A Guide on Data Analysis

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Contents

Preface **11**
How to cite this book . . . 12
More books . . . 13

1 Introduction **15**
1.1 General Recommendations . . . 16

2 Prerequisites **23**
2.1 Matrix Theory . . . 23
2.2 Probability Theory . . . 30
2.3 General Math . . . 65
2.4 Data Import/Export . . . 75
2.5 Data Manipulation . . . 82

I. BASIC **95**

3 Descriptive Statistics **95**
3.1 Numerical Measures . . . 95
3.2 Graphical Measures . . . 97
3.3 Normality Assessment . . . 98
3.4 Bivariate Statistics . . . 103
3.5 Summary . . . 111

4 Basic Statistical Inference **121**
4.1 One Sample Inference . . . 123
4.2 Two Sample Inference . . . 133
4.3 Categorical Data Analysis . . . 143
4.4 Divergence Metrics and Test for Comparing Distributions . . . 151

II. REGRESSION **159**

5 Linear Regression **159**

5.1 Ordinary Least Squares . . . 160
5.2 Feasible Generalized Least Squares . . . 204
5.3 Weighted Least Squares . . . 211
5.4 Generalized Least Squares . . . 212
5.5 Feasible Prais Winsten . . . 213
5.6 Feasible group level Random Effects . . . 214
5.7 Ridge Regression . . . 215
5.8 Principal Component Regression . . . 215
5.9 Robust Regression . . . 216
5.10 Maximum Likelihood . . . 216

6 Non-linear Regression 225
6.1 Inference . . . 225
6.2 Non-linear Least Squares . . . 230

7 Generalized Linear Models 257
7.1 Logistic Regression . . . 257
7.2 Probit Regression . . . 267
7.3 Binomial Regression . . . 268
7.4 Poisson Regression . . . 271
7.5 Negative Binomial Regression . . . 274
7.6 Multinomial . . . 275
7.7 Generalization . . . 283

8 Linear Mixed Models 301
8.1 Dependent Data . . . 301
8.2 Estimation . . . 309
8.3 Inference . . . 315
8.4 Information Criteria . . . 317
8.5 Split-Plot Designs . . . 318
8.6 Repeated Measures in Mixed Models . . . 323
8.7 Unbalanced or Unequally Spaced Data . . . 325
8.8 Application . . . 325

9 Nonlinear and Generalized Linear Mixed Models 341
9.1 Estimation . . . 343
9.2 Application . . . 348
9.3 Summary . . . 369

III. RAMIFICATIONS 373

10 Model Specification 373
10.1 Nested Model . . . 373
10.2 Non-Nested Model . . . 374
10.3 Heteroskedasticity . . . 376

11 Imputation (Missing Data) 379
11.1 Assumptions . . . 380
11.2 Solutions to Missing data . . . 382
11.3 Criteria for Choosing an Effective Approach . . . 402
11.4 Another Perspective . . . 403
11.5 Diagnosing the Mechanism . . . 404
11.6 Application . . . 405

12 Data 419
12.1 Cross-Sectional . . . 419
12.2 Time Series . . . 419
12.3 Repeated Cross Sections . . . 425
12.4 Panel Data . . . 426

13 Variable Transformation 457
13.1 Continuous Variables . . . 457
13.2 Categorical Variables . . . 473

14 Hypothesis Testing 475
14.1 Types of hypothesis testing . . . 476
14.2 Wald test . . . 479
14.3 The likelihood ratio test . . . 485
14.4 Lagrange Multiplier (Score) . . . 486
14.5 Two One-Sided Tests (TOST) Equivalence Testing . . . 486

15 Marginal Effects 487
15.1 Delta Method . . . 488
15.2 Average Marginal Effect Algorithm . . . 489
15.3 Packages . . . 491

16 Prediction and Estimation 499
16.1 Prediction . . . 499
16.2 Parameter Estimation . . . 499
16.3 Causation versus Prediction . . . 500

17 Moderation 503
17.1 emmeans package . . . 504
17.2 probmod package . . . 513
17.3 interactions package . . . 514
17.4 interactionR package . . . 533
17.5 sjPlot package . . . 533

IV. CAUSAL INFERENCE 537

18 Causal Inference 537
18.1 Treatment effect types . . . 542

A. EXPERIMENTAL DESIGN 555

19 Experimental Design 555
19.1 Notes . . . 558
19.2 Semi-random Experiment . . . 561
19.3 Rerandomization . . . 564
19.4 Two-Stage Randomized Experiments with Interference and Non-compliance . . . 566

20 Sampling 567
20.1 Simple Sampling . . . 567
20.2 Stratified Sampling . . . 568
20.3 Unequal Probability Sampling . . . 570
20.4 Balanced Sampling . . . 571

21 Analysis of Variance (ANOVA) 573
21.1 Completely Randomized Design (CRD) . . . 574
21.2 Nonparametric ANOVA . . . 609
21.3 Sample Size Planning for ANOVA . . . 611
21.4 Randomized Block Designs . . . 613
21.5 Nested Designs . . . 619
21.6 Single Factor Covariance Model . . . 623

22 Multivariate Methods 627
22.1 MANOVA . . . 650
22.2 Principal Components . . . 668
22.3 Factor Analysis . . . 679
22.4 Discriminant Analysis . . . 695

B. QUASI-EXPERIMENTAL DESIGN 721

23 Quasi-experimental 721
23.1 Natural Experiments . . . 722

24 Regression Discontinuity 727
24.1 Estimation and Inference . . . 730
24.2 Specification Checks . . . 731
24.3 Fuzzy RD Design . . . 746
24.4 Regression Kink Design . . . 747
24.5 Multi-cutoff . . . 748
24.6 Multi-score . . . 748
24.7 Steps for Sharp RD . . . 748
24.8 Steps for Fuzzy RD . . . 748
24.9 Steps for RDiT (Regression Discontinuity in Time) . . . 749
24.10 Evaluation of an RD . . . 752
24.11 Applications . . . 754

25 Synthetic Difference-in-Differences **761**
25.1 Understanding . . . 762
25.2 Application . . . 767

26 Difference-in-differences **779**
26.1 Visualization . . . 780
26.2 Simple Dif-n-dif . . . 783
26.3 Notes . . . 787
26.4 Standard Errors . . . 796
26.5 Examples . . . 796
26.6 One Difference . . . 801
26.7 Two-way Fixed-effects . . . 802
26.8 Multiple periods and variation in treatment timing . . . 808
26.9 Staggered Dif-n-dif . . . 811
26.10 Multiple Treatments . . . 889
26.11 Mediation Under DiD . . . 890
26.12 Assumptions . . . 890

27 Changes-in-Changes **899**
27.1 Application . . . 901

28 Synthetic Control **913**
28.1 Applications . . . 918
28.2 Augmented Synthetic Control Method . . . 934
28.3 Synthetic Control with Staggered Adoption . . . 934
28.4 Bayesian Synthetic Control . . . 934
28.5 Generalized Synthetic Control . . . 934
28.6 Other Advances . . . 934

29 Event Studies **935**
29.1 Other Issues . . . 939
29.2 Testing . . . 943
29.3 Sample . . . 945
29.4 Biases . . . 950
29.5 Long-run event studies . . . 951
29.6 Aggregation . . . 957
29.7 Heterogeneity in the event effect . . . 958
29.8 Expected Return Calculation . . . 959
29.9 Application . . . 961

30 Instrumental Variables **969**
30.1 Framework . . . 972
30.2 Estimation . . . 975
30.3 Inference . . . 980
30.4 Testing Assumptions . . . 988
30.5 Negative R^2 . . . 999

30.6 Treatment Intensity 1000
30.7 Control Function 1001
30.8 New Advances 1008

31 Matching Methods **1011**
31.1 Selection on Observables 1023
31.2 Selection on Unobservables 1043

32 Interrupted Time Series **1053**
32.1 Autocorrelation 1059
32.2 Multiple Groups 1061

C. OTHER CONCERNS **1065**

33 Endogeneity **1065**
33.1 Endogenous Treatment 1067
33.2 Endogenous Sample Selection 1096

34 Other Biases **1115**
34.1 Aggregation Bias 1117
34.2 Contamination Bias 1125
34.3 Survivorship Bias 1125
34.4 Publication Bias 1128

35 Controls **1133**
35.1 Bad Controls 1133
35.2 Good Controls 1147
35.3 Neutral Controls 1162
35.4 Choosing Controls 1172

36 Mediation **1175**
36.1 Traditional Approach 1175
36.2 Causal Inference Approach 1189
36.3 Model-based causal mediation analysis 1192

37 Directed Acyclic Graph **1199**
37.1 Basic Notations 1199

V. MISCELLANEOUS **1203**

38 Report **1203**
38.1 One summary table 1204
38.2 Model Comparison 1206
38.3 Changes in an estimate 1212
38.4 Standard Errors 1213

38.5 Coefficient Uncertainty and Distribution 1214
38.6 Descriptive Tables 1215
38.7 Visualizations and Plots 1217

39 Exploratory Data Analysis 1223

40 Sensitivity Analysis/ Robustness Check 1225
40.1 Specification curve 1225
40.2 Coefficient stability 1241
40.3 Omitted Variable Bias Quantification 1242

41 Replication and Synthetic Data 1245
41.1 The Replication Standard 1245
41.2 Synthetic Data: An Overview 1247
41.3 Application 1248

A Appendix 1255
A.1 Git 1255
A.2 Short-cut 1257
A.3 Function short-cut 1257
A.4 Citation 1259
A.5 Install all necessary packages/libaries on your local machine . . . 1259

B Bookdown cheat sheet 1263
B.1 Operation 1263
B.2 Math Expression/ Syntax 1264
B.3 Table 1268

Preface

This book is an effort to simplify and demystify the complex process of data analysis, making it accessible to a wide audience. While I do not claim to be a professional statistician, econometrician, or data scientist, I firmly believe in the value of learning through teaching and practical application. Writing this book has been as much a learning journey for me as I hope it will be for you.

The intended audience includes those with little to no experience in statistics, econometrics, or data science, as well as individuals with a budding interest in these fields who are eager to deepen their knowledge. While my primary domain of interest is marketing, the principles and methods discussed in this book are universally applicable to any discipline that employs scientific methods or data analysis.

I hope this book provides a valuable starting point for aspiring statisticians, econometricians, and data scientists, empowering you to navigate the fascinating world of causal inference and data analysis with confidence.

How to cite this book

1. APA (7th edition):

Nguyen, M. (2020). *A Guide on Data Analysis*. Bookdown.

https://bookdown.org/mike/data_analysis/

2. MLA (8th edition):

Nguyen, Mike. *A Guide on Data Analysis*. Bookdown, 2020. **https://bookdown.org/mike/data_analysis/**

3. Chicago (17th edition):

Nguyen, Mike. 2020. *A Guide on Data Analysis*. Bookdown. **https://bookdown.org/mike/data_analysis/**

4. Harvard:

Nguyen, M. (2020) *A Guide on Data Analysis*. Bookdown. Available at: **https://bookdown.org/mike/data_analysis/**

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@book{nguyen2020guide,
  title={A Guide on Data Analysis},
  author={Nguyen, Mike},
  year={2020},
  publisher={Bookdown},
```

```
  url={https://bookdown.org/mike/data_analysis/}
}
```

More books

More books by the author can be found here:

- Advanced Data Analysis: the second book in the data analysis series, which covers machine learning models (with a focus on prediction)
- Marketing Research
- Communication Theory

Chapter 1

Introduction

Since the turn of the century, we have witnessed remarkable advancements and innovations, particularly in statistics, information technology, computer science, and the rapidly emerging field of data science. However, one challenge of these developments is the overuse of **buzzwords** like *big data*, *machine learning*, and *deep learning*. While these terms are powerful in context, they can sometimes obscure the foundational principles underlying their application.

Every substantive field often has its own specialized metric subfield, such as:

- **Econometrics** in economics
- **Psychometrics** in psychology
- **Chemometrics** in chemistry
- **Sabermetrics** in sports analytics
- **Biostatistics** in public health and medicine

To the layperson, these disciplines are often grouped under broader terms like:

- **Data Science**
- **Applied Statistics**
- **Computational Social Science**

As exciting as it is to explore these new tools and techniques, I must admit that retaining these concepts can be challenging. For me, the most effective way to internalize and apply these ideas has been to document the data analysis process from start to finish.

With that in mind, let's dive in and explore the fascinating world of data analysis together.

1.1 General Recommendations

- The journey of mastering data analysis is fueled by practice and repetition. The more lines of code you write, the more functions you familiarize yourself with, and the more you experiment, the more enjoyable and rewarding this process becomes.
- Readers can approach this book in several ways:
  - **Focused Learning**: If you are interested in specific methods or tools, you can jump directly to the relevant section by navigating through the table of contents.
  - **Sequential Learning**: To follow a traditional path of data analysis, start with the Linear Regression section.
  - **Experimental Approach**: If you are interested in designing experiments and testing hypotheses, explore the Analysis of Variance (ANOVA) section.
- For those primarily interested in applications and less concerned with theoretical foundations, focus on the summary and application sections of each chapter.

- If a concept is unclear, consider researching the topic online. This book serves as a guide, and external resources like tutorials or articles can provide additional insights.
- To customize the code examples provided in this book, use R's built-in help functions. For instance:
  - To learn more about a specific function, type `help(function_name)` or `?function_name` in the R console.
  - For example, to find details about the `hist` function, type `?hist` or `help(hist)` in the console.
- Additionally, searching online is a powerful resource (e.g., Google, ChatGPT, etc.). Different practitioners often use various R packages to achieve similar results. For instance, if you need to create a histogram in R, a simple search like *"histogram in R"* will provide multiple approaches and examples.

By adopting these strategies, you can tailor your learning experience and maximize the value of this book.

Tools of statistics

- Probability Theory
- Mathematical Analysis
- Computer Science
- Numerical Analysis
- Database Management

Code Replication

This book was built with R version 4.2.3 (2023-03-15 ucrt) and the following packages:

package	version	source
abind	1.4-5	CRAN (R 4.2.0)
agridat	1.21	CRAN (R 4.2.3)
ape	5.7-1	CRAN (R 4.2.3)
assertthat	0.2.1	CRAN (R 4.2.3)
backports	1.4.1	CRAN (R 4.2.0)
bookdown	0.35	CRAN (R 4.2.3)
boot	1.3-28.1	CRAN (R 4.2.3)
broom	1.0.5	CRAN (R 4.2.3)
bslib	0.6.1	CRAN (R 4.2.3)
cachem	1.0.8	CRAN (R 4.2.3)
callr	3.7.3	CRAN (R 4.2.3)
car	3.1-2	CRAN (R 4.2.3)
carData	3.0-5	CRAN (R 4.2.3)
cellranger	1.1.0	CRAN (R 4.2.3)

package	version	source
cli	3.6.1	CRAN (R 4.2.3)
coda	0.19-4	CRAN (R 4.2.3)
colorspace	2.1-0	CRAN (R 4.2.3)
corpcor	1.6.10	CRAN (R 4.2.0)
crayon	1.5.2	CRAN (R 4.2.3)
cubature	2.1.0	CRAN (R 4.2.3)
curl	5.1.0	CRAN (R 4.2.3)
data.table	1.14.8	CRAN (R 4.2.3)
DBI	1.2.0	CRAN (R 4.2.3)
dbplyr	2.4.0	CRAN (R 4.2.3)
desc	1.4.3	CRAN (R 4.2.3)
devtools	2.4.5	CRAN (R 4.2.3)
digest	0.6.31	CRAN (R 4.2.3)
dplyr	1.1.2	CRAN (R 4.2.3)
ellipsis	0.3.2	CRAN (R 4.2.3)
evaluate	0.23	CRAN (R 4.2.3)
extrafont	0.19	CRAN (R 4.2.2)
extrafontdb	1.0	CRAN (R 4.2.0)
fansi	1.0.4	CRAN (R 4.2.3)
faraway	1.0.8	CRAN (R 4.2.3)
fastmap	1.1.1	CRAN (R 4.2.3)
forcats	1.0.0	CRAN (R 4.2.3)
foreign	0.8-84	CRAN (R 4.2.3)
fs	1.6.3	CRAN (R 4.2.3)
generics	0.1.3	CRAN (R 4.2.3)
ggplot2	3.4.4	CRAN (R 4.2.3)
glue	1.6.2	CRAN (R 4.2.3)
gtable	0.3.4	CRAN (R 4.2.3)
haven	2.5.3	CRAN (R 4.2.3)
Hmisc	5.1-0	CRAN (R 4.2.3)
hms	1.1.3	CRAN (R 4.2.3)
htmltools	0.5.7	CRAN (R 4.2.3)
htmlwidgets	1.6.2	CRAN (R 4.2.3)
httr	1.4.7	CRAN (R 4.2.3)
investr	1.4.2	CRAN (R 4.2.3)
jpeg	0.1-10	CRAN (R 4.2.2)
jquerylib	0.1.4	CRAN (R 4.2.3)
jsonlite	1.8.8	CRAN (R 4.2.3)
kableExtra	1.3.4	CRAN (R 4.2.3)
knitr	1.45	CRAN (R 4.2.3)
lattice	0.21-8	CRAN (R 4.2.3)
latticeExtra	0.6-30	CRAN (R 4.2.3)
lifecycle	1.0.4	CRAN (R 4.2.3)
lme4	1.1-35.1	CRAN (R 4.2.3)

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ltm	1.2-0	CRAN (R 4.2.3)
lubridate	1.9.2	CRAN (R 4.2.3)
magrittr	2.0.3	CRAN (R 4.2.3)
MASS	7.3-60	CRAN (R 4.2.3)
matlib	0.9.6	CRAN (R 4.2.3)
Matrix	1.6-1	CRAN (R 4.2.3)
MCMCglmm	2.35	CRAN (R 4.2.3)
memoise	2.0.1	CRAN (R 4.2.3)
mgcv	1.9-0	CRAN (R 4.2.3)
minqa	1.2.6	CRAN (R 4.2.3)
modelr	0.1.11	CRAN (R 4.2.3)
munsell	0.5.0	CRAN (R 4.2.3)
nlme	3.1-163	CRAN (R 4.2.3)
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nlstools	2.0-0	CRAN (R 4.2.3)
nnet	7.3-19	CRAN (R 4.2.3)
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openxlsx	4.2.5.2	CRAN (R 4.2.3)
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pillar	1.9.0	CRAN (R 4.2.3)
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pkgconfig	2.0.3	CRAN (R 4.2.3)
pkgload	1.3.3	CRAN (R 4.2.3)
png	0.1-8	CRAN (R 4.2.2)
ppsr	0.0.2	CRAN (R 4.2.3)
prettyunits	1.2.0	CRAN (R 4.2.3)
processx	3.8.2	CRAN (R 4.2.3)
ps	1.7.5	CRAN (R 4.2.3)
pscl	1.5.5.1	CRAN (R 4.2.3)
purrr	1.0.2	CRAN (R 4.2.3)
R6	2.5.1	CRAN (R 4.2.3)
RColorBrewer	1.1-3	CRAN (R 4.2.0)
Rcpp	1.0.11	CRAN (R 4.2.3)
readr	2.1.4	CRAN (R 4.2.3)
readxl	1.4.3	CRAN (R 4.2.3)
remotes	2.4.2.1	CRAN (R 4.2.3)
reprex	2.0.2	CRAN (R 4.2.3)
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rio	1.0.1	CRAN (R 4.2.3)
rlang	1.1.1	CRAN (R 4.2.3)
RLRsim	3.1-8	CRAN (R 4.2.3)
rmarkdown	2.25	CRAN (R 4.2.3)

package	version	source
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rstudioapi	0.15.0	CRAN (R 4.2.3)
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sass	0.4.8	CRAN (R 4.2.3)
scales	1.3.0	CRAN (R 4.2.3)
sessioninfo	1.2.2	CRAN (R 4.2.3)
stringi	1.7.12	CRAN (R 4.2.2)
stringr	1.5.1	CRAN (R 4.2.3)
svglite	2.1.1	CRAN (R 4.2.3)
systemfonts	1.0.5	CRAN (R 4.2.3)
tensorA	0.36.2	CRAN (R 4.2.0)
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#>  language (EN)
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#>
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#>  mime          0.12    2021-09-28 [1] CRAN (R 4.2.0)
#>  miniUI        0.1.1.1 2018-05-18 [1] CRAN (R 4.2.3)
#>  munsell       0.5.0   2018-06-12 [1] CRAN (R 4.2.3)
#>  pillar        1.9.0   2023-03-22 [1] CRAN (R 4.2.3)
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#>  profvis       0.3.8   2023-05-02 [1] CRAN (R 4.2.3)
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#>  remotes       2.4.2.1 2023-07-18 [1] CRAN (R 4.2.3)
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#>
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#>
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Chapter 2

Prerequisites

This chapter serves as a concise review of fundamental concepts in Matrix Theory and Probability Theory.

If you are confident in your understanding of these topics, you can proceed directly to the Descriptive Statistics section to begin exploring applied data analysis.

2.1 Matrix Theory

Matrix A represents the original matrix. It's a 2x2 matrix with elements a_{ij}, where i represents the row and j represents the column.

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

A' is the transpose of A. The transpose of a matrix flips its rows and columns.

$$A' = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix}$$

Fundamental properties and rules of matrices, essential for understanding operations in linear algebra:

$$
\begin{aligned}
(\mathbf{ABC})' &= \mathbf{C}'\mathbf{B}'\mathbf{A}' && \text{(Transpose reverses order in a product)} \\
\mathbf{A}(\mathbf{B}+\mathbf{C}) &= \mathbf{AB}+\mathbf{AC} && \text{(Distributive property)} \\
\mathbf{AB} &\neq \mathbf{BA} && \text{(Multiplication is not commutative)} \\
(\mathbf{A}')' &= \mathbf{A} && \text{(Double transpose is the original matrix)} \\
(\mathbf{A}+\mathbf{B})' &= \mathbf{A}'+\mathbf{B}' && \text{(Transpose of a sum is the sum of transposes)} \\
(\mathbf{AB})' &= \mathbf{B}'\mathbf{A}' && \text{(Transpose reverses order in a product)} \\
(\mathbf{AB})^{-1} &= \mathbf{B}^{-1}\mathbf{A}^{-1} && \text{(Inverse reverses order in a product)} \\
\mathbf{A}+\mathbf{B} &= \mathbf{B}+\mathbf{A} && \text{(Addition is commutative)} \\
\mathbf{AA}^{-1} &= \mathbf{I} && \text{(Matrix times its inverse is identity)}
\end{aligned}
$$

These properties are critical in solving systems of equations, optimizing models, and performing data transformations.

If a matrix $\mathbf{A}$ has an inverse, it is called **invertible**. If $\mathbf{A}$ does not have an inverse, it is referred to as **singular**.

The product of two matrices $\mathbf{A}$ and $\mathbf{B}$ is computed as:

$$
\begin{aligned}
\mathbf{A} &= \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \\
&= \begin{bmatrix} a_{11}b_{11} + a_{12}b_{21} + a_{13}b_{31} & \sum_{i=1}^{3} a_{1i}b_{i2} & \sum_{i=1}^{3} a_{1i}b_{i3} \\ \sum_{i=1}^{3} a_{2i}b_{i1} & \sum_{i=1}^{3} a_{2i}b_{i2} & \sum_{i=1}^{3} a_{2i}b_{i3} \end{bmatrix}
\end{aligned}
$$

Quadratic Form

Let $\mathbf{a}$ be a 3×1 vector. The quadratic form involving a matrix $\mathbf{B}$ is given by:

$$
\mathbf{a}'\mathbf{Ba} = \sum_{i=1}^{3} \sum_{j=1}^{3} a_i b_{ij} a_j
$$

Length of a Vector

The **length** (or 2-norm) of a vector $\mathbf{a}$, denoted as $||\mathbf{a}||$, is defined as the square root of the inner product of the vector with itself:

$$
||\mathbf{a}|| = \sqrt{\mathbf{a}'\mathbf{a}}
$$

2.1.1 Rank of a Matrix

The **rank** of a matrix refers to:

- The dimension of the space spanned by its columns (or rows).

- The number of linearly independent columns or rows.

For an $n \times k$ matrix $\mathbf{A}$ and a $k \times k$ matrix $\mathbf{B}$, the following properties hold:

- $\text{rank}(\mathbf{A}) \leq \min(n, k)$
- $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}') = \text{rank}(\mathbf{A}'\mathbf{A}) = \text{rank}(\mathbf{A}\mathbf{A}')$
- $\text{rank}(\mathbf{AB}) = \min(\text{rank}(\mathbf{A}), \text{rank}(\mathbf{B}))$
- $\mathbf{B}$ is invertible (non-singular) if and only if $\text{rank}(\mathbf{B}) = k$.

2.1.2 Inverse of a Matrix

In scalar algebra, if $a = 0$, then $1/a$ does not exist.

In matrix algebra, a matrix is invertible if it is **non-singular**, meaning it has a non-zero determinant and its inverse exists. A square matrix $\mathbf{A}$ is invertible if there exists another square matrix $\mathbf{B}$ such that:

$$\mathbf{AB} = \mathbf{I} \quad \text{(Identity Matrix)}.$$

In this case, $\mathbf{A}^{-1} = \mathbf{B}$.

For a 2×2 matrix:

$$\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

The inverse is:

$$\mathbf{A}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

This inverse exists only if $ad - bc \neq 0$, where $ad - bc$ is the determinant of $\mathbf{A}$.

For a partitioned block matrix:

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} (\mathbf{A} - \mathbf{BD^{-1}C})^{-1} & -(\mathbf{A} - \mathbf{BD^{-1}C})^{-1}\mathbf{BD^{-1}} \\ -\mathbf{D^{-1}C}(\mathbf{A} - \mathbf{BD^{-1}C})^{-1} & \mathbf{D^{-1}} + \mathbf{D^{-1}C}(\mathbf{A} - \mathbf{BD^{-1}C})^{-1}\mathbf{BD^{-1}} \end{bmatrix}$$

This formula assumes that $\mathbf{D}$ and $\mathbf{A} - \mathbf{BD^{-1}C}$ are invertible.

Properties of the Inverse for Non-Singular Matrices

1. $(\mathbf{A^{-1}})^{-1} = \mathbf{A}$

2. For a non-zero scalar b, $(\mathbf{bA})^{-1} = \mathbf{b^{-1}A^{-1}}$

3. For a matrix $\mathbf{B}$, $(\mathbf{BA})^{-\mathbf{1}} = \mathbf{B}^{-\mathbf{1}}\mathbf{A}^{-\mathbf{1}}$ (only if $\mathbf{B}$ is non-singular).

4. $(\mathbf{A}^{-\mathbf{1}})' = (\mathbf{A}')^{-\mathbf{1}}$ (the transpose of the inverse equals the inverse of the transpose).

5. Never notate $\mathbf{1}/\mathbf{A}$; use $\mathbf{A}^{-\mathbf{1}}$ instead.

Notes: - The determinant of a matrix determines whether it is invertible. For square matrices, a determinant of 0 means the matrix is **singular** and has no inverse.
- Always verify the conditions for invertibility, particularly when dealing with partitioned or block matrices.

2.1.3 Definiteness of a Matrix

A symmetric square $k \times k$ matrix $\mathbf{A}$ is classified based on the following conditions:

- **Positive Semi-Definite (PSD)**: $\mathbf{A}$ is PSD if, for any non-zero $k \times 1$ vector $\mathbf{x}$:
$$\mathbf{x}'\mathbf{A}\mathbf{x} \geq \mathbf{0}.$$

- **Negative Semi-Definite (NSD)**: $\mathbf{A}$ is NSD if, for any non-zero $k \times 1$ vector $\mathbf{x}$:
$$\mathbf{x}'\mathbf{A}\mathbf{x} \leq \mathbf{0}.$$

- **Indefinite**: $\mathbf{A}$ is indefinite if it is neither PSD nor NSD.

The **identity matrix** is always positive definite (PD).

Example

Let $\mathbf{x} = (x_1, x_2)'$, and consider a 2×2 identity matrix $\mathbf{I}$:

$$\begin{aligned}
\mathbf{x}'\mathbf{I}\mathbf{x} &= (x_1, x_2) \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\
&= (x_1, x_2) \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\
&= x_1^2 + x_2^2 \geq 0.
\end{aligned}$$

Thus, $\mathbf{I}$ is PD because $\mathbf{x}'\mathbf{I}\mathbf{x} > 0$ for all non-zero $\mathbf{x}$.

Properties of Definiteness

1. Any variance-covariance matrix is PSD.
2. A matrix $\mathbf{A}$ is PSD if and only if there exists a matrix $\mathbf{B}$ such that:
$$\mathbf{A} = \mathbf{B}'\mathbf{B}.$$

3. If $\mathbf{A}$ is PSD, then $\mathbf{B}'\mathbf{A}\mathbf{B}$ is also PSD for any conformable matrix $\mathbf{B}$.

4. If $\mathbf{A}$ and $\mathbf{C}$ are non-singular, then $\mathbf{A} - \mathbf{C}$ is PSD if and only if $\mathbf{C}^{-1} - \mathbf{A}^{-1}$ is PSD.
5. If $\mathbf{A}$ is PD (or ND), then $\mathbf{A}^{-1}$ is also PD (or ND).

Notes

- An **indefinite** matrix $\mathbf{A}$ is neither PSD nor NSD. This concept does not have a direct counterpart in scalar algebra.
- If a square matrix is PSD and invertible, then it is PD.

Examples of Definiteness

1. **Invertible / Indefinite**:
$$\begin{bmatrix} -1 & 0 \\ 0 & 10 \end{bmatrix}$$

2. **Non-Invertible / Indefinite**:
$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

3. **Invertible / PSD**:
$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

4. **Non-Invertible / PSD**:
$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

2.1.4 Matrix Calculus

Consider a scalar function $y = f(x_1, x_2, \dots, x_k) = f(x)$, where x is a $1 \times k$ row vector.

2.1.4.1 Gradient (First-Order Derivative)

The gradient, or the first-order derivative of $f(x)$ with respect to the vector x, is given by:

$$\frac{\partial f(x)}{\partial x} = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \frac{\partial f(x)}{\partial x_2} \\ \vdots \\ \frac{\partial f(x)}{\partial x_k} \end{bmatrix}.$$

2.1.4.2 Hessian (Second-Order Derivative)

The Hessian, or the second-order derivative of $f(x)$ with respect to x, is a symmetric matrix defined as:

$$\frac{\partial^2 f(x)}{\partial x \partial x'} = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial x_1^2} & \frac{\partial^2 f(x)}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_k} \\ \frac{\partial^2 f(x)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(x)}{\partial x_2^2} & \cdots & \frac{\partial^2 f(x)}{\partial x_2 \partial x_k} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f(x)}{\partial x_k \partial x_1} & \frac{\partial^2 f(x)}{\partial x_k \partial x_2} & \cdots & \frac{\partial^2 f(x)}{\partial x_k^2} \end{bmatrix}.$$

2.1.4.3 Derivative of a Scalar Function with Respect to a Matrix

Let $f(\mathbf{X})$ be a scalar function, where $\mathbf{X}$ is an $n \times p$ matrix. The derivative is:

$$\frac{\partial f(\mathbf{X})}{\partial \mathbf{X}} = \begin{bmatrix} \frac{\partial f(\mathbf{X})}{\partial x_{11}} & \cdots & \frac{\partial f(\mathbf{X})}{\partial x_{1p}} \\ \vdots & \ddots & \vdots \\ \frac{\partial f(\mathbf{X})}{\partial x_{n1}} & \cdots & \frac{\partial f(\mathbf{X})}{\partial x_{np}} \end{bmatrix}.$$

2.1.4.4 Common Matrix Derivatives

1. If $\mathbf{a}$ is a vector and $\mathbf{A}$ is a matrix independent of $\mathbf{y}$:
   - $\frac{\partial \mathbf{a}'\mathbf{y}}{\partial \mathbf{y}} = \mathbf{a}$
   - $\frac{\partial \mathbf{y}'\mathbf{y}}{\partial \mathbf{y}} = 2\mathbf{y}$
   - $\frac{\partial \mathbf{y}'\mathbf{A}\mathbf{y}}{\partial \mathbf{y}} = (\mathbf{A} + \mathbf{A}')\mathbf{y}$
2. If $\mathbf{X}$ is symmetric:
   - $\frac{\partial |\mathbf{X}|}{\partial x_{ij}} = \begin{cases} X_{ii}, & i = j \\ X_{ij}, & i \neq j \end{cases}$ where X_{ij} is the (i, j)-th cofactor of $\mathbf{X}$.
3. If $\mathbf{X}$ is symmetric and $\mathbf{A}$ is a matrix independent of $\mathbf{X}$:
   - $\frac{\partial \mathrm{tr}(\mathbf{X}\mathbf{A})}{\partial \mathbf{X}} = \mathbf{A} + \mathbf{A}' - \mathrm{diag}(\mathbf{A})$.
4. If $\mathbf{X}$ is symmetric, let $\mathbf{J}_{ij}$ be a matrix with 1 at the (i, j)-th position and 0 elsewhere:
   - $\frac{\partial \mathbf{X}^{-1}}{\partial x_{ij}} = \begin{cases} -\mathbf{X}^{-1}\mathbf{J}_{ii}\mathbf{X}^{-1}, & i = j \\ -\mathbf{X}^{-1}(\mathbf{J}_{ij} + \mathbf{J}_{ji})\mathbf{X}^{-1}, & i \neq j \end{cases}.$

2.1.5 Optimization in Scalar and Vector Spaces

Optimization is the process of finding the minimum or maximum of a function. The conditions for optimization differ depending on whether the function involves a scalar or a vector. Below is a comparison of scalar and vector optimization:

Condition	**Scalar Optimization**	**Vector Optimization**
First-Order Condition	$\frac{\partial f(x_0)}{\partial x} = 0$	$\frac{\partial f(x_0)}{\partial x} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$
Second-Order Condition	$\frac{\partial^2 f(x_0)}{\partial x^2} > 0$	$\frac{\partial^2 f(x_0)}{\partial x \partial x'} > 0$
For **convex** functions, this implies a **minimum**.		
For **concave** functions, this implies a **maximum**.	$\frac{\partial^2 f(x_0)}{\partial x^2} < 0$	$\frac{\partial^2 f(x_0)}{\partial x \partial x'} < 0$

Key Concepts

1. **First-Order Condition**:
   - The **first-order derivative** of the function must equal zero at a critical point. This holds for both scalar and vector functions:
     - In the scalar case, $\frac{\partial f(x)}{\partial x} = 0$ identifies critical points.
     - In the vector case, $\frac{\partial f(x)}{\partial x}$ is a **gradient vector**, and the condition is satisfied when all elements of the gradient are zero.
2. **Second-Order Condition**:
   - The **second-order derivative** determines whether the critical point is a minimum, maximum, or saddle point:
     - For scalar functions, $\frac{\partial^2 f(x)}{\partial x^2} > 0$ implies a **local minimum**, while $\frac{\partial^2 f(x)}{\partial x^2} < 0$ implies a **local maximum**.
     - For vector functions, the Hessian matrix $\frac{\partial^2 f(x)}{\partial x \partial x'}$ must be:
       * **Positive Definite**: For a **minimum** (convex function).
       * **Negative Definite**: For a **maximum** (concave function).
       * **Indefinite**: For a **saddle point** (neither minimum nor maximum).
3. **Convex and Concave Functions**:
   - A function $f(x)$ is:
     - **Convex** if $\frac{\partial^2 f(x)}{\partial x^2} > 0$ or the Hessian $\frac{\partial^2 f(x)}{\partial x \partial x'}$ is positive definite.
     - **Concave** if $\frac{\partial^2 f(x)}{\partial x^2} < 0$ or the Hessian is negative definite.
   - Convexity ensures global optimization for minimization problems, while concavity ensures global optimization for maximization problems.
4. **Hessian Matrix**:
   - In vector optimization, the Hessian $\frac{\partial^2 f(x)}{\partial x \partial x'}$ plays a crucial role in determining the nature of critical points:

- Positive definite Hessian: All eigenvalues are positive.
- Negative definite Hessian: All eigenvalues are negative.
- Indefinite Hessian: Eigenvalues have mixed signs.

2.2 Probability Theory

2.2.1 Axioms and Theorems of Probability

1. Let S denote the sample space of an experiment. Then:

$$P[S] = 1$$

(The probability of the sample space is always 1.)

2. For any event A:

$$P[A] \geq 0$$

(Probabilities are always non-negative.)

3. Let $A_1, A_2, A_3, ...$ be a finite or infinite collection of mutually exclusive events. Then:

$$P[A_1 \cup A_2 \cup A_3 ...] = P[A_1] + P[A_2] + P[A_3] + ...$$

(The probability of the union of mutually exclusive events is the sum of their probabilities.)

4. The probability of the empty set is:

$$P[\emptyset] = 0$$

5. The complement rule:

$$P[A'] = 1 - P[A]$$

6. The probability of the union of two events:

$$P[A_1 \cup A_2] = P[A_1] + P[A_2] - P[A_1 \cap A_2]$$

2.2.1.1 Conditional Probability

The conditional probability of A given B is defined as:

$$P[A|B] = \frac{P[A \cap B]}{P[B]}, \quad \text{provided } P[B] \neq 0.$$

2.2.1.2 Independent Events

Two events A and B are independent if and only if:

1. $P[A \cap B] = P[A]P[B]$
2. $P[A|B] = P[A]$
3. $P[B|A] = P[B]$

A collection of events $A_1, A_2, \dots, A_n$ is independent if and only if every subcollection is independent.

2.2.1.3 Multiplication Rule

The probability of the intersection of two events can be calculated as:

$$P[A \cap B] = P[A|B]P[B] = P[B|A]P[A].$$

2.2.1.4 Bayes' Theorem

Let $A_1, A_2, \dots, A_n$ be a collection of mutually exclusive events whose union is S, and let B be an event with $P[B] \neq 0$. Then, for any event A_j $(j = 1, 2, \dots, n)$:

$$P[A_j|B] = \frac{P[B|A_j]P[A_j]}{\sum_{i=1}^{n} P[B|A_i]P[A_i]}.$$

2.2.1.5 Jensen's Inequality

- If $g(x)$ is convex, then:

$$E[g(X)] \geq g(E[X])$$

- If $g(x)$ is concave, then:

$$E[g(X)] \leq g(E[X]).$$

2.2.1.6 Law of Iterated Expectations

The **law of iterated expectations** states:

$$E[Y] = E[E[Y|X]].$$

2.2.1.7 Correlation and Independence

The strength of the relationship between random variables can be ranked from strongest to weakest as:

1. **Independence**:
   - $f(x, y) = f_X(x)f_Y(y)$
   - $f_{Y|X}(y|x) = f_Y(y)$ and $f_{X|Y}(x|y) = f_X(x)$

- $E[g_1(X)g_2(Y)] = E[g_1(X)]E[g_2(Y)]$

2. **Mean Independence** (implied by independence):
   - Y is mean independent of X if:
   $$E[Y|X] = E[Y].$$
   - $E[Xg(Y)] = E[X]E[g(Y)]$
3. **Uncorrelatedness** (implied by independence and mean independence):
   - $\text{Cov}(X, Y) = 0$
   - $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$
   - $E[XY] = E[X]E[Y]$

2.2.2 Central Limit Theorem

The **Central Limit Theorem** states that for a sufficiently large sample size ($n \geq 25$), the sampling distribution of the sample mean or proportion approaches a normal distribution, regardless of the population's original distribution.

Let $X_1, X_2, \dots, X_n$ be a random sample of size n from a distribution X with mean μ and variance σ^2. Then, for large n:

1. The sample mean $\bar{X}$ is approximately normal:
$$\mu_{\bar{X}} = \mu, \quad \sigma^2_{\bar{X}} = \frac{\sigma^2}{n}.$$
2. The sample proportion $\hat{p}$ is approximately normal:
$$\mu_{\hat{p}} = p, \quad \sigma^2_{\hat{p}} = \frac{p(1-p)}{n}.$$
3. The difference in sample proportions $\hat{p}_1 - \hat{p}_2$ is approximately normal:
$$\mu_{\hat{p}_1 - \hat{p}_2} = p_1 - p_2, \quad \sigma^2_{\hat{p}_1 - \hat{p}_2} = \frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}.$$
4. The difference in sample means $\bar{X}_1 - \bar{X}_2$ is approximately normal:
$$\mu_{\bar{X}_1 - \bar{X}_2} = \mu_1 - \mu_2, \quad \sigma^2_{\bar{X}_1 - \bar{X}_2} = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}.$$
5. The following random variables are approximately standard normal:
   - $\frac{\bar{X}-\mu}{\sigma/\sqrt{n}}$
   - $\frac{\hat{p}-p}{\sqrt{\frac{p(1-p)}{n}}}$
   - $\frac{(\hat{p}_1-\hat{p}_2)-(p_1-p_2)}{\sqrt{\frac{p_1(1-p_1)}{n_1}+\frac{p_2(1-p_2)}{n_2}}}$
   - $\frac{(\bar{X}_1-\bar{X}_2)-(\mu_1-\mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_2^2}{n_2}}}$

2.2.2.1 Limiting Distribution of the Sample Mean

If $\{X_i\}_{i=1}^n$ is an iid random sample from a distribution with finite mean μ and finite variance σ^2, the sample mean $\bar{X}$ scaled by $\sqrt{n}$ has the following limiting distribution:

$$\sqrt{n}(\bar{X} - \mu) \xrightarrow{d} N(0, \sigma^2).$$

Standardizing the sample mean gives:

$$\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \xrightarrow{d} N(0, 1).$$

Notes:

- The CLT holds for most random samples from any distribution (continuous, discrete, or unknown).
- It extends to the multivariate case: A random sample of a random vector converges to a multivariate normal distribution.

2.2.2.2 Asymptotic Variance and Limiting Variance

Asymptotic Variance (Avar):

$$Avar(\sqrt{n}(\bar{X} - \mu)) = \sigma^2.$$

- Refers to the variance of the limiting distribution of an estimator as the sample size (n) approaches infinity.
- It characterizes the variability of the scaled estimator $\sqrt{n}(\bar{x} - \mu)$ in its asymptotic distribution (e.g., normal distribution).

Limiting Variance ($\lim_{n\to\infty} Var$)

$$\lim_{n\to\infty} Var(\sqrt{n}(\bar{x} - \mu)) = \sigma^2$$

- Represents the value that the actual variance of $\sqrt{n}(\bar{x} - \mu)$ converges to as $n \to \infty$.

For a well-behaved estimator,

$$Avar(\sqrt{n}(\bar{X} - \mu)) = \lim_{n\to\infty} Var(\sqrt{n}(\bar{x} - \mu)) = \sigma^2.$$

However, **asymptotic variance is not necessarily equal to the limiting value of the variance** because asymptotic variance is derived from the limiting distribution, while limiting variance is a convergence result of the sequence of variances.

$$Avar(.) \neq lim_{n\to\infty} Var(.)$$

- Both the asymptotic variance $Avar$ and the limiting variance $\lim_{n\to\infty} Var$ are numerically equal to σ^2, but their conceptual definitions differ.
- $Avar(\cdot) \neq \lim_{n\to\infty} Var(\cdot)$. This emphasizes that while the numerical result may match, their derivation and meaning differ:
  - $Avar$ depends on the asymptotic (large-sample) distribution of the estimator.
  - $\lim_{n\to\infty} Var(\cdot)$ involves the sequence of variances as n grows.

Cases where the two do not match:

1. **Sample Quantiles**: Consider the sample quantile of order p, for some $0 < p < 1$. Under regularity conditions, the asymptotic distribution of the sample quantile is normal, with a variance that depends on p and the density of the distribution at the p-th quantile. However, the variance of the sample quantile itself does not necessarily converge to this limit as the sample size grows.
2. **Bootstrap Methods**: When using bootstrapping techniques to estimate the distribution of a statistic, the bootstrap distribution might converge to a different limiting distribution than the original statistic. In these cases, the variance of the bootstrap distribution (or the bootstrap variance) might differ from the limiting variance of the original statistic.
3. **Statistics with Randomly Varying Asymptotic Behavior**: In some cases, the asymptotic behavior of a statistic can vary randomly depending on the sample path. For such statistics, the asymptotic variance might not provide a consistent estimate of the limiting variance.
4. **M-estimators with Varying Asymptotic Behavior**: M-estimators can sometimes have different asymptotic behaviors depending on the tail behavior of the underlying distribution. For heavy-tailed distributions, the variance of the estimator might not stabilize even as the sample size grows large, making the asymptotic variance different from the variance of any limiting distribution.

2.2.3 Random Variable

Random variables can be categorized as either **discrete** or **continuous**, with distinct properties and functions defining each type.

	Discrete Variable	**Continuous Variable**
Definition	A random variable is discrete if it can assume at most a finite or countably infinite number of values.	A random variable is continuous if it can assume any value in some interval or intervals of real numbers, with $P(X = x) = 0$.

	Discrete Variable	Continuous Variable
Density Function	A function f is called a density for X if: 1. $f(x) \geq 0$ 2. $\sum_x f(x) = 1$ 3. $f(x) = P(X = x)$ for x real	A function f is called a density for X if: 1. $f(x) \geq 0$ for x real 2. $\int_{-\infty}^{\infty} f(x)\,dx = 1$ 3. $P[a \leq X \leq b] = \int_a^b f(x)\,dx$ for a, b real
Cumulative Distribution Function	$F(x) = P(X \leq x)$	$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(t)\,dt$
$E[H(X)]$	$\sum_x H(x)f(x)$	$\int_{-\infty}^{\infty} H(x)f(x)\,dx$
$\mu = E[X]$	$\sum_x xf(x)$	$\int_{-\infty}^{\infty} xf(x)\,dx$
Ordinary Moments	$\sum_x x^k f(x)$	$\int_{-\infty}^{\infty} x^k f(x)\,dx$
Moment Generating Function	$m_X(t) = E[e^{tX}] = \sum_x e^{tx} f(x)$	$m_X(t) = E[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f(x)\,dx$

Expected Value Properties

- $E[c] = c$ for any constant c.
- $E[cX] = cE[X]$ for any constant c.
- $E[X + Y] = E[X] + E[Y]$.
- $E[XY] = E[X]E[Y]$ (if X and Y are independent).

Variance Properties

- $\mathrm{Var}(c) = 0$ for any constant c.
- $\mathrm{Var}(cX) = c^2\mathrm{Var}(X)$ for any constant c.
- $\mathrm{Var}(X) \geq 0$.
- $\mathrm{Var}(X) = E[X^2] - (E[X])^2$.
- $\mathrm{Var}(X + c) = \mathrm{Var}(X)$.
- $\mathrm{Var}(X + Y) = \mathrm{Var}(X) + \mathrm{Var}(Y)$ (if X and Y are independent).

The standard deviation σ is given by:

$$\sigma = \sqrt{\sigma^2} = \sqrt{\mathrm{Var}(X)}.$$

2.2.3.1 Multivariate Random Variables

Suppose $y_1, \ldots, y_p$ are random variables with means $\mu_1, \ldots, \mu_p$. Then:

$$\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_p \end{bmatrix}, \quad E[\mathbf{y}] = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_p \end{bmatrix} = \mu.$$

The covariance between y_i and y_j is $\sigma_{ij} = \text{Cov}(y_i, y_j)$. The variance-covariance (or dispersion) matrix is:

$$= (\sigma_{ij}) = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1} & \sigma_{p2} & \cdots & \sigma_{pp} \end{bmatrix}.$$

And is symmetric with $(p+1)p/2$ unique parameters.

Alternatively, let $u_{p\times 1}$ and $v_{v\times 1}$ be random vectors with means $_{\mathbf{u}}$ and $_{\mathbf{v}}$. then

$$_{\mathbf{uv}} = cov(\mathbf{u}, \mathbf{v}) = E[(\mathbf{u} - \ _{\mathbf{u}})(\mathbf{v} - \ _{\mathbf{v}})']$$

$\Sigma_{uv} \neq \Sigma_{vu}$ (but $\Sigma_{uv} = \Sigma'_{vu}$)

Properties of Covariance Matrices

1. **Symmetry**: $' = \ .$
2. **Eigen-Decomposition** (spectral decomposition,symmetric decomposition): $= \ ,$ where is a matrix of eigenvectors such that $' = \mathbf{I}$ (orthonormal), and is a diagonal matrix with eigenvalues $(\lambda_1, ..., \lambda_p)$ on the diagonal.
3. **Non-Negative Definiteness**: $\mathbf{a}\ \mathbf{a} \geq 0$ for any $\mathbf{a} \in R^p$. Equivalently, the eigenvalues of , $\lambda_1 \geq ... \geq \lambda_p \geq 0$
4. **Generalized Variance**: $| \ | = \lambda_1 ... \lambda_p \geq 0$.
5. **Trace**: $\text{tr}(\ ) = \lambda_1 + \cdots + \lambda_p = \sigma_{11} + \cdots + \sigma_{pp} = \sum \sigma_{ii}$ = sum of variances (total variance).

Note: is required to be positive definite. This implies that all eigenvalues are positive, and has an inverse $^{-1}$, such that $^{-1} = \mathbf{I}_{p\times p} = \ ^{-1}$

2.2.3.2 Correlation Matrices

The correlation coefficient ρ_{ij} and correlation matrix $\mathbf{R}$ are defined as:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}}, \quad \mathbf{R} = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{21} & 1 & \cdots & \rho_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p1} & \rho_{p2} & \cdots & 1 \end{bmatrix}.$$

where $\rho_{ii} = 1 \forall i$

2.2.3.3 Linear Transformations

Let $\mathbf{A}$ and $\mathbf{B}$ be matrices of constants, and $\mathbf{c}$ and $\mathbf{d}$ be vectors of constants. Then:

- $E[\mathbf{Ay} + \mathbf{c}] = \mathbf{A}_{\mathbf{y}} + \mathbf{c}$.
- $\text{Var}(\mathbf{Ay} + \mathbf{c}) = \mathbf{A}_{\mathbf{y}}\mathbf{A}'$.
- $\text{Cov}(\mathbf{Ay} + \mathbf{c}, \mathbf{By} + \mathbf{d}) = \mathbf{A}_{\mathbf{y}}\mathbf{B}'$.

2.2.4 Moment Generating Function (MGF)

2.2.4.1 Properties of the Moment Generating Function

1. $\left.\frac{d^k(m_X(t))}{dt^k}\right|_{t=0} = E[X^k]$ (The k-th derivative at $t = 0$ gives the k-th moment of X).
2. $\mu = E[X] = m'_X(0)$ (The first derivative at $t = 0$ gives the mean).
3. $E[X^2] = m''_X(0)$ (The second derivative at $t = 0$ gives the second moment).

2.2.4.2 Theorems Involving MGFs

Let $X_1, X_2, \dots, X_n, Y$ be random variables with MGFs $m_{X_1}(t), m_{X_2}(t), \dots, m_{X_n}(t), m_Y(t)$:

1. If $m_{X_1}(t) = m_{X_2}(t)$ for all t in some open interval about 0, then X_1 and X_2 have the same distribution.
2. If $Y = \alpha + \beta X_1$, then:
$$m_Y(t) = e^{\alpha t} m_{X_1}(\beta t).$$
3. If $X_1, X_2, \dots, X_n$ are independent and $Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n$, where $\alpha_0, \alpha_1, \dots, \alpha_n$ are constants, then:
$$m_Y(t) = e^{\alpha_0 t} m_{X_1}(\alpha_1 t) m_{X_2}(\alpha_2 t) \dots m_{X_n}(\alpha_n t).$$
4. Suppose $X_1, X_2, \dots, X_n$ are independent normal random variables with means $\mu_1, \mu_2, \dots, \mu_n$ and variances $\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2$. If $Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n$, then:
   - Y is normally distributed.
   - Mean: $\mu_Y = \alpha_0 + \alpha_1\mu_1 + \alpha_2\mu_2 + \cdots + \alpha_n\mu_n$.
   - Variance: $\sigma_Y^2 = \alpha_1^2\sigma_1^2 + \alpha_2^2\sigma_2^2 + \cdots + \alpha_n^2\sigma_n^2$.

2.2.5 Moments

Moment	Uncentered	Centered
1st	$E[X] = \mu = \text{Mean}(X)$	
2nd	$E[X^2]$	$E[(X-\mu)^2] = \text{Var}(X) = \sigma^2$

Moment	Uncentered	Centered
3rd	$E[X^3]$	$E[(X-\mu)^3]$
4th	$E[X^4]$	$E[(X-\mu)^4]$

- **Skewness**: $\text{Skewness}(X) = \frac{E[(X-\mu)^3]}{\sigma^3}$
- **Kurtosis**: $\text{Kurtosis}(X) = \frac{E[(X-\mu)^4]}{\sigma^4}$

2.2.5.1 Conditional Moments

For a random variable Y given $X = x$:

1. **Expected Value**:

$$E[Y|X=x] = \begin{cases} \sum_y y f_Y(y|x) & \text{for discrete RV,} \\ \int_y y f_Y(y|x)\,dy & \text{for continuous RV.} \end{cases}$$

2. **Variance**:

$$\text{Var}(Y|X=x) = \begin{cases} \sum_y (y - E[Y|X=x])^2 f_Y(y|x) & \text{for discrete RV,} \\ \int_y (y - E[Y|X=x])^2 f_Y(y|x)\,dy & \text{for continuous RV.} \end{cases}$$

2.2.5.2 Multivariate Moments

1. **Expected Value**:

$$E\begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} E[X] \\ E[Y] \end{bmatrix} = \begin{bmatrix} \mu_X \\ \mu_Y \end{bmatrix}.$$

2. **Variance-Covariance Matrix**:

$$\text{Var}\begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} \text{Var}(X) & \text{Cov}(X,Y) \\ \text{Cov}(X,Y) & \text{Var}(Y) \end{bmatrix} = \begin{bmatrix} E[(X-\mu_X)^2] & E[(X-\mu_X)(Y-\mu_Y)] \\ E[(X-\mu_X)(Y-\mu_Y)] & E[(Y-\mu_Y)^2] \end{bmatrix}.$$

2.2.5.3 Properties of Moments

1. $E[aX + bY + c] = aE[X] + bE[Y] + c$
2. $\text{Var}(aX + bY + c) = a^2\text{Var}(X) + b^2\text{Var}(Y) + 2ab\text{Cov}(X,Y)$
3. $\text{Cov}(aX + bY, cX + dY) = ac\text{Var}(X) + bd\text{Var}(Y) + (ad + bc)\text{Cov}(X,Y)$
4. Correlation: $\rho_{XY} = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y}$

2.2.6 Distributions

2.2.6.1 Conditional Distributions

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)}$$

If X and Y are independent:

$$f_{X|Y}(x|y) = f_X(x).$$

2.2.6.2 Discrete Distributions

2.2.6.2.1 Bernoulli Distribution A random variable X follows a Bernoulli distribution, denoted as $X \sim \text{Bernoulli}(p)$, if it represents a single trial with:

- Success probability p
- Failure probability $q = 1 - p$.

Density Function

$$f(x) = p^x(1-p)^{1-x}, \quad x \in \{0, 1\}$$

CDF: Use table or manual computation.

PDF

```
hist(
    mc2d::rbern(1000, prob = 0.5),
    main = "Histogram of Bernoulli Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

Mean

$$\mu = E[X] = p$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = p(1-p)$$

2.2.6.2.2 Binomial Distribution $X \sim B(n, p)$ is the number of successes in n independent Bernoulli trials, where:

- n is the number of trials
- p is the success probability.
- The trials are identical and independent, and probability of success (p) and probability of failure ($q = 1 - p$) remains the same for all trials.

Density Function

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x = 0, 1, \ldots, n$$

PDF

```r
hist(
    rbinom(1000, size = 100, prob = 0.5),
    main = "Histogram of Binomial Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = (1 - p + pe^t)^n$$

Mean

$$\mu = np$$

Variance

$$\sigma^2 = np(1 - p)$$

2.2.6.2.3 Poisson Distribution $X \sim \text{Poisson}(\lambda)$ models the number of occurrences of an event in a fixed interval, with average rate λ.

- Arises with Poisson process, which involves observing discrete events in a continuous "interval" of time, length, or space.

- The random variable X is the number of occurrences of the event within an interval of s units.
- The parameter λ is the average number of occurrences of the event in question per measurement unit. For the distribution, we use the parameter $k = \lambda s$.

Density Function

$$f(x) = \frac{e^{-k}k^x}{x!}, \quad x = 0, 1, 2, ...$$

CDF

PDF

```
hist(rpois(1000, lambda = 5),
     main = "Histogram of Poisson Distribution",
     xlab = "Value",
     ylab = "Frequency")
```

MGF

$$m_X(t) = e^{k(e^t - 1)}$$

Mean

$$\mu = E(X) = k$$

Variance

$$\sigma^2 = Var(X) = k$$

2.2.6.2.4 Geometric Distribution $X \sim \mathrm{G}(p)$ models the number of trials needed to obtain the first success, with:

- p: probability of success
- $q = 1 - p$: probability of failure.
- The experiment consists of a series of trails. The outcome of each trial can be classed as being either a "success" (s) or "failure" (f). (i.e., Bernoulli trial).
- The trials are identical and independent in the sense that the outcome of one trial has no effect on the outcome of any other (i..e, lack of memory - momerylessness). The probability of success (p) and probability of failure ($q = 1 - p$) remains the same from trial to trial.

Density Function

$$f(x) = p(1-p)^{x-1}, \quad x = 1, 2, ...$$

CDF

$$F(x) = 1 - (1-p)^x$$

PDF

```
hist(rgeom(1000, prob = 0.5),
     main = "Histogram of Geometric Distribution",
     xlab = "Value",
     ylab = "Frequency")
```

MGF

$$m_X(t) = \frac{pe^t}{1-(1-p)e^t}, \quad t < -\ln(1-p)$$

Mean

$$\mu = \frac{1}{p}$$

Variance

$$\sigma^2 = \frac{1-p}{p^2}$$

2.2.6.2.5 Hypergeometric Distribution $X \sim \mathrm{H}(N, r, n)$ models the number of successes in a sample of size n drawn without replacement from a population of size N, where:

- r objects have the trait of interest
- $N - r$ do not have the trait.

Density Function

$$f(x) = \frac{\binom{r}{x}\binom{N-r}{n-x}}{\binom{N}{n}}, \quad \max(0, n-(N-r)) \leq x \leq \min(n, r)$$

PDF

```
hist(
    rhyper(1000, m = 50, n = 20, k = 30),
    main = "Histogram of Hypergeometric Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

Mean

$$\mu = E[X] = \frac{nr}{N}$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = n\frac{r}{N}\frac{N-r}{N}\frac{N-n}{N-1}$$

Note: For large N (when $\frac{n}{N} \leq 0.05$), the hypergeometric distribution can be approximated by a binomial distribution with $p = \frac{r}{N}$.

2.2.6.3 Continuous Distributions

2.2.6.3.1 Uniform Distribution Defined over an interval (a, b), where the probabilities are "equally likely" for subintervals of equal length.

Density Function:

$$f(x) = \frac{1}{b-a}, \quad a < x < b$$

CDF

$$F(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & \text{if } x > b \end{cases}$$

PDF

```
hist(
    runif(1000, min = 0, max = 1),
    main = "Histogram of Uniform Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = \begin{cases} \frac{e^{tb}-e^{ta}}{t(b-a)} & \text{if } t \neq 0 \\ 1 & \text{if } t = 0 \end{cases}$$

Mean

$$\mu = E[X] = \frac{a+b}{2}$$

Variance

$$\sigma^2 = \text{Var}(X) = \frac{(b-a)^2}{12}$$

2.2.6.3.2 Gamma Distribution The gamma distribution is used to define the exponential and χ^2 distributions.

The **gamma function** is defined as:

$$\Gamma(\alpha) = \int_0^\infty z^{\alpha-1} e^{-z} dz, \quad \alpha > 0$$

Properties of the Gamma Function:

- $\Gamma(1) = 1$
- For $\alpha > 1$, $\Gamma(\alpha) = (\alpha - 1)\Gamma(\alpha - 1)$
- If n is an integer and $n > 1$, then $\Gamma(n) = (n - 1)!$

Density Function:

$$f(x) = \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta}, \quad x > 0$$

CDF (for $\alpha = n$, and $x > 0$ a positive integer):

$$F(x, n, \beta) = 1 - \sum_{k=0}^{n-1} \frac{(\frac{x}{\beta})^k e^{-x/\beta}}{k!}$$

PDF:

```
hist(
    rgamma(n = 1000, shape = 5, rate = 1),
    main = "Histogram of Gamma Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = (1 - \beta t)^{-\alpha}, \quad t < \frac{1}{\beta}$$

Mean

$$\mu = E[X] = \alpha\beta$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = \alpha\beta^2$$

2.2.6.3.3 Normal Distribution The normal distribution, denoted as $N(\mu, \sigma^2)$, is symmetric and bell-shaped with parameters μ (mean) and σ^2 (variance). It is also known as the Gaussian distribution.

Density Function:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \quad -\infty < x < \infty,\ \sigma > 0$$

CDF: Use table or numerical methods.

PDF

```r
hist(
    rnorm(1000, mean = 0, sd = 1),
    main = "Histogram of Normal Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = e^{\mu t + \frac{\sigma^2 t^2}{2}}$$

Mean

$$\mu = E[X]$$

Variance

$$\sigma^2 = \mathrm{Var}(X)$$

Standard Normal Random Variable:

- The normal random variable Z with mean $\mu = 0$ and standard deviation $\sigma = 1$ is called a standard normal random variable.

- Any normal random variable X with mean μ and standard deviation σ can be converted to the standard normal random variable Z:

$$Z = \frac{X - \mu}{\sigma}$$

Normal Approximation to the Binomial Distribution:

Let X be binomial with parameters n and p. For large n:

- If $p \leq 0.5$ and $np > 5$, or
- If $p > 0.5$ and $n(1-p) > 5$,

X is approximately normally distributed with mean $\mu = np$ and standard deviation $\sigma = \sqrt{np(1-p)}$.

When using the normal approximation, add or subtract 0.5 as needed for the continuity correction.

Discrete Approximate Normal (Corrected):

Table 2.4: **Normal Probability Rule**

Discrete	Approximate Normal (corrected)
$P(X = c)$	$P(c - 0.5 < Y < c + 0.5)$
$P(X < c)$	$P(Y < c - 0.5)$
$P(X \leq c)$	$P(Y < c + 0.5)$
$P(X > c)$	$P(Y > c + 0.5)$
$P(X \geq c)$	$P(Y > c - 0.5)$

If X is normally distributed with parameters μ and σ, then

- $P(-\sigma < X - \mu < \sigma) \approx .68$
- $P(-2\sigma < X - \mu < 2\sigma) \approx .95$
- $P(-3\sigma < X - \mu < 3\sigma) \approx .997$

2.2.6.3.4 Logistic Distribution The logistic distribution is a continuous probability distribution commonly used in logistic regression and other types of statistical modeling. It resembles the normal distribution but has heavier tails, allowing for more extreme values. - The logistic distribution is symmetric around μ. - Its heavier tails make it useful for modeling outcomes with occasional extreme values.

Density Function

$$f(x;\mu,s) = \frac{e^{-(x-\mu)/s}}{s\left(1+e^{-(x-\mu)/s}\right)^2}, \quad -\infty < x < \infty$$

where μ is the location parameter (mean) and $s > 0$ is the scale parameter.

CDF

$$F(x;\mu,s) = \frac{1}{1+e^{-(x-\mu)/s}}, \quad -\infty < x < \infty$$

PDF

```
hist(
    rlogis(1000, location = 0, scale = 1),
    main = "Histogram of Logistic Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

The MGF of the logistic distribution does not exist because its expected value diverges for most t.

Mean

$$\mu = E[X] = \mu$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = \frac{\pi^2 s^2}{3}$$

2.2.6.3.5 Laplace Distribution The Laplace distribution, also known as the double exponential distribution, is a continuous probability distribution often used in economics, finance, and engineering. It is characterized by a peak at its mean and heavier tails compared to the normal distribution.

- The Laplace distribution is symmetric around μ.
- It has heavier tails than the normal distribution, making it suitable for modeling data with more extreme outliers.

Density Function

$$f(x; \mu, b) = \frac{1}{2b} e^{-|x-\mu|/b}, \quad -\infty < x < \infty$$

where μ is the location parameter (mean) and $b > 0$ is the scale parameter.

CDF

$$F(x; \mu, b) = \begin{cases} \frac{1}{2} e^{(x-\mu)/b} & \text{if } x < \mu \\ 1 - \frac{1}{2} e^{-(x-\mu)/b} & \text{if } x \geq \mu \end{cases}$$

PDF

```r
hist(
    VGAM::rlaplace(1000, location = 0, scale = 1),
    main = "Histogram of Laplace Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = \frac{e^{\mu t}}{1 - b^2 t^2}, \quad |t| < \frac{1}{b}$$

Mean

$$\mu = E[X] = \mu$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = 2b^2$$

2.2.6.3.6 Log-normal Distribution The log-normal distribution is denoted as Lognormal(μ, σ^2).

PDF

```
hist(rlnorm(n = 1000, meanlog = 0, sdlog = 1), main="Histogram of Log-normal Distribution", xlab=
```

2.2.6.3.7 Lognormal Distribution The lognormal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. It is often used to model variables that are positively skewed, such as income or biological measurements.

- The lognormal distribution is positively skewed.
- It is useful for modeling data that cannot take negative values and is often used in finance and environmental studies.

Density Function

$$f(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-(\ln(x)-\mu)^2/(2\sigma^2)}, \quad x > 0$$

where μ is the mean of the underlying normal distribution and $\sigma > 0$ is the standard deviation.

CDF

The cumulative distribution function of the lognormal distribution is given by:

$$F(x;\mu,\sigma) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{\ln(x)-\mu}{\sigma\sqrt{2}}\right)\right], \quad x > 0$$

PDF

```
hist(
    rlnorm(1000, meanlog = 0, sdlog = 1),
```

```
    main = "Histogram of Lognormal Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

The moment generating function (MGF) of the lognormal distribution does not exist in a simple closed form.

Mean

$$E[X] = e^{\mu+\sigma^2/2}$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = \left(e^{\sigma^2} - 1\right) e^{2\mu+\sigma^2}$$

2.2.6.3.8 Exponential Distribution The exponential distribution, denoted as $\mathrm{Exp}(\lambda)$, is a special case of the gamma distribution with $\alpha = 1$.

- It is commonly used to model the time between independent events that occur at a constant rate. It is often applied in reliability analysis and queuing theory.
- The exponential distribution is memoryless, meaning the probability of an event occurring in the future is independent of the past.

- It is commonly used to model waiting times, such as the time until the next customer arrives or the time until a radioactive particle decays.

Density Function

$$f(x) = \frac{1}{\beta} e^{-x/\beta}, \quad x, \beta > 0$$

CDF

$$F(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 - e^{-x/\beta} & \text{if } x > 0 \end{cases}$$

PDF

```
hist(rexp(n = 1000, rate = 1),
     main = "Histogram of Exponential Distribution",
     xlab = "Value",
     ylab = "Frequency")
```

MGF

$$m_X(t) = (1 - \beta t)^{-1}, \quad t < 1/\beta$$

Mean

$$\mu = E[X] = \beta$$

Variance

$$\sigma^2 = \text{Var}(X) = \beta^2$$

2.2.6.3.9 Chi-Squared Distribution The chi-squared distribution is a continuous probability distribution commonly used in statistical inference, particularly in hypothesis testing and construction of confidence intervals for variance. It is also used in goodness-of-fit tests.

- The chi-squared distribution is defined only for positive values.
- It is often used to model the distribution of the sum of the squares of k independent standard normal random variables.

Density Function

$$f(x;k) = \frac{1}{2^{k/2}\Gamma(k/2)} x^{k/2-1} e^{-x/2}, \quad x \geq 0$$

where k is the degrees of freedom and Γ is the gamma function.

CDF

The cumulative distribution function of the chi-squared distribution is given by:

$$F(x;k) = \frac{\gamma(k/2, x/2)}{\Gamma(k/2)}, \quad x \geq 0$$

where γ is the lower incomplete gamma function.

PDF

```
hist(
    rchisq(1000, df = 5),
    main = "Histogram of Chi-Squared Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_X(t) = (1-2t)^{-k/2}, \quad t < \frac{1}{2}$$

Mean

$$E[X] = k$$

Variance

$$\sigma^2 = \mathrm{Var}(X) = 2k$$

2.2.6.3.10 Student's T Distribution The Student's t-distribution, denoted as $T(v)$, is defined by:

$$T = \frac{Z}{\sqrt{\chi_v^2/v}},$$

where Z is a standard normal random variable and χ_v^2 follows a chi-squared distribution with v degrees of freedom.

The Student's T distribution is a continuous probability distribution used in statistical inference, particularly for estimating population parameters when the sample size is small and/or the population variance is unknown. It is similar to

the normal distribution but has heavier tails, which makes it more robust for small sample sizes.

- The Student's T distribution is symmetric around 0.
- It has heavier tails than the normal distribution, making it useful for dealing with outliers or small sample sizes.

Density Function

$$f(x;u) = \frac{\Gamma((u+1)/2)}{\sqrt{u\pi}\Gamma(u/2)} \left(1 + \frac{x^2}{u}\right)^{-(u+1)/2}$$

where u is the degrees of freedom and $\Gamma(x)$ is the Gamma function.

CDF

The cumulative distribution function of the Student's T distribution is more complex and typically evaluated using numerical methods.

PDF

```
hist(
    rt(1000, df = 5),
    main = "Histogram of Student's T Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

The moment generating function (MGF) of the Student's T distribution does not exist in a simple closed form.

Mean

For $u > 1$:

$$E[X] = 0$$

Variance

For $u > 2$:

$$\sigma^2 = \mathrm{Var}(X) = \frac{u}{u-2}$$

2.2.6.3.11 F Distribution The F-distribution, denoted as $F(d_1, d_2)$, is strictly positive and used to compare variances.

Definition:

$$F = \frac{\chi^2_{d_1}/d_1}{\chi^2_{d_2}/d_2},$$

where $\chi^2_{d_1}$ and $\chi^2_{d_2}$ are independent chi-squared random variables with degrees of freedom d_1 and d_2, respectively.

The distribution is asymmetric and never negative.

The F distribution arises frequently as the null distribution of a test statistic, especially in the context of comparing variances, such as in analysis of variance (ANOVA).

Density Function

$$f(x; d_1, d_2) = \frac{\sqrt{\frac{(d_1 x)^{d_1} d_2^{d_2}}{(d_1 x + d_2)^{d_1+d_2}}}}{xB\left(\frac{d_1}{2}, \frac{d_2}{2}\right)}, \quad x > 0$$

where d_1 and d_2 are the degrees of freedom and B is the beta function.

CDF

The cumulative distribution function of the F distribution is typically evaluated using numerical methods.

PDF

```r
hist(
    rf(1000, df1 = 5, df2 = 2),
    main = "Histogram of F Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

The moment generating function (MGF) of the F distribution does not exist in a simple closed form.

Mean

For $d_2 > 2$:

$$E[X] = \frac{d_2}{d_2 - 2}$$

Variance

For $d_2 > 4$:

$$\sigma^2 = \mathrm{Var}(X) = \frac{2d_2^2(d_1 + d_2 - 2)}{d_1(d_2 - 2)^2(d_2 - 4)}$$

2.2.6.3.12 Cauchy Distribution The Cauchy distribution is a continuous probability distribution that is often used in physics and has heavier tails than the normal distribution. It is notable because it does not have a finite mean or variance.

- The Cauchy distribution does not have a finite mean or variance.
- The Central Limit Theorem and Weak Law of Large Numbers do not apply to the Cauchy distribution.

Density Function

$$f(x; x_0, \gamma) = \frac{1}{\pi\gamma\left[1 + \left(\frac{x-x_0}{\gamma}\right)^2\right]}$$

where x_0 is the location parameter and $\gamma > 0$ is the scale parameter.

CDF

The cumulative distribution function of the Cauchy distribution is given by:

$$F(x; x_0, \gamma) = \frac{1}{\pi}\arctan\left(\frac{x - x_0}{\gamma}\right) + \frac{1}{2}$$

PDF

```r
hist(
    rcauchy(1000, location = 0, scale = 1),
    main = "Histogram of Cauchy Distribution",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

The MGF of the Cauchy distribution does not exist.

Mean

The mean of the Cauchy distribution is undefined.

Variance

The variance of the Cauchy distribution is undefined.

2.2.6.3.13 Multivariate Normal Distribution Let y be a p-dimensional multivariate normal (MVN) random variable with mean μ and variance-covariance matrix Σ. The density function of y is given by:

$$f(\mathbf{y}) = \frac{1}{(2\pi)^{p/2}|\ |^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{y}-\mu)'\Sigma^{-1}(\mathbf{y}-\mu)\right)$$

where $|\ |$ represents the determinant of the variance-covariance matrix Σ, and $\mathbf{y} \sim N_p(\ ,\ )$.

Properties:

- Let $\mathbf{A}_{r\times p}$ be a fixed matrix. Then $\mathbf{Ay} \sim N_r(\mathbf{A}\ , \mathbf{A}\ \mathbf{A}')$. Note that $r \leq p$, and all rows of $\mathbf{A}$ must be linearly independent to guarantee that $\mathbf{A}\ \mathbf{A}'$ is non-singular.
- Let $\mathbf{G}$ be a matrix such that $^{-\mathbf{1}} = \mathbf{GG}'$. Then $\mathbf{G}'\mathbf{y} \sim N_p(\mathbf{G}'\ , \mathbf{I})$ and $\mathbf{G}'(\mathbf{y} -\ ) \sim N_p(\mathbf{0}, \mathbf{I})$.

- Any fixed linear combination of $y_1, \dots, y_p$, say $\mathbf{c}'\mathbf{y}$, follows $\mathbf{c}'\mathbf{y} \sim N_1(\mathbf{c}' \ , \mathbf{c}' \ \mathbf{c})$.

Large Sample Properties

Suppose that $y_1, \dots, y_n$ are a random sample from some population with mean μ and variance-covariance matrix Σ:

$$\mathbf{Y} \sim MVN(\ , \ )$$

Then:

- $\bar{\mathbf{y}} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{y}_i$ is a consistent estimator for .
- $\mathbf{S} = \frac{1}{n-1}\sum_{i=1}^{n}(\mathbf{y}_i - \bar{\mathbf{y}})(\mathbf{y}_i - \bar{\mathbf{y}})'$ is a consistent estimator for .
- **Multivariate Central Limit Theorem**: Similar to the univariate case, $\sqrt{n}(\bar{\mathbf{y}} - \mu) \sim N_p(\mathbf{0}, \ )$ when n is large relative to p (e.g., $n \geq 25p$), which is equivalent to $\bar{\mathbf{y}} \sim N_p(\ , \ /\mathbf{n})$.
- **Wald's Theorem**: $n(\bar{\mathbf{y}} - \mu)'\mathbf{S^{-1}}(\bar{\mathbf{y}} - \mu) \sim \chi^2_{(p)}$ when n is large relative to p.

Density Function

$$f(\mathbf{x}; \mu, \Sigma) = \frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \Sigma^{-1}(\mathbf{x} - \mu)\right)$$

where μ is the mean vector, Σ is the covariance matrix, $\mathbf{x} \in \mathbb{R}^k$ and k is the number of variables.

CDF

The cumulative distribution function of the multivariate normal distribution does not have a simple closed form and is typically evaluated using numerical methods.

PDF

```r
k <- 2
n <- 1000
mu <- c(0, 0)
sigma <- matrix(c(1, 0.5, 0.5, 1), nrow = k)
library(MASS)
hist(
    mvrnorm(n, mu = mu, Sigma = sigma)[,1],
    main = "Histogram of MVN Distribution (1st Var)",
    xlab = "Value",
    ylab = "Frequency"
)
```

MGF

$$m_{\mathbf{X}}(\mathbf{t}) = \exp\left(\mu^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T\Sigma\mathbf{t}\right)$$

Mean

$$E[\mathbf{X}] = \mu$$

Variance

$$\mathrm{Var}(\mathbf{X}) = \Sigma$$

2.3 General Math

2.3.1 Number Sets

Notation	Denotes	Examples
$\emptyset$	Empty set	No members
$\mathbb{N}$	Natural numbers	$\{1, 2, ...\}$
$\mathbb{Z}$	Integers	$\{..., -1, 0, 1, ...\}$
$\mathbb{Q}$	Rational numbers	Including fractions
$\mathbb{R}$	Real numbers	Including all finite decimals, irrational numbers

Notation	Denotes	Examples
$\mathbb{C}$	Complex numbers	Including numbers of the form $a + bi$ where $i^2 = -1$

2.3.2 Summation Notation and Series

2.3.2.1 Chebyshev's Inequality

Let X be a random variable with mean μ and standard deviation σ. For any positive number k, Chebyshev's Inequality states:

$$P(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2}$$

This provides a probabilistic bound on the deviation of X from its mean and does not require X to follow a normal distribution.

2.3.2.2 Geometric Sum

For a geometric series of the form $\sum_{k=0}^{n-1} ar^k$, the sum is given by:

$$\sum_{k=0}^{n-1} ar^k = a\frac{1 - r^n}{1 - r} \quad \text{where } r \neq 1$$

2.3.2.3 Infinite Geometric Series

When $|r| < 1$, the geometric series converges to:

$$\sum_{k=0}^{\infty} ar^k = \frac{a}{1 - r}$$

2.3.2.4 Binomial Theorem

The binomial expansion for $(x + y)^n$ is:

$$(x + y)^n = \sum_{k=0}^{n} \binom{n}{k} x^{n-k} y^k \quad \text{where } n \geq 0$$

2.3.2.5 Binomial Series

For non-integer exponents α:

$$\sum_{k=0}^{\infty} \binom{\alpha}{k} x^k = (1+x)^\alpha \quad \text{where } |x| < 1$$

2.3.2.6 Telescoping Sum

A telescoping sum simplifies as intermediate terms cancel, leaving:

$$\sum_{a \le k < b} \Delta F(k) = F(b) - F(a) \quad \text{where } a, b \in \mathbb{Z}, a \le b$$

2.3.2.7 Vandermonde Convolution

The Vandermonde convolution identity is:

$$\sum_{k=0}^{n} \binom{r}{k} \binom{s}{n-k} = \binom{r+s}{n} \quad \text{where } n \in \mathbb{Z}$$

2.3.2.8 Exponential Series

The exponential function e^x can be represented as:

$$\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x \quad \text{where } x \in \mathbb{C}$$

2.3.2.9 Taylor Series

The Taylor series expansion for a function $f(x)$ about $x = a$ is:

$$\sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} (x-a)^k = f(x)$$

For $a = 0$, this becomes the **Maclaurin series**.

2.3.2.10 Maclaurin Series for e^z

A special case of the Taylor series, the Maclaurin expansion for e^z is:

$$e^z = 1 + z + \frac{z^2}{2!} + \frac{z^3}{3!} + \cdots$$

2.3.2.11 Euler's Summation Formula

Euler's summation formula connects sums and integrals:

$$\sum_{a \le k < b} f(k) = \int_a^b f(x)\,dx + \sum_{k=1}^{m} \frac{B_k}{k!} \left[f^{(k-1)}(x) \right]_a^b + (-1)^{m+1} \int_a^b \frac{B_m(x - \lfloor x \rfloor)}{m!} f^{(m)}(x)\,dx$$

Here, B_k are Bernoulli numbers.

- **For** $m = 1$ (Trapezoidal Rule):

$$\sum_{a \le k < b} f(k) \approx \int_a^b f(x)\,dx - \frac{1}{2}(f(b) - f(a))$$

2.3.3 Taylor Expansion

A differentiable function, $G(x)$, can be written as an infinite sum of its derivatives. More specifically, if $G(x)$ is infinitely differentiable and evaluated at a, its Taylor expansion is:

$$G(x) = G(a) + \frac{G'(a)}{1!}(x-a) + \frac{G''(a)}{2!}(x-a)^2 + \frac{G'''(a)}{3!}(x-a)^3 + ...$$

This expansion is valid within the radius of convergence.

2.3.4 Law of Large Numbers

Let $X_1, X_2, ...$ be an infinite sequence of independent and identically distributed (i.i.d.) random variables with finite mean μ and variance σ^2. The **Law of Large Numbers (LLN)** states that the sample average:

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i$$

converges to the expected value μ as $n \to \infty$. This can be expressed as:

$$\bar{X}_n \to \mu \quad (\text{as } n \to \infty).$$

2.3.4.1 Variance of the Sample Mean

The variance of the sample mean decreases as the sample size increases:

$$Var(\bar{X}_n) = Var\left(\frac{1}{n}\sum_{i=1}^{n} X_i\right) = \frac{\sigma^2}{n}.$$

$$\begin{aligned} Var(\bar{X}_n) &= Var(\frac{1}{n}(X_1 + ... + X_n)) = Var\left(\frac{1}{n}\sum_{i=1}^{n} X_i\right) \\ &= \frac{1}{n^2} Var(X_1 + ... + X_n) \\ &= \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n} \end{aligned}$$

Note: The connection between the Law of Large Numbers and the Normal Distribution lies in the Central Limit Theorem. The CLT states that, regardless of the original distribution of a dataset, the distribution of the sample means will tend to follow a normal distribution as the sample size becomes larger.

The difference between [Weak Law] and [Strong Law] regards the mode of convergence.

2.3.4.2 Weak Law of Large Numbers

The **Weak Law of Large Numbers** states that the sample average converges in probability to the expected value:

$$\bar{X}_n \xrightarrow{p} \mu \quad \text{as } n \to \infty.$$

Formally, for any $\epsilon > 0$:

$$\lim_{n\to\infty} P(|\bar{X}_n - \mu| > \epsilon) = 0.$$

Additionally, the sample mean of an i.i.d. random sample ($\{X_i\}_{i=1}^n$) from any population with a finite mean and variance is a consistent estimator of the population mean μ:

$$plim(\bar{X}_n) = plim\left(\frac{1}{n}\sum_{i=1}^{n} X_i\right) = \mu.$$

2.3.4.3 Strong Law of Large Numbers

The **Strong Law of Large Numbers** states that the sample average converges almost surely to the expected value:

$$\bar{X}_n \xrightarrow{a.s.} \mu \quad \text{as } n \to \infty.$$

Equivalently, this can be expressed as:

$$P\left(\lim_{n\to\infty} \bar{X}_n = \mu\right) = 1.$$

2.3.5 Law of Iterated Expectation

The **Law of Iterated Expectation** states that for random variables X and Y:

$$E(X) = E(E(X|Y)).$$

This means the expected value of X can be obtained by first calculating the conditional expectation $E(X|Y)$ and then taking the expectation of this quantity over the distribution of Y.

2.3.6 Convergence

2.3.6.1 Convergence in Probability

As $n \to \infty$, an estimator (random variable) θ_n is said to converge in probability to a constant c if:

$$\lim_{n\to\infty} P(|\theta_n - c| \geq \epsilon) = 0 \quad \text{for any } \epsilon > 0.$$

This is denoted as:

$$plim(\theta_n) = c \quad \text{or equivalently, } \theta_n \xrightarrow{p} c.$$

Properties of Convergence in Probability:

1. **Slutsky's Theorem**: For a continuous function $g(\cdot)$, if $plim(\theta_n) = \theta$, then:

$$plim(g(\theta_n)) = g(\theta)$$

2. If $\gamma_n \xrightarrow{p} \gamma$, then:
   - $plim(\theta_n + \gamma_n) = \theta + \gamma$,
   - $plim(\theta_n \gamma_n) = \theta\gamma$,
   - $plim(\theta_n/\gamma_n) = \theta/\gamma$ (if $\gamma \neq 0$).
3. These properties extend to random vectors and matrices.

2.3.6.2 Convergence in Distribution

As $n \to \infty$, the distribution of a random variable X_n may converge to another ("fixed") distribution. Formally, X_n with CDF $F_n(x)$ converges in distribution to X with CDF $F(x)$ if:

$$\lim_{n\to\infty} |F_n(x) - F(x)| = 0$$

at all points of continuity of $F(x)$. This is denoted as:

$$X_n \xrightarrow{d} X \quad \text{or equivalently, } F(x) \text{ is the limiting distribution of } X_n.$$

Asymptotic Properties:

- $E(X)$: Limiting mean (asymptotic mean).
- $Var(X)$: Limiting variance (asymptotic variance).

Note: Limiting expectations and variances do not necessarily match the expectations and variances of X_n:

$$E(X) \neq \lim_{n\to\infty} E(X_n),$$
$$Avar(X_n) \neq \lim_{n\to\infty} Var(X_n).$$

Properties of Convergence in Distribution:

1. **Continuous Mapping Theorem**: For a continuous function $g(\cdot)$, if $X_n \xrightarrow{d} X$, then:

$$g(X_n) \xrightarrow{d} g(X).$$

2. If $Y_n \xrightarrow{d} c$ (a constant), then:
   - $X_n + Y_n \xrightarrow{d} X + c$,
   - $Y_n X_n \xrightarrow{d} cX$,

- $X_n/Y_n \xrightarrow{d} X/c$ (if $c \neq 0$).

3. These properties also extend to random vectors and matrices.

2.3.6.3 Summary: Properties of Convergence

Convergence in Probability	Convergence in Distribution
Slutsky's Theorem: For a continuous $g(\cdot)$, if $plim(\theta_n) = \theta$, then $plim(g(\theta_n)) = g(\theta)$	Continuous Mapping Theorem: For a continuous $g(\cdot)$, if $X_n \xrightarrow{d} X$, then $g(X_n) \xrightarrow{d} g(X)$
If $\gamma_n \xrightarrow{p} \gamma$, then:	If $Y_n \xrightarrow{d} c$, then:
$plim(\theta_n + \gamma_n) = \theta + \gamma$	$X_n + Y_n \xrightarrow{d} X + c$
$plim(\theta_n \gamma_n) = \theta\gamma$	$Y_n X_n \xrightarrow{d} cX$
$plim(\theta_n/\gamma_n) = \theta/\gamma$ (if $\gamma \neq 0$)	$X_n/Y_n \xrightarrow{d} X/c$ (if $c \neq 0$)

Relationship between Convergence Types:

Convergence in Probability is stronger than Convergence in Distribution. Therefore:

- Convergence in Distribution does not guarantee Convergence in Probability.

2.3.7 Sufficient Statistics and Likelihood

2.3.7.1 Likelihood

The **likelihood** describes the degree to which the observed data supports a particular value of a parameter θ.

- The exact value of the likelihood is **not meaningful**; only relative comparisons matter.
- Likelihood is **informative** when comparing parameter values, helping identify which values of θ are more plausible given the data.

For a single observation $Y = y$, the likelihood function is:

$$L(\theta_0; y) = P(Y = y|\theta = \theta_0) = f_Y(y; \theta_0)$$

2.3.7.2 Likelihood Ratio

The **likelihood ratio** compares the relative likelihood of two parameter values θ_0 and θ_1 given the data:

$$\frac{L(\theta_0; y)}{L(\theta_1; y)}$$

A likelihood ratio greater than 1 implies that θ_0 is more likely than θ_1, given the observed data.

2.3.7.3 Likelihood Function

For a given sample, the likelihood for all possible values of θ forms the **likelihood function**:

$$L(\theta) = L(\theta; y) = f_Y(y; \theta).$$

For a sample of size n, assuming independence among observations:

$$L(\theta) = \prod_{i=1}^{n} f_i(y_i; \theta).$$

Taking the natural logarithm of the likelihood gives the **log-likelihood function**:

$$l(\theta) = \sum_{i=1}^{n} \log f_i(y_i; \theta).$$

The log-likelihood function is particularly useful in optimization problems, as logarithms convert products into sums, simplifying computation.

2.3.7.4 Sufficient Statistics

A statistic $T(y)$ is **sufficient** for a parameter θ if it summarizes all the information in the data about θ. Formally, by the **Factorization Theorem**, $T(y)$ is sufficient for θ if:

$$L(\theta; y) = c(y)L^*(\theta; T(y)),$$

where:

- $c(y)$ is a function of the data independent of θ.
- $L^*(\theta; T(y))$ is a function that depends on θ and $T(y)$.

In other words, the likelihood function can be rewritten in terms of $T(y)$ alone, without loss of information about θ.

Example:

For a sample of i.i.d. observations $Y_1, Y_2, \dots, Y_n$ from a normal distribution $N(\mu, \sigma^2)$:

- The sample mean $\bar{Y}$ is sufficient for μ.
- The sufficient statistic conveys all the information about μ contained in the data.

2.3.7.5 Nuisance Parameters

Parameters that are not of direct interest in the analysis but are necessary to model the data are called **nuisance parameters**.

Profile Likelihood: To handle nuisance parameters, replace them with their maximum likelihood estimates (MLEs) in the likelihood function, creating a **profile likelihood** for the parameter of interest.

2.3.8 Parameter Transformations

Transformations of parameters are often used to improve interpretability or statistical properties of models.

2.3.8.1 Log-Odds Transformation

The **log-odds transformation** is commonly used in logistic regression and binary classification problems. It transforms probabilities (which are bounded between 0 and 1) to the real line:

$$\text{Log odds} = g(\theta) = \ln\left(\frac{\theta}{1-\theta}\right),$$

where θ represents a probability (e.g., the success probability in a Bernoulli trial).

2.3.8.2 General Parameter Transformations

For a parameter θ and a transformation $g(\cdot)$:

- If $\theta \in (a, b)$, $g(\theta)$ may map θ to a different range (e.g., $\mathbb{R}$).
- Useful transformations include:
  - Logarithmic: $g(\theta) = \ln(\theta)$ for $\theta > 0$.
  - Exponential: $g(\theta) = e^{\theta}$ for unconstrained θ.
  - Square root: $g(\theta) = \sqrt{\theta}$ for $\theta \geq 0$.

Jacobian Adjustment for Transformations: If transforming a parameter in Bayesian inference, the Jacobian of the transformation must be included to ensure proper posterior scaling.

2.3.8.3 Applications of Parameter Transformations

1. **Improving Interpretability**:
   - Probabilities can be transformed to odds or log-odds for logistic models.
   - Rates can be transformed logarithmically for multiplicative effects.
2. **Statistical Modeling**:
   - Variance-stabilizing transformations (e.g., log for Poisson data or arcsine for proportions).
   - Regularization or simplification of complex relationships.
3. **Optimization**:
   - Transforming constrained parameters (e.g., probabilities or positive scales) to unconstrained scales simplifies optimization algorithms.

2.4 Data Import/Export

Extended Manual by R

Table 2.7: Table by Rio Vignette

Format	Typical Extension	Import Package	Export Package	Installed by Default
Comma-separated data	.csv	**data.table**	**data.table**	Yes
Pipe-separated data	.psv	**data.table**	**data.table**	Yes
Tab-separated data	.tsv	**data.table**	**data.table**	Yes

Format	Typical Extension	Import Package	Export Package	Installed by Default
CSVY (CSV + YAML metadata header)	.csvy	**data.table**	**data.table**	Yes
SAS	.sas7bdat	**haven**	**haven**	Yes
SPSS	.sav	**haven**	**haven**	Yes
SPSS (compressed)	.zsav	**haven**	**haven**	Yes
Stata	.dta	**haven**	**haven**	Yes
SAS XPORT	.xpt	**haven**	**haven**	Yes
SPSS Portable	.por	**haven**		Yes
Excel	.xls	**readxl**		Yes
Excel	.xlsx	**readxl**	**openxlsx**	Yes
R syntax	.R	**base**	**base**	Yes
Saved R objects	.RData, .rda	**base**	**base**	Yes
Serialized R objects	.rds	**base**	**base**	Yes
Epiinfo	.rec	**foreign**		Yes
Minitab	.mtp	**foreign**		Yes
Systat	.syd	**foreign**		Yes
"XBASE" database files	.dbf	**foreign**	**foreign**	Yes
Weka Attribute-Relation File Format	.arff	**foreign**	**foreign**	Yes
Data Interchange Format	.dif	**utils**		Yes
Fortran data	no recognized extension	**utils**		Yes
Fixed-width format data	.fwf	**utils**	**utils**	Yes
gzip comma-separated data	.csv.gz	**utils**	**utils**	Yes
Apache Arrow (Parquet)	.parquet	**arrow**	**arrow**	No
EViews	.wf1	**hexView**		No

Format	Typical Extension	Import Package	Export Package	Installed by Default
Feather R/Python interchange format	.feather	**feather**	**feather**	No
Fast Storage	.fst	**fst**	**fst**	No
JSON	.json	**jsonlite**	**jsonlite**	No
Matlab	.mat	**rmatio**	**rmatio**	No
OpenDocument Spreadsheet	.ods	**readODS**	**readODS**	No
HTML Tables	.html	**xml2**	**xml2**	No
Shallow XML documents	.xml	**xml2**	**xml2**	No
YAML	.yml	**yaml**	**yaml**	No
Clipboard	default is tsv	**clipr**	**clipr**	No
Google Sheets	as Comma-separated data			

R limitations:

- By default, R use 1 core in CPU
- R puts data into memory (limit around 2-4 GB), while SAS uses data from files on demand
- Categorization
  - Medium-size file: within RAM limit, around 1-2 GB
  - Large file: 2-10 GB, there might be some workaround solution
  - Very large file > 10 GB, you have to use distributed or parallel computing

Solutions:

- buy more RAM
- HPC packages
  - Explicit Parallelism
  - Implicit Parallelism
  - Large Memory
  - Map/Reduce

- specify number of rows and columns, typically including command `nrow =`
- Use packages that store data differently
  - `bigmemory`, `biganalytics`, `bigtabulate` , `synchronicity`, `bigalgebra`, `bigvideo` use C++ to store matrices, but also support one class type
  - For multiple class types, use `ff` package
- Very Large datasets use
  - `RHaddop` package
  - `HadoopStreaming`
  - `Rhipe`

2.4.1 Medium size

```
library("rio")
```

To import multiple files in a directory

```
str(import_list(dir()), which = 1)
```

To export a single data file

```
export(data, "data.csv")
export(data,"data.dta")
export(data,"data.txt")
export(data,"data_cyl.rds")
export(data,"data.rdata")
export(data,"data.R")
export(data,"data.csv.zip")
export(data,"list.json")
```

To export multiple data files

```
export(list(mtcars = mtcars, iris = iris), "data_file_type")
# where data_file_type should substituted with the extension listed above
```

To convert between data file types

```
# convert Stata to SPSS
convert("data.dta", "data.sav")
```

2.4.2 Large size

2.4.2.1 Cloud Computing: Using AWS for Big Data

Amazon Web Service (AWS): Compute resources can be rented at approximately $1/hr. Use AWS to process large datasets without overwhelming your local machine.

2.4.2.2 Importing Large Files as Chunks

```
file_in <- file("in.csv", "r")  # Open a connection to the file
chunk_size <- 100000            # Define chunk size
x <- readLines(file_in, n = chunk_size)  # Read data in chunks
close(file_in)                  # Close the file connection
```

2.4.2.2.1 Using Base R

```
library(data.table)
mydata <- fread("in.csv", header = TRUE)  # Fast and memory-efficient
```

2.4.2.2.2 Using the `data.table` Package

```
library(ff)
x <- read.csv.ffdf(
  file = "file.csv",
  nrow = 10,          # Total rows
  header = TRUE,      # Include headers
  VERBOSE = TRUE,     # Display progress
  first.rows = 10000, # Initial chunk
  next.rows = 50000,  # Subsequent chunks
  colClasses = NA
)
```

2.4.2.2.3 Using the `ff` Package

```
library(bigmemory)
my_data <- read.big.matrix('in.csv', header = TRUE)
```

2.4.2.2.4 Using the `bigmemory` Package

```
library(sqldf)
my_data <- read.csv.sql('in.csv')
```

```
# Example: Filtering during import
iris2 <- read.csv.sql("iris.csv",
    sql = "SELECT * FROM file WHERE Species = 'setosa'")
```

2.4.2.2.5 Using the sqldf Package

```
library(RMySQL)
```

2.4.2.2.6 Using the RMySQL Package RQLite package

- Download SQLite, pick "A bundle of command-line tools for managing SQLite database files" for Window 10
- Unzip file, and open `sqlite3.exe`.
- Type in the prompt
  - `sqlite> .cd 'C:\Users\data'` specify path to your desired directory
  - `sqlite> .open database_name.db` to open a database
  - To import the CSV file into the database
    - `sqlite> .mode csv` specify to SQLite that the next file is .csv file
    - `sqlite> .import file_name.csv datbase_name` to import the csv file to the database
  - `sqlite> .exit` After you're done, exit the sqlite program

```
library(DBI)
library(dplyr)
library("RSQLite")
setwd("")
con <- dbConnect(RSQLite::SQLite(), "data_base.db")
tbl <- tbl(con, "data_table")
tbl %>%
    filter() %>%
    select() %>%
    collect() # to actually pull the data into the workspace
dbDisconnect(con)
```

```
library(arrow)
data <- read_csv_arrow("file.csv")
```

2.4.2.2.7 Using the arrow Package

```
library(vroom)
```

```r
# Import a compressed CSV file
compressed <- vroom_example("mtcars.csv.zip")
data <- vroom(compressed)
```

2.4.2.2.8 Using the `vroom` Package

```r
s = fread("sample.csv")
```

2.4.2.2.9 Using the `data.table` Package

```r
test = ff::read.csv.ffdf(file = "")
object.size(test) # Highest memory usage

test1 = data.table::fread(file = "")
object.size(test1) # Lowest memory usage

test2 = readr::read_csv(file = "")
object.size(test2) # Second lowest memory usage

test3 = vroom::vroom(file = "")
object.size(test3) # Similar to read_csv
```

2.4.2.2.10 Comparisons Regarding Storage Space To work with large datasets, you can compress them into `csv.gz` format. However, typically, R requires loading the entire dataset before exporting it, which can be impractical for data over 10 GB. In such cases, processing the data sequentially becomes necessary. Although `read.csv` is slower compared to `readr::read_csv`, it can handle connections and allows for sequential looping, making it useful for large files.

Currently, `readr::read_csv` does not support the `skip` argument efficiently for large data. Even if you specify `skip`, the function reads all preceding lines again. For instance, if you run `read_csv(file, n_max = 100, skip = 0)` followed by `read_csv(file, n_max = 200, skip = 100)`, the first 100 rows are re-read. In contrast, `read.csv` can continue from where it left off without re-reading previous rows.

If you encounter an error such as:

"Error in (function (con, what, n = 1L, size = NA_integer_, signed = TRUE): can only read from a binary connection",

you can modify the connection mode from `"r"` to `"rb"` (read binary). Although the `file` function is designed to detect the appropriate format automatically, this workaround can help resolve the issue when it does not behave as expected.

2.4.2.3 Sequential Processing for Large Data

```
# Open file for sequential reading
file_conn <- file("file.csv", open = "r")
while (TRUE) {
  # Read a chunk of data
  data_chunk <- read.csv(file_conn, nrows = 1000)
  if (nrow(data_chunk) == 0) break  # Stop if no more rows
  # Process the chunk here
}
close(file_conn)  # Close connection
```

2.5 Data Manipulation

```
# Load required packages
library(tidyverse)
library(lubridate)

# ----------------------------
# Data Structures in R
# ----------------------------

# Create vectors
x <- c(1, 4, 23, 4, 45)
n <- c(1, 3, 5)
g <- c("M", "M", "F")

# Create a data frame
df <- data.frame(n, g)
df  # View the data frame
#>   n g
#> 1 1 M
#> 2 3 M
#> 3 5 F
str(df)  # Check its structure
#> 'data.frame':    3 obs. of  2 variables:
#>  $ n: num  1 3 5
#>  $ g: chr  "M" "M" "F"

# Using tibble for cleaner outputs
df <- tibble(n, g)
df  # View the tibble
#> # A tibble: 3 x 2
#>       n g
```

```
#>   <dbl> <chr>
#> 1     1 M
#> 2     3 M
#> 3     5 F
str(df)
#> tibble [3 x 2] (S3: tbl_df/tbl/data.frame)
#>  $ n: num [1:3] 1 3 5
#>  $ g: chr [1:3] "M" "M" "F"

# Create a list
lst <- list(x, n, g, df)
lst  # Display the list
#> [[1]]
#> [1]  1  4 23  4 45
#>
#> [[2]]
#> [1] 1 3 5
#>
#> [[3]]
#> [1] "M" "M" "F"
#>
#> [[4]]
#> # A tibble: 3 x 2
#>       n g
#>   <dbl> <chr>
#> 1     1 M
#> 2     3 M
#> 3     5 F

# Name list elements
lst2 <- list(num = x, size = n, sex = g, data = df)
lst2  # Named list elements are easier to reference
#> $num
#> [1]  1  4 23  4 45
#>
#> $size
#> [1] 1 3 5
#>
#> $sex
#> [1] "M" "M" "F"
#>
#> $data
#> # A tibble: 3 x 2
#>       n g
#>   <dbl> <chr>
```

```
#> 1     1 M
#> 2     3 M
#> 3     5 F

# Another list example with numeric vectors
lst3 <- list(
  x = c(1, 3, 5, 7),
  y = c(2, 2, 2, 4, 5, 5, 5, 6),
  z = c(22, 3, 3, 3, 5, 10)
)
lst3
#> $x
#> [1] 1 3 5 7
#>
#> $y
#> [1] 2 2 2 4 5 5 5 6
#>
#> $z
#> [1] 22  3  3  3  5 10

# Find means of list elements
# One at a time
mean(lst3$x)
#> [1] 4
mean(lst3$y)
#> [1] 3.875
mean(lst3$z)
#> [1] 7.666667

# Using lapply to calculate means
lapply(lst3, mean)
#> $x
#> [1] 4
#>
#> $y
#> [1] 3.875
#>
#> $z
#> [1] 7.666667

# Simplified output with sapply
sapply(lst3, mean)
#>        x        y        z
#> 4.000000 3.875000 7.666667
```

```r
# Tidyverse alternative: map() function
map(lst3, mean)
#> $x
#> [1] 4
#>
#> $y
#> [1] 3.875
#>
#> $z
#> [1] 7.666667

# Tidyverse with numeric output: map_dbl()
map_dbl(lst3, mean)
#>        x        y        z
#> 4.000000 3.875000 7.666667

# ----------------------------
# Binding Data Frames
# ----------------------------

# Create tibbles for demonstration
dat01 <- tibble(x = 1:5, y = 5:1)
dat02 <- tibble(x = 10:16, y = x / 2)
dat03 <- tibble(z = runif(5))  # 5 random numbers from (0, 1)

# Row binding
bind_rows(dat01, dat02, dat01)
#> # A tibble: 17 x 2
#>        x     y
#>    <int> <dbl>
#>  1     1   5
#>  2     2   4
#>  3     3   3
#>  4     4   2
#>  5     5   1
#>  6    10   5
#>  7    11   5.5
#>  8    12   6
#>  9    13   6.5
#> 10    14   7
#> 11    15   7.5
#> 12    16   8
#> 13     1   5
#> 14     2   4
#> 15     3   3
```

```
#> 16     4   2
#> 17     5   1

# Add a new identifier column with .id
bind_rows(dat01, dat02, .id = "id")
#> # A tibble: 12 x 3
#>    id        x     y
#>    <chr> <int> <dbl>
#>  1 1         1   5
#>  2 1         2   4
#>  3 1         3   3
#>  4 1         4   2
#>  5 1         5   1
#>  6 2        10   5
#>  7 2        11   5.5
#>  8 2        12   6
#>  9 2        13   6.5
#> 10 2        14   7
#> 11 2        15   7.5
#> 12 2        16   8

# Use named inputs for better identification
bind_rows("dat01" = dat01, "dat02" = dat02, .id = "id")
#> # A tibble: 12 x 3
#>    id        x     y
#>    <chr> <int> <dbl>
#>  1 dat01     1   5
#>  2 dat01     2   4
#>  3 dat01     3   3
#>  4 dat01     4   2
#>  5 dat01     5   1
#>  6 dat02    10   5
#>  7 dat02    11   5.5
#>  8 dat02    12   6
#>  9 dat02    13   6.5
#> 10 dat02    14   7
#> 11 dat02    15   7.5
#> 12 dat02    16   8

# Bind a list of data frames
list01 <- list("dat01" = dat01, "dat02" = dat02)
bind_rows(list01, .id = "source")
#> # A tibble: 12 x 3
#>    source     x     y
#>    <chr>  <int> <dbl>
```

```
#>  1 dat01      1   5
#>  2 dat01      2   4
#>  3 dat01      3   3
#>  4 dat01      4   2
#>  5 dat01      5   1
#>  6 dat02     10   5
#>  7 dat02     11   5.5
#>  8 dat02     12   6
#>  9 dat02     13   6.5
#> 10 dat02     14   7
#> 11 dat02     15   7.5
#> 12 dat02     16   8

# Column binding
bind_cols(dat01, dat03)
#> # A tibble: 5 x 3
#>       x     y      z
#>   <int> <int>  <dbl>
#> 1     1     5 0.508
#> 2     2     4 0.824
#> 3     3     3 0.0374
#> 4     4     2 0.577
#> 5     5     1 0.988

# -----------------------------
# String Manipulation
# -----------------------------

names <- c("Ford, MS", "Jones, PhD", "Martin, Phd", "Huck, MA, MLS")

# Remove everything after the first comma
str_remove(names, pattern = ", [[:print:]]+")
#> [1] "Ford"   "Jones"  "Martin" "Huck"

# Explanation: [[:print:]]+ matches one or more printable characters

# -----------------------------
# Reshaping Data
# -----------------------------

# Wide format data
wide <- data.frame(
  name = c("Clay", "Garrett", "Addison"),
  test1 = c(78, 93, 90),
  test2 = c(87, 91, 97),
```

```
  test3 = c(88, 99, 91)
)

# Long format data
long <- data.frame(
  name = rep(c("Clay", "Garrett", "Addison"), each = 3),
  test = rep(1:3, 3),
  score = c(78, 87, 88, 93, 91, 99, 90, 97, 91)
)

# Summary statistics
aggregate(score ~ name, data = long, mean)  # Mean score per student
#>      name    score
#> 1 Addison 92.66667
#> 2    Clay 84.33333
#> 3 Garrett 94.33333
aggregate(score ~ test, data = long, mean)  # Mean score per test
#>   test    score
#> 1    1 87.00000
#> 2    2 91.66667
#> 3    3 92.66667

# Line plot of scores over tests
ggplot(long,
       aes(
           x = factor(test),
           y = score,
           color = name,
           group = name
       )) +
    geom_point() +
    geom_line() +
    xlab("Test") +
    ggtitle("Test Scores by Student")
```

```
# Reshape wide to long
pivot_longer(wide, test1:test3, names_to = "test", values_to = "score")
#> # A tibble: 9 x 3
#>   name    test  score
#>   <chr>   <chr> <dbl>
#> 1 Clay    test1    78
#> 2 Clay    test2    87
#> 3 Clay    test3    88
#> 4 Garrett test1    93
#> 5 Garrett test2    91
#> 6 Garrett test3    99
#> 7 Addison test1    90
#> 8 Addison test2    97
#> 9 Addison test3    91

# Use names_prefix to clean column names
pivot_longer(
    wide,
    -name,
    names_to = "test",
    values_to = "score",
    names_prefix = "test"
)
#> # A tibble: 9 x 3
#>   name    test  score
#>   <chr>   <chr> <dbl>
```

```
#> 1 Clay    1        78
#> 2 Clay    2        87
#> 3 Clay    3        88
#> 4 Garrett 1        93
#> 5 Garrett 2        91
#> 6 Garrett 3        99
#> 7 Addison 1        90
#> 8 Addison 2        97
#> 9 Addison 3        91

# Reshape long to wide with explicit id_cols argument
pivot_wider(
  long,
  id_cols = name,
  names_from = test,
  values_from = score
)
#> # A tibble: 3 x 4
#>   name      `1`   `2`   `3`
#>   <chr>   <dbl> <dbl> <dbl>
#> 1 Clay       78    87    88
#> 2 Garrett    93    91    99
#> 3 Addison    90    97    91

# Add a prefix to the resulting columns
pivot_wider(
  long,
  id_cols = name,
  names_from = test,
  values_from = score,
  names_prefix = "test"
)
#> # A tibble: 3 x 4
#>   name    test1 test2 test3
#>   <chr>   <dbl> <dbl> <dbl>
#> 1 Clay       78    87    88
#> 2 Garrett    93    91    99
#> 3 Addison    90    97    91
```

The verbs of data manipulation

- `select`: selecting (or not selecting) columns based on their names (eg: select columns Q1 through Q25)
- `slice`: selecting (or not selecting) rows based on their position (eg: select rows 1:10)
- `mutate`: add or derive new columns (or variables) based on existing

columns (eg: create a new column that expresses measurement in cm based on existing measure in inches)
- `rename`: rename variables or change column names (eg: change "GraduationRate100" to "grad100")
- `filter`: selecting rows based on a condition (eg: all rows where gender = Male)
- `arrange`: ordering rows based on variable(s) numeric or alphabetical order (eg: sort in descending order of Income)
- `sample`: take random samples of data (eg: sample 80% of data to create a "training" set)
- `summarize`: condense or aggregate multiple values into single summary values (eg: calculate median income by age group)
- `group_by`: convert a tbl into a grouped tbl so that operations are performed "by group"; allows us to summarize data or apply verbs to data by groups (eg, by gender or treatment)
- the pipe: `%>%`
  - Use Ctrl + Shift + M (Win) or Cmd + Shift + M (Mac) to enter in RStudio
  - The pipe takes the output of a function and "pipes" into the first argument of the next function.
  - new pipe is `|>` It should be identical to the old one, except for certain special cases.
- `:=` (Walrus operator): similar to `=` , but for cases where you want to use the `glue` package (i.e., dynamic changes in the variable name in the left-hand side)

Writing function in R

Tunneling

`{{` (called curly-curly) allows you to tunnel data-variables through arg-variables (i.e., function arguments)

```
library(tidyverse)
# ----------------------------
# Writing Functions with {{ }}
# ----------------------------

# Define a custom function using {{ }}
get_mean <- function(data, group_var, var_to_mean) {
  data %>%
    group_by({{group_var}}) %>%
    summarize(mean = mean({{var_to_mean}}, na.rm = TRUE))
}

# Apply the function
data("mtcars")
```

```r
mtcars %>%
  get_mean(group_var = cyl, var_to_mean = mpg)
#> # A tibble: 3 x 2
#>     cyl  mean
#>   <dbl> <dbl>
#> 1     4  26.7
#> 2     6  19.7
#> 3     8  15.1

# Dynamically name the resulting variable
get_mean <- function(data, group_var, var_to_mean, prefix = "mean_of") {
  data %>%
    group_by({{group_var}}) %>%
    summarize("{prefix}_{{var_to_mean}}" := mean({{var_to_mean}}, na.rm = TRUE))
}

# Apply the modified function
mtcars %>%
  get_mean(group_var = cyl, var_to_mean = mpg)
#> # A tibble: 3 x 2
#>     cyl mean_of_mpg
#>   <dbl>       <dbl>
#> 1     4        26.7
#> 2     6        19.7
#> 3     8        15.1
```

I. BASIC

Chapter 3

Descriptive Statistics

When you have an area of interest that you want to research, a problem that you want to solve, a relationship that you want to investigate, theoretical and empirical processes will help you.

Estimand is defined as "a quantity of scientific interest that can be calculated in the population and does not change its value depending on the data collection design used to measure it (i.e., it does not vary with sample size and survey design, or the number of non-respondents, or follow-up efforts)." (Rubin, 1996)

Estimands include:

- population means
- Population variances
- correlations
- factor loading
- regression coefficients

3.1 Numerical Measures

There are differences between a population and a sample

Measures of	Category	Population	Sample
-	What is it?	Reality	A small fraction of reality (inference)
-	Characteristics described by	Parameters	Statistics

Measures of	Category	Population	Sample
Central Tendency	Mean	$\mu = E(Y)$	$\hat{\mu} = \overline{y}$
Central Tendency	Median	50-th percentile	$y_{(\frac{n+1}{2})}$
Dispersion	Variance	$\sigma^2 = var(Y)$ $= E(Y - \mu^2)$	$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(y_i - \overline{y})^2$
Dispersion	Coefficient of Variation	$\frac{\sigma}{\mu}$	$\frac{s}{\overline{y}}$
Dispersion	Interquartile Range	difference between 25th and 75th percentiles. Robust to outliers	
Shape	Skewness Standardized 3rd central moment (unitless)	$g_1 = \frac{\mu_3}{\mu_2^{3/2}}$	$\hat{g_1} = \frac{m_3}{m_2 sqrt(m_2)}$
Shape	Central moments	$\mu = E(Y)$ $\mu_2 = \sigma^2 = E(Y - \mu)^2$ $\mu_3 = E(Y - \mu)^3$ $\mu_4 = E(Y - \mu)^4$ |	$m_2 = \sum_{i=1}^{n}(y_1 - \overline{y})^2/n$ $m_3 = \sum_{i=1}^{n}(y_1 - \overline{y})^3/n$
Shape	Kurtosis (peakedness and tail thickness) Standardized 4th central moment	$g_2^* = \frac{E(Y-\mu)^4}{\sigma^4}$	$\hat{g_2} = \frac{m_4}{m_2^2} - 3$

Note:

- Order Statistics: $y_{(1)}, y_{(2)}, ..., y_{(n)}$ where $y_{(1)} < y_{(2)} < ... < y_{(n)}$
- Coefficient of variation: standard deviation over mean. This metric is stable, dimensionless statistic for comparison.
- Symmetric: mean = median, skewness = 0
- Skewed right: mean > median, skewness > 0
- Skewed left: mean < median, skewness < 0
- Central moments: $\mu = E(Y)$, $\mu_2 = \sigma^2 = E(Y - \mu)^2$, $\mu_3 = E(Y - \mu)^3$, $\mu_4 = E(Y - \mu)^4$
- For normal distributions, $\mu_3 = 0$, so $g_1 = 0$

- $\hat{g_1}$ is distributed approximately as $N(0, 6/n)$ if sample is from a normal population. (valid when $n > 150$)
  - For large samples, inference on skewness can be based on normal tables with 95% confidence interval for g_1 as $\hat{g_1} \pm 1.96\sqrt{6/n}$
  - For small samples, special tables from Snedecor and Cochran 1989, Table A 19(i) or Monte Carlo test

Kurtosis > 0 (leptokurtic)	heavier tail	compared to a normal distribution with the same σ (e.g., t-distribution)
Kurtosis < 0 (platykurtic)	lighter tail	compared to a normal distribution with the same σ

- For a normal distribution, $g_2^* = 3$. Kurtosis is often redefined as: $g_2 = \frac{E(Y-\mu)^4}{\sigma^4} - 3$ where the 4th central moment is estimated by $m_4 = \sum_{i=1}^{n}(y_i - \overline{y})^4/n$
  - the asymptotic sampling distribution for $\hat{g_2}$ is approximately $N(0, 24/n)$ (with $n > 1000$)
  - large sample on kurtosis uses standard normal tables
  - small sample uses tables by Snedecor and Cochran, 1989, Table A 19(ii) or Geary 1936

```
data = rnorm(100)
library(e1071)
skewness(data)
#> [1] -0.5285128
kurtosis(data)
#> [1] 0.6497711
```

3.2 Graphical Measures

3.2.1 Shape

It's a good habit to label your graph, so others can easily follow.

```
data = rnorm(100)

# Histogram
hist(data,labels = T,col="grey",breaks = 12)

# Interactive histogram
pacman::p_load("highcharter")
hchart(data)

# Box-and-Whisker plot
```

```r
boxplot(count ~ spray, data = InsectSprays,col = "lightgray",main="boxplot")

# Notched Boxplot
boxplot(len~supp*dose, data=ToothGrowth, notch=TRUE,
  col=(c("gold","darkgreen")),
  main="Tooth Growth", xlab="Suppliment and Dose")
# If notches differ -> medians differ

# Stem-and-Leaf Plots
stem(data)


# Bagplot - A 2D Boxplot Extension
pacman::p_load(aplpack)
attach(mtcars)
bagplot(wt,mpg, xlab="Car Weight", ylab="Miles Per Gallon",
  main="Bagplot Example")
```

Others more advanced plots

```r
# boxplot.matrix()  #library("sfsmisc")
# boxplot.n()       #library("gplots")
# vioplot()         #library("vioplot")
```

3.2.2 Scatterplot

```r
# pairs(mtcars)
```

3.3 Normality Assessment

Since Normal (Gaussian) distribution has many applications, we typically want/ wish our data or our variable is normal. Hence, we have to assess the normality based on not only Numerical Measures but also Graphical Measures

3.3.1 Graphical Assessment

```r
pacman::p_load("car")
qqnorm(precip, ylab = "Precipitation [in/yr] for 70 US cities")
qqline(precip)
```

The straight line represents the theoretical line for normally distributed data. The dots represent real empirical data that we are checking. If all the dots fall on the straight line, we can be confident that our data follow a normal distribution. If our data wiggle and deviate from the line, we should be concerned with the normality assumption.

3.3.2 Summary Statistics

Sometimes it's hard to tell whether your data follow the normal distribution by just looking at the graph. Hence, we often have to conduct statistical test to aid our decision. Common tests are

- Methods based on normal probability plot
  - Correlation Coefficient with Normal Probability Plots
  - Shapiro-Wilk Test
- Methods based on empirical cumulative distribution function
  - Anderson-Darling Test
  - Kolmogorov-Smirnov Test
  - Cramer-von Mises Test
  - Jarque–Bera Test

3.3.2.1 Methods based on normal probability plot

3.3.2.1.1 Correlation Coefficient with Normal Probability Plots (Looney and Gulledge Jr, 1985) (Shapiro and Francia, 1972) The correlation coefficient between $y_{(i)}$ and m_i^* as given on the normal probability plot:

$$W^* = \frac{\sum_{i=1}^{n}(y_{(i)} - \bar{y})(m_i^* - 0)}{(\sum_{i=1}^{n}(y_{(i)} - \bar{y})^2 \sum_{i=1}^{n}(m_i^* - 0)^2)\cdot 5}$$

where $\bar{m}^* = 0$

Pearson product moment formula for correlation:

$$\hat{p} = \frac{\sum_{i-1}^{n}(y_i - \bar{y})(x_i - \bar{x})}{(\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2)\cdot 5}$$

- When the correlation is 1, the plot is exactly linear and normality is assumed.
- The closer the correlation is to zero, the more confident we are to reject normality
- Inference on W* needs to be based on special tables (Looney and Gulledge Jr, 1985)

```
library("EnvStats")
gofTest(data,test="ppcc")$p.value #Probability Plot Correlation Coefficient
#> [1] 0.02720557
```

3.3.2.1.2 Shapiro-Wilk Test (Shapiro and Wilk, 1965)

$$W = (\frac{\sum_{i=1}^{n} a_i(y_{(i)} - \bar{y})(m_i^* - 0)}{(\sum_{i=1}^{n} a_i^2(y_{(i)} - \bar{y})^2 \sum_{i=1}^{n}(m_i^* - 0)^2)\cdot 5})^2$$

where $a_1, .., a_n$ are weights computed from the covariance matrix for the order statistics.

- Researchers typically use this test to assess normality. (n < 2000) Under normality, W is close to 1, just like W^*. Notice that the only difference between W and W* is the "weights".

```
gofTest(data,test="sw")$p.value #Shapiro-Wilk is the default.
#> [1] 0.03744017
```

3.3.2.2 Methods based on empirical cumulative distribution function

The formula for the empirical cumulative distribution function (CDF) is:

$F_n(t)$ = estimate of probability that an observation $\leq$ t = (number of observation $\leq$ t)/n

This method requires large sample sizes. However, it can apply to distributions other than the normal (Gaussian) one.

```r
# Empirical CDF hand-code
plot.ecdf(data,verticals = T, do.points=F)
```

3.3.2.2.1 Anderson-Darling Test The Anderson-Darling statistic (Anderson and Darling, 1952):

$$A^2 = \int_{-\infty}^{\infty} (F_n(t) = F(t))^2 \frac{dF(t)}{F(t)(1-F(t))}$$

- a weight average of squared deviations (it weights small and large values of t more)

For the normal distribution,

$A^2 = -(\sum_{i=1}^{n}(2i-1)(ln(p_i) + ln(1-p_{n+1-i}))/n - n$

where $p_i = \Phi(\frac{y_{(i)}-\bar{y}}{s})$, the probability that a standard normal variable is less than $\frac{y_{(i)}-\bar{y}}{s}$

- Reject normal assumption when A^2 is too large
- Evaluate the null hypothesis that the observations are randomly selected from a normal population based on the critical value provided by (Marsaglia and Marsaglia, 2004) and (Stephens, 1974)
- This test can be applied to other distributions:
  - Exponential
  - Logistic

- Gumbel
- Extreme-value
- Weibull: log(Weibull) = Gumbel
- Gamma
- Logistic
- Cauchy
- von Mises
- Log-normal (two-parameter)

Consult (Stephens, 1974) for more detailed transformation and critical values.

```
gofTest(data,test="ad")$p.value #Anderson-Darling
#> [1] 0.04245868
```

3.3.2.2.2 Kolmogorov-Smirnov Test

- Based on the largest absolute difference between empirical and expected cumulative distribution
- Another deviation of K-S test is Kuiper's test

```
gofTest(data,test="ks")$p.value #Komogorov-Smirnov
#> [1] 0.4097154
```

3.3.2.2.3 Cramer-von Mises Test

- Based on the average squared discrepancy between the empirical distribution and a given theoretical distribution. Each discrepancy is weighted equally (unlike Anderson-Darling test weights end points more heavily)

```
gofTest(data,test="cvm")$p.value #Cramer-von Mises
#> [1] 0.06912725
```

3.3.2.2.4 Jarque–Bera Test (Bera and Jarque, 1981)

Based on the skewness and kurtosis to test normality.

$JB = \frac{n}{6}(S^2 + (K-3)^2/4)$ where S is the sample skewness and K is the sample kurtosis

$S = \frac{\hat{\mu_3}}{\hat{\sigma}^3} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^3/n}{(\sum_{i=1}^{n}(x_i-\bar{x})^2/n)^{\frac{3}{2}}}$

$K = \frac{\hat{\mu_4}}{\hat{\sigma}^4} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4/n}{(\sum_{i=1}^{n}(x_i-\bar{x})^2/n)^2}$

recall $\hat{\sigma^2}$ is the estimate of the second central moment (variance) $\hat{\mu_3}$ and $\hat{\mu_4}$ are the estimates of third and fourth central moments.

If the data comes from a normal distribution, the JB statistic asymptotically has a chi-squared distribution with two degrees of freedom.

The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being zero.

3.4 Bivariate Statistics

Correlation between

- Two Continuous variables
- Two Discrete variables
- Categorical and Continuous

	Categorical	Continuous
Categorical	Phi coefficient Cramer's V Tschuprow's T Freeman's Theta Epsilon-squared Goodman Kruskal's Gamma Somers' D Kendall's Tau-b Yule's Q and Y Tetrachoric Correlation Polychoric Correlation	
Continuous	Point-Biserial Correlation Logistic Regression	Pearson Correlation Spearman Correlation

Questions to keep in mind:

1. Is the relationship linear or non-linear?
2. If the variable is continuous, is it normal and homoskadastic?
3. How big is your dataset?

3.4.1 Two Continuous

```
n = 100 # (sample size)

data = data.frame(A = sample(1:20, replace = TRUE, size = n),
                  B = sample(1:30, replace = TRUE, size = n))
```

3.4.1.1 Pearson Correlation

- Good with linear relationship

```
library(Hmisc)
rcorr(data$A, data$B, type="pearson")
#>       x     y
#> x  1.00 -0.13
#> y -0.13  1.00
#>
#> n= 100
#>
#>
#> P
#>   x      y
#> x        0.1984
#> y 0.1984
```

3.4.1.2 Spearman Correlation

```
library(Hmisc)
rcorr(data$A, data$B, type="spearman")
#>       x     y
#> x  1.00 -0.13
#> y -0.13  1.00
#>
#> n= 100
#>
#>
#> P
#>   x     y
#> x       0.203
#> y 0.203
```

3.4.2 Categorical and Continuous

3.4.2.1 Point-Biserial Correlation

Similar to the Pearson correlation coefficient, the point-biserial correlation coefficient is between -1 and 1 where:

- -1 means a perfectly negative correlation between two variables
- 0 means no correlation between two variables
- 1 means a perfectly positive correlation between two variables

```
x <- c(0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0)
y <- c(12, 14, 17, 17, 11, 22, 23, 11, 19, 8, 12)

#calculate point-biserial correlation
```

```
cor.test(x, y)
#>
#>  Pearson's product-moment correlation
#>
#> data:  x and y
#> t = 0.67064, df = 9, p-value = 0.5193
#> alternative hypothesis: true correlation is not equal to 0
#> 95 percent confidence interval:
#>  -0.4391885  0.7233704
#> sample estimates:
#>       cor
#> 0.2181635
```

Alternatively

```
ltm::biserial.cor(y,x, use = c("all.obs"), level = 2)
#> [1] 0.2181635
```

3.4.2.2 Logistic Regression

See 3.4.2.2

3.4.3 Two Discrete

3.4.3.1 Distance Metrics

Some consider distance is not a correlation metric because it isn't unit independent (i.e., if you scale the distance, the metrics will change), but it's still a useful proxy. Distance metrics are more likely to be used for similarity measure.

- Euclidean Distance
- Manhattan Distance
- Chessboard Distance
- Minkowski Distance
- Canberra Distance
- Hamming Distance
- Cosine Distance
- Sum of Absolute Distance
- Sum of Squared Distance
- Mean-Absolute Error

3.4.3.2 Statistical Metrics

3.4.3.2.1 Chi-squared test

3.4.3.2.1.1 Phi coefficient

- 2 binary

```
dt = matrix(c(1,4,3,5), nrow = 2)
dt
#>      [,1] [,2]
#> [1,]    1    3
#> [2,]    4    5
psych::phi(dt)
#> [1] -0.18
```

3.4.3.2.1.2 Cramer's V

- between nominal categorical variables (no natural order)

$$\text{Cramer's V} = \sqrt{\frac{\chi^2/n}{\min(c-1, r-1)}}$$

where

- χ^2 = Chi-square statistic
- n = sample size
- r = # of rows
- c = # of columns

```
library('lsr')
n = 100 # (sample size)
set.seed(1)
data = data.frame(A = sample(1:5, replace = TRUE, size = n),
                  B = sample(1:6, replace = TRUE, size = n))


cramersV(data$A, data$B)
#> [1] 0.1944616
```

Alternatively,

- `ncchisq` noncentral Chi-square
- `nchisqadj` Adjusted noncentral Chi-square
- `fisher` Fisher Z transformation

- `fisheradj` bias correction Fisher z transformation

```
DescTools::CramerV(data, conf.level = 0.95,method = "ncchisqadj")
#>  Cramer V    lwr.ci    upr.ci
#> 0.3472325 0.3929964 0.4033053
```

3.4.3.2.1.3 Tschuprow's T

- 2 nominal variables

```
DescTools::TschuprowT(data)
#> [1] 0.1100808
```

3.4.3.3 Ordinal Association (Rank correlation)

- Good with non-linear relationship

```
n = 100 # (sample size)
set.seed(1)
dt = table(data.frame(
    A = sample(1:4, replace = TRUE, size = n), # ordinal
    B = sample(1:3, replace = TRUE, size = n)  # nominal
))
dt
#>    B
#> A    1  2  3
#>   1  7 11  9
#>   2 11  6 14
#>   3  7 11  4
#>   4  6  4 10
```

3.4.3.3.1 Ordinal and Nominal

3.4.3.3.1.1 Freeman's Theta

- Ordinal and nominal

```
# this package is not available for R >= 4.0.0
rcompanion::freemanTheta(dt, group = "column")
# because column is the grouping variable (i.e., nominal)
```

3.4.3.3.1.2 Epsilon-squared

- Ordinal and nominal

```
# this package is not available for R >= 4.0.0
rcompanion::epsilonSquared(dt,group = "column" )
# because column is the grouping variable (i.e., nominal)
```

```
n = 100 # (sample size)
set.seed(1)
dt = table(data.frame(
    A = sample(1:4, replace = TRUE, size = n), # ordinal
    B = sample(1:3, replace = TRUE, size = n)  # ordinal
))
dt
#>    B
#> A    1  2  3
#>   1  7 11  9
#>   2 11  6 14
#>   3  7 11  4
#>   4  6  4 10
```

3.4.3.3.2 Two Ordinal

3.4.3.3.2.1 Goodman Kruskal's Gamma

- 2 ordinal variables

```
DescTools::GoodmanKruskalGamma(dt, conf.level = 0.95)
#>        gamma       lwr.ci       upr.ci
#>  0.006781013 -0.229032069  0.242594095
```

3.4.3.3.2.2 Somers' D

- or Somers' Delta
- 2 ordinal variables

```
DescTools::SomersDelta(dt, conf.level = 0.95)
#>       somers       lwr.ci       upr.ci
#>  0.005115859 -0.172800185  0.183031903
```

3.4.3.3.2.3 Kendall's Tau-b

- 2 ordinal variables

```
DescTools::KendallTauB(dt, conf.level = 0.95)
#>        tau_b       lwr.ci       upr.ci
#>  0.004839732 -0.163472443  0.173151906
```

3.4.3.3.2.4 Yule's Q and Y

- 2 ordinal variables

Special version (2×2) of the Goodman Kruskal's Gamma coefficient.

	Variable 1	
Variable 2	a	b
	c	d

$$\text{Yule's Q} = \frac{ad - bc}{ad + bc}$$

We typically use Yule's Q in practice while Yule's Y has the following relationship with Q.

$$\text{Yule's Y} = \frac{\sqrt{ad} - \sqrt{bc}}{\sqrt{ad} + \sqrt{bc}}$$

$$Q = \frac{2Y}{1 + Y^2}$$

$$Y = \frac{1 = \sqrt{1 - Q^2}}{Q}$$

```
n = 100 # (sample size)
set.seed(1)
dt = table(data.frame(A = sample(c(0, 1), replace = TRUE, size = n),
                      B = sample(c(0, 1), replace = TRUE, size = n)))
dt
#>    B
#> A    0  1
#>   0 25 24
#>   1 28 23

DescTools::YuleQ(dt)
#> [1] -0.07778669
```

3.4.3.3.2.5 Tetrachoric Correlation

- is a special case of Polychoric Correlation when both variables are binary

```
library(psych)

n = 100 # (sample size)

data = data.frame(A = sample(c(0, 1), replace = TRUE, size = n),
```

```
                  B = sample(c(0, 1), replace = TRUE, size = n))

#view table
head(data)
#>   A B
#> 1 1 0
#> 2 1 0
#> 3 0 0
#> 4 1 0
#> 5 1 0
#> 6 1 0

table(data)
#>    B
#> A    0  1
#>   0 21 23
#>   1 34 22


#calculate tetrachoric correlation
tetrachoric(data)
#> Call: tetrachoric(x = data)
#> tetrachoric correlation
#>   A    B
#> A  1.0
#> B -0.2  1.0
#>
#>  with tau of
#>     A     B
#> -0.15  0.13
```

3.4.3.3.2.6 Polychoric Correlation

- between ordinal categorical variables (natural order).
- Assumption: Ordinal variable is a discrete representation of a latent normally distributed continuous variable. (Income = low, normal, high).

```
library(polycor)

n = 100 # (sample size)

data = data.frame(A = sample(1:4, replace = TRUE, size = n),
                  B = sample(1:6, replace = TRUE, size = n))

head(data)
#>   A B
```

```
#> 1 1 3
#> 2 1 1
#> 3 3 5
#> 4 2 3
#> 5 3 5
#> 6 4 4


#calculate polychoric correlation between ratings
polychor(data$A, data$B)
#> [1] 0.01607982
```

3.5 Summary

```
library(tidyverse)

data("mtcars")
df = mtcars %>%
    dplyr::select(cyl, vs, carb)


df_factor = df %>%
    dplyr::mutate(
        cyl = factor(cyl),
        vs = factor(vs),
        carb = factor(carb)
    )
# summary(df)
str(df)
#> 'data.frame':    32 obs. of  3 variables:
#>  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
#>  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
#>  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
str(df_factor)
#> 'data.frame':    32 obs. of  3 variables:
#>  $ cyl : Factor w/ 3 levels "4","6","8": 2 2 1 2 3 2 3 1 1 2 ...
#>  $ vs  : Factor w/ 2 levels "0","1": 1 1 2 2 1 2 1 2 2 2 ...
#>  $ carb: Factor w/ 6 levels "1","2","3","4",..: 4 4 1 1 2 1 4 2 2 4 ...
```

Get the correlation table for continuous variables only

```
cor(df)
#>             cyl         vs       carb
#> cyl   1.0000000 -0.8108118  0.5269883
#> vs   -0.8108118  1.0000000 -0.5696071
```

	cyl	vs	carb
cyl	1	.	.
vs	−0.81	1	.
carb	0.53	−0.57	1

```
#> carb  0.5269883 -0.5696071  1.0000000

# only complete obs
# cor(df, use = "complete.obs")
```

Alternatively, you can also have the

```
Hmisc::rcorr(as.matrix(df), type = "pearson")
#>        cyl    vs  carb
#> cyl   1.00 -0.81  0.53
#> vs   -0.81  1.00 -0.57
#> carb  0.53 -0.57  1.00
#>
#> n= 32
#>
#>
#> P
#>      cyl    vs     carb
#> cyl         0.0000 0.0019
#> vs   0.0000        0.0007
#> carb 0.0019 0.0007
```

```
modelsummary::datasummary_correlation(df)
```

```
ggcorrplot::ggcorrplot(cor(df))
```

Different comparison between different correlation between different types of variables (i.e., continuous vs. categorical) can be problematic. Moreover, the problem of detecting non-linear vs. linear relationship/correlation is another one. Hence, a solution is that using mutual information from information theory (i.e., knowing one variable can reduce uncertainty about the other).

To implement mutual information, we have the following approximations

$$\downarrow \text{prediction error} \approx \downarrow \text{uncertainty} \approx \downarrow \text{association strength}$$

More specifically, following the X2Y metric, we have the following steps:

1. Predict y without x (i.e., baseline model)
    1. Average of y when y is continuous
    2. Most frequent value when y is categorical
2. Predict y with x (e.g., linear, random forest, etc.)
3. Calculate the prediction error difference between 1 and 2

To have a comprehensive table that could handle

- continuous vs. continuous
- categorical vs. continuous
- continuous vs. categorical
- categorical vs. categorical

the suggested model would be Classification and Regression Trees (CART). But we can certainly use other models as well.

The downfall of this method is that you might suffer

1. Symmetry: $(x, y) \neq (y, x)$
2. Comparability : Different pair of comparison might use different metrics (e.g., misclassification error vs. MAE)

```
library(ppsr)

iris <- iris %>%
  select(1:3)

# ppsr::score_df(iris) # if you want a dataframe
ppsr::score_matrix(iris,
                   do_parallel = TRUE,
                   n_cores = parallel::detectCores() / 2)
#>              Sepal.Length Sepal.Width Petal.Length
#> Sepal.Length   1.00000000  0.04632352    0.5491398
#> Sepal.Width    0.06790301  1.00000000    0.2376991
#> Petal.Length   0.61608360  0.24263851    1.0000000

# if you want a similar correlation matrix
ppsr::score_matrix(df,
                   do_parallel = TRUE,
                   n_cores = parallel::detectCores() / 2)
#>             cyl        vs      carb
#> cyl  1.00000000 0.3982789 0.2092533
#> vs   0.02514286 1.0000000 0.2000000
#> carb 0.30798148 0.2537309 1.0000000
```

```
corrplot::corrplot(cor(df))
```

Alternatively,

```
PerformanceAnalytics::chart.Correlation(df, histogram = T, pch = 19)
```

```
heatmap(as.matrix(df))
```

More general form,

```
ppsr::visualize_pps(
    df = iris,
    do_parallel = TRUE,
    n_cores = parallel::detectCores() / 2
)
```

```
ppsr::visualize_correlations(
    df = iris
)
```

Both heat map and correlation at the same time

```
ppsr::visualize_both(
    df = iris,
    do_parallel = TRUE,
    n_cores = parallel::detectCores() / 2
)
```

More elaboration with `ggplot2`

```
ppsr::visualize_pps(
    df = iris,
    color_value_high = 'red',
    color_value_low = 'yellow',
    color_text = 'black'
) +
    ggplot2::theme_classic() +
    ggplot2::theme(plot.background =
                       ggplot2::element_rect(fill = "lightgrey")) +
    ggplot2::theme(title = ggplot2::element_text(size = 15)) +
    ggplot2::labs(
        title = 'Correlation aand Heatmap',
        subtitle = 'Subtitle',
        caption = 'Caption',
        x = 'More info'
    )
```

Correlation aand Heatmap
Subtitle
target
Sepal.Length
Sepal.Width
Petal.Length
1.00
0.05
0.55
0.07
1.00
0.24
0.62
0.24
1.00
Sepal.Length
Sepal.Width
Petal.Length
More info
Caption
pps
1.0
0.8
0.6
0.4
0.2
0.0

Chapter 4

Basic Statistical Inference

1. One Sample Inference
2. Two Sample Inference
3. Categorical Data Analysis
4. Divergence Metrics and Test for Comparing Distributions

- Make **inferences** (an interpretation) about the true parameter value β based on our estimator/estimate
- Test whether our underlying assumptions (about the true population parameters, random variables, or model specification) hold true.

Testing does not

- Confirm with 100% a hypothesis is true
- Confirm with 100% a hypothesis is false
- Tell you how to interpret the estimate value (Economic vs. Practical vs. Statistical Significance)

Hypothesis: Translate an objective in better understanding the results in terms of specifying a value (or sets of values) in which our population parameters should/should not lie.

- **Null hypothesis** (H_0): A statement about the population parameter that we take to be true in which we would need the data to provide substantial evidence that against it.
  - Can be either a single value (ex: $H_0 : \beta = 0$) or a set of values (ex: $H_0 : \beta_1 \geq 0$)
  - Will generally be the value you would not like the population parameter to be (subjective)
    - $H_0 : \beta_1 = 0$ means you would like to see a non-zero coefficient
    - $H_0 : \beta_1 \geq 0$ means you would like to see a negative effect
  - "Test of Significance" refers to the two-sided test: $H_0 : \beta_j = 0$

- **Alternative hypothesis** (H_a or H_1) (Research Hypothesis): All other possible values that the population parameter may be if the null hypothesis does not hold.

Type I Error

Error made when H_0 is rejected when, in fact, H_0 is true.
The probability of committing a Type I error is α (known as **level of significance** of the test)

Type I error (α): probability of rejecting H_0 when it is true.

Legal analogy: In U.S. law, a defendant is presumed to be "innocent until proven guilty".
If the null hypothesis is that a person is innocent, the Type I error is the probability that you conclude the person is guilty when he is innocent.

Type II Error

Type II error level (β): probability that you fail to reject the null hypothesis when it is false.

In the legal analogy, this is the probability that you fail to find the person guilty when he or she is guilty.

Error made when H_0 is not rejected when, in fact, H_1 is true
The probability of committing a Type II error is β (known as the **power** of the test)

Random sample of size n: A collection of n independent random variables taken from the distribution X, each with the same distribution as X.

Sample mean

$$\bar{X} = (\sum_{i=1}^{n} X_i)/n$$

Sample Median

$\tilde{x}$ = the middle observation in a sample of observation order from smallest to largest (or vice versa).

If n is odd, $\tilde{x}$ is the middle observation,
If n is even, $\tilde{x}$ is the average of the two middle observations.

Sample variance

$$S^2 = \frac{\sum_{i=1}^{n}(X_i = \bar{X})^2}{n-1} = \frac{n\sum_{i=1}^{n} X_i^2 - (\sum_{i=1}^{n} X_i)^2}{n(n-1)}$$

Sample standard deviation

$$S = \sqrt{S^2}$$

Sample proportions

$$\hat{p} = \frac{X}{n} = \frac{\text{number in the sample with trait}}{\text{sample size}}$$

$$\widehat{p_1 - p_2} = \hat{p_1} - \hat{p_2} = \frac{X_1}{n_1} - \frac{X_2}{n_2} = \frac{n_2 X_1 = n_1 X_2}{n_1 n_2}$$

Estimators
Point Estimator
$\hat{\theta}$ is a statistic used to approximate a population parameter θ

Point estimate
The numerical value assumed by $\hat{\theta}$ when evaluated for a given sample

Unbiased estimator
If $E(\hat{\theta}) = \theta$, then $\hat{\theta}$ is an unbiased estimator for θ

1. $\bar{X}$ is an unbiased estimator for μ
2. S^2 is an unbiased estimator for σ^2
3. $\hat{p}$ is an unbiased estimator for p
4. $\widehat{p_1 - p_2}$ is an unbiased estimator for $p_1 - p_2$
5. $\bar{X}_1 - \bar{X}_2$ is an unbiased estimator for $\mu_1 - \mu_2$

Note: S is a biased estimator for σ

Distribution of the sample mean

If $\bar{X}$ is the sample mean based on a random sample of size n drawn from a normal distribution X with mean μ and standard deviation σ, the $\bar{X}$ is normally distributed, with mean $\mu_{\bar{X}} = \mu$ and variance $\sigma^2_{\bar{X}} = Var(\bar{X}) = \frac{\sigma^2}{n}$. Then the **standard error of the mean** is: $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$

4.1 One Sample Inference

$Y_i \sim i.i.d. N(\mu, \sigma^2)$

i.i.d. standards for "independent and identically distributed"

Hence, we have the following model:

$Y_i = \mu + \epsilon_i$ where

- $\epsilon_i \sim^{iid} N(0, \sigma^2)$
- $E(Y_i) = \mu$
- $Var(Y_i) = \sigma^2$
- $\bar{y} \sim N(\mu, \sigma^2/n)$

4.1.1 The Mean

When σ^2 is estimated by s^2, then

$$\frac{\bar{y}-\mu}{s/\sqrt{n}} \sim t_{n-1}$$

Then, a $100(1-\alpha)\%$ confidence interval for μ is obtained from:

$$1-\alpha = P(-t_{\alpha/2;n-1} \leq \frac{\bar{y}-\mu}{s/\sqrt{n}} \leq t_{\alpha/2;n-1}) = P(\bar{y}-(t_{\alpha/2;n-1})s/\sqrt{n} \leq \mu \leq \bar{y}+(t_{\alpha/2;n-1})s/\sqrt{n})$$

And the interval is

$$\bar{y} \pm (t_{\alpha/2;n-1})s/\sqrt{n}$$

and $s/\sqrt{n}$ is the standard error of $\bar{y}$

If the experiment were repeated many times, $100(1-\alpha)\%$ of these intervals would contain μ

	Confidence Interval $100(1-\alpha)$	Sample Sizes Confidence α, Error d	Hypothesis Testing Test Statistic
When σ^2 is known, X is normal (or $n \geq 25$)	$\bar{X} \pm z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$	$n \approx \frac{z^2_{\alpha/2}\sigma^2}{d^2}$	$z = \frac{\bar{X}-\mu_0}{\sigma/\sqrt{n}}$
When σ^2 is unknown, X is normal (or $n \geq 25$)	$\bar{X} \pm t_{\alpha/2}\frac{s}{\sqrt{n}}$	$n \approx \frac{z^2_{\alpha/2}s^2}{d^2}$	$t = \frac{\bar{X}-\mu_0}{s/\sqrt{n}}$

4.1.1.1 For Difference of Means $(\mu_1 - \mu_2)$, Independent Samples

	$100(1-\alpha)$ Confidence Interval	Hypothesis Testing Test Statistic
When σ^2 is known	$\bar{X}_1 - \bar{X}_2 \pm z_{\alpha/2}\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$	$z = \frac{(\bar{X}_1-\bar{X}_2)-(\mu_1-\mu_2)_0}{\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_2^2}{n_2}}}$

	$100(1-\alpha)$ Confidence Interval	Hypothesis Testing Test Statistic	
When σ^2 is unknown, Variances Assumed EQUAL	$\bar{X}_1 - \bar{X}_2 \pm t_{\alpha/2}\sqrt{s_p^2(\frac{1}{n_1}+\frac{1}{n_2})}$	$t = \frac{(\bar{X}_1-\bar{X}_2)-(\mu_1-\mu_2)_0}{\sqrt{s_p^2(\frac{1}{n_1}+\frac{1}{n_2})}}$	Pooled Variance: $s_p^2 = \frac{(n_1-1)s_1^2-(n_2-1)s_2^2}{n_1+n_2-2}$ Degrees of Freedom: $\gamma = n_1+n_2-2$
When σ^2 is unknown, Variances Assumed UNEQUAL	$\bar{X}_1 - \bar{X}_2 \pm t_{\alpha/2}\sqrt{(\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2})}$	$t = \frac{(\bar{X}_1-\bar{X}_2)-(\mu_1-\mu_2)_0}{\sqrt{(\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2})}}$	Degrees of Freedom: $\gamma = \frac{(\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2})^2}{\frac{(\frac{s_1^2}{n_1})^2}{n_1-1}+\frac{(\frac{s_2^2}{n_2})^2}{n_2-1}}$

4.1.1.2 For Difference of Means ($\mu_1 - \mu_2$), Paired Samples (D = X-Y)

$100(1-\alpha)$ Confidence Interval

$$\bar{D} \pm t_{\alpha/2}\frac{s_d}{\sqrt{n}}$$

Hypothesis Testing Test Statistic

$$t = \frac{\bar{D} - D_0}{s_d/\sqrt{n}}$$

4.1.1.3 Difference of Two Proportions

Mean

$$\hat{p_1} - \hat{p_2}$$

Variance

$$\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}$$

$100(1-\alpha)$ Confidence Interval

$$\hat{p_1} - \hat{p_2} + z_{\alpha/2}\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}$$

Sample Sizes, Confidence α, Error d
(Prior Estimate fo $\hat{p_1}, \hat{p_2}$)

$$n \approx \frac{z^2_{\alpha/2}[p_1(1-p_1)+p_2(1-p_2)]}{d^2}$$

(No Prior Estimates for $\hat{p}$)

$$n \approx \frac{z^2_{\alpha/2}}{2d^2}$$

Hypothesis Testing - Test Statistics

Null Value $(p_1 - p_2) \neq 0$

$$z = \frac{(\hat{p_1} - \hat{p_2}) - (p_1 - p_2)_0}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}}$$

Null Value $(p_1 - p_2)_0 = 0$

$$z = \frac{\hat{p_1} - \hat{p_2}}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where

$$\hat{p} = \frac{x_1 + x_2}{n_1 + n_2} = \frac{n_1\hat{p_1} + n_2\hat{p_2}}{n_1 + n_2}$$

4.1.2 Single Variance

$$1-\alpha = P(\chi^2_{1-\alpha/2;n-1}) \leq (n-1)s^2/\sigma^2 \leq \chi^2_{\alpha/2;n-1}) = P(\frac{(n-1)s^2}{\chi^2_{\alpha/2}} \leq \sigma^2 \leq \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}})$$

and a $100(1-\alpha)\%$ confidence interval for σ^2 is:

$$(\frac{(n-1)s^2}{\chi^2_{\alpha/2;n-1}}, \frac{(n-1)s^2}{\chi^2_{1-\alpha/2;n-1}})$$

Confidence limits for σ^2 are obtained by computing the positive square roots of these limits

Equivalently,

$100(1-\alpha)$ Confidence Interval

$$L_1 = \frac{(n-1)s^2}{\chi^2_{\alpha/2}} L_1 = \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}}$$

Hypothesis Testing Test Statistic

$$\chi^2 = \frac{(n-1)s^2}{\sigma_0^2}$$

4.1.3 Single Proportion (p)

Confidence Interval $100(1-\alpha)$	Sample Sizes Confidence α, Error d (prior estimate for $\hat{p}$)	(No prior estimate for $\hat{p}$)	Hypothesis Testing Test Statistic
$\hat{p} \pm z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$	$n \approx \frac{z^2_{\alpha/2}\hat{p}(1-\hat{p})}{d^2}$	$n \approx \frac{z^2_{\alpha/2}}{4d^2}$	$z = \frac{\hat{p}-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$

4.1.4 Power

Formally, power (for the test of the mean) is given by:

$$\pi(\mu) = 1 - \beta = P(\text{test rejects } H_0|\mu)$$

To evaluate the power, one needs to know the distribution of the test statistic if the null hypothesis is false.

For 1-sided z-test where $H_0 : \mu \leq \mu_0$
$H_A : \mu > 0$

The power is:

$$\begin{aligned}
\pi(\mu) &= P(\bar{y} > \mu_0 + z_\alpha \sigma/\sqrt{n}|\mu) \\
&= P(Z = \frac{\bar{y}-\mu}{\sigma/\sqrt{n}} > z_\alpha + \frac{\mu_0-\mu}{\sigma/\sqrt{n}}|\mu) \\
&= 1 - \Phi(z_\alpha + \frac{(\mu_0-\mu)\sqrt{n}}{\sigma}) \\
&= \Phi(-z_\alpha + \frac{(\mu-\mu_0)\sqrt{n}}{\sigma})
\end{aligned}$$

where $1 - \Phi(x) = \Phi(-x)$ since the normal pdf is symmetric

Power is correlated to the difference in $\mu - \mu_0$, sample size n, variance σ^2, and the α-level of the test (through z_α)
Equivalently, power can be increased by making α large, σ^2 smaller, or n larger.

For 2-sided z-test is:

$$\pi(\mu) = \Phi(-z_{\alpha/2} + \frac{(\mu_0-\mu)\sqrt{n}}{\sigma}) + \Phi(-z_{\alpha/2} + \frac{(\mu-\mu_0)\sqrt{n}}{\sigma})$$

4.1.5 Sample Size

4.1.5.1 1-sided Z-test

Example: to show that the mean response μ under the treatment is higher than the mean response μ_0 without treatment (show that the treatment effect $\delta = \mu - \mu_0$ is large)

Because power is an increasing function of $\mu - \mu_0$, it is only necessary to find n that makes the power equal to $1 - \beta$ at $\mu = \mu_0 + \delta$

Hence, we have

$$\pi(\mu_0 + \delta) = \Phi(-z_\alpha + \frac{\delta\sqrt{n}}{\sigma}) = 1 - \beta$$

Since $\Phi(z_\beta) = 1 - \beta$, we have

$$-z_\alpha + \frac{\delta\sqrt{n}}{\sigma} = z_\beta$$

Then n is

$$n = (\frac{(z_\alpha + z_\beta)\sigma}{\delta})^2$$

Then, we need larger samples, when

- the sample variability is large (σ is large)
- α is small (z_α is large)
- power $1 - \beta$ is large (z_β is large)
- The magnitude of the effect is smaller (δ is small)

Since we don't know δ and σ. We can base σ on previous studies, pilot studies. Or, obtain an estimate of σ by anticipating the range of the observation (without outliers). divide this range by 4 and use the resulting number as an approximate estimate of σ. For normal (distribution) data, this is reasonable.

4.1.5.2 2-sided Z-test

We want to know the min n, required to guarantee $1 - \beta$ power when the treatment effect $\delta = |\mu - \mu_0|$ is at least greater than 0. Since the power function for the 2-sided is increasing and symmetric in $|\mu - \mu_0|$, we only need to find n that makes the power equal to $1 - \beta$ when $\mu = \mu_0 + \delta$

$$n = (\frac{(z_{\alpha/2} + z_\beta)\sigma}{\delta})^2$$

We could also use the confidence interval approach. If we require that an α-level two-sided CI for μ be

$$\bar{y} \pm D$$

where $D = z_{\alpha/2}\sigma/\sqrt{n}$ gives

$$n = (\frac{z_{\alpha/2}\sigma}{D})^2$$

(round up to the nearest integer)

```
data = rnorm(100)
t.test(data, conf.level=0.95)
#>
#>  One Sample t-test
#>
#> data:  data
#> t = -1.7813, df = 99, p-value = 0.07793
#> alternative hypothesis: true mean is not equal to 0
#> 95 percent confidence interval:
#>  -0.40186463  0.02165643
#> sample estimates:
#>  mean of x
#> -0.1901041
```

$$H_0 : \mu \geq 30 H_a : \mu < 30$$

```
t.test(data, mu=30,alternative="less")
#>
#>  One Sample t-test
#>
#> data:  data
#> t = -282.88, df = 99, p-value < 2.2e-16
#> alternative hypothesis: true mean is less than 30
#> 95 percent confidence interval:
#>         -Inf -0.01290305
#> sample estimates:
#>  mean of x
#> -0.1901041
```

4.1.6 Note

For t-tests, the sample and power are not as easy as z-test.

$$\pi(\mu) = P(\frac{\bar{y} - \mu_0}{s/\sqrt{n}} > t_{n-1;\alpha}|\mu)$$

when $\mu > \mu_0$ (i.e., $\mu - \mu_0 = \delta$), the random variable $(\bar{y} - \mu_0)/(s/\sqrt{n})$ does not have a [Student's t distribution][Student T], but rather is distributed as a non-central t-distribution with non-centrality parameter $\delta\sqrt{n}/\sigma$ and d.f. of $n - 1$

- The power is an increasing function of this non-centrality parameter (note, when $\delta = 0$ the distribution is usual Student's t-distribution).
- To evaluate power, one must consider numerical procedure or use special charts

Approximate Sample Size Adjustment for t-test. We use an adjustment to the z-test determination for sample size.

Let $v = n - 1$, where n is sample size derived based on the z-test power. Then the 2-sided t-test sample size (approximate) is given:

$$n^* = \frac{(t_{v;\alpha/2} + t_{v;\beta})^2\sigma^2}{\delta^2}$$

4.1.7 One-sample Non-parametric Methods

```
lecture.data = c(0.76, 0.82, 0.80, 0.79, 1.06, 0.83,-0.43,-0.34, 3.34, 2.33)
```

4.1.7.1 Sign Test

If we want to test $H_0 : \mu_{(0.5)} = 0; H_a : \mu_{(0.5)} > 0$ where $\mu_{(0.5)}$ is the population median. We can

(1) Count the number of observation (y_i's) that exceed 0. Denote this number by s_+, called the number of plus signs. Let $s_- = n - s_+$, which is the number of minus signs.
(2) Reject H_0 if s_+ is large or equivalently, if s_- is small.

To determine how large s_+ must be to reject H_0 at a given significance level, we need to know the distribution of the corresponding random variable S_+ under the null hypothesis, which is a binomial with p = 1/2,w hen the null is true.

To work out the null distribution using the binomial formula, we have α-level test rejects H_0 if $s_+ \geq b_{n,\alpha}$, where $b_{n,\alpha}$ is the upper α critical point of the $Bin(n, 1/2)$ distribution. Both S_+ and S_- have this same distribution ($S = S_+ = S_-$).

$$\text{p-value} = P(S \geq s_+) = \sum_{i=s_+}^{n} \binom{n}{i}(\frac{1}{2})^n$$

equivalently,

$$P(S \leq s_-) = \sum_{i=0}^{s_-} \binom{n}{i} (\frac{1}{2})^2$$

For large sample sizes, we could use the normal approximation for the binomial, in which case reject H_0 if

$$s_+ \geq n/2 + 1/2 + z_\alpha \sqrt{n/4}$$

For the 2-sided test, we use the tests statistic $s_{max} = max(s_+, s_-)$ or $s_{min} = min(s_+, s_-)$. An α-level test rejects H_0 if the p-value is $\leq \alpha$, where the p-value is computed from:

$$p - value = 2 \sum_{i=s_{max}}^{n} \binom{n}{i} (\frac{1}{2})^n = s \sum_{i=0}^{s_{min}} \binom{n}{i} (\frac{1}{2})^n$$

Equivalently, rejecting H_0 if $s_{max} \geq b_{n,\alpha/2}$

A large sample normal approximation can be used, where

$$z = \frac{s_{max} - n/2 - 1/2}{\sqrt{n/4}}$$

and reject H_0 at α if $z \geq z_{\alpha/2}$

However, treatment of 0 is problematic for this test.

- Solution 1: randomly assign 0 to the positive or negative (2 researchers might get different results).
- Solution 2: count each 0 as a contribution 1/2 toward s_+ and s_- (but then could not apply the binomial distribution)
- Solution 3: ignore 0 (reduces the power of test due to decreased sample size).

```
binom.test(sum(lecture.data > 0), length(lecture.data))
#>
#>  Exact binomial test
#>
#> data:  sum(lecture.data > 0) and length(lecture.data)
#> number of successes = 8, number of trials = 10, p-value = 0.1094
#> alternative hypothesis: true probability of success is not equal to 0.5
#> 95 percent confidence interval:
#>  0.4439045 0.9747893
#> sample estimates:
```

```
#> probability of success
#>                    0.8
# alternative = "greater" or alternative = "less"
```

4.1.7.2 Wilcoxon Signed Rank Test

Since the Sign Test could not consider the magnitude of each observation from 0, the Wilcoxon Signed Rank Test improves by taking account the ordered magnitudes of the observation, but it will impose the requirement of symmetric to this test (while Sign Test does not)

$$H_0 : \mu_{0.5} = 0 H_a : \mu_{0.5} > 0$$

(assume no ties or same observations)

The signed rank test procedure:

1. rank order the observation y_i in terms of their absolute values. Let r_i be the rank of y_i in this ordering. Since we assume no ties, the ranks r_i are uniquely determined and are a permutation of the integers $1, 2, ..., n$.

2. Calculate w_+, which is the sum of the ranks of the positive values, and w_-, which is the sum of the ranks of the negative values. Note that $w_+ + w_- = r_1 + r_2 + ... = 1 + 2 + ... + n = n(n+1)/2$

3. Reject H_0 if w_+ is large (or if w_- is small)

To know what is large or small with regard to w_+ and w_-, we need the distribution of W_+ and W_- when the null is true.

Since these null distributions are identical and symmetric, the p-value is $P(W \geq w_+) = P(W \leq w_-)$

An α-level test rejects the null if the p-value is $\leq \alpha$, or if $w_+ \geq w_{n,\alpha}$, where $w_{n,\alpha}$ is the upper α critical point of the null distribution of W.

This distribution of W has a special table. For large n, the distribution of W is approximately normal.

$$z = \frac{w_+ - n(n+1)/4 - 1/2}{\sqrt{n(n+1)(2n+1)/24}}$$

The test rejects H_0 at level α if

$$w_+ \geq n(n+1)/4 + 1/2 + z_\alpha \sqrt{n(n+1)(2n+1)/24} \approx w_{n,\alpha}$$

For the 2-sided test, we use $w_{max} = max(w_+, w_-)$ or $w_{min} = min(w_+, w_-)$, with p-value given by:

$$p - value = 2P(W \geq w_{max}) = 2P(W \leq w_{min})$$

Same as Sign Test,we ignore 0. In some cases where some of the $|y_i|$'s may be tied for the same rank, we simply assign each of the tied ranks the average rank (or "midrank").

Example, if $y_1 = -1$, $y_3 = 3$ and $y_3 = -3$, and $y_4 = 5$, then $r_1 = 1$, $r_2 = r_3 = (2+3)/2 = 2.5$, $r_4 = 4$

```
wilcox.test(lecture.data)
#>
#>  Wilcoxon signed rank exact test
#>
#> data:  lecture.data
#> V = 52, p-value = 0.009766
#> alternative hypothesis: true location is not equal to 0
# does not use normal approximation
# (using the underlying W distribution)

wilcox.test(lecture.data,exact=F)
#>
#>  Wilcoxon signed rank test with continuity correction
#>
#> data:  lecture.data
#> V = 52, p-value = 0.01443
#> alternative hypothesis: true location is not equal to 0
# uses normal approximation
```

4.2 Two Sample Inference

4.2.1 Means

Suppose we have 2 sets of observations,

- $y_1, ..., y_{n_y}$
- $x_1, ..., x_{n_x}$

that are random samples from two independent populations with means μ_y and μ_x and variances σ_y^2,σ_x^2. Our goal is to compare μ_x and μ_y or $\sigma_y^2 = \sigma_x^2$

4.2.1.1 Large Sample Tests

Assume that n_y and n_x are large (≥ 30). Then,

$$E(\bar{y} - \bar{x}) = \mu_y - \mu_x Var(\bar{y} - \bar{x}) = \sigma_y^2/n_y + \sigma_x^2/n_x$$

Then,

$$Z = \frac{\bar{y} - \bar{x} - (\mu_y - \mu_x)}{\sqrt{\sigma_y^2/n_y + \sigma_x^2/n_x}} \sim N(0,1)$$

(according to Central Limit Theorem). For large samples, we can replace variances by their unbiased estimators (s_y^2, s_x^2), and get the same large sample distribution.

An approximate $100(1-\alpha)\%$ CI for $\mu_y - \mu_x$ is given by:

$$\bar{y} - \bar{x} \pm z_{\alpha/2}\sqrt{s_y^2/n_y + s_x^2/n_x}$$

$$H_0 : \mu_y - \mu_x = \delta_0 H_A : \mu_y - \mu_x \neq \delta_0$$

at the α-level with the statistic:

$$z = \frac{\bar{y} - \bar{x} - \delta_0}{\sqrt{s_y^2/n_y + s_x^2/n_x}}$$

and reject H_0 if $|z| > z_{\alpha/2}$

If $\delta =)$, it means that we are testing whether two means are equal.

4.2.1.2 Small Sample Tests

If the two samples are from normal distribution, iid $N(\mu_y, \sigma_y^2)$ and iid $N(\mu_x, \sigma_x^2)$ and the two samples are independent, we can do inference based on the [t-distribution][Student T]

Then we have 2 cases

- Equal Variance
- Unequal Variance

4.2.1.2.1 Equal variance Assumptions

- iid: so that $var(\bar{y}) = \sigma_y^2/n_y; var(\bar{x}) = \sigma_x^2/n_x$

- Independence between samples: No observation from one sample can influence any observation from the other sample, to have

$$\begin{aligned} var(\bar{y} - \bar{x}) &= var(\bar{y}) + var\bar{x} - 2cov(\bar{y}, \bar{x}) \\ &= var(\bar{y}) + var\bar{x} \\ &= \sigma_y^2/n_y + \sigma_x^2/n_x \end{aligned}$$

- Normality: Justifies the use of the [t-distribution][Student T]

Let $\sigma^2 = \sigma_y^2 = \sigma_x^2$. Then, s_y^2 and s_x^2 are both unbiased estimators of σ^2. We then can pool them.

Then the pooled variance estimate is

$$s^2 = \frac{(n_y - 1)s_y^2 + (n_x - 1)s_x^2}{(n_y - 1) + (n_x - 1)}$$

has $n_y + n_x - 2$ df.

Then the test statistic

$$T = \frac{\bar{y} - \bar{x} - (\mu_y - \mu_x)}{s\sqrt{1/n_y + 1/n_x}} \sim t_{n_y+n_x-2}$$

$100(1-\alpha)\%$ CI for $\mu_y - \mu_x$ is

$$\bar{y} - \bar{x} \pm (t_{n_y+n_x-2})s\sqrt{1/n_y + 1/n_x}$$

Hypothesis testing:

$$H_0 : \mu_y - \mu_x = \delta_0 H_1 : \mu_y - \mu_x \neq \delta_0$$

we reject H_0 if $|t| > t_{n_y+n_x-2;\alpha/2}$

4.2.1.2.2 Unequal Variance Assumptions

1. Two samples are independent
    1. Scatter plots
    2. Correlation coefficient (if normal)
2. Independence of observation in each sample
    1. Test for serial correlation
3. For each sample, homogeneity of variance
    1. Scatter plots
    2. Formal tests
4. Normality

5. Equality of variances (homogeneity of variance between samples)

    1. F-test

    2. Barlett test

    3. [Modified Levene Test]

To compare 2 normal $\sigma_y^2 \neq \sigma_x^2$, we use the test statistic:

$$T = \frac{\bar{y} - \bar{x} - (\mu_y - \mu_x)}{\sqrt{s_y^2/n_y + s_x^2/n_x}}$$

In this case, T does not follow the [t-distribution][Student T] (its distribution depends on the ratio of the unknown variances σ_y^2, σ_x^2). In the case of small sizes, we can can approximate tests by using the Welch-Satterthwaite method (Satterthwaite, 1946). We assume T can be approximated by a [t-distribution][Student T], and adjust the degrees of freedom.

Let $w_y = s_y^2/n_y$ and $w_x = s_x^2/n_x$ (the w's are the square of the respective standard errors)
Then, the degrees of freedom are

$$v = \frac{(w_y + w_x)^2}{w_y^2/(n_y - 1) + w_x^2/(n_x - 1)}$$

Since v is usually fractional, we truncate down to the nearest integer.

$100(1-\alpha)\%$ CI for $\mu_y - \mu_x$ is

$$\bar{y} - \bar{x} \pm t_{v,\alpha/2}\sqrt{s_y^2/n_y + s_x^2/n_x}$$

Reject H_0 if $|t| > t_{v,\alpha/2}$, where

$$t = \frac{\bar{y} - \bar{x} - \delta_0}{\sqrt{s_y^2/n_y + s_x^2/n_x}}$$

4.2.2 Variances

$$F_{ndf,ddf} = \frac{s_1^2}{s_2^2}$$

where $s_1^2 > s_2^2, ndf = n_1 - 1, ddf = n_2 - 1$

4.2.2.1 F-test

Test

$$H_0 : \sigma_y^2 = \sigma_x^2 H_a : \sigma_y^2 \neq \sigma_x^2$$

Consider the test statistic,

$$F = \frac{s_y^2}{s_x^2}$$

Reject H_0 if

- $F > f_{n_y-1,n_x-1,\alpha/2}$ or
- $F < f_{n_y-1,n_x-1,1-\alpha/2}$

Where $F > f_{n_y-1,n_x-1,\alpha/2}$ and $F < f_{n_y-1,n_x-1,1-\alpha/2}$ are the upper and lower $\alpha/2$ critical points of an [F-distribution][F-Distribution], with a n_y-1 and n_x-1 degrees of freedom.

Note

- This test depends heavily on the assumption Normality.
- In particular, it could give to many significant results when observations come from long-tailed distributions (i.e., positive kurtosis).
- If we cannot find support for normality, then we can use nonparametric tests such as the Modified Levene Test (Brown-Forsythe Test)

```
data(iris)
irisVe=iris$Petal.Width[iris$Species=="versicolor"]
irisVi=iris$Petal.Width[iris$Species=="virginica"]

var.test(irisVe,irisVi)
#>
#>  F test to compare two variances
#>
#> data:  irisVe and irisVi
#> F = 0.51842, num df = 49, denom df = 49, p-value = 0.02335
#> alternative hypothesis: true ratio of variances is not equal to 1
#> 95 percent confidence interval:
#>  0.2941935 0.9135614
#> sample estimates:
#> ratio of variances
#>          0.5184243
```

4.2.2.2 Modified Levene Test (Brown-Forsythe Test)

- considers averages of absolute deviations rather than squared deviations. Hence, less sensitive to long-tailed distributions.

- This test is still good for normal data

For each sample, we consider the absolute deviation of each observation form the median:

$$d_{y,i} = |y_i - y_{.5}| d_{x,i} = |x_i - x_{.5}|$$

Then,

$$t_L^* = \frac{\bar{d}_y - \bar{d}_x}{s\sqrt{1/n_y + 1/n_x}}$$

The pooled variance s^2 is given by:

$$s^2 = \frac{\sum_i^{n_y}(d_{y,i} - \bar{d}_y)^2 + \sum_j^{n_x}(d_{x,i} - \bar{d}_x)^2}{n_y + n_x - 2}$$

- If the error terms have constant variance and n_y and n_x are not extremely small, then $t_L^* \sim t_{n_x+n_y-2}$

- We reject the null hypothesis when $|t_L^*| > t_{n_y+n_x-2;\alpha/2}$

- This is just the two-sample t-test applied to the absolute deviations.

```
dVe=abs(irisVe-median(irisVe))
dVi=abs(irisVi-median(irisVi))
t.test(dVe,dVi,var.equal=T)
#>
#>  Two Sample t-test
#>
#> data:  dVe and dVi
#> t = -2.5584, df = 98, p-value = 0.01205
#> alternative hypothesis: true difference in means is not equal to 0
#> 95 percent confidence interval:
#>  -0.12784786 -0.01615214
#> sample estimates:
#> mean of x mean of y
#>     0.154     0.226

# small samples t-test
t.test(irisVe,irisVi,var.equal=F)
```

```
#>
#>  Welch Two Sample t-test
#>
#> data:  irisVe and irisVi
#> t = -14.625, df = 89.043, p-value < 2.2e-16
#> alternative hypothesis: true difference in means is not equal to 0
#> 95 percent confidence interval:
#>  -0.7951002 -0.6048998
#> sample estimates:
#> mean of x mean of y
#>     1.326     2.026
```

4.2.3 Power

Consider $\sigma_y^2 = \sigma_x^2 = \sigma^2$
Under the assumption of equal variances, we take size samples from both groups $(n_y = n_x = n)$

For 1-sided testing,

$$H_0 : \mu_y - \mu_x \leq 0 H_a : \mu_y - \mu_x > 0$$

α-level z-test rejects H_0 if

$$z = \frac{\bar{y} - \bar{x}}{\sigma\sqrt{2/n}} > z_\alpha$$

$$\pi(\mu_y - \mu_x) = \Phi(-z_\alpha + \frac{\mu_y - \mu_x}{\sigma}\sqrt{n/2})$$

We need sample size n that give at least $1 - \beta$ power when $\mu_y - \mu_x = \delta$, where δ is the smallest difference that we want to see.

Power is given by:

$$\Phi(-z_\alpha + \frac{\delta}{\sigma}\sqrt{n/2}) = 1 - \beta$$

4.2.4 Sample Size

Then, the sample size is

$$n = 2(\frac{\sigma(z_\alpha + z_\beta}{\delta})^2$$

For 2-sided test, replace z_α with $z_{\alpha/2}$.
As with the one-sample case, to perform an exact 2-sample t-test sample size calculation, we must use a non-central [t-distribution][Student T].

A correction that gives the approximate t-test sample size can be obtained by using the z-test n value in the formula:

$$n^* = 2(\frac{\sigma(t_{2n-2;\alpha} + t_{2n-2;\beta})}{\delta})^2$$

where we use $\alpha/2$ for the two-sided test

4.2.5 Matched Pair Designs

We have two treatments

Subject	Treatment A	Treatment B	Difference
1	y_1	x_1	$d_1 = y_1 - x_1$
2	y_2	x_2	$d_2 = y_2 - x_2$
.	.	.	.
n	y_n	x_n	$d_n = y_n - x_n$

we assume $y_i \sim^{iid} N(\mu_y, \sigma_y^2)$ and $x_i \sim^{iid} N(\mu_x, \sigma_x^2)$, but since y_i and x_i are measured on the same subject, they are correlated.

Let

$$\mu_D = E(y_i - x_i) = \mu_y - \mu_x \sigma_D^2 = var(y_i - x_i) = Var(y_i) + Var(x_i) - 2cov(y_i, x_i)$$

If the matching induces **positive** correlation, then the variance of the difference of the measurements is reduced as compared to the independent case. This is the point of Matched Pair Designs. Although covariance can be negative, giving a larger variance of the difference than the independent sample case, usually the covariance is positive. This means both y_i and x_i are large for many of the same subjects, and for others, both measurement are small. (we still assume that various subjects respond independently of each other, which is necessary for the iid assumption within groups).

Let $d_i = y_i - x_i$, then

- $\bar{d} = \bar{y} - \bar{x}$ is the sample mean of the d_i
- $s_d^2 = \frac{1}{n-1} \sum_{i=1}^n (d_i - \bar{d})^2$ is the sample variance of the difference

Once the data are converted to differences, we are back to One Sample Inference and can use its tests and CIs.

4.2.6 Nonparametric Tests for Two Samples

For Matched Pair Designs, we can use the One-sample Non-parametric Methods.

Assume that Y and X are random variables with CDF F_y and F_x. then, Y is **stochastically** larger than X for all real number u, $P(Y > u) \geq P(X > u)$.

Equivalently, $P(Y \leq u) \leq P(X \leq u)$, which is $F_Y(u) \leq F_X(u)$, same thing as $F_Y < F_X$

If two distributions are identical, except that one is shifted relative to the other, then each of distribution can be indexed by a location parameter, say θ_y and θ_x. In this case, $Y > X$ if $\theta_y > \theta_x$

Consider the hypotheses,

$$H_0 : F_Y = F_X H_a : F_Y < F_X$$

where the alternative is an upper one-sided alternative.

- We can also consider the lower one-sided alternative

$$H_a : F_Y > F_X \text{ or} H_a : F_Y < F_X \text{ or } F_Y > F_X$$

- In this case, we don't use $H_a : F_Y \neq F_X$ as that allows arbitrary differences between the distributions, without requiring one be stochastically larger than the other.

If the distributions only differ in terms of their location parameters, we can focus hypothesis tests on the parameters (e.g., $H_0 : \theta_y = \theta_x$ vs. $\theta_y > \theta_x$)

We have 2 equivalent nonparametric tests that consider the hypothesis mentioned above

1. Wilcoxon rank test

2. Mann-Whitney U test

4.2.6.1 Wilcoxon rank test

1. Combine all $n = n_y + n_x$ observations and rank them in ascending order.

2. Sum the ranks of the y's and x's separately. Let w_y and w_x be these sums. $(w_y + w_x = 1 + 2 + ... + n = n(n+1)/2)$

3. Reject H_0 if w_y is large (equivalently, w_x is small)

Under H_0, any arrangement of the y's and x's is equally likely to occur, and there are $(n_y + n_x)!/(n_y! n_x!)$ possible arrangements.

- Technically, for each arrangement we can compute the values of w_y and w_x, and thus generate the distribution of the statistic under the null hypothesis.

- This could lead to computationally intensive.

```
wilcox.test(
    irisVe,
    irisVi,
    alternative = "two.sided",
    conf.level = 0.95,
    exact = F,
    correct = T
)
#>
#>  Wilcoxon rank sum test with continuity correction
#>
#> data:  irisVe and irisVi
#> W = 49, p-value < 2.2e-16
#> alternative hypothesis: true location shift is not equal to 0
```

4.2.6.2 Mann-Whitney U test

The Mann-Whitney test is computed as follows:

1. Compare each y_i with each x_i.
   Let u_y be the number of pairs in which $y_i > x_i$ Let u_x be the number of pairs in which $y_i < x_i$. (assume there are no ties). There are $n_y n_x$ such comparisons and $u_y + u_x = n_y n_x$.

2. Reject H_0 if u_y is large (or u_x is small)

Mann-Whitney U test and Wilcoxon rank test are related:

$$u_y = w_y - n_y(n_y + 1)/2 u_x = w_x - n_x(n_x + 1)/2$$

An α-level test rejects H_0 if $u_y \geq u_{n_y, n_x, \alpha}$, where $u_{n_y, n_x, \alpha}$ is the upper α critical point of the null distribution of the random variable, U.

The p-value is defined to be $P(Y \geq u_y) = P(U \leq u_x)$. One advantage of Mann-Whitney U test is that we can use either u_y or u_x to carry out the test.

For large n_y and n_x, the null distribution of U can be well approximated by a normal distribution with mean $E(U) = n_y n_x/2$ and variance $var(U) = n_y n_x(n+1)/12$. A large sample z-test can be based on the statistic:

$$z = \frac{u_y - n_y n_x/2 - 1/2}{\sqrt{n_y n_x (n+1)/12}}$$

The test rejects H_0 at level α if $z \geq z_\alpha$ or if $u_y \geq u_{n_y, n_x, \alpha}$ where

$$u_{n_y, n_x, \alpha} \approx n_y n_x/2 + 1/2 + z_\alpha \sqrt{n_y n_x (n+1)/12}$$

For the 2-sided test, we use the test statistic $u_{max} = max(u_y, u_x)$ and $u_{min} = min(u_y, u_x)$ and p-value is given by

$$p - value = 2P(U \geq u_{max}) = 2P(U \leq u_{min})$$

Since we assume there are no ties (when $y_i = x_j$), we count 1/2 towards both u_y and u_x. Even though the sampling distribution is not the same, but large sample approximation is still reasonable,

4.3 Categorical Data Analysis

Categorical Data Analysis when we have categorical outcomes

- Nominal variables: no logical ordering (e.g., sex)
- Ordinal variables: logical order, but relative distances between values are not clear (e.g., small, medium, large)

The distribution of one variable changes when the level (or values) of the other variable change. The row percentages are different in each column.

4.3.1 Inferences for Small Samples

The approximate tests based on the asymptotic normality of $\hat{p}_1 - \hat{p}_2$ do not apply for small samples.

Using **Fisher's Exact Test** to evaluate $H_0 : p_1 = p_2$

- Assume X_1 and X_2 are independent Binomial
- Let x_1 and x_2 be the corresponding observed values.
- Let $n = n_1 + n_2$ be the total sample size
- $m = x_1 + x_2$ be the observed number of successes.
- By assuming that m (total successes) is fixed, and conditioning on this value, one can show that the conditional distribution of the number of successes from sample 1 is [Hypergeometric]

- If we want to test $H_0 : p_1 = p_2$ and $H_a : p_1 \neq p_2$, we have

$$Z^2 = (\frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}(1-\hat{p})(1/n_1 + 1/n_2)}})^2 \sim \chi^2_{1,\alpha}$$

where $\chi^2_{1,\alpha}$ is the upper α percentage point for the central [Chi-squared] with one d.f.

This extends to the contingency table setting: whether the observed frequencies are equal to those expected under a null hypothesis of no association.

4.3.2 Test of Association

Pearson Chi-square test statistic is

$$\chi^2 = \sum_{\text{all categories}} \frac{(observed - epxected)^2}{expected}$$

Comparison of proportions for several independent surveys or experiments

	Experiment 1	Experiment 2	...	Experiment k
Number of successes	x_1	x_2	...	x_k
Number of failures	$n_1 - x_1$	$n_2 - x_2$	...	$n_k - x_k$
	n_1	n_2	...	n_k

$H_0 : p_1 = p_2 = \cdots = p_k$ vs. the alternative that the null is not true (at least one pair are not equal).

We estimate the common value of the probability of success on a single trial assuming H_0 is true:

$$\hat{p} = \frac{x_1 + x_2 + ... + x_k}{n_1 + n_2 + ... + n_k}$$

we use table of expected counts when H_0 is true:

success	$n_1\hat{p}$	$n_2\hat{p}$	...	$n_k\hat{p}$
failure	$n_1(1-\hat{p})$	$n_2(1-\hat{p})$	...	$n_k(1-\hat{p})$
	n_1	n_2	...	n_k

$$\chi^2 = \sum_{\text{all cells in table}} \frac{(observed - expected)^2}{expected}$$

with $k - 1$ degrees of freedom

4.3.2.1 Two-way Count Data

	1	2	...	j	...	c	Row Total
1	n_{11}	n_{12}	...	n_{1j}	...	n_{1c}	$n_{1.}$
2	n_{21}	n_{22}	...	n_{2j}	...	n_{2c}	$n_{2.}$
.	.	.	.	.	.	.	.
r	n_{r1}	n_{r2}	...	n_{rj}	...	n_{rc}	$n_{r.}$
Column Total	$n_{.1}$	$n_{.2}$	...	$n_{.j}$	...	$n_{.c}$	n

Design 1
total sample size fixed $n =$ constant (e.g., survey on job satisfaction and income); both row and column totals are random variables

Design 2
Fix the sample size in each group (in each row) (e.g., Drug treatments success or failure); fixed number of participants for each treatment; independent random samples from the two row populations.

These different sampling designs imply two different probability models.

4.3.2.2 Total Sample Size Fixed

Design 1

random sample of size n drawn from a single population, and sample units are cross-classified into r row categories and c column

This results in an $r \times c$ table of observed counts

$n_{ij} = 1, ..., r; j = 1, ..., c$

Let p_{ij} be the probability of classification into cell (i, j) and $\sum_{i=1}^{r} \sum_{j=1}^{c} p_{ij} = 1$.
Let N_{ij} be the random variable corresponding to n_{ij}
The joint distribution of the N_{ij} is multinomial with unknown parameters p_{ij}

Denote the row variable by X and column variable by Y, then $p_{ij} = P(X = i, Y = j)$ and $p_{i.} = P(X = i)$ and $p_{.j} = P(Y = j)$ are the marginal probabilities.

The null hypothesis that X and Y are statistically independent (i.e., no association) is just:

$$H_0 : p_{ij} = P(X = i, Y = j) = P(X = i)P(Y = j) = p_{i.}p_{.j} H_a : p_{ij} \neq p_{i.}p_{.j}$$

for all i, j.

4.3.2.3 Row Total Fixed

Design 2

Random samples of sizes $n_1, ..., n_r$ are drawn independently from $r \geq 2$ row populations. In this case, the 2-way table row totals are $n_{i.} = n_i$ for $i = 1, ..., r$.

The counts from each row are modeled by independent multinomial distributions.

X is fixed, Y is observed.

Then, p_{ij} represent conditional probabilities $p_{ij} = P(Y = j|X = i)$

The null hypothesis is the probability of response j is the same, regardless of the row population (i.e., no association):

$$\begin{cases} H_0 : p_{ij} = P(Y = j|X = i) = p_j & \text{for all } i, j = 1, 2, ..., c \\ \text{or } H_0 : (p_{i1}, p_{i2}, ..., p_{ic}) = (p_1, p_2, ..., p_c) & \text{for all } i \\ H_a : (p_{i1}, p_{i2}, ..., p_{ic}) & \text{are not the same for all } i \end{cases}$$

Although the hypotheses to be tested are different for two sampling designs, **The χ^2 test is identical**

We have estimated expected frequencies:

$$\hat{e}_{ij} = \frac{n_{i.} n_{.j}}{n}$$

The Chi-square statistic is

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(n_{ij} - \hat{e}_{ij})^2}{\hat{e}_{ij}} \sim \chi_{(r-1)(c-1)}$$

α-level test rejects H_0 if $\chi^2 > \chi^2_{(r-1)(c-1),\alpha}$

4.3.2.4 Pearson Chi-square Test

- Determine whether an association exists
- Sometimes, H_0 represents the model whose validity is to be tested. Contrast this with the conventional formulation of H_0 as the hypothesis that is to be disproved. The goal in this case is not to disprove the model, but to see whether data are consistent with the model and if deviation can be attributed to chance.
- These tests do not measure the strength of an association.

- These tests depend on and reflect the sample size - double the sample size by copying each observation, double the χ^2 statistic even thought the strength of the association does not change.

- The Pearson Chi-square Test is not appropriate when more than about 20% of the cells have an expected cell frequency of less than 5 (large-sample p-values not appropriate).

- When the sample size is small the exact p-values can be calculated (this is prohibitive for large samples); calculation of the exact p-values assumes that the column totals and row totals are fixed.

```
july.x=480
july.n=1000
sept.x=704
sept.n=1600
```

$$H_0 : p_J = 0.5 H_a : p_J < 0.5$$

```
prop.test(
    x = july.x,
    n = july.n,
    p = 0.5,
    alternative = "less",
    correct = F
)
#>
#>  1-sample proportions test without continuity correction
#>
#> data:  july.x out of july.n, null probability 0.5
#> X-squared = 1.6, df = 1, p-value = 0.103
#> alternative hypothesis: true p is less than 0.5
#> 95 percent confidence interval:
#>  0.0000000 0.5060055
#> sample estimates:
#>    p
#> 0.48
```

$$H_0 : p_J = p_S H_a : p_j \neq p_S$$

```
prop.test(
    x = c(july.x, sept.x),
    n = c(july.n, sept.n),
    correct = F
)
```

```
#>
#>  2-sample test for equality of proportions without continuity correction
#>
#> data:  c(july.x, sept.x) out of c(july.n, sept.n)
#> X-squared = 3.9701, df = 1, p-value = 0.04632
#> alternative hypothesis: two.sided
#> 95 percent confidence interval:
#>  0.0006247187 0.0793752813
#> sample estimates:
#> prop 1 prop 2
#>   0.48   0.44
```

4.3.3 Ordinal Association

- An ordinal association implies that as one variable increases, the other tends to increase or decrease (depending on the nature of the association).

- For tests for variables with two or more levels, the levels must be in a logical ordering.

4.3.3.1 Mantel-Haenszel Chi-square Test

The Mantel-Haenszel Chi-square Test is more powerful for testing ordinal associations, but does not test for the strength of the association.

This test is presented in the case where one has a series of 2×2 tables that examine the same effects under different conditions (If there are K such tables, we have $2 \times 2 \times K$ table)

In stratum k, given the marginal totals $(n_{.1k}, n_{.2k}, n_{1.k}, n_{2.k})$, the sampling model for cell counts is the [Hypergeometric] (knowing n_{11k} determines $(n_{12k}, n_{21k}, n_{22k})$, given the marginal totals)

Assuming conditional independence, the [Hypergeometric] mean and variance of n_{11k} are

$$m_{11k} = E(n_{11k}) = \frac{n_{1.k} n_{.1k}}{n_{..k}} var(n_{11k}) = \frac{n_{1.k} n_{2.k} n_{.1k} n_{.2k}}{n_{..k}^2 (n_{..k} - 1)}$$

To test conditional independence, Mantel and Haenszel proposed

$$M^2 = \frac{(|\sum_k n_{11k} - \sum_k m_{11k}| - .5)^2}{\sum_k var(n_{11k})} \sim \chi_1^2$$

This method can be extended to general $I \times J \times K$ tables.

$(2 \times 2 \times 3)$ table

```r
Bron = array(
    c(20, 9, 382, 214, 10, 7, 172, 120, 12, 6, 327, 183),
    dim = c(2, 2, 3),
    dimnames = list(
        Particulate = c("High", "Low"),
        Bronchitis = c("Yes", "No"),
        Age = c("15-24", "25-39", "40+")
    )
)
margin.table(Bron, c(1, 2))
#>            Bronchitis
#> Particulate Yes  No
#>        High  42 881
#>        Low   22 517
# assess whether the relationship between
# Bronchitis by Particulate Level varies by Age
library(samplesizeCMH)
marginal_table = margin.table(Bron, c(1, 2))
odds.ratio(marginal_table)
#> [1] 1.120318

#  whether these odds vary by age.
# The conditional odds can be calculated using the original table.
apply(Bron, 3, odds.ratio)
#>     15-24     25-39       40+
#> 1.2449098 0.9966777 1.1192661

# Mantel-Haenszel Test
mantelhaen.test(Bron, correct = T)
#>
#>  Mantel-Haenszel chi-squared test with continuity correction
#>
#> data:  Bron
#> Mantel-Haenszel X-squared = 0.11442, df = 1, p-value = 0.7352
#> alternative hypothesis: true common odds ratio is not equal to 1
#> 95 percent confidence interval:
#>  0.6693022 1.9265813
#> sample estimates:
#> common odds ratio
#>          1.135546
```

4.3.3.1.1 McNemar's Test special case of Mantel-Haenszel Chi-square Test

```r
vote = cbind(c(682, 22), c(86, 810))
mcnemar.test(vote, correct = T)
#>
#>  McNemar's Chi-squared test with continuity correction
#>
#> data:  vote
#> McNemar's chi-squared = 36.75, df = 1, p-value = 1.343e-09
```

4.3.3.2 Spearman Rank Correlation

To test for the strength of association between two ordinally scaled variables, we can use Spearman Rank Correlation statistic

Let X and Y be two random variables measured on an ordinal scale. Consider n pairs of observations (x_i, y_i), $i = 1, \dots, n$

The Spearman Rank Correlation coefficient (denoted by r_S is calculated using the Pearson correlation formula, but based on the ranks of x_i and y_i).

Spearman Rank Correlation be calculated

1. Assign ranks to x_i's and y_i's separately. Let $u_i = rank(x_i)$ and $v_i = rank(y_i)$

2. Calculate r_S using the formula for the Pearson correlation coefficient, but applied to the ranks:

$$r_S = \frac{\sum_{i=1}^{n}(u_i - \bar{u})(v_i - \bar{v})}{\sqrt{(\sum_{i=1}^{n}(u_i - \bar{u})^2)(\sum_{i=1}^{n}(v_i - \bar{v})^2)}}$$

r_S ranges between -1 and +1 , with

- $r_S = -1$ if there is a perfect negative monotone association
- $r_S = +1$ if there is a perfect positive monotone association between X and Y.

To test

- H_0 : X and Y independent
- H_a: X and Y positively associated

For large n (e.g., $n \geq 10$),

$$r_S \sim N(0, 1/(n-1))$$

Then,

$$Z = r_s\sqrt{n-1} \sim N(0,1)$$

4.4 Divergence Metrics and Test for Comparing Distributions

Similarity among distributions using divergence statistics, which is different from

- Deviation statistics: difference between the realization of a variable and some value (e.g., mean). Statistics of the deviation distributions consist of standard deviation, average absolute deviation, median absolute deviation , maximum absolute deviation.
- Deviance statistics: goodness-of-fit statistic for statistical models (comparable to the sum of squares of residuals in OLS to cases that use ML estimation). Usually used in generalized linear models.

Divergence statistics is a statistical distance (different from metrics)

- Divergences do not require symmetry
- Divergences generalize squared distance (instead of linear distance). Hence, fail the triangle inequity

Can be used for

- Detecting data drift in machine learning
- Feature selections
- Variational Auto Encoder
- Detect similarity between policies (i.e., distributions) in reinforcement learning
- To see consistency in two measured variables of two constructs.

Techniques

- Kullback-Leibler Divergence
- Jensen-Shannon Divergence
- Kolmogorov-Smirnov Test

Packages

- `entropy`
- `philentropy`

4.4.1 Kullback-Leibler Divergence

- Also known as relative entropy
- Not a metric (does not satisfy the triangle inequality)
- Can be generalized to the multivariate case
- Measure the similarity between two discrete probability distributions
  - P = true data distribution
  - Q = predicted data distribution
- It quantifies info loss when moving from P to Q (i.e., information loss when P is approximated by Q)

Discrete

$$D_{KL}(P||Q) = \sum_i P_i \log(\frac{P_i}{Q_i})$$

Continuous

$$D_{KL}(P||Q) = \int P(x) \log(\frac{P(x)}{Q(x)})dx$$

where

- $K \in [0, \infty)$ from similar to diverge
- Non-symmetric between two distributions: $D_{KL}(P|Q) \neq D_{KL}(Q|P)$

```
library(philentropy)
# philentropy::dist.diversity(rbind(X = 1:10 / sum(1:10),
#                                   Y = 1:20 / sum(1:20)),
#                               p = 2,
#                               unit = "log2")


# continuous
KL(rbind(X = 1:10 / sum(1:10), Y = 1:10 / sum(1:10)), unit = "log2")
#> kullback-leibler
#>                0

# discrete
KL(rbind(X = 1:10, Y = 1:10), est.prob = "empirical")
#> kullback-leibler
#>                0
```

4.4.2 Jensen-Shannon Divergence

- Also known as info radius or total divergence to the average

$$D_{JS}(P||Q) = \frac{1}{2}(D_{KL}(P||M) + D_{KL}(Q||M))$$

where

- $M = \frac{1}{2}(P + Q)$ is a mixed distribution
- $D_{JS} \in [0, 1]$ for $\log_2$ and $D_{JS} \in [0, \ln(2)]$ for $\log_e$

```
library(philentropy)
# continous
JSD(rbind(X = 1:10, Y = 1:20), unit = "log2")
#> jensen-shannon
#>       20.03201

# discrete
JSD(rbind(X = 1:10, Y = 1:20), est.prob = "empirical")
#> jensen-shannon
#>     0.06004756
```

4.4.3 Wasserstein Distance

- measure the distance between two empirical CDFs

$$W = \int_{x \in R} |E(x) - F(X)|^p$$

- This is also a test statistics

```
set.seed(1)
transport::wasserstein1d(rnorm(100), rnorm(100, mean = 1))
#> [1] 0.8533046

set.seed(1)
# Wasserstein metric
twosamples::wass_stat(rnorm(100), rnorm(100, mean = 1))
#> [1] 0.8533046

set.seed(1)
# permutation-based tw sample test using Wasserstein metric
twosamples::wass_test(rnorm(100), rnorm(100, mean = 1))
#> Test Stat   P-Value
#> 0.8533046 0.0002500
```

4.4.4 Kolmogorov-Smirnov Test

- Can be used for continuous distribution

H_0: Empirical distribution follows a specified distribution

H_1: Empirical distribution does not follow a specified distribution

- Using non-parametric

$$D = \max |P(X) - Q(X)|$$

- $D \in [0, 1]$ from the densities are evenly distributed to not evenly distributed

```
library(entropy)
library(tidyverse)

lst = list(sample_1 = c(1:20), sample_2 = c(2:30), sample_3 = c(3:30))

expand.grid(1:length(lst), 1:length(lst)) %>%
    rowwise() %>%
    mutate(KL = KL.empirical(lst[[Var1]], lst[[Var2]]))
#> # A tibble: 9 x 3
#> # Rowwise:
#>    Var1  Var2     KL
#>   <int> <int>  <dbl>
#> 1     1     1 0
#> 2     2     1 0.150
#> 3     3     1 0.183
#> 4     1     2 0.704
#> 5     2     2 0
#> 6     3     2 0.0679
#> 7     1     3 0.622
#> 8     2     3 0.0870
#> 9     3     3 0
```

To use the test for discrete date, use bootstrap version of the KS test (bypass the continuity requirement)

```
Matching::ks.boot(Tr = c(0:10), Co = c(0:10))
#> $ks.boot.pvalue
#> [1] 1
#>
#> $ks
#>
#>  Exact two-sample Kolmogorov-Smirnov test
#>
#> data:  Tr and Co
```

```
#> D = 0, p-value = 1
#> alternative hypothesis: two-sided
#>
#>
#> $nboots
#> [1] 1000
#>
#> attr(,"class")
#> [1] "ks.boot"
```

II. REGRESSION

Chapter 5

Linear Regression

- Estimating parameters -> parametric (finite parameters)
- Estimating functions -> non-parametric

Estimator Desirable Properties

1. **Unbiased**
2. **Consistency**

- $plim\hat{\beta}_n = \beta$
- based on the law of large numbers, we can derive consistency
- More observations means more precise, closer to the true value.

3. **Efficiency**

- Minimum variance in comparison to another estimator.
  - OLS is BLUE (best linear unbiased estimator) means that OLS is the most efficient among the class of linear unbiased estimator Gauss-Markov Theorem
  - If we have correct distributional assumptions, then the Maximum Likelihood is asymptotically efficient among consistent estimators.

5.1 Ordinary Least Squares

The most fundamental model in statistics or econometric is a OLS linear regression. OLS = Maximum likelihood when the error term is assumed to be normally distributed.

Regression is still great if the underlying CEF (conditional expectation function) is not linear. Because regression has the following properties:

1. For $E[Y_i|X_{1i}, \dots, X_{Ki}] = a + \sum_{k=1}^{K} b_k X_{ki}$ (i.e., the CEF of Y_i on $X_{1i}, \dots, X_{Ki}$ is linear, then the regression of Y_i on $X_{1i}, \dots, X_{Ki}$ is the CEF
2. For $E[Y_i|X_{1i}, \dots, X_{Ki}]$ is a nonlinear function of the conditioning variables, the regression of Y_i on $X_{1i}, \dots, X_{Ki}$ will give you the best linear approximation to the nonlinear CEF (i.e., minimize the expected squared deviation between the fitted values from the linear model and the CEF).

5.1.1 Simple Regression (Basic Model)

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

- Y_i: response (dependent) variable at i-th observation
- β_0, β_1: regression parameters for intercept and slope.
- X_i: known constant (independent or predictor variable) for i-th observation
- ϵ_i: random error term

$$\begin{aligned} E(\epsilon_i) &= 0 \\ var(\epsilon_i) &= \sigma^2 \\ cov(\epsilon_i, \epsilon_j) &= 0 \text{ for all } i \neq j \end{aligned}$$

Y_i is random since ϵ_i is:

$$\begin{aligned} E(Y_i) &= E(\beta_0 + \beta_1 X_i + \epsilon_i) \\ &= E(\beta_0) + E(\beta_1 X_i) + E(\epsilon) \\ &= \beta_0 + \beta_1 X_i \end{aligned}$$

$$\begin{aligned} var(Y_i) &= var(\beta_0 + \beta_1 X_i + \epsilon_i) \\ &= var(\epsilon_i) \\ &= \sigma^2 \end{aligned}$$

Since $cov(\epsilon_i, \epsilon_j) = 0$ (uncorrelated), the outcome in any one trail has no effect on the outcome of any other. Hence, Y_i, Y_j are uncorrelated as well (conditioned on the X's)

Note
Least Squares does not require a distributional assumption

Relationship between bivariate regression and covariance

Covariance between 2 variables:

$$C(X_i, Y_i) = E[(X_i - E[X_i])(Y_i - E[Y_i])]$$

Which has the following properties

1. $C(X_i, X_i) = \sigma_X^2$
2. If either $E(X_i) = 0 | E(Y_i) = 0$, then $Cov(X_i, Y_i) = E[X_i Y_i]$
3. Given $W_i = a + bX_i$ and $Z_i = c + dY_i$, then $Cov(W_i, Z_i) = bdC(X_i, Y_i)$

For the bivariate regression, the slope is

$$\beta = \frac{Cov(Y_i, X_i)}{Var(X_i)}$$

To extend this to a multivariate case

$$\beta_k = \frac{C(Y_i, \tilde{X}_{ki})}{Var(\tilde{X}_{ki})}$$

Where $\tilde{X}_{ki}$ is the residual from a regression of X_{ki} on the $K-1$ other covariates included in the model

And intercept

$$\alpha = E[Y_i] - \beta E(X_i)$$

5.1.1.1 Estimation

Deviation of Y_i from its expected value:

$$Y_i - E(Y_i) = Y_i - (\beta_0 + \beta_1 X_i)$$

Consider the sum of the square of such deviations:

$$Q = \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_i)^2$$

$$b_1 = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n} (X_i - \bar{X})^2}$$

$$b_0 = \frac{1}{n}(\sum_{i=1}^{n} Y_i - b_1 \sum_{i=1}^{n} X_i) = \bar{Y} - b_1 \bar{X}$$

5.1.1.2 Properties of Least Least Estimators

$$
\begin{aligned}
E(b_1) &= \beta_1 \\
E(b_0) &= E(\bar{Y}) - \bar{X}\beta_1 \\
E(\bar{Y}) &= \beta_0 + \beta_1\bar{X} \\
E(b_0) &= \beta_0 \\
var(b_1) &= \frac{\sigma^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \\
var(b_0) &= \sigma^2(\frac{1}{n} + \frac{\bar{X}^2}{\sum(X_i - \bar{X})^2})
\end{aligned}
$$

$var(b_1) \to 0$ as more measurements are taken at more X_i values (unless X_i is at its mean value)
$var(b_0) \to 0$ as n increases when the X_i values are judiciously selected.

Mean Square Error

$$MSE = \frac{SSE}{n-2} = \frac{\sum_{i=1}^{n} e_i^2}{n-2} = \frac{\sum(Y_i - \hat{Y}_i)^2}{n-2}$$

Unbiased estimator of MSE:

$$E(MSE) = \sigma^2$$

$$
\begin{aligned}
s^2(b_1) = \widehat{var(b_1)} &= \frac{MSE}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \\
s^2(b_0) = \widehat{var(b_0)} &= MSE(\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2})
\end{aligned}
$$

$$
\begin{aligned}
E(s^2(b_1)) &= var(b_1) \\
E(s^2(b_0)) &= var(b_0)
\end{aligned}
$$

5.1.1.3 Residuals

$$e_i = Y_i - \hat{Y} = Y_i - (b_0 + b_1 X_i)$$

- e_i is an estimate of $\epsilon_i = Y_i - E(Y_i)$
- ϵ_i is always unknown since we don't know the true β_0, β_1

$$\sum_{i=1}^{n} e_i = 0$$

$$\sum_{i=1}^{n} X_i e_i = 0$$

Residual properties

1. $E[e_i] = 0$
2. $E[X_i e_i] = 0$ and $E[\hat{Y}_i e_i] = 0$

5.1.1.4 Inference

Normality Assumption

- Least Squares estimation does not require assumptions of normality.
- However, to do inference on the parameters, we need distributional assumptions.
- Inference on β_0, β_1 and Y_h are not extremely sensitive to moderate departures from normality, especially if the sample size is large.
- Inference on Y_{pred} is very sensitive to the normality assumptions.

Normal Error Regression Model

$$Y_i \sim N(\beta_0 + \beta_1 X_i, \sigma^2)$$

5.1.1.4.1 β_1 Under the normal error model,

$$b_1 \sim N(\beta_1, \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2})$$

A linear combination of independent normal random variable is normally distributed

Hence,

$$\frac{b_1 - \beta_1}{s(b_1)} \sim t_{n-2}$$

A $(1-\alpha)100\%$ confidence interval for β_1 is

$$b_1 \pm t_{t-\alpha/2;n-2} s(b_1)$$

5.1.1.4.2 β_0 Under the normal error model, the sampling distribution for b_0 is

$$b_0 \sim N(\beta_0, \sigma^2(\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^n (X_i - \bar{X})^2}))$$

Hence,

$$\frac{b_0 - \beta_0}{s(b_0)} \sim t_{n-2}$$

A $(1-\alpha)100\%$ confidence interval for β_0 is

$$b_0 \pm t_{1-\alpha/2;n-2} s(b_0)$$

5.1.1.4.3 Mean Response Let X_h denote the level of X for which we wish to estimate the mean response

- We denote the mean response when $X = X_h$ by $E(Y_h)$
- A point estimator of $E(Y_h)$ is $\hat{Y}_h$:

$$\hat{Y}_h = b_0 + b_1 X_h$$

Note

$$\begin{aligned} E(\bar{Y}_h) &= E(b_0 + b_1 X_h) \\ &= \beta_0 + \beta_1 X_h \\ &= E(Y_h) \end{aligned}$$

(unbiased estimator)

$$\begin{aligned} var(\hat{Y}_h) &= var(b_0 + b_1 X_h) \\ &= var(\hat{Y} + b_1(X_h - \bar{X})) \\ &= var(\bar{Y}) + (X_h - \bar{X})^2 var(b_1) + 2(X_h - \bar{X}) cov(\bar{Y}, b_1) \\ &= \frac{\sigma^2}{n} + (X_h - \bar{X})^2 \frac{\sigma^2}{\sum (X_i - \bar{X})^2} \\ &= \sigma^2 (\frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}) \end{aligned}$$

Since $cov(\bar{Y}, b_1) = 0$ due to the iid assumption on ϵ_i

An estimate of this variance is

$$s^2(\hat{Y}_h) = MSE(\frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2})$$

the sampling distribution for the mean response is

$$\hat{Y}_h \sim N(E(Y_h), var(\hat{Y}_h))$$
$$\frac{\hat{Y}_h - E(Y_h)}{s(\hat{Y}_h)} \sim t_{n-2}$$

A $100(1-\alpha)\%$ CI for $E(Y_h)$ is

$$\hat{Y}_h \pm t_{1-\alpha/2;n-2} s(\hat{Y}_h)$$

5.1.1.4.4 Prediction of a new observation Regarding the Mean Response, we are interested in estimating **mean** of the distribution of Y given a certain X.

Now, we want to **predict** an individual outcome for the distribution of Y at a given X. We call Y_{pred}

Estimation of mean response versus prediction of a new observation:

- the point estimates are the same in both cases: $\hat{Y}_{pred} = \hat{Y}_h$
- It is the variance of the prediction that is different; hence, prediction intervals are different than confidence intervals. The prediction variance must consider:
  - Variation in the mean of the distribution of Y
  - Variation within the distribution of Y

We want to predict: mean response + error

$$\beta_0 + \beta_1 X_h + \epsilon$$

Since $E(\epsilon) = 0$, use the least squares predictor:

$$\hat{Y}_h = b_0 + b_1 X_h$$

The variance of the predictor is

$$\begin{aligned} var(b_0 + b_1 X_h + \epsilon) &= var(b_0 + b_1 X_h) + var(\epsilon) \\ &= \sigma^2(\frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}) + \sigma^2 \\ &= \sigma^2(1 + \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}) \end{aligned}$$

An estimate of the variance is given by

$$s^2(pred) = MSE(1 + \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2})$$

and

$$\frac{Y_{pred} - \hat{Y}_h}{s(pred)} \sim t_{n-2}$$

$100(1-\alpha)\%$ prediction interval is

$$\bar{Y}_h \pm t_{1-\alpha/2;n-2} s(pred)$$

The prediction interval is very sensitive to the distributional assumption on the errors, ϵ

5.1.1.4.5 Confidence Band We want to know the confidence interval for the entire regression line, so we can draw conclusions about any and all mean response fo the entire regression line $E(Y) = \beta_0 + \beta_1 X$ rather than for a given response Y

Working-Hotelling Confidence Band

For a given X_h, this band is

$$\hat{Y}_h \pm W s(\hat{Y}_h)$$

where $W^2 = 2F_{1-\alpha;2,n-2}$, which is just 2 times the F-stat with 2 and $n-2$ degrees of freedom

- the interval width will change with each X_h (since $s(\hat{Y}_h)$ changes)
- the boundary values for this confidence band will always define a hyperbole containing the regression line
- will be smallest at $X = \bar{X}$

5.1.1.5 ANOVA

Partitioning the Total Sum of Squares: Consider the corrected Total sum of squares:

$$SSTO = \sum_{i=1}^{n}(Y_i - \bar{Y})^2$$

Measures the overall dispersion in the response variable
We use the term corrected because we correct for mean, the uncorrected total sum of squares is given by $\sum Y_i^2$

use $\hat{Y}_i = b_0 + b_1 X_i$ to estimate the conditional mean for Y at X_i

$$\begin{aligned}
\sum_{i=1}^{n}(Y_i - \bar{Y})^2 &= \sum_{i=1}^{n}(Y_i - \hat{Y}_i + \hat{Y}_i - \bar{Y})^2 \\
&= \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 + \sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2 + 2\sum_{i=1}^{n}(Y_i - \hat{Y}_i)(\hat{Y}_i - \bar{Y}) \\
&= \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 + \sum_{i=1}^{n}(\bar{Y}_i - \bar{Y})^2 \\
STTO &= SSE + SSR
\end{aligned}$$

where SSR is the regression sum of squares, which measures how the conditional mean varies about a central value.

The cross-product term in the decomposition is 0:

$$\begin{aligned}
\sum_{i=1}^{n}(Y_i - \hat{Y}_i)(\hat{Y}_i - \bar{Y}) &= \sum_{i=1}^{n}(Y_i - \bar{Y} - b_1(X_i - \bar{X}))(\bar{Y} + b_1(X_i - \bar{X}) - \bar{Y}) \\
&= b_1 \sum_{i=1}^{n}(Y_i - \bar{Y})(X_i - \bar{X}) - b_1^2 \sum_{i=1}^{n}(X_i - \bar{X})^2 \\
&= b_1 \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \sum_{i=1}^{n}(X_i - \bar{X})^2 - b_1^2 \sum_{i=1}^{n}(X_i - \bar{X})^2 \\
&= b_1^2 \sum_{i=1}^{n}(X_i - \bar{X})^2 - b_1^2 \sum_{i=1}^{n}(X_i - \bar{X})^2 \\
&= 0
\end{aligned}$$

and

$$\begin{aligned}
SSTO &= SSR + SSE \\
(n - 1d.f) &= (1d.f.) + (n - 2d.f.)
\end{aligned}$$

Source of Variation	Sum of Squares	df	Mean Square	F
Regression (model)	SSR	1	MSR = SSR/df	MSR/MSE

Source of Variation	Sum of Squares	df	Mean Square	F
Error	SSE	$n-2$	MSE = SSE/df	
Total (Corrected)	SSTO	$n-1$		

$$E(MSE) = \sigma^2$$
$$E(MSR) = \sigma^2 + \beta_1^2 \sum_{i=1}^{n} (X_i - \bar{X})^2$$

- If $\beta_1 = 0$, then these two expected values are the same
- if $\beta_1 \neq 0$ then E(MSR) will be larger than E(MSE)

which means the ratio of these two quantities, we can infer something about β_1

Distribution theory tells us that if $\epsilon_i \sim iidN(0, \sigma^2)$ and assuming $H_0 : \beta_1 = 0$ is true,

$$\frac{MSE}{\sigma^2} \sim \chi^2_{n-2}$$
$$\frac{MSR}{\sigma^2} \sim \chi^2_1 \text{ if } \beta_1 = 0$$

where these two chi-square random variables are independent.

Since the ratio of 2 independent chi-square random variable follows an F distribution, we consider:

$$F = \frac{MSR}{MSE} \sim F_{1,n-2}$$

when $\beta_1 = 0$. Thus, we reject $H_0 : \beta_1 = 0$ (or $E(Y_i) =$ constant) at α if

$$F > F_{1-\alpha;1,n-2}$$

this is the only null hypothesis that can be tested with this approach.

Coefficient of Determination

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

where $0 \leq R^2 \leq 1$

Interpretation: The proportionate reduction of the total variation in Y after fitting a linear model in X.

It is not really correct to say that R^2 is the "variation in Y explained by X".

R^2 is related to the correlation coefficient between Y and X:

$$R^2 = (r)^2$$

where $r = corr(x, y)$ is an estimate of the Pearson correlation coefficient. Also, note

$$\begin{aligned} b_1 &= (\frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{\sum_{i=1}^n (X_i - \bar{X})^2})^{1/2} \\ r &= \frac{s_y}{s_x} r \end{aligned}$$

Lack of Fit

$Y_{11}, Y_{21}, \ldots, Y_{n_1,1}$: n_1 repeat obs at X_1

$Y_{1c}, Y_{2c}, \ldots, Y_{n_c,c}$: n_c repeat obs at X_c

So, there are c distinct X values.

Let $\bar{Y}_j$ be the mean over replicates for X_j

Partition the Error Sum of Squares:

$$\begin{aligned} \sum_i \sum_j (Y_{ij} - \hat{Y}_{ij})^2 &= \sum_i \sum_j (Y_{ij} - \bar{Y}_j + \bar{Y}_j + \hat{Y}_{ij})^2 \\ &= \sum_i \sum_j (Y_{ij} - \bar{Y}_j)^2 + \sum_i \sum_j (\bar{Y}_j - \hat{Y}_{ij})^2 + \text{cross product term} \\ &= \sum_i \sum_j (Y_{ij} - \bar{Y}_j)^2 + \sum_j n_j (\bar{Y}_j - \hat{Y}_{ij})^2 \\ SSE &= SSPE + SSLF \end{aligned}$$

- SSPE: "pure error sum of squares" has $n - c$ degrees of freedom since we need to estimate c means
- SSLF: "lack of fit sum of squares" has $c-2$ degrees of freedom (the number of unique X values - number of parameters used to specify the conditional mean regression model)

$$MSPE = \frac{SSPE}{df_{pe}} = \frac{SSPE}{n-c}$$
$$MSLF = \frac{SSLF}{df_{lf}} = \frac{SSLF}{c-2}$$

The **F-test for Lack-of-Fit** tests

$$H_0 : Y_{ij} = \beta_0 + \beta_1 X_i + \epsilon_{ij}, \epsilon_{ij} \sim iidN(0, \sigma^2)$$
$$H_a : Y_{ij} = \alpha_0 + \alpha_1 X_i + f(X_i, Z_1, ...) + \epsilon^*_{ij}, \epsilon^*_{ij} \sim iidN(0, \sigma^2)$$

$E(MSPE) = \sigma^2$ under either H_0, H_a

$E(MSLF) = \sigma^2 + \frac{\sum n_j (f(X_i, ...))^2}{n-2}$ in general and

$E(MSLF) = \sigma^2$ when H_0 is true

We reject H_0 (i.e., the model $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$ is not adequate) if

$$F = \frac{MSLF}{MSPE} > F_{1-\alpha;c-2,n-c}$$

Failing to reject H_0 does not imply that $H_0 : Y_{ij} = \beta_0 + \beta_1 X_i + \epsilon_{ij}$ is exactly true, but it suggests that this model may provide a reasonable approximation to the true model.

Source of Variation	Sum of Squares	df	Mean Square	F
Regression	SSR	1	MSR	MSR / MSE
Error	SSE	$n-2$	MSE	
Lack of fit	SSLF	$c-2$	MSLF	MSLF / MSPE
Pure Error	SSPE	$n-c$	MSPE	
Total (Corrected)	SSTO	$n-1$		

Repeat observations have an effect on R^2:

- It is impossible for R^2 to attain 1 when repeat obs. exist (SSE can't be 0)
- The maximum R^2 attainable in this situation:

$$R^2_{max} = \frac{SSTo - SSPE}{SSTO}$$

- Not all levels of X need have repeat observations.

- Typically, when H_0 is appropriate, one still uses MSE as the estimate for σ^2 rather than MSPE, Since MSE has more degrees of freedom, sometimes people will pool these estimates.

Joint Inference
The confidence coefficient for both β_0 and β_1 considered simultaneously is $\leq \alpha$

Let

- $\bar{A}_1$ be the event that the first interval covers β_0
- $\bar{A}_2$ be the event that the second interval covers β_1

$$P(\bar{A}_1) = 1 - \alpha$$
$$P(\bar{A}_2) = 1 - \alpha$$

The probability that both $\bar{A}_1$ and $\bar{A}_2$

$$\begin{aligned} P(\bar{A}_1 \cap \bar{A}_2) &= 1 - P(\bar{A}_1 \cup \bar{A}_2) \\ &= 1 - P(A_1) - P(A_2) + P(A_1 \cap A_2) \\ &\geq 1 - P(A_1) - P(A_2) \\ &= 1 - 2\alpha \end{aligned}$$

If β_0 and β_1 have separate 95% confidence intervals, the joint (family) confidence coefficient is at least $1-2(0.05) = 0.9$. This is called a **Bonferroni Inequality**

We could use a procedure in which we obtained $1 - \alpha/2$ confidence intervals for the two regression parameters separately, then the joint (Bonferroni) family confidence coefficient would be at least $1 - \alpha$

The $1 - \alpha$ joint Bonferroni confidence interval for β_0 and β_1 is given by calculating:

$$b_0 \pm Bs(b_0)$$
$$b_1 \pm Bs(b_1)$$

where $B = t_{1-\alpha/4;n-2}$

Interpretation: If repeated samples were taken and the joint $(1 - \alpha)$ intervals for β_0 and β_1 were obtained, $(1 - \alpha)100\%$ of the joint intervals would contain the true pair (β_0, β_1). That is, in $\alpha \times 100\%$ of the samples, one or both intervals would not contain the true value.

- The Bonferroni interval is **conservative**. It is a lower bound and the joint intervals will tend to be correct more than $(1-\alpha)100\%$ of the time (lower power). People usually consider a larger α for the Bonferroni joint tests (e.g, $\alpha = 0.1$)

- The Bonferroni procedure extends to testing more than 2 parameters. Say we are interested in testing $\beta_0, \beta_1, ..., \beta_{g-1}$ (g parameters to test). Then, the joint Bonferroni interval is obtained by calculating the $(1-\alpha/g)$ 100% level interval for each separately.
- For example, if $\alpha = 0.05$ and $g = 10$, each individual test is done at the $1 - \frac{.05}{10}$ level. For 2-sided intervals, this corresponds to using $t_{1-\frac{0.05}{2(10)};n-p}$ in the CI formula. This procedure works best if g is relatively small, otherwise the intervals for each individual parameter are very wide and the test is way too conservative.
- b_0, b_1 are usually correlated (negatively if $\bar{X} > 0$ and positively if $\bar{X} < 0$)
- Other multiple comparison procedures are available.

5.1.1.6 Assumptions

- Linearity of the regression function
- Error terms have constant variance
- Error terms are independent
- No outliers
- Error terms are normally distributed
- No Omitted variables

5.1.1.7 Diagnostics

- Constant Variance
  - Plot residuals vs. X
- Outliers
  - plot residuals vs. X
  - box plots
  - stem-leaf plots
  - scatter plots

We could use standardize the residuals to have unit variance. These standardized residuals are called studentized residuals:

$$r_i = \frac{e_i - \bar{e}}{s(e_i)} = \frac{e_i}{s(e_i)}$$

A simplified standardization procedure gives semi-studentized residuals:

$$e_i^* = \frac{e_i - \bar{e}}{\sqrt{MSE}} = \frac{e_i}{\sqrt{MSE}}$$

Non-independent of Error Terms

- plot residuals vs. time

Residuals e_i are not independent random variables because they involve the fitted values $\hat{Y}_i$, which are based on the same fitted regression function.

If the sample size is large, the dependency among e_i is relatively unimportant.

To detect non-independence, it helps to plot the residual for the i-th response vs. the $(i-1)$-th

Non-normality of Error Terms

to detect non-normality (distribution plots of residuals, box plots of residuals, stem-leaf plots of residuals, normal probability plots of residuals)

- Need relatively large sample sizes.
- Other types of departure affect the distribution of the residuals (wrong regression function, non-constant error variance,...)

5.1.1.7.1 Objective Tests of Model Assumptions

- Normality
  - Use Methods based on empirical cumulative distribution function to test on residuals.
- Constancy of error variance
  - Brown-Forsythe Test (Modified Levene Test)
  - Breusch-Pagan Test (Cook-Weisberg Test)

5.1.1.8 Remedial Measures

If the simple linear regression is not appropriate, one can:

- more complicated models
- transformations on X and/or Y (may not be "optimal" results)

Remedial measures based on deviations:

- Non-linearity:
  - Transformations
  - more complicated models
- Non-constant error variance:
  - Weighted Least Squares
  - Transformations
- Correlated errors:
  - serially correlated error models (times series)
- Non-normality

- Additional variables: multiple regression.
- Outliers:
  - Robust estimation.

5.1.1.8.1 Transformations use transformations of one or both variables before performing the regression analysis.
The properties of least-squares estimates apply to the transformed regression, not the original variable.

If we transform the Y variable and perform regression to get:

$$g(Y_i) = b_0 + b_1 X_i$$

Transform back:

$$\hat{Y}_i = g^{-1}(b_0 + b_1 X_i)$$

$\hat{Y}_i$ will be biased. we can correct this bias.

Box-Cox Family Transformations

$$Y' = Y^{\lambda}$$

where λ is a parameter to be determined from the data.

λ	Y'
2	Y^2
0.5	$\sqrt{Y}$
0	$ln(Y)$
-0.5	$1/\sqrt{Y}$
-1	$1/Y$

To pick λ, we can do estimation by:

- trial and error
- maximum likelihood
- numerical search

Variance Stabilizing Transformations

A general method for finding a variance stabilizing transformation, when the standard deviation is a function of the mean, is the **delta method** - an application of a Taylor series expansion.

$$\sigma = \sqrt{var(Y)} = f(\mu)$$

where $\mu = E(Y)$ and $f(\mu)$ is some smooth function of the mean.

Consider the transformation $h(Y)$. Expand this function in a Taylor series about μ. Then,

$$h(Y) = h(\mu) + h'(\mu)(Y - \mu) + \text{small terms}$$

we want to select the function h(.) so that the variance of h(Y) is nearly constant for all values of $\mu = E(Y)$:

$$\begin{aligned} const &= var(h(Y)) \\ &= var(h(\mu) + h'(\mu)(Y - \mu)) \\ &= (h'(\mu))^2 var(Y - \mu) \\ &= (h'(\mu))^2 var(Y) \\ &= (h'(\mu))^2 (f(\mu))^2 \end{aligned}$$

we must have,

$$h'(\mu) \propto \frac{1}{f(\mu)}$$

then,

$$h(\mu) = \int \frac{1}{f(\mu)} d\mu$$

Example: For the Poisson distribution: $\sigma^2 = var(Y) = E(Y) = \mu$

Then,

$$\begin{aligned} \sigma = f(\mu) &= \sqrt{mu} \\ h'(\mu) &\propto \frac{1}{\mu} = \mu^{-.5} \end{aligned}$$

Then, the variance stabilizing transformation is:

$$h(\mu) = \int \mu^{-.5} d\mu = \frac{1}{2}\sqrt{\mu}$$

hence, $\sqrt{Y}$ is used as the variance stabilizing transformation.

If we don't know $f(\mu)$

1. Trial and error. Look at residuals plots
2. Ask researchers about previous studies or find published results on similar experiments and determine what transformation was used.
3. If you have multiple observations Y_{ij} at the same X values, compute $\bar{Y}_i$ and s_i and plot them
   If $s_i \propto \bar{Y}_i^{\lambda}$ then consider $s_i = a\bar{Y}_i^{\lambda}$ or $ln(s_i) = ln(a) + \lambda ln(\bar{Y}_i)$. So regression the natural log of s_i on the natural log of $\bar{Y}_i$ gives $\hat{a}$ and $\hat{\lambda}$ and suggests the form of $f(\mu)$ If we don't have multiple obs, might still be able to "group" the observations to get $\bar{Y}_i$ and s_i.

Transformation	Situation	Comments
$\sqrt{Y}$	$var(\epsilon_i) = kE(Y_i)$	counts from Poisson dist
$sqrtY + \sqrt{Y+1}$	$var(\epsilon_i) = kE(Y_i)$	small counts or zeroes
$log(Y)$	$var(\epsilon_i) = k(E(Y_i))^2$	positive integers with wide range
$log(Y+1)$	$var(\epsilon_i) = k(E(Y_i))^2$	some counts zero
1/Y	$var(\epsilon_i) = k(E(Y_i))^4$	most responses near zero, others large
$arcsin(\sqrt{Y})$	$var(\epsilon_i) = kE(Y_i)(1-E(Y_i))$	data are binomial proportions or %

5.1.2 Multiple Linear Regression

Geometry of Least Squares

$$\begin{aligned}\hat{\mathbf{y}} &= \mathbf{Xb} \\ &= \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \\ &= \mathbf{Hy}\end{aligned}$$

sometimes $\mathbf{H}$ is denoted as $\mathbf{P}$.

$\mathbf{H}$ is the projection operator.

$$\hat{\mathbf{y}} = \mathbf{Hy}$$

is the projection of y onto the linear space spanned by the columns of $\mathbf{X}$ (model space). The dimension of the model space is the rank of $\mathbf{X}$.

