NATIONAL CENTRE FOR RESEARCH METHODS

Economic and Social Research Council

UNIVERSITY OF Southampton

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NATIONAL CENTRE FOR RESEARCH METHODS

Multilevel and Longitudinal Statistical Modelling for Qualitative Researchers

15th November 2024 10:00 am to 4:00 pm

Professor Vernon Gayle vernon.gayle@ed.ac.uk
@Profbigvern

https://github.com/vernongayle/ncrm_longitudinal_and_multilevel_models_for_qualitative_researcher_2024

Table 3. Linear regression model (survey weighted) for school GCSE attainment Year 11 (GCSE points score): beta values.

		1990–99	2001[a]	2003[a]
YCS cohort	1990	0.00		
	1993	**4.78**		
	1995	**7.95**		
	1997	**7.21**		
	1999	**10.88**		
Gender	Girls	0.00	0.00	0.00
	Boys	**−4.73**	**−5.01**	**−5.53**
Ethnicity	White	0.00	0.00	0.00
	Black	**−3.43**	−1.19	−2.80
	Indian	**3.00**	**4.87**	**8.25**
	Pakistani	**−2.01**	0.75	−1.98
	Bangladeshi	**3.28**	**7.92**	**4.77**
	Other Asian	**6.46**	**8.42**	1.72
	Other	0.84	1.11	**2.77**
Housing tenure	Owned / mortgage	0.00	0.00	0.00
	Rented	**−7.37**	**−7.69**	**−10.74**
	Others	**−2.67**	**−5.79**	−15.99
Household type	Mother and father	0.00	0.00	0.00
	Mother Only	**−1.19**	**−1.10**	**−2.00**
	Father only	**−2.94**	**−6.21**	**−8.16**
	Other household	**−7.98**	**−8.44**	**−10.01**
Parental education	Non-graduates	0.00	0.00	0.00
	Graduates	**4.95**	**4.23**	**6.35**
Parents' social classification (NS-SEC)	1.1 Large Employers and Higher Managerial	**4.53**	**3.83**	1.10
	1.2 Higher Professional Occupations	**6.44**	**8.02**	**3.98**
	2 Lower Managerial and Professional Occupations	**2.43**	**2.70**	1.31
	3 Intermediate Occupations	0.00	0.00	0.00
	4 Small Employers and Own Account Workers	**−4.72**	**−2.78**	**−4.68**
	5 Lower Supervisory and Technical Occupations	**−5.09**	**−5.33**	**−6.77**
	6 Semi-routine Occupations	**−6.96**	**−5.22**	**−7.78**
	7 Routine Occupations	**−9.14**	**−7.69**	**−10.54**
Constant		**33.83**	**44.77**	**51.22**
R^2		0.24	0.18	0.21
n		54,236	12,934	10,269

Note: Significant variables highlighted in bold.
[a]For the 2001 and 2003 school year cohorts, an alternative point score was deposited with data that include other qualifications (e.g. GCSE short courses).

Table 5. Normalized mathematics KS2 score response for Staffordshire, with pupils assigned to KS2 test score school by using models of increasing complexity†

Variable	*Results for the following models:*		
	A	*B*	*C*
Fixed effects			
Intercept	−0.011	−0.195	−0.093
Age in months		0.029 (0.003)	−0.014 (0.002)
KS1 mathematics score			0.754 (0.006)
Random parameters			
Between-junior-school variance	0.094 (0.011)	0.095 (0.011)	0.053 (0.006)
Between-pupil variance	0.795 (0.012)	0.784 (0.012)	0.301 (0.004)
VPC	0.11	0.11	0.15
Deviance (−2 log-likelihood)	25107.1	24989.0	15987.9

†Estimates with standard errors in parentheses.

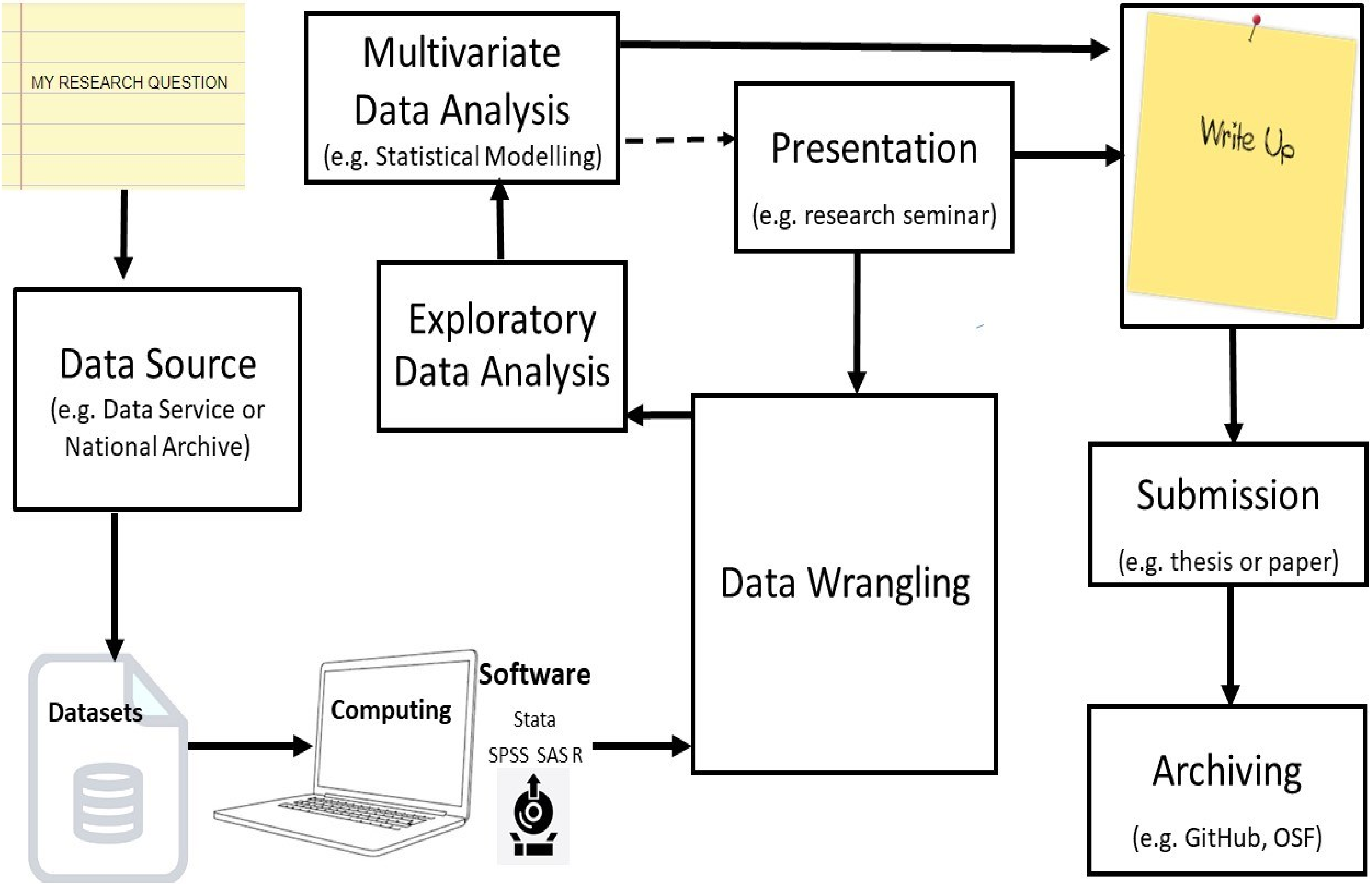
Statistical Concepts and

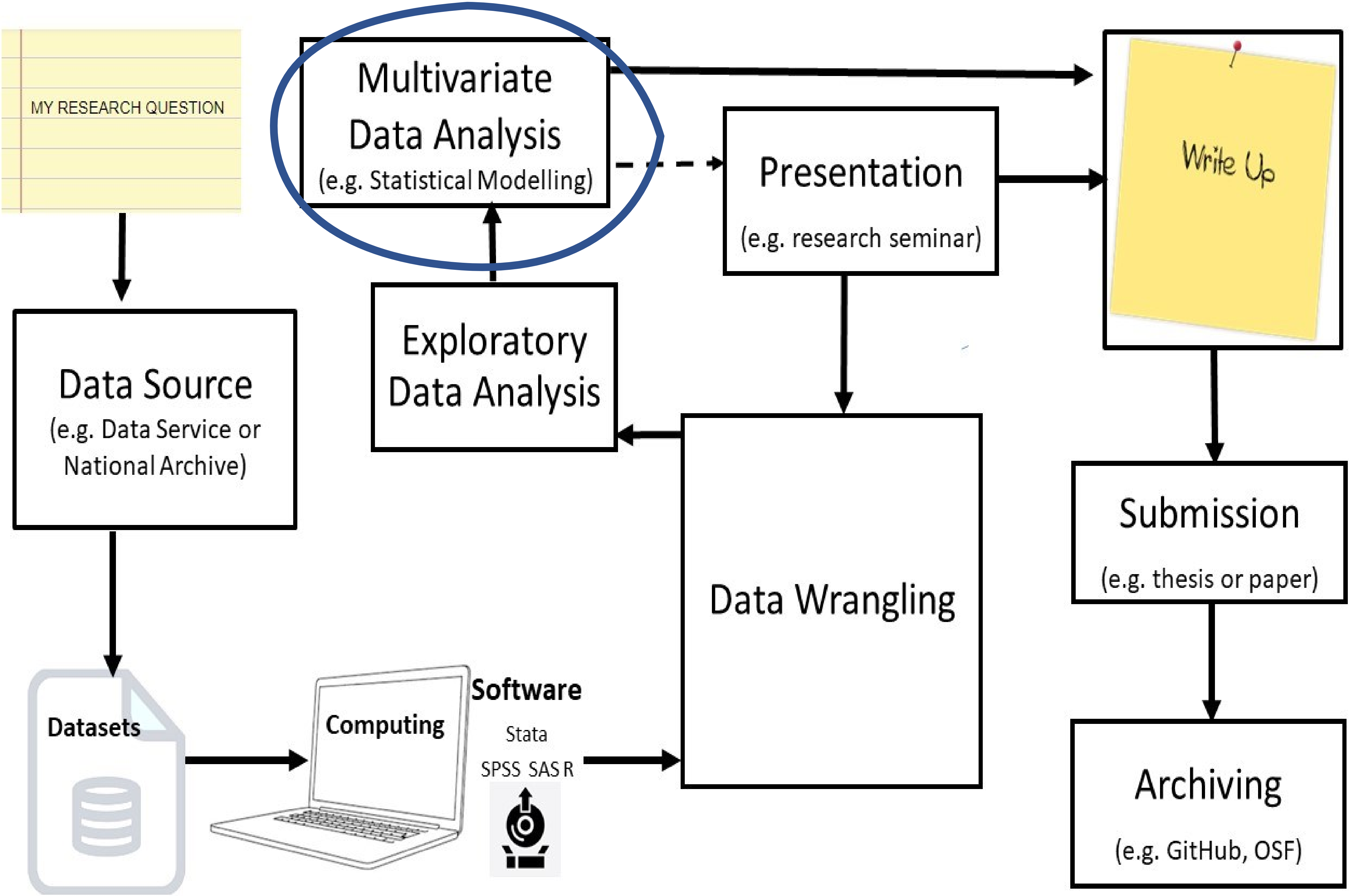
Statistical Thinking

Part 1

The social world is complex!

In the non-experimental social sciences we must use more comprehensive statistical methods which might better help us to identify, and then quantify, the multifaceted relationships that characterise contemporary social life


MY RESEARCH QUESTION
Multivariate Data Analysis
(e.g. Statistical Modelling)
Presentation
(e.g. research seminar)
Write Up
Data Source
(e.g. Data Service or National Archive)
Exploratory Data Analysis
Data Wrangling
Submission
(e.g. thesis or paper)
Datasets
Computing
Software
Stata
SPSS SAS R
Archiving
(e.g. GitHub, OSF)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Fundamental Concepts (probably revision)

- Variables
  - – measures of social science concepts
- Cases
  - Distinctive entities
  - People, firms, farms, hospitals, schools, local authorities, regions, nation states, animals

The Variable by Case Matrix

ID	LONDON	AGE	DEGREE
001	0	21	0
002	1	22	1
003	1	25	1

ID - IDENTIFICATON NUMBER

BORN IN LONDON - 0=NO; 1=YES

AGE - YEARS

DEGREE - 0=NO; 1=YES

Outcome Variables

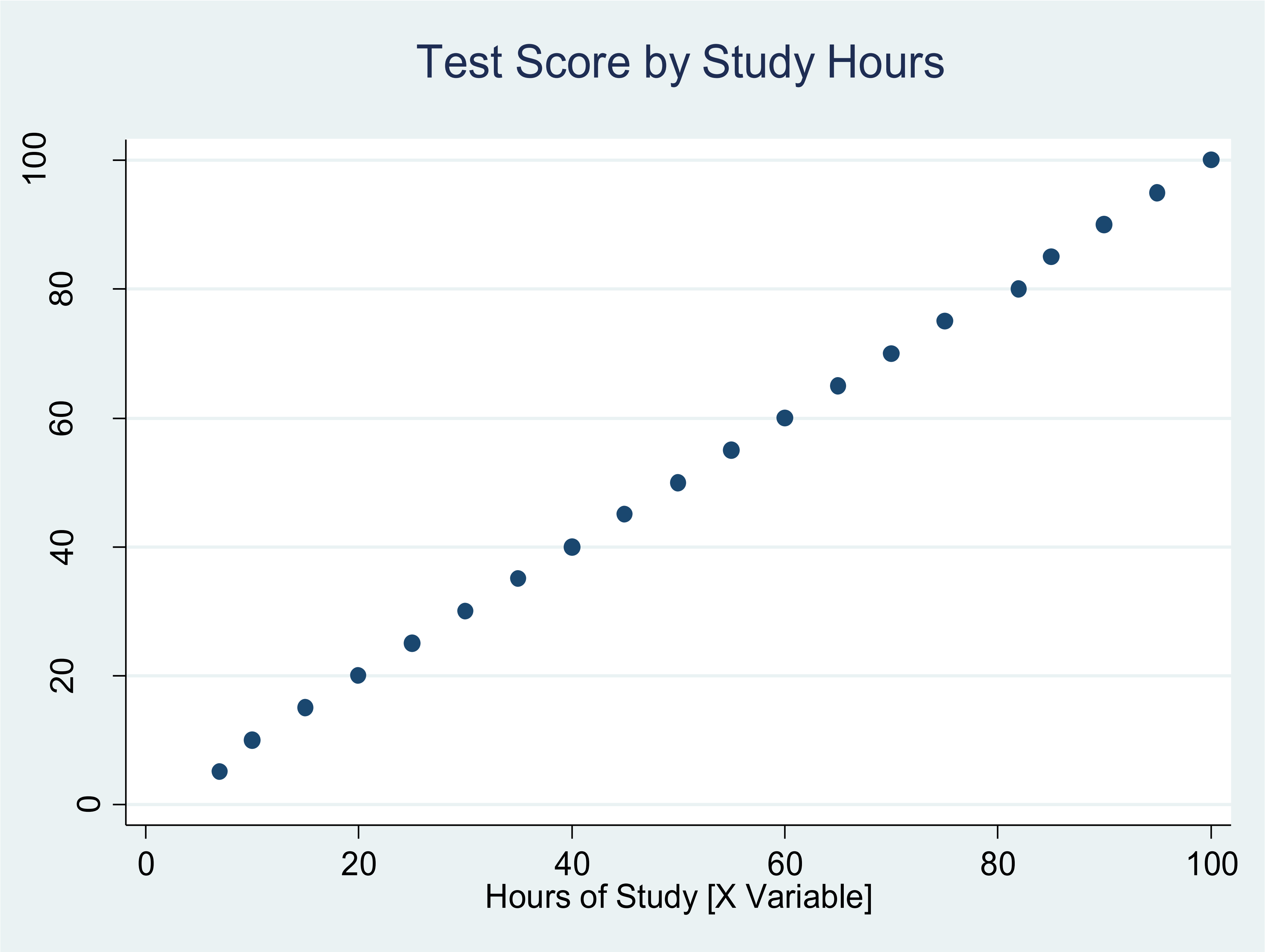
- Outcome variables
  - Y variable; Dependent variable; DV

- Educational test score
- Life expectancy (years)
- Number of criminal convictions
- Numerous health outcomes
- Subjective wellbeing (SWB) measures

Explanatory variables

- X variables
- These variables explain outcome variables

- Hours of study
- Gender
- Ethnicity
- Socioeconomic classifications
- Age
- Housing tenure (type)


Test Score by Study Hours
0
20
40
60
80
100
0
20
40
60
80
100
Hours of Study [X Variable]

Continuous Variables

- Age in years
- Number of years of service
- Time taken to arrive at traffic incident
- Number of arrests in last twelve months

aage12	**Age at 1.12.1991**
Record Type	AINDRESP
Questionnaire	Derived Variable

Mean	Std Dev	Minimum	Maximum
44.52	18.47	15	97

Value Label	Value	Frequency	%	Valid %
Age given	1	10264	100.0	100.0

Categorical variables

- Marital Status

What is your legal marital status, are you..

- Religion

Do you regard yourself as belonging to any particular religion? If Yes. Which?

- Ethnicity

Could you look at this card (V2) please and tell me which of these groups you consider you belong to?

amlstat	**Present legal marital status**
Record Type	AINDRESP
Questionnaire	Individual (4)
Question Number and Text	AD12 : What is your legal marital status, are you..

Value Label	Value	Frequency	%	Valid %
Married	1	6041	58.9	58.9
Separated	2	202	2.0	2.0
Divorced	3	599	5.8	5.8
Widowed	4	876	8.5	8.5
Never married	5	2531	24.7	24.7
Missing or wild	-9	14	.1	Missing
Refused	-2	1	.0	Missing

Valid cases	**10249**	**Missing cases**	**15**

Question Route	ALL RESPONDENTS
Index Terms	Marital and Cohabitation History

aoprlg1	**Religion**
Record Type	AINDRESP
Questionnaire	Individual (85)
Question Number and Text	AV11 : Do you regard yourself as belonging to any particular religion? If Yes. Which?

Value Label	Value	Frequency	%	Valid %
No religion	1	3793	37.0	38.3
C of E /Anglican	2	3546	34.5	35.8
Roman Catholic	3	907	8.8	9.2
Presbyt/C of Scot	4	412	4.0	4.2
Methodist	5	340	3.3	3.4
Baptist	6	97	.9	1.0
Congregation/URC	7	55	.5	.6
Other Christian	8	242	2.4	2.4
Christian	9	253	2.5	2.6
Muslim/Islam	10	84	.8	.8
Hindu	11	37	.4	.4
Jewish	12	31	.3	.3
Sikh	13	38	.4	.4
Other	14	63	.6	.6
Missing or wild	-9	10	.1	Missing

arace	**Ethnic group membership**
Record Type	AINDRESP
Questionnaire	Individual (86)
Question Number and Text	AV14 : Could you look at this card (V2) please and tell me which of these groups you consider you belong to?

Value Label	Value	Frequency	%	Valid %
White	1	9503	92.6	96.1
Black-Carib	2	67	.7	.7
Black-African	3	45	.4	.5
Black-Other	4	26	.3	.3
Indian	5	107	1.0	1.1
Pakistani	6	44	.4	.4
Bangladeshi	7	8	.1	.1
Chinese	8	10	.1	.1
Other ethnic grp	9	83	.8	.8
Missing or wild	-9	10	.1	Missing
Proxy respondent	-7	352	3.4	Missing
Refused	-2	9	.1	Missing

Valid cases	**9893**	**Missing cases**	**371**

Levels of Measurement (types of variables)

Continuous variables

Categorical variables

This is presented in much more confusing terms in most statistics text books however!

You can read more (e.g. Blaikie 2003, p.22-7)

Statistical Significance

Statistical significance is a fundamental concept in statistical analyse, and *p values* are a central tool

Significance tests are used in the social sciences and are common the natural sciences, medicine and engineering

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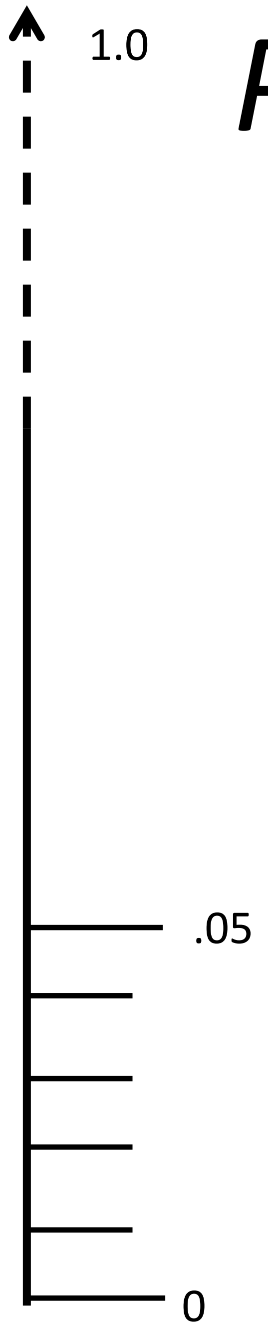
Statistical Significance (in a nutshell)

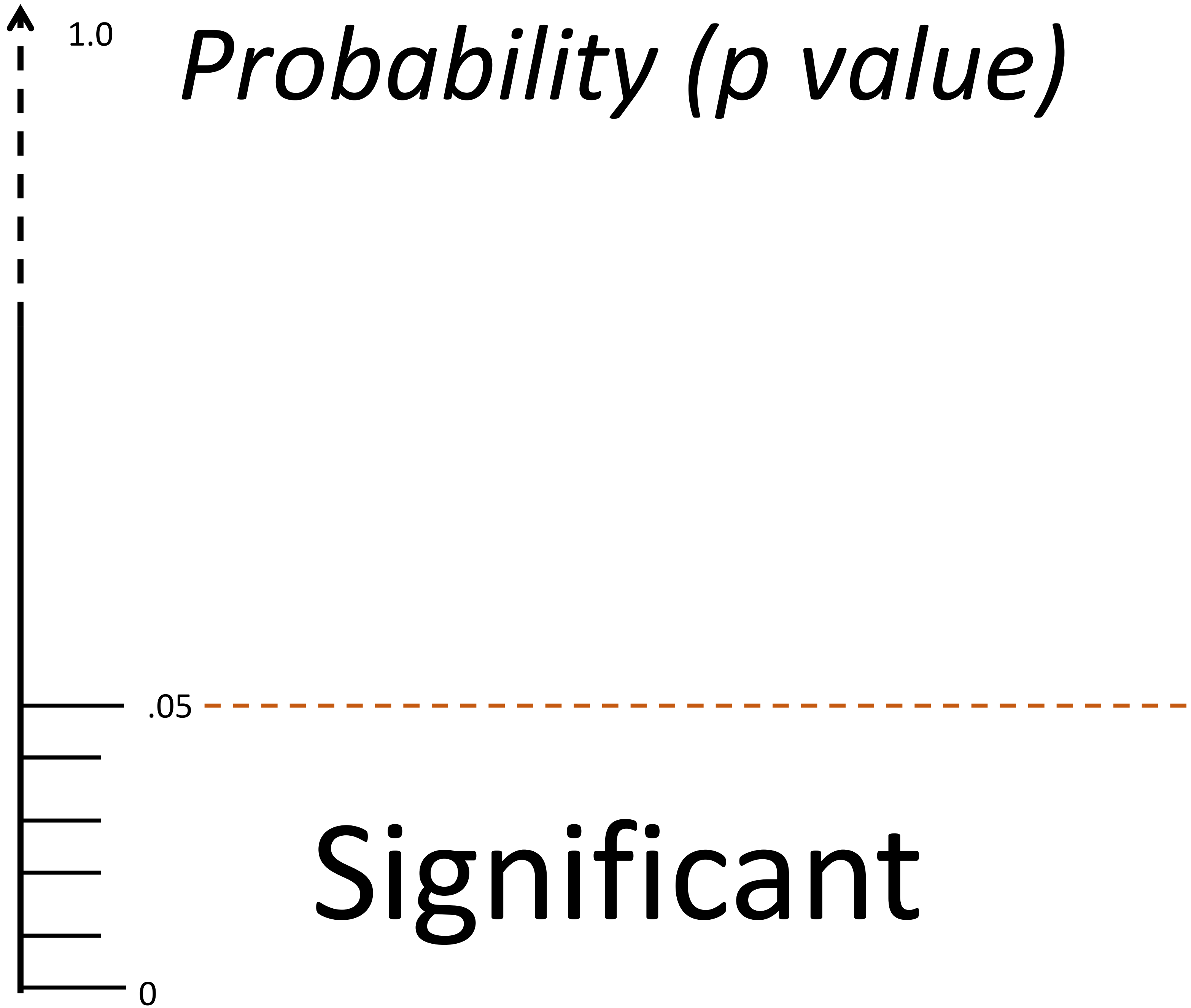
The idea of statistical significance is straightforward - if a p-value is small enough, then we say the results are statistically significant

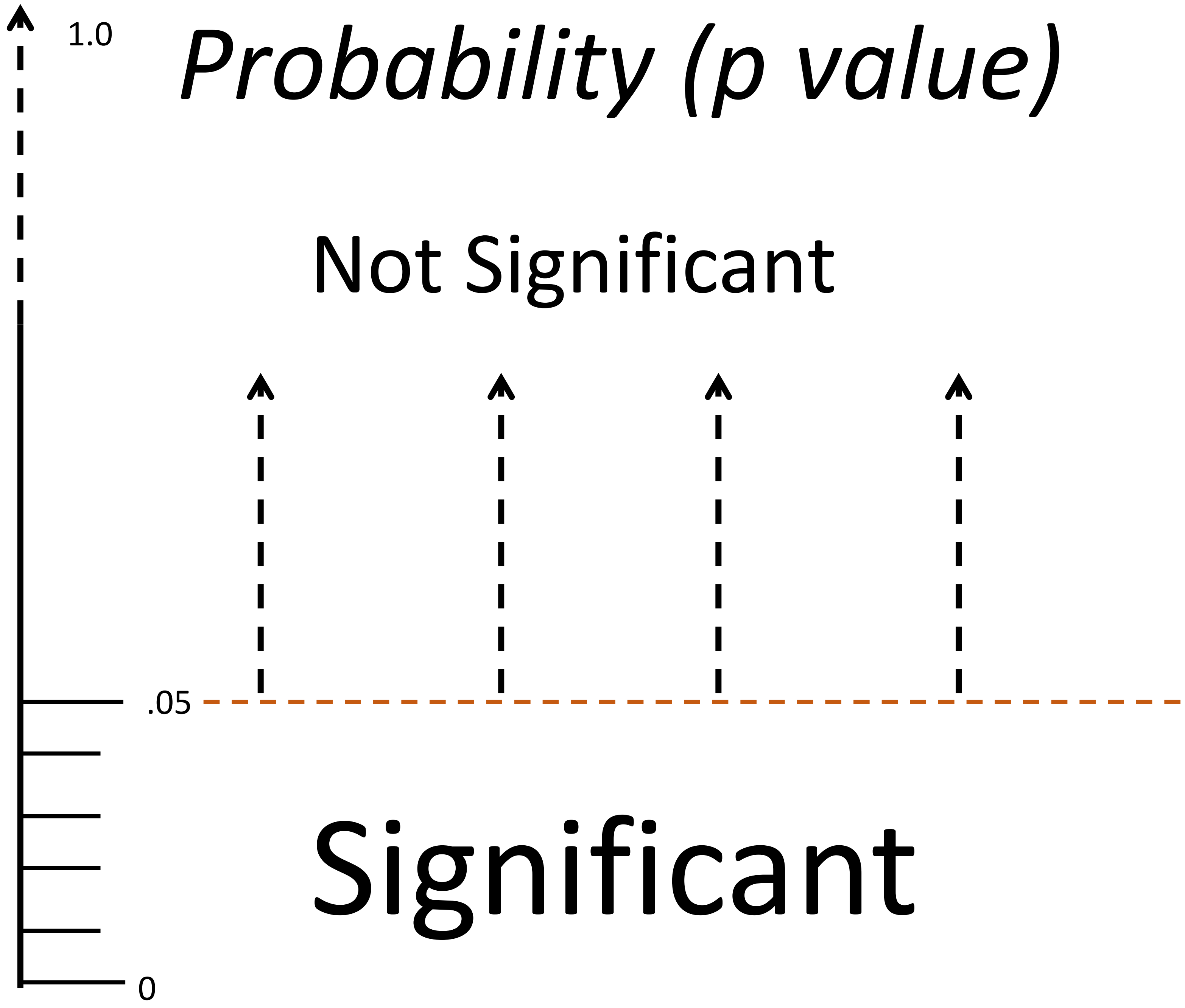
(Spieglehalter 2019).

Probability (p value)



Small number (close to 0) = **Significant**


1.0
Probability (p value)
.05
Significant
0


1.0
Probability (p value)
Not Significant
.05
Significant
0

Assay

<u>Not</u> Significant

Significant

Assay

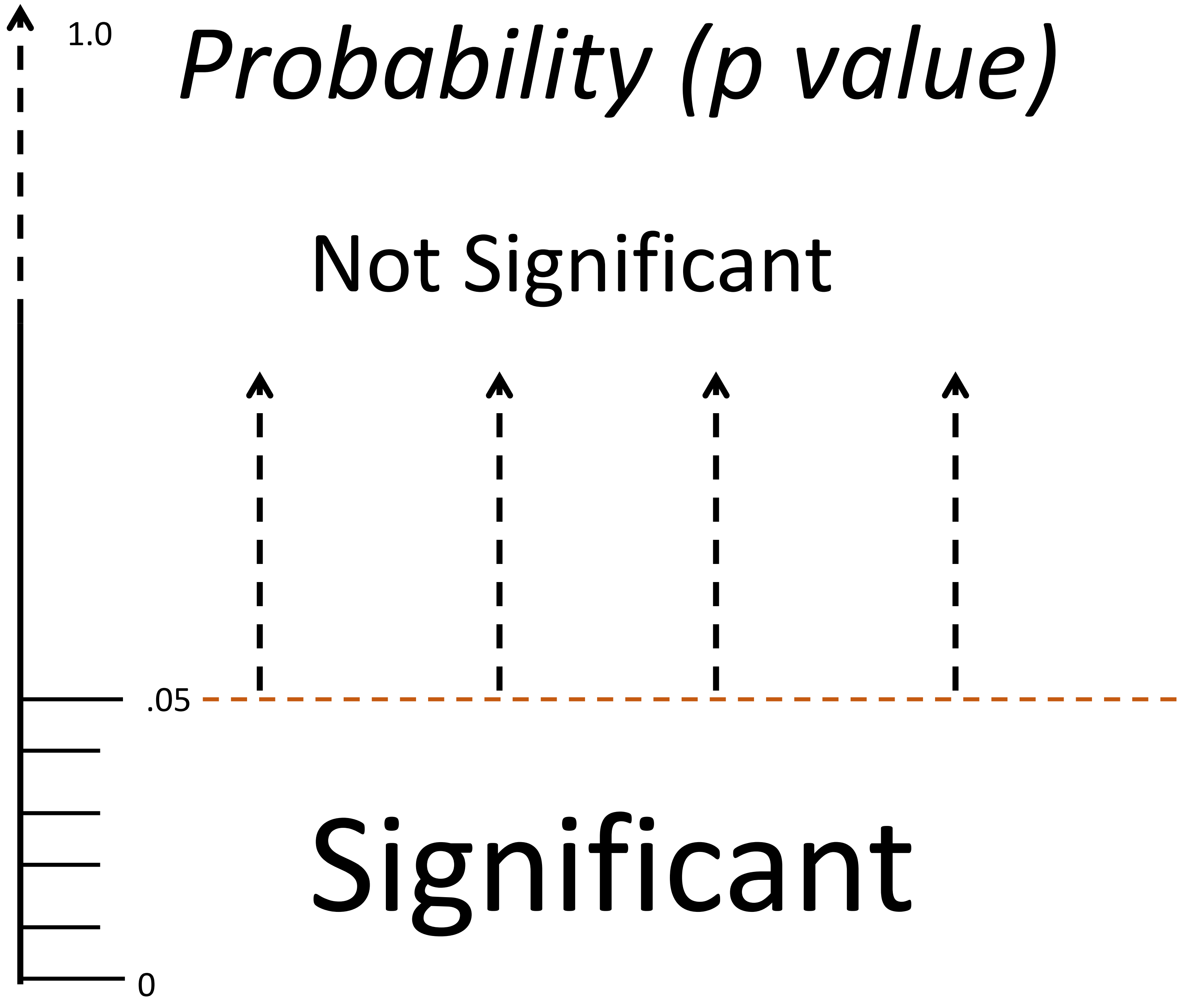
Not Pregnant

Pregnant

Assay

Fail

Pass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Not Significant
.05
Significant
0

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The idea of statistical significance is straightforward - if a p-value is small enough, then we say the results are statistically significant (Speiglehalter 2019)

Spiegelhalter, D., 2019. *The art of statistics: Learning from data*. Penguin UK.

Karl Pearson (1857–1936) studied maths at Cambridge and taught at University College London, in addition to his impressive work in statistics he leaves a troubling legacy

Brian Tarran, News, Significance, Volume 17, Issue 2, April 2020, Pages 4–5, https://doi.org/10.1111/1740-9713.01367

