Applications

Of Data Science

Modeling in the Tidyverse

Applications of Data Science - Class 5

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The Problem

Inconsistency, Inextensibility

```r
n <- 10000
x1 <- runif(n)
x2 <- runif(n)
t <- 1 + 2 * x1 + 3 * x2
y <- rbinom(n, 1, 1 / (1 + exp(-t)))
```

```r
glm(y ~ x1 + x2, family = "binomial")
```

```r
glmnet(as.matrix(cbind(x1, x2)), as.factor(y), family = "binomial'
```

```r
randomForest(as.factor(y) ~ x1 + x2)
```

```r
gbm(y ~ x1 + x2, data = data.frame(x1 = x1, x2 = x2, y = y))
```

Compare this with `sklearn`

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,
  GradientBoostingClassifier

LogisticRegression(penalty='none').fit(X, y)

LogisticRegression(penalty='l2', C=0.001).fit(X, y)

RandomForestClassifier(n_estimators=100).fit(X, y)

GradientBoostingClassifier(n_estimators=100).fit(X, y)
```

Detour: A Regression Problem

IPF-Lifts: Predicting Bench Lifting

- Dataset was published as part of the TidyTuesday intiative
- Comes from Open Powerlifting
- Wikipedia: Powerlifting is a strength sport that consists of three attempts at maximal weight on three lifts: squat, bench press, and deadlift

The raw data has over 40K rows: for each athlete, for each event, stats about athlete gender, age and weight, and the maximal weight lifted in the 3 types of Powerlifting.

We will be predicting `best3bench_kg` based on a few predictors, no missing values:

```
library(lubridate)

ipf_lifts <- read_csv("https://raw.githubusercontent.com/rfordatas

ipf_lifts <- ipf_lifts %>%
  drop_na(best3bench_kg, age) %>%
  filter(between(age, 18, 100), best3bench_kg > 0, equipment != "W
  select(sex, event, equipment, age, division, bodyweight_kg, best
  drop_na() %>%
  mutate(year = year(date), month = month(date),
         dayofweek = wday(date)) %>%
  select(-date) %>%
  mutate_if(is.character, as.factor)

dim(ipf_lifts)
```

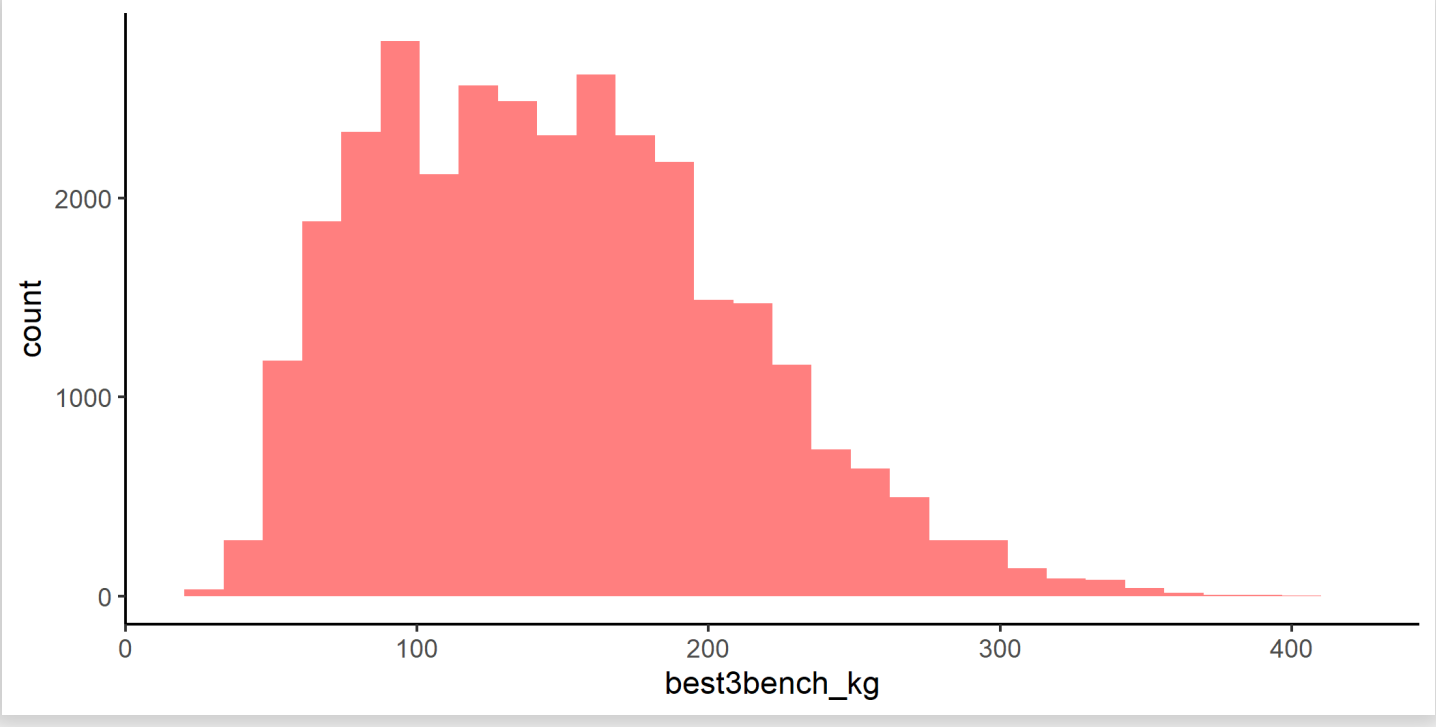
```
## [1] 32047    11
```

```
glimpse(ipf_lifts)
```

```
## Observations: 32,047
## Variables: 11
## $ sex            <fct> F, F, F, F, F, F, F, F, F, F, F, F, F, F, F, F, ..
## $ event          <fct> SBD, SBD, SBD, SBD, SBD, SBD, SBD, SBD, SBD, SBD..
## $ equipment      <fct> Single-ply, Single-ply, Single-ply, Single-ply, ..
## $ age            <dbl> 33.5, 34.5, 23.5, 27.5, 37.5, 25.5, 33.5, 26.0, ..
## $ division       <fct> Open, Open, Open, Open, Open, Open, Open, Open, ..
## $ bodyweight_kg  <dbl> 44, 44, 44, 44, 44, 44, 48, 48, 48, 48, 48, 48, ..
## $ best3bench_kg  <dbl> 60.0, 62.5, 62.5, 60.0, 65.0, 45.0, 62.5, 77.5, ..
## $ meet_name      <fct> World Powerlifting Championships, World Powerlif..
## $ year           <dbl> 1989, 1989, 1989, 1989, 1989, 1989, 1989, 1989, ..
## $ month          <dbl> 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, ..
## $ dayofweek      <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ..
```

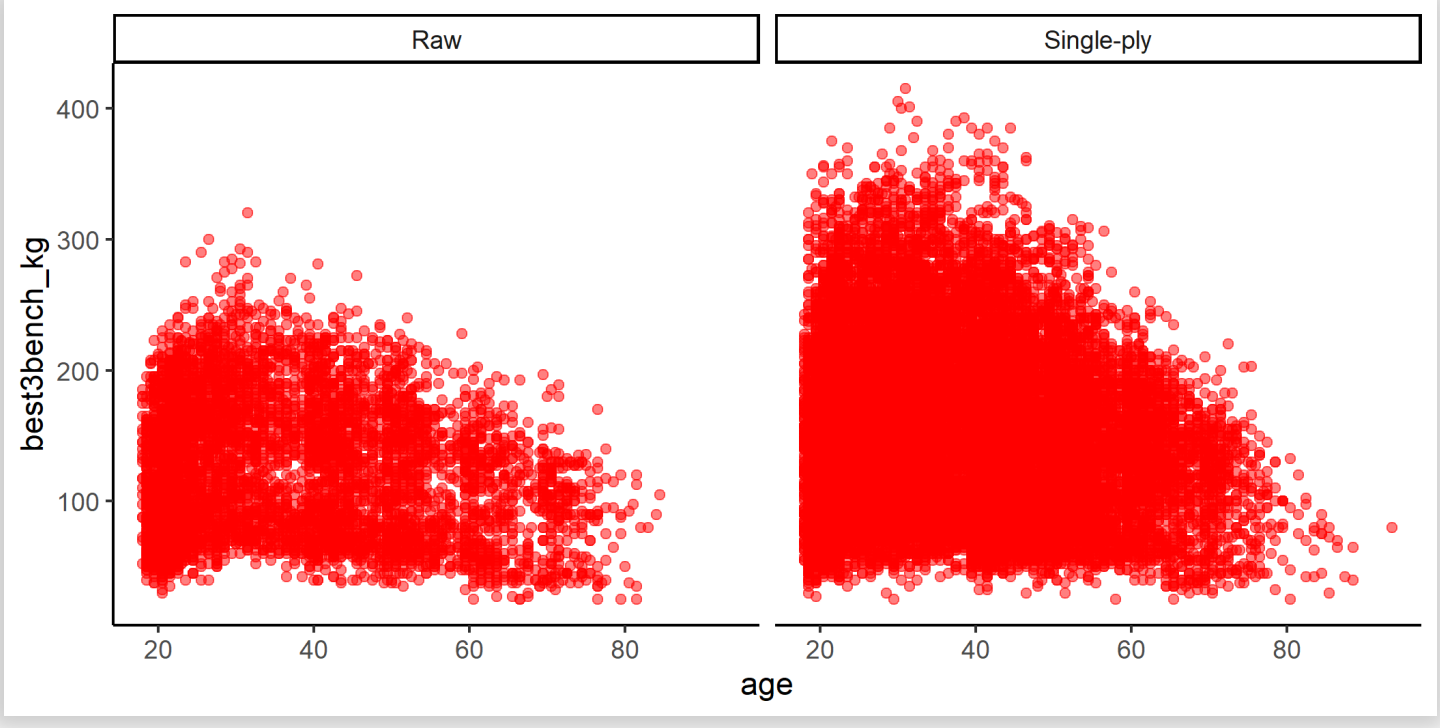
See the dependent variable distribution:

```
ggplot(ipf_lifts, aes(best3bench_kg)) +
  geom_histogram(fill = "red", alpha = 0.5) +
  theme_classic()
```



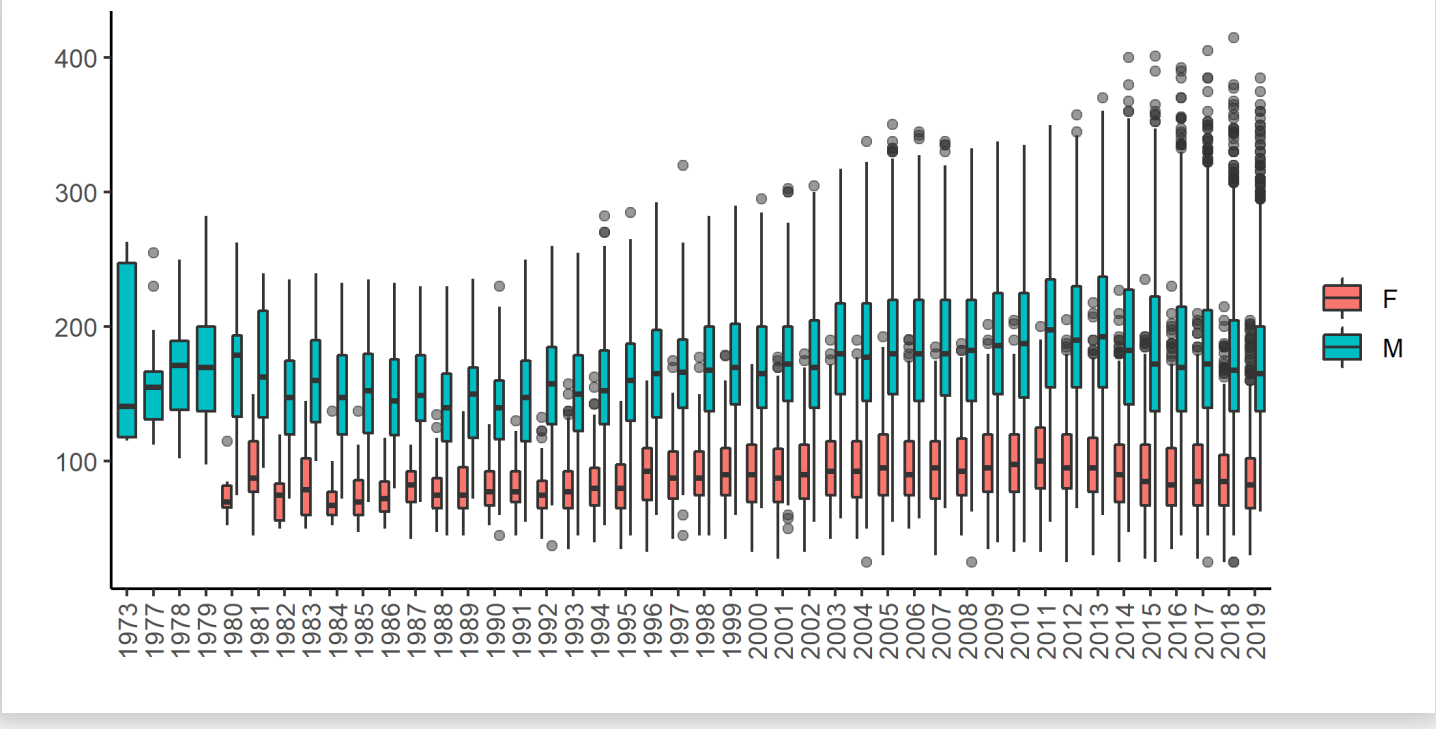
See it vs. say age, facetted by equipment:

```
ggplot(ipf_lifts, aes(age, best3bench_kg)) +
  geom_point(color = "red", alpha = 0.5) +
  facet_wrap(~ equipment) +
  theme_classic()
```



See it vs. year, by gender:

```
ggplot(ipf_lifts, aes(factor(year), best3bench_kg, fill = sex)) +
  geom_boxplot(outlier.alpha = 0.5) +
  labs(fill = "", x = "", y = "") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust =
```



Maybe add age^2 and $year^2$ to make Linear Regression's life easier?

```
ipf_lifts <- ipf_lifts %>%
  mutate(age2 = age ^ 2, year2 = year ^2)
```

End of Detour

WARNING

What you're about to see is not a good modeling/prediction flow. This is just an intro to tidy modeling. Some of the issues with how things are done here will be raised, some will have to wait till later in the course.

The Present Solution: `caret`

Split Data

```
library(caret)

train_idx <- createDataPartition(ipf_lifts$best3bench_kg,
                                 p = 0.6, list = FALSE)

ipf_tr <- ipf_lifts[train_idx, ]
ipf_te <- ipf_lifts[-train_idx, ]

library(glue)
glue("train no. of rows: {nrow(ipf_tr)}
     test no. of rows: {nrow(ipf_te)}")
```

```
## train no. of rows: 19230
## test no. of rows: 12817
```

Here you might consider some preprocessing.

`caret` has some nice documentation here.

Tuning and Modeling

Define general methodology, e.g. 10-fold Cross-Validation:

```
fit_control <- trainControl(method = "cv", number = 5)

ridge_grid <- expand.grid(alpha=0, lambda = 10^seq(-3, 1, length =
lasso_grid <- expand.grid(alpha=1, lambda = 10^seq(-3, 1, length =
rf_grid <- expand.grid(splitrule = "variance",
                       min.node.size = seq(10, 30, 10),
                       mtry = seq(2, 10, 2))

mod_ridge <- train(best3bench_kg ~ ., data = ipf_tr, method = "glm
                   trControl = fit_control, tuneGrid = ridge_grid,
                   metric = "RMSE")

mod_lasso <- train(best3bench_kg ~ ., data = ipf_tr, method = "glm
                   trControl = fit_control, tuneGrid = lasso_grid,
                   metric = "RMSE")

mod_rf <- train(best3bench_kg ~ ., data = ipf_tr, method = "ranger
                   trControl = fit_control, tuneGrid = rf_grid,
                   num.trees = 50, metric = "RMSE")
```

Evaluating Models

```
mod_ridge
```

```
## glmnet
##
## 19230 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15385, 15385, 15383, 15383, 15384
## Resampling results across tuning parameters:
##
##   lambda        RMSE      Rsquared   MAE
##    0.001000000  26.82721  0.8110942  20.47454
##    0.001206793  26.82721  0.8110942  20.47454
##    0.001456348  26.82721  0.8110942  20.47454
##    0.001757511  26.82721  0.8110942  20.47454
##    0.002120951  26.82721  0.8110942  20.47454
##    0.002559548  26.82721  0.8110942  20.47454
##    0.003088844  26.82721  0.8110942  20.47454
##    0.003727594  26.82721  0.8110942  20.47454
##    0.004498433  26.82721  0.8110942  20.47454
##    0.005428675  26.82721  0.8110942  20.47454
##    0.006551286  26.82721  0.8110942  20.47454
##    0.007906043  26.82721  0.8110942  20.47454
```

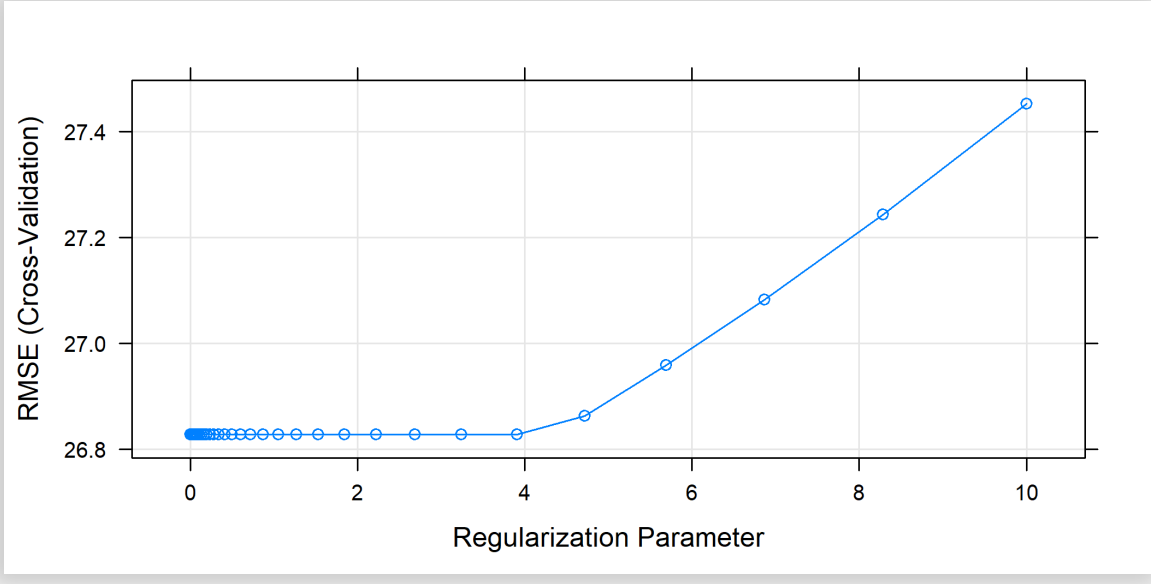
```
mod_lasso
```

```
## glmnet
##
## 19230 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15385, 15383, 15384, 15385, 15383
## Resampling results across tuning parameters:
##
##   lambda        RMSE      Rsquared   MAE
##    0.001000000  26.40433  0.8151910  20.18166
##    0.001206793  26.40433  0.8151910  20.18166
##    0.001456348  26.40433  0.8151910  20.18166
##    0.001757511  26.40433  0.8151910  20.18166
##    0.002120951  26.40433  0.8151910  20.18166
##    0.002559548  26.40433  0.8151910  20.18166
##    0.003088844  26.40433  0.8151910  20.18166
##    0.003727594  26.40433  0.8151910  20.18166
##    0.004498433  26.40433  0.8151910  20.18166
##    0.005428675  26.40433  0.8151910  20.18166
##    0.006551286  26.40433  0.8151910  20.18166
##    0.007906043  26.40433  0.8151910  20.18166
##    0.009540955  26.40433  0.8151910  20.18166
##    0.011513954  26.40433  0.8151910  20.18166
##    0.013894955  26.40433  0.8151910  20.18166
##    0.016768329  26.40433  0.8151910  20.18166
```

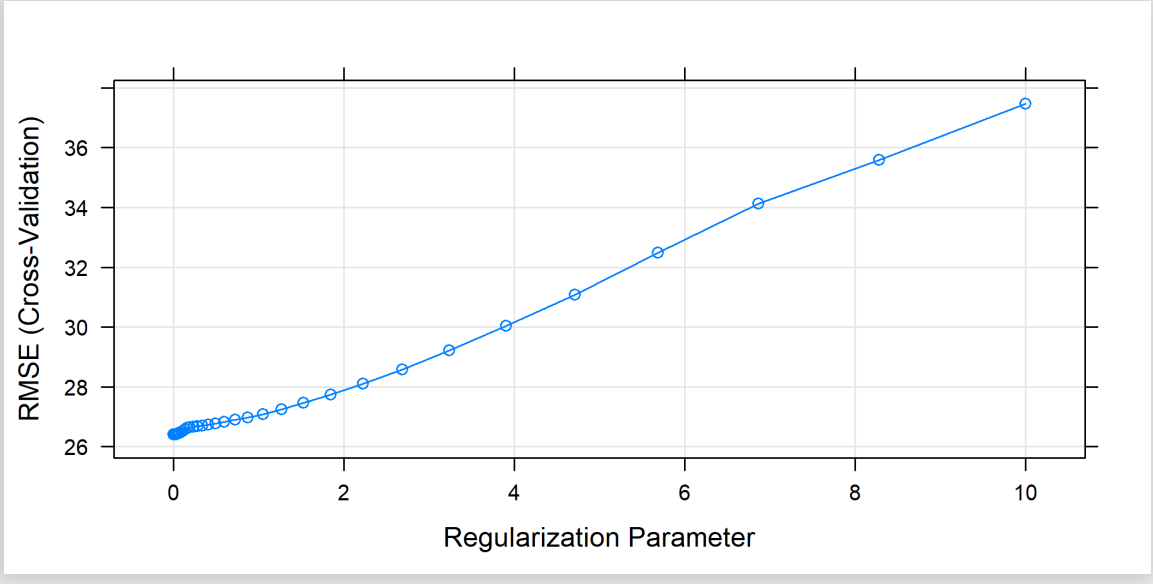
```
mod_rf
```

```
## Random Forest
##
## 19230 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15384, 15384, 15384, 15385, 15383
## Resampling results across tuning parameters:
##
##   min.node.size  mtry  RMSE      Rsquared   MAE
##   10              2    44.46119  0.7126922  35.75270
##   10              4    33.22558  0.7903895  26.03864
##   10              6    28.34899  0.8210037  21.87503
##   10              8    25.75484  0.8373422  19.74784
##   10             10    24.59800  0.8445753  18.76416
##   20              2    44.12560  0.7140751  35.35874
##   20              4    33.38484  0.7892705  26.15563
##   20              6    28.76182  0.8186550  22.23829
##   20              8    25.71983  0.8371620  19.72128
##   20             10    24.63315  0.8440852  18.80395
##   30              2    43.48024  0.7332561  34.84502
##   30              4    34.31972  0.7807501  26.94342
##   30              6    28.61490  0.8192508  22.10767
##   30              8    25.83251  0.8365044  19.80986
##   30             10    24.74613  0.8434765  18.90919
##
```

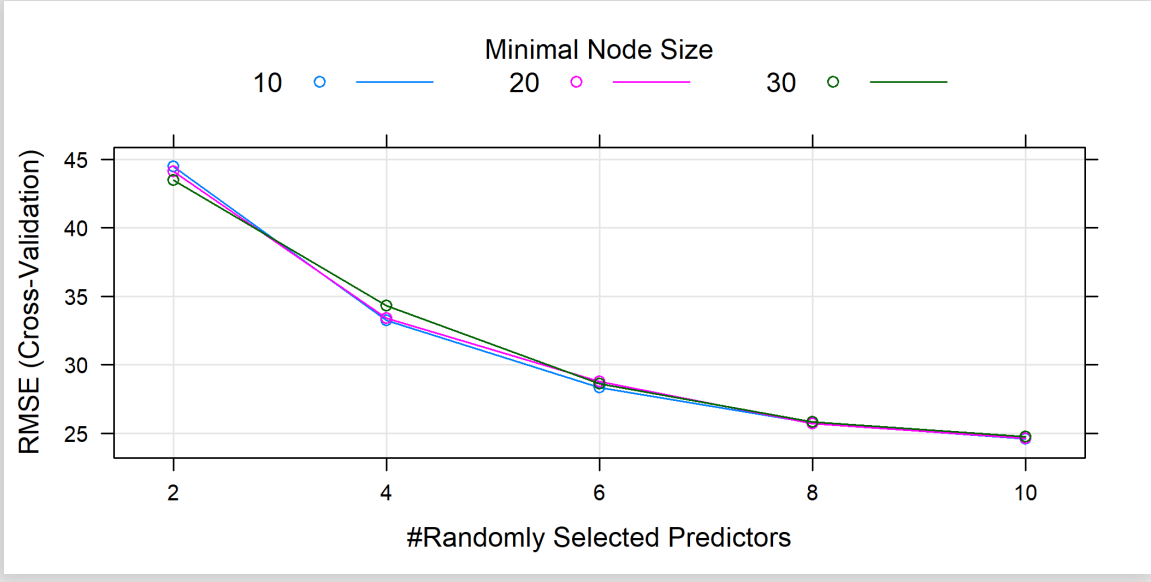
```
plot(mod_ridge)
```



```
plot(mod_lasso)
```



```
plot(mod_rf)
```

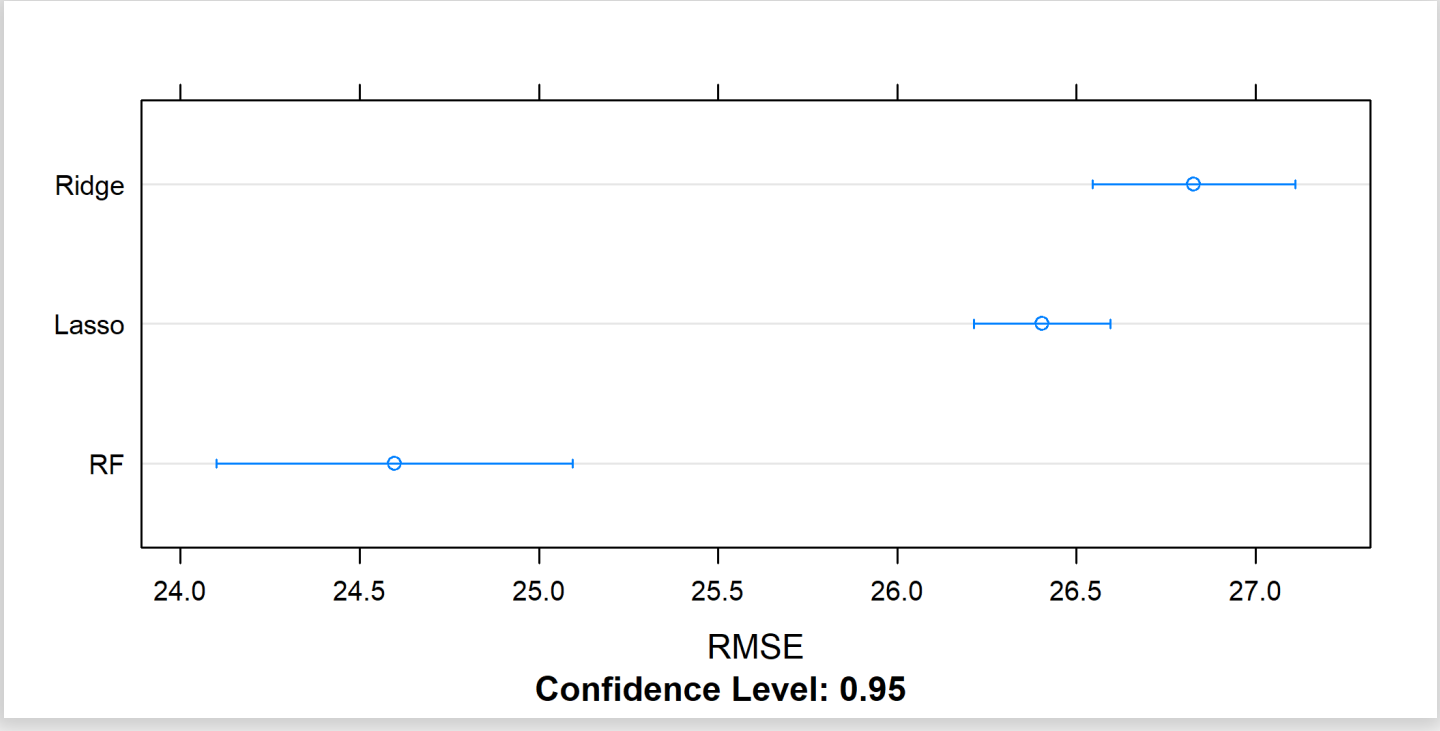

Minimal Node Size
10
20
30
RMSE (Cross-Validation)
45
40
35
30
25
2
4
6
8
10
#Randomly Selected Predictors

Comparing Models

```
resamps <- resamples(list(Ridge = mod_ridge,
                          Lasso = mod_lasso,
                          RF = mod_rf))
summary(resamps)
```

```
##
## Call:
## summary.resamples(object = resamps)
##
## Models: Ridge, Lasso, RF
## Number of resamples: 5
##
## MAE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## Ridge 20.21697 20.40482 20.47514 20.47454 20.60721 20.66855    0
## Lasso 20.03314 20.08440 20.11722 20.18166 20.19072 20.48283    0
## RF    18.33264 18.57500 18.64885 18.76416 19.00912 19.25519    0
##
## RMSE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## Ridge 26.59173 26.63820 26.80070 26.82721 26.96887 27.13656    0
## Lasso 26.21031 26.36819 26.36904 26.40433 26.43962 26.63447    0
## RF    24.21951 24.29361 24.44555 24.59800 24.88725 25.14407    0
##
```

```
dotplot(resamps, metric = "RMSE")
```



Predicting

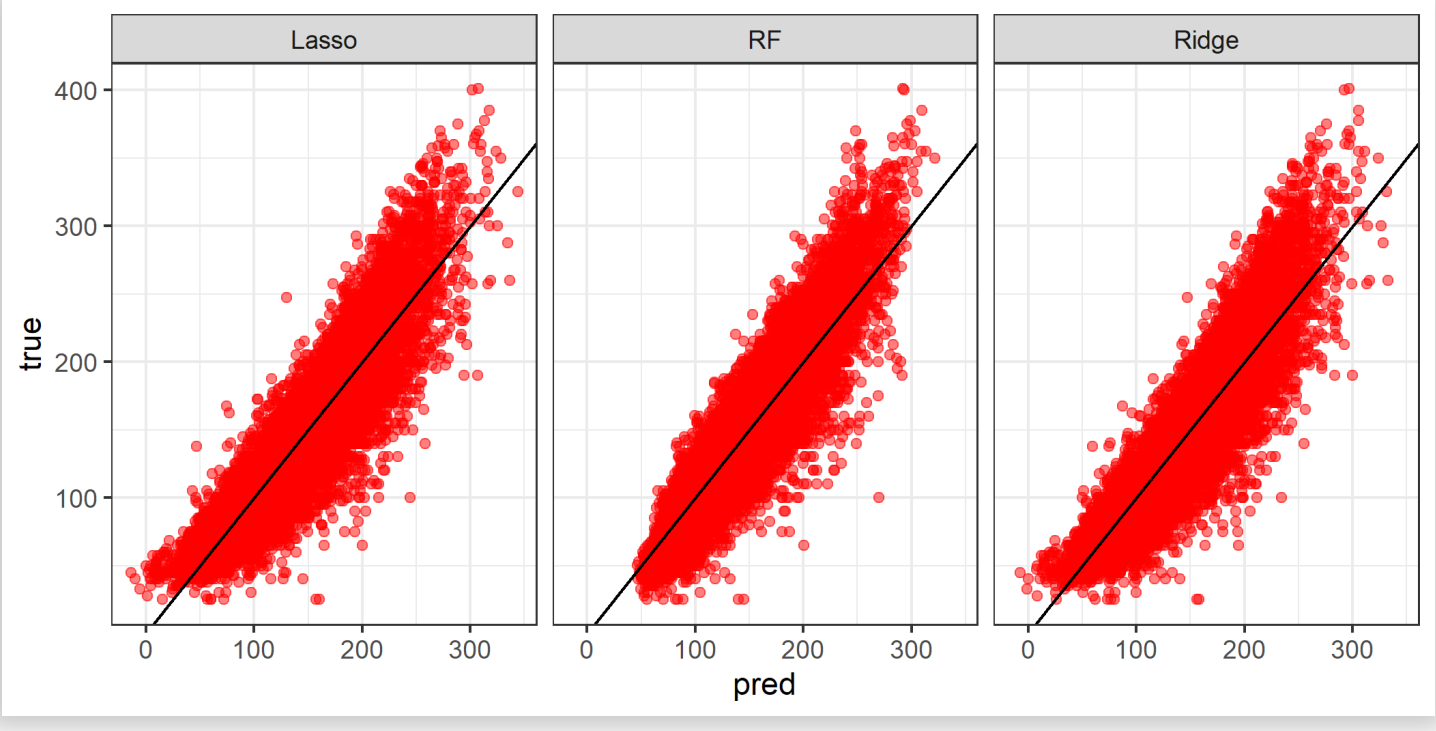
```
pred_ridge <- predict(mod_ridge, newdata = ipf_te)
pred_lasso <- predict(mod_lasso, newdata = ipf_te)
pred_rf <- predict(mod_rf, newdata = ipf_te)

rmse_ridge <- RMSE(pred_ridge, ipf_te$best3bench_kg)
rmse_lasso <- RMSE(pred_lasso, ipf_te$best3bench_kg)
rmse_rf <- RMSE(pred_rf, ipf_te$best3bench_kg)

glue("Test RMSE Ridge: {format(rmse_ridge, digits = 3)}
     Test RMSE Lassoe: {format(rmse_lasso, digits = 3)}
     Test RMSE RF: {format(rmse_rf, digits = 3)}")
```

```
## Test RMSE Ridge: 26.5
## Test RMSE Lassoe: 26
## Test RMSE RF: 24.3
```

⚠ Is using a "regular" regression model the natural approach for these data?

Ask yourself what is this model good for, if at all 😮

```
bind_rows(
  tibble(method = "Ridge", pred = pred_ridge, true = ipf_te$best3k
  tibble(method = "Lasso", pred = pred_lasso, true = ipf_te$best3k
  tibble(method = "RF", pred = pred_rf, true = ipf_te$best3bench_k
  ggplot(aes(pred, true)) +
  geom_point(color = "red", alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0) +
  facet_wrap(~ method) +
  theme_bw()
```



The Future Solution: `tidymodels`

Inspired by Julia Silge

Packages under tidymodels

- `paresnip`: tidy `caret`
- `dials` and `tune`: specifying and tuning model parameters
- `rsample`: sampling, data partitioning
- `recipes` and `embed`: preprocessing and creating model matrices
- `infer`: tidy statistics
- `yardstick`: measuring models performance
- `broom`: convert models output into tidy tibbles

And more.

> ⚠ All `tidymodels` packages are under development!

Split Data

The `initial_split()` function is from the `rsample` package:

```
library(tidymodels)

ipf_split_obj <- ipf_lifts %>%
  initial_split(prop = 0.6, strata = equipment)

ipf_tr <- training(ipf_split_obj)
ipf_te <- testing(ipf_split_obj)

glue("train no. of rows: {nrow(ipf_tr)}
     test no. of rows: {nrow(ipf_te)}")
```

```
## train no. of rows: 19229
## test no. of rows: 12818
```

```
print(ipf_split_obj)
```

```
## <19229/12818/32047>
```

Preprocess (but we're not gonna use it)

The `recipe()` function is from the `recipes` package. It allows you to specify a python-like pipe you can later apply to any dataset, including all preprocessing steps:

```
ipf_rec <- recipe(best3bench_kg ~ ., data = ipf_tr)
ipf_rec
```

```
## Data Recipe
##
## Inputs:
##
##       role #variables
##    outcome          1
##  predictor         12
```

`recipes` contains more preprocessing `step_`s than you imagine:

```
ipf_rec <-  ipf_rec %>%
  step_normalize(all_numeric())
```

After you have your `recipe` you need to `prep()` materials...

```
ipf_rec <- ipf_rec %>% prep(ipf_tr)

ipf_rec
```

```
## Data Recipe
##
## Inputs:
##
##       role #variables
##    outcome          1
##  predictor         12
##
## Training data contained 19229 data points and no missing data.
##
## Operations:
##
## Centering and scaling for age, bodyweight_kg, year, month, ... [trained]
```

At this point our `recipe` has all necessary `sd` and `means` for numeric variables.

And then we `bake()`:

```
ipf_tr2 <- ipf_rec %>% bake(ipf_tr)
ipf_te2 <- ipf_rec %>% bake(ipf_te)

glue("mean of age in orig training: {format(mean(ipf_tr$age), digi
     mean of age in baked training: {format(mean(ipf_tr2$age), dig
```

```
## mean of age in orig training: 36.6, sd: 14.3
## mean of age in baked training: 0, sd: 1
```

```
glue("mean of age in orig testing: {format(mean(ipf_te$age), digit
     mean of age in baked testing: {format(mean(ipf_te2$age), digi
```

```
## mean of age in orig testing: 36.7, sd: 14.2
## mean of age in baked testing: 0, sd: 0.994
```

Or you can do it all in a single pipe:

```
ipf_rec <- recipe(best3bench_kg ~ ., data = ipf_tr) %>%
  step_normalize(all_numeric()) %>%
  prep(ipf_tr)

ipf_tr2 <- ipf_rec %>% bake(ipf_tr)
ipf_te2 <- ipf_rec %>% bake(ipf_te)

glue("mean of age in orig training: {format(mean(ipf_tr$age), digi
     mean of age in baked training: {format(mean(ipf_tr2$age), dig
```

```
## mean of age in orig training: 36.6, sd: 14.3
## mean of age in baked training: 0, sd: 1
```

```
glue("mean of age in orig testing: {format(mean(ipf_te$age), digit
     mean of age in baked testing: {format(mean(ipf_te2$age), digi
```

```
## mean of age in orig testing: 36.7, sd: 14.2
## mean of age in baked testing: 0, sd: 0.994
```

Modeling

For now let us use the original `ipf_tr` data.

Functions `linear_reg()` and `set_engine()` are from the `parsnip` package:

```
mod_ridge_spec <- linear_reg(mixture = 0, penalty = 0.001) %>%
  set_engine(engine = "glmnet")

mod_ridge_spec
```

```
## Linear Regression Model Specification (regression)
##
## Main Arguments:
##   penalty = 0.001
##   mixture = 0
##
## Computational engine: glmnet
```

```
mod_ridge <- mod_ridge_spec %>%
  fit(best3bench_kg ~ ., data = ipf_tr)

mod_ridge
```

```
## parsnip model object
##
## Fit in:  51ms
## Call:  glmnet::glmnet(x = as.matrix(x), y = y, family = "gaussian",
##
##     Df    %Dev Lambda
## 1   51 0.00000  43490
## 2   51 0.00396  39620
## 3   51 0.00435  36100
## 4   51 0.00477  32900
## 5   51 0.00523  29970
## 6   51 0.00574  27310
## 7   51 0.00629  24880
## 8   51 0.00690  22670
## 9   51 0.00757  20660
## 10  51 0.00830  18820
## 11  51 0.00910  17150
## 12  51 0.00998  15630
## 13  51 0.01094  14240
## 14  51 0.01200  12980
## 15  51 0.01315  11820
## 16  51 0.01442  10770
## 17  51 0.01580   9815
## 18  51 0.01731   8943
```

In a single pipe:

```
mod_lasso <- linear_reg(mixture = 1, penalty = 0.001) %>%
  set_engine(engine = "glmnet") %>%
  fit(best3bench_kg ~ ., data = ipf_tr)

mod_lasso
```

```
## parsnip model object
##
## Fit in:  61ms
## Call:  glmnet::glmnet(x = as.matrix(x), y = y, family = "gaussian",
##
##    Df    %Dev Lambda
## 1   0 0.00000 43.490
## 2   1 0.08583 39.620
## 3   2 0.15840 36.100
## 4   2 0.23960 32.900
## 5   2 0.30710 29.970
## 6   2 0.36310 27.310
## 7   2 0.40960 24.880
## 8   2 0.44820 22.670
## 9   2 0.48030 20.660
## 10  2 0.50690 18.820
## 11  2 0.52900 17.150
## 12  2 0.54730 15.630
## 13  2 0.56250 14.240
## 14  2 0.57520 12.980
```

Can also use `fit_xy()` a-la `sklearn`:

```
mod_rf <- rand_forest(mode = "regression", mtry = 4, trees = 50, r
  set_engine("ranger") %>%
  fit_xy(x = ipf_tr[, -7],
         y = ipf_tr$best3bench_kg)

mod_rf
```

```
## parsnip model object
##
## Fit in:  671msRanger result
##
## Call:
##  ranger::ranger(formula = formula, data = data, mtry = ~4, num.trees = ~
##
## Type:                             Regression
## Number of trees:                  50
## Sample size:                      19229
## Number of independent variables:  12
## Mtry:                             4
## Target node size:                 30
## Variable importance mode:         none
## Splitrule:                        variance
## OOB prediction error (MSE):       561.2796
## R squared (OOB):                  0.8499749
```

Notice how easy it is to get the model's results in a tidy way using the `tidy()` function:

```
tidy(mod_ridge)
```

```
## # A tibble: 5,200 x 5
##    term                 step  estimate lambda dev.ratio
##    <chr>               <dbl>     <dbl>  <dbl>     <dbl>
##  1 (Intercept)             1  1.49e+ 2 43487.  2.60e-36
##  2 sexM                    1  8.48e-35 43487.  2.60e-36
##  3 eventSB                 1 -8.72e-36 43487.  2.60e-36
##  4 eventSBD                1 -2.38e-35 43487.  2.60e-36
##  5 equipmentSingle-ply     1  2.96e-35 43487.  2.60e-36
##  6 age                     1 -5.60e-37 43487.  2.60e-36
##  7 divisionJuniors         1 -5.27e-36 43487.  2.60e-36
##  8 divisionLight           1 -2.22e-35 43487.  2.60e-36
##  9 divisionMasters 1       1 -1.59e-36 43487.  2.60e-36
## 10 divisionMasters 2       1 -1.53e-35 43487.  2.60e-36
## # ... with 5,190 more rows
```

Predicting

```
results_test <- mod_ridge %>%
  predict(new_data = ipf_te, penalty = 0.001) %>%
  mutate(
    truth = ipf_te$best3bench_kg,
    method = "Ridge"
  ) %>%
  bind_rows(mod_lasso %>%
    predict(new_data = ipf_te) %>%
    mutate(
      truth = ipf_te$best3bench_kg,
      method = "Lasso"
  )) %>%
  bind_rows(mod_rf %>%
    predict(new_data = ipf_te) %>%
    mutate(
      truth = ipf_te$best3bench_kg,
      method = "RF"
  ))

dim(results_test)
```

```
## [1] 38454     3
```

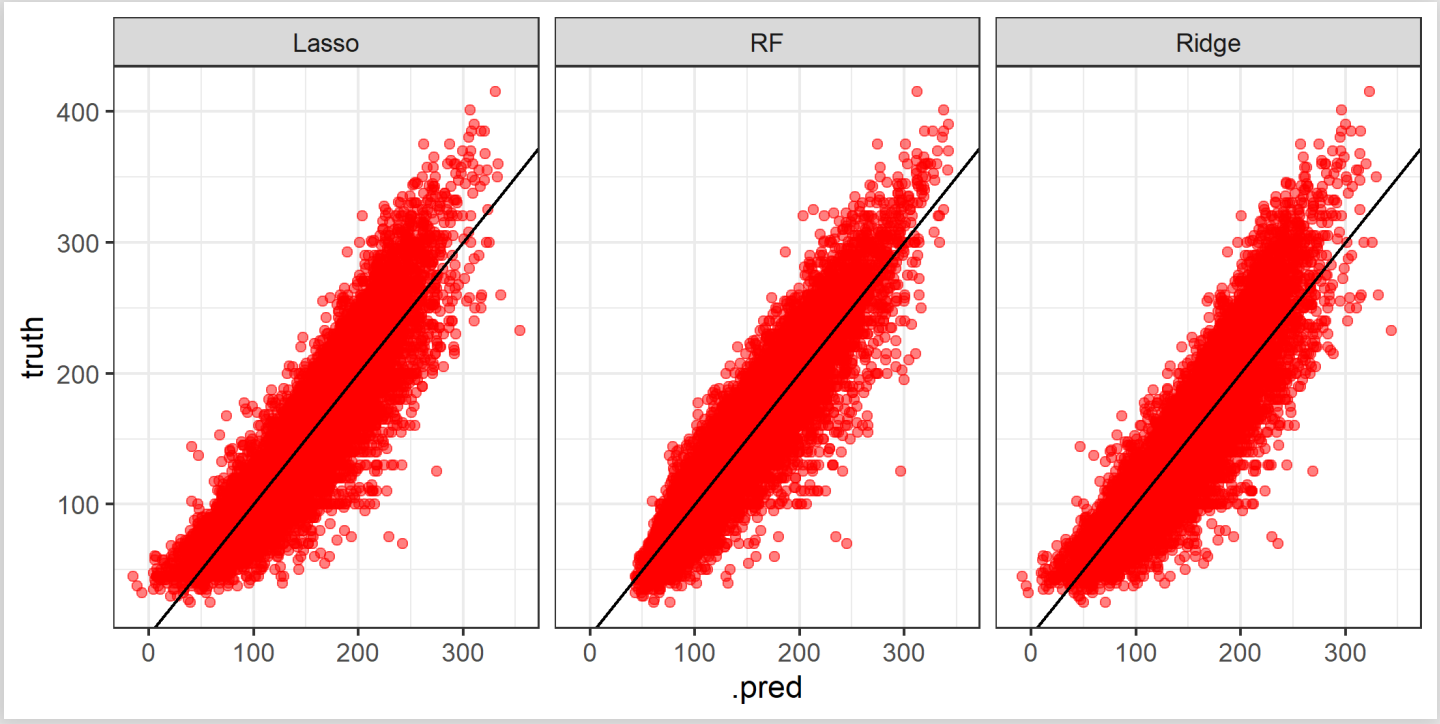
Comparing Models

The package `yardstick` has tons of performance metrics:

```
results_test %>%
  group_by(method) %>%
  yardstick::rmse(truth = truth, estimate = .pred)
```

```
## # A tibble: 3 x 4
##   method .metric .estimator .estimate
##   <chr>  <chr>   <chr>          <dbl>
## 1 Lasso  rmse    standard        26.4
## 2 RF     rmse    standard        23.8
## 3 Ridge  rmse    standard        26.9
```

```
results_test %>%
  ggplot(aes(.pred, truth)) +
  geom_point(color = "red", alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0) +
  facet_wrap(~ method) +
  theme_bw()
```



Tuning

This isn't completely clear to me, but it seems to work:

Define your model spec, using `tune()` from the `tune` package (needs to be installed separately) for a paramter you wish to tune:

```
library(tune)

mod_rf_spec <- rand_forest(mode = "regression",
                           mtry = tune("mtry"),
                           min_n = tune("min_n")) %>%
  set_engine("ranger")
```

Define the `grid` on which you train your params, with the `dials` package:

```
rf_grid <- grid_regular(mtry(range(2, 10)), min_n(range(10, 30)),
                        levels = c(5, 3))

rf_grid
```

```
## # A tibble: 15 x 2
##     mtry min_n
##    <int> <int>
##  1     2    10
##  2     4    10
##  3     6    10
##  4     8    10
##  5    10    10
##  6     2    20
##  7     4    20
##  8     6    20
##  9     8    20
## 10    10    20
## 11     2    30
## 12     4    30
## 13     6    30
## 14     8    30
## 15    10    30
```

Split your data into a few folds for Cross Validation with `vfold_cv()` from the `rsample` package:

```
cv_splits <- vfold_cv(ipf_tr, v = 5)

cv_splits
```

```
## #  5-fold cross-validation
## # A tibble: 5 x 2
##   splits               id
##   <named list>         <chr>
## 1 <split [15.4K/3.8K]> Fold1
## 2 <split [15.4K/3.8K]> Fold2
## 3 <split [15.4K/3.8K]> Fold3
## 4 <split [15.4K/3.8K]> Fold4
## 5 <split [15.4K/3.8K]> Fold5
```

Now perform cross validation with `tune_grid()` from the `tune` package:

```
tune_res <- tune_grid(recipe(best3bench_kg ~ ., data = ipf_tr),
                      model = mod_rf_spec,
                      resamples = cv_splits,
                      grid = rf_grid,
                      metrics = metric_set(rmse))
tune_res
```

```
## #  5-fold cross-validation
## # A tibble: 5 x 4
##   splits               id    .metrics          .notes
## * <list>               <chr> <list>            <list>
## 1 <split [15.4K/3.8K]> Fold1 <tibble [15 x 5]> <tibble [0 x 1]>
## 2 <split [15.4K/3.8K]> Fold2 <tibble [15 x 5]> <tibble [0 x 1]>
## 3 <split [15.4K/3.8K]> Fold3 <tibble [15 x 5]> <tibble [0 x 1]>
## 4 <split [15.4K/3.8K]> Fold4 <tibble [15 x 5]> <tibble [0 x 1]>
## 5 <split [15.4K/3.8K]> Fold5 <tibble [15 x 5]> <tibble [0 x 1]>
```

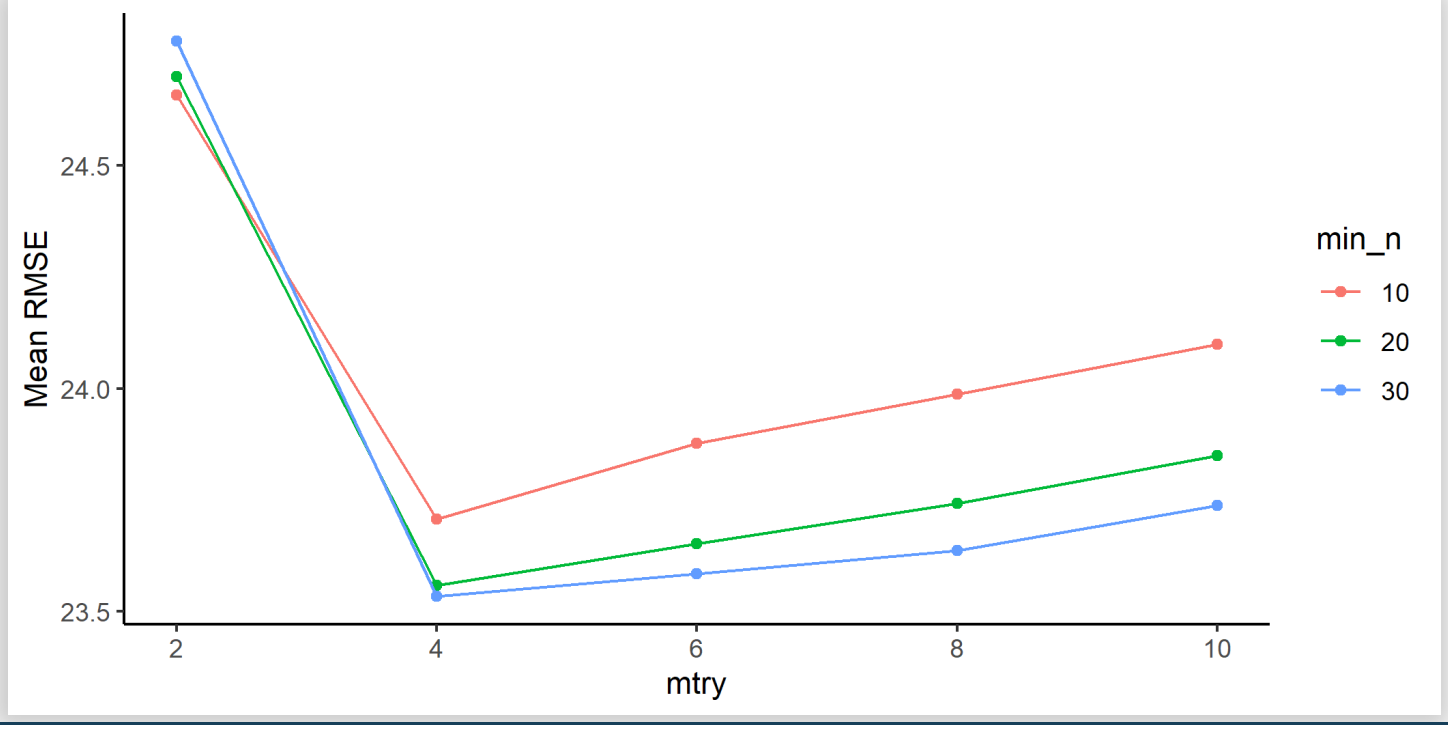
Collect the mean metric across folds:

```
estimates <- collect_metrics(tune_res)

estimates
```

```
## # A tibble: 15 x 7
##     mtry min_n .metric .estimator  mean     n std_err
##    <int> <int> <chr>   <chr>      <dbl> <int>   <dbl>
##  1     2    10 rmse    standard    24.7     5   0.197
##  2     2    20 rmse    standard    24.7     5   0.190
##  3     2    30 rmse    standard    24.8     5   0.192
##  4     4    10 rmse    standard    23.7     5   0.186
##  5     4    20 rmse    standard    23.6     5   0.192
##  6     4    30 rmse    standard    23.5     5   0.181
##  7     6    10 rmse    standard    23.9     5   0.191
##  8     6    20 rmse    standard    23.7     5   0.186
##  9     6    30 rmse    standard    23.6     5   0.186
## 10     8    10 rmse    standard    24.0     5   0.203
## 11     8    20 rmse    standard    23.7     5   0.185
## 12     8    30 rmse    standard    23.6     5   0.185
## 13    10    10 rmse    standard    24.1     5   0.206
## 14    10    20 rmse    standard    23.8     5   0.181
## 15    10    30 rmse    standard    23.7     5   0.183
```

Choose best paramter:

```
estimates %>%
  mutate(min_n = factor(min_n)) %>%
  ggplot(aes(x = mtry, y = mean, color = min_n)) +
  geom_point() +
  geom_line() +
  labs(y = "Mean RMSE") +
  theme_classic()
```



`infer`: Tidy Statistics

Statistical Q1

Is there a relation between men and women and the type of equipment they use in 2019? Assume observations are independent.

```
sex_vs_equipment <- ipf_lifts %>%
  filter(year == 2019) %>%
  select(sex, equipment) %>%
  table()

sex_vs_equipment
```

```
##     equipment
## sex Raw Single-ply
##   F 678         186
##   M 854         287
```

```
prop.table(sex_vs_equipment, margin = 1)
```

```
##     equipment
## sex        Raw Single-ply
##   F 0.7847222  0.2152778
##   M 0.7484663  0.2515337
```

Statistical Q2

Is there a difference between men and women age in 2019? Assume observations are independent.

```
ipf_lifts %>%
  filter(year == 2019) %>%
  group_by(sex) %>% summarise(avg = mean(age), sd = sd(age), n = n
```

```
## # A tibble: 2 x 4
##   sex     avg    sd     n
##   <fct> <dbl> <dbl> <int>
## 1 F      36.0  15.5   864
## 2 M      38.8  16.7  1141
```

Same Problem!

Varied interface, varied output.

```
prop.test(sex_vs_equipment[,1], rowSums(sex_vs_equipment))
```

```
##
##     2-sample test for equality of proportions with continuity
##     correction
##
## data:  sex_vs_equipment[, 1] out of rowSums(sex_vs_equipment)
## X-squared = 3.3872, df = 1, p-value = 0.0657
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.001975717  0.074487646
## sample estimates:
##    prop 1    prop 2
## 0.7847222 0.7484663
```

```
t.test(age ~ sex, data = ipf_lifts %>% filter(year == 2019))
```

```
##
##     Welch Two Sample t-test
##
## data:  age by sex
## t = -3.8797, df = 1921.8, p-value = 0.0001081
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -4.228319 -1.388844
## sample estimates:
## mean in group F mean in group M
##        35.97801        38.78659
```

The `generics::tidy()` Approach

(Also available when you load several other packages, like `broom` and `yardstick`)

```
tidy(prop.test(sex_vs_equipment[,1], rowSums(sex_vs_equipment)))
```

```
## # A tibble: 1 x 9
##   estimate1 estimate2 statistic p.value parameter conf.low conf.high met
##       <dbl>     <dbl>     <dbl>   <dbl>     <dbl>    <dbl>     <dbl> <ch
## 1     0.785     0.748      3.39  0.0657         1 -0.00198    0.0745 2-s
## # ... with 1 more variable: alternative <chr>
```

```
tidy(t.test(age ~ sex, data = ipf_lifts %>% filter(year == 2019)))
```

```
## # A tibble: 1 x 10
##   estimate estimate1 estimate2 statistic p.value parameter conf.low
##      <dbl>     <dbl>     <dbl>     <dbl>   <dbl>     <dbl>    <dbl>
## 1    -2.81      36.0      38.8     -3.88 1.08e-4     1922.    -4.23
## # ... with 3 more variables: conf.high <dbl>, method <chr>,
## #   alternative <chr>
```

The `infer` Approach

> infer implements an expressive grammar to perform statistical inference that coheres with the tidyverse design framework

4 main verbs for a typical flow:

- `specify()` - dependent/independent variables, formula
- `hypothesize()` - declare the null hypothesis
- `generate()` - generate data reflecting the null hypothesis (the permutation/bootstrap approach)
- `calculate()` - calculate a distribution of statistics from the generated data, from which you can extract conclusion based on a p-value for example

`infer` Diff in Proportions Test

Get the observed statistic (here manually in order to not confuse you, there *is* a way via `infer`):

```
#    equipment
# sex Raw Single-ply
#   F 678         186
#   M 854         287
p_F <- sex_vs_equipment[1, 1] / (sum(sex_vs_equipment[1, ]))
p_M <- sex_vs_equipment[2, 1] / (sum(sex_vs_equipment[2, ]))
obs_diff <- p_F - p_M
obs_diff
```

```
## [1] 0.03625596
```

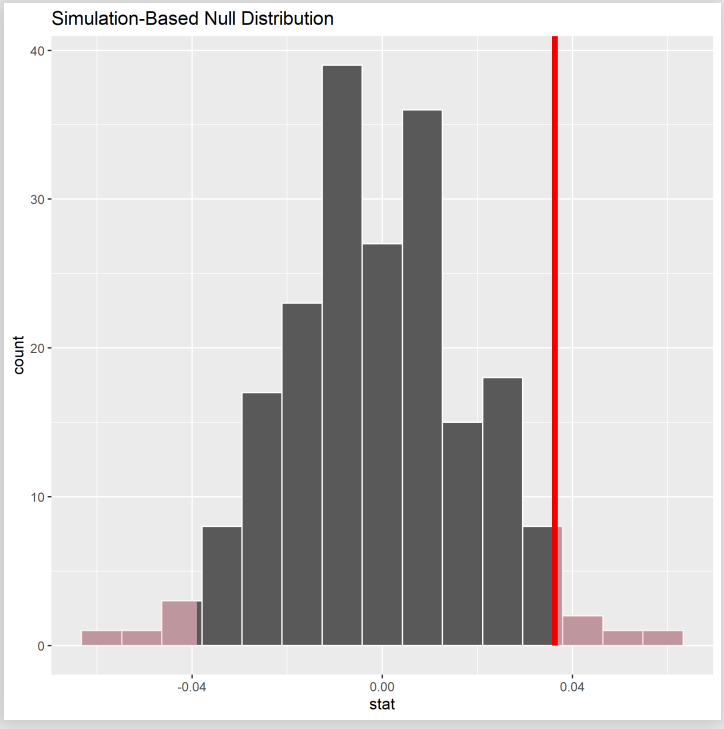
Get distribution of the difference in proportions under null hypothesis

```
diff_null_perm <- ipf_lifts %>%
  filter(year == 2019) %>%
  specify(equipment ~ sex, success = "Raw") %>%
  hypothesize(null = "independence") %>%
  generate(reps = 200, type = "permute") %>%
  calculate(stat = "diff in props", order = c("F", "M"))

diff_null_perm
```

```
## # A tibble: 200 x 2
##    replicate     stat
##        <int>    <dbl>
##  1         1 -0.0126
##  2         2 -0.00645
##  3         3  0.0200
##  4         4 -0.0492
##  5         5 -0.0248
##  6         6  0.00168
##  7         7  0.0200
##  8         8 -0.00442
##  9         9 -0.00645
## 10        10  0.00168
## # ... with 190 more rows
```

Visualize the permuted difference null distribution and the p-value

```
visualize(diff_null_perm) +
  shade_p_value(obs_stat = obs_diff, direction = "two_sided")
```



Get the actual p-value:

```
diff_null_perm %>%
  get_p_value(obs_stat = obs_diff, direction = "two_sided")
```

```
## # A tibble: 1 x 1
##   p_value
##     <dbl>
## 1    0.07
```

`infer` t Test (independent samples)

Get the observed statistic (here via `infer`):

```
obs_t <- ipf_lifts %>%
  filter(year == 2019) %>%
  specify(age ~ sex) %>%
  calculate(stat = "t", order = c("F", "M"))
obs_t
```

```
## # A tibble: 1 x 1
##    stat
##   <dbl>
## 1 -3.88
```

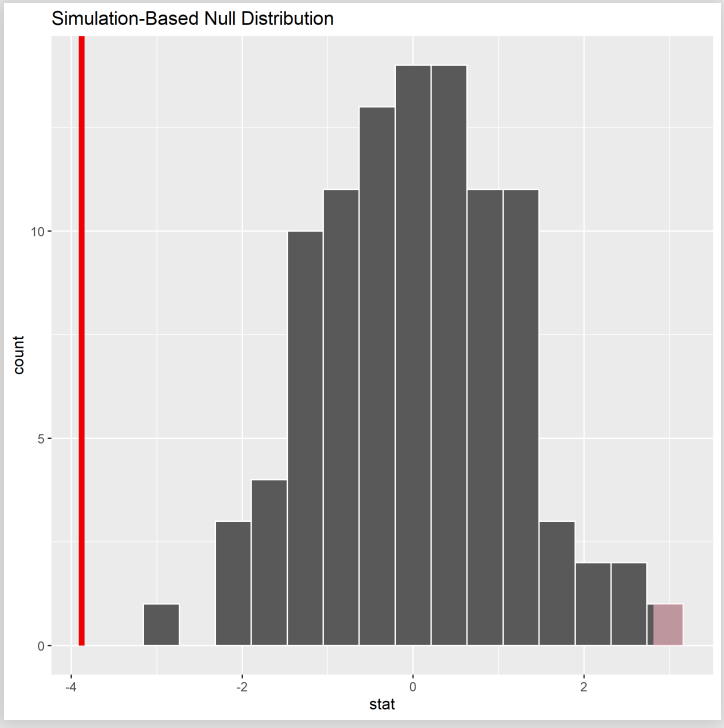
Get distribution of the t statistic under null hypothesis

```
t_null_perm <- ipf_lifts %>%
  filter(year == 2019) %>%
  specify(age ~ sex) %>%
  hypothesize(null = "independence") %>%
  generate(reps = 100, type = "permute") %>%
  calculate(stat = "t", order = c("F", "M"))

t_null_perm
```

```
## # A tibble: 100 x 2
##    replicate    stat
##        <int>   <dbl>
##  1         1 -0.450
##  2         2 -0.268
##  3         3  1.20
##  4         4  1.14
##  5         5  1.04
##  6         6  0.0967
##  7         7  0.908
##  8         8  0.456
##  9         9 -0.758
## 10        10 -0.575
## # ... with 90 more rows
```

Visualize the permuted t statistic null distribution and the two-sided p-value

```
visualize(t_null_perm) +
  shade_p_value(obs_stat = obs_t, direction = "two_sided")
```



Get the actual p-value:

```
t_null_perm %>%
  get_p_value(obs_stat = obs_t, direction = "two_sided")
```

```
## # A tibble: 1 x 1
##   p_value
##     <dbl>
## 1       0
```