Homework 3 - Ames Housing Dataset

In [1]:
```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import xgboost as xgb
from sklearn.model_selection import KFold
from sklearn.metrics import make_scorer
from sklearn.model_selection import permutation_test_score
import math
from sklearn.metrics.pairwise import euclidean_distances
from sklearn.preprocessing import MinMaxScaler
```

In [2]:
```
import warnings
from scipy.spatial.distance import squareform
from scipy.spatial.distance import pdist
import plotly_express as px
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.manifold import TSNE
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_error, r2_score
warnings.filterwarnings('ignore')
#To display atmost 1000 rows
pd.options.display.max_rows=1000
```

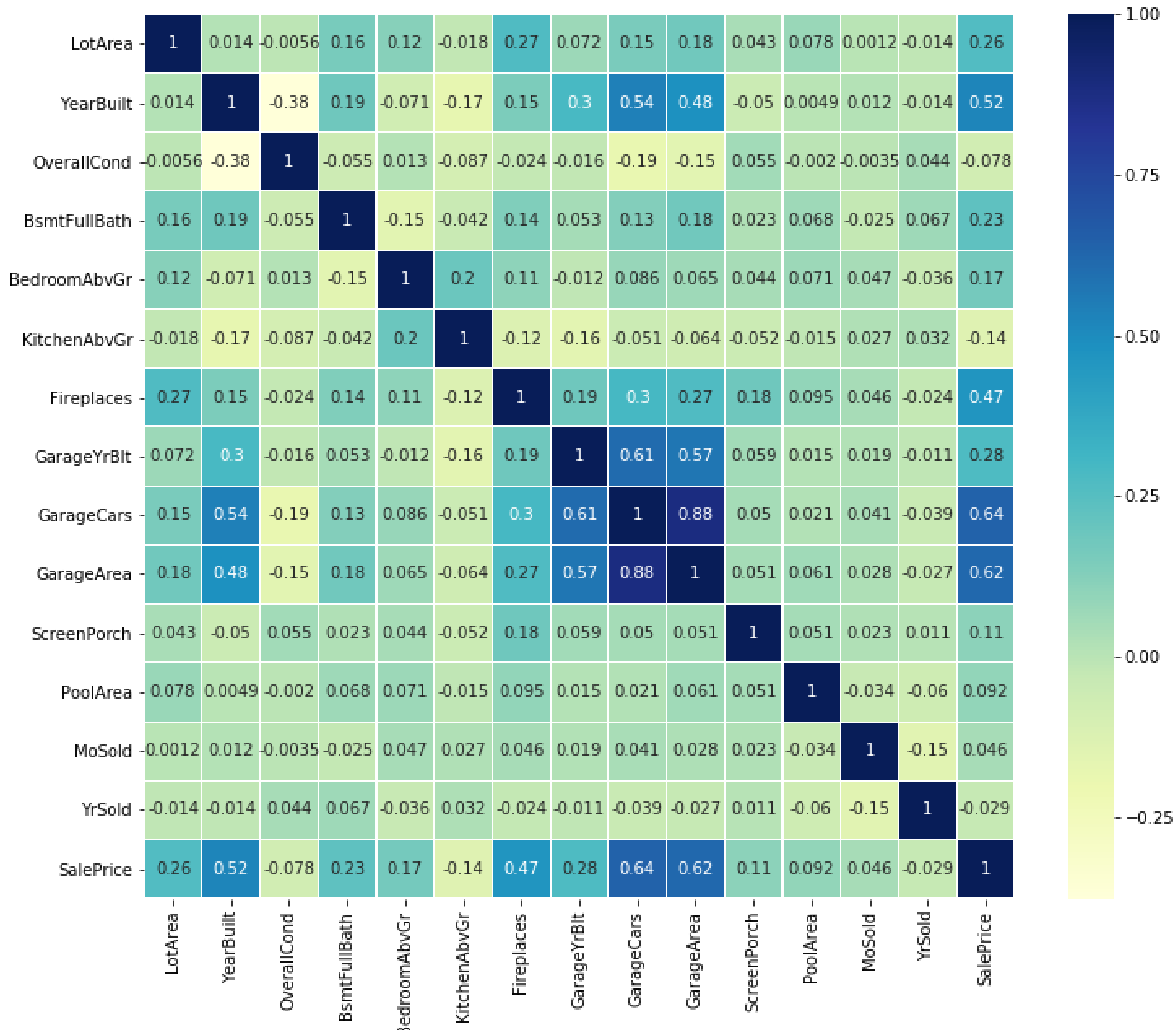
In [4]:
```
# *********** LOADING DATA FILES ******************
#importing train.csv file and test.csv files
train= pd.read_csv('train.csv')
test=pd.read_csv('test.csv')
# train= pd.read_csv('/kaggle/input/house-prices-advanced-regression-technique
s/train.csv')
# test=pd.read_csv('/kaggle/input/house-prices-advanced-regression-techniques/
test.csv')

#function to obtain the numeric columns of the data set and replace the NA val
ues with the mean values
def num_data(df):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    numdf = df.select_dtypes(include=numerics)
    for column in numdf.columns:
        numdf[column].fillna(numdf[column].mean(), inplace=True)
        numdf[column]=numdf[column].astype(int)
    return numdf
```

In [33]:
```
#************cleaning the data********************
#replacing numeric values in training and testing data with mean values
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
numdf = train.select_dtypes(include=numerics)
for column in numdf.columns:
    train.fillna(train[column].mean(),inplace=True)

numdf1 = test.select_dtypes(include=numerics)
for column in numdf1.columns:
    test.fillna(test[column].mean(),inplace=True)
```

Part 1 - Pairwise Correlations

In [34]:
```
#select 15 columns from the given training dataset and create a new dataframe
df_select=num_data(train[['LotArea','YearBuilt','OverallCond', 'BsmtFullBath',
'BedroomAbvGr', 'KitchenAbvGr', 'Fireplaces',
       'GarageYrBlt','GarageCars', 'GarageArea', 'ScreenPorch', 'PoolArea', 'M
oSold', 'YrSold', 'SalePrice']])
#obtain a pariwise pearson correlation between all the columns in the modified
data frame
pearsoncorr = df_select.corr(method='pearson')
#plot a heatmap for the pearson correlation computed above
_, ax = plt.subplots(figsize =(12, 10))
sns.heatmap(pearsoncorr, ax = ax, cmap ="YlGnBu", linewidths = 0.1, annot= Tru
e)
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7f053fd65780>



In [35]:
```
#obtain the most positive correlations
high = np.where(pearsoncorr>0.5)
high = [(pearsoncorr.index[x], pearsoncorr.columns[y]) for x, y in zip(*high)
                                        if x != y and x < y]
#print most positive correlations
high
```

Out[35]:
```
[('YearBuilt', 'GarageCars'),
 ('YearBuilt', 'SalePrice'),
 ('GarageYrBlt', 'GarageCars'),
 ('GarageYrBlt', 'GarageArea'),
 ('GarageCars', 'GarageArea'),
 ('GarageCars', 'SalePrice'),
 ('GarageArea', 'SalePrice')]
```

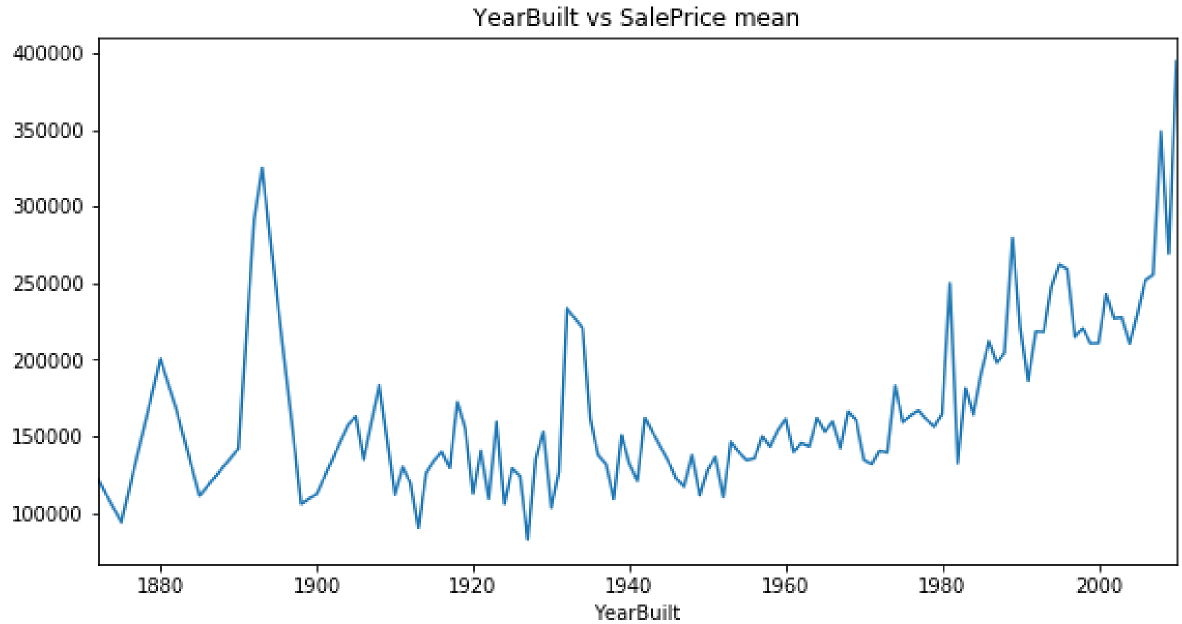
In [36]:
```
#obtain the most negative correlations
low = np.where(pearsoncorr<-0.35)
low = [(pearsoncorr.index[x], pearsoncorr.columns[y]) for x, y in zip(*low)
                                        if x != y and x < y]
#print most negative correlations
low
```

Out[36]:
```
[('YearBuilt', 'OverallCond')]
```

Out of the correlations made, the most positive is between garagecars and garagearea(0.88).The most negative is between yearbuilt and overallcond(-0.38).

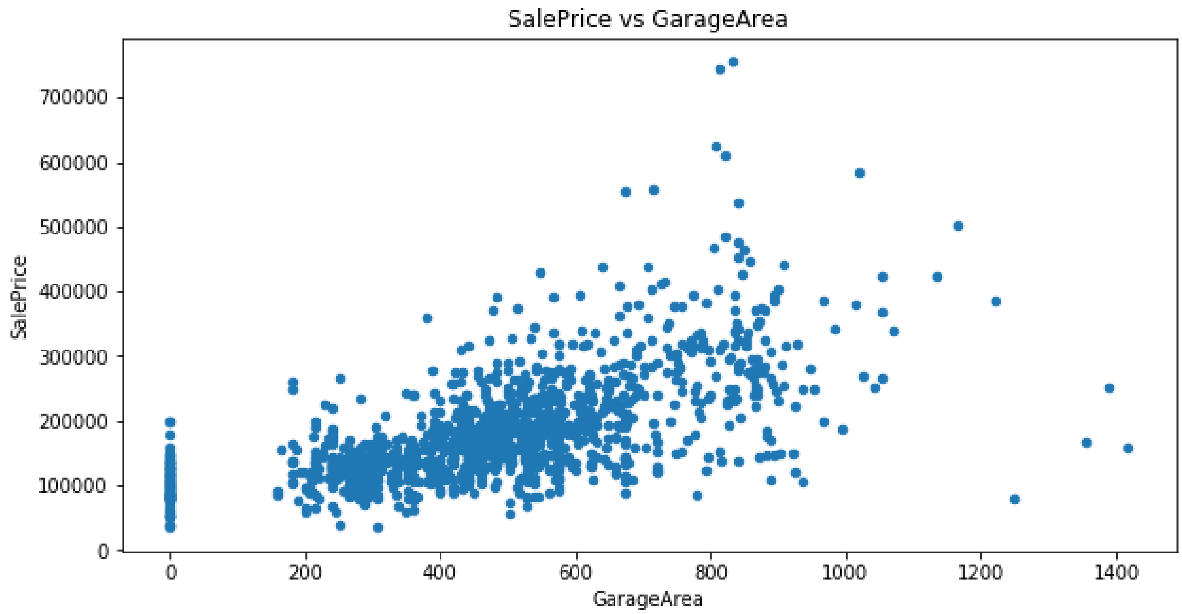
Part 2 - Informative Plots

In [37]:
```
#line chart
train.groupby('YearBuilt')['SalePrice'].mean().plot(kind='line',title='YearBuilt vs SalePrice mean',figsize=(10,5))
plt.show()
```



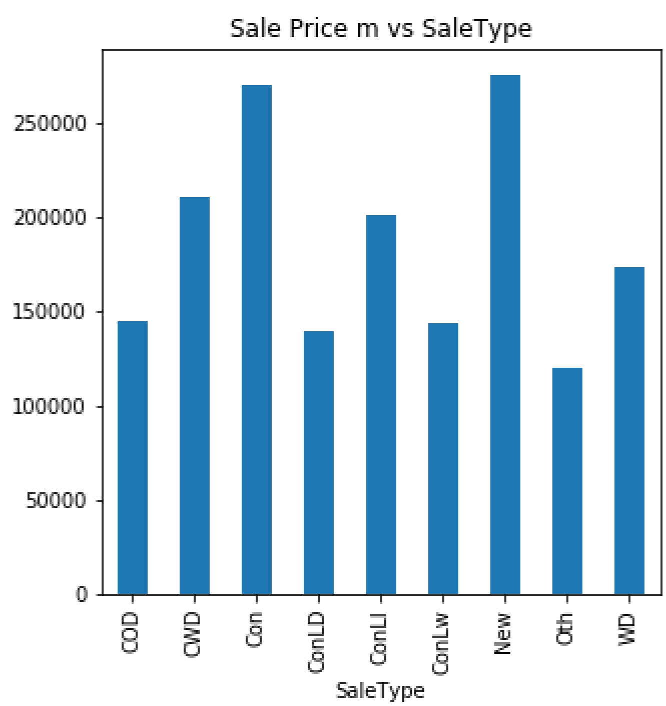
This plot shows the mean of the Sale prices of the houses built in a particular year. Here, we can see that the Sale Price is not steadily increasing or decreasing from 1880- 2000. It's also noticeable that the mean of the sale price of the houses built after 2000 is higher than others. Interesting thing to notice here is that the mean sale price of the houses built between 1880-1900 also are quite high. This can be because of few houses built in that period of time.

In [38]:
```
#scatter plot
train.plot.scatter(x ='GarageArea', y ='SalePrice',figsize=(10,5), title='Sale
Price vs GarageArea')
plt.show()
```



No dependency is noticed between the sale price of the house and its garage area. There are houses with high garage area which were sold for a cheaper price and also most houses with garage area between 200 and 400 have a sale price between 10000 and 20000

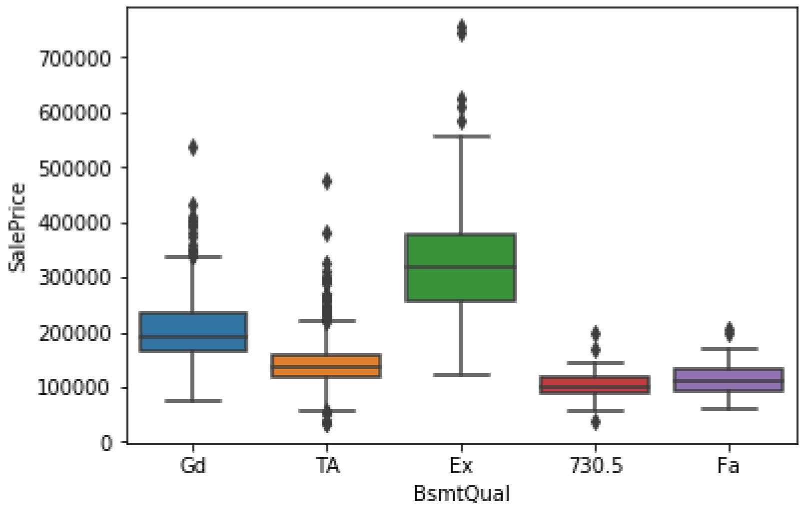
In [39]:
```
#bar graph
train.groupby('SaleType')['SalePrice'].mean().plot(kind='bar',title='Sale Pric
e m vs SaleType',figsize=(5,5))
plt.show()
```



We can notice that New Homes which are just constructed have the highest sale price mean. Also houses sold on contracts with 15% down payment have the second highest mean. Contracts with low down payment have the second lowest sale price mean.

In [40]:
```
#boxplot
sns.boxplot(x='BsmtQual', y='SalePrice', data=train)
```

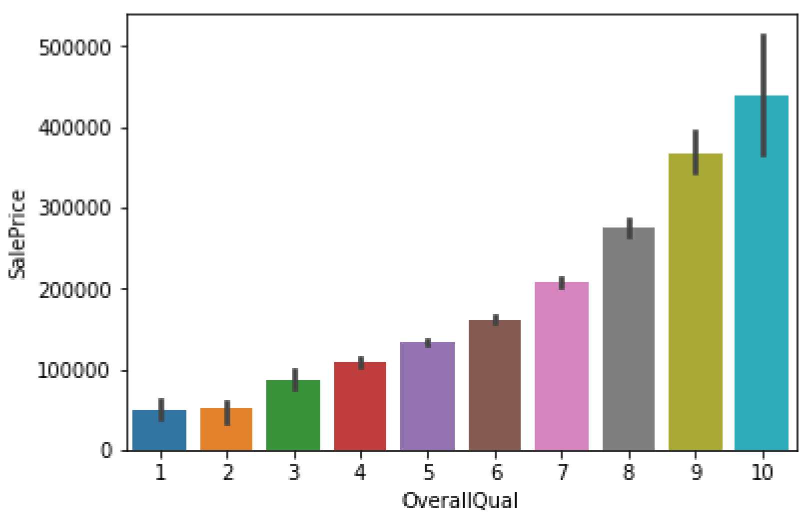
Out[40]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0520208438>
```



From the above plot, we can see that the basement quality is a very important parameter which would affect the sale price of the house. As we can see the houses with excellent quality have higher mean sale price than all the others.

In [41]:
```
sns.barplot(train.OverallQual,train.SalePrice)
```

Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f05200e4320>
```



Overall material and finish of the house is an important paramter for determining the sale price. The houses are ranked from 10 to 1 based on their overall quality. Clearly, houses with rank 10 have the highest sale price mean and houses with ranks 2 and 1 almost have the same sale price mean.

Part 3 - Handcrafted Scoring Function

In [42]:
```
#A scoring function based on the few qualities of the house.
numdata=num_data(train)
numdata['Desirability']= (numdata['YearBuilt']*0.5)+(numdata['OverallQual']*0.25)+(numdata['FullBath']*0.2)+(numdata['1stFlrSF']*0.1)+(numdata['TotRmsAbvGrd']*0.3)
numdata.sort_values('Desirability').head(10)
```

Out[42]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemod
1100	1101	30	60	8400	2	5	1920	1
705	706	190	70	5600	4	5	1930	1
533	534	20	50	5000	1	3	1946	1
968	969	50	50	5925	3	6	1910	1
29	30	30	60	6324	4	6	1927	1
1137	1138	50	54	6342	5	8	1875	1
61	62	75	60	7200	5	7	1920	1
155	156	50	60	9600	6	5	1924	1
125	126	190	60	6780	6	8	1935	1
329	330	70	60	6402	5	5	1920	1

10 rows × 39 columns

The top ten desirable houses are: ID 1298 1299 496 497 523 524 1024 1025 1373 1374 440 441 1044 1045 691 692 898 899 224 225

Least desirable houses are: ID 1100 1101 705 706 533 534 968 969 29 30 1137 1138 61 62 155 156 125 126 329 330

I considered different columns based on their correlation with the Sale Price column. I continued to tweak this by alloting each column a different weight based on it's relation with the sale price. I inserted a new column called 'Desirability' into the dataset which will contain these values. Based on this, I sorted the dataframe based on the desirability values and obtained the top 10 desirable and least desirable houses.

Part 4 - Pairwise Distance Function

In [43]:
```
#using euclidean distances and minmax scalar
euc_dist=pd.DataFrame(euclidean_distances(numdata))
euc_dist.head(5)
```

Out[43]:

	0	1	2	3	4	5	
0	0.000000	27052.126479	15263.957024	68512.881614	41913.177298	65751.050005	985
1	27052.126479	0.000000	42052.210419	41523.870425	68676.125756	38783.662944	1255
2	15263.957024	42052.210419	0.000000	83518.747377	26679.103038	80558.015317	835
3	68512.881614	41523.870425	83518.747377	0.000000	110105.268760	5587.984338	1670
4	41913.177298	68676.125756	26679.103038	110105.268760	0.000000	107010.549313	571

5 rows × 1460 columns

In [44]:
```
scaler = MinMaxScaler()
print(scaler.fit(euc_dist))
dist=pd.DataFrame(scaler.transform(euc_dist))
dist.head(5)
```

```
MinMaxScaler(copy=True, feature_range=(0, 1))
```

Out[44]:

	0	1	2	3	4	5	6	7	8	
0	0.000000	0.047159	0.028713	0.111379	0.082986	0.107426	0.219847	0.015807	0.125768	0.
1	0.049485	0.000000	0.079103	0.067504	0.135975	0.063366	0.280042	0.033473	0.082746	0.
2	0.027922	0.073308	0.000000	0.135774	0.052823	0.131618	0.186373	0.042403	0.149918	0.
3	0.125327	0.072387	0.157104	0.000000	0.218003	0.009130	0.372659	0.108119	0.017082	0.
4	0.076670	0.119720	0.050185	0.178995	0.000000	0.174836	0.127577	0.090356	0.192516	0.

5 rows × 1460 columns

In [45]:
```
subgroup = train.groupby(['SaleType', 'HouseStyle']).size().unstack().fillna(0
)
distfun=pd.DataFrame(
    squareform(pdist(subgroup.loc[['WD', 'New', 'CWD','COD','ConLD','ConLI','C
onLw','Oth','Con']])),
    columns = ['WD', 'New', 'CWD','COD','ConLD','ConLI','ConLw','Oth','Con'],
    index = ['WD', 'New', 'CWD','COD','ConLD','ConLI','ConLw','Oth','Con']
)
distfun
```

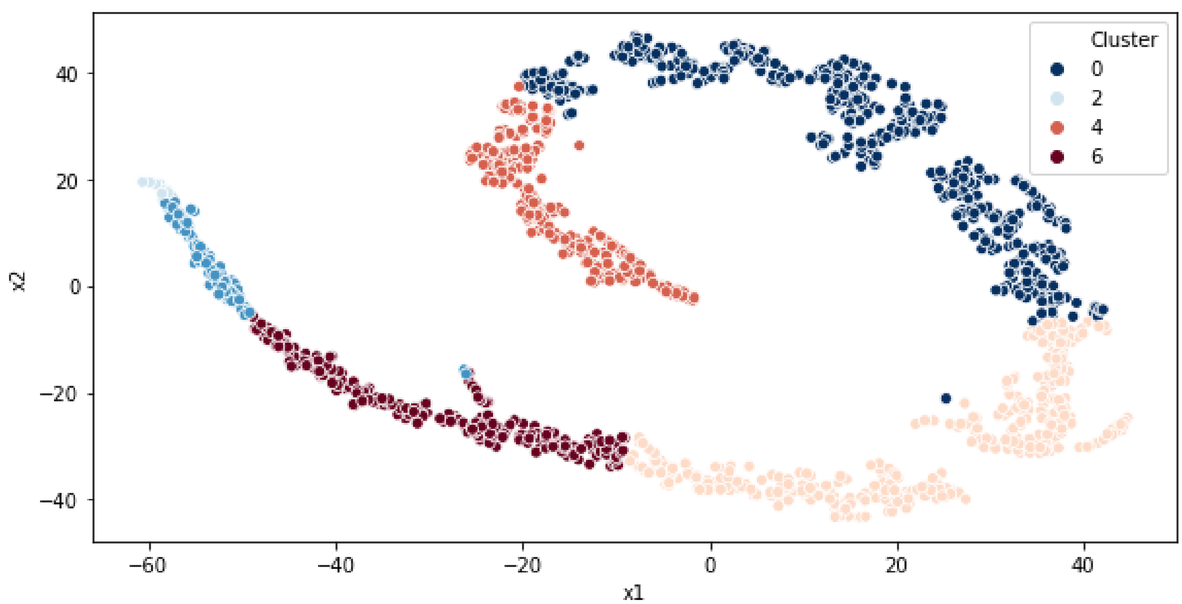
Out[45]:

	WD	New	CWD	COD	ConLD	ConLI	ConLw
WD	0.000000	653.252631	737.269964	710.012676	734.898632	736.004076	736.516123
New	653.252631	0.000000	86.625631	60.456596	84.658136	85.246701	85.772956
CWD	737.269964	86.625631	0.000000	29.715316	3.872983	1.732051	1.732051
COD	710.012676	60.456596	29.715316	0.000000	26.795522	28.635642	28.809721
ConLD	734.898632	84.658136	3.872983	26.795522	0.000000	3.741657	3.464102
ConLI	736.004076	85.246701	1.732051	28.635642	3.741657	0.000000	1.414214
ConLw	736.516123	85.772956	1.732051	28.809721	3.464102	1.414214	0.000000
Oth	736.426507	85.445889	2.645751	28.178006	3.464102	2.449490	2.000000
Con	737.545253	86.614087	1.414214	29.916551	4.582576	1.732051	1.732051

I used euclidean distance to see the similarity/dissimilarity between all the houses(pairwise). It is seen that the more the distance, the dissimilar are the two houses. I also used pdist to compare different housetypes and see their similarity. I also used minmaxscalar to obtain the distances between 0 and 1 to make the comparison simpler.

Part 5 - Clustering

In [46]:
```
usemod = numdata
pca = PCA(n_components=30).fit(usemod)
evr=np.cumsum(pca.explained_variance_ratio_)
pca = PCA(n_components=9).fit(usemod)
_pca = pca.fit_transform(usemod)
clusters = range(1,20)
kmeans = [KMeans(i) for i in clusters]
score = [kmeans[i].fit(usemod).score(usemod) for i in range(len(kmeans))]
kmeans = KMeans(n_clusters=6, random_state=40)
Xkmeans = kmeans.fit_predict(_pca)
others = numdata.SalePrice.reset_index(drop=True)
sprice = numdata.SalePrice
_TSNE = TSNE(n_components=2).fit_transform(_pca)
fin = pd.concat([pd.DataFrame(_TSNE),pd.DataFrame(Xkmeans),

                       pd.DataFrame(others), pd.DataFrame(sprice)],axis=1)

fin.columns = ['x1','x2','Cluster','Neighbours','SalePrice']
plt.figure(figsize=(10,5))
sns.scatterplot(x="x1", y="x2", hue="Cluster", palette="RdBu_r", data=fin)
plt.show()
```



Using kmeans, I clustered the data based on the matrix mentioned above. Here different clusters are formed based on their similarity. The clustering is done with respect to the sale price. I only considered the numerical columns of the training data to do this clustering. Different dataframes are combined to obtain this cluster representation

Part 6 - Linear Regression

In [47]:
```
numeric_data =num_data(train)
X=numeric_data.drop(columns=['SalePrice'])
y=numeric_data['SalePrice']
Xtest=num_data(test)
lin_model = LinearRegression()
lin_model.fit(X, y)
y_test_predict = lin_model.predict(Xtest)
print("accuracy score:",lin_model.score(X,y))
```

```
accuracy score: 0.8165649232788081
```

In [48]:
```
X=numeric_data.drop(columns=['SalePrice','OverallCond'])
lin_model = LinearRegression()
lin_model.fit(X, y)
Xtest1=Xtest.drop(columns=['OverallCond'])
y_test_predict = lin_model.predict(Xtest1)
print("accuracy score:",lin_model.score(X,y))
```

```
accuracy score: 0.813189357593816
```

In [49]:
```
X=numeric_data.drop(columns=['SalePrice','YearBuilt'])
lin_model = LinearRegression()
lin_model.fit(X, y)
Xtest2=Xtest.drop(columns=['YearBuilt'])
y_test_predict = lin_model.predict(Xtest2)
print("accuracy score:",lin_model.score(X,y))
```

```
accuracy score: 0.8122127745034409
```

In [50]:
```
X=numeric_data.drop(columns=['SalePrice','GarageCars'])
lin_model = LinearRegression()
lin_model.fit(X, y)
Xtest3=Xtest.drop(columns=['YearBuilt'])
y_test_predict = lin_model.predict(Xtest3)
print("accuracy score:",lin_model.score(X,y))
```

```
accuracy score: 0.8129421884896492
```

This linear regression model is 81.6% accurate. Here, we are using all the numerical columns in the training data set to predict the value of the sale price. This numerical data is preprocessed (check the code mentioned for num_data function explanation). I tried to find the most important variable by removing it from the list of independent columns to see if the absence of that variable is impacting the accuracy of sale price prediction or not. YearBuilt is one of the important variables since removal of YearBuilt from the list of variables decreased the accuracy by 0.4%

Part 7 - External Dataset

This data consists of the different region names and the value of housing per sqr foot in different time periods. This dataset can be helpful in predicting the sale price better since we can use the rate of the housing in different regions during different time periods. For example,

RegionName	Sta	SizeRank	1996-04	1996-05	1996-06	1996-07	1996-08	1996-09	1996-10	1996-11	1996-12	1997-01
United States	NA	0	65	65	65	65	65	65	65	65	65	65
New York	NY	1	103	103	103	102	102	102	102	102	102	103
Los Angeles-Long Beach-Anaheim	CA	2	116	117	117	116	116	116	116	116	116	117
Chicago	IL	3	94	94	94	95	94	94	94	94	95	95
Dallas-Fort Worth	TX	4	52	52	52	52	52	52	52	52	52	53
Philadelphia	PA	5	68	68	68	68	68	67	67	67	67	67
Houston	TX	6										
Washington	DC	7	96	96	96	95	95	95	95	95	95	95
Miami-Fort Lauderdale	FL	8	67	67	67	67	67	66	66	66	66	66
Atlanta	GA	9	59	58	59	59	59	59	60	60	61	61
Boston	MA	10	96	96	96	96	96	96	96	97	97	98
San Francisco	CA	11	143	143	143	143	143	144	144	144	144	146

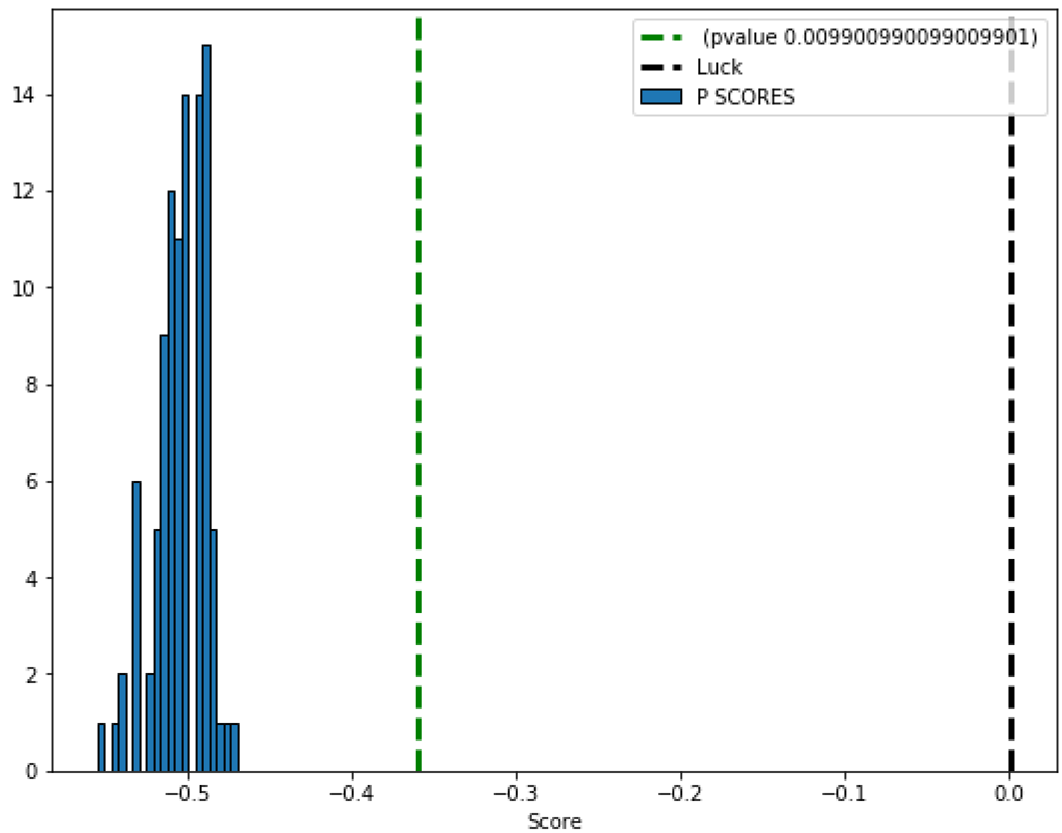
It can be noted that the rate of the housing per square foot didn't differ much over years but it varies a lot from area to area. Using this dataset we can predict sale prices in a better way since we know how much it costs in a particular city.

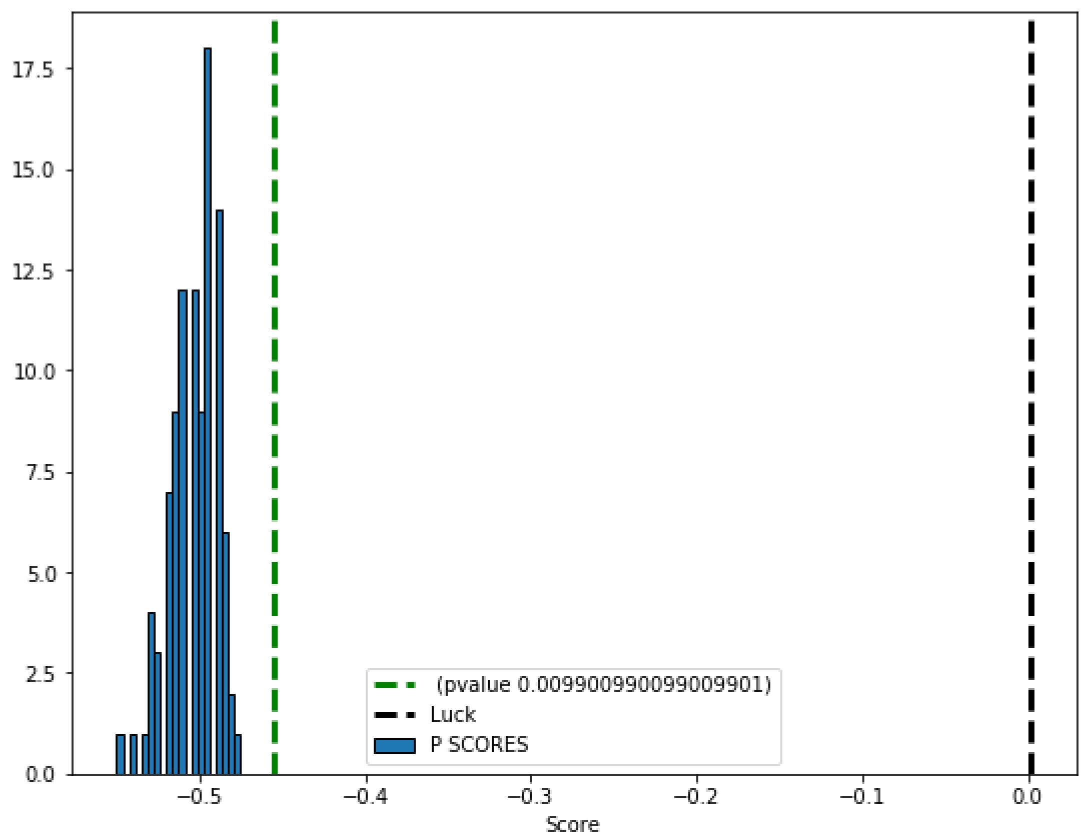
Part 8 - Permutation Test

In [17]:
```
def fn_rmse(y_true, y_pred):
        e = np.sqrt(mean_squared_error(y_true, y_pred))
        rmse = round(e, 2)
        return rmse

def pScore(col):
    X = train[col]
    y = np.log(train['SalePrice'])
    n_classes = np.unique(y).size
    random = np.random.RandomState(seed=77)
    E = random.normal(size=(len(X), 2200))
    X = np.c_[X, E]
    reg = LinearRegression()
    k = KFold(2)
    score = make_scorer(fn_rmse, greater_is_better=False)
    score, permutation_scores, pvalue = permutation_test_score (reg, X, y, sco
ring=score, cv=k, n_permutations=100, n_jobs=1,verbose=0)
    plt.figure(figsize=(9,7))
    plt.hist(permutation_scores, 20, label='P SCORES', edgecolor='black')
    ylim = plt.ylim()
    plt.plot(2 * [score], ylim, '--g', linewidth=3, label=' (pvalue %s)' % pva
lue)
    plt.plot(2 * [1. / n_classes], ylim, '--k', linewidth=3, label='Luck')
    plt.ylim(ylim)
    plt.legend()
    plt.xlabel('Score')
    plt.show();
```

In [18]:
```
%%javascript
IPython.OutputArea.auto_scroll_threshold = 9999;
```

In [ ]:
```
list1=['OverallQual','GarageCars','GarageArea','MasVnrArea','GrLivArea','YearB
uilt','KitchenAbvGr','BedroomAbvGr',
       'YrSold','FirePlaces']

for l in list1:
    pScore(l)
```


(pvalue 0.009900990099009901)
Luck
P SCORES
14
12
10
8
6
4
2
0
−0.5
−0.4
−0.3
−0.2
−0.1
0.0
Score


(pvalue 0.009900990099009901)
Luck
P SCORES
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−0.5
−0.4
−0.3
−0.2
−0.1
0.0
Score

I considered 10 columns namely 'OverallQual','GarageCars','GarageArea','MasVnrArea','GrLivArea','YearBuilt','KitchenAbvGr','BedroomAbvGr', 'YrSold','FirePlaces' to get the pscore for them. For this I used permutation_test_score, kfold, mean squared error and make_scorer

Part 9 - Final Result

In [7]:
```
train1= pd.read_csv('train.csv')
test1=pd.read_csv('test.csv')
# train1= pd.read_csv('/kaggle/input/house-prices-advanced-regression-techniqu
es/train.csv')
# test1=pd.read_csv('/kaggle/input/house-prices-advanced-regression-technique
s/test.csv')
#dropping columns which have null values
data_irr = train1.dropna(axis=1)
removecols = [col for col in train1.columns
                                 if train1[col].isnull().any()]
ctrain1 = train1.drop(removecols, axis=1)
ctest1 = test1.drop(removecols, axis=1)
#label encoding for categorical variables
from sklearn import preprocessing
for col in ctrain1.columns:
    if ctrain1[col].dtypes=='object':
        lbl=preprocessing.LabelEncoder()
        lbl.fit(list(train1[col].values))
        ctrain1[col]=lbl.transform(list(ctrain1[col].values))

for col in ctest1.columns:
    if ctest1[col].dtypes=='object':
        lbl=preprocessing.LabelEncoder()
        lbl.fit(list(ctest1[col].values))
        ctest1[col]=lbl.transform(list(ctest1[col].values))
```

In [8]:
```
#replacing NAN in numerical columns by mode value
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
numdf = ctrain1.select_dtypes(include=numerics)
for column in numdf.columns:
    ctrain1.fillna(ctrain1[column].mode()[0],inplace=True)

numdf1 = ctest1.select_dtypes(include=numerics)
for column in numdf1.columns:
    ctest1.fillna(ctest1[column].mode()[0],inplace=True)
```

In [9]:
```
#splitting the train dataset
y=ctrain1[['SalePrice']]
X=ctrain1.drop(columns=['SalePrice'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random
_state=0)
```

In [10]:
```
#random forest regressor
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
reg = RandomForestRegressor(n_estimators = 100, random_state = 0)
reg.fit(X_train, y_train)
y_pred = reg.predict(X_test)
pred = reg.predict(ctest1)
out=pd.DataFrame(pred,ctest1.Id,['SalePrice'])
out.to_csv('outfin1.csv')
```

In [11]:
```
#xgb regressor
xg_reg = xgb.XGBRegressor(learning_rate=0.05,n_estimators=2000)
xg_reg.fit(X_train,y_train)
preds = xg_reg.predict(X_test)
predxg = xg_reg.predict(ctest1)
out=pd.DataFrame(predxg,ctest1.Id,['SalePrice'])
out.to_csv('xgb2.csv')
```

In [12]:
```
#lightgbm
import lightgbm as lgb
lgbmod = lgb.LGBMRegressor(objective='regression',num_leaves=10,learning_rate=
0.05, n_estimators=750)
lgbmod.fit(X_train,y_train)
lgb_pred = lgbmod.predict(ctest1.values)
out=pd.DataFrame(lgb_pred,ctest1.Id,['SalePrice'])
out.to_csv('lightgbm2.csv')
```

In [13]:
```
#gradient boosting regressor
from sklearn import ensemble, tree, linear_model
gboost = ensemble.GradientBoostingRegressor(learning_rate=0.05, max_depth=3,
                                               min_samples_leaf=20, min_sample
s_split=10, n_estimators=3500)
gboost.fit(X_train, y_train)
gboost_pred = gboost.predict(ctest1.values)
out=pd.DataFrame(gboost_pred,ctest1.Id,['SalePrice'])
out.to_csv('gboost2.csv')
```

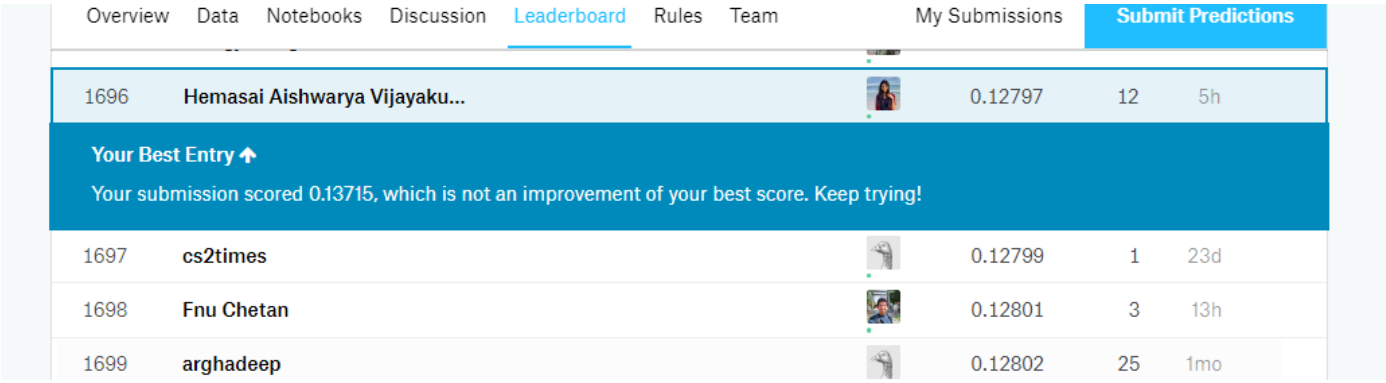
Preprocessing of data: Dropped columns with null values. Performed label encoding on all the categorical variables in test and training data. After that, replaced NANs with mode values in numerical columns. Modelling: For modelling of the data to predict sale price, I initially used RandomForest Regressor which gave a score of 0.14 On using XGBRegressor with learning rate of 0.05 the score improved to 0.13. The best score 0.12 was obtained using Light GBM model with n_estimators=750 and learning rate=0.05. GradientBoosting Regressor also gave around 0.13 as the score.

Kaggle Link: [https://www.kaggle.com/aishwaryavhs07 (https://www.kaggle.com/aishwaryavhs07)](https://www.kaggle.com/aishwaryavhs07)

Highest Rank: 1696

Score: 0.12797

Number of entries: 12



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