Pearson's r

+1 **Strong**

Weak

0

Weak

-1 **Strong**

Pearson's r

+1 **Strong**

POSITIVE

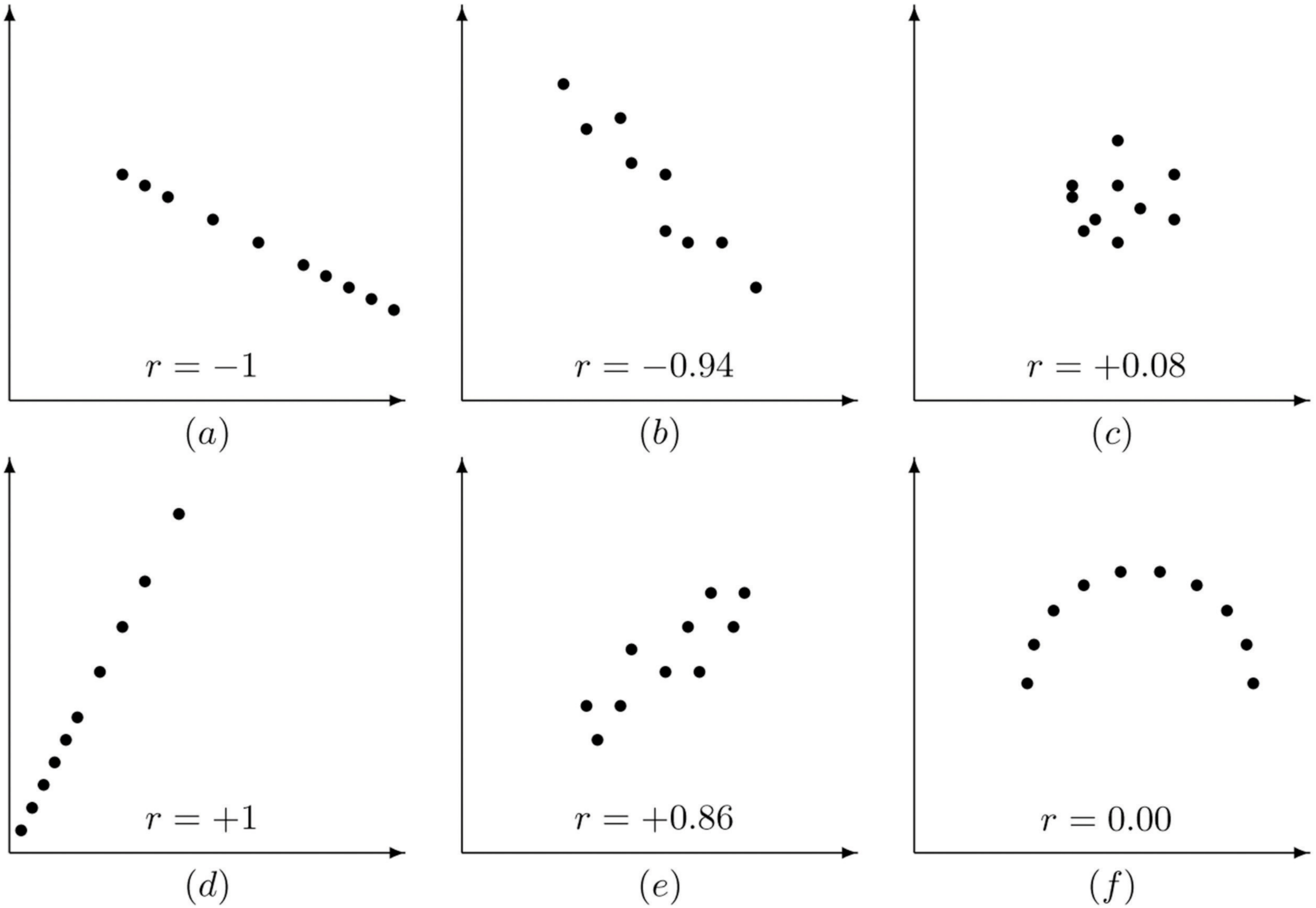
Weak

0

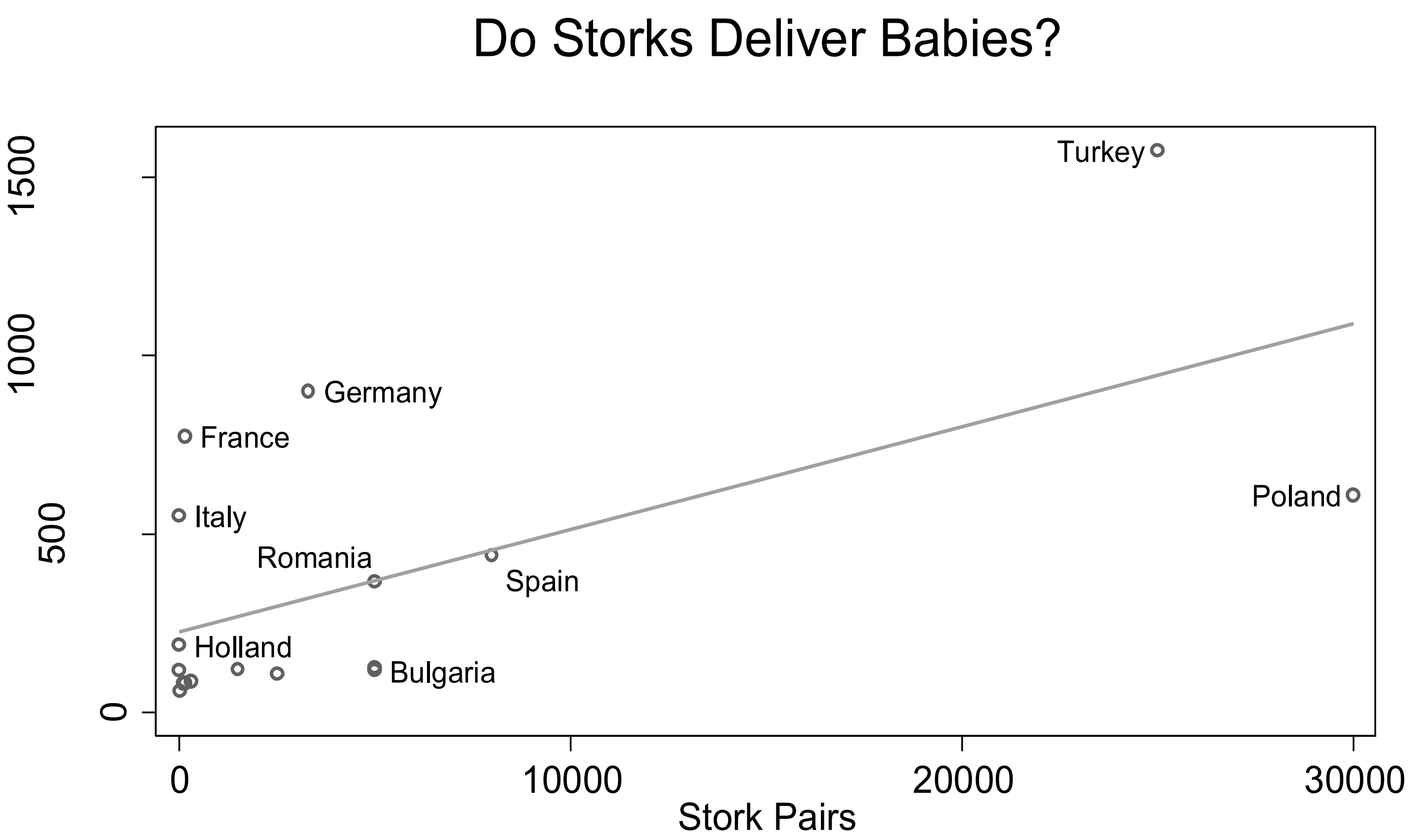
Weak

NEGATIVE

-1 **Strong**



https://saylordotorg.github.io/text_introductory-statistics/section_14/07aa5db140b70615a15e8631c2d7a2c4.jpg

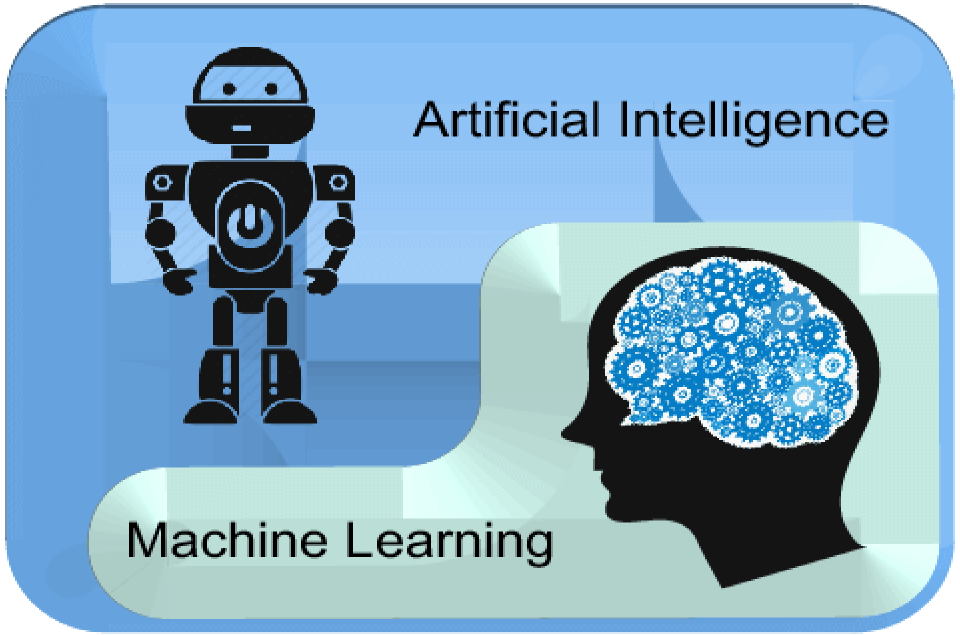


p=.008; r=.62

Mathews, R. 'Storks Deliver Babies (p=0.008)'
Teaching Statistics. Volume 22, Number 2, Summer 2000

p = .008

r = .62




Correlation
Causality

Correlation is <u>**NOT**</u> Causation

Correlation tests for a relationship between two variables

A 'social science imagination' must be applied when assessing the causal nexus

Multivariate Relationships in Data

Part 2

The social world is complex and messy but multivariate analyses using statistical models provide a formal approach to evaluate data, test ideas and investigate research questions.

Statistical models help us deal with the messy complexity of the social world.

This is my humble opinion…

Experimental Methods	Causal Analysis
Quasi Experimental Methods	(Weaker) Causal Analysis
Multivariate analysis of Observational Data	Sophisticated Description

More Terminology

- **Univariate** – a single variable outcome variable (Y)

- **Bivariate** – two variables

  - One outcome variable (Y) and one explanatory variable (X)

- **Multivariate** – three (or many more) variables

  - One outcome variable (Y) and many explanatory variables (X)
  - This is the ‘cheddar’ (see Urban Dictionary)

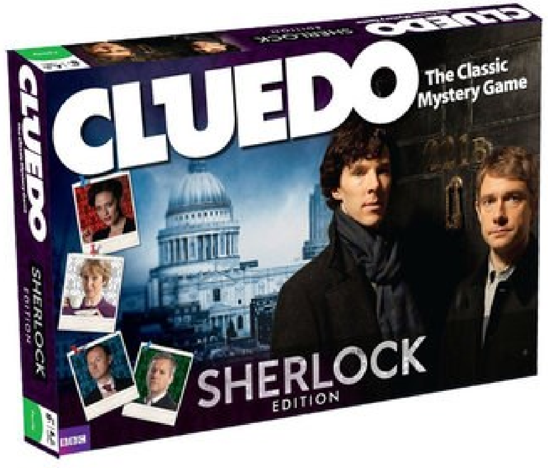
(More advanced multivariate analyses have multiple outcomes too)

Multivariate Data Analysis

John Tukey – Exploratory Data Analysis

Explanatory variables (X) should have the means, the motive and the opportunity to commit the crime of changing the Y variable –

Robert Luskin, University of Texas



Gayle, V., Murray, S. and Connelly, R., 2016. Young people and school General Certificate of Secondary Education attainment: Looking for the 'missing middle'. *British Journal of Sociology of Education*, *37*(3), pp.350-370.

GCSE
(score)

←

Explanatory variables

gender
ethnicity
housing tenure
household type
parental education
parent's socio-economic class (NS-SEC)

https://www.tandfonline.com/doi/pdf/10.1080/01425692.2014.935292

Alternative Terminology

- Multivariate Analysis
- Statistical Model
- Linear Regression
- Regression Model
- Generalized Linear Model (glm)

The two overall aims of a generalized linear model are

i. to indicate which of the explanatory variables are important
ii. to estimate the relative influence of the explanatory variables

1. A generalized linear model will estimate how much of the variability in the outcome variable is explained by the set of explanatory variables that are included in the model
2. A generalized linear model will indicate which of the explanatory variables included in the model are statistically significant
3. A generalized linear model will indicate the direction of the relationship between the specific explanatory variable and the outcome variable
4. A generalized linear model will estimate the strength of the relationship between the explanatory variable and the outcome variable, once all of the other variables in the model have been considered

Example Regression Models (SPSS outputs)

This is a dataset that is similar to data in the US High School Beyond Study

n = 200

Science Test Score

Statistics

science score

N	Valid	200
	Missing	0
Mean		51.85
Median		53.00
Mode		50
Std. Deviation		9.901
Minimum		26
Maximum		74

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	female, math score[b]	.	Enter

a. Dependent Variable: science score

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.640[a]	.410	.404	7.645

a. Predictors: (Constant), female, math score

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7993.550	2	3996.775	68.384	<.001[b]
	Residual	11513.950	197	58.446		
	Total	19507.500	199			

a. Dependent Variable: science score

b. Predictors: (Constant), female, math score

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.118	3.167		5.721	<.001
	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

1. A generalized linear model will estimate how much of the variability in the outcome variable is explained by the set of explanatory variables that are included in the model

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a. Dependent Variable: science score

R^2 = Model Explanation / Total to be Explained

Model Summary

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1	.640[a]	.410	.404	7.645

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Adjusted R Squared – adjusted for the number of variables in the model

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.640[a]	.410	.404	7.645

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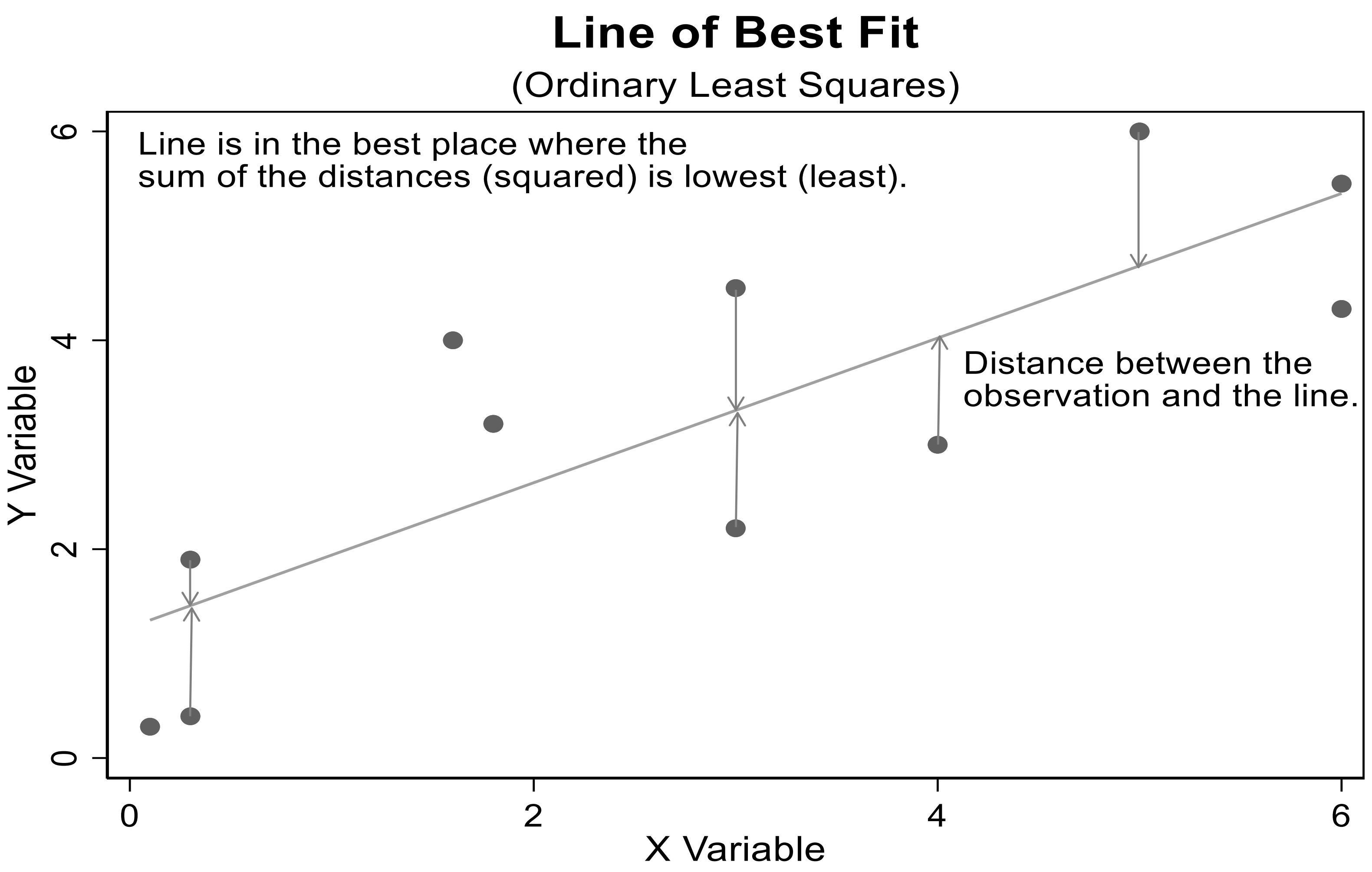
$1-((1 - R^2)(n-1) / (n- k – 1))$

The Line of Best Fit (Ordinary Least Squares)



In linear regression models that are estimated using OLS the total sum of squares (TSS) can be understood as the sum of the squared differences between the value of the observation and its expected value for all cases in the analysis

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a. Dependent Variable: science score

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The TSS has two components

First, the model sum of squares (MSS) is a measure of the variability that is explained by the explanatory variables in the model

Second, the residual sum of squares (RSS) is the ‘residual’ variability that cannot be explained by the model

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7993.550	2	3996.775	68.384	<.001[b]
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	Total	19507.500	199			

a. Dependent Variable: science score

b. Predictors: (Constant), female, math score

R^2 = Model Explanation / Total to be Explained

$R^2 = 7993.550 / 19507.500$

$R^2 = .41$

Model Summary

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Mean Square = Sum of Squares / df

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a. Dependent Variable: science score

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The F-statistic is derived by dividing the mean square for the model (MSM) by the mean square residual (MSR)

F = Mean Square Model/ Mean Square Residual

ANOVA[a]

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F Test and significance value

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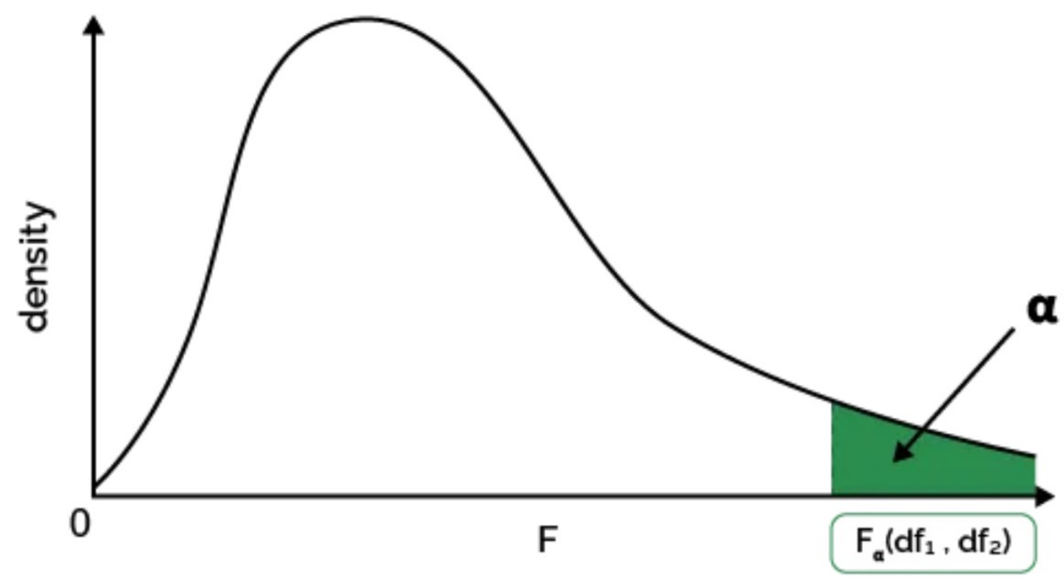

