FINAL REPORT

Making Houses More Appealing to Buyers

Abstract

Exploratory Data Analysis and Machine Learning Algorithms on a Housing Dataset to support which home improvement may positively affect the Selling Price

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Introduction

Background

The housing market is the target of several studies because it affects an important part of the society. Moreover, it involves large amounts of money, especially if we are dealing with a family's entire life's worth of savings or future earnings in the form of loans.

Every owner wants to make a good deal when selling their properties. The most significant actions an owner can take to get a better evaluation of their houses are performing house upgrades. But there are so many possible enhancements available, wouldn't it be great if we could identify which services would impact the selling price the most?

Proposal

This study is the first two parts of a more ambitious study that would recommend homeowners and home brokers which home improvements would greatly impact the selling price. The outcome of the complete version of the study would be a "portfolio" of possible home upgrades, alongside with the cost and duration of the project, and the estimated increase in the selling price. This would be presented to homeowners and home brokers, giving them the opportunity to either sell a "harder-to-sell" house faster or to maximize their profits.

As far as this study is concerned, the first part would be to identify which house features are immutable, like location, type of dwelling, etc. and which features can be affected by house projects. The immutable features will be used in the future to classify a house, therefore they will be called "classifying variables". The second group are the ones that the owners can act upon with house projects, therefore they are the "actionable variables".

Our final deliverable is a Machine Learning model capable of providing good predictions for a random house. This way, we could apply the model to a specific house and provide a list of "actionable variables" that have the most positive impact on the selling price.

Out of the scope of this study, but vital to the success of this business, is to identify which home project will affect one or more of the "studied variables". The next step would be to get quotes and time estimates for these home projects. For that, services from a company like Homestars can be used, where home professionals are easily found, as well as quotes and time estimates for home projects.

Some of the "classifying variables" can be used for acquiring the estimates. Once this part is done, the portfolio will be complete and it will be possible to recommend which home improvement will better impact the selling price of a house, taking the time and resources available for home projects into consideration. This is the reason why this part is crucial: it is possible to find that the cost of the upgrade may be greater than the impact on the selling price, voiding the findings of this study.

Dataset

The dataset used for this study is the Ames Housing Dataset, which presents 79 explanatory variables describing several aspects of residential homes in Ames, Iowa, United States. The dataset can be found following the link below:

https://www.kaggle.com/c/house-prices-advanced-regression-techniques/overview

Once this study is finalized, with minor adjustments, the algorithms generated may be applied for different regions.

Data Wrangling

Checking for errors on categorical columns

The document "data_description.txt" shows all the allowed values for each categorical data. Let us list all unique values on each categorical column to look for mistyped data. IMPORTANT: there are 3 categorical columns that are represented by numbers ('MSSubClass','OverallQual','OverallCond'). Please note the highlighted line where we added those 3 columns.

```
import pandas as pd
df = pd.read_csv('house_price.csv, header=0, index_col='Id')
dfnumbers = df._get_numeric_data()
catcols = set(df.columns) - set(dfnumbers.columns)
catcols = catcols.union(set(['MSSubClass','OverallQual','OverallCond']))
for col in catcols:
    print(col, ' - ',df[col].unique())
```

Here is a part of the output

```
GarageQual  -  ['TA' 'Fa' 'Gd' nan 'Ex' 'Po']
Foundation  -  ['PConc' 'CBlock' 'BrkTil' 'Wood' 'Slab' 'Stone']
CentralAir  -  ['Y' 'N']
ExterQual  -  ['Gd' 'TA' 'Ex' 'Fa']
BsmtExposure  -  ['No' 'Gd' 'Mn' 'Av' nan]
MSZoning  -  ['RL' 'RM' 'C (all)' 'FV' 'RH']
RoofStyle  -  ['Gable' 'Hip' 'Gambrel' 'Mansard' 'Flat' 'Shed']
```

With a quick inspection, we notice some NaNs that are not "missing data". The highlighted nan, for example, means "no garage", but it could also mean "missing data" in other columns. We will investigate that later.

Comparing the output with the data description, we noticed small errors that are quite easy to miss if we inspect manually. So, we created a .csv file called "AllPossibleValuesForCatCols.csv", using the data_description.txt as the source, to list all possible values those categorical columns may have. We will import this file as a Dataframe and match the actual values found on the dataset with the possible values for that column. This way we can find typos easier. This is the code to find all typos:

```
df = pd.read_csv('train.csv', header=0, index_col='Id')
dfAll = pd.read_csv('AllPossibleValuesForCatCols.csv', header=0)
dfAll = dfAll.applymap(lambda x: x.strip() if isinstance(x, str) else x)
diffs = {}
for col in dfAll.columns:
    diffs[col] = set(df[col]) - set(dfAll[col])
for key, value in diffs.items():
    if(len(value)>0): print(key, ' - ',value)
```

Analyzing the output,

```
MSZoning  -  {'C (all)'}
Neighborhood  -  {'NAmes'}
BldgType  -  {'Duplex', '2fmCon', 'Twnhs'}
Exterior2nd  -  {'Wd Shng', 'CmentBd', 'Brk Cmn'}
```

we noticed some small variations on the text of some columns, compared to the data_description data. To match the values exactly, we changed the following, by running this code:

```
df.BldgType = df.BldgType.replace('Twnhs', 'TwnhsI')
df.BldgType = df.BldgType.replace('Duplex', 'Duplx')
df.BldgType = df.BldgType.replace('2fmCon', '2FmCon')
df.MSZoning = df.MSZoning.replace('C (all)', 'C')
df.Exterior2nd = df.Exterior2nd.replace('Wd Shng', 'WdShing')
df.Exterior2nd = df.Exterior2nd.replace('CmentBd', 'CemntBd')
df.Exterior2nd = df.Exterior2nd.replace('Brk Cmn', 'BrkComm')
df.Neighborhood = df.Neighborhood.replace('NAmes', 'Names')
```

- Column **BldgType**: “Duplex” should be “Duplx” and “2fmCon” should be “2FmCon”. “Twnhs” should be “TwnhsI”.
- Column **MSZoning:** “C (all)” should be “C”
- Column **Exterior2nd:** “Wd Shng” should be “WdShing” because wecan see “Wd Shng” on the data. “CmentBd” should be “CemntBd” and “Brk Cmn” should be “BrkComm”
- Column **Neighborhood**: “NAmes” should be “Names” (meaning North Ames)

If we run the same code again to check typos, the output is empty, meaning the code ran successfully.

Back to the unique values from all columns, a few other things that caught our attention. Below are the modifications we performed on the columns **MasVnrType** and **MasVnrArea,** performed by the code below:

```
df = df.replace({'MasVnrType':{np.nan : 'None'}, 'MasVnrArea': {np.nan : 0}}, value = None)
print(df[['MasVnrType', 'MasVnrArea']][(df.MasVnrType == 'None') & (df.MasVnrArea > 0)])
df.MasVnrArea = df.MasVnrArea.replace(1.0,0.0)
print(df[['MasVnrType', 'MasVnrArea']][df.MasVnrArea > 0].MasVnrType.value_counts())
for index, row in df.iterrows():
    if((row['MasVnrType'] == 'None') & (row['MasVnrArea'] > 0)):
        df.loc[index, 'MasVnrType'] = 'BrkFace'
```

There are 8 values that are “None” values and NaN on the MasVnrType column. Replace NaN with ‘None’ on column MasVnrType and replace NaN with 0 on the MasVnrArea column.

When the MasVnrType is None, MasVnrArea should be zero. Analysing this table,

Id	MasVnrType	MasVnrArea
625	None	288.0
774	None	1.0
1231	None	1.0
1301	None	344.0
1335	None	312.0

generated by the code above, we find values different than zero, which is not what we expected. To deal with that, the two records with Areas = 1.0 will be replaced by Area = 0.0, and the other three values will be replaced by the most common Masonry veneer type, which is type = ‘BrkFace’.

This type of consistency will be checked for every column later. For example, if the house has no garage, all columns related to “garage” should show NA.

Cleaning NaN from categorical columns

We already know that missing values are stored as NaN. The code below

```
nulls = df.isnull().sum()
catcolswithnan = set(dfAll.columns) & set(nulls[nulls>0].index)
for col in catcolswithnan:
    print(col, ' - ',df[col].unique())
```

lists the categorical columns with their unique values. Analyzing the output

```
PoolQC  -  [nan 'Ex' 'Fa' 'Gd']
Alley  -  [nan 'Grvl' 'Pave']
BsmtQual  -  ['Gd' 'TA' 'Ex' nan 'Fa']
BsmtCond  -  ['TA' 'Gd' nan 'Fa' 'Po']
Electrical  -  ['SBrkr' 'FuseF' 'FuseA' 'FuseP' 'Mix' nan]
BsmtExposure  -  ['No' 'Gd' 'Mn' 'Av' nan]
GarageCond  -  ['TA' 'Fa' nan 'Gd' 'Po' 'Ex']
BsmtFinType2  -  ['Unf' 'BLQ' nan 'ALQ' 'Rec' 'LwQ' 'GLQ']
GarageType  -  ['Attchd' 'Detchd' 'BuiltIn' 'CarPort' nan 'Basment' '2Types']
GarageQual  -  ['TA' 'Fa' 'Gd' nan 'Ex' 'Po']
GarageFinish  -  ['RFn' 'Unf' 'Fin' nan]
Fence  -  [nan 'MnPrv' 'GdWo' 'GdPrv' 'MnWw']
FireplaceQu  -  [nan 'TA' 'Gd' 'Fa' 'Ex' 'Po']
BsmtFinType1  -  ['GLQ' 'ALQ' 'Unf' 'Rec' 'BLQ' nan 'LwQ']
MiscFeature  -  [nan 'Shed' 'Gar2' 'Othr' 'TenC']
```

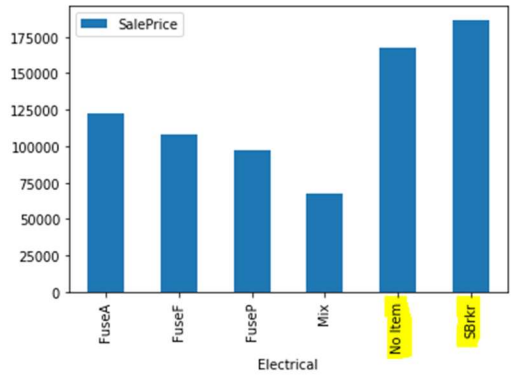
we notice that, for all columns, it makes sense to replace nan with “No Item”, except for the column “Electrical”, because It does not make sense not to have an electrical system.

After replacing all NaN from the above columns with “No Item”, this code

```
print(df[df.Electrical == 'No Item']['Electrical'].count())
#plot code 6
df[['Electrical', 'SalePrice']].groupby('Electrical').mean().plot(kind = 'bar')
plt.show()

df.Electrical = df.Electrical.replace('No Item', 'SBrkr')
```

performs the following operations on the “Electrical” column:

- Finds the number of records we are dealing with
- Checks how the price of this house stands against the other types of electrical systems.



- Replace “No Item” by “SBrkr”

Cleaning NaN from numerical columns

The code below

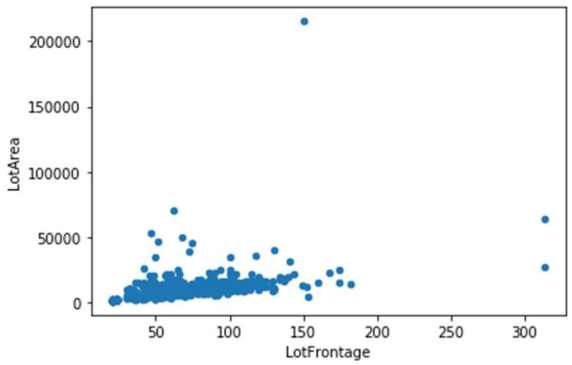
```
dfNumericCols = set(df.columns) - set(dfAll.columns)
dfNumeric = df[list(dfNumericCols)]
print(dfNumeric.isnull().sum()[dfNumeric.isnull().sum()>0])
print(df[['GarageType', 'GarageYrBlt']][df.GarageYrBlt.isnull()].GarageType.unique())
df[['LotFrontage', 'LotArea']].plot(x = 'LotFrontage', y = 'LotArea', kind = 'scatter')
df[['LotFrontage', 'LotArea']].plot(x = 'LotFrontage', y = 'LotArea',
                                    xlim=(0,150), ylim=(0,20000), kind = 'scatter')
```

performs the following operations:

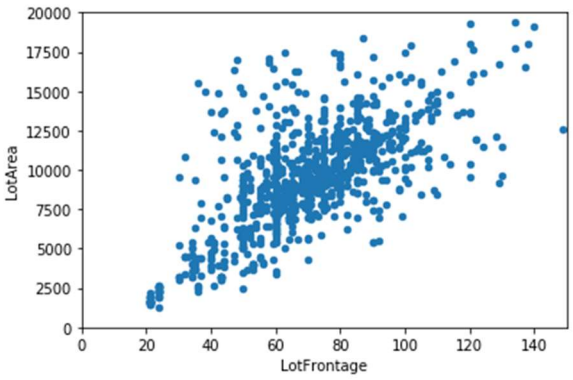
- Create a DataFrame with only the numeric columns;
- Inspect the NaN with this table, generated by code above

```
GarageYrBlt     81
LotFrontage    259
```

  - Column **GarageYrBlt**: Hopefully, those NaN are for houses without a igarage. Check the unique values of the column GarageType when GarageYrBlt is NaN
  - Column **LotFrontage**: those are legitimate NaNs, too many to discard. Inspecting the columns, we found a **LotArea.** Maybe a scatter plot



    will show a relationship between those two variables
    - We can easily identify the presence of outliers on both dimensions. To better identify the relationship, let us “zoom in” in the plot



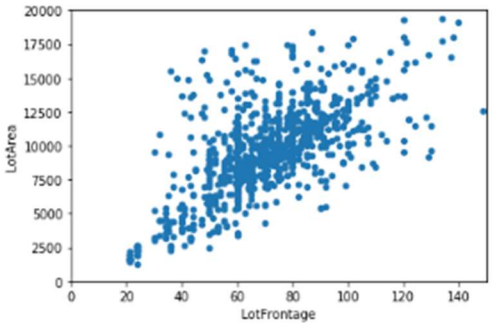
- As suspected, there is a big correlation between those two variables.

Filling those 259 NaN from LotFrontage with values that are proportional to the column LotArea makes sense. To do that, we will find the equation that best represents the linear regression between these two columns and apply it to replace the NaNs. We used LinearRegression() from scikit learn to find that equation, as shown below:

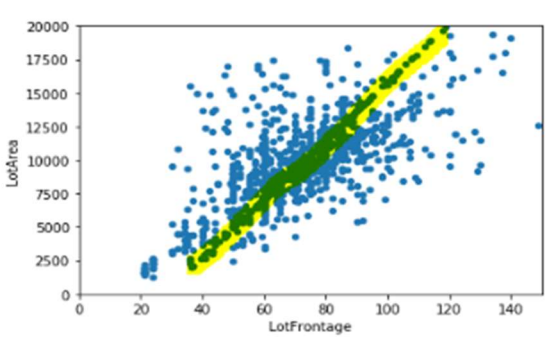
```
#filter out NaN
dfLotTrain = df[np.logical_not(np.isnan(df['LotFrontage']))]
dfLotTest = df[np.isnan(df['LotFrontage'])]

#apply method
model = LinearRegression()
model.fit(dfLotTrain['LotArea'].values.reshape(-1, 1), dfLotTrain['LotFrontage'].values.reshape(-1, 1))
aux = model.predict(dfLotTest['LotArea'].values.reshape(-1, 1))
dfLotTest = dfLotTest.assign(LotFrontage=aux)
```

Here is the before and after this procedure:

BEFORE



AFTER



Consistency among columns

If a house has no garage, all columns related to “garage” should reflect this fact. We have already done this for MasVnrType column on item 1 of this report, now let us take the same approach for garage, Basement, fireplace, pool, and miscellaneous features. Please check the long code below:

```
#Garage
collist = ['GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond']
df.GarageType== 'No Item'
myDict = {}

for col in collist:
    myDict[col] = []

for index, row in df.iterrows():
    if(df.loc[index, 'GarageType'] == 'No Item'):
        for col in collist:
            myDict[col].append(row[col])

dfGarage = pd.DataFrame(myDict)

for col in dfGarage.columns:
    print(col, '- ', dfGarage[col].unique())

#Basement
collist = ['BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2',
           'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath']
df.BsmtQual == 'No Item'
myDict = {}

for col in collist:
    myDict[col] = []

for index, row in df.iterrows():
    if(df.loc[index, 'BsmtQual'] == 'No Item'):
        for col in collist:
            myDict[col].append(row[col])

dfBsmt = pd.DataFrame(myDict)

for col in dfBsmt.columns:
    print(col, '- ', dfBsmt[col].unique())

#Fireplace
 print(df[['Fireplaces', 'FireplaceQu']][(df.FireplaceQu == 'No Item') & (df.Fireplaces != 0 )])

#Pool
print(df[['PoolArea', 'PoolQC']][(df.PoolQC == 'No Item') & (df.PoolArea != 0 )])

#miscellaneous
print(df[['MiscFeature', 'MiscVal']][(df.MiscFeature == 'No Item') & (df.MiscVal != 0 )])
```

which resulted in empty outputs only, meaning no action needs to be taken.

Checking for outliers

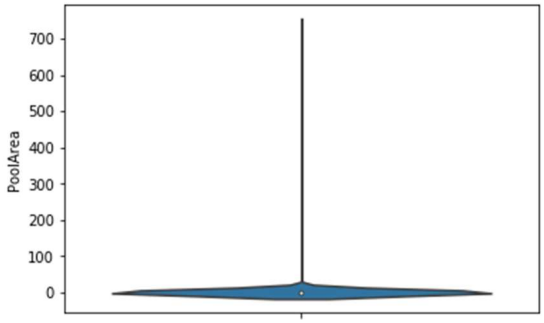
In this section, we are going through a few relevant numerical columns to inspect outliers and decide whether to keep or discard them.

- Violin plots to help inspect the variables

We used this code

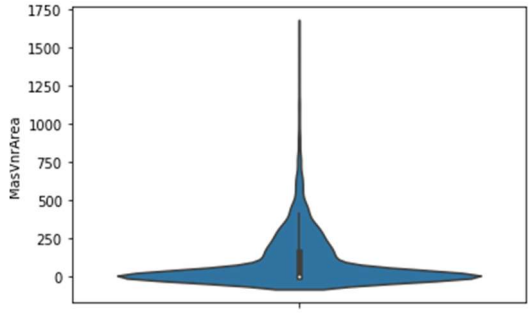
```
for col in dfNumericCols:
    ax = sns.violinplot(y=col, data=df)
    plt.show()
```

to plot violin plots to spot outliers on the other variables. Inspecting each one of the curves, the following called our attention:



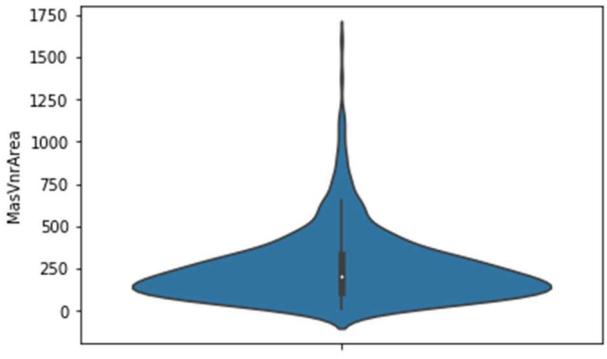
Looking back into the data, this behavior is expected as we only have 7 values different than 0. Maybe this data can help predict house selling prices for specific cases, so we will keep this column as-is.

The same argument goes to columns 3SsdPorch, BsmtFinSF2, LowQualFinSF, MiscVal, ScreenPorch and BsmtHalfBath.



This variable has more than 500 samples different than zero, so let us see if we can find outliers in a violin distribution that ignores the zeros. Here is the code and output

```
ax = sns.violinplot(y='MasVnrArea', data = df[df.MasVnrArea > 0])
```



Now this distribution has only a few outliers that can be useful for some cases and may have a combined effect with other variables, so we will keep it as is.

Exploratory data Analysis - EDA

Our EDA is mainly presented on a Jupyter Notebook called “Story Telling.ipynb”, which is found in the same Github repository. We will show our findings below, but please refer to the original file for more details.

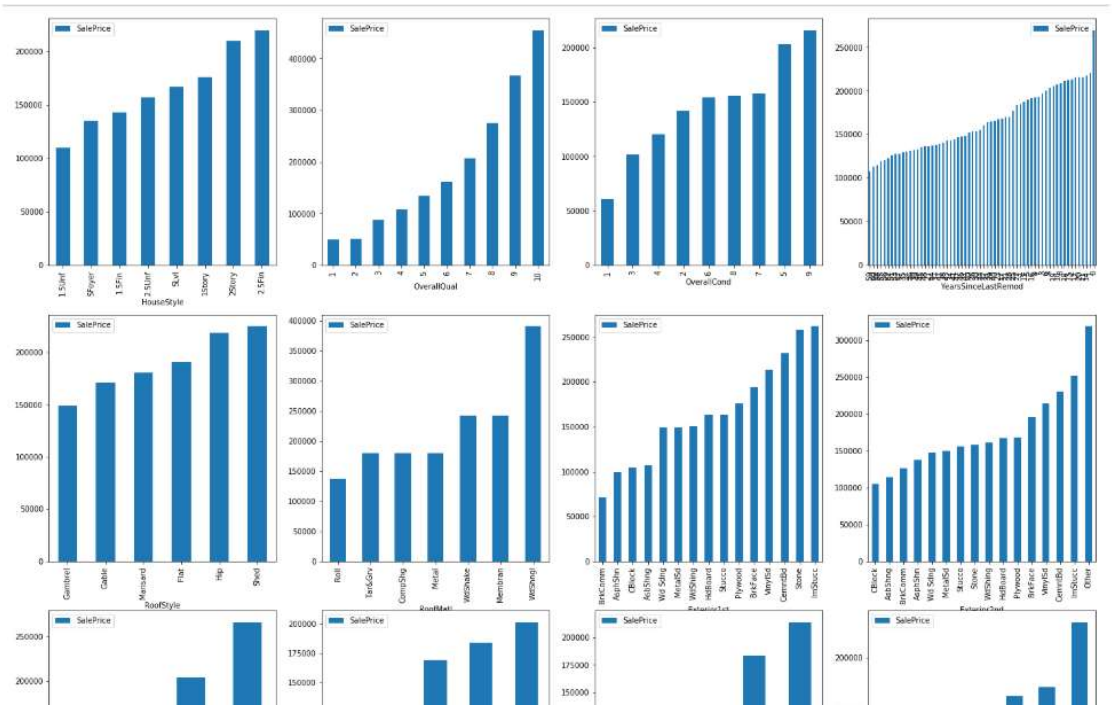
Actionable variables X Selling Price

With the following codes

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math

df = pd.read_csv("DatasetTreated.csv", index_col='Id', header=0)
varList = ['HouseStyle','OverallQual','OverallCond','YearsSinceLastRemod','RoofStyle','RoofMatl','Exterior1st','Exterior2nd',
           'MasVnrType','ExterCond','BsmtCond','BsmtFinType1','BsmtFinType2','HeatingQC','CentralAir','KitchenQual',
           'Functional','PavedDrive','PoolQC','Fence']

fig, axes = plt.subplots(nrows=5, ncols=4)
i=0
j=0
for col in varList:
    df[[col, 'SalePrice']].groupby(col).mean().sort_values('SalePrice').plot(kind="bar", ax=axes[i,j], figsize=(25,35))
    j+=1
    if(j==4):
        j=0
        i+=1

plt.show()
```

```
fig, axes = plt.subplots(nrows=5, ncols=4)
i=0
j=0
for col in varList:
    ax = df[col].value_counts().plot(kind='bar', ax=axes[i,j], figsize=(25,35),title = col)
    for p in ax.patches:
        # get_x pulls left or right; get_height pushes up or down
        ax.text(p.get_x()+.12, p.get_height()+3,
            str(p.get_height()))

    j+=1
    if(j==4):
        j=0
        i+=1

plt.show()
```

we generated several charts at once. This way, we were able to visualize the association of all variables with the Selling Price. You may check part of the output below:



Let us analyse the generated outputs.

a. Roof Style and Roof Material

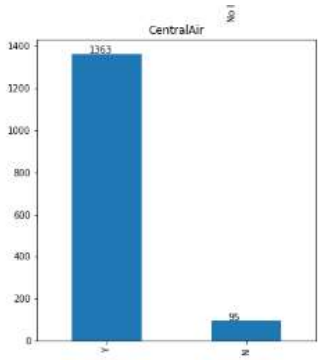
Roof styles are predominantly "Gable" with material "standard Shingle". As we have very few observations of the other types of Roof and types of material, we cannot draw statistically relevant conclusions. As a result, this variable will not be among those we will suggest being improved.

b. Pool Quality

Not enough houses with pools to draw significant conclusions. Improving the quality of the pool will not be suggested to owners.

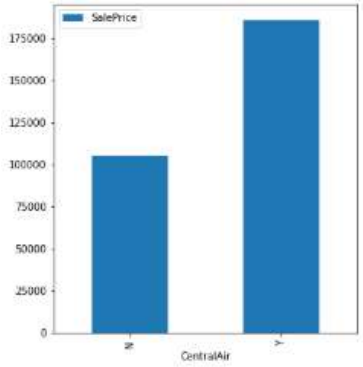
c. Central Air

Most of the houses on this sample have central air, as shown below:



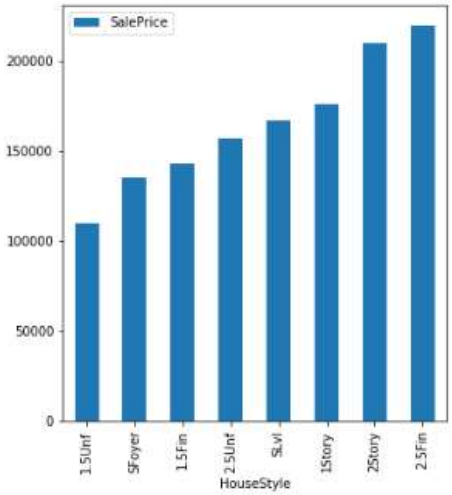
which means that it is possible to find houses with several combinations of the other variables that have that feature. In other words, a buyer will either look for another house or make a low offer. We understand it is not a simple

service but, comparing a house with central air with a similar one without central air, we notice an increment of $80,000 on average, as seen below.



d. Price based on number of stories

We were not expecting the average selling price of a 1 story house being more expensive than a one and a half story (finished or unfinished) and more expensive than a two stories house with 2nd level unfinished.

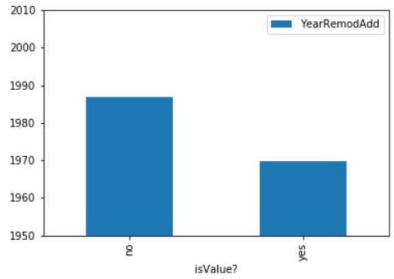


We investigated this and found that:

- 1.5 and 2 stories houses with 2nd level unfinished are located in "poor" neighborhoods

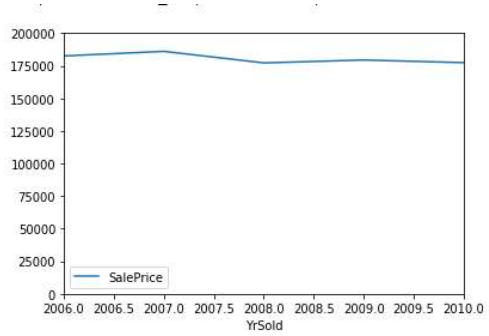
```
 STYLE   - % ON POOR NEIGHBORHOODS
1.5Unf   -  71.0%
1.5Fin   -  73.0%
2.5Unf   -  91.0%
```

- 1.5 and 2 stories houses with 2nd level unfinished are older



e. Selling prices do not increase along the years

We do not need to take into consideration the inflation over the years, as the average selling price does not change significantly

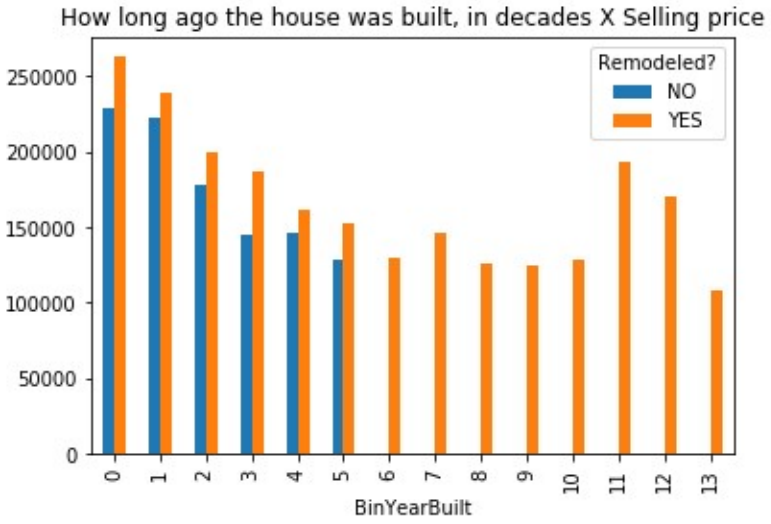


f. Basement improvement

The jump on the average selling price when the basement finished area goes from any category to Good Living Quarters is enormous. It is almost $100,000.00. Which means: if the owner is improving their basement, they better make a great job. Otherwise, the basement may fall into an average quality and they will lose the investment.

g. Difference in price between remodelled houses X non-remodelled houses

We were able to prove that the difference in price of remodelled houses is indeed more expensive than non-remodelled houses, which is the cornerstone of our project. The following plot helps us see that:



Another interesting fact this chart shows is that every house built more than 60 years ago has undergone a house improvement.

Inferential Statistics

The last chart presented in the previous section is by far the most important we produced in this report because it makes the whole project viable. With that in mind, this section will apply hypothesis test to confirm what the data is showing us.

Considering that the smallest difference between the prices was shown for houses in bin 4 (built between 40 - 49 years before selling), if we can prove that the difference in the mean price for houses that were remodelled and houses that were not is statistically significant, the other houses, that fit other bins, will also be significant.

Let us find the p-value associated with the following hypothesis test (1-sided):

For houses built between 40 to 49 years ago:

H0: Mean(remodelled) – Mean(not-remodelled) = 0

H1: Mean(remodelled) – Mean(not-remodelled) > 0

We will estimate the mean and the standard deviation from the sample and use t-statistic.

Using python code,

```
dfBin4 = df[df.BinYearBuilt == 4]
groupRemod = dfBin4[dfBin4['Remodeled?']=='yes']['SalePrice']
groupNoRemod = dfBin4[dfBin4['Remodeled?']=='no']['SalePrice']

import scipy.stats as stats
stats.ttest_ind(a=groupRemod,b=groupNoRemod)
```

```
Ttest_indResult(statistic=2.61985113389767, pvalue=0.009547840858910668)
```

we notice that the p-value is less then 1%, confirming that we should reject our null hypotheses and accept that remodelled houses tend to be sold for more.

Machine Learning Models

To confidently suggest home improvements to homeowners, we need to predict the future value of their property after the job is done. In this section, we are analysing a few machine learning models to help us in this crucial matter. It is important to note that not all models tested are shown in the table for the sake of simplicity, because a lot of parameters tweaking was done to generate this table.

For all models:

- We used all columns: Categorical, numeric and the ones created during visual analysis;
- To use the categorical data, we first added the data from the "test.csv" file to the training data, then we generated dummy columns. Later we removed the test data and trained the model. This way, we guarantee that the columns on both training and testing dataset are the same.

Below is a table that summarizes all our efforts. There are links to the codes in the Appendix, a quick description of each model and their respective scores*.

ID	Model Family	Description	Kaggle Score*	Local Score**
1	LinearRegression()	- The column "LotFrontage" had the missing values filled by an equation determined on Excel; - Data not normalized	0.19883	-
2	LinearRegression()	- The column "LotFrontage" had the missing values filled by an equation determined on Excel; - Data normalized	1.55232	-
3	LinearRegression()	- Column "LotFrontage" calculated with LinearRegression(); - Data not normalized	0.19921	0.09799
4	LassoCV()	CV = 3 Alpha = 100	0.15103	0.87345
5	LassoCV()	CV = 5 Alpha = 110	0.15297	-
6	SVC()	Did not work. Predicted all rows with the same values	-	-
7	LinearSVC()	No parameters tweaking	0.40867	
8	ElasticNet()	-Pipeline with StandardScaler and GridSearchCV - L1_ratio = 0.74	0.15345	0.84387
9	ElasticNet()	- Without StandardScaler - Execution cancelled after 2 hours	-	-
10	RandomForest()	- 'RF__max_depth': 3	0.32349	-
11	RandomForest()	- 'RF__max_depth': 4 GridSearchCV → cv = 5	0.30828	-
12	RandomForest()	- 'RF__max_depth': 7, - 'RF__n_estimators': 110 - GridSearchCV → cv = 5	0.25614	-

13	RandomForest()	- 'RF__max_depth': 8, - 'RF__n_estimators': 200 - GridSearchCV → cv = 5	0.25075	0.01027
14	GradientBoosting()	All parameters default	0.13650	-
15	GradientBoosting()	- 'grad__learning_rage': 0.05 - 'grad__n_estimators': 1000	0.13327	0.90036

*Score obtained by submitting the predictions to the Kaggle competition. The Benchmark score is 0.40890. For the testing dataset, we do not have access to the actual values of the properties selling prices.

**R square scores calculated from the training dataset, where 20% of the data was used as the testing dataset, to compare the predictions with the actual selling prices. Here is the code we used to split the data:

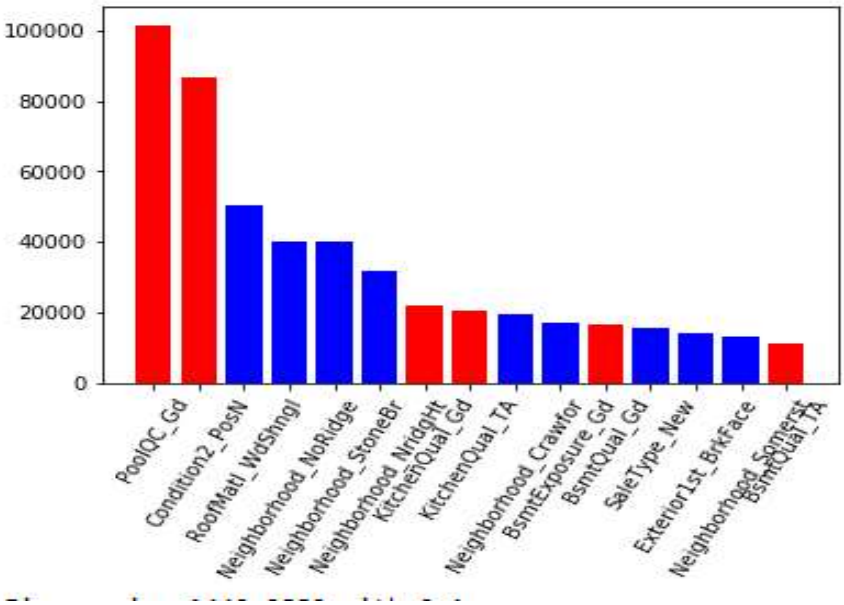
```
# -*- coding: utf-8 -*-
"""
Created on Wed Apr 15 19:47:24 2020

@author: Rafael"""

import pandas as pd
from sklearn.linear_model import LassoCV
from sklearn.model_selection import train_test_split

#read training file
df = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)

#Separate last column (target)
X = df.iloc[:, 0:-1]
y = df.iloc[:, -1]

#generate dummy columns
X = pd.get_dummies(X, drop_first = True)

#train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#run the model
#MY MODEL HERE
reg.fit(X_train, y_train)

#calculate Score
print(reg.score(X_test, y_test))
```

* We replaced line 25 by the models being evaluated to generate the column of local errors.

Using the best model (ID=15, GradientBoostingRegressor()), we are now interested to check which features impact the selling price the most. Using this code

```
df_feat = pd.DataFrame(index=X_aux.columns, data={'Reg_Coef':reg.coef_})
df_feat['Signal'] = df_feat.apply(lambda x: 'Pos' if(x['Reg_Coef']>0) else 'Neg', axis=1)
df_feat['Abs'] = df_feat.apply(lambda x: np.abs(x['Reg_Coef']), axis=1)
df_feat = df_feat.sort_values(by=['Abs'], ascending=False).head(15)

plt.bar(df_feat.index, df_feat.Abs, color=df_feat.Signal.map({'Pos':'blue', 'Neg':'red'}))
plt.xticks(rotation=60)
plt.figure(figsize=(20,40))
plt.show()
```

We generate the following bar chart:



Red and blue columns are the features that affect negatively and positively the Selling Price, respectively.

For our purposes, we can confidently apply this model to potential homeowners willing to sell their property and suggest which home improvement would better increase their selling price.

Conclusion

With the help of charts, we were able to Explore our dataset and expose some interesting findings, the most important of them being the increment on the Selling price of a house after improvement. We were able to prove with 99% confidence that houses that undergo home improvements tend to be sold for more, validating our hypothesis and our project.

Finally, we built a robust Machine Learning model, capable of supporting decisions to homeowners. The model may be applied in specific cases. For example, by simply imputing data about a house, the owner will be able to learn how much the value of his house will increase in case they finish remodelling their basement. With this increment in mind, the owner may take a proper decision regarding hiring home improvement services to finish their basement.

Ideally, the second part of this project would be to contact home improvement service providers, get a quote for generic jobs, and offer the owners a list of home improvements along with their cost and the expected increment on the final Selling Price. As stated on the introduction, this is not part of the scope of this project.

Appendix

Please find the codes used to test different Machine Learning models

3 – LinearRegression

```
import pandas as pd
from sklearn.linear_model import LinearRegression

df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data from the testing dataset will alse be present
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)

reg = LinearRegression()
reg.fit(X_train, y_train)

#print(X_train.columns)
#print(X_test.columns)
#print(reg.predict(X_test))

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': reg.predict(X_test)})
result.to_csv("submission_Rafael3.csv", index=False)
```

5 – LassoCV

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LassoCV

df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data from the testing dataset will alse be present
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)

#reg = LassoCV(cv=5, alphas=[10, 60, 100, 200, 500, 1000], max_iter=10000, random_state=0).fit(X_train, y_train)
reg = LassoCV(cv=5, alphas=[110], max_iter=10000, random_state=0).fit(X_train, y_train)

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': reg.predict(X_test)})
result.to_csv("submission_Rafael_LassoCVBest.csv", index=False)
```

6 - SVC

```
@author: Rafael
"""
import pandas as pd
from sklearn.svm import LinearSVC

df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data f
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)

reg = LinearSVC(max_iter=10000).fit(X_train, y_train)

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': reg.predict(X_test)})
result.to_csv("submission_Rafael5.csv", index=False)
```

9 - ElasticNet()

```
@author: Rafael
"""
import pandas as pd
import numpy as np
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import ElasticNet

df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data from the testing dataset will alse be present
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)

steps = [('scaler', StandardScaler()), ('elasticnet', ElasticNet(max_iter=100000))]
pipeline = Pipeline(steps)

parameters = {'elasticnet__l1_ratio':np.linspace(0,1,100)}
#parameters = {'l1_ratio':np.linspace(0,1,100)}

reg = GridSearchCV(pipeline, param_grid=parameters)
#reg = GridSearchCV(ElasticNet(max_iter=100000), param_grid=parameters)
reg.fit(X_train, y_train)

#print(X_train.columns)
#print(X_test.columns)
#print(reg.predict(X_test))

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': reg.predict(X_test)})
result.to_csv("submission_Rafael7.csv", index=False)
```

13 - RandomForest()

```
@author: Rafael
"""
import pandas as pd
import numpy as np
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier

df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data from the testing dataset will alse be present
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)

steps = [('scaler', StandardScaler()), ('RF', RandomForestClassifier(random_state=0))]
pipeline = Pipeline(steps)

parameters = {'RF__max_depth':np.arange(2,10), 'RF__n_estimators':np.arange(100,600,100)}
#parameters = {'l1_ratio':np.linspace(0,1,100)}

reg = GridSearchCV(pipeline, param_grid=parameters, cv=5)
#reg = GridSearchCV(ElasticNet(max_iter=100000), param_grid=parameters)
reg.fit(X_train, y_train)

print(reg.best_params_)

#print(X_train.columns)
#print(X_test.columns)
#print(reg.predict(X_test))

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': reg.predict(X_test)})
result.to_csv("submission_Rafael8diff.csv", index=False)
```

15 - GradientBoosting()

```
@author: Rafael
"""
import pandas as pd
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.ensemble import GradientBoostingRegressor


df_train = pd.read_csv('DatasetTreated.csv', index_col=0, header=0)
df_test = pd.read_csv('DatasetTreated_test.csv', index_col=0, header=0)

X_aux = df_train.iloc[:, 0:-1]
y_train = df_train.iloc[:, -1]

#save the number of the last row in the training dataset. Useful to unappend later
lastRow = X_aux.shape[0]

#append test dataset, so when the dummy columns are generated, any categorical data from the testing dataset will alse be present
X_aux = X_aux.append(df_test)

#generate dummy columns
X_aux = pd.get_dummies(X_aux, drop_first = True)
#X_aux.to_csv("cols_train_all.csv", index=False)

#split back to train/test
X_train = X_aux.iloc[:lastRow,:]
X_test = X_aux.iloc[lastRow:,:]

#generate csvs to check
#X_train.to_csv("cols_train.csv", index=False)
#X_test.to_csv("cols_test.csv", index=False)
steps = [('scaler', StandardScaler()), ('gradient', GradientBoostingRegressor(random_state=0, learning_rate=0.05, n_estimators=1000))]
pipeline = Pipeline(steps)

#parameters = {'gradient__learning_rate':[0.01, 0.05, 0.1], 'gradient__n_estimators':[500, 1000, 1500, 2000]}
#parameters = {'l1_ratio':np.linspace(0,1,100)}

#reg = GridSearchCV(pipeline, param_grid=parameters, cv=5, scoring='r2')
pipeline.fit(X_train, y_train)

#print(reg.score(X_test, y_test))

#print(X_train.columns)
#print(X_test.columns)
#print(reg.predict(X_test))

result = pd.DataFrame({'Id':X_test.index, 'SalePrice': pipeline.predict(X_test)})
result.to_csv("submission_Rafael_gradBoostCV.csv", index=False)
```