Logistic Regression

May 23, 2022

1 Imports

[1]:
```
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Load the data

[2]:
```
heart_data = pd.read_csv('heart.csv')
heart_data.head()
```

[2]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
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

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

3 Data exploration

[3]:
```
heart_data.shape
```

[3]:
```
(303, 14)
```

[4]:
```
heart_data.describe()
```

[4]:

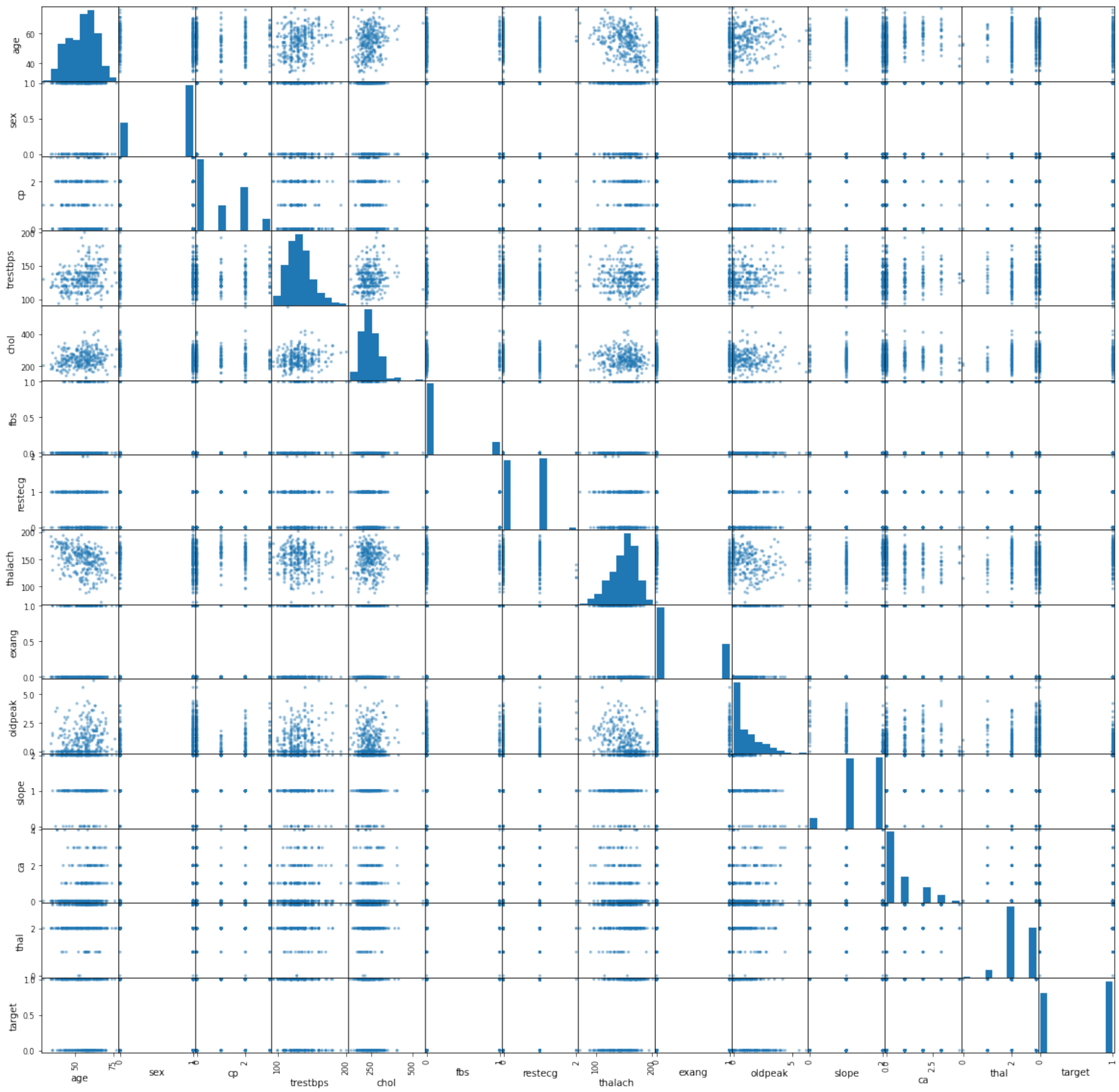
```
              age         sex          cp    trestbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean    54.366337    0.683168    0.966997  131.623762  246.264026    0.148515
std      9.082101    0.466011    1.032052   17.538143   51.830751    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     thalach       exang     oldpeak       slope          ca  \
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

             thal      target
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
```

[5]:

```
pd.plotting.scatter_matrix(heart_data, figsize=(20, 20))
plt.savefig('scatter_matrix.jpg')
plt.show()
```



[6]:
```
heart_data.corr()
```

[6]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.098447 -0.068653  0.279351  0.213678  0.121308
sex      -0.098447  1.000000 -0.049353 -0.056769 -0.197912  0.045032
cp       -0.068653 -0.049353  1.000000  0.047608 -0.076904  0.094444
trestbps  0.279351 -0.056769  0.047608  1.000000  0.123174  0.177531
chol      0.213678 -0.197912 -0.076904  0.123174  1.000000  0.013294
fbs       0.121308  0.045032  0.094444  0.177531  0.013294  1.000000
restecg  -0.116211 -0.058196  0.044421 -0.114103 -0.151040 -0.084189
thalach  -0.398522 -0.044020  0.295762 -0.046698 -0.009940 -0.008567
exang     0.096801  0.141664 -0.394280  0.067616  0.067023  0.025665
oldpeak   0.210013  0.096093 -0.149230  0.193216  0.053952  0.005747
slope    -0.168814 -0.030711  0.119717 -0.121475 -0.004038 -0.059894
```

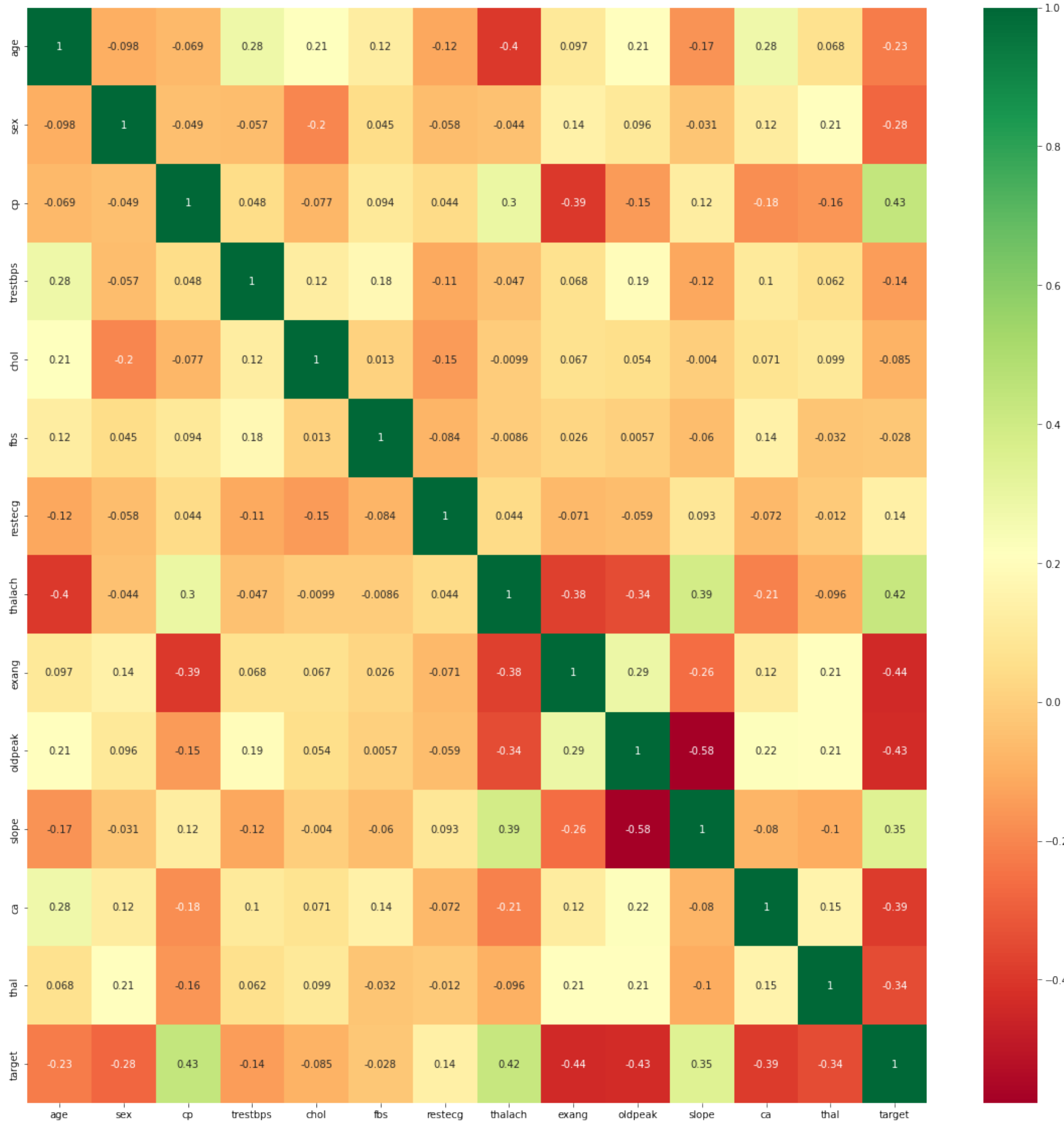
```
ca        0.276326  0.118261 -0.181053  0.101389  0.070511  0.137979
thal      0.068001  0.210041 -0.161736  0.062210  0.098803 -0.032019
target   -0.225439 -0.280937  0.433798 -0.144931 -0.085239 -0.028046

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.116211 -0.398522  0.096801  0.210013 -0.168814  0.276326
sex      -0.058196 -0.044020  0.141664  0.096093 -0.030711  0.118261
cp        0.044421  0.295762 -0.394280 -0.149230  0.119717 -0.181053
trestbps -0.114103 -0.046698  0.067616  0.193216 -0.121475  0.101389
chol     -0.151040 -0.009940  0.067023  0.053952 -0.004038  0.070511
fbs      -0.084189 -0.008567  0.025665  0.005747 -0.059894  0.137979
restecg   1.000000  0.044123 -0.070733 -0.058770  0.093045 -0.072042
thalach   0.044123  1.000000 -0.378812 -0.344187  0.386784 -0.213177
exang    -0.070733 -0.378812  1.000000  0.288223 -0.257748  0.115739
oldpeak  -0.058770 -0.344187  0.288223  1.000000 -0.577537  0.222682
slope     0.093045  0.386784 -0.257748 -0.577537  1.000000 -0.080155
ca       -0.072042 -0.213177  0.115739  0.222682 -0.080155  1.000000
thal     -0.011981 -0.096439  0.206754  0.210244 -0.104764  0.151832
target    0.137230  0.421741 -0.436757 -0.430696  0.345877 -0.391724

              thal    target
age       0.068001 -0.225439
sex       0.210041 -0.280937
cp       -0.161736  0.433798
trestbps  0.062210 -0.144931
chol      0.098803 -0.085239
fbs      -0.032019 -0.028046
restecg  -0.011981  0.137230
thalach  -0.096439  0.421741
exang     0.206754 -0.436757
oldpeak   0.210244 -0.430696
slope    -0.104764  0.345877
ca        0.151832 -0.391724
thal      1.000000 -0.344029
target   -0.344029  1.000000
```

