In [0]:
```
import numpy as np
import pandas as pd
import sklearn
from sklearn import preprocessing
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import roc_curve,auc,recall_score,precision_score,accurac
y_score,f1_score
from sklearn.metrics import confusion_matrix,average_precision_score,recall_sc
ore
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [143]:
```
from sklearn import datasets
boston=datasets.load_boston()
boston.feature_names
'''here we are trying BUILDING LINEAR REGRESSION TO PREDICT HOUSING PRICE
TO DO THIS WE HAVE LOADDED BOSTON DATASET READILY AVAILABLE IN SKLEARN
we have following features which will help us determine and predict what would
be the housing price based
on data given from the below input features.
CRIM     -per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 s
q.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0
 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by t
own
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's  '''
```

Out[143]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

Out[143]:
```
"here we are trying BUILDING LINEAR REGRESSION TO PREDICT HOUSING PRICE\nTO D
O THIS WE HAVE LOADDED BOSTON DATASET READILY AVAILABLE IN SKLEARN\nwe have f
ollowing features which will help us determine and predict what would be the
housing price based\non data given from the below input features.\nCRIM     -
per capita crime rate by town\n        - ZN       proportion of residential l
and zoned for lots over 25,000 sq.ft.\n        - INDUS    proportion of non-r
etail business acres per town\n        - CHAS     Charles River dummy variabl
e (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nitric oxides
concentration (parts per 10 million)\n        - RM       average number of ro
oms per dwelling\n        - AGE      proportion of owner-occupied units built
prior to 1940\n        - DIS      weighted distances to five Boston employmen
t centres\n        - RAD      index of accessibility to radial highways\n
- TAX      full-value property-tax rate per $10,000\n        - PTRATIO  pupil
-teacher ratio by town\n        - B        1000(Bk - 0.63)^2 where Bk is the
proportion of blacks by town\n        - LSTAT    % lower status of the popula
tion\n        - MEDV     Median value of owner-occupied homes in $1000's  "
```

In [144]:
```
'''here we find that our dataset contains 13 features and 560 rows of data is
 available to us for all these input features'''
print('\n')
boston.data.shape
```

Out[144]:
```
'here we find that our dataset contains 13 features and 560 rows of data is a
vailable to us for all these input features'
```

Out[144]:
```
(506, 13)
```

In [145]:
```
'''here we are listing out all the input features name'''
print('\n')
boston.feature_names
```

Out[145]:
```
'here we are listing out all the input features name'
```

Out[145]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [146]:
```
'''our target variable is Housing price and following are the data for Actual
 Housing price already available to us'''
print('\n')
boston.target
```

Out[146]:
```
'our target variable is Housing price and following are the data for Actual H
ousing price already available to us'
```

Out[146]:
```
array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15. ,
       18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
       15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
       13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
       21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
       35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
       19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
       20.8, 21.2, 20.3, 28. , 23.9, 24.8, 22.9, 23.9, 26.6, 22.5, 22.2,
       23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
       33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
       21.7, 22.8, 18.8, 18.7, 18.5, 18.3, 21.2, 19.2, 20.4, 19.3, 22. ,
       20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
       23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
       15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
       17. , 15.6, 13.1, 41.3, 24.3, 23.3, 27. , 50. , 50. , 50. , 22.7,
       25. , 50. , 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
       23.2, 24.6, 29.9, 37.2, 39.8, 36.2, 37.9, 32.5, 26.4, 29.6, 50. ,
       32. , 29.8, 34.9, 37. , 30.5, 36.4, 31.1, 29.1, 50. , 33.3, 30.3,
       34.6, 34.9, 32.9, 24.1, 42.3, 48.5, 50. , 22.6, 24.4, 22.5, 24.4,
       20. , 21.7, 19.3, 22.4, 28.1, 23.7, 25. , 23.3, 28.7, 21.5, 23. ,
       26.7, 21.7, 27.5, 30.1, 44.8, 50. , 37.6, 31.6, 46.7, 31.5, 24.3,
       31.7, 41.7, 48.3, 29. , 24. , 25.1, 31.5, 23.7, 23.3, 22. , 20.1,
       22.2, 23.7, 17.6, 18.5, 24.3, 20.5, 24.5, 26.2, 24.4, 24.8, 29.6,
       42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
       36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
       32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
       20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
       20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
       22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
       21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
       19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
       32.7, 16.5, 23.9, 31.2, 17.5, 17.2, 23.1, 24.5, 26.6, 22.9, 24.1,
       18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
       16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
       13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
        7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
       12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
       27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
        8.8,  8.4, 16.7, 14.2, 20.8, 13.4, 11.7,  8.3, 10.2, 10.9, 11. ,
        9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4,  9.6,  8.7,  8.4, 12.8,
       10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13. , 13.4,
       15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20. , 16.4, 17.7,
       19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
       29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
       20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
       23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9])
```

In [147]:
```
'''here we created a dataframe comprising of all input features available to u
s'''
print('\n')
boston_df=pd.DataFrame(boston.data,columns=boston.feature_names)
boston_df
```

Out[147]:
```
'here we created a dataframe comprising of all input features available to u
s'
```

Out[147]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	L
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	
...	...	...	...	...	...	...	...	...	...	...	...	...	
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	

506 rows × 13 columns

In [148]:
```
'''here we are trying to snowball and determine first five rows of sample data
available for the input features'''
print('\n')
boston_df.head()
```

Out[148]:
```
'here we are trying to snowball and determine first five rows of sample data
available for the input features'
```

Out[148]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.

In [149]:
```
'''hear we added Target variable also in our dataframe and snowballing first f
ive rows of sample data available
for the input features as well as of the target variable'''
boston_df['House_Price']=boston.target
print('\n')
boston_df.head()
```

Out[149]:
```
'hear we added Target variable also in our dataframe and snowballing first fi
ve rows of sample data available \nfor the input features as well as of the t
