# Modeling Run Performance

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## Garmin Data Modeling

The two most obvious primary target variables are average speed (avg_spd) in miles per hour, and average pace (avg_pace_sec) in seconds. A higher average speed and a lower average pace are the desired outcome when measuring performance over time. Reviewing the results of the two preliminary linear regression models, the more desirable variable is average pace, as it has stronger relationships with other variables.

```
# Create preliminary model

prelim_spd <- lm(avg_spd ~ ., df)
summary(prelim_spd)
```

```
##
## Call:
## lm(formula = avg_spd ~ ., data = df)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.187959 -0.029389 -0.000816  0.028251  0.219902
##
## Coefficients: (1 not defined because of singularities)
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -6.402e+00  5.019e-01 -12.755  < 2e-16 ***
## distance                  1.031e-02  7.272e-03   1.417 0.157270
## avg_hr                    4.347e-03  1.026e-03   4.236 2.84e-05 ***
## max_hr                   -1.052e-03  6.662e-04  -1.579 0.115059
## avg_run_cadence           4.733e-02  1.259e-03  37.584  < 2e-16 ***
## max_run_cadence           1.806e-04  2.388e-04   0.756 0.449921
## total_ascent             -5.052e-05  7.741e-05  -0.653 0.514341
## total_decent              6.208e-05  7.328e-05   0.847 0.397386
## avg_stride                5.142e+00  1.294e-01  39.720  < 2e-16 ***
## min_elevation             3.616e-04  1.058e-04   3.418 0.000697 ***
## max_elevation            -2.596e-05  1.096e-04  -0.237 0.812852
## avg_pace_sec             -1.011e-03  3.465e-04  -2.916 0.003745 **
## best_pace_sec            -9.307e-05  1.039e-04  -0.896 0.370737
## `sweat_loss(ml)`         -4.945e-05  1.336e-04  -0.370 0.711397
## aerobic_TE               -8.122e-02  1.663e-02  -4.885 1.51e-06 ***
## aerobic_fctImpacting     -5.322e-03  9.255e-03  -0.575 0.565576
## aerobic_fctMaintaining    2.091e-02  1.771e-02   1.181 0.238502
## aerobic_fctOverreaching   4.604e-02  1.427e-02   3.225 0.001365 **
## anaerobic_value           1.303e-02  1.097e-02   1.187 0.235838
```

```
## anaerobic_fctMaintaining  -4.067e-03  1.741e-02  -0.234 0.815458
## anaerobic_fctNo Benefit   -4.778e-02  3.440e-02  -1.389 0.165630
## anaerobic_fctSome Benefit -6.501e-02  2.583e-02  -2.517 0.012246 *
## max_spd                   -3.014e-03  2.567e-03  -1.174 0.241070
## short_distanceY            1.336e-02  1.906e-02   0.701 0.483817
## middle_distanceY           1.843e-02  1.414e-02   1.303 0.193186
## long_distanceY                    NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04525 on 392 degrees of freedom
## Multiple R-squared:  0.9978, Adjusted R-squared:  0.9976
## F-statistic:  7263 on 24 and 392 DF,  p-value: < 2.2e-16
```

```
prelim_pace <- lm(avg_pace_sec ~ ., df)
summary(prelim_pace)
```

```
##
## Call:
## lm(formula = avg_pace_sec ~ ., data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.013  -3.313  -0.427   3.011  47.420
##
## Coefficients: (1 not defined because of singularities)
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                1.185e+03  6.190e+01  19.143  < 2e-16 ***
## distance                  -4.443e+00  1.027e+00  -4.326 1.93e-05 ***
## avg_hr                     3.786e-01  1.501e-01   2.522  0.01206 *
## max_hr                    -8.380e-03  9.638e-02  -0.087  0.93075
## avg_run_cadence           -1.787e+00  3.790e-01  -4.715 3.37e-06 ***
## max_run_cadence            5.933e-03  3.445e-02   0.172  0.86337
## total_ascent              -9.885e-03  1.116e-02  -0.886  0.37613
## total_decent               3.999e-03  1.057e-02   0.378  0.70547
## avg_stride                -2.333e+02  4.015e+01  -5.811 1.29e-08 ***
## min_elevation             -2.627e-02  1.542e-02  -1.703  0.08930 .
## max_elevation              2.642e-02  1.575e-02   1.678  0.09417 .
## best_pace_sec              2.566e-02  1.494e-02   1.718  0.08661 .
## `sweat_loss(ml)`           9.787e-02  1.862e-02   5.257 2.41e-07 ***
## aerobic_TE                -8.762e+00  2.429e+00  -3.606  0.00035 ***
## aerobic_fctImpacting      -4.257e+00  1.318e+00  -3.231  0.00134 **
## aerobic_fctMaintaining     5.590e+00  2.542e+00   2.199  0.02849 *
## aerobic_fctOverreaching    5.209e+00  2.069e+00   2.518  0.01220 *
## anaerobic_value           -1.135e+00  1.584e+00  -0.716  0.47435
## anaerobic_fctMaintaining   2.063e+00  2.509e+00   0.822  0.41144
## anaerobic_fctNo Benefit    1.926e-01  4.972e+00   0.039  0.96913
## anaerobic_fctSome Benefit  1.513e+00  3.754e+00   0.403  0.68709
## avg_spd                   -2.101e+01  7.205e+00  -2.916  0.00374 **
## max_spd                    6.393e-02  3.708e-01   0.172  0.86321
## short_distanceY           -5.004e-01  2.750e+00  -0.182  0.85569
## middle_distanceY          -1.782e-01  2.044e+00  -0.087  0.93054
## long_distanceY                    NA         NA      NA       NA
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.525 on 392 degrees of freedom
## Multiple R-squared:  0.9901, Adjusted R-squared:  0.9895
## F-statistic:  1641 on 24 and 392 DF,  p-value: < 2.2e-16
```

The ultimate goal of this model is to utilize data leading up to a performance event. As many races take place on Sunday and the typical long-distance run in this data set takes place on Sunday, the final linear regression model will begin with predicting Sunday performance.

To being predicting run performance, an initial linear regression model will be built below using all available data. Based on the preliminary linear regression above, an aerobic training effect that has a high impact (value between 4 and 4.9) is strongly related to average pace. This variable will be the target variable in the logistic regression that follows.

```
set.seed(456)
# Split data into training and testing sets
df_split <- initial_split(df, prop = 3/4)

train_df <- training(df_split)
test_df <- testing(df_split)

# Create recipe
pace_rec <- recipe(avg_hr ~ ., data = train_df)

summary(pace_rec)
```

```
## # A tibble: 22 x 4
##    variable        type    role      source
##    <chr>           <chr>   <chr>     <chr>
##  1 distance        numeric predictor original
##  2 max_hr          numeric predictor original
##  3 avg_run_cadence numeric predictor original
##  4 max_run_cadence numeric predictor original
##  5 total_ascent    numeric predictor original
##  6 total_decent    numeric predictor original
##  7 avg_stride      numeric predictor original
##  8 min_elevation   numeric predictor original
##  9 max_elevation   numeric predictor original
## 10 avg_pace_sec    numeric predictor original
## # ... with 12 more rows
```

```
lm_pace <- linear_reg() %>%
  set_engine("lm")

pace_wflow <- workflow()%>%
  add_model(lm_pace) %>%
  add_recipe(pace_rec)

pace_fit <- pace_wflow %>%
  fit(data = train_df)

tidy(pace_fit)
```

```
## # A tibble: 26 x 5
##    term             estimate std.error statistic  p.value
##    <chr>               <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)      59.0      31.4         1.88  6.14e- 2
##  2 distance         -4.45      0.590      -7.54  6.24e-13
##  3 max_hr            0.168     0.0359      4.67  4.68e- 6
##  4 avg_run_cadence  -0.200     0.144      -1.39  1.65e- 1
##  5 max_run_cadence  -0.0358    0.0132     -2.72  6.88e- 3
##  6 total_ascent     -0.00706   0.00455    -1.55  1.22e- 1
##  7 total_decent      0.00335   0.00421     0.797 4.26e- 1
##  8 avg_stride      -30.8      15.7        -1.97  5.01e- 2
##  9 min_elevation    -0.0145    0.00626    -2.31  2.14e- 2
## 10 max_elevation    -0.000661  0.00630    -0.105 9.17e- 1
## # ... with 16 more rows
```

```
predict(pace_fit, test_df)
```

```
## Warning in predict.lm(object = object$fit, newdata = new_data, type =
## "response"): prediction from a rank-deficient fit may be misleading
```

```
## # A tibble: 105 x 1
##    .pred
##    <dbl>
##  1  168.
##  2  167.
##  3  164.
##  4  167.
##  5  165.
##  6  171.
##  7  166.
##  8  172.
##  9  166.
## 10  164.
## # ... with 95 more rows
```

```
pace_aug <- augment(pace_fit, test_df)
```

```
## Warning in predict.lm(object = object$fit, newdata = new_data, type =
## "response"): prediction from a rank-deficient fit may be misleading
```

```
pace_aug %>% select(avg_pace_sec, .pred)
```

```
## # A tibble: 105 x 2
##    avg_pace_sec .pred
##           <dbl> <dbl>
##  1          447  168.
##  2          449  167.
##  3          432  164.
##  4          438  167.
##  5          391  165.
##  6          414  171.
```

```
## 7           419  166.
## 8           432  172.
## 9           444  166.
## 10          430  164.
## # ... with 95 more rows
```

The R Mean-Squared Error for this model is 5.41. In other words, this model can predict average pace within 5.41 seconds.

```r
pace_error <- pace_aug %>%
  rmse(truth = avg_pace_sec, .pred)

pace_error
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard        322.
```

The most significant variables (based on p-value) are average heart rate, average cadence, average stride, and aerobic training effect. The binary variable aerobic_fct_Impacting had a good p-value, as well, but that value is related to aerobic training effect, so it is left out of this analysis. As an attempt to improve the quality of the model, only the variables with the highest p-values will be included in this analysis.

```r
set.seed(456)
# Split data into training and testing sets
df_split <- initial_split(df, prop = 3/4)

train_df <- training(df_split)
test_df <- testing(df_split)

# Create recipe
pace_rec_2 <- recipe(avg_pace_sec ~ avg_hr + avg_run_cadence + avg_stride + aerobic_TE, data = train_df

summary(pace_rec_2)
```

```
## # A tibble: 5 x 4
##   variable        type    role      source
##   <chr>           <chr>   <chr>     <chr>
## 1 avg_hr          numeric predictor original
## 2 avg_run_cadence numeric predictor original
## 3 avg_stride      numeric predictor original
## 4 aerobic_TE      numeric predictor original
## 5 avg_pace_sec    numeric outcome   original
```

```r
lreg <- linear_reg() %>%
  set_engine("lm")

pace_wflow_2 <- workflow()%>%
  add_model(lreg) %>%
  add_recipe(pace_rec_2)
```

```r
pace_fit_2 <- pace_wflow_2 %>%
  fit(data = train_df)

tidy(pace_fit_2)
```

```
## # A tibble: 5 x 5
##   term            estimate std.error statistic   p.value
##   <chr>              <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)     1462.       19.6       74.7  6.99e-199
## 2 avg_hr             0.212     0.138      1.53 1.26e-  1
## 3 avg_run_cadence   -3.17      0.146    -21.7  7.28e- 64
## 4 avg_stride      -376.        7.15     -52.6  1.04e-155
## 5 aerobic_TE        -8.36      1.02      -8.17 8.05e- 15
```

```r
predict(pace_fit_2, test_df)
```

```
## # A tibble: 105 x 1
##    .pred
##    <dbl>
##  1  452.
##  2  450.
##  3  444.
##  4  441.
##  5  390.
##  6  414.
##  7  431.
##  8  429.
##  9  446.
## 10  441.
## # ... with 95 more rows
```

```r
pace_aug_2 <- augment(pace_fit_2, test_df)

pace_aug_2 %>% select(avg_pace_sec, .pred)
```

```
## # A tibble: 105 x 2
##    avg_pace_sec .pred
##           <dbl> <dbl>
##  1          447  452.
##  2          449  450.
##  3          432  444.
##  4          438  441.
##  5          391  390.
##  6          414  414.
##  7          419  431.
##  8          432  429.
##  9          444  446.
## 10          430  441.
## # ... with 95 more rows
```

Reviewing the results, the quality of the model decreased slightly. However, it seems that average pace will be a good target variable in exploring performance improvements.

```
pace_error_2 <- pace_aug_2 %>%
  rmse(truth = avg_pace_sec, .pred)

pace_error_2
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard        7.24
```

## Logistic Regression

### All Variables

This first logistic regression is meant to predict whether an activity highly impacts aerobic training. This variable is relevant because it is the highest measure for aerobic conditioning without being over-reaching. In this analysis, calories and other variables related to aerobic training effect were removed.

```
set.seed(456)

df2 <- df %>% mutate(high_impact = ifelse(aerobic_fct == "Highly Impacting", 1,0))
df2$high_impact <- factor(df2$high_impact)

# Split data into training and testing sets
df2_split <- initial_split(df2, prop = 3/4)

train_df2 <- training(df2_split)
test_df2 <- testing(df2_split)

# Create recipe. Use all variables except aerobic_TE and related
aerobic_rec <- recipe(high_impact ~ short_distance + middle_distance + long_distance +
                        max_spd + avg_spd + anaerobic_value + `sweat_loss(ml)` + best_pace_sec +
                        avg_pace_sec + max_elevation + min_elevation + avg_stride +
                        total_decent + total_ascent + max_run_cadence + avg_run_cadence +
                        max_hr + avg_hr + distance, data = train_df2)

summary(aerobic_rec)
```

```
## # A tibble: 20 x 4
##    variable        type    role      source
##    <chr>           <chr>   <chr>     <chr>
##  1 short_distance  nominal predictor original
##  2 middle_distance nominal predictor original
##  3 long_distance   nominal predictor original
##  4 max_spd         numeric predictor original
##  5 avg_spd         numeric predictor original
##  6 anaerobic_value numeric predictor original
##  7 sweat_loss(ml)  numeric predictor original
##  8 best_pace_sec   numeric predictor original
##  9 avg_pace_sec    numeric predictor original
## 10 max_elevation   numeric predictor original
## 11 min_elevation   numeric predictor original
```

```
## 12 avg_stride      numeric predictor original
## 13 total_decent    numeric predictor original
## 14 total_ascent    numeric predictor original
## 15 max_run_cadence numeric predictor original
## 16 avg_run_cadence numeric predictor original
## 17 max_hr          numeric predictor original
## 18 avg_hr          numeric predictor original
## 19 distance        numeric predictor original
## 20 high_impact     nominal outcome   original
```

```
log_reg <- logistic_reg() %>%
  set_engine("glm")

aero_wkfl <- workflow()%>%
  add_model(log_reg) %>%
  add_recipe(aerobic_rec)

aero_fit <- aero_wkfl %>%
  fit(data = train_df2)

tidy(aero_fit)
```

```
## # A tibble: 20 x 5
##    term               estimate std.error statistic  p.value
##    <chr>                 <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)       -52.5     143.         -0.366   0.714
##  2 short_distanceY    -0.129     1.62       -0.0796  0.937
##  3 middle_distanceY    1.22      1.07        1.15    0.251
##  4 long_distanceY     NA        NA          NA      NA
##  5 max_spd            -0.769     1.12       -0.686   0.492
##  6 avg_spd           -20.8       6.50       -3.20    0.00138
##  7 anaerobic_value    -1.00      0.536      -1.87    0.0615
##  8 `sweat_loss(ml)`    0.0196    0.0289      0.677   0.498
##  9 best_pace_sec      -0.0201    0.0376     -0.536   0.592
## 10 avg_pace_sec       -0.106     0.120      -0.884   0.377
## 11 max_elevation      -0.0422    0.0158     -2.67    0.00756
## 12 min_elevation       0.0410    0.0135      3.03    0.00245
## 13 avg_stride         87.3      37.8         2.31    0.0209
## 14 total_decent        0.00683   0.00776     0.880   0.379
## 15 total_ascent        0.00178   0.00776     0.229   0.819
## 16 max_run_cadence     0.0432    0.0265      1.63    0.104
## 17 avg_run_cadence     0.727     0.351       2.07    0.0384
## 18 max_hr              0.00227   0.0959      0.0237  0.981
## 19 avg_hr              0.240     0.0828      2.91    0.00366
## 20 distance           -0.519     1.39       -0.375   0.708
```

```
predict(aero_fit, test_df2)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
## # A tibble: 105 x 1
```

```
##    .pred_class
##    <fct>
##  1 0
##  2 0
##  3 0
##  4 0
##  5 0
##  6 0
##  7 0
##  8 1
##  9 1
## 10 0
## # ... with 95 more rows
```

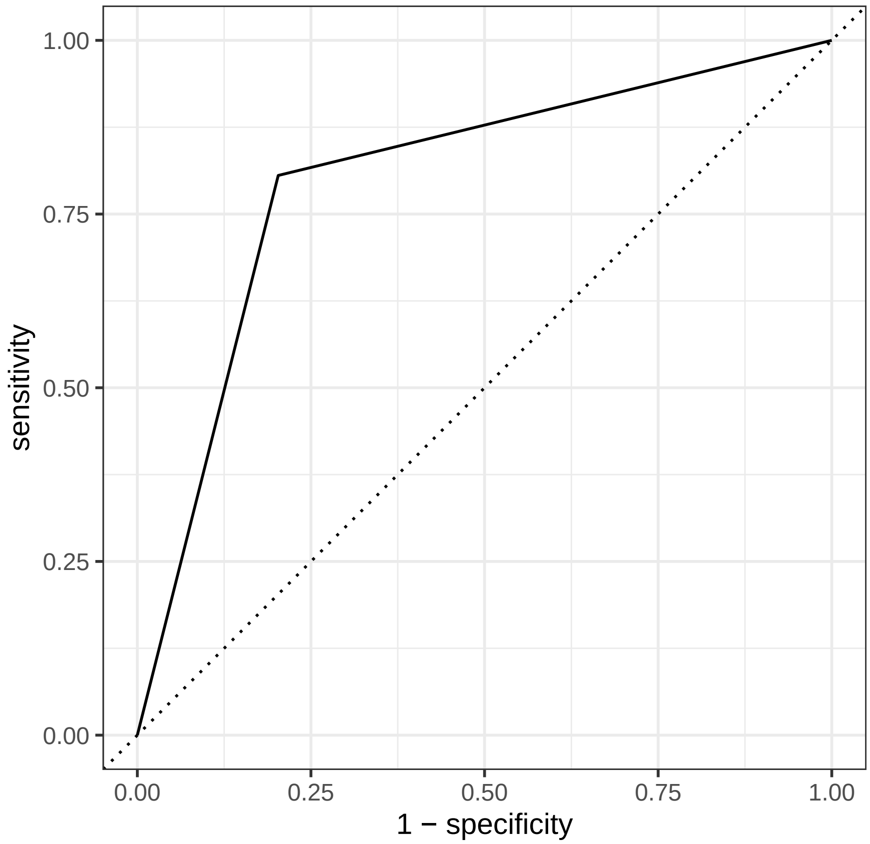
```r
aero_aug <- augment(aero_fit, test_df2)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```r
aero_aug %>% select(high_impact, .pred_class)
```

```
## # A tibble: 105 x 2
##    high_impact .pred_class
##    <fct>       <fct>
##  1 0           0
##  2 0           0
##  3 0           0
##  4 0           0
##  5 0           0
##  6 0           0
##  7 0           0
##  8 1           1
##  9 1           1
## 10 0           0
## # ... with 95 more rows
```

```r
aero_aug$.pred_class <- as.character(aero_aug$.pred_class)
aero_aug$.pred_class <- as.numeric(aero_aug$.pred_class)

aero_aug %>%
  roc_curve(truth = high_impact, .pred_class, event_level="second") %>%
  autoplot()
```




```
aero_aug %>%
  roc_auc(truth = high_impact, .pred_class, event_level="second")
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc binary         0.801
```

The first logistic regression is a good predictive model. The next step is to select fewer variables to see those increase the reliability of the model.

```
# Create recipe. Use all variables except aerobic_TE and related
aerobic_rec2 <- recipe(high_impact ~ middle_distance + avg_spd + min_elevation + avg_stride +
                       avg_run_cadence + avg_hr, data = train_df2)

summary(aerobic_rec2)
```

```
## # A tibble: 7 x 4
##   variable        type    role      source
##   <chr>           <chr>   <chr>     <chr>
## 1 middle_distance nominal predictor original
## 2 avg_spd         numeric predictor original
## 3 min_elevation   numeric predictor original
## 4 avg_stride      numeric predictor original
```

```
## 5 avg_run_cadence numeric predictor original
## 6 avg_hr          numeric predictor original
## 7 high_impact     nominal outcome   original
```

```
log_reg <- logistic_reg() %>%
  set_engine("glm")

aero_wkfl2 <- workflow()%>%
  add_model(log_reg) %>%
  add_recipe(aerobic_rec2)

aero_fit2 <- aero_wkfl2 %>%
  fit(data = train_df2)

tidy(aero_fit2)
```

```
## # A tibble: 7 x 5
##   term              estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)      -159.      36.8         -4.32 1.58e- 5
## 2 middle_distanceY    2.72     0.385        7.07 1.56e-12
## 3 avg_spd           -17.9      4.48        -3.99 6.51e- 5
## 4 min_elevation      -0.0139   0.00647     -2.14 3.22e- 2
## 5 avg_stride         92.7     24.7          3.75 1.79e- 4
## 6 avg_run_cadence     0.938    0.243        3.86 1.11e- 4
## 7 avg_hr              0.217    0.0482       4.51 6.58e- 6
```

```
predict(aero_fit2, test_df2)
```

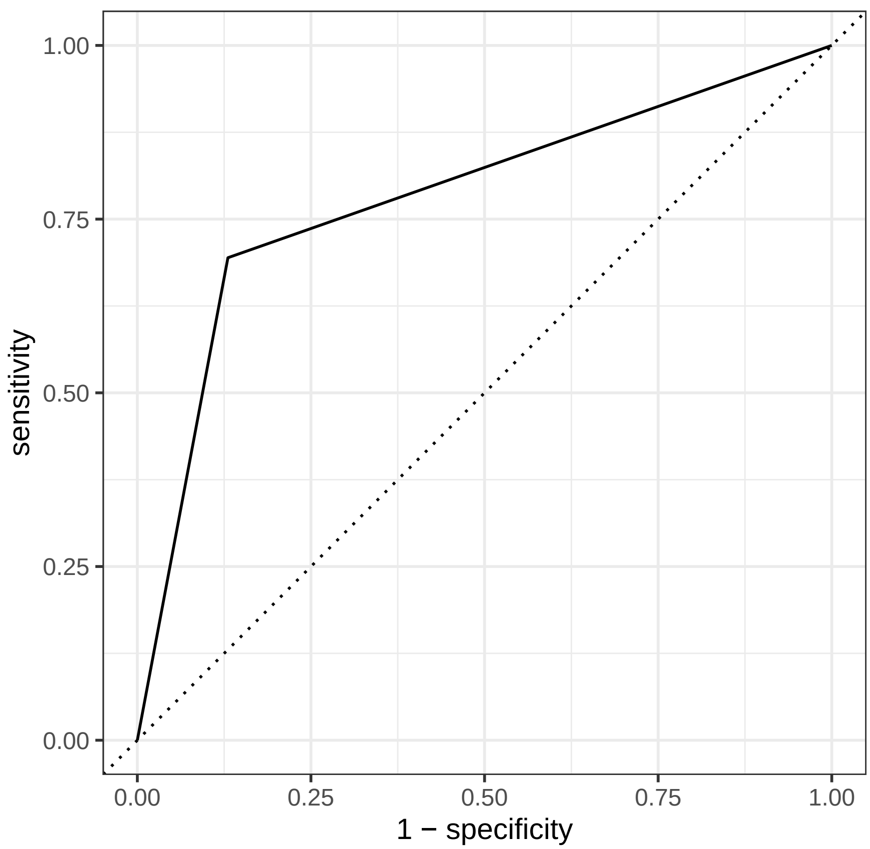
```
## # A tibble: 105 x 1
##    .pred_class
##    <fct>
##  1 0
##  2 0
##  3 0
##  4 0
##  5 0
##  6 0
##  7 0
##  8 1
##  9 1
## 10 0
## # ... with 95 more rows
```

```
aero_aug2 <- augment(aero_fit2, test_df2)

aero_aug2 %>% select(high_impact, .pred_class)
```

```
## # A tibble: 105 x 2
##    high_impact .pred_class
##    <fct>       <fct>
##  1 0           0
```

```
##   2 0           0
##   3 0           0
##   4 0           0
##   5 0           0
##   6 0           0
##   7 0           0
##   8 1           1
##   9 1           1
## 10 0           0
## # ... with 95 more rows
```

```
aero_aug2$.pred_class <- as.character(aero_aug2$.pred_class)
aero_aug2$.pred_class <- as.numeric(aero_aug2$.pred_class)

aero_aug2 %>%
  roc_curve(truth = high_impact, .pred_class, event_level = "second") %>%
  autoplot()
```




```
aero_aug2 %>%
  roc_auc(truth = high_impact, .pred_class, event_level = "second")
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc binary         0.782
```

Both of these models are acceptable for predicting whether a run highly impacts performance. These analyses provide a good starting point for building a more complex model that can predict good performance. The possible next step is to use k-fold cross validation to predict when good performance will happen given a series of events.

Thinking more about the aim of this project, the goal is to predict the quality of a workouts without favoring workouts that are fast. In a distance running training plan, a good-quality workout could be a lactate threshold run at race pace, or it could be a recovery run that is two or three minutes slower than race pace. One target variable that can account for these two types of workouts (and the spectrum of workouts in between) is heart rate. The idea here is that a recovery run would have a much lower heart rate, while a threshold run would have a higher heart rate. when more observations are available, many models for different workout types could be deployed (ex. one model for threshold runs, one model for easy runs, one model for recovery runs, etc). Having a target average heart rate set going into a workout would be beneficial for athletes without coaches who need to strike a balance between quality training sessions and preventing over- or under-training.

```
prelim_hr <- lm(avg_hr ~ ., df)
summary(prelim_hr)
```

```
##
## Call:
## lm(formula = avg_hr ~ ., data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.6496 -1.1084 -0.0108  1.2731 11.3369
##
## Coefficients: (1 not defined because of singularities)
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               3.806e+01  2.867e+01   1.327 0.185135
## distance                 -2.319e+00  3.308e-01  -7.011 1.04e-11 ***
## max_hr                    1.788e-01  3.087e-02   5.793 1.42e-08 ***
## avg_run_cadence          -1.310e-01  1.299e-01  -1.009 0.313782
## max_run_cadence          -3.027e-02  1.140e-02  -2.656 0.008234 **
## total_ascent             -1.618e-03  3.726e-03  -0.434 0.664323
## total_decent             -2.063e-04  3.530e-03  -0.058 0.953421
## avg_stride               -1.593e+01  1.394e+01  -1.143 0.253788
## min_elevation            -3.760e-03  5.163e-03  -0.728 0.466867
## max_elevation             2.508e-03  5.273e-03   0.476 0.634659
## avg_pace_sec              4.218e-02  1.672e-02   2.522 0.012058 *
## best_pace_sec             9.256e-03  4.981e-03   1.858 0.063909 .
## `sweat_loss(ml)`          2.218e-02  6.331e-03   3.504 0.000511 ***
## aerobic_TE                1.164e+01  5.774e-01  20.165  < 2e-16 ***
## aerobic_fctImpacting      7.975e-01  4.438e-01   1.797 0.073111 .
## aerobic_fctMaintaining    1.284e+00  8.513e-01   1.508 0.132373
## aerobic_fctOverreaching  -4.027e-01  6.957e-01  -0.579 0.563063
## anaerobic_value           3.691e-01  5.288e-01   0.698 0.485545
## anaerobic_fctMaintaining -5.187e-01  8.377e-01  -0.619 0.536189
## anaerobic_fctNo Benefit   1.741e+00  1.657e+00   1.051 0.294059
## anaerobic_fctSome Benefit 5.963e-01  1.253e+00   0.476 0.634353
## avg_spd                   1.007e+01  2.377e+00   4.236 2.84e-05 ***
## max_spd                   3.969e-01  1.221e-01   3.250 0.001254 **
## short_distanceY          -1.968e+00  9.124e-01  -2.157 0.031627 *
## middle_distanceY         -2.243e+00  6.726e-01  -3.335 0.000935 ***
```

```
## long_distanceY                     NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.178 on 392 degrees of freedom
## Multiple R-squared:  0.9485, Adjusted R-squared:  0.9454
## F-statistic: 300.9 on 24 and 392 DF,  p-value: < 2.2e-16
```

In this section, the random forest model will use k-fold cross validation and train with all variables. After more consideration about the project aims, average pace was selected as the target variable. Strictly using the aerobic training effect variable would essentially just copy the work Garmin already does.

```r
pacman::p_load(tidymodels, ranger, parallel)

cores <- parallel::detectCores()

set.seed(456)

# Split data into training and testing sets
df_split <- initial_split(df, prop = 3/4)

train_df <- training(df_split)
test_df <- testing(df_split)

# Create recipe
rf_rec <- recipe(avg_hr ~ ., data = train_df) %>%
          step_dummy(all_nominal_predictors())

folds <- vfold_cv(train_df, v = 10, repeats = 5, strata = avg_hr)

summary(rf_rec)
```

```
## # A tibble: 22 x 4
##    variable        type    role      source
##    <chr>           <chr>   <chr>     <chr>
##  1 distance        numeric predictor original
##  2 max_hr          numeric predictor original
##  3 avg_run_cadence numeric predictor original
##  4 max_run_cadence numeric predictor original
##  5 total_ascent    numeric predictor original
##  6 total_decent    numeric predictor original
##  7 avg_stride      numeric predictor original
##  8 min_elevation   numeric predictor original
##  9 max_elevation   numeric predictor original
## 10 avg_pace_sec    numeric predictor original
## # ... with 12 more rows
```

```r
rf_mod <- rand_forest(mtry = tune(), min_n = tune(), trees = 1000) %>%
  set_engine("ranger", num.threads = cores) %>%
  set_mode("regression")

rf_wf <- workflow() %>%
  add_model(rf_mod) %>%
```

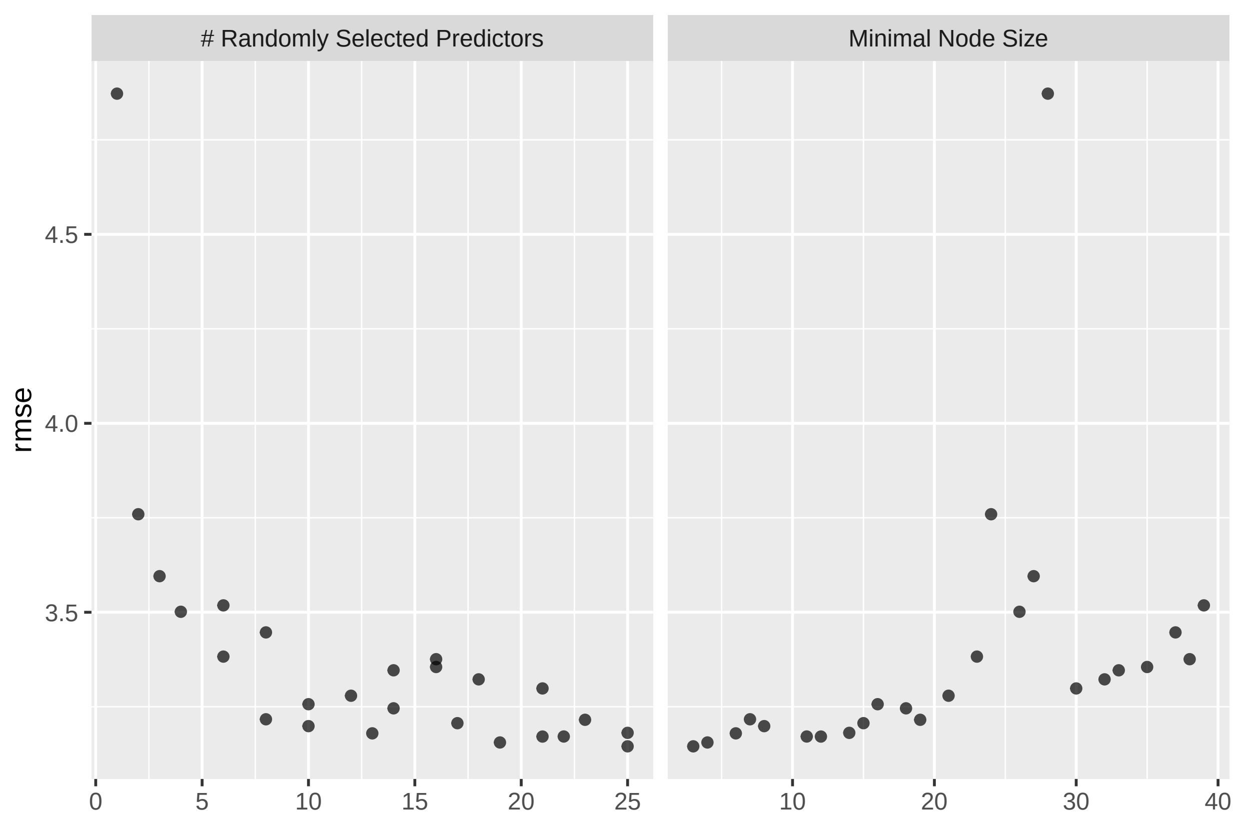
```
  add_recipe(rf_rec)

rf_res <- rf_wf %>%
  tune_grid(folds,
            grid = 25,
            control = control_grid(save_pred = TRUE),
            metrics = metric_set(rmse))
```

```
## i Creating pre-processing data to finalize unknown parameter: mtry
```

```
rf_res %>%
  show_best(metric = "rmse")
```

```
## # A tibble: 5 x 8
##    mtry min_n .metric .estimator  mean     n std_err .config
##   <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1    25     3 rmse    standard    3.15    50  0.0705 Preprocessor1_Model14
## 2    19     4 rmse    standard    3.16    50  0.0692 Preprocessor1_Model17
## 3    21    12 rmse    standard    3.17    50  0.0688 Preprocessor1_Model06
## 4    22    11 rmse    standard    3.17    50  0.0690 Preprocessor1_Model12
## 5    13     6 rmse    standard    3.18    50  0.0681 Preprocessor1_Model13
```

```
autoplot(rf_res)
```



```r
rf_best <- rf_res %>%
  select_best(metric = "rmse")
rf_res %>% collect_predictions()
```

```
## # A tibble: 39,000 x 8
##    id      id2    .pred  .row  mtry min_n avg_hr .config
##    <chr>   <chr>  <dbl> <int> <int> <int>  <dbl> <chr>
##  1 Repeat1 Fold01  166.    10     8     7    164 Preprocessor1_Model01
##  2 Repeat1 Fold01  158.    15     8     7    157 Preprocessor1_Model01
##  3 Repeat1 Fold01  168.    27     8     7    169 Preprocessor1_Model01
##  4 Repeat1 Fold01  144.    36     8     7    149 Preprocessor1_Model01
##  5 Repeat1 Fold01  172.    37     8     7    173 Preprocessor1_Model01
##  6 Repeat1 Fold01  171.    49     8     7    178 Preprocessor1_Model01
##  7 Repeat1 Fold01  169.    92     8     7    169 Preprocessor1_Model01
##  8 Repeat1 Fold01  160.    96     8     7    157 Preprocessor1_Model01
##  9 Repeat1 Fold01  165.   105     8     7    167 Preprocessor1_Model01
## 10 Repeat1 Fold01  154.   114     8     7    158 Preprocessor1_Model01
## # ... with 38,990 more rows
```

```r
final_rf_wf <- rf_wf %>%
  finalize_workflow(rf_best)

final_fit_rf <- final_rf_wf %>%
  last_fit(df_split)

final_fit_rf %>% collect_metrics()
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard       2.89  Preprocessor1_Model1
## 2 rsq     standard       0.881 Preprocessor1_Model1
```

```r
rf_rmse <-
  rf_res %>%
  collect_predictions(parameters = rf_best) %>%
  rmse(avg_hr, .pred) %>%
  mutate(model = "Random Forest")
rf_rmse
```

```
## # A tibble: 1 x 4
##   .metric .estimator .estimate model
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard        3.18 Random Forest
```

This model predicts average pace within 3.2 seconds. In an attempt to improve the accuracy, some variables will be eliminated. This model ran with 21 predictors. The next iteration will eliminate four predictors: max_hr(highly-correlated with avg_hr), min_elevation, max_elevation, and sweat_loss(ml).

```r
set.seed(456)
```

```r
#get rid of max_hr,min_elevation, max_elevation, and sweat_loss
df1 <- df %>% select(-max_hr, -min_elevation, -max_elevation, -`sweat_loss(ml)`)

# Split data into training and testing sets
df1_split <- initial_split(df1, prop = 3/4)

train_df1 <- training(df1_split)
test_df1 <- testing(df1_split)

# Create recipe
rf_rec <- recipe(avg_hr ~ ., data = train_df1) %>%
          step_dummy(all_nominal_predictors())

folds <- vfold_cv(train_df, v = 10, repeats = 5, strata = avg_hr)

summary(rf_rec)
```

```
## # A tibble: 18 x 4
##    variable          type    role      source
##    <chr>             <chr>   <chr>     <chr>
##  1 distance          numeric predictor original
##  2 avg_run_cadence   numeric predictor original
##  3 max_run_cadence   numeric predictor original
##  4 total_ascent      numeric predictor original
##  5 total_decent      numeric predictor original
##  6 avg_stride        numeric predictor original
##  7 avg_pace_sec      numeric predictor original
##  8 best_pace_sec     numeric predictor original
##  9 aerobic_TE        numeric predictor original
## 10 aerobic_fct       nominal predictor original
## 11 anaerobic_value   numeric predictor original
## 12 anaerobic_fct     nominal predictor original
## 13 avg_spd           numeric predictor original
## 14 max_spd           numeric predictor original
## 15 short_distance    nominal predictor original
## 16 middle_distance   nominal predictor original
## 17 long_distance     nominal predictor original
## 18 avg_hr            numeric outcome   original
```

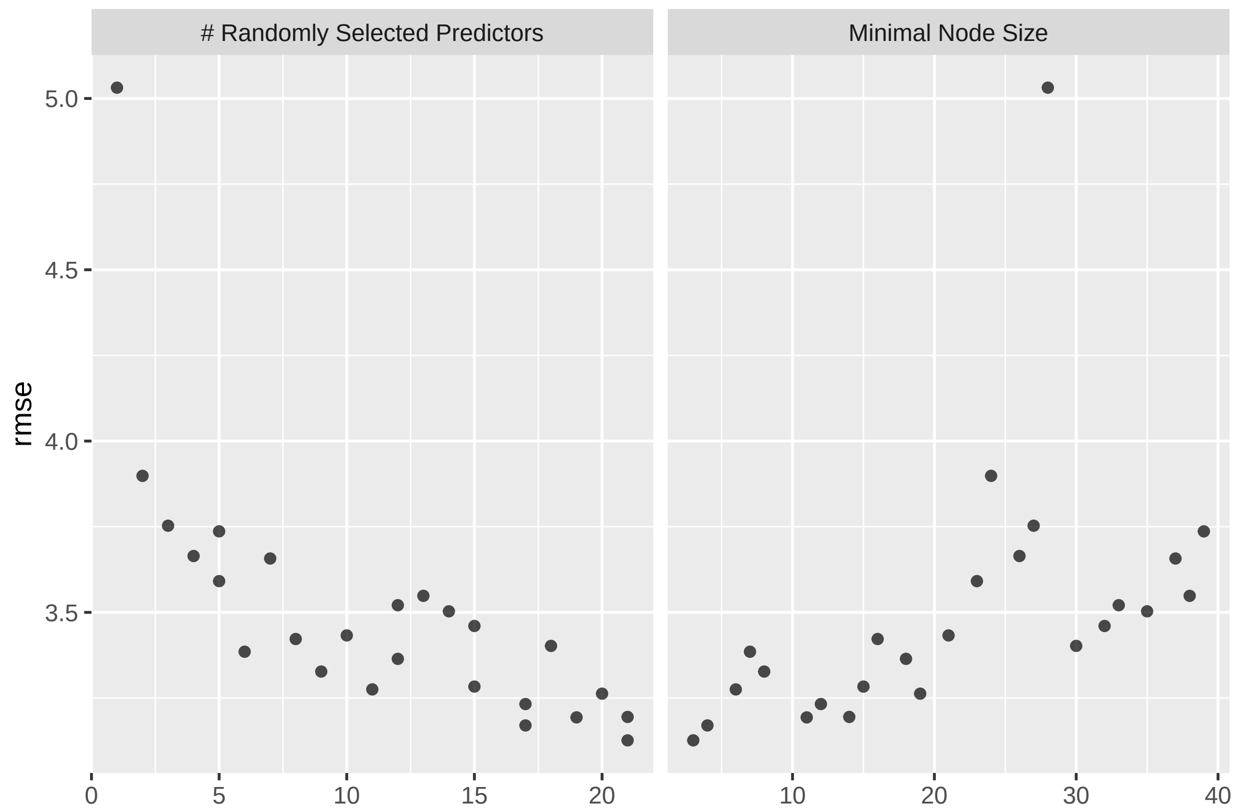
```r
rf_mod <- rand_forest(mtry = tune(), min_n = tune(), trees = 1000) %>%
  set_engine("ranger", num.threads = cores) %>%
  set_mode("regression")

rf_wf <- workflow() %>%
  add_model(rf_mod) %>%
  add_recipe(rf_rec)

rf_res <- rf_wf %>%
  tune_grid(folds,
            grid = 25,
            control = control_grid(save_pred = TRUE),
            metrics = metric_set(rmse))
```

```
## i Creating pre-processing data to finalize unknown parameter: mtry
```

```
rf_res %>%
  show_best(metric = "rmse")
```

```
## # A tibble: 5 x 8
##    mtry min_n .metric .estimator  mean     n std_err .config
##   <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1    21     3 rmse    standard    3.13    50  0.0763 Preprocessor1_Model14
## 2    17     4 rmse    standard    3.17    50  0.0753 Preprocessor1_Model17
## 3    19    11 rmse    standard    3.19    50  0.0758 Preprocessor1_Model12
## 4    21    14 rmse    standard    3.19    50  0.0763 Preprocessor1_Model09
## 5    17    12 rmse    standard    3.23    50  0.0749 Preprocessor1_Model06
```

```
autoplot(rf_res)
```




```
rf_best <- rf_res %>%
  select_best(metric = "rmse")
rf_res %>% collect_predictions()
```

```
## # A tibble: 39,000 x 8
##    id      id2    .pred  .row  mtry min_n avg_hr .config
##    <chr>   <chr>  <dbl> <int> <int> <int>  <dbl> <chr>
##  1 Repeat1 Fold01  167.    10     6     7    164 Preprocessor1_Model01
```

```
##   2 Repeat1 Fold01  159.    15     6     7    157 Preprocessor1_Model01
##   3 Repeat1 Fold01  167.    27     6     7    169 Preprocessor1_Model01
##   4 Repeat1 Fold01  143.    36     6     7    149 Preprocessor1_Model01
##   5 Repeat1 Fold01  171.    37     6     7    173 Preprocessor1_Model01
##   6 Repeat1 Fold01  170.    49     6     7    178 Preprocessor1_Model01
##   7 Repeat1 Fold01  169.    92     6     7    169 Preprocessor1_Model01
##   8 Repeat1 Fold01  160.    96     6     7    157 Preprocessor1_Model01
##   9 Repeat1 Fold01  165.   105     6     7    167 Preprocessor1_Model01
## 10 Repeat1 Fold01  153.   114     6     7    158 Preprocessor1_Model01
## # ... with 38,990 more rows
```

```r
final_rf_wf <- rf_wf %>%
  finalize_workflow(rf_best)

final_fit_rf <- final_rf_wf %>%
  last_fit(df1_split)

final_fit_rf %>% collect_metrics()
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard       3.04  Preprocessor1_Model1
## 2 rsq     standard       0.867 Preprocessor1_Model1
```

```r
rf_rmse <-
  rf_res %>%
  collect_predictions(parameters = rf_best) %>%
  rmse(avg_hr, .pred) %>%
  mutate(model = "Random Forest")
rf_rmse
```

```
## # A tibble: 1 x 4
##   .metric .estimator .estimate model
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard        3.17 Random Forest
```

The accuracy (measured by RMSE) improved slightly to 3.17. Try dropping more variables. This time, ascent, descent, aerobic factors and anaerobic factors.

Try running the model with tuned parameters.

```r
set.seed(456)

#get rid of max_hr,min_elevation, max_elevation, and sweat_loss
df1 <- df %>% select(-max_hr, -min_elevation, -max_elevation, -`sweat_loss(ml)`)

# Split data into training and testing sets
df1_split <- initial_split(df1, prop = 3/4)

train_df1 <- training(df1_split)
test_df1 <- testing(df1_split)
```

```r
# Create recipe
rf_rec <- recipe(avg_hr ~ ., data = train_df1) %>%
          step_dummy(all_nominal_predictors())

folds <- vfold_cv(train_df, v = 10, repeats = 5, strata = avg_hr)

summary(rf_rec)
```

```
## # A tibble: 18 x 4
##    variable         type    role      source
##    <chr>            <chr>   <chr>     <chr>
##  1 distance         numeric predictor original
##  2 avg_run_cadence  numeric predictor original
##  3 max_run_cadence  numeric predictor original
##  4 total_ascent     numeric predictor original
##  5 total_decent     numeric predictor original
##  6 avg_stride       numeric predictor original
##  7 avg_pace_sec     numeric predictor original
##  8 best_pace_sec    numeric predictor original
##  9 aerobic_TE       numeric predictor original
## 10 aerobic_fct      nominal predictor original
## 11 anaerobic_value  numeric predictor original
## 12 anaerobic_fct    nominal predictor original
## 13 avg_spd          numeric predictor original
## 14 max_spd          numeric predictor original
## 15 short_distance   nominal predictor original
## 16 middle_distance  nominal predictor original
## 17 long_distance    nominal predictor original
## 18 avg_hr           numeric outcome   original
```

```r
rf_mod <- rand_forest(mtry = 6, min_n = 7, trees = 1000) %>%
  set_engine("ranger", num.threads = cores) %>%
  set_mode("regression")

rf_wf <- workflow() %>%
  add_model(rf_mod) %>%
  add_recipe(rf_rec)

rf_res <- rf_wf %>%
  tune_grid(folds,
            grid = 25,
            control = control_grid(save_pred = TRUE),
            metrics = metric_set(rmse))
```

```
## Warning: No tuning parameters have been detected, performance will be evaluated
## using the resamples with no tuning. Did you want to [tune()] parameters?
```

```r
rf_res %>%
  show_best(metric = "rmse")
```

```
## # A tibble: 1 x 6
##   .metric .estimator  mean     n std_err .config
```

```
##   <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1 rmse    standard    3.39    50  0.0696 Preprocessor1_Model1
```

```
rf_best <- rf_res %>%
  select_best(metric = "rmse")
rf_res %>% collect_predictions()
```

```
## # A tibble: 1,560 x 6
##    id      id2    .pred  .row avg_hr .config
##    <chr>   <chr>  <dbl> <int>  <dbl> <chr>
##  1 Repeat1 Fold01  167.    10    164 Preprocessor1_Model1
##  2 Repeat1 Fold01  159.    15    157 Preprocessor1_Model1
##  3 Repeat1 Fold01  167.    27    169 Preprocessor1_Model1
##  4 Repeat1 Fold01  143.    36    149 Preprocessor1_Model1
##  5 Repeat1 Fold01  171.    37    173 Preprocessor1_Model1
##  6 Repeat1 Fold01  170.    49    178 Preprocessor1_Model1
##  7 Repeat1 Fold01  169.    92    169 Preprocessor1_Model1
##  8 Repeat1 Fold01  160.    96    157 Preprocessor1_Model1
##  9 Repeat1 Fold01  164.   105    167 Preprocessor1_Model1
## 10 Repeat1 Fold01  153.   114    158 Preprocessor1_Model1
## # ... with 1,550 more rows
```

```
final_rf_wf <- rf_wf %>%
  finalize_workflow(rf_best)

final_fit_rf <- final_rf_wf %>%
  last_fit(df1_split)

final_fit_rf %>% collect_metrics()
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard       3.23  Preprocessor1_Model1
## 2 rsq     standard       0.850 Preprocessor1_Model1
```

```
rf_rmse <-
  rf_res %>%
  collect_predictions(parameters = rf_best) %>%
  rmse(avg_hr, .pred) %>%
  mutate(model = "Random Forest")
rf_rmse
```

```
## # A tibble: 1 x 4
##   .metric .estimator .estimate model
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard        3.42 Random Forest
```

This final Random Forest model has a greater RMSE value than the previous one. One of the concerns with the dataset is the greater number of features (21 total predictors avialable). LASSO may be a good option to automate feature selection.

```r
set.seed(456)
# Split data into training and testing sets
df_split <- initial_split(df, prop = 3/4)

train_df <- training(df_split)
test_df <- testing(df_split)

# Create recipe
lasso_rec <- recipe(avg_hr ~ ., data = train_df)

# create folds
folds <- vfold_cv(train_df, v = 10, repeats = 5, strata = avg_hr)

summary(lasso_rec)
```

```
## # A tibble: 22 x 4
##    variable        type    role      source
##    <chr>           <chr>   <chr>     <chr>
##  1 distance        numeric predictor original
##  2 max_hr          numeric predictor original
##  3 avg_run_cadence numeric predictor original
##  4 max_run_cadence numeric predictor original
##  5 total_ascent    numeric predictor original
##  6 total_decent    numeric predictor original
##  7 avg_stride      numeric predictor original
##  8 min_elevation   numeric predictor original
##  9 max_elevation   numeric predictor original
## 10 avg_pace_sec    numeric predictor original
## # ... with 12 more rows
```

```r
lasso_mod <- linear_reg(penalty = tune(), mixture = 1) %>%
  set_engine("lm")

lasso_wkfl <- workflow() %>%
  add_model(lasso_mod) %>%
  add_recipe(lasso_rec)
```

```r
# create penalty grid for tuning
lasso_grid <- tibble(penalty = 10^seq(-4, -1, length.out = 30))

# lowest penalties
lasso_grid %>% top_n(-5)
```

```
## Selecting by penalty
```

```
## # A tibble: 5 x 1
##    penalty
##      <dbl>
## 1 0.0001
## 2 0.000127
## 3 0.000161
## 4 0.000204
## 5 0.000259
```

```r
#highest penalties
lasso_grid %>% top_n(5)
```

```
## Selecting by penalty
```

```
## # A tibble: 5 x 1
##   penalty
##     <dbl>
## 1  0.0386
## 2  0.0489
## 3  0.0621
## 4  0.0788
## 5  0.1
```

```r
lasso_res <- lasso_wkfl %>%
  tune_grid(folds,
            grid = lasso_grid,
            control = control_grid(save_pred = TRUE),
            metrics = metric_set(rmse))
```

```
## Warning: No tuning parameters have been detected, performance will be evaluated
## using the resamples with no tuning. Did you want to [tune()] parameters?
```

```
## ! Fold01, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold02, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold03, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold04, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold05, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold06, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold07, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold08, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold09, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold10, Repeat1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold01, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold02, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold03, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold04, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold05, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold06, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold07, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold08, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold09, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold10, Repeat2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold01, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold02, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold03, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold04, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold05, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold06, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold07, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold08, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold09, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold10, Repeat3: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold01, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold02, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold03, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold04, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold05, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold06, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold07, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
## ! Fold08, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold09, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold10, Repeat4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold01, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold02, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold03, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold04, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold05, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold06, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold07, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold08, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold09, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
## ! Fold10, Repeat5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
top_models <- lasso_res %>%
  show_best("rmse")
top_models
```

```
## # A tibble: 1 x 6
##   .metric .estimator  mean     n std_err .config
##   <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1 rmse    standard    2.31    50  0.0670 Preprocessor1_Model1
```

```
lasso_best <- lasso_res %>%
  select_best("rmse")
lasso_best
```

```
## # A tibble: 1 x 1
##   .config
##   <chr>
## 1 Preprocessor1_Model1
```

```
final_lasso_wf <- lasso_wkfl %>%
  finalize_workflow(lasso_best)

final_lasso_fit <- final_lasso_wf %>%
  last_fit(df_split)
```

```
## ! train/test split: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```
final_lasso_fit %>% collect_metrics()
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard       2.78  Preprocessor1_Model1
## 2 rsq     standard       0.895 Preprocessor1_Model1
```

The LASSO model does improve the RMSE and is likely the best path forward. The next steps in this project will be to further tune this model.