# Basics of Statistical Learning

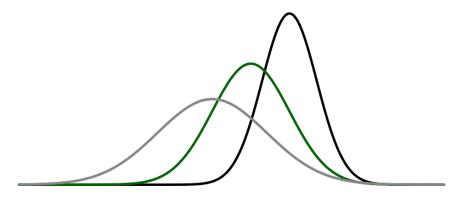
David Dalpiaz 2019-08-30

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## **Preface**



Welcome to Basics of Statistical Learning!

- TODO: Warning about development.
- TODO: Warning about PDF version.
- TODO: Transfer acknowledgements.
- TODO: discuss https://daviddalpiaz.github.io/r4sl/

## License



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## Chapter 1

## Introduction

```
library(readr)
library(tibble)
library(dplyr)
library(purrr)
library(ggplot2)
library(ggridges)
library(lubridate)
library(randomForest)
library(rpart)
library(rpart.plot)
library(cluster)
library(caret)
library(factoextra)
library(rsample)
library(janitor)
library(rvest)
library(dendextend)
library(knitr)
library(kableExtra)
library(ggthemes)
```

- TODO: Show package messaging? check conflicts!
- TODO: Should this be split into three analyses with different packages?

## 1.1 Regression: Powerlifting

#### 1.1.1 Background

- TODO: https://www.openpowerlifting.org/
- TODO: https://en.wikipedia.org/wiki/Powerlifting

#### 1.1.2 Data

- TODO: Why readr::col\_factor() and not just col\_factor()?
- TODO: Characters should be character and "categories" should be factors.
- TODO: Is na.omit() actually a good idea?

```
pl = read_csv("data/pl.csv", col_types = cols(Sex = readr::col_factor()))
pl
## # A tibble: 3,604 x 8
##
     Name
                     Sex
                          Bodyweight
                                       Age Squat Bench Deadlift Total
##
     <chr>
                    <fct>
                               <dbl> <dbl> <dbl> <dbl> <
                                                        <dbl> <dbl>
## 1 Ariel Stier
                    F
                                60
                                       32 128.
                                                 72.5
                                                         150
                                                               350
## 2 Nicole Bueno
                                60
                                       26 110
                                                 60
                                                         135
                                                               305
## 3 Lisa Peterson F
                                67.5
                                       28 118.
                                                 67.5
                                                         138. 322.
## 4 Shelby Bandula F
                                67.5
                                       26 92.5 67.5
                                                         140
                                                               300
                                       28 92.5 62.5
                                                         132. 288.
## 5 Lisa Lindhorst F
                                67.5
## 6 Laura Burnett
                     F
                                67.5
                                       30 90
                                                 45
                                                         108. 242.
## 7 Suzette Bradley F
                               75
                                       38 125
                                                 75
                                                         158. 358.
## 8 Norma Romero
                     F
                                75
                                       20 92.5 42.5
                                                         125
                                                               260
## 9 Georgia Andrews F
                                82.5
                                       29 108.
                                                 52.5
                                                         120
                                                               280
## 10 Christal Bundang F
                                90
                                        30 100
                                                 55
                                                         125
                                                               280
## # ... with 3,594 more rows
```

#### 1.1.3 EDA

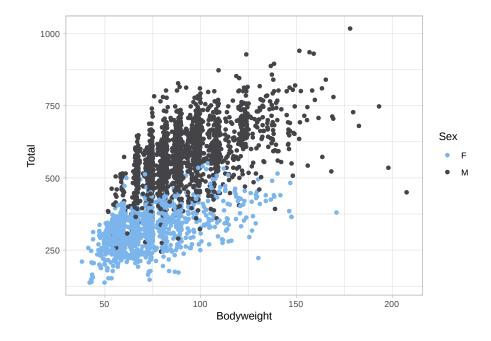
```
set.seed(1)

# test-train split
pl_tst_trn_split = initial_split(pl, prop = 0.80)
pl_trn = training(pl_tst_trn_split)
pl_tst = testing(pl_tst_trn_split)

# estimation-validation split
pl_est_val_split = initial_split(pl_trn, prop = 0.80)
```

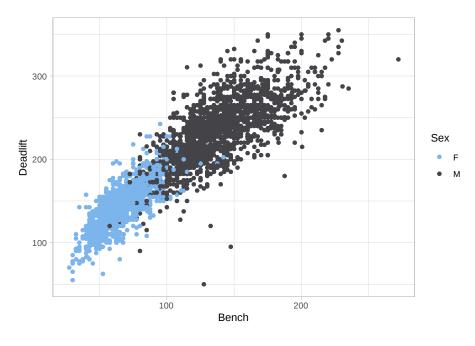
```
pl_est = training(pl_est_val_split)
pl_val = testing(pl_est_val_split)
rm(pl)
```

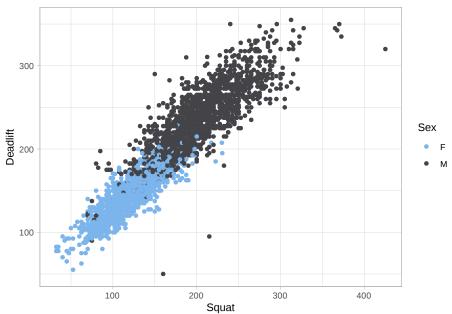
- TODO: Train can be used however you want. (Including EDA.)
- TODO: Test can only be used after all model decisions have been made!





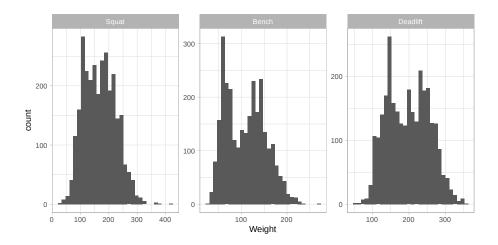




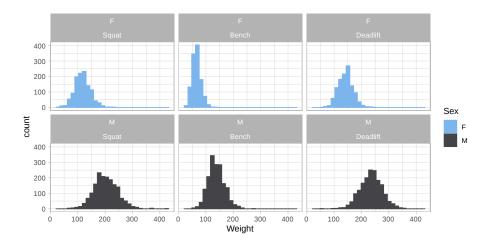


pl\_trn\_tidy\$Lift = factor(pl\_trn\_tidy\$Lift, levels = c("Squat", "Bench", "Deadlift"))

TODO: https://www.tidyverse.org/
TODO: https://en.wikipedia.org/wiki/Tidy\_data
TODO: http://vita.had.co.nz/papers/tidy-data.pdf





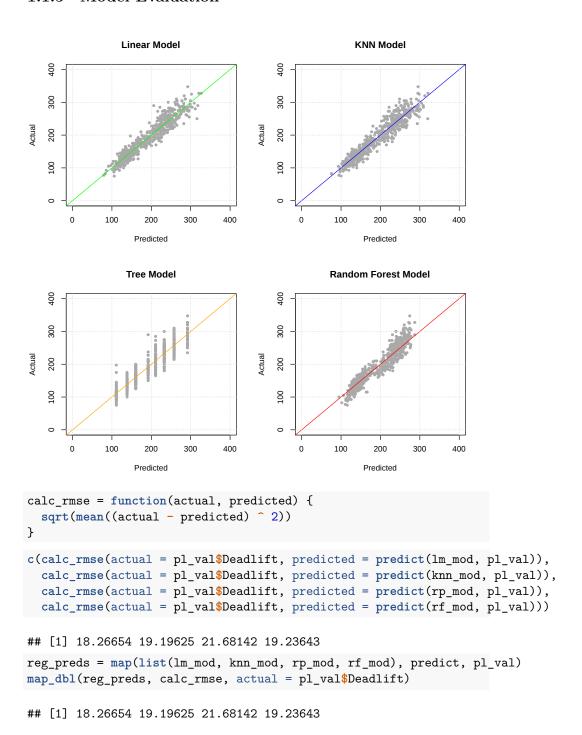


#### 1.1.4 Modeling

```
dl_mod_form = formula(Deadlift ~ Sex + Bodyweight + Age + Squat + Bench)
set.seed(1)
lm_mod = lm(dl_mod_form, data = pl_est)
knn_mod = caret::knnreg(dl_mod_form, data = pl_est)
rf_mod = randomForest(dl_mod_form, data = pl_est)
rp_mod = rpart(dl_mod_form, data = pl_est)
```

- TODO: Note: we are not using Name. Why? We are not using Total. Why?
- TODO: look what happens with Total! You'll see it with lm(), you'll be optimistic with randomForest().
- TODO: What variables are allowed? (With respect to real world problem.)
- TODO: What variables lead to the best predictions?

#### 1.1.5 Model Evaluation



• TODO: Never supply data = df to predict(). You have been warned.

```
knitr::include_graphics("img/sim-city.jpg")
```



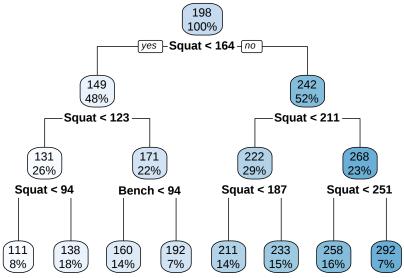
```
calc_mae = function(actual, predicted) {
  mean(abs(actual - predicted))
}
map_dbl(reg_preds, calc_mae, actual = pl_val$Deadlift)
```

```
## [1] 14.38953 14.99748 17.14823 15.28626
```

```
reg_results = tibble(
  Model = c("Linear", "KNN", "Tree", "Forest"),
  RMSE = map_dbl(reg_preds, calc_rmse, actual = pl_val$Deadlift),
  MAE = map_dbl(reg_preds, calc_mae, actual = pl_val$Deadlift))
```

Model	RMSE	MAE
Linear	18.26654	14.38953
KNN	19.19625	14.99748
Tree	21.68142	17.14823
Forest	19.23643	15.28626

### 1.1.6 Discussion



```
lm_mod_final = lm(dl_mod_form, data = pl_trn)
calc_rmse(actual = pl_tst$Deadlift,
          predicted = predict(lm_mod_final, pl_tst))
## [1] 22.29668
  • TODO: Is this a good model?
  • TODO: Is this model useful?
william_biscarri = tibble(
  Name = "William Biscarri",
  Age = 28,
  Sex = "M",
  Bodyweight = 83,
  Squat = 130,
  Bench = 90
predict(lm_mod_final, william_biscarri)
##
         1
## 175.495
```

## 1.2 Classification: Handwritten Digits

#### 1.2.1 Background

- TODO: https://en.wikipedia.org/wiki/MNIST\_database
- TODO: http://yann.lecun.com/exdb/mnist/

#### 1.2.2 Data

- TODO: How is this data pre-processed?
- TODO: https://gist.github.com/daviddalpiaz/ae62ae5ccd0bada4b9acd6dbc9008706
- TODO: https://github.com/itsrainingdata/mnistR
- TODO: https://pjreddie.com/projects/mnist-in-csv/
- TODO: http://varianceexplained.org/r/digit-eda/

```
mnist_trn = read_csv(file = "data/mnist_train_subest.csv")
mnist_tst = read_csv(file = "data/mnist_test.csv")

mnist_trn_y = as.factor(mnist_trn$X1)
mnist_tst_y = as.factor(mnist_tst$X1)

mnist_trn_x = mnist_trn[, -1]
mnist_tst_x = mnist_tst[, -1]
```

- TODO: If we were going to tune a model, we would need a validation split as well. We're going to be lazy and just fit a single random forest.
- TODO: This is an agreed upon split.

#### 1.2.3 EDA



#### 1.2.4 Modeling

```
set.seed(42)
mnist_rf = randomForest(x = mnist_trn_x, y = mnist_trn_y, ntree = 100)
```

#### 1.2.5 Model Evaluation

```
mnist_tst_pred = predict(mnist_rf, mnist_tst_x)
mean(mnist_tst_pred == mnist_tst_y)
## [1] 0.8839
table(predicted = mnist_tst_pred, actual = mnist_tst_y)
##
            actual
## predicted
                     1
                          2
                              3
                                        5
                                             6
                                                   7
                                                       8
                                                             9
                        14
##
          0 959
                    0
                              6
                                   1
                                       15
                                             22
                                                   1
                                                       10
                                                            10
##
           1
                0 1112
                         5
                              5
                                       16
##
           2
                    2 928
                             31
                                   3
                                        5
                                             19
                                                  24
                                                       17
                                                            8
                1
##
           3
                0
                    2
                        11
                             820
                                   1
                                       24
                                             0
                                                  1
                                                      13
                                                           13
           4
##
               4
                    0
                        13
                                 839
                                       21
                                             39
                                                  11
                                                      18
                                                            40
                             1
##
           5
               3
                             88
                                   3 720
                                                  1
                                                      25
                                                            9
                    1
                         1
                                            18
           6
               7
                    2
                                                            2
##
                       15
                              3
                                  25
                                       15
                                            848
                                                   0
                                                       18
##
           7
               2
                    1
                        29
                             24
                                   1
                                       14
                                             2 928
                                                      15
                                                           30
##
           8
               4
                             22
                                    5
                                                      797
                    14
                       13
                                       19
                                              5
                                                   4
                                                             3
##
                   1
                         3
                            10 103
                                       43
                                                 49
                                                      56 888
```

#### 1.2.6 Discussion

```
par(mfrow = c(3, 3))
plot_mistake(actual = 6, predicted = 4)
```

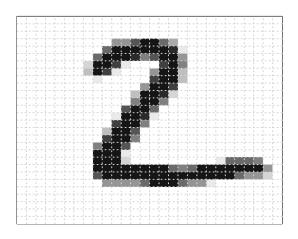
```
mnist_obs_to_check = 2
predict(mnist_rf, mnist_tst_x[mnist_obs_to_check, ], type = "prob")[1, ]

## 0 1 2 3 4 5 6 7 8 9
## 0.09 0.03 0.25 0.14 0.02 0.14 0.25 0.01 0.05 0.02

mnist_tst_y[mnist_obs_to_check]

## [1] 2
## Levels: 0 1 2 3 4 5 6 7 8 9
```

show\_digit(mnist\_tst\_x[mnist\_obs\_to\_check, ])



## 1.3 Clustering: NBA Players

## 1.3.1 Background

- https://www.youtube.com/watch?v=cuLprHh\_BRg
- $\bullet \ \, https://www.youtube.com/watch?v=1FBwSO\_1Mb8$
- $\bullet \ \, https://www.basketball-reference.com/leagues/NBA\_2019.html$

#### 1.3.2 Data

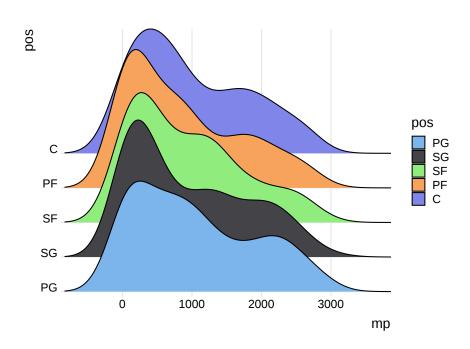
- $\bullet \ \ https://www.basketball-reference.com/leagues/NBA\_2019\_totals.html$

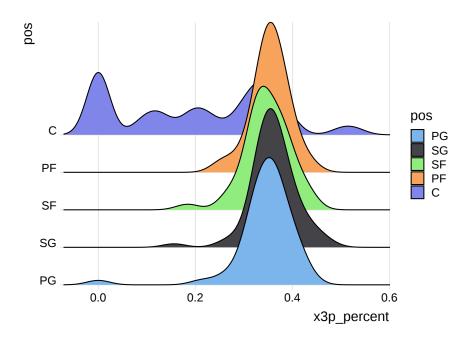
- https://www.basketball-reference.com/leagues/NBA\_2019\_per\_poss. html
- https://www.basketball-reference.com/leagues/NBA\_2019\_advanced.

```
nba = scrape_nba_season_player_stats()
nba$pos = factor(nba$pos, levels = c("PG", "SG", "SF", "PF", "C"))
```

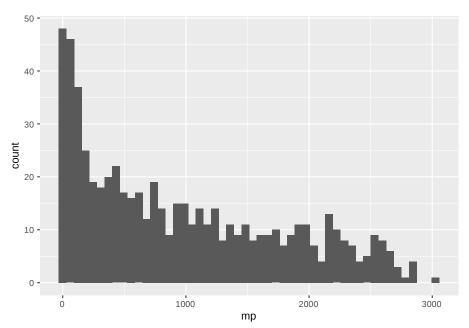
```
## # A tibble: 100 x 93
##
      player_team pos
                                                                fga fg_percent
                           age tm
                                                           fg
                                              gs
                                                     mp
                                         g
##
      <chr>
                  <fct> <dbl> <chr> <dbl> <dbl> <dbl> <dbl>
                                                        <dbl> <dbl>
                                                                          <dbl>
    1 Álex Abrin~ SG
                            25 OKC
                                        31
                                               2
                                                    588
                                                           56
                                                                157
                                                                         0.357
    2 Quincy Acy~ PF
                            28 PHO
                                                                         0.222
##
                                        10
                                               0
                                                    123
                                                            4
                                                                 18
##
    3 Jaylen Ada~ PG
                            22 ATL
                                        34
                                               1
                                                    428
                                                           38
                                                                110
                                                                         0.345
##
    4 Steven Ada~ C
                            25 OKC
                                        80
                                              80
                                                   2669
                                                          481
                                                                809
                                                                         0.595
##
   5 Bam Adebay~ C
                            21 MIA
                                        82
                                                   1913
                                                                486
                                                                         0.576
                                              28
                                                          280
    6 Deng Adel ~ SF
##
                            21 CLE
                                        19
                                               3
                                                    194
                                                           11
                                                                 36
                                                                         0.306
##
    7 DeVaughn A~ SG
                            25 DEN
                                         7
                                               0
                                                     22
                                                                 10
                                                                         0.3
                                                            3
##
   8 LaMarcus A~ C
                            33 SAS
                                        81
                                              81
                                                   2687
                                                          684
                                                               1319
                                                                         0.519
##
    9 Rawle Alki~ SG
                            21 CHI
                                        10
                                                    120
                                                           13
                                                                 39
                                                                         0.333
                                               1
## 10 Grayson Al~ SG
                            23 UTA
                                        38
                                               2
                                                    416
                                                           67
                                                                178
                                                                         0.376
## # ... with 90 more rows, and 83 more variables: x3p <dbl>, x3pa <dbl>,
       x3p_percent <dbl>, x2p <dbl>, x2pa <dbl>, x2p_percent <dbl>,
## #
       e_fg_percent <dbl>, ft <dbl>, fta <dbl>, ft_percent <dbl>, orb <dbl>,
## #
       drb <dbl>, trb <dbl>, ast <dbl>, stl <dbl>, blk <dbl>, tov <dbl>,
## #
       pf <dbl>, pts <dbl>, fg_pm <dbl>, fga_pm <dbl>, fg_percent_pm <dbl>,
## #
       x3p_pm <dbl>, x3pa_pm <dbl>, x3p_percent_pm <dbl>, x2p_pm <dbl>,
## #
       x2pa_pm <dbl>, x2p_percent_pm <dbl>, ft_pm <dbl>, fta_pm <dbl>,
## #
       ft_percent_pm <dbl>, orb_pm <dbl>, drb_pm <dbl>, trb_pm <dbl>,
## #
       ast_pm <dbl>, stl_pm <dbl>, blk_pm <dbl>, tov_pm <dbl>, pf_pm <dbl>,
## #
       pts_pm <dbl>, fg_pp <dbl>, fga_pp <dbl>, fg_percent_pp <dbl>,
## #
       x3p_pp <dbl>, x3pa_pp <dbl>, x3p_percent_pp <dbl>, x2p_pp <dbl>,
## #
       x2pa_pp <dbl>, x2p_percent_pp <dbl>, ft_pp <dbl>, fta_pp <dbl>,
## #
       ft_percent_pp <dbl>, orb_pp <dbl>, drb_pp <dbl>, trb_pp <dbl>,
## #
       ast_pp <dbl>, stl_pp <dbl>, blk_pp <dbl>, tov_pp <dbl>, pf_pp <dbl>,
## #
       pts_pp <dbl>, o_rtg_pp <dbl>, d_rtg_pp <dbl>, per <dbl>,
## #
       ts_percent <dbl>, x3p_ar <dbl>, f_tr <dbl>, orb_percent <dbl>,
## #
       drb_percent <dbl>, trb_percent <dbl>, ast_percent <dbl>,
## #
       stl_percent <dbl>, blk_percent <dbl>, tov_percent <dbl>,
## #
       usg_percent <dbl>, ows <dbl>, dws <dbl>, ws <dbl>, ws_48 <dbl>,
## #
       obpm <dbl>, dbpm <dbl>, bpm <dbl>, vorp <dbl>
```

## 1.3.3 EDA



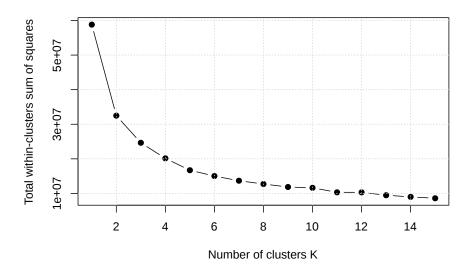






```
nba_for_clustering = nba %>%
  filter(mp > 2000) %>%
  column_to_rownames("player_team") %>%
  select(-pos, -tm)
```

#### 1.3.4 Modeling



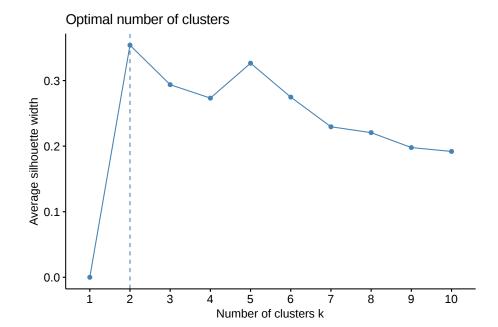
- TODO: K-Means likes clusters of roughly equal size.
- TODO: http://varianceexplained.org/r/kmeans-free-lunch/

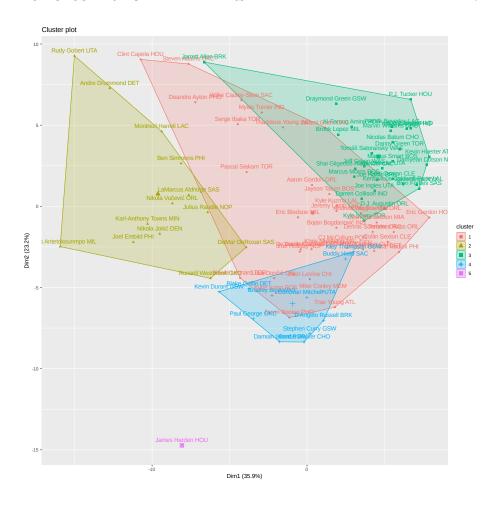
```
nba_hc = hclust(dist(nba_for_clustering))
nba_hc_clust = cutree(nba_hc, k = 5)
table(nba_hc_clust)
```

```
## nba_hc_clust
## 1 2 3 4 5
## 38 13 28 11 1
```

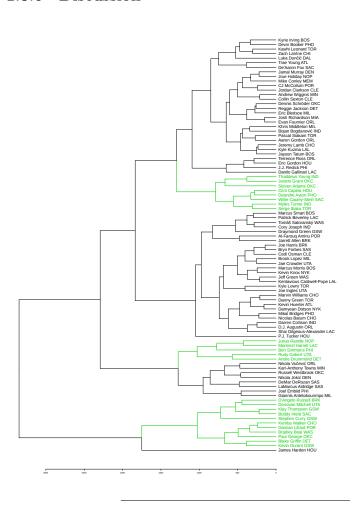
#### 1.3.5 Model Evaluation







## 1.3.6 Discussion



## Chapter 2

# Computing

This is not a book about R.

- TODO: Set of readings to do. (R4DS, ADVR, ?)
- Applied Statistics with R
- R for Data Science
- Advanced R
- Hands-On Programming with R

#### 2.1 Resources

#### 2.1.1 R

- Efficient R programming
- R Programming for Data Science
- R Graphics Cookbook
- Modern Dive
- ? The tidyverse Website
  - ? dplyr Website
  - ? readr Website
  - ? tibble Website
  - ? forcats Website

#### 2.1.2 RStudio

 $\bullet \ \ https://resources.rstudio.com/rstudio-cheatsheets/rstudio-ide-cheat-sheet$ 

• https://resources.rstudio.com/

### 2.1.3 R Markdown

- $\bullet \ \ https://resources.rstudio.com/rstudio-cheatsheets/rmarkdown-2-0-cheat-sheet$
- https://bookdown.org/yihui/rmarkdown/
- $\bullet \ \, \rm https://daring fireball.net/projects/markdown/basics$
- https://guides.github.com/features/mastering-markdown/
- https://commonmark.org/

### 2.2 BSL Idioms

Things here supercede everythign above.

## 2.2.1 Style

• https://style.tidyverse.org/