Housing Data Analysis

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Introduction

This data analysis project set out to answer two questions: 1. Which variables are most important to determining the sale price of a house? 2. Are there natural clusters of houses that can be derived and explained from within the data and what do those clusters correspond to?

The dataset we set out to analyze was found on the Kaggle Competition: "House Prices: Advanced Regression Techniques." The original data comes from the Ames City Assessor's Office in the form of a data dump from their records system. The initial Excel file contained 113 variables describing 3970 property sales that had occurred in this city between 2006 and 2010. This data was obtained by Prof. De Cock (from Truman State University) who removed variables that required special knowledge or previous calculations for their use, leaving us with the 80 variable dataset we have now.

Loading and cleaning the data

The first step in the data analysis process is data cleaning. This dataset needed quite a bit of cleaning. Many of the variables were only valid in some situations, like PoolQC - a variable that encodes the quality of a pool. In the data descriptions, it stated that if a house didn't have a pool, the variable was encoded as NA. This also artificially inflated the number of rows that were missing values when in fact the NA was simply coding for the lack of an attribute (pool, garage, deck, etc.).

Therefore, we decided that for all of the variables that used NA to encode a missing attribute, we replaced the NA values for a factor "None" to explicitely encode for that missing attribute. This brought the number of complete observations up from 0 to 1451 out of 1460.

```
## [1] "Initial complete observations:  0"
```

```
## [1] "Complete observations coded for missing attributes:  1451"
```

Exploratory Data Analysis

A summary of the data shows that many variables have levels with only a few observations in them. For example, the RoofMatl variable (which describes the material of the roof) has 8 different options, clay tile, standard composite shingle, membrane, metal, roll, gravel and tar, wood shakes, and wood shingles. However, out of all 1460 observations, clay tile, membrane, metal, and roll roofs only have one observation, wood shake has 5 observations, and wood shingle has 6.

A similar pattern is true for many other categorical variables, where certain categories are very sparsely represented. This is potentially a problem for building cross validated models due to the fact that a model that is trained on a subset of the data is unlikely to see many examples of all categories and thus might be unable to accurately model the relationships between the categories and sale price.

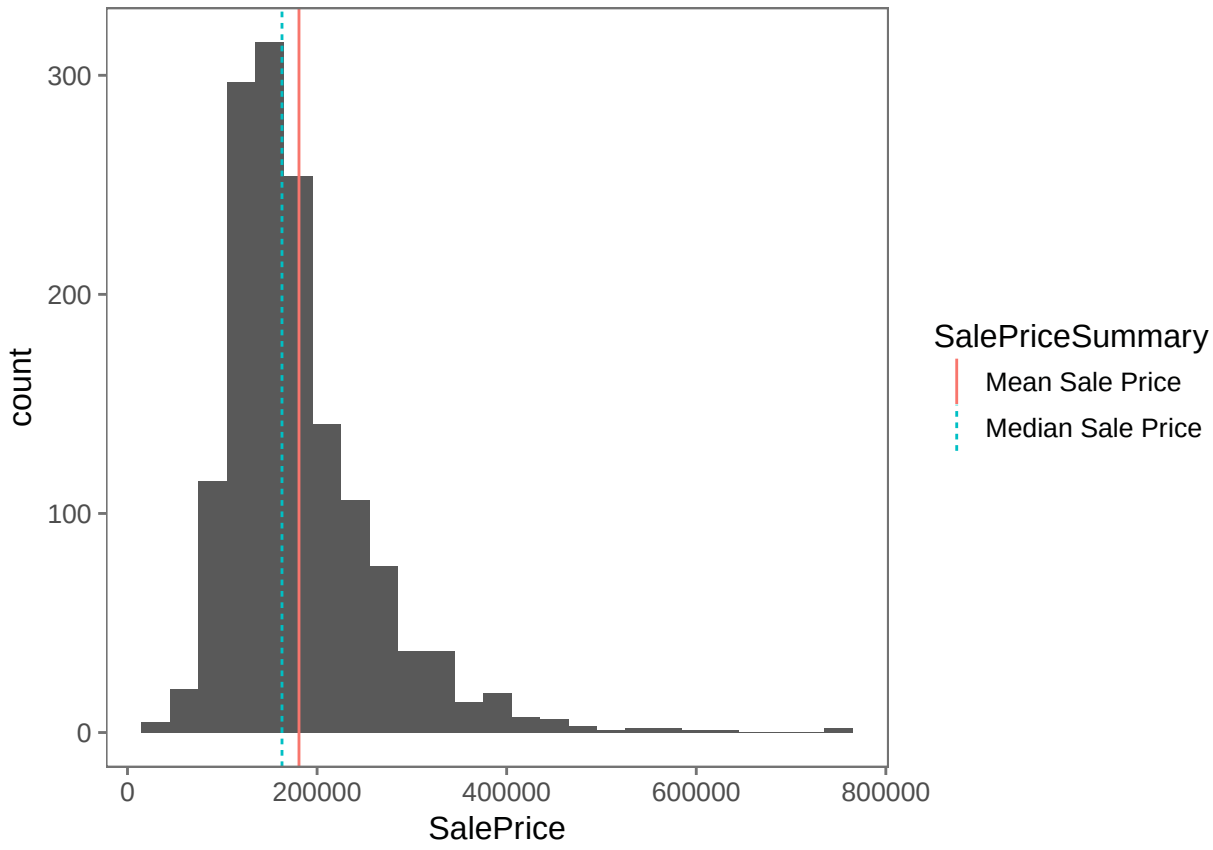
```
##        Id           MSSubClass       MSZoning     LotFrontage
##  Min.   :   1.0   Min.   : 20.0   C (all):  10   Min.   :  0.00
##  1st Qu.: 365.8   1st Qu.: 20.0   FV     :  65   1st Qu.: 42.00
##  Median : 730.5   Median : 50.0   RH     :  16   Median : 63.00
##  Mean   : 730.5   Mean   : 56.9   RL     :1151   Mean   : 57.62
```

```
##  3rd Qu.:1095.2   3rd Qu.: 70.0   RM     : 218   3rd Qu.: 79.00
##  Max.   :1460.0   Max.   :190.0                  Max.   :313.00
##
##     LotArea        Street      Alley      LotShape  LandContour
##  Min.   :  1300   Grvl:   6   Grvl:  50   IR1:484   Bnk:  63
##  1st Qu.:  7554   Pave:1454   Pave:  41   IR2: 41   HLS:  50
##  Median :  9478               None:1369   IR3: 10   Low:  36
##  Mean   : 10517                           Reg:925   Lvl:1311
##  3rd Qu.: 11602
##  Max.   :215245
##
##   Utilities      LotConfig    LandSlope   Neighborhood   Condition1
##  AllPub:1459   Corner : 263   Gtl:1382   NAmes  :225   Norm   :1260
##  NoSeWa:   1   CulDSac:  94   Mod:  65   CollgCr:150   Feedr  :  81
##                FR2    :  47   Sev:  13   OldTown:113   Artery :  48
##                FR3    :   4              Edwards:100   RRAn   :  26
##                Inside :1052              Somerst: 86   PosN   :  19
##                                          Gilbert: 79   RRAe   :  11
##                                          (Other):707   (Other):  15
##    Condition2     BldgType      HouseStyle   OverallQual
##  Norm   :1445   1Fam  :1220   1Story :726   Min.   : 1.000
##  Feedr  :   6   2fmCon:  31   2Story :445   1st Qu.: 5.000
##  Artery :   2   Duplex:  52   1.5Fin :154   Median : 6.000
##  PosN   :   2   Twnhs :  43   SLvl   : 65   Mean   : 6.099
##  RRNn   :   2   TwnhsE: 114   SFoyer : 37   3rd Qu.: 7.000
##  PosA   :   1                 1.5Unf : 14   Max.   :10.000
##  (Other):   2                 (Other): 19
##   OverallCond      YearBuilt     YearRemodAdd    RoofStyle
##  Min.   :1.000   Min.   :1872   Min.   :1950   Flat   :  13
##  1st Qu.:5.000   1st Qu.:1954   1st Qu.:1967   Gable  :1141
##  Median :5.000   Median :1973   Median :1994   Gambrel:  11
##  Mean   :5.575   Mean   :1971   Mean   :1985   Hip    : 286
##  3rd Qu.:6.000   3rd Qu.:2000   3rd Qu.:2004   Mansard:   7
##  Max.   :9.000   Max.   :2010   Max.   :2010   Shed   :   2
##
##     RoofMatl     Exterior1st   Exterior2nd    MasVnrType    MasVnrArea
##  CompShg:1434   VinylSd:515   VinylSd:504   BrkCmn : 15   Min.   :   0.0
##  Tar&Grv:  11   HdBoard:222   MetalSd:214   BrkFace:445   1st Qu.:   0.0
##  WdShngl:   6   MetalSd:220   HdBoard:207   None   :864   Median :   0.0
##  WdShake:   5   Wd Sdng:206   Wd Sdng:197   Stone  :128   Mean   : 103.7
##  ClyTile:   1   Plywood:108   Plywood:142   NA's   :  8   3rd Qu.: 166.0
##  Membran:   1   CemntBd: 61   CmentBd: 60                 Max.   :1600.0
##  (Other):   2   (Other):128   (Other):136                 NA's   :8
##  ExterQual ExterCond  Foundation  BsmtQual   BsmtCond    BsmtExposure
##  Ex: 52    Ex:   3   BrkTil:146   Ex  :121   Fa  :  45   Av  :221
##  Fa: 14    Fa:  28   CBlock:634   Fa  : 35   Gd  :  65   Gd  :134
##  Gd:488    Gd: 146   PConc :647   Gd  :618   Po  :   2   Mn  :114
##  TA:906    Po:   1   Slab  : 24   TA  :649   TA  :1311   No  :953
##            TA:1282   Stone :  6   None: 37   None:  37   None: 38
##                      Wood  :  3
##
##  BsmtFinType1   BsmtFinSF1     BsmtFinType2   BsmtFinSF2
##  ALQ :220     Min.   :   0.0   ALQ :  19    Min.   :   0.00
##  BLQ :148     1st Qu.:   0.0   BLQ :  33    1st Qu.:   0.00
```

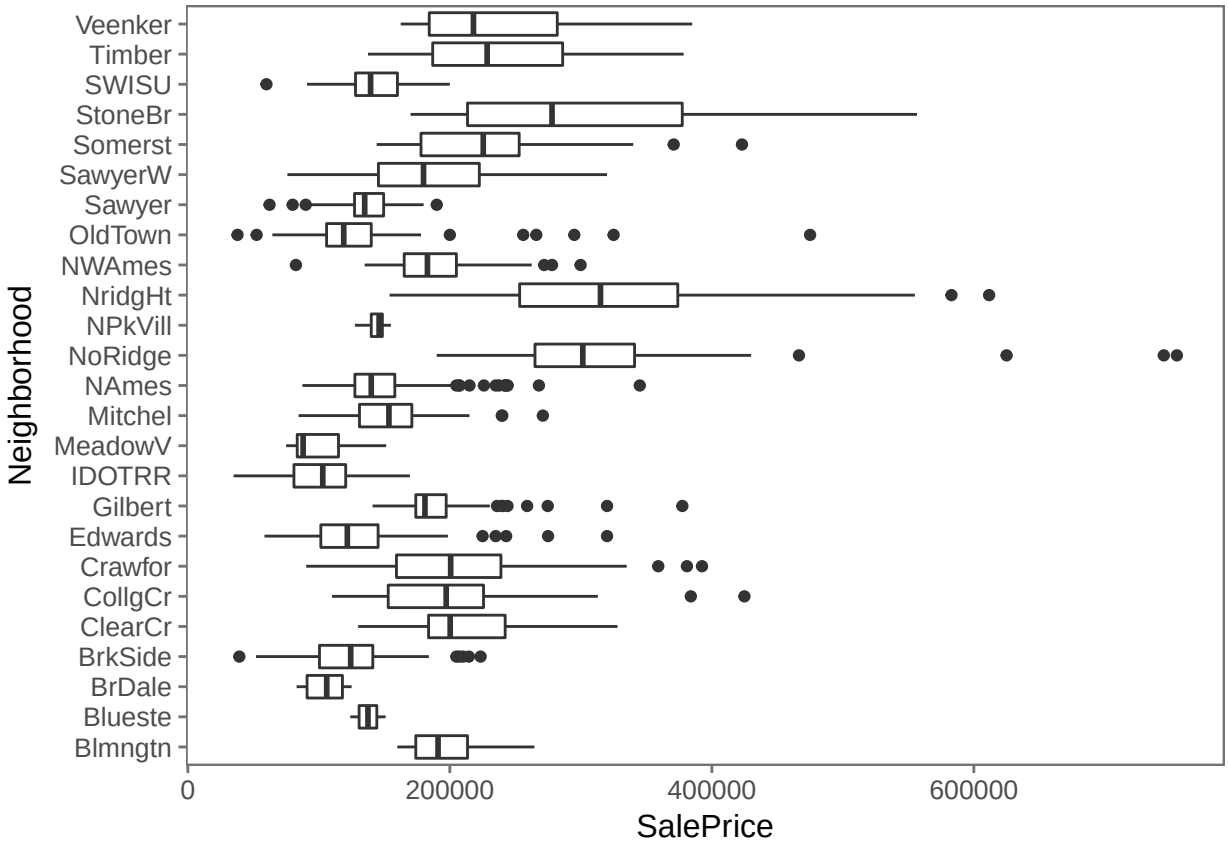
```
##  GLQ :418     Median : 383.5   GLQ :  14    Median :   0.00
##  LwQ : 74     Mean   : 443.6   LwQ :  46    Mean   :  46.55
##  Rec :133     3rd Qu.: 712.2   Rec :  54    3rd Qu.:   0.00
##  Unf :430     Max.   :5644.0   Unf :1256    Max.   :1474.00
##  None: 37                      None:  38
##    BsmtUnfSF       TotalBsmtSF      Heating     HeatingQC CentralAir
##  Min.   :   0.0   Min.   :   0.0   Floor:   1   Ex:741    N:  95
##  1st Qu.: 223.0   1st Qu.: 795.8   GasA :1428   Fa: 49    Y:1365
##  Median : 477.5   Median : 991.5   GasW :  18   Gd:241
##  Mean   : 567.2   Mean   :1057.4   Grav :   7   Po:  1
##  3rd Qu.: 808.0   3rd Qu.:1298.2   OthW :   2   TA:428
##  Max.   :2336.0   Max.   :6110.0   Wall :   4
##
##  Electrical     X1stFlrSF      X2ndFlrSF     LowQualFinSF
##  FuseA:  94   Min.   : 334   Min.   :   0   Min.   :  0.000
##  FuseF:  27   1st Qu.: 882   1st Qu.:   0   1st Qu.:  0.000
##  FuseP:   3   Median :1087   Median :   0   Median :  0.000
##  Mix  :   1   Mean   :1163   Mean   : 347   Mean   :  5.845
##  SBrkr:1334   3rd Qu.:1391   3rd Qu.: 728   3rd Qu.:  0.000
##  NA's :   1   Max.   :4692   Max.   :2065   Max.   :572.000
##
##    GrLivArea     BsmtFullBath     BsmtHalfBath        FullBath
##  Min.   : 334   Min.   :0.0000   Min.   :0.00000   Min.   :0.000
##  1st Qu.:1130   1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:1.000
##  Median :1464   Median :0.0000   Median :0.00000   Median :2.000
##  Mean   :1515   Mean   :0.4253   Mean   :0.05753   Mean   :1.565
##  3rd Qu.:1777   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:2.000
##  Max.   :5642   Max.   :3.0000   Max.   :2.00000   Max.   :3.000
##
##     HalfBath       BedroomAbvGr    KitchenAbvGr   KitchenQual
##  Min.   :0.0000   Min.   :0.000   Min.   :0.000   Ex:100
##  1st Qu.:0.0000   1st Qu.:2.000   1st Qu.:1.000   Fa: 39
##  Median :0.0000   Median :3.000   Median :1.000   Gd:586
##  Mean   :0.3829   Mean   :2.866   Mean   :1.047   TA:735
##  3rd Qu.:1.0000   3rd Qu.:3.000   3rd Qu.:1.000
##  Max.   :2.0000   Max.   :8.000   Max.   :3.000
##
##   TotRmsAbvGrd    Functional    Fireplaces    FireplaceQu   GarageType
##  Min.   : 2.000   Maj1:  14   Min.   :0.000   Ex  : 24    2Types :  6
##  1st Qu.: 5.000   Maj2:   5   1st Qu.:0.000   Fa  : 33    Attchd :870
##  Median : 6.000   Min1:  31   Median :1.000   Gd  :380    Basment: 19
##  Mean   : 6.518   Min2:  34   Mean   :0.613   Po  : 20    BuiltIn: 88
##  3rd Qu.: 7.000   Mod :  15   3rd Qu.:1.000   TA  :313    CarPort:  9
##  Max.   :14.000   Sev :   1   Max.   :3.000   None:690    Detchd :387
##                   Typ :1360                               None   : 81
##  GarageFinish   GarageCars      GarageArea     GarageQual  GarageCond
##  Fin :352     Min.   :0.000   Min.   :   0.0   Ex  :   3   Ex  :   2
##  RFn :422     1st Qu.:1.000   1st Qu.: 334.5   Fa  :  48   Fa  :  35
##  Unf :605     Median :2.000   Median : 480.0   Gd  :  14   Gd  :   9
##  None: 81     Mean   :1.767   Mean   : 473.0   Po  :   3   Po  :   7
##               3rd Qu.:2.000   3rd Qu.: 576.0   TA  :1311   TA  :1326
##               Max.   :4.000   Max.   :1418.0   None:  81   None:  81
##
##  PavedDrive   WoodDeckSF      OpenPorchSF     EnclosedPorch
```

```
##  N:  90     Min.   :  0.00   Min.   :  0.00   Min.   :  0.00
##  P:  30     1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.00
##  Y:1340     Median :  0.00   Median : 25.00   Median :  0.00
##             Mean   : 94.24   Mean   : 46.66   Mean   : 21.95
##             3rd Qu.:168.00   3rd Qu.: 68.00   3rd Qu.:  0.00
##             Max.   :857.00   Max.   :547.00   Max.   :552.00
##
##    X3SsnPorch      ScreenPorch        PoolArea        PoolQC
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.000   Ex  :   2
##  1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.000   Fa  :   2
##  Median :  0.00   Median :  0.00   Median :  0.000   Gd  :   3
##  Mean   :  3.41   Mean   : 15.06   Mean   :  2.759   None:1453
##  3rd Qu.:  0.00   3rd Qu.:  0.00   3rd Qu.:  0.000
##  Max.   :508.00   Max.   :480.00   Max.   :738.000
##
##    Fence      MiscFeature    MiscVal             MoSold
##  GdPrv:  59   Gar2:   2   Min.   :    0.00   Min.   : 1.000
##  GdWo :  54   Othr:   2   1st Qu.:    0.00   1st Qu.: 5.000
##  MnPrv: 157   Shed:  49   Median :    0.00   Median : 6.000
##  MnWw :  11   TenC:   1   Mean   :   43.49   Mean   : 6.322
##  None :1179   None:1406   3rd Qu.:    0.00   3rd Qu.: 8.000
##                           Max.   :15500.00   Max.   :12.000
##
##      YrSold        SaleType    SaleCondition    SalePrice
##  Min.   :2006   WD     :1267   Abnorml: 101   Min.   : 34900
##  1st Qu.:2007   New    : 122   AdjLand:   4   1st Qu.:129975
##  Median :2008   COD    :  43   Alloca :  12   Median :163000
##  Mean   :2008   ConLD  :   9   Family :  20   Mean   :180921
##  3rd Qu.:2009   ConLI  :   5   Normal :1198   3rd Qu.:214000
##  Max.   :2010   ConLw  :   5   Partial: 125   Max.   :755000
##                 (Other):   9
```

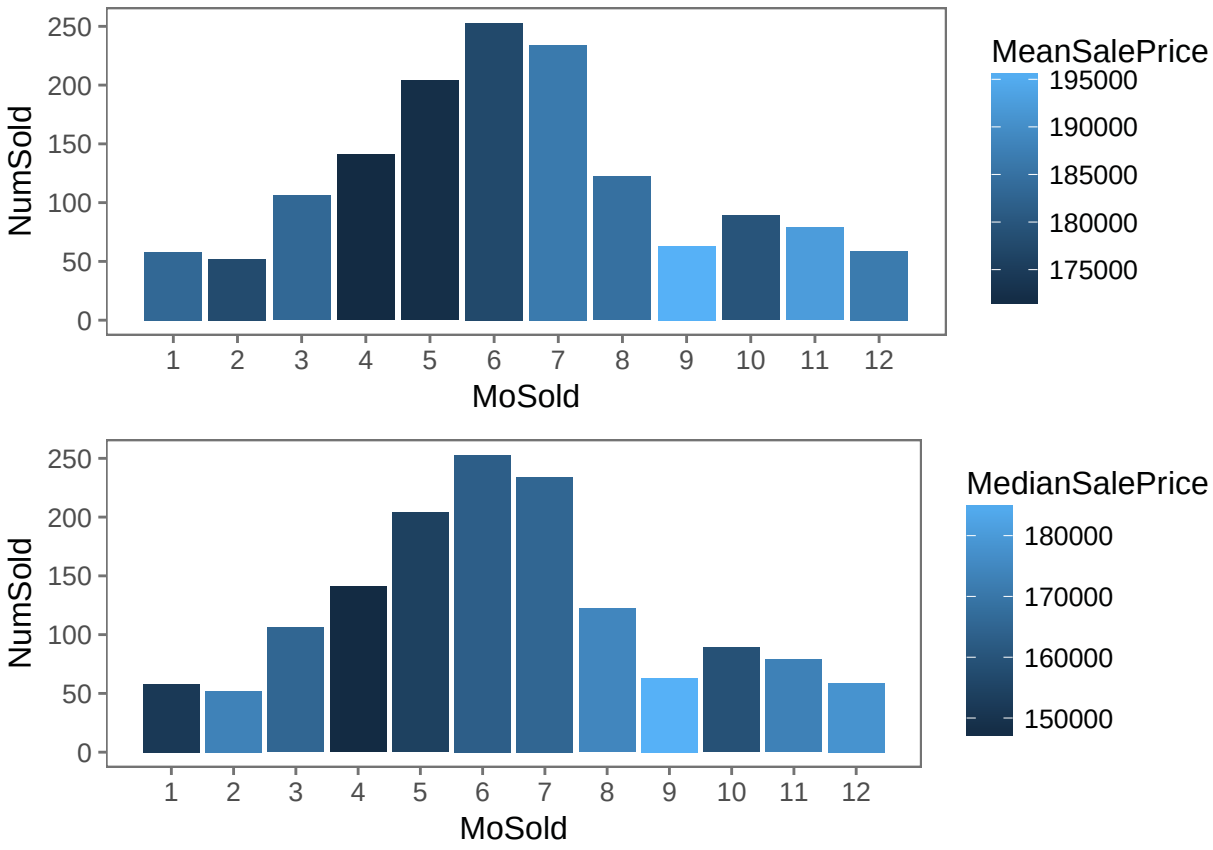
Then with some data visualization we find that the sale price of homes has a positively skewed distribution, with the median sale price of a house ($163,000.00) being significantly less than the average sale price of a house ($180,921.20).



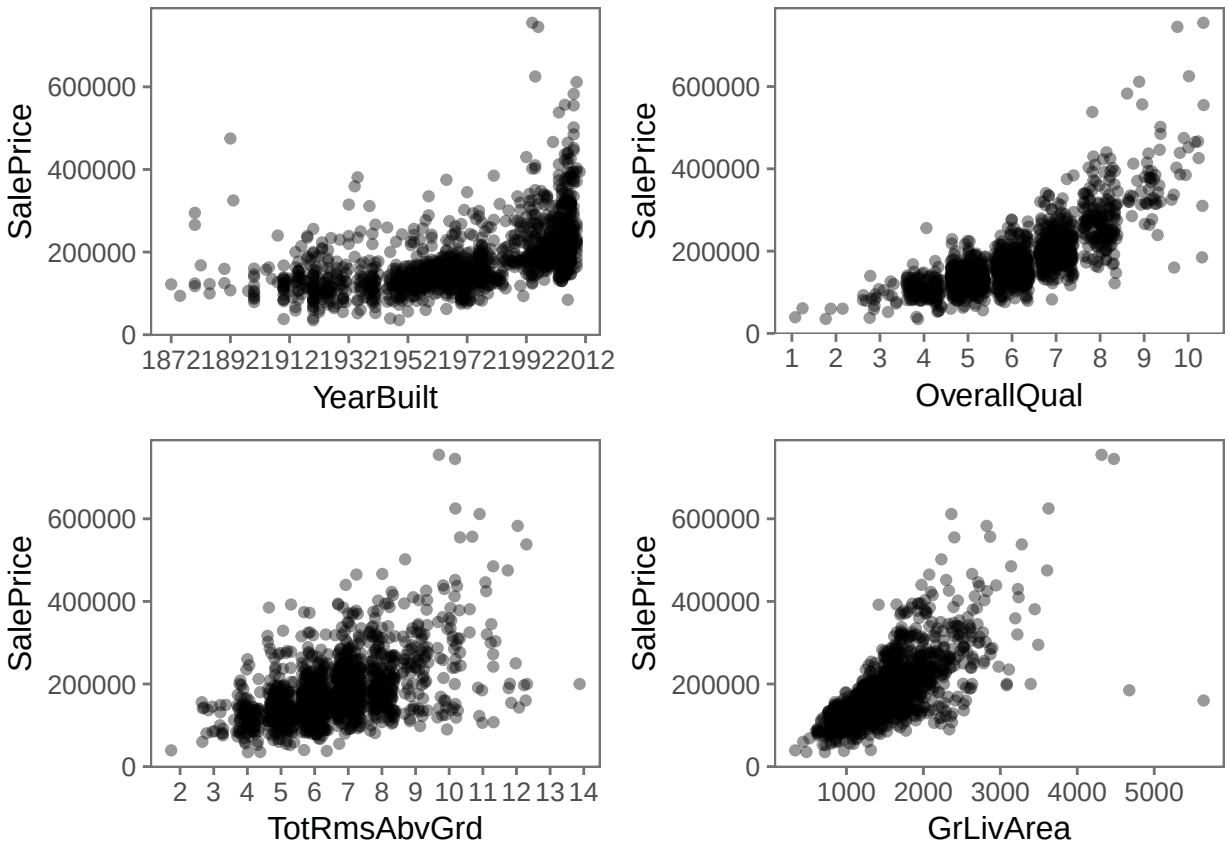
A boxplot comparing the sale prices for all of the different neighborhoods shows that there are some neighborhoods that clearly have much higher average and median sale prices than others. This indicates that Neighborhood is likely an importat indicator for sale price.



We also wanted to see if which month a house was purchased in has any effect on the sale price of the house. Based on the plots of the number of sales per month, colored by the mean and median sale price for each month, it seems like house sale prices are lower and more frequent as the summer starts (April, May), but that buying a house in September is going to be much more expensive then during other months.



In the plots of sale price and the year built (YearBuilt), overall house quality (OverallQual), total number of rooms above ground (TotRmsAbvGrd), and above grade living area square feet (GrLivArea), it becomes clear that these three variables are positively correlated with sale price.

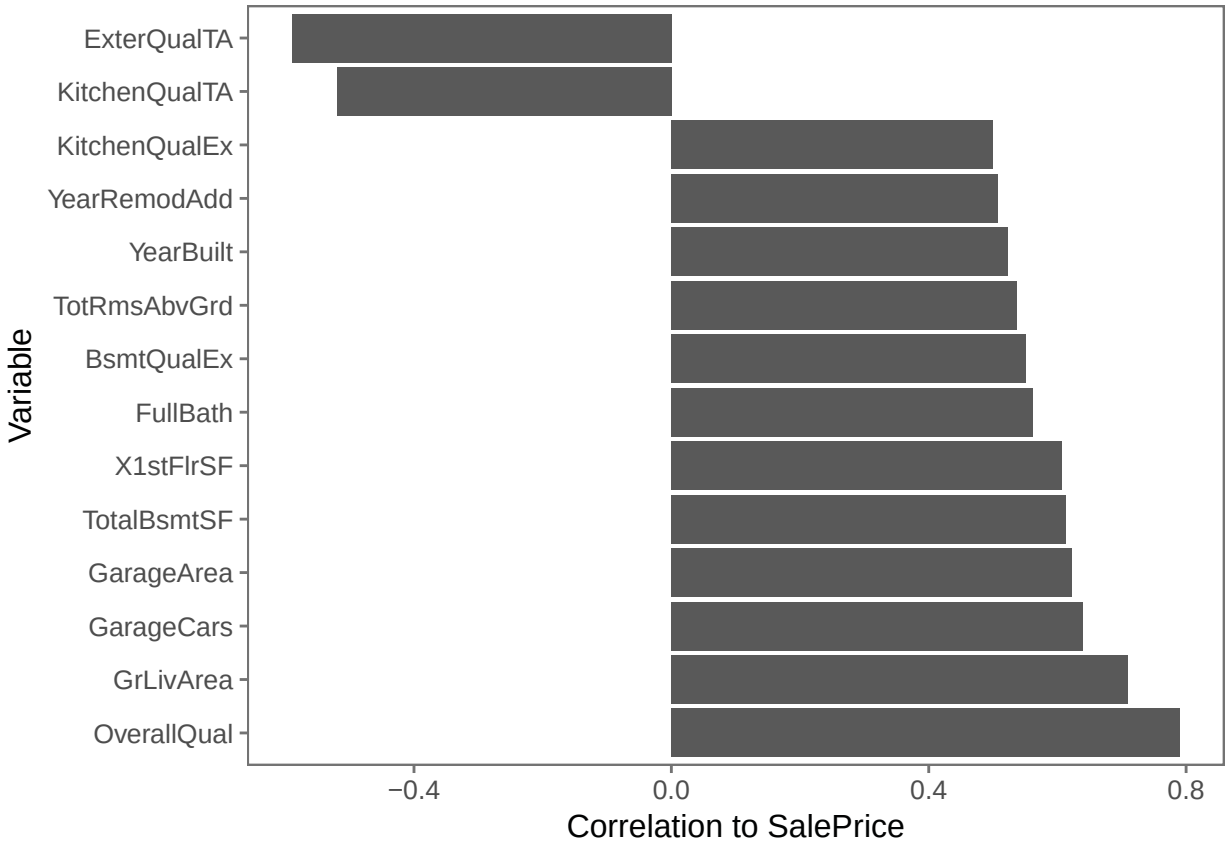


Because year built, overall house quality, total number of rooms above ground, and above grade living area square feet seemed correlated with SalePrice, we wanted to definitively test said correlation and see if there are other variables that are highly correlated with SalePrice.

However, since correlation requires numeric variables, and since many of our variables are factors, we decided to use a technique known as one hot variable encoding. With this technique, each variable with n factors is expanded into n variables that take the value 1 if the data has that factor and 0 otherwise.

For example, the variable Street with its two possible factors 'Gravl' and 'Pave' becomes two variables: StreetGravl and StreetPave that are either 0 or 1.

With this new encoding we calculated the correlation and then plotted the variables with absolute correlation values larger than 0.5.



Removing NA values

Because some predictive models don't allow for NA values, we want to do some data imputation. The data was imputed using random forests. This imputed data can be used in conjunction with the one-hot encoded data to compare and contrast the various predictions.

Starting Predictive Modeling

The first step in predictive modeling is splitting the data into training and test sets.

We did this by using the createDataPartition function from the caret package in order to get training and testing sets that have values of SalePrice that are evenly split across the dataset.

We created training and testing sets for the full data, the imputed data, the one hot encoded data, and the one hot encoded data with NA values removed.

First Research Question

The first model we tried out was a simple decision tree. We created decision trees on all of our training sets and calculated the cross-validated RMSE for each. We also averaged the predictions from each decision tree and calculated the cross-validated RMSE for that. Overall, the predictions from the decision trees weren't too inaccurate, though they tended to underpredict sale price for more expensive homes. Furthermore, the

average of the predictions from all three trees has the lowest RMSE, suggesting that a random forest might increase the accuracy of the model.

We then decided to answer our second research question: Which variables are most important to determining the sale price of a house?

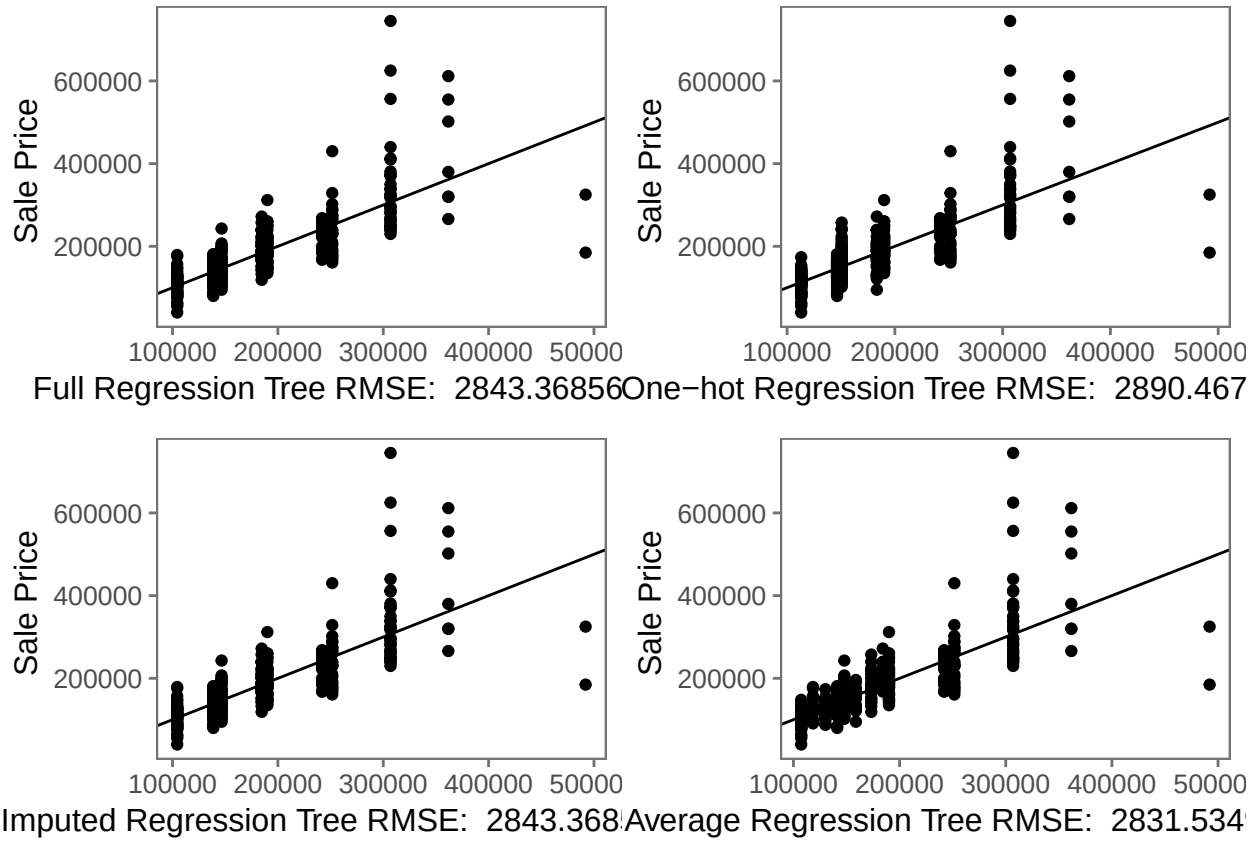
To do this, we inspected the individual decision trees the algorithm constructed. Each algorithm constructed a decision tree that has 11 leaf nodes of sale price bins that are reached with either 3 or 4 splits.

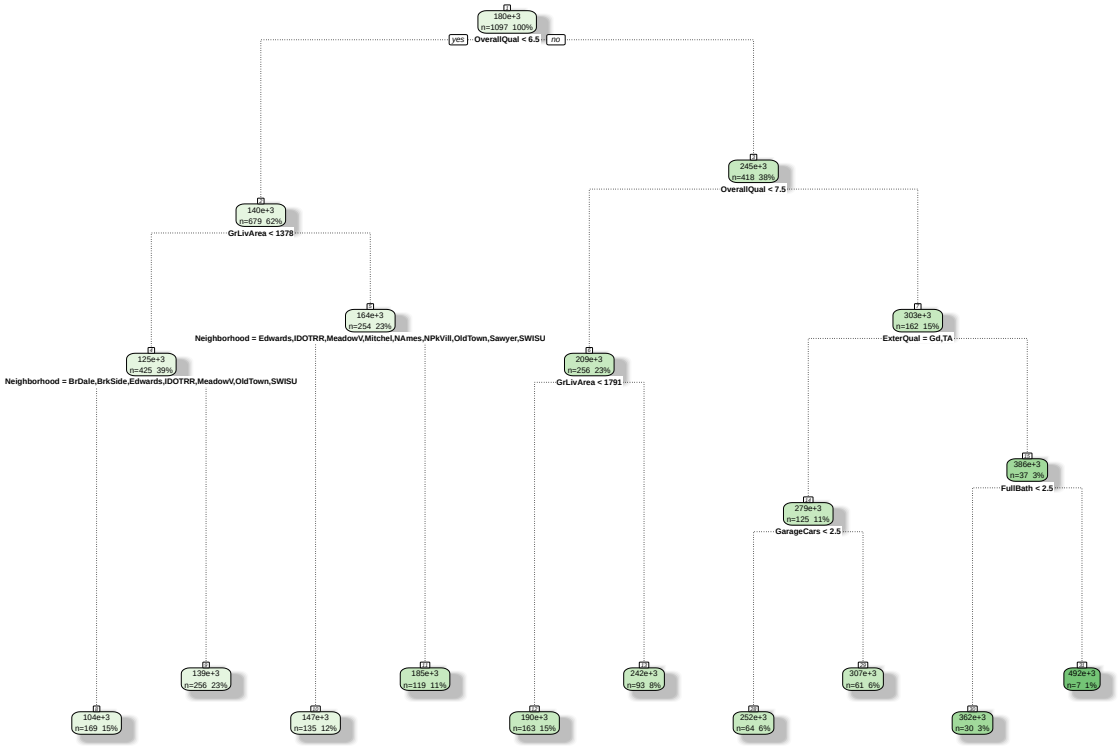
From these, it becomes immediately obvious that the overall quality of a house is the most important factor to sale price, as it was used for all three trees for the first and second level splits. The third level splits are equally in agreement, for all three models use above grade living area square feet to split this level. After that, the trees are not as synonomous, though they do contain similar information about the important variables in prediction sale price.

All three models use the size of garage in car capacity to determine the data with the 3rd and 4th lowest sale price nodes and the finished square feet of the basement type 1 to determine the 4th and 5th highest sale price nodes.

Where the decision trees diverge is the variable used to split between the 2 lowest sale price nodes. For the full data and the imputed data the input data point is assigned to the lowest node if it is in any of the neighborhoods Briardale, Brookside, Edwards, Iowa DOT and Rail Road, Meadow Village, Old Town, or South & West of Iowa State University. However, for the one-hot encoded data the input data point is assigned to the lowest sale price node if the total basement square feet is less than 1008 ft^2.

When you look at the box plots comparing the two splits, the neighborhood split has a smaller interquartile range within sale price than the total basement square feet split. This may explain why the one-hot encoded decision tree has a slightly worse RMSE than the other two models.





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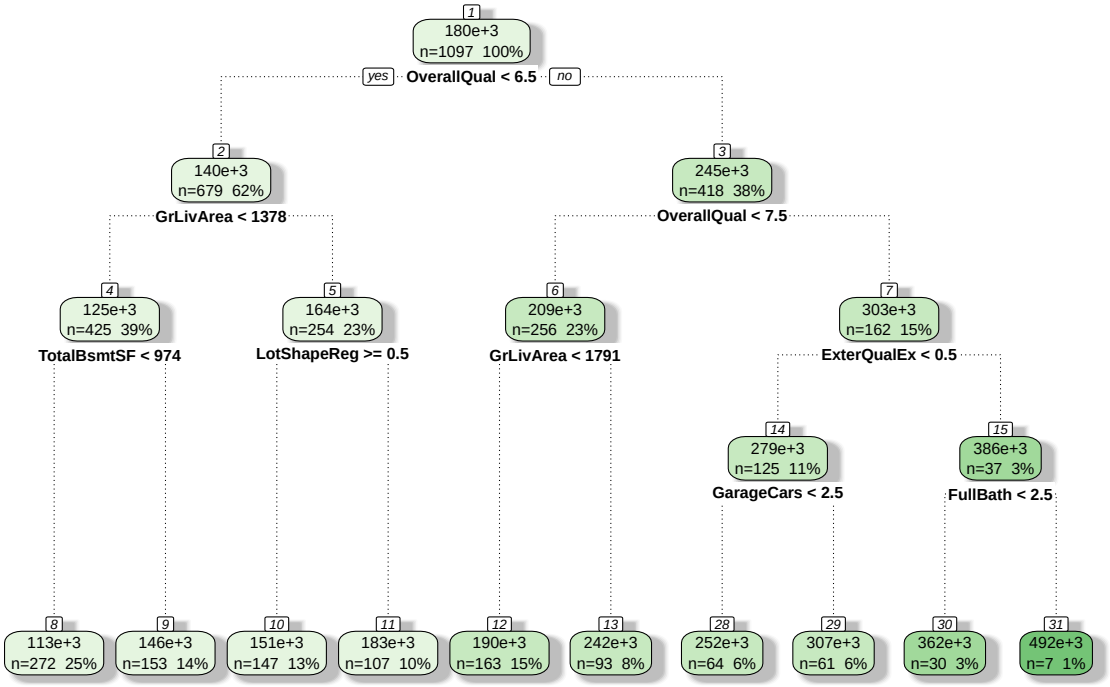
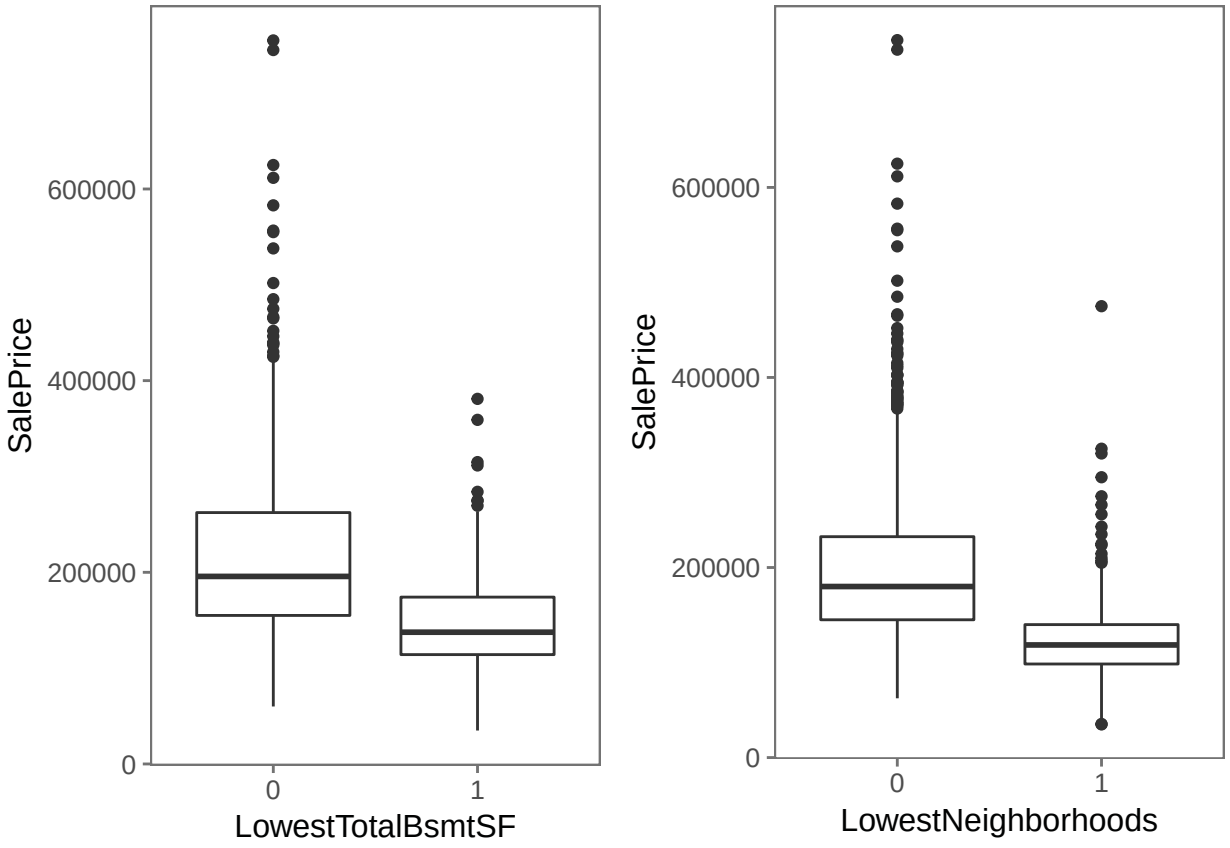


Rattle 2017−May−16 05:28:52 baf14



The next method we used to attempt to answer our research question is linear regression. Due to some of the factor variables having extremely sparse categories (as discussed above) when the data was split into training and testing sets the testing set occasionally had factors that were missing from the training set. To overcome this, we manually added the factors that were missing, but this understandably caused some deficiencies in the model and its predictions.

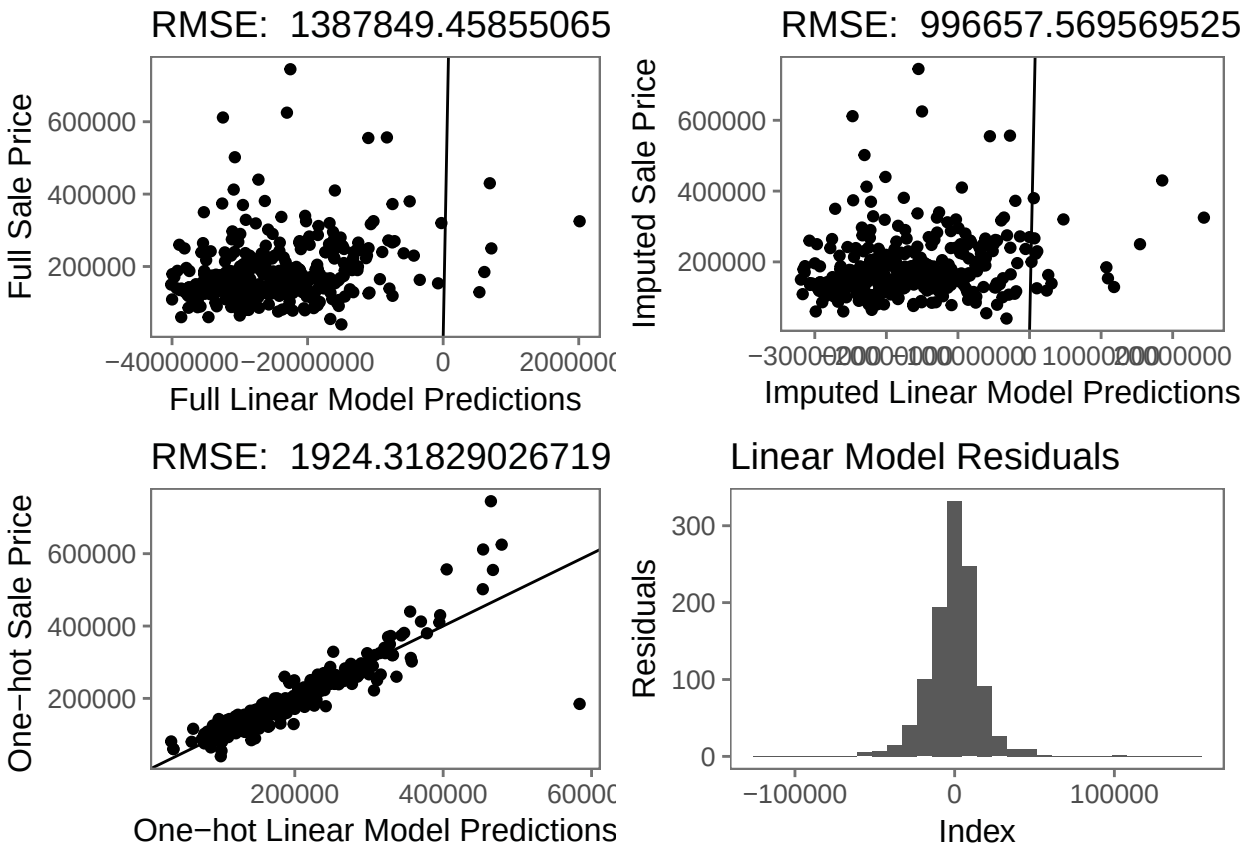
The linear models fit on the full dataset and the imputed dataset entirely failed to predict sale price, likely due to the lack of factor representation. However, the one-hot encoded data will always represent every factor category as a variable, even if that variable contains only zeros in the training split. The predictions from the one hot encoded data fit the data rather well with an adjusted R^2 of 0.9157 and RMSE of 1540.92.

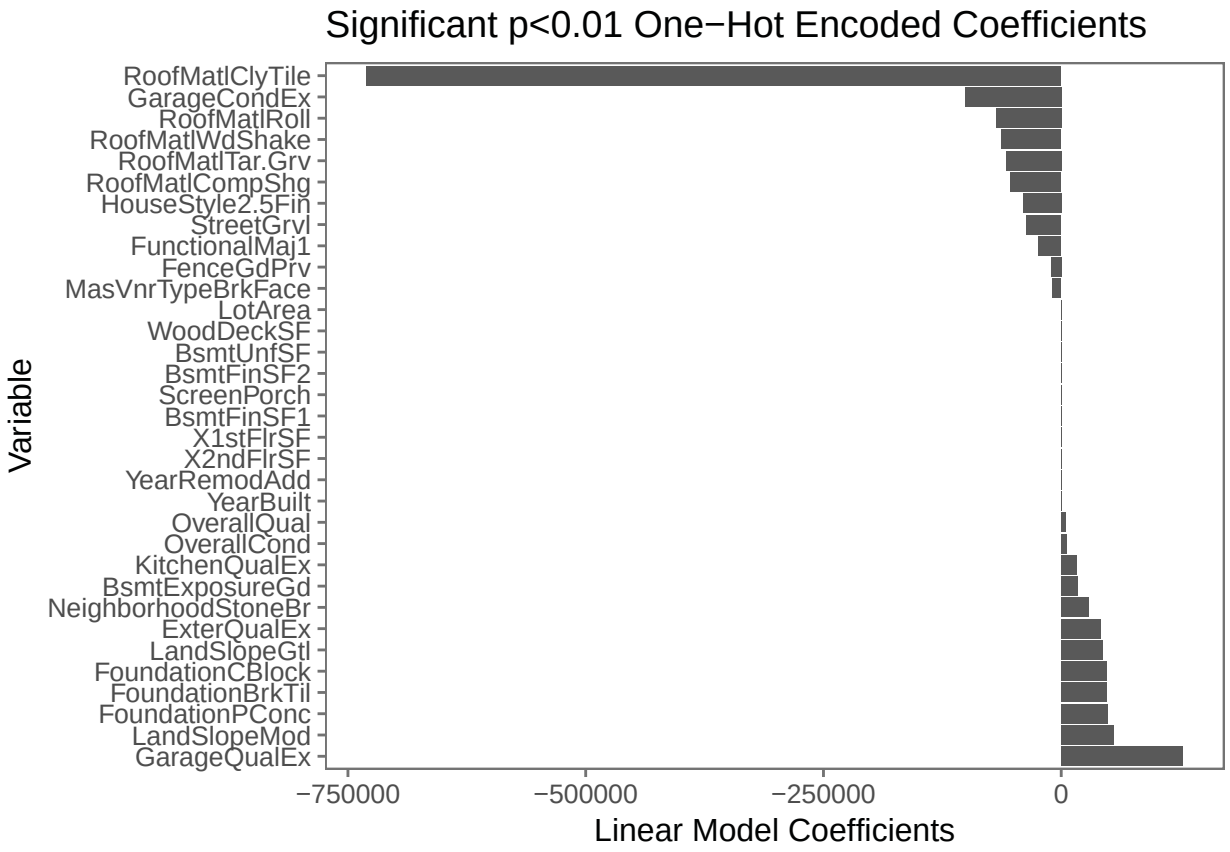
However, when examining the statistically significant coefficients of the model in order to answer our research question, it becomes clear that interpreting the outputs of a model with such sparsely represented factors gives nonsensical results - e.g. that houses with a roof material of clay tile are worth $600,000 less than those without clay roofs and that being adjacent to a near positive off-site feature–park, greenbelt, etc. makes your house worth almost $200,000 less.

