Supervised Machine Learning: Regression - Final Assignment

Instructions:

In this Assignment, you will demonstrate the data regression skills you have learned by completing this course. You are expected to leverage a wide variety of tools, but also this report should focus on present findings, insights, and next steps. You may include some visuals from your code output, but this report is intended as a summary of your findings, not as a code review.

The grading will center around 5 main points:

1. Does the report include a section describing the data?
2. Does the report include a paragraph detailing the main objective(s) of this analysis?
3. Does the report include a section with variations of linear regression models and specifies which one is the model that best suits the main objective(s) of this analysis.
4. Does the report include a clear and well-presented section with key findings related to the main objective(s) of the analysis?
5. Does the report highlight possible flaws in the model and a plan of action to revisit this analysis with additional data or different predictive modeling techniques?

Import the required libraries

The following required modules are pre-installed in the Skills Network Labs environment. However if you run this notebook commands in a different Jupyter environment (e.g. Watson Studio or Ananconda) you will need to install these libraries by removing the `#` sign before `!mamba` in the code cell below.

In [1]:
```
# All Libraries required for this lab are listed below. The libraries pre-ir
# !mamba install -qy pandas==1.3.4 numpy==1.21.4 seaborn==0.9.0 matplotlib==
# Note: If your environment doesn't support "!mamba install", use "!pip inst
```

In [2]:
```
!pip install imbalanced-learn==0.8.0
```

```
Requirement already satisfied: imbalanced-learn==0.8.0 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (0.8.0)
Requirement already satisfied: numpy>=1.13.3 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from imbalanced-learn==0.8.0) (1.21.6)
Requirement already satisfied: scipy>=0.19.1 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from imbalanced-learn==0.8.0) (1.7.3)
Requirement already satisfied: scikit-learn>=0.24 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from imbalanced-learn==0.8.0) (1.0.2)
Requirement already satisfied: joblib>=0.11 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from imbalanced-learn==0.8.0) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /home/jupyterlab/conda/envs/python/lib/python3.7/site-packages (from scikit-learn>=0.24->imbalanced-learn==0.8.0) (3.1.0)
```

In [3]:
```
!pip install lime
```

```
Requirement already satisfied: lime in /home/jupyterlab/conda/envs/python/li
b/python3.7/site-packages (0.2.0.1)
Requirement already satisfied: matplotlib in /home/jupyterlab/conda/envs/pyth
on/lib/python3.7/site-packages (from lime) (3.5.3)
Requirement already satisfied: numpy in /home/jupyterlab/conda/envs/python/li
b/python3.7/site-packages (from lime) (1.21.6)
Requirement already satisfied: scipy in /home/jupyterlab/conda/envs/python/li
b/python3.7/site-packages (from lime) (1.7.3)
Requirement already satisfied: tqdm in /home/jupyterlab/conda/envs/python/li
b/python3.7/site-packages (from lime) (4.60.0)
Requirement already satisfied: scikit-learn>=0.18 in /home/jupyterlab/conda/e
nvs/python/lib/python3.7/site-packages (from lime) (1.0.2)
Requirement already satisfied: scikit-image>=0.12 in /home/jupyterlab/conda/e
nvs/python/lib/python3.7/site-packages (from lime) (0.17.2)
Requirement already satisfied: networkx>=2.0 in /home/jupyterlab/conda/envs/p
ython/lib/python3.7/site-packages (from scikit-image>=0.12->lime) (2.7)
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,>=4.3.0 in /home/jupyter
lab/conda/envs/python/lib/python3.7/site-packages (from scikit-image>=0.12->l
ime) (8.1.0)
Requirement already satisfied: imageio>=2.3.0 in /home/jupyterlab/conda/envs/
python/lib/python3.7/site-packages (from scikit-image>=0.12->lime) (2.4.1)
Requirement already satisfied: tifffile>=2019.7.26 in /home/jupyterlab/conda/
envs/python/lib/python3.7/site-packages (from scikit-image>=0.12->lime) (202
0.6.3)
Requirement already satisfied: PyWavelets>=1.1.1 in /home/jupyterlab/conda/en
vs/python/lib/python3.7/site-packages (from scikit-image>=0.12->lime) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /home/jupyterlab/conda/envs/py
thon/lib/python3.7/site-packages (from matplotlib->lime) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /home/jupyterlab/conda/en
vs/python/lib/python3.7/site-packages (from matplotlib->lime) (4.38.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /home/jupyterlab/conda/en
vs/python/lib/python3.7/site-packages (from matplotlib->lime) (1.4.4)
Requirement already satisfied: packaging>=20.0 in /home/jupyterlab/conda/env
s/python/lib/python3.7/site-packages (from matplotlib->lime) (23.1)
Requirement already satisfied: pyparsing>=2.2.1 in /home/jupyterlab/conda/env
s/python/lib/python3.7/site-packages (from matplotlib->lime) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in /home/jupyterlab/cond
a/envs/python/lib/python3.7/site-packages (from matplotlib->lime) (2.8.2)
Requirement already satisfied: joblib>=0.11 in /home/jupyterlab/conda/envs/py
thon/lib/python3.7/site-packages (from scikit-learn>=0.18->lime) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /home/jupyterlab/cond
a/envs/python/lib/python3.7/site-packages (from scikit-learn>=0.18->lime) (3.
1.0)
Requirement already satisfied: typing-extensions in /home/jupyterlab/conda/en
vs/python/lib/python3.7/site-packages (from kiwisolver>=1.0.1->matplotlib->li
me) (4.5.0)
Requirement already satisfied: six>=1.5 in /home/jupyterlab/conda/envs/pytho
n/lib/python3.7/site-packages (from python-dateutil>=2.7->matplotlib->lime)
(1.16.0)
```

In [4]:
```
## Import packages here
import pandas as pd
import numpy as np
import imblearn
import lime.lime_tabular
```

```
from matplotlib.pyplot import figure
from sklearn.utils import shuffle
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.model_selection import train_test_split, learning_curve
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score, precisior
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassif

from imblearn.under_sampling import RandomUnderSampler
from sklearn import metrics
from sklearn.inspection import permutation_importance
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
from collections import Counter
```

Importing the Dataset

Before you begin, you will need to choose a data set that you feel passionate about. You can brainstorm with your peers about great public data sets using the discussion board in this module.

Read your chosen dataset into pandas dataframe:

In [5]:
```
hf_df = pd.read_csv("heart.csv", index_col=False)
hf_df.head()
```

Out[5]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR
0	40	M	ATA	140	289	0	Normal	172
1	49	F	NAP	160	180	0	Normal	156
2	37	M	ATA	130	283	0	ST	98
3	48	F	ASY	138	214	0	Normal	108
4	54	M	NAP	150	195	0	Normal	122

In [6]:
```
hf_df.describe()
```

Out[6]:

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	He
count	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000	9
mean	53.510893	132.396514	198.799564	0.233115	136.809368	0.887364	
std	9.432617	18.514154	109.384145	0.423046	25.460334	1.066570	
min	28.000000	0.000000	0.000000	0.000000	60.000000	-2.600000	
25%	47.000000	120.000000	173.250000	0.000000	120.000000	0.000000	
50%	54.000000	130.000000	223.000000	0.000000	138.000000	0.600000	
75%	60.000000	140.000000	267.000000	0.000000	156.000000	1.500000	
max	77.000000	200.000000	603.000000	1.000000	202.000000	6.200000	

In [7]:
```
hf_df[hf_df['Cholesterol'] == 0]
```

Out[7]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxH
293	65	M	ASY	115	0	0	Normal	9
294	32	M	TA	95	0	1	Normal	12
295	61	M	ASY	105	0	1	Normal	11
296	50	M	ASY	145	0	1	Normal	13
297	57	M	ASY	110	0	1	ST	1
...	...	...	...	...	...	...	...	
514	43	M	ASY	122	0	0	Normal	12
515	63	M	NAP	130	0	1	ST	16
518	48	M	NAP	102	0	1	ST	11
535	56	M	ASY	130	0	0	LVH	12
536	62	M	NAP	133	0	1	ST	11

172 rows × 12 columns

In [8]:
```
hf_df['Cholesterol'].replace(0, np.nan, inplace=True)
```

In [9]:
```
hf_df[hf_df['Cholesterol'] == 0]
```

Out[9]:

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR

In [10]:
```
hf_df.Cholesterol.isnull().sum()
```

Out[10]: 172

In [11]:
```
hf_df['Cholesterol'] = hf_df.groupby(['Age'])['Cholesterol'].transform(lambc
```

In [12]:
```
hf_df.Cholesterol.isnull().sum()
```

Out[12]: 1

In [13]:
```
null_data = hf_df[hf_df.isnull().any(axis=1)]
null_data
```

Out[13]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxH
375	73	F	NAP	160	NaN	0	ST	1:

In [14]:
```
hf_df.groupby('HeartDisease')['Cholesterol'].mean()
```

Out[14]:
```
HeartDisease
0    238.968979
1    249.683470
Name: Cholesterol, dtype: float64
```

In [15]:
```
hf_df['Cholesterol'][375] = 249
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/ipykernel_laun
cher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [16]:
```
hf_df.Cholesterol.isnull().sum()
```

Out[16]: 0

In [17]:
```
hf_df.head()
```

Out[17]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR
0	40	M	ATA	140	289.0	0	Normal	172
1	49	F	NAP	160	180.0	0	Normal	156
2	37	M	ATA	130	283.0	0	ST	98
3	48	F	ASY	138	214.0	0	Normal	108
4	54	M	NAP	150	195.0	0	Normal	122

In [18]:
```
hf_df.shape
```

Out[18]: (918, 12)

In [19]:
```
hf_df.corr()
```

Out[19]:

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	He
Age	1.000000	0.254399	0.061333	0.198039	-0.382045	0.258612	
RestingBP	0.254399	1.000000	0.078055	0.070193	-0.112135	0.164803	
Cholesterol	0.061333	0.078055	1.000000	0.046174	-0.023454	0.053113	
FastingBS	0.198039	0.070193	0.046174	1.000000	-0.131438	0.052698	
MaxHR	-0.382045	-0.112135	-0.023454	-0.131438	1.000000	-0.160691	
Oldpeak	0.258612	0.164803	0.053113	0.052698	-0.160691	1.000000	
HeartDisease	0.282039	0.107589	0.099180	0.267291	-0.400421	0.403951	

In [20]:
```
hf_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Age             918 non-null    int64  
 1   Sex             918 non-null    object 
 2   ChestPainType   918 non-null    object 
 3   RestingBP       918 non-null    int64  
 4   Cholesterol     918 non-null    float64
 5   FastingBS       918 non-null    int64  
 6   RestingECG      918 non-null    object 
 7   MaxHR           918 non-null    int64  
 8   ExerciseAngina  918 non-null    object 
 9   Oldpeak         918 non-null    float64
 10  ST_Slope        918 non-null    object 
 11  HeartDisease    918 non-null    int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 86.2+ KB
```

In [21]:
```
data = hf_df.copy()
```

In [22]:
```
data.columns
```

Out[22]:
```
Index(['Age', 'Sex', 'ChestPainType', 'RestingBP', 'Cholesterol', 'FastingB
S',
       'RestingECG', 'MaxHR', 'ExerciseAngina', 'Oldpeak', 'ST_Slope',
       'HeartDisease'],
      dtype='object')
```

In [23]:
```
data.ExerciseAngina.value_counts()
```

Out[23]:
```
N    547
Y    371
Name: ExerciseAngina, dtype: int64
```

In [24]:
```
columns = ['Age','Sex','ChestPainType', 'RestingBP', 'Cholesterol', 'Fasting
```

In [25]:
```
data['RestingECG'].value_counts()
```

Out[25]:
```
Normal    552
LVH       188
ST        178
Name: RestingECG, dtype: int64
```

In [26]:
```
X = data[['Age', 'Sex', 'ChestPainType', 'RestingBP', 'Cholesterol', 'Fastir
```

In [27]:
```
y = data["HeartDisease"]
```

In [28]:
```
print(type(X))
```

```
<class 'numpy.ndarray'>
```

In [29]:
```
from sklearn import preprocessing
le_sex = preprocessing.LabelEncoder()
le_sex.fit(['F','M'])
X[:,1] = le_sex.transform(X[:,1])

le_CPT = preprocessing.LabelEncoder()
le_CPT.fit([ 'ASY', 'NAP', 'ATA', 'TA'])
X[:,2] = le_CPT.transform(X[:,2])


le_RECG = preprocessing.LabelEncoder()
le_RECG.fit([ 'Normal', 'LVH', 'ST'])
X[:,6] = le_RECG.transform(X[:,6])

le_Ang = preprocessing.LabelEncoder()
le_Ang.fit(['Y','N'])
X[:,8] = le_Ang.transform(X[:,8])

le_ST = preprocessing.LabelEncoder()
le_ST.fit(['Flat','Up', 'Down'])
X[:,10] = le_ST.transform(X[:,10])

X[0:10]
```

Out[29]:
```
array([[40, 1, 1, 140, 289.0, 0, 1, 172, 0, 0.0, 2],
       [49, 0, 2, 160, 180.0, 0, 1, 156, 0, 1.0, 1],
       [37, 1, 1, 130, 283.0, 0, 2, 98, 0, 0.0, 2],
       [48, 0, 0, 138, 214.0, 0, 1, 108, 1, 1.5, 1],
       [54, 1, 2, 150, 195.0, 0, 1, 122, 0, 0.0, 2],
       [39, 1, 2, 120, 339.0, 0, 1, 170, 0, 0.0, 2],
       [45, 0, 1, 130, 237.0, 0, 1, 170, 0, 0.0, 2],
       [54, 1, 1, 110, 208.0, 0, 1, 142, 0, 0.0, 2],
       [37, 1, 0, 140, 207.0, 0, 1, 130, 1, 1.5, 1],
       [48, 0, 1, 120, 284.0, 0, 1, 120, 0, 0.0, 2]], dtype=object)
```

In [30]:
```
X.astype(int)
```

Out[30]:
```
array([[40,  1,  1, ...,  0,  0,  2],
       [49,  0,  2, ...,  0,  1,  1],
       [37,  1,  1, ...,  0,  0,  2],
       ...,
       [57,  1,  0, ...,  1,  1,  1],
       [57,  0,  1, ...,  0,  0,  1],
       [38,  1,  2, ...,  0,  0,  2]])
```

In [31]:
```
y_raw = data['HeartDisease']
```

In [32]:
```
print(type(y_raw))
```

```
<class 'pandas.core.series.Series'>
```

In [33]:
```
X_raw = pd.DataFrame(X)
```

In [34]:
```
X_raw.columns=['Age', 'Sex', 'ChestPainType', 'RestingBP', 'Cholesterol', 'F
```

In [35]:
```
print(type(X_raw))
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [36]:
```
X_raw.head()
```

Out[36]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR
0	40	1	1	140	289.0	0	1	172
1	49	0	2	160	180.0	0	1	156
2	37	1	1	130	283.0	0	2	98
3	48	0	0	138	214.0	0	1	108
4	54	1	2	150	195.0	0	1	122

In [37]:
```
X_raw.ST_Slope.value_counts()
```

Out[37]:
```
1    460
2    395
0     63
Name: ST_Slope, dtype: int64
```

In [38]:
```
data.ST_Slope.value_counts()
```

Out[38]:
```
Flat    460
Up      395
Down     63
Name: ST_Slope, dtype: int64
```

In [39]:
```
data['HeartDisease'].value_counts()
```

Out[39]:
```
1    508
0    410
Name: HeartDisease, dtype: int64
```

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, ra
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (734, 11) (734,)
Test set: (184, 11) (184,)
```

In [41]:
```
print(type(y_test))
```

```
<class 'pandas.core.series.Series'>
```

In [42]:
```
print(type(X_train))
```

```
<class 'numpy.ndarray'>
```

In [43]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
```

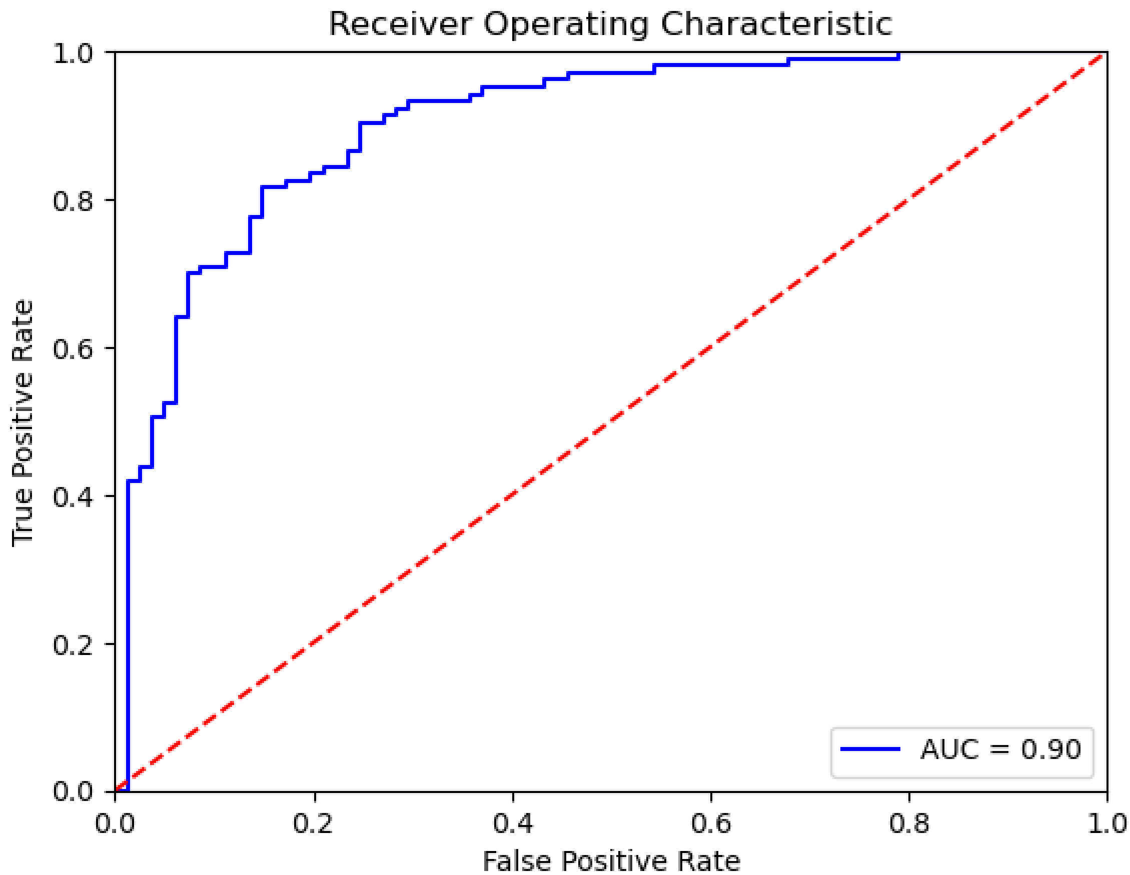
In [44]:
```
from sklearn.linear_model import LogisticRegression

LR = LogisticRegression()
LR = LR.fit(X_train, y_train)
X_test = scaler.transform(X_test)
y_pred = LR.predict(X_test)
```

In [45]:
```
LR.coef_
```

Out[45]:
```
array([[ 0.17235441,  0.65054992, -0.63411103,  0.00592034,  0.20700175,
         0.52852459, -0.06883613, -0.37277718,  0.55797386,  0.37626126,
        -1.04366219]])
```

In [46]:
```
probs = LR.predict_proba(X_test)

import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification

preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)
```

In [47]:
```
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [48]:
```
def evaluate_metrics(yt, yp):
    results_pos = {}
    results_pos['accuracy'] = accuracy_score(yt, yp)
    precision, recall, f_beta, _ = precision_recall_fscore_support(yt, yp)
    results_pos['recall'] = recall
    results_pos['precision'] = precision
    results_pos['f1score'] = f_beta
    return results_pos
```

In [49]:
```
result = evaluate_metrics(y_test, y_pred)
result
```

Out[49]:
```
{'accuracy': 0.8315217391304348,
 'recall': array([0.75308642, 0.89320388]),
 'precision': array([0.84722222, 0.82142857]),
 'f1score': array([0.79738562, 0.85581395])}
```

In [50]:
```
results = []
results.append(result)
```

In [51]:
```
from sklearn.model_selection import GridSearchCV

parameters = [{'solver': ['lbfgs', 'liblinear']},
              {'penalty':['none', 'l2']},
              {'C':[0.001, 0.01, 0.1, 1, 10, 100]}]
```

```
grid_search = GridSearchCV(estimator = LR,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 5,
                           verbose=0)


grid_search.fit(X_train, y_train)
best_params = grid_search.best_params_
best_params
```

Out[51]: {'penalty': 'none'}

In [52]:

```
from sklearn.svm import LinearSVC

linSVC = LinearSVC()
linSVC = linSVC.fit(X_train, y_train)
y_predsvc = linSVC.predict(X_test)
result_linsvc = evaluate_metrics(y_test, y_predsvc)
results.append(result_linsvc)
result_linsvc
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/sklearn/svm/_b
ase.py:1208: ConvergenceWarning: Liblinear failed to converge, increase the n
umber of iterations.
  ConvergenceWarning,
```

Out[52]:

```
{'accuracy': 0.8315217391304348,
 'recall': array([0.75308642, 0.89320388]),
 'precision': array([0.84722222, 0.82142857]),
 'f1score': array([0.79738562, 0.85581395])}
```

In [53]:

```
from sklearn.svm import SVC

model = SVC()
model.fit(X_train, y_train.values.ravel())
preds = model.predict(X_test)
result_svc = evaluate_metrics(y_test, preds)
result_svc
results.append(result_svc)
```

In [54]:

```
params_grid = { 'C':[1, 10, 100], 'kernel':['poly','rbf','sigmoid']}

model = SVC()

grid_search = GridSearchCV(estimator = model, param_grid = params_grid, scor

grid_search.fit(X_train, y_train.values.ravel())
best_params = grid_search.best_params_
best_params
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

Out[54]: {'C': 1, 'kernel': 'rbf'}

In [55]:

```
model = SVC(kernel = 'rbf')
model.fit(X_train, y_train.values.ravel())
```

```
preds = model.predict(X_test)
evaluate_metrics(y_test, preds)
result_svc2 = evaluate_metrics(y_test, preds)
results.append(result_svc2)
```

In [56]:
```
params_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, 15, 20],
    'min_samples_leaf': [1, 2, 5]
}
model = DecisionTreeClassifier(random_state=123)
grid_search = GridSearchCV(estimator = model,
                        param_grid = params_grid,
                        scoring='f1',
                        cv = 5, verbose = 1)
grid_search.fit(X_train, y_train.values.ravel())
best_params = grid_search.best_params_
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
```

In [57]:
```
best_params
```

Out[57]:
```
{'criterion': 'gini', 'max_depth': 5, 'min_samples_leaf': 5}
```

In [58]:
```
dtc = DecisionTreeClassifier(criterion = 'gini', max_depth = 5)
dtc = dtc.fit(X_train, y_train)
y_dtc = dtc.predict(X_test)
```

In [59]:
```
result_dtc = evaluate_metrics(y_test, y_dtc)
result_dtc
results.append(result_dtc)
```

In [60]:
```
from sklearn.ensemble import RandomForestClassifier
rc = RandomForestClassifier()
rc = rc.fit(X_train, y_train)
y_rc = rc.predict(X_test)
```

In [61]:
```
result_rc = evaluate_metrics(y_test, y_rc)
results.append(result_rc)
result_rc
```

Out[61]:
```
{'accuracy': 0.8586956521739131,
 'recall': array([0.7654321 , 0.93203883]),
 'precision': array([0.89855072, 0.83478261]),
 'f1score': array([0.82666667, 0.88073394])}
```

In [62]:
```
LR = LogisticRegression()
LR = LR.fit(X_train, y_train)
X_test = scaler.transform(X_test)
y_pred = LR.predict(X_test)
```

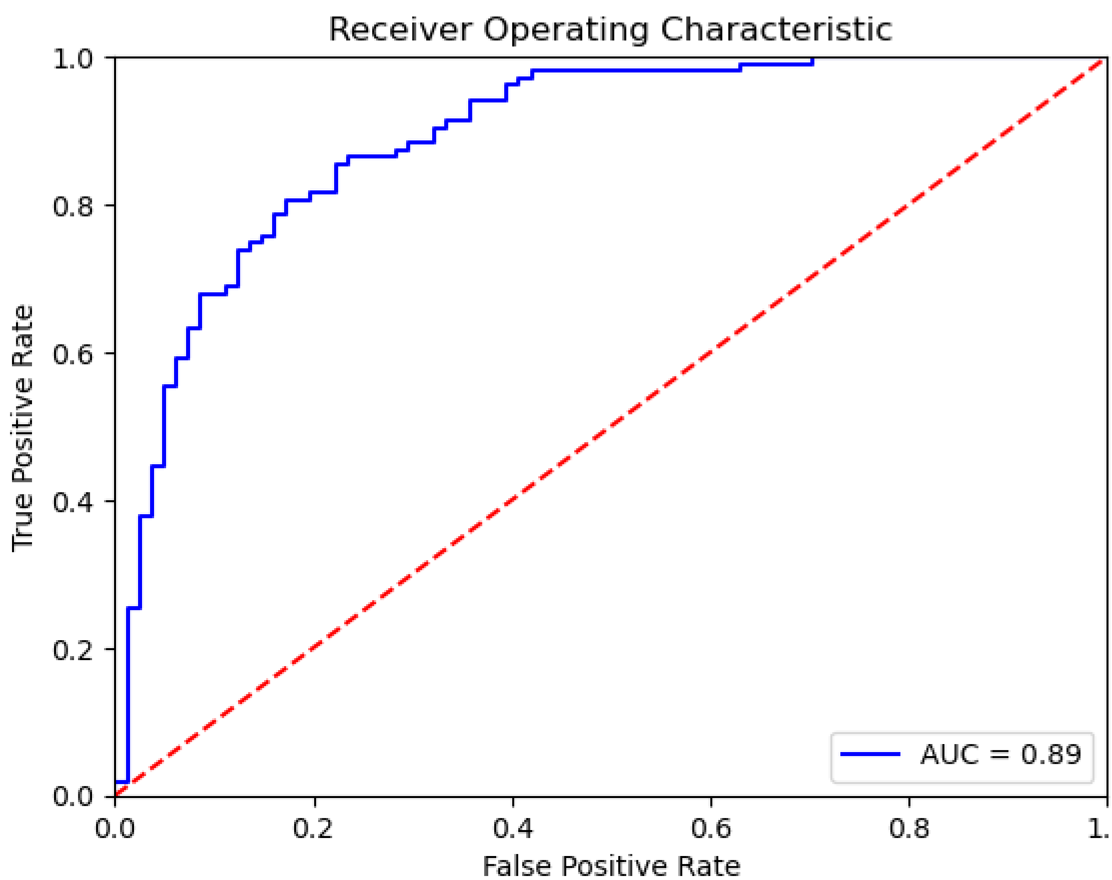
In [63]:
```
probs = LR.predict_proba(X_test)

import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
```

```
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)
```

In [64]:
```
evaluate_metrics(y_test, y_pred)
```

Out[64]:
```
{'accuracy': 0.8043478260869565,
 'recall': array([0.67901235, 0.90291262]),
 'precision': array([0.84615385, 0.78151261]),
 'f1score': array([0.75342466, 0.83783784])}
```

In [65]:
```
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [66]:
```
from sklearn.inspection import permutation_importance, plot_partial_depender
```

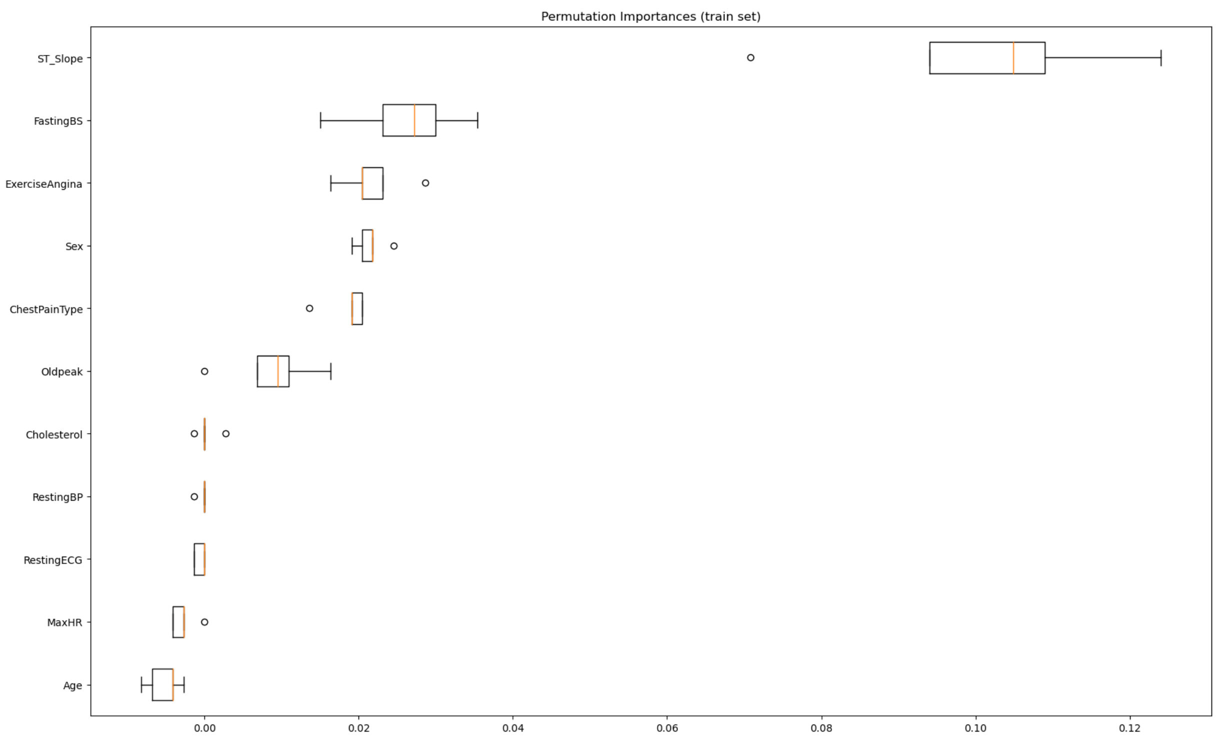
In [67]:
```
f_importances = permutation_importance(estimator=LR, X=X_train, y=y_train, r
```

In [68]:
```
f_importances.importances.shape
```

Out[68]: (11, 5)

In [69]:
```
def visualize_feature_importance(importance_array):
    # Sort the array based on mean value
    sorted_idx = importance_array.importances_mean.argsort()
    # Visualize the feature importances using boxplot
    fig, ax = plt.subplots()
    fig.set_figwidth(16)
    fig.set_figheight(10)
    fig.tight_layout()
    ax.boxplot(importance_array.importances[sorted_idx].T,
               vert=False, labels=df.columns[sorted_idx])
    ax.set_title("Permutation Importances (train set)")
    plt.show()
```

In [70]:
```
df= pd.DataFrame(X_train, columns= ['Age', 'Sex', 'ChestPainType', 'RestingE
       'RestingECG', 'MaxHR', 'ExerciseAngina', 'Oldpeak', 'ST_Slope'])
visualize_feature_importance(f_importances)
```

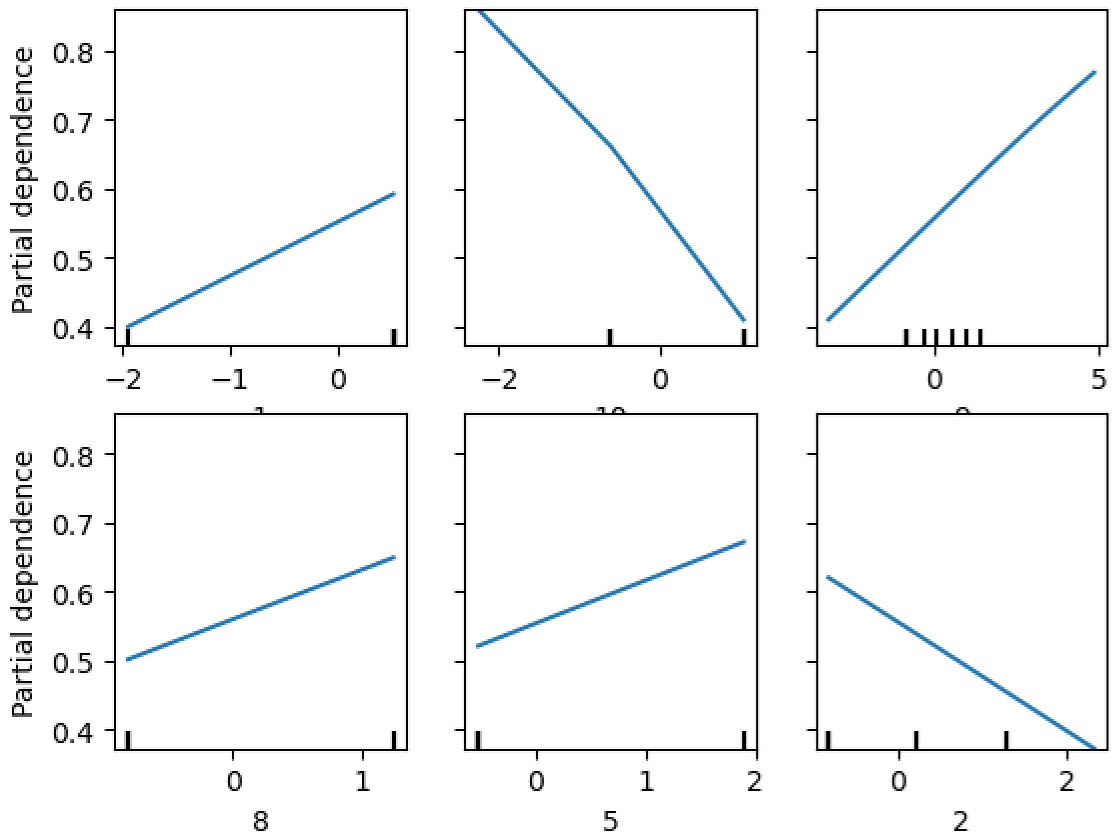


In [71]:
```
imp_features2 = ['Sex', 'ChestPainType', 'Oldpeak' 'ExerciseAngina', 'Fastir
imp_features = ['1', '10', '9', '8', '5', '2']
```

In [72]:
```
plot_partial_dependence(estimator=LR, X=X_train, features = imp_features, ra
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/sklearn/utils/
deprecation.py:87: FutureWarning: Function plot_partial_dependence is depreca
ted; Function `plot_partial_dependence` is deprecated in 1.0 and will be remo
ved in 1.2. Use PartialDependenceDisplay.from_estimator instead
  warnings.warn(msg, category=FutureWarning)
```

Out[72]: <sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x7fc358154c50>



In [73]:
```
X_train, X_test, y_train, y_test = train_test_split(X_raw, y_raw, test_size=
```

In [74]:
```
# Define a black-box random forest model
black_box_model = RandomForestClassifier(random_state = 123, max_depth=25,
                                         max_features=10, n_estimators=100,
                                         bootstrap=True)
# Train the model
black_box_model.fit(X_train, y_train.values.ravel())
```

Out[74]: RandomForestClassifier(max_depth=25, max_features=10, random_state=123)

In [75]:
```
#predicting test set
y_blackbox = black_box_model.predict(X_test)
```

In [76]:
```
metrics.roc_auc_score(y_test, y_blackbox)
```

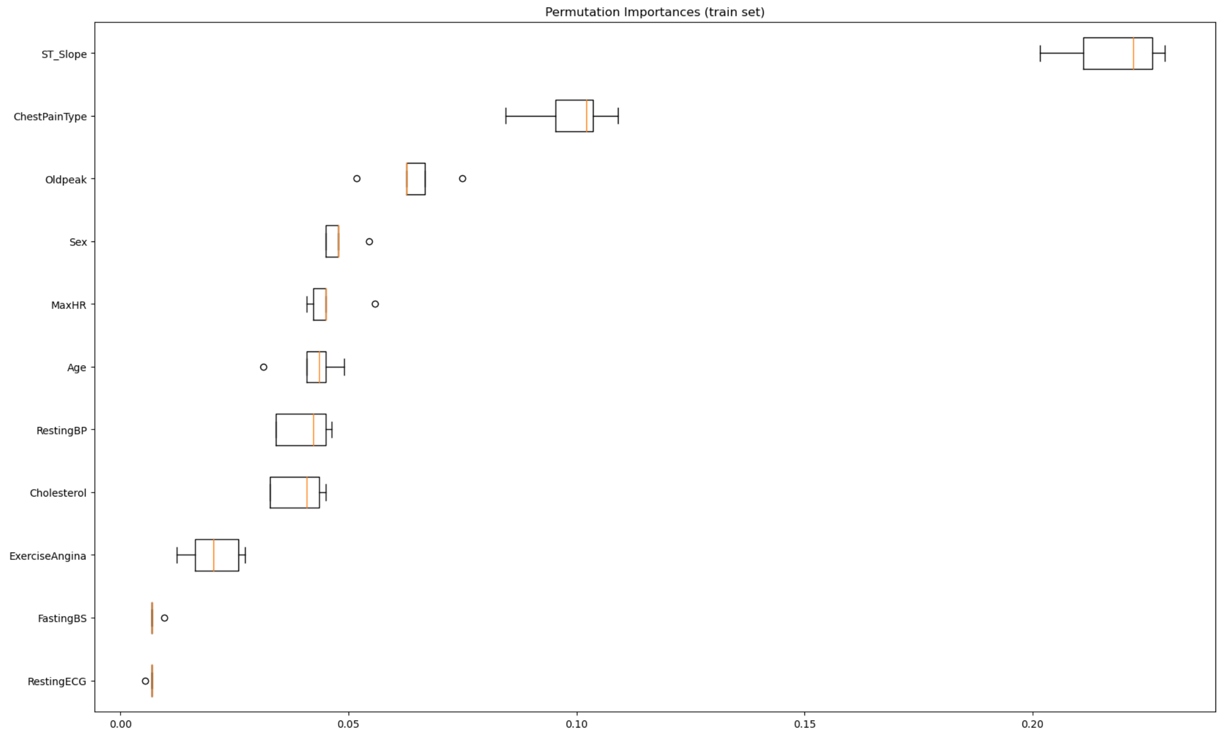
Out[76]: 0.8510282161645146

In [77]:
```
result_blackbox = evaluate_metrics(y_test, y_blackbox)
results.append(result_blackbox)
result_blackbox
```

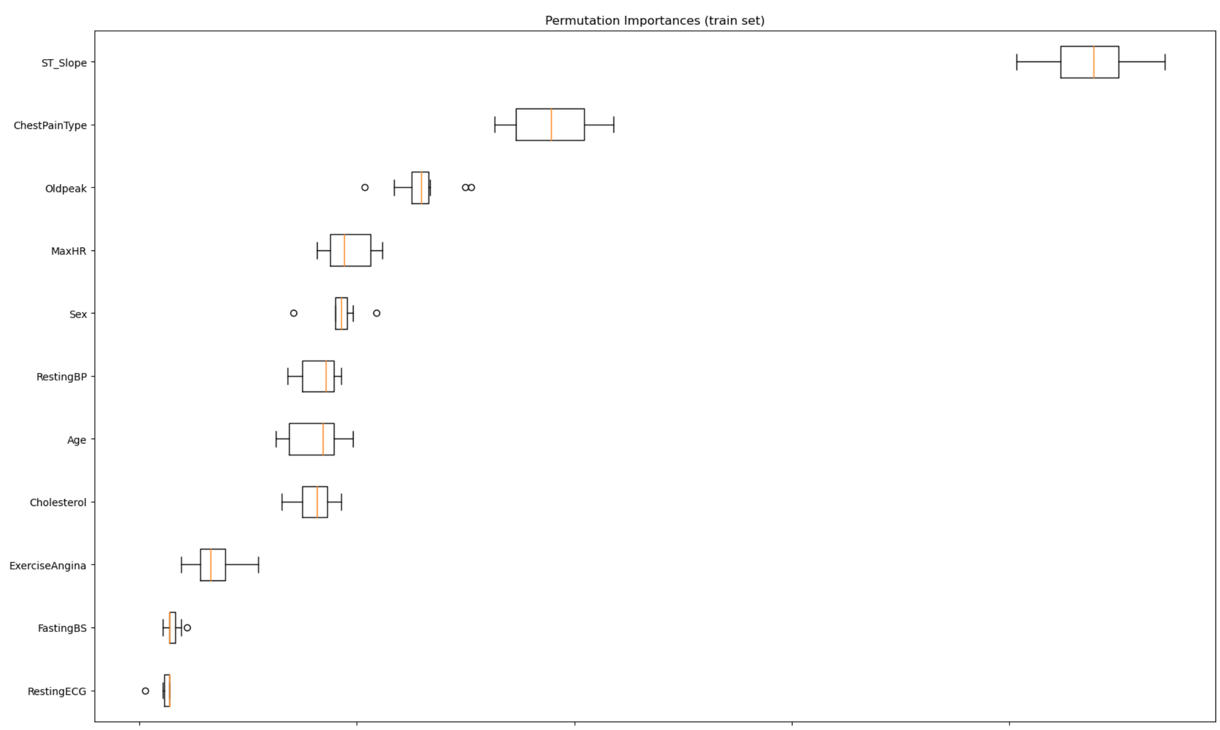
Out[77]:
```
{'accuracy': 0.8586956521739131,
 'recall': array([0.7804878 , 0.92156863]),
 'precision': array([0.88888889, 0.83928571]),
 'f1score': array([0.83116883, 0.87850467])}
```

In [78]:
```
feature_importances = permutation_importance(estimator=black_box_model, X =
                                            random_state=123, n_jobs=2)
```

In [79]:
```
visualize_feature_importance(feature_importances)
```



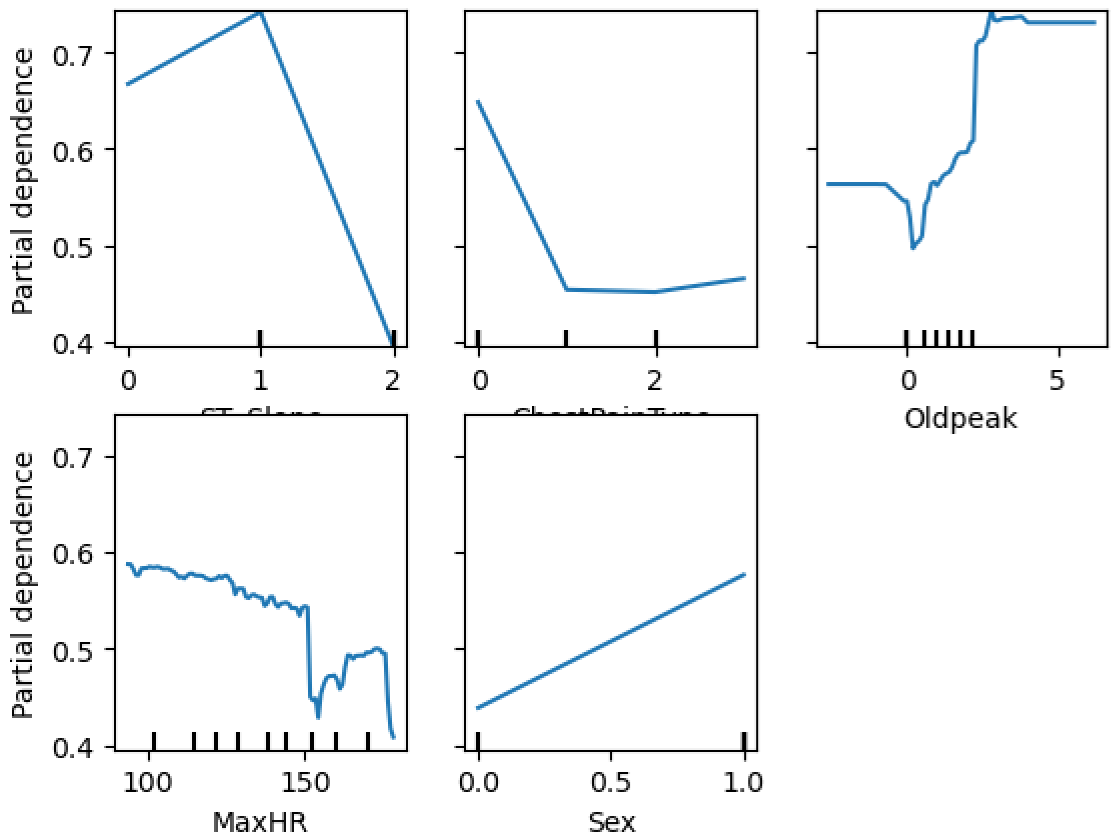
In [80]:
```
feature_importances = permutation_importance(estimator=black_box_model, X =
                                            random_state=123, n_jobs=2)

visualize_feature_importance(feature_importances)
```



In [81]:
```
important_features = ['ST_Slope', 'ChestPainType', 'Oldpeak', 'MaxHR', 'Sex'
"arguments: "
" - estimator: the black box model"
" - X is the training data X"
" - features are the important features we are interested"
plot_partial_dependence(estimator=black_box_model,
                        X=X_train,
                        features=important_features,
                        random_state=123)
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/sklearn/utils/
deprecation.py:87: FutureWarning: Function plot_partial_dependence is depreca
ted; Function `plot_partial_dependence` is deprecated in 1.0 and will be remo
ved in 1.2. Use PartialDependenceDisplay.from_estimator instead
  warnings.warn(msg, category=FutureWarning)
```

Out[81]:
```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x
7fc358082090>
```



In [82]:
```
min_max_scaler = StandardScaler()
X_test_minmax = min_max_scaler.fit_transform(X_test)
```

In [83]:
```
lm_surrogate = LogisticRegression(max_iter=1000,
                                  random_state=123, penalty='l1', solver='li
lm_surrogate.fit(X_test_minmax, y_blackbox)
```

Out[83]:
```
LogisticRegression(max_iter=1000, penalty='l1', random_state=123,
                   solver='liblinear')
```

In [84]:
```
y_surrogate = lm_surrogate.predict(X_test_minmax)
```

In [85]:
```
metrics.accuracy_score(y_blackbox, y_surrogate)
```

Out[85]:
```
0.9184782608695652
```

In [86]:
```
metrics.roc_auc_score(y_blackbox, y_surrogate)
```

Out[86]:
```
0.9231150793650794
```

In [87]:
```
evaluate_metrics(y_blackbox, y_surrogate)
```

Out[87]:
```
{'accuracy': 0.9184782608695652,
 'recall': array([0.94444444, 0.90178571]),
 'precision': array([0.86075949, 0.96190476]),
 'f1score': array([0.90066225, 0.93087558])}
```

In [88]:
```
def get_feature_coefs(regression_model):
    coef_dict = {}
    # Filter coefficients less than 0.01
    for coef, feat in zip(regression_model.coef_[0, :], X_test.columns):
        if abs(coef) >= 0.01:
            coef_dict[feat] = coef
    # Sort coefficients
    coef_dict = {k: v for k, v in sorted(coef_dict.items(), key=lambda item:
    return coef_dict
```

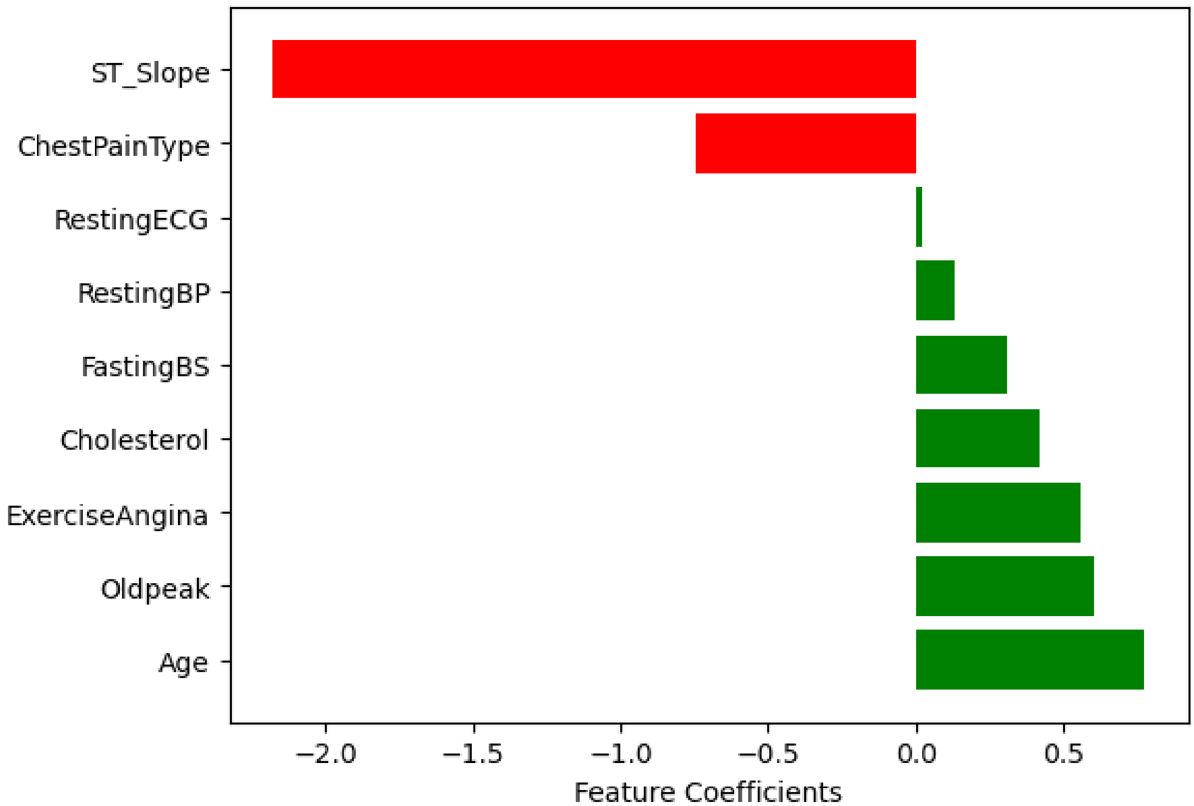
In [89]:
```
coef_dict = get_feature_coefs(lm_surrogate)
coef_dict
```

Out[89]:
```
{'ST_Slope': -2.17525789623819,
 'ChestPainType': -0.7434431511859994,
 'RestingECG': 0.020118255598450253,
 'RestingBP': 0.1294785493778037,
 'FastingBS': 0.3065041516136047,
 'Cholesterol': 0.42180751617652945,
 'ExerciseAngina': 0.5576187733807246,
 'Oldpeak': 0.6008967955476152,
 'Age': 0.7761895394364545}
```

In [90]:
```
# Generate bar colors based on if value is negative or positive
def get_bar_colors(values):
    color_vals = []
    for val in values:
        if val <= 0:
            color_vals.append('r')
        else:
            color_vals.append('g')
    return color_vals

# Visualize coefficients
def visualize_coefs(coef_dict):
    features = list(coef_dict.keys())
    values = list(coef_dict.values())
    y_pos = np.arange(len(features))
    color_vals = get_bar_colors(values)
    plt.rcdefaults()
```

```
    fig, ax = plt.subplots()
    ax.barh(y_pos, values, align='center', color=color_vals)
    ax.set_yticks(y_pos)
    ax.set_yticklabels(features)
    # labels read top-to-bottom
    ax.invert_yaxis()
    ax.set_xlabel('Feature Coefficients')
    ax.set_title('')
    plt.show()
```

In [91]:
```
visualize_coefs(coef_dict)
```



In [92]:
```
explainer = lime.lime_tabular.LimeTabularExplainer(
    # Set the training dataset to be X_test.values (2-D Numpy array)
    training_data=X_test.values,
    # Set the mode to be classification
    mode='classification',
    # Set class names to be `Not Changing` and `Changing`
    class_names = ['No HD', 'Heart Disease'],
    # Set feature names
    feature_names=list(X_train.columns),
    random_state=123,
    verbose=True)
```

In [103…
```
instance_index = 8
selected_instance = X_test.iloc[[instance_index]]
lime_test_instance = selected_instance.values.reshape(-1)
selected_instance
```

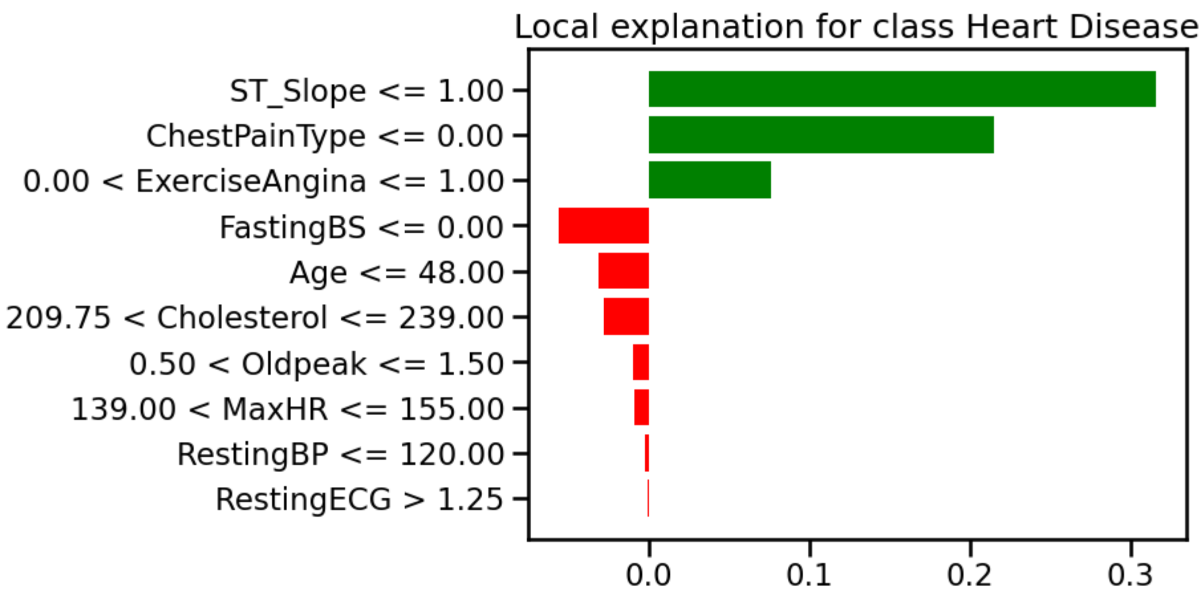
Out[103]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxI
183	46	1	0	110	238.0	0	2	1

In [104…

```
exp = explainer.explain_instance(
                                  # Instance to explain
                                  lime_test_instance,
                                  # The prediction from black-box model
                                  black_box_model.predict_proba,
                                  # Use max 10 features
                                  num_features=10)
exp.as_pyplot_figure();
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/sklearn/base.p
y:451: UserWarning: X does not have valid feature names, but RandomForestClas
sifier was fitted with feature names
  "X does not have valid feature names, but"
Intercept 0.3101596731386885
Prediction_local [0.77808863]
Right: 0.94
```



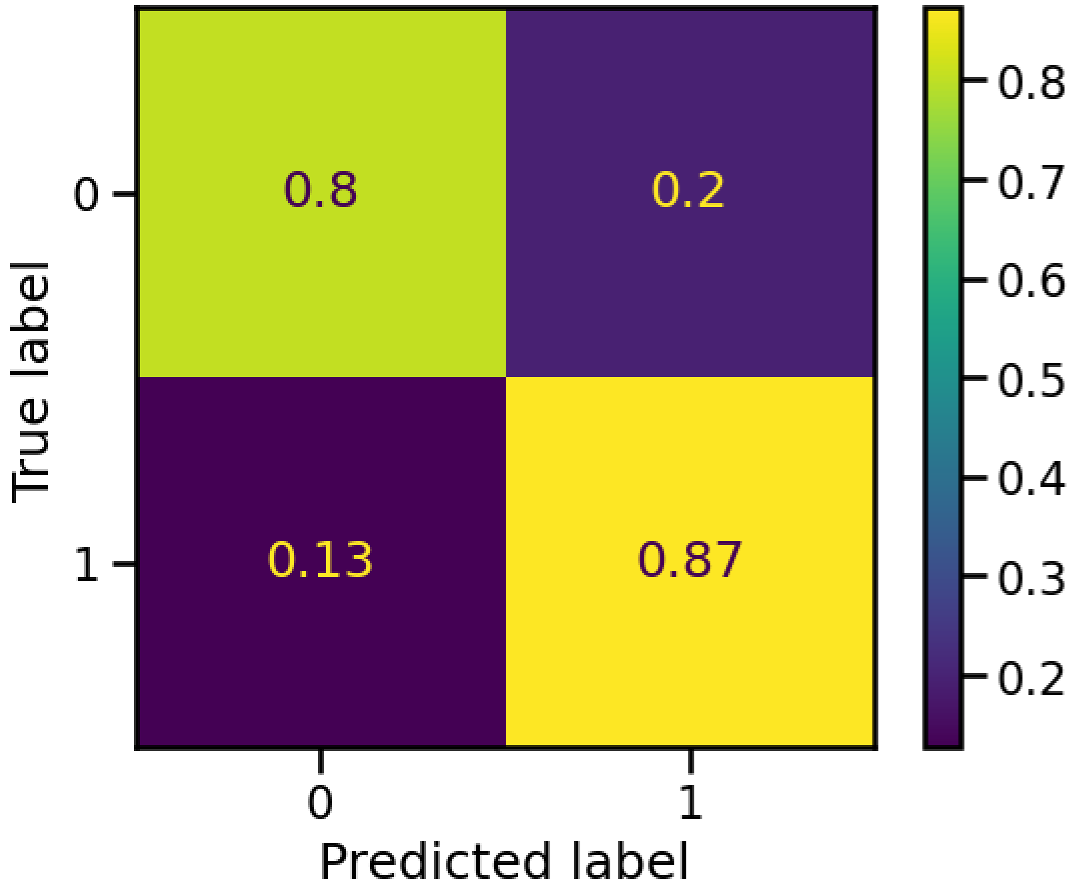
In [ ]:
```
def visualize_eval_metrics(results):
    df = pd.DataFrame(data=results)
    #table = pd.pivot_table(df, values='type', index=['accuracy', 'precision
    #                 columns=['type'])
    #df = df.set_index('type').transpose()
    print(df)
    x = np.arange(4)
    original = df.iloc[0, 1:].values
    width = 0.2
    figure(figsize=(12, 10), dpi=80)
    plt.bar(x-0.2, original, width, color='#95a5a6')
    plt.bar(x, class_weight, width, color='#d35400')
    plt.xticks(x, ['Accuracy', 'Recall','Precision', 'Fscore'])
    plt.xlabel("Evaluation Metrics")
    plt.ylabel("Score")
    plt.show()
```

In [96]:
```
result_lrsurrogate = evaluate_metrics(y_test, y_surrogate)
results.append(result_lrsurrogate)
result_lrsurrogate
```

Out[96]:
```
{'accuracy': 0.842391304347826,
 'recall': array([0.80487805, 0.87254902]),
 'precision': array([0.83544304, 0.84761905]),
 'f1score': array([0.81987578, 0.85990338])}
```

In [97]:
```
cf = confusion_matrix(y_test, y_surrogate, normalize='true')
```

In [98]:
```
from sklearn.metrics import classification_report, accuracy_score, confusion
import seaborn as sns


sns.set_context('talk')
disp = ConfusionMatrixDisplay(confusion_matrix=cf,display_labels=LR.classes_
disp.plot()
plt.show()
```



In [99]:
```
results_df = pd.DataFrame(results).T
results_df.columns = ['LR','LinSVC', 'SVC','SVC-rbf', 'DecisionTree','RF', '
results_df
```

Out[99]:

	LR	LinSVC	SVC	
accuracy	0.831522	0.831522	0.858696	
recall	[0.7530864197530864, 0.8932038834951457]	[0.7530864197530864, 0.8932038834951457]	[0.7654320987654321, 0.9320388349514563]	[0.765 0.932
precision	[0.8472222222222222, 0.8214285714285714]	[0.8472222222222222, 0.8214285714285714]	[0.8985507246376812, 0.8347826086956521]	[0.898 0.834
f1score	[0.7973856209150327, 0.8558139534883721]	[0.7973856209150327, 0.8558139534883721]	[0.8266666666666668, 0.8807339449541284]	[0.826 0.880

Once you have selected a data set, you will produce the deliverables listed below and submit them to one of your peers for review. Treat this exercise as an opportunity to produce analysis that are ready to highlight your analytical skills for a senior audience, for example, the Chief Data Officer, or the Head of Analytics at your company. Sections required in your report:

- Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation.
- Brief description of the data set you chose and a summary of its attributes.

- Brief summary of data exploration and actions taken for data cleaning and feature engineering.
- Summary of training at least three linear regression models which should be variations that cover using a simple linear regression as a baseline, adding polynomial effects, and using a regularization regression. Preferably, all use the same training and test splits, or the same cross-validation method.
- A paragraph explaining which of your regressions you recommend as a final model that best fits your needs in terms of accuracy and explainability.
- Summary Key Findings and Insights, which walks your reader through the main drivers of your model and insights from your data derived from your linear regression model.
- Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model adding specific data features to achieve a better explanation or a better prediction.