# **House Prices Kaggle**

Load all the packages needed

```
library(tidymodels)
## Registered S3 method overwritten by 'tune':
     method
##
                                 from
     required_pkgs.model_spec parsnip
## -- Attaching packages ----- tidymodels
0.1.3 --
## v broom 0.7.9 v recipes 0.1.16
## v dials 0.0.10 v rsample 0.1.0
## v dplyr 1.0.7 v tibble 3.1.4
## v ggplot2 3.3.5 v tidyr 1.1.3
## v infer 1.0.0 v tune 0.1.6
## v modeldata 0.1.1 v workflows 0.2.3
## v parsnip 0.1.7 v workflowsets 0.1.0
## v purrr 0.3.4 v yardstick 0.0.8
## -- 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()
## * Use tidymodels prefer() to resolve common conflicts.
library(tidyverse)
## -- Attaching packages ----- tidyverse
1.3.1 --
## v readr 2.0.1 v forcats 0.5.1
## v stringr 1.4.0
## -- Conflicts ------
tidyverse_conflicts() --
## x readr::col_factor() masks scales::col_factor()
library(skimr)
library(parsnip)
library(ranger)
```

```
library(yardstick)
library(glmnet)
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
## The following objects are masked from 'package:tidyr':
##
##
       expand, pack, unpack
## Loaded glmnet 4.1-2
library(earth)
## Loading required package: Formula
## Loading required package: plotmo
## Loading required package: plotrix
## Attaching package: 'plotrix'
## The following object is masked from 'package:scales':
##
##
       rescale
## Loading required package: TeachingDemos
Load the data sets
setwd("~/R projects/House Prices")
train <- read_csv("train.csv")</pre>
## Rows: 1460 Columns: 81
## -- Column specification -----
## Delimiter: ","
## chr (43): MSZoning, Street, Alley, LotShape, LandContour, Utilities,
LotConf...
## dbl (38): Id, MSSubClass, LotFrontage, LotArea, OverallQual, OverallCond,
Ye...
##
```

## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show\_col\_types = FALSE` to quiet this

message.

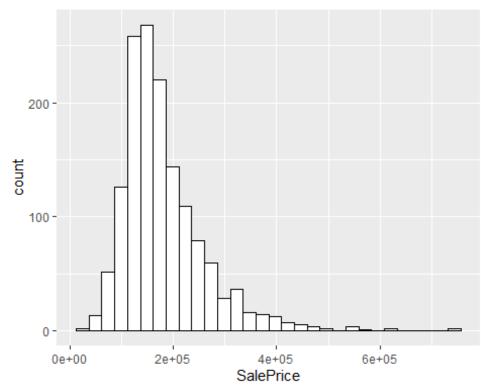
test <- read\_csv("test.csv")</pre>

## Rows: 1459 Columns: 80

```
## -- Column specification ------
## Delimiter: ","
## chr (43): MSZoning, Street, Alley, LotShape, LandContour, Utilities,
LotConf...
## dbl (37): Id, MSSubClass, LotFrontage, LotArea, OverallQual, OverallCond,
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

EDA Lets look at how the SalePrices are distributed

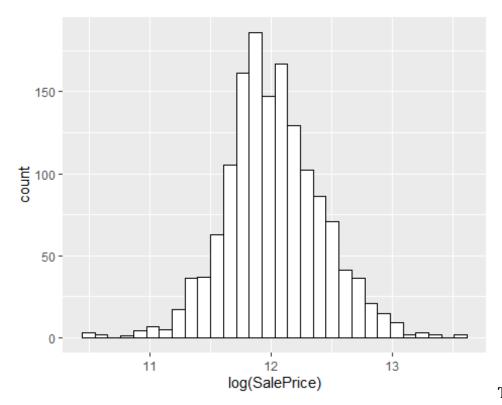
```
ggplot(train,
       aes(x = SalePrice)) +
  geom_histogram(fill = "white", color = "black")
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



I don't like the

shape of the distribution of SalePrice so lets try making it look more symmetric with a log transformation.

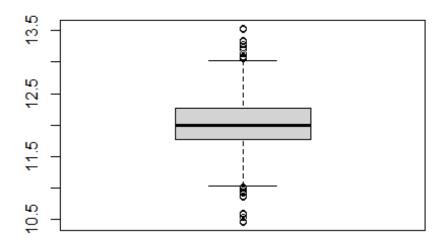
```
ggplot(train, aes(x = log(SalePrice))) +
  geom_histogram(fill = "white", color = "black")
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



This is much better.

We could try more kinds of transformations like inverse, power or BoxCox but I think this looks good enough. However, lets do the transformation and then remove observations that have a boxplot's definition of outlier for SalePrice.

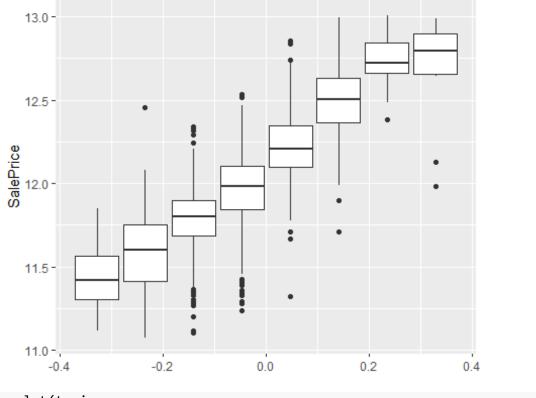
```
train$SalePrice <- log(train$SalePrice)
sale_upper <- boxplot(train$SalePrice)$stats[5]
sale_lower <- boxplot(train$SalePrice)$stats[1]</pre>
```



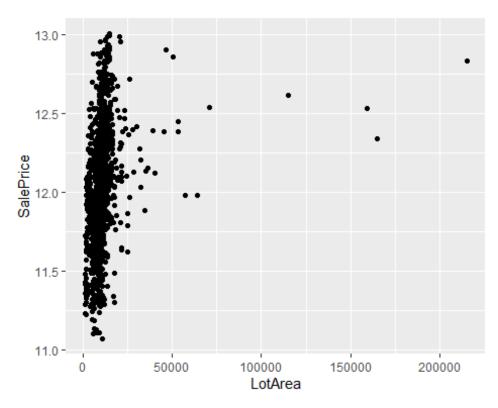
```
train <- train %>%
  filter(SalePrice < sale_upper, SalePrice > sale_lower)
```

Lets check some other features and their relationship to SalePrice

```
ggplot(train,
    aes(y = SalePrice,
        group = OverallQual)) +
    geom_boxplot()
```



```
ggplot(train,
    aes(y = SalePrice,
        x = LotArea)) +
    geom_point()
```



Data Cleaning

Now it is time to clean our datasets. For this I combine the train and test dataset. I am going to remove columns which have more that 25% missing values. Also I remove Street and Utilties because they have a very small variance.

```
test$SalePrice <- 0
full <- rbind(test, train)
skim(full)</pre>
```

## Data summary

Name full
Number of rows 2889
Number of columns 81

\_\_\_\_\_

## Column type frequency:

character 43 numeric 38

\_\_\_\_\_

Group variables None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
MSZoning	4	1.00	2	7	0	5	0
Street	0	1.00	4	4	0	2	0
Alley	2694	0.07	4	4	0	2	0
LotShape	0	1.00	3	3	0	4	0
LandContour	0	1.00	3	3	0	4	0
Utilities	2	1.00	6	6	0	2	0
LotConfig	0	1.00	3	7	0	5	0
LandSlope	0	1.00	3	3	0	3	0
Neighborhood	0	1.00	5	7	0	25	0
Condition1	0	1.00	4	6	0	9	0
Condition2	0	1.00	4	6	0	8	0
BldgType	0	1.00	4	6	0	5	0
HouseStyle	0	1.00	4	6	0	8	0
RoofStyle	0	1.00	3	7	0	6	0
RoofMatl	0	1.00	4	7	0	8	0
Exterior1st	1	1.00	5	7	0	15	0
Exterior2nd	1	1.00	5	7	0	16	0
MasVnrType	23	0.99	4	7	0	4	0
ExterQual	0	1.00	2	2	0	4	0
ExterCond	0	1.00	2	2	0	5	0
Foundation	0	1.00	4	6	0	6	0
BsmtQual	79	0.97	2	2	0	4	0
BsmtCond	80	0.97	2	2	0	4	0
BsmtExposure	80	0.97	2	2	0	4	0
BsmtFinType1	77	0.97	3	3	0	6	0
BsmtFinType2	78	0.97	3	3	0	6	0
Heating	0	1.00	4	5	0	6	0
HeatingQC	0	1.00	2	2	0	5	0
CentralAir	0	1.00	1	1	0	2	0
Electrical	1	1.00	3	5	0	5	0
KitchenQual	1	1.00	2	2	0	4	0
Functional	2	1.00	3	4	0	7	0
FireplaceQu	1406	0.51	2	2	0	5	0
GarageType	148	0.95	6	7	0	6	0
GarageFinish	150	0.95	3	3	0	3	0

GarageQual	150	0.95	2	2	0	5	0
GarageCond	150	0.95	2	2	0	5	0
PavedDrive	0	1.00	1	1	0	3	0
PoolQC	2880	0.00	2	2	0	3	0
Fence	2325	0.20	4	5	0	4	0
MiscFeature	2786	0.04	4	4	0	4	0
SaleType	1	1.00	2	5	0	9	0
SaleCondition	0	1.00	6	7	0	6	0

# Variable type: numeric

skim_vari	n_mis	complete								
able	sing	_rate	mean	sd	p0	p25	p50	p75	p100	hist
Id	0	1.00	1467. 00	843. 50	1	737. 00	147 5.0	2197. 00	2919.0 0	
MSSubCla ss	0	1.00	57.28	42.5 8	20	20.0	50.0	70.00	190.00	<b>-</b>
LotFronta ge	484	0.83	69.19	23.2 1	21	59.0 0	68.0	80.00	313.00	<b>L</b>
LotArea	0	1.00	1013 8.54	7856 .52	13 00	7476 .00	945 2.0	1152 0.00	21524 5.00	<b>I</b>
OverallQu al	0	1.00	6.09	1.38	1	5.00	6.0	7.00	10.00	<b>I</b>
OverallCo nd	0	1.00	5.57	1.11	1	5.00	5.0	6.00	9.00	 
YearBuilt	0	1.00	1971. 40	30.1 8	18 72	1954 .00	197 3.0	2001. 00	2010.0 0	_ <b></b>
YearRem odAdd	0	1.00	1984. 33	20.8	19 50	1965 .00	199 3.0	2004. 00	2010.0 0	
MasVnrAr ea	22	0.99	100.6	175. 11	0	0.00	0.0	164.0 0	1600.0 0	<b>I</b>
BsmtFinS F1	1	1.00	439.6 4	451. 19	0	0.00	370. 0	732.2 5	5644.0 0	<b>I</b>
BsmtFinS F2	1	1.00	49.80	169. 70	0	0.00	0.0	0.00	1526.0 0	<b>I</b>
BsmtUnfS F	1	1.00	560.0 2	438. 48	0	219. 75	467. 0	806.0 0	2336.0 0	<b>I</b>
TotalBsm tSF	1	1.00	1049. 46	433. 68	0	793. 00	989. 5	1299. 25	6110.0 0	<b>L</b>

1stFlrSF	0	1.00	1157. 57	386. 76	40 7	879. 00	108 2.0	1383. 00	5095.0	<b>L</b>
2ndFlrSF	0	1.00	335.0 3	425. 12	0	0.00	0.0	704.0 0	1862.0 0	<b></b> _
LowQualF inSF	0	1.00	4.55	45.4 2	0	0.00	0.0	0.00	1064.0 0	<b>■</b>
GrLivArea	0	1.00	1497. 15	492. 11	40 7	1128 .00	144 4.0	1740. 00	5642.0 0	<b>II</b> _
BsmtFull Bath	2	1.00	0.43	0.53	0	0.00	0.0	1.00	3.00	<b>II</b> _
BsmtHalf Bath	2	1.00	0.06	0.25	0	0.00	0.0	0.00	2.00	<b>■</b>
FullBath	0	1.00	1.57	0.55	0	1.00	2.0	2.00	4.00	<b>-</b> ■
HalfBath	0	1.00	0.38	0.50	0	0.00	0.0	1.00	2.00	<b>I</b> _•
Bedroom AbvGr	0	1.00	2.86	0.82	0	2.00	3.0	3.00	8.00	- <b>L</b>
KitchenA bvGr	0	1.00	1.04	0.21	0	1.00	1.0	1.00	3.00	<b>-</b> ■-
TotRmsA bvGrd	0	1.00	6.44	1.54	3	5.00	6.0	7.00	15.00	<b>-1</b>
Fireplaces	0	1.00	0.60	0.64	0	0.00	1.0	1.00	4.00	<b>II</b> _
GarageYr Blt	150	0.95	1978. 07	25.5 4	18 95	1960 .00	197 9.0	2002. 00	2207.0 0	<b>_I</b> _
GarageCa rs	1	1.00	1.77	0.75	0	1.00	2.0	2.00	5.00	<b>-</b>
GarageAr ea	1	1.00	472.9 2	212. 98	0	322. 75	480. 0	576.0 0	1488.0 0	<b></b> -
WoodDec kSF	0	1.00	93.73	126. 27	0	0.00	0.0	168.0 0	1424.0 0	<b>■</b>
OpenPorc hSF	0	1.00	47.19	66.8 5	0	0.00	26.0	70.00	742.00	<b>■</b>
Enclosed Porch	0	1.00	23.09	64.3 1	0	0.00	0.0	0.00	1012.0 0	<b>■</b>
3SsnPorc h	0	1.00	2.63	25.3 2	0	0.00	0.0	0.00	508.00	<b>I</b>

```
1.00
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ScreenPo
               0
                             15.89
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rch
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MiscVal
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                                      70
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MoSold
               0
                       1.00
                                     2.71
                                                4.00
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                                                                     12.00
                              6.22
                                            1
YrSold
                                     1.31
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                       1.00
                             2007.
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                                               2007
                                                       200
                                                             2009.
                                                                    2010.0
                                79
                                           06
                                                 .00
                                                       8.0
                                                               00
                                                                         0
SalePrice
               0
                       1.00
                              5.95
                                     6.02
                                            0
                                                0.00
                                                       0.0
                                                             12.00
                                                                     13.01
remove_cols <- colnames(full)[colSums(is.na(full)) > (0.25 * nrow(full))]
full <- full %>%
  select(!remove cols)
## Note: Using an external vector in selections is ambiguous.
## i Use `all of(remove cols)` instead of `remove cols` to silence this
message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
full <- full %>%
  select(!c(Street, Utilities))
train <- full %>%
  filter(SalePrice != 0)
test <- full %>%
  filter(SalePrice == 0)
```

Now we split the training data

```
set.seed(135)
data_split <- initial_split(train, strata = "SalePrice", prop = 0.80)
house_test <- testing(data_split)
house_train <- training(data_split)</pre>
```

Here I am doing all the preprocessing.

```
house_rec <- recipe(SalePrice ~., data = house_train) %>%
  step_impute_mode(all_nominal_predictors()) %>%
  step_impute_mean(all_numeric_predictors()) %>%
  update_role(Id, new_role = "ID") %>%
  step_dummy(all_nominal_predictors()) %>%
  step_impute_median(all_predictors()) %>%
  step_BoxCox(all_numeric_predictors()) %>%
  step_nzv(all_predictors()) %>%
  step_normalize(all_numeric_predictors())
```

#### Modeling

For some of the models I will be tuning the hyperparameters and will be doing so using a 5-fold crossvalidation.

```
set.seed(123)
folds <- vfold_cv(house_train, v = 5)</pre>
```

Random Forest Model - Model

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

Random Forest - Workflow

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

Random Forest - Grid for tuning

```
rf_grid <- grid_regular(
  mtry(range = c(10, 30)),
  min_n(range = c(2, 8)),
  levels = 5
)</pre>
```

Random Forest - Tune and update the parameters

```
set.seed(345)
tune_res <- tune_grid(</pre>
  rf_wf,
  resamples = folds,
  grid = rf grid
)
## ! Fold1: preprocessor 1/1, model 1/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 2/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 3/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 4/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 5/25 (predictions): There are new levels
in a fa...
```

```
## ! Fold1: preprocessor 1/1, model 6/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 7/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 8/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 9/25 (predictions): There are new levels
in a fa...
## ! Fold1: preprocessor 1/1, model 10/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 11/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 12/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 13/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 14/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 15/25 (predictions): There are new levels
## ! Fold1: preprocessor 1/1, model 16/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 17/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 18/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 19/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 20/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 21/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 22/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 23/25 (predictions): There are new levels
in a f...
```

```
## ! Fold1: preprocessor 1/1, model 24/25 (predictions): There are new levels
in a f...
## ! Fold1: preprocessor 1/1, model 25/25 (predictions): There are new levels
in a f...
## ! Fold2: preprocessor 1/1, model 1/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 2/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 3/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 4/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 5/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 6/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 7/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 8/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 9/25 (predictions): There are new levels
in a fa...
## ! Fold2: preprocessor 1/1, model 10/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 11/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 12/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 13/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 14/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 15/25 (predictions): There are new levels
in a f...
## ! Fold2: preprocessor 1/1, model 16/25 (predictions): There are new levels
in a f...
```

```
## ! Fold2: preprocessor 1/1, model 17/25 (predictions): There are new levels
in a f...
## ! Fold2: preprocessor 1/1, model 18/25 (predictions): There are new levels
in a f...
## ! Fold2: preprocessor 1/1, model 19/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 20/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 21/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 22/25 (predictions): There are new levels
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## ! Fold2: preprocessor 1/1, model 23/25 (predictions): There are new levels
## ! Fold2: preprocessor 1/1, model 24/25 (predictions): There are new levels
in a f...
## ! Fold2: preprocessor 1/1, model 25/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 1/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 2/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 3/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 4/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 5/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 6/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 7/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 8/25 (predictions): There are new levels
in a fa...
## ! Fold3: preprocessor 1/1, model 9/25 (predictions): There are new levels
in a fa...
```

```
## ! Fold3: preprocessor 1/1, model 10/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 11/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 12/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 13/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 14/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 15/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 16/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 17/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 18/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 19/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 20/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 21/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 22/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 23/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 24/25 (predictions): There are new levels
in a f...
## ! Fold3: preprocessor 1/1, model 25/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 1/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 2/25 (predictions): There are new levels
in a fa...
```

```
## ! Fold4: preprocessor 1/1, model 3/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 4/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 5/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 6/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 7/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 8/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 9/25 (predictions): There are new levels
in a fa...
## ! Fold4: preprocessor 1/1, model 10/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 11/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 12/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 13/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 14/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 15/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 16/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 17/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 18/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 19/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 20/25 (predictions): There are new levels
in a f...
```

```
## ! Fold4: preprocessor 1/1, model 21/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 22/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 23/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 24/25 (predictions): There are new levels
in a f...
## ! Fold4: preprocessor 1/1, model 25/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 1/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 2/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 3/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 4/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 5/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 6/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 7/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 8/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 9/25 (predictions): There are new levels
in a fa...
## ! Fold5: preprocessor 1/1, model 10/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 11/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 12/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 13/25 (predictions): There are new levels
in a f...
```

```
## ! Fold5: preprocessor 1/1, model 14/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 15/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 16/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 17/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 18/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 19/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 20/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 21/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 22/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 23/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 24/25 (predictions): There are new levels
in a f...
## ! Fold5: preprocessor 1/1, model 25/25 (predictions): There are new levels
in a f...
best rmse <- select best(tune res, "rmse")</pre>
final_rf <- finalize_model(</pre>
  rf_mod,
  best rmse
rf wf <- rf wf %>%
  update model(final rf)
```

Random Forest - Fit the model

```
rf_fit <- fit(rf_wf, data = house_train)</pre>
```

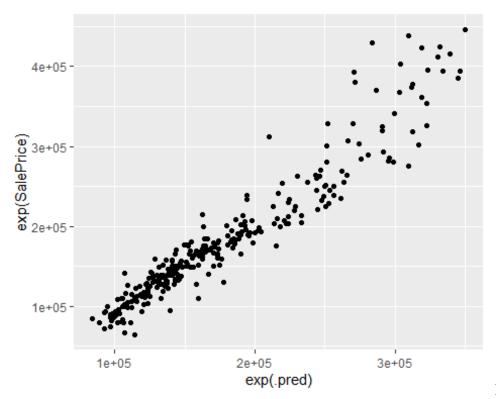
Random Forest - Predict and find the RMSE

```
rf_pred <- rf_fit %>%
  predict(new_data = house_test)
## Warning: There are new levels in a factor: Artery
```

```
## Warning: There are new levels in a factor: Other
## Warning: There are new levels in a factor: Floor
rf_pred <- bind_cols(rf_pred, house_test %>% select(SalePrice))
rf_pred
## # A tibble: 288 x 2
      .pred SalePrice
##
               <dbl>
     <dbl>
##
## 1 12.5
                12.6
## 2 11.7
                11.7
## 3 11.8
                11.8
## 4 11.9
                11.9
## 5
      11.8
                11.8
      12.2
                12.1
## 6
  7
      12.1
                12.0
##
## 8 11.9
                11.9
## 9 11.7
                11.6
## 10 12.6
                13.0
## # ... with 278 more rows
rmse(rf_pred, truth = exp(SalePrice), estimate = exp(.pred))
## # A tibble: 1 x 3
##
     .metric .estimator .estimate
##
     <chr>
            <chr>>
                           <dbl>
                          29029.
## 1 rmse
            standard
```

Random Forest - Plot the predictions against the actual SalePrice and see if there any postProcesses that can be done.

```
ggplot(data = rf_pred, aes(x = exp(.pred), y = exp(SalePrice))) +
  geom_point()
```



Does not look like

any postProcessing is needed.

LASSO Model Same Process as with Random Forest

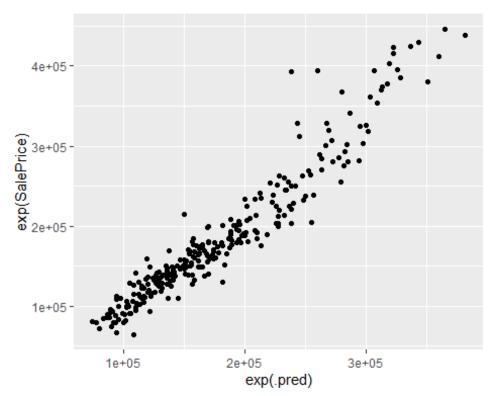
```
lasso_model <- linear_reg(penalty = tune(), mixture = tune()) %>%
  set_engine("glmnet")
lasso_wf <- workflow() %>%
  add_recipe(house_rec) %>%
  add_model(lasso_model)
lasso_grid <- grid_regular(</pre>
  penalty(), # The tune package has default values for penalty() and
mixture() so no need to give them any
  mixture(),
  levels = 5
set.seed(345)
tune_res_las <- tune_grid(</pre>
  lasso_wf,
  resamples = folds,
  grid = lasso_grid
## ! Fold1: preprocessor 1/1, model 1/5 (predictions): There are new levels
in a fac...
```

```
## ! Fold1: preprocessor 1/1, model 2/5 (predictions): There are new levels
in a fac...
## ! Fold1: preprocessor 1/1, model 3/5 (predictions): There are new levels
in a fac...
## ! Fold1: preprocessor 1/1, model 4/5 (predictions): There are new levels
in a fac...
## ! Fold1: preprocessor 1/1, model 5/5 (predictions): There are new levels
in a fac...
## ! Fold1: internal: A correlation computation is required, but `estimate`
is const...
## ! Fold2: preprocessor 1/1, model 1/5 (predictions): There are new levels
in a fac...
## ! Fold2: preprocessor 1/1, model 2/5 (predictions): There are new levels
in a fac...
## ! Fold2: preprocessor 1/1, model 3/5 (predictions): There are new levels
in a fac...
## ! Fold2: preprocessor 1/1, model 4/5 (predictions): There are new levels
in a fac...
## ! Fold2: preprocessor 1/1, model 5/5 (predictions): There are new levels
## ! Fold2: internal: A correlation computation is required, but `estimate`
is const...
## ! Fold3: preprocessor 1/1, model 1/5 (predictions): There are new levels
in a fac...
## ! Fold3: preprocessor 1/1, model 2/5 (predictions): There are new levels
in a fac...
## ! Fold3: preprocessor 1/1, model 3/5 (predictions): There are new levels
in a fac...
## ! Fold3: preprocessor 1/1, model 4/5 (predictions): There are new levels
in a fac...
## ! Fold3: preprocessor 1/1, model 5/5 (predictions): There are new levels
in a fac...
## ! Fold3: internal: A correlation computation is required, but `estimate`
is const...
## ! Fold4: preprocessor 1/1, model 1/5 (predictions): There are new levels
in a fac...
```

```
## ! Fold4: preprocessor 1/1, model 2/5 (predictions): There are new levels
in a fac...
## ! Fold4: preprocessor 1/1, model 3/5 (predictions): There are new levels
in a fac...
## ! Fold4: preprocessor 1/1, model 4/5 (predictions): There are new levels
in a fac...
## ! Fold4: preprocessor 1/1, model 5/5 (predictions): There are new levels
in a fac...
## ! Fold4: internal: A correlation computation is required, but `estimate`
is const...
## ! Fold5: preprocessor 1/1, model 1/5 (predictions): There are new levels
in a fac...
## ! Fold5: preprocessor 1/1, model 2/5 (predictions): There are new levels
in a fac...
## ! Fold5: preprocessor 1/1, model 3/5 (predictions): There are new levels
in a fac...
## ! Fold5: preprocessor 1/1, model 4/5 (predictions): There are new levels
in a fac...
## ! Fold5: preprocessor 1/1, model 5/5 (predictions): There are new levels
in a fac...
## ! Fold5: internal: A correlation computation is required, but `estimate`
is const...
best rmse_las <- select_best(tune_res_las, "rmse")</pre>
final las <- finalize model(</pre>
  lasso model,
  best_rmse_las
lasso wf <- lasso wf %>%
  update_model(final_las)
LASSO - Fit the model
lasso fit <- fit(lasso wf, data = house train)</pre>
LASSO - Predict and evaluate using RMSE
lasso pred <- lasso fit %>%
  predict(new_data = house_test)
## Warning: There are new levels in a factor: Artery
## Warning: There are new levels in a factor: Other
```

#### LASSO - Check for any potential postProcessing

```
ggplot(data = lasso_pred, aes(x = exp(.pred), y = exp(SalePrice))) +
  geom_point()
```



Looks good, no

postProcessing required

MARS Model For the MARS model I am not going to use parameter tuning

```
mars_model <- mars(mode = "regression") %>%
  set_engine("earth")

mars_wf <- workflow() %>%
  add_recipe(house_rec) %>%
  add_model(mars_model)

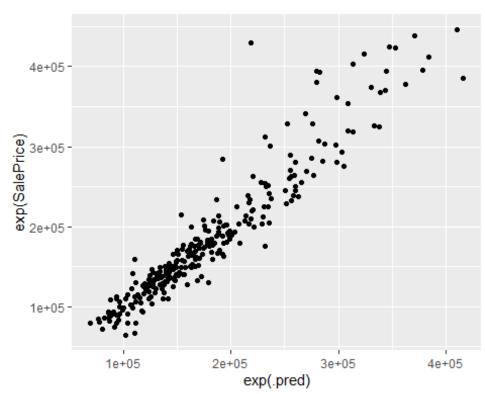
mars_fit <- fit(mars_wf, data = house_train)</pre>
```

#### MARS - Prediction and evaluate using RMSE

```
mars_pred <- mars_fit %>%
  predict(new_data = house_test)
## Warning: There are new levels in a factor: Artery
## Warning: There are new levels in a factor: Other
## Warning: There are new levels in a factor: Floor
mars_pred <- bind_cols(mars_pred, house_test %>% select(SalePrice))
rmse(mars_pred, truth = exp(SalePrice), estimate = exp(.pred))
## # A tibble: 1 x 3
     .metric .estimator .estimate
##
     <chr>>
             <chr>>
                            <dhl>
## 1 rmse
             standard
                           28164.
```

#### MARS - Check for any postProcessing

```
ggplot(data = mars_pred, aes(x = exp(.pred), y = exp(SalePrice))) +
  geom_point()
```



Looks good, no

postProcessing required.

Submission From the RMSE scores it looks like the LASSO model worked best so that is what I am going to use for the final prediction.

```
lasso_final_fit <- fit(lasso_wf, data = train)
lasso_final_pred <- predict(lasso_final_fit, new_data = test)
lasso_final_pred <- bind_cols(test %>% select(Id), exp(lasso_final_pred))
names(lasso_final_pred)[2] <- "SalePrice"

write_csv(lasso_final_pred, "tidymodels_pred.csv")</pre>
```

This gave me a 0.13401 score on Kaggle.