Gradient Boosted Trees

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

%matplotlib inline
# sns.set_style("whitegrid")
```

In [2]:

```
df=pd.read_csv("https://raw.githubusercontent.com/training-ml/Files/main/heart_disease.csv"
df.head()
```

Out[2]:

	Unnamed: 0	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca
0	0	63	1	3	145	233	1	0	150	0	2.3	0	0
1	1	37	1	2	130	250	0	1	187	0	3.5	0	0
2	2	41	0	1	130	204	0	0	172	0	1.4	2	0
3	3	56	1	1	120	236	0	1	178	0	0.8	2	0
4	4	57	0	0	120	354	0	1	163	1	0.6	2	0

In [3]:

```
df.drop('Unnamed: 0', axis=1,inplace=True)
```

In [4]:

```
df.describe()
```

Out[4]:

	age	sex	cp	trestbps	chol	fbs	restecg	
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	30
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	14
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	2
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	7
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	13
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	15
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	16
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	20

In [5]:

```
# Checking for missing values
df.isna().sum()
```

Out[5]:

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

In [6]:

```
#Just find correlation of feature vs target using corrwith
df.drop('target',axis=1).corrwith(df.target)
```

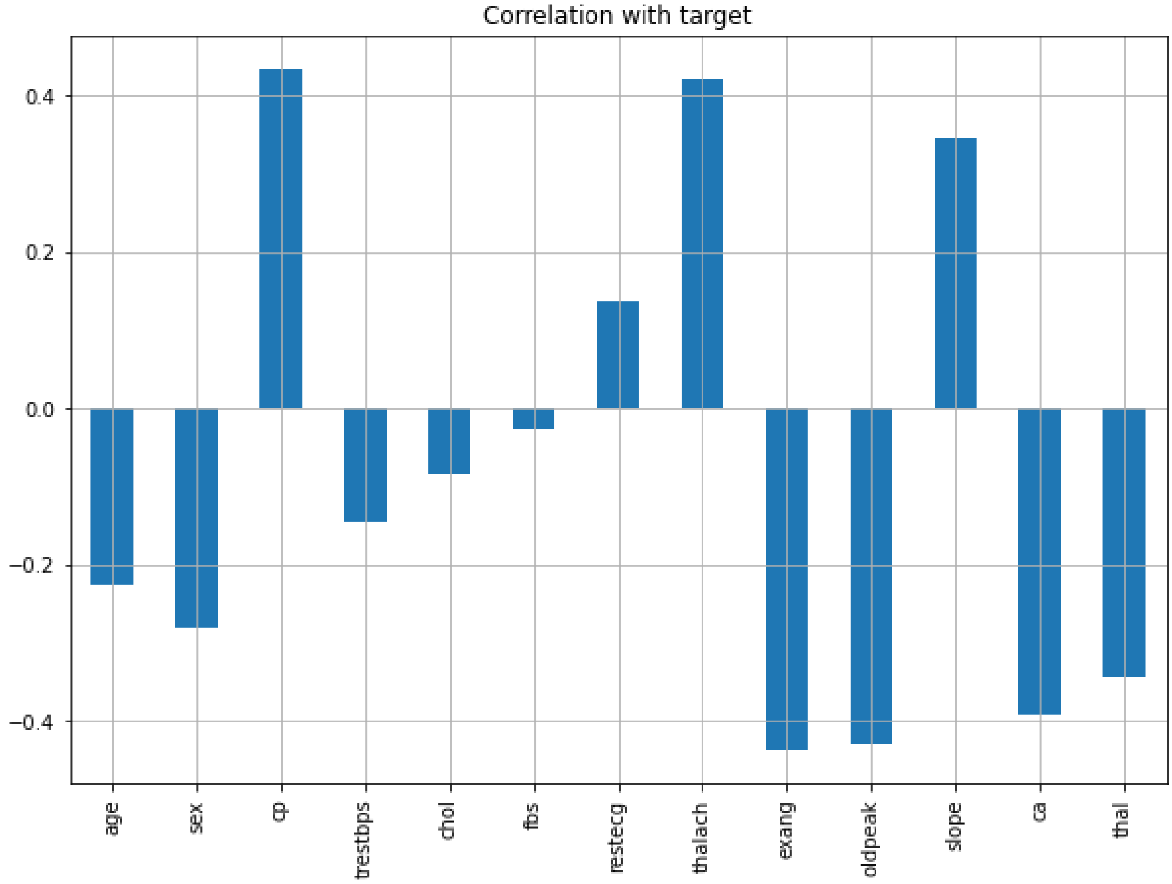
Out[6]:

```
age        -0.225439
sex        -0.280937
cp          0.433798
trestbps   -0.144931
chol       -0.085239
fbs        -0.028046
restecg     0.137230
thalach     0.421741
exang      -0.436757
oldpeak    -0.430696
slope       0.345877
ca         -0.391724
thal       -0.344029
dtype: float64
```

Visualize the correlation

In [7]:

```
df.drop('target',axis=1).corrwith(df.target).plot(kind='bar',grid=True,figsize=(10,7),
                                                   title="Correlation with target")
plt.show()
```



Let's work on feature selection and see if that can help us building better model.

Model building using SelectPercentile features

In [8]:

```
from sklearn.feature_selection import SelectPercentile
from sklearn.feature_selection import chi2
```

when we apply chi2 we get p values for all feature. Based on the p values. it will select top 80% of features.

Example- If p-value <0.05, it will reject null hypothesis. Default null hypothesis is , there is no relation b/w feature and Target

In [9]:

```
#Instantiate selectpercentile and fit (feature, Label)
x=df.drop(['target'], axis=1)
y=df.target
SPercentile =SelectPercentile(score_func=chi2,percentile=80)
SPercentile= SPercentile.fit(x,y)
```

In [10]:

```
#Seperate the features to check p_values
cols=SPercentile.get_support(indices=True) # to return index numbers instead of boolean
print('Feature Index=', cols)

features=x.columns[cols]
print('Features=',list(features))
```

```
Feature Index= [ 0  1  2  3  4  7  8  9 10 11]
Features= ['age', 'sex', 'cp', 'trestbps', 'chol', 'thalach', 'exang', 'oldp
eak', 'slope', 'ca']
```

In [11]:

```
df_scores=pd.DataFrame({'features':x.columns,'chi2score':SPercentile.scores_,'pValue':SPerc
df_scores.sort_values(by='chi2score',ascending=False)
```

Out[11]:

	features	chi2score	pValue
7	thalach	188.320472	7.395102e-43
9	oldpeak	72.644253	1.552583e-17
11	ca	66.440765	3.605677e-16
2	cp	62.598098	2.534982e-15
8	exang	38.914377	4.428074e-10
4	chol	23.936394	9.957148e-07
0	age	23.286624	1.395673e-06
3	trestbps	14.823925	1.180286e-04
10	slope	9.804095	1.741237e-03
1	sex	7.576835	5.912318e-03
12	thal	5.791853	1.610061e-02
6	restecg	2.978271	8.438939e-02
5	fbs	0.202934	6.523632e-01

Let's print the top 80% features

In [12]:

```
# create subset of selected features

x=df[features]
y=df.target
```

In [13]:

```
#Import Libs
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

scaler=StandardScaler()
x_scaler=scaler.fit_transform(x)
x_train,x_test,y_train,y_test=train_test_split(x_scaler,y,test_size=0.3,random_state=42)
```

GradientBoostingClassifier

In [14]:

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [15]:

```
gbdt_clf=GradientBoostingClassifier()
gbdt_clf.fit(x_train,y_train)
pred=gbdt_clf.predict(x_train)
gbdt_clf_report=pd.DataFrame(classification_report(y_train,pred,output_dict=True))
print("\n==============================Train Result==============================")

print(f"Accuracy score:{accuracy_score(y_train,pred)* 100 :.2f}%")
print("==============================================")
print(f"CLASSIFICATION REPORT : \n{gbdt_clf_report}")
print("==================================================")
print(f"confusion Matrix: \n{confusion_matrix(y_train,pred)}\n")


#**************************Test Score********************************

pred = gbdt_clf.predict(x_test)
clf_report=pd.DataFrame(classification_report(y_test,pred,output_dict=True))

print("\n==============================Test Result==============================")

print(f"Accuracy score:{accuracy_score(y_test,pred)* 100 :.2f}%")
print("==============================================")
print(f"CLASSIFICATION REPORT : \n{clf_report}")
print("==================================================")
print(f"confusion Matrix: \n{confusion_matrix(y_test,pred)}\n")
```

```
==============================Train Result==============================
Accuracy score:100.00%
==============================================
CLASSIFICATION REPORT :
              0      1  accuracy  macro avg  weighted avg
precision   1.0    1.0       1.0        1.0           1.0
recall      1.0    1.0       1.0        1.0           1.0
f1-score    1.0    1.0       1.0        1.0           1.0
support    97.0  115.0       1.0      212.0         212.0
==================================================
confusion Matrix:
[[ 97   0]
 [  0 115]]


==============================Test Result==============================
Accuracy score:83.52%
==============================================
CLASSIFICATION REPORT :
                   0          1  accuracy  macro avg  weighted avg
precision   0.809524   0.857143  0.835165   0.833333      0.835688
recall      0.829268   0.840000  0.835165   0.834634      0.835165
f1-score    0.819277   0.848485  0.835165   0.833881      0.835325
support    41.000000  50.000000  0.835165  91.000000     91.000000
==================================================
confusion Matrix:
[[34  7]
 [ 8 42]]
```

In [16]:

```
#Let's try if we can improve the performance of our model using parameter tuning
```

Hyperparameter tuning

In [17]:

```
from sklearn.model_selection import GridSearchCV
```

In [33]:

```
grid_param = {
       'max_depth' : range(4,8),
       'min_samples_split':range(2,8,2),
       'learning_rate':np.arange(0.1,0.3)
}
```

In [34]:

```
grid=GridSearchCV(GradientBoostingClassifier(),param_grid=grid_param)
grid.fit(x_train,y_train)
```

Out[34]:

```
GridSearchCV(estimator=GradientBoostingClassifier(),
             param_grid={'learning_rate': array([0.1]),
                         'max_depth': range(4, 8),
                         'min_samples_split': range(2, 8, 2)})
```

In [35]:

```
grid.best_params_
```

Out[35]:

```
{'learning_rate': 0.1, 'max_depth': 4, 'min_samples_split': 4}
```

In [39]:

```
gbdt_clf=GradientBoostingClassifier(
max_depth=4,min_samples_split=2,learning_rate=0.05)
gbdt_clf.fit(x_train,y_train)
pred=gbdt_clf.predict(x_train)
gbdt_clf_report=pd.DataFrame(classification_report(y_train,pred,output_dict=True))
print("\n==============================Train Result==============================")

print(f"Accuracy score:{accuracy_score(y_train,pred)* 100 :.2f}%")
print("==============================================")
print(f"CLASSIFICATION REPORT : \n{gbdt_clf_report}")
print("==================================================")
print(f"confusion Matrix: \n{confusion_matrix(y_train,pred)}\n")


#***************************Test Score********************************

pred = gbdt_clf.predict(x_test)
clf_report=pd.DataFrame(classification_report(y_test,pred,output_dict=True))

print("\n==============================Test Result==============================")

print(f"Accuracy score:{accuracy_score(y_test,pred)* 100 :.2f}%")
print("==============================================")
print(f"CLASSIFICATION REPORT : \n{clf_report}")
print("==================================================")
print(f"confusion Matrix: \n{confusion_matrix(y_test,pred)}\n")
```

```
==============================Train Result==============================
Accuracy score:100.00%
==============================================
CLASSIFICATION REPORT :
              0      1  accuracy  macro avg  weighted avg
precision   1.0    1.0       1.0        1.0           1.0
recall      1.0    1.0       1.0        1.0           1.0
f1-score    1.0    1.0       1.0        1.0           1.0
support    97.0  115.0       1.0      212.0         212.0
==================================================
confusion Matrix:
[[ 97   0]
 [  0 115]]


==============================Test Result==============================
Accuracy score:85.71%
==============================================
CLASSIFICATION REPORT :
                   0          1  accuracy  macro avg  weighted avg
precision   0.818182   0.893617  0.857143   0.855899      0.859630
recall      0.878049   0.840000  0.857143   0.859024      0.857143
f1-score    0.847059   0.865979  0.857143   0.856519      0.857455
support    41.000000  50.000000  0.857143  91.000000     91.000000
==================================================
confusion Matrix:
[[36  5]
```

```
 [ 8 42]]
```

You can still tune the parameter with different range and try to improve the score

In [ ]: