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 code that justifies your answer as well as answer the questions. We also ask that code be commented to make it easier to follow.

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

pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import pairwise_distances
from scipy import stats
from scipy.stats import norm,skew
from scipy.special import boxcox1p
from scipy.stats import boxcox_normmax
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
import warnings
warnings.filterwarnings('ignore')


import os
#print(os.listdir("../input"))

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

##SEABORN STYLINNG
color = sns.color_palette()
sns.set_style('darkgrid')
import warnings
def ignore_warn(*args, **kwargs):
    pass
warnings.warn = ignore_warn #ignore annoying warning (from sklearn and seaborn)
```

```
pd.set_option('display.float_format', lambda x: '{:.3f}'.format(x)) #Limiting floats output to 3 decimal points
pd.set_option('display.max_columns', 500)
pd.set_option('display.max_rows', 500)
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

#train=pd.read_csv("/kaggle/input/house-prices-advanced-regression-techniques/train.csv")
#test=pd.read_csv("/kaggle/input/house-prices-advanced-regression-techniques/test.csv")
train= pd.read_csv("/content/drive/My Drive/DSF-3Housing/train.csv")
test = pd.read_csv("/content/drive/My Drive/DSF-3Housing/test.csv")

externalData = pd.read_csv("/content/drive/My Drive/DSF-3Housing/external.csv")
print(" Train data :",train.shape)
print(" Test data :",test.shape)


##Backing up dataframe
train0=pd.DataFrame(train)
test0=pd.DataFrame(test)

##Drop Id column
train.drop("Id", axis = 1, inplace = True)
test.drop("Id", axis = 1, inplace = True)
print(" Train data :",train.shape)
print(" Test data :",test.shape)
```

```
Mounted at /content/drive
 Train data : (1460, 81)
 Test data : (1459, 80)
 Train data : (1460, 80)
 Test data : (1459, 79)
```

Part 1 - Pairwise Correlations

Question1 : Features selected :

SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.

LotFrontage: Linear feet of street connected to property

OverallQual: Overall material and finish quality

OverallCond: Overall condition rating

Fireplaces: Number of fireplaces

YearBuilt: Original construction date

TotalBsmtSF: Total square feet of basement area

FullBath: Full bathrooms above grade

MiscVal: Value of miscellaneous feature

Bedroom: Number of bedrooms above basement level

Kitchen: Number of kitchens

GarageArea: Size of garage in square feet

PoolArea: Pool area in square feet

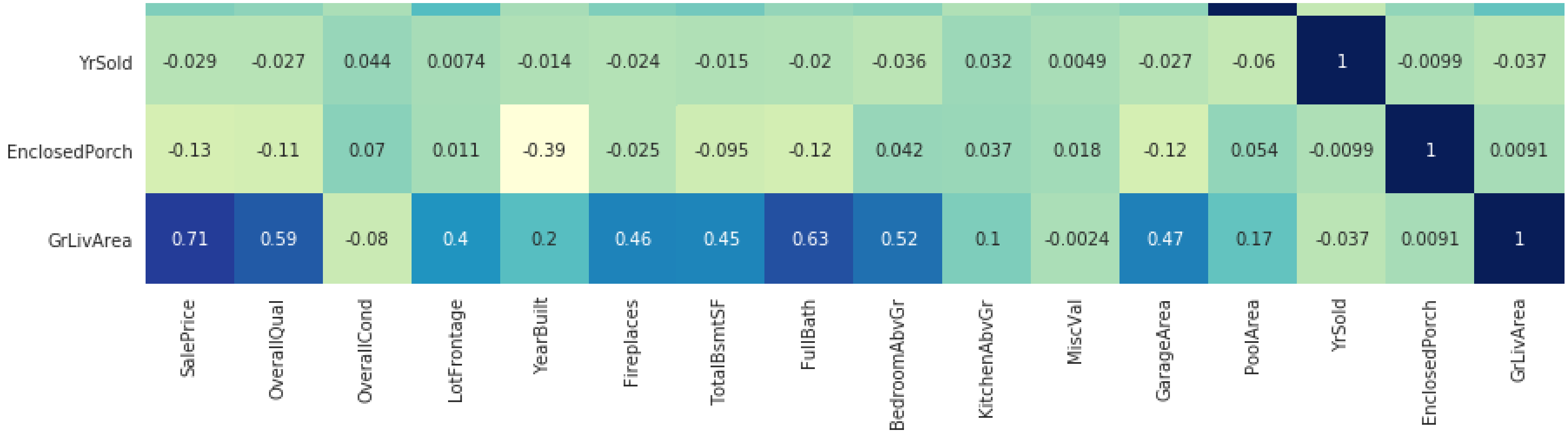
YrSold: Year Sold

EnclosedPorch: Enclosed porch area in square feet

GrLivArea: Living Area

```
# TODO: show visualization


train.isna().any()


train_Q1 = train[['SalePrice','OverallQual', 'OverallCond','LotFrontage','YearBuilt', 'Fireplaces'  ,'TotalBsmtSF',
                  'FullBath' , 'BedroomAbvGr' , 'KitchenAbvGr'  ,'MiscVal'
                  , 'GarageArea' ,  'PoolArea' , 'YrSold'  , 'EnclosedPorch' , 'GrLivArea' ]]
##ain_Q1 = train.iloc[:,0:2] # Remember that Python does not slice inclusive of the ending index.
print(train_Q1.columns.values)
#Correlation map to see how features are correlated with SalePrice
corrmat = train_Q1.corr()
plt.subplots(figsize=(20,15))
sns.heatmap(corrmat, vmax=.9 , square=True, annot=True,  cmap="YlGnBu")
```

```
['SalePrice' 'OverallQual' 'OverallCond' 'LotFrontage' 'YearBuilt'
 'Fireplaces' 'TotalBsmtSF' 'FullBath' 'BedroomAbvGr' 'KitchenAbvGr'
 'MiscVal' 'GarageArea' 'PoolArea' 'YrSold' 'EnclosedPorch' 'GrLivArea']
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3eec28ac8>
```



Most positive and negative correlations

Positve Correlations: Correlation<-> Score

SalePrice <->OverallQual | 0.79

SalePrice <->FullBath | 0.63

SalePrice <->BedroomAbvGr | 0.52

SalePrice<->GarageArea | 0.47

SalePrice <-> GrLivArea | 0.71

YearBuilt <-> GarageArea | 0.48

FullBath<->GrLivArea | 0.63

BedroomAbvGr<->GrLivArea | 0.52

Negative Correlations: Correlation<-> Score

GarageArea <->OverallQual | -0.15

OverallCond <->FullBath | -0.19

YearBuilt <->OverallCond | -0.38

EnclosedPorch<->GarageArea | -0.12

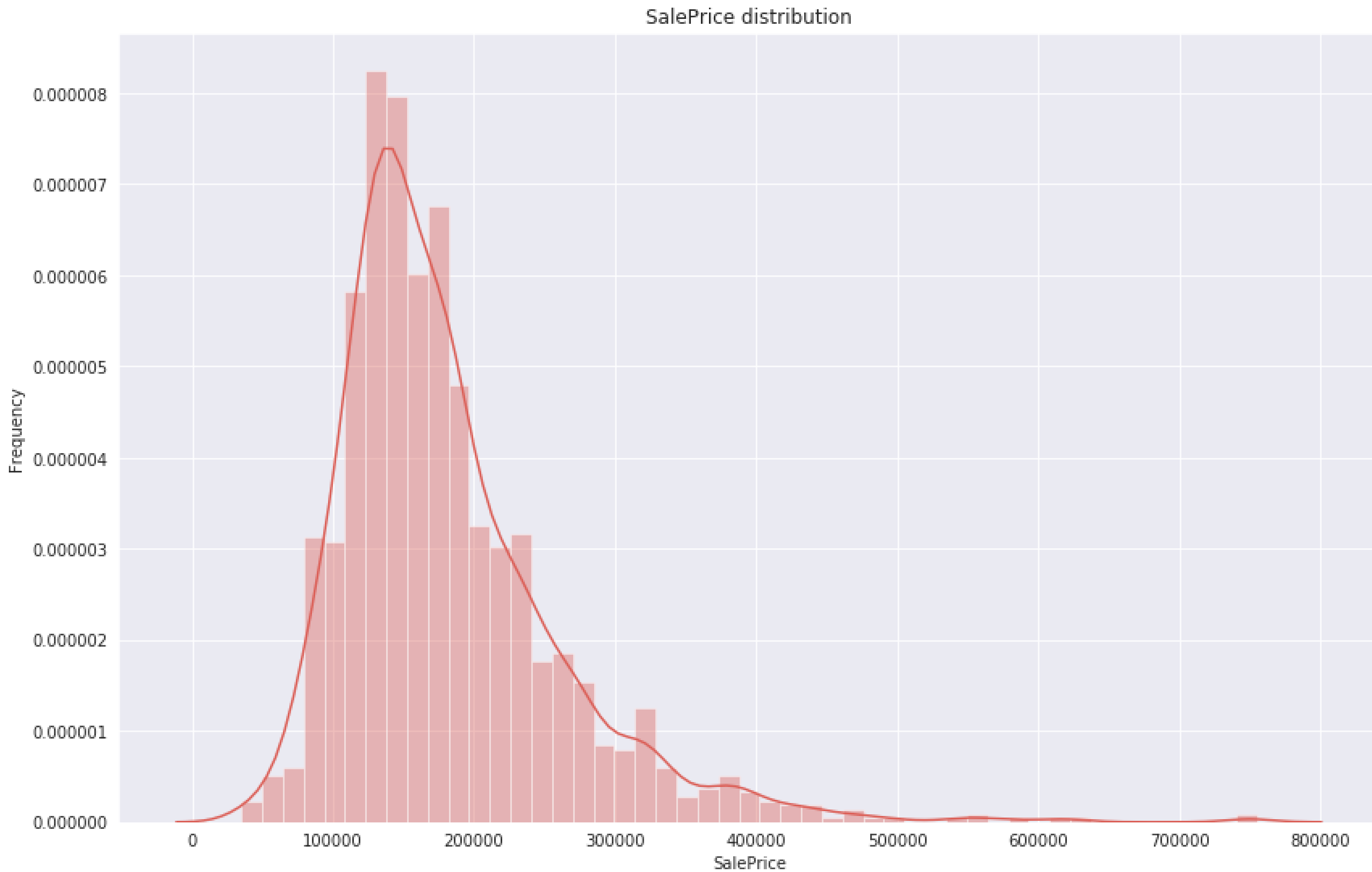
YearBuilt <-> KitchAbvGr | -0.17

YearBuilt <-> EnclosedPorch | -0.39

OverallQual <->EnclosedPorch | -0.11

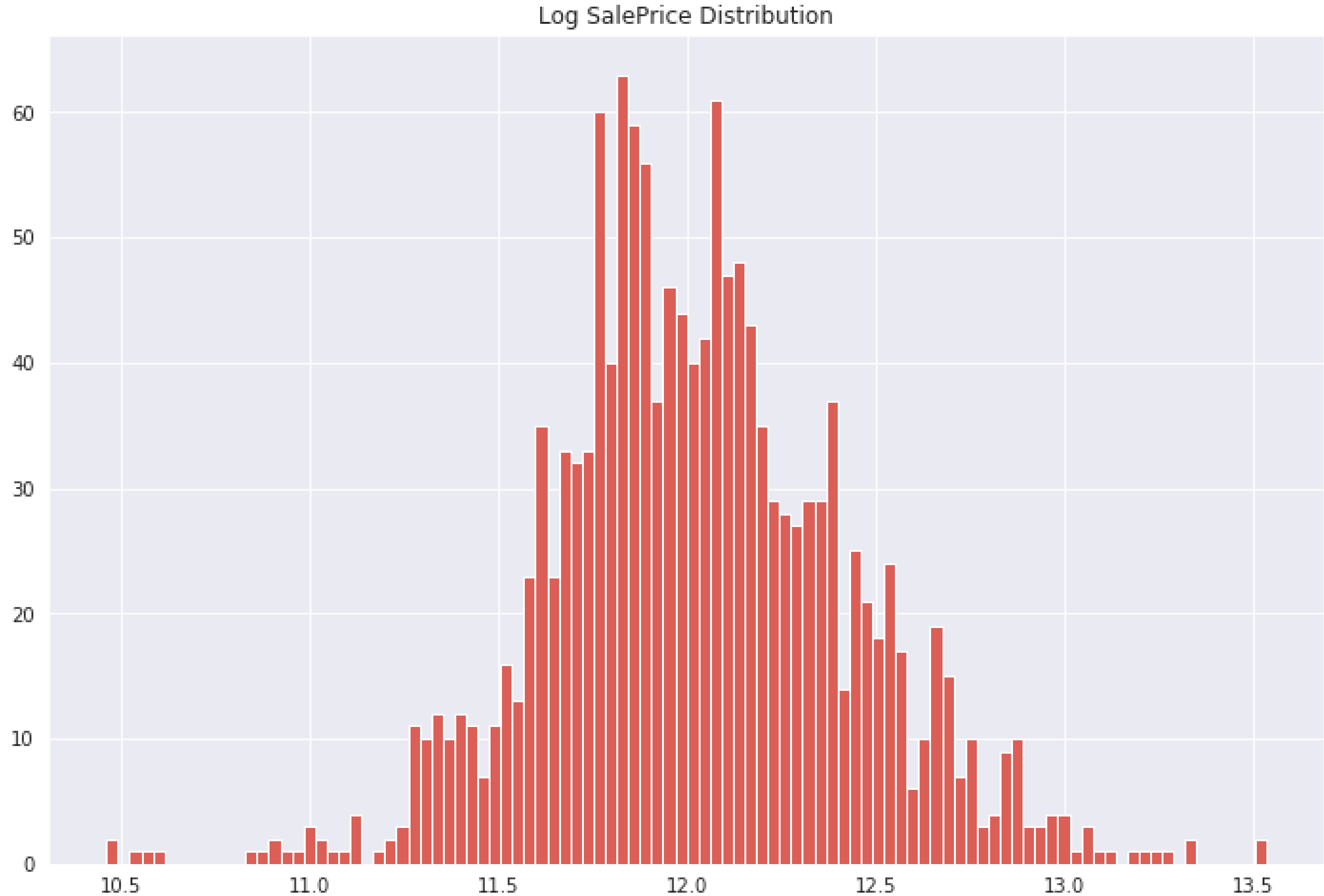
EnclosedPorch<->FullBath | -0.12

```
##SalePrice Distribution : 1
##Construct a Histogram for distribution of SalePrice

fig, ax = plt.subplots(figsize=(14, 9))
plt.ylabel('Frequency')

plt.title('SalePrice distribution')
sns.distplot(train['SalePrice'] );
```




```
##Log the SalePrice
train_X=pd.DataFrame(train)
train_X["SalePriceLog"] = np.log1p(train_X["SalePrice"])
plt.title('Log SalePrice Distribution')
train_X.SalePriceLog.hist(bins = 100, figsize=(12,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3e27b4518>
```

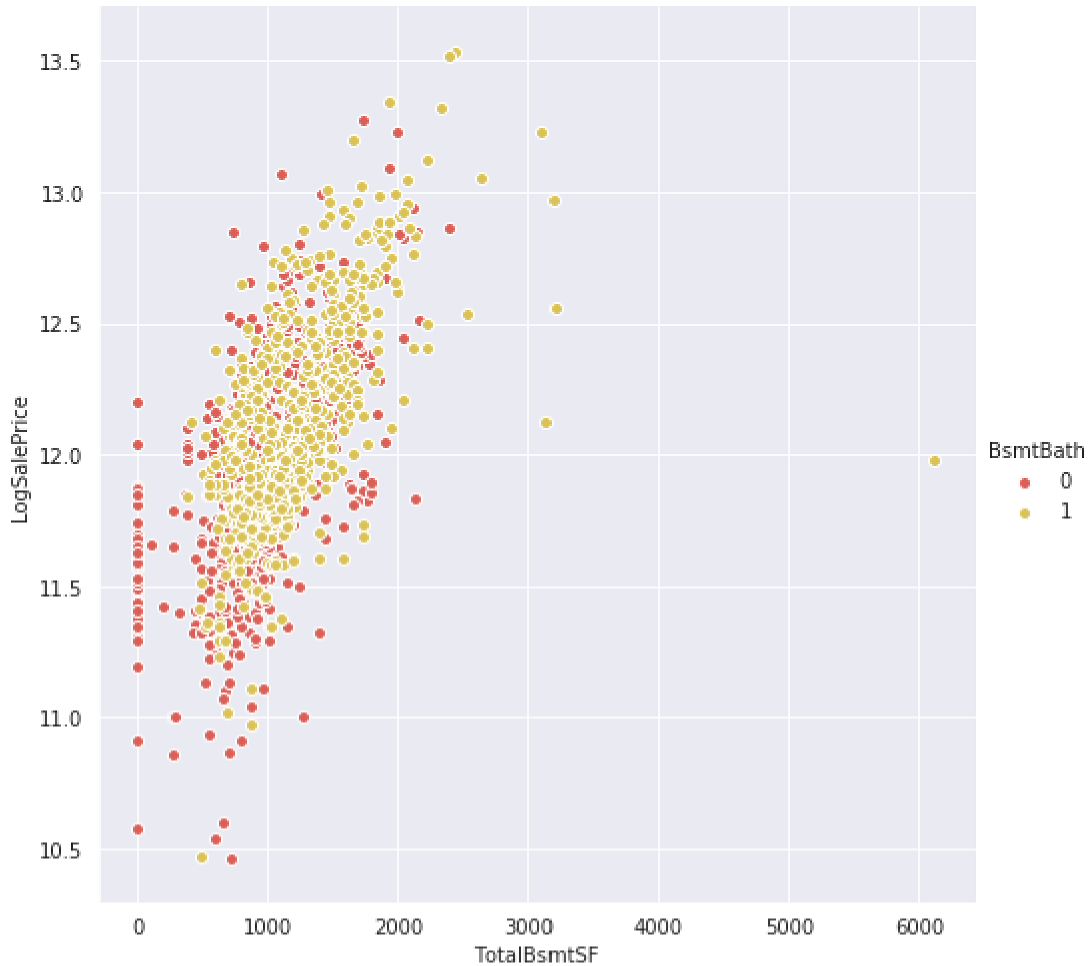


Part 2 - Informative Plots

```
# TODO: code to generate Plot 1

df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])
df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])



df_train['BsmtBath'] = 0
df_train['BsmtHalfBath'] = df_train['BsmtHalfBath'].fillna(0)
```

```
df_train['BsmtFullBath'] = df_train['BsmtFullBath'].fillna(0)

df_train.loc[(df_train['BsmtFullBath'] > 0) | (df_train['BsmtHalfBath'] > 0), 'BsmtBath'] = 1

var = 'BsmtBath'

g = sns.FacetGrid(df_train, hue='BsmtBath', size = 7)
g.map(plt.scatter, 'TotalBsmtSF', 'LogSalePrice', edgecolor="w")
g.add_legend()
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd3e27b4d30>
```



What interesting properties does Plot 1 reveal?

1. We observe that high priced houses have basement bath, and most houses priced more than the average have basement bath
2. Having Fullbath or HalfBath is same as having a bath in the basement , so we have clubbed their values to know that having any bath in basement the pricing.

```
# TODO: code to generate Plot 2


#scatterplot
train.columns.values

df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])

df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])
##df_train.LogSalePrice.hist(bins = 100)



df_train['BedroomAbvGr'] = df_train['BedroomAbvGr'].fillna(0)
df_train['KitchenAbvGr'] = df_train['KitchenAbvGr'].fillna(0)
df_train['TotRmsAbvGrd'] = df_train['TotRmsAbvGrd'].fillna(0)
df_train['HalfBath'] = df_train['HalfBath'].fillna(0)
df_train['FullBath'] = df_train['FullBath'].fillna(0)


df_train['TotBath'] = df_train.FullBath + df_train.HalfBath
df_train['TotRoomsBath'] = df_train.TotRmsAbvGrd + df_train.TotBath



g = sns.FacetGrid(df_train, hue='TotRoomsBath', size = 8)
g.map(plt.scatter, 'GrLivArea', 'LogSalePrice', edgecolor="w")
g.add_legend()

#https://towardsdatascience.com/data-cleaning-and-feature-engineering-in-python-b4d448366022
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd3e2dc7d30>
```

What interesting properties does Plot 2 reveal?

1. There is a linear relation between GrLivArea and the SaePrice of house except a few outliers

2. Also we can observe that number of rooms and bath increases as the SalePrice increases. Also the Toal LivingArea of the house combines all the s Rooms+Bathrooms
3. Also observe that the total number of bathrooms+Rooms higher for higher priced houses. And the average number of rooms+bathrooms is 12.

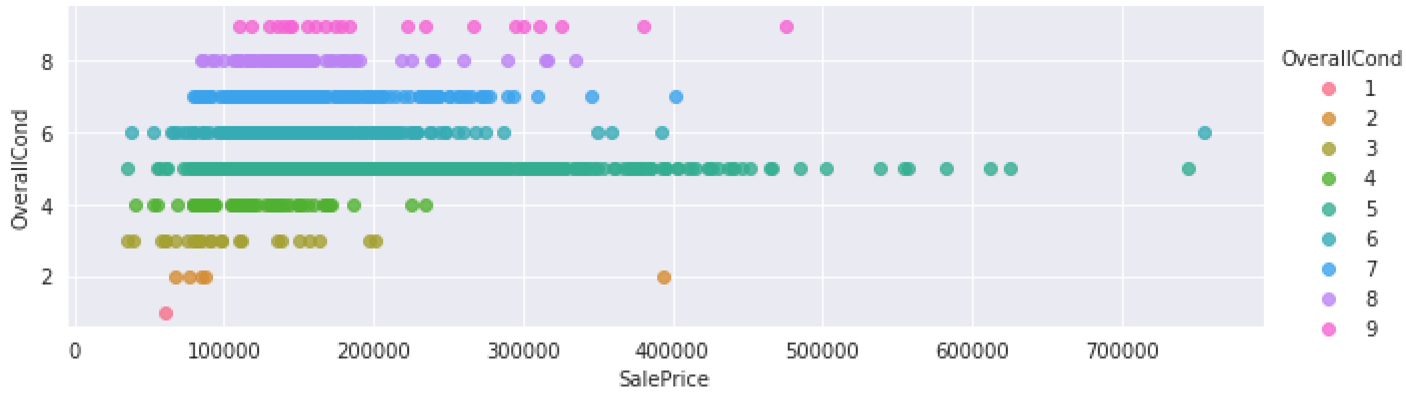
```
# TODO: code to generate Plot 3
```

```
###sns.lmplot( x='SalePrice', y='OverallQual' , data=train,fit_reg=False, # No regression line   hue='OverallQual' , size=3, aspect=3)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd3e36826d8>
```


```
sns.lmplot( x='SalePrice', y='OverallCond' , data=train,fit_reg=False,    hue='OverallCond' , size=3, aspect=3)   # Color by OverallCo
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd3e3d31400>
```



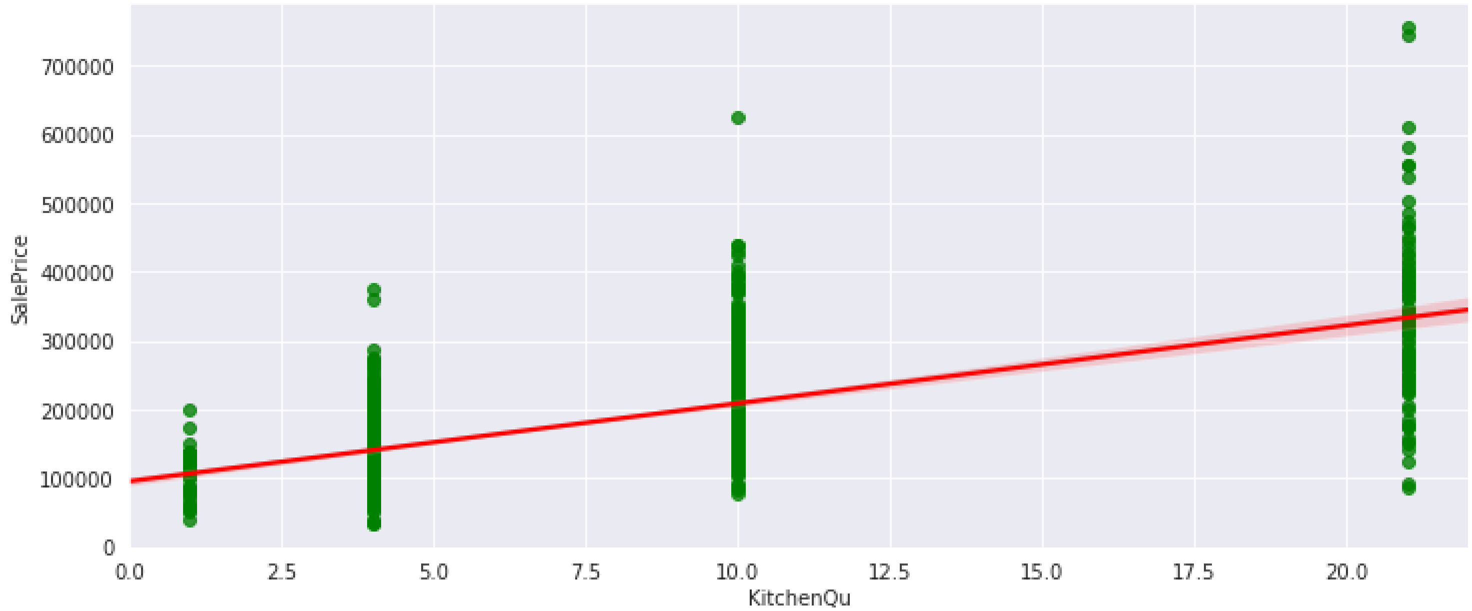
What interesting properties does Plot 3 reveal?

1. Overall quality of the house is assigned a metric for from 1 to 10 , 10 being the highest value
2. We observe that SalePrice of the house with high "Overall quality" value is also higher
3. But this is not in the case of "OverAll Condition" values. SalePrice does not increase linearly with the increase in "OverAll Condition" value

```
# TODO: code to generate Plot 4



df_train=pd.DataFrame(train)

df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])

df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])
##df_train.LogSalePrice.hist(bins = 100)


df_train['KitchenQual'] = df_train['KitchenQual'].fillna('None')


df_train.loc[df_train.KitchenQual == 'None', 'KitchenQu'] = 0
df_train.loc[df_train.KitchenQual == 'Fa', 'KitchenQu'] = 1
df_train.loc[df_train.KitchenQual == 'TA', 'KitchenQu'] = 4
df_train.loc[df_train.KitchenQual == 'Gd', 'KitchenQu'] = 10
df_train.loc[df_train.KitchenQual == 'Ex', 'KitchenQu'] = 21


## 3. Regplot
```

```
plt.figure(figsize=(12,5))##fig, ax =plt.subplots(1,2, figsize=(12,5))
sns.regplot(x='KitchenQu', y='SalePrice' , data=train,fit_reg=True, scatter_kws={"color": "green"}, line_kws={"color": "red"})
plt.ylim(0, None)
plt.xlim(0, None)
```

```
(0, 22.004061775789268)
```



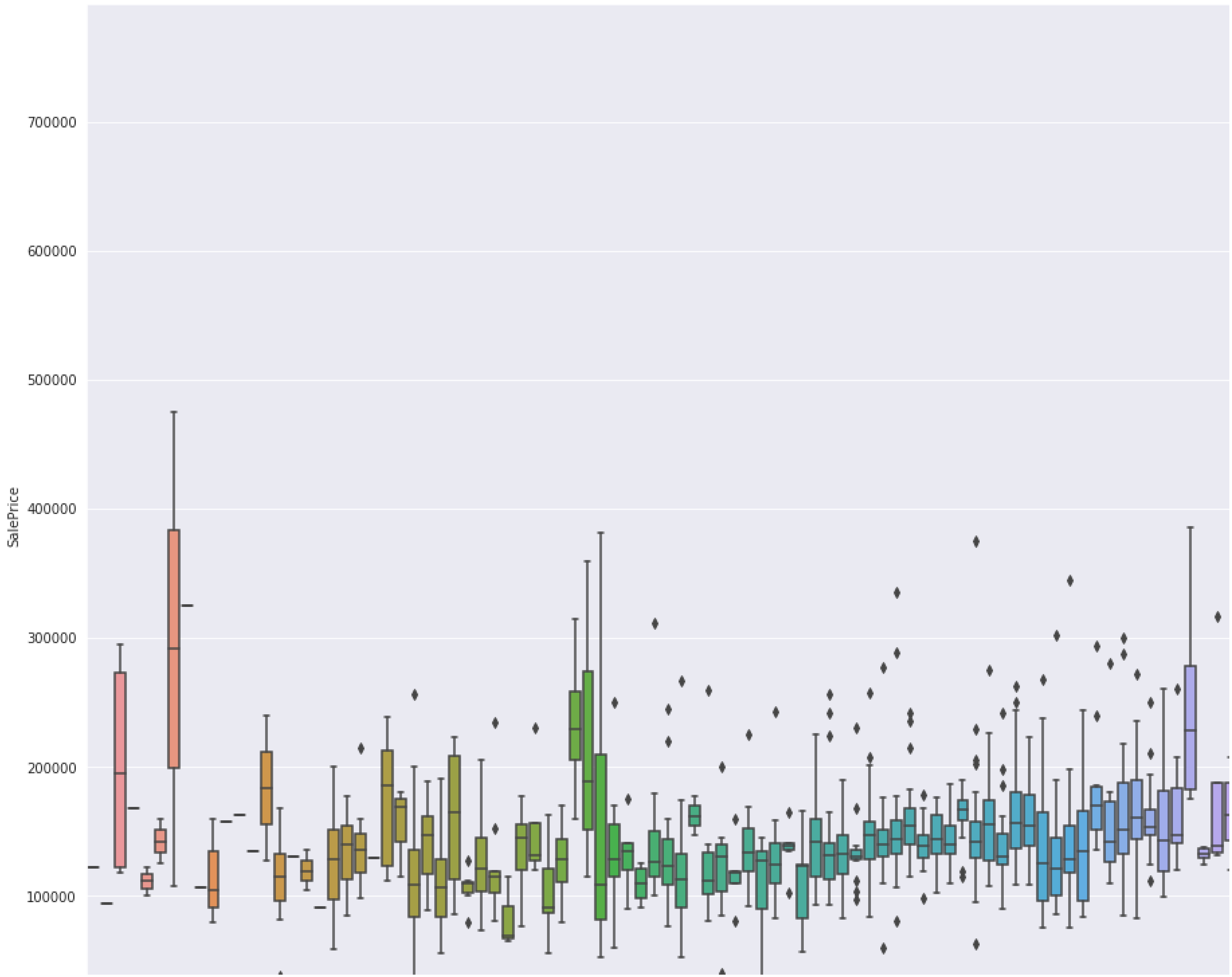
What interesting properties does Plot 4 reveal?

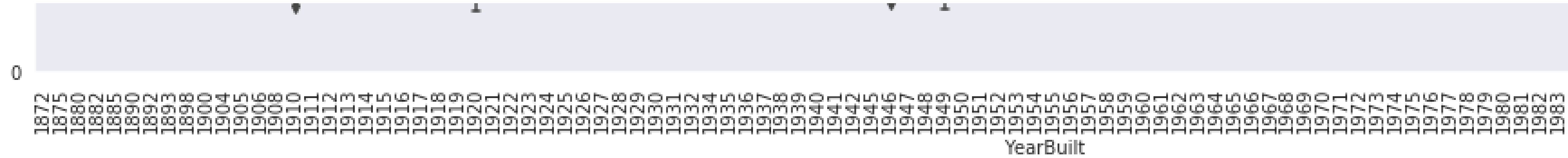
1. Quality of the Kitchen affects the Price of the house
2. Price of the house linearly increases with the increase in KitchQuality. We have been given a metric for evalutaing the Kitchen Quality. So from the ı see that any house in the Price range can have high Kitchen Quality value range from lowest(0) to the highest value(20)

```
# TODO: code to generate Plot 5
```

```
df_train=pd.DataFrame(train)
```

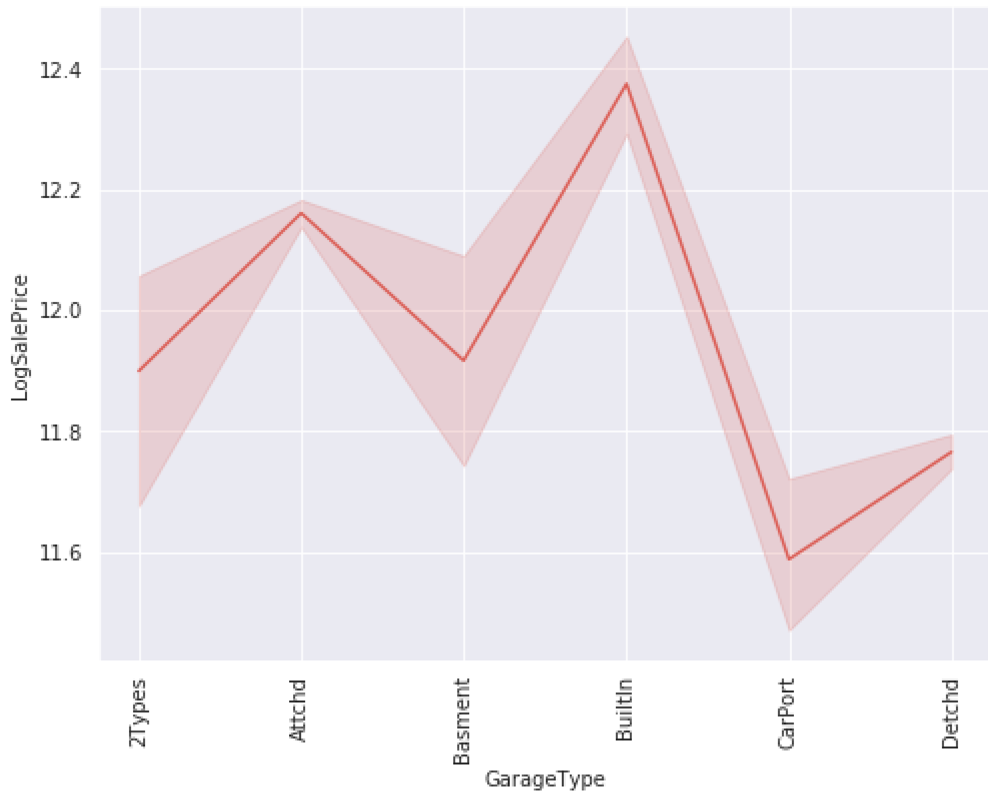
```
## 4. Box Plot

"""var = 'YearBuilt'
data = pd.concat([df_train['SalePrice'], df_train[var]], axis=1)
f, ax = plt.subplots(figsize=(16, 8))
fig = sns.boxplot(x=var, y="SalePrice", data=data)
"""


plt.figure(figsize=(20,14))


df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])
sns.boxplot(x='YearBuilt', y='SalePrice', data=train0)
##fig.axis(ymin=0, ymax=800000);
plt.xticks(rotation=90);
# df2.plot.barh(stacked=True);
```


700000
600000
500000
400000
300000
200000
100000
SalePrice

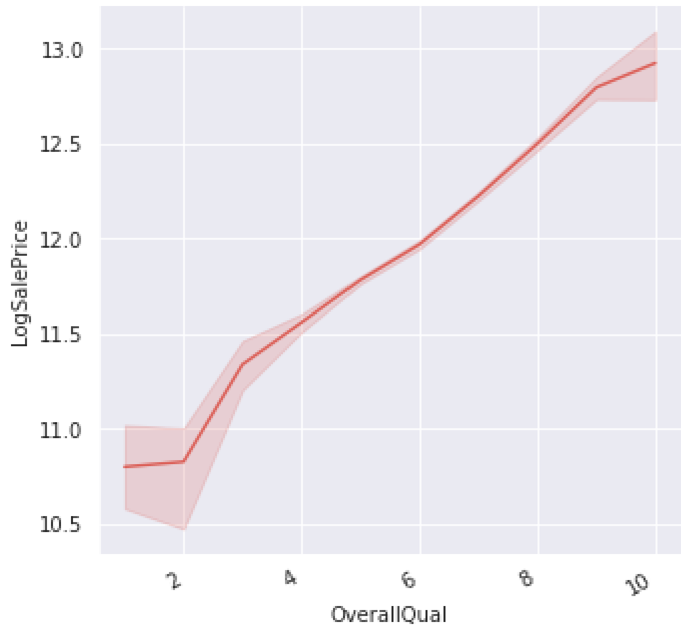


We see that the year in which the house is built affects pricing. The more recent the house is built , the house would be more priced.

```
# overallqual/saleprice

df_train=pd.DataFrame(train)
df_train["LogSalePrice"] = np.log1p(df_train["SalePrice"])
#plt.figure(figsize=(20,14))


f, ax = plt.subplots(figsize=(8, 6))
ax = sns.lineplot(x="GarageType", y="LogSalePrice", data=df_train)
plt.xticks(rotation=90);
#fig.axis(ymin=0, ymax=800000);
```




```
g = sns.relplot(x="OverallQual", y="LogSalePrice", kind="line", data=df_train)
g.fig.autofmt_xdate()
```



What interesting properties does Plot 5 reveal?

It shows linear relationship between OverallQual and LogSalePrice

Part 3 - Handcrafted Scoring Function

```
# TODO: code for scoring function


####################################
##Combining train and Test data
####################################

train_1=pd.DataFrame(train0)
test_1=pd.DataFrame(test0)


##Drop Id column
train_1.drop("Id", axis = 1, inplace = True)
```

```
test_1.drop("Id", axis = 1, inplace = True)


# Dropping columns
train_1 = train_1[train_1.GrLivArea < 4000]
train_1.reset_index(drop=True, inplace=True)
dataY = train_1.SalePrice
train_1.drop("SalePrice", axis = 1, inplace = True)


print(" Train data after dropping columns :",train_1.shape)
print(" Test data after dropping columns:",test_1.shape)


traintest_2 = pd.concat((train_1, test_1)).reset_index(drop=True)
print("Traintest data shape",traintest_2.shape)


## Missing values to be handled in Encoded function below
### Step 1:[](http://) Identify the missing values columns
traintest_2_na = traintest_2.isnull().sum()
traintest_2_na = traintest_2_na[traintest_2_na>0]
traintest_2_na.sort_values(ascending=False)


cols=['PoolQC', 'MiscFeature','Alley', 'Fence', 'FireplaceQu','LotFrontage','GarageFinish',
      'GarageQual','GarageCond', 'GarageType' , 'BsmtExposure', 'BsmtCond', 'BsmtQual',
      'BsmtFinType2', 'BsmtFinType1', 'BsmtFinType2' , 'MasVnrType' , 'MasVnrArea']


### Step 2: Identify the unique values in columns with most missing values[]
#for col in cols:
    #print(col, traintest_2[col].unique())


#### Observations:
###We observe that these columns : [BsmtCond ,BsmtQual ,GarageQual ,GarageCond ,FireplaceQu ,PoolQC  ] have a ranking for their values

####Also all the missing values columns , we would fill in None or 0 values for Nan.
```

```
 Train data after dropping columns : (1456, 79)
 Test data after dropping columns: (1459, 79)
Traintest data shape (2915, 79)
```

Step 1. : Imputing values /Preprocessing

```
def DataCleaningEncoding(wholeDataX):


    dataX=pd.DataFrame(wholeDataX)


    ########################################################

    ##pd.concat((train, test)).reset_index(drop=True)
    #print("Before dataX size is :",dataX.shape)

    #print("dataX columns :",dataX.columns.values)

    ########################################################

    ##Filling missing values with None  as mentioned in the observation
    for col in ('PoolQC','MiscFeature','Alley','Fence','FireplaceQu' , 'GarageQual' , 'GarageFinish' , 'HeatingQC',
           'KitchenQual', 'GarageType' ,'GarageCond','BsmtQual', 'BsmtCond', 'BsmtExposure','BsmtFinType1', 'BsmtFinType2','ExterQual'
            'MasVnrType','FireplaceQu','GarageQual','BsmtFinSF1'):
        dataX[col] = dataX[col].fillna('None')


    dataX['BsmtFinSF2'] = dataX['BsmtFinSF2'].fillna(0.0)


    ##Filling missing values with 0
    cols=['GarageYrBlt','GarageArea','GarageCars','BsmtUnfSF',
                'TotalBsmtSF', 'BsmtFullBath','BsmtHalfBath','LotArea','GarageYrBlt',
            'MasVnrArea','MSSubClass']
    for col in cols:
        dataX[col] = dataX[col].fillna(0)
    #print(dataX['BsmtFinType1'].unique())
    #print(dataX['BsmtFinType2'].unique())




    # Both columns have only one missing value. We will just substitute in the most common string
    cols = ['MSZoning','Exterior1st','Exterior2nd','SaleType','Electrical']
    for col in cols:
        dataX[col] = dataX[col].fillna(dataX[col].mode()[0])

    ##Custom
    ##Dropping Utilities as it has a lot of null values
    dataX = dataX.drop(['Utilities'], axis=1)

    dataX["Functional"] = dataX["Functional"].fillna("Typ")
```

```
dataX["LotFrontage"] = dataX.groupby("Neighborhood")["LotFrontage"].transform(lambda x: x.fillna(x.median()))
# 'RL' is by far the most common value. So we can fill in missing values with 'RL'
dataX['MSZoning'] = dataX.groupby('MSSubClass')['MSZoning'].transform(lambda x: x.fillna(x.mode()[0]))

########################################################
##remaining missing values
for col in dataX.columns:
    dataX[col] = dataX[col].fillna('None')
##Changing the ranking to numeric metrics
rank_dict = {None: 0, "0": 0, "None": 0, "Po": 1, "Fa": 2, "TA": 3, "Gd": 4, "Ex": 5}


cols=['KitchenQual', 'GarageQual'  ,'FireplaceQu' ,'ExterQual', 'ExterCond' ,'BsmtQual' , 'BsmtCond',
 'HeatingQC'  ,'GarageCond', 'PoolQC']


dataX['GarageQual']=dataX['GarageQual'].map(rank_dict).astype(int)
dataX['FireplaceQu']=dataX['FireplaceQu'].map(rank_dict).astype(int)
dataX['ExterQual']=dataX['ExterQual'].map(rank_dict).astype(int)
dataX['ExterCond']=dataX['ExterCond'].map(rank_dict).astype(int)
dataX['BsmtQual']=dataX['BsmtQual'].map(rank_dict).astype(int)
dataX['BsmtCond']=dataX['BsmtCond'].map(rank_dict).astype(int)
dataX['HeatingQC']=dataX['HeatingQC'].map(rank_dict).astype(int)
dataX['GarageCond']=dataX['GarageCond'].map(rank_dict).astype(int)
dataX['PoolQC']=dataX['PoolQC'].map(rank_dict).astype(int)






dataX= dataX.drop(["BsmtFinType2"],axis=1)
dataX= dataX.drop(["BsmtFinType1"] , axis=1)

dataX= dataX.drop(['KitchenQual'] , axis=1)


dataX["Functional"] = dataX["Functional"].map(
    {None: 0, "Sal": 1, "Sev": 2, "Maj2": 3, "Maj1": 4,
     "Mod": 5, "Min2": 6, "Min1": 7, "Typ": 8}).astype(int)

dataX["GarageFinish"] = dataX["GarageFinish"].map(
    {None: 0, "None": 0, "Unf": 1, "RFn": 2, "Fin": 3}).astype(int)

dataX["Fence"] = dataX["Fence"].map({None: 0,  "None": 0, "MnWw": 1, "GdWo": 2, "MnPrv": 3, "GdPrv": 4}).astype(int)



########################################################
##Step: 2 Label Encoding
########################################################
###label encoding
```

```
labelencode = LabelEncoder()

##MSZoning
dataX['MSZoning']=dataX['MSZoning'].fillna('RL', inplace=True)
labelencode.fit(dataX['MSZoning'].unique())
dataX['MSZoning'] = labelencode.transform(dataX['MSZoning'])
##Exterior1st
dataX['Exterior1st']=dataX['Exterior1st'].fillna('Other', inplace=True)
labelencode.fit(dataX['Exterior1st'].unique())
dataX['Exterior1st'] = labelencode.transform(dataX['Exterior1st'])

##Exterior2nd
dataX['Exterior2nd']=dataX['Exterior2nd'].fillna('Other', inplace=True)
labelencode.fit(dataX['Exterior2nd'].unique())
dataX['Exterior2nd'] = labelencode.transform(dataX['Exterior2nd'])
##"SaleType
dataX['SaleType']=dataX['SaleType'].fillna('Other', inplace=True)
labelencode.fit(dataX['SaleType'].unique())
dataX['SaleType'] = labelencode.transform(dataX['SaleType'])
##MasVnrType
dataX['MasVnrType']=dataX['MasVnrType'].fillna('N', inplace=True)
labelencode.fit(dataX['MasVnrType'].unique())
dataX['MasVnrType']= labelencode.transform(dataX['MasVnrType'])


##remaining missing values
for col in dataX.columns:
    dataX[col] = dataX[col].fillna('None')


##print("Before encode",dataX.dtypes)
##'BsmtFinType2','BsmtFinType1',


##'BsmtFinSF2',

cols=[     'Condition2','HouseStyle', 'RoofMatl', 'GarageType','Electrical', 'ExterQual', 'ExterCond','HeatingQC',
       'PoolQC','MiscFeature','LandContour','Heating','BldgType','SaleCondition',  'Foundation' , 'RoofStyle',
       'LotShape', 'PavedDrive', 'Street', 'Alley', 'CentralAir', 'MSSubClass', 'OverallCond',
    'YrSold', 'MoSold','Condition1','GarageQual','GarageCond', 'FireplaceQu',
      'Functional', 'Fence', 'BsmtExposure', 'GarageFinish', 'LandSlope',
      'Neighborhood', 'LotConfig' ]
for col in cols:
    #labelencode = LabelEncoder()
    labelencode.fit(dataX[col].unique())
    dataX[col] = labelencode.transform(dataX[col].values)




##Drop Features:
```

```
    dataX = dataX.drop(['MasVnrArea', 'OpenPorchSF',  'BsmtFinSF1','2ndFlrSF','BsmtFinSF2'], axis=1)




    scaler = StandardScaler()
    scaler.fit(dataX)

    scaled = scaler.transform(dataX)






    ##remaining missing values
    for col in dataX.columns:
        dataX[col] = dataX[col].fillna('None')


    #Check remaining missing values if any
    dataX_na = (dataX.isnull().sum() / len(dataX)) * 100
    dataX_na = dataX_na.drop(dataX_na[dataX_na == 0].index).sort_values(ascending=False)
    missing_data = pd.DataFrame({'Missing Ratio' :dataX_na})
    #print(missing_data)

    ##print(dataX.dtypes)
    # shape
    #print('Shape dataX: ',(dataX.shape))
    return dataX
```

Step: 2 Label Encoding

```
dataY1 = pd.DataFrame(dataY)
dataX1=pd.DataFrame(traintest_2)



encodedData=DataCleaningEncoding(dataX1)


trainData = encodedData.iloc[:len(dataY1), :]
testData = encodedData.iloc[len(dataY1):, :]
print("test",testData.shape)
print("trainData",trainData.shape)
print("dataY1",dataY1.shape)
```

```
print("encodedData",encodedData.shape)
```

```
test (1459, 70)
trainData (1456, 70)
dataY1 (1456, 1)
encodedData (2915, 70)
```

Scoring Function

For scoring function we consider the following columns for scoring:

1. OverallQual
2. TotalBsmtSF
3. OverallQual
4. FullBath
5. GarageArea
6. GrLivArea
7. TotRmsAbvGrd
8. Fireplaces
9. WoodDeckSF
10. YearBuilt

```
dataX3=pd.DataFrame(dataX1)
X3=pd.DataFrame(dataX1)
dataY3 = pd.DataFrame(dataY)


##DataFrame for scoring function
dataX3=dataX3[['OverallQual',
'TotalBsmtSF',
'OverallQual',
'FullBath',
'GarageArea',
'GrLivArea',
'TotRmsAbvGrd',
'Fireplaces',
'WoodDeckSF',
'YearBuilt']]


scoringColumns=['OverallQual',
```

```
'TotalBsmtSF',
'OverallQual',
'FullBath',
'GarageArea',
'GrLivArea',
'TotRmsAbvGrd',
'Fireplaces',
'WoodDeckSF',
'YearBuilt']
```

```
2915 10
```

Using the scoring columns , get the “desirability” of the houses

```
#Check remaining missing values if any
#dataX3_na = (dataX3.isnull().sum() / len(dataX3)) * 100
#dataX3_na = dataX3_na.drop(dataX3_na[dataX3_na == 0].index).sort_values(ascending=False)
#missing_data = pd.DataFrame({'Missing Ratio' :dataX3_na})
#print(missing_data)


dataX3.head()
rows=dataX3.shape[0]
columns=dataX3.shape[1]
print(rows,columns)

rank=list()



##Calculate the scoringFunctionValue
for row in range(rows):
  sum=0
  for col in range(columns):
    dataValue=dataX3.iloc[row][col]
    sum+=dataValue
    #print(row1)
  rank.append(sum)
```

After we have got the score for each ,we add the score at the end of the dataframe

```
#print(rank)

rankdf=pd.DataFrame(rank)

rankdf.head()

X3["ScoringFunctionValue"]=rankdf
X3 = X3.sort_values(by ='ScoringFunctionValue', ascending=False )


##Change the order of the columns
cols = list(X3.columns)
cols = [cols[-1]] + cols[:-1]
X3 = X3[cols]
```

	ScoringFunctionValue	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
1818	2954.000	30	C (all)	72.000	9392	Pave	None	Reg	Lvl	AllPub
708	2946.000	30	RL	56.000	4130	Pave	None	IR1	Lvl	AllPub
2118	2934.000	30	RM	nan	6120	Pave	None	Reg	Lvl	AllPub
1098	2902.000	30	RL	60.000	8400	Pave	None	Reg	Bnk	AllPub
1215	2871.000	50	RM	52.000	6240	Pave	None	Reg	Lvl	AllPub
1810	2869.000	30	RM	50.000	5925	Pave	None	Reg	Lvl	AllPub
1581	2837.000	30	RL	67.000	8777	Pave	None	Reg	Lvl	AllPub
2887	2686.000	30	C (all)	69.000	12366	Pave	None	Reg	Lvl	AllPub
1843	2617.000	20	RL	nan	9000	Pave	None	Reg	Lvl	AllPub
532	2285.000	20	RL	50.000	5000	Pave	None	Reg	Low	AllPub

What is the ten most desirable houses?

```
X3.head(10)
```

	ScoringFunctionValue	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
2545	13937.000	20	RL	128.000	39290	Pave	None	IR1	Bnk	AllPub
496	9260.000	20	RL	nan	12692	Pave	None	IR1	Lvl	AllPub
2678	9088.000	60	RL	114.000	17242	Pave	None	IR1	Lvl	AllPub
2818	8987.000	75	RL	60.000	19800	Pave	None	Reg	Lvl	AllPub
1475	8755.000	20	RL	110.000	14300	Pave	None	Reg	HLS	AllPub
1167	8754.000	60	RL	118.000	35760	Pave	None	IR1	Lvl	AllPub
1659	8465.000	20	RL	105.000	13693	Pave	None	Reg	Lvl	AllPub
1369	8417.000	20	RL	nan	11400	Pave	None	Reg	Lvl	AllPub
2749	8398.000	190	RL	94.000	22136	Pave	None	Reg	Lvl	AllPub
767	8308.000	60	RL	47.000	53504	Pave	None	IR2	HLS	AllPub

What is the ten least desirable houses?

```
X3.tail(10)
```

	ScoringFunctionValue	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
1818	2954.000	30	C (all)	72.000	9392	Pave	None	Reg	Lvl	AllPub
708	2946.000	30	RL	56.000	4130	Pave	None	IR1	Lvl	AllPub
2118	2934.000	30	RM	nan	6120	Pave	None	Reg	Lvl	AllPub
1098	2902.000	30	RL	60.000	8400	Pave	None	Reg	Bnk	AllPub
1215	2871.000	50	RM	52.000	6240	Pave	None	Reg	Lvl	AllPub
1810	2869.000	30	RM	50.000	5925	Pave	None	Reg	Lvl	AllPub
1581	2837.000	30	RL	67.000	8777	Pave	None	Reg	Lvl	AllPub
2887	2686.000	30	C (all)	69.000	12366	Pave	None	Reg	Lvl	AllPub
1843	2617.000	20	RL	nan	9000	Pave	None	Reg	Lvl	AllPub
532	2285.000	20	RL	50.000	5000	Pave	None	Reg	Low	AllPub

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

Selected these columns which attribute more to the SalePrice of the houses. Encoded these columns so that an equation can be formed which returns th scoringFucntionValue for that house.

1. OverallQual
2. TotalBsmtSF
3. OverallQual
4. FullBath
5. GarageArea
6. GrLivArea
7. TotRmsAbvGrd
8. Fireplaces
9. WoodDeckSF
10. YearBuilt

Part 4 - Pairwise Distance Function

Step 1

We want the scoring function to based upon the columns which describe the layout and size of the houses. So we select these columns to get a better pa distance function. Example if there were 2 room houses and 3 room houses , distance between same-number-of-room houses should be less than differ number-of-room houses.

```
# TODO: code for distance function

from sklearn.metrics.pairwise import euclidean_distances
from scipy.spatial.distance import pdist
train_Q4=pd.DataFrame(dataX1)
X4=pd.DataFrame(dataX1)
dataY4 = pd.DataFrame(dataY)


encodedData=DataCleaningEncoding(train_Q4)


trainData = encodedData.iloc[:len(dataY4), :]
testData = encodedData.iloc[len(dataY4):, :]
print("test",testData.shape)
print("trainData",trainData.shape)
print("dataY4",dataY4.shape)

print("encodedData",encodedData.shape)

train_Q4=pd.DataFrame(trainData)


columns=['OverallQual',
'TotalBsmtSF',
'OverallQual',
'FullBath',
'GarageArea',
'GrLivArea',
'TotRmsAbvGrd',
'Fireplaces',
'WoodDeckSF',
'YearBuilt']

pairwiseDistFunctionDf=train_Q4[['OverallQual','TotalBsmtSF','OverallQual','FullBath','GarageArea','GrLivArea','TotRmsAbvGrd','Firepla
```

```
pairwiseDist=euclidean_distances(pairwiseDistFunctionDf, pairwiseDistFunctionDf)
#print(pd.DataFrame(pairwiseDist))
```

```
Empty DataFrame
Columns: [Missing Ratio]
Index: []
Shape dataX:  (2915, 71)
test (1459, 71)
trainData (1456, 71)
dataY4 (1456, 1)
encodedData (2915, 71)
```

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

The distance function works well when correlated columns are chosen for finding the distance. f we select attributes that constribute less towards the Sa
the distance function does not work well. It gives larger distance for the houses which are much similar if we include them.

So following columns give a good distance function.

1. OverallQual
2. TotalBsmtSF
3. OverallQual
4. FullBath
5. GarageArea
6. GrLivArea
7. TotRmsAbvGrd
8. Fireplaces
9. WoodDeckSF
10. YearBuilt

Part 5 - Clustering

```
# TODO: code for clustering and visualization
```

```
import pandas as pd
from scipy import stats
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import AgglomerativeClustering
from sklearn.preprocessing import MinMaxScaler
from sklearn.datasets import load_digits
from sklearn.preprocessing import normalize
from sklearn.manifold import TSNE



train_Q5=pd.DataFrame(dataX1)
X5=pd.DataFrame(dataX1)
dataY5 = pd.DataFrame(dataY)


encodedData=DataCleaningEncoding(train_Q5)


trainData = encodedData.iloc[:len(dataY5), :]
testData = encodedData.iloc[len(dataY5):, :]
#print("test",testData.shape)  #print("trainData",trainData.shape)  #print("dataY5",dataY5.shape)  #print("encodedData",encodedData.sh
train_Q5=pd.DataFrame(trainData)
data=train_Q5##.values

clustering= AgglomerativeClustering(n_clusters=6, affinity='euclidean', linkage='ward')
clustering.fit(data)

print(clustering.labels_)
# MinMax scale the data so that it fits nicely onto the 0.0->1.0 axes of the plot.
scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(data)
#data_scaled=pd.DataFrame(data_scaled)


X, y = load_digits(return_X_y=True)
tsne = TSNE()
X_embedded = tsne.fit_transform(X)



##As we can see, the model managed to take a 64-dimensional dataset and project it on to a 2-dimensional space in such a way that simi


palette = sns.color_palette("bright", 10)
sns.scatterplot(X_embedded[:,0], X_embedded[:,1], hue=y, legend='full')
```

```
[0 0 0 ... 0 0 0]
<matplotlib.axes._subplots.AxesSubplot at 0x7fd3e2c5d7b8>
```

How well do the clusters reflect neighborhood boundaries? Write a discussion on what your clusters capture and how well they work.

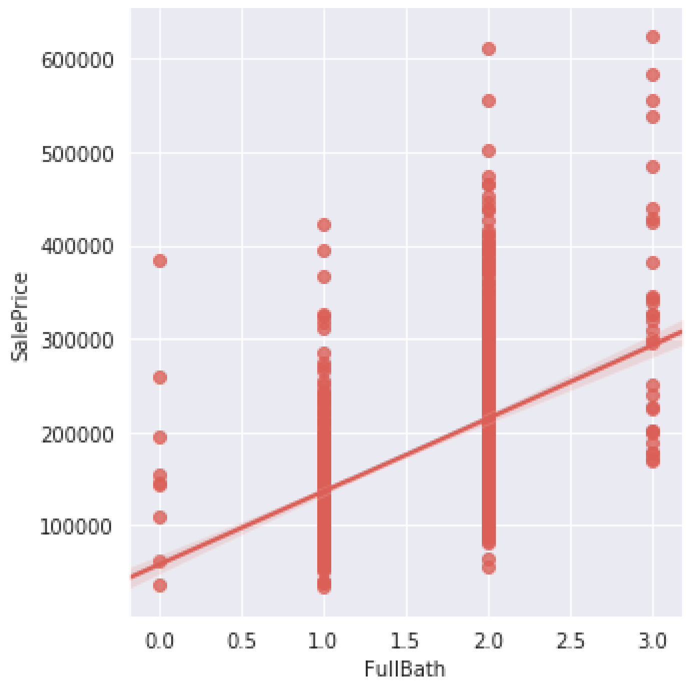
Clusters clearly attribute the Neighbourhood boundaries as seen in the plot. The clusters is formed on the similarity on the most highly ranked columns a similarity in their data , all those houses are clubbed together.

Part 6 - Linear Regression

```
# TODO: code for linear regression
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as seabornInstance
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
%matplotlib inline
```

```
train_Q6=pd.DataFrame(dataX1)
X6=pd.DataFrame(dataX1)
dataY6 = pd.DataFrame(dataY)
encodedData=DataCleaningEncoding(train_Q6)
trainData = encodedData.iloc[:len(dataY6), :]
testData = encodedData.iloc[len(dataY6):, :]


####columns for linear regression
columns=['OverallQual','TotalBsmtSF','OverallQual','FullBath','GarageArea','GrLivArea','TotRmsAbvGrd',
'Fireplaces','YearBuilt']


X=trainData[['OverallQual','TotalBsmtSF','OverallQual','FullBath','GarageArea','GrLivArea','TotRmsAbvGrd',
'Fireplaces','YearBuilt']]

Xplot1=trainData[['OverallQual','TotalBsmtSF','OverallQual','FullBath','GarageArea','GrLivArea','TotRmsAbvGrd',
'Fireplaces','YearBuilt']]
Xplot1["SalePrice"]=dataY6[["SalePrice"]]
sns.lmplot(x='FullBath', y='SalePrice', data=Xplot1)
```

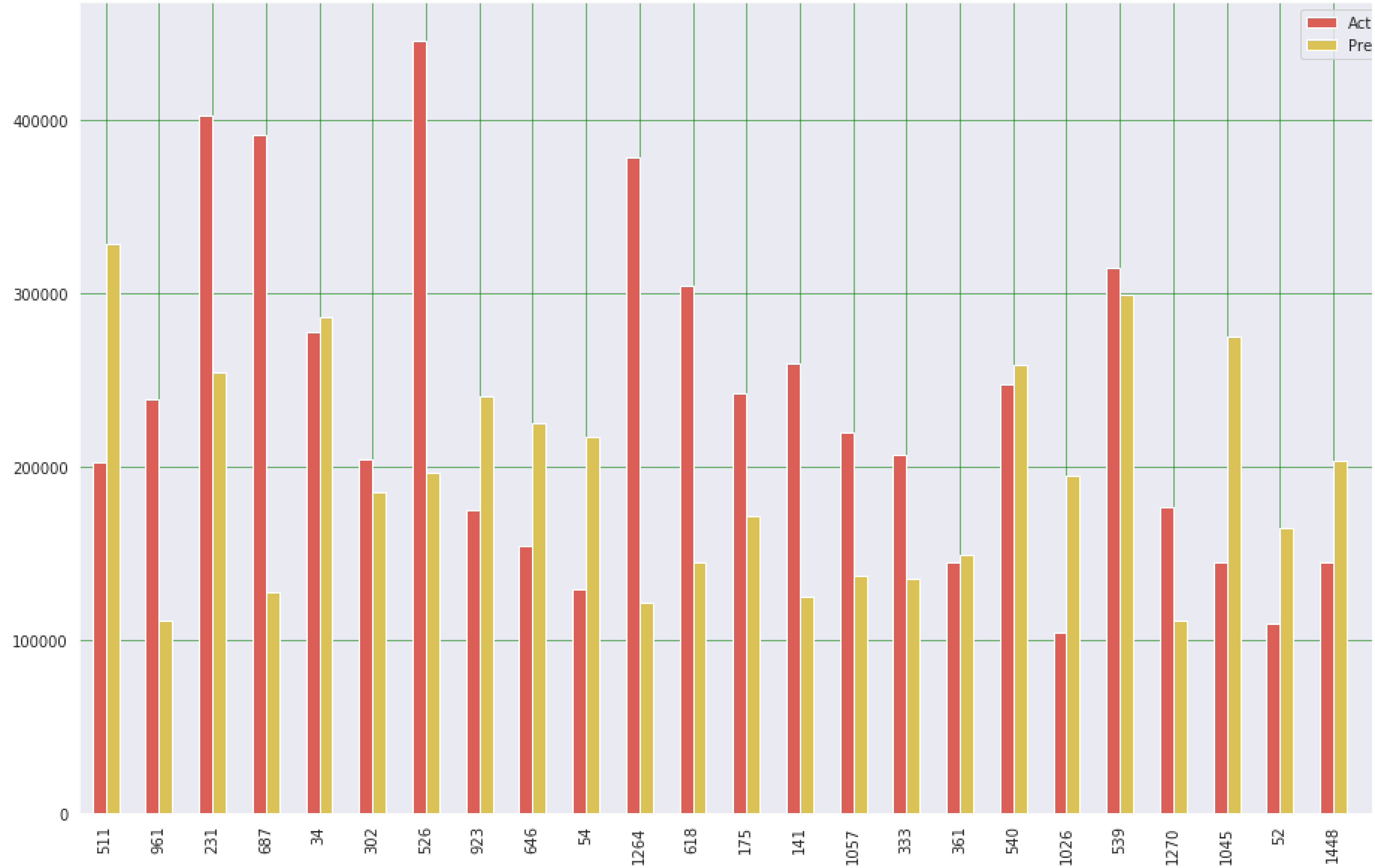
```
Empty DataFrame
Columns: [Missing Ratio]
Index: []
Shape dataX:  (2915, 71)
<seaborn.axisgrid.FacetGrid at 0x7fd3e37bcef0>
```




```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as seabornInstance
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
%matplotlib inline


regressor = LinearRegression()


X_train, X_test, y_train, y_test = train_test_split(X, dataY6, test_size=0.2, random_state=0)


regressor.fit(X_train, y_train) #training the algorithm
```

```
#To retrieve the intercept:
print(regressor.intercept_)
#For retrieving the slope:
print(regressor.coef_)
X_test=testData[['OverallQual','TotalBsmtSF','OverallQual','FullBath','GarageArea','GrLivArea','TotRmsAbvGrd',
'Fireplaces','YearBuilt']]
y_pred = regressor.predict(X_test)

df=pd.DataFrame()

df["Actual"] =  y_test["SalePrice"]
df["Predict"] =  pd.DataFrame(y_pred)

df1 = df.head(25)
df1.plot(kind='bar',figsize=(16,10))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```

```
[-836308.81001022]
[[ 8621.31102994    37.29511908  8621.31102993 -6127.63148473
    44.2095773     59.0967969   -303.56916061  7582.41934704
   390.14213802]]
```




```
print('Mean Absolute Error:', metrics.mean_absolute_error(df["Actual"], df["Predict"]))
print('Mean Squared Error:', metrics.mean_squared_error(df["Actual"], df["Predict"]))
```

```
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(df["Actual"], df["Predict"]) ))
```

```
Mean Absolute Error: 79544.54726169552
Mean Squared Error: 10607436615.848024
Root Mean Squared Error: 102992.41047692798
```

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

Our algorithm considered the following columns

1. 'OverallQual'
2. 'TotalBsmtSF'
3. 'OverallQual'
4. 'FullBath'
5. 'GarageArea'
6. 'GrLivArea'
7. 'TotRmsAbvGrd',
8. 'Fireplaces'
9. 'YearBuilt'

This means that our algorithm was not very accurate but can still make reasonably good predictions.

Part 7 - External Dataset

```
# TODO: code to import external dataset and test


externalData.head()
externalData.isna().any()


column1=pd.DataFrame()
column1=externalData[['taxvaluedollarcnt']]
column1['taxvaluedollarcnt'] = column1['taxvaluedollarcnt'].fillna(0)
```

```
print(column1.shape)



train_Q6=pd.DataFrame(dataX1)
X6=pd.DataFrame(dataX1)
dataY6 = pd.DataFrame(dataY)
print(train_Q6.shape)

encodedData=DataCleaningEncoding(train_Q6)
column1SelectedTrain=column1.iloc[:len(dataY6), :]



print(column1SelectedTrain.shape)

trainData = encodedData.iloc[:len(dataY6), :]
testData = encodedData.iloc[len(dataY6):, :]


column1SelectedTest=column1.iloc[:len(testData), :]
print(column1SelectedTest.shape)


##Adding external dataset
trainData["taxvaluedollarcnt"]=pd.DataFrame(column1SelectedTrain)
trainData.head()

testData["taxvaluedollarcnt"]=pd.DataFrame(column1SelectedTest)
testData.head()
```

```
(2491, 1)
(2915, 79)
(1456, 1)
(1459, 1)
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	LotConfig	LandSlope	Neighborh
1456	0	0	80.000	11622	1	1	3	3	4	0	
1457	0	0	81.000	14267	1	1	0	3	0	0	
1458	5	0	74.000	13830	1	1	0	3	4	0	
1459	5	0	78.000	9978	1	1	0	3	4	0	
1460	11	0	43.000	5005	1	1	0	1	4	0	

```
from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsIC
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clone
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
import lightgbm as lgb

##Define a cross validation strategy
###Validation function
#"""
n_folds = 5

def rmsle_cv(model):
    kf = KFold(n_folds, shuffle=True, random_state=42).get_n_splits(trainData.values)
    rmse= np.sqrt(-cross_val_score(model, trainData.values, dataY6, scoring="neg_mean_squared_error", cv = kf))
    return(rmse)  #"""
```

```
GBoost = GradientBoostingRegressor(n_estimators=3000, learning_rate=0.05,
                                   max_depth=4, max_features='sqrt',
                                   min_samples_leaf=15, min_samples_split=10,
                                   loss='huber', random_state =5)


score = rmsle_cv(GBoost)
print("Gradient Boosting score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()) ,score)
```

```
Gradient Boosting score: 22640.9354 (1917.4683)
 [21704.44435388 23858.22812401 23731.13616916 19319.50520034
 24591.36334436]
```

Describe the dataset and whether this data helps with prediction.

I used a dataset on the housing prices to get the "taxvaluedollarcnt". The tax rate for house linearly affects the housing prices. More the tax, more would rate of the house. Using this column , I ran the model to see the mean squared error , and it actually reduced the error. For Gradient Boosting , it was Grad Boosting score: 22502.1931 (2156.0775) with original data which went down to Gradient Boosting score: 22640.9354 (1917.4683).

Part 8 - Permutation Test

```
# TODO: code for all permutation tests



from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import permutation_test_score
from sklearn import datasets
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score
from sklearn import metrics

dataY8 = pd.DataFrame(dataY)
dataX8=pd.DataFrame(traintest_2)

encodedData=DataCleaningEncoding(dataX1)


trainData8 = encodedData.iloc[:len(dataY8), :]
testData8 = encodedData.iloc[len(dataY8):, :]
```

```
cols=['LotFrontage','YrSold'  ,'EnclosedPorch', 'FullBath' , 'TotalBsmtSF', 'YearBuilt','Fireplaces' ,
      'Condition1' , 'Exterior1st' , 'BsmtFullBath' ]
newDataX=pd.DataFrame()


for col in cols:
    trainColX=pd.DataFrame(trainData8[col])
    testColX=pd.DataFrame(testData8[col])
    # Create linear regression object
    linear_regr = linear_model.LinearRegression()
    # Train the model using the training sets
    linear_regr.fit(trainColX, dataY8)

    # Make predictions using the testing set
    y_pred = linear_regr.predict(testColX)

    score, permutation_scores, pvalue = permutation_test_score(linear_regr, trainColX, dataY8, cv=2, n_permutations=120)
    predY=linear_regr.predict(trainColX)

    print('Root-mean-squared Error of the Log(SalePrice) for Column : ',col," : ", np.sqrt(metrics.mean_squared_log_error(dataY8, prec
    print('P-value for Column : ',col," : ",pvalue )
```

```
Root-mean-squared Error of the Log(SalePrice) for Column :  LotFrontage  :  0.3746480252101541
P-value for Column :  LotFrontage  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  YrSold  :  0.4036412753499791
P-value for Column :  YrSold  :  0.9090909090909091
Root-mean-squared Error of the Log(SalePrice) for Column :  EnclosedPorch  :  0.3997828901926548
P-value for Column :  EnclosedPorch  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  FullBath  :  0.32896715515846786
P-value for Column :  FullBath  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  TotalBsmtSF  :  0.3260794686890968
P-value for Column :  TotalBsmtSF  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  YearBuilt  :  0.3407702001914169
P-value for Column :  YearBuilt  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  Fireplaces  :  0.34825579742170126
P-value for Column :  Fireplaces  :  0.008264462809917356
Root-mean-squared Error of the Log(SalePrice) for Column :  Condition1  :  0.40083952649533716
P-value for Column :  Condition1  :  0.2231404958677686
Root-mean-squared Error of the Log(SalePrice) for Column :  Exterior1st  :  0.4038649236343497
P-value for Column :  Exterior1st  :  0.6942148760330579
Root-mean-squared Error of the Log(SalePrice) for Column :  BsmtFullBath  :  0.3915748476064666
P-value for Column :  BsmtFullBath  :  0.008264462809917356
```

Describe the results.

Randomly selected variables gave lower probability of occurrence than these variables. Depending on the correlation with SalePrice , we picked up these colummns for permutation test.

Part 9 - Final Result

```
########################################################
##Step: 3 Modelling
########################################################
from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsIC
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clone
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
import lightgbm as lgb

##Define a cross validation strategy
###Validation function
#"""
n_folds = 5

def rmsle_cv(model):
    kf = KFold(n_folds, shuffle=True, random_state=42).get_n_splits(trainData.values)
    rmse= np.sqrt(-cross_val_score(model, trainData.values, dataY1, scoring="neg_mean_squared_error", cv = kf))
    return(rmse)  #"""




lasso = make_pipeline(RobustScaler(), Lasso(alpha =0.0005, random_state=1))
score = rmsle_cv(lasso)
print("\nLasso score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()) ,score)

model = lasso.fit(trainData, dataY1)
submitPredict_lasso=model.predict(testData)
print("testdata",testData.shape)

ENet = make_pipeline(RobustScaler(), ElasticNet(alpha=0.0005, l1_ratio=.9, random_state=3))
score = rmsle_cv(ENet)
```

```
print("ElasticNet score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()),score)
model = ENet.fit(trainData, dataY1)
submitPredict_enet=model.predict(testData)


#"""
GBoost = GradientBoostingRegressor(n_estimators=3000, learning_rate=0.05,
                                   max_depth=4, max_features='sqrt',
                                   min_samples_leaf=15, min_samples_split=10,
                                   loss='huber', random_state =5)


score = rmsle_cv(GBoost)
print("Gradient Boosting score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()) ,score)

model = GBoost.fit(trainData, dataY1)
submitPredict_gboost=model.predict(testData)#"""

submitPredict_lasso=pd.DataFrame(submitPredict_lasso)
submitPredict_lasso.to_csv("submitPredict_lasso.csv", index = "True")


submitPredict_gboost=pd.DataFrame(submitPredict_gboost)
submitPredict_gboost.to_csv("submitPredict_gboost.csv", index = True)

submitPredict_enet=pd.DataFrame(submitPredict_enet)
submitPredict_enet.to_csv("submitPredict_enet.csv", index = "True")

a1=submitPredict_enet


a1['Id'] = range(1, len(a1) + 1)
a1.to_csv("a1.csv", index = "False")
```

```
Lasso score: 27826.4437 (1497.8703)
 [27562.26596648 25373.03944072 29027.23702812 27458.59069698
 29711.08552904]
testdata (1459, 71)
ElasticNet score: 27801.4137 (1499.4474)
 [27447.94844167 25375.39895067 29019.98693725 27457.56946101
 29706.16494445]
Gradient Boosting score: 22502.1931 (2156.0775)
 [21758.36820591 24125.49683498 23661.29303226 18599.02216718
 24366.78531735]
```

```
from google.colab import files

#a1.to_csv("a1.csv", index = "True")
submitPredict_enet.to_csv("submitPredict_enet.csv", index = False)
files.download('submitPredict_enet.csv')
```

Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderboard as confirmation. Be sure to prov
to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with SBU.

```
submitPredict_gboost.to_csv("submitPredict_gboost.csv", index = True)
files.download('submitPredict_gboost.csv')
```

```
submitPredict_lasso.to_csv("submitPredict_lasso.csv", index = "True")
files.download('submitPredict_lasso.csv')
```

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

Highest Rank: 908

Score: 0.1195

Number of entries: 4

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901	**alim90**	0.11943	53	2d
902	**Damilya Saduakhas**	0.11944	1	2d
903	**UNKERS**	0.11944	21	21d
904	**Aveena Kottwani**	0.11950	4	6m

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905	**Shailendra Kumar**	0.11955	1	1mo
906	**Alex Lc**	0.11955	5	2mo
907	**Jon Walwyn**	0.11955	1	9d

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submitPredict_gboost.csv	3 minutes ago	160 seconds	0 seconds	0.11950

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