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 text to answer the questions. We also ask that code be commented to make it easier to follow.

In [112]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
from sklearn.cluster import KMeans
from sklearn.feature_selection import f_regression
from sklearn.model_selection import permutation_test_score
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold

pd.set_option("display.max_columns", 500)
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

data_set = pd.read_csv("/Users/mkondeti/Desktop/Data Science Fundamentals/h
data_set = data_set.set_index('Id')
```

The above statements import libraries which will be used in this assignment. The training data which is a csv file is read as a dataframe using pandas dataframe. The dataframe is then indexed with "Id" column as index of the dataframe.

In [113]:
```
_set[["MSSubClass", "LotFrontage", "LotArea", "Neighborhood", "BldgType", "H
    "Exterior1st", "ExterQual", "BsmtQual", "KitchenQual", "Functional", "G
    "LandContour", "TotalBsmtSF", "GrLivArea","LowQualFinSF","GarageCond","
     "GarageCars", "TotRmsAbvGrd", "BedroomAbvGr", "FullBath", "YrSold", "S
```

Out[113]:

	MSSubClass	LotFrontage	LotArea	Neighborhood	BldgType	HouseStyle	OverallQual	YearBuilt
Id								
1	60	65.0	8450	CollgCr	1Fam	2Story	7	2003
2	20	80.0	9600	Veenker	1Fam	1Story	6	1976
3	60	68.0	11250	CollgCr	1Fam	2Story	7	2001
4	70	60.0	9550	Crawfor	1Fam	2Story	7	1915
5	60	84.0	14260	NoRidge	1Fam	2Story	8	2000

The above statement selects multiple columns from "data_set" dataframe and points the resultant dataframe to the df variable. The columns are selected for the first two questions.

Note : The above data is a subset of the actual complete dataframe.

In [114]:
```
df.isnull().sum()
```

Out[114]:
```
MSSubClass         0
LotFrontage      259
LotArea            0
Neighborhood       0
BldgType           0
HouseStyle         0
OverallQual        0
YearBuilt          0
YearRemodAdd       0
Exterior1st        0
ExterQual          0
BsmtQual          37
KitchenQual        0
Functional         0
GarageArea         0
SaleType           0
SaleCondition      0
LandContour        0
TotalBsmtSF        0
GrLivArea          0
LowQualFinSF       0
GarageCond        81
PoolArea           0
GarageQual        81
OpenPorchSF        0
WoodDeckSF         0
GarageCars         0
TotRmsAbvGrd       0
BedroomAbvGr       0
FullBath           0
YrSold             0
SalePrice          0
dtype: int64
```

In [115]:
```
df.dtypes
```

Out[115]:
```
MSSubClass         int64
LotFrontage      float64
LotArea            int64
Neighborhood      object
BldgType          object
HouseStyle        object
OverallQual        int64
YearBuilt          int64
YearRemodAdd       int64
Exterior1st       object
ExterQual         object
BsmtQual          object
KitchenQual       object
Functional        object
GarageArea         int64
SaleType          object
SaleCondition     object
LandContour       object
TotalBsmtSF        int64
GrLivArea          int64
LowQualFinSF       int64
GarageCond        object
PoolArea           int64
GarageQual        object
OpenPorchSF        int64
WoodDeckSF         int64
GarageCars         int64
TotRmsAbvGrd       int64
BedroomAbvGr       int64
FullBath           int64
YrSold             int64
SalePrice          int64
dtype: object
```

The above two statements indicate the total of null values and data types of columns in the selected dataframe(df)

Part 1 - Pairwise Correlations

In [116]:
```
def function(input):
    if (input == 'Ex'):
        return 10
    elif (input == 'Gd'):
        return 8
    elif (input == 'TA'):
        return 6
    elif (input == 'Fa'):
        return 4
    elif (input == 'Po' ):
        return 2
    else:
        return 0
```

In [117]:
```
df['TotalSqft'] = TotalSqft = data_set["1stFlrSF"]+data_set["TotalBsmtSF"]+
df['KitchenQualIndex'] =KitchenQualIndex = data_set['KitchenQual'].apply(fu
df['BsmtQualIndex']=BsmtQualIndex=data_set['BsmtQual'].apply(function)
```

In [118]:
```
df[['KitchenQualIndex', 'BsmtQualIndex', 'TotalSqft']].head()
```

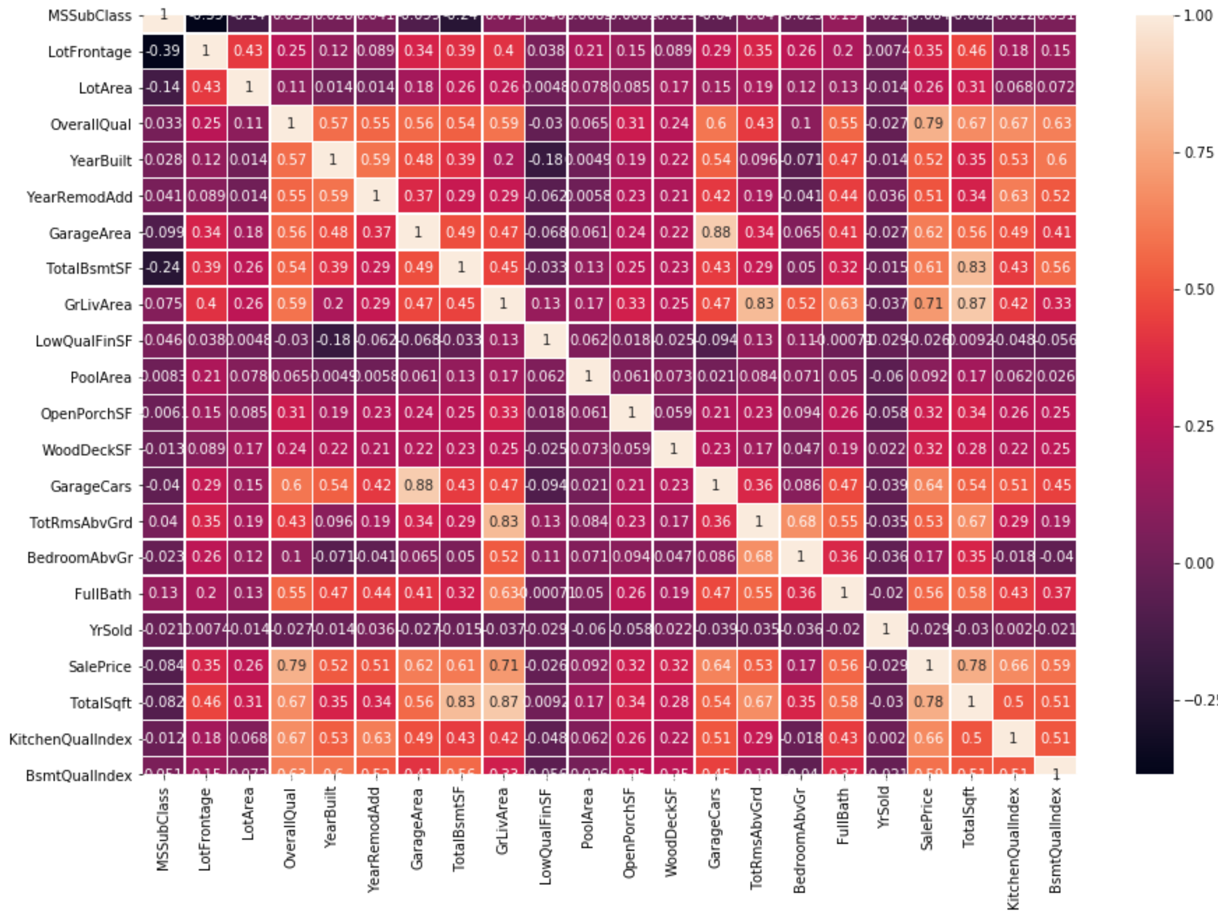
Out[118]:

	KitchenQualIndex	BsmtQualIndex	TotalSqft
Id			
1	8	8	2566
2	6	8	2524
3	8	8	2706
4	8	6	2473
5	8	8	3343

The above statements compute totalsqft as summation of 1stFlrSF, TotalBsmtSF and 2nd FlrSF Function converts categorical feature 'Bsmtqal' into discrete values. The values are mapped to values based on the relative importance.

In [119]:
```python
plt.figure(figsize=(15, 10))
sns.heatmap(df.corr(), annot = True, linewidth=0.5)
```

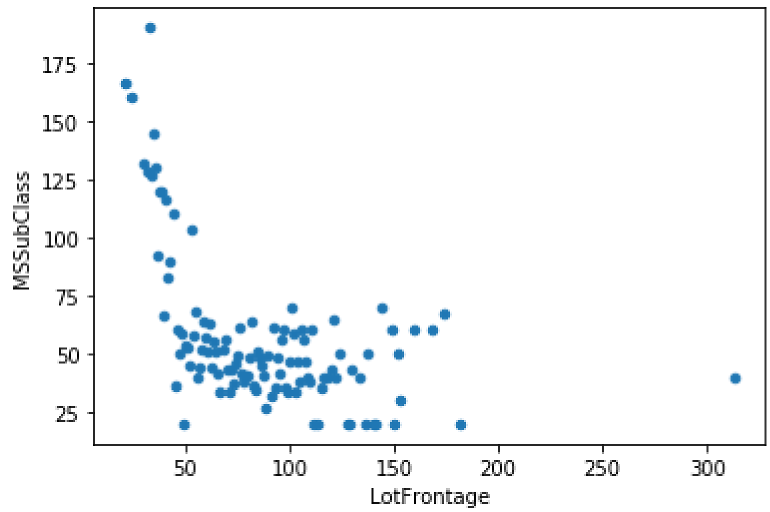
Out[119]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1e71c910>



From the above heatmap, we can see the corelarions between various columns of the dataframe.

In [120]:
```
group1 = df.groupby('LotFrontage').MSSubClass.mean()
group1 = group1.to_frame()
group1.reset_index(inplace=True)
group1.plot(kind = 'scatter', x = "LotFrontage", y="MSSubClass")
```

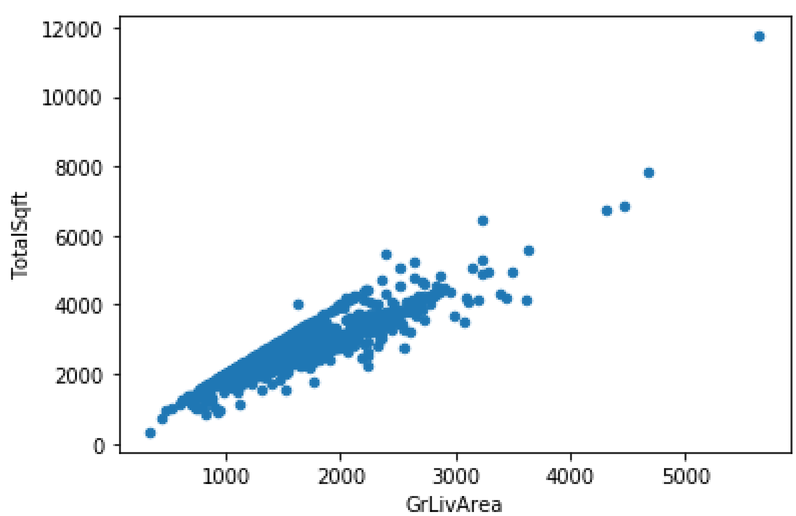
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1cc18f90>



This plot between LotFrontage and BsmtQualIndex tells that both variables have negative corelation between them. Even in the heatmap, both these variables have a corelation of -0.39 LotFrontage and BsmtQualIndex have most negative corelation.

In [121]:
```
group2 = df.groupby('GrLivArea').TotalSqft.mean()
group2 = group2.to_frame()
group2.reset_index(inplace=True)
group2.plot(kind = 'scatter', x = "GrLivArea", y="TotalSqft")
```

Out[121]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1cc91650>



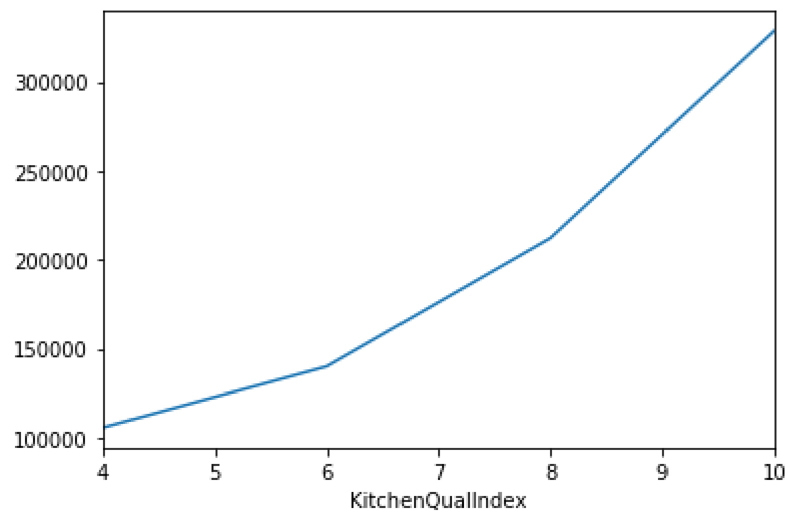
The above scatter plot between "GrLivArea" and "TotalSqft" shows positive corelation This is also evident from the heatmap which tells us that a corelation of 0.87 is between features "GrLivArea" and "TotalSqft". So, corelation between "GrLivArea" and "TotalSqft" is the maximum corelation.

Discuss most positive and negative correlations.

Part 2 - Informative Plots

In [122]:
```
group = df.groupby('KitchenQualIndex')['SalePrice'].mean()
group.plot(kind = 'line')
```

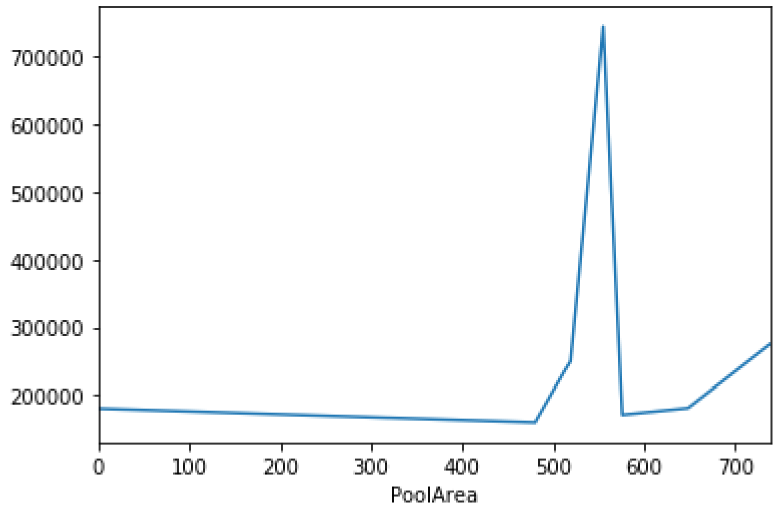
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1cbd2350>



The above plot is a line graph between KitchenQualIndex and SalePrice. We can see that both of these features have a positive corelation and we can infer that KitchenQuality is an important factor in determining the price of a given proeprty. From this, we can also infer that Women have crucial role in purchase of a house since they care a lot about Kitchen.

In [123]:
```
group = df.groupby('PoolArea')['SalePrice'].mean()
group.plot(kind = 'line')
```

Out[123]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c74f310>

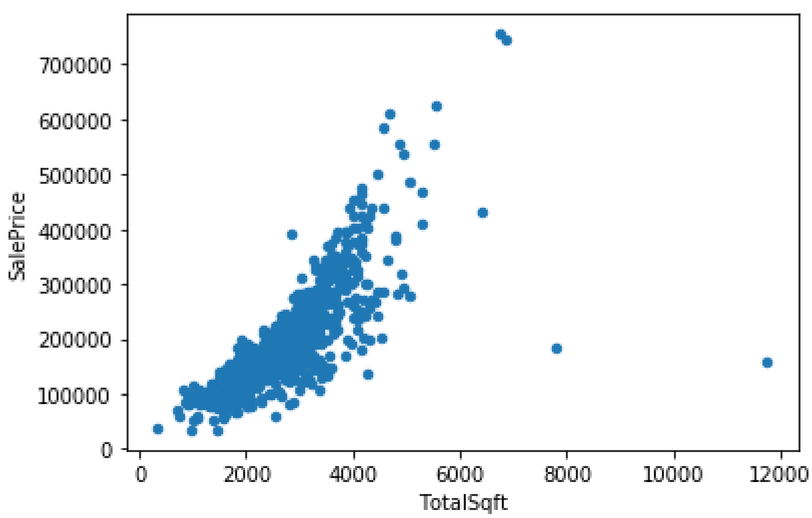


This line graph between "PoolArea" and "SalePrice" demonstrates that PoolArea doesn't influence the SalePrice and this makes first line graph even more meaningful.

What interesting properties does Plot 1 reveal?

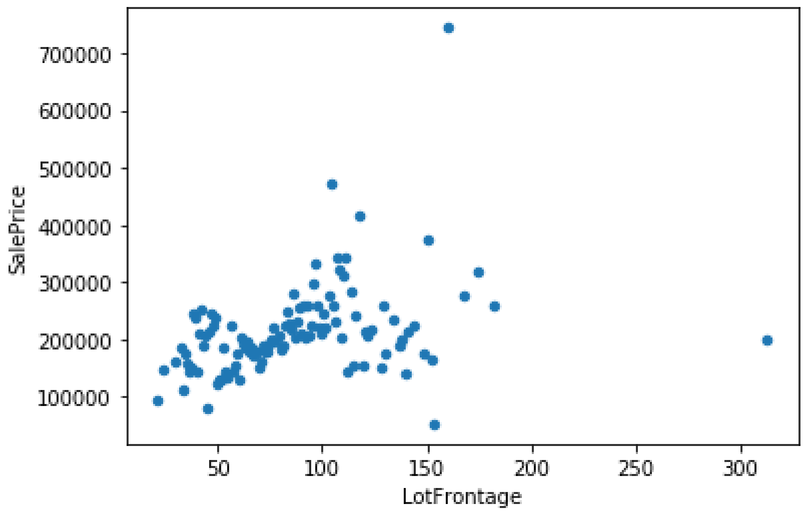
In [124]:
```
group2 = df.groupby('TotalSqft').SalePrice.mean()
group2 = group2.to_frame()
group2.reset_index(inplace=True)
group2.plot(kind = 'scatter', x = "TotalSqft", y="SalePrice")
```

Out[124]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1cd59650>



In [125]:
```
group3 = df.groupby('LotFrontage').SalePrice.mean()
group3 = group3.to_frame()
group3.reset_index(inplace=True)
group3.plot(kind = 'scatter', x = "LotFrontage", y="SalePrice")
```

Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1ce35fd0>

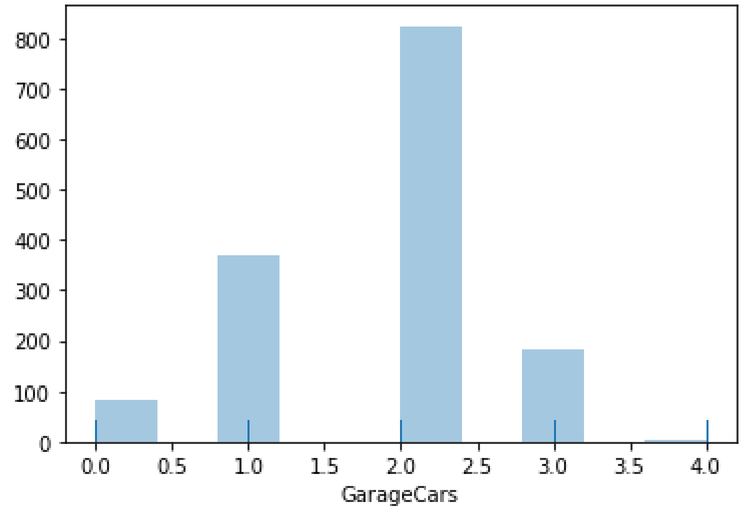


The Scatter plot is between "TotalSqft" and "SalePrice" As we can see in the figure, as TotalSqft increases, the SalePrice increases which is natural for any house sale. But, with second figure we can infer that as LotFrontage value increases, the SalePrice value is not increasing. So, people are more inclined to buy a house which has more living area and less inclined to spend more money on LotFrontage. In a way, people are more inclined to buy flats in apartments than buy independent houses.

What interesting properties does Plot 2 reveal?

In [126]:
```
group3 = df['GarageCars']


sns.distplot(group3, bins=10, kde=False, rug=True);
```

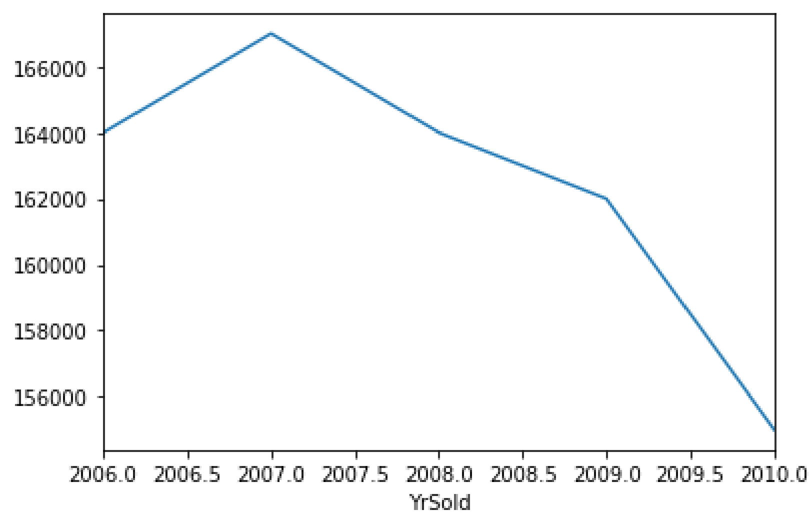


From the bar diagram, we can see that more number of families use two cars per house and very few pople use three cars. We can find almost zero families using four cars. Hence, two cars per house is the norm according to the dataset.

What interesting properties does Plot 3 reveal?

In [127]:
```
group = df.groupby('YrSold')['SalePrice'].median()
group.plot(kind = 'line')
```

Out[127]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1cedf890>

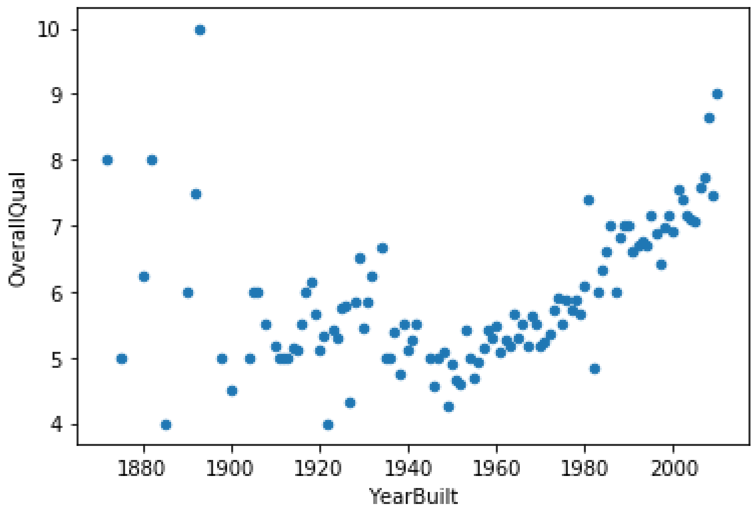


The above scatter plot is between 'YrSold' and 'SalePrice'. As we can see from the graph, the selling price od houses were highest at 2007 i.e before recession. After recession has it, mainly housing market was affected badly. The selling price of houses have gone down when compared with pre recession time. This trend is evident from the line plot.

What interesting properties does Plot 4 reveal?

In [128]:
```
group3 = df.groupby('YearBuilt').OverallQual.mean()
group3 = group3.to_frame()
group3.reset_index(inplace=True)
group3.plot(kind = 'scatter', x = "YearBuilt", y="OverallQual")
```

Out[128]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1f455190>



The above scatter plot is between "YearBuilt" and "OverallQual". As we can see, after 1960's the overallQual of the house kep't increasing. This can be due to the advancements in building technology and better standard of living of people which allowed people to afford better quality of houses.

What interesting properties does Plot 5 reveal?

Part 3 - Handcrafted Scoring Function

In [129]:
```
df2 = data_set[["LotFrontage", "OverallQual", "YearRemodAdd",
                "ExterQual", "BsmtQual", "Functional", "GarageArea", "SaleTy
               "LandContour", "TotalBsmtSF", "GrLivArea", 'LandSlope',"BsmtF
                ]]
df2.head(10)
```

Out[129]:

	LotFrontage	OverallQual	YearRemodAdd	ExterQual	BsmtQual	Functional	GarageArea	SaleTy
Id								
1	65.0	7	2003	Gd	Gd	Typ	548	\
2	80.0	6	1976	TA	Gd	Typ	460	\
3	68.0	7	2002	Gd	Gd	Typ	608	\
4	60.0	7	1970	TA	TA	Typ	642	\
5	84.0	8	2000	Gd	Gd	Typ	836	\
6	85.0	5	1995	TA	Gd	Typ	480	\
7	75.0	8	2005	Gd	Ex	Typ	636	\
8	NaN	7	1973	TA	Gd	Typ	484	\
9	51.0	7	1950	TA	TA	Min1	468	\
10	50.0	5	1950	TA	TA	Typ	205	\

In the above statements, I have selected features which are important while buying a house and saved that dataframe into a new variable called df2

In [130]:
```
#functions to be applied for categorical values and for scaling numerical v
def func_lot(input):
    if (input <= 313 and input >= 80):
        return 10
    if (input < 80 and input >= 69):
        return 7.5
    if (input < 69 and input >= 59):
        return 5
    if (input < 59):
        return 2.5

def func_street(input):
    if (input == 'Pave'):
        return 10
    if (input == 'Gravel'):
        return 0

def func_year_remod(input):
    if (input <= 2010 and input >= 2004):
        return 10
    if (input < 2004 and input >= 1994):
        return 7.5
    if (input < 1994 and input >= 1967):
        return 5
    if (input < 1967 ):
        return 2.5

def func_functional(input):
    if (input == "Typ"):
        return 10
    elif (input == 'Min1'):
        return 8
    elif (input == 'Min2'):
        return 6
    elif (input == 'Mod'):
        return 4
    elif (input == 'Maj1' ):
        return 2
    elif (input == 'Maj2' ):
        return 0
    elif (input == 'Sev' ):
        return -2
    elif (input == 'Sal' ):
        return -4

def func_garage(input):
    if (input <= 1418 and input >= 576):
        return 10
    if (input < 576 and input >= 480):
        return 7.5
    if (input < 480 and input >= 334):
        return 5
    if (input < 334 ):
        return 2.5
```

```
def func_SaleType(input):
    if (input == 'WD'):
        return 10
    elif (input == 'CWD'):
        return 10
    elif (input == 'VWD'):
        return 9
    elif (input == 'New'):
        return 8
    elif (input == 'COD'):
        return 7
    elif (input == 'Con' ):
        return 6
    elif (input == 'ConLw' ):
        return 5
    elif (input == 'ConLI' ):
        return 4
    elif (input == 'ConLD' ):
        return 3
    elif (input == 'Oth' ):
        return 2

def func_LandContour(input):
    if (input == 'Lvl'):
        return 10
    elif (input == 'Bnk'):
        return 7.5
    elif (input == 'HLS'):
        return 5
    elif (input == 'Low'):
        return 2.5

def func_TotalBsmtSF(input):
    if (input <= 6110 and input >= 1298.25):
        return 10
    if (input < 1298.25 and input >= 991.5):
        return 7.5
    if (input < 991.5 and input >= 795.75):
        return 5
    if (input < 795.75 ):
        return 2.5

def func_GrLivArea(input):
    if (input <= 5642 and input >= 1776.75):
        return 10
    if (input < 1776.75 and input >= 1464):
        return 7.5
    if (input < 1464 and input >= 1129.5):
        return 5
    if (input < 1129.5 and input >= 334 ):
        return 2.5


def func_LandSlope(input):
    if (input == 'Gtl'):
        return 10
    elif (input == 'Mod'):
```

```
        return 5
    elif (input == 'Sev'):
        return 0

def func_TotalSqft(input):
    if (input <= 11752 and input >= 3004):
        return 10
    if (input < 3004 and input >= 2474):
        return 7.5
    if (input < 2474 and input >= 2009.5):
        return 5
    if (input < 2009.5 and input >= 334 ):
        return 2.5

df2['TotalSqft'] = data_set["1stFlrSF"]+data_set["TotalBsmtSF"]+data_set["2
df2['KitchenQualIndex'] = data_set['KitchenQual'].apply(function)
df2['BsmtQualIndex']=BsmtQualIndex=data_set['BsmtQual'].apply(function)


df2['LotFrontage'] = df2['LotFrontage'].apply(func_lot)
df2['YearRemodAdd'] = df2['YearRemodAdd'].apply(func_year_remod)
df2['ExterQual'] = df2['ExterQual'].apply(function)
df2['BsmtQual'] = df2['BsmtQual'].apply(function)
df2['Functional'] = df2['Functional'].apply(func_functional)
df2['GarageArea'] = df2['GarageArea'].apply(func_garage)
df2['SaleType'] = df2['SaleType'].apply(func_SaleType)
df2['LandContour'] = df2['LandContour'].apply(func_LandContour)
df2['TotalBsmtSF'] = df2['TotalBsmtSF'].apply(func_TotalBsmtSF)
df2['GrLivArea'] = df2['GrLivArea'].apply(func_GrLivArea)
df2['LandSlope'] = df2['LandSlope'].apply(func_LandSlope)
df2['TotalSqft'] = df2['TotalSqft'].apply(func_TotalSqft)
df2.fillna(0, inplace = True)

df2.head(10)
```

Out[130]:

Id	LotFrontage	OverallQual	YearRemodAdd	ExterQual	BsmtQual	Functional	GarageArea	SaleTy
1	5.0	7	7.5	8	8	10	7.5	
2	10.0	6	5.0	6	8	10	5.0	
3	5.0	7	7.5	8	8	10	10.0	
4	5.0	7	5.0	6	6	10	10.0	
5	10.0	8	7.5	8	8	10	10.0	
6	10.0	5	7.5	6	8	10	7.5	
7	7.5	8	10.0	8	10	10	10.0	
8	0.0	7	5.0	6	8	10	7.5	
9	2.5	7	2.5	6	6	8	5.0	
10	2.5	5	2.5	6	6	10	2.5	

In the above code contains the functions which are applied on the 'df2' dataframe. For Continous variables, scaling is done based on the relative percentile of the value For Categorical values, features are scaled into integers values from 0 - 10 After functions are defined, then the relative columns are apllied by the respective function and the resulatant dataframe first 10 values are printed above.

In [131]:

```
#Handcrafted Scoring function
df2["rating"] = (3*df2["LotFrontage"] + 10*df2["OverallQual"] + 4*df2["Year
                 4*df2["ExterQual"] +  4*df2["BsmtQual"] + 8*df2["Functional"]
                      + 5*df2["LandContour"] +  4*df2["TotalBsmtSF"] +  6*df2["
                     10*df2['TotalSqft']+8*df2['KitchenQualIndex']+6*df2['BsmtQ
```

This is the main code for handpicked function. Here variuous features are multipled with scalar values from 0 - 10 and the sum of respective multiples is stored in a new column named as 'rating'

In [132]:

```
#Top 10 most desirable houses
#dataframe is sorted in descending order based on values in 'value' column
df2.sort_values(by = ['rating'], ascending = False)[:10]
```

Out[132]:

	LotFrontage	OverallQual	YearRemodAdd	ExterQual	BsmtQual	Functional	GarageArea	Sale
Id								
441	10.0	10	10.0	10	10	10	10.0	
516	10.0	10	10.0	10	10	10	10.0	
1443	10.0	10	10.0	10	10	10	10.0	
692	10.0	10	7.5	10	10	10	10.0	
933	10.0	9	10.0	10	10	10	10.0	
390	10.0	10	10.0	10	10	10	10.0	
826	10.0	10	10.0	10	10	10	10.0	
541	10.0	9	10.0	10	10	10	10.0	
225	10.0	10	7.5	10	10	10	10.0	
1244	10.0	10	10.0	10	10	10	10.0	

In [133]:
```
#ten least desirable houses
#dataframe is sorted in ascending order based on values in 'value' column c
df2.sort_values(by = ['rating'], ascending = True)[:10]
```

Out[133]:

	LotFrontage	OverallQual	YearRemodAdd	ExterQual	BsmtQual	Functional	GarageArea	Sale
Id								
376	0.0	1	2.5	4	4	2	2.5	
534	2.5	1	2.5	4	0	10	2.5	
637	2.5	2	2.5	4	6	2	2.5	
706	7.5	4	2.5	4	0	4	2.5	
750	2.5	4	2.5	6	0	4	2.5	
1322	0.0	3	2.5	6	0	10	2.5	
1046	0.0	3	2.5	6	0	6	5.0	
343	0.0	3	2.5	6	0	10	5.0	
1036	0.0	4	2.5	6	0	10	2.5	
1001	7.5	3	2.5	6	0	8	7.5	

My scoring function takes important features that are influential in determining the sale price of house. Then, it multiples each feature based on the relative influences it has in SalePrice. The summation of all the products is stored in a column called as "result".

Part 4 - Pairwise Distance Function

In [134]:
```
list1 = ["Neighborhood", "BldgType", "OverallQual", "YearBuilt", "YearRemoc
                "BsmtQual", "KitchenQual", "Functional", "GarageArea", "Sale
                "TotalBsmtSF", "GrLivArea","LowQualFinSF","GarageQual",
                "GarageCars", "TotRmsAbvGrd", "FullBath","YrSold"]

cont_list2 = ["MSSubClass", "LotFrontage", "LotArea","OverallQual", "Overal
              "TotalBsmtSF", "1stFlrSF", "2ndFlrSF", "LowQualFinSF","GrLivAr
             "MasVnrArea", "BsmtFinSF1", "HalfBath", "BedroomAbvGr", "Kitche
             "GarageCars", "GarageArea", "WoodDeckSF","OpenPorchSF", "Enclos
              "MoSold", "YrSold"]


category_list = ["MSZoning", "Street", "LotShape", "LandContour", "Utilitie
                 "Condition1", "Condition2", "BldgType", "HouseStyle", "Roof
                 "Exterior2nd", "MasVnrType", "ExterQual", "ExterCond", "Fou
                 "BsmtFinType1", "BsmtFinType2", "Heating", "HeatingQC", "Ce
                 "FireplaceQu", "GarageType", "GarageFinish", "GarageQual",

df = data_set

df[cont_list2].fillna(df[cont_list2].mean(), inplace = True)
df[category_list].fillna(df[category_list].mode(), inplace = True)
df.fillna(0, inplace = True)
```

Here, I declared two lists for categorical and continous values. Then, NaN in the dataframe are replaced with mean and mode for continous and categorical fields respectively.

In [135]:
```
train_data_set = pd.read_csv("/Users/mkondeti/Desktop/Data Science Fundamen
test_data_set = pd.read_csv("/Users/mkondeti/Desktop/Data Science Fundament

submit = test_data_set['Id']
sale_price = train_data_set["SalePrice"]

train_data_set = train_data_set.drop("SalePrice", axis = 1)
submit = submit.to_frame()
TotalData = pd.merge(train_data_set, test_data_set, how = 'outer')

TotalData1 = TotalData.set_index('Id')
TotalData1[cont_list2].fillna(TotalData1[cont_list2].median(), inplace = Tr
TotalData1[category_list].fillna(TotalData1[category_list].mode(), inplace
TotalData1.fillna(0, inplace = True)

#one Hot Encoding
TotalData1 = TotalData1[list1]

TotalData1 = pd.get_dummies(TotalData1)

one_hot_df = TotalData1[0:train_data_set.shape[0]]
one_hot_df2 = TotalData1[train_data_set.shape[0] :]
```

In [136]:
```
from sklearn.metrics.pairwise import euclidean_distances
k = euclidean_distances(one_hot_df, one_hot_df)
```

Part 5 - Clustering

In [137]:

```
kmeans = KMeans(n_clusters=5, random_state=0).fit(one_hot_df)
one_hot_df['cluster'] = kmeans.labels_

groupby = one_hot_df.groupby('cluster')

groupby.describe()
```

Out[137]:

	OverallQual								YearBuilt			
	count	mean	std	min	25%	50%	75%	max	count	mean	std	mi
cluster												
0	580.0	5.134483	0.956308	1.0	5.0	5.0	6.0	8.0	580.0	1959.201724	24.895686	18
1	143.0	7.468531	1.209145	5.0	7.0	8.0	8.0	10.0	143.0	1977.545455	34.545689	18
2	394.0	6.241117	1.016522	3.0	6.0	6.0	7.0	10.0	394.0	1970.005076	34.189860	18
3	338.0	6.958580	1.239101	4.0	6.0	7.0	8.0	10.0	338.0	1990.372781	19.254737	19
4	5.0	9.600000	0.894427	8.0	10.0	10.0	10.0	10.0	5.0	1999.400000	7.536577	19

5 rows × 648 columns

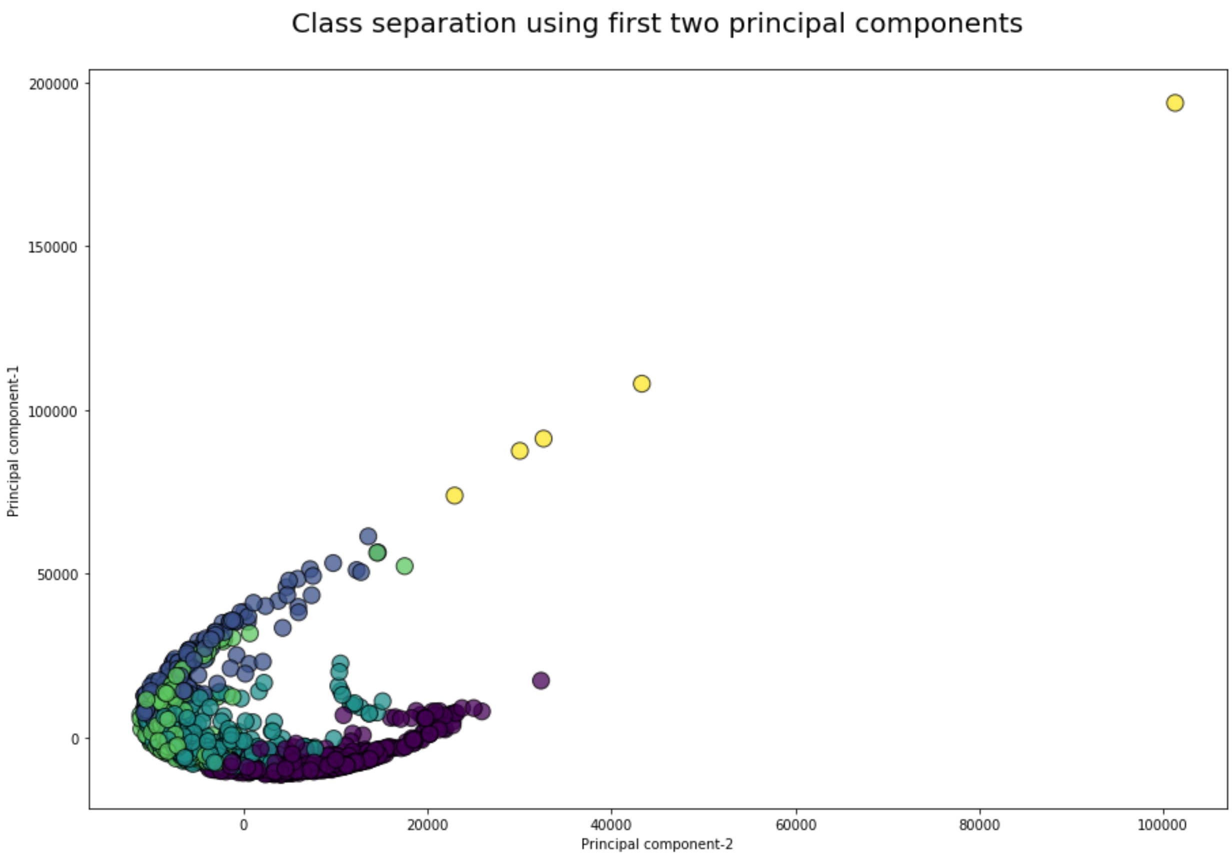
In [138]:

```
cluster = PCA(n_components=4)


k_cluster = cluster.fit_transform(k)
k_cluster = pd.DataFrame(data=k_cluster)
plt.figure(figsize=(15,10))
plt.scatter(k_cluster[1],k_cluster[0], c= kmeans.labels_.astype(float),edge

plt.title("Class separation using first two principal components\n",fontsiz
plt.xlabel("Principal component-2",fontsize=10)
plt.ylabel("Principal component-1",fontsize=10)

plt.show()
```



The above graph gives clusters of one_hot_encoded data which was fed by dataframe.

Part 6 - Linear Regression

In [139]:
```
= ["Neighborhood", "BldgType", "OverallQual", "YearBuilt", "YearRemodAdd",
          "BsmtQual", "KitchenQual", "Functional", "GarageArea", "SaleType",
          "TotalBsmtSF", "GrLivArea","LowQualFinSF","GarageQual",
          "GarageCars", "TotRmsAbvGrd", "FullBath","YrSold"]

= ["LotFrontage", "OverallQual", "YearRemodAdd",
          "ExterQual", "BsmtQual", "Functional", "GarageArea", "SaleType",
         "LandContour", "TotalBsmtSF", "GrLivArea", 'LandSlope', "TotRmsAbvG
          ]

list2 = ["MSSubClass", "LotFrontage", "LotArea","OverallQual", "OverallCond"
        "TotalBsmtSF", "1stFlrSF", "2ndFlrSF", "LowQualFinSF","GrLivArea", "
       "MasVnrArea", "BsmtFinSF1", "HalfBath", "BedroomAbvGr", "KitchenAbvGr
       "GarageCars", "GarageArea", "WoodDeckSF","OpenPorchSF", "EnclosedPorc
        "MoSold", "YrSold"]


ory_list = ["MSZoning", "Street", "LotShape", "LandContour", "Utilities", "L
           "Condition1", "Condition2", "BldgType", "HouseStyle", "RoofStyle"
           "Exterior2nd", "MasVnrType", "ExterQual", "ExterCond", "Foundatio
           "BsmtFinType1", "BsmtFinType2", "Heating", "HeatingQC", "CentralA
           "FireplaceQu", "GarageType", "GarageFinish", "GarageQual", "Garag
```

I've defined three lists in the above line. These lists will be used on the train and test datasets. list2 will used for feature selection on one_hot_encoded data frame. cont_list2 will be used to filter continous features from the given dataframe. category_listwill be used to filter out categorical features from given data frame.

In [140]:
```
train_data_set = pd.read_csv("/Users/mkondeti/Desktop/Data Science Fundamen
test_data_set = pd.read_csv("/Users/mkondeti/Desktop/Data Science Fundament

submit = test_data_set['Id']
sale_price = train_data_set["SalePrice"]

train_data_set = train_data_set.drop("SalePrice", axis = 1)
submit = submit.to_frame()
TotalData = pd.merge(train_data_set, test_data_set, how = 'outer')
```

Initially I imported train data and test data from local machine and then extracting "SalePrice" column from data frame. Later, I've dropped the 'SalePrice' column since 'SalePrice' is not required to be in the train data data frame. Lastly, I've merged train data and test data using outer merge command. The resultant frame is stored using TotalData variable.

In [141]:
```
TotalData1 = TotalData.set_index('Id')
TotalData1[cont_list2].fillna(TotalData1[cont_list2].median(), inplace = Tr
TotalData1[category_list].fillna(TotalData1[category_list].mode(), inplace
TotalData1.fillna(0, inplace = True)


TotalData1 = TotalData1[list1]
#one Hot Encoding
TotalData1 = pd.get_dummies(TotalData1)

one_hot_df = TotalData1[0:train_data_set.shape[0]]
one_hot_df2 = TotalData1[train_data_set.shape[0] :]
```

Here, I've used "cont_list2" and "category_list" to fill NaN values with median and mode respectively in the dataframe. Later, I've filled remaining NaN values with zero's. Then, we filtered the TotalData using "list1". get_dummies does one hot encoding of the data frame and then I've separated the train data and test data into two different variables.

In [142]:
```
model = LinearRegression()
model.fit(one_hot_df, sale_price)

list2 = model.coef_
max = list2.max()
max2 = 2
for i in range(len(list2)):
    if list2[i] == max:
        max2 = i

print(one_hot_df.columns[76])

submit['SalePrice'] = model.predict(one_hot_df2)
submit.to_csv( "/Users/mkondeti/Desktop/Data Science Fundamentals/submit.cs
```

```
GarageQual_Ex
```

In [143]:
```
list2 = model.coef_
max = list2.max()
max2 = 2
for i in range(len(list2)):
    if list2[i] == max:
        max2 = i

print(one_hot_df.columns[76] + ' is the most important feature.')
```

```
GarageQual_Ex is the most important feature.
```

As mentioned in the above code snippet, GarageQual_Ex is the most important variable in the above linear regression model.

I've used Linear Regression model for predicting the SalePrice and stored the result locally.

The predictive score for the above linear regression model was 0.167

In [144]:
```
#lasse regression model
#model = linear_model.Lasso(alpha=.1)
#model.fit(one_hot_df, sale_price)
#submit['SalePrice'] = model.predict(one_hot_df2)
#submit.to_csv( "/Users/mkondeti/Desktop/Data Science Fundamentals/submit.c

#Ridge regression model
#model2 = linear_model.Ridge(alpha=.5)
#model2.fit(one_hot_df, sale_price)
#submit['SalePrice'] = model2.predict(one_hot_df2)
#submit.to_csv( "/Users/mkondeti/Desktop/Data Science Fundamentals/submit.c
```

Part 7 - External Dataset

In [145]:
```
#building a new dataframe after merging with actual data frame and external
external_data_set = pd.read_excel("/Users/mkondeti/Desktop/Data Science Fun
external_data_set = external_data_set.iloc[2:]
#merging
TotalData2 = pd.merge(TotalData1, external_data_set, how = 'left', left_on
one_hot = TotalData2[0:train_data_set.shape[0]]
one_hot2 = TotalData2[train_data_set.shape[0] :]
#linear regression
model = LinearRegression()
model.fit(one_hot, sale_price)
submit['SalePrice'] = model.predict(one_hot2)
#saving the resultant .csv file
submit.to_csv( "/Users/mkondeti/Desktop/Data Science Fundamentals/submit_ex
```

The kaggle score for the above model is 0.16636 which is similar to the actual linear regression score of 0.16713 Hence, there hasn't been much change after adding the external data set to the total dataset.

The above mentioned dataset consists of multiple features which are common to the train_data_set and among those common features 'SalePrice' and 'SaleDate' can be used to extend our train data set.

Part 8 - Permutation Test

In [ ]:
```
#f_reg = f_regression(one_hot_df, sale_price)

variables=[ "OverallQual", "YearBuilt", "YearRemodAdd",
                  "GarageArea", "TotalBsmtSF", "GrLivArea","LowQualFinSF",
               "GarageCars", "TotRmsAbvGrd", "YrSold"]

one_hot_df_variables = one_hot_df[variables]
svm = SVC(kernel='linear')
cumulative_value = StratifiedKFold(2)
for item in variables:

    score, permutation_scores, pvalue = permutation_test_score(svm, one_hot
                                    scoring="accuracy", cv=cumulative_value
```

In [ ]:
```
def rmse(y, y_pred):
     return np.sqrt(np.mean((y_pred - y)**2))
rmse_scorer = make_scorer(rmse, greater_is_better=False)
cumulative_value = StratifiedKFold(2)
for item in variables:
    score, permutation_scores, pvalue = permutation_test_score(
     svm,one_hot_df[item], sale_price, scoring=rmse_scorer, cv=cumulative_v
    print("Root mean square error for"+variables[i],score)
```

In [146]:
```
f_regression(one_hot_df[variables], sale_price )[1].round(3)
```

Out[146]:
```
array([0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.328, 0.   , 0.   ,
       0.269])
```

I have given 10 variables for the p-test and stored the features in a variable. After performing p-test on the train_data_set data frame, we can see that only two variables have 0.328 and 0.269 values. Except these two, all the other variables have zero values. These variables are "LowQualFinSF" and "YrSold". So, these values have very less impact on predicting the sale_price.

Part 9 - Final Result

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 provide a link to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with SBU.

Kaggle Link: [https://www.kaggle.com/mkondeti (https://www.kaggle.com/mkondeti)](https://www.kaggle.com/mkondeti)

Highest Rank: 3529

Score: 0.16713

Number of entries: 6

I've calculated linear regression, Ridge, Lasso regression models and linear regression gave me the best score out of the three models.