Kaggle Challenge: Predicting Housing Prices

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Introduction

Challenge: Predicting Housing Prices in Ames, Iowa using various machine learning techniques

Data:

- Train Data Set**:** 1460 Observations x 80 Variables (Including Response Variable: Sale Price)
- Test Data Set: 1459 Observations x 79 Variables

Useful Links:

- **Kaggle Homepage: https://www.kaggle.com/c/house-prices-advanced-regression-techniques**
- **Data Description: https://storage.googleapis.com/kaggle-competitions-data/kaggle/5407/data_description.txt**

Understanding the Data

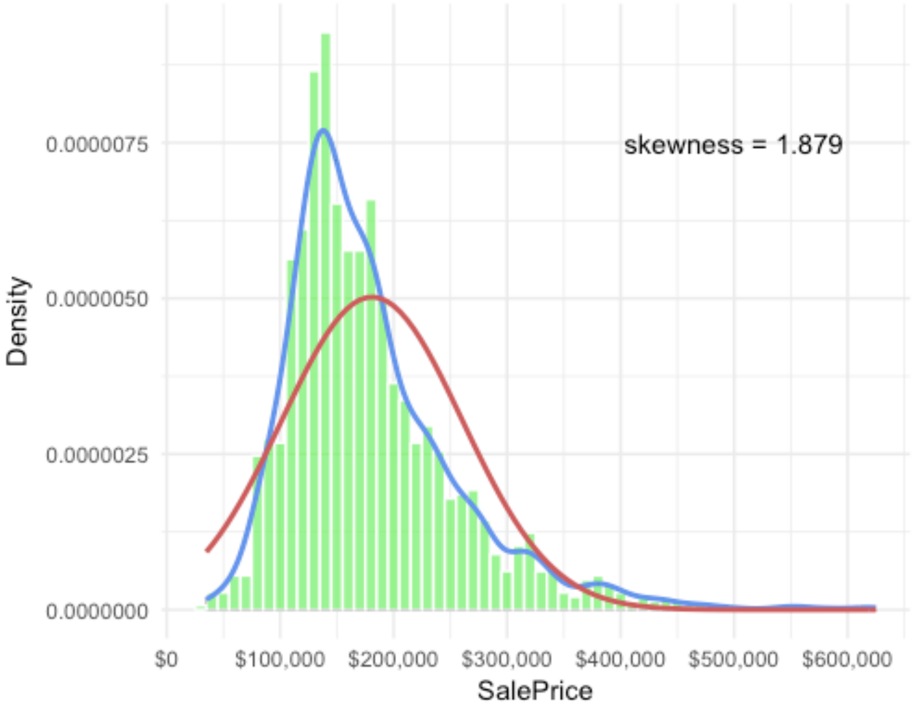
Total Predictor Variables Provided: 79

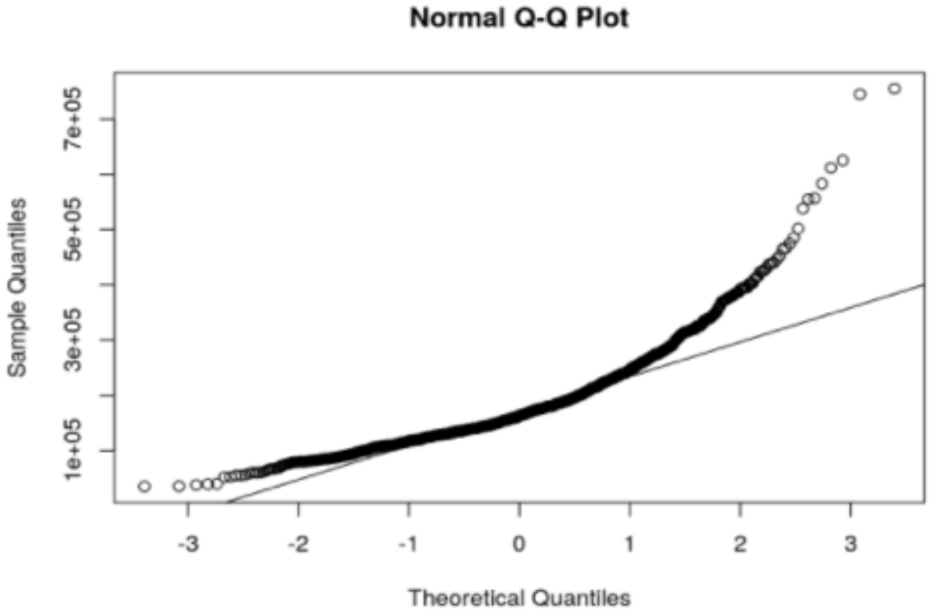
- Continuous Variables: 28
- Categorical Variables: 51

Combined test and train data sets to get a holistic view of each variable

- (i.e., total missing values, total categories in categorical variable)

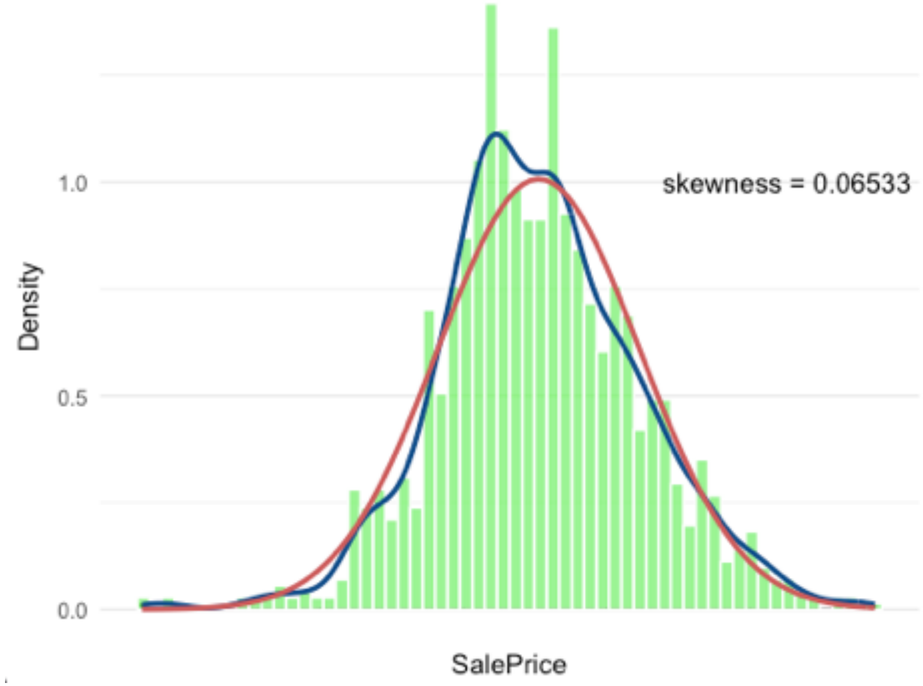
Processing the Data: Response Variable

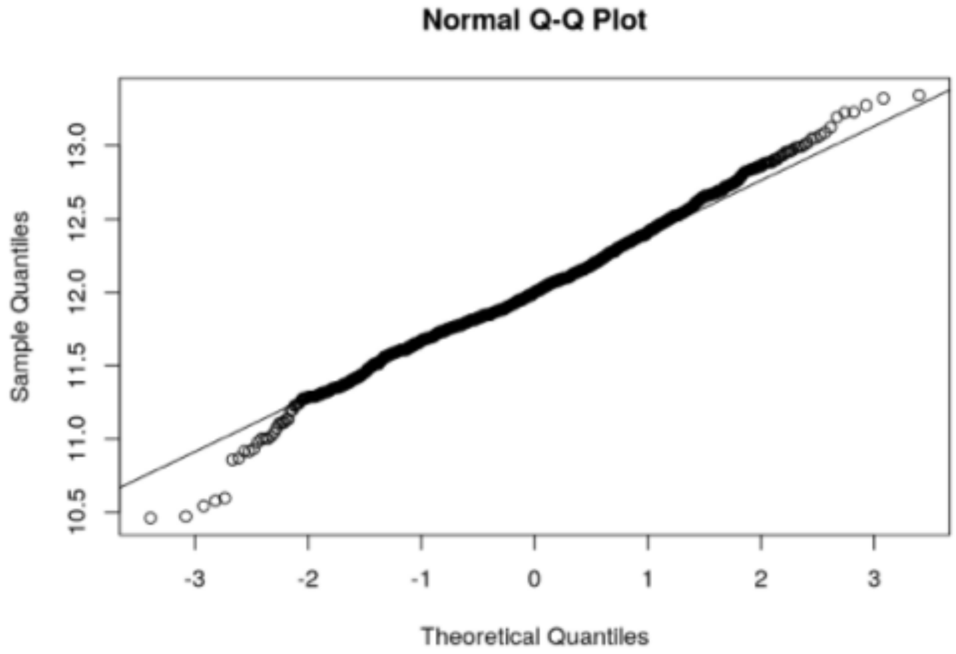




Processing the Data: Response Variable

Treat response variable with log + 1 transformation

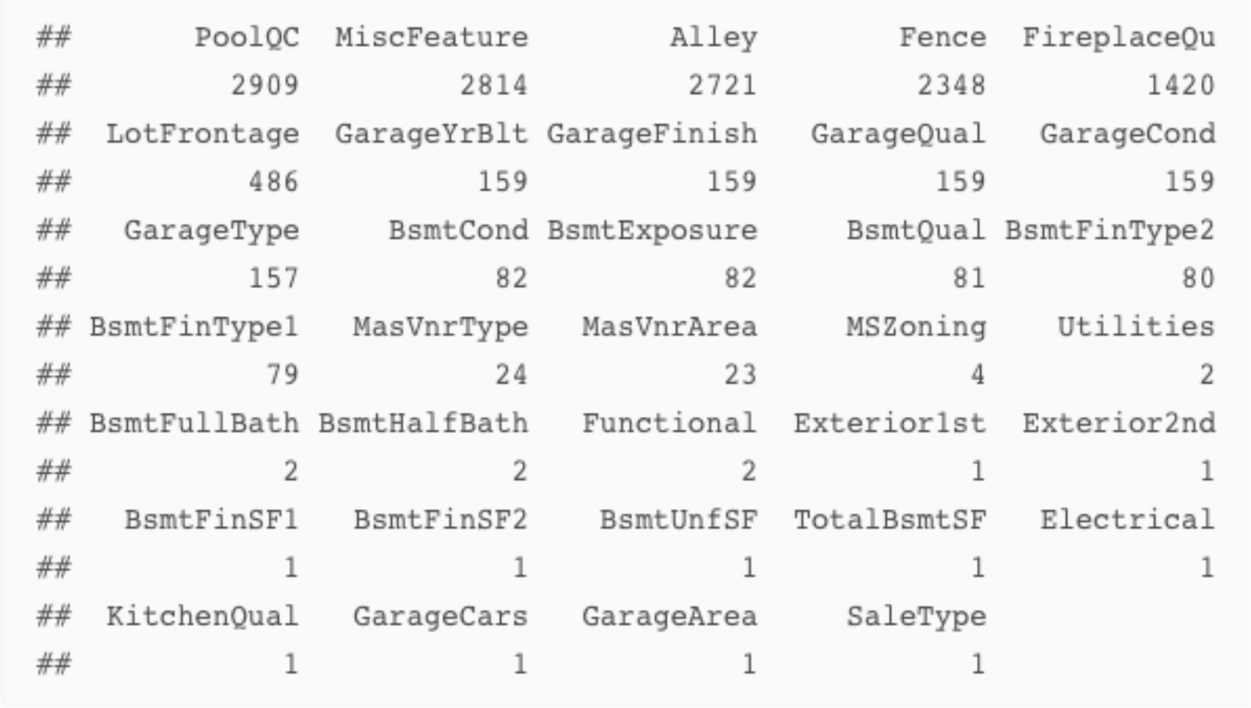



Normal Q-Q Plot

Remember to inverse log before submitting to Kaggle

Processing the Data: Overview of Missingness

34 predictors with missing values



```
##       PoolQC  MiscFeature        Alley        Fence  FireplaceQu
##         2909         2814         2721         2348         1420
##  LotFrontage  GarageYrBlt GarageFinish   GarageQual   GarageCond
##          486          159          159          159          159
##   GarageType     BsmtCond BsmtExposure     BsmtQual BsmtFinType2
##          157           82           82           81           80
## BsmtFinType1   MasVnrType   MasVnrArea     MSZoning    Utilities
##           79           24           23            4            2
## BsmtFullBath BsmtHalfBath   Functional  Exterior1st  Exterior2nd
##            2            2            2            1            1
##   BsmtFinSF1   BsmtFinSF2    BsmtUnfSF  TotalBsmtSF   Electrical
##            1            1            1            1            1
##  KitchenQual   GarageCars   GarageArea     SaleType
##            1            1            1            1
```

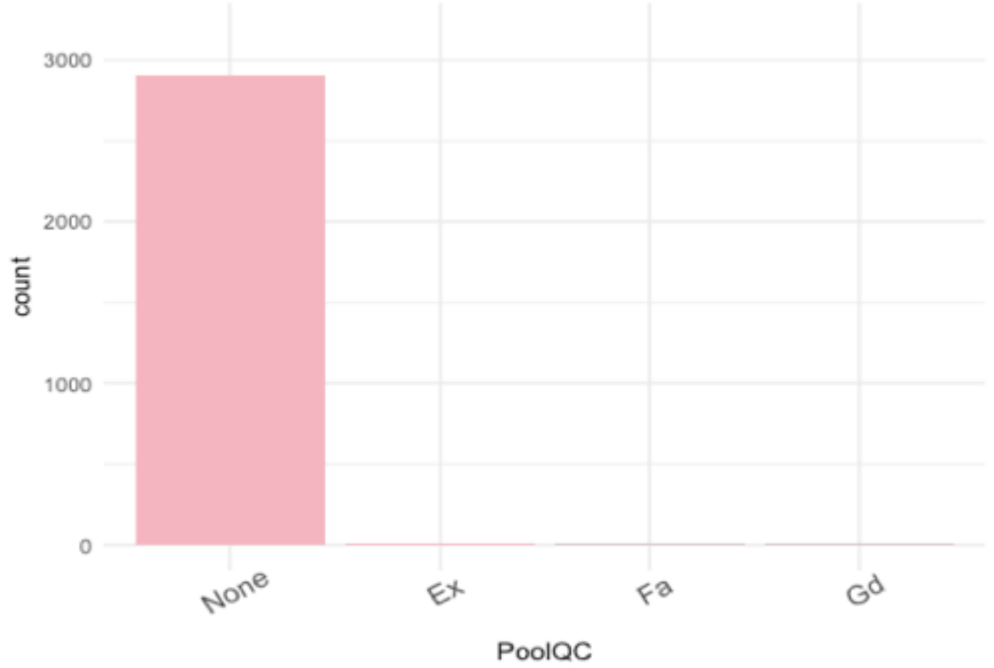
Processing the Data: Handling Missing Data

1) Are data really missing?

Ex. Pool Quality

- 2909 out of 2919 observations have ”NA” values
  - Most NAs are due to houses not having pools

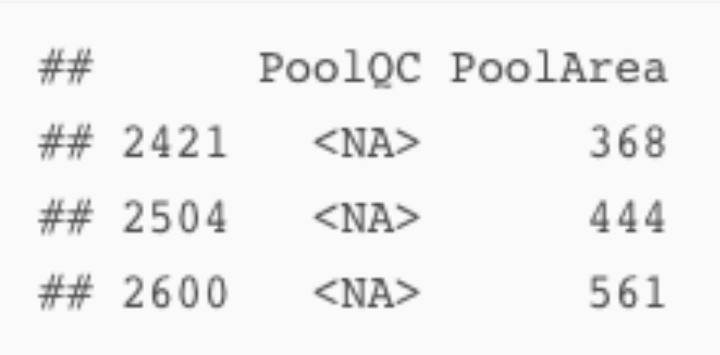
- Solution:
  - Replace (most) NAs with new category: “None”



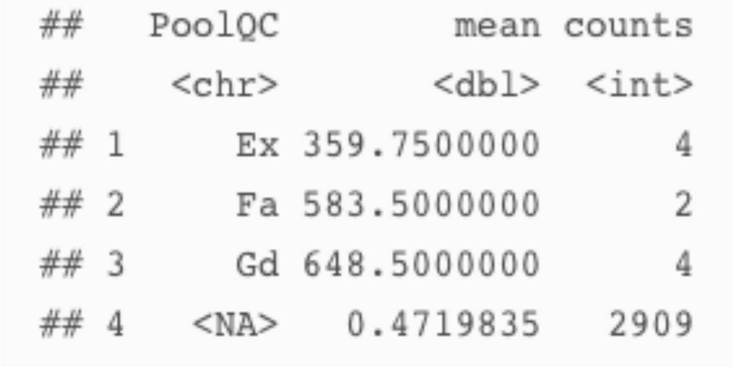
Processing the Data: Handling Missing Data

2) Not all NA values indicate a missing feature

Ex. Pool Quality



```
##         PoolQC PoolArea
## 2421    <NA>        368
## 2504    <NA>        444
## 2600    <NA>        561
```



```
##    PoolQC          mean counts
##     <chr>         <dbl>  <int>
## 1      Ex 359.7500000      4
## 2      Fa 583.5000000      2
## 3      Gd 648.5000000      4
## 4    <NA>     0.4719835   2909
```

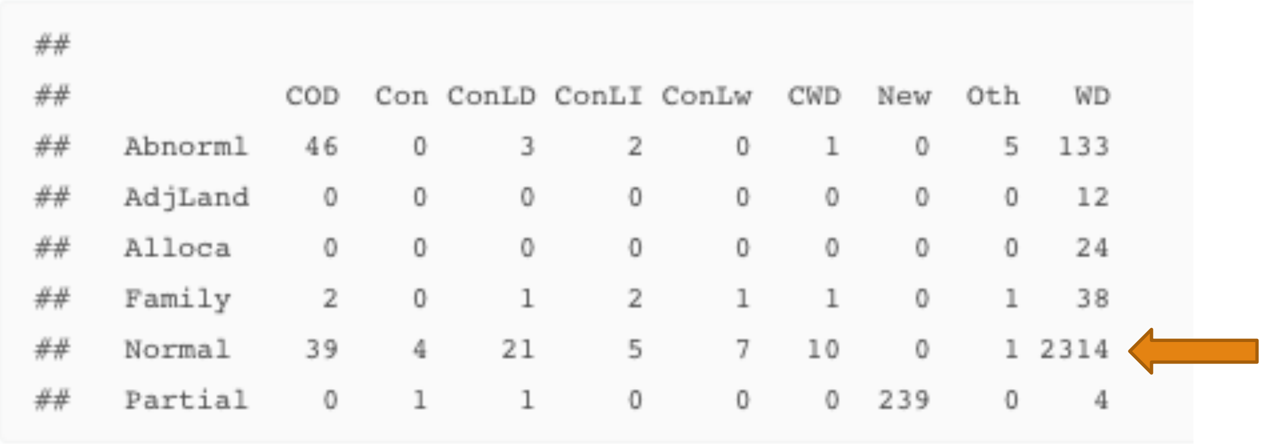
- Solution: Use related numerical variable to impute categorical variable
  - Calculate average area of each pool class within Pool Quality and fill for NAs

Processing the Data: Handling Missing Data

2) Not all NA values indicate a missing feature

Ex. Sale Type (1 Missing observation, but we know Sale Condition)

- Solution: Use related categorical variables to impute
  - For Sale Condition that is “Normal” we see by far most common Sale Type value is “WD” and we can impute.



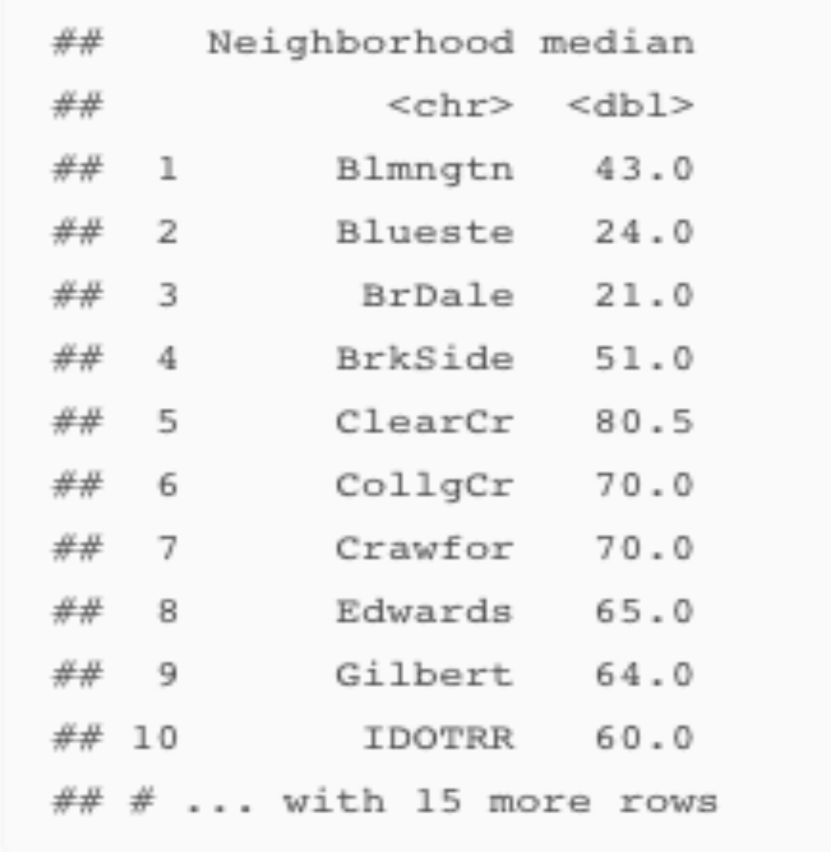
```
##
##              COD  Con ConLD ConLI ConLw  CWD  New  Oth   WD
##   Abnorml     46    0     3     2     0    1    0    5  133
##   AdjLand      0    0     0     0     0    0    0    0   12
##   Alloca       0    0     0     0     0    0    0    0   24
##   Family       2    0     1     2     1    1    0    1   38
##   Normal      39    4    21     5     7   10    0    1 2314
##   Partial      0    1     1     0     0    0  239    0    4
```

Processing the Data: Handling Missing Data

3) Use domain knowledge

Ex. Lot Frontage (486 NAs)

- Houses in close proximity likely have similar lot areas
- Solution: use categorical variable to impute numerical
    - Use median Lot Frontage by neighborhood to impute missing value

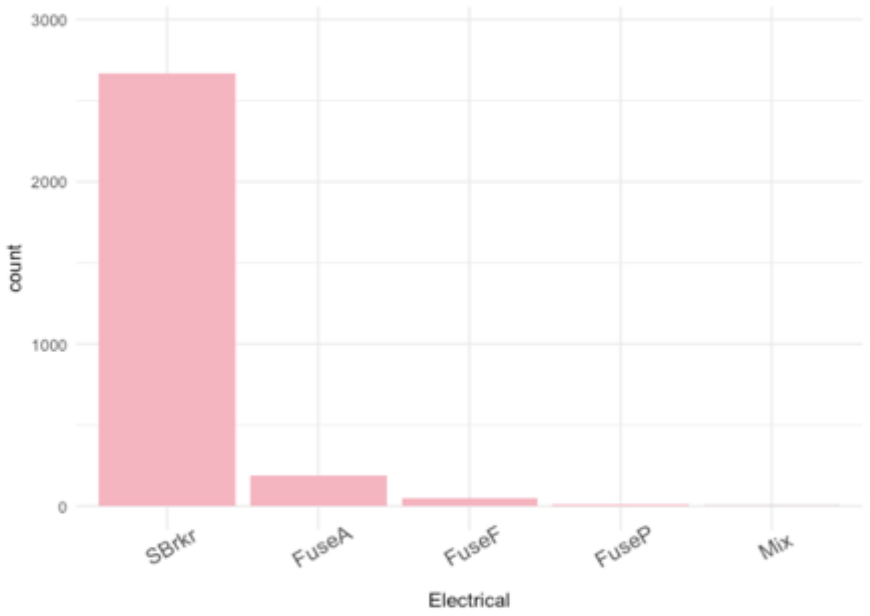


```
##     Neighborhood median
##            <chr>  <dbl>
##  1       Blmngtn   43.0
##  2       Blueste   24.0
##  3        BrDale   21.0
##  4       BrkSide   51.0
##  5       ClearCr   80.5
##  6       CollgCr   70.0
##  7       Crawfor   70.0
##  8       Edwards   65.0
##  9       Gilbert   64.0
## 10        IDOTRR   60.0
## # ... with 15 more rows
```

Processing the Data: Handling Missing Data

4) Variables with little to no relation to other variables

Ex. Electrical

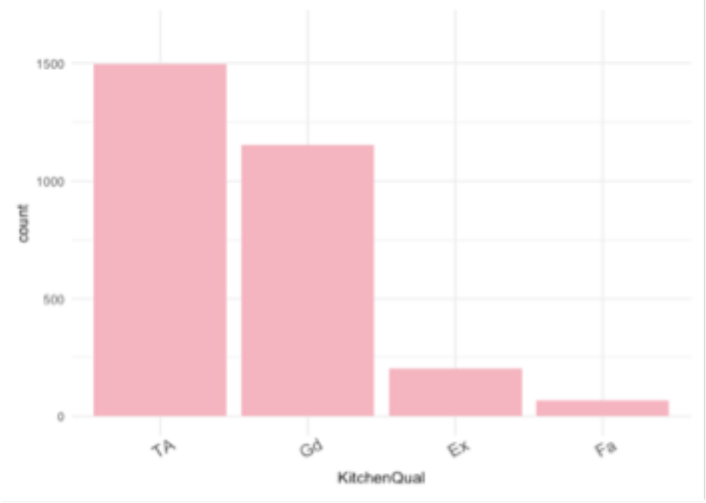


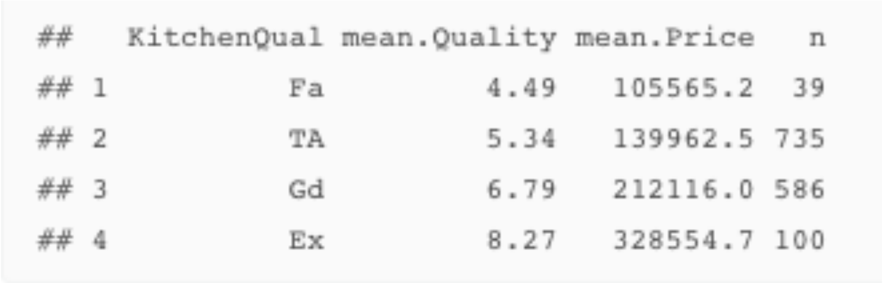
- Solution: Impute by most commonly occurring class within variable

Processing the Data: Categorical Variables (Ordinal)

Some machine learning algorithms cannot handle non-numerical values

Ex. Kitchen Quality





```
##   KitchenQual mean.Quality mean.Price   n
## 1          Fa         4.49   105565.2  39
## 2          TA         5.34   139962.5 735
## 3          Gd         6.79   212116.0 586
## 4          Ex         8.27   328554.7 100
```

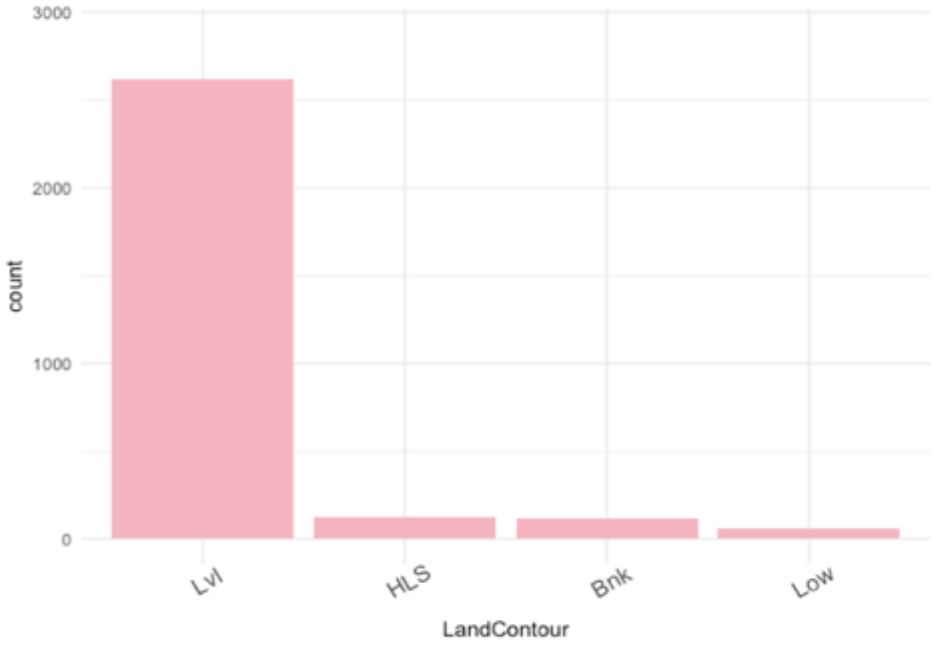
('None' = 0, 'Po' = 1, 'Fa' = 2, 'TA' = 3, 'Gd' = 4, 'Ex' = 5)

- Solution: Use average Sale Price to assign ordered numerical values to categories

Processing the Data: Categorical Variables (Nominal)

Some machine learning algorithms cannot handle non-numerical values

Ex. Land Contour



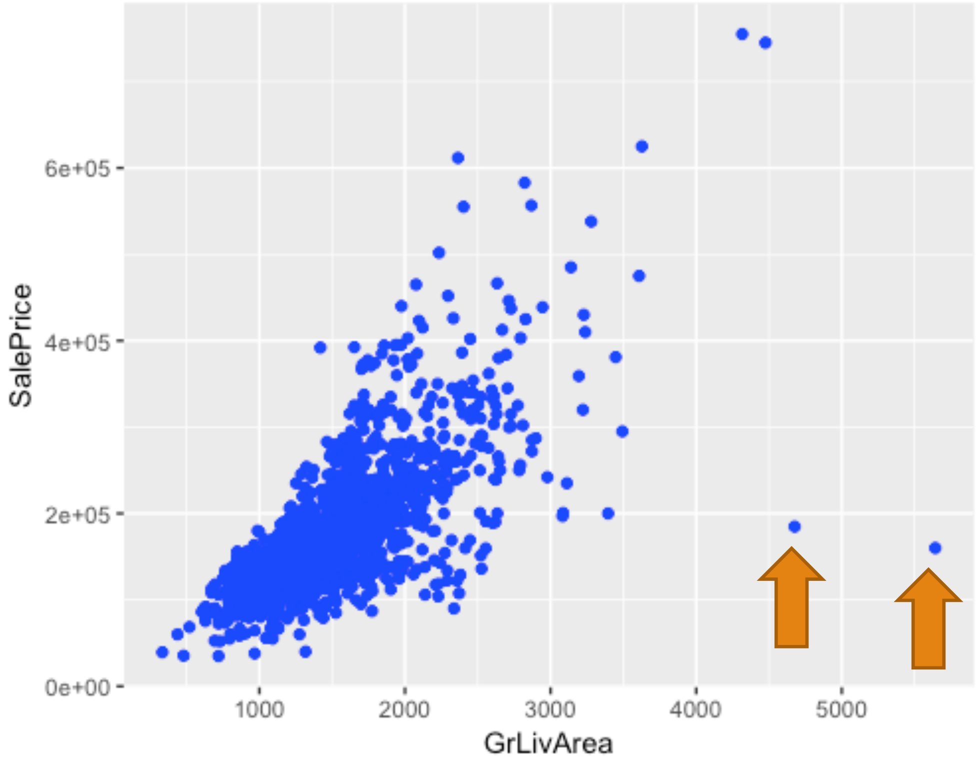
◦ Solution: One-hot encoding technique: binarizing classes of each variable

Processing the Data: Outliers

Some observations may be abnormally far from other values

Ex. Ground Living Area vs Sale Price

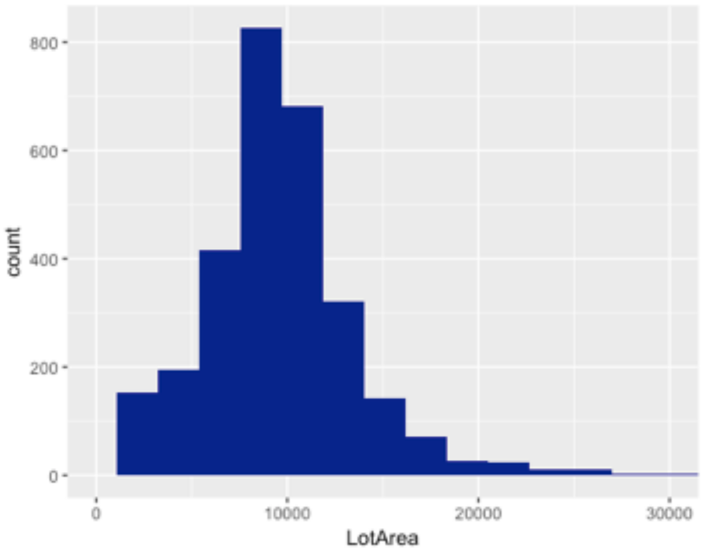
- Two points with very large area but very low sale price
- Solution: Remove outliers

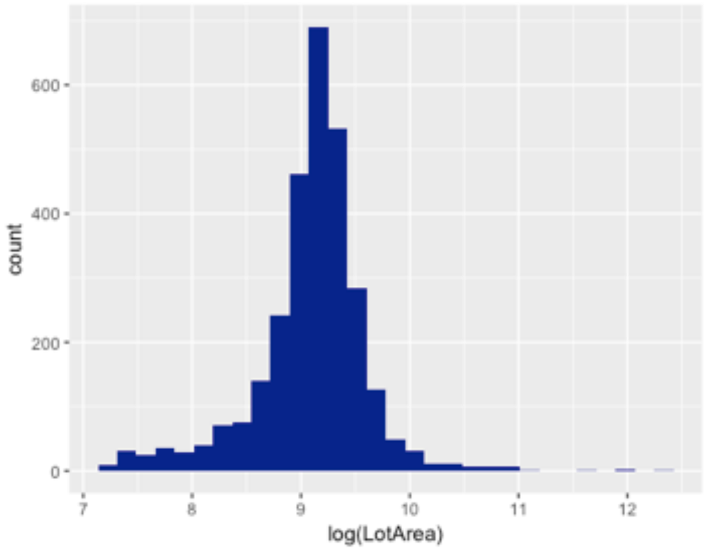


Processing the Data: Skewness and Scaling

Distributions of some variables may be highly skewed

Ex. Lot Area



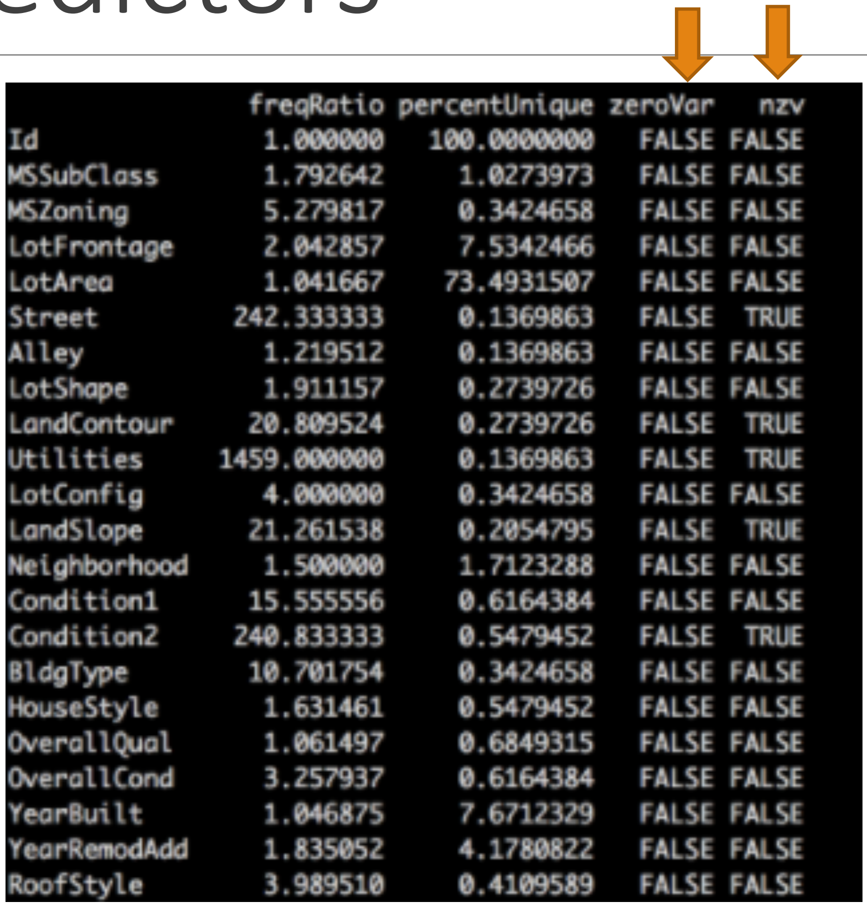


- Solution: Log + 1 Transformation

Processing the Data:
Near Zero Variance Predictors

Low variance predictors add little value to models

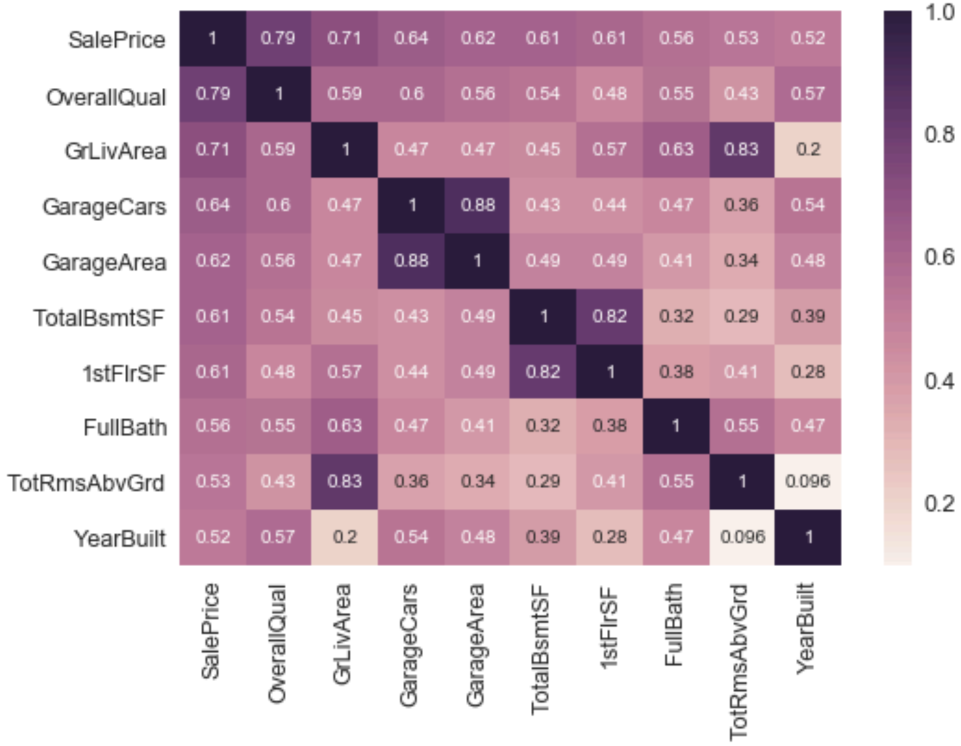
- Calculate ratio of most frequent vs. second most frequent value
- Ratios >> 1 suggest very low variance
- Solution: Remove near zero predictors with cutoffs of 95:5



```
              freqRatio percentUnique zeroVar   nzv
Id             1.000000   100.0000000   FALSE FALSE
MSSubClass     1.792642     1.0273973   FALSE FALSE
MSZoning       5.279817     0.3424658   FALSE FALSE
LotFrontage    2.042857     7.5342466   FALSE FALSE
LotArea        1.041667    73.4931507   FALSE FALSE
Street       242.333333     0.1369863   FALSE  TRUE
Alley          1.219512     0.1369863   FALSE FALSE
LotShape       1.911157     0.2739726   FALSE FALSE
LandContour   20.809524     0.2739726   FALSE  TRUE
Utilities   1459.000000     0.1369863   FALSE  TRUE
LotConfig      4.000000     0.3424658   FALSE FALSE
LandSlope     21.261538     0.2054795   FALSE  TRUE
Neighborhood   1.500000     1.7123288   FALSE FALSE
Condition1    15.555556     0.6164384   FALSE FALSE
Condition2   240.833333     0.5479452   FALSE  TRUE
BldgType      10.701754     0.3424658   FALSE FALSE
HouseStyle     1.631461     0.5479452   FALSE FALSE
OverallQual    1.061497     0.6849315   FALSE FALSE
OverallCond    3.257937     0.6164384   FALSE FALSE
YearBuilt      1.046875     7.6712329   FALSE FALSE
YearRemodAdd   1.835052     4.1780822   FALSE FALSE
RoofStyle      3.989510     0.4109589   FALSE FALSE
```

Processing the Data: Numerical Variables

Top10 Numerical Variables With Greatest Covariance vs. SalePrice



	SalePrice	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF	1stFlrSF	FullBath	TotRmsAbvGrd	YearBuilt
SalePrice	1	0.79	0.71	0.64	0.62	0.61	0.61	0.56	0.53	0.52
OverallQual	0.79	1	0.59	0.6	0.56	0.54	0.48	0.55	0.43	0.57
GrLivArea	0.71	0.59	1	0.47	0.47	0.45	0.57	0.63	0.83	0.2
GarageCars	0.64	0.6	0.47	1	0.88	0.43	0.44	0.47	0.36	0.54
GarageArea	0.62	0.56	0.47	0.88	1	0.49	0.49	0.41	0.34	0.48
TotalBsmtSF	0.61	0.54	0.45	0.43	0.49	1	0.82	0.32	0.29	0.39
1stFlrSF	0.61	0.48	0.57	0.44	0.49	0.82	1	0.38	0.41	0.28
FullBath	0.56	0.55	0.63	0.47	0.41	0.32	0.38	1	0.55	0.47
TotRmsAbvGrd	0.53	0.43	0.83	0.36	0.34	0.29	0.41	0.55	1	0.096
YearBuilt	0.52	0.57	0.2	0.54	0.48	0.39	0.28	0.47	0.096	1

As expected, important quantitative factors to consider are space/size, date, overall quality.

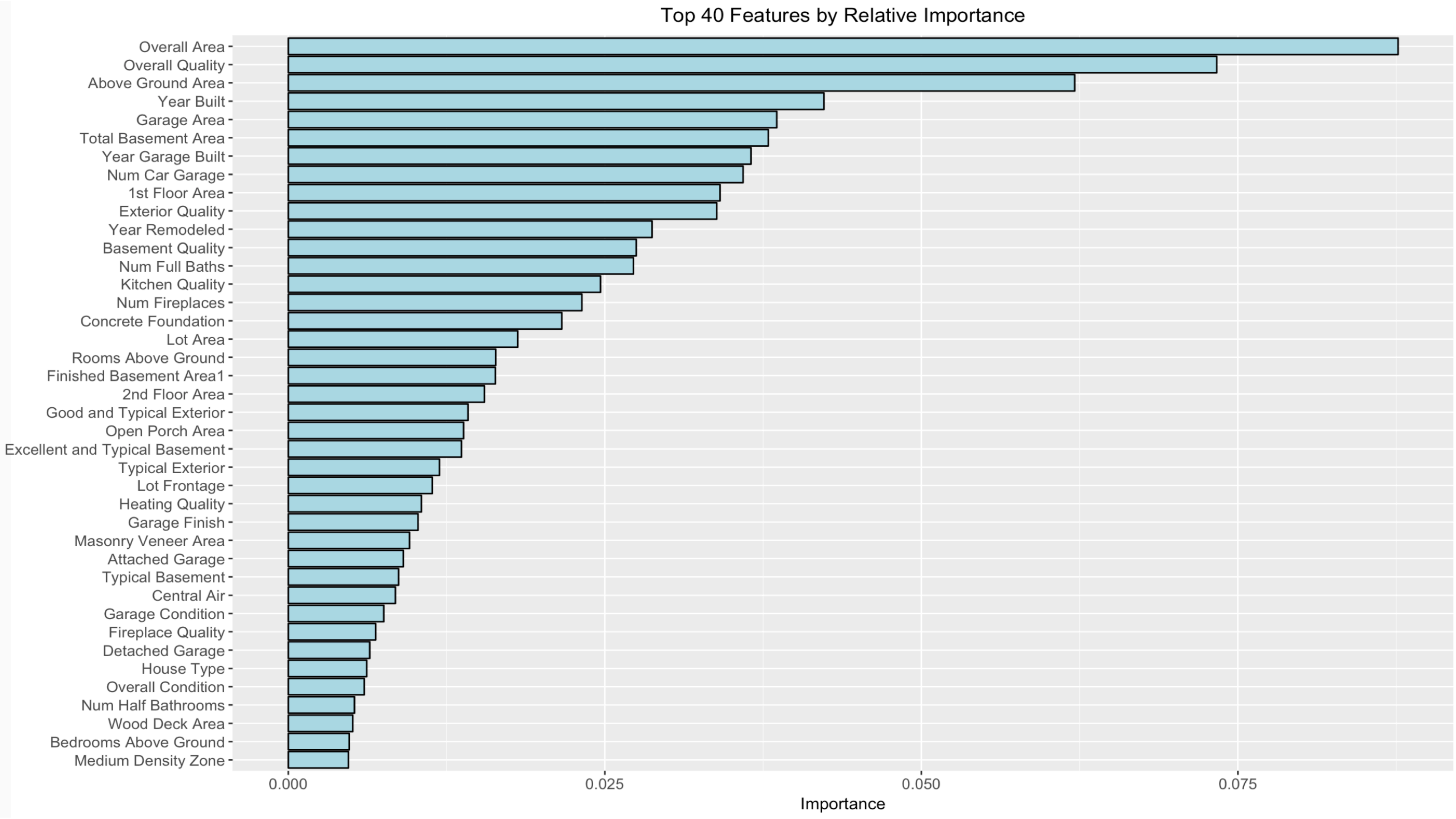
Feature Engineering

Ideas for new features:

- Remodeled – Year Built not equal to Year Additional Remodeling
- Seasonality – Combine Month Sold and Year Sold
- New House – Year Built same as Year Sold
- Total Area – sum all variables denoting square footage
- Inside Area – sum all variables denoting square footage referring to space inside the house
- Overall Basement – Basement Quality and Basement Condition
- Overall Condition – Condition 1 and Condition 2
- Overall Quality – External Quality and External Condition
- Overall Sale – Sale Type and Sale Condition
- Sale and Condtion – Sale Type and Overall Condition

Models

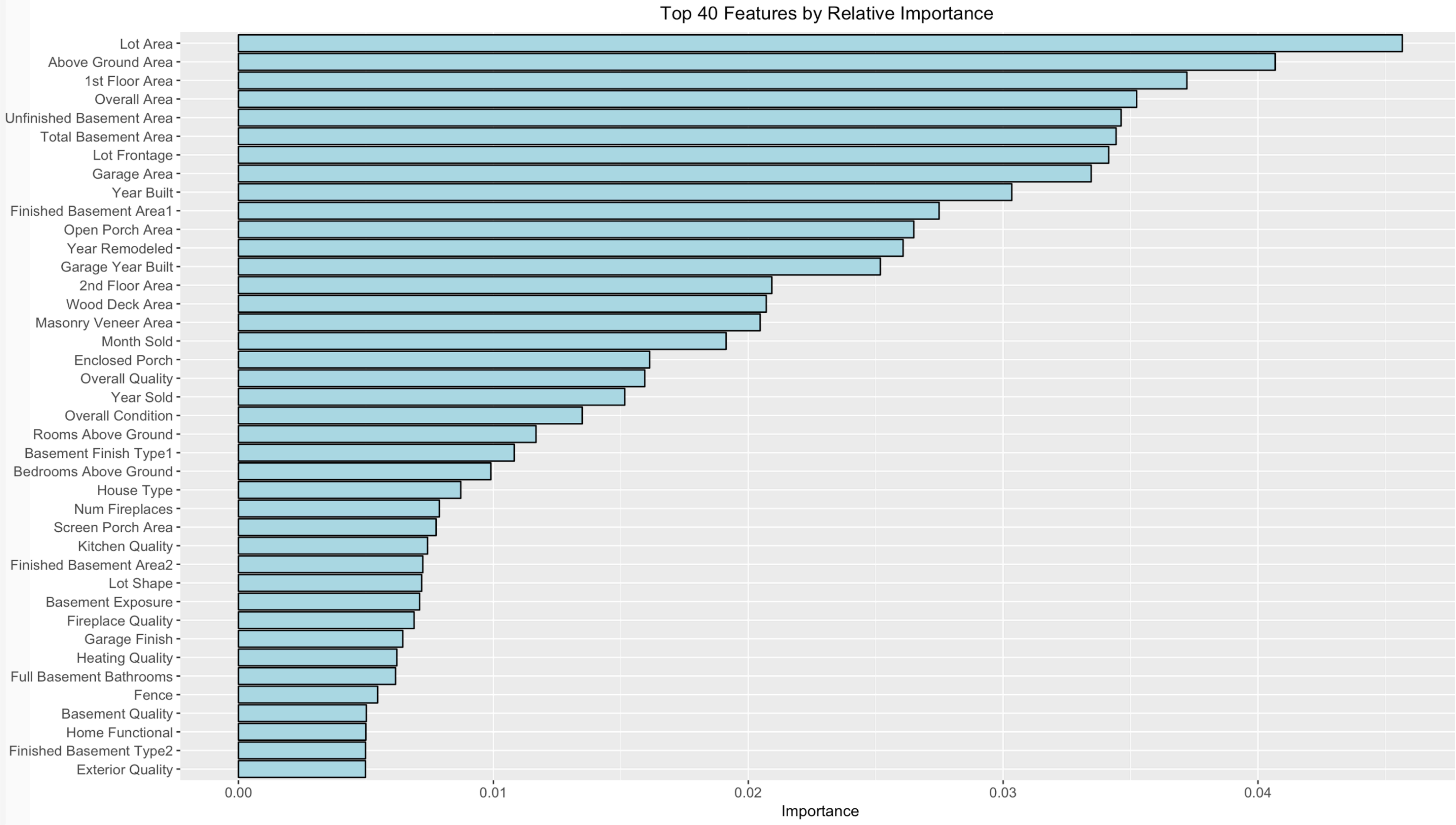
	Pros	Cons	Hyperparameters	Cross-Validated RMSE Score	Kaggle Score
Random Forest	Lower variance, Decorrelates data, Scale invariant	High bias, Difficult to interpret	Num features = 48, Num trees = 1000	0.14997	0.14758



Top 40 Features by Relative Importance

Models

	Pros	Cons	Hyperparameters	Cross-Validated RMSE Score	Kaggle Score
Random Forest	Lower variance, Decorrelates data, Scale invariant	High bias, Difficult to interpret	Num features = 48, Num trees = 1000	0.14997	0.14758
Gradient Boost	**Feature scaling not needed, High accuracy**	**Computationally expensive, Overfitting**	**Num trees = 1000, Depth = 2, Num Features = sqrt, Samples/leaf = 15, Learning rate = 0.05**	**0.1128**	**0.12421**

Top 40 Features by Relative Importance
Lot Area
Above Ground Area
1st Floor Area
Overall Area
Unfinished Basement Area
Total Basement Area
Lot Frontage
Garage Area
Year Built
Finished Basement Area1
Open Porch Area
Year Remodeled
Garage Year Built
2nd Floor Area
Wood Deck Area
Masonry Veneer Area
Month Sold
Enclosed Porch
Overall Quality
Year Sold
Overall Condition
Rooms Above Ground
Basement Finish Type1
Bedrooms Above Ground
House Type
Num Fireplaces
Screen Porch Area
Kitchen Quality
Finished Basement Area2
Lot Shape
Basement Exposure
Fireplace Quality
Garage Finish
Heating Quality
Full Basement Bathrooms
Fence
Basement Quality
Home Functional
Finished Basement Type2
Exterior Quality
0.00
0.01
0.02
0.03
0.04
Importance

Models

	Pros	Cons	Hyperparameters	Cross-Validated RMSE Score	Kaggle Score
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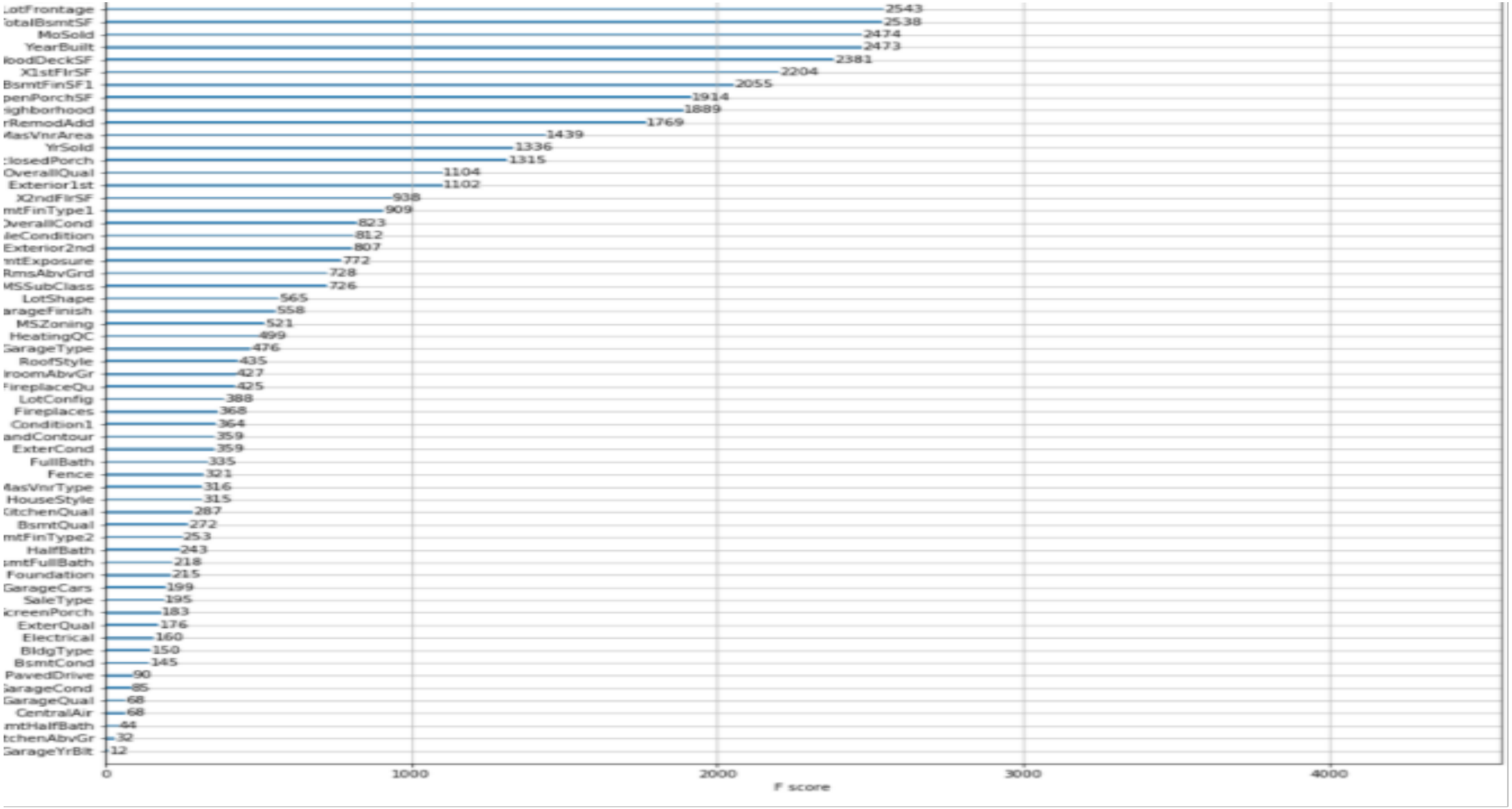
Gradient Boost	Feature scaling not needed, High accuracy	Computationally expensive, Overfitting	Num trees = 1000, Depth = 2, Num Features = sqrt, Samples/leaf = 15, Learning rate = 0.05	0.1128	0.12421
XGBoost	**Extremely fast,** **Allows parallel computing**	**Difficult to interpret,** **Overfits vs gradient boosting**	**Num trees = 2724,** **Max depth = 30,** **Gamma = 0.0,** **Minimum child weight = 4**	**0.13642**	**0.13082**

Top 40 Features by Relative Importance XGBoost



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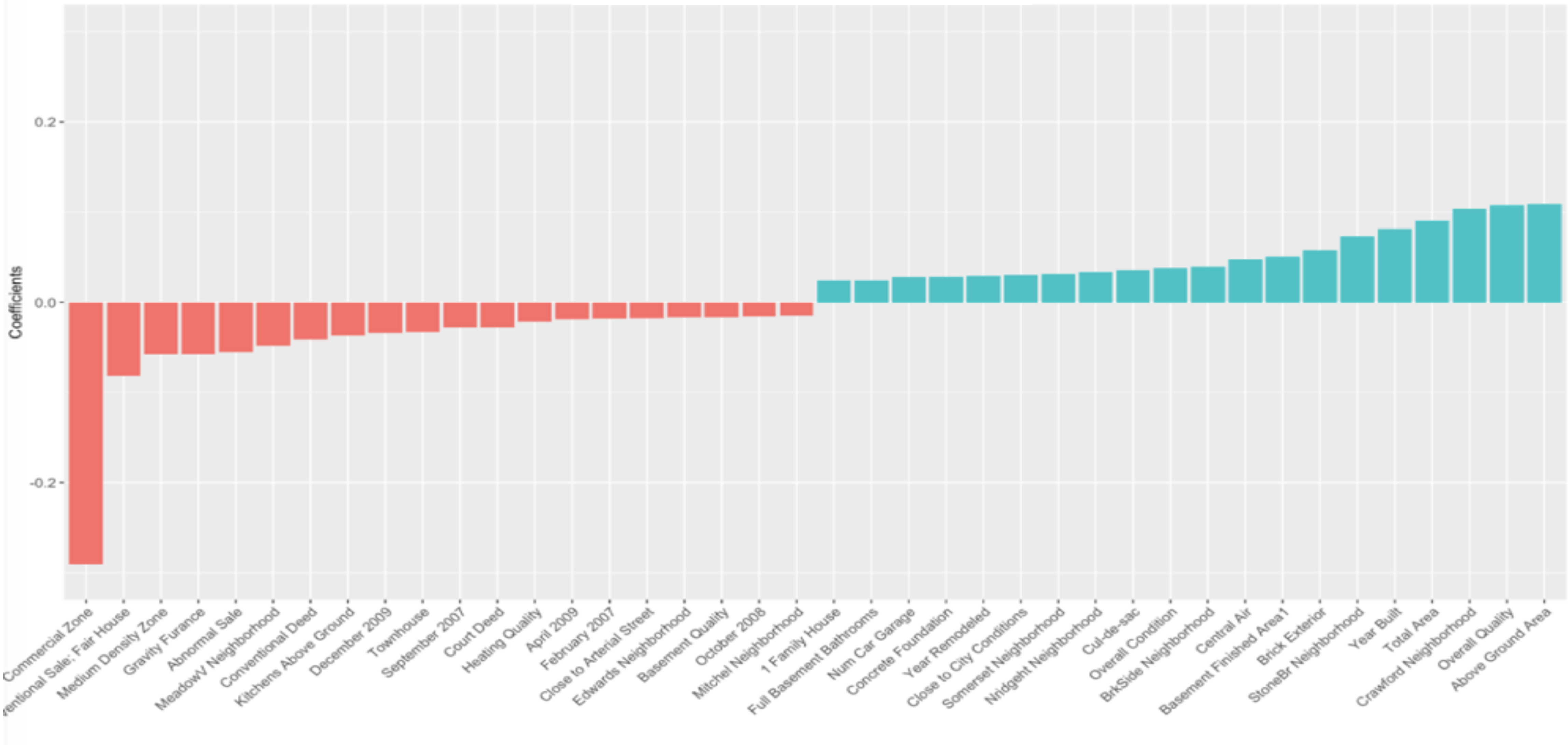
XGBoost	Extremely fast, Allows parallel computing	Difficult to interpret, Overfits vs gradient boosting	Num trees = 2724, Max depth = 30, Gamma = 0.0, Minimum child weight = 4	0.13642	0.13082
Regularize Linear Regression	**Easily interpretable, Computationally inexpensive, Less prone to overfitting**	**Requires scaled variables, Requires numerical variables**	**Lambda = 0.0005, Alpha = 0.9**	**0.1111**	**0.11922**

Coefficients of Top 40 Predictors



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XGBoost	Extremely fast, Allows parallel computing	Difficult to interpret, Overfits vs gradient boosting	Num trees = 2724, Max depth = 30, Gamma = 0.0, Minimum child weight = 4	0.13642	0.13082
Regularize Linear Regression	Easily interpretable, Computationally inexpensive, Less prone to overfitting	Requires scaled variables, Requires numerical variables	Lambda = 0.0005, Alpha = 0.9	0.1111	0.11922
Ensembling	**Can improve accuracy**	**Lose interpretability**	**Lasso, Enet, Gradient Boost, Gradient Boost Lite**	**0.1071**	**0.11751**

Conclusions

Prediction

Our RMSE yields an error of: ≈ ± \$9000 for average sale price (\$181000)

What Drives Sale Price?

Size, Age

Overall Quality/Condition

Neighborhood (both good and bad)

Commercial Zone

Year sold (housing crash)

Questions?