The code below ensures that when cells have multiple outputs all outputs are seen, not just the last one which is the default.

In [1]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

Objective 0

Importing necessary packages to perform EDA on the Ames Data Set.

In [2]:
```
import numpy as np
import pandas as pd
import os
import pickle
```

Ensuring the datasets are in my current directory. Once confirmed, I import the data as a pandas dataframe, amesDF.

In [3]:
```
os.listdir()
```

Out[3]:
```
['.DS_Store',
 '.ipynb_checkpoints',
 'amesDF.pickle',
 'amesNumDFclean.pickle',
 'amesNumDFclean2.pickle',
 'amesSelDF.pickle',
 'Assigment_1_Objective_5.docx',
 'Assigment_1_Objective_5.pdf',
 'assign-1-radon-data.pickle',
 'Chapter_2_Housing.ipynb',
 'DataDocumentation.txt',
 'datasets',
 'decock.pdf',
 'Exercise_2.zip',
 'Jonah MunizAssignment-1.ipynb',
 'JonahMuniz_Assignment1.docx',
 'JonahMuniz_Assignment1.pdf',
 'Jonah_Muniz_Assignment_2.ipynb',
 'Jonah_Muniz_Assignment_2_Objective_6.docx',
 'Maronna2011_Article_AlanJulianIzenman2008ModernMul.pdf',
 'Modern Multivariate Statistical Techniques_Regression, Classification, and Manifold Learning.pdf',
 'RF.pickleDB',
```

```
'sqlite-tools-osx-x86-3340100',
'Web_Login_Discussion.pptx',
'__MACOSX',
'~$nahMuniz_Assignment1.docx']
```

In [4]:
```
amesDF=pd.read_pickle('amesDF.pickle')
```

Now that the data has been imported I call dtypes on the dataframe to get an understanding on the data types in the dataframe as well as the count of each type. Right away I notice 32 int64 and 2 float 64 columns. Due to the fact that kmeans need numeric data only, I need to convert the 32 int 64 columns to float dtypes and create a new num dataframe.

In [5]:
```
amesDF.dtypes.value_counts()
```

Out[5]:
```
object     40
int64      32
float64     2
dtype: int64
```

In [6]:
```
amesNumDF=amesDF.select_dtypes(include=np.number).astype('float')
```

In [7]:
```
amesNumDF.dtypes.value_counts()
```

Out[7]:
```
float64    34
dtype: int64
```

The columns in the new num dataframe can be seen below.

In [8]:
```
amesNumDF.columns
```

Out[8]:
```
Index(['Lot_Frontage', 'Lot_Area', 'Year_Built', 'Year_Remod_Add',
       'Mas_Vnr_Area', 'BsmtFin_SF_1', 'BsmtFin_SF_2', 'Bsmt_Unf_SF',
       'Total_Bsmt_SF', 'First_Flr_SF', 'Second_Flr_SF', 'Gr_Liv_Area',
       'Bsmt_Full_Bath', 'Bsmt_Half_Bath', 'Full_Bath', 'Half_Bath',
       'Bedroom_AbvGr', 'Kitchen_AbvGr', 'TotRms_AbvGrd', 'Fireplaces',
       'Garage_Cars', 'Garage_Area', 'Wood_Deck_SF', 'Open_Porch_SF',
       'Enclosed_Porch', 'Three_season_porch', 'Screen_Porch', 'Pool_Area',
       'Misc_Val', 'Mo_Sold', 'Year_Sold', 'Sale_Price', 'Longitude',
       'Latitude'],
      dtype='object')
```

In [9]:
```
amesNumDF.describe()
```

Out[9]:

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Mas_Vnr_Area	BsmtFin_SF_1	BsmtFin_SF_2	Bsmt_Unf_SF	Total_Bsmt_SF	Fi
count	2930.000000	2930.000000	2930.000000	2930.000000	2930.000000	2930.000000	2930.000000	2930.000000	2930.000000	29
mean	57.647782	10147.921843	1971.356314	1984.266553	101.096928	4.177474	49.705461	559.071672	1051.255631	11
std	33.499441	7880.017759	30.245361	20.860286	178.634545	2.233372	169.142089	439.540571	440.968018	3
min	0.000000	1300.000000	1872.000000	1950.000000	0.000000	0.000000	0.000000	0.000000	0.000000	3
25%	43.000000	7440.250000	1954.000000	1965.000000	0.000000	3.000000	0.000000	219.000000	793.000000	8
50%	63.000000	9436.500000	1973.000000	1993.000000	0.000000	3.000000	0.000000	465.500000	990.000000	10
75%	78.000000	11555.250000	2001.000000	2004.000000	162.750000	7.000000	0.000000	801.750000	1301.500000	13
max	313.000000	215245.000000	2010.000000	2010.000000	1600.000000	7.000000	1526.000000	2336.000000	6110.000000	50

8 rows × 34 columns

In [100…

```
amesNumDF['Gr_Liv_Area'].describe()
```

Out[100…

```
count    2930.000000
mean     1499.690444
std       505.508887
min       334.000000
25%      1126.000000
50%      1442.000000
75%      1742.750000
max      5642.000000
Name: Gr_Liv_Area, dtype: float64
```

The assignment calls for removing rows where the house sqft is larger than 4,000 due to these rows being outliers in the data. This is done below be creating a new data set where above ground living area square feet is less than 4,000. This removes 5 rows from the data.

