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.

```
# TODO: code and runtime results
from google.colab import drive
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
sns.set()
```

```
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Ai

Enter your authorization code:
··········
Mounted at /content/drive
```

```
cd '/content/drive/My Drive/DSF/Homework_3/house-prices-advanced-regression-techniques'
```

```
/content/drive/My Drive/DSF/Homework_3/house-prices-advanced-regression-techniques
```

Part 1 - Pairwise Correlations

```
# TODO: show visualization
df_train=pd.read_csv('train.csv')
```

```
df_train_clean=df_train.copy()
```

```
isna=df_train_clean.isna().sum()
```

```
df_train_clean.drop(['MiscFeature','PoolQC','Fence','Alley'], axis=1, inplace=True)
```

```
df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='object']]=df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='object']].fillna(df_train_clean.mode().iloc[0])
df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='int64']]=df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='int64']].fillna(df_train_clean.mean())
df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='float64']]=df_train_clean[df_train_clean.columns[df_train_clean.dtypes=='float64']].fillna(df_train_clean.mean())
df_train_clean.shape
```

```
(1460, 77)
```

```
df_train_P1=df_train_clean.copy()
```

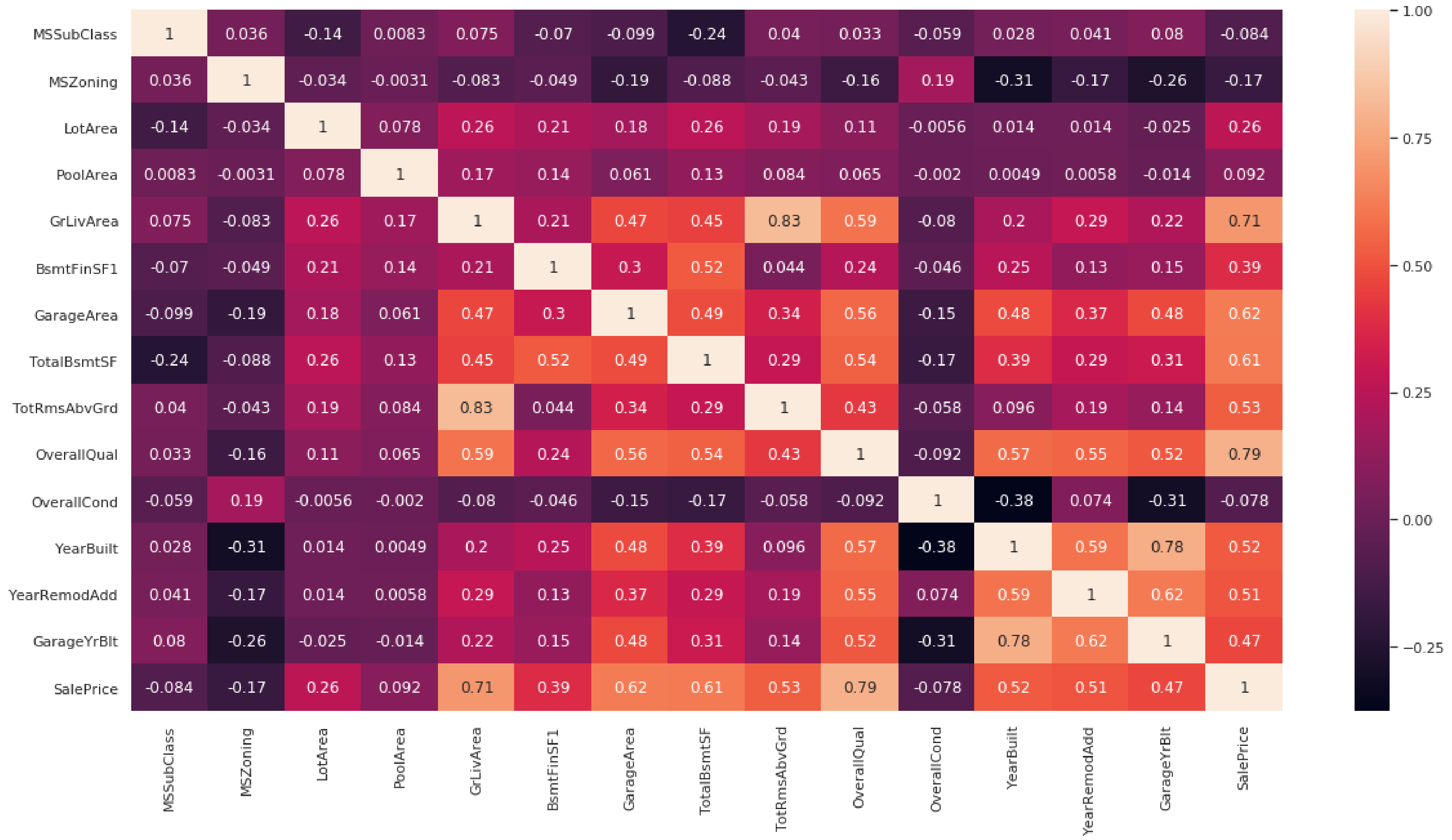
```
df_train_P1=df_train_P1[['MSSubClass',
 'MSZoning',
 'LotArea',
 'PoolArea',
 'GrLivArea',
 'BsmtFinSF1',
 'GarageArea',
 'TotalBsmtSF',
 'TotRmsAbvGrd',
 'OverallQual',
 'OverallCond',
 'YearBuilt',
 'YearRemodAdd',
 'GarageYrBlt',
 'SalePrice']]
```

```
cat_cols = df_train_P1.dtypes==object
cat_cols = df_train_P1.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_train_P1[cat_cols] = df_train_P1[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))
```

```
corr_pearson = df_train_P1.corr()

plt.figure(figsize=[20,10])
ax = sns.heatmap(corr_pearson,annot=True)
```



	MSSubClass	MSZoning	LotArea	PoolArea	GrLivArea	BsmtFinSF1	GarageArea	TotalBsmtSF	TotRmsAbvGrd	OverallQual	OverallCond	YearBuilt	YearRemodAdd	GarageYrBlt	SalePrice
MSSubClass	1	0.036	-0.14	0.0083	0.075	-0.07	-0.099	-0.24	0.04	0.033	-0.059	0.028	0.041	0.08	-0.084
MSZoning	0.036	1	-0.034	-0.0031	-0.083	-0.049	-0.19	-0.088	-0.043	-0.16	0.19	-0.31	-0.17	-0.26	-0.17
LotArea	-0.14	-0.034	1	0.078	0.26	0.21	0.18	0.26	0.19	0.11	-0.0056	0.014	0.014	-0.025	0.26
PoolArea	0.0083	-0.0031	0.078	1	0.17	0.14	0.061	0.13	0.084	0.065	-0.002	0.0049	0.0058	-0.014	0.092
GrLivArea	0.075	-0.083	0.26	0.17	1	0.21	0.47	0.45	0.83	0.59	-0.08	0.2	0.29	0.22	0.71
BsmtFinSF1	-0.07	-0.049	0.21	0.14	0.21	1	0.3	0.52	0.044	0.24	-0.046	0.25	0.13	0.15	0.39
GarageArea	-0.099	-0.19	0.18	0.061	0.47	0.3	1	0.49	0.34	0.56	-0.15	0.48	0.37	0.48	0.62
TotalBsmtSF	-0.24	-0.088	0.26	0.13	0.45	0.52	0.49	1	0.29	0.54	-0.17	0.39	0.29	0.31	0.61
TotRmsAbvGrd	0.04	-0.043	0.19	0.084	0.83	0.044	0.34	0.29	1	0.43	-0.058	0.096	0.19	0.14	0.53
OverallQual	0.033	-0.16	0.11	0.065	0.59	0.24	0.56	0.54	0.43	1	-0.092	0.57	0.55	0.52	0.79
OverallCond	-0.059	0.19	-0.0056	-0.002	-0.08	-0.046	-0.15	-0.17	-0.058	-0.092	1	-0.38	0.074	-0.31	-0.078
YearBuilt	0.028	-0.31	0.014	0.0049	0.2	0.25	0.48	0.39	0.096	0.57	-0.38	1	0.59	0.78	0.52
YearRemodAdd	0.041	-0.17	0.014	0.0058	0.29	0.13	0.37	0.29	0.19	0.55	0.074	0.59	1	0.62	0.51
GarageYrBlt	0.08	-0.26	-0.025	-0.014	0.22	0.15	0.48	0.31	0.14	0.52	-0.31	0.78	0.62	1	0.47
SalePrice	-0.084	-0.17	0.26	0.092	0.71	0.39	0.62	0.61	0.53	0.79	-0.078	0.52	0.51	0.47	1

```
del [[df_train_P1,corr_pearson]]
```

Discuss most positive and negative correlations.

The features have been decided by analysing the data_description.txt file and the training dataset.

Highest Positive Correlation = 0.83 (GrLivArea and TotRmsAbvGrd)

This signifies that more the ground living area, more the number of rooms.

Least Negative Correlation = -0.38 (OverallCond and YearBuilt)

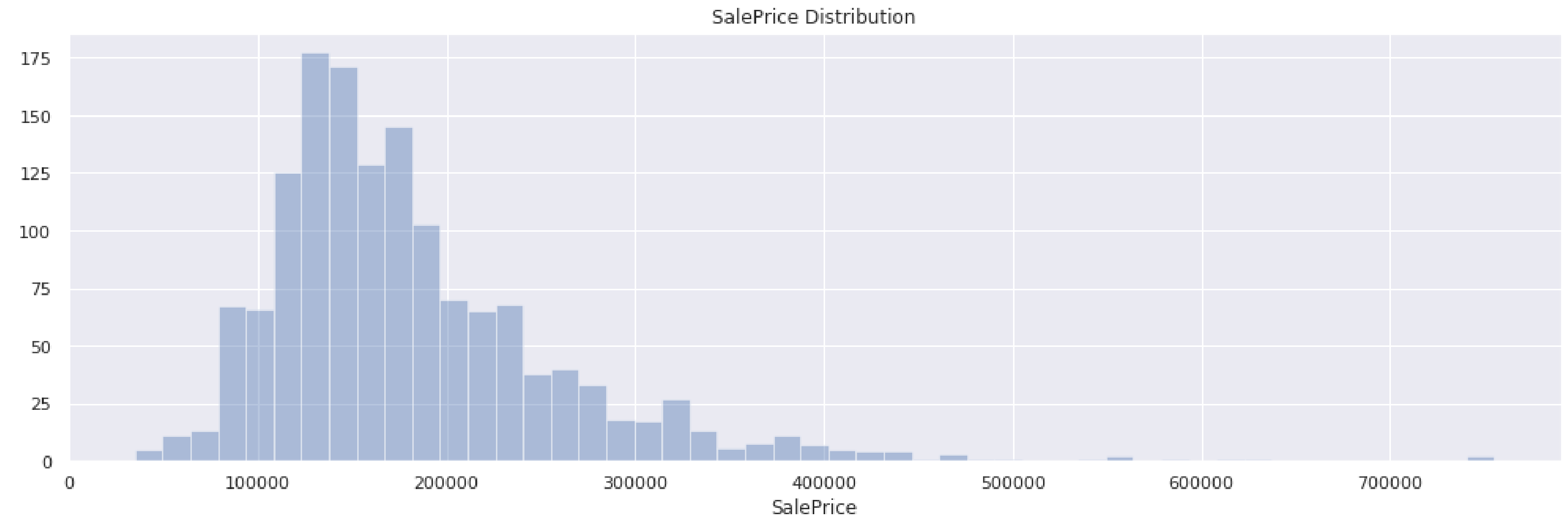
This signifies that the OverallCond will mostly be opposite to the year the house was built in. Therefore, hihger the overall condition, earlier the house was built.

Part 2 - Informative Plots

```
# TODO: code to generate Plot 1
df_train_P2=df_train.copy()

plt.figure(figsize=(17,5))
sns.distplot(df_train_P2['SalePrice'],kde=False).set_title('SalePrice Distribution')
```

```
Text(0.5, 1.0, 'SalePrice Distribution')
```



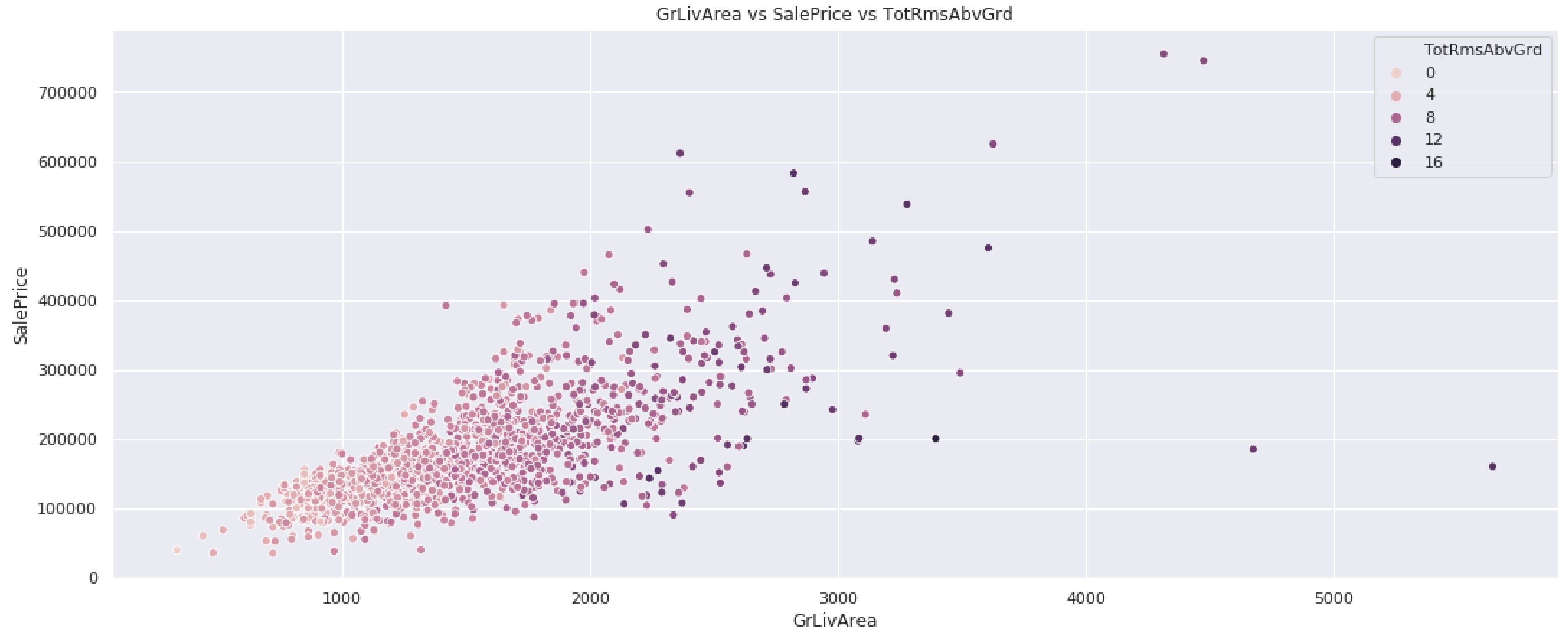
What interesting properties does Plot 1 reveal?