[7]:

```
plt.figure(figsize=(20,20))
sns.heatmap(heart_data.corr(),annot=True,cmap="RdYlGn")
plt.savefig('corr.jpg')
plt.show()
```



4 Logistic Regression

[8]:
```python
class LogiReg:
    def __init__(self, lr=0.001, iters_num=100, log=True):
        self.lr = lr
        self.iters_num = iters_num
        self.weights = None
        self.log = log
```

```
    def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))


    def b_intercept(self, X):
        intercept = np.ones((X.shape[0], 1))
        # concatinate them to the value of X
        return np.concatenate((intercept, X), axis=1)


    def fit (self, X, y):
        # initialize parameters
        X = self.b_intercept(X)
        self.weights = np.zeros(X.shape[1])

        # gradient descent
        for i in range(self.iters_num):

            z = np.dot(X, self.weights)
            # apply sigmoid function
            y_pred = self.sigmoid(z)

            # compute gradients
            grad = np.dot(X.T, (y_pred - y)) / y.size
            self.weights -= self.lr * grad

            # new W * Xi
            new_z = np.dot(X, self.weights)
            y_pred = self.sigmoid(new_z)

            # calculate loss
            loss = self.loss(y_pred, y)
            if i % 100 == 0 and self.log:
                print(f'iteration #{i}, loss = {loss}')


    def loss(self, y_pred, y):
        return (-y * np.log(y_pred) - (1 - y) * np.log(1 - y_pred)).mean()

    # predict the probability values
    def predict_prob(self, X):
        X = self.b_intercept(X)
        z = np.dot(X, self.weights)
        return self.sigmoid(z)

    # predict the actual values 0 or 1 using round
    def predict(self, X):
```

```
        return self.predict_prob(X).round()
```

[9]:
```
model = LogiReg(0.01, 3000)
```

5 Data preprocessing

[10]:
```
# creating features and labels matrices
X = heart_data.drop(['target'], axis=1) # axis =1 because of we deal with␣
↪coloumn
y = heart_data['target']
```

[11]:
```
# normalization step
X = (X-X.mean())/X.std()
```

[12]:
```
# train test splitting
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

6 All features

6.0.1 Model training

[13]:
```
model.fit(X_train, y_train)
```

```
iteration #0, loss = 0.6899513425649656
iteration #100, loss = 0.5080874138342651
iteration #200, loss = 0.4434654806586477
iteration #300, loss = 0.4126782301146911
iteration #400, loss = 0.395135628962435
iteration #500, loss = 0.3839824082850972
iteration #600, loss = 0.37636232794764624
iteration #700, loss = 0.37088798112082094
iteration #800, loss = 0.3668077919367627
iteration #900, loss = 0.36368039187628926
iteration #1000, loss = 0.36123006516245904
iteration #1100, loss = 0.35927600560309153
iteration #1200, loss = 0.35769492735406383
iteration #1300, loss = 0.356400366595718
iteration #1400, loss = 0.35532858424449393
iteration #1500, loss = 0.354434174928488
iteration #1600, loss = 0.35368184113103557
iteration #1700, loss = 0.3530447876229182
iteration #1800, loss = 0.3525021822418355
iteration #1900, loss = 0.3520376211278857
iteration #2000, loss = 0.3516380404969885
iteration #2100, loss = 0.3512929309376693
```

```
iteration #2200, loss = 0.3509937609081084
iteration #2300, loss = 0.3507335475692134
iteration #2400, loss = 0.3505065331009784
iteration #2500, loss = 0.3503079376649882
iteration #2600, loss = 0.3501337688128113
iteration #2700, loss = 0.349980672976371З
iteration #2800, loss = 0.34984581868595993
iteration #2900, loss = 0.34972680395795647
```

6.0.2 Evaluation

[14]:
```python
def accuracy(y, y_pred):
    accuracy = np.mean(y == y_pred)
    return accuracy

def plot_regression(X, y, model):
    plt.figure(figsize=(10, 6))
    plt.scatter(X[y == 0][:, 0], X[y == 0][:, 1], color='b', label='0')
    plt.scatter(X[y == 1][:, 0], X[y == 1][:, 1], color='r', label='1')
    plt.legend()
    x1_min, x1_max = X[:,0].min(), X[:,0].max(),
    x2_min, x2_max = X[:,1].min(), X[:,1].max(),
    xx1, xx2 = np.meshgrid(np.linspace(x1_min, x1_max), np.linspace(x2_min,␣
 ↪x2_max))
    grid = np.c_[xx1.ravel(), xx2.ravel()]
    probs = model.predict_prob(grid).reshape(xx1.shape)
    plt.contour(xx1, xx2, probs, [0.5], linewidths=1, colors='black')
    plt.show()
```

[15]:
```python
predictions = model.predict(X_test)
print("Accuracy:", accuracy(y_test, predictions))
```

```
Accuracy: 0.8360655737704918
```

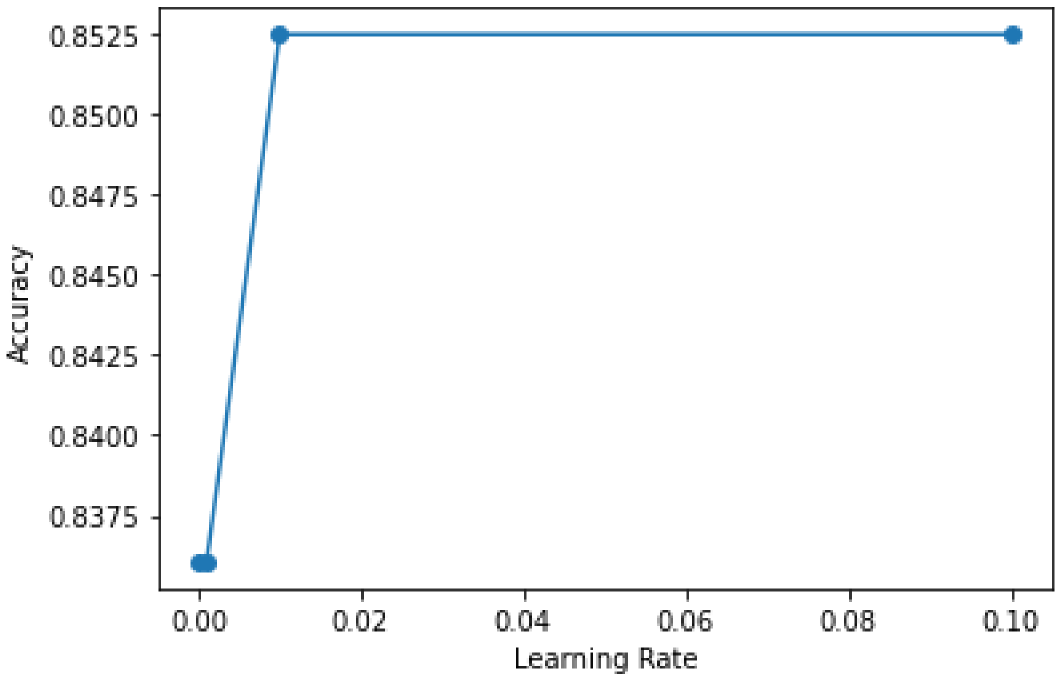
7 Learning rate

[16]:
```python
lrs = [0.1, 0.01, 0.001, 0.0001]
acc = list()
for lr in lrs:
    model = LogiReg(lr, 10000, False)
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    acc.append(accuracy(y_test, predictions))

best_lr = lrs[acc.index(max(acc))]
print('Best learning rate is', best_lr)
```

```
Best learning rate is 0.1
```

[17]:
```
plt.plot(lrs, acc, '-o')
plt.xlabel('Learning Rate')
plt.ylabel('Accuracy')
plt.savefig('lrs.jpg')
plt.show()
```



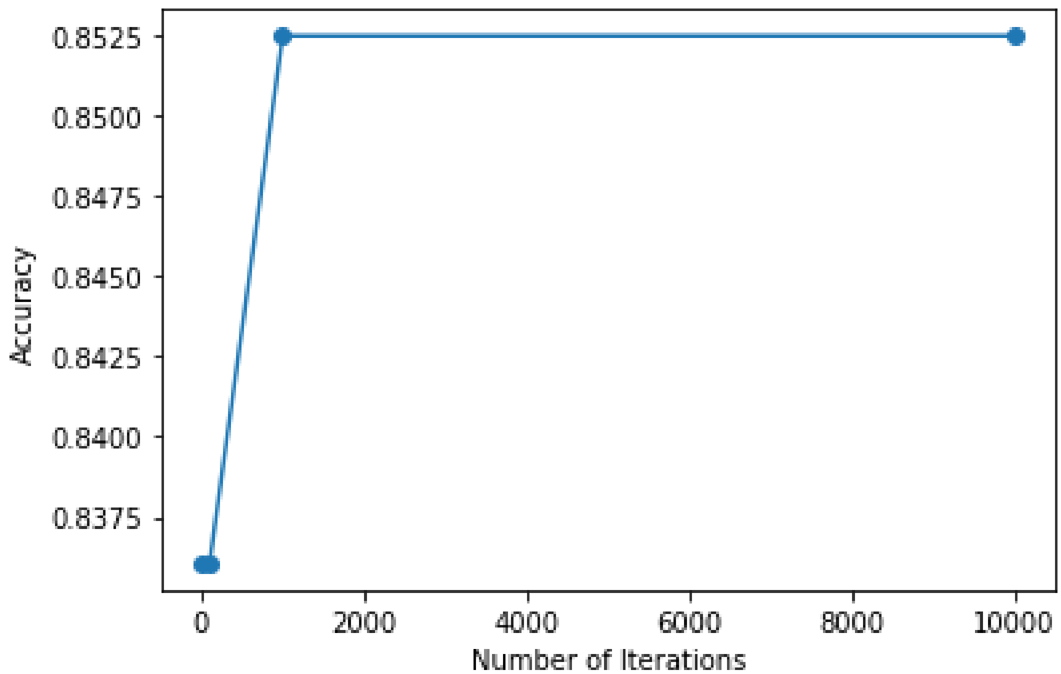
8 Number of iterations

[18]:
```
its = [10, 100, 1000, 10000]
acc = list()
for it in its:
    model = LogiReg(best_lr, it, False)
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    acc.append(accuracy(y_test, predictions))

best_it = its[acc.index(max(acc))]
print('Best number of iterations is', best_it)
```