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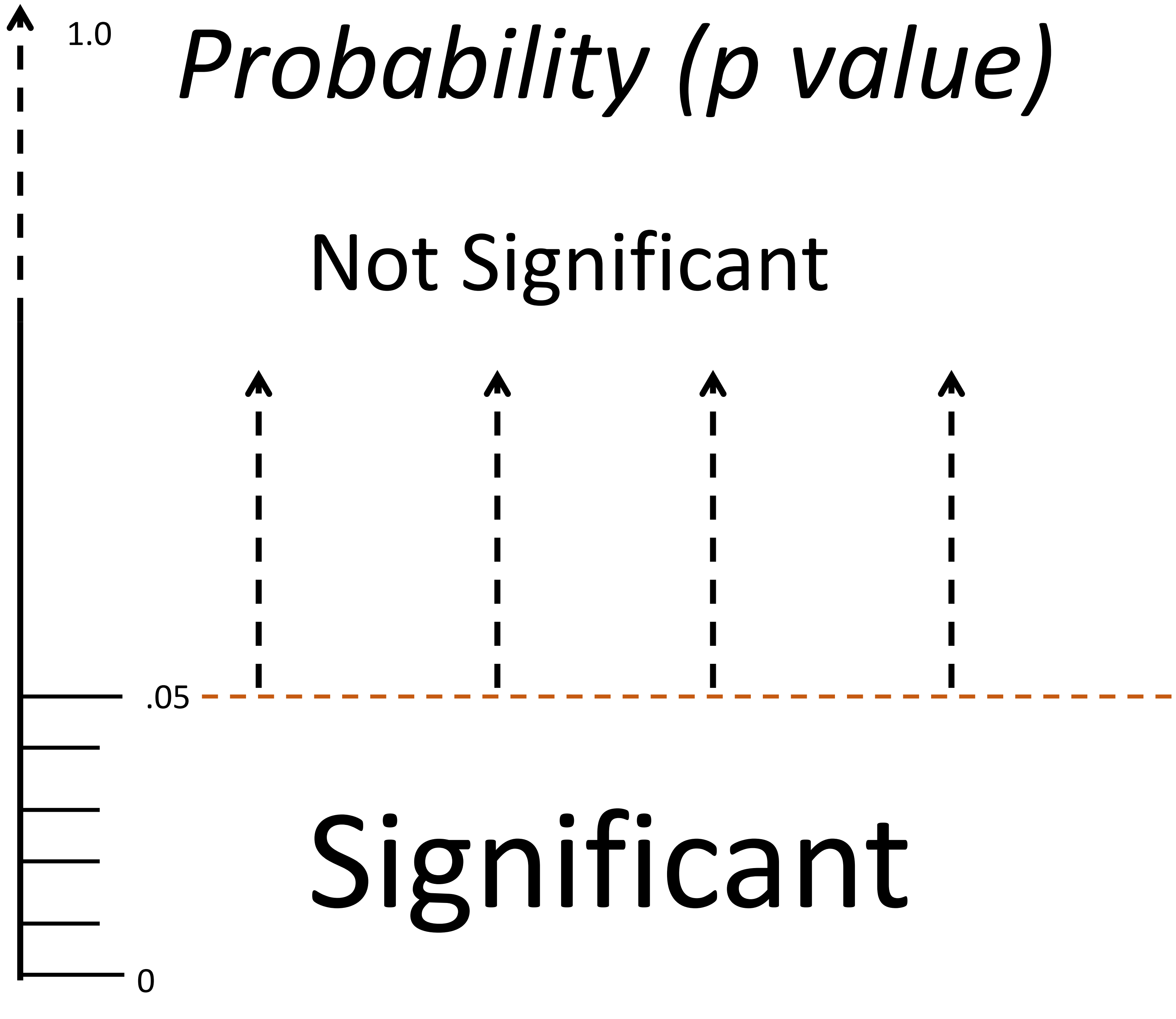
2. A generalized linear model will indicate which of the explanatory variables included in the model are statistically significant



1.0
Probability (p value)
Not Significant
.05
Significant
0

Coefficients[a]

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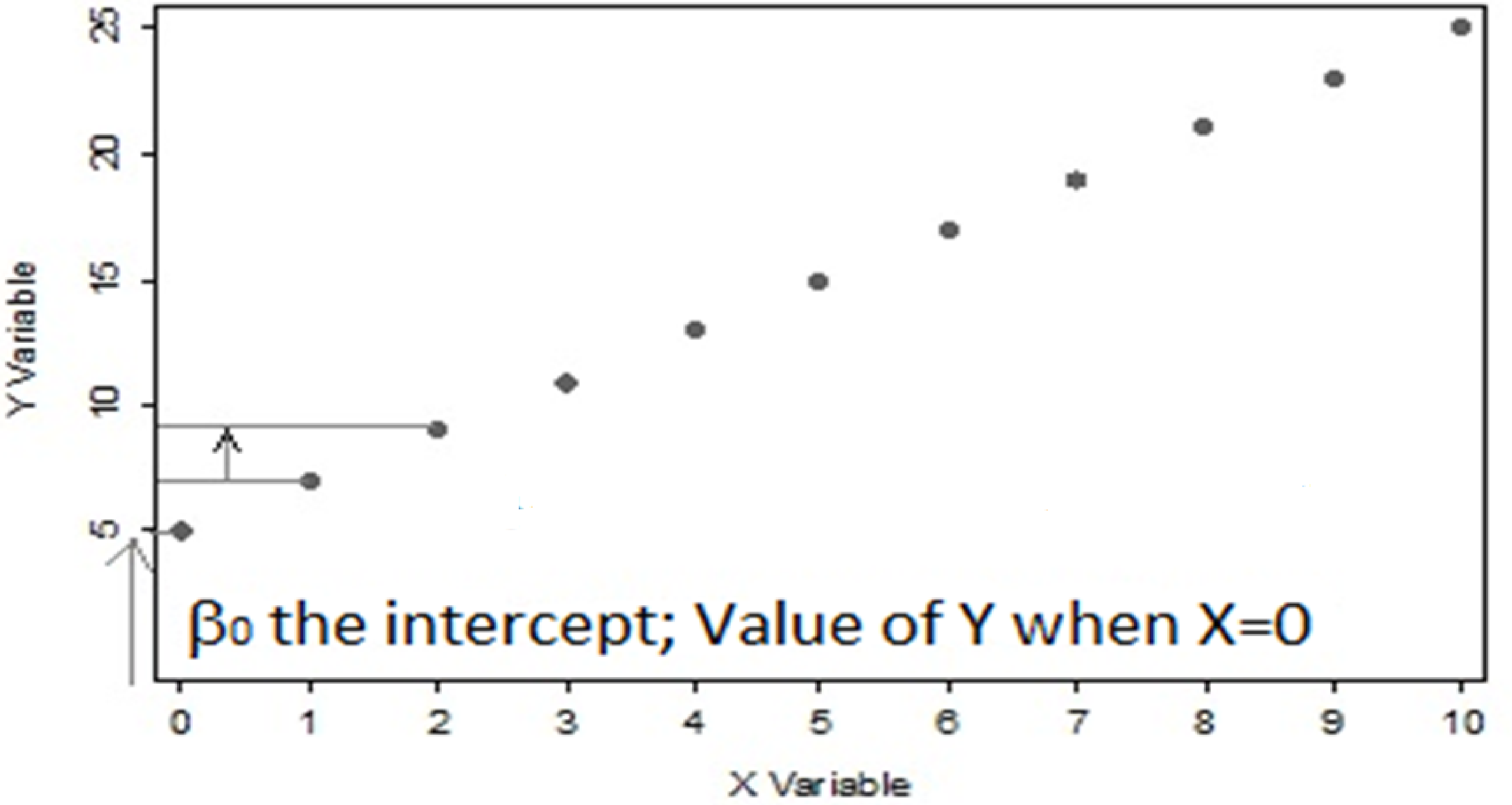
2. A generalized linear model will indicate which of the explanatory variables included in the model are statistically significant
3. A generalized linear model will indicate the direction of the relationship between the specific explanatory variable and the outcome variable

$$\boxed{Y_i} = \boxed{\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki}} + \varepsilon_i$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki} + \varepsilon_i$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki} + \varepsilon_i$$

The Intercept (β_o)



Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	18.118	3.167		5.721	<.001
	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

$$Y_i = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki} + \varepsilon_i$$

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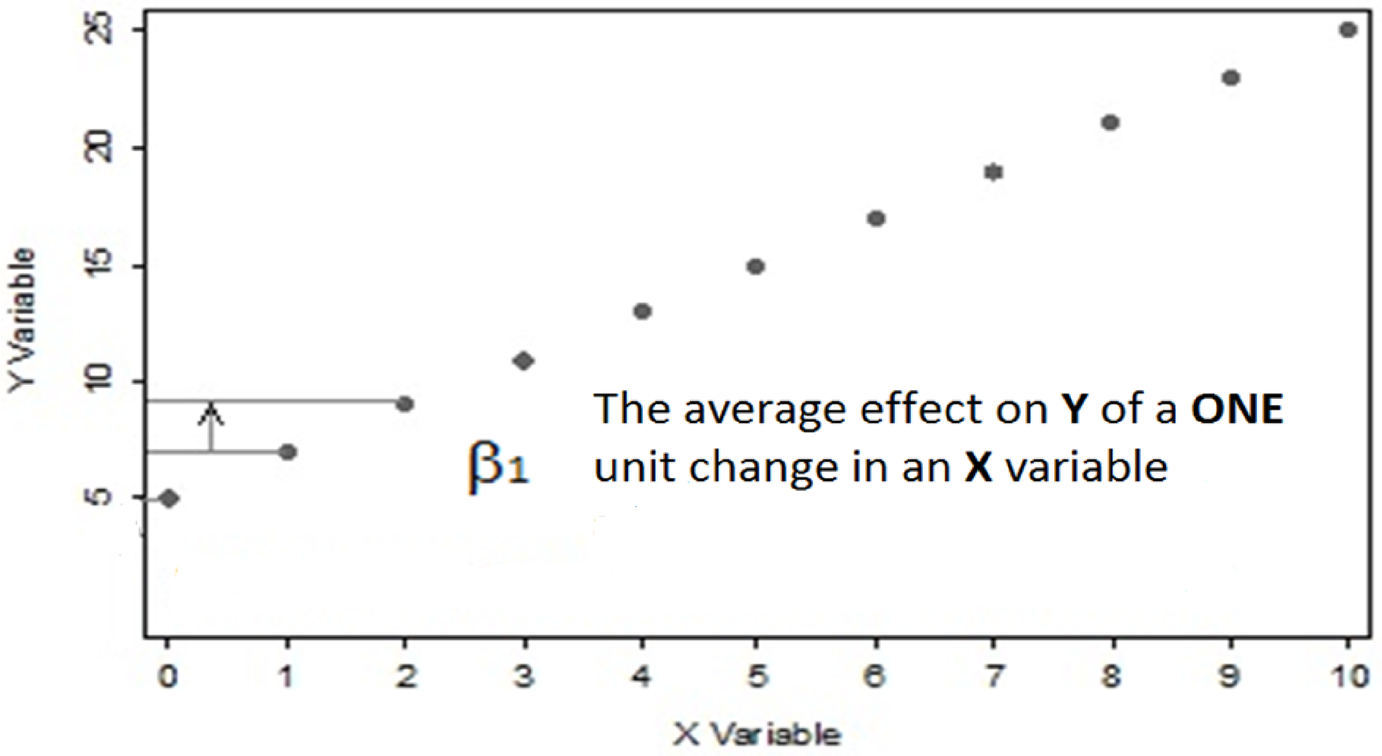
The Average Effect of the Explanatory Variable on the Outcome (β_1)



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	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

1. A generalized linear model will estimate how much of the variability in the outcome variable is explained by the set of explanatory variables that are included in the model
2. A generalized linear model will indicate which of the explanatory variables included in the model are statistically significant
3. A generalized linear model will indicate the direction of the relationship between the specific explanatory variable and the outcome variable
4. A generalized linear model will estimate the strength of the relationship between the explanatory variable and the outcome variable, once all of the other variables in the model have been considered

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
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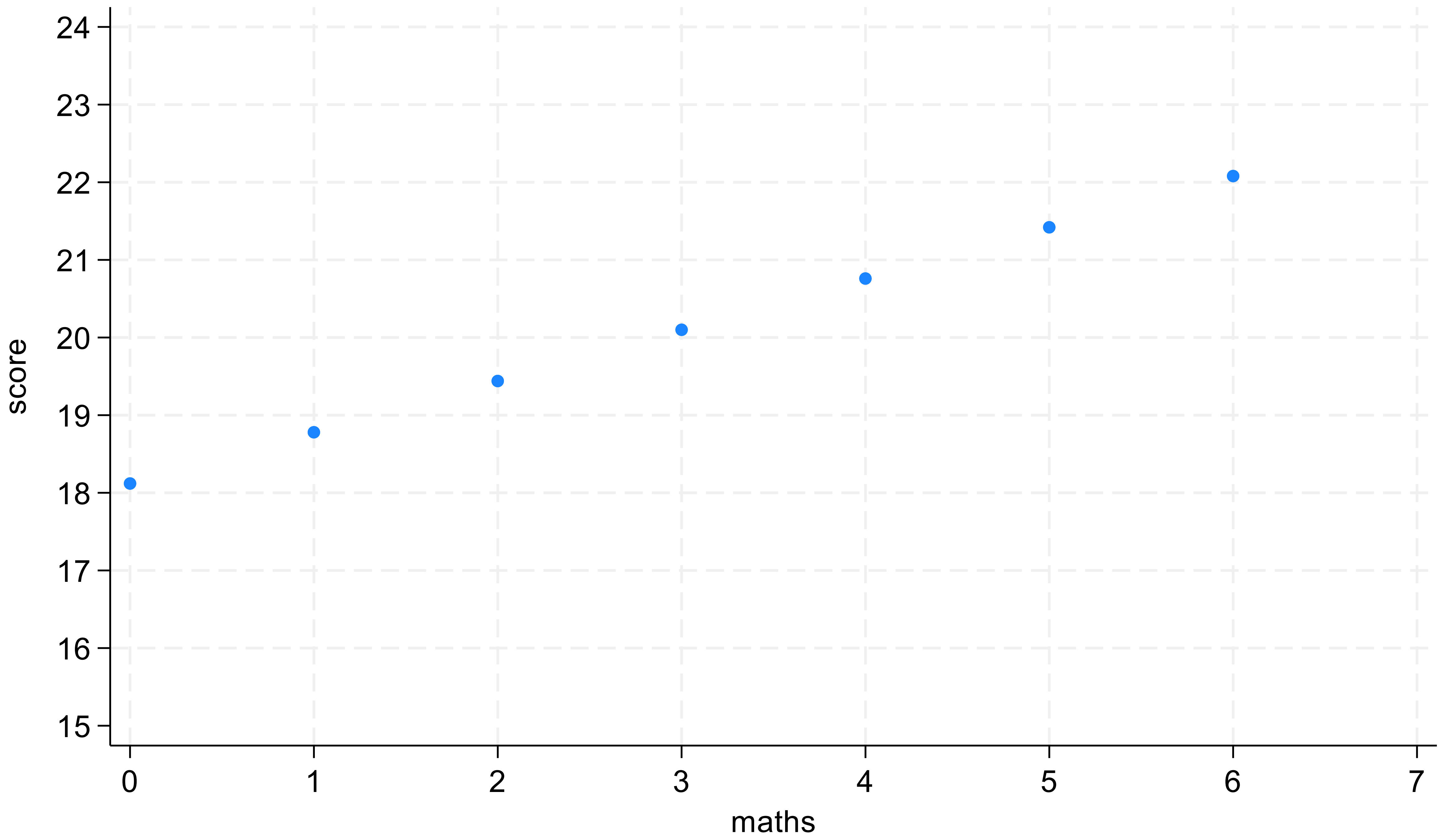
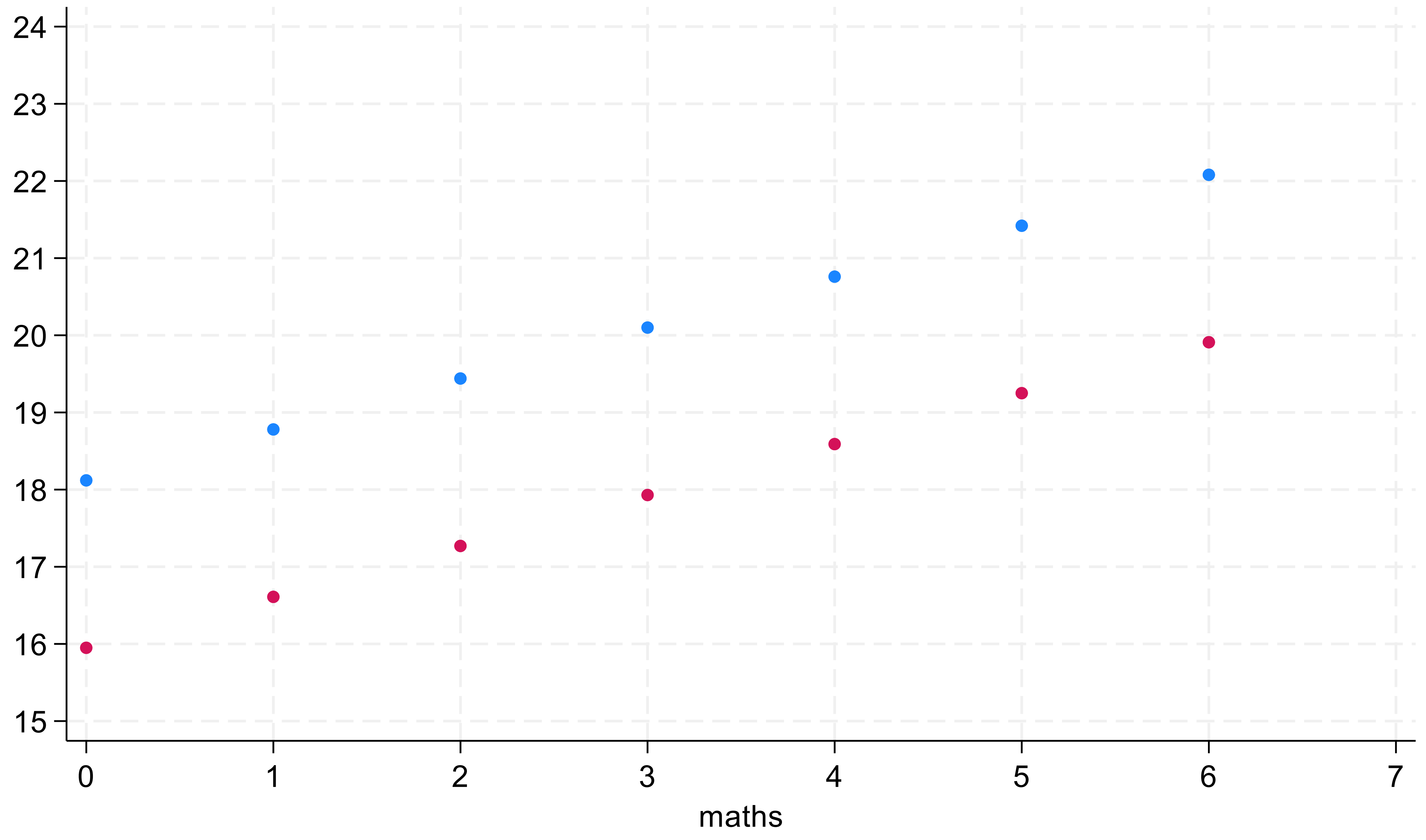
	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score



24
23
22
21
20
19
18
17
16
15
score
0
1
2
3
4
5
6
7
maths


24
23
22
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19
18
17
16
15
0
1
2
3
4
5
6
7
maths

Standard Error (s.e.)

A measure of the precision with which the regression coefficient is measured (small s.e. indicates better precision)

(if a coefficient is large compared with its standard error, then it is probably different from 0)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
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	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

The *t* statistic

$$t = \beta / se$$

Simple guide: when *t* is greater than plus or minus 2 then the variable is significant

And… if β is twice the s.e. the variable is significant

p value

$$t = \beta / se$$

With associated degrees of freedom ($n - k$)

The t statistic

$$t = \beta/se$$
$$t = -2.168/1.086$$
$$t = -1.997$$

Coefficients[a]

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	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	female, math score[b]	.	Enter

a. Dependent Variable: science score

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.640[a]	.410	.404	7.645

a. Predictors: (Constant), female, math score

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7993.550	2	3996.775	68.384	<.001[b]
	Residual	11513.950	197	58.446		
	Total	19507.500	199			

a. Dependent Variable: science score

b. Predictors: (Constant), female, math score

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.118	3.167		5.721	<.001
	math score	.663	.058	.628	11.460	<.001
	female	-2.168	1.086	-.109	-1.997	.047

a. Dependent Variable: science score

The social world is complex and messy but multivariate analyses using statistical models provide a formal approach to evaluate data, test ideas and investigate research questions.

Statistical models help us deal with the messy complexity of the social world.

Putting this all together…

Part 2.5

Young people and school General Certificate of Secondary Education attainment: looking for the 'missing middle'

Vernon Gayle, Susan Murray & Roxanne Connelly

To cite this article: Vernon Gayle, Susan Murray & Roxanne Connelly (2016) Young people and school General Certificate of Secondary Education attainment: looking for the 'missing middle', British Journal of Sociology of Education, 37:3, 350-370, DOI: 10.1080/01425692.2014.935292

To link to this article: https://doi.org/10.1080/01425692.2014.935292

Gayle, V., Murray, S. and Connelly, R., 2016. Young people and school General Certificate of Secondary Education attainment: Looking for the ‘missing middle’. *British Journal of Sociology of Education*, *37*(3), pp.350-370.

https://www.tandfonline.com/doi/pdf/10.1080/01425692.2014.935292

Table 3 [2003 Cohort p.364]

GCSE
(score)

Explanatory variables

gender
ethnicity
housing tenure
household type
parental education
parent’s socio-economic class (NS-SEC)

Table 3. Linear regression model (survey weighted) for school GCSE attainment Year 11 (GCSE points score): beta values.

		1990–99	2001[a]	2003[a]
YCS cohort	1990	0.00		
	1993	**4.78**		
	1995	**7.95**		
	1997	**7.21**		
	1999	**10.88**		
Gender	Girls	0.00	0.00	0.00
	Boys	**−4.73**	**−5.01**	**−5.53**
Ethnicity	White	0.00	0.00	0.00
	Black	**−3.43**	−1.19	−2.80
	Indian	**3.00**	**4.87**	**8.25**
	Pakistani	**−2.01**	0.75	−1.98
	Bangladeshi	**3.28**	**7.92**	**4.77**
	Other Asian	**6.46**	**8.42**	1.72
	Other	0.84	1.11	**2.77**
Housing tenure	Owned / mortgage	0.00	0.00	0.00
	Rented	**−7.37**	**−7.69**	**−10.74**
	Others	**−2.67**	**−5.79**	−15.99
Household type	Mother and father	0.00	0.00	0.00
	Mother Only	**−1.19**	**−1.10**	**−2.00**
	Father only	**−2.94**	**−6.21**	**−8.16**
	Other household	**−7.98**	**−8.44**	**−10.01**
Parental education	Non-graduates	0.00	0.00	0.00
	Graduates	**4.95**	**4.22**	**6.35**
Parents' social classification (NS-SEC)	1.1 Large Employers and Higher Managerial	**4.53**	**3.83**	1.10
	1.2 Higher Professional Occupations	**6.44**	**8.02**	**3.98**
	2 Lower Managerial and Professional Occupations	**2.43**	**2.70**	1.31
	3 Intermediate Occupations	0.00	0.00	0.00
	4 Small Employers and Own Account Workers	**−4.72**	**−2.78**	**−4.68**
	5 Lower Supervisory and Technical Occupations	**−5.09**	**−5.33**	**−6.77**
	6 Semi-routine Occupations	**−6.96**	**−5.22**	**−7.78**
	7 Routine Occupations	**−9.14**	−7.69	**−10.54**
Constant		**33.83**	**44.77**	**51.22**
R^2		0.24	0.18	0.21
n		54,236	12,934	10,269

Note: Significant variables highlighted in bold.
[a]For the 2001 and 2003 school year cohorts, an alternative point score was deposited with data that include other qualifications (e.g. GCSE short courses).

Constant	**33.83**	**44.77**	**51.22**
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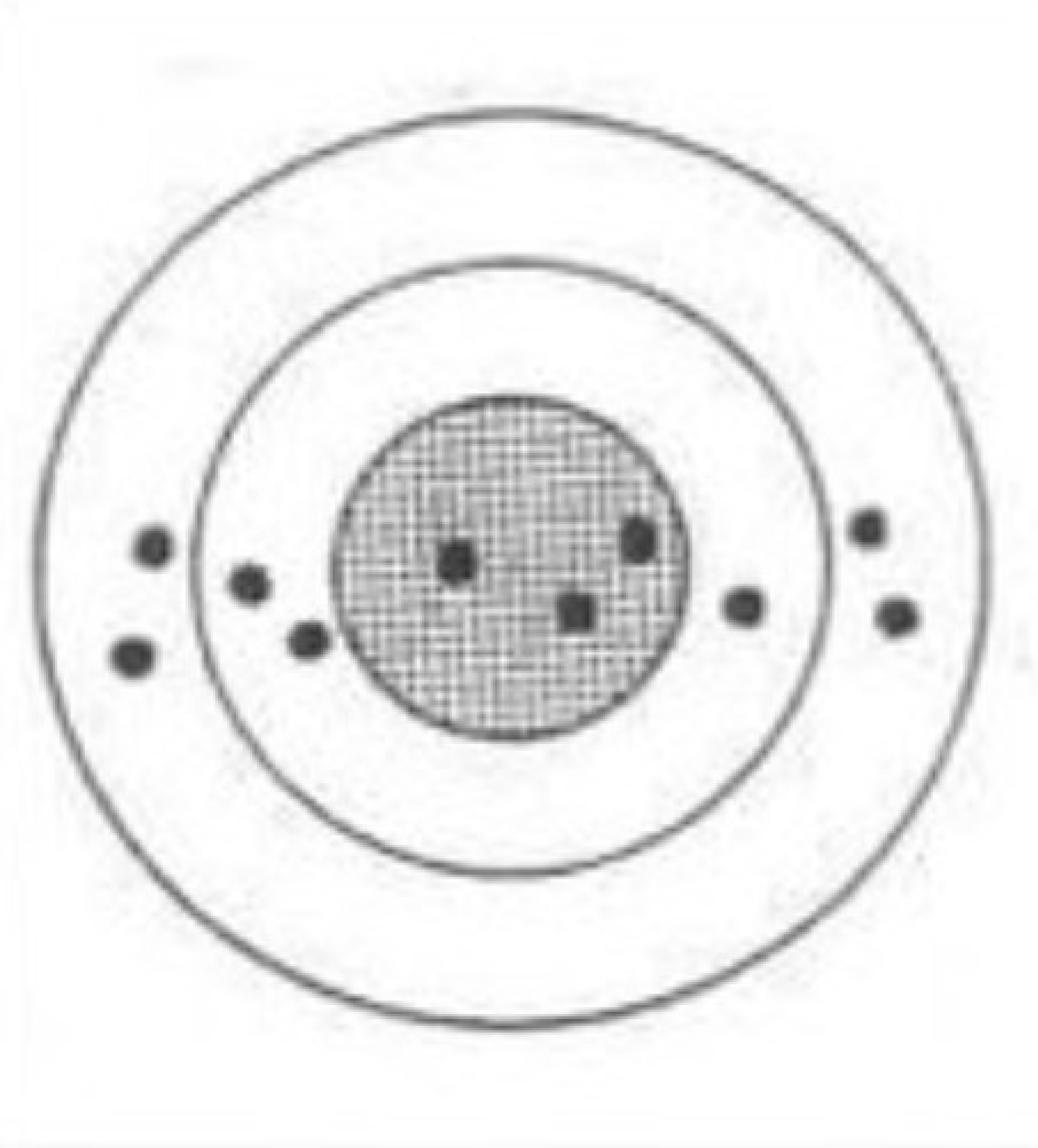
Clusters and Hierarchies

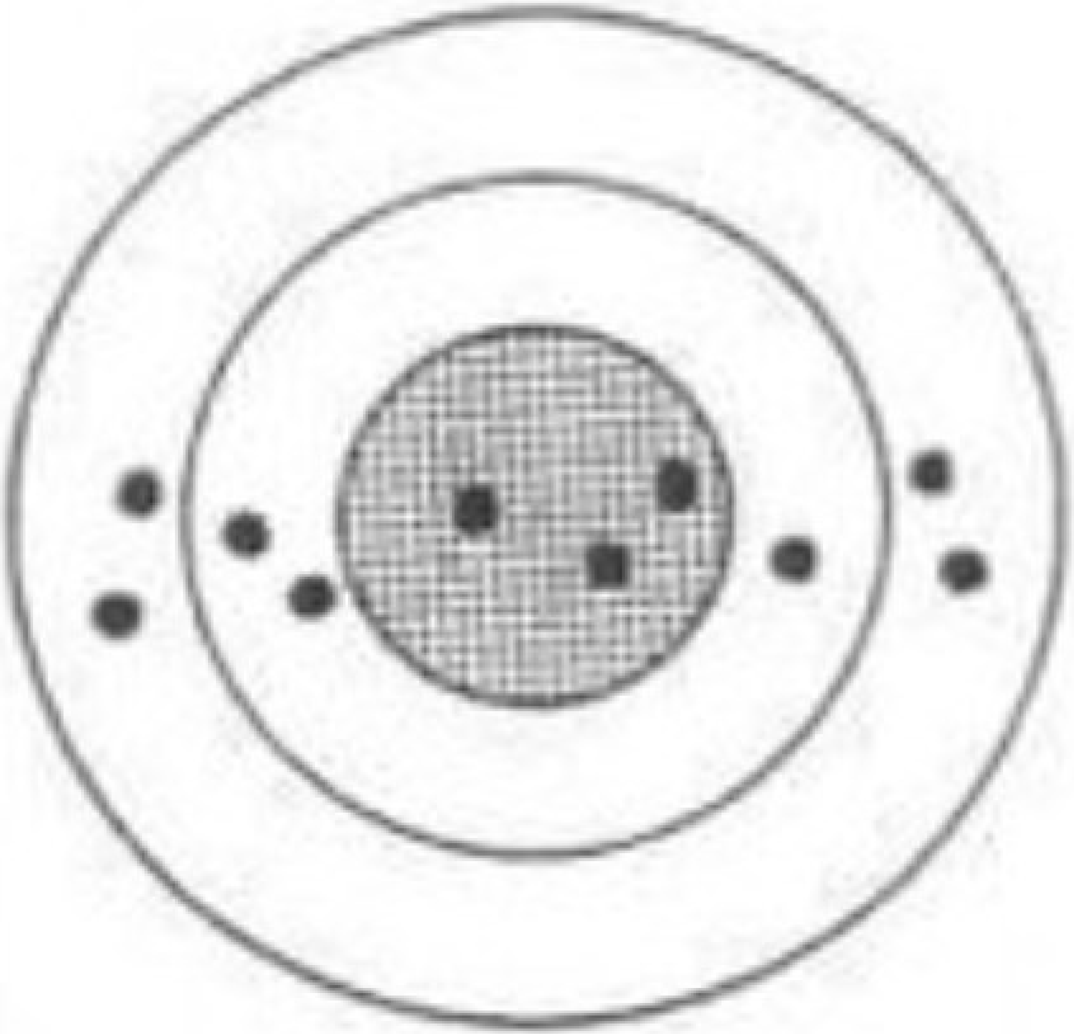
Part 3

Some Thought Experiments

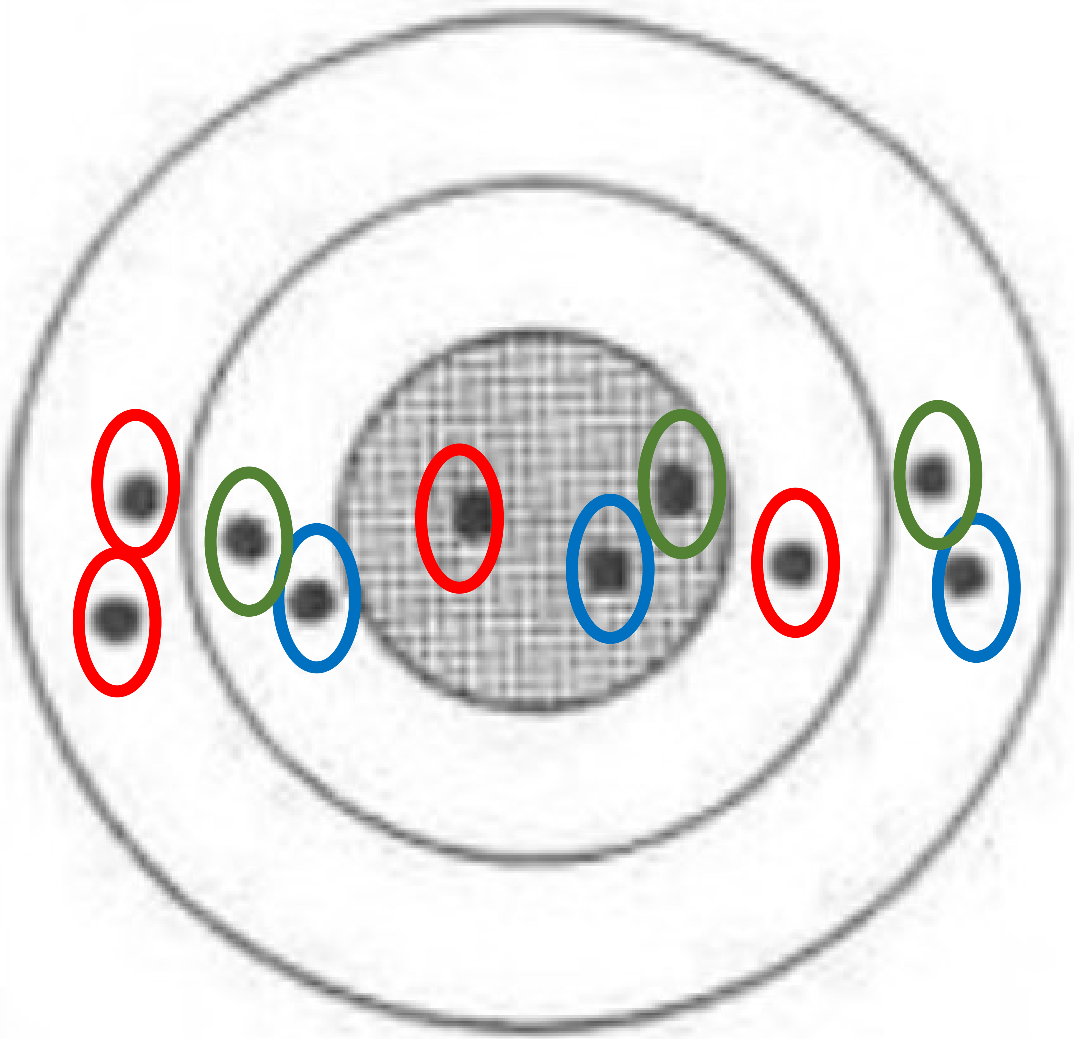
Like all thought experiments they are a bit contrived!

10 shots at a target





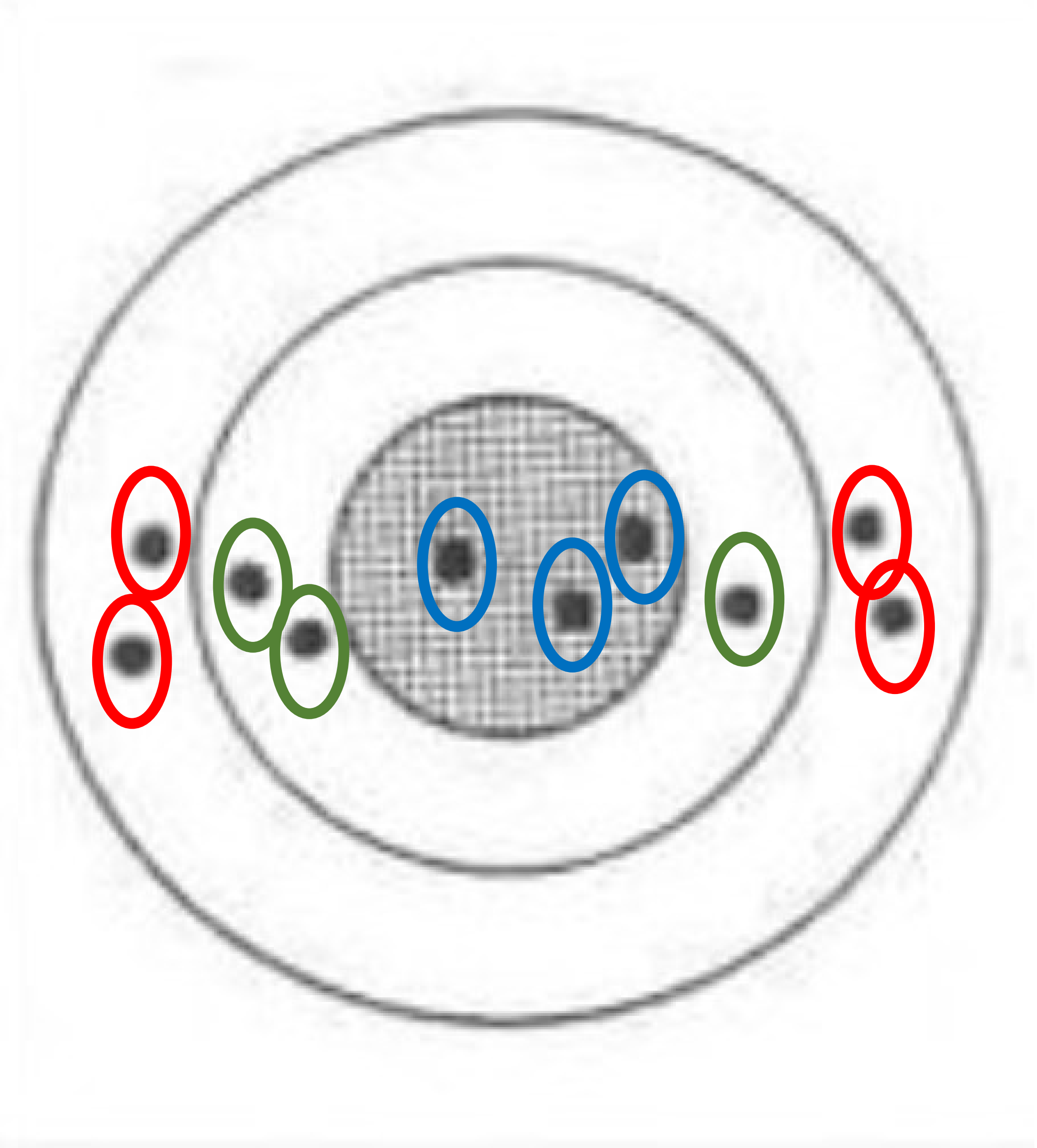
4 are from school A
3 are from school B
3 are from school C



4 are from school A

3 are from school B

3 are from school C

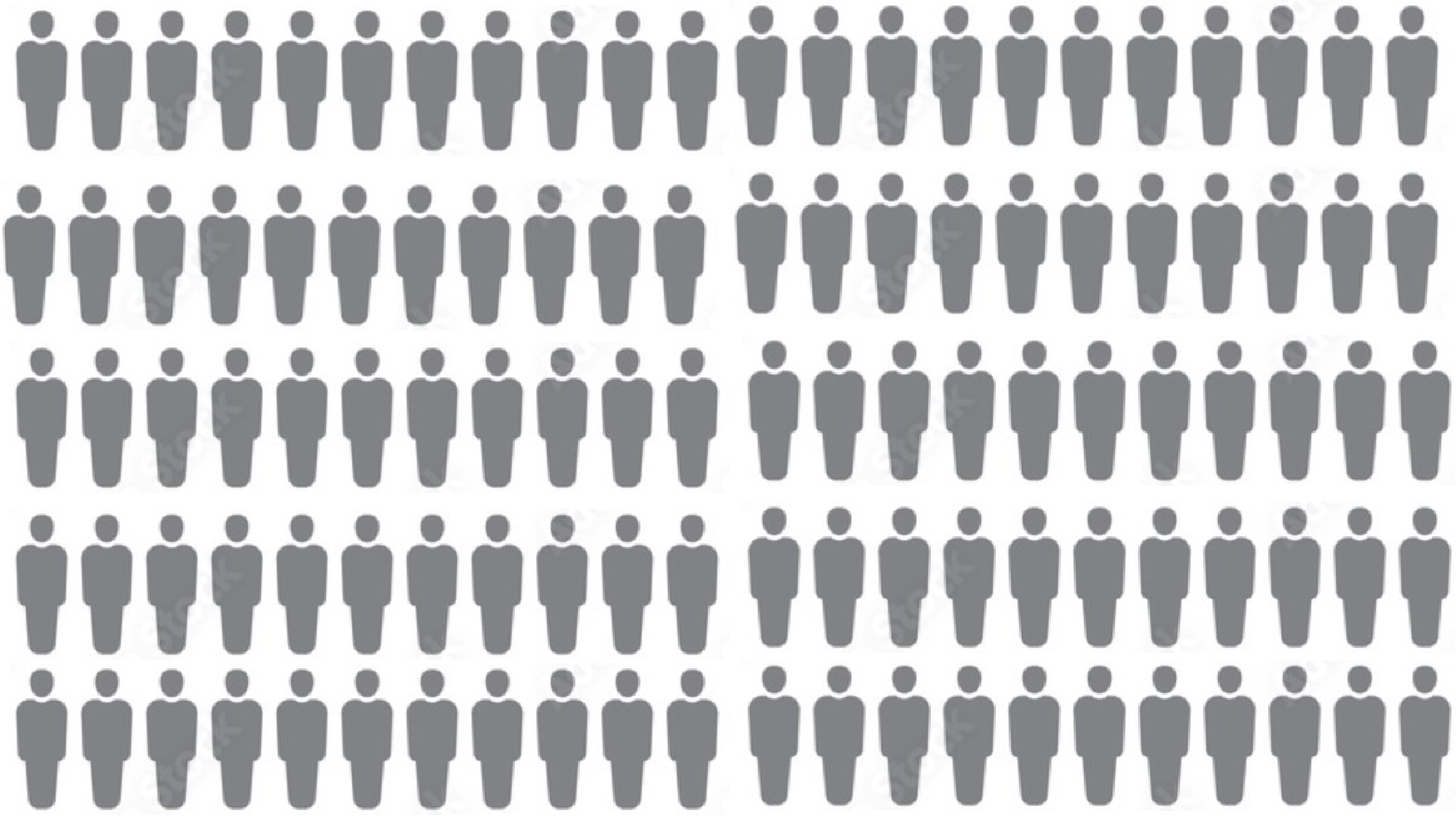


4 are from school A

3 are from school B

3 are from school C

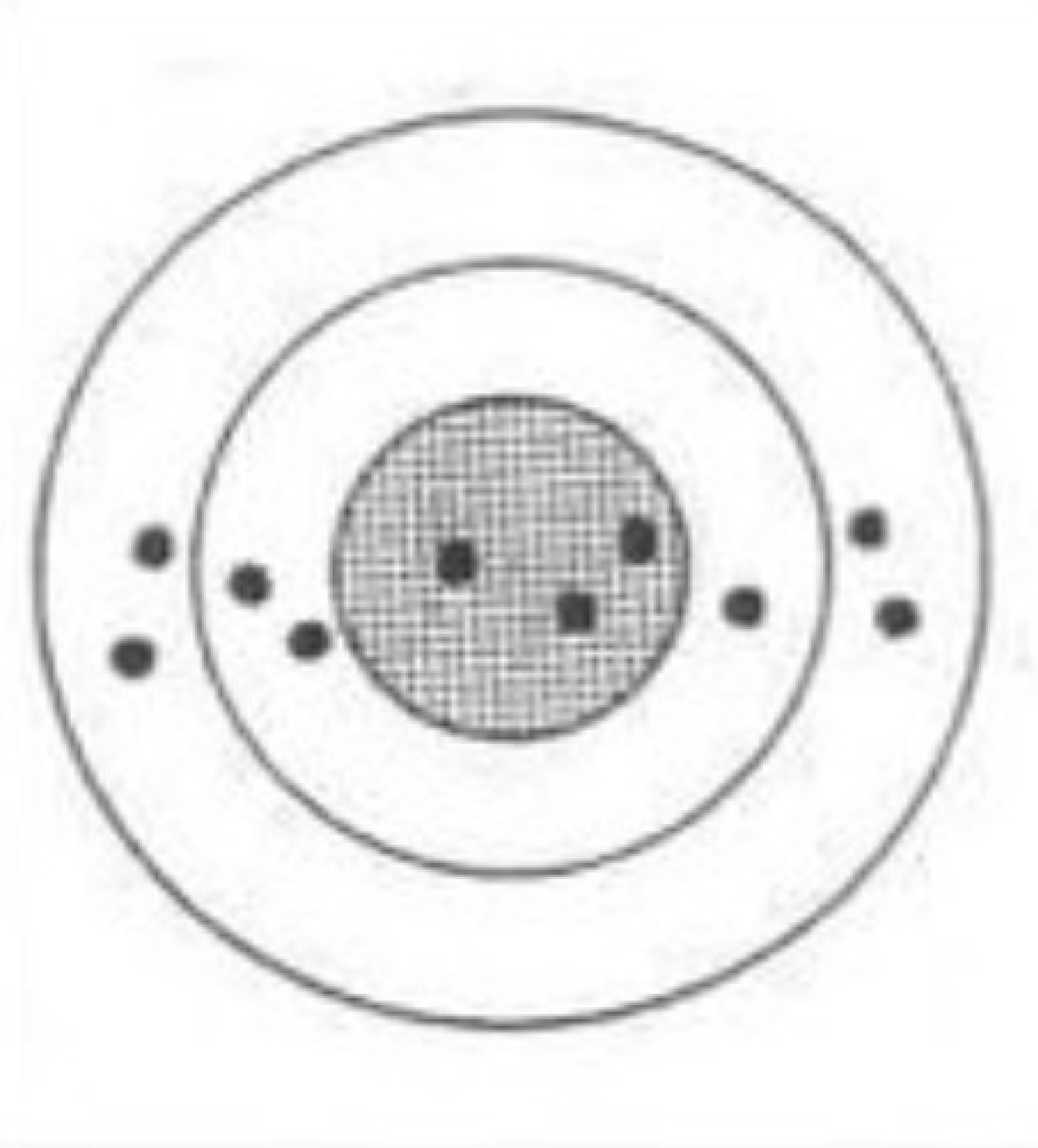
100 Observations

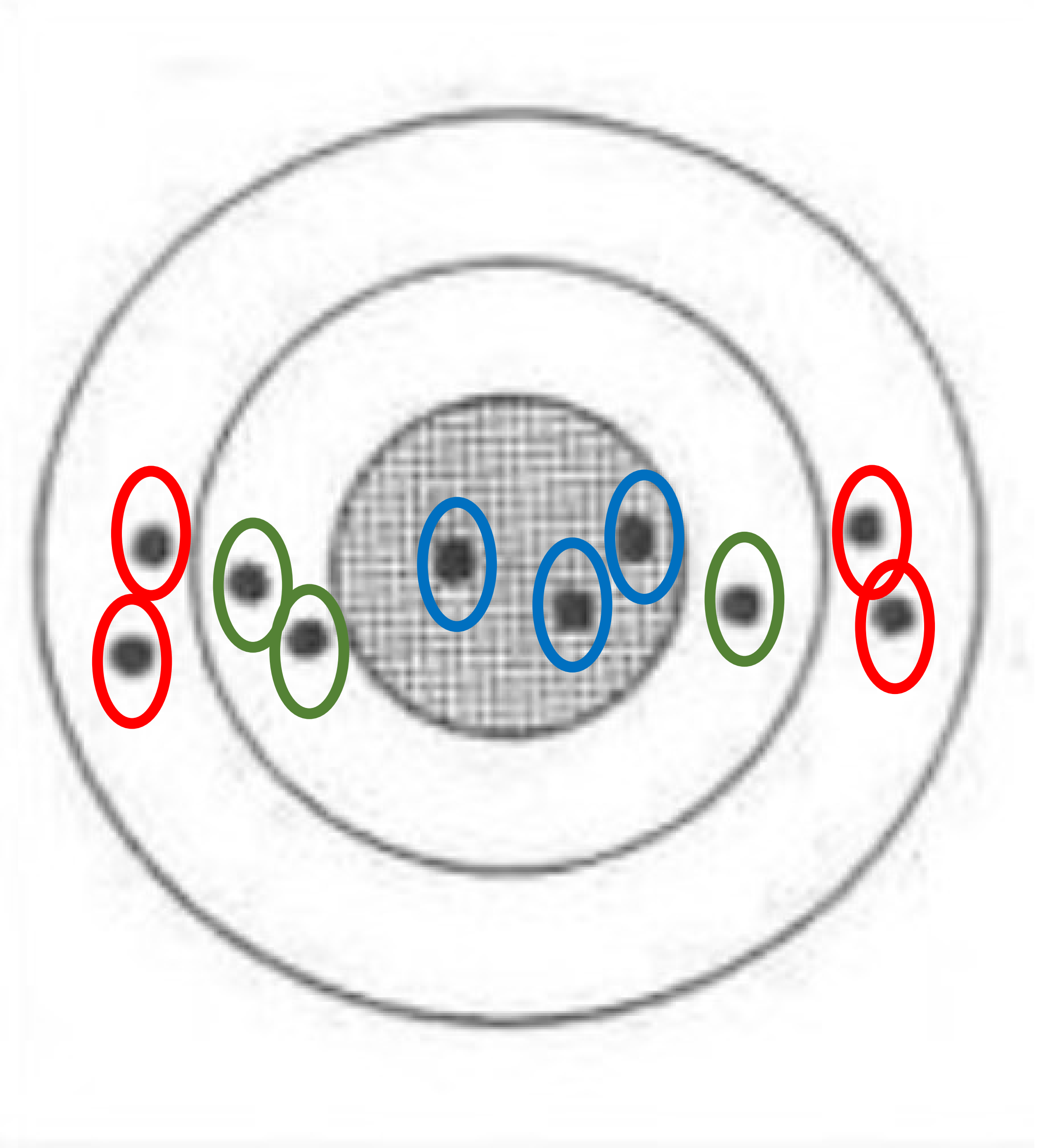


Is data from 100 observations from 100 cases

the same thing as 100 observations from 10 cases?

10 shots at a target





4 are from school A

3 are from school B

3 are from school C

Independence of Observation Assumption

A common assumption in statistical analyses is that observations in the sample are independent of each other

When Data Violates the Independence Assumption

In practice estimates effects might be okay but estimates of precision will be affects

Why?

Because data from 100 observations from 100 cases
is not quite the same thing as
100 observations from only 10 cases?

Adjustment for Clustering

Robust standard errors are sometimes known as Huber/White sandwich estimates of variance (see White, 1984, Huber, 1967)

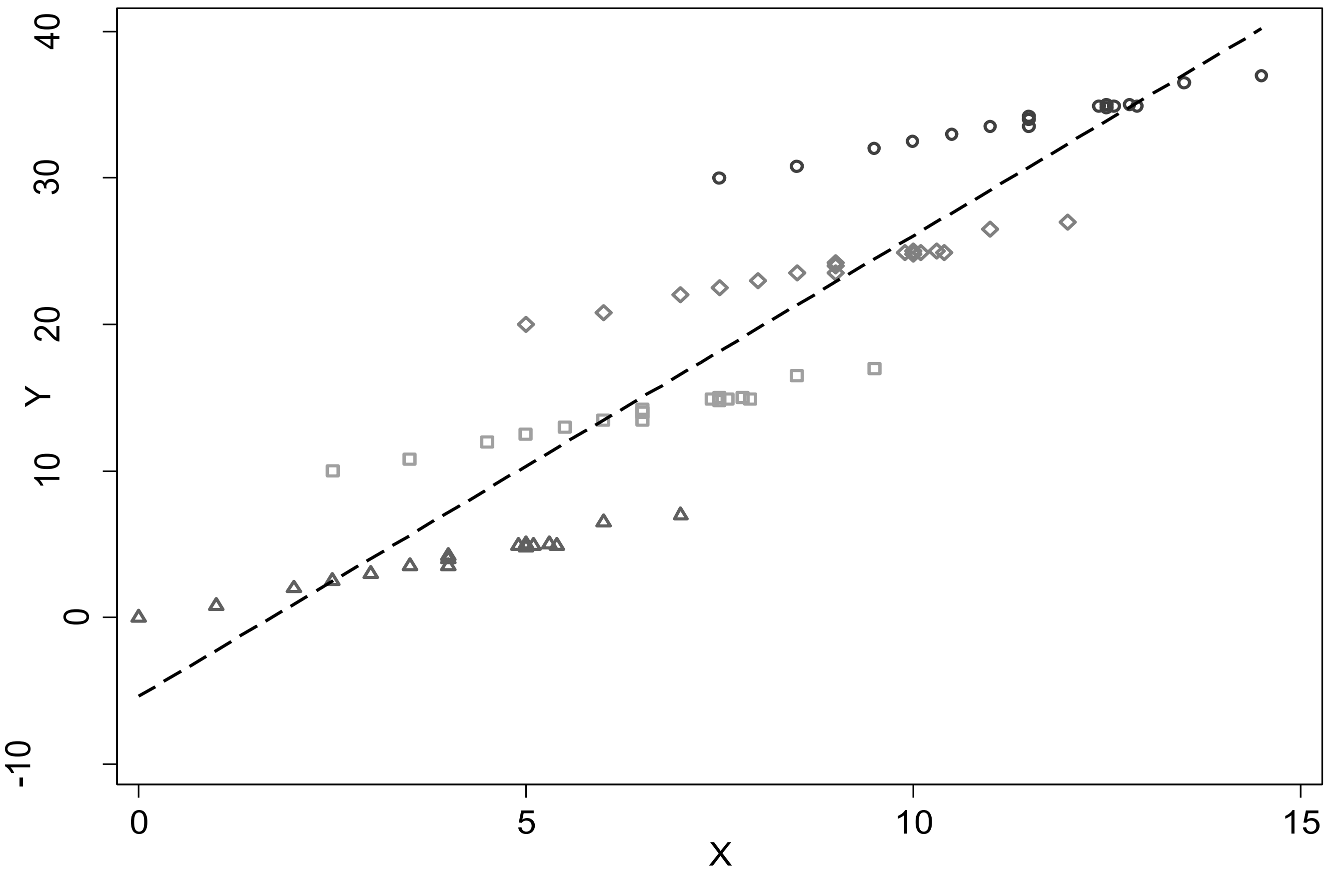
Adjustment for Clustering

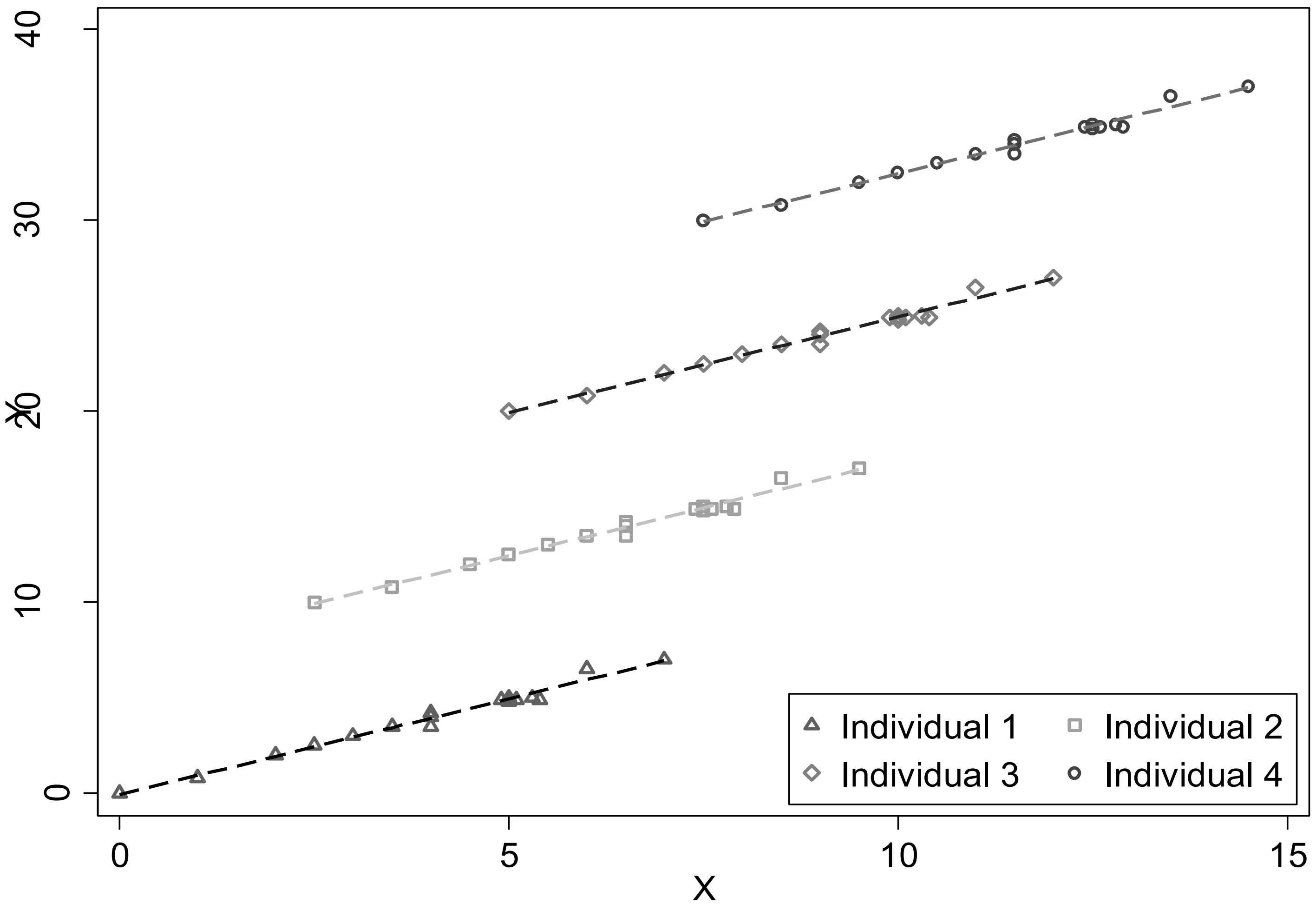
Robust standard errors

Are correcting for the clustering

They will tend to be larger than conventional standard errors

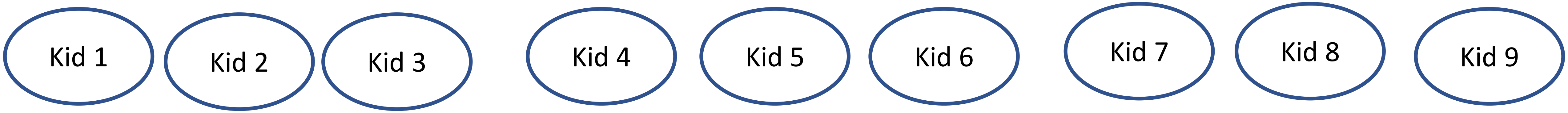
Another Thought Experiment…



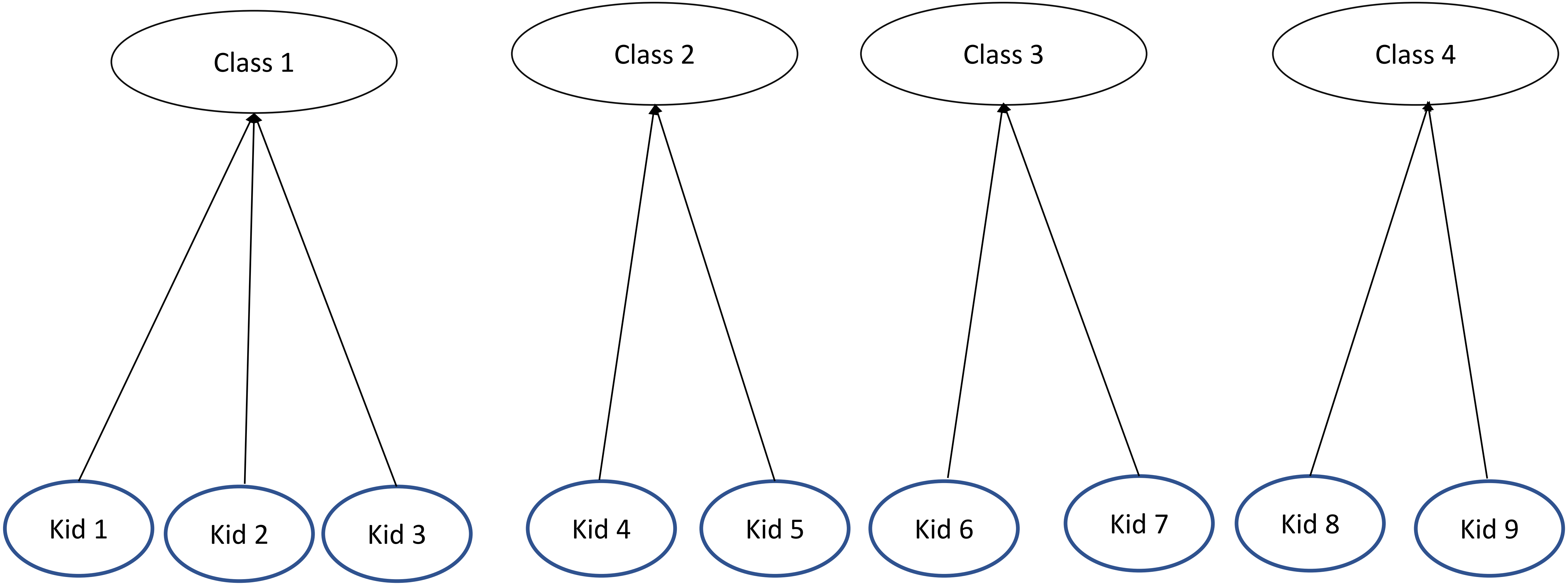

Y
X
0
10
20
30
40
0
5
10
15
Individual 1
Individual 2
Individual 3
Individual 4

Possible Structures in Social Science Data

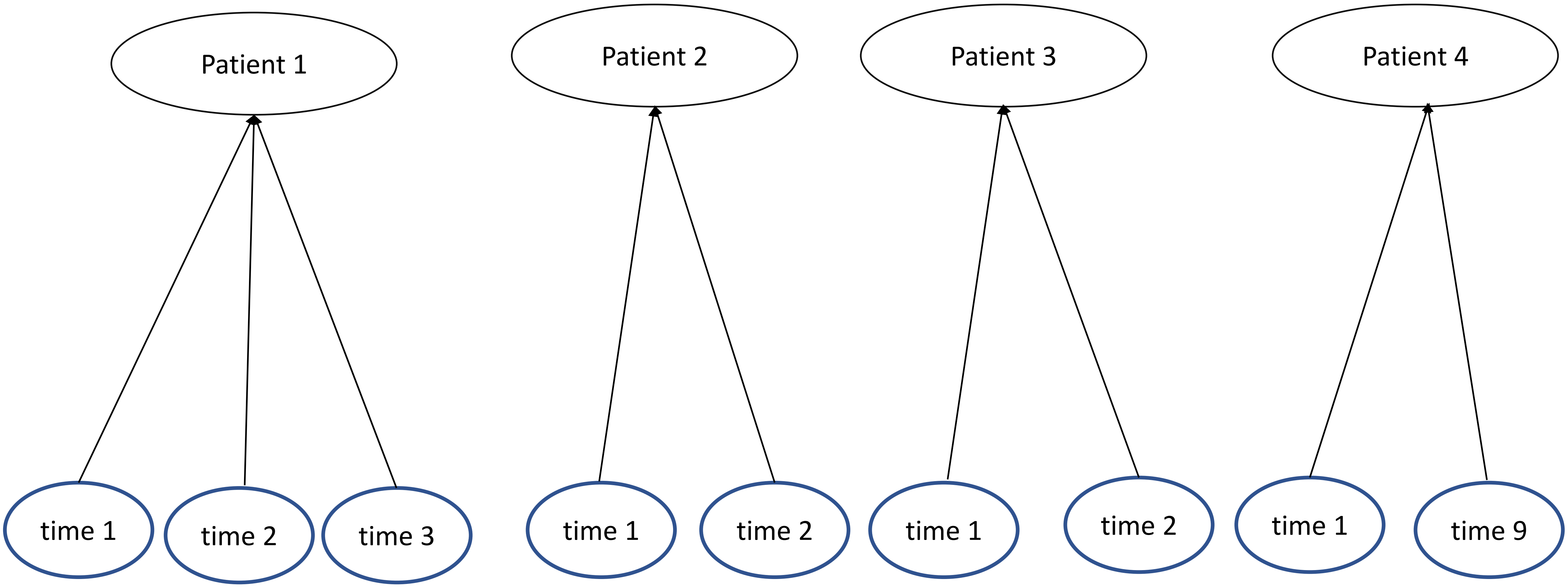
Education Example



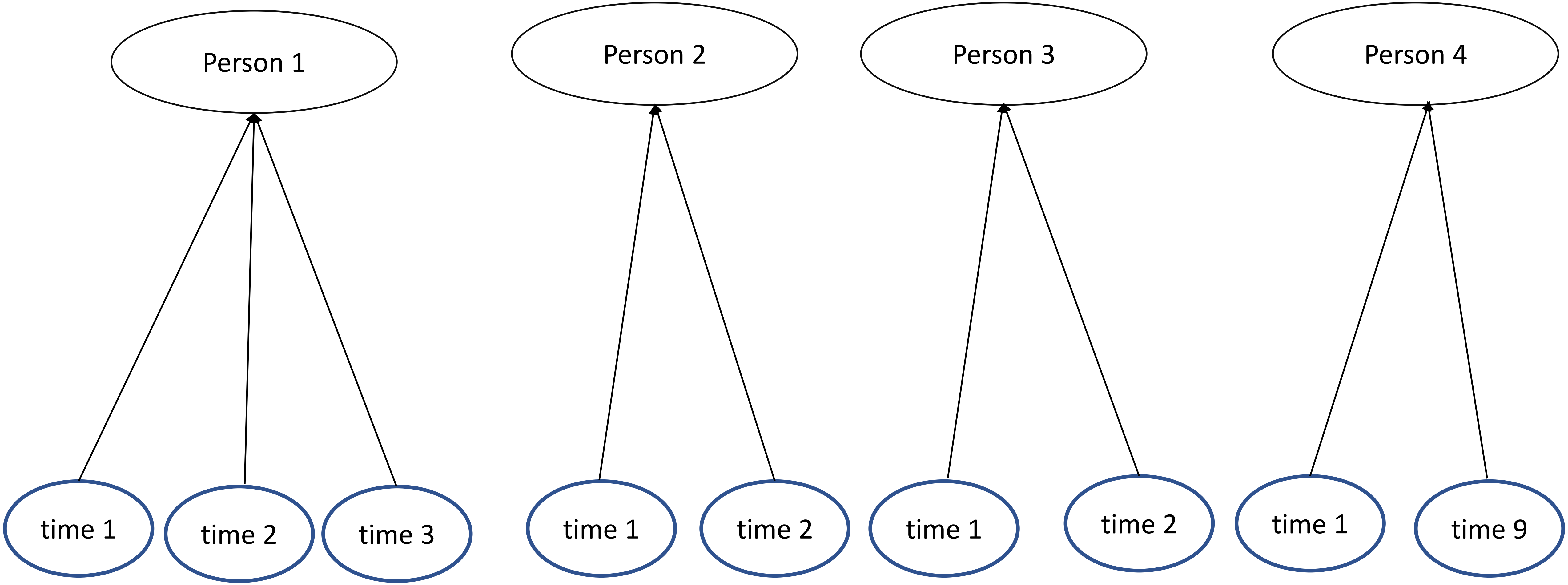
A Simple Education Example



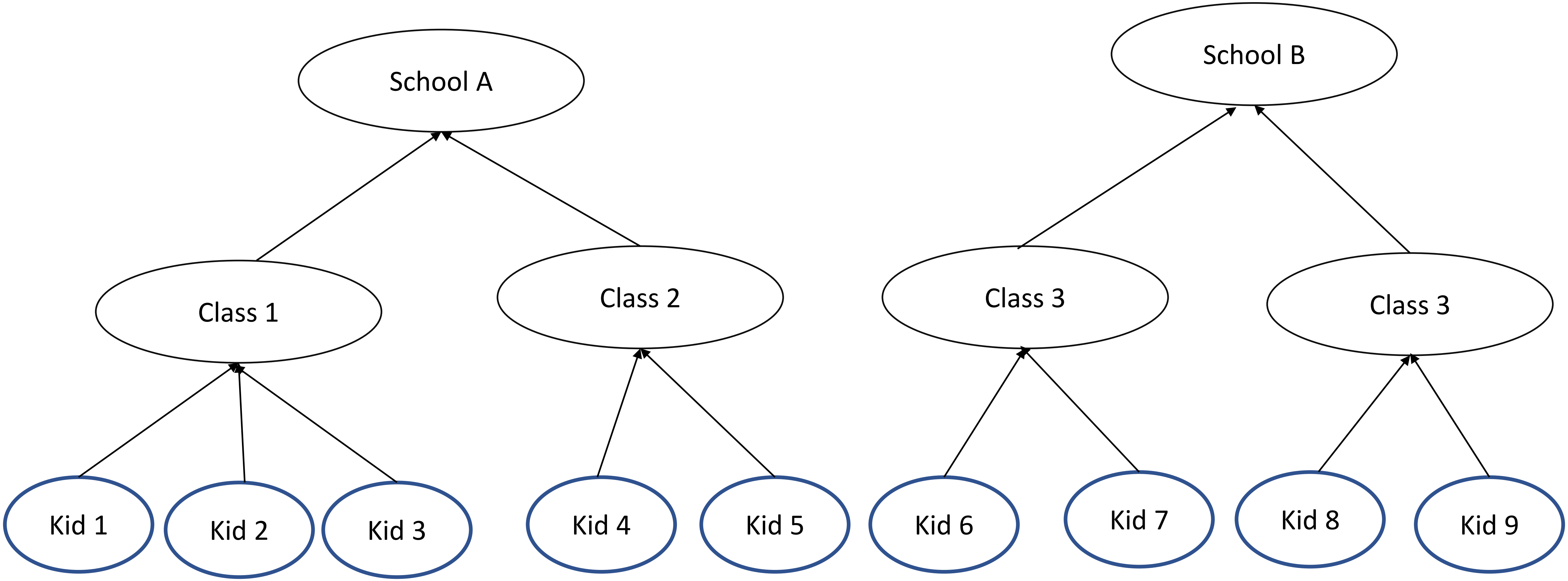
Medical (a separate literature but the same underlying data structure)

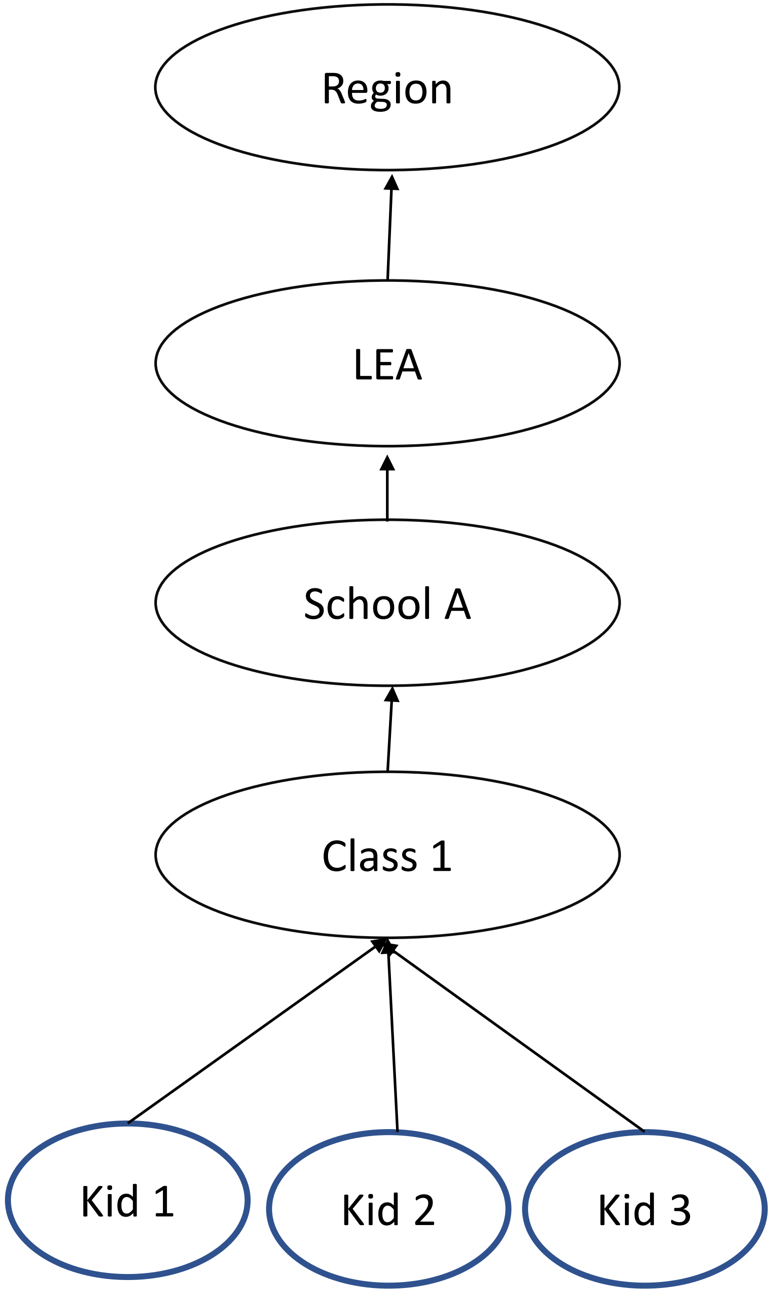


Repeated Measures Example (longitudinal)



Education Example





Education Example

This is conceptual but in practice researchers are unlikely to have suitable data to estimate a model with so many levels!

Models in Action

Part 4

Goldstein, H., Burgess, S. and McConnell, B., 2007. Modelling the effect of pupil mobility on school differences in educational achievement. *Journal of the royal statistical society series A: statistics in society*, *170*(4), pp.941-954.

Modelling the effect of pupil mobility on school differences in educational achievement

Harvey Goldstein, Simon Burgess and Brendon McConnell

University of Bristol, UK

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Summary. The recently introduced national pupil database in England allows the tracking of every child through the compulsory phases of the state education system. The data from key stage 2 for three local education authorities are studied, following cohorts of pupils through their schooling. The mobility of pupils among schools is studied in detail by using multiple-membership multilevel models that include prior achievement and other predictors and the results are compared with traditional 'value-added' approaches that ignore pupil mobility. The analysis also includes a cross-classification of junior and infant schools attended. The results suggest that some existing conclusions about schooling effects may need to be revised.

Keywords: Cross-classified model; Educational attainment; Mobility; Multilevel model; Multiple-membership model; National pupil database; Pupil level annual school census; Random effects; School effectiveness; Value added; Variance components

1. Introduction

Since the early 1980s educational researchers have developed models for judging the comparative performance of schools and other institutions by using what have come to be known as 'value-added' techniques (see Goldstein *et al.* (1993) and Raudenbush and Bryk (1989) for early discussions). Typical applications have compared the performance of pupils in public examinations or on the basis of routine test scores. In essence these models attempt to adjust simple comparisons of school mean values by using measures of pupil prior achievement and other variables to take account of selection and other procedures that are associated with pupils' achievements but not related to any effect that the schools themselves may have on achievement. Thus, a simple two-level, variance components, model based on data from a random sample of schools can be written as follows where subscript i refers to the pupil, and j to the school:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + u_j + e_{ij}, \qquad u_j \sim N(0, \sigma_u^2), \quad e_{ij} \sim N(0, \sigma_e^2); \qquad (1)$$

Table 5. Normalized mathematics KS2 score response for Staffordshire, with pupils assigned to KS2 test score school by using models of increasing complexity†

Variable	*Results for the following models:*		
	A	*B*	*C*
Fixed effects			
Intercept	−0.011	−0.195	−0.093
Age in months		0.029 (0.003)	−0.014 (0.002)
KS1 mathematics score			0.754 (0.006)
Random parameters			
Between-junior-school variance	0.094 (0.011)	0.095 (0.011)	0.053 (0.006)
Between-pupil variance	0.795 (0.012)	0.784 (0.012)	0.301 (0.004)
VPC	0.11	0.11	0.15
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†Estimates with standard errors in parentheses.

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Age in months		0.029 (0.003)	−0.014 (0.002)
KS1 mathematics score			0.734 (0.006)
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Is the estimate twice as big as the standard error?

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A very confusing aspect of the terminology in one branch of multilevel modelling is that the explanatory variables are know as 'fixed effects'

This is often confused with something else called a 'fixed effects model'

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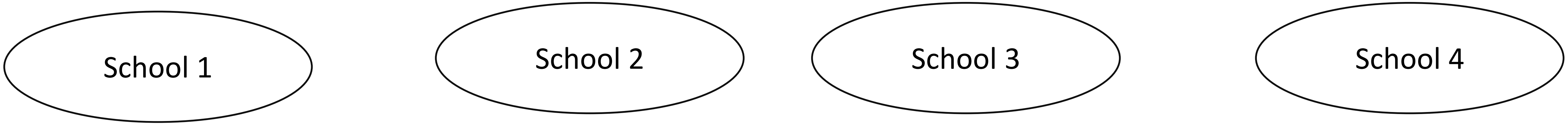
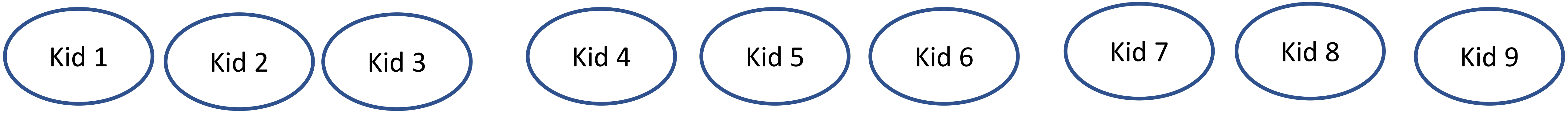
Between Junior School Variance



Between Pupil Variance



Total Variance = Between pupil variance + Between junior school variance

VPC is the Variance Partition Coefficient

$$\text{VPC} = \frac{\text{Between junior school variance}}{\text{Between pupil variance} + \text{Between junior school variance}}$$

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$$0.094 / (0.094 + 0.795) = 0.11$$

Deviance is an overall measure of the model

Model A Deviance 25107.1

Model B Deviance 24989.0

Model C Deviance 15987.9

A smaller Deviance is a good thing

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Look at the estimate and s.e. for the KS1 mathematics

For swots only

Model A Deviance 25107.1

Model B Deviance 24989.0 change in Deviance 118.1 @ 1.df

Model C Deviance 15987.9 change in Deviance 9,001.1 @ 1 df

The change in Deviance follows a chi-square distributions with associated degrees of freedom

The critical value of chi-square @ 1 df = 3.81 ($p<.05$)

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Goldstein et al. (2007 p. 947- 948) …

“Model C is the most common or traditional value-added analysis where we additionally condition on the KS1 mathematics score by using a linear term which is sufficient to describe the relationship.

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The relationship with age in the value-added model is now negative so that given their KS1 performance the younger children do better, indicating that they tend to ‘catch up’ over this period. See also Goldstein and Fogelman (1974) for a similar finding.”

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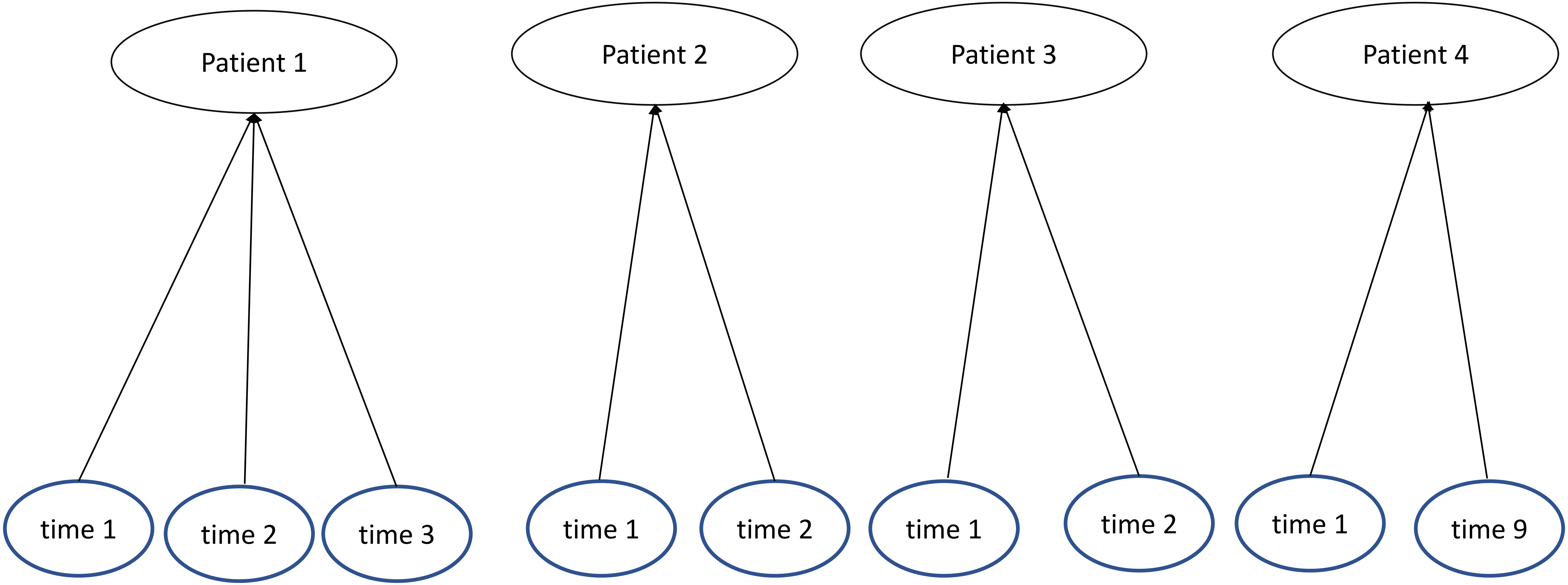
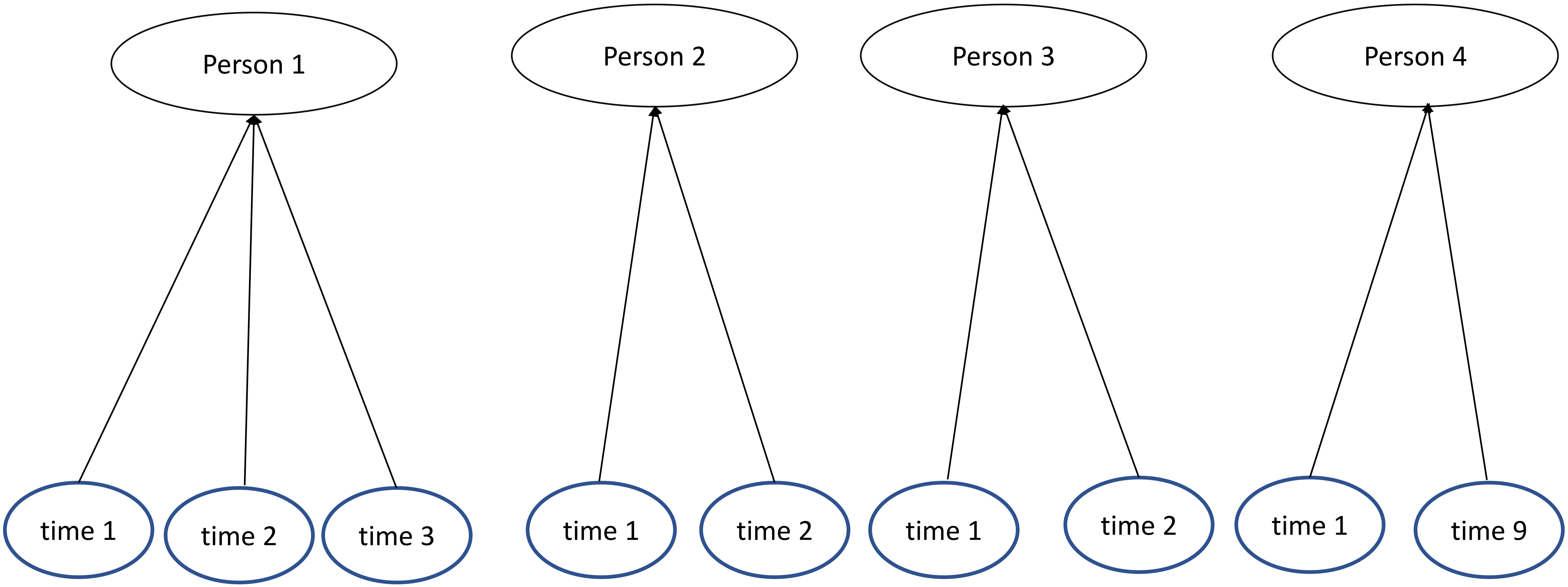
Even when the notation looks like it is written in Greek you can still engage with the analysis!

Frailty Models in Epidemiology



Repeated Measures Example (longitudinal)



	(1) Panel RE	(2) Multilevel
Zpaynu2		
zjbhrs	3.983***	3.983***
	(0.723)	(0.721)
zjbcssm	2.975***	2.975***
	(0.425)	(0.415)
pacssm	4.075***	4.075***
	(0.759)	(0.757)
graduate	195.5***	195.5***
	(32.05)	(31.91)
zregage	9.742*	9.742*
	(4.820)	(4.820)

	(1) Panel RE	(2) Multilevel
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zregage	9.742*	9.742*
	(4.820)	(4.820)

_cons	449.7***	449.7***
	(46.94)	(46.84)
sigma_u		
_cons	358.2***	
	(10.18)	
sigma_e		
_cons	251.9***	
	(2.734)	
lns1_1_1		
_cons		5.881***
		(0.0284)
lnsig_e		
_cons		5.529***
		(0.0109)
N	5097	5097

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Software logs sigma_u and sigma_e

These are all versions of something called a random effects model

The underlying maths and estimation is the same!

Educational researchers tend to think in terms of multilevel models
Geographers tend to think in terms of multilevel models

Economists tend to think in terms of longitudinal models (panel models)

Epidemiologists tend to think in terms of frailty models

Conclusions & Final Remarks

Part 5

Who's Afraid of…

- A standard statistical model?
- A multilevel model?
- A longitudinal model (i.e. a panel model)?

Some Concluding Remarks

- Many research questions can be answered with single-level analyses!

- Some research questions require multilevel analyses
  - when there are hierarchical structures (e.g. pupils nested in schools)
  - when there are other clusters (e.g. local geographies)
  - sometimes clusters are a nuisance sometimes they are substantively important

- Beware - there might not be suitable measures (especially at the higher-levels to estimate models)

Some Concluding Remarks

- Many research questions can be answered without longitudinal data
- Some research questions require longitudinal data
  - when studying individual level change (or stability) over time
  - when studying growth or development
- Cohort studies and panel studies provide suitable data

Tools of the Trade

Stata https://www.stata.com/

SPSS https://www.ibm.com/uk-en/analytics/spss-statistics-software

SAS https://www.sas.com/

R https://www.r-project.org/

Python https://www.python.org/
(https://www.statsmodels.org/stable/index.html)

MLwiN https://www.bristol.ac.uk/cmm/software/mlwin/

In practice the programming languages look quite similar

Stata

```
logit admit gre gpa
```

SPSS

```
logistic regression admit with gre gpa.
```

SAS

```
proc logistic data="c:\data\binary" descending;
 class rank / param=ref ;
 model admit = gre gpa;
 run ;
```

R

```
mylogit <- glm(admit ~ gre + gpa, data = mydata, family = "binomial")
```

Python

```
independentVar = [`gre’, `gpa’,`Int’]
logReg = sm.Logit(df[`admit’] , df[independentVar])
answer = logReg.fit( )
```

Considerations

1. Supervisor’s expertise
2. Peer group (e.g. other PhD students)
3. Departmental access and support
4. University licenses
5. Data format and meta data (e.g. UK Data Service)
6. Academic subject area
7. Academic job market
8. Non-academic job market

Where next?

NCRM Playlist Multilevel Model – Ian Brunton-Smith

Https://www.youtube.com/playlist?list=PL-XAd1-IhZXZxcWfV0ErYVwPSvGzZ2Lup

methodsMcr Mark Tranmer Multilevel Modelling

https://youtu.be/_lrB-ZaLQE0

Sheffield DTP Andrew Bell

https://www.youtube.com/watch?v=_7sp2-aJFUI

Historical Interview with the late Harvey Goldstein
https://www.youtube.com/watch?v=qG037-GDfm8

Final Thought…

Angrist and Pischke (2008) playfully remarked that if applied research was easy then theorists would do it!

They also reassure readers that applied research is not as hard as the dense pages of Econometrica might lead us to believe https://www.ncrm.ac.uk/surveys/edin

Please add the course title and date at the start of the survey

Multilevel and Longitudinal Statistical Modelling for Qualitative Researchers 15th November 2024

Professor Vernon Gayle vernon.gayle@ed.ac.uk
@Profbigvern

https://github.com/vernongayle/ncrm_longitudinal_and_multilevel_models_for_qualitative_researcher_2024