In [ ]:
```
# This Heart Attack data Logistic Regression model is based on the 'heart.csv' file (h
# More info on this dataset:


# Age : Age of the patient
# Sex : Sex of the patient
# cp : Chest Pain type
#             Value 0: typical angina
#             Value 1: atypical angina
#             Value 2: non-anginal pain
#             Value 3: asymptomatic


# trtbps : resting blood pressure (in mm Hg)
# chol: cholesterol in mg/dl fetched via BMI sensor
# fbs: (fasting blood sugar > 120 mg/dl)
#             1 = true
#             0 = false


# rest_ecg: resting electrocardiographic results
#             Value 0: normal
#             Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevat
#             Value 2: showing probable or definite left ventricular hypertrophy by Est


# thalach: maximum heart rate achieved
# exang: exercise induced angina
#             1 = yes
#             0 = no


# old peak: ST depression induced by exercise relative to rest
# slp: the slope of the peak exercise ST segment
#             0 = unsloping
#             1 = flat
#             2 = downsloping


# caa: number of major vessels (0-3)
# thall : thalassemia
#             0 = null
#             1 = fixed defect
#             2 = normal
#             3 = reversable defect


# output: diagnosis of heart disease (angiographic disease status)
#             0: < 50% diameter narrowing. less chance of heart disease
#             1: > 50% diameter narrowing. more chance of heart disease
```

In [1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

```
from sklearn.metrics import classification_report, confusion_matrix
import shap
import xgboost
from termcolor import colored as cl #text customization
```

In [2]:
```
# Phase 1: import data

data = pd.read_csv('heart.csv')
print(data.head())

print('\n', data.describe())
```

```
   age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng  oldpeak  slp  \
0   63    1   3     145   233    1        0       150     0      2.3    0   
1   37    1   2     130   250    0        1       187     0      3.5    0   
2   41    0   1     130   204    0        0       172     0      1.4    2   
3   56    1   1     120   236    0        1       178     0      0.8    2   
4   57    0   0     120   354    0        1       163     1      0.6    2   

   caa  thall  output  
0    0      1       1  
1    0      2       1  
2    0      2       1  
3    0      2       1  
4    0      2       1  

               age         sex          cp      trtbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000   
mean    54.366337    0.683168    0.966997  131.623762  246.264026    0.148515   
std      9.082101    0.466011    1.032052   17.538143   51.830751    0.356198   
min     29.000000    0.000000    0.000000   94.000000  126.000000    0.000000   
25%     47.500000    0.000000    0.000000  120.000000  211.000000    0.000000   
50%     55.000000    1.000000    1.000000  130.000000  240.000000    0.000000   
75%     61.000000    1.000000    2.000000  140.000000  274.500000    0.000000   
max     77.000000    1.000000    3.000000  200.000000  564.000000    1.000000   

          restecg    thalachh        exng     oldpeak         slp         caa  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000   
mean     0.528053  149.646865    0.326733    1.039604    1.399340    0.729373   
std      0.525860   22.905161    0.469794    1.161075    0.616226    1.022606   
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000   
25%      0.000000  133.500000    0.000000    0.000000    1.000000    0.000000   
50%      1.000000  153.000000    0.000000    0.800000    1.000000    0.000000   
75%      1.000000  166.000000    1.000000    1.600000    2.000000    1.000000   
max      2.000000  202.000000    1.000000    6.200000    2.000000    4.000000   

            thall      output  
count  303.000000  303.000000  
mean     2.313531    0.544554  
std      0.612277    0.498835  
min      0.000000    0.000000  
25%      2.000000    0.000000  
50%      2.000000    1.000000  
75%      3.000000    1.000000  
max      3.000000    1.000000  
```

In [3]:
```
# Phase 2: Splitting dataset into X and y based on row and column using iloc[]
#          and reshaping X-variable before training and testing

X = data.iloc[:, :-1]
```

```
y = data.iloc[:, -1]

print('\nChecking X-variable before scaling\n', X)
print('\nChecking values in y\n', y)


# data partitioning
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
print('\nChecking X-variable values after scaling\n', X_train)



# Checking training and testing samples for train_test_split
print('\nChecking data partitioning\nX_train samples: {}\n\nX_test samples: {}\n\ny_tr
```

```
Checking X-variable before scaling
      age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng  oldpeak  slp  \
0     63    1   3     145   233    1        0       150     0      2.3    0
1     37    1   2     130   250    0        1       187     0      3.5    0
2     41    0   1     130   204    0        0       172     0      1.4    2
3     56    1   1     120   236    0        1       178     0      0.8    2
4     57    0   0     120   354    0        1       163     1      0.6    2
..   ...  ...  ..     ...   ...  ...      ...       ...   ...      ...  ...
298   57    0   0     140   241    0        1       123     1      0.2    1
299   45    1   3     110   264    0        1       132     0      1.2    1
300   68    1   0     144   193    1        1       141     0      3.4    1
301   57    1   0     130   131    0        1       115     1      1.2    1
302   57    0   1     130   236    0        0       174     0      0.0    1

     caa  thall
0      0      1
1      0      2
2      0      2
3      0      2
4      0      2
..   ...    ...
298    0      3
299    0      3
300    2      3
301    1      3
302    1      2

[303 rows x 13 columns]

Checking values in y
 0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: output, Length: 303, dtype: int64

Checking X-variable values after scaling
 [[-0.71097084  0.75757049 -0.92209456 ...  0.94593254 -0.66285492
   -0.42543801]
 [-0.37873576  0.75757049 -0.92209456 ... -0.62483617  2.5797597
    1.2857682 ]
 [-0.48948078 -1.32000918 -0.92209456 ...  0.94593254 -0.66285492
   -0.42543801]
 ...
 [-0.48948078 -1.32000918  0.03709576 ...  0.94593254 -0.66285492
   -0.42543801]
 [-2.26140122 -1.32000918  0.03709576 ...  0.94593254 -0.66285492
   -0.42543801]
 [-0.26799073  0.75757049 -0.92209456 ...  0.94593254  2.5797597
    1.2857682 ]]

Checking data partitioning
X_train samples: [[-0.71097084  0.75757049 -0.92209456 ...  0.94593254 -0.66285492
```

```
  -0.42543801]
 [-0.37873576  0.75757049 -0.92209456 ... -0.62483617  2.5797597
   1.2857682 ]
 [-0.48948078 -1.32000918 -0.92209456 ...  0.94593254 -0.66285492
  -0.42543801]
 ...
 [-0.48948078 -1.32000918  0.03709576 ...  0.94593254 -0.66285492
  -0.42543801]
 [-2.26140122 -1.32000918  0.03709576 ...  0.94593254 -0.66285492
  -0.42543801]
 [-0.26799073  0.75757049 -0.92209456 ...  0.94593254  2.5797597
   1.2857682 ]]

X_test samples:      age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng  oldpea
k  slp  \
189   41    1   0     110   172    0        0       158     0      0.0    2
277   57    1   1     124   261    0        1       141     0      0.3    2
23    61    1   2     150   243    1        1       137     1      1.0    1
100   42    1   3     148   244    0        0       178     0      0.8    2
38    65    0   2     155   269    0        1       148     0      0.8    2
..   ...  ...  ..     ...   ...  ...      ...       ...   ...      ...  ...
116   41    1   2     130   214    0        0       168     0      2.0    1
184   50    1   0     150   243    0        0       128     0      2.6    1
226   62    1   1     120   281    0        0       103     0      1.4    1
63    41    1   1     135   203    0        1       132     0      0.0    1
276   58    1   0     146   218    0        1       105     0      2.0    1

     caa  thall
189    0      3
277    0      3
23     0      2
100    2      2
38     0      2
..   ...    ...
116    0      2
184    0      3
226    1      3
63     0      1
276    1      3

[122 rows x 13 columns]

y_train samples: 56     1
250    0
109    1
173    0
216    0
      ..
185    0
245    0
108    1
125    1
97     1
Name: output, Length: 181, dtype: int64

y_test samples: 189    0
277    0
23     1
100    1
38     1
```

```
       ..
116    1
184    0
226    0
63     1
276    0
Name: output, Length: 122, dtype: int64
```

In [4]:

```
# Phase 3: Creating the model
# Understanding LR parameters:
#               solver = a string ('liblinear' by deafult) that decides what solver to
#               multi-class = a string ('ovr' by default) decides the approach to use
#                             'ovr' says to make the binary fit for each class
#                              'multinomial' says to apply the multinomial loss fit
#               C = a positive floating-point number (1.0 by default) that defines the
#               random_state = an integer, an instance of numpy.RandomState, or None (

model = LogisticRegression(solver='liblinear', C=0.5, multi_class='ovr', random_state=
model.fit(X_train, y_train)

print('\nChecking LR output string\n', cl(model, attrs = ['bold']))
print('\nChecking LR coefficients: \n', model.coef_)
print('\nChecking LR intercept: \n', model.intercept_)
```

```
Checking LR output string
 LogisticRegression(C=0.5, multi_class='ovr', random_state=0, solver='liblinear')

Checking LR coefficients:
 [[-4.55118365e-02 -7.10529980e-01  8.47203745e-01 -4.78566647e-01
  -2.29197623e-01 -6.78570178e-04  1.86813165e-01  6.77556904e-01
  -4.92139834e-01 -3.82959521e-01  8.00958423e-02 -4.71220027e-01
  -3.78816464e-01]]

Checking LR intercept:
 [0.3701171]
```

In [5]:

```
# Phase 4:Evaluating the model: returns the matrix of probabilities

X_test = scaler.transform(X_test)
y_pred = model.predict(X_test)
confusion_matrix(y_test, y_pred)
```

Out[5]:

```
array([[44, 17],
       [ 7, 54]], dtype=int64)
```

In [6]:

```
train_score = model.score(X_train, y_train)
test_score = model.score(X_test, y_test)
print('\nTrain score is: \n', train_score)
print('\nTest score is: \n', test_score)
```

```
Train score is:
 0.8342541436464088

Test score is:
 0.8032786885245902
```

In [7]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.72      0.79        61
           1       0.76      0.89      0.82        61

    accuracy                           0.80       122
   macro avg       0.81      0.80      0.80       122
weighted avg       0.81      0.80      0.80       122
```

In [8]:

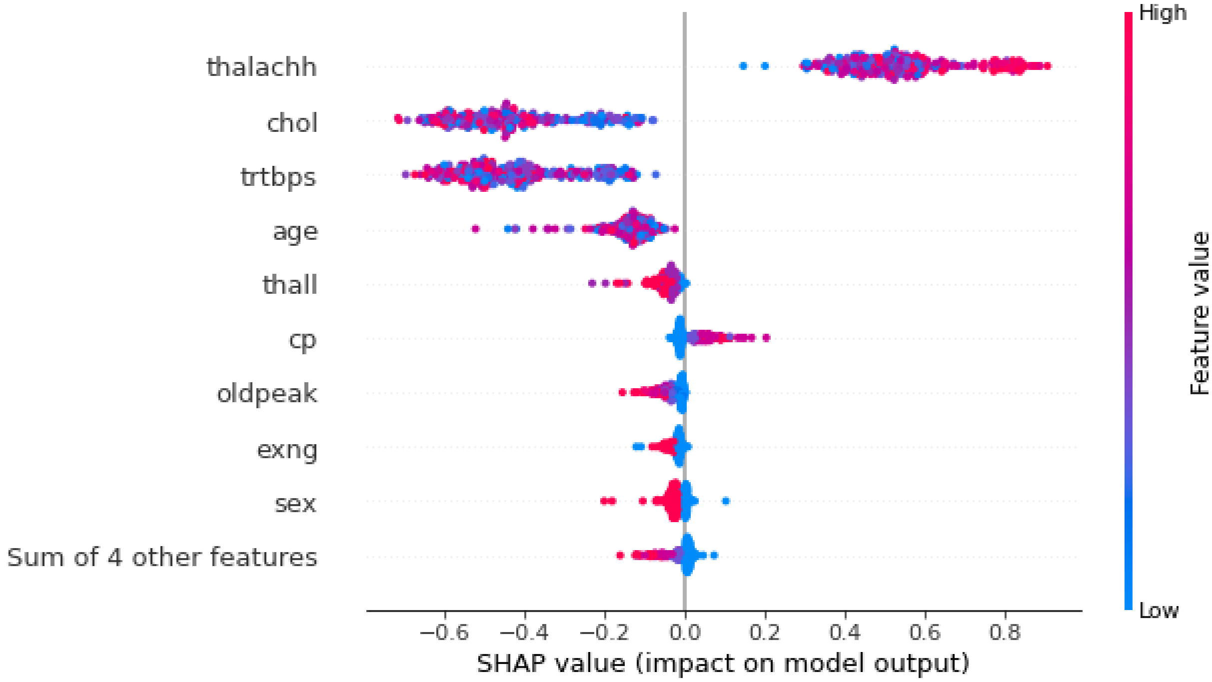
```
# Phase 5: Creating SHAP explainer object
#          Creating feature_names array to store features to be able to use in shap pl
#          Finding 'best' way to represent dataset using SHAP visualization


feature_names = []
for feature in X.columns.tolist():
    feature_names.append(feature)
print('\nChecking feature names in columns from X-variable: \n', feature_names)


explainer = shap.Explainer(model.predict, X_test, feature_names=feature_names)
shap_values = explainer(X)




# for-loop goes through shap_values which stores .base_values, .values, .data while al
#            through feature_names to assign respective shap_value to its correspondir
# Break the inner loop to execute string based on length of the feature_names array or
#            will repeat string format all # of times of length in feature_names
print('\nArray of SHAP values with added feature_names: \n')
for name in feature_names:
    print('\n')
    for value in shap_values:
        print('"{}" data and values \n{}'.format(name, value))
        break


# By default, a SHAP beeswarm plot will take the mean absolute value of each feature
#             over all the instances (rows) of the dataset
# Each point on the chart is one SHAP value for a prediction and feature
# Red color means higher value of a feature. Blue means lower value of a feature.
# We can get the general sense of features' directionality impact based on the distrib
#            the red and blue dots
shap.plots.beeswarm(shap_values)


# In this chart, the x-axis stands for the SHAP value and the y-axis has all the featu
shap.summary_plot(shap_values, feature_names, plot_type='bar')



# Interesting SHAP scatter plot summary of all SHAP values for each feature
shap.plots.scatter(shap_values[:,:])


# for-loop for SHAP scatter plots to show correlation between different features
for feature in feature_names:
    shap.plots.scatter(shap_values[:, feature], color=shap_values)
```

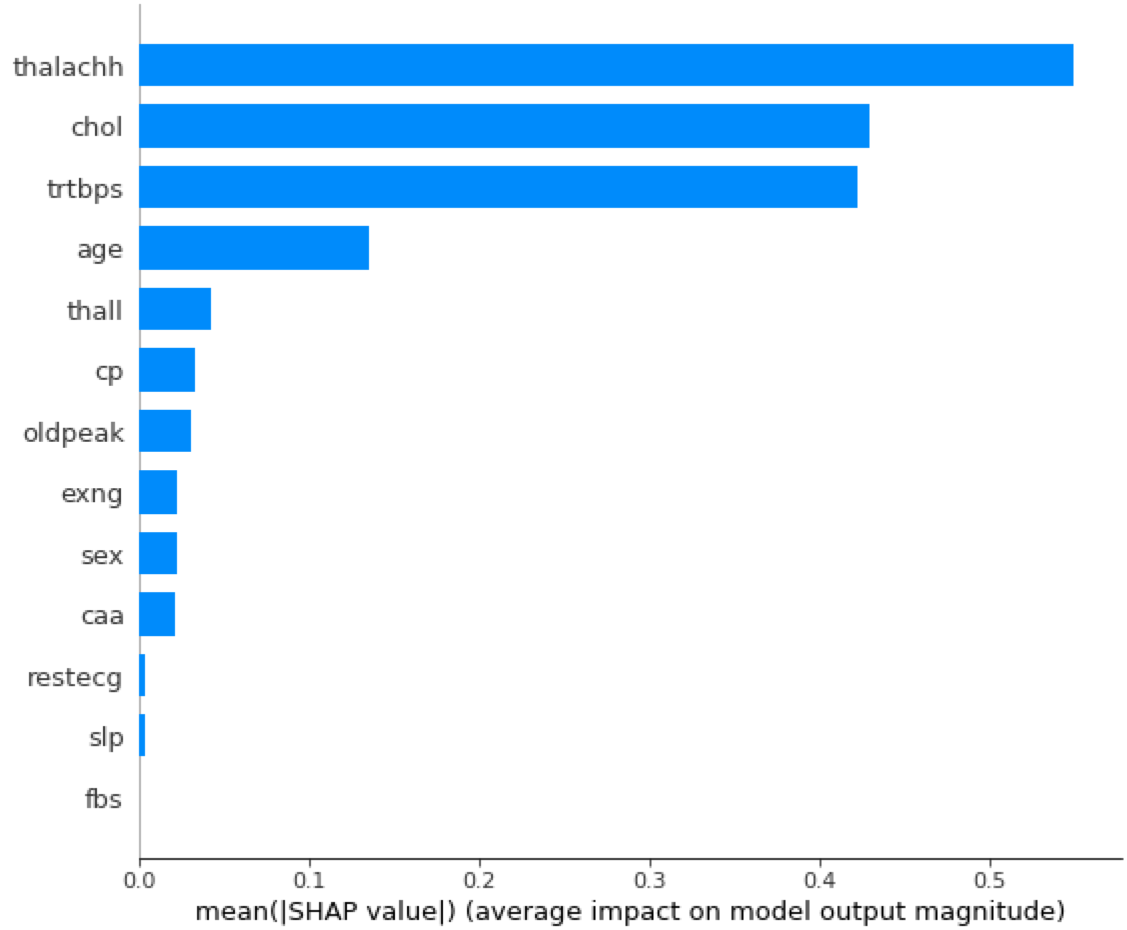
```
Checking feature names in columns from X-variable:
 ['age', 'sex', 'cp', 'trtbps', 'chol', 'fbs', 'restecg', 'thalachh', 'exng', 'oldpea
k', 'slp', 'caa', 'thall']

Array of SHAP values with added feature_names:



"age" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"sex" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"cp" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"trtbps" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])
```

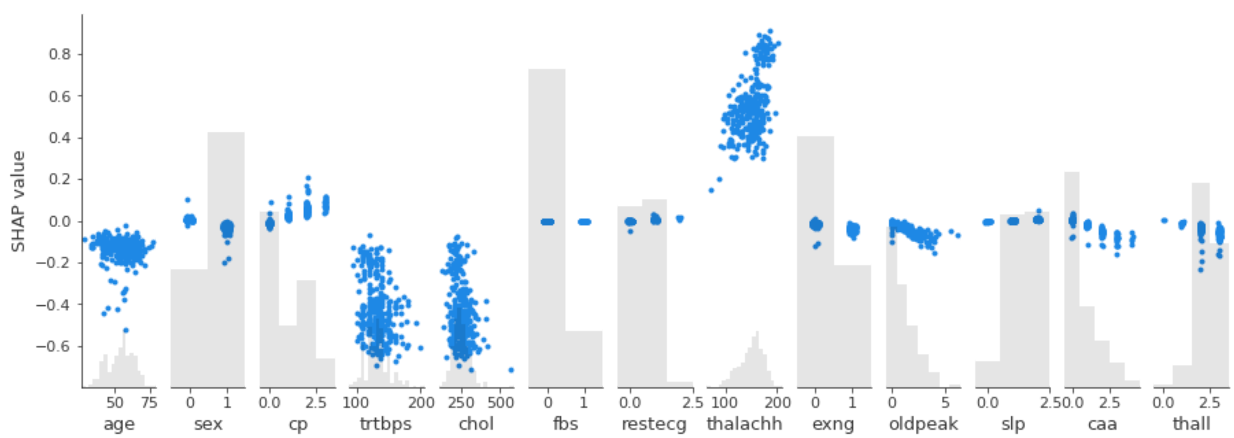
```
.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"chol" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"fbs" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"restecg" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"thalachh" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])
```

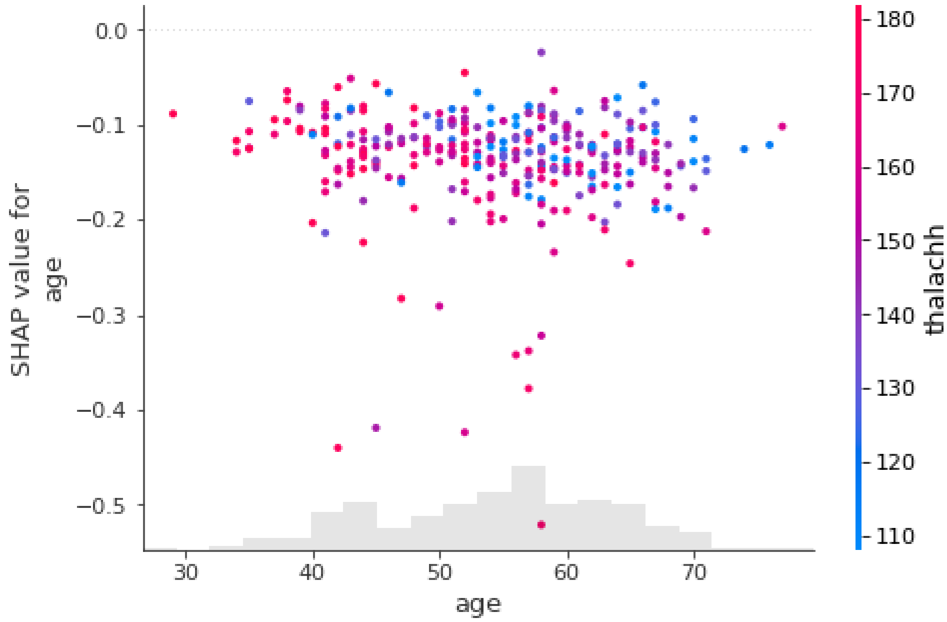
```
.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"exng" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"oldpeak" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"slp" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"caa" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])
```

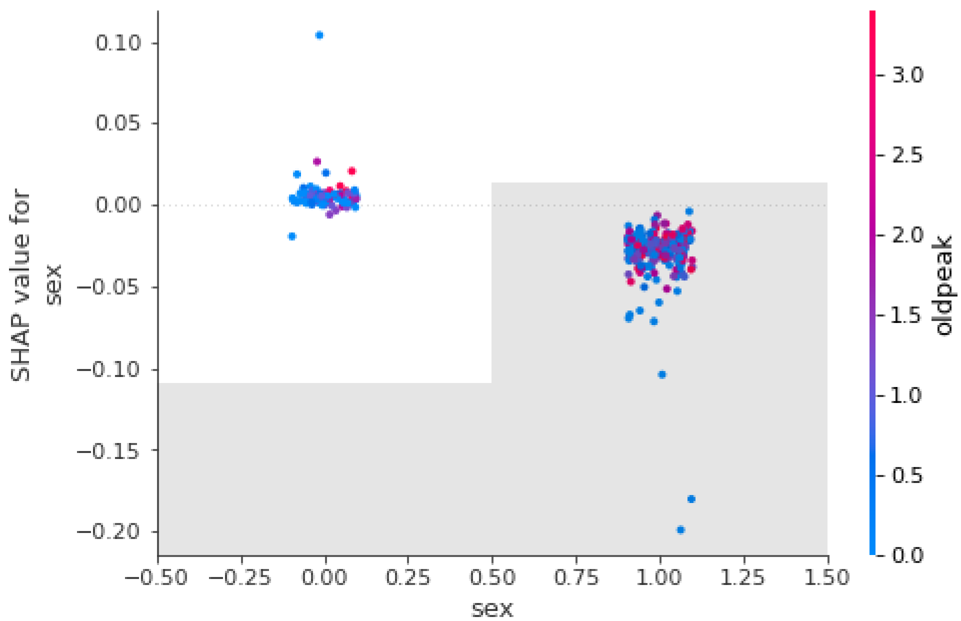
```
.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])


"thall" data and values
.values =
array([-1.47777778e-01, -1.16666667e-02,  9.58333333e-02, -5.23888889e-01,
       -5.00277778e-01,  0.00000000e+00, -5.55555556e-04,  4.37222222e-01,
       -1.11111111e-03, -5.72222222e-02, -2.77777778e-04,  9.72222222e-03,
       -1.00000000e-02])

.base_values =
0.71

.data =
array([ 63. ,   1. ,   3. , 145. , 233. ,   1. ,   0. , 150. ,   0. ,
         2.3,   0. ,   0. ,   1. ])
```

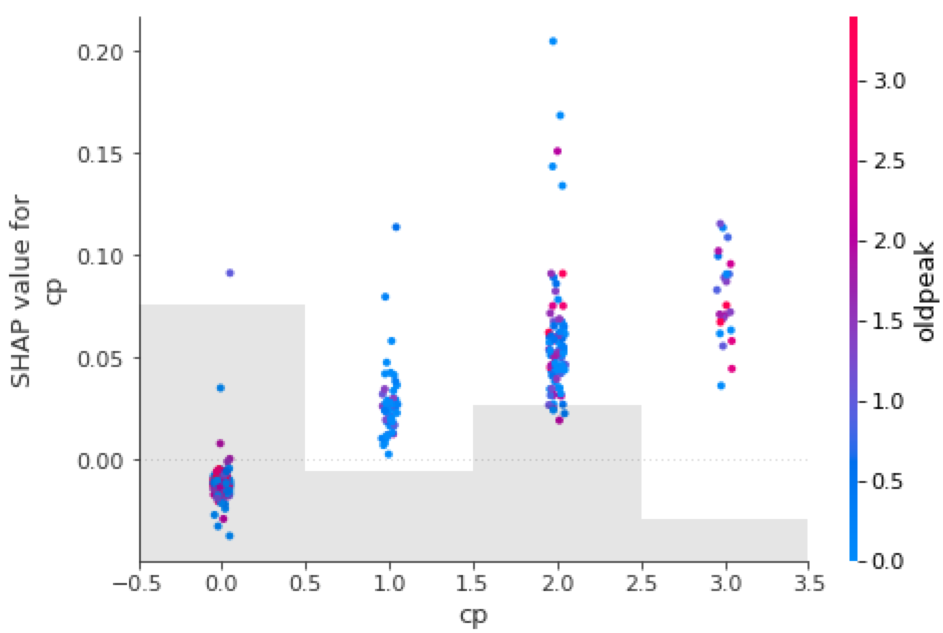


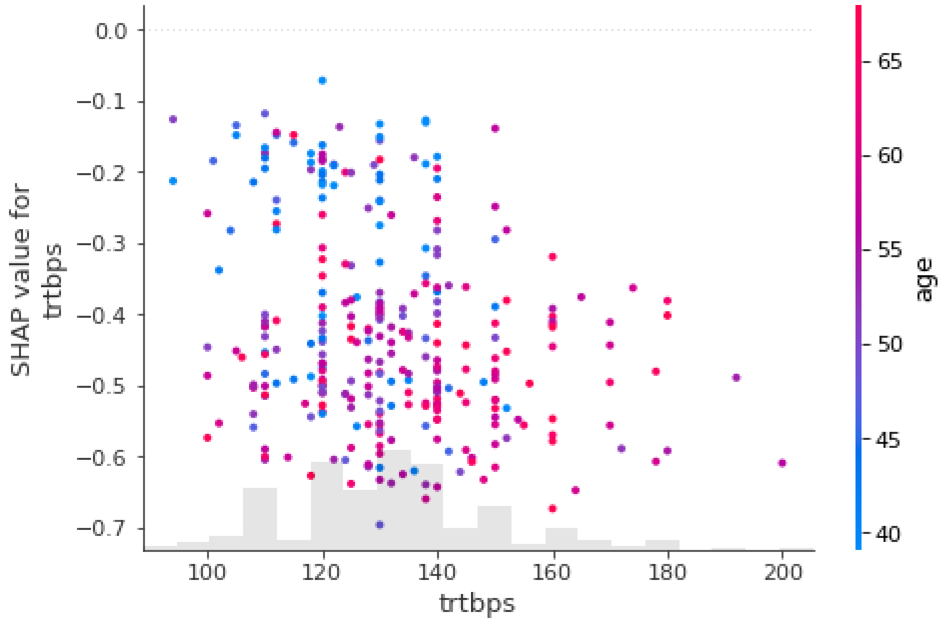

thalachh
chol
trtbps
age
thall
cp
oldpeak
exng
sex
caa
restecg
slp
fbs
0.0
0.1
0.2
0.3
0.4
0.5
mean(|SHAP value|) (average impact on model output magnitude)

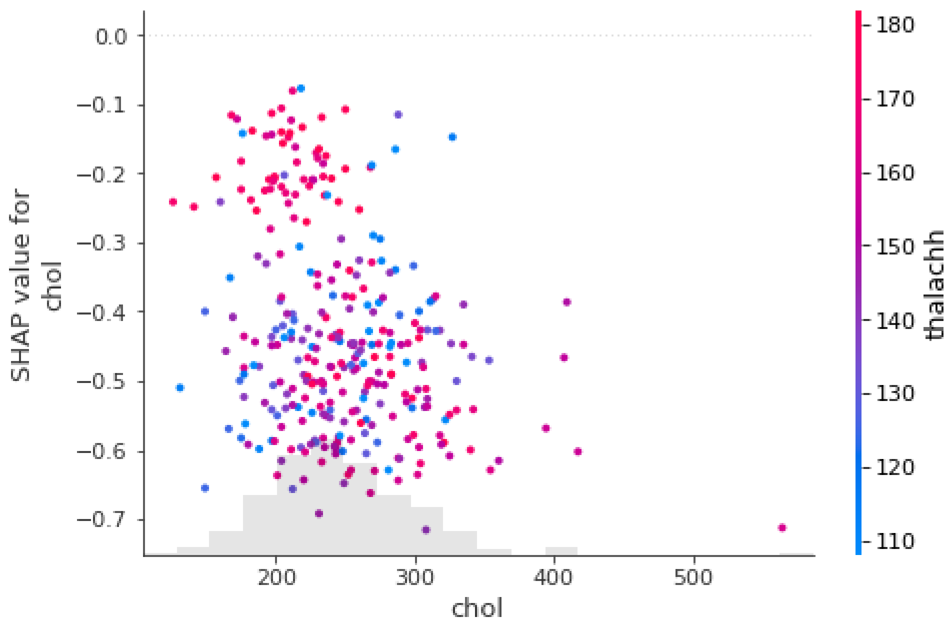

SHAP value
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
age
sex
cp
trtbps
chol
fbs
restecg
thalachh
exng
oldpeak
slp
caa
thall

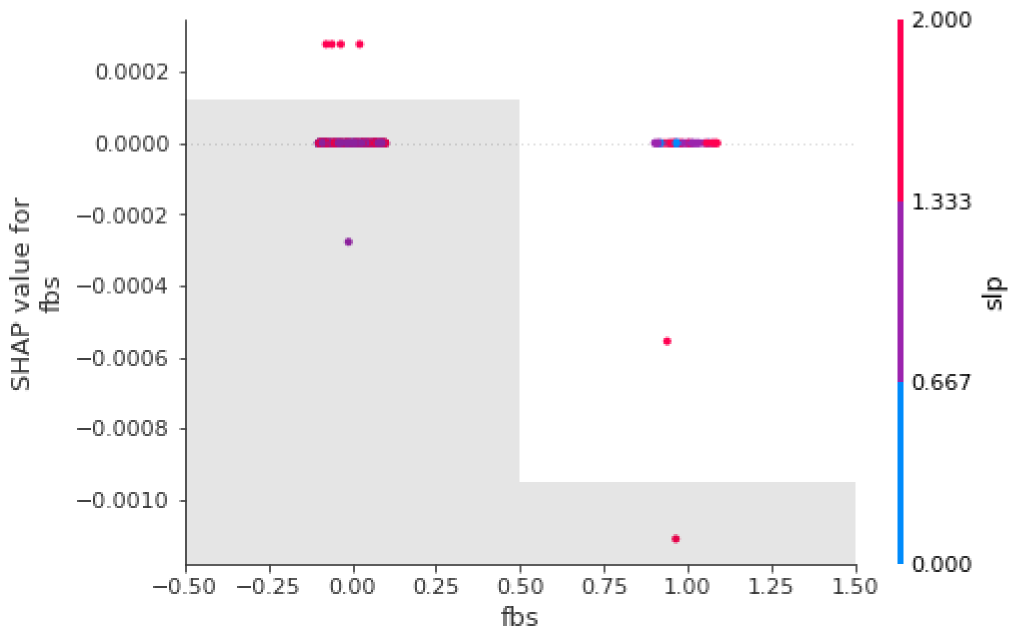

SHAP value for
age
age
thalachh
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
30
40
50
60
70
180
170
160
150
140
130
120
110

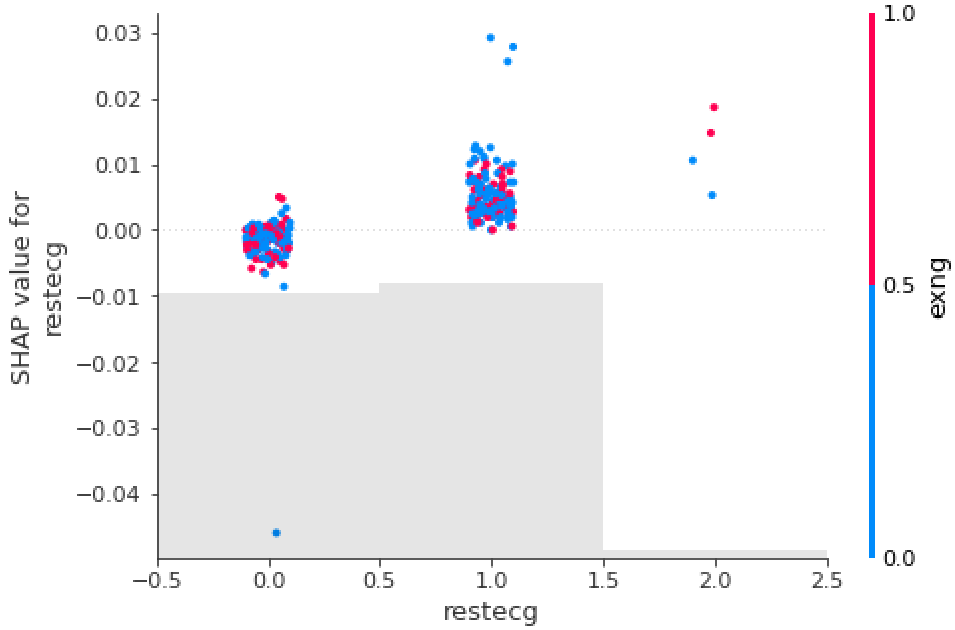

SHAP value for
sex
sex
oldpeak
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
3.0
2.5
2.0
1.5
1.0
0.5
0.0


SHAP value for
cp
cp
oldpeak
0.20
0.15
0.10
0.05
0.00
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0

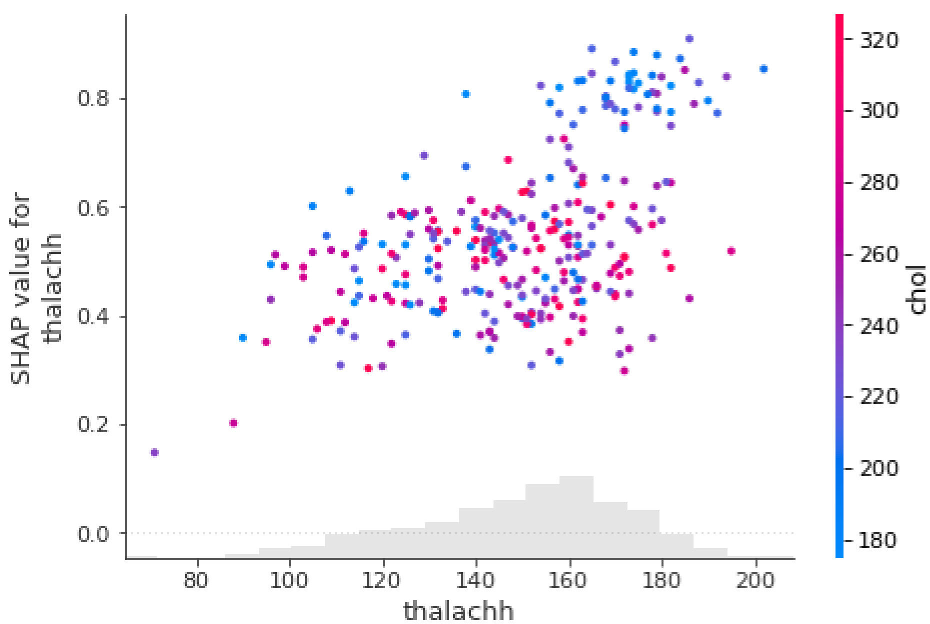

SHAP value for trtbps
trtbps
age
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
−0.7
100
120
140
160
180
200
65
60
55
50
45
40


SHAP value for chol
chol
thalachh
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
−0.7
200
300
400
500
180
170
160
150
140
130
120
110

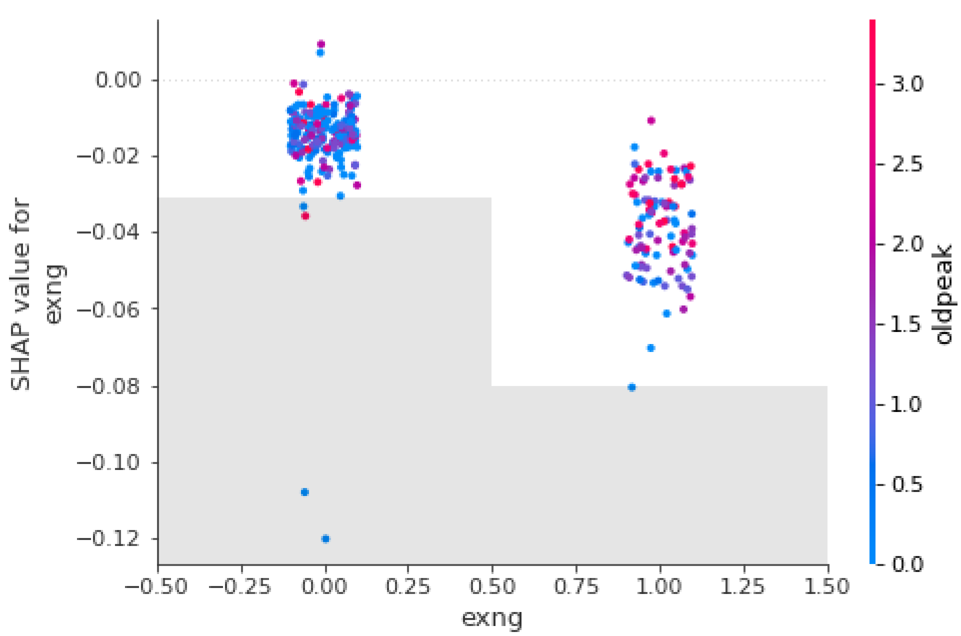

SHAP value for fbs
fbs
slp
0.0002
0.0000
−0.0002
−0.0004
−0.0006
−0.0008
−0.0010
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
2.000
1.333
0.667
0.000



