R for FinTech

Jasmine Dumas

2016-10-30

Contents

Chapter 1

Introduction

1.1 Welcome

Welcome to **R for FinTech**! This guidebook has emphasis on "FinTech" or Financial Technology applications in data analysis. Examples and packages in this guidebook will highlight common methods in computational programming for banking, insurance, and investing.

1.2 The purpose of this book

When starting out in a new industry or a new programming language like R, it can be difficult to learn how to apply industry-specific methods given the vast amount of R packages available and the sparsity of relative examples using financial data on question and answer forums. The purpose of this book is to provide introductory resources and modular code examples to enable the effective communication and translation of financial data to actionable-insights.

1.3 How this book is organized

The organization of this guidebook is inspired by the book **R for Data Science** from Garrett Grolemund and Hadley Wickham which explores each step of the data science process from acquiring data on the web to communicating the outputs with dynamic reports and dashboards. Each section of the guidebook is meant to follow the typical data science workflow when followed in order however when jumping into existing projects which is a common approach in industry, the sections can be referenced as needed as standalone tutorials.

1.4 Prerequisites

If you don't already have R or RStudio:

- Download R at https://www.r-project.org/alt-home/
- Download RStudio at https://www.rstudio.com/products/rstudio/download/


Getting started with R Programming in FinTech
R for FinTech
An Introductory Guide
O RLY?
Jasmine Dumas

Figure 1.1:

Chapter 2

Import

2.1 Introduction

The first step in the typical data science project involves importing data into R. There are numerous packages for different data types all with varying preferences on speed and efficiency. Here are some R packages for importing data into R:

2.2 Tabular Data

Tabular data consists of variables, observations and values to form data frames. This is the most common format of organized data and many packages are developed to work with this type of data.

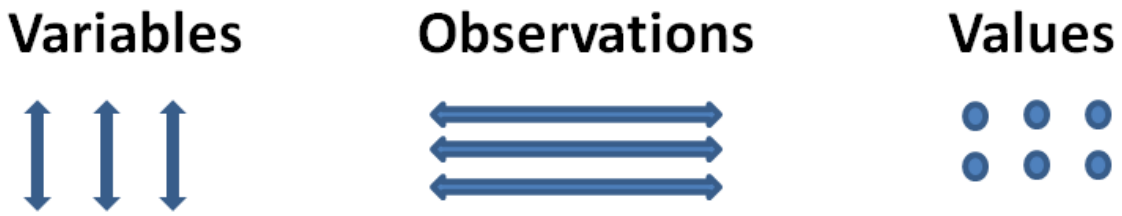


Figure 2.1:

2.2.1 readr

`readr`: Read flat/tabular text files from disk (or a connection). readr has some benefits over the base/utils version as smart column type parsing and not automatically converting strings into factors.

2.2.1.1 Examples

- Here is an example of credit card applications data set from the UCI Machine Learning Repository using `readr`:

```
library(readr)
cc_apps <- read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/credit-screening/crx.data
head(cc_apps)
```

```
## # A tibble: 6 × 16
##      X1    X2    X3    X4    X5    X6    X7    X8    X9   X10   X11   X12
##   <chr> <dbl> <dbl> <chr> <chr> <chr> <chr> <dbl> <chr> <chr> <chr> <chr>
## 1     b 30.83 0.000     u     g     w     v  1.25     t     t    01     f
## 2     a 58.67 4.460     u     g     q     h  3.04     t     t    06     f
## 3     a 24.50 0.500     u     g     q     h  1.50     t     f     0     f
## 4     b 27.83 1.540     u     g     w     v  3.75     t     t    05     t
## 5     b 20.17 5.625     u     g     w     v  1.71     t     f     0     f
## 6     b 32.08 4.000     u     g     m     v  2.50     t     f     0     t
## # ... with 4 more variables: X13 <chr>, X14 <chr>, X15 <int>, X16 <chr>
```

2.2.2 readxl

`readxl`: Import excel files into R. Supports '.xls' via the embedded 'libxls' C library (http://sourceforge.net/projects/libxls/) and '.xlsx' via the embedded 'RapidXML' C++ library (http://rapidxml.sourceforge.net). Works on Windows, Mac and Linux without external dependencies.

2.2.2.1 Examples

- Here is an example from the default of credit card clients data set from the UCI Machine Learning Repository using `readxl`:

```
# download the excel file first from the link
library(readxl)
default_cc <- read_excel("default of credit card clients.xls")

# alternative reading from a URL
require(RCurl)
require(gdata)
url <- "http://archive.ics.uci.edu/ml/machine-learning-databases/00350/default%20of%20credit%20card%20c
default_cc <- read.xls(url)

head(default_cc)
```

```
##    X        X1  X2        X3       X4  X5    X6    X7    X8    X9   X10
## 1 ID LIMIT_BAL SEX EDUCATION MARRIAGE AGE PAY_0 PAY_2 PAY_3 PAY_4 PAY_5
## 2  1     20000   2         2        1  24     2     2    -1    -1    -2
## 3  2    120000   2         2        2  26    -1     2     0     0     0
## 4  3     90000   2         2        2  34     0     0     0     0     0
## 5  4     50000   2         2        1  37     0     0     0     0     0
## 6  5     50000   1         2        1  57    -1     0    -1     0     0
##     X11       X12       X13       X14       X15       X16       X17
## 1 PAY_6 BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 BILL_AMT5 BILL_AMT6
## 2    -2      3913      3102       689         0         0         0
## 3     2      2682      1725      2682      3272      3455      3261
## 4     0     29239     14027     13559     14331     14948     15549
## 5     0     46990     48233     49291     28314     28959     29547
## 6     0      8617      5670     35835     20940     19146     19131
##        X18       X19       X20       X21       X22       X23
```

```
## 1 PAY_AMT1 PAY_AMT2 PAY_AMT3 PAY_AMT4 PAY_AMT5 PAY_AMT6
## 2        0      689        0        0        0        0
## 3        0     1000     1000     1000        0     2000
## 4     1518     1500     1000     1000     1000     5000
## 5     2000     2019     1200     1100     1069     1000
## 6     2000    36681    10000     9000      689      679
##                            Y
## 1 default payment next month
## 2                           1
## 3                           1
## 4                           0
## 5                           0
## 6                           0
```

2.3 Hierarchical Data

Hierarchical Data is a tree-structure data format such as XML, HTML, JSON. Popular methods for accessing this data are known as **web scraping** or **web data mining** when the goal is to parse data on a web page into a analysis-ready format such as a data frame.

2.3.1 jsonlite

`jsonlite`: A fast JSON parser and generator optimized for statistical data and the web.

2.3.1.1 Examples

TBD

2.3.2 xml2

`xml2`: Work with XML files using a simple, consistent interface. Built on top of the 'libxml2' C library.

2.3.2.1 Examples

TBD

2.3.3 rvest

`rvest`: Wrappers around the 'xml2' and 'httr' packages to make it easy to download, then manipulate, HTML and XML.

2.3.3.1 Examples

TBD

2.4 Relational Data

Relational Data consists of a collection of data items (tables) organized as a set based on the data contents and its relation.

2.4.1 DBI

`DBI`: A database interface definition for communication between R and relational database management systems. All classes in this package are virtual and need to be extended by the various R/DBMS implementations.

2.4.1.1 Examples

TBD

2.4.2 RMySQL

`RMySQL`: Implements 'DBI' Interface to 'MySQL' and 'MariaDB' Databases.

2.4.2.1 Examples

TBD

2.4.2.2 RPostgreSQL

`RPostgreSQL`:Database interface and PostgreSQL driver for R This package provides a Database Interface (DBI) compliant driver for R to access PostgreSQL database systems. In order to build and install this package from source, PostgreSQL itself must be present your system to provide PostgreSQL functionality via its libraries and header files. These files are provided as postgresql-devel package under some Linux distributions. On Microsoft Windows system the attached libpq library source will be used. A wiki and issue tracking system for the package are available at Google Code at https://code.google.com/p/rpostgresql/

2.4.2.3 Examples

TBD

2.5 Distributed Data

Distributed Data consists of non-relational formats with quick access to data over a large number of nodes (data spread over many different computers).

2.5.1 sparklyr

`sparklyr`: Filter and aggregate Spark datasets then bring them into R for analysis and visualization.

2.5.1.1 Examples

TBD

2.6 Additional Import Methods

Different Data Formats: The R programming language and environment is continuously increasing its capacity with new packages to work with different types of proprietory data formats from statistical software packages that are used on industry teams.

2.6.1 haven

`haven`: Import and Export 'SPSS', 'Stata' and 'SAS' Files.

2.6.1.1 Examples

Here is an example from Macquarie University data repository for the applied finance and actuarial studies of importing a SAS data set:

```
library(haven)
claims <- read_sas("http://www.businessandeconomics.mq.edu.au/our_departments/Applied_Finance_and_Actua
head(claims)
```

```
## # A tibble: 6 × 33
##          ID KIDSDRIV   PLCYDATE TRAVTIME    CAR_USE POLICYNO BLUEBOOK
##       <chr>    <dbl>     <date>    <dbl>      <chr>    <dbl>    <dbl>
## 1 100058542        0 1996-03-17 17.09181    Private 36292520     9860
## 2 100093408        0 1993-07-26 17.98656    Private 31958061     1500
## 3 100208113        0 1994-06-06 47.00727 Commercial 42433312    30460
## 4 100237269        0 1999-01-19 31.24381    Private 49896544    16580
## 5  10042968        0 1999-05-18 13.96243 Commercial 79298192    23030
## 6 100737644        0 1996-02-28 45.79204    Private 43393435    20730
## # ... with 26 more variables: INITDATE <date>, RETAINED <dbl>,
## #   NPOLICY <dbl>, CAR_TYPE <chr>, RED_CAR <chr>, OLDCLAIM <dbl>,
## #   CLM_FREQ <dbl>, REVOLKED <chr>, MVR_PTS <dbl>, CLM_AMT <dbl>,
## #   CLM_DATE <date>, CLM_FLAG <chr>, BIRTH <date>, AGE <dbl>,
## #   HOMEKIDS <dbl>, YOJ <dbl>, INCOME <dbl>, GENDER <chr>, MARRIED <chr>,
## #   PARENT1 <chr>, JOBCLASS <chr>, MAX_EDUC <chr>, HOME_VAL <dbl>,
## #   SAMEHOME <dbl>, DENSITY <chr>, YEARQTR <chr>
```

2.6.2 foreign

`foreign`: Functions for reading and writing data stored by some versions of Epi Info, Minitab, S, SAS, SPSS, Stata, Systat and Weka and for reading and writing some dBase files.

