Homework8

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This homework will explore basics of predictive modeling using an online-available data set concerning bike data in Seoul, South Korea.

First, let's get our libraries set:

```
Warning: package 'tidymodels' was built under R version 4.3.3

-- Attaching packages -------------------------------------- tidymodels 1.2.0 --

v broom        1.0.5     v recipes      1.1.0
v dials        1.3.0     v rsample      1.2.1
v dplyr        1.1.4     v tibble       3.2.1
v ggplot2      3.5.1     v tidyr        1.3.1
v infer        1.0.7     v tune         1.2.1
v modeldata    1.4.0     v workflows    1.1.4
v parsnip      1.2.1     v workflowsets 1.1.0
v purrr        1.0.2     v yardstick    1.3.1

Warning: package 'dials' was built under R version 4.3.3

Warning: package 'scales' was built under R version 4.3.3

Warning: package 'dplyr' was built under R version 4.3.3

Warning: package 'ggplot2' was built under R version 4.3.3

Warning: package 'infer' was built under R version 4.3.3

Warning: package 'modeldata' was built under R version 4.3.3
```

```
Warning: package 'parsnip' was built under R version 4.3.3

Warning: package 'purrr' was built under R version 4.3.3

Warning: package 'recipes' was built under R version 4.3.3

Warning: package 'rsample' was built under R version 4.3.3

Warning: package 'tidyr' was built under R version 4.3.3

Warning: package 'tune' was built under R version 4.3.3

Warning: package 'workflows' was built under R version 4.3.3

Warning: package 'workflowsets' was built under R version 4.3.3

Warning: package 'yardstick' was built under R version 4.3.3

-- Conflicts ----------------------------------------- tidymodels_conflicts() --
x purrr::discard() masks scales::discard()
x dplyr::filter()  masks stats::filter()
x dplyr::lag()     masks stats::lag()
x recipes::step()  masks stats::step()
* Dig deeper into tidy modeling with R at https://www.tmwr.org


Attaching package: 'lubridate'

The following objects are masked from 'package:base':

    date, intersect, setdiff, union
```

EDA

Next, let's load the data in and resolve the known error mentioned in the instructions. We can specify the fileEncoding and avoid checking names to solve the problem:

```r
data = read.csv("SeoulBikeData.csv", fileEncoding = "Latin1", check.names = F)
```

Great, now we can go ahead with our EDA to make sure everything looks good. First, lets check for missing values:

```r
sum(is.na(data))
```

```
[1] 0
```

Sweet, no missing values. makes for a good start. Next, we'll take a look at the column types, rename to avoid strange variable names, and change our categorical variables to factors. The instructions say to change our variable names later in the process, but I'd rather they be in a clean format for the rest of the EDA!

```r
summary(data)
```

```
     Date            Rented Bike Count      Hour       Temperature(°C)
 Length:8760        Min.   :   0.0    Min.   : 0.00   Min.   :-17.80
 Class :character   1st Qu.: 191.0    1st Qu.: 5.75   1st Qu.:  3.50
 Mode  :character   Median : 504.5    Median :11.50   Median : 13.70
                    Mean   : 704.6    Mean   :11.50   Mean   : 12.88
                    3rd Qu.:1065.2    3rd Qu.:17.25   3rd Qu.: 22.50
                    Max.   :3556.0    Max.   :23.00   Max.   : 39.40
  Humidity(%)    Wind speed (m/s) Visibility (10m) Dew point temperature(°C)
 Min.   : 0.00   Min.   :0.000    Min.   :  27     Min.   :-30.600
 1st Qu.:42.00   1st Qu.:0.900    1st Qu.: 940     1st Qu.: -4.700
 Median :57.00   Median :1.500    Median :1698     Median :  5.100
 Mean   :58.23   Mean   :1.725    Mean   :1437     Mean   :  4.074
 3rd Qu.:74.00   3rd Qu.:2.300    3rd Qu.:2000     3rd Qu.: 14.800
 Max.   :98.00   Max.   :7.400    Max.   :2000     Max.   : 27.200
 Solar Radiation (MJ/m2)  Rainfall(mm)     Snowfall (cm)       Seasons
 Min.   :0.0000          Min.   : 0.0000   Min.   :0.00000   Length:8760
 1st Qu.:0.0000          1st Qu.: 0.0000   1st Qu.:0.00000   Class :character
 Median :0.0100          Median : 0.0000   Median :0.00000   Mode  :character
 Mean   :0.5691          Mean   : 0.1487   Mean   :0.07507
 3rd Qu.:0.9300          3rd Qu.: 0.0000   3rd Qu.:0.00000
 Max.   :3.5200          Max.   :35.0000   Max.   :8.80000
   Holiday          Functioning Day
 Length:8760        Length:8760
 Class :character   Class :character
```

```
 Mode  :character   Mode  :character
```

```
colnames(data) = c('Date', 'NumBikes', "Hour", "Temperature", "Humidity",
                   "WindSpeed","Visibility", "DewPointTemp", "SolarRad", "Rainfall"
                   , "Snowfall", "Season", "Holiday", "FunctioningDay" )

data$Season = as.factor(data$Season)
data$Holiday = as.factor(data$Holiday)
data$FunctioningDay = as.factor(data$FunctioningDay)
levels(data$Season)
```

```
[1] "Autumn" "Spring" "Summer" "Winter"
```

```
levels(data$Holiday)
```

```
[1] "Holiday"    "No Holiday"
```

```
levels(data$FunctioningDay)
```

```
[1] "No"  "Yes"
```

Great, now we can see that everything looks good with our numerical variables, our variable names are no longer likely to cause an issue, and our categorical variables are appropriately recast as factors! Next, we will change the date into a workable arithmetic form using lubridate:

```
typeof(data$Date) # currently character
```

```
[1] "character"
```

```
data$Date = lubridate::dmy(data$Date)
typeof(data$Date) # now it's a double!
```

```
[1] "double"
```

Now that we have cleaned the data up, we will do some summary stats, specifically looking at bike rental count, rainfall, and snowfall. We'll also examine these across some categorical variables, such as FunctioningDay, Holiday, and Season:

```
data |> # check bike numbers by season
  group_by(FunctioningDay) |>
  summarize(mean = mean(NumBikes), sd = sd(NumBikes))# Non-functioning days mean no bikes!
```

```
# A tibble: 2 x 3
  FunctioningDay  mean    sd
  <fct>          <dbl> <dbl>
1 No                 0     0
2 Yes              729.  642.
```

```
sum(data$FunctioningDay == "No") # 295 of the data points can be excluded
```

```
[1] 295
```

```
sub_data = subset(data, data$FunctioningDay == "Yes") # we can ignore days that are not func


sub_data |> # check bike numbers by season
  group_by(Season) |>
  summarize(mean = mean(NumBikes), sd = sd(NumBikes))
```

```
# A tibble: 4 x 3
  Season  mean    sd
  <fct>  <dbl> <dbl>
1 Autumn  924.  618.
2 Spring  746.  619.
3 Summer 1034.  690.
4 Winter  226.  150.
```

```
sub_data |> # check bike numbers by holiday
  group_by(Holiday) |>
  summarize(mean = mean(NumBikes), sd = sd(NumBikes))
```

```
# A tibble: 2 x 3
  Holiday     mean    sd
  <fct>      <dbl> <dbl>
1 Holiday     529.  574.
2 No Holiday  739.  644.
```

```r
sub_data |> # check rain  by season
  group_by(Season) |>
  summarize(mean = mean(Rainfall),  sd = sd(Rainfall))
```

```
# A tibble: 4 x 3
  Season   mean    sd
  <fct>   <dbl> <dbl>
1 Autumn 0.118  0.890
2 Spring 0.187  1.21
3 Summer 0.253  1.59
4 Winter 0.0328 0.423
```

```r
sub_data |> # check snowfall by season
  group_by(Season) |>
  summarize(mean = mean(Snowfall),  sd = sd(Snowfall))
```

```
# A tibble: 4 x 3
  Season   mean    sd
  <fct>   <dbl> <dbl>
1 Autumn 0.0635 0.522
2 Spring 0      0
3 Summer 0      0
4 Winter 0.248  0.698
```

We see that summer appears to have the highest number of bike rentals, and winter has the fewest. Bike rentals are more common on Non-Holidays, so they are likely being used to commute to work. Finally, we see from our tables that snowfall is most plentiful in winter, while rainfall is most plentiful in summer.

Next up, let's summarize across hours so that we can collapse each day into a single observation.

```r
clean_data = sub_data |>
  group_by(Date, Season, Holiday) |>
  summarize(TotBikes = sum(NumBikes), TotRain = sum(Rainfall), TotSnow = sum(Snowfall), Mean
```

```
`summarise()` has grouped output by 'Date', 'Season'. You can override using
the `.groups` argument.
```

```r
head(clean_data)
```

```
# A tibble: 6 x 12
# Groups:   Date, Season [6]
  Date       Season Holiday    TotBikes TotRain TotSnow MeanTemp MeanHumid
  <date>     <fct>  <fct>         <int>   <dbl>   <dbl>    <dbl>     <dbl>
1 2017-12-01 Winter No Holiday     9539     0       0    -2.45        45.9
2 2017-12-02 Winter No Holiday     8523     0       0     1.32        62.0
3 2017-12-03 Winter No Holiday     7222     4       0     4.88        81.5
4 2017-12-04 Winter No Holiday     8729     0.1     0    -0.304       52.5
5 2017-12-05 Winter No Holiday     8307     0       0    -4.46        36.4
6 2017-12-06 Winter No Holiday     6669     1.3     8.6   0.0458      70.8
# i 4 more variables: MeanWindSpeed <dbl>, MeanVis <dbl>, MeanDewPoint <dbl>,
#   MeanSolar <dbl>
```

Great, now we have our final data set for training. Let's recreate our basic summaries and do some plots on this cleaned data. We'll also report some correlations. Let's first recreate our summary stats:

```r
clean_data |> # check bike numbers by season
  group_by(Season) |>
  summarize(mean = mean(TotBikes), sd = sd(TotBikes))
```

```
# A tibble: 4 x 3
  Season   mean    sd
  <fct>   <dbl> <dbl>
1 Autumn 22099. 6711.
2 Spring 17910. 8357.
3 Summer 24818. 7297.
4 Winter  5413. 1808.
```

```r
clean_data |> # check bike numbers by holiday
  group_by(Holiday) |>
  summarize(mean = mean(TotBikes), sd = sd(TotBikes))
```

```
# A tibble: 2 x 3
  Holiday      mean     sd
  <fct>       <dbl>  <dbl>
1 Holiday    12700. 10504.
2 No Holiday 17727.  9862.
```

```
clean_data |> # check rain  by season
  group_by(Season) |>
  summarize(mean = mean(TotRain),  sd = sd(TotRain))
```

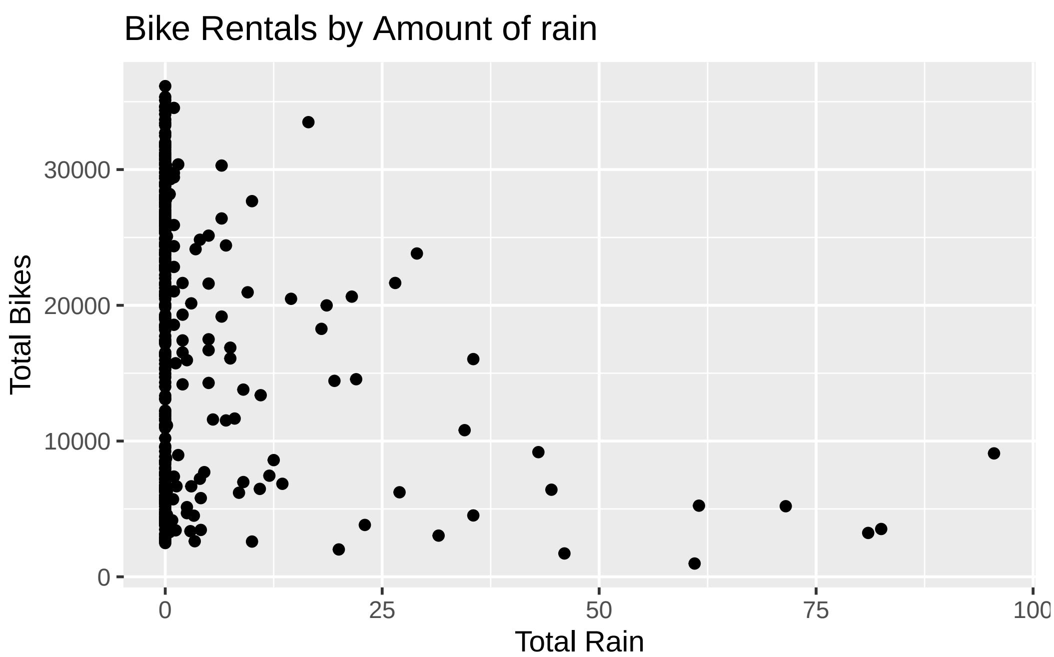
```
# A tibble: 4 x 3
  Season  mean    sd
  <fct>  <dbl> <dbl>
1 Autumn 2.81   8.61
2 Spring 4.49  12.7
3 Summer 6.08  17.0
4 Winter 0.788  3.28
```

```
clean_data |> # check snowfall by season
  group_by(Season) |>
  summarize(mean = mean(TotSnow),  sd = sd(TotSnow))
```

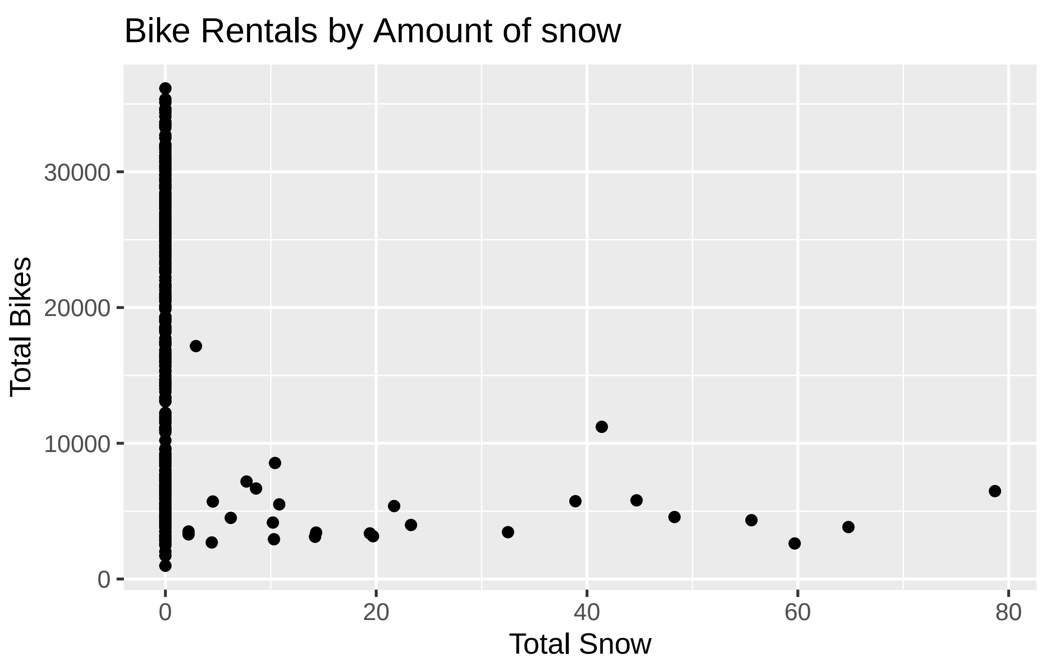
```
# A tibble: 4 x 3
  Season  mean    sd
  <fct>  <dbl> <dbl>
1 Autumn  1.52  9.83
2 Spring  0     0
3 Summer  0     0
4 Winter  5.94 14.0
```

We see that the same trends hold; more bikes in summer, more bikes on non-holidays, more rain in summer, and more snow in winter. Next, let's plot some of the numerical variables:

```
ggplot(clean_data, aes(x = TotRain, y = TotBikes)) +
       geom_point() +
       labs(x = 'Total Rain', y = 'Total Bikes', title = 'Bike Rentals by Amount of rain')
```

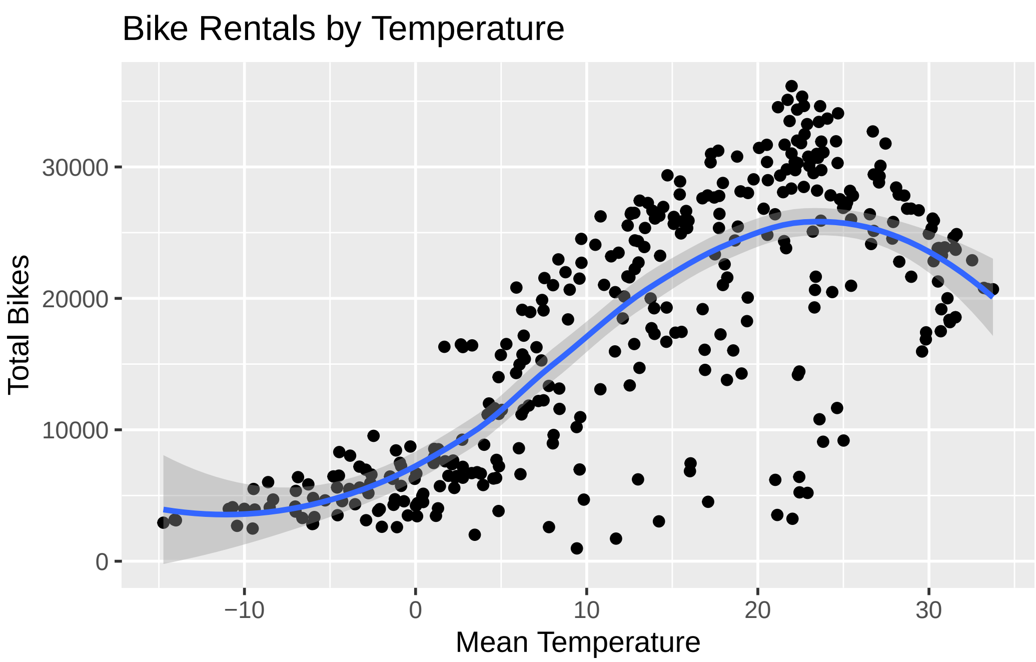



```
ggplot(clean_data, aes(x = TotSnow, y = TotBikes)) +
       geom_point() +
       labs(x = 'Total Snow', y = 'Total Bikes', title = 'Bike Rentals by Amount of snow')
```



```r
ggplot(clean_data, aes(x = MeanTemp, y = TotBikes)) +
       geom_point() +
       geom_smooth() +
       labs(x = 'Mean Temperature', y = 'Total Bikes', title = 'Bike Rentals by Temperature')
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



These plots make sense. We see a lot more bike rentals when there is low snow and low rain. Also, we see that the number of bikes increase as temperature increases, until a certain point. These plots appear to be accurately capturing info about how weather influence bike riding behavior!

Finally, let's plot some correlations:

```r
cor(clean_data[sapply(clean_data, is.numeric)])
```

```
             TotBikes     TotRain     TotSnow     MeanTemp   MeanHumid
TotBikes   1.00000000 -0.23910905 -0.26529110  0.753076732  0.03588697
TotRain   -0.23910905  1.00000000 -0.02313404  0.144517274  0.52864263
TotSnow   -0.26529110 -0.02313404  1.00000000 -0.266963662  0.06539191
MeanTemp   0.75307673  0.14451727 -0.26696366  1.000000000  0.40416749
MeanHumid  0.03588697  0.52864263  0.06539191  0.404167486  1.00000000
```

```
MeanWindSpeed -0.19288142 -0.10167578  0.02088156 -0.260721792 -0.23425778
MeanVis        0.16599375 -0.22199387 -0.10188902  0.002336683 -0.55917733
MeanDewPoint   0.65047655  0.26456621 -0.20955286  0.962796255  0.63204729
MeanSolar      0.73589290 -0.32270413 -0.23343056  0.550274301 -0.27444967
              MeanWindSpeed      MeanVis MeanDewPoint   MeanSolar
TotBikes        -0.19288142  0.165993749    0.6504765  0.73589290
TotRain         -0.10167578 -0.221993866    0.2645662 -0.32270413
TotSnow          0.02088156 -0.101889019   -0.2095529 -0.23343056
MeanTemp        -0.26072179  0.002336683    0.9627963  0.55027430
MeanHumid       -0.23425778 -0.559177334    0.6320473 -0.27444967
MeanWindSpeed    1.00000000  0.206022636   -0.2877032  0.09612635
MeanVis          0.20602264  1.000000000   -0.1535516  0.27139591
MeanDewPoint    -0.28770322 -0.153551591    1.0000000  0.38315713
MeanSolar        0.09612635  0.271395906    0.3831571  1.00000000
```

We can see some impressive correlations here. For example, Mean Temp, Mean Dew Point, and Mean Solar are all quite positively correlated with total number of bike rentals. These are likely all tied into the weather we commented on above - when the weather is nice, people are more likely to rent bikes, thus leading to higher correlation values! We should be able to do some nice prediction on this data given the strengths of these correlations, although we might be at risk of overfitting if we aren't careful.

Modeling the Data

Now we can prep our model for prediction! First, let's make our test and training sets:

```r
set.seed(42)
splits = initial_split(clean_data, prop = 0.75, strata = "Season")
train = training(splits)
test = testing(splits)

head(train)
```

```
# A tibble: 6 x 12
# Groups:   Date, Season [6]
  Date       Season Holiday    TotBikes TotRain TotSnow MeanTemp MeanHumid
  <date>     <fct>  <fct>         <int>   <dbl>   <dbl>    <dbl>     <dbl>
1 2018-09-01 Autumn No Holiday    26010     0         0     25.5      61.2
2 2018-09-02 Autumn No Holiday    26881     0         0     25.0      54.5
3 2018-09-03 Autumn No Holiday    10802    34.5       0     23.6      82.2
4 2018-09-04 Autumn No Holiday    29529     0         0     23.3      71.6
```

```
5 2018-09-05 Autumn No Holiday    31114     0          0     23.8      61.8
6 2018-09-06 Autumn No Holiday    27838     0          0     24.2      70.8
# i 4 more variables: MeanWindSpeed <dbl>, MeanVis <dbl>, MeanDewPoint <dbl>,
#   MeanSolar <dbl>
```

```r
nrow(train)
```

```
[1] 263
```

```r
head(test)
```

```
# A tibble: 6 x 12
# Groups:   Date, Season [6]
  Date       Season Holiday    TotBikes TotRain TotSnow MeanTemp MeanHumid
  <date>     <fct>  <fct>         <int>   <dbl>   <dbl>    <dbl>     <dbl>
1 2017-12-01 Winter No Holiday     9539     0          0   -2.45       45.9
2 2017-12-03 Winter No Holiday     7222     4          0    4.88       81.5
3 2017-12-04 Winter No Holiday     8729     0.1        0   -0.304      52.5
4 2017-12-08 Winter No Holiday     8032     0          0   -3.82       41.8
5 2017-12-13 Winter No Holiday     6019     0          0   -8.62       41.2
6 2017-12-15 Winter No Holiday     7198     0          0   -3.28       50.5
# i 4 more variables: MeanWindSpeed <dbl>, MeanVis <dbl>, MeanDewPoint <dbl>,
#   MeanSolar <dbl>
```

```r
nrow(test)
```

```
[1] 90
```

Everything appears to be in order with our test and training sets, and we have stratified by Season as requested. Next up, we'll make three recipes, train our three MLR models, and then compare their performances:

```r
# All three of our recipes will use the same recipes. However, model 1 will only include all

# Recipe 1: all numeric variables, no interactions
bike_rec1 = recipe(TotBikes ~., data = clean_data) |>
  step_date(Date, features = "dow") |>
  step_mutate(DayType = factor(if_else(wday(Date) %in% c(1,7), "Weekend", "Weekday"), levels
  step_normalize(all_numeric_predictors()) |>
  step_dummy(Season, Holiday, DayType) |>
```

```r
  step_rm(Date_dow, Date) #|>
  #prep(training = clean_data) |>
  #bake(clean_data) # let's make sure it worked as planned!

# Recipe 2: all numeric variables, some interactions
bike_rec2 = recipe(TotBikes ~., data = clean_data) |>
  step_date(Date, features = "dow") |>
  step_mutate(DayType = factor(if_else(wday(Date) %in% c(1,7), "Weekend", "Weekday"), levels
  step_normalize(all_numeric_predictors()) |>
  step_dummy(Season, Holiday, DayType) |>
  step_rm(Date_dow, Date) |>
  step_interact(~ Season_Spring:Holiday_No.Holiday +
                Season_Summer:Holiday_No.Holiday +
                Season_Winter:Holiday_No.Holiday +
                Season_Spring:TotRain + Season_Summer:TotRain +
                Season_Winter:TotRain +
                MeanTemp:TotRain)

# Recipe 3: all numeric variables, some interacitons, & quad term
bike_rec3 = recipe(TotBikes ~., data = clean_data) |>
  step_date(Date, features = "dow") |>
  step_mutate(DayType = factor(if_else(wday(Date) %in% c(1,7), "Weekend", "Weekday"), levels
  step_normalize(all_numeric_predictors()) |>
  step_dummy(Season, Holiday, DayType) |>
  step_rm(Date_dow, Date) |>
  step_interact(~ Season_Spring:Holiday_No.Holiday +
                Season_Summer:Holiday_No.Holiday +
                Season_Winter:Holiday_No.Holiday +
                Season_Spring:TotRain + Season_Summer:TotRain +
                Season_Winter:TotRain +
                MeanTemp:TotRain) |>
  step_poly(TotRain, TotSnow, MeanTemp, MeanHumid, MeanWindSpeed,
            MeanVis, MeanDewPoint , MeanSolar, degree = 2)
```

After prepping and baking the data, we can see that everything seems to be in order! Now, we can declare our model and set up our workflow:

```r
bike_mod = linear_reg() %>%
  set_engine("lm")

bike_wfl1 = workflow() |>
  add_recipe(bike_rec1) |>
```

```
  add_model(bike_mod)

bike_wfl2 = workflow() |>
  add_recipe(bike_rec2) |>
  add_model(bike_mod)

bike_wfl3 = workflow() |>
  add_recipe(bike_rec3) |>
  add_model(bike_mod)
```

Cool, now we have the workflows for each of our models ready to! Let's set up the 10-fold cross validation next:

```
bike_cv10 = vfold_cv(clean_data, 10) # same CV for all models
set.seed(42)

bike_cv_fits1 = bike_wfl1 |>
  fit_resamples(bike_cv10)
bike_cv_fits1 |>
  collect_metrics()
```

```
# A tibble: 2 x 6
  .metric .estimator     mean     n  std_err .config
  <chr>   <chr>         <dbl> <int>    <dbl> <chr>
1 rmse    standard   4107.       10 129.     Preprocessor1_Model1
2 rsq     standard      0.829    10   0.0164 Preprocessor1_Model1
```

```
bike_cv_fits2 = bike_wfl2 |>
  fit_resamples(bike_cv10)
bike_cv_fits2 |>
  collect_metrics()
```

```
# A tibble: 2 x 6
  .metric .estimator     mean     n  std_err .config
  <chr>   <chr>         <dbl> <int>    <dbl> <chr>
1 rmse    standard   4211.       10 128.     Preprocessor1_Model1
2 rsq     standard      0.820    10   0.0162 Preprocessor1_Model1
```

```
bike_cv_fits3 = bike_wfl3 |>
  fit_resamples(bike_cv10)
bike_cv_fits3 |>
  collect_metrics()
```

```
# A tibble: 2 x 6
  .metric .estimator     mean     n  std_err .config
  <chr>   <chr>         <dbl> <int>    <dbl> <chr>
1 rmse    standard   3997.       10 148.     Preprocessor1_Model1
2 rsq     standard      0.836    10   0.0125 Preprocessor1_Model1
```

After fitting all three models, we see that the first one has the lowest RMSE. Also, this first model is the simplest of the set! We will use recipe 1 on the full training set and then use collect_metrics() to find the test RMSE:

```
final_mod = last_fit(bike_wfl1, split = splits)
clean_final_mod = collect_metrics(final_mod)
clean_final_mod
```

```
# A tibble: 2 x 4
  .metric .estimator .estimate .config
  <chr>   <chr>          <dbl> <chr>
1 rmse    standard    3863.    Preprocessor1_Model1
2 rsq     standard       0.843 Preprocessor1_Model1
```

And finally, we can obtain the final model coefficient table:

```
final_fits = extract_fit_parsnip(final_mod)
final_coef = tidy(final_fits)
final_coef
```

```
# A tibble: 14 x 5
   term               estimate std.error statistic  p.value
   <chr>                 <dbl>     <dbl>     <dbl>    <dbl>
 1 (Intercept)          18545.     1394.    13.3   7.20e-31
 2 TotRain              -1781.      347.    -5.13  5.87e- 7
 3 TotSnow               -193.      286.    -0.672 5.02e- 1
 4 MeanTemp             -6113.     4938.    -1.24  2.17e- 1
 5 MeanHumid            -3701.     1822.    -2.03  4.33e- 2
 6 MeanWindSpeed         -834.      296.    -2.81  5.30e- 3
```

```
 7 MeanVis               -411.      377.    -1.09  2.76e- 1
 8 MeanDewPoint         11795.     5752.     2.05  4.13e- 2
 9 MeanSolar             3949.      456.     8.65  6.34e-16
10 Season_Spring        -5027.      839.    -6.00  7.09e- 9
11 Season_Summer        -3941.      998.    -3.95  1.02e- 4
12 Season_Winter        -8353.     1127.    -7.41  1.90e-12
13 Holiday_No.Holiday    2024.     1294.     1.56  1.19e- 1
14 DayType_Weekday       2291.      570.     4.02  7.72e- 5
```

And there we have it! We can see how the various different parameters are expected to impact bike rentals in this specific town, and could use these to predict how well our bikes may fair depending on the weather, season, and other variables.

Homework 9 New Material

For this portion of HW9, we will fit 4 new models: a tuned LASSO, a tuned Regression Tree, a tuned Bagged Tree, and a tuned Random Forest. We'll do them in this order, then compare the best tuned version of each to the MLR model from HW8. We'll report model fittings, and then train our best model on the full data set!

Tuned LASSO Model

Recall that our data is already split as follows, which we will use for these new models too:

> splits = initial_split(clean_data, prop = 0.75, strata = "Season")
>
> train = training(splits)
>
> test = testing(splits)
>
> bike_cv10 = vfold_cv(clean_data, 10)

```r
# let's throw all of our numeric predictors into the LASSO, so that it can effectively help u
set.seed(42)
LASSO_rec = bike_rec1 # we can use the same basic recipe as with our MLR from last time - thi

# tune the penalty term, and specify LASSO instead of elastic net
LASSO_spec = linear_reg(penalty=tune(), mixture = 1) |>
  set_engine("glmnet")

LASSO_wkf = workflow() |>
  add_recipe(LASSO_rec)|>
  add_model(LASSO_spec)

LASSO_grid = LASSO_wkf |>
  tune_grid(resamples = bike_cv10,
            grid = grid_regular(penalty(), levels = 200))
```

```
Warning: package 'glmnet' was built under R version 4.3.2
```

```
Warning: package 'Matrix' was built under R version 4.3.3
```

```r
lowest_rmse = LASSO_grid |>
  select_best(metric = 'rmse')

LASSO_final = LASSO_wkf |>
  finalize_workflow(lowest_rmse) |>
  fit(train) # we will use tidy(LASSO_final) late to produce the coefficients table

LASSO_wkf |>
  finalize_workflow(lowest_rmse) |>
  last_fit(splits, metrics = metric_set(rmse,mae)) |>
  collect_metrics()
```

```
# A tibble: 2 x 4
  .metric .estimator .estimate .config
  <chr>   <chr>          <dbl> <chr>
1 rmse    standard       3838. Preprocessor1_Model1
2 mae     standard       3118. Preprocessor1_Model1
```

```r
# produce the coefs as requested
tidy(LASSO_final)
```

```
# A tibble: 14 x 3
   term               estimate      penalty
   <chr>                 <dbl>        <dbl>
 1 (Intercept)          18421. 0.0000000001
 2 TotRain              -1936. 0.0000000001
 3 TotSnow               -228. 0.0000000001
 4 MeanTemp                 0  0.0000000001
 5 MeanHumid            -1480. 0.0000000001
 6 MeanWindSpeed         -816. 0.0000000001
 7 MeanVis               -281. 0.0000000001
 8 MeanDewPoint          4620. 0.0000000001
 9 MeanSolar             3872. 0.0000000001
10 Season_Spring        -4968. 0.0000000001
11 Season_Summer        -3738. 0.0000000001
12 Season_Winter        -8185. 0.0000000001
13 Holiday_No.Holiday    2011. 0.0000000001
14 DayType_Weekday       2325. 0.0000000001
```

```
# also produce the coefs for MLR model 1
final_coef
```

```
# A tibble: 14 x 5
   term               estimate std.error statistic  p.value
   <chr>                 <dbl>     <dbl>     <dbl>    <dbl>
 1 (Intercept)          18545.     1394.    13.3   7.20e-31
 2 TotRain              -1781.      347.    -5.13  5.87e- 7
 3 TotSnow               -193.      286.    -0.672 5.02e- 1
 4 MeanTemp             -6113.     4938.    -1.24  2.17e- 1
 5 MeanHumid            -3701.     1822.    -2.03  4.33e- 2
 6 MeanWindSpeed         -834.      296.    -2.81  5.30e- 3
 7 MeanVis               -411.      377.    -1.09  2.76e- 1
 8 MeanDewPoint         11795.     5752.     2.05  4.13e- 2
 9 MeanSolar             3949.      456.     8.65  6.34e-16
10 Season_Spring        -5027.      839.    -6.00  7.09e- 9
11 Season_Summer        -3941.      998.    -3.95  1.02e- 4
12 Season_Winter        -8353.     1127.    -7.41  1.90e-12
13 Holiday_No.Holiday    2024.     1294.     1.56  1.19e- 1
14 DayType_Weekday       2291.      570.     4.02  7.72e- 5
```

We see that the values of errors values are around RMSE = 3837 and MAE = 3117. This LASSO example is a great example of the power of this model workflow - we were able to easily recycle the recipe from our earlier project and effectively construct another type of model with ease! Our coefficient tables let us see how the MLR and LASSO models differ - it's interesting to note that temperature has been reduced to 0 in the LASSO model, yet temperature is one of the most important variables in our Bagged model!

Tuned Regression Tree Model

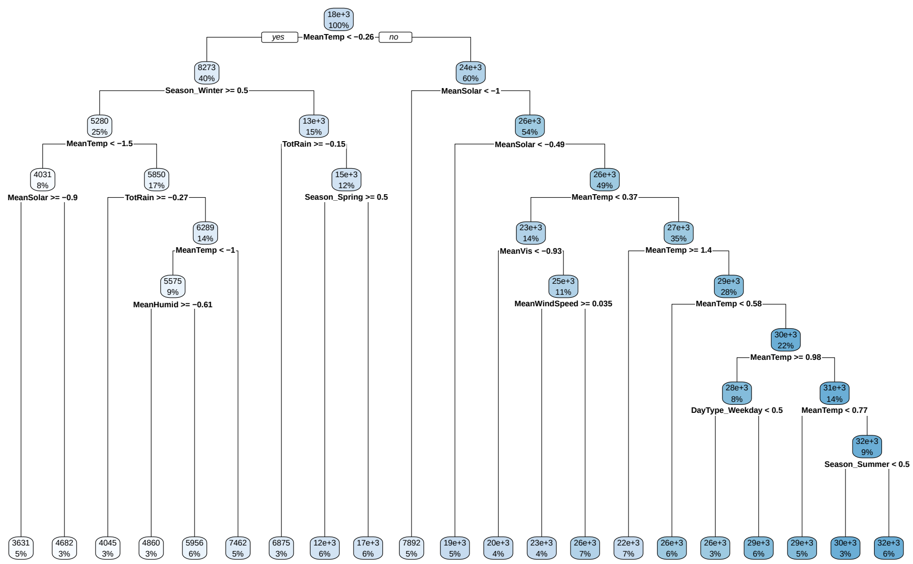
Again, we can recycle the recipe from our earlier model for the sake of our regression tree:

```
set.seed(42)
RegTree_rec = bike_rec1

RegTree_mod = decision_tree(tree_depth = tune(), min_n = 20, cost_complexity = tune()) |>
  set_engine("rpart") |>
  set_mode("regression")

RegTree_wkf = workflow() |>
  add_recipe(RegTree_rec) |>
  add_model(RegTree_mod)

#RegTree_wkf |> tune_grid(resamples = #bike_cv10) |>
#  collect_metrics()

RegTree_grid = grid_regular(cost_complexity(), tree_depth(), levels = c(10,5))

RegTree_fits = RegTree_wkf |>
  tune_grid(resamples = bike_cv10, grid = RegTree_grid)


RegTree_best_params = select_best(RegTree_fits, metric = "rmse")

RegTree_final_wkf = RegTree_wkf |>
  finalize_workflow(RegTree_best_params)

RegTree_final_fit = RegTree_final_wkf |>
  last_fit(splits,metrics = metric_set(rmse,mae))

RegTree_final_fit |>
  collect_metrics()
```

```
# A tibble: 2 x 4
  .metric .estimator .estimate .config
```

```
  <chr>   <chr>          <dbl> <chr>
1 rmse    standard       4104. Preprocessor1_Model1
2 mae     standard       3022. Preprocessor1_Model1
```

```r
# plot the final fit
RegTree_final_fit %>%
  extract_fit_engine() %>%
  rpart.plot::rpart.plot(roundint = FALSE)
```



We see that the MAE for this model is lower than for the LASSO, but our RMSE is higher. The diagram is hard to read because the font is so small, but is shows how we are making our decisions as we move down the branches!

Tuned Bagged Tree model

Next up, let's run the bagged tree model:

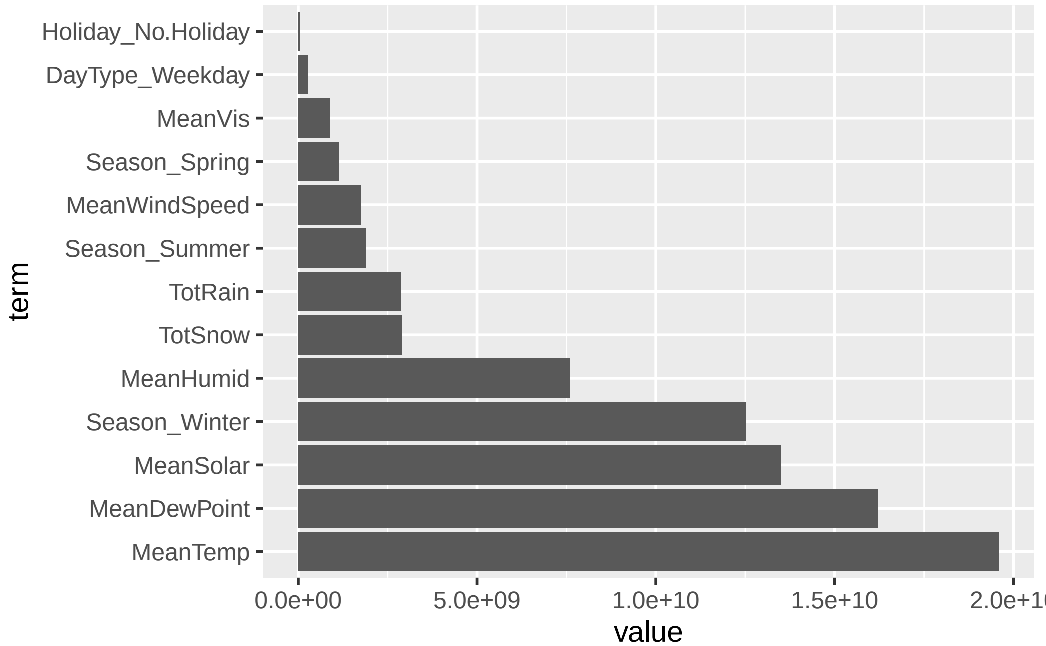
```r
library(baguette)
```

```
Warning: package 'baguette' was built under R version 4.3.3
```

```r
set.seed(42)
Bag_rec = bike_rec1 # recycle the same recipe

Bag_spec = bag_tree(tree_depth = tune(), min_n = 10, cost_complexity = tune()) |>
  set_engine("rpart") |>
  set_mode("regression")

Bag_wkf = workflow() |>
  add_recipe(Bag_rec) |>
  add_model(Bag_spec)

Bag_grid = grid_regular(cost_complexity(), tree_depth(), levels = c(10,5))

Bag_fit = Bag_wkf |>
  tune_grid(resamples = bike_cv10, grid = Bag_grid)

Bag_best_params = select_best(Bag_fit, metric = 'rmse')

Bag_final_wkf = Bag_wkf |>
  finalize_workflow(Bag_best_params)

Bag_final_fit = Bag_final_wkf |>
  last_fit(splits, metrics = metric_set(rmse,mae))

Bag_final_fit |>
  collect_metrics()
```

```
# A tibble: 2 x 4
  .metric .estimator .estimate .config
  <chr>   <chr>          <dbl> <chr>
1 rmse    standard       3424. Preprocessor1_Model1
2 mae     standard       2740. Preprocessor1_Model1
```

```r
# variable importance chart for the bagged model:
Bag_final_model = extract_fit_engine(Bag_final_fit)
Bag_final_model$imp |>
  mutate(term = factor(term, levels = term)) |>
  ggplot(aes(x = term, y = value)) +
  geom_bar(stat ="identity") +
  coord_flip()
```



In this case, we again see that our MAE is lower than our RMSE! Furthermore, the Test RMSE for our bagged model is better than either of the previous models. Right now, RMSE = 3434 is the number to beat for our next model. Also, we can see that it looks like the temperature and dew point are both the most important variables for this model! This is interesting to see, since our LASSO model pushed temperature to zero.

Tuned Random Forest

Finally, let's run our tuned Random Forest. This is similar to the Bagged model, but a bit different:

```
library(ranger)
```

```
Warning: package 'ranger' was built under R version 4.3.3
```

```
set.seed(42)
RF_rec = bike_rec1 # recycle the same recipe

RF_spec = rand_forest(mtry = tune()) |>
  set_engine("ranger", importance = "permutation") |>
  set_mode("regression")
```

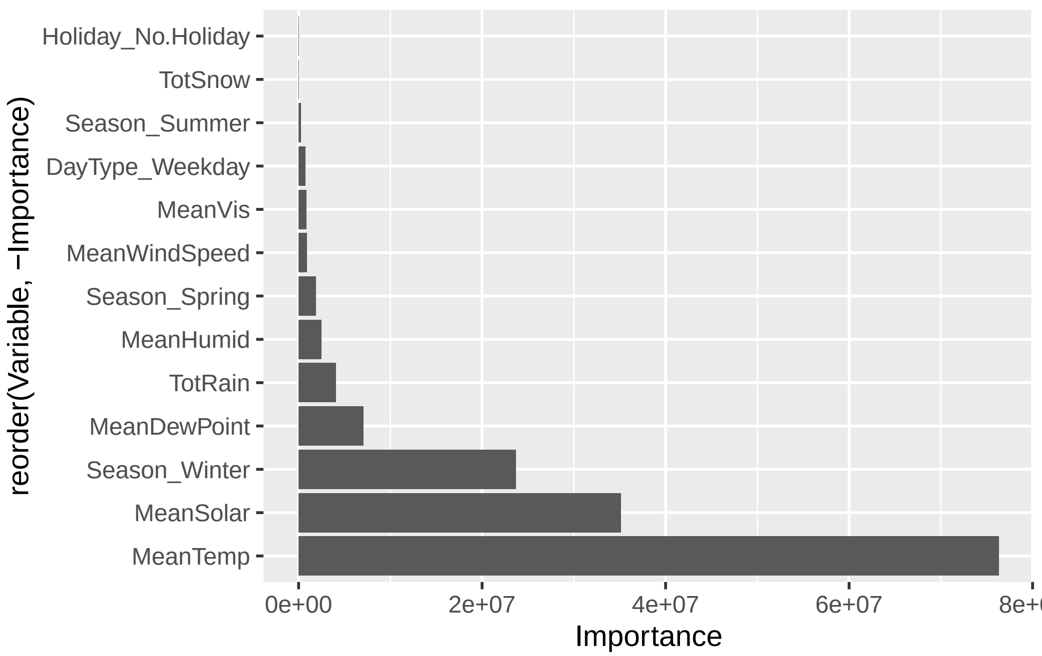
```r
RF_wkf = workflow() |>
  add_recipe(RF_rec) |>
  add_model(RF_spec)

# grid is simple enough that we don't need to specify it in advance
RF_fit = RF_wkf |>
  tune_grid(resamples = bike_cv10, grid = 7)
```

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

```r
RF_best_params = select_best(RF_fit, metric = 'rmse')

RF_final_wkf = RF_wkf |>
  finalize_workflow(RF_best_params)

RF_final_fit = RF_final_wkf |>
  last_fit(splits, metrics = metric_set(rmse,mae))

RF_final_fit |>
  collect_metrics()
```

```
# A tibble: 2 x 4
  .metric .estimator .estimate .config
  <chr>   <chr>          <dbl> <chr>
1 rmse    standard       3344. Preprocessor1_Model1
2 mae     standard       2699. Preprocessor1_Model1
```

```r
# need to extract to get our var importances differently for a ranger-engine model
RF_extracted_model = RF_final_fit |>
  extract_fit_parsnip()

RF_imp_values = enframe(RF_extracted_model$fit$variable.importance, name = "Variable", value
  arrange(Importance)

ggplot(RF_imp_values, aes(x = reorder(Variable, -Importance), y = Importance)) +
  geom_bar(stat = "identity") +
  coord_flip()
```



We have a winner! The Test RMSE for our random forest is 3343, the lowest that we have yet seen including the MLR models from HW8! The variable importance plots indicates that temperature is by far the most important of the variables, while holiday doesn't seem to have much importance in the model.