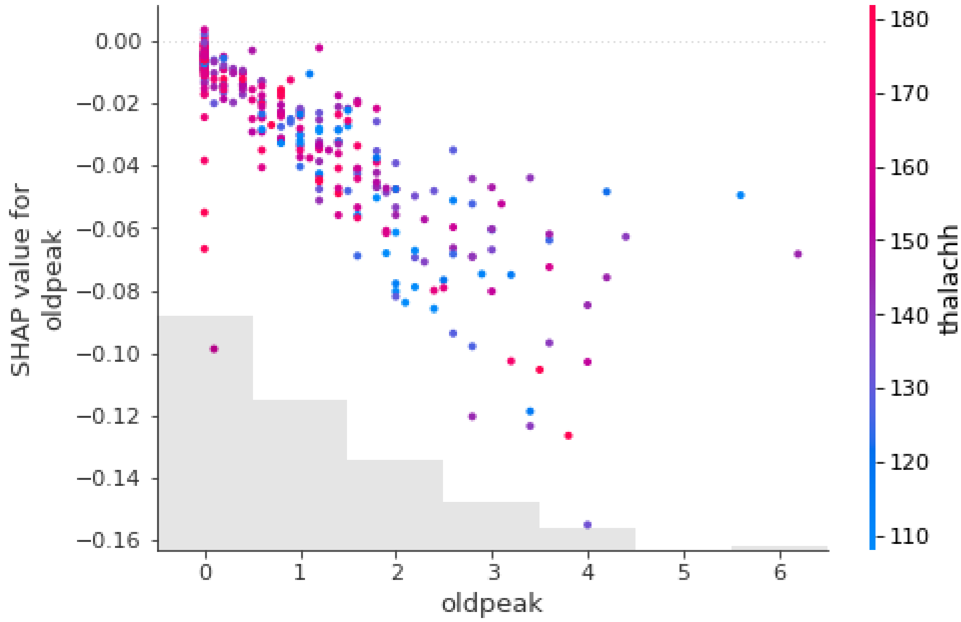
SHAP value for restecg
restecg
exng
0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
−0.04
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.5
1.0



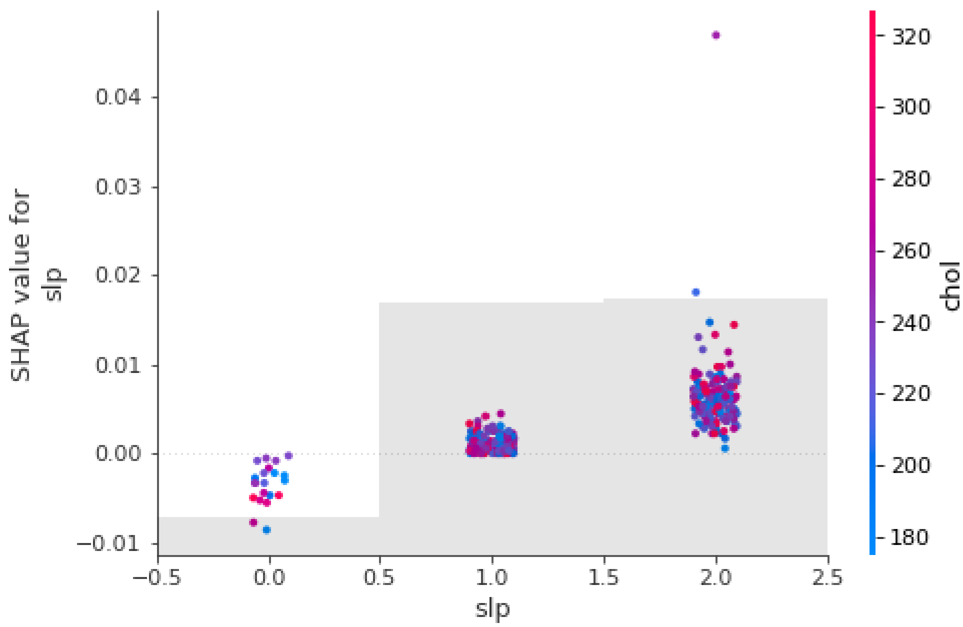
SHAP value for thalachh
thalachh
chol
0.0
0.2
0.4
0.6
0.8
80
100
120
140
160
180
200
180
200
220
240
260
280
300
320



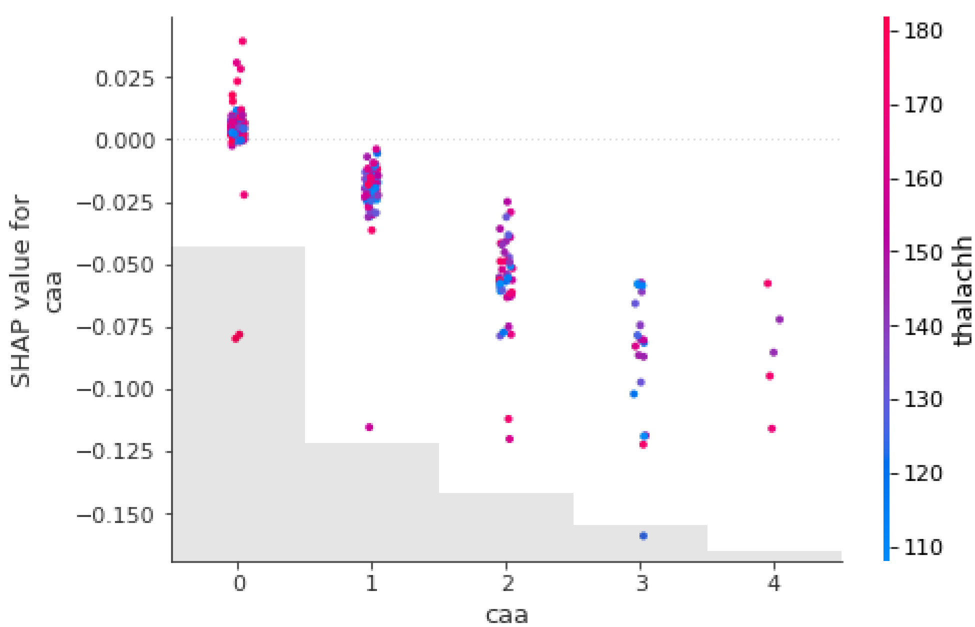
SHAP value for exng
exng
oldpeak
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
−0.12
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
0.0
0.5
1.0
1.5
2.0
2.5
3.0



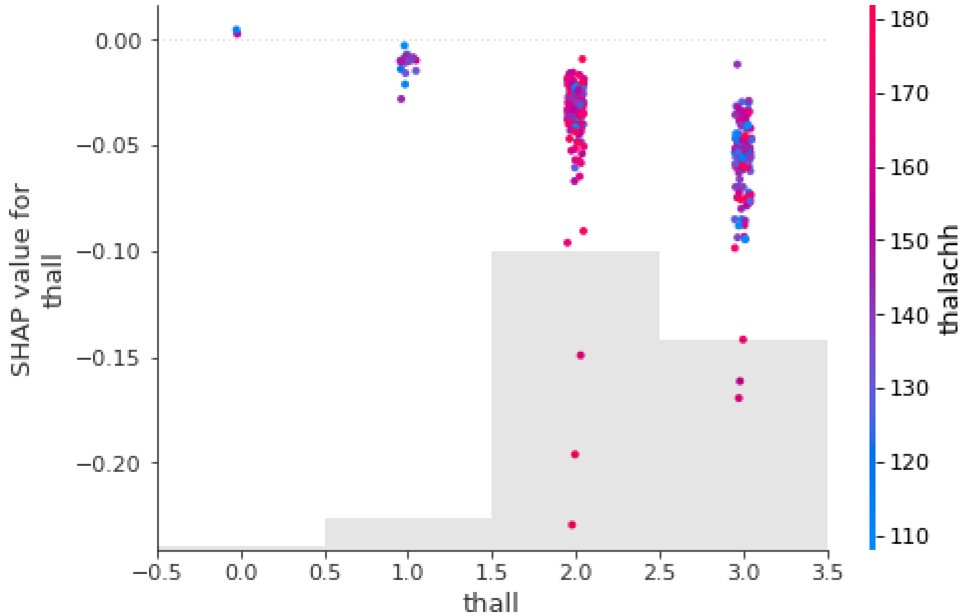
SHAP value for oldpeak
oldpeak
thalachh



SHAP value for slp
slp
chol



SHAP value for caa
caa
thalachh



In [9]:

```
# References to put code together, compile, and test run of a Logistic Regression mode
#           Splitting CSV Into Trainand Test Data by Nishank Sharma: https://medium.co
#           Logistic Regression in Python by Mirko Stojiljkovic: https://realpython.co
#           How to interpret machine learning (ML) models with SHAP values by Xiaoyou
#           SHAP explainer and models: https://www.mage.ai/blog/how-to-interpret-expla
#           Dataset taken from: https://www.kaggle.com/datasets/rashikrahmanpritom/hea
#           scikit learn: https://scikit-learn.org/stable/modules/generated/sklearn.pr
#           SHAP Force Plots for Classification by Max Steele: https://medium.com/mlea
#           Machine Learning - Logistic Regression with Python by Nikhil Adithyan: htt
```