arget variable'
```

Out[149]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.

In [150]:
```
'''here we got more discriptions of the input variable and also target variabl
e i.e. House_Price and
those desriptions are like getting mean,std devaiation,min,max,and data in 2
5%,50% and 75% quartile for all the listed
input features as well as the target variable'''
boston_df.describe()
```

Out[150]:
```
'here we got more discriptions of the input variable and also target variable
i.e. House_Price and\nthose desriptions are like getting mean,std devaiation,
min,max,and data in 25%,50% and 75% quartile for all the listed\ninput featur
es as well as the target variable'
```

Out[150]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12

In [151]:
```
'''here we are fetermine how the input and target variables are
coorelated among themselves.we determine the strength and direction of correla
tion.
for example we find that LSTAT IS negatively correlated with housing price and
value is -0.74
that means that for increase in LSTAT there is going to be decrease in housing
price.so LSAT is
negatively coorelated with house price and coorelation strength is 0.74.'''
x=boston_df.corr()
x
```

Out[151]:
```
'here we are fetermine how the input and target variables are\ncoorelated amo
ng themselves.we determine the strength and direction of correlation.\nfor ex
ample we find that LSTAT IS negatively correlated with housing price and valu
e is -0.74\nthat means that for increase in LSTAT there is going to be decrea
se in housing price.so LSAT is\nnegatively coorelated with house price and co
orelation strength is 0.74.'
```

Out[151]:

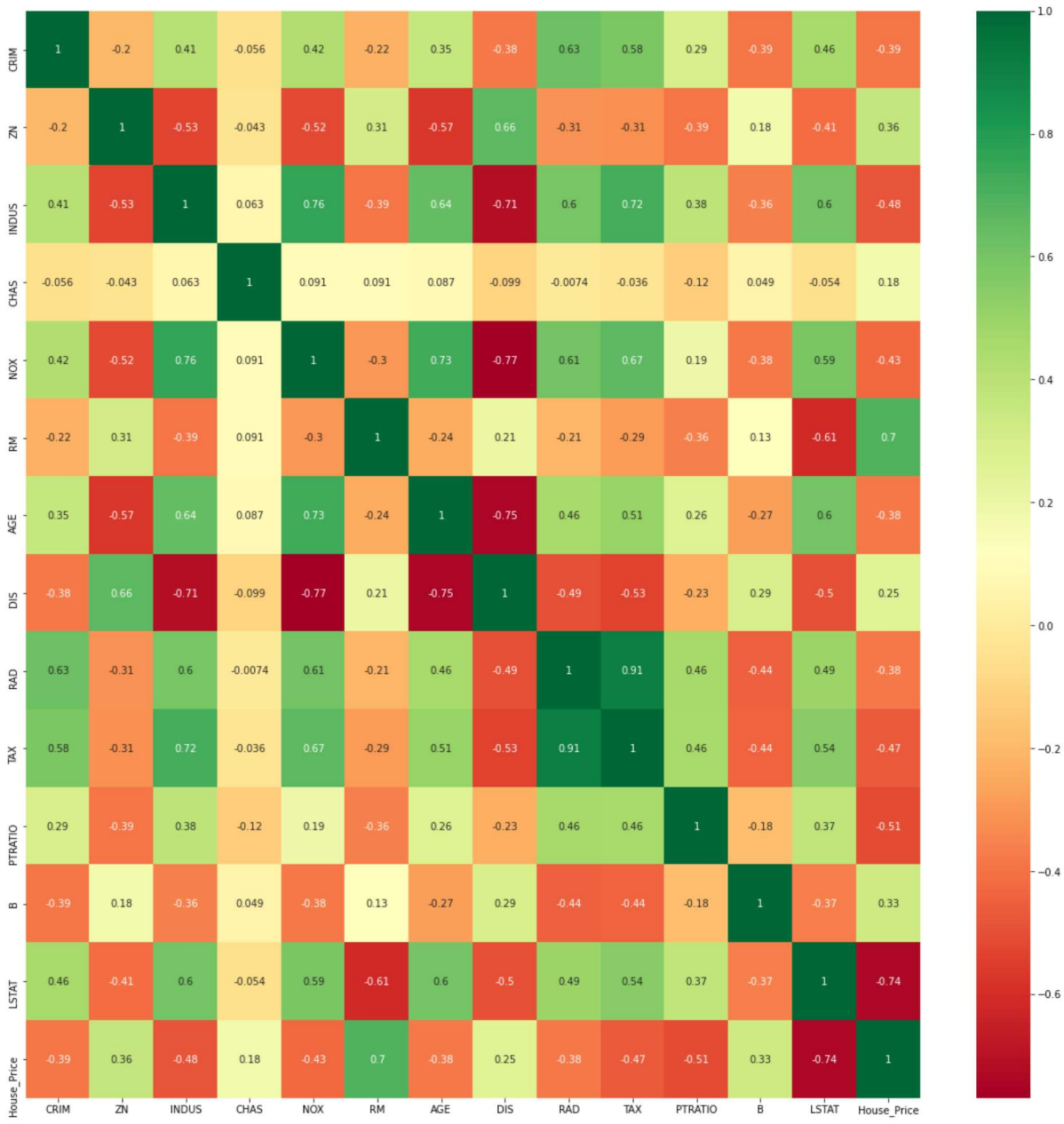
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.3796
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.6644
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.7080
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.0991
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.7692
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.2052
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.7478
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.0000
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.4945
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.5344
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.2324
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.2915
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.4969
House_Price	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.2499

In [152]:
```
'''here we plot heatmap for the coorelation between input features and target
 variable.
#AS PER THE HEATMAP,PTRATIO IS -0.51 INDUS=-0.48,TAX is -0.47,LSTAT is  -0.74.
SO THEY ARE  highly NEGATIVE CORRELATED
#WITH House_price meaning with decrease in THEIR VALUES,HOUSE_PRICE INCREASE
S.'''
import matplotlib.pyplot as plt
%matplotlib inline
plt.subplots(figsize=(20,20))
sns.heatmap(x,cmap='RdYlGn',annot=True)
plt.show()
```

Out[152]: 'here we plot heatmap for the coorelation between input features and target v
ariable.\n#AS PER THE HEATMAP,PTRATIO IS -0.51 INDUS=-0.48,TAX is -0.47,LSTAT
is -0.74. SO THEY ARE highly NEGATIVE CORRELATED \n#WITH House_price meanin
g with decrease in THEIR VALUES,HOUSE_PRICE INCREASES.'

Out[152]: (<Figure size 1440x1440 with 1 Axes>,
<matplotlib.axes._subplots.AxesSubplot at 0x7fb54d59a588>)

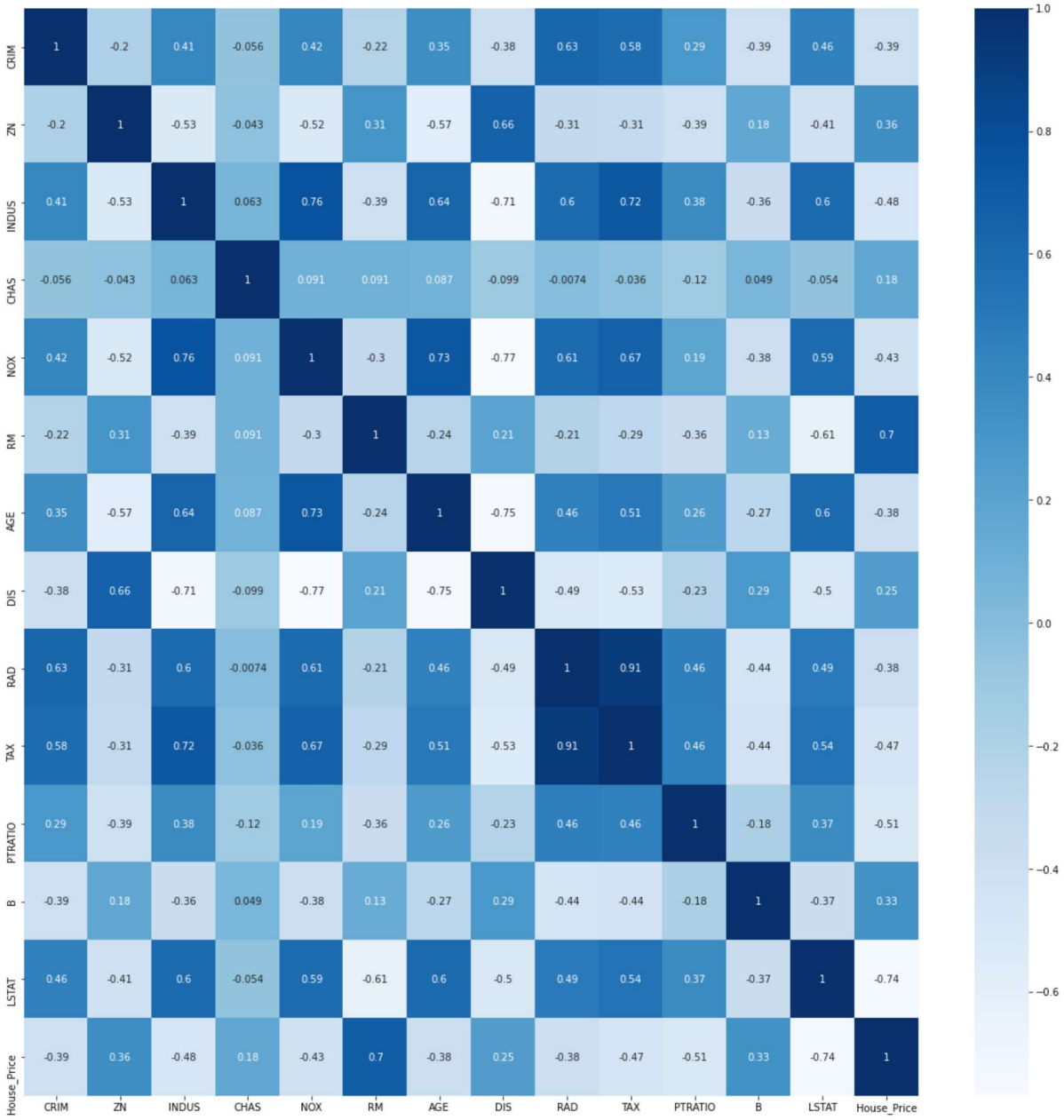
Out[152]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb54d59a588>



In [153]:
```
plt.subplots(figsize=(20,20))
sns.heatmap(x,cmap='Blues',annot=True)
plt.show()
```

Out[153]:
```
(<Figure size 1440x1440 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7fb54d6c5eb8>)
```

Out[153]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb54d6c5eb8>
```



