In [251]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
```

Data pre-processing

In [252]:

```
train_data = pd.read_csv('train_temp.csv')
test_data = pd.read_csv('test_temp.csv')
neighbour_arr = train_data['Neighborhood']
id_arr = train_data['Id']
saleprice_arr = train_data['SalePrice']
```

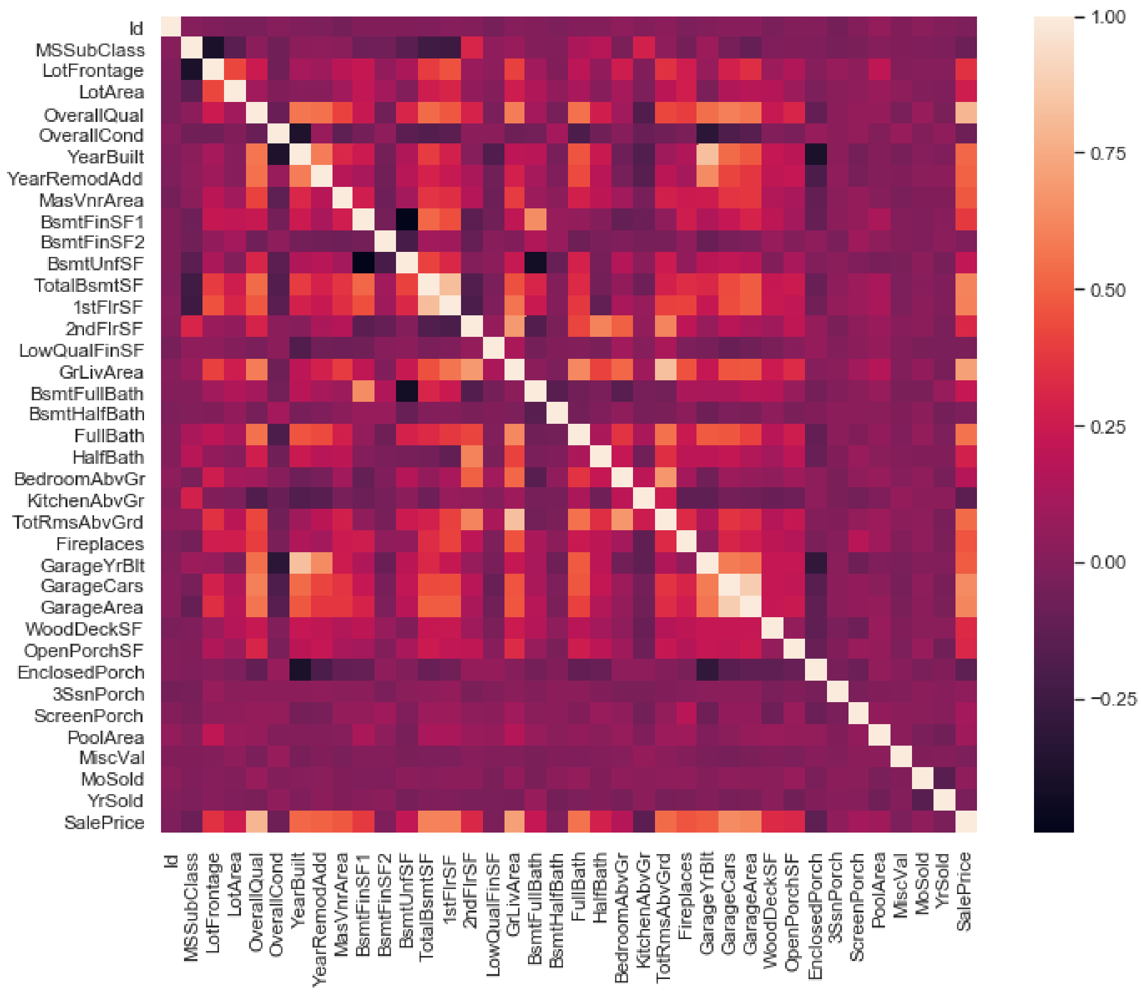
Homework 3 - Ames Housing Dataset

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.

Part 1 - Pairwise Correlations

In [253]:

```
#correlation matrix
import matplotlib.pyplot as plt
import seaborn as sns
corrmat = train_data.corr(method='pearson')
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, square=True);
```



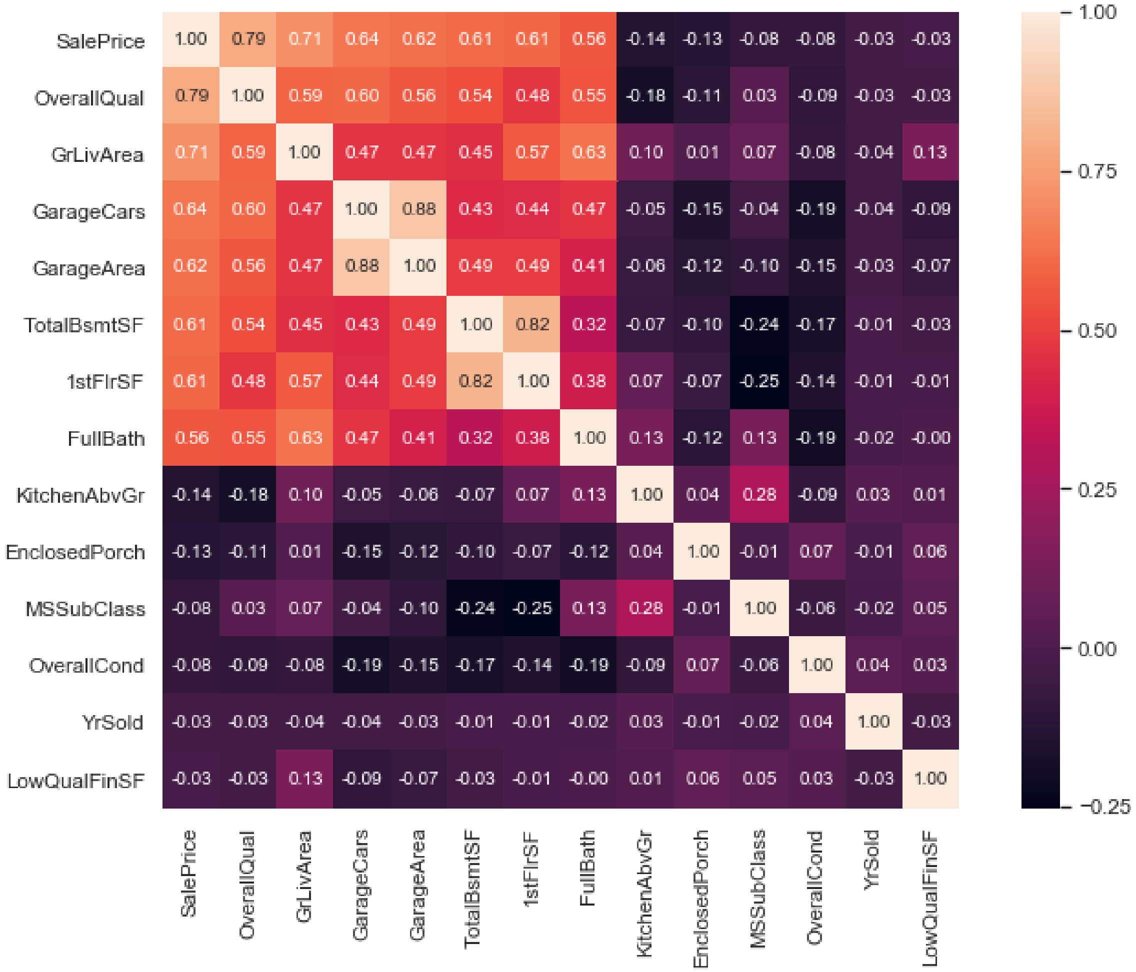
In [254]:

```
cols_large = corrmat.nlargest(8, 'SalePrice')['SalePrice']
cols_small = corrmat.nsmallest(6, 'SalePrice')['SalePrice']
cols = cols_large.index.append(cols_small.index)
```

We are trying to find correlation between SalePrice and features which perform well and badly with it.

In [255]:

```
cm = np.corrcoef(train_data[cols].values.T)
sns.set(font_scale=1.05)
f, ax = plt.subplots(figsize=(12, 8))
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':
10}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```



In [256]:

```
min_cm = np.min(cm)
```

In [257]:

```
min_cm
```

Out[257]:

```
-0.25175835187837947
```

From the heatmap, the least correlation is between 1stFlrSF and MSSubClass which is -0.25 and maximum correlation leaving 1 is 0.88 between GarageArea and GarageCars

Part 2 - Informative Plots

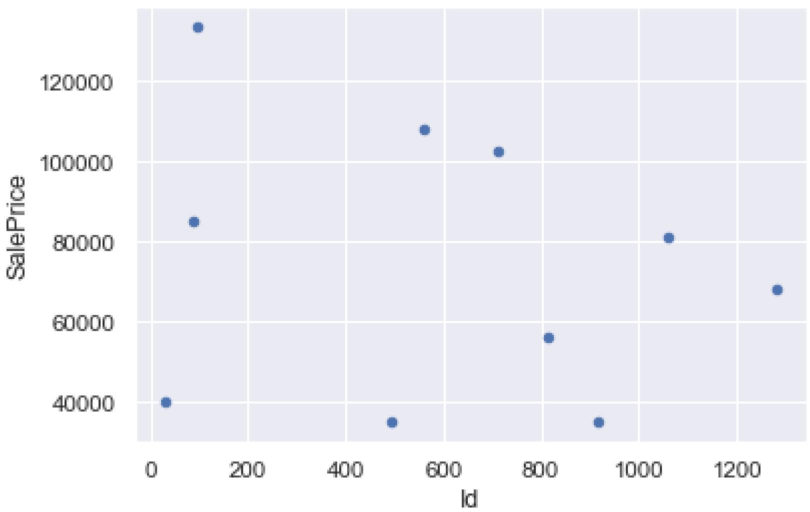
In [258]:

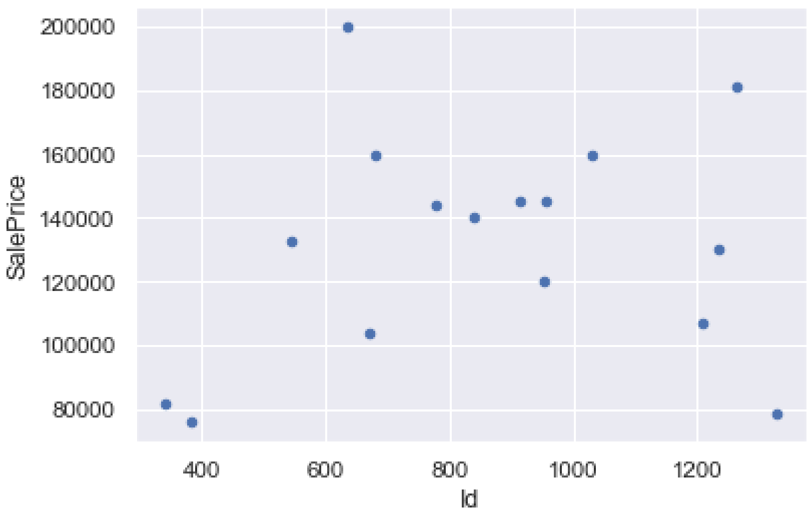
```
train_data_MsZoning_C = train_data[train_data['MSZoning']=='C (all)']
train_data_MsZoning_C.plot(x='Id', y='SalePrice', kind = 'scatter')
train_data_MsZoning_RH = train_data[train_data['MSZoning']=='RH']
train_data_MsZoning_RH.plot(x='Id', y='SalePrice', kind = 'scatter')
train_data_MsZoning_RM = train_data[train_data['MSZoning']=='RM']
train_data_MsZoning_RM.plot(x='Id', y='SalePrice', kind = 'scatter')
train_data_MsZoning_RL = train_data[train_data['MSZoning']=='RL']
train_data_MsZoning_RL.plot(x='Id', y='SalePrice', kind = 'scatter')
train_data_MsZoning_FV = train_data[train_data['MSZoning']=='FV']
train_data_MsZoning_FV.plot(x='Id', y='SalePrice', kind = 'scatter')
```

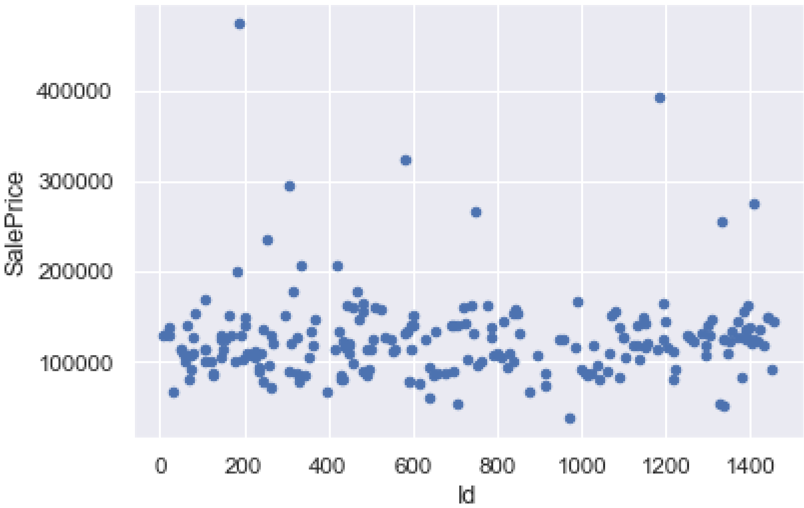
```
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
```

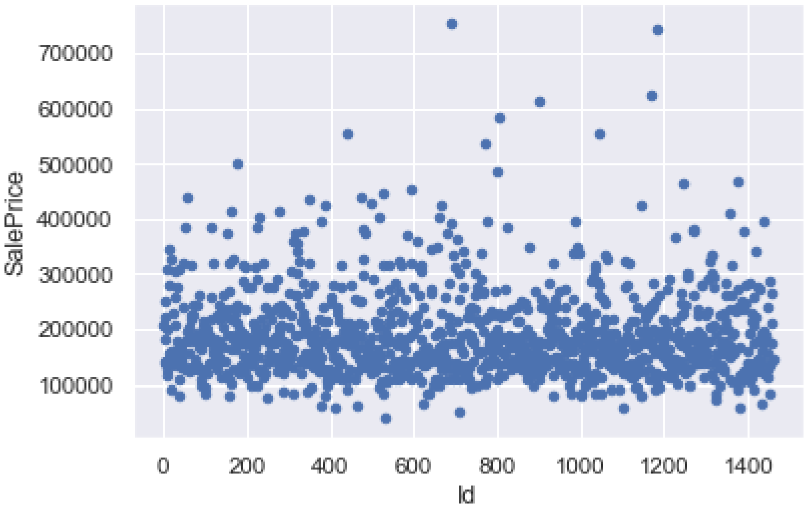
Out[258]:

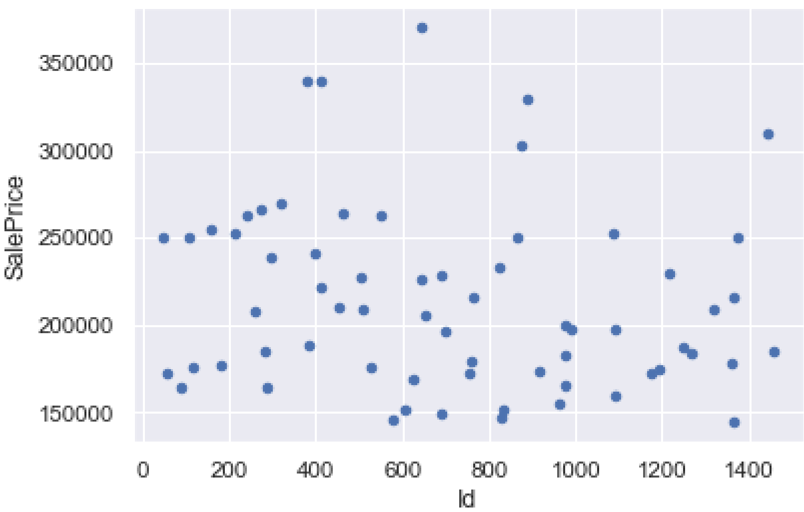
```
<matplotlib.axes._subplots.AxesSubplot at 0x215c0c87b38>
```






SalePrice
400000
300000
200000
100000
0
200
400
600
800
1000
1200
1400
Id


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
200
400
600
800
1000
1200
1400
Id


SalePrice
350000
300000
250000
200000
150000
0
200
400
600
800
1000
1200
1400
Id

The following are the notations for MSZoning given in the kaggle website:

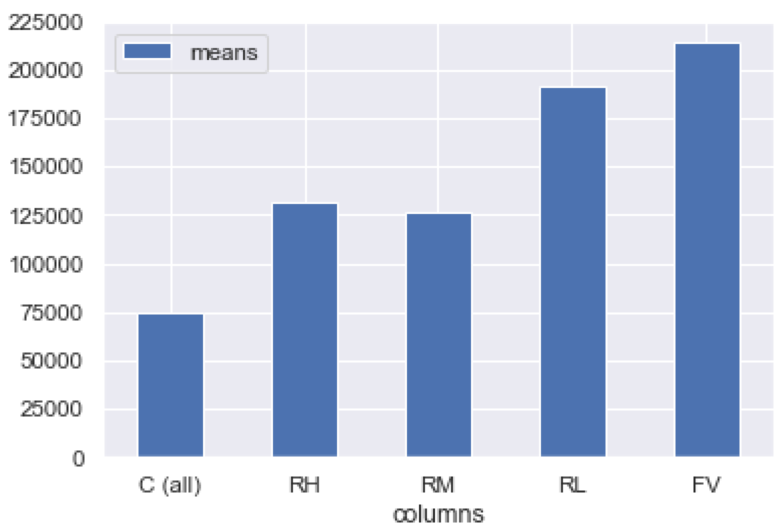
- A Agriculture - *missing*
- C Commercial
- FV Floating Village Residential
- I Industrial - *missing*
- RH Residential High Density
- RL Residential Low Density
- RP Residential Low Density Park - *missing*
- RM Residential Medium Density We only have 5 of the above. Of which, Commercial housing generally has high price, but isn't desirable. Residencies come next. High density needn't necessarily mean desirable but it could mean it's closer to a place where all facilities are available. On the other hand, low density needn't mean the area is costly and hence the density is lesser. It could also mean the location is not good. But, in general, High densities are desirable and low densitity housing is not. Finally comes floating villages. Let's check how the dataset varies.

In [259]:

```
mean_C = np.mean(train_data_MsZoning_C['SalePrice'])
mean_RH = np.mean(train_data_MsZoning_RH['SalePrice'])
mean_RM = np.mean(train_data_MsZoning_RM['SalePrice'])
mean_RL = np.mean(train_data_MsZoning_RL['SalePrice'])
mean_FV = np.mean(train_data_MsZoning_FV['SalePrice'])
d = {'columns':['C (all)','RH','RM','RL','FV'],'means':[mean_C,mean_RH,mean_RM,mean_RL,
mean_FV]}
df = pd.DataFrame(data=d)
df.plot.bar(x='columns', y='means', rot=0)
```

Out[259]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x215c0d046a0>
```



In [260]:

```
train_data['SalePrice'].groupby(train_data['Neighborhood']).mean()
```

Out[260]:

```
Neighborhood
Blmngtn    194870.882353
Blueste    137500.000000
BrDale     104493.750000
BrkSide    124834.051724
ClearCr    212565.428571
CollgCr    197965.773333
Crawfor    210624.725490
Edwards    128219.700000
Gilbert    192854.506329
IDOTRR     100123.783784
MeadowV     98576.470588
Mitchel    156270.122449
NAmes      145847.080000
NPkVill    142694.444444
NWAmes     189050.068493
NoRidge    335295.317073
NridgHt    316270.623377
OldTown    128225.300885
SWISU      142591.360000
Sawyer     136793.135135
SawyerW    186555.796610
Somerst    225379.837209
StoneBr    310499.000000
Timber     242247.447368
Veenker    238772.727273
Name: SalePrice, dtype: float64
```

In [261]:

```
c1_fv = train_data_MsZoning_FV[train_data_MsZoning_FV['SalePrice']>=mean_FV]
c2_fv = train_data_MsZoning_FV[train_data_MsZoning_FV['SalePrice']<mean_FV]
c3_fv = train_data_MsZoning_FV[train_data_MsZoning_FV['SalePrice']>=mean_RL]
c1 = train_data_MsZoning_RL[train_data_MsZoning_RL['SalePrice']>=mean_RL]
c2 = train_data_MsZoning_RL[train_data_MsZoning_RL['SalePrice']<mean_RL]
c3 = train_data_MsZoning_RL[train_data_MsZoning_RL['SalePrice']>=mean_RH]
```

In [262]:

```
(len(c1)/(len(c1)+len(c2)))*100
```

Out[262]:

```
37.35881841876629
```

In [263]:

```
(len(c3)/(len(c1)+len(c2)))*100
```

Out[263]:

```
80.36490008688098
```

In [264]:

```
(len(c3_fv)/(len(c1_fv)+len(c2_fv)))*100
```

Out[264]:

```
56.92307692307692
```

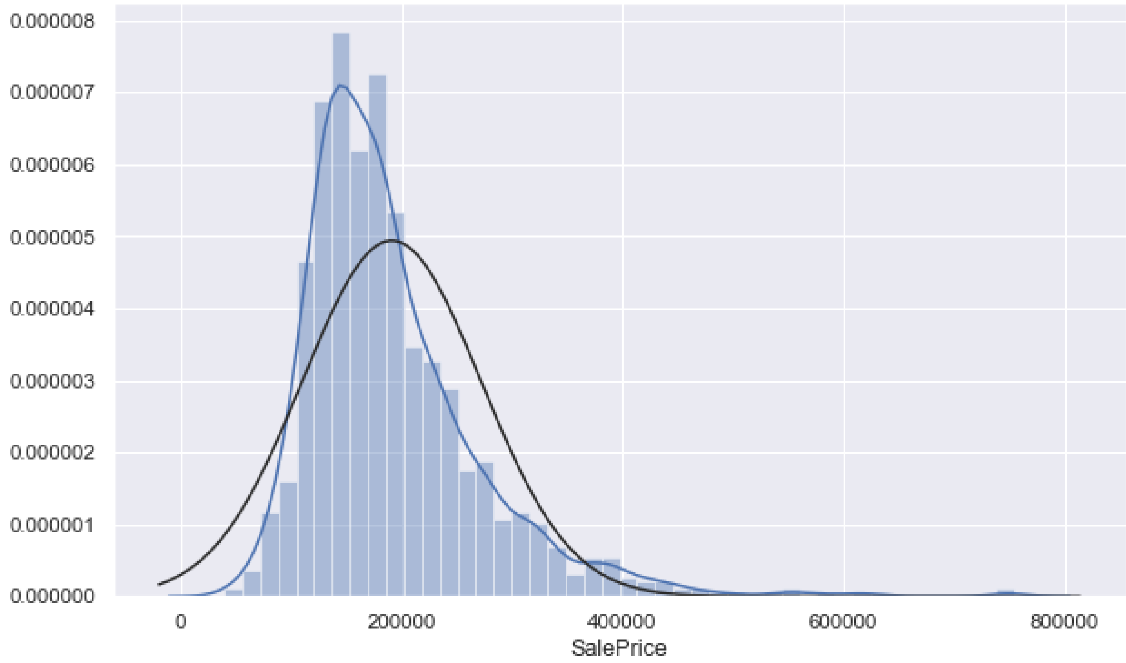
- There are too few points from plot above, however, average for commercial housing is around 74528
- For Residential High, the average is quite high which is 131558.375. This is greater than commercial types. Then, it might mean, commercial housing may not even have minimal facilities, making them much less desirable than expected, reducing the demand for them. Evenually making less costlier to live. Next one is Residential Medium.
- We have a large dataset of Residential medium density and the average is quite good. Much more than expected value and as expected, is less than Residential High density.
- Residential Low density have a surprisingly high price. With, 37% being greater than the mean value which is 191004.9 and 80% being greater than the High density mean. Our original expectation seems wrong and people seem preferable to stay in places of low densities with good features.
- Floating village as the name suggested, misled into estimating wrongly. 56% of the dataset lie above the mean of low densities and probably they're near lakeside and have a scenic view, and therefore are highly priced.

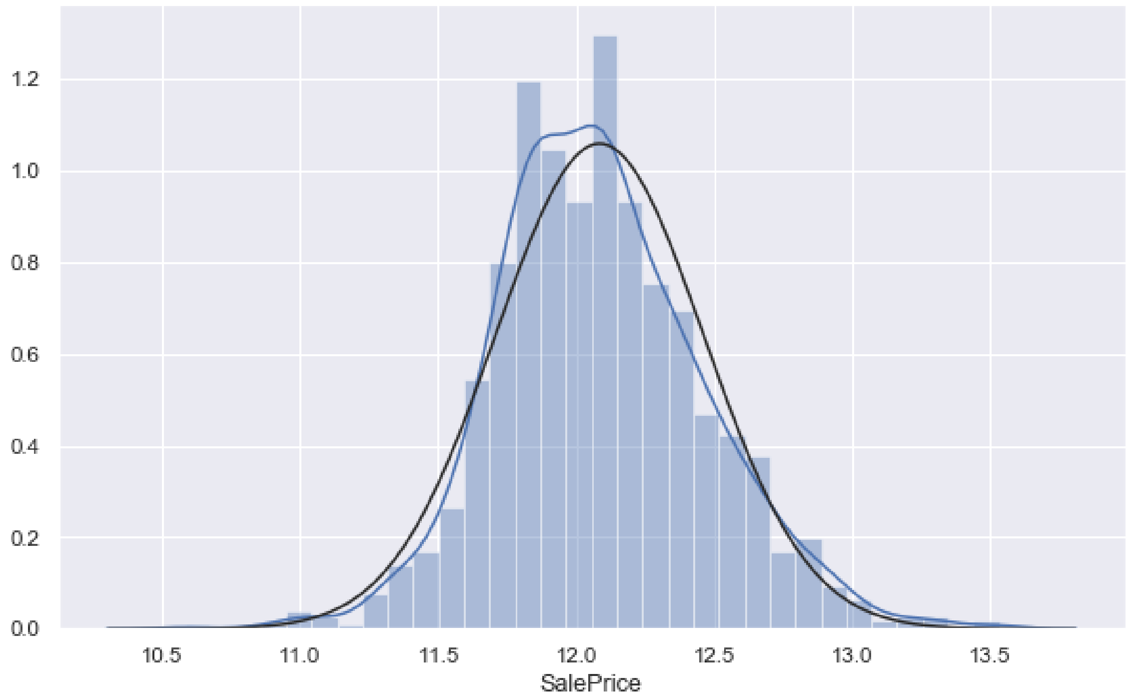
In [265]:

```
import seaborn as sns
from scipy.stats import norm
plt.figure(figsize=[10,6])
sns.distplot(train_data_MsZoning_RL.SalePrice, fit=norm)
plt.figure(figsize=[10,6])
sns.distplot(np.log(train_data_MsZoning_RL.SalePrice), fit=norm)
```

Out[265]:

<matplotlib.axes._subplots.AxesSubplot at 0x215c0db5438>





The Residency Low density plot didn't properly fit the normal distribution(right skewed) and therefore smoothing was required and applying logarithm yielded the right fit.

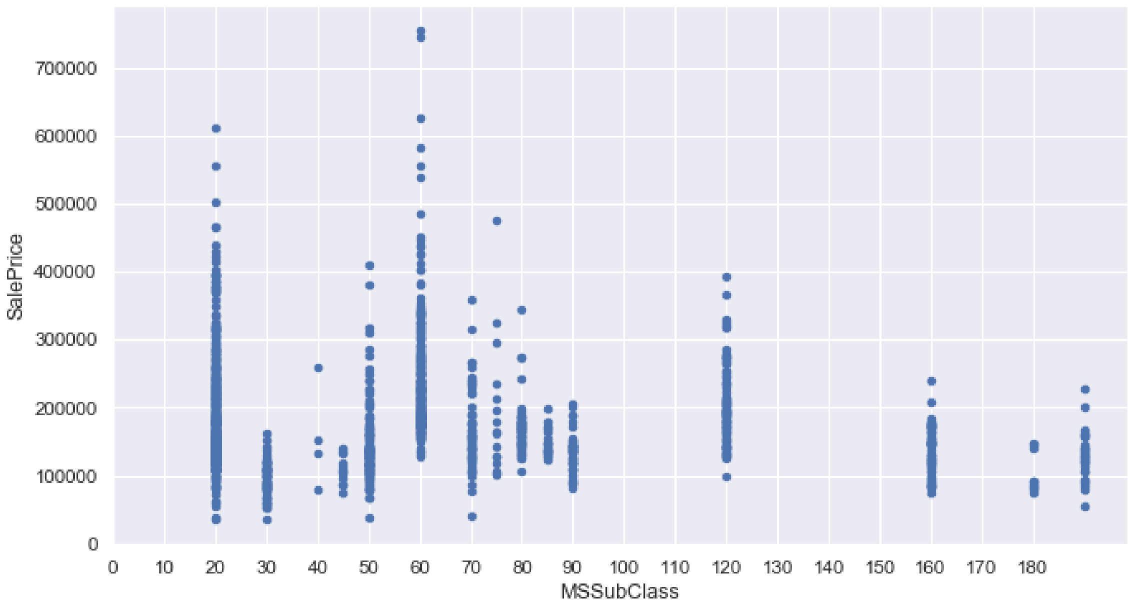
In [266]:

```
train_data.plot(x='MSSubClass', y='SalePrice', kind = 'scatter',xticks=range(0,190,10),
figsize=(11,6))
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which shoul
d be avoided as value-mapping will have precedence in case its length matc
hes with 'x' & 'y'.  Please use a 2-D array with a single row if you reall
y want to specify the same RGB or RGBA value for all points.
```

Out[266]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x215c0cfa550>
```



In [267]:

```
m_20 = np.mean(train_data[train_data['MSSubClass']==20]['SalePrice'])
m_60 = np.mean(train_data[train_data['MSSubClass']==60]['SalePrice'])
m_120 = np.mean(train_data[train_data['MSSubClass']==120]['SalePrice'])
```

In [268]:

```
m_20
```

Out[268]:

```
185224.81156716417
```

In [269]:

```
m_60
```

Out[269]:

```
239948.5016722408
```

In [270]:

```
m_120
```

Out[270]:

```
200779.0804597701
```

```
    20  1-STORY 1946 & NEWER ALL STYLES
    60  2-STORY 1946 & NEWER
    120  1-STORY PUD (Planned Unit Development) - 1946 & NEWER
```

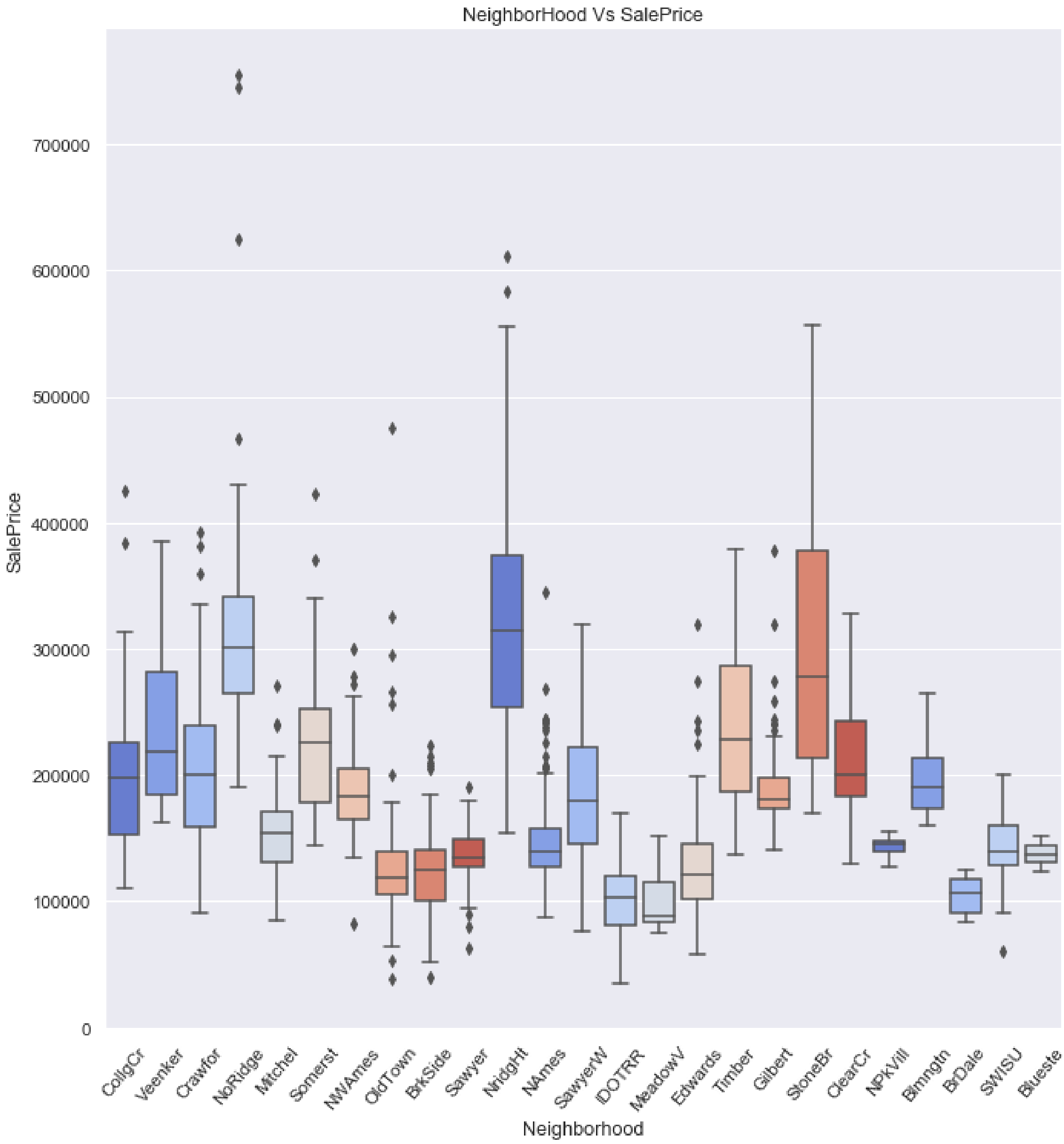
Selecting these 3, Subclass 60 seems to be doing the best followed by 120 and then 20.

In [271]:

```
sns.set_palette("cubehelix")
sns.catplot(x="Neighborhood", y="SalePrice",
            kind="box", dodge=False, data=train_data, height=10, palette=sns.color_pale
tte("coolwarm", 10))
plt.xticks(rotation=50);
plt.title('NeighborHood Vs SalePrice')
```

Out[271]:

```
Text(0.5, 1.0, 'NeighborHood Vs SalePrice')
```


NeighborHood Vs SalePrice
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
CollgCr
Veenker
Crawfor
NoRidge
Mitchel
Somerst
NWAmes
OldTown
BrkSide
Sawyer
NridgHt
NAmes
SawyerW
IDOTRR
MeadowV
Edwards
Timber
Gilbert
StoneBr
ClearCr
NPkVill
Blmngtn
BrDale
SWISU
Blueste
Neighborhood

As we can see, neighborhood plays a keyfactor in determining SalePrice. For few neighborhoods like NoRidge, NridgHT,StoneBr the averages are quite high while for others it is a lot lesser

In [272]:

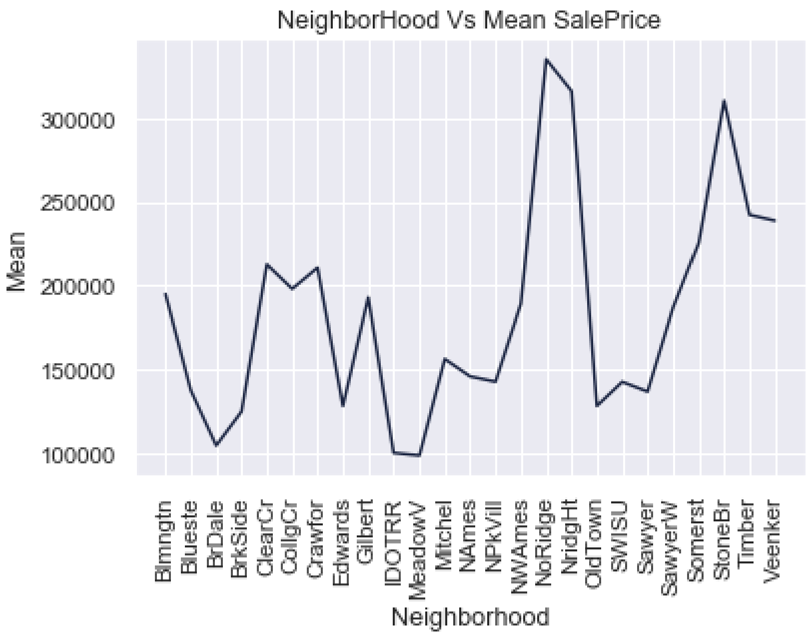
```
neighborhood = np.unique(train_data["Neighborhood"])
mean_arr=[]
for neigh in neighborhood:
    mean_arr.append(np.mean(train_data[train_data["Neighborhood"]==neigh]["SalePrice"
]))
df = pd.DataFrame({"Neighborhood":neighborhood,"Mean":mean_arr})
```

In [273]:

```
plt.plot(df["Neighborhood"], df["Mean"])
plt.xticks(rotation=90);
plt.xlabel('Neighborhood')
plt.ylabel('Mean')
plt.title('NeighborHood Vs Mean SalePrice')
```

Out[273]:

```
Text(0.5, 1.0, 'NeighborHood Vs Mean SalePrice')
```



The above plot shows the average values of various neighborhoods as a line chart. We can see NoRidge, DridgHt, StoneBr dominates the most and others follow.

Part 3 - Handcrafted Scoring Function

In [274]:

```
def scorefunc(input_data,params,weights,powers):
    if len(params)!=len(weights) or len(params)!=len(powers):
        return False
    output = 0
    for i in range(len(params)):
        output+= (input_data[params[i]]*weights[i])**powers[i]
    return output
```

In [275]:

```
import pandas as pd
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
train_data = pd.read_csv('train_temp.csv')
train_data = train_data.drop('Id',axis=1)
col_miss_val = [col for col in train_data.columns if train_data[col].isnull().any()]
for col in col_miss_val:
    if(train_data[col].dtype == np.dtype('O')):
         train_data[col]=train_data[col].fillna(train_data[col].value_counts().index[0
])    #replace nan with most frequent
    else:
        train_data[col] = train_data[col].fillna(train_data[col].median())
LE = LabelEncoder()
for col in train_data.select_dtypes(include=['object']):
    train_data[col] = LE.fit_transform(train_data[col])
score_params = ['GrLivArea', 'YearBuilt', 'GarageArea', 'OverallCond','PoolQC']
weights = [1/np.mean(train_data[score_params[0]]),1/np.mean(train_data[score_params[1
]]),
           1/np.mean(train_data[score_params[2]]),1/np.mean(train_data[score_params[3
]]),1]
powers = [2,1,1,1,1]
train_data['desirability'] = scorefunc(train_data,score_params,weights,powers)
```

In [276]:

```
train_data_sorted_desc = train_data.sort_values(by=['desirability'], ascending=False)
train_data_sorted_desc.head(10)
```

Out[276]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
1298	60	3	313.0	63887	1	0	2	0
523	60	3	130.0	40094	1	0	0	0
691	60	3	104.0	21535	1	0	0	3
1182	60	3	160.0	15623	1	0	0	3
185	75	4	90.0	22950	1	0	1	3
1268	50	3	69.0	14100	1	0	0	3
304	75	4	87.0	18386	1	0	3	3
1169	60	3	118.0	35760	1	0	0	3
769	60	3	47.0	53504	1	0	1	1
798	60	3	104.0	13518	1	0	3	3

10 rows × 81 columns

Having a greater ground living area, the year built, garage area, overall condition and pool have been considered highly desirable. These 10 are the most desirable based on these factors. And we can see their saleprice is quite good.

In [277]:

```
train_data_sorted = train_data.sort_values(by=['desirability'])
train_data_sorted.head(10)
```

Out[277]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
375	30	3	69.0	10020	1	0	0	2
533	20	3	50.0	5000	1	0	3	2
636	30	4	51.0	6120	1	0	3	3
620	30	3	45.0	8248	1	0	3	3
1337	30	4	153.0	4118	1	0	0	0
1325	30	4	40.0	3636	1	0	3	3
1143	20	3	69.0	9000	1	0	3	3
287	20	3	69.0	8125	1	0	0	3
250	30	3	55.0	5350	1	0	0	3
495	30	0	60.0	7879	1	0	3	3

10 rows × 81 columns

These 10 are the least desirable based on these factors. And we can see their saleprice is quite low.

In [278]:

```
train_data['desirability'].corr(train_data['SalePrice'])
```

Out[278]:

0.7350642709249529

The scoring function seems to work fine since it's in good correlation with the SalePrice(needn't be but it's a good indicator). With 0.74(rounded) correlation, the scoring function has done fine.

Part 4 - Pairwise Distance Function

In [279]:

```
#from sklearn.metrics import pairwise_distances
'''import pandas as pd
from sklearn import preprocessing
train_data = pd.read_csv('train_temp.csv')
train_data = train_data.drop('Id',axis=1)
col_miss_val = [col for col in train_data.columns if train_data[col].isnull().any()]
for col in col_miss_val:
    if(train_data[col].dtype == np.dtype('O')):
         train_data[col]=train_data[col].fillna(train_data[col].value_counts().index
[0])    #replace nan with most frequent
    else:
        train_data[col] = train_data[col].fillna(train_data[col].median())
LE = LabelEncoder()
for col in train_data.select_dtypes(include=['object']):
    train_data[col] = LE.fit_transform(train_data[col])

x = train_data.values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
train_data = pd.DataFrame(x_scaled,columns=train_data.columns)'''
#ds = pairwise_distances(train_data)
```

Out[279]:

```
"import pandas as pd\nfrom sklearn import preprocessing\ntrain_data = pd.r
ead_csv('train_temp.csv')\ntrain_data = train_data.drop('Id',axis=1)\ncol_
miss_val = [col for col in train_data.columns if train_data[col].isnull().
any()]\nfor col in col_miss_val:\n    if(train_data[col].dtype == np.dtype
('O')):\n         train_data[col]=train_data[col].fillna(train_data[col].v
alue_counts().index[0])    #replace nan with most frequent\n    else:\n
train_data[col] = train_data[col].fillna(train_data[col].median()) \nLE =
LabelEncoder()\nfor col in train_data.select_dtypes(include=['object']):\n
train_data[col] = LE.fit_transform(train_data[col])\n    \nx = train_data.
values #returns a numpy array\nmin_max_scaler = preprocessing.MinMaxScaler
()\nx_scaled = min_max_scaler.fit_transform(x)\ntrain_data = pd.DataFrame
(x_scaled,columns=train_data.columns)"
```

In [280]:

```
#from sklearn.metrics import pairwise_distances
import pandas as pd
from sklearn import preprocessing
train_data = pd.read_csv('train_temp.csv')
test_data = pd.read_csv('test_temp.csv')
train_id_arr = train_data['Id']
test_id_arr = test_data['Id']
train_data_copy = train_data
test_data_copy = test_data
train_data_copy = train_data_copy.drop("Id", axis = 1)
test_data_copy = test_data_copy.drop("Id", axis = 1)

keys_to_fill_na = [ "FireplaceQu","PoolQC","Alley", "BsmtQual", "BsmtCond", "BsmtExposu
re", "BsmtFinType1",
                    "BsmtFinType2", "GarageType", "GarageFinish", "GarageQual",
                    "GarageCond", "Fence"]
for key in keys_to_fill_na:
    train_data_copy[key].fillna("NA", inplace=True)
    test_data_copy[key].fillna("NA", inplace=True)
keys_to_fill_none = [ "MiscFeature","MasVnrType"]
for key in keys_to_fill_none:
    train_data_copy[key].fillna("None", inplace=True)
    test_data_copy[key].fillna("None", inplace=True)

#Enumerate Subclass and sold column data as below
dict1 = {20 : "Sub20", 30 : "Sub30", 40 : "Sub40", 45 : "Sub45",50 : "Sub50", 60 : "Sub
60", 70 : "Sub70", 75 : "Sub75",
         80 : "Sub80", 85 : "Sub85", 90 : "Sub90", 120 : "Sub120", 150 : "Sub150", 160
: "Sub160", 180 : "Sub180",
         190 : "Sub190"}
dict2 = {1 : "Jan", 2 : "Feb", 3 : "Mar", 4 : "Apr", 5 : "May", 6 : "Jun", 7 : "Jul", 8
: "Aug", 9 : "Sep", 10 : "Oct",
         11 : "Nov", 12 : "Dec"}
train_data_copy = train_data_copy.replace({"MSSubClass" : dict1,"MoSold" : dict2})
test_data_copy = test_data_copy.replace({"MSSubClass" : dict1,"MoSold" : dict2})

col_missing = []
for col in train_data_copy.columns:
    if len(np.unique(train_data_copy[col].isnull()))>1:
        col_missing.append(col)
for missing_col in col_missing:
    if train_data_copy[missing_col].dtype=='float64':
        train_data_copy[missing_col] = np.nanmedian(train_data_copy[missing_col])
    if train_data_copy[missing_col].dtype=='int64':
        train_data_copy[missing_col] = np.nanmedian(train_data_copy[missing_col])

col_missing_test = []
for col in test_data_copy.columns:
    if len(np.unique(test_data_copy[col].isnull()))>1:
        col_missing_test.append(col)
for missing_col in col_missing_test:
    if test_data_copy[missing_col].dtype=='float64':
        test_data_copy[missing_col] = np.nanmedian(test_data_copy[missing_col])
    if test_data_copy[missing_col].dtype=='int64':
        test_data_copy[missing_col] = np.nanmedian(test_data_copy[missing_col])

train_data_copy.drop("LotFrontage", axis=1, inplace=True)
test_data_copy.drop("LotFrontage", axis=1, inplace=True)
```

```
keys_to_fill_mode = ['Electrical', 'Exterior1st', 'Exterior2nd', 'Functional','KitchenQ
ual','MSZoning','SaleType','Utilities']
for key in keys_to_fill_mode:
    train_data_copy[key]=train_data_copy[key].fillna(train_data_copy[key].mode()[0])
#replace nan with most frequent
    test_data_copy[key]=test_data_copy[key].fillna(test_data_copy[key].mode()[0])    #r
eplace nan with most frequent

#Add new features to train and test data based on quality of the house and number of ba
throoms
train_data_copy["TotalSF"] = train_data_copy["GrLivArea"] + train_data_copy["TotalBsmtS
F"]
test_data_copy["TotalSF"] = test_data_copy["GrLivArea"] + test_data_copy["TotalBsmtSF"]

train_data_copy["TotalFlrSF"] = train_data_copy["1stFlrSF"] + train_data_copy["2ndFlrS
F"]
test_data_copy["TotalFlrSF"] = test_data_copy["1stFlrSF"] + test_data_copy["2ndFlrSF"]

train_data_copy["TotalBath"] = train_data_copy["BsmtFullBath"] + ((1/2)*train_data_copy
["BsmtHalfBath"])+ train_data_copy["FullBath"] + ((1/2) * train_data_copy["HalfBath"])
test_data_copy["TotalBath"] = test_data_copy["BsmtFullBath"] + ((1/2)*test_data_copy["B
smtHalfBath"]) + test_data_copy["FullBath"] + ((1/2) * test_data_copy["HalfBath"])
#multiplied by 1/2 because it's mentioned half

train_data_copy["TotalPorchSF"] = train_data_copy["OpenPorchSF"] + train_data_copy["Enc
losedPorch"] + train_data_copy["3SsnPorch"] + train_data_copy["ScreenPorch"]
test_data_copy["TotalPorchSF"] = test_data_copy["OpenPorchSF"] + test_data_copy["Enclos
edPorch"] + test_data_copy["3SsnPorch"] + test_data_copy["ScreenPorch"]

cat_train = train_data_copy.select_dtypes(include=[np.object])
cat_test = test_data_copy.select_dtypes(include=[np.object])
cat_train_test = pd.concat([cat_train,cat_test])
cat_onehot = pd.get_dummies(cat_train_test, columns=cat_train_test.columns)
cat_train_encod = cat_onehot[:cat_train.shape[0]]
cat_test_encod = cat_onehot[cat_train.shape[0]:]
train_filtered = pd.concat([train_data_copy, cat_train_encod],axis=1)
test_filtered = pd.concat([test_data_copy, cat_test_encod],axis=1)

#y_train = np.log(train_filtered['SalePrice'])
#train_filtered.drop(['SalePrice'], axis = 1, inplace=True)
train_filtered = train_filtered.select_dtypes(exclude=['object'])
test_filtered = test_filtered.select_dtypes(exclude=['object'])

x = train_filtered.values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
train_filtered = pd.DataFrame(x_scaled,columns=train_filtered.columns)
```

In [281]:

```
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
pca = PCA(n_components=50)
principalComponents = pca.fit_transform(train_filtered)
principalDf = pd.DataFrame(data = principalComponents)
X_embedded = TSNE(n_components=2).fit_transform(principalDf)
X_embedded.shape
```

Out[281]:

```
(1460, 2)
```

In [282]:

```
def pairwise_man(x,y): #Manhatan metric
    if len(x) != len(y):
        return False
    else:
        return sum([abs(a-b) for a,b in zip(x,y)])
```

In [283]:

```
def pairwise_euc(x,y): #Eucledian metric
    if len(x) != len(y):
        return False
    else:
        return np.sqrt(sum([(a-b)**2 for a,b in zip(x,y)]))
```

In [284]:

```
distance = []
for i in range(len(X_embedded)):
    dist = []
    for j in range(len(X_embedded)):
        dist.append(pairwise_euc(X_embedded[i], X_embedded[j]))
    distance.append(dist)
```

In [285]:

```
distance_man = []
for i in range(len(X_embedded)):
    dist = []
    for j in range(len(X_embedded)):
        dist.append(pairwise_man(X_embedded[i], X_embedded[j]))
    distance_man.append(dist)
```

In [286]:

```
n_true = 0
n_false = 0
for i in range(len(distance)):
    unsorted_arr = distance[i]
    sorted_arr = np.sort(distance[i])
    ii = np.where(unsorted_arr == sorted_arr[1])[0]#ignoring 0
    if neighbour_arr[ii[0]]==neighbour_arr[i]:
        n_true=n_true+1
    else:
        n_false=n_false+1
```

In [287]:

```
(n_true/(n_true+n_false))*100
```

Out[287]:

```
50.890410958904106
```

1. Implemented one hot encoding and did some feature engineering before applying pairwise distances.
2. Normalized the data using min-max scaler and then reduced 300+ dimensions to 50 using PCA.
3. Finally used tsne and reduced the dimensions to 2.
4. Then applied the handcrafted euclidean distance function and obtained the distance vector using O(n^2).
5. Finally we check if the nearest distance point contain the same neighbourhood. If it contains, we increment the true and if it doesn't we increment false.
6. We obtain the above by sorting distance array and taking the one with least pair-wise distance. Then we get the index of the element from the original dataset and check if we have the same neighborhood from the neighborhood array
7. Obtained approximately 51% times neighbourhood matching the nearest.

Part 5 - Clustering

In [288]:

```
import sys
import numpy
numpy.set_printoptions(threshold=sys.maxsize)
```

In [289]:

```
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(affinity='precomputed', compute_full_tree='auto',
                        connectivity=None,
                        linkage='single', memory=None, n_clusters=10,
                        pooling_func='deprecated').fit(distance)
```

In [290]:

```
labels = clustering.labels_
x_embeddf = pd.DataFrame(X_embedded)
```

In [291]:

```
to_plot = pd.DataFrame()
to_plot['Id'] = train_data['Id']
to_plot['x_coord'] = x_embeddf[0]
to_plot['y_coord'] = x_embeddf[1]
to_plot['clusters'] = clustering.labels_
```

In [292]:

```
import seaborn as sns
plt.figure(figsize=[14,8])
ax = sns.scatterplot(x="x_coord", y="y_coord",hue="clusters",legend="full",palette=sns.
color_palette("hls", 10),data=to_plot);
```

In [293]:

```
import numpy as np
import operator
df_main = pd.DataFrame()
for i in range(0,10):
    neigh = neighbour_arr[labels==i]
    unique, counts = np.unique(neigh, return_counts=True)
    d = dict(zip(unique, counts))
    sorted_d = sorted(d.items(), key=operator.itemgetter(1),reverse=True)
    percent = (sorted_d[0][1]/sum(d.values()))*100
    neighbor = sorted_d[0][0]
    count = sorted_d[0][1]
    df = pd.DataFrame({'centre': i,'Neighborhood': neighbor,'count':count,'percent':per
cent}, index = [i])
    print(df)
```

```
   centre Neighborhood  count    percent
0       0      Edwards     10  27.777778
   centre Neighborhood  count    percent
1       1      Mitchel      1  33.333333
   centre Neighborhood  count    percent
2       2        NAmes    209  15.714286
   centre Neighborhood  count  percent
3       3      Edwards      4    100.0
   centre Neighborhood  count    percent
4       4      SawyerW      2  33.333333
   centre Neighborhood  count  percent
5       5      OldTown      1    100.0
   centre Neighborhood  count    percent
6       6      Edwards     19  25.675676
   centre Neighborhood  count  percent
7       7      BrkSide      1    100.0
   centre Neighborhood  count  percent
8       8      Crawfor      3    100.0
   centre Neighborhood  count  percent
9       9      Mitchel      2    100.0
```

In [294]:

```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=10, random_state=0).fit(X_embedded)
kmeans_to_plot = pd.DataFrame()
kmeans_to_plot['Id'] = train_data['Id']
kmeans_to_plot['x_coord'] = x_embeddf[0]
kmeans_to_plot['y_coord'] = x_embeddf[1]
kmeans_to_plot['clusters'] = kmeans.labels_
```

In [295]:

```
import seaborn as sns
plt.figure(figsize=[14,8])
ax = sns.scatterplot(x="x_coord", y="y_coord",hue="clusters",legend="full",palette=sns.
color_palette("hls", 10)
                     ,data=kmeans_to_plot);
```

In [296]:

```
import operator
import numpy as np
df_main = pd.DataFrame()
for i in range(0,10):
    neigh = neighbour_arr[kmeans.labels_==i]
    unique, counts = np.unique(neigh, return_counts=True)
    d = dict(zip(unique, counts))
    if(len(d)>0):
        sorted_d = sorted(d.items(), key=operator.itemgetter(1),reverse=True)
        percent = (sorted_d[0][1]/sum(d.values()))*100
        neighbor = sorted_d[0][0]
        count = sorted_d[0][1]
        df = pd.DataFrame({'centre': i,'Neighborhood': neighbor,'count':count,'percent'
:percent}, index = [i])
        print(df)
```

```
   centre Neighborhood  count    percent
0       0      Gilbert     41  27.702703
   centre Neighborhood  count    percent
1       1        NAmes    107  59.776536
   centre Neighborhood  count    percent
2       2      CollgCr     48  35.294118
   centre Neighborhood  count    percent
3       3      Edwards     24  17.142857
   centre Neighborhood  count    percent
4       4      Somerst     48  33.333333
   centre Neighborhood  count    percent
5       5      Edwards     29  26.126126
   centre Neighborhood  count    percent
6       6        NAmes     47  30.322581
   centre Neighborhood  count    percent
7       7       NWAmes     35  23.026316
   centre Neighborhood  count    percent
8       8      OldTown     74  56.060606
   centre Neighborhood  count    percent
9       9      NridgHt     50  30.674847
```

We applied two algorithms here, Agglomerative and kmeans.

1. Agglomerative takes distance matrix(handwritten output of euclidean given here) as input and gives out the cluster labels, from which we determine the cluster it belongs too. As we can see from graphs above, agglomerative does non-uniform clustering with centre 1 occupying the majority of data, which contained 'NAmes'. However, the clusters have a clear separation of the neighborhoods in this form of clustering
2. Kmeans takes input as X_embedded, which is the output of tsne and clusters using euclidean by default and performs clustering. Contrasting to previous case, kmeans does smaller clusters and one can see 'NAmes' appears majority in 2 neighborhoods. Kmeans makes sure every cluster is uniformly distributed and therefore the results appear as such.

Part 6 - Linear Regression

In [297]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn import linear_model
from sklearn import metrics
train_data = pd.read_csv('train_temp.csv')
x = train_data
y = train_data['SalePrice']
col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most 
frequent
    else:
        x[col] = train_data[col].fillna(x[col].median())
LE = LabelEncoder()
for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
lm = linear_model.LinearRegression()
x = x.drop(['Id','SalePrice'],axis=1)
model = lm.fit(x,y)
y_fit = model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_fit))
RMSE
```

Out[297]:

```
30022.875211221748
```

In [298]:

```
y_ = np.log(y)
model = lm.fit(x,y_)
y_fit = model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y_, y_fit))
RMSE
```

Out[298]:

```
0.13357330661378403
```

In [299]:

```
import operator
coeffs = model.coef_
index_max, value_max = max(enumerate(coeffs), key=operator.itemgetter(1))
index_min, value_min = min(enumerate(coeffs), key=operator.itemgetter(1))
```

In [300]:

```
value_min
```

Out[300]:

```
-0.22144831525522518
```

In [301]:

```
x.columns[index_min]
```

Out[301]:

```
'PoolQC'
```

In [302]:

```
value_max
```

Out[302]:

```
0.1877445046910877
```

In [303]:

```
x.columns[index_max]
```

Out[303]:

```
'Street'
```

1. Applying all the dataset on the model yields an RMSE of 30000, which is quite huge.
2. Now, if we apply on log plot, we get 0.1335. By applying inverse log we can convert to the required format.
3. The one with the maximum absolute weight contributes greatly towards the linear regression model. As we can see, PoolQC has a negative coefficient of value 0.22 and it is the most important one. And in positive coefficients, Street has the maximum.

Part 7 - External Dataset

In [304]:

```
import pandas as pd
train_data = pd.read_csv('train_temp.csv')
test_data = pd.read_csv('test_temp.csv')
x = train_data
add_data = {}
national_burglary_rate = 430.4
national_assault_rate= 248.9
national_robbery_rate = 98
national_rape_rate = 41.7
national_murder_rate = 5.3
national_car_theft_rate = 237.4
#https://en.wikipedia.org/wiki/Crime_in_the_United_States - national average rates

#Searched all the cities from here and added here
#In case of missing data, we substituted with Ames city average
#https://www.addressreport.com/report/neighborhood/ames-ia/somerset-ames-ia/?display=tr
ue


#first five are household_income,renters,sales_tax,property_tax and remaining are under
stood

ames_average = [46358,0.56,0.07,2479,
                (1-0.30)*national_burglary_rate,(1-0.66)*national_assault_rate,
                (1-0.94)*national_robbery_rate,(1-0.0)*national_rape_rate,
                (1-0.81)*national_murder_rate,(1-0.67)*national_car_theft_rate]

add_data['Blmngtn'] = [95256,0.16,0.07,3742,
                      (1-0.05)*national_burglary_rate,(1-0.70)*national_assault_rate,
                      (1-0.98)*national_robbery_rate,(1-0.54)*national_rape_rate,
                      (1-0.79)*national_murder_rate,(1-0.77)*national_car_theft_rate]

add_data['Blueste'] = ames_average #missing data

add_data['BrDale'] = [45558,0.60,0.07,1785,
                      (1-0.14)*national_burglary_rate,(1-0.58)*national_assault_rate,
                      (1-0.94)*national_robbery_rate,(1-0.26)*national_rape_rate,
                      (1-0.89)*national_murder_rate,(1-0.70)*national_car_theft_rate]

add_data['BrkSide'] = ames_average #missing data

add_data['ClearCr'] = ames_average #missing data

add_data['CollgCr'] = [66875,0.45,0.07,2616,
            (1-0.26)*national_burglary_rate,(1-0.64)*national_assault_rate,
            (1-0.93)*national_robbery_rate,(1+0.11)*national_rape_rate,
            (1-0.92)*national_murder_rate,(1-0.54)*national_car_theft_rate]

add_data['Crawfor'] = ames_average #missing data

add_data['Edwards'] = ames_average #missing data

add_data['Gilbert'] = ames_average #missing data

add_data['IDOTRR'] = ames_average #missing data

add_data['MeadowV'] = [53962,0.49,0.07,1521,
            (1-0.52)*national_burglary_rate,(1-0.77)*national_assault_rate,
            (1-0.92)*national_robbery_rate,(1+0.22)*national_rape_rate,
```

```
            (1-0.78)*national_murder_rate,(1-0.46)*national_car_theft_rate]

add_data['Mitchel'] = ames_average #missing data

add_data['NAmes'] = ames_average #missing data

add_data['NoRidge'] = ames_average #missing data

add_data['NPkVill'] = ames_average #missing data

add_data['NridgHt'] = [95256,0.16,0.07,5478,
            (1-0.05)*national_burglary_rate,(1-0.70)*national_assault_rate,
            (1-0.98)*national_robbery_rate,(1-0.54)*national_rape_rate,
            (1-0.79)*national_murder_rate,(1-0.77)*national_car_theft_rate]

add_data['NWAmes'] = ames_average #missing data

add_data['OldTown'] = ames_average #missing data

add_data['SWISU'] = ames_average #missing data

add_data['Sawyer'] = ames_average #missing data

add_data['SawyerW'] = ames_average #missing data

add_data['Somerst'] = [84600,0.38,0.07,2314,
            (1+0.09)*national_burglary_rate,(1-0.60)*national_assault_rate,
            (1-0.97)*national_robbery_rate,(1-0.39)*national_rape_rate,
            (1-0.78)*national_murder_rate,(1-0.69)*national_car_theft_rate]

add_data['StoneBr'] = [95256,0.16,0.07,4369,
            (1-0.05)*national_burglary_rate,(1-0.70)*national_assault_rate,
            (1-0.98)*national_robbery_rate,(1-0.54)*national_rape_rate,
            (1-0.79)*national_murder_rate,(1-0.77)*national_car_theft_rate]

add_data['Timber'] = ames_average #missing data

add_data['Veenker'] = ames_average #missing data


x = train_data
x['household_income'] = 0
x['renters'] = 0
x['sales_tax'] = 0
x['property_tax'] = 0
x['burglary_rate'] = 0
x['assault_rate'] = 0
x['robbery_rate'] = 0
x['rape_rate'] = 0
x['murder_rate'] = 0
x['car_theft_rate'] = 0

keyset = ['household_income','renters','sales_tax','property_tax','burglary_rate','assa
ult_rate','robbery_rate',
        'rape_rate','murder_rate','car_theft_rate']

#for key in add_data:
#    for i in range(len(keyset)):
#        print(add_data[key][i])
#        x[x['Neighborhood']==key][keyset[i]] = add_data[key][i]
```

```
household_arr = []
renters_arr = []
sales_tax_arr = []
property_tax_arr=[]
burglary_rate_arr=[]
assault_rate_arr=[]
robbery_rate_arr=[]
rape_rate_arr=[]
murder_rate_arr=[]
car_theft_rate_arr=[]
for i in range(len(x)):
    neighborhood = x.iloc[i]['Neighborhood']
    household_arr.append(add_data[neighborhood][0])
    renters_arr.append(add_data[neighborhood][1])
    sales_tax_arr.append(add_data[neighborhood][2])
    property_tax_arr.append(add_data[neighborhood][3])
    burglary_rate_arr.append(add_data[neighborhood][4])
    assault_rate_arr.append(add_data[neighborhood][5])
    robbery_rate_arr.append(add_data[neighborhood][6])
    rape_rate_arr.append(add_data[neighborhood][7])
    murder_rate_arr.append(add_data[neighborhood][8])
    car_theft_rate_arr.append(add_data[neighborhood][9])
x['household_income']=household_arr
x['renters']=renters_arr
x['sales_tax']=sales_tax_arr
x['property_tax']=property_tax_arr
x['burglary_rate']=burglary_rate_arr
x['assault_rate']=assault_rate_arr
x['robbery_rate']=robbery_rate_arr
x['rape_rate']=rape_rate_arr
x['murder_rate']=murder_rate_arr
x['car_theft_rate']=car_theft_rate_arr


x_test = test_data
x_test['household_income'] = 0
x_test['renters'] = 0
x_test['sales_tax'] = 0
x_test['property_tax'] = 0
x_test['burglary_rate'] = 0
x_test['assault_rate'] = 0
x_test['robbery_rate'] = 0
x_test['rape_rate'] = 0
x_test['murder_rate'] = 0
x_test['car_theft_rate'] = 0

household_arr_test = []
renters_arr_test = []
sales_tax_arr_test = []
property_tax_arr_test=[]
burglary_rate_arr_test=[]
assault_rate_arr_test=[]
robbery_rate_arr_test=[]
rape_rate_arr_test=[]
murder_rate_arr_test=[]
car_theft_rate_arr_test=[]
for i in range(len(x_test)):
    neighborhood = x_test.iloc[i]['Neighborhood']
    household_arr_test.append(add_data[neighborhood][0])
    renters_arr_test.append(add_data[neighborhood][1])
    sales_tax_arr_test.append(add_data[neighborhood][2])
```

```
    property_tax_arr_test.append(add_data[neighborhood][3])
    burglary_rate_arr_test.append(add_data[neighborhood][4])
    assault_rate_arr_test.append(add_data[neighborhood][5])
    robbery_rate_arr_test.append(add_data[neighborhood][6])
    rape_rate_arr_test.append(add_data[neighborhood][7])
    murder_rate_arr_test.append(add_data[neighborhood][8])
    car_theft_rate_arr_test.append(add_data[neighborhood][9])
x_test['household_income']=household_arr_test
x_test['renters']=renters_arr_test
x_test['sales_tax']=sales_tax_arr_test
x_test['property_tax']=property_tax_arr_test
x_test['burglary_rate']=burglary_rate_arr_test
x_test['assault_rate']=assault_rate_arr_test
x_test['robbery_rate']=robbery_rate_arr_test
x_test['rape_rate']=rape_rate_arr_test
x_test['murder_rate']=murder_rate_arr_test
x_test['car_theft_rate']=car_theft_rate_arr_test
```

In [305]:

```
#Baseline Model
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from scipy import stats
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score
import base64
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn import linear_model
from sklearn import metrics
test_data = pd.read_csv('test_temp.csv')
#x = train_data
y = x['SalePrice']


col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most
frequent
    else:
        x[col] = x[col].fillna(x[col].median())
test_col_miss_val = [col for col in test_data.columns if test_data[col].isnull().any()]
for col in test_col_miss_val:
    if(test_data[col].dtype == np.dtype('O')):
        test_data[col] = test_data[col].fillna(test_data[col].value_counts().index[0])
#replace nan with most frequent
    else:
        test_data[col] = test_data[col].fillna(test_data[col].median())
LE = LabelEncoder()
for col in test_data.select_dtypes(include=['object']):
    test_data[col] = LE.fit_transform(test_data[col])

for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
y = x["SalePrice"]
y = np.log(y+1)
x = x.drop(['Id','SalePrice'],axis=1)
lm = linear_model.LinearRegression()
model = lm.fit(x,y)
y_pred = model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
residual = y - y_pred
z = np.abs(stats.zscore(residual))
outliers1=np.where(abs(z) > abs(z).std() * 3)[0]
x = x.drop(outliers1)
y = y.drop(outliers1)
lm.fit(x, y)
y_pred = lm.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
```

```
0.13068097305285897
0.09094826262107804
```

1. Obtained the national averages from [https://en.wikipedia.org/wiki/Crime_in_the_United_States (https://en.wikipedia.org/wiki/Crime_in_the_United_States)](https://en.wikipedia.org/wiki/Crime_in_the_United_States).
2. Then used [https://www.addressreport.com (https://www.addressreport.com)](https://www.addressreport.com) and obtained household_income,renters,sales_tax,property_tax,burglary_rate, assault_rate, robbery_rate, rape_rate, murder_rate, car_theft_rate for available neighborhoods within Ames and filled the missing data with average rates in Ames city.
3. Then appended the dataset to the original one and applied Linear regression model.
4. We got an RMSE smaller than the previous(0.090<0.0093), making our assumptions valid that crime and income factors do impact the SalePrice

Part 8 - Permutation Test

In [306]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn import linear_model
from sklearn.model_selection import permutation_test_score
train_data = pd.read_csv('train_temp.csv')
x = train_data
y = np.log(train_data['SalePrice'])
col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most 
frequent
    else:
        x[col] = train_data[col].fillna(x[col].median())
LE = LabelEncoder()
for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
```

In [307]:

```
lm = linear_model.LinearRegression()
x = x.drop(['Id','SalePrice'],axis=1)
ten_variables = ['OverallQual', 'GrLivArea','GarageCars','GarageArea','TotalBsmtSF','1s
tFlrSF','FullBath',
                'YearBuilt','GarageFinish','HeatingQC']
for i in range(len(ten_variables)):
    z = np.array(x[ten_variables[i]])
    z=np.reshape(z,(z.shape[0],1))
    model = lm.fit(z,y)
    p_value = permutation_test_score(model,z,y,n_permutations=100)
    print(p_value)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.6662141142239526, array([-2.02756334e-03, -6.90362761e-03, -2.76302822e
-03, -3.20248134e-05,
       -1.73549804e-03, -3.65261092e-04, -4.29779841e-03, -1.03059442e-03,
       -5.59690431e-03, -8.91864518e-03, -2.17393594e-03, -1.07519103e-03,
       -4.28092880e-03, -4.95740262e-03, -6.31858375e-03, -1.46594218e-03,
       -3.69676729e-03, -7.42087989e-03, -5.92302887e-03, -1.00800626e-03,
       -1.10959652e-02, -5.94655675e-03, -5.80500479e-03, -6.38010217e-03,
       -2.49115151e-03, -2.12385487e-03, -3.65991819e-03, -5.70071257e-04,
       -7.54425074e-03, -3.29459214e-03, -6.96533492e-03, -2.24177085e-03,
       -6.78704158e-03, -9.81676320e-03, -4.32468506e-03, -1.74235056e-03,
       -1.01697479e-02, -3.64507296e-03,  1.40456887e-03, -2.86992789e-03,
        2.22059695e-04, -3.34137835e-03, -7.35697146e-03, -2.24688282e-03,
        7.34864175e-04, -3.29791046e-03, -4.67343358e-03, -2.57094652e-02,
       -1.19000533e-02, -3.02189407e-03,  3.29546578e-03, -1.97373421e-03,
       -2.81011262e-03, -2.54797111e-03, -7.86019320e-03, -6.69829898e-03,
       -8.27481306e-03, -5.95713001e-03, -1.95021036e-03, -6.73218321e-03,
       -6.28636816e-03, -2.09772194e-03, -2.02107398e-03, -1.23499928e-02,
       -5.47012151e-03, -1.10045768e-02, -8.39030090e-04, -3.06974812e-03,
       -3.32266168e-03, -6.79022340e-03, -1.94211032e-04,  1.29873172e-03,
       -1.28578178e-03, -1.26885265e-04, -1.04635315e-03,  4.21194483e-06,
       -4.71599706e-04, -1.03879536e-03, -1.25440483e-03, -2.82881852e-03,
       -1.49852124e-03, -1.26391841e-03, -6.97069123e-03, -4.21523218e-03,
       -5.95452211e-03, -9.88867005e-03, -7.24711561e-04, -3.29351702e-03,
       -1.28372651e-03, -1.72271533e-03, -1.77800403e-03, -2.41511900e-03,
       -1.01838923e-02, -3.97350531e-03, -1.42360902e-03, -2.62408375e-03,
       -4.49925076e-03, -2.61899255e-03,  1.17370517e-05, -7.08957541e-0
3]), 0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.47791328554743356, array([-4.67389525e-05, -6.84398277e-03, -3.30837045
e-03, -3.53525856e-03,
       -7.41875945e-04, -1.26304867e-03, -5.19112675e-03, -5.56469005e-03,
       -3.77319691e-03, -8.88801420e-03, -5.90713183e-03, -1.03754246e-03,
       -1.07241999e-02, -2.11982548e-03, -7.97112649e-03,  1.87549676e-04,
       -5.09422836e-03, -8.02568159e-03, -9.31452628e-03,  4.01524848e-04,
       -1.02069211e-02, -6.91141121e-03, -7.49052738e-03, -5.35758673e-03,
       -2.57556951e-03, -2.25610547e-03, -3.79257351e-03, -1.07028385e-03,
       -3.92868340e-03, -8.65957988e-04, -1.04395870e-02, -7.69350074e-04,
       -8.56937717e-03, -7.07419844e-03, -2.23330510e-03, -7.78735330e-04,
       -1.11071123e-02, -1.71516777e-03, -3.64571862e-03, -4.71642093e-03,
       -3.42919758e-04, -3.58556811e-03, -8.86545039e-03, -2.82672216e-03,
       -8.15531414e-04, -6.75115779e-03, -3.29836968e-03, -2.75537859e-02,
       -1.17278169e-02, -2.19899989e-03, -1.38093482e-03, -9.89065606e-04,
       -1.07317768e-03, -4.23503735e-03, -9.29105458e-03, -7.35991895e-04,
       -1.03529648e-02, -6.94919282e-03, -3.15010292e-03, -6.45732449e-03,
       -7.23927577e-03, -3.16463179e-03, -3.91444360e-03, -1.16515815e-02,
       -4.70108570e-03, -9.75604931e-03, -3.89956253e-03, -6.56461162e-04,
       -1.17430664e-03, -9.97246169e-03, -2.58239402e-03,  7.09537435e-04,
        5.94171243e-05, -4.71111641e-04, -1.56221714e-03, -1.77178391e-03,
       -1.02372623e-03, -2.66426258e-03, -2.62566446e-03, -1.71384553e-03,
       -1.39548907e-03, -5.64979265e-04, -4.42065267e-03, -5.48013135e-03,
       -7.33659891e-03, -8.06255752e-03, -2.28784250e-03, -3.02980371e-03,
       -1.86056842e-03, -5.67492310e-03, -1.08101315e-03, -1.36273115e-03,
       -9.24996797e-03, -4.57955738e-03, -3.00730802e-04, -9.28743039e-03,
       -3.77564164e-03, -2.10591925e-03,  6.52657432e-03, -6.40156642e-0
3]), 0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.46010392375143994, array([-8.61964270e-04, -6.32973940e-03, -1.65795255
e-03, -3.81699395e-03,
       -1.09099577e-03, -3.59730511e-04, -4.30094908e-03, -5.66027637e-03,
       -6.73542564e-03, -7.20940257e-03, -5.81139946e-03, -1.63206878e-06,
       -1.35281871e-03, -4.87545419e-03, -4.50857547e-03, -4.03204901e-04,
       -3.70172749e-03, -7.51852505e-03, -6.95444793e-03, -1.08051542e-03,
       -9.94586231e-03, -8.47085369e-03, -7.59217450e-03, -3.64298515e-03,
       -7.54297998e-04, -7.16004702e-03, -4.63945731e-03, -1.25534630e-03,
       -8.11453418e-03, -4.76141712e-03, -8.25336611e-03,  1.18078417e-03,
       -7.48034939e-03, -5.11836982e-03, -2.01509337e-03, -6.23657137e-04,
       -1.20760130e-02, -2.54846221e-03, -4.57758835e-03, -9.32503248e-03,
        1.71101125e-04, -6.70865918e-03, -6.43823395e-03, -7.16945698e-03,
       -6.77907824e-04, -2.88445483e-03, -1.11814933e-02, -2.50214188e-02,
       -1.42429930e-02,  3.83814684e-04, -1.78316879e-03, -2.67522668e-03,
       -2.01164429e-03, -2.95903343e-03, -9.05921635e-03, -2.39465416e-03,
       -5.91217251e-03, -5.13806923e-03, -3.53751782e-03, -6.55791852e-03,
       -7.61370621e-03, -1.30123765e-03, -4.81501157e-03, -1.00682973e-02,
       -4.37136218e-03, -1.17689179e-02, -8.42659621e-04, -4.25926990e-03,
       -7.55787103e-04, -3.27035825e-03, -1.42139330e-04, -2.93652731e-03,
       -9.59849453e-04, -1.66824127e-03, -6.92843085e-04, -3.03285249e-03,
       -1.85998248e-03, -4.65618347e-03, -3.65308972e-03, -2.31095653e-03,
       -1.95699346e-03, -8.47713669e-04, -4.26708981e-03, -3.99001790e-03,
       -6.28071175e-03, -7.70203719e-03, -7.94473792e-04, -3.08744967e-03,
       -4.20873354e-04, -1.02954966e-03, -5.39376718e-03, -3.29010081e-03,
       -1.01740531e-02, -5.47492006e-03, -2.00548889e-03, -5.93590682e-03,
       -5.56955188e-03, -1.22787090e-03, -4.40187765e-04, -6.43805086e-0
3]), 0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.4163606862775098, array([-0.00057852, -0.00511996, -0.00275775, -0.0032
9453, -0.00244458,
       -0.00088817, -0.00455772, -0.0047295 , -0.00651798, -0.00847311,
       -0.00422129,  0.00050265, -0.00211002, -0.00421799, -0.00418059,
       -0.00010424, -0.00212349, -0.00719471, -0.00976843, -0.0013786 ,
       -0.00969827, -0.00466952, -0.00615121, -0.00340859, -0.00093548,
       -0.00821896, -0.00487301, -0.00112883, -0.00819968, -0.00344929,
       -0.00781665, -0.00105148, -0.00724916, -0.00625466, -0.00265164,
       -0.00093021, -0.01038011, -0.00211887, -0.0064422 , -0.00676158,
        0.00016167, -0.00505403, -0.00596588, -0.00793154, -0.00211987,
       -0.00293212, -0.01172494, -0.02707124, -0.01547461, -0.000504  ,
        0.00046976, -0.00276583, -0.00129702, -0.00291052, -0.00715873,
       -0.00092459, -0.00635286, -0.0044321 , -0.00267022, -0.00706158,
       -0.00751481, -0.00253878, -0.00447347, -0.00904321, -0.00449306,
       -0.01194926, -0.0007559 , -0.00226258, -0.00149126, -0.00262464,
       -0.00079881, -0.0028385 , -0.00512423, -0.00103581, -0.00162104,
       -0.00074775, -0.0029217 , -0.00508567, -0.00392739, -0.002005  ,
       -0.00078879, -0.00094167, -0.00607693, -0.00397662, -0.00729859,
       -0.008965  , -0.00119229, -0.0044708 , -0.00013213, -0.00116266,
       -0.00777423, -0.00299712, -0.00984491, -0.00415695, -0.00089727,
       -0.00405935, -0.00558166, -0.00138172, -0.00049004, -0.00709078]),
0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.36381300464568067, array([-0.00163398, -0.00383374, -0.00335363, -0.012
85209, -0.00185876,
       -0.00082711, -0.00408359, -0.00591877, -0.00344053, -0.00804996,
       -0.00449682,  0.00161778, -0.00352238, -0.00696726, -0.00600034,
       -0.00526628, -0.00412635, -0.00743742, -0.00633408, -0.00253619,
       -0.00709668, -0.00655566, -0.00516459, -0.00509843, -0.00494872,
       -0.00571743, -0.00198463, -0.0014704 , -0.00380574, -0.00086098,
       -0.00908927, -0.00443001, -0.00818223, -0.00736967, -0.00117717,
       -0.00109211, -0.00993737, -0.00823593, -0.00181361, -0.00224716,
        0.00052877, -0.00550252, -0.00348656, -0.00260855, -0.00077353,
       -0.00259138, -0.00826924, -0.02268668, -0.01281074, -0.00061737,
       -0.00060713, -0.00264117, -0.00191019, -0.00287422, -0.0043694 ,
       -0.0001752 , -0.00560091, -0.00724977, -0.00151635, -0.00730097,
       -0.00694953, -0.00502485, -0.00348929, -0.01210623, -0.00552819,
       -0.0165282 , -0.00099367, -0.00321685,  0.00039809, -0.01224598,
        0.0002892 , -0.00531371, -0.00242942,  0.00080666, -0.00039491,
       -0.0012503 , -0.00025173, -0.0036006 , -0.00381348, -0.00319929,
       -0.00196841, -0.00071529, -0.00404911, -0.0038775 , -0.00739134,
       -0.00821603, -0.00139504, -0.00217716, -0.00166127, -0.00393566,
       -0.00504635, -0.00265525, -0.01149414, -0.00536921,  0.00025729,
       -0.00355535, -0.00519843, -0.00047104, -0.00040944, -0.00729223]),
0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.34811127945711773, array([ 0.00261247, -0.00366721, -0.00296434, -0.006
10886, -0.00388074,
       -0.00164239, -0.00453493, -0.00616054, -0.00306994, -0.00758306,
       -0.00739667, -0.00099793, -0.00300327, -0.00330107, -0.00709168,
       -0.00722355, -0.00093152, -0.00744742, -0.00673672, -0.00357165,
       -0.00877695, -0.01061073, -0.0052714 , -0.00442366, -0.00479763,
       -0.00248377, -0.00343825, -0.00329637, -0.00528941, -0.00042735,
       -0.01080339, -0.0019792 , -0.00874897, -0.0073968 , -0.00121652,
       -0.00194538, -0.0086483 , -0.00556355, -0.00200707, -0.0067012 ,
       -0.00017747, -0.00939609, -0.00624273, -0.00210152, -0.00234863,
       -0.00392707, -0.00349252, -0.02450075, -0.01320986, -0.00133141,
       -0.00166187, -0.00292224, -0.00256785, -0.00261349, -0.00634405,
       -0.00038391, -0.00553147, -0.00423557, -0.0024136 , -0.00689498,
       -0.00770518, -0.00510518, -0.0006732 , -0.01153512, -0.00547309,
       -0.01489312, -0.00056312, -0.0009589 ,  0.000336  , -0.01672949,
       -0.00326074, -0.00238481, -0.00139721,  0.00132722, -0.00035984,
        0.00026351, -0.00072741, -0.00135986, -0.00350547, -0.00152432,
       -0.00085938, -0.00174222, -0.00605266, -0.00427261, -0.00827685,
       -0.01070729, -0.00210054, -0.00295651, -0.00312674, -0.00758782,
       -0.00273843, -0.00374445, -0.01050167, -0.00596339, -0.00042253,
       -0.0031506 , -0.00375691, -0.00018139,  0.00288196, -0.00660445]),
0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.35178576192334315, array([-0.00396584, -0.00463686, -0.00365379, -0.002
4781 , -0.00149306,
       -0.00180163, -0.00372296, -0.00329111, -0.00739232, -0.00699188,
       -0.00455476, -0.00068557, -0.00394741, -0.0011483 , -0.00726645,
       -0.00316551, -0.00205591, -0.0069429 , -0.01091456, -0.00390259,
       -0.01111194, -0.00743126, -0.00447155, -0.005691  , -0.00278997,
       -0.00334452, -0.00262323, -0.00243162, -0.00437529, -0.00099061,
       -0.00555949, -0.0014447 , -0.00749846, -0.00480538, -0.00274449,
       -0.00057704, -0.0140717 , -0.00246597,  0.00051122, -0.0026713 ,
       -0.00332985, -0.00128685, -0.00490344, -0.00186486, -0.0028092 ,
       -0.00428507, -0.00688727, -0.02421271, -0.01082453, -0.00200049,
        0.00038878, -0.00314202, -0.00138424, -0.00406817, -0.00912418,
       -0.00073362, -0.00615087, -0.00722834, -0.00522881, -0.00586031,
       -0.00912155, -0.00353516, -0.00150794, -0.01295196, -0.00554197,
       -0.00905143, -0.00178269,  0.00114859, -0.00119998, -0.00361198,
       -0.00099644, -0.00218277, -0.00150172, -0.00398744, -0.00166104,
       -0.00067368, -0.00222949,  0.00068195, -0.00214784, -0.00240262,
       -0.00188421, -0.00351862, -0.00209904, -0.00260371, -0.0054388 ,
       -0.00957657, -0.00073974, -0.00483064,  0.00219994, -0.00123011,
       -0.00212953, -0.00169904, -0.01214722, -0.00848818, -0.00125346,
       -0.00150793, -0.00488396, -0.00219933,  0.00452896, -0.00838816]),
0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.342290077614468, array([-2.52538386e-03, -3.00911365e-03, -2.21251393e-
05, -7.37395480e-03,
       -3.89513110e-04, -1.62944433e-03, -4.48922803e-03, -5.76210771e-03,
       -8.88047970e-03, -8.48633641e-03, -1.46773054e-03, -2.90897817e-04,
       -1.81519811e-03, -2.27602760e-03, -7.97037349e-03, -1.17901372e-03,
       -2.26858992e-03, -7.37447863e-03, -4.43450105e-03, -2.73426056e-03,
       -1.47167573e-02, -1.82345264e-03, -1.29690271e-02, -5.07459678e-03,
       -1.98430766e-03, -4.97234948e-03, -3.25898026e-03, -1.00081351e-03,
       -4.30435162e-03, -7.15562712e-03, -5.90424030e-03, -6.74789632e-03,
       -6.75543718e-03, -6.28370542e-03, -9.57164368e-03, -4.12392809e-03,
       -1.06391366e-02, -5.15798285e-03, -5.12072684e-03, -4.74976622e-03,
        4.14666491e-04,  1.98364706e-03, -6.69631484e-03, -2.66943814e-03,
       -2.17885373e-03, -1.98016843e-03, -6.93379006e-03, -2.63255071e-02,
       -1.16251820e-02, -1.00761298e-03, -1.22135014e-04, -2.19730374e-03,
       -2.08187295e-03, -3.60007982e-03, -8.24594723e-03,  9.31145224e-04,
       -6.59456190e-03, -1.03043392e-02, -3.04441889e-03, -6.50255366e-03,
       -8.99065915e-03, -3.85196377e-03, -1.41107275e-03, -1.17686334e-02,
       -5.15679489e-03, -1.02840434e-02, -3.05988064e-03, -1.76537197e-03,
       -4.20945945e-03, -1.28182823e-03, -5.03500419e-03, -1.04799056e-03,
       -9.31999865e-05, -1.72569433e-03, -1.38245817e-03, -1.48826301e-03,
        1.14426460e-04, -4.01933667e-03, -2.25737038e-03, -1.55299016e-03,
       -2.23286299e-03, -1.67001862e-03, -3.89776841e-03, -1.01227976e-03,
       -9.95130282e-03, -8.16712702e-03, -5.79760074e-03, -4.72254581e-03,
       -3.12649332e-03, -1.03519126e-03, -1.22807894e-03, -9.01889141e-04,
       -6.51433018e-03, -4.47772058e-03, -7.58773003e-04, -4.06976212e-03,
       -6.45457205e-03, -2.48493956e-03, -9.15831068e-04, -8.04055594e-0
3]), 0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.3283287511176459, array([-0.00131677, -0.00363536, -0.00330971, -0.0025
7581, -0.0034798 ,
       -0.00281606, -0.00462244, -0.00507538, -0.00511925, -0.00766422,
       -0.00476233, -0.00119251, -0.0012353 , -0.00660834, -0.00627435,
       -0.00177842, -0.00120735, -0.00857824, -0.00533845, -0.00276293,
       -0.01165271, -0.00311463, -0.00657594, -0.00510047, -0.00089974,
       -0.00735758, -0.00270826, -0.00164931, -0.0048052 , -0.00062883,
       -0.00868673, -0.00516597, -0.00710423, -0.01181889, -0.00104367,
       -0.00428092, -0.01041658, -0.00318389,  0.00085803, -0.00269145,
       -0.00027763,  0.00116384, -0.00657489, -0.00388294, -0.00246265,
       -0.00269215, -0.00457577, -0.02578662, -0.01792277, -0.00024536,
        0.00109058, -0.00288164, -0.00256763, -0.00297821, -0.00429849,
       -0.00301799, -0.00512793, -0.00570113, -0.00325455, -0.00994441,
       -0.00918082, -0.00535302, -0.00175169, -0.01130845, -0.00554787,
       -0.00951564, -0.00135544, -0.00058745, -0.00196642, -0.0012358 ,
       -0.00043492, -0.00132456,  0.00046969, -0.00040384, -0.00179676,
       -0.00265673, -0.00094624, -0.0007785 , -0.00275786, -0.0031023 ,
       -0.00069836, -0.00129955, -0.00338839, -0.00507401, -0.00731945,
       -0.00684183,  0.00090248, -0.0065366 , -0.00147836, -0.00126369,
       -0.00600726, -0.00192371, -0.00978424, -0.00425401, -0.00088066,
       -0.00388978, -0.00581225, -0.00477945,  0.00159402, -0.00581598]),
0.009900990099009901)
```

```
C:\Users\srika\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:2053: FutureWarning: You should specify a value for 'cv' instead of rel
ying on the default value. The default value will change from 3 to 5 in ve
rsion 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
(0.17853279498655886, array([-0.00096383, -0.00161312, -0.00606382,  0.005
85076, -0.00219263,
       -0.00595456, -0.00678218, -0.00393919, -0.00310253, -0.00766898,
       -0.00262   , -0.00102411, -0.00046672, -0.00867462, -0.0089557 ,
        0.00145604, -0.00410548, -0.00870397, -0.00704776, -0.0042171 ,
       -0.00792149, -0.00439065, -0.00950146, -0.00349096, -0.00829444,
       -0.00268008, -0.00181653, -0.00021647, -0.0046054 , -0.00164621,
       -0.0054333 ,  0.00025656, -0.00599106, -0.00621379, -0.00346574,
       -0.00044764, -0.01288109, -0.00655306, -0.00053793, -0.00373386,
       -0.00144392, -0.00032138, -0.00683028, -0.00209247, -0.00120527,
       -0.00643022, -0.00034315, -0.0240867 , -0.01147638, -0.00036164,
       -0.00019305, -0.00231704, -0.00184081, -0.00256352, -0.00404301,
       -0.00177605, -0.00486215, -0.00463642, -0.00425196, -0.00673893,
       -0.01067801, -0.00366775, -0.00077686, -0.01201848, -0.0051456 ,
       -0.00946507,  0.00148226, -0.00070914, -0.0018229 , -0.00245105,
        0.00151014, -0.004234  , -0.00016605, -0.00094548, -0.00190525,
       -0.00141584, -0.00416919, -0.00318929, -0.00298203, -0.00067753,
       -0.0011978 ,  0.00086495, -0.00735593, -0.00583115, -0.00625893,
       -0.00832869, -0.00350399, -0.00392658, -0.0044959 , -0.00486331,
       -0.00068524, -0.00389204, -0.01200714, -0.00449223, -0.00214263,
       -0.0054772 , -0.00859206, -0.0011383 ,  0.00041993, -0.00629153]),
0.009900990099009901)
```

1. If p-value<0.05, then it means our hypothesis is correct and that's what we obtained. All the p-tests passed here.
2. The p-value, which approximates the probability that the score would be obtained by chance. This is calculated as:

   (C + 1) / (n_permutations + 1) Where C is the number of permutations whose score >= the true score.
3. The best possible p-value is 1/(n_permutations + 1), which happened in this case.
4. For all the 100 permutations, the true score, 0.8036 has contradicted in all the cases, making C=0.
5. The p-value is therefore 1/101 = 0.0099 as obtained

Part 9 - Final Result

In [308]:

```
#Baseline Model
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from scipy import stats
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score
import base64
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn import linear_model
from sklearn import metrics
test_data = pd.read_csv('test_temp.csv')
train_data = pd.read_csv('train_temp.csv')
x = train_data
y = x['SalePrice']


col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most frequent
    else:
        x[col] = x[col].fillna(x[col].median())
test_col_miss_val = [col for col in test_data.columns if test_data[col].isnull().any()]
for col in test_col_miss_val:
    if(test_data[col].dtype == np.dtype('O')):
        test_data[col] = test_data[col].fillna(test_data[col].value_counts().index[0])
#replace nan with most frequent
    else:
        test_data[col] = test_data[col].fillna(test_data[col].median())
LE = LabelEncoder()
for col in test_data.select_dtypes(include=['object']):
    test_data[col] = LE.fit_transform(test_data[col])

for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
y = x["SalePrice"]
y = np.log(y+1)
x = x.drop(['Id','SalePrice'],axis=1)
lm = linear_model.LinearRegression()
model = lm.fit(x,y)
y_pred = model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
residual = y - y_pred
z = np.abs(stats.zscore(residual))
outliers1=np.where(abs(z) > abs(z).std() * 3)[0]
x = x.drop(outliers1)
y = y.drop(outliers1)
lm.fit(x, y)
y_pred = lm.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)

x_test = test_data.drop('Id',axis=1)
x_test.shape
y_pred_test = lm.predict(x_test)
d1 = {'Id': test_data['Id'], 'SalePrice': np.exp(y_pred_test)-1}
```

```
df1 = pd.DataFrame(data=d1)
df1.to_csv("output_baseline1.csv")
```

```
0.13357226973052294
0.09251472149062581
```

In [309]:

```
#Advanced Model
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from scipy import stats
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score
import base64
train_data = pd.read_csv('train_temp.csv')
x = train_data
col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most frequent
    else:
        x[col] = train_data[col].fillna(x[col].median())
LE = LabelEncoder()
for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
test_col_miss_val = [col for col in test_data.columns if test_data[col].isnull().any()]
for col in test_col_miss_val:
    if(test_data[col].dtype == np.dtype('O')):
        test_data[col] = test_data[col].fillna(test_data[col].value_counts().index[0])
#replace nan with most frequent
    else:
        test_data[col] = test_data[col].fillna(test_data[col].median())
for col in test_data.select_dtypes(include=['object']):
    test_data[col] = LE.fit_transform(test_data[col])

x = x.drop(['Id','SalePrice'],axis=1)
y = train_data["SalePrice"]
x.shape
y = np.log(y+1)
RR= Ridge(15)
RR.fit(x, y)
y_pred = RR.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
residual = y - y_pred
z = np.abs(stats.zscore(residual))
outliers1=np.where(abs(z) > abs(z).std() * 3)[0]
x = x.drop(outliers1)
y = y.drop(outliers1)
RR.fit(x, y)
y_pred = RR.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
x_test = test_data.drop('Id',axis=1)
x_test.shape
y_pred_test = RR.predict(x_test)
d1 = {'Id': test_data['Id'], 'SalePrice': np.exp(y_pred_test)-1}
df1 = pd.DataFrame(data=d1)
df1.to_csv("output.csv")
```

```
0.13434636652740095
0.09371815082320259
```

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from scipy import stats
import xgboost as xgb
train_data = pd.read_csv('train_temp.csv')
x = train_data
col_miss_val = [col for col in x.columns if x[col].isnull().any()]
for col in col_miss_val:
    if(x[col].dtype == np.dtype('O')):
         x[col]=x[col].fillna(x[col].value_counts().index[0])    #replace nan with most
frequent
    else:
        x[col] = train_data[col].fillna(x[col].median())
LE = LabelEncoder()
for col in x.select_dtypes(include=['object']):
    x[col] = LE.fit_transform(x[col])
test_col_miss_val = [col for col in test_data.columns if test_data[col].isnull().any()]
for col in test_col_miss_val:
    if(test_data[col].dtype == np.dtype('O')):
        test_data[col] = test_data[col].fillna(test_data[col].value_counts().index[0])
#replace nan with most frequent
    else:
        test_data[col] = test_data[col].fillna(test_data[col].median())
for col in test_data.select_dtypes(include=['object']):
    test_data[col] = LE.fit_transform(test_data[col])

x = x.drop(['Id','SalePrice'],axis=1)
y = train_data["SalePrice"]
x.shape
y = np.log(y+1)
xgb_model = xgb.XGBRegressor(colsample_bytree=0.4,
                 gamma=0,
                 learning_rate=0.07,
                 max_depth=3,
                 min_child_weight=1.5,
                 n_estimators=10000,
                 reg_alpha=0.75,
                 reg_lambda=0.45,
                 subsample=0.6,
                 seed=42)
xgb_model.fit(x,y)
y_pred = xgb_model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
residual = y - y_pred
z = np.abs(stats.zscore(residual))
outliers1=np.where(abs(z) > abs(z).std() * 3)[0]
x = x.drop(outliers1)
y = y.drop(outliers1)
xgb_model.fit(x, y)
y_pred = xgb_model.predict(x)
RMSE = np.sqrt(metrics.mean_squared_error(y, y_pred))
print(RMSE)
x_test = test_data.drop('Id',axis=1)
x_test.shape
y_pred_test = xgb_model.predict(x_test)
d1 = {'Id': test_data['Id'], 'SalePrice': np.exp(y_pred_test)-1}
df1 = pd.DataFrame(data=d1)
df1.to_csv("output_xgb.csv")
```

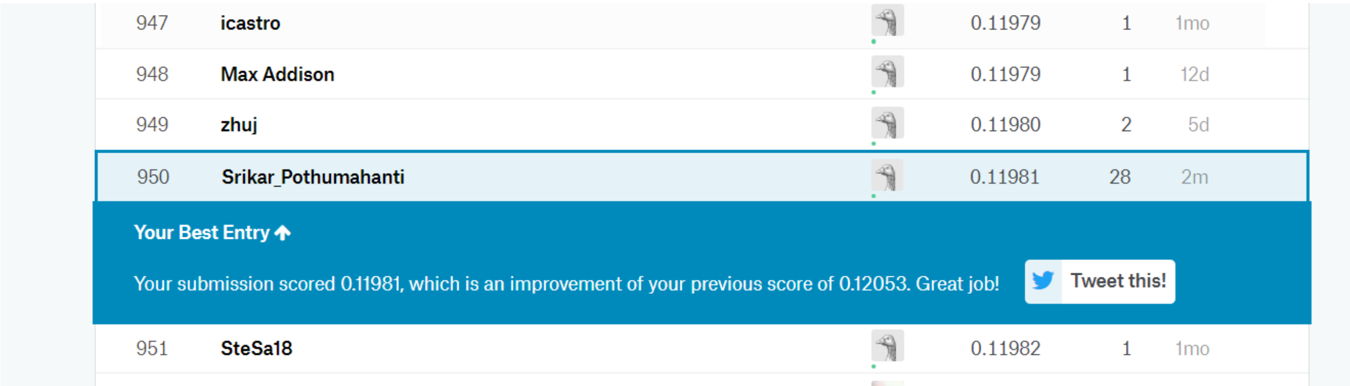
Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderboard as confirmation. Be sure to provide a link to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with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

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

Highest Rank: 950

Score: 0.11981

Number of entries: 28



947	icastro	0.11979	1	1mo
948	Max Addison	0.11979	1	12d
949	zhuj	0.11980	2	5d
950	Srikar_Pothumahanti	0.11981	28	2m
951	SteSa18	0.11982	1	1mo

In [ ]: