Homework 3 - Ames Housing Dataset

For all parts below, answer all parts as shown in the Google document for Homework 3. Be sure to include both cod
answer the questions. We also ask that code be commented to make it easier to follow.

Part 1 - Pairwise Correlations

I have taken the following columns for finding the Pearson Correlation Coefficient between them. All of them are nu
in the correlation analysis as I feel that would be pretty helpful to analyse the correlation of different variables with t
candidates to include in our prediction model.

1) LotFrontage
2) LotArea 3) OverallQual 4) OverallCond 5) SalePrice 6) GarageArea 7) TotRmsAbvGrd 8) TotalBsmtSF 9) YearRem
BedroomAbvGr 13) GarageYrBlt 14) 2ndFlrSF 15) LowQualFinSF

```
#importing all the necessary libraries

import pandas as pd
from pandas import *
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from scipy.stats.stats import pearsonr
import itertools
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import KMeans
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import r2_score
!pip install xgboost
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
from sklearn.kernel_ridge import KernelRidge
from sklearn import linear_model
from sklearn import preprocessing

train_houses = pd.read_csv('C:/Fall2019/DSF/Assignment2/Data/train.csv')
train_houses.head()
```

```
Requirement already satisfied: xgboost in c:\users\rutvi\appdata\local\continuum\anacond
Requirement already satisfied: scipy in c:\users\rutvi\appdata\local\continuum\anaconda3
Requirement already satisfied: numpy in c:\users\rutvi\appdata\local\continuum\anaconda3
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl

5 rows × 81 columns

```
train_houses_correlation_columns = train_houses[['LotFrontage', 'LotArea', 'OverallQual', 'Ov
train_houses_not_null = train_houses_correlation_columns.dropna(axis = 0, how='any')
correlations = {}
columns = ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'SalePrice', 'GarageArea',

for col_a, col_b in itertools.combinations(columns, 2):
    correlations[col_a + '__' + col_b] = pearsonr(train_houses_not_null.loc[:, col_a], train_

correlation_result = DataFrame.from_dict(correlations, orient='index')
correlation_result.columns = ['PCC', 'p-value']
correlation_result = correlation_result[['PCC']]
correlation_result = correlation_result.sort_values(by=['PCC'], ascending=False)
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  print(correla
```

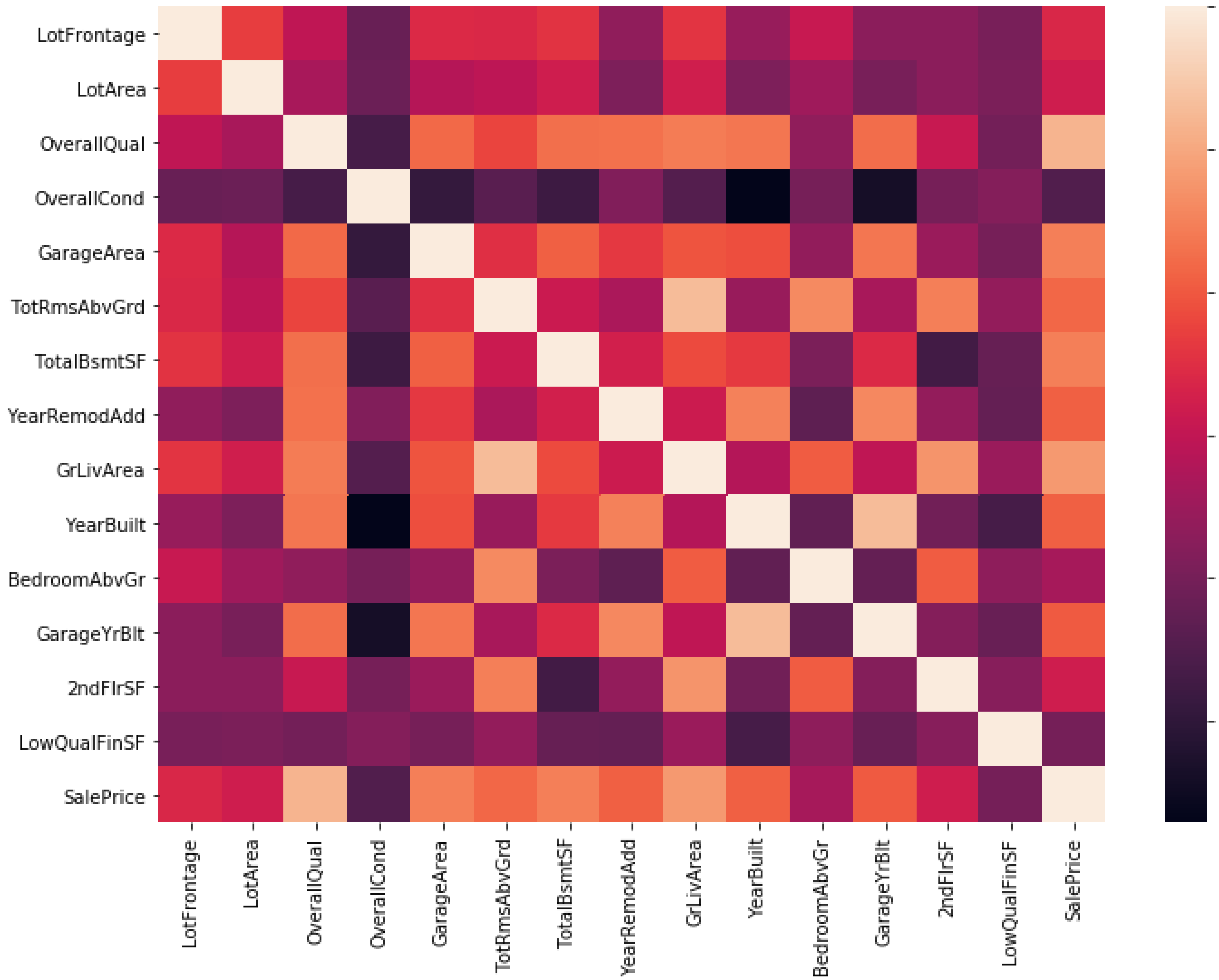
```
                                   PCC
YearBuilt__GarageYrBlt        0.824558
TotRmsAbvGrd__GrLivArea       0.823793
OverallQual__SalePrice        0.799069
SalePrice__GrLivArea          0.704202
GrLivArea__2ndFlrSF           0.687342
TotRmsAbvGrd__BedroomAbvGr    0.650929
YearRemodAdd__GarageYrBlt     0.647651
YearRemodAdd__YearBuilt       0.625157
SalePrice__GarageArea         0.620812
TotRmsAbvGrd__2ndFlrSF        0.617704
SalePrice__TotalBsmtSF        0.617345
OverallQual__GrLivArea        0.606944
GarageArea__GarageYrBlt       0.592711
OverallQual__YearBuilt        0.590791
OverallQual__YearRemodAdd     0.571944
OverallQual__TotalBsmtSF      0.565761
OverallQual__GarageYrBlt      0.561982
OverallQual__GarageArea       0.552446
SalePrice__TotRmsAbvGrd       0.544031
SalePrice__YearBuilt          0.525195
GarageArea__TotalBsmtSF       0.523317
SalePrice__YearRemodAdd       0.520913
BedroomAbvGr__2ndFlrSF        0.511138
GrLivArea__BedroomAbvGr       0.510335
SalePrice__GarageYrBlt        0.504690
GarageArea__GrLivArea         0.487904
GarageArea__YearBuilt         0.471922
TotalBsmtSF__GrLivArea        0.464377
OverallQual__TotRmsAbvGrd     0.447723
LotFrontage__LotArea          0.421760
TotalBsmtSF__YearBuilt        0.409777
GarageArea__YearRemodAdd      0.408310
LotFrontage__GrLivArea        0.396957
LotFrontage__TotalBsmtSF      0.388917
GarageArea__TotRmsAbvGrd      0.380526
LotFrontage__GarageArea       0.357199
TotalBsmtSF__GarageYrBlt      0.353830
LotFrontage__TotRmsAbvGrd     0.349225
LotFrontage__SalePrice        0.345879
TotalBsmtSF__YearRemodAdd     0.309803
LotArea__GrLivArea            0.307297
SalePrice__2ndFlrSF           0.302984
LotArea__TotalBsmtSF          0.302551
LotArea__SalePrice            0.299455
YearRemodAdd__GrLivArea       0.289624
TotRmsAbvGrd__TotalBsmtSF     0.281844
LotFrontage__BedroomAbvGr     0.270695
OverallQual__2ndFlrSF         0.270101
GrLivArea__GarageYrBlt        0.243457
LotFrontage__OverallQual      0.243025
LotArea__TotRmsAbvGrd         0.238426
LotArea__GarageArea           0.211345
GrLivArea__YearBuilt          0.204875
TotRmsAbvGrd__YearRemodAdd    0.179377
LotArea__OverallQual          0.167328
TotRmsAbvGrd__GarageYrBlt     0.164382
```

```
SalePrice__BedroomAbvGr      0.161764
LotArea__BedroomAbvGr        0.137770
GrLivArea__LowQualFinSF      0.121840
GarageArea__2ndFlrSF         0.121342
TotRmsAbvGrd__YearBuilt      0.118799
LotFrontage__YearBuilt       0.109935
TotRmsAbvGrd__LowQualFinSF   0.102376
YearRemodAdd__2ndFlrSF       0.102239
GarageArea__BedroomAbvGr     0.091884
OverallQual__BedroomAbvGr    0.089983
LotFrontage__YearRemodAdd    0.086702
BedroomAbvGr__LowQualFinSF   0.082355
LotArea__2ndFlrSF            0.074124
LotFrontage__2ndFlrSF        0.073978
LotFrontage__GarageYrBlt     0.070250
2ndFlrSF__LowQualFinSF       0.062342
OverallCond__LowQualFinSF    0.048900
GarageYrBlt__2ndFlrSF        0.048563
OverallCond__YearRemodAdd    0.037491
LotArea__YearBuilt           0.028729
LotArea__YearRemodAdd        0.026420
TotalBsmtSF__BedroomAbvGr    0.024150
LotArea__LowQualFinSF        0.020070
LotArea__GarageYrBlt         0.013292
LotFrontage__LowQualFinSF    0.011040
OverallCond__2ndFlrSF        0.007294
OverallCond__BedroomAbvGr    0.006689
GarageArea__LowQualFinSF     0.005406
SalePrice__LowQualFinSF     -0.001897
OverallQual__LowQualFinSF   -0.008694
YearBuilt__2ndFlrSF         -0.012444
LotArea__OverallCond        -0.034330
LotFrontage__OverallCond    -0.046745
GarageYrBlt__LowQualFinSF   -0.046795
TotalBsmtSF__LowQualFinSF   -0.048074
YearRemodAdd__LowQualFinSF -0.053900
BedroomAbvGr__GarageYrBlt   -0.055587
YearBuilt__BedroomAbvGr     -0.065047
YearRemodAdd__BedroomAbvGr -0.078837
OverallCond__TotRmsAbvGrd   -0.095429
OverallCond__GrLivArea      -0.112204
OverallCond__SalePrice      -0.125475
YearBuilt__LowQualFinSF     -0.164479
OverallQual__OverallCond    -0.164751
TotalBsmtSF__2ndFlrSF       -0.178859
OverallCond__TotalBsmtSF    -0.194055
OverallCond__GarageArea     -0.226959
OverallCond__GarageYrBlt    -0.343965
OverallCond__YearBuilt      -0.426921
```

```
a4_dims = (11.7, 8.27)
fig, ax = plt.subplots(figsize=a4_dims)
sns.heatmap(train_houses_not_null.corr(),ax=ax)
```

```
print("Heatmap for the correlation co-efficients")
```

```
Heatmap for the correlation co-efficients
```



Discuss most positive and negative correlations.

Most Positive Correlations:

1) YearBuilt__GarageYrBlt 0.824558

This correlation tells us that the earlier the house was built, the earlier they built the garage. Most of the houses hav
subtracted the year the house was built from the year the garage was built. Most of the values were 0, which means
built.

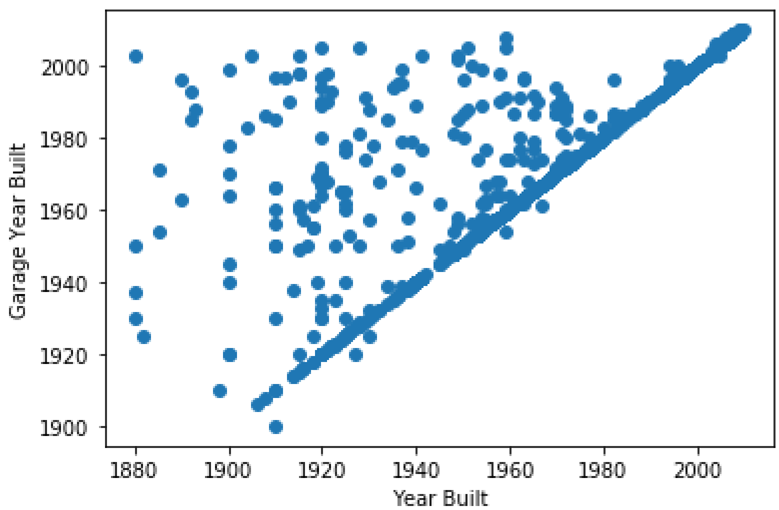
One interesting thing I found out while taking the difference of the years was that some differences were negative. T
the house. It may possibly be a mistake or the garage was built first and then it was extended to a house!

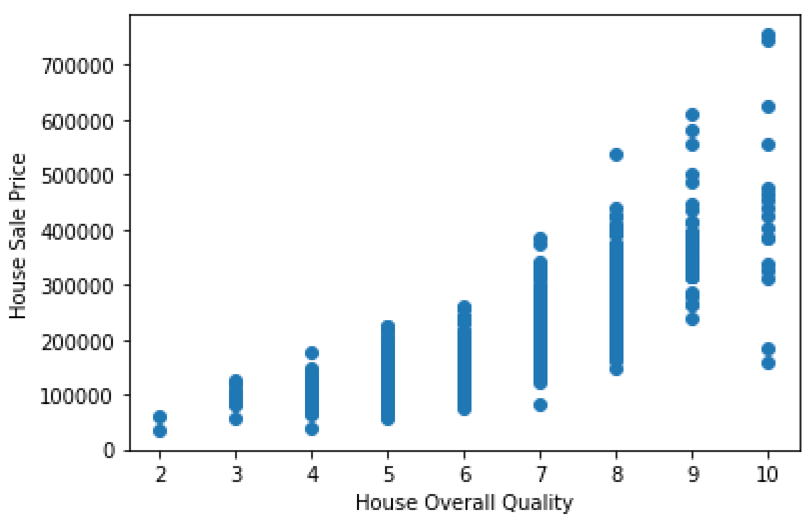
2) OverallQual__SalePrice 0.799069

Even this should not come as a surprise as this is the expected behaviour. The better the quality of the house, the hi
this can be seen below. One interesting thing to note here is that each overall quality has some range of Sale Price.
increase the overall quality. For example, 'Overall Quality' --> 2 has a range of Sale Price somewhere between 10,000
Sale Price of 50,000 t o 1,30,000. The ranges for overall quality are overlapping, but the maximum value of 'Sale Pric

```
plt.scatter(train_houses_not_null['YearBuilt'], train_houses_not_null['GarageYrBlt'])
```

```
plt.scatter(train_houses_not_null['YearBuilt'], train_houses_not_null['GarageYrBlt'])
plt.xlabel('Year Built')
plt.ylabel('Garage Year Built')
plt.show()


plt.scatter(train_houses_not_null['OverallQual'], train_houses_not_null['SalePrice'])
plt.xlabel('House Overall Quality')
plt.ylabel('House Sale Price')
plt.show()
```





Most negative correlations:

1) OverallCond__YearBuilt -0.426921

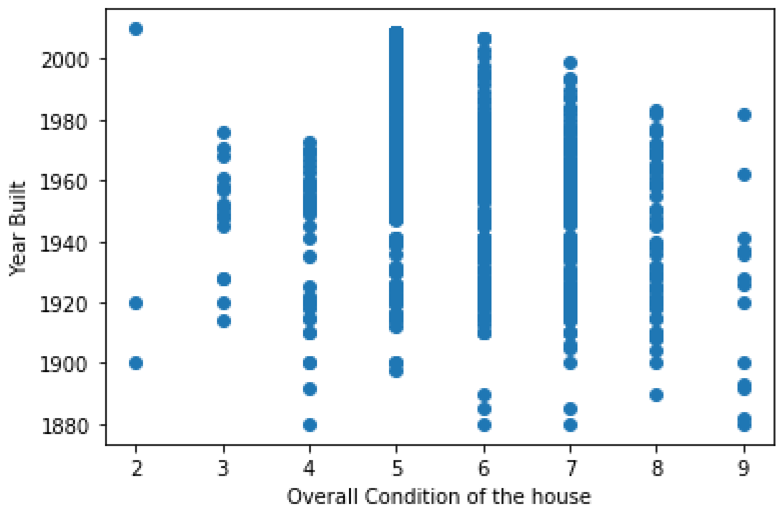
This correlation tells us that the earlier the house was built, the overall condition deteriorated Although, it's not a stro the house was also remodelled. This is proven by the fact that 'YearRemodAdd' and 'OverallQual' of the house is cor house was remodeled is given by the column 'YearRemodAdd'.

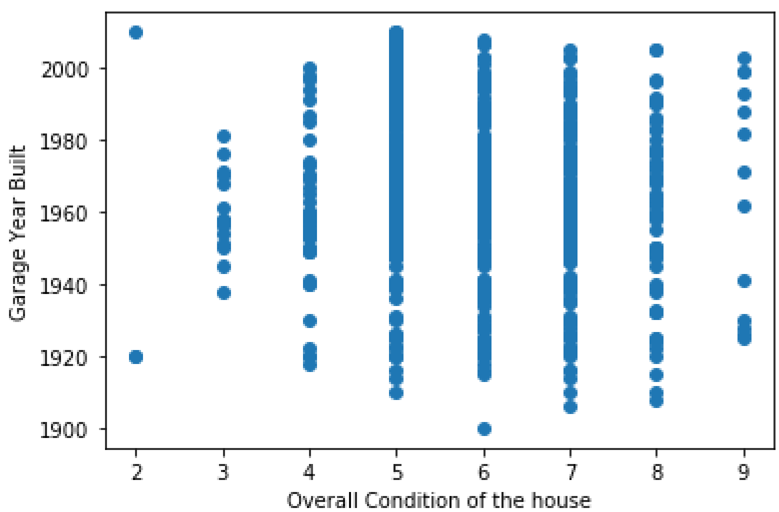
2) OverallCond__GarageYrBlt -0.343965

This correlation tells us about the relation between the overall condition of the house and the year the garage was bı condition of the house.

The scatter plots for both of these negative correlations can be seen below.

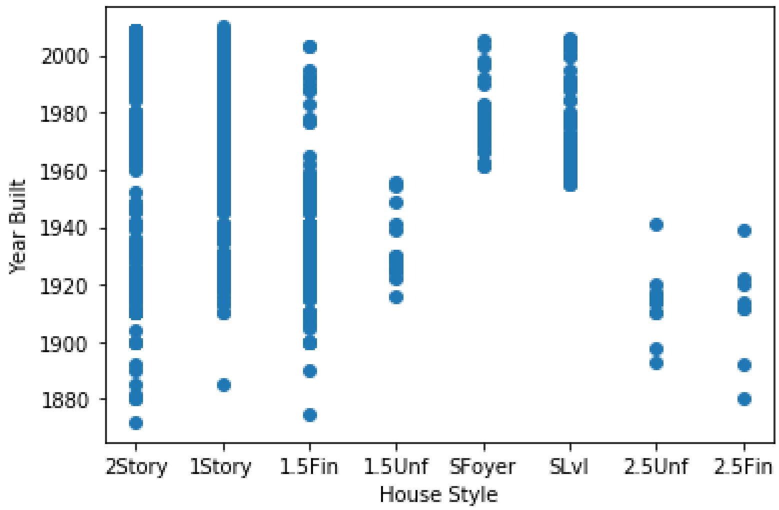
```
plt.scatter(train_houses_not_null['OverallCond'], train_houses_not_null['YearBuilt'])
plt.xlabel('Overall Condition of the house')
plt.ylabel('Year Built')
plt.show()

plt.scatter(train_houses_not_null['OverallCond'], train_houses_not_null['GarageYrBlt'])
plt.xlabel('Overall Condition of the house')
plt.ylabel('Garage Year Built')
plt.show()
```





Part 2 - Informative Plots

```
# code to generate Plot 1

# Scatter Plot of House Style v/s Year Built
plt.scatter(train_houses['HouseStyle'], train_houses['YearBuilt'])
plt.xlabel('House Style')
plt.ylabel('Year Built')
plt.show()
```



What interesting properties does Plot 1 reveal?

The most interesting properties that the Plot 1 reveal are the ranges of years for which a particular house style was

The most popular version of the house people preferred in Ames was 2Story building.

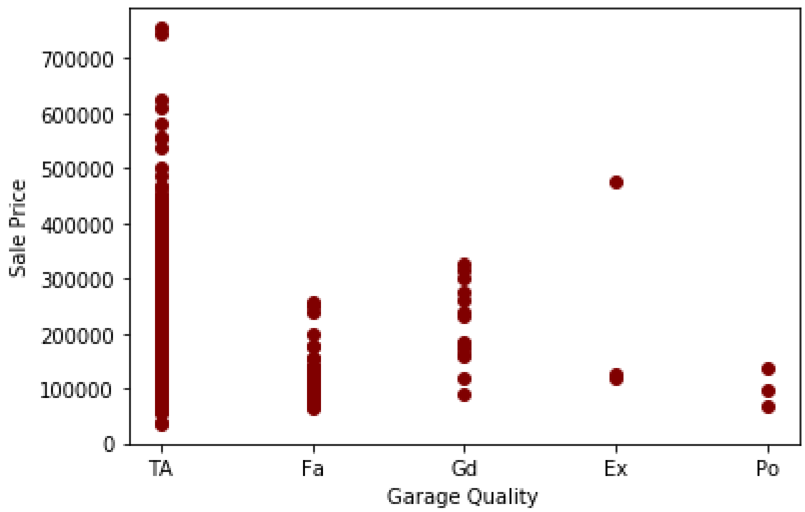
For example, the construction for 2Story house style began way back in 1800s and it was built evenly till late 2000s

There were a few instances of 1Story buildings in 1880's and then the construction of 1Story buildings stopped until

The most rare house styles are 1.5Unf, 2.5Unf and 2.5Fin. They were present on on-off basis.

It would be pretty interesting to know the reasons behind why such patterns are observed. Why the construction of a
particular period of time. It may reveal some very interesting back-stories.

```
# code to generate Plot 2

# Scatter plot of Garage Quality vs Sale Price
garagequal_saleprice_notnull = train_houses[['GarageQual', 'SalePrice']].dropna(axis=0, how='
plt.scatter(garagequal_saleprice_notnull['GarageQual'], garagequal_saleprice_notnull['SalePri
plt.xlabel('Garage Quality')
plt.ylabel('Sale Price')
plt.show()
```



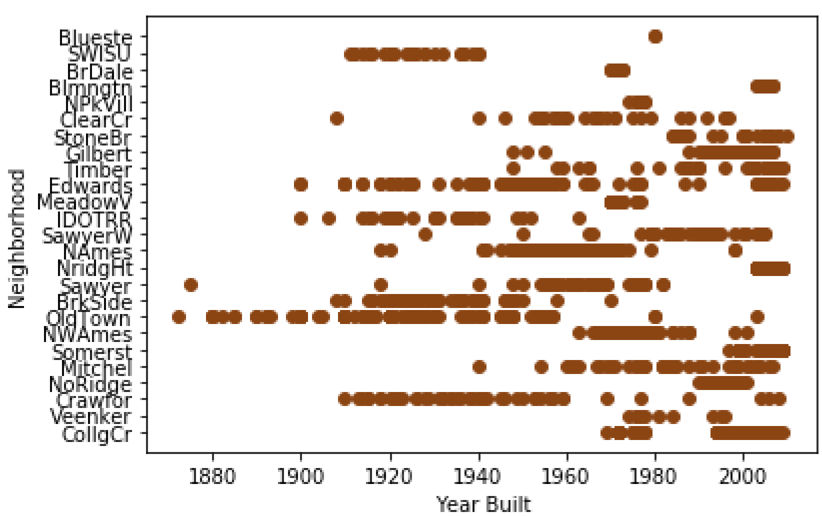
What interesting properties does Plot 2 reveal?

TA - Typical Fa - Fair Gd - Good Ex - Excellent Po - Poor Plot 2 reveals that SalePrice is dependent on Garage Quality l
seeing that Poor garage quality houses have SalePrice mostly on the lower side of the spectrum. Fair, which is a gra
SalePrice. Good garage quality has slightly higher range of values than Fair.

But one interesting thing to note here is that Typical Garage quality is distributed nicely among all the SalePrices anc
garage quality bracket. This tells us that once the Garage Quality reaches a level of Typical, the customer does not fe
But, if the garage quality is below typical, like Poor or Fair, it may affect the price of the house severely and negativel

This tells us the subtlety or the nuance of the effect of Garage Quality on SalePrice.

```
# code to generate Plot 3

# Scatter plot of Neighborhood v/s the year the houses were built there.
plt.scatter(train_houses['YearBuilt'], train_houses['Neighborhood'],color='saddlebrown')
plt.xlabel('Year Built')
plt.ylabel('Neighborhood')
plt.show()
```



What interesting properties does Plot 3 reveal?

Plot 3 reveals interesting things about the year the neighborhood was developed in the city of Ames. We can find ou neighborhoods which were developed quite early.

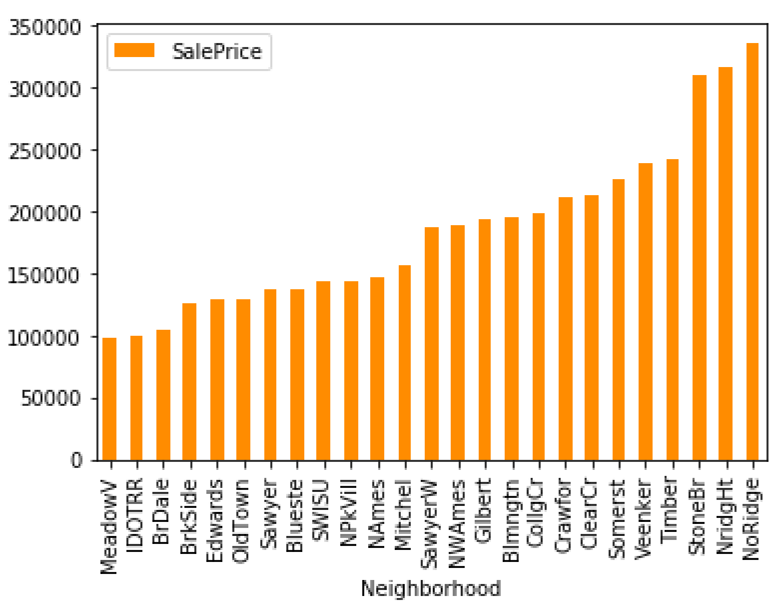
For example, Old Town neighborhood has construction started quite early in 1800s. Blmngtn is a new neighborhood constructed in around 2000s.

There are some areas in which the construction started and continued for a few years or decades and then stopped

It would be interesting to know the reasons behind these gaps. And the reasons behind those gaps could lead to soı

```
# code to generate Plot 4

# Bar graph of neighborhood v/s mean SalePrice
new_data = pd.read_csv('C:/Fall2019/DSF/Assignment2/Data/train.csv')
new_data.Neighborhood.head()
groupby_neighborhood = new_data[['Neighborhood', 'SalePrice']]

neighborhoods = new_data.Neighborhood.unique().tolist()
#neighborhoods_list = neighborhoods.values().tolist()
groupby_neighborhood.shape
ng = groupby_neighborhood.groupby('Neighborhood').mean()
ng = ng.sort_values(by='SalePrice')
print(ng.head())
plot1 = (ng).plot(kind='bar', color='darkorange')
fig= plt.figure(figsize=(6,3))
```

```
                 SalePrice
Neighborhood
MeadowV       98576.470588
IDOTRR       100123.783784
BrDale       104493.750000
BrkSide      124834.051724
Edwards      128219.700000
```

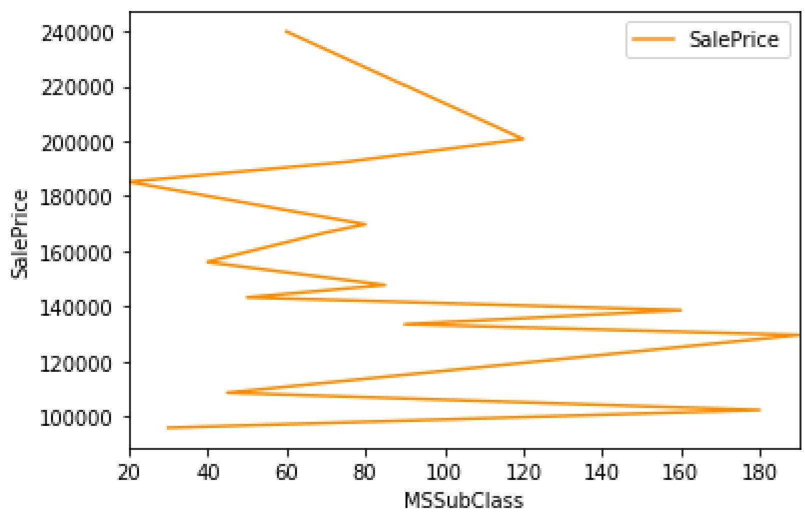


What interesting properties does Plot 4 reveal?

This line chart reveals the relation between the Neighborhood and the Sale Price.

```
# code to generate Plot 5

# Line Graph of MSSubClass v/s SalePrice

MSSubClasses = train_houses.MSSubClass.unique().tolist()
MSSub = train_houses[['MSSubClass', 'SalePrice']]
mg = MSSub.groupby('MSSubClass').mean()
mg = mg.sort_values(by='SalePrice')
print(mg.head())
plot1 = (mg).plot(color='darkorange')
plt.xlabel('MSSubClass')
plt.ylabel('SalePrice')
plt.show()
```

```
                SalePrice
MSSubClass
30           95829.724638
180         102300.000000
45          108591.666667
190         129613.333333
90          133541.076923
```



What interesting properties does Plot 5 reveal?

This plot shows the average SalePrice for a group of MSSubClass.

Part 3 - Handcrafted Scoring Function

```
# TODO: code for scoring function

# Finding correlation between ordinal variables and sale price
ordinal_saleprice = train_houses[['ExterQual', 'ExterCond','BsmtQual', 'BsmtCond', 'HeatingQC
 'GarageCond', 'SalePrice']]
mapper = {'Ex':5, 'Gd':4, 'TA':3, 'Fa':2, 'Po':1}
new_ordinal_saleprice = ordinal_saleprice.replace(mapper)
```

```
new_ordinal_saleprice.fillna(0, inplace=True)

corr1 = new_ordinal_saleprice.corr()
# print(corr1)
house_score_columns = ['OverallQual', 'YearBuilt', 'TotalBsmtSF', 'GrLivArea', 'GarageArea','
house_score_exterqual_ordinal = train_houses[house_score_columns].replace(mapper)
house_score_exterqual_ordinal.fillna(0, inplace=True)
house_score_exterqual_ordinal.head()
corr = house_score_exterqual_ordinal.corr()

corr_saleprice_values = corr['SalePrice'].tolist()
corr_saleprice_values.pop()

# print(corr_saleprice_values)

weights = []
sum = 0
for idx in range(len(corr_saleprice_values)):
    sum+=corr_saleprice_values[idx]

for idx in range(len(corr_saleprice_values)):
    weights.append(corr_saleprice_values[idx]/sum)

house_score_saleprice_dropped = house_score_exterqual_ordinal.drop(columns=['SalePrice'])

# Calculate the maximum possible score
max_score = 0
max_columns = house_score_exterqual_ordinal.max()

max_columns_list = max_columns.tolist()

# Removing the SalePrice column
max_columns_list.pop()

# Find the maximum score possible by multiplying the maximum value in each column with its we
for index in range(len(max_columns_list)):
    max_score+=max_columns_list[index]*weights[index]

column_index = 0;
scores = []
for row in house_score_saleprice_dropped.iterrows():
    score = 0
    for column_index in range(len(weights)):
        score+=row[1][column_index]*weights[column_index]
    score = (score*100)/max_score
    scores.append(score)

house_score_exterqual_ordinal['score'] = scores
house_score_sorted = house_score_exterqual_ordinal.sort_values(by=['score'],ascending=False)
house_score_sorted.insert(0, 'Id', train_houses[['Id']])
display(house_score_sorted.head(10))
```

```
print( Ten most desirable houses )


Id_SalePrice_Score = house_score_sorted[['Id', 'SalePrice', 'score']]
display(Id_SalePrice_Score. head(10))
# train_houses['score'] = scores
# train_houses_sorted = train_houses.sort_values(by=['score'], ascending=False)

# Fetching the 10 most desirable houses
# train_houses_sorted.head(10)
```

	Id	OverallQual	YearBuilt	TotalBsmtSF	GrLivArea	GarageArea	TotRmsAbvGrd	Ex
1298	1299	10	2008	6110	5642	1418	12	
523	524	10	2007	3138	4676	884	11	
1182	1183	10	1996	2396	4476	813	10	
691	692	10	1994	2444	4316	832	10	
496	497	8	1992	3200	3228	546	10	
1169	1170	10	1995	1930	3627	807	10	
440	441	10	2008	3094	2402	672	10	
1373	1374	10	2001	2633	2633	804	8	
1353	1354	8	1995	2033	3238	666	9	
798	799	9	2008	1926	3140	820	11	

```
Ten most desirable houses
```

	Id	SalePrice	score
1298	1299	160000	99.978223
523	524	184750	70.691236
1182	1183	745000	64.011294
691	692	755000	63.264750
496	497	430000	58.221686
1169	1170	625000	54.814496
440	441	555000	52.445614
1373	1374	466500	52.016900
1353	1354	410000	51.697533
798	799	485000	51.397749

What is the ten most desirable houses?

The IDs of the ten most desirable houses (as can be seen in the table above with all column values) are:

Id SalePrice score 1299 160000 99.978223 524 184750 70.691236 1183 745000 64.011294 692 755000 63.26475(
54.814496 441 555000 52.445614 1374 466500 52.016900 1354 410000 51.697533 799 485000 51.397749

```
# Fetching the 10 least desirable houses
house_score_sorted_ascending = house_score_exterqual_ordinal.sort_values(by=['score'])
house_score_sorted_ascending.insert(0, 'Id', train_houses[['Id']])
display(house_score_sorted_ascending.head(10))
print("Ten least desirable houses")
```

	Id	OverallQual	YearBuilt	TotalBsmtSF	GrLivArea	GarageArea	TotRmsAbvGrd	Ex
533	534	1	1946	0	334	0	2	
1100	1101	2	1920	290	438	246	3	
1218	1219	4	1947	0	912	0	3	
710	711	3	1935	270	729	0	5	
1321	1322	3	1949	0	720	287	4	
636	637	2	1936	264	800	0	4	
528	529	4	1920	528	605	0	5	
1323	1324	4	1940	420	708	0	5	
705	706	4	1930	0	1092	0	7	
1035	1036	4	1957	0	845	290	5	

```
Ten least desirable houses
```

What is the ten least desirable houses?

The IDs of the ten least desirable houses (as can be seen in the table above with all column values) are:

Id SalePrice score

534 39300 12.971542 1101 60000 17.025584 1219 80500 17.241422 711 52000 17.557500 1322 72500 17.69130!
1324 82500 18.366807 706 55000 18.472395 1036 84000 18.680118

Describe your scoring function and how well you think it worked.

The notion of desirability was attached to the sense of cost. So, for the scoring function, I used the correlation matri
correlations with 'Sale Price' were the most significant among all the variables. I selected those variables to be used
correlations, I was not getting significant enough correlation with 'Sale Price'. The highest negative correlation was a
negative correlations.

The variables which were selected based on the correlation with 'Sale Price' are:

```
Variable             Correlation with SalePrice
```

1) OverallQual 0.790982 2) YearBuilt 0.522897 3) TotalBsmtSF 0.613581 4) GrLivArea 0.708624 5) GarageArea 0.62
0.682639 8) KitchenQual 0.659600

The last two variables 'ExterQual' and 'KitchenQual' were ordinal variables and converted to numerical values by map
4,'Typical' : 3, 'Fair':2, 'Poor':1, 'NA':0}

The scoring functions calculates a weight to be given to each variable depending upon the extent of its correlation w
score for a particular row by multiplying the weights of the column with the column value.

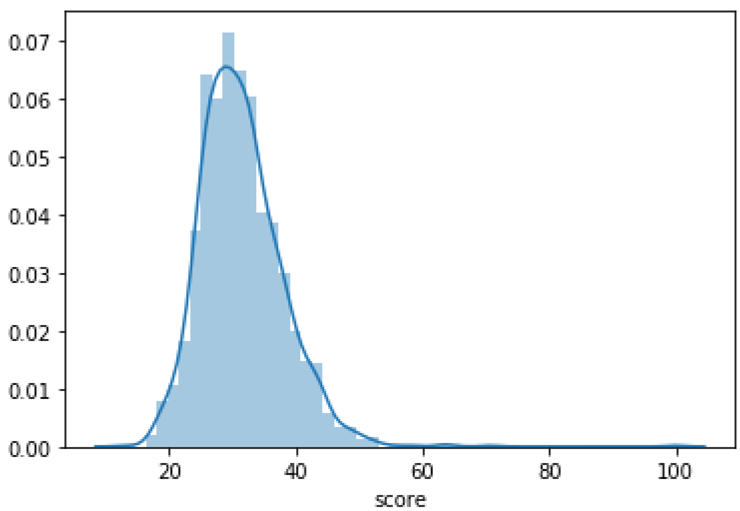
The maximum possible score is calculated and then each score is divided by the maximum possible score and mult
of 100.

If you have a look at the table for the most desirable houses, the top desirable house (ie ID: 1299 sits comfortably at
the second position is at 70.69 This is because of the excellent values of the variables of that particular house. The
highest SalePrice among the whole data. So, I would say that the scoring function works pretty well.

If you have a look at the 10 least desirable houses, they have terrible values of the variables and these things are eve
Price of the house are among the lowest in the whole dataset.

```
# The distribution of the scoring function can be plotted as below
# Most of our houses have a score of 20-60 and there are very few houses which are above 60.
sns.distplot(house_score_sorted_ascending['score'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x195509ae9b0>
```



Part 4 - Pairwise Distance Function

Here, we need to find homes that are similar to each other. This means that homes that are of similar make, similar
house style and many more properties of the house. We will ignore the attributes of the house such as quality of gar
variables are not dependent on the neighborhood. Same quality of the houses can be found in different neighborhoo
related to physical properties of the house.

For assigning distances between a pair of categorical variable values, we will first label encode the categorical varia

```
#  code for distance function
# For each categorical column
# We fit a label encoder, transform our column and
# add it to our new dataframe
cat_columns = {'MSSubClass', 'MSZoning', 'Street', 'Condition1', 'Condition2', 'BldgType','Ho
```

```
dist_houses = train_houses[['Id', 'Neighborhood']]
train_houses_dist = train_houses[['Id', 'Neighborhood', 'MSSubClass', 'MSZoning', 'Street', '

train_houses_dist = train_houses_dist.dropna(how='any')
display(train_houses_dist.shape)


train_houses_dist.head()
train_houses_dist_ohe = train_houses_dist[['MSSubClass', 'MSZoning', 'Street', 'Condition1',

distance_cols = ['LotFrontage', 'LotArea', 'YearBuilt', 'GrLivArea','GarageArea']
distance_data = train_houses[distance_cols]
distance_data.fillna(0, inplace=True)
from sklearn.metrics.pairwise import euclidean_distances


# Calculating the Euclidian distances between two rows in the data
eu_dist = euclidean_distances(distance_data, distance_data)

# getting the normalized euclidian distances

origin = [[0 for i in range(len(eu_dist[0]))] for j in range(len(eu_dist))]
eu_dist_norm = euclidean_distances(eu_dist,origin)

print(eu_dist_norm)
```

```
(1378, 17)
C:\Users\rutvi\AppData\Local\Continuum\anaconda3\lib\site-packages\pandas\core\frame.py:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexi
  downcast=downcast, **kwargs)
[[390036.26774442 390036.26774442 390036.26774442 ... 390036.26774442
  390036.26774442 390036.26774442]
 [383599.423876   383599.423876   383599.423876   ... 383599.423876
  383599.423876   383599.423876  ]
 [383074.67415114 383074.67415114 383074.67415114 ... 383074.67415114
  383074.67415114 383074.67415114]
 ...
 [387385.43792456 387385.43792456 387385.43792456 ... 387385.43792456
  387385.43792456 387385.43792456]
 [383562.17986136 383562.17986136 383562.17986136 ... 383562.17986136
  383562.17986136 383562.17986136]
 [382717.60433249 382717.60433249 382717.60433249 ... 382717.60433249
  382717.60433249 382717.60433249]]
```

```
print(eu_dist)
```

```
[[   0.         1237.70028682 2801.67610548 ...  915.87389962
  1449.96379265 1578.86446537]
 [1237.70028682    0.         1737.74250106 ... 1232.12539946
   311.07073151  384.19656427]
 [2801.67610548 1737.74250106    0.         ... 2304.89045293
  1728.98178128 1454.7982678 ]
 ...
 [ 915.87389962 1232.12539946 2304.89045293 ...    0.
  1431.25748906 1406.1699755 ]
 [1449.96379265  311.07073151 1728.98178128 ... 1431.25748906
    0.          285.75164042]
 [1578.86446537  384.19656427 1454.7982678  ... 1406.1699755
   285.75164042    0.        ]]
```

How well does the distance function work? When does it do well/badly?

I have calculated the Distance matrix between some of the variables. The notion of distance is attached to the neigh similar and hence tend to have a less distance between them.

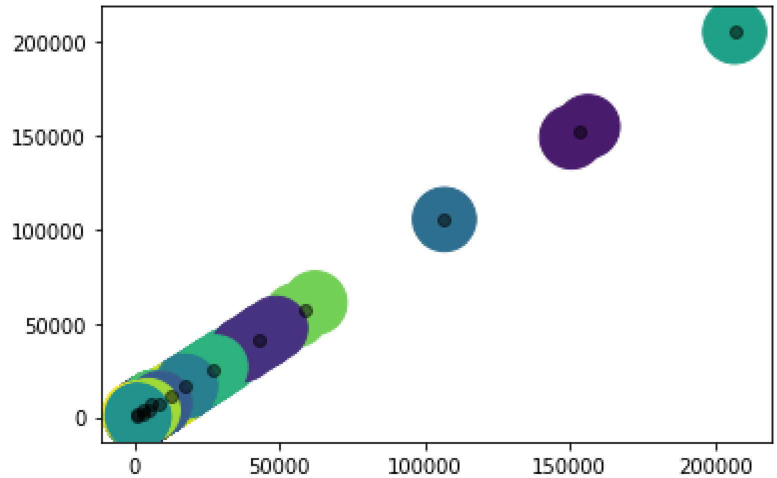
Part 5 - Clustering

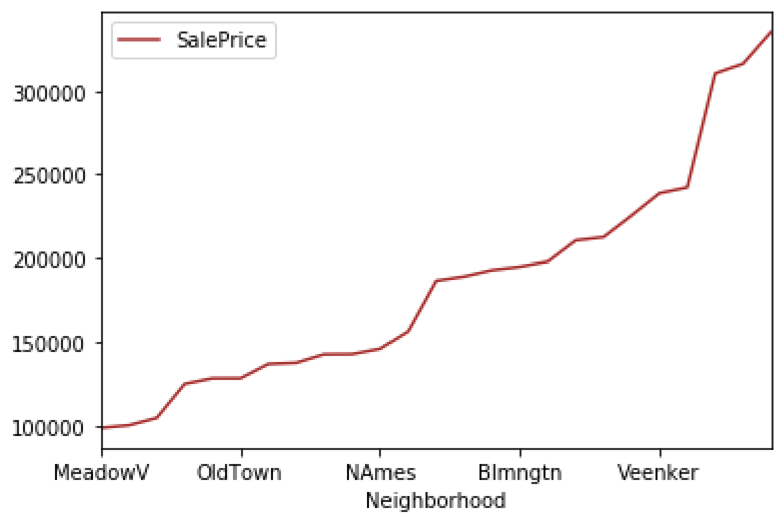
```
#code for clustering and visualization

display(train_houses_dist_ohe.head())
ohe_dist_houses = pd.get_dummies(train_houses_dist_ohe)
ohe_dist_houses.shape

ohe_dist_houses_with_ids_neighbors = pd.concat([dist_houses, ohe_dist_houses], axis=1)

# Agglomerative clustering
cluster = AgglomerativeClustering(n_clusters=15, affinity='euclidean', linkage='ward')
display(cluster.fit_predict(distance_data))


# k means clustering
kmeans = KMeans(n_clusters=15)
kmeans.fit(eu_dist)
y_kmeans = kmeans.predict(eu_dist)

plt.scatter(eu_dist[:,0], eu_dist[:,1], c=y_kmeans, s=1000,cmap='viridis')

centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='black', alpha=0.5);


new_data_1 = pd.read_csv('C:/Fall2019/DSF/Assignment2/Data/train.csv')
groupby_neighborhood_1 = new_data[['Neighborhood', 'SalePrice']]

neighborhoods_1 = new_data_1.Neighborhood.unique().tolist()
ng1 = groupby_neighborhood.groupby('Neighborhood').mean()
```

```
ng1 = groupby_neighborhood.groupby('Neighborhood').mean()
ng1 = ng.sort_values(by='SalePrice')
plot1 = (ng1).plot(color='brown')
fig= plt.figure(figsize=(6,3))
```

	MSSubClass	MSZoning	Street	Condition1	Condition2	BldgType	HouseStyle	RoofStyle
0	60	RL	Pave	Norm	Norm	1Fam	2Story	Gable
1	20	RL	Pave	Feedr	Norm	1Fam	1Story	Gable
2	60	RL	Pave	Norm	Norm	1Fam	2Story	Gable
3	70	RL	Pave	Norm	Norm	1Fam	2Story	Gable
4	60	RL	Pave	Norm	Norm	1Fam	2Story	Gable

```
array([10, 10,  0, ..., 10, 10, 10], dtype=int64)
```






```
<Figure size 432x216 with 0 Axes>
```

How well do the clusters reflect neighborhood boundaries? Write a discussion on what your clusters capture and ho

I have applied agglomerative and k means clustering. The boundaries were reflected more clearly in the k means clu clusters to be 15 for optimal performance of k means clustering. The number of possible neighborhoods is 25. Hen reflected clearly here.

The plot above is highly reflective of 'Neighborhood' and the mean 'SalePrice'. So, the points lying around 0-50000 ar
range and the cheapest neighborhood is reflected in those points.

Part 6 - Linear Regression

```
#  code for linear regression

# We will use those variables for predicting the sale price which have the highest correlatio
house_score_exterqual_ordinal_neighbors['logSalePrice'] = np.log(house_score_exterqual_ordina
X = house_score_exterqual_ordinal_neighbors[['OverallQual', 'YearBuilt' , 'GrLivArea', 'Garag
y = house_score_exterqual_ordinal_neighbors[['logSalePrice']]

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.01,random_state=0)
regr = linear_model.LinearRegression()
regr.fit(X_train, y_train)

y_pred = regr.predict(X_test)

accuracy = regr.score(X_test, y_test)
#print(accuracy)

# Prints the r2 score for the linear regression model

print(r2_score(y_test, y_pred))

test_file = pd.read_csv('C:/Fall2019/DSF/Assignment2/Data/test.csv')
test_file_variables = test_file[['OverallQual', 'YearBuilt' , 'GrLivArea', 'GarageArea','Exte
mapper = {'Ex':5, 'Gd':4, 'TA':3, 'Fa':2, 'Po':1}

test_file_variables_ordinal = test_file_variables.replace(mapper)
test_file_variables_ordinal_neighbor = test_file_variables_ordinal.replace(neighbor_mapper)
test_file_variables_ordinal_neighbor.fillna(0, inplace=True)
test_file_predict = regr.predict(test_file_variables_ordinal_neighbor)


sampleSubmission = pd.read_csv("C:/Fall2019/DSF/Assignment2/Data/sample_submission.csv")
sampleSubmission['SalePrice'] = np.exp(test_file_predict)

sampleSubmission.to_csv("C:/Fall2019/DSF/Assignment2/Data/sampleSubmission1.csv")
sampleSubmission.shape
```

```
(15, 1)
15
0.9267547638773315
(1459, 2)
```

```
# Converting the categorical nominal variable 'Neighborhood' to ordinal variable according to

neighborhood = train_houses[['Neighborhood', 'SalePrice']]
```

```
neighborhood = train_houses[['Neighborhood','SalePrice']]
neighborGroupBy = neighborhood.groupby(by='Neighborhood').mean()
#print(neighborGroupBy)
neighborGroupBy.sort_values(by='SalePrice')
neighbor_mapper = {'MeadowV':1,
'IDOTRR':2,
'BrDale':3,
'BrkSide':4,
'Edwards':5,
'OldTown':6,
'Sawyer':7,
'Blueste':8,
'SWISU':9,
'NPkVill':10,
'NAmes':11,
'Mitchel':12,
'SawyerW':13,
'NWAmes':14,
'Gilbert':15,
'Blmngtn':16,
'CollgCr':17,
'Crawfor':18,
'ClearCr':19,
'Somerst':20,
'Veenker':21,
'Timber':22,
'StoneBr':23,
'NridgHt':24,
'NoRidge':25}

house_score_exterqual_ordinal['Neighborhood'] = train_houses[['Neighborhood']]
house_score_exterqual_ordinal_neighbors = house_score_exterqual_ordinal.replace(neighbor_mapp
display(house_score_exterqual_ordinal_neighbors.head())
```

	OverallQual	YearBuilt	TotalBsmtSF	GrLivArea	GarageArea	TotRmsAbvGrd	ExterQual
0	7	2003	856	1710	548	8	4
1	6	1976	1262	1262	460	6	3
2	7	2001	920	1786	608	6	4
3	7	1915	756	1717	642	7	3
4	8	2000	1145	2198	836	9	4

How well/badly does it work? Which are the most important variables?

So, I experimented with many variables. Mostly numerical variables which has a significant correlation with the Sale of the neighborhood with the SalePrice as this is true in most parts of the world. For example, prices of houses in M houses in Stony Brook! So, I included neighborhood in the linear regression model for prediction.

Part 7 - External Dataset

```
# code to import external dataset and test

ownership_rate = pd.read_csv('C:/Fall2019/DSF/Assignment2/Data/IAHOWN.csv')
ownership_rate['DATE'] = pd.to_datetime(ownership_rate['DATE'])
ownership_rate['DATE'] = ownership_rate['DATE'].dt.year
display(ownership_rate.head())

house_with_yr_sold = house_score_exterqual_ordinal_neighbors
house_with_yr_sold['YrSold'] = train_houses['YrSold']
merged = pd.merge(house_with_yr_sold, ownership_rate, left_on = 'YrSold', right_on = 'DATE')
display(merged.head())

X_merged = merged[['OverallQual', 'YearBuilt' , 'GrLivArea', 'GarageArea','ExterQual','Kitche
y_merged = merged[['logSalePrice']]
X_merged_train,X_merged_test,y_merged_train,y_merged_test=train_test_split(X_merged,y_merged,
regr_merged = linear_model.LinearRegression()
regr_merged.fit(X_merged_train, y_merged_train)

y_pred_merged = regr_merged.predict(X_merged_test)

#print(accuracy)

# Prints the r2 score for the linear regression model
print("Accuracy after merging the external data: ")
print(r2_score(y_merged_test, y_pred_merged))
print('')
print("Accuracy before merging the external data: ")
print('0.92675')
```

	DATE	IAHOWN
0	1984	71.3
1	1985	69.9
2	1986	69.2
3	1987	67.7
4	1988	68.3

	OverallQual	YearBuilt	TotalBsmtSF	GrLivArea	GarageArea	TotRmsAbvGrd	ExterQual
0	7	2003	856	1710	548	8	4
1	7	2001	920	1786	608	6	4
2	8	2000	1145	2198	836	9	4
3	7	1931	952	1774	468	8	3
4	5	1939	991	1077	205	5	3

```
Accuracy after merging the external data:
0.8656861406433914

Accuracy before merging the external data:
0.92675
```

Describe the dataset and whether this data helps with prediction.

There is a dataset of Homeownership Rate for the state of Iowa, which I found on FRED Economic Data website (htt

This dataset talks about the rate of ownership of the houses inthe state of Iowa for a particular year starting from th

I integrated this dataset in my train data to check whether the ownership rate of the houses affected the sale price c affect the SalePrice of the house as more the ownership rate of the year, more the people are buying the houses anc increase proportionally.

In the external dataset, first I extracted the year from the date provided. Then, I merged the two tables based on year the house was sold in the original data which makes sense because we would check the home ownership rate only

As we can see from the code above that the accuracy of the simple linear regression model decreases from approx. with the original data, we would not be using it for further prediction as this will only become a hindrance for us in pr

So, this data clearly does not help with the prediction.

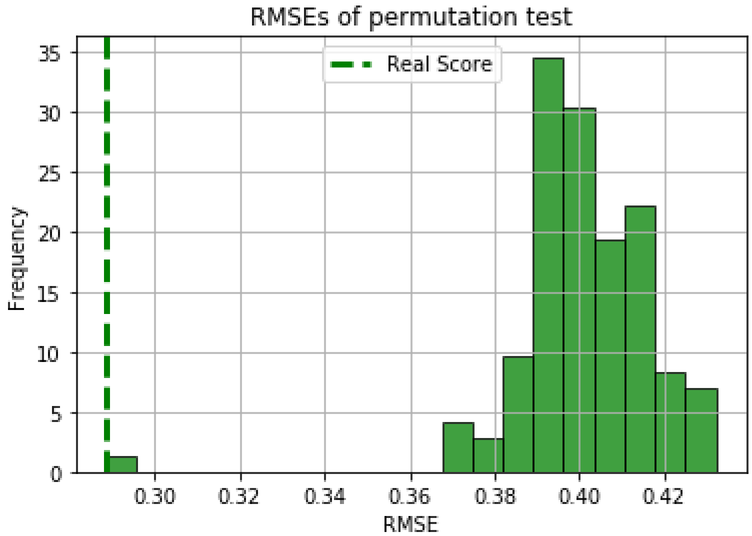
Part 8 - Permutation Test

```
# Create a redundant data frame for doing permutation tests and add all the permutation colum
permutation_df = house_score_exterqual_ordinal_neighbors

# Meaningless variables to be included for permutation tests = LandContour, LotConfig, LandSl
permutation_df['LandContour'] = train_houses['LandContour']
```

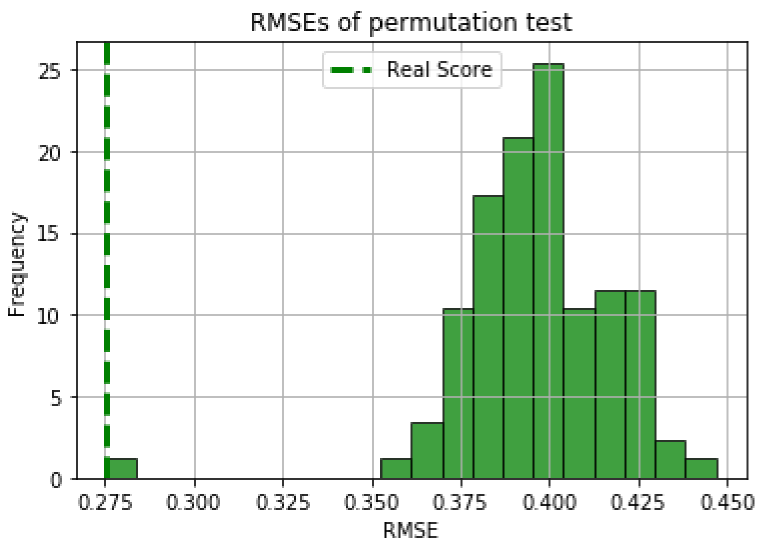
```
permutation_df['LotConfig'] = train_houses['LotConfig']
permutation_df['LandSlope'] = train_houses['LandSlope']
permutation_df['Condition1'] = train_houses['Condition1']
permutation_df['Condition2'] = train_houses['Condition2']

permutation_df.fillna(0,inplace=True)

le_LandContour = preprocessing.LabelEncoder()
le_LotConfig = preprocessing.LabelEncoder()
le_LandSlope = preprocessing.LabelEncoder()
le_Condition1 = preprocessing.LabelEncoder()
le_Condition2 = preprocessing.LabelEncoder()
permutation_df['LotConfig'] = le_LotConfig.fit_transform(permutation_df['LotConfig'])
permutation_df['LandContour'] = le_LandContour.fit_transform(permutation_df['LandContour'])
permutation_df['LandSlope'] = le_LandSlope.fit_transform(permutation_df['LandSlope'])
permutation_df['Condition1'] = le_Condition1.fit_transform(permutation_df['Condition1'])
permutation_df['Condition2'] = le_Condition2.fit_transform(permutation_df['Condition1'])


# TODO: code for all permutation tests

# Variables selected for p test:
# Meaningful
    # 'OverallQual',
    # 'GrLivArea',
    # 'GarageArea',
    # 'ExterQual',
    # 'KitchenQual',

# Meaningless
    # 'LandContour',
    # 'LotConfig',
    # 'LandSlope',
    # 'Condition1',
    # 'Condition2'

# A simple function to return random permutation of the data
def permute(df):
    df = df.copy()
    df.apply(np.random.shuffle)
    return df

permutation_columns = ['OverallQual', 'GrLivArea', 'GarageArea', 'ExterQual', 'KitchenQual','
X_whole = house_score_exterqual_ordinal_neighbors[['OverallQual','GrLivArea', 'GarageArea','E
y_whole = house_score_exterqual_ordinal_neighbors[['logSalePrice']]

# iterate through all the columns selected for permutation testing
# Prepare the training data for that single column only by taking 100 random permutations
# Perform simple linear regression for that column
# Calculate the Root of Mean Square Error (RMSE)
# Append the 100 values of RMSE in a list
for col in permutation_columns:
```

```
    rmse_perm = []
    print("Column: ", col)
    for _ in range(100):

        X_perm = permute(X_whole[[col]])
        y_perm = permute(y_whole)
        X_train_perm,X_test_perm,y_train_perm,y_test_perm=train_test_split(X_perm,y_perm,test
        regr_perm = linear_model.LinearRegression()
        regr_perm.fit(X_train_perm, y_train_perm)
        y_pred_perm = regr_perm.predict(X_test_perm)
        rms = np.sqrt(mean_squared_error(y_test_perm, y_pred_perm))
        rmse_perm.append(rms)

    # Train the model with the real values of the data
    X_train_real,X_test_real,y_train_real,y_test_real = train_test_split(X_whole[[col]],y_who
    # with sklearn
    regr_real = linear_model.LinearRegression()
    regr_real.fit(X_train_real, y_train_real)
    y_pred_real = regr_real.predict(X_test_real)
    rms_real = np.sqrt(mean_squared_error(y_test_real, y_pred_real))

    # append the real result to the rmse list
    rmse_perm.append(rms_real)

    # Plot the graphs for 10 different columns RMSEs and highlight the RMSE of the real data
    n, bins, patches = plt.hist(rmse_perm, 20, density=True, facecolor='g', alpha=0.75, edgec
    ylim = plt.ylim()
    plt.plot(2 * [rmse_perm[100]], ylim, '--g', linewidth=3,
             label='Real Score')
    plt.ylim(ylim)
    plt.legend()
    plt.xlabel('Score')
    plt.xlabel('RMSE')
    plt.ylabel('Frequency')
    plt.title('RMSEs of permutation test')
    plt.grid(True)
    plt.show()

    # Get the pvalue from the permutation scores
    rmse_perm.sort()
    pos = rmse_perm.index(rms_real)
    pvalue = pos/101
    print("PValue with column :", col)
    pvalue = round(pvalue, 3)
    print(pvalue)

    # Added to print new lines between plots
    print('')
    print('')
    print('')
```

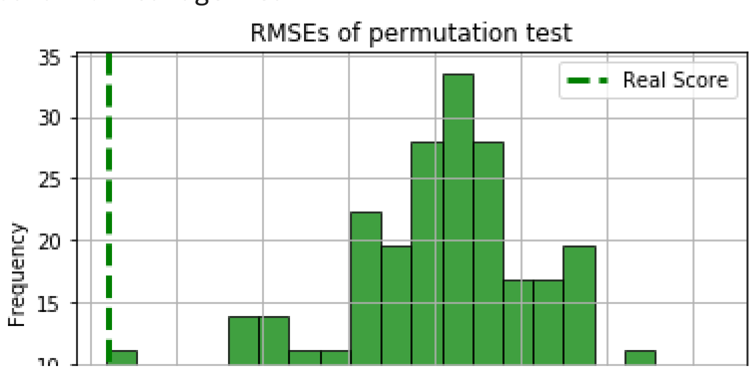
```
Automatically created module for IPython interactive environment
Column:  OverallQual
```

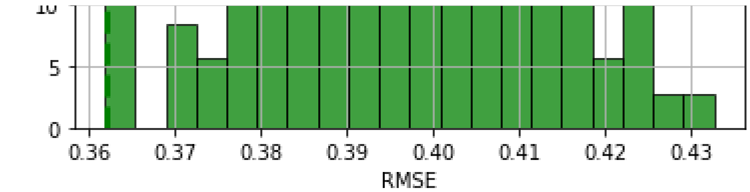



```
PValue with column : OverallQual
0.0


Column:  GrLivArea
```



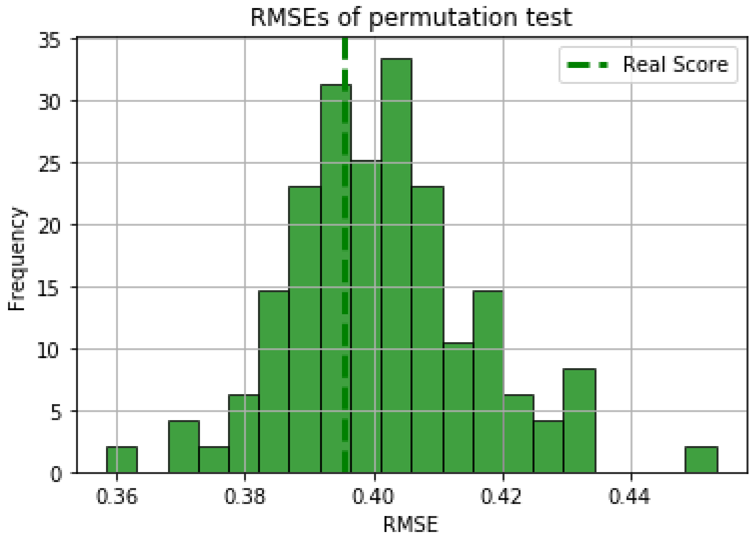

```
PValue with column : GrLivArea
0.0


Column:  GarageArea
```





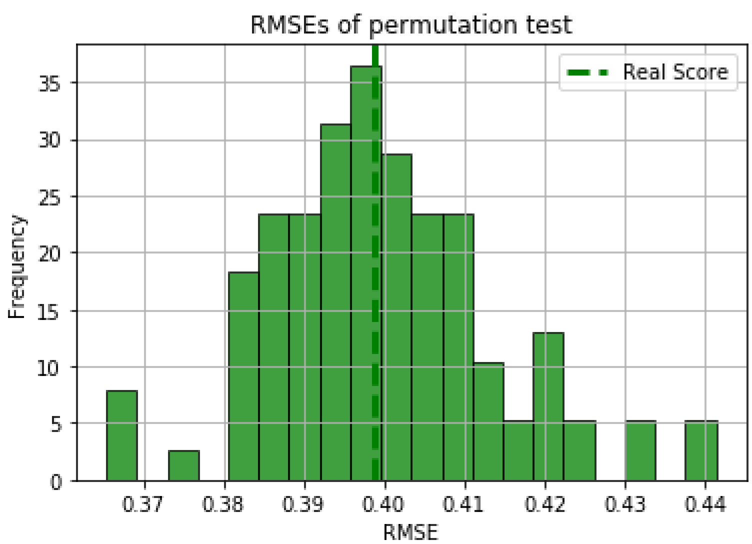

```
PValue with column : GarageArea
0.01
```

```
Column:  ExterQual
```




```
PValue with column : ExterQual
0.347
```

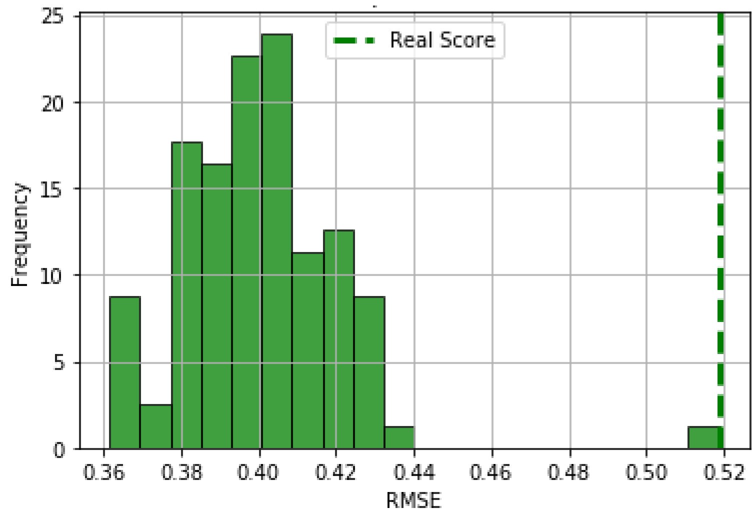
```
Column:  KitchenQual
```



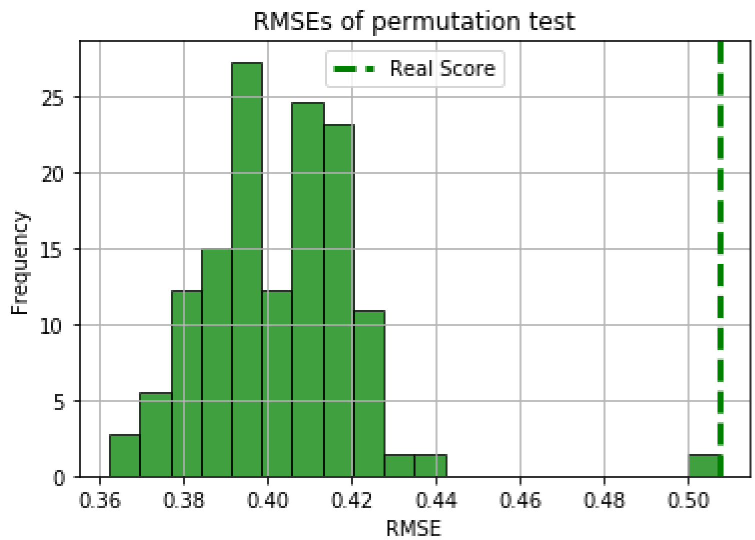

```
PValue with column : KitchenQual
0.505
```

```
Column:  LandContour
```

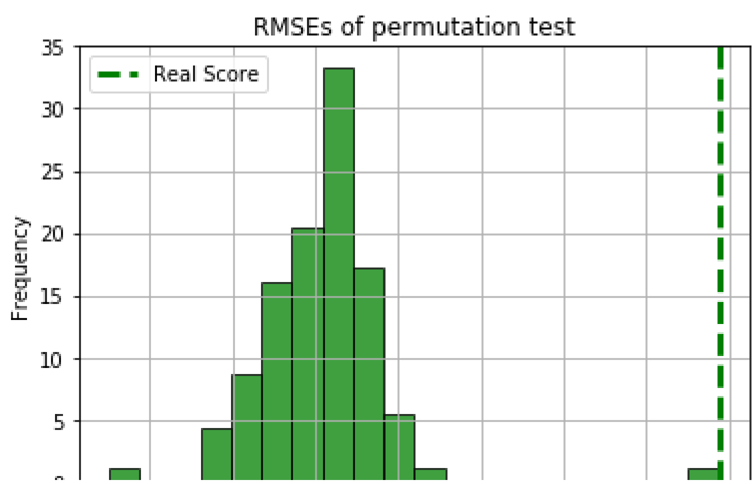
RMSEs of permutation test

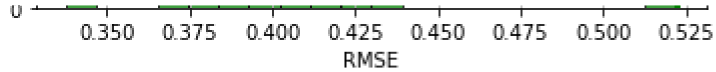



```
PValue with column : LandContour
0.99


Column:  LotConfig
```



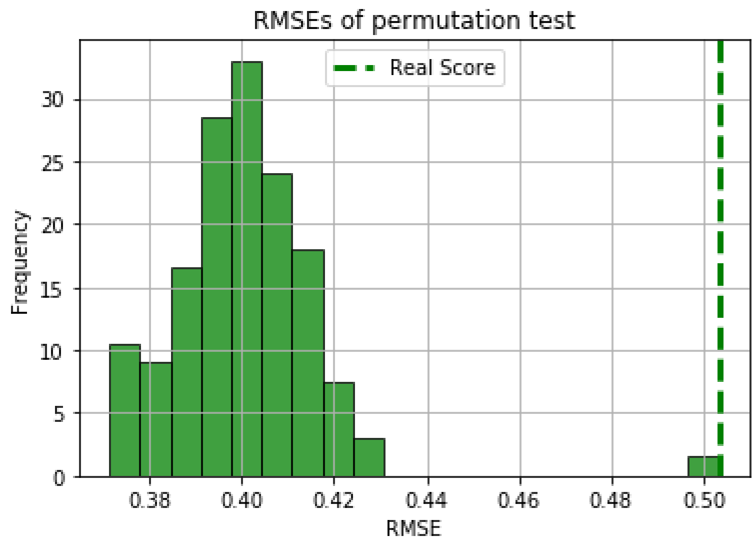

```
PValue with column : LotConfig
0.99


Column:  LandSlope
```





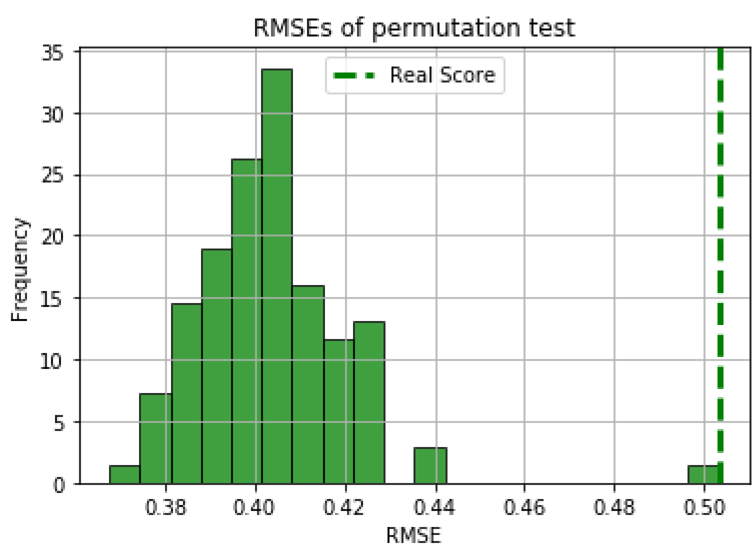

```
PValue with column : LandSlope
0.99
```

```
Column:  Condition1
```




```
PValue with column : Condition1
0.99
```

```
Column:  Condition2
```




```
PValue with column : Condition2
0.99
```

Permutation test results description

The first 3 meaningful variables such as OverallQual, GarageArea , GrLivArea have very low pvalues almost equal to to the SalePrice and hence it is statistically significant

The next 2 variables ie KitchenQual and ExterQual, which we considered to be quite meaningful ended up have a pva may not be as astatistically significant as we thought them to be.

The meaningless variables have very high pvalues of 0.99 which means that our intuition was right and those variab meaningless with respect to the prediction of the SalePrice.

Describe the results.

XGBoost Model

```
# XGBoost Model

model = XGBRegressor(n_estimators = 1000, #100-1000
    learning_rate = 0.01, #increase while decreasing n_trees
    max_depth = 5, #increase incrementally by 1; default 6, increasing can lead to overfit
    colsample_bytree = 0.3, # 0.3 to 0.8
    gamma = 0) #0, 1 or 5

model.fit(X_train, y_train)
xgb_preds = model.predict(X_test) #store the predictions for xgbregressor
rmse = np.sqrt(mean_squared_error(y_test, xgb_preds))
print(rmse)


test_file_predict2 = model.predict(test_file_variables_ordinal_neighbor)


sampleSubmission2 = pd.read_csv("C:/Fall2019/DSF/Assignment2/Data/sample_submission.csv")
sampleSubmission2['SalePrice'] = np.exp(test_file_predict2)

sampleSubmission2.to_csv("C:/Fall2019/DSF/Assignment2/Data/sampleSubmission2.csv")
sampleSubmission2.shape
print(len(xgb_preds))
```

Kernel Ridge Regression Model

```
# Kernel Ridge Regression:

clf = KernelRidge(alpha=1.0)
clf.fit(X_train, y_train)

test_file_predict3 = clf.predict(test_file_variables_ordinal_neighbor)


sampleSubmission3 = pd.read_csv("C:/Fall2019/DSF/Assignment2/Data/sample_submission.csv")
sampleSubmission3['SalePrice'] = np.exp(test_file_predict3)
```

```
sampleSubmission3['SalePrice'] = np.exp(test_file_predict3)

sampleSubmission3.to_csv("C:/Fall2019/DSF/Assignment2/Data/sampleSubmission3.csv")
sampleSubmission3.shape
print(len(test_file_predict3))
```

Lasso Regression

```
# Lasso Regression

clf2 = linear_model.Lasso(alpha=0.1)
clf2.fit(X_train, y_train)

test_file_predict4 = clf2.predict(test_file_variables_ordinal_neighbor)


sampleSubmission4 = pd.read_csv("C:/Fall2019/DSF/Assignment2/Data/sample_submission.csv")
sampleSubmission4['SalePrice'] = np.exp(test_file_predict4)

sampleSubmission4.to_csv("C:/Fall2019/DSF/Assignment2/Data/sampleSubmission4.csv")
```

Comparison of Different Models

1) Linear Regression Model: (done in 6th question)

This model did not perform very well as expected. Linear Regression model just finds the linear relationship betwee variable. When I uploaded the results to Kaggle, I was getting a score of 0.1924

2) XGBoost Model:

This model improved the model significantly and gave the Kaggle score of 0.1349 and a rank of 2234. This was the models.

3) Kernel Ridge Regression:

This model did not give much accuracy as compared to other models. It gave Kaggle score of 0.3675.

4) Lasso Regression:

This model performed on the same lines as that of baseline Linear Regression and gave the accuracy of around 0.2

Hence, XGBoost gives the best result for the prediction of the test task.

Part 9 - Final Result

Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderb to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face

Kaggle Link: https://www.kaggle.com/rutvikparekh

Highest Rank: 2234

Score: 0.13495

Number of entries: 10

The screenshot of my ranking is uploaded on Google Drive.

https://drive.google.com/file/d/1Yqk5MNLMGGpiv13kAPbWUPgAyGLjYzNB/view?usp=sharing