In [154]:
```
'''data preparation and/or cleaning operation
clearly we find that input feature CHAS has weak correlation of 0.18 and simil
arly DIS has weak correlation of 0.25
so we can remove these input features before building the model.'''
#STEP1=CREATE FEATURES AND LABEL
x=boston_df.drop(['CHAS','DIS','House_Price'],axis=1)
print('\n')
x.head()
y=boston_df['House_Price']
y.head()
```

Out[154]:
```
'data preparation and/or cleaning operation\nclearly we find that input featu
re CHAS has weak correlation of 0.18 and similarly DIS has weak correlation o
f 0.25\nso we can remove these input features before building the model.'
```

Out[154]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.538	6.575	65.2	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.469	6.421	78.9	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.469	7.185	61.1	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.458	6.998	45.8	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.458	7.147	54.2	3.0	222.0	18.7	396.90	5.33

Out[154]:
```
0    24.0
1    21.6
2    34.7
3    33.4
4    36.2
Name: House_Price, dtype: float64
```

In [155]:
```
x.shape
y.shape
```

Out[155]:
```
(506, 11)
```

Out[155]:
```
(506,)
```

In [156]:
```
#SCALE ALL VALUES BETWEEN 0 AND 1
#HERE WE ARE TRYING TO CONVERT UNSTANDARDIZED COEFFICIENTS TO STANDARDIZED COE
FFICIENTS AND ALSO LIMITING COEFFICIENTS VALUES BETWEEN 0 AND 1
import sklearn
from sklearn.preprocessing import MinMaxScaler
scld=MinMaxScaler(feature_range=(0,1))
arr_scld=scld.fit_transform(x)
x_scld=pd.DataFrame(arr_scld,columns=x.columns)
x_scld.head()
x_scld.describe()
```

Out[156]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	
0	0.000000	0.18	0.067815	0.314815	0.577505	0.641607	0.000000	0.208015	0.287234	1.0000
1	0.000236	0.00	0.242302	0.172840	0.547998	0.782698	0.043478	0.104962	0.553191	1.0000
2	0.000236	0.00	0.242302	0.172840	0.694386	0.599382	0.043478	0.104962	0.553191	0.9897
3	0.000293	0.00	0.063050	0.150206	0.658555	0.441813	0.086957	0.066794	0.648936	0.9942
4	0.000705	0.00	0.063050	0.150206	0.687105	0.528321	0.086957	0.066794	0.648936	1.0000

Out[156]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506
mean	0.040544	0.113636	0.391378	0.349167	0.521869	0.676364	0.371713	0
std	0.096679	0.233225	0.251479	0.238431	0.134627	0.289896	0.378576	0
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0
25%	0.000851	0.000000	0.173387	0.131687	0.445392	0.433831	0.130435	0
50%	0.002812	0.000000	0.338343	0.314815	0.507281	0.768280	0.173913	0
75%	0.041258	0.125000	0.646628	0.491770	0.586798	0.938980	1.000000	0
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1

In [157]:
```
'''STEP2 SPLIT TEST AND TRAIN
here we are creating seperate test and train samples with 25% test and 70% tra
in samples
we will build model on train sample and evaluate the model on test sample'''
train_x,test_x,train_y,test_y=train_test_split(x_scld,y,test_size=0.25,random_
state=1)
train_x.shape
test_x.shape
train_y.shape
test_y.shape
```

Out[157]:
```
'STEP2 SPLIT TEST AND TRAIN\nhere we are creating seperate test and train sam
ples with 25% test and 70% train samples\nwe will build model on train sample
and evaluate the model on test sample'
```

Out[157]:
```
(379, 11)
```

Out[157]:
```
(127, 11)
```

Out[157]:
```
(379,)
```

Out[157]:
```
(127,)
```

In [158]:
```
type(train_x)
```

Out[158]:
```
pandas.core.frame.DataFrame
```

In [159]:
```
type(train_y)
```

Out[159]:
```
pandas.core.series.Series
```

In [160]:
```
#STEP 3:CREATE INSTANT OF THE MODEL
from sklearn.linear_model import LinearRegression
lm=LinearRegression()
lm
```

Out[160]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [0]:
```
lm?
```

In [162]:
```
#STEP 4:FIT THE MODEL
lm.fit(train_x,train_y)
```

Out[162]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [163]:
```
#STEP5 PREDICT USING THE TRAINED MODEL
predicted_values=lm.predict(test_x)
predicted_values
```

Out[163]:
```
array([29.5336412 , 27.58230169, 20.61861473, 22.41492046, 19.95109785,
       20.52525149, 28.13947259, 19.34127244, 22.7264299 , 25.38599744,
       28.12828099, 28.53267076, 19.86733775, 24.94076899, 23.03840341,
       20.09299449, 16.49998253, 38.0327241 , 28.54019243,  9.5109598 ,
       21.65098929, 17.87141616, 26.11205305, 25.14665072, 29.34363159,
       10.64324809, 14.04648809, 21.33377124, 35.47210997, 14.52666643,
       26.3404152 , 17.90005463, 39.27010486, 19.08663922, 23.10732596,
       17.99262948, 18.38914067, 29.45119642,  8.21138158, 21.32879432,
       24.2302001 , 23.78150418, 29.39517959, 16.06158042, 19.49595338,
       14.08940901, 38.67450474, 18.24188668, 27.09054988, 18.97070932,
       25.19606247, 26.72790448, 27.33356386, 27.64490369,  4.17826575,
       27.30896908,  9.38880425, 25.25941849, 17.55435813, 36.35046933,
       20.23053355, 27.47587765, 16.34383728, 18.19995103,  8.08459159,
       30.2500781 , 37.65026693, 25.20624099, 26.85399563, 26.38369384,
       24.37317708,  6.32314305, 16.43078639, 21.5059822 , 18.39885533,
       22.28896909, 31.27320515, 28.44076289, 27.69434479, 30.65681521,
       18.35805318, 23.43193467, 32.50371903, 14.05567802, 24.08739264,
       30.54098311, 17.95557939, 24.83818916, 18.32169587, 17.06457142,
       26.02937502, 40.49930773, 14.45747921, 25.74179832, 14.88351358,
       25.86275577, 21.55457025, 27.70643842, 36.68574941, 18.14114963,
       15.89543249, 18.55030063, 25.63856474, 24.7090281 ,  7.50265659,
       22.61946285, 14.71739896, 30.97287803, 23.11975216, 23.82946935,
       37.27463092, 27.81626698, 14.07975012, 32.07671613, 34.90193244,
       33.43286971, 21.2841254 , 15.12276312, 30.83097093, 37.96526412,
       21.55053263, 16.76538643, 28.0454918 , 20.07885884, 27.8984897 ,
       19.54985378, 27.40234327])
```

In [164]:
```
#STEP6-EVALUATE MODEL PERFORMANCE
from sklearn.metrics import mean_absolute_error
print("MEAN ABSOLUTE ERROR (MAE) FOR TEST DATA IS")
round(mean_absolute_error(predicted_values,test_y),3)
```

```
MEAN ABSOLUTE ERROR (MAE) FOR TEST DATA IS
```

Out[164]:
```
3.871
```

In [165]:
```
from sklearn import metrics
print("MEAN SQUARE ERROR (MSE) FOR TEST DATA IS")
np.round(metrics.mean_squared_error(test_y,predicted_values),0)
```

```
MEAN SQUARE ERROR (MSE) FOR TEST DATA IS
```

Out[165]:
```
25.0
```

In [166]:
```
from sklearn.metrics import median_absolute_error
print("MEDIAN ABSOLUTE ERROR (MAE) FOR TEST DATA IS")
round(median_absolute_error(predicted_values,test_y))
```

```
MEDIAN ABSOLUTE ERROR (MAE) FOR TEST DATA IS
```

Out[166]:
```
3.0
```

In [167]:
```
print(lm.coef_)
df_m=pd.DataFrame({'features':x_scld.columns,'coeff':lm.coef_})
```

```
[ -8.128503     0.87511848   3.65857823  -6.34943641  17.03835315
   3.66793138   7.36447978  -5.91226465 -10.88027562   2.95463795
 -21.22615166]
```

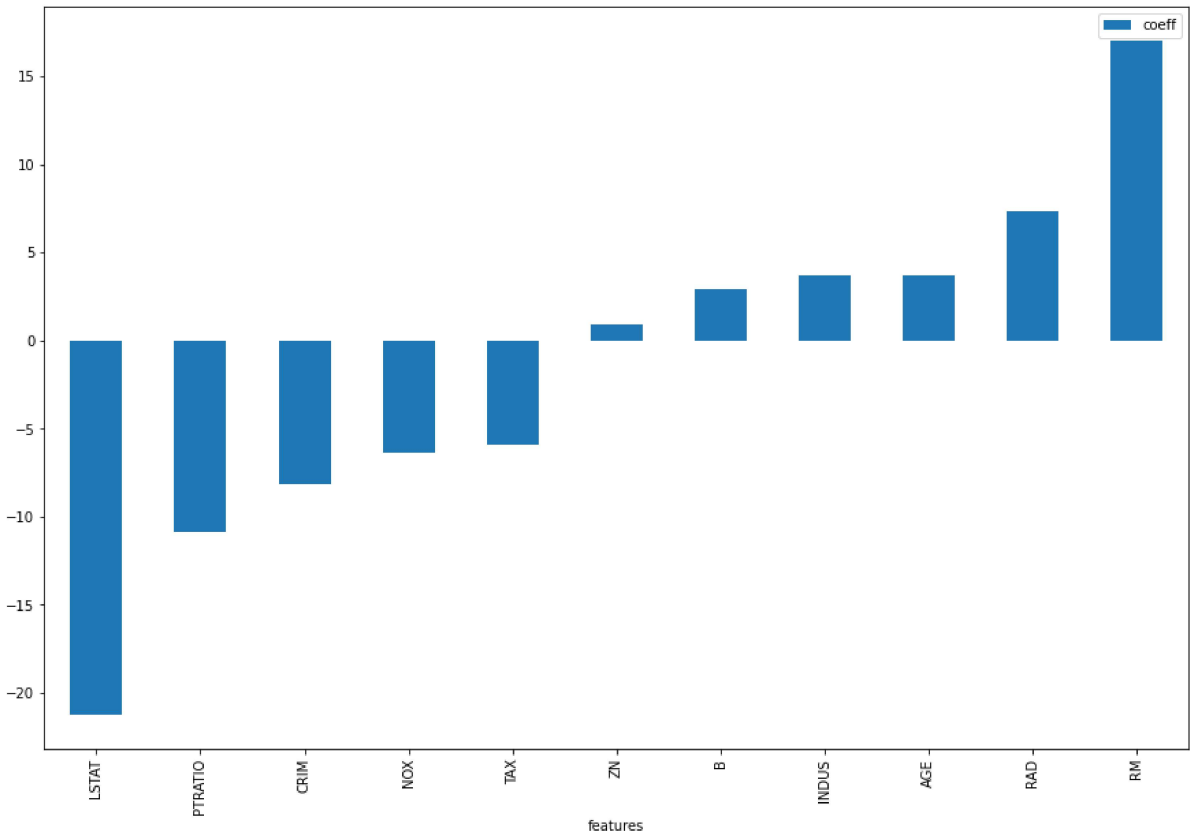
In [0]:
```
df_m=df_m.sort_values(by=['coeff'])
```

In [169]:
```
df_m
```

Out[169]:

	features	coeff
10	LSTAT	-21.226152
8	PTRATIO	-10.880276
0	CRIM	-8.128503
3	NOX	-6.349436
7	TAX	-5.912265
1	ZN	0.875118
9	B	2.954638
2	INDUS	3.658578
5	AGE	3.667931
6	RAD	7.364480
4	RM	17.038353

In [170]:
```
df_m.plot(x='features',y='coeff',kind='bar',figsize=(15,10))
plt.show();
```



In [171]:
```
"R-SQUARE VALUE FOR TEST DATA IS"
np.round(lm.score(test_x,test_y)*100,0)
```

Out[171]: 'R-SQUARE VALUE FOR TEST DATA IS'

Out[171]: 75.0

In [172]:
```
"R-SQUARE VALUE FOR TRAIN DATA IS"
np.round(lm.score(train_x,train_y)*100,0)
```

Out[172]: 'R-SQUARE VALUE FOR TRAIN DATA IS'

Out[172]: 68.0

In [173]:
```
type(pd.DataFrame({'features':x.columns,'coeff':lm.coef_}))
```

Out[173]: pandas.core.frame.DataFrame

In [174]:
```
#INVERSE SCALING TO REVERT BACK TO SAME SCALE
df1=pd.DataFrame(scld.inverse_transform(x_scld),columns=x.columns)
df1.head()
x.head()
```

Out[174]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.538	6.575	65.2	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.469	6.421	78.9	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.469	7.185	61.1	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.458	6.998	45.8	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.458	7.147	54.2	3.0	222.0	18.7	396.90	5.33

Out[174]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.538	6.575	65.2	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.469	6.421	78.9	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.469	7.185	61.1	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.458	6.998	45.8	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.458	7.147	54.2	3.0	222.0	18.7	396.90	5.33

In [0]:
```
#In the last step we are appending the predicted house prices into
#the original data and computing the error in estimation for the test data.
fdf=pd.concat([test_x,test_y],1)
```

In [176]:
```
fdf['Predicted']=np.round(predicted_values,1)
fdf['Prediction_Error']=fdf['House_Price']-fdf['Predicted']
fdf
```

Out[176]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	
307	0.000483	0.330	0.063050	0.179012	0.630006	0.694130	0.260870	0.066794	0.617021	1.0
343	0.000215	0.550	0.121701	0.203704	0.600690	0.550978	0.173913	0.349237	0.531915	1.0
47	0.002506	0.000	0.236437	0.129630	0.473079	0.850669	0.086957	0.087786	0.563830	0.9
67	0.000580	0.125	0.205645	0.049383	0.443955	0.190525	0.130435	0.301527	0.670213	0.9
362	0.041271	0.000	0.646628	0.792181	0.345085	0.960865	1.000000	0.914122	0.808511	0.9
...	...	...	...	...	...	...	...	...	...	
41	0.001361	0.000	0.236437	0.129630	0.614869	0.000000	0.086957	0.087786	0.563830	0.9
361	0.043054	0.000	0.646628	0.792181	0.515424	0.908342	1.000000	0.914122	0.808511	0.8
289	0.000412	0.525	0.178152	0.041152	0.575589	0.205973	0.217391	0.202290	0.425532	0.9
498	0.002617	0.000	0.338343	0.411523	0.470971	0.642636	0.217391	0.389313	0.702128	1.0
293	0.000858	0.000	0.493402	0.106996	0.491665	0.159629	0.130435	0.194656	0.361702	1.0

127 rows × 14 columns

In [177]:
```
'''Here we will use churn dataset to perform Logistic regression which is one
 of the classification
type of Supervised Model Building procedure.'''
df=pd.read_csv("churn.csv")
```

Out[177]:
```
'Here we will use churn dataset to perform Logistic regression which is one o
f the classification \ntype of Supervised Model Building procedure.'
```

In [178]:
```
'''we can find that our churn datset has 21 variables each comprising
of 7043 rows of data.This include the input features as well as the Target var
iable'''
print('\n')
df.shape
```

Out[178]:
```
'we can find that our churn datset has 21 variables each comprising\nof 7043
rows of data.This include the input features as well as the Target variable'
```

Out[178]:
```
(7043, 21)
```

In [179]:
```
type(df)
```

Out[179]:
```
pandas.core.frame.DataFrame
```

In [180]:
```
'''hear we included Target variable also in our dataframe and snowballing firs
t five rows of sample data available
for the input features as well as of the target variable'''
print('\n')
df.head()
```

Out[180]:
```
'hear we included Target variable also in our dataframe and snowballing first
five rows of sample data available \nfor the input features as well as of the
target variable'
```

Out[180]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service
4	9237-HQITU	Female	0	No	No	2	Yes	No

In [181]:
```
'''hear we included Target variable also in our dataframe and snowballing last
five rows of sample data available
for the input features as well as of the target variable'''
print('\n')
df.tail()
```

Out[181]:
```
'hear we included Target variable also in our dataframe and snowballing last
five rows of sample data available \nfor the input features as well as of the
target variable'
```

Out[181]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLin
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Y
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Y
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phc serv
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Y
7042	3186-AJIEK	Male	0	No	No	66	Yes	

In [182]:
```
df.size
```

Out[182]: 147903

In [183]:
```
'''from the below function we find that we have 21 variables and each one has
 7043 rows meaning to
say that we don't have missing value for any of the variables
Churn is our target variable which is also a catigorical variable having two o
utcomes
i.e. yes or no.hence by building the logistic regression
model we will decide the precison,recall  and accuracy for churn is equal to y
es
and also churn is equal to no.
here SeniorCitizen,tenure  and MonthlyCharges are all numeric variables i.e. s
cale features.
remaining other features are all categorical variables'''
print('\n')
df.info()
```

Out[183]:
```
"from the below function we find that we have 20 variables and each one has 7
043 rows meaning to\nsay that we don't have missing value for any of the vari
ables\nChurn is our target variable which is also a catigorical variable havi
ng two outcomes \ni.e. yes or no.hence by building the logistic regression \n
model we will decide the precison,recall  and accuracy for churn is equal to
yes\nand also churn is equal to no.\nhere SeniorCitizen,tenure  and MonthlyCh
arges are all numeric variables i.e. scale features.\nremaining other feature
s are all categorical variables"


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [184]:
```
#here we found that none of the variables has any missing values
pd.isnull(df).any()
```

Out[184]:
```
customerID          False
gender              False
SeniorCitizen       False
Partner             False
Dependents          False
tenure              False
PhoneService        False
MultipleLines       False
InternetService     False
OnlineSecurity      False
OnlineBackup        False
DeviceProtection    False
TechSupport         False
StreamingTV         False
StreamingMovies     False
Contract            False
PaperlessBilling    False
PaymentMethod       False
MonthlyCharges      False
TotalCharges        False
Churn               False
dtype: bool
```

In [185]:
```
pd.isnull(df).sum()
```

Out[185]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [186]:
```
'''here we got more discriptions of the SeniorCitizen,tenure  and MonthlyCharg
es as they are all numeric variables i.e. scale features. and
those desriptions are like getting mean,std devaiation,min,max,and data in 2
5%,50% and 75% quartile for the listed
input features '''
print('\n')
df.describe()
```

Out[186]:
```
'here we got more discriptions of the SeniorCitizen,tenure  and MonthlyCharge
s as they are all numeric variables i.e. scale features. and\nthose desriptio
ns are like getting mean,std devaiation,min,max,and data in 25%,50% and 75% q
uartile for the listed\ninput features '
```

Out[186]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

In [187]:
```
'''DUMMY CODING USING THE LOOP STRUCTURE here we converted yes and no to 1 and
0
for all categorical variables including the target variable i.e. churn'''
print('\n')
for col in df.columns:
  if df[col].dtype=='object':
    df[col]=pd.Categorical(df[col]).codes
    df.head(5)
```

Out[187]: 'DUMMY CODING USING THE LOOP STRUCTURE here we converted yes and no to 1 and 0 \nfor all categorical variables including the target variable i.e. churn'

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	Female	0	Yes	No	1	No	No phone service
1	3962	Male	0	No	No	34	Yes	No
2	2564	Male	0	No	No	2	Yes	No
3	5535	Male	0	No	No	45	No	No phone service
4	6511	Female	0	No	No	2	Yes	No

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	Yes	No	1	No	No phone service
1	3962	1	0	No	No	34	Yes	No
2	2564	1	0	No	No	2	Yes	No
3	5535	1	0	No	No	45	No	No phone service
4	6511	0	0	No	No	2	Yes	No

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	No	1	No	No phone service
1	3962	1	0	0	No	34	Yes	No
2	2564	1	0	0	No	2	Yes	No
3	5535	1	0	0	No	45	No	No phone service
4	6511	0	0	0	No	2	Yes	No

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	No	No phone service
1	3962	1	0	0	0	34	Yes	No
2	2564	1	0	0	0	2	Yes	No
3	5535	1	0	0	0	45	No	No phone service
4	6511	0	0	0	0	2	Yes	No

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	0	No phone service
1	3962	1	0	0	0	34	1	No
2	2564	1	0	0	0	2	1	No
3	5535	1	0	0	0	45	0	No phone service
4	6511	0	0	0	0	2	1	No

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	0	1
1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
3	5535	1	0	0	0	45	0	1
4	6511	0	0	0	0	2	1	0

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	0	1
1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
3	5535	1	0	0	0	45	0	1
4	6511	0	0	0	0	2	1	0

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	0	1
1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
3	5535	1	0	0	0	45	0	1
4	6511	0	0	0	0	2	1	0

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	5375	0	0	1	0	1	0	1
1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
3	5535	1	0	0	0	45	0	1
4	6511	0	0	0	0	2	1	0

Out[187]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
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1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
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	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
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	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
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1	3962	1	0	0	0	34	1	0
2	2564	1	0	0	0	2	1	0
3	5535	1	0	0	0	45	0	1
4	6511	0	0	0	0	2	1	0

In [188]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   int16  
 1   gender            7043 non-null   int8   
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   int8   
 4   Dependents        7043 non-null   int8   
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   int8   
 7   MultipleLines     7043 non-null   int8   
 8   InternetService   7043 non-null   int8   
 9   OnlineSecurity    7043 non-null   int8   
 10  OnlineBackup      7043 non-null   int8   
 11  DeviceProtection  7043 non-null   int8   
 12  TechSupport       7043 non-null   int8   
 13  StreamingTV       7043 non-null   int8   
 14  StreamingMovies   7043 non-null   int8   
 15  Contract          7043 non-null   int8   
 16  PaperlessBilling  7043 non-null   int8   
 17  PaymentMethod     7043 non-null   int8   
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   int16  
 20  Churn             7043 non-null   int8   
dtypes: float64(1), int16(2), int64(2), int8(16)
memory usage: 302.8 KB
```

In [189]:
```
'''data preparation and/or cleaning operation
clearly we find that input feature customerID and TotalCharges are irrelevant
 in determining
whether target variable i.e. churn will be 0 or 1
so we can remove these input features before building the model.'''
print('\n')
x=df.drop(['customerID','TotalCharges','Churn'],axis=1)
x.head()
```

Out[189]:
```
'data preparation and/or cleaning operation\nclearly we find that input featu
re customerID and TotalCharges are irrelevant in determining\nwhether target
variable i.e. churn will be 0 or 1\nso we can remove these input features bef
ore building the model.'
```

Out[189]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServi
0	0	0	1	0	1	0	1	
1	1	0	0	0	34	1	0	
2	1	0	0	0	2	1	0	
3	1	0	0	0	45	0	1	
4	0	0	0	0	2	1	0	

In [190]:
```
y=df['Churn']
y.head()
```

Out[190]:
```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int8
```

In [192]:
```
#create test and train data 70% and 30% split
train_x,test_x,train_y,test_y=train_test_split(x,y,test_size=0.3)
train_x.shape
test_x.shape
train_x.shape
train_y.shape
```

Out[192]: (4930, 18)

Out[192]: (2113, 18)

Out[192]: (4930, 18)

Out[192]: (4930,)

In [0]:
```
#BUILD A LOGISTIC REGRESSION MODEL
from sklearn.linear_model import LogisticRegression
log=LogisticRegression(max_iter=1000)
```

In [194]:
```
log.fit(train_x,train_y)
```

Out[194]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [195]:
```
log.coef_
```

Out[195]:
```
array([[ 0.02065473,  0.21040511,  0.04477025, -0.25185287, -0.03378192,
        -1.11659143,  0.07953846,  0.27110324, -0.27666299, -0.14602112,
        -0.04057135, -0.2982555 ,  0.00136595,  0.01744049, -0.60625901,
         0.42492908,  0.07404845,  0.02800835]])
```

In [0]:
```
#FIND OUT KEY PREDICTOR OF CHURN
coeff=pd.concat([pd.DataFrame(x.columns),pd.DataFrame(np.transpose(log.coef_
))],axis=1)
```

In [197]:
```
coeff.columns=("variables","coeff")
coeff.sort_values("variables",ascending=True)
```

Out[197]:

	variables	coeff
14	Contract	-0.606259
3	Dependents	-0.251853
10	DeviceProtection	-0.040571
7	InternetService	0.271103
17	MonthlyCharges	0.028008
6	MultipleLines	0.079538
9	OnlineBackup	-0.146021
8	OnlineSecurity	-0.276663
15	PaperlessBilling	0.424929
2	Partner	0.044770
16	PaymentMethod	0.074048
5	PhoneService	-1.116591
1	SeniorCitizen	0.210405
13	StreamingMovies	0.017440
12	StreamingTV	0.001366
11	TechSupport	-0.298255
0	gender	0.020655
4	tenure	-0.033782

In [198]:
```
#GENERATE MODEL DIAGNOSTICS
classes=log.predict(test_x)
print(classes.size)
```

```
2113
```

In [199]:
```
print("positive cases in test data:",test_y[test_y==1].shape[0])
print("Negative cases in Test Data:",test_y[test_y==0].shape[0])
```

```
positive cases in test data: 562
Negative cases in Test Data: 1551
```

In [200]:
```
#PRECISION AND RECALL
print("ACCUIRACY SCORE")
print(metrics.accuracy_score(test_y,classes))
```

```
ACCUIRACY SCORE
0.8007572172266919
```

In [201]:
```
#PRECISION RECALL MATRIX
print("precision/recall Metrics")
print(metrics.classification_report(test_y,classes))
```

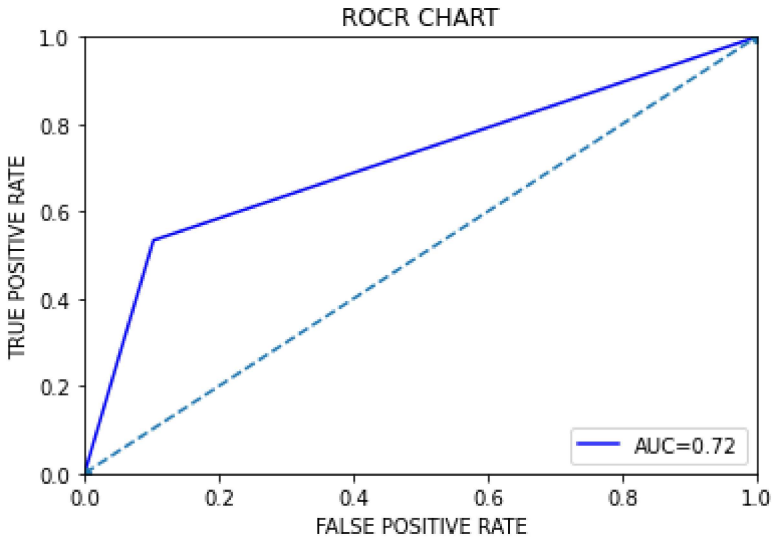
```
precision/recall Metrics
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1551
           1       0.65      0.53      0.59       562

    accuracy                           0.80      2113
   macro avg       0.75      0.72      0.73      2113
weighted avg       0.79      0.80      0.79      2113
```

In [202]:
```
#AUC
print("AUC")
auc=metrics.roc_auc_score(test_y,classes)
auc
```

```
AUC
```

Out[202]:
```
0.7156466612058343
```

In [203]:
```
'''ROC CHART:from ROC CHART we find that Area under curve is 70.94% which is p
retty significant'''
print('\n')
fpr,tpr,th=roc_curve(test_y,classes)
roc_auc=metrics.auc(fpr,tpr)
import matplotlib.pyplot as plt
plt.title("ROCR CHART")
plt.plot(fpr,tpr,'b',label="AUC=%0.2F"%roc_auc)
plt.legend(loc="lower right")
plt.plot([0,1],[0,1],"o--")
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel("TRUE POSITIVE RATE")
plt.xlabel("FALSE POSITIVE RATE")
plt.show();
```



In [204]:
```
#CONFUSION MATRIX
print("CONFUSION MATRIX")
cf=metrics.confusion_matrix(test_y,classes)
lbl1=["Predicted 0","Predicted 1"]
lbl2=["True 0","True 1"]
sns.heatmap(cf,annot=True,cmap="Greens",fmt="d",xticklabels=lbl1,yticklabels=l
bl2)
plt.show()
```

```
CONFUSION MATRIX
```

Out[204]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb54d1ab4e0>
```