2.6.2.1 Examples

TBD

2.6.3 *Zipped Data*

Accessing Zipped Data files: Zip archives are actually more a 'filesystem' with content, meta data, and/or documentation.

1. Create a temp file. file name (eg tempfile())
2. Use download.file() to download the file into the temp object that is being reserved for the file

3. Use unzip() to extract the target file from temp file by reading the meta data on what specific data set you want which is contained in the zip file
4. Remove the temp file via unlink()

```
temp <- tempfile()
download.file("http://archive.ics.uci.edu/ml/machine-learning-databases/00222/bank.zip",temp)
unzip(temp, "bank.csv")
bank_marketing <- read.csv("bank.csv", sep=";") # sometimes its the default
unlink(temp)
head(bank_marketing)
```

```
##   age         job marital education default balance housing loan  contact
## 1  30  unemployed married   primary      no    1787      no   no cellular
## 2  33    services married secondary      no    4789     yes  yes cellular
## 3  35  management  single  tertiary      no    1350     yes   no cellular
## 4  30  management married  tertiary      no    1476     yes  yes  unknown
## 5  59 blue-collar married secondary      no       0     yes   no  unknown
## 6  35  management  single  tertiary      no     747      no   no cellular
##   day month duration campaign pdays previous poutcome  y
## 1  19   oct       79        1    -1        0  unknown no
## 2  11   may      220        1   339        4  failure no
## 3  16   apr      185        1   330        1  failure no
## 4   3   jun      199        4    -1        0  unknown no
## 5   5   may      226        1    -1        0  unknown no
## 6  23   feb      141        2   176        3  failure no
```

Chapter 3

Tidy

3.1 Introduction

Reshaping the data is an important (if necessary) step to exploratory data analysis and preparatory data cleaning for modeling or creating specialized visualization. Further concepts about *tidy data* can be found in this paper Tidy Data.

The principles of tidy data are:

1. Each variable forms a column
2. Each observation forms a row
3. Each type of observational unit forms a table

3.1.1 tidyr

- `tidyr`: An evolution of 'reshape2'. It's designed specifically for data tidying (not general reshaping or aggregating) and works well with 'dplyr' data pipelines. Tidy data complements R's vectorized operations. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R.

3.1.1.1 Examples

```
library(tidyr)
library(insuranceData)
library(magrittr)
data("AutoBi")
head(AutoBi)
```

```
##   CASENUM ATTORNEY CLMSEX MARITAL CLMINSUR SEATBELT CLMAGE   LOSS
## 1       5        1      1      NA        2        1     50 34.940
## 2      13        2      2       2        1        1     28 10.892
## 3      66        2      1       2        2        1      5  0.330
## 4      71        1      1       1        2        2     32 11.037
## 5      96        2      1       4        2        1     30  0.138
## 6      97        1      2       1        2        1     35  0.309
```

```
# create an interaction column
g <- AutoBi %>%  unite(col = MARITAL_CLMAGE, MARITAL, CLMAGE, sep = "*")
```

```
head(g)
```

```
##   CASENUM ATTORNEY CLMSEX MARITAL_CLMAGE CLMINSUR SEATBELT   LOSS
## 1       5        1      1          NA*50        2        1 34.940
## 2      13        2      2           2*28        1        1 10.892
## 3      66        2      1            2*5        2        1  0.330
## 4      71        1      1           1*32        2        2 11.037
## 5      96        2      1           4*30        2        1  0.138
## 6      97        1      2           1*35        2        1  0.309
```

Not all data that needs to be *tidied* comes in "long" format (i.e. the `spread()` function), so this data set below is put into tidy or cleaned format using base R functions and general manipulation. This data set has its observations stored in the row names field, delimited with a semicolon ";". The original column contains a mis-transformed value for the population density metric. The only variables' names are also a concatenation of the entire data set's column names delimited with a period ".".

- Data dictionary
- Original source data used in the insuranceData package

```
library(insuranceData)
library(magrittr)
data("Thirdparty")

head(Thirdparty) # rownames have column values
```

```
##                                      lga.sd.claims.accidents.ki.population.pop_density
## ASHFIELD;1;1103;2304;920;124850;0                                              499001
## AUBURN;1;1939;2660;1465;143500;0                                               148379
## BANKSTOWN;1;4339;7381;3864;470700;0                                            205407
## BAULKHAMHILLS;1;1491;3217;1554;311300;0                                         25879
## BLACKTOWN;1;3801;6655;4175;584900;0                                             81222
## BOTANY;1;387;2013;854;106350;0                                                 178143
```

```
cols = strsplit(colnames(Thirdparty) , "." , fixed=T)   # a new vector to use later
dput(unlist(cols))
```

```
## c("lga", "sd", "claims", "accidents", "ki", "population", "pop_density"
## )
```

```
rows2df <- sapply(rownames(Thirdparty), strsplit, ";", USE.NAMES = FALSE)

tidy_3PD <- data.frame(matrix(unlist(rows2df), nrow = nrow(Thirdparty), byrow=T))
colnames(tidy_3PD) <- c("lga", "sd", "claims", "accidents", "ki", "population",
"pop_density")
tidy_3PD$pop_density <- Thirdparty$lga.sd.claims.accidents.ki.population.pop_density / 1000000

head(tidy_3PD)
```

```
##             lga sd claims accidents   ki population pop_density
## 1      ASHFIELD  1   1103      2304  920     124850    0.499001
## 2        AUBURN  1   1939      2660 1465     143500    0.148379
## 3     BANKSTOWN  1   4339      7381 3864     470700    0.205407
## 4 BAULKHAMHILLS  1   1491      3217 1554     311300    0.025879
## 5     BLACKTOWN  1   3801      6655 4175     584900    0.081222
## 6        BOTANY  1    387      2013  854     106350    0.178143
```

Every variable forms a column and every observation forms a row which makes for a table!

Chapter 4

Transform

4.1 Introduction

Transforming cleaned data to create summaries and aggregations is an common part of the data analysis process along with extracting out data to create new features. With SQL-like commands you can answer numerous questions in the exploratory phase of a analysis prior to building a model with `dplyr`.

4.1.1 dplyr

`dplyr`: A fast, consistent tool for working with data frame like objects, both in memory and out of memory.

4.1.1.1 Examples

```
library(dplyr)
library(insuranceData)
library(magrittr)
data("AutoBi")

# summary of loss by whether or not the claimant was wearing a seatbelt/child restraint

AutoBi %>% group_by(SEATBELT, MARITAL) %>%
           summarise(mLOSS = median(LOSS))
```

```
## Source: local data frame [10 x 3]
## Groups: SEATBELT [?]
##
##    SEATBELT MARITAL mLOSS
##       <int>   <int> <dbl>
## 1         1       1 2.641
## 2         1       2 1.780
## 3         1       3 1.703
## 4         1       4 3.845
## 5         1      NA 3.120
## 6         2       1 3.919
## 7         2       2 2.328
## 8        NA       1 1.985
## 9        NA       2 1.433
```

```
## 10       NA       NA 2.364
```

Chapter 5

Visualization

5.1 Introduction

Data Visualization allows for the effective translation of data and processes into business applicable decisions that can explain key metrics. Ploting data prior to analysis can give key insights on variables and distributions.

5.2 Exploratory Visualization

Exploratory visualization involoves learning descriptive details prior to modeling efforts. Preemptive results from visualizing distributions can lead to more informed approachs in variable transformation, error distribution selection, parameter tunning.

5.2.1 ggplot2

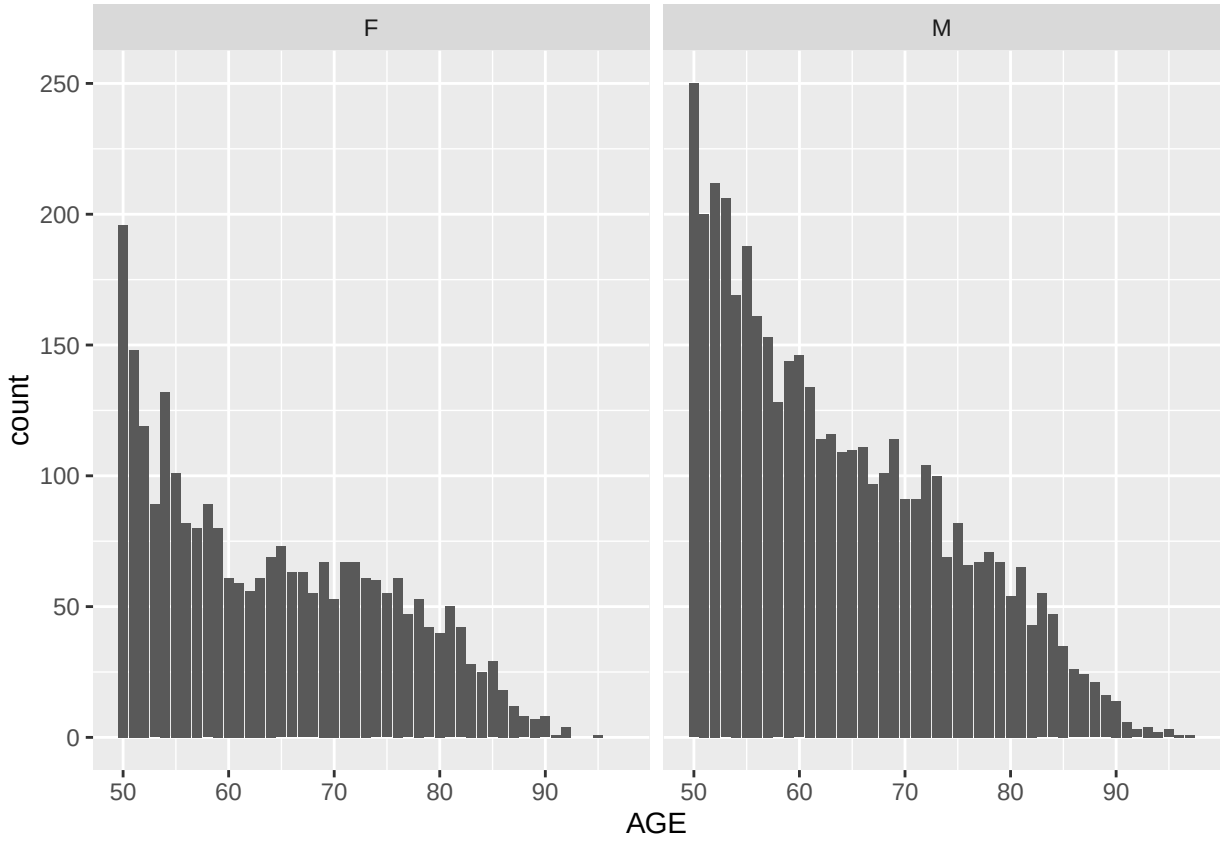
`ggplot2`: An implementation of the grammar of graphics in R. It combines the advantages of both base and lattice graphics: conditioning and shared axes are handled automatically, and you can still build up a plot step by step from multiple data sources. It also implements a sophisticated multidimensional conditioning system and a consistent interface to map data to aesthetic attributes.

5.2.1.1 Examples:

```
library(ggplot2)
library(insuranceData)
data("AutoClaims")
head(AutoClaims)
```

```
##      STATE CLASS GENDER AGE    PAID
## 1 STATE 14   C6       M  97 1134.44
## 2 STATE 15   C6       M  96 3761.24
## 3 STATE 15   C11      M  95 7842.31
## 4 STATE 15   F6       F  95 2384.67
## 5 STATE 15   F6       M  95  650.00
## 6 STATE 15   F6       M  95  391.12
```

```
g <- ggplot(AutoClaims, aes(x = AGE)) +
            geom_bar() +
            facet_grid(. ~ GENDER)
g
```



```
library(ggplot2)
library(insuranceData)


g2 <- ggplot(AutoClaims, aes(x = AGE, y = PAID, color = GENDER)) +
            geom_point() +
            geom_text(aes(label = STATE)) +
            theme_classic()
g2
```

5.3 Interactive Visualization

5.3.1 plotly

`plotly`: Easily translate 'ggplot2' graphs to an interactive web-based version and/or create custom web-based visualizations directly from R. Once uploaded to a 'plotly' account, 'plotly' graphs (and the data behind them) can be viewed and modified in a web browser.

5.3.1.1 Examples

```
suppressPackageStartupMessages(library(plotly))
library(insuranceData)
data("AutoCollision")
head(AutoCollision)
```

```
##   Age Vehicle_Use Severity Claim_Count
## 1   A    Pleasure   250.48          21
## 2   A  DriveShort   274.78          40
## 3   A   DriveLong   244.52          23
## 4   A    Business   797.80           5
## 5   B    Pleasure   213.71          63
## 6   B  DriveShort   298.60         171
```

```
plot_ly(AutoCollision, x = Severity, y = Claim_Count, mode = "markers",
        color = Severity, size = Severity)
```

5.4 Other visualization packages

- rcharts
- leaflet
- ggvis
- htmlwidget
- googleVis

Chapter 6

Model

Build Models

6.1 LM

- `lm()`: In statistics, the term linear model is used for drawing primary associations with a response (dependent variable) and covariate(s) (independent variable(s)) as a regression analysis technique. Source: Wikipedia

Examples:

```
library(insuranceData)
data("AutoCollision")
head(AutoCollision)
```

```
##   Age Vehicle_Use Severity Claim_Count
## 1   A    Pleasure   250.48          21
## 2   A  DriveShort   274.78          40
## 3   A   DriveLong   244.52          23
## 4   A    Business   797.80           5
## 5   B    Pleasure   213.71          63
## 6   B  DriveShort   298.60         171
```

```
fit <- lm(Severity ~ Vehicle_Use + Age + Claim_Count, data = AutoCollision)
summary(fit)
```

```
##
## Call:
## lm(formula = Severity ~ Vehicle_Use + Age + Claim_Count, data = AutoCollision)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -130.430  -24.580   -1.353   23.368  274.270
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             523.0303    51.1632  10.223 2.18e-09 ***
## Vehicle_UseDriveLong   -150.3807    50.6663  -2.968 0.007603 **
## Vehicle_UseDriveShort  -198.6347    65.8048  -3.019 0.006786 **
## Vehicle_UsePleasure    -184.4265    40.9901  -4.499 0.000219 ***
```

```
## AgeB                  -105.7532    58.6628  -1.803 0.086521 .
## AgeC                  -128.0870    65.4756  -1.956 0.064546 .
## AgeD                  -137.4725    68.6554  -2.002 0.058992 .
## AgeE                  -206.6701    70.2024  -2.944 0.008026 **
## AgeF                  -195.6402    97.7303  -2.002 0.059052 .
## AgeG                  -183.3416    85.0540  -2.156 0.043476 *
## AgeH                  -173.1478    71.6721  -2.416 0.025387 *
## Claim_Count              0.1000     0.1468   0.681 0.503380
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 81.67 on 20 degrees of freedom
## Multiple R-squared:  0.6472, Adjusted R-squared:  0.4532
## F-statistic: 3.336 on 11 and 20 DF,  p-value: 0.009379
```

```
# this is not the best model we could have constructed as the lm assumes the error distribution of the
```

6.2 GLM

- `glm()`: In statistics, the generalized linear model (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value. Source: Wikipedia

Examples:

```
library(insuranceData)
data("AutoCollision")

fit <- glm(Severity ~ Vehicle_Use + Age + Claim_Count, data = AutoCollision, family = Gamma(link = "inv
summary(fit)
```

```
##
## Call:
## glm(formula = Severity ~ Vehicle_Use + Age + Claim_Count, family = Gamma(link = "inverse"),
##     data = AutoCollision)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -0.36252  -0.07729   0.00388   0.06376   0.23788
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             1.576e-03  1.939e-04   8.131 9.07e-08 ***
## Vehicle_UseDriveLong    1.206e-03  2.750e-04   4.388 0.000284 ***
## Vehicle_UseDriveShort   1.752e-03  3.760e-04   4.659 0.000151 ***
## Vehicle_UsePleasure     2.096e-03  2.671e-04   7.847 1.57e-07 ***
## AgeB                    7.881e-04  2.954e-04   2.668 0.014762 *
## AgeC                    8.927e-04  3.411e-04   2.617 0.016503 *
## AgeD                    9.567e-04  3.660e-04   2.614 0.016604 *
## AgeE                    2.040e-03  4.331e-04   4.710 0.000134 ***
## AgeF                    1.381e-03  5.526e-04   2.500 0.021237 *
## AgeG                    1.353e-03  4.600e-04   2.942 0.008068 **
```

```
## AgeH                   1.395e-03  3.902e-04   3.575 0.001894 **
## Claim_Count           -8.694e-08  9.419e-07  -0.092 0.927375
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Gamma family taken to be 0.02045281)
##
##     Null deviance: 3.20647  on 31  degrees of freedom
## Residual deviance: 0.42585  on 20  degrees of freedom
## AIC: 335.24
##
## Number of Fisher Scoring iterations: 4
```

```
r_squared = 1 - ( fit$deviance / fit$df.null ) # psuedo r2 for GLMs

r_squared
```

```
## [1] 0.9862631
```

```
# this model explains much more variance now that the error distribution has been specified correctly
```

- Probability distributions from the exponential family

    1. Claim Counts: **Multiplicative Poisson** model forms fit due to the poisson distribution is invariant to meatures of time.
    2. Frequency: **Multiplicative Poisson** model forms fit due to the poisson distribution is invariant to meatures of time.
    3. Severity: **Multiplicative Gamma** model forms fit because the gamma distribution is invariant to measures of currency.
    4. Retension and New Business: **Binomial with logit** model form fits becasue the binomial distribution is invariant to measures of success or failure.

6.3 GBM

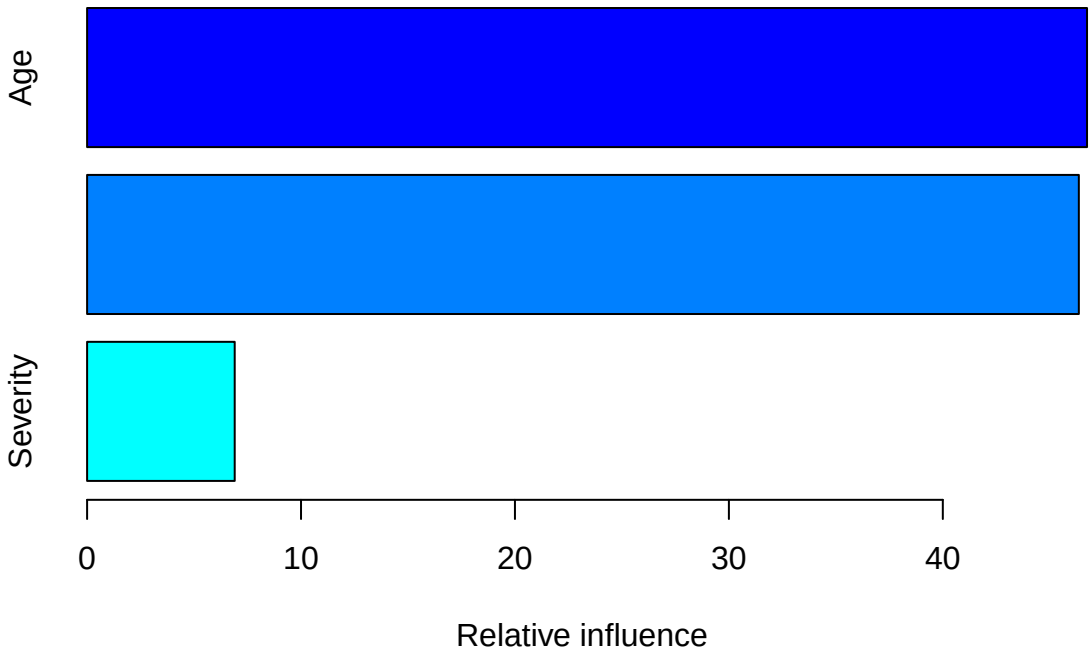
Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function. Source: Wikipedia

- Parameter tuning is prudent in machine learning!

Examples:

```
library(insuranceData)
data("AutoCollision")
library(gbm)

# let's build a a GBM model which combines some weak learners into a strong learner as to boost the pre
fit <- gbm(Claim_Count ~ Vehicle_Use + Age + Severity, data=AutoCollision, distribution = "poisson", n.
summary(fit)
```




```
##                     var   rel.inf
## Age                 Age 46.741540
## Vehicle_Use Vehicle_Use 46.358522
## Severity       Severity  6.899939
```

6.4 Ensemble learning

In statistics and machine learning, ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone. Source: Wikipedia

- h2o / stacking

6.5 Additional Machine Learning Techniques

- `xgboost`: Extreme Gradient Boosting, which is an efficient implementation of gradient boosting framework. This package is its R interface. The package includes efficient linear model solver and tree learning algorithms. The package can automatically do parallel computation on a single machine which could be more than 10 times faster than existing gradient boosting packages. It supports various objective functions, including regression, classification and ranking. The package is made to be extensible, so that users are also allowed to define their own objectives easily.
- `TDboost`: A boosted Tweedie compound Poisson model using the gradient boosting. It is capable of fitting a flexible nonlinear Tweedie compound Poisson model (or a gamma model) and capturing interactions among predictors.
- `glmnet`: lasso, ridge, elasticnet: Extremely efficient procedures for fitting the entire lasso (least absolute shrinkage and selection operator) or elastic-net regularization path for linear regression, logistic and multinomial regression models, Poisson regression and the Cox model. Two recent additions are the multiple-response Gaussian, and the grouped multinomial. The algorithm uses cyclical coordinate descent in a path-wise fashion.
- `randomForest`: Classification and regression based on a forest of trees using random inputs.

- K-means / K-mediods: K Means Clustering is an unsupervised learning algorithm that tries to cluster data based on their similarity. Available in the base `stats` package

Chapter 7

Communicate

In Data Science our role is to be translators. We are tasked with translating buisness-driven inquires to discovering implicit knowledge from data and transforming knowledge into actionable results.

7.1 Tools for Communication and Reproducible Research

- `knitr`: Provides a general-purpose tool for dynamic report generation in R using Literate Programming techniques.
- `rmarkdown`: Convert R Markdown documents into a variety of formats (HTML, Word, PDF, Notebooks, Presentaions, dashboards).
- Bookdown (meta): Output formats and utilities for authoring books with R Markdown.
- `shiny`: Makes it incredibly easy to build interactive web applications with R. Automatic "reactive" binding between inputs and outputs and extensive pre-built widgets make it possible to build beautiful, responsive, and powerful applications with minimal effort.
- `flexdashboard`: Format for converting an R Markdown document to a grid oriented dashboard. The dashboard flexibly adapts the size of it's components to the containing web page.

Chapter 8

References

1. Yihui Xie (NA). bookdown: Authoring Books with R Markdown. R package version 0.1.15. https://github.com/rstudio/bookdown
2. Hadley Wickham, Jim Hester and Romain Francois (2016). readr: Read Tabular Data. R package version 1.0.0. https://CRAN.R-project.org/package=readr
3. Hadley Wickham (2016). readxl: Read Excel Files. R package version 0.1.1. https://CRAN.R-project.org/package=readxl
4. Jeroen Ooms (2014). The jsonlite Package: A Practical and Consistent Mapping Between JSON Data and R Objects. arXiv:1403.2805 [stat.CO] URL http://arxiv.org/abs/1403.2805.
5. Hadley Wickham and James Hester (2016). xml2: Parse XML. R package version 1.0.0. https://CRAN.R-project.org/package=xml2
6. Hadley Wickham (2016). rvest: Easily Harvest (Scrape) Web Pages. R package version 0.3.2. https://CRAN.R-project.org/package=rvest
7. R Special Interest Group on Databases (R-SIG-DB), Hadley Wickham and Kirill Müller (2016). DBI: R Database Interface. R package version 0.5. https://CRAN.R-project.org/package=DBI
8. Jeroen Ooms, David James, Saikat DebRoy, Hadley Wickham and Jeffrey Horner (2016). RMySQL: Database Interface and 'MySQL' Driver for R. R package version 0.10.9. https://CRAN.R-project.org/package=RMySQL
9. Joe Conway, Dirk Eddelbuettel, Tomoaki Nishiyama, Sameer Kumar Prayaga and Neil Tiffin (2016). RPostgreSQL: R interface to the PostgreSQL database system. R package version 0.4-1. https://CRAN.R-project.org/package=RPostgreSQL
10. Javier Luraschi, Kevin Ushey, JJ Allaire and The Apache Software Foundation (2016). sparklyr: R Interface to Apache Spark. R package version 0.4. https://CRAN.R-project.org/package=sparklyr
11. Hadley Wickham and Evan Miller (2016). haven: Import and Export 'SPSS', 'Stata' and 'SAS' Files. R package version 1.0.0. https://CRAN.R-project.org/package=haven
12. R Core Team (2015). foreign: Read Data Stored by Minitab, S, SAS, SPSS, Stata, Systat, Weka, dBase, ... R package version 0.8-66. https://CRAN.R-project.org/package=foreign

8.1 Session Info

```
## Session info -------------------------------------------------------------
```

```
##  setting  value
##  version  R version 3.3.1 (2016-06-21)
##  system   x86_64, darwin13.4.0
##  ui       X11
##  language (EN)
##  collate  en_US.UTF-8
```

```
##  tz       America/New_York
##  date     2016-10-30

## Packages -----------------------------------------------------------------

##  package       * version  date       source
##  assertthat      0.1      2013-12-06 CRAN (R 3.3.0)
##  base64enc       0.1-3    2015-07-28 CRAN (R 3.3.0)
##  bitops        * 1.0-6    2013-08-17 CRAN (R 3.3.0)
##  bookdown        0.1.15   2016-10-04 Github (rstudio/bookdown@c0b02d4)
##  colorspace      1.2-6    2015-03-11 CRAN (R 3.3.0)
##  curl            1.2      2016-08-13 CRAN (R 3.3.0)
##  DBI             0.5      2016-08-11 CRAN (R 3.3.0)
##  devtools        1.12.0   2016-06-24 CRAN (R 3.3.0)
##  digest          0.6.10   2016-08-02 CRAN (R 3.3.0)
##  dplyr         * 0.5.0    2016-06-24 CRAN (R 3.3.0)
##  evaluate        0.9      2016-04-29 CRAN (R 3.3.0)
##  formatR         1.4      2016-05-09 CRAN (R 3.3.0)
##  gbm           * 2.1.1    2015-03-11 CRAN (R 3.3.0)
##  gdata         * 2.17.0   2015-07-04 CRAN (R 3.3.0)
##  ggplot2       * 2.1.0    2016-03-01 CRAN (R 3.3.0)
##  gridExtra       2.2.1    2016-02-29 CRAN (R 3.3.0)
##  gtable          0.2.0    2016-02-26 CRAN (R 3.3.0)
##  gtools          3.5.0    2015-05-29 CRAN (R 3.3.0)
##  haven         * 1.0.0    2016-09-23 CRAN (R 3.3.0)
##  htmltools       0.3.5    2016-03-21 CRAN (R 3.3.0)
##  htmlwidgets     0.7      2016-08-02 CRAN (R 3.3.0)
##  httpuv          1.3.3    2015-08-04 CRAN (R 3.3.0)
##  httr            1.2.1    2016-07-03 cran (@1.2.1)
##  insuranceData * 1.0      2014-09-04 CRAN (R 3.3.0)
##  jsonlite        1.0      2016-07-01 CRAN (R 3.3.0)
##  knitr           1.14.9   2016-10-04 Github (yihui/knitr@63407ab)
##  labeling        0.3      2014-08-23 CRAN (R 3.3.0)
##  lattice       * 0.20-33  2015-07-14 CRAN (R 3.3.1)
##  lazyeval        0.2.0    2016-06-12 CRAN (R 3.3.0)
##  magrittr      * 1.5      2014-11-22 CRAN (R 3.3.0)
##  Matrix          1.2-6    2016-05-02 CRAN (R 3.3.1)
##  memoise         1.0.0    2016-01-29 CRAN (R 3.3.0)
##  mime            0.5      2016-07-07 CRAN (R 3.3.0)
##  miniUI          0.1.1    2016-01-15 cran (@0.1.1)
##  munsell         0.4.3    2016-02-13 CRAN (R 3.3.0)
##  plotly        * 3.6.0    2016-05-18 CRAN (R 3.3.0)
##  plyr            1.8.4    2016-06-08 CRAN (R 3.3.0)
##  R6              2.1.3    2016-08-19 CRAN (R 3.3.0)
##  Rcpp            0.12.6   2016-07-19 CRAN (R 3.3.0)
##  RCurl         * 1.95-4.8 2016-03-01 CRAN (R 3.3.0)
##  readr         * 1.0.0    2016-08-03 CRAN (R 3.3.0)
##  readxl        * 0.1.1    2016-03-28 CRAN (R 3.3.0)
##  reshape2        1.4.1    2014-12-06 CRAN (R 3.3.0)
##  rmarkdown       1.1      2016-10-16 CRAN (R 3.3.1)
##  rstudioapi      0.6      2016-06-27 CRAN (R 3.3.0)
##  scales          0.4.0    2016-02-26 CRAN (R 3.3.0)
##  shiny           0.14     2016-09-10 cran (@0.14)
##  stringi         1.1.1    2016-05-27 CRAN (R 3.3.0)
##  stringr         1.1.0    2016-08-19 CRAN (R 3.3.0)
```

```
##  survival      * 2.39-5   2016-06-26 CRAN (R 3.3.0)
##  tibble          1.2      2016-08-26 CRAN (R 3.3.0)
##  tidyr         * 0.6.0    2016-08-12 CRAN (R 3.3.0)
##  viridis         0.3.4    2016-03-12 CRAN (R 3.3.0)
##  webshot         0.3.2    2016-08-04 Github (wch/webshot@52891c1)
##  withr           1.0.2    2016-06-20 CRAN (R 3.3.0)
##  xtable          1.8-2    2016-02-05 CRAN (R 3.3.0)
##  yaml            2.1.13   2014-06-12 CRAN (R 3.3.0)
```

Chapter 9

Learning Resources

9.1 R Programming Resources

- **R for Data Science**
- bookdown: Authoring Books with R Markdown
- Data Science Curated List from Author Jasmine Dumas
- Applied Predictive Modeling
- R in Finance Conference

9.2 Financial Technology Resources

9.2.1 Social

- Simple Finance Blog
- Wharton FinTech Group, Blog
- #fintech on Twitter

9.2.2 Articles

- 8 Ways Financial Technology Will Evolve in 2016 by JOHN BOITNOTT, Journalist and digital consultant
- Predicting the future of financial technology by Mashable
- HOW CRYPTOCURRENCIES ARE BEGINNING TO SHAPE FINTECH EDUCATION IN COLLEGES by Angela Ruth at due

9.2.3 Education

- Fintech Basics from Udemy
- Investment Management Specialization from Coursera
- Bitcoin and Cryptocurrency Technologies from Coursera
- Economics & Finance Courses from edX

Bibliography