It can observed that the data is skewed.

We can see that most number of houses cost in the range of 120000 and 180000 (approximately). Moreover, there are significantly lower number of houses which are ultra expensive, even compared to the ultra cheap houses.

```
# TODO: code to generate Plot 2
plt.figure(figsize=(18,7))
sns.scatterplot(x="GrLivArea", y="SalePrice",hue='TotRmsAbvGrd',data=df_train_P2).set_title('GrLivArea vs SalePrice vs TotRmsAbvGrd')
```

```
Text(0.5, 1.0, 'GrLivArea vs SalePrice vs TotRmsAbvGrd')
```



What interesting properties does Plot 2 reveal?

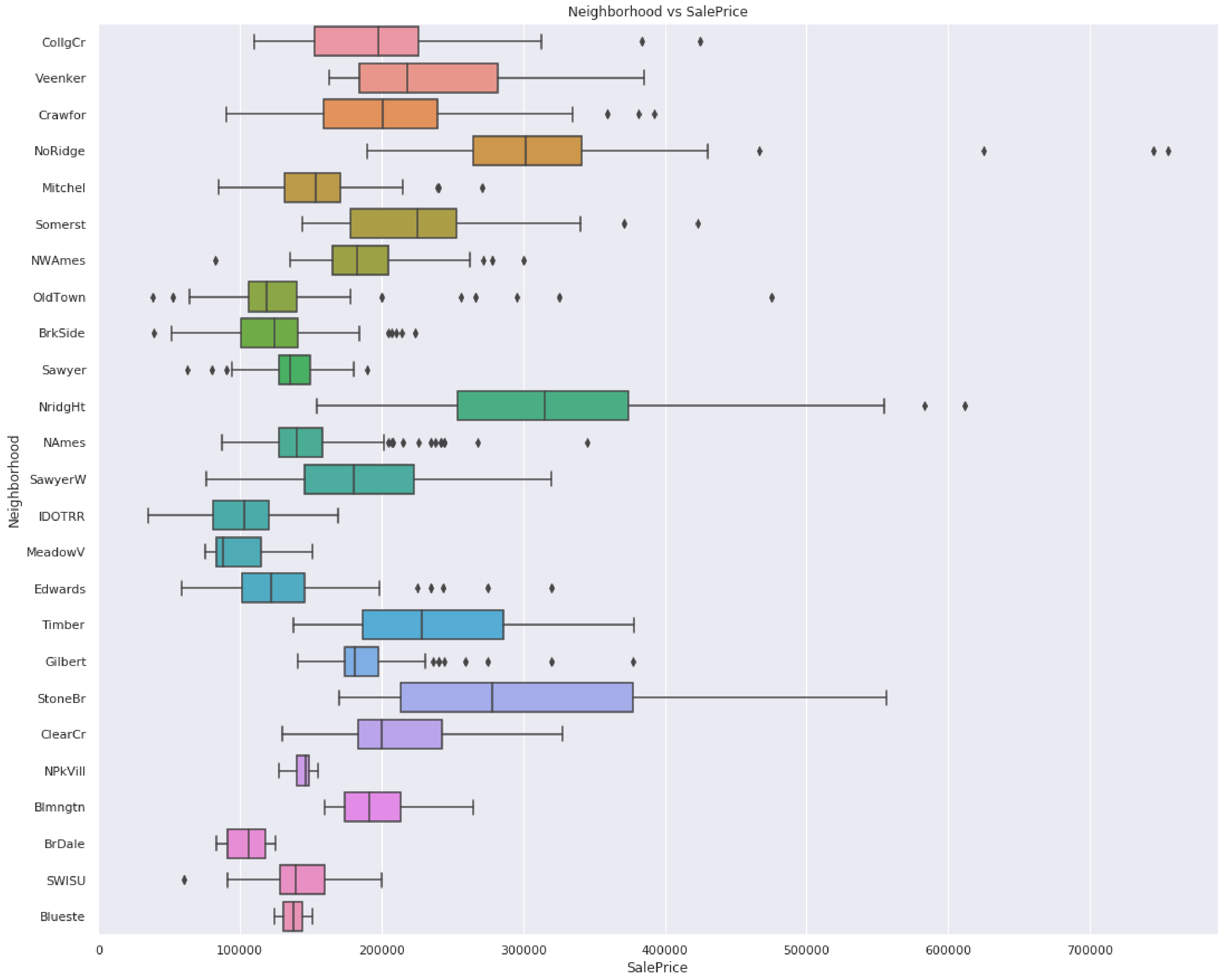
As the Ground Living Area increases, the Sale Price also increases. This is a linear relationship.

The Total number of rooms increases, in effect the Ground Living Area also increases. The more the area, the more the number of rooms.

```
# TODO: code to generate Plot 3

plt.figure(figsize=(18,15))
# sns.countplot(x="Neighborhood", y="SalePrice",data=df_train_P2).set_title('GrLivArea vs SalePrice')
sns.boxplot(x="SalePrice", y="Neighborhood",data=df_train_P2).set_title('Neighborhood vs SalePrice')
```

```
Text(0.5, 1.0, 'Neighborhood vs SalePrice')
```



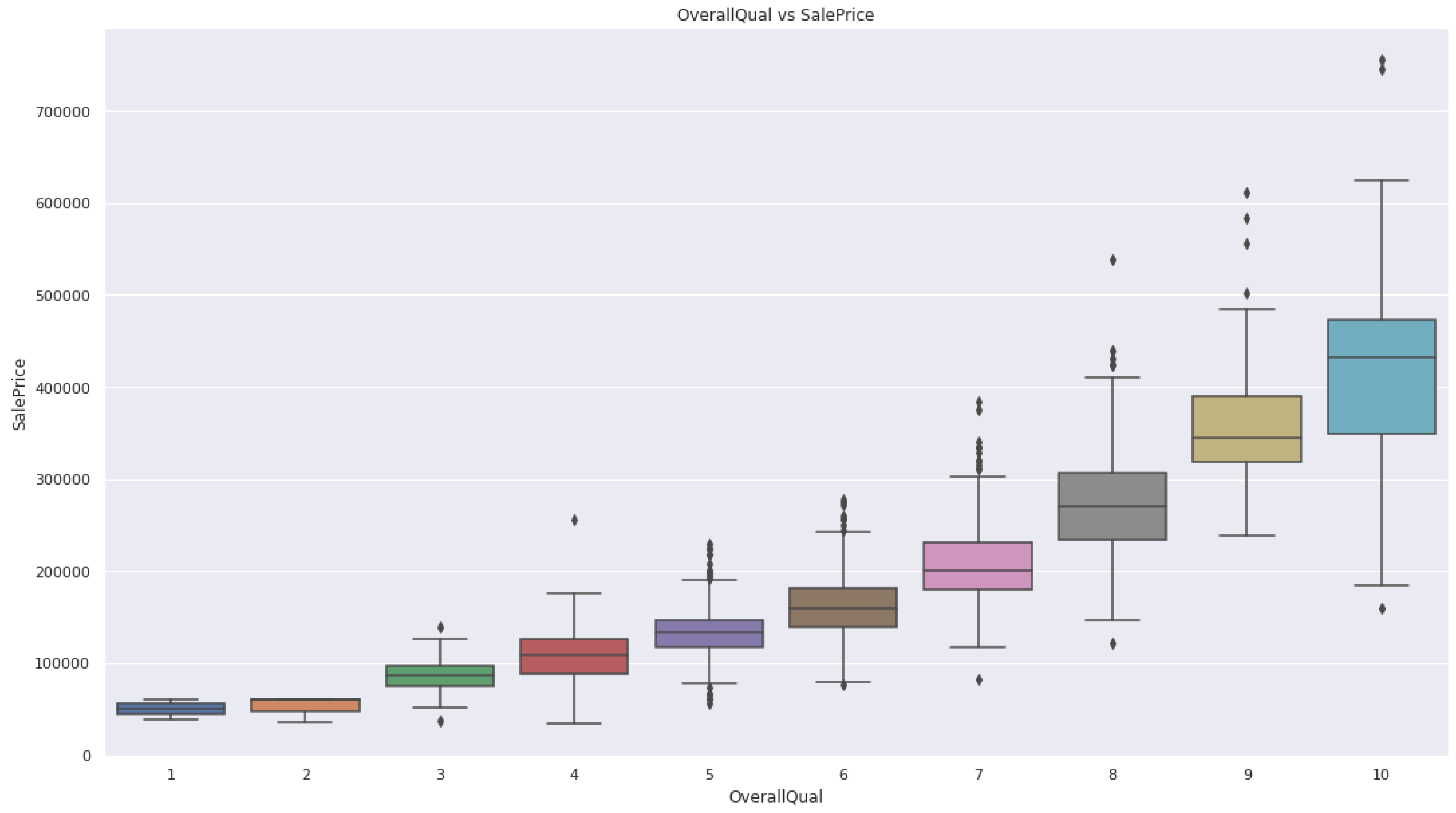
What interesting properties does Plot 3 reveal?

We can infer that the different neighborhoods have different range of SalePrice. The neighborhoods with the most expensive houses are 'NirdigHt' and 'StoneBr'.

Also, the maximum range of SalePrice is for 'StoneBr'.

```
# # TODO: code to generate Plot 4
# OverallQual
plt.figure(figsize=(18,10))
sns.boxplot(y="SalePrice", x="OverallQual",data=df_train_P2).set_title('OverallQual vs SalePrice')
```

```
Text(0.5, 1.0, 'OverallQual vs SalePrice')
```



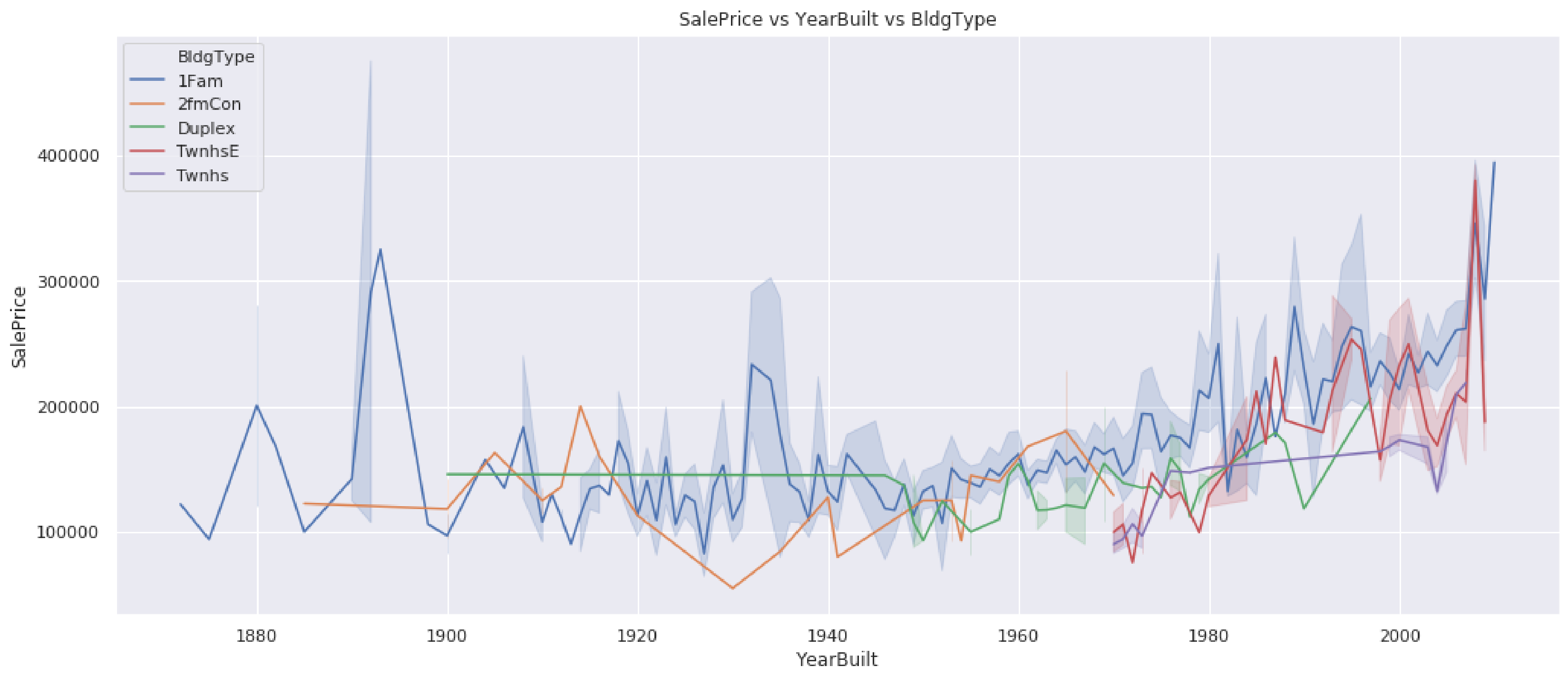
What interesting properties does Plot 4 reveal?

We can infer that as the Overall Quality of the houses increases, the cost of the houses increases.

It can also be observed with this increase, even the range of SalePrice increases with the increase in Overall Quality.

```
# TODO: code to generate Plot 5
plt.figure(figsize=(17,7))
sns.lineplot(y='SalePrice', x='YearBuilt',markers=True, dashes=False,data=df_train_P2,hue='BldgType').set_title('SalePrice vs YearBuilt vs BldgType')
```

```
Text(0.5, 1.0, 'SalePrice vs YearBuilt vs BldgType')
```



What interesting properties does Plot 5 reveal?

1. Initially 'Single-family Detached' were the type of houses that existed and were sold until the year 1885.
2. After 1880 'Two-family Conversion' were the kind of houses that were sold. Although, Single-family houses still dominated the market.
3. 'Duplex' houses started being sold after the year 1900. It was sold at a constant rate for a few years. But after the year 1950, it's frequency dropped.
4. 'Townhouse End Unit' and 'Townhouse Inside Unit' houses, both these type of houses started being sold after 1970. In the years around 2000, the Single family and Townhouse End Unit have similar frequency of sale.

```
del [df_train_P2]
```

Part 3 - Handcrafted Scoring Function

```
# TODO: code for scoring function
df_train_P3=df_train_clean.copy()

cat_cols = df_train_P3.dtypes==object
cat_cols = df_train_P3.columns[cat_cols].tolist()
```

```python
le = preprocessing.LabelEncoder()
df_train_P3[cat_cols] = df_train_P3[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

corr_pearson = df_train_P3.corr()



df_train_P3_pos_corr_SalePrice=corr_pearson['SalePrice'].copy()

df_train_P3=df_train_P3[df_train_P3_pos_corr_SalePrice.index]
df_train_P3_pos_corr_SalePrice.drop(labels = ['Id'],inplace=True)
df_train_P3_pos_corr_SalePrice.drop(labels = ['SalePrice'],inplace=True)


sum_P3=df_train_P3_pos_corr_SalePrice.values.sum()

for index,val in df_train_P3_pos_corr_SalePrice.iteritems():
    df_train_P3_pos_corr_SalePrice[index]=val/sum_P3

ID=df_train_P3['Id']
SalePrice=df_train_P3['SalePrice']
df_train_P3.drop(['Id','SalePrice'], axis=1, inplace=True)

df_train_P3['Score'] = df_train_P3.dot(df_train_P3_pos_corr_SalePrice)
df_train_P3['Id']=ID
df_train_P3['SalePrice']=SalePrice


df_train_P3.set_index('Id', inplace=True)
print("Top 10 Desirable Houses: \n")
print(df_train_P3.nlargest(10,'Score'))
print("\n\n\nTop 10 Least Houses: \n")
print(df_train_P3.nsmallest(10,'Score'))
```

```
Top 10 Desirable Houses:

      MSSubClass  MSZoning  LotFrontage  ...  SaleCondition        Score  SalePrice
Id                                       ...                                       
314           20         3   150.000000  ...              4  7153.467444     375000
336          190         3    70.049958  ...              4  5610.096576     228950
250           50         3    70.049958  ...              4  5465.431619     277000
707           20         3    70.049958  ...              4  4218.995842     302000
1299          60         3   313.000000  ...              5  3832.971051     160000
452           20         3    62.000000  ...              4  2820.391025     280000
770           60         3    47.000000  ...              4  2613.168367     538000
524           60         3   130.000000  ...              5  2593.580812     184750
54            20         3    68.000000  ...              4  2365.389059     385000
385           60         3    70.049958  ...              4  2352.933094     240000

[10 rows x 77 columns]



Top 10 Least Houses:

      MSSubClass  MSZoning  LotFrontage  ...  SaleCondition       Score  SalePrice
Id                                       ...                                      
615          180         4         21.0  ...              4  509.965402      75500
534           20         3         50.0  ...              4  515.925022      39300
650          180         4         21.0  ...              4  517.607789      84500
1450         180         4         21.0  ...              0  526.609439      92000
435          180         4         21.0  ...              4  539.036952      81000
1040         180         4         21.0  ...              4  543.143620      80000
490          180         4         21.0  ...              4  546.509015      86000
711           30         3         56.0  ...              4  575.489965      52000
838          160         4         21.0  ...              4  575.580639     100000
76           180         4         21.0  ...              4  577.000160      91000

[10 rows x 77 columns]
```

```
del [[df_train_P3,df_train_P3_pos_corr_SalePrice,ID,corr_pearson]]
```

What is the ten most desirable houses?

The ten most desirable houses are with the Id:

1. **314**
2. **336**
3. **250**
4. **707**
5. **1299**
6. **452**
7. **770**

8. **524**
9. **54**
10. **385**

What is the ten least desirable houses?

The ten least desirable houses are with the Id:

1. **615**
2. **534**
3. **650**
4. **1450**
5. **435**
6. **1040**
7. **490**
8. **711**
9. **838**
10. **76**

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

The scoring function is based on the correaltion of the features with the target feature, i.e SalePrice. The features have been given weights based on their correlation value. The correlation values have been normlaized such that the summation of their weights will be 1.

The intuition behind the scoring function was that the more desirable houses will have higher cost. This is evident if we check the trend for different features, for example MSSubclass, 20 and 60 subclass give more desirability to the house.

Part 4 - Pairwise Distance Function

```
# TODO: code for distance function
from scipy.spatial import distance

df_train_P4=df_train_clean.copy()

cat_cols = df_train_P4.dtypes==object
cat_cols = df_train_P4.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_train_P4[cat_cols] = df_train_P4[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))
```

```
len_df_P4=len(df_train_P4.index)
SalePrice_dist = np.zeros(shape=(len_df_P4,len_df_P4))

for i in range(len_df_P4):
  for j in range (len_df_P4):
    dist = df_train_P4['SalePrice'].values[i]-df_train_P4['SalePrice'].values[j]
    SalePrice_dist[i][j]=abs(dist)
```

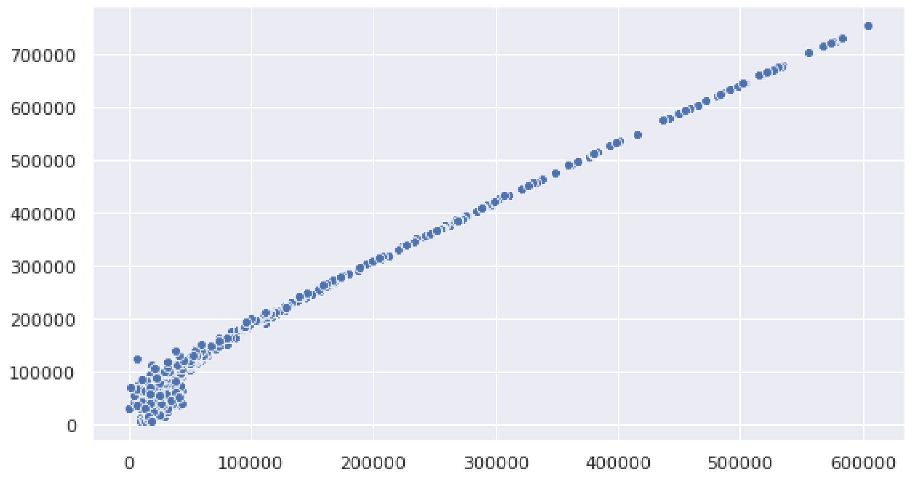
```
df_train_P4_dist = df_train_P4.drop("SalePrice", axis=1)
pdf = distance.cdist(df_train_P4_dist, df_train_P4_dist, lambda x, y: np.sqrt(sum((x-y)**3)))
```

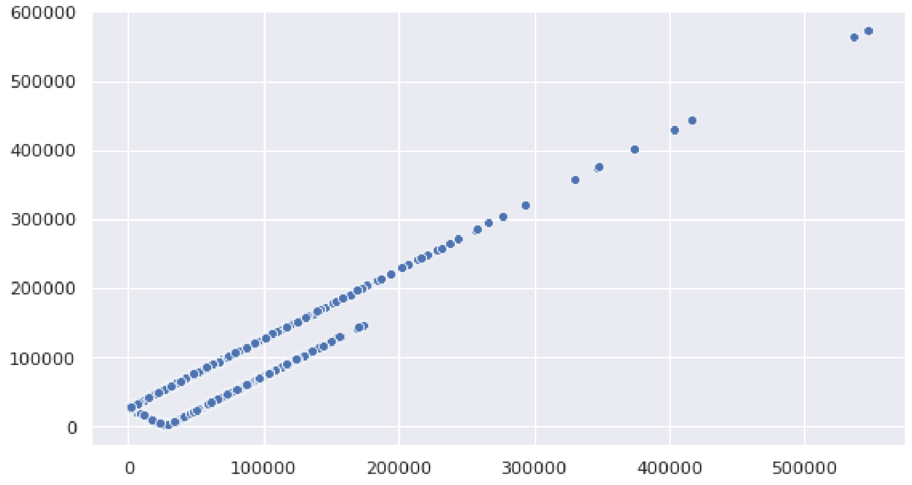
```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:10: RuntimeWarning: invalid value encountered in sqrt
  # Remove the CWD from sys.path while we load stuff.
```

```
fig, ax =plt.subplots(1,2,figsize=(20,5),sharex=False)

sns.scatterplot(x=pdf[0], y=pdf[1],ax=ax[0])
sns.scatterplot(x=SalePrice_dist[0], y=SalePrice_dist[1],ax=ax[1])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe5db0b8320>
```





```
del [[df_train_P4,df_train_P4_dist]]
```

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

'pdf' is pairwise distance function. The distance matrix 'pdf' is the square root of the cube of differences between tuples. The values returned by pds is very quite close to the difference of SalePrice for these tuples. The graph of pds is similar to the sale price difference matrix graph. Therefore, the distance function pdf works well.

Part 5 - Clustering

```
# TODO: code for clustering and visualization
from sklearn.cluster import KMeans
from sklearn.manifold import TSNE


df_train_P5=df_train_clean.copy()

cat_cols = df_train_P5.dtypes==object
cat_cols = df_train_P5.columns[cat_cols].tolist()
```

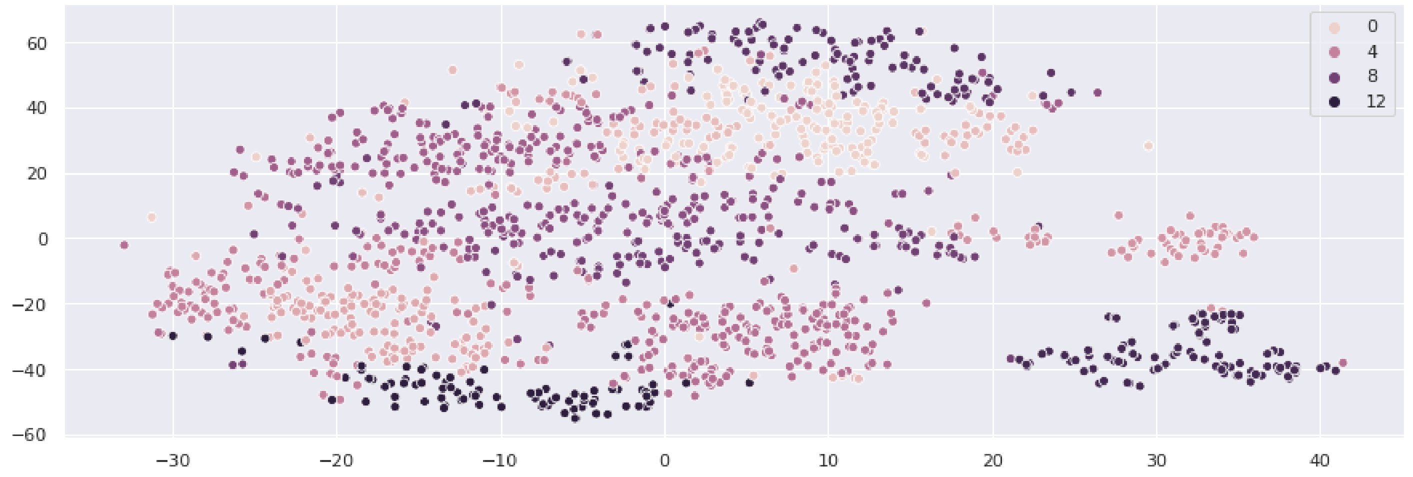
```
le = preprocessing.LabelEncoder()
df_train_P5[cat_cols] = df_train_P5[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))
```

```
df_train_P5_numpy = df_train_P5.values
min_max_scaler = preprocessing.MinMaxScaler()
df_train_P5_numpy_scaled = min_max_scaler.fit_transform(df_train_P5_numpy)
df_train_P5_numpy_scaled = pd.DataFrame(df_train_P5_numpy_scaled)

kmeans = KMeans(n_clusters=12)
kmeans.fit(df_train_P5_numpy_scaled)
y_kmeans = kmeans.predict(df_train_P5_numpy_scaled)
df_train_P5_embedded = TSNE(n_components=2).fit_transform(df_train_P5_numpy_scaled)
```

```
plt.figure(figsize=(15, 5))
sns.scatterplot(x=df_train_P5_embedded[:, 0], y=df_train_P5_embedded[:, 1], hue=y_kmeans)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe5d6455198>
```



```
del [[df_train_P5,df_train_P5_numpy_scaled,df_train_P5_embedded,df_train_P5_numpy]]
```

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

The above figure shows the clustering of the data values based on a distance metric. K means clustering algorithm clusters the data into K number of clusters. For this case, k is 12 as seen in the above figure. Distance metric used by the algorithm is euclidean distance. Data belonging to clusters are evidently seperated from other clusters.

Part 6 - Linear Regression

```
# TODO: code for linear regression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

df_train_P6=df_train_clean.copy()

cat_cols = df_train_P6.dtypes==object
cat_cols = df_train_P6.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_train_P6[cat_cols] = df_train_P6[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

train, test = train_test_split(df_train_P6,train_size=0.9)
Y_train = train['SalePrice']
Y_test = test['SalePrice']
```

```
X_train = train[['OverallQual']]
X_test = test[['OverallQual']]

model = LinearRegression().fit(X_train, Y_train)
Y_pred = model.predict(X_test)

score = model.score(X_train, Y_train)
print('Score:', score)
rms = np.sqrt(mean_squared_error(np.log(Y_test), np.log(Y_pred)))
print('RMSE:', rms)
```

```
Score: 0.6311497446095071
RMSE: 0.2734483899139265
```

```
X_train = train[['GrLivArea']]
X_test = test[['GrLivArea']]

model = LinearRegression().fit(X_train, Y_train)
Y_pred = model.predict(X_test)

score = model.score(X_train, Y_train)
print('Score:', score)
rms = np.sqrt(mean_squared_error(np.log(Y_test), np.log(Y_pred)))
print('RMSE:', rms)
```

```
Score: 0.5302720481602266
RMSE: 0.28914610273793423
```

```
X_train = train[['GarageArea']]
X_test = test[['GarageArea']]

model = LinearRegression().fit(X_train, Y_train)
Y_pred = model.predict(X_test)

score = model.score(X_train, Y_train)
print('Score:', score)
rms = np.sqrt(mean_squared_error(np.log(Y_test), np.log(Y_pred)))
print('RMSE:', rms)
```

```
Score: 0.3918833171674463
RMSE: 0.30724191331455497
```

```
X_train = train[['TotalBsmtSF']]
X_test = test[['TotalBsmtSF']]
```

```
model = LinearRegression().fit(X_train, Y_train)
Y_pred = model.predict(X_test)

score = model.score(X_train, Y_train)
print('Score:', score)
rms = np.sqrt(mean_squared_error(np.log(Y_test), np.log(Y_pred)))
print('RMSE:', rms)
```

```
Score: 0.415074487551893
RMSE: 0.3215171082696571
```

```
X_train=train[['MSSubClass',
 'MSZoning',
 'LotArea',
 'PoolArea',
 'GrLivArea',
 'BsmtFinSF1',
 'GarageArea',
 'TotalBsmtSF',
 'TotRmsAbvGrd',
 'OverallQual',
 'OverallCond',
 'YearBuilt',
 'YearRemodAdd',
 'GarageYrBlt']]

X_test=test[['MSSubClass',
 'MSZoning',
 'LotArea',
 'PoolArea',
 'GrLivArea',
 'BsmtFinSF1',
 'GarageArea',
 'TotalBsmtSF',
 'TotRmsAbvGrd',
 'OverallQual',
 'OverallCond',
 'YearBuilt',
 'YearRemodAdd',
 'GarageYrBlt']]
```

```
model = LinearRegression().fit(X_train, Y_train)
Y_pred = model.predict(X_test)

score = model.score(X_train, Y_train)
print('Score:', score)
rms = np.sqrt(mean_squared_error(np.log(Y_test), np.log(Y_pred)))
print('RMSE:', rms)
```

```
Score: 0.8279703865918338
RMSE: 0.19112994456471255
```

```
del [df_train_P6]
```

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

Top 4 features have been considered from Part 1.

By performing linear regression, we observed the following:

OverallQual:

Score: 0.6265082886069024

RMSE: 0.3007400199641814

GrLivArea:

Score: 0.49773266615921447

RMSE: 0.27367496499224914

GarageArea:

Score: 0.3888393328909978

RMSE: 0.3296042039134672

TotalBsmtSF:

Score: 0.3703938829550786

RMSE: 0.30523419334378066

Group of Features:

Apart from the indvidual features, the 14 features from Part 1 have been used and performed liner regression on, it resulted in:

Score: 0.7861095260374218

RMSE: 0.1788936967919409

From these features we can see that **Group of Features** is the best set of features with highest score and lowest Root Mean Squared Error compared to indvidual features.

Part 7 - External Dataset

```
# TODO: code to import external dataset and test
from lightgbm import LGBMRegressor

df_train_P7=df_train.copy()

df_external=pd.read_excel('externalDataSet.xls')

df_test=pd.read_csv('test.csv')
df_test_external=df_test.copy()

df_external.rename(columns={"Order": "Id"}, inplace = True)
df_train_P7 = pd.merge(df_external[['Id','PID']], df_train_P7, on='Id', how='right')
df_test_external = pd.merge(df_external[['Id','PID']], df_test_external, on='Id', how='right')


df_train_P7.columns = df_train_P7.columns.str.replace(' ', '')


df_external.drop(['Id'], axis=1, inplace=True)

Test_T_ID_external=df_test_external['Id']
```

```
df_test_external.drop(['Id','MiscFeature','PoolQC','Fence','Alley'], axis=1, inplace=True)
df_test_external[df_test_external.columns[df_test_external.dtypes=='object']]=df_test_external[df_test_external.columns[df_test_external.dtypes=='object']].fillna(df_test_external.mode().iloc[
df_test_external[df_test_external.columns[df_test_external.dtypes=='int64']]=df_test_external[df_test_external.columns[df_test_external.dtypes=='int64']].fillna(df_test_external.mean())
df_test_external[df_test_external.columns[df_test_external.dtypes=='float64']]=df_test_external[df_test_external.columns[df_test_external.dtypes=='float64']].fillna(df_test_external.mean())

df_train_P7.drop(['Id','MiscFeature','PoolQC','Fence','Alley'], axis=1, inplace=True)
df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='object']]=df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='object']].fillna(df_train_P7.mode().iloc[0])
df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='int64']]=df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='int64']].fillna(df_train_P7.mean())
df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='float64']]=df_train_P7[df_train_P7.columns[df_train_P7.dtypes=='float64']].fillna(df_train_P7.mean())
```

```
X = df_train_P7[[col for col in df_train_P7.columns if col != 'SalePrice']]
Y = df_train_P7['SalePrice']
```

```
cat_cols = X.dtypes==object
cat_cols = X.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
X[cat_cols] = X[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

cat_cols = df_test_external.dtypes==object
cat_cols = df_test_external.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_test_external[cat_cols] = df_test_external[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))
```

```
gbm=LGBMRegressor(objective='regression',learning_rate=0.05, n_estimators=300)
# train
gbm.fit(X,Y)

print('Accuracy of gbm regression on training set: {:.2f}'
     .format(gbm.score(X, Y)))
Y_pred_gbm=gbm.predict(df_test_external)

gbmResult = {'Id':Test_T_ID_external, 'SalePrice':Y_pred_gbm}
df_gbmResult = pd.DataFrame(gbmResult)
df_gbmResult.head()
df_gbmResult.shape

df_gbmResult.to_csv('submissionLgbm_external.csv',index=False)
```

Describe the dataset and whether this data helps with prediction.

The dataset is an extension of the Ames Housing dataset which was compiled by Dean De Cock. Refernce: http://jse.amstat.org/v19n3/decock.pdf

Source: http://www.amstat.org/publications/jse/v19n3/decock/AmesHousing.xls

This dataset has an extra column, 'PID' which is the Parcel Identification Number assigned to each property within the Ames Assessor's system.

The dataset was trained with the best model from Part 9. The external dataset does not improve the prediction, this can be seen by the drop in the Kaggle Score.

External dataset Kaggle Score: 0.13383

```
del [[df_external,df_gbmResult,df_test_external,df_train_P7]]
```

Part 8 - Permutation Test

```
# TODO: code for all permutation tests
from mlxtend.evaluate import permutation_test

df_train_P8=df_train_clean.copy()

cat_cols = df_train_P8.dtypes==object
cat_cols = df_train_P8.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_train_P8[cat_cols] = df_train_P8[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

X = df_train_P8[[col for col in df_train_P8.columns if col != 'SalePrice']]
Y = df_train_P8['SalePrice']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)

# Choose 10 variables few are good and few are bad
cols = [ 'GrLivArea','Utilities','MoSold','TotalBsmtSF', 'TotRmsAbvGrd','SaleCondition','MSSubClass','MSZoning', 'LotArea','PoolArea','OverallCond']

print("P-Test:\n")
for c in cols:
  regr = LinearRegression()
  regr.fit(np.reshape(X_train[c].values, (-1, 1)), np.reshape(Y_train.values, (-1, 1)))
  Y_pred = regr.predict(np.reshape(X_test[c].values, (-1, 1)))
  p_value = permutation_test(Y_pred.flatten(), Y_test, method='approximate', func=lambda x, y: mean_squared_error(x,y), seed=0)
  print(c, p_value)
```

```
P-Test:

GrLivArea 1.0
Utilities 0.558
MoSold 0.59
TotalBsmtSF 1.0
TotRmsAbvGrd 1.0
SaleCondition 0.963
MSSubClass 0.632
MSZoning 0.745
LotArea 0.924
PoolArea 0.55
OverallCond 0.633
```

```
del [df_train_P8]
```

For few of the features, the p_value is low which suggests that the actual output we received is right, whereas for some features, this is not the case. This shows that these features aren't relevant and the actual output we received wasn't right for these individual features.

Part 9 - Final Result

Preprocessing of data and library imports

```
from sklearn import preprocessing
from sklearn.svm import SVR
from sklearn.linear_model import Lasso
import xgboost as xgb
```

```
df_train_P9=df_train_clean.copy()
df_test=pd.read_csv('test.csv')
```

```
df_train_P9.drop(['Id'], axis=1, inplace=True)

Test_T_ID=df_test['Id']

df_test.drop(['Id','MiscFeature','PoolQC','Fence','Alley'], axis=1, inplace=True)
df_test[df_test.columns[df_test.dtypes=='object']]=df_test[df_test.columns[df_test.dtypes=='object']].fillna(df_test.mode().iloc[0])
df_test[df_test.columns[df_test.dtypes=='int64']]=df_test[df_test.columns[df_test.dtypes=='int64']].fillna(df_test.mean())
df_test[df_test.columns[df_test.dtypes=='float64']]=df_test[df_test.columns[df_test.dtypes=='float64']].fillna(df_test.mean())
```

```
X = df_train_P9[[col for col in df_train_P9.columns if col != 'SalePrice']]
Y = df_train_P9['SalePrice']
```

```
cat_cols = X.dtypes==object
cat_cols = X.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
X[cat_cols] = X[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

cat_cols = df_test.dtypes==object
cat_cols = df_test.columns[cat_cols].tolist()

le = preprocessing.LabelEncoder()
df_test[cat_cols] = df_test[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))
```

Linear Regression

Kaggle Score :0.17117

```
# linearRegressor = LinearRegression()
# linearRegressor.fit(X,Y)
# print('Accuracy of Linear regression on training set: {:.2f}'
#      .format(linearRegressor.score(X, Y)))
# Y_pred=linearRegressor.predict(df_test)

# linearRegressorResult = {'Id':Test_T_ID, 'SalePrice':Y_pred}
# df_linearRegressorResult = pd.DataFrame(linearRegressorResult)
# df_linearRegressorResult.head()
# df_linearRegressorResult.shape

# df_linearRegressorResult.to_csv('submissionlinearRegressor.csv',index=False)
```

Accuracy : 0.85

SVR

Kaggle Score: 0.41889

```
# SVR_regressor = SVR(kernel='rbf')
# SVR_regressor.fit(X,Y)

# print('Accuracy of SVR_regressor on training set: {:.2f}'
#      .format(SVR_regressor.score(X, Y)))
# Y_pred_svr=SVR_regressor.predict(df_test)

# SVR_regressorResult = {'Id':Test_T_ID, 'SalePrice':Y_pred_svr}
# df_SVR_regressorResult = pd.DataFrame(SVR_regressorResult)
# df_SVR_regressorResult.head()
# df_SVR_regressorResult.shape

# df_SVR_regressorResult.to_csv('submissionSVR_regressor.csv',index=False)
```

Accuracy: 0.05

Lasso

Kaggle Score: 0.17119

```
# lasso = Lasso()
# lasso.fit(X,Y)
# print('Accuracy of Lasso regression on training set: {:.2f}'
#      .format(lasso.score(X, Y)))
# Y_pred_lasso=lasso.predict(df_test)

# lassoResult = {'Id':Test_T_ID, 'SalePrice':Y_pred_lasso}
# df_lassoResult = pd.DataFrame(lassoResult)
# df_lassoResult.head()
# df_lassoResult.shape

# df_lassoResult.to_csv('submissionLasso.csv',index=False)
```

Accuracy : 0.85

XGBoost

Kaggle Score: 0.45206

```
# df_train_P9_xgb=df_train.copy()
# df_test=pd.read_csv('test.csv')

# df_train_P9_xgb.drop(['Id'], axis=1, inplace=True)


# Test_T_ID=df_test['Id']

# df_test.drop(['Id'], axis=1, inplace=True)

# X = df_train_P9_xgb[[col for col in df_train_P9_xgb.columns if col != 'SalePrice']]
# Y = df_train_P9_xgb['SalePrice']


# cat_cols = X.dtypes==object
# cat_cols = X.columns[cat_cols].tolist()
# le = preprocessing.LabelEncoder()
# X[cat_cols] = X[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))

# cat_cols = df_test.dtypes==object
# cat_cols = df_test.columns[cat_cols].tolist()

# le = preprocessing.LabelEncoder()
# df_test[cat_cols] = df_test[cat_cols].apply(lambda col: le.fit_transform(col.astype(str)))



# xg_reg = xgb.XGBRegressor(objective ='reg:linear', colsample_bytree = 0.3, learning_rate = 0.1,
#                 max_depth = 5, alpha = 10, n_estimators = 10)
# xg_reg.fit(X,Y)
# print('Accuracy of XGB regression on training set: {:.2f}'
#      .format(xg_reg.score(X, Y)))
# Y_pred_xg_reg=xg_reg.predict(df_test)

# xg_regResult = {'Id':Test_T_ID, 'SalePrice':Y_pred_xg_reg}
# df_xg_regResult = pd.DataFrame(xg_regResult)
# df_xg_regResult.head()
# df_xg_regResult.shape

# # df_xg_regResult.to_csv('submissionXGB.csv',index=False)
```

Accuracy: 0.08

LightGBM :

Kaggle Score: 0.13215

```
gbm=LGBMRegressor(objective='regression',learning_rate=0.05, n_estimators=300)
gbm.fit(X,Y)

print('Accuracy of gbm regression on training set: {:.2f}'
     .format(gbm.score(X, Y)))
Y_pred_gbm=gbm.predict(df_test)

gbmResult = {'Id':Test_T_ID, 'SalePrice':Y_pred_gbm}
df_gbmResult = pd.DataFrame(gbmResult)
df_gbmResult.head()
df_gbmResult.shape

df_gbmResult.to_csv('submissionLgbm.csv',index=False)
```

```
Accuracy of gbm regression on training set: 0.99
```

Accuracy : 0.99

```
del [[df_train_P9,df_gbmResult]]
```

Kaggle Information

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/arnnav

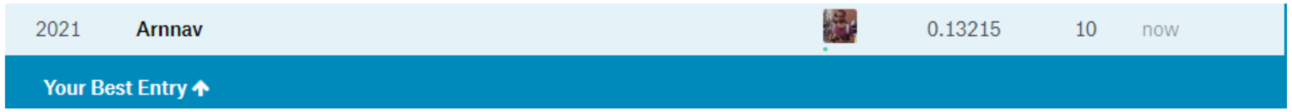
Highest Rank: 2021

Score: 0.13215

Number of entries: 10

INCLUDE IMAGE OF YOUR KAGGLE RANKING

```
from google.colab import files
from IPython.display import Image
Image('/content/drive/My Drive/DSF/Homework_3/HW3_Kaggle.png',width=800)
```



2021	**Arnnav**	0.13215	10	now