Facts:

1. $\mathbf{H}$ is symmetric (i.e., $\mathbf{H} = \mathbf{H}'$)

2. $\mathbf{HH} = \mathbf{H}$

$$\begin{aligned}\mathbf{HH} &= \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' \\ &= \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{I}\mathbf{X}' \\ &= \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\end{aligned}$$

3. $\mathbf{H}$ is an $n \times n$ matrix with $rank(\mathbf{H}) = rank(\mathbf{X})$

4. $(\mathbf{I} - \mathbf{H}) = \mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ is also a projection operator. It projects onto the $n-k$ dimensional space that is orthogonal to the k dimensional space spanned by the columns of $\mathbf{X}$
5. $\mathbf{H}(\mathbf{I} - \mathbf{H}) = (\mathbf{I} - \mathbf{H})\mathbf{H} = \mathbf{0}$

Partition of uncorrected total sum of squares:

$$\begin{aligned}\mathbf{y}'\mathbf{y} &= \hat{\mathbf{y}}'\hat{\mathbf{y}} + \mathbf{e}'\mathbf{e} \\ &= (\mathbf{H}\mathbf{y})'(\mathbf{H}\mathbf{y}) + ((\mathbf{I} - \mathbf{H})\mathbf{y})'((\mathbf{I} - \mathbf{H})\mathbf{y}) \\ &= \mathbf{y}'\mathbf{H}'\mathbf{H}\mathbf{y} + \mathbf{y}'(\mathbf{I} - \mathbf{H})'(\mathbf{I} - \mathbf{H})\mathbf{y} \\ &= \mathbf{y}'\mathbf{H}\mathbf{y} + \mathbf{y}'(\mathbf{I} - \mathbf{H})\mathbf{y}\end{aligned}$$

or partition for the corrected total sum of squares:

$$\mathbf{y}'(\mathbf{I} - \mathbf{H_1})\mathbf{y} = \mathbf{y}'(\mathbf{H} - \mathbf{H_1})\mathbf{y} + \mathbf{y}'(\mathbf{I} - \mathbf{H})\mathbf{y}$$

where $H_1 = \frac{1}{n}J = 1'(1'1)1$

Source	SS	df	MS	F
Regression	$SSR = \mathbf{y}'(\mathbf{H} - \frac{\mathbf{1}}{\mathbf{n}}\mathbf{J})\mathbf{y}$	$p-1$	$SSR/(p-1)$	MSR/MSE
Error	$SSE = \mathbf{y}'(\mathbf{I} - \mathbf{H})\mathbf{y}$	$n-p$	$SSE/(n-p)$	
Total	$\mathbf{y}'\mathbf{y} - \mathbf{y}'\mathbf{J}\mathbf{y}/\mathbf{n}$	$n-1$		

Equivalently, we can express

$$\mathbf{Y} = \mathbf{X} + (\mathbf{Y} - \mathbf{X})$$

where

- $\hat{\mathbf{Y}} = \mathbf{X}$ = sum of a vector of fitted values
- $\mathbf{e} = (\mathbf{Y} - \mathbf{X}) =$ residual
- $\mathbf{Y}$ is the $n \times 1$ vector in a n-dimensional space R^n
- $\mathbf{X}$ is an $n \times p$ full rank matrix. and its columns generate a p-dimensional subspace of R^n. Hence, any estimator $\mathbf{X}$ is also in this subspace.

We choose least squares estimator that minimize the distance between $\mathbf{Y}$ and $\mathbf{X}$, which is the **orthogonal projection** of $\mathbf{Y}$ onto $\mathbf{X}$.

$$\begin{aligned}
||\mathbf{Y} - \mathbf{X}\hat{\beta}||^2 &= ||\mathbf{Y} - \mathbf{X}\,||^2 + ||\mathbf{X}\,||^2 \\
&= (\mathbf{Y} - \mathbf{X}\,)'(\mathbf{Y} - \mathbf{X}\,) + (\mathbf{X}\,)'(\mathbf{X}\,) \\
&= (\mathbf{Y} - \mathbf{X}\,)'\mathbf{Y} - (\mathbf{Y} - \mathbf{X}\,)'\mathbf{X}\,\hat{}\,'\mathbf{X}'\mathbf{X} \\
&= (\mathbf{Y} - \mathbf{X}\,)'\mathbf{Y} \hat{}\,'\mathbf{X}'\mathbf{X}(\mathbf{X}\mathbf{X}')^{-\mathbf{1}}\mathbf{X}'\mathbf{Y} \\
&= \mathbf{Y}'\mathbf{Y} - \hat{}\,'\mathbf{X}'\mathbf{Y} \hat{}\,'\mathbf{X}'\mathbf{Y}
\end{aligned}$$

where the norm of a $(p \times 1)$ vector $\mathbf{a}$ is defined by:

$$||\mathbf{a}|| = \sqrt{\mathbf{a}'\mathbf{a}} = \sqrt{\sum_{i=1}^{p} a_i^2}$$

Coefficient of Multiple Determination

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

Adjusted Coefficient of Multiple Determination

$$R_a^2 = 1 - \frac{SSE/(n-p)}{SSTO/(n-1)} = 1 - \frac{(n-1)SSE}{(n-p)SSTO}$$

Sequential and Partial Sums of Squares:

In a regression model with coefficients $\beta = (\beta_0, \beta_1, ..., \beta_{p-1})'$, we denote the uncorrected and corrected SS by

$$\begin{aligned}
SSM &= SS(\beta_0, \beta_1, ..., \beta_{p-1}) \\
SSM_m &= SS(\beta_0, \beta_1, ..., \beta_{p-1}|\beta_0)
\end{aligned}$$

There are 2 decompositions of SSM_m:

- **Sequential SS**: (not unique -depends on order, also referred to as Type I SS, and is the default of `anova()` in R)

$$SSM_m = SS(\beta_1|\beta_0) + SS(\beta_2|\beta_0, \beta_1) + ... + SS(\beta_{p-1}|\beta_0, ..., \beta_{p-2})$$

- **Partial SS**: (use more in practice - contribution of each given all of the others)

$$SSM_m = SS(\beta_1|\beta_0, \beta_2, ..., \beta_{p-1}) + ... + SS(\beta_{p-1}|\beta_0, \beta_1, ..., \beta_{p-2})$$

5.1.3 OLS Assumptions

- A1 Linearity
- A2 Full rank
- A3 Exogeneity of Independent Variables
- A4 Homoskedasticity
- A5 Data Generation (random Sampling)
- A6 Normal Distribution

5.1.3.1 A1 Linearity

$$A1 : y = \mathbf{x}\beta + \epsilon \tag{5.1}$$

Not restrictive

- x can be nonlinear transformation including interactions, natural log, quadratic

With A3 (Exogeneity of Independent), linearity can be restrictive

5.1.3.1.1 Log Model

Model	Form	Interpretation of β	In words
Level-Level	$y = \beta_0 + \beta_1 x + \epsilon$	$\Delta y = \beta_1 \Delta x$	A unit change in x will result in β_1 unit change in y
Log-Level	$ln(y) = \beta_0 + \beta_1 x + \epsilon$	$\%\Delta y = 100\beta_1 \Delta x$	A unit change in x result in 100 β_1 % change in y
Level-Log	$y = \beta_0 + \beta_1 ln(x) + \epsilon$	$\Delta y = (\beta_1/100)\%\Delta x$	One percent change in x result in $\beta_1/100$ units change in y
Log-Log	$ln(y) = \beta_0 + \beta_1 ln(x) + \epsilon$	$\%\Delta y = \beta_1 \%\Delta x$	One percent change in x result in β_1 percent change in y

5.1.3.1.2 Higher Orders $y = \beta_0 + x_1\beta_1 + x_1^2\beta_2 + \epsilon$

$$\frac{\partial y}{\partial x_1} = \beta_1 + 2x_1\beta_2$$

- The effect of x_1 on y depends on the level of x_1
- The partial effect at the average $= \beta_1 + 2E(x_1)\beta_2$
- Average Partial Effect $= E(\beta_1 + 2x_1\beta_2)$

5.1.3.1.3 Interactions $y = \beta_0 + x_1\beta_1 + x_2\beta_2 + x_1x_2\beta_3 + \epsilon$

- β_1 is the average effect on y for a unit change in x_1 when $x_2 = 0$
- $\beta_1 + x_2\beta_3$ is the partial effect of x_1 on y which depends on the level of x_2

5.1.3.2 A2 Full rank

$$A2 : rank(E(x'x)) = k \tag{5.2}$$

also known as **identification condition**

- columns of **x** cannot be written as a linear function of the other columns
- which ensures that each parameter is unique and exists in the population regression equation

5.1.3.3 A3 Exogeneity of Independent Variables

$$A3 : E[\epsilon|x_1, x_2, ..., x_k] = E[\epsilon|\mathbf{x}] = 0 \tag{5.3}$$

strict exogeneity

- also known as **mean independence** check back on Correlation and Independence
- by the Law of Iterated Expectations $E(\epsilon) = 0$, which can be satisfied by always including an intercept.
- independent variables do not carry information for prediction of ϵ
- A3 implies $E(y|x) = x\beta$, which means the conditional mean function must be a linear function of x A1 Linearity

5.1.3.3.1 A3a Weaker Exogeneity Assumption

Exogeneity of Independent variables

A3a: $E(\mathbf{x_i'}\epsilon_i) = 0$

- x_i is **uncorrelated** with ϵ_i Correlation and Independence
- Weaker than **mean independence** A3
  - A3 implies A3a, not the reverse
  - No causality interpretations
  - Cannot test the difference

5.1.3.4 A4 Homoskedasticity

$$A4 : Var(\epsilon|x) = Var(\epsilon) = \sigma^2 \tag{5.4}$$

- Variation in the disturbance to be the same over the independent variables

5.1.3.5 A5 Data Generation (random Sampling)

$$A5 : y_i, x_{i1}, ..., x_{ik-1} : i = 1, ..., n \tag{5.5}$$

is a random sample

- random sample mean samples are independent and identically distributed (iid) from a joint distribution of $(y, \mathbf{x})$
- with A3 and A4, we have
  - **Strict Exogeneity**: $E(\epsilon_i | x_1, ..., x_n) = 0$. independent variables do not carry information for prediction of ϵ
  - **Non-autocorrelation**: $E(\epsilon_i \epsilon_j | x_1, ..., x_n) = 0$ The error term is uncorrelated across the draws conditional on the independent variables $\rightarrow A4 : Var(\epsilon|\mathbf{X}) = Var(\epsilon) = \sigma^2 I_n$
- In times series and spatial settings, A5 is less likely to hold.

5.1.3.5.1 A5a A stochastic process $\{x_t\}_{t=1}^T$ is **stationary** if for every collection fo time indices $\{t_1, t_2, ..., t_m\}$, the joint distribution of

$$x_{t_1}, x_{t_2}, ..., x_{t_m}$$

is the same as the joint distribution of

$$x_{t_1+h}, x_{t_2+h}, ..., x_{t_m+h}$$

for any $h \geq 1$

- The joint distribution for the first ten observation is the same for the next ten, etc.
- Independent draws automatically satisfies this

A stochastic process $\{x_t\}_{t=1}^T$ is **weakly stationary** if x_t and x_{t+h} are "almost independent" as h increases without bounds.

- two observation that are very far apart should be "almost independent"

Common Weakly Dependent Processes

1. Moving Average process of order 1 (MA(1))

MA(1) means that there is only one period lag.

$$\begin{aligned} y_t &= u_t + \alpha_1 u_{t-1} \\ E(y_t) &= E(u_t) + \alpha_1 E(u_{t-1}) = 0 \\ Var(y_t) &= var(u_t) + \alpha_1 var(u_{t-1}) \\ &= \sigma^2 + \alpha_1^2 \sigma^2 \\ &= \sigma^2(1 + \alpha_1^2) \end{aligned}$$

where u_t is drawn iid over t with variance σ^2

An increase in the absolute value of α_1 increases the variance

When the MA(1) process can be **inverted** ($|\alpha| < 1$ then

$$u_t = y_t - \alpha_1 u_{t-1}$$

called the autoregressive representation (express current observation in term of past observation).

We can expand it to more than 1 lag, then we have MA(q) process

$$y_t = u_t + \alpha_1 u_{t-1} + ... + \alpha_q u_{t-q}$$

where $u_t \sim WN(0, \sigma^2)$

- Covariance stationary: irrespective of the value of the parameters.
- Invertibility when $\alpha < 1$
- The conditional mean of MA(q) depends on the q lags (long-term memory).
- In MA(q), all autocorrelations beyond q are 0.

$$\begin{aligned} Cov(y_t, y_{t-1}) &= Cov(u_t + \alpha_1 u_{t-1}, u_{t-1} + \alpha_1 u_{t-2}) \\ &= \alpha_1 var(u_{t-1}) \\ &= \alpha_1 \sigma^2 \end{aligned}$$

$$\begin{aligned} Cov(y_t, y_{t-2}) &= Cov(u_t + \alpha_1 u_{t-1}, u_{t-2} + \alpha_1 u_{t-3}) \\ &= 0 \end{aligned}$$

An MA models a linear relationship between the dependent variable and the current and past values of a stochastic term.

2. Auto regressive process of order 1 (AR(1))

$$y_t = \rho y_{t-1} + u_t, |\rho| < 1$$

where u_t is drawn iid over t with variance σ^2

$$\begin{aligned} Cov(y_t, y_{t-1}) &= Cov(\rho y_{t-1} + u - t, y_{t-1}) \\ &= \rho Var(y_{t-1}) \\ &= \rho \frac{\sigma^2}{1-\rho^2} \end{aligned}$$

$$Cov(y_t, y_{t-h}) = \rho^h \frac{\sigma^2}{1-\rho^2}$$

Stationarity: in the continuum of t, the distribution of each t is the same

$$\begin{aligned} E(y_t) = E(y_{t-1}) = ... = E(y_0) \\ y_1 = \rho y_0 + u_1 \end{aligned}$$

where the initial observation $y_0 = 0$

Assume $E(y_t) = 0$

$$\begin{aligned} y_t &= \rho^t y_{t-t} + \rho^{t-1} u_1 + \rho^{t-2} u_2 + ... + \rho u_{t-1} + u_t \\ &= \rho^t y_0 + \rho^{t-1} u_1 + \rho^{t-2} u_2 + ... + \rho u_{t-1} + u_t \end{aligned}$$

Hence, y_t is the weighted of all of the u_t time observations before. y will be correlated with all the previous observations as well as future observations.

$$\begin{aligned} Var(y_t) &= Var(\rho y_{t-1} + u_t) \\ &= \rho^2 Var(y_{t-1}) + Var(u_t) + 2\rho Cov(y_{t-1} u_t) \\ &= \rho^2 Var(y_{t-1}) + \sigma^2 \end{aligned}$$

Hence,

$$Var(y_t) = \frac{\sigma^2}{1-\rho^2}$$

to have Variance constantly over time, then $\rho \neq 1$ or -1.

Then stationarity requires $\rho \neq 1$ or -1. weakly dependent process $|\rho| < 1$

To estimate the AR(1) process, we use **Yule-Walker Equation**

$$\begin{aligned} y_t &= \epsilon_t + \phi y_{t-1} \\ y_t y_{t-\tau} &= \epsilon_t y_{t-\tau} + \phi y_{t-1} y_{t-\tau} \end{aligned}$$

For $\tau \geq 1$, we have

$$\gamma\tau = \phi\gamma(\tau - 1)$$

$$\rho_t = \phi^t$$

when you generalize to p-th order autoregressive process, AR(p):

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \epsilon_t$$

AR(p) process is **covariance stationary**, and decay in autocorrelations.

When we combine MA(q) and AR(p), we have ARMA(p,q) process, where you can see seasonality. For example, ARMA(1,1)

$$y_t = \phi y_{t-1} + \epsilon_t + \alpha\epsilon_{t-1}$$

Random Walk process

$$y_t = y_0 + \sum_{s=1}^{t} u_t$$

- not stationary : when $y_0 = 0$ then $E(y_t) = 0$, but $Var(y_t) = t\sigma^2$. Further along in the spectrum, the variance will be larger
- not weakly dependent: $Cov(\sum_{s=1}^{t} u_s, \sum_{s=1}^{t-h} u_s) = (t-h)\sigma^2$. So the covariance (fixed) is not diminishing as h increases

Assumption A5a: $\{y_t, x_{t1}, .., x_{tk-1}\}$

where $t = 1, ..., T$ are **stationary and weakly dependent processes**.

Alternative [Weak Law], Central Limit Theorem
If z_t is a weakly dependent stationary process with a finite first absolute moment and $E(z_t) = \mu$, then

$$T^{-1} \sum_{t=1}^{T} z_t \to^p \mu$$

If additional regulatory conditions hold (Greene, 1990), then

$$\sqrt{T}(\bar{z} - \mu) \to^d N(0, B)$$

where $B = Var(z_t) + 2\sum_{h=1}^{\infty} Cov(z_t, z_{t-h})$

5.1.3.6 A6 Normal Distribution

$$A6 : \epsilon|\mathbf{x} \sim N(0, \sigma^2 I_n) \tag{5.6}$$

The error term is normally distributed

From A1-A3, we have **identification** (also known as **Orthogonality Condition**) of the population parameter β

$$\begin{aligned}
y &= x\beta + \epsilon && \text{A1} \\
x'y &= x'x\beta + x'\epsilon \\
E(x'y) &= E(x'x)\beta + E(x'\epsilon) \\
E(x'y) &= E(x'x)\beta && \text{A3} \\
[E(x'x)]^{-1}E(x'y) &= [E(x'x)]^{-1}E(x'x)\beta && \text{A2} \\
[E(x'x)]^{-1}E(x'y) &= \beta
\end{aligned}$$

β is the row vector of parameters that produces the best predictor of y we choose the min of γ :

$$\underset{\gamma}{\text{argmin}} E((y - x\gamma)^2)$$

First Order Condition

$$\begin{aligned}
\frac{\partial((y - x\gamma)^2)}{\partial\gamma} &= 0 \\
-2E(x'(y - x\gamma)) &= 0 \\
E(x'y) - E(x'x\gamma) &= 0 \\
E(x'y) &= E(x'x)\gamma \\
(E(x'x))^{-1}E(x'y) &= \gamma
\end{aligned}$$

Second Order Condition

$$\begin{aligned}
\frac{\partial^2 E((y - x\gamma)^2)}{\partial\gamma'^2} &= 0 \\
E(\frac{\partial(y - x\partial)^2)}{\partial\gamma\partial\gamma'}) &= 2E(x'x)
\end{aligned}$$

If A3 holds, then $2E(x'x)$ is PSD $\rightarrow$ minimum

5.1.4 Theorems

5.1.4.1 Frisch-Waugh-Lovell Theorem

$$\mathbf{y} = \mathbf{X} \ + \ = \mathbf{X_1} \ _1 + \mathbf{X_2} \ _2 +$$

Equivalently,

$$\begin{pmatrix} X_1'X_1 & X_1'X_2 \\ X_2'X_1 & X_2'X_2 \end{pmatrix} \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix} = \begin{pmatrix} X_1'y \\ X_2'y \end{pmatrix}$$

Hence,

$$\hat{}_{\mathbf{1}} = (\mathbf{X_1'X_1})^{-\mathbf{1}}\mathbf{X_1'y} - (\mathbf{X_1'X_1})^{-\mathbf{1}}\mathbf{X_1'X_2}\hat{}_{\mathbf{2}}$$

1. Betas from the multiple regression are not the same as the betas from each of the individual simple regression
2. Different set of X will affect all the coefficient estimates.
3. If $X_1'X_2 = 0$ or $\hat{\beta}_2 = 0$, then 1 and 2 do not hold.

5.1.4.2 Gauss-Markov Theorem

For a linear regression model

$$\mathbf{y} = \mathbf{X} \ +$$

Under A1, A2, A3, A4, OLS estimator defined as

$$\hat{\beta} = (\mathbf{X'X})^{-\mathbf{1}}\mathbf{X'y}$$

is the minimum variance linear (in y) unbiased estimator of β

Let $\tilde{\beta} = \mathbf{Cy}$, be another linear estimator where $\mathbf{C}$ is $k \times n$ and only function of $\mathbf{X}$), then for it be unbiased,

$$\begin{aligned} E(\tilde{\beta}|\mathbf{X}) &= E(\mathbf{Cy}|\mathbf{X}) \\ &= E(\mathbf{CX} \ + \mathbf{C} \ |\mathbf{X}) \\ &= \mathbf{CX} \end{aligned}$$

which equals the true parameter β only if $\mathbf{CX} = \mathbf{I}$
Equivalently, $\tilde{\beta} = \beta + \mathbf{C}\epsilon$ and the variance of the estimator is $Var(\tilde{\beta}|\mathbf{X}) = \sigma^2\mathbf{CC'}$

To show minimum variance,

$$
\begin{aligned}
&= \sigma^2(\mathbf{C} - (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}')(\mathbf{C} - (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}')' \\
&= \sigma^2(\mathbf{C}\mathbf{C}' - \mathbf{C}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}) - (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\mathbf{C} + (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}) \\
&= \sigma^2(\mathbf{C}\mathbf{C}' - (\mathbf{X}'\mathbf{X})^{-\mathbf{1}} - (\mathbf{X}'\mathbf{X})^{-\mathbf{1}} + (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}) \\
&= \sigma^2\mathbf{C}\mathbf{C}' - \sigma^2(\mathbf{X}'\mathbf{X})^{-1} \\
&= Var(\tilde{\beta}|\mathbf{X}) - Var(\hat{\beta}|\mathbf{X})
\end{aligned}
$$

Hierarchy of OLS Assumptions

Identification Data Description	Unbiasedness Consistency	Gauss- Markov (BLUE) Asymptotic Inference (z and Chi-squared)	Classical LM (BUE) Small-sample Inference (t and F)
Variation in **X**	Variation in **X**	Variation in **X**	Variation in **X**
	Random Sampling	Random Sampling	Random Sampling
	Linearity in Parameters	Linearity in Parameters	Linearity in Parameters
	Zero Conditional Mean	Zero Conditional Mean	Zero Conditional Mean
		H homoskedasticity	**H** homoskedasticity Normality of Errors

5.1.5 Variable Selection

depends on

- Objectives or goals
- Previously acquired expertise
- Availability of data
- Availability of computer software

Let $P-1$ be the number of possible X variables

5.1.5.1 Mallows's C_p Statistic

(Mallows, 1973, Technometrics, 15, 661-675)

A measure of the predictive ability of a fitted model

Let $\hat{Y}_{ip}$ be the predicted value of Y_i using the model with p parameters.

The total standardized mean square error of prediction is:

$$\begin{aligned}\Gamma_p &= \frac{\sum_{i=1}^{n} E(\hat{Y}_{ip} - E(Y_i))^2}{\sigma^2} \\ &= \frac{\sum_{i=1}^{n}[E(\hat{Y}_{ip}) - E(Y_i)]^2 + \sum_{i=1}^{n} var(\hat{Y}_{ip})}{\sigma^2}\end{aligned}$$

the first term in the numerator is the (bias)^2 term and the 2nd term is the prediction variance term.

- bias term decreases as more variables are added to the model.
- if we assume the full model ($p = P$) is the true model, then $E(\hat{Y}_{ip}) - E(Y_i) = 0$ and the bias is 0.
- Prediction variance increase as more variables are added to the model $\sum var(\hat{Y}_{ip}) = p\sigma^2$
- thus, a tradeoff between bias and variance terns is achieved by minimizing Γ_p.
- Since Γ_p is unknown (due to β). we use an estimate: $C_p = \frac{SSE_p}{\hat{\sigma}^2} - (n-2p)$ which is an unbiased estimate of Γ_p
- As more variables are added to the model, the SSE_p decreases but 2p increases. where $\hat{\sigma^2} = MSE(X_1, .., X_{P-1})$ the MSE with all possible X variables in the model.
- when there is no bias then $E(C_p) \approx p$. Thus, good models have C_p close to p.
- Prediction: consider models with $C_p \leq p$
- Parameter estimation: consider models with $C_p \leq 2p - (P-1)$. Fewer variables should be eliminated from the model to avoid excess bias in the estimates.

5.1.5.2 Akaike Information Criterion (AIC)

$$AUC = nln(\frac{SSE_p}{n}) + 2p$$

- increasing p (number of parameters) leads first-term decreases, and second-term increases.
- We want model with small values of AIC. If the AIC increases when a parameter is added to the model, that parameter is not needed.
- AIC represents a tradeoff between precision of fit against the number of parameters used.

5.1.5.3 Bayes (or Schwarz) Information Criterion

$$BIC = n\ln(\frac{SSE_p}{n}) + (\ln n)p$$

The coefficient in front of p tends to penalize more heavily models with a larger number of parameters (as compared to AIC).

5.1.5.4 Prediction Error Sum of Squares (PRESS)

$$PRESS_p = \sum_{i=1}^{n}(Y_i - \hat{Y}_{i(i)})^2$$

where $\hat{Y}_{i(i)}$ is the prediction of the i-th response when the i-th observation is not used, obtained for the model with p parameters.

- evaluates the predictive ability of a postulated model by omitting one observation at a time.

- We want small $PRESS_p$ values

- It can be computationally intensive when you have large p.

5.1.5.5 Best Subsets Algorithm

- "leap and bounds" algorithm of (Furnival and Wilson, 2000) combines comparison of SSE for different subset models with control over the sequence in which the subset regression are computed.

- Guarantees finding the best m subset regressions within each subset size with less computational burden than all possible subsets.

```
library("leaps")
regsubsets()
```

5.1.5.6 Stepwise Selection Procedures

The **forward stepwise** procedure:

- finds a plausible subset sequentially.
- at each step, a variable is added or deleted.

- criterion for adding or deleting is based on SSE, R^2, t, or F-statistic.

Note:

- Instead of using exact F-values, computer packages usually specify the equivalent "significance" level. For example, SLE is the "significance" level to enter, and SLS is the "significance" level to stay. The SLE and SLS are guides rather than true tests of significance.

- The choice of SLE and SLS represents a balancing of opposing tendencies. Use of large SLE values tends to result in too many predictor variables; models with small SLE tend to be under-specified resulting in σ^2 being badly overestimated.

- As for choice of SLE, can choose between 0.05 and 0.5.

- If SLE > SLS then a cycling pattern may occur. Although most computer packages can detect can stop when it happens. A quick fix: SLS = SLE /2 (Bendel and Afifi, 1977).

- If SLE < SLS then the procedure is conservative and may lead variables with low contribution to be retained.

- Order of variable entry does not matter.

Automated Selection Procedures:

- Forward selection: Same idea as forward stepwise except it doesn't test if variables should be dropped once enter. (not as good as forward stepwise).

- Backward Elimination: begin with all variables and identifies the one with the smallest F-value to be dropped.

5.1.6 Diagnostics

5.1.6.1 Normality of errors

could use Methods based on normal probability plot or Methods based on empirical cumulative distribution function

or plots such as

```
y = 1:100
x = rnorm(100)
qqplot(x,y)
```

5.1.6.2 Influential observations/outliers

5.1.6.2.1 Hat matrix

$$\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}$$

where $\hat{\mathbf{Y}} = \mathbf{HY}, \mathbf{e} = (\mathbf{I} - \mathbf{H})\mathbf{Y}$ and $var(\mathbf{e}) = \sigma^2(\mathbf{I} - \mathbf{H})$

- $\sigma^2(e_i) = \sigma^2(1 - h_{ii})$, where h_{ii} is the i-th element of the main diagonal of $\mathbf{H}$ (must be between 0 and 1).
- $\sum_{i=1}^{n} h_{ii} = p$
- $cov(e_i, e_j) = -h_{ii}\sigma^2$ where $i \neq j$
- Estimate: $s^2(e_i) = MSE(1 - h_{ii})$
- Estimate: $\hat{cov}(e_i, e_j) = -h_{ij}(MSE)$; if model assumption are correct, this covariance is very small for large data sets.
- If $\mathbf{x}_i = [1X_{i,1}...X_{i,p-1}]'$ (the vector of X-values for a given response), then $h_{ii} = \mathbf{x_i'}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{x_i}$ (depends on relative positions of the design points $X_{i,1}, ..., X_{i,p-1}$)

5.1.6.2.2 Studentized Residuals

$$r_i = \frac{e_i}{s(e_i)}$$
$$r_i \sim N(0, 1)$$

where $s(e_i) = \sqrt{MSE(1-h_{ii})}$. r_i is called the studentized residual or standardized residual.

- you can use the semi-studentized residual before, $e_i^* = e_i\sqrt{MSE}$. This doesn't take into account the different variances for each e_i.

We would want to see the model without a particular value. You delete the i-th case, fit the regression to the remaining $n-1$ cases, get estimated responses for the i-th case, $\hat{Y}_{i(i)}$, and find the difference, called the **deleted residual**:

$$\begin{aligned} d_i &= Y_i - \hat{Y}_{i(i)} \\ &= \frac{e_i}{1-h_{ii}} \end{aligned}$$

we don't need to recompute the regression model for each case

As h_{ii} increases, d_i increases.

$$s^2(d_i) = \frac{MSE_{(i)}}{1-h_{ii}}$$

where $MSE_{(i)}$ is the mean square error when the i-th case is omitted.

Let

$$t_i = \frac{d_i}{s(d_i)} = \frac{e_i}{\sqrt{MSE_{(i)}(1-h_{ii})}}$$

be the **studentized deleted residual**, which follows a t-distribution with $n-p-1$ df.

$$(n-p)MSE = (n-p-1)MSE_{(i)} + \frac{e_i^2}{1-h_{ii}}$$

hence, we do not need to fit regressions for each case and

$$t_i = e_i(\frac{n-p-1}{SSE(1-h_{ii}) - e_i^2})^{1/2}$$

The outlying Y-observations are those cases whose studentized deleted residuals are large in absolute value. If there are many residuals to consider, a Bonferroni critical value can be can $(t_{1-\alpha/2n;n-p-1})$

Outlying X Observations

Recall, $0 \leq h_{ii} \leq 1$ and $\sum_{i=1}^n h_{ii} = p$ (the total number of parameters)

A large h_{ii} indicates that the i-th case is distant from the center of all X observations (the **leverage** of the i-th case). That is, a large value suggests that the observation exercises substantial leverage in determining the fitted value $\hat{Y}_i$

We have $\hat{\mathbf{Y}} = \mathbf{HY}$, a linear combination of Y-values; h_{ii} is the weight of the observation Y_i; so h_{ii} measures the role of the X values in determining how important Y_i is in affecting the $\hat{Y}_i$.

Large h_{ii} implies $var(e_i)$ is small, so larger h_{ii} implies that $\hat{Y}_i$ is close to Y_i

- small data sets: $h_{ii} > .5$ suggests "large".
- large data sets: $h_{ii} > \frac{2p}{n}$ is "large.

Using the hat matrix to identify extrapolation:

- Let $\mathbf{x_{new}}$ be a vector containing the X values for which an inference about a mean response or a new observation is to be made.
- Let $\mathbf{X}$ be the data design matrix used to fit the data. Then, if $h_{new,new} = \mathbf{x_{new}}(\mathbf{X'X})^{-1}\mathbf{x_{new}}$ is within the range of leverage values (h_{ii}) for cases in the data set, no extrapolation is involved; otherwise; extrapolation is indicated.

Identifying Influential Cases:

by influential we mean that exclusion of an observation causes major changes int he fitted regression. (not all outliers are influential)

- Influence on Single Fitted Values: DFFITS
- Influence on All Fitted Values: Cook's D
- Influence on the Regression Coefficients: DFBETAS

5.1.6.2.3 DFFITS Influence on Single Fitted Values: DFFITS

$$
\begin{aligned}
(DFFITS)_i &= \frac{\hat{Y}_i - \hat{Y}_{i(i)}}{\sqrt{MSE_{(i)}h_{ii}}} \\
&= t_i(\frac{h_{ii}}{1-h_{ii}})^{1/2}
\end{aligned}
$$

- the standardized difference between the i-th fitted value with all observations and with the i-th case removed.
- studentized deleted residual multiplied by a factor that is a function fo the i-th leverage value.
- influence if:
  - small to medium data sets: $|DFFITS| > 1$
  - large data sets: $|DFFITS| > 2\sqrt{p/n}$

5.1.6.2.4 Cook's D Influence on All Fitted Values: Cook's D

$$\begin{aligned} D_i &= \frac{\sum_{j=1}^{n}(\hat{Y}_j - \hat{Y}_{j(i)})^2}{p(MSE)} \\ &= \frac{e_i^2}{p(MSE)}(\frac{h_{ii}}{(1-h_{ii})^2}) \end{aligned}$$

gives the influence of i-th case on all fitted values.

If e_i increases or h_{ii} increases, then D_i increases.

D_i is a percentile of an $F_{(p,n-p)}$ distribution. If the percentile is greater than .5(50%) then the i-th case has major influence. In practice, if $D_i > 4/n$, then the i-th case has major influence.

5.1.6.2.5 DFBETAS Influence on the Regression Coefficients: DFBETAS

$$(DFBETAS)_{k(i)} = \frac{b_k - b_{k(i)}}{\sqrt{MSE_{(i)}c_{kk}}}$$

for $k = 0, ..., p-1$ and c_{kk} is the k-th diagonal element of $\mathbf{X}'\mathbf{X}^{-1}$

Influence of the i-th case on each regression coefficient b_k $(k = 0, \dots, p-1)$ is the difference between the estimated regression coefficients based on all n cases and the regression coefficients obtained when the i-th case is omitted $(b_{k(i)})$

- small data sets: $|DFBETA| > 1$
- large data sets: $|DFBETA| > 2\sqrt{n}$
- Sign of DFBETA inculcates whether inclusion of a case leads to an increase or a decrease in estimates of the regression coefficient.

5.1.6.3 Collinearity

Multicollinearity refers to correlation among explanatory variables.

- large changes in the estimated regression coefficient when a predictor variable is added or deleted, or when an observation is altered or deleted.

- non insignificant results in individual tests on regression coefficients for important predictor variables.

- estimated regression coefficients with an algebraic sign that is the opposite of that expected from theoretical consideration or prior experience.

- large coefficients of simple correlation between pairs of predictor variables in the correlation matrix.

- wide confidence intervals for the regression coefficients representing important predictor variables.

When some of X variables are so highly correlated that the inverse $(X'X)^{-1}$ does not exist or is very computationally unstable.

Correlated Predictor Variables: if some X variables are "perfectly" correlated, the system is undetermined and there are an infinite number of models that fit the data. That is, if $X'X$ is singular, then $(X'X)^{-1}$ doesn't exist. Then,

- parameters cannot be interpreted ($\mathbf{b} = (\mathbf{X'X})^{-1}\mathbf{X'y}$)

- sampling variability is infinite ($\mathbf{s^2(b)} = \mathbf{MSE(X'X)^{-1}}$)

5.1.6.3.1 VIFs Let R_k^2 be the coefficient of multiple determination when X_k is regressed on the $p-2$ other X variables in the model. Then,

$$VIF_k = \frac{1}{1-R_k^2}$$

- large values indicate that a near collinearity is causing the variance of b_k to be inflated, $var(b_k) \propto \sigma^2(VIF_k)$

- Typically, the rule of thumb is that $VIF > 4$ mean you should see why this is the case, and $VIF_k > 10$ indicates a serious problem collinearity problem that could result in poor parameters estimates.

- the mean of all VIF's provide an estimate of the ratio of the true multicollinearity to a model where the X variables are uncorrelated

- serious multicollinearity if $avg(VIF) >> 1$

5.1.6.3.2 Condition Number Condition Number

spectral decomposition

$$\mathbf{X'X} = \sum_{i=1}^{p} \lambda_i \mathbf{u_i u_i'}$$

where λ_i is the eigenvalue and $\mathbf{u}_i$ is the eigenvector. $\lambda_1 > ... > \lambda_p$ and the eigenvecotrs are orthogonal:

$$\begin{cases} \mathbf{u_i'u_j} = 0 & \text{for } i \neq j \\ 1 & \text{for } i = j \end{cases}$$

The condition number is then

$$k = \sqrt{\frac{\lambda_{max}}{\lambda_{min}}}$$

- values $k > 30$ are cause for concern
- values $30 < k < 100$ imply moderate dependencies.
- values $k > 100$ imply strong collinearity

Condition index

$$\delta_i = \sqrt{\frac{\lambda_{max}}{\lambda_i}}$$

where $i = 1, ..., p$

we can find the proportion of the total variance associated with the k-th regression coefficient and the i-th eigen mode:

$$\frac{u_{ik}^2/\lambda_i}{\sum_j (u_{jk}^2/\lambda_j)}$$

These variance proportions can be helpful for identifying serious collinearity

- the condition index must be large
- the variance proportions must be large (>,5) for at least two regression coefficients.

5.1.6.4 Constancy of Error Variance

5.1.6.4.1 Brown-Forsythe Test (Modified Levene Test)

- Does not depend on normality
- Applicable when error variance increases or decreases with X
- relatively large sample size needed (so we can ignore dependency between residuals)
- Split residuals into 2 groups $(e_{i1}, i = 1, ..., n_1; e_{i2}, j = 1, ..., n_2)$
- Let $d_{i1} = |e_{i1} - \tilde{e}_1|$ where $\tilde{e}_1$ is the median of group 1.
- Let $d_{j2} = |e_{j2} - \tilde{e}_2|$.

- Then, a 2-sample t-test:

$$t_L = \frac{\bar{d}_1 - \bar{d}_2}{s\sqrt{1/n_1 + 1/n_2}}$$

where

$$s^2 = \frac{\sum_i (d_{i1} - \bar{d}_1)^2 + \sum_j (d_{j2} - \bar{d}_2)^2}{n-2}$$

If $|t_L| > t_{1-\alpha/2;n-2}$ conclude the error variance is not constant.

5.1.6.4.2 Breusch-Pagan Test (Cook-Weisberg Test) Assume the error terms are independent and normally distributed, and

$$\sigma_i^2 = \gamma_0 + \gamma_1 X_i$$

Constant error variance corresponds to $\gamma_1 = 0$, i.e., test

- $H_0 : \gamma_1 = 0$
- $H_1 : \gamma_1 \neq 0$

by regressing the squared residuals on X in the usual manner. Obtain the regression sum of squares from this: SSR^* (the SSR from the regression of e_i^2 on X_i). Then, define

$$X_{BP}^2 = \frac{SSR^*/2}{(SSE/n)^2}$$

where SSE is the error sum of squares from the regression of Y on X.

If $H_0 : \gamma_1 = 0$ holds and n is reasonably large, X_{BP}^2 follows approximately the χ^2 distribution with 1 d.f. We reject H_0 (Homogeneous variance) if $X_{BP}^2 > \chi^2_{1-\alpha;1}$

5.1.6.5 Independence

5.1.6.5.1 Plots

5.1.6.5.2 Durbin-Watson

5.1.6.5.3 Time-series

5.1.6.5.4 Spatial Statistics

5.1.7 Model Validation

- split data into 2 groups: training (model building) sample and validation (prediction) sample.

- the model MSE will tend to underestimate the inherent variability in making future predictions. to consider actual predictive ability, consider mean squared prediction error (MSPE):

$$MSPE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n^*}$$

  - where Y_i is the known value of the response variable in the i-th validation case.
  - $\hat{Y}_i$ is the predicted value based on a model fit with the training data set.
  - n^* is the number of cases in the validation set.

- we want MSPE to be close to MSE (in which MSE is not biased); so look at the the ratio MSPE / MSE (closer to 1, the better).

5.1.8 Finite Sample Properties

- n is fixed

- **Bias** On average, how close is our estimate to the true value

  - $Bias = E(\hat{\beta}) - \beta$ where β is the true parameter value and $\hat{\beta}$ is the estimator for β

  - An estimator is **unbiased** when

    * $Bias = E(\hat{\beta}) - \beta = 0$ or $E(\hat{\beta}) = \beta$
    * means that the estimator will produce estimates that are, on average, equal to the value it it trying to estimate

- **Distribution of an estimator**: An estimator is a function of random variables (data)

- **Standard Deviation**: the spread of the estimator.

OLS

Under A1 A2 A3, OLS is unbiased

$$
\begin{aligned}
E(\hat{\beta}) &= E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\mathbf{y}) && \text{A2} \\
&= E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'(\mathbf{X}\ +\ )) && \text{A1} \\
&= E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\mathbf{X}\ + (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\ ) \\
&= E(\beta + (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\ ) \\
&= \beta + E((\mathbf{X}'\mathbf{X}^{-\mathbf{1}}\ )) \\
&= \beta + E(E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\ |\mathbf{X})) && \text{LIE} \\
&= \beta + E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'E(\ |\mathbf{X})) \\
&= \beta + E((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'0)) && \text{A3} \\
&= \beta
\end{aligned}
$$

where LIE stands for Law of Iterated Expectation

If A3 does not hold, then OLS will be **biased**

From **Frisch-Waugh-Lovell Theorem**, if we have the omitted variable $\hat{\beta}_2 \neq 0$ and $\mathbf{X_1'X_2} \neq 0$, then the omitted variable will cause OLS estimator to be biased.

Under A1 A2 A3 A4, we have the conditional variance of the OLS estimator as follows]

$$
\begin{aligned}
Var(\hat{\beta}|\mathbf{X}) &= Var(\beta + (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\ |\mathbf{X}) && \text{A1-A2} \\
&= Var((\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\ |\mathbf{X}) \\
&= \mathbf{X}'\mathbf{X}^{-\mathbf{1}}\mathbf{X}'Var(\epsilon|\mathbf{X})\mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}} \\
&= \mathbf{X}'\mathbf{X}^{-\mathbf{1}}\mathbf{X}'\sigma^2 I\mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}} && \text{A4} \\
&= \sigma^2\mathbf{X}'\mathbf{X}^{-\mathbf{1}}\mathbf{X}'I\mathbf{X}(\mathbf{X}'\mathbf{X})^{-\mathbf{1}} \\
&= \sigma^2(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}
\end{aligned}
$$

Sources of variation

1. $\sigma^2 = Var(\epsilon_i|\mathbf{X})$
   - The amount of unexplained variation ϵ_i is large relative to the explained $\mathbf{x_i}$ variation
2. "Small" $Var(x_{i1}), Var(x_{i1}), ..$
   - Not a lot of variation in $\mathbf{X}$ (no information)
   - small sample size
3. "Strong" correlation between the explanatory variables
   - x_{i1} is highly correlated with a linear combination of 1, x_{i2}, x_{i3}, ...
   - include many irrelevant variables will contribute to this.
   - If x_1 is perfectly determined in the regression $\rightarrow$ **Perfect Collinearity** $\rightarrow$ A2 is violated.

- If x_1 is highly correlated with a linear combination of other variables, then we have **Multicollinearity**

5.1.8.1 Check for Multicollinearity

Variance Inflation Factor (VIF) Rule of thumb $VIF \geq 10$ is large

$$VIF = \frac{1}{1 - R_1^2}$$

- **Multicollinearity and VIF:**
  - High VIFs with indicator variables are normal and not problematic.
  - VIF is generally not useful for detecting multicollinearity concerns in models with fixed effects.
- **Overemphasis on Multicollinearity:**
  - Multicollinearity inflates standard errors and widens confidence intervals but does not bias results.
  - If key variables have narrow confidence intervals, multicollinearity is not an issue.
- **Goldberger's Insight** (Goldberger, 1991)**:**
  - Multicollinearity is akin to small sample size ("micronumerosity").
  - Large standard errors are expected with highly correlated independent variables.
- **Practical Implications:**
  - Evaluate whether confidence intervals for key variables are sufficiently narrow.
  - If not, the study is inconclusive, and a larger dataset or redesigned study is needed.

5.1.8.2 Standard Errors

- $Var(\hat{\beta}|\mathbf{X}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}$ is the variance of the estimate $\hat{\beta}$
- **Standard Errors** are estimators/estimates of the standard deviation (square root of the variance) of the estimator $\hat{\beta}$
- Under A1-A5, then we can estimate $\sigma^2 = Var(\epsilon^2|\mathbf{X})$ the standard errors as

$$\begin{aligned} s^2 &= \frac{1}{n-k}\sum_{i=1}^{n} e_i^2 \\ &= \frac{1}{n-k} SSR \end{aligned}$$

- degrees of freedom adjustment: because $e_i \neq \epsilon_i$ and are estimated using k estimates for β, we lose degrees of freedom in our variance estimate.
- $s = \sqrt{s^2}$ is a biased estimator for the standard deviation (Jensen's Inequality)

Standard Errors for $\hat{\beta}$

$$\begin{aligned} SE(\hat{\beta}_{j-1}) &= s\sqrt{[(\mathbf{X}'\mathbf{X})^{-1}]_{jj}} \\ &= \frac{s}{\sqrt{SST_{j-1}(1-R^2_{j-1})}} \end{aligned}$$

where SST_{j-1} and R^2_{j-1} from the following regression

x_{j-1} on 1, x_1,... x_{j-2},x_j,x_{j+1}, ..., x_{k-1}

Summary of Finite Sample Properties

- Under A1-A3: OLS is unbiased
- Under A1-A4: The variance of the OLS estimator is $Var(\hat{\beta}|\mathbf{X}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-\mathbf{1}}$
- Under A1-A4, A6: OLS estimator $\hat{\beta} \sim N(\beta, \sigma^2(\mathbf{X}'\mathbf{X})^{-\mathbf{1}})$
- Under A1-A4, Gauss-Markov Theorem holds $\rightarrow$ OLS is BLUE
- Under A1-A5, the above standard errors are unbiased estimator of standard deviation for $\hat{\beta}$

5.1.9 Large Sample Properties

- Let $n \rightarrow \infty$
- A perspective that allows us to evaluate the "quality" of estimators when finite sample properties are not informative, or impossible to compute
- Consistency, asymptotic distribution, asymptotic variance

Motivation

- Finite Sample Properties need strong assumption A1 A3 A4 A6
- Other estimation such as GLS, MLE need to be analyzed using Large Sample Properties

Let $\mu(\mathbf{X}) = E(y|\mathbf{X})$ be the **Conditional Expectation Function**

- $\mu(\mathbf{X})$ is the minimum mean squared predictor (over all possible functions)

$$minE((y - f(\mathbf{X}))^2)$$

under A1 and A3,

$$\mu(\mathbf{X}) = \mathbf{X}\beta$$

Then the **linear projection**

$$L(y|1, \mathbf{X}) = \gamma_0 + \mathbf{X}Var(X)^{-1}Cov(X, Y)$$

where $\mathbf{X}Var(X)^{-1}Cov(X, Y) = \gamma$

is the minimum mean squared linear approximation to be conditional mean function

$$(\gamma_0, \gamma) = argminE((E(y|\mathbf{X}) - (a + \mathbf{Xb})^2)$$

- OLS is always **consistent** for the linear projection, but not necessarily unbiased.
- Linear projection has no causal interpretation
- Linear projection does not depend on assumption A1 and A3

Evaluating an estimator using large sample properties:

- Consistency: measure of centrality
- Limiting Distribution: the shape of the scaled estimator as the sample size increases
- Asymptotic variance: spread of the estimator with regards to its limiting distribution.

An estimator $\hat{\theta}$ is consistent for θ if $\hat{\theta}_n \to^p \theta$

- As n increases, the estimator converges to the population parameter value.
- Unbiased does not imply consistency and consistency does not imply unbiased.

Based on [Weak Law] of Large Numbers

$$\begin{aligned}
\hat{\beta} &= (\mathbf{X'X})^{-\mathbf{1}}\mathbf{X'y} \\
&= (\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'x_i})^{-\mathbf{1}} \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'y_i} \\
&= (n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'x_i})^{-\mathbf{1}} n^{-1} \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'y_i}
\end{aligned}$$

$$\begin{aligned}
plim(\hat{\beta}) &= plim((n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'x_i})^{-\mathbf{1}} n^{-1} \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'y_i}) \\
&= plim((n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'x_i})^{-\mathbf{1}}) plim(n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'y_i}) \\
&= (plim(n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'x_i})^{-\mathbf{1}}) plim(n^{-1}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{x_i'y_i}) \text{ due to A2, A5} \\
&= E(\mathbf{x_i'x_i})^{-1} E(\mathbf{x_i'y_i})
\end{aligned}$$

$$E(\mathbf{x_i'x_i})^{-1}E(\mathbf{x_i'y_i}) = \beta + E(\mathbf{x_i'x_i})^{-1}E(\mathbf{x_i'}\ _{\mathbf{i}})$$

Under A1, A2, A3a, A5 OLS is consistent, but not guarantee unbiased.

Under A1, A2, A3a, A5, and $\mathbf{x_i'x_i}$ has finite first and second moments (CLT), $Var(\mathbf{x_i'}\epsilon_i) = \mathbf{B}$

- $(n^{-1}\sum_{i=1}^{n}\mathbf{x_i'x_i})^{-1} \to^p (E(\mathbf{x_i'x_i}))^{-1}$
- $\sqrt{n}(n^{-1}\sum_{i=1}^{n}\mathbf{x_i'}\epsilon_i) \to^d N(0,\mathbf{B})$

$$\sqrt{n}(\hat{\beta}-\beta) = (n^{-1}\sum_{i=1}^{n}\mathbf{x_i'x_i})^{-1}\sqrt{n}(n^{-1}\sum_{i=1}^{n}\mathbf{x_i'x_i}) \to^d N(0,\Sigma)$$

where $\Sigma = (E(\mathbf{x_i'x_i}))^{-1}\mathbf{B}(E(\mathbf{x_i'x_i}))^{-1}$

- holds under A3a
- Do not need A4 and A6 to apply CLT
  - If A4 does not hold, then $\mathbf{B} = Var(\mathbf{x_i'}\epsilon_i) = \sigma^2 E(x_i'x_i)$ which means $\Sigma = \sigma^2(E(\mathbf{x_i'x_i}))^{-1}$, use standard errors

Heteroskedasticity can be from

- Limited dependent variable
- Dependent variables with large/skewed ranges

Solving Asymptotic Variance

$$\begin{aligned}
\Sigma &= (E(\mathbf{x_i'x_i}))^{-1}\mathbf{B}(E(\mathbf{x_i'x_i}))^{-1} \\
&= (E(\mathbf{x_i'x_i}))^{-1}Var(\mathbf{x_i'}\epsilon_i)(E(\mathbf{x_i'x_i}))^{-1} \\
&= (E(\mathbf{x_i'x_i}))^{-1}E[(\mathbf{x_i'}\epsilon_i - 0)(\mathbf{x_i'}\epsilon_i - 0)](E(\mathbf{x_i'x_i}))^{-1} && \text{A3a} \\
&= (E(\mathbf{x_i'x_i}))^{-1}E[E(\ ^{\mathbf{2}}_{\mathbf{i}}|\mathbf{x_i})\mathbf{x_i'x_i}](E(\mathbf{x_i'x_i}))^{-1} && \text{LIE} \\
&= (E(\mathbf{x_i'x_i}))^{-1}\sigma^2 E(\mathbf{x_i'x_i})(E(\mathbf{x_i'x_i}))^{-1} && \text{A4} \\
&= \sigma^2(E(\mathbf{x_i'x_i}))
\end{aligned}$$

Under A1, A2, A3a, A4, A5:

$$\sqrt{n}(\hat{\beta}-\beta) \to^d N(0,\sigma^2(E(\mathbf{x_i'x_i}))^{-1})$$

- The Asymptotic variance is approximation for the variance in the scaled random variable for $\sqrt{n}(\hat{\beta}-\beta)$ when n is large.
- use $Avar(\sqrt{n}(\hat{\beta}-\beta))/n$ as an approximation for finite sample variance for large n:

$$Avar(\sqrt{n}(\hat{\beta}-\beta)) \approx Var(\sqrt{n}(\hat{\beta}-\beta))$$
$$Avar(\sqrt{n}(\hat{\beta}-\beta))/n \approx Var(\sqrt{n}(\hat{\beta}-\beta))/n = Var(\hat{\beta})$$

- $Avar(.)$ does not behave the same way as $Var(.)$

$$\begin{aligned} Avar(\sqrt{n}(\hat{\beta}-\beta))/n &\neq Avar(\sqrt{n}(\hat{\beta}-\beta)/\sqrt{n}) \\ &\neq Avar(\hat{\beta}) \end{aligned}$$

In Finite Sample Properties, we calculate standard errors as an estimate for the conditional standard deviation:

$$SE_{fs}(\hat{\beta}_{j-1}) = \sqrt{\hat{Var}(\hat{\beta}_{j-1}|\mathbf{X})} = \sqrt{s^2[(\mathbf{X}'\mathbf{X})^{-1}]_{jj}}$$

In Large Sample Properties, we calculate standard errors as an estimate for the square root of asymptotic variance

$$SE_{ls}(\hat{\beta}_{j-1}) = \sqrt{\hat{Avar}(\sqrt{n}\hat{\beta}_{j-1})/n} = \sqrt{s^2[(\mathbf{X}'\mathbf{X})^{-1}]_{jj}}$$

Hence, the standard error estimator is the same for finite sample and large sample.

- Same estimator, but conceptually estimating two different things.
- Valid under weaker assumptions: the assumptions needed to produce a consistent estimator for the finite sample conditional variance (A1-A5) are stronger than those needed to produce a consistent estimator for the asymptotic variance (A1,A2,A3a,A4,A5)

Suppose that $y_1, ..., y_n$ are a random sample from some population with mean μ and variance-covariance matrix Σ

- $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ is a consistent estimator for μ
- $S = \frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})(y_i - \bar{y})'$ is a consistent estimator for Σ.
- Multivariate Central limit Theorem: Similar to the univariate case, $\sqrt{n}(\bar{y}-\mu) \sim N_p(0, \Sigma)$, when n is large relative to p (e.g., $n \geq 25p$). Equivalently, $\bar{y} \sim N_p(\mu, \Sigma/n)$.
- Wald's Theorem: $n(\bar{y}-\mu)'S^{-1}(\bar{y}-\mu) \sim \chi^2_{(p)}$ when n is large relative to p.

5.2 Feasible Generalized Least Squares

Motivation for a more efficient estimator

- Gauss-Markov Theorem holds under A1-A4
- A4: $Var(\epsilon|\mathbf{X}) = \sigma^2 I_n$
  - Heteroskedasticity: $Var(\epsilon_i|\mathbf{X}) \neq \sigma^2 I_n$
  - Serial Correlation: $Cov(\epsilon_i, \epsilon_j|\mathbf{X}) \neq 0$
- Without A4, how can we know which unbiased estimator is the most efficient?

Original (unweighted) model:

$$\mathbf{y} = \mathbf{X} \ +$$

Suppose A1-A3 hold, but A4 does not hold,

$$\mathbf{Var}(\ |\mathbf{X}) = \ \neq \ ^{\mathbf{2}}\mathbf{I_n}$$

We will try to use OLS to estimate the transformed (weighted) model

$$\mathbf{wy} = \mathbf{wX} \ + \mathbf{w}$$

We need to choose $\mathbf{w}$ so that

$$\mathbf{w'w} = \ ^{\mathbf{-1}}$$

then $\mathbf{w}$ (full-rank matrix) is the **Cholesky decomposition** of $^{\mathbf{-1}}$ (full-rank matrix)

In other words, $\mathbf{w}$ is the squared root of Ω (squared root version in matrix)

$$\begin{aligned} \Omega &= var(\epsilon|X) \\ \Omega^{-1} &= var(\epsilon|X)^{-1} \end{aligned}$$

Then, the transformed equation (IGLS) will have the following properties.

$$\begin{aligned} \hat{\ }_{\mathbf{IGLS}} &= (\mathbf{X'w'wX})^{\mathbf{-1}}\mathbf{X'w'wy} \\ &= (\mathbf{X'} \ ^{\mathbf{-1}}\mathbf{X})^{\mathbf{-1}}\mathbf{X'} \ ^{\mathbf{-1}}\mathbf{y} \\ &= \ + \mathbf{X'} \ ^{\mathbf{-1}}\mathbf{X'} \ ^{\mathbf{-1}} \end{aligned}$$

Since A1-A3 hold for the unweighted model

$$\begin{aligned}
\mathbf{E}\hat{(}_{\mathbf{IGLS}}|\mathbf{X}) &= E(\ + (\mathbf{X}'^{\ -1}\mathbf{X}'^{\ -1}\ )|X) \\
&= \ + \mathbf{E}(\mathbf{X}'^{\ -1}\mathbf{X}'^{\ -1}\ )|\mathbf{X}) \\
&= \ + \mathbf{X}'^{\ -1}\mathbf{X}'^{\ -1}\mathbf{E}(\ |\mathbf{X}) \qquad \text{since A3} : E(\epsilon|X) = 0 \\
&=
\end{aligned}$$

$\rightarrow$ IGLS estimator is unbiased

$$\begin{aligned}
\mathbf{Var}(\mathbf{w}\ |\mathbf{X}) &= \mathbf{w}\mathbf{Var}(\ |\mathbf{X})\mathbf{w}' \\
&= \mathbf{w}\ \mathbf{w}' \\
&= \mathbf{w}(\mathbf{w}'\mathbf{w})^{-1}\mathbf{w}' \qquad \text{since w is a full-rank matrix} \\
&= \mathbf{w}\mathbf{w}^{-1}(\mathbf{w}')^{-1}\mathbf{w}' \\
&= \mathbf{I_n}
\end{aligned}$$

$\rightarrow$ A4 holds for the transformed (weighted) equation

Then, the variance for the estimator is

$$\begin{aligned}
Var(\hat{\beta}_{IGLS}|\mathbf{X}) &= \mathbf{Var}(\ + (\mathbf{X}'^{\ -1}\mathbf{X})^{-1}\mathbf{X}'^{\ -1}\ |\mathbf{X}) \\
&= \mathbf{Var}((\mathbf{X}'^{\ -1}\mathbf{X})^{-1}\mathbf{X}'^{\ -1}\ |\mathbf{X}) \\
&= (\mathbf{X}'^{\ -1}\mathbf{X})^{-1}\mathbf{X}'^{\ -1}\mathbf{Var}(\ |\mathbf{X})\ ^{-1}\mathbf{X}(\mathbf{X}'^{\ -1}\mathbf{X})^{-1} \quad \text{because A4 holds} \\
&= (\mathbf{X}'^{\ -1}\mathbf{X})^{-1}\mathbf{X}'^{\ -1}\ \ ^{-1}\ ^{-1}\mathbf{X}(\mathbf{X}'^{\ -1}\mathbf{X})^{-1} \\
&= (\mathbf{X}'^{\ -1}\mathbf{X})^{-1}
\end{aligned}$$

Let $A = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' - (\mathbf{X}'^{\ -1}\mathbf{X})\mathbf{X}'^{\ -1}$ then

$$Var(\hat{\beta}_{OLS}|X) - Var(\hat{\beta}_{IGLS}|X) = A\Omega A'$$

And Ω is Positive Semi Definite, then $A\Omega A'$ also PSD, then IGLS is more efficient

The name **Infeasible** comes from the fact that it is impossible to compute this estimator.

$$\mathbf{w} = \begin{pmatrix} w_{11} & 0 & 0 & ... & 0 \\ w_{21} & w_{22} & 0 & ... & 0 \\ w_{31} & w_{32} & w_{33} & ... & ... \\ w_{n1} & w_{n2} & w_{n3} & ... & w_{nn} \end{pmatrix}$$

With $n(n+1)/2$ number of elements and n observations $\rightarrow$ infeasible to estimate. (number of equation > data)

Hence, we need to make assumption on Ω to make it feasible to estimate $\mathbf{w}$:

1. Heteroskedasticity : multiplicative exponential model
2. AR(1)
3. Cluster

5.2.1 Heteroskedasticity

$$\begin{aligned} Var(\epsilon_i|x_i) &= E(\epsilon^2|x_i) \neq \sigma^2 \\ &= h(x_i) = \sigma_i^2 (\text{variance of the error term is a function of x}) \end{aligned} \tag{5.7}$$

For our model,

$$\begin{aligned} y_i &= x_i\beta + \epsilon_i \\ (1/\sigma_i)y_i &= (1/\sigma_i)x_i\beta + (1/\sigma_i)\epsilon_i \end{aligned}$$

then, from (5.7)

$$\begin{aligned} Var((1/\sigma_i)\epsilon_i|X) &= (1/\sigma_i^2)Var(\epsilon_i|X) \\ &= (1/\sigma_i^2)\sigma_i^2 \\ &= 1 \end{aligned}$$

then the weight matrix $\mathbf{w}$ in the matrix equation

$$\mathbf{wy} = \mathbf{wX} \ + \mathbf{w}$$

$$\mathbf{w} = \begin{pmatrix} 1/\sigma_1 & 0 & 0 & ... & 0 \\ 0 & 1/\sigma_2 & 0 & ... & 0 \\ 0 & 0 & 1/\sigma_3 & ... & . \\ . & . & . & . & 0 \\ 0 & 0 & . & . & 1/\sigma_n \end{pmatrix}$$

Infeasible Weighted Least Squares

1. Assume we know σ_i^2 (Infeasible)
2. The IWLS estimator is obtained as the least squared estimated for the following weighted equation

$$(1/\sigma_i)y_i = (1/\sigma_i)\mathbf{x}_i\beta + (1/\sigma_i)\epsilon_i$$

- Usual standard errors for the weighted equation are valid if $Var(\epsilon|\mathbf{X}) = \sigma_i^2$
- If $Var(\epsilon|\mathbf{X}) \neq \sigma_i^2$ then heteroskedastic robust standard errors are valid.

Problem: We do not know $\sigma_i^2 = Var(\epsilon_i|\mathbf{x_i}) = E(\epsilon_i^2|\mathbf{x}_i)$

- One observation ϵ_i cannot estimate a sample variance estimate σ_i^2

- Model ϵ_i^2 as reasonable (strictly positive) function of x_i and independent error v_i (strictly positive)

$$\epsilon_i^2 = v_i exp(\mathbf{x_i}\ )$$

Then we can apply a log transformation to recover a linear in parameters model,

$$ln(\epsilon_i^2) = \mathbf{x_i}\ + ln(v_i)$$

where $ln(v_i)$ is independent $\mathbf{x}_i$

We do not observe ϵ_i * OLS residual (e_i) as an approximate

5.2.2 Serial Correlation

$$Cov(\epsilon_i, \epsilon_j|\mathbf{X}) \neq 0$$

Under covariance stationary,

$$Cov(\epsilon_i, \epsilon_j|\mathbf{X}) = Cov(\epsilon_i, \epsilon_{i+h}|\mathbf{x_i}, \mathbf{x_{i+h}}) = \gamma_h$$

And the variance covariance matrix is

$$Var(\epsilon|\mathbf{X}) = \Omega = \begin{pmatrix} \sigma^2 & \gamma_1 & \gamma_2 & \cdots & \gamma_{n-1} \\ \gamma_1 & \sigma^2 & \gamma_1 & \cdots & \gamma_{n-2} \\ \gamma_2 & \gamma_1 & \sigma^2 & \cdots & \cdots \\ . & . & . & . & \gamma_1 \\ \gamma_{n-1} & \gamma_{n-2} & . & \gamma_1 & \sigma^2 \end{pmatrix}$$

There n parameters to estimate - need some sort fo structure to reduce number of parameters to estimate.

- Time Series
  - Effect of inflation and deficit on Treasury Bill interest rates
- Cross-sectional
  - Clustering

5.2.2.1 AR(1)

$$y_t = \beta_0 + x_t\beta_1 + \epsilon_t$$
$$\epsilon_t = \rho\epsilon_{t-1} + u_t$$

and the variance covariance matrix is

$$Var(\epsilon|\mathbf{X}) = \frac{\sigma_u^2}{1-\rho}\begin{pmatrix} 1 & \rho & \rho^2 & ... & \rho^{n-1} \\ \rho & 1 & \rho & ... & \rho^{n-2} \\ \rho^2 & \rho & 1 & . & . \\ . & . & . & . & \rho \\ \rho^{n-1} & \rho^{n-2} & . & \rho & 1 \end{pmatrix}$$

Hence, there is only 1 parameter to estimate: ρ

- Under A1, A2, A3a, A5a, OLS is consistent and asymptotically normal
- Use Newey West Standard Errors for valid inference.
- Apply Infeasible Cochrane Orcutt (as if we knew ρ)
- Because

$$u_t = \epsilon_t - \rho\epsilon_{t-1}$$

satisfies A3, A4, A5 we'd like to to transform the above equation to one that has u_t as the error.

$$\begin{aligned} y_t - \rho y_{t-1} &= (\beta_0 + x\beta_1 + \epsilon_t) - \rho(\beta_0 + x_{t-1}\beta_1 + \epsilon_{t-1}) \\ &= (1-\rho)\beta_0 + (x_t - \rho x_{t-1})\beta_1 + u_t \end{aligned}$$

5.2.2.1.1 Infeasible Cochrane Orcutt

1. Assume that we know ρ (Infeasible)
2. The ICO estimator is obtained as the least squared estimated for the following weighted first difference equation

$$y_t - \rho y_{t-1} = (1-\rho)\beta_0 + (x_t - \rho x_{t-1})\beta_1 + u_t$$

- Usual standard errors for the weighted first difference equation are valid if the errors truly follow an AR(1) process
- If the serial correlation is generated from a more complex dynamic process then Newey-West HAC standard errors are valid

Problem We do not know ρ

- ρ is the correlation between ϵ_t and ϵ_{t-1}: estimate using OLS residuals (e_i) as proxy

$$\hat{\rho} = \frac{\sum_{t=1}^{T} e_t e_{t-1}}{\sum_{t=1}^{T} e_t^2}$$

which can be obtained from the OLS regression of

$$e_t = \rho e_{t-1} + u_t$$

where we suppress the intercept.

- We are losing an observation
- By taking the first difference we are dropping the first observation

$$y_1 = \beta_0 + x_1\beta_1 + \epsilon_1$$

- Feasiable Prais Winsten Transformation applies the Infeasible Cochrane Orcutt but includes a weighted version of the first observation

$$(\sqrt{1-\rho^2})y_1 = \beta_0 + (\sqrt{1-\rho^2})x_1\beta_1 + (\sqrt{1-\rho^2})\epsilon_1$$

5.2.2.2 Cluster

$$y_{gi} = \mathbf{x}_{gi}\beta + \epsilon_{gi}$$

$$Cov(\epsilon_{gi}, \epsilon_{hj}) \begin{cases} = 0 & \text{for } g \neq h \text{ and any pair (i,j)} \\ \neq 0 & \text{for any (i,j) pair} \end{cases}$$

Intra-group Correlation
Each individual in a single group may be correlated but independent across groups.

- A4 is violated. usual standard errors for OLS are valid.
- Use **cluster robust standard errors** for OLS.

Suppose there are 3 groups with different n

$$Var(\epsilon|\mathbf{X}) = \Omega = \begin{pmatrix} \sigma^2 & \delta^1_{12} & \delta^1_{13} & 0 & 0 & 0 \\ \delta^1_{12} & \sigma^2 & \delta^1_{23} & 0 & 0 & 0 \\ \delta^1_{13} & \delta^1_{23} & \sigma^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2 & \delta^2_{12} & 0 \\ 0 & 0 & 0 & \delta^2_{12} & \sigma^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2 \end{pmatrix}$$

where $Cov(\epsilon_{gi}, \epsilon_{gj}) = \delta^g_{ij}$ and $Cov(\epsilon_{gi}, \epsilon_{hj}) = 0$ for any i and j

Infeasible Generalized Least Squares (Cluster)

1. Assume that σ^2 and δ^g_{ij} are known, plug into Ω and solve for the inverse Ω^{-1} (infeasible)
2. The Infeasible Generalized Least Squares Estimator is

$$\hat{\beta}_{IGLS} = (\mathbf{X}'^{\,-1}\mathbf{X})^{-1}\mathbf{X}'^{\,-1}\mathbf{y}$$

Problem * We do not know σ^2 and δ_{ij}^g + Can make assumptions about data generating process that is causing the clustering behavior. - Will give structure to $Cov(\epsilon_{gi}, \epsilon_{gj}) = \delta_{ij}^g$ which makes it feasible to estimate - if the assumptions are wrong then we should use cluster robust standard errors.

Solution Assume **group level random effects** specification in the error

$$\begin{aligned} y_{gi} &= \mathbf{g}_i\beta + c_g + u_{gi} \\ Var(c_g|\mathbf{x}_i) &= \sigma_c^2 \\ Var(u_{gi}|\mathbf{x}_i) &= \sigma_u^2 \end{aligned}$$

where c_g and u_{gi} are independent of each other, and mean independent of $\mathbf{x}_i$

- c_g captures the common group shocks (independent across groups)
- u_{gi} captures the individual shocks (independent across individuals and groups)

Then the error variance is

$$Var(\epsilon|\mathbf{X}) = \Omega = \begin{pmatrix} \sigma_c^2 + \sigma_u^2 & \sigma_c^2 & \sigma_c^2 & 0 & 0 & 0 \\ \sigma_c^2 & \sigma^2 + \sigma_u^2 & \sigma_c^2 & 0 & 0 & 0 \\ \sigma_c^2 & \sigma_c^2 & \sigma^2 + \sigma_u^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2 + \sigma_u^2 & \sigma_c^2 & 0 \\ 0 & 0 & 0 & \sigma_c^2 & \sigma^2 + \sigma_u^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2 + \sigma_u^2 \end{pmatrix}$$

Use Feasible group level Random Effects

5.3 Weighted Least Squares

1. Estimate the following equation using OLS

$$y_i = \mathbf{x}_i\beta + \epsilon_i$$

and obtain the residuals $e_i = y_i - \mathbf{x}_i\hat{\beta}$

2. Transform the residual and estimate the following by OLS,

$$ln(e_i^2) = \mathbf{x}_i\gamma + ln(v_i)$$

and obtain the predicted values $g_i = \mathbf{x}_i\hat{\gamma}$

3. The weights will be the untransformed predicted outcome,

$$\hat{\sigma}_i = \sqrt{exp(g_i)}$$

4. The FWLS (Feasible WLS) estimator is obtained as the least squared estimated for the following weighted equation

$$(1/\hat{\sigma}_i)y_i = (1/\hat{\sigma}_i)\mathbf{x}_i\beta + (1/\hat{\sigma}_i)\epsilon_i$$

Properties of the FWLS

- The infeasible WLS estimator is unbiased under A1-A3 for the unweighted equation.
- The FWLS estimator is NOT an unbiased estimator.
- The FWLS estimator is consistent under A1, A2, (for the unweighted equation), A5, and $E(\mathbf{x}_i'\epsilon_i/\sigma_i^2) = 0$
  - A3a is not sufficient for the above equation
  - A3 is sufficient for the above equation.
- The FWLS estimator is asymptotically more efficient than OLS if the errors have multiplicative exponential heteroskedasticity.
  - If the errors are truly multiplicative exponential heteroskedasticity, then usual standard errors are valid
  - If we believe that there may be some mis-specification with the **multiplicative exponential model**, then we should report heteroskedastic robust standard errors.

5.4 Generalized Least Squares

Consider

$$\mathbf{y} = \mathbf{X} \ +$$

where,

$$var(\epsilon) = \mathbf{G} = \begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ . & . & . & . \\ g_{n1} & . & . & g_{nn} \end{pmatrix}$$

The variances are heterogeneous, and the errors are correlated.

$$\hat{\mathbf{b}}_{\mathbf{G}} = (\mathbf{X}'\mathbf{G}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{G}^{-1}\mathbf{Y}$$

if we know G, we can estimate **b** just like OLS. However, we do not know G. Hence, we model the structure of G.

5.5 Feasible Prais Winsten

Weighting Matrix

$$\mathbf{w} = \begin{pmatrix} \sqrt{1-\hat{\rho}^2} & 0 & 0 & ... & 0 \\ -\hat{\rho} & 1 & 0 & ... & 0 \\ 0 & -\hat{\rho} & 1 & & . \\ . & . & . & . & 0 \\ 0 & . & 0 & -\hat{\rho} & 1 \end{pmatrix}$$

1. Estimate the following equation using OLS

$$y_t = \mathbf{x}_t\beta + \epsilon_t$$

and obtain the residuals $e_t = y_t - \mathbf{x}_t\hat{\beta}$

2. Estimate the correlation coefficient for the AR(1) process by estimating the following by OLS (without no intercept)

$$e_t = \rho e_{t-1} + u_t$$

3. Transform the outcome and independent variables **wy** and **wX** respectively (weight matrix as stated).
4. The FPW estimator is obtained as the least squared estimated for the following weighted equation

$$\mathbf{wy} = \mathbf{wX} \ + \mathbf{w}$$

Properties of FeasiblePrais Winsten Estimator

- The Infeasible PW estimator is under A1-A3 for the unweighted equation
- The FPW estimator is biased
- The FPW is consistent under A1 A2 A5 and

$$E((\mathbf{x_t} - \ \mathbf{x_{t-1}})')(\epsilon_t - \rho\epsilon_{t-1}) = 0$$

- A3a is not sufficient for the above equation
- A3 is sufficient for the above equation
- The FPW estimator is asymptotically more efficient than OLS if the errors are truly generated as AR(1) process

  - If the errors are truly generated as AR(1) process then usual standard errors are valid
  - If we are concerned that there may be a more complex dependence structure of heteroskedasticity, then we use Newey West Standard Errors

5.6 Feasible group level Random Effects

1. Estimate the following equation using OLS

$$y_{gi} = \mathbf{x}_{gi}\beta + \epsilon_{gi}$$

and obtain the residuals $e_{gi} = y_{gi} - \mathbf{x}_{gi}\hat{\beta}$ 2. Estimate the variance using the usual $s^2 estimator

$$s^2 = \frac{1}{n-k}\sum_{i=1}^{n} e_i^2$$

as an estimator for $\sigma_c^2 + \sigma_u^2$ and estimate the within group correlation,

$$\hat{\sigma}_c^2 = \frac{1}{G}\sum_{g=1}^{G}(\frac{1}{\sum_{i=1}^{n_g-1} i}\sum_{i\neq j}\sum_{j}^{n_g} e_{gi}e_{gj})$$

and plug in the estimates to obtain $\hat{\Omega}$

3. The feasible group level RE estimator is obtained as

$$\hat{\beta} = (\mathbf{X}^{\wedge\,-1}\mathbf{X})^{-1}\mathbf{X}^{\wedge\,-1}\mathbf{y}$$

Properties of the Feasible group level Random Effects Estimator

- The infeasible group RE estimator is a linear estimator and is unbiased under A1-A3 for the unweighted equation
  - A3 requires $E(\epsilon_{gi}|\mathbf{x}_i) = E(c_g|\mathbf{x}_i) + (u_{gi}|\mathbf{x}_i) = 0$ so we generally assume $E(c_g|\mathbf{x}_i) + (u_{gi}|\mathbf{x}_i) = 0$. The assumption $E(c_g|\mathbf{x}_i) = 0$ is generally called **random effects assumption**
- The Feasible group level Random Effects is biased
- The Feasible group level Random Effects is consistent under A1-A3a, and A5a for the unweighted equation.
  - A3a requires $E(\mathbf{x}_i'\epsilon_{gi}) = E(\mathbf{x}_i'c_g) + (\mathbf{x}_i'u_{gi}) = 0$

- The Feasible group level Random Effects estimator is asymptotically more efficient than OLS if the errors follow the random effects specification
  - If the errors do follow the random effects specification than the usual standard errors are consistent
  - If there might be a more complex dependence structure or heteroskedasticity, then we need cluster robust standard errors.

5.7 Ridge Regression

When we have the Collinearity problem, we could use the Ridge regression.

The main problem with multicollinearity is that $\mathbf{X}'\mathbf{X}$ is "ill-conditioned". The idea for ridge regression: adding a constant to the diagonal of $\mathbf{X}'\mathbf{X}$ improves the conditioning

$$\mathbf{X}'\mathbf{X} + c\mathbf{I}(c > 0)$$

The choice of c is hard. The estimator

$$\mathbf{b}^R = (\mathbf{X}'\mathbf{X} + c\mathbf{I})^{-1}\mathbf{X}'\mathbf{y}$$

is **biased**.

- It has smaller variance than the OLS estimator; as c increases, the bias increases but the variance decreases.
- Always exists some value of c for which the ridge regression estimator has a smaller total MSE than the OLS
- The optimal c varies with application and data set.
- To find the "optimal" c we could use "ridge trace".

We plot the values of the $p-1$ parameter estimates for different values of c, simultaneously.

- Typically, as c increases toward 1 the coefficients decreases to 0.
- The values of the VIF tend to decrease rapidly as c gets bigger than 0. The VIF values begin to change slowly as $c \to 1$.
- Then we can examine the ridge trace and VIF values and chooses the smallest value of c where the regression coefficients first become stable in the ridge trace and the VIF values have become sufficiently small (which is very subjective).
- Typically, this procedure is applied to the standardized regression model.

5.8 Principal Component Regression

This also addresses the problem of multicollinearity

5.9 Robust Regression

- To address the problem of influential cases.
- Can be used when a known functional form is to be fitted, and when the errors are not normal due to a few outlying cases.

5.9.1 Least Absolute Residuals (LAR) Regression

also known as minimum L_1-norm regression.

$$L_1 = \sum_{i=1}^{n} |Y_i - (\beta_0 + \beta_1 X_{i1} + .. + \beta_{p-1} X_{i,p-1})$$

which is not sensitive to outliers and inadequacies of the model specification.

5.9.2 Least Median of Squares (LMS) Regression

$$median\{[Y_i - (\beta_0 - \beta_1 X_{i1} + ... + \beta_{p-1} X_{i,p-1})]^2\}$$

5.9.3 Iteratively Reweighted Least Squares (IRLS) Robust Regression

- uses Weighted Least Squares to lessen the influence of outliers.
- the weights w_i are inversely proportional to how far an outlying case is (e.g., based on the residual)
- the weights are revised iteratively until a robust fit

Process:

Step 1: Choose a weight function for weighting the cases.
Step 2: obtain starting weights for all cases.
Step 3: Use the starting weights in WLS and obtain the residuals from the fitted regression function.
Step 4: use the residuals in Step 3 to obtain revised weights.
Step 5: continue until convergence.

Note:

- If you don't know the form of the regression function, consider using non-parametric regression (e.g., locally weighted regression, regression trees, projection pursuit, neural networks, smoothing splines, loess, wavelets).
- could use to detect outliers or confirm OLS.

5.10 Maximum Likelihood

Premise: find values of the parameters that maximize the probability of observing the data In other words, we try to maximize the value of theta in the

likelihood function

$$L(\theta) = \prod_{i=1}^{n} f(y_i|\theta)$$

$f(y|\theta)$ is the probability density of observing a single value of Y given some value of θ $f(y|\theta)$ can be specify as various type of distributions. You can review back section Distributions. For example, if y is a dichotomous variable, then

$$L(\theta) = \prod_{i=1}^{n} \theta^{y_i}(1-\theta)^{1-y_i}$$

$\hat{\theta}$ is the Maximum Likelihood estimate if $L(\hat{\theta}) > L(\theta_0)$ for all values of θ_0 in the parameter space.

5.10.1 Motivation for MLE

Suppose we know the conditional distribution of y given x:

$$f_{Y|X}(y, x; \theta)$$

where θ is the unknown parameter of distribution. Sometimes we are only concerned with the unconditional distribution $f_Y(y; \theta)$

Then given a sample of iid data, we can calculate the joint distribution of the entire sample,

$$f_{Y_1,\ldots,Y_n|X_1,\ldots,X_n(y_1,\ldots y_n,x_1,\ldots,x_n;\theta)} = \prod_{i=1}^{n} f_{Y|X}(y_i, x_i; \theta)$$

The joint distribution evaluated at the sample is the likelihood (probability) that we observed this particular sample (depends on θ)

Idea for MLE: Given a sample, we choose our estimates of the parameters that gives the highest likelihood (probability) of observing our particular sample

$$max_\theta \prod_{i=1}^{n} f_{Y|X}(y_i, x_i; \theta)$$

Equivalently,

$$max_\theta \prod_{i=1}^{n} ln(f_{Y|X}(y_i, x_i; \theta))$$

Solving for the Maximum Likelihood Estimator

1. Solve First Order Condition

$$\frac{\partial}{\partial \theta} \sum_{i=1}^{n} ln(f_{Y|X}(y_i, x_i; \hat{\theta}_{MLE})) = 0$$

where $\hat{\theta}_{MLE}$ is defined.

2. Evaluate Second Order Condition

$$\frac{\partial^2}{\partial \theta^2} \sum_{i=1}^{n} ln(f_{Y|X}(y_i, x_i; \hat{\theta}_{MLE})) < 0$$

where the above condition ensures we can solve for a maximum

Examples:
Unconditional Poisson Distribution: Number of products ordered on Amazon within an hour, number of website visits a day for a political campaign.

Exponential Distribution: Length of time until an earthquake occurs, length of time a car battery lasts.

$$f_{Y|X}(y, x; \theta) = exp(-y/x\theta)/x\theta$$
$$f_{Y_1,..Y_n|X_1,...,X_n(y_1,...,y_n,x_1,...,x_n;\theta)} = \prod_{i=1}^{n} exp(-y_i/x_i\theta)/x_i\theta$$

5.10.2 Assumption

- **High Level Regulatory Assumptions** is the sufficient condition used to show large sample properties
  - Hence, for each MLE, we will need to either assume or verify if the regulatory assumption holds.
- observations are independent and have the same density function.
- Under multivariate normal assumption, maximum likelihood yields consistent estimates of the means and the covariance matrix for multivariate distribution with finite fourth moments (Little, 1988)

To find the MLE, we usually differentiate the **log-likelihood** function and set it equal to 0.

$$\frac{d}{d\theta} l(\theta) = 0$$

This is the **score** equation

Our confidence in the MLE is quantified by the "pointedness" of the log-likelihood

$$I_O(\theta) = \frac{d^2}{d\theta^2} l(\theta) = 0$$

called the **observed information**

while

$$I(\theta) = E[I_O(\theta; Y)]$$

is the expected information. (also known as Fisher Information). which we base our variance of the estimator.

$$V(\hat{\Theta}) \approx I(\theta)^{-1}$$

Consistency of MLE
Suppose that y_i and x_i are iid drawn from the true conditional pdf $f_{Y|X}(y_i, x_i; \theta_0)$. If the following regulatory assumptions hold,

- R1: If $\theta \neq \theta_0$ then $f_{Y|X}(y_i, x_i; \theta) \neq f_{Y|X}(y_i, x_i; \theta_0)$
- R2: The set Θ that contains the true parameters θ_0 is compact
- R3: The log-likelihood $ln(f_{Y|X}(y_i, x_i; \theta_0))$ is continuous at each θ with probability 1
- R4: $E(sup_{\theta \in \Theta} |ln(f_{Y|X}(y_i, x_i; \theta_0))|)$

then the MLE estimator is consistent,

$$\hat{\theta}_{MLE} \rightarrow^p \theta_0$$

Asymptotic Normality of MLE

Suppose that y_1 and x_i are iid drawn from the true conditional pdf $f_{Y|X}(y_i, x_i; \theta)$. If R1-R4 and the following hold

- R5: θ_0 is in the interior of the set Θ
- R6: $f_{Y|X}(y_i, x_i; \theta)$ is twice continuously differentiable in θ and $f_{Y|X}(y_i, x_i; \theta) > 0$ for a neighborhood $N \in \Theta$ around θ_0
- R7: $\int sup_{\theta \in N} ||\partial f_{Y|X}(y_i, x_i; \theta) \partial\theta || d(y, x) < \infty$, $\int sup_{\theta \in N} ||\partial^2 f_{Y|X}(y_i, x_i; \theta)/\partial\theta\partial\theta' || d(y, x) < \infty$ and $E(sup_{\theta \in N} ||\partial^2 ln(f_{Y|X}(y_i, x_i; \theta))/\partial\theta\partial\theta' ||) < \infty$
- R8: The information matrix $I(\theta_0) = Var(\partial f_{Y|X}(y, x_i; \theta_0)/\partial\theta)$ exists and is non-singular

then the MLE estimator is asymptotically normal,

$$\sqrt{n}(\hat{\theta}_{MLE} - \theta_0) \rightarrow^d N(0, I(\theta_0)^{-1})$$

5.10.3 Properties

(1) Consistent: estimates are approximately unbiased in large samples

(2) Asymptotically efficient: approximately smaller standard errors compared to other estimator

(3) Asymptotically normal: with repeated sampling, the estimates will have an approximately normal distribution. Suppose that $\hat{\theta}_n$ is the MLE for θ based on n independent observations. then $\hat{\theta}_n \sim N(\theta, H^{-1})$.

- where H is called the Fisher information matrix. It contains the expected values of the second partial derivatives of the log-likelihood function. The (i.j)th element of H is $-E(\frac{\partial^2 l(\theta)}{\partial\theta_i \partial\theta_j})$
- We can estimate H by finding the form determined above, and evaluating it at $\theta = \hat{\theta}_n$

(4) Invariance: MLE for $g(\theta) = g(\hat{\theta})$ for any function g(.)

$$\hat{\Theta} \approx^d (\theta, I(\theta)\hat{^{-1}}))$$

Explicit vs Implicit MLE

- If we solve the score equation to get an expression of MLE, then it's called **explicit**
- If there is no closed form for MLE, and we need some algorithms to derive its expression, it's called **implicit**

Large Sample Property of MLE

Implicit in these theorems is the assumption that we know what the conditional distribution,

$$f_{Y|X}(y_i, x_i; \theta_0)$$

but just do now know the exact parameter value.

- Any Distributional mis-specification will result in inconsistent parameter estimates.
- Quasi-MLE: Particular settings/ assumption that allow for certain types of distributional mis-specification (Ex: as long as the distribution is part of

particular class or satisfies a particular assumption, then estimating with a wrong distribution will not lead to inconsistent parameter estimates).
- non-parametric/ Semi-parametric estimation: no or very little distributional assumption are made. (hard to implement, derive properties, and interpret)

The asymptotic variance of the MLE achieves the **Cramer-Rao Lower Bound** (Cramér, 1999, Rao (1992))

- The **Cramer-Rao Lower Bound** is a lower brand for the asymptotic variance of a consistent and asymptotically normally distributed estimator.
- If an estimator achieves the lower bound then it is the most efficient estimator.

The maximum Likelihood estimator (assuming the distribution is correctly specified and R1-R8 hold) is the most efficient consistent and asymptotically normal estimator. * most efficient among ALL consistent estimators (not limited to unbiased or linear estimators).

Note

- ML is better choice for binary, strictly positive, count, or inherent heteroskedasticity than linear model.
- ML will assume that we know the conditional distribution of the outcome, and derive an estimator using that information.
  - Adds an assumption that we know the distribution (which is similar to A6 Normal Distribution in linear model)
  - will produce a more efficient estimator.

5.10.4 Compare to OLS

MLE is not a cure for most of OLS problems:

- To do joint inference in MLE, we typically use log-likelihood calculation, instead of F-score
- Functional form affects estimation of MLE and OLS.
- Perfect Collinearity/Multicollinearity: highly correlated are likely to yield large standard errors.
- Endogeneity (Omitted variables bias, Simultaneous equations): Like OLS, MLE is also biased against this problem

5.10.5 Application

Other applications of MLE

- Corner Solution
  - Ex: hours worked, donations to charity

  - Estimate with Tobit

- Non-negative count
  - Ex: Numbers of arrest, Number of cigarettes smoked a day
  - Estimate with Poisson regression

- Multinomial Choice
  - Ex: Demand for cars, votes for primary election
  - Estimate with mutinomial probit or logit

- Ordinal Choice
  - Ex: Levels of Happiness, Levels of Income
  - Ordered Probit

Model for binary Response
A binary variable will have a [Bernoulli] distribution:

$$f_Y(y_i; p) = p^{y_i}(1-p)^{(1-y_i)}$$

where p is the probability of success. The conditional distribution is:

$$f_{Y|X}(y_i, x_i; p(.)) = p(x_i)^{y_i}(1-p(x_i))^{(1-y_i)}$$

So choose $p(x_i)$ to be a reasonable function of x_i and unknown parameters θ

We can use **latent variable model** as probability functions

$$\begin{aligned} y_i &= 1\{y_i^* > 0\} \\ y_i^* &= x_i\beta - \epsilon_i \end{aligned}$$

- y_i^* is a latent variable (unobserved) that is not well-defined in terms of units/magnitudes
- ϵ_i is a mean 0 unobserved random variable.

We can rewrite the model without the latent variable,

$$y_i = 1\{x_i beta > \epsilon_i\}$$

Then the probability function,

$$\begin{aligned} p(x_i) &= P(y_i = 1|x_i) \\ &= P(x_i\beta > \epsilon_i|x_i) \\ &= F_{\epsilon|X}(x_i\beta|x_i) \end{aligned}$$

then we need to choose a conditional distribution for ϵ_i. Hence, we can make additional strong independence assumption

ϵ_i is independent of x_i

Then the probability function is simply,

$$p(x_i) = F_\epsilon(x_i\beta)$$

The probability function is also the conditional expectation function,

$$E(y_i|x_i) = P(y_i = 1|x_i) = F_\epsilon(x_i\beta)$$

so we allow the conditional expectation function to be non-linear.

Common distributional assumption

1. **Probit**: Assume ϵ_i is standard normally distributed, then $F_\epsilon(.) = \Phi(.)$ is the standard normal CDF.

2. **Logit**: Assume ϵ_i is standard logistically distributed, then $F_\epsilon(.) = \Lambda(.)$ is the standard normal CDF.

Step to derive

1. Choose a distribution (normal or logistic) and plug into the following log likelihood,

$$ln(f_{Y|X}(y_i, x_i; \beta)) = y_i ln(F_\epsilon(x_i\beta)) + (1 - y_i)ln(1 - F_\epsilon(x_i\beta))$$

2. Solve the MLE by finding the Maximum of

$$\hat{\beta}_{MLE} = argmax \sum_{i=1}^{n} ln(f_{Y|X}(y_i, x_i; \beta))$$

Properties of the Probit and Logit Estimators

- Probit or Logit is consistent and asymptotically normal if
  - A2 Full rank holds: $E(x_i'x_i)$ exists and is non-singular
  - A5 Data Generation (random Sampling) (or A5a) holds: {y_i,x_i} are iid (or stationary and weakly dependent).
  - Distributional assumptions on ϵ_i hold: Normal/Logistic and independent of x_i
- Under the same assumptions, Probit or Logit is also asymptotically efficient with asymptotic variance,

$$I(\beta_0)^{-1} = [E(\frac{(f_\epsilon(x_i\beta_0))^2}{F_\epsilon(x_i\beta_0)(1 - F_\epsilon(x_i\beta_0))} x_i' x_i)]^{-1}$$

where $F_\epsilon(x_i\beta_0)$ is the probability density function (derivative of the CDF)

5.10.5.1 Interpretation

β is the average response in the latent variable associated with a change in x_i

- Magnitudes do not have meaning
- Direction does have meaning

The **partial effect** for a Non-linear binary response model

$$\begin{aligned} E(y_i|x_i) &= F_\epsilon(x_i\beta) \\ PE(x_{ij}) &= \frac{\partial E(y_i|x_i)}{\partial x_{ij}} = f_\epsilon(x_i\beta)\beta_j \end{aligned}$$

- The partial effect is the coefficient parameter β_j multiplied by a scaling factor $f_\epsilon(x_i\beta)$

- The scaling factor depends on x_i so the partial effect changes depending on what x_i is

Single value for the partial effect

- **Partial Effect at the Average (PEA)** is the partial effect for an average individual

$$f_\epsilon(\bar{x}\hat{\beta})\hat{\beta}_j$$

- **Average Partial Effect (APE)** is the average of all partial effect for each individual.

$$\frac{1}{n}\sum_{i=1}^{n} f_\epsilon(x_i\hat{\beta})\hat{\beta}_j$$

In the linear model, $APE = PEA$.

In a non-linear model (e.g., binary response), $APE \neq PEA$

Chapter 6

Non-linear Regression

Definition: models in which the derivatives of the mean function with respect to the parameters depend on one or more of the parameters.

To approximate data, we can approximate the function

- by a high-order polynomial
- by a linear model (e.g., a Taylor expansion around X's)
- a collection of locally linear models or basis function

but it would not easy to interpret, or not enough data, or can't interpret them globally.

intrinsically nonlinear models:

$$Y_i = f(\mathbf{x_i};\ ) + \epsilon_i$$

where $f(\mathbf{x_i};\ )$ is a nonlinear function relating $E(Y_i)$ to the independent variables x_i

- $\mathbf{x}_i$ is a $k \times 1$ vector of independent variables (fixed).
- is a $p \times 1$ vector of parameters.
- ϵ_is are iid variables mean 0 and variance σ^2. (sometimes it's normal).

6.1 Inference

Since $Y_i = f(\mathbf{x}_i, \theta) + \epsilon_i$, where $\epsilon_i \sim iid(0, \sigma^2)$, we can obtain $\hat{\theta}$ by minimizing $\sum_{i=1}^{n}(Y_i - f(x_i, \theta))^2$ and estimate $s^2 = \hat{\sigma}_\epsilon^2 = \frac{\sum_{i=1}^{n}(Y_i - f(x_i,\theta))^2}{n-p}$

6.1.1 Linear Function of the Parameters

If we assume $\epsilon_i \sim N(0, \sigma^2)$, then

$$\hat{\theta} \sim AN(\ , \sigma^2[\mathbf{F}(\theta)'\mathbf{F}(\theta)]^{-1})$$

where AN = asymptotic normality

Asymptotic means we have enough data to make inference (As your sample size increases, this becomes more and more accurate (to the true value)).

Since we want to do inference on linear combinations of parameters or contrasts.

If we have $\ = (\theta_0, \theta_1, \theta_2)'$ and we want to look at $\theta_1 - \theta_2$; we can define vector $\mathbf{a} = (0, 1, -1)'$, consider inference for $\mathbf{a}'$

Rules for expectation and variance of a fixed vector $\mathbf{a}$ and random vector $\mathbf{Z}$;

$$E(\mathbf{a}'\mathbf{Z}) = \mathbf{a}'E(\mathbf{Z})$$
$$var(\mathbf{a}'\mathbf{Z}) = \mathbf{a}'var(\mathbf{Z})\mathbf{a}$$

Then,

$$\mathbf{a}\hat{\ } \sim AN(\mathbf{a}'\ , \sigma^2\mathbf{a}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{a})$$

and $\mathbf{a}\hat{\ }$ is asymptotically independent of s^2 (to order 1/n) then

$$\frac{\mathbf{a}\hat{\ } - \mathbf{a}'}{s(\mathbf{a}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{a})^{1/2}} \sim t_{n-p}$$

to construct $100(1-\alpha)\%$ confidence interval for $\mathbf{a}'$

$$\mathbf{a}'\ \pm t_{(1-\alpha/2, n-p)} s(\mathbf{a}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{a})^{1/2}$$

Suppose $\mathbf{a}' = (0, ..., j, ..., 0)$. Then, a confidence interval for the j-th element of is

$$\hat{\theta}_j \pm t_{(1-\alpha/2, n-p)} s\sqrt{\hat{c}^j}$$

where $\hat{c}^j$ is the j-th diagonal element of $[\mathbf{F}\hat{(\ )}'\mathbf{F}\hat{(\ )}]^{-1}$

```
#set a seed value
set.seed(23)

#Generate x as 100 integers using seq function
x <- seq(0, 100, 1)

#Generate y as a*e^(bx)+c
y <- runif(1, 0, 20) * exp(runif(1, 0.005, 0.075) * x) + runif(101, 0, 5)
```

```
# visualize
plot(x, y)
```

```
#define our data frame
datf = data.frame(x, y)

#define our model function
mod = function(a, b, x)
    a * exp(b * x)
```

In this example, we can get the starting values by using linearized version of the function $\log y = \log a + bx$. Then, we can fit a linear regression to this and use our estimates as starting values

```
#get starting values by linearizing
lin_mod = lm(log(y) ~ x, data = datf)

#convert the a parameter back from the log scale; b is ok
astrt = exp(as.numeric(lin_mod$coef[1]))
bstrt = as.numeric(lin_mod$coef[2])
print(c(astrt, bstrt))
#> [1] 14.07964761  0.01855635
```

with `nls`, we can fit the nonlinear model via least squares

```
nlin_mod = nls(y ~ mod(a, b, x),
               start = list(a = astrt, b = bstrt),
```

```
                data = datf)

#look at model fit summary
summary(nlin_mod)
#>
#> Formula: y ~ mod(a, b, x)
#>
#> Parameters:
#>    Estimate Std. Error t value Pr(>|t|)
#> a 13.603909   0.165390   82.25   <2e-16 ***
#> b  0.019110   0.000153  124.90   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.542 on 99 degrees of freedom
#>
#> Number of iterations to convergence: 3
#> Achieved convergence tolerance: 7.006e-07

#add prediction to plot
plot(x, y)
lines(x, predict(nlin_mod), col = "red")
```

6.1.2 Nonlinear

Suppose that $h(\theta)$ is a nonlinear function of the parameters. We can use Taylor series about θ

$$h(\hat{\theta}) \approx h(\theta) + \mathbf{h}'[\hat{\theta} - \theta]$$

where $\mathbf{h} = (\frac{\partial h}{\partial \theta_1}, ..., \frac{\partial h}{\partial \theta_p})'$

with

$$\begin{aligned} E(\hat{\theta}) &\approx \theta \\ var(\hat{\theta}) &\approx \sigma^2[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-1} \\ E(h(\hat{\theta})) &\approx h(\theta) \\ var(h(\hat{\theta})) &\approx \sigma^2\mathbf{h}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{h} \end{aligned}$$

Thus,

$$h(\hat{\theta}) \sim AN(h(\theta), \sigma^2\mathbf{h}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{h})$$

and an approximate $100(1-\alpha)\%$ confidence interval for $h(\theta)$ is

$$h(\hat{\theta}) \pm t_{(1-\alpha/2;n-p)}s(\mathbf{h}'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{h})^{1/2}$$

where $\mathbf{h}$ and $\mathbf{F}(\theta)$ are evaluated at $\hat{\theta}$

Regarding **prediction interval** for Y at $x = x_0$

$$\begin{aligned} Y_0 &= f(x_0;\theta) + \epsilon_0, \epsilon_0 \sim N(0, \sigma^2) \\ \hat{Y}_0 &= f(x_0, \hat{\theta}) \end{aligned}$$

As $n \to \infty$, $\hat{\theta} \to \theta$, so we

$$f(x_0, \hat{\theta}) \approx f(x_0, \theta) + \mathbf{f}_0(\ )'[\hat{\theta} - \theta]$$

where

$$f_0(\theta) = (\frac{\partial f(x_0, \theta)}{\partial \theta_1}, .., \frac{\partial f(x_0, \theta)}{\partial \theta_p})'$$

(note: this $f_0(\theta)$ is different from $f(\theta)$).

$$\begin{aligned} Y_0 - \hat{Y}_0 &\approx Y_0 - f(x_0, \theta) - f_0(\theta)'[\hat{\theta} - \theta] \\ &= \epsilon_0 - f_0(\theta)'[\hat{\theta} - \theta] \end{aligned}$$

$$\begin{aligned} E(Y_0 - \hat{Y}_0) &\approx E(\epsilon_0)E(\hat{\theta} - \theta) = 0 \\ var(Y_0 - \hat{Y}_0) &\approx var(\epsilon_0 - (\mathbf{f_0}(\ )'\uparrow\ -\ ])) \\ &= \sigma^2 + \sigma^2 \mathbf{f_0}(\ )'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{f_0}(\ ) \\ &= \sigma^2(1 + \mathbf{f_0}(\ )'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{f_0}(\ )) \end{aligned}$$

Hence, combining

$$Y_0 - \hat{Y}_0 \sim AN(0, \sigma^2(1 + \mathbf{f_0}(\ )'[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{f_0}(\ )))$$

Note:

Confidence intervals for the mean response Y_i (which is different from prediction intervals) can be obtained similarly.

6.2 Non-linear Least Squares

- The LS estimate of θ, $\hat{\theta}$ is the set of parameters that minimizes the residual sum of squares:

$$S(\hat{\theta}) = SSE(\hat{\theta}) = \sum_{i=1}^{n} \{Y_i - f(\mathbf{x_i}; \hat{\theta})\}^2$$

- to obtain the solution, we can consider the partial derivatives of $S(\theta)$ with respect to each θ_j and set them to 0, which gives a system of p equations. Each normal equation is

$$\frac{\partial S(\theta)}{\partial \theta_j} = -2 \sum_{i=1}^{n} \{Y_i - f(\mathbf{x}_i; \theta)\}[\frac{\partial(\mathbf{x}_i; \theta)}{\partial \theta_j}] = 0$$

- but we can't obtain a solution directly/analytically for this equation.

Numerical Solutions

- Grid search
  - A "grid" of possible parameter values and see which one minimize the residual sum of squares.
  - finer grid = greater accuracy
  - could be inefficient, and hard when p is large.
- Gauss-Newton Algorithm
  - we have an initial estimate of θ denoted as $\hat{\theta}^{(0)}$

– use a Taylor expansions of $f(\mathbf{x}_i;\theta)$ as a function of θ about the point $\widehat{\theta}^{(0)}$

$$\begin{aligned} Y_i &= f(x_i;\theta) + \epsilon_i \\ &= f(x_i;\theta) + \sum_{j=1}^{p}\{\frac{\partial f(x_i;\theta)}{\partial \theta_j}\}_{\theta=\widehat{\theta}^{(0)}}(\theta_j - \widehat{\theta}^{(0)}) + \text{remainder} + \epsilon_i \end{aligned}$$

Equivalently,

In matrix notation,

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ . \\ Y_n \end{bmatrix}$$

$$\mathbf{f}(\widehat{\theta}^{(0)}) = \begin{bmatrix} f(\mathbf{x_1}, \hat{}^{(0)}) \\ . \\ f(\mathbf{x_n}, \hat{}^{(0)}) \end{bmatrix}$$

$$= \begin{bmatrix} \epsilon_1 \\ . \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{F}(\widehat{\theta}^{(0)}) = \begin{bmatrix} \frac{\partial f(x_1,)}{\partial \theta_1} & \cdots & \frac{\partial f(x_1,)}{\partial \theta_p} \\ . & . & . \\ \frac{\partial f(x_n,)}{\partial \theta_1} & \cdots & \frac{\partial f(x_n,)}{\partial \theta_p} \end{bmatrix}_{\theta=\widehat{\theta}^{(0)}}$$

Hence,

$$\mathbf{Y} = \mathbf{f}(\widehat{\theta}^{(0)}) + \mathbf{F}(\widehat{\theta}^{(0)})(\theta - \widehat{\theta}^{(0)}) + \epsilon + \text{remainder}$$

where we assume that the remainder is small and the error term is only assumed to be iid with mean 0 and variance σ^2.

We can rewrite the above equation as

$$\mathbf{Y} - \mathbf{f}(\widehat{\theta}^{(0)}) \approx \mathbf{F}(\widehat{\theta}^{(0)})(\theta - \widehat{\theta}^{(0)}) + \epsilon$$

where it is in the form of linear model. After we solve for $(\theta - \widehat{\theta}^{(0)})$ and let it equal to $\widehat{\delta}^{(1)}$
Then we new estimate is given by adding the Gauss increment adjustment to the initial estimate $\widehat{\theta}^{(1)} = \widehat{\theta}^{(0)} + \widehat{\delta}^{(1)}$
We can repeat this process.

Gauss-Newton Algorithm Steps:

1. initial estimate $\hat{\theta}^{(0)}$, set j = 0
2. Taylor series expansion and calculate $\mathbf{f}(\hat{\theta}^{(j)})$ and $\mathbf{F}(\hat{\theta}^{(j)})$
3. Use OLS to get $\hat{\delta}^{(j+1)}$
4. get the new estimate $\hat{\theta}^{(j+1)}$, return to step 2
5. continue until "convergence"
6. With the final parameter estimate $\hat{\theta}$, we can estimate σ^2 if $\epsilon \sim (\mathbf{0}, \sigma^2\mathbf{I})$ by

$$\hat{\sigma}^2 = \frac{1}{n-p}(\mathbf{Y} - \mathbf{f}(x;\hat{\theta}))'(\mathbf{Y} - \mathbf{f}(x;\hat{\theta}))$$

Criteria for convergence

1. Minor change in the objective function (SSE = residual sum of squares)

$$\frac{|SSE(\hat{\theta}^{(j+1)}) - SSE(\hat{\theta}^{(j)})|}{SSE(\hat{\theta}^{(j)})} < \gamma_1$$

2. Minor change in the parameter estimates

$$|\hat{\theta}^{(j+1)} - \hat{\theta}^{(j)}| < \gamma_2$$

3. "residual projection" criterion of (Bates and Watts, 1981)

6.2.1 Alternative of Gauss-Newton Algorithm

6.2.1.1 Gauss-Newton Algorithm

Normal equations:

$$\frac{\partial SSE(\theta)}{\partial \theta} = 2\mathbf{F}(\theta)'[\mathbf{Y} - \mathbf{f}(\theta)]$$

$$\begin{aligned}
\hat{\theta}^{(j+1)} &= \hat{\theta}^{(j)} + \hat{\delta}^{(j+1)} \\
&= \hat{\theta}^{(j)} + [\mathbf{F}((\hat{\theta})^{(j)})'\mathbf{F}(\hat{\theta}^{(j)})]^{-1}\mathbf{F}(\hat{\theta})^{(j)} \\
&= \hat{\theta}^{(j)} - \frac{1}{2}[\mathbf{F}(\hat{\theta}^{(j)})'\mathbf{F}(\hat{\theta}^{(j)})]^{-1}\frac{\partial SSE(\hat{\theta}^{(j)})}{\partial \theta}
\end{aligned}$$

where

- $\frac{\partial SSE(\hat{\theta}^{(j)})}{\partial \theta}$ is a gradient vector (points in the direction in which the SSE increases most rapidly). This path is known as steepest ascent.
- $[\mathbf{F}(\hat{\theta}^{(j)})'\mathbf{F}(\hat{\theta}^{(j)})]^{-1}$ indicates how far to move
- $-1/2$: indicator of the direction of steepest descent.

6.2.1.2 Modified Gauss-Newton Algorithm

To avoid overstepping (the local min), we can use the modified Gauss-Newton Algorithm. We define a new proposal for θ

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} + \alpha_j \hat{\delta}^{(j+1)}, 0 < \alpha_j < 1$$

where

- α_j (called the "learning rate"): is used to modify the step length.

We could also have $\alpha \times 1/2$, but typically it is assumed to be absorbed into the learning rate.

A way to choose α_j, we can use **step halving**

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} + \frac{1}{2^k}\hat{\delta}^{(j+1)}$$

where

- k is the smallest non-negative integer such that

  $$SSE(\hat{\theta}^{(j)} + \frac{1}{2^k}\hat{\delta}^{(j+1)}) < SSE(\hat{\theta}^{(j)})$$

  which means we try $\hat{\delta}^{(j+1)}$, then $\hat{\delta}^{(j+1)}/2$, $\hat{\delta}^{(j+1)}/4$, etc.

The most general form of the convergence algorithm is

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j \mathbf{A}_j \frac{\partial Q(\hat{\theta}^{(j)})}{\partial \theta}$$

where

- $\mathbf{A}_j$ is a positive definite matrix
- α_j is the learning rate
- $\frac{\partial Q(\hat{\theta}^{(j)})}{\partial \theta}$is the gradient based on some objective function Q (a function of θ), which is typically the SSE in nonlinear regression applications (e.g., cross-entropy for classification).

Refer back to the **Modified Gauss-Newton Algorithm**, we can see it is in this form

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j [\mathbf{F}(\hat{\theta}^{(j)})' \mathbf{F}(\hat{\theta}^{(j)})]^{-1} \frac{\partial SSE(\hat{\theta}^{(j)})}{\partial \theta}$$

where Q = SSE, $[\mathbf{F}(\hat{\theta}^{(j)})' \mathbf{F}(\hat{\theta}^{(j)})]^{-1} = \mathbf{A}$

6.2.1.3 Steepest Descent

(also known just "gradient descent")

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j \mathbf{I}_{p\times p} \frac{\partial \mathbf{Q}(\hat{\theta}^{(j)})}{\partial \theta}$$

- slow to converge, moves rapidly initially.
- could be use for starting values

6.2.1.4 Levenberg -Marquardt

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j [\mathbf{F}(\hat{\theta}^{(j)})' \mathbf{F}(\hat{\theta}^{(j)}) + \tau \mathbf{I}_{p\times p}] \frac{\partial \mathbf{Q}(\hat{\theta}^{(j)})}{\partial \theta}$$

which is a compromise between the Gauss-Newton Algorithm and the Steepest Descent.

- best when $\mathbf{F}(\hat{\theta}^{(j)})' \mathbf{F}(\hat{\theta}^{(j)})$ is nearly singular ($\mathbf{F}(\hat{\theta}^{(j)})$ isn't of full rank)
- similar to ridge regression
- If $SSE(\hat{\theta}^{(j+1)}) < SSE(\hat{\theta}^{(j)})$, then $\tau = \tau/10$ for the next iteration. Otherwise, $\tau = 10\tau$

6.2.1.5 Newton-Raphson

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j [\frac{\partial^2 Q(\hat{\theta}^{(j)})}{\partial \theta \partial \theta'}]^{-1} \frac{\partial \mathbf{Q}(\hat{\theta}^{(j)})}{\partial \theta}$$

The **Hessian matrix** can be rewritten as:

$$\frac{\partial^2 Q(\hat{\theta}^{(j)})}{\partial \theta \partial \theta'} = 2\mathbf{F}((\hat{\theta})^{(j)})' \mathbf{F}(\hat{\theta}^{(j)}) - 2\sum_{i=1}^{n} [Y_i - f(x_i;\theta)] \frac{\partial^2 f(x_i;\theta)}{\partial \theta \partial \theta'}$$

which contains the same term that Gauss-Newton Algorithm, combined with one containing the second partial derivatives of f(). (methods that require the second derivatives of the objective function are known as "second-order methods".) However, the last term $\frac{\partial^2 f(x_i;\theta)}{\partial \theta \partial \theta'}$ can sometimes be non-singular.

6.2.1.6 Quasi-Newton

update θ according to

$$\hat{\theta}^{(j+1)} = \hat{\theta}^{(j)} - \alpha_j \mathbf{H}_j^{-1} \frac{\partial \mathbf{Q}(\hat{\theta}^{(j)})}{\partial \theta}$$

where H_j is a symmetric positive definite approximation to the Hessian, which gets closer as $j \to \infty$.

- $\mathbf{H}_j$ is computed iteratively

- Among first-order methods (where only first derivatives are required), this method performs best.

6.2.1.7 Derivative Free Methods

- **secant Method**: like Gauss-Newton Algorithm, but calculates the derivatives numerically from past iterations.
- **Simplex Methods**
- **Genetic Algorithm**
- **Differential Evolution Algorithms**
- **Particle Swarm Optimization**
- **Ant Colony Optimization**

6.2.2 Practical Considerations

To converge, algorithm need good initial estimates.

- Starting values:
  - Prior or theoretical info
  - A grid search or a graph of $SSE(\theta)$
  - could also use OLS to get starting values.
  - Model interpretation: if you have some idea regarding the form of the objective function, then you can try to guess the initial value.
  - Expected Value Parameterization
- Constrained Parameters: (constraints on parameters like $\theta_i > a, a < \theta_i < b$)
  - fit the model first to see if the converged parameter estimates satisfy the constraints.
  - if they don't satisfy, then try re-parameterizing

6.2.2.1 Failure to converge

- $SSE(\theta)$ may be "flat" in a neighborhood of the minimum.
- You can try different or "better" starting values.
- Might suggest the model is too complex for the data, might consider simpler model.

6.2.2.2 Convergence to a Local Minimum

- Linear least squares has the property that $SSE(\theta) = (\mathbf{Y} - \mathbf{X}\ )'(\mathbf{Y} - \mathbf{X}\ )$, which is quadratic and has a unique minimum (or maximum).

- Nonlinear east squares need not have a unique minimum
- Using different starting values can help
- If the dimension of θ is low, graph $SSE(\theta)$ as a function of θ_i
- Different algorithm can help (e.g., genetic algorithm, particle swarm)

To converge, algorithms need good initial estimates.

- Starting values:
  - prior or theoretical info
  - A grid search or a graph
  - OLS estimates as starting values
  - Model interpretation
  - Expected Value Parameterization
- Constrained Parameters:
  - try the model without the constraints first.
  - If the resulted parameter estimates does not satisfy the constraint, try re-parameterizing

```
# Grid search
# choose grid of a and b values
aseq = seq(10,18,.2)
bseq = seq(.001,.075,.001)

na = length(aseq)
nb = length(bseq)
SSout = matrix(0,na*nb,3) #matrix to save output
cnt = 0
for (k in 1:na){
   for (j in 1:nb){
      cnt = cnt+1
      ypred = mod(aseq[k],bseq[j],x) #evaluate model w/ these parms
      ss = sum((y-ypred)^2)  #this is our SSE objective function
      #save values of a, b, and SSE
      SSout[cnt,1]=aseq[k]
      SSout[cnt,2]=bseq[j]
      SSout[cnt,3]=ss
   }
}
#find minimum SSE and associated a,b values
mn_indx = which.min(SSout[,3])
astrt = SSout[mn_indx,1]
bstrt = SSout[mn_indx,2]
#now, run nls function with these starting values
nlin_modG=nls(y~mod(a,b,x),start=list(a=astrt,b=bstrt))
```

```
nlin_modG
#> Nonlinear regression model
#>   model: y ~ mod(a, b, x)
#>    data: parent.frame()
#>        a        b
#> 13.60391  0.01911
#>  residual sum-of-squares: 235.5
#>
#> Number of iterations to convergence: 3
#> Achieved convergence tolerance: 2.293e-07
# Note, the package `nls_multstart` will allow you
# to do a grid search without programming your own loop
```

For prediction interval

```
plotFit(
  nlin_modG,
  interval = "both",
  pch = 19,
  shade = TRUE,
  col.conf = "skyblue4",
  col.pred = "lightskyblue2",
  data = datf
)
```

Based on the forms of your function, you can also have programmed starting values from `nls` function (e.e.g, logistic growth, asymptotic regression, etc).

```r
apropos("^SS")
#>  [1] "ss"          "SSasymp"     "SSasympOff"  "SSasympOrig" "SSbiexp"
#>  [6] "SSD"         "SSfol"       "SSfpl"       "SSgompertz"  "SSlogis"
#> [11] "SSmicmen"    "SSout"       "SSweibull"
```

For example, a logistic growth model:

$$P = \frac{K}{1 + exp(P_0 + rt)} + \epsilon$$

where

- P = population at time t
- K = carrying capacity
- r = population growth rate

but in `R` you have slight different parameterization:

$$P = \frac{asym}{1 + exp(\frac{xmid - t}{scal})}$$

where

- $asym$ = carrying capacity
- $xmid$ = the x value at the inflection point of the curve
- $scal$ = scaling parameter.

Hence, you have

- $K = asym$
- $r = -1/scal$
- $P_0 = -rxmid$

```r
# simulated data
time <- c(1, 2, 3, 5, 10, 15, 20, 25, 30, 35)
population <-
    c(2.8, 4.2, 3.5, 6.3, 15.7, 21.3, 23.7, 25.1, 25.8, 25.9)
plot(time, population, las = 1, pch = 16)
```

```
# model fitting
logisticModelSS <- nls(population ~ SSlogis(time, Asym, xmid, scal))
summary(logisticModelSS)
#>
#> Formula: population ~ SSlogis(time, Asym, xmid, scal)
#>
#> Parameters:
#>      Estimate Std. Error t value Pr(>|t|)
#> Asym  25.5029     0.3666   69.56 3.34e-11 ***
#> xmid   8.7347     0.3007   29.05 1.48e-08 ***
#> scal   3.6353     0.2186   16.63 6.96e-07 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.6528 on 7 degrees of freedom
#>
#> Number of iterations to convergence: 1
#> Achieved convergence tolerance: 1.908e-06
coef(logisticModelSS)
#>      Asym      xmid      scal
#> 25.502890  8.734698  3.635333
```

Other parameterization

```
#convert to other parameterization
Ks = as.numeric(coef(logisticModelSS)[1])
rs = -1 / as.numeric(coef(logisticModelSS)[3])
```

```
Pos = -rs * as.numeric(coef(logisticModelSS)[2])
#let's refit with these parameters
logisticModel <-
    nls(population ~ K / (1 + exp(Po + r * time)),
        start = list(Po = Pos, r = rs, K = Ks))
summary(logisticModel)
#>
#> Formula: population ~ K/(1 + exp(Po + r * time))
#>
#> Parameters:
#>    Estimate Std. Error t value Pr(>|t|)
#> Po  2.40272    0.12702   18.92 2.87e-07 ***
#> r  -0.27508    0.01654  -16.63 6.96e-07 ***
#> K  25.50289    0.36665   69.56 3.34e-11 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.6528 on 7 degrees of freedom
#>
#> Number of iterations to convergence: 0
#> Achieved convergence tolerance: 1.924e-06
```

```
#note: initial values =  solution (highly unusual, but ok)
plot(time, population, las = 1, pch = 16)
lines(time, predict(logisticModel), col = "red")
```

If can also define your own self-starting function if your models are uncommon

(built in `nls`)

Example is based on (Schabenberger and Pierce, 2001)

```
#Load data
dat <- read.table("images/dat.txt", header = T)
# plot
dat.plot <-
    ggplot(dat) + geom_point(aes(
        x = no3,
        y = ryp,
        color = as.factor(depth)
    )) +
    labs(color = 'Depth (cm)') + xlab('Soil NO3') +
    ylab('relative yield percent')

dat.plot
```

The suggested model (known as plateau model) is

$$E(Y_{ij}) = (\beta_{0j} + \beta_{1j} N_{ij}) I_{N_{ij} \leq \alpha_j} + (\beta_{0j} + \beta_{1j} \alpha_j) I_{N_{ij} > \alpha_j}$$

where

- N is an observation
- i is a particular observation
- j = 1,2 corresponding to depths (30,60)

```
#First define model as a function
nonlinModel <- function(predictor, b0, b1, alpha) {
    ifelse(predictor <= alpha,
           #if observation less than cutoff simple linear model
           b0 + b1 * predictor,
           b0 + b1 * alpha) #otherwise flat line
}
```

define `selfStart` function. Because we defined our model to be linear in the first part and then plateau (remain constant) we can use the first half of our predictors (sorted by increasing value) to get an initial estimate for the slope and intercept of the model, and the last predictor value (alpha) can be the starting value for the plateau parameter.

```
nonlinModelInit <- function(mCall, LHS, data) {
    # sort data by increasing predictor value -
    # done so we can just use the low level
    # no3 conc to fit a simple model
    xy <- sortedXyData(mCall[['predictor']], LHS, data)
    n <- nrow(xy)
    #For the first half of the data a simple linear model is fit
    lmFit <- lm(xy[1:(n / 2), 'y'] ~ xy[1:(n / 2), 'x'])
    b0 <- coef(lmFit)[1]
    b1 <- coef(lmFit)[2]
    # for the cut off to the flat part select the last
    # x value used in creating linear model
    alpha <- xy[(n / 2), 'x']
    value <- c(b0, b1, alpha)
    names(value) <- mCall[c('b0', 'b1', 'alpha')]
    value
}
```

combine model and custom function to calculate starting values.

```
SS_nonlinModel <- selfStart(nonlinModel,nonlinModelInit,c('b0','b1','alpha'))
```

```
# Above code defined model and selfStart now just need to call it for each of the depti
sep30_nls <-
    nls(ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha),
        data = dat[dat$depth == 30,])

sep60_nls <-
    nls(ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha),
        data = dat[dat$depth == 60,])

par(mfrow = c(1, 2))
plotFit(
```

```
    sep30_nls,
    interval = "both",
    pch = 19,
    shade = TRUE,
    col.conf = "skyblue4",
    col.pred = "lightskyblue2",
    data = dat[dat$depth == 30,],
    main = 'Results 30 cm depth',
    ylab = 'relative yield percent',
    xlab = 'Soil NO3 concentration',
    xlim = c(0, 120)
)
plotFit(
    sep60_nls,
    interval = "both",
    pch = 19,
    shade = TRUE,
    col.conf = "lightpink4",
    col.pred = "lightpink2",
    data = dat[dat$depth == 60,],
    main = 'Results 60 cm depth',
    ylab = 'relative yield percent',
    xlab = 'Soil NO3 concentration',
    xlim = c(0, 120)
)
```

```
summary(sep30_nls)
#>
#> Formula: ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha)
#>
#> Parameters:
#>       Estimate Std. Error t value Pr(>|t|)
#> b0     15.1943     2.9781   5.102 6.89e-07 ***
#> b1      3.5760     0.1853  19.297  < 2e-16 ***
#> alpha  23.1324     0.5098  45.373  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 8.258 on 237 degrees of freedom
#>
#> Number of iterations to convergence: 6
#> Achieved convergence tolerance: 3.608e-09
summary(sep60_nls)
#>
#> Formula: ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha)
#>
#> Parameters:
#>       Estimate Std. Error t value Pr(>|t|)
#> b0      5.4519     2.9785    1.83   0.0684 .
#> b1      5.6820     0.2529   22.46   <2e-16 ***
#> alpha  16.2863     0.2818   57.80   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 7.427 on 237 degrees of freedom
#>
#> Number of iterations to convergence: 5
#> Achieved convergence tolerance: 8.571e-09
```

Instead of modeling the depths model separately we model them together - so there is a common slope, intercept, and plateau.

```
red_nls <-
  nls(ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha),
      data = dat)

summary(red_nls)
#>
#> Formula: ryp ~ SS_nonlinModel(predictor = no3, b0, b1, alpha)
#>
#> Parameters:
#>       Estimate Std. Error t value Pr(>|t|)
```

```
#> b0      8.7901     2.7688   3.175   0.0016 **
#> b1      4.8995     0.2207  22.203   <2e-16 ***
#> alpha  18.0333     0.3242  55.630   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 9.13 on 477 degrees of freedom
#>
#> Number of iterations to convergence: 7
#> Achieved convergence tolerance: 7.126e-09

par(mfrow = c(1, 1))
plotFit(
  red_nls,
  interval = "both",
  pch = 19,
  shade = TRUE,
  col.conf = "lightblue4",
  col.pred = "lightblue2",
  data = dat,
  main = 'Results combined',
  ylab = 'relative yield percent',
  xlab = 'Soil NO3 concentration'
)
```

Examine residual values for the combined model.

```
library(nlstools)
# using nlstools nlsResiduals function to get some quick residual plots
# can also use test.nlsResiduals(resid)
# https://www.rdocumentation.org/packages/nlstools/versions/1.0-2
resid <- nlsResiduals(red_nls)
plot(resid)
```

can we test whether the parameters for the two soil depth fits are significantly different? To know if the combined model is appropriate, we consider a parameterization where we let the parameters for the 60cm model be equal to the parameters from the 30cm model plus some increment:

$$\beta_{02} = \beta_{01} + d_0$$
$$\beta_{12} = \beta_{11} + d_1$$
$$\alpha_2 = \alpha_1 + d_a$$

We can implement this in the following function:

```
nonlinModelF <- function(predictor,soildep,b01,b11,a1,d0,d1,da){
   b02 = b01 + d0 #make 60cm parms = 30cm parms + increment
   b12 = b11 + d1
   a2 = a1 + da

   y1 = ifelse(predictor<=a1,
        #if observation less than cutoff simple linear model
         b01+b11*predictor,
         b01+b11*a1) # otherwise flat line
```

```
   y2 = ifelse(predictor<=a2,
               b02+b12*predictor,
               b02+b12*a2)
   y =  y1*(soildep == 30) + y2*(soildep == 60)  #combine models
   return(y)
}
```

Starting values are easy now because we fit each model individually.

```
Soil_full = nls(
    ryp ~ nonlinModelF(
        predictor = no3,
        soildep = depth,
        b01,
        b11,
        a1,
        d0,
        d1,
        da
    ),
    data = dat,
    start = list(
        b01 = 15.2,
        b11 = 3.58,
        a1 = 23.13,
        d0 = -9.74,
        d1 = 2.11,
        da = -6.85
    )
)

summary(Soil_full)
#>
#> Formula: ryp ~ nonlinModelF(predictor = no3, soildep = depth, b01, b11,
#>     a1, d0, d1, da)
#>
#> Parameters:
#>     Estimate Std. Error t value Pr(>|t|)
#> b01  15.1943     2.8322   5.365 1.27e-07 ***
#> b11   3.5760     0.1762  20.291  < 2e-16 ***
#> a1   23.1324     0.4848  47.711  < 2e-16 ***
#> d0   -9.7424     4.2357  -2.300   0.0219 *
#> d1    2.1060     0.3203   6.575 1.29e-10 ***
#> da   -6.8461     0.5691 -12.030  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#>
#> Residual standard error: 7.854 on 474 degrees of freedom
#>
#> Number of iterations to convergence: 1
#> Achieved convergence tolerance: 3.742e-06
```

So, the increment parameters, d_1,d_2,d_a are all significantly different from 0, suggesting that we should have two models here.

6.2.3 Model/Estimation Adequacy

(Bates and Watts, 1980) assess nonlinearity in terms of 2 components of curvature:

- **Intrinsic nonlinearity**: the degree of bending and twisting in $f(\theta)$; our estimation approach assumes that the true function is relatively flat (planar) in the neighborhood fo $\hat{\theta}$, which would not be true if $f()$ has a lot of "bending" in the neighborhood of $\hat{\theta}$ (independent of parameterization)
  - If bad, the distribution of residuals will be seriously distorted
  - slow to converge
  - difficult to identify (could use this function `rms.curve`)
  - Solution:
    * could use higher order Taylor expansions estimation
    * Bayesian method
- **Parameter effects nonlinearity**: degree to which curvature (nonlinearity) is affected by choice of θ (data dependent; dependent on parameterization)
  - leads to problems with inference on $\hat{\theta}$
  - `rms.curve` in `MASS` can identify
  - bootstrap-based inference can also be used
  - Solution: try to reparaemterize.

```
#check parameter effects and intrinsic curvature

modD = deriv3(~ a*exp(b*x), c("a","b"),function(a,b,x) NULL)

nlin_modD = nls(y ~ modD(a, b, x),
                start = list(a = astrt, b = bstrt),
                data = datf)

rms.curv(nlin_modD)
#> Parameter effects: c^theta x sqrt(F) = 0.0626
#>         Intrinsic: c^iota  x sqrt(F) = 0.0062
```

In linear model, we have Linear Regression, we have goodness of fit measure as R^2:

$$\begin{aligned} R^2 &= \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO} \\ &= \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \end{aligned}$$

but not valid in the nonlinear case because the error sum of squares and model sum of squares do not add to the total corrected sum of squares

$$SSR + SSE \neq SST$$

but we can use pseudo-R^2:

$$R^2_{pseudo} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

But we can't interpret this as the proportion of variability explained by the model. We should use as a relative comparison of different models.

Residual Plots: standardize, similar to OLS. useful when the intrinsic curvature is small:

The studentized residuals

$$r_i = \frac{e_i}{s\sqrt{1 - \hat{c}_i}}$$

where $\hat{c}_i$is the i-th diagonal of $\hat{\mathbf{H}} = \mathbf{F}(\ )[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{F}(\ )'$

We could have problems of

- Collinearity: the condition number of $[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}$ should be less than 30. Follow (Magel and Hertsgaard, 1987); reparameterize if possible
- Leverage: Like OLS, but consider $\hat{\mathbf{H}} = \mathbf{F}(\ )[\mathbf{F}(\ )'\mathbf{F}(\ )]^{-\mathbf{1}}\mathbf{F}(\ )'$ (also known as "tangent plant hat matrix") (St Laurent and Cook, 1992)
- Heterogeneous Errors: weighted Non-linear Least Squares
- Correlated Errors:
  - Generalized Nonlinear Least Squares
  - Nonlinear Mixed Models
  - Bayesian methods

6.2.4 Application

$$y_i = \frac{\theta_0 + \theta_1 x_i}{1 + \theta_2 \exp(0.4x_i)} + \epsilon_i$$

where $i = 1, .., n$

Get the starting values

```
plot(my_data)
```

We notice that $Y_{max} = \theta_0 + \theta_1 x_i$ in which we can find x_i from data

```
max(my_data$y)
#> [1] 2.6722
my_data$x[which.max(my_data$y)]
#> [1] 0.0094
```

hence, $x = 0.0094$ when $y = 2.6722$ when we have the first equation as

$$2.6722 = \theta_0 + 0.0094\theta_1$$

$$\theta_0 + 0.0094\theta_1 + 0\theta_2 = 2.6722$$

Secondly, we notice that we can obtain the "average" of y when

$$1 + \theta_2 exp(0.4x) = 2$$

then we can find this average numbers of x and y

```
# find mean y
mean(my_data$y)
#> [1] -0.0747864

# find y closest to its mean
my_data$y[which.min(abs(my_data$y - (mean(my_data$y))))]
#> [1] -0.0773


# find x closest to the mean y
my_data$x[which.min(abs(my_data$y - (mean(my_data$y))))]
#> [1] 11.0648
```

we have the second equation

$$1 + \theta_2 exp(0.4 * 11.0648) = 2$$

$$0\theta_1 + 0\theta_1 + 83.58967\theta_2 = 1$$

Thirdly, we can plug in the value of x closest to 1 to find the value of y

```
# find value of x closet to 1
my_data$x[which.min(abs(my_data$x - 1))]
#> [1] 0.9895

# find index of x closest to 1
match(my_data$x[which.min(abs(my_data$x - 1))], my_data$x)
#> [1] 14

# find y value
my_data$y[match(my_data$x[which.min(abs(my_data$x - 1))], my_data$x)]
#> [1] 1.4577
```

hence we have

$$1.457 = \frac{\theta_0 + \theta_1 * 0.9895}{1 + \theta_2 exp(0.4 * 0.9895)}$$

$$1.457 + 2.164479 * \theta_2 = \theta_0 + \theta_1 * 0.9895$$

$$\theta_0 + \theta_1 * 0.9895 - 2.164479 * \theta_2 = 1.457$$

with 3 equations, we can solve them to get the starting value for $\theta_0, \theta_1, \theta_2$

$$\theta_0 + 0.0094\theta_1 + 0\theta_2 = 2.6722$$

$$0\theta_1 + 0\theta_1 + 83.58967\theta_2 = 1$$

$$\theta_0 + \theta_1 * 0.9895 - 2.164479 * \theta_2 = 1.457$$

```
library(matlib)
A = matrix(
    c(0, 0.0094, 0, 0, 0, 83.58967, 1, 0.9895,-2.164479),
    nrow = 3,
    ncol = 3,
    byrow = T
)
b = c(2.6722, 1, 1.457)
showEqn(A, b)
#> 0*x1 + 0.0094*x2        + 0*x3  =  2.6722
#> 0*x1      + 0*x2 + 83.58967*x3  =       1
#> 1*x1 + 0.9895*x2 - 2.164479*x3  =   1.457
Solve(A, b, fractions = F)
#> x1      =  -279.80879739
#>   x2    =   284.27659574
#>     x3  =      0.0119632
```

Construct manually Gauss-Newton Algorithm

```
#starting value
theta_0_strt = -279.80879739
theta_1_strt =  284.27659574
theta_2_strt = 0.0119632

#model
mod_4 = function(theta_0, theta_1, theta_2, x) {
    (theta_0 + theta_1 * x) / (1 + theta_2 * exp(0.4 * x))
}

#define a function
f_4 = expression((theta_0 + theta_1 * x) / (1 + theta_2 * exp(0.4 * x)))

#take the first derivative
df_4.d_theta_0 = D(f_4, 'theta_0')

df_4.d_theta_1 = D(f_4, 'theta_1')
```

```
df_4.d_theta_2 = D(f_4, 'theta_2')

# save the result of all iterations
theta_vec = matrix(c(theta_0_strt, theta_1_strt, theta_2_strt))
delta = matrix(NA, nrow = 3, ncol = 1)

f_theta = as.matrix(eval(
    f_4,
    list(
        x = my_data$x,
        theta_0 = theta_vec[1, 1],
        theta_1 = theta_vec[2, 1],
        theta_2 = theta_vec[3, 1]
    )
))

i = 1

repeat {
    F_theta_0 = as.matrix(cbind(
        eval(
            df_4.d_theta_0,
            list(
                x = my_data$x,
                theta_0 = theta_vec[1, i],
                theta_1 = theta_vec[2, i],
                theta_2 = theta_vec[3, i]
            )
        ),
        eval(
            df_4.d_theta_1,
            list(
                x = my_data$x,
                theta_0 = theta_vec[1, i],
                theta_1 = theta_vec[2, i],
                theta_2 = theta_vec[3, i]
            )
        ),
        eval(
            df_4.d_theta_2,
            list(
                x = my_data$x,
                theta_0 = theta_vec[1, i],
                theta_1 = theta_vec[2, i],
                theta_2 = theta_vec[3, i]
```

```
            )
        )
    ))
    delta[, i] = (solve(t(F_theta_0) %*% F_theta_0)) %*% t(F_theta_0) %*% (my_data$y -
    theta_vec = cbind(theta_vec, matrix(NA, nrow = 3, ncol = 1))
    theta_vec[, i + 1] = theta_vec[, i] + delta[, i]
    i = i + 1

    f_theta = cbind(f_theta, as.matrix(eval(
        f_4,
        list(
            x = my_data$x,
            theta_0 = theta_vec[1, i],
            theta_1 = theta_vec[2, i],
            theta_2 = theta_vec[3, i]
        )
    )))
    delta = cbind(delta, matrix(NA, nrow = 3, ncol = 1))

    #convergence criteria based on SSE
    if (abs(sum((my_data$y - f_theta[, i]) ^ 2) - sum((my_data$y - f_theta[, i - 1]) ^
        break
    }
}
delta
#>               [,1]        [,2]        [,3]       [,4]       [,5]       [,6]
#> [1,]  2.811840e+02 -0.03929013  0.43160654  0.6904856  0.6746748  0.4056460
#> [2,] -2.846545e+02  0.03198446 -0.16403964 -0.2895487 -0.2933345 -0.1734087
#> [3,] -1.804567e-05  0.01530258  0.05137285  0.1183271  0.1613129  0.1160404
#>             [,7] [,8]
#> [1,]  0.09517681   NA
#> [2,] -0.03928239   NA
#> [3,]  0.03004911   NA
theta_vec
#>              [,1]        [,2]        [,3]        [,4]       [,5]       [,6]
#> [1,] -279.8087974  1.37521388  1.33592375  1.76753029  2.4580158  3.1326907
#> [2,]  284.2765957 -0.37788712 -0.34590266 -0.50994230 -0.7994910 -1.0928255
#> [3,]    0.0119632  0.01194515  0.02724773  0.07862059  0.1969477  0.3582607
#>            [,7]       [,8]
#> [1,]  3.5383367  3.6335135
#> [2,] -1.2662342 -1.3055166
#> [3,]  0.4743011  0.5043502

head(f_theta)
#>           [,1]     [,2]     [,3]     [,4]     [,5]     [,6]     [,7]     [,8]
```

```
#> [1,] -273.8482 1.355410 1.297194 1.633802 2.046023 2.296554 2.389041 2.404144
#> [2,] -209.0859 1.268192 1.216738 1.514575 1.863098 2.059505 2.126009 2.135969
#> [3,] -190.3323 1.242916 1.193433 1.480136 1.810629 1.992095 2.051603 2.060202
#> [4,] -177.1891 1.225196 1.177099 1.456024 1.774000 1.945197 1.999945 2.007625
#> [5,] -148.5872 1.186618 1.141549 1.403631 1.694715 1.844154 1.888953 1.894730
#> [6,] -119.9585 1.147980 1.105961 1.351301 1.615968 1.744450 1.779859 1.783866

# estimate sigma^2

sigma2 = 1 / (nrow(my_data) - 3) * (t(my_data$y - (f_theta[, ncol(f_theta)]))) %*%
    (my_data$y - (f_theta[, ncol(f_theta)])) # p = 3
sigma2
#>           [,1]
#> [1,] 0.0801686
```

After 8 iterations, my function has converged. And objective function value at convergence is

```
sum((my_data$y - f_theta[,i])^2)
#> [1] 19.80165
```

and the parameters of θs are

```
theta_vec[,ncol(theta_vec)]
#> [1]  3.6335135 -1.3055166  0.5043502
```

and the asymptotic variance covariance matrix is

```
as.numeric(sigma2)*as.matrix(solve(crossprod(F_theta_0)))
#>             [,1]        [,2]        [,3]
#> [1,]  0.11552571 -0.04817428  0.02685848
#> [2,] -0.04817428  0.02100861 -0.01158212
#> [3,]  0.02685848 -0.01158212  0.00703916
```

Issue that I encounter in this problem was that it was very sensitive to starting values. when I tried the value of 1 for all θs, I have vastly different parameter estimates. Then, I try to use the model interpretation to try to find reasonable starting values.

Check with predefined function in `nls`

```
nlin_4 = nls(
    y ~ mod_4(theta_0, theta_1, theta_2, x),
    start = list(
        theta_0 = -279.80879739 ,
        theta_1 = 284.27659574 ,
        theta_2 = 0.0119632
    ),
    data = my_data
```

```
)
nlin_4
#> Nonlinear regression model
#>   model: y ~ mod_4(theta_0, theta_1, theta_2, x)
#>    data: my_data
#> theta_0 theta_1 theta_2
#>  3.6359 -1.3064  0.5053
#>  residual sum-of-squares: 19.8
#>
#> Number of iterations to convergence: 9
#> Achieved convergence tolerance: 2.294e-07
```

Chapter 7

Generalized Linear Models

Even though we call it generalized linear model, it is still under the paradigm of non-linear regression, because the form of the regression model is non-linear. The name generalized linear model derived from the fact that we have $\mathbf{x_i'}$ (which is linear form) in the model.

7.1 Logistic Regression

$$p_i = f(\mathbf{x}_i; \beta) = \frac{exp(\mathbf{x_i'})}{1 + exp(\mathbf{x_i'})}$$

Equivalently,

$$logit(p_i) = log(\frac{p_i}{1 + p_i}) = \mathbf{x_i'}$$

where $\frac{p_i}{1+p_i}$is the **odds**.

In this form, the model is specified such that **a function of the mean response is linear**. Hence, **Generalized Linear Models**

The likelihood function

$$L(p_i) = \prod_{i=1}^{n} p_i^{Y_i}(1 - p_i)^{1-Y_i}$$

where $p_i = \frac{\mathbf{x_i'}}{1+\mathbf{x_i'}}$ and $1 - p_i = (1 + exp(\mathbf{x_i'}))^{-1}$

Hence, our objective function is

$$Q(\beta) = log(L(\beta)) = \sum_{i=1}^{n} Y_i \mathbf{x_i'} - \sum_{i=1}^{n} log(1 + exp(\mathbf{x_i'}))$$

we could maximize this function numerically using the optimization method above, which allows us to find numerical MLE for $\hat{\beta}$. Then we can use the standard asymptotic properties of MLEs to make inference.

Property of MLEs is that parameters are asymptotically unbiased with sample variance-covariance matrix given by the **inverse Fisher information matrix**

$$\hat{\beta} \dot{\sim} AN(\beta, [\mathbf{I}(\beta)]^{-1})$$

where the **Fisher Information matrix**, $\mathbf{I}(\beta)$ is

$$\begin{aligned}\mathbf{I}(\beta) &= E[\frac{\partial \log(L(\beta))}{\partial(\beta)} \frac{\partial \log(L(\beta))}{\partial \beta'}] \\ &= E[(\frac{\partial \log(L(\beta))}{\partial \beta_i} \frac{\partial \log(L(\beta))}{\partial \beta_j})_{ij}]\end{aligned}$$

Under **regularity conditions**, this is equivalent to the negative of the expected value of the Hessian Matrix

$$\begin{aligned}\mathbf{I}(\beta) &= -E[\frac{\partial^2 \log(L(\beta))}{\partial \beta \partial \beta'}] \\ &= -E[(\frac{\partial^2 \log(L(\beta))}{\partial \beta_i \partial \beta_j})_{ij}]\end{aligned}$$

Example:

$$x_i'\beta = \beta_0 + \beta_1 x_i$$

$$\begin{aligned}-\frac{\partial^2 \ln(L(\beta))}{\partial \beta_0^2} &= \sum_{i=1}^{n} \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)} - [\frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)}]^2 = \sum_{i=1}^{n} p_i(1-p_i) \\ -\frac{\partial^2 \ln(L(\beta))}{\partial \beta_1^2} &= \sum_{i=1}^{n} \frac{x_i^2 \exp(x_i'\beta)}{1+\exp(x_i'\beta)} - [\frac{x_i \exp(x_i'\beta)}{1+\exp(x_i'\beta)}]^2 = \sum_{i=1}^{n} x_i^2 p_i(1-p_i) \\ -\frac{\partial^2 \ln(L(\beta))}{\partial \beta_0 \partial \beta_1} &= \sum_{i=1}^{n} \frac{x_i \exp(x_i'\beta)}{1+\exp(x_i'\beta)} - x_i[\frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)}]^2 = \sum_{i=1}^{n} x_i p_i(1-p_i)\end{aligned}$$

Hence,

$$\mathbf{I}(\beta) = \begin{bmatrix} \sum_i p_i(1-p_i) & \sum_i x_i p_i(1-p_i) \\ \sum_i x_i p_i(1-p_i) & \sum_i x_i^2 p_i(1-p_i) \end{bmatrix}$$

Inference

Likelihood Ratio Tests

To formulate the test, let $\beta = [\beta_1', \beta_2']'$. If you are interested in testing a hypothesis about β_1, then we leave β_2 unspecified (called **nuisance parameters**). β_1 and β_2 can either a **vector** or **scalar**, or β_2 can be null.

Example: $H_0 : \beta_1 = \beta_{1,0}$ (where $\beta_{1,0}$ is specified) and $\hat{\beta}_{2,0}$ be the MLE of β_2 under the restriction that $\beta_1 = \beta_{1,0}$. The likelihood ratio test statistic is

$$-2\log\Lambda = -2[\log(L(\beta_{1,0}, \hat{\beta}_{2,0})) - \log(L(\hat{\beta}_1, \hat{\beta}_2))]$$

where

- the first term is the value fo the likelihood for the fitted restricted model
- the second term is the likelihood value of the fitted unrestricted model

Under the null,

$$-2\log\Lambda \sim \chi^2_\upsilon$$

where υ is the dimension of β_1

We reject the null when $-2\log\Lambda > \chi^2_{\upsilon,1-\alpha}$

Wald Statistics

Based on

$$\hat{\beta} \sim AN(\beta, [\mathbf{I}(\beta)^{-1}])$$

$$H_0 : \mathbf{L}\hat{\beta} = 0$$

where $\mathbf{L}$ is a $q \times p$ matrix with q linearly independent rows. Then

$$W = (\mathbf{L}\hat{\ })'(\mathbf{L}[\mathbf{I}(\hat{\ })]^{-\mathbf{1}}\mathbf{L}')^{-1}(\mathbf{L}\hat{\ })$$

under the null hypothesis

Confidence interval

$$\hat{\beta}_i \pm 1.96\hat{s}^2_{ii}$$

where $\hat{s}_{ii}^2$ is the i-th diagonal of $[\mathbf{I}(\hat{\ })]^{-1}$

If you have

- large sample size, the likelihood ratio and Wald tests have similar results.
- small sample size, the likelihood ratio test is better.

Logistic Regression: Interpretation of β

For single regressor, the model is

$$logit\{\hat{p}_{x_i}\} \equiv logit(\hat{p}_i) = \log(\frac{\hat{p}_i}{1-\hat{p}_i}) = \hat{\beta}_0 + \hat{\beta}_1 x_i$$

When $x = x_i + 1$

$$logit\{\hat{p}_{x_i+1}\} = \hat{\beta}_0 + \hat{\beta}(x_i + 1) = logit\{\hat{p}_{x_i}\} + \hat{\beta}_1$$

Then,

$$\begin{aligned} logit\{\hat{p}_{x_i+1}\} - logit\{\hat{p}_{x_i}\} &= log\{odds[\hat{p}_{x_i+1}]\} - log\{odds[\hat{p}_{x_i}]\} \\ &= log(\frac{odds[\hat{p}_{x_i+1}]}{odds[\hat{p}_{x_i}]}) = \hat{\beta}_1 \end{aligned}$$

and

$$exp(\hat{\beta}_1) = \frac{odds[\hat{p}_{x_i+1}]}{odds[\hat{p}_{x_i}]}$$

the estimated **odds ratio**

the estimated odds ratio, when there is a difference of c units in the regressor x, is $exp(c\hat{\beta}_1)$. When there are multiple covariates, $exp(\hat{\beta}_k)$ is the estimated odds ratio for the variable x_k, assuming that all of the other variables are held constant.

Inference on the Mean Response

Let $x_h = (1, x_{h1}, ..., x_{h,p-1})'$. Then

$$\hat{p}_h = \frac{exp(\mathbf{x}_\mathbf{h}'\hat{\ })}{1 + exp(\mathbf{x}_\mathbf{h}'\hat{\ })}$$

and $s^2(\hat{p}_h) = \mathbf{x}_\mathbf{h}'[\mathbf{I}(\hat{\ })]^{-\mathbf{1}}\mathbf{x}_\mathbf{h}$

For new observation, we can have a cutoff point to decide whether y = 0 or 1.

7.1.1 Application

```
library(kableExtra)
library(dplyr)
library(pscl)
library(ggplot2)
library(faraway)
library(nnet)
library(agridat)
library(nlstools)
```

Logistic Regression

$x \sim Unif(-0.5, 2.5)$. Then $\eta = 0.5 + 0.75x$

```
set.seed(23) #set seed for reproducibility
x <- runif(1000, min = -0.5, max = 2.5)
eta1 <- 0.5 + 0.75 * x
```

Passing η's into the inverse-logit function, we get

$$p = \frac{\exp(\eta)}{1 + \exp(\eta)}$$

where $p \in [0, 1]$

Then, we generate $y \sim Bernoulli(p)$

```
p <- exp(eta1) / (1 + exp(eta1))
y <- rbinom(1000, 1, p)
BinData <- data.frame(X = x, Y = y)
```

Model Fit

```
Logistic_Model <- glm(formula = Y ~ X,
                      family = binomial, # family = specifies the response distribution
                      data = BinData)
summary(Logistic_Model)
#>
#> Call:
#> glm(formula = Y ~ X, family = binomial, data = BinData)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -2.2317   0.4153   0.5574   0.7922   1.1469
#>
#> Coefficients:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  0.46205    0.10201   4.530 5.91e-06 ***
```

```
#> X            0.78527    0.09296   8.447  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#>     Null deviance: 1106.7  on 999  degrees of freedom
#> Residual deviance: 1027.4  on 998  degrees of freedom
#> AIC: 1031.4
#>
#> Number of Fisher Scoring iterations: 4
nlstools::confint2(Logistic_Model)
#>                 2.5 %    97.5 %
#> (Intercept) 0.2618709 0.6622204
#> X           0.6028433 0.9676934
OddsRatio <- coef(Logistic_Model) %>% exp
OddsRatio
#> (Intercept)           X
#>    1.587318    2.192995
```

Based on the odds ratio, when

- $x = 0$, the odds of success of 1.59
- $x = 1$, the odds of success increase by a factor of 2.19 (i.e., 119.29% increase).

Deviance Tests

- H_0: No variables are related to the response (i.e., model with just the intercept)
- H_1: At least one variable is related to the response

```
Test_Dev <- Logistic_Model$null.deviance - Logistic_Model$deviance
p_val_dev <- 1 - pchisq(q = Test_Dev, df = 1)
```

Since we see the p-value of 0, we reject the null that no variables are related to the response

Deviance residuals

```
Logistic_Resids <- residuals(Logistic_Model, type = "deviance")
plot(
    y = Logistic_Resids,
    x = BinData$X,
    xlab = 'X',
    ylab = 'Deviance Resids'
)
```

However, this plot is not informative. Hence, we can can see the residuals plots that are grouped into bins based on prediction values.

```
plot_bin <- function(Y,
                     X,
                     bins = 100,
                     return.DF = FALSE) {
    Y_Name <- deparse(substitute(Y))
    X_Name <- deparse(substitute(X))
    Binned_Plot <- data.frame(Plot_Y = Y, Plot_X = X)
    Binned_Plot$bin <-
        cut(Binned_Plot$Plot_X, breaks = bins) %>% as.numeric
    Binned_Plot_summary <- Binned_Plot %>%
        group_by(bin) %>%
        summarise(
            Y_ave = mean(Plot_Y),
            X_ave = mean(Plot_X),
            Count = n()
        ) %>% as.data.frame
    plot(
        y = Binned_Plot_summary$Y_ave,
        x = Binned_Plot_summary$X_ave,
        ylab = Y_Name,
        xlab = X_Name
    )
    if (return.DF)
        return(Binned_Plot_summary)
```

```
}


plot_bin(Y = Logistic_Resids,
         X = BinData$X,
         bins = 100)
```

We can also see the predicted value against the residuals.

```
Logistic_Predictions <- predict(Logistic_Model, type = "response")
plot_bin(Y = Logistic_Resids, X = Logistic_Predictions, bins = 100)
```

We can also look at a binned plot of the logistic prediction versus the true category

```
NumBins <- 10
Binned_Data <- plot_bin(
    Y = BinData$Y,
    X = Logistic_Predictions,
    bins = NumBins,
    return.DF = TRUE
)
Binned_Data
#>    bin     Y_ave     X_ave Count
#> 1    1 0.5833333 0.5382095    72
#> 2    2 0.5200000 0.5795887    75
#> 3    3 0.6567164 0.6156540    67
#> 4    4 0.7014925 0.6579674    67
#> 5    5 0.6373626 0.6984765    91
#> 6    6 0.7500000 0.7373341    72
#> 7    7 0.7096774 0.7786747    93
#> 8    8 0.8503937 0.8203819   127
#> 9    9 0.8947368 0.8601232   133
#> 10  10 0.8916256 0.9004734   203
abline(0, 1, lty = 2, col = 'blue')
```

Formal deviance test

Hosmer-Lemeshow test

Null hypothesis: the observed events match the expected evens

$$X^2_{HL} = \sum_{j=1}^{J} \frac{(y_j - m_j \hat{p}_j)^2}{m_j \hat{p}_j (1 - \hat{p}_j)}$$

where

- within the j-th bin, y_j is the number of successes
- m_j = number of observations
- $\hat{p}_j$ = predicted probability

Under the null hypothesis, $X^2_{HLL} \sim \chi^2_{J-1}$

```
HL_BinVals <-
    (Binned_Data$Count * Binned_Data$Y_ave - Binned_Data$Count * Binned_Data$X_ave) ^ 2
HLpval <- pchisq(q = sum(HL_BinVals),
                 df = NumBins,
                 lower.tail = FALSE)
HLpval
#> [1] 0.9999989
```

Since p-value = 0.99, we do not reject the null hypothesis (i.e., the model is fitting well).

7.2 Probit Regression

$$E(Y_i) = p_i = \Phi(\mathbf{x_i'}\ )$$

where $\Phi()$ is the CDF of a $N(0,1)$ random variable.

Other models (e..g, t–distribution; log-log; I complimentary log-log)

We let $Y_i = 1$ success, $Y_i = 0$ no success.

- assume $Y \sim Ber$ and $p_i = P(Y_i = 1)$, the success probability.
- consider a logistic regression with the response function $logit(p_i) = x_i'\beta$

Confusion matrix

	Predicted	
Truth	1	0
1	True Positive (TP)	False Negative (FN)
0	False Positive (FP)	True Negative (TN)

Sensitivity: ability to identify positive results

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity: ability to identify negative results

$$\text{Specificity} = \frac{TN}{TN + FP}$$

False positive rate: Type I error (1- specificity)

$$\text{False Positive Rate} = \frac{FP}{TN + FP}$$

False Negative Rate: Type II error (1-sensitivity)

$$\text{False Negative Rate} = \frac{FN}{TP + FN}$$

	Predicted	
Truth	1	0
1	Sensitivity	False Negative Rate
0	False Positive Rate	Specificity

7.3 Binomial Regression

Binomial

Here, cancer case = successes, and control case = failures.

```
data("esoph")
head(esoph, n = 3)
#>   agegp     alcgp    tobgp ncases ncontrols
#> 1 25-34 0-39g/day 0-9g/day      0        40
#> 2 25-34 0-39g/day    10-19      0        10
#> 3 25-34 0-39g/day    20-29      0         6
plot(
  esoph$ncases / (esoph$ncases + esoph$ncontrols) ~ esoph$alcgp,
  ylab = "Proportion",
  xlab = 'Alcohol consumption',
  main = 'Esophageal Cancer data'
)
```

```
class(esoph$agegp) <- "factor"
class(esoph$alcgp) <- "factor"
class(esoph$tobgp) <- "factor"
```

```
#  only the alcohol consumption as a predictor
model <- glm(cbind(ncases, ncontrols) ~ alcgp, data = esoph, family = binomial)
summary(model)
#>
#> Call:
#> glm(formula = cbind(ncases, ncontrols) ~ alcgp, family = binomial,
```

```
#>     data = esoph)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -4.0759  -1.2037  -0.0183   1.0928   3.7336
#>
#> Coefficients:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  -2.5885     0.1925 -13.444  < 2e-16 ***
#> alcgp40-79    1.2712     0.2323   5.472 4.46e-08 ***
#> alcgp80-119   2.0545     0.2611   7.868 3.59e-15 ***
#> alcgp120+     3.3042     0.3237  10.209  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#>     Null deviance: 367.95  on 87  degrees of freedom
#> Residual deviance: 221.46  on 84  degrees of freedom
#> AIC: 344.51
#>
#> Number of Fisher Scoring iterations: 5
```

```
#Coefficient Odds
coefficients(model) %>% exp
#> (Intercept)  alcgp40-79 alcgp80-119   alcgp120+
#>  0.07512953  3.56527094  7.80261593 27.22570533
deviance(model)/df.residual(model)
#> [1] 2.63638
model$aic
#> [1] 344.5109
```

```
# alcohol consumption and age as predictors
better_model <-
    glm(cbind(ncases, ncontrols) ~ agegp + alcgp,
        data = esoph,
        family = binomial)
summary(better_model)
#>
#> Call:
#> glm(formula = cbind(ncases, ncontrols) ~ agegp + alcgp, family = binomial,
#>     data = esoph)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -2.2395  -0.7186  -0.2324   0.7930   3.3538
```

```
#>
#> Coefficients:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  -6.1472     1.0419  -5.900 3.63e-09 ***
#> agegp35-44    1.6311     1.0800   1.510 0.130973
#> agegp45-54    3.4258     1.0389   3.297 0.000976 ***
#> agegp55-64    3.9435     1.0346   3.811 0.000138 ***
#> agegp65-74    4.3568     1.0413   4.184 2.87e-05 ***
#> agegp75+      4.4242     1.0914   4.054 5.04e-05 ***
#> alcgp40-79    1.4343     0.2448   5.859 4.64e-09 ***
#> alcgp80-119   2.0071     0.2776   7.230 4.84e-13 ***
#> alcgp120+     3.6800     0.3763   9.778  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#>     Null deviance: 367.95  on 87  degrees of freedom
#> Residual deviance: 105.88  on 79  degrees of freedom
#> AIC: 238.94
#>
#> Number of Fisher Scoring iterations: 6
```

```
better_model$aic #smaller AIC is better
#> [1] 238.9361
coefficients(better_model) %>% exp
#>  (Intercept)   agegp35-44   agegp45-54   agegp55-64   agegp65-74     agegp75+
#>  0.002139482  5.109601844 30.748594216 51.596634690 78.005283850 83.448437749
#>   alcgp40-79  alcgp80-119    alcgp120+
#>  4.196747169  7.441782227 39.646885126
pchisq(
    q = model$deviance - better_model$deviance,
    df = model$df.residual - better_model$df.residual,
    lower = FALSE
)
#> [1] 2.713923e-23
```

```
# specify link function as probit
Prob_better_model <- glm(
    cbind(ncases, ncontrols) ~ agegp + alcgp,
    data = esoph,
    family = binomial(link = probit)
)
summary(Prob_better_model)
#>
#> Call:
```

```
#> glm(formula = cbind(ncases, ncontrols) ~ agegp + alcgp, family = binomial(link = probit),
#>     data = esoph)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -2.1325  -0.6877  -0.1661   0.7654   3.3258
#>
#> Coefficients:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  -3.3741     0.4922  -6.855 7.13e-12 ***
#> agegp35-44    0.8562     0.5081   1.685 0.092003 .
#> agegp45-54    1.7829     0.4904   3.636 0.000277 ***
#> agegp55-64    2.1034     0.4876   4.314 1.61e-05 ***
#> agegp65-74    2.3374     0.4930   4.741 2.13e-06 ***
#> agegp75+      2.3694     0.5275   4.491 7.08e-06 ***
#> alcgp40-79    0.8080     0.1330   6.076 1.23e-09 ***
#> alcgp80-119   1.1399     0.1558   7.318 2.52e-13 ***
#> alcgp120+     2.1204     0.2060  10.295  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#>     Null deviance: 367.95  on 87  degrees of freedom
#> Residual deviance: 104.48  on 79  degrees of freedom
#> AIC: 237.53
#>
#> Number of Fisher Scoring iterations: 6
```

7.4 Poisson Regression

From the Poisson distribution

$$
\begin{aligned}
f(Y_i) &= \frac{\mu_i^{Y_i} exp(-\mu_i)}{Y_i!}, Y_i = 0, 1, .. \\
E(Y_i) &= \mu_i \\
var(Y_i) &= \mu_i
\end{aligned}
$$

which is a natural distribution for counts. We can see that the variance is a function of the mean. If we let $\mu_i = f(\mathbf{x_i};\ )$, it would be similar to Logistic Regression since we can choose $f()$ as $\mu_i = \mathbf{x_i'}\ , \mu_i = \exp(\mathbf{x_i'}\ ), \mu_i = \log(\mathbf{x_i'}\ )$

7.4.1 Application

Count Data and Poisson regression

```
data(bioChemists, package = "pscl")
bioChemists <- bioChemists %>%
    rename(
        Num_Article = art, #articles in last 3 years of PhD
        Sex = fem, #coded 1 if female
        Married = mar, #coded 1 if married
        Num_Kid5 = kid5, #number of childeren under age 6
        PhD_Quality = phd, #prestige of PhD program
        Num_MentArticle = ment #articles by mentor in last 3 years
    )
hist(bioChemists$Num_Article, breaks = 25, main = 'Number of Articles')
```

```
Poisson_Mod <- glm(Num_Article ~ ., family=poisson, bioChemists)
summary(Poisson_Mod)
#>
#> Call:
#> glm(formula = Num_Article ~ ., family = poisson, data = bioChemists)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -3.5672  -1.5398  -0.3660   0.5722   5.4467
#>
#> Coefficients:
#>                  Estimate Std. Error z value Pr(>|z|)
```

```
#> (Intercept)      0.304617   0.102981   2.958   0.0031 **
#> SexWomen        -0.224594   0.054613  -4.112 3.92e-05 ***
#> MarriedMarried   0.155243   0.061374   2.529   0.0114 *
#> Num_Kid5        -0.184883   0.040127  -4.607 4.08e-06 ***
#> PhD_Quality      0.012823   0.026397   0.486   0.6271
#> Num_MentArticle  0.025543   0.002006  12.733  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for poisson family taken to be 1)
#>
#>     Null deviance: 1817.4  on 914  degrees of freedom
#> Residual deviance: 1634.4  on 909  degrees of freedom
#> AIC: 3314.1
#>
#> Number of Fisher Scoring iterations: 5
```

Residual of 1634 with 909 df isn't great.

We see Pearson χ^2

```
Predicted_Means <- predict(Poisson_Mod,type = "response")
X2 <- sum((bioChemists$Num_Article - Predicted_Means)^2/Predicted_Means)
X2
#> [1] 1662.547
pchisq(X2,Poisson_Mod$df.residual, lower.tail = FALSE)
#> [1] 7.849882e-47
```

With interaction terms, there are some improvements

```
Poisson_Mod_All2way <- glm(Num_Article ~ .^2, family=poisson, bioChemists)
Poisson_Mod_All3way <- glm(Num_Article ~ .^3, family=poisson, bioChemists)
```

Consider the $\hat{\phi} = \frac{\text{deviance}}{df}$

```
Poisson_Mod$deviance / Poisson_Mod$df.residual
#> [1] 1.797988
```

This is evidence for over-dispersion. Likely cause is missing variables. And remedies could either be to include more variables or consider random effects.

A quick fix is to force the Poisson Regression to include this value of ϕ, and this model is called "Quasi-Poisson".

```
phi_hat = Poisson_Mod$deviance/Poisson_Mod$df.residual
summary(Poisson_Mod,dispersion = phi_hat)
#>
#> Call:
#> glm(formula = Num_Article ~ ., family = poisson, data = bioChemists)
```

```
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -3.5672  -1.5398  -0.3660   0.5722   5.4467
#>
#> Coefficients:
#>                 Estimate Std. Error z value Pr(>|z|)
#> (Intercept)      0.30462    0.13809   2.206  0.02739 *
#> SexWomen        -0.22459    0.07323  -3.067  0.00216 **
#> MarriedMarried   0.15524    0.08230   1.886  0.05924 .
#> Num_Kid5        -0.18488    0.05381  -3.436  0.00059 ***
#> PhD_Quality      0.01282    0.03540   0.362  0.71715
#> Num_MentArticle  0.02554    0.00269   9.496  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for poisson family taken to be 1.797988)
#>
#>     Null deviance: 1817.4  on 914  degrees of freedom
#> Residual deviance: 1634.4  on 909  degrees of freedom
#> AIC: 3314.1
#>
#> Number of Fisher Scoring iterations: 5
```

Or directly rerun the model as

```
quasiPoisson_Mod <- glm(Num_Article ~ ., family=quasipoisson, bioChemists)
```

Quasi-Poisson is not recommended, but Negative Binomial Regression that has an extra parameter to account for over-dispersion is.

7.5 Negative Binomial Regression

```
library(MASS)
NegBinom_Mod <- MASS::glm.nb(Num_Article ~ .,bioChemists)
summary(NegBinom_Mod)
#>
#> Call:
#> MASS::glm.nb(formula = Num_Article ~ ., data = bioChemists, init.theta = 2.26438769
#>     link = log)
#>
#> Deviance Residuals:
#>     Min       1Q   Median       3Q      Max
#> -2.1678  -1.3617  -0.2806   0.4476   3.4524
#>
```

```
#> Coefficients:
#>                  Estimate Std. Error z value Pr(>|z|)
#> (Intercept)      0.256144   0.137348   1.865 0.062191 .
#> SexWomen        -0.216418   0.072636  -2.979 0.002887 **
#> MarriedMarried   0.150489   0.082097   1.833 0.066791 .
#> Num_Kid5        -0.176415   0.052813  -3.340 0.000837 ***
#> PhD_Quality      0.015271   0.035873   0.426 0.670326
#> Num_MentArticle  0.029082   0.003214   9.048  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for Negative Binomial(2.2644) family taken to be 1)
#>
#>     Null deviance: 1109.0  on 914  degrees of freedom
#> Residual deviance: 1004.3  on 909  degrees of freedom
#> AIC: 3135.9
#>
#> Number of Fisher Scoring iterations: 1
#>
#>
#>               Theta:  2.264
#>           Std. Err.:  0.271
#>
#>  2 x log-likelihood:  -3121.917
```

We can see the dispersion is 2.264 with SE = 0.271, which is significantly different from 1, indicating over-dispersion. Check Over-Dispersion for more detail

7.6 Multinomial

If we have more than two categories or groups that we want to model relative to covariates (e.g., we have observations $i = 1, ..., n$ and groups/ covariates $j = 1, 2, ..., J$), multinomial is our candidate model

Let

- p_{ij} be the probability that the i-th observation belongs to the j-th group
- Y_{ij} be the number of observations for individual i in group j; An individual will have observations $Y_{i1}, Y_{i2}, ...Y_{iJ}$
- assume the probability of observing this response is given by a multinomial distribution in terms of probabilities p_{ij}, where $\sum_{j=1}^{J} p_{ij} = 1$. For interpretation, we have a baseline category $p_{i1} = 1 - \sum_{j=2}^{J} p_{ij}$

The link between the mean response (probability) p_{ij} and a linear function of the covariates

$$\eta_{ij} = \mathbf{x}'_{\mathbf{i}\ \mathbf{j}} = \log \frac{p_{ij}}{p_{i1}}, j = 2, .., J$$

We compare p_{ij} to the baseline p_{i1}, suggesting

$$p_{ij} = \frac{\exp(\eta_{ij})}{1 + \sum_{i=2}^{J} \exp(\eta_{ij})}$$

which is known as **multinomial logistic** model.

Note:

- Softmax coding for multinomial logistic regression: rather than selecting a baseline class, we treat all K class symmetrically - equally important (no baseline).

$$P(Y = k|X = x) = \frac{exp(\beta_{k1} + \cdots + \beta_{k_p x_p})}{\sum_{l=1}^{K} exp(\beta_{l0} + \cdots + \beta_{l_p x_p})}$$

then the log odds ratio between k-th and k'-th classes is

$$\log(\frac{P(Y = k|X = x)}{P(Y = k'|X = x)}) = (\beta_{k0} - \beta_{k'0}) + \cdots + (\beta_{kp} - \beta_{k'p})x_p$$

```
library(faraway)
library(dplyr)
data(nes96, package="faraway")
head(nes96,3)
#>   popul TVnews selfLR ClinLR DoleLR     PID age  educ   income    vote
#> 1     0      7 extCon extLib    Con  strRep  36    HS $3Kminus    Dole
#> 2   190      1 sliLib sliLib sliCon weakDem  20  Coll $3Kminus Clinton
#> 3    31      7    Lib    Lib    Con weakDem  24 BAdeg $3Kminus Clinton
```

We try to understand their political strength

```
table(nes96$PID)
#>
#>  strDem weakDem  indDem  indind  indRep weakRep  strRep
#>     200     180     108      37      94     150     175
nes96$Political_Strength <- NA
nes96$Political_Strength[nes96$PID %in% c("strDem", "strRep")] <-
    "Strong"
nes96$Political_Strength[nes96$PID %in% c("weakDem", "weakRep")] <-
    "Weak"
nes96$Political_Strength[nes96$PID %in% c("indDem", "indind", "indRep")] <-
```

```
    "Neutral"
nes96 %>% group_by(Political_Strength) %>% summarise(Count = n())
#> # A tibble: 3 x 2
#>   Political_Strength Count
#>   <chr>              <int>
#> 1 Neutral              239
#> 2 Strong               375
#> 3 Weak                 330
```

visualize the political strength variable

```
library(ggplot2)
Plot_DF <- nes96 %>%
    mutate(Age_Grp = cut_number(age, 4)) %>%
    group_by(Age_Grp, Political_Strength) %>%
    summarise(count = n()) %>%
    group_by(Age_Grp) %>%
    mutate(etotal = sum(count), proportion = count / etotal)

Age_Plot <- ggplot(
    Plot_DF,
    aes(
        x        = Age_Grp,
        y        = proportion,
        group    = Political_Strength,
        linetype = Political_Strength,
        color    = Political_Strength
    )
) +
    geom_line(size = 2)
Age_Plot
```

Fit the multinomial logistic model:

model political strength as a function of age and education

```
library(nnet)
Multinomial_Model <-
    multinom(Political_Strength ~ age + educ, nes96, trace = F)
summary(Multinomial_Model)
#> Call:
#> multinom(formula = Political_Strength ~ age + educ, data = nes96,
#>     trace = F)
#>
#> Coefficients:
#>        (Intercept)          age     educ.L     educ.Q     educ.C      educ^4
#> Strong -0.08788729  0.010700364 -0.1098951 -0.2016197 -0.1757739 -0.02116307
#> Weak    0.51976285 -0.004868771 -0.1431104 -0.2405395 -0.2411795  0.18353634
#>            educ^5     educ^6
#> Strong -0.1664377 -0.1359449
#> Weak   -0.1489030 -0.2173144
#>
#> Std. Errors:
#>        (Intercept)         age    educ.L    educ.Q    educ.C    educ^4
#> Strong   0.3017034 0.005280743 0.4586041 0.4318830 0.3628837 0.2964776
#> Weak     0.3097923 0.005537561 0.4920736 0.4616446 0.3881003 0.3169149
#>           educ^5    educ^6
#> Strong 0.2515012 0.2166774
#> Weak   0.2643747 0.2199186
#>
```

```
#> Residual Deviance: 2024.596
#> AIC: 2056.596
```

Alternatively, stepwise model selection based AIC

```
Multinomial_Step <- step(Multinomial_Model,trace = 0)
#> trying - age
#> trying - educ
#> trying - age
Multinomial_Step
#> Call:
#> multinom(formula = Political_Strength ~ age, data = nes96, trace = F)
#>
#> Coefficients:
#>        (Intercept)          age
#> Strong -0.01988977  0.009832916
#> Weak    0.59497046 -0.005954348
#>
#> Residual Deviance: 2030.756
#> AIC: 2038.756
```

compare the best model to the full model based on deviance

```
pchisq(q = deviance(Multinomial_Step) - deviance(Multinomial_Model),
df = Multinomial_Model$edf-Multinomial_Step$edf,lower=F)
#> [1] 0.9078172
```

We see no significant difference

Plot of the fitted model

```
PlotData <- data.frame(age = seq(from = 19, to = 91))
Preds <-
  PlotData %>% bind_cols(data.frame(predict(
    object = Multinomial_Step,
    PlotData, type = "probs"
  )))

plot(
  x       = Preds$age,
  y       = Preds$Neutral,
  type    = "l",
  ylim    = c(0.2, 0.6),
  col     = "black",
  ylab    = "Proportion",
  xlab    = "Age"
)
```

```
lines(x   = Preds$age,
      y   = Preds$Weak,
      col = "blue")
lines(x   = Preds$age,
      y   = Preds$Strong,
      col = "red")

legend(
  'topleft',
  legend  = c('Neutral', 'Weak', 'Strong'),
  col     = c('black', 'blue', 'red'),
  lty     = 1
)
```

```
predict(Multinomial_Step,data.frame(age = 34)) # predicted result (categoriy of politi
#> [1] Weak
#> Levels: Neutral Strong Weak
predict(Multinomial_Step,data.frame(age = c(34,35)),type="probs") # predicted result o
#>     Neutral    Strong      Weak
#> 1 0.2597275 0.3556910 0.3845815
#> 2 0.2594080 0.3587639 0.3818281
```

If categories are ordered (i.e., ordinal data), we must use another approach (still multinomial, but use cumulative probabilities).

Another example

```r
library(agridat)
dat <- agridat::streibig.competition
# See Schaberger and Pierce, pages 370+
# Consider only the mono-species barley data (no competition from Sinapis)
gammaDat <- subset(dat, sseeds < 1)
gammaDat <-
    transform(gammaDat,
              x = bseeds,
              y = bdwt,
              block = factor(block))
# Inverse yield looks like it will be a good fit for Gamma's inverse link
ggplot(gammaDat, aes(x = x, y = 1 / y)) +
    geom_point(aes(color = block, shape = block)) +
    xlab('Seeding Rate') +
    ylab('Inverse yield') +
    ggtitle('Streibig Competion - Barley only')
```

$$Y \sim Gamma$$

because Gamma is non-negative as opposed to Normal. The canonical Gamma link function is the inverse (or reciprocal) link

$$\eta_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \beta_2 x_{ij}^2$$
$$Y_{ij} = \eta_{ij}^{-1}$$

The linear predictor is a quadratic model fit to each of the j-th blocks. A different model (not fitted) could be one with common slopes: `glm(y ~ x + I(x^2),…)`

```
# linear predictor is quadratic, with separate intercept and slope per block
m1 <-
    glm(y ~ block + block * x + block * I(x ^ 2),
        data = gammaDat,
        family = Gamma(link = "inverse"))
summary(m1)
#>
#> Call:
#> glm(formula = y ~ block + block * x + block * I(x^2), family = Gamma(link = "invers
#>     data = gammaDat)
#>
#> Deviance Residuals:
#>      Min        1Q    Median        3Q       Max
#> -1.21708  -0.44148   0.02479   0.17999   0.80745
#>
#> Coefficients:
#>                  Estimate Std. Error t value Pr(>|t|)
#> (Intercept)     1.115e-01  2.870e-02   3.886 0.000854 ***
#> blockB2        -1.208e-02  3.880e-02  -0.311 0.758630
#> blockB3        -2.386e-02  3.683e-02  -0.648 0.524029
#> x              -2.075e-03  1.099e-03  -1.888 0.072884 .
#> I(x^2)          1.372e-05  9.109e-06   1.506 0.146849
#> blockB2:x       5.198e-04  1.468e-03   0.354 0.726814
#> blockB3:x       7.475e-04  1.393e-03   0.537 0.597103
#> blockB2:I(x^2) -5.076e-06  1.184e-05  -0.429 0.672475
#> blockB3:I(x^2) -6.651e-06  1.123e-05  -0.592 0.560012
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for Gamma family taken to be 0.3232083)
#>
#>     Null deviance: 13.1677  on 29  degrees of freedom
#> Residual deviance:  7.8605  on 21  degrees of freedom
#> AIC: 225.32
#>
#> Number of Fisher Scoring iterations: 5
```

For predict new value of x

```
newdf <-
    expand.grid(x = seq(0, 120, length = 50), block = factor(c('B1', 'B2', 'B3')))

newdf$pred <- predict(m1, new = newdf, type = 'response')
```

```
ggplot(gammaDat, aes(x = x, y = y)) +
    geom_point(aes(color = block, shape = block)) +
    xlab('Seeding Rate') + ylab('Inverse yield') +
    ggtitle('Streibig Competion - Barley only Predictions') +
    geom_line(data = newdf, aes(
        x = x,
        y = pred,
        color = block,
        linetype = block
    ))
```

7.7 Generalization

We can see that Poisson regression looks similar to logistic regression. Hence, we can generalize to a class of modeling. Thanks to Nelder and Wedderburn (1972), we have the **generalized linear models** (GLMs). Estimation is generalize in these models.

Exponential Family
The theory of GLMs is developed for data with distribution given y the **exponential family**.
The form of the data distribution that is useful for GLMs is

$$f(y;\theta,\phi) = \exp(\frac{\theta y - b(\theta)}{a(\phi)} + c(y,\phi))$$

where

- θ is called the natural parameter
- ϕ is called the dispersion parameter

Note:

This family includes the [Gamma], [Normal], [Poisson], and other. For all parameterization of the exponential family, check this link

Example

if we have $Y \sim N(\mu, \sigma^2)$

$$\begin{aligned} f(y;\mu,\sigma^2) &= \frac{1}{(2\pi\sigma^2)^{1/2}} \exp(-\frac{1}{2\sigma^2}(y-\mu)^2) \\ &= \exp(-\frac{1}{2\sigma^2}(y^2 - 2y\mu + \mu^2) - \frac{1}{2}\log(2\pi\sigma^2)) \\ &= \exp(\frac{y\mu - \mu^2/2}{\sigma^2} - \frac{y^2}{2\sigma^2} - \frac{1}{2}\log(2\pi\sigma^2)) \\ &= \exp(\frac{\theta y - b(\theta)}{a(\phi)} + c(y,\phi)) \end{aligned}$$

where

- $\theta = \mu$
- $b(\theta) = \frac{\mu^2}{2}$
- $a(\phi) = \sigma^2 = \phi$
- $c(y,\phi) = -\frac{1}{2}(\frac{y^2}{\phi} + \log(2\pi\sigma^2))$

Properties of GLM exponential families

1. $E(Y) = b'(\theta)$ where $b'(\theta) = \frac{\partial b(\theta)}{\partial \theta}$ (here ' is "prime", not transpose)

2. $var(Y) = a(\phi)b''(\theta) = a(\phi)V(\mu)$.

   - $V(\mu)$ is the *variance function*; however, it is only the variance in the case that $a(\phi) = 1$

3. If $a(), b(), c()$ are identifiable, we will derive expected value and variance of Y.

Example

Normal distribution

$$
\begin{aligned}
b'(\theta) &= \frac{\partial b(\mu^2/2)}{\partial \mu} = \mu \\
V(\mu) &= \frac{\partial^2(\mu^2/2)}{\partial \mu^2} = 1 \\
\rightarrow var(Y) &= a(\phi) = \sigma^2
\end{aligned}
$$

Poisson distribution

$$
\begin{aligned}
f(y, \theta, \phi) &= \frac{\mu^y \exp(-\mu)}{y!} \\
&= \exp(y \log(\mu) - \mu - \log(y!)) \\
&= \exp(y\theta - \exp(\theta) - \log(y!))
\end{aligned}
$$

where

- $\theta = \log(\mu)$
- $a(\phi) = 1$
- $b(\theta) = \exp(\theta)$
- $c(y, \phi) = \log(y!)$

Hence,

$$
\begin{aligned}
E(Y) &= \frac{\partial b(\theta)}{\partial \theta} = \exp(\theta) = \mu \\
var(Y) &= \frac{\partial^2 b(\theta)}{\partial \theta^2} = \mu
\end{aligned}
$$

Since $\mu = E(Y) = b'(\theta)$

In GLM, we take some monotone function (typically nonlinear) of μ to be linear in the set of covariates

$$g(\mu) = g(b'(\theta)) = \mathbf{x}'$$

Equivalently,

$$\mu = g^{-1}(\mathbf{x}' \ )$$

where $g(.)$ is the **link function** since it links mean response ($\mu = E(Y)$) and a linear expression of the covariates

Some people use $\eta = \mathbf{x}'$ where $\eta =$ the "linear predictor"

GLM is composed of 2 components

The **random component**:

- is the distribution chosen to model the response variables $Y_1, ..., Y_n$
- is specified by the choice fo $a(), b(), c()$ in the exponential form
- Notation:
  - Assume that there are n **independent** response variables $Y_1, ..., Y_n$ with densities

    $$f(y_i; \theta_i, \phi) = \exp(\frac{\theta_i y_i - b(\theta_i)}{a(\phi)} + c(y_i, \phi))$$

    notice each observation might have different densities
  - Assume that ϕ is constant for all $i = 1, ..., n$, but θ_i will vary. $\mu_i = E(Y_i)$ for all i.

The **systematic component**

- is the portion of the model that gives the relation between μ and the covariates $\mathbf{x}$
- consists of 2 parts:
  - the *link* function, $g(.)$
  - the *linear predictor*, $\eta = \mathbf{x}'$
- Notation:
  - assume $g(\mu_i) = \mathbf{x}' \ = \eta_i$ where $\ = (\beta_1, ..., \beta_p)'$
  - The parameters to be estimated are $\beta_1, ...\beta_p, \phi$

The Canonical Link

To choose $g(.)$, we can use **canonical link function** (Remember: Canonical link is just a special case of the link function)

If the link function $g(.)$ is such $g(\mu_i) = \eta_i = \theta_i$, the natural parameter, then $g(.)$ is the canonical link.

- $b(\theta)$ = cumulant moment generating function
- $g(\mu)$ is the link function, which relates the linear predictor to the mean and is required to be monotone increasing, continuously differentiable and invertible.

Equivalently, we can think of canonical link function as

$$\gamma^{-1} \circ g^{-1} = I$$

which is the identity. Hence,

$$\theta = \eta$$

The inverse link

$g^{-1}(.)$ is also known as the mean function, take linear predictor output (ranging from $-\infty$ to ∞) and transform it into a different scale.

- **Exponential**: converts $\mathbf{X}$ into a curve that is restricted between 0 and ∞ (which you can see that is useful in case you want to convert a linear predictor into a non-negative value). $\lambda = \exp(y) = \mathbf{X}$
- **Inverse Logit** (also known as logistic): converts $\mathbf{X}$ into a curve that is restricted between 0 and 1, which is useful in case you want to convert a linear predictor to a probability. $\theta = \frac{1}{1+\exp(-y)} = \frac{1}{1+\exp(-\mathbf{X})}$
  - $y =$ linear predictor value
  - $\theta =$ transformed value

The **identity link** is that

$$\eta_i = g(\mu_i) = \mu_i$$
$$\mu_i = g^{-1}(\eta_i) = \eta_i$$

Link	$\eta_i = g(\mu_i)$	$\mu_i = g^{-1}(\eta_i)$
Identity	μ_i	η_i
Log	$\log_e \mu_i$	e^{η_i}
Inverse	μ_i^{-1}	η_i^{-1}
Inverse-square	μ_i^{-2}	$\eta_i^{-1/2}$
Square-root	$\sqrt{\mu_i}$	η_i^2
Logit	$\log_e \frac{\mu_i}{1-\mu_i}$	$\frac{1}{1+e^{-\eta_i}}$
Probit	$\Phi^{-1}(\mu_i)$	$\Phi(\eta_i)$
Log-log	$-\log_e[-\log_e(\mu_i)]$	$\exp[-\exp(-\eta_i)]$
Complementary log-log	$\log_e[-\log_e(1-\mu_i)]$	$1-\exp[-\exp(\eta_i)]$

NOTE: μ_i is the expected value of the response; η_i is the linear predictor; and $\Phi(\cdot)$ is the cumulative distribution function of the standard-normal distribution.

Table 15.1 Generalized Linear Models 15.1 the Structure of Generalized Linear Models

More example on the link functions and their inverses can be found on page 380

Example

Normal random component

- Mean Response: $\mu_i = \theta_i$
- Canonical Link: $g(\mu_i) = \mu_i$ (the identity link)

Binomial random component

- Mean Response: $\mu_i = \frac{n_i \exp(\theta)}{1+\exp(\theta_i)}$ and $\theta(\mu_i) = \log(\frac{p_i}{1-p_i}) = \log(\frac{\mu_i}{n_i-\mu_i})$
- Canonical link: $g(\mu_i) = \log(\frac{\mu_i}{n_i-\mu_i})$ (logit link)

Poisson random component

- Mean Response: $\mu_i = \exp(\theta_i)$
- Canonical Link: $g(\mu_i) = \log(\mu_i)$

Gamma random component:

- Mean response: $\mu_i = -\frac{1}{\theta_i}$ and $\theta(\mu_i) = -\mu_i^{-1}$
- Canonical Link: $g(\mu_i) = -\frac{1}{\mu_i}$

Inverse Gaussian random

- Canonical Link: $g(\mu_i) = \frac{1}{\mu_i^2}$

7.7.1 Estimation

- MLE for parameters of the **systematic component (**β)
- Unification of derivation and computation (thanks to the exponential forms)
- No unification for estimation of the dispersion parameter (ϕ)

7.7.1.1 Estimation of β

We have

$$
\begin{aligned}
f(y_i;\theta_i,\phi) &= \exp(\frac{\theta_i y_i - b(\theta_i)}{a(\phi)} + c(y_i,\phi)) \\
E(Y_i) &= \mu_i = b'(\theta) \\
var(Y_i) &= b''(\theta)a(\phi) = V(\mu_i)a(\phi) \\
g(\mu_i) &= \mathbf{x}_i'\beta = \eta_i
\end{aligned}
$$

If the log-likelihood for a single observation is $l_i(\beta,\phi)$. The log-likelihood for all n observations is

$$
\begin{aligned}
l(\beta,\phi) &= \sum_{i=1}^{n} l_i(\beta,\phi) \\
&= \sum_{i=1}^{n} (\frac{\theta_i y_i - b(\theta_i)}{a(\phi)} + c(y_i,\phi))
\end{aligned}
$$

Using MLE to find β, we use the chain rule to get the derivatives

$$
\begin{aligned}
\frac{\partial l_i(\beta,\phi)}{\partial \beta_j} &= \frac{\partial l_i(\beta,\phi)}{\partial \theta_i} \times \frac{\partial \theta_i}{\partial \mu_i} \times \frac{\partial \mu_i}{\partial \eta_i} \times \frac{\partial \eta_i}{\partial \beta_j} \\
&= \sum_{i=1}^{n} (\frac{y_i - \mu_i}{a(\phi)} \times \frac{1}{V(\mu_i)} \times \frac{\partial \mu_i}{\partial \eta_i} \times x_{ij})
\end{aligned}
$$

If we let

$$
w_i \equiv ((\frac{\partial \eta_i}{\partial \mu_i})^2 V(\mu_i))^{-1}
$$

Then,

$$
\frac{\partial l_i(\beta,\phi)}{\partial \beta_j} = \sum_{i=1}^{n} (\frac{y_i \mu_i}{a(\phi)} \times w_i \times \frac{\partial \eta_i}{\partial \mu_i} \times x_{ij})
$$

We can also get the second derivatives using the chain rule.

Example:

For the

$$
Newton - Raphson
$$

algorithm, we need

$$
-E(\frac{\partial^2 l(\beta,\phi)}{\partial \beta_j \partial \beta_k})
$$

where (j,k)-th element of the **Fisher information matrix** $\mathbf{I}(\beta)$

Hence,

$$
-E(\frac{\partial^2 l(\beta,\phi)}{\partial \beta_j \partial \beta_k}) = \sum_{i=1}^{n} \frac{w_i}{a(\phi)} x_{ij} x_{ik}
$$

for the (j,k)th element

If Bernoulli model with logit link function (which is the canonical link)

$$
\begin{aligned}
b(\theta) &= \log(1+\exp(\theta)) = \log(1+\exp(\mathbf{x}'\ )) \\
a(\phi) &= 1 \\
c(y_i,\phi) &= 0 \\
E(Y) = b'(\theta) &= \frac{\exp(\theta)}{1+\exp(\theta)} = \mu = p \\
\eta = g(\mu) &= \log(\frac{\mu}{1-\mu}) = \theta = \log(\frac{p}{1-p}) = \mathbf{x}'
\end{aligned}
$$

For Y_i, i = 1,.., the log-likelihood is

$$
l_i(\beta,\phi) = \frac{y_i\theta_i - b(\theta_i)}{a(\phi)} + c(y_i,\phi) = y_i\mathbf{x}_i'\beta - \log(1+\exp(\mathbf{x}'\ ))
$$

Additionally,

$$
\begin{aligned}
V(\mu_i) &= \mu_i(1-\mu_i) = p_i(1-p_i) \\
\frac{\partial\mu_i}{\partial\eta_i} &= p_i(1-p_i)
\end{aligned}
$$

Hence,

$$
\begin{aligned}
\frac{\partial l(\beta,\phi)}{\partial\beta_j} &= \sum_{i=1}^{n}[\frac{y_i-\mu_i}{a(\phi)} \times \frac{1}{V(\mu_i)} \times \frac{\partial\mu_i}{\partial\eta_i} \times x_{ij}] \\
&= \sum_{i=1}^{n}(y_i-p_i) \times \frac{1}{p_i(1-p_i)} \times p_i(1-p_i) \times x_{ij} \\
&= \sum_{i=1}^{n}(y_i-p_i)x_{ij} \\
&= \sum_{i=1}^{n}(y_i - \frac{\exp(\mathbf{x_i'}\ )}{1+\exp(\mathbf{x_i'}\ )})x_{ij}
\end{aligned}
$$

then

$$
w_i = ((\frac{\partial\eta_i}{\partial\mu_i})^2 V(\mu_i))^{-1} = p_i(1-p_i)
$$

$$
\mathbf{I}_{jk}(\ ) = \sum_{i=1}^{n}\frac{w_i}{a(\phi)}x_{ij}x_{ik} = \sum_{i=1}^{n}p_i(1-p_i)x_{ij}x_{ik}
$$

The **Fisher-scoring** algorithm for the MLE of is

$$\begin{pmatrix} \beta_1 \\ \beta_2 \\ . \\ . \\ . \\ \beta_p \end{pmatrix}^{(m+1)} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ . \\ . \\ . \\ \beta_p \end{pmatrix}^{(m)} + \mathbf{I}^{-1}(\ ) \begin{pmatrix} \frac{\partial l(\beta,\phi)}{\partial \beta_1} \\ \frac{\partial l(\beta,\phi)}{\partial \beta_2} \\ . \\ . \\ . \\ \frac{\partial l(\beta,\phi)}{\partial \beta_p} \end{pmatrix} |_{\beta=\beta^{(m)}}$$

Similar to

$$Newton - Raphson$$

expect the matrix of second derivatives by the expected value of the second derivative matrix.

In matrix notation,

$$\begin{aligned} \frac{\partial l}{\partial \beta} &= \frac{1}{a(\phi)} \mathbf{X'W}\ (\mathbf{y} -\ ) \\ &= \frac{1}{a(\phi)} \mathbf{F'V^{-1}}(\mathbf{y} -\ ) \end{aligned}$$

$$\mathbf{I}(\beta) = \frac{1}{a(\phi)} \mathbf{X'WX} = \frac{1}{a(\phi)} \mathbf{F'V^{-1}F}$$

where

- $\mathbf{X}$ is an $n \times p$ matrix of covariates
- $\mathbf{W}$ is an $n \times n$ diagonal matrix with (i,i)-th element given by w_i
- an $n \times n$ diagonal matrix with (i,i)-th element given by $\frac{\partial \eta_i}{\partial \mu_i}$
- $\mathbf{F} =$ - an $n \times p$ matrix with i-th row $\frac{\partial \mu_i}{\partial \beta} = (\frac{\partial \mu_i}{\partial \eta_i})\mathbf{x}_i'$
- $\mathbf{V}$ an $n \times n$ diagonal matrix with (i,i)-th element given by $V(\mu_i)$

Setting the derivative of the log-likelihood equal to 0, ML estimating equations are

$$\mathbf{F'V^{-1}y} = \mathbf{F'V^{-1}}$$

where all components of this equation expect y depends on the parameters β

Special Cases

If one has a canonical link, the estimating equations reduce to

$$\mathbf{X'y} = \mathbf{X'}$$

If one has an identity link, then

$$\mathbf{X'V^{-1}y} = \mathbf{X'V^{-1}X}$$

which gives the generalized least squares estimator

Generally, we can rewrite the Fisher-scoring algorithm as

$$\beta^{(m+1)} = \beta^{(m)} + (\mathbf{\hat{F}'\hat{V}^{-1}\hat{F}})^{\mathbf{-1}}\mathbf{\hat{F}'\hat{V}^{-1}}(\mathbf{y} - \hat{\ })$$

Since $\hat{F}, \hat{V}, \hat{\mu}$ depend on β, we evaluate at $\beta^{(m)}$

From starting values $\beta^{(0)}$, we can iterate until convergence.

Notes:

- if $a(\phi)$ is a constant or of the form $m_i\phi$ with known m_i, then ϕ cancels.

7.7.1.2 Estimation of ϕ

2 approaches:

1. MLE

$$\frac{\partial l_i}{\partial \phi} = \frac{(\theta_i y_i - b(\theta_i)a'(\phi))}{a^2(\phi)} + \frac{\partial c(y_i, \phi)}{\partial \phi}$$

the MLE of ϕ solves

$$\frac{a^2(\phi)}{a'(\phi)} \sum_{i=1}^{n} \frac{\partial c(y_i, \phi)}{\partial \phi} = \sum_{i=1}^{n} (\theta_i y_i - b(\theta_i))$$

- Situation others than normal error case, expression for $\frac{\partial c(y,\phi)}{\partial \phi}$ are not simple
- Even for the canonical link and $a(\phi)$ constant, there is no nice general expression for $-E(\frac{\partial^2 l}{\partial \phi^2})$, so the unification GLMs provide for estimation of β breaks down for ϕ

2. Moment Estimation ("Bias Corrected χ^2")
   - The MLE is not conventional approach to estimation of ϕ in GLMS.
   - For the exponential family $var(Y) = V(\mu)a(\phi)$. This implies

$$a(\phi) = \frac{var(Y)}{V(\mu)} = \frac{E(Y-\mu)^2}{V(\mu)}$$
$$a(\hat{\phi}) = \frac{1}{n-p} \sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{V(\hat{\mu})}$$

   where p is the dimension of β

- GLM with canonical link function $g(.) = (b'(.))^{-1}$

$$g(\mu) = \theta = \eta = \mathbf{x}'$$
$$\mu = g^{-1}(\eta) = b'(\eta)$$

- so the method estimator for $a(\phi) = \phi$ is

$$\hat{\phi} = \frac{1}{n-p} \sum_{i=1}^{n} \frac{(y_i - g^{-1}(\hat{\eta}_i))^2}{V(g^{-1}(\hat{\eta}_i))}$$

7.7.2 Inference

We have

$$\hat{var}(\beta) = a(\phi)(\hat{\mathbf{F}}'\hat{\mathbf{V}}\hat{\mathbf{F}})^{-1}$$

where

- $\mathbf{V}$ is an $n \times n$ diagonal matrix with diagonal elements given by $V(\mu_i)$
- $\mathbf{F}$ is an $n \times p$ matrix given by $\mathbf{F} = \frac{\partial \mu}{\partial \beta}$
- Both $\mathbf{V}, \mathbf{F}$ are dependent on the mean μ, and thus β. Hence, their estimates $(\hat{\mathbf{V}}, \hat{\mathbf{F}})$ depend on $\hat{\beta}$.

$$H_0 : \mathbf{L} \ = \mathbf{d}$$

where $\mathbf{L}$ is a q x p matrix with a **Wald** test

$$W = (\mathbf{L}\hat{} \ - \mathbf{d})'(\mathbf{a}(\ )\mathbf{L}(\hat{\mathbf{F}}'\hat{\mathbf{V}}^{-\mathbf{1}}\hat{\mathbf{F}})\mathbf{L}')^{-\mathbf{1}}(\mathbf{L}\hat{} \ - \mathbf{d})$$

which follows χ^2_q distribution (asymptotically), where q is the rank of $\mathbf{L}$

In the simple case $H_0 : \beta_j = 0$ gives $W = \frac{\hat{\beta}_j^2}{\hat{var}(\hat{\beta}_j)} \sim \chi^2_1$ asymptotically

Likelihood ratio test

$$\Lambda = 2(l(\hat{\beta}_f) - l(\hat{\beta}_r)) \sim \chi^2_q$$

where

- q is the number of constraints used to fit the reduced model $\hat{\beta}_r$, and $\hat{\beta}_r$ is the fit under the full model.

Wald test is easier to implement, but likelihood ratio test is better (especially for small samples).

7.7.3 Deviance

Deviance is necessary for goodness of fit, inference and for alternative estimation of the dispersion parameter. We define and consider Deviance from a likelihood ratio perspective.

- Assume that ϕ is known. Let $\tilde{\theta}$ denote the full and $\hat{\theta}$ denote the reduced model MLEs. Then, the likelihood ratio (2 times the difference in log-likelihoods) is
$$2\sum_{i=1}^{n}\frac{y_i(\tilde{\theta}_i-\hat{\theta}_i)-b(\tilde{\theta}_i)+b(\hat{\theta}_i)}{a_i(\phi)}$$
- For exponential families, $\mu = E(y) = b'(\theta)$, so the natural parameter is a function of $\mu : \theta = \theta(\mu) = b'^{-1}(\mu)$, and the likelihood ratio turns into
$$2\sum_{i=1}^{m}\frac{y_i\{\theta(\tilde{\mu}_i-\theta(\hat{\mu}_i)\}-b(\theta(\tilde{\mu}_i))+b(\theta(\hat{\mu}_i))}{a_i(\phi)}$$
- Comparing a fitted model to "the fullest possible model", which is the **saturated model**: $\tilde{\mu}_i = y_i$, i = 1,..,n. If $\tilde{\theta}_i^* = \theta(y_i), \hat{\theta}_i^* = \theta(\hat{\mu})$, the likelihood ratio is
$$2\sum_{i=1}^{n}\frac{y_i(\tilde{\theta}_i^*-\hat{\theta}_i^*+b(\hat{\theta}_i^*))}{a_i(\phi)}$$
- (McCullagh, 2019) specify $a(\phi) = \phi$, then the likelihood ratio can be written as
$$D^*(\mathbf{y},\hat{\ }) = \frac{2}{\phi}\sum_{i=1}^{n}\{y_i(\tilde{\theta}_i^*-\hat{\theta}_i^*)-b(\tilde{\theta}_i^*)+b(\hat{\theta}_i^*)\}$$
where
- $D^*(\mathbf{y},\hat{\ }) =$ **scaled deviance**
- $D(\mathbf{y},\hat{\ }) = \phi D^*(\mathbf{y},\hat{\ }) =$ **deviance**

Note:

- in some random component distributions, we can write $a_i(\phi) = \phi m_i$, where
  - m_i is some known scalar that may change with the observations. Then, the scaled deviance components are divided by m_i:
$$D^*(\mathbf{y},\hat{\ }) \equiv 2\sum_{i=1}^{n}\{y_i(\tilde{\theta}_i^*-\hat{\theta}_i^*)-b(\tilde{\theta}_i^*)+b(\hat{\theta}_i^*)\}/(\phi m_i)$$

- $D^*(\mathbf{y}, \hat{\ }) = \sum_{i=1}^n d_i$m where d_i is the deviance contribution from the i-th observation.
- D is used in model selection
- D^* is used in goodness of fit tests (as it is a likelihood ratio statistic).

$$D^*(\mathbf{y}, \hat{\ }) = 2\{l(\mathbf{y}, \tilde{\ }) - l(\mathbf{y}, \hat{\ })\}$$

- d_i are used to form **deviance residuals**

Normal

We have

$$\begin{aligned}
\theta &= \mu \\
\phi &= \sigma^2 \\
b(\theta) &= \frac{1}{2}\theta^2 \\
a(\phi) &= \phi
\end{aligned}$$

Hence,

$$\begin{aligned}
\tilde{\theta}_i &= y_i \\
\hat{\theta}_i &= \hat{\mu}_i = g^{-1}(\hat{\eta}_i)
\end{aligned}$$

And

$$\begin{aligned}
D &= 2\sum_{1=1}^n Y_i^2 - y_i\hat{\mu}_i - \frac{1}{2}y_i^2 + \frac{1}{2}\hat{\mu}_i^2 \\
&= \sum_{i=1}^n y_i^2 - 2y_i\hat{\mu}_i + \hat{\mu}_i^2 \\
&= \sum_{i=1}^n (y_i - \hat{\mu}_i)^2
\end{aligned}$$

which is the **residual sum of squares**

Poisson

$$
\begin{aligned}
f(y) &= \exp\{y\log(\mu) - \mu - \log(y!)\} \\
\theta &= \log(\mu) \\
b(\theta) &= \exp(\theta) \\
a(\phi) &= 1 \\
\tilde{\theta}_i &= \log(y_i) \\
\hat{\theta}_i &= \log(\hat{\mu}_i) \\
\hat{\mu}_i &= g^{-1}(\hat{\eta}_i)
\end{aligned}
$$

Then,

$$
\begin{aligned}
D &= 2\sum_{i=1}^{n} y_i \log(y_i) - y_i \log(\hat{\mu}_i) - y_i + \hat{\mu}_i \\
&= 2\sum_{i=1}^{n} y_i \log(\frac{y_i}{\hat{\mu}_i}) - (y_i - \hat{\mu}_i)
\end{aligned}
$$

and

$$
d_i = 2\{y_i \log(\frac{y_i}{\hat{\mu}}) - (y_i - \hat{\mu}_i)\}
$$

7.7.3.1 Analysis of Deviance

The difference in deviance between a reduced and full model, where q is the difference in the number of free parameters, has an asymptotic χ^2_q. The likelihood ratio test

$$
D^*(\mathbf{y}; \hat{}_{\mathbf{r}}) - D^*(\mathbf{y}; \hat{}_{\mathbf{f}}) = 2\{l(\mathbf{y}; \hat{}_{\mathbf{f}}) - l(\mathbf{y}; \hat{}_{\mathbf{r}})\}
$$

this comparison of models is **Analysis of Deviance**. GLM uses this analysis for model selection.

An estimation of ϕ is

$$
\hat{\phi} = \frac{D(\mathbf{y}; \hat{})}{n-p}
$$

where p = number of parameters fit.

Excessive use of χ^2 test could be problematic since it is asymptotic (McCullagh, 2019)

7.7.3.2 Deviance Residuals

We have $D = \sum_{i=1}^{n} d_i$. Then, we define **deviance residuals**

$$r_{D_i} = \text{sign}(y_i - \hat{\mu}_i)\sqrt{d_i}$$

Standardized version of deviance residuals is

$$r_{s,i} = \frac{y_i - \hat{\mu}}{\hat{\sigma}(1 - h_{ii})^{1/2}}$$

Let $\mathbf{H^{GLM}} = \mathbf{W^{1/2}X(X'WX)^{-1}X'W^{-1/2}}$, where $\mathbf{W}$ is an $n \times n$ diagonal matrix with (i, i)-th element given by w_i (see Estimation of β). Then Standardized deviance residuals is equivalently

$$r_{s,D_i} = \frac{r_{D_i}}{\{\hat{\phi}(1 - h_{ii}^{glm}\}^{1/2}}$$

where h_{ii}^{glm} is the i-th diagonal of $\mathbf{H}^{GLM}$

7.7.3.3 Pearson Chi-square Residuals

Another χ^2 statistic is **Pearson** χ^2 statistics: (assume $m_i = 1$)

$$X^2 = \sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{V(\hat{\mu}_i)}$$

where $\hat{\mu}_i$ is the fitted mean response fo the model of interest.

The **Scaled Pearson** χ^2 statistic is given by $\frac{X^2}{\phi} \sim \chi^2_{n-p}$ where p is the number of parameters estimated. Hence, the **Pearson** χ^2 residuals are

$$X_i^2 = \frac{(y_i - \hat{\mu}_i)^2}{V(\hat{\mu}_i)}$$

If we have the following assumptions:

- Independent samples
- No over-dispersion: If $\phi = 1$, $\frac{D(\mathbf{y}\hat{;})}{n-p}$ and $\frac{X^2}{n-p}$ have a value substantially larger 1 indicates **improperly specified model** or **overdispersion**
- Multiple groups

then $\frac{X^2}{\phi}$ and $D^*(\mathbf{y}\hat{;})$ both follow χ^2_{n-p}

7.7.4 Diagnostic Plots

- Standardized residual Plots:
  - plot(r_{s,D_i}, $\hat{\mu}_i$) or plot(r_{s,D_i}, $T(\hat{\mu}_i)$) where $T(\hat{\mu}_i)$ is transformation($\hat{\mu}_i$) called **constant information scale**:
  - plot(r_{s,D_i}, $\hat{\eta}_i$)

Random Component	$T(\hat{\mu}_i)$
Normal	$\hat{\mu}$
Poisson	$2\sqrt{\mu}$
Binomial	$2\sin^{-1}(\sqrt{\hat{\mu}})$
Gamma	$2\log(\hat{\mu})$
Inverse Gaussian	$-2\hat{\mu}^{-1/2}$

- If we see:
  - Trend, it means we might have a wrong link function, or choice of scale
  - Systematic change in range of residuals with a change in $T(\hat{\mu})$ (incorrect random component) (systematic $\neq$ random)
- plot($|r_{D_i}|, \hat{\mu}_i$) to check **Variance Function**.

7.7.5 Goodness of Fit

To assess goodness of fit, we can use

- Deviance
- Pearson Chi-square Residuals

In nested model, we could use likelihood-based information measures:

$$
\begin{aligned}
AIC &= -2l(\hat{\ }) + 2p \\
AICC &= -2l(\hat{\ }) + 2p(\frac{n}{n-p-1}) \\
BIC &= 2l(\hat{\mu}) + p\log(n)
\end{aligned}
$$

where

- $l(\hat{\mu})$ is the log-likelihood evaluated at the parameter estimates
- p is the number of parameters
- n is the number of observations.

Note: you have to use the same data with the same model (i.e., same link function, same random underlying random distribution). but you can have different number of parameters.

Even though statisticians try to come up with measures that are similar to R^2, in practice, it is not so appropriate. For example, they compare the log-likelihood of the fitted model against the that of a model with just the intercept:

$$R_p^2 = 1 - \frac{l(\hat{\mu})}{l(\hat{\mu}_0)}$$

For certain specific random components such as binary response model, we have rescaled generalized R^2

$$\bar{R}^2 = \frac{R_*^2}{\max(R_*^2)} = \frac{1 - \exp\{-\frac{2}{n}(l(\hat{\mu}) - l(\hat{\mu}_0)\}}{1 - \exp\{\frac{2}{n} l(\hat{\mu}_0)\}}$$

7.7.6 Over-Dispersion

Random Components	$var(Y)$	$V(\mu)$
Binomial	$var(Y) = n\mu(1-\mu)$	$V(\mu) = \phi n\mu(1-\mu)$ where $m_i = n$
Poisson	$var(Y) = \mu$	$V(\mu) = \phi\mu$

In both cases $\phi = 1$. Recall $b''(\theta) = V(\mu)$ check Estimation of ϕ.

If we find

- $\phi > 1$: over-dispersion (i.e., too much variation for an independent binomial or Poisson distribution).
- $\phi < 1$: under-dispersion (i.e., too little variation for an independent binomial or Poisson distribution).

If we have either over or under-dispersion, it means we might have unspecified random component, we could

- Select a different random component distribution that can accommodate over or under-dispersion (e.g., negative binomial, Conway-Maxwell Poisson)
- use Nonlinear and Generalized Linear Mixed Models to handle random effects in generalized linear models.

Chapter 8

Linear Mixed Models

8.1 Dependent Data

Forms of dependent data:

- Multivariate measurements on different individuals: (e.g., a person's blood pressure, fat, etc are correlated)
- Clustered measurements: (e.g., blood pressure measurements of people in the same family can be correlated).
- Repeated measurements: (e.g., measurement of cholesterol over time can be correlated) "If data are collected repeatedly on experimental material to which treatments were applied initially, the data is a repeated measure." (Schabenberger and Pierce, 2001)
- Longitudinal data: (e.g., individual's cholesterol tracked over time are correlated): "data collected repeatedly over time in an observational study are termed longitudinal." (Schabenberger and Pierce, 2001)
- Spatial data: (e.g., measurement of individuals living in the same neighborhood are correlated)

Hence, we like to account for these correlations.

Linear Mixed Model (LMM), also known as **Mixed Linear Model** has 2 components:

- **Fixed effect** (e.g, gender, age, diet, time)
- **Random effects** representing individual variation or auto correlation/spatial effects that imply **dependent (correlated) errors**

Review Two-Way Mixed Effects ANOVA

We choose to model the random subject-specific effect instead of including dummy subject covariates in our model because:

- reduction in the number of parameters to estimate
- when you do inference, it would make more sense that you can infer from a population (i.e., random effect).

LLM Motivation

In a repeated measurements analysis where Y_{ij} is the response for the i-th individual measured at the j-th time,

$i = 1, ..., N$; $j = 1, ..., n_i$

$$\mathbf{Y}_i = \begin{pmatrix} Y_{i1} \\ . \\ . \\ . \\ Y_{in_i} \end{pmatrix}$$

is all measurements for subject i.

<u>*Stage 1: (Regression Model)*</u> how the response changes over time for the i-th subject

$$\mathbf{Y_i} = \mathbf{Z_i}\ _{\mathbf{i}} + \ _{\mathbf{i}}$$

where

- Z_i is an $n_i \times q$ matrix of known covariates
- β_i is an unknown $q \times 1$ vector of subjective -specific coefficients (regression coefficients different for each subject)
- ϵ_i are the random errors (typically $\sim N(0, \sigma^2 I)$)

We notice that there are two many β to estimate here. Hence, this is the motivation for the second stage

<u>*Stage 2: (Parameter Model)*</u>

$$_{\mathbf{i}} = \mathbf{K_i}\ + \mathbf{b_i}$$

where

- K_i is a $q \times p$ matrix of known covariates
- β is a $p \times 1$ vector of unknown parameter
- $\mathbf{b}_i$ are independent $N(0, D)$ random variables

This model explain the observed variability between subjects with respect to the subject-specific regression coefficients, β_i. We model our different coefficient (β_i) with respect to β.

Example:

Stage 1:

$$Y_{ij} = \beta_{1i} + \beta_{2i} t_{ij} + \epsilon_{ij}$$

where

- $j = 1, .., n_i$

In the matrix notation,

$$\mathbf{Y_i} = \begin{pmatrix} Y_{i1} \\ . \\ Y_{in_i} \end{pmatrix}; \mathbf{Z}_i = \begin{pmatrix} 1 & t_{i1} \\ . & . \\ 1 & t_{in_i} \end{pmatrix}$$

$$\beta_i = \begin{pmatrix} \beta_{1i} \\ \beta_{2i} \end{pmatrix}; \epsilon_i = \begin{pmatrix} \epsilon_{i1} \\ . \\ \epsilon_{in_i} \end{pmatrix}$$

Thus,

$$\mathbf{Y_i} = \mathbf{Z_i}\ _{\mathbf{i}} + \ _{\mathbf{i}}$$

Stage 2:

$$\begin{aligned} \beta_{1i} &= \beta_0 + b_{1i} \\ \beta_{2i} &= \beta_1 L_i + \beta_2 H_i + \beta_3 C_i + b_{2i} \end{aligned}$$

where L_i, H_i, C_i are indicator variables defined to 1 as the subject falls into different categories.

Subject specific intercepts do not depend upon treatment, with β_0 (the average response at the start of treatment), and $\beta_1, \beta_2, \beta_3$ (the average time effects for each of three treatment groups).

$$\begin{aligned} \mathbf{K}_i &= \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & L_i & H_i & C_i \end{pmatrix} \\ \beta &= (\beta_0, \beta_1, \beta_2, \beta_3)' \\ \mathbf{b}_i &= \begin{pmatrix} b_{1i} \\ b_{2i} \end{pmatrix} \\ \beta_i &= \mathbf{K_i} + \mathbf{b_i} \end{aligned}$$

To get $\hat{\beta}$, we can fit the model sequentially:

1. Estimate $\hat{\beta}_i$ in the first stage

2. Estimate $\hat{\beta}$ in the second stage by replacing β_i with $\hat{\beta}_i$

However, problems arise from this method:

- information is lost by summarizing the vector $\mathbf{Y}_i$ solely by $\hat{\beta}_i$
- we need to account for variability when replacing β_i with its estimate
- different subjects might have different number of observations.

To address these problems, we can use **Linear Mixed Model** (Laird and Ware, 1982)

Substituting stage 2 into stage 1:

$$\mathbf{Y}_i = \mathbf{Z}_i\mathbf{K}_i\beta + \mathbf{Z}_i\mathbf{b}_i + {}_i$$

Let $\mathbf{X}_i = \mathbf{Z}_i\mathbf{K}_i$ be an $n_i \times p$ matrix . Then, the LMM is

$$\mathbf{Y}_i = \mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i + {}_i$$

where

- $i = 1, .., N$
- β are the fixed effects, which are common to all subjects
- $\mathbf{b}_i$ are the subject specific random effects. $\mathbf{b}_i \sim N_q(\mathbf{0}, \mathbf{D})$
- ${}_i \sim N_{n_i}(\mathbf{0}, {}_\mathbf{i})$
- $\mathbf{b}_i$ and ϵ_i are independent
- $\mathbf{Z}_{i(n_i \times q})$ and $\mathbf{X}_{i(n_i \times p})$ are matrices of known covariates.

Equivalently, in the hierarchical form, we call **conditional** or **hierarchical** formulation of the linear mixed model

$$\begin{aligned} \mathbf{Y}_i|\mathbf{b}_i &\sim N(\mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i, {}_i) \\ \mathbf{b}_i &\sim N(\mathbf{0}, \mathbf{D}) \end{aligned}$$

for $i = 1, .., N$. denote the respective functions by $f(\mathbf{Y}_i|\mathbf{b}_i)$ and $f(\mathbf{b}_i)$

In general,

$$\begin{aligned} f(A, B) &= f(A|B)f(B) \\ f(A) &= \int f(A, B)dB = \int f(A|B)f(B)dB \end{aligned}$$

In the LMM, the marginal density of $\mathbf{Y}_i$ is

$$f(\mathbf{Y}_i) = \int f(\mathbf{Y}_i|\mathbf{b}_i)f(\mathbf{b}_i)d\mathbf{b}_i$$

which can be shown

$$\mathbf{Y}_i \sim N(\mathbf{X_i}\ , \mathbf{Z_i D Z_i'} + \ _{\mathbf{i}})$$

This is the **marginal** formulation of the linear mixed model

Notes:

We no longer have $Z_i b_i$ in the mean, but add error in the variance (marginal dependence in Y). kinda of averaging out the common effect. Technically, we shouldn't call it averaging the error b (adding it to the variance covariance matrix), it should be called adding random effect

Continue with our example

$$Y_{ij} = (\beta_0 + b_{1i}) + (\beta_1 L_i + \beta_2 H_i + \beta_3 C_i + b_{2i})t_{ij} + \epsilon_{ij}$$

for each treatment group

$$Y_{ik} = \begin{cases} \beta_0 + b_{1i} + (\beta_1 + \ b_{2i})t_{ij} + \epsilon_{ij} & L \\ \beta_0 + b_{1i} + (\beta_2 + \ b_{2i})t_{ij} + \epsilon_{ij} & H \\ \beta_0 + b_{1i} + (\beta_3 + \ b_{2i})t_{ij} + \epsilon_{ij} & C \end{cases}$$

- Intercepts and slopes are all subject specific
- Different treatment groups have different slops, but the same intercept.

In the hierarchical model form

$$\begin{aligned} \mathbf{Y}_i|\mathbf{b}_i &\sim N(\mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i,\ _i) \\ \mathbf{b}_i &\sim N(\mathbf{0}, \mathbf{D}) \end{aligned}$$

X will be in the form of

$$\beta = (\beta_0, \beta_1, \beta_2, \beta_3)'$$

$$\begin{aligned} \mathbf{X}_i &= \mathbf{Z}_i\mathbf{K}_i \\ &= \begin{bmatrix} 1 & t_{i1} \\ 1 & t_{i2} \\ . & . \\ 1 & t_{in_i} \end{bmatrix} \times \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & L_i & H_i & C_i \end{bmatrix} \\ &= \begin{bmatrix} 1 & t_{i1}L_i & t_{i1}H_i & T_{i1}C_i \\ 1 & t_{i2}L_i & t_{i2}H_i & T_{i2}C_i \\ . & . & . & . \\ 1 & t_{in_i}L_i & t_{in_i}H_i & T_{in_i}C_i \end{bmatrix} \end{aligned}$$

$$\mathbf{b}_i = \begin{pmatrix} b_{1i} \\ b_{2i} \end{pmatrix}$$

$$D = \begin{pmatrix} d_{11} & d_{12} \\ d_{12} & d_{22} \end{pmatrix}$$

Assuming $_i = \sigma^2 \mathbf{I}_{n_i}$, which is called **conditional independence**, meaning the response on subject i are independent conditional on $\mathbf{b}_i$ and β

In the marginal model form

$$Y_{ij} = \beta_0 + \beta_1 L_i t_{ij} + \beta_2 H_i t_{ij} + \beta_3 C_i t_{ij} + \eta_{ij}$$

where $\eta_i \sim N(\mathbf{0}, \mathbf{Z}_i \mathbf{D} \mathbf{Z}_i' + \ _i)$

Equivalently,

$$\mathbf{Y_i} \sim \mathbf{N}(\mathbf{X_i}\ , \mathbf{Z_i} \mathbf{D} \mathbf{Z_i'} + \ _\mathbf{i})$$

In this case that $n_i = 2$

$$\begin{aligned} \mathbf{Z_i} \mathbf{D} \mathbf{Z_i'} &= \begin{pmatrix} 1 & t_{i1} \\ 1 & t_{i2} \end{pmatrix} \begin{pmatrix} d_{11} & d_{12} \\ d_{12} & d_{22} \end{pmatrix} \begin{pmatrix} 1 & 1 \\ t_{i1} & t_{i2} \end{pmatrix} \\ &= \begin{pmatrix} d_{11} + 2d_{12}t_{i1} + d_{22}t_{i1}^2 & d_{11} + d_{12}(t_{i1} + t_{i2}) + d_{22}t_{i1}t_{i2} \\ d_{11} + d_{12}(t_{i1} + t_{i2}) + d_{22}t_{i1}t_{i2} & d_{11} + 2d_{12}t_{i2} + d_{22}t_{i2}^2 \end{pmatrix} \end{aligned}$$

$$var(Y_{i1}) = d_{11} + 2d_{12}t_{i1} + d_{22}t_{i1}^2 + \sigma^2$$

On top of correlation in the errors, the marginal implies that the variance function of the response is quadratic over time, with positive curvature d_{22}

8.1.1 Random-Intercepts Model

If we remove the random slopes,

- the assumption is that all variability in subject-specific slopes can be attributed to treatment differences
- the model is random-intercepts model. This has subject specific intercepts, but the same slopes within each treatment group.

$$\begin{aligned}\mathbf{Y}_i|b_i &\sim N(\mathbf{X}_i\beta + 1b_i, \Sigma_i)\\ b_i &\sim N(0, d_{11})\end{aligned}$$

The marginal model is then ($_i = \sigma^2\mathbf{I}$)

$$\mathbf{Y}_i \sim N(\mathbf{X}_i\beta, 11'd_{11} + \sigma^2\mathbf{I})$$

The marginal covariance matrix is

$$\begin{aligned}cov(\mathbf{Y}_i) &= 11'd_{11} + \sigma^2 I\\ &= \begin{pmatrix} d_{11}+\sigma^2 & d_{11} & ... & d_{11}\\ d_{11} & d_{11}+\sigma^2 & d_{11} & ...\\ . & . & . & .\\ d_{11} & ... & ... & d_{11}+\sigma^2\end{pmatrix}\end{aligned}$$

the associated correlation matrix is

$$corr(\mathbf{Y}_i) = \begin{pmatrix} 1 & \rho & ... & \rho\\ \rho & 1 & \rho & ...\\ . & . & . & .\\ \rho & ... & ... & 1\end{pmatrix}$$

where $\rho \equiv \frac{d_{11}}{d_{11}+\sigma^2}$

Thu, we have

- constant variance over time
- equal, positive correlation between any two measurements from the same subject
- a covariance structure that is called **compound symmetry**, and ρ is called the **intra-class correlation**
- that when ρ is large, the **inter-subject variability** (d_{11}) is large relative to the intra-subject variability (σ^2)

8.1.2 Covariance Models

If the conditional independence assumption, ($_{\mathbf{i}} = {}^{\mathbf{2}}\mathbf{I}_{\mathbf{n_i}}$). Consider, $\epsilon_i = \epsilon_{(1)i} + \epsilon_{(2)i}$, where

- $\epsilon_{(1)i}$ is a "serial correlation" component. That is, part of the individual's profile is a response to time-varying stochastic processes.
- $\epsilon_{(2)i}$ is the measurement error component, and is independent of $\epsilon_{(1)i}$

Then

$$\mathbf{Y_i} = \mathbf{X_i} \ + \mathbf{Z_i b_i} + \ _{\mathbf{(1)i}} + \ _{\mathbf{(2)i}}$$

where

- $\mathbf{b_i} \sim N(\mathbf{0}, \mathbf{D})$
- $\epsilon_{(2)i} \sim N(\mathbf{0}, \ ^{\mathbf{2}}\mathbf{I_{n_i}})$
- $\epsilon_{(1)i} \sim N(\mathbf{0}, \ ^{\mathbf{2}}\mathbf{H_i})$
- $\mathbf{b}_i$ and ϵ_i are mutually independent

To model the structure of the $n_i \times n_i$ correlation (or covariance) matrix $\mathbf{H}_i$. Let the (j,k)th element of $\mathbf{H}_i$ be $h_{ijk} = g(t_{ij}t_{ik})$. that is a function of the times t_{ij} and t_{ik} , which is assumed to be some function of the "distance' between the times.

$$h_{ijk} = g(|t_{ij} - t_{ik}|)$$

for some decreasing function $g(.)$ with $g(0) = 1$ (for correlation matrices).

Examples of this type of function:

- Exponential function: $g(|t_{ij} - t_{ik}|) = \exp(-\phi|t_{ij} - t_{ik}|)$
- Gaussian function: $g(|t_{ij} - t_{ik}|) = \exp(-\phi(t_{ij} - t_{ik})^2)$

Similar structures could also be used for $\mathbf{D}$ matrix (of $\mathbf{b}$)

Example: Autoregressive Covariance Structure

A first order Autoregressive Model (AR(1)) has the form

$$\alpha_t = \phi\alpha_{t-1} + \eta_t$$

where $\eta_t \sim iidN(0, \sigma_\eta^2)$

Then, the covariance between two observations is

$$cov(\alpha_t, \alpha_{t+h}) = \frac{\sigma_\eta^2 \phi^{|h|}}{1 - \phi^2}$$

for $h = 0, \pm 1, \pm 2, ...; |\phi| < 1$

Hence,

$$corr(\alpha_t, \alpha_{t+h}) = \phi^{|h|}$$

If we let $\alpha_T = (\alpha_1, ...\alpha_T)'$, then

$$corr(\alpha_T) = \begin{bmatrix} 1 & \phi^1 & \phi^2 & ... & \phi^2 \\ \phi^1 & 1 & \phi^1 & ... & \phi^{T-1} \\ \phi^2 & \phi^1 & 1 & ... & \phi^{T-2} \\ . & . & . & . & . \\ \phi^T & \phi^{T-1} & \phi^{T-2} & ... & 1 \end{bmatrix}$$

Notes:

- The correlation decreases as time lag increases
- This matrix structure is known as a **Toeplitz** structure
- More complicated covariance structures are possible, which is critical component of spatial random effects models and time series models.
- Often, we don't need both random effects $\mathbf{b}$ and $\epsilon_{(1)i}$

More in the Time Series section

8.2 Estimation

$$\mathbf{Y}_i = \mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i + \epsilon_i$$

where $\beta, \mathbf{b}_i, \mathbf{D},\ _i$ we must obtain estimation from the data

- $,\mathbf{D},\ _i$ are unknown, but fixed, parameters, and must be estimated from the data
- $\mathbf{b}_i$ is a random variable. Thus, we can't estimate these values, but we can predict them. (i.e., you can't estimate a random thing).

If we have

- $\hat{\beta}$ as an estimator of β
- $\hat{\mathbf{b}}_i$ as a predictor of $\mathbf{b}_i$

Then,

- The population average estimate of $\mathbf{Y}_i$ is $\hat{\mathbf{Y}}_i = \mathbf{X}_i\hat{\beta}$
- The subject-specific prediction is $\hat{\mathbf{Y}}_i = \mathbf{X}_i\hat{\beta} + \mathbf{Z}_i\hat{b}_i$

According to (Henderson, 1975), estimating equations known as the mixed model equations:

$$\begin{bmatrix} \hat{\beta} \\ \hat{\mathbf{b}} \end{bmatrix} = \begin{bmatrix} \mathbf{X}'^{\ -1}\mathbf{X} & \mathbf{X}'^{\ -1}\mathbf{Z} \\ \mathbf{Z}'^{\ -1}\mathbf{X} & \mathbf{Z}'^{\ -1}\mathbf{Z} + \mathbf{B}^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{X}'^{\ -1}\mathbf{Y} \\ \mathbf{Z}'^{\ -1}\mathbf{Y} \end{bmatrix}$$

where

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ . \\ \mathbf{y}_N \end{bmatrix}; \mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ . \\ \mathbf{X}_N \end{bmatrix}; \mathbf{b} = \begin{bmatrix} \mathbf{b}_1 \\ . \\ \mathbf{b}_N \end{bmatrix}; \epsilon = \begin{bmatrix} \epsilon_1 \\ . \\ \epsilon_N \end{bmatrix}$$

$$cov(\epsilon) = \ , \mathbf{Z} = \begin{bmatrix} \mathbf{Z}_1 & 0 & ... & 0 \\ 0 & \mathbf{Z}_2 & ... & 0 \\ . & . & . & . \\ 0 & 0 & ... & \mathbf{Z}_n \end{bmatrix}, \mathbf{B} = \begin{bmatrix} \mathbf{D} & 0 & ... & 0 \\ 0 & \mathbf{D} & ... & 0 \\ . & . & . & . \\ 0 & 0 & ... & \mathbf{D} \end{bmatrix}$$

The model has the form

$$\begin{aligned} \mathbf{Y} &= \mathbf{X} \ + \mathbf{Zb} + \\ \mathbf{Y} &\sim N(\mathbf{X} \ , \mathbf{ZBZ}' + \ ) \end{aligned}$$

If $\mathbf{V} = \mathbf{ZBZ}' + \ $, then the solutions to the estimating equations can be

$$\begin{aligned} \hat{\beta} &= (\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{Y} \\ \hat{\mathbf{b}} &= \mathbf{BZ}'\mathbf{V}^{-1}(\mathbf{Y} - \mathbf{X} \ ) \end{aligned}$$

The estimate $\hat{\beta}$ is a generalized least squares estimate.

The predictor, $\hat{\mathbf{b}}$ is the best linear unbiased predictor (BLUP), for $\mathbf{b}$

$$\begin{aligned} E(\hat{\beta}) &= \beta \\ var(\hat{\beta}) &= (\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1} \\ E(\hat{\mathbf{b}}) &= 0 \end{aligned}$$

$$var(\hat{\mathbf{b}} - \mathbf{b}) = \mathbf{B} - \mathbf{BZ}'\mathbf{V}^{-1}\mathbf{ZB} + \mathbf{BZ}'\mathbf{V}^{-1}\mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{B}$$

The variance here is the variance of the prediction error (mean squared prediction error, MSPE), which is more meaningful than $var(\hat{\mathbf{b}})$, since MSPE accounts for both variance and bias in the prediction.

To derive the mixed model equations, consider

$$= \mathbf{Y} - \mathbf{X} \ - \mathbf{Zb}$$

Let $T = \sum_{i=1}^{N} n_i$ be the total number of observations (i.e., the length of $\mathbf{Y}, \epsilon$) and Nq the length of $\mathbf{b}$. The joint distribution of $\mathbf{b}$, is

$$f(\mathbf{b}, \ ) = \frac{1}{(2\pi)^{(T+Nq)/2}} \begin{vmatrix} \mathbf{B} & 0 \\ 0 & \end{vmatrix}^{-1/2} \exp\left(-\frac{1}{2} \begin{bmatrix} \mathbf{b} \\ \mathbf{Y} - \mathbf{X} \ - \mathbf{Zb} \end{bmatrix}' \begin{bmatrix} \mathbf{B} & 0 \\ 0 & \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{b} \\ \mathbf{Y} - \mathbf{X} \ - \mathbf{Zb} \end{bmatrix} \right)$$

Maximization of $f(\mathbf{b}, \epsilon)$ with respect to $\mathbf{b}$ and β requires minimization of

$$\begin{aligned} Q &= \begin{bmatrix} \mathbf{b} \\ \mathbf{Y} - \mathbf{X} \ - \mathbf{Zb} \end{bmatrix}' \begin{bmatrix} \mathbf{B} & 0 \\ 0 & \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{b} \\ \mathbf{Y} - \mathbf{X} \ - \mathbf{Zb} \end{bmatrix} \\ &= \mathbf{b}'\mathbf{B}^{-1}\mathbf{b} + (\mathbf{Y} - \mathbf{X} \ - \mathbf{Zb})' \ ^{-1}(\mathbf{Y} - \mathbf{X} \ - \mathbf{Zb}) \end{aligned}$$

Setting the derivatives of Q with respect to $\mathbf{b}$ and to zero leads to the system of equations:

$$\begin{aligned} \mathbf{X}' \ ^{-1}\mathbf{X} \ + \mathbf{X}' \ ^{-1}\mathbf{Zb} &= \mathbf{X}' \ ^{-1}\mathbf{Y} \\ (\mathbf{Z}' \ ^{-1}\mathbf{Z} + \mathbf{B}^{-1})\mathbf{b} + \mathbf{Z}' \ ^{-1}\mathbf{X} \ &= \mathbf{Z}' \ ^{-1}\mathbf{Y} \end{aligned}$$

Rearranging

$$\begin{bmatrix} \mathbf{X}' \ ^{-1}\mathbf{X} & \mathbf{X}' \ ^{-1}\mathbf{Z} \\ \mathbf{Z}' \ ^{-1}\mathbf{X} & \mathbf{Z}' \ ^{-1}\mathbf{Z} + \mathbf{B}^{-1} \end{bmatrix} \begin{bmatrix} \beta \\ \mathbf{b} \end{bmatrix} = \begin{bmatrix} \mathbf{X}' \ ^{-1}\mathbf{Y} \\ \mathbf{Z}' \ ^{-1}\mathbf{Y} \end{bmatrix}$$

Thus, the solution to the mixed model equations give:

$$\begin{bmatrix} \hat{\beta} \\ \hat{\mathbf{b}} \end{bmatrix} = \begin{bmatrix} \mathbf{X}' \ ^{-1}\mathbf{X} & \mathbf{X}' \ ^{-1}\mathbf{Z} \\ \mathbf{Z}' \ ^{-1}\mathbf{X} & \mathbf{Z}' \ ^{-1}\mathbf{Z} + \mathbf{B}^{-1} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{X}' \ ^{-1}\mathbf{Y} \\ \mathbf{Z}' \ ^{-1}\mathbf{Y} \end{bmatrix}$$

Equivalently,

Bayes' theorem

$$f(\mathbf{b}|\mathbf{Y}) = \frac{f(\mathbf{Y}|\mathbf{b})f(\mathbf{b})}{\int f(\mathbf{Y}|\mathbf{b})f(\mathbf{b})d\mathbf{b}}$$

where

- $f(\mathbf{Y}|\mathbf{b})$ is the "likelihood"
- $f(\mathbf{b})$ is the prior
- the denominator is the "normalizing constant"
- $f(\mathbf{b}|\mathbf{Y})$ is the posterior distribution

In this case

$$\begin{aligned} \mathbf{Y}|\mathbf{b} &\sim N(\mathbf{X} \ + \mathbf{Zb}, \ ) \\ \mathbf{b} &\sim N(\mathbf{0}, \mathbf{B}) \end{aligned}$$

The posterior distribution has the form

$$\mathbf{b}|\mathbf{Y} \sim N(\mathbf{BZ}'\mathbf{V}^{-1}(\mathbf{Y} - \mathbf{X} \ ), (\mathbf{Z}' \ ^{-1}\mathbf{Z} + \mathbf{B}^{-1})^{-1})$$

Hence, the best predictor (based on squared error loss)

$$E(\mathbf{b}|\mathbf{Y}) = \mathbf{B}\mathbf{Z}'\mathbf{V}^{-1}(\mathbf{Y} - \mathbf{X}\ )$$

8.2.1 Estimating V

If we have $\tilde{\mathbf{V}}$ (estimate of $\mathbf{V}$), then we can estimate:

$$\hat{\beta} = (\mathbf{X}'\tilde{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'\tilde{\mathbf{V}}^{-1}\mathbf{Y}$$
$$\hat{\mathbf{b}} = \mathbf{B}\mathbf{Z}'\tilde{\mathbf{V}}^{-1}(\mathbf{Y} - \mathbf{X}\ )$$

where **b** is **EBLUP** (estimated BLUP) or **empirical Bayes estimate**

Note:

- $\hat{var}(\hat{\beta})$ is a consistent estimator of $var(\hat{\beta})$ if $\tilde{\mathbf{V}}$ is a consistent estimator of $\mathbf{V}$
- However, $\hat{var}(\hat{\beta})$ is biased since the variability arises from estimating $\mathbf{V}$ is not accounted for in the estimate.
- Hence, $\hat{var}(\hat{\beta})$ underestimates the true variability

Ways to estimate **V**

- Maximum Likelihood Estimation (MLE)
- Restricted Maximum Likelihood (REML)
- Estimated Generalized Least Squares
- Bayesian Hierarchical Models (BHM)

8.2.1.1 Maximum Likelihood Estimation (MLE)

Grouping unknown parameters in Σ and B under a parameter vector θ. Under MLE, $\hat{\theta}$ and $\hat{\beta}$ maximize the likelihood $\mathbf{y} \sim N(\mathbf{X}\ , \mathbf{V}(\ ))$. Synonymously, $-2\log L(\mathbf{y};\ ,\ )$:

$$-2l(\ ,\ , \mathbf{y}) = \log|\mathbf{V}(\ )| + (\mathbf{y} - \mathbf{X}\ )'\mathbf{V}(\ )^{-1}(\mathbf{y} - \mathbf{X}\ ) + N\log(2\pi)$$

- Step 1: Replace β with its maximum likelihood (where θ is known $\hat{\beta} = (\mathbf{X}'\mathbf{V}(\ )^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}(\ )^{-1}\mathbf{y}$
- Step 2: Minimize the above equation with respect to θ to get the estimator $\hat{\theta}_{MLE}$
- Step 3: Substitute $\hat{\theta}_{MLE}$ back to get $\hat{\beta}_{MLE} = (\mathbf{X}'\mathbf{V}(\ _{\mathbf{MLE}})^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}(\ _{\mathbf{MLE}})^{-1}\mathbf{y}$
- Step 4: Get $\hat{\mathbf{b}}_{MLE} = \mathbf{B}\hat{(}\ _{\mathbf{MLE}})\mathbf{Z}'\mathbf{V}\hat{(}\ _{\mathbf{MLE}})^{-1}(\mathbf{y} - \mathbf{X}\ _{\mathbf{MLE}})$

Note:

- $\hat{\theta}$ are typically negatively biased due to unaccounted fixed effects being estimated, which we could try to account for.

8.2.1.2 Restricted Maximum Likelihood (REML)

REML accounts for the number of estimated mean parameters by adjusting the objective function. Specifically, the likelihood of linear combination of the elements of $\mathbf{y}$ is accounted for.

We have $\mathbf{K}'\mathbf{y}$, where $\mathbf{K}$ is any $N \times (N-p)$ full-rank contrast matrix, which has columns orthogonal to the $\mathbf{X}$ matrix (that is $\mathbf{K}'\mathbf{X} = 0$). Then,

$$\mathbf{K}'\mathbf{y} \sim N(0, \mathbf{K}'\mathbf{V}(\ )\mathbf{K})$$

where β is no longer in the distribution

We can proceed to maximize this likelihood for the contrasts to get $\hat{\theta}_{REML}$, which does not depend on the choice of $\mathbf{K}$. And $\hat{\beta}$ are based on $\hat{\theta}$

Comparison REML and MLE

- Both methods are based upon the likelihood principle, and have desired properties for the estimates:
  - consistency
  - asymptotic normality
  - efficiency
- ML estimation provides estimates for fixed effects, while REML can't
- In balanced models, REML is identical to ANOVA
- REML accounts for df for the fixed effects int eh model, which is important when $\mathbf{X}$ is large relative to the sample size
- Changing has no effect on the REML estimates of θ
- REML is less sensitive to outliers than MLE
- MLE is better than REML regarding model comparisons (e.g., AIC or BIC)

8.2.1.3 Estimated Generalized Least Squares

MLE and REML rely upon the Gaussian assumption. To overcome this issue, EGLS uses the first and second moments.

$$\mathbf{Y}_i = \mathbf{X}_i\beta + \mathbf{Z}_i\mathbf{b}_i + \epsilon_i$$

where

- $\epsilon_i \sim (\mathbf{0},\ _{\mathbf{i}})$
- $\mathbf{b}_i \sim (\mathbf{0}, \mathbf{D})$

- $cov(\epsilon_i, \mathbf{b}_i) = 0$

Then the EGLS estimator is

$$\begin{aligned}\hat{\beta}_{GLS} &= \{\sum_{i=1}^{n} \mathbf{X_i'V_i}(\ )^{-1}\mathbf{X_i}\}^{-1} \sum_{i=1}^{n} \mathbf{X_i'V_i}(\ )^{-1}\mathbf{Y_i} \\ &= \{\mathbf{X'V}(\ )^{-1}\mathbf{X}\}^{-1}\mathbf{X'V}(\ )^{-1}\mathbf{Y}\end{aligned}$$

depends on the first two moments

- $E(\mathbf{Y}_i) = \mathbf{X}_i\beta$
- $var(\mathbf{Y}_i) = \mathbf{V}_i$

EGLS use $\hat{\mathbf{V}}$ for $\mathbf{V}(\ )$

$$\hat{\beta}_{EGLS} = \{\mathbf{X'\hat{V}^{-1}X}\}^{-1}\mathbf{X'\hat{V}^{-1}Y}$$

Hence, the fixed effects estimators for the MLE, REML, and EGLS are of the same form, except for the estimate of $\mathbf{V}$

In case of non-iterative approach, EGLS can be appealing when $\mathbf{V}$ can be estimated without much computational burden.

8.2.1.4 Bayesian Hierarchical Models (BHM)

Joint distribution cane be decomposed hierarchically in terms of the product of conditional distributions and a marginal distribution

$$f(A, B, C) = f(A|B, C)f(B|C)f(C)$$

Applying to estimate $\mathbf{V}$

$$\begin{aligned}f(\mathbf{Y},\ ,\mathbf{b},\ ) &= f(\mathbf{Y}|\ ,\mathbf{b},\ )f(\mathbf{b}|\ ,\ )f(\ |\ )f(\ ) && \text{based on probability decomposition} \\ &= f(\mathbf{Y}|\ ,\mathbf{b},\ )f(\mathbf{b}|\ )f(\ )f(\ ) && \text{based on simplifying modeling assumptions}\end{aligned}$$

elaborate on the second equality, if we assume conditional independence (e.g., given θ, no additional info about $\mathbf{b}$ is given by knowing β), then we can simply from the first equality

Using Bayes' rule

$$f(\ ,\mathbf{b},\ |\mathbf{Y}) \propto f(\mathbf{Y}|\ ,\mathbf{b},\ )f(\mathbf{b}|\ )f(\ )f(\ )$$

where

$$\mathbf{Y}|\ ,\mathbf{b},\ \sim \mathbf{N}(\mathbf{X}\ +\mathbf{Zb},\ (\ ))$$
$$\mathbf{b}|\ \sim \mathbf{N}(\mathbf{0},\mathbf{B}(\ ))$$

and we also have to have prior distributions for $f(\beta), f(\theta)$

With normalizing constant, we can obtain the posterior distribution. Typically, we can't get analytical solution right away. Hence, we can use Markov Chain Monte Carlo (MCMC) to obtain samples from the posterior distribution.

Bayesian Methods:

- account for the uncertainty in parameters estimates and accommodate the propagation of that uncertainty through the model
- can adjust prior information (i.e., priori) in parameters
- Can extend beyond Gaussian distributions
- but hard to implement algorithms and might have problem converging

8.3 Inference

8.3.1 Parameters β

8.3.1.1 Wald test

We have

$$\hat{}\ (\ ) = \{\mathbf{X'V^{-1}}(\ )\mathbf{X}\}^{\mathbf{-1}}\mathbf{X'V^{-1}}(\ )\mathbf{Y}$$
$$var(\hat{\beta}(\theta)) = \{\mathbf{X'V^{-1}}(\ )\mathbf{X}\}^{\mathbf{-1}}$$

We can use $\hat{\theta}$ in place of θ to approximate Wald test

$$H_0 : \mathbf{A}\ = \mathbf{d}$$

With

$$W = (\mathbf{A}\hat{}\ - \mathbf{d})'[\mathbf{A}(\mathbf{X'}\hat{\mathbf{V}}^{\mathbf{-1}}\mathbf{X})^{\mathbf{-1}}\mathbf{A}']^{\mathbf{-1}}(\mathbf{A}\hat{}\ - \mathbf{d})$$

where $W \sim \chi^2_{rank(A)}$ under H_0 is true. However, it does not take into account variability from using $\hat{\theta}$ in place of θ, hence the standard errors are underestimated

8.3.1.2 F-test

Alternatively, we can use the modified F-test, suppose we have $var(\mathbf{Y}) = \sigma^2\mathbf{V}(\theta)$, then

$$F^* = \frac{(\mathbf{A\hat{\beta}} - \mathbf{d})'[\mathbf{A}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{A}']^{-1}(\mathbf{A\hat{\beta}} - \mathbf{d})}{\hat{\sigma}^2 \text{rank}(A)}$$

where $F^* \sim f_{rank(A),den(df)}$ under the null hypothesis. And den(df) needs to be approximated from the data by either:

- Satterthwaite method
- Kenward-Roger approximation

Under balanced cases, the Wald and F tests are similar. But for small sample sizes, they can differ in p-values. And both can be reduced to t-test for a single β

8.3.1.3 Likelihood Ratio Test

$$H_0 : \beta \in \Theta_{\beta,0}$$

where $\Theta_{\beta,0}$ is a subspace of the parameter space, Θ_β of the fixed effects β . Then

$$-2\log\lambda_N = -2\log\{\frac{\hat{L}_{ML,0}}{\hat{L}_{ML}}\}$$

where

- $\hat{L}_{ML,0}$, $\hat{L}_{ML}$ are the maximized likelihood obtained from maximizing over $\Theta_{\beta,0}$ and Θ_β
- $-2\log\lambda_N \dot{\sim} \chi^2_{df}$ where df is the difference in the dimension (i.e., number of parameters) of $\Theta_{\beta,0}$ and Θ_β

This method is not applicable for REML. But REML can still be used to test for covariance parameters between nested models.

8.3.2 Variance Components

- For ML and REML estimator, $\hat{\theta} \sim N(\theta, I(\theta))$ for large samples
- Wald test in variance components is analogous to the fixed effects case (see 8.3.1.1)
  - However, the normal approximation depends largely on the true value of θ. It will fail if the true value of θ is close to the boundary of the parameter space Θ_θ (i.e., $\sigma^2 \approx 0$)

  - Typically works better for covariance parameter, than variance parameters.

- The likelihood ratio tests can also be used with ML or REML estimates. However, the same problem of parameters

8.4 Information Criteria

- account for the likelihood and the number of parameters to assess model comparison.

8.4.1 Akaike's Information Criteria (AIC)

Derived as an estimator of the expected Kullback discrepancy between the true model and a fitted candidate model

$$AIC = -2l(\hat{\theta}, \hat{\beta}) + 2q$$

where

- $l(\hat{\theta}, \hat{\beta})$ is the log-likelihood
- q = the effective number of parameters; total of fixed and those associated with random effects (variance/covariance; those not estimated to be on a boundary constraint)

Note:

- In comparing models that differ in their random effects, this method is not advised to due the inability to get the correct number of effective parameters).
- We prefer smaller AIC values.
- If your program uses $l - q$ then we prefer larger AIC values (but rarely).
- can be used for mixed model section, (e.g., selection of the covariance structure), but the sample size must be very large to have adequate comparison based on the criterion
- Can have a large negative bias (e.g., when sample size is small but the number of parameters is large) due to the penalty term can't approximate the bias adjustment adequately

8.4.2 Corrected AIC (AICC)

- developed by (Hurvich and Tsai, 1989)
- correct small-sample adjustment
- depends on the candidate model class
- Only if you have fixed covariance structure, then AICC is justified, but not general covariance structure

8.4.3 Bayesian Information Criteria (BIC)

$$BIC = -2l(\hat{\theta}, \hat{\beta}) + q \log n$$

where n = number of observations.

- we prefer smaller BIC value
- BIC and AIC are used for both REML and MLE if we have the same mean structure. Otherwise, in general, we should prefer MLE

With our example presented at the beginning of Linear Mixed Models,

$$Y_{ik} = \begin{cases} \beta_0 + b_{1i} + (\beta_1 + \ b_{2i})t_{ij} + \epsilon_{ij} & L \\ \beta_0 + b_{1i} + (\beta_2 + \ b_{2i})t_{ij} + \epsilon_{ij} & H \\ \beta_0 + b_{1i} + (\beta_3 + \ b_{2i})t_{ij} + \epsilon_{ij} & C \end{cases}$$

where

- $i = 1, .., N$
- $j = 1, .., n_i$ (measures at time t_{ij})

Note:

- we have subject-specific intercepts,

$$\begin{aligned} \mathbf{Y}_i | b_i &\sim N(\mathbf{X}_i \beta + 1 b_i, \sigma^2 \mathbf{I}) \\ b_i &\sim N(0, d_{11}) \end{aligned}$$

here, we want to estimate β, σ^2, d_{11} and predict b_i

8.5 Split-Plot Designs

- Typically used in the case that you have two factors where one needs much larger units than the other.

Example:

A: 3 levels (large units)

B: 2 levels (small units)

- A and B levels are randomized into 4 blocks.
- But it differs from Randomized Block Designs. In each block, both have one of the 6 (3x2) treatment combinations. But Randomized Block Designs assign in each block randomly, while split-plot does not randomize this step.
- Moreover, because A needs to be applied in large units, factor A is applied only once in each block while B can be applied multiple times.

Hence, we have our model

If A is our factor of interest

$$Y_{ij} = \mu + \rho_i + \alpha_j + e_{ij}$$

where

- i = replication (block or subject)
- j = level of Factor A
- μ = overall mean
- ρ_i = variation due to the i-th block
- $e_{ij} \sim N(0, \sigma_e^2)$ = whole plot error

If B is our factor of interest

$$Y_{ijk} = \mu + \phi_{ij} + \beta_k + \epsilon_{ijk}$$

where

- ϕ_{ij} = variation due to the ij-th main plot
- β_k = Factor B effect
- $\epsilon_{ijk} \sim N(0, \sigma_\epsilon^2)$ = subplot error
- $\phi_{ij} = \rho_i + \alpha_j + e_{ij}$

Together, the split-plot model

$$Y_{ijk} = \mu + \rho_i + \alpha_j + e_{ij} + \beta_k + (\alpha\beta)_{jk} + \epsilon_{ijk}$$

where

- i = replicate (blocks or subjects)
- j = level of factor A
- k = level of factor B
- μ = overall mean
- ρ_i = effect of the block
- α_j = main effect of factor A (fixed)
- $e_{ij} = (\rho\alpha)_{ij}$ = block by factor A interaction (the whole plot error, random)
- β_k = main effect of factor B (fixed)
- $(\alpha\beta)_{jk}$ = interaction between factors A and B (fixed)
- ϵ_{ijk} = subplot error (random)

We can approach sub-plot analysis based on

- the ANOVA perspective
  - Whole plot comparisons
    - Compare factor A to the whole plot error (i.e., α_j to e_{ij})

    - Compare the block to the whole plot error (i.e., ρ_i to e_{ij})
  - Sub-plot comparisons:
    - Compare factor B to the subplot error (β to ϵ_{ijk})
    - Compare the AB interaction to the subplot error ($(\alpha\beta)_{jk}$ to ϵ_{ijk})
- the mixed model perspective

$$\mathbf{Y} = \mathbf{X} \ + \mathbf{Zb} +$$

8.5.1 Application

8.5.1.1 Example 1

$$y_{ijk} = \mu + i_i + v_j + (iv)_{ij} + f_k + \epsilon_{ijk}$$

where

- y_{ijk} = observed yield
- μ = overall average yield
- i_i = irrigation effect
- v_j = variety effect
- $(iv)_{ij}$ = irrigation by variety interaction
- f_k = random field (block) effect
- ϵ_{ijk} = residual
- because variety-field combination is only observed once, we can't have the random interaction effects between variety and field

```
library(ggplot2)
data(irrigation, package = "faraway")
summary(irrigation)
#>      field   irrigation variety     yield
#>  f1     :2   i1:4       v1:8    Min.   :34.80
#>  f2     :2   i2:4       v2:8    1st Qu.:37.60
#>  f3     :2   i3:4               Median :40.15
#>  f4     :2   i4:4               Mean   :40.23
#>  f5     :2                      3rd Qu.:42.73
#>  f6     :2                      Max.   :47.60
#>  (Other):4
head(irrigation, 4)
#>   field irrigation variety yield
#> 1    f1         i1      v1  35.4
#> 2    f1         i1      v2  37.9
#> 3    f2         i2      v1  36.7
#> 4    f2         i2      v2  38.2
ggplot(irrigation,
       aes(
```

```
        x     = field,
        y     = yield,
        shape = irrigation,
        color = variety
      )) +
  geom_point(size = 3)
```

```
sp_model <-
    lmerTest::lmer(yield ~ irrigation * variety
                   + (1 |field), irrigation)
summary(sp_model)
#> Linear mixed model fit by REML. t-tests use Satterthwaite's method [
#> lmerModLmerTest]
#> Formula: yield ~ irrigation * variety + (1 | field)
#>    Data: irrigation
#>
#> REML criterion at convergence: 45.4
#>
#> Scaled residuals:
#>     Min      1Q  Median      3Q     Max
#> -0.7448 -0.5509  0.0000  0.5509  0.7448
#>
#> Random effects:
#>  Groups   Name        Variance Std.Dev.
#>  field    (Intercept) 16.200   4.025
#>  Residual              2.107   1.452
#> Number of obs: 16, groups:  field, 8
```

```
#>
#> Fixed effects:
#>                        Estimate Std. Error     df t value Pr(>|t|)
#> (Intercept)              38.500      3.026  4.487  12.725 0.000109 ***
#> irrigationi2              1.200      4.279  4.487   0.280 0.791591
#> irrigationi3              0.700      4.279  4.487   0.164 0.877156
#> irrigationi4              3.500      4.279  4.487   0.818 0.454584
#> varietyv2                 0.600      1.452  4.000   0.413 0.700582
#> irrigationi2:varietyv2   -0.400      2.053  4.000  -0.195 0.855020
#> irrigationi3:varietyv2   -0.200      2.053  4.000  -0.097 0.927082
#> irrigationi4:varietyv2    1.200      2.053  4.000   0.584 0.590265
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Correlation of Fixed Effects:
#>             (Intr) irrgt2 irrgt3 irrgt4 vrtyv2 irr2:2 irr3:2
#> irrigation2 -0.707
#> irrigation3 -0.707  0.500
#> irrigation4 -0.707  0.500  0.500
#> varietyv2   -0.240  0.170  0.170  0.170
#> irrgtn2:vr2  0.170 -0.240 -0.120 -0.120 -0.707
#> irrgtn3:vr2  0.170 -0.120 -0.240 -0.120 -0.707  0.500
#> irrgtn4:vr2  0.170 -0.120 -0.120 -0.240 -0.707  0.500  0.500

anova(sp_model, ddf = c("Kenward-Roger"))
#> Type III Analysis of Variance Table with Kenward-Roger's method
#>                    Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
#> irrigation         2.4545 0.81818     3     4  0.3882 0.7685
#> variety            2.2500 2.25000     1     4  1.0676 0.3599
#> irrigation:variety 1.5500 0.51667     3     4  0.2452 0.8612
```

Since p-value of the interaction term is insignificant, we consider fitting without it.

```
library(lme4)
sp_model_additive <- lmer(yield ~ irrigation + variety
                          + (1 | field), irrigation)
anova(sp_model_additive,sp_model,ddf = "Kenward-Roger")
#> Data: irrigation
#> Models:
#> sp_model_additive: yield ~ irrigation + variety + (1 | field)
#> sp_model: yield ~ irrigation * variety + (1 | field)
#>                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
#> sp_model_additive    7 83.959 89.368 -34.980   69.959
#> sp_model            10 88.609 96.335 -34.305   68.609 1.3503  3     0.7172
```

Since p-value of χ^2 test is insignificant, we can't reject the additive model is already sufficient. Looking at AIC and BIC, we can also see that we would prefer the additive model

Random Effect Examination

`exactRLRT` test

- H_0: Var(random effect) (i.e., σ^2)= 0
- H_a: Var(random effect) (i.e., σ^2) > 0

```
sp_model <- lme4::lmer(yield ~ irrigation * variety
                       + (1 | field), irrigation)
library(RLRsim)
exactRLRT(sp_model)
#>
#>  simulated finite sample distribution of RLRT.
#>
#>  (p-value based on 10000 simulated values)
#>
#> data:
#> RLRT = 6.1118, p-value = 0.0075
```

Since the p-value is significant, we reject H_0

8.6 Repeated Measures in Mixed Models

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \delta_{i(k)} + \epsilon_{ijk}$$

where

- i-th group (fixed)
- j-th (repeated measure) time effect (fixed)
- k-th subject
- $\delta_{i(k)} \sim N(0, \sigma_\delta^2)$ (k-th subject in the i-th group) and $\epsilon_{ijk} \sim N(0, \sigma^2)$ (independent error) are random effects ($i = 1, .., n_A, j = 1, .., n_B, k = 1, ..., n_i$)

hence, the variance-covariance matrix of the repeated observations on the k-th subject of the i-th group, $\mathbf{Y}_{ik} = (Y_{i1k}, .., Y_{in_Bk})'$, will be

$$
\begin{aligned}
_{subject} &= \begin{pmatrix} \sigma_\delta^2 + \sigma^2 & \sigma_\delta^2 & ... & \sigma_\delta^2 \\ \sigma_\delta^2 & \sigma_\delta^2 + \sigma^2 & ... & \sigma_\delta^2 \\ . & . & . & . \\ \sigma_\delta^2 & \sigma_\delta^2 & ... & \sigma_\delta^2 + \sigma^2 \end{pmatrix} \\
&= (\sigma_\delta^2 + \sigma^2) \begin{pmatrix} 1 & \rho & ... & \rho \\ \rho & 1 & ... & \rho \\ . & . & . & . \\ \rho & \rho & ... & 1 \end{pmatrix} \qquad \text{product of a scalar and a correlation matrix}
\end{aligned}
$$

where $\rho = \frac{\sigma_\delta^2}{\sigma_\delta^2 + \sigma^2}$, which is the compound symmetry structure that we discussed in Random-Intercepts Model

But if you only have repeated measurements on the subject over time, AR(1) structure might be more appropriate

Mixed model for a repeated measure

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where

- ϵ_{ijk} combines random error of both the whole and subplots.

In general,

$$\mathbf{Y} = \mathbf{X} \ +$$

where

- $\epsilon \sim N(0, \sigma^2\ )$ where is block diagonal if the random error covariance is the same for each subject

The variance covariance matrix with AR(1) structure is

$$_{subject} = \sigma^2 \begin{pmatrix} 1 & \rho & \rho^2 & ... & \rho^{n_B - 1} \\ \rho & 1 & \rho & ... & \rho^{n_B - 2} \\ . & . & . & . & . \\ \rho^{n_B - 1} & \rho^{n_B - 2} & \rho^{n_B - 3} & ... & 1 \end{pmatrix}$$

Hence, the mixed model for a repeated measure can be written as

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where

- ϵ_{ijk} = random error of whole and subplots

Generally,

$$\mathbf{Y} = \mathbf{X} \ +$$

where $\epsilon \sim N(0, \ ^{\mathbf{2}} \ )$ and Σ = block diagonal if the random error covariance is the same for each subject.

8.7 Unbalanced or Unequally Spaced Data

Consider the model

$$Y_{ikt} = \beta_0 + \beta_{0i} + \beta_1 t + \beta_{1i} t + \beta_2 t^2 + \beta_{2i} t^2 + \epsilon_{ikt}$$

where

- $i = 1, 2$ (groups)
- $k = 1, ..., n_i$ (individuals)
- $t = (t_1, t_2, t_3, t_4)$ (times)
- β_{2i} = common quadratic term
- β_{1i} = common linear time trends
- β_{0i} = common intercepts

Then, we assume the variance-covariance matrix of the repeated measurements collected on a particular subject over time has the form

$$_{ik} = \sigma^2 \begin{pmatrix} 1 & \rho^{t_2-t_1} & \rho^{t_3-t_1} & \rho^{t_4-t_1} \\ \rho^{t_2-t_1} & 1 & \rho^{t_3-t_2} & \rho^{t_4-t_2} \\ \rho^{t_3-t_1} & \rho^{t_3-t_2} & 1 & \rho^{t_4-t_3} \\ \rho^{t_4-t_1} & \rho^{t_4-t_2} & \rho^{t_4-t_3} & 1 \end{pmatrix}$$

which is called "power" covariance model

We can consider $\beta_{2i}, \beta_{1i}, \beta_{0i}$ accordingly to see whether these terms are needed in the final model

8.8 Application

R Packages for mixed models

- `nlme`
  - has nested structure
  - flexible for complex design

  - not user-friendly

- `lme4`
  - computationally efficient
  - user-friendly
  - can handle non-normal response
  - for more detailed application, check Fitting Linear Mixed-Effects Models Using lme4

- Others
  - Bayesian setting: `MCMCglmm`, `brms`
  - For genetics: `ASReml`

8.8.1 Example 1 (Pulps)

Model:

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

where

- $i = 1, .., a$ groups for random effect α_i
- $j = 1, ..., n$ individuals in each group
- $\alpha_i \sim N(0, \sigma_\alpha^2)$ is random effects
- $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$ is random effects
- Imply compound symmetry model where the intraclass correlation coefficient is: $\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\epsilon^2}$
- If factor a does not explain much variation, low correlation within the levels: $\sigma_\alpha^2 \to 0$ then $\rho \to 0$
- If factor a explain much variation, high correlation within the levels $\sigma_\alpha^2 \to \infty$ hence, $\rho \to 1$

```
data(pulp, package = "faraway")
plot(
    y    = pulp$bright,
    x    = pulp$operator,
    xlab = "Operator",
    ylab = "Brightness"
)
```

```
pulp %>% dplyr::group_by(operator) %>%
    dplyr::summarise(average = mean(bright))
#> # A tibble: 4 x 2
#>   operator average
#>   <fct>      <dbl>
#> 1 a           60.2
#> 2 b           60.1
#> 3 c           60.6
#> 4 d           60.7
```

`lmer` application

```
library(lme4)
mixed_model <-
    lmer(
        # pipe (i..e, | ) denotes random-effect terms
        formula = bright ~ 1 + (1 |operator),
         data = pulp)
summary(mixed_model)
#> Linear mixed model fit by REML ['lmerMod']
#> Formula: bright ~ 1 + (1 | operator)
#>    Data: pulp
#>
#> REML criterion at convergence: 18.6
#>
#> Scaled residuals:
#>     Min      1Q  Median      3Q     Max
#> -1.4666 -0.7595 -0.1244  0.6281  1.6012
```

```
#>
#> Random effects:
#>  Groups   Name        Variance Std.Dev.
#>  operator (Intercept) 0.06808  0.2609
#>  Residual             0.10625  0.3260
#> Number of obs: 20, groups:  operator, 4
#>
#> Fixed effects:
#>             Estimate Std. Error t value
#> (Intercept)  60.4000     0.1494   404.2
coef(mixed_model)
#> $operator
#>   (Intercept)
#> a    60.27806
#> b    60.14088
#> c    60.56767
#> d    60.61340
#>
#> attr(,"class")
#> [1] "coef.mer"
fixef(mixed_model)   # fixed effects
#> (Intercept)
#>        60.4
confint(mixed_model) # confidence interval
#>                 2.5 %     97.5 %
#> .sig01       0.000000  0.6178987
#> .sigma       0.238912  0.4821845
#> (Intercept) 60.071299 60.7287012
ranef(mixed_model)   # random effects
#> $operator
#>   (Intercept)
#> a  -0.1219403
#> b  -0.2591231
#> c   0.1676679
#> d   0.2133955
#>
#> with conditional variances for "operator"
VarCorr(mixed_model) # random effects standard deviation
#>  Groups   Name        Std.Dev.
#>  operator (Intercept) 0.26093
#>  Residual             0.32596
re_dat = as.data.frame(VarCorr(mixed_model))

# rho based on the above formula
rho = re_dat[1, 'vcov'] / (re_dat[1, 'vcov'] + re_dat[2, 'vcov'])
```

```
rho
#> [1] 0.3905354
```

To Satterthwaite approximation for the denominator df, we use `lmerTest`

```
library(lmerTest)
summary(lmerTest::lmer(bright ~ 1 + (1 | operator), pulp))$coefficients
#>             Estimate Std. Error df  t value     Pr(>|t|)
#> (Intercept)     60.4  0.1494434  3 404.1664 3.340265e-08
confint(mixed_model)[3, ]
#>   2.5 %  97.5 %
#> 60.0713 60.7287
```

In this example, we can see that the confidence interval computed by `confint` in `lmer` package is very close is `confint` in `lmerTest` model.

`MCMglmm` application

under the Bayesian framework

```
library(MCMCglmm)
mixed_model_bayes <-
    MCMCglmm(
        bright ~ 1,
        random =  ~ operator,
        data = pulp,
        verbose = FALSE
    )
summary(mixed_model_bayes)$solutions
#>             post.mean l-95% CI u-95% CI eff.samp pMCMC
#> (Intercept)  60.38821 60.08119 60.70809     1000 0.001
```

this method offers the confidence interval slightly more positive than `lmer` and `lmerTest`

8.8.1.1 Prediction

```
# random effects prediction (BLUPs)
ranef(mixed_model)$operator
#>   (Intercept)
#> a  -0.1219403
#> b  -0.2591231
#> c   0.1676679
#> d   0.2133955

# prediction for each categories
fixef(mixed_model) + ranef(mixed_model)$operator
#>   (Intercept)
```

```
#> a    60.27806
#> b    60.14088
#> c    60.56767
#> d    60.61340

# equivalent to the above method
predict(mixed_model, newdata = data.frame(operator = c('a', 'b', 'c', 'd')))
#>        1        2        3        4
#> 60.27806 60.14088 60.56767 60.61340
```

use `bootMer()` to get bootstrap-based confidence intervals for predictions.

Another example using GLMM in the context of blocking

Penicillin data

```
data(penicillin, package = "faraway")
summary(penicillin)
#>  treat    blend       yield
#>  A:5   Blend1:4   Min.   :77
#>  B:5   Blend2:4   1st Qu.:81
#>  C:5   Blend3:4   Median :87
#>  D:5   Blend4:4   Mean   :86
#>        Blend5:4   3rd Qu.:89
#>                   Max.   :97
library(ggplot2)
ggplot(penicillin, aes(
    y     = yield,
    x     = treat,
    shape = blend,
    color = blend
)) +
    # treatment = fixed effect
    # blend = random effects
    geom_point(size = 3) +
    xlab("Treatment")
```

```
library(lmerTest) # for p-values
mixed_model <- lmerTest::lmer(yield ~ treat + (1 | blend),
                              data = penicillin)
summary(mixed_model)
#> Linear mixed model fit by REML. t-tests use Satterthwaite's method [
#> lmerModLmerTest]
#> Formula: yield ~ treat + (1 | blend)
#>    Data: penicillin
#>
#> REML criterion at convergence: 103.8
#>
#> Scaled residuals:
#>     Min      1Q  Median      3Q     Max
#> -1.4152 -0.5017 -0.1644  0.6830  1.2836
#>
#> Random effects:
#>  Groups   Name        Variance Std.Dev.
#>  blend    (Intercept) 11.79    3.434
#>  Residual             18.83    4.340
#> Number of obs: 20, groups:  blend, 5
#>
#> Fixed effects:
#>             Estimate Std. Error     df t value Pr(>|t|)
#> (Intercept)   84.000      2.475 11.075  33.941 1.51e-12 ***
#> treatB         1.000      2.745 12.000   0.364   0.7219
#> treatC         5.000      2.745 12.000   1.822   0.0935 .
```

```
#> treatD         2.000      2.745 12.000   0.729   0.4802
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Correlation of Fixed Effects:
#>        (Intr) treatB treatC
#> treatB -0.555
#> treatC -0.555  0.500
#> treatD -0.555  0.500  0.500

#The BLUPs for the each blend
ranef(mixed_model)$blend
#>        (Intercept)
#> Blend1   4.2878788
#> Blend2  -2.1439394
#> Blend3  -0.7146465
#> Blend4   1.4292929
#> Blend5  -2.8585859
```

Examine treatment effect

```
anova(mixed_model) # p-value based on lmerTest
#> Type III Analysis of Variance Table with Satterthwaite's method
#>       Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
#> treat     70  23.333     3    12  1.2389 0.3387
```

Since the p-value is greater than 0.05, we can't reject the null hypothesis that there is no treatment effect.

```
library(pbkrtest)
# REML is not appropriate for testing fixed effects, it should be ML
full_model <-
    lmer(yield ~ treat + (1 | blend),
         penicillin,
         REML = FALSE)
null_model <- lmer(yield ~ 1 + (1 | blend),
                   penicillin,
                   REML = FALSE)

# use  Kenward-Roger approximation for df
KRmodcomp(full_model, null_model)
#> large : yield ~ treat + (1 | blend)
#> small : yield ~ 1 + (1 | blend)
#>          stat     ndf     ddf F.scaling p.value
#> Ftest  1.2389  3.0000 12.0000         1  0.3387
```

Since the p-value is greater than 0.05, and consistent with our previous obser-

vation, we conclude that we can't reject the null hypothesis that there is no treatment effect.

8.8.2 Example 2 (Rats)

```
rats <- read.csv(
    "images/rats.dat",
    header = F,
    sep = ' ',
    col.names = c('Treatment', 'rat', 'age', 'y')
)

# log transformed age
rats$t <- log(1 + (rats$age - 45) / 10)
```

We are interested in whether treatment effect induces changes over time.

```
rat_model <-
    # treatment = fixed effect, rat = random effects
    lmerTest::lmer(y ~ t:Treatment + (1 | rat),
                   data = rats)
summary(rat_model)
#> Linear mixed model fit by REML. t-tests use Satterthwaite's method [
#> lmerModLmerTest]
#> Formula: y ~ t:Treatment + (1 | rat)
#>    Data: rats
#>
#> REML criterion at convergence: 932.4
#>
#> Scaled residuals:
#>      Min       1Q   Median       3Q      Max
#> -2.25574 -0.65898 -0.01163  0.58356  2.88309
#>
#> Random effects:
#>  Groups   Name        Variance Std.Dev.
#>  rat      (Intercept) 3.565    1.888
#>  Residual             1.445    1.202
#> Number of obs: 252, groups:  rat, 50
#>
#> Fixed effects:
#>                Estimate Std. Error       df t value Pr(>|t|)
#> (Intercept)     68.6074     0.3312  89.0275  207.13   <2e-16 ***
#> t:Treatmentcon   7.3138     0.2808 247.2762   26.05   <2e-16 ***
#> t:Treatmenthig   6.8711     0.2276 247.7097   30.19   <2e-16 ***
#> t:Treatmentlow   7.5069     0.2252 247.5196   33.34   <2e-16 ***
#> ---
```

```
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Correlation of Fixed Effects:
#>             (Intr) t:Trtmntc t:Trtmnth
#> t:Tretmntcn -0.327
#> t:Tretmnthg -0.340  0.111
#> t:Tretmntlw -0.351  0.115     0.119
anova(rat_model)
#> Type III Analysis of Variance Table with Satterthwaite's method
#>             Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
#> t:Treatment 3181.9  1060.6     3 223.21  734.11 < 2.2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Since the p-value is significant, we can be confident concluding that there is a treatment effect

```
library(agridat)
library(latticeExtra)
dat <- harris.wateruse
# Compare to Schabenberger & Pierce, fig 7.23
useOuterStrips(
    xyplot(
        water ~ day | species * age,
        dat,
        as.table = TRUE,
        group = tree,
        type = c('p', 'smooth'),
        main = "harris.wateruse 2 species, 2 ages (10 trees each)"
    )
)
```

Remove outliers

```
dat <- subset(dat, day!=268)
```

Plot between age and species

```
xyplot(
    water ~ day | tree,
    dat,
    subset   = age == "A2" & species == "S2",
    as.table = TRUE,
    type     = c('p', 'smooth'),
    ylab     = "Water use profiles of individual trees",
    main     = "harris.wateruse (Age 2, Species 2)"
)
```

```
# Rescale day for nicer output,
# and convergence issues, add quadratic term
dat <- transform(dat, ti = day / 100)
dat <- transform(dat, ti2 = ti * ti)
# Start with a subgroup: age 2, species 2
d22 <- droplevels(subset(dat, age == "A2" & species == "S2"))
```

`lme` function from `nlme` package

```
library(nlme)

## We use pdDiag() to get uncorrelated random effects
m1n <- lme(
    water ~ 1 + ti + ti2,
    #intercept, time and time-squared = fixed effects
    data = d22,
    na.action = na.omit,
    random = list(tree = pdDiag(~ 1 + ti + ti2))
    # random intercept, time
    # and time squared per tree = random effects
)
ranef(m1n)
#>     (Intercept)            ti           ti2
#> T04   0.1985796  1.609864e-09  4.990101e-10
#> T05   0.3492827  2.487690e-10 -4.845287e-11
#> T19  -0.1978989 -7.681202e-10 -1.961453e-10
#> T23   0.4519003 -3.270426e-10 -2.413583e-10
#> T38  -0.6457494 -1.608770e-09 -3.298010e-10
```

```
#> T40   0.3739432  3.264705e-10 -2.543109e-11
#> T49   0.8620648  9.021831e-10 -5.402247e-12
#> T53  -0.5655049 -8.279040e-10 -4.579291e-11
#> T67  -0.4394623 -3.485113e-10  2.147434e-11
#> T71  -0.3871552  7.930610e-10  3.718993e-10
```

```
fixef(m1n)
#> (Intercept)          ti         ti2
#>  -10.798799   12.346704   -2.838503
summary(m1n)
#> Linear mixed-effects model fit by REML
#>   Data: d22
#>        AIC     BIC    logLik
#>   276.5142 300.761 -131.2571
#>
#> Random effects:
#>  Formula: ~1 + ti + ti2 | tree
#>  Structure: Diagonal
#>         (Intercept)           ti          ti2  Residual
#> StdDev:   0.5187869 1.438333e-05 3.864019e-06 0.3836614
#>
#> Fixed effects:  water ~ 1 + ti + ti2
#>                  Value Std.Error  DF   t-value p-value
#> (Intercept) -10.798799 0.8814666 227 -12.25094       0
#> ti           12.346704 0.7827112 227  15.77428       0
#> ti2          -2.838503 0.1720614 227 -16.49704       0
#>  Correlation:
#>     (Intr) ti
#> ti  -0.979
#> ti2  0.970 -0.997
#>
#> Standardized Within-Group Residuals:
#>         Min          Q1         Med          Q3         Max
#> -3.07588246 -0.58531056  0.01210209  0.65402695  3.88777402
#>
#> Number of Observations: 239
#> Number of Groups: 10
```

`lmer` function from `lme4` package

```
m1lmer <-
    lmer(water ~ 1 + ti + ti2 + (ti + ti2 ||
                                    tree),
         data = d22,
         na.action = na.omit)
ranef(m1lmer)
```

```
#> $tree
#>     (Intercept) ti ti2
#> T04   0.1985796  0   0
#> T05   0.3492827  0   0
#> T19  -0.1978989  0   0
#> T23   0.4519003  0   0
#> T38  -0.6457494  0   0
#> T40   0.3739432  0   0
#> T49   0.8620648  0   0
#> T53  -0.5655049  0   0
#> T67  -0.4394623  0   0
#> T71  -0.3871552  0   0
#>
#> with conditional variances for "tree"
```

Notes:

- `||` double pipes= uncorrelated random effects
- To remove the intercept term:
  - `(0+ti|tree)`
  - `(ti-1|tree)`

```
fixef(m1lmer)
#> (Intercept)          ti         ti2
#>  -10.798799   12.346704   -2.838503
m1l <-
    lmer(water ~ 1 + ti + ti2
         + (1 | tree) + (0 + ti | tree)
         + (0 + ti2 | tree), data = d22)
ranef(m1l)
#> $tree
#>     (Intercept) ti ti2
#> T04   0.1985796  0   0
#> T05   0.3492827  0   0
#> T19  -0.1978989  0   0
#> T23   0.4519003  0   0
#> T38  -0.6457494  0   0
#> T40   0.3739432  0   0
#> T49   0.8620648  0   0
#> T53  -0.5655049  0   0
#> T67  -0.4394623  0   0
#> T71  -0.3871552  0   0
#>
#> with conditional variances for "tree"
fixef(m1l)
```

```
#> (Intercept)          ti         ti2
#>  -10.798799   12.346704   -2.838503
```

To include structured covariance terms, we can use the following way

```
m2n <- lme(
    water ~ 1 + ti + ti2,
    data = d22,
    random = ~ 1 | tree,
    cor = corExp(form =  ~ day | tree),
    na.action = na.omit
)
ranef(m2n)
#>     (Intercept)
#> T04   0.1929971
#> T05   0.3424631
#> T19  -0.1988495
#> T23   0.4538660
#> T38  -0.6413664
#> T40   0.3769378
#> T49   0.8410043
#> T53  -0.5528236
#> T67  -0.4452930
#> T71  -0.3689358
fixef(m2n)
#> (Intercept)          ti         ti2
#>  -11.223310   12.712094   -2.913682
summary(m2n)
#> Linear mixed-effects model fit by REML
#>   Data: d22
#>        AIC      BIC   logLik
#>   263.3081 284.0911 -125.654
#>
#> Random effects:
#>  Formula: ~1 | tree
#>         (Intercept)  Residual
#> StdDev:   0.5154042 0.3925777
#>
#> Correlation Structure: Exponential spatial correlation
#>  Formula: ~day | tree
#>  Parameter estimate(s):
#>    range
#> 3.794624
#> Fixed effects:  water ~ 1 + ti + ti2
#>                  Value Std.Error  DF   t-value p-value
#> (Intercept) -11.223310 1.0988725 227 -10.21348       0
```

```
#> ti           12.712094 0.9794235 227  12.97916       0
#> ti2          -2.913682 0.2148551 227 -13.56115       0
#>  Correlation:
#>     (Intr) ti
#> ti  -0.985
#> ti2  0.976 -0.997
#>
#> Standardized Within-Group Residuals:
#>         Min          Q1         Med          Q3         Max
#> -3.04861039 -0.55703950  0.00278101  0.62558762  3.80676991
#>
#> Number of Observations: 239
#> Number of Groups: 10
```

Chapter 9

Nonlinear and Generalized Linear Mixed Models

- NLMMs extend the nonlinear model to include both fixed effects and random effects
- GLMMs extend the generalized linear model to include both fixed effects and random effects.

A nonlinear mixed model has the form of

$$Y_{ij} = f(\mathbf{x_{ij}}, \ , \ _{\mathbf{i}}) + \epsilon_{ij}$$

for the j-th response from cluster (or subject) i ($i = 1, ..., n$), where

- $j = 1, ..., n_i$
- are the fixed effects
- $_i$ are the random effects for cluster i
- $\mathbf{x}_{ij}$ are the regressors or design variables
- $f(.)$ is nonlinear mean response function

A GLMM can be written as:

we assume

$$y_i|\alpha_i \sim \text{indep } f(y_i|\alpha)$$

and $f(y_i| \ )$ is an exponential family distribution,

$$f(y_i|\alpha) = \exp[\frac{y_i\theta_i - b(\theta_i)}{a(\phi)} - c(y_i, \phi)]$$

The conditional mean of y_i is related to θ_i

$$\mu_i = \frac{\partial b(\theta_i)}{\partial \theta_i}$$

The transformation of this mean will give us the desired linear model to model both the fixed and random effects.

$$\begin{aligned} E(y_i|\alpha) &= \mu_i \\ g(\mu_i) &= \mathbf{x_i'} \ + \mathbf{z_i'} \end{aligned}$$

where $g()$ is a known link function and μ_i is the conditional mean. We can see similarity to GLM

We also have to specify the random effects distribution

$$\alpha \sim f(\alpha)$$

which is similar to the specification for mixed models.

Moreover, law of large number applies to fixed effects so that you know it is a normal distribution. But here, you can specify α subjectively.

Hence, we can show NLMM is a special case of the GLMM

$$\begin{aligned} \mathbf{Y}_i &= \mathbf{f}(\mathbf{x}_i, \ , \ _i) + \ _i \\ \mathbf{Y}_i &= \mathbf{g}^{-1}(\mathbf{x}_i'\beta + \mathbf{z}_i' \ _i) + \ _i \end{aligned}$$

where the inverse link function corresponds to a nonlinear transformation of the fixed and random effects.

Note:

- we can't derive the analytical formulation of the marginal distribution because nonlinear combination of normal variables is not normally distributed, even in the case of additive error (e_i) and random effects (α_i) are both normal.

Consequences of having random effects

The marginal mean of y_i is

$$E(y_i) = E_\alpha(E(y_i|\alpha)) = E_\alpha(\mu_i) = E(g^{-1}(\mathbf{x_i'} \ + \mathbf{z_i'} \ ))$$

Because $g^{-1}()$ is nonlinear, this is the most simplified version we can go for.

In special cases such as log link ($g(\mu) = \log \mu$ or $g^{-1}() = \exp()$) then

$$E(y_i) = E(\exp(\mathbf{x_i'} + \mathbf{z_i'})) = \exp(\mathbf{x_i'})E(\exp(\mathbf{z}_i'\alpha))$$

which is the moment generating function of α evaluated at $\mathbf{z}_i$

Marginal variance of y_i

$$\begin{aligned} var(y_i) &= var_\alpha(E(y_i|\alpha)) + E_\alpha(var(y_i|\alpha)) \\ &= var(\mu_i) + E(a(\phi)V(\mu_i)) \\ &= var(g^{-1}(\mathbf{x_i'} + \mathbf{z_i'})) + E(a(\phi)V(g^{-1}(\mathbf{x_i'} + \mathbf{z_i'}))) \end{aligned}$$

Without specific assumption about $g()$ and/or the conditional distribution of $\mathbf{y}$, this is the most simplified version.

Marginal covariance of y

In a linear mixed model, random effects introduce a dependence among observations which share any random effect in common

$$\begin{aligned} cov(y_i, y_j) &= cov_\alpha(E(y_i|\ ), E(y_j|\ )) + E_\alpha(cov(y_i, y_j|\ )) \\ &= cov(\mu_i, \mu_j) + E(0) \\ &= cov(g^{-1}(\mathbf{x}_i'\beta + \mathbf{z}_i'\ ), g^{-1}(\mathbf{x}_j'\beta + \mathbf{z}_j'\ )) \end{aligned}$$

- Important: conditioning to induce the covariability

Example:

Repeated measurements on the subjects.

Let y_{ij} be the j-th count taken on the i-th subject.

then, the model is $y_{ij}| \sim$ indep $Pois(\mu_{ij})$. Here

$$\log(\mu_{ij}) = \mathbf{x}_{ij}'\beta + \alpha_i$$

where $\alpha_i \sim iidN(0, \sigma_\alpha^2)$

which is a log-link with a random patient effect.

9.1 Estimation

In linear mixed models, the marginal likelihood for $\mathbf{y}$ is the integration of the random effects from the hierarchical formulation

$$f(\mathbf{y}) = \int f(\mathbf{y}|\alpha)f(\alpha)d\alpha$$

For linear mixed models, we assumed that the 2 component distributions were Gaussian with linear relationships, which implied the marginal distribution was also linear and Gaussian and allows us to solve this integral analytically.

On the other hand, GLMMs, the distribution for $f(\mathbf{y}|\alpha)$ is not Gaussian in general, and for NLMMs, the functional form between the mean response and the random (and fixed) effects is nonlinear. In both cases, we can't perform the integral analytically, which means we have to solve it

- numerically and/or
- linearize the inverse link function.

9.1.1 Estimation by Numerical Integration

The marginal likelihood is

$$L(\beta; \mathbf{y}) = \int f(\mathbf{y}|\alpha) f(\alpha) d\alpha$$

Estimation fo the fixed effects requires $\frac{\partial l}{\partial \beta}$, where l is the log-likelihood

One way to obtain the marginal inference is to numerically integrate out the random effects through

- numerical quadrature
- Laplace approximation
- Monte Carlo methods

When the dimension of is relatively low, this is easy. But when the dimension of α is high, additional approximation is required.

9.1.2 Estimation by Linearization

Idea: Linearized version of the response (known as working response, or pseudo-response) called $\tilde{y}_i$ and then the conditional mean is

$$E(\tilde{y}_i|\alpha) = \mathbf{x}_i'\beta + \mathbf{z}_i'\alpha$$

and also estimate $var(\tilde{y}_i|\alpha)$. then, apply Linear Mixed Models estimation as usual.

The difference is only in how the linearization is done (i.e., how to expand $f(\mathbf{x},\ ,\ )$ or the inverse link function

9.1.2.1 Penalized quasi-likelihood

(PQL)

This is the more popular method

$$\tilde{y}_i^{(k)} = \hat{\eta}_i^{(k-1)} + (y_i - \hat{\mu}_i^{(k-1)})\frac{d\eta}{d\mu}|\hat{\eta}_i^{(k-1)}$$

where

- $\eta_i = g(\mu_i)$ is the linear predictor
- $k =$ iteration of the optimization algorithm

The algorithm updates $\tilde{y}_i$ after each linear mixed model fit using $E(\tilde{y}_i|\alpha)$ and $var(\tilde{y}_i|\alpha)$

Comments:

- Easy to implement
- Inference is only asymptotically correct due to the linearizaton
- Biased estimates are likely for binomial response with small groups and worst for Bernoulli response. Similarly for Poisson models with small counts. (Faraway, 2016)
- Hypothesis testing and confidence intervals also have problems.

9.1.2.2 Generalized Estimating Equations

(GEE)

Let a marginal generalized linear model for the mean of y as a function of the predictors, which means we linearize the mean response function and assume a dependent error structure

Example
Binary data:

$$logit(E(\mathbf{y})) = \mathbf{X}\beta$$

If we assume a "working covariance matrix", $\mathbf{V}$ the the elements of $\mathbf{y}$, then the maximum likelihood equations for estimating β is

$$\mathbf{X'V^{-1}y} = \mathbf{X'V^{-1}}E(\mathbf{y})$$

If $\mathbf{V}$ is correct, then unbiased estimating equations

We typically define $\mathbf{V} = \mathbf{I}$. Solutions to unbiased estimating equation give consistent estimators.

In practice, we assume a covariance structure, and then do a logistic regression, and calculate its large sample variance

Let $y_{ij}, j = 1, .., n_i, i = 1, .., K$ be the j-th measurement on the i-th subject.

$$\mathbf{y}_i = \begin{pmatrix} y_{i1} \\ \cdot \\ y_{in_i} \end{pmatrix}$$

with mean

$$_i = \begin{pmatrix} \mu_{i1} \\ \cdot \\ \mu_{in_i} \end{pmatrix}$$

and

$$\mathbf{x}_{ij} = \begin{pmatrix} X_{ij1} \\ \cdot \\ X_{ijp} \end{pmatrix}$$

Let $\mathbf{V}_i = cov(\mathbf{y}_i)$, then based on(Liang and Zeger, 1986) GEE estimates for β can be obtained from solving the equation:

$$S(\beta) = \sum_{i=1}^{K} \frac{\partial \ _i'}{\partial \beta} \mathbf{V}^{-1}(\mathbf{y}_i - \ _i) = 0$$

Let $\mathbf{R}_i(\mathbf{c})$ be an $n_i \times n_i$ "working" correlation matrix specified up to some parameters $\mathbf{c}$. Then, $\mathbf{V}_i = a(\phi)\mathbf{B}_i^{1/2}\mathbf{R}(\mathbf{c})\mathbf{B}_i^{1/2}$, where $\mathbf{B}_i$ is an $n_i \times n_i$ diagonal matrix with $V(\mu_{ij})$ on the j-th diagonal

If $\mathbf{R}(\mathbf{c})$ is the true correlation matrix of $\mathbf{y}_i$, then $\mathbf{V}_i$ is the true covariance matrix

The working correlation matrix must be estimated iteratively by a fitting algorithm:

1. Compute the initial estimate of β (using GLM under the independence assumption)
2. Compute the working correlation matrix $\mathbf{R}$ based upon studentized residuals
3. Compute the estimate covariance $\hat{\mathbf{V}}_i$

4. Update β according to

$$\beta_{r+1} = \beta_r + (\sum_{i=1}^{K} \frac{\partial \ _i'}{\partial \beta} \hat{\mathbf{V}}_i^{-1} \frac{\partial \ _i}{\partial \beta})$$

5. Iterate until the algorithm converges

Note: Inference based on likelihoods is not appropriate because this is not a likelihood estimator

9.1.3 Estimation by Bayesian Hierarchical Models

Bayesian Estimation

$$f(\ , \ |\mathbf{y}) \propto f(\mathbf{y}| \ , \ )f(\ )f(\ )$$

Numerical techniques (e.g., MCMC) can be used to find posterior distribution. This method is best in terms of not having to make simplifying approximation and fully accounting for uncertainty in estimation and prediction, but it could be complex, time-consuming, and computationally intensive.

Implementation Issues:

- No valid joint distribution can be constructed from the given conditional model and random parameters
- The mean/ variance relationship and the random effects lead to constraints on the marginal covariance model
- Difficult to fit computationally

2 types of estimation approaches:

1. Approximate the objective function (marginal likelihood) through integral approximation
    1. Laplace methods
    2. Quadrature methods
    3. Monte Carlo integration
2. Approximate the model (based on Taylor series linearization)

Packages in R

- GLMM: `MASS:glmmPQL` `lme4::glmer` `glmmTMB`
- NLMM: `nlme::nlme`; `lme4::nlmer` `brms::brm`
- Bayesian: `MCMCglmm` ; `brms:brm`

Example: Non-Gaussian Repeated measurements

- When the data are Gaussian, then Linear Mixed Models
- When the data are non-Gaussian, then Nonlinear and Generalized Linear Mixed Models

9.2 Application

9.2.1 Binomial (CBPP Data)

```
data(cbpp,package = "lme4")
head(cbpp)
#>   herd incidence size period
#> 1    1         2   14      1
#> 2    1         3   12      2
#> 3    1         4    9      3
#> 4    1         0    5      4
#> 5    2         3   22      1
#> 6    2         1   18      2
```

PQL

Pro:

- Linearizes the response to have a pseudo-response as the mean response (like LMM)
- computationally efficient

Cons:

- biased for binary, Poisson data with small counts
- random effects have to be interpreted on the link scale
- can't interpret AIC/BIC value

```
library(MASS)
pql_cbpp <-
    glmmPQL(
        cbind(incidence, size - incidence) ~ period,
        random  = ~ 1 | herd,
        data    = cbpp,
        family  = binomial(link = "logit"),
        verbose = F
    )
summary(pql_cbpp)
#> Linear mixed-effects model fit by maximum likelihood
#>   Data: cbpp
#>   AIC BIC logLik
#>    NA  NA     NA
```

```
#>
#> Random effects:
#>  Formula: ~1 | herd
#>         (Intercept) Residual
#> StdDev:   0.5563535 1.184527
#>
#> Variance function:
#>  Structure: fixed weights
#>  Formula: ~invwt
#> Fixed effects:  cbind(incidence, size - incidence) ~ period
#>                 Value Std.Error DF   t-value p-value
#> (Intercept) -1.327364 0.2390194 38 -5.553372  0.0000
#> period2     -1.016126 0.3684079 38 -2.758156  0.0089
#> period3     -1.149984 0.3937029 38 -2.920944  0.0058
#> period4     -1.605217 0.5178388 38 -3.099839  0.0036
#>  Correlation:
#>         (Intr) perid2 perid3
#> period2 -0.399
#> period3 -0.373  0.260
#> period4 -0.282  0.196  0.182
#>
#> Standardized Within-Group Residuals:
#>        Min         Q1        Med         Q3        Max
#> -2.0591168 -0.6493095 -0.2747620  0.5170492  2.6187632
#>
#> Number of Observations: 56
#> Number of Groups: 15
```

```
exp(0.556)
#> [1] 1.743684
```

is how the herd specific outcome odds varies.

We can interpret the fixed effect coefficients just like in GLM. Because we use logit link function here, we can say that the log odds of the probability of having a case in period 2 is -1.016 less than period 1 (baseline).

```
summary(pql_cbpp)$tTable
#>                 Value Std.Error DF   t-value      p-value
#> (Intercept) -1.327364 0.2390194 38 -5.553372 2.333216e-06
#> period2     -1.016126 0.3684079 38 -2.758156 8.888179e-03
#> period3     -1.149984 0.3937029 38 -2.920944 5.843007e-03
#> period4     -1.605217 0.5178388 38 -3.099839 3.637000e-03
```

Numerical Integration

Pro:

- more accurate

Con:

- computationally expensive
- won't work for complex models.

```
library(lme4)
numint_cbpp <-
    glmer(
        cbind(incidence, size - incidence) ~
            period + (1 | herd),
        data = cbpp,
        family = binomial(link = "logit")
    )
summary(numint_cbpp)
#> Generalized linear mixed model fit by maximum likelihood (Laplace
#>   Approximation) [glmerMod]
#>  Family: binomial  ( logit )
#> Formula: cbind(incidence, size - incidence) ~ period + (1 | herd)
#>    Data: cbpp
#>
#>      AIC      BIC   logLik deviance df.resid
#>    194.1    204.2    -92.0    184.1       51
#>
#> Scaled residuals:
#>     Min      1Q  Median      3Q     Max
#> -2.3816 -0.7889 -0.2026  0.5142  2.8791
#>
#> Random effects:
#>  Groups Name        Variance Std.Dev.
#>  herd   (Intercept) 0.4123   0.6421
#> Number of obs: 56, groups:  herd, 15
#>
#> Fixed effects:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  -1.3983     0.2312  -6.048 1.47e-09 ***
#> period2      -0.9919     0.3032  -3.272 0.001068 **
#> period3      -1.1282     0.3228  -3.495 0.000474 ***
#> period4      -1.5797     0.4220  -3.743 0.000182 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Correlation of Fixed Effects:
#>         (Intr) perid2 perid3
#> period2 -0.363
```

```
#> period3 -0.340  0.280
#> period4 -0.260  0.213  0.198
```

For small data set, the difference between two approaches are minimal

```
library(rbenchmark)
benchmark(
    "MASS" = {
        pql_cbpp <-
            glmmPQL(
                cbind(incidence, size - incidence) ~ period,
                random = ~ 1 | herd,
                data = cbpp,
                family = binomial(link = "logit"),
                verbose = F
            )
    },
    "lme4" = {
        glmer(
            cbind(incidence, size - incidence) ~ period + (1 | herd),
            data = cbpp,
            family = binomial(link = "logit")
        )
    },
    replications = 50,
    columns = c("test", "replications", "elapsed", "relative"),
    order = "relative"
)
#>   test replications elapsed relative
#> 1 MASS           50    3.69    1.000
#> 2 lme4           50    7.58    2.054
```

In numerical integration, we can set `nAGQ > 1` to switch the method of likelihood evaluation, which might increase accuracy

```
library(lme4)
numint_cbpp_GH <-
    glmer(
        cbind(incidence, size - incidence) ~ period + (1 | herd),
        data = cbpp,
        family = binomial(link = "logit"),
        nAGQ = 20
    )
summary(numint_cbpp_GH)$coefficients[, 1] -
    summary(numint_cbpp)$coefficients[, 1]
#>   (Intercept)       period2       period3       period4
```

```
#> -0.0008808634  0.0005160912  0.0004066218  0.0002644629
```

Bayesian approach to GLMMs

- assume the fixed effects parameters have distribution
- can handle models with intractable result under traditional methods
- computationally expensive

```
library(MCMCglmm)
Bayes_cbpp <-
    MCMCglmm(
        cbind(incidence, size - incidence) ~ period,
        random  = ~ herd,
        data    = cbpp,
        family  = "multinomial2",
        verbose = FALSE
    )
summary(Bayes_cbpp)
#>
#>  Iterations = 3001:12991
#>  Thinning interval  = 10
#>  Sample size  = 1000
#>
#>  DIC: 538.3852
#>
#>  G-structure:  ~herd
#>
#>      post.mean  l-95% CI u-95% CI eff.samp
#> herd   0.02602 1.164e-16   0.1944    53.97
#>
#>  R-structure:  ~units
#>
#>       post.mean l-95% CI u-95% CI eff.samp
#> units     1.115    0.158    2.163    304.9
#>
#>  Location effects: cbind(incidence, size - incidence) ~ period
#>
#>             post.mean l-95% CI u-95% CI eff.samp  pMCMC
#> (Intercept)   -1.5298  -2.1566  -0.8140    875.6 <0.001 ***
#> period2       -1.2500  -2.3851  -0.2880    780.4  0.020 *
#> period3       -1.4018  -2.5983  -0.3816    800.8  0.006 **
#> period4       -1.9360  -3.1710  -0.7034    432.9  0.004 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- `MCMCglmm` fits a residual variance component (useful with dispersion issues)

```
# explains less variability
apply(Bayes_cbpp$VCV,2,sd)
#>      herd     units
#> 0.1074491 0.5582551
```

```
summary(Bayes_cbpp)$solutions
#>             post.mean  l-95% CI   u-95% CI eff.samp pMCMC
#> (Intercept) -1.529801 -2.156645 -0.8139842 875.5644 0.001
#> period2     -1.249981 -2.385050 -0.2879657 780.4308 0.020
#> period3     -1.401787 -2.598287 -0.3815690 800.8027 0.006
#> period4     -1.936025 -3.171037 -0.7033584 432.9481 0.004
```

interpret Bayesian "credible intervals" similarly to confidence intervals

Make sure you make post-hoc diagnoses

```
library(lattice)
xyplot(as.mcmc(Bayes_cbpp$Sol), layout = c(2, 2))
```

There is no trend, well-mixed

```
xyplot(as.mcmc(Bayes_cbpp$VCV),layout=c(2,1))
```

For the herd variable, a lot of them are 0, which suggests problem. To fix the instability in the herd effect sampling, we can either

- modify the prior distribution on the herd variation

- increases the number of iteration

```
library(MCMCglmm)
Bayes_cbpp2 <-
    MCMCglmm(
        cbind(incidence, size - incidence) ~ period,
        random = ~ herd,
        data   = cbpp,
        family = "multinomial2",
        nitt   = 20000,
        burnin = 10000,
        prior  = list(G = list(list(
            V  = 1, nu = .1
        ))),
        verbose = FALSE
    )
xyplot(as.mcmc(Bayes_cbpp2$VCV), layout = c(2, 1))
```

To change the shape of priors, in `MCMCglmm` use:

- `V` controls for the location of the distribution (default = 1)
- `nu` controls for the concentration around V (default = 0)

9.2.2 Count (Owl Data)

```
library(glmmTMB)
library(dplyr)
data(Owls, package = "glmmTMB")
Owls <- Owls %>%
    rename(Ncalls = SiblingNegotiation)
```

In a typical Poisson model, λ (Poisson mean), is model as $\log(\lambda) = \mathbf{x}'$ But if the response is the rate (e.g., counts per BroodSize), we could model it as $\log(\lambda/b) = \mathbf{x}'$, equivalently $\log(\lambda) = \log(b) + \mathbf{x}'$ where b is BroodSize. Hence, we "offset" the mean by the log of this variable.

```
owls_glmer <-
    glmer(
        Ncalls ~ offset(log(BroodSize))
        + FoodTreatment * SexParent +
            (1 | Nest),
        family = poisson,
        data = Owls
    )
summary(owls_glmer)
```

```
#> Generalized linear mixed model fit by maximum likelihood (Laplace
#>   Approximation) [glmerMod]
#>  Family: poisson  ( log )
#> Formula: Ncalls ~ offset(log(BroodSize)) + FoodTreatment * SexParent +
#>     (1 | Nest)
#>    Data: Owls
#>
#>      AIC      BIC   logLik deviance df.resid
#>   5212.8   5234.8  -2601.4   5202.8      594
#>
#> Scaled residuals:
#>     Min      1Q  Median      3Q     Max
#> -3.5529 -1.7971 -0.6842  1.2689 11.4312
#>
#> Random effects:
#>  Groups Name        Variance Std.Dev.
#>  Nest   (Intercept) 0.2063   0.4542
#> Number of obs: 599, groups:  Nest, 27
#>
#> Fixed effects:
#>                                    Estimate Std. Error z value Pr(>|z|)
#> (Intercept)                         0.65585    0.09567   6.855 7.12e-12 ***
#> FoodTreatmentSatiated              -0.65612    0.05606 -11.705  < 2e-16 ***
#> SexParentMale                      -0.03705    0.04501  -0.823   0.4104
#> FoodTreatmentSatiated:SexParentMale  0.13135    0.07036   1.867   0.0619 .
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Correlation of Fixed Effects:
#>             (Intr) FdTrtS SxPrnM
#> FdTrtmntStt -0.225
#> SexParentMl -0.292  0.491
#> FdTrtmS:SPM  0.170 -0.768 -0.605
```

- nest explains a relatively large proportion of the variability (its standard deviation is larger than some coefficients)
- the model fit isn't great (deviance of 5202 on 594 df)

```
# Negative binomial model
owls_glmerNB <-
    glmer.nb(Ncalls ~ offset(log(BroodSize))
             + FoodTreatment * SexParent
             + (1 | Nest), data = Owls)

c(Deviance = round(summary(owls_glmerNB)$AICtab["deviance"], 3),
```

```
  df = summary(owls_glmerNB)$AICtab["df.resid"])
#> Deviance.deviance       df.df.resid
#>          3483.616           593.000
```

There is an improvement using negative binomial considering over-dispersion

```
hist(Owls$Ncalls,breaks=30)
```

To account for too many 0s in these data, we can use zero-inflated Poisson (ZIP) model.

- `glmmTMB` can handle ZIP GLMMs since it adds automatic differentiation to existing estimation strategies.

```
library(glmmTMB)
owls_glmm <-
    glmmTMB(
        Ncalls ~ FoodTreatment * SexParent + offset(log(BroodSize)) +
            (1 | Nest),
        ziformula =  ~ 0,
        family = nbinom2(link = "log"),
        data = Owls
    )
owls_glmm_zi <-
    glmmTMB(
        Ncalls ~ FoodTreatment * SexParent + offset(log(BroodSize)) +
            (1 | Nest),
        ziformula =  ~ 1,
```

```
        family = nbinom2(link = "log"),
        data = Owls
    )
# Scale Arrival time to use as a covariate for zero-inflation parameter
Owls$ArrivalTime <- scale(Owls$ArrivalTime)
owls_glmm_zi_cov <- glmmTMB(
    Ncalls ~ FoodTreatment * SexParent +
        offset(log(BroodSize)) +
        (1 | Nest),
    ziformula =  ~ ArrivalTime,
    family = nbinom2(link = "log"),
    data = Owls
)
as.matrix(anova(owls_glmm, owls_glmm_zi))
#>              Df      AIC      BIC    logLik deviance    Chisq Chi Df
#> owls_glmm     6 3495.610 3521.981 -1741.805 3483.610       NA     NA
#> owls_glmm_zi  7 3431.646 3462.413 -1708.823 3417.646 65.96373      1
#>                Pr(>Chisq)
#> owls_glmm              NA
#> owls_glmm_zi 4.592983e-16
as.matrix(anova(owls_glmm_zi, owls_glmm_zi_cov))
#>                  Df      AIC      BIC    logLik deviance    Chisq Chi Df
#> owls_glmm_zi      7 3431.646 3462.413 -1708.823 3417.646       NA     NA
#> owls_glmm_zi_cov  8 3422.532 3457.694 -1703.266 3406.532 11.11411      1
#>                    Pr(>Chisq)
#> owls_glmm_zi               NA
#> owls_glmm_zi_cov 0.0008567362
summary(owls_glmm_zi_cov)
#>  Family: nbinom2  ( log )
#> Formula:
#> Ncalls ~ FoodTreatment * SexParent + offset(log(BroodSize)) +      (1 | Nest)
#> Zero inflation:          ~ArrivalTime
#> Data: Owls
#>
#>      AIC      BIC   logLik deviance df.resid
#>   3422.5   3457.7  -1703.3   3406.5      591
#>
#> Random effects:
#>
#> Conditional model:
#>  Groups Name        Variance Std.Dev.
#>  Nest   (Intercept) 0.07487  0.2736
#> Number of obs: 599, groups:  Nest, 27
#>
#> Dispersion parameter for nbinom2 family (): 2.22
```

```
#>
#> Conditional model:
#>                                   Estimate Std. Error z value Pr(>|z|)
#> (Intercept)                        0.84778    0.09961   8.511  < 2e-16 ***
#> FoodTreatmentSatiated             -0.39529    0.13742  -2.877  0.00402 **
#> SexParentMale                     -0.07025    0.10435  -0.673  0.50079
#> FoodTreatmentSatiated:SexParentMale  0.12388    0.16449   0.753  0.45138
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Zero-inflation model:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  -1.3018     0.1261  -10.32  < 2e-16 ***
#> ArrivalTime   0.3545     0.1074    3.30 0.000966 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We can see ZIP GLMM with an arrival time covariate on the zero is best.

- arrival time has a positive effect on observing a nonzero number of calls
- interactions are non significant, the food treatment is significant (fewer calls after eating)
- nest variability is large in magnitude (without this, the parameter estimates change)

9.2.3 Binomial

```r
library(agridat)
library(ggplot2)
library(lme4)
library(spaMM)
data(gotway.hessianfly)
dat <- gotway.hessianfly
dat$prop <- dat$y / dat$n

ggplot(dat, aes(x = lat, y = long, fill = prop)) +
    geom_tile() +
    scale_fill_gradient(low = 'white', high = 'black') +
    geom_text(aes(label = gen, color = block)) +
    ggtitle('Gotway Hessian Fly')
```

- Fixed effects (β) = genotype
- Random effects (α) = block

```
flymodel <-
    glmer(
        cbind(y, n - y) ~ gen + (1 | block),
        data   = dat,
        family = binomial,
        nAGQ   = 5
    )
summary(flymodel)
#> Generalized linear mixed model fit by maximum likelihood (Adaptive
#>   Gauss-Hermite Quadrature, nAGQ = 5) [glmerMod]
#>  Family: binomial  ( logit )
#> Formula: cbind(y, n - y) ~ gen + (1 | block)
#>    Data: dat
#>
#>      AIC      BIC   logLik deviance df.resid
#>    162.2    198.9    -64.1    128.2       47
#>
#> Scaled residuals:
#>      Min       1Q   Median       3Q      Max
#> -2.38644 -1.01188  0.09631  1.03468  2.75479
#>
#> Random effects:
#>  Groups Name        Variance Std.Dev.
#>  block  (Intercept) 0.001022 0.03196
```

```
#> Number of obs: 64, groups:  block, 4
#>
#> Fixed effects:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)   1.5035     0.3914   3.841 0.000122 ***
#> genG02       -0.1939     0.5302  -0.366 0.714644
#> genG03       -0.5408     0.5103  -1.060 0.289260
#> genG04       -1.4342     0.4714  -3.043 0.002346 **
#> genG05       -0.2037     0.5429  -0.375 0.707486
#> genG06       -0.9783     0.5046  -1.939 0.052533 .
#> genG07       -0.6041     0.5111  -1.182 0.237235
#> genG08       -1.6774     0.4907  -3.418 0.000630 ***
#> genG09       -1.3984     0.4725  -2.960 0.003078 **
#> genG10       -0.6817     0.5333  -1.278 0.201181
#> genG11       -1.4630     0.4843  -3.021 0.002522 **
#> genG12       -1.4591     0.4918  -2.967 0.003010 **
#> genG13       -3.5528     0.6600  -5.383 7.31e-08 ***
#> genG14       -2.5073     0.5264  -4.763 1.90e-06 ***
#> genG15       -2.0872     0.4851  -4.302 1.69e-05 ***
#> genG16       -2.9697     0.5383  -5.517 3.46e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Equivalently, we can use `MCMCglmm` , for a Bayesian approach

```
library(coda)
Bayes_flymodel <- MCMCglmm(
    cbind(y, n - y) ~ gen ,
    random  = ~ block,
    data    = dat,
    family  = "multinomial2",
    verbose = FALSE
)
plot(Bayes_flymodel$Sol[, 1], main = dimnames(Bayes_flymodel$Sol)[[2]][1])
```

```
autocorr.plot(Bayes_flymodel$Sol[, 1], main = dimnames(Bayes_flymodel$Sol)[[2]][1])
```

9.2.4 Example from (Schabenberger and Pierce, 2001) section 8.4.1

```
dat2 <- read.table("images/YellowPoplarData_r.txt")
names(dat2) <- c('tn', 'k', 'dbh', 'totht',
                 'dob', 'ht', 'maxd', 'cumv')
```

```
dat2$t <- dat2$dob / dat2$dbh
dat2$r <- 1 - dat2$dob / dat2$totht
```

The cumulative volume relates to the complementary diameter (subplots were created based on total tree height)

```
library(ggplot2)
library(dplyr)
dat2 <- dat2 %>% group_by(tn) %>% mutate(
    z = case_when(
        totht < 74 & totht >= 0 ~ 'a: 0-74ft',
        totht < 88 & totht >= 74 ~ 'b: 74-88',
        totht < 95 & totht >= 88 ~ 'c: 88-95',
        totht < 99 & totht >= 95 ~ 'd: 95-99',
        totht < 104 & totht >= 99 ~ 'e: 99-104',
        totht < 109 & totht >= 104 ~ 'f: 104-109',
        totht < 115 & totht >= 109 ~ 'g: 109-115',
        totht < 120 & totht >= 115 ~ 'h: 115-120',
        totht < 140 & totht >= 120 ~ 'i: 120-150',
    )
)
ggplot(dat2, aes(x = r, y = cumv)) +
    geom_point(size = 0.5) +
    facet_wrap(vars(z))
```

The proposed non-linear model:

$$V_{id_j} = (\beta_0 + (\beta_1 + b_{1i})\frac{D_i^2 H_i}{1000})(\exp[-(\beta_2 + b_{2i})t_{ij}\exp(\beta_3 t_{ij})]) + e_{ij}$$

where

- b_{1i}, b_{2i} are random effects
- e_{ij} are random errors

```
library(nlme)
tmp <-
    nlme(
        cumv ~ (b0 + (b1 + u1) *
                    (dbh * dbh * totht / 1000)) *
            (exp(-(b2 + u2) * (t / 1000) * exp(b3 * t))),
        data = dat2,
        fixed = b0 + b1 + b2 + b3 ~ 1,
        # 1 on the right hand side of the formula indicates
        # a single fixed effects for the corresponding parameters
        random = list(pdDiag(u1 + u2 ~ 1)),
        #uncorrelated random effects
        groups = ~ tn,
        #group on trees so each tree w/ have u1 and u2
        start = list(fixed = c(
            b0 = 0.25,
            b1 = 2.3,
            b2 = 2.87,
            b3 = 6.7
        ))
    )
summary(tmp)
#> Nonlinear mixed-effects model fit by maximum likelihood
#>   Model: cumv ~ (b0 + (b1 + u1) * (dbh * dbh * totht/1000)) * (exp(-(b2 +      u2)
#>   Data: dat2
#>        AIC      BIC    logLik
#>   31103.73 31151.33 -15544.86
#>
#> Random effects:
#>  Formula: list(u1 ~ 1, u2 ~ 1)
#>  Level: tn
#>  Structure: Diagonal
#>                u1       u2 Residual
#> StdDev: 0.1508094 0.447829 2.226361
#>
#> Fixed effects:  b0 + b1 + b2 + b3 ~ 1
#>       Value  Std.Error   DF  t-value p-value
```

```
#> b0 0.249386 0.12894687 6297   1.9340  0.0532
#> b1 2.288832 0.01266804 6297 180.6776  0.0000
#> b2 2.500497 0.05606685 6297  44.5985  0.0000
#> b3 6.848871 0.02140677 6297 319.9395  0.0000
#>  Correlation:
#>    b0     b1     b2
#> b1 -0.639
#> b2  0.054  0.056
#> b3 -0.011 -0.066 -0.850
#>
#> Standardized Within-Group Residuals:
#>           Min            Q1           Med            Q3           Max
#> -6.694575e+00 -3.081861e-01 -8.904304e-05  3.469469e-01  7.855665e+00
#>
#> Number of Observations: 6636
#> Number of Groups: 336
nlme::intervals(tmp)
#> Approximate 95% confidence intervals
#>
#>  Fixed effects:
#>           lower      est.     upper
#> b0 -0.003318061 0.2493855 0.5020892
#> b1  2.264006036 2.2888322 2.3136584
#> b2  2.390620340 2.5004973 2.6103743
#> b3  6.806919342 6.8488713 6.8908232
#>
#>  Random Effects:
#>   Level: tn
#>            lower      est.     upper
#> sd(u1) 0.1376084 0.1508094 0.1652768
#> sd(u2) 0.4056209 0.4478290 0.4944291
#>
#>  Within-group standard error:
#>    lower     est.    upper
#> 2.187258 2.226361 2.266162
```

- Little different from the book because of different implementation of non-linear mixed models.

```
library(cowplot)
nlmmfn <- function(fixed,rand,dbh,totht,t){
  b0 <- fixed[1]
  b1 <- fixed[2]
  b2 <- fixed[3]
  b3 <- fixed[4]
  u1 <- rand[1]
```

```
  u2 <- rand[2]
  #just made so we can predict w/o random effects
  return((b0+(b1+u1)*(dbh*dbh*totht/1000))*(exp(-(b2+u2)*(t/1000)*exp(b3*t))))
}



#Tree 1
pred1 <- data.frame(seq(1, 24, length.out = 100))
names(pred1) <- 'dob'
pred1$tn <- 1
pred1$dbh <- unique(dat2[dat2$tn == 1, ]$dbh)
pred1$t <- pred1$dob / pred1$dbh
pred1$totht <- unique(dat2[dat2$tn == 1, ]$totht)
pred1$r <- 1 - pred1$dob / pred1$totht


pred1$test <- predict(tmp, pred1)
pred1$testno <-
    nlmmfn(
        fixed = tmp$coefficients$fixed,
        rand = c(0, 0),
        pred1$dbh,
        pred1$totht,
        pred1$t
    )

p1 <-
    ggplot(pred1) +
    geom_line(aes(x = r, y = test, color = 'with random')) +
    geom_line(aes(x = r, y = testno, color = 'No random')) +
    labs(colour = "") +
    geom_point(data = dat2[dat2$tn == 1, ], aes(x = r, y = cumv)) +
    ggtitle('Tree 1') + theme(legend.position = "none")


#Tree 151
pred151        <- data.frame(seq(1, 21, length.out = 100))
names(pred151) <- 'dob'
pred151$tn     <- 151
pred151$dbh    <- unique(dat2[dat2$tn == 151, ]$dbh)
pred151$t      <- pred151$dob / pred151$dbh
pred151$totht  <- unique(dat2[dat2$tn == 151, ]$totht)
pred151$r      <- 1 - pred151$dob / pred151$totht
```

```
pred151$test <- predict(tmp, pred151)
pred151$testno <-
    nlmmfn(
        fixed = tmp$coefficients$fixed,
        rand = c(0, 0),
        pred151$dbh,
        pred151$totht,
        pred151$t
    )

p2 <-
    ggplot(pred151) +
    geom_line(aes(x = r, y = test, color = 'with random')) +
    geom_line(aes(x = r, y = testno, color = 'No random')) +
    labs(colour = "") +
    geom_point(data = dat2[dat2$tn == 151,], aes(x = r, y = cumv)) +
    ggtitle('Tree 151') +
    theme(legend.position = "none")


#Tree 279
pred279        <- data.frame(seq(1, 9, length.out = 100))
names(pred279) <- 'dob'
pred279$tn     <- 279
pred279$dbh    <- unique(dat2[dat2$tn == 279, ]$dbh)
pred279$t      <- pred279$dob / pred279$dbh
pred279$totht  <- unique(dat2[dat2$tn == 279, ]$totht)
pred279$r      <- 1 - pred279$dob / pred279$totht


pred279$test <- predict(tmp, pred279)
pred279$testno <-
    nlmmfn(
        fixed = tmp$coefficients$fixed,
        rand = c(0, 0),
        pred279$dbh,
        pred279$totht,
        pred279$t
    )

p3 <-
    ggplot(pred279) +
    geom_line(aes(x = r, y = test, color = 'with random')) +
    geom_line(aes(x = r, y = testno, color = 'No random')) +
    labs(colour = "") +
```

```
    geom_point(data = dat2[dat2$tn == 279, ], aes(x = r, y = cumv)) +
    ggtitle('Tree 279') +
    theme(legend.position = "none")

plot_grid(p1, p2, p3)
```

red line = predicted observations based on the common fixed effects

teal line = tree-specific predictions with random effects

9.3 Summary

Generalized Linear Mixed Model
Non-linear Mixed Model
Linear Mixed Model
Generalized Linear Model
Non-linear Regression
Linear Regression

III. RAMIFICATIONS

Chapter 10

Model Specification

Test whether underlying assumptions hold true

- Nested Model (A1/A3)
- Non-Nested Model (A1/A3)
- Heteroskedasticity (A4)

10.1 Nested Model

$$\begin{aligned} y &= \beta_0 + x_1\beta_1 + x_2\beta - 2 + x_3\beta_3 + \epsilon && \text{unrestricted model} \\ y &= \beta_0 + x_1\beta_1 + \epsilon && \text{restricted model} \end{aligned}$$

Unrestricted model is always longer than the restricted model
The restricted model is "nested" within the unrestricted model
To determine which variables should be included or exclude, we could use the same Wald Test

Adjusted R^2

- R^2 will always increase with more variables included
- Adjusted R^2 tries to correct by penalizing inclusion of unnecessary variables.

$$\begin{aligned} R^2 &= 1 - \frac{SSR/n}{SST/n} \\ R^2_{adj} &= 1 - \frac{SSR/(n-k)}{SST/(n-1)} \\ &= 1 - \frac{(n-1)(1-R^2)}{(n-k)} \end{aligned}$$

- R^2_{adj} increases if and only if the t-statistic on the additional variable is greater than 1 in absolute value.
- R^2_{adj} is valid in models where there is no heteroskedasticity
- there fore it **should not** be used in determining which variables should be included in the model (the t or F-tests are more appropriate)

10.1.1 Chow test

Should we run two different regressions for two groups?

10.2 Non-Nested Model

compare models with different non-nested specifications

10.2.1 Davidson-Mackinnon test

10.2.1.1 Independent Variable

Should the independent variables be logged? (decide between non-nested alternatives)

$$y = \beta_0 + x_1\beta_1 + x_2\beta_2 + \epsilon \quad \text{(level eq)}$$
$$y = \beta_0 + ln(x_1)\beta_1 + x_2\beta_2 + \epsilon \quad \text{(log eq)}$$

1. Obtain predict outcome when estimating the model in log equation $\check{y}$ and then estimate the following auxiliary equation,

$$y = \beta_0 + x_1\beta_1 + x_2\beta_2 + \check{y}\gamma + error$$

and evaluate the t-statistic for the null hypothesis $H_0 : \gamma = 0$

2. Obtain predict outcome when estimating the model in the level equation $\hat{y}$, then estimate the following auxiliary equation,

$$y = \beta_0 + ln(x_1)\beta_1 + x_2\beta_2 + \check{y}\gamma + error$$

and evaluate the t-statistic for the null hypothesis $H_0 : \gamma = 0$

- If you reject the null in the (1) step but fail to reject the null in the second step, then the log equation is preferred.
- If fail to reject the null in the (1) step but reject the null in the (2) step then, level equation is preferred.
- If reject in both steps, then you have statistical evidence that neither model should be used and should re-evaluate the functional form of your model.

- If fail to reject in both steps, you do not have sufficient evidence to prefer one model over the other. You can compare the R^2_{adj} to choose between the two models.

$$y = \beta_0 + ln(x)\beta_1 + \epsilon$$
$$y = \beta_0 + x(\beta_1) + x^2\beta_2 + \epsilon$$

- Compare which better fits the data
- Compare standard R^2 is unfair because the second model is less parsimonious (more parameters to estimate)
- The R^2_{adj} will penalize the second model for being less parsimonious + Only valid when there is no heteroskedasticity (A4 holds)
- Should only compare after a Davidson-Mackinnon test

10.2.1.2 Dependent Variable

$$y = \beta_0 + x_1\beta_1 + \epsilon \quad \text{level eq}$$
$$ln(y) = \beta_0 + x_1\beta_1 + \epsilon \quad \text{log eq}$$

- In the level model, regardless of how big y is, x has a constant effect (i.e., one unit change in x_1 results in a β_1 unit change in y)
- In the log model, the larger in y is, the effect of x is stronger (i.e., one unit change in x_1 could increase y from 1 to $1+\beta_1$ or from 100 to 100+100xβ_1)
- Cannot compare R^2 or R^2_{adj} because the outcomes are complement different, the scaling is different (SST is different)

We need to "un-transform" the $ln(y)$ back to the same scale as y and then compare,

1. Estimate the model in the log equation to obtain the predicted outcome $\widehat{ln(y)}$
2. "Un-transform" the predicted outcome

$$\widehat{m} = exp(\widehat{ln(y)})$$

3. Estimate the following model (without an intercept)

$$y = \alpha\widehat{m} + error$$

and obtain predicted outcome $\widehat{y}$

4. Then take the square of the correlation between $\widehat{y}$ and y as a scaled version of the R^2 from the log model that can now compare with the usual R^2 in the level model.

10.3 Heteroskedasticity

- Using roust standard errors are always valid
- If there is significant evidence of heteroskedasticity implying A4 does not hold
  - Gauss-Markov Theorem no longer holds, OLS is not BLUE.
  - Should consider using a better linear unbiased estimator (Weighted Least Squares or Generalized Least Squares)

10.3.1 Breusch-Pagan test

A4 implies

$$E(\epsilon_i^2|\mathbf{x_i}) = \sigma^2$$

$$\epsilon_i^2 = \gamma_0 + x_{i1}\gamma_1 + ... + x_{ik-1}\gamma_{k-1} + error$$

and determining whether or not $\mathbf{x}_i$ has any predictive value

- if $\mathbf{x}_i$ has predictive value, then the variance changes over the levels of $\mathbf{x}_i$ which is evidence of heteroskedasticity
- if $\mathbf{x}_i$ does not have predictive value, the variance is constant for all levels of $\mathbf{x}_i$

The Breusch-Pagan test for heteroskedasticity would compute the F-test of total significance for the following model

$$e_i^2 = \gamma_0 + x_{i1}\gamma_1 + ... + x_{ik-1}\gamma_{k-1} + error$$

A low p-value means we reject the null of homoskedasticity

However, Breusch-Pagan test cannot detect heteroskedasticity in non-linear form

10.3.2 White test

test heteroskedasticity would allow for a non-linear relationship by computing the F-test of total significance for the following model (assume there are three independent random variables)

$$\begin{aligned} e_i^2 &= \gamma_0 + x_i\gamma_1 + x_{i2}\gamma_2 + x_{i3}\gamma_3 \\ &+ x_{i1}^2\gamma_4 + x_{i2}^2\gamma_5 + x_{i3}^2\gamma_6 \\ &+ (x_{i1} \times x_{i2})\gamma_7 + (x_{i1} \times x_{i3})\gamma_8 + (x_{i2} \times x_{i3})\gamma_9 + error \end{aligned}$$

A low p-value means we reject the null of homoskedasticity

Equivalently, we can compute LM as $LM = nR^2_{e^2}$ where the $R^2_{e^2}$ come from the regression with the squared residual as the outcome

- The LM statistic has a $[\chi^2_k]$[Chi-squared] distribution

Chapter 11

Imputation (Missing Data)

Imputation is a statistical procedure where you replace missing data with *some reasonable values*

- Unit imputation = single data point
- Item imputation = single feature value

Imputation is usually seen as the illegitimate child of statistical analysis. Several reasons that contribute to these negative views could be:

(1) Peopled hardly do imputation correctly (which will introduce bias to your estimates)
(2) Imputation can only be applied to a small range of problems correctly

If you have missing data on y (dependent variable), you probably would not be able to do any imputation appropriately. However, if you have certain type of missing data (e.g., non-random missing data) in the x's variable (independent variables), then you can still salvage your collected data points with imputation.

We also need to talk why you would want to do imputation in the first place. If your purpose is inference/ explanation (valid statistical inference not optimal point prediction), then imputation would not offer much help (Rubin, 1996). However, if your purpose is prediction, you would want your standard error to be reduced by including information (non-missing data) on other variables of a data point. Then imputation could be the tool that you're looking for.

For most software packages, it will use listwise deletion or casewise deletion to have complete case analysis (analysis with only observations with all information). Not until recently that statistician can propose some methods that are a bit better than listwise deletion which are maximum likelihood and multiple imputation.

"Judging the quality of missing data procedures by their ability to recreate the

individual missing values (according to hit rate, mean square error, etc) does not lead to choosing procedures that result in valid inference", (Rubin, 1996)

Missing data can make it more challenging to big datasets.

11.1 Assumptions

11.1.1 Missing Completely at Random (MCAR)

Missing Completely at Random, MCAR, means there is no relationship between the missingness of the data and any values, observed or missing. Those missing data points are a random subset of the data. There is nothing systematic going on that makes some data more likely to be missing than others.

The probability of missing data on a variable is unrelated to the value of it or to the values of any other variables in the data set.

Note: the "missingness" on Y can be correlated with the "missingness" on X We can compare the value of other variables for the observations with missing data, and observations without missing data. If we reject the t-test for mean difference, we can say there is evidence that the data are not MCAR. But we cannot say that our data are MCAR if we fail to reject the t-test.

- the propensity for a data point to be missing is completely random.
- There's no relationship between whether a data point is missing and any values in the data set, missing or observed.
- The missing data are just a random subset of the data.

Methods include:

- Universal singular value thresholding (Chatterjee, 2015) (can only recover the mean, not the whole true distribution).
- Softimputet: (Hastie et al., 2015) (doesn't work well under "Limited" - missing not at random).
- Synthetic nearest neighbor (Agarwal et al., 2023) (still work okay under missing not at random). Available on GitHub: syntheticNN

11.1.2 Missing at Random (MAR)

Missing at Random, MAR, means there is a systematic relationship between the propensity of missing values and the observed data, but not the missing data. Whether an observation is missing has nothing to do with the missing values, but it does have to do with the values of an individual's observed variables. So, for example, if men are more likely to tell you their weight than women, weight is MAR.

MAR is weaker than MCAR

$$P(Y_{missing}|Y, X) = P(Y_{missing}|X)$$

The probability of Y missing given Y and X equal to the probability of of Y missing given X. However, it is impossible to provide evidence to the MAR condition.

- the propensity for a data point to be missing is not related to the missing data, but it is related to some of the observed data. In another word, there is a systematic relationship between the propensity of missing values and the observed data, but not the missing data.
  - For example, if men are more likely to tell you their weight than women, weight is MAR
- MAR requires that the cause of the missing data is unrelated to the missing values but may be related to the observed values of other variables.
- MAR means that the missing values are related to observed values on other variables. As an example of CD missing data, missing income data may be unrelated to the actual income values but are related to education. Perhaps people with more education are less likely to reveal their income than those with less education

11.1.3 Ignorable

The missing data mechanism is ignorable when

(1) The data are MAR
(2) the parameters in the function of the missing data process are unrelated to the parameters (of interest) that need to be estimated.

In this case, you actually don't need to model the missing data mechanisms unless you would like to improve on your accuracy, in which case you still need to be very rigorous about your approach to improve efficiency in your parameters.

11.1.4 Nonignorable

Missing Not at Random, MNAR, means there is a relationship between the propensity of a value to be missing and its values.

Example: people with the lowest education are missing on education or the sickest people are most likely to drop out of the study.

MNAR is called Nonignorable because the missing data mechanism itself has to be modeled as you deal with the missing data. You have to include some model for why the data are missing and what the likely values are.

Hence, in the case of nonignorable, the data are not MAR. Then, your parameters of interest will be biased if you do not model the missing data mechanism.

One of the most widely used approach for nonignorable missing data is (Heckman, 1976)

- Another name: Missing Not at Random (MNAR): there is a relationship between the propensity of a value to be missing and its values
  - For example, people with low education will be less likely to report it
- We need to model why the data are missing and what the likely values are.
- the missing data mechanism is related to the missing values
- It commonly occurs when people do not want to reveal something very personal or unpopular about themselves
- Complete case analysis can give highly biased results for NI missing data. If proportionally more low and moderate income individuals are left in the sample because high income people are missing, an estimate of the mean income will be lower than the actual population mean.

One can use instrument that can predict the nonresponse process in outcome variable, and unrelated to the outcome of the population to correct for this missingness (but you still have to use complete cases) (Sun et al., 2018; Tchetgen Tchetgen and Wirth, 2017)

11.2 Solutions to Missing data

11.2.1 Listwise Deletion

Also known as complete case deletion only where you only retain cases with complete data for all features.

Advantages:

- Can be applied to any statistical test (SEM, multi-level regression, etc.)
- In the case of MCAR, both the parameters estimates and its standard errors are unbiased.
- In the case of MAR among independent variables (not depend on the values of dependent variables), then listwise deletion parameter estimates can still be unbiased. (Little, 1992) For example, you have a model $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$ if the probability of missing data on $X1$ is independent of Y, but dependent on the value of $X1$ and $X2$, then the model estimates are still unbiased.
  - The missing data mechanism the depends on the values of the independent variables are the same as stratified sampling. And stratified sampling does not bias your estimates

  - In the case of logistic regression, if the probability of missing data on any variable depends on the value of the dependent variable, but independent of the value of the independent variables, then the listwise deletion will yield biased intercept estimate, but consistent estimates of the slope and their standard errors (Vach and Vach, 1994). However, logistic regression will still fail if the probability of missing data is dependent on both the value of the dependent and independent variables.
  - Under regression analysis, listwise deletion is more robust than maximum likelihood and multiple imputation when MAR assumption is violated.

Disadvantages:

- It will yield a larger standard errors than other more sophisticated methods discussed later.
- If the data are not MCAR, but MAR, then your listwise deletion can yield biased estimates.
- In other cases than regression analysis, other sophisticated methods can yield better estimates compared to listwise deletion.

11.2.2 Pairwise Deletion

This method could only be used in the case of linear models such as linear regression, factor analysis, or SEM. The premise of this method based on that the coefficient estimates are calculated based on the means, standard deviations, and correlation matrix. Compared to listwise deletion, we still utilized as many correlation between variables as possible to compute the correlation matrix.

Advantages:

- If the true missing data mechanism is MCAR, pair wise deletion will yield consistent estimates, and unbiased in large samples
- Compared to listwise deletion: (Glasser, 1964)
  - If the correlation among variables are low, pairwise deletion is more efficient estimates than listwise
  - If the correlations among variables are high, listwise deletion is more efficient than pairwise.

Disadvantages:

- If the data mechanism is MAR, pairwise deletion will yield biased estimates.
- In small sample, sometimes covariance matrix might not be positive definite, which means coefficients estimates cannot be calculated.

Note: You need to read carefully on how your software specify the sample size because it will alter the standard errors.

11.2.3 Dummy Variable Adjustment

Also known as Missing Indicator Method or Proxy Variable

Add another variable in the database to indicate whether a value is missing.

Create 2 variables

$$D = \begin{cases} 1 & \text{data on X are missing} \\ 0 & \text{otherwise} \end{cases}$$

$$X^* = \begin{cases} X & \text{data are available} \\ c & \text{data are missing} \end{cases}$$

Note: A typical choice for c is usually the mean of X

Interpretation:

- Coefficient of D is the the difference in the expected value of Y between the group with data and the group without data on X.
- Coefficient of X^* is the effect of the group with data on Y

Disadvantages:

- This method yields biased estimates of the coefficient even in the case of MCAR (Jones, 1996)

11.2.4 Imputation

11.2.4.1 Mean, Mode, Median Imputation

- Bad:
  - Mean imputation does not preserve the relationships among variables
  - Mean imputation leads to An Underestimate of Standard Errors $\rightarrow$ you're making Type I errors without realizing it.
  - Biased estimates of variances and covariances (Haitovsky, 1968)
  - In high-dimensions, mean substitution cannot account for dependence structure among features.

11.2.4.2 Maximum Likelihood

When missing data are MAR and monotonic (such as in the case of panel studies), ML can be adequately in estimating coefficients.

Monotonic means that if you are missing data on X1, then that observation also has missing data on all other variables that come after it.

ML can generally handle linear models, log-linear model, but beyond that, ML still lacks both theory and software to implement.

11.2.4.2.1 Expectation-Maximization Algorithm (EM Algorithm) An iterative process:

(1) Other variables are used to impute a value (Expectation).
(2) Check whether the value is most likely (Maximization).
(3) If not, it re-imputes a more likely value.

You start your regression with your estimates based on either listwise deletion or pairwise deletion. After regressing missing variables on available variables, you obtain a regression model. Plug the missing data back into the original model, with modified variances and covariances For example, if you have missing data on X_{ij} you would regress it on available data of $X_{i(j)}$, then plug the expected value of X_{ij} back with its X_{ij}^2 turn into $X_{ij}^2 + s_{j(j)}^2$ where $s_{j(j)}^2$ stands for the residual variance from regressing X_{ij} on $X_{i(j)}$ With the new estimated model, you rerun the process until the estimates converge.

Advantages:

(1) Easy to use
(2) Preserves the relationship with other variables (important if you use Factor Analysis or Linear Regression later on), but best in the case of Factor Analysis, which doesn't require standard error of individuals item.

Disadvantages:

(1) Standard errors of the coefficients are incorrect (biased usually downward - underestimate)
(2) Models with overidentification, the estimates will not be efficient

11.2.4.2.2 Direct ML (raw maximum likelihood) Advantages

(1) Efficient estimates and correct standard errors.

Disadvantages:

(1) Hard to implements

11.2.4.3 Multiple Imputation

MI is designed to use "the Bayesian model-based approach to *create* procedures, and the frequentist (randomization-based approach) to *evaluate* procedures". (Rubin, 1996)

MI estimates have the same properties as ML when the data is MAR

- Consistent
- Asymptotically efficient
- Asymptotically normal

MI can be applied to any type of model, unlike Maximum Likelihood that is only limited to a small set of models.

A drawback of MI is that it will produce slightly different estimates every time you run it. To avoid such problem, you can set seed when doing your analysis to ensure its reproducibility.

11.2.4.3.1 Single Random Imputation Random draws form the residual distribution of each imputed variable and add those random numbers to the imputed values.

For example, if we have missing data on X, and it's MCAR, then

(1) Regress X on Y (Listwise Deletion method) to get its residual distribution.

(2) For every missing value on X, we substitute with $\tilde{x_i} = \hat{x_i} + \rho u_i$ where

- u_i is a random draw from a standard normal distribution
- x_i is the predicted value from the regression of X and Y
- ρ is the standard deviation of the residual distribution of X regressed on Y.

However, the model you run with the imputed data still thinks that your data are collected, not imputed, which leads your standard error estimates to be too low and test statistics too high.

To address this problem, we need to repeat the imputation process which leads us to repeated imputation or multiple random imputation.

11.2.4.3.2 Repeated Imputation "Repeated imputations are draws from the posterior predictive distribution of the missing values under a specific model , a particular Bayesian model for both the data and the missing mechanism".(Rubin, 1996)

Repeated imputation, also known as, multiple random imputation, allows us to have multiple "completed" data sets. The variability across imputations will adjust the standard errors upward.

The estimate of the standard error of $\bar{r}$ (mean correlation estimates between X and Y) is

$$SE(\bar{r}) = \sqrt{\frac{1}{M}\sum_k s_k^2 + (1+\frac{1}{M})(\frac{1}{M-1})\sum_k (r_k - \bar{r})^2}$$

where M is the number of replications, r_k is the the correlation in replication k, s_k is the estimated standard error in replication k.

However, this method still considers the parameter in predicting $\tilde{x}$ is still fixed, which means we assume that we are using the true parameters to predict $\tilde{x}$. To overcome this challenge, we need to introduce variability into our model for $\tilde{x}$ by treating the parameters as a random variables and use Bayesian posterior distribution of the parameters to predict the parameters.

However, if your sample is large and the proportion of missing data is small, the extra Bayesian step might not be necessary. If your sample is small or the proportion of missing data is large, the extra Bayesian step is necessary.

Two algorithms to get random draws of the regression parameters from its posterior distribution:

- Data Augmentation
- Sampling importance/resampling (SIR)

Authors have argued for SIR superiority due to its computer time (King et al., 2001)

11.2.4.3.2.1 Data Augmentation Steps for data augmentation:

(1) Choose starting values for the parameters (e.g., for multivariate normal, choose means and covariance matrix). These values can come from previous values, expert knowledge, or from listwise deletion or pairwise deletion or EM estimation.
(2) Based on the current values of means and covariances calculate the coefficients estimates for the equation that variable with missing data is regressed on all other variables (or variables that you think will help predict the missing values, could also be variables that are not in the final estimation model)
(3) Use the estimates in step (2) to predict values for missing values. For each predicted value, add a random error from the residual normal distribution for that variable.
(4) From the "complete" data set, recalculate the means and covariance matrix. And take a random draw from the posterior distribution of the means and covariances with Jeffreys' prior.
(5) Using the random draw from step (4), repeat step (2) to (4) until the means and covariances stabilize (converged).

The iterative process allows us to get random draws from the joint posterior distribution of both data nd parameters, given the observed data.

Rules of thumb regarding convergence:

- The higher the proportion of missing, the more iterations
- the rate of convergence for EM algorithm should be the minimum threshold for DA.
- You can also check if your distribution has been converged by diagnostic statistics Can check Bayesian Diagnostics for some introduction.

Types of chains

1. **Parallel**: Run a separate chain of iterations for each of data set. Different starting values are encouraged. For example, one could use bootstrap to generate different data set with replacement, and for each data set, calculate the starting values by EM estimates.

- Pro: Run faster, and less likely to have dependence in the resulting data sets.
- Con: Sometimes it will not converge

2. **Sequential** one long chain of data augmentation cycles. After burn-in and thinning, you will have to data sets

   - Pro: Converged to the true posterior distribution is more likely.
   - Con: The resulting data sets are likely to be dependent. Remedies can be thinning and burn-in.

Note on Non-normal or categorical data The normal-based methods still work well, but you will need to do some transformation. For example,

- If the data is skewed, then log-transform, then impute the exponentiate to have the missing data back to its original metric.
- If the data is proportion, logit-transform, impute, then de-transform the missing data.

If you want to impute non-linear relationship, such as interaction between 2 variables and 1 variable is categorical. You can do separate imputation for different levels of that variable separately, then combined for the final analysis.

- If all variables that have missing data are categorical, then **unrestricted multinomial model** or **log-linear model** is recommended.
- If a single categorical variable, **logistic (logit) regression** would be sufficient.

11.2.4.4 Nonparametric/ Semiparametric Methods

11.2.4.4.1 Hot Deck Imputation

- Used by U.S. Census Bureau for public datasets
- approximate Bayesian bootstrap
- A randomly chosen value from an individual in the sample who has similar values on other variables. In other words, find all the sample subjects who are similar on other variables, then randomly choose one of their values on the missing variable.

When we have n_1 cases with complete data on Y and n_0 cases with missing data on Y

- Step 1: From n_1, take a random sample (with replacement) of n_1 cases
- Step 2: From the retrieved sample take a random sample (with replacement) of n_0 cases
- Step 3: Assign the n_0 cases in step 2 to n_0 missing data cases.
- Step 4: Repeat the process for every variable.
- Step 5: For multiple imputation, repeat the four steps multiple times.

Note:

- If we skip step 1, it reduce variability for estimating standard errors.
- Good:
  - Constrained to only possible values.
  - Since the value is picked at random, it adds some variability, which might come in handy when calculating standard errors.
- Challenge: how can you define "similar" here.

11.2.4.4.2 Cold Deck Imputation Contrary to Hot Deck, Cold Deck choose value systematically from an observation that has similar values on other variables, which remove the random variation that we want.

Donor samples of "cold-deck" imputation come from a different data set.

11.2.4.4.3 Predictive Mean Matching Steps:

1. Regress Y on X (matrix of covariates) for the n_1 (i.e., non-missing cases) to get coefficients b (a $k \times 1$ vector) and residual variance estimates s^2
2. Draw randomly from the posterior predictive distribution of the residual variance (assuming a noninformative prior) by calculating $\frac{(n_1-k)s^2}{\chi^2}$, where χ^2 is a random draw from a $\chi^2_{n_1-k}$ and let $s^2_{[1]}$ be an i-th random draw
3. Randomly draw from the posterior distribution of the coefficients b, by drawing from $MVN(b, s^2_{[1]}(X'X)^{-1})$, where X is an $n_1 \times k$ matrix of X values. Then we have b_1
4. Using step 1, we can calculate standardized residuals for n_1 cases: $e_i = \frac{y_i - bx_i}{\sqrt{s^2(1-k/n_1)}}$
5. Randomly draw a sample (with replacement) of n_0 from the n_1 residuals in step 4
6. With n_0 cases, we can calculate imputed values of Y: $y_i = b_{[1]}x_i + s_{[1]}e_i$ where e_i are taken from step 5, and $b_{[1]}$ taken from step 3, and $s_{[1]}$ taken from step 2.
7. Repeat steps 2 through 6 except for step 4.

Notes:

- can be used for multiple variables where each variable is imputed using all other variables as predictor.
- can also be used for heteroskedasticity in imputed values.

Example from Statistics Globe

```
set.seed(918273) # Seed
N  <- 3000                                      # Sample size
y  <- round(runif(N,-10, 10))                   # Target variable Y
x1 <- y + round(runif(N, 0, 50))                # Auxiliary variable 1
x2 <- round(y + 0.25 * x1 + rnorm(N,-3, 15))    # Auxiliary variable 2
x3 <- round(0.1 * x1 + rpois(N, 2))             # Auxiliary variable 3
```

```
# (categorical variable)
x4 <- as.factor(round(0.02 * y + runif(N)))   # Auxiliary variable 4

# Insert 20% missing data in Y
y[rbinom(N, 1, 0.2) == 1] <- NA

data <- data.frame(y, x1, x2, x3, x4)         # Store data in dataset
head(data) # First 6 rows of our data
#>    y x1  x2 x3 x4
#> 1  8 38  -3  6  1
#> 2  1 50  -9  5  0
#> 3  5 43  20  5  1
#> 4 NA  9  13  3  0
#> 5 -4 40 -10  6  0
#> 6 NA 29  -6  5  1

library("mice") # Load mice package

##### Impute data via predictive mean matching (single imputation)#####

imp_single <- mice(data, m = 1, method = "pmm") # Impute missing values
#>
#>  iter imp variable
#>   1   1  y
#>   2   1  y
#>   3   1  y
#>   4   1  y
#>   5   1  y
data_imp_single <- complete(imp_single)         # Store imputed data
# head(data_imp_single)

# Since single imputation underestiamtes stnadard errors,
# we use multiple imputaiton

##### Predictive mean matching (multiple imputation) #####

# Impute missing values multiple times
imp_multi <- mice(data, m = 5, method = "pmm")
#>
#>  iter imp variable
#>   1   1  y
#>   1   2  y
#>   1   3  y
#>   1   4  y
#>   1   5  y
```

```
#>   2   1  y
#>   2   2  y
#>   2   3  y
#>   2   4  y
#>   2   5  y
#>   3   1  y
#>   3   2  y
#>   3   3  y
#>   3   4  y
#>   3   5  y
#>   4   1  y
#>   4   2  y
#>   4   3  y
#>   4   4  y
#>   4   5  y
#>   5   1  y
#>   5   2  y
#>   5   3  y
#>   5   4  y
#>   5   5  y
data_imp_multi_all <-
    # Store multiply imputed data
    complete(imp_multi,
             "repeated",
             include = TRUE)

data_imp_multi <-
    # Combine imputed Y and X1-X4 (for convenience)
    data.frame(data_imp_multi_all[, 1:6], data[, 2:5])

head(data_imp_multi)
#>   y.0 y.1 y.2 y.3 y.4 y.5 x1  x2 x3 x4
#> 1   8   8   8   8   8   8 38  -3  6  1
#> 2   1   1   1   1   1   1 50  -9  5  0
#> 3   5   5   5   5   5   5 43  20  5  1
#> 4  NA   1  -2  -4   9  -8  9  13  3  0
#> 5  -4  -4  -4  -4  -4  -4 40 -10  6  0
#> 6  NA   4   7   7   6   0 29  -6  5  1
```

Example from UCLA Statistical Consulting

```
library(mice)
library(VIM)
library(lattice)
library(ggplot2)
## set observations to NA
```

```r
anscombe <- within(anscombe, {
    y1[1:3] <- NA
    y4[3:5] <- NA
})
## view
head(anscombe)
#>   x1 x2 x3 x4   y1   y2    y3   y4
#> 1 10 10 10  8   NA 9.14  7.46 6.58
#> 2  8  8  8  8   NA 8.14  6.77 5.76
#> 3 13 13 13  8   NA 8.74 12.74   NA
#> 4  9  9  9  8 8.81 8.77  7.11   NA
#> 5 11 11 11  8 8.33 9.26  7.81   NA
#> 6 14 14 14  8 9.96 8.10  8.84 7.04

## check missing data patterns
md.pattern(anscombe)
```

```
#>   x1 x2 x3 x4 y2 y3 y1 y4
#> 6  1  1  1  1  1  1  1  1 0
#> 2  1  1  1  1  1  1  1  0 1
#> 2  1  1  1  1  1  1  0  1 1
#> 1  1  1  1  1  1  1  0  0 2
#>    0  0  0  0  0  0  3  3 6

## Number of observations per patterns for all pairs of variables
p <- md.pairs(anscombe)
p
```

```
#> $rr
#>    x1 x2 x3 x4 y1 y2 y3 y4
#> x1 11 11 11 11  8 11 11  8
#> x2 11 11 11 11  8 11 11  8
#> x3 11 11 11 11  8 11 11  8
#> x4 11 11 11 11  8 11 11  8
#> y1  8  8  8  8  8  8  8  6
#> y2 11 11 11 11  8 11 11  8
#> y3 11 11 11 11  8 11 11  8
#> y4  8  8  8  8  6  8  8  8
#>
#> $rm
#>    x1 x2 x3 x4 y1 y2 y3 y4
#> x1  0  0  0  0  3  0  0  3
#> x2  0  0  0  0  3  0  0  3
#> x3  0  0  0  0  3  0  0  3
#> x4  0  0  0  0  3  0  0  3
#> y1  0  0  0  0  0  0  0  2
#> y2  0  0  0  0  3  0  0  3
#> y3  0  0  0  0  3  0  0  3
#> y4  0  0  0  0  2  0  0  0
#>
#> $mr
#>    x1 x2 x3 x4 y1 y2 y3 y4
#> x1  0  0  0  0  0  0  0  0
#> x2  0  0  0  0  0  0  0  0
#> x3  0  0  0  0  0  0  0  0
#> x4  0  0  0  0  0  0  0  0
#> y1  3  3  3  3  0  3  3  2
#> y2  0  0  0  0  0  0  0  0
#> y3  0  0  0  0  0  0  0  0
#> y4  3  3  3  3  2  3  3  0
#>
#> $mm
#>    x1 x2 x3 x4 y1 y2 y3 y4
#> x1  0  0  0  0  0  0  0  0
#> x2  0  0  0  0  0  0  0  0
#> x3  0  0  0  0  0  0  0  0
#> x4  0  0  0  0  0  0  0  0
#> y1  0  0  0  0  3  0  0  1
#> y2  0  0  0  0  0  0  0  0
#> y3  0  0  0  0  0  0  0  0
#> y4  0  0  0  0  1  0  0  3
```

- `rr` = number of observations where both pairs of values are observed
- `rm` = the number of observations where both variables are missing values

- `mr` = the number of observations where the first variable's value (e.g. the row variable) is observed and second (or column) variable is missing
- `mm` = the number of observations where the second variable's value (e.g. the col variable) is observed and first (or row) variable is missing

```
## Margin plot of y1 and y4
marginplot(anscombe[c(5, 8)], col = c("blue", "red", "orange"))
```

```
## 5 imputations for all missing values
imp1 <- mice(anscombe, m = 5)
#>
#>  iter imp variable
#>   1   1  y1  y4
#>   1   2  y1  y4
#>   1   3  y1  y4
#>   1   4  y1  y4
#>   1   5  y1  y4
#>   2   1  y1  y4
#>   2   2  y1  y4
#>   2   3  y1  y4
#>   2   4  y1  y4
#>   2   5  y1  y4
#>   3   1  y1  y4
#>   3   2  y1  y4
#>   3   3  y1  y4
#>   3   4  y1  y4
#>   3   5  y1  y4
```

```
#>   4   1  y1  y4
#>   4   2  y1  y4
#>   4   3  y1  y4
#>   4   4  y1  y4
#>   4   5  y1  y4
#>   5   1  y1  y4
#>   5   2  y1  y4
#>   5   3  y1  y4
#>   5   4  y1  y4
#>   5   5  y1  y4

## linear regression for each imputed data set - 5 regression are run
fitm <- with(imp1, lm(y1 ~ y4 + x1))
summary(fitm)
#> # A tibble: 15 x 6
#>    term        estimate std.error statistic p.value  nobs
#>    <chr>          <dbl>     <dbl>     <dbl>   <dbl> <int>
#>  1 (Intercept)    8.60      2.67      3.23  0.0121     11
#>  2 y4            -0.533     0.251    -2.12  0.0667     11
#>  3 x1             0.334     0.155     2.16  0.0628     11
#>  4 (Intercept)    4.19      2.93      1.43  0.190      11
#>  5 y4            -0.213     0.273    -0.782 0.457      11
#>  6 x1             0.510     0.167     3.05  0.0159     11
#>  7 (Intercept)    6.51      2.35      2.77  0.0244     11
#>  8 y4            -0.347     0.215    -1.62  0.145      11
#>  9 x1             0.395     0.132     3.00  0.0169     11
#> 10 (Intercept)    5.48      3.02      1.81  0.107      11
#> 11 y4            -0.316     0.282    -1.12  0.295      11
#> 12 x1             0.486     0.173     2.81  0.0230     11
#> 13 (Intercept)    7.12      1.81      3.92  0.00439    11
#> 14 y4            -0.436     0.173    -2.53  0.0355     11
#> 15 x1             0.425     0.102     4.18  0.00308    11

## pool coefficients and standard errors across all 5 regression models
pool(fitm)
#> Class: mipo    m = 5
#>          term m   estimate       ubar           b           t dfcom       df
#> 1 (Intercept) 5  6.3808015 6.72703243 2.785088109 10.06913816     8 3.902859
#> 2          y4 5 -0.3690455 0.05860053 0.014674911  0.07621042     8 4.716160
#> 3          x1 5  0.4301588 0.02191260 0.004980516  0.02788922     8 4.856052
#>         riv    lambda       fmi
#> 1 0.4968172 0.3319158 0.5254832
#> 2 0.3005074 0.2310693 0.4303733
#> 3 0.2727480 0.2142985 0.4143230
```

```
## output parameter estimates
summary(pool(fitm))
#>          term   estimate std.error statistic       df    p.value
#> 1 (Intercept)  6.3808015 3.1731905  2.010847 3.902859 0.11643863
#> 2          y4 -0.3690455 0.2760624 -1.336819 4.716160 0.24213491
#> 3          x1  0.4301588 0.1670007  2.575791 4.856052 0.05107581
```

11.2.4.4.4 Stochastic Imputation `Regression imputation + random residual = Stochastic Imputation`

Most multiple imputation is based off of some form of stochastic regression imputation.

Good:

- Has all the advantage of Regression Imputation
- and also has the random components

Bad:

- might lead to implausible values (e.g. negative values)
- can't handle heteroskadastic data

Note
Multiple Imputation usually based on some form of stochastic regression imputation.

```
# Income data

set.seed(91919)                                # Set seed
N <- 1000                                      # Sample size

income <- round(rnorm(N, 0, 500))              # Create some synthetic income data
income[income < 0] <- income[income < 0] * (- 1)

x1 <- income + rnorm(N, 1000, 1500)            # Auxiliary variables
x2 <- income + rnorm(N, - 5000, 2000)

income[rbinom(N, 1, 0.1) == 1] <- NA           # Create 10% missingness in income

data_inc_miss <- data.frame(income, x1, x2)
```

Single stochastic regression imputation

```
imp_inc_sri  <- mice(data_inc_miss, method = "norm.nob", m = 1)
#>
#>  iter imp variable
#>   1   1  income
#>   2   1  income
```

```
#>   3   1  income
#>   4   1  income
#>   5   1  income
data_inc_sri <- complete(imp_inc_sri)
```

Single predictive mean matching

```
imp_inc_pmm  <- mice(data_inc_miss, method = "pmm", m = 1)
#>
#>  iter imp variable
#>   1   1  income
#>   2   1  income
#>   3   1  income
#>   4   1  income
#>   5   1  income
data_inc_pmm <- complete(imp_inc_pmm)
```

Stochastic regression imputation contains negative values

```
data_inc_sri$income[data_inc_sri$income < 0]
#> [1]  -66.055957  -96.980053  -28.921432   -4.175686  -54.480798  -27.207102
#> [7] -143.603500  -80.960488
# No values below 0
data_inc_pmm$income[data_inc_pmm$income < 0]
#> numeric(0)
```

Evidence for heteroskadastic data

```
# Heteroscedastic data

set.seed(654654)                              # Set seed
N <- 1:5000                                   # Sample size

a <- 0
b <- 1
sigma2 <- N^2
eps <- rnorm(N, mean = 0, sd = sqrt(sigma2))

y <- a + b * N + eps                          # Heteroscedastic variable
x <- 30 * N + rnorm(N[length(N)], 1000, 200) # Correlated variable

y[rbinom(N[length(N)], 1, 0.3) == 1] <- NA   # 30% missing

data_het_miss <- data.frame(y, x)
```

Single stochastic regression imputation

```
imp_het_sri  <- mice(data_het_miss, method = "norm.nob", m = 1)
#>
#>  iter imp variable
#>   1   1  y
#>   2   1  y
#>   3   1  y
#>   4   1  y
#>   5   1  y
data_het_sri <- complete(imp_het_sri)
```

Single predictive mean matching

```
imp_het_pmm  <- mice(data_het_miss, method = "pmm", m = 1)
#>
#>  iter imp variable
#>   1   1  y
#>   2   1  y
#>   3   1  y
#>   4   1  y
#>   5   1  y
data_het_pmm <- complete(imp_het_pmm)
```

Comparison between predictive mean matching and stochastic regression imputation

```
par(mfrow = c(1, 2))                                # Both plots in one graphic

# Plot of observed values
plot(x[!is.na(data_het_sri$y)],
     data_het_sri$y[!is.na(data_het_sri$y)],
     main = "",
     xlab = "X",
     ylab = "Y")
# Plot of missing values
points(x[is.na(y)], data_het_sri$y[is.na(y)],
       col = "red")

# Title of plot
title("Stochastic Regression Imputation",
      line = 0.5)

# Regression line
abline(lm(y ~ x, data_het_sri),
       col = "#1b98e0", lwd = 2.5)

# Legend
```

```r
legend(
  "topleft",
  c("Observed Values", "Imputed Values", "Regression Y ~ X"),
  pch = c(1, 1, NA),
  lty = c(NA, NA, 1),
  col = c("black", "red", "#1b98e0")
)

# Plot of observed values
plot(x[!is.na(data_het_pmm$y)],
     data_het_pmm$y[!is.na(data_het_pmm$y)],
     main = "",
     xlab = "X",
     ylab = "Y")


# Plot of missing values
points(x[is.na(y)], data_het_pmm$y[is.na(y)],
       col = "red")

# Title of plot
title("Predictive Mean Matching",
      line = 0.5)
abline(lm(y ~ x, data_het_pmm),
       col = "#1b98e0", lwd = 2.5)

# Legend
legend(
  "topleft",
  c("Observed Values", "Imputed Values", "Regression Y ~ X"),
  pch = c(1, 1, NA),
  lty = c(NA, NA, 1),
  col = c("black", "red", "#1b98e0")
)

mtext(
  "Imputation of Heteroscedastic Data",
  # Main title of plot
  side = 3,
  line = -1.5,
  outer = TRUE,
  cex = 2
)
```

11.2.4.5 Regression Imputation

Also known as conditional mean imputation Missing value is based (regress) on other variables.

- Good:
  - Maintain the relationship with other variables (i.e., preserve dependence structure among features, unlike 11.2.4.1).
  - If the data are MCAR, least-squares coefficients estimates will be consistent, and approximately unbiased in large samples (Gourieroux and Monfort, 1981)
    - Can have improvement on efficiency by using weighted least squares (Beale and Little, 1975) or generalized least squares (Gourieroux and Monfort, 1981).
- Bad:
  - No variability left. treated data as if they were collected.
  - Underestimate the standard errors and overestimate test statistics

11.2.4.6 Interpolation and Extrapolation

An estimated value from other observations from the same individual. It usually only works in longitudinal data.

11.2.4.7 K-nearest neighbor (KNN) imputation

The above methods are model-based imputation (regression).
This is an example of neighbor-based imputation (K-nearest neighbor).

For every observation that needs to be imputed, the algorithm identifies 'k' closest observations based on some types distance (e.g., Euclidean) and computes the weighted average (weighted based on distance) of these 'k' obs.

For a discrete variable, it uses the most frequent value among the k nearest neighbors.

- Distance metrics: Hamming distance.

For a continuous variable, it uses the mean or mode.

- Distance metrics:
  - Euclidean
  - Mahalanobis
  - Manhattan

11.2.4.8 Bayesian Ridge regression implementation

11.2.4.9 Matrix Completion

Impute items missing at random while accounting for dependence between features by using principal components, which is known as **matrix completion** (James et al., 2013, Sec 12.3)

Consider an $n \times p$ feature matrix, $\mathbf{X}$, with element x_{ij}, some of which are missing.

Similar to 22.2, we can approximate the matrix $\mathbf{X}$ in terms of its leading PCs.

We consider the M principal components that optimize

$$\min_{\mathbf{A} \in \mathbb{R}^{n \times M}, \mathbf{B} \in \mathbb{R}^{p \times M}} \left\{ \sum_{(i,j) \in \mathcal{O}} (x_{ij} - \sum_{m=1}^{M} a_{im} b_{jm})^2 \right\}$$

where $\mathcal{O}$ is the set of all observed pairs indices (i, j), a subset of the possible $n \times p$ pairs

Once this minimization is solved,

- One can impute a missing observation, x_{ij}, with $\hat{x}_{ij} = \sum_{m=1}^{M} \hat{a}_{im} \hat{b}_{jm}$ where $\hat{a}_{im}, \hat{b}_{jm}$ are the (i, m) and $(j.m)$ elements, respectively, of the matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ from the minimization, and
- One can approximately recover the M principal component scores and loadings, as we did when the data were complete

The challenge here is to solve this minimization problem: the eigen-decomposition non longer applies (as in 22.2

Hence, we have to use iterative algorithm (James et al., 2013, Alg 12.1)

1. Create a complete data matrix $\tilde{\mathbf{X}}$ of dimension $n \times p$ of which the (i, j) element equals

$$\tilde{x}_{ij} = \begin{cases} x_{ij} & \text{if } (i,j) \in \mathcal{O} \\ \bar{x}_j & \text{if } (i,j) \notin \mathcal{O} \end{cases}$$

where $\bar{x}_j$ is the average of the observed values for the jth variable in the incomplete data matrix $\mathbf{X}$

$\mathcal{O}$ indexes the observations that are observed in $\mathbf{X}$

2. Repeat these 3 steps until some objectives are met

a. Solve

$$\min_{\mathbf{A} \in R^{n \times M}, \mathbf{B} \in R^{p \times M}} \{ \sum_{(i,j) \in \mathcal{O}} (x_{ij} - \sum_{m=1}^{M} a_{im} b_{jm})^2 \}$$

by computing the principal components of $\tilde{\mathbf{X}}$

b. For each element $(i, j) \notin \mathcal{O}$, set $\tilde{x}_{ij} \leftarrow \sum_{m=1}^{M} \hat{a}_{im} \hat{b}_{jm}$

c. Compute the objective

$$\sum_{(i,j \in \mathcal{O})} (x_{ij} - \sum_{m=1}^{M} \hat{a}_{im} \hat{b}_{jm})^2$$

3. Return the estimated missing entries $\tilde{x}_{ij}, (i, j) \notin \mathcal{O}$

11.2.5 Other methods

- For panel data, or clustered data, use `pan` package by Schafer (1997)

11.3 Criteria for Choosing an Effective Approach

Criteria for an ideal technique in treating missing data:

1. Unbiased parameter estimates
2. Adequate power
3. Accurate standard errors (p-values, confidence intervals)

The Multiple Imputation and Full Information Maximum Likelihood are the the most ideal candidate. Single imputation will generally lead to underestimation of standard errors.

11.4 Another Perspective

Model bias can arisen from various factors including:

- Imputation method
- Missing data mechanism (MCAR vs. MAR)
- Proportion of the missing data
- Information available in the data set

Since the imputed observations are themselves estimates, their values have corresponding random error. But when you put in that estimate as a data point, your software doesn't know that. So it overlooks the extra source of error, resulting in too-small standard errors and too-small p-values. So multiple imputation comes up with multiple estimates.

Because multiple imputation have a random component, the multiple estimates are slightly different. This re-introduces some variation that your software can incorporate in order to give your model accurate estimates of standard error. Multiple imputation was a huge breakthrough in statistics about 20 years ago. It solves a lot of problems with missing data (though, unfortunately not all) and if done well, leads to unbiased parameter estimates and accurate standard errors. If your rate of missing data is very, very small (2-3%) it doesn't matter what technique you use.

Remember that there are three goals of multiple imputation, or any missing data technique:

- Unbiased parameter estimates in the final analysis (regression coefficients, group means, odds ratios, etc.)
- accurate standard errors of those parameter estimates, and therefore, accurate p-values in the analysis
- adequate power to find meaningful parameter values significant.

Hence,

1. Don't round off imputations for dummy variables. Many common imputation techniques, like MCMC, require normally distributed variables. Suggestions for imputing categorical variables were to dummy code them, impute them, then round off imputed values to 0 or 1. Recent research, however, has found that rounding off imputed values actually leads to biased parameter estimates in the analysis model. You actually get better results by leaving the imputed values at impossible values, even though it's counter-intuitive.

2. Don't transform skewed variables. Likewise, when you transform a variable to meet normality assumptions before imputing, you not only are changing the distribution of that variable but the relationship between that variable and the others you use to impute. Doing so can lead to imputing outliers, creating more bias than just imputing the skewed variable.

3. Use more imputations. The advice for years has been that 5-10 imputations are adequate. And while this is true for unbiasedness, you can get inconsistent results if you run the multiple imputation more than once. (Bodner, 2008) recommends having as many imputations as the percentage of missing data. Since running more imputations isn't any more work for the data analyst, there's no reason not to.

4. Create multiplicative terms before imputing. When the analysis model contains a multiplicative term, like an interaction term or a quadratic, create the multiplicative terms first, then impute. Imputing first, and then creating the multiplicative terms actually biases the regression parameters of the multiplicative term (Von Hippel, 2009)

11.5 Diagnosing the Mechanism

11.5.1 MAR vs. MNAR

The only true way to distinguish between MNAR and MAR is to measure some of that missing data.

It's a common practice among professional surveyors to, for example, follow-up on a paper survey with phone calls to a group of the non-respondents and ask a few key survey items. This allows you to compare respondents to non-respondents.

If their responses on those key items differ by very much, that's good evidence that the data are MNAR.

However in most missing data situations, we can't get a hold of the missing data. So while we can't test it directly, we can examine patterns in the data get an idea of what's the most likely mechanism.

The first thing in diagnosing randomness of the missing data is to use your substantive scientific knowledge of the data and your field. The more sensitive the issue, the less likely people are to tell you. They're not going to tell you as much about their cocaine usage as they are about their phone usage.

Likewise, many fields have common research situations in which non-ignorable data is common. Educate yourself in your field's literature.

11.5.2 MCAR vs. MAR

There is a very useful test for MCAR, Little's test.

A second technique is to create dummy variables for whether a variable is missing.

1 = missing 0 = observed

You can then run t-tests and chi-square tests between this variable and other variables in the data set to see if the missingness on this variable is related to the values of other variables.

For example, if women really are less likely to tell you their weight than men, a chi-square test will tell you that the percentage of missing data on the weight variable is higher for women than men.

11.6 Application

```
library(visdat)
library(naniar)
library(ggplot2)
vis_miss()



ggplot(data, aes(x, y)) +
  geom_miss_point() +
  facet_wrap( ~ group)

gg_miss_var(data, facet = group)

gg_miss_upset(data)

gg_miss_fct(x = variable1, fct = variable2)
```

Read more on The Missing Book by Nicholas Tierney & Allison Horst

How many imputation:

Usually 5. (unless you have extremely high portion of missing, in which case you probably need to check your data again)

According to Rubin, the relative efficiency of an estimate based on m imputations to infinity imputation is approximately

$$(1 + \frac{\lambda}{m})^{-1}$$

where λ is the rate of missing data

Example 50% of missing data means an estimate based on 5 imputation has standard deviation that is only 5% wider compared to an estimate based on infinity imputation
($\sqrt{1+0.5/5} = 1.049$)

```
library(missForest)

#load data
data <- iris

#Generate 10% missing values at Random
set.seed(1)
iris.mis <- prodNA(iris, noNA = 0.1)

#remove categorical variables
iris.mis.cat <- iris.mis
iris.mis <- subset(iris.mis, select = -c(Species))
```

11.6.1 Imputation with mean / median / mode

```
# whole data set
e1071::impute(iris.mis, what = "mean")        # replace with mean
e1071::impute(iris.mis, what = "median")      # replace with median

# by variables
Hmisc::impute(iris.mis$Sepal.Length, mean)    # mean
Hmisc::impute(iris.mis$Sepal.Length, median)  # median
Hmisc::impute(iris.mis$Sepal.Length, 0)       # replace specific number
```

check accuracy

```
# library(DMwR2)
# actuals <- iris$Sepal.Width[is.na(iris.mis$Sepal.Width)]
# predicteds <- rep(mean(iris$Sepal.Width, na.rm=T), length(actuals))
# regr.eval(actuals, predicteds)
```

11.6.2 KNN

```
# library(DMwR2)
# # iris.mis[,!names(iris.mis) %in% c("Sepal.Length")]
# # data should be this line. But since knn cant work with 3 or less variables,
# # we need to use at least 4 variables.
#
# # knn is not appropriate for categorical variables
# knnOutput <-
#   knnImputation(data = iris.mis.cat,
```

```
#                   #k = 10,
#                   meth = "median" # could use "median" or "weighAvg")
#                   # should exclude the dependent variable: Sepal.Length
#                   anyNA(knnOutput)
```

```
# library(DMwR2)
# actuals <- iris$Sepal.Width[is.na(iris.mis$Sepal.Width)]
# predicteds <- knnOutput[is.na(iris.mis$Sepal.Width), "Sepal.Width"]
# regr.eval(actuals, predicteds)
```

Compared to MAPE (mean absolute percentage error) of mean imputation, we see almost always see improvements.

11.6.3 rpart

For categorical (factor) variables, `rpart` can handle

```
library(rpart)
class_mod <-
  rpart(
    Species ~ . - Sepal.Length,
    data = iris.mis.cat[!is.na(iris.mis.cat$Species),],
    method = "class",
    na.action = na.omit
  )  # since Species is a factor, and exclude dependent variable "Sepal.Length"

anova_mod <-
  rpart(
    Sepal.Width ~ . - Sepal.Length,
    data = iris.mis[!is.na(iris.mis$Sepal.Width),],
    method = "anova",
    na.action = na.omit
  )  # since Sepal.Width is numeric.


species_pred <-
  predict(class_mod, iris.mis.cat[is.na(iris.mis.cat$Species),])


width_pred <-
  predict(anova_mod, iris.mis[is.na(iris.mis$Sepal.Width),])
```

11.6.4 MICE (Multivariate Imputation via Chained Equations)

Assumption: data are MAR

It imputes data per variable by specifying an imputation model for each variable

Example

We have $X_1, X_2, .., X_k$. If X_1 has missing data, then it is regressed on the rest of the variables. Same procedure applies if X_2 has missing data. Then, predicted values are used in place of missing values.

By default,

- **Continuous variables** use linear regression.
- **Categorical Variables** use logistic regression.

Methods in MICE:

- PMM (Predictive Mean Matching) – For numeric variables
- `logreg`(Logistic Regression) – For Binary Variables(with 2 levels)
- `polyreg` (Bayesian polytomous regression) – For Factor Variables (>= 2 levels)
- Proportional odds model (ordered, >= 2 levels)

```
# load package
library(mice)
library(VIM)

# check missing values
md.pattern(iris.mis)
```

```
#>     Sepal.Width Sepal.Length Petal.Length Petal.Width
#> 100           1            1            1           1  0
#> 15            1            1            1           0  1
```

```
#> 8              1            1            0            1  1
#> 2              1            1            0            0  2
#> 11             1            0            1            1  1
#> 1              1            0            1            0  2
#> 1              1            0            0            1  2
#> 1              1            0            0            0  3
#> 7              0            1            1            1  1
#> 3              0            1            0            1  2
#> 1              0            0            1            1  2
#>               11           15           15           19 60
```

```
#plot the missing values
aggr(
  iris.mis,
  col = mdc(1:2),
  numbers = TRUE,
  sortVars = TRUE,
  labels = names(iris.mis),
  cex.axis = .7,
  gap = 3,
  ylab = c("Proportion of missingness", "Missingness Pattern")
)
```

```
#>
#>  Variables sorted by number of missings:
#>      Variable      Count
#>   Petal.Width 0.12666667
```

```
#>  Sepal.Length 0.10000000
#>  Petal.Length 0.10000000
#>   Sepal.Width 0.07333333
```

```
mice_plot <- aggr(
  iris.mis,
  col = c('navyblue', 'yellow'),
  numbers = TRUE,
  sortVars = TRUE,
  labels = names(iris.mis),
  cex.axis = .7,
  gap = 3,
  ylab = c("Missing data", "Pattern")
)
```

```
#>
#>  Variables sorted by number of missings:
#>      Variable      Count
#>   Petal.Width 0.12666667
#>  Sepal.Length 0.10000000
#>  Petal.Length 0.10000000
#>   Sepal.Width 0.07333333
```

Impute Data

```
imputed_Data <-
    mice(
```

```
        iris.mis,
        m = 5, # number of imputed datasets
        maxit = 50, # number of iterations taken to impute missing values
        method = 'pmm', # method used in imputation.
        # Here, we used predictive mean matching


        # other methods can be
        # "pmm": Predictive mean matching
        # "midastouch" : weighted predictive mean matching
        # "sample": Random sample from observed values
        # "cart": classification and regression trees
        # "rf": random forest imputations.
        # "2lonly.pmm": Level-2 class predictive mean matching
        # Other methods based on whether variables are
        # (1) numeric, (2) binary, (3) ordered, (4), unordered
        seed = 500
    )
```

```
summary(imputed_Data)
#> Class: mids
#> Number of multiple imputations:  5
#> Imputation methods:
#> Sepal.Length  Sepal.Width Petal.Length  Petal.Width
#>        "pmm"        "pmm"        "pmm"        "pmm"
#> PredictorMatrix:
#>              Sepal.Length Sepal.Width Petal.Length Petal.Width
#> Sepal.Length            0           1            1           1
#> Sepal.Width             1           0            1           1
#> Petal.Length            1           1            0           1
#> Petal.Width             1           1            1           0

#make a density plot
densityplot(imputed_Data)
```

```
#the red (imputed values) should be similar to the blue (observed)
```

Check imputed dataset

```
# 1st dataset
completeData <- complete(imputed_Data,1)

# 2nd dataset
complete(imputed_Data,2)
```

Regression model using imputed datasets

```
# regression model
fit <-
  with(data = imputed_Data,
       exp = lm(Sepal.Width ~ Sepal.Length + Petal.Width))

#combine results of all 5 models
combine <- pool(fit)
summary(combine)
#>           term   estimate  std.error statistic       df      p.value
#> 1  (Intercept)  1.8963130 0.32453912  5.843095 131.0856 3.838556e-08
#> 2 Sepal.Length  0.2974293 0.06679204  4.453066 130.2103 1.802241e-05
#> 3  Petal.Width -0.4811603 0.07376809 -6.522608 108.8253 2.243032e-09
```

11.6.5 Amelia

- Use bootstrap based EMB algorithm (faster and robust to impute many variables including cross sectional, time series data etc)
- Use parallel imputation feature using multicore CPUs.

Assumptions

- All variables follow Multivariate Normal Distribution (MVN). Hence, this package works best when data is MVN, or transformation to normality.
- Missing data is Missing at Random (MAR)

Steps:

1. m bootstrap samples and applies EMB algorithm to each sample. Then we have m different estimates of mean and variances.
2. the first set of estimates are used to impute first set of missing values using regression, then second set of estimates are used for second set and so on.

However, Amelia is different from MICE

- MICE imputes data on variable by variable basis whereas MVN uses a joint modeling approach based on multivariate normal distribution.
- MICE can handle different types of variables while the variables in MVN need to be normally distributed or transformed to approximate normality.
- MICE can manage imputation of variables defined on a subset of data whereas MVN cannot.

```
library(Amelia)
data("iris")
#seed 10% missing values
iris.mis <- prodNA(iris, noNA = 0.1)
```

- idvars – keep all ID variables and other variables which you don't want to impute
- noms – keep nominal variables here

```
#specify columns and run amelia
amelia_fit <-
  amelia(iris.mis,
         m = 5,
         parallel = "multicore",
         noms = "Species")
#> -- Imputation 1 --
#>
#>   1  2  3  4  5  6  7  8
#>
#> -- Imputation 2 --
#>
#>   1  2  3  4  5  6  7  8
```

```
#>
#> -- Imputation 3 --
#>
#>   1  2  3  4  5
#>
#> -- Imputation 4 --
#>
#>   1  2  3  4  5  6  7
#>
#> -- Imputation 5 --
#>
#>   1  2  3  4  5  6  7

# access imputed outputs
# amelia_fit$imputations[[1]]
```

11.6.6 missForest

- an implementation of random forest algorithm (a non parametric imputation method applicable to various variable types). Hence, no assumption about function form of f. Instead, it tries to estimate f such that it can be as close to the data points as possible.
- builds a random forest model for each variable. Then it uses the model to predict missing values in the variable with the help of observed values.
- It yields out of bag imputation error estimate. Moreover, it provides high level of control on imputation process.
- Since bagging works well on categorical variable too, we don't need to remove them here.

```
library(missForest)
#impute missing values, using all parameters as default values
iris.imp <- missForest(iris.mis)
# check imputed values
# iris.imp$ximp
```

- check imputation error
- NRMSE is normalized mean squared error. It is used to represent error derived from imputing continuous values.
- PFC (proportion of falsely classified) is used to represent error derived from imputing categorical values.

```
iris.imp$OOBerror
#>      NRMSE        PFC
#> 0.13631893 0.04477612

#comparing actual data accuracy
```

```
iris.err <- mixError(iris.imp$ximp, iris.mis, iris)
iris.err
#>     NRMSE       PFC
#> 0.1501524 0.0625000
```

This means categorical variables are imputed with 5% error and continuous variables are imputed with 14% error.

This can be improved by tuning the values of `mtry` and `ntree` parameter.

- `mtry` refers to the number of variables being randomly sampled at each split.
- `ntree` refers to number of trees to grow in the forest.

11.6.7 Hmisc

- `impute()` function imputes missing value using user defined statistical method (mean, max, mean). It's default is median.

- `aregImpute()` allows mean imputation using additive regression, bootstrapping, and predictive mean matching.

1. In bootstrapping, different bootstrap resamples are used for each of multiple imputations. Then, a flexible additive model (non parametric regression method) is fitted on samples taken with replacements from original data and missing values (acts as dependent variable) are predicted using non-missing values (independent variable).

2. it uses predictive mean matching (default) to impute missing values. Predictive mean matching works well for continuous and categorical (binary & multi-level) without the need for computing residuals and maximum likelihood fit.

Note

- For predicting categorical variables, Fisher's optimum scoring method is used.
- `Hmisc` automatically recognizes the variables types and uses bootstrap sample and predictive mean matching to impute missing values.
- `missForest` can outperform `Hmisc` if the observed variables have sufficient information.

Assumption

- linearity in the variables being predicted.

```
library(Hmisc)
# impute with mean value
iris.mis$imputed_age <- with(iris.mis, impute(Sepal.Length, mean))
```

```
# impute with random value
iris.mis$imputed_age2 <-
  with(iris.mis, impute(Sepal.Length, 'random'))

# could also use min, max, median to impute missing value

# using argImpute
impute_arg <-
  # argImpute() automatically identifies the variable type
  # and treats them accordingly.
  aregImpute(
    ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width +
      Species,
    data = iris.mis,
    n.impute = 5
  )
#> Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8

impute_arg # R-squares are for predicted missing values.
#>
#> Multiple Imputation using Bootstrap and PMM
#>
#> aregImpute(formula = ~Sepal.Length + Sepal.Width + Petal.Length +
#>     Petal.Width + Species, data = iris.mis, n.impute = 5)
#>
#> n: 150   p: 5    Imputations: 5      nk: 3
#>
#> Number of NAs:
#> Sepal.Length  Sepal.Width Petal.Length  Petal.Width      Species
#>           11           11           13           24           16
#>
#>              type d.f.
#> Sepal.Length    s    2
#> Sepal.Width     s    2
#> Petal.Length    s    2
#> Petal.Width     s    2
#> Species         c    2
#>
```

```
#> Transformation of Target Variables Forced to be Linear
#>
#> R-squares for Predicting Non-Missing Values for Each Variable
#> Using Last Imputations of Predictors
#> Sepal.Length  Sepal.Width Petal.Length  Petal.Width      Species
#>        0.907        0.660        0.978        0.963        0.993

# check imputed variable Sepal.Length
impute_arg$imputed$Sepal.Length
#>     [,1] [,2] [,3] [,4] [,5]
#> 19   5.2  5.2  5.2  5.8  5.7
#> 21   5.1  5.0  5.1  5.7  5.4
#> 31   4.8  5.0  5.2  5.0  4.8
#> 35   4.6  4.9  4.9  4.9  4.8
#> 49   5.0  5.1  5.1  5.1  5.1
#> 62   6.2  5.7  6.0  6.4  5.6
#> 65   5.5  5.5  5.2  5.8  5.5
#> 67   6.5  5.8  5.8  6.3  6.5
#> 82   5.2  5.1  5.7  5.8  5.5
#> 113  6.4  6.5  7.4  7.2  6.3
#> 122  6.2  5.8  5.5  5.8  6.7
```

11.6.8 mi

1. allows graphical diagnostics of imputation models and convergence of imputation process.
2. uses Bayesian version of regression models to handle issue of separation.
3. automatically detects irregularities in data (e.g., high collinearity among variables).
4. adds noise to imputation process to solve the problem of additive constraints.

```
library(mi)
# default values of parameters
# 1. rand.imp.method as "bootstrap"
# 2. n.imp (number of multiple imputations) as 3
# 3. n.iter ( number of iterations) as 30
mi_data <- mi(iris.mis, seed = 335)
summary(mi_data)
```

Chapter 12

Data

There are multiple ways to categorize data. For example,

- Qualitative vs. Quantitative:

Qualitative	Quantitative
in-depth interviews, documents, focus groups, case study, ethnography. open-ended questions. observations in words	experiments, observation in words, survey with closed-end questions, structured interviews
language, descriptive	quantities, numbers
Text-based	Numbers-based
Subjective	Objectivity

12.1 Cross-Sectional

12.2 Time Series

$$y_t = \beta_0 + x_{t1}\beta_1 + x_{t2}\beta_2 + ... + x_{t(k-1)}\beta_{k-1} + \epsilon_t$$

Examples

- Static Model
  - $y_t = \beta_0 + x_1\beta_1 + x_2\beta_2 - x_3\beta_3 - \epsilon_t$
- Finite Distributed Lag model
  - $y_t = \beta_0 + pe_t\delta_0 + pe_{t-1}\delta_1 + pe_{t-2}\delta_2 + \epsilon_t$
  - **Long Run Propensity (LRP)** is $LRP = \delta_0 + \delta_1 + \delta_2$

- Dynamic Model
  - $GDP_t = \beta_0 + \beta_1 GDP_{t-1} - \epsilon_t$

Finite Sample Properties for Time Series:

- A1-A3: OLS is unbiased
- A1-A4: usual standard errors are consistent and Gauss-Markov Theorem holds (OLS is BLUE)
- A1-A6, A6: Finite Sample Wald Test (t-test and F-test) are valid

A3 might not hold under time series setting

- Spurious Time Trend - solvable
- Strict vs Contemporaneous Exogeneity - not solvable

In time series data, there are many processes:

- Autoregressive model of order p: AR(p)
- Moving average model of order q: MA(q)
- Autoregressive model of order p and moving average model of order q: ARMA(p,q)
- Autoregressive conditional heteroskedasticity model of order p: ARCH(p)
- Generalized Autoregressive conditional heteroskedasticity of orders p and q; GARCH(p.q)

12.2.1 Deterministic Time trend

Both the dependent and independent variables are trending over time

Spurious Time Series Regression

$$y_t = \alpha_0 + t\alpha_1 + v_t$$

and x takes the form

$$x_t = \lambda_0 + t\lambda_1 + u_t$$

- $\alpha_1 \neq 0$ and $\lambda_1 \neq 0$
- v_t and u_t are independent
- there is no relationship between y_t and x_t

If we estimate the regression,

$$y_t = \beta_0 + x_t\beta_1 + \epsilon_t$$

so the true $\beta_1 = 0$

- Inconsistent: $plim(\widehat{\beta}_1) = \frac{\alpha_1}{\lambda_1}$

- Invalid Inference: $|t| \to^d \infty$ for $H_0 : \beta_1 = 0$, will always reject the null as $n \to \infty$
- Uninformative R^2: $plim(R^2) = 1$ will be able to perfectly predict as $n \to \infty$

We can rewrite the equation as

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t$$
$$\epsilon_t = \alpha_1 t + v_t$$

where $\beta_0 = \alpha_0$ and $\beta_1 = 0$. Since x_t is a deterministic function of time, ϵ_t is correlated with x_t and we have the usual omitted variable bias.
Even when y_t and x_t are related ($\beta_1 \neq 0$) but they are both trending over time, we still get spurious results with the simple regression on y_t on x_t

Solutions to Spurious Trend

1. Include time trend t as an additional control
   - consistent parameter estimates and valid inference
2. Detrend both dependent and independent variables and then regress the detrended outcome on detrended independent variables (i.e., regress residuals $\hat{u}_t$ on residuals $\hat{v}_t$)
   - Detrending is the same as partialing out in the Frisch-Waugh-Lovell Theorem
     - Could allow for non-linear time trends by including t t^2, and $\exp(t)$
     - Allow for seasonality by including indicators for relevant "seasons" (quarters, months, weeks).

A3 does not hold under:

- Feedback Effect
  - ϵ_t influences next period's independent variables
- Dynamic Specification
  - include last time period outcome as an explanatory variable
- Dynamically Complete
  - For finite distrusted lag model, the number of lags needs to be absolutely correct.

12.2.2 Feedback Effect

$$y_t = \beta_0 + x_t \beta_1 + \epsilon_t$$

A3

$$E(\epsilon_t|\mathbf{X}) = E(\epsilon_t|x_1, x_2, ..., x_t, x_{t+1}, ..., x_T)$$

will not equal 0, because y_t will likely influence $x_{t+1}, .., x_T$

- A3 is violated because we require the error to be uncorrelated with all time observation of the independent regressors (**strict exogeneity**)

12.2.3 Dynamic Specification

$$y_t = \beta_0 + y_{t-1}\beta_1 + \epsilon_t$$

$$E(\epsilon_t|\mathbf{X}) = E(\epsilon_t|y_1, y_2, ..., y_t, y_{t+1}, ..., y_T)$$

will not equal 0, because y_t and ϵ_t are inherently correlated

- A3 is violated because we require the error to be uncorrelated with all time observation of the independent regressors (**strict exogeneity**)
- Dynamic Specification is not allowed under A3

12.2.4 Dynamically Complete

$$y_t = \beta_0 + x_t\delta_0 + x_{t-1}\delta_1 + \epsilon_t$$

$$E(\epsilon_t|\mathbf{X}) = E(\epsilon_t|x_1, x_2, ..., x_t, x_{t+1}, ..., x_T)$$

will not equal 0, because if we did not include enough lags, x_{t-2} and ϵ_t are correlated

- A3 is violated because we require the error to be uncorrelated with all time observation of the independent regressors (strict exogeneity)
- Can be corrected by including more lags (but when stop?)

Without A3

- OLS is biased
- Gauss-Markov Theorem
- Finite Sample Properties are invalid

then, we can

- Focus on Large Sample Properties
- Can use A3a instead of A3

A3a in time series become

$$A3a : E(\mathbf{x}_t'\epsilon_t) = 0$$

only the regressors in this time period need to be independent from the error in this time period (**Contemporaneous Exogeneity**)

- ϵ_t can be correlated with $..., x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2}, ...$
- can have a dynamic specification $y_t = \beta_0 + y_{t-1}\beta_1 + \epsilon_t$

Deriving Large Sample Properties for Time Series

- Assumptions A1, A2, A3a
- [Weak Law] and Central Limit Theorem depend on A5
  - x_t and ϵ_t are dependent over t
  - without [Weak Law] or Central Limit Theorem depend on A5, we cannot have Large Sample Properties for OLS
  - Instead of A5, we consider A5a
- Derivation of the Asymptotic Variance depends on A4
  - time series setting introduces **Serial Correlation**: $Cov(\epsilon_t, \epsilon_s) \neq 0$

under A1, A2, A3a, and A5a, OLS estimator is **consistent**, and **asymptotically normal**

12.2.5 Highly Persistent Data

If $y_t, \mathbf{x}_t$ are not weakly dependent stationary process

- y_t and y_{t-h} are not almost independent for large h
- A5a does not hold and OLS is not **consistent** and does not have a limiting distribution.
- Example + Random Walk $y_t = y_{t-1} + u_t$ + Random Walk with a drift: $y_t = \alpha + y_{t-1} + u_t$

Solution First difference is a stationary process

$$y_t - y_{t-1} = u_t$$

- If u_t is a weakly dependent process (also called integrated of order 0) then y_t is said to be difference-stationary process (integrated of order 1)
- For regression, if $\{y_t, \mathbf{x}_t\}$ are random walks (integrated at order 1), can consistently estimate the first difference equation

$$\begin{aligned} y_t - y_{t-1} &= (\mathbf{x}_t - \mathbf{x}_{t-1}\beta + \epsilon_t - \epsilon_{t-1}) \\ \Delta y_t &= \Delta\mathbf{x}\beta + \Delta u_t \end{aligned}$$

Unit Root Test

$$y_t = \alpha + \alpha y_{t-1} + u_t$$

tests if $\rho = 1$ (integrated of order 1)

- Under the null $H_0 : \rho = 1$, OLS is not consistent or asymptotically normal.
- Under the alternative $H_a : \rho < 1$, OLS is consistent and asymptotically normal.
- usual t-test is not valid, will need to use the transformed equation to produce a valid test.

Dickey-Fuller Test

$$\Delta y_t = \alpha + \theta y_{t-1} + v_t$$

where $\theta = \rho - 1$

- $H_0 : \theta = 0$ and $H_a : \theta < 0$
- Under the null, Δy_t is weakly dependent but y_{t-1} is not.
- Dickey and Fuller derived the non-normal asymptotic distribution. If you reject the null then y_t is not a random walk.

Concerns with the standard Dickey Fuller Test
1. Only considers a fairly simplistic dynamic relationship

$$\Delta y_t = \alpha + \theta y_{t-1} + \gamma_1 \Delta_{t-1} + .. + \gamma_p \Delta_{t-p} + v_t$$

- with one additional lag, under the null Δ_{y_t} is an AR(1) process and under the alternative y_t is an AR(2) process.
- Solution: include lags of Δ_{y_t} as controls.

2. Does not allow for time trend

$$\Delta y_t = \alpha + \theta y_{t-1} + \delta t + v_t$$

- allows y_t to have a quadratic relationship with t
- Solution: include time trend (changes the critical values).

Adjusted Dickey-Fuller Test

$$\Delta y_t = \alpha + \theta y_{t-1} + \delta t + \gamma_1 \Delta y_{t-1} + ... + \gamma_p \Delta y_{t-p} + v_t$$

where $\theta = 1 - \rho$

- $H_0 : \theta_1 = 0$ and $H_a : \theta_1 < 0$
- Under the null, Δy_t is weakly dependent but y_{t-1} is not
- Critical values are different with the time trend, if you reject the null then y_t is not a random walk.

12.2.5.0.1 Newey West Standard Errors If A4 does not hold, we can use Newey West Standard Errors (HAC - Heteroskedasticity Autocorrelation Consistent)

$$\hat{B} = T^{-1}\sum_{t=1}^{T} e_t^2 \mathbf{x_t'x_t} + \sum_{h=1}^{g}(1-\frac{h}{g+1})T^{-1}\sum_{t=h+1}^{T} e_t e_{t-h}(\mathbf{x_t'x_{t-h}} + \mathbf{x_{t-h}'x_t})$$

- estimates the covariances up to a distance g part
- downweights to insure $\hat{B}$ is PSD
- How to choose g:
  - For yearly data: $g = 1$ or 2 is likely to account for most of the correlation
  - For quarterly or monthly data: g should be larger ($g = 4$ or 8 for quarterly and $g = 12$ or 14 for monthly)
  - can also take integer part of $4(T/100)^{2/9}$ or integer part of $T^{1/4}$

Testing for Serial Correlation

1. Run OLS regression of y_t on $\mathbf{x_t}$ and obtain residuals e_t
2. Run OLS regression of e_t on $\mathbf{x}_t, e_{t-1}$ and test whether coefficient on e_{t-1} is significant.
3. Reject the null of no serial correlation if the coefficient is significant at the 5% level.
   - Test using heteroskedastic robust standard errors
   - can include $e_{t-2}, e_{t-3}, ..$ in step 2 to test for higher order serial correlation (t-test would now be an F-test of joint significance)

12.3 Repeated Cross Sections

For each time point (day, month, year, etc.), a set of data is sampled. This set of data can be different among different time points.

For example, you can sample different groups of students each time you survey.

Allowing structural change in pooled cross section

$$y_i = \mathbf{x}_i\beta + \delta_1 y_1 + ... + \delta_T y_T + \epsilon_i$$

Dummy variables for all but one time period

- allows different intercept for each time period
- allows outcome to change on average for each time period

Allowing for structural change in pooled cross section

$$y_i = \mathbf{x}_i\beta + \mathbf{x}_i y_1\gamma_1 + ... + \mathbf{x}_i y_T\gamma_T + \delta_1 y_1 + ... + \delta_T y_T + \epsilon_i$$

Interact x_i with time period dummy variables

- allows different slopes for each time period
- allows effects to change based on time period (**structural break**)
- Interacting all time period dummies with x_i can produce many variables - use hypothesis testing to determine which structural breaks are needed.

12.3.1 Pooled Cross Section

$$y_i = \mathbf{x_i} \ + \mathbf{x_i} \times \mathbf{y1}_{\ \mathbf{1}} + ... + \mathbf{x_i} \times \mathbf{yT}_{\ \mathbf{T}} + \ _{\mathbf{1}}\mathbf{y_1} + ... + \ _{\mathbf{T}}\mathbf{y_T} + \ _{\mathbf{i}}$$

Interact x_i with time period dummy variables

- allows different slopes for each time period
- allows effect to change based on time period (structural break)
  - interacting all time period dummies with x_i can produce many variables - use hypothesis testing to determine which structural breaks are needed.

12.4 Panel Data

Detail notes in R can be found here

Follows an individual over T time periods.

Panel data structure is like having n samples of time series data

Characteristics

- Information both across individuals and over time (cross-sectional and time-series)
- N individuals and T time periods
- Data can be either
  - Balanced: all individuals are observed in all time periods
  - Unbalanced: all individuals are not observed in all time periods.
- Assume correlation (clustering) over time for a given individual, with independence over individuals.

Types

- Short panel: many individuals and few time periods.
- Long panel: many time periods and few individuals

- Both: many time periods and many individuals

Time Trends and Time Effects

- Nonlinear
- Seasonality
- Discontinuous shocks

Regressors

- Time-invariant regressors $x_{it} = x_i$ for all t (e.g., gender, race, education) have zero within variation
- Individual-invariant regressors $x_{it} = x_t$ for all i (e.g., time trend, economy trends) have zero between variation

Variation for the dependent variable and regressors

- Overall variation: variation over time and individuals.
- Between variation: variation between individuals
- Within variation: variation within individuals (over time).

Estimate	Formula
Individual mean	$\bar{x_i} = \frac{1}{T}\sum_t x_{it}$
Overall mean	$\bar{x} = \frac{1}{NT}\sum_i \sum_t x_{it}$
Overall Variance	$s_O^2 = \frac{1}{NT-1}\sum_i \sum_t (x_{it} - \bar{x})^2$
Between variance	$s_B^2 = \frac{1}{N-1}\sum_i (\bar{x_i} - \bar{x})^2$
Within variance	$s_W^2 = \frac{1}{NT-1}\sum_i \sum_t (x_{it} - \bar{x_i})^2 = \frac{1}{NT-1}\sum_i \sum_t (x_{it} - \bar{x_i} + \bar{x})^2$

Note: $s_O^2 \approx s_B^2 + s_W^2$

Since we have n observation for each time period t, we can control for each time effect separately by including time dummies (time effects)

$$y_{it} = \mathbf{x_{it}} \ + d_1\delta_1 + ... + d_{T-1}\delta_{T-1} + \epsilon_{it}$$

Note: we cannot use these many time dummies in time series data because in time series data, our n is 1. Hence, there is no variation, and sometimes not enough data compared to variables to estimate coefficients.

Unobserved Effects Model Similar to group clustering, assume that there is a random effect that captures differences across individuals but is constant in time.

$$y_i t = \mathbf{x_{it}} \ + d_1\delta_1 + ... + d_{T-1}\delta_{T-1} + c_i + u_{it}$$

where

- $c_i + u_{it} = \epsilon_{it}$
- c_i unobserved individual heterogeneity (effect)
- u_{it} idiosyncratic shock
- ϵ_{it} unobserved error term.

12.4.1 Pooled OLS Estimator

If c_i is uncorrelated with x_{it}

$$E(\mathbf{x'_{it}}(c_i + u_{it})) = 0$$

then A3a still holds. And we have Pooled OLS consistent.

If A4 does not hold, OLS is still consistent, but not efficient, and we need cluster robust SE.

Sufficient for A3a to hold, we need

- **Exogeneity** for u_{it} A3a (contemporaneous exogeneity): $E(\mathbf{x'_{it}}u_{it}) = 0$ time varying error
- **Random Effect Assumption** (time constant error): $E(\mathbf{x'_{it}}c_i) = 0$

Pooled OLS will give you consistent coefficient estimates under A1, A2, A3a (for both u_{it} and RE assumption), and A5 (randomly sampling across i).

12.4.2 Individual-specific effects model

- If we believe that there is unobserved heterogeneity across individual (e.g., unobserved ability of an individual affects y), If the individual-specific effects are correlated with the regressors, then we have the Fixed Effects Estimator. and if they are not correlated we have the Random Effects Estimator.

12.4.2.1 Random Effects Estimator

Random Effects estimator is the Feasible GLS estimator that assumes u_{it} is serially uncorrelated and homoskedastic

- Under A1, A2, A3a (for both u_{it} and RE assumption) and A5 (randomly sampling across i), RE estimator is consistent.
  - If A4 holds for u_{it}, RE is the most efficient estimator
  - If A4 fails to hold (may be heteroskedasticity across i, and serial correlation over t), then RE is not the most efficient, but still more efficient than pooled OLS.

12.4.2.2 Fixed Effects Estimator

also known as **Within Estimator** uses within variation (over time)

If the **RE assumption** is not hold ($E(\mathbf{x'_{it}}c_i) \neq 0$), then A3a does not hold ($E(\mathbf{x'_{it}}\epsilon_i) \neq 0$).

Hence, the OLS and RE are inconsistent/biased (because of omitted variable bias)

However, FE can only fix bias due to time-invariant factors (both observables and unobservables) correlated with treatment (not time-variant factors that correlated with the treatment).

The traditional FE technique is flawed when lagged dependent variables are included in the model. (Nickell, 1981) (Narayanan and Nair, 2013)

With measurement error in the independent, FE will exacerbate the errors-in-the-variables bias.

12.4.2.2.1 Demean Approach To deal with violation in c_i, we have

$$y_{it} = \mathbf{x_{it}} \ + c_i + u_{it}$$

$$\bar{y_i} = \bar{\mathbf{x}}_\mathbf{i}\beta + c_i + \bar{u_i}$$

where the second equation is the time averaged equation

using **within transformation**, we have

$$y_{it} - \bar{y_i} = (\mathbf{x_{it}} - \bar{\mathbf{x}}_\mathbf{i})\beta + u_{it} - \bar{u_i}$$

because c_i is time constant.

The Fixed Effects estimator uses POLS on the transformed equation

$$y_{it} - \bar{y_i} = (\mathbf{x_{it}} - \bar{\mathbf{x}}_\mathbf{i})\beta + d_1\delta_1 + ... + d_{T-2}\delta_{T-2} + u_{it} - \bar{u_i}$$

- we need A3 (strict exogeneity) ($E((\mathbf{x_{it}} - \bar{\mathbf{x}}_\mathbf{i})'(u_{it} - \bar{u_i}) = 0$) to have FE consistent.
- Variables that are time constant will be absorbed into c_i. Hence we cannot make inference on time constant independent variables.
  - If you are interested in the effects of time-invariant variables, you could consider the OLS or **between estimator**
- It's recommended that you should still use cluster robust standard errors.

12.4.2.2.2 Dummy Approach Equivalent to the within transformation (i.e., mathematically equivalent to Demean Approach), we can have the fixed effect estimator be the same with the dummy regression

$$y_{it} = x_{it}\beta + d_1\delta_1 + ... + d_{T-2}\delta_{T-2} + c_1\gamma_1 + ... + c_{n-1}\gamma_{n-1} + u_{it}$$

where

$$c_i = \begin{cases} 1 & \text{if observation is i} \\ 0 & \text{otherwise} \end{cases}$$

- The standard error is incorrectly calculated.
- the FE within transformation is controlling for any difference across individual which is allowed to correlated with observables.

12.4.2.2.3 First-difference Approach Economists typically use this approach

$$y_{it} - y_{i(t-1)} = (\mathbf{x}_{it} - \mathbf{x}_{i(t-1)})\beta + +(u_{it} - u_{i(t-1)})$$

12.4.2.2.4 Fixed Effects Summary

- The three approaches are **almost** equivalent.
  - Demean Approach is mathematically equivalent to Dummy Approach
  - If you have only 1 period, all 3 are the same.
- Since fixed effect is a within estimator, only **status changes** can contribute to β variation.
  - Hence, with a small number of changes then the standard error for β will explode
- Status changes mean subjects change from (1) control to treatment group or (2) treatment to control group. Those who have status change, we call them **switchers**.
  - Treatment effect is typically **non-directional**.
  - You can give a parameter for the direction if needed.
- Issues:
  - You could have fundamental difference between switchers and non-switchers. Even though we can't definitive test this, but providing descriptive statistics on switchers and non-switchers can give us confidence in our conclusion.

  - Because fixed effects focus on bias reduction, you might have larger variance (typically, with fixed effects you will have less df)

- If the true model is random effect, economists typically don't care, especially when c_i is the random effect and $c_i \perp x_{it}$ (because RE assumption is that it is unrelated to x_{it}). The reason why economists don't care is because RE wouldn't correct bias, it only improves efficiency over OLS.
- You can estimate FE for different units (not just individuals).
- FE removes bias from time invariant factors but not without costs because it uses within variation, which imposes strict exogeneity assumption on u_{it}: $E[(x_{it} - \bar{x}_i)(u_{it} - \bar{u}_{it})] = 0$

Recall

$$Y_{it} = \beta_0 + X_{it}\beta_1 + \alpha_i + u_{it}$$

where $\epsilon_{it} = \alpha_i + u_{it}$

$$\hat{\sigma}_\epsilon^2 = \frac{SSR_{OLS}}{NT - K}$$

$$\hat{\sigma}_u^2 = \frac{SSR_{FE}}{NT - (N + K)} = \frac{SSR_{FE}}{N(T - 1) - K}$$

It's ambiguous whether your variance of error changes up or down because SSR can increase while the denominator decreases.

FE can be unbiased, but not consistent (i.e., not converging to the true effect)

12.4.2.2.5 FE Examples

12.4.2.2.6 Blau (1999)

- Intergenerational mobility
- If we transfer resources to low income family, can we generate upward mobility (increase ability)?

Mechanisms for intergenerational mobility

1. Genetic (policy can't affect) (i.e., ability endowment)
2. Environmental indirect
3. Environmental direct

$$\frac{\%\Delta\text{Human capital}}{\%\Delta\text{income}}$$

4. Financial transfer

Income measures:

1. Total household income
2. Wage income
3. Non-wage income
4. Annual versus permanent income

Core control variables:

Bad controls are those jointly determined with dependent variable

Control by mother = choice by mother

Uncontrolled by mothers:

- mother race
- location of birth
- education of parents
- household structure at age 14

$$Y_{ijt} = X_{jt}\beta_i + I_{jt}\alpha_i + \epsilon_{ijt}$$

where

- i = test
- j = individual (child)
- t = time

Grandmother's model

Since child is nested within mother and mother nested within grandmother, the fixed effect of child is included in the fixed effect of mother, which is included in the fixed-effect of grandmother

$$Y_{ijgmt} = X_{it}\beta_i + I_{jt}\alpha_i + \gamma_g + u_{ijgmt}$$

where

- i = test, j = kid, m = mother, g = grandmother
- where γ_g includes γ_m includes γ_j

Grandma fixed-effect

Pros:

- control for some genetics + fixed characteristics of how mother are raised
- can estimate effect of parameter income

Con:

- Might not be a sufficient control

Common to cluster a the fixed-effect level (common correlated component)

Fixed effect exaggerates attenuation bias

Error rate on survey can help you fix this (plug in the number only , but not the uncertainty associated with that number).

12.4.2.2.7 Babcock (2010)

$$T_{ijct} = \alpha_0 + S_{jct}\alpha_1 + X_{ijct}\alpha_2 + u_{ijct}$$

where

- S_{jct} is the average class expectation
- $X_{ijct}\alpha_2$ is the individual characteristics
- i student
- j instructor
- c course
- t time

$$T_{ijct} = \beta_0 + S_{jct}\beta_1 + X_{ijct}\beta_2 + \mu_{jc} + \epsilon_{ijct}$$

where μ_{jc} is instructor by course fixed effect (unique id), which is different from $(\theta_j + \delta_c)$

1. Decrease course shopping because conditioned on available information (μ_{jc}) (class grade and instructor's info).
2. Grade expectation change even though class materials stay the same

Identification strategy is

- Under (fixed) time-varying factor that could bias my coefficient (simultaneity)

$$Y_{ijt} = X_{it}\beta_1 + \text{Teacher Experience}_{jt}\beta_2 + \text{Teacher education}_{jt}\beta_3 + \text{Teacher score}_{it}\beta_4 + \cdots + \epsilon_{ijt}$$

Drop teacher characteristics, and include teacher dummy effect

$$Y_{ijt} = X_{it}\alpha + \Gamma_{it}\theta_j + u_{ijt}$$

where α is the within teacher (conditional on teacher fixed effect) and $j = 1 \rightarrow (J-1)$

Nuisance in the sense that we don't about the interpretation of α

The least we can say about θ_j is the teacher effect conditional on student test score.

$$Y_{ijt} = X_{it}\gamma + \epsilon_{ijt}$$

γ is between within (unconditional) and e_{ijt} is the prediction error

$$e_{ijt} = T_{it}\delta_j + \tilde{e}_{ijt}$$

where δ_j is the mean for each group

$$Y_{ijkt} = Y_{ijkt-1} + X_{it}\beta + T_{it}\tau_j + (W_i + P_k + \epsilon_{ijkt})$$

where

- Y_{ijkt-1} = lag control
- τ_j = teacher fixed time
- W_i is the student fixed effect
- P_k is the school fixed effect
- $u_{ijkt} = W_i + P_k + \epsilon_{ijkt}$

And we worry about selection on class and school

Bias in τ (for 1 teacher) is

$$\frac{1}{N_j}\sum_{i=1}^{N}(W_i + P_k + \epsilon_{ijkt})$$

where N_j = the number of student in class with teacher j

then we can $P_k + \frac{1}{N_j}\sum_{i=1}^{N_j}(W_i + \epsilon_{ijkt})$

Shocks from small class can bias τ

$$\frac{1}{N_j}\sum_{i=1}^{N_j}\epsilon_{ijkt} \neq 0$$

which will inflate the teacher fixed effect

Even if we create random teacher fixed effect and put it in the model, it still contains bias mentioned above which can still τ (but we do not know the way it will affect - whether more positive or negative).

If teachers switch schools, then we can estimate both teacher and school fixed effect (**mobility web** thin vs. thick)

Mobility web refers to the web of switchers (i.e., from one status to another).

$$Y_{ijkt} = Y_{ijk(t-1)}\alpha + X_{it}\beta + T_{it}\tau + P_k + \epsilon_{ijkt}$$

If we demean (fixed-effect), τ (teacher fixed effect) will go away

If you want to examine teacher fixed effect, we have to include teacher fixed effect

Control for school, the article argues that there is no selection bias

For $\frac{1}{N_j}\sum_{i=1}^{N_j}\epsilon_{ijkt}$ (teacher-level average residuals), $var(\tau)$ does not change with N_j (Figure 2 in the paper). In words, the quality of teachers is not a function of the number of students

If $var(\tau) = 0$ it means that teacher quality does not matter

Spin-off of Measurement Error: Sampling error or estimation error

$$\hat{\tau}_j = \tau_j + \lambda_j$$

$$var(\hat{\tau}) = var(\tau + \lambda)$$

Assume $cov(\tau_j, \lambda_j) = 0$ (reasonable) In words, your randomness in getting children does not correlation with teacher quality.

Hence,

$$var(\hat{\tau}) = var(\tau) + var(\lambda)$$
$$var(\tau) = var(\hat{\tau}) - var(\lambda)$$

We have $var(\hat{\tau})$ and we need to estimate $var(\lambda)$

$$var(\lambda) = \frac{1}{J}\sum_{j=1}^{J}\hat{\sigma}_j^2$$

where $\hat{\sigma}_j^2$ is the squared standard error of the teacher j (a function of n)

Hence,

$$\frac{var(\tau)}{var(\hat{\tau})} = \text{reliability} = \text{true variance signal}$$

also known as how much noise in $\hat{\tau}$ and

$$1 - \frac{var(\tau)}{var(\hat{\tau})} = \text{noise}$$

Even in cases where the true relationship is that τ is a function of N_j, then our recovery method for λ is still not affected

To examine our assumption

$$\hat{\tau}_j = \beta_0 + X_j\beta_1 + \epsilon_j$$

Regressing teacher fixed-effect on teacher characteristics should give us R^2 close to 0, because teacher characteristics cannot predict sampling error ($\hat{\tau}$ contain sampling error)

12.4.3 Tests for Assumptions

We typically don't test heteroskedasticity because we will use robust covariance matrix estimation anyway.

Dataset

```
library("plm")
data("EmplUK", package="plm")
data("Produc", package="plm")
data("Grunfeld", package="plm")
data("Wages", package="plm")
```

12.4.3.1 Poolability

also known as an F test of stability (or Chow test) for the coefficients

H_0: All individuals have the same coefficients (i.e., equal coefficients for all individuals).

H_a Different individuals have different coefficients.

Notes:

- Under a within (i.e., fixed) model, different intercepts for each individual are assumed
- Under random model, same intercept is assumed

```
library(plm)
plm::pooltest(inv~value+capital, data=Grunfeld, model="within")
#>
#>  F statistic
#>
#> data:  inv ~ value + capital
#> F = 5.7805, df1 = 18, df2 = 170, p-value = 1.219e-10
#> alternative hypothesis: unstability
```

Hence, we reject the null hypothesis that coefficients are stable. Then, we should use the random model.

12.4.3.2 Individual and time effects

use the Lagrange multiplier test to test the presence of individual or time or both (i.e., individual and time).

Types:

- `honda`: (Honda, 1985) Default
- `bp`: (Breusch and Pagan, 1980) for unbalanced panels
- `kw`: (King and Wu, 1997) unbalanced panels, and two-way effects
- `ghm`: (Gourieroux et al., 1982): two-way effects

```
pFtest(inv~value+capital, data=Grunfeld, effect="twoways")
#>
#>  F test for twoways effects
#>
#> data:  inv ~ value + capital
#> F = 17.403, df1 = 28, df2 = 169, p-value < 2.2e-16
#> alternative hypothesis: significant effects
pFtest(inv~value+capital, data=Grunfeld, effect="individual")
#>
#>  F test for individual effects
#>
#> data:  inv ~ value + capital
#> F = 49.177, df1 = 9, df2 = 188, p-value < 2.2e-16
#> alternative hypothesis: significant effects
pFtest(inv~value+capital, data=Grunfeld, effect="time")
#>
#>  F test for time effects
#>
#> data:  inv ~ value + capital
#> F = 0.23451, df1 = 19, df2 = 178, p-value = 0.9997
#> alternative hypothesis: significant effects
```

12.4.3.3 Cross-sectional dependence/contemporaneous correlation

- Null hypothesis: residuals across entities are not correlated.

```
pcdtest(inv~value+capital, data=Grunfeld, model="within")
#>
#>  Pesaran CD test for cross-sectional dependence in panels
#>
#> data:  inv ~ value + capital
#> z = 4.6612, p-value = 3.144e-06
#> alternative hypothesis: cross-sectional dependence
```

12.4.3.3.1 Global cross-sectional dependence

12.4.3.3.2 Local cross-sectional dependence use the same command, but supply matrix `w` to the argument.

```
pcdtest(inv~value+capital, data=Grunfeld, model="within")
#>
#>  Pesaran CD test for cross-sectional dependence in panels
#>
#> data:  inv ~ value + capital
#> z = 4.6612, p-value = 3.144e-06
#> alternative hypothesis: cross-sectional dependence
```

12.4.3.4 Serial Correlation

- Null hypothesis: there is no serial correlation
- usually seen in macro panels with long time series (large N and T), not seen in micro panels (small T and large N)
- Serial correlation can arise from individual effects(i.e., time-invariant error component), or idiosyncratic error terms (e..g, in the case of AR(1) process). But typically, when we refer to serial correlation, we refer to the second one.
- Can be
  - **marginal** test: only 1 of the two above dependence (but can be biased towards rejection)
  - **joint** test: both dependencies (but don't know which one is causing the problem)
  - **conditional** test: assume you correctly specify one dependence structure, test whether the other departure is present.

12.4.3.4.1 Unobserved effect test

- semi-parametric test (the test statistic $W \dot{\sim} N$ regardless of the distribution of the errors) with $H_0 : \sigma_\mu^2 = 0$ (i.e., no unobserved effects in the residuals), favors pooled OLS.
  - Under the null, covariance matrix of the residuals = its diagonal (off-diagonal = 0)
- It is robust against both **unobserved effects** that are constant within every group, and any kind of **serial correlation**.

```
pwtest(log(gsp) ~ log(pcap) + log(pc) + log(emp) + unemp, data = Produc)
#>
#>  Wooldridge's test for unobserved individual effects
#>
#> data:  formula
#> z = 3.9383, p-value = 8.207e-05
#> alternative hypothesis: unobserved effect
```

Here, we reject the null hypothesis that the no unobserved effects in the residuals. Hence, we will exclude using pooled OLS.

12.4.3.4.2 Locally robust tests for random effects and serial correlation

- A joint LM test for **random effects** and **serial correlation** assuming normality and homoskedasticity of the idiosyncratic errors [Baltagi and Li (1991)](Baltagi and Li, 1995)

```
pbsytest(log(gsp) ~ log(pcap) + log(pc) + log(emp) + unemp,
         data = Produc,
         test = "j")
#>
#>  Baltagi and Li AR-RE joint test
#>
#> data:  formula
#> chisq = 4187.6, df = 2, p-value < 2.2e-16
#> alternative hypothesis: AR(1) errors or random effects
```

Here, we reject the null hypothesis that there is no presence of **serial correlation,** and **random effects**. But we still do not know whether it is because of serial correlation, of random effects or of both

To know the departure from the null assumption, we can use Bera et al. (2001)'s test for first-order serial correlation or random effects (both under normality and homoskedasticity assumption of the error).

BSY for serial correlation

```
pbsytest(log(gsp) ~ log(pcap) + log(pc) + log(emp) + unemp,
         data = Produc)
#>
#>  Bera, Sosa-Escudero and Yoon locally robust test
#>
#> data:  formula
#> chisq = 52.636, df = 1, p-value = 4.015e-13
#> alternative hypothesis: AR(1) errors sub random effects
```

BSY for random effects

```
pbsytest(log(gsp)~log(pcap)+log(pc)+log(emp)+unemp,
         data=Produc,
         test="re")
#>
#>  Bera, Sosa-Escudero and Yoon locally robust test (one-sided)
#>
#> data:  formula
#> z = 57.914, p-value < 2.2e-16
#> alternative hypothesis: random effects sub AR(1) errors
```

Since BSY is only locally robust, if you "know" there is no serial correlation, then this test is based on LM test is more superior:

```
plmtest(inv ~ value + capital, data = Grunfeld,
        type = "honda")
#>
#>  Lagrange Multiplier Test - (Honda)
#>
#> data:  inv ~ value + capital
#> normal = 28.252, p-value < 2.2e-16
#> alternative hypothesis: significant effects
```

On the other hand, if you know there is no random effects, to test for serial correlation, use (Breusch, 1978)-(Godfrey, 1978)'s test

```
lmtest::bgtest()
```

If you "know" there are random effects, use (Baltagi and Li, 1995)'s. to test for serial correlation in both AR(1) and MA(1) processes.

H_0: Uncorrelated errors.

Note:

- one-sided only has power against positive serial correlation.
- applicable to only balanced panels.

```
pbltest(
    log(gsp) ~ log(pcap) + log(pc) + log(emp) + unemp,
    data = Produc,
    alternative = "onesided"
)
#>
#>  Baltagi and Li one-sided LM test
#>
#> data:  log(gsp) ~ log(pcap) + log(pc) + log(emp) + unemp
#> z = 21.69, p-value < 2.2e-16
#> alternative hypothesis: AR(1)/MA(1) errors in RE panel model
```

General serial correlation tests

- applicable to random effects model, OLS, and FE (with large T, also known as long panel).
- can also test higher-order serial correlation

```
plm::pbgtest(plm::plm(inv ~ value + capital,
                      data = Grunfeld,
                      model = "within"),
             order = 2)
#>
#>  Breusch-Godfrey/Wooldridge test for serial correlation in panel models
#>
#> data:  inv ~ value + capital
#> chisq = 42.587, df = 2, p-value = 5.655e-10
#> alternative hypothesis: serial correlation in idiosyncratic errors
```

in the case of short panels (small T and large n), we can use

```
pwartest(log(emp) ~ log(wage) + log(capital), data=EmplUK)
#>
#>  Wooldridge's test for serial correlation in FE panels
#>
#> data:  plm.model
#> F = 312.3, df1 = 1, df2 = 889, p-value < 2.2e-16
#> alternative hypothesis: serial correlation
```

12.4.3.5 Unit roots/stationarity

- Dickey-Fuller test for stochastic trends.
- Null hypothesis: the series is non-stationary (unit root)
- You would want your test to be less than the critical value (p<.5) so that there is evidence there is not unit roots.

12.4.3.6 Heteroskedasticity

- Breusch-Pagan test
- Null hypothesis: the data is homoskedastic
- If there is evidence for heteroskedasticity, robust covariance matrix is advised.
- To control for heteroskedasticity: Robust covariance matrix estimation (Sandwich estimator)
  - "white1" - for general heteroskedasticity but no serial correlation (check serial correlation first). Recommended for random effects.
  - "white2" - is "white1" restricted to a common variance within groups. Recommended for random effects.
  - "arellano" - both heteroskedasticity and serial correlation. Recommended for fixed effects

12.4.4 Model Selection

12.4.4.1 POLS vs. RE

The continuum between RE (used FGLS which more assumption) and POLS check back on the section of FGLS

Breusch-Pagan LM test

- Test for the random effect model based on the OLS residual
- Null hypothesis: variances across entities is zero. In another word, no panel effect.
- If the test is significant, RE is preferable compared to POLS

12.4.4.2 FE vs. RE

- RE does not require strict exogeneity for consistency (feedback effect between residual and covariates)

Hypothesis	If true
$H_0 : Cov(c_i, \mathbf{x_{it}}) = 0$	$\hat{\beta}_{RE}$ is consistent and efficient, while $\hat{\beta}_{FE}$ is consistent
$H_0 : Cov(c_i, \mathbf{x_{it}}) \neq 0$	$\hat{\beta}_{RE}$ is inconsistent, while $\hat{\beta}_{FE}$ is consistent

Hausman Test

For the Hausman test to run, you need to assume that

- strict exogeneity hold
- A4 to hold for u_{it}

Then,

- Hausman test statistic: $H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'(V(\hat{\beta}_{RE}) - V(\hat{\beta}_{FE}))(\hat{\beta}_{RE} - \hat{\beta}_{FE}) \sim \chi^2_{n(X)}$ where $n(X)$ is the number of parameters for the time-varying regressors.
- A low p-value means that we would reject the null hypothesis and prefer FE
- A high p-value means that we would not reject the null hypothesis and consider RE estimator.

```
gw <- plm(inv ~ value + capital, data = Grunfeld, model = "within")
gr <- plm(inv ~ value + capital, data = Grunfeld, model = "random")
phtest(gw, gr)
#>
#>  Hausman Test
#>
#> data:  inv ~ value + capital
#> chisq = 2.3304, df = 2, p-value = 0.3119
#> alternative hypothesis: one model is inconsistent
```

- Violation Estimator
- Basic Estimator
- Instrumental variable Estimator
- Variable Coefficients estimator
- Generalized Method of Moments estimator
- General FGLS estimator
- Means groups estimator
- CCEMG
- Estimator for limited dependent variables

12.4.5 Summary

- All three estimators (POLS, RE, FE) require A1, A2, A5 (for individuals) to be consistent. Additionally,
- POLS is consistent under A3a(for u_{it}): $E(\mathbf{x}'_{it}u_{it}) = 0$, and RE Assumption $E(\mathbf{x}'_{it}c_i) = 0$
  - If A4 does not hold, use cluster robust SE but POLS is not efficient
- RE is consistent under A3a(for u_{it}): $E(\mathbf{x}'_{it}u_{it}) = 0$, and RE Assumption $E(\mathbf{x}'_{it}c_i) = 0$
  - If A4 (for u_{it}) holds then usual SE are valid and RE is most efficient
  - If A4 (for u_{it}) does not hold, use cluster robust SE ,and RE is no longer most efficient (but still more efficient than POLS)
- FE is consistent under A3 $E((\mathbf{x}_{it} - \bar{\mathbf{x}}_{it})'(u_{it} - \bar{u}_{it})) = 0$
  - Cannot estimate effects of time constant variables

- A4 generally does not hold for $u_{it} - \bar{u}_{it}$ so cluster robust SE are needed

Note: A5 for individual (not for time dimension) implies that you have A5a for the entire data set.

Estimator / True Model	POLS	RE	FE
POLS	Consistent	Consistent	Inconsistent
FE	Consistent	Consistent	Consistent
RE	Consistent	Consistent	Inconsistent

Based on table provided by Ani Katchova

12.4.6 Application

12.4.6.1 `plm` package

Recommended application of `plm` can be found here and here by Yves Croissant

```
#install.packages("plm")
library("plm")

library(foreign)
Panel <- read.dta("http://dss.princeton.edu/training/Panel101.dta")

attach(Panel)
Y <- cbind(y)
X <- cbind(x1, x2, x3)

# Set data as panel data
pdata <- pdata.frame(Panel, index = c("country", "year"))

# Pooled OLS estimator
pooling <- plm(Y ~ X, data = pdata, model = "pooling")
summary(pooling)

# Between estimator
between <- plm(Y ~ X, data = pdata, model = "between")
summary(between)

# First differences estimator
firstdiff <- plm(Y ~ X, data = pdata, model = "fd")
summary(firstdiff)

# Fixed effects or within estimator
fixed <- plm(Y ~ X, data = pdata, model = "within")
```

```r
summary(fixed)

# Random effects estimator
random <- plm(Y ~ X, data = pdata, model = "random")
summary(random)

# LM test for random effects versus OLS
# Accept Null, then OLS, Reject Null then RE
plmtest(pooling, effect = "individual", type = c("bp"))
# other type: "honda", "kw"," "ghm"; other effect : "time" "twoways"


# B-P/LM and Pesaran CD (cross-sectional dependence) test
# Breusch and Pagan's original LM statistic
pcdtest(fixed, test = c("lm"))
# Pesaran's CD statistic
pcdtest(fixed, test = c("cd"))

# Serial Correlation
pbgtest(fixed)

# stationary
library("tseries")
adf.test(pdata$y, k = 2)

# LM test for fixed effects versus OLS
pFtest(fixed, pooling)

# Hausman test for fixed versus random effects model
phtest(random, fixed)

# Breusch-Pagan heteroskedasticity
library(lmtest)
bptest(y ~ x1 + factor(country), data = pdata)

# If there is presence of heteroskedasticity
## For RE model
coeftest(random) #orginal coef

# Heteroskedasticity consistent coefficients
coeftest(random, vcovHC)

t(sapply(c("HC0", "HC1", "HC2", "HC3", "HC4"), function(x)
    sqrt(diag(
        vcovHC(random, type = x)
```

```
    )))) #show HC SE of the coef
# HC0 - heteroskedasticity consistent. The default.
# HC1,HC2, HC3 - Recommended for small samples.
# HC3 gives less weight to influential observations.
# HC4 - small samples with influential observations
# HAC - heteroskedasticity and autocorrelation consistent

## For FE model
coeftest(fixed) # Original coefficients
coeftest(fixed, vcovHC) # Heteroskedasticity consistent coefficients

# Heteroskedasticity consistent coefficients (Arellano)
coeftest(fixed, vcovHC(fixed, method = "arellano"))

t(sapply(c("HC0", "HC1", "HC2", "HC3", "HC4"), function(x)
    sqrt(diag(
        vcovHC(fixed, type = x)
    )))) #show HC SE of the coef
```

Advanced

Other methods to estimate the random model:

- `"swar"`: *default* (Swamy and Arora, 1972)
- `"walhus"`: (Wallace and Hussain, 1969)
- `"amemiya"`: (Amemiya, 1971)
- `"nerlove"`" (Nerlove, 1971)

Other effects:

- Individual effects: *default*
- Time effects: `"time"`
- Individual and time effects: `"twoways"`

Note: no random two-ways effect model for `random.method = "nerlove"`

```
amemiya <-
    plm(
        Y ~ X,
        data = pdata,
        model = "random",
        random.method = "amemiya",
        effect = "twoways"
    )
```

To call the estimation of the variance of the error components

```
ercomp(Y ~ X,
       data = pdata,
```

```
        method = "amemiya",
        effect = "twoways")
```

Check for the unbalancedness. Closer to 1 indicates balanced data (Ahrens and Pincus, 1981)

```
punbalancedness(random)
```

Instrumental variable

- "bvk": default (Balestra and Varadharajan-Krishnakumar, 1987)
- "baltagi": (Baltagi, 1981)
- "am" (Amemiya and MaCurdy, 1986)
- "bms": (Breusch et al., 1989)

```
instr <-
    plm(
        Y ~ X | X_ins,
        data = pdata,
        random.method = "ht",
        model = "random",
        inst.method = "baltagi"
    )
```

12.4.6.1.1 Other Estimators

```
fixed_pvcm  <- pvcm(Y ~ X, data = pdata, model = "within")
random_pvcm <- pvcm(Y ~ X, data = pdata, model = "random")
```

12.4.6.1.1.1 Variable Coefficients Model More details can be found here

12.4.6.1.1.2 Generalized Method of Moments Estimator Typically use in dynamic models. Example is from plm package

```
z2 <- pgmm(
    log(emp) ~ lag(log(emp), 1) + lag(log(wage), 0:1) +
        lag(log(capital), 0:1) | lag(log(emp), 2:99) +
        lag(log(wage), 2:99) + lag(log(capital), 2:99),
    data = EmplUK,
    effect = "twoways",
    model = "onestep",
    transformation = "ld"
)
summary(z2, robust = TRUE)
```

12.4.6.1.1.3 General Feasible Generalized Least Squares Models Assume there is no cross-sectional correlation Robust against intragroup heteroskedasticity and serial correlation. Suited when n is much larger than T (long panel) However, inefficient under group-wise heteorskedasticity.

```
# Random Effects
zz <-
    pggls(log(emp) ~ log(wage) + log(capital),
          data = EmplUK,
          model = "pooling")

# Fixed
zz <-
    pggls(log(emp) ~ log(wage) + log(capital),
          data = EmplUK,
          model = "within")
```

12.4.6.2 `fixest` package

Available functions

- `feols`: linear models
- `feglm`: generalized linear models
- `femlm`: maximum likelihood estimation
- `feNmlm`: non-linear in RHS parameters
- `fepois`: Poisson fixed-effect
- `fenegbin`: negative binomial fixed-effect

Notes

- can only work for `fixest` object

Examples by the package's authors

```
library(fixest)
data(airquality)

# Setting a dictionary
setFixest_dict(
    c(
        Ozone   = "Ozone (ppb)",
        Solar.R = "Solar Radiation (Langleys)",
        Wind    = "Wind Speed (mph)",
        Temp    = "Temperature"
    )
)
```

```r
# On multiple estimations: see the dedicated vignette
est = feols(
    Ozone ~ Solar.R + sw0(Wind + Temp) | csw(Month, Day),
    data = airquality,
    cluster = ~ Day
)

etable(est)
#>                                          est.1              est.2
#> Dependent Var.:                     Ozone (ppb)        Ozone (ppb)
#>
#> Solar Radiation (Langleys) 0.1148*** (0.0234)   0.0522* (0.0202)
#> Wind Speed (mph)                                -3.109*** (0.7986)
#> Temperature                                      1.875*** (0.3671)
#> Fixed-Effects:              ------------------- -------------------
#> Month                                       Yes                Yes
#> Day                                          No                 No
#> __________________________ ___________________ ___________________
#> S.E.: Clustered                        by: Day            by: Day
#> Observations                               111                111
#> R2                                     0.31974            0.63686
#> Within R2                              0.12245            0.53154
#>
#>                                          est.3              est.4
#> Dependent Var.:                     Ozone (ppb)        Ozone (ppb)
#>
#> Solar Radiation (Langleys) 0.1078** (0.0329)   0.0509* (0.0236)
#> Wind Speed (mph)                                -3.289*** (0.7777)
#> Temperature                                      2.052*** (0.2415)
#> Fixed-Effects:              ----------------- -------------------
#> Month                                       Yes                Yes
#> Day                                         Yes                Yes
#> __________________________ _________________ ___________________
#> S.E.: Clustered                        by: Day            by: Day
#> Observations                               111                111
#> R2                                     0.58018            0.81604
#> Within R2                              0.12074            0.61471
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# in latex
etable(est, tex = T)
#> \begingroup
#> \centering
```

```
#> \begin{tabular}{lcccc}
#>    \tabularnewline \midrule \midrule
#>    Dependent Variable: & \multicolumn{4}{c}{Ozone (ppb)}\\
#>    Model:                      & (1)            & (2)            & (3)            &
#>    \midrule
#>    \emph{Variables}\\
#>    Solar Radiation (Langleys) & 0.1148$^{***}$ & 0.0522$^{**}$  & 0.1078$^{***}$ &
#>                               & (0.0234)       & (0.0202)       & (0.0329)       &
#>    Wind Speed (mph)           &                & -3.109$^{***}$ &                &
#>                               &                & (0.7986)       &                &
#>    Temperature                &                & 1.875$^{***}$  &                &
#>                               &                & (0.3671)       &                &
#>    \midrule
#>    \emph{Fixed-effects}\\
#>    Month                      & Yes            & Yes            & Yes            &
#>    Day                        &                &                & Yes            &
#>    \midrule
#>    \emph{Fit statistics}\\
#>    Observations               & 111            & 111            & 111            &
#>    R$^2$                      & 0.31974        & 0.63686        & 0.58018        &
#>    Within R$^2$               & 0.12245        & 0.53154        & 0.12074        &
#>    \midrule \midrule
#>    \multicolumn{5}{l}{\emph{Clustered (Day) standard-errors in parentheses}}\\
#>    \multicolumn{5}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
#> \end{tabular}
#> \par\endgroup


# get the fixed-effects coefficients for 1 model
fixedEffects = fixef(est[[1]])
summary(fixedEffects)
#> Fixed_effects coefficients
#> Number of fixed-effects for variable Month is 5.
#>  Mean = 19.6 Variance = 272
#>
#> COEFFICIENTS:
#>   Month:     5     6     7     8     9
#>          3.219 8.288 34.26 40.12 12.13

# see the fixed effects for one dimension
fixedEffects$Month
#>         5         6         7         8         9
#>  3.218876  8.287899 34.260812 40.122257 12.130971

plot(fixedEffects)
```

For multiple estimation

```
# set up
library(fixest)

# let R know the base dataset (the biggest/ultimate
# dataset that includes everything in your analysis)
base = iris

# rename variables
names(base) = c("y1", "y2", "x1", "x2", "species")

res_multi = feols(
    c(y1, y2) ~ x1 + csw(x2, x2 ^ 2) |
        sw0(species),
    data = base,
    fsplit = ~ species,
    lean = TRUE,
    vcov = "hc1" # can also clustered at the fixed effect level
)
# it's recommended to use vcov at
# estimation stage, not summary stage

summary(res_multi, "compact")
#>          sample   fixef lhs                rhs     (Intercept)                x1
#> 1  Full sample 1        y1 x1 + x2           4.19*** (0.104)  0.542*** (0.076)
#> 2  Full sample 1        y1 x1 + x2 + I(x2^2) 4.27*** (0.101)  0.719*** (0.082)
```

```
#> 3  Full sample 1        y2 x1 + x2           3.59*** (0.103) -0.257*** (0.066)
#> 4  Full sample 1        y2 x1 + x2 + I(x2^2) 3.68*** (0.097)    -0.030 (0.078)
#> 5  Full sample species  y1 x1 + x2                             0.906*** (0.076)
#> 6  Full sample species  y1 x1 + x2 + I(x2^2)                   0.900*** (0.077)
#> 7  Full sample species  y2 x1 + x2                               0.155* (0.073)
#> 8  Full sample species  y2 x1 + x2 + I(x2^2)                     0.148. (0.075)
#> 9  setosa      1        y1 x1 + x2           4.25*** (0.474)     0.399 (0.325)
#> 10 setosa      1        y1 x1 + x2 + I(x2^2) 4.00*** (0.504)     0.405 (0.325)
#> 11 setosa      1        y2 x1 + x2           2.89*** (0.416)     0.247 (0.305)
#> 12 setosa      1        y2 x1 + x2 + I(x2^2) 2.82*** (0.423)     0.248 (0.304)
#> 13 setosa      species  y1 x1 + x2                               0.399 (0.325)
#> 14 setosa      species  y1 x1 + x2 + I(x2^2)                     0.405 (0.325)
#> 15 setosa      species  y2 x1 + x2                               0.247 (0.305)
#> 16 setosa      species  y2 x1 + x2 + I(x2^2)                     0.248 (0.304)
#> 17 versicolor  1        y1 x1 + x2           2.38*** (0.423)  0.934*** (0.166)
#> 18 versicolor  1        y1 x1 + x2 + I(x2^2)   0.323 (1.44)   0.901*** (0.164)
#> 19 versicolor  1        y2 x1 + x2           1.25*** (0.275)     0.067 (0.095)
#> 20 versicolor  1        y2 x1 + x2 + I(x2^2)   0.097 (1.01)      0.048 (0.099)
#> 21 versicolor  species  y1 x1 + x2                             0.934*** (0.166)
#> 22 versicolor  species  y1 x1 + x2 + I(x2^2)                   0.901*** (0.164)
#> 23 versicolor  species  y2 x1 + x2                               0.067 (0.095)
#> 24 versicolor  species  y2 x1 + x2 + I(x2^2)                     0.048 (0.099)
#> 25 virginica   1        y1 x1 + x2             1.05. (0.539)  0.995*** (0.090)
#> 26 virginica   1        y1 x1 + x2 + I(x2^2)   -2.39 (2.04)   0.994*** (0.088)
#> 27 virginica   1        y2 x1 + x2             1.06. (0.572)     0.149 (0.107)
#> 28 virginica   1        y2 x1 + x2 + I(x2^2)    1.10 (1.76)      0.149 (0.108)
#> 29 virginica   species  y1 x1 + x2                             0.995*** (0.090)
#> 30 virginica   species  y1 x1 + x2 + I(x2^2)                   0.994*** (0.088)
#> 31 virginica   species  y2 x1 + x2                               0.149 (0.107)
#> 32 virginica   species  y2 x1 + x2 + I(x2^2)                     0.149 (0.108)
#>                  x2          I(x2^2)
#> 1   -0.320. (0.170)
#> 2  -1.52*** (0.307) 0.348*** (0.075)
#> 3    0.364* (0.142)
#> 4  -1.18*** (0.313) 0.446*** (0.074)
#> 5    -0.006 (0.163)
#> 6     0.290 (0.408)   -0.088 (0.117)
#> 7  0.623*** (0.114)
#> 8    0.951* (0.472)   -0.097 (0.125)
#> 9    0.712. (0.418)
#> 10    2.51. (1.47)     -2.91 (2.10)
#> 11    0.702 (0.560)
#> 12     1.27 (2.39)    -0.911 (3.28)
#> 13   0.712. (0.418)
#> 14    2.51. (1.47)     -2.91 (2.10)
```

```
#> 15    0.702 (0.560)
#> 16     1.27 (2.39)    -0.911 (3.28)
#> 17   -0.320 (0.364)
#> 18     3.01 (2.31)     -1.24 (0.841)
#> 19 0.929*** (0.244)
#> 20    2.80. (1.65)    -0.695 (0.583)
#> 21   -0.320 (0.364)
#> 22     3.01 (2.31)     -1.24 (0.841)
#> 23 0.929*** (0.244)
#> 24    2.80. (1.65)    -0.695 (0.583)
#> 25    0.007 (0.205)
#> 26    3.50. (2.09)    -0.870 (0.519)
#> 27 0.535*** (0.122)
#> 28    0.503 (1.56)     0.008 (0.388)
#> 29    0.007 (0.205)
#> 30    3.50. (2.09)    -0.870 (0.519)
#> 31 0.535*** (0.122)
#> 32    0.503 (1.56)     0.008 (0.388)

# call the first 3 estimated models only
etable(res_multi[1:3],

       # customize the headers
       headers = c("mod1", "mod2", "mod3"))
#>                   res_multi[1:3].1   res_multi[1:3].2    res_multi[1:3].3
#>                               mod1               mod2                mod3
#> Dependent Var.:                 y1                 y1                  y2
#>
#> Constant         4.191*** (0.1037)  4.266*** (0.1007)   3.587*** (0.1031)
#> x1              0.5418*** (0.0761) 0.7189*** (0.0815) -0.2571*** (0.0664)
#> x2               -0.3196. (0.1700) -1.522*** (0.3072)    0.3640* (0.1419)
#> x2 square                          0.3479*** (0.0748)
#> _______________ __________________ __________________ ___________________
#> S.E. type       Heteroskedas.-rob. Heteroskedas.-rob. Heteroskedast.-rob.
#> Observations                   150                150                 150
#> R2                         0.76626            0.79456             0.21310
#> Adj. R2                    0.76308            0.79034             0.20240
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

12.4.6.2.1 Multiple estimation (Left-hand side)

- When you have multiple interested dependent variables

```
etable(feols(c(y1, y2) ~ x1 + x2, base))
#>                 feols(c(y1, y2)..1 feols(c(y1, y2) ..2
#> Dependent Var.:                 y1                  y2
#>
#> Constant         4.191*** (0.0970)   3.587*** (0.0937)
#> x1              0.5418*** (0.0693) -0.2571*** (0.0669)
#> x2               -0.3196* (0.1605)    0.3640* (0.1550)
#> _______________ __________________ __________________
#> S.E. type                      IID                 IID
#> Observations                   150                 150
#> R2                         0.76626             0.21310
#> Adj. R2                    0.76308             0.20240
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

To input a list of dependent variable

```
depvars <- c("y1", "y2")

res <- lapply(depvars, function(var) {
    res <- feols(xpd(..lhs ~ x1 + x2, ..lhs = var), data = base)
    # summary(res)
})
etable(res)
#>                            model 1             model 2
#> Dependent Var.:                 y1                  y2
#>
#> Constant         4.191*** (0.0970)   3.587*** (0.0937)
#> x1              0.5418*** (0.0693) -0.2571*** (0.0669)
#> x2               -0.3196* (0.1605)    0.3640* (0.1550)
#> _______________ __________________ __________________
#> S.E. type                      IID                 IID
#> Observations                   150                 150
#> R2                         0.76626             0.21310
#> Adj. R2                    0.76308             0.20240
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

12.4.6.2.2 Multiple estimation (Right-hand side) Options to write the functions

- `sw` (stepwise): sequentially analyze each elements
  - `y ~ sw(x1, x2)` will be estimated as `y ~ x1` and `y ~ x2`
- `sw0` (stepwise 0): similar to `sw` but also estimate a model without the elements in the set first

  - `y ~ sw(x1, x2)` will be estimated as `y ~ 1` and `y ~ x1` and `y ~ x2`

- `csw` (cumulative stepwise): sequentially add each element of the set to the formula
  - `y ~ csw(x1, x2)` will be estimated as `y ~ x1` and `y ~ x1 + x2`

- `csw0` (cumulative stepwise 0): similar to `csw` but also estimate a model without the elements in the set first
  - `y ~ csw(x1, x2)` will be estimated as `y~ 1 y ~ x1` and `y ~ x1 + x2`

- `mvsw` (multiverse stepwise): all possible combination of the elements in the set (it will get large very quick).
  - `mvsw(x1, x2, x3)` will be `sw0(x1, x2, x3, x1 + x2, x1 + x3, x2 + x3, x1 + x2 + x3)`

```
etable(feols(y1 ~ x1 + x2, fsplit = ~ species, data = base))
#>                   feols(y1 ~ x1 +..1 feols(y1 ~ x1 ..2 feols(y1 ~ x1 +..3
#> Sample (species)        Full sample             setosa          versicolor
#> Dependent Var.:                  y1                 y1                  y1
#>
#> Constant          4.191*** (0.0970) 4.248*** (0.4114)  2.381*** (0.4493)
#> x1               0.5418*** (0.0693)   0.3990 (0.2958) 0.9342*** (0.1693)
#> x2                -0.3196* (0.1605)   0.7121 (0.4874)   -0.3200 (0.4024)
#> ________________ __________________ __________________ __________________
#> S.E. type                       IID                IID                 IID
#> Observations                    150                 50                  50
#> R2                          0.76626            0.11173             0.57432
#> Adj. R2                     0.76308            0.07393             0.55620
#>
#>                   feols(y1 ~ x1 +..4
#> Sample (species)          virginica
#> Dependent Var.:                  y1
#>
#> Constant            1.052* (0.5139)
#> x1               0.9946*** (0.0893)
#> x2                  0.0071 (0.1795)
#> ________________ __________________
#> S.E. type                       IID
#> Observations                     50
#> R2                          0.74689
#> Adj. R2                     0.73612
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

12.4.6.2.3 Split sample estimation

12.4.6.2.4 Standard Errors

- `iid`: errors are homoskedastic and independent and identically distributed
- `hetero`: errors are heteroskedastic using White correction
- `cluster`: errors are correlated within the cluster groups
- `newey_west`: (Newey and West, 1986) use for time series or panel data. Errors are heteroskedastic and serially correlated.
  - `vcov = newey_west ~ id + period` where `id` is the subject id and `period` is time period of the panel.
  - to specify lag period to consider `vcov = newey_west(2) ~ id + period` where we're considering 2 lag periods.
- `driscoll_kraay` (Driscoll and Kraay, 1998) use for panel data. Errors are cross-sectionally and serially correlated.
  - `vcov = discoll_kraay ~ period`
- `conley`: (Conley, 1999) for cross-section data. Errors are spatially correlated
  - `vcov = conley ~ latitude + longitude`
  - to specify the distance cutoff, `vcov = vcov_conley(lat = "lat", lon = "long", cutoff = 100, distance = "spherical")`, which will use the `conley()` helper function.
- `hc`: from the `sandwich` package
  - `vcov = function(x) sandwich::vcovHC(x, type = "HC1"))`

To let R know which SE estimation you want to use, insert `vcov = vcov_type ~ variables`

12.4.6.2.5 Small sample correction To specify that R needs to use small sample correction add

```
ssc = ssc(adj = T, cluster.adj = T)
```

Chapter 13

Variable Transformation

`trafo` vignette

13.1 Continuous Variables

Purposes:

- To change the scale of the variables
- To transform skewed data distribution to normal distribution

13.1.1 Standardization

$$x_i' = \frac{x_i - \bar{x}}{s}$$

when you have a few large numbers

13.1.2 Min-max scaling

$$x_i' = \frac{x_i - x_{max}}{x_{max} - x_{min}}$$

dependent on the min and max values, which makes it sensitive to outliers.

best to use when you have values in a fixed interval.

13.1.3 Square Root/Cube Root

- When variables have positive skewness or residuals have positive heteroskasticity.
- Frequency counts variable

- Data have many 0 or extremely small values.

13.1.4 Logarithmic

- Variables have positively skewed distribution

Formula	In case
$x_i' = \log(x_i)$	cannot work zero because `log(0) = -Inf`
$x_i' = \log(x_i + 1)$	variables with 0
$x_i' = \log(x_i + c)$	
$x_i' = \frac{x_i}{\lvert x_i \rvert} \log \lvert x_i \rvert$	variables with negative values
$x_i'^{\lambda} = \log(x_i + \sqrt{x_i^2 + \lambda})$	generalized log transformation

For the general case of $\log(x_i + c)$, choosing a constant is rather tricky.

The choice of the constant is critically important, especially when you want to do inference. It can dramatically change your model fit (see (Ekwaru and Veugelers, 2018) for the independent variable case).

Chen and Roth (2023) show that in causal inference problem, log transformation of values with meaningful 0 is problematic. But there are solutions for each approach (e.g., DID, IV).

However, assuming that you do not have 0s because of

- Censoring
- No measurement errors (stemming from measurement tools)

We can proceed choosing `c` (it's okay if your 0's are represent really small values).

```
data(cars)
cars$speed %>% head()
#> [1] 4 4 7 7 8 9

log(cars$speed) %>% head()
#> [1] 1.386294 1.386294 1.945910 1.945910 2.079442 2.197225

# log(x+1)
log1p(cars$speed) %>% head()
#> [1] 1.609438 1.609438 2.079442 2.079442 2.197225 2.302585
```

13.1.5 Exponential

- Negatively skewed data
- Underlying logarithmic trend (e.g., survival, decay)

13.1.6 Power

- Variables have negatively skewed distribution

13.1.7 Inverse/Reciprocal

- Variables have platykurtic distribution

- Data are positively skewed

- Ratio data

```
data(cars)
head(cars$dist)
#> [1]  2 10  4 22 16 10
plot(cars$dist)
```

```
plot(1/(cars$dist))
```

13.1.8 Hyperbolic arcsine

- Variables with positively skewed distribution

13.1.9 Ordered Quantile Norm

- (Bartlett, 1947)

$$x_i' = \Phi^{-1}(\frac{rank(x_i) - 1/2}{length(x)})$$

```
ord_dist <- bestNormalize::orderNorm(cars$dist)
ord_dist
#> orderNorm Transformation with 50 nonmissing obs and ties
#>  - 35 unique values
#>  - Original quantiles:
#>   0%  25%  50%  75% 100%
#>    2   26   36   56  120
ord_dist$x.t %>% hist()
```

13.1.10 Arcsinh

- Proportion variable (0-1)

```
cars$dist %>% hist()
```

```
# cars$dist %>% MASS::truehist()

as_dist <- bestNormalize::arcsinh_x(cars$dist)
```

```
as_dist
#> Standardized asinh(x) Transformation with 50 nonmissing obs.:
#>  Relevant statistics:
#>  - mean (before standardization) = 4.230843
#>  - sd (before standardization) = 0.7710887
as_dist$x.t %>% hist()
```

$$arcsinh(Y) = \log(\sqrt{1+Y^2} + Y)$$

Paper	Interpretation
Azoulay et al. (2019)	Elasticity
Faber and Gaubert (2019)	Percentage
Hjort and Poulsen (2019)	Percentage
Johnson (2020)	Percentage
Beerli et al. (2021)	Percentage
Norris et al. (2021)	Percentage
Berkouwer and Dean (2022)	Percentage
Cabral et al. (2022)	Elasticity
Carranza et al. (2022)	Percentage
Mirenda et al. (2022)	Percentage

For a simple regression model, $Y = \beta X$

When both Y and X are transformed, the coefficient estimate represents elasticity, indicating the percentage change in Y for a 1% change in X.

When only Y is in transformed and X is in raw form, the coefficient estimate represents the percentage change in Y for a one-unit change in X.

13.1.11 Lambert W x F Transformation

`LambertW` package

- Using moments to normalize data.
- Usually need to compare with the Box-Cox Transformation and Yeo-Johnson Transformation
- Can handle skewness, heavy-tailed.

```
data(cars)
head(cars$dist)
#> [1]  2 10  4 22 16 10
cars$dist %>% hist()
```

```
l_dist <- LambertW::Gaussianize(cars$dist)
# small fix
l_dist %>% hist()
```

13.1.12 Inverse Hyperbolic Sine (IHS) transformation

- Proposed by (Johnson, 1949)
- Can be applied to real numbers.

$$\begin{aligned} f(x,\theta) &= \frac{\sinh^{-1}(\theta x)}{\theta} \\ &= \frac{\log(\theta x + (\theta^2 x^2 + 1)^{1/2})}{\theta} \end{aligned}$$

13.1.13 Box-Cox Transformation

$$y^\lambda = \beta x + \epsilon$$

to fix non-linearity in the error terms

work well between (-3,3) (i.e., small transformation).

or with independent variables

$$x_i'^\lambda = \begin{cases} \frac{x_i^\lambda - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \log(x_i) & \text{if } \lambda = 0 \end{cases}$$

And the two-parameter version is

$$x_i'(\lambda_1, \lambda_2) = \begin{cases} \frac{(x_i+\lambda_2)^{\lambda_1}-1}{} & \text{if } \lambda_1 \neq 0 \\ \log(x_i + \lambda_2) & \text{if } \lambda_1 = 0 \end{cases}$$

More advances

- (Manly, 1976)

- (Bickel and Doksum, 1981; Box and Cox, 1981)

```
library(MASS)
data(cars)
mod <- lm(cars$speed ~ cars$dist, data = cars)
# check residuals
plot(mod)
```

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(cars$speed ~ cars$dist)
39
2
23
−2
−1
0
1
2

Scale−Location
√|Standardized residuals|
Fitted values
lm(cars$speed ~ cars$dist)
23
2
39
0.0
0.5
1.0
1.5
10
15
20
25

```
bc <- boxcox(mod, lambda = seq(-3, 3))
```

```
# best lambda
bc$x[which(bc$y == max(bc$y))]
#> [1] 1.242424

# model with best lambda
mod_lambda = lm(cars$speed ^ (bc$x[which(bc$y == max(bc$y))]) ~ cars$dist,
```

```
                 data = cars)
plot(mod_lambda)
```

```r
# 2-parameter version
two_bc = geoR::boxcoxfit(cars$speed)
two_bc
#> Fitted parameters:
#>    lambda      beta   sigmasq
#>  1.028798 15.253008 31.935297
#>
#> Convergence code returned by optim: 0
```

```r
plot(two_bc)
```

```r
# bestNormalize
bc_dist <- bestNormalize::boxcox(cars$dist)
bc_dist
#> Standardized Box Cox Transformation with 50 nonmissing obs.:
#>  Estimated statistics:
```

```
#>  - lambda = 0.4950628
#>  - mean (before standardization) = 10.35636
#>  - sd (before standardization) = 3.978036
bc_dist$x.t %>% hist()
```

13.1.14 Yeo-Johnson Transformation

Similar to Box-Cox Transformation (when $\lambda = 1$), but allows for negative value

$$x_i'^{\lambda} = \begin{cases} \frac{(x_i+1)^{\lambda}-1}{\lambda} & \text{if } \lambda \neq 0, x_i \geq 0 \\ \log(x_i+1) & \text{if } \lambda = 0, x_i \geq 0 \\ \frac{-[(-x_i+1)^{2-\lambda}-1]}{2-\lambda} & \text{if } \lambda \neq 2, x_i < 0 \\ -\log(-x_i+1) & \text{if } \lambda = 2, x_i < 0 \end{cases}$$

```
data(cars)
yj_speed <- bestNormalize::yeojohnson(cars$speed)
yj_speed$x.t %>% hist()
```

13.1.15 RankGauss

- Turn values into ranks, then ranks to values under normal distribution.

13.1.16 Summary

Automatically choose the best method to normalize data (code by `bestNormalize`)

```
bestdist <- bestNormalize::bestNormalize(cars$dist)
bestdist$x.t %>% hist()
```

```
boxplot(log10(bestdist$oos_preds), yaxt = "n")
```

```
# axis(2, at = log10(c(.1, .5, 1, 2, 5, 10)),
#      labels = c(.1, .5, 1, 2, 5, 10))
```

13.2 Categorical Variables

Purposes

- To transform to continuous variable (for machine learning models) (e.g., encoding/ embedding in text mining)

Approaches:

- One-hot encoding
- Label encoding
- Feature hashing
- Binary encoding
- Base N encoding
- Frequency encoding
- Target encoding
- Ordinal encoding
- Helmert encoding
- Mean encoding
- Weight of evidence encoding
- Probability ratio encoding
- Backward difference encoding
- Leave one out encoding
- James-Stein encoding
- M-estimator encoding
- Thermometer encoding

Chapter 14

Hypothesis Testing

Error types:

- Type I Error (False Positive):
  - Reality: nope
  - Diagnosis/Analysis: yes
- Type II Error (False Negative):
  - Reality: yes
  - Diagnosis/Analysis: nope

Power: The probability of rejecting the null hypothesis when it is actually false

Note:

- Always written in terms of the population parameter (β) not the estimator/estimate ($\hat{\beta}$)
- Sometimes, different disciplines prefer to use β (i.e., standardized coefficient), or $\mathbf{b}$ (i.e., unstandardized coefficient)
  - β and $\mathbf{b}$ are similar in interpretation; however, β is scale free. Hence, you can see the relative contribution of β to the dependent variable. On the other hand, $\mathbf{b}$ can be more easily used in policy decisions.
  - $$\beta_j = \mathbf{b}\frac{s_{x_j}}{s_y}$$
- Assuming the null hypothesis is true, what is the (asymptotic) distribution of the estimator
- Two-sided

$$H_0 : \beta_j = 0$$
$$H_1 : \beta_j \neq 0$$

then under the null, the OLS estimator has the following distribution

$$A1 - A3a, A5 : \sqrt{n}\hat{\beta}_j \sim N(0, Avar(\sqrt{n}\hat{\beta}_j))$$

- For the one-sided test, the null is a set of values, so now you choose the worst case single value that is hardest to prove and derive the distribution under the null
- One-sided

$$H_0 : \beta_j \geq 0$$
$$H_1 : \beta_j < 0$$

then the hardest null value to prove is $H_0 : \beta_j = 0$. Then under this specific null, the OLS estimator has the following asymptotic distribution

$$A1 - A3a, A5 : \sqrt{n}\hat{\beta}_j \sim N(0, Avar(\sqrt{n}\hat{\beta}_j))$$

14.1 Types of hypothesis testing

$H_0 : \theta = \theta_0$

$H_1 : \theta \neq \theta_0$

How far away / extreme θ can be if our null hypothesis is true

Assume that our likelihood function for q is $L(q) = q^{30}(1-q)^{70}$ **Likelihood function**

```
q = seq(0, 1, length = 100)
L = function(q) {
    q ^ 30 * (1 - q) ^ 70
}

plot(q,
     L(q),
     ylab = "L(q)",
     xlab = "q",
     type = "l")
```

Log-Likelihood function

```
q = seq(0, 1, length = 100)
l = function(q) {
    30 * log(q) + 70 * log(1 - q)
}
plot(q,
     l(q) - l(0.3),
     ylab = "l(q) - l(qhat)",
     xlab = "q",
     type = "l")
abline(v = 0.2)
```

Figure from(Fox, 1997)

typically, The likelihood ratio test (and Lagrange Multiplier (Score)) performs better with small to moderate sample sizes, but the Wald test only requires one maximization (under the full model).

14.2 Wald test

$$W = (\hat{\theta} - \theta_0)'[cov(\hat{\theta})]^{-1}(\hat{\theta} - \theta_0)$$
$$W \sim \chi^2_q$$

where $cov(\hat{\theta})$ is given by the inverse Fisher Information matrix evaluated at $\hat{\theta}$ and q is the rank of $cov(\hat{\theta})$, which is the number of non-redundant parameters in θ

Alternatively,

$$t_W = \frac{(\hat{\theta} - \theta_0)^2}{I(\theta_0)^{-1}} \sim \chi^2_{(v)}$$

where v is the degree of freedom.

Equivalently,

$$s_W = \frac{\hat{\theta} - \theta_0}{\sqrt{I(\hat{\theta})^{-1}}} \sim Z$$

How far away in the distribution your sample estimate is from the hypothesized population parameter.

For a null value, what is the probability you would have obtained a realization "more extreme" or "worse" than the estimate you actually obtained?

Significance Level (α) and Confidence Level ($1 - \alpha$)

- The significance level is the benchmark in which the probability is so low that we would have to reject the null
- The confidence level is the probability that sets the bounds on how far away the realization of the estimator would have to be to reject the null.

Test Statistics

- Standardized (transform) the estimator and null value to a test statistic that always has the same distribution
- Test Statistic for the OLS estimator for a single hypothesis

$$T = \frac{\sqrt{n}(\hat{\beta}_j - \beta_{j0})}{\sqrt{n}SE(\hat{\beta}_j)} \sim^a N(0,1)$$

Equivalently,

$$T = \frac{(\hat{\beta}_j - \beta_{j0})}{SE(\hat{\beta}_j)} \sim^a N(0,1)$$

the test statistic is another random variable that is a function of the data and null hypothesis.

- T denotes the random variable test statistic
- t denotes the single realization of the test statistic

Evaluating Test Statistic: determine whether or not we reject or fail to reject the null hypothesis at a given significance / confidence level

Three equivalent ways

1. Critical Value
2. P-value
3. Confidence Interval
4. Critical Value

For a given significance level, will determine the critical value (c)

- One-sided: $H_0 : \beta_j \geq \beta_{j0}$

$$P(T < c|H_0) = \alpha$$

Reject the null if $t < c$

- One-sided: $H_0 : \beta_j \leq \beta_{j0}$

$$P(T > c|H_0) = \alpha$$

Reject the null if $t > c$

- Two-sided: $H_0 : \beta_j \neq \beta_{j0}$

$$P(|T| > c|H_0) = \alpha$$

Reject the null if $|t| > c$

2. p-value

Calculate the probability that the test statistic was worse than the realization you have

- One-sided: $H_0 : \beta_j \geq \beta_{j0}$

$$\text{p-value} = P(T < t|H_0)$$

- One-sided: $H_0 : \beta_j \leq \beta_{j0}$

$$\text{p-value} = P(T > t|H_0)$$

- Two-sided: $H_0 : \beta_j \neq \beta_{j0}$

$$\text{p-value} = P(|T| < t|H_0)$$

reject the null if p-value $< \alpha$

3. Confidence Interval

Using the critical value associated with a null hypothesis and significance level, create an interval

$$CI(\hat{\beta}_j)_\alpha = [\hat{\beta}_j - (c \times SE(\hat{\beta}_j)), \hat{\beta}_j + (c \times SE(\hat{\beta}_j))]$$

If the null set lies outside the interval then we reject the null.

- We are not testing whether the true population value is close to the estimate, we are testing that given a field true population value of the parameter, how like it is that we observed this estimate.
- Can be interpreted as we believe with $(1-\alpha) \times 100\%$ probability that the confidence interval captures the true parameter value.

With stronger assumption (A1-A6), we could consider Finite Sample Properties

$$T = \frac{\hat{\beta}_j - \beta_{j0}}{SE(\hat{\beta}_j)} \sim T(n-k)$$

- This above distributional derivation is strongly dependent on A4 and A5
- T has a student t-distribution because the numerator is normal and the denominator is χ^2.
- Critical value and p-values will be calculated from the student t-distribution rather than the standard normal distribution.
- $n \to \infty$, $T(n-k)$ is asymptotically standard normal.

Rule of thumb

- if $n-k > 120$: the critical values and p-values from the t-distribution are (almost) the same as the critical values and p-values from the standard normal distribution.
- if $n-k < 120$
  - if (A1-A6) hold then the t-test is an exact finite distribution test

  - if (A1-A3a, A5) hold, because the t-distribution is asymptotically normal, computing the critical values from a t-distribution is still a valid asymptotic test (i.e., not quite the right critical values and p0values, the difference goes away as $n \to \infty$)

14.2.1 Multiple Hypothesis

- test multiple parameters as the same time
  - $H_0 : \beta_1 = 0$ & $\beta_2 = 0$
  - $H_0 : \beta_1 = 1$ & $\beta_2 = 0$
- perform a series of simply hypothesis does not answer the question (joint distribution vs. two marginal distributions).
- The test statistic is based on a restriction written in matrix form.

$$y = \beta_0 + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + \epsilon$$

Null hypothesis is $H_0 : \beta_1 = 0$ & $\beta_2 = 0$ can be rewritten as $H_0 : \mathbf{R}\beta - \mathbf{q} = 0$ where

- $\mathbf{R}$ is a $m \times k$ matrix where m is the number of restrictions and k is the number of parameters. $\mathbf{q}$ is a $k \times 1$ vector
- $\mathbf{R}$ "picks up" the relevant parameters while $\mathbf{q}$ is a the null value of the parameter

$$\mathbf{R} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \mathbf{q} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

Test Statistic for OLS estimator for a multiple hypothesis

$$F = \frac{(\mathbf{R}\hat{} - \mathbf{q})\hat{\Sigma}^{-1}(\mathbf{R}\hat{} - \mathbf{q})}{m} \sim^a F(m, n-k)$$

- $\hat{\Sigma}^{-1}$ is the estimator for the asymptotic variance-covariance matrix
  - if A4 holds, both the homoskedastic and heteroskedastic versions produce valid estimator
  - If A4 does not hold, only the heteroskedastic version produces valid estimators.
- When $m = 1$, there is only a single restriction, then the F-statistic is the t-statistic squared.
- F distribution is strictly positive, check [F-Distribution] for more details.

14.2.2 Linear Combination

Testing multiple parameters as the same time

$$H_0 : \beta_1 - \beta_2 = 0$$
$$H_0 : \beta_1 - \beta_2 > 0$$
$$H_0 : \beta_1 - 2 \times \beta_2 = 0$$

Each is a single restriction on a function of the parameters.

Null hypothesis:

$$H_0 : \beta_1 - \beta_2 = 0$$

can be rewritten as

$$H_0 : \mathbf{R}\beta - \mathbf{q} = 0$$

where $\mathbf{R}$=(0 1 -1 0 0) and $\mathbf{q} = 0$

14.2.3 Estimate Difference in Coefficients

There is no package to estimate for the difference between two coefficients and its CI, but a simple function created by Katherine Zee can be used to calculate this difference. Some modifications might be needed if you don't use standard `lm` model in R.

```
difftest_lm <- function(x1, x2, model) {
    diffest <-
        summary(model)$coef[x1, "Estimate"] - summary(model)$coef[x2, "Estimate"]

    vardiff <- (summary(model)$coef[x1, "Std. Error"] ^ 2 +
                    summary(model)$coef[x2, "Std. Error"] ^ 2) - (2 * (vcov(model)[x1, x2]))
    # variance of x1 + variance of x2 - 2*covariance of x1 and x2
    diffse <- sqrt(vardiff)
    tdiff <- (diffest) / (diffse)
    ptdiff <- 2 * (1 - pt(abs(tdiff), model$df, lower.tail = T))
    upr <-
        # will usually be very close to 1.96
        diffest + qt(.975, df = model$df) * diffse
    lwr <- diffest + qt(.025, df = model$df) * diffse
    df <- model$df
    return(list(
        est = round(diffest, digits = 2),
        t = round(tdiff, digits = 2),
```

```
        p = round(ptdiff, digits = 4),
        lwr = round(lwr, digits = 2),
        upr = round(upr, digits = 2),
        df = df
    ))
}
```

14.2.4 Application

```
library("car")

# Multiple hypothesis
mod.davis <- lm(weight ~ repwt, data=Davis)
linearHypothesis(mod.davis, c("(Intercept) = 0", "repwt = 1"),white.adjust = TRUE)
#> Linear hypothesis test
#>
#> Hypothesis:
#> (Intercept) = 0
#> repwt = 1
#>
#> Model 1: restricted model
#> Model 2: weight ~ repwt
#>
#> Note: Coefficient covariance matrix supplied.
#>
#>   Res.Df Df      F  Pr(>F)
#> 1    183
#> 2    181  2 3.3896 0.03588 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Linear Combination
mod.duncan <- lm(prestige ~ income + education, data=Duncan)
linearHypothesis(mod.duncan, "1*income - 1*education = 0")
#> Linear hypothesis test
#>
#> Hypothesis:
#> income - education = 0
#>
#> Model 1: restricted model
#> Model 2: prestige ~ income + education
#>
#>   Res.Df    RSS Df Sum of Sq      F Pr(>F)
#> 1     43 7518.9
```

```
#> 2     42 7506.7  1    12.195 0.0682 0.7952
```

14.2.5 Nonlinear

Suppose that we have q nonlinear functions of the parameters

$$\mathbf{h}(\theta) = \{h_1(\theta), ..., h_q(\theta)\}'$$

The,n, the Jacobian matrix ($\mathbf{H}(\theta)$), of rank q is

$$\mathbf{H}_{q\times p}(\theta) = \begin{pmatrix} \frac{\partial h_1(\theta)}{\partial \theta_1} & \cdots & \frac{\partial h_1(\theta)}{\partial \theta_p} \\ . & . & . \\ \frac{\partial h_q(\theta)}{\partial \theta_1} & \cdots & \frac{\partial h_q(\theta)}{\partial \theta_p} \end{pmatrix}$$

where the null hypothesis $H_0 : \mathbf{h}(\theta) = 0$ can be tested against the 2-sided alternative with the Wald statistic

$$W = \frac{\mathbf{h}(\hat{\ })'\{\mathbf{H}(\hat{\ })[\mathbf{F}(\hat{\ })'\mathbf{F}(\hat{\ })]^{-\mathbf{1}}\mathbf{H}(\hat{\ })'\}^{-\mathbf{1}}\mathbf{h}(\hat{\ })}{s^2 q} \sim F_{q,n-p}$$

14.3 The likelihood ratio test

$$t_{LR} = 2[l(\hat{\theta}) - l(\theta_0)] \sim \chi^2_v$$

where v is the degree of freedom.

Compare the height of the log-likelihood of the sample estimate in relation to the height of log-likelihood of the hypothesized population parameter

Alternatively,

This test considers a ratio of two maximizations,

$$L_r = \text{maximized value of the likelihood under } H_0 \text{ (the reduced model)}$$
$$L_f = \text{maximized value of the likelihood under } H_0 \cup H_a \text{ (the full model)}$$

Then, the likelihood ratio is:

$$\Lambda = \frac{L_r}{L_f}$$

which can't exceed 1 (since L_f is always at least as large as $L - r$ because L_r is the result of a maximization under a restricted set of the parameter values).

The likelihood ratio statistic is:

$$-2ln(\Lambda) = -2ln(L_r/L_f) = -2(l_r - l_f)$$
$$\lim_{n\to\infty}(-2ln(\Lambda)) \sim \chi^2_v$$

where v is the number of parameters in the full model minus the number of parameters in the reduced model.

If L_r is much smaller than L_f (the likelihood ratio exceeds $\chi^2_{\alpha,v}$), then we reject he reduced model and accept the full model at $\alpha \times 100\%$ significance level

14.4 Lagrange Multiplier (Score)

$$t_S = \frac{S(\theta_0)^2}{I(\theta_0)} \sim \chi^2_v$$

where v is the degree of freedom.

Compare the slope of the log-likelihood of the sample estimate in relation to the slope of the log-likelihood of the hypothesized population parameter

14.5 Two One-Sided Tests (TOST) Equivalence Testing

This is a good way to test whether your population effect size is within a range of practical interest (e.g., if the effect size is 0).

```
library(TOSTER)
```

Chapter 15

Marginal Effects

In cases without polynomials or interactions, it can be easy to interpret the marginal effect.

For example,

$$Y = \beta_1 X_1 + \beta_2 X_2$$

where β are the marginal effects.

Numerical derivation is easier than analytical derivation.

- We need to choose values for all the variables to calculate the marginal effect of X

Analytical derivation

$$f'(x) \equiv \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

E.g., $f(x) = X^2$

$$\begin{aligned} f'(x) &= \lim_{h \to 0} \frac{(x+h)^2 - x^2}{h} \\ &= \frac{x^2 + 2xh + h^2 - x^2}{h} \\ &= \frac{2xh + h^2}{h} \\ &= 2x + h \\ &= 2x \end{aligned}$$

For numerically approach, we "just" need to find a small h to plug in our function. However, you also need a large enough h to have numerically accurate computation (Gould et al., 2010, chapter 1)

Numerically approach

One-sided derivative

$$\begin{aligned} f'(x) &= \lim_{h \to 0} \frac{(x+h)^2 - x^2}{h} \\ &\approx \frac{f(x+h) - f(x)}{h} \end{aligned}$$

Alternatively, two-sided derivative

$$f_2'(x) \approx \frac{f(x+h) - f(x-h)}{2h}$$

Marginal effects for

- discrete variables (also known as incremental effects) are the change in $E[Y|X]$ for a one unit change in X
- continuous variables are the change in $E[Y|X]$ for very small changes in X (not unit changes), because it's a derivative, which is a limit when $h \to 0$

	Analytical derivation	Numerical derivation
Marginal Effects	Rules of expectations	Approximate analytical solution
Standard Errors	Rules of variances	Delta method using the asymptotic errors (vcov matrix)

15.1 Delta Method

- approximate the mean and variance of a function of random variables using a first-order Taylor approximation
- A semi-parametric method
- Alternative approaches:
  - Analytically derive a probability function for the margin
  - Simulation/Bootstrapping
- Resources:
  - Advanced: modmarg
  - Intermediate: UCLA stat
  - Simple: Another one

Let $G(\beta)$ be a function of the parameters β, then

$$var(G(\beta)) \approx \nabla G(\beta) cov(\beta) \nabla G(\beta)'$$

where

- $\nabla G(\beta)$ = the gradient of the partial derivatives of $G(\beta)$ (also known as the Jacobian)

15.2 Average Marginal Effect Algorithm

For one-sided derivative $\frac{\partial p(\mathbf{X},\beta)}{\partial X}$ in the probability scale

1. Estimate your model
2. For each observation i
    1. Calculate $\hat{Y}_{i0}$ which is the prediction in the probability scale using observed values
    2. Increase X (variable of interest) by a "small" amount h ($X_{new} = X + h$)
        - When X is continuous, $h = (|\bar{X}| + 0.001) \times 0.001$ where $\bar{X}$ is the mean value of X
        - When X is discrete, $h = 1$
    3. Calculate $\hat{Y}_{i1}$ which is the prediction in the probability scale using new X and other variables' observed vales.
    4. Calculate the difference between the two predictions as fraction of h: $\frac{\bar{Y}_{i1} - \bar{Y}_{i0}}{h}$
3. Average numerical derivative is $E[\frac{\bar{Y}_{i1} - \bar{Y}_{i0}}{h}] \approx \frac{\partial p(Y|\mathbf{X},\beta)}{\partial X}$

Two-sided derivatives

1. Estimate your model
2. For each observation i
    1. Calculate $\hat{Y}_{i0}$ which is the prediction in the probability scale using observed values
    2. Increase X (variable of interest) by a "small" amount h ($X_1 = X + h$) and decrease X (variable of interest) by a "small" amount h ($X_2 = X - h$)
        - When X is continuous, $h = (|\bar{X}| + 0.001) \times 0.001$ where $\bar{X}$ is the mean value of X
        - When X is discrete, $h = 1$
    3. Calculate $\hat{Y}_{i1}$ which is the prediction in the probability scale using new X_1 and other variables' observed vales.
    4. Calculate $\hat{Y}_{i2}$ which is the prediction in the probability scale using new X_2 and other variables' observed vales.
    5. Calculate the difference between the two predictions as fraction of h: $\frac{\bar{Y}_{i1} - \bar{Y}_{i2}}{2h}$

3. Average numerical derivative is $E[\frac{\bar{Y}_{i1}-\bar{Y}_{i2}}{2h}] \approx \frac{\partial p(Y|\mathbf{X},\beta)}{\partial X}$

```
library(margins)
library(tidyverse)

data("mtcars")
mod <- lm(mpg ~ cyl * disp * hp, data = mtcars)
margins::margins(mod) %>% summary()
#>  factor     AME     SE       z      p    lower   upper
#>     cyl -4.0592 3.7614 -1.0792 0.2805 -11.4313  3.3130
#>    disp -0.0350 0.0132 -2.6473 0.0081  -0.0610 -0.0091
#>      hp -0.0284 0.0185 -1.5348 0.1248  -0.0647  0.0079

# function for variable
get_mae <- function(mod, var = "disp") {
    data = mod$model

    pred <- predict(mod)

    if (class(mod$model[[{
        {
            var
        }
    }]]) == "numeric") {
        h = (abs(mean(mod$model[[var]])) + 0.01) * 0.01
    } else {
        h = 1
    }

    data[[{
        {
            var
        }
    }]] <- data[[{
{
var
}
}]] - h

    pred_new <- predict(mod, newdata = data)

    mean(pred - pred_new) / h
}

get_mae(mod, var = "disp")
#> [1] -0.03504546
```

15.3 Packages

15.3.1 MarginalEffects

`MarginalEffects` package is a successor of `margins` and `emtrends` (faster, more efficient, more adaptable). Hence, this is advocated to be used.

- A limitation is that there is no readily function to correct for multiple comparisons. Hence, one can use the `p.adjust` function to overcome this disadvantage.

Definitions from the package:

- **Marginal effects** are slopes or derivatives (i.e., effect of changes in a variable on the outcome)
  - `margins` package defines marginal effects as "partial derivatives of the regression equation with respect to each variable in the model for each unit in the data."
- **Marginal means** are averages or integrals (i.e., marginalizing across rows of a prediction grid)

To customize your plot using `plot_cme` (which is a `ggplot` class), you can check this post by the author of the `MarginalEffects` package

Causal inference with the parametric g-formula

- Because the plug-in g estimator is equivalent to the average contrast in the `marginaleffects` package.

To get predicted values

```
library(marginaleffects)
library(tidyverse)
data(mtcars)

mod <- lm(mpg ~ hp * wt * am, data = mtcars)
predictions(mod) %>% head()
#>
#>  Estimate Std. Error    z Pr(>|z|)     S 2.5 % 97.5 %
#>      22.5      0.884 25.4   <0.001 471.7  20.8   24.2
#>      20.8      1.194 17.4   <0.001 223.3  18.5   23.1
#>      25.3      0.709 35.7   <0.001 922.7  23.9   26.7
#>      20.3      0.704 28.8   <0.001 601.5  18.9   21.6
#>      17.0      0.712 23.9   <0.001 416.2  15.6   18.4
#>      19.7      0.875 22.5   <0.001 368.8  17.9   21.4
#>
#> Columns: rowid, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, mpg, hp
# for specific reference values
predictions(mod, newdata = datagrid(am = 0, wt = c(2, 4)))
```

```
#>
#>  am wt Estimate Std. Error    z Pr(>|z|)     S 2.5 % 97.5 %  hp
#>   0  2     22.0       2.04 10.8   <0.001  87.4  18.0   26.0 147
#>   0  4     16.6       1.08 15.3   <0.001 173.8  14.5   18.7 147
#>
#> Columns: rowid, estimate, std.error, statistic, p.value, s.value, conf.low, conf.hi
plot_cap(mod, condition = c("hp","wt"))
```

```
# Average Margianl Effects
mfx <- marginaleffects(mod, variables = c("hp", "wt"))
summary(mfx)
#>
#>  Term    Contrast Estimate Std. Error     z Pr(>|z|)   2.5 % 97.5 %
#>    hp mean(dY/dX)  -0.0381     0.0128 -2.98  0.00291 -0.0631 -0.013
#>    wt mean(dY/dX)  -3.9391     1.0858 -3.63  < 0.001 -6.0672 -1.811
#>
#> Columns: term, contrast, estimate, std.error, statistic, p.value, conf.low, conf.hi

# Group-Average Marginal Effects
marginaleffects::marginaleffects(mod, by = "hp", variables = "am")
#>
#>  Term          Contrast  hp Estimate Std. Error      z Pr(>|z|)   S  2.5 %
#>    am mean(1) - mean(0)  52    3.976       5.20  0.764    0.445 1.2  -6.22
#>    am mean(1) - mean(0)  62   -2.774       2.51 -1.107    0.268 1.9  -7.68
#>    am mean(1) - mean(0)  65    2.999       4.13  0.725    0.468 1.1  -5.10
#>    am mean(1) - mean(0)  66    2.025       3.48  0.582    0.561 0.8  -4.80
#>    am mean(1) - mean(0)  91    1.858       2.76  0.674    0.500 1.0  -3.54
```

```
#>    am mean(1) - mean(0)  93    1.201       2.35  0.511    0.609 0.7  -3.40
#>    am mean(1) - mean(0)  95   -1.832       1.97 -0.931    0.352 1.5  -5.69
#>    am mean(1) - mean(0)  97    0.708       2.04  0.347    0.728 0.5  -3.28
#>    am mean(1) - mean(0) 105   -2.682       2.37 -1.132    0.258 2.0  -7.32
#>    am mean(1) - mean(0) 109   -0.237       1.59 -0.149    0.881 0.2  -3.35
#>    am mean(1) - mean(0) 110   -0.640       1.57 -0.407    0.684 0.5  -3.73
#>    am mean(1) - mean(0) 113    4.081       3.94  1.037    0.300 1.7  -3.63
#>    am mean(1) - mean(0) 123   -2.098       2.10 -0.998    0.318 1.7  -6.22
#>    am mean(1) - mean(0) 150   -1.429       1.90 -0.753    0.452 1.1  -5.15
#>    am mean(1) - mean(0) 175   -0.416       1.56 -0.266    0.790 0.3  -3.48
#>    am mean(1) - mean(0) 180   -1.381       2.47 -0.560    0.576 0.8  -6.22
#>    am mean(1) - mean(0) 205   -2.873       6.24 -0.460    0.645 0.6 -15.11
#>    am mean(1) - mean(0) 215   -2.534       6.95 -0.364    0.716 0.5 -16.16
#>    am mean(1) - mean(0) 230   -1.477       7.07 -0.209    0.835 0.3 -15.34
#>    am mean(1) - mean(0) 245    1.115       2.28  0.488    0.625 0.7  -3.36
#>    am mean(1) - mean(0) 264    2.106       2.29  0.920    0.358 1.5  -2.38
#>    am mean(1) - mean(0) 335    4.027       3.24  1.243    0.214 2.2  -2.32
#>  97.5 %
#>   14.18
#>    2.14
#>   11.10
#>    8.85
#>    7.26
#>    5.80
#>    2.02
#>    4.70
#>    1.96
#>    2.87
#>    2.45
#>   11.79
#>    2.02
#>    2.29
#>    2.64
#>    3.46
#>    9.36
#>   11.09
#>   12.39
#>    5.59
#>    6.59
#>   10.38
#>
#> Columns: term, contrast, hp, estimate, std.error, statistic, p.value, s.value, conf.low, conf.

# Marginal effects at representative values
marginaleffects::marginaleffects(mod,
```

```
                                newdata = datagrid(am = 0,
                                                   wt = c(2, 4)))
#>
#>  Term Contrast am wt Estimate Std. Error      z Pr(>|z|)   S   2.5 %   97.5 %
#>    am    1 - 0  0  2   2.5465     2.7860  0.914   0.3607 1.5 -2.9139  8.00694
#>    am    1 - 0  0  4  -2.9661     3.0381 -0.976   0.3289 1.6 -8.9207  2.98852
#>    hp    dY/dX  0  2  -0.0598     0.0283 -2.115   0.0344 4.9 -0.1153 -0.00439
#>    hp    dY/dX  0  4  -0.0309     0.0187 -1.654   0.0981 3.3 -0.0676  0.00572
#>    wt    dY/dX  0  2  -2.6762     1.4194 -1.885   0.0594 4.1 -5.4582  0.10587
#>    wt    dY/dX  0  4  -2.6762     1.4199 -1.885   0.0595 4.1 -5.4591  0.10676
#>
#> Columns: rowid, term, contrast, estimate, std.error, statistic, p.value, s.value, c

# Marginal Effects at the Mean
marginaleffects::marginaleffects(mod, newdata = "mean")
#>
#>  Term Contrast Estimate Std. Error      z Pr(>|z|)    S  2.5 %  97.5 %
#>    am    1 - 0  -0.8086    1.52383 -0.531  0.59568  0.7 -3.795  2.1781
#>    hp    dY/dX  -0.0323    0.00956 -3.375  < 0.001 10.4 -0.051 -0.0135
#>    wt    dY/dX  -3.7959    1.21310 -3.129  0.00175  9.2 -6.174 -1.4183
#>
#> Columns: rowid, term, contrast, estimate, std.error, statistic, p.value, s.value, c
```

```
# counterfactual
comparisons(mod, variables = list(am = 0:1)) %>% summary()
#>
#>  Term          Contrast Estimate Std. Error      z Pr(>|z|) 2.5 % 97.5 %
#>    am mean(1) - mean(0)  -0.0481       1.85 -0.026    0.979 -3.68   3.58
#>
#> Columns: term, contrast, estimate, std.error, statistic, p.value, conf.low, conf.hi
```

15.3.2 margins

- Marginal effects are partial derivative of the regression equation with respect to each variable in the model for each unit in the data
- Average Partial Effects: the contribution of each variable the outcome scale, conditional on the other variables involved in the link function transformation of the linear predictor
- Average Marginal Effects: the marginal contribution of each variable on the scale of the linear predictor.
- Average marginal effects are the mean of these unit-specific partial derivatives over some sample

`margins` package gives the marginal effects of models (a replication of the

`margins` command in Stata).

`prediction` package gives the unit-specific and sample average predictions of models (similar to the predictive margins in Stata).

```
library(margins)

# examples by the package's authors
mod <- lm(mpg ~ cyl * hp + wt, data = mtcars)
summary(mod)
#>
#> Call:
#> lm(formula = mpg ~ cyl * hp + wt, data = mtcars)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -3.3440 -1.4144 -0.6166  1.2160  4.2815
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 52.017520   4.916935  10.579 4.18e-11 ***
#> cyl         -2.742125   0.800228  -3.427  0.00197 **
#> hp          -0.163594   0.052122  -3.139  0.00408 **
#> wt          -3.119815   0.661322  -4.718 6.51e-05 ***
#> cyl:hp       0.018954   0.006645   2.852  0.00823 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 2.242 on 27 degrees of freedom
#> Multiple R-squared:  0.8795, Adjusted R-squared:  0.8616
#> F-statistic: 49.25 on 4 and 27 DF,  p-value: 5.065e-12
```

In cases where you have interaction or polynomial terms, the coefficient estimates cannot be interpreted as the marginal effects of X on Y. Hence, if you want to know the average marginal effects of each variable then

```
summary(margins(mod))
#>  factor     AME     SE       z      p   lower   upper
#>     cyl  0.0381 0.5999  0.0636 0.9493 -1.1376  1.2139
#>      hp -0.0463 0.0145 -3.1909 0.0014 -0.0748 -0.0179
#>      wt -3.1198 0.6613 -4.7176 0.0000 -4.4160 -1.8236

# equivalently
margins_summary(mod)
#>  factor     AME     SE       z      p   lower   upper
#>     cyl  0.0381 0.5999  0.0636 0.9493 -1.1376  1.2139
#>      hp -0.0463 0.0145 -3.1909 0.0014 -0.0748 -0.0179
```

```
#>      wt -3.1198 0.6613 -4.7176 0.0000 -4.4160 -1.8236

plot(margins(mod))
```

Marginal effects at the mean (**MEM**):

- Marginal effects at the mean values of the sample
- For discrete variables, it's called average discrete change (**ADC**)

Average Marginal Effect (**AME**)

- An average of the marginal effects at each value of the sample

Marginal Effects at representative values (**MER**)

```
margins(mod, at = list(hp = 150))
#>  at(hp)    cyl       hp    wt
#>     150 0.1009 -0.04632 -3.12

margins(mod, at = list(hp = 150)) %>% summary()
#>  factor       hp     AME     SE       z      p   lower   upper
#>     cyl 150.0000  0.1009 0.6128  0.1647 0.8692 -1.1001  1.3019
#>      hp 150.0000 -0.0463 0.0145 -3.1909 0.0014 -0.0748 -0.0179
#>      wt 150.0000 -3.1198 0.6613 -4.7175 0.0000 -4.4160 -1.8236
```

15.3.3 mfx

Works well with Generalized Linear Models/`glm` package

For technical details, see the package vignette

Model	Dependent Variable	Syntax
Probit	Binary	`probitmfx`
Logit	Binary	`logitmfx`
Poisson	Count	`poissonmfx`
Negative Binomial	Count	`negbinmfx`
Beta	Rate	`betamfx`

```
library(mfx)
data("mtcars")
poissonmfx(formula = vs ~ mpg * cyl * disp, data = mtcars)
#> Call:
#> poissonmfx(formula = vs ~ mpg * cyl * disp, data = mtcars)
#>
#> Marginal Effects:
#>                     dF/dx   Std. Err.       z  P>|z|
#> mpg           1.4722e-03  8.7531e-03  0.1682 0.8664
#> cyl           6.6420e-03  3.9263e-02  0.1692 0.8657
#> disp          1.5899e-04  9.4555e-04  0.1681 0.8665
#> mpg:cyl      -3.4698e-04  2.0564e-03 -0.1687 0.8660
#> mpg:disp     -7.6794e-06  4.5545e-05 -0.1686 0.8661
#> cyl:disp     -3.3837e-05  1.9919e-04 -0.1699 0.8651
#> mpg:cyl:disp  1.6812e-06  9.8919e-06  0.1700 0.8650
```

This package can only give the marginal effect for each variable in the `glm` model, but not the average marginal effect that we might look for.

Chapter 16

Prediction and Estimation

Prediction and Estimation (or Causal Inference) serve distinct roles in understanding and modeling data.

16.1 Prediction

- **Definition**: Prediction, denoted as $\hat{y}$, is about creating an algorithm for predicting the outcome variable y from predictors x.
- **Goal**: The primary goal is loss minimization, aiming for model accuracy on unseen data:

$$\hat{f} \approx \min E_{(y,x)} L(f(x), y)$$

- **Applications in Economics**:
  - Measure variables.
  - Embed prediction tasks within parameter estimation or treatment effects.
  - Control for observed confounders.

16.2 Parameter Estimation

- **Definition**: Parameter estimation, represented by $\hat{\beta}$, focuses on estimating the relationship between y and x.
- **Goal**: The aim is consistency, ensuring that models perform well on the training data:

$$E[\hat{f}] = f$$

- **Challenges**:
  - High-dimensional spaces can lead to covariance among variables and multicollinearity.
  - This leads to the bias-variance tradeoff (Hastie et al., 2009).

16.3 Causation versus Prediction

Understanding the relationship between causation and prediction is crucial in statistical modeling.

Let Y be an outcome variable dependent on X, and our aim is to manipulate X to maximize a payoff function $\pi(X, Y)$ (Kleinberg et al., 2015). The decision on X hinges on:

$$\begin{aligned}\frac{d\pi(X,Y)}{dX} &= \frac{\partial \pi}{\partial X}(Y) + \frac{\partial \pi}{\partial Y}\frac{\partial Y}{\partial X} \\ &= \frac{\partial \pi}{\partial X}(\text{Prediction}) + \frac{\partial \pi}{\partial Y}(\text{Causation})\end{aligned}$$

Empirical work is essential for estimating the derivatives in this equation:

- $\frac{\partial Y}{\partial X}$ is required for causal inference to determine X's effect on Y,
- $\frac{\partial \pi}{\partial X}$ is required for prediction of Y.

Figure 16.1: (SICSS 2018 - Sendhil Mullainathan's presentation slide)

Chapter 17

Moderation

- Spotlight Analysis: Compare the mean of the dependent of the two groups (treatment and control) at every value (Simple Slopes Analysis)
- Floodlight Analysis: is spotlight analysis on the whole range of the moderator (Johnson-Neyman intervals)

Other Resources:

- `BANOVAL` : floodlight analysis on Bayesian ANOVA models
- `cSEM` : `doFloodlightAnalysis` in SEM model
- (Spiller et al., 2013)

Terminology:

- Main effects (slopes): coefficients that do no involve interaction terms
- Simple slope: when a continuous independent variable interact with a moderating variable, its slope at a particular level of the moderating variable
- Simple effect: when a categorical independent variable interacts with a moderating variable, its effect at a particular level of the moderating variable.

Example:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 X \times M$$

where

- β_0 = intercept
- β_1 = simple effect (slope) of X (independent variable)

- β_2 = simple effect (slope) of M (moderating variable)
- β_3 = interaction of X and M

Three types of interactions:

1. Continuous by continuous
2. Continuous by categorical
3. Categorical by categorical

When interpreting the three-way interactions, one can use the slope difference test (Dawson and Richter, 2006)

17.1 emmeans package

```
install.packages("emmeans")
```

```
library(emmeans)
```

Data set is from UCLA seminar where `gender` and `prog` are categorical

```
dat <- readRDS("data/exercise.rds") %>%
    mutate(prog = factor(prog, labels = c("jog", "swim", "read"))) %>%
    mutate(gender = factor(gender, labels = c("male", "female")))
```

17.1.1 Continuous by continuous

```
contcont <- lm(loss~hours*effort,data=dat)
summary(contcont)
#>
#> Call:
#> lm(formula = loss ~ hours * effort, data = dat)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -29.52 -10.60  -1.78  11.13  34.51
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   7.79864   11.60362   0.672   0.5017
#> hours        -9.37568    5.66392  -1.655   0.0982 .
#> effort       -0.08028    0.38465  -0.209   0.8347
#> hours:effort  0.39335    0.18750   2.098   0.0362 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 13.56 on 896 degrees of freedom
```

```
#> Multiple R-squared:  0.07818,    Adjusted R-squared:  0.07509
#> F-statistic: 25.33 on 3 and 896 DF,  p-value: 9.826e-16
```

Simple slopes for a continuous by continuous model

Spotlight analysis (Aiken and West, 2005): usually pick 3 values of moderating variable:

- Mean Moderating Variable + $\sigma\times$ (Moderating variable)
- Mean Moderating Variable
- Mean Moderating Variable - $\sigma\times$ (Moderating variable)

```
effar <- round(mean(dat$effort) + sd(dat$effort), 1)
effr  <- round(mean(dat$effort), 1)
effbr <- round(mean(dat$effort) - sd(dat$effort), 1)
```

```
# specify list of points
mylist <- list(effort = c(effbr, effr, effar))

# get the estimates
emtrends(contcont, ~ effort, var = "hours", at = mylist)
#>  effort hours.trend    SE  df lower.CL upper.CL
#>    24.5       0.261 1.352 896   -2.392     2.91
#>    29.7       2.307 0.915 896    0.511     4.10
#>    34.8       4.313 1.308 896    1.745     6.88
#>
#> Confidence level used: 0.95

# plot
mylist <- list(hours = seq(0, 4, by = 0.4),
               effort = c(effbr, effr, effar))
emmip(contcont, effort ~ hours, at = mylist, CIs = TRUE)
```

```
# statistical test for slope difference
emtrends(
    contcont,
    pairwise ~ effort,
    var = "hours",
    at = mylist,
    adjust = "none"
)
#> $emtrends
#>  effort hours.trend    SE  df lower.CL upper.CL
#>    24.5       0.261 1.352 896   -2.392     2.91
#>    29.7       2.307 0.915 896    0.511     4.10
#>    34.8       4.313 1.308 896    1.745     6.88
#>
#> Results are averaged over the levels of: hours
#> Confidence level used: 0.95
#>
#> $contrasts
#>  contrast                estimate    SE  df t.ratio p.value
#>  effort24.5 - effort29.7    -2.05 0.975 896  -2.098  0.0362
#>  effort24.5 - effort34.8    -4.05 1.931 896  -2.098  0.0362
#>  effort29.7 - effort34.8    -2.01 0.956 896  -2.098  0.0362
#>
#> Results are averaged over the levels of: hours
```

The 3 p-values are the same as the interaction term.

For publication, we use

```
library(ggplot2)

# data
mylist <- list(hours = seq(0, 4, by = 0.4),
               effort = c(effbr, effr, effar))
contcontdat <-
    emmip(contcont,
          effort ~ hours,
          at = mylist,
          CIs = TRUE,
          plotit = FALSE)
contcontdat$feffort <- factor(contcontdat$effort)
levels(contcontdat$feffort) <- c("low", "med", "high")

# plot
p  <-
    ggplot(data = contcontdat,
           aes(x = hours, y = yvar, color = feffort)) +
    geom_line()
p1 <-
    p +
    geom_ribbon(aes(ymax = UCL, ymin = LCL, fill = feffort),
                     alpha = 0.4)
p1  + labs(x = "Hours",
           y = "Weight Loss",
           color = "Effort",
           fill = "Effort")
```

17.1.2 Continuous by categorical

```
# use Female as basline
dat$gender <- relevel(dat$gender, ref = "female")

contcat <- lm(loss ~ hours * gender, data = dat)
summary(contcat)
#>
#> Call:
#> lm(formula = loss ~ hours * gender, data = dat)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -27.118 -11.350  -1.963  10.001  42.376
#>
#> Coefficients:
#>                   Estimate Std. Error t value Pr(>|t|)
#> (Intercept)          3.335      2.731   1.221    0.222
#> hours                3.315      1.332   2.489    0.013 *
#> gendermale           3.571      3.915   0.912    0.362
#> hours:gendermale    -1.724      1.898  -0.908    0.364
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 14.06 on 896 degrees of freedom
#> Multiple R-squared:  0.008433,   Adjusted R-squared:  0.005113
```

```
#> F-statistic:  2.54 on 3 and 896 DF,  p-value: 0.05523
```

Get simple slopes by each level of the categorical moderator

```
emtrends(contcat, ~ gender, var = "hours")
#>  gender hours.trend   SE  df lower.CL upper.CL
#>  female        3.32 1.33 896    0.702     5.93
#>  male          1.59 1.35 896   -1.063     4.25
#>
#> Confidence level used: 0.95

# test difference in slopes
emtrends(contcat, pairwise ~ gender, var = "hours")
#> $emtrends
#>  gender hours.trend   SE  df lower.CL upper.CL
#>  female        3.32 1.33 896    0.702     5.93
#>  male          1.59 1.35 896   -1.063     4.25
#>
#> Confidence level used: 0.95
#>
#> $contrasts
#>  contrast      estimate  SE  df t.ratio p.value
#>  female - male     1.72 1.9 896   0.908  0.3639
# which is the same as the interaction term
```

```
# plot
(mylist <- list(
    hours = seq(0, 4, by = 0.4),
    gender = c("female", "male")
))
#> $hours
#>  [1] 0.0 0.4 0.8 1.2 1.6 2.0 2.4 2.8 3.2 3.6 4.0
#>
#> $gender
#> [1] "female" "male"
emmip(contcat, gender ~ hours, at = mylist, CIs = TRUE)
```

17.1.3 Categorical by categorical

```
# relevel baseline
dat$prog   <- relevel(dat$prog, ref = "read")
dat$gender <- relevel(dat$gender, ref = "female")
```

```
catcat <- lm(loss ~ gender * prog, data = dat)
summary(catcat)
#>
#> Call:
#> lm(formula = loss ~ gender * prog, data = dat)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -19.1723  -4.1894  -0.0994   3.7506  27.6939
#>
#> Coefficients:
#>                     Estimate Std. Error t value Pr(>|t|)
#> (Intercept)          -3.6201     0.5322  -6.802 1.89e-11 ***
#> gendermale           -0.3355     0.7527  -0.446    0.656
#> progjog               7.9088     0.7527  10.507  < 2e-16 ***
#> progswim             32.7378     0.7527  43.494  < 2e-16 ***
#> gendermale:progjog    7.8188     1.0645   7.345 4.63e-13 ***
#> gendermale:progswim  -6.2599     1.0645  -5.881 5.77e-09 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#>
#> Residual standard error: 6.519 on 894 degrees of freedom
#> Multiple R-squared:  0.7875, Adjusted R-squared:  0.7863
#> F-statistic: 662.5 on 5 and 894 DF,  p-value: < 2.2e-16
```

Simple effects

```
emcatcat <- emmeans(catcat, ~ gender*prog)

# differences in predicted values
contrast(emcatcat,
         "revpairwise",
         by = "prog",
         adjust = "bonferroni")
#> prog = read:
#>  contrast      estimate    SE  df t.ratio p.value
#>  male - female   -0.335 0.753 894  -0.446  0.6559
#>
#> prog = jog:
#>  contrast      estimate    SE  df t.ratio p.value
#>  male - female    7.483 0.753 894   9.942  <.0001
#>
#> prog = swim:
#>  contrast      estimate    SE  df t.ratio p.value
#>  male - female   -6.595 0.753 894  -8.762  <.0001
```

Plot

```
emmip(catcat, prog ~ gender,CIs=TRUE)
```

Bar graph

```
catcatdat <- emmip(catcat,
                   gender ~ prog,
                   CIs = TRUE,
                   plotit = FALSE)
p <-
    ggplot(data = catcatdat,
           aes(x = prog, y = yvar, fill = gender)) +
    geom_bar(stat = "identity", position = "dodge")

p1 <-
    p + geom_errorbar(
        position = position_dodge(.9),
        width = .25,
        aes(ymax = UCL, ymin = LCL),
        alpha = 0.3
    )
p1  + labs(x = "Program", y = "Weight Loss", fill = "Gender")
```

17.2 probmod package

- Not recommend: package has serious problem with subscript.

```
install.packages("probemod")
```

```
library(probemod)

myModel <-
    lm(loss ~ hours * gender, data = dat %>%
           select(loss, hours, gender))
jnresults <- jn(myModel,
                dv = 'loss',
                iv = 'hours',
                mod = 'gender')


pickapoint(
    myModel,
    dv = 'loss',
    iv = 'hours',
    mod = 'gender',
    alpha = .01
)

plot(jnresults)
```

17.3 interactions package

- Recommend

```
install.packages("interactions")
```

17.3.1 Continuous interaction

- (at least one of the two variables is continuous)

```
library(interactions)
library(jtools) # for summ()
states <- as.data.frame(state.x77)
fiti <- lm(Income ~ Illiteracy * Murder + `HS Grad`, data = states)
summ(fiti)
```

Observations	50
Dependent variable	Income
Type	OLS linear regression

F(4,45)	10.65
R^2	0.49
Adj. R^2	0.44

	Est.	S.E.	t val.	p
(Intercept)	1414.46	737.84	1.92	0.06
Illiteracy	753.07	385.90	1.95	0.06
Murder	130.60	44.67	2.92	0.01
‘HS Grad‘	40.76	10.92	3.73	0.00
Illiteracy:Murder	-97.04	35.86	-2.71	0.01

Standard errors: OLS

For continuous moderator, the three values chosen are:

- -1 SD above the mean
- The mean
- -1 SD below the mean

```
interact_plot(fiti,
              pred = Illiteracy,
              modx = Murder,

              # if you don't want the plot to mean-center
              # centered = "none",
```

```
# exclude the mean value of the moderator
# modx.values = "plus-minus",

# split moderator's distribution into 3 groups
# modx.values = "terciles"

plot.points = T, # overlay data


# different shape for differennt levels of the moderator
point.shape = T,

# if two data points are on top one another,
# this moves them apart by little
jitter = 0.1,

# other appearance option
x.label = "X label",
y.label = "Y label",
main.title = "Title",
legend.main = "Legend Title",
colors = "blue",

# include confidence band
interval = TRUE,
int.width = 0.9,
robust = TRUE # use robust SE
)
```

To include weights from the regression inn the plot

```
fiti <- lm(Income ~ Illiteracy * Murder,
           data = states,
           weights = Population)

interact_plot(fiti,
              pred = Illiteracy,
              modx = Murder,
              plot.points = TRUE)
```

Partial Effect Plot

```
library(ggplot2)
data(cars)
fitc <- lm(cty ~ year + cyl * displ + class + fl + drv,
           data = mpg)
summ(fitc)
```

Observations	234
Dependent variable	cty
Type	OLS linear regression

F(16,217)	99.73
R^2	0.88
Adj. R^2	0.87

```
interact_plot(
    fitc,
    pred = displ,
    modx = cyl,
    # the observed data is based on displ, cyl, and model error
    partial.residuals = TRUE,
    modx.values = c(4, 5, 6, 8)
)
```

	Est.	S.E.	t val.	p
(Intercept)	-200.98	47.01	-4.28	0.00
year	0.12	0.02	5.03	0.00
cyl	-1.86	0.28	-6.69	0.00
displ	-3.56	0.66	-5.41	0.00
classcompact	-2.60	0.93	-2.80	0.01
classmidsize	-2.63	0.93	-2.82	0.01
classminivan	-4.41	1.04	-4.24	0.00
classpickup	-4.37	0.93	-4.68	0.00
classsubcompact	-2.38	0.93	-2.56	0.01
classsuv	-4.27	0.87	-4.92	0.00
fld	6.34	1.69	3.74	0.00
fle	-4.57	1.66	-2.75	0.01
flp	-1.92	1.59	-1.21	0.23
flr	-0.79	1.57	-0.50	0.61
drvf	1.40	0.40	3.52	0.00
drvr	0.49	0.46	1.06	0.29
cyl:displ	0.36	0.08	4.56	0.00

Standard errors: OLS

Check linearity assumption in the model

Plot the lines based on the subsample (red line), and whole sample (black line)

```r
x_2 <- runif(n = 200, min = -3, max = 3)
w   <- rbinom(n = 200, size = 1, prob = 0.5)
err <- rnorm(n = 200, mean = 0, sd = 4)
y_2 <- 2.5 - x_2 ^ 2 - 5 * w + 2 * w * (x_2 ^ 2) + err

data_2 <- as.data.frame(cbind(x_2, y_2, w))

model_2 <- lm(y_2 ~ x_2 * w, data = data_2)
summ(model_2)
```

Observations	200
Dependent variable	y_2
Type	OLS linear regression

F(3,196)	1.40
R^2	0.02
Adj. R^2	0.01

	Est.	S.E.	t val.	p
(Intercept)	0.06	0.53	0.12	0.91
x_2	0.55	0.31	1.79	0.07
w	0.54	0.75	0.72	0.47
x_2:w	-0.68	0.44	-1.53	0.13

Standard errors: OLS

```r
interact_plot(
    model_2,
    pred = x_2,
    modx = w,
    linearity.check = TRUE,
    plot.points = TRUE
)
```

17.3.1.1 Simple Slopes Analysis

- continuous by continuous variable interaction (still work for binary)
- conditional slope of the variable of interest (i.e., the slope of X when we hold M constant at a value)

Using `sim_slopes` it will

- mean-center all variables except the variable of interest
- For moderator that is
  - Continuous, it will pick mean, and plus/minus 1 SD
  - Categorical, it will use all factor

`sim_slopes` requires

- A regression model with an interaction term)
- Variable of interest (`pred =`)
- Moderator: (`modx =`)

```
sim_slopes(fiti,
           pred = Illiteracy,
           modx = Murder,
           johnson_neyman = FALSE)
#> SIMPLE SLOPES ANALYSIS
#>
#> Slope of Illiteracy when Murder =  5.420973 (- 1 SD):
```

```
#>
#>     Est.     S.E.   t val.      p
#> -------- -------- -------- ------
#>   -71.59   268.65    -0.27   0.79
#>
#> Slope of Illiteracy when Murder =  8.685043 (Mean):
#>
#>      Est.     S.E.   t val.      p
#> --------- -------- -------- ------
#>   -437.12   175.82    -2.49   0.02
#>
#> Slope of Illiteracy when Murder = 11.949113 (+ 1 SD):
#>
#>      Est.     S.E.   t val.      p
#> --------- -------- -------- ------
#>   -802.66   145.72    -5.51   0.00

# plot the coefficients
ss <- sim_slopes(fiti,
                 pred = Illiteracy,
                 modx = Murder,
                 modx.values = c(0, 5, 10))
plot(ss)
```

```
# table
ss <- sim_slopes(fiti,
```

```
                  pred = Illiteracy,
                  modx = Murder,
                  modx.values = c(0, 5, 10))
library(huxtable)
as_huxtable(ss)
```

Table 17.1

Value of Murder	Slope of Illiteracy
Value of Murder	slope
0.00	535.50 (458.77)
5.00	-24.44 (282.48)
10.00	-584.38 (152.37)***

17.3.1.2 Johnson-Neyman intervals

To know all the values of the moderator for which the slope of the variable of interest will be statistically significant, we can use the Johnson-Neyman interval (Johnson and Neyman, 1936)

Even though we kind of know that the alpha level when implementing the Johnson-Neyman interval is not correct (Bauer and Curran, 2005), not until recently that there is a correction for the type I and II errors (Esarey and Sumner, 2018).

Since Johnson-Neyman inflates the type I error (comparisons across all values of the moderator)

```
sim_slopes(
    fiti,
    pred = Illiteracy,
    modx = Murder,
    johnson_neyman = TRUE,
    control.fdr = TRUE,
    # correction for type I and II

    # include conditional intecepts
    # cond.int = TRUE,

    robust = "HC3",
    # rubust SE
```

```
    # don't mean-centered non-focal variables
    # centered = "none",
    jnalpha = 0.05
)
#> JOHNSON-NEYMAN INTERVAL
#>
#> When Murder is OUTSIDE the interval [-11.70, 8.75], the slope of Illiteracy
#> is p < .05.
#>
#> Note: The range of observed values of Murder is [1.40, 15.10]
#>
#> Interval calculated using false discovery rate adjusted t = 2.33
#>
#> SIMPLE SLOPES ANALYSIS
#>
#> Slope of Illiteracy when Murder =  5.420973 (- 1 SD):
#>
#>     Est.     S.E.   t val.      p
#> -------- -------- -------- ------
#>   -71.59   256.60    -0.28   0.78
#>
#> Slope of Illiteracy when Murder =  8.685043 (Mean):
#>
#>      Est.     S.E.   t val.      p
#> --------- -------- -------- ------
#>   -437.12   191.07    -2.29   0.03
#>
#> Slope of Illiteracy when Murder = 11.949113 (+ 1 SD):
#>
#>      Est.     S.E.   t val.      p
#> --------- -------- -------- ------
#>   -802.66   178.75    -4.49   0.00
```

For plotting, we can use `johnson_neyman`

```
johnson_neyman(fiti,
               pred = Illiteracy,
               modx = Murder,

               # correction for type I and II
               control.fdr = TRUE,
               alpha = .05)
#> JOHNSON-NEYMAN INTERVAL
#>
#> When Murder is OUTSIDE the interval [-22.57, 8.52], the slope of Illiteracy
#> is p < .05.
```

```
#>
#> Note: The range of observed values of Murder is [1.40, 15.10]
#>
#> Interval calculated using false discovery rate adjusted t = 2.33
```

Note:

- y-axis is the **conditional slope** of the variable of interest

17.3.1.3 3-way interaction

```
# fita3 <-
#     lm(rating ~ privileges * critical * learning,
#        data = attitude)
#
# probe_interaction(
#     fita3,
#     pred = critical,
#     modx = learning,
#     mod2 = privileges,
#     alpha = .1
# )


mtcars$cyl <- factor(mtcars$cyl,
                     labels = c("4 cylinder", "6 cylinder", "8 cylinder"))
fitc3 <- lm(mpg ~ hp * wt * cyl, data = mtcars)
```

```
interact_plot(fitc3,
              pred = hp,
              modx = wt,
              mod2 = cyl) +
    theme_apa(legend.pos = "bottomright")
```

Johnson-Neyman 3-way interaction

```
library(survey)
data(api)

dstrat <- svydesign(
    id = ~ 1,
    strata = ~ stype,
    weights = ~ pw,
    data = apistrat,
    fpc = ~ fpc
)

regmodel3 <-
    survey::svyglm(api00 ~ avg.ed * growth * enroll, design = dstrat)

sim_slopes(
    regmodel3,
    pred = growth,
    modx = avg.ed,
    mod2 = enroll,
```

```
    jnplot = TRUE
)
#> ############### While enroll (2nd moderator) =  153.0518 (- 1 SD) ##############
#>
#> JOHNSON-NEYMAN INTERVAL
#>
#> When avg.ed is OUTSIDE the interval [2.75, 3.82], the slope of growth is p
#> < .05.
#>
#> Note: The range of observed values of avg.ed is [1.38, 4.44]
#>
#> SIMPLE SLOPES ANALYSIS
#>
#> Slope of growth when avg.ed = 2.085002 (- 1 SD):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   1.25   0.32     3.86   0.00
#>
#> Slope of growth when avg.ed = 2.787381 (Mean):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   0.39   0.22     1.75   0.08
#>
#> Slope of growth when avg.ed = 3.489761 (+ 1 SD):
#>
#>    Est.   S.E.   t val.      p
#> ------- ------ -------- ------
#>   -0.48   0.35    -1.37   0.17
#>
#> ################ While enroll (2nd moderator) =  595.2821 (Mean) ###############
#>
#> JOHNSON-NEYMAN INTERVAL
#>
#> When avg.ed is OUTSIDE the interval [2.84, 7.83], the slope of growth is p
#> < .05.
#>
#> Note: The range of observed values of avg.ed is [1.38, 4.44]
#>
#> SIMPLE SLOPES ANALYSIS
#>
#> Slope of growth when avg.ed = 2.085002 (- 1 SD):
#>
#>   Est.   S.E.   t val.      p
```

```
#> ------ ------ -------- ------
#>   0.72   0.22     3.29   0.00
#>
#> Slope of growth when avg.ed = 2.787381 (Mean):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   0.34   0.16     2.16   0.03
#>
#> Slope of growth when avg.ed = 3.489761 (+ 1 SD):
#>
#>    Est.   S.E.   t val.      p
#> ------- ------ -------- ------
#>   -0.04   0.24    -0.16   0.87
#>
#> ############### While enroll (2nd moderator) = 1037.5125 (+ 1 SD) ##############
#>
#> JOHNSON-NEYMAN INTERVAL
#>
#> The Johnson-Neyman interval could not be found. Is the p value for your
#> interaction term below the specified alpha?
#>
#> SIMPLE SLOPES ANALYSIS
#>
#> Slope of growth when avg.ed = 2.085002 (- 1 SD):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   0.18   0.31     0.58   0.56
#>
#> Slope of growth when avg.ed = 2.787381 (Mean):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   0.29   0.20     1.49   0.14
#>
#> Slope of growth when avg.ed = 3.489761 (+ 1 SD):
#>
#>   Est.   S.E.   t val.      p
#> ------ ------ -------- ------
#>   0.40   0.27     1.49   0.14
```

Report

```
ss3 <-
    sim_slopes(regmodel3,
               pred = growth,
               modx = avg.ed,
               mod2 = enroll)
plot(ss3)
```

```
as_huxtable(ss3)
```

Table 17.2

enroll = 153	
Value of avg.ed	Slope of growth
Value of avg.ed	slope
2.09	1.25 (0.32)***
2.79	0.39 (0.22)#
enroll = 595.28	
Value of avg.ed	Slope of growth
3.49	-0.48 (0.35)
2.09	0.72 (0.22)**
2.79	0.34 (0.16)*
enroll = 1037.51	
Value of avg.ed	Slope of growth
3.49	-0.04 (0.24)
2.09	0.18 (0.31)
2.79	0.29 (0.20)
3.49	0.40 (0.27)

17.3.2 Categorical interaction

```
library(ggplot2)
mpg2 <- mpg %>%
    mutate(cyl = factor(cyl))

mpg2["auto"] <- "auto"
mpg2$auto[mpg2$trans %in% c("manual(m5)", "manual(m6)")] <- "manual"
mpg2$auto <- factor(mpg2$auto)
mpg2["fwd"] <- "2wd"
```

```r
mpg2$fwd[mpg2$drv == "4"] <- "4wd"
mpg2$fwd <- factor(mpg2$fwd)
## Drop the two cars with 5 cylinders (rest are 4, 6, or 8)
mpg2 <- mpg2[mpg2$cyl != "5", ]
## Fit the model
fit3 <- lm(cty ~ cyl * fwd * auto, data = mpg2)

library(jtools) # for summ()
summ(fit3)
```

Observations	230
Dependent variable	cty
Type	OLS linear regression

F(11,218)	61.37
R^2	0.76
Adj. R^2	0.74

	Est.	S.E.	t val.	p
(Intercept)	21.37	0.39	54.19	0.00
cyl6	-4.37	0.54	-8.07	0.00
cyl8	-8.37	0.67	-12.51	0.00
fwd4wd	-2.91	0.76	-3.83	0.00
automanual	1.45	0.57	2.56	0.01
cyl6:fwd4wd	0.59	0.96	0.62	0.54
cyl8:fwd4wd	2.13	0.99	2.15	0.03
cyl6:automanual	-0.76	0.90	-0.84	0.40
cyl8:automanual	0.71	1.18	0.60	0.55
fwd4wd:automanual	-1.66	1.07	-1.56	0.12
cyl6:fwd4wd:automanual	1.29	1.52	0.85	0.40
cyl8:fwd4wd:automanual	-1.39	1.76	-0.79	0.43

Standard errors: OLS

```r
cat_plot(fit3,
         pred = cyl,
         modx = fwd,
         plot.points = T)
```

```
#line plots
cat_plot(
    fit3,
    pred = cyl,
    modx = fwd,
    geom = "line",
    point.shape = TRUE,
    # colors = "Set2", # choose color
    vary.lty = TRUE
)
```

```
# bar plot
cat_plot(
    fit3,
    pred = cyl,
    modx = fwd,
    geom = "bar",
    interval = T,
    plot.points = TRUE
)
```

17.4 interactionR package

- For publication purposes
- Following
  - (Knol and VanderWeele, 2012) for presentation
  - (Hosmer and Lemeshow, 1992) for confidence intervals based on the delta method
  - (Zou, 2008) for variance recovery "mover" method
  - (Assmann et al., 1996) for bootstrapping

```
install.packages("interactionR")
```

17.5 sjPlot package

- For publication purposes (recommend, but more advanced)
- link

IV. CAUSAL INFERENCE

Chapter 18

Causal Inference

After all of the mambo jumbo that we have learned so far, I want to now talk about the concept of causality. We usually say that correlation is not causation. Then, what is causation?
One of my favorite books has explained this concept beautifully (Pearl and Mackenzie, 2018). And I am just going to quickly summarize the gist of it from my understanding. I hope that it can give you an initial grasp on the concept so that later you can continue to read up and develop a deeper understanding.

It's important to have a deep understanding regarding the method research. However, one needs to be aware of its limitation. As mentioned in various sections throughout the book, we see that we need to ask experts for number as our baseline or visit literature to gain insight from past research.

Here, we dive in a more conceptual side statistical analysis as a whole, regardless of particular approach.

You probably heard scientists say correlation doesn't mean causation. There are ridiculous spurious correlations that give a firm grip on what the previous phrase means. The pioneer who tried to use regression to infer causation in social science was Yule (1899) (but it was a fatal attempt where he found relief policy increases poverty). To make a causal inference from statistics, **the equation (function form) must be stable** under intervention (i.e., variables are manipulated). Statistics is used to be a causality-free enterprise in the past.

Not until the development of path analysis by Sewall Wright in the 1920s that the discipline started to pay attention to causation. Then, it remained dormant until the Causal Revolution (quoted Judea Pearl's words). This revolution introduced the calculus of causation which includes (1) causal diagrams), and (2) a symbolic language

The world has been using $P(Y|X)$ (statistics use to derive this), but what we want is to compare the difference between

- $P(Y|do(X))$: treatment group
- $P(Y|do(not - X))$: control group

Hence, we can see a clear difference between $P(Y|X) \neq P(Y|do(X))$

The conclusion we want to make from data is counterfactuals: **What would have happened had we not do X?**

To teach a robot to make inference, we need inference engine

FIGURE I. How an "inference engine" combines data with causal knowledge to produce answers to queries of interest. The dashed box is not part of the engine but is required for building it. Arrows could also be drawn from boxes 4 and 9 to box 1, but I have opted to keep the diagram simple.

Figure 18.1: p. 12 (Pearl and Mackenzie, 2018)

Levels of cognitive ability to be a causal learner:

1. Seeing
2. Doing
3. Imagining

Ladder of causation (associated with levels of cognitive ability as well):

1. Association: conditional probability, correlation, regression
2. Intervention
3. Counterfactuals

Level	Activity	Questions	Examples
Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in Y?	What does a symptom tell me about a disease?
Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?	What if I spend more time learning, will my result change?
Counterfactuals $P(y_x\|x', y')$	Imagining	Why? was it X that caused Y? What if I had acted differently	What if I stopped smoking a year ago?

Table by (Pearl, 2019, p. 57)

You cannot define causation from probability alone

If you say X causes Y if X raises the probability of Y." On the surface, it might sound intuitively right. But when we translate it to probability notation: $P(Y|X) > P(Y)$, it can't be more wrong. Just because you are seeing X (1st level), it **doesn't mean** the probability of Y increases.

It could be either that (1) X causes Y, or (2) Z affects both X and Y. Hence, people might use **control variables**, which translate: $P(Y|X, Z = z) > P(Y|Z = z)$, then you can be more confident in your probabilistic observation. However, the question is how can you choose Z

With the invention of the do-operator, now you can represent X causes Y as

$$P(Y|do(X)) > P(Y)$$

and with the help of causal diagram, now you can answer questions at the 2nd level (Intervention)

Note: people under econometrics might still use "Granger causality" and "vector autoregression" to use the probability language to represent causality (but it's not).

The 7 tools for Structural Causal Model framework (Pearl, 2019):

1. Encoding Causal Assumptions - transparency and testability (with graphical representation)
2. Do-calculus and the control of confounding: "back-door"
3. The algorithmization of Counterfactuals
4. Mediation Analysis and the Assessment of Direct and Indirect Effects

5. Adaptability, External validity and Sample Selection Bias: are still researched under "domain adaptation", "transfer learning"
6. Recovering from missing data
7. Causal Discovery:
    1. d-separation
    2. Functional decomposition (Hoyer et al., 2008)
    3. Spontaneous local changes (Pearl, 2014)

List of packages to do causal inference in R

Simpson's Paradox:

- A statistical association seen in an entire population is reversed in subpopulation.

Structural Causal Model accompanies graphical causal model to create more efficient language to represent causality

Structural Causal Model is the solution to the curse of dimensionality (i.e., large numbers of variable p, and small dataset n) thanks to product decomposition. It allows us to solve problems without knowing the function, parameters, or distributions of the error terms.

Suppose you have a causal chain $X \to Y \to Z$:

$$P(X = x, Y = y, Z = z) = P(X = x)P(Y = y|X = x)P(Z = z|Y = y)$$

Experimental Design	Quasi-experimental Design
Experimentalist	Observationalist
Experimental Data	Observational Data
Random Assignment (reduce treatment imbalance)	Random Sampling (reduce sample selection error)

Criticisms of quasi-experimental versus experimental designs:

- Quasi-experimental methods don't approximate well experimental results. For example,
    - LaLonde (1986) shows Matching Methods, Difference-in-differences, Tobit-2 (Heckman-type) can't approximate the experimental estimates.

Tools in a hierarchical order

1. Experimental Design: Randomized Control Trials (Gold standard): Tier 1

2. Quasi-experimental
    1. Regression Discontinuity
    2. Synthetic Difference-in-Differences
    3. Difference-In-Differences
    4. Synthetic Control
    5. Event Studies
    6. Fixed Effects Estimator 12.4.2.2
    7. Endogenous Treatment: mostly Instrumental Variables
    8. Matching Methods
    9. Interrupted Time Series
    10. Endogenous Sample Selection 33.2: mostly Heckman's correction

Internal vs. External Validity

- Internal Validity: Economists and applied scientists largely care about.
- External Validity: Localness might affect your external validity.

For many economic policies, there is a difference between **treatment** and **intention to treat**.

For example, we might have an effective vaccine (i.e., intention to treat), but it does not mean that everybody will take it (i.e., treatment).

There are four types of subjects that we deal with:

- **Non-switchers**: we don't care about non-switchers because even if we introduce or don't introduce the intervention, it won't affect them.
    - **Always takers**
    - **Never takers**
- **Switchers**
    - **Compliers**: defined as those who respect the intervention.
        * We only care about compliers because when we introduce the intervention, they will do something. When we don't have any interventions, they won't do it.
        * Tools above are used to identify the causal impact of an intervention on compliers
        * If we have only **compliers** in our dataset, then **intention to treatment = treatment effect**.

- **Defiers**: those who will go to the opposite direction of your treatment.
  - We typically aren't interested in defiers because they will do the opposite of what we want them to do. And they are typically a small group; hence, we just assume they don't exist.

	Treatment Assignment	Control Assignment
Compliers	Treated	No Treated
Always-takers	Treated	Treated
Never-takers	Not treated	No treated
Defiers	Not treated	Treated

Directional Bias due to selection into treatment comes from 2 general opposite sources

1. **Mitigation-based**: select into treatment to combat a problem
2. **Preference-based**: select into treatment because units like that kind of treatment.

18.1 Treatment effect types

This section is based on Paul Testa's note

Terminology:

- Quantities of causal interest (i.e., treatment effect types)
- Estimands: parameters of interest
- Estimators: procedures to calculate hesitates for the parameters of interest

Sources of bias (according to prof. Luke Keele)

$$\begin{aligned}&\text{Estimator - True Causal Effect}\\&= \text{Hidden bias + Misspecification bias + Statistical Noise}\\&= \text{Due to design + Due to modeling + Due to finite sample}\end{aligned}$$

18.1.1 Average Treatment Effects

Average treatment effect (ATE) is the difference in means of the treated and control groups

Randomization under Experimental Design can provide an unbiased estimate of ATE.

Let $Y_i(1)$ denote the outcome of individual i under treatment and

$Y_i(0)$ denote the outcome of individual i under control

Then, the treatment effect for individual i is the difference between her outcome under treatment and control

$$\tau_i = Y_i(1) - Y_i(0)$$

Without a time machine or dimension portal, we can only observe one of the two event: either individual i experiences the treatment or she doesn't.

Then, the ATE as a quantity of interest can come in handy since we can observe across all individuals

$$ATE = \frac{1}{N}\sum_{i=1}^{N}\tau_i = \frac{\sum_1^N Y_i(1)}{N} - \frac{\sum_i^N Y_i(0)}{N}$$

With random assignment (i.e., treatment assignment is independent of potential outcome and observables and unobservables), the observed means difference between the two groups is an unbiased estimator of the average treatment effect

$$E(Y_i(1)|D=1) = E(Y_i(1)|D=0) = E(Y_i(1))E(Y_i(0)|D=1) = E(Y_i(0)|D=0) = E(Y_i(0))$$

$$ATE = E(Y_i(1)) - E(Y_i(0))$$

Alternatively, we can write the potential outcomes model in a regression form

$$Y_i = Y_i(0) + [Y_i(1) - Y_i(0)]D_i$$

Let $\beta_{0i} = Y_i(0); \beta_{1i} = Y_i(1) - Y_i(0)$, we have

$$Y_i = \beta_{0i} + \beta_{1i}D_i$$

where

- β_{0i} = outcome if the unit did not receive any treatment
- β_{1i} = treatment effect (i.e., random coefficients for each unit i)

To understand endogeneity (i.e., nonrandom treatment assignment), we can examine a standard linear model

$$
\begin{aligned}
Y_i &= \beta_{0i} + \beta_{1i} D_i \\
&= (\bar{\beta}_0 + \epsilon_{0i}) + (\bar{\beta}_1 + \epsilon_{1i}) D_i \\
&= \bar{\beta}_0 + \epsilon_{0i} + \bar{\beta}_1 D_i + \epsilon_{1i} D_i
\end{aligned}
$$

When you have random assignment, $E(\epsilon_{0i}) = E(\epsilon_{1i}) = 0$

- No selection bias: $D_i \perp e_{0i}$
- Treatment effect is independent of treatment assignment: $D_i \perp e_{1i}$

But otherwise, residuals can correlate with D_i

For estimation,

- $\hat{\beta}_1^{OLS}$ is identical to difference in means (i.e., $Y_i(1) - Y_i(0)$)
- In case of heteroskedasticity (i.e., $\epsilon_{0i} + D_i \epsilon_{1i} \neq 0$), this residual's variance depends on X when you have heterogeneous treatment effects (i.e., $\epsilon_{1i} \neq 0$)
  - Robust SE should still give consistent estimate of $\hat{\beta}_1$ in this case
  - Alternatively, one can use two-sample t-test on difference in means with unequal variances.

18.1.2 Conditional Average Treatment Effects

Treatment effects can be different for different groups of people. In words, treatment effects can vary across subgroups.

To examine the heterogeneity across groups (e.g., men vs. women), we can estimate the conditional average treatment effects (CATE) for each subgroup

$$CATE = E(Y_i(1) - Y_i(0) | D_i, X_i))$$

18.1.3 Intent-to-treat Effects

When we encounter non-compliance (either people suppose to receive treatment don't receive it, or people suppose to be in the control group receive the treatment), treatment receipt is not independent of potential outcomes and confounders.

In this case, the difference in observed means between the treatment and control groups is not Average Treatment Effects, but Intent-to-treat Effects (ITT). In words, ITT is the treatment effect on those who **receive** the treatment

18.1.4 Local Average Treatment Effects

Instead of estimating the treatment effects of those who **receive** the treatment (i.e., Intent-to-treat Effects), you want to estimate the treatment effect of those who actually **comply** with the treatment. This is the local average treatment effects (LATE) or complier average causal effects (CACE). I assume we don't use CATE to denote complier average treatment effect because it was reserved for conditional average treatment effects.

- Using random treatment assignment as an instrument, we can recover the effect of treatment on compliers.

- As the percent of compliers increases, Intent-to-treat Effects and Local Average Treatment Effects converge

- Rule of thumb: SE(LATE) = SE(ITT)/(share of compliers)

- LATE estimate is always greater than the ITT estimate

- LATE can also be estimated using a pure placebo group (Gerber et al., 2010).

- Partial compliance is hard to study, and IV/2SLS estimator is biased, we have to use Bayesian (Long et al., 2010; Jin and Rubin, 2009, 2008).

18.1.4.1 One-sided noncompliance

- One-sided noncompliance is when in the sample, we only have compliers and never-takers
- With the exclusion restriction (i.e., excludability), never-takers have the same results in the treatment or control group (i.e., never treated)
- With random assignment, we can have the same number of never-takers in the treatment and control groups
- Hence,

$$LATE = \frac{ITT}{\text{share of compliers}}$$

18.1.4.2 Two-sided noncompliance

- Two-sided noncompliance is when in the sample, we have compliers, never-takers, and always-takers
- To estimate LATE, beyond excludability like in the One-sided noncompliance case, we need to assume that there is no defiers (i.e., monotonicity assumption) (this is excusable in practical studies)

$$LATE = \frac{ITT}{\text{share of compliers}}$$

18.1.5 Population vs. Sample Average Treatment Effects

See (Imai et al., 2008) for when the sample average treatment effect (SATE) diverges from the population average treatment effect (PATE).

To stay consistent, this section uses notations from (Imai et al., 2008)'s paper.

In a finite population N, we observe n observations ($N >> n$), where half is in the control and half is in the treatment group.

With unknown data generating process, we have

$$I_i = \begin{cases} 1 \text{ if unit i is in the sample} \\ 0 \text{ otherwise} \end{cases}$$

$$T_i = \begin{cases} 1 \text{ if unit i is in the treatment group} \\ 0 \text{ if unit i is in the control group} \end{cases}$$

$$\text{potential outcome} = \begin{cases} Y_i(1) \text{ if } T_i = 1 \\ Y_i(0) \text{ if } T_i = 0 \end{cases}$$

Observed outcome is

$$Y_i|I_i = 1 = T_iY_i(1) + (1 - T_i)Y_i(0)$$

Since we can never observed both outcome for the same individual, the treatment effect is always unobserved for unit i

$$TE_i = Y_i(1) - Y_i(0)$$

Sample average treatment effect is

$$SATE = \frac{1}{n} \sum_{i \in \{I_i = 1\}} TE_i$$

Population average treatment effect is

$$PATE = \frac{1}{N} \sum_{i=1}^{N} TE_i$$

Let X_i be observables and U_i be unobservables for unit i

The baseline estimator for SATE and PATE is

$$\begin{aligned} D = & \frac{1}{n/2} \sum_{i \in (I_i = 1, T_i = 1)} Y_i - \frac{1}{n/2} \sum_{i \in (I_i = 1, T_i = 0)} Y_i \\ & = \text{observed sample mean of the treatment group} \\ & - \text{observed sample mean of the control group} \end{aligned}$$

Let Δ be the estimation error (deviation from the truth), under an additive model

$$Y_i(t) = g_t(X_i) + h_t(U_i)$$

The decomposition of the estimation error is

$$\begin{aligned} PATE - D = \Delta = & \Delta_S + \Delta_T \\ & = (PATE - SATE) + (SATE - D) \\ & = \text{sample selection} + \text{treatment imbalance} \\ & = (\Delta_{S_X} + \Delta_{S_U}) + (\Delta_{T_X} + \Delta_{T_U}) \\ & = (\text{selection on observed} + \text{selection on unobserved}) \\ & + (\text{treatment imbalance in observed} + \text{unobserved}) \end{aligned}$$

18.1.5.1 Estimation Error from Sample Selection

Also known as sample selection error

$$\Delta_S = PATE - SATE = \frac{N-n}{N}(NATE - SATE)$$

where NATE is the non-sample average treatment effect (i.e., average treatment effect for those in the population but not in your sample:

$$NATE = \sum_{i \in (I_i = 0)} \frac{TE_i}{N-n}$$

From the equation, to have zero sample selection error (i.e., $\Delta_S = 0$), we can either

- Get $N = n$ by redefining your sample as the population of interest
- $NATE = SATE$ (e.g., TE_i is constant over i in both your selected sample, and those in the population that you did not select)

Note

- When you have heterogeneous treatment effects, **random sampling** can only warrant **sample selection bias**, not **sample selection error**.
- Since we can rarely know the true underlying distributions of the observables (X) and unobservables (U), we cannot verify whether the empirical distributions of your observables and unobservables for those in your sample is identical to that of your population (to reduce Δ_S). For special case,
  - Say you have census of your population, you can adjust for the observables X to reduce Δ_{S_X}, but still you cannot adjust your unobservables (U)
  - Say you are willing to assume TE_i is constant over
    * X_i, then $\Delta_{S_X} = 0$
    * U_i, then $\Delta_U = 0$

18.1.5.2 Estimation Error from Treatment Imbalance

Also known as treatment imbalance error

$$\Delta_T = SATE - D$$

$\Delta_T \to 0$ when treatment and control groups are balanced (i.e., identical empirical distributions) for both observables (X) and unobservables (U)

However, in reality, we can only readjust for observables, not unobservables.

	Blocking	**Matching Methods**
Definition	Random assignment within strata based on pre-treatment observables	Dropping, repeating or grouping observations to balance covariates between the treatment and control group (Rubin, 1973)
Time	Before randomization of treatments	After randomization of treatments
What if the set of covariates used to adjust is irrelevant?	Nothing happens	In the worst case scenario (e.g., these variables are uncorrelated with the treatment assignment, but correlated with the post-treatment variables), matching induces bias that is greater than just using the unadjusted difference in means
Benefits	$\Delta_{T_X} = 0$ (no imbalance on observables). But we don't know its effect on unobservables imbalance (might reduce if the unobservables are correlated with the observables)	Reduce model dependence, bias, variance, mean-square error

18.1.6 Average Treatment Effects on the Treated and Control

Average Effect of treatment on the Treated (ATT) is

$$\begin{aligned} ATT &= E(Y_i(1) - Y_i(0)|D_i = 1) \\ &= E(Y_i(1)|D_i = 1) - E(Y_i(0)|D_i = 1) \end{aligned}$$

Average Effect of treatment on the Control (ATC) (i.e., the effect **would be** for those weren't treated) is

$$\begin{aligned} ATC &= E(Y_i(1) - Y_i(0)|D_i = 0) \\ &= E(Y_i(1)|D_i = 0) - E(Y_i(0)|D_i = 0) \end{aligned}$$

Under random assignment and full compliance,

$$ATE = ATT = ATC$$

Sample average treatment effect on the treated is

$$SATT = \frac{1}{n} \sum_i TE_i$$

where

- TE_i is the treatment effect for unit i
- n is the number of treated units in the sample
- i belongs the subset (i.e., sample) of the population of interest that is treated.

Population average treatment effect on the treated is

$$PATT = \frac{1}{N} \sum_i TE_i$$

where

- TE_i is the treatment effect for unit i
- N is the number of treated units in the population
- i belongs to the population of interest that is treated.

18.1.7 Quantile Average Treatment Effects

Instead of the middle point estimate (ATE), we can also understand the changes in the distribution the outcome variable due to the treatment.

Using quantile regression and more assumptions (Abadie et al., 2002; Chernozhukov and Hansen, 2005), we can have consistent estimate of quantile treatment effects (QTE), with which we can make inference regarding a given quantile.

18.1.8 Mediation Effects

With additional assumptions (i.e., sequential ignorability (Imai et al., 2010a; Bullock and Ha, 2011)), we can examine the mechanism of the treatment on the outcome.

Under the causal framework,

- the indirect effect of treatment via a mediator is called average causal mediation effect (ACME)
- the direct effect of treatment on outcome is the average direct effect (ADE)

More in the Mediation Section 36

18.1.9 Log-odds Treatment Effects

For binary outcome variable, we might be interested in the log-odds of success. See (Freedman, 2008) on how to estimate a consistent causal effect.

Alternatively, attributable effects (Rosenbaum, 2002) can also be appropriate for binary outcome.

A. EXPERIMENTAL DESIGN

Chapter 19

Experimental Design

- Randomized Control Trials (RCT) or Experiments have always been and are likely to continue in the future to be the holy grail of causal inference, because of
  - unbiased estimates
  - elimination of confounding factors on average (covariate imbalance is always possible. Hence, you want to do Rerandomization to achieve platinum standard set by (Tukey, 1993))
- RCT means you have two group treatment (or experimental) gorp and control group. Hence, as you introduce the treatment (your exogenous variable) to the treatment group, the only expected difference in the outcomes of the two group should be due to the treatment.
- Subjects from the same population will be **randomly assigned** to either treatment or control group. This random assignment give us the confidence that changes in the outcome variable will be due only the treatment, not any other source (variable).
- It can be easier for hard science to have RCT because they can introduce the treatment, and have control environments. But it's hard for social scientists because their subjects are usually human, and some treatment can be hard to introduce, or environments are uncontrollable. Hence, social scientists have to develop different tools (Quasi-experimental) to recover causal inference or to recreate the treatment and control group environment.
- With RCT, you can easily establish internal validity
- Even though random assignment is not the same thing as *ceteris paribus* (i.e., holding everything else constant), it should have the same effect (i.e., under random manipulation, *other things equal* can be observed, on average, across treatment and control groups).

Selection Problem

Assume we have

- binary treatment $D_i = (0, 1)$
- outcome of interest Y_i for individual i
  - Y_{0i} are those were **not treated**
  - Y_{1i} are those were **treated**

$$\text{Potential Outcome} = \begin{cases} Y_{1i} \text{ if } D_i = 1 \\ Y_{0i} \text{ if } D_i = 0 \end{cases}$$

Then, what we observe in the outcome variable is

$$Y_i = Y_{0i} + (Y_{1i} - Y_{0i})D_i$$

It's likely that Y_{1i} and Y_{0i} both have their own distributions (i.e., different treatment effect for different people). Since we can't see both outcomes for the same individual (unless we have a time machine), then we can only make inference regarding the average outcome of those who were treated and those who were not.

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= (E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]) + (E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]) \\ &= (E[Y_{1i} - Y_{0i}|D_i = 1]) + (E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]) \end{aligned}$$

Observed difference in treatment = Average treatment effect on the treated + Selection bias

- **The average treatment effect** is the average between between a person who is treated and the same person (in another parallel universe) who is not treated
- **The selection bias** is the difference between those who were treated and those who weren't treated

With **random assignment** of treatment (D_i) under Experimental Design, we can have D_i independent of potential outcomes

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0)] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0)] \quad D_i \perp Y_i \\ &= E[Y_{1i} - Y_{0i}|D_i = 1] \\ &= E[Y_{1i} - Y_{0i}] \end{aligned}$$

Another representation under regression

Suppose that you know the effect is

$$Y_{1i} - Y_{0i} = \rho$$

The observed outcome variable (for an individual) can be rewritten as

$$\begin{aligned} Y_i &= E(Y_{0i}) + (Y_{1i} - Y_{0i})D_i + [Y_{0i} - E(Y_{0i})] \\ &= \alpha + \rho D_i + \eta_i \end{aligned}$$

where η_i = random variation of Y_{0i}

Hence, the conditional expectation of an individual outcome on treatment status is

$$\begin{aligned} E[Y_i|D_i = 1] &= \alpha + \rho \quad &+E[\eta_i|D_i = 1] \\ E[Y_i|D_i = 0] &= \alpha \quad &+E[\eta_i|D_i = 0] \end{aligned}$$

Thus,

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = \rho + E[\eta_i|D_i = 1] - E[\eta_i|D_i = 0]$$

where $E[\eta_i|D_i = 1] - E[\eta_i|D_i = 0]$ is the selection bias - correlation between the regression error term (η_i), and the regressor (D_i)

Under regression, we have

$$E[\eta_i|D_i = 1] - E[\eta_i|D_i = 0] = E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$$

which is the difference in outcomes between **those who weren't treated get treated** and **those who weren't treated stay untreated**

Say you have control variables (X_i), that is **uncorrelated with the treatment** (D_i), then you can include in your model, and it won't (in principle) affect your estimate of the treatment effect (ρ) with an added benefit of reducing the residual variance, which subsequently reduces the standard error of other estimates.

$$Y_i = \alpha + \rho D_i + X_i'\gamma + \eta_i$$

Examples:

- Bertrand and Mullainathan (2004) randomly assign race to a job application to study the effect of race on callbacks.

19.1 Notes

For outcomes with 0s, we can't use log-like transformation, because it's sensitive to outcome unit (Chen and Roth, 2023). For info on this issue, check [Zero-valued Outcomes]. We should use:

- **Percentage changes in the Average**: by using Poisson QMLE, we can interpret the coefficients of the effect of treatment on the treated group relative to the mean of the control group.
- **Extensive vs. Intensive Margins**: Distinguish the treatment effect on the intensive (outcome: 10 to 11) vs. extensive margins (outcome: 0 to 1).
  - To get the bounds for the intensive-margin, use Lee (2009) (assuming that treatment has a monotonic effect on outcome)

```r
set.seed(123) # For reproducibility
library(tidyverse)

n <- 1000 # Number of observations
p_treatment <- 0.5 # Probability of being treated

# Step 1: Generate the treatment variable D
D <- rbinom(n, 1, p_treatment)

# Step 2: Generate potential outcomes
# Untreated potential outcome (mostly zeroes)
Y0 <- rnorm(n, mean = 0, sd = 1) * (runif(n) < 0.3)

# Treated potential outcome (shifting both the probability of being positive - extensi
Y1 <- Y0 + rnorm(n, mean = 2, sd = 1) * (runif(n) < 0.7)

# Step 3: Combine effects based on treatment
Y_observed <- (1 - D) * Y0 + D * Y1

# Add explicit zeroes to model situations with no effect
Y_observed[Y_observed < 0] <- 0


data <-
    data.frame(
        ID = 1:n,
        Treatment = D,
        Outcome = Y_observed,
        X = rnorm(n)
    ) |>
    # whether outcome is positive
    dplyr::mutate(positive = Outcome > 0)
```

```
# Viewing the first few rows of the dataset
head(data)
#>   ID Treatment   Outcome          X positive
#> 1  1         0 0.0000000  1.4783345    FALSE
#> 2  2         1 2.2369379 -1.4067867     TRUE
#> 3  3         0 0.0000000 -1.8839721    FALSE
#> 4  4         1 3.2192276 -0.2773662     TRUE
#> 5  5         1 0.6649693  0.4304278     TRUE
#> 6  6         0 0.0000000 -0.1287867    FALSE

hist(data$Outcome)
```

- **Percentage changes in the Average**

```
library(fixest)
res_pois <-
    fepois(
        fml = Outcome ~ Treatment + X,
        data = data,
        vcov = "hetero"
    )
etable(res_pois)
#>                           res_pois
#> Dependent Var.:            Outcome
#>
#> Constant        -2.223*** (0.1440)
#> Treatment        2.579*** (0.1494)
```

```
#> X                   0.0235 (0.0406)
#> --------------- ------------------
#> S.E. type       Heteroskedas.-rob.
#> Observations                 1,000
#> Squared Cor.               0.33857
#> Pseudo R2                  0.26145
#> BIC                        1,927.9
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

To calculate the proportional effect

```
# proportional effect
exp(coefficients(res_pois)["Treatment"]) - 1
#> Treatment
#>  12.17757

# SE
exp(coefficients(res_pois)["Treatment"]) *
    sqrt(res_pois$cov.scaled["Treatment", "Treatment"])
#> Treatment
#>  1.968684
```

Hence, we conclude that the treatment effect is 1215% higher for the treated group as compared to the control group.

- **Extensive vs. Intensive Margins**

Here, we can estimate the intensive-margin treatment effect (i.e., the treatment effect for "always-takers").

```
res <- causalverse::lee_bounds(
    df = data,
    d = "Treatment",
    m = "positive",
    y = "Outcome",
    numdraws = 10
) |>
    causalverse::nice_tab(2)
print(res)
#>          term estimate std.error
#> 1 Lower bound    -0.22      0.09
#> 2 Upper bound     2.77      0.14
```

Since in this case, the bounds contains 0, we can't say much about the intensive margin for always-takers.

If we aim to examine the sensitivity of always-takers, we should consider scenar-

ios where the average outcome of compliers are $100 \times c\%$ lower or higher than that of always-takers.

We assume that $E(Y(1)|Complier) = (1-c)E(Y(1)|Always-taker)$

```
set.seed(1)
c_values = c(.1, .5, .7)

combined_res <- bind_rows(lapply(c_values, function(c) {
    res <- causalverse::lee_bounds(
        df = data,
        d = "Treatment",
        m = "positive",
        y = "Outcome",
        numdraws = 10,
        c_at_ratio = c
    )

    res$c_value <- as.character(c)
    return(res)
}))

combined_res |>
    dplyr::select(c_value, everything()) |>
    causalverse::nice_tab()
#>   c_value           term estimate std.error
#> 1     0.1 Point estimate     6.60      0.71
#> 2     0.5 Point estimate     2.54      0.13
#> 3     0.7 Point estimate     1.82      0.08
```

- If we assume $c = 0.1$ (i.e., under treatment, compliers would have an outcome equal to 10% of the outcome of always-takers), then the intensive-margin effect for always-takers is 6.6 more in the unit of the outcome.
- If we assume $c = 0.5$ (i.e., under treatment, compliers would have an outcome equal to 50% of the outcome of always-takers), then the intensive-margin effect for always-takers is 2.54 more in the unit of the outcome.

19.2 Semi-random Experiment

Chicago Open Enrollment Program (Cullen et al., 2005)

- Students can apply to "choice" schools
- Many schools are oversubscribed (Demand > Supply)
- Resolve scarcity via random lotteries

- Non-random enrollment, we only have random lottery which mean the above

Let

$$\delta_j = E(Y_i|Enroll_{ij} = 1; Apply_{ij} = 1) - E(Y_i|Enroll_{ij} = 0; Apply_{ij} = 1)$$

and

$$\theta_j = E(Y_i|Win_{ij} = 1; Apply_{ij} = 1) - E(Y_i|Win_{ij} = 0; Apply_{ij} = 1)$$

Hence, we can clearly see that $\delta_j \neq \theta_j$ because you can only enroll, but you cannot ensure that you will win. Thus, **intention to treat is different from treatment effect**.

Non-random enrollment, we only have random lottery which means we can only estimate θ_j

To recover the true treatment effect, we can use

$$\delta_j = \frac{E(Y_i|W_{ij} = 1; A_{ij} = 1) - E(Y_i|W_{ij} = 0; A_{ij} = 1)}{P(Enroll_{ij} = 1|W_{ij} = 1; A_{ij} = 1) - P(Enroll_{ij} = 1|W_{ij} = 0; A_{ij} = 1)}$$

where

- δ_j = treatment effect
- W = Whether students win the lottery
- A = Whether student apply for the lottery
- i = application
- j = school

Say that we have

10 win

Number students	Type	Selection effect	Treatment effect	Total effect
1	Always Takers	+0.2	+1	+1.2
2	Compliers	0	+1	+1
7	Never Takers	-0.1	0	-0.1

10 lose

Number students	Type	Selection effect	Treatment effect	Total effect
1	Always Takers	+0.2	+1	+1.2
2	Compliers	0	0	0
7	Never Takers	-0.1	0	-0.1

Intent to treatment = Average effect of who you give option to choose

$$\begin{aligned} E(Y_i|W_{ij}=1;A_{ij}=1) &= \frac{1*(1.2)+2*(1)+7*(-0.1)}{10} \\ &= 0.25 \end{aligned}$$

$$\begin{aligned} E(Y_i|W_{ij}=0;A_{ij}=1) &= \frac{1*(1.2)+2*(0)+7*(-0.1)}{10} \\ &= 0.05 \end{aligned}$$

Hence,

$$\begin{aligned} \text{Intent to treatment} &= 0.25-0.05=0.2 \\ \text{Treatment effect} &= 1 \end{aligned}$$

$$\begin{aligned} P(Enroll_{ij}=1|W_{ij}=1;A_{ij}=1) &= \frac{1+2}{10}=0.3 \\ P(Enroll_{ij}=1|W_{ij}=0;A_{ij}=1) &= \frac{1}{10}=0.1 \end{aligned}$$

$$\text{Treatment effect} = \frac{0.2}{0.3-0.1}=1$$

After knowing how to recover the treatment effect, we turn our attention to the main model

$$Y_{ia}=\delta W_{ia}+\lambda L_{ia}+e_{ia}$$

where

- W = whether a student wins a lottery
- L = whether student enrolls in the lottery
- δ = intent to treat

Hence,

- Conditional on lottery, the δ is valid
- But without lottery, your δ is not random
- Winning and losing are only identified within lottery
- Each lottery has multiple entries. Thus, we can have within estimator

We can also include other control variables ($X_i\theta$)

$$Y_{ia} = \delta_1 W_{ia} + \lambda_1 L_{ia} + X_i\theta + u_{ia}$$

$$\begin{aligned} &E(\delta) = E(\delta_1) \\ &E(\lambda) \neq E(\lambda_1) \quad \text{because choosing a lottery is not random} \end{aligned}$$

Including ($X_i\theta$) just shifts around control variables (i.e., reweighting of lottery), which would not affect your treatment effect $E(\delta)$

19.3 Rerandomization

- Since randomization only balances baseline covariates on average, imbalance in variables due to random chance can still happen.
- In case that you have a "bad" randomization (i.e., imbalance for important baseline covariates), (Morgan and Rubin, 2012) introduce the idea of rerandomization.
- Rerandomization is checking balance during the randomization process (before the experiment), to eliminate bad allocation (i.e., those with unacceptable balance).
- The greater the number of variables, the greater the likelihood that at least one covariate would be imbalanced across treatment groups.
  - Example: For 10 covariates, the probability of a significant difference at $\alpha = .05$ for at least one covariate is $1 - (1 - .05)^{10} = 0.4 = 40\%$
- Rerandomization increase treatment effect estimate precision if the covariates are correlated with the outcome.
  - Improvement in precision for treatment effect estimate depends on (1) improvement in covariate balance and (2) correlation between covariates and the outcome.
- You also need to take into account rerandomization into your analysis when making inference.
- Rerandomization is equivalent to increasing our sample size.

- Alternatives include
  - Stratified randomization (Johansson and Schultzberg, 2022)
  - Matched randomization (Greevy et al., 2004; Kapelner and Krieger, 2014)
  - Minimization (Pocock and Simon, 1975)

Rerandomization Criterion

- Acceptable randomization is based on a function of covariate matrix $\mathbf{X}$ and vector of treatment assignments $\mathbf{W}$

$$W_i = \begin{cases} 1 \text{ if treated} \\ 0 \text{ if control} \end{cases}$$

- Mahalanobis Distance, M, can be used as criteria for acceptable balance

Let M be the multivariate distance between groups means

$$\begin{aligned} M &= (\bar{\mathbf{X}}_T - \bar{\mathbf{X}}_C)' cov(\bar{\mathbf{X}}_T - \bar{\mathbf{X}}_C)^{-1} (\bar{\mathbf{X}}_T - \bar{\mathbf{X}}_C) \\ &= (\frac{1}{n_T} + \frac{1}{n_C})^{-1} (\bar{\mathbf{X}}_T - \bar{\mathbf{X}}_C)' cov(\mathbf{X})^{-1} (\bar{\mathbf{X}}_T - \bar{\mathbf{X}}_C) \end{aligned}$$

With large sample size and "pure" randomization $M \sim \chi^2_k$ where k is the number of covariates to be balanced

Then let p_a be the probability of accepting a randomization. Choosing appropriate p_a is a tradeoff between balance and time.

Then the rule of thumb is re-randomize when $M > a$

19.4 Two-Stage Randomized Experiments with Interference and Noncompliance

(Imai et al., 2021a)

Chapter 20

Sampling

20.1 Simple Sampling

Simple (random) Sampling

```
library(dplyr)
iris_df <- iris
set.seed(1)
sample_n(iris_df, 10)
#>    Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
#> 1           5.8         2.7          4.1         1.0 versicolor
#> 2           6.4         2.8          5.6         2.1  virginica
#> 3           4.4         3.2          1.3         0.2     setosa
#> 4           4.3         3.0          1.1         0.1     setosa
#> 5           7.0         3.2          4.7         1.4 versicolor
#> 6           5.4         3.0          4.5         1.5 versicolor
#> 7           5.4         3.4          1.7         0.2     setosa
#> 8           7.6         3.0          6.6         2.1  virginica
#> 9           6.1         2.8          4.7         1.2 versicolor
#> 10          4.6         3.4          1.4         0.3     setosa
```

```
library(sampling)
# set unique id number for each row
iris_df$id = 1:nrow(iris_df)

# Simple random sampling with replacement
srswor(10, length(iris_df$id))
#>   [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 1
#>  [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
#>  [75] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0
#> [112] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

```
#> [149] 0 0

# Simple random sampling without replacement (sequential method)
srswor1(10, length(iris_df$id))
#>   [1] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#>  [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#>  [75] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#> [112] 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0
#> [149] 0 0

# Simple random sampling with replacement
srswr(10, length(iris_df$id))
#>   [1] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 1 0 0 0 0 0
#>  [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
#>  [75] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
#> [112] 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
#> [149] 0 0
```

```
library(survey)
data("api")
srs_design <- svydesign(data = apistrat,
                        weights = ~pw,
                        fpc = ~fpc,
                        id = ~1)
```

```
library(sampler)
rsamp(albania,
      n = 260,
      over = 0.1, # desired oversampling proportion
      rep = F)
```

Identify missing points between sample and collected data

```
alsample <- rsamp(df = albania, 544)
alreceived <- rsamp(df = alsample, 390)
rmissing(sampdf = alsample,
         colldf = alreceived,
         col_name = qvKod)
```

20.2 Stratified Sampling

A stratum is a subset of the population that has at least one common characteristic.

Steps:

1. Identify relevant stratums and their representation in the population.

2. Randomly sample to select a sufficient number of subjects from each stratum.

Stratified sampling reduces sampling error.

```
library(dplyr)
# by number of rows
sample_iris <- iris %>%
    group_by(Species) %>%
    sample_n(5)
sample_iris
#> # A tibble: 15 x 5
#> # Groups:   Species [3]
#>    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
#>           <dbl>       <dbl>        <dbl>       <dbl> <fct>
#>  1          4.4         3            1.3         0.2 setosa
#>  2          5.2         3.5          1.5         0.2 setosa
#>  3          5.1         3.8          1.5         0.3 setosa
#>  4          5.2         3.4          1.4         0.2 setosa
#>  5          4.5         2.3          1.3         0.3 setosa
#>  6          5.5         2.5          4           1.3 versicolor
#>  7          7           3.2          4.7         1.4 versicolor
#>  8          6.7         3            5           1.7 versicolor
#>  9          6.1         2.9          4.7         1.4 versicolor
#> 10          5.5         2.4          3.8         1.1 versicolor
#> 11          6.4         2.7          5.3         1.9 virginica
#> 12          6.4         2.8          5.6         2.1 virginica
#> 13          6.4         3.2          5.3         2.3 virginica
#> 14          6.8         3.2          5.9         2.3 virginica
#> 15          7.2         3.6          6.1         2.5 virginica

# by fraction
sample_iris <- iris %>%
    group_by(Species) %>%
    sample_frac(size = .15)
sample_iris
#> # A tibble: 24 x 5
#> # Groups:   Species [3]
#>    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
#>           <dbl>       <dbl>        <dbl>       <dbl> <fct>
#>  1          5.5         4.2          1.4         0.2 setosa
#>  2          5           3            1.6         0.2 setosa
#>  3          5.2         4.1          1.5         0.1 setosa
#>  4          4.6         3.1          1.5         0.2 setosa
#>  5          5.1         3.7          1.5         0.4 setosa
#>  6          4.8         3.4          1.9         0.2 setosa
```

```
#>  7          5.1         3.3          1.7         0.5 setosa
#>  8          5.5         3.5          1.3         0.2 setosa
#>  9          5           2.3          3.3         1   versicolor
#> 10          5.6         2.9          3.6         1.3 versicolor
#> # i 14 more rows
```

```
library(sampler)
# Stratified sample using proportional allocation without replacement
ssamp(df=albania, n=360, strata=qarku, over=0.1)
#> # A tibble: 395 x 45
#>    qarku  Q_ID bashkia   BAS_ID zaz   njesiaAdministrative COM_ID qvKod zgjedhes
#>    <fct> <int> <fct>      <int> <fct> <fct>                 <int> <fct>    <int>
#>  1 Berat     1 Berat         11 ZAZ ~ "Berat "               1101 "\"3~      558
#>  2 Berat     1 Berat         11 ZAZ ~ "Berat "               1101 "\"3~      815
#>  3 Berat     1 Berat         11 ZAZ ~ "Sinje"                1108 "\"3~      419
#>  4 Berat     1 Kucove        13 ZAZ ~ "Lumas"                1104 "\"3~      237
#>  5 Berat     1 Kucove        13 ZAZ ~ "Kucove"               1201 "\"3~      562
#>  6 Berat     1 Skrapar       17 ZAZ ~ "Corovode"             1303 "\"3~      829
#>  7 Berat     1 Berat         11 ZAZ ~ "Roshnik"              1107 "\"3~      410
#>  8 Berat     1 Ura Vajg~     19 ZAZ ~ "Ura Vajgurore"        1110 "\"3~      708
#>  9 Berat     1 Kucove        13 ZAZ ~ "Perondi"              1203 "\"3~      835
#> 10 Berat     1 Kucove        13 ZAZ ~ "Kucove"               1201 "\"3~      907
#> # i 385 more rows
#> # i 36 more variables: meshkuj <int>, femra <int>, totalSeats <int>,
#> #   vendndodhja <fct>, ambienti <fct>, totalVoters <int>, femVoters <int>,
#> #   maleVoters <int>, unusedBallots <int>, damagedBallots <int>,
#> #   ballotsCast <int>, invalidVotes <int>, validVotes <int>, lsi <int>,
#> #   ps <int>, pkd <int>, sfida <int>, pr <int>, pd <int>, pbdksh <int>,
#> #   adk <int>, psd <int>, ad <int>, frd <int>, pds <int>, pdiu <int>, ...
```

Identify number of missing points by strata between sample and collected data

```
alsample <- rsamp(df = albania, 544)
alreceived <- rsamp(df = alsample, 390)
smissing(
    sampdf = alsample,
    colldf = alreceived,
    strata = qarku,
    col_name = qvKod
)
```

20.3 Unequal Probability Sampling

```
UPbrewer()
UPmaxentropy()
```

```
UPmidzuno()
UPmidzunopi2()
UPmultinomial()
UPpivotal()
UPrandompivotal()
UPpoisson()
UPsampford()
UPsystematic()
UPrandomsystematic()
UPsystematicpi2()
UPtille()
UPtillepi2()
```

20.4 Balanced Sampling

- Purpose: to get the same means in the population and the sample for all the auxiliary variables
- Balanced sampling is different from purposive selection

Balancing equations

$$\sum_{k \in S} \frac{\mathbf{x}_k}{\pi_k} = \sum_{k \in U} \mathbf{x}_k$$

where $\mathbf{x}_k$ is a vector of auxiliary variables

20.4.1 Cube

- flight phase
- landing phase

```
samplecube()
fastflightcube()
landingcube()
```

20.4.2 Stratification

- Try to replicate the population based on the original multivariate histogram

```
library(survey)
data("api")
srs_design <- svydesign(data = apistrat,
                        weights = ~pw,
```

```
                          fpc = ~fpc,
                          strata = ~stype,
                          id = ~1)
```

```
balancedstratification()
```

20.4.3 Cluster

```
library(survey)
data("api")
srs_design <- svydesign(data = apiclus1,
                          weights = ~pw,
                          fpc = ~fpc,
                          id = ~dnum)
```

```
balancedcluster()
```

20.4.4 Two-stage

```
library(survey)
data("api")
srs_design <- svydesign(data = apiclus2,
                          fpc = ~fpc1 + fpc2,
                          id = ~ dnum + snum)
```

```
balancedtwostage()
```

Chapter 21

Analysis of Variance (ANOVA)

ANOVA is using the same underlying mechanism as linear regression. However, the angle that ANOVA chooses to look at is slightly different from the traditional linear regression. It can be more useful in the case with **qualitative variables** and **designed experiments**.

Experimental Design

- **Factor**: explanatory or predictor variable to be studied in an investigation
- **Treatment** (or Factor Level): "value" of a factor applied to the experimental unit
- **Experimental Unit**: person, animal, piece of material, etc. that is subjected to treatment(s) and provides a response
- **Single Factor Experiment**: one explanatory variable considered
- **Multifactor Experiment**: more than one explanatory variable
- **Classification Factor**: A factor that is not under the control of the experimenter (observational data)
- **Experimental Factor**: assigned by the experimenter

Basics of experimental design:

- Choices that a statistician has to make:
  - set of treatments
  - set of experimental units
  - treatment assignment (selection bias)
  - measurement (measurement bias, blind experiments)
- Advancements in experimental design:

1. **Factorial Experiments**:
   consider multiple factors at the same time (interaction)
2. **Replication**: repetition of experiment
   - assess mean squared error
   - control over precision of experiment (power)
3. **Randomization**
   - Before R.A. Fisher (1900s), treatments were assigned systematically or subjectively
   - randomization: assign treatments to experimental units at random, which averages out systematic effects that cannot be control by the investigator
4. **Local control**: Blocking or Stratification
   - Reduce experimental errors and increase power by placing restrictions on the randomization of treatments to experimental units.

Randomization may also eliminate correlations due to time and space.

21.1 Completely Randomized Design (CRD)

Treatment factor A with $a \geq 2$ treatments levels. Experimental units are randomly assigned to each treatment. The number of experimental units in each group can be

- equal (balanced): n
- unequal (unbalanced): n_i for the i-th group (i = 1,...,a).

The total sample size is $N = \sum_{i=1}^{a} n_i$

Possible assignments of units to treatments are $k = \frac{N!}{n_1! n_2! \ldots n_a!}$

Each has probability 1/k of being selected. Each experimental unit is measured with a response Y_{ij}, in which j denotes unit and i denotes treatment.

Treatment

	1	2	...	a
	Y_{11}	Y_{21}	...	Y_{a1}
	Y_{12}	...	...	...
	...	...	...	...
Sample Mean	$\bar{Y}_{1.}$	$\bar{Y}_{2.}$	...	$\bar{Y}_{a.}$
Sample SD	s_1	s_2	...	s_a

where $\bar{Y}_{i.} = \frac{1}{n_i}\sum_{j=1}^{n_i} Y_{ij}$

$s_i^2 = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}(Y_{ij} - \bar{Y}_i)^2$

And the grand mean is $\bar{Y}_{..} = \frac{1}{N}\sum_i \sum_j Y_{ij}$

21.1.1 Single Factor Fixed Effects Model

also known as Single Factor (One-Way) ANOVA or ANOVA Type I model.

Partitioning the Variance

The total variability of the Y_{ij} observation can be measured as the deviation of Y_{ij} around the overall mean $\bar{Y}_{..}$: $Y_{ij} - \bar{Y}_{..}$

This can be rewritten as:

$$\begin{aligned} Y_{ij} - \bar{Y}_{..} &= Y_{ij} - \bar{Y}_{..} + \bar{Y}_{i.} - \bar{Y}_{i.} \\ &= (\bar{Y}_{i.} - \bar{Y}_{..}) + (Y_{ij} - \bar{Y}_{i.}) \end{aligned}$$

where

- the first term is the *between* treatment differences (i.e., the deviation of the treatment mean from the overall mean)
- the second term is *within* treatment differences (i.e., the deviation of the observation around its treatment mean)

$$\begin{aligned} \sum_i \sum_j (Y_{ij} - \bar{Y}_{..})^2 &= \sum_i n_i(\bar{Y}_{i.} - \bar{Y}_{..})^2 + \sum_i \sum_j (Y_{ij} - \bar{Y}_{i.})^2 \\ SSTO &= SSTR + SSE \\ total\ SS &= treatment\ SS + error\ SS \\ (N-1)\ d.f. &= (a-1)\ d.f. + (N-a)\ d.f. \end{aligned}$$

we lose a d.f. for the total corrected SSTO because of the estimation of the mean ($\sum_i \sum_j (Y_{ij} - \bar{Y}_{..}) = 0$)
And, for the SSTR $\sum_i n_i(\bar{Y}_{i.} - \bar{Y}_{..}) = 0$

Accordingly, $MSTR = \frac{SST}{a-1}$ and $MSR = \frac{SSE}{N-a}$

ANOVA Table

Source of Variation	SS	df	MS
Between Treatments	$\sum_i n_i(\bar{Y}_{i.} - \bar{Y}_{..})^2$	a-1	SSTR/(a-1)
Error (within treatments)	$\sum_i \sum_j (Y_{ij} - \bar{Y}_{i.})^2$	N-a	SSE/(N-a)

Source of Variation	SS	df	MS
Total (corrected)	$\sum_i n_i(\bar{Y}_{i.} - \bar{Y}_{..})^2$	N-1	

Linear Model Explanation of ANOVA

21.1.1.1 Cell means model

$$Y_{ij} = \mu_i + \epsilon_ij$$

where

- Y_{ij} response variable in j-th subject for the i-th treatment
- μ_i: parameters (fixed) representing the unknown population mean for the i-th treatment
- ϵ_{ij} independent $N(0, \sigma^2)$ errors
- $E(Y_{ij}) = \mu_i$ $var(Y_{ij}) = var(\epsilon_{ij}) = \sigma^2$
- All observations have the same variance

Example:

$a = 3$ (3 treatments) $n_1 = n_2 = n_3 = 2$

$$\begin{pmatrix} Y_{11} \\ Y_{12} \\ Y_{21} \\ Y_{22} \\ Y_{31} \\ Y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{21} \\ \epsilon_{22} \\ \epsilon_{31} \\ \epsilon_{32} \end{pmatrix}$$

$$\mathbf{y} = \mathbf{X} \ +$$

$X_{k,ij} = 1$ if the k-th treatment is used

$X_{k,ij} = 0$ Otherwise

Note: no intercept term.

$$\begin{aligned}
\mathbf{b} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} &= (\mathbf{x}'\mathbf{x})^{-1}\mathbf{x}'\mathbf{y} \\
&= \begin{bmatrix} n_1 & 0 & 0 \\ 0 & n_2 & 0 \\ 0 & 0 & n_3 \end{bmatrix}^{-1} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \qquad (21.1) \\
&= \begin{bmatrix} \bar{Y_1} \\ \bar{Y_2} \\ \bar{Y_3} \end{bmatrix}
\end{aligned}$$

is the BLUE (best linear unbiased estimator) for $\beta = [\mu_1\mu_2\mu_3]'$

$$E(\mathbf{b}) = \beta$$

$$var(\mathbf{b}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1} = \sigma^2 \begin{bmatrix} 1/n_1 & 0 & 0 \\ 0 & 1/n_2 & 0 \\ 0 & 0 & 1/n_3 \end{bmatrix}$$

$var(b_i) = var(\hat{\mu_i}) = \sigma^2/n_i$ where $\mathbf{b} \sim N(\beta, \sigma^2(\mathbf{X}'\mathbf{X})^{-1})$

$$\begin{aligned}
MSE &= \frac{1}{N-a}\sum_i\sum_j (Y_{ij} - \bar{Y_{i.}})^2 \\
&= \frac{1}{N-a}\sum_i [(n_i - 1)\frac{\sum_i (Y_{ij} - \bar{Y_{i.}})^2}{n_i - 1}] \\
&= \frac{1}{N-a}\sum_i (n_i - 1)s_1^2
\end{aligned}$$

We have $E(s_i^2) = \sigma^2$

$E(MSE) = \frac{1}{N-a}\sum_i (n_i - 1)\sigma^2 = \sigma^2$

Hence, MSE is an unbiased estimator of σ^2, regardless of whether the treatment means are equal or not.

$E(MSTR) = \sigma^2 + \frac{\sum_i n_i(\mu_i - \mu_.)^2}{a-1}$

where $\mu_. = \frac{\sum_{i=1}^a n_i\mu_i}{\sum_{i=1}^a n_i}$

If all treatment means are equals $(=\mu_.)$, $E(MSTR) = \sigma^2$.

Then we can use an F-test for the equality of all treatment means:

$$H_0 : \mu_1 = \mu_2 = .. = \mu_a$$

$$H_a : not\ all\ \mu_i\ are\ equal$$

$F = \frac{MSTR}{MSE}$
where large values of F support H_a (since MSTR will tend to exceed MSE when H_a holds)
and F near 1 support H_0 (upper tail test)

Equivalently, when H_0 is true, $F \sim f_{(a-1,N-a)}$

- If $F \leq f_{(a-1,N-a;1-\alpha)}$, we cannot reject H_0
- If $F \geq f_{(a-1,N-a;1-\alpha)}$, we reject H_0

Note: If $a = 2$ (2 treatments), F-test = two sample t-test

21.1.1.2 Treatment Effects (Factor Effects)

Besides Cell means model, we have another way to formalize one-way ANOVA:

$$Y_{ij} = \mu + \tau_i + \epsilon_{ij}$$

where

- Y_{ij} is the j-th response for the i-th treatment
- τ_i is i-th treatment effect
- μ constant component, common to all observations
- ϵ_{ij} independent random errors $\sim N(0, \sigma^2)$

For example, $a = 3$, $n_1 = n_2 = n_3 = 2$

$$\begin{pmatrix} Y_{11} \\ Y_{12} \\ Y_{21} \\ Y_{22} \\ Y_{31} \\ Y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \tau_3 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{21} \\ \epsilon_{22} \\ \epsilon_{31} \\ \epsilon_{32} \end{pmatrix} \tag{21.2}$$

$$\mathbf{y} = \mathbf{X}\ +$$

However,

$$\mathbf{X}'\mathbf{X} = \begin{pmatrix} \sum_i n_i & n_1 & n_2 & n_3 \\ n_1 & n_1 & 0 & 0 \\ n_2 & 0 & n_2 & 0 \\ n_3 & 0 & 0 & n_3 \end{pmatrix}$$

is **singular** thus does not exist, **b** is insolvable (infinite solutions)

Hence, we have to impose restrictions on the parameters to a model matrix **X** of full rank.

Whatever restriction we use, we still have:

$E(Y_{ij}) = \mu + \tau_i = \mu_i = mean\ response\ for\ i-th\ treatment$

21.1.1.2.1 Restriction on sum of tau $\sum_{i=1}^{a} \tau_i = 0$

implies

$$\mu = \mu + \frac{1}{a}\sum_{i=1}^{a}(\mu + \tau_i)$$

is the average of the treatment mean (grand mean) (overall mean)

$$\begin{aligned}\tau_i &= (\mu + \tau_i) - \mu = \mu_i - \mu \\ &= \text{treatment mean} - \text{grand mean} \\ &= \text{treatment effect}\end{aligned}$$

$$\tau_a = -\tau_1 - \tau_2 - ... - \tau_{a-1}$$

Hence, the mean for the a-th treatment is

$$\mu_a = \mu + \tau_a = \mu - \tau_1 - \tau_2 - ... - \tau_{a-1}$$

Hence, the model need only "a" parameters:

$$\mu, \tau_1, \tau_2, .., \tau_{a-1}$$

Equation (21.2) becomes

$$\begin{pmatrix} Y_{11} \\ Y_{12} \\ Y_{21} \\ Y_{22} \\ Y_{31} \\ Y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & -1 & -1 \\ 1 & -1 & -1 \end{pmatrix} \begin{pmatrix} \mu \\ \tau_1 \\ \tau_2 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{21} \\ \epsilon_{22} \\ \epsilon_{31} \\ \epsilon_{32} \end{pmatrix} \tag{21.3}$$

$$\mathbf{y} = \mathbf{X}\ +$$

where $\beta \equiv [\mu, \tau_1, \tau_2]'$

Equation (21.1) with $\sum_i \tau_i = 0$ becomes

$$
\begin{aligned}
\mathbf{b} = \begin{bmatrix} \hat{\mu} \\ \hat{\tau}_1 \\ \hat{\tau}_2 \end{bmatrix} &= (\mathbf{x}'\mathbf{x})^{-1}\mathbf{x}'\mathbf{y} \\
&= \begin{bmatrix} \sum_i n_i & n_1 - n_3 & n_2 - n_3 \\ n_1 - n_3 & n_1 + n_3 & n_3 \\ n_2 - n_3 & n_3 & n_2 - n_3 \end{bmatrix}^{-1} \begin{bmatrix} Y_{..} \\ Y_{1.} - Y_{3.} \\ Y_{2.} - Y_{3.} \end{bmatrix} \\
&= \begin{bmatrix} \frac{1}{3}\sum_{i=1}^{3} \bar{Y}_{i.} \\ \bar{Y}_{1.} - \frac{1}{3}\sum_{i=1}^{3} \bar{Y}_{i.} \\ \bar{Y}_{2.} - \frac{1}{3}\sum_{i=1}^{3} \bar{Y}_{i.} \end{bmatrix} \\
&= \begin{bmatrix} \hat{\mu} \\ \hat{\tau}_1 \\ \hat{\tau}_2 \end{bmatrix}
\end{aligned}
$$

and $\hat{\tau}_3 = -\hat{\tau}_1 - \hat{\tau}_2 = \bar{Y}_3 - \frac{1}{3}\sum_i \bar{Y}_{i.}$

21.1.1.2.2 Restriction on first tau In R, `lm()` uses the restriction $\tau_1 = 0$

For the previous example, for $n_1 = n_2 = n_3 = 2$, and $\tau_1 = 0$.

Then the treatment means can be written as:

$$
\begin{aligned}
\mu_1 &= \mu + \tau_1 = \mu + 0 = \mu \\
\mu_2 &= \mu + \tau_2 \\
\mu_3 &= \mu + \tau_3
\end{aligned}
$$

Hence, μ is the mean response for the first treatment

In the matrix form,

$$
\begin{pmatrix} Y_{11} \\ Y_{12} \\ Y_{21} \\ Y_{22} \\ Y_{31} \\ Y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu \\ \tau_2 \\ \tau_3 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{21} \\ \epsilon_{22} \\ \epsilon_{31} \\ \epsilon_{32} \end{pmatrix}
$$

$$
\mathbf{y} = \mathbf{X} \ +
$$

$\beta = [\mu, \tau_2, \tau_3]'$

$$\mathbf{b} = \begin{bmatrix} \hat{\mu} \\ \hat{\tau_2} \\ \hat{\tau_3} \end{bmatrix} = (\mathbf{x}'\mathbf{x})^{-1}\mathbf{x}'\mathbf{y}$$

$$= \begin{bmatrix} \sum_i n_i & n_2 & n_3 \\ n_2 & n_2 & 0 \\ n_3 & 0 & n_3 \end{bmatrix}^{-1} \begin{bmatrix} Y_{..} \\ Y_{2.} \\ Y_{3.} \end{bmatrix}$$

$$= \begin{bmatrix} \bar{Y_{1.}} \\ \bar{Y_{2.}} - \bar{Y_{1.}} \\ \bar{Y_{3.}} - \bar{Y_{1.}} \end{bmatrix}$$

$$E(\mathbf{b}) = \beta = \begin{bmatrix} \mu \\ \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 - \mu_1 \\ \mu_3 - \mu_1 \end{bmatrix}$$

$$\begin{aligned} var(\mathbf{b}) &= \sigma^2(\mathbf{X}'\mathbf{X})^{-1} \\ var(\hat{\mu}) &= var(\bar{Y_{1.}}) = \sigma^2/n_1 \\ var(\hat{\tau_2}) &= var(\bar{Y_{2.}} - \bar{Y_{1.}}) = \sigma^2/n_2 + \sigma^2/n_1 \\ var(\hat{\tau_3}) &= var(\bar{Y_{3.}} - \bar{Y_{1.}}) = \sigma^2/n_3 + \sigma^2/n_1 \end{aligned}$$

Note For all three parameterization, the ANOVA table is the same

- Model 1: $Y_{ij} = \mu_i + \epsilon_{ij}$
- Model 2: $Y_{ij} = \mu + \tau_i + \epsilon_{ij}$ where $\sum_i \tau_i = 0$
- Model 3: $Y_{ij} = \mu + \tau_i + \epsilon_{ij}$ where $\tau_1 = 0$

All models have the same calculation for $\hat{Y}$ as

$$\hat{\mathbf{Y}} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = \mathbf{PY} = \mathbf{Xb}$$

ANOVA Table

Source of Variation	SS	df	MS	F
Between Treatments	$\sum_i n_i(\bar{Y_{i.}} - \bar{Y_{..}})^2 = \mathbf{Y}'(\mathbf{P} - \mathbf{P_1})\mathbf{Y}$	a-1	$\frac{SSTR}{a-1}$	$\frac{MSTR}{MSE}$
Error (within treatments)	$\sum_i \sum_j (Y_{ij} - \bar{Y_{i.}})^2 = \mathbf{e}'\mathbf{e}$	N-a	$\frac{SSE}{N-a}$	

Source of Variation	SS	df	MS	F
Total (corrected)	$\sum_i n_i(\bar{Y_{i.}} - \bar{Y_{..}})^2 = \mathbf{Y'Y} - \mathbf{Y'P_1Y}$	N-1		

where $\mathbf{P_1} = \frac{1}{n}\mathbf{J}$

The F-statistic here has $(a-1, N-a)$ degrees of freedom, which gives the same value for all three parameterization, but the hypothesis test is written a bit different:

$$H_0 : \mu_1 = \mu_2 = ... = \mu_a$$
$$H_0 : \mu + \tau_1 = \mu + \tau_2 = ... = \mu + \tau_a$$
$$H_0 : \tau_1 = \tau_2 = ... = \tau_a$$

The F-test here serves as a preliminary analysis, to see if there is any difference at different factors. For more in-depth analysis, we consider different testing of treatment effects.

21.1.1.3 Testing of Treatment Effects

- A Single Treatment Mean μ_i
- A Differences Between Treatment Means
- A Contrast Among Treatment Means
- A Linear Combination of Treatment Means

21.1.1.3.1 Single Treatment Mean We have $\hat{\mu_i} = \bar{Y_{i.}}$ where

- $E(\bar{Y_{i.}}) = \mu_i$
- $var(\bar{Y_i}) = \sigma^2/n_i$ estimated by $s^2(\bar{Y_{i.}}) = MSE/n_i$

Since $\frac{\bar{Y_{i.}} - \mu_i}{s(\bar{Y_{i.}})} \sim t_{N-a}$ and the confidence interval for μ_i is $\bar{Y_{i.}} \pm t_{1-\alpha/2;N-a} s(\bar{Y_{i.}})$, then we can do a t-test for the means difference with some constant c

$$H_0 : \mu_i = c$$
$$H_1 : \mu_i \neq c$$

where

$$T = \frac{\bar{Y_{i.}} - c}{s(\bar{Y_{i.}})}$$

follows t_{N-a} when H_0 is true.
If $|T| > t_{1-\alpha/2;N-a}$, we can reject H_0

21.1.1.3.2 Differences Between Treatment Means Let $D = \mu_i - \mu_i'$, also known as **pairwise comparison**
D can be estimated by $\hat{D} = \bar{Y_i} - \bar{Y_i}'$ is unbiased ($E(\hat{D}) = \mu_i - \mu_i'$)

Since $\bar{Y_i}$ and $\bar{Y_i}'$ are independent, then

$$var(\hat{D}) = var(\bar{Y_i}) + var(\bar{Y_{i'}}) = \sigma^2(1/n_i + 1/n_i')$$

can be estimated with

$$s^2(\hat{D}) = MSE(1/n_i + 1/n_i')$$

With the single treatment inference,

$$\frac{\hat{D} - D}{s(\hat{D})} \sim t_{N-a}$$

hence,

$$\hat{D} \pm t_{(1-\alpha/2;N-a)} s(\hat{D})$$

Hypothesis tests:

$$H_0 : \mu_i = \mu_i'$$
$$H_a : \mu_i \neq \mu_i'$$

can be tested by the following statistic

$$T = \frac{\hat{D}}{s(\hat{D})} \sim t_{1-\alpha/2;N-a}$$

reject H_0 if $|T| > t_{1-\alpha/2;N-a}$

21.1.1.3.3 Contrast Among Treatment Means generalize the comparison of two means, we have **contrasts**

A contrast is a linear combination of treatment means:

$$L = \sum_{i=1}^{a} c_i \mu_i$$

where each c_i is non-random constant and sum to 0:

$$\sum_{i=1}^{a} c_i = 0$$

An unbiased estimator of a contrast L is

$$\hat{L} = \sum_{i=1}^{a} c_i \bar{Y}_{i.}$$

and $E(\hat{L}) = L$. Since the $\bar{Y}_{i.}$, i = 1,..., a are independent.

$$\begin{aligned} var(\hat{L}) &= var(\sum_{i=1}^{a} c_i \bar{Y}_{i.}) = \sum_{i=1}^{a} var(c_i \bar{Y}_i) \\ &= \sum_{i=1}^{a} c_i^2 var(\bar{Y}_i) = \sum_{i=1}^{a} c_i^2 \sigma^2 / n_i \\ &= \sigma^2 \sum_{i=1}^{a} c_i^2 / n_i \end{aligned}$$

Estimation of the variance:

$$s^2(\hat{L}) = MSE \sum_{i=1}^{a} \frac{c_i^2}{n_i}$$

$\hat{L}$ is normally distributed (since it is a linear combination of independent normal random variables).

Then, since SSE/σ^2 is χ^2_{N-a}

$$\frac{\hat{L} - L}{s(\hat{L})} \sim t_{N-a}$$

A $1 - \alpha$ confidence limits are given by

$$\hat{L} \pm t_{1-\alpha/2;N-a} s(\hat{L})$$

Hypothesis testing

$$\begin{aligned} H_0 &: L = 0 \\ H_a &: L \neq 0 \end{aligned}$$

with

$$T = \frac{\hat{L}}{s(\hat{L})}$$

reject H_0 if $|T| > t_{1-\alpha/2;N-a}$

21.1.1.3.4 Linear Combination of Treatment Means just like contrast $L = \sum_{i=1}^{a} c_i\mu_i$ but no restrictions on the c_i coefficients.

Tests on a single treatment mean, two treatment means, and contrasts can all be considered form the same perspective.

$$H_0 : \sum c_i\mu_i = c$$
$$H_a : \sum c_i\mu_i \neq c$$

The test statistics (t-stat) can be considered equivalently as F-tests; $F = (T)^2$ where $F \sim F_{1,N-a}$. Since the numerator degrees of freedom is always 1 in these cases, we refer to them as single-degree-of-freedom tests.

Multiple Contrasts

To test simultaneously $k \geq 2$ contrasts, let $T_1, ..., T_k$ be the t-stat. The joint distribution of these random variables is a multivariate t-distribution (the tests are dependent since they re based on the same data).

Limitations for comparing multiple contrasts:

1. The confidence coefficient $1 - \alpha$ only applies to a particular estimate, not a series of estimates; similarly, the Type I error rate, α, applies to a particular test, not a series of tests. Example: 3 t-tests at $\alpha = 0.05$, if tests are independent (which they are not), $0.95^3 = 0.857$ (thus $\alpha - 0.143$ not 0.05)

2. The confidence coefficient $1 - \alpha$ and significance level α are appropriate only if the test was not suggest by the data.

   - often, the results of an experiment suggest important (i.e.,..g, potential significant) relationships.
   - the process of studying effects suggests by the data is called **data snooping**

Multiple Comparison Procedures:

- Tukey
- Scheffe
- Bonferroni

21.1.1.3.4.1 Tukey All pairwise comparisons of factor level means. All pairs $D = \mu_i - \mu_i'$ or all tests of the form:

$$H_0 : \mu_i - \mu_i' = 0$$
$$H_a : \mu_i - \mu_i' \neq 0$$

- When all sample sizes are equal ($n_1 = n_2 = ... = n_a$) then the Tukey method family confidence coefficient is exactly $1 - \alpha$ and the significance level is exactly α

- When the sample sizes are not equal, the family confidence coefficient is greater than $1 - \alpha$ (i.e., the significance level is less than α) so the test **conservative**

- Tukey considers the **studentized range distribution**. If we have $Y_1, .., Y_r$, observations from a normal distribution with mean α and variance σ^2. Define:
$$w = max(Y_i) - min(Y_i)$$
as the range of the observations. Let s^2 be an estimate of σ^2 with v degrees of freedom. Then,
$$q(r, v) = \frac{w}{s}$$
is called the studentized range. The distribution of q uses a special table.

Notes

- when we are not interested in testing all pairwise comparison,s the confidence coefficient for the family of comparisons under consideration will be greater than $1 - \alpha$ (with the significance level less than α)
- Tukey can be used for "data snooping" as long as the effects to be studied on the basis of preliminary data analysis are pairwise comparisons.

21.1.1.3.4.2 Scheffe This method applies when the family of interest is the set of possible contrasts among the treatment means:

$$L = \sum_{i=1}^{a} c_i \mu_i$$

where $\sum_{i=1}^{a} c_i = 0$

That is, the family of all possible contrasts L or

$$H_0 : L = 0$$
$$H_a : L \neq 0$$

The family confidence level for the Scheffe procedure is exactly $1-\alpha$ (i.e., significance level $= \alpha$) whether the sample sizes are equal or not.

For simultaneous confidence intervals,

$$\hat{L} \pm Ss(\hat{L})$$

where $\hat{L} = \sum c_i \bar{Y}_{i.}$, $s^2(\hat{L}) = MSE \sum c_i^2/n_i$ and $S^2 = (a-1)f_{1-\alpha;a-1,N-a}$

The Scheffe procedure considers

$$F = \frac{\hat{L}^2}{(a-1)s^2(\hat{L})}$$

where we reject H_0 at the family significance level α if $F > f_{(1-\alpha;a-1,N-a)}$

Note

- Since applications of the Scheffe never involve all conceivable contrasts, the **finite family** confidence coefficient will be larger than $1-\alpha$, so $1-\alpha$ is a lower bound. Thus, people often consider a larger α (e.g., 90% confidence interval)
- Scheffe can be used for "data scooping" since the family of statements contains all possible contrasts.
- If only pairwise comparisons are to be considered, The Tukey procedure gives narrower confidence limits.

21.1.1.3.4.3 Bonferroni Applicable whether the sample sizes are equal or unequal.

For the confidence intervals,

$$\hat{L} \pm Bs(\hat{L})$$

where $B = t_{(1-\alpha/(2g);N-a)}$ and g is the number of comparisons in the family.

Hypothesis testing

$$H_0 : L = 0$$
$$H_a : L \neq 0$$

Let $T = \frac{\hat{L}}{s(\hat{L})}$ and reject H_0 if $|T| > t_{1-\alpha/(2g),N-a}$

Notes

- If all pairwise comparisons are of interest, the Tukey procedure is superior (narrower confidence intervals). If not, Bonferroni may be better.

- Bonferroni is better than Scheffe when the number of contrasts is about the same as the treatment levels (or less).
- Recommendation: compute all threes and pick the smallest.
- Bonferroni can't be used for **data snooping**

21.1.1.3.4.4 Fisher's LSD does not control for family error rate

use t-stat for testing

$$H_0 : \mu_i = \mu_j$$

t-stat

$$t = \frac{\bar{y}_i - \bar{y}_j}{\sqrt{MSE(\frac{1}{n_i} + \frac{1}{n_j})}}$$

21.1.1.3.4.5 Newman-Keuls Do not recommend using this test since it has less power than ANOVA.

21.1.1.3.5 Multiple comparisons with a control

21.1.1.3.5.1 Dunnett We have a groups where the last group is the control group, and the $a-1$ treatment groups.

Then, we compare treatment groups to the control group. Hence, we have $a-1$ contrasts (i.e., $a-1$ pairwise comparisons)

21.1.1.3.6 Summary When choosing a multiple contrast method:

- Pairwise
  - Equal groups sizes: Tukey
  - Unequal groups sizes: Tukey, Scheffe
- Not pairwise
  - with control: Dunnett
  - general: Bonferroni, Scheffe

21.1.2 Single Factor Random Effects Model

Also known as ANOVA Type II models.

Treatments are chosen at from from larger population. We extend inference to all treatments in the population and not restrict our inference to those treatments that happened to be selected for the study.

21.1.2.1 Random Cell Means

$$Y_{ij} = \mu_i + \epsilon_{ij}$$

where

- $\mu_i \sim N(\mu, \sigma_\mu^2)$ and independent
- $\epsilon_{ij} \sim N(0, \sigma^2)$ and independent

μ_i and ϵ_{ij} are mutually independent for $i = 1, ..., a; j = 1, ..., n$

With all treatment sample sizes are equal

$$\begin{aligned} E(Y_{ij}) &= E(\mu_i) = \mu \\ var(Y_{ij}) &= var(\mu_i) + var(\epsilon_i) = \sigma_\mu^2 + \sigma^2 \end{aligned}$$

Since Y_{ij} are not independent

$$\begin{aligned} cov(Y_{ij}, Y_{ij'}) &= E(Y_{ij}Y_{ij'}) - E(Y_{ij})E(Y_{ij'}) \\ &= E(\mu_i^2 + \mu_i\epsilon_{ij'} + \mu_i\epsilon_{ij} + \epsilon_{ij}\epsilon_{ij'}) - \mu^2 \\ &= \sigma_\mu^2 + \mu^2 - \mu^2 && \text{if} j \neq j' \\ &= \sigma_\mu^2 && \text{if} j \neq j' \end{aligned}$$

$$\begin{aligned} cov(Y_{ij}, Y_{i'j'}) &= E(\mu_i\mu_{i'} + \mu_i\epsilon_{i'j'} + \mu_{i'}\epsilon_{ij} + \epsilon_{ij}\epsilon_{i'j'}) - \mu^2 \\ &= \mu^2 - \mu^2 && \text{if } i \neq i' \\ &= 0 \end{aligned}$$

Hence,

- all observations have the same variance
- any two observations from the same treatment have covariance σ_μ^2
- The correlation between any two responses from the same treatment:

$$\rho(Y_{ij}, Y_{ij'}) = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma^2} \quad j \neq j'$$

Inference

Intraclass Correlation Coefficient

$$\frac{\sigma_\mu^2}{\sigma^2 + \sigma_\mu^2}$$

which measures the proportion of total variability of Y_{ij} accounted for by the variance of μ_i

$$H_0 : \sigma_\mu^2 = 0$$
$$H_a : \sigma_\mu^2 \neq 0$$

H_0 implies $\mu_i = \mu$ for all i, which can be tested by the F-test in ANOVA.

The understandings of the Single Factor Fixed Effects Model and the Single Factor Random Effects Model are different, the ANOVA is same for the one factor model. The difference is in the expected mean squares

Random Effects Model	**Fixed Effects** Model
$E(MSE) = \sigma^2$	$E(MSE) = \sigma^2$
$E(MSTR) = \sigma^2 - n\sigma_\mu^2$	$E(MSTR) = \sigma^2 + \frac{\sum_i n_i(\mu_i - \mu)^2}{a-1}$

If σ_μ^2, then MSE and MSTR have the same expectation (σ^2). Otherwise, $E(MSTR) > E(MSE)$. Large values of the statistic

$$F = \frac{MSTR}{MSE}$$

suggest we reject H_0.

Since $F \sim F_{(a-1,a(n-1))}$ when H_0 holds. If $F > f_{(1-\alpha;a-1,a(n-1))}$ we reject H_0.

If sample sizes are not equal, F-test can still be used, but the df are $a-1$ and $N-a$.

21.1.2.1.1 Estimation of μ An unbiased estimator of $E(Y_{ij}) = \mu$ is the grand mean: $\hat{\mu} = \hat{Y}_{..}$

The variance of this estimator is

$$\begin{aligned} var(\bar{Y}_{..}) &= var(\sum_i \bar{Y}_{i.}/a) \\ &= \frac{1}{a^2}\sum_i var(\bar{Y}_{i.}) \\ &= \frac{1}{a^2}\sum_i (\sigma_\mu^2 + \sigma^2/n) \\ &= \frac{1}{a^2}(\sigma_\mu^2 + \sigma^2/n) \\ &= \frac{n\sigma_\mu^2 + \sigma^2}{an} \end{aligned}$$

An unbiased estimator of this variance is $s^2(\bar{Y}) = \frac{MSTR}{an}$. Thus $\frac{\bar{Y}_{..} - \mu}{s(\bar{Y}_{..})} \sim t_{a-1}$

A $1-\alpha$ confidence interval is $\bar{Y}_{..} \pm t_{(1-\alpha/2;a-1)} s(\bar{Y}_{..})$

21.1.2.1.2 Estimation of $\sigma_\mu^2/(\sigma_\mu^2+\sigma^2)$ In the random and fixed effects model, MSTR and MSE are independent. When the sample sizes are equal ($n_i = n$ for all i),

$$\frac{\frac{MSTR}{n\sigma_\mu^2+\sigma^2}}{\frac{MSE}{\sigma^2}} \sim f_{(a-1,a(n-1))}$$

$$P(f_{(\alpha/2;a-1,a(n-1))} \leq \frac{\frac{MSTR}{n\sigma_\mu^2+\sigma^2}}{\frac{MSE}{\sigma^2}} \leq f_{(1-\alpha/2;a-1,a(n-1))}) = 1-\alpha$$

$$L = \frac{1}{n}(\frac{MSTR}{MSE}(\frac{1}{f_{(1-\alpha/2;a-1,a(n-1))}})-1)$$
$$U = \frac{1}{n}(\frac{MSTR}{MSE}(\frac{1}{f_{(\alpha/2;a-1,a(n-1))}})-1)$$

The lower and upper (L^*, U^*) confidence limits for $\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma^2}$

$$L^* = \frac{L}{1+L}$$
$$U^* = \frac{U}{1+U}$$

If the lower limit for $\frac{\sigma_\mu^2}{\sigma^2}$ is negative, it is customary to set $L = 0$.

21.1.2.1.3 Estimation of σ^2 $a(n-1)MSE/\sigma^2 \sim \chi^2_{a(n-1)}$, the $(1-\alpha)$ confidence interval for σ^2:

$$\frac{a(n-1)MSE}{\chi^2_{1-\alpha/2;a(n-1)}} \leq \sigma^2 \leq \frac{a(n-1)MSE}{\chi^2_{\alpha/2;a(n-1)}}$$

can also be used in case sample sizes are not equal - then df is N-a.

21.1.2.1.4 Estimation of σ_μ^2 $E(MSE) = \sigma^2$ $E(MSTR) = \sigma^2 + n\sigma_\mu^2$. Hence,

$$\sigma_\mu^2 = \frac{E(MSTR)-E(MSE)}{n}$$

An unbiased estimator of σ_μ^2 is given by

$$s_\mu^2 = \frac{MSTR - MSE}{n}$$

if $s_\mu^2 < 0$, set $s_\mu^2 = 0$

If sample sizes are not equal,

$$s_\mu^2 = \frac{MSTR - MSE}{n'}$$

where $n' = \frac{1}{a-1}(\sum_i n_i - \frac{\sum_i n_i^2}{\sum_i n_i})$

no exact confidence intervals for σ_μ^2, but we can approximate intervals.

Satterthewaite Procedure can be used to construct approximate confidence intervals for linear combination of expected mean squares
A linear combination:

$$\sigma_\mu^2 = \frac{1}{n}E(MSTR) + (-\frac{1}{n})E(MSE)$$

$$S = d_1 E(MS_1) + .. + d_h E(MS_h)$$

where d_i are coefficients.

An unbiased estimator of S is

$$\hat{S} = d_1 MS_1 + ... + d_h MS_h$$

Let df_i be the degrees of freedom associated with the mean square MS_i. The **Satterthwaite** approximation:

$$\frac{(df)\hat{S}}{S} \sim \chi^2_{df}$$

where

$$df = \frac{(d_1 MS_1 + ... + d_h MS_h)^2}{(d_1 MS_1)^2/df_1 + ... + (d_h MS_h)^2/df_h}$$

An approximate $1 - \alpha$ confidence interval for S:

$$\frac{(df)\hat{S}}{\chi^2_{1-\alpha/2;df}} \leq S \leq \frac{(df)\hat{S}}{\chi^2_{\alpha/2;df}}$$

For the single factor random effects model

$$\frac{(df)s_\mu^2}{\chi^2_{1-\alpha/2;df}} \leq \sigma_\mu^2 \leq \frac{(df)s_\mu^2}{\chi^2_{\alpha/2;df}}$$

where

$$df = \frac{(sn_\mu^2)^2}{\frac{(MSTR)^2}{a-1} + \frac{(MSE)^2}{a(n-1)}}$$

21.1.2.2 Random Treatment Effects Model

$$\tau_i = \mu_i - E(\mu_i) = \mu_i - \mu$$

we have $\mu_i = \mu + \tau_i$ and

$$Y_{ij} = \mu + \tau_i + \epsilon_{ij}$$

where

- μ = constant, common to all observations
- $\tau_i \sim N(0, \sigma_\tau^2)$ independent (random variables)
- $\epsilon_{ij} \sim N(0, \sigma^2)$ independent.
- τ_i, ϵ_{ij} are independent (i=1,...,a; j =1,..,n)
- our model is concerned with only balanced single factor ANOVA.

Diagnostics Measures

- Non-constant error variance (plots, Levene test, Hartley test).
- Non-independence of errors (plots, Durban-Watson test).
- Outliers (plots, regression methods).
- Non-normality of error terms (plots, Shapiro-Wilk, Anderson-Darling).
- Omitted Variable Bias (plots)

Remedial

- Weighted Least Squares
- Transformations
- Non-parametric Procedures.

Note

- Fixed effect ANOVA is relatively robust to
  - non-normality
  - unequal variances when sample sizes are approximately equal; at least the F-test and multiple comparisons. However, single comparisons of treatment means are sensitive to unequal variances.

- Lack of independence can seriously affect both fixed and random effect ANVOA.

21.1.3 Two Factor Fixed Effect ANOVA

The multi-factor experiment is

- more efficient
- provides more info
- gives more validity to the findings.

21.1.3.1 Balanced

Assumption:

- All treatment sample sizes are equal
- All treatment means are of equal importance

Assume:

- Factor A has `a` levels and Factor B has `b` levels. All $a \times b$ factor levels are considered.
- The number of treatments for each level is n. $N = abn$ observations in the study.

21.1.3.1.1 Cell Means Model

$$Y_{ijk} = \mu_{ij} + \epsilon_{ijk}$$

where

- μ_{ij} are fixed parameters (cell means)
- $i = 1, ..., a =$ the levels of Factor A
- $j = 1, ..., b =$ the levels of Factor B.
- $\epsilon_{ijk} \sim$ indep $N(0, \sigma^2)$ for $i = 1, ..., a$, $j = 1, .., b$ and $k = 1, .., n$

And

$$E(Y_{ijk}) = \mu_{ij}$$
$$var(Y_{ijk}) = var(\epsilon_{ijk}) = \sigma^2$$

Hence,

$$Y_{ijk} \sim \text{indep } N(\mu_{ij}, \sigma^2)$$

And the model is

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon$$

Thus,

$$\begin{aligned} E(\mathbf{Y}) &= \mathbf{X}\beta \\ var(\mathbf{Y}) &= \sigma^2\mathbf{I} \end{aligned}$$

Interaction

$$(\alpha\beta)_{ij} = \mu_{ij} - (\mu_{..} + \alpha_i + \beta_j)$$

where

- $\mu_{..} = \sum_i \sum_j \mu_{ij}/ab$ is the grand mean
- $\alpha_i = \mu_{i.} - \mu_{..}$ is the main effect for factor A at the i-th level
- $\beta_j = \mu_{.j} - \mu_{..}$ is the main effect for factor B at the j-th level
- $(\alpha\beta)_{ij}$ is the interaction effect when factor A is at the i-th level and factor B is at the j-th level.
- $(\alpha\beta)_{ij} = \mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..}$

Examine interactions:

- Examine whether all μ_{ij} can be expressed as the sums $\mu_{..} + \alpha_i + \beta_j$
- Examine whether the difference between the mean responses for any two levels of factor B is the same for all levels of factor A.
- Examine whether the difference between the mean response for any two levels of factor A is the same for all levels of factor B
- Examine whether the treatment mean curves for the different factor levels in a treatment plot are parallel.

For $j = 1, ..., b$

$$\begin{aligned} \sum_i (\alpha\beta)_{ij} &= \sum_i (\mu_{ij} - \mu_{..} - \alpha_i - \beta_j) \\ &= \sum_i \mu_{ij} - a\mu_{..} - \sum_i \alpha_i - a\beta_j \\ &= a\mu_{.j} - a\mu_{..} - \sum_i (\mu_{i.} - \mu_{..}) - a(\mu_{.j} - \mu_{..}) \\ &= a\mu_{.j} - a\mu_{..} - a\mu_{..} + a\mu_{..} - a(\mu_{.j} - \mu_{..}) \\ &= 0 \end{aligned}$$

Similarly, $\sum_j (\alpha\beta) = 0, i = 1, ..., a$ and $\sum_i \sum_j (\alpha\beta)_{ij} = 0$, $\sum_i \alpha_i = 0$, $\sum_j \beta_j = 0$

21.1.3.1.2 Factor Effects Model

$$\mu_{ij} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij}$$
$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where

- $\mu_{..}$ is a constant
- α_i are constants subject to the restriction $\sum_i \alpha_i = 0$
- β_j are constants subject to the restriction $\sum_j \beta_j = 0$
- $(\alpha\beta)_{ij}$ are constants subject to the restriction $\sum_i (\alpha\beta)_{ij} = 0$ for $j = 1, ..., b$ and $\sum_j (\alpha\beta)_{ij} = 0$ for $i = 1, ..., a$
- $\epsilon_{ijk} \sim$ indep $N(0, \sigma^2)$ for $k = 1, .., n$

We have

$$E(Y_{ijk}) = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij}$$
$$var(Y_{ijk}) = \sigma^2$$
$$Y_{ijk} \sim N(\mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij}, \sigma^2)$$

We have $1 + a + b + ab$ parameters. But there are ab parameters in the Cell Means Model. In the Factor Effects Model, the restrictions limit the number of parameters that can be estimated:

$$1 \text{ for } \mu_{..}$$
$$(a-1) \text{ for } \alpha_i$$
$$(b-1) \text{ for } \beta_j$$
$$(a-1)(b-1) \text{ for } (\alpha\beta)_{ij}$$

Hence, there are

$$1 + a - 1 + b - 1 + ab - a - b + 1 = ab$$

parameters in the model.

We can have several restrictions when considering the model in the form $\mathbf{Y} = \mathbf{X}\beta + \epsilon$

One way:

$$\alpha_a = \alpha_1 - \alpha_2 - ... - \alpha_{a-1}$$
$$\beta_b = -\beta_1 - \beta_2 - ... - \beta_{b-1}$$
$$(\alpha\beta)_{ib} = -(\alpha\beta)_{i1} - (\alpha\beta)_{i2} - ... - (\alpha\beta)_{i,b-1}; i = 1, .., a$$
$$(\alpha\beta)_{aj} = -(\alpha\beta)_{1j} - (\alpha\beta)_{2j} - ... - (\alpha\beta)_{a-1,j}; j = 1, .., b$$

We can fit the model by least squares or maximum likelihood

Cell Means Model
minimize

$$Q = \sum_i \sum_j \sum_k (Y_{ijk} - \mu_{ij})^2$$

estimators

$$\begin{aligned} \hat{\mu}_{ij} &= \bar{Y}_{ij} \\ \hat{Y}_{ijk} &= \bar{Y}_{ij} \\ e_{ijk} = Y_{ijk} - \hat{Y}_{ijk} &= Y_{ijk} - \bar{Y}_{ij} \end{aligned}$$

Factor Effects Model

$$Q = \sum_i \sum_j \sum_k (Y_{ijk} - \mu_{..} - \alpha_i = \beta_j - (\alpha\beta)_{ij})^2$$

subject to the restrictions

$$\begin{aligned} \sum_i \alpha_i &= 0 \\ \sum_j \beta_j &= 0 \\ \sum_i (\alpha\beta)_{ij} &= 0 \\ \sum_j (\alpha\beta)_{ij} &= 0 \end{aligned}$$

estimators

$$\begin{aligned} \hat{\mu}_{..} &= \bar{Y}_{...} \\ \hat{\alpha}_i &= \bar{Y}_{i..} - \bar{Y}_{...} \\ \hat{\beta}_j &= \bar{Y}_{.j.} - \bar{Y}_{...} \\ (\hat{\alpha\beta})_{ij} &= \bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...} \end{aligned}$$

The fitted values

$$\hat{Y}_{ijk} = \bar{Y}_{...} + (\bar{Y}_{i..} - \bar{Y}_{...}) + (\bar{Y}_{.j.} - \bar{Y}_{...}) + (\bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...}) = \bar{Y}_{ij.}$$

where

$$e_{ijk} = Y_{ijk} - \bar{Y}_{ij.}$$
$$e_{ijk} \sim \text{ indep } (0, \sigma^2)$$

and

$$\begin{aligned} s^2_{\hat{\mu}_{..}} &= \frac{MSE}{nab} \\ s^2_{\hat{\alpha}_i} &= MSE(\frac{1}{nb} - \frac{1}{nab}) \\ s^2_{\hat{\beta}_j} &= MSE(\frac{1}{na} - \frac{1}{nab}) \\ s^2_{(\hat{\alpha\beta})_{ij}} &= MSE(\frac{1}{n} - \frac{1}{na} - \frac{1}{nb} + \frac{1}{nab}) \end{aligned}$$

21.1.3.1.2.1 Partitioning the Total Sum of Squares

$$Y_{ijk} - \bar{Y}_{...} = \bar{Y}_{ij.} - \bar{Y}_{...} + Y_{ijk} - \bar{Y}_{ij.}$$

$Y_{ijk} - \bar{Y}_{...}$: Total deviation
$\bar{Y}_{ij.} - \bar{Y}_{...}$: Deviation of treatment mean from overall mean
$Y_{ijk} - \bar{Y}_{ij.}$: Deviation of observation around treatment mean (residual).

$$\sum_i \sum_j \sum_k (Y_{ijk} - \bar{Y}_{...})^2 = n \sum_i \sum_j (\bar{Y}_{ij.} - \bar{Y}_{...})^2 + \sum_i \sum_j sum_k (Y_{ijk} - \bar{ij.})^2$$
$$SSTO = SSTR + SSE$$

(cross product terms are 0)

$$\bar{Y}_{ij.} - \bar{Y}_{...} = \bar{Y}_{i..} - \bar{Y}_{...} + \bar{Y}_{.j.} - \bar{Y}_{...} + \bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...}$$

squaring and summing:

$$\begin{aligned} n \sum_i \sum_j (\bar{Y}_{ij.} - \bar{Y}_{...})^2 &= nb \sum_i (\bar{Y}_{i..} - \bar{Y}_{...})^2 + na \sum_j (\bar{Y}_{.j.} - \bar{Y}_{...})^2 \\ &\quad + n \sum_i \sum_j (\bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...})^2 \\ SSTR &= SSA + SSB + SSAB \end{aligned}$$

The interaction term from

$$SSAB = SSTO - SSE - SSA - SSB$$
$$SSAB = SSTR - SSA - SSB$$

where

- SSA is the factor A sum of squares (measures the variability of the estimated factor A level means $\bar{Y}_{i..}$)- the more variable, the larger SSA
- SSB is the factor B sum of squares
- $SSAB$ is the interaction sum of squares, measuring the variability of the estimated interactions.

21.1.3.1.2.2 Partitioning the df $N = abn$ cases and ab treatments.

For one-way ANOVA and regression, the partition has df:

$$SS : SSTO = SSTR + SSE$$

$$df : N - 1 = (ab - 1) + (N - ab)$$

we must further partition the $ab - 1$ df with SSTR

$$SSTR = SSA + SSB + SSAB$$

$$ab - 1 = (a - 1) + (b - 1) + (a - 1)(b - 1)$$

- $df_{SSA} = a - 1$: a treatment deviations but 1 df is lost due to the restriction $\sum(\bar{Y}_{i..} - \bar{Y}_{...}) = 0$

- $df_{SSB} = b - 1$: b treatment deviations but 1 df is lost due to the restriction $\sum(\bar{Y}_{.j.} - \bar{Y}_{...}) = 0$

- $df_{SSAB} = (a - 1)(b - 1) = (ab - 1) - (a - 1) - (b - 1)$: ab interactions, there are (a+b-1) restrictions, so df = ab-a-(b-1)= (a-1)(b-1)

21.1.3.1.2.3 Mean Squares

$$MSA = \frac{SSA}{a - 1}$$
$$MSB = \frac{SSB}{b - 1}$$
$$MSAB = \frac{SSAB}{(a - 1)(b - 1)}$$

The expected mean squares are

$$
\begin{aligned}
E(MSE) &= \sigma^2 \\
E(MSA) &= \sigma^2 + nb\frac{\sum \alpha_i^2}{a-1} = \sigma^2 + nb\frac{\sum(\sum_{i.} - \mu_{..})^2}{a-1} \\
E(MSB) &= \sigma^2 + na\frac{\sum \beta_i^2}{b-1} = \sigma^2 + na\frac{\sum(\sum_{.j} - \mu_{..})^2}{b-1} \\
E(MSAB) &= \sigma^2 + n\frac{\sum\sum(\alpha\beta)_{ij}^2}{(a-1)(b-1)} = \sigma^2 + n\frac{\sum(\mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..})^2}{(a-1)(b-1)}
\end{aligned}
$$

If there are no factor A main effects (all $\mu_{i.} = 0$ or $\alpha_i = 0$) the MSA and MSE have the same expectation; otherwise MSA > MSE. Same for factor B, and interaction effects. which case we can examine F-statistics.

Interaction

$$
\begin{aligned}
H_0 &: \mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..} = 0 \qquad \text{for all i,j} \\
H_a &: \mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..} \neq 0 \quad \text{for some i,j}
\end{aligned}
$$

or

$$
\begin{aligned}
H_0 &: \text{All}(\alpha\beta)_{ij} = 0 \\
H_a &: \text{Not all}(\alpha\beta) = 0
\end{aligned}
$$

Let $F = \frac{MSAB}{MSE}$. When H_0 is true $F \sim f_{((a-1)(b-1),ab(n-1))}$. So reject H_0 when $F > f_{((a-1)(b-1),ab(n-1))}$

Factor A main effects:

$$
\begin{aligned}
H_0 &: \mu_{1.} = \mu_{2.} = ... = \mu_{a.} \\
H_a &: \text{Not all } \mu_{i.} \text{ are equal}
\end{aligned}
$$

or

$$
\begin{aligned}
H_0 &: \alpha_1 = ... = \alpha_a = 0 \\
H_a &: \text{Not all } \alpha_i \text{ are equal to } 0
\end{aligned}
$$

$F = \frac{MSA}{MSE}$ and reject H_0 if $F > f_{(1-\alpha;a-1,ab(n-1))}$

21.1.3.1.2.4 Two-way ANOVA

Source of Variation	SS	df	MS	F
Factor A	SSA	$a-1$	$MSA = SSA/(a-1)$	MSA/MSE
Factor B	SSB	$b-1$	$MSB = SSB/(b-1)$	MSB/MSE
AB interactions	$SSAB$	$(a-1)(b-1)$	$MSAB = SSAB/MSE$	
Error	SSE	$ab(n-1)$	$MSE = SSE/ab(n-1)$	
Total (corrected)	$SSTO$	$abn-1$		

Doing 2-way ANOVA means you always check interaction first, because if there are significant interactions, checking the significance of the main effects becomes moot.

The main effects concern the mean responses for levels of one factor averaged over the levels of the other factor. When interaction is present, we can't conclude that a given factor has no effect, even if these averages are the same. It means that the effect of the factor depends on the level of the other factor.

On the other hand, if you can establish that there is no interaction, then you can consider inference on the factor main effects, which are then said to be **additive**.
And we can also compare factor means like the Single Factor Fixed Effects Model using Tukey, Scheffe, Bonferroni.

We can also consider contrasts in the 2-way model

$$L = \sum c_i \mu_i$$

where $\sum c_i = 0$
which is estimated by

$$\hat{L} = \sum c_i \bar{Y}_{i..}$$

with variance

$$\sigma^2(\hat{L}) = \frac{\sigma^2}{bn} \sum c_i^2$$

and variance estimate

$$\frac{MSE}{bn} \sum c_i^2$$

Orthogonal Contrasts

$$L_1 = \sum c_i \mu_i, \sum c_i = 0$$
$$L_2 = \sum d_i \mu_i, \sum d_i = 0$$

these contrasts are said to be **orthogonal** if

$$\sum \frac{c_i d_i}{n_i} = 0$$

in balanced case $\sum c_i d_i = 0$

$$\begin{aligned} cov(\hat{L}_1, \hat{L}_2) &= cov(\sum_i c_i \bar{Y}_{i..}, \sum_l d_l \bar{Y}_{l..}) \\ &= \sum_i \sum_l c_i d_l cov(\bar{Y}_{i..}, \bar{Y}_{l..}) \\ &= \sum_i c_i d_i \frac{\sigma^2}{bn} = 0 \end{aligned}$$

Orthogonal contrasts can be used to further partition the model sum of squares. There are many sets of orthogonal contrasts and thus, many ways to partition the sum of squares.

A special set of orthogonal contrasts that are used when the levels of a factor can be assigned values on a metric scale are called **orthogonal polynomials**

Coefficients can be found for the special case of

- equal spaced levels (e.g., (0 15 30 45 60))
- equal sample sizes ($n_1 = n_2 = ... = n_{ab}$)

We can define the SS for a given contrast:

$$SS_L = \frac{\hat{L}^2}{\sum_{i=1}^a (c_i^2/bn_i)}$$

$$T = \frac{\hat{L}}{\sqrt{MSE \sum_{i=1}^a (c_i^2/bn_i)}} \sim t$$

Moreover,

$$t^2_{(1-\alpha/2;df)} = F_{(1-\alpha;1,df)}$$

So,

$$\frac{SS_L}{MSE} \sim F_{(1-\alpha;1,df_{MSE})}$$

all contrasts have d.f = 1

21.1.3.2 Unbalanced

We could have unequal numbers of replications for all treatment combinations:

- Observational studies
- Dropouts in designed studies
- Larger sample sizes for inexpensive treatments
- Sample sizes to match population makeup.

Assume that each factor combination has at least 1 observation (no empty cells)

Consider the same model as:

$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where sample sizes are: n_{ij}:

$$\begin{aligned} n_{i.} &= \sum_j n_{ij} \\ n_{.j} &= \sum_i n_{ij} \\ n_T &= \sum_i \sum_j n_{ij} \end{aligned}$$

Problem here is that

$$SSTO \neq SSA + SSB + SSAB + SSE$$

(the design is **non-orthogonal**)

- For $i = 1, ..., a-1$,

$$u_i = \begin{cases} +1 & \text{if the obs is from the i-th level of Factor 1} \\ -1 & \text{if the obs is from the a-th level of Factor 1} \\ 0 & \text{otherwise} \end{cases}$$

- For $j = 1, ..., b-1$

$$v_i = \begin{cases} +1 & \text{if the obs is from the j-th level of Factor 1} \\ -1 & \text{if the obs is from the b-th level of Factor 1} \\ 0 & \text{otherwise} \end{cases}$$

We can use these indicator variables as predictor variables and $\mu_{..}, \alpha_i, \beta_j, (\alpha\beta)_{ij}$ as unknown parameters.

$$Y = \mu_{..} + \sum_{i=1}^{a-1} \alpha_i u_i + \sum_{j=1}^{b-1} \beta_j v_j + \sum_{i=1}^{a-1} \sum_{j=1}^{b-1} (\alpha\beta)_{ij} u_i v_j + \epsilon$$

To test hypotheses, we use the extra sum of squares idea.

For interaction effects

$$H_0 : all(\alpha\beta)_{ij} = 0$$
$$H_a : \text{not all } (\alpha\beta)_{ij} = 0$$

Or to test

$$H_0 : \beta_1 = \beta_2 = \beta_3 = 0$$
$$H_a : \text{not all } \beta_j = 0$$

Analysis of Factor Means

(e.g., contrasts) is analogous to the balanced case, with modifications in the formulas for means and standard errors to account for unequal sample sizes.

Or , we can fit the cell means model and consider it from a regression perspective

If you have empty cells (i.e., some factor combinations have no observation), then the equivalent regression approach can't be used. But you can still do partial analyses

21.1.4 Two-Way Random Effects ANOVA

$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ij}$$

where

- $\mu_{..}$: constant
- $\alpha_i \sim N(0, \sigma_\alpha^2), i = 1, .., a$ (independent)
- $\beta_j \sim N(0, \sigma_\beta^2), j = 1, .., b$ (independent)
- $(\alpha\beta)_{ij} \sim N(0, \sigma_{\alpha\beta}^2), i = 1, ..., a, j = 1, .., b$ (independent)
- $\epsilon_{ijk} \sim N(0, \sigma^2)$ (independent)

All $\alpha_i, \beta_j, (\alpha\beta)_{ij}$ are pairwise independent

Theoretical means, variances, and covariances are

$$\begin{aligned} E(Y_{ijk}) &= \mu_{..} \\ var(Y_{ijk}) &= \sigma_Y^2 = \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_{\alpha\beta}^2 + \sigma^2 \end{aligned}$$

So

$Y_{ijk} \sim N(\mu_{..}, \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_{\alpha\beta}^2 + \sigma^2)$

$$\begin{aligned} cov(Y_{ijk}, Y_{ij'k'}) &= \sigma_\alpha^2, j \neq j' \\ cov(Y_{ijk}, Y_{i'jk'}) &= \sigma_\beta^2, i \neq i' \\ cov(Y_{ijk}, Y_{ijk'}) &= \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_{\alpha\beta}^2, k \neq k' \\ cov(Y_{ijk}, Y_{i'j'k'}) &=, i \neq i', j \neq j' \end{aligned}$$

21.1.5 Two-Way Mixed Effects ANOVA

21.1.5.1 Balanced

One fixed factor, while other is random treatment levels, we have a **mixed effects model** or a **mixed model**

Restricted mixed model for 2-way ANOVA:

$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where

- $\mu_{..}$: constant
- α_i: fixed effects with constraints subject to restriction $\sum \alpha_i = 0$
- $\beta_j \sim indepN(0, \sigma_\beta^2)$
- $(\alpha\beta)_{ij} \sim N(0, \frac{a-1}{a}\sigma_{\alpha\beta}^2)$ subject to restriction $\sum_i (\alpha\beta)_{ij} = 0$ for all j, the variance here is written as the proportion for convenience; it makes the expected mean squares simpler (other assumed $var((\alpha\beta)_{ij} = \sigma_{\alpha\beta}^2)$
- $cov((\alpha\beta)_{ij}, (\alpha\beta)_{i'j'}) = -\frac{1}{a}\sigma_{\alpha\beta}^2, i \neq i'$
- $\epsilon_{ijk} \sim indepN(0, \sigma^2)$
- $\beta_j, (\alpha\beta)_{ij}, \epsilon_{ijk}$ are pairwise independent

Two-way mixed models are written in an "unrestricted" form, with no restrictions on the interaction effects $(\alpha\beta)_{ij}$, they are pairwise independent.

Let $\beta^*, (\alpha\beta)_{ij}^*$ be the unrestricted random effects, and $(\bar{\alpha\beta})_{ij}^*$ the means averaged over the fixed factor for each level of random factor B.

$$\beta_j = \beta_j^* + (\bar{\alpha\beta})_{ij}^*$$
$$(\alpha\beta)_{ij} = (\alpha\beta)_{ij}^* - (\bar{\alpha\beta})_{ij}^*$$

Some consider the restricted model to be more general. but here we consider the restricted form.

$$E(Y_{ijk}) = \mu_{..} + \alpha_i$$
$$var(Y_{ijk}) = \sigma_\beta^2 + \frac{a-1}{a}\sigma_{\alpha\beta}^2 + \sigma^2$$

Responses from the same random factor (B) level are correlated

$$cov(Y_{ijk}, Y_{ijk'}) = E(Y_{ijk}Y_{ijk'}) - E(Y_{ijk})E(Y_{ijk'})$$
$$= \sigma_\beta^2 + \frac{a-1}{a}\sigma_{\alpha\beta}^2, k \neq k'$$

Similarly,

$$cov(Y_{ijk}, Y_{i'jk'}) = \sigma_\beta^2 - \frac{1}{a}\sigma_{\alpha\ \beta}^2, i \neq i'$$
$$cov(Y_{ijk}, Y_{i'j'k'}) = 0, j \neq j'$$

Hence, you can see that the only way you don't have dependence in the Y is when they don't share the same random effect.

An advantage of the **restricted mixed model** is that 2 observations from the same random factor b level can be positively or negatively correlated. In the **unrestricted model**, they can only be positively correlated.

Mean Square	Fixed ANOVA (A, B Fixed)	Random ANOVA (A,B random)	Mixed ANVOA (A fixed, B random)
MSA	a - 1	$\sigma^2 + nb\frac{\sum \alpha_i^2}{a-1}$	$\sigma^2 + nb\sigma_\alpha^2 + n\sigma_{\alpha\beta}^2$
MSB	b-1	$\sigma^2 + na\frac{\sum \beta_j^2}{b-1}$	$\sigma^2 + na\sigma_\beta^2 + n\sigma_{\alpha\beta}^2$
MSAB	(a-1)(b-1)	$\sigma^2 + n\frac{\sum\sum(\alpha\beta)_{ij}^2}{(a-1)(b-1)}$	$\sigma^2 + n\sigma_{\alpha\beta}^2$
MSE	(n-1)ab	σ^2	σ^2

For fixed, random, and mixed models (balanced), the ANOVA table sums of squares calculations are identical. (also true for df and mean squares). The only difference is with the expected mean squares, thus the test statistics.

In Random ANOVA, we test

$$H_0 : \sigma^2 = 0$$
$$H_a : \sigma^2 > 0$$

by considering $F = \frac{MSA}{MSAB} \sim F_{a-1;(a-1)(b-1)}$

The same test statistic is used for mixed models, but in that case we are testing null hypothesis that all of the $\alpha_i = 0$

The test statistic different for the same null hypothesis under the fixed effects model.

Test for effects of	Fixed ANOVA (A&B fixed)	Random ANOVA (A&B random)	Mixed ANOVA (A fixed, B random)
Factor A	$\frac{MSA}{MSE}$	$\frac{MSA}{MSAB}$	$\frac{MSA}{MSAB}$
Factor B	$\frac{MSB}{MSE}$	$\frac{MSB}{MSAB}$	$\frac{MSB}{MSE}$
AB interactions	$\frac{MSAB}{MSE}$	$\frac{MSAB}{MSE}$	$\frac{MSAB}{MSE}$

Estimation Of Variance Components

In random and mixed effects models, we are interested in estimating the **variance components**
Variance component σ^2_β in the mixed ANOVA.

$$E(\sigma^2_\beta) = \frac{E(MSB) - E(MSE)}{na} = \frac{\sigma^2 + na\sigma^2_\beta - \sigma^2}{na} = \sigma^2_\beta$$

which can be estimated with

$$\hat{\sigma}^2_\beta = \frac{MSB - MSE}{na}$$

Confidence intervals for variance components can be constructed (approximately) by using the **Satterthwaite** procedure or the MLS procedure (like the 1-way random effects)

Estimation of Fixed Effects in Mixed Models

$$
\begin{aligned}
\hat{\alpha}_i &= \bar{Y}_{i..} - \bar{Y}_{...} \\
\hat{\mu}_{i.} &= \bar{Y}_{...} + (\bar{Y}_{i..} - \bar{Y}_{...}) = \bar{Y}_{i..} \\
\sigma^2(\hat{\alpha}_i) &= \frac{\sigma^2 + n\sigma^2_{\alpha\beta}}{bn} = \frac{E(MSAB)}{bn} \\
s^2(\hat{\alpha}_i) &= \frac{MSAB}{bn}
\end{aligned}
$$

Contrasts on the **Fixed Effects**

$$
\begin{aligned}
L &= \sum c_i \alpha_i \\
\sum c_i &= 0 \\
\hat{L} &= \sum c_i \hat{\alpha}_i \\
\sigma^2(\hat{L}) &= \sum c_i^2 \sigma^2(\hat{\alpha}_i) \\
s^2(\hat{L}) &= \frac{MSAB}{bn} \sum c_i^2
\end{aligned}
$$

Confidence intervals and tests can be constructed as usual

21.1.5.2 Unbalanced

For a mixed model with a = 2, b = 4

$$
\begin{aligned}
Y_{ijk} &= \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk} \\
var(\beta_j) &= \sigma^2_\beta \\
var((\alpha\beta)_{ij}) &= \frac{2-1}{2}\sigma^2_{\alpha\beta} = \frac{\sigma^2_{\alpha\beta}}{2} \\
var(\epsilon_{ijk}) &= \sigma^2 \\
E(Y_{ijk}) &= \mu_{..} + \alpha_i \\
var(Y_{ijk}) &= \sigma^2_\beta + \frac{\sigma^2_{\alpha\beta}}{2} + \sigma^2 \\
cov(Y_{ijk}, Y_{ijk'}) &= \sigma^2 + \frac{\sigma^2_{\alpha\beta}}{2}, k \neq k' \\
cov(Y_{ijk}, Y_{i'jk'}) &= \sigma^2_\beta - \frac{\sigma^2_{\alpha\beta}}{2}, i \neq i' \\
cov(Y_{ijk}, Y_{i'j'k'}) &= 0, j \neq j'
\end{aligned}
$$

assume

$$
\mathbf{Y} \sim N(\mathbf{X}\beta, M)
$$

where M is block diagonal

density function

$$f(\mathbf{Y}) = \frac{1}{(2\pi)^{N/2}|M|^{1/2}} exp(-\frac{1}{2}(\mathbf{Y} - \mathbf{X}\ )'\mathbf{M^{-1}}(\mathbf{Y} - \mathbf{X}\ ))$$

if we knew the variance components, we could use GLS:

$$\hat{\beta}_{GLS} = (\mathbf{X}'\mathbf{M^{-1}}\mathbf{X})^{-1}\mathbf{X}'\mathbf{M^{-1}}\mathbf{Y}$$

but we usually don't know the variance components $\sigma^2, \sigma^2_\beta, \sigma^2_{\alpha\beta}$ that make up M
Another way to get estimates is by **Maximum likelihood estimation**

we try to maximize its log

$$\ln L = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|M| - \frac{1}{2}(\mathbf{Y} - \mathbf{X}\ )'\ ^{-1}(\mathbf{Y} - \mathbf{X}\ )$$

21.2 Nonparametric ANOVA

21.2.1 Kruskal-Wallis

Generalization of independent samples Wilcoxon Rank sum test for 2 independent samples (like F-test of one-way ANOVA is a generalization to several independent samples of the two sample t-test)

Consider the one-way case:

We have

- $a \geq 2$ treatments
- n_i is the sample size for the i-th treatment
- Y_{ij} is the j-th observation from the i-th treatment.
- we make **no** assumption of normality
- We only assume that observations on the i-th treatment are a random sample from the continuous CDF F_i, i = 1,..,n, and are mutually independent.

$$H_0 : F_1 = F_2 = ... = F_a$$
$$H_a : F_i < F_j \text{ for some } i \neq j$$

or if distribution is from the location-scale family, $H_0 : \theta_1 = \theta_2 = ... = \theta_a$)

Procedure

- Rank all $N = \sum_{i=1}^{a} n_i$ observations in ascending order. Let $r_{ij} = rank(Y_{ij})$, note $\sum_i \sum_j r_{ij} = 1 + 2.. + N = \frac{N(N+1)}{2}$

- Calculate the rank sums and averages:

$$r_{i.} = \sum_{j=1}^{n_i} r_{ij}$$

and

$$\bar{r}_{i.} = \frac{r_{i.}}{n_i}, i = 1, .., a$$

- Calculate the test statistic on the ranks:

$$\chi^2_{KW} = \frac{SSTR}{\frac{SSTO}{N-1}}$$

where $SSTR = \sum n_i(\bar{r}_{i.} - \bar{r}_{..})^2$ and $SSTO = \sum\sum(\bar{r}_{ij} - \bar{r}_{..})^2$
- For large n_i ($\geq$ 5 observations) the Kruskal-Wallis statistic is approximated by a χ^2_{a-1} distribution when all the treatment means are equal. Hence, reject H_0 if $\chi^2_{KW} > \chi^2_{(1-\alpha;a-1)}$.

- If sample sizes are small, one can exhaustively work out all possible distinct ways of assigning N ranks to the observations from a treatments and calculate the value of the KW statistic in each case ($\frac{N!}{n_1!..n_a!}$ possible combinations). Under H_0 all of these assignments are equally likely.

21.2.2 Friedman Test

When the responses $Y_{ij} = 1, .., n, j = 1, .., r$ in a randomized complete block design are not normally distributed (or do not have constant variance), a non-parametric test is more helpful.

A distribution-free rank-based test for comparing the treatments in this setting is the Friedman test. Let F_{ij} be the CDF of random Y_{ij}, corresponding to the observed value y_{ij}

Under the null hypothesis, F_{ij} are identical for all treatments j separately for each block i.

$$H_0 : F_{i1} = F_{i2} = ... = F_{ir} \text{ for all i}$$
$$H_a : F_{ij} < F_{ij'} \text{ for some } j \neq j' \text{ for all } i$$

For location parameter distributions, treatment effects can be tested:

$$H_0 : \tau_1 = \tau_2 = ... = \tau_r$$
$$H_a : \tau_j > \tau_{j'} \text{ for some } j \neq j'$$

Procedure

- Rank observations from the r treatments separately within each block (in ascending order; if ties, each tied observation is given the mean of ranks involved). Let the ranks be called r_{ij}

- Calculate the Friedman test statistic

$$\chi_F^2 = \frac{SSTR}{\frac{SSTR+SSE}{n(r-1)}}$$

where

$$SSTR = n\sum(\bar{r}_{.j} - \bar{r}_{..})^2$$
$$SSE = \sum\sum(r_{ij} - \bar{r}_{.j})^2$$
$$\bar{r}_{.j} = \frac{\sum_i r_{ij}}{n}$$
$$\bar{r}_{..} = \frac{r+1}{2}$$

If there is no ties, it can be rewritten as

$$\chi_F^2 = [\frac{12}{nr(n+1)}\sum_j r_{.j}^2] - 3n(r+1)$$

with large number of blocks, χ_F^2 is approximately χ_{r-1}^2 under H_0. Hence, we reject H_0 if $\chi_F^2 > \chi_{(1-\alpha;r-1)}^2$
The exact null distribution for χ_F^2 can be derived since there are r! possible ways of assigning ranks 1,2,...,r to the r observations within each block. There are n blocks and thus $(r!)^n$ possible assignments to the ranks, which are equally likely when H_0 is true.

21.3 Sample Size Planning for ANOVA

21.3.1 Balanced Designs

21.3.1.1 Single Factor Studies

21.3.1.1.1 Fixed cell means

$$P(F > f_{(1-\alpha;a-1,N-a)}|\phi) = 1 - \beta$$

where ϕ is the non-centrality **parameter** (measures how unequal the treatment means μ_i are)

$$\phi = \frac{1}{\sigma}\sqrt{\frac{n}{a}\sum_i(\mu_i - \mu_.)^2}, (n_i \equiv n)$$

and

$$\mu_{.} = \frac{\sum \mu_i}{a}$$

To decide on the power probabilities we use the non-central F distribution.

We could use the power table directly when effects are fixed and design is balanced by using **minimum range** of factor level means for your desired differences

$$\Delta = \max(\mu_i) - \min(\mu_i)$$

Hence, we need

- α level
- Δ
- σ
- β

Notes:

- When Δ/σ is small greatly affects sample size, but if Δ/σ is large.
- Reducing α or β increases the required sample sizes.
- Error in estimating σ can make a large difference.

21.3.1.2 Multi-factor Studies

The same noncentral F tables can be used here

For two-factor fixed effect model

Test for interactions:

$$\begin{aligned}
\phi &= \frac{1}{\sigma}\sqrt{\frac{n\sum\sum(\alpha\beta_{ij})^2}{(a-1)(b-1)+1}} = \frac{1}{\sigma}\sqrt{\frac{n\sum\sum(\mu_{ij}-\mu_{i.}-\mu_{.j}+\mu_{..})^2}{(a-1)(b-1)+1}} \\
\upsilon_1 &= (a-1)(b-1) \\
\upsilon_2 &= ab(n-1)
\end{aligned}$$

Test for Factor A main effects:

$$\begin{aligned}
\phi &= \frac{1}{\sigma}\sqrt{\frac{nb\sum\alpha_i^2}{a}} = \frac{1}{\sigma}\sqrt{\frac{nb\sum(\mu_{i.}-\mu_{..})^2}{a}} \\
\upsilon_1 &= a-1 \\
\upsilon_2 &= ab(n-1)
\end{aligned}$$

Test for Factor B main effects:

$$\phi = \frac{1}{\sigma}\sqrt{\frac{na\sum\beta_j^2}{b}} = \frac{1}{\sigma}\sqrt{\frac{na\sum(\mu_{.j}-\mu_{..})^2}{b}}$$
$$\upsilon_1 = b-1$$
$$\upsilon_2 = ab(n-1)$$

Procedure:

1. Specify the minimum range of Factor A means
2. Obtain sample sizes with $r = a$. The resulting sample size is bn, from which n can be obtained.
3. Repeat the first 2 steps for Factor B minimum range.
4. Choose the greater number of sample size between A and B.

21.3.2 Randomized Block Experiments

Analogous to completely randomized designs . The power of the F-test for treatment effects for randomized block design uses the same non-centrality parameter as completely randomized design:

$$\phi = \frac{1}{\sigma}\sqrt{\frac{n}{r}\sum(\mu_i-\mu_.)^2}$$

However, the power level is different from the randomized block design because

- error variance σ^2 is different
- df(MSE) is different.

21.4 Randomized Block Designs

To improve the precision of treatment comparisons, we can reduce variability among the experimental units. We can group experimental units into **blocks** so that each block contains relatively homogeneous units.

- Within each block, random assignment treatments to units (separate random assignment for each block)
- The number of units per block is a multiple of the number of factor combinations.
- Commonly, use each treatment once in each block.

Benefits of **Blocking**

- Reduction in variability of estimators for treatment means
  - Improved power for t-tests and F-tests
  - Narrower confidence intervals

  - Smaller MSE

- Compare treatments under different conditions (related to different blocks).

Loss from **Blocking** (little to lose)

- If you don't do blocking well, you waste df on negligible block effects that could have been used to estimate σ^2
- Hence, the df for t-tests and denominator df for F-tests will be reduced without reducing MSE and small loss of power for both tests.

Consider

$$Y_{ij} = \mu_{..} + \rho_i + \tau_j + \epsilon_{ij}$$

where

- $i = 1, 2, \ldots, n$
- $j = 1, 2, \ldots, r$
- $\mu_{..}$: overall mean response, averaging across all blocks and treatments
- ρ_i: block effect, average difference in response for i-th block ($\sum \rho_i = 0$)
- τ_j treatment effect, average across blocks ($\sum \tau_j = 0$)
- $\epsilon_{ij} \sim iidN(0, \sigma^2)$: random experimental error.

Here, we assume that the block and treatment effects are additive. The difference in average response for any pair of treatments i the same **within** each block

$$(\mu_{..} + \rho_i + \tau_j) - (\mu_{..} + \rho_i + \tau_j') = \tau_j - \tau_j'$$

for all $i = 1, .., n$ blocks

$$\begin{aligned}
\hat{\mu} &= \bar{Y}_{..} \\
\hat{\rho}_i &= \bar{Y}_{i.} - \bar{Y}_{..} \\
\hat{\tau}_j &= \bar{Y}_{.j} - \bar{Y}_{..}
\end{aligned}$$

Hence,

$$\begin{aligned}
\hat{Y}_{ij} &= \bar{Y}_{..} + (\bar{Y}_{i.} - \bar{Y}_{..}) + (\bar{Y}_{.j} - \bar{Y}_{..}) = \bar{Y}_{i.} + \bar{Y}_{.j} - \bar{Y}_{..} \\
e_{ij} &= Y_{ij} - \hat{Y}_{ij} = Y_{ij} - \bar{Y}_{i.} - \bar{Y}_{.j} + \bar{Y}_{..}
\end{aligned}$$

ANOVA table

Source of Variation	SS	df	Fixed Treatments E(MS)	Random Treatments E(MS)
Blocks	$r\sum_i(\bar{Y}_{i.}-\bar{Y}_{..})^2$	$n-1$	$\sigma^2+r\frac{\sum\rho_i^2}{n-1}$	$\sigma^2+r\frac{\sum\rho_i^2}{n-1}$
Treatments	$n\sum_j(\bar{Y}_{.j}-\bar{Y}_{..})^2$	$r-1$	$\sigma^2+n\frac{\sum\tau_j^2}{r-1}$	$\sigma^2+n\sigma_\tau^2$
Error	$\sum_i\sum_j(Y_{ij}-\bar{Y}_{i.}-\bar{Y}_{.j}+\bar{Y}_{..})^2$	$(n-1)(r-1)$	σ^2	σ^2
Total	$SSTO$	$nr-1$		

F-tests

$$H_0:\tau_1=\tau_2=...=\tau_r=0 \qquad \text{Fixed Treatment Effects}$$
$$H_a:\text{not all } \tau_j=0$$

$$H_0:\sigma_\tau^2=0 \quad \text{Random Treatment Effects}$$
$$H_a:\sigma_\tau^2\neq 0$$

In both cases $F=\frac{MSTR}{MSE}$, reject H_0 if $F>f_{(1-\alpha;r-1,(n-1)(r-1))}$

we don't use F-test to compare blocks, because

- We have a priori that blocs are different
- Randomization is done "within" block.

To estimate the efficiency that was gained by blocking (relative to completely randomized design).

$$\hat{\sigma}_{CR}^2=\frac{(n-1)MSBL+n(r-1)MSE}{nr-1}$$
$$\hat{\sigma}_{RB}^2=MSE$$
$$\frac{\hat{\sigma}_{CR}^2}{\hat{\sigma}_{RB}^2}=\text{above 1}$$

then a completely randomized experiment would

$$(\frac{\hat{\sigma}_{CR}^2}{\hat{\sigma}_{RB}^2}-1)\%$$

more observations than the randomized block design to get the same MSE

If batches are randomly selected then they are random effects. That is , if the experiment was repeated, a new sample of i batches would be selected,d yielding new values for $\rho_1, \rho_2, ..., \rho_i$ then.

$$\rho_1, \rho_2, ..., \rho_j \sim N(0, \sigma_\rho^2)$$

Then,

$$Y_{ij} = \mu_{..} + \rho_i + \tau_j + \epsilon_{ij}$$

where

- $\mu_{..}$ fixed
- ρ_i: random iid $N(0, \sigma_p^2)$
- τ_j fixed (or random) $\sum \tau_j = 0$
- $\epsilon_{ij} \sim iidN(0, \sigma^2)$

Fixed Treatment

$$E(Y_{ij}) = \mu_{..} + \tau_j$$
$$var(Y_{ij}) = \sigma_\rho^2 + \sigma^2$$

$$cov(Y_{ij}, Y_{ij'}) = \sigma^2, j \neq j' \text{ treatments within same block are correlated}$$
$$cov(Y_{ij}, Y_{i'j'}) = 0, i \neq i', j \neq j'$$

Correlation between 2 observations in the same block

$$\frac{\sigma_\rho^2}{\sigma^2 + \sigma_\rho^2}$$

The expected MS for the additive fixed treatment effect, random block effect is

Source	SS	E(MS)
Blocks	SSBL	$\sigma^2 + r\sigma_\rho^2$
Treatment	SSTR	$\sigma^2 + n\frac{\sum \tau_j^2}{r-1}$
Error	SSE	σ^2

Interactions and Blocks

without replications within each block for each treatment, we can't consider interaction between block and treatment when the block effect is fixed. Hence, only in the random block effect, we have

$$Y_{ij} = \mu_{..} + \rho_i + \tau_j + (\rho\tau)_{ij} + \epsilon_{ij}$$

where

- $\mu_{..}$ constant
- $\rho_i \sim iddN(0, \sigma_\rho^2)$ random
- τ_j fixed ($\sum \tau_j = 0$)
- $(\rho\tau)_{ij} \sim N(0, \frac{r-1}{r}\sigma_{\rho\tau}^2)$ with $\sum_j (\rho\tau)_{ij} = 0$ for all i
- $cov((\rho\tau)_{ij}, (\rho\tau)_{ij'}) = -\frac{1}{r}\sigma_{\rho\tau}^2$ for $j \neq j'$
- $\epsilon_{ij} \sim iidN(0, \sigma^2)$ random

Note: a special case of mixed 2-factor model with 1 observation per "cell"

$$E(Y_{ij}) = \mu_{..} + \tau_j$$
$$var(Y_{ij}) = \sigma_\rho^2 + \frac{r-1}{r}\sigma_{\rho\tau}^2 + \sigma^2$$

$$cov(Y_{ij}, Y_{ij'}) = \sigma_\rho^2 - \frac{1}{r}\sigma_{\rho\tau}^2, j \neq j' \text{ obs from the same block are correlated}$$
$$cov(Y_{ij}, Y_{i'j'}) = 0, i \neq i', j \neq j' \text{ obs from different blocks are independent}$$

The sum of squares and degrees of freedom for interaction model are the same as those for the additive model. The difference exists only with the expected mean squares

Source	SS	df	E(MS)
Blocks	$SSBL$	$n-1$	$\sigma^2 + r\sigma_\rho^2$
Treatment	$SSTR$	$r-1$	$\sigma^2 + \sigma_{\rho\tau}^2 + n\frac{\sum \tau_j^2}{r-1}$
Error	SSE	$(n-1)(r-1)$	$\sigma^2 + \sigma_{\rho\tau}^2$

- No exact test is possible for block effects when interaction is present (Not important if blocks are used primarily to reduce experimental error variability)

- $E(MSE) = \sigma^2 + \sigma_{\rho\tau}^2$ the error term variance and interaction variance $\sigma_{\rho\tau}^2$. We can't estimate these components separately with this model. The two are **confounded**.

- If more than 1 observation per treatment block combination, one can consider interaction with fixed block effects, which is called **generalized randomized block designs** (multifactor analysis).

21.4.1 Tukey Test of Additivity

(Tukey's 1 df test for additivity)

formal test of interaction effects between blocks and treatments for a randomized block design. can also considered for testing additivity in 2-way analyses when there is only one observation per cell.

we consider a less restricted interaction term

$$(\rho\tau)_{ij} = D\rho_i\tau_j(\text{D: Constant})$$

So,

$$Y_{ij} = \mu_{..} + \rho_i + \tau_j + D\rho_i\tau_j + \epsilon_{ij}$$

the least square estimate or MLE for D

$$\hat{D} = \frac{\sum_i \sum_j \rho_i\tau_j Y_{ij}}{\sum_i \rho_i^2 \sum_j \tau_j^2}$$

replacing the parameters by their estimates

$$\hat{D} = \frac{\sum_i \sum_j (\bar{Y}_{i.} - \bar{Y}_{..})(\bar{Y}_{.j} - \bar{Y}_{..})Y_{ij}}{\sum_i (\bar{Y}_{i.} - \bar{Y}_{..})^2 \sum_j (\bar{Y}_{.j} - \bar{Y}_{..})^2}$$

Thus, the interaction sum of squares

$$SSint = \sum_i \sum_j \hat{D}^2 (\bar{Y}_{i.} - \bar{Y}_{..})^2 (\bar{Y}_{.j} - \bar{Y}_{..})^2$$

The ANOVA decomposition

$$SSTO = SSBL + SSTR + SSint + SSRem$$

where $SSRem$: remainder sum of squares

$$SSRem = SSTO - SSBL - SSTR - SSint$$

if $D = 0$ (i.e., no interactions of the type $D\rho_i\tau_j$). $SSint$ and $SSRem$ are independent $\chi^2_{1,rn-r-n}$.

If $D = 0$,

$$F = \frac{SSint/1}{SSRem/(rn-r-n)} \sim f_{(1-\alpha;rn-r-n)}$$

if

$$H_0 : D = 0 \text{ no interaction present}$$
$$H_a : D \neq 0 \text{ interaction of form } D\rho_i\tau_j \text{ present}$$

we reject H_0 if $F > f_{(1-\alpha;1,nr-r-n)}$

21.5 Nested Designs

Let μ_{ij} be the mean response when factor A is at the i-th level and factor B is at the j-th level.
If the factors are crossed, the j-th level of B is the same for all levels of A.
If factor B is nested within A, the j-th level of B when A is at level 1 has nothing in common with the j-th level of B when A is at level 2.

Factors that can't be manipulated are designated as **classification factors**, as opposed to **experimental factors** (i.e., you assign to the experimental units).

21.5.1 Two-Factor Nested Designs

- Consider B is nested within A.
- both factors are fixed
- All treatment means are equally important.

Mean responses

$$\mu_{i.} = \sum_j \mu_{ij}/b$$

Main effect factor A

$$\alpha_i = \mu_{i.} - \mu_{..}$$

where $\mu_{..} = \frac{\mu_{ij}}{ab} = \frac{\sum_i \mu_{i.}}{a}$ and $\sum_i \alpha_i = 0$

Individual effects of B is denoted as $\beta_{j(i)}$ where $j(i)$ indicates the j-th level of factor B is nested within the it-h level of factor A

$$\begin{aligned}\beta_{j(i)} &= \mu_{ij} - \mu_{i.} \\ &= \mu_{ij} - \alpha_i - \mu_{..} \\ \sum_j \beta_{j(i)} &= 0, i = 1, ..., a\end{aligned}$$

$\beta_{j(i)}$ is the **specific effect** of the j-th level of factor B nested within the i-th level of factor A. Hence,

$$\mu_{ij} \equiv \mu_{..} + \alpha_i + \beta_{j(i)} \equiv \mu_{..} + (\mu_{i.} - \mu_{..}) + (\mu_{ij} - \mu_{i.})$$

Model

$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_{j(i)} + \epsilon_{ijk}$$

where

- Y_{ijk} response for the k-th treatment when factor A is at the i-th level and factor B is at the j-th level ($i = 1, .., a; j = 1, .., b; k = 1, ..n$)
- $\mu_{..}$ constant
- α_i constants subject to restriction $\sum_i \alpha_i = 0$
- $\beta_{j(i)}$ constants subject to restriction $\sum_j \beta_{j(i)} = 0$ for all i
- $\epsilon_{ijk} \sim iidN(0, \sigma^2)$

$$\begin{aligned} E(Y_{ijk}) &= \mu_{..} + \alpha_i + \beta_{j(i)} \\ var(Y_{ijk}) &= \sigma^2 \end{aligned}$$

there is no interaction term in a nested model

ANOVA for Two-Factor Nested Designs

Least Squares and MLE estimates

Parameter	Estimator
$\mu_{..}$	$\bar{Y}_{...}$
α_i	$\bar{Y}_{i..} - \bar{Y}_{...}$
$\beta_{j(i)}$	$\bar{Y}_{ij.} - \bar{Y}_{i..}$
$\hat{Y}_{ijk}$	$\bar{Y}_{ij.}$

residual $e_{ijk} = Y_{ijk} - \bar{Y}_{ijk}$

$$\begin{aligned} SSTO &= SSA + SSB(A) + SSE \\ \sum_i \sum_j \sum_k (Y_{ijk} - \bar{Y}_{...})^2 &= bn \sum_i (\bar{Y}_{i..} - \bar{Y}_{...})^2 + n \sum_i \sum_j (\bar{Y}_{ij.} - \bar{Y}_{i..})^2 \\ &\quad + \sum_i \sum_j \sum_k (Y_{ijk} - \bar{Y}_{ij.})^2 \end{aligned}$$

ANOVA Table

Source of Variation	SS	df	MS	E(MS)
Factor A	SSA	$a-1$	MSA	$\sigma^2 + bn\frac{\sum \alpha_i^2}{a-1}$
Factor B	$SSB(A)$	$a(b-1)$	$MSB(A)$	$\sigma^2 + n\frac{\|\|\|um \sum eta_{i)}^2}{a(b-1)}$
Error	SSE	$ab(n-1)$	MSE	σ^2
Total	$SSTO$	$abn-1$		

Tests For Factor Effects

$$H_0: \text{ All } \alpha_i = 0$$
$$H_a: \text{ not all } \alpha_i = 0$$

$F = \frac{MSA}{MSE} \sim f_{(1-\alpha;a-1,(n-1)ab)}$ reject if $F > f$

$$H_0: \text{ All } \beta_{j(i)} = 0$$
$$H_a: \text{ not all } \beta_{j(i)} = 0$$

$F = \frac{MSB(A)}{MSE} \sim f_{(1-\alpha;a(b-1),(n-1)ab)}$ reject $F > f$

Testing Factor Effect Contrasts

$L = \sum c_i \mu_i$ where $\sum c_i = 0$

$$\hat{L} = \sum c_i \bar{Y}_{i..}$$
$$\hat{L} \pm t_{(1-\alpha/2;df)} s(\hat{L})$$

where $s^2(\hat{L}) = \sum c_i^2 s^2(\bar{Y}_{i..})$, where $s^2(\bar{Y}_{i..}) = \frac{MSE}{bn}, df = ab(n-1)$

Testing Treatment Means

$L = \sum c_i \mu_{.j}$ estimated by $\hat{L} = \sum c_i \bar{Y}_{ij}$ with confidence limits:

$$\hat{L} \pm t_{(1-\alpha/2;(n-1)ab)} s(\hat{L})$$

where

$$s^2(\hat{L}) = \frac{MSE}{n} \sum c_i^2$$

Unbalanced Nested Two-Factor Designs

If there are different number of levels of factor B for different levels of factor A, then the design is called **unbalanced**

The model

$$
\begin{aligned}
Y_{ijk} &= \mu_{..} + \alpha_i + \beta_{j(i)} + \epsilon_{ijk} \\
\sum_{i=1}^{2} \alpha_i &= 0 \\
\sum_{j=1}^{3} \beta_{j(1)} &= 0 \\
\sum_{j=1}^{2} \beta_{j(2)} &= 0
\end{aligned}
$$

where

- $i = 1, 2; j = 1, .., b_i; k = 1, .., n_{ij}$
- $b_1 = 3, b_2 = 2, n_{11} = n_{13} = 2, n_{12} = 1, n_{21} = n_{22} = 2$
- $\alpha_1, \beta_{1(1)}, \beta_{2(1)}, \beta_{1(2)}$ are parameters.

And constraints: $\alpha_2 = -\alpha_1, \beta_{3(1)} = -\beta_{1(1)} - \beta_{2(1)}, \beta_{2(2)} = -\beta_{1(2)}$

4 indicator variables

$$X_1 = \begin{cases} 1 & \text{if obs from school 1} \\ -1 & \text{if obs from school 2} \end{cases} \tag{21.4}$$

$$X_2 = \begin{cases} 1 & \text{if obs from instructor 1 in school 1} \\ -1 & \text{if obs from instructor 3 in school 1} \\ 0 & \text{otherwise} \end{cases} \tag{21.5}$$

$$X_3 = \begin{cases} 1 & \text{if obs from instructor 2 in school 1} \\ -1 & \text{if obs from instructor 3 in school 1} \\ 0 & \text{otherwise} \end{cases} \tag{21.6}$$

$$X_4 = \begin{cases} 1 & \text{if obs from instructor 1 in school 1} \\ -1 & \text{if obs from instructor 2 in school 1} \\ 0 & \text{otherwise} \end{cases} \tag{21.7}$$

Regression Full Model

$$Y_{ijk} = \mu_{..} + \alpha_1 X_{ijk1} + \beta_{1(1)} X_{ijk2} + \beta_{2(1)} X_{ijk3} + \beta_{1(2)} X_{ijk4} + \epsilon_{ijk}$$

Random Factor Effects

If

$$\alpha_1 \sim iidN(0, \sigma_\alpha^2)$$
$$\beta_{j(i)} \sim iidN(0, \sigma_\beta^2)$$

Mean Square	Expected Mean Squares A fixed, B random	Expected Mean Squares A random, B random
MSA	$\sigma^2 + n\sigma_\beta^2 + bn\frac{\sum \alpha_i^2}{a-1}$	$\sigma^2 + bn\sigma_\alpha^2 + n\sigma_\beta^2$
MSB(A)	$\sigma^2 + n\sigma_\beta^2$	$\sigma^2 + n\sigma_\beta^2$
MSE	σ^2	σ^2

Test Statistics

Factor A	$\frac{MSA}{MSB(A)}$	$\frac{MSA}{MSB(A)}$
Factor B(A)	$\frac{MSB(A)}{MSE}$	$\frac{MSB(A)}{MSE}$

Another way to increase the precision of treatment comparisons by reducing variability is to use regression models to adjust for differences among experimental units (also known as **analysis of covariance**).

21.6 Single Factor Covariance Model

$$Y_{ij} = \mu_. + \tau_i + \gamma(X_{ij} - \bar{X}_{..}) + \epsilon_{ij}$$

for $i = 1, ..., r; j = 1, .., n_i$

where

- $\mu_.$ overall mean
- τ_i: fixed treatment effects ($\sum \tau_i = 0$)
- γ: fixed regression coefficient effect between X and Y
- X_{ij} covariate (not random)
- $\epsilon_{ij} \sim iidN(0, \sigma^2)$: random errors

If we just use γX_{ij} as the regression term (rather than $\gamma(X_{ij} - \bar{X}_{..})$), then $\mu_.$ is no longer the overall mean; thus we need to centered mean.

$$E(Y_{ij}) = \mu_. + \tau_i + \gamma(X_{ij} - \bar{X}_{..})$$
$$var(Y_{ij}) = \sigma^2$$

$Y_{ij} \sim N(\mu_{ij}, \sigma^2)$,

where

$$\mu_{ij} = \mu_{.} + \tau_i + \gamma(X_{ij} - \bar{X}_{..})$$
$$\sum \tau_i = 0$$

Thus, the mean response (μ_{ij}) is a regression line with intercept $\mu_{.} + \tau_i$ and slope γ for each treatment $$i.

Assumption:

- All treatment regression lines have the same slope
- when treatment interact with covariate X (non-parallel slopes), covariance analysis is **not** appropriate. in which case we should use separate regression lines.

More complicated regression features (e.g., quadratic, cubic) or additional covariates e.g.,

$$Y_{ij} = \mu_{.} + \tau_i + \gamma_1(X_{ij1} - \bar{X}_{..2}) + \gamma_2(X_{ij2} - \bar{X}_{..2}) + \epsilon_{ij}$$

Regression Formulation

We can use indicator variables for treatments

$$l_1 = \begin{cases} 1 & \text{if case is from treatment 1} \\ -1 & \text{if case is from treatment r} \\ 0 & \text{otherwise} \end{cases}$$

.

.

$$l_{r-1} = \begin{cases} 1 & \text{if case is from treatment r-1} \\ -1 & \text{if case is from treatment r} \\ 0 & \text{otherwise} \end{cases}$$

Let $x_{ij} = X_{ij} - \bar{X}_{..}$. the regression model is

$$Y_{ij} = \mu_{.} + \tau_1 l_{ij,1} + .. + \tau_{r-1} l_{ij,r-1} + \gamma x_{ij} + \epsilon_{ij}$$

where $I_{ij,1}$ is the indicator variable l_1 for the j-th case from treatment i. The treatment effect $\tau_1, ..\tau_{r-1}$ are just regression coefficients for the indicator variables.

We could use the same diagnostic tools for this case.

Inference

Treatment effects

$$H_0 : \tau_1 = \tau_2 = ... = 0$$
$$H_a : \text{not all } \tau_i = 0$$

$$\text{Full Model} : Y_{ij} = \mu_. + \tau_i + \gamma X_{ij} + \epsilon_{ij}$$
$$\text{Reduced Model} : Y_{ij} = \mu_. + \gamma X_{ij} + \epsilon_{ij}$$

$$F = \frac{SSE(R) - SSE(F)}{(N-2) - (N-(r+1))} / \frac{SSE(F)}{N-(r+1)} \sim F_{(r-1, N-(r+1))}$$

If we are interested in comparisons of treatment effects.
For example, r - 3. We estimate $\tau_1, \tau_2, \tau_3 = -\tau_1 - \tau_2$

Comparison	Estimate	Variance of Estimator
$\tau_1 - \tau_2$	$\hat{\tau}_1 - \hat{\tau}_2$	$var(\hat{\tau}_1) + var(\hat{\tau}_2) - 2cov(\hat{\tau}_1\hat{\tau}_2)$
$\tau_1 - \tau_3$	$2\hat{\tau}_1 + \hat{\tau}_2$	$4var(\hat{\tau}_1) + var(\hat{\tau}_2) - 4cov(\hat{\tau}_1\hat{\tau}_2)$
$\tau_2 - \tau_3$	$\hat{\tau}_1 + 2\hat{\tau}_2$	$var(\hat{\tau}_1) + 4var(\hat{\tau}_2) - 4cov(\hat{\tau}_1\hat{\tau}_2)$

Testing for Parallel Slopes

Example:

r = 3

$$Y_{ij} = \mu_. + \tau_1 I_{ij,1} + \tau_2 I_{ij,2} + \gamma X_{ij} + \beta_1 I_{ij,1} X_{ij} + \beta_2 I_{ij,2} X_{ij} + \epsilon_{ij}$$

where β_1, β_2: interaction coefficients.

$$H_0 : \beta_1 = \beta_2 = 0$$
$$H_a : \text{at least one} \beta \neq 0$$

If we can't reject H_0 using F-test then we have evidence that the slopes are parallel

Adjusted Means

The means in response after adjusting for the covariate effect

$$Y_{i.}(adj) = \bar{Y}_{i.} - \hat{\gamma}(\bar{X}_{i.} - \bar{X}_{..})$$

Chapter 22

Multivariate Methods

$y_1, ..., y_p$ are possibly correlated random variables with means $\mu_1, ..., \mu_p$

$$\mathbf{y} = \begin{pmatrix} y_1 \\ . \\ y_p \end{pmatrix}$$

$$E(\mathbf{y}) = \begin{pmatrix} \mu_1 \\ . \\ \mu_p \end{pmatrix}$$

Let $\sigma_{ij} = cov(y_i, y_j)$ for $i, j = 1, ..., p$

$$= (\sigma_{ij}) = \begin{pmatrix} \sigma_{11} & \sigma_{22} & ... & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & ... & \sigma_{2p} \\ . & . & . & . \\ \sigma_{p1} & \sigma_{p2} & ... & \sigma_{pp} \end{pmatrix}$$

where (symmetric) is the variance-covariance or dispersion matrix

Let $\mathbf{u}_{p\times 1}$ and $\mathbf{v}_{q\times 1}$ be random vectors with means μ_u and μ_v . Then

$$_{uv} = cov(\mathbf{u}, \mathbf{v}) = E[(\mathbf{u} - \mu_u)(\mathbf{v} - \mu_v)']$$

in which $_{uv} \neq {}_{vu}$ and $_{uv} = {}'_{vu}$

Properties of Covariance Matrices

1. Symmetric $' =$

2. Non-negative definite $\mathbf{a}'\ \mathbf{a} \geq 0$ for any $\mathbf{a} \in R^p$, which is equivalent to eigenvalues of , $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p \geq 0$
3. $|\ | = \lambda_1 \lambda_2 ... \lambda_p \geq 0$ (**generalized variance**) (the bigger this number is, the more variation there is
4. $trace(\ ) = tr(\ ) = \lambda_1 + ... + \lambda_p = \sigma_{11} + ... + \sigma_{pp}$ = sum of variance (**total variance**)

Note:

- is typically required to be positive definite, which means all eigenvalues are positive, and has an inverse $^{-1}$ such that $^{-1} = \mathbf{I}_{p \times p} = \ ^{-1}$

Correlation Matrices

$$\rho_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}}$$

$$\mathbf{R} = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2p} \\ . & . & . & . \\ \rho_{p1} & \rho_{p2} & \cdots & \rho_{pp} \end{pmatrix}$$

where ρ_{ij} is the correlation, and $\rho_{ii} = 1$ for all i

Alternatively,

$$\mathbf{R} = [diag(\ )]^{-1/2}\ [diag(\ )]^{-1/2}$$

where $diag(\ )$ is the matrix which has the σ_{ii}'s on the diagonal and 0's elsewhere

and $\mathbf{A}^{1/2}$ (the square root of a symmetric matrix) is a symmetric matrix such as $\mathbf{A} = \mathbf{A}^{1/2}\mathbf{A}^{1/2}$

Equalities

Let

- $\mathbf{x}$ and $\mathbf{y}$ be random vectors with means μ_x and μ_y and variance -variance matrices $_x$ and $_y$.
- $\mathbf{A}$ and $\mathbf{B}$ be matrices of constants and $\mathbf{c}$ and $\mathbf{d}$ be vectors of constants

Then

- $E(\mathbf{Ay} + \mathbf{c}) = \mathbf{A}\mu_y + c$
- $var(\mathbf{Ay} + \mathbf{c}) = \mathbf{A}var(\mathbf{y})\mathbf{A}' = \mathbf{A}\ _{\mathbf{y}}\mathbf{A}'$
- $cov(\mathbf{Ay} + \mathbf{c}, \mathbf{By} + \mathbf{d}) = \mathbf{A}\ _{\mathbf{y}}\mathbf{B}'$
- $E(\mathbf{Ay} + \mathbf{Bx} + \mathbf{c}) = \mathbf{A}\ _{\mathbf{y}} + \mathbf{B}\ _{\mathbf{x}} + \mathbf{c}$

- $var(\mathbf{Ay} + \mathbf{Bx} + \mathbf{c}) = \mathbf{A}\ _{\mathbf{y}}\mathbf{A}' + \mathbf{B}\ _{\mathbf{x}}\mathbf{B}' + \mathbf{A}\ _{\mathbf{yx}}\mathbf{B}' + \mathbf{B}\ '_{\mathbf{yx}}\mathbf{A}'$

Multivariate Normal Distribution

Let $\mathbf{y}$ be a multivariate normal (MVN) random variable with mean μ and variance . Then the density of $\mathbf{y}$ is

$$f(\mathbf{y}) = \frac{1}{(2\pi)^{p/2}|\ |^{1/2}} \exp(-\frac{1}{2}(\mathbf{y} - \ )'\ ^{-\mathbf{1}}(\mathbf{y} - \ ))$$

$\mathbf{y} \sim N_p(\mu,\ )$

22.0.1 Properties of MVN

- Let $\mathbf{A}_{r\times p}$ be a fixed matrix. Then $\mathbf{Ay} \sim N_r(\mathbf{A}\ , \mathbf{A}\ \mathbf{A}')$. $r \leq p$ and all rows of $\mathbf{A}$ must be linearly independent to guarantee that $\mathbf{A}\ \mathbf{A}'$ is non-singular.
- Let $\mathbf{G}$ be a matrix such that $^{-1} = \mathbf{GG}'$. Then $\mathbf{G}'\mathbf{y} \sim N_p(\mathbf{G}'\ , \mathbf{I})$ and $\mathbf{G}'(\mathbf{y} - \ ) \sim N_p(0, \mathbf{I})$
- Any fixed linear combination of $y_1, ..., y_p$ (say $\mathbf{c}'\mathbf{y}$) follows $\mathbf{c}'\mathbf{y} \sim N_1(\mathbf{c}'\ , \mathbf{c}'\ \mathbf{c})$
- Define a partition, $[\mathbf{y}_1', \mathbf{y}_2']'$ where
  - $\mathbf{y}_1$ is $p_1 \times 1$
  - $\mathbf{y}_2$ is $p_2 \times 1$,
  - $p_1 + p_2 = p$
  - $p_1, p_2 \geq 1$ Then

$$\begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} {}_{11} & {}_{12} \\ {}_{21} & {}_{22} \end{pmatrix}\right)$$

- The marginal distributions of $\mathbf{y}_1$ and $\mathbf{y}_2$ are $\mathbf{y}_1 \sim N_{p1}(\ _{\mathbf{1}},\ _{\mathbf{11}})$ and $\mathbf{y}_2 \sim N_{p2}(\ _{\mathbf{2}},\ _{\mathbf{22}})$
- Individual components $y_1, ..., y_p$ are all normally distributed $y_i \sim N_1(\mu_i, \sigma_{ii})$
- The conditional distribution of $\mathbf{y}_1$ and $\mathbf{y}_2$ is normal
  - $\mathbf{y}_1|\mathbf{y}_2 \sim N_{p1}(\ _{\mathbf{1}} +\ _{\mathbf{12}}\ ^{-\mathbf{1}}_{\mathbf{22}}(\mathbf{y}_{\mathbf{2}} -\ _{\mathbf{2}}),\ _{\mathbf{11}} -\ _{\mathbf{12}}\ ^{-\mathbf{1}}_{\mathbf{22}}\ _{\mathbf{21}})$
    - In this formula, we see if we know (have info about) $\mathbf{y}_2$, we can re-weight $\mathbf{y}_1$'s mean, and the variance is reduced because we know more about $\mathbf{y}_1$ because we know $\mathbf{y}_2$
  - which is analogous to $\mathbf{y}_2|\mathbf{y}_1$. And $\mathbf{y}_1$ and $\mathbf{y}_2$ are independently distrusted only if $_{12} = 0$

- If $\mathbf{y} \sim N(\ ,\ )$ and is positive definite, then $(\mathbf{y} - \ )' \ ^{-\mathbf{1}}(\mathbf{y} - \ ) \sim \chi^2_{(p)}$
- If $\mathbf{y}_i$ are independent $N_p(\ _i,\ _i)$ random variables, then for fixed matrices $\mathbf{A}_{i(m\times p)}$, $\sum_{i=1}^k \mathbf{A}_i\mathbf{y}_i \sim N_m(\sum_{i=1}^k \mathbf{A}_i\ _i, \sum_{i=1}^k \mathbf{A}_i\ _i\mathbf{A}_i)$

Multiple Regression

$$\begin{pmatrix} Y \\ \mathbf{x} \end{pmatrix} \sim N_{p+1}\left(\begin{bmatrix} \mu_y \\ \ _x \end{bmatrix}, \begin{bmatrix} \sigma^2_Y & \ _{yx} \\ \ _{yx} & \ _{xx} \end{bmatrix}\right)$$

The conditional distribution of Y given x follows a univariate normal distribution with

$$\begin{aligned} E(Y|\mathbf{x}) &= \mu_y + \ _{yx}\Sigma^{-1}_{xx}(\mathbf{x} - \mu_x) \\ &= \mu_y - \Sigma_{yx}\Sigma^{-1}_{xx}\mu_x + \Sigma_{yx}\Sigma^{-1}_{xx}\mathbf{x} \\ &= \beta_0 + \ '\mathbf{x} \end{aligned}$$

where $\beta = (\beta_1, ..., \beta_p)' = \ ^{-1}_{xx}\ ^{\prime}_{yx}$ (e.g., analogous to $(\mathbf{x}'\mathbf{x})^{-\mathbf{1}}\mathbf{x}'\mathbf{y}$ but not the same if we consider Y_i and $\mathbf{x}_i$, $i = 1, .., n$ and use the empirical covariance formula: $var(Y|\mathbf{x}) = \sigma^2_Y - \ _{\mathbf{yx}}\ ^{-\mathbf{1}}_{\mathbf{xx}}\ ^{\prime}_{\mathbf{yx}})$

Samples from Multivariate Normal Populations

A random sample of size n, $\mathbf{y}_1, .., \mathbf{y}_n$ from $N_p(\ ,\ )$. Then

- Since $\mathbf{y}_1, ..., \mathbf{y}_n$ are iid, their sample mean, $\bar{\mathbf{y}} = \sum_{i=1}^n \mathbf{y}_i/n \sim N_p(\ ,\ /n)$. that is, $\bar{\mathbf{y}}$ is an unbiased estimator of
- The $p \times p$ sample variance-covariance matrix, $\mathbf{S}$ is $\mathbf{S} = \frac{1}{n-1}\sum_{i=1}^n(\mathbf{y}_i - \bar{\mathbf{y}})(\mathbf{y}_i - \bar{\mathbf{y}})' = \frac{1}{n-1}(\sum_{i=1}^n \mathbf{y}_i\mathbf{y}_i' - n\bar{\mathbf{y}}\bar{\mathbf{y}}')$
  - where $\mathbf{S}$ is symmetric, unbiased estimator of and has $p(p+1)/2$ random variables.
- $(n-1)\mathbf{S} \sim W_p(n-1,\ )$ is a Wishart distribution with n-1 degrees of freedom and expectation $(n-1)$. The Wishart distribution is a multivariate extension of the Chi-squared distribution.
- $\bar{\mathbf{y}}$ and $\mathbf{S}$ are independent
- $\bar{\mathbf{y}}$ and $\mathbf{S}$ are sufficient statistics. (All of the info in the data about and is contained in $\bar{\mathbf{y}}$ and $\mathbf{S}$, regardless of sample size).

Large Sample Properties

$\mathbf{y}_1, ..., \mathbf{y}_n$ are a random sample from some population with mean and variance-covariance matrix

- $\bar{\mathbf{y}}$ is a consistent estimator for μ
- $\mathbf{S}$ is a consistent estimator for

- **Multivariate Central Limit Theorem**: Similar to the univariate case, $\sqrt{n}(\bar{\mathbf{y}} - \mu) \dot{\sim} N_p(\mathbf{0}, \ )$ where n is large relative to p ($n \geq 25p$), which is equivalent to $\bar{\mathbf{y}} \dot{\sim} N_p(\mu, \ /n)$
- **Wald's Theorem**: $n(\bar{\mathbf{y}} - \mu)' \mathbf{S}^{-1} (\bar{\mathbf{y}} - \mu)$ when n is large relative to p.

Maximum Likelihood Estimation for MVN

Suppose iid $\mathbf{y}_1, ...\mathbf{y}_n \sim N_p(\mu, \ )$, the likelihood function for the data is

$$\begin{aligned} L(\mu, \ ) &= \prod_{j=1}^{n} (\frac{1}{(2\pi)^{p/2} | \ |^{1/2}} \exp(-\frac{1}{2} (\mathbf{y}_j - \mu)' \ ^{-1}) (\mathbf{y}_j - \mu)) \\ &= \frac{1}{(2\pi)^{np/2} | \ |^{n/2}} \exp(-\frac{1}{2} \sum_{j=1}^{n} (\mathbf{y}_j - \mu)' \ ^{-1}) (\mathbf{y}_j - \mu) \end{aligned}$$

Then, the MLEs are

$$\hat{\mu} = \bar{\mathbf{y}}$$

$$\hat{} = \frac{n-1}{n} \mathbf{S}$$

using derivatives of the log of the likelihood function with respect to μ and

Properties of MLEs

- Invariance: If $\hat{\theta}$ is the MLE of θ, then the MLE of $h(\theta)$ is $h(\hat{\theta})$ for any function h(.)
- Consistency: MLEs are consistent estimators, but they are usually biased
- Efficiency: MLEs are efficient estimators (no other estimator has a smaller variance for large samples)
- Asymptotic normality: Suppose that $\hat{\theta}_n$ is the MLE for θ based upon n independent observations. Then $\hat{\theta}_n \dot{\sim} N(\theta, \mathbf{H}^{-1})$
  - $\mathbf{H}$ is the Fisher Information Matrix, which contains the expected values of the second partial derivatives fo the log-likelihood function. the (i,j)th element of $\mathbf{H}$ is $-E(\frac{\partial^2 l(\ )}{\partial \theta_i \partial \theta_j})$
  - we can estimate $\mathbf{H}$ by finding the form determined above, and evaluate it at $\theta = \hat{\theta}_n$
- Likelihood ratio testing: for some null hypothesis, H_0 we can form a likelihood ratio test
  - The statistic is: $\Lambda = \frac{\max_{H_0} l(\ , |\mathbf{Y})}{\max l(\mu, |\mathbf{Y})}$

  - For large n, $-2\log\Lambda \sim \chi^2_{(v)}$ where v is the number of parameters in the unrestricted space minus the number of parameters under H_0

Test of Multivariate Normality

- Check univariate normality for each trait (X) separately
  - Can check

$$NormalityAssessment$$

  - The good thing is that if any of the univariate trait is not normal, then the joint distribution is not normal (see again [m]). If a joint multivariate distribution is normal, then the marginal distribution has to be normal.
  - However, marginal normality of all traits does not imply joint MVN
  - Easily rule out multivariate normality, but not easy to prove it
- Mardia's tests for multivariate normality
  - Multivariate skewness is

$$\beta_{1,p} = E[(\mathbf{y} - \ )'\ ^{-1}(\mathbf{x} - \ )]^3$$

  - where $\mathbf{x}$ and $\mathbf{y}$ are independent, but have the same distribution (note: β here is not regression coefficient)
  - Multivariate kurtosis is defined as
  -

$$\beta_{2,p} - E[(\mathbf{y} - \ )'\ ^{-1}(\mathbf{x} - \ )]^2$$

  - For the MVN distribution, we have $\beta_{1,p} = 0$ and $\beta_{2,p} = p(p+2)$
  - For a sample of size n, we can estimate

$$\hat{\beta}_{1,p} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}^2$$

$$\hat{\beta}_{2,p} = \frac{1}{n}\sum_{i=1}^{n} g_{ii}^2$$

    * where $g_{ij} = (\mathbf{y}_i - \bar{\mathbf{y}})'\mathbf{S}^{-1}(\mathbf{y}_j - \bar{\mathbf{y}})$. Note: $g_{ii} = d_i^2$ where d_i^2 is the Mahalanobis distance
  - (Mardia, 1970) shows for large n

$$\kappa_1 = \frac{n\hat{\beta}_{1,p}}{6} \dot{\sim} \chi^2_{p(p+1)(p+2)/6}$$

$$\kappa_2 = \frac{\hat{\beta}_{2,p} - p(p+2)}{\sqrt{8p(p+2)/n}} \sim N(0,1)$$

  * Hence, we can use κ_1 and κ_2 to test the null hypothesis of MVN.
  * When the data are non-normal, normal theory tests on the mean are sensitive to $\beta_{1,p}$, while tests on the covariance are sensitive to $\beta_{2,p}$

- Alternatively, Doornik-Hansen test for multivariate normality (Doornik and Hansen, 2008)
- Chi-square Q-Q plot
  - Let $\mathbf{y}_i, i = 1, ..., n$ be a random sample sample from $N_p(\ , \ )$
  - Then $\mathbf{z}_i = \ ^{-1/2}(\mathbf{y}_i - \ ), i = 1, ..., n$ are iid $N_p(\mathbf{0}, \mathbf{I})$. Thus, $d_i^2 = \mathbf{z}_i'\mathbf{z}_i \sim \chi_p^2, i = 1, ..., n$
  - plot the ordered d_i^2 values against the qualities of the χ_p^2 distribution. When normality holds, the plot should approximately resemble a straight lien passing through the origin at a 45 degree
  - it requires large sample size (i.e., sensitive to sample size). Even if we generate data from a MVN, the tail of the Chi-square Q-Q plot can still be out of line.
- If the data are not normal, we can
  - ignore it
  - use nonparametric methods
  - use models based upon an approximate distribution (e.g., GLMM)
  - try performing a transformation

```
library(heplots)
library(ICSNP)
library(MVN)
library(tidyverse)

trees = read.table("images/trees.dat")
names(trees) <- c("Nitrogen","Phosphorous","Potassium","Ash","Height")
str(trees)
#> 'data.frame':    26 obs. of  5 variables:
#>  $ Nitrogen   : num  2.2 2.1 1.52 2.88 2.18 1.87 1.52 2.37 2.06 1.84 ...
#>  $ Phosphorous: num  0.417 0.354 0.208 0.335 0.314 0.271 0.164 0.302 0.373 0.265 ...
#>  $ Potassium  : num  1.35 0.9 0.71 0.9 1.26 1.15 0.83 0.89 0.79 0.72 ...
#>  $ Ash        : num  1.79 1.08 0.47 1.48 1.09 0.99 0.85 0.94 0.8 0.77 ...
#>  $ Height     : int  351 249 171 373 321 191 225 291 284 213 ...
```

```r
summary(trees)
#>     Nitrogen      Phosphorous       Potassium           Ash
#>  Min.   :1.130   Min.   :0.1570   Min.   :0.3800   Min.   :0.4500
#>  1st Qu.:1.532   1st Qu.:0.1963   1st Qu.:0.6050   1st Qu.:0.6375
#>  Median :1.855   Median :0.2250   Median :0.7150   Median :0.9300
#>  Mean   :1.896   Mean   :0.2506   Mean   :0.7619   Mean   :0.8873
#>  3rd Qu.:2.160   3rd Qu.:0.2975   3rd Qu.:0.8975   3rd Qu.:0.9825
#>  Max.   :2.880   Max.   :0.4170   Max.   :1.3500   Max.   :1.7900
#>      Height
#>  Min.   : 65.0
#>  1st Qu.:122.5
#>  Median :181.0
#>  Mean   :196.6
#>  3rd Qu.:276.0
#>  Max.   :373.0
cor(trees, method = "pearson") # correlation matrix
#>              Nitrogen Phosphorous Potassium       Ash    Height
#> Nitrogen    1.0000000   0.6023902 0.5462456 0.6509771 0.8181641
#> Phosphorous 0.6023902   1.0000000 0.7037469 0.6707871 0.7739656
#> Potassium   0.5462456   0.7037469 1.0000000 0.6710548 0.7915683
#> Ash         0.6509771   0.6707871 0.6710548 1.0000000 0.7676771
#> Height      0.8181641   0.7739656 0.7915683 0.7676771 1.0000000

# qq-plot
gg <- trees %>%
    pivot_longer(everything(), names_to = "Var", values_to = "Value") %>%
    ggplot(aes(sample = Value)) +
    geom_qq() +
    geom_qq_line() +
    facet_wrap("Var", scales = "free")
gg
```

```
# Univariate normality
sw_tests <- apply(trees, MARGIN = 2, FUN = shapiro.test)
sw_tests
#> $Nitrogen
#>
#>  Shapiro-Wilk normality test
#>
#> data:  newX[, i]
#> W = 0.96829, p-value = 0.5794
#>
#>
#> $Phosphorous
#>
#>  Shapiro-Wilk normality test
#>
#> data:  newX[, i]
#> W = 0.93644, p-value = 0.1104
#>
#>
#> $Potassium
#>
#>  Shapiro-Wilk normality test
#>
#> data:  newX[, i]
#> W = 0.95709, p-value = 0.3375
#>
```

```
#>
#> $Ash
#>
#>  Shapiro-Wilk normality test
#>
#> data:  newX[, i]
#> W = 0.92071, p-value = 0.04671
#>
#>
#> $Height
#>
#>  Shapiro-Wilk normality test
#>
#> data:  newX[, i]
#> W = 0.94107, p-value = 0.1424
# Kolmogorov-Smirnov test
ks_tests <- map(trees, ~ ks.test(scale(.x),"pnorm"))
ks_tests
#> $Nitrogen
#>
#>  Asymptotic one-sample Kolmogorov-Smirnov test
#>
#> data:  scale(.x)
#> D = 0.12182, p-value = 0.8351
#> alternative hypothesis: two-sided
#>
#>
#> $Phosphorous
#>
#>  Asymptotic one-sample Kolmogorov-Smirnov test
#>
#> data:  scale(.x)
#> D = 0.17627, p-value = 0.3944
#> alternative hypothesis: two-sided
#>
#>
#> $Potassium
#>
#>  Asymptotic one-sample Kolmogorov-Smirnov test
#>
#> data:  scale(.x)
#> D = 0.10542, p-value = 0.9348
#> alternative hypothesis: two-sided
#>
#>
```

```
#> $Ash
#>
#>  Asymptotic one-sample Kolmogorov-Smirnov test
#>
#> data:  scale(.x)
#> D = 0.14503, p-value = 0.6449
#> alternative hypothesis: two-sided
#>
#>
#> $Height
#>
#>  Asymptotic one-sample Kolmogorov-Smirnov test
#>
#> data:  scale(.x)
#> D = 0.1107, p-value = 0.9076
#> alternative hypothesis: two-sided

# Mardia's test, need large sample size for power
mardia_test <-
    mvn(
        trees,
        mvnTest = "mardia",
        covariance = FALSE,
        multivariatePlot = "qq"
    )

mardia_test$multivariateNormality
#>              Test         Statistic            p value Result
#> 1 Mardia Skewness  29.7248528871795   0.720544267457 78    YES
#> 2 Mardia Kurtosis -1.67743173185383 0.0934580886477281    YES
#> 3             MVN              <NA>               <NA>    YES

# Doornik-Hansen's test
dh_test <-
    mvn(
        trees,
        mvnTest = "dh",
        covariance = FALSE,
        multivariatePlot = "qq"
    )
```

```
dh_test$multivariateNormality
#>              Test        E df      p value MVN
#> 1 Doornik-Hansen 161.9446 10 1.285352e-29  NO

# Henze-Zirkler's test
hz_test <-
    mvn(
        trees,
        mvnTest = "hz",
        covariance = FALSE,
        multivariatePlot = "qq"
    )
hz_test$multivariateNormality
#>             Test        HZ   p value MVN
#> 1 Henze-Zirkler 0.7591525 0.6398905 YES
# The last column indicates whether dataset follows a multivariate normality or not (i

# Royston's test
# can only apply for 3 < obs < 5000 (because of Shapiro-Wilk's test)
royston_test <-
    mvn(
        trees,
        mvnTest = "royston",
        covariance = FALSE,
        multivariatePlot = "qq"
    )
royston_test$multivariateNormality
```

```
#>      Test        H    p value MVN
#> 1 Royston 9.064631 0.08199215 YES


# E-statistic
estat_test <-
    mvn(
        trees,
        mvnTest = "energy",
        covariance = FALSE,
        multivariatePlot = "qq"
    )
estat_test$multivariateNormality
#>          Test Statistic p value MVN
#> 1 E-statistic  1.091101   0.526 YES
```

22.0.2 Mean Vector Inference

In the univariate normal distribution, we test $H_0 : \mu = \mu_0$ by using

$$T = \frac{\bar{y} - \mu_0}{s/\sqrt{n}} \sim t_{n-1}$$

under the null hypothesis. And reject the null if $|T|$ is large relative to $t_{(1-\alpha/2, n-1)}$ because it means that seeing a value as large as what we observed is rare if the null is true

Equivalently,

$$T^2 = \frac{(\bar{y} - \mu_0)^2}{s^2/n} = n(\bar{y} - \mu_0)(s^2)^{-1}(\bar{y} - \mu_0) \sim f_{(1,n-1)}$$

22.0.2.1 Natural Multivariate Generalization

$$\begin{aligned} H_0 : & \ = \ _0 \\ H_a : & \ \neq \ _0 \end{aligned}$$

Define **Hotelling's** T^2 by

$$T^2 = n(\bar{\mathbf{y}} - \ _0)'\mathbf{S}^{-1}(\bar{\mathbf{y}} - \ _0)$$

which can be viewed as a generalized distance between $\bar{\mathbf{y}}$ and $\ _0$

Under the assumption of normality,

$$F = \frac{n-p}{(n-1)p} T^2 \sim f_{(p,n-p)}$$

and reject the null hypothesis when $F > f_{(1-\alpha,p,n-p)}$

- The T^2 test is invariant to changes in measurement units.
  - If $\mathbf{z} = \mathbf{C}\mathbf{y} + \mathbf{d}$ where $\mathbf{C}$ and $\mathbf{d}$ do not depend on $\mathbf{y}$, then $T^2(\mathbf{z}) - T^2(\mathbf{y})$
- The T^2 test can be derived as a **likelihood ratio** test of $H_0 : \mu = \mu_0$

22.0.2.2 Confidence Intervals

22.0.2.2.1 Confidence Region An "exact" $100(1-\alpha)\%$ confidence region for is the set of all vectors, $\mathbf{v}$, which are "close enough" to the observed mean vector, $\bar{\mathbf{y}}$ to satisfy

$$n(\bar{\mathbf{y}} - {}_0)'\mathbf{S}^{-1}(\bar{\mathbf{y}} - {}_0) \leq \frac{(n-1)p}{n-p} f_{(1-\alpha,p,n-p)}$$

- $\mathbf{v}$ are just the mean vectors that are not rejected by the T^2 test when $\bar{\mathbf{y}}$ is observed.

In case that you have 2 parameters, the confidence region is a "hyper-ellipsoid".

In this region, it consists of all ${}_0$ vectors for which the T^2 test would not reject H_0 at significance level α

Even though the confidence region better assesses the joint knowledge concerning plausible values of , people typically include confidence statement about the individual component means. We'd like all of the separate confidence statements to hold **simultaneously** with a specified high probability. Simultaneous confidence intervals: intervals **against** any statement being incorrect

22.0.2.2.1.1 Simultaneous Confidence Statements

- Intervals based on a rectangular confidence region by projecting the previous region onto the coordinate axes:

$$\bar{y}_i \pm \sqrt{\frac{(n-1)p}{n-p} f_{(1-\alpha,p,n-p)} \frac{s_{ii}}{n}}$$

for all $i = 1, .., p$

which implied confidence region is conservative; it has at least $100(1-\alpha)\%$

Generally, simultaneous $100(1-\alpha)\%$ confidence intervals for all linear combinations , $\mathbf{a}$ of the elements of the mean vector are given by

$$\mathbf{a}'\bar{\mathbf{y}} \pm \sqrt{\frac{(n-1)p}{n-p} f_{(1-\alpha,p,n-p)} \frac{\mathbf{a}'\mathbf{S}\mathbf{a}}{n}}$$

- works for any arbitrary linear combination $\mathbf{a}' = a_1\mu_1 + ... + a_p\mu_p$, which is a projection onto the axis in the direction of $\mathbf{a}$
- These intervals have the property that the probability that at least one such interval does not contain the appropriate $\mathbf{a}'$ is no more than α
- These types of intervals can be used for "data snooping" (like

  $$Scheffe$$

)

22.0.2.2.1.2 One μ at a time

- One at a time confidence intervals:

$$\bar{y}_i \pm t_{(1-\alpha/2,n-1} \sqrt{\frac{s_{ii}}{n}}$$

- Each of these intervals has a probability of $1-\alpha$ of covering the appropriate μ_i
- But they ignore the covariance structure of the p variables
- If we only care about k simultaneous intervals, we can use "one at a time" method with the

  $$Bonferroni$$

  correction.
- This method gets more conservative as the number of intervals k increases.

22.0.3 General Hypothesis Testing

22.0.3.1 One-sample Tests

$$H_0 : \mathbf{C} = \mathbf{0}$$

where

- $\mathbf{C}$ is a $c \times p$ matrix of rank c where $c \leq p$

We can test this hypothesis using the following statistic

$$F = \frac{n-c}{(n-1)c} T^2$$

where $T^2 = n(\mathbf{C}\bar{\mathbf{y}})'(\mathbf{CSC}')^{-1}(\mathbf{C}\bar{\mathbf{y}})$

Example:

$$H_0 : \mu_1 = \mu_2 = ... = \mu_p$$

Equivalently,

$$\begin{aligned} \mu_1 - \mu_2 &= 0 \\ &\vdots \\ \mu_{p-1} - \mu_p &= 0 \end{aligned}$$

a total of $p-1$ tests. Hence, we have $\mathbf{C}$ as the $p-1 \times p$ matrix

$$\mathbf{C} = \begin{pmatrix} 1 & -1 & 0 & ... & 0 \\ 0 & 1 & -1 & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & 1 & -1 \end{pmatrix}$$

number of rows $= c = p-1$

Equivalently, we can also compare all of the other means to the first mean. Then, we test $\mu_1 - \mu_2 = 0, \mu_1 - \mu_3 = 0, ..., \mu_1 - \mu_p = 0$, the $(p-1) \times p$ matrix $\mathbf{C}$ is

$$\mathbf{C} = \begin{pmatrix} -1 & 1 & 0 & ... & 0 \\ -1 & 0 & 1 & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -1 & 0 & ... & 0 & 1 \end{pmatrix}$$

The value of T^2 is invariant to these equivalent choices of $\mathbf{C}$

This is often used for **repeated measures designs**, where each subject receives each treatment once over successive periods of time (all treatments are administered to each unit).

Example:

Let y_{ij} be the response from subject i at time j for $i = 1, .., n, j = 1, ..., T$. In this case, $\mathbf{y}_i = (y_{i1}, ..., y_{iT})', i = 1, ..., n$ are a random sample from $N_T(\ ,\ )$

Let $n = 8$ subjects, $T = 6$. We are interested in $\mu_1, .., \mu_6$

$$H_0 : \mu_1 = \mu_2 = ... = \mu_6$$

Equivalently,

$$\mu_1 - \mu_2 = 0$$
$$\mu_2 - \mu_3 = 0$$
$$...$$
$$\mu_5 - \mu_6 = 0$$

We can test orthogonal polynomials for 4 equally spaced time points. To test for example the null hypothesis that quadratic and cubic effects are jointly equal to 0, we would define $\mathbf{C}$

$$\mathbf{C} = \begin{pmatrix} 1 & -1 & -1 & 1 \\ -1 & 3 & -3 & 1 \end{pmatrix}$$

22.0.3.2 Two-Sample Tests

Consider the analogous two sample multivariate tests.

Example: we have data on two independent random samples, one sample from each of two populations

$$\mathbf{y}_{1i} \sim N_p(\ _{\mathbf{1}},\ )$$
$$\mathbf{y}_{2j} \sim N_p(\ _{\mathbf{2}},\ )$$

We **assume**

- normality
- equal variance-covariance matrices
- independent random samples

We can summarize our data using the **sufficient statistics** $\bar{\mathbf{y}}_1, \mathbf{S}_1, \bar{\mathbf{y}}_2, \mathbf{S}_2$ with respective sample sizes, n_1, n_2

Since we assume that $_1 = \ _2 = \ $, compute a pooled estimate of the variance-covariance matrix on $n_1 + n_2 - 2$ df

$$\mathbf{S} = \frac{(n_1 - 1)\mathbf{S}_1 + (n_2 - 1)\mathbf{S}_2}{(n_1 - 1) + (n_2 - 1)}$$

$$H_0 : \ _1 = \ _2$$
$$H_a : \ _1 \neq \ _2$$

At least one element of the mean vectors is different

We use

- $\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2$ to estimate $\mu_1 - \mu_2$

- **S** to estimate

  Note: because we assume the two populations are independent, there is no covariance

  $cov(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2) = var(\bar{\mathbf{y}}_1) + var(\bar{\mathbf{y}}_2) = \frac{1}{n_1} + \frac{2}{n_2} = (\frac{1}{n_1} + \frac{1}{n_2})$

Reject H_0 if

$$\begin{aligned} T^2 &= (\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2)'\{\mathbf{S}(\frac{1}{n_1} + \frac{1}{n_2})\}^{-1}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2) \\ &= \frac{n_1 n_2}{n_1 + n_2}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2)'\{\mathbf{S}\}^{-1}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2) \\ &\geq \frac{(n_1 + n_2 - 2)p}{n_1 + n_2 - p - 1} f_{(1-\alpha, n_1+n_2-p-1)} \end{aligned}$$

or equivalently, if

$$F = \frac{n_1 + n_2 - p - 1}{(n_1 + n_2 - 2)p} T^2 \geq f_{(1-\alpha, p, n_1+n_2-p-1)}$$

A $100(1-\alpha)\%$ confidence region for $\mu_1 - \mu_2$ consists of all vector δ which satisfy

$$\frac{n_1 n_2}{n_1 + n_2}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2 - \ )'\mathbf{S}^{-1}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2 - \ ) \leq \frac{(n_1 + n_2 - 2)p}{n_1 + n_2 - p - 1} f_{(1-\alpha, p, n_1+n_2-p-1)}$$

The simultaneous confidence intervals for all linear combinations of $\mu_1 - \mu_2$ have the form

$$\mathbf{a}'(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2) \pm \sqrt{\frac{(n_1 + n_2 - 2)p}{n_1 + n_2 - p - 1} f_{(1-\alpha, p, n_1+n_2-p-1)}} \times \sqrt{\mathbf{a}'\mathbf{S}\mathbf{a}(\frac{1}{n_1} + \frac{1}{n_2})}$$

Bonferroni intervals, for k combinations

$$(\bar{y}_{1i} - \bar{y}_{2i}) \pm t_{(1-\alpha/2k, n_1+n_2-2)} \sqrt{(\frac{1}{n_1} + \frac{1}{n_2}) s_{ii}}$$

22.0.3.3 Model Assumptions

If model assumption are not met

- Unequal Covariance Matrices

- If $n_1 = n_2$ (large samples) there is little effect on the Type I error rate and power fo the two sample test
- If $n_1 > n_2$ and the eigenvalues of ${}_1\,{}_2^{-1}$ are less than 1, the Type I error level is inflated
- If $n_1 > n_2$ and some eigenvalues of ${}_1\,{}_2^{-1}$ are greater than 1, the Type I error rate is too small, leading to a reduction in power

- Sample Not Normal
  - Type I error level of the two sample T^2 test isn't much affect by moderate departures from normality if the two populations being sampled have similar distributions
  - One sample T^2 test is much more sensitive to lack of normality, especially when the distribution is skewed.
  - Intuitively, you can think that in one sample your distribution will be sensitive, but the distribution of the difference between two similar distributions will not be as sensitive.
  - Solutions:
    * Transform to make the data more normal
    * Large large samples, use the χ^2 (Wald) test, in which populations don't need to be normal, or equal sample sizes, or equal variance-covariance matrices
      · $H_0 : \mu_1 - \mu_2 = 0$ use $(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2)'(\frac{1}{n_1}\mathbf{S}_1 + \frac{1}{n_2}\mathbf{S}_2)^{-1}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2) \dot{\sim} \chi^2_{(p)}$

22.0.3.3.1 Equal Covariance Matrices Tests With independent random samples from k populations of p-dimensional vectors. We compute the sample covariance matrix for each, $\mathbf{S}_i$, where $i = 1, ..., k$

$$H_0 : {}_1 = {}_2 = ... = {}_k =$$
$$H_a : \text{at least 2 are different}$$

Assume H_0 is true, we would use a pooled estimate of the common covariance matrix,

$$\mathbf{S} = \frac{\sum_{i=1}^k (n_i - 1)\mathbf{S}_i}{\sum_{i=1}^k (n_i - 1)}$$

with $\sum_{i=1}^k (n_i - 1)$

22.0.3.3.1.1 Bartlett's Test (a modification of the likelihood ratio test). Define

$$N = \sum_{i=1}^{k} n_i$$

and (note: || are determinants here, not absolute value)

$$M = (N-k)\log|\mathbf{S}| - \sum_{i=1}^{k}(n_i - 1)\log|\mathbf{S}_i|$$

$$C^{-1} = 1 - \frac{2p^2+3p-1}{6(p+1)(k-1)}\{\sum_{i=1}^{k}(\frac{1}{n_i-1}) - \frac{1}{N-k}\}$$

- Reject H_0 when $MC^{-1} > \chi^2_{1-\alpha,(k-1)p(p+1)/2}$
- If not all samples are from normal populations, MC^{-1} has a distribution which is often shifted to the right of the nominal χ^2 distribution, which means H_0 is often rejected even when it is true (the Type I error level is inflated). Hence, it is better to test individual normality first, or then multivariate normality before you do Bartlett's test.

22.0.3.4 Two-Sample Repeated Measurements

- Define $\mathbf{y}_{hi} = (y_{hi1}, ..., y_{hit})'$ to be the observations from the i-th subject in the h-th group for times 1 through T
- Assume that $\mathbf{y}_{11}, ..., \mathbf{y}_{1n_1}$ are iid $N_t(\ _1,\ )$ and that $\mathbf{y}_{21}, ..., \mathbf{y}_{2n_2}$ are iid $N_t(\ _2,\ )$
- $H_0 : \mathbf{C}(\ _1 -\ _2) = \mathbf{0}_c$ where $\mathbf{C}$ is a $c \times t$ matrix of rank c where $c \leq t$
- The test statistic has the form

$$T^2 = \frac{n_1 n_2}{n_1+n_2}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2)'\mathbf{C}'(\mathbf{CSC}')^{-1}\mathbf{C}(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2)$$

where $\mathbf{S}$ is the pooled covariance estimate. Then,

$$F = \frac{n_1+n_2-c-1}{(n_1+n_2-2)c}T^2 \sim f_{(c,n_1+n_2-c-1)}$$

when H_0 is true

If the null hypothesis $H_0 : \mu_1 = \mu_2$ is rejected. A weaker hypothesis is that the profiles for the two groups are parallel.

$$\mu_{11} - \mu_{21} = \mu_{12} - \mu_{22}$$
$$\vdots$$
$$\mu_{1t-1} - \mu_{2t-1} = \mu_{1t} - \mu_{2t}$$

The null hypothesis matrix term is then

$H_0 : \mathbf{C}(\mu_1 - \mu_2) = \mathbf{0}_c$, where $c = t - 1$ and

$$\mathbf{C} = \begin{pmatrix} 1 & -1 & 0 & \dots & 0 \\ 0 & 1 & -1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & -1 \end{pmatrix}_{(t-1)\times t}$$

```
# One-sample Hotelling's T^2 test
#  Create data frame
plants <- data.frame(
    y1 = c(2.11, 2.36, 2.13, 2.78, 2.17),
    y2 = c(10.1, 35.0, 2.0, 6.0, 2.0),
    y3 = c(3.4, 4.1, 1.9, 3.8, 1.7)
)

# Center the data with
# the hypothesized means and make a matrix
plants_ctr <- plants %>%
    transmute(y1_ctr = y1 - 2.85,
              y2_ctr = y2 - 15.0,
              y3_ctr = y3 - 6.0) %>%
    as.matrix()

# Use anova.mlm to calculate Wilks' lambda
onesamp_fit <- anova(lm(plants_ctr ~ 1), test = "Wilks")
onesamp_fit
#> Analysis of Variance Table
#>
#>             Df    Wilks approx F num Df den Df  Pr(>F)
#> (Intercept)  1 0.054219   11.629      3      2 0.08022 .
#> Residuals    4
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

can't reject the null of hypothesized vector of means

```
# Paired-Sample Hotelling's T^2 test
library(ICSNP)
```

```r
#  Create data frame
waste <- data.frame(
    case = 1:11,
    com_y1 = c(6, 6, 18, 8, 11, 34, 28, 71, 43, 33, 20),
    com_y2 = c(27, 23, 64, 44, 30, 75, 26, 124, 54, 30, 14),
    state_y1 = c(25, 28, 36, 35, 15, 44, 42, 54, 34, 29, 39),
    state_y2 = c(15, 13, 22, 29, 31, 64, 30, 64, 56, 20, 21)
)

# Calculate the difference between commercial and state labs
waste_diff <- waste %>%
    transmute(y1_diff = com_y1 - state_y1,
              y2_diff = com_y2 - state_y2)
# Run the test
paired_fit <- HotellingsT2(waste_diff)
# value T.2 in the output corresponds to
# the approximate F-value in the output from anova.mlm
paired_fit
#>
#>  Hotelling's one sample T2-test
#>
#> data:  waste_diff
#> T.2 = 6.1377, df1 = 2, df2 = 9, p-value = 0.02083
#> alternative hypothesis: true location is not equal to c(0,0)
```

reject the null that the two labs' measurements are equal

```r
# Independent-Sample Hotelling's T^2 test with Bartlett's test

# Read in data
steel <- read.table("images/steel.dat")
names(steel) <- c("Temp", "Yield", "Strength")
str(steel)
#> 'data.frame':    12 obs. of  3 variables:
#>  $ Temp    : int  1 1 1 1 1 2 2 2 2 2 ...
#>  $ Yield   : int  33 36 35 38 40 35 36 38 39 41 ...
#>  $ Strength: int  60 61 64 63 65 57 59 59 61 63 ...

# Plot the data
ggplot(steel, aes(x = Yield, y = Strength)) +
    geom_text(aes(label = Temp), size = 5) +
    geom_segment(aes(
        x = 33,
        y = 57.5,
        xend = 42,
        yend = 65
```

```
    ), col = "red")
```

```
# Bartlett's test for equality of covariance matrices
# same thing as Box's M test in the multivariate setting
bart_test <- boxM(steel[, -1], steel$Temp)
bart_test # fail to reject the null of equal covariances
#>
#>  Box's M-test for Homogeneity of Covariance Matrices
#>
#> data:  steel[, -1]
#> Chi-Sq (approx.) = 0.38077, df = 3, p-value = 0.9442

# anova.mlm
twosamp_fit <-
    anova(lm(cbind(Yield, Strength) ~ factor(Temp),
             data = steel),
          test = "Wilks")
twosamp_fit
#> Analysis of Variance Table
#>
#>               Df    Wilks approx F num Df den Df    Pr(>F)
#> (Intercept)    1 0.001177   3818.1      2      9 6.589e-14 ***
#> factor(Temp)   1 0.294883     10.8      2      9  0.004106 **
#> Residuals     10
#> ---
```

```
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# ICSNP package
twosamp_fit2 <-
    HotellingsT2(cbind(steel$Yield, steel$Strength) ~
                     factor(steel$Temp))
twosamp_fit2
#>
#>  Hotelling's two sample T2-test
#>
#> data:  cbind(steel$Yield, steel$Strength) by factor(steel$Temp)
#> T.2 = 10.76, df1 = 2, df2 = 9, p-value = 0.004106
#> alternative hypothesis: true location difference is not equal to c(0,0)
```

reject null. Hence, there is a difference in the means of the bivariate normal distributions

22.1 MANOVA

Multivariate Analysis of Variance

One-way MANOVA

Compare treatment means for h different populations

Population 1: $\mathbf{y}_{11}, \mathbf{y}_{12}, \dots, \mathbf{y}_{1n_1} \sim iddN_p(\ _1,\ )$

$\vdots$

Population h: $\mathbf{y}_{h1}, \mathbf{y}_{h2}, \dots, \mathbf{y}_{hn_h} \sim iddN_p(\ _h,\ )$

Assumptions

1. Independent random samples from h different populations
2. Common covariance matrices
3. Each population is multivariate **normal**

Calculate the summary statistics $\bar{\mathbf{y}}_i, \mathbf{S}$ and the pooled estimate of the covariance matrix $\mathbf{S}$

Similar to the univariate one-way ANVOA, we can use the effects model formulation $\ _i = \ + \ _i$, where

- $\ _i$ is the population mean for population i
- is the overall mean effect
- $\ _i$ is the treatment effect of the i-th treatment.

For the one-way model: $\mathbf{y}_{ij} = \mu + \tau_i + \epsilon_{ij}$ for $i = 1, .., h; j = 1, ..., n_i$ and $\epsilon_{ij} \sim N_p(\mathbf{0},\ )$

However, the above model is over-parameterized (i.e., infinite number of ways to define and the $_i$'s such that they add up to μ_i. Thus we can constrain by having

$$\sum_{i=1}^{h} n_i \tau_i = 0$$

or

$$_h = 0$$

The observational equivalent of the effects model is

$$\begin{aligned}\mathbf{y}_{ij} &= \bar{\mathbf{y}} + (\bar{\mathbf{y}}_i - \bar{\mathbf{y}}) + (\mathbf{y}_{ij} - \bar{\mathbf{y}}_i) \\ &= \text{overall sample mean} + \text{treatement effect} + \text{residual (under univariate ANOVA)}\end{aligned}$$

After manipulation

$$\sum_{i=1}^{h}\sum_{j=1}^{n_i}(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}})(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}})' = \sum_{i=1}^{h} n_i(\bar{\mathbf{y}}_i - \bar{\mathbf{y}})(\bar{\mathbf{y}}_i - \bar{\mathbf{y}})' + \sum_{i=1}^{h}\sum_{j=1}^{n_i}(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}})(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}}_i)'$$

LHS = Total corrected sums of squares and cross products (SSCP) matrix

RHS =

- 1st term = Treatment (or between subjects) sum of squares and cross product matrix (denoted H;B)
- 2nd term = residual (or within subject) SSCP matrix denoted (E;W)

Note:

$$\mathbf{E} = (n_1 - 1)\mathbf{S}_1 + ... + (n_h - 1)\mathbf{S}_h = (n - h)\mathbf{S}$$

MANOVA table

Table 22.1: MONOVA table

Source	SSCP	df
Treatment	$\mathbf{H}$	$h - 1$
Residual (error)	$\mathbf{E}$	$\sum_{i=1}^{h} n_i - h$

Source	SSCP	df
Total Corrected	$\mathbf{H}+\mathbf{E}$	$\sum_{i=1}^{h} n_i - 1$

$$H_0 : \tau_1 = \tau_2 = \cdots = \tau_h = \mathbf{0}$$

We consider the relative "sizes" of $\mathbf{E}$ and $\mathbf{H}+\mathbf{E}$

Wilk's Lambda

Define Wilk's Lambda

$$\Lambda^* = \frac{|\mathbf{E}|}{|\mathbf{H}+\mathbf{E}|}$$

Properties:

1. Wilk's Lambda is equivalent to the F-statistic in the univariate case
2. The exact distribution of Λ^* can be determined for especial cases.
3. For large sample sizes, reject H_0 if

$$-(\sum_{i=1}^{h} n_i - 1 - \frac{p+h}{2}) \log(\Lambda^*) > \chi^2_{(1-\alpha, p(h-1))}$$

22.1.1 Testing General Hypotheses

- h different treatments
- with the i-th treatment
- applied to n_i subjects that
- are observed for p repeated measures.

Consider this a p dimensional obs on a random sample from each of h different treatment populations.

$$\mathbf{y}_{ij} = \ + \ _i + \ _{ij}$$

for $i = 1, .., h$ and $j = 1, .., n_i$

Equivalently,

$$\mathbf{Y} = \mathbf{XB} +$$

where $n = \sum_{i=1}^{h} n_i$ and with restriction $_h = 0$

$$\mathbf{Y}_{(n\times p)} = \begin{bmatrix} \mathbf{y}'_{11} \\ \vdots \\ \mathbf{y}'_{1n_1} \\ \vdots \\ \mathbf{y}'_{hn_h} \end{bmatrix}, \mathbf{B}_{(h\times p)} = \begin{bmatrix} ' \\ ' \\ 1 \\ \vdots \\ ' \\ h-1 \end{bmatrix}, \ _{(n\times p)} = \begin{bmatrix} \epsilon'_{11} \\ \vdots \\ \epsilon'_{1n_1} \\ \vdots \\ \epsilon'_{hn_h} \end{bmatrix}$$

$$\mathbf{X}_{(n\times h)} = \begin{bmatrix} 1 & 1 & 0 & ... & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & 1 & 0 & ... & 0 \\ \vdots & \vdots & \vdots & ... & \vdots \\ 1 & 0 & 0 & ... & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & 0 & 0 & ... & 0 \end{bmatrix}$$

Estimation

$$\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$$

Rows of $\mathbf{Y}$ are independent (i.e., $var(\mathbf{Y}) = \mathbf{I}_n \otimes$, an $np \times np$ matrix, where $\otimes$ is the Kronecker product).

$$H_0 : \mathbf{LBM} = 0$$
$$H_a : \mathbf{LBM} \neq 0$$

where

- $\mathbf{L}$ is a $g \times h$ matrix of full row rank ($g \leq h$) = comparisons across groups
- $\mathbf{M}$ is a $p \times u$ matrix of full column rank ($u \leq p$) = comparisons across traits

The general treatment corrected sums of squares and cross product is

$$\mathbf{H} = \mathbf{M}'\mathbf{Y}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}'[\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}']^{-1}\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}\mathbf{M}$$

or for the null hypothesis $H_0 : \mathbf{LBM} = \mathbf{D}$

$$\mathbf{H} = (\mathbf{L}\hat{\mathbf{B}}\mathbf{M} - \mathbf{D})'[\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}]^{-1}(\mathbf{L}\hat{\mathbf{B}}\mathbf{M} - \mathbf{D})$$

The general matrix of residual sums of squares and cross product

$$\mathbf{E} = \mathbf{M}'\mathbf{Y}'[\mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}']\mathbf{Y}\mathbf{M} = \mathbf{M}'[\mathbf{Y}'\mathbf{Y} - \hat{\mathbf{B}}'(\mathbf{X}'\mathbf{X})^{-1}\hat{\mathbf{B}}]\mathbf{M}$$

We can compute the following statistic eigenvalues of $\mathbf{HE}^{-1}$

- Wilk's Criterion: $\Lambda^* = \frac{|\mathbf{E}|}{|\mathbf{H}+\mathbf{E}|}$. The df depend on the rank of $\mathbf{L}, \mathbf{M}, \mathbf{X}$
- Lawley-Hotelling Trace: $U = tr(\mathbf{HE}^{-1})$
- Pillai Trace: $V = tr(\mathbf{H}(\mathbf{H} + \mathbf{E}^{-1})$
- Roy's Maximum Root: largest eigenvalue of $\mathbf{HE}^{-1}$

If H_0 is true and n is large, $-(n - 1 - \frac{p+h}{2}) \ln \Lambda^* \sim \chi^2_{p(h-1)}$. Some special values of p and h can give exact F-dist under H_0

```r
# One-way MANOVA

library(car)
library(emmeans)
library(profileR)
library(tidyverse)

## Read in the data
gpagmat <- read.table("images/gpagmat.dat")

## Change the variable names
names(gpagmat) <- c("y1", "y2", "admit")

## Check the structure
str(gpagmat)
#> 'data.frame':    85 obs. of  3 variables:
#>  $ y1   : num  2.96 3.14 3.22 3.29 3.69 3.46 3.03 3.19 3.63 3.59 ...
#>  $ y2   : int  596 473 482 527 505 693 626 663 447 588 ...
#>  $ admit: int  1 1 1 1 1 1 1 1 1 1 ...


## Plot the data
gg <- ggplot(gpagmat, aes(x = y1, y = y2)) +
    geom_text(aes(label = admit, col = as.character(admit))) +
    scale_color_discrete(name = "Admission",
                         labels = c("Admit", "Do not admit", "Borderline")) +
    scale_x_continuous(name = "GPA") +
    scale_y_continuous(name = "GMAT")

## Fit one-way MANOVA
oneway_fit <- manova(cbind(y1, y2) ~ admit, data = gpagmat)
summary(oneway_fit, test = "Wilks")
#>           Df  Wilks approx F num Df den Df    Pr(>F)
#> admit      1 0.6126   25.927      2     82 1.881e-09 ***
#> Residuals 83
```

```
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

reject the null of equal multivariate mean vectors between the three admmission groups

```
# Repeated Measures MANOVA


## Create data frame
stress <- data.frame(
    subject = 1:8,
    begin = c(3, 2, 5, 6, 1, 5, 1, 5),
    middle = c(3, 4, 3, 7, 4, 7, 1, 2),
    final = c(6, 7, 4, 7, 6, 7, 3, 5)
)
```

- If independent = time with 3 levels -> univariate ANOVA (require sphericity assumption (i.e., the variances for all differences are equal))
- If each level of independent time as a separate variable -> MANOVA (does not require sphericity assumption)

```
## MANOVA
stress_mod <- lm(cbind(begin, middle, final) ~ 1, data = stress)
idata <-
    data.frame(time = factor(
        c("begin", "middle", "final"),
        levels = c("begin", "middle", "final")
    ))
repeat_fit <-
    Anova(
        stress_mod,
        idata = idata,
        idesign = ~ time,
        icontrasts = "contr.poly"
    )
summary(repeat_fit)
#>
#> Type III Repeated Measures MANOVA Tests:
#>
#> ------------------------------------------
#>
#> Term: (Intercept)
#>
#>  Response transformation matrix:
#>        (Intercept)
#> begin             1
```

```
#> middle           1
#> final            1
#>
#> Sum of squares and products for the hypothesis:
#>             (Intercept)
#> (Intercept)        1352
#>
#> Multivariate Tests: (Intercept)
#>                  Df test stat approx F num Df den Df     Pr(>F)
#> Pillai            1  0.896552 60.66667      1      7 0.00010808 ***
#> Wilks             1  0.103448 60.66667      1      7 0.00010808 ***
#> Hotelling-Lawley  1  8.666667 60.66667      1      7 0.00010808 ***
#> Roy               1  8.666667 60.66667      1      7 0.00010808 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> ------------------------------------------
#>
#> Term: time
#>
#>  Response transformation matrix:
#>               time.L     time.Q
#> begin  -7.071068e-01  0.4082483
#> middle -7.850462e-17 -0.8164966
#> final   7.071068e-01  0.4082483
#>
#> Sum of squares and products for the hypothesis:
#>           time.L   time.Q
#> time.L 18.062500 6.747781
#> time.Q  6.747781 2.520833
#>
#> Multivariate Tests: time
#>                  Df test stat approx F num Df den Df   Pr(>F)
#> Pillai            1 0.7080717 7.276498      2      6 0.024879 *
#> Wilks             1 0.2919283 7.276498      2      6 0.024879 *
#> Hotelling-Lawley  1 2.4254992 7.276498      2      6 0.024879 *
#> Roy               1 2.4254992 7.276498      2      6 0.024879 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
#>
#>             Sum Sq num Df Error SS den Df F value    Pr(>F)
#> (Intercept) 450.67      1    52.00      7 60.6667 0.0001081 ***
#> time         20.58      2    24.75     14  5.8215 0.0144578 *
```

```
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#>
#> Mauchly Tests for Sphericity
#>
#>      Test statistic p-value
#> time         0.7085 0.35565
#>
#>
#> Greenhouse-Geisser and Huynh-Feldt Corrections
#>  for Departure from Sphericity
#>
#>       GG eps Pr(>F[GG])
#> time 0.77429    0.02439 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#>         HF eps Pr(>F[HF])
#> time 0.9528433 0.01611634
```

can't reject the null hypothesis of sphericity, hence univariate ANOVA is also appropriate.We also see linear significant time effect, but no quadratic time effect

```
## Polynomial contrasts
# What is the reference for the marginal means?
ref_grid(stress_mod, mult.name = "time")
#> 'emmGrid' object with variables:
#>     1 = 1
#>     time = multivariate response levels: begin, middle, final

# marginal means for the levels of time
contr_means <- emmeans(stress_mod, ~ time, mult.name = "time")
contrast(contr_means, method = "poly")
#>  contrast  estimate    SE df t.ratio p.value
#>  linear        2.12 0.766  7   2.773  0.0276
#>  quadratic     1.38 0.944  7   1.457  0.1885
```

```
# MANOVA



## Read in Data
heart <- read.table("images/heart.dat")
names(heart) <- c("drug", "y1", "y2", "y3", "y4")
## Create a subject ID nested within drug
```

```
heart <- heart %>%
    group_by(drug) %>%
    mutate(subject = row_number()) %>%
    ungroup()
str(heart)
#> tibble [24 x 6] (S3: tbl_df/tbl/data.frame)
#>  $ drug   : chr [1:24] "ax23" "ax23" "ax23" "ax23" ...
#>  $ y1     : int [1:24] 72 78 71 72 66 74 62 69 85 82 ...
#>  $ y2     : int [1:24] 86 83 82 83 79 83 73 75 86 86 ...
#>  $ y3     : int [1:24] 81 88 81 83 77 84 78 76 83 80 ...
#>  $ y4     : int [1:24] 77 82 75 69 66 77 70 70 80 84 ...
#>  $ subject: int [1:24] 1 2 3 4 5 6 7 8 1 2 ...

## Create means summary for profile plot,
# pivot longer for plotting with ggplot
heart_means <- heart %>%
    group_by(drug) %>%
    summarize_at(vars(starts_with("y")), mean) %>%
    ungroup() %>%
    pivot_longer(-drug, names_to = "time", values_to = "mean") %>%
    mutate(time = as.numeric(as.factor(time)))
gg_profile <- ggplot(heart_means, aes(x = time, y = mean)) +
    geom_line(aes(col = drug)) +
    geom_point(aes(col = drug)) +
    ggtitle("Profile Plot") +
    scale_y_continuous(name = "Response") +
    scale_x_discrete(name = "Time")
gg_profile
```

```
## Fit model
heart_mod <- lm(cbind(y1, y2, y3, y4) ~ drug, data = heart)
man_fit <- car::Anova(heart_mod)
summary(man_fit)
#>
#> Type II MANOVA Tests:
#>
#> Sum of squares and products for error:
#>         y1       y2       y3      y4
#> y1 641.00 601.750 535.250 426.00
#> y2 601.75 823.875 615.500 534.25
#> y3 535.25 615.500 655.875 555.25
#> y4 426.00 534.250 555.250 674.50
#>
#> ------------------------------------------
#>
#> Term: drug
#>
#> Sum of squares and products for the hypothesis:
#>         y1        y2        y3    y4
#> y1 567.00 335.2500  42.7500 387.0
#> y2 335.25 569.0833 404.5417 367.5
#> y3  42.75 404.5417 391.0833 171.0
#> y4 387.00 367.5000 171.0000 316.0
#>
#> Multivariate Tests: drug
#>                  Df test stat  approx F num Df den Df     Pr(>F)
```

```
#> Pillai            2  1.283456  8.508082      8     38 1.5010e-06 ***
#> Wilks             2  0.079007 11.509581      8     36 6.3081e-08 ***
#> Hotelling-Lawley  2  7.069384 15.022441      8     34 3.9048e-09 ***
#> Roy               2  6.346509 30.145916      4     19 5.4493e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

reject the null hypothesis of no difference in means between treatments

```
## Contrasts
heart$drug <- factor(heart$drug)
L <- matrix(c(0, 2,
              1, -1,-1, -1), nrow = 3, byrow = T)
colnames(L) <- c("bww9:ctrl", "ax23:rest")
rownames(L) <- unique(heart$drug)
contrasts(heart$drug) <- L
contrasts(heart$drug)
#>      bww9:ctrl ax23:rest
#> ax23         0         2
#> bww9         1        -1
#> ctrl        -1        -1

# do not set contrast L if you do further analysis (e.g., Anova, lm)
# do M matrix instead

M <- matrix(c(1, -1, 0, 0,
              0, 1, -1, 0,
              0, 0, 1, -1), nrow = 4)
## update model to test contrasts
heart_mod2 <- update(heart_mod)
coef(heart_mod2)
#>                  y1         y2        y3    y4
#> (Intercept)   75.00 78.9583333 77.041667 74.75
#> drugbww9:ctrl  4.50  5.8125000  3.562500  4.25
#> drugax23:rest -2.25  0.7708333  1.979167 -0.75

# Hypothesis test for bww9 vs control after transformation M
# same as linearHypothesis(heart_mod, hypothesis.matrix = c(0,1,-1), P = M)
bww9vctrl <-
    car::linearHypothesis(heart_mod2,
                          hypothesis.matrix = c(0, 1, 0),
                          P = M)
bww9vctrl
#>
#>  Response transformation matrix:
#>    [,1] [,2] [,3]
```

```
#> y1    1    0    0
#> y2   -1    1    0
#> y3    0   -1    1
#> y4    0    0   -1
#>
#> Sum of squares and products for the hypothesis:
#>          [,1]   [,2]     [,3]
#> [1,]  27.5625 -47.25  14.4375
#> [2,] -47.2500  81.00 -24.7500
#> [3,]  14.4375 -24.75   7.5625
#>
#> Sum of squares and products for error:
#>          [,1]     [,2]    [,3]
#> [1,]  261.375 -141.875  28.000
#> [2,] -141.875  248.750 -19.375
#> [3,]   28.000  -19.375 219.875
#>
#> Multivariate Tests:
#>                  Df test stat approx F num Df den Df Pr(>F)
#> Pillai            1 0.2564306 2.184141      3     19 0.1233
#> Wilks             1 0.7435694 2.184141      3     19 0.1233
#> Hotelling-Lawley  1 0.3448644 2.184141      3     19 0.1233
#> Roy               1 0.3448644 2.184141      3     19 0.1233

bww9vctrl <-
    car::linearHypothesis(heart_mod,
                          hypothesis.matrix = c(0, 1, -1),
                          P = M)
bww9vctrl
#>
#>  Response transformation matrix:
#>    [,1] [,2] [,3]
#> y1    1    0    0
#> y2   -1    1    0
#> y3    0   -1    1
#> y4    0    0   -1
#>
#> Sum of squares and products for the hypothesis:
#>          [,1]   [,2]     [,3]
#> [1,]  27.5625 -47.25  14.4375
#> [2,] -47.2500  81.00 -24.7500
#> [3,]  14.4375 -24.75   7.5625
#>
#> Sum of squares and products for error:
#>          [,1]     [,2]    [,3]
```

```
#> [1,]  261.375 -141.875  28.000
#> [2,] -141.875  248.750 -19.375
#> [3,]   28.000  -19.375 219.875
#>
#> Multivariate Tests:
#>                  Df test stat approx F num Df den Df Pr(>F)
#> Pillai            1 0.2564306 2.184141      3     19 0.1233
#> Wilks             1 0.7435694 2.184141      3     19 0.1233
#> Hotelling-Lawley  1 0.3448644 2.184141      3     19 0.1233
#> Roy               1 0.3448644 2.184141      3     19 0.1233
```

there is no significant difference in means between the control and `bww9` drug

```
# Hypothesis test for ax23 vs rest after transformation M
axx23vrest <-
    car::linearHypothesis(heart_mod2,
                          hypothesis.matrix = c(0, 0, 1),
                          P = M)
axx23vrest
#>
#>  Response transformation matrix:
#>    [,1] [,2] [,3]
#> y1    1    0    0
#> y2   -1    1    0
#> y3    0   -1    1
#> y4    0    0   -1
#>
#> Sum of squares and products for the hypothesis:
#>           [,1]       [,2]      [,3]
#> [1,]  438.0208  175.20833 -395.7292
#> [2,]  175.2083   70.08333 -158.2917
#> [3,] -395.7292 -158.29167  357.5208
#>
#> Sum of squares and products for error:
#>          [,1]     [,2]    [,3]
#> [1,]  261.375 -141.875  28.000
#> [2,] -141.875  248.750 -19.375
#> [3,]   28.000  -19.375 219.875
#>
#> Multivariate Tests:
#>                  Df test stat approx F num Df den Df     Pr(>F)
#> Pillai            1  0.855364 37.45483      3     19 3.5484e-08 ***
#> Wilks             1  0.144636 37.45483      3     19 3.5484e-08 ***
#> Hotelling-Lawley  1  5.913921 37.45483      3     19 3.5484e-08 ***
#> Roy               1  5.913921 37.45483      3     19 3.5484e-08 ***
#> ---
```

```
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

axx23vrest <-
    car::linearHypothesis(heart_mod,
                          hypothesis.matrix = c(2, -1, 1),
                          P = M)
axx23vrest
#>
#>  Response transformation matrix:
#>    [,1] [,2] [,3]
#> y1    1    0    0
#> y2   -1    1    0
#> y3    0   -1    1
#> y4    0    0   -1
#>
#> Sum of squares and products for the hypothesis:
#>           [,1]       [,2]      [,3]
#> [1,]  402.5208  127.41667 -390.9375
#> [2,]  127.4167   40.33333 -123.7500
#> [3,] -390.9375 -123.75000  379.6875
#>
#> Sum of squares and products for error:
#>          [,1]     [,2]    [,3]
#> [1,]  261.375 -141.875  28.000
#> [2,] -141.875  248.750 -19.375
#> [3,]   28.000  -19.375 219.875
#>
#> Multivariate Tests:
#>                  Df test stat approx F num Df den Df     Pr(>F)
#> Pillai            1  0.842450 33.86563      3     19 7.9422e-08 ***
#> Wilks             1  0.157550 33.86563      3     19 7.9422e-08 ***
#> Hotelling-Lawley  1  5.347205 33.86563      3     19 7.9422e-08 ***
#> Roy               1  5.347205 33.86563      3     19 7.9422e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

there is a significant difference in means between ax23 drug treatment and the rest of the treatments

22.1.2 Profile Analysis

Examine similarities between the treatment effects (between subjects), which is useful for longitudinal analysis. Null is that all treatments have the same average effect.

$$H_0 : \mu_1 = \mu_2 = \cdots = \mu_h$$

Equivalently,

$$H_0 : \tau_1 = \tau_2 = \cdots = \tau_h$$

The exact nature of the similarities and differences between the treatments can be examined under this analysis.

Sequential steps in profile analysis:

1. Are the profiles **parallel**? (i.e., is there no interaction between treatment and time)
2. Are the profiles **coincidental**? (i.e., are the profiles identical?)
3. Are the profiles **horizontal**? (i.e., are there no differences between any time points?)

If we reject the null hypothesis that the profiles are parallel, we can test

- Are there differences among groups within some subset of the total time points?
- Are there differences among time points in a particular group (or groups)?
- Are there differences within some subset of the total time points in a particular group (or groups)?

Example

- 4 times (p = 4)
- 3 treatments (h=3)

22.1.2.1 Parallel Profile

Are the profiles for each population identical expect for a mean shift?

$$\begin{aligned} H_0 : \mu_{11} - \mu_{21} - \mu_{12} - \mu_{22} &= \cdots = \mu_{1t} - \mu_{2t} \\ \mu_{11} - \mu_{31} - \mu_{12} - \mu_{32} &= \cdots = \mu_{1t} - \mu_{3t} \\ &\cdots \end{aligned}$$

for $h - 1$ equations

Equivalently,

$$H_0 : \mathbf{LBM} = \mathbf{0}$$

$$\mathbf{LBM} = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} \mu_{11} & \cdots & \mu_{14} \\ \mu_{21} & \cdots & \mu_{24} \\ \mu_{31} & \cdots & \mu_{34} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} = \mathbf{0}$$

where this is the cell means parameterization of $\mathbf{B}$

The multiplication of the first 2 matrices $\mathbf{LB}$ is

$$\begin{bmatrix} \mu_{11} - \mu_{21} & \mu_{12} - \mu_{22} & \mu_{13} - \mu_{23} & \mu_{14} - \mu_{24} \\ \mu_{11} - \mu_{31} & \mu_{12} - \mu_{32} & \mu_{13} - \mu_{33} & \mu_{14} - \mu_{34} \end{bmatrix}$$

which is the differences in treatment means at the same time

Multiplying by $\mathbf{M}$, we get the comparison across time

$$\begin{bmatrix} (\mu_{11} - \mu_{21}) - (\mu_{12} - \mu_{22}) & (\mu_{11} - \mu_{21}) - (\mu_{13} - \mu_{23}) & (\mu_{11} - \mu_{21}) - (\mu_{14} - \mu_{24}) \\ (\mu_{11} - \mu_{31}) - (\mu_{12} - \mu_{32}) & (\mu_{11} - \mu_{31}) - (\mu_{13} - \mu_{33}) & (\mu_{11} - \mu_{31}) - (\mu_{14} - \mu_{34}) \end{bmatrix}$$

Alternatively, we can also use the effects parameterization

$$\mathbf{LBM} = \begin{bmatrix} 0 & 1 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} \mu' \\ \tau_1' \\ \tau_2' \\ \tau_3' \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} = \mathbf{0}$$

In both parameterizations, $rank(\mathbf{L}) = h - 1$ and $rank(\mathbf{M}) = p - 1$

We could also choose $\mathbf{L}$ and $\mathbf{M}$ in other forms

$$\mathbf{L} = \begin{bmatrix} 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix}$$

and

$$\mathbf{M} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & -1 \end{bmatrix}$$

and still obtain the same result.

22.1.2.2 Coincidental Profiles

After we have evidence that the profiles are parallel (i.e., fail to reject the parallel profile test), we can ask whether they are identical?

Given profiles are **parallel**, then if the sums of the components of μ_i are identical for all the treatments, then the profiles are **identical**.

$$H_0 : \mathbf{1}'_p \mu_1 = \mathbf{1}'_p \mu_2 = \cdots = \mathbf{1}'_p \mu_h$$

Equivalently,

$$H_0 : \mathbf{LBM} = \mathbf{0}$$

where for the cell means parameterization

$$\mathbf{L} = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix}$$

and

$$\mathbf{M} = \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix}'$$

multiplication yields

$$\begin{bmatrix} (\mu_{11} + \mu_{12} + \mu_{13} + \mu_{14}) - (\mu_{31} + \mu_{32} + \mu_{33} + \mu_{34}) \\ (\mu_{21} + \mu_{22} + \mu_{23} + \mu_{24}) - (\mu_{31} + \mu_{32} + \mu_{33} + \mu_{34}) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Different choices of $\mathbf{L}$ and $\mathbf{M}$ can yield the same result

22.1.2.3 Horizontal Profiles

Given that we can't reject the null hypothesis that all h profiles are the same, we can ask whether all of the elements of the common profile equal? (i.e., horizontal)

$$H_0 : \mathbf{LBM} = \mathbf{0}$$

$$\mathbf{L} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

and

$$\mathbf{M} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & -1 \end{bmatrix}$$

hence,

$$\begin{bmatrix} (\mu_{11} - \mu_{12}) & (\mu_{12} - \mu_{13}) & (\mu_{13} + \mu_{14}) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$$

Note:

- If we fail to reject all 3 hypotheses, then we fail to reject the null hypotheses of both no difference between treatments and no differences between traits.

Test	Equivalent test for
Parallel profile	Interaction
Coincidental profile	main effect of between-subjects factor
Horizontal profile	main effect of repeated measures factor

```
profile_fit <-
    pbg(
        data = as.matrix(heart[, 2:5]),
        group = as.matrix(heart[, 1]),
        original.names = TRUE,
        profile.plot = FALSE
    )
summary(profile_fit)
#> Call:
#> pbg(data = as.matrix(heart[, 2:5]), group = as.matrix(heart[,
#>     1]), original.names = TRUE, profile.plot = FALSE)
#>
#> Hypothesis Tests:
#> $`Ho: Profiles are parallel`
#>   Multivariate.Test Statistic  Approx.F num.df den.df      p.value
#> 1             Wilks 0.1102861 12.737599      6     38 7.891497e-08
#> 2            Pillai 1.0891707  7.972007      6     40 1.092397e-05
#> 3  Hotelling-Lawley 6.2587852 18.776356      6     36 9.258571e-10
#> 4               Roy 5.9550887 39.700592      3     20 1.302458e-08
#>
#> $`Ho: Profiles have equal levels`
#>             Df Sum Sq Mean Sq F value  Pr(>F)
#> group        2  328.7  164.35   5.918 0.00915 **
#> Residuals   21  583.2   27.77
#> ---
```

```
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> $`Ho: Profiles are flat`
#>          F df1 df2      p-value
#> 1 14.30928   3  19 4.096803e-05
# reject null hypothesis of parallel profiles
# reject the null hypothesis of coincidental profiles
# reject the null hypothesis that the profiles are flat
```

22.1.3 Summary

22.2 Principal Components

- Unsupervised learning
- find important features
- reduce the dimensions of the data set
- "decorrelate" multivariate vectors that have dependence.
- uses eigenvector/eigvenvalue decomposition of covariance (correlation) matrices.

According to the "spectral decomposition theorem", if $_{p\times p}$ i s a positive semi-definite, symmetric, real matrix, then there exists an orthogonal matrix $\mathbf{A}$ such

that $\mathbf{A}'\ \mathbf{A} = \Lambda$ where Λ is a diagonal matrix containing the eigenvalues

$$= \begin{pmatrix} \lambda_1 & 0 & ... & 0 \\ 0 & \lambda_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \lambda_p \end{pmatrix}$$

$$\mathbf{A} = \begin{pmatrix} \mathbf{a}_1 & \mathbf{a}_2 & ... & \mathbf{a}_p \end{pmatrix}$$

the i-th column of $\mathbf{A}$, $\mathbf{a}_i$, is the i-th $p \times 1$ eigenvector of that corresponds to the eigenvalue, λ_i , where $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p$. Alternatively, express in matrix decomposition:

$$= \mathbf{A}\ \mathbf{A}'$$

$$= \mathbf{A} \begin{pmatrix} \lambda_1 & 0 & ... & 0 \\ 0 & \lambda_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \lambda_p \end{pmatrix} \mathbf{A}' = \sum_{i=1}^{p} \lambda_i \mathbf{a}_i \mathbf{a}_i'$$

where the outer product $\mathbf{a}_i \mathbf{a}_i'$ is a $p \times p$ matrix of rank 1.

For example,

$\mathbf{x} \sim N_2(\ , \ )$

$$= \begin{pmatrix} 5 \\ 12 \end{pmatrix}; \ = \begin{pmatrix} 4 & 1 \\ 1 & 2 \end{pmatrix}$$

```
library(MASS)
mu = as.matrix(c(5, 12))
Sigma = matrix(c(4, 1, 1, 2), nrow = 2, byrow = T)
sim <- mvrnorm(n = 1000, mu = mu, Sigma = Sigma)
plot(sim[, 1], sim[, 2])
```

Here,

$$\mathbf{A} = \begin{pmatrix} 0.9239 & -0.3827 \\ 0.3827 & 0.9239 \end{pmatrix}$$

Columns of $\mathbf{A}$ are the eigenvectors for the decomposition

Under matrix multiplication ($\mathbf{A}'\ \mathbf{A}$ or $\mathbf{A}'\mathbf{A}$), the off-diagonal elements equal to 0

Multiplying data by this matrix (i.e., projecting the data onto the orthogonal axes); the distribution of the resulting data (i.e., "scores") is

$$N_2(\mathbf{A}'\ , \mathbf{A}'\ \mathbf{A}) = N_2(\mathbf{A}'\ ,\ )$$

Equivalently,

$$\mathbf{y} = \mathbf{A}'\mathbf{x} \sim N\left[\begin{pmatrix} 9.2119 \\ 9.1733 \end{pmatrix}, \begin{pmatrix} 4.4144 & 0 \\ 0 & 1.5859 \end{pmatrix}\right]$$

```
A_matrix = matrix(c(0.9239, -0.3827, 0.3827, 0.9239),
                  nrow = 2,
                  byrow = T)
t(A_matrix) %*% A_matrix
#>          [,1]     [,2]
#> [1,] 1.000051 0.000000
#> [2,] 0.000000 1.000051
```

```
sim1 <-
    mvrnorm(
        n = 1000,
        mu = t(A_matrix) %*% mu,
        Sigma = t(A_matrix) %*% Sigma %*% A_matrix
    )
plot(sim1[, 1], sim1[, 2])
```

No more dependence in the data structure, plot

Notes:

- The i-th eigenvalue is the variance of a linear combination of the elements of $\mathbf{x}$; $var(y_i) = var(\mathbf{a_i'x}) = \lambda_i$
- The values on the transformed set of axes (i.e., the y_i's) are called the scores. These are the orthogonal projections of the data onto the "new principal component axes
- Variances of y_1 are greater than those for any other possible projection

Covariance matrix decomposition and projection onto orthogonal axes = PCA

22.2.1 Population Principal Components

$p \times 1$ vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ which are iid with $var(\mathbf{x}_i) =$

- The first PC is the linear combination $y_1 = \mathbf{a}_1'\mathbf{x} = a_{11}x_1 + \cdots + a_{1p}x_p$ with $\mathbf{a}_1'\mathbf{a}_1 = 1$ such that $var(y_1)$ is the maximum of all linear combinations of $\mathbf{x}$ which have unit length

- The second PC is the linear combination $y_1 = \mathbf{a}_2'\mathbf{x} = a_{21}x_1 + \cdots + a_{2p}x_p$ with $\mathbf{a}_2'\mathbf{a}_2 = 1$ such that $var(y_1)$ is the maximum of all linear combinations of $\mathbf{x}$ which have unit length and uncorrelated with y_1 (i.e., $cov(\mathbf{a}_1'\mathbf{x}, \mathbf{a}_2'\mathbf{x}) = 0$
- continues for all y_i to y_p

$\mathbf{a}_i$'s are those that make up the matrix $\mathbf{A}$ in the symmetric decomposition $\mathbf{A}'\ \mathbf{A} =$, where $var(y_1) = \lambda_1, \ldots, var(y_p) = \lambda_p$ And the total variance of $\mathbf{x}$ is

$$\begin{aligned} var(x_1) + \cdots + var(x_p) &= tr(\Sigma) = \lambda_1 + \cdots + \lambda_p \\ &= var(y_1) + \cdots + var(y_p) \end{aligned}$$

Data Reduction

To reduce the dimension of data from p (original) to k dimensions without much "loss of information", we can use properties of the population principal components

- Suppose $\approx \sum_{i=1}^{k} \lambda_i \mathbf{a}_i \mathbf{a}_i'$. Even thought the true variance-covariance matrix has rank p , it can be be well approximate by a matrix of rank k (k <p)
- New "traits" are linear combinations of the measured traits. We can attempt to make meaningful interpretation fo the combinations (with orthogonality constraints).
- The proportion of the total variance accounted for by the j-th principal component is

$$\frac{var(y_j)}{\sum_{i=1}^{p} var(y_i)} = \frac{\lambda_j}{\sum_{i=1}^{p} \lambda_i}$$

- The proportion of the total variation accounted for by the first k principal components is $\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i}$
- Above example , we have $4.4144/(4+2) = .735$ of the total variability can be explained by the first principal component

22.2.2 Sample Principal Components

Since is unknown, we use

$$\mathbf{S} = \frac{1}{n-1} \sum_{i=1}^{n} (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})'$$

Let $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \ldots \geq \hat{\lambda}_p \geq 0$ be the eigenvalues of $\mathbf{S}$ and $\hat{\mathbf{a}}_1, \hat{\mathbf{a}}_2, \ldots, \hat{\mathbf{a}}_p$ denote the eigenvectors of $\mathbf{S}$

Then, the i-th sample principal component score (or principal component or score) is

$$\hat{y}_{ij} = \sum_{k=1}^{p} \hat{a}_{ik} x_{kj} = \hat{\mathbf{a}}_i' \mathbf{x}_j$$

Properties of Sample Principal Components

- The estimated variance of $y_i = \hat{\mathbf{a}}_i' \mathbf{x}_j$ is $\hat{\lambda}_i$
- The sample covariance between $\hat{y}_i$ and $\hat{y}_{i'}$ is 0 when $i \neq i'$
- The proportion of the total sample variance accounted for by the i-th sample principal component is $\frac{\hat{\lambda}_i}{\sum_{k=1}^{p} \hat{\lambda}_k}$
- The estimated correlation between the i-th principal component score and the l-th attribute of $\mathbf{x}$ is

$$r_{x_l, \hat{y}_i} = \frac{\hat{a}_{il} \sqrt{\lambda_i}}{\sqrt{s_{ll}}}$$

- The correlation coefficient is typically used to interpret the components (i.e., if this correlation is high then it suggests that the l-th original trait is important in the i-th principle component). According to Johnson et al. (2002), pp.433-434, $r_{x_l, \hat{y}_i}$ only measures the univariate contribution of an individual X to a component Y without taking into account the presence of the other X's. Hence, some prefer $\hat{a}_{il}$ coefficient to interpret the principal component.
- $r_{x_l, \hat{y}_i}; \hat{a}_{il}$ are referred to as "loadings"

To use k principal components, we must calculate the scores for each data vector in the sample

$$\mathbf{y}_j = \begin{pmatrix} y_{1j} \\ y_{2j} \\ \vdots \\ y_{kj} \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1' \mathbf{x}_j \\ \hat{\mathbf{a}}_2' \mathbf{x}_j \\ \vdots \\ \hat{\mathbf{a}}_k' \mathbf{x}_j \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1' \\ \hat{\mathbf{a}}_2' \\ \vdots \\ \hat{\mathbf{a}}_k' \end{pmatrix} \mathbf{x}_j$$

Issues:

- Large sample theory exists for eigenvalues and eigenvectors of sample covariance matrices if inference is necessary. But we do not do inference with PCA, we only use it as exploratory or descriptive analysis.
- PC is not invariant to changes in scale (Exception: if all trait are rescaled by multiplying by the same constant, such as feet to inches).

- PCA based on the correlation matrix $\mathbf{R}$ is different than that based on the covariance matrix
- PCA for the correlation matrix is just rescaling each trait to have unit variance
- Transform $\mathbf{x}$ to $\mathbf{z}$ where $z_{ij} = (x_{ij} - \bar{x}_i)/\sqrt{s_{ii}}$ where the denominator affects the PCA
- After transformation, $cov(\mathbf{z}) = \mathbf{R}$
- PCA on $\mathbf{R}$ is calculated in the same way as that on $\mathbf{S}$ (where $\hat{\lambda}_1 + \cdots + \hat{\lambda}_p = p$)
- The use of $\mathbf{R}, \mathbf{S}$ depends on the purpose of PCA.
  * If the scale of the observations if different, covariance matrix is more preferable. but if they are dramatically different, analysis can still be dominated by the large variance traits.
- How many PCs to use can be guided by
  * Scree Graphs: plot the eigenvalues against their indices. Look for the "elbow" where the steep decline in the graph suddenly flattens out; or big gaps.
  * minimum Percent of total variation (e.g., choose enough components to have 50% or 90%). can be used for interpretations.
  * Kaiser's rule: use only those PC with eigenvalues larger than 1 (applied to PCA on the correlation matrix) - ad hoc
  * Compare to the eigenvalue scree plot of data to the scree plot when the data are randomized.

22.2.3 Application

PCA on the covariance matrix is usually not preferred due to the fact that PCA is not invariant to changes in scale. Hence, PCA on the correlation matrix is more preferred

This also addresses the problem of multicollinearity

The eigvenvectors may differ by a multiplication of -1 for different implementation, but same interpretation.

```
library(tidyverse)
## Read in and check data
stock <- read.table("images/stock.dat")
names(stock) <- c("allied", "dupont", "carbide", "exxon", "texaco")
str(stock)
#> 'data.frame':    100 obs. of  5 variables:
```

```
#>  $ allied : num  0 0.027 0.1228 0.057 0.0637 ...
#>  $ dupont : num  0 -0.04485 0.06077 0.02995 -0.00379 ...
#>  $ carbide: num  0 -0.00303 0.08815 0.06681 -0.03979 ...
#>  $ exxon  : num  0.0395 -0.0145 0.0862 0.0135 -0.0186 ...
#>  $ texaco : num  0 0.0435 0.0781 0.0195 -0.0242 ...

## Covariance matrix of data
cov(stock)
#>               allied       dupont      carbide        exxon       texaco
#> allied  0.0016299269 0.0008166676 0.0008100713 0.0004422405 0.0005139715
#> dupont  0.0008166676 0.0012293759 0.0008276330 0.0003868550 0.0003109431
#> carbide 0.0008100713 0.0008276330 0.0015560763 0.0004872816 0.0004624767
#> exxon   0.0004422405 0.0003868550 0.0004872816 0.0008023323 0.0004084734
#> texaco  0.0005139715 0.0003109431 0.0004624767 0.0004084734 0.0007587370

## Correlation matrix of data
cor(stock)
#>            allied    dupont   carbide     exxon    texaco
#> allied  1.0000000 0.5769244 0.5086555 0.3867206 0.4621781
#> dupont  0.5769244 1.0000000 0.5983841 0.3895191 0.3219534
#> carbide 0.5086555 0.5983841 1.0000000 0.4361014 0.4256266
#> exxon   0.3867206 0.3895191 0.4361014 1.0000000 0.5235293
#> texaco  0.4621781 0.3219534 0.4256266 0.5235293 1.0000000

# cov(scale(stock)) # give the same result

## PCA with covariance
cov_pca <- prcomp(stock)
# uses singular value decomposition for calculation and an N -1 divisor
# alternatively, princomp can do PCA via spectral decomposition,
# but it has worse numerical accuracy

# eigen values
cov_results <- data.frame(eigen_values = cov_pca$sdev ^ 2)
cov_results %>%
    mutate(proportion = eigen_values / sum(eigen_values),
           cumulative = cumsum(proportion))
#>   eigen_values proportion cumulative
#> 1 0.0035953867 0.60159252  0.6015925
#> 2 0.0007921798 0.13255027  0.7341428
#> 3 0.0007364426 0.12322412  0.8573669
#> 4 0.0005086686 0.08511218  0.9424791
#> 5 0.0003437707 0.05752091  1.0000000
# first 2 PCs account for 73% variance in the data
```

```r
# eigen vectors
cov_pca$rotation # prcomp calls rotation
#>               PC1         PC2        PC3         PC4         PC5
#> allied  0.5605914  0.73884565 -0.1260222  0.28373183 -0.20846832
#> dupont  0.4698673 -0.09286987 -0.4675066 -0.68793190  0.28069055
#> carbide 0.5473322 -0.65401929 -0.1140581  0.50045312 -0.09603973
#> exxon   0.2908932 -0.11267353  0.6099196 -0.43808002 -0.58203935
#> texaco  0.2842017  0.07103332  0.6168831  0.06227778  0.72784638
# princomp calls loadings.

# first PC = overall average
# second PC compares Allied to Carbide

## PCA with correlation
#same as scale(stock) %>% prcomp
cor_pca <- prcomp(stock, scale = T)



# eigen values
cor_results <- data.frame(eigen_values = cor_pca$sdev ^ 2)
cor_results %>%
    mutate(proportion = eigen_values / sum(eigen_values),
           cumulative = cumsum(proportion))
#>   eigen_values proportion cumulative
#> 1    2.8564869 0.57129738  0.5712974
#> 2    0.8091185 0.16182370  0.7331211
#> 3    0.5400440 0.10800880  0.8411299
#> 4    0.4513468 0.09026936  0.9313992
#> 5    0.3430038 0.06860076  1.0000000

# first egiven values corresponds to less variance
# than PCA based on the covariance matrix

# eigen vectors
cor_pca$rotation
#>               PC1        PC2        PC3        PC4        PC5
#> allied  0.4635405 -0.2408499  0.6133570 -0.3813727  0.4532876
#> dupont  0.4570764 -0.5090997 -0.1778996 -0.2113068 -0.6749814
#> carbide 0.4699804 -0.2605774 -0.3370355  0.6640985  0.3957247
#> exxon   0.4216770  0.5252647 -0.5390181 -0.4728036  0.1794482
#> texaco  0.4213291  0.5822416  0.4336029  0.3812273 -0.3874672
# interpretation of PC2 is different from above:
# it is a comparison of Allied, Dupont and Carbid to Exxon and Texaco
```

Covid Example

To reduce collinearity problem in this dataset, we can use principal components as regressors.

```
load('images/MOcovid.RData')
covidpca <- prcomp(ndat[,-1],scale = T,center = T)

covidpca$rotation[,1:2]
#>                                                          PC1         PC2
#> X..Population.in.Rural.Areas                       0.32865838  0.05090955
#> Area..sq..miles.                                   0.12014444 -0.28579183
#> Population.density..sq..miles.                    -0.29670124  0.28312922
#> Literacy.rate                                     -0.12517700 -0.08999542
#> Families                                          -0.25856941  0.16485752
#> Area.of.farm.land..sq..miles.                      0.02101106 -0.31070363
#> Number.of.farms                                   -0.03814582 -0.44809679
#> Average.value.of.all.property.per.farm..dollars. -0.05410709  0.14404306
#> Estimation.of.rurality..                          -0.19040210  0.12089501
#> Male..                                             0.02182394 -0.09568768
#> Number.of.Physcians.per.100.000                   -0.31451606  0.13598026
#> average.age                                        0.29414708  0.35593459
#> X0.4.age.proportion                               -0.11431336 -0.23574057
#> X20.44.age.proportion                             -0.32802128 -0.22718550
#> X65.and.over.age.proportion                        0.30585033  0.32201626
#> prop..White..nonHisp                               0.35627561 -0.14142646
#> prop..Hispanic                                    -0.16655381 -0.15105342
#> prop..Black                                       -0.33333359  0.24405802


# Variability of each principal component: pr.var
pr.var <- covidpca$sdev ^ 2
# Variance explained by each principal component: pve
pve <- pr.var / sum(pr.var)
plot(
    pve,
    xlab = "Principal Component",
    ylab = "Proportion of Variance Explained",
    ylim = c(0, 0.5),
    type = "b"
)
```

```
plot(
    cumsum(pve),
    xlab = "Principal Component",
    ylab = "Cumulative Proportion of Variance Explained",
    ylim = c(0, 1),
    type = "b"
)
```

```
# the first six principe account for around 80% of the variance.


#using base lm function for PC regression
pcadat <- data.frame(covidpca$x[, 1:6])
pcadat$y <- ndat$Y
pcr.man <- lm(log(y) ~ ., pcadat)
mean(pcr.man$residuals ^ 2)
#> [1] 0.03453371

#comparison to lm w/o prin comps
lm.fit <- lm(log(Y) ~ ., data = ndat)
mean(lm.fit$residuals ^ 2)
#> [1] 0.02335128
```

MSE for the PC-based model is larger than regular regression, because models with a large degree of collinearity can still perform well.

`pcr` function in `pls` can be used for fitting PC regression (it will select the optimal number of components in the model).

22.3 Factor Analysis

Purpose

- Using a few linear combinations of underlying unobservable (latent) traits, we try to describe the covariance relationship among a large number of measured traits
- Similar to PCA, but factor analysis is **model based**

More details can be found on PSU stat or UMN stat

Let $\mathbf{y}$ be the set of p measured variables

$E(\mathbf{y}) =$

$var(\mathbf{y}) =$

We have

$$\begin{aligned}\mathbf{y} - &= \mathbf{L}\mathbf{f} + \epsilon \\ &= \begin{pmatrix} l_{11}f_1 + l_{12}f_2 + \cdots + l_{tm}f_m \\ \vdots \\ l_{p1}f_1 + l_{p2}f_2 + \cdots + l_{pm}f_m \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_p \end{pmatrix}\end{aligned}$$

where

- $\mathbf{y} - \quad =$ the p centered measurements
- $\mathbf{L} = p \times m$ matrix of factor loadings
- $\mathbf{f} =$ unobserved common factors for the population
- $\quad =$ random errors (i.e., variation that is not accounted for by the common factors).

We want m (the number of factors) to be much smaller than p (the number of measured attributes)

Restrictions on the model

- $E(\epsilon) = \mathbf{0}$
- $var(\epsilon) = \Psi_{p\times p} = diag(\psi_1, \dots, \psi_p)$
- $\quad, \mathbf{f}$ are independent
- Additional assumption could be $E(\mathbf{f}) = \mathbf{0}, var(\mathbf{f}) = \mathbf{I}_{m\times m}$ (known as the orthogonal factor model) , which imposes the following covariance structure on $\mathbf{y}$

$$\begin{aligned} var(\mathbf{y}) = \quad &= var(\mathbf{Lf} + \quad) \\ &= var(\mathbf{Lf}) + var(\epsilon) \\ &= \mathbf{L}var(\mathbf{f})\mathbf{L}' + \\ &= \mathbf{LIL}' + \\ &= \mathbf{LL}' + \end{aligned}$$

Since is diagonal, the off-diagonal elements of $\mathbf{LL}'$ are σ_{ij}, the co variances in , which means $cov(y_i, y_j) = \sum_{k=1}^{m} l_{ik} l_{jk}$ and the covariance of $\mathbf{y}$ is completely determined by the m factors ($m << p$)

$var(y_i) = \sum_{k=1}^{m} l_{ik}^2 + \psi_i$ where ψ_i is the **specific variance** and the summation term is the i-th **communality** (i.e., portion of the variance of the i-th variable contributed by the m common factors ($h_i^2 = \sum_{k=1}^{m} l_{ik}^2$)

The factor model is only uniquely determined up to an orthogonal transformation of the factors.

Let $\mathbf{T}_{m\times m}$ be an orthogonal matrix $\mathbf{TT}' = \mathbf{T}'\mathbf{T} = \mathbf{I}$ then

$$\begin{aligned} \mathbf{y} - \quad &= \mathbf{Lf} + \epsilon \\ &= \mathbf{LTT}'\mathbf{f} + \epsilon \\ &= \mathbf{L}^*(\mathbf{T}'\mathbf{f}) + \epsilon \quad \text{where } \mathbf{L}^* = \mathbf{LT} \end{aligned}$$

and

$$
\begin{aligned}
&= \mathbf{L}\mathbf{L}' + \\
&= \mathbf{L}\mathbf{T}\mathbf{T}'\mathbf{L} + \\
&= (\mathbf{L}^*)(\mathbf{L}^*)' +
\end{aligned}
$$

Hence, any orthogonal transformation of the factors is an equally good description of the correlations among the observed traits.

Let $\mathbf{y} = \mathbf{C}\mathbf{x}$, where $\mathbf{C}$ is any diagonal matrix, then $\mathbf{L}_y = \mathbf{C}\mathbf{L}_x$ and $_y = \mathbf{C}\ _x\mathbf{C}$

Hence, we can see that factor analysis is also invariant to changes in scale

22.3.1 Methods of Estimation

To estimate $\mathbf{L}$

1. Principal Component Method
2. Principal Factor Method
3. 22.3.1.3

22.3.1.1 Principal Component Method

Spectral decomposition

$$
\begin{aligned}
&= \lambda_1 \mathbf{a}_1 \mathbf{a}_1' + \cdots + \lambda_p \mathbf{a}_p \mathbf{a}_p' \\
&= \mathbf{A}\ \mathbf{A}' \\
&= \sum_{k=1}^{m} \lambda + k \mathbf{a}_k \mathbf{a}_k' + \sum_{k=m+1}^{p} \lambda_k \mathbf{a}_k \mathbf{a}_k' \\
&= \sum_{k=1}^{m} l_k l_k' + \sum_{k=m+1}^{p} \lambda_k \mathbf{a}_k \mathbf{a}_k'
\end{aligned}
$$

where $l_k = \mathbf{a}_k \sqrt{\lambda_k}$ and the second term is not diagonal in general.

Assume

$$
\psi_i = \sigma_{ii} - \sum_{k=1}^{m} l_{ik}^2 = \sigma_{ii} - \sum_{k=1}^{m} \lambda_i a_{ik}^2
$$

then

$$
\approx \mathbf{L}\mathbf{L}' +
$$

To estimate $\mathbf{L}$ and Ψ , we use the expected eigenvalues and eigenvectors from $\mathbf{S}$ or $\mathbf{R}$

- The estimated factor loadings don't change as the number of actors increases
- The diagonal elements of $\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{}$ are equal to the diagonal elements of $\mathbf{S}$ and $\mathbf{R}$, but the covariances may not be exactly reproduced
- We select m so that the off-diagonal elements close to the values in $\mathbf{S}$ (or to make the off-diagonal elements of $\mathbf{S} - \hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{}$ small)

22.3.1.2 Principal Factor Method

Consider modeling the correlation matrix, $\mathbf{R} = \mathbf{L}\mathbf{L}' + \quad$. Then

$$\mathbf{L}\mathbf{L}' = \mathbf{R} - \quad = \begin{pmatrix} h_1^2 & r_{12} & \dots & r_{1p} \\ r_{21} & h_2^2 & \dots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \dots & h_p^2 \end{pmatrix}$$

where $h_i^2 = 1 - \psi_i$ (the communality)

Suppose that initial estimates are available for the communalities, $(h_1^*)^2, (h_2^*)^2, \dots, (h_p^*)^2$, then we can regress each trait on all the others, and then use the r^2 as h^2

The estimate of $\mathbf{R} - \quad$ at step k is

$$(\mathbf{R} - \quad)_k = \begin{pmatrix} (h_1^*)^2 & r_{12} & \dots & r_{1p} \\ r_{21} & (h_2^*)^2 & \dots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \dots & (h_p^*)^2 \end{pmatrix} = \mathbf{L}_k^*(\mathbf{L}_k^*)'$$

where

$$\mathbf{L}_k^* = (\sqrt{\hat{\lambda}_1^* \hat{\mathbf{a}}_1^*, \dots \hat{\lambda}_m^* \hat{\mathbf{a}}_m^*})$$

and

$$\hat{\psi}_{i,k}^* = 1 - \sum_{j=1}^{m} \hat{\lambda}_i^* (\hat{a}_{ij}^*)^2$$

we used the spectral decomposition on the estimated matrix $(\mathbf{R} - \quad)$ to calculate the $\hat{\lambda}_i^* s$ and the $\hat{\mathbf{a}}_i^* s$

After updating the values of $(\hat{h}_i^*)^2 = 1 - \hat{\psi}_{i,k}^*$ we will use them to form a new $\mathbf{L}_{k+1}^*$ via another spectral decomposition. Repeat the process

Notes:

- The matrix $(\mathbf{R} - \ )_k$ is not necessarily positive definite
- The principal component method is similar to principal factor if one considers the initial communalities are $h^2 = 1$
- if m is too large, some communalities may become larger than 1, causing the iterations to terminate. To combat, we can
  - fix any communality that is greater than 1 at 1 and then continues.
  - continue iterations regardless of the size of the communalities. However, results can be outside fo the parameter space.

22.3.1.3 Maximum Likelihood Method

Since we need the likelihood function, we make the additional (critical) assumption that

- $\mathbf{y}_j \sim N(\ ,\ )$ for $j = 1, .., n$
- $\mathbf{f} \sim N(\mathbf{0}, \mathbf{I})$
- $\epsilon_j \sim N(\mathbf{0},\ )$

and restriction

- $\mathbf{L}'\ ^{-1}\mathbf{L} =$ where is a diagonal matrix. (since the factor loading matrix is not unique, we need this restriction).

Notes:

- Finding MLE can be computationally expensive
- we typically use other methods for exploratory data analysis
- Likelihood ratio tests could be used for testing hypotheses in this framework (i.e., Confirmatory Factor Analysis)

22.3.2 Factor Rotation

$\mathbf{T}_{m\times m}$ is an orthogonal matrix that has the property that

$$\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{} = \hat{\mathbf{L}}^*(\hat{\mathbf{L}}^*)' + \hat{}$$

where $\mathbf{L}^* = \mathbf{LT}$

This means that estimated specific variances and communalities are not altered by the orthogonal transformation.

Since there are an infinite number of choices for $\mathbf{T}$, some selection criterion is necessary

For example, we can find the orthogonal transformation that maximizes the objective function

$$\sum_{j=1}^{m}[\frac{1}{p}\sum_{i=1}^{p}(\frac{l_{ij}^{*2}}{h_i})^2 - \{\frac{\gamma}{p}\sum_{i=1}^{p}(\frac{l_{ij}^{*2}}{h_i})^2\}^2]$$

where $\frac{l_{ij}^{*2}}{h_i}$ are "scaled loadings", which gives variables with small communalities more influence.

Different choices of γ in the objective function correspond to different orthogonal rotation found in the literature;

1. Varimax $\gamma = 1$ (rotate the factors so that each of the p variables should have a high loading on only one factor, but this is not always possible).
2. Quartimax $\gamma = 0$
3. Equimax $\gamma = m/2$
4. Parsimax $\gamma = \frac{p(m-1)}{p+m-2}$
5. Promax: non-orthogonal or olique transformations
6. Harris-Kaiser (HK): non-orthogonal or oblique transformations

22.3.3 Estimation of Factor Scores

Recall

$$(\mathbf{y}_j - \ ) = \mathbf{L}_{p\times m}\mathbf{f}_j + \epsilon_j$$

If the factor model is correct then

$$var(\epsilon_j) = \ = diag(\psi_1, \dots, \psi_p)$$

Thus we could consider using weighted least squares to estimate $\mathbf{f}_j$, the vector of factor scores for the j-th sampled unit by

$$\begin{aligned}\hat{\mathbf{f}} &= (\mathbf{L}'\ ^{-1}\mathbf{L})^{-1}\mathbf{L}'\ ^{-1}(\mathbf{y}_j - \ ) \\ &\approx (\mathbf{L}'\ ^{-1}\mathbf{L})^{-1}\mathbf{L}'\ ^{-1}(\mathbf{y}_j - \bar{\mathbf{y}})\end{aligned}$$

22.3.3.1 The Regression Method

Alternatively, we can use the regression method to estimate the factor scores

Consider the joint distribution of $(\mathbf{y}_j - \ )$ and $\mathbf{f}_j$ assuming multivariate normality, as in the maximum likelihood approach. then,

$$\begin{pmatrix} \mathbf{y}_j - \\ \mathbf{f}_j \end{pmatrix} \sim N_{p+m}\left(\begin{bmatrix} \mathbf{L}\mathbf{L}' + & \mathbf{L} \\ \mathbf{L}' & \mathbf{I}_{m\times m} \end{bmatrix}\right)$$

when the m factor model is correct

Hence,

$$E(\mathbf{f}_j|\mathbf{y}_j - \ ) = \mathbf{L}'(\mathbf{L}\mathbf{L}' + \ )^{-1}(\mathbf{y}_j - \ )$$

notice that $\mathbf{L}'(\mathbf{L}\mathbf{L}' + \ )^{-1}$ is an $m \times p$ matrix of regression coefficients

Then, we use the estimated conditional mean vector to estimate the factor scores

$$\hat{\mathbf{f}}_j = \hat{\mathbf{L}}'(\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{} \ )^{-1}(\mathbf{y}_j - \bar{\mathbf{y}})$$

Alternatively, we could reduce the effect of possible incorrect determination fo the number of factors m by using $\mathbf{S}$ as a substitute for $\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{} \ \ \

```
#> Tract1        5700      12.8       2500          270      25000
#> Tract2        1000      10.9        600           10      10000
#> Tract3        3400       8.8       1000           10       9000
#> Tract4        3800      13.6       1700          140      25000
#> Tract5        4000      12.8       1600          140      25000
#> Tract6        8200       8.3       2600           60      12000
#> Tract7        1200      11.4        400           10      16000
#> Tract8        9100      11.5       3300           60      14000
#> Tract9        9900      12.5       3400          180      18000
#> Tract10       9600      13.7       3600          390      25000
#> Tract11       9600       9.6       3300           80      12000
#> Tract12       9400      11.4       4000          100      13000

# Correlation matrix
cor_mat <- cor(Harman.5)
cor_mat
#>              population  schooling employment professional housevalue
#> population   1.00000000 0.00975059  0.9724483    0.4388708 0.02241157
#> schooling    0.00975059 1.00000000  0.1542838    0.6914082 0.86307009
#> employment   0.97244826 0.15428378  1.0000000    0.5147184 0.12192599
#> professional 0.43887083 0.69140824  0.5147184    1.0000000 0.77765425
#> housevalue   0.02241157 0.86307009  0.1219260    0.7776543 1.00000000

## Principal Component Method with Correlation
cor_pca <- prcomp(Harman.5, scale = T)
# eigen values
cor_results <- data.frame(eigen_values = cor_pca$sdev ^ 2)

cor_results <- cor_results %>%
    mutate(
        proportion = eigen_values / sum(eigen_values),
        cumulative = cumsum(proportion),
        number = row_number()
    )
cor_results
#>   eigen_values  proportion cumulative number
#> 1   2.87331359 0.574662719  0.5746627      1
#> 2   1.79666009 0.359332019  0.9339947      2
#> 3   0.21483689 0.042967377  0.9769621      3
#> 4   0.09993405 0.019986811  0.9969489      4
#> 5   0.01525537 0.003051075  1.0000000      5

# Scree plot of Eigenvalues
scree_gg <- ggplot(cor_results, aes(x = number, y = eigen_values)) +
    geom_line(alpha = 0.5) +
```

```
    geom_text(aes(label = number)) +
    scale_x_continuous(name = "Number") +
    scale_y_continuous(name = "Eigenvalue") +
    theme_bw()
scree_gg
```

```
screeplot(cor_pca, type = 'lines')
```

```r
## Keep 2 factors based on scree plot and eigenvalues
factor_pca <- principal(Harman.5, nfactors = 2, rotate = "none")
factor_pca
#> Principal Components Analysis
#> Call: principal(r = Harman.5, nfactors = 2, rotate = "none")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>               PC1   PC2   h2    u2 com
#> population   0.58  0.81 0.99 0.012 1.8
#> schooling    0.77 -0.54 0.89 0.115 1.8
#> employment   0.67  0.73 0.98 0.021 2.0
#> professional 0.93 -0.10 0.88 0.120 1.0
#> housevalue   0.79 -0.56 0.94 0.062 1.8
#>
#>                        PC1  PC2
#> SS loadings           2.87 1.80
#> Proportion Var        0.57 0.36
#> Cumulative Var        0.57 0.93
#> Proportion Explained  0.62 0.38
#> Cumulative Proportion 0.62 1.00
#>
#> Mean item complexity =  1.7
#> Test of the hypothesis that 2 components are sufficient.
#>
#> The root mean square of the residuals (RMSR) is  0.03
#>  with the empirical chi square  0.29  with prob <  0.59
#>
#> Fit based upon off diagonal values = 1

# factor 1 = overall socioeconomic health
# factor 2 = contrast of the population and employment against school and house value


## Ssquared multiple correlation (SMC) prior, no rotation
factor_pca_smc <- fa(
    Harman.5,
    nfactors = 2,
    fm = "pa",
    rotate = "none",
    SMC = TRUE
)
factor_pca_smc
#> Factor Analysis using method =  pa
#> Call: fa(r = Harman.5, nfactors = 2, rotate = "none", SMC = TRUE, fm = "pa")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>               PA1   PA2   h2      u2 com
```

```
#> population   0.62  0.78 1.00 -0.0027 1.9
#> schooling    0.70 -0.53 0.77  0.2277 1.9
#> employment   0.70  0.68 0.96  0.0413 2.0
#> professional 0.88 -0.15 0.80  0.2017 1.1
#> housevalue   0.78 -0.60 0.96  0.0361 1.9
#>
#>                        PA1  PA2
#> SS loadings           2.76 1.74
#> Proportion Var        0.55 0.35
#> Cumulative Var        0.55 0.90
#> Proportion Explained  0.61 0.39
#> Cumulative Proportion 0.61 1.00
#>
#> Mean item complexity =  1.7
#> Test of the hypothesis that 2 factors are sufficient.
#>
#> df null model =  10  with the objective function =  6.38 with Chi Square =  54.25
#> df of  the model are 1  and the objective function was  0.34
#>
#> The root mean square of the residuals (RMSR) is  0.01
#> The df corrected root mean square of the residuals is  0.03
#>
#> The harmonic n.obs is  12 with the empirical chi square  0.02  with prob <  0.88
#> The total n.obs was  12  with Likelihood Chi Square =  2.44  with prob <  0.12
#>
#> Tucker Lewis Index of factoring reliability =  0.596
#> RMSEA index =  0.336  and the 90 % confidence intervals are  0 0.967
#> BIC =  -0.04
#> Fit based upon off diagonal values = 1

## SMC prior, Promax rotation
factor_pca_smc_pro <- fa(
    Harman.5,
    nfactors = 2,
    fm = "pa",
    rotate = "Promax",
    SMC = TRUE
)
factor_pca_smc_pro
#> Factor Analysis using method =  pa
#> Call: fa(r = Harman.5, nfactors = 2, rotate = "Promax", SMC = TRUE,
#>     fm = "pa")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>                PA1   PA2   h2      u2 com
#> population   -0.11  1.02 1.00 -0.0027 1.0
```

```
#> schooling     0.90 -0.11 0.77  0.2277 1.0
#> employment    0.02  0.97 0.96  0.0413 1.0
#> professional  0.75  0.33 0.80  0.2017 1.4
#> housevalue    1.01 -0.14 0.96  0.0361 1.0
#>
#>                        PA1  PA2
#> SS loadings           2.38 2.11
#> Proportion Var        0.48 0.42
#> Cumulative Var        0.48 0.90
#> Proportion Explained  0.53 0.47
#> Cumulative Proportion 0.53 1.00
#>
#>  With factor correlations of
#>      PA1  PA2
#> PA1 1.00 0.25
#> PA2 0.25 1.00
#>
#> Mean item complexity =  1.1
#> Test of the hypothesis that 2 factors are sufficient.
#>
#> df null model =  10  with the objective function =  6.38 with Chi Square =  54.25
#> df of  the model are 1  and the objective function was  0.34
#>
#> The root mean square of the residuals (RMSR) is  0.01
#> The df corrected root mean square of the residuals is  0.03
#>
#> The harmonic n.obs is  12 with the empirical chi square  0.02  with prob <  0.88
#> The total n.obs was  12  with Likelihood Chi Square =  2.44  with prob <  0.12
#>
#> Tucker Lewis Index of factoring reliability =  0.596
#> RMSEA index =  0.336  and the 90 % confidence intervals are  0 0.967
#> BIC =  -0.04
#> Fit based upon off diagonal values = 1

## SMC prior, varimax rotation
factor_pca_smc_var <- fa(
    Harman.5,
    nfactors = 2,
    fm = "pa",
    rotate = "varimax",
    SMC = TRUE
)
## Make a data frame of the loadings for ggplot2
factors_df <-
    bind_rows(
```

```
        data.frame(
            y = rownames(factor_pca_smc$loadings),
            unclass(factor_pca_smc$loadings)
        ),
        data.frame(
            y = rownames(factor_pca_smc_pro$loadings),
            unclass(factor_pca_smc_pro$loadings)
        ),
        data.frame(
            y = rownames(factor_pca_smc_var$loadings),
            unclass(factor_pca_smc_var$loadings)
        ),
        .id = "Rotation"
    )
flag_gg <- ggplot(factors_df) +
    geom_vline(aes(xintercept = 0)) +
    geom_hline(aes(yintercept = 0)) +
    geom_point(aes(
        x = PA2,
        y = PA1,
        col = y,
        shape = y
    ), size = 2) +
    scale_x_continuous(name = "Factor 2", limits = c(-1.1, 1.1)) +
    scale_y_continuous(name = "Factor1", limits = c(-1.1, 1.1)) +
    facet_wrap("Rotation", labeller = labeller(Rotation = c(
        "1" = "Original", "2" = "Promax", "3" = "Varimax"
    ))) +
    coord_fixed(ratio = 1) # make aspect ratio of each facet 1

flag_gg
```

```
# promax and varimax did a good job to assign trait to a particular factor

factor_mle_1 <- fa(
    Harman.5,
    nfactors = 1,
    fm = "mle",
    rotate = "none",
    SMC = TRUE
)
factor_mle_1
#> Factor Analysis using method =  ml
#> Call: fa(r = Harman.5, nfactors = 1, rotate = "none", SMC = TRUE, fm = "mle")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>               ML1    h2     u2 com
#> population   0.97 0.950 0.0503   1
#> schooling    0.14 0.021 0.9791   1
#> employment   1.00 0.995 0.0049   1
#> professional 0.51 0.261 0.7388   1
#> housevalue   0.12 0.014 0.9864   1
#>
#>                 ML1
#> SS loadings    2.24
#> Proportion Var 0.45
#>
#> Mean item complexity =  1
#> Test of the hypothesis that 1 factor is sufficient.
```

```
#>
#> df null model =  10  with the objective function =  6.38 with Chi Square =  54.25
#> df of  the model are 5  and the objective function was  3.14
#>
#> The root mean square of the residuals (RMSR) is  0.41
#> The df corrected root mean square of the residuals is  0.57
#>
#> The harmonic n.obs is  12 with the empirical chi square  39.41  with prob <  2e-07
#> The total n.obs was  12  with Likelihood Chi Square =  24.56  with prob <  0.00017
#>
#> Tucker Lewis Index of factoring reliability =  0.022
#> RMSEA index =  0.564  and the 90 % confidence intervals are  0.374 0.841
#> BIC =  12.14
#> Fit based upon off diagonal values = 0.5
#> Measures of factor score adequacy
#>                                                   ML1
#> Correlation of (regression) scores with factors   1.00
#> Multiple R square of scores with factors          1.00
#> Minimum correlation of possible factor scores     0.99

factor_mle_2 <- fa(
    Harman.5,
    nfactors = 2,
    fm = "mle",
    rotate = "none",
    SMC = TRUE
)
factor_mle_2
#> Factor Analysis using method =  ml
#> Call: fa(r = Harman.5, nfactors = 2, rotate = "none", SMC = TRUE, fm = "mle")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>                ML2  ML1   h2    u2 com
#> population   -0.03 1.00 1.00 0.005 1.0
#> schooling     0.90 0.04 0.81 0.193 1.0
#> employment    0.09 0.98 0.96 0.036 1.0
#> professional  0.78 0.46 0.81 0.185 1.6
#> housevalue    0.96 0.05 0.93 0.074 1.0
#>
#>                        ML2  ML1
#> SS loadings           2.34 2.16
#> Proportion Var        0.47 0.43
#> Cumulative Var        0.47 0.90
#> Proportion Explained  0.52 0.48
#> Cumulative Proportion 0.52 1.00
#>
```

```
#> Mean item complexity =  1.1
#> Test of the hypothesis that 2 factors are sufficient.
#>
#> df null model =  10  with the objective function =  6.38 with Chi Square =  54.25
#> df of  the model are 1  and the objective function was  0.31
#>
#> The root mean square of the residuals (RMSR) is  0.01
#> The df corrected root mean square of the residuals is  0.05
#>
#> The harmonic n.obs is  12 with the empirical chi square  0.05  with prob <  0.82
#> The total n.obs was  12  with Likelihood Chi Square =  2.22  with prob <  0.14
#>
#> Tucker Lewis Index of factoring reliability =  0.658
#> RMSEA index =  0.307  and the 90 % confidence intervals are  0 0.945
#> BIC =  -0.26
#> Fit based upon off diagonal values = 1
#> Measures of factor score adequacy
#>                                                   ML2  ML1
#> Correlation of (regression) scores with factors   0.98 1.00
#> Multiple R square of scores with factors          0.95 1.00
#> Minimum correlation of possible factor scores     0.91 0.99

factor_mle_3 <- fa(
    Harman.5,
    nfactors = 3,
    fm = "mle",
    rotate = "none",
    SMC = TRUE
)
factor_mle_3
#> Factor Analysis using method =  ml
#> Call: fa(r = Harman.5, nfactors = 3, rotate = "none", SMC = TRUE, fm = "mle")
#> Standardized loadings (pattern matrix) based upon correlation matrix
#>                ML2  ML1   ML3   h2     u2 com
#> population   -0.12 0.98 -0.11 0.98 0.0162 1.1
#> schooling     0.89 0.15  0.29 0.90 0.0991 1.3
#> employment    0.00 1.00  0.04 0.99 0.0052 1.0
#> professional  0.72 0.52 -0.10 0.80 0.1971 1.9
#> housevalue    0.97 0.13 -0.09 0.97 0.0285 1.1
#>
#>                        ML2  ML1  ML3
#> SS loadings           2.28 2.26 0.11
#> Proportion Var        0.46 0.45 0.02
#> Cumulative Var        0.46 0.91 0.93
#> Proportion Explained  0.49 0.49 0.02
```

```
#> Cumulative Proportion 0.49 0.98 1.00
#>
#> Mean item complexity =  1.2
#> Test of the hypothesis that 3 factors are sufficient.
#>
#> df null model =  10  with the objective function =  6.38 with Chi Square =  54.25
#> df of  the model are -2  and the objective function was  0
#>
#> The root mean square of the residuals (RMSR) is  0
#> The df corrected root mean square of the residuals is  NA
#>
#> The harmonic n.obs is  12 with the empirical chi square  0  with prob <  NA
#> The total n.obs was  12  with Likelihood Chi Square =  0  with prob <  NA
#>
#> Tucker Lewis Index of factoring reliability =  1.318
#> Fit based upon off diagonal values = 1
#> Measures of factor score adequacy
#>                                                   ML2  ML1  ML3
#> Correlation of (regression) scores with factors   0.99 1.00 0.82
#> Multiple R square of scores with factors          0.98 1.00 0.68
#> Minimum correlation of possible factor scores     0.96 0.99 0.36
```

The output info for the null hypothesis of no common factors is in the statement "The degrees of freedom for the null model .."

The output info for the null hypothesis that number of factors is sufficient is in the statement "The total number of observations was …"

One factor is not enough, two is sufficient, and not enough data for 3 factors (df of -2 and NA for p-value). Hence, we should use 2-factor model.

22.4 Discriminant Analysis

Suppose we have two or more different populations from which observations could come from. Discriminant analysis seeks to determine which of the possible population an observation comes from while making as few mistakes as possible

- This is an alternative to logistic approaches with the following advantages:
  - when there is clear separation between classes, the parameter estimates for the logic regression model can be **surprisingly** unstable, while discriminant approaches do not suffer
  - If X is normal in each of the classes and the sample size is small, then discriminant approaches can be more accurate

Notation

Similar to MANOVA, let $\mathbf{y}_{j1}, \mathbf{y}_{j2}, \dots, \mathbf{y}_{in_j} \sim iid f_j(\mathbf{y})$ for $j = 1, \dots, h$

Let $f_j(\mathbf{y})$ be the density function for population j . Note that each vector $\mathbf{y}$ contain measurements on all p traits

1. Assume that each observation is from one of h possible populations.
2. We want to form a discriminant rule that will allocate an observation $\mathbf{y}$ to population j when $\mathbf{y}$ is in fact from this population

22.4.1 Known Populations

The maximum likelihood discriminant rule for assigning an observation $\mathbf{y}$ to one of the h populations allocates $\mathbf{y}$ to the population that gives the largest likelihood to $\mathbf{y}$

Consider the likelihood for a single observation $\mathbf{y}$, which has the form $f_j(\mathbf{y})$ where j is the true population.

Since j is unknown, to make the likelihood as large as possible, we should choose the value j which causes $f_j(\mathbf{y})$ to be as large as possible

Consider a simple univariate example. Suppose we have data from one of two binomial populations.

- The first population has $n = 10$ trials with success probability $p = .5$
- The second population has $n = 10$ trials with success probability $p = .7$
- to which population would we assign an observation of $y = 7$
- Note:
  - $f(y = 7|n = 10, p = .5) = .117$
  - $f(y = 7|n = 10, p = .7) = .267$ where $f(.)$ is the binomial likelihood.
  - Hence, we choose the second population

Another example

We have 2 populations, where

- First population: $N(\mu_1, \sigma_1^2)$
- Second population: $N(\mu_2, \sigma_2^2)$

The likelihood for a single observation is

$$f_j(y) = (2\pi\sigma_j^2)^{-1/2} \exp\{-\frac{1}{2}(\frac{y - \mu_j}{\sigma_j})^2\}$$

Consider a likelihood ratio rule

$$\begin{aligned}\Lambda &= \frac{\text{likelihood of y from pop 1}}{\text{likelihood of y from pop 2}} \\ &= \frac{f_1(y)}{f_2(y)} \\ &= \frac{\sigma_2}{\sigma_1}\exp\{-\frac{1}{2}[(\frac{y-\mu_1}{\sigma_1})^2 - (\frac{y-\mu_2}{\sigma_2})^2]\}\end{aligned}$$

Hence, we classify into

- pop 1 if $\Lambda > 1$
- pop 2 if $\Lambda < 1$
- for ties, flip a coin

Another way to think:

we classify into population 1 if the "standardized distance" of y from μ_1 is less than the "standardized distance" of y from μ_2 which is referred to as a **quadratic discriminant rule**.

(Significant simplification occurs in th special case where $\sigma_1 = \sigma_2 = \sigma^2$)

Thus, we classify into population 1 if

$$(y-\mu_2)^2 > (y-\mu_1)^2$$

or

$$|y-\mu_2| > |y-\mu_1|$$

and

$$-2\log(\Lambda) = -2y\frac{(\mu_1-\mu_2)}{\sigma^2} + \frac{(\mu_1^2-\mu_2^2)}{\sigma^2} = \beta y + \alpha$$

Thus, we classify into population 1 if this is less than 0.

Discriminant classification rule is linear in y in this case.

22.4.1.1 Multivariate Expansion

Suppose that there are 2 populations

- $N_p(\ _1,\ _1)$
- $N_p(\ _2,\ _2)$

$$
\begin{aligned}
-2\log(\frac{f_1(\mathbf{x})}{f_2(\mathbf{x})}) &= \log|\ _1| + (\mathbf{x} - \ _1)'\ _1^{-1}(\mathbf{x} - \ _1) \\
&\quad - [\log|\ _2| + (\mathbf{x} - \ _2)'\ _2^{-1}(\mathbf{x} - \ _2)]
\end{aligned}
$$

Again, we classify into population 1 if this is less than 0, otherwise, population 2. And like the univariate case with non-equal variances, this is a quadratic discriminant rule.

And if the covariance matrices are equal: $_1 = \ _2 = \ _1$ classify into population 1 if

$$
(\ _1 - \ _2)'\ ^{-1}\mathbf{x} - \frac{1}{2}(\ _1 - \ _2)'\ ^{-1}(\ _1 - \ _2) \geq 0
$$

This linear discriminant rule is also referred to as **Fisher's linear discriminant function**

By **assuming the covariance matrices are equal, we assume that the shape and orientation fo the two populations must be the same (which can be a strong restriction)**

In other words, for each variable, it can have different mean but the same variance.

- Note: LDA Bayes decision boundary is linear. Hence, quadratic decision boundary might lead to better classification. Moreover, the assumption of same variance/covariance matrix across all classes for Gaussian densities imposes the linear rule, if we allow the predictors in each class to follow MVN distribution with class-specific mean vectors and variance/covariance matrices, then it is **Quadratic Discriminant Analysis.** But then, you will have more parameters to estimate (which gives more flexibility than LDA) at the cost of more variance (bias -variance tradeoff).

When $_1, \ _2, \ $ are known, the probability of misclassification can be determined:

$$
\begin{aligned}
P(2|1) &= P(\text{calssify into pop 2| x is from pop 1}) \\
&= P((\ _1 - \ _2)'\ ^{-1}\mathbf{x} \leq \frac{1}{2}(\ _1 - \ _2)'\ ^{-1}(\ _1 - \ _2)|\mathbf{x} \sim N(\mu_1, \ ) \\
&= \Phi(-\frac{1}{2}\delta)
\end{aligned}
$$

where

- $\delta^2 = (\ _1 - \ _2)'\ ^{-1}(\ _1 - \ _2)$
- Φ is the standard normal CDF

Suppose there are h possible populations, which are distributed as $N_p(\ _p,\ )$. Then, the maximum likelihood (linear) discriminant rule allocates $\mathbf{y}$ to population j where j minimizes the squared Mahalanobis distance

$$(\mathbf{y} - \ _j)' \ ^{-1}(\mathbf{y} - \ _j)$$

22.4.1.2 Bayes Discriminant Rules

If we know that population j has prior probabilities π_j (assume $\pi_j > 0$) we can form the Bayes discriminant rule.

This rule allocates an observation $\mathbf{y}$ to the population for which $\pi_j f_j(\mathbf{y})$ is maximized.

Note:

- **Maximum likelihood discriminant rule** is a special case of the **Bayes discriminant rule**, where it sets all the $\pi_j = 1/h$

Optimal Properties of Bayes Discriminant Rules

- let p_{ii} be the probability of correctly assigning an observation from population i
- then one rule (with probabilities p_{ii}) is as good as another rule (with probabilities p'_{ii}) if $p_{ii} \geq p'_{ii}$ for all $i = 1, \ldots, h$
- The first rule is better than the alternative if $p_{ii} > p'_{ii}$ for at least one i.
- A rule for which there is no better alternative is called admissible
- Bayes Discriminant Rules are admissible
- If we utilized prior probabilities, then we can form the posterior probability of a correct allocation, $\sum_{i=1}^{h} \pi_i p_{ii}$
- Bayes Discriminant Rules have the largest possible posterior probability of correct allocation with respect to the prior
- These properties show that **Bayes Discriminant rule is our best approach**.

Unequal Cost

- We want to consider the cost misallocation
  - Define c_{ij} to be the cost associated with allocation a member of population j to population i.
- Assume that
  - $c_{ij} > 0$ for all $i \neq j$
  - $c_{ij} = 0$ if $i = j$

- We could determine the expected amount of loss for an observation allocated to population i as $\sum_j c_{ij} p_{ij}$ where the $p_{ij}s$ are the probabilities of allocating an observation from population j into population i
- We want to minimize the amount of loss expected for our rule. Using a Bayes Discrimination, allocate $\mathbf{y}$ to the population j which minimizes $\sum_{k \neq j} c_{ij} \pi_k f_k(\mathbf{y})$
- We could assign equal probabilities to each group and get a maximum likelihood type rule. here, we would allocate $\mathbf{y}$ to population j which minimizes $\sum_{k \neq j} c_{jk} f_k(\mathbf{y})$

Example:

Two binomial populations, each of size 10, with probabilities $p_1 = .5$ and $p_2 = .7$

And the probability of being in the first population is .9

However, suppose the cost of inappropriately allocating into the first population is 1 and the cost of incorrectly allocating into the second population is 5.

In this case, we pick population 1 over population 2

In general, we consider two regions, R_1 and R_2 associated with population 1 and 2:

$$R_1 : \frac{f_1(\mathbf{x})}{f_2(\mathbf{x})} \geq \frac{c_{12}\pi_2}{c_{21}\pi_1}$$

$$R_2 : \frac{f_1(\mathbf{x})}{f_2(\mathbf{x})} < \frac{c_{12}\pi_2}{c_{21}\pi_1}$$

where c_{12} is the cost of assigning a member of population 2 to population 1.

22.4.1.3 Discrimination Under Estimation

Suppose we know the form of the distributions for populations of interests, but we still have to estimate the parameters.

Example:

we know the distributions are multivariate normal, but we have to estimate the means and variances

The maximum likelihood discriminant rule allocates an observation $\mathbf{y}$ to population j when j maximizes the function

$$f_j(\mathbf{y}|\hat{\theta})$$

where $\hat{\theta}$ are the maximum likelihood estimates of the unknown parameters

For instance, we have 2 multivariate normal populations with distinct means, but common variance covariance matrix

MLEs for $_1$ and $_2$ are $\bar{\mathbf{y}}_1$ and $\bar{\mathbf{y}}_2$and common is $\mathbf{S}$.

Thus, an estimated discriminant rule could be formed by substituting these sample values for the population values

22.4.1.4 Native Bayes

- The challenge with classification using Bayes' is that we don't know the (true) densities, $f_k, k = 1, \dots, K$, while LDA and QDA make **strong multivariate normality assumptions** to deal with this.
- Naive Bayes makes only one assumption: **within the k-th class, the p predictors are independent (i.e,, for** $k = 1, \dots, K$

$$f_k(x) = f_{k1}(x_1) \times f_{k2}(x_2) \times \cdots \times f_{kp}(x_p)$$

where f_{kj} is the density function of the j-th predictor among observation in the k-th class.

This assumption allows the use of joint distribution without the need to account for dependence between observations. However, this (native) assumption can be unrealistic, but still works well in cases where the number of sample (n) is not large relative to the number of features (p).

With this assumption, we have

$$P(Y = k|X = x) = \frac{\pi_k \times f_{k1}(x_1) \times \cdots \times f_{kp}(x_p)}{\sum_{l=1}^{K} \pi_l \times f_{l1}(x_1) \times \dots f_{lp}(x_p)}$$

we only need to estimate the one-dimensional density function f_{kj} with either of these approaches:

- When X_j is quantitative, assume it has a univariate normal distribution (with independence): $X_j|Y = k \sim N(\mu_{jk}, \sigma_{jk}^2)$ which is more restrictive than QDA because it assumes predictors are independent (e.g., a diagonal covariance matrix)
- When X_j is quantitative, use a kernel density estimator Kernel Methods ; which is a smoothed histogram
- When X_j is qualitative, we count the promotion of training observations for the j-th predictor corresponding to each class.

22.4.1.5 Comparison of Classification Methods

Assuming we have K classes and K is the baseline from (James , Witten, Hastie, and Tibshirani book)

Comparing the log odds relative to the K class

22.4.1.5.1 Logistic Regression

$$\log(\frac{P(Y=k|X=x)}{P(Y=K|X=x)}) = \beta_{k0} + \sum_{j=1}^{p} \beta_{kj} x_j$$

22.4.1.5.2 LDA

$$\log(\frac{P(Y=k|X=x)}{P(Y=K|X=x)} = a_k + \sum_{j=1}^{p} b_{kj} x_j$$

where a_k and b_{kj} are functions of $\pi_k, \pi_K, \mu_k, \mu_K$,

Similar to logistic regression, LDA assumes the log odds is linear in x

Even though they look like having the same form, the parameters in logistic regression are estimated by MLE, where as LDA linear parameters are specified by the prior and normal distributions

We expect LDA to outperform logistic regression when the normality assumption (approximately) holds, and logistic regression to perform better when it does not

22.4.1.5.3 QDA

$$\log(\frac{P(Y=k|X=x}{P(Y=K|X=x}) = a_k + \sum_{j=1}^{p} b_{kj} x_j + \sum_{j=1}^{p} \sum_{l=1}^{p} c_{kjl} x_j x_l$$

where a_k, b_{kj}, c_{kjl} are functions $\pi_k, \pi_K, \mu_k, \mu_K, \ _k, \ _K$

22.4.1.5.4 Naive Bayes

$$\log(\frac{P(Y=k|X=x)}{P(Y=K|X=x}) = a_k + \sum_{j=1}^{p} g_{kj}(x_j)$$

where $a_k = \log(\pi_k/\pi_K)$ and $g_{kj}(x_j) = \log(\frac{f_{kj}(x_j)}{f_{Kj}(x_j)})$ which is the form of generalized additive model

22.4.1.5.5 Summary

- LDA is a special case of QDA
- LDA is robust when it comes to high dimensions
- Any classifier with a linear decision boundary is a special case of naive Bayes with $g_{kj}(x_j) = b_{kj}x_j$, which means LDA is a special case of naive Bayes. LDA assumes that the features are normally distributed with a common within-class covariance matrix, and naive Bayes assumes independence of the features.
- Naive bayes is also a special case of LDA with restricted to a diagonal matrix with diagonals, σ^2 (another notation $diag(\ )$) assuming $f_{kj}(x_j) = N(\mu_{kj}, \sigma_j^2)$
- QDA and naive Bayes are not special case of each other. In principal,e naive Bayes can produce a more flexible fit by the choice of $g_{kj}(x_j)$, but it's restricted to only purely additive fit, but QDA includes multiplicative terms of the form $c_{kjl}x_jx_l$
- None of these methods uniformly dominates the others: the choice of method depends on the true distribution of the predictors in each of the K classes, n and p (i.e., related to the bias-variance tradeoff).

Compare to the non-parametric method (KNN)

- KNN would outperform both LDA and logistic regression when the decision boundary is highly nonlinear, but can't say which predictors are most important, and requires many observations
- KNN is also limited in high-dimensions due to the curse of dimensionality
- Since QDA is a special type of nonlinear decision boundary (quadratic), it can be considered as a compromise between the linear methods and KNN classification. QDA can have fewer training observations than KNN but not as flexible.

From simulation:

True decision boundary	Best performance
Linear	LDA + Logistic regression
Moderately nonlinear	QDA + Naive Bayes
Highly nonlinear (many training, p is not large)	KNN

- like linear regression, we can also introduce flexibility by including transformed features $\sqrt{X}, X^2, X^3$

22.4.2 Probabilities of Misclassification

When the distribution are exactly known, we can determine the misclassification probabilities exactly. however, when we need to estimate the population parameters, we have to estimate the probability of misclassification

- Naive method
  - Plugging the parameters estimates into the form for the misclassification probabilities results to derive at the estimates of the misclassification probability.
  - But this will tend to be optimistic when the number of samples in one or more populations is small.
- Resubstitution method
  - Use the proportion of the samples from population i that would be allocated to another population as an estimate of the misclassification probability
  - But also optimistic when the number of samples is small
- Jack-knife estimates:
  - The above two methods use observation to estimate both parameters and also misclassification probabilities based upon the discriminant rule
  - Alternatively, we determine the discriminant rule based upon all of the data except the k-th observation from the j-th population
  - then, determine if the k-th observation would be misclassified under this rule
  - perform this process for all n_j observation in population j . An estimate fo the misclassification probability would be the fraction of n_j observations which were misclassified
  - repeat the process for other $i \neq j$ populations
  - This method is more reliable than the others, but also computationally intensive
- Cross-Validation

Summary

Consider the group-specific densities $f_j(\mathbf{x})$ for multivariate vector $\mathbf{x}$.

Assume equal misclassifications costs, the Bayes classification probability of $\mathbf{x}$ belonging to the j-th population is

$$p(j|\mathbf{x}) = \frac{\pi_j f_j(\mathbf{x})}{\sum_{k=1}^{h} \pi_k f_k(\mathbf{x})}$$

$j = 1, \ldots, h$

where there are h possible groups.

We then classify into the group for which this probability of membership is largest

Alternatively, we can write this in terms of a **generalized squared distance** formation

$$D_j^2(\mathbf{x}) = d_j^2(\mathbf{x}) + g_1(j) + g_2(j)$$

where

- $d_j^2(\mathbf{x}) = (\mathbf{x} - \ _j)'\mathbf{V}_j^{-1}(\mathbf{x} - \ _j)$ is the squared Mahalanobis distance from $\mathbf{x}$ to the centroid of group j, and
  - $\mathbf{V}_j = \mathbf{S}_j$ if the within group covariance matrices are not equal
  - $\mathbf{V}_j = \mathbf{S}_p$ if a pooled covariance estimate is appropriate

and

$$g_1(j) = \begin{cases} \ln|\mathbf{S}_j| & \text{within group covariances are not equal} \\ 0 & \text{pooled covariance} \end{cases}$$

$$g_2(j) = \begin{cases} -2\ln\pi_j & \text{prior probabilities are not equal} \\ 0 & \text{prior probabilities are equal} \end{cases}$$

then, the posterior probability of belonging to group j is

$$p(j|\mathbf{x}) = \frac{\exp(-.5D_j^2(\mathbf{x}))}{\sum_{k=1}^{h} \exp(-.5D_k^2(\mathbf{x}))}$$

where $j = 1, \ldots, h$

and $\mathbf{x}$ is classified into group j if $p(j|\mathbf{x})$ is largest for $j = 1, \ldots, h$ (or, $D_j^2(\mathbf{x})$ is smallest).

22.4.2.1 Assessing Classification Performance

For binary classification, confusion matrix

	Predicted class			
		- or Null	+ or Null	Total
True Class	- or Null	True Neg (TN)	False Pos (FP)	N
	+ or Null	False Neg (FN)	True Pos (TP)	P
	Total	N*	P*	

and table 4.6 from (James et al., 2013)

Name	Definition	Synonyms
False Pos rate	FP/N	Type I error, 1 0 Specificity
True Pos. rate	TP/P	1 - Type II error, power, sensitivity, recall
Pos Pred. value	TP/P*	Precision, 1 - false discovery promotion
Neg. Pred. value	TN/N*	

ROC curve (receiver Operating Characteristics) is a graphical comparison between **sensitivity** (true positive) and **specificity** (= 1 - false positive)

y-axis = true positive rate

x-axis = false positive rate

as we change the threshold rate for classifying an observation as from 0 to 1

AUC (area under the ROC) ideally would equal to 1, a bad classifier would have AUC = 0.5 (pure chance)

22.4.3 Unknown Populations/ Nonparametric Discrimination

When your multivariate data are not Gaussian, or known distributional form at all, we can use the following methods

22.4.3.1 Kernel Methods

We approximate $f_j(\mathbf{x})$ by a kernel density estimate

$$\hat{f}_j(\mathbf{x}) = \frac{1}{n_j} \sum_{i=1}^{n_j} K_j(\mathbf{x} - \mathbf{x}_i)$$

where

- $K_j(.)$ is a kernel function satisfying $\int K_j(\mathbf{z}) d\mathbf{z} = 1$

- $\mathbf{x}_i$, $i = 1, \dots, n_j$ is a random sample from the j-th population.

Thus, after finding $\hat{f}_j(\mathbf{x})$ for each of the h populations, the posterior probability of group membership is

$$p(j|\mathbf{x}) = \frac{\pi_j \hat{f}_j(\mathbf{x})}{\sum_{k-1}^{h} \pi_k \hat{f}_k(\mathbf{x})}$$

where $j = 1, \dots, h$

There are different choices for the kernel function:

- Uniform
- Normal
- Epanechnikov
- Biweight
- Triweight

We these kernels, we have to pick the "radius" (or variance, width, window width, bandwidth) of the kernel, which is a smoothing parameter (the larger the radius, the more smooth the kernel estimate of the density).

To select the smoothness parameter, we can use the following method

If we believe the populations were close to multivariate normal, then

$$R = (\frac{4/(2p+1)}{n_j})^{1/(p+1}$$

But since we do not know for sure, we might choose several different values and select one that vies the best out of sample or cross-validation discrimination.

Moreover, you also have to decide whether to use different kernel smoothness for different populations, which is similar to the individual and pooled covariances in the classical methodology.

22.4.3.2 Nearest Neighbor Methods

The nearest neighbor (also known as k-nearest neighbor) method performs the classification of a new observation vector based on the group membership of its nearest neighbors. In practice, we find

$$d_{ij}^2(\mathbf{x}, \mathbf{x}_i) = (\mathbf{x}, \mathbf{x}_i) V_j^{-1} (\mathbf{x}, \mathbf{x}_i)$$

which is the distance between the vector $\mathbf{x}$ and the i-th observation in group j

We consider different choices for $\mathbf{V}_j$

For example,

$$\begin{aligned}
\mathbf{V}_j &= \mathbf{S}_p \\
\mathbf{V}_j &= \mathbf{S}_j \\
\mathbf{V}_j &= \mathbf{I} \\
\mathbf{V}_j &= diag(\mathbf{S}_p)
\end{aligned}$$

We find the k observations that are closest to $\mathbf{x}$ (where users pick k). Then we classify into the most common population, weighted by the prior.

22.4.3.3 Modern Discriminant Methods

Note:

Logistic regression (with or without random effects) is a flexible model-based procedure for classification between two populations.

The extension of logistic regression to the multi-group setting is polychotomous logistic regression (or, mulinomial regression).

The machine learning and pattern recognition are growing with strong focus on nonlinear discriminant analysis methods such as:

- radial basis function networks
- support vector machines
- multiplayer perceptrons (neural networks)

The general framework

$$g_j(\mathbf{x}) = \sum_{l=1}^{m} w_{jl}\phi_l(\mathbf{x};\ _l) + w_{j0}$$

where

- $j = 1, \dots, h$
- m nonlinear basis functions ϕ_l, each of which has n_m parameters given by $\theta_l = \{\theta_{lk} : k = 1, \dots, n_m\}$

We assign $\mathbf{x}$ to the j-th population if $g_j(\mathbf{x})$ is the maximum for all $j = 1, \dots, h$

Development usually focuses on the choice and estimation of the basis functions, ϕ_l and the estimation of the weights w_{jl}

More details can be found (Webb et al., 2011)

22.4.4 Application

```
library(class)
library(klaR)
library(MASS)
library(tidyverse)

## Read in the data
crops <- read.table("images/crops.txt")
names(crops) <- c("crop", "y1", "y2", "y3", "y4")
str(crops)
#> 'data.frame':    36 obs. of  5 variables:
#>  $ crop: chr  "Corn" "Corn" "Corn" "Corn" ...
#>  $ y1  : int  16 15 16 18 15 15 12 20 24 21 ...
#>  $ y2  : int  27 23 27 20 15 32 15 23 24 25 ...
#>  $ y3  : int  31 30 27 25 31 32 16 23 25 23 ...
#>  $ y4  : int  33 30 26 23 32 15 73 25 32 24 ...


## Read in test data
crops_test <- read.table("images/crops_test.txt")
names(crops_test) <- c("crop", "y1", "y2", "y3", "y4")
str(crops_test)
#> 'data.frame':    5 obs. of  5 variables:
#>  $ crop: chr  "Corn" "Soybeans" "Cotton" "Sugarbeets" ...
#>  $ y1  : int  16 21 29 54 32
#>  $ y2  : int  27 25 24 23 32
#>  $ y3  : int  31 23 26 21 62
#>  $ y4  : int  33 24 28 54 16
```

22.4.4.1 LDA

Default prior is proportional to sample size and `lda` and `qda` do not fit a constant or intercept term

```
## Linear discriminant analysis
lda_mod <- lda(crop ~ y1 + y2 + y3 + y4,
               data = crops)
lda_mod
#> Call:
#> lda(crop ~ y1 + y2 + y3 + y4, data = crops)
#>
#> Prior probabilities of groups:
#>     Clover       Corn     Cotton   Soybeans Sugarbeets
#>  0.3055556  0.1944444  0.1666667  0.1666667  0.1666667
#>
```

```
#> Group means:
#>                  y1       y2       y3       y4
#> Clover     46.36364 32.63636 34.18182 36.63636
#> Corn       15.28571 22.71429 27.42857 33.14286
#> Cotton     34.50000 32.66667 35.00000 39.16667
#> Soybeans   21.00000 27.00000 23.50000 29.66667
#> Sugarbeets 31.00000 32.16667 20.00000 40.50000
#>
#> Coefficients of linear discriminants:
#>              LD1          LD2         LD3          LD4
#> y1 -6.147360e-02  0.009215431 -0.02987075 -0.014680566
#> y2 -2.548964e-02  0.042838972  0.04631489  0.054842132
#> y3  1.642126e-02 -0.079471595  0.01971222  0.008938745
#> y4  5.143616e-05 -0.013917423  0.05381787 -0.025717667
#>
#> Proportion of trace:
#>    LD1    LD2    LD3    LD4
#> 0.7364 0.1985 0.0576 0.0075

## Look at accuracy on the training data
lda_fitted <- predict(lda_mod,newdata = crops)
# Contingency table
lda_table <- table(truth = crops$crop, fitted = lda_fitted$class)
lda_table
#>             fitted
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          6    0      3        0          2
#>   Corn            0    6      0        1          0
#>   Cotton          3    0      1        2          0
#>   Soybeans        0    1      1        3          1
#>   Sugarbeets      1    1      0        2          2
# accuracy of 0.5 is just random (not good)

## Posterior probabilities of membership
crops_post <- cbind.data.frame(crops,
                               crop_pred = lda_fitted$class,
                               lda_fitted$posterior)
crops_post <- crops_post %>%
    mutate(missed = crop != crop_pred)
head(crops_post)
#>   crop y1 y2 y3 y4 crop_pred     Clover      Corn    Cotton  Soybeans
#> 1 Corn 16 27 31 33      Corn 0.08935164 0.4054296 0.1763189 0.2391845
#> 2 Corn 15 23 30 30      Corn 0.07690181 0.4558027 0.1420920 0.2530101
#> 3 Corn 16 27 27 26      Corn 0.09817815 0.3422454 0.1365315 0.3073105
#> 4 Corn 18 20 25 23      Corn 0.10521511 0.3633673 0.1078076 0.3281477
```

```
#> 5 Corn 15 15 31 32      Corn 0.05879921 0.5753907 0.1173332 0.2086696
#> 6 Corn 15 32 32 15  Soybeans 0.09723648 0.3278382 0.1318370 0.3419924
#>   Sugarbeets missed
#> 1 0.08971545  FALSE
#> 2 0.07219340  FALSE
#> 3 0.11573442  FALSE
#> 4 0.09546233  FALSE
#> 5 0.03980738  FALSE
#> 6 0.10109590   TRUE
# posterior shows that posterior of corn membership is much higher than the prior

## LOOCV
# leave-one-out cross validation for linear discriminant analysis
# cannot run the predict function using the object with CV = TRUE
# because it returns the within sample predictions
lda_cv <- lda(crop ~ y1 + y2 + y3 + y4,
              data = crops, CV = TRUE)
# Contingency table
lda_table_cv <- table(truth = crops$crop, fitted = lda_cv$class)
lda_table_cv
#>             fitted
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          4    3      1        0          3
#>   Corn            0    4      1        2          0
#>   Cotton          3    0      0        2          1
#>   Soybeans        0    1      1        3          1
#>   Sugarbeets      2    1      0        2          1

## Predict the test data
lda_pred <- predict(lda_mod, newdata = crops_test)

## Make a contingency table with truth and most likely class
table(truth=crops_test$crop, predict=lda_pred$class)
#>             predict
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          0    0      1        0          0
#>   Corn            0    1      0        0          0
#>   Cotton          0    0      0        1          0
#>   Soybeans        0    0      0        1          0
#>   Sugarbeets      1    0      0        0          0
```

LDA didn't do well on both within sample and out-of-sample data.

22.4.4.2 QDA

```
## Quadratic discriminant analysis
qda_mod <- qda(crop ~ y1 + y2 + y3 + y4,
               data = crops)

## Look at accuracy on the training data
qda_fitted <- predict(qda_mod, newdata = crops)
# Contingency table
qda_table <- table(truth = crops$crop, fitted = qda_fitted$class)
qda_table
#>             fitted
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          9    0      0        0          2
#>   Corn            0    7      0        0          0
#>   Cotton          0    0      6        0          0
#>   Soybeans        0    0      0        6          0
#>   Sugarbeets      0    0      1        1          4

## LOOCV
qda_cv <- qda(crop ~ y1 + y2 + y3 + y4,
              data = crops, CV = TRUE)
# Contingency table
qda_table_cv <- table(truth = crops$crop, fitted = qda_cv$class)
qda_table_cv
#>             fitted
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          9    0      0        0          2
#>   Corn            3    2      0        0          2
#>   Cotton          3    0      2        0          1
#>   Soybeans        3    0      0        2          1
#>   Sugarbeets      3    0      1        1          1

## Predict the test data
qda_pred <- predict(qda_mod, newdata = crops_test)
## Make a contingency table with truth and most likely class
table(truth = crops_test$crop, predict = qda_pred$class)
#>             predict
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          1    0      0        0          0
#>   Corn            0    1      0        0          0
#>   Cotton          0    0      1        0          0
#>   Soybeans        0    0      0        1          0
#>   Sugarbeets      0    0      0        0          1
```

22.4.4.3 KNN

knn uses design matrices of the features.

```
## Design matrices
X_train <- crops %>%
    dplyr::select(-crop)
X_test <- crops_test %>%
    dplyr::select(-crop)
Y_train <- crops$crop
Y_test <- crops_test$crop

## Nearest neighbors with 2 neighbors
knn_2 <- knn(X_train, X_train, Y_train, k = 2)
table(truth = Y_train, fitted = knn_2)
#>             fitted
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          8    0      2        1          0
#>   Corn            0    6      0        1          0
#>   Cotton          0    0      5        0          1
#>   Soybeans        0    0      0        3          3
#>   Sugarbeets      0    0      1        1          4

## Accuracy
mean(Y_train==knn_2)
#> [1] 0.7222222

## Performance on test data
knn_2_test <- knn(X_train, X_test, Y_train, k = 2)
table(truth = Y_test, predict = knn_2_test)
#>             predict
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          1    0      0        0          0
#>   Corn            0    1      0        0          0
#>   Cotton          0    0      0        0          1
#>   Soybeans        0    0      0        1          0
#>   Sugarbeets      0    0      0        0          1

## Accuracy
mean(Y_test==knn_2_test)
#> [1] 0.8

## Nearest neighbors with 3 neighbors
knn_3 <- knn(X_train, X_train, Y_train, k = 3)
table(truth = Y_train, fitted = knn_3)
#>             fitted
```

```
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          8    0      2        1          0
#>   Corn            0    6      0        1          0
#>   Cotton          1    1      4        0          0
#>   Soybeans        1    0      0        4          1
#>   Sugarbeets      0    0      0        2          4

## Accuracy
mean(Y_train==knn_3)
#> [1] 0.7222222

## Performance on test data
knn_3_test <- knn(X_train, X_test, Y_train, k = 3)
table(truth = Y_test, predict = knn_3_test)
#>             predict
#> truth        Clover Corn Cotton Soybeans Sugarbeets
#>   Clover          1    0      0        0          0
#>   Corn            0    1      0        0          0
#>   Cotton          0    0      1        0          0
#>   Soybeans        0    0      0        1          0
#>   Sugarbeets      0    0      0        0          1

## Accuracy
mean(Y_test==knn_3_test)
#> [1] 1
```

22.4.4.4 Stepwise

Stepwise discriminant analysis using the `stepclass` in function in the `klaR` package.

```
step <- stepclass(
    crop ~ y1 + y2 + y3 + y4,
    data = crops,
    method = "qda",
    improvement = 0.15
)
#> correctness rate: 0.45;  in: "y1";  variables (1): y1
#>
#>  hr.elapsed min.elapsed sec.elapsed
#>        0.00        0.00        0.16

step$process
#>    step var varname result.pm
#> 0 start   0      --      0.00
#> 1    in   1      y1      0.45
```

```
step$performance.measure
#> [1] "correctness rate"
```

Iris Data

```
library(dplyr)
data('iris')
set.seed(1)
samp <-
    sample.int(nrow(iris), size = floor(0.70 * nrow(iris)), replace = F)

train.iris <- iris[samp,] %>% mutate_if(is.numeric,scale)
test.iris <- iris[-samp,] %>% mutate_if(is.numeric,scale)

library(ggplot2)
iris.model <- lda(Species ~ ., data = train.iris)
#pred
pred.lda <- predict(iris.model, test.iris)
table(truth = test.iris$Species, prediction = pred.lda$class)
#>             prediction
#> truth        setosa versicolor virginica
#>   setosa         15          0         0
#>   versicolor      0         17         0
#>   virginica       0          0        13

plot(iris.model)
```

```
iris.model.qda <- qda(Species~.,data=train.iris)
#pred
pred.qda <- predict(iris.model.qda,test.iris)
table(truth=test.iris$Species,prediction=pred.qda$class)
#>              prediction
#> truth         setosa versicolor virginica
#>   setosa         15          0         0
#>   versicolor      0         16         1
#>   virginica       0          0        13
```

22.4.4.5 PCA with Discriminant Analysis

we can use both PCA for dimension reduction in discriminant analysis

```
zeros <- as.matrix(read.table("images/mnist0_train_b.txt"))
nines <- as.matrix(read.table("images/mnist9_train_b.txt"))
train <- rbind(zeros[1:1000, ], nines[1:1000, ])
train <- train / 255 #divide by 255 per notes (so ranges from 0 to 1)
train <- t(train) #each column is an observation
image(matrix(train[, 1], nrow = 28), main = 'Example image, unrotated')
```

```
test <- rbind(zeros[2501:3000, ], nines[2501:3000, ])
test <- test / 255
test <- t(test)
y.train <- c(rep(0, 1000), rep(9, 1000))
```

```
y.test <- c(rep(0, 500), rep(9, 500))


library(MASS)
pc <- prcomp(t(train))
train.large <- data.frame(cbind(y.train, pc$x[, 1:10]))
large <- lda(y.train ~ ., data = train.large)
#the test data set needs to be constucted w/ the same 10 princomps
test.large <- data.frame(cbind(y.test, predict(pc, t(test))[, 1:10]))
pred.lda <- predict(large, test.large)
table(truth = test.large$y.test, prediction = pred.lda$class)
#>      prediction
#> truth   0   9
#>     0 491   9
#>     9   5 495

large.qda <- qda(y.train~.,data=train.large)
#prediction
pred.qda <- predict(large.qda,test.large)
table(truth=test.large$y.test,prediction=pred.qda$class)
#>      prediction
#> truth   0   9
#>     0 493   7
#>     9   3 497
```

B.
QUASI-EXPERIMENTAL DESIGN

Chapter 23

Quasi-experimental

In most cases, it means that you have pre- and post-intervention data.

Great resources for causal inference include Causal Inference Mixtape and Recent Advances in Micro, especially if you like to read about the history of causal inference as a field as well (codes for Stata, R, and Python).

Libraries in R:

- Econometrics
- Causal Inference

Identification strategy for any quasi-experiment (No ways to prove or formal statistical test, but you can provide plausible argument and evidence)

1. Where the exogenous variation comes from (by argument and institutional knowledge)
2. Exclusion restriction: Evidence that the variation in the exogenous shock and the outcome is due to no other factors
    1. The stable unit treatment value assumption (SUTVA) states that the treatment of unit i affect only the outcome of unit i (i.e., no spillover to the control groups)

All quasi-experimental methods involve a tradeoff between power and support for the exogeneity assumption (i.e., discard variation in the data that is not exogenous).

Consequently, we don't usually look at R^2 (Ebbes et al., 2011). And it can even be misleading to use R^2 as the basis for model comparison.

Clustering should be based on the design, not the expectations of correlation (Abadie et al., 2023). With a **small sample**, you should use the **wild bootstrap procedure** (Cameron et al., 2008) to correct for the downward bias (see (Cai et al., 2022)for additional assumptions).

Typical robustness check: recommended by (Goldfarb et al., 2022)

- Different controls: show models with and without controls. Typically, we want to see the change in the estimate of interest. See (Altonji et al., 2005) for a formal assessment based on Rosenbaum bounds (i.e., changes in the estimate and threat of Omitted variables on the estimate). For specific applications in marketing, see (Manchanda et al., 2015) (Shin et al., 2012)
- Different functional forms
- Different window of time (in longitudinal setting)
- Different dependent variables (those that are related) or different measures of the dependent variables
- Different control group size (matched vs. un-matched samples)
- Placebo tests: see each placebo test for each setting below.

Showing the mechanism:

- Mediation analysis
- Moderation analysis
  - Estimate the model separately (for different groups)
  - Assess whether the three-way interaction between the source of variation (e.g., under DID, cross-sectional and time series) and group membership is significant.

External Validity:

- Assess how representative your sample is
- Explain the limitation of the design.
- Use quasi-experimental results in conjunction with structural models: see (Anderson et al., 2015; Einav et al., 2010; Chung et al., 2014)

Limitation

1. What is your identifying assumptions or identification strategy
2. What are threats to the validity of your assumptions?
3. What you do to address it? And maybe how future research can do to address it.

23.1 Natural Experiments

Reusing the same natural experiments for research, particularly when employing identical methods to determine the treatment effect in a given setting, can pose problems for hypothesis testing.

Simulations show that when $N_{\text{Outcome}} >> N_{\text{True effect}}$, more than 50% of statistically significant findings may be false positives (Heath et al., 2023, p.2331).

Solutions:

- Bonferroni correction
- Romano and Wolf (2005) and Romano and Wolf (2016) correction: recommended
- Benjamini and Yekutieli (2001) correction
- Alternatively, refer to the rules of thumb from Table AI (Heath et al., 2023, p.2356).

When applying multiple testing corrections, we can either use (but they will give similar results anyway (Heath et al., 2023, p.2335)):

1. **Chronological Sequencing**: Outcomes are ordered by the date they were first reported, with multiple testing corrections applied in this sequence. This method progressively raises the statistical significance threshold as more outcomes are reviewed over time.
2. **Best Foot Forward Policy**: Outcomes are ordered from most to least likely to be rejected based on experimental data. Used primarily in clinical trials, this approach gives priority to intended treatment effects, which are subjected to less stringent statistical requirements. New outcomes are added to the sequence as they are linked to the primary treatment effect.

```r
# Romano-Wolf correction
library(fixest)
library(wildrwolf)

head(iris)
#>   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
#> 1          5.1         3.5          1.4         0.2  setosa
#> 2          4.9         3.0          1.4         0.2  setosa
#> 3          4.7         3.2          1.3         0.2  setosa
#> 4          4.6         3.1          1.5         0.2  setosa
#> 5          5.0         3.6          1.4         0.2  setosa
#> 6          5.4         3.9          1.7         0.4  setosa

fit1 <- feols(Sepal.Width ~ Sepal.Length , data = iris)
fit2 <- feols(Petal.Length ~ Sepal.Length, data = iris)
fit3 <- feols(Petal.Width ~ Sepal.Length, data = iris)

res <- rwolf(
  models = list(fit1, fit2, fit3),
  param = "Sepal.Length",
  B = 500
```

```
)
#>
  |
  |                                                                      |   0%
  |
  |=========================                                             |  33%
  |
  |=================================================                     |  67%
  |
  |======================================================================| 100%

res
#>   model   Estimate Std. Error   t value     Pr(>|t|) RW Pr(>|t|)
#> 1     1 -0.0618848 0.04296699 -1.440287    0.1518983 0.131736527
#> 2     2   1.858433 0.08585565  21.64602 1.038667e-47 0.001996008
#> 3     3  0.7529176 0.04353017  17.29645 2.325498e-37 0.001996008
```

For all other tests, one can use `multtest::mt.rawp2adjp` which includes:

- Bonferroni
- Holm (1979)
- Šidák (1967)
- Hochberg (1988)
- Benjamini and Hochberg (1995)
- Benjamini and Yekutieli (2001)
- Adaptive Benjamini and Hochberg (2000)
- Two-stage Benjamini et al. (2006)

Permutation adjusted p-values for simple multiple testing procedures

```
# BiocManager::install("multtest")
library(multtest)

procs <-
    c("Bonferroni",
      "Holm",
      "Hochberg",
      "SidakSS",
      "SidakSD",
      "BH",
      "BY",
      "ABH",
      "TSBH")

mt.rawp2adjp(
    # p-values
    runif(10),
```

```
    procs) |> causalverse::nice_tab()
#>    adjp.rawp adjp.Bonferroni adjp.Holm adjp.Hochberg adjp.SidakSS adjp.SidakSD
#> 1       0.12               1         1          0.75         0.72         0.72
#> 2       0.22               1         1          0.75         0.92         0.89
#> 3       0.24               1         1          0.75         0.94         0.89
#> 4       0.29               1         1          0.75         0.97         0.91
#> 5       0.36               1         1          0.75         0.99         0.93
#> 6       0.38               1         1          0.75         0.99         0.93
#> 7       0.44               1         1          0.75         1.00         0.93
#> 8       0.59               1         1          0.75         1.00         0.93
#> 9       0.65               1         1          0.75         1.00         0.93
#> 10      0.75               1         1          0.75         1.00         0.93
#>    adjp.BH adjp.BY adjp.ABH adjp.TSBH_0.05 index h0.ABH h0.TSBH
#> 1     0.63       1     0.63           0.63     2     10      10
#> 2     0.63       1     0.63           0.63     6     10      10
#> 3     0.63       1     0.63           0.63     8     10      10
#> 4     0.63       1     0.63           0.63     3     10      10
#> 5     0.63       1     0.63           0.63    10     10      10
#> 6     0.63       1     0.63           0.63     1     10      10
#> 7     0.63       1     0.63           0.63     7     10      10
#> 8     0.72       1     0.72           0.72     9     10      10
#> 9     0.72       1     0.72           0.72     5     10      10
#> 10    0.75       1     0.75           0.75     4     10      10
```

Chapter 24

Regression Discontinuity

- A regression discontinuity occurs when there is a discrete change (jump) in treatment likelihood in the distribution of a continuous (or roughly continuous) variable (i.e., **running/forcing/assignment variable**).
  - Running variable can also be time, but the argument for time to be continuous is hard to argue because usually we do not see increment of time (e.g., quarterly or annual data). Unless we have minute or hour data, then we might be able to argue for it.
- Review paper (Imbens and Lemieux, 2008; Lee and Lemieux, 2010)
- Other readings:
  - https://ies.ed.gov/ncee/wwc/Docs/ReferenceResources/wwc_rd.pdf
  - https://ies.ed.gov/ncee/wwc/Docs/ReferenceResources/wwc_rdd_standards_122315.pdf
- (Thistlethwaite and Campbell, 1960): first paper to use RD in the context of merit awards on future academic outcomes.
- RD is a localized experiment at the cutoff point
  - Hence, we always have to qualify (perfunctory) our statement in research articles that "our research might not generalize to beyond the bandwidth."
- In reality, RD and experimental (from random assignment) estimates are very similar ((Chaplin et al., 2018); Mathematica). But still, it's hard to prove empirically for every context (there might be future study that finds a huge difference between local estimate - causal - and overall estimate - random assignment.

- Threats: only valid near threshold: inference at threshold is valid on average. Interestingly, random experiment showed the validity already.
- Tradeoff between efficiency and bias
- Regression discontinuity is under the framework of Instrumental Variable (structural IV) argued by (Angrist and Lavy, 1999) and a special case of the Matching Methods (matching at one point) argued by (Heckman et al., 1999).
- The hard part is to find a setting that can apply, but once you find one, it's easy to apply
- We can also have multiple cutoff lines. However, for each cutoff line, there can only be one breakup point
- RD can have multiple coinciding effects (i.e., joint distribution or bundled treatment), then RD effect in this case would be the joint effect.
- As the running variable becomes more discrete your framework should be Interrupted Time Series, but for more granular levels you can use RD. When you have infinite data (or substantially large) the two frameworks are identical. RD is always better than Interrupted Time Series
- Multiple alternative model specifications that produce consistent results are more reliable (parametric - linear regression with polynomials terms, and non-parametric - local linear regression). This is according to (Lee and Lemieux, 2010), one straightforward method to ease the linearity assumption is by incorporating polynomial functions of the forcing variable. The choice of polynomial terms can be determined based on the data.
  - . According to (Gelman and Imbens, 2019), accounting for global high-order polynomials presents three issues: (1) imprecise estimates due to noise, (2) sensitivity to the polynomial's degree, and (3) inadequate coverage of confidence intervals. To address this, researchers should instead employ estimators that rely on local linear or quadratic polynomials or other smooth functions.
- RD should be viewed more as a description of a data generating process, rather than a method or approach (similar to a randomized experiment)
- RD is close to
  - other quasi-experimental methods in the sense that it's based on the discontinuity at a threshold
  - randomized experiments in the sense that it's local randomization.

There are several types of Regression Discontinuity:

1. Sharp RD: Change in treatment probability at the cutoff point is 1

- Kink design: Instead of a discontinuity in the level of running variable, we have a discontinuity in the slope of the function (while the function/level can remain continuous) (Nielsen et al., 2010). See (Böckerman et al., 2018) for application, and (Card et al., 2015) for theory.

2. Kink RD
3. Fuzzy RD: Change in treatment probability less than 1
4. Fuzzy Kink RD
5. RDiT: running variable is time.

Others:

- Multiple cutoff
- Multiple Scores
- Geographic RD
- Dynamic Treatments
- Continuous Treatments

Consider

$$D_i = 1_{X_i > c}$$

$$D_i = \begin{cases} D_i = 1 \text{ if } X_i > C \\ D_i = 0 \text{ if } X_i < C \end{cases}$$

where

- D_i = treatment effect
- X_i = score variable (continuous)
- c = cutoff point

Identification (Identifying assumptions) of RD:

Average Treatment Effect at the cutoff (Continuity-based)

$$\begin{aligned} \alpha_{SRDD} &= E[Y_{1i} - Y_{0i} | X_i = c] \\ &= E[Y_{1i} | X_i = c] - E[Y_{0i} | X_i = c] \\ &= \lim_{x \to c^+} E[Y_{1i} | X_i = c] - \lim_{x \to c^=} E[Y_{0i} | X_i = c] \end{aligned}$$

Average Treatment Effect in a neighborhood (Local Randomization-based):

$$\begin{aligned}\alpha_{LR} &= E[Y_{1i} - Y_{0i}|X_i \in W] \\ &= \frac{1}{N_1} \sum_{X_i \in W, T_i=1} Y_i - \frac{1}{N_0} \sum_{X_i \in W, T_i=0} Y_i\end{aligned}$$

RDD estimates the local average treatment effect (LATE), at the cutoff point which is not at the individual or population levels.

Since researchers typically care more about the internal validity, than external validity, localness affects only external validity.

Assumptions:

- Independent assignment
- Continuity of conditional regression functions
  - $E[Y(0)|X = x]$ and $E[Y(1)|X = x]$ are continuous in x.
- RD is valid if cutpoint is **exogenous (i.e., no endogenous selection)** and running variable is **not manipulable**
- Only treatment(s) (e.g., could be joint distribution of multiple treatments) cause discontinuity or jump in the outcome variable
- All other factors are **smooth** through the cutoff (i.e., threshold) value. (we can also test this assumption by seeing no discontinuity in other factors). If they "jump", they will bias your causal estimate

Threats to RD

- Variables (other than treatment) change discontinuously at the cutoff
  - We can test for jumps in these variables (including pre-treatment outcome)
- Multiple discontinuities for the assignment variable
- Manipulation of the assignment variable
  - At the cutoff point, check for continuity in the density of the assignment variable.

24.1 Estimation and Inference

24.1.1 Local Randomization-based

Additional Assumption: Local Randomization approach assumes that inside the chosen window $W = [c - w, c + w]$ are assigned to treatment as good as random:

1. Joint probability distribution of scores for units inside the chosen window W is known

2. Potential outcomes are not affected by value of the score

This approach is stronger than the Continuity-based because we assume the regressions are continuously at c and unaffected by the running variable within window W

Because we can choose the window W (within which random assignment is plausible), the sample size can typically be small.

To choose the window W, we can base on either

1. where the pre-treatment covariate-balance is observed
2. independent tests between outcome and score
3. domain knowledge

To make inference, we can either use

- (Fisher) randomization inference
- (Neyman) design-based

24.1.2 Continuity-based

- also known as the local polynomial method
  - as the name suggests, global polynomial regression is not recommended (because of lack of robustness, and over-fitting and Runge's phenomenon)

Step to estimate local polynomial regression

1. Choose polynomial order and weighting scheme
2. Choose bandwidth that has optimal MSE or coverage error
3. Estimate the parameter of interest
4. Examine robust bias-correct inference

24.2 Specification Checks

1. Balance Checks
2. Sorting/Bunching/Manipulation
3. Placebo Tests
4. Sensitivity to Bandwidth Choice

24.2.1 Balance Checks

- Also known as checking for Discontinuities in Average Covariates
- Null Hypothesis: The average effect of covariates on pseudo outcomes (i.e., those qualitatively cannot be affected by the treatment) is 0.

- If this hypothesis is rejected, you better have a good reason to why because it can cast serious doubt on your RD design.

24.2.2 Sorting/Bunching/Manipulation

- Also known as checking for A Discontinuity in the Distribution of the Forcing Variable
- Also known as clustering or density test
- Formal test is McCrary sorting test (McCrary, 2008) or (Cattaneo et al., 2019)
- Since human subjects can manipulate the running variable to be just above or below the cutoff (assuming that the running variable is manipulable), especially when the cutoff point is known in advance for all subjects, this can result in a discontinuity in the distribution of the running variable at the cutoff (i.e., we will see "bunching" behavior right before or after the cutoff)>
  - People would like to sort into treatment if it's desirable. The density of the running variable would be 0 just below the threshold
  - People would like to be out of treatment if it's undesirable
- (McCrary, 2008) proposes a density test (i.e., a formal test for manipulation of the assignment variable).
  - H_0: The continuity of the density of the running variable (i.e., the covariate that underlies the assignment at the discontinuity point)
  - H_a: A jump in the density function at that point
  - Even though it's not a requirement that the density of the running must be continuous at the cutoff, but a discontinuity can suggest manipulations.
- (Zhang and Rubin, 2003; Lee, 2009; Aronow et al., 2019) offers a guide to know when you should warrant the manipulation
- Usually it's better to know your research design inside out so that you can suspect any manipulation attempts.
  - We would suspect the direction of the manipulation. And typically, it's one-way manipulation. In cases where we might have both ways, theoretically they would cancel each other out.
- We could also observe partial manipulation in reality (e.g., when subjects can only imperfectly manipulate). But typically, as we treat it like fuzzy RD, we would not have identification problems. But complete manipulation would lead to serious identification issues.

- Remember: even in cases where we fail to reject the null hypothesis for the density test, we could not rule out completely that identification problem exists (just like any other hypotheses)
- Bunching happens when people self-select to a specific value in the range of a variable (e.g., key policy thresholds).
- Review paper (Kleven, 2016)
- **This test can only detect manipulation that changes the distribution of the running variable**. If you can choose the cutoff point or you have 2-sided manipulation, this test will fail to detect it.
- Histogram in bunching is similar to a density curve (we want narrower bins, wider bins bias elasticity estimates)
- We can also use bunching method to study individuals' or firm's responsiveness to changes in policy.
- Under RD, we assume that we don't have any manipulation in the running variable. However, bunching behavior is a manipulation by firms or individuals. Thus, violating this assumption.
  - Bunching can fix this problem by estimating what densities of individuals would have been without manipulation (i.e., manipulation-free counterfactual).
  - **The fraction of persons who manipulated** is then calculated by comparing the observed distribution to manipulation-free counterfactual distributions.
  - Under RD, we do not need this step because the observed and manipulation-free counterfactual distributions are assumed to be the same. RD assume there is no manipulation (i.e., assume the manipulation-free counterfactual distribution)

When running variable and outcome variable are simultaneously determined, we can use a modified RDD estimator to have consistent estimate. (Bajari et al., 2011)

- **Assumptions**:
  - Manipulation is **one-sided**: People move one way (i.e., either below the threshold to above the threshold or vice versa, but not to or away the threshold), which is similar to the monotonicity assumption under instrumental variable 33.1.3.1
  - Manipulation is **bounded** (also known as regularity assumption): so that we can use people far away from this threshold to derive at our counterfactual distribution [Blomquist et al. (2021)](Bertanha et al., 2021)

Steps:

1. Identify the window in which the running variable contains bunching behavior. We can do this step empirically based on Bosch et al. (2020). Additionally robustness test is needed (i.e., varying the manipulation window).
2. Estimate the manipulation-free counterfactual
3. Calculating the standard errors for inference can follow (Chetty et al., 2016) where we bootstrap re-sampling residuals in the estimation of the counts of individuals within bins (large data can render this step unnecessary).

If we pass the bunching test, we can move on to the Placebo Test

McCrary (2008) test

A jump in the density at the threshold (i.e., discontinuity) hold can serve as evidence for sorting around the cutoff point

```
library(rdd)

# you only need the runing variable and the cutoff point

# Example by the package's authors
#No discontinuity
x<-runif(1000,-1,1)
DCdensity(x,0)
```

```
#> [1] 0.8254815

#Discontinuity
```

```
x<-runif(1000,-1,1)
x<-x+2*(runif(1000,-1,1)>0&x<0)
DCdensity(x,0)
```

```
#> [1] 0.02607091
```

Cattaneo et al. (2019) test

```
library(rddensity)

# Example by the package's authors
# Continuous Density
set.seed(1)
x <- rnorm(2000, mean = -0.5)
rdd <- rddensity(X = x, vce = "jackknife")
summary(rdd)
#>
#> Manipulation testing using local polynomial density estimation.
#>
#> Number of obs =       2000
#> Model =               unrestricted
#> Kernel =              triangular
#> BW method =           estimated
#> VCE method =          jackknife
#>
#> c = 0                 Left of c           Right of c
#> Number of obs         1376                624
#> Eff. Number of obs    354                 345
```

```
#> Order est. (p)        2                    2
#> Order bias (q)        3                    3
#> BW est. (h)           0.514                0.609
#>
#> Method                T                    P > |T|
#> Robust                -0.6798              0.4966
#>
#>
#> P-values of binomial tests (H0: p=0.5).
#>
#> Window Length / 2          <c     >=c    P>|T|
#> 0.036                      28      20    0.3123
#> 0.072                      46      39    0.5154
#> 0.107                      68      59    0.4779
#> 0.143                      94      79    0.2871
#> 0.179                     122     103    0.2301
#> 0.215                     145     130    0.3986
#> 0.250                     163     156    0.7370
#> 0.286                     190     176    0.4969
#> 0.322                     214     200    0.5229
#> 0.358                     249     218    0.1650

# you have to specify your own plot (read package manual)
```

24.2.3 Placebo Tests

- Also known as Discontinuities in Average Outcomes at Other Values
- We should not see any jumps at other values (either $X_i < c$ or $X_i \geq c$)
  - Use the same bandwidth you use for the cutoff, and move it along the running variable: testing for a jump in the conditional mean of the outcome at the median of the running variable.
- Also known as falsification checks
- Before and after the cutoff point, we can run the placebo test to see whether X's are different).
- The placebo test is where you expect your coefficients to be not different from 0.
- This test can be used for
  - Testing no discontinuity in predetermined variables:
  - Testing other discontinuities

  - Placebo outcomes: we should see any changes in other outcomes that shouldn't have changed.
  - Inclusion and exclusion of covariates: RDD parameter estimates should not be sensitive to the inclusion or exclusion of other covariates.
- This is analogous to Experimental Design where we cannot only test whether the observables are similar in both treatment and control groups (if we reject this, then we don't have random assignment), but we cannot test unobservables.

Balance on observable characteristics on both sides

$$Z_i = \alpha_0 + \alpha_1 f(x_i) + [I(x_i \geq c)]\alpha_2 + [f(x_i) \times I(x_i \geq c)]\alpha_3 + u_i$$

where

- x_i is the running variable
- Z_i is other characteristics of people (e.g., age, etc)

Theoretically, Z_i should no be affected by treatment. Hence, $E(\alpha_2) = 0$

Moreover, when you have multiple Z_i, you typically have to simulate joint distribution (to avoid having significant coefficient based on chance).

The only way that you don't need to generate joint distribution is when all Z_i's are independent (unlikely in reality).

Under RD, you shouldn't have to do any Matching Methods. Because just like when you have random assignment, there is no need to make balanced dataset before and after the cutoff. If you have to do balancing, then your RD assumptions are probably wrong in the first place.

24.2.4 Sensitivity to Bandwidth Choice

- Methods for bandwidth selection
  - Ad-hoc or substantively driven
  - Data driven: cross validation
  - Conservative approach: (Calonico et al., 2020)
- The objective is to minimize the mean squared error between the estimated and actual treatment effects.
- Then, we need to see how sensitive our results will be dependent on the choice of bandwidth.
- In some cases, the best bandwidth for testing covariates may not be the best bandwidth for treating them, but it may be close.

```r
# find optimal bandwidth by Imbens-Kalyanaraman
rdd::IKbandwidth(running_var,
                 outcome_var,
                 cutpoint = "",
                 kernel = "triangular") # can also pick other kernels
```

24.2.5 Manipulation Robust Regression Discontinuity Bounds

- McCrary (2008) linked density jumps at cutoffs in RD studies to potential manipulation.
  - If no jump is detected, researchers proceed with RD analysis; if detected, they halt using the cutoff for inference.
  - Some studies use the "doughnut-hole" method, excluding near-cutoff observations and extrapolating, which contradicts RD principles.
    - False negative could be due to a small sample size and can lead to biased estimates, as units near the cutoff may still differ in unobserved ways.
    - Even correct rejections of no manipulation may overlook that the data can still be informative despite modest manipulation.
    - Gerard et al. (2020) introduces a systematic approach to handle potentially manipulated variables in RD designs, addressing both concerns.
- The model introduces two types of unobservable units in RD designs:
  - **always-assigned** units, which are always on one side of the cutoff,
  - **potentially-assigned** units, which fit traditional RD assumptions.
    - The standard RD model is a subset of this broader model, which assumes no always-assigned units.
- Identifying assumption: manipulation occurs through one-sided selection.
- The approach does not make a binary decision on manipulation in RD designs but assesses its extent and worst-case impact.

Two steps are used:

1. Determining the proportion of always-assigned units using the discontinuity at the cutoff
2. Bounding treatment effects based on the most extreme feasible outcomes for these units.

- For sharp RD designs, bounds are established by trimming extreme outcomes near the cutoff; for fuzzy designs, the process involves more complex adjustments due to additional model constraints.
- Extensions of the study use covariate information and economic behavior assumptions to refine these bounds and identify covariate distributions among unit types at the cutoff.

Setup

Independent data points (X_i, Y_i, D_i), where X_i is the running variable, Y_i is the outcome, and D_i indicates treatment status (1 if treated, 0 otherwise). Treatment is assigned based on $X_i \geq c$.

The design is *sharp* if $D_i = I(X_i \geq c)$ and *fuzzy* otherwise.

The population is divided into:

- **Potentially-assigned units** ($M_i = 0$): Follow the standard RD framework, with potential outcomes $Y_i(d)$ and potential treatment states $D_i(x)$.
- **Always-assigned units** ($M_i = 1$): These units do not require potential outcomes or states, and always have X_i values beyond the cutoff.

Assumptions

1. **Local Independence and Continuity**:
   - $P(D = 1|X = c^+, M = 0) > P(D = 1|X = c^-, M = 0)$
   - No defiers: $P(D^+ \geq D^-|X = c, M = 0) = 1$
   - Continuity in potential outcomes and states at c.
   - $F_{X|M=0}(x)$ is differentiable at c, with a positive derivative.
2. **Smoothness of the Running Variable among Potentially-Assigned Units**:
   - The derivative of $F_{X|M=0}(x)$ is continuous at c.
3. **Restrictions on Always-Assigned Units**:
   - $P(X \geq c|M = 1) = 1$ and $F_{X|M=1}(x)$ is right-differentiable (or left-differentiable) at c.
   - This (local) one-sided manipulation assumption allows identification of the proportion of always-assigned units among all units close to the cutoff.

When always-assigned unit exist, the RD design is fuzzy because we have

1. Treated and untreated units among the potentially-assigned (below and above the cutoff)
2. Always-assigned units (above the cutoff).

Causal Effects of Interest

causal effects among potentially-assigned units:

$$\Gamma = E[Y(1) - Y(0)|X = c, D^+ > D^-, M = 0]$$

This parameter represents the local average treatment effect (LATE) for the subgroup of "compliers"—units that receive treatment if and only if their running variable X_i exceeds a certain cutoff.

The parameter Γ captures the causal effect of changes in the cutoff level on treatment status among potentially-assigned compliers.

RD designs with a manipulated running variable	**"Doughnut-Hole" RD Designs**:
• Focuses on actual observations at the cutoff, not hypothetical true values. • Provides a direct and observable estimate of causal effects, without reliance on hypothetical constructs.	• Exclude observations around the cutoff and use extrapolation from the trends outside this excluded range to infer causal effects at the cutoff • Assumes a hypothetical population existing in a counterfactual scenario without manipulation. • Requires strong assumptions about the nature of manipulation and the minimal impact of extrapolation biases.

Identification of τ in RD Designs

- Identification challenges arise due to the inability to distinguish always-assigned from potentially-assigned units, thus Γ is not point identified. We establish sharp bounds on Γ
- These bounds are supported by the stochastic dominance of the potential outcome CDFs over observed distributions.

Unit Types and Notation:

- C_0: Potentially-assigned compliers.
- A_0: Potentially-assigned always-takers.
- N_0: Potentially-assigned never-takers.
- T_1: Always-assigned treated units.
- U_1: Always-assigned untreated units.

The measure τ , representing the proportion of always-assigned units near the cutoff, is point identified by the discontinuity in the observed running variable density f_X at the cutoff

Sharp RD:

- Units to the left of the cutoff are potentially assigned units. The distribution of their observed outcomes (Y) are the outcomes $Y(0)$ of potentially-assigned compliers (C_0) at the cutoff.

- To determine the bounds on the treatment effect (Γ), we need to assess the distribution of treated outcomes ($Y(1)$) for the same potentially-assigned compliers at the cutoff.
- Information regarding the treated outcomes ($Y(1)$) comes exclusively from the subpopulation of treated units, which includes both potentially-assigned compliers (C_0) and those always assigned units (T_1).
- With τ point identified, we can estimate sharp bounds on Γ.

Fuzzy RD:

Table 24.2: Note: Table on page 848 (Gerard et al., 2020)

Subpopulation	Types of units
$X = c^+, D = 1$	C_0, A_0, T_1
$X = c^-, D = 1$	A_0
$X = c^+, D = 0$	N_0, U_1
$X = c^-, D = 0$	C_0, N_0

- **Unit Types and Combinations**: There are five distinct unit types and four combinations of treatment assignments and decisions relevant to the analysis. These distinctions are important because they affect how potential outcomes are analyzed and bounded.
- **Outcome Distributions**: The analysis involves estimating the distribution of potential outcomes (both treated and untreated) among potentially-assigned compliers at the cutoff.
- **Three-Step Process**:
  1. **Potential Outcomes Under Treatment**: Bounds on the distribution of treated outcomes are determined using data from treated units.
  2. **Potential Outcomes Under Non-Treatment**: Bounds on the distribution of untreated outcomes are derived using data from untreated units.
  3. **Bounds on Parameters of Interest**: Using the bounds from the first two steps, sharp upper and lower bounds on the local average treatment effect are derived.
- **Extreme Value Consideration**: The bounds for treatment effects are based on "extreme" scenarios under worst-case assumptions about the distribution of potential outcomes, making them sharp but empirically relevant within the data constraints.

Extensions:

- **Quantile Treatment Effects**: alternative to average effects by focusing on different quantiles of the outcome distribution, which are less affected by extreme values.
- **Applicability to Discrete Outcomes**
- **Behavioral Assumptions Impact**: Assuming a high likelihood of treatment among always-assigned units can narrow the bounds of treatment effects by refining the analysis of potential outcomes.
- **Utilization of Covariates**: Incorporating covariates measured prior to treatment can refine the bounds on treatment effects and help target policies by identifying covariate distributions among different unit types.

Notes:

- Quantile Treatment Effects (QTEs): QTE bounds are less sensitive to the tails of the outcome distribution, making them tighter than ATE bounds.
  - Inference on ATEs is sensitive to the extent of manipulation, with confidence intervals widening significantly with small degrees of assumed manipulation.
  - Inference on QTEs is less affected by manipulation, remaining meaningful even with larger degrees of manipulation.
- Alternative Inference Strategy when manipulation is believed to be unlikely. Try different hypothetical values of τ

```
devtools::install_github("francoisgerard/rdbounds/R")
```

```
library(formattable)
library(data.table)
library(rdbounds)
set.seed(123)
df <- rdbounds_sampledata(10000, covs = FALSE)
#> [1] "True tau: 0.117999815082062"
#> [1] "True treatment effect on potentially-assigned: 2"
#> [1] "True treatment effect on right side of cutoff: 2.35399944524618"
head(df)
#>            x        y treatment
#> 1 -1.2532616 3.489563         0
#> 2 -0.5146925 3.365232         0
#> 3  3.4853777 6.193533         0
#> 4  0.1576616 8.820440         1
#> 5  0.2890962 4.791972         0
#> 6  3.8350019 7.316907         0

rdbounds_est <-
    rdbounds(
```

```
        y = df$y,
        x = df$x,
        # covs = as.factor(df$cov),
        treatment = df$treatment,
        c = 0,
        discrete_x = FALSE,
        discrete_y = FALSE,
        bwsx = c(.2, .5),
        bwy = 1,

        # for median effect use
        # type = "qte",
        # percentiles = .5,

        kernel = "epanechnikov",
        orders = 1,
        evaluation_ys = seq(from = 0, to = 15, by = 1),
        refinement_A = TRUE,
        refinement_B = TRUE,
        right_effects = TRUE,
        yextremes = c(0, 15),
        num_bootstraps = 5
    )
#> [1] "The proportion of always-assigned units just to the right of the cutoff is estimated to b
#> [1] "2024-05-13 19:26:14 Estimating CDFs for point estimates"
#> [1] "2024-05-13 19:26:14 .....Estimating CDFs for units just to the right of the cutoff"
#> [1] "2024-05-13 19:26:16 Estimating CDFs with nudged tau (tau_star)"
#> [1] "2024-05-13 19:26:16 .....Estimating CDFs for units just to the right of the cutoff"
#> [1] "2024-05-13 19:26:18 Beginning parallelized output by bootstrap.."
#> [1] "2024-05-13 19:26:24 Computing Confidence Intervals"
#> [1] "2024-05-13 19:26:33 Time taken:0.32 minutes"
```

```
rdbounds_summary(rdbounds_est, title_prefix = "Sample Data Results")
#> [1] "Time taken: 0.32 minutes"
#> [1] "Sample size: 10000"
#> [1] "Local Average Treatment Effect:"
#> $tau_hat
#> [1] 0.04209028
#>
#> $tau_hat_CI
#> [1] 0.1671043 0.7765031
#>
#> $takeup_increase
#> [1] 0.7521208
#>
```

```
#> $takeup_increase_CI
#> [1] 0.7065353 0.7977063
#>
#> $TE_SRD_naive
#> [1] 1.770963
#>
#> $TE_SRD_naive_CI
#> [1] 1.541314 2.000612
#>
#> $TE_SRD_bounds
#> [1] 1.569194 1.912681
#>
#> $TE_SRD_CI
#> [1] -0.1188634  3.5319468
#>
#> $TE_SRD_covs_bounds
#> [1] NA NA
#>
#> $TE_SRD_covs_CI
#> [1] NA NA
#>
#> $TE_FRD_naive
#> [1] 2.356601
#>
#> $TE_FRD_naive_CI
#> [1] 1.995430 2.717772
#>
#> $TE_FRD_bounds
#> [1] 1.980883 2.362344
#>
#> $TE_FRD_CI
#> [1] -0.6950823  4.6112538
#>
#> $TE_FRD_bounds_refinementA
#> [1] 1.980883 2.357499
#>
#> $TE_FRD_refinementA_CI
#> [1] -0.6950823  4.6112538
#>
#> $TE_FRD_bounds_refinementB
#> [1] 1.980883 2.351411
#>
#> $TE_FRD_refinementB_CI
#> [1] -0.6152215  4.2390830
#>
```

```
#> $TE_FRD_covs_bounds
#> [1] NA NA
#>
#> $TE_FRD_covs_CI
#> [1] NA NA
#>
#> $TE_SRD_CIs_manipulation
#> [1] NA NA
#>
#> $TE_FRD_CIs_manipulation
#> [1] NA NA
#>
#> $TE_SRD_right_bounds
#> [1] 1.376392 2.007746
#>
#> $TE_SRD_right_CI
#> [1] -5.036752  5.889137
#>
#> $TE_FRD_right_bounds
#> [1] 1.721121 2.511504
#>
#> $TE_FRD_right_CI
#> [1] -6.663269  7.414185
```

```
rdbounds_est_tau <-
    rdbounds(
        y = df$y,
        x = df$x,
        # covs = as.factor(df$cov),
        treatment = df$treatment,
        c = 0,
        discrete_x = FALSE,
        discrete_y = FALSE,
        bwsx = c(.2, .5),
        bwy = 1,
        kernel = "epanechnikov",
        orders = 1,
        evaluation_ys = seq(from = 0, to = 15, by = 1),
        refinement_A = TRUE,
        refinement_B = TRUE,
        right_effects = TRUE,
        potential_taus = c(.025, .05, .1, .2),
        yextremes = c(0, 15),
        num_bootstraps = 5
    )
```

```
#> [1] "The proportion of always-assigned units just to the right of the cutoff is est
#> [1] "2024-05-13 19:26:34 Estimating CDFs for point estimates"
#> [1] "2024-05-13 19:26:34 .....Estimating CDFs for units just to the right of the cu
#> [1] "2024-05-13 19:26:35 Estimating CDFs with nudged tau (tau_star)"
#> [1] "2024-05-13 19:26:35 .....Estimating CDFs for units just to the right of the cu
#> [1] "2024-05-13 19:26:38 Beginning parallelized output by bootstrap.."
#> [1] "2024-05-13 19:26:44 Estimating CDFs with fixed tau value of: 0.025"
#> [1] "2024-05-13 19:26:44 Estimating CDFs with fixed tau value of: 0.05"
#> [1] "2024-05-13 19:26:44 Estimating CDFs with fixed tau value of: 0.1"
#> [1] "2024-05-13 19:26:44 Estimating CDFs with fixed tau value of: 0.2"
#> [1] "2024-05-13 19:26:45 Beginning parallelized output by bootstrap x fixed tau.."
#> [1] "2024-05-13 19:26:49 Computing Confidence Intervals"
#> [1] "2024-05-13 19:27:00 Time taken:0.43 minutes"
```

```
causalverse::plot_rd_aa_share(rdbounds_est_tau) # For SRD (default)
```

```
# causalverse::plot_rd_aa_share(rdbounds_est_tau, rd_type = "FRD")  # For FRD
```

24.3 Fuzzy RD Design

When you have cutoff that does not perfectly determine treatment, but creates a discontinuity in the likelihood of receiving the treatment, you need another instrument

For those that are close to the cutoff, we create an instrument for D_i

$$Z_i = \begin{cases} 1 & \text{if } X_i \geq c \\ 0 & \text{if } X_c < c \end{cases}$$

Then, we can estimate the effect of the treatment for compliers only (i.e., those treatment D_i depends on Z_i)

The LATE parameter

$$\lim_{c-\epsilon \leq X \leq c+\epsilon, \epsilon \to 0} \left(\frac{E(Y|Z=1) - E(Y|Z=0)}{E(D|Z=1) - E(D|Z=0)} \right)$$

equivalently, the canonical parameter:

$$\frac{lim_{x \downarrow c} E(Y|X=x) - \lim_{x \uparrow c} E(Y|X=x)}{\lim_{x \downarrow c} E(D|X=x) - \lim_{x \uparrow c} E(D|X=x)}$$

Two equivalent ways to estimate

1. First
    1. Sharp RDD for Y
    2. Sharp RDD for D
    3. Take the estimate from step 1 divide by that of step 2
2. Second: Subset those observations that are close to c and run instrumental variable Z

24.4 Regression Kink Design

- If the slope of the treatment intensity changes at the cutoff (instead of the level of treatment assignment), we can have regression kink design
- Example: unemployment benefits

Sharp Kink RD parameter

$$\alpha_{KRD} = \frac{\lim_{x \downarrow c} \frac{d}{dx} E[Y_i|X_i = x] - \lim_{x \uparrow c} \frac{d}{dx} E[Y_i|X_i = x]}{\lim_{x \downarrow c} \frac{d}{dx} b(x) - \lim_{x \uparrow c} \frac{d}{dx} b(x)}$$

where $b(x)$ is a known function inducing "kink"

Fuzzy Kink RD parameter

$$\alpha_{KRD} = \frac{\lim_{x \downarrow c} \frac{d}{dx} E[Y_i|X_i = x] - \lim_{x \uparrow c} \frac{d}{dx} E[Y_i|X_i = x]}{\lim_{x \downarrow c} \frac{d}{dx} E[D_i|X_i = x] - \lim_{x \uparrow c} \frac{d}{dx} E[D_i|X_i = x]}$$

24.5 Multi-cutoff

$$\tau(x, c) = E[Y_{1i} - Y_{0i}|X_i = x, C_i = c]$$

24.6 Multi-score

Multi-score (in multiple dimensions) (e.g., math and English cutoff for certain honor class):

$$\tau(x_1, x_2) = E[Y_{1i} - Y_{0i}|X_{1i} = x_1, X_{2i} = x]$$

24.7 Steps for Sharp RD

1. Graph the data by computing the average value of the outcome variable over a set of bins (large enough to see a smooth graph, and small enough to make the jump around the cutoff clear).
2. Run regression on both sides of the cutoff to get the treatment effect
3. Robustness checks:
    1. Assess possible jumps in other variables around the cutoff
    2. Hypothesis testing for bunching
    3. Placebo tests
    4. Varying bandwidth

24.8 Steps for Fuzzy RD

1. Graph the data by computing the average value of the outcome variable over a set of bins (large enough to see a smooth graph, and small enough to make the jump around the cutoff clear).
2. Graph the probability of treatment
3. Estimate the treatment effect using 2SLS
4. Robustness checks:
    1. Assess possible jumps in other variables around the cutoff
    2. Hypothesis testing for bunching
    3. Placebo tests
    4. Varying bandwidth

24.9 Steps for RDiT (Regression Discontinuity in Time)

Notes:

- Additional assumption: Time-varying confounders change smoothly across the cutoff date
- Typically used in policy implementation in the same date for all subjects, but can also be used for cases where implementation dates are different between subjects. In the second case, researchers typically use different RDiT specification for each time series.
- Sometimes the date of implementation is not randomly assigned by chosen strategically. Hence, RDiT should be thought of as the "discontinuity at a threshold" interpretation of RD (not as "local randomization"). (Hausman and Rapson, 2018, p. 8)
- Normal RD uses variation in the N dimension, while RDiT uses variation in the T dimension
- Choose polynomials based on BIC typically. And can have either global polynomial or pre-period and post-period polynomial for each time series (but usually the global one will perform better)
- Could use **augmented local linear** outlined by (Hausman and Rapson, 2018, p. 12), where estimate the model with all the control first then take the residuals to include in the model with the RDiT treatment (remember to use bootstrapping method to account for the first-stage variance in the second stage).

Pros:

- can overcome cases where there is no cross-sectional variation in treatment implementation (DID is not feasible)
  - There are papers that use both RDiT and DID to (1) see the differential treatment effects across individuals/ space (Auffhammer and Kellogg, 2011) or (2) compare the 2 estimates where the control group's validity is questionable (Gallego et al., 2013).
- Better than pre/post comparison because it can include flexible controls
- Better than event studies because it can use long-time horizons (may not be too relevant now since the development long-time horizon event studies), and it can use higher-order polynomials time control variables.

Cons:

- Taking observation for from the threshold (in time) can bias your estimates because of unobservables and time-series properties of the data generating process.
- (McCrary, 2008) test is not possible (see Sorting/Bunching/Manipulation) because when the density of the running (time) is uniform, you can't use

the test.

- Time-varying unobservables may impact the dependent variable discontinuously
- Error terms are likely to include persistence (serially correlated errors)
- Researchers cannot model time-varying treatment under RDiT
  - In a small enough window, the local linear specification is fine, but the global polynomials can either be too big or too small (Hausman and Rapson, 2018)

Biases

- Time-Varying treatment Effects
  - increase sample size either by
    * more granular data (greater frequency): will not increase power because of the problem of serial correlation
    * increasing time window: increases bias from other confounders
  - 2 additional assumption:
    * Model is correctly specified (with all confoudners or global polynomial approximation)
    * Treatment effect is correctly specified (whether it's smooth and constant, or varies)
    * These 2 assumptions do not interact (we don't want them to interact - i.e., we don't want the polynomial correlated with the unobserved variation in the treatment effect)
  - There usually a difference between short-run and long-run treatment effects, but it's also possibly that the bias can stem from the over-fitting problem of the polynomial specification. (Hausman and Rapson, 2018, p. 544)
- Autoregression (serial dependence)
  - Need to use **clustered standard errors** to account for serial dependence in the residuals
  - In the case of serial dependence in ϵ_{it}, we don't have a solution, including a lagged dependent variable would misspecify the model (probably find another research project)
  - In the case of serial dependence in y_{it}, with long window, it becomes fuzzy to what you try to recover. You can include the **lagged dependent variable** (bias can still come from the time-varying treatment or over-fitting of the global polynomial)

- Sorting and Anticipation Effects
  - Cannot run the (McCrary, 2008) because the density of the time running variable is uniform
  - Can still run tests to check discontinuities in other covariates (you want no discontinuities) and discontinuities in the outcome variable at other placebo thresholds (you don't want discontinuities)
  - Hence, it's hard to argue for the causal effect here because it could be the total effect of the causal treatment and the unobserved sorting/anticipation/adaptation/avoidance effects. You can only argue that there is no such behavior

Recommendations for robustness check following (Hausman and Rapson, 2018, p. 549)

1. Plot the raw data and residuals (after removing confounders or trend). With varying polynomial and local linear controls, inconsistent results can be a sign of time-varying treatment effects.
2. Using global polynomial, you could overfit, then show polynomial with different order and alternative local linear bandwidths. If the results are consistent, you're okay
3. Placebo Tests: estimate another RD (1) on another location or subject (that did not receive the treatment) or (2) use another date.
4. Plot RD discontinuity on continuous controls
5. Donut RD to see if avoiding the selection close to the cutoff would yield better results (Barreca et al., 2011)
6. Test for auto-regression (using only pre-treatment data). If there is evidence for autoregression, include the lagged dependent variable
7. Augmented local linear (no need to use global polynomial and avoid overfitting)
   1. Use full sample to exclude the effect of important predictors
   2. Estimate the conditioned second stage on a smaller sample bandwidth

Examples from (Hausman and Rapson, 2018, p. 534) in

econ

- (Davis, 2008): Air quality
- (Auffhammer and Kellogg, 2011): Air quality
- (Chen et al., 2018): Air quality
- (De Paola et al., 2013): car accidents
- (Gallego et al., 2013): air quality
- (Bento et al., 2014): Traffic
- (Anderson, 2014): Traffic

- (Burger et al., 2014): Car accidents
- (Brodeur et al., 2021): Covid19 lock-downs on well-being

marketing

- (Busse et al., 2006, Busse et al. (2013)): Vehicle prices
- (Chen et al., 2009a): Customer Satisfaction
- (Busse et al., 2010): Vehicle prices
- (Davis and Kahn, 2010): vehicle prices

24.10 Evaluation of an RD

- Evidence for (either formal tests or graphs)
  - Treatment and outcomes change discontinuously at the cutoff, while other variables and pre-treatment outcomes do not.
  - No manipulation of the assignment variable.
- Results are robust to various functional forms of the forcing variable
- Is there any other (unobserved) confound that could cause the discontinuous change at the cutoff (i.e., multiple forcing variables / bundling of institutions)?
- External Validity: How likely the result at the cutoff will generalize?

General Model

$$Y_i = \beta_0 + f(x_i)\beta_1 + [I(x_i \geq c)]\beta_2 + \epsilon_i$$

where $f(x_i)$ is any functional form of x_i

Simple case

When $f(x_i) = x_i$ (linear function)

$$Y_i = \beta_0 + x_i\beta_1 + [I(x_i \geq c)]\beta_2 + \epsilon_i$$

RD gives you β_2 (causal effect) of X on Y at the cutoff point

In practice, everyone does

$$Y_i = \alpha_0 + f(x)\alpha_1 + [I(x_i \geq c)]\alpha_2 + [f(x_i) \times [I(x_i \geq c)]\alpha_3 + u_i$$

where we estimate different slope on different sides of the line

and if you estimate α_3 to be no different from 0 then we return to the simple case

Notes:

- Sparse data can make α_3 large differential effect
- People are very skeptical when you have complex $f(x_i)$, usual simple function forms (e.g., linear, squared term, etc.) should be good. However, if you still insist, then **non-parametric estimation** can be your best bet.

Bandwidth of c (window)

- Closer to c can give you lower bias, but also efficiency
- Wider c can increase bias, but higher efficiency.
- Optimal bandwidth is very controversial, but usually we have to do it in the appendix for research article anyway.
- We can either
  - drop observations outside of bandwidth or
  - weight depends on how far and close to c

24.11 Applications

Examples in marketing:

- (Narayanan and Kalyanam, 2015)
- (Hartmann et al., 2011): nonparametric estimation and guide to identifying causal marketing mix effects

Packages in R (see (Thoemmes et al., 2017) for detailed comparisons): all can handle both sharp and fuzzy RD

- `rdd`
- `rdrobust` estimation, inference and plot
- `rddensity` discontinuity in density tests (Sorting/Bunching/Manipulation) using local polynomials and binomial test
- `rdlocrand` covariate balance, binomial tests, window selection
- `rdmulti` multiple cutoffs and multiple scores
- `rdpower` power, sample selection
- `rddtools`

Package	rdd	rdrobust	rddtools
Coefficient estimator bandwidth selectors	Local linear regression (Imbens and Kalyanaraman, 2012)	local polynomial regression (Calonico et al., 2020) (Imbens and Kalyanaraman, 2012) (Calonico et al., 2014)	local polynomial regression (Imbens and Kalyanaraman, 2012)
Kernel functions	Epanechnikov Gaussian	Epanechnikov	Gaussian
• Triangular			
• Rectangular			
Bias Correction		Local polynomial regression	
Covariate options	Include	Include	Include Residuals
Assumptions testing	McCrary sorting		McCrary sorting Equality of covariates distribution and mean

based on table 1 (Thoemmes et al., 2017) (p. 347)

24.11.1 Example 1

Example by Leihua Ye

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + u_i$$

$$X_i = \begin{cases} 1, W_i \geq c \\ 0, W_i < c \end{cases}$$

```
#cutoff point = 3.5
GPA <- runif(1000, 0, 4)
future_success <- 10 + 2 * GPA + 10 * (GPA >= 3.5) + rnorm(1000)
#install and load the package 'rddtools'
#install.packages("rddtools")
library(rddtools)
data <- rdd_data(future_success, GPA, cutpoint = 3.5)
```

```r
# plot the dataset
plot(
    data,
    col =  "red",
    cex = 0.1,
    xlab =  "GPA",
    ylab =  "future_success"
)
```

```r
# estimate the sharp RDD model
rdd_mod <- rdd_reg_lm(rdd_object = data, slope =  "same")
summary(rdd_mod)
#>
#> Call:
#> lm(formula = y ~ ., data = dat_step1, weights = weights)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -2.90364 -0.70348  0.00278  0.66828  3.00603
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 16.90704    0.06637  254.75   <2e-16 ***
#> D           10.09058    0.11063   91.21   <2e-16 ***
#> x            1.97078    0.03281   60.06   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#>
#> Residual standard error: 0.9908 on 997 degrees of freedom
#> Multiple R-squared:  0.9654, Adjusted R-squared:  0.9654
#> F-statistic: 1.392e+04 on 2 and 997 DF,  p-value: < 2.2e-16
```

```
# plot the RDD model along with binned observations
plot(
    rdd_mod,
    cex = 0.1,
    col =  "red",
    xlab =  "GPA",
    ylab =  "future_success"
)
```

24.11.2 Example 2

Bowblis and Smith (2021)

Occupational licensing can either increase or decrease market efficiency:

- More information means more efficiency
- Increased entry barriers (i.e., friction) increase efficiency

Components of RD

- Running variable
- Cutoff: 120 beds or above
- Treatment: you have to have the treatment before the cutoff point.

Under OLS

$$Y_i = \alpha_0 + X_i\alpha_1 + LW_i\alpha_2 + \epsilon_i$$

where

- LW_i Licensed/certified workers (in fraction format for each center).
- Y_i = Quality of service

Bias in α_2

- Mitigation-based: terrible quality can lead to more hiring, which negatively bias α_2
- Preference-based: places that have higher quality staff want to keep high quality staffs.

Under RD

$$\begin{aligned} Y_{ist} = \beta_0 &+ [I(Bed \geq 121)_{ist}]\beta_1 + f(Size_{ist})\beta_2 \\ &+ [f(Size_{ist}) \times I(Bed \geq 121)_{ist}]\beta_3 \\ &+ X_{it}\delta + \gamma_s + \theta_t + \epsilon_{ist} \end{aligned}$$

where

- s = state
- t = year
- i = hospital

This RD is fuzzy

- If right near the threshold (bandwidth), we have states with different sorting (i.e., non-random), then we need the fixed-effect for state s. But then your RD assumption wrong anyway, then you won't do it in the first place
- Technically, we could also run the fixed-effect regression, but because it's lower in the causal inference hierarchy. Hence, we don't do it.
- Moreover, in the RD framework, we don't include t before treatment (but in the FE we have to include before and after)
- If we include π_i for each hospital, then we don't have variation in the causal estimates (because hardly any hospital changes their bed size in the panel)
- When you have β_1 as the intent to treat (because the treatment effect does not coincide with the intent to treat)

- You cannot take those fuzzy cases out, because it will introduce the selection bias.
- Note that we cannot drop cases based on behavioral choice (because we will exclude non-compliers), but we can drop when we have particular behaviors ((e.g., people like round numbers).

Thus, we have to use Instrument variable 33.1.3.1

Stage 1:

$$\begin{aligned} QSW_{ist} = \alpha_0 &+ [I(Bed \geq 121)_{ist}]\alpha_1 + f(Size_{ist})\alpha_2 \\ &+ [f(Size_{ist}) \times I(Bed \geq 121)_{ist}]\alpha_3 \\ &+ X_{it}\delta + \gamma_s + \theta_t + \epsilon_{ist} \end{aligned}$$

(Note: you should have different fixed effects and error term - $\delta, \gamma_s, \theta_t, \epsilon_{ist}$ from the first equation, but I ran out of Greek letters)

Stage 2:

$$\begin{aligned} Y_{ist} = \gamma_0 &+ \gamma_1 Q\hat{W}S_{ist} + f(Size_{ist})\delta_2 \\ &+ [f(Size_{ist}) \times I(Bed \geq 121)]\delta_3 \\ &+ X_{it}\lambda + \eta_s + \tau_t + u_{ist} \end{aligned}$$

- The bigger the jump (discontinuity), the more similar the 2 coefficients ($\gamma_1 \approx \beta_1$) where γ_1 is the average treatment effect (of exposing to the policy)
- β_1 will always be closer to 0 than γ_1
- Figure 1 shows bunching at every 5 units cutoff, but 120 is still out there.
- If we have manipulable bunching, there should be decrease at 130
- Since we have limited number of mass points (at the round numbers), we should clustered standard errors by the mass point

24.11.3 Example 3

Replication of (Carpenter and Dobkin, 2009) by Philipp Leppert, dataset from here

24.11.4 Example 4

For a detailed application, see (Thoemmes et al., 2017) where they use `rdd`, `rdrobust`, `rddtools`

Chapter 25

Synthetic Difference-in-Differences

by (Arkhangelsky et al., 2021)

also known as weighted double-differencing estimators

- Setting: Researchers use panel data to study effects of policy changes.
  - Panel data: repeated observations across time for various units.
  - Some units exposed to policy at different times than others.
- Policy changes often aren't random across units or time.
  - Challenge: Observed covariates might not lead to credible conclusions of no confounding (Imbens and Rubin, 2015)
- To estimate the effects, either
  - Difference-in-differences (DID) method widely used in applied economics.
  - Synthetic Control (SC) methods offer alternative approach for comparative case studies.
- Difference between DID and SC:
  - DID: used with many policy-exposed units; relies on "parallel trends" assumption.
  - SC: used with few policy-exposed units; compensates lack of parallel trends by reweighting units based on pre-exposure trends.
- **New proposition**: Synthetic Difference in Differences (SDID).
  - Combines features of DID and SC.

  - Reweights and matches pre-exposure trends (similar to SC).
  - Invariant to additive unit-level shifts, valid for large-panel inference (like DID).
- Attractive features:
  - SDID provides consistent and asymptotically normal estimates.
  - SDID performs on par with or better than DID in traditional DID settings.
    * where DID can only handle completely random treatment assignment, SDID can handle cases where treatment assignment is correlated with some time or unit latent factors.
  - Similarly, SDID is as good as or better than SC in traditional SC settings.
  - Uniformly random treatment assignment results in unbiased outcomes for all methods, but SDID is more precise.
  - SDID reduces bias effectively for non-uniformly random assignments.
  - SDID's double robustness is akin to the augmented inverse probability weighting estimator (Ben-Michael et al., 2021, Scharfstein et al. (1999)).
  - Very much similar to augmented SC estimator by (Ben-Michael et al., 2021; Arkhangelsky et al., 2021, p. 4112)

Ideal case to use SDID estimator is when

- $N_{ctr} \approx T_{pre}$
- Small T_{post}
- $N_{tr} < \sqrt{N_{ctr}}$

Applications in marketing:

- Lambrecht et al. (2024): TV ads on online browsing and sales.
- Keller et al. (2024): soda tax on marketing effectiveness.

25.1 Understanding

Consider a traditional time-series cross-sectional data

Let Y_{it} denote the outcome for unit i in period t

A balanced panel of N units and T time periods

- $W_{it} \in \{0, 1\}$ is the binary treatment
- N_c never-treated units (control)
- N_t treated units after time T_{pre}

Steps:

1. Find unit weights $\hat{w}^{sdid}$ such that $\sum_{i=1}^{N_c} \hat{w}_i^{sdid} Y_{it} \approx N_t^{-1} \sum_{i=N_c+1}^{N} Y_{it} \forall t = 1, \dots, T_{pre}$ (i.e., pre-treatment trends in outcome of the treated similar to those of control units) (similar to SC).
2. Find time weights $\hat{\lambda}_t$ such that we have a balanced window (i.e., posttreatment outcomes for control units differ consistently from their weighted average pretreatment outcomes).
3. Estimate the average causal effect of treatment

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau,\mu,\alpha,\beta} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{w}_i^{sdid} \hat{\lambda}_t^{sdid}\}$$

Better than DiD estimator because τ^{did} does not consider time or unit weights

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau,\mu,\alpha,\beta} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2\}$$

Better than SC estimator because τ^{sc} lacks unit fixed effete and time weights

$$(\hat{\tau}^{sc}, \hat{\mu}, \hat{\beta}) = \arg \min_{\tau,\mu,\beta} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \beta_t - W_{it}\tau)^2 \hat{w}_i^{sdid}\}$$

	DID	**SC**	**SDID**
Primary Assumption	Absence of intervention leads to parallel evolution across states.	Reweights unexposed states to match pre-intervention outcomes of treated state.	Reweights control units to ensure a parallel time trend with the treated pre-intervention trend.
Reliability Concern	Can be unreliable when pre-intervention trends aren't parallel.	Accounts for non-parallel pre-intervention trends by reweighting.	Uses reweighting to adjust for non-parallel pre-intervention trends.

	DID	SC	SDID
Treatment of Time Periods	All pre-treatment periods are given equal weight.	Doesn't specifically emphasize equal weight for pre-treatment periods.	Focuses only on a subset of pre-intervention time periods, selected based on historical outcomes.
Goal with Reweighting	N/A (doesn't use reweighting).	To match treated state as closely as possible before the intervention.	Make trends of control units parallel (not necessarily identical) to the treated pre-intervention.

Alternatively, think of our parameter of interest as:

$$\hat{\tau} = \hat{\delta}_t - \sum_{i=1}^{N_c} \hat{w}_i \hat{\delta}_i$$

where $\hat{\delta}_t = \frac{1}{N_t} \sum_{i=N_c+1}^{N} \hat{\delta}_i$

Method	Sample Weight	Adjusted outcomes ($\hat{\delta}_i$)	Interpretation
SC	$\hat{w}^{sc} = \min_{w \in R} l_{unit}(w)$	$\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it}$	Unweighted treatment period averages
DID	$\hat{w}_i^{did} = N_c^{-1}$	$\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \frac{1}{T_{pre}} \sum_{t=1}^{T_{pre}} Y_{it}$	Unweighted differences between average treatment period and pretreatment outcome
SDID	$(\hat{w}_0, \hat{w}^{sdid}) = \min l_{unit}(w_0, w)$	$\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} Y_{it}$	Weighted differences between average treatment period and pretreatment outcome

- The SDID estimator uses weights:
  - Makes two-way fixed effect regression "local."
  - Emphasizes units similar in their past to treated units.
  - Prioritizes periods resembling treated periods.
- Benefits of this localization:
  1. **Robustness**: Using similar units and periods boosts estimator's robustness.

2. **Improved Precision**: Weights can eliminate predictable outcome components.
   - The SEs of SDID are smaller than those of SC and DID
   - Caveat: If there's minor systematic heterogeneity in outcomes, unequal weighting might reduce precision compared to standard DID.

- Weight Design:
  - **Unit Weights**: Makes average outcome for treated units roughly parallel to the weighted average for control units.
  - **Time Weights**: Ensures posttreatment outcomes for control units differ consistently from their weighted average pretreatment outcomes.
- Weights enhance DID's plausibility:
  - Raw data often lacks parallel time trends for treated/control units.
  - Similar techniques (e.g., adjusting for covariates or selecting specific time periods) were used before (Callaway and Sant'Anna, 2021).
  - SDID automates this process, applying a similar logic to weight both units and time periods.
- Time Weights in SDID:
  - Removes bias and boosts precision (i.e., minimizes the influence of time periods vastly different from posttreatment periods).
- Argument for Unit Fixed Effects:
  1. **Flexibility**: Increases model flexibility and thereby bolsters robustness.
  2. **Enhanced Precision**: Unit fixed effects explain a significant portion of outcome variation.
- SC Weighting & Unit Fixed Effects:
  - Under certain conditions, SC weighting can inherently account for unit fixed effects.
    - For example, when the weighted average outcome for control units in pretreatment is the same as that of the treated units. (unlikely in reality)
  - The use of unit fixed effect in synthetic control regression (i.e., synthetic control with intercept) was proposed before in Doudchenko and Imbens (2016) and Ferman and Pinto (2021) (called DIFP)

More details on application

1. Choose unit weights

- Regularization Parameter:
  - Equal to the size of a typical one-period outcome change for control units in the pre-period, then multiplied by a scaling factor (Arkhangelsky et al., 2021, p. 4092).
- Relation to SC Weights:
  - SDID weights are similar to those used in (Abadie et al., 2010) except two distinctions:
    1. Inclusion of an Intercept Term:
       * The weights in SynthDiD do not necessarily make the control pre-trends perfectly match the treated trends, just make them parallel.
       * This flexibility comes from the use of unit fixed effects, which can absorb any consistent differences between units.
    2. Regularization Penalty:
       * Adopted from Doudchenko and Imbens (2016) .
       * Enhances the dispersion and ensures the uniqueness of the weights.
  - DID weights are identical to those used in (Abadie et al., 2010) without intercept and regularization penalty and 1 treated unit.

2. Choose time weights

- Also include an intercept term, but no regularization (because correlated observations within time periods for the same unit is plausible, but not across units within the same period).

Note: To account for time-varying variables in the weights, one can use the residuals of the regression of the observed outcome on these time-varying variables, instead of the observed outcomes themselves ($Y_{it}^{res} = Y_{it} - X_{it}\hat{\beta}$, where $\hat{\beta}$ come from $Y = \beta X_{it}$).

The SDID method can account for systematic effects, often referred to as unit effects or unit heterogeneity, which influence treatment assignment (i.e., when treatment assignment is correlated with these systematic effects). Consequently, it provides unbiased estimates, especially valuable when there's a suspicion that the treatment might be influenced by persistent, unit-specific attributes.

Even in cases where we have completely random assignment, SDID, DiD, and SC are unbiased, but SynthDiD has the smallest SE.

25.2 Application

SDID Algorithm

1. Compute regularization parameter ζ

$$\zeta = (N_t T_{post})^{1/4} \hat{\sigma}$$

where

$$\hat{\sigma}^2 = \frac{1}{N_c(T_{pre}-1)} \sum_{i=1}^{N_c} \sum_{t=1}^{T_{re}-1} (\Delta_{it} - \hat{\Delta})^2$$

- $\Delta_{it} = Y_{i(t+1)} - Y_{it}$
- $\hat{\Delta} = \frac{1}{N_c(T_{pre}-1)} \sum_{i=1}^{N_c} \sum_{t=1}^{T_{pre}-1} \Delta_{it}$

2. Compute unit weights $\hat{w}^{sdid}$

$$(\hat{w}_0, \hat{w}^{sidid}) = \arg \min_{w_0 \in R, w \in \Omega} l_{unit}(w_0, w)$$

where

- $l_{unit}(w_0, w) = \sum_{t=1}^{T_{pre}} (w_0 + \sum_{i=1}^{N_c} w_i Y_{it} - \frac{1}{N_t} \sum_{i=N_c+1}^{N} Y_{it})^2 + \zeta^2 T_{pre} ||w||_2^2$
- $\Omega = \{w \in R_+^N : \sum_{i=1}^{N_c} w_i = 1, w_i = N_t^{-1} \forall i = N_c + 1, \dots, N\}$

3. Compute time weights $\hat{\lambda}^{sdid}$

$$(\hat{\lambda}_0, \hat{\lambda}^{sdid}) = \arg \min_{\lambda_0 \in R, \lambda \in \Lambda} l_{time}(\lambda_0, \lambda)$$

where

- $l_{time}(\lambda_0, \lambda) = \sum_{i=1}^{N_c} (\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it})^2$
- $\Lambda = \{\lambda \in R_+^T : \sum_{t=1}^{T_{pre}} \lambda_t = 1, \lambda_t = T_{post}^{-1} \forall t = T_{pre} + 1, \dots, T\}$

4. Compute the SDID estimator

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau, \mu, \alpha, \beta} \{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{w}_i^{sdid} \hat{\lambda}_t^{sdid}$$

SE Estimation

- Under certain assumptions (errors, samples, and interaction properties between time and unit fixed effects) detailed in (Arkhangelsky et al., 2019, p. 4107), SDID is asymptotically normal and zero-centered
- Using its asymptotic variance, conventional confidence intervals can be applied to SDID.

$$\tau \in \hat{\tau}^{sdid} \pm z_{\alpha/2}\sqrt{\hat{V}_\tau}$$

- There are 3 approaches for variance estimation in confidence intervals:
  1. **Clustered Bootstrap (Efron, 1992):**
     - Independently resample units.
     - Advantages: Simple to use; robust performance in large panels due to natural approach to inference with panel data where observations of the same unit might be correlated.
     - Disadvantage: Computationally expensive.
  2. **Jackknife (Miller, 1974):**
     - Applied to weighted SDID regression with fixed weights.
     - Generally conservative and precise when treated and control units are sufficiently similar.
     - Not recommended for some methods, like the SC estimator, due to potential biases.
     - Appropriate for jackknifing DID without random weights.
  3. **Placebo Variance Estimation:**
     - Can used in cases with only one treated unit or large panels.
     - Placebo evaluations swap out the treated unit for untreated ones to estimate noise.
     - Relies on homoskedasticity across units.
     - Depends on homoskedasticity across units. It hinges on the empirical distribution of residuals from placebo estimators on control units.
     - The validity of the placebo method hinges on consistent noise distribution across units. One treated unit makes nonparametric variance estimation difficult, necessitating homoskedasticity for feasible inference. Detailed analysis available in Conley and Taber (2011).

All algorithms are from Arkhangelsky et al. (2021), p. 4109:

Bootstrap Variance Estimation

1. For each b from $1 \to B$:
   - Sample N rows from $(\mathbf{Y}, \mathbf{W})$ to get $(\mathbf{Y}^{(b)}, \mathbf{W}^{(b)})$ with replacement.
   - If the sample lacks treated or control units, resample.
   - Calculate $\tau^{(b)}$ using $(\mathbf{Y}^{(b)}, \mathbf{W}^{(b)})$.
2. Calculate variance: $\hat{V}_\tau = \frac{1}{B}\sum_{b=1}^{B}(\hat{\tau}^b - \frac{1}{B}\sum_{b=1}^{B}\hat{\tau}^b)^2$

Jackknife Variance Estimation

1. For each i from $1 \to N$:
   1. Calculate $\hat{\tau}^{(-i)}$: $\arg\min_{\tau,\{\alpha_j,\beta_t\}} \sum_{j\neq,i,t}(\mathbf{Y}_{jt} - \alpha_j - \beta_t - \tau\mathbf{W}_{it})^2\hat{w}_j\hat{\lambda}_t$
2. Calculate: $\hat{V}_\tau = (N-1)N^{-1}\sum_{i=1}^{N}(\hat{\tau}^{(-i)} - \hat{\tau})^2$

Placebo Variance Estimation

1. For each b from $1 \to B$
   1. Sample N_t out of N_c without replacement to get the "placebo" treatment
   2. Construct a placebo treatment matrix $\mathbf{W}_c^b$ for the controls
   3. Calculate $\hat{\tau}$ based on $(\mathbf{Y}_c, \mathbf{W}_c^b)$
2. Calculate $\hat{V}_\tau = \frac{1}{B}\sum_{b=1}^{B}(\hat{\tau}^b - \frac{1}{B}\sum_{b=1}^{B}\hat{\tau}^b)^2$

25.2.1 Block Treatment

Code provided by the `synthdid` package

```
library(synthdid)
library(tidyverse)

# Estimate the effect of California Proposition 99 on cigarette consumption
data('california_prop99')

setup = synthdid::panel.matrices(synthdid::california_prop99)

tau.hat = synthdid::synthdid_estimate(setup$Y, setup$N0, setup$T0)

# se = sqrt(vcov(tau.hat, method = 'placebo'))

plot(tau.hat) + causalverse::ama_theme()
```

```
setup = synthdid::panel.matrices(synthdid::california_prop99)

# Run for specific estimators
results_selected = causalverse::panel_estimate(setup,
                                               selected_estimators = c("synthdid", "dic

results_selected
#> $synthdid
#> $synthdid$estimate
#> synthdid: -15.604 +- NA. Effective N0/N0 = 16.4/38~0.4. Effective T0/T0 = 2.8/19~0.
#>
#> $synthdid$std.error
#> [1] 10.05324
#>
#>
#> $did
#> $did$estimate
#> synthdid: -27.349 +- NA. Effective N0/N0 = 38.0/38~1.0. Effective T0/T0 = 19.0/19~1
#>
#> $did$std.error
#> [1] 15.81479
#>
#>
#> $sc
#> $sc$estimate
#> synthdid: -19.620 +- NA. Effective N0/N0 = 3.8/38~0.1. Effective T0/T0 = Inf/19~Inf
#>
```

```
#> $sc$std.error
#> [1] 11.16422

# to access more details in the estimate object
summary(results_selected$did$estimate)
#> $estimate
#> [1] -27.34911
#>
#> $se
#>      [,1]
#> [1,]   NA
#>
#> $controls
#>                 estimate 1
#> Wyoming              0.026
#> Wisconsin            0.026
#> West Virginia        0.026
#> Virginia             0.026
#> Vermont              0.026
#> Utah                 0.026
#> Texas                0.026
#> Tennessee            0.026
#> South Dakota         0.026
#> South Carolina       0.026
#> Rhode Island         0.026
#> Pennsylvania         0.026
#> Oklahoma             0.026
#> Ohio                 0.026
#> North Dakota         0.026
#> North Carolina       0.026
#> New Mexico           0.026
#> New Hampshire        0.026
#> Nevada               0.026
#> Nebraska             0.026
#> Montana              0.026
#> Missouri             0.026
#> Mississippi          0.026
#> Minnesota            0.026
#> Maine                0.026
#> Louisiana            0.026
#> Kentucky             0.026
#> Kansas               0.026
#> Iowa                 0.026
#> Indiana              0.026
#> Illinois             0.026
```

```
#> Idaho                0.026
#> Georgia              0.026
#> Delaware             0.026
#> Connecticut          0.026
#>
#> $periods
#>      estimate 1
#> 1988      0.053
#> 1987      0.053
#> 1986      0.053
#> 1985      0.053
#> 1984      0.053
#> 1983      0.053
#> 1982      0.053
#> 1981      0.053
#> 1980      0.053
#> 1979      0.053
#> 1978      0.053
#> 1977      0.053
#> 1976      0.053
#> 1975      0.053
#> 1974      0.053
#> 1973      0.053
#> 1972      0.053
#> 1971      0.053
#>
#> $dimensions
#>           N1           N0 N0.effective           T1           T0 T0.effective
#>            1           38           38           12           19           19
```

```
causalverse::process_panel_estimate(results_selected)
#>     Method Estimate    SE
#> 1 SYNTHDID   -15.60 10.05
#> 2      DID   -27.35 15.81
#> 3       SC   -19.62 11.16
```

25.2.2 Staggered Adoption

To apply to staggered adoption settings using the SDID estimator (see examples in Arkhangelsky et al. (2021), p. 4115 similar to Ben-Michael et al. (2022)), we can:

1. Apply the SDID estimator repeatedly, once for every adoption date.
2. Using Ben-Michael et al. (2022) 's method, form matrices for each adoption date. Apply SDID and average based on treated unit/time-period

fractions.

3. Create multiple samples by splitting the data up by time periods. Each sample should have a consistent adoption date.

For a formal note on this special case, see Porreca (2022). It compares the outcomes from using SynthDiD with those from other estimators:

- Two-Way Fixed Effects (TWFE),
- The group time average treatment effect estimator from Callaway and Sant'Anna (2021),
- The partially pooled synthetic control method estimator from Ben-Michael et al. (2021), in a staggered treatment adoption context.
- The findings reveal that SynthDiD produces a different estimate of the average treatment effect compared to the other methods.
  - Simulation results suggest that these differences could be due to the SynthDiD's data generating process assumption (a latent factor model) aligning more closely with the actual data than the additive fixed effects model assumed by traditional DiD methods.

To explore heterogeneity of treatment effect, we can do subgroup analysis (Berman and Israeli, 2022, p. 1092)

Method	**Advantages**	**Disadvantages**	**Procedure**
Split Data into Subsets	Compares treated units to control units within the same subgroup.	Each subset uses a different synthetic control, making it challenging to compare effects across subgroups.	1. Split the data into separate subsets for each subgroup. 2. Compute synthetic DID effects for each subset.

Method	Advantages	Disadvantages	Procedure
Control Group Comprising All Non-adopters	Control weights match pretrends well for each treated subgroup.	Each control unit receives a different weight for each treatment subgroup, making it difficult to compare results due to varying synthetic controls.	1. Use a control group consisting of all non-adopters in each balanced panel cohort analysis. 2. Switch treatment units to the subgroup being analyzed. 3. Perform `synthdid` analysis.
Use All Data to Estimate Synthetic Control Weights **(recommend)**	All units have the same synthetic control.	Pretrend match may not be as accurate since it aims to match the average outcome of all treated units, not just a specific subgroup.	1. Use all the data to estimate the synthetic DID control weights. 2. Compute treatment effects using only the treated subgroup units as the treatment units.

```
library(tidyverse)
df <- fixest::base_stagg |>
   dplyr::mutate(treatvar = if_else(time_to_treatment >= 0, 1, 0)) |>
   dplyr::mutate(treatvar = as.integer(if_else(year_treated > (5 + 2), 0, treatvar)))
```

```r
est <- causalverse::synthdid_est_ate(
  data               = df,
  adoption_cohorts   = 5:7,
  lags               = 2,
  leads              = 2,
  time_var           = "year",
  unit_id_var        = "id",
  treated_period_var = "year_treated",
  treat_stat_var     = "treatvar",
  outcome_var        = "y"
)
#> adoption_cohort: 5
#> Treated units: 5 Control units: 65
#> adoption_cohort: 6
#> Treated units: 5 Control units: 60
#> adoption_cohort: 7
#> Treated units: 5 Control units: 55

data.frame(
    Period = names(est$TE_mean_w),
    ATE    = est$TE_mean_w,
    SE     = est$SE_mean_w
) |>
    causalverse::nice_tab()
#>    Period   ATE   SE
#> 1      -2 -0.05 0.22
#> 2      -1  0.05 0.22
#> 3       0 -5.07 0.80
#> 4       1 -4.68 0.51
#> 5       2 -3.70 0.79
#> 6 cumul.0 -5.07 0.80
#> 7 cumul.1 -4.87 0.55
#> 8 cumul.2 -4.48 0.53


causalverse::synthdid_plot_ate(est)
```

```
est_sub <- causalverse::synthdid_est_ate(
  data               = df,
  adoption_cohorts   = 5:7,
  lags               = 2,
  leads              = 2,
  time_var           = "year",
  unit_id_var        = "id",
  treated_period_var = "year_treated",
  treat_stat_var     = "treatvar",
  outcome_var        = "y",
  # a vector of subgroup id (from unit id)
  subgroup           =  c(
    # some are treated
    "11", "30", "49" ,
    # some are control within this period
    "20", "25", "21")
)
#> adoption_cohort: 5
#> Treated units: 3 Control units: 65
#> adoption_cohort: 6
#> Treated units: 0 Control units: 60
#> adoption_cohort: 7
#> Treated units: 0 Control units: 55

data.frame(
    Period = names(est_sub$TE_mean_w),
    ATE = est_sub$TE_mean_w,
```

```
    SE = est_sub$SE_mean_w
) |>
    causalverse::nice_tab()
#>    Period   ATE   SE
#> 1      -2  0.32 0.44
#> 2      -1 -0.32 0.44
#> 3       0 -4.29 1.68
#> 4       1 -4.00 1.52
#> 5       2 -3.44 2.90
#> 6 cumul.0 -4.29 1.68
#> 7 cumul.1 -4.14 1.52
#> 8 cumul.2 -3.91 1.82

causalverse::synthdid_plot_ate(est)
```

Plot different estimators

```
library(causalverse)
methods <- c("synthdid", "did", "sc", "sc_ridge", "difp", "difp_ridge")

estimates <- lapply(methods, function(method) {
  synthdid_est_ate(
    data               = df,
    adoption_cohorts   = 5:7,
    lags               = 2,
    leads              = 2,
    time_var           = "year",
```

```
    unit_id_var        = "id",
    treated_period_var = "year_treated",
    treat_stat_var     = "treatvar",
    outcome_var        = "y",
    method = method
  )
})

plots <- lapply(seq_along(estimates), function(i) {
  causalverse::synthdid_plot_ate(estimates[[i]],
                                 title = methods[i],
                                 theme = causalverse::ama_theme(base_size = 6))
})

gridExtra::grid.arrange(grobs = plots, ncol = 2)
```

Chapter 26

Difference-in-differences

List of packages

Examples in marketing

- (Liaukonyte et al., 2015): TV ad on online shopping
- (Wang et al., 2018): political ad source and message tone on vote shares and turnout using discontinuities in the level of political ads at the borders
- (Datta et al., 2018): streaming service on total music consumption using timing of users adoption of a music streaming service
- (Janakiraman et al., 2018): data breach announcement affect customer spending using timing of data breach and variation whether customer info was breached in that event
- (Israeli, 2018): digital monitoring and enforcement on violations using enforcement of min ad price policies
- (Ramani and Srinivasan, 2019): firms respond to foreign direct investment liberalization using India's reform in 1991.
- (Pattabhiramaiah et al., 2019): paywall affects readership
- (Akca and Rao, 2020): aggregators for airlines business effect
- (Lim et al., 2020): nutritional labels on nutritional quality for other brands in a category using variation in timing of adoption of nutritional labels across categories
- (Guo et al., 2020): payment disclosure laws effect on physician prescription behavior using Timing of the Massachusetts open payment law as the exogenous shock
- (He et al., 2022): using Amazon policy change to examine the causal impact of fake reviews on sales, average ratings.
- (Peukert et al., 2022): using European General data protection Regulation, examine the impact of policy change on website usage.

Examples in econ:

- (Rosenzweig and Wolpin, 2000)
- (Angrist and Krueger, 2001)
- (Fuchs-Schündeln and Hassan, 2016): macro

Show the mechanism via

- Mediation Under DiD analysis: see (Habel et al., 2021)
- Moderation analysis: see (Goldfarb and Tucker, 2011)

Steps to trust DID:

1. Visualize the treatment rollout (e.g., `panelView`).
2. Document the number of treated units in each cohort (e.g., control and treated).
3. Visualize the trajectory of average outcomes across cohorts (if you have multiple periods).
4. Parallel Trends Conduct an event-study analysis with and without covariates.
5. For the case with covariates, check for overlap in covariates between treated and control groups to ensure control group validity (e.g., if the control is relatively small than the treated group, you might not have overlap, and you have to make extrapolation).
6. Conduct sensitivity analysis for parallel trend violations (e.g., `honestDiD`).

26.1 Visualization

```
library(panelView)
library(fixest)
library(tidyverse)
base_stagg <- fixest::base_stagg |>
    # treatment status
    dplyr::mutate(treat_stat = dplyr::if_else(time_to_treatment < 0, 0, 1)) |>
    select(id, year, treat_stat, y)

head(base_stagg)
#>   id year treat_stat           y
#> 2 90    1          0  0.01722971
#> 3 89    1          0 -4.58084528
#> 4 88    1          0  2.73817174
#> 5 87    1          0 -0.65103066
#> 6 86    1          0 -5.33381664
#> 7 85    1          0  0.49562631
```

```r
panelView::panelview(
    y ~ treat_stat,
    data = base_stagg,
    index = c("id", "year"),
    xlab = "Year",
    ylab = "Unit",
    display.all = F,
    gridOff = T,
    by.timing = T
)
```

```r
# alternatively specification
panelView::panelview(
    Y = "y",
    D = "treat_stat",
    data = base_stagg,
    index = c("id", "year"),
    xlab = "Year",
    ylab = "Unit",
    display.all = F,
    gridOff = T,
    by.timing = T
)
```

```r
# Average outcomes for each cohort
panelView::panelview(
    data = base_stagg,
    Y = "y",
    D = "treat_stat",
    index = c("id", "year"),
    by.timing = T,
    display.all = F,
    type = "outcome",
    by.cohort = T
)
#> Number of unique treatment histories: 10
```

26.2 Simple Dif-n-dif

- A tool developed intuitively to study "natural experiment", but its uses are much broader.
- Fixed Effects Estimator is the foundation for DID
- Why is dif-in-dif attractive? Identification strategy: Inter-temporal variation between groups
  - **Cross-sectional estimator** helps avoid omitted (unobserved) **common trends**
  - **Time-series estimator** helps overcome omitted (unobserved) **cross-sectional differences**

Consider

- $D_i = 1$ treatment group
- $D_i = 0$ control group
- $T = 1$ After the treatment
- $T = 0$ Before the treatment

	After (T = 1)	Before (T = 0)
Treated $D_i = 1$	$E[Y_{1i}(1)\|D_i = 1]$	$E[Y_{0i}(0)\|D)i = 1]$
Control $D_i = 0$	$E[Y_{0i}(1)\|D_i = 0]$	$E[Y_{0i}(0)\|D_i = 0]$

missing $E[Y_{0i}(1)|D=1]$

The Average Treatment Effect on Treated (ATT)

$$\begin{aligned} E[Y_1(1) - Y_0(1)|D=1] = &\{E[Y(1)|D=1] - E[Y(1)|D=0]\} \\ &- \{E[Y(0)|D=1] - E[Y(0)|D=0]\} \end{aligned}$$

More elaboration:

- For the treatment group, we isolate the difference between being treated and not being treated. If the untreated group would have been affected in a different way, the DiD design and estimate would tell us nothing.
- Alternatively, because we can't observe treatment variation in the control group, we can't say anything about the treatment effect on this group.

Extension

1. **More than 2 groups** (multiple treatments and multiple controls), and more than 2 period (pre and post)

$$Y_{igt} = \alpha_g + \gamma_t + \beta I_{gt} + \delta X_{igt} + \epsilon_{igt}$$

where

- α_g is the group-specific fixed effect
- γ_t = time specific fixed effect
- β = dif-in-dif effect
- I_{gt} = interaction terms (n treatment indicators x n post-treatment dummies) (capture effect heterogeneity over time)

This specification is the "two-way fixed effects DiD" - **TWFE** (i.e., 2 sets of fixed effects: group + time).

- However, if you have Staggered Dif-n-dif (i.e., treatment is applied at different times to different groups). TWFE is really bad.

2. **Long-term Effects**

To examine the dynamic treatment effects (that are not under rollout/staggered design), we can create a centered time variable,

Centered Time Variable	Period
...	
$t = -1$	2 periods before treatment period
$t = 0$	Last period right before treatment period Remember to use this period as reference group
$t = 1$	Treatment period

Centered Time Variable	Period
…	

By interacting this factor variable, we can examine the dynamic effect of treatment (i.e., whether it's fading or intensifying)

$$
\begin{aligned}
Y &= \alpha_0 + \alpha_1 Group + \alpha_2 Time \\
&+ \beta_{-T_1} Treatment + \beta_{-(T_1-1)} Treatment + \cdots + \beta_{-1} Treatment \\
&+ \beta_1 + \cdots + \beta_{T_2} Treatment
\end{aligned}
$$

where

- β_0 is used as the reference group (i.e., drop from the model)
- T_1 is the pre-treatment period
- T_2 is the post-treatment period

With more variables (i.e., interaction terms), coefficients estimates can be less precise (i.e., higher SE).

3. DiD on the relationship, not levels. Technically, we can apply DiD research design not only on variables, but also on coefficients estimates of some other regression models with before and after a policy is implemented.

Goal:

1. Pre-treatment coefficients should be non-significant $\beta_{-T_1}, \ldots, \beta_{-1} = 0$ (similar to the Placebo Test)
2. Post-treatment coefficients are expected to be significant $\beta_1, \ldots, \beta_{T_2} \neq 0$
    - You can now examine the trend in post-treatment coefficients (i.e., increasing or decreasing)

```
library(tidyverse)
library(fixest)

od <- causaldata::organ_donations %>%

    # Treatment variable
    dplyr::mutate(California = State == 'California') %>%
    # centered time variable
    dplyr::mutate(center_time = as.factor(Quarter_Num - 3))
# where 3 is the reference period precedes the treatment period

class(od$California)
#> [1] "logical"
class(od$State)
```

```
#> [1] "character"

cali <- feols(Rate ~ i(center_time, California, ref = 0) |
                  State + center_time,
              data = od)

etable(cali)
#>                                              cali
#> Dependent Var.:                              Rate
#>
#> California x center_time = -2    -0.0029 (0.0051)
#> California x center_time = -1   0.0063** (0.0023)
#> California x center_time = 1  -0.0216*** (0.0050)
#> California x center_time = 2  -0.0203*** (0.0045)
#> California x center_time = 3    -0.0222* (0.0100)
#> Fixed-Effects:                 -------------------
#> State                                         Yes
#> center_time                                   Yes
#> ____________________________ ___________________
#> S.E.: Clustered                           by: State
#> Observations                                    162
#> R2                                          0.97934
#> Within R2                                   0.00979
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

iplot(cali, pt.join = T)
```

```
coefplot(cali)
```

26.3 Notes

- Matching Methods
  - Match treatment and control based on pre-treatment observables
  - Modify SEs appropriately (Heckman et al., 1997). It's might be eas-

ier to just use the Doubly Robust DiD (Sant'Anna and Zhao, 2020) where you just need either matching or regression to work in order to identify your treatment effect

  - Whereas the group fixed effects control for the group time-invariant effects, it does not control for selection bias (i.e., certain groups are more likely to be treated than others). Hence, with these backdoor open (i.e., selection bias) between (1) propensity to be treated and (2) dynamics evolution of the outcome post-treatment, matching can potential close these backdoor.
  - Be careful when matching time-varying covariates because you might encounter "regression to the mean" problem, where pre-treatment periods can have an unusually bad or good time (that is out of the ordinary), then the post-treatment period outcome can just be an artifact of the regression to the mean (Daw and Hatfield, 2018). This problem is not of concern to time-invariant variables.
  - Matching and DiD can use pre-treatment outcomes to correct for selection bias. From real world data and simulation, (Chabé-Ferret, 2015) found that matching generally underestimates the average causal effect and gets closer to the true effect with more number of pre-treatment outcomes. When selection bias is symmetric around the treatment date, DID is still consistent when implemented symmetrically (i.e., the same number of period before and after treatment). In cases where selection bias is asymmetric, the MC simulations show that Symmetric DiD still performs better than Matching.

- It's always good to show results with and without controls because
  - If the controls are fixed within group or within time, then those should be absorbed under those fixed effects
  - If the controls are dynamic across group and across, then your parallel trends assumption is not plausible.
- Under causal inference, R^2 is not so important.

For count data, one can use the fixed-effects Poisson pseudo-maximum likelihood estimator (PPML) (Athey and Imbens, 2006, Puhani (2012)) (For applied papers, see Burtch et al. (2018) in management and He et al. (2021) in marketing). This also allows for robust standard errors under over-dispersion (Wooldridge, 1999).

- This estimator outperforms a log OLS when data have many 0s(Silva and Tenreyro, 2011), since log-OLS can produce biased estimates (O'Hara and Kotze, 2010) under heteroskedascity (Silva and Tenreyro, 2006).
- For those thinking of negative binomial with fixed effects, there isn't an estimator right now (Allison and Waterman, 2002).

For [Zero-valued Outcomes], we have to distinguish the treatment effect on the intensive (outcome: 10 to 11) vs. extensive margins (outcome: 0 to 1), and we can't readily interpret the treatment coefficient of log-transformed outcome regression as percentage change (Chen and Roth, 2023). Alternatively, we can either focus on

- **Proportional treatment effects**: $\theta_{ATT\%} = \frac{E(Y_{it}(1)|D_i=1,Post_t=1)-E(Y_{it}(0)|D_i=1,Post_t=1)}{E(Y_{it}(0)|D_i=1,Post_t=1}$ (i.e., percentage change in treated group's average post-treatment outcome). Instead of relying on the parallel trends assumption in levels, we could also rely on parallel trends assumption in ratio (Wooldridge, 2023).
  - We can use Poisson QMLE to estimate the treatment effect: $Y_{it} = \exp(\beta_0 + D_i \times \beta_1 Post_t + \beta_2 D_i + \beta_3 Post_t + X_{it})\epsilon_{it}$ and $\hat{\theta}_{ATT\%} = \exp(\hat{\beta}_1 - 1)$.
  - To examine the parallel trends assumption in ratio holds, we can also estimate a dynamic version of the Poisson QMLE: $Y_{it} = \exp(\lambda_t + \beta_2 D_i + \sum_{r \neq -1} \beta_r D_i \times (RelativeTime_t = r)$, we would expect $\exp(\hat{\beta}_r) - 1 = 0$ for $r < 0$.
  - Even if we see the plot of these coefficients are 0, we still should run sensitivity analysis (Rambachan and Roth, 2023) to examine violation of this assumption (see Prior Parallel Trends Test).
- **Log Effects with Calibrated Extensive-margin value**: due to problem with the mean value interpretation of the proportional treatment effects with outcomes that are heavy-tailed, we might be interested in the extensive margin effect. Then, we can explicit model how much weight we put on the intensive vs. extensive margin (Chen and Roth, 2023, p. 39).

1. **Proportional treatment effects**

```r
set.seed(123) # For reproducibility

n <- 500 # Number of observations per group (treated and control)
# Generating IDs for a panel setup
ID <- rep(1:n, times = 2)

# Defining groups and periods
Group <- rep(c("Control", "Treated"), each = n)
Time <- rep(c("Before", "After"), times = n)
Treatment <- ifelse(Group == "Treated", 1, 0)
Post <- ifelse(Time == "After", 1, 0)

# Step 1: Generate baseline outcomes with a zero-inflated model
lambda <- 20 # Average rate of occurrence
zero_inflation <- 0.5 # Proportion of zeros
Y_baseline <-
```

```r
    ifelse(runif(2 * n) < zero_inflation, 0, rpois(2 * n, lambda))

# Step 2: Apply DiD treatment effect on the treated group in the post-treatment period
Treatment_Effect <- Treatment * Post
Y_treatment <-
    ifelse(Treatment_Effect == 1, rpois(n, lambda = 2), 0)

# Incorporating a simple time trend, ensuring outcomes are non-negative
Time_Trend <- ifelse(Time == "After", rpois(2 * n, lambda = 1), 0)

# Step 3: Combine to get the observed outcomes
Y_observed <- Y_baseline + Y_treatment + Time_Trend

# Ensure no negative outcomes after the time trend
Y_observed <- ifelse(Y_observed < 0, 0, Y_observed)

# Create the final dataset
data <-
    data.frame(
        ID = ID,
        Treatment = Treatment,
        Period = Post,
        Outcome = Y_observed
    )

# Viewing the first few rows of the dataset
head(data)
#>   ID Treatment Period Outcome
#> 1  1         0      0       0
#> 2  2         0      1      25
#> 3  3         0      0       0
#> 4  4         0      1      20
#> 5  5         0      0      19
#> 6  6         0      1       0
```

```r
library(fixest)
res_pois <-
    fepois(Outcome ~ Treatment + Period + Treatment * Period,
           data = data,
           vcov = "hetero")
etable(res_pois)
#>                              res_pois
#> Dependent Var.:               Outcome
#>
#> Constant           2.249*** (0.0717)
```

```
#> Treatment           0.1743. (0.0932)
#> Period               0.0662 (0.0960)
#> Treatment x Period   0.0314 (0.1249)
#> ------------------ -----------------
#> S.E. type          Heteroskeda.-rob.
#> Observations                   1,000
#> Squared Cor.                 0.01148
#> Pseudo R2                    0.00746
#> BIC                         15,636.8
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Average percentage change
exp(coefficients(res_pois)["Treatment:Period"]) - 1
#> Treatment:Period
#>       0.03191643

# SE using delta method
exp(coefficients(res_pois)["Treatment:Period"]) *
    sqrt(res_pois$cov.scaled["Treatment:Period", "Treatment:Period"])
#> Treatment:Period
#>        0.1288596
```

In this example, the DID coefficient is not significant. However, say that it's significant, we can interpret the coefficient as 3 percent increase in posttreatment period due to the treatment.

```
library(fixest)

base_did_log0 <- base_did |>
    mutate(y = if_else(y > 0, y, 0))

res_pois_es <-
    fepois(y ~ x1 + i(period, treat, 5) | id + period,
           data = base_did_log0,
           vcov = "hetero")

etable(res_pois_es)
#>                             res_pois_es
#> Dependent Var.:                       y
#>
#> x1                   0.1895*** (0.0108)
#> treat x period = 1    -0.2769 (0.3545)
#> treat x period = 2    -0.2699 (0.3533)
#> treat x period = 3     0.1737 (0.3520)
#> treat x period = 4    -0.2381 (0.3249)
```

```
#> treat x period = 6     0.3724 (0.3086)
#> treat x period = 7    0.7739* (0.3117)
#> treat x period = 8    0.5028. (0.2962)
#> treat x period = 9   0.9746** (0.3092)
#> treat x period = 10  1.310*** (0.3193)
#> Fixed-Effects:      ------------------
#> id                                Yes
#> period                            Yes
#> ------------------- ------------------
#> S.E. type           Heteroskedas.-rob.
#> Observations                    1,080
#> Squared Cor.                  0.51131
#> Pseudo R2                     0.34836
#> BIC                           5,868.8
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
iplot(res_pois_es)
```

This parallel trend is the "ratio" version as in Wooldridge (2023) :

$$\frac{E(Y_{it}(0)|D_i = 1, Post_t = 1)}{E(Y_{it}(0)|D_i = 1, Post_t = 0)} = \frac{E(Y_{it}(0)|D_i = 0, Post_t = 1)}{E(Y_{it}(0)|D_i = 0, Post_t = 0)}$$

which means without treatment, the average percentage change in the mean outcome for treated group is identical to that of the control group.

2. **Log Effects with Calibrated Extensive-margin value**

If we want to study the treatment effect on a concave transformation of the outcome that is less influenced by those in the distribution's tail, then we can perform this analysis.

Steps:

1. Normalize the outcomes such that 1 represents the minimum non-zero and positve value (i.e., divide the outcome by its minimum non-zero and positive value).
2. Estimate the treatment effects for the new outcome

$$m(y) = \begin{cases} \log(y) & \text{for } y > 0 \\ -x & \text{for } y = 0 \end{cases}$$

The choice of x depends on what the researcher is interested in:

Value of x	Interest
$x = 0$	The treatment effect in logs where all zero-valued outcomes are set to equal the minimum non-zero value (i.e., we exclude the extensive-margin change between 0 and y_{min})
$x > 0$	Setting the change between 0 and y_{min} to be valued as the equivalent of a x log point change along the intensive margin.

```
library(fixest)
base_did_log0_cali <- base_did_log0 |>
    # get min
    mutate(min_y = min(y[y > 0])) |>

    # normalized the outcome
    mutate(y_norm = y / min_y)

my_regression <-
    function(x) {
        base_did_log0_cali <-
            base_did_log0_cali %>% mutate(my = ifelse(y_norm == 0,-x,
                                                      log(y_norm)))
        my_reg <-
            feols(
                fml = my ~ x1 + i(period, treat, 5) | id + period,
                data = base_did_log0_cali,
                vcov = "hetero"
            )
```

```
        return(my_reg)
    }

xvec <- c(0, .1, .5, 1, 3)
reg_list <- purrr::map(.x = xvec, .f = my_regression)


iplot(reg_list,
      pt.col =  1:length(xvec),
      pt.pch = 1:length(xvec))
legend("topleft",
       col = 1:length(xvec),
       pch = 1:length(xvec),
       legend = as.character(xvec))
```

```
etable(
    reg_list,
    headers = list("Extensive-margin value (x)" = as.character(xvec)),
    digits = 2,
    digits.stats = 2
)
#>                                   model 1        model 2        model 3
#> Extensive-margin value (x)              0            0.1            0.5
#> Dependent Var.:                        my             my             my
#>
```

```
#> x1                          0.43*** (0.02) 0.44*** (0.02) 0.46*** (0.03)
#> treat x period = 1            -0.92 (0.67)   -0.94 (0.69)    -1.0 (0.73)
#> treat x period = 2            -0.41 (0.66)   -0.42 (0.67)   -0.43 (0.71)
#> treat x period = 3            -0.34 (0.67)   -0.35 (0.68)   -0.38 (0.73)
#> treat x period = 4             -1.0 (0.67)    -1.0 (0.68)    -1.1 (0.73)
#> treat x period = 6             0.44 (0.66)    0.44 (0.67)    0.45 (0.72)
#> treat x period = 7             1.1. (0.64)    1.1. (0.65)    1.2. (0.70)
#> treat x period = 8             1.1. (0.64)    1.1. (0.65)     1.1 (0.69)
#> treat x period = 9            1.7** (0.65)   1.7** (0.66)    1.8* (0.70)
#> treat x period = 10          2.4*** (0.62)  2.4*** (0.63)  2.5*** (0.68)
#> Fixed-Effects:              -------------- -------------- --------------
#> id                                     Yes            Yes            Yes
#> period                                 Yes            Yes            Yes
#> -------------------------- -------------- -------------- --------------
#> S.E. type                   Heterosk.-rob. Heterosk.-rob. Heterosk.-rob.
#> Observations                         1,080          1,080          1,080
#> R2                                    0.43           0.43           0.43
#> Within R2                             0.26           0.26           0.25
#>
#>                                    model 4        model 5
#> Extensive-margin value (x)               1              3
#> Dependent Var.:                         my             my
#>
#> x1                          0.49*** (0.03) 0.62*** (0.04)
#> treat x period = 1             -1.1 (0.79)     -1.5 (1.0)
#> treat x period = 2            -0.44 (0.77)   -0.51 (0.99)
#> treat x period = 3            -0.43 (0.78)    -0.60 (1.0)
#> treat x period = 4             -1.2 (0.78)     -1.5 (1.0)
#> treat x period = 6             0.45 (0.77)     0.46 (1.0)
#> treat x period = 7              1.2 (0.75)     1.3 (0.97)
#> treat x period = 8              1.2 (0.74)     1.3 (0.96)
#> treat x period = 9             1.8* (0.75)    2.1* (0.97)
#> treat x period = 10          2.7*** (0.73)  3.2*** (0.94)
#> Fixed-Effects:              -------------- --------------
#> id                                     Yes            Yes
#> period                                 Yes            Yes
#> -------------------------- -------------- --------------
#> S.E. type                   Heterosk.-rob. Heterosk.-rob.
#> Observations                         1,080          1,080
#> R2                                    0.42           0.41
#> Within R2                             0.25           0.24
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We have the dynamic treatment effects for different hypothesized extensive-

margin value of $x \in (0, .1, .5, 1, 3, 5)$

The first column is when the zero-valued outcome equal to $y_{min,y>0}$ (i.e., there is no different between the minimum outcome and zero outcome - $x = 0$)

For this particular example, as the extensive margin increases, we see an increase in the effect magnitude. The second column is when we assume an extensive-margin change from 0 to $y_{min,y>0}$ is equivalent to a 10 (i.e., 0.1×100) log point change along the intensive margin.

26.4 Standard Errors

Serial correlation is a big problem in DiD because (Bertrand et al., 2004)

1. DiD often uses long time series
2. Outcomes are often highly positively serially correlated
3. Minimal variation in the treatment variable over time within a group (e.g., state).

To overcome this problem:

- Using parametric correction (standard AR correction) is not good.
- Using nonparametric (e.g., **block bootstrap**- keep all obs from the same group such as state together) is good when number of groups is large.
- Remove time series dimension (i.e., aggregate data into 2 periods: pre and post). This still works with small number of groups (See (Donald and Lang, 2007) for more notes on small-sample aggregation).
- Empirical and arbitrary variance-covariance matrix corrections work only in large samples.

26.5 Examples

Example by Philipp Leppert replicating Card and Krueger (1994)

Example by Anthony Schmidt

26.5.1 Example by Doleac and Hansen (2020)

- The purpose of banning a checking box for ex-criminal was banned because we thought that it gives more access to felons
- Even if we ban the box, employers wouldn't just change their behaviors. But then the unintended consequence is that employers statistically discriminate based on race

3 types of ban the box

1. Public employer only
2. Private employer with government contract

3. All employers

Main identification strategy

- If any county in the Metropolitan Statistical Area (MSA) adopts ban the box, it means the whole MSA is treated. Or if the state adopts "ban the ban," every county is treated

Under Simple Dif-n-dif

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 treat_i + \beta_2(Post_t \times Treat_i) + \epsilon_{it}$$

But if there is no common post time, then we should use Staggered Dif-n-dif

$$\begin{aligned} E_{imrt} = \alpha &+ \beta_1 BTB_{imt} W_{imt} + \beta_2 BTB_{mt} + \beta_3 BTB_{mt} H_{imt} \\ &+ \delta_m + D_{imt}\beta_5 + \lambda_{rt} + \delta_m \times f(t)\beta_7 + e_{imrt} \end{aligned}$$

where

- i = person; m = MSA; r = region (US regions e.g., Midwest) ; r = region; t = year
- W = White; B = Black; H = Hispanic
- $\beta_1 BTB_{imt} W_{imt} + \beta_2 BTB_{mt} + \beta_3 BTB_{mt} H_{imt}$ are the 3 dif-n-dif variables (BTB = "ban the box")
- δ_m = dummy for MSI
- D_{imt} = control for people
- λ_{rt} = region by time fixed effect
- $\delta_m \times f(t)$ = linear time trend within MSA (but we should not need this if we have good pre-trend)

If we put $\lambda_r - \lambda_t$ (separately) we will more broad fixed effect, while λ_{rt} will give us deeper and narrower fixed effect.

Before running this model, we have to drop all other races. And $\beta_1, \beta_2, \beta_3$ are not collinear because there are all interaction terms with BTB_{mt}

If we just want to estimate the model for black men, we will modify it to be

$$E_{imrt} = \alpha + BTB_{mt}\beta_1 + \delta_m + D_{imt}\beta_5 + \lambda_{rt} + (\delta_m \times f(t))\beta_7 + e_{imrt}$$

$$\begin{aligned} E_{imrt} = \alpha &+ BTB_{m(t-3t)}\theta_1 + BTB_{m(t-2)}\theta_2 + BTB_{mt}\theta_4 \\ &+ BTB_{m(t+1)}\theta_5 + BTB_{m(t+2)}\theta_6 + BTB_{m(t+3t)}\theta_7 \\ &+ [\delta_m + D_{imt}\beta_5 + \lambda_r + (\delta_m \times (f(t))\beta_7 + e_{imrt}] \end{aligned}$$

We have to leave $BTB_{m(t-1)}\theta_3$ out for the category would not be perfect collinearity

So the year before BTB $(\theta_1, \theta_2, \theta_3)$ should be similar to each other (i.e., same pre-trend). Remember, we only run for places with BTB.

If θ_2 is statistically different from θ_3 (baseline), then there could be a problem, but it could also make sense if we have pre-trend announcement.

26.5.2 Example from Princeton

```
library(foreign)
mydata = read.dta("http://dss.princeton.edu/training/Panel101.dta") %>%
    # create a dummy variable to indicate the time when the treatment started
    dplyr::mutate(time = ifelse(year >= 1994, 1, 0)) %>%
    # create a dummy variable to identify the treatment group
    dplyr::mutate(treated = ifelse(country == "E" |
                                       country == "F" | country == "G" ,
                                   1,
                                   0)) %>%
    # create an interaction between time and treated
    dplyr::mutate(did = time * treated)
```

estimate the DID estimator

```
didreg = lm(y ~ treated + time + did, data = mydata)
summary(didreg)
#>
#> Call:
#> lm(formula = y ~ treated + time + did, data = mydata)
#>
#> Residuals:
#>        Min         1Q     Median         3Q        Max
#> -9.768e+09 -1.623e+09  1.167e+08  1.393e+09  6.807e+09
#>
#> Coefficients:
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  3.581e+08  7.382e+08   0.485   0.6292
#> treated      1.776e+09  1.128e+09   1.575   0.1200
#> time         2.289e+09  9.530e+08   2.402   0.0191 *
#> did         -2.520e+09  1.456e+09  -1.731   0.0882 .
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 2.953e+09 on 66 degrees of freedom
#> Multiple R-squared:  0.08273,    Adjusted R-squared:  0.04104
#> F-statistic: 1.984 on 3 and 66 DF,  p-value: 0.1249
```

The `did` coefficient is the differences-in-differences estimator. Treat has a negative effect

26.5.3 Example by Card and Krueger (1993)

found that increase in minimum wage increases employment

Experimental Setting:

- New Jersey (treatment) increased minimum wage
- Penn (control) did not increase minimum wage

		After	Before	
Treatment	NJ	A	B	A - B
Control	PA	C	D	C - D
		A - C	B - D	(A - B) - (C - D)

where

- A - B = treatment effect + effect of time (additive)
- C - D = effect of time
- (A - B) - (C - D) = dif-n-dif

The identifying assumptions:

- Can't have **switchers**
- PA is the control group
  - is a good counter factual
  - is what NJ would look like if they hadn't had the treatment

$$Y_{jt} = \beta_0 + NJ_j\beta_1 + POST_t\beta_2 + (NJ_j \times POST_t)\beta_3 + X_{jt}\beta_4 + \epsilon_{jt}$$

where

- j = restaurant
- NJ = dummy where $1 = NJ$, and $0 = PA$
- $POST$ = dummy where $1 = post$, and $0 = pre$

Notes:

- We don't need β_4 in our model to have unbiased β_3, but including it would give our coefficients efficiency
- If we use ΔY_{jt} as the dependent variable, we don't need $POST_t\beta_2$ anymore

- Alternative model specification is that the authors use NJ high wage restaurant as control group (still choose those that are close to the border)
- The reason why they can't control for everything (PA + NJ high wage) is because it's hard to interpret the causal treatment
- Dif-n-dif utilizes similarity in pretrend of the dependent variables. However, this is neither a necessary nor sufficient for the identifying assumption.
  - It's not sufficient because they can have multiple treatments (technically, you could include more control, but your treatment can't interact)
  - It's not necessary because trends can be parallel after treatment
- However, we can't never be certain; we just try to find evidence consistent with our theory so that dif-n-dif can work.
- Notice that we don't need before treatment the **levels of the dependent variable** to be the same (e.g., same wage average in both NJ and PA), dif-n-dif only needs **pre-trend (i.e., slope)** to be the same for the two groups.

26.5.4 Example by Butcher et al. (2014)

Theory:

- Highest achieving students are usually in hard science. Why?
  - Hard to give students students the benefit of doubt for hard science
  - How unpleasant and how easy to get a job. Degrees with lower market value typically want to make you feel more pleasant

Under OLS

$$E_{ij} = \beta_0 + X_i\beta_1 + G_j\beta_2 + \epsilon_{ij}$$

where

- X_i = student attributes
- β_2 = causal estimate (from grade change)
- E_{ij} = Did you choose to enroll in major j
- G_j = grade given in major j

Examine $\hat{\beta}_2$

- Negative bias: Endogenous response because department with lower enrollment rate will give better grade

- Positive bias: hard science is already having best students (i.e., ability), so if they don't their grades can be even lower

Under dif-n-dif

$$Y_{idt} = \beta_0 + POST_t\beta_1 + Treat_d\beta_2 + (POST_t \times Treat_d)\beta_3 + X_{idt} + \epsilon_{idt}$$

where

- Y_{idt} = grade average

	Intercept	Treat	Post	Treat*Post
Treat Pre	1	1	0	0
Treat Post	1	1	1	1
Control Pre	1	0	0	0
Control Post	1	0	1	0
	Average for pre-control β_0			

A more general specification of the dif-n-dif is that

$$Y_{idt} = \alpha_0 + (POST_t \times Treat_d)\alpha_1 + \theta_d + \delta_t + X_{idt} + u_{idt}$$

where

- $(\theta_d + \delta_t)$ richer , more df than $Treat_d\beta_2 + Post_t\beta_1$ (because fixed effects subsume Post and treat)
- α_1 should be equivalent to β_3 (if your model assumptions are correct)

26.6 One Difference

The regression formula is as follows (Liaukonytė et al., 2023):

$$y_{ut} = \beta \text{Post}_t + \gamma_u + \gamma_w(t) + \gamma_l + \gamma_g(u)p(t) + \epsilon_{ut}$$

where

- y_{ut}: Outcome of interest for unit u in time t.
- Post_t: Dummy variable representing a specific post-event period.
- β: Coefficient measuring the average change in the outcome after the event relative to the pre-period.
- γ_u: Fixed effects for each unit.
- $\gamma_w(t)$: Time-specific fixed effects to account for periodic variations.

- γ_l: Dummy variable for a specific significant period (e.g., a major event change).
- $\gamma_g(u)p(t)$: Group x period fixed effects for flexible trends that may vary across different categories (e.g., geographical regions) and periods.
- ϵ_{ut}: Error term.

This model can be used to analyze the impact of an event on the outcome of interest while controlling for various fixed effects and time-specific variations, but using units themselves pre-treatment as controls.

26.7 Two-way Fixed-effects

A generalization of the dif-n-dif model is the two-way fixed-effects models where you have multiple groups and time effects. But this is not a designed-based, non-parametric causal estimator (Imai and Kim, 2021)

When applying TWFE to multiple groups and multiple periods, the supposedly causal coefficient is the weighted average of all two-group/two-period DiD estimators in the data where some of the weights can be negative. More specifically, the weights are proportional to group sizes and treatment indicator's variation in each pair, where units in the middle of the panel have the highest weight.

The canonical/standard TWFE only works when

- Effects are homogeneous across units and across time periods (i.e., no dynamic changes in the effects of treatment). See (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Borusyak et al., 2021) for details. Similarly, it relies on the assumption of **linear additive effects** (Imai and Kim, 2021)
  - Have to argue why treatment heterogeneity is not a problem (e.g., plot treatment timing and decompose treatment coefficient using Goodman-Bacon Decomposition) know the percentage of observation are never treated (because as the never-treated group increases, the bias of TWFE decreases, with 80% sample to be never-treated, bias is negligible). The problem is worsen when you have long-run effects.
  - Need to manually drop two relative time periods if everyone is eventually treated (to avoid multicollinearity). Programs might do this randomly and if it chooses to drop a post-treatment period, it will create biases. The choice usually -1, and -2 periods.
  - Treatment heterogeneity can come in because (1) it might take some time for a treatment to have measurable changes in outcomes or (2) for each period after treatment, the effect can be different (phase in or increasing effects).
- 2 time periods.

Within this setting, TWFE works because, using the baseline (e.g., control units where their treatment status is unchanged across time periods), the comparison can be

- Good for
  - Newly treated units vs. control
  - Newly treated units vs not-yet treated
- Bad for
  - Newly treated vs. already treated (because already treated cannot serve as the potential outcome for the newly treated).
  - Strict exogeneity (i.e., time-varying confounders, feedback from past outcome to treatment) (Imai and Kim, 2019)
  - Specific functional forms (i.e., treatment effect homogeneity and no carryover effects or anticipation effects) (Imai and Kim, 2019)

Note: Notation for this section is consistent with (ark, 2020)

$$Y_{it} = \alpha_i + \lambda_t + \tau W_{it} + \beta X_{it} + \epsilon_{it}$$

where

- Y_{it} is the outcome
- α_i is the unit FE
- λ_t is the time FE
- τ is the causal effect of treatment
- W_{it} is the treatment indicator
- X_{it} are covariates

When $T = 2$, the TWFE is the traditional DiD model

Under the following assumption, $\hat{\tau}_{OLS}$ is unbiased:

1. homogeneous treatment effect
2. parallel trends assumptions
3. linear additive effects (Imai and Kim, 2021)

Remedies for TWFE's shortcomings

- (Goodman-Bacon, 2021): diagnostic robustness tests of the TWFE DiD and identify influential observations to the DiD estimate (Goodman-Bacon Decomposition)
- (Callaway and Sant'Anna, 2021): 2-step estimation with a bootstrap procedure that can account for autocorrelation and clustering,

  - the parameters of interest are the group-time average treatment effects, where each group is defined by when it was first treated (Multiple periods and variation in treatment timing)
  - Comparing post-treatment outcomes fo groups treated in a period against a similar group that is never treated (using matching).
  - Treatment status cannot switch (once treated, stay treated for the rest of the panel)
  - Package: `did`
- (Sun and Abraham, 2021): a specialization of (Callaway and Sant'Anna, 2021) in the event-study context.
  - They include lags and leads in their design
  - have cohort-specific estimates (similar to group-time estimates in (Callaway and Sant'Anna, 2021)
  - They propose the "interaction-weighted" estimator.
  - Package: `fixest`
- (Imai and Kim, 2021)
  - Different from (Callaway and Sant'Anna, 2021) because they allow units to switch in and out of treatment.
  - Based on matching methods, to have weighted TWFE
  - Package: `wfe` and `PanelMatch`
- (Gardner, 2022): two-stage DiD
  - `did2s`
- In cases with an unaffected unit (i.e., never-treated), using the exposure-adjusted difference-in-differences estimators can recover the average treatment effect (De Chaisemartin and d'Haultfoeuille, 2020). However, if you want to see the treatment effect heterogeneity (in cases where the true heterogeneous treatment effects vary by the exposure rate), exposure-adjusted did still fails (Sun and Shapiro, 2022).
- (ark, 2020): see below

To be robust against

1. time- and unit-varying effects

We can use the reshaped inverse probability weighting (RIPW)- TWFE estimator

With the following assumptions:

- SUTVA

- Binary treatment: $\mathbf{W}_i = (W_{i1}, \dots, W_{it})$ where $\mathbf{W}_i \sim {}_i$ generalized propensity score (i.e., each person treatment likelihood follow π regardless of the period)

Then, the unit-time specific effect is $\tau_{it} = Y_{it}(1) - Y_{it}(0)$

Then the Doubly Average Treatment Effect (DATE) is

$$\tau(\xi) = \sum_{T=1}^{T} \xi_t \left(\frac{1}{n} \sum_{i=1}^{n} \tau_{it} \right)$$

where

- $\frac{1}{n}\sum_{i=1}^{n} \tau_{it}$ is the unweighted effect of treatment across units (i.e., time-specific ATE).
- $\xi = (\xi_1, \dots, \xi_t)$ are user-specific weights for each time period.
- This estimand is called DATE because it's weighted (averaged) across both time and units.

A special case of DATE is when both time and unit-weights are equal

$$\tau_{eq} = \frac{1}{nT} \sum_{t=1}^{T} \sum_{i=1}^{n} \tau_{it}$$

Borrowing the idea of inverse propensity-weighted least squares estimator in the cross-sectional case that we reweight the objective function via the treatment assignment mechanism:

$$\hat{\tau} \triangleq \arg\min_{\tau} \sum_{i=1}^{n} (Y_i - \mu - W_i \tau)^2 \frac{1}{\pi_i(W_i)}$$

where

- the first term is the least squares objective
- the second term is the propensity score

In the panel data case, the IPW estimator will be

$$\hat{\tau}_{IPW} \triangleq \arg\min_{\tau} \sum_{i=1}^{n} \sum_{t=1}^{T} (Y_{it} - \alpha_i - \lambda_t - W_{it}\tau)^2 \frac{1}{\pi_i(W_i)}$$

Then, to have DATE that users can specify the structure of time weight, we use reshaped IPW estimator (ark, 2020)

$$\hat{\tau}_{RIPW}(\Pi) \triangleq \arg\min_{\tau} \sum_{i=1}^{n} \sum_{t=1}^{T} (Y_{it} - \alpha_i - \lambda_t - W_{it}\tau)^2 \frac{\Pi(W_i)}{\pi_i(W_i)}$$

where it's a function of a data-independent distribution Π that depends on the support of the treatment path $\mathbb{S} = \cup_i Supp(W_i)$

This generalization can transform to

- IPW-TWFE estimator when $\Pi \sim Unif(\mathbb{S})$
- randomized experiment when $\Pi = \pi_i$

To choose Π, we don't need to data, we just need possible assignments in your setting.

- For most practical problems (DiD, staggered, transient), we have closed form solutions
- For generic solver, we can use nonlinear programming (e..g, BFGS algorithm)

As argued in (Imai and Kim, 2021) that TWFE is not a non-parametric approach, it can be subjected to incorrect model assumption (i.e., model dependence).

- Hence, they advocate for matching methods for time-series cross-sectional data (Imai and Kim, 2021)
- Use `wfe` and `PanelMatch` to apply their paper.

This package is based on (Somaini and Wolak, 2016)

```
# dataset
library(bacondecomp)
df <- bacondecomp::castle
```

```
# devtools::install_github("paulosomaini/xtreg2way")

library(xtreg2way)
# output <- xtreg2way(y,
#                     data.frame(x1, x2),
#                     iid,
#                     tid,
#                     w,
#                     noise = "1",
#                     se = "1")

# equilvalently
output <- xtreg2way(l_homicide ~ post,
                    df,
```

```
                    iid = df$state, # group id
                    tid = df$year, # time id
                    # w, # vector of weight
                    se = "1")
output$betaHat
#>                  [,1]
#> l_homicide 0.08181162
output$aVarHat
#>              [,1]
#> [1,] 0.003396724

# to save time, you can use your structure in the
# last output for a new set of variables
# output2 <- xtreg2way(y, x1, struc=output$struc)
```

Standard errors estimation options

Set	Estimation
`se = "0"`	Assume homoskedasticity and no within group correlation or serial correlation
`se = "1"` (default)	robust to heteroskadasticity and serial correlation (Arellano, 1987)
`se = "2"`	robust to heteroskedasticity, but assumes no correlation within group or serial correlation
`se = "11"`	Aerllano SE with df correction performed by Stata xtreg (Somaini and Wolak, 2021)

Alternatively, you can also do it manually or with the `plm` package, but you have to be careful with how the SEs are estimated

```
library(multiwayvcov) # get vcov matrix
library(lmtest) # robust SEs estimation

# manual
output3 <- lm(l_homicide ~ post + factor(state) + factor(year),
              data = df)

# get variance-covariance matrix
vcov_tw <- multiwayvcov::cluster.vcov(output3,
                        cbind(df$state, df$year),
                        use_white = F,
                        df_correction = F)

# get coefficients
```

```r
coeftest(output3, vcov_tw)[2,]
#>   Estimate Std. Error    t value   Pr(>|t|)
#> 0.08181162 0.05671410 1.44252696 0.14979397
```

```r
# using the plm package
library(plm)

output4 <- plm(l_homicide ~ post,
               data = df,
               index = c("state", "year"),
               model = "within",
               effect = "twoways")

# get coefficients
coeftest(output4, vcov = vcovHC, type = "HC1")
#>
#> t test of coefficients:
#>
#>      Estimate Std. Error t value Pr(>|t|)
#> post 0.081812   0.057748  1.4167   0.1572
```

As you can see, differences stem from SE estimation, not the coefficient estimate.

26.8 Multiple periods and variation in treatment timing

This is an extension of the DiD framework to settings where you have

- more than 2 time periods
- different treatment timing

When treatment effects are heterogeneous across time or units, the standard Two-way Fixed-effects is inappropriate.

Notation is consistent with `did` package (Callaway and Sant'Anna, 2021)

- $Y_{it}(0)$ is the potential outcome for unit i
- $Y_{it}(g)$ is the potential outcome for unit i in time period t if it's treated in period g
- Y_{it} is the observed outcome for unit i in time period t

$$Y_{it} = \begin{cases} Y_{it} = Y_{it}(0) & \forall i \in \text{never-treated group} \\ Y_{it} = 1\{G_i > t\}Y_{it}(0) + 1\{G_i \leq t\}Y_{it}(G_i) & \forall i \in \text{other groups} \end{cases}$$

- G_i is the time period when i is treated
- C_i is a dummy when i belongs to the **never-treated** group
- D_{it} is a dummy for whether i is treated in period t

Assumptions:

- Staggered treatment adoption: once treated, a unit cannot be untreated (revert)
- Parallel trends assumptions (conditional on covariates):
  - Based on never-treated units: $E[Y_t(0) - Y_{t-1}(0)|G = g] = E[Y_t(0) - Y_{t-1}(0)|C = 1]$
    - Without treatment, the average potential outcomes for group g equals the average potential outcomes for the never-treated group (i.e., control group), which means that we have (1) enough data on the never-treated group (2) the control group is similar to the eventually treated group.
  - Based on not-yet treated units: $E[Y_t(0) - Y_{t-1}(0)|G = g] = E[Y_t(0) - Y_{t-1}(0)|D_s = 0, G \neq g]$
    - Not-yet treated units by time s ($s \geq t$) can be used as comparison groups to calculate the average treatment effects for the group first treated in time g
    - Additional assumption: pre-treatment trends across groups (Marcus and Sant'Anna, 2021)
- Random sampling
- Irreversibility of treatment (once treated, cannot be untreated)
- Overlap (the treatment propensity $e \in [0, 1]$)

Group-Time ATE

- This is the equivalent of the average treatment effect in the standard case (2 groups, 2 periods) under multiple time periods.

$$ATT(g, t) = E[Y_t(g) - Y_t(0)|G = g]$$

which is the average treatment effect for group g in period t

- Identification: When the parallel trends assumption based on
  - Never-treated units: $ATT(g, t) = E[Y_t - Y_{g-1}|G = g] - E[Y_t - Y_{g-1}|C = 1] \forall t \geq g$
  - Not-yet-treated units: $ATT(g, t) = E[Y_t - Y_{g-1}|G = g] - E[Y_t - Y_{g-1}|D_t = 0, G \neq g] \forall t \geq g$

- Identification: when the parallel trends assumption only holds conditional on covariates and based on
  - Never-treated units: $ATT(g,t) = E[Y_t - Y_{g-1}|X, G = g] - E[Y_t - Y_{g-1}|X, C = 1] \forall t \geq g$
  - Not-yet-treated units: $ATT(g,t) = E[Y_t - Y_{g-1}|X, G = g] - E[Y_t - Y_{g-1}|X, D_t = 0, G \neq g] \forall t \geq g$
  - This is plausible when you have suspected selection bias that can be corrected by using covariates (i.e., very much similar to matching methods to have plausible parallel trends).

Possible parameters of interest are:

1. Average treatment effect per group

$$\theta_S(g) = \frac{1}{\tau - g + 1} \sum_{t=2}^{\tau} \mathbb{1}\{\leq t\} ATT(g,t)$$

2. Average treatment effect across groups (that were treated) (similar to average treatment effect on the treated in the canonical case)

$$\theta_S^O := \sum_{g=2}^{\tau} \theta_S(g) P(G = g)$$

3. Average treatment effect dynamics (i.e., average treatment effect for groups that have been exposed to the treatment for e time periods):

$$\theta_D(e) := \sum_{g=2}^{\tau} \mathbb{1}\{g + e \leq \tau\} ATT(g, g+e) P(G = g | G + e \leq \tau)$$

4. Average treatment effect in period t for all groups that have treated by period t)

$$\theta_C(t) = \sum_{g=2}^{\tau} \mathbb{1}\{g \leq t\} ATT(g,t) P(G = g | g \leq t)$$

5. Average treatment effect by calendar time

$$\theta_C = \frac{1}{\tau - 1} \sum_{t=2}^{\tau} \theta_C(t)$$

26.9 Staggered Dif-n-dif

See Wing et al. (2024) checklist.

Recommendations by Baker et al. (2022)

- TWFE DiD regressions are suitable for single treatment periods or when treatment effects are homogeneous, provided there's a solid rationale for effect homogeneity.
- For TWFE staggered DiD, researchers should evaluate bias risks, plot treatment timings to check for variations, and use decompositions like Goodman-Bacon (2021) when possible. If decompositions aren't feasible (e.g., unbalanced panel), the percentage of never-treated units can indicate bias severity. Expected treatment effect variability should also be discussed.
- In TWFE staggered DiD event studies, avoid binning time periods without evidence of uniform effects. Use full relative-time indicators, justify reference periods, and be wary of multicollinearity causing bias.
- To address treatment timing and bias concerns, use alternative estimators like stacked regressions, Sun and Abraham (2021), Callaway and Sant'Anna (2021), or separate regressions for each event with "clean" controls.
- Justify the selection of comparison groups (not-yet treated, last treated, never treated) and ensure the parallel-trends assumption holds, especially when anticipating no effects for certain groups.

Notes:

- When subjects are treated at different point in time (variation in treatment timing across units), we have to use staggered DiD (also known as DiD event study or dynamic DiD).
- For design where a treatment is applied and units are exposed to this treatment at all time afterward, see (Athey and Imbens, 2022)

For example, basic design (Stevenson and Wolfers, 2006)

$$\begin{aligned} Y_{it} = & \sum_k \beta_k Treatment_{it}^k + \sum_i \eta_i State_i \\ & + \sum_t \lambda_t Year_t + Controls_{it} + \epsilon_{it} \end{aligned}$$

where

- $Treatment_{it}^k$ is a series of dummy variables equal to 1 if state i is treated k years ago in period t
- SE is usually clustered at the group level (occasionally time level).

- To avoid collinearity, the period right before treatment is usually chosen to drop.

The more general form of TWFE (Sun and Abraham, 2021):

First, define the relative period bin indicator as

$$D_{it}^{l} = \mathbf{1}(t - E_i = l)$$

where it's an indicator function of unit i being l periods from its first treatment at time t

1. **Static** specification

$$Y_{it} = \alpha_i + \lambda_t + \mu_g \sum_{l \geq 0} D_{it}^{l} + \epsilon_{it}$$

where

- α_i is the the unit FE
- λ_t is the time FE
- μ_g is the coefficient of interest $g = [0, T)$
- we exclude all periods before first adoption.

2. **Dynamic** specification

$$Y_{it} = \alpha_i + \lambda_t + \sum_{\substack{l=-K \\ l \neq -1}}^{L} \mu_l D_{it}^{l} + \epsilon_{it}$$

where we have to exclude some relative periods to avoid multicollinearity problem (e.g., either period right before treatment, or the treatment period).

In this setting, we try to show that the treatment and control groups are not statistically different (i.e., the coefficient estimates before treatment are not different from 0) to show pre-treatment parallel trends.

However, this two-way fixed effects design has been criticized by Sun and Abraham (2021); Callaway and Sant'Anna (2021); Goodman-Bacon (2021). When researchers include leads and lags of the treatment to see the long-term effects of the treatment, these leads and lags can be biased by effects from other periods, and pre-trends can falsely arise due to treatment effects heterogeneity.

Applying the new proposed method, finance and accounting researchers find that in many cases, the causal estimates turn out to be null (Baker et al., 2022).

Assumptions of Staggered DID

- **Rollout Exogeneity** (i.e., exogeneity of treatment adoption): if the treatment is randomly implemented over time (i.e., unrelated to variables that could also affect our dependent variables)
  - Evidence: Regress adoption on pre-treatment variables. And if you find evidence of correlation, include linear trends interacted with pre-treatment variables (Hoynes and Schanzenbach, 2009)
  - Evidence: (Deshpande and Li, 2019, p. 223)
    * Treatment is random: Regress treatment status at the unit level to all pre-treatment observables. If you have some that are predictive of treatment status, you might have to argue why it's not a worry. At best, you want this.
    * Treatment timing is random: Conditional on treatment, regress timing of the treatment on pre-treatment observables. At least, you want this.
- **No confounding events**
- **Exclusion restrictions**
  - ***No-anticipation assumption***: future treatment time do not affect current outcomes
  - ***Invariance-to-history assumption***: the time a unit under treatment does not affect the outcome (i.e., the time exposed does not matter, just whether exposed or not). This presents causal effect of early or late adoption on the outcome.
- And all the assumptions in listed in the Multiple periods and variation in treatment timing
- Auxiliary assumptions:
  - Constant treatment effects across units
  - Constant treatment effect over time
  - Random sampling
  - Effect Additivity

Remedies for staggered DiD (Baker et al., 2022):

- Each treated cohort is compared to appropriate controls (not-yet-treated, never-treated)
  - (Goodman-Bacon, 2021)
  - (Callaway and Sant'Anna, 2021) consistent for average ATT. more complicated but also more flexible than (Sun and Abraham, 2021)
    * (Sun and Abraham, 2021) (a special case of (Callaway and Sant'Anna, 2021))

  - (De Chaisemartin and d'Haultfoeuille, 2020)
  - (Borusyak et al., 2021)
- Stacked DID (biased but simple):
  - (Gormley and Matsa, 2011)
  - (Cengiz et al., 2019)
  - (Deshpande and Li, 2019)

26.9.1 Stacked DID

Notations following these slides

$$Y_{it} = \beta_{FE} D_{it} + A_i + B_t + \epsilon_{it}$$

where

- A_i is the group fixed effects
- B_t is the period fixed effects

Steps

1. Choose Event Window
2. Enumerate Sub-experiments
3. Define Inclusion Criteria
4. Stack Data
5. Specify Estimating Equation

Event Window

Let

- κ_a be the length of the pre-event window
- κ_b be the length of the post-event window

By setting a common event window for the analysis, we essentially exclude all those events that do not meet this criteria.

Sub-experiments

Let T_1 be the earliest period in the dataset

T_T be the last period in the dataset

Then, the collection of all policy adoption periods that are under our event window is

$$\Omega_A = \{A_i | T_1 + \kappa_a \leq A_i \leq T_T - \kappa_b\}$$

where these events exist

- at least κ_a periods after the earliest period
- at least κ_b periods before the last period

Let $d = 1, \dots, D$ be the index column of the sub-experiments in Ω_A

and ω_d be the event date of the d-th sub-experiment (e.g., ω_1 = adoption date of the 1st experiment)

Inclusion Criteria

1. Valid treated Units
   - Within sub-experiment d, all treated units have the same adoption date
   - This makes sure a unit can only serve as a treated unit in only 1 sub-experiment
2. Clean controls
   - Only units satisfying $A_i > \omega_d + \kappa_b$ are included as controls in sub-experiment d
   - This ensures controls are only
     - never treated units
     - units that are treated in far future
   - But a unit can be control unit in multiple sub-experiments (need to correct SE)
3. Valid Time Periods
   - All observations within sub-experiment d are from time periods within the sub-experiment's event window
   - This ensures in sub-experiment d, only observations satisfying $\omega_d - \kappa_a \leq t \leq \omega_d + \kappa_b$ are included

```r
library(did)
library(tidyverse)
library(fixest)

data(base_stagg)

# first make the stacked datasets
# get the treatment cohorts
cohorts <- base_stagg %>%
    select(year_treated) %>%
    # exclude never-treated group
    filter(year_treated != 10000) %>%
    unique() %>%
    pull()

# make formula to create the sub-datasets
getdata <- function(j, window) {
```

```
    #keep what we need
    base_stagg %>%
        # keep treated units and all units not treated within -5 to 5
        # keep treated units and all units not treated within -window to window
        filter(year_treated == j | year_treated > j + window) %>%
        # keep just year -window to window
        filter(year >= j - window & year <= j + window) %>%
        # create an indicator for the dataset
        mutate(df = j)
}

# get data stacked
stacked_data <- map_df(cohorts, ~ getdata(., window = 5)) %>%
    mutate(rel_year = if_else(df == year_treated, time_to_treatment, NA_real_)) %>%
    fastDummies::dummy_cols("rel_year", ignore_na = TRUE) %>%
    mutate(across(starts_with("rel_year_"), ~ replace_na(., 0)))

# get stacked value
stacked <-
    feols(
        y ~ `rel_year_-5` + `rel_year_-4` + `rel_year_-3` +
            `rel_year_-2` + rel_year_0 + rel_year_1 + rel_year_2 + rel_year_3 +
            rel_year_4 + rel_year_5 |
            id ^ df + year ^ df,
        data = stacked_data
    )$coefficients

stacked_se = feols(
    y ~ `rel_year_-5` + `rel_year_-4` + `rel_year_-3` +
        `rel_year_-2` + rel_year_0 + rel_year_1 + rel_year_2 + rel_year_3 +
        rel_year_4 + rel_year_5 |
        id ^ df + year ^ df,
    data = stacked_data
)$se

# add in 0 for omitted -1
stacked <- c(stacked[1:4], 0, stacked[5:10])
stacked_se <- c(stacked_se[1:4], 0, stacked_se[5:10])


cs_out <- att_gt(
    yname = "y",
    data = base_stagg,
    gname = "year_treated",
    idname = "id",
```

```
    # xformla = "~x1",
    tname = "year"
)
cs <-
    aggte(
        cs_out,
        type = "dynamic",
        min_e = -5,
        max_e = 5,
        bstrap = FALSE,
        cband = FALSE
    )



res_sa20 = feols(y ~ sunab(year_treated, year) |
                     id + year, base_stagg)
sa = tidy(res_sa20)[5:14, ] %>% pull(estimate)
sa = c(sa[1:4], 0, sa[5:10])

sa_se = tidy(res_sa20)[6:15, ] %>% pull(std.error)
sa_se = c(sa_se[1:4], 0, sa_se[5:10])

compare_df_est = data.frame(
    period = -5:5,
    cs = cs$att.egt,
    sa = sa,
    stacked = stacked
)

compare_df_se = data.frame(
    period = -5:5,
    cs = cs$se.egt,
    sa = sa_se,
    stacked = stacked_se
)

compare_df_longer <- compare_df_est %>%
    pivot_longer(!period, names_to = "estimator", values_to = "est") %>%

    full_join(compare_df_se %>%
                  pivot_longer(!period, names_to = "estimator", values_to = "se")) %>%

    mutate(upper = est +  1.96 * se,
           lower = est - 1.96 * se)
```

```
ggplot(compare_df_longer) +
    geom_ribbon(aes(
        x = period,
        ymin = lower,
        ymax = upper,
        group = estimator
    )) +
    geom_line(aes(
        x = period,
        y = est,
        group = estimator,
        col = estimator
    ),
    linewidth = 1) +
    causalverse::ama_theme()
```

Stack Data

Estimating Equation

$$Y_{itd} = \beta_0 + \beta_1 T_{id} + \beta_2 P_{td} + \beta_3 (T_{id} \times P_{td}) + \epsilon_{itd}$$

where

- $T_{id} = 1$ if unit i is treated in sub-experiment d, 0 if control
- $P_{td} = 1$ if it's the period after the treatment in sub-experiment d

Equivalently,

$$Y_{itd} = \beta_3(T_{id} \times P_{td}) + \theta_{id} + \gamma_{td} + \epsilon_{itd}$$

β_3 averages all the time-varying effects into a single number (can't see the time-varying effects)

Stacked Event Study

Let $YSE_{td} = t - \omega_d$ be the "time since event" variable in sub-experiment d

Then, $YSE_{td} = -\kappa_a, \dots, 0, \dots, \kappa_b$ in every sub-experiment

In each sub-experiment, we can fit

$$Y_{it}^d = \sum_{j=-\kappa_a}^{\kappa_b} \beta_j^d \times 1(TSE_{td} = j) + \sum_{m=-\kappa_a}^{\kappa_b} \delta_j^d (T_{id} \times 1(TSE_{td} = j)) + \theta_i^d + \epsilon_{it}^d$$

- Different set of event study coefficients in each sub-experiment

$$Y_{itd} = \sum_{j=-\kappa_a}^{\kappa_b} \beta_j \times 1(TSE_{td} = j) + \sum_{m=-\kappa_a}^{\kappa_b} \delta_j (T_{id} \times 1(TSE_{td} = j)) + \theta_{id} + \epsilon_{itd}$$

Clustering

- Clustered at the unit x sub-experiment level (Cengiz et al., 2019)
- Clustered at the unit level (Deshpande and Li, 2019)

26.9.2 Goodman-Bacon Decomposition

Paper: (Goodman-Bacon, 2021)

For an excellent explanation slides by the author, see

Takeaways:

- A pairwise DID (τ) gets more weight if the change is close to the middle of the study window
- A pairwise DID (τ) gets more weight if it includes more observations.

Code from `bacondecomp` vignette

```
library(bacondecomp)
library(tidyverse)
data("castle")
castle <- bacondecomp::castle %>%
```

```
    dplyr::select("l_homicide", "post", "state", "year")
head(castle)
#>   l_homicide post   state year
#> 1   2.027356    0 Alabama 2000
#> 2   2.164867    0 Alabama 2001
#> 3   1.936334    0 Alabama 2002
#> 4   1.919567    0 Alabama 2003
#> 5   1.749841    0 Alabama 2004
#> 6   2.130440    0 Alabama 2005


df_bacon <- bacon(
    l_homicide ~ post,
    data = castle,
    id_var = "state",
    time_var = "year"
)
#>                        type  weight  avg_est
#> 1 Earlier vs Later Treated 0.05976 -0.00554
#> 2 Later vs Earlier Treated 0.03190  0.07032
#> 3     Treated vs Untreated 0.90834  0.08796

# weighted average of the decomposition
sum(df_bacon$estimate * df_bacon$weight)
#> [1] 0.08181162
```

Two-way Fixed effect estimate

```
library(broom)
fit_tw <- lm(l_homicide ~ post + factor(state) + factor(year),
             data = bacondecomp::castle)
head(tidy(fit_tw))
#> # A tibble: 6 x 5
#>   term                     estimate std.error statistic   p.value
#>   <chr>                       <dbl>     <dbl>     <dbl>     <dbl>
#> 1 (Intercept)                 1.95      0.0624    31.2   2.84e-118
#> 2 post                        0.0818    0.0317     2.58  1.02e-  2
#> 3 factor(state)Alaska        -0.373     0.0797    -4.68  3.77e-  6
#> 4 factor(state)Arizona        0.0158    0.0797     0.198 8.43e-  1
#> 5 factor(state)Arkansas      -0.118     0.0810    -1.46  1.44e-  1
#> 6 factor(state)California    -0.108     0.0810    -1.34  1.82e-  1
```

Hence, naive TWFE fixed effect equals the weighted average of the Bacon decomposition (= 0.08).

```r
library(ggplot2)

ggplot(df_bacon) +
    aes(
        x = weight,
        y = estimate,
        # shape = factor(type),
        color = type
    ) +
    labs(x = "Weight", y = "Estimate", shape = "Type") +
    geom_point() +
    causalverse::ama_theme()
```

With time-varying controls that can identify variation within-treatment timing group, the"early vs. late" and "late vs. early" estimates collapse to just one estimate (i.e., both treated).

26.9.3 DID with in and out treatment condition

26.9.3.1 Panel Match

Imai and Kim (2021)

This case generalizes the staggered adoption setting, allowing units to vary in treatment over time. For N units across T time periods (with potentially unbalanced panels), let X_{it} represent treatment and Y_{it} the outcome for unit i at time t. We use the two-way linear fixed effects model:

$$Y_{it} = \alpha_i + \gamma_t + \beta X_{it} + \epsilon_{it}$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$. Here, α_i and γ_t are unit and time fixed effects. They capture time-invariant unit-specific and unit-invariant time-specific unobserved confounders, respectively. We can express these as $\alpha_i = h(\mathbf{U}_i)$ and $\gamma_t = f(\mathbf{V}_t)$, with $\mathbf{U}_i$ and $\mathbf{V}_t$ being the confounders. The model doesn't assume a specific form for $h(.)$ and $f(.)$, but that they're additive and separable given binary treatment.

The least squares estimate of β leverages the covariance in outcome and treatment (Imai and Kim, 2021, p. 406). Specifically, it uses the within-unit and within-time variations. Many researchers prefer the two fixed effects (2FE) estimator because it adjusts for both types of unobserved confounders without specific functional-form assumptions, but this is wrong (Imai and Kim, 2019). We do need functional-form assumption (i.e., linearity assumption) for the 2FE to work (Imai and Kim, 2021, p. 406)

- **Two-Way Matching Estimator**:
  - It can lead to mismatches; units with the same treatment status get matched when estimating counterfactual outcomes.
  - Observations need to be matched with opposite treatment status for correct causal effects estimation.
  - Mismatches can cause attenuation bias.
  - The 2FE estimator adjusts for this bias using the factor K, which represents the net proportion of proper matches between observations with opposite treatment status.
- **Weighting in 2FE**:
  - Observation (i, t) is weighted based on how often it acts as a control unit.
  - The weighted 2FE estimator still has mismatches, but fewer than the standard 2FE estimator.
  - Adjustments are made based on observations that neither belong to the same unit nor the same time period as the matched observation.
  - This means there are challenges in adjusting for unit-specific and time-specific unobserved confounders under the two-way fixed effect framework.
- **Equivalence & Assumptions**:
  - Equivalence between the 2FE estimator and the DID estimator is dependent on the linearity assumption.

  - The multi-period DiD estimator is described as an average of two-time-period, two-group DiD estimators applied during changes from control to treatment.

- **Comparison with DiD**:
  - In simple settings (two time periods, treatment given to one group in the second period), the standard nonparametric DiD estimator equals the 2FE estimator.
  - This doesn't hold in multi-period DiD designs where units change treatment status multiple times at different intervals.
  - Contrary to popular belief, the unweighted 2FE estimator isn't generally equivalent to the multi-period DiD estimator.
  - While the multi-period DiD can be equivalent to the weighted 2FE, some control observations may have negative regression weights.

- **Conclusion**:
  - Justifying the 2FE estimator as the DID estimator isn't warranted without imposing the linearity assumption.

Application (Imai et al., 2021b)

- **Matching Methods**:
  - Enhance the validity of causal inference.
  - Reduce model dependence and provide intuitive diagnostics (Ho et al., 2007)
  - Rarely utilized in analyzing time series cross-sectional data.
  - The proposed matching estimators are more robust than the standard two-way fixed effects estimator, which can be biased if mis-specified
  - Better than synthetic controls (e.g., (Xu, 2017)) because it needs less data to achieve good performance and and adapt the the context of unit switching treatment status multiple times.

- Notes:
  - Potential carryover effects (treatment may have a long-term effect), leading to post-treatment bias.

- **Proposed Approach**:
  1. Treated observations are matched with control observations from other units in the same time period with the same treatment history up to a specified number of lags.
  2. Standard matching and weighting techniques are employed to further refine the matched set.

3. Apply a DiD estimator to adjust for time trend.

4. The goal is to have treated and matched control observations with similar covariate values.

- **Assessment**:
  - The quality of matches is evaluated through covariate balancing.

- **Estimation**:
  - Both short-term and long-term average treatment effects on the treated (ATT) are estimated.

```
library(PanelMatch)
```

Treatment Variation plot

- Visualize the variation of the treatment across space and time

- Aids in discerning whether the treatment fluctuates adequately over time and units or if the variation is primarily clustered in a subset of data.

```
DisplayTreatment(
    unit.id = "wbcode2",
    time.id = "year",
    legend.position = "none",
    xlab = "year",
    ylab = "Country Code",
    treatment = "dem",

    hide.x.tick.label = TRUE, hide.y.tick.label = TRUE,
    # dense.plot = TRUE,
    data = dem
)
```

1. Select F (i.e., the number of leads - time periods after treatment). Driven by what authors are interested in estimating:

- $F = 0$ is the contemporaneous effect (short-term effect)
- $F = n$ is the the treatment effect on the outcome two time periods after the treatment. (cumulative or long-term effect)

2. Select L (number of lags to adjust).

- Driven by the identification assumption.
- Balances bias-variance tradeoff.
- Higher L values increase credibility but reduce efficiency by limiting potential matches.

Model assumption:

- No spillover effect assumed.
- Carryover effect allowed up to L periods.
- Potential outcome for a unit depends neither on others' treatment status nor on its past treatment after L periods.

After defining causal quantity with parameters L and F.

- Focus on the average treatment effect of treatment status change.
- $\delta(F, L)$ is the average causal effect of treatment change (ATT), F periods post-treatment, considering treatment history up to L periods.
- Causal quantity considers potential future treatment reversals, meaning treatment could revert to control before outcome measurement.

Also possible to estimate the average treatment effect of treatment reversal on the reversed (ART).

Choose L, F based on specific needs.

- A large L value:
  - Increases the credibility of the limited carryover effect assumption.
  - Allows more past treatments (up to $t - L$) to influence the outcome $Y_{i,t+F}$.
  - Might reduce the number of matches and lead to less precise estimates.
- Selecting an appropriate number of lags
  - Researchers should base this choice on substantive knowledge.
  - Sensitivity of empirical results to this choice should be examined.
- The choice of F should be:
  - Substantively motivated.
  - Decides whether the interest lies in short-term or long-term causal effects.
  - A large F value can complicate causal effect interpretation, especially if many units switch treatment status during the F lead time period.

Identification Assumption

- Parallel trend assumption conditioned on treatment, outcome (excluding immediate lag), and covariate histories.
- Doesn't require strong unconfoundedness assumption.
- Cannot account for unobserved time-varying confounders.
- Essential to examine outcome time trends.
  - Check if they're parallel between treated and matched control units using pre-treatment data
- **Constructing the Matched Sets**:
  - For each treated observation, create matched control units with identical treatment history from $t - L$ to $t - 1$.
  - Matching based on treatment history helps control for carryover effects.
  - Past treatments often act as major confounders, but this method can correct for it.

  - Exact matching on time period adjusts for time-specific unobserved confounders.
  - Unlike staggered adoption methods, units can change treatment status multiple times.
  - Matched set allows treatment switching in and out of treatment
- **Refining the Matched Sets**:
  - Initially, matched sets adjust only for treatment history.
  - Parallel trend assumption requires adjustments for other confounders like past outcomes and covariates.
  - Matching methods:
    * Match each treated observation with up to J control units.
    * Distance measures like Mahalanobis distance or propensity score can be used.
    * Match based on estimated propensity score, considering pretreatment covariates.
    * Refined matched set selects most similar control units based on observed confounders.
  - Weighting methods:
    * Assign weight to each control unit in a matched set.
    * Weights prioritize more similar units.
    * Inverse propensity score weighting method can be applied.
    * Weighting is a more generalized method than matching.

The Difference-in-Differences Estimator:

- Using refined matched sets, the ATT (Average Treatment Effect on the Treated) of policy change is estimated.
- For each treated observation, estimate the counterfactual outcome using the weighted average of control units in the refined set.
- The DiD estimate of the ATT is computed for each treated observation, then averaged across all such observations.
- For noncontemporaneous treatment effects where $F > 0$:
  - The ATT doesn't specify future treatment sequence.
  - Matched control units might have units receiving treatment between time t and $t + F$.

  - Some treated units could return to control conditions between these times.

Checking Covariate Balance:

- The proposed methodology offers the advantage of checking covariate balance between treated and matched control observations.
- This check helps to see if treated and matched control observations are comparable with respect to observed confounders.
- Once matched sets are refined, covariate balance examination becomes straightforward.
- Examine the mean difference of each covariate between a treated observation and its matched controls for each pretreatment time period.
- Standardize this difference using the standard deviation of each covariate across all treated observations in the dataset.
- Aggregate this covariate balance measure across all treated observations for each covariate and pretreatment time period.
- Examine balance for lagged outcome variables over multiple pretreatment periods and time-varying covariates.
  - This helps evaluate the validity of the parallel trend assumption underlying the proposed DiD estimator.

Relations with Linear Fixed Effects Regression Estimators:

- The standard DiD estimator is equivalent to the linear two-way fixed effects regression estimator when:
  - Only two time periods exist.
  - Treatment is given to some units exclusively in the second period.
- This equivalence doesn't extend to multiperiod DiD designs, where:
  - More than two time periods are considered.
  - Units might receive treatment multiple times.
- Despite this, many researchers relate the use of the two-way fixed effects estimator to the DiD design.

Standard Error Calculation:

- Approach:
  - Condition on the weights implied by the matching process.
  - These weights denote how often an observation is utilized in matching (Imbens and Rubin, 2015)
- Context:

  - Analogous to the conditional variance seen in regression models.
  - Resulting standard errors don't factor in uncertainties around the matching procedure.
  - They can be viewed as a measure of uncertainty conditional upon the matching process (Ho et al., 2007).

Key Findings:

- Even in conditions favoring OLS, the proposed matching estimator displayed higher robustness to omitted relevant lags than the linear regression model with fixed effects.
- The robustness offered by matching came at a cost - reduced statistical power.
- This emphasizes the classic statistical tradeoff between bias (where matching has an advantage) and variance (where regression models might be more efficient).

Data Requirements

- The treatment variable is binary:
  - 0 signifies "assignment" to control.
  - 1 signifies assignment to treatment.
- Variables identifying units in the data must be: Numeric or integer.
- Variables identifying time periods should be: Consecutive numeric/integer data.
- Data format requirement: Must be provided as a standard `data.frame` object.

Basic functions:

1. Utilize treatment histories to create matching sets of treated and control units.
2. Refine these matched sets by determining weights for each control unit in the set.
   - Units with higher weights have a larger influence during estimations.

Matching on Treatment History:

- Goal is to match units transitioning from untreated to treated status with control units that have similar past treatment histories.
- Setting the Quantity of Interest (`qoi =`)
  - `att` average treatment effect on treated units
  - `atc` average treatment effect of treatment on the control units

- `art` average effect of treatment reversal for units that experience treatment reversal

- `ate` average treatment effect

```
library(PanelMatch)
# All examples follow the package's vignette
# Create the matched sets
PM.results.none <-
    PanelMatch(
        lag = 4,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "none",
        data = dem,
        match.missing = TRUE,
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )

# visualize the treated unit and matched controls
DisplayTreatment(
    unit.id = "wbcode2",
    time.id = "year",
    legend.position = "none",
    xlab = "year",
    ylab = "Country Code",
    treatment = "dem",
    data = dem,
    matched.set = PM.results.none$att[1],
    # highlight the particular set
    show.set.only = TRUE
)
```

Control units and the treated unit have identical treatment histories over the lag window (1988-1991)

```
DisplayTreatment(
    unit.id = "wbcode2",
    time.id = "year",
    legend.position = "none",
    xlab = "year",
    ylab = "Country Code",
    treatment = "dem",
    data = dem,
    matched.set = PM.results.none$att[2],
    # highlight the particular set
    show.set.only = TRUE
)
```

This set is more limited than the first one, but we can still see that we have exact past histories.

- **Refining Matched Sets**
  - Refinement involves assigning weights to control units.
  - Users must:
    1. Specify a method for calculating unit similarity/distance.
    2. Choose variables for similarity/distance calculations.
- **Select a Refinement Method**
  - Users determine the refinement method via the **`refinement.method`** argument.
  - Options include:
    * `mahalanobis`
    * `ps.match`
    * `CBPS.match`
    * `ps.weight`
    * `CBPS.weight`
    * `ps.msm.weight`
    * `CBPS.msm.weight`
    * `none`

  - Methods with "match" in the name and Mahalanobis will assign equal weights to similar control units.
  - "Weighting" methods give higher weights to control units more similar to treated units.

- **Variable Selection**
  - Users need to define which covariates will be used through the **`covs.formula`** argument, a one-sided formula object.
  - Variables on the right side of the formula are used for calculations.
  - "Lagged" versions of variables can be included using the format: **`I(lag(name.of.var, 0:n))`**.

- **Understanding `PanelMatch` and `matched.set` objects**
  - The **`PanelMatch` function** returns a **`PanelMatch` object**.
  - The most crucial element within the `PanelMatch` object is the **matched.set object**.
  - Within the `PanelMatch` object, the matched.set object will have names like att, art, or atc.
  - If **`qoi = ate`**, there will be two matched.set objects: att and atc.

- **Matched.set Object Details**
  - matched.set is a named list with added attributes.
  - Attributes include:
    * Lag
    * Names of treatment
    * Unit and time variables
  - Each list entry represents a matched set of treated and control units.
  - Naming follows a structure: **`[id variable].[time variable]`**.
  - Each list element is a vector of control unit ids that match the treated unit mentioned in the element name.
  - Since it's a matching method, weights are only given to the **`size.match`** most similar control units based on distance calculations.

```r
# PanelMatch without any refinement
PM.results.none <-
    PanelMatch(
        lag = 4,
        time.id = "year",
```

```
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "none",
        data = dem,
        match.missing = TRUE,
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )

# Extract the matched.set object
msets.none <- PM.results.none$att

# PanelMatch with refinement
PM.results.maha <-
    PanelMatch(
        lag = 4,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "mahalanobis", # use Mahalanobis distance
        data = dem,
        match.missing = TRUE,
        covs.formula = ~ tradewb,
        size.match = 5,
        qoi = "att" ,
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )
msets.maha <- PM.results.maha$att
```

```
# these 2 should be identical because weights are not shown
msets.none |> head()
#>   wbcode2 year matched.set.size
#> 1       4 1992               74
#> 2       4 1997                2
#> 3       6 1973               63
#> 4       6 1983               73
#> 5       7 1991               81
#> 6       7 1998                1
```

```
msets.maha |> head()
#>   wbcode2 year matched.set.size
#> 1       4 1992               74
#> 2       4 1997                2
#> 3       6 1973               63
#> 4       6 1983               73
#> 5       7 1991               81
#> 6       7 1998                1
# summary(msets.none)
# summary(msets.maha)
```

Visualizing Matched Sets with the plot method

- Users can visualize the distribution of the matched set sizes.
- A red line, by default, indicates the count of matched sets where treated units had no matching control units (i.e., empty matched sets).
- Plot adjustments can be made using `graphics::plot`.

```
plot(msets.none)
```

Comparing Methods of Refinement

- Users are encouraged to:
  - Use substantive knowledge for experimentation and evaluation.
  - Consider the following when configuring `PanelMatch`:
    1. The number of matched sets.

    2. The number of controls matched to each treated unit.
    3. Achieving covariate balance.
  - **Note**: Large numbers of small matched sets can lead to larger standard errors during the estimation stage.
  - Covariates that aren't well balanced can lead to undesirable comparisons between treated and control units.
  - Aspects to consider include:
    * Refinement method.
    * Variables for weight calculation.
    * Size of the lag window.
    * Procedures for addressing missing data (refer to **`match.missing`** and **`listwise.delete`** arguments).
    * Maximum size of matched sets (for matching methods).

- **Supportive Features:**
  - **`print`**, **`plot`**, and **`summary`** methods assist in understanding matched sets and their sizes.
  - **`get_covariate_balance`** helps evaluate covariate balance:
    * Lower values in the covariate balance calculations are preferred.

```
PM.results.none <-
    PanelMatch(
        lag = 4,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "none",
        data = dem,
        match.missing = TRUE,
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )
PM.results.maha <-
    PanelMatch(
        lag = 4,
        time.id = "year",
```

```
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "mahalanobis",
        data = dem,
        match.missing = TRUE,
        covs.formula = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )

# listwise deletion used for missing data
PM.results.listwise <-
    PanelMatch(
        lag = 4,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "mahalanobis",
        data = dem,
        match.missing = FALSE,
        listwise.delete = TRUE,
        covs.formula = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        use.diagonal.variance.matrix = TRUE
    )

# propensity score based weighting method
PM.results.ps.weight <-
    PanelMatch(
        lag = 4,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        refinement.method = "ps.weight",
        data = dem,
        match.missing = FALSE,
        listwise.delete = TRUE,
```

```
        covs.formula = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        size.match = 5,
        qoi = "att",
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE
    )

get_covariate_balance(
    PM.results.none$att,
    data = dem,
    covariates = c("tradewb", "y"),
    plot = FALSE
)
#>         tradewb            y
#> t_4 -0.07245466  0.291871990
#> t_3 -0.20930129  0.208654876
#> t_2 -0.24425207  0.107736647
#> t_1 -0.10806125 -0.004950238

get_covariate_balance(
    PM.results.maha$att,
    data = dem,
    covariates = c("tradewb", "y"),
    plot = FALSE
)
#>         tradewb          y
#> t_4  0.04558637 0.09701606
#> t_3 -0.03312750 0.10844046
#> t_2 -0.01396793 0.08890753
#> t_1  0.10474894 0.06618865


get_covariate_balance(
    PM.results.listwise$att,
    data = dem,
    covariates = c("tradewb", "y"),
    plot = FALSE
)
#>         tradewb          y
#> t_4  0.05634922 0.05223623
#> t_3 -0.01104797 0.05217896
#> t_2  0.01411473 0.03094133
#> t_1  0.06850180 0.02092209
```

```r
get_covariate_balance(
    PM.results.ps.weight$att,
    data = dem,
    covariates = c("tradewb", "y"),
    plot = FALSE
)
#>         tradewb          y
#> t_4 0.014362590 0.04035905
#> t_3 0.005529734 0.04188731
#> t_2 0.009410044 0.04195008
#> t_1 0.027907540 0.03975173
```

get__covariate__balance Function Options:

- Allows for the generation of plots displaying covariate balance using **`plot = TRUE`**.

- Plots can be customized using arguments typically used with the base R **`plot`** method.

- Option to set **`use.equal.weights = TRUE`** for:

  - Obtaining the balance of unrefined sets.

  - Facilitating understanding of the refinement's impact.

```r
# Use equal weights
get_covariate_balance(
    PM.results.ps.weight$att,
    data = dem,
    use.equal.weights = TRUE,
    covariates = c("tradewb", "y"),
    plot = TRUE,
    # visualize by setting plot to TRUE
    ylim = c(-1, 1)
)
```

```
# Compare covariate balance to refined sets
# See large improvement in balance
get_covariate_balance(
    PM.results.ps.weight$att,
    data = dem,
    covariates = c("tradewb", "y"),
    plot = TRUE,
    # visualize by setting plot to TRUE
    ylim = c(-1, 1)
)
```

```
balance_scatter(
    matched_set_list = list(PM.results.maha$att,
                            PM.results.ps.weight$att),
    data = dem,
    covariates = c("y", "tradewb")
)
```

`PanelEstimate`

- **Standard Error Calculation Methods**
  - There are different methods available:
    - **Bootstrap** (default method with 1000 iterations).
    - **Conditional**: Assumes independence across units, but not time.
    - **Unconditional**: Doesn't make assumptions of independence across units or time.
  - For `qoi` values set to `att`, `art`, or `atc` (Imai et al., 2021b):
    - You can use analytical methods for calculating standard errors, which include both "conditional" and "unconditional" methods.

```
PE.results <- PanelEstimate(
    sets              = PM.results.ps.weight,
    data              = dem,
    se.method         = "bootstrap",
    number.iterations = 1000,
    confidence.level  = .95
)

# point estimates
PE.results[["estimates"]]
#>       t+0       t+1       t+2       t+3       t+4
#> 0.2609565 0.9630847 1.2851017 1.7370930 1.4871846

# standard errors
PE.results[["standard.error"]]
#>       t+0       t+1       t+2       t+3       t+4
#> 0.6399349 1.0304938 1.3825265 1.7625951 2.1672629


# use conditional method
PE.results <- PanelEstimate(
    sets             = PM.results.ps.weight,
    data             = dem,
    se.method        = "conditional",
    confidence.level = .95
)

# point estimates
PE.results[["estimates"]]
#>       t+0       t+1       t+2       t+3       t+4
#> 0.2609565 0.9630847 1.2851017 1.7370930 1.4871846
```

```r
# standard errors
PE.results[["standard.error"]]
#>       t+0       t+1       t+2       t+3       t+4
#> 0.4844805 0.8170604 1.1171942 1.4116879 1.7172143

summary(PE.results)
#> Weighted Difference-in-Differences with Propensity Score
#> Matches created with 4 lags
#>
#> Standard errors computed with conditional  method
#>
#> Estimate of Average Treatment Effect on the Treated (ATT) by Period:
#> $summary
#>      estimate std.error       2.5%    97.5%
#> t+0 0.2609565 0.4844805 -0.6886078 1.210521
#> t+1 0.9630847 0.8170604 -0.6383243 2.564494
#> t+2 1.2851017 1.1171942 -0.9045586 3.474762
#> t+3 1.7370930 1.4116879 -1.0297644 4.503950
#> t+4 1.4871846 1.7172143 -1.8784937 4.852863
#>
#> $lag
#> [1] 4
#>
#> $qoi
#> [1] "att"

plot(PE.results)
```

Moderating Variables

```
# moderating variable
dem$moderator <- 0
dem$moderator <- ifelse(dem$wbcode2 > 100, 1, 2)

PM.results <-
    PanelMatch(
        lag                          = 4,
        time.id                      = "year",
        unit.id                      = "wbcode2",
        treatment                    = "dem",
        refinement.method            = "mahalanobis",
        data                         = dem,
        match.missing                = TRUE,
        covs.formula                 = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        size.match                   = 5,
        qoi                          = "att",
        outcome.var                  = "y",
        lead                         = 0:4,
        forbid.treatment.reversal    = FALSE,
        use.diagonal.variance.matrix = TRUE
    )
PE.results <-
    PanelEstimate(sets      = PM.results,
                  data      = dem,
                  moderator = "moderator")
```

```
# Each element in the list corresponds to a level in the moderator
plot(PE.results[[1]])
```

```
plot(PE.results[[2]])
```

To write up for journal submission, you can follow the following report:

In this study, closely aligned with the research by (Acemoglu et al., 2019), two

key effects of democracy on economic growth are estimated: the impact of democratization and that of authoritarian reversal. The treatment variable, X_{it}, is defined to be one if country i is democratic in year t, and zero otherwise.

The Average Treatment Effect for the Treated (ATT) under democratization is formulated as follows:

$$\begin{aligned}\delta(F,L) = \mathbb{E}\big\{&Y_{i,t+F}(X_{it}=1, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L}) \\ &-Y_{i,t+F}(X_{it}=0, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L}) | X_{it}=1, X_{i,t-1}=0\big\}\end{aligned}$$

In this framework, the treated observations are countries that transition from an authoritarian regime $X_{it-1} = 0$ to a democratic one $X_{it} = 1$. The variable F represents the number of leads, denoting the time periods following the treatment, and L signifies the number of lags, indicating the time periods preceding the treatment.

The ATT under authoritarian reversal is given by:

$$\begin{aligned}&\mathbb{E}\big[Y_{i,t+F}(X_{it}=0, X_{i,t-1}=1, \{X_{i,t-l}\}_{l=2}^{L}) \\ &-Y_{i,t+F}(X_{it}=1, X_{it-1}=1, \{X_{i,t-l}\}_{l=2}^{L}) | X_{it}=0, X_{i,t-1}=1\big]\end{aligned}$$

The ATT is calculated conditioning on 4 years of lags ($L = 4$) and up to 4 years following the policy change $F = 1, 2, 3, 4$. Matched sets for each treated observation are constructed based on its treatment history, with the number of matched control units generally decreasing when considering a 4-year treatment history as compared to a 1-year history.

To enhance the quality of matched sets, methods such as Mahalanobis distance matching, propensity score matching, and propensity score weighting are utilized. These approaches enable us to evaluate the effectiveness of each refinement method. In the process of matching, we employ both up-to-five and up-to-ten matching to investigate how sensitive our empirical results are to the maximum number of allowed matches. For more information on the refinement process, please see the Web Appendix

> The Mahalanobis distance is expressed through a specific formula. We aim to pair each treated unit with a maximum of J control units, permitting replacement, denoted as $|\mathcal{M}_{it} \leq J|$. The average Mahalanobis distance between a treated and each control unit over time is computed as:
>
> $$S_{it}(i') = \frac{1}{L}\sum_{l=1}^{L}\sqrt{(\mathbf{V}_{i,t-l} - \mathbf{V}_{i',t-l})^T \,{}^{-1}_{i,t-l}(\mathbf{V}_{i,t-l} - \mathbf{V}_{i',t-l})}$$
>
> For a matched control unit $i' \in \mathcal{M}_{it}$, $\mathbf{V}_{it'}$ represents the time-varying covariates to adjust for, and ${}_{it'}$ is the sample covariance

matrix for $\mathbf{V}_{it'}$. Essentially, we calculate a standardized distance using time-varying covariates and average this across different time intervals.

In the context of propensity score matching, we employ a logistic regression model with balanced covariates to derive the propensity score. Defined as the conditional likelihood of treatment given pre-treatment covariates (Rosenbaum and Rubin, 1983), the propensity score is estimated by first creating a data subset comprised of all treated and their matched control units from the same year. This logistic regression model is then fitted as follows:

$$\begin{aligned} & e_{it}(\{\mathbf{U}_{i,t-l}\}_{l=1}^{L}) \\ & = Pr(X_{it} = 1 | \mathbf{U}_{i,t-1}, \dots, \mathbf{U}_{i,t-L}) \\ & = \frac{1}{1 = \exp(-\sum_{l=1}^{L} \beta_l^T \mathbf{U}_{i,t-l})} \end{aligned}$$

where $\mathbf{U}_{it'} = (X_{it'}, \mathbf{V}_{it'}^T)^T$. Given this model, the estimated propensity score for all treated and matched control units is then computed. This enables the adjustment for lagged covariates via matching on the calculated propensity score, resulting in the following distance measure:

$$S_{it}(i') = |\text{logit}\{\hat{e}_{it}(\{\mathbf{U}_{i,t-l}\}_{l=1}^{L})\} - \text{logit}\{\hat{e}_{i't}(\{\mathbf{U}_{i',t-l}\}_{l=1}^{L})\}|$$

Here, $\hat{e}_{i't}(\{\mathbf{U}_{i,t-l}\}_{l=1}^{L})$ represents the estimated propensity score for each matched control unit $i' \in \mathcal{M}_{it}$.

Once the distance measure $S_{it}(i')$ has been determined for all control units in the original matched set, we fine-tune this set by selecting up to J closest control units, which meet a researcher-defined caliper constraint C. All other control units receive zero weight. This results in a refined matched set for each treated unit (i, t):

$$\mathcal{M}_{it}^{*} = \{i' : i' \in \mathcal{M}_{it}, S_{it}(i') < C, S_{it} \leq S_{it}^{(J)}\}$$

$S_{it}^{(J)}$ is the Jth smallest distance among the control units in the original set $\mathcal{M}_{it}$.

For further refinement using weighting, a weight is assigned to each control unit i' in a matched set corresponding to a treated unit (i, t), with greater weight accorded to more similar units. We utilize inverse propensity score weighting, based on the propensity score model mentioned earlier:

$$w_{it}^{i'} \propto \frac{\hat{e}_{i't}(\{\mathbf{U}_{i,t-l}\}_{l=1}^{L})}{1-\hat{e}_{i't}(\{\mathbf{U}_{i,t-l}\}_{l=1}^{L})}$$

In this model, $\sum_{i' \in \mathcal{M}_{it}} w_{it}^{i'} = 1$ and $w_{it}^{i'} = 0$ for $i' \notin \mathcal{M}_{it}$. The model is fitted to the complete sample of treated and matched control units.

Checking Covariate Balance A distinct advantage of the proposed methodology over regression methods is the ability it offers researchers to inspect the covariate balance between treated and matched control observations. This facilitates the evaluation of whether treated and matched control observations are comparable regarding observed confounders. To investigate the mean difference of each covariate (e.g., $V_{it'j}$, representing the j-th variable in $\mathbf{V}_{it'}$) between the treated observation and its matched control observation at each pre-treatment time period (i.e., $t' < t$), we further standardize this difference. For any given pretreatment time period, we adjust by the standard deviation of each covariate across all treated observations in the dataset. Thus, the mean difference is quantified in terms of standard deviation units. Formally, for each treated observation (i,t) where $D_{it} = 1$, we define the covariate balance for variable j at the pretreatment time period $t-l$ as:

$$B_{it}(j,l) = \frac{V_{i,t-l,j} - \sum_{i' \in \mathcal{M}_{it}} w_{it}^{i'} V_{i',t-l,j}}{\sqrt{\frac{1}{N_1-1}\sum_{i'=1}^{N}\sum_{t'=L+1}^{T-F} D_{i't'}(V_{i',t'-l,j} - \bar{V}_{t'-l,j})^2}} \quad (26.1)$$

where $N_1 = \sum_{i'=1}^{N}\sum_{t'=L+1}^{T-F} D_{i't'}$ denotes the total number of treated observations and $\bar{V}_{t-l,j} = \sum_{i=1}^{N} D_{i,t-l,j}/N$. We then aggregate this covariate balance measure across all treated observations for each covariate and pre-treatment time period:

$$\bar{B}(j,l) = \frac{1}{N_1}\sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it} B_{it}(j,l) \quad (26.2)$$

Lastly, we evaluate the balance of lagged outcome variables over several pre-treatment periods and that of time-varying covariates. This examination aids in assessing the validity of the parallel trend assumption integral to the DiD estimator justification.

In Figure **??**, we demonstrate the enhancement of covariate balance thank to the refinement of matched sets. Each scatter plot contrasts the absolute standardized mean difference, as detailed in Equation (26.2), before (horizontal axis) and after (vertical axis) this refinement. Points below the 45-degree line indicate an improved standardized mean balance for certain time-varying covariates post-refinement. The majority of variables benefit from this refinement process.

Notably, the propensity score weighting (bottom panel) shows the most significant improvement, whereas Mahalanobis matching (top panel) yields a more modest improvement.

```
library(PanelMatch)
library(causalverse)

runPanelMatch <- function(method, lag, size.match=NULL, qoi="att") {

    # Default parameters for PanelMatch
    common.args <- list(
        lag = lag,
        time.id = "year",
        unit.id = "wbcode2",
        treatment = "dem",
        data = dem,
        covs.formula = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        qoi = qoi,
        outcome.var = "y",
        lead = 0:4,
        forbid.treatment.reversal = FALSE,
        size.match = size.match  # setting size.match here for all methods
    )

    if(method == "mahalanobis") {
        common.args$refinement.method <- "mahalanobis"
        common.args$match.missing <- TRUE
        common.args$use.diagonal.variance.matrix <- TRUE
    } else if(method == "ps.match") {
        common.args$refinement.method <- "ps.match"
        common.args$match.missing <- FALSE
        common.args$listwise.delete <- TRUE
    } else if(method == "ps.weight") {
        common.args$refinement.method <- "ps.weight"
        common.args$match.missing <- FALSE
        common.args$listwise.delete <- TRUE
    }

    return(do.call(PanelMatch, common.args))
}

methods <- c("mahalanobis", "ps.match", "ps.weight")
lags <- c(1, 4)
sizes <- c(5, 10)
```

You can either do it sequentailly

```r
res_pm <- list()

for(method in methods) {
    for(lag in lags) {
        for(size in sizes) {
            name <- paste0(method, ".", lag, "lag.", size, "m")
            res_pm[[name]] <- runPanelMatch(method, lag, size)
        }
    }
}

# Now, you can access res_pm using res_pm[["mahalanobis.1lag.5m"]] etc.

# for treatment reversal
res_pm_rev <- list()

for(method in methods) {
    for(lag in lags) {
        for(size in sizes) {
            name <- paste0(method, ".", lag, "lag.", size, "m")
            res_pm_rev[[name]] <- runPanelMatch(method, lag, size, qoi = "art")
        }
    }
}
```

or in parallel

```r
library(foreach)
library(doParallel)
registerDoParallel(cores = 4)
# Initialize an empty list to store results
res_pm <- list()

# Replace nested for-loops with foreach
results <-
  foreach(
    method = methods,
    .combine = 'c',
    .multicombine = TRUE,
    .packages = c("PanelMatch", "causalverse")
  ) %dopar% {
    tmp <- list()
    for (lag in lags) {
      for (size in sizes) {
        name <- paste0(method, ".", lag, "lag.", size, "m")
        tmp[[name]] <- runPanelMatch(method, lag, size)
```

```
      }
    }
    tmp
  }

# Collate results
for (name in names(results)) {
  res_pm[[name]] <- results[[name]]
}

# Treatment reversal
# Initialize an empty list to store results
res_pm_rev <- list()

# Replace nested for-loops with foreach
results_rev <-
  foreach(
    method = methods,
    .combine = 'c',
    .multicombine = TRUE,
    .packages = c("PanelMatch", "causalverse")
  ) %dopar% {
    tmp <- list()
    for (lag in lags) {
      for (size in sizes) {
        name <- paste0(method, ".", lag, "lag.", size, "m")
        tmp[[name]] <-
          runPanelMatch(method, lag, size, qoi = "art")
      }
    }
    tmp
  }

# Collate results
for (name in names(results_rev)) {
  res_pm_rev[[name]] <- results_rev[[name]]
}


stopImplicitCluster()
```

```
library(gridExtra)

# Updated plotting function
create_balance_plot <- function(method, lag, sizes, res_pm, dem) {
```

```
    matched_set_lists <- lapply(sizes, function(size) {
        res_pm[[paste0(method, ".", lag, "lag.", size, "m")]]$att
    })

    return(
        balance_scatter_custom(
            matched_set_list = matched_set_lists,
            legend.title = "Possible Matches",
            set.names = as.character(sizes),
            legend.position = c(0.2, 0.8),

            # for compiled plot, you don't need x,y, or main labs
            x.axis.label = "",
            y.axis.label = "",
            main = "",
            data = dem,
            dot.size = 5,
            # show.legend = F,
            them_use = causalverse::ama_theme(base_size = 32),
            covariates = c("y", "tradewb")
        )
    )
}

plots <- list()

for (method in methods) {
    for (lag in lags) {
        plots[[paste0(method, ".", lag, "lag")]] <-
            create_balance_plot(method, lag, sizes, res_pm, dem)
    }
}

# # Arranging plots in a 3x2 grid
# grid.arrange(plots[["mahalanobis.1lag"]],
#              plots[["mahalanobis.4lag"]],
#              plots[["ps.match.1lag"]],
#              plots[["ps.match.4lag"]],
#              plots[["ps.weight.1lag"]],
#              plots[["ps.weight.4lag"]],
#              ncol=2, nrow=3)


# Standardized Mean Difference of Covariates
library(gridExtra)
```

```r
library(grid)

# Create column and row labels using textGrob
col_labels <- c("1-year Lag", "4-year Lag")
row_labels <- c("Maha Matching", "PS Matching", "PS Weigthing")

major.axes.fontsize = 40
minor.axes.fontsize = 30

png(
    file.path(getwd(), "images", "did_balance_scatter.png"),
    width = 1200,
    height = 1000
)

# Create a list-of-lists, where each inner list represents a row
grid_list <- list(
    list(
        nullGrob(),
        textGrob(col_labels[1], gp = gpar(fontsize = minor.axes.fontsize)),
        textGrob(col_labels[2], gp = gpar(fontsize = minor.axes.fontsize))
    ),

    list(textGrob(
        row_labels[1],
        gp = gpar(fontsize = minor.axes.fontsize),
        rot = 90
    ), plots[["mahalanobis.1lag"]], plots[["mahalanobis.4lag"]]),

    list(textGrob(
        row_labels[2],
        gp = gpar(fontsize = minor.axes.fontsize),
        rot = 90
    ), plots[["ps.match.1lag"]], plots[["ps.match.4lag"]]),

    list(textGrob(
        row_labels[3],
        gp = gpar(fontsize = minor.axes.fontsize),
        rot = 90
    ), plots[["ps.weight.1lag"]], plots[["ps.weight.4lag"]])
)

# "Flatten" the list-of-lists into a single list of grobs
grobs <- do.call(c, grid_list)
```

```r
grid.arrange(
    grobs = grobs,
    ncol = 3,
    nrow = 4,
    widths = c(0.15, 0.42, 0.42),
    heights = c(0.15, 0.28, 0.28, 0.28)
)

grid.text(
    "Before Refinement",
    x = 0.5,
    y = 0.03,
    gp = gpar(fontsize = major.axes.fontsize)
)
grid.text(
    "After Refinement",
    x = 0.03,
    y = 0.5,
    rot = 90,
    gp = gpar(fontsize = major.axes.fontsize)
)
dev.off()
#> pdf
#>   2
```

Note: Scatter plots display the standardized mean difference of each covariate j and lag year l as defined in Equation (26.2) before (x-axis) and after (y-axis) matched set refinement. Each plot includes varying numbers of possible matches for each matching method. Rows represent different matching/weighting methods, while columns indicate adjustments for various lag lengths.

```r
# Step 1: Define configurations
configurations <- list(
    list(refinement.method = "none", qoi = "att"),
    list(refinement.method = "none", qoi = "art"),
    list(refinement.method = "mahalanobis", qoi = "att"),
    list(refinement.method = "mahalanobis", qoi = "art"),
    list(refinement.method = "ps.match", qoi = "att"),
    list(refinement.method = "ps.match", qoi = "art"),
    list(refinement.method = "ps.weight", qoi = "att"),
    list(refinement.method = "ps.weight", qoi = "art")
)

# Step 2: Use lapply or loop to generate results
results <- lapply(configurations, function(config) {
    PanelMatch(
```

```
        lag                        = 4,
        time.id                    = "year",
        unit.id                    = "wbcode2",
        treatment                  = "dem",
        data                       = dem,
        match.missing              = FALSE,
        listwise.delete            = TRUE,
        size.match                 = 5,
        outcome.var                = "y",
        lead                       = 0:4,
        forbid.treatment.reversal  = FALSE,
        refinement.method          = config$refinement.method,
        covs.formula               = ~ I(lag(tradewb, 1:4)) + I(lag(y, 1:4)),
        qoi                        = config$qoi
    )
})

# Step 3: Get covariate balance and plot
plots <- mapply(function(result, config) {
    df <- get_covariate_balance(
        if (config$qoi == "att")
            result$att
        else
            result$art,
        data = dem,
        covariates = c("tradewb", "y"),
        plot = F
    )
    causalverse::plot_covariate_balance_pretrend(df, main = "", show_legend = F)
}, results, configurations, SIMPLIFY = FALSE)

# Set names for plots
names(plots) <- sapply(configurations, function(config) {
    paste(config$qoi, config$refinement.method, sep = ".")
})
```

To export

```
library(gridExtra)
library(grid)

# Column and row labels
col_labels <-
    c("None",
      "Mahalanobis",
      "Propensity Score Matching",
```

```
      "Propensity Score Weighting")
row_labels <- c("ATT", "ART")

# Specify your desired fontsize for labels
minor.axes.fontsize <- 16
major.axes.fontsize <- 20

png(file.path(getwd(), "images", "p_covariate_balance.png"), width=1200, height=1000)

# Create a list-of-lists, where each inner list represents a row
grid_list <- list(
    list(
        nullGrob(),
        textGrob(col_labels[1], gp = gpar(fontsize = minor.axes.fontsize)),
        textGrob(col_labels[2], gp = gpar(fontsize = minor.axes.fontsize)),
        textGrob(col_labels[3], gp = gpar(fontsize = minor.axes.fontsize)),
        textGrob(col_labels[4], gp = gpar(fontsize = minor.axes.fontsize))
    ),

    list(
        textGrob(
            row_labels[1],
            gp = gpar(fontsize = minor.axes.fontsize),
            rot = 90
        ),
        plots$att.none,
        plots$att.mahalanobis,
        plots$att.ps.match,
        plots$att.ps.weight
    ),

    list(
        textGrob(
            row_labels[2],
            gp = gpar(fontsize = minor.axes.fontsize),
            rot = 90
        ),
        plots$art.none,
        plots$art.mahalanobis,
        plots$art.ps.match,
        plots$art.ps.weight
    )
)

# "Flatten" the list-of-lists into a single list of grobs
```

```r
grobs <- do.call(c, grid_list)

# Arrange your plots with text labels
grid.arrange(
    grobs   = grobs,
    ncol    = 5,
    nrow    = 3,
    widths  = c(0.1, 0.225, 0.225, 0.225, 0.225),
    heights = c(0.1, 0.45, 0.45)
)

# Add main x and y axis titles
grid.text(
    "Refinement Methods",
    x  = 0.5,
    y  = 0.01,
    gp = gpar(fontsize = major.axes.fontsize)
)
grid.text(
    "Quantities of Interest",
    x   = 0.02,
    y   = 0.5,
    rot = 90,
    gp  = gpar(fontsize = major.axes.fontsize)
)

dev.off()
```

```r
library(knitr)
include_graphics(file.path(getwd(), "images", "p_covariate_balance.png"))
```

Note: Each graph displays the standardized mean difference, as outlined in Equation (26.2), plotted on the vertical axis across a pre-treatment duration of four years represented on the horizontal axis. The leftmost column illustrates the balance prior to refinement, while the subsequent three columns depict the covariate balance post the application of distinct refinement techniques. Each individual line signifies the balance of a specific variable during the pre-treatment phase.The red line is tradewb and blue line is the lagged outcome variable.

In Figure **??**, we observe a marked improvement in covariate balance due to the implemented matching procedures during the pre-treatment period. Our analysis prioritizes methods that adjust for time-varying covariates over a span of four years preceding the treatment initiation. The two rows delineate the standardized mean balance for both treatment modalities, with individual lines representing the balance for each covariate.

Across all scenarios, the refinement attributed to matched sets significantly enhances balance. Notably, using propensity score weighting considerably mitigates imbalances in confounders. While some degree of imbalance remains evident in the Mahalanobis distance and propensity score matching techniques, the standardized mean difference for the lagged outcome remains stable throughout the pre-treatment phase. This consistency lends credence to the validity of the proposed DiD estimator.

Estimation Results

We now detail the estimated ATTs derived from the matching techniques. Figure below offers visual representations of the impacts of treatment initiation (upper panel) and treatment reversal (lower panel) on the outcome variable for a duration of 5 years post-transition, specifically, (F = 0, 1, ..., 4). Across the five methods (columns), it becomes evident that the point estimates of effects associated with treatment initiation consistently approximate zero over the 5-year window. In contrast, the estimated outcomes of treatment reversal are notably negative and maintain statistical significance through all refinement techniques during the initial year of transition and the 1 to 4 years that follow, provided treatment reversal is permissible. These effects are notably pronounced, pointing to an estimated reduction of roughly X% in the outcome variable.

Collectively, these findings indicate that the transition into the treated state from its absence doesn't invariably lead to a heightened outcome. Instead, the transition from the treated state back to its absence exerts a considerable negative effect on the outcome variable in both the short and intermediate terms. Hence, the positive effect of the treatment (if we were to use traditional DiD) is actually driven by the negative effect of treatment reversal.

```
# sequential
# Step 1: Apply PanelEstimate function

# Initialize an empty list to store results
res_est <- vector("list", length(res_pm))

# Iterate over each element in res_pm
for (i in 1:length(res_pm)) {
  res_est[[i]] <- PanelEstimate(
    res_pm[[i]],
    data = dem,
    se.method = "bootstrap",
    number.iterations = 1000,
    confidence.level = .95
  )
  # Transfer the name of the current element to the res_est list
  names(res_est)[i] <- names(res_pm)[i]
}

# Step 2: Apply plot_PanelEstimate function

# Initialize an empty list to store plot results
res_est_plot <- vector("list", length(res_est))

# Iterate over each element in res_est
for (i in 1:length(res_est)) {
    res_est_plot[[i]] <-
```

```
        plot_PanelEstimate(res_est[[i]],
                           main = "",
                           theme_use = causalverse::ama_theme(base_size = 14))
    # Transfer the name of the current element to the res_est_plot list
    names(res_est_plot)[i] <- names(res_est)[i]
}

# check results
# res_est_plot$mahalanobis.1lag.5m


# Step 1: Apply PanelEstimate function for res_pm_rev

# Initialize an empty list to store results
res_est_rev <- vector("list", length(res_pm_rev))

# Iterate over each element in res_pm_rev
for (i in 1:length(res_pm_rev)) {
  res_est_rev[[i]] <- PanelEstimate(
    res_pm_rev[[i]],
    data = dem,
    se.method = "bootstrap",
    number.iterations = 1000,
    confidence.level = .95
  )
  # Transfer the name of the current element to the res_est_rev list
  names(res_est_rev)[i] <- names(res_pm_rev)[i]
}

# Step 2: Apply plot_PanelEstimate function for res_est_rev

# Initialize an empty list to store plot results
res_est_plot_rev <- vector("list", length(res_est_rev))

# Iterate over each element in res_est_rev
for (i in 1:length(res_est_rev)) {
    res_est_plot_rev[[i]] <-
        plot_PanelEstimate(res_est_rev[[i]],
                           main = "",
                           theme_use = causalverse::ama_theme(base_size = 14))
  # Transfer the name of the current element to the res_est_plot_rev list
  names(res_est_plot_rev)[i] <- names(res_est_rev)[i]
}
```

```r
# parallel
library(doParallel)
library(foreach)

# Detect the number of cores to use for parallel processing
num_cores <- 4

# Register the parallel backend
cl <- makeCluster(num_cores)
registerDoParallel(cl)

# Step 1: Apply PanelEstimate function in parallel
res_est <-
    foreach(i = 1:length(res_pm), .packages = "PanelMatch") %dopar% {
        PanelEstimate(
            res_pm[[i]],
            data = dem,
            se.method = "bootstrap",
            number.iterations = 1000,
            confidence.level = .95
        )
    }

# Transfer names from res_pm to res_est
names(res_est) <- names(res_pm)

# Step 2: Apply plot_PanelEstimate function in parallel
res_est_plot <-
    foreach(
        i = 1:length(res_est),
        .packages = c("PanelMatch", "causalverse", "ggplot2")
    ) %dopar% {
        plot_PanelEstimate(res_est[[i]],
                           main = "",
                           theme_use = causalverse::ama_theme(base_size = 10))
    }

# Transfer names from res_est to res_est_plot
names(res_est_plot) <- names(res_est)



# Step 1: Apply PanelEstimate function for res_pm_rev in parallel
res_est_rev <-
    foreach(i = 1:length(res_pm_rev), .packages = "PanelMatch") %dopar% {
```

```
        PanelEstimate(
            res_pm_rev[[i]],
            data = dem,
            se.method = "bootstrap",
            number.iterations = 1000,
            confidence.level = .95
        )
    }

# Transfer names from res_pm_rev to res_est_rev
names(res_est_rev) <- names(res_pm_rev)

# Step 2: Apply plot_PanelEstimate function for res_est_rev in parallel
res_est_plot_rev <-
    foreach(
        i = 1:length(res_est_rev),
        .packages = c("PanelMatch", "causalverse", "ggplot2")
    ) %dopar% {
        plot_PanelEstimate(res_est_rev[[i]],
                           main = "",
                           theme_use = causalverse::ama_theme(base_size = 10))
    }

# Transfer names from res_est_rev to res_est_plot_rev
names(res_est_plot_rev) <- names(res_est_rev)

# Stop the cluster
stopCluster(cl)
```

To export

```
library(gridExtra)
library(grid)

# Column and row labels
col_labels <- c("Mahalanobis 5m",
                "Mahalanobis 10m",
                "PS Matching 5m",
                "PS Matching 10m",
                "PS Weighting 5m")

row_labels <- c("ATT", "ART")

# Specify your desired fontsize for labels
minor.axes.fontsize <- 16
major.axes.fontsize <- 20
```

```r
png(file.path(getwd(), "images", "p_did_est_in_n_out.png"), width=1200, height=1000)

# Create a list-of-lists, where each inner list represents a row
grid_list <- list(
  list(
    nullGrob(),
    textGrob(col_labels[1], gp = gpar(fontsize = minor.axes.fontsize)),
    textGrob(col_labels[2], gp = gpar(fontsize = minor.axes.fontsize)),
    textGrob(col_labels[3], gp = gpar(fontsize = minor.axes.fontsize)),
    textGrob(col_labels[4], gp = gpar(fontsize = minor.axes.fontsize)),
    textGrob(col_labels[5], gp = gpar(fontsize = minor.axes.fontsize))
  ),

  list(
    textGrob(row_labels[1], gp = gpar(fontsize = minor.axes.fontsize), rot = 90),
    res_est_plot$mahalanobis.1lag.5m,
    res_est_plot$mahalanobis.1lag.10m,
    res_est_plot$ps.match.1lag.5m,
    res_est_plot$ps.match.1lag.10m,
    res_est_plot$ps.weight.1lag.5m
  ),

  list(
    textGrob(row_labels[2], gp = gpar(fontsize = minor.axes.fontsize), rot = 90),
    res_est_plot_rev$mahalanobis.1lag.5m,
    res_est_plot_rev$mahalanobis.1lag.10m,
    res_est_plot_rev$ps.match.1lag.5m,
    res_est_plot_rev$ps.match.1lag.10m,
    res_est_plot_rev$ps.weight.1lag.5m
  )
)

# "Flatten" the list-of-lists into a single list of grobs
grobs <- do.call(c, grid_list)

# Arrange your plots with text labels
grid.arrange(
  grobs   = grobs,
  ncol    = 6,
  nrow    = 3,
  widths  = c(0.1, 0.18, 0.18, 0.18, 0.18, 0.18),
  heights = c(0.1, 0.45, 0.45)
)

# Add main x and y axis titles
```

```
grid.text(
  "Methods",
  x  = 0.5,
  y  = 0.02,
  gp = gpar(fontsize = major.axes.fontsize)
)
grid.text(
  "",
  x   = 0.02,
  y   = 0.5,
  rot = 90,
  gp  = gpar(fontsize = major.axes.fontsize)
)

dev.off()
```

```
library(knitr)
include_graphics(file.path(getwd(), "images", "p_did_est_in_n_out.png"))
```

26.9.3.2 Counterfactual Estimators

- Also known as **imputation approach** (Liu et al., 2022)
- This class of estimator consider observation treatment as missing data. Models are built using data from the control units to impute conterfactuals for the treated observations.
- It's called counterfactual estimators because they predict outcomes as if the treated observations had not received the treatment.
- Advantages:
  - Avoids negative weights and biases by not using treated observations for modeling and applying uniform weights.
  - Supports various models, including those that may relax strict exogeneity assumptions.
- Methods including
  - Fixed-effects conterfactual estimator (FEct) (DiD is a special case):
    * Based on the Two-way Fixed-effects, where assumes linear additive functional form of unobservables based on unit and time FEs. But FEct fixes the improper weighting of TWFE by comparing within each matched pair (where each pair is the treated observation and its predicted counterfactual that is the weighted sum of all untreated observations).
  - Interactive Fixed Effects conterfactual estimator (IFEct) (Gobillon and Magnac, 2016, Xu (2017)):
    * When we suspect unobserved time-varying confounder, FEct fails. Instead, IFEct uses the factor-augmented models to relax the strict exogeneity assumption where the effects of

unobservables can be decomposed to unit FE + time FE + unit x time FE.
    * Generalized Synthetic Controls are a subset of IFEct when treatments don't revert.
  - Matrix completion (MC) (Athey et al., 2021):
    * Generalization of factor-augmented models. Different from IFEct which uses hard impute, MC uses soft impute to regularize the singular values when decomposing the residual matrix.
    * Only when latent factors (of unobservables) are strong and sparse, IFEct outperforms MC.
  - [Synthetic Controls] (case studies)

Identifying Assumptions:

1. **Function Form**: Additive separability of observables, unobservables, and idiosyncratic error term.
   - Hence, these models are scale dependent (Athey and Imbens, 2006) (e.g., log-transform outcome can invadiate this assumption).
2. **Strict Exogeneity**: Conditional on observables and unobservables, potential outcomes are independent of treatment assignment (i.e., baseline quasi-randomization)
   - In DiD, where unobservables = unit + time FEs, this assumption is the parallel trends assumption
3. **Low-dimensional Decomposition (Feasibility Assumption)**: Unobservable effects can be decomposed in low-dimension.
   - For the case that $U_{it} = f_t \times \lambda_i$ where f_t = common time trend (time FE), and λ_i = unit heterogeneity (unit FE). If $U_{it} = f_t \times \lambda_i$, DiD can satisfy this assumption. But this assumption is weaker than that of DID, and allows us to control for unobservables based on data.

Estimation Procedure:

1. Using all control observations, estimate the functions of both observable and unobservable variables (relying on Assumptions 1 and 3).
2. Predict the counterfactual outcomes for each treated unit using the obtained functions.
3. Calculate the difference in treatment effect for each treated individual.
4. By averaging over all treated individuals, you can obtain the Average Treatment Effect on the Treated (ATT).

Notes:

- Use jackknife when number of treated units is small (Liu et al., 2022, p.166).

26.9.3.2.1 Imputation Method Liu et al. (2022) can also account for treatment reversals and heterogeneous treatment effects.

Other imputation estimators include

- [@gardner2022two and @borusyak2021revisiting]
- Brown et al. (2023)

```
library(fect)

PanelMatch::dem

model.fect <-
    fect(
        Y = "y",
        D = "dem",
        X = "tradewb",
        data = na.omit(PanelMatch::dem),
        method = "fe",
        index = c("wbcode2", "year"),
        se = TRUE,
        parallel = TRUE,
        seed = 1234,
        # twfe
        force = "two-way"
    )
print(model.fect$est.avg)

plot(model.fect)

plot(model.fect, stats = "F.p")
```

F-test H_0: residual averages in the pre-treatment periods = 0

To see treatment reversal effects

```
plot(model.fect, stats = "F.p", type = 'exit')
```

26.9.3.2.2 Placebo Test By selecting a part of the data and excluding observations within a specified range to improve the model fitting, we then evaluate whether the estimated Average Treatment Effect (ATT) within this range significantly differs from zero. This approach helps us analyze the periods before treatment.

If this test fails, either the functional form or strict exogeneity assumption is problematic.

```
out.fect.p <-
    fect(
        Y = "y",
        D = "dem",
```

```
        X = "tradewb",
        data = na.omit(PanelMatch::dem),
        method = "fe",
        index = c("wbcode2", "year"),
        se = TRUE,
        placeboTest = TRUE,
        # using 3 periods
        placebo.period = c(-2, 0)
    )
plot(out.fect.p, proportion = 0.1, stats = "placebo.p")
```

26.9.3.2.3 (No) Carryover Effects Test The placebo test can be adapted to assess carryover effects by masking several post-treatment periods instead of pre-treatment ones. If no carryover effects are present, the average prediction error should approximate zero. For the carryover test, set `carryoverTest = TRUE`. Specify a post-treatment period range in carryover.period to exclude observations for model fitting, then evaluate if the estimated ATT significantly deviates from zero.

Even if we have carryover effects, in most cases of the staggered adoption setting, researchers are interested in the cumulative effects, or aggregated treatment effects, so it's okay.

```
out.fect.c <-
    fect(
        Y = "y",
        D = "dem",
        X = "tradewb",
        data = na.omit(PanelMatch::dem),
        method = "fe",
        index = c("wbcode2", "year"),
        se = TRUE,
        carryoverTest = TRUE,
        # how many periods of carryover
        carryover.period = c(1, 3)
    )
plot(out.fect.c,  stats = "carryover.p")
```

We have evidence of carryover effects.

26.9.3.3 Matrix Completion

Applications in marketing:

- Bronnenberg et al. (2020)

To estimate average causal effects in panel data with units exposed to treatment

intermittently, two literatures are pivotal:

- **Unconfoundedness** (Imbens and Rubin, 2015): Imputes missing potential control outcomes for treated units using observed outcomes from similar control units in previous periods.
- **Synthetic Control** (Abadie et al., 2010): Imputes missing control outcomes for treated units using weighted averages from control units, matching lagged outcomes between treated and control units.

Both exploit missing potential outcomes under different assumptions:

- Unconfoundedness assumes time patterns are stable across units.
- Synthetic control assumes unit patterns are stable over time.

Once regularization is applied, both approaches are applicable in similar settings (Athey et al., 2021).

Matrix Completion method, nesting both, is based on matrix factorization, focusing on imputing missing matrix elements assuming:

1. Complete matrix = low-rank matrix + noise.
2. Missingness is completely at random.

It's distinguished by not imposing factorization restrictions but utilizing regularization to define the estimator, particularly effective with the nuclear norm as a regularizer for complex missing patterns (Athey et al., 2021).

Contributions of Athey et al. (2021) matrix completion include:

1. Recognizing structured missing patterns allowing time correlation, enabling staggered adoption.
2. Modifying estimators for unregularized unit and time fixed effects.
3. Performing well across various T and N sizes, unlike unconfoundedness and synthetic control, which falter when $T >> N$ or $N >> T$, respectively.

Identifying Assumptions:

1. SUTVA: Potential outcomes indexed only by the unit's contemporaneous treatment.
2. No dynamic effects (it's okay under staggered adoption, it gives a different interpretation of estimand).

Setup:

- $Y_{it}(0)$ and $Y_{it}(1)$ represent potential outcomes of Y_{it}.
- W_{it} is a binary treatment indicator.

Aim to estimate the average effect for the treated:

$$\tau = \frac{\sum_{(i,t):W_{it}=1}[Y_{it}(1) - Y_{it}(0)]}{\sum_{i,t} W_{it}}$$

We observe all relevant values for $Y_{it}(1)$

We want to impute missing entries in the $Y(0)$ matrix for treated units with $W_{it} = 1$.

Define $\mathcal{M}$ as the set of pairs of indices (i,t), where $i \in N$ and $t \in T$, corresponding to missing entries with $W_{it} = 1$; $\mathcal{O}$ as the set of pairs of indices corresponding to observed entries in $Y(0)$ with $W_{it} = 0$.

Data is conceptualized as two $N \times T$ matrices, one incomplete and one complete:

$$Y = \begin{pmatrix} Y_{11} & Y_{12} & ? & \cdots & Y_{1T} \\ ? & ? & Y_{23} & \cdots & ? \\ Y_{31} & ? & Y_{33} & \cdots & ? \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Y_{N1} & ? & Y_{N3} & \cdots & ? \end{pmatrix},$$

and

$$W = \begin{pmatrix} 0 & 0 & 1 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 1 \\ 0 & 1 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \cdots & 1 \end{pmatrix},$$

where

$$W_{it} = \begin{cases} 1 & \text{if } (i,t) \in \mathcal{M}, \\ 0 & \text{if } (i,t) \in \mathcal{O}, \end{cases}$$

is an indicator for the event that the corresponding component of Y, that is Y_{it}, is missing.

Patterns of missing data in $\mathbf{Y}$:

- Block (treatment) structure with 2 special cases
  - Single-treated-period block structure (Imbens and Rubin, 2015)
  - Single-treated-unit block structure (Abadie et al., 2010)
- Staggered Adoption

Shape of matrix $\mathbf{Y}$:

- Thin ($N >> T$)
- Fat ($T >> N$)
- Square ($N \approx T$)

Combinations of patterns of missingness and shape create different literatures:

- Horizontal Regression = Thin matrix + single-treated-period block (focusing on cross-section correlation patterns)
- Vertical Regression = Fat matrix + single-treated-unit block (focusing on time-series correlation patterns)
- TWFE = Square matrix

To combine, we can exploit both stable patterns over time, and across units (e.g., TWFE, interactive FEs or matrix completion).

For the same factor model

$$\mathbf{Y} = \mathbf{U}\mathbf{V}^T +$$

where $\mathbf{U}$ is $N \times R$ and $\mathbf{V}$ is $T \times R$

The interactive FE literature focuses on a fixed number of factors R in $\mathbf{U}, \mathbf{V}$, while matrix completion focuses on impute $\mathbf{Y}$ using some forms regularization (e.g., nuclear norm).

- We can also estimate the number of factors R (Bai and Ng, 2002, Moon and Weidner (2015))

To use the nuclear norm minimization estimator, we must add a penalty term to regularize the objective function. However, before doing so, we need to explicitly estimate the time (λ_t) and unit (μ_i) fixed effects implicitly embedded in the missing data matrix to reduce the bias of the regularization term.

Specifically,

$$Y_{it} = L_{it} + \sum_{p=1}^{P}\sum_{q=1}^{Q} X_{ip}H_{pq}Z_{qt} + \mu_i + \lambda_t + V_{it}\beta + \epsilon_{it}$$

where

- X_{ip} is a matrix of p variables for unit i
- Z_{qt} is a matrix of q variables for time t
- V_{it} is a matrix of time-varying variables.

Lasso-type l_1 norm ($||H|| = \sum_{p=1}^{p}\sum_{q=1}^{Q}|H_{pq}|$) is used to shrink $H \to 0$

There are several options to regularize L:

1. Frobenius (i.e., Ridge): not informative since it imputes missing values as 0.
2. Nuclear Norm (i.e., Lasso): computationally feasible (using SOFT-IMPUTE algorithm (Mazumder et al., 2010)).
3. Rank (i.e., Subset selection): not computationally feasible

This method allows to

- use more covariates
- leverage data from treated units (can be used when treatment effect is constant and pattern of missing is not complex).
- have autocorrelated errors
- have weighted loss function (i.e., take into account the probability of outcomes for a unit being missing)

26.9.4 Gardner (2022) and Borusyak et al. (2021)

- Estimate the time and unit fixed effects separately
- Known as the imputation method (Borusyak et al., 2021) or two-stage DiD (Gardner, 2022)

```
# remotes::install_github("kylebutts/did2s")
library(did2s)
library(ggplot2)
library(fixest)
library(tidyverse)
data(base_stagg)


est <- did2s(
    data = base_stagg |> mutate(treat = if_else(time_to_treatment >= 0, 1, 0)),
    yname = "y",
    first_stage = ~ x1 | id + year,
    second_stage = ~ i(time_to_treatment, ref = c(-1,-1000)),
    treatment = "treat" ,
    cluster_var = "id"
)

fixest::esttable(est)
#>                                        est
#> Dependent Var.:                          y
#>
#> time_to_treatment = -9  0.3518** (0.1332)
#> time_to_treatment = -8  -0.3130* (0.1213)
#> time_to_treatment = -7    0.0894 (0.2367)
```

```
#> time_to_treatment = -6    0.0312 (0.2176)
#> time_to_treatment = -5   -0.2079 (0.1519)
#> time_to_treatment = -4   -0.1152 (0.1438)
#> time_to_treatment = -3   -0.0127 (0.1483)
#> time_to_treatment = -2    0.1503 (0.1440)
#> time_to_treatment = 0  -5.139*** (0.3680)
#> time_to_treatment = 1  -3.480*** (0.3784)
#> time_to_treatment = 2  -2.021*** (0.3055)
#> time_to_treatment = 3   -0.6965. (0.3947)
#> time_to_treatment = 4    1.070** (0.3501)
#> time_to_treatment = 5   2.173*** (0.4456)
#> time_to_treatment = 6   4.449*** (0.3680)
#> time_to_treatment = 7   4.864*** (0.3698)
#> time_to_treatment = 8   6.187*** (0.2702)
#> ---------------------- ------------------
#> S.E. type                          Custom
#> Observations                          950
#> R2                                0.62486
#> Adj. R2                           0.61843
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

fixest::iplot(
    est,
    main = "Event study",
    xlab = "Time to treatment",
    ref.line = -1
)
```

```
coefplot(est)
```

```
mult_est <- did2s::event_study(
    data = fixest::base_stagg |>
        dplyr::mutate(year_treated = dplyr::if_else(year_treated == 10000, 0, year_treated)),
    gname = "year_treated",
    idname = "id",
    tname = "year",
```

```
    yname = "y",
    estimator = "all"
)
#> Error in purrr::map(., function(y) { : i In index: 1.
#> i With name: y.
#> Caused by error in `.subset2()`:
#> ! no such index at level 1
did2s::plot_event_study(mult_est)
```

Borusyak et al. (2021) `didimputation`

This version is currently not working

```
library(didimputation)
library(fixest)
data("base_stagg")

did_imputation(
    data = base_stagg,
    yname = "y",
    gname = "year_treated",
    tname = "year",
    idname = "id"
)
```

26.9.5 De Chaisemartin and d'Haultfoeuille (2020)

use `twowayfeweights` from GitHub (De Chaisemartin and d'Haultfoeuille, 2020)

- Average instant treatment effect of changes in the treatment
  - This relaxes the no-carryover-effect assumption.
- Drawbacks:
  - Cannot observe treatment effects that manifest over time.

There still isn't a good package for this estimator.

```
# remotes::install_github("shuo-zhang-ucsb/did_multiplegt")
library(DIDmultiplegt)
library(fixest)
library(tidyverse)

data("base_stagg")

res <-
    did_multiplegt(
        df = base_stagg |>
            dplyr::mutate(treatment = dplyr::if_else(time_to_treatment < 0, 0, 1)),
        Y        = "y",
        G        = "year_treated",
        T        = "year",
        D        = "treatment",
        controls = "x1",
        # brep     = 20, # getting SE will take forever
        placebo  = 5,
        dynamic  = 5,
        average_effect = "simple"
    )

head(res)
#> $effect
#> treatment
#> -5.214207
#>
#> $N_effect
#> [1] 675
#>
#> $N_switchers_effect
#> [1] 45
#>
#> $dynamic_1
```

```
#> [1] -3.63556
#>
#> $N_dynamic_1
#> [1] 580
#>
#> $N_switchers_effect_1
#> [1] 40
```

I don't recommend the `TwoWayFEWeights` since it only gives the aggregated average treatment effect over all post-treatment periods, but not for each period.

```
library(TwoWayFEWeights)

res <- twowayfeweights(
    data = base_stagg |> dplyr::mutate(treatment = dplyr::if_else(time_to_treatment < 0
    Y = "y",
    G = "year_treated",
    T = "year",
    D = "treatment",
    summary_measures = T
)

print(res)
#> Under the common trends assumption, beta estimates a weighted sum of 45 ATTs.
#> 41 ATTs receive a positive weight, and 4 receive a negative weight.
#>
#> ------------------------------------------
#> Treat. var: treatment    ATTs    Σ weights
#> ------------------------------------------
#> Positive weights           41       1.0238
#> Negative weights            4      -0.0238
#> ------------------------------------------
#> Total                      45            1
#> ------------------------------------------
#>
#> Summary Measures:
#>   TWFE Coefficient ( _fe): -3.4676
#>   min  (Δ) compatible with  _fe and Δ_TR = 0: 4.8357
#>   min  (Δ) compatible with  _fe and Δ_TR of a different sign: 36.1549
#>   Reference: Corollary 1, de Chaisemartin, C and D'Haultfoeuille, X (2020a)
#>
#> The development of this package was funded by the European Union (ERC, REALLYCREDIB
```

26.9.6 Callaway and Sant'Anna (2021)

- `staggered` package

- Group-time average treatment effect

```
library(staggered)
library(fixest)
data("base_stagg")

# simple weighted average
staggered(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "simple"
)
#>     estimate        se se_neyman
#> 1 -0.7110941 0.2211943 0.2214245

# cohort weighted average
staggered(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "cohort"
)
#>    estimate        se se_neyman
#> 1 -2.724242 0.2701093 0.2701745

# calendar weighted average
staggered(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "calendar"
)
#>     estimate        se se_neyman
#> 1 -0.5861831 0.1768297 0.1770729

res <- staggered(
    df = base_stagg,
    i = "id",
    t = "year",
```

```
    g = "year_treated",
    y = "y",
    estimand = "eventstudy",
    eventTime = -9:8
)
head(res)
#>      estimate        se se_neyman eventTime
#> 1  0.20418779 0.1045821 0.1045821        -9
#> 2 -0.06215104 0.1669703 0.1670886        -8
#> 3  0.02744671 0.1413273 0.1420377        -7
#> 4 -0.02131747 0.2203695 0.2206338        -6
#> 5 -0.30690897 0.2015697 0.2036412        -5
#> 6  0.05594029 0.1908101 0.1921745        -4


ggplot(
    res |> mutate(
        ymin_ptwise = estimate + 1.96 * se,
        ymax_ptwise = estimate - 1.96 * se
    ),
    aes(x = eventTime, y = estimate)
) +
    geom_pointrange(aes(ymin = ymin_ptwise, ymax = ymax_ptwise)) +
    geom_hline(yintercept = 0) +
    xlab("Event Time") +
    ylab("Estimate") +
    causalverse::ama_theme()
```

```
# Callaway and Sant'Anna estimator for the simple weighted average
staggered_cs(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "simple"
)
#>     estimate        se se_neyman
#> 1 -0.7994889 0.4484987 0.4486122

# Sun and Abraham estimator for the simple weighted average
staggered_sa(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "simple"
)
#>     estimate        se se_neyman
#> 1 -0.7551901 0.4407818 0.4409525
```

Fisher's Randomization Test (i.e., permutation test)

H_0: $TE = 0$

```r
staggered(
    df = base_stagg,
    i = "id",
    t = "year",
    g = "year_treated",
    y = "y",
    estimand = "simple",
    compute_fisher = T,
    num_fisher_permutations = 100
)
#>     estimate        se se_neyman fisher_pval fisher_pval_se_neyman
#> 1 -0.7110941 0.2211943 0.2214245           0                     0
#>   num_fisher_permutations
#> 1                     100
```

26.9.7 Sun and Abraham (2021)

This paper utilizes the Cohort Average Treatment Effects on the Treated (CATT), which measures the cohort-specific average difference in outcomes relative to those never treated, offering a more detailed analysis than Goodman-Bacon (2021). In scenarios lacking a never-treated group, this method designates the last cohort to be treated as the control group.

Parameter of interest is the cohort-specific ATT l periods from int ital treatment period e

$$CATT = E[Y_{i,e+I} - Y^{\infty}_{i,e+I} | E_i = e]$$

This paper uses an **interaction-weighted estimator** in a panel data setting, where the original paper Gibbons et al. (2018) used the same idea in a cross-sectional setting.

- Callaway and Sant'Anna (2021) explores group-time average treatment effects, employing cohorts that have not yet been treated as controls, and permits conditioning on time-varying covariates.
- Athey and Imbens (2022) examines the treatment effect in relation to the counterfactual outcome of the always-treated group, diverging from the conventional focus on the never-treated.
- Borusyak et al. (2021) presumes a uniform treatment effect across cohorts, effectively simplifying CATT to ATT.

Identifying Assumptions for dynamic TWFE:

1. **Parallel Trends**: Baseline outcomes follow parallel trends across cohorts before treatment.

- This gives us all CATT (including own, included bins, and excluded bins)

2. **No Anticipatory Behavior**: There is no effect of the treatment during pre-treatment periods, indicating that outcomes are not influenced by the anticipation of treatment.

3. **Treatment Effect Homogeneity**: The treatment effect is consistent across cohorts for each relative period. Each adoption cohort should have the same path of treatment effects. In other words, the trajectory of each treatment cohort is similar. Compare to other designs:

    1. Athey and Imbens (2022) assume heterogeneity of treatment effects vary over adoption cohorts, but not over time.

    2. Borusyak et al. (2021) assume heterogeneity of treatment effects vary over time, but not over adoption cohorts.

    3. Callaway and Sant'Anna (2021) assume heterogeneity of treatment effects vary over time and across cohorts.

    4. De Chaisemartin and D'haultfœuille (2023) assume heterogeneity of treatment effects vary across groups and over time.

    5. Goodman-Bacon (2021) assume heterogeneity either "vary across units but not over time" or "vary over time but not across units".

    6. Sun and Abraham (2021) allows for treatment effect heterogeneity across units and time.

Sources of Heterogeneous Treatment Effects

- Adoption cohorts can differ based on certain covariates. Similarly, composition of units within each adoption cohort is different.

- The response to treatment varies among cohorts if units self-select their initial treatment timing based on anticipated treatment effects. However, this self-selection is still compatible with the parallel trends assumption. This is true if units choose based on an evaluation of baseline outcomes - that is, if baseline outcomes are similar (following parallel trends), then we might not see selection into treatment based on the evaluation of the baseline outcome.

- Treatment effects can vary across cohorts due to calendar time-varying effects, such as changes in economic conditions.

Notes:

- If you do TWFE, you actually have to drop 2 terms to avoid multicollinearity:

    - Period right before treatment (this one was known before this paper)

  - Drop or bin or trim a distant lag period (this one was clarified by the paper). The reason is before of the multicollinearity in the linear relationship between TWFE and the relative period indicators.

- Contamination of the treatment effect estimates from excluded periods is a type of "normalization". To avoid this, we have to assume that all pre-treatment periods have the same CATT.
  - Sun and Abraham (2021) estimation method gives reasonable weights to CATT (i..e, weights that sum to 1, and are non negative). They estimate the weighted average of CATT where the weights are shares of cohorts that experience at least l periods after to treatment, normalized by the size of total periods g.

- Aggregation of CATT is similar to that of Callaway and Sant'Anna (2021)

Application

can use `fixest` in r with `sunab` function

```
library(fixest)
data("base_stagg")
res_sa20 = feols(y ~ x1 + sunab(year_treated, year) | id + year, base_stagg)
iplot(res_sa20)
```

```
summary(res_sa20, agg = "att")
#> OLS estimation, Dep. Var.: y
#> Observations: 950
#> Fixed-effects: id: 95,  year: 10
#> Standard-errors: Clustered (id)
```

```
#>      Estimate Std. Error  t value  Pr(>|t|)
#> x1   0.994678   0.018378 54.12293 < 2.2e-16 ***
#> ATT -1.133749   0.205070 -5.52858 2.882e-07 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.921817     Adj. R2: 0.887984
#>                  Within R2: 0.876406
```

```r
summary(res_sa20, agg = c("att" = "year::[^-]"))
#> OLS estimation, Dep. Var.: y
#> Observations: 950
#> Fixed-effects: id: 95,  year: 10
#> Standard-errors: Clustered (id)
#>                       Estimate Std. Error   t value   Pr(>|t|)
#> x1                    0.994678   0.018378 54.122928  < 2.2e-16 ***
#> year::-9:cohort::10   0.351766   0.359073  0.979649 3.2977e-01
#> year::-8:cohort::9    0.033914   0.471437  0.071937 9.4281e-01
#> year::-8:cohort::10  -0.191932   0.352896 -0.543876 5.8781e-01
#> year::-7:cohort::8   -0.589387   0.736910 -0.799809 4.2584e-01
#> year::-7:cohort::9    0.872995   0.493427  1.769249 8.0096e-02 .
#> year::-7:cohort::10   0.019512   0.603411  0.032336 9.7427e-01
#> year::-6:cohort::7   -0.042147   0.865736 -0.048683 9.6127e-01
#> year::-6:cohort::8   -0.657571   0.573257 -1.147078 2.5426e-01
#> year::-6:cohort::9    0.877743   0.533331  1.645775 1.0315e-01
#> year::-6:cohort::10  -0.403635   0.347412 -1.161832 2.4825e-01
#> year::-5:cohort::6   -0.658034   0.913407 -0.720418 4.7306e-01
#> year::-5:cohort::7   -0.316974   0.697939 -0.454158 6.5076e-01
#> year::-5:cohort::8   -0.238213   0.469744 -0.507113 6.1326e-01
#> year::-5:cohort::9    0.301477   0.604201  0.498968 6.1897e-01
#> year::-5:cohort::10  -0.564801   0.463214 -1.219308 2.2578e-01
#> year::-4:cohort::5   -0.983453   0.634492 -1.549984 1.2451e-01
#> year::-4:cohort::6    0.360407   0.858316  0.419900 6.7552e-01
#> year::-4:cohort::7   -0.430610   0.661356 -0.651102 5.1657e-01
#> year::-4:cohort::8   -0.895195   0.374901 -2.387816 1.8949e-02 *
#> year::-4:cohort::9   -0.392478   0.439547 -0.892914 3.7418e-01
#> year::-4:cohort::10   0.519001   0.597880  0.868069 3.8757e-01
#> year::-3:cohort::4    0.591288   0.680169  0.869324 3.8688e-01
#> year::-3:cohort::5   -1.000650   0.971741 -1.029749 3.0577e-01
#> year::-3:cohort::6    0.072188   0.652641  0.110609 9.1216e-01
#> year::-3:cohort::7   -0.836820   0.804275 -1.040465 3.0079e-01
#> year::-3:cohort::8   -0.783148   0.701312 -1.116691 2.6697e-01
#> year::-3:cohort::9    0.811285   0.564470  1.437251 1.5397e-01
#> year::-3:cohort::10   0.527203   0.320051  1.647250 1.0285e-01
#> year::-2:cohort::3    0.036941   0.673771  0.054828 9.5639e-01
```

```
#> year::-2:cohort::4   0.832250   0.859544  0.968246 3.3541e-01
#> year::-2:cohort::5  -1.574086   0.525563 -2.995051 3.5076e-03 **
#> year::-2:cohort::6   0.311758   0.832095  0.374666 7.0875e-01
#> year::-2:cohort::7  -0.558631   0.871993 -0.640638 5.2332e-01
#> year::-2:cohort::8   0.429591   0.305270  1.407250 1.6265e-01
#> year::-2:cohort::9   1.201899   0.819186  1.467188 1.4566e-01
#> year::-2:cohort::10 -0.002429   0.682087 -0.003562 9.9717e-01
#> att                 -1.133749   0.205070 -5.528584 2.8820e-07 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.921817     Adj. R2: 0.887984
#>                  Within R2: 0.876406

# alternatively
summary(res_sa20, agg = c("att" = "year::[012345678]")) |>
    etable(digits = 2)
#>                           summary(res_..
#> Dependent Var.:                        y
#>
#> x1                        0.99*** (0.02)
#> year = -9 x cohort = 10    0.35 (0.36)
#> year = -8 x cohort = 9     0.03 (0.47)
#> year = -8 x cohort = 10   -0.19 (0.35)
#> year = -7 x cohort = 8    -0.59 (0.74)
#> year = -7 x cohort = 9    0.87. (0.49)
#> year = -7 x cohort = 10    0.02 (0.60)
#> year = -6 x cohort = 7    -0.04 (0.87)
#> year = -6 x cohort = 8    -0.66 (0.57)
#> year = -6 x cohort = 9     0.88 (0.53)
#> year = -6 x cohort = 10   -0.40 (0.35)
#> year = -5 x cohort = 6    -0.66 (0.91)
#> year = -5 x cohort = 7    -0.32 (0.70)
#> year = -5 x cohort = 8    -0.24 (0.47)
#> year = -5 x cohort = 9     0.30 (0.60)
#> year = -5 x cohort = 10   -0.56 (0.46)
#> year = -4 x cohort = 5    -0.98 (0.63)
#> year = -4 x cohort = 6     0.36 (0.86)
#> year = -4 x cohort = 7    -0.43 (0.66)
#> year = -4 x cohort = 8   -0.90* (0.37)
#> year = -4 x cohort = 9    -0.39 (0.44)
#> year = -4 x cohort = 10    0.52 (0.60)
#> year = -3 x cohort = 4     0.59 (0.68)
#> year = -3 x cohort = 5     -1.0 (0.97)
#> year = -3 x cohort = 6     0.07 (0.65)
#> year = -3 x cohort = 7    -0.84 (0.80)
```

```
#> year = -3 x cohort = 8    -0.78 (0.70)
#> year = -3 x cohort = 9     0.81 (0.56)
#> year = -3 x cohort = 10    0.53 (0.32)
#> year = -2 x cohort = 3     0.04 (0.67)
#> year = -2 x cohort = 4     0.83 (0.86)
#> year = -2 x cohort = 5   -1.6** (0.53)
#> year = -2 x cohort = 6     0.31 (0.83)
#> year = -2 x cohort = 7    -0.56 (0.87)
#> year = -2 x cohort = 8     0.43 (0.31)
#> year = -2 x cohort = 9      1.2 (0.82)
#> year = -2 x cohort = 10  -0.002 (0.68)
#> att                     -1.1*** (0.21)
#> Fixed-Effects:          --------------
#> id                                Yes
#> year                              Yes
#> ------------------------ --------------
#> S.E.: Clustered                 by: id
#> Observations                       950
#> R2                             0.90982
#> Within R2                      0.87641
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Using the same syntax as `fixest`

```r
# devtools::install_github("kylebutts/fwlplot")
library(fwlplot)
fwl_plot(y ~ x1, data = base_stagg)
```

```
fwl_plot(y ~ x1 | id + year, data = base_stagg, n_sample = 100)
```

```
fwl_plot(y ~ x1 | id + year, data = base_stagg, n_sample = 100, fsplit = ~ treated)
```

26.9.8 Wooldridge (2022)

use etwfe(Extended two-way Fixed Effects) (Wooldridge, 2022)

26.9.9 Doubly Robust DiD

Also known as the locally efficient doubly robust DiD (Sant'Anna and Zhao, 2020)

Code example by the authors

The package (not method) is rather limited application:

- Use OLS (cannot handle `glm`)
- Canonical DiD only (cannot handle DDD).

```
library(DRDID)
data("nsw_long")
eval_lalonde_cps <-
    subset(nsw_long, nsw_long$treated == 0 | nsw_long$sample == 2)
head(eval_lalonde_cps)
#>   id year treated age educ black married nodegree dwincl      re74 hisp
#> 1  1 1975      NA  42   16     0       1        0     NA     0.000    0
#> 2  1 1978      NA  42   16     0       1        0     NA     0.000    0
#> 3  2 1975      NA  20   13     0       0        0     NA  2366.794    0
#> 4  2 1978      NA  20   13     0       0        0     NA  2366.794    0
#> 5  3 1975      NA  37   12     0       1        0     NA 25862.322    0
#> 6  3 1978      NA  37   12     0       1        0     NA 25862.322    0
```

```
#>   early_ra sample experimental         re
#> 1       NA      2            0     0.0000
#> 2       NA      2            0   100.4854
#> 3       NA      2            0  3317.4678
#> 4       NA      2            0  4793.7451
#> 5       NA      2            0 22781.8555
#> 6       NA      2            0 25564.6699


# locally efficient doubly robust DiD Estimators for the ATT
out <-
    drdid(
        yname = "re",
        tname = "year",
        idname = "id",
        dname = "experimental",
        xformla = ~ age + educ + black + married + nodegree + hisp + re74,
        data = eval_lalonde_cps,
        panel = TRUE
    )
summary(out)
#>  Call:
#> drdid(yname = "re", tname = "year", idname = "id", dname = "experimental",
#>     xformla = ~age + educ + black + married + nodegree + hisp +
#>         re74, data = eval_lalonde_cps, panel = TRUE)
#> ------------------------------------------------------------------
#>  Further improved locally efficient DR DID estimator for the ATT:
#>
#>    ATT     Std. Error  t value    Pr(>|t|)  [95% Conf. Interval]
#> -901.2703   393.6247   -2.2897     0.022    -1672.7747  -129.766
#> ------------------------------------------------------------------
#>  Estimator based on panel data.
#>  Outcome regression est. method: weighted least squares.
#>  Propensity score est. method: inverse prob. tilting.
#>  Analytical standard error.
#> ------------------------------------------------------------------
#>  See Sant'Anna and Zhao (2020) for details.



# Improved locally efficient doubly robust DiD estimator
# for the ATT, with panel data
# drdid_imp_panel()

# Locally efficient doubly robust DiD estimator for the ATT,
```

```
# with panel data
# drdid_panel()

# Locally efficient doubly robust DiD estimator for the ATT,
# with repeated cross-section data
# drdid_rc()

# Improved locally efficient doubly robust DiD estimator for the ATT,
# with repeated cross-section data
# drdid_imp_rc()
```

26.9.10 Augmented/Forward DID

- DID Methods for Limited Pre-Treatment Periods:

Method	Scenario	Approach
Augmented DID (Li and Van den Bulte, 2023)	Treatment outcome is outside the range of control units	Constructs the treatment counterfactual using a scaled average of control units
Forward DID (Li, 2024)	Treatment outcome is within the range of control units	Uses a forward selection algorithm to choose relevant control units before applying DID

26.10 Multiple Treatments

When you have 2 treatments in a setting, you should always try to model both of them under one regression to see whether they are significantly different.

- Never use one treated groups as control for the other, and run separate regression.
- Could check this answer

$$
\begin{aligned}
Y_{it} = \alpha + \gamma_1 Treat1_i + \gamma_2 Treat2_i + \lambda Post_t \\
+ \delta_1(Treat1_i \times Post_t) + \delta_2(Treat2_i \times Post_t) + \epsilon_{it}
\end{aligned}
$$

(Fricke, 2017)

(De Chaisemartin and D'haultfœuille, 2023) video code

26.11 Mediation Under DiD

Check this post

26.12 Assumptions

- **Parallel Trends**: Difference between the treatment and control groups remain constant if there were no treatment.
  - should be used in cases where
    - you observe before and after an event
    - you have treatment and control groups
  - not in cases where
    - treatment is not random
    - confounders.
  - To support we use
    - Placebo test
    - Prior Parallel Trends Test
- **Linear additive effects** (of group/unit specific and time-specific):
  - If they are not additively interact, we have to use the weighted 2FE estimator (Imai and Kim, 2021)
  - Typically seen in the Staggered Dif-n-dif
- No anticipation: There is no causal effect of the treatment before its implementation.

Possible issues

- Estimate dependent on functional form:
  - When the size of the response depends (nonlinearly) on the size of the intervention, we might want to look at the the difference in the group with high intensity vs. low.
- Selection on (time–varying) unobservables
  - Can use the overall sensitivity of coefficient estimates to hidden bias using Rosenbaum Bounds
- Long-term effects
  - Parallel trends are more likely to be observed over shorter period (window of observation)
- Heterogeneous effects

  - Different intensity (e.g., doses) for different groups.

- Ashenfelter dip (Ashenfelter and Card, 1985) (job training program participant are more likely to experience an earning drop prior enrolling in these programs)
  - Participants are systemically different from nonparticipants before the treatment, leading to the question of permanent or transitory changes.
  - A fix to this transient endogeneity is to calculate long-run differences (exclude a number of periods symmetrically around the adoption/ implementation date). If we see a sustained impact, then we have strong evidence for the causal impact of a policy. (Proserpio and Zervas, 2017a) (Heckman and Smith, 1999) (Jepsen et al., 2014) (Li et al., 2011)

- Response to event might not be immediate (can't be observed right away in the dependent variable)
  - Using lagged dependent variable Y_{it-1} might be more appropriate (Blundell and Bond, 1998)

- Other factors that affect the difference in trends between the two groups (i.e., treatment and control) will bias your estimation.

- Correlated observations within a group or time

- Incidental parameters problems (Lancaster, 2000): it's always better to use individual and time fixed effect.

- When examining the effects of variation in treatment timing, we have to be careful because negative weights (per group) can be negative if there is a heterogeneity in the treatment effects over time. Example: [Athey and Imbens (2022)](Borusyak et al., 2021)(Goodman-Bacon, 2021). In this case you should use new estimands proposed by @callaway2021difference(De Chaisemartin and d'Haultfoeuille, 2020), in the `did` package. If you expect lags and leads, see (Sun and Abraham, 2021)

- (Gibbons et al., 2018) caution when we suspect the treatment effect and treatment variance vary across groups

26.12.1 Prior Parallel Trends Test

1. Plot the average outcomes over time for both treatment and control group before and after the treatment in time.
2. Statistical test for difference in trends (**using data from before the treatment period**)

$$Y = \alpha_g + \beta_1 T + \beta_2 T \times G + \epsilon$$

where

- Y = the outcome variable
- α_g = group fixed effects
- T = time (e.g., specific year, or month)
- β_2 = different time trends for each group

Hence, if $\beta_2 = 0$ provides evidence that there are no differences in the trend for the two groups prior the time treatment.

You can also use different functional forms (e..g, polynomial or nonlinear).

If $\beta_2 \neq 0$ statistically, possible reasons can be:

- Statistical significance can be driven by large sample
- Or the trends are so consistent, and just one period deviation can throw off the trends. Hence, statistical statistical significance.

Technically, we can still salvage the research by including time fixed effects, instead of just the before-and-after time fixed effect (actually, most researchers do this mechanically anyway nowadays). However, a side effect can be that the time fixed effects can also absorb some part your treatment effect as well, especially in cases where the treatment effects vary with time (i.e., stronger or weaker over time) (Wolfers, 2003).

Debate:

- (Kahn-Lang and Lang, 2020) argue that DiD will be more plausible when the treatment and control groups are similar not only in **trends**, but also in **levels**. Because when we observe dissimilar in levels prior to the treatment, why is it okay to think that this will not affect future trends?
  - Show a plot of the dependent variable's time series for treated and control groups and also a similar plot with matched sample. (Ryan et al., 2019) show evidence of matched DiD did well in the setting of non-parallel trends (at least in health care setting).
  - In the case that we don't have similar levels ex ante between treatment and control groups, functional form assumptions matter and we need justification for our choice.
- Pre-trend statistical tests: (Roth, 2022) provides evidence that these test are usually under powered.
  - See PretrendsPower and pretrends packages for correcting this.
- Parallel trends assumption is specific to both the transformation and units of the outcome (Roth and Sant'Anna, 2023)
  - See falsification test (H_0: parallel trends is insensitive to functional form).

```r
library(tidyverse)
library(fixest)
od <- causaldata::organ_donations %>%
    # Use only pre-treatment data
    filter(Quarter_Num <= 3) %>%
    # Treatment variable
    dplyr::mutate(California = State == 'California')

# use my package
causalverse::plot_par_trends(
    data = od,
    metrics_and_names = list("Rate" = "Rate"),
    treatment_status_var = "California",
    time_var = list(Quarter_Num = "Time"),
    display_CI = F
)
#> [[1]]
```

```r
# do it manually
# always good but plot the dependent out
od |>
    # group by treatment status and time
    dplyr::group_by(California, Quarter) |>
    dplyr::summarize_all(mean) |>
    dplyr::ungroup() |>
    # view()
```

```
ggplot2::ggplot(aes(x = Quarter_Num, y = Rate, color = California)) +
ggplot2::geom_line() +
causalverse::ama_theme()
```

```
# but it's also important to use statistical test
prior_trend <- fixest::feols(Rate ~ i(Quarter_Num, California) | State + Quarter,
               data = od)

fixest::coefplot(prior_trend, grid = F)
```

```
fixest::iplot(prior_trend, grid = F)
```

This is alarming since one of the periods is significantly different from 0, which means that our parallel trends assumption is not plausible.

In cases where you might have violations of parallel trends assumption, check (Rambachan and Roth, 2023)

- Impose restrictions on how different the post-treatment violations of parallel trends can be from the pre-trends.

- Partial identification of causal parameter
- Sensitivity analysis

```
# https://github.com/asheshrambachan/HonestDiD
# remotes::install_github("asheshrambachan/HonestDiD")
# library(HonestDiD)
```

Alternatively, Ban and Kedagni (2022) propose a method that with an information set (i.e., pre-treatment covariates), and an assumption on the selection bias in the post-treatment period (i.e., lies within the convex hull of all selection biases), they can still identify a set of ATT, and with stricter assumption on selection bias from the policymakers perspective, they can also have a point estimate.

Alternatively, we can use the `pretrends` package to examine our assumptions (Roth, 2022)

26.12.2 Placebo Test

Procedure:

1. Sample data only in the period before the treatment in time.
2. Consider different fake cutoff in time, either
    1. Try the whole sequence in time
    2. Generate random treatment period, and use **randomization inference** to account for sampling distribution of the fake effect.
3. Estimate the DiD model but with the post-time = 1 with the fake cutoff
4. A significant DiD coefficient means that you violate the parallel trends! You have a big problem.

Alternatively,

- When data have multiple control groups, drop the treated group, and assign another control group as a "fake" treated group. But even if it fails (i.e., you find a significant DiD effect) among the control groups, it can still be fine. However, this method is used under Synthetic Control

Code by theeffectbook.net

```
library(tidyverse)
library(fixest)

od <- causaldata::organ_donations %>%
    # Use only pre-treatment data
    dplyr::filter(Quarter_Num <= 3) %>%

    # Create fake treatment variables
    dplyr::mutate(
        FakeTreat1 = State == 'California' &
```

```
            Quarter %in% c('Q12011', 'Q22011'),
        FakeTreat2 = State == 'California' &
            Quarter == 'Q22011'
    )


clfe1 <- fixest::feols(Rate ~ FakeTreat1 | State + Quarter,
               data = od)
clfe2 <- fixest::feols(Rate ~ FakeTreat2 | State + Quarter,
               data = od)

fixest::etable(clfe1,clfe2)
#>                            clfe1            clfe2
#> Dependent Var.:             Rate             Rate
#>
#> FakeTreat1TRUE  0.0061 (0.0051)
#> FakeTreat2TRUE                  -0.0017 (0.0028)
#> Fixed-Effects:  --------------- ----------------
#> State                        Yes              Yes
#> Quarter                      Yes              Yes
#> _______________ _______________ ________________
#> S.E.: Clustered       by: State        by: State
#> Observations                 81               81
#> R2                      0.99377          0.99376
#> Within R2               0.00192          0.00015
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We would like the "supposed" DiD to be insignificant.

26.12.3 Assumption Violations

1. Endogenous Timing

If the timing of units can be influenced by strategic decisions in a DID analysis, an instrumental variable approach with a control function can be used to control for endogeneity in timing.

2. Questionable Counterfactuals

In situations where the control units may not serve as a reliable counterfactual for the treated units, matching methods such as propensity score matching or generalized random forest can be utilized. Additional methods can be found in Matching Methods.

26.12.4 Robustness Checks

- Placebo DiD (if the DiD estimate $\neq 0$, parallel trend is violated, and original DiD is biased):
  - Group: Use fake treatment groups: A population that was **not** affect by the treatment
  - Time: Redo the DiD analysis for period before the treatment (expected treatment effect is 0) (e.g., for previous year or period).
- Possible alternative control group: Expected results should be similar
- Try different windows (further away from the treatment point, other factors can creep in and nullify your effect).
- Treatment Reversal (what if we don't see the treatment event)
- Higher-order polynomial time trend (to relax linearity assumption)
- Test whether other dependent variables that should not be affected by the event are indeed unaffected.
  - Use the same control and treatment period (DiD $\neq 0$, there is a problem)
- The **triple-difference strategy** involves examining the interaction between the **treatment variable** and **the probability of being affected by the program**, and the group-level participation rate. The identification assumption is that there are no differential trends between high and low participation groups in early versus late implementing countries.

Chapter 27

Changes-in-Changes

- **Introduction**
  - The Changes-in-Changes (CiC) estimator, introduced by Athey and Imbens (2006), is an alternative to the Difference-in-Differences (DiD) strategy.
  - Unlike traditional DiD, which estimates the Average Treatment Effect on the Treated (ATT), CiC focuses on the Quantile Treatment Effect on the Treated (QTT).
  - QTT captures the difference between potential outcome distributions for treated units at a specific quantile.
  - **Beyond Averages:** Policymakers often look beyond average program impacts, considering how benefits are distributed across different groups.
    - **Job Training Example:** Two programs with the same negative average impact may be treated differently: one benefiting high earners might be rejected, while one benefiting low earners could be approved.
    - **Traditional Methods' Limitations:** Methods like linear regression, which assume uniform effects, fail to capture important distributional differences.
    - **QTEs' Advantage:** QTE methods are tailored for analyzing how treatment effects vary across different segments of a population.
  - **QTE vs. ATE:** While QTEs provide detailed insights into distributional impacts, they also allow for the recovery of ATEs. However, ATEs are usually identified under weaker assumptions, making QTEs more suitable for exploring the shape of treatment effects rather than just their central tendency.
- **Key Concepts**

  - **Quantile Treatment Effect on the Treated (QTT):** Difference in quantiles of treated units' potential outcome distributions.
  - **Rank Preservation:** Assumes each unit's rank remains constant across potential outcome distributions—this is a strong assumption.
  - **Counterfactual Distribution:** Estimation focuses on determining this distribution for the treated units in period 1.

- **Estimating QTT**
  - CiC uses four distributions from a 2x2 DiD design:
    1. $F_{Y(0),00}$: CDF of $Y(0)$ for control units in period 0.
    2. $F_{Y(0),10}$: CDF of $Y(0)$ for treatment units in period 0.
    3. $F_{Y(0),01}$: CDF of $Y(0)$ for control units in period 1.
    4. $F_{Y(1),11}$: CDF of $Y(1)$ for treatment units in period 1.
  - QTT is defined as the difference between the inverses of $F_{Y(1),11}$ and the counterfactual distribution $F_{Y(0),11}$ at quantile q:

$$\Delta_\theta^{QTT} = F_{Y(1),11}^{-1}(\theta) - F_{Y(0),11}^{-1}(\theta)$$

- **Estimation Process**
  - **Counterfactual CDF:**

$$\hat{F}_{Y(0),11}(y) = F_{y,01}\left(F_{y,00}^{-1}\left(F_{y,10}(y)\right)\right)$$

  - **Equivalent Expression:**

$$\hat{F}_{Y(0),11}^{-1}(\theta) = F_{y,01}^{-1}\left(F_{y,00}\left(F_{y,10}^{-1}(\theta)\right)\right)$$

  - **Treatment Effect Estimate:**

$$\hat{\Delta}_\theta^{CIC} = F_{Y(1),11}^{-1}(\theta) - \hat{F}_{Y(0),11}^{-1}(\theta)$$

  - **Equivalently:**

  Δ_θ^{CIC} is the difference between two QTE estimates:

$$\Delta_\theta^{CIC} = \Delta_{\theta,1}^{QTE} - \Delta_{\theta',0}^{QTE}$$

  where:
  - $\Delta_{\theta,1}^{QTT}$ = change over time in y at quantile θ for $D = 1$ group.
  - $\Delta_{\theta',0}^{QTU}$ = change over time in y at quantile θ' for $D = 0$ group, where q' is the quantile in the $D = 0, T = 0$ distribution corresponding to the value of y associated with quantile θ in the $D = 1, T = 0$ distribution.

- **Marketing Example**

  - Suppose a company implements a new online marketing strategy aimed at improving customer retention rates.
  - **QTT:** The goal is to estimate the effect of the strategy on customer retention rates at different quantiles (e.g., median retention rate).
  - **Rank Preservation:** Assumes customers' rank in retention distribution remains the same, regardless of the strategy—this assumption is strong and should be carefully considered.
  - **Counterfactual:** CiC helps estimate how retention rates would have changed without the new strategy by comparing it with a control group.

- **References**
  - Athey and Imbens (2006)
  - Frölich and Melly (2013): IV-based
  - Callaway and Li (2019): panel data
  - Huber et al. (2022)

- **Additional Resources**
  - Code examples available in Stata.

27.1 Application

27.1.1 ECIC package

```
library(ecic)
data(dat, package = "ecic")
mod =
  ecic(
    yvar  = lemp,          # dependent variable
    gvar  = first.treat,   # group indicator
    tvar  = year,          # time indicator
    ivar  = countyreal,    # unit ID
    dat   = dat,           # dataset
    boot  = "weighted",    # bootstrap proceduce ("no", "normal", or "weighted")
    nReps = 3             # number of bootstrap runs
    )
mod_res <- summary(mod)
mod_res
#>   perc    coefs          se
#> 1  0.1 1.206140 0.021351711
#> 2  0.2 1.316599 0.009225026
#> 3  0.3 1.449963 0.001859468
#> 4  0.4 1.583415 0.015296156
#> 5  0.5 1.739932 0.011240454
#> 6  0.6 1.915558 0.013060348
```

```
#> 7  0.7 2.114966 0.014482208
#> 8  0.8 2.363105 0.005173865
#> 9  0.9 2.779202 0.020831180

ecic_plot(mod_res)
```

27.1.2 QTE package

```
library(qte)
data(lalonde)

# randomized setting
# qte is identical to qtet
jt.rand <-
    ci.qtet(
        re78 ~ treat,
        data = lalonde.exp,
        iters = 10
    )
summary(jt.rand)
#>
#> Quantile Treatment Effect:
#>
#> tau  QTE Std. Error
#> 0.05    0.00    0.00
#> 0.1     0.00    0.00
```

```
#> 0.15    0.00    0.00
#> 0.2     0.00  179.39
#> 0.25  338.65  310.66
#> 0.3   846.40  403.44
#> 0.35 1451.51  550.40
#> 0.4  1177.72  832.39
#> 0.45 1396.08  958.97
#> 0.5  1123.55  923.72
#> 0.55 1181.54  746.56
#> 0.6  1466.51  657.59
#> 0.65 2115.04  561.46
#> 0.7  1795.12  463.82
#> 0.75 2347.49  824.58
#> 0.8  2278.12 1111.52
#> 0.85 2178.28  934.05
#> 0.9  3239.60 1313.89
#> 0.95 3979.62 1440.05
#>
#> Average Treatment Effect:    1794.34
#>   Std. Error:        545.04
ggqte(jt.rand)
```

```
# conditional independence assumption (CIA)
jt.cia <- ci.qte(
    re78 ~ treat,
    xformla =  ~ age + education,
    data = lalonde.psid,
```

```r
    iters = 10
)
summary(jt.cia)
#>
#> Quantile Treatment Effect:
#>
#> tau  QTE Std. Error
#> 0.05      0.00        0.00
#> 0.1       0.00       69.16
#> 0.15  -4433.18     1216.49
#> 0.2   -8219.15      573.30
#> 0.25 -10435.74      800.14
#> 0.3  -12232.03     1306.61
#> 0.35 -12428.30     1789.50
#> 0.4  -14195.24     1626.30
#> 0.45 -14248.66     2166.41
#> 0.5  -15538.67     2505.12
#> 0.55 -16550.71     2576.07
#> 0.6  -15595.02     2724.52
#> 0.65 -15827.52     3396.82
#> 0.7  -16090.32     3480.56
#> 0.75 -16091.49     3148.62
#> 0.8  -17864.76     3657.43
#> 0.85 -16756.71     3178.53
#> 0.9  -17914.99     2856.43
#> 0.95 -23646.22     3061.80
#>
#> Average Treatment Effect:    -13435.40
#>   Std. Error:        1637.45
ggqte(jt.cia)
```

```
jt.ciat <- ci.qtet(
    re78 ~ treat,
    xformla =  ~ age + education,
    data = lalonde.psid,
    iters = 10
)
summary(jt.ciat)
#>
#> Quantile Treatment Effect:
#>
#> tau  QTE Std. Error
#> 0.05      0.00        0.00
#> 0.1   -1018.15      547.30
#> 0.15  -3251.00     1196.05
#> 0.2   -7240.86      546.85
#> 0.25  -8379.94      301.65
#> 0.3   -8758.82      439.07
#> 0.35  -9897.44      539.91
#> 0.4  -10239.57      654.74
#> 0.45 -10751.39      836.43
#> 0.5  -10570.14      425.39
#> 0.55 -11348.96      753.11
#> 0.6  -11550.84      982.00
#> 0.65 -12203.56     1203.44
#> 0.7  -13277.72     1141.45
#> 0.75 -14011.74      940.89
```

```
#> 0.8  -14373.95      980.16
#> 0.85 -14499.18     1385.55
#> 0.9  -15008.63     1974.96
#> 0.95 -15954.05     1701.02
#>
#> Average Treatment Effect:    4266.19
#>   Std. Error:        352.88
ggqte(jt.ciat)
```

- **QTE** compares quantiles of the entire population under treatment and control, whereas **QTET** compares quantiles within the treated group itself. This difference means that QTE reflects the overall population-level impact, while QTET focuses on the treated group's specific impact.
- **CIA** enables identification of both QTE and QTET, but since QTET is conditional on treatment, it might reflect different effects than QTE, especially when the treatment effect is heterogeneous across different subpopulations. For example, the QTE could show a more generalized effect across all individuals, while the QTET may reveal stronger or weaker effects for the subgroup that actually received the treatment.

These are DID-like models

1. With the distributional difference-in-differences assumption (Fan and Yu, 2012, Callaway and Li (2019)), which is an extension of the parallel trends assumption, we can estimate QTET.

```
# distributional DiD assumption
jt.pqtet <- panel.qtet(
```

```r
    re ~ treat,
    t = 1978,
    tmin1 = 1975,
    tmin2 = 1974,
    tname = "year",
    idname = "id",
    data = lalonde.psid.panel,
    iters = 10
)
summary(jt.pqtet)
#>
#> Quantile Treatment Effect:
#>
#> tau  QTE Std. Error
#> 0.05  4779.21     1511.78
#> 0.1   1987.35      648.15
#> 0.15   842.95     3420.35
#> 0.2  -7366.04     3887.64
#> 0.25 -8449.96     1188.96
#> 0.3  -7992.15     1183.48
#> 0.35 -7429.21     1235.74
#> 0.4  -6597.37     1301.13
#> 0.45 -5519.45     1327.31
#> 0.5  -4702.88     1245.44
#> 0.55 -3904.52     1077.21
#> 0.6  -2741.80     1199.48
#> 0.65 -1507.31     1268.90
#> 0.7   -771.12     1260.84
#> 0.75   707.81     1241.03
#> 0.8    580.00      893.78
#> 0.85   821.75     1491.33
#> 0.9   -250.77     1904.54
#> 0.95 -1874.54     3129.77
#>
#> Average Treatment Effect:    2326.51
#>   Std. Error:        544.91
ggqte(jt.pqtet)
```

2. With 2 periods, the distributional DiD assumption can partially identify QTET with bounds (Fan and Yu, 2012)

```
res_bound <-
    bounds(
        re ~ treat,
        t = 1978,
        tmin1 = 1975,
        data = lalonde.psid.panel,
        idname = "id",
        tname = "year"
    )
summary(res_bound)
#>
#> Bounds on the Quantile Treatment Effect on the Treated:
#>
#> tau  Lower Bound Upper Bound
#>          tau  Lower Bound Upper Bound
#>         0.05       -51.72           0
#>          0.1     -1220.84           0
#>         0.15      -1881.9           0
#>          0.2     -2601.32           0
#>         0.25     -2916.38      485.23
#>          0.3     -3080.16      943.05
#>         0.35     -3327.89     1505.98
#>          0.4     -3240.59     2133.59
#>         0.45     -2982.51     2616.84
```

```
#>          0.5     -3108.01      2566.2
#>         0.55     -3342.66     2672.82
#>          0.6      -3491.4      3065.7
#>         0.65     -3739.74     3349.74
#>          0.7     -4647.82     2992.03
#>         0.75     -4826.78     3219.32
#>          0.8      -5801.7     2702.33
#>         0.85     -6588.61     2499.41
#>          0.9     -8953.84     2020.84
#>         0.95    -14283.61      397.04
#>
#> Average Treatment Effect on the Treated: 2326.51
plot(res_bound)
```

3. With a restrictive assumption that difference in the quantiles of the distribution of potential outcomes for the treated and untreated groups be the same for all values of quantiles, we can have the mean DiD model

```
jt.mdid <- ddid2(
    re ~ treat,
    t = 1978,
    tmin1 = 1975,
    tname = "year",
    idname = "id",
    data = lalonde.psid.panel,
    iters = 10
)
```

```r
summary(jt.mdid)
#>
#> Quantile Treatment Effect:
#>
#> tau  QTE Std. Error
#> 0.05 10616.61      551.36
#> 0.1   5019.83      323.38
#> 0.15  2388.12      229.69
#> 0.2   1033.23      226.29
#> 0.25   485.23      302.16
#> 0.3    943.05      227.36
#> 0.35   931.45      562.40
#> 0.4    945.35      925.57
#> 0.45  1205.88      820.33
#> 0.5   1362.11      618.99
#> 0.55  1279.05      615.60
#> 0.6   1618.13      742.07
#> 0.65  1834.30      961.33
#> 0.7   1326.06     1078.10
#> 0.75  1586.35      913.81
#> 0.8   1256.09      796.22
#> 0.85   723.10     1304.06
#> 0.9    251.36     1904.49
#> 0.95 -1509.92     3034.49
#>
#> Average Treatment Effect:    2326.51
#>   Std. Error:        712.66
plot(jt.mdid)
```

On top of the distributional DiD assumption, we need **copula stability** assumption (i.e., If, before the treatment, the units with the highest outcomes were improving the most, we would expect to see them improving the most in the current period too.) for these models:

Aspect	QDiD	CiC
Treatment of Time and Group	Symmetric	Asymmetric
QTET Computation	Not inherently scale-invariant	Outcome Variable Scale-Invariant

```
jt.qdid <- QDiD(
    re ~ treat,
    t = 1978,
    tmin1 = 1975,
    tname = "year",
    idname = "id",
    data = lalonde.psid.panel,
    iters = 10,
    panel = T
)

jt.cic <- CiC(
    re ~ treat,
    t = 1978,
    tmin1 = 1975,
```

```
    tname = "year",
    idname = "id",
    data = lalonde.psid.panel,
    iters = 10,
    panel = T
)
```

Chapter 28

Synthetic Control

Examples in marketing:

- (Tirunillai and Tellis, 2017): offline TV ad on Online Chatter
- (Wang et al., 2019): mobile hailing technology adoption on drivers' hourly earnings
- (Guo et al., 2020): payment disclosure laws effect on physician prescription behavior using Timing of the Massachusetts open payment law as the exogenous shock
- (Adalja et al., 2023): mandatory GMO labels had no impact on consumer demand (Using Vermont as a mandatory state)

Notes

- The SC method provides asymptotically normal estimators for various linear panel data models, given sufficiently large pre-treatment periods, making it a natural alternative to the Difference-in-differences model (Arkhangelsky and Hirshberg, 2023).
- SCM is **superior** than Matching Methods because it not only matches on covariates (i.e., pre-treatment variables), but also outcomes.
- For a review of the method, see (Abadie, 2021)
- SCMs can also be used under the Bayesian framework (Bayesian Synthetic Control) where we do not have to impose any restrictive priori (Kim et al., 2020)
- Different from Matching Methods because SCMs match on the pre-treatment outcomes in each period while Matching Methods match on the number of covariates.
- A data driven procedure to construct more comparable control groups (i.e., black box).

- To do causal inference with control and treatment group using Matching Methods, you typically have to have similar covariates in the control and the treated groups. However, if you don't methods like Propensity Scores and DID can perform rather poorly (i.e., large bias).

Advantages over Difference-in-differences

1. Maximization of the observable similarity between control and treatment (maybe also unobservables)
2. Can also be used in cases where no untreated case with similar on matching dimensions with treated cases
3. Objective selection of controls.

Advantages over linear regression

- Regression weights for the estimator will be outside of [0,1] (because regression allows extrapolation), and it will not be sparse (i.e., can be less than 0).
- No extrapolation under SCMs
- Explicitly state the fit (i.e., the weight)
- Can be estimated without the post-treatment outcomes for the control group (can't p-hack)

Advantages:

1. From the selection criteria, researchers can understand the relative importance of each candidate
2. Post-intervention outcomes are not used in synthetic. Hence, you can't retro-fit.
3. Observable similarity between control and treatment cases is maximized

Disadvantages:

1. It's hard to argue for the weights you use to create the "synthetic control"

SCM is recommended when

1. Social events to evaluate large-scale program or policy
2. Only one treated case with several control candidates.

Assumptions

- Donor subject is a good match for the synthetic control (i.e., gap between the dependent of the donor subject and that of the synthetic control should be 0 before treatment)
- Only the treated subject undergoes the treatment and not any of the subjects in the donor pool.
- No other changes to the subjects during the whole window.

- The counterfactual outcome of the treatment group can be imputed in a **linear combination** of control groups.

Identification: The exclusion restriction is met conditional on the pre-treatment outcomes.

`Synth` provides an algorithm that finds weighted combination of the comparison units where the weights are chosen such that it best resembles the values of predictors of the outcome variable for the affected units before the intervention

Setting (notation followed professor Alberto Abadie)

- $J+1$ units in periods $1, \dots, T$
- The first unit is the treated one during $T_0+1, \dots, T$
- J units are called a donor pool
- Y_{it}^I is the outcome for unit i if it's exposed to the treatment during $T_0+1, \dots T$
- Y_{it}^N is the outcome for unit i if it's not exposed to the treatment

We try to estimate the effect of treatment on the treated unit

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N$$

where we observe the first treated unit already $Y_{1t}^I = Y_{1t}$

To construct the synthetic control unit, we have to find appropriate weight for each donor in the donor pool by finding $\mathbf{W} = (w_2, \dots, w_{J=1})'$ where

- $w_j \geq 0$ for $j = 2, \dots, J+1$
- $w_2 + \dots + w_{J+1} = 1$

The "appropriate" vector $\mathbf{W}$ here is constrained to

$$\min ||\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W}||$$

where

- $\mathbf{X}_1$ is the $k \times 1$ vector of pre-treatment characteristics for the treated unit
- $\mathbf{X}_0$ is the $k \times J$ matrix of pre-treatment characteristics for the untreated units

For simplicity, researchers usually use

$$\begin{aligned} &\min ||\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W}|| \\ &= (\sum_{h=1}^{k} v_h (X_{h1} - w_2 X - h2 - \dots - w_{J+1} X_{hJ+1})^{1/2} \end{aligned}$$

where

- $v_1, \dots, v_k$ is a vector positive constants that represent the predictive power of the k predictors on Y_{1t}^N (i.e., the potential outcome of the treated without treatment) and it can be chosen either explicitly by the researcher or by data-driven methods

For penalized synthetic control (Abadie and L'hour, 2021), the minimization problem becomes

$$\min_{\mathbf{W}} ||\mathbf{X}_1 - \sum_{j=2}^{J+1} W_j \mathbf{X}_j||^2 + \lambda \sum_{j=2}^{J+1} W_j ||\mathbf{X}_1 - \mathbf{X}_j||^2$$

where

- $W_j \geq 0$ and $\sum_{j=2}^{J+1} W_j = 1$
- $\lambda > 0$ balances over-fitting of the treated and minimize the sum of pairwise distances
  - $\lambda \to 0$: pure synthetic control (i.e solution for the unpenalized estimator)
  - $\lambda \to \infty$: nearest neighbor matching

Advantages:

- For $\lambda > 0$, you have unique and sparse solution
- Reduces the interpolation bias when averaging dissimilar units
- Penalized SC never uses dissimilar units

Then the synthetic control estimator is

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

where Y_{jt} is the outcome for unit j at time t

Consideration

Under the factor model (Abadie et al., 2010)

$$Y_{it}^N = {}_t\mathbf{Z}_i + {}_{t\ i} + \epsilon_{it}$$

where

- Z_i = observables
- μ_i = unobservables

- ϵ_{it} = unit-level transitory shock (i.e., random noise)

with assumptions of $\mathbf{W}^*$ such that

$$\sum_{j=2}^{J+1} w_j^* \mathbf{Z}_j = \mathbf{Z}_1$$

$$\dots$$

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}$$

$$\sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0}$$

Basically, we assume that the synthetic control is a good counterfactual when the treated unit is not exposed to the treatment.

Then,

- the bias bound depends on close fit, which is controlled by the ratio between ϵ_{it} (transitory shock) and T_0 (the number of pre-treatment periods). In other words, you should have good fit for Y_{1t} for pre-treatment period (i.e., T_0 should be large while small variance in ϵ_{it})
- When you have poor fit, you have to use bias correction version of the synthetic control. See (Arkhangelsky et al., 2019, Abadie (2021), Ben-Michael et al. (2020))
- Overfitting can be the result of small T_0 (the number of pre-treatment periods), large J (the number of units in the donor pool), and large ϵ_{it} (noise)
  - Mitigation: put only similar units (to the treated one) in the donor pool

To make inference, we have to create a permutation distribution (by iteratively reassigning the treatment to the units in the donor pool and estimate the placebo effects in each iteration). We say there is an effect of the treatment when the magnitude of value of the treatment effect on the treated unit is extreme relative to the permutation distribution.

It's recommended to use one-sided inference. And the permutation distribution is superior to the p-values alone (because sampling-based inference is hard under SCMs either because of undefined sampling mechanism or the sample is the population).

For benchmark (permutation) distribution (e.g., uniform), see (Firpo and Possebom, 2018)

28.1 Applications

28.1.1 Example 1

by Danilo Freire

```
# install.packages("Synth")
# install.packages("gsynth")
library("Synth")
library("gsynth")
```

simulate data for 10 states and 30 years. State A receives the treatment `T = 20` after year 15.

```
set.seed(1)
year         <- rep(1:30, 10)
state        <- rep(LETTERS[1:10], each = 30)
X1           <- round(rnorm(300, mean = 2, sd = 1), 2)
X2           <- round(rbinom(300, 1, 0.5) + rnorm(300), 2)
Y            <- round(1 + 2 * X1 + rnorm(300), 2)
df           <- as.data.frame(cbind(Y, X1, X2, state, year))
df$Y         <- as.numeric(as.character(df$Y))
df$X1        <- as.numeric(as.character(df$X1))
df$X2        <- as.numeric(as.character(df$X2))
df$year      <- as.numeric(as.character(df$year))
df$state.num <- rep(1:10, each = 30)
df$state     <- as.character(df$state)
df$`T`       <- ifelse(df$state == "A" & df$year >= 15, 1, 0)
df$Y         <- ifelse(df$state == "A" & df$year >= 15,
                       df$Y + 20, df$Y)
```

```
str(df)
#> 'data.frame':    300 obs. of  7 variables:
#>  $ Y        : num  2.29 4.51 2.07 8.87 4.37 1.32 8 7.49 6.98 3.72 ...
#>  $ X1       : num  1.37 2.18 1.16 3.6 2.33 1.18 2.49 2.74 2.58 1.69 ...
#>  $ X2       : num  1.96 0.4 -0.75 -0.56 -0.45 1.06 0.51 -2.1 0 0.54 ...
#>  $ state    : chr  "A" "A" "A" "A" ...
#>  $ year     : num  1 2 3 4 5 6 7 8 9 10 ...
#>  $ state.num: int  1 1 1 1 1 1 1 1 1 1 ...
#>  $ T        : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
dataprep.out <-
    dataprep(
        df,
        predictors            = c("X1", "X2"),
        dependent             = "Y",
        unit.variable         = "state.num",
        time.variable         = "year",
```

```
        unit.names.variable   = "state",
        treatment.identifier  = 1,
        controls.identifier   = c(2:10),
        time.predictors.prior = c(1:14),
        time.optimize.ssr     = c(1:14),
        time.plot             = c(1:30)
    )


synth.out <- synth(dataprep.out)
#>
#> X1, X0, Z1, Z0 all come directly from dataprep object.
#>
#>
#> ****************
#>  searching for synthetic control unit
#>
#>
#> ****************
#> ****************
#> ****************
#>
#> MSPE (LOSS V): 9.831789
#>
#> solution.v:
#>  0.3888387 0.6111613
#>
#> solution.w:
#>  0.1115941 0.1832781 0.1027237 0.312091 0.06096758 0.03509706 0.05893735 0.05746256 0.07784853
```

```
print(synth.tables   <- synth.tab(
        dataprep.res = dataprep.out,
        synth.res    = synth.out)
      )
#> $tab.pred
#>    Treated Synthetic Sample Mean
#> X1   2.028     2.028       2.017
#> X2   0.513     0.513       0.394
#>
#> $tab.v
#>    v.weights
#> X1 0.389
#> X2 0.611
#>
#> $tab.w
```

```
#>    w.weights unit.names unit.numbers
#> 2      0.112          B            2
#> 3      0.183          C            3
#> 4      0.103          D            4
#> 5      0.312          E            5
#> 6      0.061          F            6
#> 7      0.035          G            7
#> 8      0.059          H            8
#> 9      0.057          I            9
#> 10     0.078          J           10
#>
#> $tab.loss
#>            Loss W   Loss V
#> [1,] 9.761708e-12 9.831789
```

```
path.plot(synth.res    = synth.out,
          dataprep.res = dataprep.out,
          Ylab         = c("Y"),
          Xlab         = c("Year"),
          Legend       = c("State A","Synthetic State A"),
          Legend.position = c("topleft")
)

abline(v   = 15,
       lty = 2)
```

Gaps plot:

```
gaps.plot(synth.res    = synth.out,
          dataprep.res = dataprep.out,
          Ylab         = c("Gap"),
          Xlab         = c("Year"),
          Ylim         = c(-30, 30),
          Main         = ""
)

abline(v   = 15,
       lty = 2)
```

Alternatively, `gsynth` provides options to estimate iterative fixed effects, and handle multiple treated units at tat time.

Here, we use two=way fixed effects and bootstrapped standard errors

```
gsynth.out <- gsynth(
  Y ~ `T` + X1 + X2,
  data = df,
  index = c("state", "year"),
  force = "two-way",
  CV = TRUE,
  r = c(0, 5),
  se = TRUE,
  inference = "parametric",
  nboots = 1000,
  parallel = F # TRUE
)
```

```
#> Cross-validating ...
#>  r = 0; sigma2 = 1.13533; IC = 0.95632; PC = 0.96713; MSPE = 1.65502
#>  r = 1; sigma2 = 0.96885; IC = 1.54420; PC = 4.30644; MSPE = 1.33375
#>  r = 2; sigma2 = 0.81855; IC = 2.08062; PC = 6.58556; MSPE = 1.27341*
#>  r = 3; sigma2 = 0.71670; IC = 2.61125; PC = 8.35187; MSPE = 1.79319
#>  r = 4; sigma2 = 0.62823; IC = 3.10156; PC = 9.59221; MSPE = 2.02301
#>  r = 5; sigma2 = 0.55497; IC = 3.55814; PC = 10.48406; MSPE = 2.79596
#>
#>  r* = 2
#>
#>
Simulating errors .............
Bootstrapping ...
#> ..........
```

```
plot(gsynth.out)
```

```
plot(gsynth.out, type = "counterfactual")
```

```
plot(gsynth.out, type = "counterfactual", raw = "all")
```

```
# shows estimations for the control cases
```

28.1.2 Example 2

by Leihua Ye

```r
library(Synth)
data("basque")
dim(basque) #774*17
#> [1] 774  17
head(basque)
#>   regionno     regionname year   gdpcap sec.agriculture sec.energy sec.industry
#> 1        1 Spain (Espana) 1955 2.354542              NA         NA           NA
#> 2        1 Spain (Espana) 1956 2.480149              NA         NA           NA
#> 3        1 Spain (Espana) 1957 2.603613              NA         NA           NA
#> 4        1 Spain (Espana) 1958 2.637104              NA         NA           NA
#> 5        1 Spain (Espana) 1959 2.669880              NA         NA           NA
#> 6        1 Spain (Espana) 1960 2.869966              NA         NA           NA
#>   sec.construction sec.services.venta sec.services.nonventa school.illit
#> 1               NA                 NA                    NA           NA
#> 2               NA                 NA                    NA           NA
#> 3               NA                 NA                    NA           NA
#> 4               NA                 NA                    NA           NA
#> 5               NA                 NA                    NA           NA
#> 6               NA                 NA                    NA           NA
#>   school.prim school.med school.high school.post.high popdens invest
#> 1          NA         NA          NA               NA      NA     NA
#> 2          NA         NA          NA               NA      NA     NA
#> 3          NA         NA          NA               NA      NA     NA
#> 4          NA         NA          NA               NA      NA     NA
#> 5          NA         NA          NA               NA      NA     NA
#> 6          NA         NA          NA               NA      NA     NA
```

transform data to be used in `synth()`

```r
dataprep.out <- dataprep(
    foo = basque,
    predictors = c(
        "school.illit",
        "school.prim",
        "school.med",
        "school.high",
        "school.post.high",
        "invest"
    ),
    predictors.op =  "mean",
    # the operator
    time.predictors.prior = 1964:1969,
    #the entire time frame from the #beginning to the end
    special.predictors = list(
        list("gdpcap", 1960:1969,  "mean"),
```

```
        list("sec.agriculture", seq(1961, 1969, 2), "mean"),
        list("sec.energy", seq(1961, 1969, 2), "mean"),
        list("sec.industry", seq(1961, 1969, 2), "mean"),
        list("sec.construction", seq(1961, 1969, 2), "mean"),
        list("sec.services.venta", seq(1961, 1969, 2), "mean"),
        list("sec.services.nonventa", seq(1961, 1969, 2), "mean"),
        list("popdens", 1969,  "mean")
    ),
    dependent =  "gdpcap",
    # dv
    unit.variable =  "regionno",
    #identifying unit numbers
    unit.names.variable =  "regionname",
    #identifying unit names
    time.variable =  "year",
    #time-periods
    treatment.identifier = 17,
    #the treated case
    controls.identifier = c(2:16, 18),
    #the control cases; all others #except number 17
    time.optimize.ssr = 1960:1969,
    #the time-period over which to optimize
    time.plot = 1955:1997
) #the entire time period before/after the treatment
```

where

- X_1 = the control case before the treatment
- X_0 = the control cases after the treatment
- Z_1: the treatment case before the treatment
- Z_0: the treatment case after the treatment

```
synth.out = synth(data.prep.obj = dataprep.out, method = "BFGS")
#>
#> X1, X0, Z1, Z0 all come directly from dataprep object.
#>
#>
#> ****************
#>  searching for synthetic control unit
#>
#>
#> ****************
#> ****************
#> ****************
#>
```

```
#> MSPE (LOSS V): 0.008864606
#>
#> solution.v:
#>  0.02773094 1.194e-07 1.60609e-05 0.0007163836 1.486e-07 0.002423908 0.0587055 0.26
#>
#> solution.w:
#>  2.53e-08 4.63e-08 6.44e-08 2.81e-08 3.37e-08 4.844e-07 4.2e-08 4.69e-08 0.8508145
```

Calculate the difference between the real basque region and the synthetic control

```
gaps = dataprep.out$Y1plot - (dataprep.out$Y0plot
                                    %*% synth.out$solution.w)
gaps[1:3,1]
#>       1955       1956       1957
#> 0.15023473 0.09168035 0.03716475
```

```
synth.tables = synth.tab(dataprep.res = dataprep.out,
                         synth.res = synth.out)
names(synth.tables)
#> [1] "tab.pred" "tab.v"    "tab.w"    "tab.loss"
synth.tables$tab.pred[1:13,]
#>                                        Treated Synthetic Sample Mean
#> school.illit                            39.888   256.337     170.786
#> school.prim                           1031.742  2730.104    1127.186
#> school.med                              90.359   223.340      76.260
#> school.high                             25.728    63.437      24.235
#> school.post.high                        13.480    36.153      13.478
#> invest                                  24.647    21.583      21.424
#> special.gdpcap.1960.1969                 5.285     5.271       3.581
#> special.sec.agriculture.1961.1969        6.844     6.179      21.353
#> special.sec.energy.1961.1969             4.106     2.760       5.310
#> special.sec.industry.1961.1969          45.082    37.636      22.425
#> special.sec.construction.1961.1969       6.150     6.952       7.276
#> special.sec.services.venta.1961.1969    33.754    41.104      36.528
#> special.sec.services.nonventa.1961.1969  4.072     5.371       7.111
```

Relative importance of each unit

```
synth.tables$tab.w[8:14, ]
#>    w.weights            unit.names unit.numbers
#> 9      0.000    Castilla-La Mancha            9
#> 10     0.851               Cataluna           10
#> 11     0.000  Comunidad Valenciana           11
#> 12     0.000           Extremadura           12
#> 13     0.000               Galicia           13
#> 14     0.149 Madrid (Comunidad De)           14
#> 15     0.000    Murcia (Region de)           15
```

```
# plot the changes before and after the treatment
path.plot(
    synth.res = synth.out,
    dataprep.res = dataprep.out,
    Ylab = "real per-capita gdp (1986 USD, thousand)",
    Xlab = "year",
    Ylim = c(0, 12),
    Legend = c("Basque country",
               "synthetic Basque country"),
    Legend.position = "bottomright"
)
```

```
gaps.plot(
    synth.res = synth.out,
    dataprep.res = dataprep.out,
    Ylab =  "gap in real per - capita GDP (1986 USD, thousand)",
    Xlab =  "year",
    Ylim = c(-1.5, 1.5),
    Main = NA
)
```

Doubly Robust Difference-in-Differences

Example from `DRDID` package

```
library(DRDID)
data(nsw_long)
# Form the Lalonde sample with CPS comparison group
eval_lalonde_cps <- subset(nsw_long, nsw_long$treated == 0 |
                                nsw_long$sample == 2)
```

Estimate Average Treatment Effect on Treated using Improved Locally Efficient Doubly Robust DID estimator

```
out <-
    drdid(
        yname = "re",
        tname = "year",
        idname = "id",
        dname = "experimental",
        xformla = ~ age + educ + black + married + nodegree + hisp + re74,
        data = eval_lalonde_cps,
        panel = TRUE
    )
summary(out)
#>  Call:
#> drdid(yname = "re", tname = "year", idname = "id", dname = "experimental",
#>     xformla = ~age + educ + black + married + nodegree + hisp +
#>         re74, data = eval_lalonde_cps, panel = TRUE)
#> ------------------------------------------------------------------
```

```
#>  Further improved locally efficient DR DID estimator for the ATT:
#>
#>    ATT     Std. Error  t value    Pr(>|t|)  [95% Conf. Interval]
#> -901.2703   393.6247   -2.2897     0.022    -1672.7747  -129.766
#> ------------------------------------------------------------------
#>  Estimator based on panel data.
#>  Outcome regression est. method: weighted least squares.
#>  Propensity score est. method: inverse prob. tilting.
#>  Analytical standard error.
#> -------------------------------------------------------------------
#>  See Sant'Anna and Zhao (2020) for details.
```

28.1.3 Example 3

by `Synth` package's authors

```r
library(Synth)
data("basque")
```

`synth()` requires

- X_1 vector of treatment predictors
- X_0 matrix of same variables for control group
- Z_1 vector of outcome variable for treatment group
- Z_0 matrix of outcome variable for control group

use `dataprep()` to prepare data in the format that can be used throughout the `Synth` package

```r
dataprep.out <- dataprep(
    foo = basque,
    predictors = c(
        "school.illit",
        "school.prim",
        "school.med",
        "school.high",
        "school.post.high",
        "invest"
    ),
    predictors.op = "mean",
    time.predictors.prior = 1964:1969,
    special.predictors = list(
        list("gdpcap", 1960:1969 , "mean"),
        list("sec.agriculture", seq(1961, 1969, 2), "mean"),
        list("sec.energy", seq(1961, 1969, 2), "mean"),
        list("sec.industry", seq(1961, 1969, 2), "mean"),
```

```
        list("sec.construction", seq(1961, 1969, 2), "mean"),
        list("sec.services.venta", seq(1961, 1969, 2), "mean"),
        list("sec.services.nonventa", seq(1961, 1969, 2), "mean"),
        list("popdens", 1969, "mean")
    ),
    dependent = "gdpcap",
    unit.variable = "regionno",
    unit.names.variable = "regionname",
    time.variable = "year",
    treatment.identifier = 17,
    controls.identifier = c(2:16, 18),
    time.optimize.ssr = 1960:1969,
    time.plot = 1955:1997
)
```

find optimal weights that identifies the synthetic control for the treatment group

```
synth.out <- synth(data.prep.obj = dataprep.out, method = "BFGS")
#>
#> X1, X0, Z1, Z0 all come directly from dataprep object.
#>
#>
#> ****************
#>  searching for synthetic control unit
#>
#>
#> ****************
#> ****************
#> ****************
#>
#> MSPE (LOSS V): 0.008864606
#>
#> solution.v:
#>  0.02773094 1.194e-07 1.60609e-05 0.0007163836 1.486e-07 0.002423908 0.0587055 0.26
#>
#> solution.w:
#>  2.53e-08 4.63e-08 6.44e-08 2.81e-08 3.37e-08 4.844e-07 4.2e-08 4.69e-08 0.8508145
```

```
gaps <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*% synth.out$solution.w)
gaps[1:3, 1]
#>       1955       1956       1957
#> 0.15023473 0.09168035 0.03716475
```

```
synth.tables <-
    synth.tab(dataprep.res = dataprep.out, synth.res = synth.out)
names(synth.tables) # you can pick tables to see
```

```
#> [1] "tab.pred" "tab.v"    "tab.w"    "tab.loss"
```

```
path.plot(
    synth.res = synth.out,
    dataprep.res = dataprep.out,
    Ylab = "real per-capita GDP (1986 USD, thousand)",
    Xlab = "year",
    Ylim = c(0, 12),
    Legend = c("Basque country",
               "synthetic Basque country"),
    Legend.position = "bottomright"
)
```

```
gaps.plot(
    synth.res = synth.out,
    dataprep.res = dataprep.out,
    Ylab = "gap in real per-capita GDP (1986 USD, thousand)",
    Xlab = "year",
    Ylim = c(-1.5, 1.5),
    Main = NA
)
```

You could also run placebo tests

28.1.4 Example 4

by Michael Robbins and Steven Davenport who are authors of `MicroSynth` with the following improvements:

- Standardization `use.survey = TRUE` and permutation (`perm = 250` and `jack = TRUE`) for placebo tests
- Omnibus statistic (set to `omnibus.var`) for multiple outcome variables
- incorporate multiple follow-up periods `end.post`

Notes:

- Both predictors and outcome will be used to match units before intervention
  - Outcome variable has to be **time-variant**
  - Predictors are **time-invariant**

```
# right now the package is not availabe for R version 4.2
library(microsynth)
data("seattledmi")


cov.var <-
    c(
        "TotalPop",
```

```
        "BLACK",
        "HISPANIC",
        "Males_1521",
        "HOUSEHOLDS",
        "FAMILYHOUS",
        "FEMALE_HOU",
        "RENTER_HOU",
        "VACANT_HOU"
    )
match.out <- c("i_felony", "i_misdemea", "i_drugs", "any_crime")
```

```
sea1 <- microsynth(
    seattledmi,
    idvar       = "ID",
    timevar     = "time",
    intvar      = "Intervention",
    start.pre   = 1,
    end.pre     = 12,
    end.post    = 16,
    match.out   = match.out, # outcome variable will be matched on exactly
    match.covar = cov.var, # specify covariates will be matched on exactly
    result.var  = match.out, # used to report results
    omnibus.var = match.out, # feature in the omnibus p-value
    test        = "lower",
    n.cores     = min(parallel::detectCores(), 2)
)
sea1
summary(sea1)
```

```
plot_microsynth(sea1)
```

```
sea2 <- microsynth(
    seattledmi,
    idvar = "ID",
    timevar = "time",
    intvar = "Intervention",
    start.pre = 1,
    end.pre = 12,
    end.post = c(14, 16),
    match.out = match.out,
    match.covar = cov.var,
    result.var = match.out,
    omnibus.var = match.out,
    test = "lower",
    perm = 250,
    jack = TRUE,
```

```
    n.cores = min(parallel::detectCores(), 2)
)
```

28.2 Augmented Synthetic Control Method

package: `augsynth` (Ben-Michael et al., 2021)

28.3 Synthetic Control with Staggered Adoption

references: https://ebenmichael.github.io/assets/research/jamboree.pdf (Ben-Michael et al., 2022) package: `augsynth`

28.4 Bayesian Synthetic Control

Kim et al. (2020)

Pang et al. (2022)

28.5 Generalized Synthetic Control

reference: (Xu, 2017)

- Bootstrap procedure here is biased (Li and Sonnier, 2023). Hence, we need to follow Li and Sonnier (2023) in terms of SEs estimation.

28.6 Other Advances

Sun et al. (2023) Using Multiple Outcomes to Improve SCM

- **Common Weights Across Outcomes**: This paper proposes using a single set of synthetic control weights across multiple outcomes, rather than estimating separate weights for each outcome.
- **Reduced Bias with Low-Rank Factor Model**: By balancing a vector or an index of outcomes, this approach yields lower bias bounds under a low-rank factor model, with further improvements as the number of outcomes increases.
- **Evidence**: re-analysis of the Flint water crisis's impact on educational outcome.

Chapter 29

Event Studies

The earliest paper that used event study was (Dolley, 1933)

(Campbell et al., 1998) introduced this method, which based on the efficient markets theory by (Fama, 1970)

Review:

- (McWilliams and Siegel, 1997): in management
- (Sorescu et al., 2017): in marketing

Previous marketing studies:

1. Firm-initiated activities

- (Horsky and Swyngedouw, 1987): name change
- (Chaney et al., 1991) new product announcements
- (Agrawal and Kamakura, 1995): celebrity endorsement
- (Lane and Jacobson, 1995): brand extensions
- (Houston and Johnson, 2000): joint venture
- (Geyskens et al., 2002): Internet channel (for newspapers)
- (Cornwell et al., 2005): sponsorship announcements
- (Elberse, 2007): casting announcements
- (Sorescu et al., 2007): M&A
- (Sood and Tellis, 2009): innovation payoff
- (Wiles and Danielova, 2009): product placements in movies
- (Joshi and Hanssens, 2009): movie releases

- (Wiles et al., 2010): Regulatory Reports of Deceptive Advertising
- (Boyd et al., 2010): new CMO appointments
- (Karniouchina et al., 2011): product placement
- (Wiles et al., 2012): Brand Acquisition and Disposal
- (Kalaignanam and Bahadir, 2013): corporate brand name change
- (Raassens et al., 2012): new product development outsourcing
- (Mazodier and Rezaee, 2013): sports announcements
- (Borah and Tellis, 2014): make, buy or ally for innovations
- (Homburg et al., 2014): channel expansions
- (Fang et al., 2015): Co-development agreements
- (Wu et al., 2015): horizontal collaboration in new product development
- (Fama et al., 1969): stock split

2. Non-firm-initiated activities

- (Sorescu et al., 2003): FDA approvals
- (Pandey et al., 2005): diversity elite list
- (Balasubramanian et al., 2005): high-quality achievements
- (Tellis and Johnson, 2007): quality reviews by Walter Mossberg
- (Fornell et al., 2006): customer satisfaction
- (Gielens et al., 2008): Walmart's entry into the UK market
- (Boyd and Spekman, 2008): indirect ties
- (Rao et al., 2008): FDA approvals
- (Ittner et al., 2009): customer satisfaction
- (Tipton et al., 2009): Deceptive advertising
- (Chen et al., 2009b): product recalls
- (Jacobson and Mizik, 2009): satisfaction score release
- (Karniouchina et al., 2009): Mad money with Jim Cramer
- (Wiles et al., 2010): deceptive advertising
- (Chen et al., 2012): third-party movie reviews
- (Xiong and Bharadwaj, 2013): positive and negative news
- (Gao et al., 2015): product recall
- (Malhotra and Kubowicz Malhotra, 2011): data breach

- (Bhagat et al., 1998): litigation

Potential avenues:

- Ad campaigns
- Market entry
- product failure/recalls
- Patents

Pros:

- Better than accounting based measures (e.g., profits) because managers can manipulate profits (Benston, 1985)
- Easy to do

Fun fact:

- (Dubow and Monteiro, 2006) came up with a way to gauge how 'clean' a market is. They based their measure on how much prices seemed to move in a way that suggested insider knowledge, before the release of important regulatory announcements that could affect the stock prices. Such price shifts might suggest that insider trading was occurring. Essentially, they were watching for any unusual price changes before the day of the announcement.

Events can be

- Internal (e.g., stock repurchase)
- External (e.g., macroeconomic variables)

Assumptions:

1. Efficient market theory
2. Shareholders are the most important group among stakeholders
3. The event sharply affects share price
4. Expected return is calculated appropriately

Steps:

1. Event Identification: (e.g., dividends, M&A, stock buyback, laws or regulation, privatization vs. nationalization, celebrity endorsements, name changes, or brand extensions etc. To see the list of events in US and international, see WRDS **S&P Capital IQ Key Developments**). Events must affect either cash flows or on the discount rate of firms (Sorescu et al., 2017, p. 191)
    1. Estimation window: Normal return expected return ($T_0 \to T_1$) (sometimes include days before to capture leakages).

- Recommendation by (Johnston, 2007) is to use 250 days before the event (and 45-day between the estimation window and the event window).
  - (Wiles et al., 2012) used an 90-trading-day estimation window ending 6 days before the event (this is consistent with the finance literature).
  - (Gielens et al., 2008) 260 to 10 days before or 300 to 46 days before
  - (Tirunillai and Tellis, 2012) estimation window of 255 days and ends 46 days before the event.
- Similarly, (McWilliams and Siegel, 1997) and (Fornell et al., 2006) 255 days ending 46 days before the event date
- (Sorescu et al., 2017, p. 194) suggest 100 days before the event date
- Leakage: try to cover as broad news sources as possible (LexisNexis, Factiva, and RavenPack).

2. Event window: contain the event date ($T_1 \to T_2$) (have to argue for the event window and can't do it empirically)
   - One day: (Balasubramanian et al., 2005; Boyd et al., 2010; Fornell et al., 2006)
   - Two days: (Raassens et al., 2012; Sood and Tellis, 2009)
   - Up to 10 days: (Cornwell et al., 2005; Kalaignanam and Bahadir, 2013; Sorescu et al., 2007)
3. Post Event window: $T_2 \to T_3$

2. Normal vs. Abnormal returns

$$\epsilon_{it}^* = \frac{P_{it} - E(P_{it})}{P_{it-1}} = R_{it} - E(R_{it}|X_t)$$

where

- ϵ_{it}^* = abnormal return
- R_{it} = realized (actual) return
- P = dividend-adjusted price of the stock
- $E(R_{it}|X_t)$ normal expected return

There are several model to calculate the expected return

A. Statistical Models: assumes jointly multivariate normal and iid over time (need distributional assumptions for valid finite-sample estimation) rather robust (hence, recommended)

1. Constant Mean Return Model
2. Market Model
3. Adjusted Market Return Model
4. Factor Model

B. Economic Model (strong assumption regarding investor behavior)

1. Capital Asset Pricing Model (CAPM)
2. Arbitrage Pricing Theory (APT)

29.1 Other Issues

29.1.1 Event Studies in marketing

(Skiera et al., 2017) What should be the dependent variable in marketing-related event studies?

- Based on valuation theory, Shareholder value = the value of the operating business + non-operating asset - debt (Schulze et al., 2012)
  - Many marketing events only affect the operating business value, but not non-operating assets and debt
- Ignoring the differences in firm-specific leverage effects has dual effects:
  - inflates the impact of observation pertaining to firms with large debt
  - deflates those pertaining to firms with large non-operating asset.
- It's recommended that marketing papers should report both CAR^{OB} and CAR^{SHV} and argue for whichever one more appropriate.
- Up until this paper, only two previous event studies control for financial structure: (Gielens et al., 2008) (Chaney et al., 1991)

Definitions:

- Cumulative abnormal percentage return on shareholder value (CAR^{SHV})
  - Shareholder value refers to a firm's market capitalization = share price x # of shares.
- Cumulative abnormal percentage return on the value of the operating business (CAR^{OB})
  - $CAR^{OB} = CAR^{SHV}$/leverage effect$_{before}$
  - Leverage effect = Operating business value / Shareholder value (LE describes how a 1% change in operating business translates into a percentage change in shareholder value).
  - Value of operating business = shareholder value - non-operating assets + debt
  - Leverage effect $\neq$ leverage ratio, where leverage ratio is debt / firm size
    - debt = long-term + short-term debt; long-term debt

    * firm size = book value of equity; market cap; total assets; debt + equity

- Operating assets are those used by firm in their core business operations (e..g, property, plant, equipment, natural resources, intangible asset)
- Non–operating assets (redundant assets), do not play a role in a firm's operations, but still generate some form of return (e.g., excess cash , marketable securities - commercial papers, market instruments)

Marketing events usually influence the value of a firm's operating assets (more specifically intangible assets). Then, changes in the value of the operating business can impact shareholder value.

- Three rare instances where marketing events can affect non-operating assets and debt
  - (Hall et al., 2004): excess pre-orderings can influence short-term debt
  - (Berger et al., 1997) Firing CMO increase debt as the manager's tenure is negatively associated with the firm's debt
  - (Bhaduri, 2002) production of unique products.

A marketing-related event can either influence

- value components of a firm's value (= firm's operating business, non-operating assets and its debt)
- only the operating business.

Replication of the leverage effect

$$\begin{aligned}\text{leverage effect} &= \frac{\text{operating business}}{\text{shareholder value}} \\ &= \frac{\text{(shareholder value - non-operating assets + debt)}}{\text{shareholder value}} \\ &= \frac{prcc_f \times csho - ivst + dd1 + dltt + pstk}{prcc_f \times csho}\end{aligned}$$

Compustat Data Item

Label	Variable
`prcc_f`	Share price
`csho`	Common shares outstanding
`ivst`	short-term investments (Non-operating assets)
`dd1`	long-term debt due in one year
`dltt`	long-term debt
`pstk`	preferred stock

Since WRDS no longer maintains the S&P 500 list as of the time of this writing, I can't replicate the list used in (Skiera et al., 2017) paper.

```
library(tidyverse)
df_leverage_effect <- read.csv("data/leverage_effect.csv.gz") %>%

    # get active firms only
    filter(costat == "A") %>%

    # drop missing values
    drop_na() %>%

    # create the leverage effect variable
    mutate(le = (prcc_f * csho - ivst + dd1 + dltt + pstk)/ (prcc_f * csho)) %>%

    # get shareholder value
    mutate(shv = prcc_f * csho) %>%

    # remove Infinity value for leverage effect (i.e., shareholder value = 0)
    filter_all(all_vars(!is.infinite(.))) %>%

    # positive values only
    filter_all(all_vars(. > 0)) %>%

    # get the within coefficient of variation
    group_by(gvkey) %>%
    mutate(within_var_mean_le = mean(le),
           within_var_sd_le = sd(le)) %>%
    ungroup()


# get the mean and standard deviation
mean(df_leverage_effect$le)
#> [1] 150.1087
max(df_leverage_effect$le)
#> [1] 183629.6
hist(df_leverage_effect$le)
```

```
# coefficient of variation
sd(df_leverage_effect$le) / mean(df_leverage_effect$le) * 100
#> [1] 2749.084

# Within-firm variation (similar to fig 3a)
df_leverage_effect %>%
    group_by(gvkey) %>%
    slice(1) %>%
    ungroup() %>%
    dplyr::select(within_var_mean_le, within_var_sd_le) %>%
    dplyr::mutate(cv = within_var_sd_le/ within_var_mean_le) %>%
    dplyr::select(cv) %>%
    pull() %>%
    hist()
```

29.1.2 Economic significance

Total wealth gain (loss) from the event

$$\Delta W_t = CAR_t \times MKTVAL_0$$

where

- ΔW_t = gain (loss)
- CAR_t = cumulative residuals to date t
- $MKTVAL_0$ market value of the firm before the event window

29.1.3 Statistical Power

increases with

- more firms
- less days in the event window (avoiding potential contamination from confounds)

29.2 Testing

29.2.1 Parametric Test

(Brown and Warner, 1985) provide evidence that even in the presence of non-normality, the parametric tests still perform well. Since the proportion of posi-

tive and negative abnormal returns tends to be equal in the sample (of at least 5 securities). The excess returns will coverage to normality as the sample size increases. Hence, parametric test is advocated than non-parametric one.

Low power to detect significance (Kothari and Warner, 1997)

- Power = f(sample, size, the actual size of abnormal returns, the variance of abnormal returns across firms)

29.2.1.1 T-test

Applying CLT

$$t_{CAR} = \frac{C\bar{A}R_{it}}{\sigma(CAR_{it})/\sqrt{n}}$$
$$t_{BHAR} = \frac{BH\bar{A}R_{it}}{\sigma(BHAR_{it})/\sqrt{n}}$$

Assume

- Abnormal returns are normally distributed
- Var(abnormal returns) are equal across firms
- No cross-correlation in abnormal returns.

Hence, it will be misspecified if you suspected

- Heteroskedasticity
- Cross-sectional dependence
- Technically, abnormal returns could follow non-normal distribution (but because of the design of abnormal returns calculation, it typically forces the distribution to be normal)

To address these concerns, Patell Standardized Residual (PSR) can sometimes help.

29.2.1.2 Patell Standardized Residual (PSR)

(Patell, 1976)

- Since market model uses observations outside the event window, abnormal returns contain prediction errors on top of the true residuals , and should be standardized:

$$AR_{it} = \frac{\hat{u}_{it}}{s_i\sqrt{C_{it}}}$$

where

- $\hat{u}_{it}$ = estimated residual
- s_i = standard deviation estimate of residuals (from the estimation period)
- C_{it} = a correction to account for the prediction's increased variation outside of the estimation period (Strong, 1992)

$$C_{it} = 1 + \frac{1}{T} + \frac{(R_{mt} - \bar{R}_m)^2}{\sum_t (R_{mt} - \bar{R}_m)^2}$$

where

- T = number of observations (from estimation period)
- R_{mt} = average rate of return of all stocks trading the the stock market at time t
- $\bar{R}_m = \frac{1}{T} \sum_{t=1}^{T} R_{mt}$

29.2.2 Non-parametric Test

- No assumptions about return distribution
- Sign Test (assumes symmetry in returns)
  - `binom.test()`
- Wilcoxon Signed-Rank Test (allows for non-symmetry in returns)
  - Use `wilcox.test(sample)`
- Gen Sign Test
- Corrado Rank Test

29.3 Sample

- Sample can be relative small
  - (Wiles et al., 2012) 572 acquisition announcements, 308 disposal announcements
  - Can range from 71 (Markovitch and Golder, 2008) to 3552 (Borah and Tellis, 2014)

29.3.1 Confounders

- Avoid confounding events: earnings announcements, key executive changes, unexpected stock buybacks, changes in dividends within the two-trading day window surrounding the event, mergers and acquisitions, spin-offers, stock splits, management changes, joint ventures, unexpected

dividend, IPO, debt defaults, dividend cancellations (McWilliams and Siegel, 1997)

According to (Fornell et al., 2006), need to control:

- one-day event period = day when Wall Street Journal publish ACSI announcement.
- 5 days before and after event to rule out other news (PR Newswires, Dow Jones, Business Wires)
  - M&A, Spin-offs, stock splits
  - CEO or CFO changes,
  - Layoffs, restructurings, earnings announcements, lawsuits
  - Capital IQ - Key Developments: covers almost all important events so you don't have to search on news.

(Sorescu et al., 2017) examine confounding events in the short-term windows:

- From RavenPack, 3982 US publicly traded firms, with all the press releases (2000-2013)
- 3-day window around event dates
- The difference between a sample with full observations and a sample without confounded events is negligible (non-significant).
- Conclusion: **excluding confounded observations may be unnecessary for short-term event studies.**
  - Biases can stem from researchers pick and choose events to exclude
  - As time progresses, more and more events you need to exclude which can be infeasible.

To further illustrate this point, let's do a quick simulation exercise

In this example, we will explore three types of events:

1. Focal events
2. Correlated events (i.e., events correlated with the focal events; the presence of correlated events can follow the presence of the focal event)
3. Uncorrelated events (i.e., events with dates that might randomly coincide with the focal events, but are not correlated with them).

We have the ability to control the strength of correlation between focal and correlated events in this study, as well as the number of unrelated events we wish to examine.

Let's examine the implications of including and excluding correlated and uncorrelated events on the estimates of our focal events.

```r
# Load required libraries
library(dplyr)
library(ggplot2)
library(tidyr)
library(tidyverse)

# Parameters
n                  <- 100000         # Number of observations
n_focal            <- round(n * 0.2) # Number of focal events
overlap_correlated <- 0.5            # Overlapping percentage between focal and correlated events

# Function to compute mean and confidence interval
mean_ci <- function(x) {
    m <- mean(x)
    ci <- qt(0.975, length(x)-1) * sd(x) / sqrt(length(x)) # 95% confidence interval
    list(mean = m, lower = m - ci, upper = m + ci)
}

# Simulate data
set.seed(42)
data <- tibble(
    date       = seq.Date(from = as.Date("2010-01-01"), by = "day", length.out = n), # Date seque
    focal      = rep(0, n),
    correlated = rep(0, n),
    ab_ret     = rnorm(n)
)


# Define focal events
focal_idx <- sample(1:n, n_focal)
data$focal[focal_idx] <- 1

true_effect <- 0.25

# Adjust the ab_ret for the focal events to have a mean of true_effect
data$ab_ret[focal_idx] <- data$ab_ret[focal_idx] - mean(data$ab_ret[focal_idx]) + true_effect



# Determine the number of correlated events that overlap with focal and those that don't
n_correlated_overlap <- round(length(focal_idx) * overlap_correlated)
n_correlated_non_overlap <- n_correlated_overlap

# Sample the overlapping correlated events from the focal indices
correlated_idx <- sample(focal_idx, size = n_correlated_overlap)
```

```
# Get the remaining indices that are not part of focal
remaining_idx <- setdiff(1:n, focal_idx)

# Check to ensure that we're not attempting to sample more than the available remainin
if (length(remaining_idx) < n_correlated_non_overlap) {
    stop("Not enough remaining indices for non-overlapping correlated events")
}

# Sample the non-overlapping correlated events from the remaining indices
correlated_non_focal_idx <- sample(remaining_idx, size = n_correlated_non_overlap)

# Combine the two to get all correlated indices
all_correlated_idx <- c(correlated_idx, correlated_non_focal_idx)

# Set the correlated events in the data
data$correlated[all_correlated_idx] <- 1


# Inflate the effect for correlated events to have a mean of
correlated_non_focal_idx <- setdiff(all_correlated_idx, focal_idx) # Fixing the select
data$ab_ret[correlated_non_focal_idx] <- data$ab_ret[correlated_non_focal_idx] - mean(


# Define the numbers of uncorrelated events for each scenario
num_uncorrelated <- c(5, 10, 20, 30, 40)

# Define uncorrelated events
for (num in num_uncorrelated) {
    for (i in 1:num) {
        data[paste0("uncorrelated_", i)] <- 0
        uncorrelated_idx <- sample(1:n, round(n * 0.1))
        data[uncorrelated_idx, paste0("uncorrelated_", i)] <- 1
    }
}


# Define uncorrelated columns and scenarios
unc_cols <- paste0("uncorrelated_", 1:num_uncorrelated)
results <- tibble(
    Scenario = c("Include Correlated", "Correlated Effects", "Exclude Correlated", "Exc
    MeanEffect = c(
        mean_ci(data$ab_ret[data$focal == 1])$mean,
        mean_ci(data$ab_ret[data$focal == 0 | data$correlated == 1])$mean,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0])$mean,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(data[, pas
```

```
    ),
    LowerCI = c(
        mean_ci(data$ab_ret[data$focal == 1])$lower,
        mean_ci(data$ab_ret[data$focal == 0 | data$correlated == 1])$lower,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0])$lower,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(data[, paste0("uncor
    ),
    UpperCI = c(
        mean_ci(data$ab_ret[data$focal == 1])$upper,
        mean_ci(data$ab_ret[data$focal == 0 | data$correlated == 1])$upper,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0])$upper,
        mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(data[, paste0("uncor
    )
)

# Add the scenarios for excluding 5, 10, 20, and 50 uncorrelated
for (num in num_uncorrelated) {
    unc_cols <- paste0("uncorrelated_", 1:num)
    results <- results %>%
        add_row(
            Scenario = paste("Exclude", num, "Uncorrelated"),
            MeanEffect = mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(dat
            LowerCI = mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(data[,
            UpperCI = mean_ci(data$ab_ret[data$focal == 1 & data$correlated == 0 & rowSums(data[,
        )
}


ggplot(results,
       aes(
           x = factor(Scenario, levels = Scenario),
           y = MeanEffect,
           ymin = LowerCI,
           ymax = UpperCI
       )) +
    geom_pointrange() +
    coord_flip() +
    ylab("Mean Effect") +
    xlab("Scenario") +
    ggtitle("Mean Effect of Focal Events under Different Scenarios") +
    geom_hline(yintercept = true_effect,
               linetype = "dashed",
               color = "red")
```

As depicted in the plot, the inclusion of correlated events demonstrates minimal impact on the estimation of our focal events. Conversely, excluding these correlated events can diminish our statistical power. This is true in cases of pronounced correlation.

However, the consequences of excluding unrelated events are notably more significant. It becomes evident that by omitting around 40 unrelated events from our study, we lose the ability to accurately identify the true effects of the focal events. In reality and within research, we often rely on the Key Developments database, excluding over 150 events, a practice that can substantially impair our capacity to ascertain the authentic impact of the focal events.

This little experiment really drives home the point – you better have a darn good reason to exclude an event from your study (make it super convincing)!

29.4 Biases

- Different closing time obscure estimation of the abnormal returns, check (Campbell et al., 1998)
- Upward bias in aggregating CAR + transaction prices (bid and ask)
- Cross-sectional dependence in the returns bias the standard deviation estimates downward, which inflates the test statistics when events share common dates (MacKinlay, 1997). Hence, (Jaffe, 1974) Calendar-time Portfolio Abnormal Returns (CTARs) should be used to correct for this bias.
- (Wiles et al., 2012): For events confined to relatively few industries, cross-

sectional dependence in the returns can bias the SD estimate downward, inflating the associated test statistics" (p. 47). To control for potential cross-sectional correlation in the abnormal returns, you can use time-series standard deviation test statistic (Brown and Warner, 1980)

- Sample selection bias (self-selection of firms into the event treatment) similar to omitted variable bias where the omitted variable is the private info that leads a firm to take the action.
  - See Endogenous Sample Selection for more methods to correct this bias.
  - Use Heckman model (Acharya, 1993)
    - But hard to find an instrument that meets the exclusion requirements (and strong, because weak instruments can lead to multicollinearity in the second equation)
    - Can estimate the private information unknown to investors (which is Mills ratio λ itself). Testing λ significance is to see whether private info can explain outcomes (e.g., magnitude of the CARs to the announcement).
    - Examples: (Chen et al., 2009b) (Wiles et al., 2012) (Fang et al., 2015)
  - Counterfactual observations
    - Propensity score matching:
      - Finance: (Iskandar-Datta and Jia, 2013, Doan and Iskandar-Datta (2021)) (Masulis and Nahata, 2011)
      - Marketing: (Warren and Sorescu, 2017) (Borah and Tellis, 2014) (Cao and Sorescu, 2013)
    - Switching regression: comparison between 2 specific outcomes (also account for selection on unobservables - using instruments) (Cao and Sorescu, 2013)

29.5 Long-run event studies

- Usually make an assumption that the distribution of the abnormal returns to these events has a mean of 0 (Sorescu et al., 2017, p. 192). And (Sorescu et al., 2017) provide evidence that for all events they examine the results from samples with and without confounding events do not differ.
- Long-horizon event studies face challenges due to systematic errors over time and sensitivity to model choice.

- Two main approaches are used to measure long-term abnormal stock returns
  - Buy and Hold Abnormal Returns (BHAR)
  - Long-term Cumulative Abnormal Returns (LCARs)
  - Calendar-time Portfolio Abnormal Returns (CTARs) (Jensen's Alpha): manages cross-sectional dependence better and is less sensitive to (asset pricing) model misspecification
- Two types:
  - Unexpected changes in firm specific variables (typically not announced, may not be immediately visible to all investors, impact on firm value is not straightforward): customer satisfaction scores effect on firm value (Jacobson and Mizik, 2009) or unexpected changes in marketing expenditures (Kim and McAlister, 2011) to determine mispricing.
  - Complex consequences (investors take time to learn and incorporate info): acquisition depends on integration (Sorescu et al., 2007)
- 12 - 60 months event window: (Loughran and Ritter, 1995) (Brav and Gompers, 1997)
- Example: (Dutta et al., 2018)

```r
library(crseEventStudy)

# example by the package's author
data(demo_returns)
SAR <-
    sar(event = demo_returns$EON,
        control = demo_returns$RWE,
        logret = FALSE)
mean(SAR)
#> [1] 0.006870196
```

29.5.1 Buy and Hold Abnormal Returns (BHAR)

- Classic references: (Loughran and Ritter, 1995) (Barber and Lyon, 1997) (Lyon et al., 1999)

Use a portfolio of stocks that are close matches of the current firm over the same period as benchmark, and see the difference between the firm return and that of the portfolio.

- More technical note is that it measures returns from buying stocks in event-experiencing firms and shorting stocks in similar non-event firms within the same time.

- Because of high cross-sectional correlations, BHARs' t-stat can be inflated, but its rank order is not affected (Markovitch and Golder, 2008; Sorescu et al., 2007)

To construct the portfolio, use similar

- size
- book-to-market
- momentum

Matching Procedure (Barber and Lyon, 1997):

1. Each year from July to June, all common stocks in the CRSP database are categorized into ten groups (deciles) based on their market capitalization from the previous June.

2. Within these deciles, firms are further sorted into five groups (quintiles) based on their book-to-market ratios as of December of the previous year or earlier, considering possible delays in financial statement reporting.

3. Benchmark portfolios are designed to exclude firms with specific events but include all firms that can be classified into the characteristic-based portfolios.

Similarly, Wiles et al. (2010) uses the following matching procedure:

1. All firms in the same two-digit SIC code with market values of 50% to 150% of the focal firms are selected
2. From this list, the 10 firms with the most comparable book-to-market ratios are chosen to serve as the matched portfolio (the matched portfolio can have less than 10 firms).

Calculations:

$$AR_{it} = R_{it} - E(R_{it}|X_t)$$

Cumulative Abnormal Return (CAR):

$$CAR_{it} = \sum_{t=1}^{T}(R_{it} - E(R_{it}))$$

Buy-and-Hold Abnormal Return (BHAR)

$$BHAR_{t=1}^{T} = \Pi_{t=1}^{T}(1 + R_{it}) - \Pi_{t=1}^{T}(1 + E(R_{it}))$$

where as CAR is the arithmetic sum, BHAR is the geometric sum.

- In short-term event studies, differences between CAR and BHAR are often minimal. However, in long-term studies, this difference could significantly skew results. (Barber and Lyon, 1997) shows that while BHAR is usually slightly lower than annual CAR, but it dramatically surpasses CAR when annual BHAR exceeds 28%.

To calculate the long-run return ($\Pi_{t=1}^{T}(1+E(R_{it}))$) of the benchmark portfolio, we can:

1. **With annual rebalance**: In each period, each portfolio is re-balanced and then compound mean stock returns in a portfolio over a given period:

$$\Pi_{t=1}^{T}(1+E(R_{it})) = \Pi_{t}^{T}(1+\sum_{i=s}^{n_t} w_{it}R_{it})$$

where n_t is the number of firms in period t, and w_{it} is (1) $1/n_t$ or (2) value-weight of firm i in period t.

To avoid favoring recent events, in cross-sectional event studies, researchers usually treat all events equally when studying their impact on the stock market over time. This approach helps identify any abnormal changes in stock prices, especially when dealing with a series of unplanned events.

Potential problems:

- Solution first: Form benchmark portfolios that will never change constituent firms (Mitchell and Stafford, 2000), because of these problems:
  - Newly public companies often perform worse than a balanced market index (Ritter, 1991), and this, over time, might distort long-term return expectations due to the inclusion of these new companies (a phenomenon called "new listing bias" identified by Barber and Lyon (1997)).
  - Regularly rebalancing an equal-weight portfolio can lead to overestimated long-term returns and potentially skew buy-and-hold abnormal returns (BHARs) negatively due to constant selling of winning stocks and buying of underperformers (i.e., "rebalancing bias" (Barber and Lyon, 1997)).
  - Value-weight portfolios, which favor larger market cap stocks, can be viewed as an active investment strategy that keeps buying winning stocks and selling underperformers. Over time, this approach tends to positively distort BHARs.

2. **Without annual rebalance**: Compounding the returns of the securities comprising the portfolio, followed by calculating the average across all securities

$$\Pi_{t=s}^{T}(1+E(R_{it})) = \sum_{i=s}^{n_t}(w_{is}\Pi_{t=1}^{T}(1+R_{it}))$$

where t is the investment period, R_{it} is the return on security i, n_i is the number of securities, w_{it} is either $1/n_s$ or value-weight factor of security i at initial period s. This portfolio's profits come from a simple investment where all the included stocks are given equal importance, or weighted according to their market value, as they were in a specific past period (period s). This means that it doesn't consider any stocks that were listed after this period, nor does it adjust the portfolio each month. However, one problem with this method is that the value assigned to each stock, based on its market size, needs to be corrected. This is to make sure that recent stocks don't end up having too much influence.

Fortunately, on WRDS, it will give you all types of BHAR (2x2) (equal-weighted vs. value-weighted and with annual rebalance and without annual rebalance)

- "MINWIN" is the smallest number of months a company trades after an event to be included in the study.
- "MAXWIN" is the most months that the study considers in its calculations.
  - Companies aren't excluded if they have less than MAXWIN months, unless they also have fewer than MINWIN months.
- The term "MONTH" signifies chosen months (typically 12, 24, or 36) used to work out BHAR.
  - If monthly returns are missing during the set period, matching portfolio returns fill in the gaps.

29.5.2 Long-term Cumulative Abnormal Returns (LCARs)

Formula for LCARs during the $(1, T)$ postevent horizon (Sorescu et al., 2007)

$$LCAR_{pT} = \sum_{t=1}^{t=T}(R_{it} - R_{pt})$$

where R_{it} is the rate of return of stock i in month t

R_{pt} is the rate of return on the counterfactual portfolio in month t

29.5.3 Calendar-time Portfolio Abnormal Returns (CTARs)

This section follows strictly the procedure in (Wiles et al., 2010)

A portfolio for every day in calendar time (including all securities which experience an event that time).

For each portfolio, the securities and their returns are equally weighted

1. For all portfolios, the average abnormal return are calculated as

$$AAR_{Pt} = \frac{\sum_{i=1}^{S} AR_i}{S}$$

where

- S is the number of securities in portfolio P
- AR_i is the abnormal return for the stock i in the portfolio

2. For every portfolio P, a time series estimate of $\sigma(AAR_{Pt})$ is calculated for the preceding k days, assuming that the AAR_{Pt} are independent over time.
3. Each portfolio's average abnormal return is standardized

$$SAAR_{Pt} = \frac{AAR_{Pt}}{SD(AAR_{Pt})}$$

4. Average standardized residual across all portfolio's in calendar time

$$ASAAR = \frac{1}{n}\sum_{i=1}^{255} SAAR_{Pt} \times D_t$$

where

- $D_t = 1$ when there is at least one security in portfolio t
- $D_t = 0$ when there are no security in portfolio t
- n is the number of days in which the portfolio have at least one security $n = \sum_{i=1}^{255} D_t$

5. The cumulative average standardized average abnormal returns is

$$CASSAR_{S_1,S_2} = \sum_{i=S_1}^{S_2} ASAAR$$

If the ASAAR are independent over time, then standard deviation for the above estimate is $\sqrt{S_2 - S_1 + 1}$

then, the test statistics is

$$t = \frac{CASAAR_{S_1,S_2}}{\sqrt{S_2 - S_1 + 1}}$$

Limitations

- Cannot examine individual stock difference, can only see the difference at the portfolio level.
  - One can construct multiple portfolios (based on the metrics of interest) so that firms in the same portfolio shares that same characteristics. Then, one can compare the intercepts in each portfolio.
- Low power (Loughran and Ritter, 2000), type II error is likely.

29.6 Aggregation

29.6.1 Over Time

We calculate the cumulative abnormal (CAR) for the event windows

H_0: Standardized cumulative abnormal return for stock i is 0 (no effect of events on stock performance)

H_1: SCAR is not 0 (there is an effect of events on stock performance)

29.6.2 Across Firms + Over Time

Additional assumptions: Abnormal returns of different socks are uncorrelated (rather strong), but it's very valid if event windows for different stocks do not overlap. If the windows for different overlap, follow (Bernard, 1987) and (Schipper and Thompson, 1983, Schipper and Smith (1983))

H_0: The mean of the abnormal returns across all firms is 0 (no effect)

H_1: The mean of the abnormal returns across all firms is different form 0 (there is an effect)

Parametric (empirically either one works fine) (assume abnormal returns is normally distributed) :

1. Aggregate the CAR of all stocks (Use this if the true abnormal variance is greater for stocks with higher variance)
2. Aggregate the SCAR of all stocks (Use this if the true abnormal return is constant across all stocks)

Non-parametric (no parametric assumptions):

1. Sign test:
   - Assume both the abnormal returns and CAR to be independent across stocks

    - Assume 50% with positive abnormal returns and 50% with negative abnormal return
    - The null will be that there is a positive abnormal return correlated with the event (if you want the alternative to be there is a negative relationship)
    - With skewed distribution (likely in daily stock data), the size test is not trustworthy. Hence, rank test might be better
2. Rank test
    - Null: there is no abnormal return during the event window

29.7 Heterogeneity in the event effect

$$y = X\theta + \eta$$

where

- y = CAR
- X = Characteristics that lead to heterogeneity in the event effect (i.e., abnormal returns) (e.g., firm or event specific)
- η = error term

Note:

- In cases with selection bias (firm characteristics and investor anticipation of the event: larger firms might enjoy great positive effect of an event, and investors endogenously anticipate this effect and overvalue the stock), we have to use the White's t-statistics to have the lower bounds of the true significance of the estimates.
- This technique should be employed even if the average CAR is not significantly different from 0, especially when the CAR variance is high (Boyd et al., 2010)

29.7.1 Common variables in marketing

(Sorescu et al., 2017) Table 4

- Firm size is negatively correlated with abnormal return in finance (Sorescu et al., 2017), but mixed results in marketing.
- # of event occurrences
- R&D expenditure
- Advertising expense
- Marketing investment (SG&A)
- Industry concentration (HHI, # of competitors)

- Financial leverage
- Market share
- Market size (total sales volume within the firm's SIC code)
- marketing capability
- Book to market value
- ROA
- Free cash flow
- Sales growth
- Firm age

29.8 Expected Return Calculation

29.8.1 Statistical Models

- based on statistical assumptions about the behavior of returns (e..g, multivariate normality)
- we only need to assume stable distributions (Owen and Rabinovitch, 1983)

29.8.1.1 Constant Mean Return Model

The expected normal return is the mean of the real returns

$$Ra_{it} = R_{it} - \bar{R}_i$$

Assumption:

- returns revert to its mean (very questionable)

The basic mean returns model generally delivers similar findings to more complex models since the variance of abnormal returns is not decreased considerably (Brown and Warner, 1985)

29.8.1.2 Market Model

$$R_{it} = \alpha_i + \beta R_{mt} + \epsilon_{it}$$

where

- R_{it} = stock return i in period t
- R_{mt} = market return
- ϵ_{it} = zero mean ($E(e_{it}) = 0$) error term with its own variance σ^2

Notes:

- People typically use S&P 500, CRSP value-weighed or equal-weighted index as the market portfolio.
- When $\beta = 0$, the Market Model is the Constant Mean Return Model
- better fit of the market-model, the less variance in abnormal return, and the more easy to detect the event's effect
- recommend generalized method of moments to be robust against autocorrelation and heteroskedasticity

29.8.1.3 Fama-French Model

Please note that there is a difference between between just taking the return versus taking the excess return as the dependent variable.

The correct way is to use the excess return for firm and for market (Fama and French, 2010, p. 1917).

- α_i "is the average return left unexplained by the benchmark model" (i.e., abnormal return)

29.8.1.3.1 FF3 (Fama and French, 1993)

$$\begin{aligned} E(R_{it}|X_t) - r_{ft} = \alpha_i &+ \beta_{1i}(E(R_{mt}|X_t) - r_{ft}) \\ &+ b_{2i}SML_t + b_{3i}HML_t \end{aligned}$$

where

- r_{ft} risk-free rate (e.g., 3-month Treasury bill)
- R_{mt} is the market-rate (e.g., S&P 500)
- SML: returns on small (size) portfolio minus returns on big portfolio
- HML: returns on high (B/M) portfolio minus returns on low portfolio.

29.8.1.3.2 FF4 (Sorescu et al., 2017, p. 195) suggest the use of Market Model in marketing for short-term window and Fama-French Model for the long-term window (the statistical properties of this model have not been examined the the daily setting).

(Carhart, 1997)

$$\begin{aligned} E(R_{it}|X_t) - r_{ft} = \alpha_i &+ \beta_{1i}(E(R_{mt}|X_t) - r_{ft}) \\ &+ b_{2i}SML_t + b_{3i}HML_t + b_{4i}UMD_t \end{aligned}$$

where

- UMD_t is the momentum factor (difference between high and low prior return stock portfolios) in day t.

29.8.2 Economic Model

The only difference between CAPM and APT is that APT has multiple factors (including factors beyond the focal company)

Economic models put limits on a statistical model that come from assumed behavior that is derived from theory.

29.8.2.1 Capital Asset Pricing Model (CAPM)

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

where

- $E(R_i)$ = expected firm return
- R_f = risk free rate
- $E(R_m - R_f)$ = market risk premium
- β_i = firm sensitivity

29.8.2.2 Arbitrage Pricing Theory (APT)

$$R = R_f + \Lambda f + \epsilon$$

where

- $\epsilon \sim N(0, \Psi)$
- Λ = factor loadings
- $f \sim N(\mu, \Omega)$ = general factor model
  - μ = expected risk premium vector
  - Ω = factor covariance matrix

29.9 Application

Packages:

- `eventstudies`
- `erer`
- `EventStudy`
- `AbnormalReturns`

- Event Study Tools
- estudy2
- `PerformanceAnalytics`

In practice, people usually sort portfolio because they are not sure whether the FF model is specified correctly.

Steps:

1. Sort all returns in CRSP into 10 deciles based on size.
2. In each decile, sort returns into 10 decides based on BM
3. Get the average return of the 100 portfolios for each period (i.e., expected returns of stocks given decile - characteristics)
4. For each stock in the event study: Compare the return of the stock to the corresponding portfolio based on size and BM.

Notes:

- Sorting produces outcomes that are often more conservative (e.g., FF abnormal returns can be greater than those that used sorting).
- If the results change when we do B/M first then size or vice versa, then the results are not robust (this extends to more than just two characteristics - e.g., momentum).

Examples:

Forestry:

- (Mei and Sun, 2008) M&A on financial performance (forest product)
- (Sun and Liao, 2011) litigation on firm values

```
library(erer)

# example by the package's author
data(daEsa)
hh <- evReturn(
    y = daEsa,        # dataset
    firm = "wpp",     # firm name
    y.date = "date", # date in y
    index = "sp500", # index
    est.win = 250,    # estimation window wedith in days
    digits = 3,
    event.date = 19990505, # firm event dates
    event.win = 5          # one-side event window wdith in days (default = 3, where 3
)
hh; plot(hh)
#>
#> === Regression coefficients by firm =========
```

```
#>   N firm event.date alpha.c alpha.e alpha.t alpha.p alpha.s beta.c beta.e
#> 1 1  wpp   19990505  -0.135   0.170  -0.795   0.428          0.665  0.123
#>   beta.t beta.p beta.s
#> 1  5.419  0.000    ***
#>
#> === Abnormal returns by date ================
#>    day Ait.wpp    HNt
#> 1   -5   4.564  4.564
#> 2   -4   0.534  5.098
#> 3   -3  -1.707  3.391
#> 4   -2   2.582  5.973
#> 5   -1  -0.942  5.031
#> 6    0  -3.247  1.784
#> 7    1  -0.646  1.138
#> 8    2  -2.071 -0.933
#> 9    3   0.368 -0.565
#> 10   4   4.141  3.576
#> 11   5   0.861  4.437
#>
#> === Average abnormal returns across firms ===
#>      name estimate error t.value p.value sig
#> 1 CiT.wpp    4.437 8.888   0.499   0.618
#> 2     GNT    4.437 8.888   0.499   0.618
```

Example by Ana Julia Akaishi Padula, Pedro Albuquerque (posted on LAMFO)

Example in `AbnormalReturns` package

29.9.1 Eventus

2 types of output:

1.
   - Using different estimation methods (e.g., market model to calendar-time approach)
   - Does not include event-specific returns. Hence, no regression later to determine variables that can affect abnormal stock returns.
2. Cross-sectional Analysis of Eventus: Event-specific abnormal returns (using monthly or data data) for cross-sectional analysis (under **Cross-Sectional Analysis** section)
   - Since it has the stock-specific abnormal returns, we can do regression on CARs later. But it only gives market-adjusted model. However, according to (Sorescu et al., 2017), they advocate for the use of market-adjusted model for the short-term only, and reserve the FF4 for the longer-term event studies using monthly daily.

29.9.1.1 Basic Event Study

1. Input a text file contains a firm identifier (e.g., PERMNO, CUSIP) and the event date
2. Choose market indices: equally weighted and the value weighted index (i.e., weighted by their market capitalization). And check Fama-French and Carhart factors.
3. Estimation options
   1. Estimation period: `ESTLEN = 100` is the convention so that the estimation is not impacted by outliers.
   2. Use "autodate" options: the first trading after the event date is used if the event falls on a weekend or holiday
4. Abnormal returns window: depends on the specific event
5. Choose test: either parametric (including Patell Standardized Residual (PSR)) or non-parametric

29.9.1.2 Cross-sectional Analysis of Eventus

Similar to the Basic Event Study, but now you can have event-specific abnormal returns.

29.9.2 Evenstudies

This package does not use the Fama-French model, only the market models.

This example is by the author of the package

```
library(eventstudies)
# firm and date data
data("SplitDates")
```

```r
head(SplitDates)

# stock price data
data("StockPriceReturns")
head(StockPriceReturns)
class(StockPriceReturns)

es <-
    eventstudy(
        firm.returns = StockPriceReturns,
        event.list = SplitDates,
        event.window = 5,
        type = "None",
        to.remap = TRUE,
        remap = "cumsum",
        inference = TRUE,
        inference.strategy = "bootstrap"
    )

plot(es)
```

29.9.3 EventStudy

You have to pay for the API key. (It's $10/month).

```r
library(EventStudy)
```

Example by the authors of the package

Data Prep

```r
library(tidyquant)
library(tidyverse)
library(readr)
```

```r
library("Quandl")
library("quantmod")
Quandl.auth("LDqWhYXzVd2omw4zipN2")
TWTR <- Quandl("NSE/OIL",type ="xts")
candleChart(TWTR)
```

```
addSMA(col="red") #Adding a Simple Moving Average
```

```
addEMA() #Adding an Exponential Moving Average
```

Reference market in Germany is DAX

```
# Index Data
# indexName <- c("DAX")

indexData <- tq_get("^GDAXI", from = "2014-05-01", to = "2015-12-31") %>%
    mutate(date = format(date, "%d.%m.%Y")) %>%
    mutate(symbol = "DAX")

head(indexData)
```

Create files

- 01_RequestFile.csv
- 02_FirmData.csv
- 03_MarketData.csv

Calculating abnormal returns

```
# get & set parameters for abnormal return Event Study
# we use a garch model and csv as return
# Attention: fitting a GARCH(1, 1) model is compute intensive
esaParams <- EventStudy::ARCApplicationInput$new()
esaParams$setResultFileType("csv")
esaParams$setBenchmarkModel("garch")


dataFiles <-
    c(
```

```
        "request_file" = file.path(getwd(), "data", "EventStudy", "01_requestFile.csv")
        "firm_data"    = file.path(getwd(), "data", "EventStudy", "02_firmDataPrice.csv
        "market_data"  = file.path(getwd(), "data", "EventStudy", "03_marketDataPrice.c
    )

# check data files, you can do it also in our R6 class
EventStudy::checkFiles(dataFiles)
```

```
arEventStudy <- estSetup$performEventStudy(estParams     = esaParams,
                                           dataFiles     = dataFiles,
                                           downloadFiles = T)
```

```
library(EventStudy)

apiUrl <- "https://api.eventstudytools.com"
Sys.setenv(EventStudyapiKey = "")

# The URL is already set by default
options(EventStudy.URL = apiUrl)
options(EventStudy.KEY = Sys.getenv("EventStudyapiKey"))

# use EventStudy estAPIKey function
estAPIKey(Sys.getenv("EventStudyapiKey"))

# initialize object
estSetup <- EventStudyAPI$new()
estSetup$authentication(apiKey = Sys.getenv("EventStudyapiKey"))
```

Chapter 30

Instrumental Variables

Similar to RCT, we try to introduce randomization (random assignment to treatment) to our treatment variable by using only variation in the instrument.

Logic of using an instrument:

- Use only exogenous variation to see the variation in treatment (try to exclude all endogenous variation in the treatment)
- Use only exogenous variation to see the variation in outcome (try to exclude all endogenous variation in the outcome)
- See the relationship between treatment and outcome in terms of residual variations that are exogenous to omitted variables.

Notes:

- Instruments can be used to remove attenuation bias in errors-in-variables.
- Be careful with the F-test and standard errors when you do 2SLS by hand (you need to correct them).
- Repeated use of related IVs across different studies can collectively invalidate these instruments, primarily through the violation of the exclusion restriction (Gallen, 2020). One needs to test for invalid instruments (Hausman-like test).
  - Mellon (2023) shows the widespread use of weather as an instrument in social sciences (289 studies linking weather to 195 variables) demonstrates significant exclusion violations that can overturn many IV results.
- For [Zero-valued Outcomes], we can't directly interpret the treatment coefficient of log-transformed outcome regression as percentage change (Chen and Roth, 2023). We have to distinguish the treatment effect on the

intensive (outcome: 10 to 11) vs. extensive margins (outcome: 0 to 1), and we can't readily interpret the treatment coefficient of log-transformed outcome regression as percentage change. To have percentage change interpretation, we can either do:

- Proportional LATE: estimate $\theta_{ATE\%}$ for those who are compliers under the instrument. To estimate proportional LATE,

  1. Regress $Y_i = \beta D_i + X_i + \epsilon_i$ using 2SLS with an instrument on D_i, where β is interpreted as the LATE in levels of the control group's mean for compliers.

  2. Get estimate of the control complier mean by regressing with same 2SLS regression (Abadie et al., 2002) where the final outcome is $-(D_i - 1)Y_i$, we refer to the new new estimated effect of D_i as β_{cc}

  3. The $\theta_{ATE\%}$ for compliers that are induced by the instrument is $\widehat{\beta}/\widehat{\beta}_{cc}$, where it can be interpreted directly as the percentage change for compliers that are induced by the instrument under treatment as compared to under control.

  4. SE can be obtained by non-parametric bootstrap.

  5. For specific case that the instrument is binary, θ of the intensive margin for compliers can be directly obtained by Poisson IV regression (`ivpoisson` in Stata).

- Lee (2009) bounds: we can get bounds for the average treatment effect in logs for compliers who have positive outcome regardless of treatment status (i.e., intensive-margin effect). This requires a monotonicity assumption for compliers where they should still have positive outcome regardless of treatment status.

Notes on First-stage:

- Always use the OLS regression in the first stage (regardless of the type of endogenous variables - e.g., continuous or discreet) (suggested by (Angrist and Pischke, 2009). Estimates of IV can still be consistent regardless of the form of the endogenous variables (discreet vs. continuous).

  - Alternatively, we could use "biprobit" model, but this is applicable only in cases where you have both dependent and endogenous variables to be binary.

- If you still want to continue and use logit or probit models for the first stage when you have binary variables, you have a "forbidden regression" (also 1, 2) (i.e., an incorrect extension of 2SLS to a nonlinear case).

There are several ways to understand this problem:

1. **Identification strategy**: The identification strategy in instrumental variables analysis relies on the fact that the instrumental variable affects the outcome variable only through its effect on the endogenous variable. However, when the endogenous variable is binary, the relationship between the instrumental variable and the endogenous variable is not continuous. This means that the instrumental variable can only affect the endogenous variable in discrete jumps, rather than through a continuous change. As a result, the identification of the causal effect of the endogenous variable on the outcome variable may not be possible with probit or logit regression in the first stage.

2. **Model assumptions**: Both models assume that the error term has a specific distribution (normal or logistic), and that the probability of the binary outcome is a function of the linear combination of the regressors.

   When the endogenous variable is binary, however, the distribution of the error term is not specified, as there is no continuous relationship between the endogenous variable and the outcome variable. This means that the assumptions of the probit and logit models may not hold, and the resulting estimates may not be reliable or interpretable.

3. **Issue of weak instruments**: When the instrument is weak, the variance of the inverse Mills ratio (which is used to correct for endogeneity in instrumental variables analysis) can be very large. In the case of binary endogenous variables, the inverse Mills ratio cannot be consistently estimated using probit or logit regression, and this can lead to biased and inconsistent estimates of the causal effect of the endogenous variable on the outcome variable.

Problems with weak instruments (Bound et al., 1995):

- Weak instrumental variables can produce (finite-sample) **biased** and **inconsistent** estimates of the causal effect of an endogenous variable on an outcome variable (even in the presence of large sample size)
- In a finite sample, instrumental variables (IV) estimates can be biased in the same direction as ordinary least squares (OLS) estimates. Additionally, the bias of IV estimates approaches that of OLS estimates as the correlation (R2) between the instruments and the endogenous explanatory variable approaches zero. This means that when the correlation between the instruments and the endogenous variable is weak, the bias of the IV estimates can be similar to that of the OLS estimates.
- Weak instruments are problematic because they do not have enough variation to fully capture the variation in the endogenous variable, leading to measurement error and other sources of noise in the estimates.
- Using weak instruments can produce large standard errors and low t-ratio. And when the feedback (reverse causality) is strong, the bias in IV is even greater than that of OLS (Nelson and Startz, 1988).

- Using lagged dependent variables as instruments for current values depends on serial correlations, typically low (Nelson and Startz, 1988).
- Using multiple covariates to artificially increase the first-stage R^2 does not solve this weak instrument problem (Nelson and Startz, 1988).
- Solutions:
  - use of multiple instruments
  - use of instrumental variables with higher correlation
  - use of alternative estimation methods such as limited information maximum likelihood (LIML) or two-stage least squares (2SLS) with heteroscedasticity-robust standard errors.

Instrument Validity:

1. Random assignment (Exogeneity Assumption).
2. Any effect of the instrument on the outcome must be through the endogenous variable (Relevance Assumption).

30.1 Framework

- $D_i \sim Bern$ Dummy Treatment
- Y_{0i}, Y_{1i} potential outcomes
- $Y_i = Y_{0i} + (Y_{1i} - Y_{0i})D_i$ observed outcome
- $Z_i \perp Y_{0i}, Y_{1i}$ Instrumental variables (and also correlate with D_i)

Under constant-effects and linear ($Y_{1i} - Y_{0i}$ are the same for everyone)

$$\begin{aligned} Y_{0i} &= \alpha + \eta_i \\ Y_{1i} - Y_{0i} &= \rho \\ Y_i &= Y_{0i} + D_i(Y_{1i} - Y_{0i}) \\ &= \alpha + \eta_i + D_i\rho \\ &= \alpha + \rho D_i + \eta_i \end{aligned}$$

where

- η_i is individual differences
- ρ is the difference between treated outcome and untreated outcome. Here we assume they are constant for everyone

However, we have a problem with OLS because D_i is correlated with η_i for each unit

But Z_i can come to the rescue, the causal estimate can be written as

$$\begin{aligned}\rho &= \frac{Cov(Y_i, Z_i)}{Cov(D_i, Z_i)} \\ &= \frac{Cov(Y_i, Z_i)/V(Z_i)}{Cov(D_i, Z_i)/V(Z_i)} = \frac{Reducedform}{First-stage} \\ &= \frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}\end{aligned}$$

Under heterogeneous treatment effect ($Y_{1i} - Y_{0i}$ are different for everyone) with LATE framework

$Y_i(d, z)$ denotes the potential outcome for unit i with treatment $D_i = d$ and instrument $Z_i = z$

Observed treatment status

$$D_i = D_{0i} + Z_i(D_{1i} - D_{0i})$$

where

- D_{1i} is treatment status of unit i when $z_i = 1$
- D_{0i} is treatment status of unit i when $z_i = 0$
- $D_{1i} - D_{0i}$ is the causal effect of Z_i on D_i

Assumptions

- ***Independence***: The instrument is randomly assigned (i.e., independent of potential outcomes and potential treatments)
  - $[\{Y_i(d, z); \forall d, z\}, D_{1i}, D_{0i}]\Pi Z_i$
  - This assumption let the first-stage equation be the average causal effect of Z_i on D_i

$$\begin{aligned}E[D_i|Z_i = 1] - E[D_i|Z_i = 0] &= E[D_{1i}|Z_i = 1] - E[D_{0i}|Z_i = 0] \\ &= E[D_{1i} - D_{0i}]\end{aligned}$$

  - This assumption also is sufficient for a causal interpretation of the reduced form, where we see the effect of the instrument on the outcome.

$$E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0] = E[Y_i(D_{1i}, Z_i = 1) - Y_i(D_{0i}, Z_i = 0)]$$

- ***Exclusion*** (i.e., existence of instruments (Imbens and Angrist, 1994)
  - The treatment D_i fully mediates the effect of Z_i on Y_i

$$Y_{1i} = Y_i(1, 1) = Y_i(1, 0)Y_{0i} = Y_i(0, 1) = Y_i(0, 0)$$

  - With this assumption, the observed outcome Y_i can be thought of as (assume Y_{1i}, Y_{0i} already satisfy the independence assumption)

$$\begin{aligned} Y_i &= Y_i(0, Z_i) + [Y_i(1, Z_i) - Y_i(0, Z_i)]D_i \\ &= Y_{0i} + (Y_{1i} - Y_{0i})D_i \end{aligned}$$

  - This assumption let us go from reduced-form causal effects to treatment effects (Angrist and Imbens, 1995)

- ***Monotonicity***: $D_{1i} > D_{0i} \forall i$
  - With this assumption, we have $E[D_{1i} - D_{0i}] = P[D_{1i} > D_{0i}]$
  - This assumption lets us assume that there is a first stage, in which we examine the proportion of the population that D_i is driven by Z_i
  - This assumption is used to solve to problem of the shifts between participation status back to non-participation status.
    * Alternatively, one can solve the same problem by assuming constant (homogeneous) treatment effect (Imbens and Angrist, 1994), but this is rather restrictive.
    * A third solution is the assumption that there exists a value of the instrument, where the probability of participation conditional on that value is 0 (Heckman, 1990, Angrist and Imbens (1991)).

With these three assumptions, we have the LATE theorem (Angrist and Pischke, 2009, 4.4.1)

$$\frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]} = E[Y_{1i} - Y_{0i}|D_{1i} > D_{0i}]$$

LATE assumptions allow us to go back to the types of subjects we have in Causal Inference

- Switchers:
  - Compliers: $D_{1i} > D_{0i}$
- Non-switchers:
  - Always-takers: $D_{1i} = D_{0i} = 1$
  - Never-takers: $D_{1i} = D_{0i} = 0$

Instrumental Variables can't say anything about non-switchers because treatment status D_i has no effects on them (similar to fixed effects models).

When all groups are the same, we come back to the constant-effects world.

Treatment effects on the treated is a weighted average of always-takers and compliers.

In the special case of IV in randomized trials, we have a compliance problem (when compliance is voluntary), where those in the treated will not always take the treatment (i.e., might be selection bias).

- **Intention-to-treat analysis** is valid, but contaminated by non-compliance
- IV in this case (Z_i = random assignment to the treatment; D_i = whether the unit actually received/took the treatment) can solve this problem.
- Under certain assumptions (i.e., SUTVA, random assignment, exclusion restriction, no defiers, and monotinicity), this analysis can give causal interpreation of LATE because it's the average causal effect for the compliers only.
  - Without these assumptions, it's a ratio of intention-to-treat.
- Without always-takers in this case, LATE = Treatment effects on the treated

See proof Bloom (1984) and examples Bloom et al. (1997) and Sherman and Berk (1984)

$$\frac{E[Y_i|Z_i=1]-E[Y_i|Z_i=0]}{E[D_i|Z_i=1]} = \frac{\text{Intention-to-treat effect}}{\text{Compliance rate}} = E[Y_{1i}-Y_{0i}|D_i=1]$$

30.2 Estimation

30.2.1 2SLS Estimation

A special case of IV-GMM

Examples by authors of `fixest` package

```
library(fixest)
base = iris
names(base) = c("y", "x1", "x_endo_1", "x_inst_1", "fe")
set.seed(2)
base$x_inst_2 = 0.2 * base$y + 0.2 * base$x_endo_1 + rnorm(150, sd = 0.5)
base$x_endo_2 = 0.2 * base$y - 0.2 * base$x_inst_1 + rnorm(150, sd = 0.5)

# est_iv = feols(y ~ x1 | x_endo_1  ~ x_inst_1 , base)
est_iv = feols(y ~ x1 | x_endo_1 + x_endo_2 ~ x_inst_1 + x_inst_2, base)
est_iv
#> TSLS estimation - Dep. Var.: y
#>                   Endo.    : x_endo_1, x_endo_2
#>                   Instr.   : x_inst_1, x_inst_2
#> Second stage: Dep. Var.: y
#> Observations: 150
```

```
#> Standard-errors: IID
#>              Estimate Std. Error  t value   Pr(>|t|)
#> (Intercept)  1.831380   0.411435  4.45121 1.6844e-05 ***
#> fit_x_endo_1 0.444982   0.022086 20.14744  < 2.2e-16 ***
#> fit_x_endo_2 0.639916   0.307376  2.08186 3.9100e-02 *
#> x1           0.565095   0.084715  6.67051 4.9180e-10 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.398842   Adj. R2: 0.761653
#> F-test (1st stage), x_endo_1: stat = 903.2    , p < 2.2e-16 , on 2 and 146 DoF.
#> F-test (1st stage), x_endo_2: stat =   3.25828, p = 0.041268, on 2 and 146 DoF.
#>                   Wu-Hausman: stat =   6.79183, p = 0.001518, on 2 and 144 DoF.
```

Default statistics

1. F-test first-stage (weak instrument test)
2. Wu-Hausman endogeneity test
3. Over-identifying restriction (Sargan) J-test

```r
fitstat(
    est_iv,
    type = c(
        "n", "ll", "aic", "bic", "rmse", # ll means log-likelihood

        "my", # mean dependent var

        "g", # degrees of freedom used to compute the t-test

        "r2", "ar2", "wr2", "awr2", "pr2", "apr2", "wpr2", "awpr2",

        "theta", # over-dispersion parameter in Negative Binomial models

        "f", "wf", # F-tests of nullity of the coefficients

        "wald", # Wald test of joint nullity of the coefficients

        "ivf",

        "ivf1",

        "ivf2",

        "ivfall",

        "ivwald", "ivwald1", "ivwald2", "ivwaldall",
```

```
        "cd"

        # "kpr"


        ),
    cluster = 'fe'
)
#>                 Observations: 150
#>               Log-Likelihood: -75.0
#>                          AIC: 157.9
#>                          BIC: 170.0
#>                         RMSE: 0.398842
#>               Dep. Var. mean: 5.84333
#>                            G: 3
#>                           R2: 0.766452
#>                      Adj. R2: 0.761653
#>                    Within R2: NA
#>                         awr2: NA
#>                    Pseudo R2: 0.592684
#>               Adj. Pseudo R2: 0.576383
#>             Within Pseudo R2: NA
#>                        awpr2: NA
#>              Over-dispersion: NA
#>                       F-test: stat =       1.80769, p = 0.375558, on 3 and 2 DoF.
#>           F-test (projected): NA
#>         Wald (joint nullity): stat = 539,363.2    , p < 2.2e-16 , on 3 and 146 DoF, VCOV: Clus
#> F-test (1st stage), x_endo_1: stat =     903.2    , p < 2.2e-16 , on 2 and 146 DoF.
#> F-test (1st stage), x_endo_2: stat =       3.25828, p = 0.041268, on 2 and 146 DoF.
#>           F-test (2nd stage): stat =     194.2    , p < 2.2e-16 , on 2 and 146 DoF.
#>             F-test (IV only): stat =     194.2    , p < 2.2e-16 , on 2 and 146 DoF.
#> Wald (1st stage), x_endo_1  : stat =   1,482.6    , p < 2.2e-16 , on 2 and 146 DoF, VCOV: Clus
#> Wald (1st stage), x_endo_2  : stat =       2.22157, p = 0.112092, on 2 and 146 DoF, VCOV: Clus
#>             Wald (2nd stage): stat = 539,363.2    , p < 2.2e-16 , on 2 and 146 DoF, VCOV: Clus
#>               Wald (IV only): stat = 539,363.2    , p < 2.2e-16 , on 2 and 146 DoF, VCOV: Clus
#>                 Cragg-Donald: 3.11162
```

To set default printing

```
# always add second-stage Wald test
setFixest_print(fitstat = ~ . + ivwald2)
est_iv
```

To see results from different stages

```r
# first-stage
summary(est_iv, stage = 1)

# second-stage
summary(est_iv, stage = 2)

# both stages
etable(summary(est_iv, stage = 1:2), fitstat = ~ . + ivfall + ivwaldall.p)
etable(summary(est_iv, stage = 2:1), fitstat = ~ . + ivfall + ivwaldall.p)
# .p means p-value, not statistic
# `all` means IV only
```

30.2.2 IV-GMM

This is a more general framework.

- 2SLS Estimation is a special case of IV-GMM estimator

$$Y = X\beta + u, u \sim (0, \Omega)$$

where

- X is a matrix of endogenous variables $(N \times k)$

We will use a matrix of instruments X where it has $N \times l$ dimensions (where $l \geq k$)

Then, we can have a set of l moments:

$$g_i(\beta) = Z_i' u_i = Z_i'(Y_i - X_i\beta)$$

where

- $i \in (1, N)$

Each l moment equation is a sample moment, which can be estimated by averaging over N

$$\bar{g}(\beta) = \frac{1}{N}\sum_{i=1}^{N} Z_i(Y_i - X_i\beta) = \frac{1}{N}Z'u$$

GMM then estimate β so that $\bar{g}(\hat{\beta}_{GMM}) = 0$

When $l = k$ there is a unique solution to this system of equations (and equivalent to the IV estimator)

$$\hat{\beta}_{IV} = (Z'X)^{-1}Z'Y$$

When $l > k$, we have a set of k instruments

$$\hat{X} = Z(Z'Z)^{-1}Z'X = P_Z X$$

then we can use the 2SLS estimator

$$\begin{aligned}\hat{\beta}_{2SLS} &= (\hat{X}'X)^{-1}\hat{X}'Y \\ &= (X'P_Z X)^{-1}X'P_Z Y\end{aligned}$$

Differences between 2SLS and IV-GMM:

- In the 2SLS method, when there are more instruments available than what is actually needed for the estimation, to address this, a matrix is created that only includes the necessary instruments, which simplifies the calculation.
- The IV-GMM method uses all the available instruments, but applies a weighting system to prioritize the instruments that are most relevant. This approach is useful when there are more instruments than necessary, which can make the calculation more complex. The IV-GMM method uses a criterion function to weight the estimates and improve their accuracy.
- **In short, always use IV-GMM when you have overid problems**

GMM estimator minimizes

$$J(\hat{\beta}_{GMM}) = N\bar{g}(\hat{\beta}_{GMM})'W\bar{g}(\hat{\beta}_{GMM})$$

where W is a symmetric weighting matrix $l \times l$

For an overid equation, solving the set of FOCs for the IV-GMM estimator, we should have

$$\hat{\beta}_{GMM} = (X'ZWZ'X)^{-1}X'ZWZ'Y$$

which is identical for all W matrices. The optimal $W = S^{-1}$ (Hansen, 1982) where S is the covariance matrix of the moment conditions to produce the most efficient estimator:

$$S = E[Z'uu'Z] = \lim_{N\to\infty} N^{-1}[Z'\Omega Z]$$

With a consistent estimator of S from the 2SLS residuals, the feasible IV-GMM estimator can be defined as

$$\hat{\beta}_{FEGMM} = (X'Z\hat{S}^{-1}Z'X)^{-1}X'Z\hat{S}^{-1}Z'Y$$

In cases where Ω (i.e., the vcov of the error process u) satisfy all classical assumptions

1. IID
2. $S = \sigma_u^2 I_N$
3. The optimal weighting matrix is proportional to the identity matrix

Then, IV-GMM estimator is the standard IV (or 2SLS) estimator.

For IV-GMM, you also have an additional test of overid restrictions: GMM distance (also known as Hayashi C statistic)

To account for clustering, one can use code provided by this blog

30.3 Inference

Under just-identified instrument variable model, we have

$$Y = \beta X + u$$

where $corr(u, Z) = 0$ (relevant assumption) and $corr(Z, X) \neq 0$ (exogenous assumption)

The t-ratio approach to construct the 95 CIs is

$$\hat{\beta} \pm 1.96\sqrt{\hat{V}_N(\hat{\beta})}$$

But this is wrong, and has been long recognized by those who understand the "weak instruments" problem (Staiger and Stock, 1997, Dufour (1997))

To test the null hypothesis of $\beta = \beta_0$ (Lee et al., 2022)

$$\frac{(\hat{\beta} - \beta_0)^2}{\hat{V}_N(\hat{\beta})} = \hat{t}^2 = \hat{t}_{AR}^2 \times \frac{1}{1 - \hat{\rho}\frac{\hat{t}_{AR}}{\hat{f}} + \frac{\hat{t}_{AR}^2}{\hat{f}^2}}$$

where $\hat{t}_{AR}^2 \sim \chi^2(1)$ (even with weak instruments) (Anderson and Rubin, 1949)

$$\hat{t}_{AR} = \frac{\hat{\pi}(\hat{\beta} - \beta_0)}{\sqrt{\hat{V}_N(\hat{\pi}(\hat{\beta} - \beta_0))}} \sim N(0, 1)$$

where

- $\hat{f} = \frac{\hat{\pi}}{\sqrt{\hat{V}_N(\hat{\pi})}} \sim N$

- $\hat{\pi}$ = 1st-stage coefficient
- $\hat{\rho} = COV(Zv, Zu)$ = correlation between the 1st-stage residual and an estimate of u

Even in large samples, $\hat{t}^2 \neq \hat{t}^2_{AR}$ because the right-hand term does not have a degenerate distribution. Thus, the normal t critical values wouldn't work.

The t-ratios does not match that of standard normal, but it matches the proposed density by Staiger and Stock (1997) and Stock and Yogo (2005b) .

The deviation between $\hat{t}^2, \hat{t}^2_{AR}$ depends on

1. π (i.e., correlation between the instrument and the endogenous variable)
2. $E(F)$ (i.e., strength of the first-stage)
3. Magnitude of $|\rho|$ (i.e., degree of endogeneity)

Hence, we can think of several scenarios:

1. **Worst case**: Very weak first stage ($\pi = 0$) and high degree of endogeneity ($|\rho| = 1$).

- The interval $\hat{\beta} \pm 1.96 \times SE$ does not contain the true parameter β.
- A 5 percent significance test under these conditions will incorrectly reject the null hypothesis ($\beta = \beta_0$) 100% of the time.

2. **Best case**: No endogeneity ($\rho = 0$) or very large $\hat{f}$ (very strong first-stage)

- The interval $\hat{\beta} \pm 1.96 \times SD$ accurately contains β at least 95% of the time.

3. **Intermediate case**: The performance of the interval lies between the two extremes.

Solutions: To have valid inference of $\hat{\beta} \pm 1.96 \times SE$ using t-ratio ($\hat{t}^2 \approx \hat{t}^2_{AR}$), we can either

1. Assume our problem away
    1. Assume $E(F) > 142.6$ (Lee et al., 2022) (Not much of an assumption since we can observe first-stage F-stat empirically).
    2. Assume $|\rho| < 0.565$ (Angrist and Kolesár, 2024, Lee et al. (2022)), but this defeats our motivation to use IV in the first place because we think there is a strong endogeneity bias, that's why we are trying to correct for it (circular argument).
2. Deal with it head on
    1. AR approach (Anderson and Rubin, 1949)
    2. tF Procedure (Lee et al., 2022)
    3. AK approach (Angrist and Kolesár, 2023)

Common Practices & Challenges:

- The t-ratio test is preferred by many researchers but has its pitfalls:

  - Known to over-reject (equivalently, under-cover confidence intervals), especially with weak instruments (Lee et al., 2022, Nelson and Startz (1990), Bound et al. (1995), Dufour (1997)).

- To address this:
  - The first-stage F-statistic is used as an indicator of weak instruments.
  - (Staiger and Stock, 1997, Stock and Yogo (2005b)) provided a framework to understand and correct these **distortions**.

Misinterpretations:

- Common errors in application:
  - Using a rule-of-thumb F-stat threshold of 10 instead of referring to Stock and Yogo (2005b).
  - Mislabeling intervals such as $\hat{\beta} \pm 1.96 \times \hat{se}(\hat{\beta})$ as 95% confidence intervals (when passed the $F > 10$ rule of thumb). Staiger and Stock (1997) clarified that such intervals actually represent 85% confidence when using $F > 16.38$ from Stock and Yogo (2005b)
- Pretesting for weak instruments might exacerbate over-rejection of the t-ratio test mentioned above (Hall et al., 1996).
- Selective model specification (i.e., dropping certain specification) based on F-statistics also leads to significant **distortions** (Andrews et al., 2019).

30.3.1 AR approach

Validity of Anderson-Rubin Test (notated as AR) (Anderson and Rubin, 1949):

- Gives accurate results even under non-normal and homoskedastic errors (Staiger and Stock, 1997).
- Maintains validity across diverse error structures (Stock and Wright, 2000).
- Minimizes type II error among several alternative tests, in cases of:
  - Homoskedastic errors (Andrews et al., 2006, Moreira (2009)).
  - Generalized for heteroskedastic, clustered, and autocorrelated errors (Moreira and Moreira, 2019).

```r
library(ivDiag)

# AR test (robust to weak instruments)
# example by the package's authors
ivDiag::AR_test(
    data = rueda,
```

```
    Y = "e_vote_buying",
    # treatment
    D = "lm_pob_mesa",
    # instruments
    Z = "lz_pob_mesa_f",
    controls = c("lpopulation", "lpotencial"),
    cl = "muni_code",
    CI = FALSE
)
#> $Fstat
#>         F       df1       df2         p
#>   50.5097    1.0000 4350.0000    0.0000

g <- ivDiag::ivDiag(
    data = rueda,
    Y = "e_vote_buying",
    D = "lm_pob_mesa",
    Z = "lz_pob_mesa_f",
    controls = c("lpopulation", "lpotencial"),
    cl = "muni_code",
    cores = 4,
    bootstrap = FALSE
)
g$AR
#> $Fstat
#>         F       df1       df2         p
#>   50.5097    1.0000 4350.0000    0.0000
#>
#> $ci.print
#> [1] "[-1.2545, -0.7156]"
#>
#> $ci
#> [1] -1.2545169 -0.7155854
#>
#> $bounded
#> [1] TRUE
ivDiag::plot_coef(g)
```

30.3.2 tF Procedure

Lee et al. (2022) propose a new method that is aligned better with traditional econometric training than AR, where it is called the tF procedure. It incorporates both the 1st-stage F-stat and the 2SLS t-value. This method is applicable to single instrumental variable (i.e., just-identified model), including

- Randomized trials with imperfect compliance (Imbens and Angrist, 1994).
- Fuzzy Regression Discontinuity designs (Lee and Lemieux, 2010).
- Fuzzy regression kink designs (Card et al., 2015).

See Andrews et al. (2019) for a comparison between AR approach and tF Procedure.

tF Procedure:

- Adjusts the t-ratio based on the first-stage F-statistic.
- Rather than a fixed pretesting threshold, it applies an adjustment factor to 2SLS standard errors.
- Adjustment factors are provided for 95% and 99% confidence levels.

Advantages of the tF Procedure:

1. **Smooth Adjustment**:
    - Gives usable finite confidence intervals for smaller F statistic values.
    - 95% confidence is applicable for $F > 3.84$, aligning with AR's bounded 95% confidence intervals.

2. **Clear Confidence Levels**:
   - These levels incorporate effects of basing inference on the first-stage F.
   - Mirrors AR or other zero distortion procedures.
3. **Robustness**:
   - Robust against common error structures (e.g., heteroskedasticity or clustering and/or autocorrelated errors).
   - No further adjustments are necessary as long as robust variance estimators are consistently used (same robust variance estimator used for the 1st-stage as for the IV estimate).
4. **Comparison to AR**:
   - Surprisingly, with $F > 3.84$, AR's expected interval length is infinite, while tF's is finite (i.e., better).
5. **Applicability**:
   - The tF adjustment can re-evaluate published studies if the first-stage F-statistic is available.
   - Original data access is not needed.

Impacts in Applied Research:

- Lee et al. (2022) examined recent single-instrument specification studies from the American Economic Review (AER).
- Observations:
  - For at least 25% of the studied specifications, using tF increased confidence interval lengths by:
    - 49% (5% significance level).
    - 136% (1% significance level).
  - For specifications with $F > 10$ and $t > 1.96$, about 25% became statistically insignificant at the 5% level when adjusted using tF.
  - Conclusion: tF adjustments could greatly influence inferences in research employing t-ratio inferences.

Notation

- $Y = X\beta + W\gamma + u$
- $X = Z\pi + W\xi + \nu$

where

- W: Additional covariates, possibly including an intercept term.
- X: variable of interest

- Z: instruments

Key Statistics:

- t-ratio for the instrumental variable estimator: $\hat{t} = \frac{\hat{\beta}-\beta_0}{\sqrt{\hat{V}_N(\hat{\beta})}}$
- t-ratio for the first-stage coefficient: $\hat{f} = \frac{\hat{\pi}}{\sqrt{\hat{V}_N(\hat{\pi})}}$
- $\hat{F} = \hat{f}^2$

where

- $\hat{\beta}$: Instrumental variable estimator.
- $\hat{V}_N(\hat{\beta})$: Estimated variance of $\hat{\beta}$, possibly robust to deal with non-iid errors.
- $\hat{t}$: t-ratio under the null hypothesis.
- $\hat{f}$: t-ratio under the null hypothesis of $\pi = 0$.

Traditional t Inference:

- In large samples, $\hat{t}^2 \to^d t^2$
- Standard normal critical values are ± 1.96 for 5% significance level testing.

Distortions in Inference in the case of IV:

- Use of a standard normal can lead to distorted inferences even in large samples.
  - Despite large samples, t-distribution might not be normal.
- But magnitude of this distortion can be quantified.
  - Stock and Yogo (2005b) provides a formula for Wald test statistics using 2SLS.
  - t^2 formula allows for quantification of inference distortions.
  - In the just-identified case with one endogenous regressor $t^2 = f + t_{AR} + \rho f t_{AR}$ (Stock and Yogo, 2005b)
    * $\hat{f} \to^d f$ and $\bar{f} = \frac{\pi}{\sqrt{\frac{1}{N}AV(\hat{\pi})}}$ and $AV(\hat{\pi})$ is the asymptotic variance of $\hat{\pi}$
    * t_{AR} is a standard normal with $AR = t_{AR}^2$
    * ρ (degree of endogeneity) is the correlation of Zu and $Z\nu$ (when data are homoskedastic, ρ is the correlation between u and ν)

Implications of t^2 formula:

- Varies rejection rates depending on ρ value.
  - $\rho \in (0, 0.5]$ (low) the t-ratio rejects at a probability below the nominal 0.05 rate
  - $\rho = 0.8$ (high) the rejection rate can be 0.13
- In short, incorrect test size when relying solely on t^2 (based on traditional econometric understanding)

To correct for this, one can

1. Estimate the usually 2SLS standard errors
2. Multiply the SE by the adjustment factor based on the observed first-stage $\hat{F}$ stat
3. One can go back to the traditional hypothesis by using either the t-ratio of confidence intervals

Lee et al. (2022) call this adjusted SE as "0.05 tF SE".

```
library(ivDiag)
g <- ivDiag::ivDiag(
    data = rueda,
    Y = "e_vote_buying",
    D = "lm_pob_mesa",
    Z = "lz_pob_mesa_f",
    controls = c("lpopulation", "lpotencial"),
    cl = "muni_code",
    cores = 4,
    bootstrap = FALSE
)
g$tF
#>          F        cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
#> 8598.3264    1.9600   -0.9835    0.1540   -6.3872   -1.2853   -0.6817    0.0000
```

```
# example in fixest package
library(fixest)
library(tidyverse)
base = iris
names(base) = c("y", "x1", "x_endo_1", "x_inst_1", "fe")
set.seed(2)
base$x_inst_2 = 0.2 * base$y + 0.2 * base$x_endo_1 + rnorm(150, sd = 0.5)
base$x_endo_2 = 0.2 * base$y - 0.2 * base$x_inst_1 + rnorm(150, sd = 0.5)

est_iv = feols(y ~ x1 | x_endo_1 + x_endo_2 ~ x_inst_1 + x_inst_2, base)
est_iv
#> TSLS estimation - Dep. Var.: y
#>                   Endo.    : x_endo_1, x_endo_2
#>                   Instr.   : x_inst_1, x_inst_2
#> Second stage: Dep. Var.: y
#> Observations: 150
#> Standard-errors: IID
#>              Estimate Std. Error  t value   Pr(>|t|)
#> (Intercept)  1.831380   0.411435  4.45121 1.6844e-05 ***
#> fit_x_endo_1 0.444982   0.022086 20.14744  < 2.2e-16 ***
#> fit_x_endo_2 0.639916   0.307376  2.08186 3.9100e-02 *
#> x1           0.565095   0.084715  6.67051 4.9180e-10 ***
```

```
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.398842   Adj. R2: 0.761653
#> F-test (1st stage), x_endo_1: stat = 903.2    , p < 2.2e-16 , on 2 and 146 DoF.
#> F-test (1st stage), x_endo_2: stat =   3.25828, p = 0.041268, on 2 and 146 DoF.
#>                   Wu-Hausman: stat =   6.79183, p = 0.001518, on 2 and 144 DoF.

res_est_iv <- est_iv$coeftable |>
    rownames_to_column()


coef_of_interest <-
    res_est_iv[res_est_iv$rowname == "fit_x_endo_1", "Estimate"]
se_of_interest <-
    res_est_iv[res_est_iv$rowname == "fit_x_endo_1", "Std. Error"]
fstat_1st <- fitstat(est_iv, type = "ivf1")[[1]]$stat

# To get the correct SE based on 1st-stage F-stat (This result is similar without adju
# the results are the new CIS and p.value
tF(coef = coef_of_interest, se = se_of_interest, Fstat = fstat_1st) |>
    causalverse::nice_tab(5)
#>          F   cF    Coef      SE        t  CI2.5. CI97.5. p.value
#> 1 903.1628 1.96 0.44498 0.02209 20.14744 0.40169 0.48827       0

# We can try to see a different 1st-stage F-stat and how it changes the results
tF(coef = coef_of_interest, se = se_of_interest, Fstat = 2) |>
    causalverse::nice_tab(5)
#>   F    cF    Coef      SE        t  CI2.5. CI97.5. p.value
#> 1 2 18.66 0.44498 0.02209 20.14744 0.03285 0.85711 0.03432
```

30.3.3 AK approach

(Angrist and Kolesár, 2023)

30.4 Testing Assumptions

$$Y = \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

where

- X_1 are exogenous variables
- X_2 are endogenous variables
- Z are instrumental variables

If Z satisfies the relevance condition, it means $Cov(Z, X_2) \neq 0$

This is important because we need this to be able to estimate β_2 where

$$\beta_2 = \frac{Cov(Z, Y)}{Cov(Z, X_2)}$$

If Z satisfies the exogeneity condition, $E[Z\epsilon] = 0$, this can achieve by

- Z having no direct effect on Y except through X_2
- In the presence of omitted variable, Z is uncorrelated with this variable.

If we just want to know the effect of Z on Y (**reduced form**) where the coefficient of Z is

$$\rho = \frac{Cov(Y, Z)}{Var(Z)}$$

and this effect is only through X_2 (by the exclusion restriction assumption).

We can also consistently estimate the effect of Z on X (**first stage**) where the the coefficient of X_2 is

$$\pi = \frac{Cov(X_2, Z)}{Var(Z)}$$

and the IV estimate is

$$\beta_2 = \frac{Cov(Y, Z)}{Cov(X_2, Z)} = \frac{\rho}{\pi}$$

30.4.1 Relevance Assumption

- **Weak instruments**: can explain little variation in the endogenous regressor
  - Coefficient estimate of the endogenous variable will be inaccurate.
  - For cases where weak instruments are unavoidable, Moreira (2003) proposes the conditional likelihood ratio test for robust inference. This test is considered approximately optimal for weak instrument scenarios (Andrews et al., 2008; Andrews and Marmer, 2008).
- Rule of thumb:
  - Compute F-statistic in the first-stage, where it should be greater than 10. But this is discouraged now by Lee et al. (2022)
  - use `linearHypothesis()` to see only instrument coefficients.

First-Stage F-Test

In the context of a two-stage least squares (2SLS) setup where you are estimating the equation:

$$Y = X\beta + \epsilon$$

and X is endogenous, you typically estimate a first-stage regression of:

$$X = Z\pi + u$$

where Z is the instrument.

The first-stage F-test evaluates the joint significance of the instruments in this first stage:

$$F = \frac{(SSR_r - SSR_{ur})/q}{SSR_{ur}/(n-k-1)}$$

where:

- SSR_r is the sum of squared residuals from the restricted model (no instruments, just the constant).
- SSR_{ur} is the sum of squared residuals from the unrestricted model (with instruments).
- q is the number of instruments excluded from the main equation.
- n is the number of observations.
- k is the number of explanatory variables excluding the instruments.

Cragg-Donald Test

The Cragg-Donald statistic is essentially the same as the Wald statistic of the joint significance of the instruments in the first stage, and it's used specifically when you have multiple endogenous regressors. It's calculated as:

$$CD = n \times (R_{ur}^2 - R_r^2)$$

where:

- R_{ur}^2 and R_r^2 are the R-squared values from the unrestricted and restricted models respectively.
- n is the number of observations.

For one endogenous variable, the Cragg-Donald test results should align closely with those from Stock and Yogo. The Anderson canonical correlation test, a likelihood ratio test, also works under similar conditions, contrasting with Cragg-Donald's Wald statistic approach. Both are valid with one endogenous variable and at least one instrument.

Stock-Yogo Weak IV Test

The Stock-Yogo test does not directly compute a statistic like the F-test or Cragg-Donald, but rather uses pre-computed critical values to assess the strength of instruments. It often uses the eigenvalues derived from the concentration matrix:

$$S = \frac{1}{n}(Z'X)(X'Z)$$

where Z is the matrix of instruments and X is the matrix of endogenous regressors.

Stock and Yogo provide critical values for different scenarios (bias, size distortion) for a given number of instruments and endogenous regressors, based on the smallest eigenvalue of S. The test compares these eigenvalues against critical values that correspond to thresholds of permissible bias or size distortion in a 2SLS estimator.

- **Critical Values and Test Conditions**: The critical values derived by Stock and Yogo depend on the level of acceptable bias, the number of endogenous regressors, and the number of instruments. For example, with a 5% maximum acceptable bias, one endogenous variable, and three instruments, the critical value for a sufficient first stage F-statistic is 13.91. Note that this framework requires at least two overidentifying degree of freedom.

Comparison

Test	Description	Focus	Usage
First-Stage F-Test	Evaluates the joint significance of instruments in the first stage.	Predictive power of instruments for the endogenous variable.	Simplest and most direct test, widely used especially with a single endogenous variable. Rule of thumb: F $<$ 10 suggests weak instruments.
Cragg-Donald Test	Wald statistic for joint significance of instruments.	Joint strength of multiple instruments with multiple endogenous variables.	More appropriate in complex IV setups with multiple endogenous variables. Compares statistic against critical values for assessing instrument strength.

Test	Description	Focus	Usage
Stock-Yogo Weak IV Test	Compares test statistic to predetermined critical values.	Minimizing size distortions and bias from weak instruments.	Theoretical evaluation of instrument strength, ensuring the reliability of 2SLS estimates against specific thresholds of bias or size distortion.

All the mentioned tests (Stock Yogo, Cragg-Donald, Anderson canonical correlation test) assume errors are independently and identically distributed. If this assumption is violated, the Kleinbergen-Paap test is robust against violations of the iid assumption and can be applied even with a single endogenous variable and instrument, provided the model is properly identified (Baum and Schaffer, 2021).

30.4.1.1 Cragg-Donald

(Cragg and Donald, 1993)

Similar to the first-stage F-statistic

```
library(cragg)
library(AER) # for dataaset
data("WeakInstrument")

cragg_donald(
    # control variables
    X = ~ 1,
    # endogeneous variables
    D = ~ x,
    # instrument variables
    Z = ~ z,
    data = WeakInstrument
)
#> Cragg-Donald test for weak instruments:
#>
#>      Data:                          WeakInstrument
#>      Controls:                      ~1
#>      Treatments:                    ~x
#>      Instruments:                   ~z
#>
#>      Cragg-Donald Statistic:          4.566136
#>      Df:                                   198
```

Large CD statistic implies that the instruments are strong, but not in our case here. But to judge it against some critical value, we have to look at Stock-Yogo

30.4.1.2 Stock-Yogo

Stock and Yogo (2002) set the critical values such that the bias is less then 10% (default)

H_0 : Instruments are weak

H_1 : Instruments are not weak

```
library(cragg)
library(AER) # for dataaset
data("WeakInstrument")
stock_yogo_test(
    # control variables
    X = ~ 1,
    # endogeneous variables
    D = ~ x,
    # instrument variables
    Z = ~ z,
    size_bias = "bias",
    data = WeakInstrument
)
```

The CD statistic should be bigger than the set critical value to be considered strong instruments.

30.4.2 Exogeneity Assumption

The local average treatment effect (LATE) is defined as:

$$\text{LATE} = \frac{\text{reduced form}}{\text{first stage}} = \frac{\rho}{\phi}$$

This implies that the reduced form (ρ) is the product of the first stage (ϕ) and LATE:

$$\rho = \phi \times \text{LATE}$$

Thus, if the first stage (ϕ) is 0, the reduced form (ρ) should also be 0.

```
# Load necessary libraries
library(shiny)
library(AER)  # for ivreg
library(ggplot2)  # for visualization
library(dplyr)  # for data manipulation

# Function to simulate the dataset
simulate_iv_data <- function(n, beta, phi, direct_effect) {
```

```
  Z <- rnorm(n)
  epsilon_x <- rnorm(n)
  epsilon_y <- rnorm(n)
  X <- phi * Z + epsilon_x
  Y <- beta * X + direct_effect * Z + epsilon_y
  data <- data.frame(Y = Y, X = X, Z = Z)
  return(data)
}

# Function to run the simulations and calculate the effects
run_simulation <- function(n, beta, phi, direct_effect) {
  # Simulate the data
  simulated_data <- simulate_iv_data(n, beta, phi, direct_effect)

  # Estimate first-stage effect (phi)
  first_stage <- lm(X ~ Z, data = simulated_data)
  phi <- coef(first_stage)["Z"]
  phi_ci <- confint(first_stage)["Z", ]

  # Estimate reduced-form effect (rho)
  reduced_form <- lm(Y ~ Z, data = simulated_data)
  rho <- coef(reduced_form)["Z"]
  rho_ci <- confint(reduced_form)["Z", ]

  # Estimate LATE using IV regression
  iv_model <- ivreg(Y ~ X | Z, data = simulated_data)
  iv_late <- coef(iv_model)["X"]
  iv_late_ci <- confint(iv_model)["X", ]

  # Calculate LATE as the ratio of reduced-form and first-stage coefficients
  calculated_late <- rho / phi
  calculated_late_se <- sqrt(
    (rho_ci[2] - rho)^2 / phi^2 + (rho * (phi_ci[2] - phi) / phi^2)^2
  )
  calculated_late_ci <- c(calculated_late - 1.96 * calculated_late_se,
                          calculated_late + 1.96 * calculated_late_se)

  # Return a list of results
  list(phi = phi,
       phi_ci = phi_ci,
       rho = rho,
       rho_ci = rho_ci,
       direct_effect = direct_effect,
       direct_effect_ci = c(direct_effect, direct_effect),  # Placeholder for direct e
       iv_late = iv_late,
```

```
       iv_late_ci = iv_late_ci,
       calculated_late = calculated_late,
       calculated_late_ci = calculated_late_ci,
       true_effect = beta,
       true_effect_ci = c(beta, beta))  # Placeholder for true effect CI
}

# Define UI for the sliders
ui <- fluidPage(
  titlePanel("IV Model Simulation"),
  sidebarLayout(
    sidebarPanel(
      sliderInput("beta", "True Effect of X on Y (beta):", min = 0, max = 1.0, value = 0.5, step
      sliderInput("phi", "First Stage Effect (phi):", min = 0, max = 1.0, value = 0.7, step = 0.1
      sliderInput("direct_effect", "Direct Effect of Z on Y:", min = -0.5, max = 0.5, value = 0,
    ),
    mainPanel(
      plotOutput("dotPlot")
    )
  )
)

# Define server logic to run the simulation and generate the plot
server <- function(input, output) {
  output$dotPlot <- renderPlot({
    # Run simulation
    results <- run_simulation(n = 1000, beta = input$beta, phi = input$phi, direct_effect = input

    # Prepare data for plotting
    plot_data <- data.frame(
      Effect = c("First Stage (phi)", "Reduced Form (rho)", "Direct Effect", "LATE (Ratio)", "LAT
      Value = c(results$phi, results$rho, results$direct_effect, results$calculated_late, results
      CI_Lower = c(results$phi_ci[1], results$rho_ci[1], results$direct_effect_ci[1], results$cal
      CI_Upper = c(results$phi_ci[2], results$rho_ci[2], results$direct_effect_ci[2], results$cal
    )

    # Create dot plot with confidence intervals
    ggplot(plot_data, aes(x = Effect, y = Value)) +
      geom_point(size = 3) +
      geom_errorbar(aes(ymin = CI_Lower, ymax = CI_Upper), width = 0.2) +
      labs(title = "IV Model Effects",
           y = "Coefficient Value") +
      coord_cartesian(ylim = c(-1, 1)) +  # Limits the y-axis to -1 to 1 but allows CI beyond
      theme_minimal() +
      theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
  })
}

# Run the application
shinyApp(ui = ui, server = server)
```

A statistically significant reduced form estimate without a corresponding first stage indicates an issue, suggesting an alternative channel linking instruments to outcomes or a direct effect of the IV on the outcome.

- **No Direct Effect**: When the direct effect is 0 and the first stage is 0, the reduced form is 0.
  - Note: Extremely rare cases with multiple additional paths that perfectly cancel each other out can also produce this result, but testing for all possible paths is impractical.
- **With Direct Effect**: When there is a direct effect of the IV on the outcome, the reduced form can be significantly different from 0, even if the first stage is 0.
  - This violates the exogeneity assumption, as the IV should only affect the outcome through the treatment variable.

To test the validity of the exogeneity assumption, we can use a sanity test:

- Identify groups for which the effects of instruments on the treatment variable are small and not significantly different from 0. The reduced form estimate for these groups should also be 0. These "no-first-stage samples" provide evidence of whether the exogeneity assumption is violated.

30.4.2.1 Overid Tests

- Wald test and Hausman test for exogeneity of X assuming Z is exogenous
  - People might prefer Wald test over Hausman test.
- Sargan (for 2SLS) is a simpler version of Hansen's J test (for IV-GMM)
- Modified J test (i.e., Regularized jacknife IV): can handle weak instruments and small sample size (Carrasco and Doukali, 2022) (also proposed a regularized F-test to test relevance assumption that is robust to heteroskedasticity).
- New advances: endogeneity robust inference in finite sample and sensitivity analysis of inference (Kiviet, 2020)

These tests that can provide evidence fo the validity of the over-identifying restrictions is not sufficient or necessary for the validity of the moment conditions (i.e., this assumption cannot be tested). (Deaton, 2010; Parente and Silva, 2012)

- The over-identifying restriction can still be valid even when the instruments are correlated with the error terms, but then in this case, what

you're estimating is no longer your parameters of interest.

- Rejection of the over-identifying restrictions can also be the result of **parameter heterogeneity** (Angrist et al., 2000)

Why overid tests hold no value/info?

- Overidentifying restrictions are valid irrespective of the instruments' validity
  - Whenever instruments have the same motivation and are on the same scale, the estimated parameter of interests will be very close (Parente and Silva, 2012, p. 316)
- Overidentifying restriction are invalid when each instrument is valid
  - When the effect of your parameter of interest is heterogeneous (e.g., you have two groups with two different true effects), your first instrument can be correlated with your variable of interest only for the first group and your second interments can be correlated with your variable of interest only for the second group (i.e., each instrument is valid), and if you use each instrument, you can still identify the parameter of interest. However, if you use both of them, what you estimate is a mixture of the two groups. Hence, the overidentifying restriction will be invalid (because no single parameters can make the errors of the model orthogonal to both instruments). The result may seem confusing at first because if each subset of overidentifying restrictions is valid, the full set should also be valid. However, this interpretation is flawed because the residual's orthogonality to the instruments depends on the chosen set of instruments, and therefore the set of restrictions tested when using two sets of instruments together is not the same as the union of the sets of restrictions tested when using each set of instruments separately (Parente and Silva, 2012, p. 316)

These tests (of overidentifying restrictions) should be used to check whether different instruments identify the same parameters of interest, not to check their validity

(Hausman, 1983; Parente and Silva, 2012)

30.4.2.1.1 Wald Test Assuming that Z is exogenous (a valid instrument), we want to know whether X_2 is exogenous

1st stage:

$$X_2 = \hat{\alpha} Z + \hat{\epsilon}$$

2nd stage:

$$Y = \delta_0 X_1 + \delta_1 X_2 + \delta_2 \hat{\epsilon} + u$$

where

- $\hat{\epsilon}$ is the residuals from the 1st stage

The Wald test of exogeneity assumes

$$H_0 : \delta_2 = 0 H_1 : \delta_2 \neq 0$$

If you have more than one endogenous variable with more than one instrument, δ_2 is a vector of all residuals from all the first-stage equations. And the null hypothesis is that they are jointly equal 0.

If you reject this hypothesis, it means that X_2 is **not endogenous**. Hence, for this test, we do not want to reject the null hypothesis.

If the test is not sacrificially significant, we might just don't have enough information to reject the null.

When you have a valid instrument Z, whether X_2 is endogenous or exogenous, your coefficient estimates of X_2 should still be consistent. But if X_2 is exogenous, then 2SLS will be inefficient (i.e., larger standard errors).

Intuition:

$\hat{\epsilon}$ is the supposed endogenous part of X_2, When we regress Y on $\hat{\epsilon}$ and observe that its coefficient is not different from 0. It means that the exogenous part of X_2 can explain well the impact on Y, and there is no endogenous part.

30.4.2.1.2 Hausman's Test Similar to Wald Test and identical to Wald Test when we have homoskedasticity (i.e., homogeneity of variances). Because of this assumption, it's used less often than Wald Test

30.4.2.1.3 Hansen's J

- (Hansen, 1982)
- J-test (over-identifying restrictions test): test whether **additional** instruments are exogenous
  - Can only be applied in cases where you have more instruments than endogenous variables
    - $dim(Z) > dim(X_2)$
  - Assume at least one instrument within Z is exogenous

Procedure IV-GMM:

1. Obtain the residuals of the 2SLS estimation
2. Regress the residuals on all instruments and exogenous variables.

3. Test the joint hypothesis that all coefficients of the residuals across instruments are 0 (i.e., this is true when instruments are exogenous).
    1. Compute $J = mF$ where m is the number of instruments, and F is your equation F statistic (can you use `linearHypothesis()` again).
    2. If your exogeneity assumption is true, then $J \sim \chi^2_{m-k}$ where k is the number of endogenous variables.
4. If you reject this hypothesis, it can be that
    1. The first sets of instruments are invalid
    2. The second sets of instruments are invalid
    3. Both sets of instruments are invalid

Note: This test is only true when your residuals are homoskedastic.

For a heteroskedasticity-robust J-statistic, see (Carrasco and Doukali, 2022; Li et al., 2022)

30.4.2.1.4 Sargan Test (Sargan, 1958)

Similar to Hansen's J, but it assumes homoskedasticity

- Have to be careful when sample is not collected exogenously. As such, when you have choice-based sampling design, the sampling weights have to be considered to have consistent estimates. However, even if we apply sampling weights, the tests are not suitable because the iid assumption off errors are already violated. Hence, the test is invalid in this case (Pitt, 2011).
- If one has heteroskedasticity in its design, the Sargan test is invalid (Pitt, 2011)

30.5 Negative R^2

It's okay to have negative R^2 in the 2nd stage. We care more about consistent coefficient estimates.

R^2 has no statistical meaning in instrumental variable regression or 2 or 3SLS

$$R^2 = \frac{MSS}{TSS}$$

where

- MSS = model sum of squares (TSS- RSS)
- TSS = total sum of squares ($\sum(y - \bar{y})^2$)
- RSS = residual sum of squares ($\sum(y - Xb)^2$)

If $TSS > RSS$, then we have negative RSS and negative R^2. Since the predicted values of the endogenous variables are different from the endogenous variables themselves, the error that is used to calculate RSS can be different from the

error in the second stage, and RSS in the second stage can be less than TSS. For more information, see here.

30.6 Treatment Intensity

Two-Stage Least Squares (TSLS) can be used to estimate the average causal effect of variable treatment intensity, and it "identifies a weighted average of per-unit treatment effects along the length of a causal response function" (Angrist and Imbens, 1995, p. 431). For example

- Drug dosage
- Hours of exam prep on score (Powers and Swinton, 1984)
- Cigarette smoking on birth weights (Permutt and Hebel, 1989)
- Years of education
- Class size on test score (Angrist and Lavy, 1999)
- Sibship size on earning (Lavy et al., 2006)
- Social Media Adoption

The **average causal effect** here refers to the conditional expectation of the difference in outcomes between the treated and what would have happened in the counterfactual world.

Notes:

- We do not need a linearity assumption of the relationships between the dependent variable, treatment intensities, and instruments.

Example

In their original paper, Angrist and Imbens (1995) take the example of schooling effect on earnings where they have quarters of birth as the instrumental variable.

For each additional year of schooling, there can be an increase in earnings, and each additional year can be heterogeneous (both in the sense that grade 9th to grade 10th is qualitatively different and one can change to a different school).

$$Y = \gamma_0 + \gamma_1 X_1 + \rho S + \epsilon$$

where

- S is years of schooling (i.e., endogenous regressor)
- ρ is the return to a year of schooling
- X_1 is a matrix of exogenous covariates

Schooling can also be related to the exogenous variable X_1

$$S = \delta_0 + X_1\delta_1 + X_2\delta_2 + \eta$$

where

- X_2 is an exogenous instrument
- δ_2 is the coefficient of the instrument

by using only the fitted value in the second, the TSLS can give a consistent estimate of the effect of schooling on earning

$$Y = \gamma_0 + X_1\gamma - 1 + \rho\hat{S} + \nu$$

To give ρ a causal interpretation,

1. We first have to have the SUTVA (stable unit treatment value assumption), where the potential outcomes of the same person with different years of schooling are independent.
2. When ρ has a probability limit equal to a weighted average of $E[Y_j - Y_{j-1}]\forall j$

Even though the first bullet point is not trivial, most of the time we don't have to defend much about it in a research article, the second bullet point is the harder one to argue and only apply to certain cases.

30.7 Control Function

Also known as **two-stage residual inclusion**

Resources:

- Binary outcome and binary endogenous variable application (Tchetgen Tchetgen, 2014)
  - In rare events: we use a logistic model in the 2nd stage
  - In non-rare events: use risk ratio regression in the 2nd stage
- Application in marketing for consumer choice model (Petrin and Train, 2010)

Notes

- This approach is better suited for models with nonadditive errors (e.g., discrete choice models), or binary endogenous model, binary response variable, etc.

$$Y = g(X) + UX = \pi(Z) + VE(U|Z, V) = E(U|V)E(V|Z) = 0$$

Under control function approach,

$$E(Y|Z, V) = g(X) + E(U|Z, V) = g(X) + E(U|V) = g(X) + h(V)$$

where $h(V)$ is the control function that models the endogeneity

1. Linear in parameters

a. Linear Endogenous Variables:
   - The control function function approach is identical to the usual 2SLS estimator

b. Nonlinear Endogenous Variables:
   - The control function is different from the 2SLS estimator

2. Nonlinear in parameters:
   - The CF function is superior than the 2SLS estimator

30.7.1 Simulation

```
library(fixest)
library(tidyverse)
library(modelsummary)

# Set the seed for reproducibility
set.seed(123)
n = 10000
# Generate the exogenous variable from a normal distribution
exogenous <- rnorm(n, mean = 5, sd = 1)

# Generate the omitted variable as a function of the exogenous variable
omitted <- rnorm(n, mean = 2, sd = 1)

# Generate the endogenous variable as a function of the omitted variable and the exoge
endogenous <- 5 * omitted + 2 * exogenous + rnorm(n, mean = 0, sd = 1)

# nonlinear endogenous variable
endogenous_nonlinear <- 5 * omitted^2 + 2 * exogenous + rnorm(100, mean = 0, sd = 1)

unrelated <- rexp(n, rate = 1)

# Generate the response variable as a function of the endogenous variable and the omit
response <- 4 +  3 * endogenous + 6 * omitted + rnorm(n, mean = 0, sd = 1)
```

```r
response_nonlinear <- 4 +  3 * endogenous_nonlinear + 6 * omitted + rnorm(n, mean = 0, sd = 1)

response_nonlinear_para <- 4 +  3 * endogenous ^ 2 + 6 * omitted + rnorm(n, mean = 0, sd = 1)


# Combine the variables into a data frame
my_data <-
    data.frame(
        exogenous,
        omitted,
        endogenous,
        response,
        unrelated,
        response,
        response_nonlinear,
        response_nonlinear_para
    )

# View the first few rows of the data frame
# head(my_data)

wo_omitted <- feols(response ~ endogenous + sw0(unrelated), data = my_data)
w_omitted  <- feols(response ~ endogenous + omitted + unrelated, data = my_data)


# ivreg::ivreg(response ~ endogenous + unrelated | exogenous, data = my_data)
iv <- feols(response ~ 1 + sw0(unrelated) | endogenous ~ exogenous, data = my_data)

etable(
    wo_omitted,
    w_omitted,
    iv,
    digits = 2
    # vcov = list("each", "iid", "hetero")
)
#>                   wo_omitted.1   wo_omitted.2      w_omitted          iv.1
#> Dependent Var.:       response       response       response      response
#>
#> Constant        -3.9*** (0.10) -4.0*** (0.10)  4.0*** (0.05) 15.7*** (0.59)
#> endogenous      4.0*** (0.005) 4.0*** (0.005) 3.0*** (0.004)  3.0*** (0.03)
#> unrelated                          0.03 (0.03)  0.002 (0.010)
#> omitted                                         6.0*** (0.02)
#> _______________ ______________ ______________ ______________ ______________
#> S.E. type                  IID            IID            IID           IID
#> Observations            10,000         10,000         10,000        10,000
```

```
#> R2                      0.98566        0.98567        0.99803        0.92608
#> Adj. R2                 0.98566        0.98566        0.99803        0.92607
#>
#>                            iv.2
#> Dependent Var.:        response
#>
#> Constant         15.6*** (0.59)
#> endogenous        3.0*** (0.03)
#> unrelated          0.10. (0.06)
#> omitted
#> _______________ ______________
#> S.E. type                    IID
#> Observations             10,000
#> R2                      0.92610
#> Adj. R2                 0.92608
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Linear in parameter and linear in endogenous variable

```
# manual
# 2SLS
first_stage = lm(endogenous ~ exogenous, data = my_data)
new_data = cbind(my_data, new_endogenous = predict(first_stage, my_data))
second_stage = lm(response ~ new_endogenous, data = new_data)
summary(second_stage)
#>
#> Call:
#> lm(formula = response ~ new_endogenous, data = new_data)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -77.683 -14.374  -0.107  14.289  78.274
#>
#> Coefficients:
#>                Estimate Std. Error t value Pr(>|t|)
#> (Intercept)     15.6743     2.0819   7.529 5.57e-14 ***
#> new_endogenous   3.0142     0.1039  29.025  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 21.26 on 9998 degrees of freedom
#> Multiple R-squared:  0.07771,    Adjusted R-squared:  0.07762
#> F-statistic: 842.4 on 1 and 9998 DF,  p-value: < 2.2e-16

new_data_cf = cbind(my_data, residual = resid(first_stage))
```

	(1)	(2)
(Intercept)	15.674	15.674
	(2.082)	(0.149)
new_endogenous	3.014	
	(0.104)	
endogenous		3.014
		(0.007)
residual		1.141
		(0.008)
Num.Obs.	10 000	10 000
R2	0.078	0.995
R2 Adj.	0.078	0.995
AIC	89 520.9	36 826.8
BIC	89 542.5	36 855.6
Log.Lik.	−44 757.438	−18 409.377
F	842.424	1 048 263.304
RMSE	21.26	1.53

```r
second_stage_cf = lm(response ~ endogenous + residual, data = new_data_cf)
summary(second_stage_cf)
#>
#> Call:
#> lm(formula = response ~ endogenous + residual, data = new_data_cf)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -5.360 -1.016  0.003  1.023  5.201
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 15.674265   0.149350   105.0   <2e-16 ***
#> endogenous   3.014202   0.007450   404.6   <2e-16 ***
#> residual     1.140920   0.008027   142.1   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.525 on 9997 degrees of freedom
#> Multiple R-squared:  0.9953, Adjusted R-squared:  0.9953
#> F-statistic: 1.048e+06 on 2 and 9997 DF,  p-value: < 2.2e-16

modelsummary(list(second_stage, second_stage_cf))
```

Nonlinear in endogenous variable

```r
# 2SLS
first_stage = lm(endogenous_nonlinear ~ exogenous, data = my_data)

new_data = cbind(my_data, new_endogenous_nonlinear = predict(first_stage, my_data))
second_stage = lm(response_nonlinear ~ new_endogenous_nonlinear, data = new_data)
summary(second_stage)
#>
#> Call:
#> lm(formula = response_nonlinear ~ new_endogenous_nonlinear, data = new_data)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -94.43 -52.10 -15.29  36.50 446.08
#>
#> Coefficients:
#>                          Estimate Std. Error t value Pr(>|t|)
#> (Intercept)               15.3390    11.8175   1.298    0.194
#> new_endogenous_nonlinear   3.0174     0.3376   8.938   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 69.51 on 9998 degrees of freedom
#> Multiple R-squared:  0.007927,   Adjusted R-squared:  0.007828
#> F-statistic: 79.89 on 1 and 9998 DF,  p-value: < 2.2e-16

new_data_cf = cbind(my_data, residual = resid(first_stage))
second_stage_cf = lm(response_nonlinear ~ endogenous_nonlinear + residual, data = new_d
summary(second_stage_cf)
#>
#> Call:
#> lm(formula = response_nonlinear ~ endogenous_nonlinear + residual,
#>     data = new_data_cf)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -17.5437  -0.8348   0.4614   1.4424   4.8154
#>
#> Coefficients:
#>                      Estimate Std. Error t value Pr(>|t|)
#> (Intercept)          15.33904    0.38459   39.88   <2e-16 ***
#> endogenous_nonlinear  3.01737    0.01099  274.64   <2e-16 ***
#> residual              0.24919    0.01104   22.58   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
```

	(1)	(2)
(Intercept)	15.339	15.339
	(11.817)	(0.385)
new_endogenous_nonlinear	3.017	
	(0.338)	
endogenous_nonlinear		3.017
		(0.011)
residual		0.249
		(0.011)
Num.Obs.	10 000	10 000
R2	0.008	0.999
R2 Adj.	0.008	0.999
AIC	113 211.6	44 709.6
BIC	113 233.2	44 738.4
Log.Lik.	−56 602.782	−22 350.801
F	79.887	4 752 573.052
RMSE	69.50	2.26

```
#> Residual standard error: 2.262 on 9997 degrees of freedom
#> Multiple R-squared:  0.9989, Adjusted R-squared:  0.9989
#> F-statistic: 4.753e+06 on 2 and 9997 DF,  p-value: < 2.2e-16

modelsummary(list(second_stage, second_stage_cf))
```

Nonlinear in parameters

```
# 2SLS
first_stage = lm(endogenous ~ exogenous, data = my_data)

new_data = cbind(my_data, new_endogenous = predict(first_stage, my_data))
second_stage = lm(response_nonlinear_para ~ new_endogenous, data = new_data)
summary(second_stage)
#>
#> Call:
#> lm(formula = response_nonlinear_para ~ new_endogenous, data = new_data)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -1536.5  -452.4   -80.7   368.4  3780.9
#>
#> Coefficients:
#>                 Estimate Std. Error t value Pr(>|t|)
#> (Intercept)    -1089.943     61.706  -17.66   <2e-16 ***
#> new_endogenous   119.829      3.078   38.93   <2e-16 ***
```

```
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 630.2 on 9998 degrees of freedom
#> Multiple R-squared:  0.1316, Adjusted R-squared:  0.1316
#> F-statistic:  1516 on 1 and 9998 DF,  p-value: < 2.2e-16

new_data_cf = cbind(my_data, residual = resid(first_stage))
second_stage_cf = lm(response_nonlinear_para ~ endogenous_nonlinear + residual, data =
summary(second_stage_cf)
#>
#> Call:
#> lm(formula = response_nonlinear_para ~ endogenous_nonlinear +
#>     residual, data = new_data_cf)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -961.00 -139.32  -16.02  135.57 1403.62
#>
#> Coefficients:
#>                      Estimate Std. Error t value Pr(>|t|)
#> (Intercept)          678.1593     9.9177   68.38   <2e-16 ***
#> endogenous_nonlinear  17.7884     0.2759   64.46   <2e-16 ***
#> residual              52.5016     1.1552   45.45   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 231.9 on 9997 degrees of freedom
#> Multiple R-squared:  0.8824, Adjusted R-squared:  0.8824
#> F-statistic: 3.751e+04 on 2 and 9997 DF,  p-value: < 2.2e-16

modelsummary(list(second_stage, second_stage_cf))
```

30.8 New Advances

- Combine ML and IV (Singh et al., 2020)

	(1)	(2)
(Intercept)	−1089.943	678.159
	(61.706)	(9.918)
new_endogenous	119.829	
	(3.078)	
endogenous_nonlinear		17.788
		(0.276)
residual		52.502
		(1.155)
Num.Obs.	10 000	10 000
R2	0.132	0.882
R2 Adj.	0.132	0.882
AIC	157 302.4	137 311.3
BIC	157 324.1	137 340.1
Log.Lik.	−78 648.225	−68 651.628
F	1515.642	37 505.777
RMSE	630.10	231.88

Chapter 31

Matching Methods

Matching is a process that aims to close back doors - potential sources of bias - by constructing comparison groups that are similar according to a set of matching variables. This helps to ensure that any observed differences in outcomes between the treatment and comparison groups can be more confidently attributed to the treatment itself, rather than other factors that may differ between the groups.

Matching and DiD can use pre-treatment outcomes to correct for selection bias. From real world data and simulation, (Chabé-Ferret, 2015) found that matching generally underestimates the average causal effect and gets closer to the true effect with more number of pre-treatment outcomes. When selection bias is symmetric around the treatment date, DID is still consistent when implemented symmetrically (i.e., the same number of period before and after treatment). In cases where selection bias is asymmetric, the MC simulations show that Symmetric DID still performs better than Matching.

Matching is useful, but not a general solution to causal problems (Smith and Todd, 2005)

Assumption: Observables can identify the selection into the treatment and control groups

Identification: The exclusion restriction can be met conditional on the observables

Motivation

Effect of college quality on earnings

- They ultimately estimate the treatment effect on the treated of attending a top (high ACT) versus bottom (low ACT) quartile college

Example

Aaronson et al. (2007)

Do teachers qualifications (causally) affect student test scores?

Step 1:

$$Y_{ijt} = \delta_0 + Y_{ij(t-1)}\delta_1 + X_{it}\delta_2 + Z_{jt}\delta_3 + \epsilon_{ijt}$$

There can always be another variable

Any observable sorting is imperfect

Step 2:

$$Y_{ijst} = \alpha_0 + Y_{ij(t-1)}\alpha_1 + X_{it}\alpha_2 + Z_{jt}\alpha_3 + \gamma_s + u_{isjt}$$

- $\delta_3 > 0$
- $\delta_3 > \alpha_3$
- γ_s = school fixed effect

Sorting is less within school. Hence, we can introduce the school fixed effect

Step 3:

Find schools that look like they are putting students in class randomly (or as good as random) + we run step 2

$$\begin{aligned} Y_{isjt} = Y_{isj(t-1)}\lambda + X_{it}\alpha_1 + Z_{jt}\alpha_{21} \\ + (Z_{jt} \times D_i)\alpha_{22} + \gamma_5 + u_{isjt} \end{aligned}$$

- D_{it} is an element of X_{it}
- Z_{it} = teacher experience

$$D_{it} = \begin{cases} 1 & \text{if high poverty} \\ 0 & \text{otherwise} \end{cases}$$

$H_0 : \alpha_{22} = 0$ test for effect heterogeneity whether the effect of teacher experience (Z_{jt}) is different

- For low poverty is α_{21}
- For high poverty effect is $\alpha_{21} + \alpha_{22}$

Matching is **selection on observables** and only works if you have good observables.

Sufficient identification assumption under Selection on observable/ back-door criterion (based on Bernard Koch's presentation)

- Strong conditional ignorability
  - $Y(0), Y(1) \perp T|X$
  - No hidden confounders
- Overlap
  - $\forall x \in X, t \in \{0,1\} : p(T = t|X = x > 0$
  - All treatments have non-zero probability of being observed
- SUTVA/ Consistency
  - Treatment and outcomes of different subjects are independent

Relative to OLS

1. Matching makes the **common support** explicit (and changes default from "ignore" to "enforce")
2. Relaxes linear function form. Thus, less parametric.

It also helps if you have high ratio of controls to treatments.

For detail summary (Stuart, 2010)

Matching is defined as "any method that aims to equate (or"balance") the distribution of covariates in the treated and control groups." (Stuart, 2010, pp. 1)

Equivalently, matching is a selection on observables identifications strategy.

If you think your OLS estimate is biased, a matching estimate (almost surely) is too.

Unconditionally, consider

$$\begin{aligned}
&E(Y_i^T|T) - E(Y_i^C|C) + E(Y_i^C|T) - E(Y_i^C|T) \\
&\quad = E(Y_i^T - Y_i^C|T) + [E(Y_i^C|T) - E(Y_i^C|C)] \\
&\quad = E(Y_i^T - Y_i^C|T) + \text{selection bias}
\end{aligned}$$

where $E(Y_i^T - Y_i^C|T)$ is the causal inference that we want to know.

Randomization eliminates the selection bias.

If we don't have randomization, then $E(Y_i^C|T) \neq E(Y_i^C|C)$

Matching tries to do selection on observables $E(Y_i^C|X,T) = E(Y_i^C|X,C)$

Propensity Scores basically do $E(Y_i^C|P(X),T) = E(Y_i^C|P(X),C)$

Matching standard errors will exceed OLS standard errors

The treatment should have larger predictive power than the control because you use treatment to pick control (not control to pick treatment).

The average treatment effect (ATE) is

$$\frac{1}{N_T}\sum_{i=1}^{N_T}(Y_i^T - \frac{1}{N_{C_T}}\sum_{i=1}^{N_{C_T}} Y_i^C)$$

Since there is no closed-form solution for the standard error of the average treatment effect, we have to use bootstrapping to get standard error.

Professor Gary King advocates instead of using the word "matching", we should use "**pruning**" (i.e., deleting observations). It is a preprocessing step where it prunes nonmatches to make control variables less important in your analysis.

Without Matching

- **Imbalance data** leads to **model dependence** lead to a lot of **researcher discretion** leads to **bias**

With Matching

- We have balance data which essentially erase human discretion

Table 31.1: Table @ref(tab:Gary King - International Methods Colloquium talk 2015)

Balance Covariates	Complete Randomization	Fully Exact
Observed	On average	Exact
Unobserved	On average	On average

Fully blocked is superior on

- imbalance
- model dependence
- power
- efficiency
- bias
- research costs
- robustness

Matching is used when

- Outcomes are not available to select subjects for follow-up
- Outcomes are available to improve precision of the estimate (i.e., reduce bias)

Hence, we can only observe one outcome of a unit (either treated or control), we can think of this problem as missing data as well. Thus, this section is closely related to Imputation (Missing Data)

In observational studies, we cannot randomize the treatment effect. Subjects select their own treatments, which could introduce selection bias (i.e., systematic differences between group differences that confound the effects of response variable differences).

Matching is used to

- reduce model dependence
- diagnose balance in the dataset

Assumptions of matching:

1. treatment assignment is independent of potential outcomes given the covariates
   - $T \perp (Y(0), Y(1))|X$
   - known as ignorability, or ignorable, no hidden bias, or unconfounded.
   - You typically satisfy this assumption when unobserved covariates correlated with observed covariates.
     - But when unobserved covariates are unrelated to the observed covariates, you can use sensitivity analysis to check your result, or use "design sensitivity" (Heller et al., 2009)
2. positive probability of receiving treatment for all X
   - $0 < P(T = 1|X) < 1 \forall X$
3. Stable Unit Treatment value Assumption (SUTVA)
   - Outcomes of A are not affected by treatment of B.
     - Very hard in cases where there is "spillover" effects (interactions between control and treatment). To combat, we need to reduce interactions.

Generalization

- P_t: treated population -> N_t: random sample from treated
- P_c: control population -> N_c: random sample from control
- μ_i = means ; Σ_i = variance covariance matrix of the p covariates in group i ($i = t, c$)
- $X_j = p$ covariates of individual j
- T_j = treatment assignment
- Y_j = observed outcome

- Assume: $N_t < N_c$
- Treatment effect is $\tau(x) = R_1(x) - R_0(x)$ where
  - $R_1(x) = E(Y(1)|X)$
  - $R_0(x) = E(Y(0)|X)$
- Assume: parallel trends hence $\tau(x) = \tau \forall x$
  - If the parallel trends are not assumed, an average effect can be estimated.
- Common estimands:
  - Average effect of the treatment on the treated (**ATT**): effects on treatment group
  - Average treatment effect (**ATE**): effect on both treatment and control

Steps:

1. Define "closeness": decide distance measure to be used
   1. Which variables to include:
      1. Ignorability (no unobserved differences between treatment and control)
         1. Since cost of including unrelated variables is small, you should include as many as possible (unless sample size/power doesn't allow you to because of increased variance)
         2. Do not include variables that were affected by the treatment.
         3. Note: if a matching variable (i.e., heavy drug users) is highly correlated to the outcome variable (i.e., heavy drinkers) , you will be better to exclude it in the matching set.
   2. Which distance measures: more below
2. Matching methods
   1. Nearest neighbor matching
      1. Simple (greedy) matching: performs poorly when there is competition for controls.
      2. Optimal matching: considers global distance measure
      3. Ratio matching: to combat increase bias and reduced variation when you have k:1 matching, one can use approximations by Rubin and Thomas (1996).

4. With or without replacement: with replacement is typically better, but one needs to account for dependent in the matched sample when doing later analysis (can use frequency weights to combat).

2. Subclassification, Full Matching and Weighting

   Nearest neighbor matching assign is 0 (control) or 1 (treated), while these methods use weights between 0 and 1.

   1. Subclassification: distribution into multiple subclass (e.g., 5-10)
   2. Full matching: optimal ly minimize the average of the distances between each treated unit and each control unit within each matched set.
   3. Weighting adjustments: weighting technique uses propensity scores to estimate ATE. If the weights are extreme, the variance can be large not due to the underlying probabilities, but due to the estimation procure. To combat this, use (1) weight trimming, or (2) doubly -robust methods when propensity scores are used for weighing or matching.
      1. Inverse probability of treatment weighting (IPTW) $w_i = \frac{T_i}{\hat{e}_i} + \frac{1-T_i}{1-\hat{e}_i}$
      2. Odds $w_i = T_i + (1 - T_i)\frac{\hat{e}_i}{1-\hat{e}_i}$
      3. Kernel weighting (e.g., in economics) averages over multiple units in the control group.

3. Assessing Common Support

   - common support means overlapping of the propensity score distributions in the treatment and control groups. Propensity score is used to discard control units from the common support. Alternatively, convex hull of the covariates in the multi-dimensional space.

3. Assessing the quality of matched samples (Diagnose)

   - Balance = similarity of the empirical distribution of the full set of covariates in the matched treated and control groups. Equivalently, treatment is unrelated to the covariates
     - $\tilde{p}(X|T = 1) = \tilde{p}(X|T = 0)$ where $\tilde{p}$ is the empirical distribution.
   - Numerical Diagnostics
     1. standardized difference in means of each covariate (most common), also known as"standardized bias", "standardized difference in means".

2. standardized difference of means of the propensity score (should be < 0.25) (Rubin, 2001)
3. ratio of the variances of the propensity score in the treated and control groups (should be between 0.5 and 2). (Rubin, 2001)
4. For each covariate, the ratio fo the variance of the residuals orthogonal to the propensity score in the treated and control groups.

   Note: can't use hypothesis tests or p-values because of (1) in-sample property (not population), (2) conflation of changes in balance with changes in statistical power.

- Graphical Diagnostics
  - QQ plots
  - Empirical Distribution Plot

4. Estimate the treatment effect
   1. After k:1
      1. Need to account for weights when use matching with replacement.
   2. After Subclassification and Full Matching
      1. Weighting the subclass estimates by the number of treated units in each subclass for ATT
      2. Weighting by the overall number of individual in each subclass for ATE.
   3. Variance estimation: should incorporate uncertainties in both the matching procedure (step 3) and the estimation procedure (step 4)

Notes:

- With missing data, use generalized boosted models, or multiple imputation (Qu and Lipkovich, 2009)
- Violation of ignorable treatment assignment (i.e., unobservables affect treatment and outcome). control by
  - measure pre-treatment measure of the outcome variable
  - find the difference in outcomes between multiple control groups. If there is a significant difference, there is evidence for violation.
  - find the range of correlations between unobservables and both treatment assignment and outcome to nullify the significant effect.
- Choosing between methods

  - smallest standardized difference of mean across the largest number of covariates
  - minimize the standardized difference of means of a few particularly prognostic covariates
  - fest number of large standardized difference of means (> 0.25)
  - (Diamond and Sekhon, 2013) automates the process
- In practice
  - If ATE, ask if there is enough overlap of the treated and control groups' propensity score to estimate ATE, if not use ATT instead
  - If ATT, ask if there are controls across the full range of the treated group
- Choose matching method
  - If ATE, use IPTW or full matching
  - If ATT, and more controls than treated (at least 3 times), k:1 nearest neighbor without replacement
  - If ATT, and few controls , use subclassification, full matching, and weighting by the odds
- Diagnostic
  - If balance, use regression on matched samples
  - If imbalance on few covariates, treat them with Mahalanobis
  - If imbalance on many covariates, try k:1 matching with replacement

Ways to define the distance D_{ij}

1. Exact

$$D_{ij} = \begin{cases} 0, \text{ if } X_i = X_j, \\ \infty, \text{ if } X_i \neq X_j \end{cases}$$

An advanced is Coarsened Exact Matching

2. Mahalanobis

$$D_{ij} = (X_i - X_j)' \Sigma^{-1} (X_i - X_j)$$

where

Σ = variance covariance matrix of X in the

- control group if ATT is interested

- polled treatment and control groups if ATE is interested

3. Propensity score:

$$D_{ij} = |e_i - e_j|$$

where e_k = the propensity score for individual k

An advanced is Prognosis score (Hansen, 2008), but you have to know (i.e., specify) the relationship between the covariates and outcome.

4. Linear propensity score

$$D_{ij} = |logit(e_i) - logit(e_j)|$$

The exact and Mahalanobis are not good in high dimensional or non normally distributed X's cases.

We can combine Mahalanobis matching with propensity score calipers (Rubin and Thomas, 2000)

Other advanced methods for longitudinal settings

- marginal structural models (Robins et al., 2000)
- balanced risk set matching (Li et al., 2001)

Most matching methods are based on (ex-post)

- propensity score
- distance metric
- covariates

Packages

- `cem` Coarsened exact matching
- `Matching` Multivariate and propensity score matching with balance optimization
- `MatchIt` Nonparametric preprocessing for parametric causal inference. Have nearest neighbor, Mahalanobis, caliper, exact, full, optimal, subclassification
- `MatchingFrontier` optimize balance and sample size (King et al., 2017)
- `optmatch`optimal matching with variable ratio, optimal and full matching
- `PSAgraphics` Propensity score graphics
- `rbounds` sensitivity analysis with matched data, examine ignorable treatment assignment assumption

- `twang` weighting and analysis of non-equivalent groups
- `CBPS` covariate balancing propensity score. Can also be used in the longitudinal setting with marginal structural models.
- `PanelMatch` based on Imai, Kim, and Wang (2018)

Matching	Regression
Not as sensitive to the functional form of the covariates	can estimate the effect of a continuous treatment
Easier to asses whether it's working	estimate the effect of all the variables (not just the treatment)
Easier to explain	
allows a nice visualization of an evaluation	
If you treatment is fairly rare, you may have a lot of control observations that are obviously no comparable	can estimate interactions of treatment with covariates
Less parametric	More parametric
Enforces common support (i.e., space where treatment and control have the same characteristics)	

However, the problem of **omitted variables** (i.e., those that affect both the outcome and whether observation was treated) - unobserved confounders is still present in matching methods.

Difference between matching and regression following Pischke's lecture

Suppose we want to estimate the effect of treatment on the treated

$$\begin{aligned}\delta_{TOT} &= E[Y_{1i} - Y_{0i}|D_i = 1] \\ &= E\{E[Y_{1i}|X_i, D_i = 1] \\ &- E[Y_{0i}|X_i, D_i = 1]|D_i = 1\} \quad \text{law of itereated expectations}\end{aligned}$$

Under conditional independence

$$E[Y_{0i}|X_i, D_i = 0] = E[Y_{0i}|X_i, D_i = 1]$$

then

$$\begin{aligned}\delta_{TOT} &= E\{E[Y_{1i}|X_i, D_i = 1] - E[Y_{0i}|X_i, D_i = 0]|D_i = 1\} \\ &= E\{E[y_i|X_i, D_i = 1] - E[y_i|X_i, D_i = 0]|D_i = 1\} \\ &= E[\delta_X|D_i = 1]\end{aligned}$$

where δ_X is an X-specific difference in means at covariate value X_i

When X_i is discrete, the matching estimand is

$$\delta_M = \sum_x \delta_x P(X_i = x | D_i = 1)$$

where $P(X_i = x|D_i = 1)$ is the probability mass function for X_i given $D_i = 1$ According to Bayes rule,

$$P(X_i = x|D_i = 1) = \frac{P(D_i = 1|X_i = x) \times P(X_i = x)}{P(D_i = 1)}$$

hence,

$$\begin{aligned}\delta_M &= \frac{\sum_x \delta_x P(D_i = 1|X_i = x)P(X_i = x)}{\sum_x P(D_i = 1|X_i = x)P(X_i = x)} \\ &= \sum_x \delta_x \frac{P(D_i = 1|X_i = x)P(X_i = x)}{\sum_x P(D_i = 1|X_i = x)P(X_i = x)}\end{aligned}$$

On the other hand, suppose we have regression

$$y_i = \sum_x d_{ix}\beta_x + \delta_R D_i + \epsilon_i$$

where

- d_{ix} = dummy that indicates $X_i = x$
- β_x = regression-effect for $X_i = x$
- δ_R = regression estimand where

$$\begin{aligned}\delta_R &= \frac{\sum_x \delta_x [P(D_i = 1|X_i = x)(1 - P(D_i = 1|X_i = x))]P(X_i = x)}{\sum_x [P(D_i = 1|X_i = x)(1 - P(D_i = 1|X_i = x))]P(X_i = x)} \\ &= \sum_x \delta_x \frac{[P(D_i = 1|X_i = x)(1 - P(D_i = 1|X_i = x))]P(X_i = x)}{\sum_x [P(D_i = 1|X_i = x)(1 - P(D_i = 1|X_i = x))]P(X_i = x)}\end{aligned}$$

the difference between the regression and matching estimand is the weights they use to combine the covariate specific treatment effect δ_x

Type	uses weights which depend on	interpretation	makes sense because
Matching	$P(D_i = 1\|X_i = x)$ the fraction of treated observations in a covariate cell (i.e., or the mean of D_i)	This is larger in cells with many treated observations.	we want the effect of treatment on the treated
Regression	$P(D_i = 1\|X_i = x)(1 - P(D_i = 1\|X_i))$ the variance of D_i in the covariate cell	This weight is largest in cells where there are half treated and half untreated observations. (this is the reason why we want to treat our sample so it is balanced, before running regular regression model, as mentioned above).	these cells will produce the lowest variance estimates of δ_x. If all the δ_x are the same, the most efficient estimand uses the lowest variance cells most heavily.

The goal of matching is to produce covariate balance (i.e., distributions of covariates in treatment and control groups are approximately similar as they would be in a successful randomized experiment).

31.1 Selection on Observables

31.1.1 MatchIt

Procedure typically involves (proposed by Noah Freifer using `MatchIt`)

1. planning
2. matching
3. checking (balance)
4. estimating the treatment effect

```
library(MatchIt)
data("lalonde")
```

examine `treat` on `re78`

1. Planning

- select type of effect to be estimated (e.g., mediation effect, conditional effect, marginal effect)
- select the target population
- select variables to match/balance (Austin, 2011) (VanderWeele, 2019)

2. Check Initial Imbalance

```
# No matching; constructing a pre-match matchit object
m.out0 <- matchit(
    formula(treat ~ age + educ + race
            + married + nodegree + re74 + re75, env = lalonde),
    data = data.frame(lalonde),
    method = NULL,
    # assess balance before matching
    distance = "glm" # logistic regression
)

# Checking balance prior to matching
summary(m.out0)
```

3. Matching

```
# 1:1 NN PS matching w/o replacement
m.out1 <- matchit(treat ~ age + educ,
                  data = lalonde,
                  method = "nearest",
                  distance = "glm")
m.out1
#> A matchit object
#>  - method: 1:1 nearest neighbor matching without replacement
#>  - distance: Propensity score
#>              - estimated with logistic regression
#>  - number of obs.: 614 (original), 370 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

4. Check balance

Sometimes you have to make trade-off between balance and sample size.

```
# Checking balance after NN matching
summary(m.out1, un = FALSE)
#>
#> Call:
#> matchit(formula = treat ~ age + educ, data = lalonde, method = "nearest",
#>     distance = "glm")
#>
#> Summary of Balance for Matched Data:
```

```
#>          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
#> distance        0.3080        0.3077          0.0094     0.9963    0.0033
#> age            25.8162       25.8649         -0.0068     1.0300    0.0050
#> educ           10.3459       10.2865          0.0296     0.5886    0.0253
#>          eCDF Max Std. Pair Dist.
#> distance   0.0432          0.0146
#> age        0.0162          0.0597
#> educ       0.1189          0.8146
#>
#> Sample Sizes:
#>           Control Treated
#> All           429     185
#> Matched       185     185
#> Unmatched     244       0
#> Discarded       0       0

# examine visually
plot(m.out1, type = "jitter", interactive = FALSE)
```

```
plot(
    m.out1,
    type = "qq",
    interactive = FALSE,
    which.xs = c("age")
)
```

Try Full Match (i.e., every treated matches with one control, and every control with one treated).

```
# Full matching on a probit PS
m.out2 <- matchit(treat ~ age + educ,
                  data = lalonde,
                  method = "full",
                  distance = "glm",
                  link = "probit")
m.out2
#> A matchit object
#>  - method: Optimal full matching
#>  - distance: Propensity score
#>              - estimated with probit regression
#>  - number of obs.: 614 (original), 614 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

Checking balance again

```
# Checking balance after full matching
summary(m.out2, un = FALSE)
#>
#> Call:
#> matchit(formula = treat ~ age + educ, data = lalonde, method = "full",
#>     distance = "glm", link = "probit")
#>
#> Summary of Balance for Matched Data:
```

```
#>          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
#> distance        0.3082        0.3081          0.0023     0.9815    0.0028
#> age            25.8162       25.8035          0.0018     0.9825    0.0062
#> educ           10.3459       10.2315          0.0569     0.4390    0.0481
#>          eCDF Max Std. Pair Dist.
#> distance   0.0270          0.0382
#> age        0.0249          0.1110
#> educ       0.1300          0.9805
#>
#> Sample Sizes:
#>               Control Treated
#> All            429.       185
#> Matched (ESS)  145.23     185
#> Matched        429.       185
#> Unmatched        0.         0
#> Discarded        0.         0

plot(summary(m.out2))
```

Exact Matching

```
# Full matching on a probit PS
m.out3 <-
    matchit(
        treat ~ age + educ,
        data = lalonde,
        method = "exact"
```

```
    )
m.out3
#> A matchit object
#>  - method: Exact matching
#>  - number of obs.: 614 (original), 332 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

Subclassfication

```
m.out4 <- matchit(
    treat ~ age + educ,
    data = lalonde,
    method = "subclass"
)
m.out4
#> A matchit object
#>  - method: Subclassification (6 subclasses)
#>  - distance: Propensity score
#>              - estimated with logistic regression
#>  - number of obs.: 614 (original), 614 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ

# Or you can use in conjunction with "nearest"
m.out4 <- matchit(
    treat ~ age + educ,
    data = lalonde,
    method = "nearest",
    option = "subclass"
)
m.out4
#> A matchit object
#>  - method: 1:1 nearest neighbor matching without replacement
#>  - distance: Propensity score
#>              - estimated with logistic regression
#>  - number of obs.: 614 (original), 370 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

Optimal Matching

```
m.out5 <- matchit(
    treat ~ age + educ,
    data = lalonde,
    method = "optimal",
```

```
    ratio = 2
)
m.out5
#> A matchit object
#>  - method: 2:1 optimal pair matching
#>  - distance: Propensity score
#>              - estimated with logistic regression
#>  - number of obs.: 614 (original), 555 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

Genetic Matching

```
m.out6 <- matchit(
    treat ~ age + educ,
    data = lalonde,
    method = "genetic"
)
m.out6
#> A matchit object
#>  - method: 1:1 genetic matching without replacement
#>  - distance: Propensity score
#>              - estimated with logistic regression
#>  - number of obs.: 614 (original), 370 (matched)
#>  - target estimand: ATT
#>  - covariates: age, educ
```

4. Estimating the Treatment Effect

```
# get matched data
m.data1 <- match.data(m.out1)

head(m.data1)
#>      treat age educ   race married nodegree re74 re75       re78  distance
#> NSW1     1  37   11  black       1        1    0    0  9930.0460 0.2536942
#> NSW2     1  22    9 hispan       0        1    0    0  3595.8940 0.3245468
#> NSW3     1  30   12  black       0        0    0    0 24909.4500 0.2881139
#> NSW4     1  27   11  black       0        1    0    0  7506.1460 0.3016672
#> NSW5     1  33    8  black       0        1    0    0   289.7899 0.2683025
#> NSW6     1  22    9  black       0        1    0    0  4056.4940 0.3245468
#>      weights subclass
#> NSW1       1        1
#> NSW2       1       98
#> NSW3       1      109
#> NSW4       1      120
#> NSW5       1      131
#> NSW6       1      142
```

```r
library("lmtest") #coeftest
library("sandwich") #vcovCL

# imbalance matched dataset
fit1 <- lm(re78 ~ treat + age + educ ,
           data = m.data1,
           weights = weights)

coeftest(fit1, vcov. = vcovCL, cluster = ~subclass)
#>
#> t test of coefficients:
#>
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -174.902   2445.013 -0.0715 0.943012
#> treat       -1139.085    780.399 -1.4596 0.145253
#> age           153.133     55.317  2.7683 0.005922 **
#> educ          358.577    163.860  2.1883 0.029278 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

`treat` coefficient = estimated ATT

```r
# balance matched dataset
m.data2 <- match.data(m.out2)

fit2 <- lm(re78 ~ treat + age + educ ,
           data = m.data2, weights = weights)

coeftest(fit2, vcov. = vcovCL, cluster = ~subclass)
#>
#> t test of coefficients:
#>
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 2151.952   3141.152  0.6851  0.49355
#> treat       -725.184    703.297 -1.0311  0.30289
#> age          120.260     53.933  2.2298  0.02612 *
#> educ         175.693    241.694  0.7269  0.46755
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

When reporting, remember to mention

1. the matching specification (method, and additional options)
2. the distance measure (e.g., propensity score)
3. other methods, and rationale for the final chosen method.
4. balance statistics of the matched dataset.

5. number of matched, unmatched, discarded
6. estimation method for treatment effect.

31.1.2 designmatch

This package includes

- `distmatch` optimal distance matching
- `bmatch` optimal bipartile matching
- `cardmatch` optimal cardinality matching
- `profmatch` optimal profile matching
- `nmatch` optimal nonbipartile matching

```
library(designmatch)
```

31.1.3 MatchingFrontier

As mentioned in `MatchIt`, you have to make trade-off (also known as bias-variance trade-off) between balance and sample size. An automated procedure to optimize this trade-off is implemented in `MatchingFrontier` (King et al., 2017), which solves this joint optimization problem.

Following `MatchingFrontier` guide

```
# library(devtools)
# install_github('ChristopherLucas/MatchingFrontier')
library(MatchingFrontier)
data("lalonde")
# choose var to match on
match.on <-
    colnames(lalonde)[!(colnames(lalonde) %in% c('re78', 'treat'))]
match.on

# Mahanlanobis frontier (default)
mahal.frontier <-
    makeFrontier(
        dataset = lalonde,
        treatment = "treat",
        match.on = match.on
    )
mahal.frontier

# L1 frontier
L1.frontier <-
    makeFrontier(
```

```
        dataset = lalonde,
        treatment = 'treat',
        match.on = match.on,
        QOI = 'SATT',
        metric = 'L1',
        ratio = 'fixed'
    )
L1.frontier

# estimate effects along the frontier

# Set base form
my.form <-
    as.formula(re78 ~ treat + age + black + education
               + hispanic + married + nodegree + re74 + re75)

# Estimate effects for the mahalanobis frontier
mahal.estimates <-
    estimateEffects(
        mahal.frontier,
        're78 ~ treat',
        mod.dependence.formula = my.form,
        continuous.vars = c('age', 'education', 're74', 're75'),
        prop.estimated = .1,
        means.as.cutpoints = TRUE
    )

# Estimate effects for the L1 frontier
L1.estimates <-
    estimateEffects(
        L1.frontier,
        're78 ~ treat',
        mod.dependence.formula = my.form,
        continuous.vars = c('age', 'education', 're74', 're75'),
        prop.estimated = .1,
        means.as.cutpoints = TRUE
    )

# Plot covariates means
# plotPrunedMeans()


# Plot estimates (deprecated)
# plotEstimates(
#     L1.estimates,
```

```
#     ylim = c(-10000, 3000),
#     cex.lab = 1.4,
#     cex.axis = 1.4,
#     panel.first = grid(NULL, NULL, lwd = 2,)
# )

# Plot estimates
plotMeans(L1.frontier)


# parallel plot
parallelPlot(
    L1.frontier,
    N = 400,
    variables = c('age', 're74', 're75', 'black'),
    treated.col = 'blue',
    control.col = 'gray'
)

# export matched dataset
# take 400 units
matched.data <- generateDataset(L1.frontier, N = 400)
```

31.1.4 Propensity Scores

Even though I mention the propensity scores matching method here, it is no longer recommended to use such method in research and publication (King and Nielsen, 2019) because it increases

- imbalance
- inefficiency
- model dependence: small changes in the model specification lead to big changes in model results
- bias

(Abadie and Imbens, 2016)note

- The initial estimation of the propensity score influences the large sample distribution of the estimators.
- Adjustments are made to the large sample variances of these estimators for both ATE and ATT.
  - The adjustment for the ATE estimator is either negative or zero, indicating greater efficiency when matching on an estimated propensity score versus the true score in large samples.

  - For the ATET estimator, the sign of the adjustment depends on the data generating process. Neglecting the estimation error in the propensity score can lead to inaccurate confidence intervals for the ATT estimator, making them either too large or too small.

PSM tries to accomplish complete randomization while other methods try to achieve fully blocked. Hence, you probably better off use any other methods.

Propensity is "the probability of receiving the treatment given the observed covariates." (Rosenbaum and Rubin, 1985)

Equivalently, it can to understood as the probability of being treated.

$$e_i(X_i) = P(T_i = 1|X_i)$$

Estimation using

- logistic regression
- Non parametric methods:
  - boosted CART
  - generalized boosted models (gbm)

Steps by Gary King's slides

- reduce k elements of X to scalar
- $\pi_i \equiv P(T_i = 1|X) = \frac{1}{1+e^{X_i\beta}}$
- Distance $(X_c, X_t) = |\pi_c - \pi_t|$
- match each treated unit to the nearest control unit
- control units: not reused; pruned if unused
- prune matches if distances > caliper

In the best case scenario, you randomly prune, which increases imbalance

Other methods dominate because they try to match exactly hence

- $X_c = X_t \rightarrow \pi_c = \pi_t$ (exact match leads to equal propensity scores) but
- $\pi_c = \pi_t \nrightarrow X_c = X_t$ (equal propensity scores do not necessarily lead to exact match)

Notes:

- Do not include/control for irrelevant covariates because it leads your PSM to be more random, hence more imbalance
- Do not include for (Bhattacharya and Vogt, 2007) instrumental variable in the predictor set of a propensity score matching estimator. More generally,

using variables that do not control for potential confounders, even if they are predictive of the treatment, can result in biased estimates

What you left with after pruning is more important than what you start with then throw out.

Diagnostics:

- balance of the covariates
- no need to concern about collinearity
- can't use c-stat or stepwise because those model fit stat do not apply

31.1.4.1 Look Ahead Propensity Score Matching

- (Bapna et al., 2018)

31.1.5 Mahalanobis Distance

Approximates fully blocked experiment

Distance $(X_c, X_t) = \sqrt{(X_c - X_t)' S^{-1} (X_c - X_t)}$

where S^{-1} standardize the distance

In application we use Euclidean distance.

Prune unused control units, and prune matches if distance > caliper

31.1.6 Coarsened Exact Matching

Steps from Gray King's slides International Methods Colloquium talk 2015

- Temporarily coarsen X
- Apply exact matching to the coarsened $X, C(X)$
  - sort observation into strata, each with unique values of $C(X)$
  - prune stratum with 0 treated or 0 control units
- Pass on original (uncoarsened) units except those pruned

Properties:

- Monotonic imbalance bounding (MIB) matching method
  - maximum imbalance between the treated and control chosen ex ante
- meets congruence principle
- robust to measurement error
- can be implemented with multiple imputation
- works well for multi-category treatments

Assumptions:

- Ignorability (i.e., no omitted variable bias)

More detail in (Iacus et al., 2012)

Example by package's authors

```
library(cem)
data(LeLonde)

Le <- data.frame(na.omit(LeLonde)) # remove missing data
# treated and control groups
tr <- which(Le$treated==1)
ct <- which(Le$treated==0)
ntr <- length(tr)
nct <- length(ct)

# unadjusted, biased difference in means
mean(Le$re78[tr]) - mean(Le$re78[ct])
#> [1] 759.0479

# pre-treatment covariates
vars <-
    c(
        "age",
        "education",
        "black",
        "married",
        "nodegree",
        "re74",
        "re75",
        "hispanic",
        "u74",
        "u75",
        "q1"
    )

# overall imbalance statistics
imbalance(group=Le$treated, data=Le[vars]) # L1 = 0.902
#>
#> Multivariate Imbalance Measure: L1=0.902
#> Percentage of local common support: LCS=5.8%
#>
#> Univariate Imbalance Measures:
#>
#>                statistic   type           L1 min 25%      50%       75%
```

```
#> age        -0.252373042 (diff) 5.102041e-03   0   0   0.0000   -1.0000
#> education   0.153634710 (diff) 8.463851e-02   1   0   1.0000    1.0000
#> black      -0.010322734 (diff) 1.032273e-02   0   0   0.0000    0.0000
#> married    -0.009551495 (diff) 9.551495e-03   0   0   0.0000    0.0000
#> nodegree   -0.081217371 (diff) 8.121737e-02   0  -1   0.0000    0.0000
#> re74      -18.160446880 (diff) 5.551115e-17   0   0 284.0715  806.3452
#> re75      101.501761679 (diff) 5.551115e-17   0   0 485.6310 1238.4114
#> hispanic   -0.010144756 (diff) 1.014476e-02   0   0   0.0000    0.0000
#> u74        -0.045582186 (diff) 4.558219e-02   0   0   0.0000    0.0000
#> u75        -0.065555292 (diff) 6.555529e-02   0   0   0.0000    0.0000
#> q1          7.494021189 (Chi2) 1.067078e-01  NA  NA       NA        NA
#>                  max
#> age          -6.0000
#> education     1.0000
#> black         0.0000
#> married       0.0000
#> nodegree      0.0000
#> re74      -2139.0195
#> re75        490.3945
#> hispanic      0.0000
#> u74           0.0000
#> u75           0.0000
#> q1                NA

# drop other variables that are not pre - treatmentt matching variables
todrop <- c("treated", "re78")
imbalance(group=Le$treated, data=Le, drop=todrop)
#>
#> Multivariate Imbalance Measure: L1=0.902
#> Percentage of local common support: LCS=5.8%
#>
#> Univariate Imbalance Measures:
#>
#>               statistic   type           L1 min 25%      50%       75%
#> age        -0.252373042 (diff) 5.102041e-03   0   0   0.0000   -1.0000
#> education   0.153634710 (diff) 8.463851e-02   1   0   1.0000    1.0000
#> black      -0.010322734 (diff) 1.032273e-02   0   0   0.0000    0.0000
#> married    -0.009551495 (diff) 9.551495e-03   0   0   0.0000    0.0000
#> nodegree   -0.081217371 (diff) 8.121737e-02   0  -1   0.0000    0.0000
#> re74      -18.160446880 (diff) 5.551115e-17   0   0 284.0715  806.3452
#> re75      101.501761679 (diff) 5.551115e-17   0   0 485.6310 1238.4114
#> hispanic   -0.010144756 (diff) 1.014476e-02   0   0   0.0000    0.0000
#> u74        -0.045582186 (diff) 4.558219e-02   0   0   0.0000    0.0000
#> u75        -0.065555292 (diff) 6.555529e-02   0   0   0.0000    0.0000
#> q1          7.494021189 (Chi2) 1.067078e-01  NA  NA       NA        NA
```

```
#>                  max
#> age          -6.0000
#> education     1.0000
#> black         0.0000
#> married       0.0000
#> nodegree      0.0000
#> re74      -2139.0195
#> re75        490.3945
#> hispanic      0.0000
#> u74           0.0000
#> u75           0.0000
#> q1                NA
```

automated coarsening

```
mat <-
    cem(
        treatment = "treated",
        data = Le,
        drop = "re78",
        keep.all = TRUE
    )
#>
#> Using 'treated'='1' as baseline group
mat
#>            G0  G1
#> All       392 258
#> Matched    95  84
#> Unmatched 297 174

# mat$w
```

coarsening by explicit user choice

```
# categorial variables
levels(Le$q1) # grouping option
#> [1] "agree"             "disagree"          "neutral"
#> [4] "no opinion"        "strongly agree"    "strongly disagree"
q1.grp <-
    list(
        c("strongly agree", "agree"),
        c("neutral", "no opinion"),
        c("strongly disagree", "disagree")
    ) # if you want ordered categories

# continuous variables
table(Le$education)
```

```
#>
#>   3   4   5   6   7   8   9  10  11  12  13  14  15
#>   1   5   4   6  12  55 106 146 173 113  19   9   1
educut <- c(0, 6.5, 8.5, 12.5, 17)  # use cutpoints

mat1 <-
    cem(
        treatment = "treated",
        data = Le,
        drop = "re78",
        cutpoints = list(education = educut),
        grouping = list(q1 = q1.grp)
    )
#>
#> Using 'treated'='1' as baseline group
mat1
#>            G0  G1
#> All       392 258
#> Matched   158 115
#> Unmatched 234 143
```

- Can also use progressive coarsening method to control the number of matches.
- `cem` can also handle some missingness.

31.1.7 Genetic Matching

- GM uses iterative checking process of propensity scores, which combines propensity scores and Mahalanobis distance.
  - GenMatch (Diamond and Sekhon, 2013)
- GM is arguably "superior" method than nearest neighbor or full matching in imbalanced data
- Use a genetic search algorithm to find weights for each covariate such that we have optimal balance.
- Implementation
  - could use *with replacement*
  - balance can be based on
    - paired t-tests (dichotomous variables)
    - Kolmogorov-Smirnov (multinomial and continuous)

Packages

Matching

```
library(Matching)
data(lalonde)
attach(lalonde)

#The covariates we want to match on
X = cbind(age, educ, black, hisp, married, nodegr, u74, u75, re75, re74)

#The covariates we want to obtain balance on
BalanceMat <-
    cbind(age,
          educ,
          black,
          hisp,
          married,
          nodegr,
          u74,
          u75,
          re75,
          re74,
          I(re74 * re75))

#
#Let's call GenMatch() to find the optimal weight to give each
#covariate in 'X' so as we have achieved balance on the covariates in
#'BalanceMat'. This is only an example so we want GenMatch to be quick
#so the population size has been set to be only 16 via the 'pop.size'
#option. This is *WAY* too small for actual problems.
#For details see http://sekhon.berkeley.edu/papers/MatchingJSS.pdf.
#
genout <-
    GenMatch(
        Tr = treat,
        X = X,
        BalanceMatrix = BalanceMat,
        estimand = "ATE",
        M = 1,
        pop.size = 16,
        max.generations = 10,
        wait.generations = 1
    )

#The outcome variable
Y=re78/1000
```

```r
#
# Now that GenMatch() has found the optimal weights, let's estimate
# our causal effect of interest using those weights
#
mout <-
    Match(
        Y = Y,
        Tr = treat,
        X = X,
        estimand = "ATE",
        Weight.matrix = genout
    )
summary(mout)

#
#Let's determine if balance has actually been obtained on the variables of interest
#
mb <-
    MatchBalance(
        treat ~ age + educ + black + hisp + married + nodegr
        + u74 + u75 + re75 + re74 + I(re74 * re75),
        match.out = mout,
        nboots = 500
    )
```

31.1.8 Entropy Balancing

(Hainmueller, 2012)

- Entropy balancing is a method for achieving covariate balance in observational studies with binary treatments.
- It uses a maximum entropy reweighting scheme to ensure that treatment and control groups are balanced based on sample moments.
- This method adjusts for inequalities in the covariate distributions, reducing dependence on the model used for estimating treatment effects.
- Entropy balancing improves balance across all included covariate moments and removes the need for repetitive balance checking and iterative model searching.

31.1.9 Matching for high-dimensional data

One could reduce the number of dimensions using methods such as:

- Lasso (Gordon et al., 2019)

- Penalized logistic regression (Eckles and Bakshy, 2021)
- PCA (Principal Component Analysis)
- Locality Preserving Projections (LPP) (Li et al., 2016)
- Random projection
- Autoencoders (Ramachandra, 2018)

Additionally, one could jointly does dimension reduction while balancing the distributions of the control and treated groups (Yao et al., 2018).

31.1.10 Matching for time series-cross-section data

Examples: (Scheve and Stasavage, 2012) and (Acemoglu et al., 2019)

Identification strategy:

- Within-unit over-time variation
- within-time across-units variation

See DID with in and out treatment condition for details of this method

31.1.11 Matching for multiple treatments

In cases where you have multiple treatment groups, and you want to do matching, it's important to have the same baseline (control) group. For more details, see

- (McCaffrey et al., 2013)
- (Lopez and Gutman, 2017)
- (Zhao et al., 2021): also for continuous treatment

If you insist on using the `MatchIt` package, then see this answer

31.1.12 Matching for multi-level treatments

See (Yang et al., 2016)

Package in R `shuyang1987/multilevelMatching` on Github

31.1.13 Matching for repeated treatments

https://cran.r-project.org/web/packages/twang/vignettes/iptw.pdf

package in R `twang`

31.2 Selection on Unobservables

There are several ways one can deal with selection on unobservables:

1. Rosenbaum Bounds
2. Endogenous Sample Selection (i.e., Heckman-style correction): examine the λ term to see whether it's significant (sign of endogenous selection)
3. Relative Correlation Restrictions
4. Coefficient-stability Bounds

31.2.1 Rosenbaum Bounds

Examples in marketing

- (Oestreicher-Singer and Zalmanson, 2013): A range of 1.5 to 1.8 is important for the effect of the level of community participation of users on their willingness to pay for premium services.
- (Sun and Zhu, 2013): A factor of 1.5 is essential for understanding the relationship between the launch of an ad revenue-sharing program and the popularity of content.
- (Manchanda et al., 2015): A factor of 1.6 is required for the social dollar effect to be nullified.
- (Sudhir and Talukdar, 2015): A factor of 1.9 is needed for IT adoption to impact labor productivity, and 2.2 for IT adoption to affect floor productivity.
- (Proserpio and Zervas, 2017a): A factor of 2 is necessary for the firm's use of management responses to influence online reputation.
- (Zhang et al., 2022): A factor of 1.55 is critical for the acquisition of verified images to drive demand for Airbnb properties.
- (Chae et al., 2023): A factor of 27 (not a typo) is significant in how paywall suspensions affect subsequent subscription decisions.

General

- Matching Methods are favored for estimating treatment effects in observational data, offering advantages over regression methods because
  - It reduces reliance on functional form assumptions.
  - Assumes all selection-influencing covariates are observable; estimates are unbiased if no unobserved confounders are missed.
- Concerns arise when potentially relevant covariates are unmeasured.

  - Rosenbaum Bounds assess the overall sensitivity of coefficient estimates to hidden bias (Rosenbaum and Rosenbaum, 2002) without having knowledge (e.g., direction) of the bias. Because the unboservables that cause hidden bias have to both affect selection into treatment by a factor of Γ and predictive of outcome, this method is also known as **worst case analyses** (DiPrete and Gangl, 2004).

- Can't provide precise bounds on estimates of treatment effects (see Relative Correlation Restrictions)

- Typically, we show both p-value and H-L point estimate for each level of gamma Γ

With random treatment assignment, we can use the non-parametric test (Wilcoxon signed rank test) to see if there is treatment effect.

Without random treatment assignment (i.e., observational data), we cannot use this test. With Selection on Observables, we can use this test if we believe there are no unmeasured confounders. And this is where Rosenbaum (2002) can come in to talk about the believability of this notion.

In layman's terms, consider that the treatment assignment is based on a method where the odds of treatment for a unit and its control differ by a multiplier Γ

- For example, $\Gamma = 1$ means that the odds of assignment are identical, indicating random treatment assignment.
- Another example, $\Gamma = 2$, in the same matched pair, one unit is twice as likely to receive the treatment (due to unobservables).
- Since we can't know Γ with certainty, we run sensitivity analysis to see if the results change with different values of Γ
- This bias is the product of an unobservable that influences both treatment selection and outcome by a factor Γ (omitted variable bias)

In technical terms,

- **Treatment Assignment and Probability**:
  - Consider unit j with a probability π_j of receiving the treatment, and unit i with π_i.
  - Ideally, after matching, if there's no hidden bias, we'd have $\pi_i = \pi_j$.
  - However, observing $\pi_i \neq \pi_j$ raises questions about potential biases affecting our inference. This is evaluated using the odds ratio.
- **Odds Ratio and Hidden Bias**:
  - The odds of treatment for a unit j is defined as $\frac{\pi_j}{1-\pi_j}$.
  - The odds ratio between two matched units i and j is constrained by $\frac{1}{\Gamma} \leq \frac{\pi_i/(1-\pi_i)}{\pi_j/(1-\pi_j)} \leq \Gamma$.
    - If $\Gamma = 1$, it implies an absence of hidden bias.
    - If $\Gamma = 2$, the odds of receiving treatment could differ by up to a factor of 2 between the two units.
- **Sensitivity Analysis Using Gamma**:

  - The value of Γ helps measure the potential departure from a bias-free study.
  - Sensitivity analysis involves varying Γ to examine how inferences might change with the presence of hidden biases.
- **Incorporating Unobserved Covariates**:
  - Consider a scenario where unit i has observed covariates x_i and an unobserved covariate u_i, that both affect the outcome.
  - A logistic regression model could link the odds of assignment to these covariates: $\log(\frac{\pi_i}{1-\pi_i}) = \kappa x_i + \gamma u_i$, where γ represents the impact of the unobserved covariate.
- **Steps for Sensitivity Analysis** (We could create a table of different levels of Γ to assess how the magnitude of biases can affect our evidence of the treatment effect (estimate):
  1. Select a range of values for Γ (e.g., $1 \to 2$).
  2. Assess how the p-value or the magnitude of the treatment effect (Hodges Jr and Lehmann, 2011) (for more details, see (Hollander et al., 2013)) changes with varying Γ values.
  3. Employ specific randomization tests based on the type of outcome to establish bounds on inferences.
     - report the minimum value of Γ at which the treatment treat is nullified (i.e., become insignificant). And the literature's rules of thumb is that if $\Gamma > 2$, then we have strong evidence for our treatment effect is robust to large biases (Proserpio and Zervas, 2017b)

Notes:

- If we have treatment assignment is clustered (e.g., within school, within state) we need to adjust the bounds for clustered treatment assignment (Hansen et al., 2014) (similar to clustered standard errors).

Packages

- `rbounds` (Keele, 2010)
- `sensitivitymv` (Rosenbaum, 2015)

Since we typically assess our estimate sensitivity to unboservables after matching, we first do some matching.

```
library(MatchIt)
library(Matching)
data("lalonde")

matched <- MatchIt::matchit(
    treat ~ age + educ,
    data = lalonde,
    method = "nearest"
)
```

```r
summary(matched)
#>
#> Call:
#> MatchIt::matchit(formula = treat ~ age + educ, data = lalonde,
#>     method = "nearest")
#>
#> Summary of Balance for All Data:
#>          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
#> distance        0.4203        0.4125          0.1689     1.2900    0.0431
#> age            25.8162       25.0538          0.1066     1.0278    0.0254
#> educ           10.3459       10.0885          0.1281     1.5513    0.0287
#>          eCDF Max
#> distance   0.1251
#> age        0.0652
#> educ       0.1265
#>
#> Summary of Balance for Matched Data:
#>          Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
#> distance        0.4203        0.4179          0.0520     1.1691    0.0105
#> age            25.8162       25.5081          0.0431     1.1518    0.0148
#> educ           10.3459       10.2811          0.0323     1.5138    0.0224
#>          eCDF Max Std. Pair Dist.
#> distance   0.0595          0.0598
#> age        0.0486          0.5628
#> educ       0.0757          0.3602
#>
#> Sample Sizes:
#>           Control Treated
#> All           260     185
#> Matched       185     185
#> Unmatched      75       0
#> Discarded       0       0
matched_data <- match.data(matched)

treatment_group <- subset(matched_data, treat == 1)
control_group <- subset(matched_data, treat == 0)


library(rbounds)

# p-value sensitivity
psens_res <-
    psens(treatment_group$re78,
          control_group$re78,
          Gamma = 2,
```

```
          GammaInc = .1)

psens_res
#>
#>  Rosenbaum Sensitivity Test for Wilcoxon Signed Rank P-Value
#>
#> Unconfounded estimate ....  0.0058
#>
#>  Gamma Lower bound Upper bound
#>    1.0      0.0058      0.0058
#>    1.1      0.0011      0.0235
#>    1.2      0.0002      0.0668
#>    1.3      0.0000      0.1458
#>    1.4      0.0000      0.2599
#>    1.5      0.0000      0.3967
#>    1.6      0.0000      0.5378
#>    1.7      0.0000      0.6664
#>    1.8      0.0000      0.7723
#>    1.9      0.0000      0.8523
#>    2.0      0.0000      0.9085
#>
#>  Note: Gamma is Odds of Differential Assignment To
#>  Treatment Due to Unobserved Factors
#>

# Hodges-Lehmann point estimate sensitivity
# median difference between treatment and control
hlsens_res <-
    hlsens(treatment_group$re78,
           control_group$re78,
           Gamma = 2,
           GammaInc = .1)
hlsens_res
#>
#>  Rosenbaum Sensitivity Test for Hodges-Lehmann Point Estimate
#>
#> Unconfounded estimate ....  1745.843
#>
#>  Gamma Lower bound Upper bound
#>    1.0 1745.800000      1745.8
#>    1.1 1139.100000      1865.6
#>    1.2  830.840000      2160.9
#>    1.3  533.740000      2462.4
#>    1.4  259.940000      2793.8
#>    1.5   -0.056912      3059.3
```

```
#>    1.6 -144.960000      3297.8
#>    1.7 -380.560000      3535.7
#>    1.8 -554.360000      3751.0
#>    1.9 -716.360000      4012.1
#>    2.0 -918.760000      4224.3
#>
#>  Note: Gamma is Odds of Differential Assignment To
#>  Treatment Due to Unobserved Factors
#>
```

For multiple control group matching

```
library(Matching)
library(MatchIt)

n_ratio <- 2
matched <- MatchIt::matchit(treat ~ age + educ ,
                    method = "nearest", ratio = n_ratio)
summary(matched)
matched_data <- match.data(matched)

mcontrol_res <- rbounds::mcontrol(
    y          = matched_data$re78,
    grp.id     = matched_data$subclass,
    treat.id   = matched_data$treat,
    group.size = n_ratio + 1,
    Gamma      = 2.5,
    GammaInc   = .1
)

mcontrol_res
```

`sensitivitymw` is faster than `sensitivitymw`. But `sensitivitymw` can match where matched sets can have differing numbers of controls (Rosenbaum, 2015).

```
library(sensitivitymv)
data(lead150)
head(lead150)
#>      [,1] [,2] [,3] [,4] [,5] [,6]
#> [1,] 1.40 1.23 2.24 0.96 1.90 1.14
#> [2,] 0.63 0.99 0.87 1.90 0.67 1.40
#> [3,] 1.98 0.82 0.66 0.58 1.00 1.30
#> [4,] 1.45 0.53 1.43 1.70 0.85 1.50
#> [5,] 1.60 1.70 0.63 1.05 1.08 0.92
#> [6,] 1.13 0.31 0.71 1.10 0.86 1.14
senmv(lead150,gamma=2,trim=2)
#> $pval
```

```
#> [1] 0.02665519
#>
#> $deviate
#> [1] 1.932398
#>
#> $statistic
#> [1] 27.97564
#>
#> $expectation
#> [1] 18.0064
#>
#> $variance
#> [1] 26.61524

library(sensitivitymw)
senmw(lead150,gamma=2,trim=2)
#> $pval
#> [1] 0.02665519
#>
#> $deviate
#> [1] 1.932398
#>
#> $statistic
#> [1] 27.97564
#>
#> $expectation
#> [1] 18.0064
#>
#> $variance
#> [1] 26.61524
```

31.2.2 Relative Correlation Restrictions

Examples in marketing

- (Manchanda et al., 2015): 3.23 for social dollar effect to be nullified
- (Chae et al., 2023): 6.69 (i.e., how much stronger the selection on unobservables has to be compared to the selection on observables to negate the result) for paywall suspensions affect subsequent subscription decisions
- (Sun and Zhu, 2013)

General

- Proposed by Altonji et al. (2005)
- Generalized by Krauth (2016)

- Estimate bounds of the treatment effects due to unobserved selection.

$$Y_i = X_i\beta + C_i\gamma + \epsilon_i$$

where

- β is the effect of interest
- C_i is the control variable
- Using OLS, $cor(X_i, \epsilon_i) = 0$

Under RCR analysis, we assume

$$cor(X_i, \epsilon_i) = \lambda cor(X_i, C_i\gamma)$$

where $\lambda \in (\lambda_l, \lambda_h)$

Choice of λ

- Strong assumption of no omitted variable bias (small
- If $\lambda = 0$, then $cor(X_i, \epsilon_i) = 0$
- If $\lambda = 1$, then $cor(X_i, \epsilon_i) = cor(X_i, C_i\gamma)$
- We typically examine $\lambda \in (0, 1)$

```
# remotes::install_github("bvkrauth/rcr/r/rcrbounds")
library(rcrbounds)
# rcrbounds::install_rcrpy()
data("ChickWeight")

rcr_res <-
    rcrbounds::rcr(weight ~ Time |
                        Diet, ChickWeight, rc_range = c(0, 10))
rcr_res
#>
#> Call:
#> rcrbounds::rcr(formula = weight ~ Time | Diet, data = ChickWeight,
#>     rc_range = c(0, 10))
#>
#> Coefficients:
#>     rcInf effectInf       rc0   effectL   effectH
#> 34.676505 71.989336 34.741955  7.447713  8.750492
summary(rcr_res)
#>
#> Call:
#> rcrbounds::rcr(formula = weight ~ Time | Diet, data = ChickWeight,
#>     rc_range = c(0, 10))
```

```
#>
#> Coefficients:
#>            Estimate  Std. Error    t value      Pr(>|t|)
#> rcInf     34.676505  50.1295005  0.6917385  4.891016e-01
#> effectInf 71.989336 112.5711682  0.6395007  5.224973e-01
#> rc0       34.741955  58.7169195  0.5916856  5.540611e-01
#> effectL    7.447713   2.4276246  3.0679014  2.155677e-03
#> effectH    8.750492   0.2607671 33.5567355 7.180405e-247
#> ---
#> conservative confidence interval:
#>          2.5  %  97.5  %
#> effect 2.689656 9.261586

# hypothesis test for the coefficient
rcrbounds::effect_test(rcr_res, h0 = 0)
#> [1] 0.001234233
plot(rcr_res)
```

31.2.3 Coefficient-stability Bounds

- Developed by Oster (2019)
- Assess robustness to omitted variable bias by observing:
  1. Changes in the coefficient of interest
  2. Shifts in model R^2
- Refer Masten and Poirier (2022) for reverse sign problem.

Chapter 32

Interrupted Time Series

- Regression Discontinuity in Time
- Control for
  - Seasonable trends
  - Concurrent events
- Pros (Penfold and Zhang, 2013)
  - control for long-term trends
- Cons
  - Min of 8 data points before and 8 after an intervention
  - Multiple events hard to distinguish

Notes:

- For subgroup analysis (heterogeneity in effect size), see (Harper and Bruckner, 2017)
- To interpret with control variables, see (Bottomley et al., 2019)

Interrupted time series should be used when

1. longitudinal data (outcome over time - observations before and after the intervention)
2. full population was affected at one specific point in time (or can be stacked based on intervention)

In each ITS framework, there can be 4 possible scenarios of outcome after an intervention

- No effects
- Immediate effect

- Sustained (long-term) effect (smooth)
- Both immediate and sustained effect

$$Y = \beta_0 + \beta_1 T + \beta_2 D + \beta_3 P + \epsilon$$

where

- Y is the outcome variable
  - β_0 is the baseline level of the outcome
- T is the time variable (e.g., days, weeks, etc.) passed from the start of the observation period
  - β_1 is the slope of the line before the intervention
- D is the treatment variable where 1 is after the intervention and 0 is before the intervention.
  - β_2 is the **immediate effect** after the intervention
- P is the time variable indicating time passed since the intervention (before the intervention, the value is set to 0) (to examine the sustained effect).
  - β_3 is the **sustained effect** = difference between the slope of the line prior to the intervention and the slope of the line subsequent to the intervention

Example

Create a fictitious dataset where we know the true data generating process

$$Outcome = 10 \times time + 20 \times treatment + 25 \times timesincetreatment + noise$$

```
# number of days
n = 365


# intervention at day
interven = 200

# time index from 1 to 365
time = c(1:n)

# treatment variable: before internvation = day 1 to 200,
# after intervention = day 201 to 365
treatment = c(rep(0, interven), rep(1, n - interven))
```

```r
# time since treatment
timesincetreat = c(rep(0, interven), c(1:(n - interven)))

# outcome
outcome = 10 + 15 * time + 20 * treatment +
    25 * timesincetreat + rnorm(n, mean = 0, sd = 1)

df = data.frame(outcome, time, treatment, timesincetreat)

head(df, 10)
#>      outcome time treatment timesincetreat
#> 1   24.79426    1         0              0
#> 2   41.23378    2         0              0
#> 3   54.72249    3         0              0
#> 4   71.08714    4         0              0
#> 5   84.40310    5         0              0
#> 6   99.60984    6         0              0
#> 7  114.91295    7         0              0
#> 8  130.64154    8         0              0
#> 9  142.81387    9         0              0
#> 10 160.91194   10         0              0
```

Visualize

```r
plot(df$time, df$outcome)

# intervention date
abline(v = interven, col = "blue")

# regression line
ts <- lm(outcome ~ time + treatment + timesincetreat, data = df)
lines(df$time, ts$fitted.values, col = "red")
```

```
summary(ts)
#>
#> Call:
#> lm(formula = outcome ~ time + treatment + timesincetreat, data = df)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -3.07701 -0.68627 -0.05883  0.66136  2.83087
#>
#> Coefficients:
#>                 Estimate Std. Error  t value Pr(>|t|)
#> (Intercept)    10.026599   0.139242    72.01   <2e-16 ***
#> time           14.999387   0.001201 12485.28   <2e-16 ***
#> treatment      20.232649   0.206490    97.98   <2e-16 ***
#> timesincetreat 24.999649   0.002003 12478.57   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.9809 on 361 degrees of freedom
#> Multiple R-squared:      1,  Adjusted R-squared:      1
#> F-statistic: 9.909e+08 on 3 and 361 DF,  p-value: < 2.2e-16
```

Interpretation

- Time coefficient shows before-intervention outcome trend. Positive and significant, indicating a rising trend. Every day adds 15 points.
- The treatment coefficient shows the **immediate** increase in outcome. **Im-**

mediate effect is positive and significant, increasing outcome by 20 points.

- The time since treatment coefficient reflects a change in trend subsequent to the intervention. The **sustained effect** is positive and statistically significant, showing that the outcome increases by 25 points per day after the intervention.

See Lee Rodgers et al. (2014) for suggestions

Plot of counterfactual

```
# treatment prediction
pred <- predict(ts, df)

# counterfactual dataset
new_df <-
    as.data.frame(cbind(
        time = time,
        # treatment = 0 means counterfactual
        treatment = rep(0, n),
        # time since treatment = 0 means counterfactual
        timesincetreat = rep(0)
    ))

# counterfactual predictions
pred_cf <- predict(ts, new_df)

# plot
plot(
    outcome,
    col = gray(0.2, 0.2),
    pch = 19,
    xlim  = c(1,365),
    ylim = c(0, 10000),
    xlab = "xlab",
    ylab = "ylab"
)

# regression line before treatment
lines(rep(1:interven), pred[1:interven], col = "blue", lwd = 3)

# regression line after treatment
lines(rep((interven + 1):n), pred[(interven + 1):n],
      col = "blue", lwd = 3)

# regression line after treatment (counterfactual)
```

```
lines(
    rep(interven:n),
    pred_cf[(interven):n],
    col = "yellow",
    lwd = 3,
    lty = 5
)

abline(v = interven, col = "red", lty = 2)
```

Possible threats to the validity of interrupted time series analysis (Baicker and Svoronos, 2019)

- Delayed effects (Rodgers et al., 2005) (may have to make assess some time after the intervention - do not assess the immediate dates).
- Other confounding events (Linden and Yarnold, 2016, Linden (2017))
- Intervention is introduced but later withdrawn (Linden, 2015)
- Autocorrelation (for every time series data): might cause underestimation in the standard errors (i.e., overestimating the statistical significance of the treatment effect)
- Regression to the mean: after a the short-term shock to the outcome, individuals can revert back to their initial states.
- Selection bias: only certain individuals are affected by the treatment (could use a Multiple Groups).

32.1 Autocorrelation

Assess autocorrelation from residual

```
# simple regression on time
simple_ts <- lm(outcome ~ time, data = df)

plot(resid(simple_ts))
```

```
# alternatively
acf(resid(simple_ts))
```

This is not the best example since I created this dataset. But when residuals do have autocorrelation, you should not see any patterns (i.e., points should be randomly distributed on the plot)

To formally test for autocorrelation, we can use the Durbin-Watson test

```
lmtest::dwtest(df$outcome ~ df$time)
#>
#>  Durbin-Watson test
#>
#> data:  df$outcome ~ df$time
#> DW = 0.00037525, p-value < 2.2e-16
#> alternative hypothesis: true autocorrelation is greater than 0
```

From the p-value, we know that there is autocorrelation in the time series

A solution to this problem is to use more advanced time series analysis (e.g., ARIMA - coming up in the book) to adjust for seasonality and other dependency.

```
forecast::auto.arima(df$outcome, xreg = as.matrix(df[,-1]))
#> Series: df$outcome
#> Regression with ARIMA(0,0,0) errors
#>
#> Coefficients:
#>       intercept     time  treatment  timesincetreat
#>         10.0266  14.9994    20.2326         24.9996
#> s.e.     0.1385   0.0012     0.2054          0.0020
#>
#> sigma^2 = 0.9622:  log likelihood = -508.86
```

```
#> AIC=1027.72   AICc=1027.89   BIC=1047.22
```

32.2 Multiple Groups

When you suspect that you might have confounding events or selection bias, you can add a control group that did not experience the treatment (very much similar to Difference-in-differences)

The model then becomes

$$\begin{aligned} Y = \beta_0 &+ \beta_1 time + \beta_2 treatment + \beta_3 \times timesincetreat \\ &+ \beta_4 group + \beta_5 group \times time + \beta_6 group \times treatment \\ &+ \beta_7 group \times timesincetreat \end{aligned}$$

where

- Group = 1 when the observation is under treatment and 0 under control
- β_4 = baseline difference between the treatment and control group
- β_5 = slope difference between the treatment and control group before treatment
- β_6 = baseline difference between the treatment and control group associated with the treatment.
- β_7 = difference between the sustained effect of the treatment and control group after the treatment.

C. OTHER CONCERNS

Chapter 33

Endogeneity

Refresher

A general model framework

$$\mathbf{Y} = \mathbf{X} \ +$$

where

- $\mathbf{Y} = n \times 1$
- $\mathbf{X} = n \times k$
- $\beta = k \times 1$
- $\epsilon = n \times 1$

Then, OLS estimates of coefficients are

$$\begin{aligned}
\hat{\beta}_{OLS} &= (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\mathbf{Y}) \\
&= (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'(\mathbf{X} \ + \ )) \\
&= (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\mathbf{X})\beta + (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}' \ ) \\
\hat{\beta}_{OLS} &\to \beta + (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}' \ )
\end{aligned}$$

To have unbiased estimates, we have to get rid of the second part $(\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}' \ )$

There are 2 conditions to achieve unbiased estimates:

1. $E(\epsilon|X) = 0$ (This is easy, putting an intercept can solve this issue)
2. $Cov(\mathbf{X}, \epsilon) = 0$ (This is the hard part)

We only care about omitted variable

Usually, the problem will stem Omitted Variables Bias, but we only care about omitted variable bias when

1. Omitted variables correlate with the variables we care about (X). If OMV does not correlate with X, we don't care, and random assignment makes this correlation goes to 0)
2. Omitted variables correlates with outcome/ dependent variable

There are more types of endogeneity listed below.

Types of endogeneity (See Hill et al. (2021) for a review in management):

1. Endogenous Treatment

- Omitted Variables Bias
  - Motivation
  - Ability/talent
  - Self-selection
- Feedback Effect (Simultaneity): also known as bidirectionality
- Reverse Causality: Subtle difference from Simultaneity: Technically, two variables affect each other sequentially, but in a big enough time frame, (e.g., monthly, or yearly), our coefficient will be biased just like simultaneity.
- Measurement Error

2. Endogenous Sample Selection

To deal with this problem, we have a toolbox (that has been mentioned in previous chapter 18)

Using control variables in regression is a "selection on observables" identification strategy.

In other words, if you believe you have an omitted variable, and you can measure it, including it in the regression model solves your problem. These uninterested variables are called control variables in your model.

However, this is rarely the case (because the problem is we don't have their measurements). Hence, we need more elaborate methods:

- Endogenous Treatment
- Endogenous Sample Selection

Before we get to methods that deal with bias arises from omitted variables, we consider cases where we do have measurements of a variable, but there is measurement error (bias).

33.1 Endogenous Treatment

33.1.1 Measurement Error

- Data error can stem from
  - Coding errors
  - Reporting errors

Two forms of measurement error:

1. Random (stochastic) (indeterminate error) (Classical Measurement Errors): noise or measurement errors do not show up in a consistent or predictable way.
2. Systematic (determinate error) (Non-classical Measurement Errors): When measurement error is consistent and predictable across observations.
   1. Instrument errors (e.g., faulty scale) -> calibration or adjustment
   2. Method errors (e.g., sampling errors) -> better method development + study design
   3. Human errors (e.g., judgement)

Usually the systematic measurement error is a bigger issue because it introduces "bias" into our estimates, while random error introduces noise into our estimates

- Noise -> regression estimate to 0
- Bias -> can pull estimate to upward or downward.

33.1.1.1 Classical Measurement Errors

33.1.1.1.1 Right-hand side

- Right-hand side measurement error: When the measurement is in the covariates, then we have the endogeneity problem.

Say you know the true model is

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

But you don't observe X_i, but you observe

$$\tilde{X}_i = X_i + e_i$$

which is known as classical measurement errors where we **assume** e_i is uncorrelated with X_i (i.e., $E(X_i e_i) = 0$)

Then, when you estimate your observed variables, you have (substitute X_i with $\tilde{X}_i - e_i$):

$$\begin{aligned} Y_i &= \beta_0 + \beta_1(\tilde{X}_i - e_i) + u_i \\ &= \beta_0 + \beta_1\tilde{X}_i + u_i - \beta_1 e_i \\ &= \beta_0 + \beta_1\tilde{X}_i + v_i \end{aligned}$$

In words, the measurement error in X_i is now a part of the error term in the regression equation v_i. Hence, we have an endogeneity bias.

Endogeneity arises when

$$\begin{aligned} E(\tilde{X}_i v_i) &= E((X_i + e_i)(u_i - \beta_1 e_i)) \\ &= -\beta_1 Var(e_i) \neq 0 \end{aligned}$$

Since $\tilde{X}_i$ and e_i are positively correlated, then it leads to

- a negative bias in $\hat{\beta}_1$ if the true β_1 is positive
- a positive bias if β_1 is negative

In other words, measurement errors cause **attenuation bias**, which inter turn pushes the coefficient towards 0

As $Var(e_i)$ increases or $\frac{Var(e_i)}{Var(\tilde{X})} \to 1$ then e_i is a random (noise) and $\beta_1 \to 0$ (random variable $\tilde{X}$ should not have any relation to Y_i)

Technical note:

The size of the bias in the OLS-estimator is

$$\hat{\beta}_{OLS} = \frac{cov(\tilde{X}, Y)}{var(\tilde{X})} = \frac{cov(X + e, \beta X + u)}{var(X + e)}$$

then

$$plim\hat{\beta}_{OLS} = \beta\frac{\sigma_X^2}{\sigma_X^2 + \sigma_e^2} = \beta\lambda$$

where λ is **reliability** or signal-to-total variance ratio or attenuation factor

Reliability affect the extent to which measurement error attenuates $\hat{\beta}$. The attenuation bias is

$$\hat{\beta}_{OLS} - \beta = -(1 - \lambda)\beta$$

Thus, $\hat{\beta}_{OLS} < \beta$ (unless $\lambda = 1$, in which case we don't even have measurement error).

Note:

Data transformation worsen (magnify) the measurement error

$$y = \beta x + \gamma x^2 + \epsilon$$

then, the attenuation factor for $\hat{\gamma}$ is the square of the attenuation factor for $\hat{\beta}$ (i.e., $\lambda_{\hat{\gamma}} = \lambda^2_{\hat{\beta}}$)

Adding covariates increases attenuation bias

To fix classical measurement error problem, we can

1. Find estimates of either $\sigma^2_X, \sigma^2_\epsilon$ or λ from validation studies, or survey data.
2. Endogenous Treatment Use instrument Z correlated with X but uncorrelated with ϵ
3. Abandon your project

33.1.1.1.2 Left-hand side When the measurement is in the outcome variable, econometricians or causal scientists do not care because they still have an unbiased estimate of the coefficients (the zero conditional mean assumption is not violated, hence we don't have endogeneity). However, statisticians might care because it might inflate our uncertainty in the coefficient estimates (i.e., higher standard errors).

$$\tilde{Y} = Y + v$$

then the model you estimate is

$$\tilde{Y} = \beta X + u + v$$

Since v is uncorrelated with X, then $\hat{\beta}$ is consistently estimated by OLS

If we have measurement error in Y_i, it will pass through β_1 and go to u_i

33.1.1.2 Non-classical Measurement Errors

Relaxing the assumption that X and ϵ are uncorrelated

Recall the true model we have true estimate is

$$\hat{\beta} = \frac{cov(X + \epsilon, \beta X + u)}{var(X + \epsilon)}$$

then without the above assumption, we have

$$
\begin{aligned}
plim\hat{\beta} &= \frac{\beta(\sigma_X^2 + \sigma_{X\epsilon})}{\sigma_X^2 + \sigma_\epsilon^2 + 2\sigma_{X\epsilon}} \\
&= (1 - \frac{\sigma_\epsilon^2 + \sigma_{X\epsilon}}{\sigma_X^2 + \sigma_\epsilon^2 + 2\sigma_{X\epsilon}})\beta \\
&= (1 - b_{\epsilon\tilde{X}})\beta
\end{aligned}
$$

where $b_{\epsilon\tilde{X}}$ is the covariance between $\tilde{X}$ and ϵ (also the regression coefficient of a regression of ϵ on $\tilde{X}$)

Hence, the Classical Measurement Errors is just a special case of Non-classical Measurement Errors where $b_{\epsilon\tilde{X}} = 1 - \lambda$

So when $\sigma_{X\epsilon} = 0$ (Classical Measurement Errors), increasing this covariance $b_{\epsilon\tilde{X}}$ increases the covariance increases the attenuation factor if more than half of the variance in $\tilde{X}$ is measurement error, and decreases the attenuation factor otherwise. This is also known as **mean reverting measurement error** (Bound et al., 1989, Bound et al. (2001))

A general framework for both right-hand side and left-hand side measurement error is (Bound et al., 2001):

consider the true model

$$
\mathbf{Y} = \mathbf{X} \ +
$$

then

$$
\begin{aligned}
\hat{\beta} &= (\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-\mathbf{1}}\tilde{\mathbf{X}}\tilde{\mathbf{Y}} \\
&= (\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-\mathbf{1}}\tilde{\mathbf{X}}'(\tilde{\mathbf{X}} \ - \mathbf{U} \ + \mathbf{v} + \ ) \\
&= \ + (\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-\mathbf{1}}\tilde{\mathbf{X}}'(-\mathbf{U} \ + \mathbf{v} + \ ) \\
plim\hat{\beta} &= \beta + plim(\tilde{X}'\tilde{X})^{-1}\tilde{X}'(-U\beta + v) \\
&= \beta + plim(\tilde{X}'\tilde{X})^{-1}\tilde{X}'W \begin{bmatrix} -\beta \\ 1 \end{bmatrix}
\end{aligned}
$$

Since we collect the measurement errors in a matrix $W = [U|v]$, then

$$
(-U\beta + v) = W \begin{bmatrix} -\beta \\ 1 \end{bmatrix}
$$

Hence, in general, biases in the coefficients β are regression coefficients from regressing the measurement errors on the mis-measured $\tilde{X}$

Notes:

- Instrumental Variable can help fix this problem
- There can also be measurement error in dummy variables and you can still use Instrumental Variable to fix it.

33.1.1.3 Solution to Measurement Errors

33.1.1.3.1 Correlation

$$P(\rho|data) = \frac{P(data|\rho)P(\rho)}{P(data)}$$

$$\text{Posterior Probability} \propto \text{Likelihood} \times \text{Prior Probability}$$

where

- ρ is a correlation coefficient
- $P(data|\rho)$ is the likelihood function evaluated at ρ
- $P(\rho)$ prior probability
- $P(data)$ is the normalizing constant

With sample correlation coefficient r:

$$r = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}}$$

Then the posterior density approximation of ρ is (Schisterman et al., 2003, pp.3)

$$P(\rho|x, y) \propto P(\rho)\frac{(1-\rho^2)^{(n-1)/2}}{(1-\rho \times r)^{n-(3/2)}}$$

where

- $\rho = \tanh \xi$ where $\xi \sim N(z, 1/n)$
- $r = \tanh z$

Then the posterior density follow a normal distribution where

Mean

$$\mu_{posterior} = \sigma^2_{posterior} \times (n_{prior} \times \tanh^{-1} r_{prior} + n_{likelihood} \times \tanh^{-1} r_{likelihood})$$

variance

$$\sigma^2_{posterior} = \frac{1}{n_{prior} + n_{Likelihood}}$$

To simplify the integration process, we choose prior that is

$$P(\rho) \propto (1-\rho^2)^c$$

where

- c is the weight the prior will have in estimation (i.e., $c = 0$ if no prior info, hence $P(\rho) \propto 1$)

Example:

Current study: $r_{xy} = 0.5, n = 200$

Previous study: $r_{xy} = 0.2765, (n = 50205)$

Combining two, we have the posterior following a normal distribution with the **variance** of

$$\sigma^2_{posterior} = \frac{1}{n_{prior} + n_{Likelihood}} = \frac{1}{200 + 50205} = 0.0000198393$$

Mean

$$\begin{aligned}\mu_{Posterior} &= \sigma^2_{Posterior} \times (n_{prior} \times \tanh^{-1} r_{prior} + n_{likelihood} \times \tanh^{-1} r_{likelihood}) \\ &= 0.0000198393 \times (50205 \times \tanh^{-1} 0.2765 + 200 \times \tanh^{-1} 0.5) \\ &= 0.2849415\end{aligned}$$

Hence, $Posterior \sim N(0.691, 0.0009)$, which means the correlation coefficient is $\tanh(0.691) = 0.598$ and 95% CI is

$$\mu_{posterior} \pm 1.96 \times \sqrt{\sigma^2_{Posterior}} = 0.2849415 \pm 1.96 \times (0.0000198393)^{1/2} = (0.2762115, 0.2936714)$$

Hence, the interval for posterior ρ is $(0.2693952, 0.2855105)$

If future authors suspect that they have

1. Large sampling variation
2. Measurement error in either measures in the correlation, which attenuates the relationship between the two variables

Applying this Bayesian correction can give them a better estimate of the correlation between the two.

To implement this calculation in R, see below

```r
n_new              <- 200
r_new              <- 0.5
alpha              <- 0.05

update_correlation <- function(n_new, r_new, alpha) {
    n_meta             <- 50205
    r_meta             <- 0.2765

    # Variance
    var_xi         <- 1 / (n_new + n_meta)
    format(var_xi, scientific = FALSE)

    # mean
    mu_xi          <- var_xi * (n_meta * atanh(r_meta) + n_new * (atanh(r_new)))
    format(mu_xi, scientific  = FALSE)

    # confidence interval
    upper_xi       <- mu_xi + qnorm(1 - alpha / 2) * sqrt(var_xi)
    lower_xi       <- mu_xi - qnorm(1 - alpha / 2) * sqrt(var_xi)

    # rho
    mean_rho       <- tanh(mu_xi)
    upper_rho      <- tanh(upper_xi)
    lower_rho      <- tanh(lower_xi)

    # return a list
    return(
        list(
            "mu_xi" = mu_xi,
            "var_xi" = var_xi,
            "upper_xi" = upper_xi,
            "lower_xi" = lower_xi,
            "mean_rho" = mean_rho,
            "upper_rho" = upper_rho,
            "lower_rho" = lower_rho
        )
    )
}




# Old confidence interval
r_new + qnorm(1 - alpha / 2) * sqrt(1/n_new)
#> [1] 0.6385904
```

```
r_new - qnorm(1 - alpha / 2) * sqrt(1/n_new)
#> [1] 0.3614096

testing = update_correlation(n_new = n_new, r_new = r_new, alpha = alpha)

# Updated rho
testing$mean_rho
#> [1] 0.2774723

# Updated confidence interval
testing$upper_rho
#> [1] 0.2855105
testing$lower_rho
#> [1] 0.2693952
```

33.1.2 Simultaneity

- When independent variables (X's) are jointly determined with the dependent variable Y, typically through an equilibrium mechanism, violates the second condition for causality (i.e., temporal order).
- Examples: quantity and price by demand and supply, investment and productivity, sales and advertisement

General Simultaneous (Structural) Equations

$$
\begin{aligned}
Y_i &= \beta_0 + \beta_1 X_i + u_i \\
X_i &= \alpha_0 + \alpha_1 Y_i + v_i
\end{aligned}
$$

Hence, the solutions are

$$
\begin{aligned}
Y_i &= \frac{\beta_0 + \beta_1 \alpha_0}{1 - \alpha_1 \beta_1} + \frac{\beta_1 v_i + u_i}{1 - \alpha_1 \beta_1} \\
X_i &= \frac{\alpha_0 + \alpha_1 \beta_0}{1 - \alpha_1 \beta_1} + \frac{v_i + \alpha_1 u_i}{1 - \alpha_1 \beta_1}
\end{aligned}
$$

If we run only one regression, we will have biased estimators (because of **simultaneity bias**):

$$
\begin{aligned}
Cov(X_i, u_i) &= Cov(\frac{v_i + \alpha_1 u_i}{1 - \alpha_1 \beta_1}, u_i) \\
&= \frac{\alpha_1}{1 - \alpha_1 \beta_1} Var(u_i)
\end{aligned}
$$

In an even more general model

$$\begin{cases} Y_i = \beta_0 + \beta_1 X_i + \beta_2 T_i + u_i \\ X_i = \alpha_0 + \alpha_1 Y_i + \alpha_2 Z_i + v_i \end{cases}$$

where

- X_i, Y_i are **endogenous** variables determined within the system
- T_i, Z_i are **exogenous** variables

Then, the reduced form of the model is

$$\begin{cases} Y_i = \dfrac{\beta_0 + \beta_1\alpha_0}{1-\alpha_1\beta_1} + \dfrac{\beta_1\alpha_2}{1-\alpha_1\beta_1} Z_i + \dfrac{\beta_2}{1-\alpha_1\beta_1} T_i + \tilde{u}_i \\ \quad = B_0 + B_1 Z_i + B_2 T_i + \tilde{u}_i \\ X_i = \dfrac{\alpha_0 + \alpha_1\beta_0}{1-\alpha_1\beta_1} + \dfrac{\alpha_2}{1-\alpha_1\beta_1} Z_i + \dfrac{\alpha_1\beta_2}{1-\alpha_1\beta_1} T_i + \tilde{v}_i \\ \quad = A_0 + A_1 Z_i + A_2 T_i + \tilde{v}_i \end{cases}$$

Then, now we can get consistent estimates of the reduced form parameters

And to get the original parameter estimates

$$\begin{aligned} \frac{B_1}{A_1} &= \beta_1 \\ B_2(1 - \frac{B_1 A_2}{A_1 B_2}) &= \beta_2 \\ \frac{A_2}{B_2} &= \alpha_1 \\ A_1(1 - \frac{B_1 A_2}{A_1 B_2}) &= \alpha_2 \end{aligned}$$

Rules for Identification

Order Condition (necessary but not sufficient)

$$K - k \geq m - 1$$

where

- M = number of endogenous variables in the model
- K = number of exogenous variables int he model
- m = number of endogenous variables in a given
- k = is the number of exogenous variables in a given equation

This is actually the general framework for instrumental variables

33.1.3 Endogenous Treatment Solutions

Using the OLS estimates as a reference point

```
library(AER)
library(REndo)
set.seed(421)
data("CASchools")
school <- CASchools
school$stratio <- with(CASchools, students / teachers)
m1.ols <-
    lm(read ~ stratio + english + lunch
       + grades + income + calworks + county,
       data = school)
summary(m1.ols)$coefficients[1:7,]
#>                 Estimate Std. Error     t value      Pr(>|t|)
#> (Intercept) 683.45305948 9.56214469  71.4748711 3.011667e-218
#> stratio      -0.30035544 0.25797023  -1.1643027  2.450536e-01
#> english      -0.20550107 0.03765408  -5.4576041  8.871666e-08
#> lunch        -0.38684059 0.03700982 -10.4523759  1.427370e-22
#> gradesKK-08  -1.91291321 1.35865394  -1.4079474  1.599886e-01
#> income        0.71615378 0.09832843   7.2832829  1.986712e-12
#> calworks     -0.05273312 0.06154758  -0.8567863  3.921191e-01
```

33.1.3.1 Instrumental Variable

A3a requires ϵ_i to be uncorrelated with $\mathbf{x}_i$

Assume A1 , A2, A5

$$plim(\hat{\beta}_{OLS}) = \beta + [E(\mathbf{x_i'x_i})]^{-1}E(\mathbf{x_i'}\epsilon_i)$$

A3a is the weakest assumption needed for OLS to be **consistent**

A3 fails when x_{ik} is correlated with ϵ_i

- Omitted Variables Bias: ϵ_i includes any other factors that may influence the dependent variable (linearly)
- Simultaneity Demand and prices are simultaneously determined.
- Endogenous Sample Selection we did not have iid sample
- Measurement Error

Note

- Omitted Variable: an omitted variable is a variable, omitted from the model (but is in the ϵ_i) and unobserved has predictive power towards the outcome.
- Omitted Variable Bias: is the bias (and inconsistency when looking at large sample properties) of the OLS estimator when the omitted variable.

- We cam have both positive and negative selection bias (it depends on what our story is)

The **structural equation** is used to emphasize that we are interested understanding a **causal relationship**

$$y_{i1} = \beta_0 + \mathbf{z}_i 1\beta_1 + y_{i2}\beta_2 + \epsilon_i$$

where

- y_{it} is the outcome variable (inherently correlated with ϵ_i)
- y_{i2} is the endogenous covariate (presumed to be correlated with ϵ_i)
- β_1 represents the causal effect of y_{i2} on y_{i1}
- $\mathbf{z}_{i1}$ is exogenous controls (uncorrelated with ϵ_i) ($E(z'_{1i}\epsilon_i) = 0$)

OLS is an inconsistent estimator of the causal effect β_2

If there was no endogeneity

- $E(y'_{i2}\epsilon_i) = 0$
- the exogenous variation in y_{i2} is what identifies the causal effect

If there is endogeneity

- Any wiggle in y_{i2} will shift simultaneously with ϵ_i

$$plim(\hat{\beta}_{OLS}) = \beta + [E(\mathbf{x'_i x_i})]^{-1} E(\mathbf{x'_i}\epsilon_i)$$

where

- β is the causal effect
- $[E(\mathbf{x'_i x_i})]^{-1} E(\mathbf{x'_i}\epsilon_i)$ is the endogenous effect

Hence $\hat{\beta}_{OLS}$ can be either more positive and negative than the true causal effect.

Motivation for **Two Stage Least Squares (2SLS)**

$$y_{i1} = \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \epsilon_i$$

We want to understand how movement in y_{i2} effects movement in y_{i1}, but whenever we move y_{i2}, ϵ_i also moves.

Solution
We need a way to move y_{i2} independently of ϵ_i, then we can analyze the response in y_{i1} as a causal effect

- Find an **instrumental variable(s)** z_{i2}
  - Instrument **Relevance**: when** z_{i2} moves then y_{i2} also moves
  - Instrument **Exogeneity**: when z_{i2} moves then ϵ_i does not move.

- z_{i2} is the **exogenous variation that identifies** the causal effect β_2

Finding an Instrumental variable:

- Random Assignment: + Effect of class size on educational outcomes: instrument is initial random
- Relation's Choice + Effect of Education on Fertility: instrument is parent's educational level
- Eligibility + Trade-off between IRA and 401K retirement savings: instrument is 401k eligibility

Example

Return to College

- education is correlated with ability - endogenous
- **Near 4year** as an instrument
  - Instrument Relevance: when **near** moves then education also moves
  - Instrument Exogeneity: when **near** moves then ϵ_i does not move.
- Other potential instruments; near a 2-year college. Parent's Education. Owning Library Card

$$y_{i1} = \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \epsilon_i$$

First Stage (Reduced Form) Equation:

$$y_{i2} = \pi_0 + \mathbf{z_{i1\ 1}} + \mathbf{z_{i2\ 2}} + v_i$$

where

- $\pi_0 + \mathbf{z_{i1\ 1}} + \mathbf{z_{i2\ 2}}$ is exogenous variation v_i is endogenous variation

This is called a **reduced form equation**

- Not interested in the causal interpretation of π_1 or π_2
- A linear projection of z_{i1} and z_{i2} on y_{i2} (simple correlations)
- The projections π_1 and π_2 guarantee that $E(z'_{i1}v_i) = 0$ and $E(z'_{i2}v_i) = 0$

Instrumental variable z_{i2}

- **Instrument Relevance**: $\pi_2 \neq 0$
- **Instrument Exogeneity**: $E(\mathbf{z_{i2\ i}}) = 0$

Moving only the exogenous part of y_i2 is moving

$$\tilde{y}_{i2} = \pi_0 + \mathbf{z_{i1\ 1}} + \mathbf{z_{i2\ 2}}$$

two Stage Least Squares (2SLS)

$$y_{i1} = \beta_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + y_{i2}\beta_2 + \epsilon_i$$

$$y_{i2} = \pi_0 + \mathbf{z_{i2}}_{\ \mathbf{2}} + \mathbf{v_i}$$

Equivalently,

$$y_{i1} = \beta_0 + \mathbf{z_{i1}}\beta_1 + \tilde{y}_{i2}\beta_2 + u_i \tag{33.1}$$

where

- $\tilde{y}_{i2} = \pi_0 + \mathbf{z_{i2}}_{\ \mathbf{2}}$
- $u_i = v_i\beta_2 + \epsilon_i$

The (33.1) holds for A1, A5

- A2 holds if the instrument is relevant $\pi_2 \neq 0$ + $y_{i1} = \beta_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + (\ _{\mathbf{0}} + \mathbf{z_{i1}}_{\ \mathbf{1}} + \mathbf{z_{i2}}_{\ \mathbf{2}})\beta_2 + u_i$
- A3a holds if the instrument is exogenous $E(\mathbf{z}_{i2}\epsilon_i) = 0$

$$\begin{aligned} E(\tilde{y}'_{i2}u_i) &= E((\pi_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + \mathbf{z_{i2}})(v_i\beta_2 + \epsilon_i)) \\ &= E((\pi_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + \mathbf{z_{i2}})(\epsilon_i)) \\ &= E(\epsilon_i)\pi_0 + E(\epsilon_i z_{i1})\pi_1 + E(\epsilon_i z_{i2}) \\ &= 0 \end{aligned}$$

Hence, (33.1) is consistent

The 2SLS Estimator
1. Estimate the first stage using OLS

$$y_{i2} = \pi_0 + \mathbf{z_{i2}}_{\ \mathbf{2}} + \mathbf{v_i}$$

and obtained estimated value $\hat{y}_{i2}$

2. Estimate the altered equation using OLS

$$y_{i1} = \beta_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + \hat{y}_{i2}\beta_2 + \epsilon_i$$

Properties of the 2SLS Estimator

- Under A1, A2, A3a (for z_{i1}), A5 and if the instrument satisfies the following two conditions, + **Instrument Relevance**: $\pi_2 \neq 0$ + **Instrument Exogeneity**: $E(\mathbf{z}'_{i2}\epsilon_i) = 0$ then the 2SLS estimator is consistent

- Can handle more than one endogenous variable and more than one instrumental variable

$$
\begin{aligned}
y_{i1} &= \beta_0 + z_{i1}\beta_1 + y_{i2}\beta_2 + y_{i3}\beta_3 + \epsilon_i \\
y_{i2} &= \pi_0 + z_{i1}\pi_1 + z_{i2}\pi_2 + z_{i3}\pi_3 + z_{i4}\pi_4 + v_{i2} \\
y_{i3} &= \gamma_0 + z_{i1}\gamma_1 + z_{i2}\gamma_2 + z_{i3}\gamma_3 + z_{i4}\gamma_4 + v_{i3}
\end{aligned}
$$

```
+ **IV estimator**: one endogenous variable with a single instrument
+ **2SLS estimator**: one endogenous variable with multiple instruments
+ **GMM estimator**: multiple endogenous variables with multiple instruments
```

- Standard errors produced in the second step are not correct
  - Because we do not know $\tilde{y}$ perfectly and need to estimate it in the firs step, we are introducing additional variation
  - We did not have this problem with FGLS because "the first stage was orthogonal to the second stage." This is generally not true for most multi-step procedure.
  - If A4 does not hold, need to report robust standard errors.
- 2SLS is less efficient than OLS and will always have larger standard errors.
  - First, $Var(u_i) = Var(v_i\beta_2 + \epsilon_i) > Var(\epsilon_i)$
  - Second, $\hat{y}_{i2}$ is generally highly collinear with $\mathbf{z}_{i1}$
- The number of instruments need to be at least as many or more the number of endogenous variables.

Note

- 2SLS can be combined with FGLS to make the estimator more efficient: You have the same first-stage, and in the second-stage, instead of using OLS, you can use FLGS with the weight matrix $\hat{w}$
- Generalized Method of Moments can be more efficient than 2SLS.
- In the second-stage of 2SLS, you can also use MLE, but then you are making assumption on the distribution of the outcome variable, the endogenous variable, and their relationship (joint distribution).

33.1.3.1.1 Testing Assumptions

1. Endogeneity Test: Is y_{i2} truly endogenous (i.e., can we just use OLS instead of 2SLS)?
2. Exogeneity (Cannot always test and when you can it might not be informative)

3. Relevancy (need to avoid "weak instruments")

33.1.3.1.1.1 Endogeneity Test

- 2SLS is generally so inefficient that we may prefer OLS if there is not much endogeneity
- Biased but inefficient vs efficient but biased
- Want a sense of "how endogenous" y_{i2} is
  - if "very" endogenous - should use 2SLS
  - if not "very" endogenous - perhaps prefer OLS

Invalid Test of Endogeneity: y_{i2} is endogenous if it is correlated with ϵ_i,

$$\epsilon_i = \gamma_0 + y_{i2}\gamma_1 + error_i$$

where $\gamma_1 \neq 0$ implies that there is endogeneity

- ϵ_i is not observed, but using the residuals

$$e_i = \gamma_0 + y_{i2}\gamma_1 + error_i$$

is **NOT** a valid test of endogeneity + The OLS residual, e is mechanically uncorrelated with y_{i2} (by FOC for OLS) + In every situation, γ_1 will be essentially 0 and you will never be able to reject the null of no endogeneity

Valid test of endogeneity

- If y_{i2} is not endogenous then ϵ_i and v are uncorrelated

$$\begin{aligned} y_{i1} &= \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \epsilon_i \\ y_{i2} &= \pi_0 + \mathbf{z}_{i1}\pi_1 + z_{i2}\pi_2 + v_i \end{aligned}$$

Variable Addition test: include the first stage residuals as an additional variable,

$$y_{i1} = \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \hat{v}_i\theta + error_i$$

Then the usual t-test of significance is a valid test to evaluate the following hypothesis. **note** this test requires your instrument to be valid instrument.

$$\begin{aligned} H_0 &: \theta = 0 \quad \text{(not endogenous)} \\ H_1 &: \theta \neq 0 \quad \text{(endogenous)} \end{aligned}$$

33.1.3.1.1.2 Exogeneity Why exogeneity matter?

$$E(\mathbf{z}_{i2}'\epsilon_i) = 0$$

- If A3a fails - 2SLS is also inconsistent
- If instrument is not exogenous, then we need to find a new one.
- Similar to Endogeneity Test, when there is a single instrument

$$e_i = \gamma_0 + \mathbf{z}_{i2}\gamma_1 + error_i$$
$$H_0 : \gamma_1 = 0$$

is **NOT** a valid test of endogeneity

- the OLS residual, e is mechanically uncorrelated with z_{i2}: $\hat{\gamma}_1$ will be essentially 0 and you will never be able to determine if the instrument is endogenous.

Solution

Testing Instrumental Exogeneity in an Over-identified Model

- When there is more than one exogenous instrument (per endogenous variable), we can test for instrument exogeneity.
  - When we have multiple instruments, the model is said to be over-identified.
  - Could estimate the same model several ways (i.e., can identify/ estimate β_1 more than one way)
- Idea behind the test: if the controls and instruments are truly exogenous then OLS estimation of the following regression,

$$\epsilon_i = \gamma_0 + \mathbf{z}_{i1}\gamma_1 + \mathbf{z}_{i2}\gamma_2 + error_i$$

should have a very low R^2

- if the model is **just identified** (one instrument per endogenous variable) then the $R^2 = 0$

Steps:

(1) Estimate the structural equation by 2SLS (using all available instruments) and obtain the residuals e

(2) Regress e on all controls and instruments and obtain the R^2

(3) Under the null hypothesis (all IV's are uncorrelated), $nR^2 \sim \chi^2(q)$, where q is the number of instrumental variables minus the number of endogenous variables

- if the model is just identified (one instrument per endogenous variable) then q = 0, and the distribution under the null collapses.

low p-value means you reject the null of exogenous instruments. Hence you would like to have high p-value in this test.

Pitfalls for the Overid test

- the overid test is essentially compiling the following information.
  - Conditional on first instrument being exogenous is the other instrument exogenous?
  - Conditional on the other instrument being exogenous, is the first instrument exogenous?
- If all instruments are endogenous than neither test will be valid
- really only useful if one instrument is thought to be truly exogenous (randomly assigned). even f you do reject the null, the test does not tell you which instrument is exogenous and which is endogenous.

Result	Implication
reject the null	you can be pretty sure there is an endogenous instrument, but don't know which one.
fail to reject	could be either (1) they are both exogenous, (2) they are both endogenous.

33.1.3.1.1.3 Relevancy Why Relevance matter?

$$\pi_2 \neq 0$$

- used to show A2 holds
  - If $\pi_2 = 0$ (instrument is not relevant) then A2 fails - perfect multicollinearity
  - If π_2 is close to 0 (**weak instrument**) then there is near perfect multicollinearity - 2SLS is highly inefficient (Large standard errors).
- A weak instrument will exacerbate any inconsistency due to an instrument being (even slightly) endogenous.
  - In the simple case with no controls and a single endogenous variable and single instrumental variable,

$$plim(\hat{\beta}_{2_{2SLS}}) = \beta_2 + \frac{E(z_{i2}\epsilon_i)}{E(z_{i2}y_{i2})}$$

Testing Weak Instruments

- can use t-test (or F-test for over-identified models) in the first stage to determine if there is a weak instrument problem.
- (Stock and Yogo, 2002, Stock and Yogo (2005a)): a statistical rejection of the null hypothesis in the first stage at the 5% (or even 1%) level is not enough to insure the instrument is not weak
  - Rule of Thumb: need a F-stat of at least 10 (or a t-stat of at least 3.2) to reject the null hypothesis that the instrument is weak.

Summary of the 2SLS Estimator

$$y_{i1} = \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \epsilon_i$$
$$y_{i2} = \pi_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + \mathbf{z_{i2}}_{\ \mathbf{2}} + v_i$$

- when A3a does not hold

$$E(y_{i2}'\epsilon_i) \neq 0$$

- Then the OLS estimator is no longer unbiased or consistent.
- If we have valid instruments $\mathbf{z}_{i2}$
- Relevancy (need to avoid "weak instruments"): $\pi_2 \neq 0$ Then the 2SLS estimator is consistent under A1, A2, A5a, and the above two conditions.
  - If A4 also holds, then the usual standard errors are valid.
  - If A4 does not hold then use the robust standard errors.

$$y_{i1} = \beta_0 + \mathbf{z}_{i1}\beta_1 + y_{i2}\beta_2 + \epsilon_i$$
$$y_{i2} = \pi_0 + \mathbf{z_{i1}}_{\ \mathbf{1}} + \mathbf{z_{i2}}_{\ \mathbf{2}} + v_i$$

- When A3a does hold

$$E(y_{i2}'\epsilon_i) = 0$$

and we have valid instruments, then both the OLS and 2SLS estimators are consistent.

- The OLS estimator is always more efficient
- can use the variable addition test to determine if 2SLS is need (A3a does hold) or if OLS is valid (A3a does not hold)

Sometimes we can test the assumption for instrument to be valid:

- Exogeneity : Only table when there are more instruments than endogenous variables.
- Relevancy (need to avoid "weak instruments"): Always testable, need the F-stat to be greater than 10 to rule out a weak instrument

Application

Expenditure as observed instrument

```
m2.2sls <-
    ivreg(
        read ~ stratio + english + lunch
        + grades + income + calworks + county |

            expenditure + english + lunch
        + grades + income + calworks + county ,
        data = school
    )
summary(m2.2sls)$coefficients[1:7,]
#>                 Estimate  Std. Error     t value      Pr(>|t|)
#> (Intercept) 700.47891593 13.58064436  51.5792106 8.950497e-171
#> stratio      -1.13674002  0.53533638  -2.1234126  3.438427e-02
#> english      -0.21396934  0.03847833  -5.5607753  5.162571e-08
#> lunch        -0.39384225  0.03773637 -10.4366757  1.621794e-22
#> gradesKK-08  -1.89227865  1.37791820  -1.3732881  1.704966e-01
#> income        0.62487986  0.11199008   5.5797785  4.668490e-08
#> calworks     -0.04950501  0.06244410  -0.7927892  4.284101e-01
```

33.1.3.1.2 Checklist

1. Regress the dependent variable on the instrument (reduced form). Since under OLS, we have unbiased estimate, the coefficient estimate should be significant (make sure the sign makes sense)
2. Report F-stat on the excluded instruments. F-stat < 10 means you have a weak instrument (Stock et al., 2002).
3. Present R^2 before and after including the instrument (Rossi, 2014)
4. For models with multiple instrument, present firs-t and second-stage result for each instrument separately. Overid test should be conducted (e.g., Sargan-Hansen J)
5. Hausman test between OLS and 2SLS (don't confuse this test for evidence that endogeneity is irrelevant - under invalid IV, the test is useless)
6. Compare the 2SLS with the limited information ML. If they are different, you have evidence for weak instruments.

33.1.3.2 Good Instruments

Exogeneity and Relevancy are necessary but not sufficient for IV to produce consistent estimates.

Without theory or possible explanation, you can always create a new variable that is correlated with X and uncorrelated with ϵ

For example, we want to estimate the effect of price on quantity (Reiss, 2011,

p. 960)

$$Q = \beta_1 P + \beta_2 X + \epsilon$$
$$P = \pi_1 X + \eta$$

where ϵ and η are jointly determined, $X \perp \epsilon, \eta$

Without theory, we can just create a new variable $Z = X + u$ where $E(u) = 0; u \perp X, \epsilon, \eta$

Then, Z satisfied both conditions:

- Relevancy: X correlates $P \rightarrow Z$ correlates P
- Exogeneity: $u \perp \epsilon$ (random noise)

But obviously, it's not a valid instrument (intuitively). But theoretically, relevance and exogeneity are not sufficient to identify β because of unsatisfied rank condition for identification.

Moreover, the functional form of the instrument also plays a role when choosing a good instrument. Hence, we always need to check for the robustness of our instrument.

IV methods even with valid instruments can still have poor sampling properties (finite sample bias, large sampling errors) (Rossi, 2014)

When you have a weak instrument, it's important to report it appropriately. This problem will be exacerbated if you have multiple instruments (Larcker and Rusticus, 2010).

33.1.3.2.1 Lagged dependent variable In time series data sets, we can use lagged dependent variable as an instrument because it is not influenced by current shocks. For example, Chetty et al. (2014) used lagged dependent variable in econ.

33.1.3.2.2 Lagged explanatory variable

- Common practice in applied economics: Replace suspected simultaneously determined explanatory variable with its lagged value (Reed, 2015, Bellemare et al. (2017)).
  - This practice does not avoid simultaneity bias.
  - Estimates using this method are still inconsistent.
  - Hypothesis testing becomes invalid under this approach.
  - Lagging variables changes how endogeneity bias operates, adding a "no dynamics among unobservables" assumption to the "selection on observables" assumption.

- Key conditions for appropriate use (Bellemare et al., 2017):
  - **Under unobserved confounding:**
    - No dynamics among unobservables.
    - The lagged variable X is a stationary autoregressive process.
  - **Under no unobserved confounding:**
    - No reverse causality; the causal effect operates with a one-period lag ($X_{t-1} \to Y$, $X_t \not\to Y_t$).
    - Reverse causality is contemporaneous, with a one-period lag effect.
    - Reverse causality is contemporaneous; no dynamics in Y, but dynamics exist in X ($X_{t-1} \to X$).
- **Alternative approach**: Use lagged values of the endogenous variable in IV estimation. However, IV estimation is only effective if (Reed, 2015):
  - Lagged values do not belong in the estimating equation.
  - Lagged values are sufficiently correlated with the simultaneously determined explanatory variable.
  - Lagged IVs help mitigate endogeneity if they only violate the independence assumption. However, if lagged IVs violate both the independence assumption and exclusion restriction, they may aggravate endogeneity (Wang and Bellemare, 2019).

33.1.3.3 Internal instrumental variable

- (also known as **instrument free methods**). This section is based on Raluca Gui's guide
- alternative to external instrumental variable approaches
- All approaches here assume a **continuous dependent variable**

33.1.3.3.1 Non-hierarchical Data (Cross-classified)

$$Y_t = \beta_0 + \beta_1 P_t + \beta_2 X_t + \epsilon_t$$

where

- $t = 1, .., T$ (indexes either time or cross-sectional units)
- Y_t is a $k \times 1$ response variable
- X_t is a $k \times n$ exogenous regressor
- P_t is a $k \times 1$ continuous endogenous regressor
- ϵ_t is a structural error term with $\mu_\epsilon = 0$ and $E(\epsilon^2) = \sigma^2$
- β are model parameters

The endogeneity problem arises from the correlation of P_t and ϵ_t:

$$P_t = \gamma Z_t + v_t$$

where

- Z_t is a $l \times 1$ vector of internal instrumental variables
- ν_t is a random error with $\mu_{v_t}, E(v^2) = \sigma_v^2, E(\epsilon v) = \sigma_{\epsilon v}$
- Z_t is assumed to be stochastic with distribution G
- ν_t is assumed to have density $h(\cdot)$

33.1.3.3.1.1 Latent Instrumental Variable (Ebbes et al., 2005)

assume Z_t (unobserved) to be uncorrelated with ϵ_t, which is similar to Instrumental Variable. Hence, Z_t and ν_t can't be identified without distributional assumptions

The distributions of Z_t and ν_t need to be specified such that:

(1) endogeneity of P_t is corrected
(2) the distribution of P_t is empirically close to the integral that expresses the amount of overlap of Z as it is shifted over (= the convolution between Z_t and ν_t).

When the density h(·) = Normal, then G cannot be normal because the parameters would not be identified (Ebbes et al., 2005) .

Hence,

- in the LIV model the distribution of Z_t is discrete
- in the Higher Moments Method and Joint Estimation Using Copula methods, the distribution of Z_t is taken to be skewed.

Z_t are assumed **unobserved, discrete and exogenous**, with

- an unknown number of groups m
- γ is a vector of group means.

Identification of the parameters relies on the distributional assumptions of

- P_t: a non-Gaussian distribution
- Z_t discrete with $m \geq 2$

Note:

- If Z_t is continuous, the model is unidentified
- If $P_t \sim N$, you have inefficient estimates.

```
m3.liv <- latentIV(read ~ stratio, data = school)
summary(m3.liv)$coefficients[1:7, ]
#>                  Estimate    Std. Error       z-score     Pr(>|z|)
#> (Intercept)   6.996014e+02  2.686186e+02  2.604441e+00 9.529597e-03
#> stratio      -2.272673e+00  1.367757e+01 -1.661605e-01 8.681108e-01
```

```
#> pi1          -4.896363e+01  5.526907e-08 -8.859139e+08 0.000000e+00
#> pi2           1.963920e+01  9.225351e-02  2.128830e+02 0.000000e+00
#> theta5       6.939432e-152 3.354672e-160  2.068587e+08 0.000000e+00
#> theta6        3.787512e+02  4.249457e+01  8.912932e+00 1.541524e-17
#> theta7       -1.227543e+00  4.885276e+01 -2.512741e-02 9.799653e-01
```

it will return a coefficient very different from the other methods since there is only one endogenous variable.

33.1.3.3.1.2 Joint Estimation Using Copula assume Z_t (unobserved) to be uncorrelated with ϵ_t, which is similar to Instrumental Variable. Hence, Z_t and ν_t can't be identified without distributional assumptions

(Park and Gupta, 2012) allows joint estimation of the continuous P_t and ϵ_t using Gaussian copulas, where a copula is a function that maps several conditional distribution functions (CDF) into their joint CDF).

The underlying idea is that using information contained in the observed data, one selects marginal distributions for P_t and ϵ_t. Then, the copula model constructs a flexible multivariate joint distribution that allows a wide range of correlations between the two marginals.

The method allows both continuous and discrete P_t.

In the special case of **one continuous** P_t, estimation is based on MLE
Otherwise, based on Gaussian copulas, augmented OLS estimation is used.

Assumptions:

- skewed P_t
- the recovery of the correct parameter estimates
- $\epsilon_t \sim$ normal marginal distribution. The marginal distribution of P_t is obtained using the **Epanechnikov kernel density estimator**

$$\hat{h}_p = \frac{1}{T.b} \sum_{t=1}^{T} K(\frac{p - P_t}{b})$$

  where

- P_t = endogenous variables
- $K(x) = 0.75(1 - x^2)I(||x|| \leq 1)$
- $b = 0.9T^{-1/5} \times min(s, IQR/1.34)$
  - IQR = interquartile range
  - s = sample standard deviation
  - T = n of time periods observed in the data

```
# 1.34 comes from this
diff(qnorm(c(0.25, 0.75)))
#> [1] 1.34898
```

In augmented OLS and MLE, the inference procedure occurs in two stages:

(1): the empirical distribution of P_t is computed
(2) used in it constructing the likelihood function)
Hence, the standard errors would not be correct.

So we use the sampling distributions (from bootstrapping) to get standard errors and the variance-covariance matrix. Since the distribution of the bootstrapped parameters is highly skewed, we report the percentile confidence intervals is preferable.

```
set.seed(110)
m4.cc <-
    copulaCorrection(
        read ~ stratio + english + lunch + calworks +
            grades + income + county |
            continuous(stratio),
        data = school,
        optimx.args = list(method = c("Nelder-Mead"),
                           itnmax = 60000),
        num.boots = 2,
        verbose = FALSE
    )
summary(m4.cc)$coefficients[1:7,]
#>              Point Estimate   Boots SE Lower Boots CI (95%) Upper Boots CI (95%)
#> (Intercept)   683.06900891 2.80554212                   NA                    NA
#> stratio        -0.32434608 0.02075999                   NA                    NA
#> english        -0.21576110 0.01450666                   NA                    NA
#> lunch          -0.37087664 0.01902052                   NA                    NA
#> calworks       -0.05569058 0.02076781                   NA                    NA
#> gradesKK-08    -1.92286128 0.25684614                   NA                    NA
#> income          0.73595353 0.04725700                   NA                    NA
```

we run this model with only one endogenous continuous regressor (`stratio`). Sometimes, the code will not converge, in which case you can use different

- optimization algorithm
- starting values
- maximum number of iterations

33.1.3.3.1.3 Higher Moments Method suggested by (Lewbel, 1997) to identify ϵ_t caused by **measurement error**.

Identification is achieved by using third moments of the data, with no restric-

tions on the distribution of ϵ_t
The following instruments can be used with 2SLS estimation to obtain consistent estimates:

$$
\begin{aligned}
q_{1t} &= (G_t - \bar{G}) \\
q_{2t} &= (G_t - \bar{G})(P_t - \bar{P}) \\
q_{3t} &= (G_t - \bar{G})(Y_t - \bar{Y}) \\
q_{4t} &= (Y_t - \bar{Y})(P_t - \bar{P}) \\
q_{5t} &= (P_t - \bar{P})^2 \\
q_{6t} &= (Y_t - \bar{Y})^2
\end{aligned}
$$

where

- $G_t = G(X_t)$ for any given function G that has finite third own and cross moments
- $X =$ exogenous variable

q_{5t}, q_{6t} can be used only when the measurement and ϵ_t are symmetrically distributed. The rest of the instruments does not require any distributional assumptions for ϵ_t.

Since the regressors $G(X) = X$ are included as instruments, $G(X)$ can't be a linear function of X in q_{1t}

Since this method has very strong assumptions, Higher Moments Method should only be used in case of overidentification

```
set.seed(111)
m5.hetEr <-
    hetErrorsIV(
        read ~ stratio + english + lunch + calworks + income +
            grades + county |
            stratio | IIV(income, english),
        data = school
    )
summary(m5.hetEr)$coefficients[1:7,]
#>                 Estimate  Std. Error    t value     Pr(>|t|)
#> (Intercept) 662.78791557 27.90173069 23.7543657 2.380436e-76
#> stratio       0.71480686  1.31077325  0.5453322 5.858545e-01
#> english      -0.19522271  0.04057527 -4.8113717 2.188618e-06
#> lunch        -0.37834232  0.03927793 -9.6324402 9.760809e-20
#> calworks     -0.05665126  0.06302095 -0.8989273 3.692776e-01
#> income        0.82693755  0.17236557  4.7975797 2.335271e-06
#> gradesKK-08  -1.93795843  1.38723186 -1.3969968 1.632541e-01
```

recommend using this approach to create additional instruments to use with external ones for better efficiency.

33.1.3.3.1.4 Heteroskedastic Error Approach

- using means of variables that are uncorrelated with the product of heteroskedastic errors to identify structural parameters.
- This method can be use either when you don't have external instruments or you want to use additional instruments to improve the efficiency of the IV estimator (Lewbel, 2012)
- The instruments are constructed as simple functions of data
- Model's assumptions:

$$\begin{aligned} E(X\epsilon) &= 0 \\ E(Xv) &= 0 \\ cov(Z, \epsilon v) &= 0 \\ cov(Z, v^2) &\neq 0 \text{ (for identification)} \end{aligned}$$

Structural parameters are identified by 2SLS regression of Y on X and P, using X and [Z − E(Z)] as instruments.

$$\text{instrument's strength} \propto cov((Z - \bar{Z})v, v)$$

where $cov((Z - \bar{Z})v, v)$ is the degree of heteroskedasticity of with respect to Z (Lewbel, 2012), which can be empirically tested.

If it is zero or close to zero (i.e.,the instrument is weak), you might have imprecise estimates, with large standard errors.

- Under homoskedasticity, the parameters of the model are unidentified.
- Under heteroskedasticity related to at least some elements of X, the parameters of the model are identified.

33.1.3.3.2 Hierarchical Data Multiple independent assumptions involving various random components at different levels mean that any moderate correlation between some predictors and a random component or error term can result in a significant bias of the coefficients and of the variance components. (Kim and Frees, 2007) proposed a generalized method of moments which uses both, the between and within variations of the exogenous variables, but only assumes the within variation of the variables to be endogenous.

Assumptions

- the errors at each level $\sim iidN$
- the slope variables are exogenous
- the level-1 $\epsilon \perp X, P$. If this is not the case, additional, external instruments are necessary

Hierarchical Model

$$
\begin{aligned}
Y_{cst} &= Z^1_{cst}\beta^1_{cs} + X^1_{cst}\beta_1 + \epsilon^1_{cst} \\
\beta^1_{cs} &= Z^2_{cs}\beta^2_c + X^2_{cst}\beta_2 + \epsilon^2_{cst} \\
\beta^2_c &= X^3_c\beta_3 + \epsilon^3_c
\end{aligned}
$$

Bias could stem from:

- errors at the higher two levels ($\epsilon^3_c, \epsilon^2_{cst}$) are correlated with some of the regressors
- only third level errors (ϵ^3_c) are correlated with some of the regressors

(Kim and Frees, 2007) proposed

- When all variables are assumed exogenous, the proposed estimator equals the random effects estimator
- When all variables are assumed endogenous, it equals the fixed effects estimator
- also use omitted variable test (based on the Hausman-test (Hausman, 1978) for panel data), which allows the comparison of a robust estimator and an estimator that is efficient under the null hypothesis of no omitted variables or the comparison of two robust estimators at different levels.

```
# function 'cholmod_factor_ldetA' not provided by package 'Matrix'
set.seed(113)
school$gr08 <- school$grades == "KK-06"
m7.multilevel <-
    multilevelIV(read ~ stratio + english + lunch + income + gr08 +
                     calworks + (1 | county) | endo(stratio),
                 data = school)
summary(m7.multilevel)$coefficients[1:7,]
```

Another example using simulated data

- level-1 regressors: $X_{11}, X_{12}, X_{13}, X_{14}, X_{15}$, where X_{15} is correlated with the level-2 error (i.e., endogenous).

- level-2 regressors: $X_{21}, X_{22}, X_{23}, X_{24}$

- level-3 regressors: X_{31}, X_{32}, X_{33}

We estimate a three-level model with X15 assumed endogenous. Having a three-level hierarchy, `multilevelIV()` returns five estimators, from the most robust to omitted variables (FE_L2), to the most efficient (REF) (i.e. lowest mean squared error).

- The random effects estimator (REF) is efficient assuming no omitted variables

- The fixed effects estimator (FE) is unbiased and asymptotically normal even in the presence of omitted variables.
- Because of the efficiency, the random effects estimator is preferable if you think there is no omitted. variables
- The robust estimator would be preferable if you think there is omitted variables.

```
# function 'cholmod_factor_ldetA' not provided by package 'Matrix''
data(dataMultilevelIV)
set.seed(114)
formula1 <-
    y ~ X11 + X12 + X13 + X14 + X15 + X21 + X22 + X23 + X24 +
    X31 + X32 + X33 + (1 | CID) + (1 | SID) | endo(X15)
m8.multilevel <-
    multilevelIV(formula = formula1, data = dataMultilevelIV)
coef(m8.multilevel)

summary(m8.multilevel, "REF")
```

True $\beta_{X_{15}} = -1$. We can see that some estimators are bias because X_{15} is correlated with the level-two error, to which only FE_L2 and GMM_L2 are robust

To select the appropriate estimator, we use the omitted variable test.

In a three-level setting, we can have different estimator comparisons:

- Fixed effects vs. random effects estimators: Test for omitted level-two and level-three omitted effects, simultaneously, one compares FE_L2 to REF. But we will not know at which omitted variables exist.

- Fixed effects vs. GMM estimators: Once the existence of omitted effects is established but not sure at which level, we test for level-2 omitted effects by comparing FE_L2 vs GMM_L3. If you reject the null, the omitted variables are at level-2 The same is accomplished by testing FE_L2 vs. GMM_L2, since the latter is consistent only if there are no omitted effects at level-2.

- Fixed effects vs. fixed effects estimators: We can test for omitted level-2 effects, while allowing for omitted level-3 effects by comparing FE_L2 vs. FE_L3 since FE_L2 is robust against both level-2 and level-3 omitted effects while FE_L3 is only robust to level-3 omitted variables.

Summary, use the omitted variable test comparing `REF vs. FE_L2` first.

- If the null hypothesis is rejected, then there are omitted variables either at level-2 or level-3

- Next, test whether there are level-2 omitted effects, since testing for omit-

ted level three effects relies on the assumption there are no level-two omitted effects. You can use any of these pair of comparisons:

  - `FE_L2 vs. FE_L3`
  - `FE_L2 vs. GMM_L2`

- If no omitted variables at level-2 are found, test for omitted level-3 effects by comparing either

  - `FE_L3` vs. `GMM_L3`
  - `GMM_L2` vs. `GMM_L3`

```
summary(m8.multilevel, "REF")
# compare REF with all the other estimators. Testing REF (the most efficient estimator) against F
```

Since the null hypothesis is rejected (p = 0.000139), there is bias in the random effects estimator.

To test for level-2 omitted effects (regardless of level-3 omitted effects), we compare FE_L2 versus FE_L3

```
summary(m8.multilevel,"FE_L2")
```

The null hypothesis of no omitted level-2 effects is rejected ($p = 3.92e - 05$). Hence, there are omitted effects at level-two. We should use FE_L2 which is consistent with the underlying data that we generated (level-2 error correlated with $X_1 5$, which leads to biased FE_L3 coefficients.

The omitted variable test between FE_L2 and GMM_L2 should reject the null hypothesis of no omitted level-2 effects (p-value is 0).

If we assume an endogenous variable as exogenous, the RE and GMM estimators will be biased because of the wrong set of internal instrumental variables. To increase our confidence, we should compare the omitted variable tests when the variable is considered endogenous vs. exogenous to get a sense whether the variable is truly endogenous.

33.1.3.4 Proxy Variables

- Can be in place of the omitted variable
- will not be able to estimate the effect of the omitted variable
- will be able to reduce some endogeneity caused bye the omitted variable
- but it can have Measurement Error. Hence, you have to be extremely careful when using proxies.

Criteria for a proxy variable:

1. The proxy is correlated with the omitted variable.
2. Having the omitted variable in the regression will solve the problem of endogeneity

3. The variation of the omitted variable unexplained by the proxy is uncorrelated with all independent variables, including the proxy.

IQ test can be a proxy for ability in the regression between wage explained education.

For the third requirement

$$ability = \gamma_0 + \gamma_1 IQ + \epsilon$$

where ϵ is uncorrelated with education and IQ test.

33.2 Endogenous Sample Selection

- Also known as sample selection or self-selection problem or incidental truncation.
- The omitted variable is how people were selected into the sample

Some disciplines consider nonresponse bias and selection bias as sample selection.

- When unobservable factors that affect who is in the sample are independent of unobservable factors that affect the outcome, the sample selection is not endogenous. Hence, the sample selection is ignorable and estimator that ignores sample selection is still consistent.
- when the unobservable factors that affect who is included in the sample are correlated with the unobservable factors that affect the outcome, the sample selection is endogenous and not ignorable, because estimators that ignore endogenous sample selection are not consistent (we don't know which part of the observable outcome is related to the causal relationship and which part is due to different people were selected for the treatment and control groups).

Assumptions: - The unobservables that affect the treatment selection and the outcome are jointly distributed as bivariate normal.

Notes:

- If you don't have strong exclusion restriction, identification is driven by the assumed non linearity in the functional form (through inverse Mills ratio). E.g., the estimate depend on the bivariate normal distribution of the error structure:
  - With strong exclusion restriction for the covariate in the correction equation, the variation in this variable can help identify the control for selection

  - With weak exclusion restriction, and the variable exists in both steps, it's the assumed error structure that identifies the control for selection (Heckman and Navarro-Lozano, 2004).

- In management, Wolfolds and Siegel (2019) found that papers should have valid exclusion conditions, because without these, simulations show that results using the Heckman method are less reliable than those obtained with OLS.

- There are differences between Heckman Sample Selection vs. Heckman-type correction

	Heckman Sample Selection Model	**Heckman-Type Corrections**
When	Only observes one sample (treated), addressing selection bias directly.	Two samples are observed (treated and untreated), known as the control function approach.
Model	Probit	OLS (even for dummy endogenous variable)
Integration of 1st stage	Also include a term (called Inverse Mills ratio) besides the endogenous variable.	Decompose the endogenous variable to get the part that is uncorrelated with the error terms of the outcome equation. Either use the predicted endogenous variable directly or include the residual from the first-stage equation.
Advantages and Assumptions	Provides a direct test for endogeneity via the coefficient of the inverse Mills ratio but requires the assumption of joint normality of errors.	Does not require the assumption of joint normality, but can't test for endogeneity directly.

To deal with [Sample Selection], we can

- Randomization: participants are randomly selected into treatment and control.
- Instruments that determine the treatment status (i.e., treatment vs. control) but not the outcome (Y)
- Functional form of the selection and outcome processes: originated from (Heckman, 1976), later on generalize by (Amemiya, 1984)

We have our main model

$$\mathbf{y}^* = \mathbf{xb} +$$

However, the pattern of missingness (i.e., censored) is related to the unobserved (latent) process:

$$\mathbf{z}^* = \mathbf{w} \ + \mathbf{u}$$

and

$$z_i = \begin{cases} 1 & \text{if } z_i^* > 0 \\ 0 & \text{if } z_i^* \leq 0 \end{cases}$$

Equivalently, $z_i = 1$ (y_i is observed) when

$$u_i \geq -w_i\gamma$$

Hence, the probability of observed y_i is

$$\begin{aligned} P(u_i \geq -w_i\gamma) &= 1 - \Phi(-w_i\gamma) \\ &= \Phi(w_i\gamma) \qquad \text{symmetry of the standard normal distribution} \end{aligned}$$

We will **assume**

- the error term of the selection $\mathbf{u} \sim \mathbf{N}(\mathbf{0}, \mathbf{I})$
- $Var(u_i) = 1$ for identification purposes

Visually, $P(u_i \geq -w_i\gamma)$ is the shaded area.

```
x = seq(-3, 3, length = 200)
y = dnorm(x, mean = 0, sd = 1)
plot(x,
     y,
     type = "l",
     main = bquote("Probabibility distribution of" ~ u[i]))
x = seq(0.3, 3, length = 100)
y = dnorm(x, mean = 0, sd = 1)
polygon(c(0.3, x, 3), c(0, y, 0), col = "gray")
text(1, 0.1, bquote(1 - Phi ~ (-w[i] ~ gamma)))
arrows(-0.5, 0.1, 0.3, 0, length = .15)
text(-0.5, 0.12, bquote(-w[i] ~ gamma))
legend(
    "topright",
    "Gray = Prob of Observed",
```

```
    pch = 1,
    title = "legend",
    inset = .02
)
```

Hence in our observed model, we see

$$y_i = x_i\beta + \epsilon_i \text{when } z_i = 1 \tag{33.2}$$

and the joint distribution of the selection model (u_i), and the observed equation (ϵ_i) as

$$\begin{bmatrix} u \\ \epsilon \end{bmatrix} \sim^{iid} N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & \sigma_\epsilon^2 \end{bmatrix}\right)$$

The relation between the observed and selection models:

$$\begin{aligned} E(y_i|y_i \text{ observed}) &= E(y_i|z^* > 0) \\ &= E(y_i| - w_i\gamma) \\ &= \mathbf{x}_i\beta + E(\epsilon_i|u_i > -w_i\gamma) \\ &= \mathbf{x}_i\beta + \rho\sigma_\epsilon \frac{\phi(w_i\gamma)}{\Phi(w_i\gamma)} \end{aligned}$$

where $\frac{\phi(w_i\gamma)}{\Phi(w_i\gamma)}$ is the Inverse Mills Ratio. and $\rho\sigma_\epsilon \frac{\phi(w_i\gamma)}{\Phi(w_i\gamma)} \geq 0$

A property of IMR: Its derivative is: $IMR'(x) = -xIMR(x) - IMR(x)^2$

Great visualization of special cases of correlation patterns among data and errors by professor Rob Hick

Note:

(Bareinboim and Pearl, 2014) is an excellent summary of cases that we can still do causal inference in case of selection bias. I'll try to summarize their idea here:

Let X be an action, Y be an outcome, and S be a binary indicator of entry into the data pool where ($S = 1 =$ in the sample, $S = 0 =$ out of sample) and Q be the conditional distribution $Q = P(y|x)$.

Usually we want to understand , but because of S, we only have $P(y, x|S = 1)$. Hence, we'd like to recover $P(y|x)$ from $P(y, x|S = 1)$

- If both X and Y affect S, we can't unbiasedly estimate $P(y|x)$

In the case of Omitted variable bias (U) and sample selection bias (S), you have unblocked extraneous "flow" of information between X and Y, which causes spurious correlation for X and Y. Traditionally, we would recover Q by parametric assumption of

(1) The data generating process (e.g., Heckman 2-step)
(2) Type of data-generating model (e..g, treatment-dependent or outcome-dependent)
(3) Selection's probability $P(S = 1|Pa_s)$ with non-parametrically based causal graphical models, the authors proposed more robust way to model misspecification regardless of the type of data-generating model, and do not require selection's probability. Hence, you can recover Q
    - Without external data
    - With external data
    - Causal effects with the Selection-backdoor criterion

33.2.1 Tobit-2

also known as Heckman's standard sample selection model
Assumption: joint normality of the errors

Data here is taken from Mroz (1984).

We want to estimate the log(wage) for married women, with education, experience, experience squared, and a dummy variable for living in a big city. But we can only observe the wage for women who are working, which means a lot of married women in 1975 who were out of the labor force are unaccounted for. Hence, an OLS estimate of the wage equation would be bias due to sample selection. Since we have data on non-participants (i.e., those who are not working for pay), we can correct for the selection process.

The Tobit-2 estimates are consistent

33.2.1.1 Example 1

```
library(sampleSelection)
library(dplyr)
# 1975 data on married women's pay and labor-force participation
# from the Panel Study of Income Dynamics (PSID)
data("Mroz87")
head(Mroz87)
#>   lfp hours kids5 kids618 age educ   wage repwage hushrs husage huseduc huswage
#> 1   1  1610     1       0  32   12 3.3540    2.65   2708     34      12  4.0288
#> 2   1  1656     0       2  30   12 1.3889    2.65   2310     30       9  8.4416
#> 3   1  1980     1       3  35   12 4.5455    4.04   3072     40      12  3.5807
#> 4   1   456     0       3  34   12 1.0965    3.25   1920     53      10  3.5417
#> 5   1  1568     1       2  31   14 4.5918    3.60   2000     32      12 10.0000
#> 6   1  2032     0       0  54   12 4.7421    4.70   1040     57      11  6.7106
#>   faminc    mtr motheduc fatheduc unem city exper  nwifeinc wifecoll huscoll
#> 1  16310 0.7215       12        7  5.0    0    14 10.910060    FALSE   FALSE
#> 2  21800 0.6615        7        7 11.0    1     5 19.499981    FALSE   FALSE
#> 3  21040 0.6915       12        7  5.0    0    15 12.039910    FALSE   FALSE
#> 4   7300 0.7815        7        7  5.0    0     6  6.799996    FALSE   FALSE
#> 5  27300 0.6215       12       14  9.5    1     7 20.100058     TRUE   FALSE
#> 6  19495 0.6915       14        7  7.5    1    33  9.859054    FALSE   FALSE
Mroz87 = Mroz87 %>%
    mutate(kids = kids5 + kids618)

library(nnet)
library(ggplot2)
library(reshape2)
```

2-stage Heckman's model:

(1) probit equation estimates the selection process (who is in the labor force?)
(2) the results from 1st stage are used to construct a variable that captures the selection effect in the wage equation. This correction variable is called the **inverse Mills ratio**.

```
# OLS: log wage regression on LF participants only
ols1 = lm(log(wage) ~ educ + exper + I(exper ^ 2) + city,
          data = subset(Mroz87, lfp == 1))
# Heckman's Two-step estimation with LFP selection equation
heck1 = heckit(
    selection = lfp ~ age + I(age ^ 2) + kids + huswage + educ,
    # the selection process, l
    # fp = 1 if the woman is participating in the labor force
    outcome = log(wage) ~ educ + exper + I(exper ^ 2) + city,
    data = Mroz87
)
```

```
summary(heck1$probit)
#> --------------------------------------------
#> Probit binary choice model/Maximum Likelihood estimation
#> Newton-Raphson maximisation, 4 iterations
#> Return code 1: gradient close to zero (gradtol)
#> Log-Likelihood: -482.8212
#> Model: Y == '1' in contrary to '0'
#> 753 observations (325 'negative' and 428 'positive') and 6 free parameters (df = 74
#> Estimates:
#>                  Estimate  Std. error t value   Pr(> t)
#> XS(Intercept) -4.18146681  1.40241567 -2.9816  0.002867 **
#> XSage          0.18608901  0.06517476  2.8552  0.004301 **
#> XSI(age^2)    -0.00241491  0.00075857 -3.1835  0.001455 **
#> XSkids        -0.14955977  0.03825079 -3.9100 9.230e-05 ***
#> XShuswage     -0.04303635  0.01220791 -3.5253  0.000423 ***
#> XSeduc         0.12502818  0.02277645  5.4894 4.034e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> Significance test:
#> chi2(5) = 64.10407 (p=1.719042e-12)
#> --------------------------------------------
summary(heck1$lm)
#>
#> Call:
#> lm(formula = YO ~ -1 + XO + imrData$IMR1, subset = YS == 1, weights = weightsNoNA)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -3.09494 -0.30953  0.05341  0.36530  2.34770
#>
#> Coefficients:
#>                 Estimate Std. Error t value Pr(>|t|)
#> XO(Intercept) -0.6143381  0.3768796  -1.630  0.10383
#> XOeduc         0.1092363  0.0197062   5.543 5.24e-08 ***
#> XOexper        0.0419205  0.0136176   3.078  0.00222 **
#> XOI(exper^2)  -0.0008226  0.0004059  -2.026  0.04335 *
#> XOcity         0.0510492  0.0692414   0.737  0.46137
#> imrData$IMR1   0.0551177  0.2111916   0.261  0.79423
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.6674 on 422 degrees of freedom
#> Multiple R-squared:  0.7734, Adjusted R-squared:  0.7702
#> F-statistic:   240 on 6 and 422 DF,  p-value: < 2.2e-16
```

Use only variables that affect the selection process in the selection equation. Technically, the selection equation and the equation of interest could have the same set of regressors. But it is not recommended because we should only use variables (or at least one) in the selection equation that affect the selection process, but not the wage process (i.e., instruments). Here, variable `kids` fulfill that role: women with kids may be more likely to stay home, but working moms with kids would not have their wages change.

Alternatively,

```
# ML estimation of selection model
ml1 = selection(
    selection = lfp ~ age + I(age ^ 2) + kids + huswage + educ,
    outcome = log(wage) ~ educ + exper + I(exper ^ 2) + city,
    data = Mroz87
)
summary(ml1)
#> --------------------------------------------
#> Tobit 2 model (sample selection model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 3 iterations
#> Return code 8: successive function values within relative tolerance limit (reltol)
#> Log-Likelihood: -914.0777
#> 753 observations (325 censored and 428 observed)
#> 13 free parameters (df = 740)
#> Probit selection equation:
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -4.1484037  1.4109302  -2.940 0.003382 **
#> age          0.1842132  0.0658041   2.799 0.005253 **
#> I(age^2)    -0.0023925  0.0007664  -3.122 0.001868 **
#> kids        -0.1488158  0.0384888  -3.866 0.000120 ***
#> huswage     -0.0434253  0.0123229  -3.524 0.000451 ***
#> educ         0.1255639  0.0229229   5.478 5.91e-08 ***
#> Outcome equation:
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.5814781  0.3052031  -1.905  0.05714 .
#> educ         0.1078481  0.0172998   6.234 7.63e-10 ***
#> exper        0.0415752  0.0133269   3.120  0.00188 **
#> I(exper^2)  -0.0008125  0.0003974  -2.044  0.04129 *
#> city         0.0522990  0.0682652   0.766  0.44385
#>    Error terms:
#>       Estimate Std. Error t value Pr(>|t|)
#> sigma  0.66326    0.02309  28.729   <2e-16 ***
#> rho    0.05048    0.23169   0.218    0.828
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#> ---------------------------------------------
# summary(ml1$twoStep)
```

Manual

```
myprob <- probit(lfp ~ age + I( age^2 ) + kids + huswage + educ,
                 # x = TRUE,
                 # iterlim = 30,
                 data = Mroz87)
summary(myprob)
#> ---------------------------------------------
#> Probit binary choice model/Maximum Likelihood estimation
#> Newton-Raphson maximisation, 4 iterations
#> Return code 1: gradient close to zero (gradtol)
#> Log-Likelihood: -482.8212
#> Model: Y == '1' in contrary to '0'
#> 753 observations (325 'negative' and 428 'positive') and 6 free parameters (df = 74
#> Estimates:
#>                Estimate  Std. error t value   Pr(> t)
#> (Intercept) -4.18146681  1.40241567 -2.9816  0.002867 **
#> age          0.18608901  0.06517476  2.8552  0.004301 **
#> I(age^2)    -0.00241491  0.00075857 -3.1835  0.001455 **
#> kids        -0.14955977  0.03825079 -3.9100 9.230e-05 ***
#> huswage     -0.04303635  0.01220791 -3.5253  0.000423 ***
#> educ         0.12502818  0.02277645  5.4894 4.034e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> Significance test:
#> chi2(5) = 64.10407 (p=1.719042e-12)
#> ---------------------------------------------

imr <- invMillsRatio(myprob)
Mroz87$IMR1 <- imr$IMR1

manually_est <- lm(log(wage) ~ educ + exper + I( exper^2 ) + city + IMR1,
                   data = Mroz87,
                   subset = (lfp == 1))

summary(manually_est)
#>
#> Call:
#> lm(formula = log(wage) ~ educ + exper + I(exper^2) + city + IMR1,
#>     data = Mroz87, subset = (lfp == 1))
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
```

```
#> -3.09494 -0.30953  0.05341  0.36530  2.34770
#>
#> Coefficients:
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.6143381  0.3768796  -1.630  0.10383
#> educ         0.1092363  0.0197062   5.543 5.24e-08 ***
#> exper        0.0419205  0.0136176   3.078  0.00222 **
#> I(exper^2)  -0.0008226  0.0004059  -2.026  0.04335 *
#> city         0.0510492  0.0692414   0.737  0.46137
#> IMR1         0.0551177  0.2111916   0.261  0.79423
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.6674 on 422 degrees of freedom
#> Multiple R-squared:  0.1582, Adjusted R-squared:  0.1482
#> F-statistic: 15.86 on 5 and 422 DF,  p-value: 2.505e-14
```

Similarly,

```
probit_selection <-
    glm(lfp ~ age + I( age^2 ) + kids + huswage + educ,
        data = Mroz87,
        family = binomial(link = 'probit'))

# library(fixest)
# probit_selection <-
#     fixest::feglm(lfp ~ age + I( age^2 ) + kids + huswage + educ,
#         data = Mroz87,
#         family = binomial(link = 'probit'))

probit_lp <- -predict(probit_selection)
inv_mills <- dnorm(probit_lp) / (1 - pnorm(probit_lp))
Mroz87$inv_mills <- inv_mills


probit_outcome <-
    glm(
        log(wage) ~ educ + exper + I(exper ^ 2) + city + inv_mills,
        data = Mroz87,
        subset = (lfp == 1)
    )
summary(probit_outcome)
#>
#> Call:
#> glm(formula = log(wage) ~ educ + exper + I(exper^2) + city +
#>     inv_mills, data = Mroz87, subset = (lfp == 1))
```

```
#>
#> Deviance Residuals:
#>      Min        1Q    Median        3Q       Max
#> -3.09494  -0.30953   0.05341   0.36530   2.34770
#>
#> Coefficients:
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.6143383  0.3768798  -1.630  0.10383
#> educ         0.1092363  0.0197062   5.543 5.24e-08 ***
#> exper        0.0419205  0.0136176   3.078  0.00222 **
#> I(exper^2)  -0.0008226  0.0004059  -2.026  0.04335 *
#> city         0.0510492  0.0692414   0.737  0.46137
#> inv_mills    0.0551179  0.2111918   0.261  0.79423
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for gaussian family taken to be 0.4454809)
#>
#>     Null deviance: 223.33  on 427  degrees of freedom
#> Residual deviance: 187.99  on 422  degrees of freedom
#> AIC: 876.49
#>
#> Number of Fisher Scoring iterations: 2
```

```r
library("stargazer")
library("Mediana")
library("plm")
# function to calculate corrected SEs for regression
cse = function(reg) {
  rob = sqrt(diag(vcovHC(reg, type = "HC1")))
  return(rob)
}

# stargazer table
stargazer(
    # ols1,
    heck1,
    ml1,
    # manually_est,

    se = list(cse(ols1), NULL, NULL),
    title = "Married women's wage regressions",
    type = "text",
    df = FALSE,
    digits = 4,
```

```
    selection.equation = T
)
#>
#> Married women's wage regressions
#> ==================================================
#>                           Dependent variable:
#>                       ------------------------------
#>                                   lfp
#>                          Heckman        selection
#>                         selection
#>                            (1)             (2)
#> --------------------------------------------------
#> age                     0.1861***       0.1842***
#>                                         (0.0658)
#>
#> I(age2)                  -0.0024       -0.0024***
#>                                         (0.0008)
#>
#> kids                   -0.1496***      -0.1488***
#>                                         (0.0385)
#>
#> huswage                  -0.0430       -0.0434***
#>                                         (0.0123)
#>
#> educ                     0.1250         0.1256***
#>                         (0.0130)        (0.0229)
#>
#> Constant               -4.1815***      -4.1484***
#>                         (0.2032)        (1.4109)
#>
#> --------------------------------------------------
#> Observations               753             753
#> R2                       0.1582
#> Adjusted R2              0.1482
#> Log Likelihood                          -914.0777
#> rho                      0.0830      0.0505 (0.2317)
#> Inverse Mills Ratio 0.0551 (0.2099)
#> ==================================================
#> Note:                    *p<0.1; **p<0.05; ***p<0.01


stargazer(
    ols1,
    # heck1,
    # ml1,
```

```
    manually_est,

    se = list(cse(ols1), NULL, NULL),
    title = "Married women's wage regressions",
    type = "text",
    df = FALSE,
    digits = 4,
    selection.equation = T
)
#>
#> Married women's wage regressions
#> ==================================================
#>                          Dependent variable:
#>                      ----------------------------
#>                               log(wage)
#>                           (1)            (2)
#> --------------------------------------------------
#> educ                   0.1057***      0.1092***
#>                        (0.0130)       (0.0197)
#>
#> exper                  0.0411***      0.0419***
#>                        (0.0154)       (0.0136)
#>
#> I(exper2)              -0.0008*       -0.0008**
#>                        (0.0004)       (0.0004)
#>
#> city                    0.0542         0.0510
#>                        (0.0653)       (0.0692)
#>
#> IMR1                                   0.0551
#>                                       (0.2112)
#>
#> Constant               -0.5308***      -0.6143
#>                        (0.2032)       (0.3769)
#>
#> --------------------------------------------------
#> Observations             428            428
#> R2                      0.1581         0.1582
#> Adjusted R2             0.1501         0.1482
#> Residual Std. Error     0.6667         0.6674
#> F Statistic            19.8561***     15.8635***
#> ==================================================
#> Note:                  *p<0.1; **p<0.05; ***p<0.01
```

Rho is an estimate of the correlation of the errors between the selection and

wage equations. In the lower panel, the estimated coefficient on the inverse Mills ratio is given for the Heckman model. The fact that it is not statistically different from zero is consistent with the idea that selection bias was not a serious problem in this case.

If the estimated coefficient of the inverse Mills ratio in the Heckman model is not statistically different from zero, then selection bias was not a serious problem.

33.2.1.2 Example 2

This code is from R package sampleSelection

```
set.seed(0)
library("sampleSelection")
library("mvtnorm")
# bivariate normal disturbances
eps <-
    rmvnorm(500, c(0, 0), matrix(c(1, -0.7, -0.7, 1), 2, 2))

# uniformly distributed explanatory variable
# (vectors of explanatory variables for the selection)
xs <- runif(500)

# probit data generating process
ys <- xs + eps[, 1] > 0

# vectors of explanatory variables for outcome equation
xo <- runif(500)
yoX <- xo + eps[, 2] # latent outcome
yo <- yoX * (ys > 0) # observable outcome
# true intercepts = 0 and our true slopes = 1
# xs and xo are independent.
# Hence, exclusion restriction is fulfilled
summary(selection(ys ~ xs, yo ~ xo))
#> --------------------------------------------
#> Tobit 2 model (sample selection model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 5 iterations
#> Return code 1: gradient close to zero (gradtol)
#> Log-Likelihood: -712.3163
#> 500 observations (172 censored and 328 observed)
#> 6 free parameters (df = 494)
#> Probit selection equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.2228     0.1081  -2.061   0.0399 *
#> xs            1.3377     0.2014   6.642 8.18e-11 ***
#> Outcome equation:
```

```
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.0002265  0.1294178  -0.002    0.999
#> xo           0.7299070  0.1635925   4.462 1.01e-05 ***
#>    Error terms:
#>       Estimate Std. Error t value Pr(>|t|)
#> sigma   0.9190     0.0574  16.009  < 2e-16 ***
#> rho    -0.5392     0.1521  -3.544 0.000431 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> --------------------------------------------
```

without the exclusion restriction, we generate yo using xs instead of xo.

```
yoX <- xs + eps[,2]
yo <- yoX*(ys > 0)
summary(selection(ys ~ xs, yo ~ xs))
#> --------------------------------------------
#> Tobit 2 model (sample selection model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 14 iterations
#> Return code 8: successive function values within relative tolerance limit (reltol)
#> Log-Likelihood: -712.8298
#> 500 observations (172 censored and 328 observed)
#> 6 free parameters (df = 494)
#> Probit selection equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.1984     0.1114  -1.781   0.0756 .
#> xs            1.2907     0.2085   6.191 1.25e-09 ***
#> Outcome equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.5499     0.5644  -0.974  0.33038
#> xs            1.3987     0.4482   3.120  0.00191 **
#>    Error terms:
#>       Estimate Std. Error t value Pr(>|t|)
#> sigma  0.85091    0.05352  15.899   <2e-16 ***
#> rho   -0.13226    0.72684  -0.182    0.856
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> --------------------------------------------
```

We can see that our estimates are still unbiased but standard errors are substantially larger. The exclusion restriction (i.e., independent information about the selection process) has a certain identifying power that we desire. Hence, it's better to have different set of variable for the selection process from the interested equation. Without the exclusion restriction, we solely rely on the functional form identification.

33.2.2 Tobit-5

Also known as the switching regression model
Condition: There is at least one variable in X in the selection process not included in the observed process. Used when there are separate models for participants, and non-participants.

```
set.seed(0)
vc <- diag(3)
vc[lower.tri(vc)] <- c(0.9, 0.5, 0.1)
vc[upper.tri(vc)] <- vc[lower.tri(vc)]

# 3 disturbance vectors by a 3-dimensional normal distribution
eps <- rmvnorm(500, c(0,0,0), vc)
xs <- runif(500) # uniformly distributed on [0, 1]
ys <- xs + eps[,1] > 0
xo1 <- runif(500) # uniformly distributed on [0, 1]
yo1 <- xo1 + eps[,2]
xo2 <- runif(500) # uniformly distributed on [0, 1]
yo2 <- xo2 + eps[,3]
```

exclusion restriction is fulfilled when x's are independent.

```
# one selection equation and a list of two outcome equations
summary(selection(ys~xs, list(yo1 ~ xo1, yo2 ~ xo2)))
#> --------------------------------------------
#> Tobit 5 model (switching regression model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 11 iterations
#> Return code 1: gradient close to zero (gradtol)
#> Log-Likelihood: -895.8201
#> 500 observations: 172 selection 1 (FALSE) and 328 selection 2 (TRUE)
#> 10 free parameters (df = 490)
#> Probit selection equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.1550     0.1051  -1.474    0.141
#> xs            1.1408     0.1785   6.390 3.86e-10 ***
#> Outcome equation 1:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  0.02708    0.16395   0.165    0.869
#> xo1          0.83959    0.14968   5.609  3.4e-08 ***
#> Outcome equation 2:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   0.1583     0.1885   0.840    0.401
#> xo2           0.8375     0.1707   4.908 1.26e-06 ***
#>    Error terms:
#>        Estimate Std. Error t value Pr(>|t|)
```

```
#> sigma1  0.93191    0.09211  10.118   <2e-16 ***
#> sigma2  0.90697    0.04434  20.455   <2e-16 ***
#> rho1    0.88988    0.05353  16.623   <2e-16 ***
#> rho2    0.17695    0.33139   0.534    0.594
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> --------------------------------------------
```

All the estimates are close to the true values.

Example of functional form misspecification

```
set.seed(5)
eps <- rmvnorm(1000, rep(0, 3), vc)
eps <- eps^2 - 1 # subtract 1 in order to get the mean zero disturbances

# interval [-1, 0] to get an asymmetric distribution over observed choices
xs <- runif(1000, -1, 0)
ys <- xs + eps[,1] > 0
xo1 <- runif(1000)
yo1 <- xo1 + eps[,2]
xo2 <- runif(1000)
yo2 <- xo2 + eps[,3]
summary(selection(ys~xs, list(yo1 ~ xo1, yo2 ~ xo2), iterlim=20))
#> --------------------------------------------
#> Tobit 5 model (switching regression model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 4 iterations
#> Return code 3: Last step could not find a value above the current.
#> Boundary of parameter space?
#> Consider switching to a more robust optimisation method temporarily.
#> Log-Likelihood: -1665.936
#> 1000 observations: 760 selection 1 (FALSE) and 240 selection 2 (TRUE)
#> 10 free parameters (df = 990)
#> Probit selection equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.53698    0.05808  -9.245  < 2e-16 ***
#> xs           0.31268    0.09395   3.328 0.000906 ***
#> Outcome equation 1:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.70679    0.03573  -19.78   <2e-16 ***
#> xo1          0.91603    0.05626   16.28   <2e-16 ***
#> Outcome equation 2:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   0.1446        NaN     NaN      NaN
#> xo2           1.1196     0.5014   2.233   0.0258 *
```

```
#>    Error terms:
#>        Estimate Std. Error t value Pr(>|t|)
#> sigma1  0.67770    0.01760   38.50   <2e-16 ***
#> sigma2  2.31432    0.07615   30.39   <2e-16 ***
#> rho1   -0.97137        NaN     NaN      NaN
#> rho2    0.17039        NaN     NaN      NaN
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> --------------------------------------------
```

Although we still have an exclusion restriction (xo1 and xo2 are independent), we now have problems with the intercepts (i.e., they are statistically significantly different from the true values zero), and convergence problems.

If we don't have the exclusion restriction, we will have a larger variance of xs

```
set.seed(6)
xs <- runif(1000, -1, 1)
ys <- xs + eps[,1] > 0
yo1 <- xs + eps[,2]
yo2 <- xs + eps[,3]
summary(tmp <- selection(ys~xs, list(yo1 ~ xs, yo2 ~ xs), iterlim=20))
#> --------------------------------------------
#> Tobit 5 model (switching regression model)
#> Maximum Likelihood estimation
#> Newton-Raphson maximisation, 16 iterations
#> Return code 8: successive function values within relative tolerance limit (reltol)
#> Log-Likelihood: -1936.431
#> 1000 observations: 626 selection 1 (FALSE) and 374 selection 2 (TRUE)
#> 10 free parameters (df = 990)
#> Probit selection equation:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.3528     0.0424  -8.321 2.86e-16 ***
#> xs            0.8354     0.0756  11.050  < 2e-16 ***
#> Outcome equation 1:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.55448    0.06339  -8.748   <2e-16 ***
#> xs           0.81764    0.06048  13.519   <2e-16 ***
#> Outcome equation 2:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   0.6457     0.4994   1.293    0.196
#> xs            0.3520     0.3197   1.101    0.271
#>    Error terms:
#>        Estimate Std. Error t value Pr(>|t|)
#> sigma1  0.59187    0.01853  31.935   <2e-16 ***
#> sigma2  1.97257    0.07228  27.289   <2e-16 ***
```

```
#> rho1    0.15568    0.15914   0.978    0.328
#> rho2   -0.01541    0.23370  -0.066    0.947
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> ---------------------------------------------
```

Usually it will not converge. Even if it does, the results may be seriously biased.

Note

The log-likelihood function of the models might not be globally concave. Hence, it might not converge, or converge to a local maximum. To combat this, we can use

- Different starting value
- Different maximization methods.
- refer to Non-linear Least Squares for suggestions.

33.2.2.0.1 Pattern-Mixture Models

- compared to the Heckman's model where it assumes the value of the missing data is predetermined, pattern-mixture models assume missingness affect the distribution of variable of interest (e.g., Y)
- To read more, you can check NCSU, stefvanbuuren.

Chapter 34

Other Biases

In econometrics, the main objective is often to uncover causal relationships. However, coefficient estimates can be affected by various biases. Here's a list of common biases that can affect coefficient estimates:

What we've covered so far (see Linear Regression and Endogeneity):

1. **Omitted Variable Bias (OVB)**:
   - Arises when a variable that affects the dependent variable and is correlated with an independent variable is left out of the regression.
2. **Endogeneity Bias**:
   - Occurs when an error term is correlated with an independent variable. This can be due to:
     - Simultaneity: When the dependent variable simultaneously affects an independent variable.
     - Omitted variables.
     - Measurement error in the independent variable.
3. **Measurement Error**:
   - Bias introduced when variables in a model are measured with error. If the error is in an independent variable and is classical (mean zero and uncorrelated with the true value), it typically biases the coefficient towards zero.
4. **Sample Selection Bias**:
   - Arises when the sample is not randomly selected and the selection is related to the dependent variable. A classic example is the Heckman

correction for labor market studies where participants self-select into the workforce.

5. **Simultaneity Bias (or Reverse Causality)**:
   - Happens when the dependent variable causes changes in the independent variable, leading to a two-way causation.
6. **Multicollinearity**:
   - Not a bias in the strictest sense, but in the presence of high multicollinearity (when independent variables are highly correlated), coefficient estimates can become unstable and standard errors large. This makes it hard to determine the individual effect of predictors on the dependent variable.
7. **Specification Errors**:
   - Arise when the functional form of the model is incorrectly specified, e.g., omitting interaction terms or polynomial terms when they are needed.
8. **Autocorrelation (or Serial Correlation)**:
   - Occurs in time-series data when the error terms are correlated over time. This doesn't cause bias in the coefficient estimates of OLS, but it can make standard errors biased, leading to incorrect inference.
9. **Heteroskedasticity**:
   - Occurs when the variance of the error term is not constant across observations. Like autocorrelation, heteroskedasticity doesn't bias the OLS estimates but can bias standard errors.

In this section, we will mention other biases that you may encounter when conducting your research

10.
   - Introduced when data are aggregated, and analysis is conducted at this aggregate level rather than the individual level.
11. [**Survivorship Bias**] **(very much related to Sample Selection)**:
   - Arises when the sample only includes "survivors" or those who "passed" a certain threshold. Common in finance where only funds or firms that "survive" are analyzed.
12.
   - Not a bias in econometric estimation per se, but relevant in the context of empirical studies. It refers to the tendency for journals to publish only significant or positive results, leading to an overrepresentation of such results in the literature.

34.1 Aggregation Bias

Aggregation bias, also known as ecological fallacy, refers to the error introduced when data are aggregated and an analysis is conducted at this aggregate level, rather than at the individual level. This can be especially problematic in econometrics, where analysts are often concerned with understanding individual behavior.

When the relationship between variables is different at the aggregate level than at the individual level, aggregation bias can result. The bias arises when inferences about individual behaviors are made based on aggregate data.

Example: Suppose we have data on individuals' incomes and their personal consumption. At the individual level, it's possible that as income rises, consumption also rises. However, when we aggregate the data to, say, a neighborhood level, neighborhoods with diverse income levels might all have similar average consumption due to other unobserved factors.

Step 1: Create individual level data

```
set.seed(123)

# Generate data for 1000 individuals
n <- 1000

income <- rnorm(n, mean = 50, sd = 10)
consumption <- 0.5 * income + rnorm(n, mean = 0, sd = 5)

# Individual level regression
individual_lm <- lm(consumption ~ income)
summary(individual_lm)
#>
#> Call:
#> lm(formula = consumption ~ income)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -15.1394  -3.4572   0.0213   3.5436  16.4557
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -1.99596    0.82085  -2.432   0.0152 *
#> income       0.54402    0.01605  33.888   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 5.032 on 998 degrees of freedom
#> Multiple R-squared:  0.535,  Adjusted R-squared:  0.5346
```

```
#> F-statistic:  1148 on 1 and 998 DF,  p-value: < 2.2e-16
```

This would show a significant positive relationship between income and consumption.

Step 2: Aggregate data to 'neighborhood' level

```
# Assume 100 neighborhoods with 10 individuals each
n_neighborhoods <- 100

df <- data.frame(income, consumption)
df$neighborhood <- rep(1:n_neighborhoods, each = n / n_neighborhoods)

aggregate_data <- aggregate(. ~ neighborhood, data = df, FUN = mean)

# Aggregate level regression
aggregate_lm <- lm(consumption ~ income, data = aggregate_data)
summary(aggregate_lm)
#>
#> Call:
#> lm(formula = consumption ~ income, data = aggregate_data)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -4.4517 -0.9322 -0.0826  1.0556  3.5728
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -4.94338    2.60699  -1.896   0.0609 .
#> income       0.60278    0.05188  11.618   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.54 on 98 degrees of freedom
#> Multiple R-squared:  0.5794, Adjusted R-squared:  0.5751
#> F-statistic:   135 on 1 and 98 DF,  p-value: < 2.2e-16
```

If aggregation bias is present, the coefficient for income in the aggregate regression might be different from the coefficient in the individual regression, even if the individual relationship is significant and strong.

```
library(ggplot2)

# Individual scatterplot
p1 <- ggplot(df, aes(x = income, y = consumption)) +
    geom_point(aes(color = neighborhood), alpha = 0.6) +
    geom_smooth(method = "lm",
```

```
                 se = FALSE,
                 color = "black") +
    labs(title = "Individual Level Data") +
    causalverse::ama_theme()

# Aggregate scatterplot
p2 <- ggplot(aggregate_data, aes(x = income, y = consumption)) +
    geom_point(color = "red") +
    geom_smooth(method = "lm",
                se = FALSE,
                color = "black") +
    labs(title = "Aggregate Level Data") +
    causalverse::ama_theme()

# print(p1)
# print(p2)

gridExtra::grid.arrange(grobs = list(p1, p2), ncol = 2)
```

From these plots, you can see the relationship at the individual level, with each neighborhood being colored differently in the first plot. The second plot shows the aggregate data, where each point now represents a whole neighborhood.

Direction of Bias: The direction of the aggregation bias isn't predetermined. It depends on the underlying relationship and the data distribution. In some cases, aggregation might attenuate (reduce) a relationship, while in other cases, it might exaggerate it.

Relation to Other Biases: Aggregation bias is closely related to several other biases in econometrics:

1. **Specification bias**: If you don't properly account for the hierarchical structure of your data (like individuals nested within neighborhoods), your model might be mis-specified, leading to biased estimates.
2. **Measurement Error**: Aggregation can introduce or amplify measurement errors. For instance, if you aggregate noisy measures, the aggregate might not accurately represent any underlying signal.
3. **Omitted Variable Bias (see Endogeneity)**: When you aggregate data, you lose information. If the loss of this information results in omitting important predictors that are correlated with both the independent and dependent variables, it can introduce omitted variable bias.

34.1.1 Simpson's Paradox

Simpson's Paradox, also known as the Yule-Simpson effect, is a phenomenon in probability and statistics where a trend that appears in different groups of data disappears or reverses when the groups are combined. It's a striking example of how aggregated data can sometimes provide a misleading representation of the actual situation.

Illustration of Simpson's Paradox:

Consider a hypothetical scenario involving two hospitals: Hospital A and Hospital B. We want to analyze the success rates of treatments at both hospitals. When we break the data down by the severity of the cases (i.e., minor cases vs. major cases):

1. **Hospital A**:
   - Minor cases: 95% success rate
   - Major cases: 80% success rate
2. **Hospital B**:
   - Minor cases: 90% success rate
   - Major cases: 85% success rate

From this breakdown, Hospital A appears to be better in treating both minor and major cases since it has a higher success rate in both categories.

However, let's consider the overall success rates without considering case severity:

- **Hospital A**: 83% overall success rate
- **Hospital B**: 86% overall success rate

Suddenly, Hospital B seems better overall. This surprising reversal happens because the two hospitals might handle very different proportions of minor and major cases. For example, if Hospital A treats many more major cases (which have lower success rates) than Hospital B, it can drag down its overall success rate.

Causes:

Simpson's Paradox can arise due to:

1. A lurking or confounding variable that wasn't initially considered (in our example, the severity of the medical cases).
2. Different group sizes, where one group might be much larger than the other, influencing the aggregate results.

Implications:

Simpson's Paradox highlights the dangers of interpreting aggregated data without considering potential underlying sub-group structures. It underscores the importance of disaggregating data and being aware of the context in which it's analyzed.

Relation to Aggregation Bias

In the most extreme case, aggregation bias can reverse the coefficient sign of the relationship of interest (i.e., Simpson's Paradox).

Example: Suppose we are studying the effect of a new study technique on student grades. We have two groups of students: those who used the new technique (`treatment = 1`) and those who did not (`treatment = 0`). We want to see if using the new study technique is related to higher grades.

Let's assume grades are influenced by the starting ability of the students. Perhaps in our sample, many high-ability students didn't use the new technique (because they felt they didn't need it), while many low-ability students did.

Here's a setup:

1. High-ability students tend to have high grades regardless of the technique.
2. The new technique has a positive effect on grades, but this is masked by the fact that many low-ability students use it.

```r
set.seed(123)

# Generate data for 1000 students
n <- 1000

# 500 students are of high ability, 500 of low ability
ability <- c(rep("high", 500), rep("low", 500))
```

```r
# High ability students are less likely to use the technique
treatment <-
  ifelse(ability == "high", rbinom(500, 1, 0.2), rbinom(500, 1, 0.8))

# Grades are influenced by ability and treatment (new technique),
# but the treatment has opposite effects based on ability.
grades <-
  ifelse(
    ability == "high",
    rnorm(500, mean = 85, sd = 5) + treatment * -3,
    rnorm(500, mean = 60, sd = 5) + treatment * 5
  )

df <- data.frame(ability, treatment, grades)

# Regression without considering ability
overall_lm <- lm(grades ~ factor(treatment), data = df)
summary(overall_lm)
#>
#> Call:
#> lm(formula = grades ~ factor(treatment), data = df)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -33.490  -4.729   0.986   6.368  25.607
#>
#> Coefficients:
#>                     Estimate Std. Error t value Pr(>|t|)
#> (Intercept)          80.0133     0.4373   183.0   <2e-16 ***
#> factor(treatment)1 -11.7461     0.6248   -18.8   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 9.877 on 998 degrees of freedom
#> Multiple R-squared:  0.2615, Adjusted R-squared:  0.2608
#> F-statistic: 353.5 on 1 and 998 DF,  p-value: < 2.2e-16

# Regression within ability groups
high_ability_lm <-
  lm(grades ~ factor(treatment), data = df[df$ability == "high",])
low_ability_lm <-
  lm(grades ~ factor(treatment), data = df[df$ability == "low",])
summary(high_ability_lm)
#>
#> Call:
```

```
#> lm(formula = grades ~ factor(treatment), data = df[df$ability ==
#>     "high", ])
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -14.2156  -3.4813   0.1186   3.4952  13.2919
#>
#> Coefficients:
#>                    Estimate Std. Error t value Pr(>|t|)
#> (Intercept)         85.1667     0.2504 340.088  < 2e-16 ***
#> factor(treatment)1  -3.9489     0.5776  -6.837 2.37e-11 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 5.046 on 498 degrees of freedom
#> Multiple R-squared:  0.08581,    Adjusted R-squared:  0.08398
#> F-statistic: 46.75 on 1 and 498 DF,  p-value: 2.373e-11
summary(low_ability_lm)
#>
#> Call:
#> lm(formula = grades ~ factor(treatment), data = df[df$ability ==
#>     "low", ])
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -13.3717  -3.5413   0.1097   3.3531  17.0568
#>
#> Coefficients:
#>                    Estimate Std. Error t value Pr(>|t|)
#> (Intercept)         59.8950     0.4871 122.956   <2e-16 ***
#> factor(treatment)1   5.2979     0.5474   9.679   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 4.968 on 498 degrees of freedom
#> Multiple R-squared:  0.1583, Adjusted R-squared:  0.1566
#> F-statistic: 93.68 on 1 and 498 DF,  p-value: < 2.2e-16
```

From this simulation:

- The **`overall_lm`** might show that the new study technique is associated with lower grades (negative coefficient), because many of the high-ability students (who naturally have high grades) did not use it.
- The **`high_ability_lm`** will likely show that high-ability students who used the technique had slightly lower grades than high-ability students who

didn't.

- The **low_ability_lm** will likely show that low-ability students who used the technique had much higher grades than low-ability students who didn't.

This is a classic example of Simpson's Paradox: within each ability group, the technique appears beneficial, but when data is aggregated, the effect seems negative because of the distribution of the technique across ability groups.

```
library(ggplot2)

# Scatterplot for overall data
p1 <-
  ggplot(df, aes(
    x = factor(treatment),
    y = grades,
    color = ability
  )) +
  geom_jitter(width = 0.2, height = 0) +
  geom_boxplot(alpha = 0.6, outlier.shape = NA) +
  labs(title = "Overall Effect of Study Technique on Grades",
       x = "Treatment (0 = No Technique, 1 = New Technique)",
       y = "Grades")

# Scatterplot for high-ability students
p2 <-
  ggplot(df[df$ability == "high", ], aes(
    x = factor(treatment),
    y = grades,
    color = ability
  )) +
  geom_jitter(width = 0.2, height = 0) +
  geom_boxplot(alpha = 0.6, outlier.shape = NA) +
  labs(title = "Effect of Study Technique on Grades (High Ability)",
       x = "Treatment (0 = No Technique, 1 = New Technique)",
       y = "Grades")

# Scatterplot for low-ability students
p3 <-
  ggplot(df[df$ability == "low", ], aes(
    x = factor(treatment),
    y = grades,
    color = ability
  )) +
  geom_jitter(width = 0.2, height = 0) +
  geom_boxplot(alpha = 0.6, outlier.shape = NA) +
```

```
  labs(title = "Effect of Study Technique on Grades (Low Ability)",
       x = "Treatment (0 = No Technique, 1 = New Technique)",
       y = "Grades")

# print(p1)
# print(p2)
# print(p3)
gridExtra::grid.arrange(grobs = list(p1, p2, p3), ncol = 1)
```

34.2 Contamination Bias

Goldsmith-Pinkham et al. (2022) show regressions with multiple treatments and flexible controls often fail to estimate convex averages of heterogeneous treatment effects, resulting in contamination by non-convex averages of other treatments' effects.

- 3 estimation methods to avoid this bias and find significant contamination bias in observational studies, with experimental studies showing less due to lower variability in propensity scores.

34.3 Survivorship Bias

Survivorship bias refers to the logical error of concentrating on the entities that have made it past some selection process and overlooking those that didn't, typically because of a lack of visibility. This can skew results and lead to overly optimistic conclusions.

Example: If you were to analyze the success of companies based only on the ones that are still in business today, you'd miss out on the insights from all those that failed. This would give you a distorted view of what makes a successful company, as you wouldn't account for all those that had those same attributes but didn't succeed.

Relation to Other Biases:

1. **Sample Selection Bias**: Survivorship bias is a specific form of sample selection bias. While survivorship bias focuses on entities that "survive", sample selection bias broadly deals with any non-random sample.

2. **Confirmation Bias**: Survivorship bias can reinforce confirmation bias. By only looking at the "winners", we might confirm our existing beliefs about what leads to success, ignoring evidence to the contrary from those that didn't survive.

```r
set.seed(42)

# Generating data for 100 companies
n <- 100

# Randomly generate earnings; assume true average earnings is 50
earnings <- rnorm(n, mean = 50, sd = 10)

# Threshold for bankruptcy
threshold <- 40

# Only companies with earnings above the threshold "survive"
survivor_earnings <- earnings[earnings > threshold]

# Average earnings for all companies vs. survivors
true_avg <- mean(earnings)
survivor_avg <- mean(survivor_earnings)

true_avg
#> [1] 50.32515
survivor_avg
#> [1] 53.3898
```

Using a histogram to visualize the distribution of earnings, highlighting the "survivors".

```r
library(ggplot2)

df <- data.frame(earnings)

p <- ggplot(df, aes(x = earnings)) +
```

```
  geom_histogram(
    binwidth = 2,
    fill = "grey",
    color = "black",
    alpha = 0.7
  ) +
  geom_vline(aes(xintercept = true_avg, color = "True Avg"),
             linetype = "dashed",
             size = 1) +
  geom_vline(
    aes(xintercept = survivor_avg, color = "Survivor Avg"),
    linetype = "dashed",
    size = 1
  ) +
  scale_color_manual(values = c("True Avg" = "blue", "Survivor Avg" = "red"),
                     name = "Average Type") +
  labs(title = "Distribution of Company Earnings",
       x = "Earnings",
       y = "Number of Companies") +
  causalverse::ama_theme()

print(p)
```

In the plot, the "True Avg" might be lower than the "Survivor Avg", indicating that by only looking at the survivors, we overestimate the average earnings.

Remedies:

1. **Awareness**: Recognizing the potential for survivorship bias is the first step.
2. **Inclusive Data Collection**: Wherever possible, try to include data from entities that didn't "survive" in your sample.
3. **Statistical Techniques**: In cases where the missing data is inherent, methods like Heckman's two-step procedure can be used to correct for sample selection bias.
4. **External Data Sources**: Sometimes, complementary datasets can provide insights into the missing "non-survivors".
5. **Sensitivity Analysis**: Test how sensitive your results are to assumptions about the non-survivors.

34.4 Publication Bias

Publication bias occurs when the results of studies influence the likelihood of their being published. Typically, studies with significant, positive, or sensational results are more likely to be published than those with non-significant or negative results. This can skew the perceived effectiveness or results when researchers conduct meta-analyses or literature reviews, leading them to draw inaccurate conclusions.

Example: Imagine pharmaceutical research. If 10 studies are done on a new drug, and only 2 show a positive effect while 8 show no effect, but only the 2 positive studies get published, a later review of the literature might erroneously conclude the drug is effective.

Relation to Other Biases:

1. **Selection Bias**: Publication bias is a form of selection bias, where the selection (publication in this case) isn't random but based on the results of the study.
2. **Confirmation Bias**: Like survivorship bias, publication bias can reinforce confirmation bias. Researchers might only find and cite studies that confirm their beliefs, overlooking the unpublished studies that might contradict them.

Let's simulate an experiment on a new treatment. We'll assume that the treatment has no effect, but due to random variation, some studies will show significant positive or negative effects.

```r
set.seed(42)

# Number of studies
n <- 100
```

```r
# Assuming no real effect (effect size = 0)
true_effect <- 0

# Random variation in results
results <- rnorm(n, mean = true_effect, sd = 1)

# Only "significant" results get published
# (arbitrarily defining significant as abs(effect) > 1.5)
published_results <- results[abs(results) > 1.5]

# Average effect for all studies vs. published studies
true_avg_effect <- mean(results)
published_avg_effect <- mean(published_results)

true_avg_effect
#> [1] 0.03251482
published_avg_effect
#> [1] -0.3819601
```

Using a histogram to visualize the distribution of study results, highlighting the "published" studies.

```r
library(ggplot2)

df <- data.frame(results)

p <- ggplot(df, aes(x = results)) +
  geom_histogram(
    binwidth = 0.2,
    fill = "grey",
    color = "black",
    alpha = 0.7
  ) +
  geom_vline(
    aes(xintercept = true_avg_effect,
        color = "True Avg Effect"),
    linetype = "dashed",
    size = 1
  ) +
  geom_vline(
    aes(xintercept = published_avg_effect,
        color = "Published Avg Effect"),
    linetype = "dashed",
    size = 1
  ) +
  scale_color_manual(
```

```
    values = c(
      "True Avg Effect" = "blue",
      "Published Avg Effect" = "red"
    ),
    name = "Effect Type"
  ) +
  labs(title = "Distribution of Study Results",
       x = "Effect Size",
       y = "Number of Studies") +
  causalverse::ama_theme()

print(p)
```

The plot might show that the "True Avg Effect" is around zero, while the "Published Avg Effect" is likely higher or lower, depending on which studies happen to have significant results in the simulation.

Remedies:

1. **Awareness**: Understand and accept that publication bias exists, especially when conducting literature reviews or meta-analyses.
2. **Study Registries**: Encourage the use of study registries where researchers register their studies before they start. This way, one can see all initiated studies, not just the published ones.
3. **Publish All Results**: Journals and researchers should make an effort to publish negative or null results. Some journals, known as "null result journals", specialize in this.

4. **Funnel Plots and Egger's Test**: In meta-analyses, these are methods to visually and statistically detect publication bias.

5. **Use of Preprints**: Promote the use of preprint servers where researchers can upload studies before they're peer-reviewed, ensuring that results are available regardless of eventual publication status.

6. **p-curve analysis**: addresses publication bias and p-hacking by analyzing the distribution of p-values below 0.05 in research studies. It posits that a right-skewed distribution of these p-values indicates a true effect, whereas a left-skewed distribution suggests p-hacking and no true underlying effect. The method includes a "half-curve" test to counteract extensive p-hacking (Simonsohn et al., 2014a, Simonsohn et al. (2014b), Simonsohn et al. (2015)).

Chapter 35

Controls

This section follows (Cinelli et al., 2022) and code

```
library(dagitty)
library(ggdag)
```

Traditional literature usually considers adding additional control variables is harmless to analysis.

More specifically, this problem is most prevalent in the review process. Reviewers only ask authors to add more variables to "control" for such variable, which can be asked with only limited rationale. Rarely ever you will see a reviewer asks an author to remove some variables to see the behavior of the variable of interest (This is also related to Coefficient stability).

However, adding more controls is only good in limited cases.

35.1 Bad Controls

35.1.1 M-bias

Traditional textbooks (Imbens and Rubin, 2015; Angrist and Pischke, 2009) consider Z as a good control because it's a pre-treatment variable, where it correlates with the treatment and the outcome.

This is most prevalent in Matching Methods, where we are recommended to include all "pre-treatment" variables.

However, it is a bad control because it opens the back-door path $Z \leftarrow U_1 \rightarrow Z \leftarrow U_2 \rightarrow Y$

```
# cleans workspace
rm(list = ls())
```

```r
# DAG

## specify edges
model <- dagitty("dag{x->y; u1->x; u1->z; u2->z; u2->y}")

# set u as latent
latents(model) <- c("u1", "u2")

## coordinates for plotting
coordinates(model) <-  list(x = c(
    x = 1,
    u1 = 1,
    z = 2,
    u2 = 3,
    y = 3
),
y = c(
    x = 1,
    u1 = 2,
    z = 1.5,
    u2 = 2,
    y = 1
))

## ggplot
ggdag(model) + theme_dag()
```

Even though Z can correlate with both X and Y very well, it's not a confounder.

Controlling for Z can bias the $X \to Y$ estimate, because it opens the colliding path $X \leftarrow U_1 \to Z \leftarrow U_2 \leftarrow Y$

```
n <- 1e4
u1 <- rnorm(n)
u2 <- rnorm(n)
z <- u1 + u2 + rnorm(n)
x <- u1 + rnorm(n)
causal_coef <- 2
y <- causal_coef * x - 4*u2 + rnorm(n)


jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.1

	Model 1	Model 2
(Intercept)	-0.00	0.03
	(0.04)	(0.03)
x	2.02 ***	2.83 ***
	(0.03)	(0.03)
z		-1.59 ***
		(0.02)
N	10000	10000
R2	0.32	0.57

*** p < 0.001; ** p < 0.01; * p < 0.05.

Another worse variation is

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; u1->x; u1->z; u2->z; u2->y; z->y}")
```

```r
# set u as latent
latents(model) <- c("u1", "u2")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, u1=1, z=2, u2=3, y=3),
  y = c(x=1, u1=2, z=1.5, u2=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

You can't do much in this case.

- If you don't control for Z, then you have an open back-door path $X \leftarrow U_1 \rightarrow Z \rightarrow Y$, and the unadjusted estimate is biased

- If you control for Z, then you open backdoor path $X \leftarrow U_1 \rightarrow Z \leftarrow U_2 \rightarrow Y$, and the adjusted estimate is also biased

Hence, we cannot identify the causal effect in this case.

We can do sensitivity analyses to examine (Cinelli et al., 2019; Cinelli and Hazlett, 2020)

1. the plausible bounds on the strength of the direct effect of $Z \rightarrow Y$
2. the strength of the effects of the latent variables

35.1.2 Bias Amplification

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; u->x; u->y; z->x}")

# set u as latent
latents(model) <- c("u")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(z=1, x=2, u=3, y=4),
  y = c(z=1, x=1, u=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

Controlling for Z amplifies the omitted variable bias

```
n <- 1e4
z <- rnorm(n)
u <- rnorm(n)
```

```
x <- 2*z + u + rnorm(n)
y <- x + 2*u + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.2

	Model 1	Model 2
(Intercept)	-0.01	-0.00
	(0.02)	(0.02)
x	1.34 ***	2.00 ***
	(0.01)	(0.01)
z		-1.98 ***
		(0.03)
N	10000	10000
R2	0.71	0.80

*** p < 0.001; ** p < 0.01; * p < 0.05.

35.1.3 Overcontrol bias

Sometimes, this is similar to controlling for variables that are proxy of the dependent variable.

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->z; z->y}")


## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, y=3),
  y = c(x=1, z=1, y=1))
```

```
## ggplot
ggdag(model) + theme_dag()
```

If X is a proxy for Z (i.e., a mediator between Z and Y), controlling for Z is bad

```
n <- 1e4
x <- rnorm(n)
z <- x + rnorm(n)
y <- z + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Now you see that Z is significant, which is technically true, but we are interested in the causal coefficient of X on Y.

Another setting for overcontrol bias is

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->m; m->z; m->y}")


## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, m=2, z=2, y=3),
```

Table 35.3

	Model 1	Model 2
(Intercept)	0.01	0.01
	(0.01)	(0.01)
x	1.00 ***	-0.01
	(0.01)	(0.01)
z		1.01 ***
		(0.01)
N	10000	10000
R2	0.33	0.67

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
  y = c(x=2, m=2, z=1, y=2))

## ggplot
ggdag(model) + theme_dag()
```

```r
n <- 1e4
x <- rnorm(n)
m <- x + rnorm(n)
z <- m + rnorm(n)
y <- m + rnorm(n)


jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.4

	Model 1	Model 2
(Intercept)	-0.03 *	-0.02 *
	(0.01)	(0.01)
x	0.97 ***	0.49 ***
	(0.01)	(0.01)
z		0.50 ***
		(0.01)
N	10000	10000
R2	0.33	0.49

*** p < 0.001; ** p < 0.01; * p < 0.05.

Another setting for this bias is

```r
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->z; z->y; u->z; u->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, u=3, y=4),
```

```
  y = c(x=1, z=1, u=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

```
set.seed(1)
n <- 1e4
x <- rnorm(n)
u <- rnorm(n)
z <- x + u + rnorm(n)
y <- z + u + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

The total effect of X on Y is not biased (i.e., $1.01 \approx 1.48 - 0.47$).

Controlling for Z will fail to identify the direct effect of X on Y and opens the biasing path $X \to Z \leftarrow U \to Y$

35.1.4 Selection Bias

Also known as "collider stratification bias"

```
rm(list = ls())

# DAG

## specify edges
```

Table 35.5

	Model 1	Model 2
(Intercept)	-0.01	-0.01
	(0.02)	(0.01)
x	1.01 ***	-0.47 ***
	(0.02)	(0.01)
z		1.48 ***
		(0.01)
N	10000	10000
R2	0.15	0.78

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
model <- dagitty("dag{x->y; x->z; u->z;u->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, u=2, y=3),
  y = c(x=3, z=2, u=4, y=3))

## ggplot
ggdag(model) + theme_dag()
```

Adjusting Z opens the colliding path $X \to Z \leftarrow U \to Y$

```
n <- 1e4
x <- rnorm(n)
u <- rnorm(n)
z <- x + u +  rnorm(n)
y <- x + 2*u + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Another setting is

```
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; x->z; y->z}")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, y=3),
  y = c(x=2, z=1, y=2))

## ggplot
ggdag(model) + theme_dag()
```

Table 35.6

	Model 1	Model 2
(Intercept)	-0.01	0.01
	(0.02)	(0.02)
x	0.97 ***	-0.03
	(0.02)	(0.02)
z		1.00 ***
		(0.01)
N	10000	10000
R2	0.16	0.49

*** p < 0.001; ** p < 0.01; * p < 0.05.

Controlling Z opens the colliding path $X \to Z \leftarrow Y$

```
n <- 1e4
x <- rnorm(n)
y <- x + rnorm(n)
z <- x + y + rnorm(n)
```

```
jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.7

	Model 1	Model 2
(Intercept)	0.00	0.00
	(0.01)	(0.01)
x	1.03 ***	-0.00
	(0.01)	(0.01)
z		0.51 ***
		(0.00)
N	10000	10000
R2	0.51	0.76

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; y->z}")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, y=3),
  y = c(x=2, z=1, y=2))

## ggplot
ggdag(model) + theme_dag()
```

Controlling Z opens a virtual collider (a descendant of a collider).

However, if X truly has no causal effect on Y. Then, controlling for Z is valid for testing whether the effect of X on Y is 0 because X is d-separated from Y regardless of adjusting for Z

```
n <- 1e4
x <- rnorm(n)
y <- x + rnorm(n)
z <- y + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

35.2 Good Controls

35.2.1 Omitted Variable Bias Correction

This is when Z can block all back-door paths.

```
rm(list = ls())

model <- dagitty("dag{x->y; z->x; z->y}")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, y=3, z=2),
  y = c(x=1, y=1, z=2))
```

Table 35.8

	Model 1	Model 2
(Intercept)	-0.00	-0.00
	(0.01)	(0.01)
x	1.00 ***	0.50 ***
	(0.01)	(0.01)
z		0.50 ***
		(0.00)
N	10000	10000
R2	0.50	0.75

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
## ggplot
ggdag(model) + theme_dag()
```

Unadjusted estimate is biased

adjusting for Z blocks the backdoor path

```r
n <- 1e4
z <- rnorm(n)
causal_coef = 2
beta2 = 3
x <- z + rnorm(n)
y <- causal_coef * x + beta2 * z + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.9

	Model 1	Model 2
(Intercept)	0.01	-0.00
	(0.02)	(0.01)
x	3.51 ***	2.00 ***
	(0.02)	(0.01)
z		3.02 ***
		(0.01)
N	10000	10000
R2	0.82	0.97

*** p < 0.001; ** p < 0.01; * p < 0.05.

```r
# cleans workspace
rm(list = ls())

# Draw DAG

# specify edges
model <- dagitty("dag{x->y; u->z; z->x; u->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, u=3, y = 4),
  y = c(x=1, y=1, z=2, u = 3))
```

```r
## ggplot
ggdag(model) + theme_dag()
```

Unadjusted estimate is biased

adjusting for Z blocks the backdoor door path due to U

```r
n <- 1e4
u <- rnorm(n)
z <- u + rnorm(n)
causal_coef = 2
x <- z + rnorm(n)
y <- causal_coef * x + u + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Even though Z is significant, we cannot give it a causal interpretation.

```r
# cleans workspace
rm(list = ls())

# Draw DAG

# specify edges
model <- dagitty("dag{x->y; u->z; u->x; z->y}")

# set u as latent
latents(model) <- "u"
```

Table 35.10

	Model 1	Model 2
(Intercept)	0.03 *	0.03 *
	(0.01)	(0.01)
x	2.34 ***	2.01 ***
	(0.01)	(0.01)
z		0.49 ***
		(0.01)
N	10000	10000
R2	0.91	0.92

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=3, u=2, y = 4),
  y = c(x=1, y=1, z=2, u = 3))

## ggplot
ggdag(model) + theme_dag()
```

```
n     <- 1e4
u     <- rnorm(n)
z     <- u + rnorm(n)
x     <- u + rnorm(n)
causal_coef <- 2
y     <- causal_coef * x + z + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Even though Z is significant, we cannot give it a causal interpretation.

Summary

```
# cleans workspace
rm(list = ls())

# Model 1

model1 <- dagitty("dag{x->y; z->x; z->y}")

## coordinates for plotting
coordinates(model1) <-  list(
  x = c(x=1, y=3, z=2),
  y = c(x=1, y=1, z=2))



# Model 2
```

Table 35.11

	Model 1	Model 2
(Intercept)	-0.03	-0.01
	(0.02)	(0.01)
x	2.51 ***	2.01 ***
	(0.01)	(0.01)
z		1.01 ***
		(0.01)
N	10000	10000
R2	0.84	0.93

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
# specify edges
model2 <- dagitty("dag{x->y; u->z; z->x; u->y}")

# set u as latent
latents(model2) <- "u"

## coordinates for plotting
coordinates(model2) <-  list(
  x = c(x=1, z=2, u=3, y = 4),
  y = c(x=1, y=1, z=2, u = 3))



# Model 3

# specify edges
model3 <- dagitty("dag{x->y; u->z; u->x; z->y}")

# set u as latent
latents(model3) <- "u"

## coordinates for plotting
coordinates(model3) <-  list(
```

```
  x = c(x=1, z=3, u=2, y = 4),
  y = c(x=1, y=1, z=2, u = 3))

par(mfrow=c(1,3))

## ggplot
ggdag(model1) + theme_dag()
```

```
## ggplot
ggdag(model2) + theme_dag()
```

```
## ggplot
ggdag(model3) + theme_dag()
```

35.2.2 Omitted Variable Bias in Mediation Correction

Common causes of X and any mediator (between X and Y) confound the effect of X on Y

```r
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; z->x; x->m; z->m; m->y}")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, m=3, y=4),
  y = c(x=1, z=2, m=1, y=1))

## ggplot
ggdag(model) + theme_dag()
```

Z is a confounder of both the mediator M and X

```r
n     <- 1e4
z     <- rnorm(n)
x     <- z + rnorm(n)
causal_coef <- 2
m     <- causal_coef * x + z + rnorm(n)
y     <- m + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.12

	Model 1	Model 2
(Intercept)	-0.02	-0.01
	(0.02)	(0.01)
x	2.49 ***	1.97 ***
	(0.01)	(0.01)
z		1.02 ***
		(0.02)
N	10000	10000
R2	0.83	0.86

*** p < 0.001; ** p < 0.01; * p < 0.05.

```r
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; u->z; z->x; x->m; u->m; m->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, u=3, m=4, y=5),
  y = c(x=1, z=2, u=3, m=1, y=1))

## ggplot
ggdag(model) + theme_dag()
```

```
n     <- 1e4
u     <- rnorm(n)
z     <- u + rnorm(n)
x     <- z + rnorm(n)
causal_coef <- 2
m     <- causal_coef * x + u + rnorm(n)
y     <- m + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; u->z; z->m; x->m; u->x; m->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=3, u=2, m=4, y=5),
  y = c(x=1, z=2, u=3, m=1, y=1))

## ggplot
```

Table 35.13

	Model 1	Model 2
(Intercept)	-0.01	-0.01
	(0.02)	(0.02)
x	2.31 ***	2.00 ***
	(0.01)	(0.02)
z		0.49 ***
		(0.02)
N	10000	10000
R2	0.86	0.86

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
ggdag(model) + theme_dag()
```

```
n     <- 1e4
u     <- rnorm(n)
z     <- u + rnorm(n)
```

```
x     <- u + rnorm(n)
causal_coef <- 2
m     <- causal_coef * x + z + rnorm(n)
y     <- m + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Table 35.14

	Model 1	Model 2
(Intercept)	0.01	-0.00
	(0.02)	(0.01)
x	2.50 ***	1.99 ***
	(0.01)	(0.01)
z		1.02 ***
		(0.01)
N	10000	10000
R2	0.78	0.87

*** p < 0.001; ** p < 0.01; * p < 0.05.

Summary

```
# model 4
model4 <- dagitty("dag{x->y; z->x; x->m; z->m; m->y}")

## coordinates for plotting
coordinates(model4) <-  list(
  x = c(x=1, z=2, m=3, y=4),
  y = c(x=1, z=2, m=1, y=1))


# model 5
model5 <- dagitty("dag{x->y; u->z; z->x; x->m; u->m; m->y}")

# set u as latent
latents(model5) <- "u"

## coordinates for plotting
```

```r
coordinates(model5) <-  list(
  x = c(x=1, z=2, u=3, m=4, y=5),
  y = c(x=1, z=2, u=3, m=1, y=1))


# model 6

model6 <- dagitty("dag{x->y; u->z; z->m; x->m; u->x; m->y}")

# set u as latent
latents(model6) <- "u"

## coordinates for plotting
coordinates(model6) <-  list(
  x = c(x=1, z=3, u=2, m=4, y=5),
  y = c(x=1, z=2, u=3, m=1, y=1))

par(mfrow=c(1,3))

## ggplot
ggdag(model4) + theme_dag()
```

```r
## ggplot
ggdag(model5) + theme_dag()
```

```
## ggplot
ggdag(model6) + theme_dag()
```

35.3 Neutral Controls

35.3.1 Good Predictive Controls

Good for precision

```r
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; z->y}")


## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, y=2),
  y = c(x=1, z=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

Controlling for Z does not help or hurt identification, but it can increase precision (i.e., reducing SE)

```r
n <- 1e4
z <- rnorm(n)
x <- rnorm(n)
y <- x + 2 * z + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Similar coefficients, but smaller SE when controlling for Z

Table 35.15

	Model 1	Model 2
(Intercept)	0.01	0.01
	(0.02)	(0.01)
x	1.00 ***	1.01 ***
	(0.02)	(0.01)
z		2.00 ***
		(0.01)
N	10000	10000
R2	0.17	0.83

*** p < 0.001; ** p < 0.01; * p < 0.05.

Another variation is

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; x->m; z->m; m->y}")

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, m=2, y=3),
  y = c(x=1, z=2, m=1, y=1))

## ggplot
ggdag(model) + theme_dag()
```

```
n <- 1e4
z <- rnorm(n)
x <- rnorm(n)
m <- 2 * z + rnorm(n)
y <- x + 2 * m + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Controlling for Z can reduce SE

35.3.2 Good Selection Bias

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; x->z; z->w; u->w;u->y}")

# set u as latent
latents(model) <- "u"

## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, w=3, u=3, y=5),
  y = c(x=3, z=2, w=1, u=4, y=3))
```

Table 35.16

	Model 1	Model 2
(Intercept)	-0.00	-0.00
	(0.05)	(0.02)
x	0.97 ***	0.99 ***
	(0.05)	(0.02)
z		4.02 ***
		(0.02)
N	10000	10000
R2	0.04	0.77

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
## ggplot
ggdag(model) + theme_dag()
```

1. Unadjusted estimate is unbiased
2. Controlling for Z can increase SE

3. Controlling for Z while having on W can help identify X

```
n <- 1e4
x <- rnorm(n)
u <- rnorm(n)
z <- x + rnorm(n)
w <- z + u + rnorm(n)
y <- x - 2*u + rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + w), lm(y ~ x + z + w))
```

Table 35.17

	Model 1	Model 2	Model 3
(Intercept)	0.01	0.01	0.03
	(0.02)	(0.02)	(0.02)
x	0.99 ***	1.65 ***	0.99 ***
	(0.02)	(0.02)	(0.02)
w		-0.67 ***	-1.01 ***
		(0.01)	(0.01)
z			1.02 ***
			(0.02)
N	10000	10000	10000
R2	0.16	0.39	0.50

*** p < 0.001; ** p < 0.01; * p < 0.05.

35.3.3 Bad Predictive Controls

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; z->x}")
```

```r
## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=1, y=2),
  y = c(x=1, z=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

```r
n <- 1e4
z <- rnorm(n)
x <- 2 * z + rnorm(n)
y <- x + 2 * rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Similar coefficients, but greater SE when controlling for Z

Another variation is

```r
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; x->z}")


## coordinates for plotting
```

Table 35.18

	Model 1	Model 2
(Intercept)	-0.02	-0.02
	(0.02)	(0.02)
x	0.99 ***	1.00 ***
	(0.01)	(0.02)
z		-0.00
		(0.04)
N	10000	10000
R2	0.55	0.55

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
coordinates(model) <-  list(
  x = c(x=1, z=1, y=2),
  y = c(x=1, z=2, y=1))

## ggplot
ggdag(model) + theme_dag()
```

```
set.seed(1)
n <- 1e4
x <- rnorm(n)
z <- 2 * x + rnorm(n)
y <- x + 2 * rnorm(n)

jtools::export_summs(lm(y ~ x), lm(y ~ x + z))
```

Worse SE when controlling for Z $(0.02 < 0.05)$

35.3.4 Bad Selection Bias

```
# cleans workspace
rm(list = ls())

# DAG

## specify edges
model <- dagitty("dag{x->y; x->z}")


## coordinates for plotting
coordinates(model) <-  list(
  x = c(x=1, z=2, y=2),
  y = c(x=1, z=2, y=1))

## ggplot
```

Table 35.19

	Model 1	Model 2
(Intercept)	0.02	0.02
	(0.02)	(0.02)
x	1.00 ***	0.99 ***
	(0.02)	(0.05)
z		0.00
		(0.02)
N	10000	10000
R2	0.20	0.20

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
ggdag(model) + theme_dag()
```

Not all post-treatment variables are bad.

Controlling for Z is neutral, but it might hurt the precision of the causal effect.

```
library(pcalg)
library(dagitty)
library(causaleffect)
```

By providing a causal diagram, deciding the appropriateness of controls are automated.

- Fusion

- DAGitty

Guide on how to choose confounders: VanderWeele (2019)

In cases where it's hard to determine the plausibility of controls, we might need to further analysis.

`sensemakr` provides such tools.

```
library(sensemakr)
```

In simple cases, we can follow the simple rules of thumb provided by Steinmetz and Block (2022) (p. 614, Fig 2)

Fig. 2 Decision process underlying the consideration of auxiliary variables

Chapter 36

Mediation

36.1 Traditional Approach

Baron and Kenny (1986) is outdated because of step 1, but we could still see the original idea.

3 regressions

- Step 1: $X \to Y$
- Step 2: $X \to M$
- Step 3: $X + M \to Y$

where

- X = independent (causal) variable
- Y = dependent (outcome) variable
- M = mediating variable

Note: Originally, the first path from $X \to Y$ suggested by (Baron and Kenny, 1986) needs to be significant. But there are cases in which you could have indirect of X on Y without significant direct effect of X on Y (e.g., when the effect is absorbed into M, or there are two counteracting effects M_1, M_2 that cancel out each other effect).

where c is the **total effect**

Figure 36.1: Unmediated model

where

- $c' =$ **direct effect** (effect of X on Y after accounting for the indirect path)
- $ab =$ **indirect effect**

Hence,

$$\text{total effect} = \text{direct effect} + \text{indirect effect}$$
$$c = c' + ab$$

However, this simple equation does not only hold in cases of

1. Models with latent variables
2. Logistic models (only approximately). Hence, you can only calculate c as the total effect of $c' + ab$
3. Multi-level models (Bauer et al., 2006)

To measure mediation (i.e., indirect effect),

1. $1 - \frac{c'}{c}$ highly unstable (MacKinnon et al., 1995), especially in cases that c is small (not re* recommended)

2. **Product method**: $a \times b$
3. **Difference method**: $c - c'$

For linear models, we have the following assumptions:

1. No unmeasured confound between $X-Y$, $X-M$ and $M-Y$ relationships.
2. $X \nrightarrow C$ where C is a confounder between $M-Y$ relationship
3. Reliability: No errors in measurement of M (also known as reliability assumption) (can consider errors-in-variables models)

Mathematically,

$$Y = b_0 + b_1 X + \epsilon$$

b_1 does **not** need to be **significant**.

2. We examine the effect of X on M. This step requires that there is a significant effect of X on M to continue with the analysis

Mathematically,

$$M = b_0 + b_2 X + \epsilon$$

where b_2 needs to be **significant**.

3. In this step, we want to the effect of M on Y "absorbs" most of the direct effect of X on Y (or at least makes the effect smaller).

Mathematically,

$$Y = b_0 + b_4 X + b_3 M + \epsilon$$

b_4 needs to be either smaller or insignificant.

The effect of X on Y	then, M … mediates between X and Y
completely disappear (b_4 insignificant)	Fully (i.e., full mediation)
partially disappear ($b_4 < b_1$ in step 1)	Partially (i.e., partial mediation)

4. Examine the mediation effect (i.e., whether it is significant)

- Sobel Test (Sobel, 1982)
- Joint Significance Test
- Bootstrapping (Preacher and Hayes, 2004, Shrout and Bolger (2002)) (preferable)

Notes:

- Proximal mediation ($a > b$) can lead to multicollinearity and reduce statistical power, whereas distal mediation ($b > a$) is preferred for maximizing test power.
- The ideal balance for maximizing power in mediation analysis involves slightly distal mediators (i.e., path b is somewhat larger than path a) (Hoyle, 1999).
- Tests for direct effects (c and c') have lower power compared to the indirect effect (ab), making it possible for ab to be significant while c is not, even in cases where there seems to be complete mediation but no statistical evidence of a direct cause-effect relationship between X and Y without considering M (Kenny and Judd, 2014).
- The testing of ab offers a power advantage over c' because it effectively combines two tests. However, claims of complete mediation based solely on the non-significance of c' should be approached with caution, emphasizing the need for sufficient sample size and power, especially in assessing partial mediation. Or one should never make complete mediation claim (Hayes and Scharkow, 2013)

36.1.1 Assumptions

36.1.1.1 Direction

- Quick fix but not convincing: Measure X before M and Y to prevent M or Y causing X; measure M before Y to avoid Y causing M.
- Y may cause M in a feedback model.
  - Assuming $c' = 0$ (full mediation) allows for estimating models with reciprocal causal effects between M and Y via IV estimation.
  - Smith (1982) proposes treating both M and Y as outcomes with potential to mediate each other, requiring distinct instrumental variables for each that do not affect the other.

36.1.1.2 Interaction

- When M interact with X to affect Y, M is both a mediator and a mediator (Baron and Kenny, 1986).
- Interaction between XM should always be estimated.
- For the interpretation of this interaction, see (VanderWeele, 2015)

36.1.1.3 Reliability

- When mediator contains measurement errors, b, c' are biased. Possible fix: mediator = latent variable (but loss of power) (Ledgerwood and Shrout, 2011)
  - b is attenuated (closer to 0)
  - c' is
    - overestimated when $ab > 0$
    - underestiamted when $ab < 0$
- When treatment contains measurement errors, a, b are biased
  - a is attenuated
  - b is
    - overestimated when $ac' > 0$
    - underestimated when $ac' < 0$
- When outcome contains measurement errors,
  - If unstandardized, no bias
  - If standardized, attenuation bias

36.1.1.4 Confounding

- Omitted variable bias can happen to any pair of relationships
- To deal with this problem, one can either use
  - Design Strategies
  - Statistical Strategies

36.1.1.4.1 Design Strategies

- **Randomization** of treatment variable. If possible, also mediator
- **Control** for the confounder (but still only for measureable observables)

36.1.1.4.2 Statistical Strategies

- **Instrumental variable** on treatment
  - Specifically for confounder affecting the $M - Y$ pair, front-door adjustment is possible when there is a variable that completely mediates the effect of the mediator on the outcome and is unaffected by the confounder.
- **Weighting** methods (e.g., inverse propensity) See Heiss for R code

- Need strong ignorability assumption (i.e.., all confounders are included and measured without error (Westfall and Yarkoni, 2016)). Not fixable, but can be examined with robustness checks.

36.1.2 Indirect Effect Tests

36.1.2.1 Sobel Test

- developed by Sobel (1982)
- also known as the **delta method**
- not recommend because it assumes the indirect effect b has a normal distribution when it's not (MacKinnon et al., 1995).
- Mediation can occur even if direct and indirect effects oppose each other, termed "inconsistent mediation" (MacKinnon et al., 2007). This is when the mediator acts as a suppressor variable.

Standard Error

$$\sqrt{\hat{b}^2 s_{\hat{a}} + \hat{a}^2 s_b^2}$$

The test of the indirect effect is

$$z = \frac{\widehat{ab}}{\sqrt{\hat{b}^2 s_{\hat{a}} + \hat{a}^2 s_b^2}}$$

Disadvantages

- Assume a and b are independent.
- Assume ab is normally distributed.
- Does not work well for small sample sizes.
- Power of the test is low and the test is conservative as compared to Bootstrapping.

36.1.2.2 Joint Significance Test

- Effective for determining if the indirect effect is nonzero (by testing whether a and b are both statistically significant), assumes $a \perp b$.
- It's recommended to use it with other tests and has similar performance to a Bootstrapping test (Hayes and Scharkow, 2013).
- The test's accuracy can be affected by heteroscedasticity (Fossum and Montoya, 2023) but not by non-normality.

- Although helpful in computing power for the test of the indirect effect, it doesn't provide a confidence interval for the effect.

36.1.2.3 Bootstrapping

- First used by Bollen and Stine (1990)

- It allows for the calculation of confidence intervals, p-values, etc.

- It does not require $a \perp b$ and corrects for bias in the bootstrapped distribution.

- It can handle non-normality (in the sampling distribution of the indirect effect), complex models, and small samples.

- Concerns exist about the bias-corrected bootstrapping being too liberal (Fritz et al., 2012). Hence, current recommendations favor percentile bootstrap without bias correction for better Type I error rates (Tibbe and Montoya, 2022).

- A special case of bootstrapping is a proposed by where you don't need access to raw data to generate resampling, you only need $a, b, var(a), var(b), cov(a, b)$ (which can be taken from lots of primary studies)

```
result <-
    causalverse::med_ind(
        a = 0.5,
        b = 0.7,
        var_a = 0.04,
        var_b = 0.05,
        cov_ab = 0.01
    )
result$plot
```

```
library(DiagrammeR)
grViz("
digraph {
  graph []
  node [shape = plaintext]
    X [label = 'Treatment']
    Y [label = 'Outcome']
  edge [minlen = 2]
    X->Y
  { rank = same; X; Y }
}
")

grViz("
digraph {
  graph []
  node [shape = plaintext]
    X [label ='Treatment', shape = box]
    Y [label ='Outcome', shape = box]
    M [label ='Mediator', shape = box]
    IV [label ='Instrument', shape = box]
  edge [minlen = 2]
    IV->X
    X->M
    M->Y
```

```
    X->Y
  { rank = same; X; Y; M }
}
")
```

```
library(mediation)
data("boundsdata")
library(fixest)

# Total Effect
out1 <- feols(out ~ ttt, data = boundsdata)

# Indirect Effect
out2 <- feols(med ~ ttt, data = boundsdata)

# Direct and Indirect Effect
out3 <- feols(out ~ med + ttt, data = boundsdata)

# Proportion Test
# To what extent is the effect of the treatment mediated by the mediator?
coef(out2)['ttt'] * coef(out3)['med'] / coef(out1)['ttt'] * 100
#>      ttt
#> 68.63609


# Sobel Test
bda::mediation.test(boundsdata$med, boundsdata$ttt, boundsdata$out) |>
    tibble::rownames_to_column() |>
    causalverse::nice_tab(2)
#>   rowname Sobel Aroian Goodman
#> 1 z.value  4.05   4.03    4.07
#> 2 p.value  0.00   0.00    0.00
```

```
# Mediation Analysis using boot
library(boot)
set.seed(1)
mediation_fn <- function(data, i){
    # sample the dataset
    df <- data[i,]


    a_path <- feols(med ~ ttt, data = df)
    a <- coef(a_path)['ttt']
```

```
    b_path <-  feols(out ~ med + ttt, data = df)
    b <- coef(b_path)['med']

    cp <- coef(b_path)['ttt']

    # indirect effect
    ind_ef <- a*b
    total_ef <- a*b + cp
    return(c(ind_ef, total_ef))

}

boot_med <- boot(boundsdata, mediation_fn, R = 100, parallel = "multicore", ncpus = 2)
boot_med
#>
#> ORDINARY NONPARAMETRIC BOOTSTRAP
#>
#>
#> Call:
#> boot(data = boundsdata, statistic = mediation_fn, R = 100, parallel = "multicore",
#>     ncpus = 2)
#>
#>
#> Bootstrap Statistics :
#>       original        bias    std. error
#> t1* 0.04112035  0.0006346725 0.009539903
#> t2* 0.05991068 -0.0004462572 0.029556611

summary(boot_med) |>
    causalverse::nice_tab()
#>     R original bootBias bootSE bootMed
#> 1 100     0.04        0   0.01    0.04
#> 2 100     0.06        0   0.03    0.06

# confidence intervals (percentile is always recommended)
boot.ci(boot_med, type = c("norm", "perc"))
#> BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
#> Based on 100 bootstrap replicates
#>
#> CALL :
#> boot.ci(boot.out = boot_med, type = c("norm", "perc"))
#>
#> Intervals :
#> Level      Normal              Percentile
#> 95%   ( 0.0218,  0.0592 )   ( 0.0249,  0.0623 )
```

```
#> Calculations and Intervals on Original Scale
#> Some percentile intervals may be unstable

# point estimates (Indirect, and Total Effects)
colMeans(boot_med$t)
#> [1] 0.04175502 0.05946442
```

36.1.2.3.1 With Instrument Alternatively, one can use the `robmed` package

```
library(robmed)
```

Power test or use app

```
library(pwr2ppl)

# indirect path ab power
medjs(
    # X on M (path a)
    rx1m1 = .3,
    # correlation between X and Y (path c')
    rx1y  = .1,
    # correlation between M and Y (path b)
    rym1  = .3,
    # sample size
    n     = 100,
    alpha = 0.05,
    # number of mediators
    mvars = 1,
    # should use 10000
    rep   = 1000
)
```

36.1.3 Multiple Mediation

The most general package to handle multiple cases is `manymome`

See vignette for an example

```
library(manymome)
```

36.1.3.1 Multiple Mediators

- Notes
- Vignette
- Package

```r
library(mma)
```

```r
# Load required packages
library(MASS)  # for mvrnorm
library(lavaan)

# Function to generate synthetic data with correctly correlated errors for mediators
generate_data <-
  function(n = 10000,
           a1 = 0.5,
           a2 = -0.35,
           b1 = 0.7,
           b2 = 0.48,
           corr = TRUE,
           correlation_value = 0.7) {
    set.seed(12345)
    X <- rnorm(n)

    # Generate correlated errors using a multivariate normal distribution
    if (corr) {
        Sigma <- matrix(c(1, correlation_value, correlation_value, 1), nrow = 2)  # Hi
        errors <- mvrnorm(n, mu = c(0, 0), Sigma = Sigma)  # Generate correlated error
    } else {
        errors <- mvrnorm(n, mu = c(0, 0), Sigma = diag(2))  # Independent errors
    }

    M1 <- a1 * X + errors[, 1]
    M2 <- a2 * X + errors[, 2]
    Y <- b1 * M1 + b2 * M2 + rnorm(n)  # Y depends on M1 and M2

    data.frame(X = X, M1 = M1, M2 = M2, Y = Y)
}

# Ground truth for comparison
ground_truth <- data.frame(Parameter = c("b1", "b2"), GroundTruth = c(0.7, 0.48))

# Function to extract relevant estimates, standard errors, and model fit
extract_estimates_b1_b2 <- function(fit) {
    estimates <- parameterEstimates(fit)
    estimates <- estimates[estimates$lhs == "Y" & estimates$rhs %in% c("M1", "M2"), c(
    estimates$Parameter <- ifelse(estimates$rhs == "M1", "b1", "b2")
    estimates <- estimates[, c("Parameter", "est", "se")]
    fit_stats <- fitMeasures(fit, c("aic", "bic", "rmsea", "chisq"))
    return(list(estimates = estimates, fit_stats = fit_stats))
```

```r
}

# Case 1: Correlated errors for mediators (modeled correctly)
Data_corr <- generate_data(n = 10000, corr = TRUE, correlation_value = 0.7)
model_corr <- '
  Y ~ b1 * M1 + b2 * M2 + c * X
  M1 ~ a1 * X
  M2 ~ a2 * X
  M1 ~~ M2  # Correlated mediators (errors)
'
fit_corr <- sem(model = model_corr, data = Data_corr)
results_corr <- extract_estimates_b1_b2(fit_corr)

# Case 2: Uncorrelated errors for mediators (modeled correctly)
Data_uncorr <- generate_data(n = 10000, corr = FALSE)
model_uncorr <- '
  Y ~ b1 * M1 + b2 * M2 + c * X
  M1 ~ a1 * X
  M2 ~ a2 * X
'
fit_uncorr <- sem(model = model_uncorr, data = Data_uncorr)
results_uncorr <- extract_estimates_b1_b2(fit_uncorr)

# Case 3: Correlated errors, but not modeled as correlated
fit_corr_incorrect <- sem(model = model_uncorr, data = Data_corr)
results_corr_incorrect <- extract_estimates_b1_b2(fit_corr_incorrect)

# Case 4: Uncorrelated errors, but modeled as correlated
fit_uncorr_incorrect <- sem(model = model_corr, data = Data_uncorr)
results_uncorr_incorrect <- extract_estimates_b1_b2(fit_uncorr_incorrect)

# Combine all estimates for comparison
estimates_combined <- list(
    "Correlated (Correct)" = results_corr$estimates,
    "Uncorrelated (Correct)" = results_uncorr$estimates,
    "Correlated (Incorrect)" = results_corr_incorrect$estimates,
    "Uncorrelated (Incorrect)" = results_uncorr_incorrect$estimates
)

# Combine all into a single table
comparison_table <- do.call(rbind, lapply(names(estimates_combined), function(case) {
    df <- estimates_combined[[case]]
    df$Case <- case
    df
}))
```

```r
# Merge with ground truth for final comparison
comparison_table <- merge(comparison_table, ground_truth, by = "Parameter")

# Display the comparison table
comparison_table
#>   Parameter       est          se                      Case GroundTruth
#> 1        b1 0.7002984 0.013870433     Correlated (Correct)        0.70
#> 2        b1 0.6973612 0.009859426   Uncorrelated (Correct)        0.70
#> 3        b1 0.7002984 0.010010367   Correlated (Incorrect)        0.70
#> 4        b1 0.6973612 0.009859634 Uncorrelated (Incorrect)        0.70
#> 5        b2 0.4871118 0.013805615     Correlated (Correct)        0.48
#> 6        b2 0.4868318 0.010009908   Uncorrelated (Correct)        0.48
#> 7        b2 0.4871118 0.009963588   Correlated (Incorrect)        0.48
#> 8        b2 0.4868318 0.010010119 Uncorrelated (Incorrect)        0.48

# Display model fit statistics for each case
fit_stats_combined <- list(
    "Correlated (Correct)" = results_corr$fit_stats,
    "Uncorrelated (Correct)" = results_uncorr$fit_stats,
    "Correlated (Incorrect)" = results_corr_incorrect$fit_stats,
    "Uncorrelated (Incorrect)" = results_uncorr_incorrect$fit_stats
)

fit_stats_combined
#> $`Correlated (Correct)`
#>      aic      bic    rmsea    chisq
#> 77932.45 77997.34     0.00     0.00
#>
#> $`Uncorrelated (Correct)`
#>       aic       bic     rmsea     chisq
#> 84664.312 84721.995     0.000     0.421
#>
#> $`Correlated (Incorrect)`
#>       aic       bic     rmsea     chisq
#> 84453.208 84510.891     0.808  6522.762
#>
#> $`Uncorrelated (Incorrect)`
#>      aic      bic    rmsea    chisq
#> 84665.89 84730.78     0.00     0.00
```

36.1.3.1.0.1 Lavaan

36.1.3.2 Multiple Treatments

(Hayes and Preacher, 2014)

Code in Process

36.2 Causal Inference Approach

36.2.1 Example 1

from Virginia's library

```
myData <-
    read.csv('http://static.lib.virginia.edu/statlab/materials/data/mediationData.csv')

# Step 1 (no longer necessary)
model.0 <- lm(Y ~ X, myData)
summary(model.0)
#>
#> Call:
#> lm(formula = Y ~ X, data = myData)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -5.0262 -1.2340 -0.3282  1.5583  5.1622
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   2.8572     0.6932   4.122 7.88e-05 ***
#> X             0.3961     0.1112   3.564 0.000567 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.929 on 98 degrees of freedom
#> Multiple R-squared:  0.1147, Adjusted R-squared:  0.1057
#> F-statistic:  12.7 on 1 and 98 DF,  p-value: 0.0005671

# Step 2
model.M <- lm(M ~ X, myData)
summary(model.M)
#>
#> Call:
#> lm(formula = M ~ X, data = myData)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -4.3046 -0.8656  0.1344  1.1344  4.6954
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
```

```
#> (Intercept)  1.49952    0.58920   2.545   0.0125 *
#> X            0.56102    0.09448   5.938 4.39e-08 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.639 on 98 degrees of freedom
#> Multiple R-squared:  0.2646, Adjusted R-squared:  0.2571
#> F-statistic: 35.26 on 1 and 98 DF,  p-value: 4.391e-08

# Step 3
model.Y <- lm(Y ~ X + M, myData)
summary(model.Y)
#>
#> Call:
#> lm(formula = Y ~ X + M, data = myData)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -3.7631 -1.2393  0.0308  1.0832  4.0055
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   1.9043     0.6055   3.145   0.0022 **
#> X             0.0396     0.1096   0.361   0.7187
#> M             0.6355     0.1005   6.321 7.92e-09 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.631 on 97 degrees of freedom
#> Multiple R-squared:  0.373,  Adjusted R-squared:  0.3601
#> F-statistic: 28.85 on 2 and 97 DF,  p-value: 1.471e-10

# Step 4 (boostrapping)
library(mediation)
results <- mediate(
    model.M,
    model.Y,
    treat = 'X',
    mediator = 'M',
    boot = TRUE,
    sims = 500
)
summary(results)
#>
#> Causal Mediation Analysis
```

```
#>
#> Nonparametric Bootstrap Confidence Intervals with the Percentile Method
#>
#>                Estimate 95% CI Lower 95% CI Upper p-value
#> ACME             0.3565       0.2119         0.51  <2e-16 ***
#> ADE              0.0396      -0.1750         0.28   0.760
#> Total Effect     0.3961       0.1743         0.64   0.004 **
#> Prop. Mediated   0.9000       0.5042         1.94   0.004 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Sample Size Used: 100
#>
#>
#> Simulations: 500
```

- Total Effect = 0.3961 = b_1 (step 1) = total effect of X on Y without M
- Direct Effect = ADE = 0.0396 = b_4 (step 3) = direct effect of X on Y accounting for the indirect effect of M
- ACME = Average Causal Mediation Effects = $b_1 - b_4$ = 0.3961 - 0.0396 = 0.3565 = $b_2 \times b_3$ = 0.56102 * 0.6355 = 0.3565

Using `mediation` package suggested by (Imai et al., 2010a, Imai et al. (2010b)). More details of the package can be found here

2 types of Inference in this package:

1. Model-based inference:
   - Assumptions:
     - Treatment is randomized (could use matching methods to achieve this).
     - Sequential Ignorability: conditional on covariates, there is other confounders that affect the relationship between (1) treatment-mediator, (2) treatment-outcome, (3) mediator-outcome. Typically hard to argue in observational data. This assumption is for the identification of ACME (i.e., average causal mediation effects).
2. Design-based inference

Notations: we stay consistent with package instruction

- $M_i(t)$ = mediator
- T_i = treatment status $(0, 1)$
- $Y_i(t, m)$ = outcome where t = treatment, and m = mediating variables.

- X_i = vector of observed pre-treatment confounders
- Treatment effect (per unit i) = $\tau_i = Y_i(1, M_i(1)) - Y_i(0, M_i(0))$ which has 2 effects
  - Causal mediation effects: $\delta_i(t) \equiv Y_i(t, M_i(1)) - Y_i(t, M_i(0))$
  - Direct effects: $\zeta(t) \equiv Y_i(1, M_i(1)) - Y_i(0, M_i(0))$
  - summing up to the treatment effect: $\tau_i = \delta_i(t) + \zeta_i(1-t)$

More on sequential ignorability

$$\{Y_i(t', m), M_i(t)\} \perp T_i | X_i = x$$

$$Y_i(t', m) \perp M_i(t) | T_i = t, X_i = x$$

where

- $0 < P(T_i = t | X_i = x)$
- $0 < P(M_i = m | T_i = t, X_i = x)$

First condition is the standard strong ignorability condition where treatment assignment is random conditional on pre-treatment confounders.

Second condition is stronger where the mediators is also random given the observed treatment and pre-treatment confounders. This condition is satisfied only when there is no unobserved pre-treatment confounders, and post-treatment confounders, and multiple mediators that are correlated.

My understanding is that until the moment I write this note, there is **no way to test the sequential ignorability assumption**. Hence, researchers can only do sensitivity analysis to argue for their result.

36.3 Model-based causal mediation analysis

Other resources:

- here

Fit 2 models

- mediator model: conditional distribution of the mediators $M_i | T_i, X_i$
- Outcome model: conditional distribution of $Y_i | T_i, M_i, X_i$

`mediation` can accommodate almost all types of model for both mediator model and outcome model except Censored mediator model.

The update here is that estimation of ACME does not rely on product or difference of coefficients (see 36.2.1 ,

which requires very strict assumption: (1) linear regression models of mediator and outcome, (2) T_i and M_i effects are additive and no interaction

```
library(mediation)
set.seed(2014)
data("framing", package = "mediation")

med.fit <-
    lm(emo ~ treat + age + educ + gender + income, data = framing)
out.fit <-
    glm(
        cong_mesg ~ emo + treat + age + educ + gender + income,
        data = framing,
        family = binomial("probit")
    )

# Quasi-Bayesian Monte Carlo
med.out <-
    mediate(
        med.fit,
        out.fit,
        treat = "treat",
        mediator = "emo",
        robustSE = TRUE,
        sims = 100 # should be 10000 in practice
    )
summary(med.out)
#>
#> Causal Mediation Analysis
#>
#> Quasi-Bayesian Confidence Intervals
#>
#>                          Estimate 95% CI Lower 95% CI Upper p-value
#> ACME (control)             0.0791       0.0351         0.15  <2e-16 ***
#> ACME (treated)             0.0804       0.0367         0.16  <2e-16 ***
#> ADE (control)              0.0206      -0.0976         0.12    0.70
#> ADE (treated)              0.0218      -0.1053         0.12    0.70
#> Total Effect               0.1009      -0.0497         0.23    0.14
#> Prop. Mediated (control)   0.6946      -6.3109         3.68    0.14
#> Prop. Mediated (treated)   0.7118      -5.7936         3.50    0.14
#> ACME (average)             0.0798       0.0359         0.15  <2e-16 ***
#> ADE (average)              0.0212      -0.1014         0.12    0.70
#> Prop. Mediated (average)   0.7032      -6.0523         3.59    0.14
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
```

```
#> Sample Size Used: 265
#>
#>
#> Simulations: 100
```

Nonparametric bootstrap version

```
med.out <-
    mediate(
        med.fit,
        out.fit,
        boot = TRUE,
        treat = "treat",
        mediator = "emo",
        sims = 100, # should be 10000 in practice
        boot.ci.type = "bca" # bias-corrected and accelerated intervals
    )
summary(med.out)
#>
#> Causal Mediation Analysis
#>
#> Nonparametric Bootstrap Confidence Intervals with the BCa Method
#>
#>                          Estimate 95% CI Lower 95% CI Upper p-value
#> ACME (control)             0.0848       0.0424         0.14  <2e-16 ***
#> ACME (treated)             0.0858       0.0410         0.14  <2e-16 ***
#> ADE (control)              0.0117      -0.0726         0.13    0.58
#> ADE (treated)              0.0127      -0.0784         0.14    0.58
#> Total Effect               0.0975       0.0122         0.25    0.06 .
#> Prop. Mediated (control)   0.8698       1.7460       151.20    0.06 .
#> Prop. Mediated (treated)   0.8804       1.6879       138.91    0.06 .
#> ACME (average)             0.0853       0.0434         0.14  <2e-16 ***
#> ADE (average)              0.0122      -0.0756         0.14    0.58
#> Prop. Mediated (average)   0.8751       1.7170       145.05    0.06 .
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Sample Size Used: 265
#>
#>
#> Simulations: 100
```

If theoretically understanding suggests that there is treatment and mediator interaction

```
med.fit <-
    lm(emo ~ treat + age + educ + gender + income, data = framing)
```

```r
out.fit <-
    glm(
        cong_mesg ~ emo * treat + age + educ + gender + income,
        data = framing,
        family = binomial("probit")
    )
med.out <-
    mediate(
        med.fit,
        out.fit,
        treat = "treat",
        mediator = "emo",
        robustSE = TRUE,
        sims = 100
    )
summary(med.out)
#>
#> Causal Mediation Analysis
#>
#> Quasi-Bayesian Confidence Intervals
#>
#>                            Estimate 95% CI Lower 95% CI Upper p-value
#> ACME (control)              0.07417      0.02401         0.14  <2e-16 ***
#> ACME (treated)              0.09496      0.02702         0.16  <2e-16 ***
#> ADE (control)              -0.01353     -0.11855         0.11    0.76
#> ADE (treated)               0.00726     -0.11007         0.11    0.90
#> Total Effect                0.08143     -0.05646         0.19    0.26
#> Prop. Mediated (control)    0.64510    -14.31243         3.13    0.26
#> Prop. Mediated (treated)    0.98006    -17.83202         4.01    0.26
#> ACME (average)              0.08457      0.02738         0.15  <2e-16 ***
#> ADE (average)              -0.00314     -0.11457         0.12    1.00
#> Prop. Mediated (average)    0.81258    -16.07223         3.55    0.26
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Sample Size Used: 265
#>
#>
#> Simulations: 100

test.TMint(med.out, conf.level = .95) # test treatment-mediator interaction effect
#>
#>  Test of ACME(1) - ACME(0) = 0
#>
#> data:  estimates from med.out
```

```
#> ACME(1) - ACME(0) = 0.020796, p-value = 0.3
#> alternative hypothesis: true ACME(1) - ACME(0) is not equal to 0
#> 95 percent confidence interval:
#>  -0.01757310  0.07110837
```

```
plot(med.out)
```

`mediation` can be used in conjunction with any of your imputation packages.

And it can also handle **mediated moderation** or **non-binary treatment variables**, or **multi-level data**

Sensitivity Analysis for sequential ignorability

- test for unobserved pre-treatment covariates
- ρ = correlation between the residuals of the mediator and outcome regressions.
- If ρ is significant, we have evidence for violation of sequential ignorability (i.e., there is unobserved pre-treatment confounders).

```
med.fit <-
    lm(emo ~ treat + age + educ + gender + income, data = framing)
out.fit <-
    glm(
        cong_mesg ~ emo + treat + age + educ + gender + income,
        data = framing,
        family = binomial("probit")
    )
```

```r
med.out <-
    mediate(
        med.fit,
        out.fit,
        treat = "treat",
        mediator = "emo",
        robustSE = TRUE,
        sims = 100
    )
sens.out <-
    medsens(med.out,
            rho.by = 0.1, # \rho varies from -0.9 to 0.9 by 0.1
            effect.type = "indirect", # sensitivity on ACME
            # effect.type = "direct", # sensitivity on ADE
            # effect.type = "both", # sensitivity on ACME and ADE
            sims = 100)
summary(sens.out)
#>
#> Mediation Sensitivity Analysis: Average Mediation Effect
#>
#> Sensitivity Region: ACME for Control Group
#>
#>      Rho ACME(control) 95% CI Lower 95% CI Upper R^2_M*R^2_Y* R^2_M~R^2_Y~
#> [1,] 0.3        0.0062      -0.0073       0.0188         0.09       0.0493
#> [2,] 0.4       -0.0084      -0.0238       0.0017         0.16       0.0877
#>
#> Rho at which ACME for Control Group = 0: 0.3
#> R^2_M*R^2_Y* at which ACME for Control Group = 0: 0.09
#> R^2_M~R^2_Y~ at which ACME for Control Group = 0: 0.0493
#>
#>
#> Sensitivity Region: ACME for Treatment Group
#>
#>      Rho ACME(treated) 95% CI Lower 95% CI Upper R^2_M*R^2_Y* R^2_M~R^2_Y~
#> [1,] 0.3        0.0071      -0.0092       0.0213         0.09       0.0493
#> [2,] 0.4       -0.0101      -0.0295       0.0023         0.16       0.0877
#>
#> Rho at which ACME for Treatment Group = 0: 0.3
#> R^2_M*R^2_Y* at which ACME for Treatment Group = 0: 0.09
#> R^2_M~R^2_Y~ at which ACME for Treatment Group = 0: 0.0493
```

```r
plot(sens.out, sens.par = "rho", main = "Anxiety", ylim = c(-0.2, 0.2))
```

ACME confidence intervals contains 0 when $\rho \in (0.3, 0.4)$

Alternatively, using R^2 interpretation, we need to specify the direction of

confounder that affects the mediator and outcome variables in `plot` using `sign.prod = "positive"` (i.e., same direction) or `sign.prod = "negative"` (i.e., opposite direction).

```
plot(sens.out, sens.par = "R2", r.type = "total", sign.prod = "positive")
```

Chapter 37

Directed Acyclic Graph

Native R:

- `dagitty`
- `ggdag`
- `dagR`
- `r-causal`: by Center for Causal Discovery. Also available in Python

Publication-ready (with `R` and `Latex`): shinyDAG

Standalone program: DAG program by Sven Knuppel

37.1 Basic Notations

Basic building blocks of DAG

- Mediators (chains): $X \to Z \to Y$
  - controlling for Z blocks (closes) the causal impact of $X \to Y$
- Common causes (forks): $X \leftarrow Z \to Y$
  - Z (i.e., confounder) is a common cause in which it induces a non-causal association between X and Y.
  - Controlling for Z should close this association.
  - Z d-separates X from Y when it blocks (closes) all paths from X to Y (i.e., $X \perp Y|Z$). This applies to both common causes and mediators.
- Common effects (colliders): $X \to Z \leftarrow Y$
  - Not controlling for Z does not induce an association between X and Y

  - Controlling for Z induces a non-causal association between X and Y

Notes:

- A descendant of a variable behavior similarly to that variable (e.g., a descendant of Z can behave like Z and partially control for Z)
- Rule of thumb for multiple Controls: o have Causal inference $X \to Y$, we must
  - Close all backdoor path between X and Y (to eliminate spurious correlation)
  - Do not close any causal path between X and Y (any mediators).

V. MISCELLANEOUS

Chapter 38

Report

Structure

- Exploratory analysis
  - plots
  - preliminary results
  - interesting structure/features in the data
  - outliers
- Model
  - Assumptions
  - Why this model/ How is this model the best one?
  - Consideration: interactions, collinearity, dependence
- Model Fit
  - How well does it fit?
  - Are the model assumptions met?
    - Residual analysis
- Inference/ Prediction
  - Are there different way to support your inference?
- Conclusion
  - Recommendation
  - Limitation of the analysis
  - How to correct those in the future

This chapter is based on the `jtools` package. More information can be found here.

38.1 One summary table

Packages for reporting:

Summary Statistics Table:

- qwraps2
- vtable
- gtsummary
- apaTables
- stargazer

Regression Table

- gtsummary
- sjPlot,sjmisc, sjlabelled
- stargazer: recommended (Example)
- modelsummary

```
library(jtools)
data(movies)
fit <- lm(metascore ~ budget + us_gross + year, data = movies)
summ(fit)
```

Observations	831 (10 missing obs. deleted)
Dependent variable	metascore
Type	OLS linear regression

F(3,827)	26.23
R^2	0.09
Adj. R^2	0.08

	Est.	S.E.	t val.	p
(Intercept)	52.06	139.67	0.37	0.71
budget	-0.00	0.00	-5.89	0.00
us_gross	0.00	0.00	7.61	0.00
year	0.01	0.07	0.08	0.94

Standard errors: OLS

```
summ(
    fit,
    scale = TRUE,
    vifs = TRUE,
    part.corr = TRUE,
    confint = TRUE,
```

```
    pvals = FALSE
) # notice that scale here is TRUE
```

Observations	831 (10 missing obs. deleted)
Dependent variable	metascore
Type	OLS linear regression

F(3,827)	26.23
R^2	0.09
Adj. R^2	0.08

	Est.	2.5%	97.5%	t val.	VIF	partial.r	part.r
(Intercept)	63.01	61.91	64.11	112.23	NA	NA	NA
budget	-3.78	-5.05	-2.52	-5.89	1.31	-0.20	-0.20
us_gross	5.28	3.92	6.64	7.61	1.52	0.26	0.25
year	0.05	-1.18	1.28	0.08	1.24	0.00	0.00

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d. The outcome variable remains in its original units.

```
#obtain clsuter-robust SE
data("PetersenCL", package = "sandwich")
fit2 <- lm(y ~ x, data = PetersenCL)
summ(fit2, robust = "HC3", cluster = "firm")
```

Observations	5000
Dependent variable	y
Type	OLS linear regression

F(1,4998)	1310.74
R^2	0.21
Adj. R^2	0.21

	Est.	S.E.	t val.	p
(Intercept)	0.03	0.07	0.44	0.66
x	1.03	0.05	20.36	0.00

Standard errors: Cluster-robust, type = HC3

Model to Equation

```r
# install.packages("equatiomatic") # not available for R 4.2
fit <- lm(metascore ~ budget + us_gross + year, data = movies)
# show the theoretical model
equatiomatic::extract_eq(fit)
# display the actual coefficients
equatiomatic::extract_eq(fit, use_coefs = TRUE)
```

38.2 Model Comparison

```r
fit <- lm(metascore ~ log(budget), data = movies)
fit_b <- lm(metascore ~ log(budget) + log(us_gross), data = movies)
fit_c <- lm(metascore ~ log(budget) + log(us_gross) + runtime, data = movies)
coef_names <- c("Budget" = "log(budget)", "US Gross" = "log(us_gross)",
                "Runtime (Hours)" = "runtime", "Constant" = "(Intercept)")
export_summs(fit, fit_b, fit_c, robust = "HC3", coefs = coef_names)
```

Table 38.1

	Model 1	Model 2	Model 3
Budget	-2.43 ***	-5.16 ***	-6.70 ***
	(0.44)	(0.62)	(0.67)
US Gross		3.96 ***	3.85 ***
		(0.51)	(0.48)
Runtime (Hours)			14.29 ***
			(1.63)
Constant	105.29 ***	81.84 ***	83.35 ***
	(7.65)	(8.66)	(8.82)
N	831	831	831
R2	0.03	0.09	0.17

Standard errors are heteroskedasticity robust. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Another package is `modelsummary`

	(1)	(2)	(3)
(Intercept)	38.752	38.752	38.752
	(1.787)	(2.286)	(2.177)
wt	−3.167	−3.167	−3.167
	(0.741)	(0.833)	(0.819)
hp	−0.018	−0.018	−0.018
	(0.012)	(0.010)	(0.013)
cyl	−0.942	−0.942	−0.942
	(0.551)	(0.573)	(0.572)
Num.Obs.	32	32	32
R2	0.843	0.843	0.843
R2 Adj.	0.826	0.826	0.826
AIC	155.5	155.5	155.5
BIC	162.8	162.8	162.8
Log.Lik.	−72.738	−72.738	−72.738
F	50.171	31.065	32.623
RMSE	2.35	2.35	2.35
Std.Errors	IID	HC3	HC4

```r
library(modelsummary)
lm_mod <- lm(mpg ~ wt + hp + cyl, mtcars)
msummary(lm_mod, vcov = c("iid","robust","HC4"))
```

```r
modelplot(lm_mod, vcov = c("iid","robust","HC4"))
```

Another package is `stargazer`

```
library("stargazer")
stargazer(attitude)
#>
#> % Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-ma
#> % Date and time: Thu, Aug 29, 2024 - 4:28:41 PM
#> \begin{table}[!htbp] \centering
#>   \caption{}
#>   \label{}
#> \begin{tabular}{@{\extracolsep{5pt}}lccccc}
#> \\[-1.8ex]\hline
#> \hline \\[-1.8ex]
#> Statistic & \multicolumn{1}{c}{N} & \multicolumn{1}{c}{Mean} & \multicolumn{1}{c}{S
#> \hline \\[-1.8ex]
#> rating & 30 & 64.633 & 12.173 & 40 & 85 \\
#> complaints & 30 & 66.600 & 13.315 & 37 & 90 \\
#> privileges & 30 & 53.133 & 12.235 & 30 & 83 \\
#> learning & 30 & 56.367 & 11.737 & 34 & 75 \\
#> raises & 30 & 64.633 & 10.397 & 43 & 88 \\
#> critical & 30 & 74.767 & 9.895 & 49 & 92 \\
#> advance & 30 & 42.933 & 10.289 & 25 & 72 \\
#> \hline \\[-1.8ex]
#> \end{tabular}
#> \end{table}
## 2 OLS models
linear.1 <-
    lm(rating ~ complaints + privileges + learning + raises + critical,
       data = attitude)
linear.2 <-
    lm(rating ~ complaints + privileges + learning, data = attitude)
## create an indicator dependent variable, and run a probit model
attitude$high.rating <- (attitude$rating > 70)

probit.model <-
    glm(
        high.rating ~ learning + critical + advance,
        data = attitude,
        family = binomial(link = "probit")
    )
stargazer(linear.1,
          linear.2,
          probit.model,
          title = "Results",
          align = TRUE)
#>
```

```
#> % Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.h
#> % Date and time: Thu, Aug 29, 2024 - 4:28:41 PM
#> % Requires LaTeX packages: dcolumn
#> \begin{table}[!htbp] \centering
#>   \caption{Results}
#>   \label{}
#> \begin{tabular}{@{\extracolsep{5pt}}lD{.}{.}{-3} D{.}{.}{-3} D{.}{.}{-3} }
#> \\[-1.8ex]\hline
#> \hline \\[-1.8ex]
#>  & \multicolumn{3}{c}{\textit{Dependent variable:}} \\
#> \cline{2-4}
#> \\[-1.8ex] & \multicolumn{2}{c}{rating} & \multicolumn{1}{c}{high.rating} \\
#> \\[-1.8ex] & \multicolumn{2}{c}{\textit{OLS}} & \multicolumn{1}{c}{\textit{probit}} \\
#> \\[-1.8ex] & \multicolumn{1}{c}{(1)} & \multicolumn{1}{c}{(2)} & \multicolumn{1}{c}{(3)}\\
#> \hline \\[-1.8ex]
#>  complaints & 0.692^{***} & 0.682^{***} &  \\
#>   & (0.149) & (0.129) &  \\
#>   & & & \\
#>  privileges & -0.104 & -0.103 &  \\
#>   & (0.135) & (0.129) &  \\
#>   & & & \\
#>  learning & 0.249 & 0.238^{*} & 0.164^{***} \\
#>   & (0.160) & (0.139) & (0.053) \\
#>   & & & \\
#>  raises & -0.033 &  &  \\
#>   & (0.202) &  &  \\
#>   & & & \\
#>  critical & 0.015 &  & -0.001 \\
#>   & (0.147) &  & (0.044) \\
#>   & & & \\
#>  advance &  &  & -0.062 \\
#>   &  &  & (0.042) \\
#>   & & & \\
#>  Constant & 11.011 & 11.258 & -7.476^{**} \\
#>   & (11.704) & (7.318) & (3.570) \\
#>   & & & \\
#> \hline \\[-1.8ex]
#> Observations & \multicolumn{1}{c}{30} & \multicolumn{1}{c}{30} & \multicolumn{1}{c}{30} \\
#> R$^{2}$ & \multicolumn{1}{c}{0.715} & \multicolumn{1}{c}{0.715} &  \\
#> Adjusted R$^{2}$ & \multicolumn{1}{c}{0.656} & \multicolumn{1}{c}{0.682} &  \\
#> Log Likelihood &  &  & \multicolumn{1}{c}{-9.087} \\
#> Akaike Inf. Crit. &  &  & \multicolumn{1}{c}{26.175} \\
#> Residual Std. Error & \multicolumn{1}{c}{7.139 (df = 24)} & \multicolumn{1}{c}{6.863 (df = 26
#> F Statistic & \multicolumn{1}{c}{12.063$^{***}$ (df = 5; 24)} & \multicolumn{1}{c}{21.743$^{**
#> \hline
```

```
#> \hline \\[-1.8ex]
#> \textit{Note:}  & \multicolumn{3}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.
#> \end{tabular}
#> \end{table}
```

```
# Latex
stargazer(
    linear.1,
    linear.2,
    probit.model,
    title = "Regression Results",
    align = TRUE,
    dep.var.labels = c("Overall Rating", "High Rating"),
    covariate.labels = c(
        "Handling of Complaints",
        "No Special Privileges",
        "Opportunity to Learn",
        "Performance-Based Raises",
        "Too Critical",
        "Advancement"
    ),
    omit.stat = c("LL", "ser", "f"),
    no.space = TRUE
)
```

```
# ASCII text output
stargazer(
    linear.1,
    linear.2,
    type = "text",
    title = "Regression Results",
    dep.var.labels = c("Overall Rating", "High Rating"),
    covariate.labels = c(
        "Handling of Complaints",
        "No Special Privileges",
        "Opportunity to Learn",
        "Performance-Based Raises",
        "Too Critical",
        "Advancement"
    ),
    omit.stat = c("LL", "ser", "f"),
    ci = TRUE,
    ci.level = 0.90,
    single.row = TRUE
)
#>
```

```
#> Regression Results
#> ==========================================================================
#>                                          Dependent variable:
#>                            ---------------------------------------------
#>                                            Overall Rating
#>                                     (1)                      (2)
#> --------------------------------------------------------------------------
#> Handling of Complaints   0.692*** (0.447, 0.937) 0.682*** (0.470, 0.894)
#> No Special Privileges    -0.104 (-0.325, 0.118)  -0.103 (-0.316, 0.109)
#> Opportunity to Learn      0.249 (-0.013, 0.512)   0.238* (0.009, 0.467)
#> Performance-Based Raises -0.033 (-0.366, 0.299)
#> Too Critical              0.015 (-0.227, 0.258)
#> Advancement              11.011 (-8.240, 30.262) 11.258 (-0.779, 23.296)
#> --------------------------------------------------------------------------
#> Observations                        30                       30
#> R2                                 0.715                    0.715
#> Adjusted R2                        0.656                    0.682
#> ==========================================================================
#> Note:                                          *p<0.1; **p<0.05; ***p<0.01
```

```
stargazer(
    linear.1,
    linear.2,
    probit.model,
    title = "Regression Results",
    align = TRUE,
    dep.var.labels = c("Overall Rating", "High Rating"),
    covariate.labels = c(
        "Handling of Complaints",
        "No Special Privileges",
        "Opportunity to Learn",
        "Performance-Based Raises",
        "Too Critical",
        "Advancement"
    ),
    omit.stat = c("LL", "ser", "f"),
    no.space = TRUE
)
```

Correlation Table

```
correlation.matrix <-
    cor(attitude[, c("rating", "complaints", "privileges")])
stargazer(correlation.matrix, title = "Correlation Matrix")
```

38.3 Changes in an estimate

```
plot_summs(
    fit_c,
    robust = "HC3",
    coefs = coef_names,
    plot.distributions = TRUE
)
```

38.4 Standard Errors

`sandwich` vignette

Type	Applicable	Usage	Reference
`const`		Assume constant variances	
`HC`	`vcovCL`	Heterogeneity	(White, 1980)
`HC0`		White's estimator All other heterogeneity SE methods are derivatives of this. No small sample bias adjustment	
`HC1`	`vcovCL`	Uses a degrees of freedom-based correction When the number of clusters is small, `HC2` and `HC3` are better (Cameron et al., 2008)	(MacKinnon and White, 1985)
`HC2`	`vcovCL`	Better with the linear model, but still applicable for Generalized Linear Models Needs a hat (weighted) matrix	
`HC3`	`vcovCL`	Better with the linear model, but still applicable for Generalized Linear Models Needs a hat (weighted) matrix	
`HC4`	`vcovHC`		(Cribari-Neto, 2004)
`HC4m`	`vcovHC`		(Cribari-Neto et al., 2007)

Type	Applicable Usage	Reference
HC5	vcovHC	(Cribari-Neto and da Silva, 2011)

```
data(cars)
model <- lm(speed ~ dist, data = cars)
summary(model)
#>
#> Call:
#> lm(formula = speed ~ dist, data = cars)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -7.5293 -2.1550  0.3615  2.4377  6.4179
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  8.28391    0.87438   9.474 1.44e-12 ***
#> dist         0.16557    0.01749   9.464 1.49e-12 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 3.156 on 48 degrees of freedom
#> Multiple R-squared:  0.6511, Adjusted R-squared:  0.6438
#> F-statistic: 89.57 on 1 and 48 DF,  p-value: 1.49e-12
lmtest::coeftest(model, vcov. = sandwich::vcovHC(model, type = "HC1"))
#>
#> t test of coefficients:
#>
#>             Estimate Std. Error t value  Pr(>|t|)
#> (Intercept) 8.283906   0.891860  9.2883 2.682e-12 ***
#> dist        0.165568   0.019402  8.5335 3.482e-11 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

38.5 Coefficient Uncertainty and Distribution

The `ggdist` allows us to visualize uncertainty under both frequentist and Bayesian frameworks

```
library(ggdist)
```

38.6 Descriptive Tables

Export APA theme

```
data("mtcars")

library(flextable)
theme_apa(flextable(mtcars[1:5,1:5]))
```

Export to Latex

```
print(xtable::xtable(mtcars, type = "latex"),
      file = file.path(getwd(), "output", "mtcars_xtable.tex"))

# American Economic Review style
stargazer::stargazer(
    mtcars,
    title = "Testing",
    style = "aer",
    out = file.path(getwd(), "output", "mtcars_stargazer.tex")
)

# other styles include
# Administrative Science Quarterly
# Quarterly Journal of Economics
```

However, the above codes do not play well with notes. Hence, I create my own custom code that follows the AMA guidelines

```
ama_tbl <- function(data, caption, label, note, output_path) {
  library(tidyverse)
  library(xtable)
  # Function to determine column alignment
  get_column_alignment <- function(data) {
    # Start with the alignment for the header row
    alignment <- c("l", "l")

    # Check each column
    for (col in seq_len(ncol(data))[-1]) {
      if (is.numeric(data[[col]])) {
        alignment <- c(alignment, "r")  # Right alignment for numbers
      } else {
        alignment <- c(alignment, "c")  # Center alignment for other data
      }
    }

    return(alignment)
  }
```

```
  data %>%
    # bold + left align first column
    rename_with(~paste("\\multicolumn{1}{l}{\\textbf{", ., "}}"), 1) %>%
    # bold + center align all other columns
    `colnames<-`(ifelse(colnames(.) != colnames(.)[1],
                        paste("\\multicolumn{1}{c}{\\textbf{", colnames(.), "}}"),
                        colnames(.))) %>%

    xtable(caption = caption,
           label = label,
           align = get_column_alignment(data),
           auto = TRUE) %>%
    print(
      include.rownames = FALSE,
      caption.placement = "top",

      hline.after=c(-1, 0),

       # p{0.9\linewidth} sets the width of the column to 90% of the line width, and t

      add.to.row = list(pos = list(nrow(data)), # Add at the bottom of the table
                        command = c(paste0("\\hline \n \\multicolumn{",ncol(data), "}{

      # make sure your heading is untouched (because you manually change it above)
      sanitize.colnames.function = identity,

      # place a the top of the page
      table.placement = "h",

      file = output_path
    )
}
```

```
ama_tbl(
    mtcars,
    caption     = "This is caption",
    label       = "tab:this_is_label",
    note        = "this is note",
    output_path = file.path(getwd(), "output", "mtcars_custom_ama.tex")
)
```

38.7 Visualizations and Plots

You can customize your plots based on your preferred journals. Here, I am creating a custom setting for the American Marketing Association.

American-Marketing-Association-ready theme for plots

```
library(ggplot2)

# check available fonts
# windowsFonts()

# for Times New Roman
# names(windowsFonts()[windowsFonts()=="TT Times New Roman"])
```

```
# Making a theme
amatheme = theme_bw(base_size = 14, base_family = "serif") + # This is Time New Roman

    theme(
        # remove major gridlines
        panel.grid.major   = element_blank(),

        # remove minor gridlines
        panel.grid.minor   = element_blank(),

        # remove panel border
        panel.border       = element_blank(),

        line               = element_line(),

        # change font
        text               = element_text(),

        # if you want to remove legend title
        # legend.title     = element_blank(),

        legend.title       = element_text(size = rel(0.6), face = "bold"),

        # change font size of legend
        legend.text        = element_text(size = rel(0.6)),

        legend.background  = element_rect(color = "black"),

        # legend.margin    = margin(t = 5, l = 5, r = 5, b = 5),
        # legend.key       = element_rect(color = NA, fill = NA),

        # change font size of main title
```

```
        plot.title          = element_text(
            size            = rel(1.2),
            face            = "bold",
            hjust           = 0.5,
            margin          = margin(b = 15)
        ),

        plot.margin         = unit(c(1, 1, 1, 1), "cm"),

        # add black line along axes
        axis.line           = element_line(colour = "black", linewidth = .8),

        axis.ticks          = element_line(),


        # axis title
        axis.title.x        = element_text(size = rel(1.2), face = "bold"),
        axis.title.y        = element_text(size = rel(1.2), face = "bold"),

        # axis text size
        axis.text.y         = element_text(size = rel(1)),
        axis.text.x         = element_text(size = rel(1))
    )
```

Example

```
library(tidyverse)
library(ggsci)
data("mtcars")
yourplot <- mtcars %>%
    select(mpg, cyl, gear) %>%
    ggplot(., aes(x = mpg, y = cyl, fill = gear)) +
    geom_point() +
    labs(title="Some Plot")

yourplot +
    amatheme +
    # choose different color theme
    scale_color_npg()
```

```
yourplot +
    amatheme +
    scale_color_continuous()
```

Other pre-specified themes

```
library(ggthemes)
```

```r
# Stata theme
yourplot +
    theme_stata()
```

```r
# The economist theme
yourplot +
    theme_economist()
```

```
yourplot +
    theme_economist_white()
```

```
# Wall street journal theme
yourplot +
    theme_wsj()
```

```r
# APA theme
yourplot +
    jtools::theme_apa(
        legend.font.size = 24,
        x.font.size = 20,
        y.font.size = 20
    )
```

Chapter 39

Exploratory Data Analysis

```r
# load to get txhousing data
library(ggplot2)
```

Data Report

Feature Engineering

Missing Data

```r
# install.packages("DataExplorer")
library(DataExplorer)

# creat a html file that contain all reports
create_report(txhousing)

introduce() # see basic info


dummify() # create binary columns from discrete variables
split_columns() # split data into discrete and continuous parts



plot_correlation() # heatmap for discrete var
plot_intro()

plot_missing() # plot missing value
profile_missing() # profile missing values
```

```r
plot_prcomp() # plot PCA
```

Error Identification

```r
# install.packages("dataReporter")
library(dataReporter)
makeDataReport() # detailed report like DataExplorer
```

Summary statistics

```r
library(skimr)
skim() # give only few quick summary stat, not as detailed as the other two packages
```

Not so code-y process

Quick and dirty way to look at your data

```r
# install.packages("rpivotTable")
library(rpivotTable)
# give set up just like Excel table
data %>%
    rpivotTable::rpivotTable()
```

Code generation and wrangling

Shiny-app based Tableu style

```r
# install.packages("esquisse")
library(esquisse)
esquisse::esquisser()
```

Customized your daily/automatic report

```r
# install.packages("chronicle")
library(chronicle)
```

```r
# install.packages("dlookr")
# install.packages("descriptr")
```

Chapter 40

Sensitivity Analysis/ Robustness Check

40.1 Specification curve

- also known as Specification robustness graph or coefficient stability plot

Resources

- In Stata or speccurve
- (Simonsohn et al., 2020)

40.1.1 starbility

- Recommend

Installation

```
devtools::install_github('https://github.com/AakaashRao/starbility')
library(starbility)
```

Example by the package's author

```
library(tidyverse)
library(starbility)
library(lfe)
data("diamonds")
set.seed(43)
indices = sample(1:nrow(diamonds),
                 replace = F,
                 size = round(nrow(diamonds) / 20))
diamonds = diamonds[indices, ]
```

Plot different combinations of controls

```
# If you want to make the diamond dimensions as base control
base_controls = c(
  'Diamond dimensions' = 'x + y + z' # include all variables under 1 dimension
)


perm_controls = c(
  'Depth' = 'depth',
  'Table width' = 'table'
)

nonperm_fe_controls = c(
  'Clarity FE (granular)' = 'clarity',
  'Clarity FE (binary)' = 'high_clarity'
)

# Adding fixed effects
nonperm_fe_controls = c(
  'Clarity FE (granular)' = 'clarity',
  'Clarity FE (binary)' = 'high_clarity'
)

# Adding instrumental variables
instruments = 'x+y+z'

# clustering and weights
diamonds$sample_weights = runif(n = nrow(diamonds))


# robust standard errors
starb_felm_custom = function(spec, data, rhs, ...) {
  spec = as.formula(spec)
  model = lfe::felm(spec, data=data) %>% broom::tidy()

  row = which(model$term==rhs)
  coef = model[row, 'estimate'] %>% as.numeric()
  se   = model[row, 'std.error'] %>% as.numeric()
  p    = model[row, 'p.value'] %>% as.numeric()

  # 99% confidence interval
  z = qnorm(0.995)
  # one-tailed test
  return(c(coef, p/2, coef+z*se, coef-z*se))
}
```

```
plots = stability_plot(
    data = diamonds,
    lhs = 'price',
    rhs = 'carat',
    error_geom = 'ribbon', # make the plot more aesthetics
    # error_geom = 'none', # if you don't want ribbon (i.e., error bar)
    model = starb_felm_custom,
    cluster = 'cut',
    weights = 'sample_weights',
    # iv = instruments,
    perm = perm_controls,
    base = base_controls,
    # perm_fe = perm_fe_controls,

    # if you want to include fixed effects sequentially (not all combinations)
    # (e.g., you want to test country or state fixed effect, not both )
    # nonperm_fe = nonperm_fe_controls,
    # fe_always = F,  # if you want to have a model without any Fixed Effects

    # sort "asc", "desc", or by fixed effects: "asc-by-fe" or "desc-by-fe"
    sort = "asc-by-fe",

    # if you have less variables and want more aesthetics
    # control_geom = 'circle',
    # point_size = 2,
    # control_spacing = 0.3,


    # error_alpha = 0.2, # change alpha of the error geom
    # point_size = 1.5, # change the size of the coefficient points
    # control_text_size = 10, # change the size of the control labels
    # coef_ylim = c(-5000, 35000), # change the endpoints of the y-axis
    # trip_top = 3, # change the spacing between the two panels

    rel_height = 0.6
)
plots
```

```
# add comments
# replacement_coef_panel = plots[[1]] +
#   scale_y_reverse() +
#   theme(panel.grid.minor = element_blank()) +
#   geom_vline(xintercept = 41,
#              linetype = 'dashed',
#              alpha = 0.4) +
#   annotate(
#     geom = 'label',
#     x = 52,
#     y = 30000,
#     label = 'What a great\nspecification!',
#     alpha = 0.75
#   )
#
# combine_plots(replacement_coef_panel,
#               plots[[2]],
#               rel_height = 0.6)
```

Note:

- $p < 0.01$: red
- $p < 0.05$: green
- $p < 0.1$: blue
- $p > 0.1$: black

More Advanced Stuff

```r
# Step 1: Control Grid

diamonds$high_clarity = diamonds$clarity %in% c('VS1','VVS2','VVS1','IF')

base_controls = c(
  'Diamond dimensions' = 'x + y + z'
)

perm_controls = c(
  'Depth' = 'depth',
  'Table width' = 'table'
)

perm_fe_controls = c(
  'Cut FE' = 'cut',
  'Color FE' = 'color'
)
nonperm_fe_controls = c(
  'Clarity FE (granular)' = 'clarity',
  'Clarity FE (binary)' = 'high_clarity'
)

grid1 = stability_plot(data = diamonds,
                       lhs = 'price',
                       rhs = 'carat',
                       perm = perm_controls,
                       base = base_controls,
                       perm_fe = perm_fe_controls,
                       nonperm_fe = nonperm_fe_controls,
                       run_to=2)

knitr::kable(grid1 %>% head(10))
```

Diamond dimensions	Depth	Table width	Cut FE	Color FE	np_fe
1	0	0	0	0	
1	1	0	0	0	
1	0	1	0	0	
1	1	1	0	0	
1	0	0	1	0	
1	1	0	1	0	
1	0	1	1	0	
1	1	1	1	0	
1	0	0	0	1	
1	1	0	0	1	

```
# Step 2: Get model expression

grid2 = stability_plot(grid = grid1,
                       data=diamonds,
                       lhs='price',
                       rhs='carat',
                       perm=perm_controls,
                       base=base_controls,
                       run_from=2,
                       run_to=3)


knitr::kable(grid2 %>% head(10))
```

Diamond dimensions	Depth	Table width	np_fe	expr
1	0	0	0	price~carat+x+y+z|0|0|0
1	1	0	0	price~carat+x+y+z+depth|0|0|0
1	0	1	0	price~carat+x+y+z+table|0|0|0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0
1	0	0	0	price~carat+x+y+z|0|0|0
1	1	0	0	price~carat+x+y+z+depth|0|0|0
1	0	1	0	price~carat+x+y+z+table|0|0|0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0
1	0	0	0	price~carat+x+y+z|0|0|0
1	1	0	0	price~carat+x+y+z+depth|0|0|0

```
# Step 3: Estimate models
grid3 = stability_plot(grid = grid2,
                       data=diamonds,
                       lhs='price',
                       rhs='carat',
                       perm=perm_controls,
                       base=base_controls,
                       run_from=3,
                       run_to=4)

knitr::kable(grid3 %>% head(10))
```

Diamond dimensions	Depth	Table width	np_fe	expr	coef	p
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0
1	0	1	0	price~carat+x+y+z+table|0|0|0	10423.42	p<0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0	10851.31	p<0
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0
1	0	1	0	price~carat+x+y+z+table|0|0|0	10423.42	p<0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0	10851.31	p<0
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0

```
# Step 4: Get dataframe to draw
dfs = stability_plot(grid = grid3,
                     data=diamonds,
                     lhs='price',
                     rhs='carat',
                     perm=perm_controls,
                     base=base_controls,
                     run_from=4,
                     run_to=5)

coef_grid = dfs[[1]]
control_grid = dfs[[2]]

knitr::kable(coef_grid %>% head(10))
```

Diamond dimensions	Depth	Table width	np_fe	expr	coef	p
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0
1	0	1	0	price~carat+x+y+z+table|0|0|0	10423.42	p<0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0	10851.31	p<0
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0
1	0	1	0	price~carat+x+y+z+table|0|0|0	10423.42	p<0
1	1	1	0	price~carat+x+y+z+depth+table|0|0|0	10851.31	p<0
1	0	0	0	price~carat+x+y+z|0|0|0	10461.86	p<0
1	1	0	0	price~carat+x+y+z+depth|0|0|0	10808.25	p<0

```
# Step 5: plot the sensitivity graph
panels = stability_plot(data = diamonds,
                     lhs='price',
                     rhs='carat',
                     coef_grid = coef_grid,
                     control_grid = control_grid,
```

```
                        run_from=5,
                        run_to=6)

stability_plot(data = diamonds,
               lhs='price',
               rhs='carat',
               coef_panel = panels[[1]],
               control_panel = panels[[2]],
               run_from = 6,
               run_to = 7)
```

In step 2, we can modify to use other function (e.g., `glm`)

```
diamonds$above_med_price = as.numeric(diamonds$price > median(diamonds$price))

base_controls = c('Diamond dimensions' = 'x + y + z')

perm_controls = c('Depth' = 'depth',
                  'Table width' = 'table',
                  'Clarity' = 'clarity')
lhs_var = 'above_med_price'
rhs_var = 'carat'

grid1 = stability_plot(
    data = diamonds,
    lhs = lhs_var,
    rhs = rhs_var,
```

```
    perm = perm_controls,
    base = base_controls,
    fe_always = F,
    run_to = 2
)

# Create control part of formula
base_perm = c(base_controls, perm_controls)
grid1$expr = apply(grid1[, 1:length(base_perm)], 1,
                   function(x)
                     paste(base_perm[names(base_perm)[which(x == 1)]],
                           collapse = '+'))

# Complete formula with LHS and RHS variables
grid1$expr = paste(lhs_var, '~', rhs_var, '+', grid1$expr, sep = '')

knitr::kable(grid1 %>% head(10))
```

Diamond dimensions	Depth	Table width	Clarity	np_fe	expr
1	0	0	0		above_med_price~carat+x + y + z
1	1	0	0		above_med_price~carat+x + y + z+depth
1	0	1	0		above_med_price~carat+x + y + z+table
1	1	1	0		above_med_price~carat+x + y + z+depth+tal
1	0	0	1		above_med_price~carat+x + y + z+clarity
1	1	0	1		above_med_price~carat+x + y + z+depth+cla
1	0	1	1		above_med_price~carat+x + y + z+table+clar
1	1	1	1		above_med_price~carat+x + y + z+depth+tal

```
# customer function for the logit model
starb_logit = function(spec, data, rhs, ...) {
  spec = as.formula(spec)
  model = glm(spec, data=data, family='binomial', weights=data$weight) %>%
    broom::tidy()
  row = which(model$term==rhs)
  coef = model[row, 'estimate'] %>% as.numeric()
  se   = model[row, 'std.error'] %>% as.numeric()
  p    = model[row, 'p.value'] %>% as.numeric()

  return(c(coef, p, coef+1.96*se, coef-1.96*se))
}

stability_plot(grid = grid1,
               data = diamonds,
               lhs = lhs_var,
               rhs = rhs_var,
```

```
                model = starb_logit,
                perm = perm_controls,
                base = base_controls,
                fe_always = F,
                run_from=3)
```

For getting other specification (e.g., different CI)

```
library(margins)
starb_logit_enhanced = function(spec, data, rhs, ...) {
  # Unpack ...
  l = list(...)
  get_mfx = ifelse(is.null(l$get_mfx), F, T) # Set a default to F

  spec = as.formula(spec)
  if (get_mfx) {
    model = glm(spec, data=data, family='binomial', weights=data$weight) %>%
      margins() %>%
      summary
    row = which(model$factor==rhs)
    coef = model[row, 'AME'] %>% as.numeric()
    se   = model[row, 'SE'] %>% as.numeric()
    p    = model[row, 'p'] %>% as.numeric()
  } else {
    model = glm(spec, data=data, family='binomial', weights=data$weight) %>%
      broom::tidy()
    row = which(model$term==rhs)
```

```
    coef = model[row, 'estimate'] %>% as.numeric()
    se   = model[row, 'std.error'] %>% as.numeric()
    p    = model[row, 'p.value'] %>% as.numeric()
  }

  z = qnorm(0.995)
  return(c(coef, p, coef+z*se, coef-z*se))
}

stability_plot(grid = grid1,
               data = diamonds,
               lhs = lhs_var,
               rhs = rhs_var,
               model = starb_logit_enhanced,
               get_mfx = T,
               perm = perm_controls,
               base = base_controls,
               fe_always = F,
               run_from = 3)
```

To get your customized plot

```
dfs = stability_plot(grid = grid1,
               data = diamonds,
               lhs = lhs_var,
               rhs = rhs_var,
               model = starb_logit_enhanced,
```

```
                get_mfx = T,
                perm = perm_controls,
                base = base_controls,
                fe_always = F,
                run_from = 3,
                run_to = 5)

coef_grid_logit = dfs[[1]]
control_grid_logit = dfs[[2]]

min_space = 0.5

coef_plot = ggplot2::ggplot(coef_grid_logit, aes(
  x = model,
  y = coef,
  shape = p,
  group = p
)) +
  geom_linerange(aes(ymin = error_low, ymax = error_high), alpha = 0.75) +
  geom_point(size = 5, aes(col = p, fill = p), alpha = 1) +
  viridis::scale_color_viridis(discrete = TRUE, option = "D") +
  scale_shape_manual(values = c(15, 17, 18, 19)) +
  theme_classic() +
  geom_hline(yintercept = 0, linetype = 'dotted') +
  ggtitle('A custom coefficient stability plot!') +
  labs(subtitle = "Error bars represent 99% confidence intervals") +
  theme(
    axis.text.x = element_blank(),
    axis.title = element_blank(),
    axis.ticks.x = element_blank()
  ) +
  coord_cartesian(xlim = c(1 - min_space, max(coef_grid_logit$model) + min_space),
                  ylim = c(-0.1, 1.6)) +
  guides(fill = F, shape = F, col = F)


control_plot = ggplot(control_grid_logit) +
  geom_point(aes(x = model, y = y, fill=value), shape=23, size=4) +
  scale_fill_manual(values=c('#FFFFFF', '#000000')) +
  guides(fill=F) +
  scale_y_continuous(breaks = unique(control_grid_logit$y),
                     labels = unique(control_grid_logit$key),
                     limits=c(min(control_grid_logit$y)-1, max(control_grid_logit$y)+1
  scale_x_continuous(breaks=c(1:max(control_grid_logit$model))) +
  coord_cartesian(xlim=c(1-min_space, max(control_grid_logit$model)+min_space)) +
```

```
  theme_classic() +
  theme(panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank(),
        axis.title = element_blank(),
        axis.text.y = element_text(size=10),
        axis.ticks = element_blank(),
        axis.line = element_blank())

cowplot::plot_grid(coef_plot, control_plot, rel_heights=c(1,0.5),
                   align='v', ncol=1, axis='b')
```

To get different model specification (e.g., probit vs. logit)

```
starb_probit = function(spec, data, rhs, ...) {
    # Unpack ...
    l = list(...)
    get_mfx = ifelse(is.null(l$get_mfx), F, T) # Set a default to F

    spec = as.formula(spec)
    if (get_mfx) {
        model = glm(
            spec,
            data = data,
            family = binomial(link = 'probit'),
            weights = data$weight
        ) %>%
            margins() %>%
```

```
            summary
        row = which(model$factor == rhs)
        coef = model[row, 'AME'] %>% as.numeric()
        se   = model[row, 'SE'] %>% as.numeric()
        p    = model[row, 'p'] %>% as.numeric()
    } else {
        model = glm(
            spec,
            data = data,
            family = binomial(link = 'probit'),
            weights = data$weight
        ) %>%
            broom::tidy()
        row = which(model$term == rhs)
        coef = model[row, 'estimate'] %>% as.numeric()
        se   = model[row, 'std.error'] %>% as.numeric()
        p    = model[row, 'p.value'] %>% as.numeric()
    }

    z = qnorm(0.995)
    return(c(coef, p, coef + z * se, coef - z * se))
}

probit_dfs = stability_plot(
    grid = grid1,
    data = diamonds,
    lhs = lhs_var,
    rhs = rhs_var,
    model = starb_probit,
    get_mfx = T,
    perm = perm_controls,
    base = base_controls,
    fe_always = F,
    run_from = 3,
    run_to = 5
)

# We'll put the probit DFs on the left,
 #so we need to adjust the model numbers accordingly
# so the probit and logit DFs don't plot on top of one another!
coef_grid_probit = probit_dfs[[1]] %>%
    mutate(model = model + max(coef_grid_logit$model))

control_grid_probit = probit_dfs[[2]] %>%
    mutate(model = model + max(control_grid_logit$model))
```

```
coef_grid    = bind_rows(coef_grid_logit, coef_grid_probit)
control_grid = bind_rows(control_grid_logit, control_grid_probit)

panels = stability_plot(
    coef_grid = coef_grid,
    control_grid = control_grid,
    data = diamonds,
    lhs = lhs_var,
    rhs = rhs_var,
    perm = perm_controls,
    base = base_controls,
    fe_always = F,
    run_from = 5,
    run_to = 6
)

coef_plot = panels[[1]] + geom_vline(xintercept = 8.5,
                                     linetype = 'dashed',
                                     alpha = 0.8) +
    annotate(
        geom = 'label',
        x = 4.25,
        y = 1.8,
        label = 'Logit models',
        size = 6,
        fill = '#D3D3D3',
        alpha = 0.7
    ) +
    annotate(
        geom = 'label',
        x = 12.75,
        y = 1.8,
        label = 'Probit models',
        size = 6,
        fill = '#D3D3D3',
        alpha = 0.7
    ) +
    coord_cartesian(ylim = c(-0.5, 1.9))

control_plot = panels[[2]] + geom_vline(xintercept = 8.5,
                                        linetype = 'dashed',
                                        alpha = 0.8)

cowplot::plot_grid(
    coef_plot,
```

```
    control_plot,
    rel_heights = c(1, 0.5),
    align = 'v',
    ncol = 1,
    axis = 'b'
)
```

40.1.2 rdfanalysis

- Not recommend

Installation

```
devtools::install_github("joachim-gassen/rdfanalysis")
```

Example by the package's author

```
library(rdfanalysis)
load(url("https://joachim-gassen.github.io/data/rdf_ests.RData"))
plot_rdf_spec_curve(ests, "est", "lb", "ub")
```

Shiny app for readers to explore

```
design <- define_design(steps = c("read_data",
                                  "select_idvs",
                                  "treat_extreme_obs",
                                  "specify_model",
                                  "est_model"),
                        rel_dir = "vignettes/case_study_code")

shiny_rdf_spec_curve(ests, list("est", "lb", "ub"),
                     design, "vignettes/case_study_code",
                     "https://joachim-gassen.github.io/data/wb_new.csv")
```

40.2 Coefficient stability

(Oster, 2019)

- Coefficient stability can be evident against omitted variable bias.
- But coefficient stability alone can be misleading, but combing with R^2 movement, it can become informative.

Packages

- `mplot`: graphical Model stability and Variable Selection
- `robomit`: Robustness checks for omitted variable bias (implementation of

```r
library(robomit)

# estimate beta
o_beta(
  y     = "mpg",       # dependent variable
  x     = "wt",        # independent treatment variable
  con   = "hp + qsec", # related control variables
  delta = 1,           # delta
  R2max = 0.9,         # maximum R-square
  type  = "lm",        # model type
  data  = mtcars       # dataset
)
#> # A tibble: 10 x 2
#>    Name                            Value
#>    <chr>                           <dbl>
#>  1 beta*                          -2.00
#>  2 (beta*-beta controlled)^2       5.56
#>  3 Alternative Solution 1         -7.01
#>  4 (beta[AS1]-beta controlled)^2   7.05
#>  5 Uncontrolled Coefficient       -5.34
#>  6 Controlled Coefficient         -4.36
#>  7 Uncontrolled R-square           0.753
#>  8 Controlled R-square             0.835
#>  9 Max R-square                    0.9
#> 10 delta                           1
```

40.3 Omitted Variable Bias Quantification

To quantify the bias needed to change the substantive conclusion from a causal inference study.

```r
library(konfound)
pkonfound(
    est_eff = 5,
    std_err = 2,
    n_obs = 1000,
    n_covariates = 5
)
#> Robustness of Inference to Replacement (RIR):
#> To invalidate an inference,  21.506 % of the estimate would have to be due to bias.
#> This is based on a threshold of 3.925 for statistical significance (alpha = 0.05).
#>
#> To invalidate an inference,  215  observations would have to be replaced with cases
#> for which the effect is 0 (RIR = 215).
#>
```

```
#> See Frank et al. (2013) for a description of the method.
#>
#> Citation: Frank, K.A., Maroulis, S., Duong, M., and Kelcey, B. (2013).
#> What would it take to change an inference?
#> Using Rubin's causal model to interpret the
#>         robustness of causal inferences.
#> Education, Evaluation and
#>                        Policy Analysis, 35 437-460.

pkonfound(
    est_eff = 5,
    std_err = 2,
    n_obs = 1000,
    n_covariates = 5,
    to_return = "thresh_plot"
)
```

```
pkonfound(
    est_eff = 5,
    std_err = 2,
    n_obs = 1000,
    n_covariates = 5,
    to_return = "corr_plot"
)
```

To invalidate an inference
Predictor of Interest
Outcome
Rx.cv | Z =
0.134
Rx.cv | Z * Ry.cv | Z =
0.018
Ry.cv | Z =
0.134
Confounding
Variable

Chapter 41

Replication and Synthetic Data

Access to comprehensive data is pivotal for replication, especially in the realm of social sciences. Yet, often the data are inaccessible, making replication a challenge (King, 1995). This chapter dives into the nuances of replication, the exceptions to its norms, and the significance of synthetic data.

41.1 The Replication Standard

Replicability in research ensures:

- Credibility and comprehension of empirical studies.
- Continuity and progression in the discipline.
- Enhanced readership and academic citations.

For a research to be replicable, the "replication standard" is vital: it entails providing all requisite information for replication by third parties. While quantitative research can, to some extent, offer clear data, qualitative studies pose complexities due to data depth.

41.1.1 Solutions for Empirical Replication

1. **Role of Individual Authors**:
    - Authors need to vouch for the replication standard for enhancing their work's credibility.
    - Archives like the Inter-University Consortium for Political and Social Research (ICPSR) serve as depositories for replication datasets.
2. **Creation of a Replication Data Set**:

- A public data set, consisting of both original and relevant complementary data, can serve replication purposes.

3. **Professional Data Archives**:
   - Organizations like ICPSR provide solutions to data storage and accessibility problems.
4. **Educational Implications**:
   - Replication can be an excellent educational tool, and many programs now emphasize its importance.

41.1.2 Free Data Repositories

1. **Zenodo**: Hosted by CERN, it provides a place for researchers to deposit datasets. It's not subject-specific, so it caters to various disciplines.
2. **figshare**: Allows researchers to upload, share, and cite their datasets.
3. **Dryad**: Primarily for datasets associated with published articles in the biological and medical sciences.
4. **OpenICPSR**: A public-facing version of the Inter-University Consortium for Political and Social Research (ICPSR) where researchers can deposit data without any cost.
5. **Harvard Dataverse**: Hosted by Harvard University, this is an open-source repository software application dedicated to archiving, sharing, and citing research data.
6. **Mendeley Data**: A multidisciplinary, free-to-use open access data repository where researchers can upload and share their datasets.
7. **Open Science Framework (OSF)**: Offers both a platform for conducting research and a place to deposit datasets.
8. **PubMed Central**: Specific to life sciences, but it's an open repository for journal articles, preprints, and datasets.
9. **Registry of Research Data Repositories (re3data)**: While not a repository itself, it provides a global registry of research data repositories from various academic disciplines.
10. **SocArXiv**: An open archive for the social sciences.
11. **EarthArXiv**: A preprints archive for earth science.
12. **Protein Data Bank (PDB)**: For 3D structures of large biological molecules.
13. **Gene Expression Omnibus (GEO)**: A public functional genomics data repository.
14. **The Language Archive (TLA)**: Dedicated to data on languages worldwide, especially endangered languages.

15. **B2SHARE**: A platform for storing and sharing research data sets in various disciplines, especially from European research projects.

41.1.3 Exceptions to Replication

Some exceptions to the replication standard are:

1. **Confidentiality**: Sometimes data, even fragmented, is too sensitive to share.
2. **Proprietary Data**: Data sets owned by entities might restrict dissemination, but usually, parts of such data can still be shared.
3. **Rights of First Publication**: Embargos might be set, but the essential data used in a study should be accessible.

41.2 Synthetic Data: An Overview

Synthetic data, modeling real data while ensuring anonymity, is becoming pivotal in research. While promising, it has its own complexities and should be approached with caution.

41.2.1 Benefits

- Privacy preservation.
- Data fairness and augmentation.
- Acceleration in research.

41.2.2 Concerns

- Misconceptions about inherent privacy.
- Challenges with data outliers.
- Models relying solely on synthetic data can pose risks.

41.2.3 Further Insights on Synthetic Data

Synthetic data bridges the model-centric and data-centric perspectives, making it an essential tool in modern research. Analogously, it's like viewing the Mona Lisa's replica, with the real painting stored securely.

Future projects, such as utilizing the R's diamonds dataset for synthetic data generation, hold promise in demonstrating the vast potentials of this technology.

For a deeper dive into synthetic data and its applications, refer to (Jordon et al., 2022).

41.3 Application

The easiest way to create synthetic data is to use the `synthpop` package. Alternatively, you can do it manually

```
library(synthpop)
library(tidyverse)
library(performance)

# library(effectsize)
# library(see)
# library(patchwork)
# library(knitr)
# library(kableExtra)

head(iris)
#>   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
#> 1          5.1         3.5          1.4         0.2  setosa
#> 2          4.9         3.0          1.4         0.2  setosa
#> 3          4.7         3.2          1.3         0.2  setosa
#> 4          4.6         3.1          1.5         0.2  setosa
#> 5          5.0         3.6          1.4         0.2  setosa
#> 6          5.4         3.9          1.7         0.4  setosa

synthpop::codebook.syn(iris)
#> $tab
#>       variable   class nmiss perctmiss ndistinct
#> 1 Sepal.Length numeric     0         0        35
#> 2  Sepal.Width numeric     0         0        23
#> 3 Petal.Length numeric     0         0        43
#> 4  Petal.Width numeric     0         0        22
#> 5      Species  factor     0         0         3
#>                              details
#> 1                  Range: 4.3 - 7.9
#> 2                    Range: 2 - 4.4
#> 3                    Range: 1 - 6.9
#> 4                  Range: 0.1 - 2.5
#> 5 'setosa' 'versicolor' 'virginica'
#>
#> $labs
#> NULL

syn_df <- syn(iris, seed = 3)
#>
#> Synthesis
#> -----------
```

```
#>  Sepal.Length Sepal.Width Petal.Length Petal.Width Species

# check for replciated uniques
replicated.uniques(syn_df, iris)
#> $replications
#>   [1]  TRUE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE  TRUE FALSE FALSE
#>  [13]  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE
#>  [25] FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#>  [37] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#>  [49] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#>  [61] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE  TRUE
#>  [73] FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE
#>  [85] FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE  TRUE
#>  [97] FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE  TRUE FALSE FALSE
#> [109] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#> [121] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE
#> [133] FALSE  TRUE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#> [145] FALSE FALSE FALSE FALSE FALSE FALSE
#>
#> $no.uniques
#> [1] 148
#>
#> $no.replications
#> [1] 17
#>
#> $per.replications
#> [1] 11.33333


# remove replicated uniques and adds a FAKE_DATA label
# (in case a person can see his or own data in
# the replicated data by chance)

syn_df_sdc <- sdc(syn_df, iris,
                  label = "FAKE_DATA",
                  rm.replicated.uniques = T)
#> no. of replicated uniques: 17
```

```
iris |>
    GGally::ggpairs()
```

```
syn_df$syn |>
    GGally::ggpairs()
```

```
lm_ori <- lm(Sepal.Length ~ Sepal.Width + Petal.Length , data = iris)
# performance::check_model(lm_ori)
summary(lm_ori)
#>
#> Call:
```

```
#> lm(formula = Sepal.Length ~ Sepal.Width + Petal.Length, data = iris)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -0.96159 -0.23489  0.00077  0.21453  0.78557
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   2.24914    0.24797    9.07 7.04e-16 ***
#> Sepal.Width   0.59552    0.06933    8.59 1.16e-14 ***
#> Petal.Length  0.47192    0.01712   27.57  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.3333 on 147 degrees of freedom
#> Multiple R-squared:  0.8402, Adjusted R-squared:  0.838
#> F-statistic: 386.4 on 2 and 147 DF,  p-value: < 2.2e-16

lm_syn <- lm(Sepal.Length ~ Sepal.Width + Petal.Length , data = syn_df$syn)
# performance::check_model(lm_syn)
summary(lm_syn)
#>
#> Call:
#> lm(formula = Sepal.Length ~ Sepal.Width + Petal.Length, data = syn_df$syn)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -0.79165 -0.22790 -0.01448  0.15893  1.13360
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept)   2.96449    0.24538  12.081  < 2e-16 ***
#> Sepal.Width   0.39214    0.06816   5.754  4.9e-08 ***
#> Petal.Length  0.45267    0.01743  25.974  < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.3658 on 147 degrees of freedom
#> Multiple R-squared:  0.8246, Adjusted R-squared:  0.8222
#> F-statistic: 345.6 on 2 and 147 DF,  p-value: < 2.2e-16
```

Open data can be assessed for its utility in two distinct ways:

1. **General Utility**: This refers to the broad resemblances within the dataset, allowing for preliminary data exploration.

2. **Specific Utility**: This focuses on the comparability of models derived from synthetic and original datasets, emphasizing analytical reproducibility.

For General utility

```
compare(syn_df, iris)
```

Specific utility

```
# just like regular lm, but for synthetic data
lm_syn <- lm.synds(Sepal.Length ~ Sepal.Width + Petal.Length , data = syn_df)
compare(lm_syn, iris)
#>
#> Call used to fit models to the data:
#> lm.synds(formula = Sepal.Length ~ Sepal.Width + Petal.Length,
#>     data = syn_df)
#>
#> Differences between results based on synthetic and observed data:
#>              Synthetic  Observed        Diff Std. coef diff CI overlap
#> (Intercept)  2.9644900 2.2491402  0.71534988       2.884829  0.2640608
#> Sepal.Width  0.3921429 0.5955247 -0.20338187      -2.933611  0.2516161
#> Petal.Length 0.4526695 0.4719200 -0.01925058      -1.124602  0.7131064
#>
#> Measures for one synthesis and 3 coefficients
#> Mean confidence interval overlap:  0.4095944
#> Mean absolute std. coef diff:  2.314347
#>
#> Mahalanobis distance ratio for lack-of-fit (target 1.0): 3.08
#> Lack-of-fit test: 9.23442; p-value 0.0263 for test that synthesis model is
#> compatible with a chi-squared test with 3 degrees of freedom.
#>
#> Confidence interval plot:
```

```
# summary(lm_syn)
```

You basically want your lack-of-fit test to be non-significant.

Appendix A

Appendix

A.1 Git

Cheat Sheet

Cheat Sheet in different languages

Learn Git

Interactive Cheat Sheet

Ultimate Guide of Git and GitHub for R user

- Setting up Git: `git config` with `--global` option to configure user name, email, editor, etc.
- Creating a repository: `git init` to initialize a repo. Git stores all of its repo data in the `.git` directory.
- Tracking changes:
  - `git status` shows the status of the repo
    - File are stored in the project's working directory (which users see)
    - The staging area (where the next commit is being built)
    - local repo is where commits are permanently recorded
  - `git add` put files in the staging area
  - `git commit` saves the staged content as a new commit in the local repo.
    - `git commit -m "your own message"` to give a messages for the purpose of your commit.

- History
  - `git diff` shows differences between commits
  - `git checkout` recovers old version of fields
    - `git checkout HEAD` to go to the last commit
    - `git checkout <unique ID of your commit>` to go to such commit
- Ignoring
  - `.gitignore` file tells Git what files to ignore
  - `cat . gitignore *.dat results/` ignore files ending with "dat" and folder "results".
- Remotes in GitHub
  - A local git repo can be connected to one or more remote repos.
  - Use the HTTPS protocol to connect to remote repos
  - `git push` copies changes from a local repo to a remote repo
  - `git pull` copies changes from a remote repo to a local repo
- Collaborating
  - `git clone` copies remote repo to create a local repo with a remote called `origin` automatically set up
- Branching
  - `git check - b <new-branch-name`
  - `git checkout master` to switch to master branch.
- Conflicts
  - occur when 2 or more people change the same lines of the same file
  - the version control system does not allow to overwrite each other's changes blindly, but highlights conflicts so that they can be resolved.
- Licensing
  - People who incorporate General Public License (GPL'd) software into their won software must make their software also open under the GPL license; most other open licenses do not require this.
  - The Creative Commons family of licenses allow people to mix and match requirements and restrictions on attribution, creation of derivative works, further sharing and commercialization.
- Citation:

  - Add a CITATION file to a repo to explain how you want others to cite your work.

- Hosting
  - Rules regarding intellectual property and storage of sensitive info apply no matter where code and data are hosted.

A.2 Short-cut

These are shortcuts that you probably you remember when working with R. Even though it might take a bit of time to learn and use them as your second nature, but they will save you a lot of time.
Just like learning another language, the more you speak and practice it, the more comfortable you are speaking it.

function	short-cut
navigate folders in console	`" " + tab`
pull up short-cut cheat sheet	`ctrl + shift + k`
go to file/function (everything in your project)	`ctrl + .`
search everything	`cmd + shift + f`
navigate between tabs	`Crtl + shift + .`
type function faster	`snip + shift + tab`
type faster	`use tab for fuzzy match`
`cmd + up`	
`ctrl + .`	

Sometimes you can't stage a folder because it's too large. In such case, use `Terminal` pane in Rstudio then type `git add -A` to stage all changes then commit and push like usual.

A.3 Function short-cut

apply one function to your data to create a new variable: `mutate(mod=map(data,function))`
instead of using `i in 1:length(object)`: `for (i in seq_along(object))`
apply multiple function: `map_dbl`
apply multiple function to multiple variables:`map2`
`autoplot(data)` plot times series data
`mod_tidy = linear(reg) %>% set_engine('lm') %>% fit(price ~ ., data=data)` fit lm model. It could also fit other models (stan, spark, glmnet, keras)

- Sometimes, data-masking will not be able to recognize whether you're calling from environment or data variables. To bypass this, we use `.data$variable` or `.env$variable`. For example `data %>% mutate(x=.env$variable/.data$variable`

- Problems with data-masking:

  - Unexpected masking by data-var: Use `.data` and `.env` to disambiguate

  - Data-var cant get through:

  - Tunnel data-var with {{}} + Subset `.data` with [[]]
- Passing Data-variables through arguments

```
library("dplyr")
mean_by <- function(data,by,var){
    data %>%
        group_by({{{by}}}) %>%
        summarise("{{var}}":=mean({{var}})) # new name for each var will be created by
}

mean_by <- function(data,by,var){
    data %>%
        group_by({{{by}}}) %>%
        summarise("{var}":=mean({{var}})) # use single {} to glue the string, but hard
}
```

- Trouble with selection:

```
library("purrr")
name <- c("mass","height")
starwars %>% select(name) # Data-var. Here you are referring to variable named "name"

starwars %>% select(all_of((name))) # use all_of() to disambiguate when

averages <- function(data,vars){ # take character vectors with all_of()
    data %>%
        select(all_of(vars)) %>%
        map_dbl(mean,na.rm=TRUE)
}

x = c("Sepal.Length","Petal.Length")
iris %>% averages(x)
```

```
# Another way
averages <- function(data,vars){ # Tunnel selectiosn with {{}}
    data %>%
        select({{vars}}) %>%
        map_dbl(mean,na.rm=TRUE)
}

x = c("Sepal.Length","Petal.Length")
iris %>% averages(x)
```

A.4 Citation

include a citation by `[@Farjam_2015]`

cite packages used in this session

`package=ls(sessionInfo()$loadedOnly) for (i in package){print(toBibtex(citation(i)))}`

```
package=ls(sessionInfo()$loadedOnly)
for (i in package){
    print(toBibtex(citation(i)))
    }
```

A.5 Install all necessary packages/libaries on your local machine

Get a list of packages you need to install from this book (or your local device)

```
installed <- as.data.frame(installed.packages())

head(installed)
#>         Package                           LibPath Version Priority
#> abind     abind C:/Program Files/R/R-4.2.3/library   1.4-5     <NA>
#> ade4       ade4 C:/Program Files/R/R-4.2.3/library  1.7-22     <NA>
#> admisc   admisc C:/Program Files/R/R-4.2.3/library    0.33     <NA>
#> AER         AER C:/Program Files/R/R-4.2.3/library  1.2-10     <NA>
#> afex       afex C:/Program Files/R/R-4.2.3/library   1.3-0     <NA>
#> agridat agridat C:/Program Files/R/R-4.2.3/library    1.21     <NA>
#>                                                                                                  Depends
#> abind                                                                                        R (>= 1.5.0)
#> ade4                                                                                          R (>= 2.10)
#> admisc                                                                                       R (>= 3.5.0)
#> AER     R (>= 3.0.0), car (>= 2.0-19), lmtest, sandwich (>= 2.4-0),\nsurvival (>= 2.37-5), zoo
#> afex                                                                R (>= 3.5.0), lme4 (>= 1.1-8)
#> agridat                                                                                         <NA>
```

```
#>                                                                                    Imp
#> abind                                                                     methods, u
#> ade4                graphics, grDevices, methods, stats, utils, MASS, pixmap, sp,\n
#> admisc                                                                          meti
#> AER                                                          stats, Formula (>= 0.
#> afex    pbkrtest (>= 0.4-1), lmerTest (>= 3.0-0), car, reshape2,\nstats, methods, u
#> agridat
#>                   LinkingTo
#> abind                  <NA>
#> ade4    Rcpp, RcppArmadillo
#> admisc                 <NA>
#> AER                    <NA>
#> afex                   <NA>
#> agridat                <NA>
#>
#> abind
#> ade4
#> admisc
#> AER
#> afex    emmeans (>= 1.4), coin, xtable, parallel, plyr, optimx,\nnloptr, knitr, rma
#> agridat                    AER, agricolae, betareg, broom, car, coin, corrgram, des
#>         Enhances       License License_is_FOSS License_restricts_use OS_type
#> abind       <NA>   LGPL (>= 2)            <NA>                  <NA>    <NA>
#> ade4        <NA>    GPL (>= 2)            <NA>                  <NA>    <NA>
#> admisc      <NA>    GPL (>= 3)            <NA>                  <NA>    <NA>
#> AER         <NA> GPL-2 | GPL-3            <NA>                  <NA>    <NA>
#> afex        <NA>    GPL (>= 2)            <NA>                  <NA>    <NA>
#> agridat     <NA>  CC BY-SA 4.0            <NA>                  <NA>    <NA>
#>         MD5sum NeedsCompilation Built
#> abind     <NA>               no 4.2.0
#> ade4      <NA>              yes 4.2.3
#> admisc    <NA>              yes 4.2.3
#> AER       <NA>               no 4.2.3
#> afex      <NA>               no 4.2.3
#> agridat   <NA>               no 4.2.3

write.csv(installed, file.path(getwd(),'installed.csv'))
```

After having the `installed.csv` file on your new or local machine, you can just install the list of packages

```
# import the list of packages
installed <- read.csv('installed.csv')

# get the list of packages that you have on your device
baseR <- as.data.frame(installed.packages())
```

```r
# install only those that you don't have
install.packages(setdiff(installed, baseR))
```

Appendix B

Bookdown cheat sheet

```
# to see non-scientific notation a result
format(12e-17, scientific = FALSE)
#> [1] "0.00000000000000012"
```

B.1 Operation

R commands to do derivatives of a defined function Taking derivatives in R involves using the `expression, D,` and `eval` functions. You wrap the function you want to take the derivative of in expression(), then use D, then eval as follows.

simple example

```
#define a function
f=expression(sqrt(x))

#take the first derivative
df.dx=D(f,'x')
df.dx
#> 0.5 * x^-0.5

#take the second derivative
d2f.dx2=D(D(f,'x'),'x')
d2f.dx2
#> 0.5 * (-0.5 * x^-1.5)
```

Evaluate

- The first argument passed to eval is the expression you want to evaluate

- the second is a list containing the values of all quantities that are not defined elsewhere.

```
#evaluate the function at a given x
eval(f,list(x=3))
#> [1] 1.732051

#evaluate the first derivative at a given x
eval(df.dx,list(x=3))
#> [1] 0.2886751

#evaluate the second derivative at a given x
eval(d2f.dx2,list(x=3))
#> [1] -0.04811252
```

B.2 Math Expression/ Syntax

Full list

Aligning equations

```
\begin{aligned}
a & = b \\
X &\sim {Norm}(10, 3) \\
5 & \le 10
\end{aligned}
```

$$\begin{aligned}
a & = b \\
X &\sim {Norm}(10, 3) \\
5 & \le 10
\end{aligned}$$

Cross-reference equation

```
\begin{equation}
a = b
(\#eq:test)
\end{equation}
```

$$a = b \tag{B.1}$$

to refer in a sentence (B.1) (`\@ref(eq:test)`)

Math Syntax	Notation
`$\pm$`	$\pm$

Math Syntax	Notation
`$\ge$`	$\ge$
`$\le$`	$\le$
`$\neq$`	$\neq$
`$\equiv$`	$\equiv$
`$^\circ$`	$^\circ$
`$\times$`	$\times$
`$\cdot$`	$\cdot$
`$\leq$`	$\leq$
`$\geq$`	$\geq$
`\propto`	$\propto$
`$\subset$`	$\subset$
`$\subseteq$`	$\subseteq$
`$\leftarrow$`	$\leftarrow$
`$\rightarrow$`	$\rightarrow$
`$\Leftarrow$`	$\Leftarrow$
`$\Rightarrow$`	$\Rightarrow$
`$\approx$`	$\approx$
`$\mathbb{R}$`	$\mathbb{R}$
`$\sum_{n=1}^{10} n^2$`	$\sum_{n=1}^{10} n^2$
`$$\sum_{n=1}^{10} n^2$$`	$\sum_{n=1}^{10} n^2$
`$x^{n}$`	x^{n}
`$x_{n}$`	x_{n}
`$\overline{x}$`	$\overline{x}$
`$\hat{x}$`	$\hat{x}$
`$\tilde{x}$`	$\tilde{x}$
`\check{}`	$\check{}$
`\underset{\gamma}{\operatorname{argmin}}`	$\underset{\gamma}{\operatorname{argmin}}$
`$\frac{a}{b}$`	$\frac{a}{b}$
`$\frac{a}{b}$`	$\frac{a}{b}$
`$\displaystyle \frac{a}{b}$`	$\displaystyle \frac{a}{b}$
`$\binom{n}{k}$`	$\binom{n}{k}$
`$x_{1} + x_{2} + \cdots + x_{n}$`	$x_{1} + x_{2} + \cdots + x_{n}$
`$x_{1}, x_{2}, \dots, x_{n}$`	$x_{1}, x_{2}, \dots, x_{n}$
`\mathbf{x} = \langle x_{1}, x_{2}, \dots, x_{n}\rangle$`	$\mathbf{x} = \langle x_{1}, x_{2}, \dots, x_{n}\rangle$
`$x \in A$`	$x \in A$
`$\|A\|$`	$\|A\|$
`$x \in A$`	$x \in A$
`$x \subset B$`	$x \subset B$
`$x \subseteq B$`	$x \subseteq B$
`$A \cup B$`	$A \cup B$

Math Syntax	Notation
`$A \cap B$`	$A \cap B$
`$X \sim Binom(n, \pi)$`	$X \sim Binom(n, \pi)$
`$\mathrm{P}(X \le x) = \text{pbinom}(x, n, \pi)$`	$\mathrm{P}(X \le x) = \text{pbinom}(x, n, \pi)$
`$P(A \mid B)$`	$P(A \mid B)$
`$\mathrm{P}(A \mid B)$`	$\mathrm{P}(A \mid B)$
`$\{1, 2, 3\}$`	$\{1, 2, 3\}$
`$\sin(x)$`	$\sin(x)$
`$\log(x)$`	$\log(x)$
`$\int_{a}^{b}$`	$\int_{a}^{b}$
`$\left(\int_{a}^{b} f(x) \; dx\right)$`	$\left(\int_{a}^{b} f(x) \; dx\right)$
`$\left[\int_{\-infty}^{\infty} f(x) \; dx\right]$`	$\left[\int_{-\infty}^{\infty} f(x) \; dx\right]$
`$\left. F(x) \right\|_{a}^{b}$`	$\left. F(x) \right\|_{a}^{b}$
`$\sum_{x = a}^{b} f(x)$`	$\sum_{x = a}^{b} f(x)$
`$\prod_{x = a}^{b} f(x)$`	$\prod_{x = a}^{b} f(x)$
`$\lim_{x \to \infty} f(x)$`	$\lim_{x \to \infty} f(x)$
`$\displaystyle \lim_{x \to \infty} f(x)$`	$\displaystyle \lim_{x \to \infty} f(x)$
Greek Letters	
`$\alpha A$`	αA
`$\beta B$`	βB
`$\gamma \Gamma$`	$\gamma \Gamma$
`$\delta \Delta$`	$\delta \Delta$
`$\epsilon \varepsilon E$`	$\epsilon \varepsilon E$
`$\zeta Z \sigma $`	$\zeta Z \sigma$
`$\eta H$`	ηH
`$\theta \vartheta \Theta$`	$\theta \vartheta \Theta$
`$\iota I$`	ιI
`$\kappa K$`	κK
`$\lambda \Lambda$`	$\lambda \Lambda$
`$\mu M$`	μM
`$\nu N$`	νN
`$\xi\Xi$`	$\xi \Xi$
`$o O$`	$o O$
`$\pi \Pi$`	$\pi \Pi$
`$\rho\varrho P$`	$\rho \varrho P$
`$\sigma \Sigma$`	$\sigma \Sigma$
`$\tau T$`	τT
`$\upsilon \Upsilon$`	$\upsilon \Upsilon$
`$\phi \varphi \Phi$`	$\phi \varphi \Phi$
`$\chi X$`	χX

Math Syntax	Notation
`$\psi \Psi$`	$\psi\Psi$
`$\omega \Omega$`	$\omega\Omega$
`$\cdot$`	$\cdot$
`$\cdots$`	$\cdots$
`$\ddots$`	$\ddots$
`$\ldots$`	$\ldots$

Limit `P(\lim_{n\to \infty}\bar{X}_n =\mu) =1`

$$P(\lim_{n\to\infty} \bar{X}_n = \mu) = 1$$

Matrices

```
$$\begin{array}
{rrr}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{array}
$$
```

$$\begin{array}{rrr}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{array}$$

```
$$\mathbf{X} = \left[\begin{array}
{rrr}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{array}\right]
$$
```

$$\mathbf{X} = \left[\begin{array}{rrr}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{array}\right]$$

Aligning Equations

Aligning Equations with Comments

```
\begin{aligned}
    3+x &=4 && \text{(Solve for} x \text{.)}\\
    x &=4-3 && \text{(Subtract 3 from both sides.)}\\
    x &=1   && \text{(Yielding the solution.)}
\end{aligned}
```

$$\begin{aligned}
    3+x &=4 && \text{(Solve for} x \text{.)}\\
    x &=4-3 && \text{(Subtract 3 from both sides.)}\\
    x &=1   && \text{(Yielding the solution.)}
\end{aligned}$$

B.2.1 Statistics Notation

```
$$
f(y|N,p) = \frac{N!}{y!(N-y)!}\cdot p^y \cdot (1-p)^{N-y} = {{N}\choose{y}} \cdot p^y \
$$
```

$$f(y|N,p) = \frac{N!}{y!(N-y)!}\cdot p^y \cdot (1-p)^{N-y} = {{N}\choose{y}} \cdot p^y \cdot (1-p)^{N-y}$$

```
\begin{cases}
\frac{1}{b-a}&\text{for $x\in[a,b]$}\\
0&\text{otherwise}\\
\end{cases}
```

$$\begin{cases}
\frac{1}{b-a}&\text{for $x\in[a,b]$}\\
0&\text{otherwise}\\
\end{cases}$$

B.3 Table

```
+---------------+---------------+--------------------+
| Fruit         | Price         | Advantages         |
+===============+===============+====================+
| *Bananas*     | $1.34         | - built-in wrapper |
|               |               | - bright color     |
+---------------+---------------+--------------------+
| Oranges       | $2.10         | - cures scurvy     |
|               |               | - **tasty**        |
+---------------+---------------+--------------------+
```

Fruit	Price	Advantages
Bananas	$1.34	• built-in wrapper • bright color
Oranges	$2.10	• cures scurvy • **tasty**

```
(\mathbf{x}^T\mathbf{x})^{-1}\mathbf{x}^T\mathbf{y}
```

$(\mathbf{x}^T\mathbf{x})^{-1}\mathbf{x}^T\mathbf{y}$

Bibliography

(2020).

Aaronson, D., Barrow, L., and Sander, W. (2007). Teachers and student achievement in the chicago public high schools. *Journal of labor Economics*, 25(1):95–135.

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59(2):391–425.

Abadie, A., Angrist, J., and Imbens, G. (2002). Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica*, 70(1):91–117.

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1):1–35.

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505.

Abadie, A. and Imbens, G. W. (2016). Matching on the estimated propensity score. *Econometrica*, 84(2):781–807.

Abadie, A. and L'hour, J. (2021). A penalized synthetic control estimator for disaggregated data. *Journal of the American Statistical Association*, 116(536):1817–1834.

Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2019). Democracy does cause growth. *Journal of political economy*, 127(1):47–100.

Acharya, S. (1993). Value of latent information: alternative event study methods. *The Journal of Finance*, 48(1):363–385.

Adalja, A., Liaukonytė, J., Wang, E., and Zhu, X. (2023). Gmo and non-gmo labeling effects: Evidence from a quasi-natural experiment. *Marketing Science*, 42(2):233–250.

Agarwal, A., Dahleh, M., Shah, D., and Shen, D. (2023). Causal matrix completion. In *The Thirty Sixth Annual Conference on Learning Theory*, pages 3821–3826. PMLR.

Agrawal, J. and Kamakura, W. A. (1995). The economic worth of celebrity endorsers: An event study analysis. *Journal of marketing*, 59(3):56–62.

Ahrens, H. and Pincus, R. (1981). On two measures of unbalancedness in a one-way model and their relation to efficiency. *Biometrical Journal*, 23(3):227–235.

Aiken, L. S. and West, S. G. (2005). Interaction effects. *Encyclopedia of statistics in behavioral science*.

Akca, S. and Rao, A. (2020). Value of aggregators. *Marketing Science*, 39(5):893–922.

Allison, P. D. and Waterman, R. P. (2002). 7. fixed-effects negative binomial regression models. *Sociological methodology*, 32(1):247–265.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy*, 113(1):151–184.

Amemiya, T. (1971). The estimation of the variances in a variance-components model. *International Economic Review*, pages 1–13.

Amemiya, T. (1984). Tobit models: A survey. *Journal of econometrics*, 24(1-2):3–61.

Amemiya, T. and MaCurdy, T. E. (1986). Instrumental-variable estimation of an error-components model. *Econometrica: Journal of the Econometric Society*, pages 869–880.

Anderson, J. E., Larch, M., and Yotov, Y. V. (2015). Growth and trade with frictions: A structural estimation framework. Technical report, National Bureau of Economic Research.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, 104(9):2763–2796.

Anderson, T. W. and Darling, D. A. (1952). Asymptotic theory of certain" goodness of fit" criteria based on stochastic processes. *The annals of mathematical statistics*, pages 193–212.

Anderson, T. W. and Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of mathematical statistics*, 20(1):46–63.

Andrews, D. W. and Marmer, V. (2008). Exactly distribution-free inference in instrumental variables regression with possibly weak instruments. *Journal of Econometrics*, 142(1):183–200.

Andrews, D. W., Moreira, M. J., and Stock, J. H. (2006). Optimal two-sided invariant similar tests for instrumental variables regression. *Econometrica*, 74(3):715–752.

Andrews, D. W., Moreira, M. J., and Stock, J. H. (2008). Efficient two-sided nonsimilar invariant tests in iv regression with weak instruments. *Journal of Econometrics*, 146(2):241–254.

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, 11:727–753.

Angrist, J. and Imbens, G. (1991). Sources of identifying information in evaluation models.

Angrist, J. and Kolesár, M. (2023). One instrument to rule them all: The bias and coverage of just-id iv. *Journal of Econometrics*.

Angrist, J. and Kolesár, M. (2024). One instrument to rule them all: The bias and coverage of just-id iv. *Journal of Econometrics*, 240(2):105398.

Angrist, J. D., Graddy, K., and Imbens, G. W. (2000). The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish. *The Review of Economic Studies*, 67(3):499–527.

Angrist, J. D. and Imbens, G. W. (1995). Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American statistical Association*, 90(430):431–442.

Angrist, J. D. and Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic perspectives*, 15(4):69–85.

Angrist, J. D. and Lavy, V. (1999). Using maimonides' rule to estimate the effect of class size on scholastic achievement. *The Quarterly journal of economics*, 114(2):533–575.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arellano, M. (1987). Computing robust standard errors for within-groups estimators. *Oxford bulletin of Economics and Statistics*, 49(4):431–434.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2019). Synthetic difference in differences. Technical report, National Bureau of Economic Research.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118.

Arkhangelsky, D. and Hirshberg, D. (2023). Large-sample properties of the synthetic control method under selection on unobservables. *arXiv preprint arXiv:2311.13575*, 2.

Aronow, P. M., Baron, J., and Pinson, L. (2019). A note on dropping experimental subjects who fail a manipulation check. *Political Analysis*, 27(4):572–589.

Ashenfelter, O. and Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *The Review of Economics and Statistics*, 67(4):648.

Assmann, S. F., Hosmer, D. W., Lemeshow, S., and Mundt, K. A. (1996). Confidence intervals for measures of interaction. *Epidemiology*, pages 286–290.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G., and Khosravi, K. (2021). Matrix completion methods for causal panel data models. *Journal of the American Statistical Association*, 116(536):1716–1730.

Athey, S. and Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, 74(2):431–497.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79.

Auffhammer, M. and Kellogg, R. (2011). Clearing the air? the effects of gasoline content regulation on air quality. *American Economic Review*, 101(6):2687–2722.

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical statistics*, 10(2):150–161.

Azoulay, P., Fons-Rosen, C., and Zivin, J. S. G. (2019). Does science advance one funeral at a time? *American Economic Review*, 109(8):2889–2920.

Babcock, P. (2010). Real costs of nominal grade inflation? new evidence from student course evaluations. *Economic inquiry*, 48(4):983–996.

Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.

Baicker, K. and Svoronos, T. (2019). Testing the validity of the single interrupted time series design. Technical report, National Bureau of Economic Research.

Bajari, P., Hong, H., Park, M., and Town, R. (2011). Regression discontinuity designs with an endogenous forcing variable and an application to contracting in health care. Technical report, National Bureau of Economic Research.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Balasubramanian, S. K., Mathur, I., and Thakur, R. (2005). The impact of high-quality firm achievements on shareholder value: focus on malcolm baldrige and jd power and associates awards. *Journal of the Academy of Marketing Science*, 33(4):413–422.

Balestra, P. and Varadharajan-Krishnakumar, J. (1987). Full information estimations of a system of simultaneous equations with error component structure. *Econometric Theory*, 3(2):223–246.

Baltagi, B. H. (1981). Simultaneous equations with error components. *Journal of econometrics*, 17(2):189–200.

Baltagi, B. H. and Li, Q. (1991). A joint test for serial correlation and random individual effects. *Statistics & Probability Letters*, 11(3):277–280.

Baltagi, B. H. and Li, Q. (1995). Testing ar (1) against ma (1) disturbances in an error component model. *Journal of econometrics*, 68(1):133–151.

Ban, K. and Kedagni, D. (2022). Generalized difference-in-differences models: Robust bounds. *arXiv preprint arXiv:2211.06710*.

Bapna, R., Ramaprasad, J., and Umyarov, A. (2018). Monetizing freemium communities. *Mis Quarterly*, 42(3):719–A4.

Barber, B. M. and Lyon, J. D. (1997). Firm size, book-to-market ratio, and security returns: A holdout sample of financial firms. *The Journal of Finance*, 52(2):875–883.

Bareinboim, E. and Pearl, J. (2014). Transportability from multiple environments with limited experiments: Completeness results. *Advances in neural information processing systems*, 27.

Baron, R. M. and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 51(6):1173.

Barreca, A. I., Guldi, M., Lindo, J. M., and Waddell, G. R. (2011). Saving babies? revisiting the effect of very low birth weight classification. *The Quarterly Journal of Economics*, 126(4):2117–2123.

Bartlett, M. S. (1947). The use of transformations. *Biometrics*, 3(1):39–52.

Bates, D. M. and Watts, D. G. (1980). Relative curvature measures of nonlinearity. *Journal of the Royal Statistical Society: Series B (Methodological)*, 42(1):1–16.

Bates, D. M. and Watts, D. G. (1981). A relative off set orthogonality convergence criterion for nonlinear least squares. *Technometrics*, 23(2):179–183.

Bauer, D. J. and Curran, P. J. (2005). Probing interactions in fixed and multilevel regression: Inferential and graphical techniques. *Multivariate behavioral research*, 40(3):373–400.

Bauer, D. J., Preacher, K. J., and Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations. *Psychological methods*, 11(2):142.

Baum, C. and Schaffer, M. (2021). Ivreg2h: Stata module to perform instrumental variables estimation using heteroskedasticity-based instruments.

Beale, E. M. and Little, R. J. (1975). Missing values in multivariate analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, 37(1):129–145.

Beerli, A., Ruffner, J., Siegenthaler, M., and Peri, G. (2021). The abolition of immigration restrictions and the performance of firms and workers: evidence from switzerland. *American Economic Review*, 111(3):976–1012.

Bellemare, M. F., Masaki, T., and Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, 79(3):949–963.

Ben-Michael, E., Feller, A., and Rothstein, J. (2020). Varying impacts of letters of recommendation on college admissions: Approximate balancing weights for subgroup effects in observational studies. *arXiv preprint arXiv:2008.04394*.

Ben-Michael, E., Feller, A., and Rothstein, J. (2021). The augmented synthetic control method. *Journal of the American Statistical Association*, 116(536):1789–1803.

Ben-Michael, E., Feller, A., and Rothstein, J. (2022). Synthetic controls with staggered adoption. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 84(2):351–381.

Bendel, R. B. and Afifi, A. A. (1977). Comparison of stopping rules in forward "stepwise" regression. *Journal of the American Statistical association*, 72(357):46–53.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300.

Benjamini, Y. and Hochberg, Y. (2000). On the adaptive control of the false discovery rate in multiple testing with independent statistics. *Journal of educational and Behavioral Statistics*, 25(1):60–83.

Benjamini, Y., Krieger, A. M., and Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3):491–507.

Benjamini, Y. and Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of statistics*, pages 1165–1188.

Benston, G. J. (1985). The validity of profits-structure studies with particular reference to the ftc's line of business data. *The American Economic Review*, 75(1):37–67.

Bento, A., Kaffine, D., Roth, K., and Zaragoza-Watkins, M. (2014). The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector. *American Economic Journal: Economic Policy*, 6(3):1–29.

Bera, A. K. and Jarque, C. M. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte carlo evidence. *Economics letters*, 7(4):313–318.

Bera, A. K., Sosa-Escudero, W., and Yoon, M. (2001). Tests for the error component model in the presence of local misspecification. *Journal of Econometrics*, 101(1):1–23.

Berger, P. G., Ofek, E., and Yermack, D. L. (1997). Managerial entrenchment and capital structure decisions. *The journal of finance*, 52(4):1411–1438.

Berkouwer, S. B. and Dean, J. T. (2022). Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households. *American Economic Review*, 112(10):3291–3330.

Berman, R. and Israeli, A. (2022). The value of descriptive analytics: Evidence from online retailers. *Marketing Science*, 41(6):1074–1096.

Bernard, V. L. (1987). Cross-sectional dependence and problems in inference in market-based accounting research. *Journal of Accounting Research*, pages 1–48.

Bertanha, M., McCallum, A. H., and Seegert, N. (2021). Better bunching, nicer notching. *arXiv preprint arXiv:2101.01170*.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275.

Bertrand, M. and Mullainathan, S. (2004). Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *American economic review*, 94(4):991–1013.

Bhaduri, S. N. (2002). Determinants of corporate borrowing: some evidence from the indian corporate structure. *Journal of Economics and Finance*, 26(2):200–215.

Bhagat, S., Bizjak, J., and Coles, J. L. (1998). The shareholder wealth implications of corporate lawsuits. *Financial Management*, pages 5–27.

Bhattacharya, J. and Vogt, W. B. (2007). Do instrumental variables belong in propensity scores?

Bickel, P. J. and Doksum, K. A. (1981). An analysis of transformations revisited. *Journal of the american statistical association*, 76(374):296–311.

Blau, D. M. (1999). The effect of income on child development. *Review of Economics and Statistics*, 81(2):261–276.

Blomquist, S., Newey, W. K., Kumar, A., and Liang, C.-Y. (2021). On bunching and identification of the taxable income elasticity. *Journal of Political Economy*, 129(8):2320–2343.

Bloom, H. S. (1984). Accounting for no-shows in experimental evaluation designs. *Evaluation review*, 8(2):225–246.

Bloom, H. S., Orr, L. L., Bell, S. H., Cave, G., Doolittle, F., Lin, W., and Bos, J. M. (1997). The benefits and costs of jtpa title ii-a programs: Key findings from the national job training partnership act study. *Journal of human resources*, pages 549–576.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1):115–143.

Böckerman, P., Kanninen, O., and Suoniemi, I. (2018). A kink that makes you sick: The effect of sick pay on absence. *Journal of Applied Econometrics*, 33(4):568–579.

Bodner, T. E. (2008). What improves with increased missing data imputations? *Structural equation modeling: a multidisciplinary journal*, 15(4):651–675.

Bollen, K. A. and Stine, R. (1990). Direct and indirect effects: Classical and bootstrap estimates of variability. *Sociological methodology*, pages 115–140.

Borah, A. and Tellis, G. J. (2014). Make, buy, or ally? choice of and payoff from announcements of alternate strategies for innovations. *Marketing Science*, 33(1):114–133.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Bosch, N., Dekker, V., and Strohmaier, K. (2020). A data-driven procedure to determine the bunching window: an application to the netherlands. *International Tax and Public Finance*, 27:951–979.

Bottomley, C., Scott, J. A. G., and Isham, V. (2019). Analysing interrupted time series with a control. *Epidemiologic Methods*, 8(1):20180010.

Bound, J., Brown, C., and Mathiowetz, N. (2001). Measurement error in survey data. In *Handbook of econometrics*, volume 5, pages 3705–3843. Elsevier.

Bound, J., Brown, C. C., Duncan, G., and Rodgers, W. L. (1989). Measurement error in cross-sectional and longitudinal labor market surveys: Results from two validation studies.

Bound, J., Jaeger, D. A., and Baker, R. M. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American statistical association*, 90(430):443–450.

Bowblis, J. R. and Smith, A. C. (2021). Occupational licensing of social services and nursing home quality: A regression discontinuity approach. *ILR Review*, 74(1):199–223.

Box, G. E. and Cox, D. R. (1981). *An analysis of transformations revisited, rebutted*. University of Wisconsin-Madison. Mathematics Research Center.

Boyd, D. E., Chandy, R. K., and Cunha Jr, M. (2010). When do chief marketing officers affect firm value? a customer power explanation. *Journal of Marketing Research*, 47(6):1162–1176.

Boyd, D. E. and Spekman, R. E. (2008). The market value impact of indirect ties within technology alliances. *Journal of the Academy of Marketing Science*, 36:488–500.

Brav, A. and Gompers, P. A. (1997). Myth or reality? the long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies. *The journal of finance*, 52(5):1791–1821.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian economic papers*, 17(31):334–355.

Breusch, T. S., Mizon, G. E., and Schmidt, P. (1989). Efficient estimation using panel data. *Econometrica: Journal of the Econometric Society*, pages 695–700.

Breusch, T. S. and Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification in econometrics. *The review of economic studies*, 47(1):239–253.

Brodeur, A., Clark, A. E., Fleche, S., and Powdthavee, N. (2021). Covid-19, lockdowns and well-being: Evidence from google trends. *Journal of public economics*, 193:104346.

Bronnenberg, B. J., Dubé, J.-P., and Sanders, R. E. (2020). Consumer misinformation and the brand premium: A private label blind taste test. *Marketing Science*, 39(2):382–406.

Brown, N., Butts, K., and Westerlund, J. (2023). Simple Difference-in-Differences Estimation in Fixed-T Panels. Papers 2301.11358, arXiv.org.

Brown, S. J. and Warner, J. B. (1980). Measuring security price performance. *Journal of financial economics*, 8(3):205–258.

Brown, S. J. and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, 14(1):3–31.

Bullock, J. G. and Ha, S. E. (2011). Mediation analysis is harder than it looks. *Cambridge handbook of experimental political science*, 508:521.

Burger, N. E., Kaffine, D. T., and Yu, B. (2014). Did california's hand-held cell phone ban reduce accidents? *Transportation research part A: policy and practice*, 66:162–172.

Burtch, G., Carnahan, S., and Greenwood, B. N. (2018). Can you gig it? an empirical examination of the gig economy and entrepreneurial activity. *Management Science*, 64(12):5497–5520.

Busse, M., Silva-Risso, J., and Zettelmeyer, F. (2006). $1,000 cash back: The pass-through of auto manufacturer promotions. *American Economic Review*, 96(4):1253–1270.

Busse, M. R., Lacetera, N., Pope, D. G., Silva-Risso, J., and Sydnor, J. R. (2013). Estimating the effect of salience in wholesale and retail car markets. *American Economic Review*, 103(3):575–579.

Busse, M. R., Simester, D. I., and Zettelmeyer, F. (2010). "the best price you'll ever get": The 2005 employee discount pricing promotions in the us automobile industry. *Marketing science*, 29(2):268–290.

Butcher, K. F., McEwan, P. J., and Weerapana, A. (2014). The effects of an anti-grade inflation policy at wellesley college. *Journal of Economic Perspectives*, 28(3):189–204.

Cabral, M., Cui, C., and Dworsky, M. (2022). The demand for insurance and rationale for a mandate: Evidence from workers' compensation insurance. *American economic review*, 112(5):1621–1668.

Cai, Y., Canay, I. A., Kim, D., and Shaikh, A. M. (2022). On the implementation of approximate randomization tests in linear models with a small number of clusters. *Journal of Econometric Methods*, 12(1):85–103.

Callaway, B. and Li, T. (2019). Quantile treatment effects in difference in differences models with panel data. *Quantitative Economics*, 10(4):1579–1618.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230.

Calonico, S., Cattaneo, M. D., and Farrell, M. H. (2020). Optimal bandwidth choice for robust bias-corrected inference in regression discontinuity designs. *The Econometrics Journal*, 23(2):192–210.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The review of economics and statistics*, 90(3):414–427.

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., and Whitelaw, R. F. (1998). The econometrics of financial markets. *Macroeconomic Dynamics*, 2(4):559–562.

Cao, Z. and Sorescu, A. (2013). Wedded bliss or tainted love? stock market reactions to the introduction of cobranded products. *Marketing Science*, 32(6):939–959.

Card, D. and Krueger, A. B. (1993). Minimum wages and employment: A case study of the fast food industry in new jersey and pennsylvania.

Card, D., Lee, D. S., Pei, Z., and Weber, A. (2015). Inference on causal effects in a generalized regression kink design. *Econometrica*, 83(6):2453–2483.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82.

Carpenter, C. and Dobkin, C. (2009). The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age. *American Economic Journal: Applied Economics*, 1(1):164–182.

Carranza, E., Garlick, R., Orkin, K., and Rankin, N. (2022). Job search and hiring with limited information about workseekers' skills. *American Economic Review*, 112(11):3547–3583.

Carrasco, M. and Doukali, M. (2022). Testing overidentifying restrictions with many instruments and heteroscedasticity using regularised jackknife iv. *The Econometrics Journal*, 25(1):71–97.

Cattaneo, M. D., Idrobo, N., and Titiunik, R. (2019). *A practical introduction to regression discontinuity designs: Foundations*. Cambridge University Press.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Chabé-Ferret, S. (2015). Analysis of the bias of matching and difference-in-difference under alternative earnings and selection processes. *Journal of Econometrics*, 185(1):110–123.

Chae, I., Ha, J., and Schweidel, D. A. (2023). Paywall suspensions and digital news subscriptions. *Marketing Science*, 42(4):729–745.

Chaney, P. K., Devinney, T. M., and Winer, R. S. (1991). The impact of new product introductions on the market value of firms. *Journal of business*, pages 573–610.

Chaplin, D. D., Cook, T. D., Zurovac, J., Coopersmith, J. S., Finucane, M. M., Vollmer, L. N., and Morris, R. E. (2018). The internal and external validity of the regression discontinuity design: A meta-analysis of 15 within-study comparisons. *Journal of Policy Analysis and Management*, 37(2):403–429.

Chatterjee, S. (2015). Matrix estimation by universal singular value thresholding.

Chen, H., Li, Q., Kaufman, J. S., Wang, J., Copes, R., Su, Y., and Benmarhnia, T. (2018). Effect of air quality alerts on human health: a regression discontinuity analysis in toronto, canada. *The Lancet Planetary Health*, 2(1):e19–e26.

Chen, J. and Roth, J. (2023). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics*, page qjad054.

Chen, X., John, G., Hays, J. M., Hill, A. V., and Geurs, S. E. (2009a). Learning from a service guarantee quasi experiment. *Journal of marketing research*, 46(5):584–596.

Chen, Y., Ganesan, S., and Liu, Y. (2009b). Does a firm's product-recall strategy affect its financial value? an examination of strategic alternatives during product-harm crises. *Journal of Marketing*, 73(6):214–226.

Chen, Y., Liu, Y., and Zhang, J. (2012). When do third-party product reviews affect firm value and what can firms do? the case of media critics and professional movie reviews. *Journal of Marketing*, 76(2):116–134.

Chernozhukov, V. and Hansen, C. (2005). An iv model of quantile treatment effects. *Econometrica*, 73(1):245–261.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014). Measuring the impacts of teachers i: Evaluating bias in teacher value-added estimates. *American economic review*, 104(9):2593–2632.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

Chung, D. J., Steenburgh, T., and Sudhir, K. (2014). Do bonuses enhance sales productivity? a dynamic structural analysis of bonus-based compensation plans. *Marketing Science*, 33(2):165–187.

Cinelli, C., Forney, A., and Pearl, J. (2022). A crash course in good and bad controls. *Sociological Methods & Research*, page 00491241221099552.

Cinelli, C. and Hazlett, C. (2020). Making sense of sensitivity: Extending omitted variable bias. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 82(1):39–67.

Cinelli, C., Kumor, D., Chen, B., Pearl, J., and Bareinboim, E. (2019). Sensitivity analysis of linear structural causal models. In *International conference on machine learning*, pages 1252–1261. PMLR.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics*, 92(1):1–45.

Conley, T. G. and Taber, C. R. (2011). Inference with "difference in differences" with a small number of policy changes. *The Review of Economics and Statistics*, 93(1):113–125.

Cornwell, T. B., Pruitt, S. W., and Clark, J. M. (2005). The relationship between major-league sports' official sponsorship announcements and the stock prices of sponsoring firms. *Journal of the Academy of Marketing Science*, 33(4):401–412.

Cragg, J. G. and Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric theory*, 9(2):222–240.

Cramér, H. (1999). *Mathematical methods of statistics*, volume 43. Princeton university press.

Cribari-Neto, F. (2004). Asymptotic inference under heteroskedasticity of unknown form. *Computational Statistics & Data Analysis*, 45(2):215–233.

Cribari-Neto, F. and da Silva, W. B. (2011). A new heteroskedasticity-consistent covariance matrix estimator for the linear regression model. *AStA Advances in Statistical Analysis*, 95:129–146.

Cribari-Neto, F., Souza, T. C., and Vasconcellos, K. L. (2007). Inference under heteroskedasticity and leveraged data. *Communications in Statistics—Theory and Methods*, 36(10):1877–1888.

Cullen, J. B., Jacob, B. A., and Levitt, S. D. (2005). The impact of school choice on student outcomes: an analysis of the chicago public schools. *Journal of Public Economics*, 89(5-6):729–760.

Datta, H., Knox, G., and Bronnenberg, B. J. (2018). Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Science*, 37(1):5–21.

Davis, L. W. (2008). The effect of driving restrictions on air quality in mexico city. *Journal of Political Economy*, 116(1):38–81.

Davis, L. W. and Kahn, M. E. (2010). International trade in used vehicles: The environmental consequences of nafta. *American Economic Journal: Economic Policy*, 2(4):58–82.

Daw, J. R. and Hatfield, L. A. (2018). Matching and regression to the mean in difference-in-differences analysis. *Health services research*, 53(6):4138–4156.

Dawson, J. F. and Richter, A. W. (2006). Probing three-way interactions in moderated multiple regression: development and application of a slope difference test. *Journal of applied psychology*, 91(4):917.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

De Chaisemartin, C. and D'haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences estimators with several treatments. *Journal of Econometrics*, 236(2):105480.

De Paola, M., Scoppa, V., and Falcone, M. (2013). The deterrent effects of the penalty points system for driving offences: a regression discontinuity approach. *Empirical Economics*, 45:965–985.

Deaton, A. (2010). Instruments, randomization, and learning about development. *Journal of economic literature*, 48(2):424–455.

Deshpande, M. and Li, Y. (2019). Who is screened out? application costs and the targeting of disability programs. *American Economic Journal: Economic Policy*, 11(4):213–248.

Diamond, A. and Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, 95(3):932–945.

DiPrete, T. A. and Gangl, M. (2004). Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological methodology*, 34(1):271–310.

Doan, T. and Iskandar-Datta, M. (2021). Does gender in the c-suite really matter? *Journal of Accounting, Auditing & Finance*, 36(1):81–107.

Doleac, J. L. and Hansen, B. (2020). The unintended consequences of "ban the box": Statistical discrimination and employment outcomes when criminal histories are hidden. *Journal of Labor Economics*, 38(2):321–374.

Dolley, J. C. (1933). Characteristics and procedure of common stock split-ups. *Harvard business review*, 11(3):316–326.

Donald, S. G. and Lang, K. (2007). Inference with difference-in-differences and other panel data. *The review of Economics and Statistics*, 89(2):221–233.

Doornik, J. A. and Hansen, H. (2008). An omnibus test for univariate and multivariate normality. *Oxford bulletin of economics and statistics*, 70:927–939.

Doudchenko, N. and Imbens, G. W. (2016). Balancing, regression, difference-in-differences and synthetic control methods: A synthesis. Technical report, National Bureau of Economic Research.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4):549–560.

Dubow, B. and Monteiro, N. B. (2006). Measuring market cleanliness. *Available at SSRN 1019999*.

Dufour, J.-M. (1997). Some impossibility theorems in econometrics with applications to structural and dynamic models. *Econometrica: Journal of the Econometric Society*, pages 1365–1387.

Dutta, A., Knif, J., Kolari, J. W., and Pynnonen, S. (2018). A robust and powerful test of abnormal stock returns in long-horizon event studies. *Journal of Empirical Finance*, 47:1–24.

Ebbes, P., Papies, D., and Van Heerde, H. J. (2011). The sense and non-sense of holdout sample validation in the presence of endogeneity. *Marketing Science*, 30(6):1115–1122.

Ebbes, P., Wedel, M., Böckenholt, U., and Steerneman, T. (2005). Solving and testing for regressor-error (in) dependence when no instrumental variables are available: With new evidence for the effect of education on income. *Quantitative Marketing and Economics*, 3:365–392.

Eckles, D. and Bakshy, E. (2021). Bias and high-dimensional adjustment in observational studies of peer effects. *Journal of the American Statistical Association*, 116(534):507–517.

Efron, B. (1992). Bootstrap methods: another look at the jackknife. In *Breakthroughs in statistics: Methodology and distribution*, pages 569–593. Springer.

Einav, L., Finkelstein, A., and Levin, J. (2010). Beyond testing: Empirical models of insurance markets. *Annu. Rev. Econ.*, 2(1):311–336.

Ekwaru, J. P. and Veugelers, P. J. (2018). The overlooked importance of constants added in log transformation of independent variables with zero values: A proposed approach for determining an optimal constant. *Statistics in Biopharmaceutical Research*, 10(1):26–29.

Elberse, A. (2007). The power of stars: Do star actors drive the success of movies? *Journal of marketing*, 71(4):102–120.

Esarey, J. and Sumner, J. L. (2018). Marginal effects in interaction models: Determining and controlling the false positive rate. *Comparative Political Studies*, 51(9):1144–1176.

Faber, B. and Gaubert, C. (2019). Tourism and economic development: Evidence from mexico's coastline. *American Economic Review*, 109(6):2245–2293.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2):383–417.

Fama, E. F., Fisher, L., Jensen, M. C., and Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, 10(1):1–21.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The journal of finance*, 65(5):1915–1947.

Fan, Y. and Yu, Z. (2012). Partial identification of distributional and quantile treatment effects in difference-in-differences models. *Economics Letters*, 115(3):511–515.

Fang, E., Lee, J., and Yang, Z. (2015). The timing of codevelopment alliances in new product development processes: Returns for upstream and downstream partners. *Journal of Marketing*, 79(1):64–82.

Faraway, J. J. (2016). *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models*. CRC press.

Ferman, B. and Pinto, C. (2021). Synthetic controls with imperfect pretreatment fit. *Quantitative Economics*, 12(4):1197–1221.

Firpo, S. and Possebom, V. (2018). Synthetic control method: Inference, sensitivity analysis and confidence sets. *Journal of Causal Inference*, 6(2):20160026.

Fornell, C., Mithas, S., Morgeson III, F. V., and Krishnan, M. S. (2006). Customer satisfaction and stock prices: High returns, low risk. *Journal of marketing*, 70(1):3–14.

Fossum, J. L. and Montoya, A. K. (2023). When to use different inferential methods for power analysis and data analysis for between-subjects mediation. *Advances in Methods and Practices in Psychological Science*, 6(2):25152459231156606.

Fox, J. (1997). *Applied regression analysis, linear models, and related methods*. sage publications, Inc.

Freedman, D. A. (2008). Randomization does not justify logistic regression. *Statistical Science*, pages 237–249.

Fricke, H. (2017). Identification based on difference-in-differences approaches with multiple treatments. *Oxford Bulletin of Economics and Statistics*, 79(3):426–433.

Fritz, M. S., Taylor, A. B., and MacKinnon, D. P. (2012). Explanation of two anomalous results in statistical mediation analysis. *Multivariate Behavioral Research*, 47(1):61–87.

Frölich, M. and Melly, B. (2013). Unconditional quantile treatment effects under endogeneity. *Journal of Business & Economic Statistics*, 31(3):346–357.

Fuchs-Schündeln, N. and Hassan, T. A. (2016). Natural experiments in macroeconomics. In *Handbook of macroeconomics*, volume 2, pages 923–1012. Elsevier.

Furnival, G. M. and Wilson, R. W. (2000). Regressions by leaps and bounds. *Technometrics*, 42(1):69–79.

Gallego, F., Montero, J.-P., and Salas, C. (2013). The effect of transport policies on car use: Evidence from latin american cities. *Journal of Public Economics*, 107:47–62.

Gallen, T. (2020). Broken instruments. *Available at SSRN 3671850*.

Gao, H., Xie, J., Wang, Q., and Wilbur, K. C. (2015). Should ad spending increase or decrease before a recall announcement? the marketing–finance interface in product-harm crisis management. *Journal of Marketing*, 79(5):80–99.

Gardner, J. (2022). Two-stage differences in differences. *arXiv preprint arXiv:2207.05943*.

Gelman, A. and Imbens, G. (2019). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, 37(3):447–456.

Gerard, F., Rokkanen, M., and Rothe, C. (2020). Bounds on treatment effects in regression discontinuity designs with a manipulated running variable. *Quantitative Economics*, 11(3):839–870.

Gerber, A. S., Green, D. P., Kaplan, E. H., and Kern, H. L. (2010). Baseline, placebo, and treatment: Efficient estimation for three-group experiments. *Political Analysis*, 18(3):297–315.

Geyskens, I., Gielens, K., and Dekimpe, M. G. (2002). The market valuation of internet channel additions. *Journal of marketing*, 66(2):102–119.

Gibbons, C. E., Suárez Serrato, J. C., and Urbancic, M. B. (2018). Broken or fixed effects? *Journal of Econometric Methods*, 8(1):20170002.

Gielens, K., Van de Gucht, L. M., Steenkamp, J.-B. E., and Dekimpe, M. G. (2008). Dancing with a giant: The effect of wal-mart's entry into the united kingdom on the performance of european retailers. *Journal of Marketing Research*, 45(5):519–534.

Glasser, M. (1964). Linear regression analysis with missing observations among the independent variables. *Journal of the American Statistical Association*, 59(307):834–844.

Gobillon, L. and Magnac, T. (2016). Regional policy evaluation: Interactive fixed effects and synthetic controls. *Review of Economics and Statistics*, 98(3):535–551.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica: Journal of the Econometric Society*, pages 1293–1301.

Goldberger, A. S. (1991). *A course in econometrics*. Harvard University Press.

Goldfarb, A. and Tucker, C. (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, 30(3):389–404.

Goldfarb, A., Tucker, C., and Wang, Y. (2022). Conducting research in marketing with quasi-experiments. *Journal of Marketing*, 86(3):1–20.

Goldsmith-Pinkham, P., Hull, P., and Kolesár, M. (2022). Contamination bias in linear regressions. Technical report, National Bureau of Economic Research.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Gordon, B. R., Zettelmeyer, F., Bhargava, N., and Chapsky, D. (2019). A comparison of approaches to advertising measurement: Evidence from big field experiments at facebook. *Marketing Science*, 38(2):193–225.

Gormley, T. A. and Matsa, D. A. (2011). Growing out of trouble? corporate responses to liability risk. *The Review of Financial Studies*, 24(8):2781–2821.

Gould, W., Pitblado, J., and Poi, B. (2010). Maximum likelihood estimation with stata: Statacorp lp.

Gourieroux, C., Holly, A., and Monfort, A. (1982). Likelihood ratio test, wald test, and kuhn-tucker test in linear models with inequality constraints on the regression parameters. *Econometrica: journal of the Econometric Society*, pages 63–80.

Gourieroux, C. and Monfort, A. (1981). On the problem of missing data in linear models. *The Review of Economic Studies*, 48(4):579–586.

Greene, W. H. (1990). A gamma-distributed stochastic frontier model. *Journal of econometrics*, 46(1-2):141–163.

Greevy, R., Lu, B., Silber, J. H., and Rosenbaum, P. (2004). Optimal multivariate matching before randomization. *Biostatistics*, 5(2):263–275.

Guo, T., Sriram, S., and Manchanda, P. (2020). "let the sunshine in": The impact of industry payment disclosure on physician prescription behavior. *Marketing Science*, 39(3):516–539.

Habel, J., Alavi, S., and Linsenmayer, K. (2021). Variable compensation and salesperson health. *Journal of Marketing*, 85(3):130–149.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis*, 20(1):25–46.

Haitovsky, Y. (1968). Missing data in regression analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, 30(1):67–82.

Hall, A. R., Rudebusch, G. D., and Wilcox, D. W. (1996). Judging instrument relevance in instrumental variables estimation. *International Economic Review*, pages 283–298.

Hall, G. C., Hutchinson, P. J., and Michaelas, N. (2004). Determinants of the capital structures of european smes. *Journal of Business Finance & Accounting*, 31(5-6):711–728.

Hansen, B. B. (2008). The prognostic analogue of the propensity score. *Biometrika*, 95(2):481–488.

Hansen, B. B., Rosenbaum, P. R., and Small, D. S. (2014). Clustered treatment assignments and sensitivity to unmeasured biases in observational studies. *Journal of the American Statistical Association*, 109(505):133–144.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the econometric society*, pages 1029–1054.

Harper, S. and Bruckner, T. A. (2017). Did the great recession increase suicides in the usa? evidence from an interrupted time-series analysis. *Annals of epidemiology*, 27(7):409–414.

Hartmann, W., Nair, H. S., and Narayanan, S. (2011). Identifying causal marketing mix effects using a regression discontinuity design. *Marketing Science*, 30(6):1079–1097.

Hastie, T., Mazumder, R., Lee, J. D., and Zadeh, R. (2015). Matrix completion and low-rank svd via fast alternating least squares. *The Journal of Machine Learning Research*, 16(1):3367–3402.

Hastie, T., Tibshirani, R., Friedman, J. H., and Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction*, volume 2. Springer.

Hausman, C. and Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. *Annual Review of Resource Economics*, 10:533–552.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, pages 1251–1271.

Hausman, J. A. (1983). Specification and estimation of simultaneous equation models. *Handbook of econometrics*, 1:391–448.

Hayes, A. F. and Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British journal of mathematical and statistical psychology*, 67(3):451–470.

Hayes, A. F. and Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: does method really matter? *Psychological science*, 24(10):1918–1927.

He, C., Ozturk, O. C., Gu, C., and Silva-Risso, J. M. (2021). The end of the express road for hybrid vehicles: Can governments' green product incentives backfire? *Marketing Science*, 40(1):80–100.

He, S., Hollenbeck, B., and Proserpio, D. (2022). The market for fake reviews. *Marketing Science*, 41(5):896–921.

Heath, D., Ringgenberg, M. C., Samadi, M., and Werner, I. M. (2023). Reusing natural experiments. *The Journal of Finance*, 78(4):2329–2364.

Heckman, J. (1990). Varieties of selection bias. *The American Economic Review*, 80(2):313–318.

Heckman, J. and Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and statistics*, 86(1):30–57.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of economic and social measurement, volume 5, number 4*, pages 475–492. NBER.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Heckman, J. J., LaLonde, R. J., and Smith, J. A. (1999). The economics and econometrics of active labor market programs. In *Handbook of labor economics*, volume 3, pages 1865–2097. Elsevier.

Heckman, J. J. and Smith, J. A. (1999). The pre-programme earnings dip and the determinants of participation in a social programme. implications for simple programme evaluation strategies. *The Economic Journal*, 109(457):313–348.

Heller, R., Rosenbaum, P. R., and Small, D. S. (2009). Split samples and design sensitivity in observational studies. *Journal of the American Statistical Association*, 104(487):1090–1101.

Henderson, C. R. (1975). Best linear unbiased estimation and prediction under a selection model. *Biometrics*, pages 423–447.

Hill, A. D., Johnson, S. G., Greco, L. M., O'Boyle, E. H., and Walter, S. L. (2021). Endogeneity: A review and agenda for the methodology-practice divide affecting micro and macro research. *Journal of Management*, 47(1):105–143.

Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in africa. *American Economic Review*, 109(3):1032–1079.

Ho, D. E., Imai, K., King, G., and Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, 15(3):199–236.

Hochberg, Y. (1988). A sharper bonferroni procedure for multiple tests of significance. *Biometrika*, 75(4):800–802.

Hodges Jr, J. L. and Lehmann, E. L. (2011). Estimates of location based on rank tests. In *Selected Works of EL Lehmann*, pages 287–300. Springer.

Hollander, M., Wolfe, D. A., and Chicken, E. (2013). *Nonparametric statistical methods*. John Wiley & Sons.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics*, pages 65–70.

Homburg, C., Vollmayr, J., and Hahn, A. (2014). Firm value creation through major channel expansions: Evidence from an event study in the united states, germany, and china. *Journal of Marketing*, 78(3):38–61.

Honda, Y. (1985). Testing the error components model with non-normal disturbances. *The review of economic studies*, 52(4):681–690.

Horsky, D. and Swyngedouw, P. (1987). Does it pay to change your company's name? a stock market perspective. *Marketing Science*, 6(4):320–335.

Hosmer, D. W. and Lemeshow, S. (1992). Confidence interval estimation of interaction. *Epidemiology*, pages 452–456.

Houston, M. B. and Johnson, S. A. (2000). Buyer–supplier contracts versus joint ventures: Determinants and consequences of transaction structure. *Journal of marketing research*, 37(1):1–15.

Hoyer, P., Janzing, D., Mooij, J. M., Peters, J., and Schölkopf, B. (2008). Nonlinear causal discovery with additive noise models. *Advances in neural information processing systems*, 21.

Hoyle, R. H. (1999). *Statistical strategies for small sample research*. sage.

Hoynes, H. W. and Schanzenbach, D. W. (2009). Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. *American Economic Journal: Applied Economics*, 1(4):109–139.

Huber, M., Schelker, M., and Strittmatter, A. (2022). Direct and indirect effects based on changes-in-changes. *Journal of Business & Economic Statistics*, 40(1):432–443.

Hurvich, C. M. and Tsai, C.-L. (1989). Regression and time series model selection in small samples. *Biometrika*, 76(2):297–307.

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis*, 20(1):1–24.

Imai, K., Jiang, Z., and Malani, A. (2021a). Causal inference with interference and noncompliance in two-stage randomized experiments. *Journal of the American Statistical Association*, 116(534):632–644.

Imai, K., Keele, L., and Tingley, D. (2010a). A general approach to causal mediation analysis. *Psychological methods*, 15(4):309.

Imai, K., Keele, L., and Yamamoto, T. (2010b). Identification, inference and sensitivity analysis for causal mediation effects.

Imai, K. and Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science*, 63(2):467–490.

Imai, K. and Kim, I. S. (2021). On the use of two-way fixed effects regression models for causal inference with panel data. *Political Analysis*, 29(3):405–415.

Imai, K., Kim, I. S., and Wang, E. H. (2021b). Matching methods for causal inference with time-series cross-sectional data. *American Journal of Political Science*.

Imai, K., King, G., and Stuart, E. A. (2008). Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the royal statistical society: series A (statistics in society)*, 171(2):481–502.

Imbens, G. and Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of economic studies*, 79(3):933–959.

Imbens, G. and Lemieux, T. (2008). The regression discontinuity design–theory and applications. *Journal of Econometrics*.

Imbens, G. W. and Angrist, J. D. (1994). Identification and estimation of local average treatment effects. *Econometrica*, 62(2):467–475.

Imbens, G. W. and Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Iskandar-Datta, M. and Jia, Y. (2013). Valuation consequences of clawback provisions. *The Accounting Review*, 88(1):171–198.

Israeli, A. (2018). Online map enforcement: evidence from a quasi-experiment. *Marketing Science*, 37(5):710–732.

Ittner, C., Larcker, D., and Taylor, D. (2009). Commentary–the stock market's pricing of customer satisfaction. *Marketing Science*, 28(5):826–835.

Jacobson, R. and Mizik, N. (2009). The financial markets and customer satisfaction: Reexamining possible financial market mispricing of customer satisfaction. *Marketing Science*, 28(5):810–819.

Jaffe, J. F. (1974). Special information and insider trading. *The Journal of Business*, 47(3):410–428.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An introduction to statistical learning*, volume 112. Springer.

Janakiraman, R., Lim, J. H., and Rishika, R. (2018). The effect of a data breach announcement on customer behavior: Evidence from a multichannel retailer. *Journal of marketing*, 82(2):85–105.

Jepsen, C., Troske, K., and Coomes, P. (2014). The labor-market returns to community college degrees, diplomas, and certificates. *Journal of Labor Economics*, 32(1):95–121.

Jin, H. and Rubin, D. B. (2008). Principal stratification for causal inference with extended partial compliance. *Journal of the American Statistical Association*, 103(481):101–111.

Jin, H. and Rubin, D. B. (2009). Public schools versus private schools: Causal inference with partial compliance. *Journal of Educational and Behavioral Statistics*, 34(1):24–45.

Johansson, P. and Schultzberg, M. (2022). Rerandomization: A complement or substitute for stratification in randomized experiments? *Journal of Statistical Planning and Inference*, 218:43–58.

Johnson, M. S. (2020). Regulation by shaming: Deterrence effects of publicizing violations of workplace safety and health laws. *American economic review*, 110(6):1866–1904.

Johnson, N. L. (1949). Systems of frequency curves generated by methods of translation. *Biometrika*, 36(1/2):149.

Johnson, P. O. and Neyman, J. (1936). Tests of certain linear hypotheses and their application to some educational problems. *Statistical research memoirs*.

Johnson, R. A., Wichern, D. W., et al. (2002). Applied multivariate statistical analysis.

Johnston, M. A. (2007). A review of the application of event studies in marketing. *Academy of Marketing Science Review*, 2007:1.

Jones, M. P. (1996). Indicator and stratification methods for missing explanatory variables in multiple linear regression. *Journal of the American statistical association*, 91(433):222–230.

Jordon, J., Szpruch, L., Houssiau, F., Bottarelli, M., Cherubin, G., Maple, C., Cohen, S. N., and Weller, A. (2022). Synthetic data–what, why and how? *arXiv preprint arXiv:2205.03257*.

Joshi, A. M. and Hanssens, D. M. (2009). Movie advertising and the stock market valuation of studios: a case of "great expectations?". *Marketing Science*, 28(2):239–250.

Kahn-Lang, A. and Lang, K. (2020). The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications. *Journal of Business & Economic Statistics*, 38(3):613–620.

Kalaignanam, K. and Bahadir, S. C. (2013). Corporate brand name changes and business restructuring: is the relationship complementary or substitutive? *Journal of the Academy of Marketing Science*, 41:456–472.

Kapelner, A. and Krieger, A. (2014). Matching on-the-fly: Sequential allocation with higher power and efficiency. *Biometrics*, 70(2):378–388.

Karniouchina, E. V., Moore, W. L., and Cooney, K. J. (2009). Impact of mad money stock recommendations: merging financial and marketing perspectives. *Journal of Marketing*, 73(6):244–266.

Karniouchina, E. V., Uslay, C., and Erenburg, G. (2011). Do marketing media have life cycles? the case of product placement in movies. *Journal of Marketing*, 75(3):27–48.

Keele, L. (2010). An overview of rbounds: An r package for rosenbaum bounds sensitivity analysis with matched data. *White Paper. Columbus, OH*, 1:15.

Keller, K. O., Guyt, J. Y., and Grewal, R. (2024). Soda taxes and marketing conduct. *Journal of Marketing Research*, 61(3):393–410.

Kenny, D. A. and Judd, C. M. (2014). Power anomalies in testing mediation. *Psychological science*, 25(2):334–339.

Kim, J.-S. and Frees, E. W. (2007). Multilevel modeling with correlated effects. *Psychometrika*, 72(4):505–533.

Kim, M. and McAlister, L. M. (2011). Stock market reaction to unexpected growth in marketing expenditure: Negative for sales force, contingent on spending level for advertising. *Journal of Marketing*, 75(4):68–85.

Kim, S., Lee, C., and Gupta, S. (2020). Bayesian synthetic control methods. *Journal of Marketing Research*, 57(5):831–852.

King, G. (1995). Replication, replication. *PS: Political Science & Politics*, 28(3):444–452.

King, G., Honaker, J., Joseph, A., and Scheve, K. (2001). Analyzing incomplete political science data: An alternative algorithm for multiple imputation. *American political science review*, 95(1):49–69.

King, G., Lucas, C., and Nielsen, R. A. (2017). The balance-sample size frontier in matching methods for causal inference. *American journal of political science*, 61(2):473–489.

King, G. and Nielsen, R. (2019). Why propensity scores should not be used for matching. *Political analysis*, 27(4):435–454.

King, M. L. and Wu, P. X. (1997). Locally optimal one-sided tests for multiparameter hypotheses. *Econometric Reviews*, 16(2):131–156.

Kiviet, J. F. (2020). Testing the impossible: Identifying exclusion restrictions. *Journal of Econometrics*, 218(2):294–316.

Kleinberg, J., Ludwig, J., Mullainathan, S., and Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review*, 105(5):491–495.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, 8:435–464.

Knol, M. J. and VanderWeele, T. J. (2012). Recommendations for presenting analyses of effect modification and interaction. *International journal of epidemiology*, 41(2):514–520.

Kothari, S. and Warner, J. B. (1997). Measuring long-horizon security price performance. *Journal of financial economics*, 43(3):301–339.

Krauth, B. (2016). Bounding a linear causal effect using relative correlation restrictions. *Journal of Econometric Methods*, 5(1):117–141.

Laird, N. M. and Ware, J. H. (1982). Random-effects models for longitudinal data. *Biometrics*, pages 963–974.

LaLonde, R. J. (1986). Evaluating the econometric evaluations of training programs with experimental data. *The American economic review*, pages 604–620.

Lambrecht, A., Tucker, C., and Zhang, X. (2024). Tv advertising and online sales: A case study of intertemporal substitution effects for an online travel platform. *Journal of Marketing Research*, 61(2):248–270.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of econometrics*, 95(2):391–413.

Lane, V. and Jacobson, R. (1995). Stock market reactions to brand extension announcements: The effects of brand attitude and familiarity. *Journal of marketing*, 59(1):63–77.

Larcker, D. F. and Rusticus, T. O. (2010). On the use of instrumental variables in accounting research. *Journal of accounting and economics*, 49(3):186–205.

Lavy, V., Angrist, J. D., and Schlosser, A. (2006). New evidence on the causal link between the quantity and quality of children.

Ledgerwood, A. and Shrout, P. E. (2011). The trade-off between accuracy and precision in latent variable models of mediation processes. *Journal of personality and social psychology*, 101(6):1174.

Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies*, pages 1071–1102.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of economic literature*, 48(2):281–355.

Lee, D. S., McCrary, J., Moreira, M. J., and Porter, J. (2022). Valid t-ratio inference for iv. *American Economic Review*, 112(10):3260–3290.

Lee Rodgers, J., Beasley, W. H., and Schuelke, M. (2014). Graphical data analysis on the circle: Wrap-around time series plots for (interrupted) time series designs. *Multivariate Behavioral Research*, 49(6):571–580.

Lewbel, A. (1997). Constructing instruments for regressions with measurement error when no additional data are available, with an application to patents and r&d. *Econometrica: journal of the econometric society*, pages 1201–1213.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80.

Li, H., Liu, X., Chen, Y., and Fan, Y. (2022). Testing for serial correlation in autoregressive exogenous models with possible garch errors. *Entropy*, 24(8):1076.

Li, K. T. (2024). Frontiers: A simple forward difference-in-differences method. *Marketing Science*, 43(2):267–279.

Li, K. T. and Sonnier, G. P. (2023). Statistical inference for the factor model approach to estimate causal effects in quasi-experimental settings. *Journal of Marketing Research*, 60(3):449–472.

Li, K. T. and Van den Bulte, C. (2023). Augmented difference-in-differences. *Marketing Science*, 42(4):746–767.

Li, S., Vlassis, N., Kawale, J., and Fu, Y. (2016). Matching via dimensionality reduction for estimation of treatment effects in digital marketing campaigns. In *IJCAI*, volume 16, pages 3768–3774.

Li, X., Gan, C., and Hu, B. (2011). The welfare impact of microcredit on rural households in china. *The Journal of Socio-Economics*, 40(4):404–411.

Li, Y. P., Propert, K. J., and Rosenbaum, P. R. (2001). Balanced risk set matching. *Journal of the American Statistical Association*, 96(455):870–882.

Liang, K.-Y. and Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, 73(1):13–22.

Liaukonyte, J., Teixeira, T., and Wilbur, K. C. (2015). Television advertising and online shopping. *Marketing Science*, 34(3):311–330.

Liaukonytė, J., Tuchman, A., and Zhu, X. (2023). Frontiers: Spilling the beans on political consumerism: Do social media boycotts and buycotts translate to real sales impact? *Marketing Science*, 42(1):11–25.

Lim, J. H., Rishika, R., Janakiraman, R., and Kannan, P. (2020). Competitive effects of front-of-package nutrition labeling adoption on nutritional quality: evidence from facts up front–style labels. *Journal of Marketing*, 84(6):3–21.

Linden, A. (2015). Conducting interrupted time-series analysis for single-and multiple-group comparisons. *The Stata Journal*, 15(2):480–500.

Linden, A. (2017). A comprehensive set of postestimation measures to enrich interrupted time-series analysis. *The Stata Journal*, 17(1):73–88.

Linden, A. and Yarnold, P. R. (2016). Using machine learning to identify structural breaks in single-group interrupted time series designs. *Journal of Evaluation in Clinical Practice*, 22(6):855–859.

Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American statistical Association*, 83(404):1198–1202.

Little, R. J. (1992). Regression with missing x's: a review. *Journal of the American statistical association*, 87(420):1227–1237.

Liu, L., Wang, Y., and Xu, Y. (2022). A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *American Journal of Political Science*.

Long, Q., Little, R. J., and Lin, X. (2010). Estimating causal effects in trials involving multitreatment arms subject to non-compliance: a bayesian framework. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 59(3):513–531.

Looney, S. W. and Gulledge Jr, T. R. (1985). Use of the correlation coefficient with normal probability plots. *The American Statistician*, 39(1):75–79.

Lopez, M. J. and Gutman, R. (2017). Estimation of causal effects with multiple treatments: a review and new ideas. *Statistical Science*, pages 432–454.

Loughran, T. and Ritter, J. R. (1995). The new issues puzzle. *The Journal of finance*, 50(1):23–51.

Loughran, T. and Ritter, J. R. (2000). Uniformly least powerful tests of market efficiency. *Journal of financial economics*, 55(3):361–389.

Lyon, J. D., Barber, B. M., and Tsai, C.-L. (1999). Improved methods for tests of long-run abnormal stock returns. *The Journal of Finance*, 54(1):165–201.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, 35(1):13–39.

MacKinnon, D. P., Fairchild, A. J., and Fritz, M. S. (2007). Mediation analysis. *Annu. Rev. Psychol.*, 58:593–614.

MacKinnon, D. P., Warsi, G., and Dwyer, J. H. (1995). A simulation study of mediated effect measures. *Multivariate behavioral research*, 30(1):41–62.

MacKinnon, J. G. and White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of econometrics*, 29(3):305–325.

Magel, R. C. and Hertsgaard, D. (1987). A collinearity diagnostic for nonlinear regression: A collinearity diagnostic. *Communications in Statistics-Simulation and Computation*, 16(1):85–97.

Malhotra, A. and Kubowicz Malhotra, C. (2011). Evaluating customer information breaches as service failures: An event study approach. *Journal of Service Research*, 14(1):44–59.

Manchanda, P., Packard, G., and Pattabhiramaiah, A. (2015). Social dollars: The economic impact of customer participation in a firm-sponsored online customer community. *Marketing Science*, 34(3):367–387.

Manly, B. F. (1976). Exponential data transformations. *Journal of the Royal Statistical Society Series D: The Statistician*, 25(1):37–42.

Marcus, M. and Sant'Anna, P. H. (2021). The role of parallel trends in event study settings: An application to environmental economics. *Journal of the Association of Environmental and Resource Economists*, 8(2):235–275.

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 57(3):519–530.

Markovitch, D. G. and Golder, P. N. (2008). Findings—using stock prices to predict market events: Evidence on sales takeoff and long-term firm survival. *Marketing Science*, 27(4):717–729.

Marsaglia, G. and Marsaglia, J. (2004). Evaluating the anderson-darling distribution. *Journal of statistical software*, 9:1–5.

Masten, M. A. and Poirier, A. (2022). The effect of omitted variables on the sign of regression coefficients. *arXiv preprint arXiv:2208.00552*.

Masulis, R. W. and Nahata, R. (2011). Venture capital conflicts of interest: Evidence from acquisitions of venture-backed firms. *Journal of Financial and Quantitative Analysis*, 46(2):395–430.

Mazodier, M. and Rezaee, A. (2013). Are sponsorship announcements good news for the shareholders? evidence from international stock exchanges. *Journal of the Academy of Marketing Science*, 41:586–600.

Mazumder, R., Hastie, T., and Tibshirani, R. (2010). Spectral regularization algorithms for learning large incomplete matrices. *Journal of Machine Learning Research*, 11:2287–2322.

McCaffrey, D. F., Griffin, B. A., Almirall, D., Slaughter, M. E., Ramchand, R., and Burgette, L. F. (2013). A tutorial on propensity score estimation for multiple treatments using generalized boosted models. *Statistics in medicine*, 32(19):3388–3414.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, 142(2):698–714.

McCullagh, P. (2019). *Generalized linear models*. Routledge.

McWilliams, A. and Siegel, D. (1997). Event studies in management research: Theoretical and empirical issues. *Academy of management journal*, 40(3):626–657.

Mei, B. and Sun, C. (2008). Event analysis of the impact of mergers and acquisitions on the financial performance of the u.s. forest products industry. *Forest Policy and Economics*, 10(5):286–294.

Mellon, J. (2023). Rain, rain, go away: 195 potential exclusion-restriction violations for studies using weather as an instrumental variable. *Available at SSRN 3715610*.

Miller, R. G. (1974). The jackknife-a review. *Biometrika*, 61(1):1–15.

Mirenda, L., Mocetti, S., and Rizzica, L. (2022). The economic effects of mafia: Firm level evidence. *American Economic Review*, 112(8):2748–2773.

Mitchell, M. L. and Stafford, E. (2000). Managerial decisions and long-term stock price performance. *The Journal of Business*, 73(3):287–329.

Moon, H. R. and Weidner, M. (2015). Linear regression for panel with unknown number of factors as interactive fixed effects. *Econometrica*, 83(4):1543–1579.

Moreira, H. and Moreira, M. J. (2019). Optimal two-sided tests for instrumental variables regression with heteroskedastic and autocorrelated errors. *Journal of Econometrics*, 213(2):398–433.

Moreira, M. J. (2003). A conditional likelihood ratio test for structural models. *Econometrica*, 71(4):1027–1048.

Moreira, M. J. (2009). Tests with correct size when instruments can be arbitrarily weak. *Journal of Econometrics*, 152(2):131–140.

Morgan, K. L. and Rubin, D. B. (2012). Rerandomization to improve covariate balance in experiments.

Mroz, T. A. (1984). *The sensitivity of an empirical model of married women's hours of work to economic and statistical assumptions*. Stanford University.

Narayanan, S. and Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, 34(3):388–407.

Narayanan, S. and Nair, H. S. (2013). Estimating causal installed-base effects: A bias-correction approach. *Journal of Marketing Research*, 50(1):70–94.

Nelder, J. A. and Wedderburn, R. W. (1972). Generalized linear models. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 135(3):370–384.

Nelson, C. and Startz, R. (1988). The distribution of the instrumental variables estimator and its t-ratiowhen the instrument is a poor one.

Nelson, C. R. and Startz, R. (1990). The distribution of the instrumental variables estimator and its t-ratio when the instrument is a poor one. *Journal of Business*, pages S125–S140.

Nerlove, M. (1971). Further evidence on the estimation of dynamic economic relations from a time series of cross sections. *Econometrica: Journal of the Econometric Society*, pages 359–382.

Newey, W. K. and West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, pages 1417–1426.

Nielsen, H. S., Sørensen, T., and Taber, C. (2010). Estimating the effect of student aid on college enrollment: Evidence from a government grant policy reform. *American Economic Journal: Economic Policy*, 2(2):185–215.

Norris, S., Pecenco, M., and Weaver, J. (2021). The effects of parental and sibling incarceration: Evidence from ohio. *American Economic Review*, 111(9):2926–2963.

Oestreicher-Singer, G. and Zalmanson, L. (2013). Content or community? a digital business strategy for content providers in the social age. *MIS quarterly*, pages 591–616.

O'Hara, R. and Kotze, J. (2010). Do not log-transform count data. *Nature Precedings*, pages 1–1.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Owen, J. and Rabinovitch, R. (1983). On the class of elliptical distributions and their applications to the theory of portfolio choice. *The Journal of Finance*, 38(3):745–752.

Pandey, V. K., Shanahan, K. J., and Hansen, S. W. (2005). The relationship between shareholder wealth effects, diversity, and publicity as a marketing strategy. *Journal of the Academy of Marketing Science*, 33:423–431.

Pang, X., Liu, L., and Xu, Y. (2022). A bayesian alternative to synthetic control for comparative case studies. *Political Analysis*, 30(2):269–288.

Parente, P. M. and Silva, J. S. (2012). A cautionary note on tests of overidentifying restrictions. *Economics Letters*, 115(2):314–317.

Park, S. and Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science*, 31(4):567–586.

Patell, J. M. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical test. *Journal of accounting research*, pages 246–276.

Pattabhiramaiah, A., Sriram, S., and Manchanda, P. (2019). Paywalls: Monetizing online content. *Journal of marketing*, 83(2):19–36.

Pearl, J. (2014). Graphical models for probabilistic and causal reasoning. *Computing Handbook, 3rd ed.(1)*, pages 44–1.

Pearl, J. (2019). The seven tools of causal inference, with reflections on machine learning. *Communications of the ACM*, 62(3):54–60.

Pearl, J. and Mackenzie, D. (2018). *The book of why: the new science of cause and effect*. Basic books.

Penfold, R. B. and Zhang, F. (2013). Use of interrupted time series analysis in evaluating health care quality improvements. *Academic pediatrics*, 13(6):S38–S44.

Permutt, T. and Hebel, J. R. (1989). Simultaneous-equation estimation in a clinical trial of the effect of smoking on birth weight. *Biometrics*, pages 619–622.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of marketing research*, 47(1):3–13.

Peukert, C., Bechtold, S., Batikas, M., and Kretschmer, T. (2022). Regulatory spillovers and data governance: Evidence from the gdpr. *Marketing Science*, 41(4):746–768.

Pitt, M. M. (2011). Overidentification tests and causality: a second response to roodman and morduch. *Access at: http://www. brown. edu/research/projects/pitt*.

Pocock, S. J. and Simon, R. (1975). Sequential treatment assignment with balancing for prognostic factors in the controlled clinical trial. *Biometrics*, pages 103–115.

Porreca, Z. (2022). Synthetic difference-in-differences estimation with staggered treatment timing. *Economics Letters*, 220:110874.

Powers, D. E. and Swinton, S. S. (1984). Effects of self-study for coachable test item types. *Journal of Educational Psychology*, 76(2):266.

Preacher, K. J. and Hayes, A. F. (2004). Spss and sas procedures for estimating indirect effects in simple mediation models. *Behavior research methods, instruments, & computers*, 36:717–731.

Proserpio, D. and Zervas, G. (2017a). Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science*, 36(5):645–665.

Proserpio, D. and Zervas, G. (2017b). Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science*, 36(5):645–665.

Puhani, P. A. (2012). The treatment effect, the cross difference, and the interaction term in nonlinear "difference-in-differences" models. *Economics Letters*, 115(1):85–87.

Qu, Y. and Lipkovich, I. (2009). Propensity score estimation with missing values using a multiple imputation missingness pattern (mimp) approach. *Statistics in medicine*, 28(9):1402–1414.

Raassens, N., Wuyts, S., and Geyskens, I. (2012). The market valuation of outsourcing new product development. *Journal of Marketing Research*, 49(5):682–695.

Ramachandra, V. (2018). Deep learning for causal inference. *arXiv preprint arXiv:1803.00149*.

Ramani, N. and Srinivasan, R. (2019). Effects of liberalization on incumbent firms' marketing-mix responses and performance: evidence from a quasi-experiment. *Journal of marketing*, 83(5):97–114.

Rambachan, A. and Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, page rdad018.

Rao, C. R. (1992). Information and the accuracy attainable in the estimation of statistical parameters. In *Breakthroughs in Statistics: Foundations and basic theory*, pages 235–247. Springer.

Rao, R. S., Chandy, R. K., and Prabhu, J. C. (2008). The fruits of legitimacy: Why some new ventures gain more from innovation than others. *Journal of Marketing*, 72(4):58–75.

Reed, W. R. (2015). On the practice of lagging variables to avoid simultaneity. *Oxford Bulletin of Economics and Statistics*, 77(6):897–905.

Reiss, P. C. (2011). Structural workshop paper—descriptive, structural, and experimental empirical methods in marketing research. *Marketing Science*, 30(6):950–964.

Ritter, J. R. (1991). The long-run performance of initial public offerings. *The journal of finance*, 46(1):3–27.

Robins, J. M., Hernan, M. A., and Brumback, B. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*, pages 550–560.

Rodgers, J. L., John, C. A. S., and Coleman, R. (2005). Did fertility go up after the oklahoma city bombing? an analysis of births in metropolitan counties in oklahoma, 1990–1999. *Demography*, 42:675–692.

Romano, J. P. and Wolf, M. (2005). Stepwise multiple testing as formalized data snooping. *Econometrica*, 73(4):1237–1282.

Romano, J. P. and Wolf, M. (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics & Probability Letters*, 113:38–40.

Rosenbaum, P. R. (2002). Attributing effects to treatment in matched observational studies. *Journal of the American statistical Association*, 97(457):183–192.

Rosenbaum, P. R. (2015). Two r packages for sensitivity analysis in observational studies. *Observational Studies*, 1(2):1–17.

Rosenbaum, P. R. and Rosenbaum, P. R. (2002). *Overt bias in observational studies*. Springer.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rosenbaum, P. R. and Rubin, D. B. (1985). The bias due to incomplete matching. *Biometrics*, pages 103–116.

Rosenzweig, M. R. and Wolpin, K. I. (2000). Natural "natural experiments" in economics. *Journal of Economic Literature*, 38(4):827–874.

Rossi, P. E. (2014). Even the rich can make themselves poor: A critical examination of iv methods in marketing applications. *Marketing Science*, 33(5):655–672.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review*, 4(3):305–322.

Roth, J. and Sant'Anna, P. H. (2023). When is parallel trends sensitive to functional form? *Econometrica*, 91(2):737–747.

Rubin, D. B. (1973). The use of matched sampling and regression adjustment to remove bias in observational studies. *Biometrics*, pages 185–203.

Rubin, D. B. (1996). Multiple imputation after 18+ years. *Journal of the American statistical Association*, 91(434):473–489.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, 2:169–188.

Rubin, D. B. and Thomas, N. (1996). Matching using estimated propensity scores: relating theory to practice. *Biometrics*, pages 249–264.

Rubin, D. B. and Thomas, N. (2000). Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association*, 95(450):573–585.

Ryan, A. M., Kontopantelis, E., Linden, A., and Burgess Jr, J. F. (2019). Now trending: Coping with non-parallel trends in difference-in-differences analysis. *Statistical methods in medical research*, 28(12):3697–3711.

Sant'Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1):101–122.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the econometric society*, pages 393–415.

Satterthwaite, F. E. (1946). An approximate distribution of estimates of variance components. *Biometrics bulletin*, 2(6):110–114.

Schabenberger, O. and Pierce, F. J. (2001). *Contemporary statistical models for the plant and soil sciences*. CRC press.

Scharfstein, D. O., Rotnitzky, A., and Robins, J. M. (1999). Adjusting for nonignorable drop-out using semiparametric nonresponse models. *Journal of the American Statistical Association*, 94(448):1096–1120.

Scheve, K. and Stasavage, D. (2012). Democracy, war, and wealth: lessons from two centuries of inheritance taxation. *American Political Science Review*, 106(1):81–102.

Schipper, K. and Smith, A. (1983). Effects of recontracting on shareholder wealth: The case of voluntary spin-offs. *Journal of financial Economics*, 12(4):437–467.

Schipper, K. and Thompson, R. (1983). Evidence on the capitalized value of merger activity for acquiring firms. *Journal of financial Economics*, 11(1-4):85–119.

Schisterman, E. F., Moysich, K. B., England, L. J., and Rao, M. (2003). Estimation of the correlation coefficient using the bayesian approach and its applications for epidemiologic research. *BMC medical research methodology*, 3:1–4.

Schulze, C., Skiera, B., and Wiesel, T. (2012). Linking customer and financial metrics to shareholder value: The leverage effect in customer-based valuation. *Journal of Marketing*, 76(2):17–32.

Shapiro, S. S. and Francia, R. (1972). An approximate analysis of variance test for normality. *Journal of the American statistical Association*, 67(337):215–216.

Shapiro, S. S. and Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52(3/4):591–611.

Sherman, L. W. and Berk, R. A. (1984). *The Minneapolis domestic violence experiment*, volume 1. Police Foundation Washington, DC.

Shin, J., Sudhir, K., and Yoon, D.-H. (2012). When to "fire" customers: Customer cost-based pricing. *Management Science*, 58(5):932–947.

Shrout, P. E. and Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological methods*, 7(4):422.

Šidák, Z. (1967). Rectangular confidence regions for the means of multivariate normal distributions. *Journal of the American Statistical Association*, 62(318):626–633.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Silva, J. S. and Tenreyro, S. (2011). Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters*, 112(2):220–222.

Simonsohn, U., Nelson, L. D., and Simmons, J. P. (2014a). P-curve: a key to the file-drawer. *Journal of experimental psychology: General*, 143(2):534.

Simonsohn, U., Nelson, L. D., and Simmons, J. P. (2014b). p-curve and effect size: Correcting for publication bias using only significant results. *Perspectives on Psychological Science*, 9(6):666–681.

Simonsohn, U., Simmons, J. P., and Nelson, L. D. (2015). Better p-curves: Making p-curve analysis more robust to errors, fraud, and ambitious p-hacking, a reply to ulrich and miller (2015).

Simonsohn, U., Simmons, J. P., and Nelson, L. D. (2020). Specification curve analysis. *Nature Human Behaviour*, 4(11):1208–1214.

Singh, A., Hosanagar, K., and Gandhi, A. (2020). Machine learning instrument variables for causal inference. In *Proceedings of the 21st ACM Conference on Economics and Computation*, pages 835–836.

Skiera, B., Bayer, E., and Schöler, L. (2017). What should be the dependent variable in marketing-related event studies? *International Journal of Research in Marketing*, 34(3):641–659.

Smith, E. R. (1982). Beliefs, attributions, and evaluations: Nonhierarchical models of mediation in social cognition. *Journal of Personality and Social Psychology*, 43(2):248.

Smith, J. A. and Todd, P. E. (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of econometrics*, 125(1-2):305–353.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological methodology*, 13:290–312.

Somaini, P. and Wolak, F. A. (2016). An algorithm to estimate the two-way fixed effects model. *Journal of Econometric Methods*, 5(1):143–152.

Somaini, P. and Wolak, F. A. (2021). Twfem: Stata module to efficiently estimate a two-way fixed effects model based on somaini and wolak (2015).

Sood, A. and Tellis, G. J. (2009). Do innovations really pay off? total stock market returns to innovation. *Marketing Science*, 28(3):442–456.

Sorescu, A., Warren, N. L., and Ertekin, L. (2017). Event study methodology in the marketing literature: an overview. *Journal of the Academy of Marketing Science*, 45:186–207.

Sorescu, A. B., Chandy, R. K., and Prabhu, J. C. (2003). Sources and financial consequences of radical innovation: Insights from pharmaceuticals. *Journal of marketing*, 67(4):82–102.

Sorescu, A. B., Chandy, R. K., and Prabhu, J. C. (2007). Why some acquisitions do better than others: product capital as a driver of long-term stock returns. *Journal of Marketing Research*, 44(1):57–72.

Spiller, S. A., Fitzsimons, G. J., Lynch Jr, J. G., and McClelland, G. H. (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of marketing research*, 50(2):277–288.

St Laurent, R. T. and Cook, R. D. (1992). Leverage and superleverage in nonlinear regression. *Journal of the American Statistical Association*, 87(420):985–990.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557–586.

Steinmetz, H. and Block, J. (2022). Meta-analytic structural equation modeling (masem): new tricks of the trade. *Management Review Quarterly*, 72(3):605–626.

Stephens, M. A. (1974). Edf statistics for goodness of fit and some comparisons. *Journal of the American statistical Association*, 69(347):730–737.

Stevenson, B. and Wolfers, J. (2006). Bargaining in the shadow of the law: Divorce laws and family distress. *The Quarterly Journal of Economics*, 121(1):267–288.

Stock, J. and Yogo, M. (2005a). Asymptotic distributions of instrumental variables statistics with many instruments. *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*, 6:109–120.

Stock, J. H. and Wright, J. H. (2000). Gmm with weak identification. *Econometrica*, 68(5):1055–1096.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529.

Stock, J. H. and Yogo, M. (2002). Testing for weak instruments in linear iv regression.

Stock, J. H. and Yogo, M. (2005b). Testing for weak instruments in linear iv regression. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, page 80.

Strong, N. (1992). Modelling abnormal returns: A review article. *Journal of Business Finance & Accounting*, 19(4):533–553.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, 25(1):1.

Sudhir, K. and Talukdar, D. (2015). The "peter pan syndrome" in emerging markets: The productivity-transparency trade-off in it adoption. *Marketing Science*, 34(4):500–521.

Sun, B., Liu, L., Miao, W., Wirth, K., Robins, J., and Tchetgen, E. J. T. (2018). Semiparametric estimation with data missing not at random using an instrumental variable. *Statistica Sinica*, 28(4):1965.

Sun, C. and Liao, X. (2011). Effects of litigation under the endangered species act on forest firm values. *Journal of forest economics*, 17(4):388–398.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Sun, L., Ben-Michael, E., and Feller, A. (2023). Using multiple outcomes to improve the synthetic control method. *arXiv preprint arXiv:2311.16260*.

Sun, L. and Shapiro, J. M. (2022). A linear panel model with heterogeneous coefficients and variation in exposure. *Journal of Economic Perspectives*, 36(4):193–204.

Sun, M. and Zhu, F. (2013). Ad revenue and content commercialization: Evidence from blogs. *Management Science*, 59(10):2314–2331.

Swamy, P. and Arora, S. S. (1972). The exact finite sample properties of the estimators of coefficients in the error components regression models. *Econometrica: journal of the Econometric Society*, pages 261–275.

Tchetgen Tchetgen, E. (2014). A note on the control function approach with an instrumental variable and a binary outcome. *Epidemiologic methods*, 3(1):107–112.

Tchetgen Tchetgen, E. J. and Wirth, K. E. (2017). A general instrumental variable framework for regression analysis with outcome missing not at random. *Biometrics*, 73(4):1123–1131.

Tellis, G. J. and Johnson, J. (2007). The value of quality. *Marketing Science*, 26(6):758–773.

Thistlethwaite, D. L. and Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational psychology*, 51(6):309.

Thoemmes, F., Liao, W., and Jin, Z. (2017). The analysis of the regression-discontinuity design in r. *Journal of Educational and Behavioral Statistics*, 42(3):341–360.

Tibbe, T. D. and Montoya, A. K. (2022). Correcting the bias correction for the bootstrap confidence interval in mediation analysis. *Frontiers in psychology*, 13:810258.

Tipton, M. M., Bharadwaj, S. G., and Robertson, D. C. (2009). Regulatory exposure of deceptive marketing and its impact on firm value. *Journal of Marketing*, 73(6):227–243.

Tirunillai, S. and Tellis, G. J. (2012). Does chatter really matter? dynamics of user-generated content and stock performance. *Marketing Science*, 31(2):198–215.

Tirunillai, S. and Tellis, G. J. (2017). Does offline tv advertising affect online chatter? quasi-experimental analysis using synthetic control. *Marketing Science*, 36(6):862–878.

Tukey, J. W. (1993). Tightening the clinical trial. *Controlled clinical trials*, 14(4):266–285.

Vach, W. and Vach, W. (1994). Missing values and subsampling. *Logistic Regression with Missing Values in the Covariates*, pages 98–102.

VanderWeele, T. (2015). *Explanation in causal inference: methods for mediation and interaction*. Oxford University Press.

VanderWeele, T. J. (2019). Principles of confounder selection. *European journal of epidemiology*, 34:211–219.

Von Hippel, P. T. (2009). 8. how to impute interactions, squares, and other transformed variables. *Sociological methodology*, 39(1):265–291.

Wallace, T. D. and Hussain, A. (1969). The use of error components models in combining cross section with time series data. *Econometrica: Journal of the Econometric Society*, pages 55–72.

Wang, Y. and Bellemare, M. F. (2019). Lagged variables as instruments. Technical report, Working Paper, Department of Applied Economics, University of Minnesota.

Wang, Y., Lewis, M., and Schweidel, D. A. (2018). A border strategy analysis of ad source and message tone in senatorial campaigns. *Marketing Science*, 37(3):333–355.

Wang, Y., Wu, C., and Zhu, T. (2019). Mobile hailing technology and taxi driving behaviors. *Marketing Science*, 38(5):734–755.

Warren, N. L. and Sorescu, A. (2017). When 1+ 1> 2: How investors react to new product releases announced concurrently with other corporate news. *Journal of Marketing*, 81(2):64–82.

Webb, A. R., Copsey, K. D., and Cawley, G. (2011). *Statistical pattern recognition*, volume 2. Wiley Online Library.

Westfall, J. and Yarkoni, T. (2016). Statistically controlling for confounding constructs is harder than you think. *PloS one*, 11(3):e0152719.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*, pages 817–838.

Wiles, M. A. and Danielova, A. (2009). The worth of product placement in successful films: An event study analysis. *Journal of marketing*, 73(4):44–63.

Wiles, M. A., Jain, S. P., Mishra, S., and Lindsey, C. (2010). Stock market response to regulatory reports of deceptive advertising: The moderating effect of omission bias and firm reputation. *Marketing Science*, 29(5):828–845.

Wiles, M. A., Morgan, N. A., and Rego, L. L. (2012). The effect of brand acquisition and disposal on stock returns. *Journal of Marketing*, 76(1):38–58.

Wing, C., Yozwiak, M., Hollingsworth, A., Freedman, S., and Simon, K. (2024). Designing difference-in-difference studies with staggered treatment adoption: Key concepts and practical guidelines. *Annual Review of Public Health*, 45.

Wolfers, J. (2003). Is business cycle volatility costly? evidence from surveys of subjective well-being. *International finance*, 6(1):1–26.

Wolfolds, S. E. and Siegel, J. (2019). Misaccounting for endogeneity: The peril of relying on the heckman two-step method without a valid instrument. *Strategic Management Journal*, 40(3):432–462.

Wooldridge, J. M. (1999). Quasi-likelihood methods for count data. *Handbook of applied econometrics volume 2: Microeconomics*, pages 321–368.

Wooldridge, J. M. (2022). Simple approaches to nonlinear difference-in-differences with panel data. *Available at SSRN 4183726*.

Wooldridge, J. M. (2023). Simple approaches to nonlinear difference-in-differences with panel data. *The Econometrics Journal*, 26(3):C31–C66.

Wu, Q., Luo, X., Slotegraaf, R. J., and Aspara, J. (2015). Sleeping with competitors: the impact of npd phases on stock market reactions to horizontal collaboration. *Journal of the Academy of Marketing Science*, 43:490–511.

Xiong, G. and Bharadwaj, S. (2013). Asymmetric roles of advertising and marketing capability in financial returns to news: Turning bad into good and good into great. *Journal of Marketing Research*, 50(6):706–724.

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis*, 25(1):57–76.

Yang, S., Imbens, G. W., Cui, Z., Faries, D. E., and Kadziola, Z. (2016). Propensity score matching and subclassification in observational studies with multilevel treatments. *Biometrics*, 72(4):1055–1065.

Yao, L., Li, S., Li, Y., Huai, M., Gao, J., and Zhang, A. (2018). Representation learning for treatment effect estimation from observational data. *Advances in neural information processing systems*, 31.

Yule, G. U. (1899). An investigation into the causes of changes in pauperism in england, chiefly during the last two intercensal decades (part i.). *Journal of the Royal Statistical Society*, 62(2):249–295.

Zhang, J. L. and Rubin, D. B. (2003). Estimation of causal effects via principal stratification when some outcomes are truncated by "death". *Journal of Educational and Behavioral Statistics*, 28(4):353–368.

Zhang, S., Lee, D., Singh, P. V., and Srinivasan, K. (2022). What makes a good image? airbnb demand analytics leveraging interpretable image features. *Management Science*, 68(8):5644–5666.

Zhao, Q.-Y., Luo, J.-C., Su, Y., Zhang, Y.-J., Tu, G.-W., and Luo, Z. (2021). Propensity score matching with r: conventional methods and new features. *Annals of translational medicine*, 9(9).

Zou, G. Y. (2008). On the estimation of additive interaction by use of the four-by-two table and beyond. *American journal of epidemiology*, 168(2):212–224.