```
Best number of iterations is 1000
```

[19]:
```
plt.plot(its, acc, '-o')
plt.xlabel('Number of Iterations')
plt.ylabel('Accuracy')
plt.savefig('its.jpg')
plt.show()
```



9 Feature pairs (random)

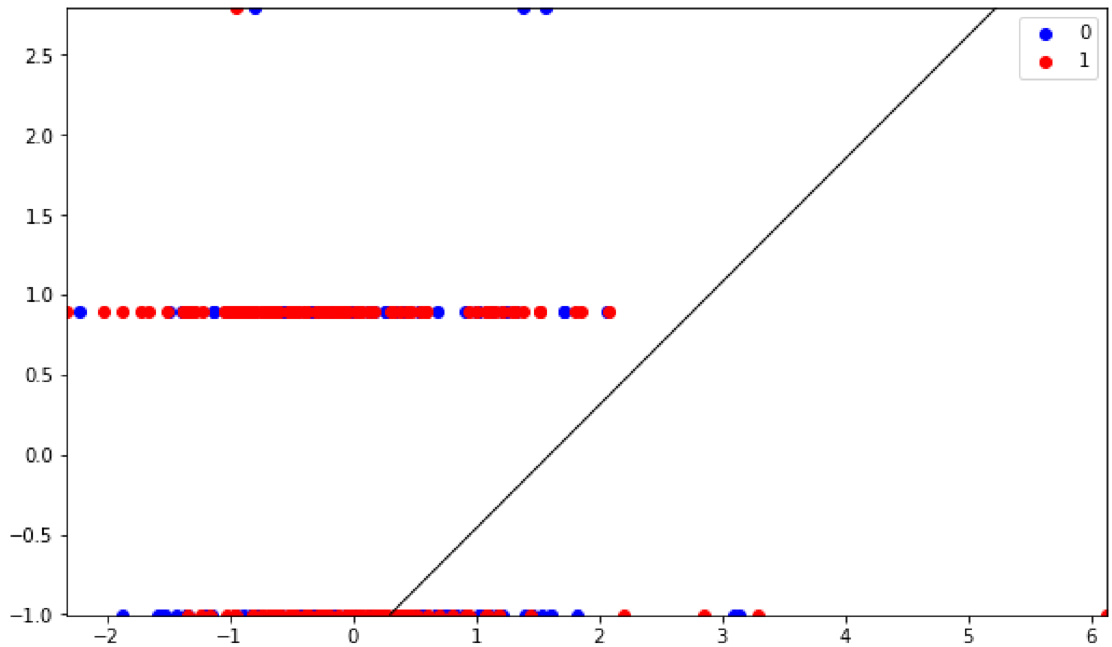
[20]:
```
def pipeline(X, y, lr=0.01, it=3000):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
    model = LogiReg(lr, it, False)
    model.fit(X_train, y_train)
    return model, round(accuracy(y_test, model.predict(X_test)), 5)*100
```

[21]:
```
for i in range(5):
    # Pick two features
    f1 = np.random.choice(X.columns.values)
    f2 = f1
    while f2 == f1:
        f2 = np.random.choice(X.columns.values)
    # Train model
    model, acc = pipeline(X[[f1, f2]], y)
```

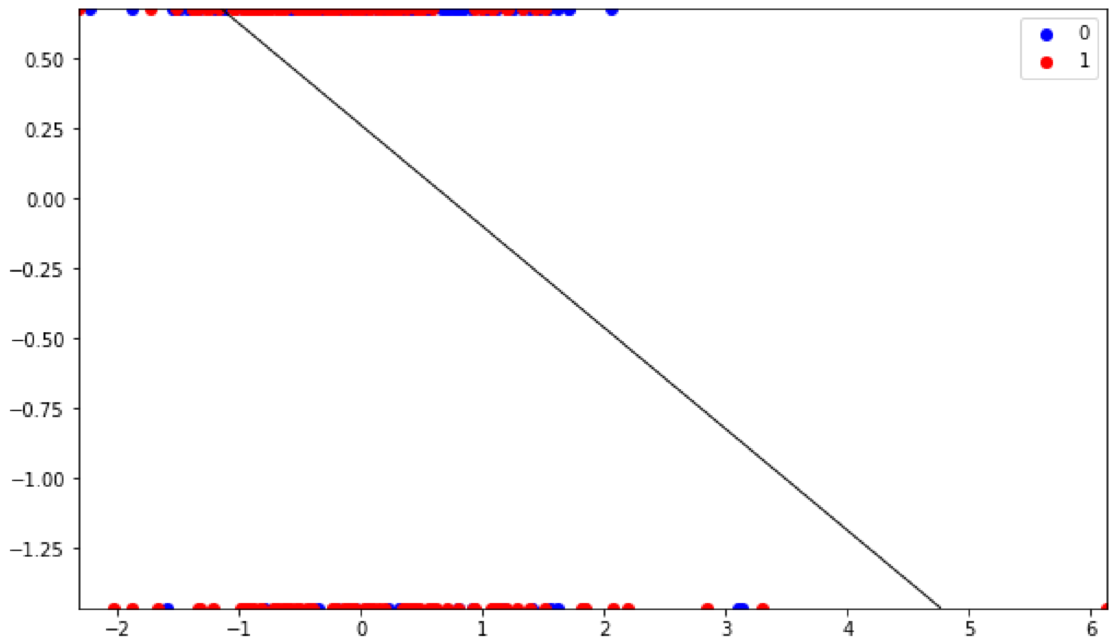
```
    print(f"Trial #{i+1} with features: {f1} and {f2}, accuracy: {acc} %")

    newX = X[[f1, f2]].to_numpy()
    plot_regression(newX, y, model)
```

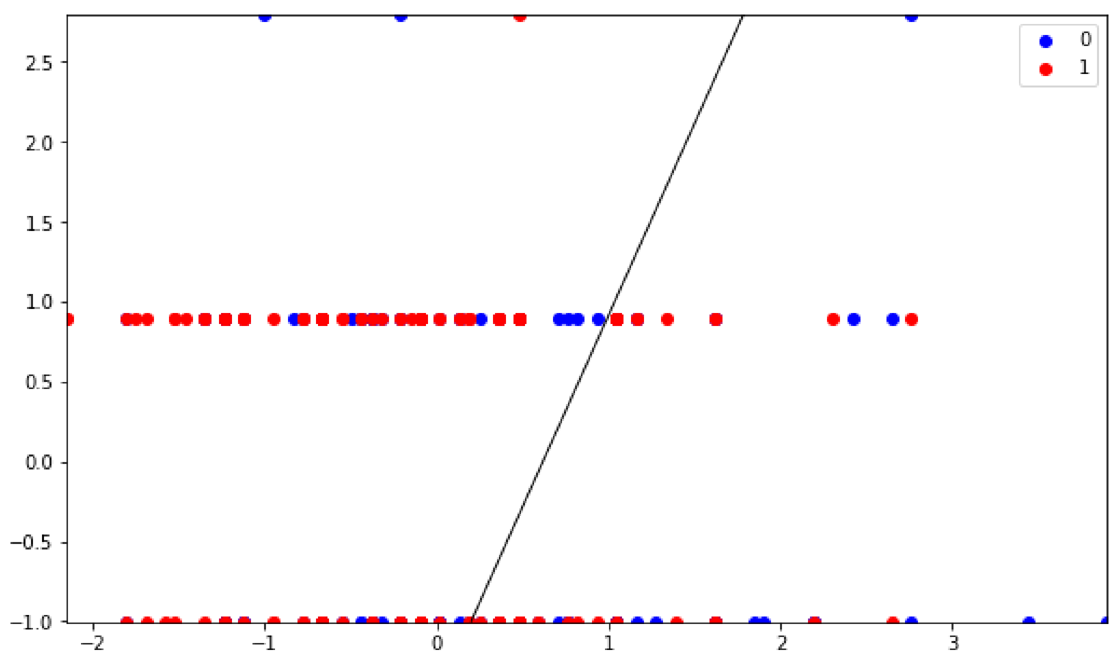
```
Trial #1 with features: chol and restecg, accuracy: 63.934000000000005 %
```



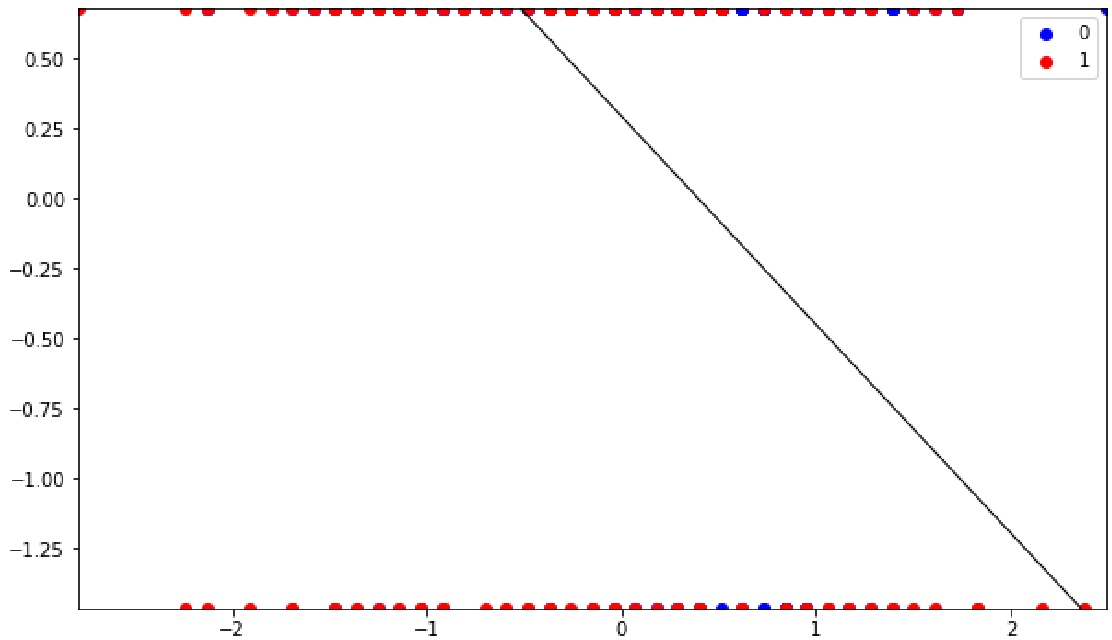

```
Trial #2 with features: chol and sex, accuracy: 49.18 %
```



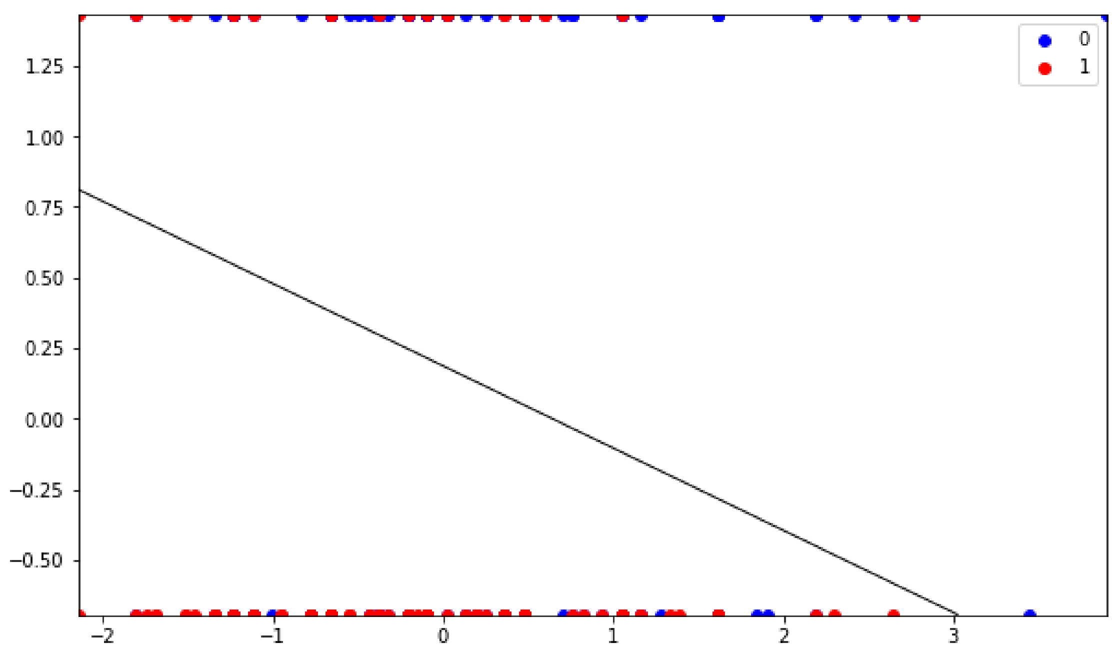
Trial #3 with features: trestbps and restecg, accuracy: 59.016000000000005 %



Trial #4 with features: age and sex, accuracy: 57.377 %



Trial #5 with features: trestbps and exang, accuracy: 72.131 %

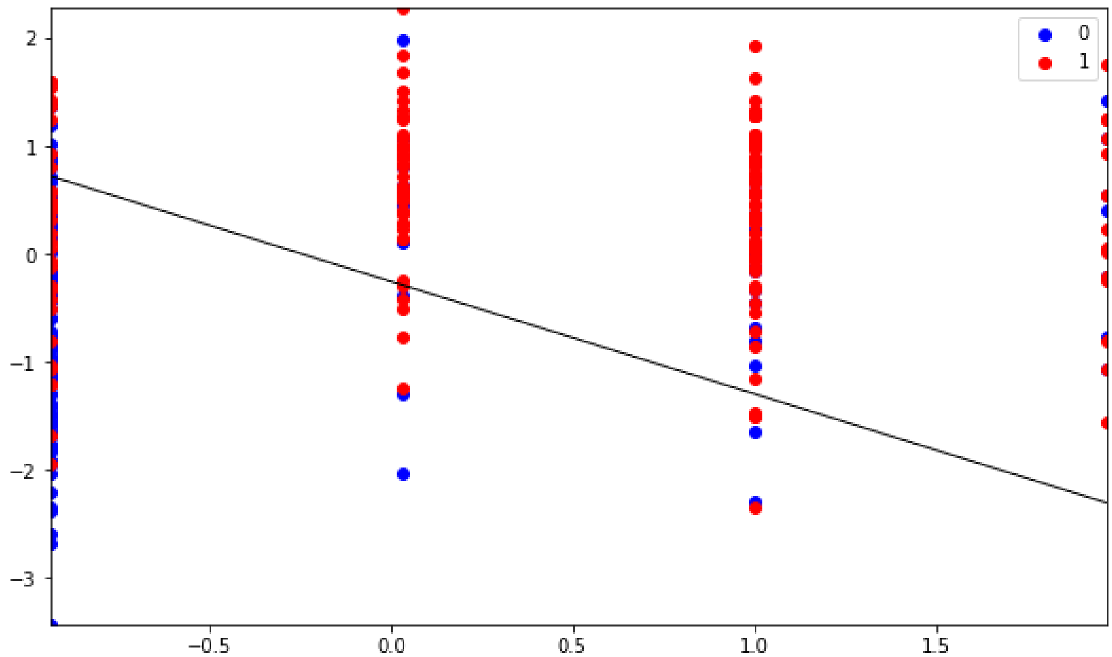


10 Feature pairs (based on correlation)

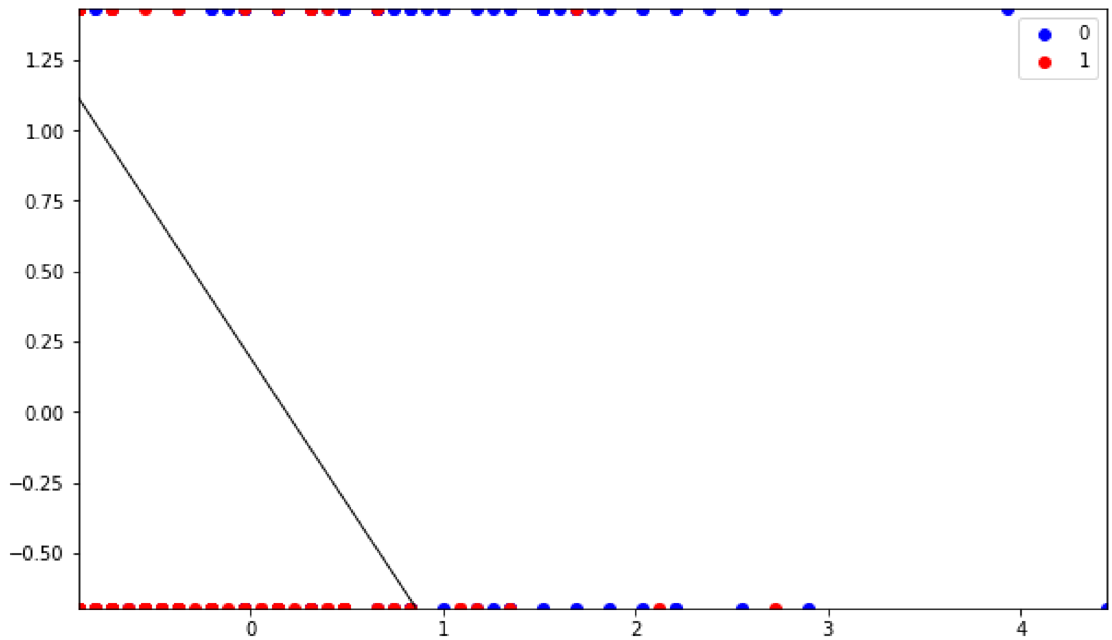
[22]:
```
pairs = [['cp', 'thalach'], ['oldpeak', 'exang'], ['ca', 'thal']]
for i, pair in enumerate(pairs):
    f1, f2 = pair
    model, acc = pipeline(X[[f1, f2]], y)
    print(f"Trial #{i+1} with features: {f1} and {f2}, accuracy: {acc} %")

    newX = X[[f1, f2]].to_numpy()
    plot_regression(newX, y, model)
```

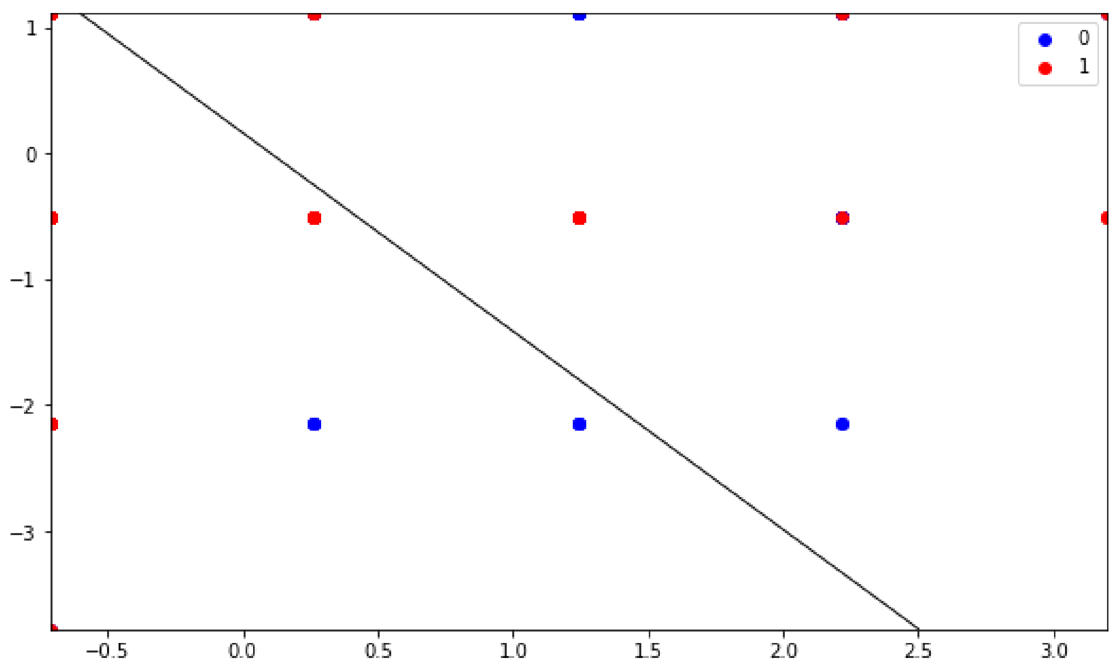
```
Trial #1 with features: cp and thalach, accuracy: 78.689 %
```




```
Trial #2 with features: oldpeak and exang, accuracy: 77.049 %
```



Trial #3 with features: ca and thal, accuracy: 70.492 %




```
[ ]:
```

[ ]:

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