Decision Tree.

In this part, we use a classification algorithm to build a model from the historical data of prices. We then use the trained decision tree to predict the price of a future house sale.

First, we import the Following Libraries:

- **numpy (as np)**
- **pandas**
- **DecisionTreeClassifier** from **sklearn.tree**

In [2]:
```
import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
```

In [3]:
```
# Importing the dataset

df = pd.read_csv("nyc-rolling-sales.csv", delimiter=",")
df.head()
```

Out[3]:

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	EASE-MENT	BUI CLA PRI
0	4	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	392	6		
1	5	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2	399	26		
2	6	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2	399	39		
3	7	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21		
4	8	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	404	55		

5 rows × 22 columns

Data processing & Exploration

In [4]:
```
#Removing unnecessary columns
del df['EASE-MENT']
del df['Unnamed: 0']
del df['ADDRESS']
del df['APARTMENT NUMBER']
```

In [5]:
```
#Checking for duplicates
sum(df.duplicated(df.columns))
```

Out[5]: 956

In [6]:
```
#Removing duplicate records
df = df.drop_duplicates(df.columns, keep='last')
sum(df.duplicated(df.columns))
```

Out[6]: 0

In [7]:
```
#Convert some of the columns to desired datatype
df['TAX CLASS AT TIME OF SALE'] = df['TAX CLASS AT TIME OF SALE'].astype
('category')
df['TAX CLASS AT PRESENT'] = df['TAX CLASS AT PRESENT'].astype('categor
y')
df['LAND SQUARE FEET'] = pd.to_numeric(df['LAND SQUARE FEET'], errors='c
oerce')
df['GROSS SQUARE FEET']= pd.to_numeric(df['GROSS SQUARE FEET'], errors=
'coerce')
df['SALE PRICE'] = pd.to_numeric(df['SALE PRICE'], errors='coerce')
df['BOROUGH'] = df['BOROUGH'].astype('category')
```

In [8]:
```python
# Convert Sale Date to Year
from datetime import datetime

for i in range(len(df)):
    if True:
        the_date = datetime.strptime(str(df['SALE DATE'][i]), '%Y-%m-%d %H:%M:%S')
        df.at[i,'SALE DATE'] = the_date.year
    else:
        df.at[i,'SALE DATE'] = int(df.at[i,'SALE DATE'])

# convert to integer
df['SALE DATE'] = df['SALE DATE'].astype(int)

df['SALE DATE'].head()
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-8-c8db02fad33a> in <module>
      4 for i in range(len(df)):
      5     if True:
----> 6         the_date = datetime.strptime(str(df['SALE DATE'][i]), '%Y-%m-%d %H:%M:%S')
      7         df.at[i,'SALE DATE'] = the_date.year
      8     else:

//anaconda3/lib/python3.7/site-packages/pandas/core/series.py in __getitem__(self, key)
    866         key = com.apply_if_callable(key, self)
    867         try:
--> 868             result = self.index.get_value(self, key)
    869 
    870             if not is_scalar(result):

//anaconda3/lib/python3.7/site-packages/pandas/core/indexes/base.py in get_value(self, series, key)
   4373         try:
   4374             return self._engine.get_value(s, k,
-> 4375                                           tz=getattr(series.dtype, 'tz', None))
   4376         except KeyError as e1:
   4377             if len(self) > 0 and (self.holds_integer() or self.is_boolean()):

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.Int64HashTable.get_item()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.Int64HashTable.get_item()

KeyError: 48
```

In [10]:

```
#checking missing values
df.columns[df.isnull().any()]
```

Out[10]:

```
Index(['LAND SQUARE FEET', 'GROSS SQUARE FEET', 'SALE PRICE'], dtype='object')
```

In [11]:
```
miss=df.isnull().sum()/len(df)
miss=miss[miss>0]
miss.sort_values(inplace=True)
miss
```

Out[11]:
```
SALE PRICE          0.168365
LAND SQUARE FEET    0.310484
GROSS SQUARE FEET   0.326371
dtype: float64
```

In [12]:
```
#Convert series to column DataFrame
miss=miss.to_frame()
#Set Column Name
miss.columns=['count']
#Set Index Name
miss.index.names=['Name']
#Create Column from Index
miss['Name']=miss.index
miss
```

Out[12]:

	count	Name
Name		
SALE PRICE	0.168365	SALE PRICE
LAND SQUARE FEET	0.310484	LAND SQUARE FEET
GROSS SQUARE FEET	0.326371	GROSS SQUARE FEET

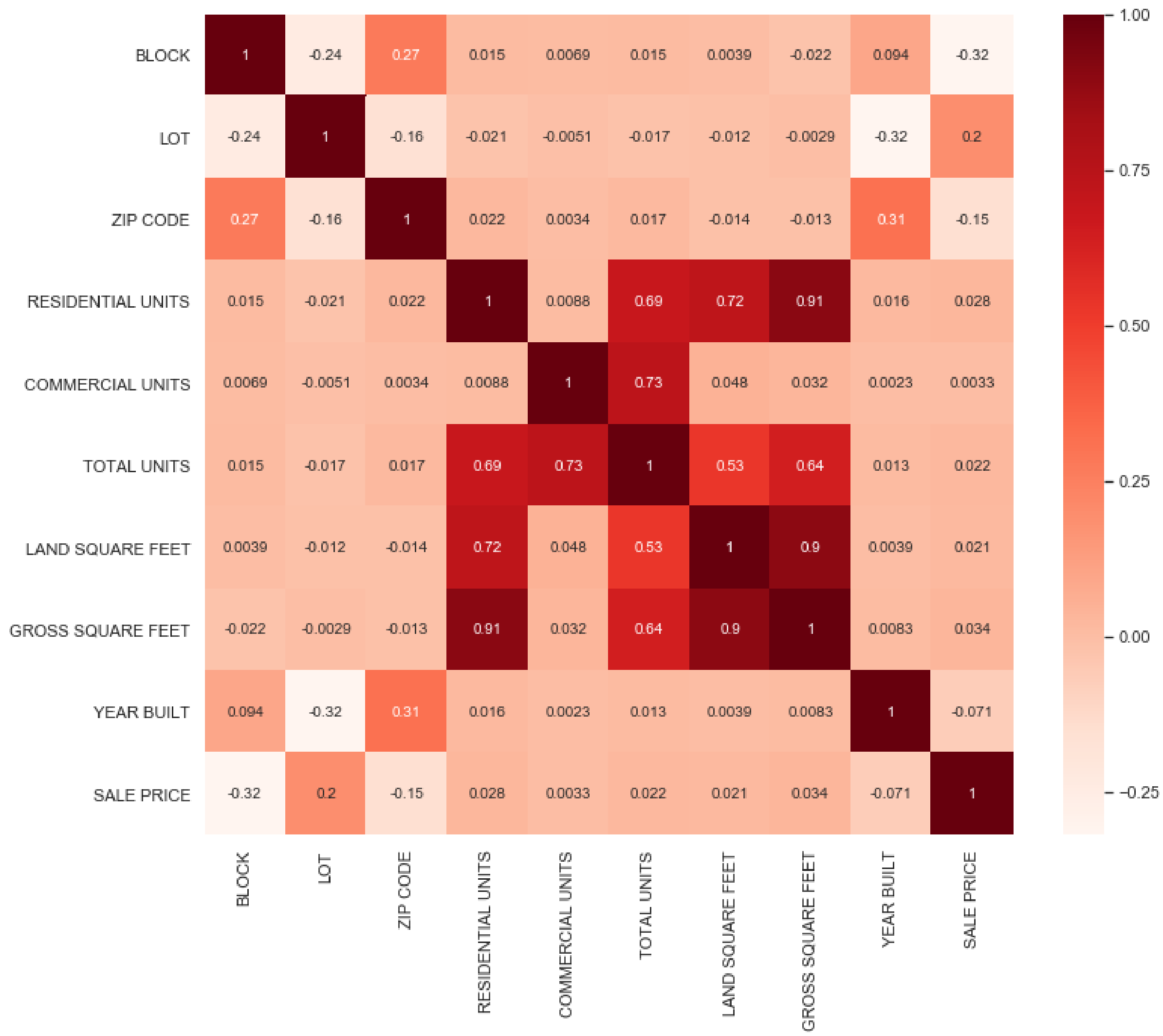
In [13]:
```
#Plot the missing values
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style='whitegrid',color_codes=True)
sns.barplot(x='Name', y='count',data=miss)
plt.xticks(rotation=90)
sns
```

Out[13]:
```
<module 'seaborn' from '//anaconda3/lib/python3.7/site-packages/seabor
n/__init__.py'>
```

In [14]:
```
#Populating mean values for missing data
df['LAND SQUARE FEET']=df['LAND SQUARE FEET'].fillna(df['LAND SQUARE FEE
T'].mean())
df['GROSS SQUARE FEET']=df['GROSS SQUARE FEET'].fillna(df['GROSS SQUARE
 FEET'].mean())
```

In [16]:
```
# Removing null observations
df = df[(df['SALE PRICE'] > 100000) & (df['SALE PRICE'] < 5000000)]
```

In [19]:
```
#Using Pearson Correlation
plt.figure(figsize=(12,10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



	BLOCK	LOT	ZIP CODE	RESIDENTIAL UNITS	COMMERCIAL UNITS	TOTAL UNITS	LAND SQUARE FEET	GROSS SQUARE FEET	YEAR BUILT	SALE PRICE
BLOCK	1	-0.24	0.27	0.015	0.0069	0.015	0.0039	-0.022	0.094	-0.32
LOT	-0.24	1	-0.16	-0.021	-0.0051	-0.017	-0.012	-0.0029	-0.32	0.2
ZIP CODE	0.27	-0.16	1	0.022	0.0034	0.017	-0.014	-0.013	0.31	-0.15
RESIDENTIAL UNITS	0.015	-0.021	0.022	1	0.0088	0.69	0.72	0.91	0.016	0.028
COMMERCIAL UNITS	0.0069	-0.0051	0.0034	0.0088	1	0.73	0.048	0.032	0.0023	0.0033
TOTAL UNITS	0.015	-0.017	0.017	0.69	0.73	1	0.53	0.64	0.013	0.022
LAND SQUARE FEET	0.0039	-0.012	-0.014	0.72	0.048	0.53	1	0.9	0.0039	0.021
GROSS SQUARE FEET	-0.022	-0.0029	-0.013	0.91	0.032	0.64	0.9	1	0.0083	0.034
YEAR BUILT	0.094	-0.32	0.31	0.016	0.0023	0.013	0.0039	0.0083	1	-0.071
SALE PRICE	-0.32	0.2	-0.15	0.028	0.0033	0.022	0.021	0.034	-0.071	1

In [20]:
```
# Most Correlations
cor_target = abs(cor["SALE PRICE"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.1]
relevant_features
```

Out[20]:
```
BLOCK          0.319305
LOT            0.195200
ZIP CODE       0.151620
SALE PRICE     1.000000
Name: SALE PRICE, dtype: float64
```

In [22]:
```
del df['SALE DATE']
```

Encoding

In [24]:

```
X = df[['BOROUGH','NEIGHBORHOOD','BUILDING CLASS CATEGORY','TAX CLASS AT PRESENT','BLOCK','LOT','BUILDING CLASS AT PRESENT','ZIP CODE','RESIDENTIAL UNITS','COMMERCIAL UNITS','TOTAL UNITS','LAND SQUARE FEET','GROSS SQUARE FEET','YEAR BUILT','TAX CLASS AT TIME OF SALE','BUILDING CLASS AT TIME OF SALE']].values
X[:, 14]
```

Out[24]:

```
array([2, 2, 2, ..., 1, 1, 1], dtype=object)
```

In [25]:

```
# Getting the dependent variables and independent variables
X = df[['BOROUGH','NEIGHBORHOOD','BUILDING CLASS CATEGORY','TAX CLASS AT PRESENT','BLOCK','LOT','BUILDING CLASS AT PRESENT','ZIP CODE','RESIDENTIAL UNITS','COMMERCIAL UNITS','TOTAL UNITS','LAND SQUARE FEET','GROSS SQUARE FEET','YEAR BUILT','TAX CLASS AT TIME OF SALE','BUILDING CLASS AT TIME OF SALE']].values

# Encoding categorical data
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder_X_1 = LabelEncoder()
X[:, 1] = labelencoder_X_1.fit_transform(X[:, 1])

labelencoder_X_2 = LabelEncoder()
X[:, 2] = labelencoder_X_2.fit_transform(X[:, 2])

labelencoder_X_3 = LabelEncoder()
X[:, 3] = labelencoder_X_3.fit_transform(X[:, 3])

labelencoder_X_6 = LabelEncoder()
X[:, 6] = labelencoder_X_6.fit_transform(X[:, 6])


labelencoder_X_16 = LabelEncoder()
X[:, 15] = labelencoder_X_16.fit_transform(X[:, 15])
```

In [26]:

```
X[0:5]
```

Out[26]:

```
array([[1, 1, 6, 7, 402, 21, 18, 10009, 10, 0, 10, 2272.0, 6794.0, 191
3,
        2, 17],
       [1, 1, 6, 7, 406, 32, 18, 10009, 8, 0, 8, 1750.0, 4226.0, 1920,
2,
        17],
       [1, 1, 8, 5, 373, 40, 20, 10009, 0, 0, 0, 3846.981435858288,
        3874.3228378618364, 1920, 2, 19],
       [1, 1, 8, 5, 373, 40, 20, 10009, 0, 0, 0, 3846.981435858288,
        3874.3228378618364, 1920, 2, 19],
       [1, 1, 8, 5, 373, 40, 20, 10009, 0, 0, 0, 3846.981435858288,
        3874.3228378618364, 1920, 2, 19]], dtype=object)
```

We then set the target variable, Sale Price

In [28]:
```
# Target variable, Sale Price

y = df['SALE PRICE'].values
y[0:5]
```

Out[28]:
```
array([3936272., 3192840.,  499000.,  529500.,  423000.])
```

Setting up the decision tree

In [29]:
```
import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
```

In [30]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Now **train_test_split** will return 4 different parameters. We will name them:
X_train, X_test, y_train, y_test

The **train_test_split** will need the parameters:
X, y, test_size=0.3, and random_state=34.
We will also try random state = 0

The **X** and **y** are the arrays required before the split, the **test_size** represents the ratio of the testing dataset, and the **random_state** ensures that we obtain the same splits.

In [31]:
```
# Splitting the training set and test set
X_train ,X_test, y_train , y_test = train_test_split(X , y, test_size =
0.3 , random_state =34)
```

In [32]:
```
# Training set
X_train.shape , y_train.shape
```

Out[32]:
```
((38173, 16), (38173,))
```

In [33]:
```
# Feature Scaling
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [34]:
```
# Checking shape of X_train and y_train. Thier shapes should match
print(X_train.shape)
print(y_train.shape)
```

```
(38173, 16)
(38173,)
```

In [35]:
```
# Also checking the shape of X_test and y_test. Thier shapes should also
match
print(X_test.shape)
print(y_test.shape)
```

```
(16361, 16)
(16361,)
```

Modeling

We will first create an instance of the **DecisionTreeClassifier** called **priceTree**.
Inside of the classifier, specify *criterion="entropy"* so we can see the information gain of each node.

In [36]:
```
priceTree = DecisionTreeClassifier(criterion="entropy", max_depth = 9)
priceTree # it shows the default parameters
```

Out[36]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dept
h=9,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

Next, we will fit the data with the training feature matrix **X_trainset** and training response vector **y_trainset**

In [37]:
```
priceTree.fit(X_train, y_train)
```

Out[37]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dept
h=9,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

Prediction

Let's make some **predictions** on the testing dataset and store it into a variable called **predTree**.

In [38]:
```
predTree = priceTree.predict(X_test)
```

We print out **predTree** and **y_test** to visually compare the prediction to the actual values.

In [39]:
```
print (predTree [0:5])
print (y_test [0:5])
```

```
[420000. 400000. 763687. 470000. 150000.]
[1270000. 2500000.  491790.  332000.  140000.]
```

Evaluation

Next, let's import **metrics** from sklearn and check the accuracy of our model.

In [40]:
```
from sklearn import metrics
import matplotlib.pyplot as plt
print("DecisionTrees's Accuracy: ", metrics.accuracy_score(y_test, predT
ree))
```

```
DecisionTrees's Accuracy:  0.015035755760650327
```

In [73]:
```
# RMSE
from sklearn.metrics import mean_squared_error
def rmse(y_test,y_pred):
      return np.sqrt(mean_squared_error(y_test,y_pred))
```

In [75]:
```
rmse(y_test,predTree)
```

Out[75]:
```
692152.7732118465
```

These are very poor scores. We will do some visulization, check feature importance and re-build the model

Feature Importance

With the very low accuracy, we would like to review the data and remove any noise that may be affecting performance

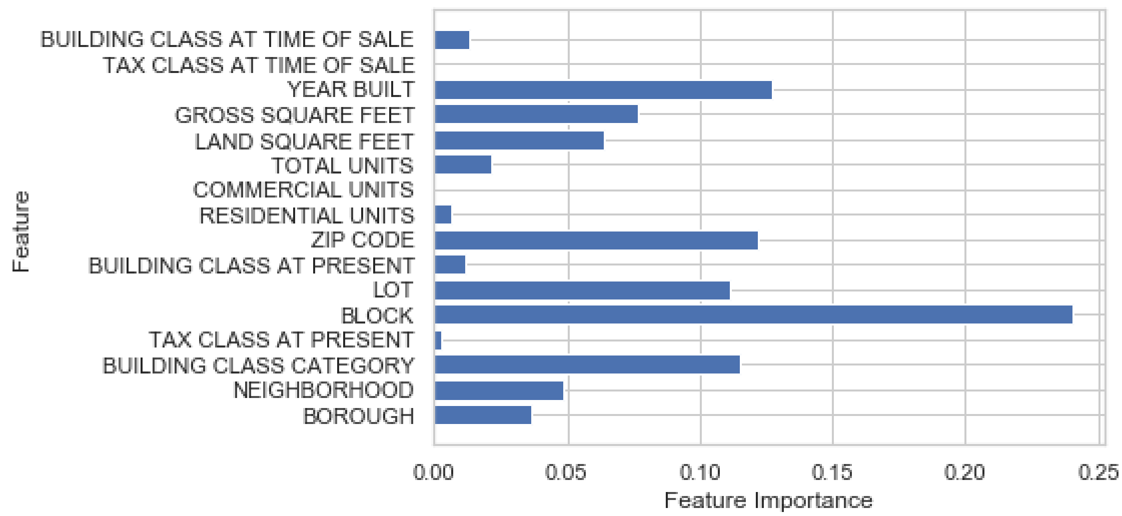
In [41]:
```
from sklearn.ensemble import ExtraTreesClassifier
```

In [42]:
```
print('Feature importances: {}'.format(priceTree.feature_importances_))
type(priceTree.feature_importances_)
```

```
Feature importances: [0.03679404 0.04857123 0.11549536 0.00308566 0.240
43385 0.11155583
 0.01218395 0.12234182 0.00657886 0.         0.02139389 0.06378611
 0.07683286 0.12721396 0.         0.01373256]
```

Out[42]:
```
numpy.ndarray
```

In [43]:
```
#Feature Importance
n_feature = X_train.shape[1]
featureNames = df.drop(columns='SALE PRICE')
featureNames = featureNames.columns.values
plt.barh(range(n_feature), priceTree.feature_importances_, align='cente
r')
plt.yticks(np.arange(n_feature), featureNames)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.show()
```



Model Re-building

We will now re-train the data using selected features

- Features with importance of less than .05 will be dropped
- We can also see that the dropped features do not correlate well with SALE PRICE
- Finally, we want to check that the top important features do not correlate much with each other

In [44]:
```
# Most Correlations
cor_target2 = abs(cor["SALE PRICE"])
#Selecting highly correlated features
relevant_features2 = cor_target2[cor_target2>0.1]
relevant_features2
```

Out[44]:
```
BLOCK         0.319305
LOT           0.195200
ZIP CODE      0.151620
SALE PRICE    1.000000
Name: SALE PRICE, dtype: float64
```

In [45]:
```
df.head()
```

Out[45]:

	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	BUILDING CLASS AT PRESENT	ZIP CODE	RE
3	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21	C4	10009	
6	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	406	32	C4	10009	
13	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	
15	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	
16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	

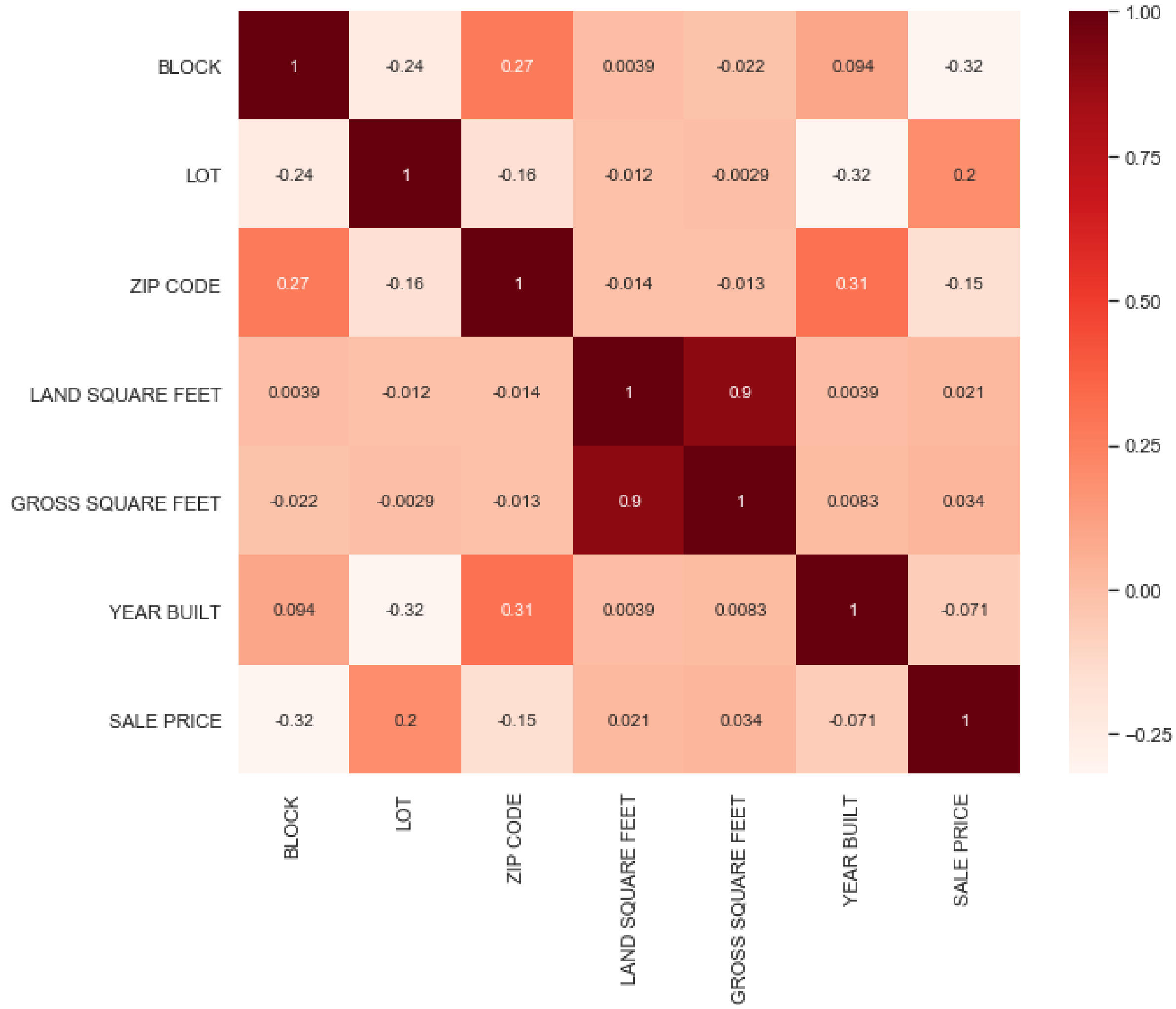
In [46]:
```
df_2 = []
df_2 = df
df_2.head()
```

Out[46]:

	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	TAX CLASS AT PRESENT	BLOCK	LOT	BUILDING CLASS AT PRESENT	ZIP CODE	RE
3	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	402	21	C4	10009	
6	1	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2B	406	32	C4	10009	
13	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	
15	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	
16	1	ALPHABET CITY	09 COOPS - WALKUP APARTMENTS	2	373	40	C6	10009	

In [47]:
```
# remove the less important features

del df_2['BUILDING CLASS AT TIME OF SALE']
del df_2['TAX CLASS AT TIME OF SALE']
del df_2['TOTAL UNITS']
del df_2['COMMERCIAL UNITS']
del df_2['RESIDENTIAL UNITS']
del df_2['BUILDING CLASS AT PRESENT']
del df_2['TAX CLASS AT PRESENT']
del df_2['NEIGHBORHOOD']
del df_2['BOROUGH']
# del df_2['SALE PRICE']  # do not delete sale data yet so we can run co
rrelation
```

In [49]:
```
#Using Pearson Correlation to check feature correlations
plt.figure(figsize=(10,8))
cor2 = df_2.corr()
sns.heatmap(cor2, annot=True, cmap=plt.cm.Reds)
plt.show()
```



In [50]:
```
# GROSS SQUARE FEET  and LAND SQUARE FEET are highly correlated with eac
h other,
# We drop LAND SQUARE FEET becuase it is slightly less correlated with S
ALE PRICE at .021

del df_2['LAND SQUARE FEET']
```

We now begin rebuilding the model

In [51]:
```
df_2.head()
```

Out[51]:

	BUILDING CLASS CATEGORY	BLOCK	LOT	ZIP CODE	GROSS SQUARE FEET	YEAR BUILT	SALE PRICE
3	07 RENTALS - WALKUP APARTMENTS	402	21	10009	6794.000000	1913	3936272.0
6	07 RENTALS - WALKUP APARTMENTS	406	32	10009	4226.000000	1920	3192840.0
13	09 COOPS - WALKUP APARTMENTS	373	40	10009	3874.322838	1920	499000.0
15	09 COOPS - WALKUP APARTMENTS	373	40	10009	3874.322838	1920	529500.0
16	09 COOPS - WALKUP APARTMENTS	373	40	10009	3874.322838	1920	423000.0

In [52]:
```
df_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 54534 entries, 3 to 84545
Data columns (total 7 columns):
BUILDING CLASS CATEGORY    54534 non-null object
BLOCK                      54534 non-null int64
LOT                        54534 non-null int64
ZIP CODE                   54534 non-null int64
GROSS SQUARE FEET          54534 non-null float64
YEAR BUILT                 54534 non-null int64
SALE PRICE                 54534 non-null float64
dtypes: float64(2), int64(4), object(1)
memory usage: 3.3+ MB
```

In [53]:
```
# Get the variables
A = df_2[['BUILDING CLASS CATEGORY','BLOCK','LOT','ZIP CODE','GROSS SQUA
RE FEET','YEAR BUILT']].values
b = df_2['SALE PRICE'].values


# Encoding categorical data
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder_A_1 = LabelEncoder()
A[:, 0] = labelencoder_A_1.fit_transform(A[:, 0])


# Target variable, Sale Price

A[0:5]
b[0:5]
```

Out[53]:
```
array([3936272., 3192840.,  499000.,  529500.,  423000.])
```

In [54]:
```
# Split  training set and test set
A_train ,A_test, b_train , b_test = train_test_split(A , b, test_size =
0.3 , random_state =34)
```

In [55]:
```
# Training set
A_train.shape , b_train.shape
```

Out[55]:
```
((38173, 6), (38173,))
```

In [56]:
```
# Feature Scaling
sc = StandardScaler()
A_train = sc.fit_transform(A_train)
A_test = sc.transform(A_test)
```

In [57]:
```
print(A_train.shape)
print(b_train.shape)

print(A_test.shape)
print(b_test.shape)
```

```
(38173, 6)
(38173,)
(16361, 6)
(16361,)
```

In [58]:
```
# 1 specify second model
priceTree_2 = DecisionTreeClassifier(criterion="entropy", max_depth = 9)
priceTree_2 # it shows the default parameters
```

Out[58]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dept
h=9,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

In [59]:
```
# 2  fit the data
priceTree_2.fit(A_train, b_train)
```

Out[59]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dept
h=9,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

In [60]:
```
# 3 Prediction
predTree_2 = priceTree_2.predict(A_test)
```

In [61]:
```
# 4 Print prediction
print (predTree_2 [0:5])
print (b_test [0:5])
```

```
[1185000.  400000. 1050000.  470000.  250000.]
[1270000. 2500000.  491790.  332000.  140000.]
```

In [62]:
```
# 5 Accuracy of predTree_2
print("DecisionTrees's Accuracy: ", metrics.accuracy_score(b_test, predT
ree_2))
```

```
DecisionTrees's Accuracy:  0.0149746348022737
```

After feature selction, the Accuracy is relatively the same!

We will build one more model using a higher max_depth

In [63]:
```
# Model using max_depth = 20

priceTree_3 = DecisionTreeClassifier(criterion="entropy", max_depth = 20
)
priceTree_3.fit(A_train, b_train)
predTree_3 = priceTree_3.predict(A_test)

print("DecisionTrees's Accuracy: ", metrics.accuracy_score(b_test, predT
ree_3))
```

```
DecisionTrees's Accuracy:  0.01772507792922193
```

F1 score, Jaccard Similarity, and RMSE

In [64]:
```
from sklearn.metrics import f1_score
f1_score(b_test, predTree_3, average='weighted')
```

```
//anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.
py:1437: UndefinedMetricWarning: F-score is ill-defined and being set t
o 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
//anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.
py:1439: UndefinedMetricWarning: F-score is ill-defined and being set t
o 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
```

Out[64]:
```
0.016880589784208252
```

In [68]:
```
from sklearn.metrics import jaccard_similarity_score
jaccard_similarity_score(b_test, predTree_3)
```

```
//anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.
py:635: DeprecationWarning: jaccard_similarity_score has been deprecate
d and replaced with jaccard_score. It will be removed in version 0.23.
This implementation has surprising behavior for binary and multiclass c
lassification tasks.
  'and multiclass classification tasks.', DeprecationWarning)
```

Out[68]: 0.01772507792922193

In [76]:
```
rmse(b_test,predTree_3)
```

Out[76]: 620436.6733025813

Conclusion

With a higher max_depth, and with feature selction, the Accuracy is still very low. It appears that Decisoin Trees is not a great option for our problem

The Accuracy may be imporved by grouping the price ranges into bins as this
is what Decision trees would be great for