Importing Libraries

In [1]:
```
import math
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score, roc_curve, auc
from dmba import adjusted_r2_score, AIC_score, BIC_score
from dmba import backward_elimination, forward_selection,stepwise_selection
import matplotlib.pylab as plt
from dmba import regressionSummary, classificationSummary, exhaustive_search
from dmba import liftChart, gainsChart
from sklearn.neighbors import KNeighborsRegressor
import seaborn as sns
from sklearn import metrics
```

Importing Dataset

In [2]:
```
## Import Dataset

house_df = pd.read_csv('HousingDataSet.csv')
house_df.head(10)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	
5	7237550310	20140512T000000	1225000.0	4	4.50	5420	101930	1.0	
6	1321400060	20140627T000000	257500.0	3	2.25	1715	6819	2.0	
7	2008000270	20150115T000000	291850.0	3	1.50	1060	9711	1.0	
8	2414600126	20150415T000000	229500.0	3	1.00	1780	7470	1.0	
9	3793500160	20150312T000000	323000.0	3	2.50	1890	6560	2.0	

10 rows × 21 columns

In [3]:
```
house_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21613 non-null  int64  
 1   date           21613 non-null  object 
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64  
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64  
 6   sqft_lot       21613 non-null  int64  
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64  
 9   view           21613 non-null  int64  
 10  condition      21613 non-null  int64  
 11  grade          21613 non-null  int64  
 12  sqft_above     21613 non-null  int64  
 13  sqft_basement  21613 non-null  int64  
 14  yr_built       21613 non-null  int64  
 15  yr_renovated   21613 non-null  int64  
 16  zipcode        21613 non-null  int64  
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64  
 20  sqft_lot15     21613 non-null  int64  
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [4]:
```
house_df.isnull().sum()
```

Out[4]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

In [5]:
```
house_df.describe()
```

Out[5]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3

Data Wrangling

In [6]:
```
#Dropping unwanted columns

new_df = house_df.drop(['id','date','zipcode','lat','long'],axis=1)
```

In [7]:
```
# replacing outlier

new_df['bedrooms'].replace(33,3,inplace =True)
```

In [8]:
```
new_df.describe()
```

Out[8]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
count	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	21613
mean	5.400881e+05	3.369454	2.114757	2079.899736	1.510697e+04	1.494309	0
std	3.671272e+05	0.907964	0.770163	918.440897	4.142051e+04	0.539989	0
min	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	0
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0
max	7.700000e+06	11.000000	8.000000	13540.000000	1.651359e+06	3.500000	1

In [9]:
```
clean_df = new_df
```

In [10]:

```
# Creating a new column with houses that were renovated and dropping the existing
clean_df['is_renovated'] = np.where(clean_df['yr_renovated'] > 0, 1, 0)


clean_df.drop('yr_renovated',axis =1,inplace = True)
```

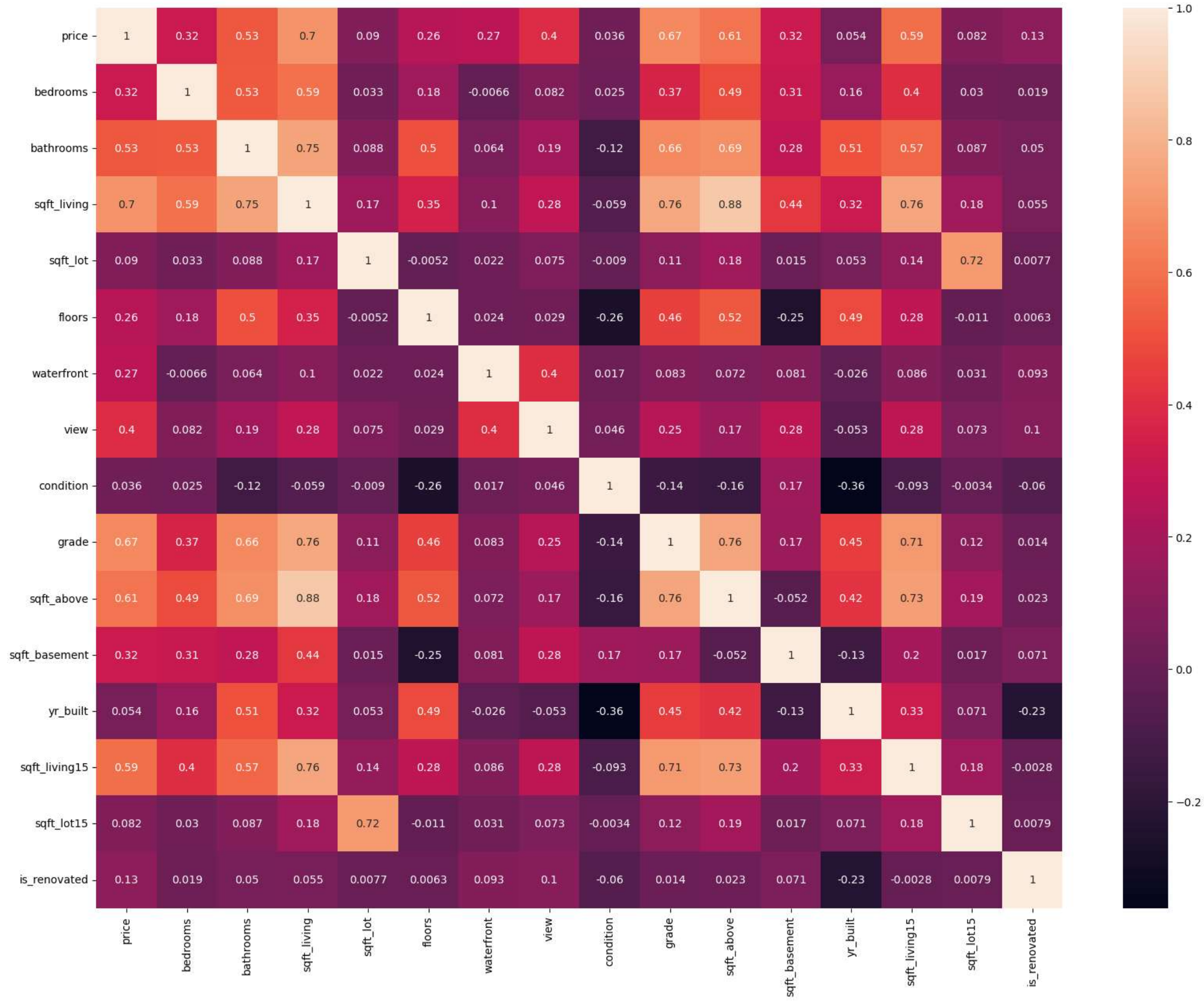
In [11]:

```
clean_df.head()
```

Out[11]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
0	221900.0	3	1.00	1180	5650	1.0	0	0	3	7
1	538000.0	3	2.25	2570	7242	2.0	0	0	3	7
2	180000.0	2	1.00	770	10000	1.0	0	0	3	6
3	604000.0	4	3.00	1960	5000	1.0	0	0	5	7
4	510000.0	3	2.00	1680	8080	1.0	0	0	3	8

In [12]:
```
cormap = clean_df.corr()
plt.figure(figsize=(20,15))
sns.heatmap(cormap, annot=True)
plt.show()
```



In [13]:
```
clean_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 16 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21613 non-null  float64
 1   bedrooms       21613 non-null  int64  
 2   bathrooms      21613 non-null  float64
 3   sqft_living    21613 non-null  int64  
 4   sqft_lot       21613 non-null  int64  
 5   floors         21613 non-null  float64
 6   waterfront     21613 non-null  int64  
 7   view           21613 non-null  int64  
 8   condition      21613 non-null  int64  
 9   grade          21613 non-null  int64  
 10  sqft_above     21613 non-null  int64  
 11  sqft_basement  21613 non-null  int64  
 12  yr_built       21613 non-null  int64  
 13  sqft_living15  21613 non-null  int64  
 14  sqft_lot15     21613 non-null  int64  
 15  is_renovated   21613 non-null  int32  
dtypes: float64(3), int32(1), int64(12)
memory usage: 2.6 MB
```

Removing columns with low correlations

In [14]:
```
# Eliminating columns with low correlation

# X = clean_df[['bedrooms','bathrooms','sqft_living','grade','sqft_above','sqft_l
X = clean_df[['bedrooms','bathrooms','sqft_living','floors','waterfront','view','
y = clean_df['price']
```

Search Algorithm

Shmueli, G., Bruce, P. C., Gedeck, P., & Patel, N. R. (2020). Data mining for Business Analytics: Concepts, techniques and applications in Python. John Wiley & Sons, Inc.

In [15]:
```
# Split the data into training and validation
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.4, random_s
```

In [16]:
```
def train_model(variables):
    model = LinearRegression()
    model.fit(train_X[list(variables)], train_y)
    return model
```

In [17]:
```
def score_model(model, variables):
    pred_y = model.predict(train_X[list(variables)])
    # we negate as score is optimized to be as low as possible
    return -adjusted_r2_score(train_y, pred_y, model)
```

In [18]:
```
allVariables = train_X.columns
results = exhaustive_search(allVariables, train_model, score_model)
data = []
for result in results:
    model = result['model']
    variables = list(result['variables'])
    AIC = AIC_score(train_y, model.predict(train_X[variables]), model)
    d = {'n': result['n'], 'r2adj': -result['score'], 'AIC':AIC}
    d.update({var: var in result['variables'] for var in allVariables})
    data.append(d)
    pd.DataFrame(data, columns=('n', 'r2adj', 'AIC') + tuple(sorted(allVariables)
```

In [19]:
```
def train_model(variables):
    model = LinearRegression()
    model.fit(train_X[list(variables)], train_y)
    return model
```

In [20]:
```
def score_model(model, variables):
    return AIC_score(train_y, model.predict(train_X[variables]), model)
```

In [21]:
```
allVariables = train_X.columns
best_model, best_variables = backward_elimination(allVariables, train_model,
                                                   score_model, verbose=True)
```

```
Variables: bedrooms, bathrooms, sqft_living, floors, waterfront, view, conditio
n, grade, sqft_above, sqft_basement, sqft_living15, sqft_lot15, is_renovated
Start: score=355731.85
Step: score=355729.85, remove sqft_living
Step: score=355728.31, remove floors
Step: score=355728.31, remove None
```

In [22]:
```
print(best_variables)
regressionSummary(test_y, best_model.predict(test_X[best_variables]))
```

```
['bedrooms', 'bathrooms', 'waterfront', 'view', 'condition', 'grade', 'sqft_abo
ve', 'sqft_basement', 'sqft_living15', 'sqft_lot15', 'is_renovated']

Regression statistics

                      Mean Error (ME) : 2872.5344
       Root Mean Squared Error (RMSE) : 241751.0270
            Mean Absolute Error (MAE) : 151751.6384
          Mean Percentage Error (MPE) : -9.3809
Mean Absolute Percentage Error (MAPE) : 31.1484
```

In [23]:
```
def train_model(variables):
    if len(variables) == 0:
        return None
    model = LinearRegression()
    model.fit(train_X[list(variables)], train_y)
    return model
```

In [24]:
```
def score_model(model, variables):
    if len(variables) == 0:
        return AIC_score(train_y, [train_y.mean()] * len(train_y), model, df=1)
    return AIC_score(train_y, model.predict(train_X[variables]), model)
```

In [25]:
```
best_model, best_variables = forward_selection(train_X.columns, train_model, scor
print(best_variables)
```

```
Variables: bedrooms, bathrooms, sqft_living, floors, waterfront, view, conditio
n, grade, sqft_above, sqft_basement, sqft_living15, sqft_lot15, is_renovated
Start: score=368124.57, constant
Step: score=359374.06, add sqft_living
Step: score=358140.16, add grade
Step: score=357006.81, add view
Step: score=356580.98, add waterfront
Step: score=356292.35, add condition
Step: score=356046.95, add is_renovated
Step: score=355890.25, add bedrooms
Step: score=355793.79, add sqft_lot15
Step: score=355755.80, add sqft_above
Step: score=355737.49, add sqft_living15
Step: score=355728.31, add bathrooms
Step: score=355728.31, add None
['sqft_living', 'grade', 'view', 'waterfront', 'condition', 'is_renovated', 'be
drooms', 'sqft_lot15', 'sqft_above', 'sqft_living15', 'bathrooms']
```

In [26]:
```
best_model, best_variables = stepwise_selection(train_X.columns, train_model, sco
print(best_variables)
```

```
Variables: bedrooms, bathrooms, sqft_living, floors, waterfront, view, conditio
n, grade, sqft_above, sqft_basement, sqft_living15, sqft_lot15, is_renovated
Start: score=368124.57, constant
Step: score=359374.06, add sqft_living
Step: score=358140.16, add grade
Step: score=357006.81, add view
Step: score=356580.98, add waterfront
Step: score=356292.35, add condition
Step: score=356046.95, add is_renovated
Step: score=355890.25, add bedrooms
Step: score=355793.79, add sqft_lot15
Step: score=355755.80, add sqft_above
Step: score=355737.49, add sqft_living15
Step: score=355728.31, add bathrooms
Step: score=355728.31, unchanged None
['sqft_living', 'grade', 'view', 'waterfront', 'condition', 'is_renovated', 'be
drooms', 'sqft_lot15', 'sqft_above', 'sqft_living15', 'bathrooms']
```

In [ ]:

Considering the algorthim results keeping only the suggested columns in forwards selection method

In [27]:
```
X = clean_df[['sqft_living', 'grade', 'view', 'waterfront', 'condition', 'is_reno
y = clean_df['price']
```

In [28]:
```
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.4, random_s
```

In [29]:
```
lm = LinearRegression()
lm.fit(train_X, train_y)
```

Out[29]:
```
▾ LinearRegression
LinearRegression()
```

In [30]:
```
print(pd.DataFrame({'Predictor': X.columns, 'coefficient': lm.coef_}))
```

```
        Predictor    coefficient
0     sqft_living     206.605994
1           grade  103193.904423
2            view   56309.834056
3      waterfront  515660.092078
4       condition   54205.970748
5    is_renovated  153779.693882
6        bedrooms  -35769.121509
7      sqft_lot15      -0.742739
8      sqft_above     -36.610041
9    sqft_living15      19.726378
10      bathrooms  -13490.921070
```

In [31]:
```
lm_pred = lm.predict(test_X)
result = pd.DataFrame({'Predicted': lm_pred, 'Actual': test_y, 'Difference': test
print(result.head(20))
```

```
          Predicted     Actual     Difference
735    5.577636e+05   365000.0 -192763.632644
2830   7.470096e+05   865000.0  117990.390639
4106   1.235944e+06  1038000.0 -197943.916013
16218  1.499047e+06  1490000.0   -9047.015439
19964  7.206953e+05   711000.0   -9695.318601
1227   3.294954e+05   211000.0 -118495.376728
18849  7.632866e+05   790000.0   26713.350967
19369  5.049273e+05   680000.0  175072.658376
20164  4.421770e+05   384500.0  -57676.968821
7139   3.356049e+05   605000.0  269395.127272
2174   5.614780e+05   638000.0   76522.000701
13342  5.841672e+05   385000.0 -199167.213395
15468  3.610636e+05   175000.0 -186063.557170
7662   4.169386e+05   365000.0  -51938.566633
16941  2.234826e+05   160000.0  -63482.603753
5304   1.166119e+06  1070000.0  -96119.308801
6377   2.363076e+05   800000.0  563692.379708
12319  1.083215e+06   795127.0 -288088.080142
18835  2.860295e+05   355000.0   68970.522520
5337   5.399390e+05   474000.0  -65938.988777
```

In [32]:
```
regressionSummary(test_y, lm.predict(test_X))
```

```
Regression statistics

                      Mean Error (ME) : 2872.5344
       Root Mean Squared Error (RMSE) : 241751.0270
            Mean Absolute Error (MAE) : 151751.6384
          Mean Percentage Error (MPE) : -9.3809
Mean Absolute Percentage Error (MAPE) : 31.1484
```

KNN

KNN = 5

In [33]:
```
knn = KNeighborsRegressor(n_neighbors=5)
knn.fit(train_X,train_y)
knn_predictions = knn.predict(test_X)
```

In [34]:
```
result_knnfive = pd.DataFrame({'Predicted': knn_predictions, 'Actual': test_y, 'D
print(result.head(20))
```

```
          Predicted     Actual     Difference
735    5.577636e+05   365000.0 -192763.632644
2830   7.470096e+05   865000.0  117990.390639
4106   1.235944e+06  1038000.0 -197943.916013
16218  1.499047e+06  1490000.0   -9047.015439
19964  7.206953e+05   711000.0   -9695.318601
1227   3.294954e+05   211000.0 -118495.376728
18849  7.632866e+05   790000.0   26713.350967
19369  5.049273e+05   680000.0  175072.658376
20164  4.421770e+05   384500.0  -57676.968821
7139   3.356049e+05   605000.0  269395.127272
2174   5.614780e+05   638000.0   76522.000701
13342  5.841672e+05   385000.0 -199167.213395
15468  3.610636e+05   175000.0 -186063.557170
7662   4.169386e+05   365000.0  -51938.566633
16941  2.234826e+05   160000.0  -63482.603753
5304   1.166119e+06  1070000.0  -96119.308801
6377   2.363076e+05   800000.0  563692.379708
12319  1.083215e+06   795127.0 -288088.080142
18835  2.860295e+05   355000.0   68970.522520
5337   5.399390e+05   474000.0  -65938.988777
```

In [35]:
```
print('Mean absolute error: {}'.format(metrics.mean_absolute_error(test_y, knn_pr
print('Mean squared error: {}'.format(metrics.mean_squared_error(test_y, knn_pred
print('Root mean squared error: {}'.format(np.sqrt(metrics.mean_squared_error(tes
```

```
Mean absolute error: 158357.05769141798
Mean squared error: 70345440921.09496
Root mean squared error: 265227.149668157
```

KNN = 10

In [36]:
```
knn = KNeighborsRegressor(n_neighbors=10)
knn.fit(train_X,train_y)
knn_predictions = knn.predict(test_X)
```

In [37]:
```
result_knnten = pd.DataFrame({'Predicted': knn_predictions, 'Actual': test_y, 'Di
print(result.head(20))
```

```
          Predicted     Actual     Difference
735    5.577636e+05   365000.0 -192763.632644
2830   7.470096e+05   865000.0  117990.390639
4106   1.235944e+06  1038000.0 -197943.916013
16218  1.499047e+06  1490000.0   -9047.015439
19964  7.206953e+05   711000.0   -9695.318601
1227   3.294954e+05   211000.0 -118495.376728
18849  7.632866e+05   790000.0   26713.350967
19369  5.049273e+05   680000.0  175072.658376
20164  4.421770e+05   384500.0  -57676.968821
7139   3.356049e+05   605000.0  269395.127272
2174   5.614780e+05   638000.0   76522.000701
13342  5.841672e+05   385000.0 -199167.213395
15468  3.610636e+05   175000.0 -186063.557170
7662   4.169386e+05   365000.0  -51938.566633
16941  2.234826e+05   160000.0  -63482.603753
5304   1.166119e+06  1070000.0  -96119.308801
6377   2.363076e+05   800000.0  563692.379708
12319  1.083215e+06   795127.0 -288088.080142
18835  2.860295e+05   355000.0   68970.522520
5337   5.399390e+05   474000.0  -65938.988777
```

In [38]:
```
print('Mean absolute error: {}'.format(metrics.mean_absolute_error(test_y, knn_pr
print('Mean squared error: {}'.format(metrics.mean_squared_error(test_y, knn_pred
print('Root mean squared error: {}'.format(np.sqrt(metrics.mean_squared_error(tes
```

```
Mean absolute error: 153539.86009715474
Mean squared error: 68241853246.204094
Root mean squared error: 261231.4170351723
```

In [ ]: