Applications

Of Data Science

Modeling in the Tidyverse

Applications of Data Science - Class 5

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The Problem

Inconsistency, Inextensibility

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

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

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

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

```
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(across(where(is.character), as.factor))

dim(ipf_lifts)
```

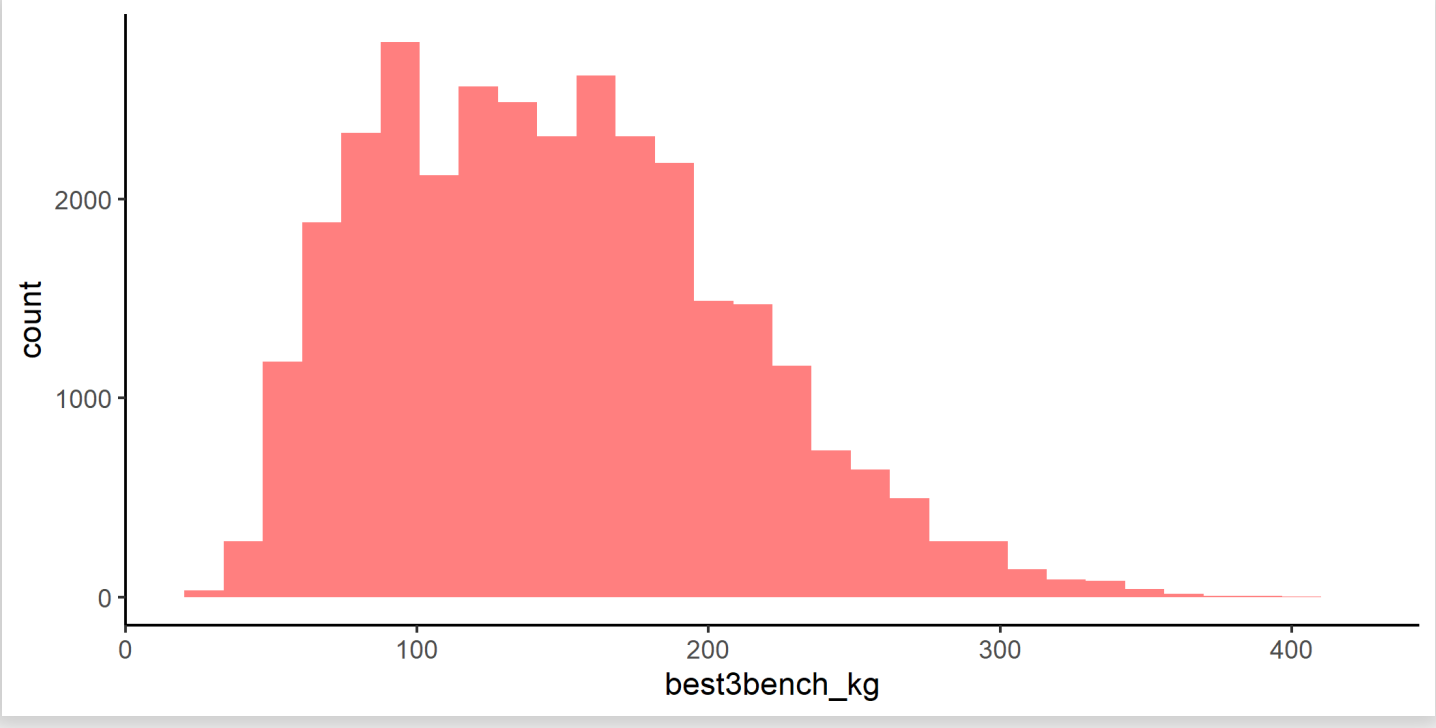
```
## [1] 32047    11
```

```
glimpse(ipf_lifts)
```

```
## Rows: 32,047
## Columns: 11
## $ sex            <fct> F, 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, S
## $ equipment      <fct> Single-ply, Single-ply, Single-ply, Single-ply, Sin
## $ age            <dbl> 33.5, 34.5, 23.5, 27.5, 37.5, 25.5, 33.5, 26.0, 33
## $ division       <fct> Open, Open, Open, Open, Open, Open, Open, Open, Ope
## $ bodyweight_kg  <dbl> 44, 44, 44, 44, 44, 44, 48, 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, 65
## $ meet_name      <fct> World Powerlifting Championships, World Powerliftin
## $ year           <dbl> 1989, 1989, 1989, 1989, 1989, 1989, 1989, 1989, 19
## $ month          <dbl> 11, 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, 2,
```

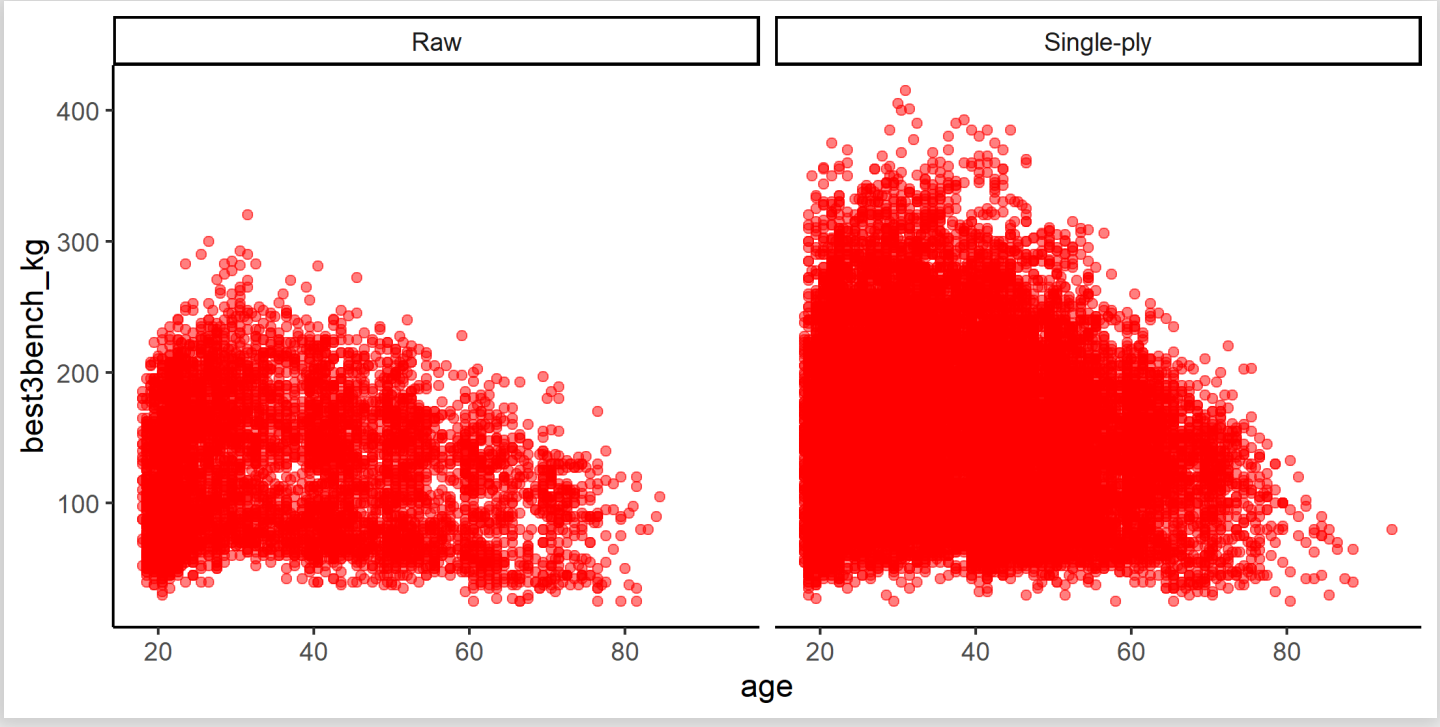
See the dependent variable distribution:

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



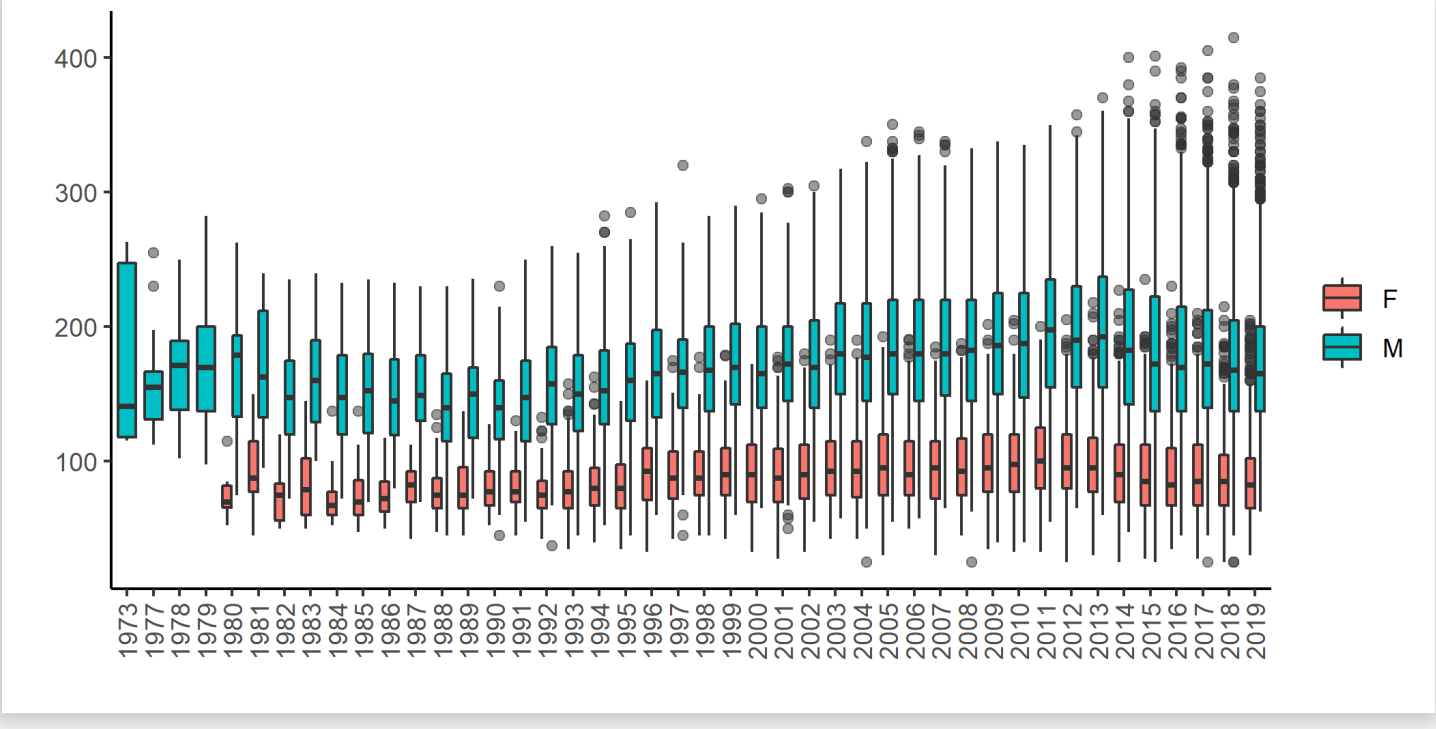
See it vs. say age, facetted by equipment:

```
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. 5-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: 15383, 15385, 15383, 15384, 15385
## Resampling results across tuning parameters:
##
##   lambda        RMSE      Rsquared   MAE
##    0.001000000  26.63908  0.8135187  20.46183
##    0.001206793  26.63908  0.8135187  20.46183
##    0.001456348  26.63908  0.8135187  20.46183
##    0.001757511  26.63908  0.8135187  20.46183
##    0.002120951  26.63908  0.8135187  20.46183
##    0.002559548  26.63908  0.8135187  20.46183
##    0.003088844  26.63908  0.8135187  20.46183
##    0.003727594  26.63908  0.8135187  20.46183
##    0.004498433  26.63908  0.8135187  20.46183
##    0.005428675  26.63908  0.8135187  20.46183
##    0.006551286  26.63908  0.8135187  20.46183
```

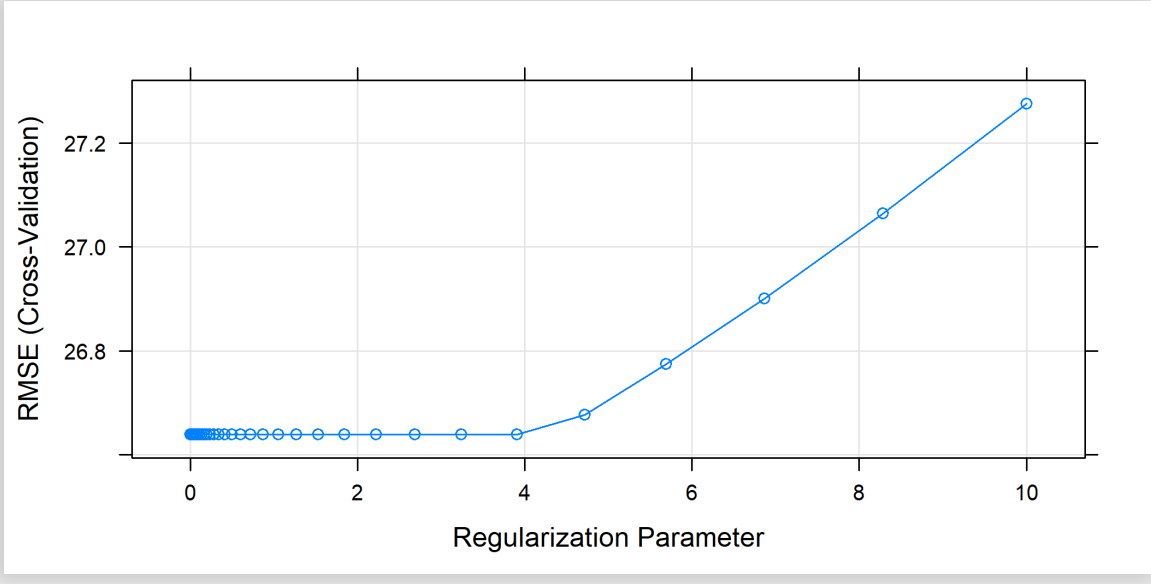
```
mod_lasso
```

```
## glmnet
##
## 19230 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15384, 15384, 15383, 15384, 15385
## Resampling results across tuning parameters:
##
##   lambda        RMSE      Rsquared   MAE
##    0.001000000  26.17362  0.8184162  20.11682
##    0.001206793  26.17362  0.8184162  20.11682
##    0.001456348  26.17362  0.8184162  20.11682
##    0.001757511  26.17362  0.8184162  20.11682
##    0.002120951  26.17362  0.8184162  20.11682
##    0.002559548  26.17362  0.8184162  20.11682
##    0.003088844  26.17362  0.8184162  20.11682
##    0.003727594  26.17362  0.8184162  20.11682
##    0.004498433  26.17362  0.8184162  20.11682
##    0.005428675  26.17362  0.8184162  20.11682
##    0.006551286  26.17362  0.8184162  20.11682
##    0.007906043  26.17362  0.8184162  20.11682
##    0.009540955  26.17362  0.8184162  20.11682
##    0.011513954  26.17362  0.8184162  20.11682
##    0.013894955  26.17362  0.8184162  20.11682
##    0.016768329  26.17362  0.8184162  20.11682
```

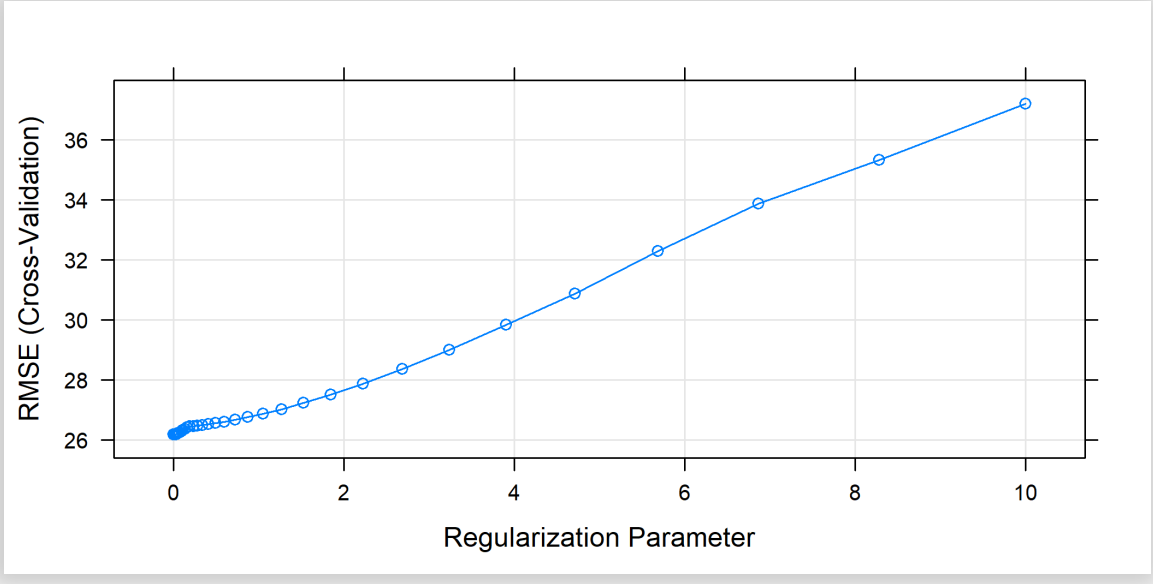
```
mod_rf
```

```
## Random Forest
##
## 19230 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 15383, 15384, 15383, 15385, 15385
## Resampling results across tuning parameters:
##
##   min.node.size  mtry  RMSE      Rsquared   MAE
##   10              2    43.98567  0.7149522  35.33115
##   10              4    33.76349  0.7849199  26.46574
##   10              6    28.13475  0.8242156  21.82625
##   10              8    25.82057  0.8380935  19.86416
##   10             10    24.36200  0.8466544  18.67136
##   20              2    43.82008  0.7278177  35.21164
##   20              4    33.57668  0.7903280  26.39480
##   20              6    28.34047  0.8207030  21.87692
##   20              8    25.66929  0.8384042  19.79244
##   20             10    24.43080  0.8465645  18.74618
##   30              2    43.79985  0.7148687  35.15808
##   30              4    33.89321  0.7833205  26.55198
##   30              6    28.60901  0.8191121  22.18501
##   30              8    26.15951  0.8342340  20.06639
##   30             10    24.48731  0.8460840  18.75604
##
```

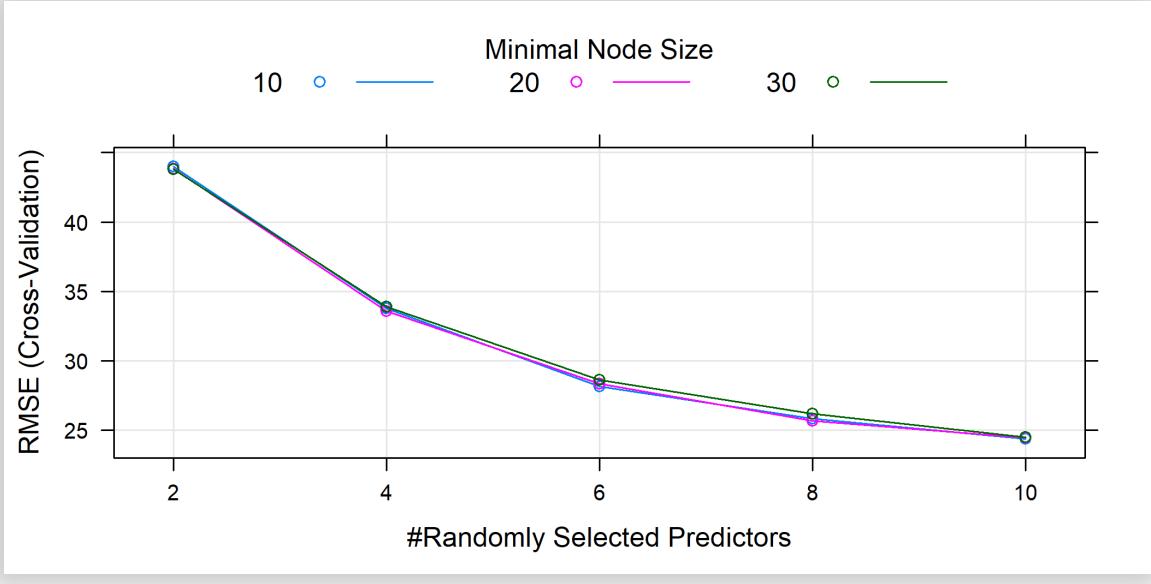
```
plot(mod_ridge)
```



```
plot(mod_lasso)
```



```
plot(mod_rf)
```

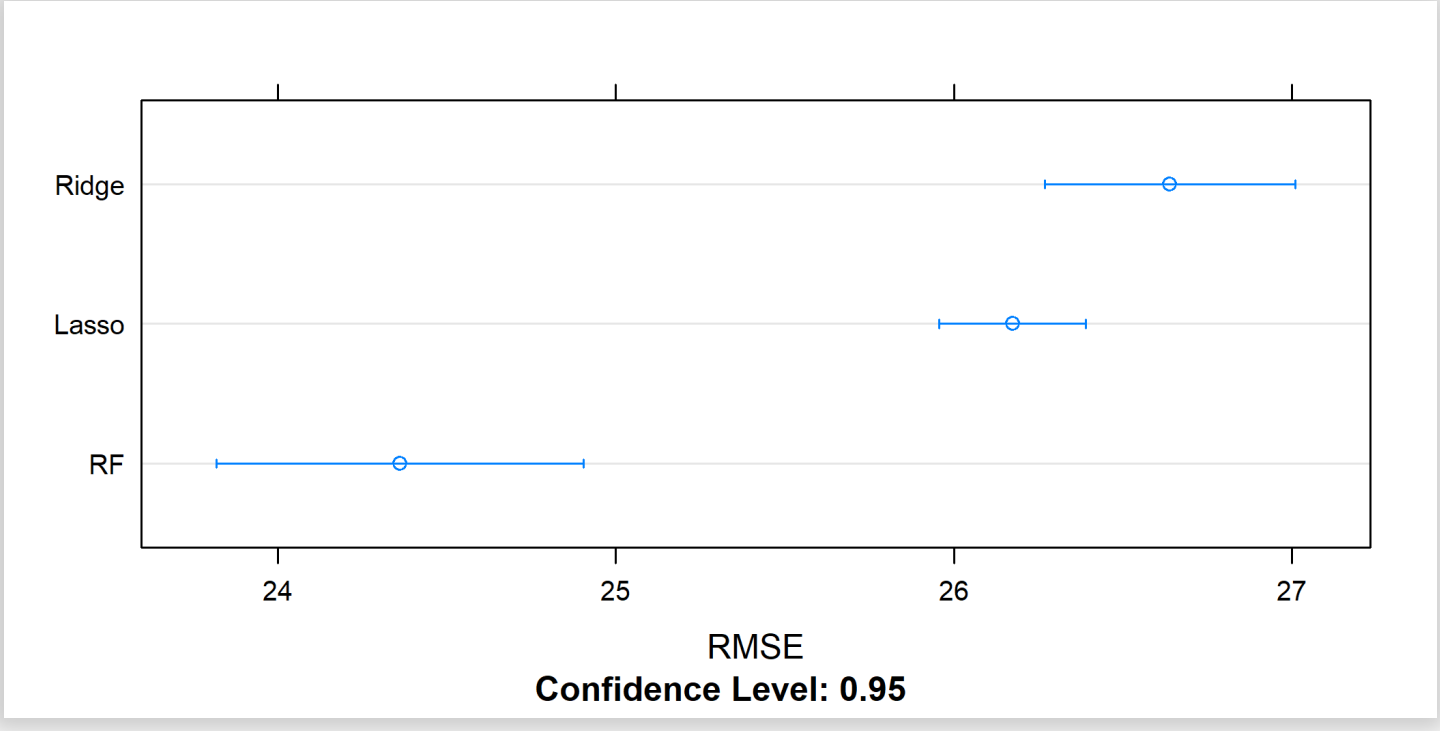

Minimal Node Size
10
20
30
RMSE (Cross-Validation)
40
35
30
25
2
4
6
8
10
#Randomly Selected Predictors

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 20.14839 20.29589 20.46453 20.46183 20.65557 20.74478    0
## Lasso 19.94215 20.01630 20.09051 20.11682 20.18540 20.34974    0
## RF    18.35277 18.48495 18.53554 18.67136 18.93460 19.04897    0
##
## RMSE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## Ridge 26.24309 26.42769 26.70235 26.63908 26.88262 26.93966    0
## Lasso 25.99027 26.04725 26.11301 26.17362 26.34091 26.37665    0
## RF    24.00869 24.06167 24.19071 24.36200 24.47448 25.07447    0
##
```

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



Predicting

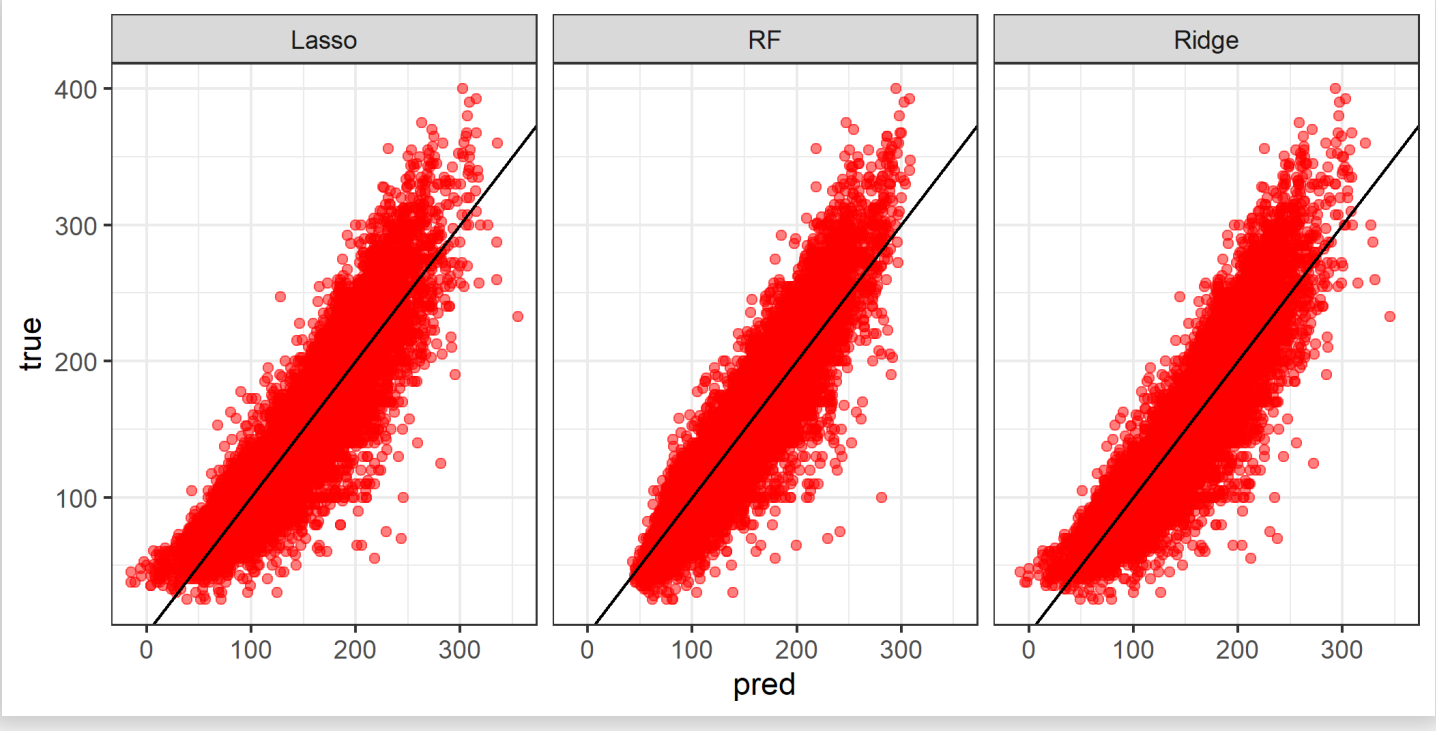
```
pred_ridge <- predict(mod_ridge, newdata = ipf_te)
pred_lasso <- predict(mod_lasso, newdata = ipf_te)
pred_rf <- predict(mod_rf, newdata = ipf_te)

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: 26.7
## Test RMSE Lassoe: 26.4
## Test RMSE RF: 24.7
```

⚠ 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

- `parsnip`: tidy `caret`
- `dials` and `tune`: specifying and tuning model parameters
- `rsample`: sampling, data partitioning
- `recipes`, `embed`, `themis`: 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)
```

```
## <Analysis/Assess/Total>
## <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.

```
ipf_rec$var_info
```

```
## # A tibble: 13 x 4
##    variable      type    role      source
##    <chr>         <chr>   <chr>     <chr>
##  1 sex           nominal predictor original
##  2 event         nominal predictor original
##  3 equipment     nominal predictor original
##  4 age           numeric predictor original
##  5 division      nominal predictor original
##  6 bodyweight_kg numeric predictor original
##  7 meet_name     nominal predictor original
##  8 year          numeric predictor original
##  9 month         numeric predictor original
## 10 dayofweek     numeric predictor original
## 11 age2          numeric predictor original
## 12 year2         numeric predictor original
## 13 best3bench_kg numeric outcome   original
```

```
ipf_rec$levels$meet_name
```

```
## $values
##  [1] "3rd World University Powerlifting Cup"
##  [2] "48th World Open Championships"
##  [3] "6th World Classic Championships"
##  [4] "Disabled Bench Press World Championships"
##  [5] "Men's World Powerlifting Championships"
##  [6] "Reykjavík International Games"
##  [7] "Student's World Cup"
##  [8] "University Powerlifting Cup"
##  [9] "Women's World Powerlifting Championship"
## [10] "Women's World Powerlifting Championships"
## [11] "World Bench Press Championships"
## [12] "World Classic Bench Press Championships"
## [13] "World Classic Powerlifting Championships"
## [14] "World Classic Powerlifting Cup"
## [15] "World Disabled Bench Press Championships"
## [16] "World Games"
## [17] "World Juniors & Sub-Juniors Championships"
## [18] "World Juniors Powerlifting Championships"
## [19] "World Masters Bench Press Championships"
## [20] "World Masters Championships"
## [21] "World Masters Powerlifting Championships"
## [22] "World Men's Powerlifting Championship"
## [23] "World Open Bench Press Championships"
## [24] "World Open Championships"
## [25] "World Powerlifting Championships"
## [26] "World Students Cup"
```

```
ipf_rec$steps[[1]]$means
```

```
##           age bodyweight_kg          year         month     dayofweek
##  3.657200e+01  8.156813e+01  2.006920e+03  7.749597e+00  3.587446e+00
##          age2         year2 best3bench_kg
##  1.539900e+03  4.027817e+06  1.481113e+02
```

```
ipf_rec$steps[[1]]$sds
```

```
##           age bodyweight_kg          year         month     dayofweek
##     14.226722     25.066822      9.375594      2.724269      1.745484
##          age2         year2 best3bench_kg
##   1186.398547  37579.912084     61.057414
```

And then we `bake()` (or `juice()`):

```
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: 14.2
## 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: 14.4
## mean of age in baked testing: 0, sd: 1.01
```

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: 14.2
## 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: 14.4
## mean of age in baked testing: 0, sd: 1.01
```

Fast Forward 10 weeks from now...

```
rec_int_topints <- recipe(pets ~ ., data = okcupid_tr) %>%
  step_textfeature(essays, prefix = "t",
                   extract_functions = my_text_funs) %>%
  update_role(essays, new_role = "discarded") %>%
  step_mutate_at(starts_with("t_"), fn = ~ifelse(is.na(.x), 0, .x)
  step_log(income, starts_with("len_"), starts_with("t_"),
           -t_essays_sent_bing, offset = 1) %>%
  step_meanimpute(income) %>%
  step_other(
    all_nominal(), -has_role("discarded"), -all_outcomes(),
    other = "all_else", threshold = 0.1) %>%
  step_novel(
    all_nominal(), -has_role("discarded"), -all_outcomes()) %>%
  step_modeimpute(all_nominal(), -has_role("discarded"), -all_outc
  step_dummy(all_nominal(), -all_outcomes(),
             -has_role("discarded"), one_hot = FALSE) %>%
  step_interact(topint_ints) %>%
  step_nzv(all_numeric(), freq_cut = 99/1) %>%
  step_upsample(pets, over_ratio = 1, seed = 42)
```

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 time:  60ms
##
## Call:  glmnet::glmnet(x = maybe_matrix(x), y = y, family = "gaussian",
##
##     Df  %Dev Lambda
## 1   51  0.00  43280
## 2   51  0.39  39440
## 3   51  0.43  35940
## 4   51  0.47  32740
## 5   51  0.52  29830
## 6   51  0.57  27180
## 7   51  0.62  24770
## 8   51  0.68  22570
## 9   51  0.75  20560
## 10  51  0.82  18740
## 11  51  0.90  17070
## 12  51  0.99  15560
## 13  51  1.08  14170
## 14  51  1.19  12910
## 15  51  1.30  11770
## 16  51  1.43  10720
## 17  51  1.56   9769
```

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 time:  40ms
##
## Call:  glmnet::glmnet(x = maybe_matrix(x), y = y, family = "gaussian",
##
##     Df  %Dev Lambda
## 1    0  0.00 43.280
## 2    1  8.53 39.440
## 3    2 16.06 35.940
## 4    2 24.11 32.740
## 5    2 30.79 29.830
## 6    2 36.33 27.180
## 7    2 40.94 24.770
## 8    2 44.76 22.570
## 9    2 47.93 20.560
## 10   2 50.57 18.740
## 11   2 52.76 17.070
## 12   2 54.57 15.560
## 13   2 56.08 14.170
```

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 time:  601ms
## Ranger result
##
## Call:
##  ranger::ranger(x = maybe_data_frame(x), y = y, mtry = min_cols(~4,
##
## 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):       561.4695
## R squared (OOB):                  0.8493916
```

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

```
tidy(mod_ridge)
```

```
## # A tibble: 52 x 3
##    term                  estimate penalty
##    <chr>                    <dbl>   <dbl>
##  1 (Intercept)          -1958.       0.001
##  2 sexM                    58.9      0.001
##  3 eventSB                -30.6      0.001
##  4 eventSBD                -9.31     0.001
##  5 equipmentSingle-ply     29.3      0.001
##  6 age                     -0.0147   0.001
##  7 divisionJuniors         -4.13     0.001
##  8 divisionLight           -8.04     0.001
##  9 divisionMasters 1       -0.251    0.001
## 10 divisionMasters 2       -9.03     0.001
## # ... with 42 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
```

```
head(results_test)
```

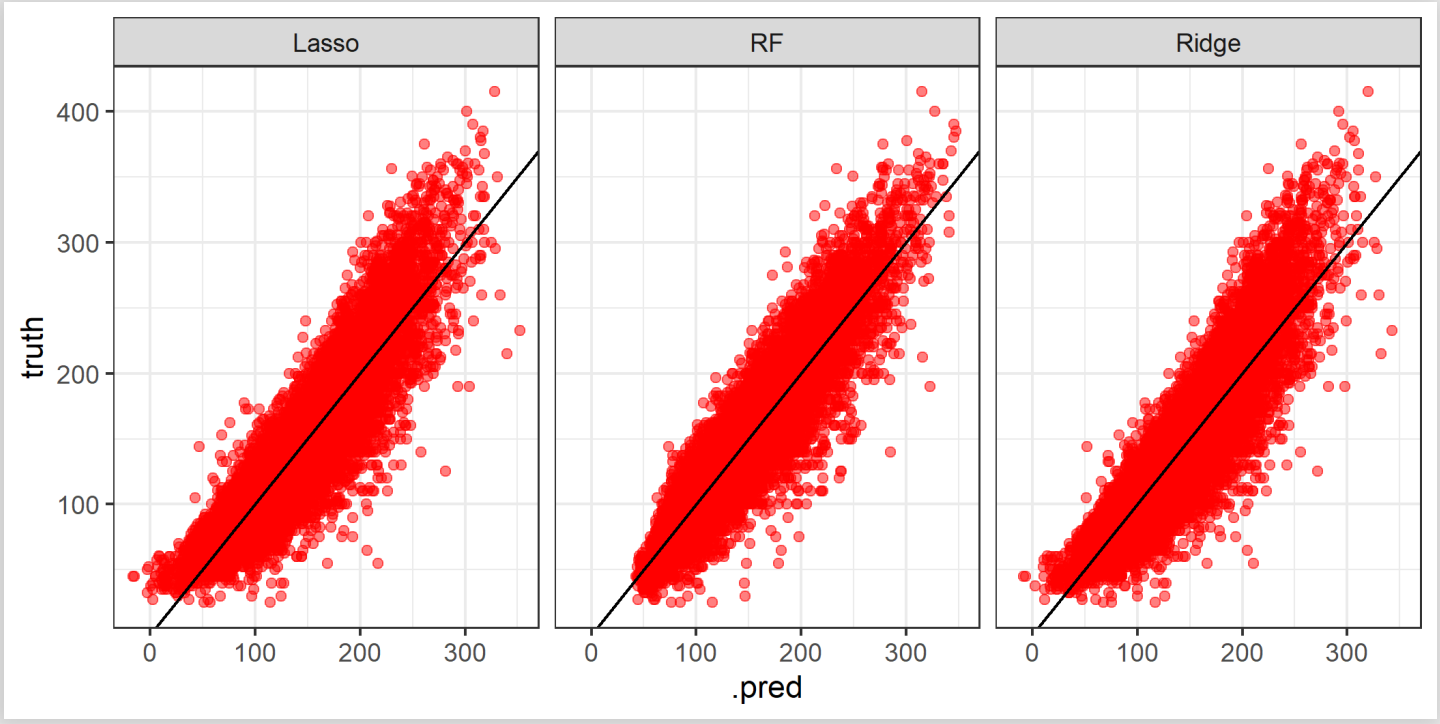
Comparing Models

The package `yardstick` has tons of performance metrics:

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

```
## # A tibble: 3 x 4
##   method .metric .estimator .estimate
##   <chr>  <chr>   <chr>          <dbl>
## 1 Lasso  rmse    standard        26.3
## 2 RF     rmse    standard        23.6
## 3 Ridge  rmse    standard        26.7
```

```
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

Define your model spec, using `tune()` from the `tune` package for a parameter you wish to tune:

```
mod_rf_spec <- rand_forest(mode = "regression",
                           mtry = tune(),
                           min_n = tune(),
                           trees = 100) %>%
  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
##   <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(mod_rf_spec,
                      recipe(best3bench_kg ~ ., data = ipf_tr),
                      resamples = cv_splits,
                      grid = rf_grid,
                      metrics = metric_set(rmse))
tune_res
```

```
## # Tuning results
## # 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 6]> <tibble [0 x 1]>
## 2 <split [15.4K/3.8K]> Fold2 <tibble [15 x 6]> <tibble [0 x 1]>
## 3 <split [15.4K/3.8K]> Fold3 <tibble [15 x 6]> <tibble [0 x 1]>
## 4 <split [15.4K/3.8K]> Fold4 <tibble [15 x 6]> <tibble [0 x 1]>
## 5 <split [15.4K/3.8K]> Fold5 <tibble [15 x 6]> <tibble [0 x 1]>
```

```
tune_res$.metrics[[1]]
```

```
## # A tibble: 15 x 6
##     mtry min_n .metric .estimator .estimate .config
##    <int> <int> <chr>   <chr>          <dbl> <chr>
##  1     2    10 rmse    standard        24.5 Preprocessor1_Model01
##  2     4    10 rmse    standard        23.6 Preprocessor1_Model02
##  3     6    10 rmse    standard        23.7 Preprocessor1_Model03
##  4     8    10 rmse    standard        23.7 Preprocessor1_Model04
##  5    10    10 rmse    standard        23.8 Preprocessor1_Model05
##  6     2    20 rmse    standard        24.5 Preprocessor1_Model06
##  7     4    20 rmse    standard        23.4 Preprocessor1_Model07
##  8     6    20 rmse    standard        23.4 Preprocessor1_Model08
##  9     8    20 rmse    standard        23.4 Preprocessor1_Model09
## 10    10    20 rmse    standard        23.4 Preprocessor1_Model10
## 11     2    30 rmse    standard        24.6 Preprocessor1_Model11
## 12     4    30 rmse    standard        23.4 Preprocessor1_Model12
## 13     6    30 rmse    standard        23.3 Preprocessor1_Model13
## 14     8    30 rmse    standard        23.3 Preprocessor1_Model14
## 15    10    30 rmse    standard        23.3 Preprocessor1_Model15
```

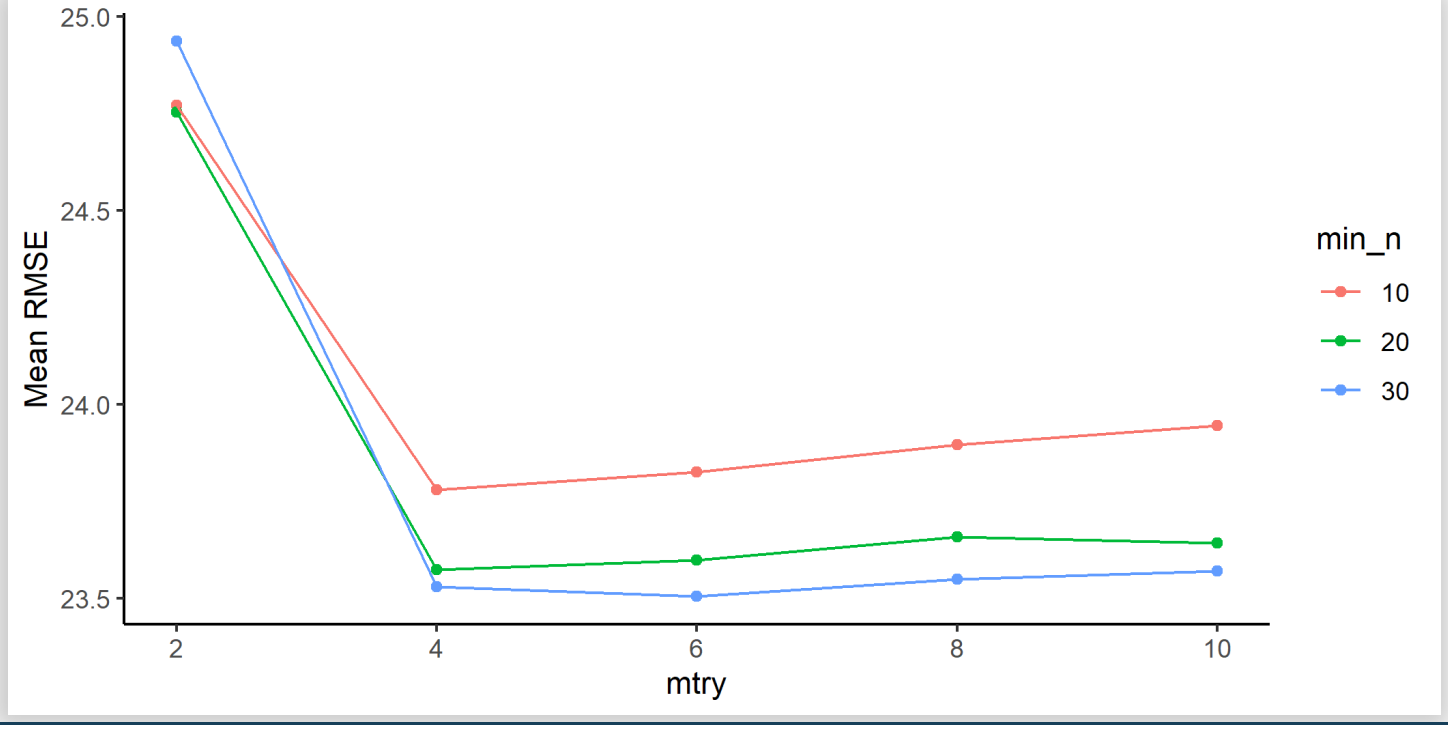
Collect the mean metric across folds:

```
estimates <- collect_metrics(tune_res)

estimates
```

```
## # A tibble: 15 x 8
##     mtry min_n .metric .estimator  mean     n std_err .config
##    <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1     2    10 rmse    standard    24.8     5   0.163 Preprocessor1_Mode
##  2     4    10 rmse    standard    23.8     5   0.129 Preprocessor1_Mode
##  3     6    10 rmse    standard    23.8     5   0.129 Preprocessor1_Mode
##  4     8    10 rmse    standard    23.9     5   0.133 Preprocessor1_Mode
##  5    10    10 rmse    standard    23.9     5   0.135 Preprocessor1_Mode
##  6     2    20 rmse    standard    24.8     5   0.214 Preprocessor1_Mode
##  7     4    20 rmse    standard    23.6     5   0.141 Preprocessor1_Mode
##  8     6    20 rmse    standard    23.6     5   0.121 Preprocessor1_Mode
##  9     8    20 rmse    standard    23.7     5   0.143 Preprocessor1_Mode
## 10    10    20 rmse    standard    23.6     5   0.142 Preprocessor1_Mode
## 11     2    30 rmse    standard    24.9     5   0.162 Preprocessor1_Mode
## 12     4    30 rmse    standard    23.5     5   0.123 Preprocessor1_Mode
## 13     6    30 rmse    standard    23.5     5   0.132 Preprocessor1_Mode
## 14     8    30 rmse    standard    23.5     5   0.145 Preprocessor1_Mode
## 15    10    30 rmse    standard    23.6     5   0.132 Preprocessor1_Mode
```

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()
```



There are of course also methods for helping us choose best params and final model.

```
best_rmse <- tune_res %>% select_best(metric = "rmse")
best_rmse
```

```
## # A tibble: 1 x 3
##    mtry min_n .config
##   <int> <int> <chr>
## 1     6    30 Preprocessor1_Model13
```

See also `?select_by_one_std_err`.

```
mod_rf_final <- finalize_model(mod_rf_spec, best_rmse)
mod_rf_final
```

```
## Random Forest Model Specification (regression)
##
## Main Arguments:
##   mtry = 6
##   trees = 100
##   min_n = 30
##
## Computational engine: ranger
```

```
mod_rf_final %>%
  fit(best3bench_kg ~ ., data = ipf_tr) %>%
  predict(new_data = ipf_te) %>%
  mutate(truth = ipf_te$best3bench_kg)
```

```
## # A tibble: 12,818 x 2
##    .pred truth
##    <dbl> <dbl>
##  1  64.1  65
##  2  73.8 100
##  3  73.8  82.5
##  4  74.5  72.5
##  5  80.3 105
##  6  80.2  75
##  7  86.2 110
##  8  87.9  85
##  9  92.8 138.
## 10  90.4 100
## # ... with 12,808 more rows
```

`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 conf
##      <dbl>     <dbl>     <dbl>     <dbl>   <dbl>     <dbl>    <dbl>
## 1    -2.81      36.0      38.8     -3.88 1.08e-4     1922.    -4.23
## # ... with 2 more variables: 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
```

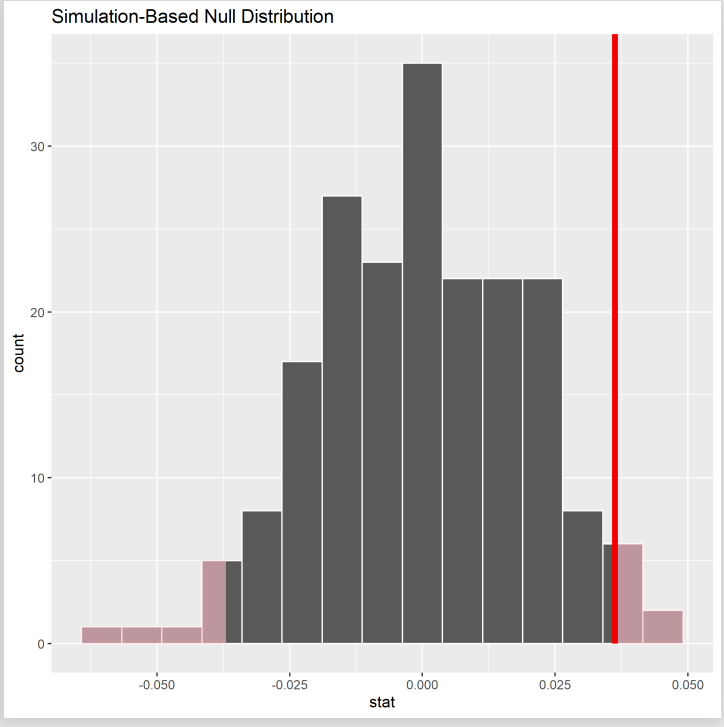
Get distribution of the difference in proportions under null hypothesis

```
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  0.0139
##  2         2 -0.0207
##  3         3  0.0200
##  4         4 -0.000353
##  5         5 -0.0126
##  6         6  0.0200
##  7         7  0.0322
##  8         8 -0.0614
##  9         9 -0.00442
## 10        10  0.00778
## # ... 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
```

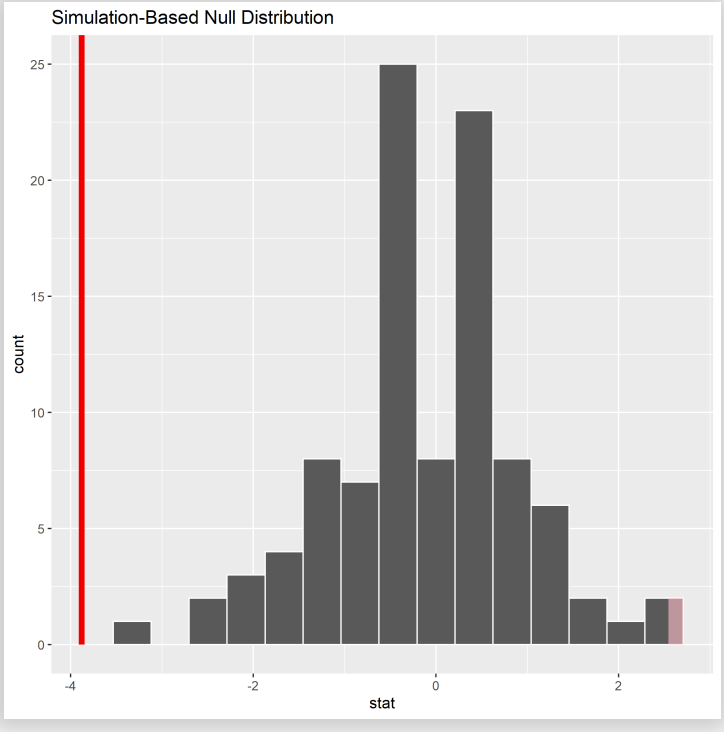
Get distribution of the t statistic under null hypothesis

```
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  0.316
##  2         2 -1.07
##  3         3  0.424
##  4         4 -0.304
##  5         5 -1.02
##  6         6 -0.259
##  7         7 -0.972
##  8         8  0.354
##  9         9 -1.51
## 10        10 -1.42
## # ... 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")
```

```
## Warning: Please be cautious in reporting a p-value of 0. This result is a
## approximation based on the number of `reps` chosen in the `generate()` st
## `?get_p_value()` for more information.

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