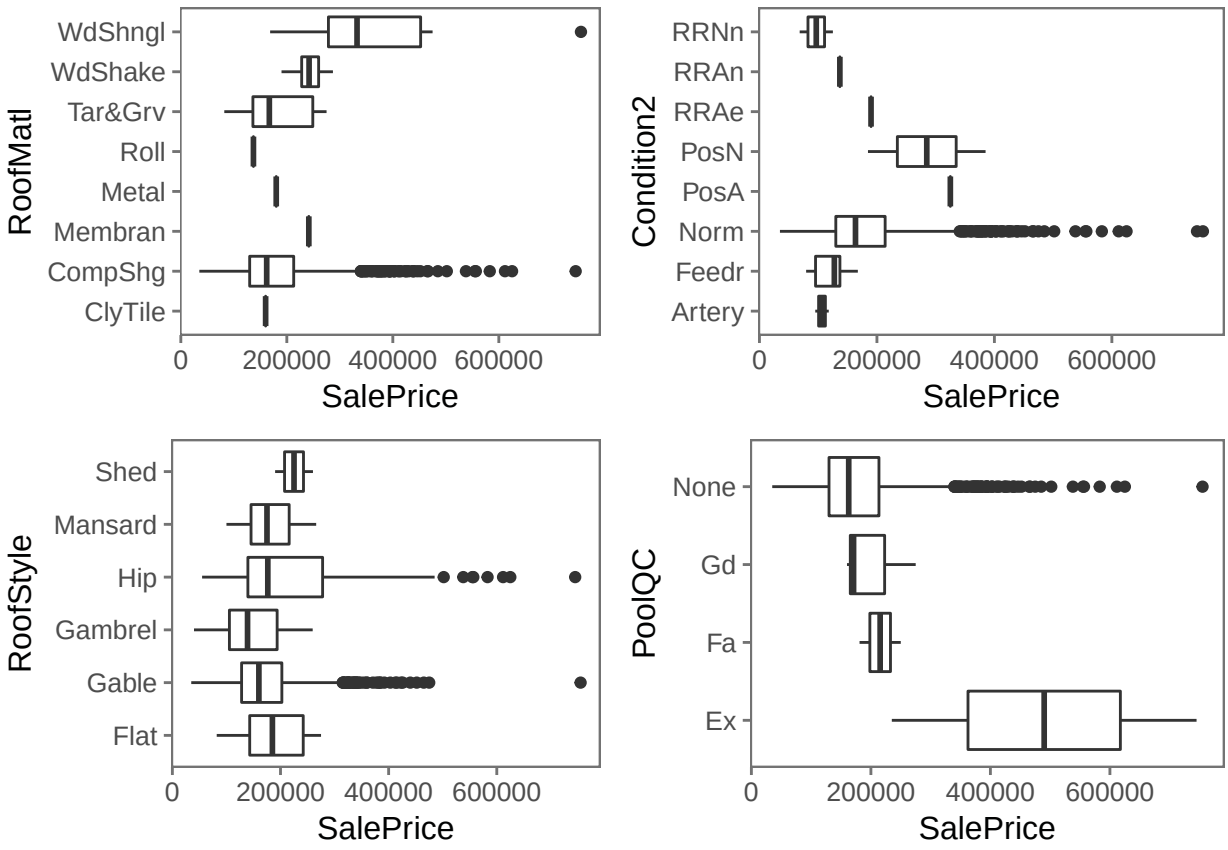
Therefore, we filtered the one-hot encoded data to only get the variables with more than 10 observations in the training set and trained a linear model on that. The RMSE is slightly higher than the previous model at 1540.92, and the adjusted R^2 is slightly lower at 0.8736, but the coefficients are much more interpretable.

From this linear model, we can say that having a quick and significant rise from street grade to building has the most significant negative impact on the sale price of a house, while being from a nice neighborhood (Northridge, Northridge Heights, Stone Brook), having excellent kitchen quality, typical functionality, and a large number of full bathrooms and garage capacity in number in cars all have a large impact on sale price.

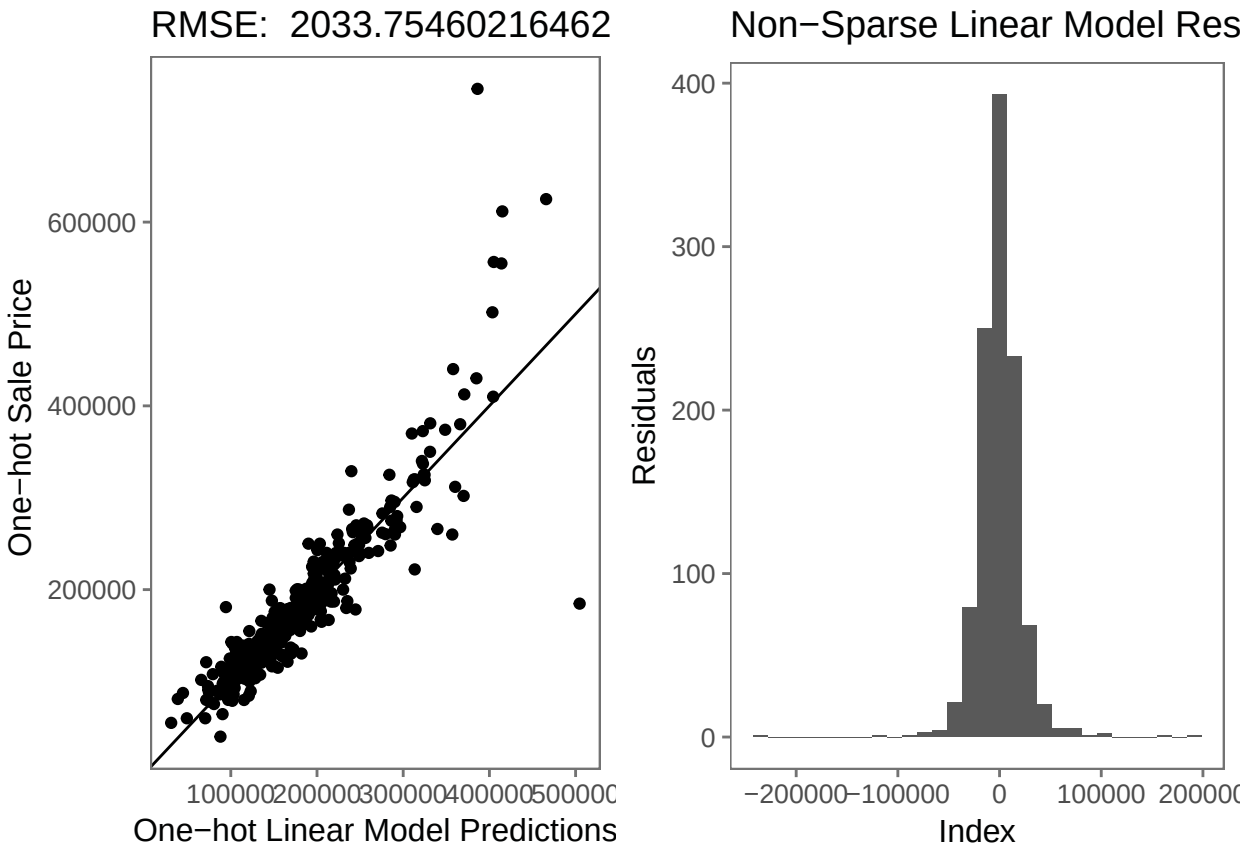
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

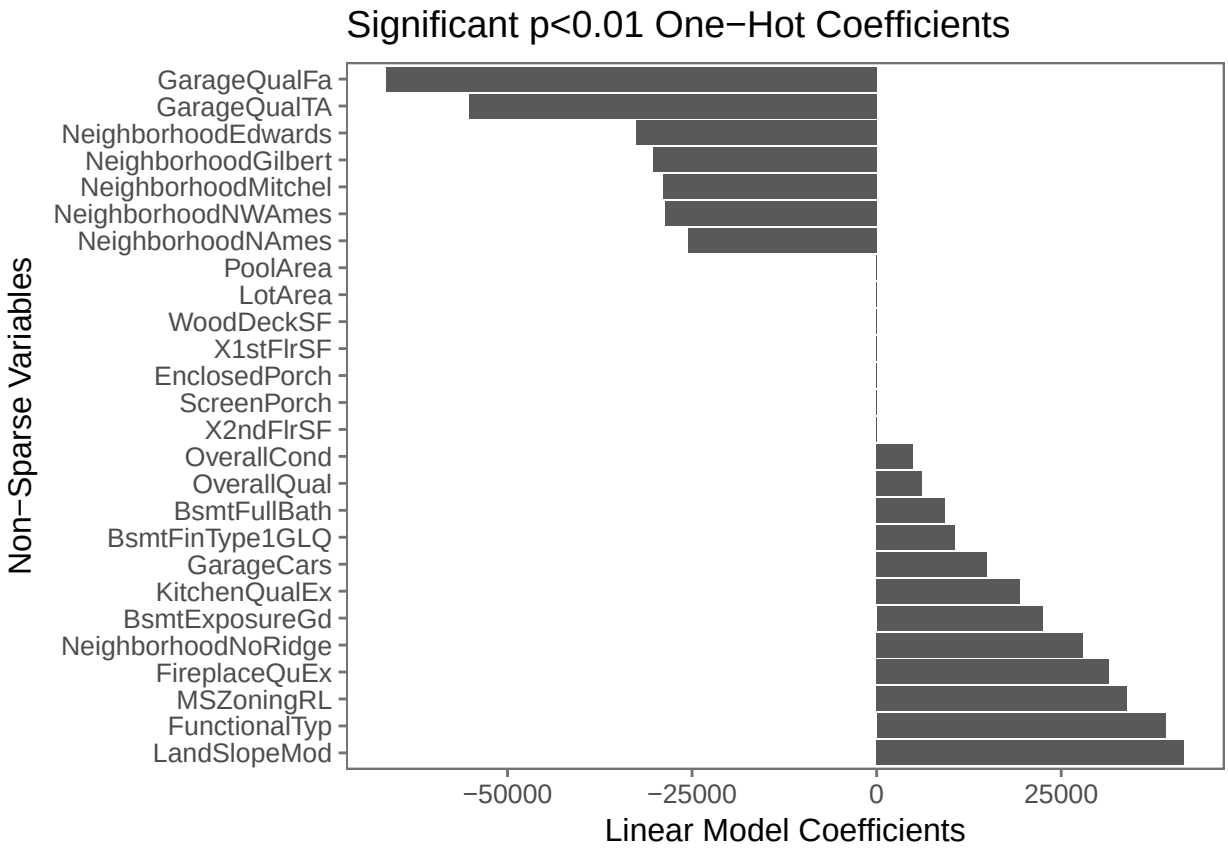

RMSE: 1387849.45855065
Full Sale Price
600000
400000
200000
−40000000
−20000000
0
Full Linear Model Predictions
RMSE: 996657.569569525
Imputed Sale Price
600000
400000
200000
Imputed Linear Model Predictions
RMSE: 1924.31829026719
One−hot Sale Price
600000
400000
200000
200000
400000
One−hot Linear Model Predictions
Linear Model Residuals
Residuals
300
200
100
0
−100000
0
100000
Index


Significant p<0.01 One−Hot Encoded Coefficients
RoofMatlClyTile
GarageCondEx
RoofMatlRoll
RoofMatlWdShake
RoofMatlTar.Grv
RoofMatlCompShg
HouseStyle2.5Fin
StreetGrvl
FunctionalMaj1
FenceGdPrv
MasVnrTypeBrkFace
LotArea
WoodDeckSF
BsmtUnfSF
BsmtFinSF2
ScreenPorch
BsmtFinSF1
X1stFlrSF
X2ndFlrSF
YearRemodAdd
YearBuilt
OverallQual
OverallCond
KitchenQualEx
BsmtExposureGd
NeighborhoodStoneBr
ExterQualEx
LandSlopeGtl
FoundationCBlock
FoundationBrkTil
FoundationPConc
LandSlopeMod
GarageQualEx
Variable
−750000
−500000
−250000
0
Linear Model Coefficients




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```


RMSE: 2033.75460216462
One−hot Sale Price
600000
400000
200000
100000
200000
300000
400000
500000
One−hot Linear Model Predictions
Non−Sparse Linear Model Res
Residuals
400
300
200
100
0
−200000
−100000
0
100000
200000
Index



Forward and backward subset selection was also used to shed some insight on our first research question. Both forward and backward selection selected the house id, overall condition, and garage area as the top 1st, 2nd, and 5th of the top five predictive variables. Where they differ is that the forward subset selection seems to select variables concerning the basement of the house, while the backward subset selection seems to select variables relating to the square feet of the house and also the kitchen quality.

These selected variables should be taken with a grain of salt because the same non-sparse variable selection process was used as with the linear models, but forward and backward subset selection identify variables that weren't identified as important by any other method. Because there are so many variables, it is too computationally intensive to calculate the best subset selection, but it is likely that forward and backward subset selection with this many variables is identifying a non-optimal solution.

```
## # A tibble: 8 × 4
##   RoofMatl n_houses avg_sale_price med_sale_price
##      <fctr>    <int>          <dbl>          <dbl>
## 1  ClyTile        1       160000.0         160000
## 2  CompShg     1434       179803.7         162000
## 3  Membran        1       241500.0         241500
## 4    Metal        1       180000.0         180000
## 5     Roll        1       137000.0         137000
## 6  Tar&Grv       11       185406.4         167000
## 7  WdShake        5       241400.0         242000
## 8  WdShngl        6       390250.0         332500
```

```
## Reordering variables and trying again:
```

```
## Reordering variables and trying again:
```

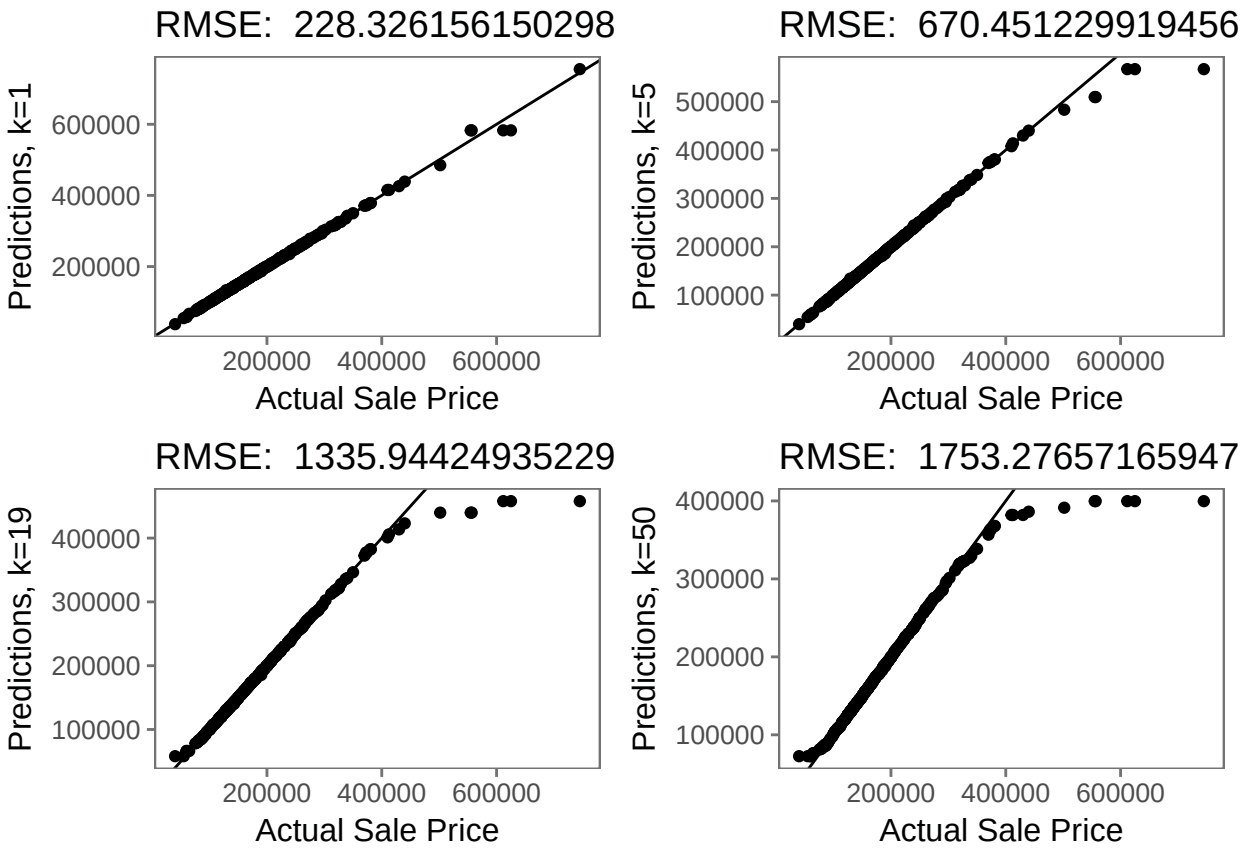
```
##   Forward.Selected.Variables Backward.Selected.Variables
```

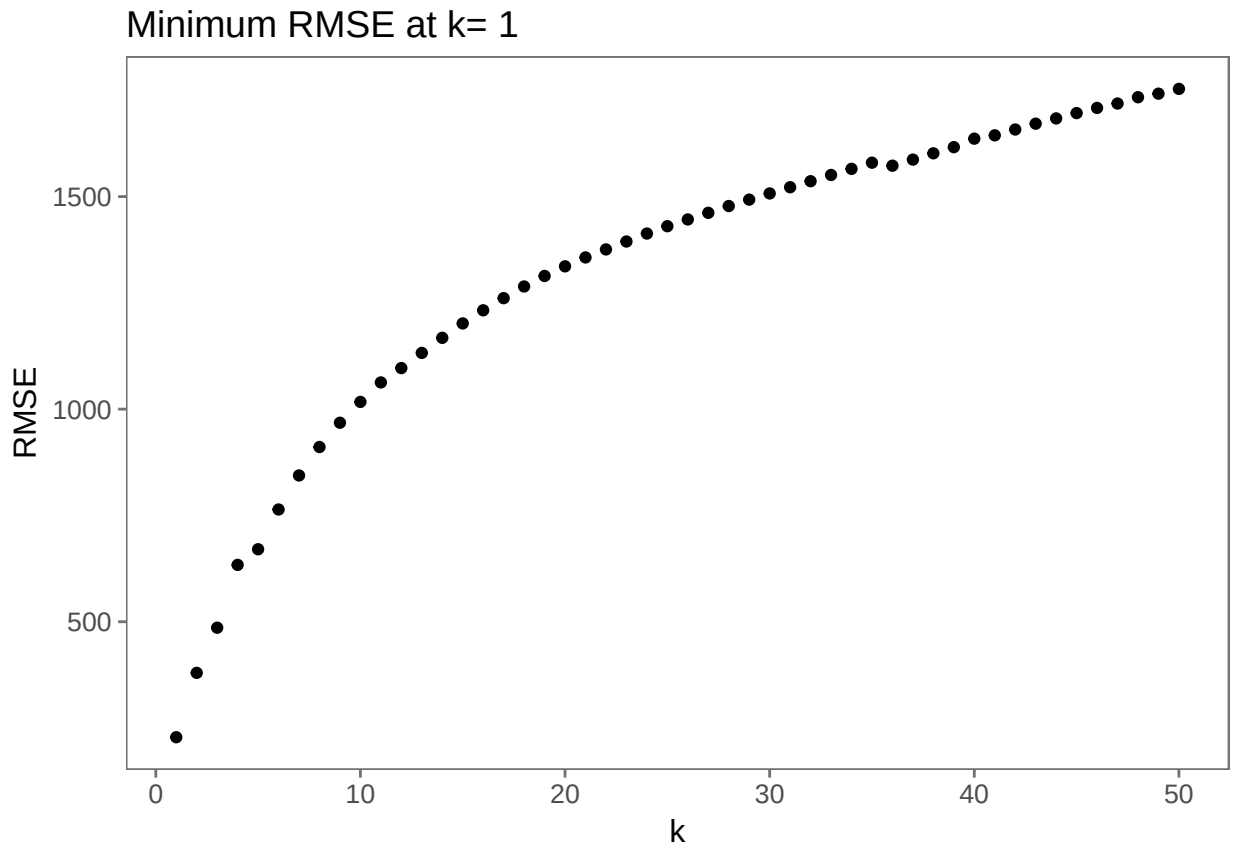
```
## 1                        Id                        Id
## 2                 StreetPave               OverallCond
## 3               OverallCond              YearRemodAdd
## 4              YearRemodAdd                X2ndFlrSF
## 5                 BsmtQualFa              LowQualFinSF
## 6               BsmtFullBath             KitchenQualFa
```

Below we applied the KNN regression on the SalePrice. The regression is basically fitting the best line to predict the SalePrice between neighbouring houses. We initially assumed 4 values of k: 1,5,19 and 50. Among the 4 values, 1 had the least root mean square error(RMSE).

We went ahead and drew a qplot to illustrate the pattern of k from 1 to 50 and its corresponding RMSE. According to the graph, 1 is the value of k with the least RMSE hence the most accurate in comparison to the others. Above 1, the RMSE gradually increase with the increasing value of k hence overfitting. This can be interpreted to mean that the sale price of each house is closest to that of only the most similar house to it, insinuating that there is a high variance in the data as well as high sparsity in the 306 dimensional space of the one-hot encoded data.

KNN regression

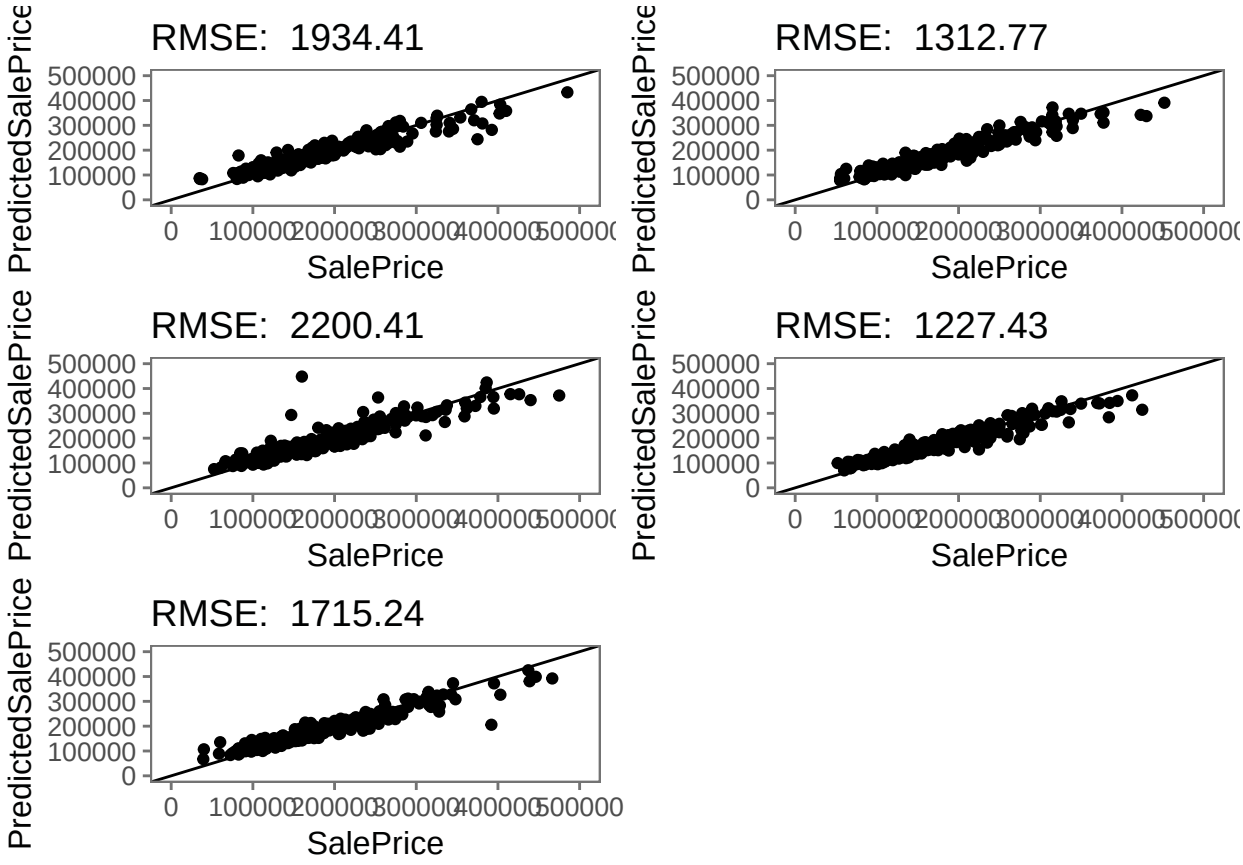




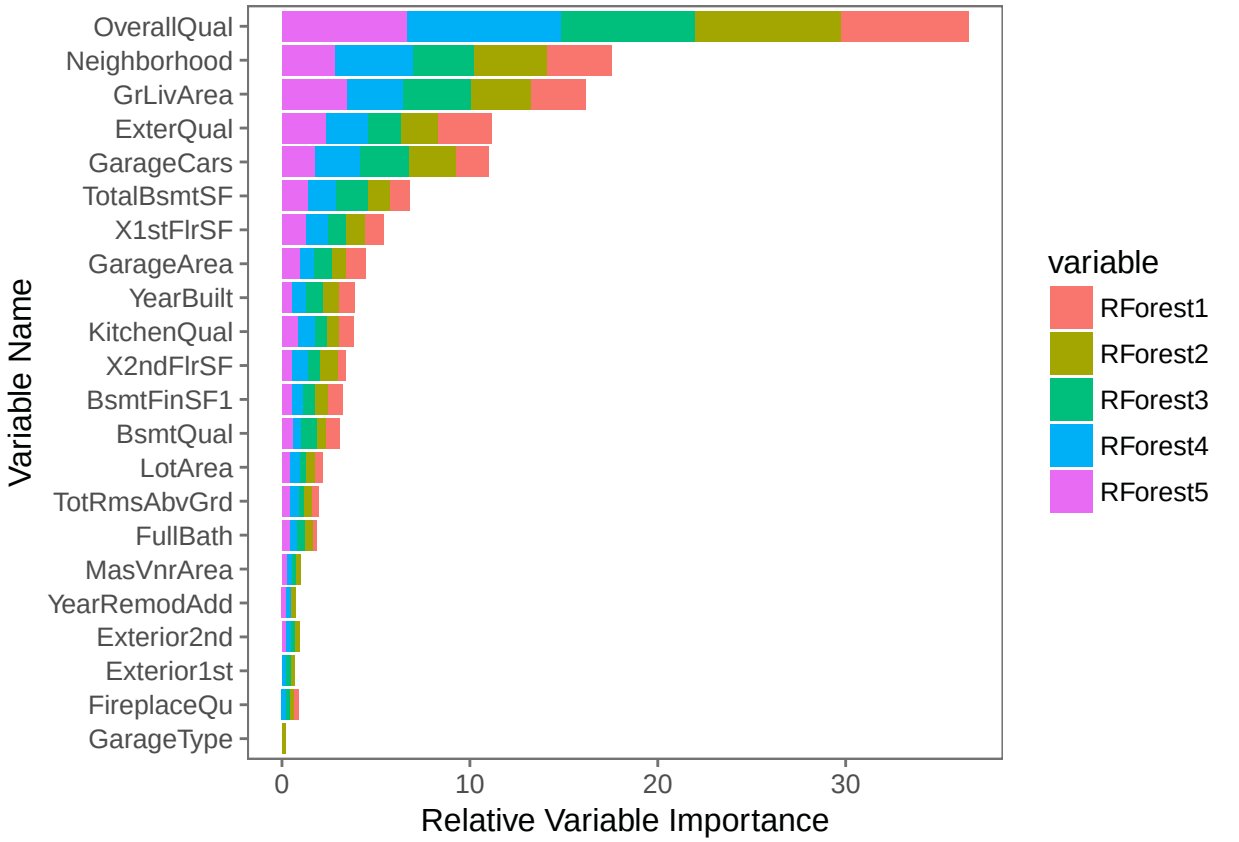
Random Forests

The next method we tried to tackle is the Random Forests, which is an ensemble method based on decision trees. As we have seen, decision trees can be understood easier but they do not predict with the same accuracy as other models. Generally, decision trees have high variance, which might lead to a very different tree for a small change in the training data. Therefore, the random forest allow us to counteract this problem.

In our random forest model, we used 5-fold cross validation to determine how the predictive accuracy could be improved by varying the number of features randomly selected at each node. The data was divided into a training set and test set in order to compare the predicted values with the true values. The figure below shows the target values versus the predicted values. As we can observe, the model is not perfect since all points do not lie along the diagonal line. Indeed, we can notice that the points found in the middle of the x-axis tend to be equally above and below the line. Nevertheless, the modelling for low sale prices or high sale prices was not as accurate. The model tends to overestimate sale prices that are low and underestimate high sale prices.

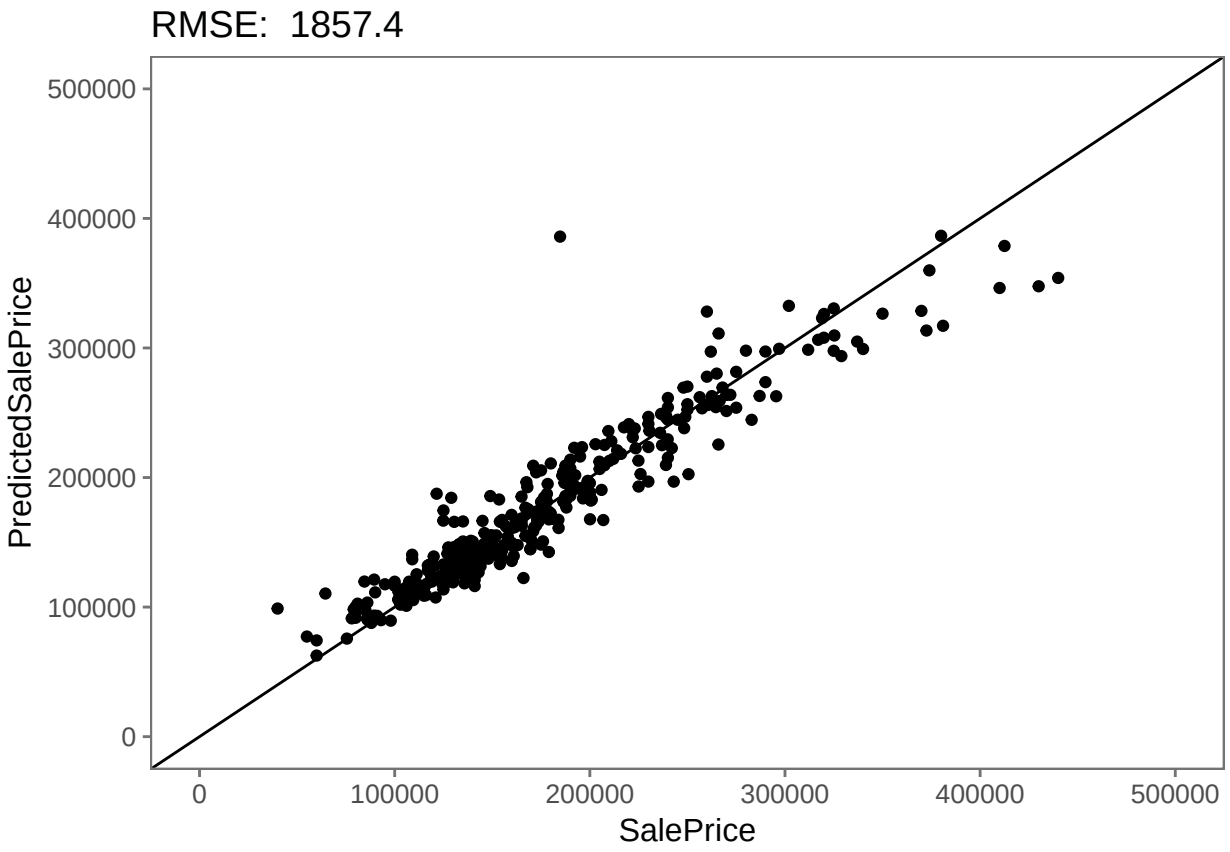


Although random forests are not easily interpretable, they could provide us with the importance of each of the predictors. In our model, we have determined that overall quality was the most important predictor, followed by the house's neighborhood and the square feet of the above ground living area. Nonetheless, the overall quality was clearly the most important one.

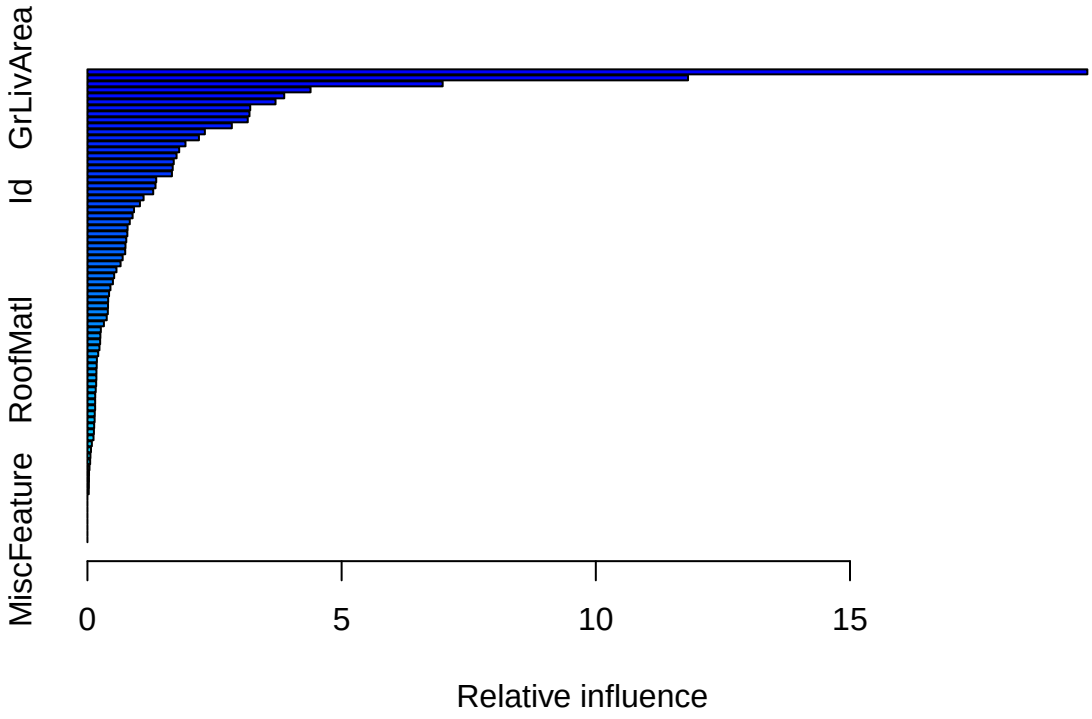


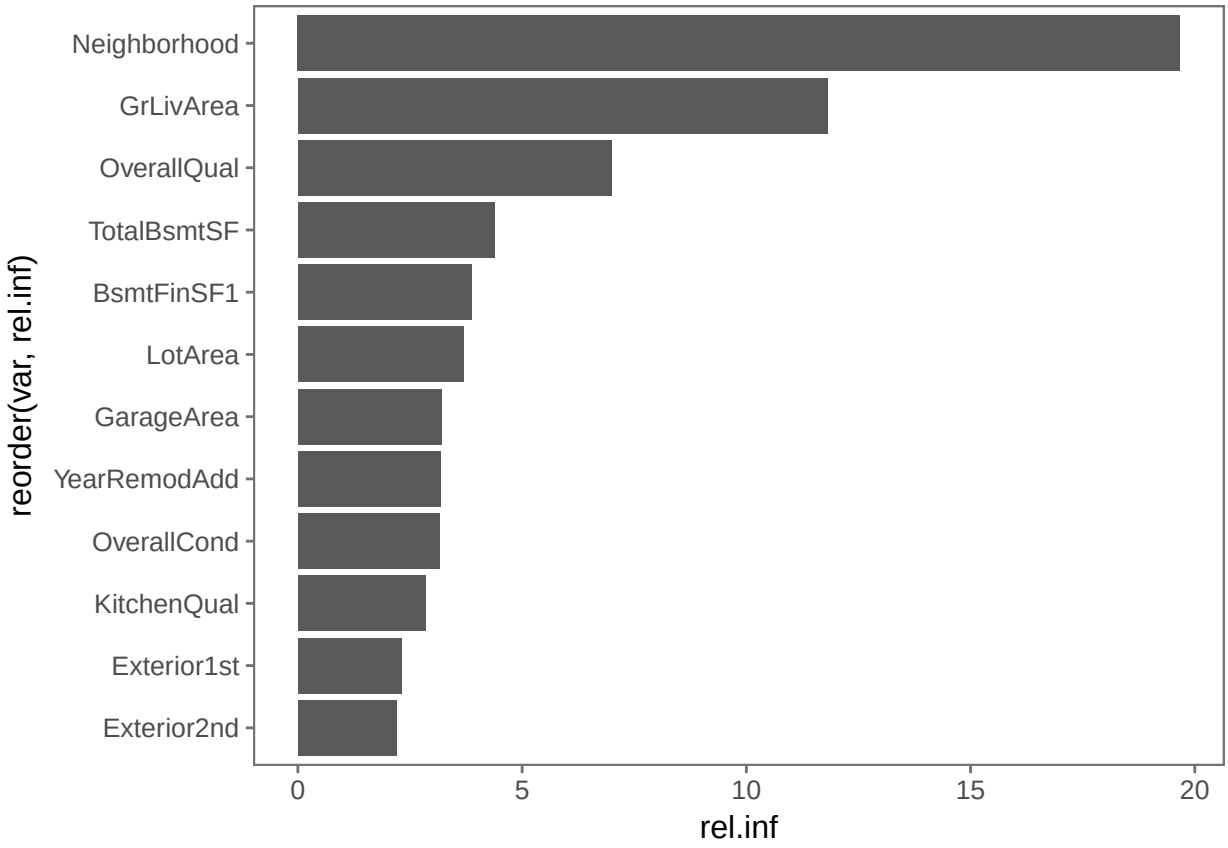
Gradient Boosting Model

Due to the fact that in our random forest model we have overestimated low sale prices and underestimated high sale prices, we can address this bias by applying some boosting techniques (such as the Gradient Boosting Model). As we can observe in the figure below, the GBM model was more accurate in our prediction than the random forests model since it is reduced the bias when overestimating sale prices that are low. However, with this method we did not manage to reduce the bias since it stills underestimate sale prices that are high.



Finally, according to the GBM model, the house's neighborhood is the most important predictor, whereas the the square feet of the above ground living area is the second one, as we can observe in the following plot.


GrLivArea
Id
RoofMatl
MiscFeature
0
5
10
15
Relative influence



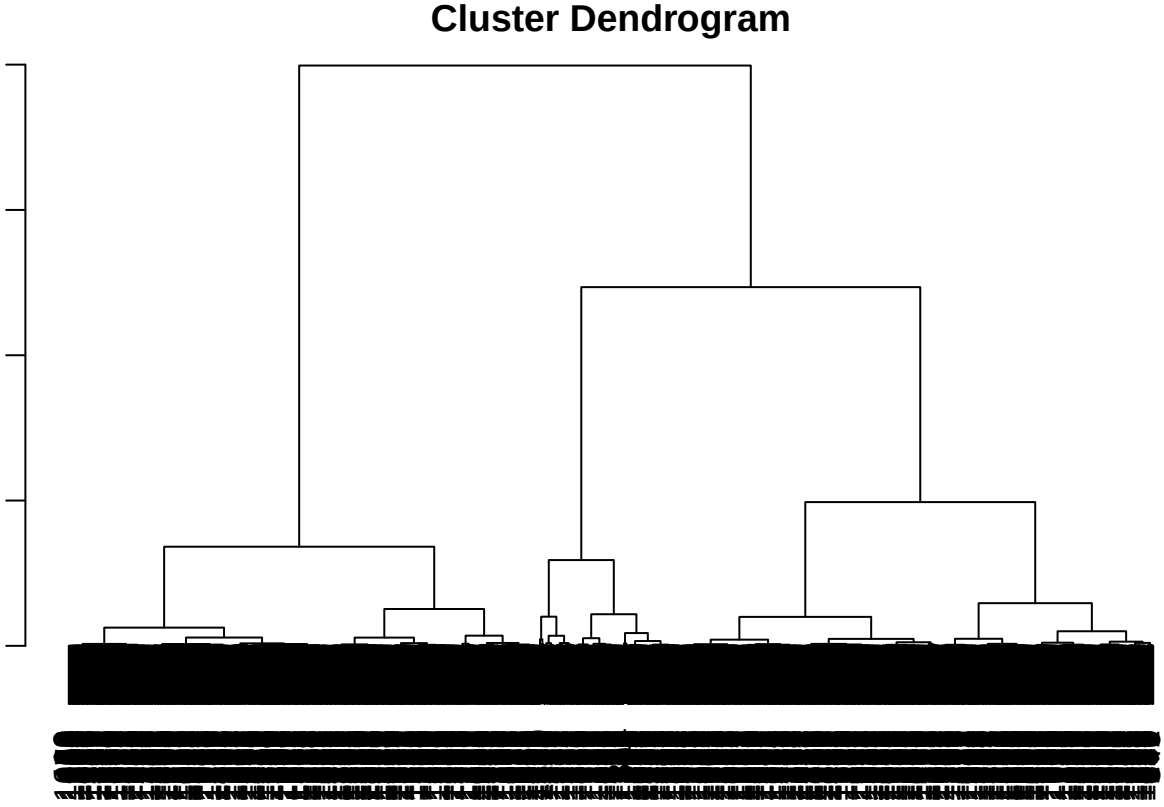
Second Research Question

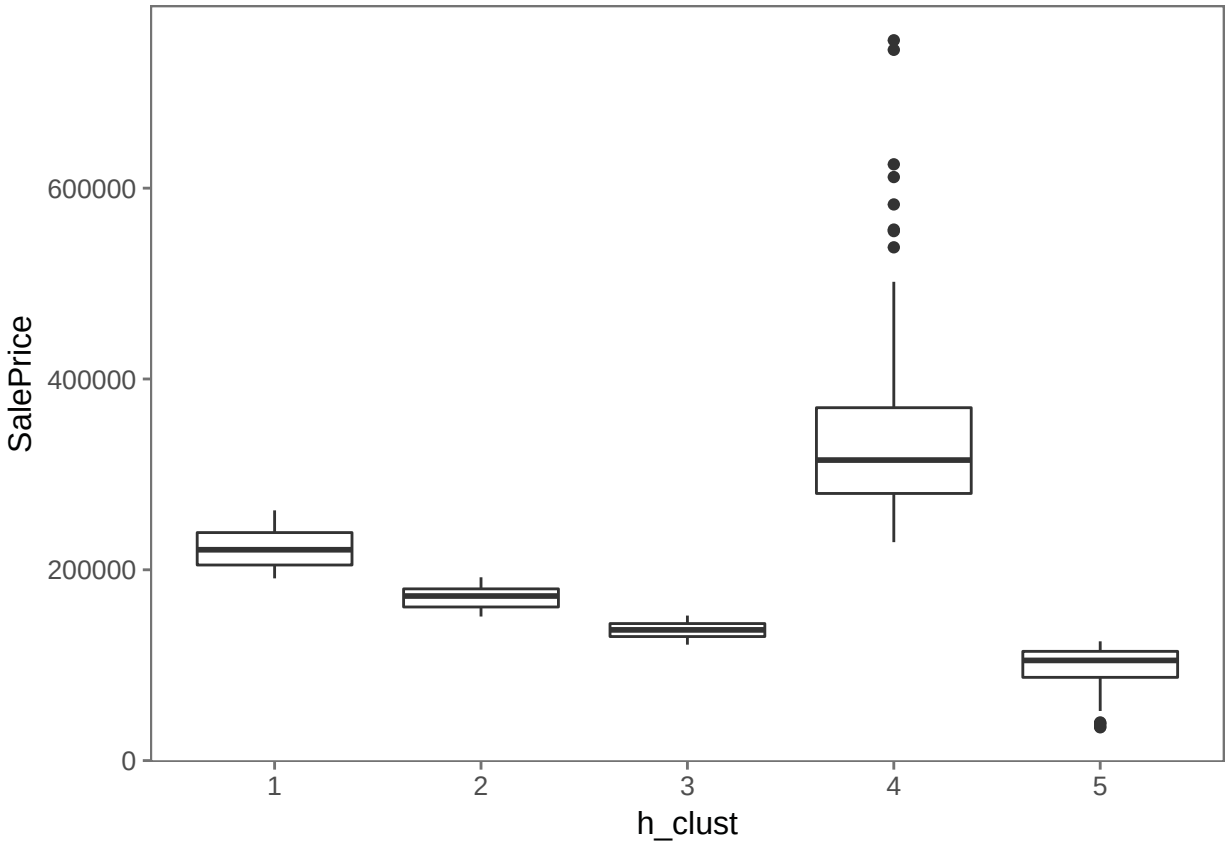
Then we started looking into answering our second research question: Are there natural clusters of houses that can be derived and explained from within the data and what do those clusters correspond to?

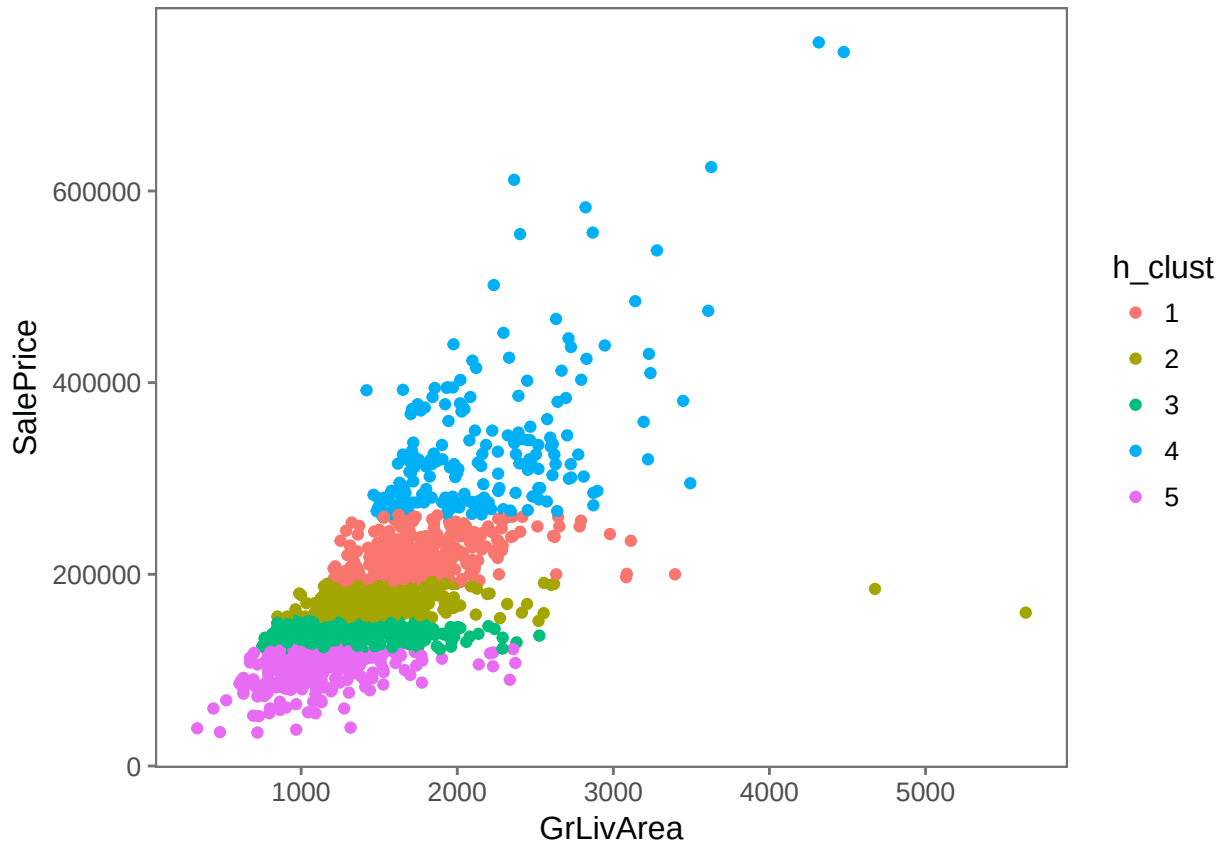
We applied hierarchical clustering in order to classify our data into 5 clusters. This contributes to a part of the answer to our research question "Are there intrinsic groupings/clusters of houses present in the data and what do these clusters represent? The clusters are formed basing on the fact that houses with similar features are within the same range of Sale Price.

We classified the clusters in 5 groups. The 5 groups represent a range of sale prices in which the dataset fall. The 4th group being the most expensive costing within the range between 300000(3e+05) to 400000(4e+05) with outliers that go beyond 600000(6e+05) while the cheapest group is the 5th group ranging from 100000(1e+05) but less than 200000(2e+05). Moreover we checked the overall quality compared to the price and the 4th group having the highest quality ranging within 7 up to 10 while the 5th group had the lowest quality ranging within 2 up to 6 with a few outliers which have 7.

Moreover, we checked as well the relationship between GrLivArea(Above grade (ground) living area square feet) and the sales price , we found that the 4th group's Gridliv area ranged between 1500 to 3500 with some outliers reaching to 4000 while the 5th group ranged between 500 to 2500. Interestingly,the second group's Gridliv area ranges between 1000 till almost 2000 however there are outliers that go beyond 5000.


Cluster Dendrogram


SalePrice
600000
400000
200000
0
1
2
3
4
5
h_clust

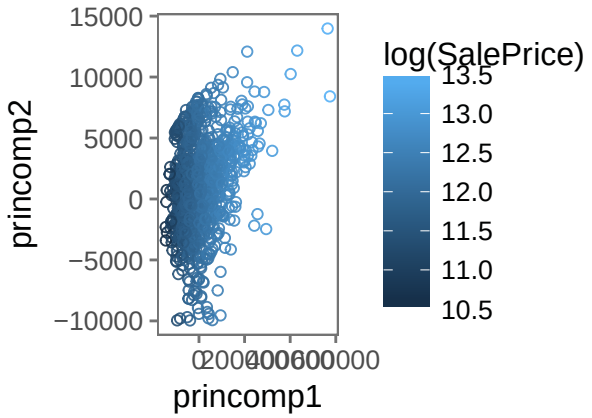


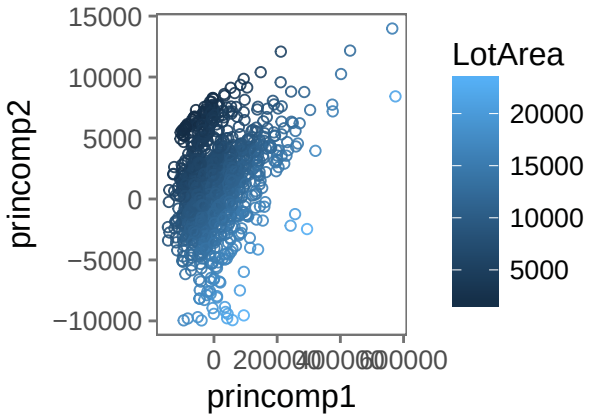
We then decided to do some dimensionality reduction to see if there were any obvious structures in the data.

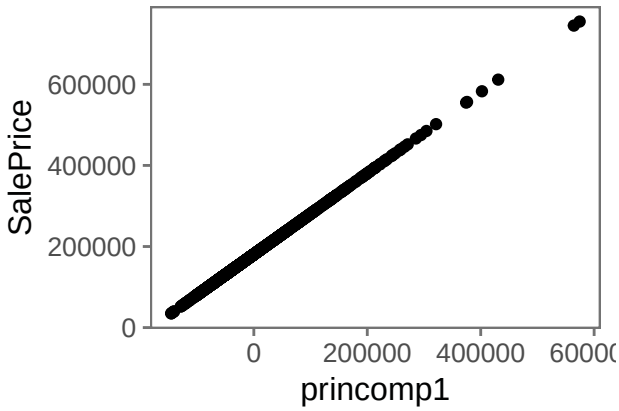
First, we computed PCA on the data with two different algorithms, then plotted them.

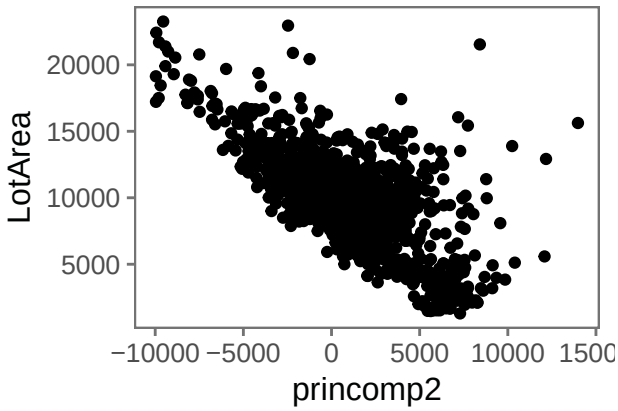
Sale price seems to almost exactly maps to the first principle component, and the second principle component is highly negatively correlated with LotArea. It is therefore obvious that much of the variation within this dataset is explained by these two variables.

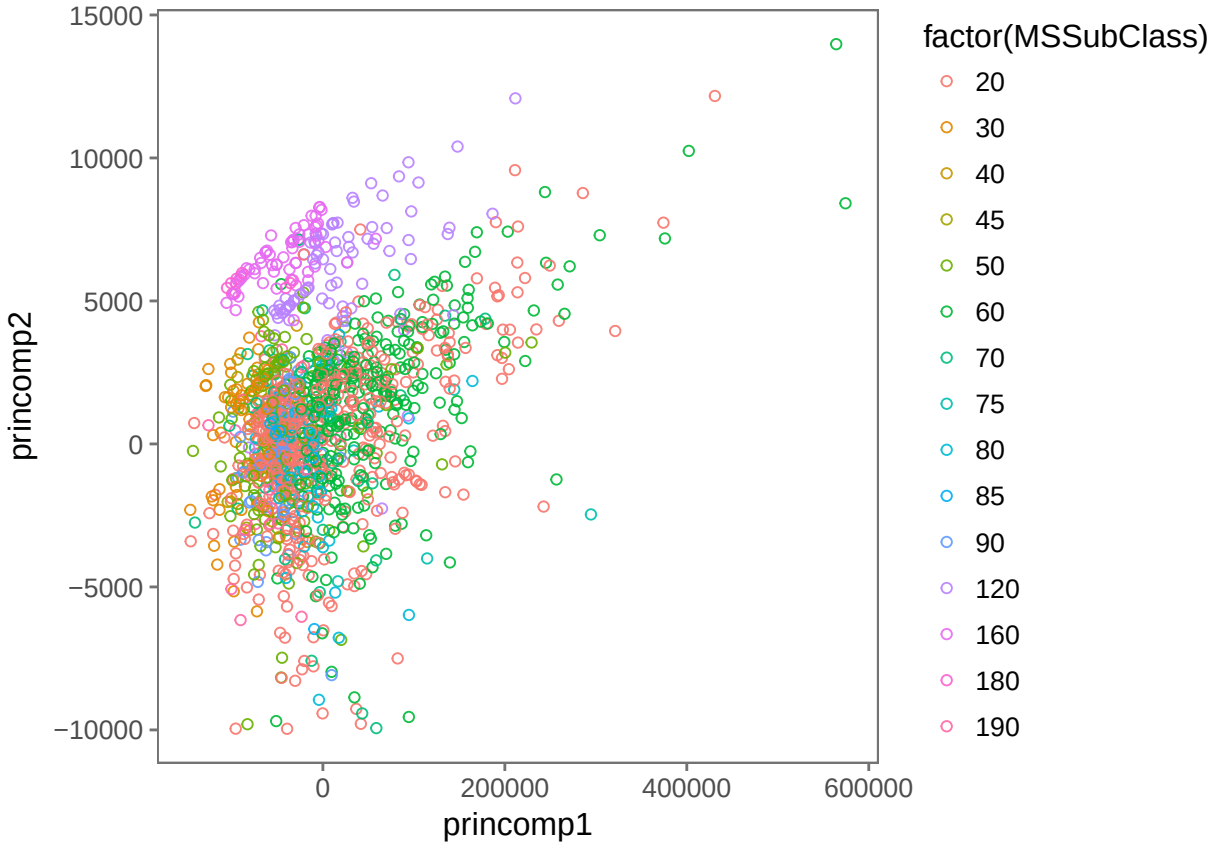
Furthermore, MSSubClass (the type of dwelling involved in the sale) also has an interesting relationship with principal component 2. The MSSubClasses 120, 160, and 180 form a cluster in the higher values of the second principal component. MSSubClasses 120, 160, and 180 are the 3 types of dwellings that are planned unit developments - communities of homes that are operated by a homeowners association to provide amenities like parks, playgrounds, pools, tennis and basketball courts, hiking trails, private gated common land and street lights or the like. It makes sense that these homes form a cluster, because homes in planned communities are often regulated to be extremely similar.

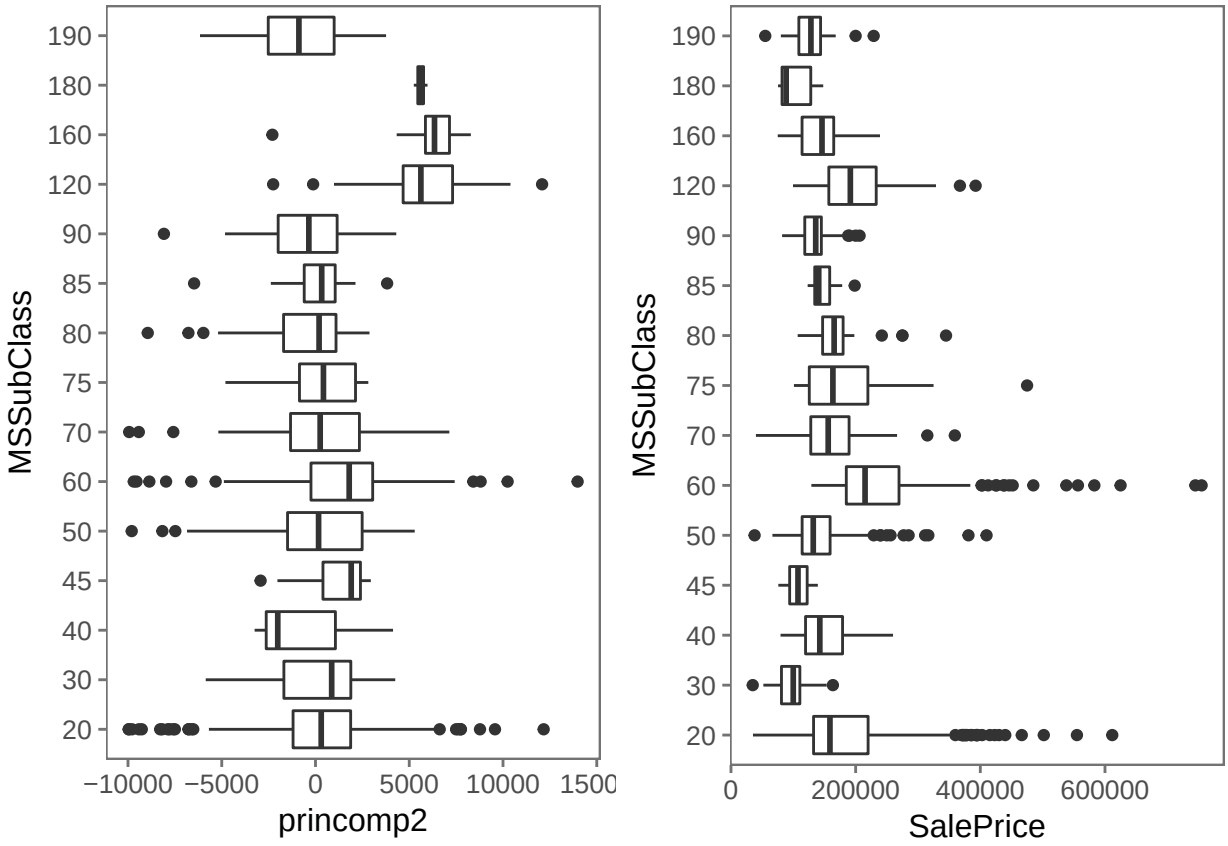

15000
10000
5000
0
−5000
−10000
princomp2
0
200000
400000
600000
princomp1
log(SalePrice)
13.5
13.0
12.5
12.0
11.5
11.0
10.5

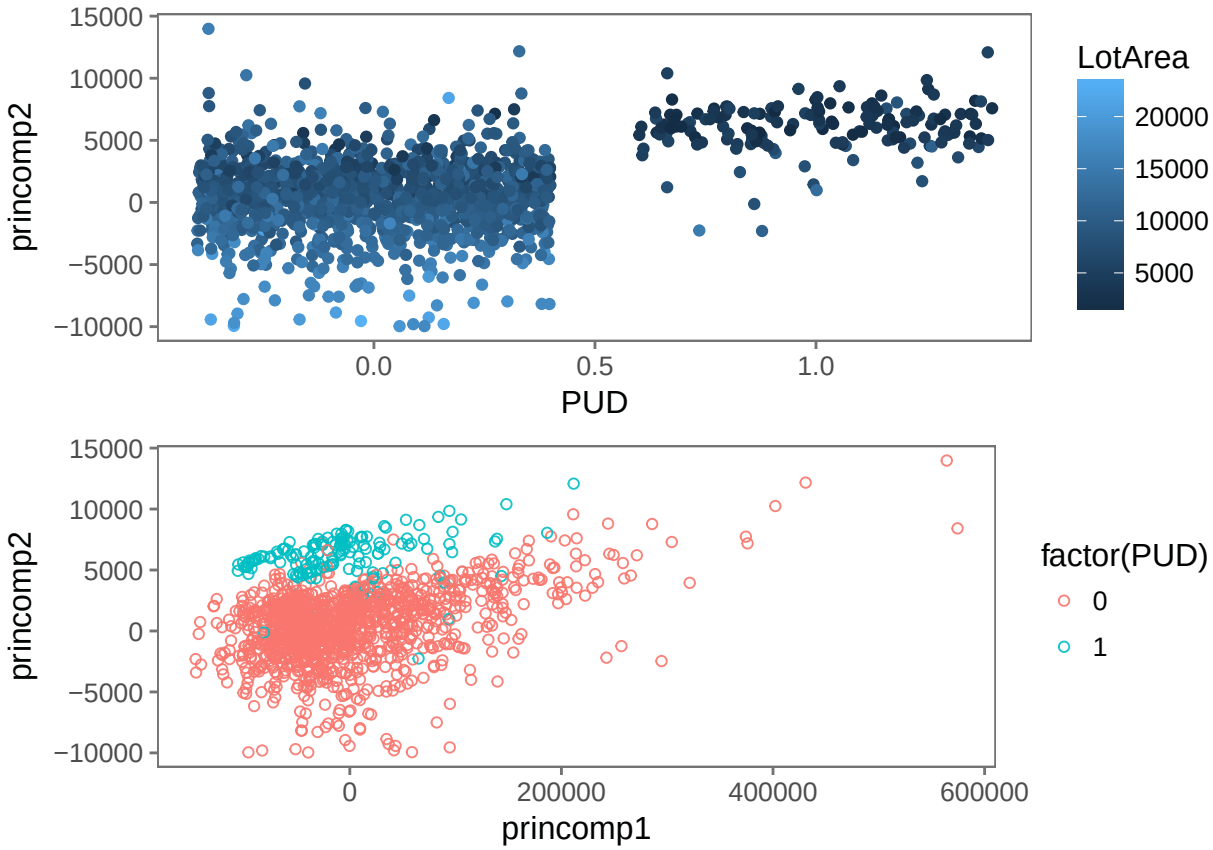

15000
10000
5000
0
−5000
−10000
princomp2
0
200000
400000
600000
princomp1
LotArea
20000
15000
10000
5000


600000
400000
200000
0
SalePrice
0
200000
400000
60000
princomp1


20000
15000
10000
5000
LotArea
−10000
−5000
0
5000
10000
1500
princomp2


15000
10000
5000
0
−5000
−10000
princomp2
0
200000
400000
600000
princomp1
factor(MSSubClass)
20
30
40
45
50
60
70
75
80
85
90
120
160
180
190

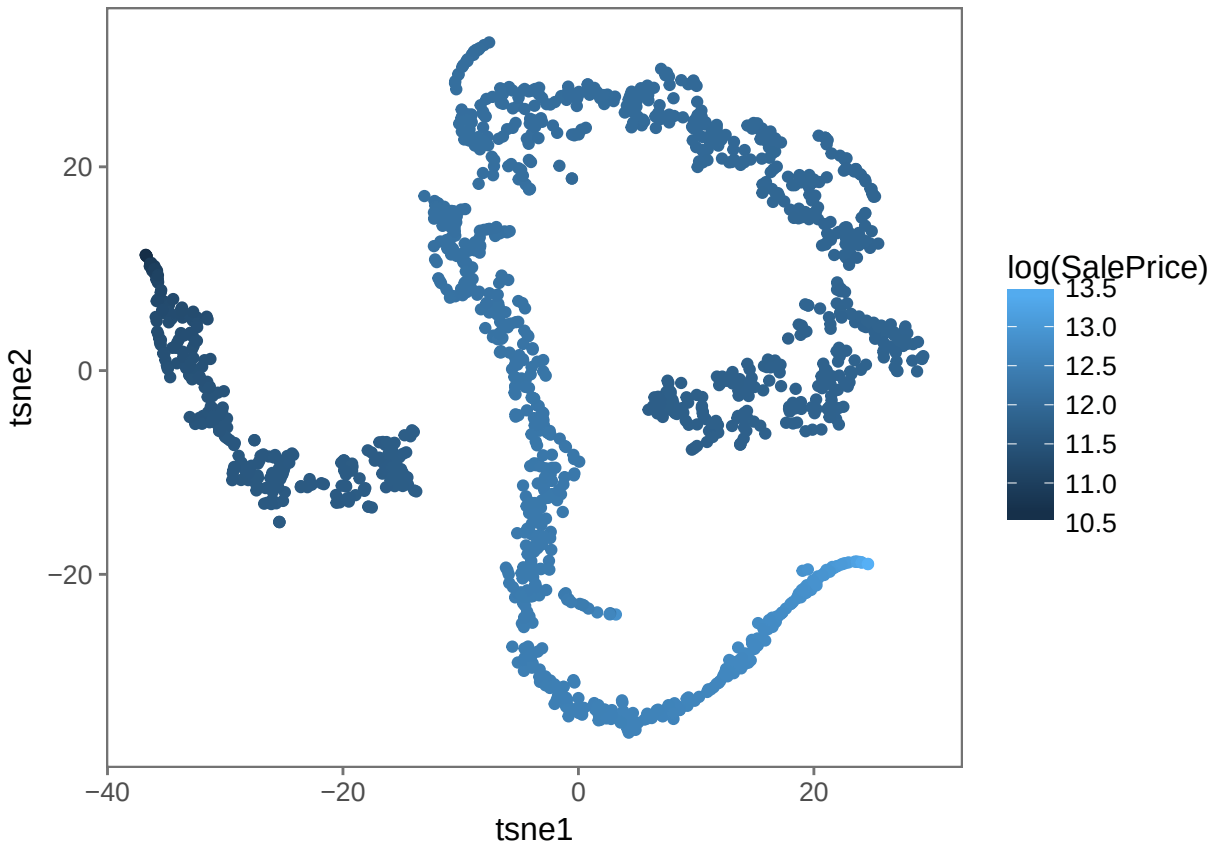

MSSubClass
190
180
160
120
90
85
80
75
70
60
50
45
40
30
20
−10000
−5000
0
5000
10000
1500
princomp2
MSSubClass
190
180
160
120
90
85
80
75
70
60
50
45
40
30
20
0
200000
400000
600000
SalePrice

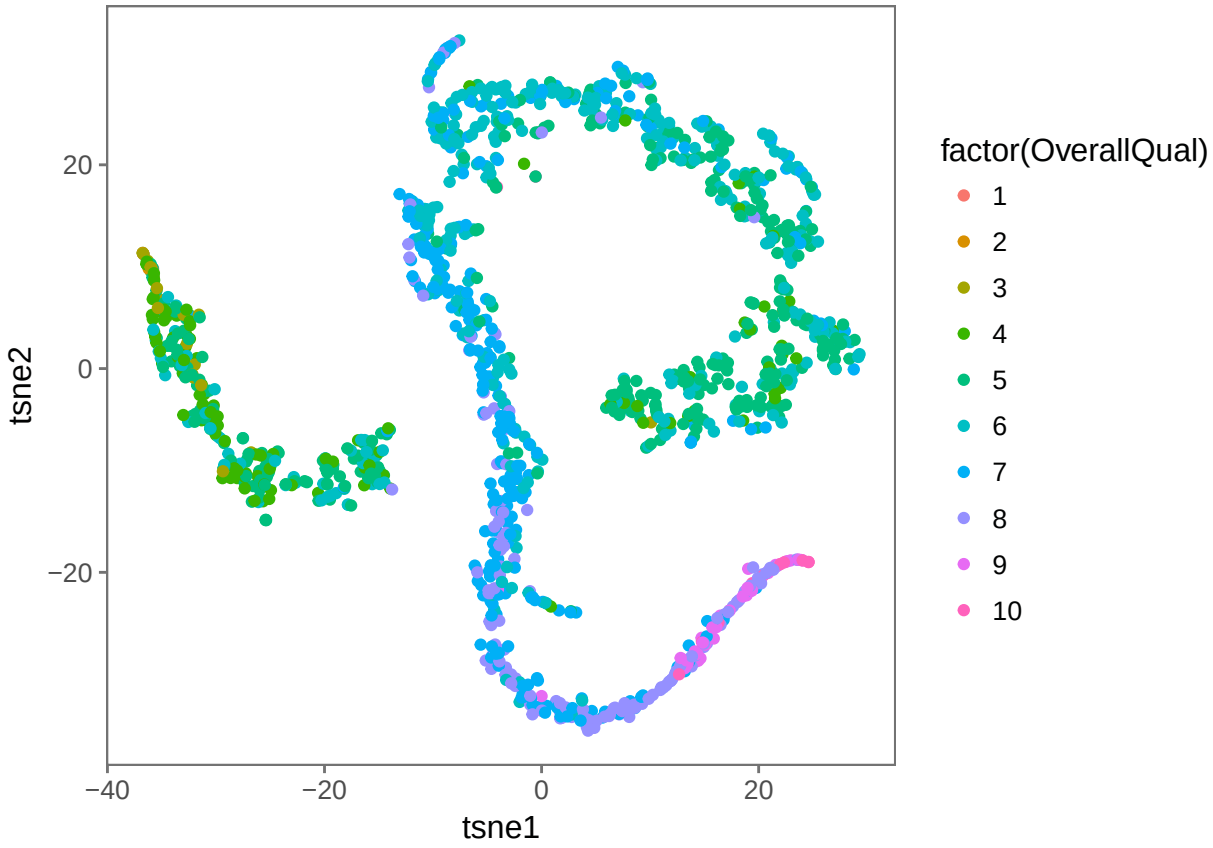


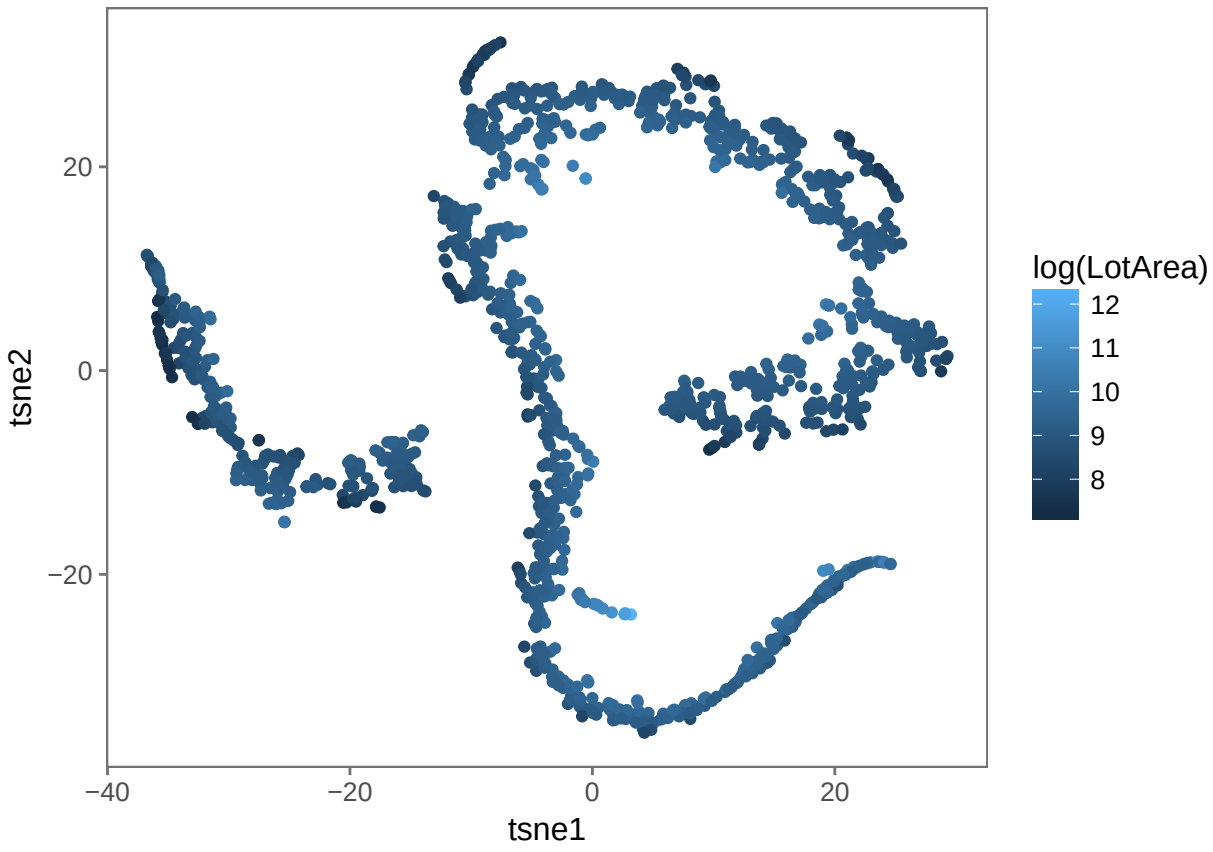
Then we decided to compare dimensionality reduction of a t-SNE plot, which stands for t-distributed Stochastic Neighbor Embedding. It is a dimensionality reduction algorithm that embeds high dimensional data into a 2 dimensional space. There is a nice R vignette about the package, a blog post about its use in R, and an interactive visualization characterizing its strengths and weaknesses.

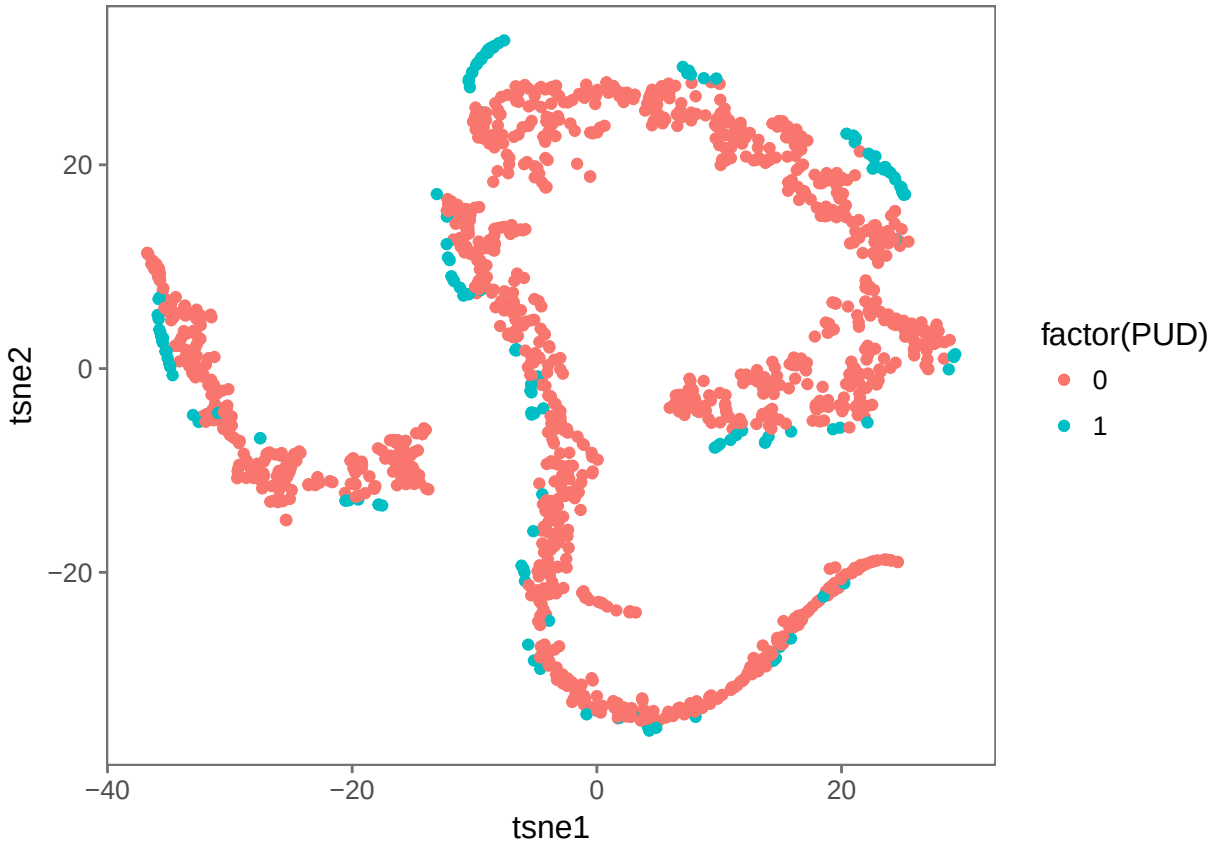
The t-SNE confirms many of the same things as the principal component analysis, namely that the majority of the variance in the dataset can be explained by the sale price (as well as variables that are correlated to the sale price like the overall quality). Also, when you plot variables that are uncorrelated with the SalePrice but correlated with the second principal component (like lot area and being a PUD) you see groupings on the outside of the main structure, and the occasional small cluster. One cluster (seen in the t-SNE plot colored by lot area) seems to point to the similarilty of more rural houses that have much higher lot area. Coloring the t-SNE plot by the PUD houses also shows some clear clusters of houses likely in the same housing development.

```
## Joining, by = c("Id", "MSSubClass", "LotFrontage", "LotArea", "OverallQual", "OverallCond", "YearBui
```


20
0
−20
tsne2
−40
−20
0
20
tsne1
log(SalePrice)
13.5
13.0
12.5
12.0
11.5
11.0
10.5


20
0
−20
tsne2
−40
−20
0
20
tsne1
factor(OverallQual)
1
2
3
4
5
6
7
8
9
10


20
0
−20
tsne2
−40
−20
0
20
tsne1
log(LotArea)
12
11
10
9
8



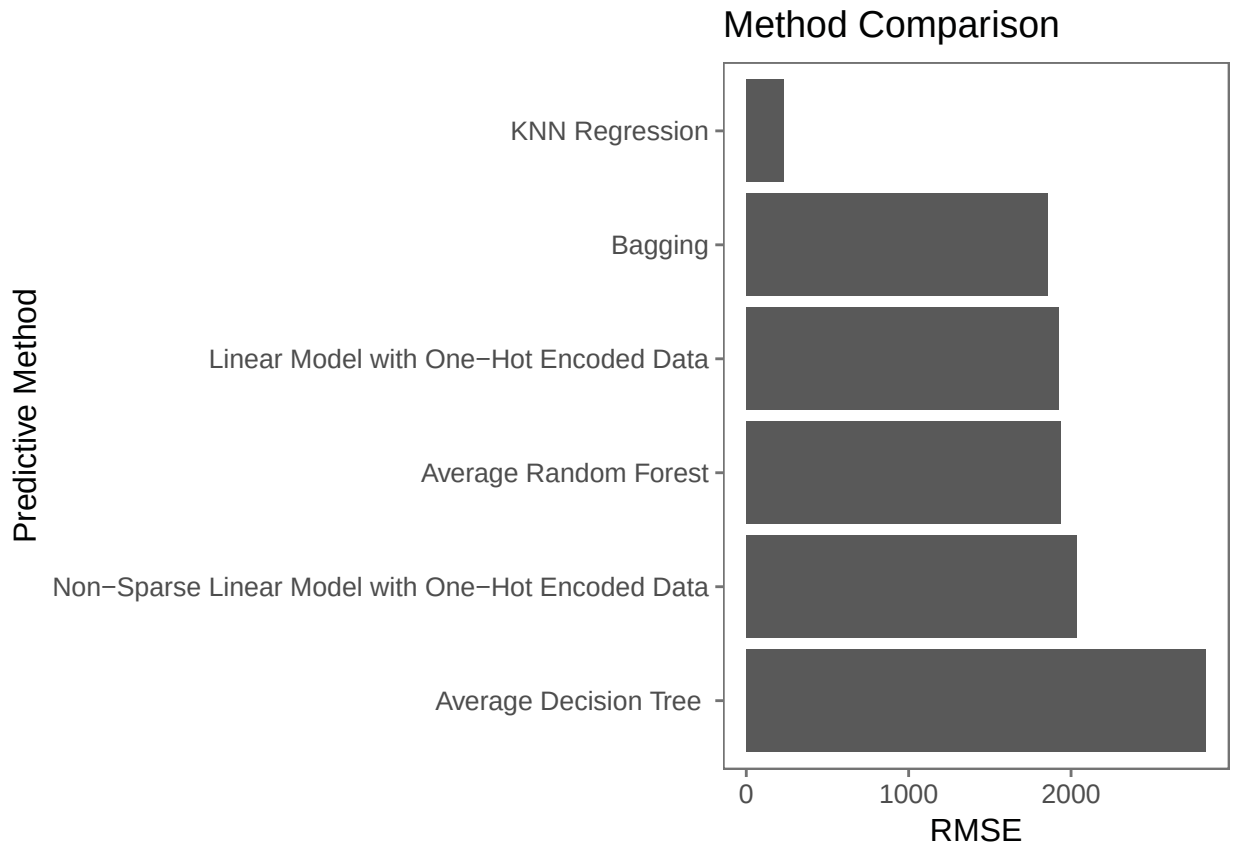
Overall Conclusion:

Overall, the answers to our research questions were interesting and diverse.

Research Question 1:

For the first research question, there are many factors that are important to predicting the sales price, but it seems like the most important (in no particular order) are the overall house quality, above grade living area square feet, neighborhood, external quality, size of garage in car capacity, and kitchen quality. These variables were determined to be important by many of the predictive algorithms we examined as well as by the exploratory data analysis and correlation analysis at the beginning of the project.

From a comparison of the RMSEs of all the different algorithms, it's obvious that the knn regression algorithm is the best fit for this data. This is likely due to the high variability in the characteristics of houses, which makes it difficult to come up with overall rules that apply to all situations like regression trees do with variable splitting and linear models do with coefficients.



Research Question 2:

From our analysis of reducing the dimensionality reduction of our data, it seems as though there are two main groupings within our data. The first is the sale price of the home. The sale price of a home is highly correlated with many other variables in the dataset and knowing the sale price can give you a good idea about other details of the home. Our analysis of hierarchical clustering isolated five clusters that map almost exactly to subsets of the sale price. The second main grouping is the amount of lot area/PUD status of a home. These groupings likely are a proxy for measuring how suburban/rural a home is, because suburban homes are often PUDs that have little individual lot area, but share land within the subdivision, and rural homes often have much more land then their city counterparts.

The price and suburban-ness of a home make sense as good metrics for explaining the variation between homes because an expensive loft in the city is quite different than an expensive suburban or rural home, as is an inexpensive suburban/rural home from a inexpensive urban home.

In short, our two research questions uncovered some interesting results from our data and we hope to post our findings on Kaggle in order to get feedback from and share our findings with the wider data science community.