In [101…

```
amesNumDF2= amesNumDF[amesNumDF['Gr_Liv_Area'] < 4000]
```

In [102…

```
amesNumDF2.describe()
```

Out[102…

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Mas_Vnr_Area	BsmtFin_SF_1	BsmtFin_SF_2	Bsmt_Unf_SF	Total_Bsmt_SF	Fi
count	2925.000000	2925.000000	2925.000000	2925.000000	2925.000000	2925.000000	2925.000000	2925.000000	2925.000000	29

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Mas_Vnr_Area	BsmtFin_SF_1	BsmtFin_SF_2	Bsmt_Unf_SF	Total_Bsmt_SF	Fi
mean	57.460855	10103.583590	1971.302906	1984.234188	99.918632	4.179487	49.790427	558.756239	1046.494359	1
std	33.075613	7781.999124	30.242474	20.861774	175.566155	2.234750	169.274143	439.667673	421.482215	3
min	0.000000	1300.000000	1872.000000	1950.000000	0.000000	0.000000	0.000000	0.000000	0.000000	3
25%	43.000000	7438.000000	1954.000000	1965.000000	0.000000	3.000000	0.000000	218.000000	792.000000	8
50%	63.000000	9428.000000	1973.000000	1993.000000	0.000000	3.000000	0.000000	464.000000	989.000000	10
75%	78.000000	11515.000000	2001.000000	2004.000000	162.000000	7.000000	0.000000	801.000000	1299.000000	13
max	313.000000	215245.000000	2010.000000	2010.000000	1600.000000	7.000000	1526.000000	2336.000000	3206.000000	38

8 rows × 34 columns

In [13]:

```
from pandas_profiling import ProfileReport
amesNumDF2Profile=ProfileReport(amesNumDF2,'ames data',explorative=True)
amesNumDF2Profile.to_notebook_iframe()
```

Overview

Overview Warnings 17 Reproduction

Dataset statistics

Number of variables	35
Number of observations	2925
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	799.9 KiB
Average record size in memory	280.0 B

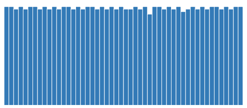
Variable types

Numeric	28
Categorical	7

Variables

df_index
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	2925	**Mean**	1463.79453
Distinct (%)	100.0%	**Minimum**	0



Based on the above profiles of each feature I have compiled a list of numerical features that I believe will be useful. My criteria for the features selected is that there needed to be less then 20% of all values being zero. Although some of these feautres may be relevant, if too many of the total rows of the feature are zero it will negatively effect the model.The new dataframe with the selected features can be seen below.

In [103…

```
amesNumDF2 = amesNumDF2[['Lot_Frontage','Lot_Area','Year_Built','Year_Remod_Add','Total_Bsmt_SF','First_Flr_SF','Gr_l
                          'Bedroom_AbvGr','TotRms_AbvGrd','Garage_Cars','Garage_Area','Sale_Price','Bsmt_Unf_SF','Yea
```

Based on the my knowledge of the data set and the features I start to search for potential erroneous data points. For example, if a house year_remod_add is less than year_build, etc.

In [104…

```
amesNumDF2.loc[amesNumDF2['Year_Built'] - amesNumDF2['Year_Remod_Add']  > 0]
```

Out[104…

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Total_Bsmt_SF	First_Flr_SF	Gr_Liv_Area	Bedroom_AbvGr	TotRms_AbvGrd	Garage_Ca
850	65.0	10739.0	2002.0	2001.0	1431.0	1444.0	1444.0	3.0	6.0	2

Dropping row 850 due to Year_Remod_Add occuring before Year_Built.

In [105…

```
amesNumDF2.drop(850)
```

Out[105…

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Total_Bsmt_SF	First_Flr_SF	Gr_Liv_Area	Bedroom_AbvGr	TotRms_AbvGrd	Garage_C
0	141.0	31770.0	1960.0	1960.0	1080.0	1656.0	1656.0	3.0	7.0	
1	80.0	11622.0	1961.0	1961.0	882.0	896.0	896.0	2.0	5.0	
2	81.0	14267.0	1958.0	1958.0	1329.0	1329.0	1329.0	3.0	6.0	
3	93.0	11160.0	1968.0	1968.0	2110.0	2110.0	2110.0	3.0	8.0	
4	74.0	13830.0	1997.0	1998.0	928.0	928.0	1629.0	3.0	6.0	
...	...	...	...	...	...	...	...	...	...	
2925	37.0	7937.0	1984.0	1984.0	1003.0	1003.0	1003.0	3.0	6.0	
2926	0.0	8885.0	1983.0	1983.0	864.0	902.0	902.0	2.0	5.0	
2927	62.0	10441.0	1992.0	1992.0	912.0	970.0	970.0	3.0	6.0	
2928	77.0	10010.0	1974.0	1975.0	1389.0	1389.0	1389.0	2.0	6.0	
2929	74.0	9627.0	1993.0	1994.0	996.0	996.0	2000.0	3.0	9.0	

2924 rows × 15 columns

Inspecting the dataframe to see if there are any rows that are duplicated in the dataframe.

In [106…
```
amesNumDF2.duplicated().sum()
```
Out[106…
```
2
```

It can be seen that there are 3 rows that are duplicated, we will remove those rows below.

In [107…
```
amesNumDF2UnDup=amesNumDF2.drop_duplicates()
amesNumDF2UnDup.duplicated().sum()
```
Out[107…
```
0
```

Saving the new cleaned DataFrame.

In [108…
```
amesNumDF2UnDup.to_pickle('amesNumDFclean.pickle')
```

Objective 1

Importing the necessary packages to complete objective 1.

In [75]:
```
import numpy as np
import pandas as pd
import os
from sklearn.cluster import KMeans, MiniBatchKMeans
%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot as skplt
from sklearn.metrics import silhouette_score, davies_bouldin_score, calinski_harabasz_score
```

In [76]:
```
os.listdir()
```
Out[76]:
```
['.DS_Store',
 '.ipynb_checkpoints',
 'amesDF.pickle',
 'amesNumDFclean.pickle',
 'amesNumDFclean2.pickle',
 'amesSelDF.pickle',
 'Assigment_1_Objective_5.docx',
 'Assigment_1_Objective_5.pdf',
 'assign-1-radon-data.pickle',
 'Chapter_2_Housing.ipynb',
```

```
 'DataDocumentation.txt',
 'datasets',
 'decock.pdf',
 'Exercise_2.zip',
 'Jonah MunizAssignment-1.ipynb',
 'JonahMuniz_Assignment1.docx',
 'JonahMuniz_Assignment1.pdf',
 'Jonah_Muniz_Assignment_2.ipynb',
 'Jonah_Muniz_Assignment_2_Objective_6.docx',
 'Maronna2011_Article_AlanJulianIzenman2008ModernMul.pdf',
 'Modern Multivariate Statistical Techniques_Regression, Classification, and Manifold Learning.pdf',
 'RF.pickleDB',
 'sqlite-tools-osx-x86-3340100',
 'Web_Login_Discussion.pptx',
 '__MACOSX',
 '~$nahMuniz_Assignment1.docx']
```

Importing the cleaned dataset from Objective 0 and calculating high level statistics for each feature.

In [77]:
```
AmesSelDF=pd.read_pickle('amesNumDFclean.pickle')
AmesSelDF.columns
```

Out[77]:
```
Index(['Lot_Frontage', 'Lot_Area', 'Year_Built', 'Year_Remod_Add',
       'Total_Bsmt_SF', 'First_Flr_SF', 'Gr_Liv_Area', 'Bedroom_AbvGr',
       'TotRms_AbvGrd', 'Garage_Cars', 'Garage_Area', 'Sale_Price',
       'Bsmt_Unf_SF', 'Year_Sold'],
      dtype='object')
```

In [78]:
```
AmesSelDF.describe()
```

Out[78]:

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Total_Bsmt_SF	First_Flr_SF	Gr_Liv_Area	Bedroom_AbvGr	TotRms_AbvGrd	G
count	2922.000000	2922.000000	2922.000000	2922.000000	2922.000000	2922.000000	2922.000000	2922.000000	2922.000000	2
mean	57.465777	10106.288159	1971.283025	1984.227242	1046.626283	1155.179671	1494.044832	2.853525	6.434292	
std	33.089491	7785.105503	30.249453	20.868256	421.139556	376.646746	486.491022	0.827735	1.558171	
min	0.000000	1300.000000	1872.000000	1950.000000	0.000000	334.000000	334.000000	0.000000	2.000000	
25%	43.000000	7440.250000	1954.000000	1965.000000	792.250000	876.000000	1125.250000	2.000000	5.000000	
50%	63.000000	9429.000000	1973.000000	1993.000000	988.500000	1082.000000	1441.000000	3.000000	6.000000	
75%	78.000000	11518.750000	2000.750000	2004.000000	1298.750000	1382.750000	1740.000000	3.000000	7.000000	

	Lot_Frontage	Lot_Area	Year_Built	Year_Remod_Add	Total_Bsmt_SF	First_Flr_SF	Gr_Liv_Area	Bedroom_AbvGr	TotRms_AbvGrd	G
max	313.000000	215245.000000	2010.000000	2010.000000	3206.000000	3820.000000	3820.000000	8.000000	14.000000	

Sale_Price is the target variable we will be training emsembles to predict later on so we will set it aside. The code below creates a new dataframe without Sale_Price as well converts the dataframe into a numpy array.It also ensures all datatypes in the array are float 32.

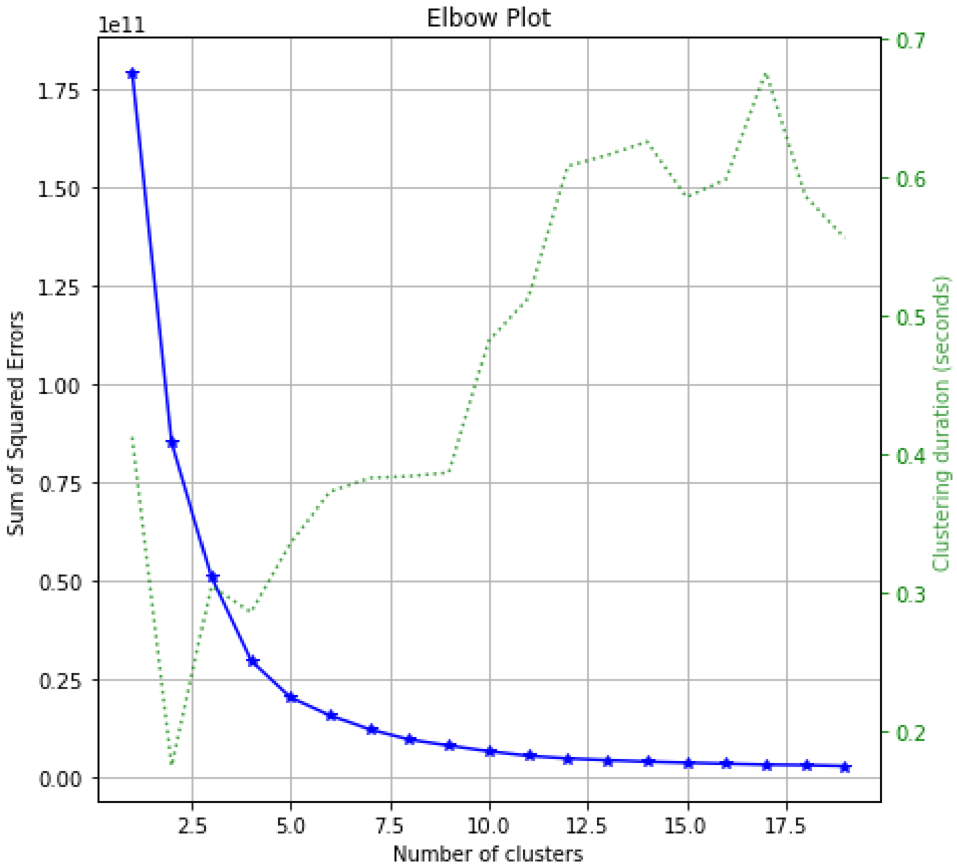
In [79]:
```
AmesClusDF=AmesSelDF.loc[:,~(AmesSelDF.columns.isin(['Sale_Price']))].astype('float32')
X=AmesClusDF.to_numpy(copy=True)
```

Using the KMeans algo I am running a for loop below to calculate the cluster breakdown, silhouette score, davies bouldin score and calinski harabasz score for cluster 2 through 12. The goal is to understand what amount of clusters maxmizes the silhouette score thus maximizing the homogenity of the clusters.

In [80]:
```
clus_sil_score = []
clus_dav_score = []
clus_cal_score = []
clus_breakdown = []
for i in range(11):
    kmMB = KMeans(n_clusters=i +2, random_state=11).fit(X)
    labelMB8=kmMB.predict(X)
    cluster_break = pd.Series(labelMB8).value_counts()
    clus_cal_score.append(calinski_harabasz_score(X,labelMB8))
    clus_dav_score.append(davies_bouldin_score(X,labelMB8))
    clus_sil_score.append(silhouette_score(X,labelMB8))
    clus_breakdown.append(cluster_break)
print(clus_sil_score,clus_dav_score,clus_cal_score)
```

```
[0.96619457, 0.7641298, 0.45700058, 0.46143505, 0.45215404, 0.46282232, 0.4153855, 0.39257067, 0.39260954, 0.3825749,
0.3538957] [0.19416140903180965, 0.49073681386804163, 0.5645511507696509, 0.5614900041442086, 0.5692813743740733, 0.5
13506436882549, 0.5631911356493917, 0.5991345213788357, 0.504469358628776, 0.5152518781937055, 0.5722997351622109] [3
234.746543419262, 3711.057107356284, 4899.119948063797, 5703.858558001865, 6065.049423364886, 6672.372729355678, 738
8.412093911824, 7762.505801103305, 8474.02163440365, 9322.967667136241, 9749.882619667407]
```

In [81]:
```
kmMB=KMeans(random_state=88)
skplt.cluster.plot_elbow_curve(kmMB,X,n_jobs=-1,cluster_ranges=range(1,20),
                               figsize=(7,7))
plt.show();
```



Looking at the silhouette scores, davies-boulden scores and the elbow plot it can be seen that the optimal number of clusters is 5. A breakdown of the counts for the 5 clusters can be seen below as well as the silhouette plot.

In [82]:

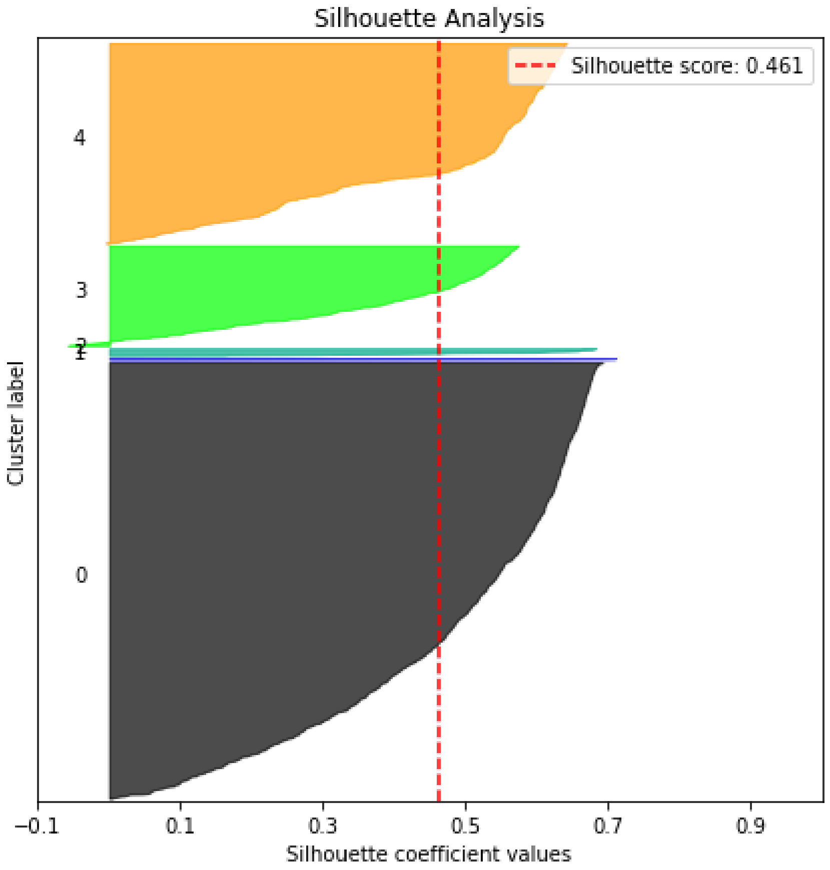
```
kmMB2 = KMeans(n_clusters=5, random_state=11).fit(X)
labels=kmMB2.predict(X)
pd.Series(labels).value_counts()
```

Out[82]:

```
0    1712
4     783
3     394
2      29
1       4
dtype: int64
```

You immediatley see that there are two very small clusters. My thinking here is that there are a few houses that have very unique features that justify their own cluster.

In [83]:
```
skplt.metrics.plot_silhouette(X, labels,figsize=(7,7))
plt.show();
```



Objective 2

Importing the necessary packages for Objective 2. Checking the current folder to ensure the right file is in there and loading the num clean dataset. I am also ensuring there are zero missing values in the dataset.

In [109…

```
import numpy as np
import pandas as pd
import os
from pickleshare import *
import re
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

In [110…

```
os.listdir()
```

Out[110…

```
['.DS_Store',
 '.ipynb_checkpoints',
 'amesDF.pickle',
 'amesNumDFclean.pickle',
 'amesNumDFclean2.pickle',
 'amesSelDF.pickle',
 'Assigment_1_Objective_5.docx',
 'Assigment_1_Objective_5.pdf',
 'assign-1-radon-data.pickle',
 'Chapter_2_Housing.ipynb',
 'DataDocumentation.txt',
 'datasets',
 'decock.pdf',
 'Exercise_2.zip',
 'Jonah MunizAssignment-1.ipynb',
 'JonahMuniz_Assignment1.docx',
 'JonahMuniz_Assignment1.pdf',
 'Jonah_Muniz_Assignment_2.ipynb',
 'Jonah_Muniz_Assignment_2_Objective_6.docx',
 'Maronna2011_Article_AlanJulianIzenman2008ModernMul.pdf',
 'Modern Multivariate Statistical Techniques_Regression, Classification, and Manifold Learning.pdf',
 'RF.pickleDB',
 'sqlite-tools-osx-x86-3340100',
 'Web_Login_Discussion.pptx',
 '__MACOSX',
 '~$nahMuniz_Assignment1.docx']
```

In [111…

```
aDF=pd.read_pickle('amesNumDFclean.pickle')
print(aDF.describe())
```

```
       Lot_Frontage       Lot_Area   Year_Built  Year_Remod_Add  \
count   2923.000000    2923.000000  2923.000000     2923.000000   
mean      57.457749   10104.400958  1971.294902     1984.234690   
```

```
std      33.086676    7784.441928    30.251093      20.868571
min       0.000000    1300.000000  1872.000000    1950.000000
25%      43.000000    7439.000000  1954.000000    1965.000000
50%      63.000000    9428.000000  1973.000000    1993.000000
75%      78.000000   11517.500000  2001.000000    2004.000000
max     313.000000  215245.000000  2010.000000    2010.000000

       Total_Bsmt_SF  First_Flr_SF  Gr_Liv_Area  Bedroom_AbvGr  TotRms_AbvGrd  \
count    2923.000000   2923.000000  2923.000000    2923.000000    2923.000000
mean     1046.799863   1155.316114  1494.065344       2.853233       6.434143
std       421.172053    376.654533   486.409033       0.827744       1.557925
min         0.000000    334.000000   334.000000       0.000000       2.000000
25%       792.500000    876.000000  1125.500000       2.000000       5.000000
50%       989.000000   1082.000000  1441.000000       3.000000       6.000000
75%      1299.500000   1383.000000  1740.000000       3.000000       7.000000
max      3206.000000   3820.000000  3820.000000       8.000000      14.000000

       Garage_Cars  Garage_Area     Sale_Price  Bsmt_Unf_SF    Year_Sold  \
count  2923.000000  2923.000000    2923.000000  2923.000000  2923.000000
mean      1.764967   471.908313  180433.115977   559.138556  2007.790626
std       0.759952   213.848497   78573.478501   439.574946     1.317479
min       0.000000     0.000000   12789.000000     0.000000  2006.000000
25%       1.000000   320.000000  129500.000000   219.000000  2007.000000
50%       2.000000   480.000000  160000.000000   465.000000  2008.000000
75%       2.000000   576.000000  213500.000000   801.000000  2009.000000
max       5.000000  1488.000000  625000.000000  2336.000000  2010.000000

           Mo_Sold
count  2923.000000
mean      6.217927
std       2.711813
min       1.000000
25%       4.000000
50%       6.000000
75%       8.000000
max      12.000000
```

Below I am doing a couple checks of the dataset to ensure that the data makes sense prior to rescaling. First check is to ensure there are zero NA values. Next I am checking that all rows where livable Sqft is greater than 4,000 is removed. I am also doing a couple logical checks of the data, ensuring that there are zero rows where the home was built after it was sold, house was remodeled before being built and any rows where the house was remolded after being sold. As it can be seen, there is one example of a house being remodeled before being built as well as being remodeled after being sold. These rows should be removed.

In [112…
```
aDF.isna().sum().sum()
```
Out[112… 0

In [113…
```
aDF2=aDF[aDF.Gr_Liv_Area<4000].copy()
aDF2.shape
```
Out[113…
```
(2923, 15)
```

In [114…
```
((aDF2.Year_Built-aDF2.Year_Sold)>0.00).value_counts()
```
Out[114…
```
False    2923
dtype: int64
```

In [115…
```
((aDF2.Year_Built-aDF2.Year_Remod_Add)>0.00).value_counts()
```
Out[115…
```
False    2922
True        1
dtype: int64
```

In [116…
```
((aDF2.Year_Remod_Add-aDF2.Year_Sold)>0.00).value_counts()
```
Out[116…
```
False    2922
True        1
dtype: int64
```

Removing the two illogical rows discovered above.

In [117…
```
aDF3=aDF2.loc[~((aDF2.Year_Built-aDF2.Year_Remod_Add)>0.00),:].copy()
aDF3.shape
```
Out[117…
```
(2922, 15)
```

In [118…
```
aDF4=aDF3.loc[~((aDF2.Year_Remod_Add-aDF2.Year_Sold)>0.00),:].copy()
aDF4.shape
```
Out[118…
```
(2921, 15)
```

Beause Mo_Sold column is not really numeric, we will have to encode the categorical values so that we represent the meaning of the categories numerically. This is done by creating dummies below. Sale_Month is removed from the dataset below and the new dummies for Mo_Sold is added to the dataset.

In [119…
```
moDummies=pd.get_dummies(aDF4.Mo_Sold,prefix="sales_mo").astype(int)
moDummies.columns
```

Out[119…
```
Index(['sales_mo_1.0', 'sales_mo_2.0', 'sales_mo_3.0', 'sales_mo_4.0',
       'sales_mo_5.0', 'sales_mo_6.0', 'sales_mo_7.0', 'sales_mo_8.0',
       'sales_mo_9.0', 'sales_mo_10.0', 'sales_mo_11.0', 'sales_mo_12.0'],
      dtype='object')
```

In [120…
```
aDF5=aDF4.loc[:,~(aDF4.columns.isin(['Sale_Month']))]
aDF6=pd.concat([aDF5,moDummies],axis=1,ignore_index=False)
aDF6.columns
```

Out[120…
```
Index(['Lot_Frontage', 'Lot_Area', 'Year_Built', 'Year_Remod_Add',
       'Total_Bsmt_SF', 'First_Flr_SF', 'Gr_Liv_Area', 'Bedroom_AbvGr',
       'TotRms_AbvGrd', 'Garage_Cars', 'Garage_Area', 'Sale_Price',
       'Bsmt_Unf_SF', 'Year_Sold', 'Mo_Sold', 'sales_mo_1.0', 'sales_mo_2.0',
       'sales_mo_3.0', 'sales_mo_4.0', 'sales_mo_5.0', 'sales_mo_6.0',
       'sales_mo_7.0', 'sales_mo_8.0', 'sales_mo_9.0', 'sales_mo_10.0',
       'sales_mo_11.0', 'sales_mo_12.0'],
      dtype='object')
```

In [121…
```
aDF6.dtypes.value_counts()
```

Out[121…
```
float64    15
int32      12
dtype: int64
```

Since the year feature is capped at 2010 and there is no relativity between the features we need to remove years, transform the feature so that it is years before 2010, and place the feature back into the dataset. First the year features are placed in a new dataset then removed from the original dataset. A transformation is then done on the new year feature dataset to transform to years before 2010. These new features are then added to the original dataset.

In [122…
```
years=['Year_Built','Year_Remod_Add','Year_Sold']
yearsDF=aDF6.loc[:,years]
aDF7=aDF6.loc[:,~(aDF6.columns.isin(years))]
```

In [123…
```
yearsDF=yearsDF.transform(lambda x: 2010-x)
yearsDF.head()
```

Out[123…

	Year_Built	Year_Remod_Add	Year_Sold
0	50.0	50.0	0.0
1	49.0	49.0	0.0
2	52.0	52.0	0.0
3	42.0	42.0	0.0
4	13.0	12.0	0.0

In [124…

```
aDF8=pd.concat([aDF7,yearsDF],axis=1)
aDF8.columns
```

Out[124…

```
Index(['Lot_Frontage', 'Lot_Area', 'Total_Bsmt_SF', 'First_Flr_SF',
       'Gr_Liv_Area', 'Bedroom_AbvGr', 'TotRms_AbvGrd', 'Garage_Cars',
       'Garage_Area', 'Sale_Price', 'Bsmt_Unf_SF', 'Mo_Sold', 'sales_mo_1.0',
       'sales_mo_2.0', 'sales_mo_3.0', 'sales_mo_4.0', 'sales_mo_5.0',
       'sales_mo_6.0', 'sales_mo_7.0', 'sales_mo_8.0', 'sales_mo_9.0',
       'sales_mo_10.0', 'sales_mo_11.0', 'sales_mo_12.0', 'Year_Built',
       'Year_Remod_Add', 'Year_Sold'],
      dtype='object')
```

Now that we have cleansed the data we can remove the target variable,Sale_Price, from the dataset. Also creating the features that will be used to train the RF models. There are 22 features in X.

In [145…

```
y=aDF8.Sale_Price.to_numpy(copy=True)
SFfeats=aDF8.columns.to_list()[:9]
salesFeats=list(filter(lambda s: s.startswith('sales_'),
                       aDF8.columns.to_list()))

RFfeatures=SFfeats+salesFeats
X=aDF8.loc[:,RFfeatures].to_numpy(copy=True)
X.shape
y.shape
```

Out[145…

```
(2921, 21)
```

Out[145…

```
(2921,)
```

Now that the target variable has been removed the dataset it is now time to split both data sets to test and train sets. The data is then saved.

In [146…
```
XTrain, XTest, yTrain, yTest = train_test_split(X,y,train_size = 0.85, test_size = 0.15, random_state=11)
trainTestData=[XTrain,XTest, yTrain, yTest]
XTrain.shape, XTest.shape, yTrain.shape, yTest.shape
```

Out[146…
```
((2482, 21), (439, 21), (2482,), (439,))
```

Creating two additional train and test sets that are scaled using StandardScaler to see if rescalling improves the performance.

In [147…
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, StandardScaler
num_pipeline = Pipeline([
        ('std_scaler', StandardScaler()),
    ])
TrainXS = num_pipeline.fit_transform(XTrain)
TestXS = num_pipeline.fit_transform(XTest)
trainTestData = [XTrain,XTest,yTrain,yTest,TrainXS,TestXS]
```

In [148…
```
RFdb=PickleShareDB('RF.pickleDB')
RFdb.clear()
```

In [149…
```
RFdb['trainTestData']=trainTestData
```

Objective 3

Importing the sklearn decomposition PCA package to perform feature reduction on the train and test dataset created in Objective 2.

In [150…
```
from sklearn.decomposition import PCA
```

Below PCA model is looking to transform the train and test datasets to only have features that are responsible for 80% or more of the variance in the data.

In [151…
```
pca80=PCA(n_components=0.80,svd_solver='full')
pca80.fit(XTrain)
trainXPCA=pca80.transform(XTrain)
testXPCA=pca80.transform(XTest)
```

Out[151…
```
PCA(n_components=0.8, svd_solver='full')
```

Examing the shape of both the train and test datasets it can be seen that one feature is responsible for 80% of the variance.

In [152…

```
trainXPCA.shape
testXPCA.shape
```

Out[152…

```
(2482, 1)
```

Out[152…

```
(439, 1)
```

Objective 4

Below I am training the first RF model using the XTrain and yTrain data set. Setting the hyperparameters as max_features = log2, out of box scoring = true, 100 trees,and the rest are set to default.

In [153…

```
RFregr=RandomForestRegressor(max_features='log2',oob_score=True,n_jobs=-1,
                            random_state=11, n_estimators = 100, max_depth = None)
RFregr.fit(XTrain,yTrain)
```

Out[153…

```
RandomForestRegressor(max_features='log2', n_jobs=-1, oob_score=True,
                      random_state=11)
```

In [154…

```
print(f'RF R Squared, Training: {RFregr.score(XTrain,yTrain):5.3f}')
print(f'RF R Squared, OOB: {RFregr.oob_score_:5.3f}')
predTesty=RFregr.predict(XTest)
print(f'Test Data R Squared: {r2_score(yTest,predTesty):4.3f}')
```

```
RF R Squared, Training: 0.974
RF R Squared, OOB: 0.812
Test Data R Squared: 0.831
```

It seems that the model is overfitting a bit with the training data. Still see a relatively high R squared value when exposing the model to unseen data, aka the test dataset.

In [156…

```
RFregr.feature_importances_
RFFeatImpDF=pd.DataFrame({'feature':RFfeatures,
                          'importance':RFregr.feature_importances_})
print('Feature importances')
RFFeatImpDF.sort_values('importance',ascending=False)
```

Out[156…

```
array([0.04707192, 0.06281027, 0.14928022, 0.11323831, 0.20866364,
       0.03010701, 0.05467705, 0.16041297, 0.13931563, 0.00248394,
       0.00339452, 0.00245607, 0.00271565, 0.00317622, 0.00329105,
```

```
       0.00360529, 0.00264682, 0.00278092, 0.00303682, 0.00284273,
       0.00199294])
Feature importances
```

Out[156…

	feature	importance
4	Gr_Liv_Area	0.208664
7	Garage_Cars	0.160413
2	Total_Bsmt_SF	0.149280
8	Garage_Area	0.139316
3	First_Flr_SF	0.113238
1	Lot_Area	0.062810
6	TotRms_AbvGrd	0.054677
0	Lot_Frontage	0.047072
5	Bedroom_AbvGr	0.030107
15	sales_mo_7.0	0.003605
10	sales_mo_2.0	0.003395
14	sales_mo_6.0	0.003291
13	sales_mo_5.0	0.003176
18	sales_mo_10.0	0.003037
19	sales_mo_11.0	0.002843
17	sales_mo_9.0	0.002781
12	sales_mo_4.0	0.002716
16	sales_mo_8.0	0.002647
9	sales_mo_1.0	0.002484
11	sales_mo_3.0	0.002456
20	sales_mo_12.0	0.001993

It can be seen when evaluating the feature importance in this first model that there are really only 3 or 4 features that dominate the model, GR_Liv_Area, Total_Bsmt_SF, First_Flr_SF and Second_Flr_SF.

Now I am training the second RF model this time using the standardized featured datasets. I kept the same model hyperparameters as I used above.

In [157…
```
RFregrS=RandomForestRegressor(max_features='log2',oob_score=True,n_jobs=-1,
                            random_state=11, n_estimators = 100, max_depth = None)
RFregrS.fit(TrainXS,yTrain)
```

Out[157…
```
RandomForestRegressor(max_features='log2', n_jobs=-1, oob_score=True,
                      random_state=11)
```

In [158…
```
print(f'RF R Squared, Training: {RFregrS.score(TrainXS,yTrain):5.3f}')
print(f'RF R Squared, OOB: {RFregrS.oob_score_:5.3f}')
predTestyS=RFregrS.predict(TestXS)
print(f'Test Data R Squared: {r2_score(yTest,predTestyS):4.3f}')
```

```
RF R Squared, Training: 0.974
RF R Squared, OOB: 0.812
Test Data R Squared: 0.824
```

It can be seen by examing the accuracy of the second RF model that it seems to be overfitting on the training data set still, as well as scoring a bit less when exposed to unseen data, aka the test set.

In [159…
```
RFregrS.feature_importances_
RFFeatImpDFS=pd.DataFrame({'feature':RFfeatures,
                           'importance':RFregrS.feature_importances_})
print('Feature importances')
RFFeatImpDFS.sort_values('importance',ascending=False)
```

Out[159…
```
array([0.04707192, 0.06281027, 0.14928022, 0.11323831, 0.20866364,
       0.03010701, 0.05467705, 0.16041297, 0.13931563, 0.00248394,
       0.00339452, 0.00245607, 0.00271565, 0.00317622, 0.00329105,
       0.00360529, 0.00264682, 0.00278092, 0.00303682, 0.00284273,
       0.00199294])
Feature importances
```

Out[159…

	feature	importance
4	Gr_Liv_Area	0.208664
7	Garage_Cars	0.160413
2	Total_Bsmt_SF	0.149280

	feature	importance
8	Garage_Area	0.139316
3	First_Flr_SF	0.113238
1	Lot_Area	0.062810
6	TotRms_AbvGrd	0.054677
0	Lot_Frontage	0.047072
5	Bedroom_AbvGr	0.030107
15	sales_mo_7.0	0.003605
10	sales_mo_2.0	0.003395
14	sales_mo_6.0	0.003291
13	sales_mo_5.0	0.003176
18	sales_mo_10.0	0.003037
19	sales_mo_11.0	0.002843
17	sales_mo_9.0	0.002781
12	sales_mo_4.0	0.002716
16	sales_mo_8.0	0.002647
9	sales_mo_1.0	0.002484
11	sales_mo_3.0	0.002456
20	sales_mo_12.0	0.001993

It can be seen above that the same features that were important in the first RF model have the same level of improtance in the second RF model trained on scaled data. It can be seen based off of the R2 values for both RF models that scaling the data using StandardScaler does not improve the models performance. This makes sense as RF is a great algo that can handle features with various scales. This is why you see very similar R2 values for both RF models.

Objective 5

Importing the AdaBoostRegressor from sklearn.ensemble.

In [160…
```
from sklearn.ensemble import AdaBoostRegressor
```

Training the AdaBoost model with the Xtrain and yTrain data. Validating the model's performance using the XTest hold out set.

In [167…
```
boost = AdaBoostRegressor(base_estimator = None, n_estimators = 100, learning_rate = 1)
boost.fit(XTrain, yTrain)
```

Out[167…
```
AdaBoostRegressor(learning_rate=1, n_estimators=100)
```

In [168…
```
print(f'Boost R Squared, Training: {boost.score(XTrain,yTrain):5.3f}')
predictions = boost.predict(XTest)
print(f'Test Data R Squared: {r2_score(yTest,predictions):4.3f}')
```

```
Boost R Squared, Training: 0.786
Test Data R Squared: 0.777
```

Quickly seeing the what the min, mean and max values are for the predictions to ensure the predicted values make sense.

In [169…
```
np.min(predictions)
np.mean(predictions)
np.max(predictions)
```

Out[169…
```
107580.86363636363
```

Out[169…
```
177915.2222996348
```

Out[169…
```
512730.3155737705
```

In [170…
```
boost.feature_importances_
boostFeatImpDFS=pd.DataFrame({'feature':RFfeatures,
                          'importance':boost.feature_importances_})
print('Feature importances')
boostFeatImpDFS.sort_values('importance',ascending=False)
```

Out[170…
```
array([1.60216165e-02, 9.12852228e-02, 2.24710843e-01, 1.33170664e-01,
       2.69051110e-01, 4.43206384e-02, 1.95245483e-02, 1.30120673e-01,
       4.04961765e-02, 2.68838243e-03, 5.53887189e-04, 0.00000000e+00,
       3.07146250e-05, 1.78308571e-07, 1.87297066e-04, 4.73258837e-03,
       5.77929809e-05, 1.44859881e-02, 6.05728362e-03, 0.00000000e+00,
       2.50439521e-03])
Feature importances
```

Out[170…

	feature	importance
4	Gr_Liv_Area	2.690511e-01
2	Total_Bsmt_SF	2.247108e-01
3	First_Flr_SF	1.331707e-01
7	Garage_Cars	1.301207e-01
1	Lot_Area	9.128522e-02
5	Bedroom_AbvGr	4.432064e-02
8	Garage_Area	4.049618e-02
6	TotRms_AbvGrd	1.952455e-02
0	Lot_Frontage	1.602162e-02
17	sales_mo_9.0	1.448599e-02
18	sales_mo_10.0	6.057284e-03
15	sales_mo_7.0	4.732588e-03
9	sales_mo_1.0	2.688382e-03
20	sales_mo_12.0	2.504395e-03
10	sales_mo_2.0	5.538872e-04
14	sales_mo_6.0	1.872971e-04
16	sales_mo_8.0	5.779298e-05
12	sales_mo_4.0	3.071463e-05
13	sales_mo_5.0	1.783086e-07
11	sales_mo_3.0	0.000000e+00
19	sales_mo_11.0	0.000000e+00

Training another AdaBoost model, this time training the model with trainXPCA and yTrain. I will be validating the model's performance using testXPCA as the hold out set.

In [171…

```
boostPCA = AdaBoostRegressor(base_estimator = None, n_estimators = 100, learning_rate = 1)
```

```
boostPCA.fit(trainXPCA, yTrain)
```

Out[171… AdaBoostRegressor(learning_rate=1, n_estimators=100)

In [172…
```
print(f'PCA Boost R Squared, Training: {boostPCA.score(trainXPCA,yTrain):5.3f}')
predictionsPCA = boostPCA.predict(testXPCA)
print(f'PCA Test Data R Squared: {r2_score(yTest,predictionsPCA):4.3f}')
```

```
PCA Boost R Squared, Training: 0.120
PCA Test Data R Squared: 0.099
```

Although the one feature that is being used to train the boost model is resposible for 80% of the variance, it does not do a great job of predicting sales price given the low R2 values shown above.

In [173…
```
np.min(predictionsPCA)
np.mean(predictionsPCA)
np.max(predictionsPCA)
```

Out[173… 113826.19047619047

Out[173… 201968.24923281829

Out[173… 344513.3905529954

Right away I notice that the min, mean and max values for boostPCA and the boost models differ significantly. This amount of variance in predictions varifies why the boost model using more than one feature has a higher R2 value.

In [ ]:

In [ ]: