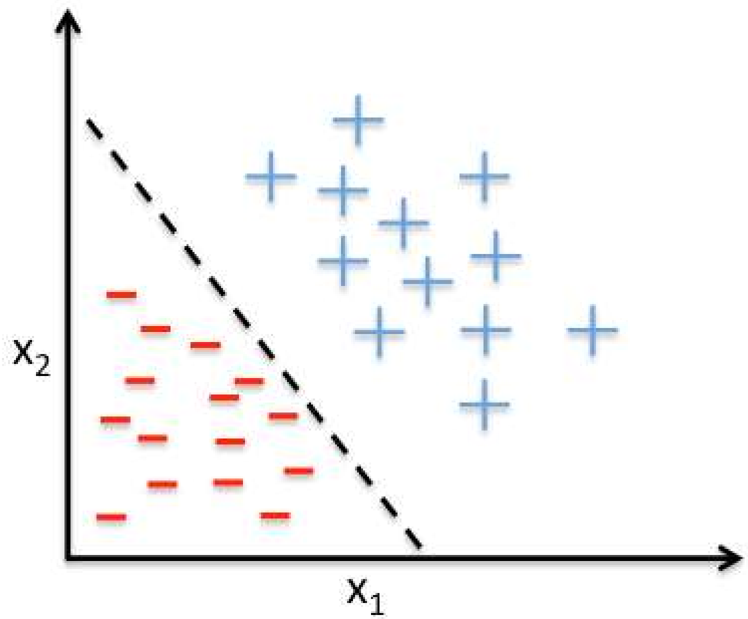
The Perceptron and Adaline is one of the oldest and simplest learning classifiers out there

What Adaline and the Perceptron have in common

- they are classifiers for binary classification
- both have a linear decision boundary
- both can learn iteratively, sample by sample (the Perceptron naturally, and Adaline via stochastic gradient descent)
- both use a threshold function



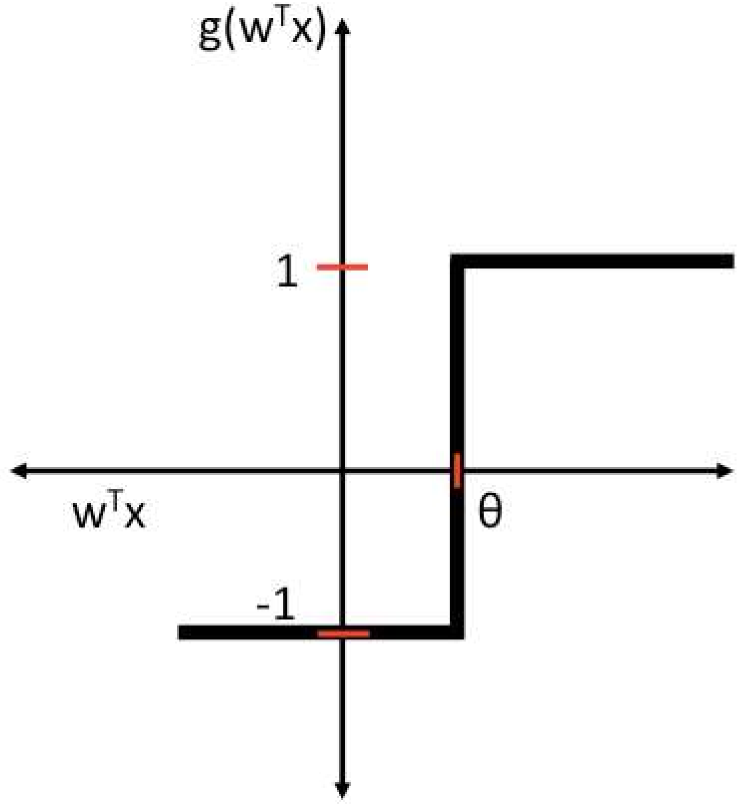
Example of a linear decision boundary for binary classification.

The first step in the two algorithms is to compute the so-called net input z as the linear combination of our feature variables x and the model weights w.

$$\begin{aligned} \mathbf{z} &= w_1 x_1 + \cdots + w_m x_m = \sum_{j=1}^{m} x_j w_j \\ &= \mathbf{w}^T \mathbf{x} \end{aligned}$$

Then, in the Perceptron and Adaline, we define a threshold function to make a prediction. I.e., if z is greater than a threshold theta usually 0, we predict class 1, and 0 otherwise:

$$g(\mathbf{z}) = \begin{cases} 1 & \text{if } \mathbf{z} \geq \theta \\ -1 & \text{otherwise.} \end{cases}$$



The difference between the 2 algorithms is that the Perceptron uses the result of the threshold function g(z) to learn the model weights while Adaline uses the net input z (where the activation function is linear) to learn the model coefficients as illustrated below

Perceptron Learning Algorithm

The perceptron learning algorithm is done sample by sample

1. Initialize weight parameters to initial values (usually small random values, rather than zero).
2. Calculate z
3. Predict of the binary output from the given features for each training sample input using the threshold function ŷ = g(z).
4. Update of the weights through the Perceptron Learning Rule.

$$w_j := w_j + \alpha(actual\ output - predicted\ output)x_j^{(i)}$$

$$w_j := w_j + \alpha(y^{(i)} - \hat{y}^{(i)})x_j^{(i)}$$

Adaline Learning Process

The Adaline learning process is done sample by sample or on all dataset. It uses gradient descent optimization function

1. Initialize weight parameters to initial values (usually small random values, rather than zero).
2. calculate z
3. apply linear activation function where Φ(z) = z
4. Update of the weights using gradient descent optimization method

$$\Delta w_j = -\alpha \frac{\partial J}{\partial w_j}$$

$$\Delta w_j = \alpha \sum_i \left(y^{(i)} - \phi(z^{(i)})\right)x_j^{(i)}$$

Where ∇ is used to denote the gradient, and α is the learning rate.

In [ ]:

```
```

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
class Perceptron:

    def __init__(self, learning_rate=0.0001 , epochs= 1000):
        self.weights = None
        self.bias = None
        self.learning_rate = learning_rate
        self.epochs = epochs


    # heaviside activation function
    def activation(self, z):
        return np.heaviside(z, 0) # haviside(z) heaviside -> activation

    def fit(self, x, y):
        n_features = x.shape[1]

        # Initializing weights and bias
        self.weights = np.zeros((n_features))
        self.bias = 0

        # Iterating until the number of epochs
        for epoch in range(self.epochs):
            # Traversing through the entire training set
            for i in range(len(x)):
                    y_pred = 0
                    for j in range(2):
                        y_pred += x.iloc[i, j] * self.weights[j]

                    y_pred += self.bias

                    if y_pred >= 0:
                        y_pred = 1
                    else:
                        y_pred = 0

                    for j in range(2):
                        self.weights[j] += self.learning_rate * (y.iloc[i] - 
                    self.bias += self.learning_rate * (y.iloc[i] - y_pred)
            return self.weights, self.bias

    def predict(self, X):
        z = np.dot(X, self.weights) + self.bias
        return self.activation(z)
```

In [3]:
```
class Adaline:
    def __init__(self, learning_rate=0.01, num_epochs=1000):
        self.learning_rate = learning_rate
        self.num_epochs = num_epochs
        self.weights = None
        self.bias = None

    def fit(self, X, y):
        num_samples, num_features = X.shape
        self.weights = np.zeros(num_features)
        self.bias = 0
        error = np.zeros(self.num_epochs)

        for epoch in range(self.num_epochs):
            net_input = np.dot(X, self.weights) + self.bias
            output = self.activation(net_input)
            error[epoch]=0.5*np.mean((output-y)**2)
            errors = output - y.T
            self.weights -= ((self.learning_rate * (X.T.dot(errors)))/np.size
            self.bias -= (self.learning_rate * np.mean(output))
            if (error[epoch]==0):break
        return self.weights ,self.bias

    def predict(self, X):
        net_input = np.dot(X, self.weights) + self.bias
        output = self.activation(net_input)
        return np.where(output >= 0.5, 1, 0)

    def activation(self, X):
        return X
```

In [4]:
```
def accuracy(y_true, y_pred):
    accuracy = np.sum(y_true == y_pred) / len(y_true)
    return accuracy
```

In [5]:
```
def MSE(y_pred, y):
    return np.mean((y_pred - y)**2)
```

In [6]:
```
df = pd.read_csv("data_banknote_authentication.csv")
df
```

Out[6]:

	variance	skewness	curtosis	entropy	class
0	3.62160	8.66610	-2.8073	-0.44699	0
1	4.54590	8.16740	-2.4586	-1.46210	0
2	3.86600	-2.63830	1.9242	0.10645	0
3	3.45660	9.52280	-4.0112	-3.59440	0
4	0.32924	-4.45520	4.5718	-0.98880	0
...	...	...	...	...	...
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

1372 rows × 5 columns

In [7]:
```
# separate the independent and dependent variables
X_data = df.iloc[ : , 0 : 2]
target = df.iloc[ : , -1]
print(X_data)
print("-"*50)
print(target)
```

```
      variance  skewness
0      3.62160   8.66610
1      4.54590   8.16740
2      3.86600  -2.63830
3      3.45660   9.52280
4      0.32924  -4.45520
...        ...       ...
1367   0.40614   1.34920
1368  -1.38870  -4.87730
1369  -3.75030 -13.45860
1370  -3.56370  -8.38270
1371  -2.54190  -0.65804

[1372 rows x 2 columns]
--------------------------------------------------
0       0
1       0
2       0
3       0
4       0
       ..
1367    1
1368    1
1369    1
1370    1
1371    1
Name: class, Length: 1372, dtype: int64
```

In [8]:
```
scale= StandardScaler()
# standardization of independent variables
scaled_data = scale.fit_transform(X_data)
print(scaled_data)
```

```
[[ 1.12180565  1.14945512]
 [ 1.44706568  1.06445293]
 [ 1.20780971 -0.77735215]
 ...
 [-1.47235682 -2.62164576]
 [-1.40669251 -1.75647104]
 [-1.04712236 -0.43982168]]
```

In [9]:
```
print(target)
```

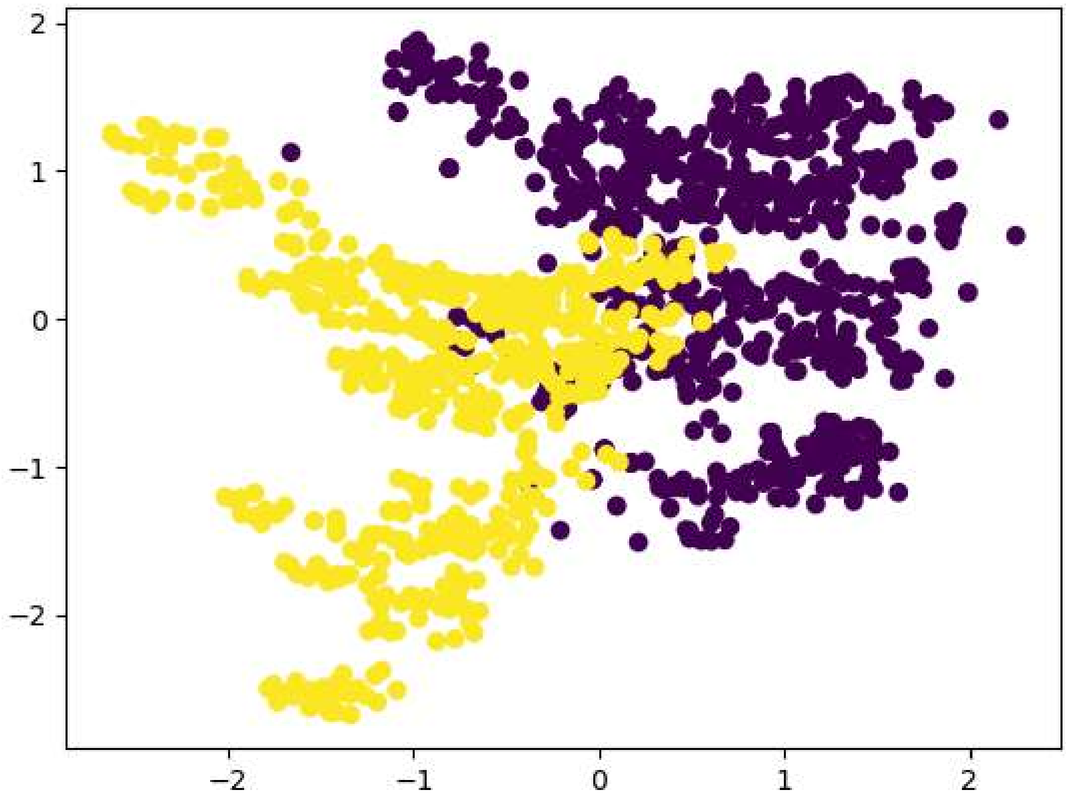
```
0       0
1       0
2       0
3       0
4       0
       ..
1367    1
1368    1
1369    1
1370    1
1371    1
Name: class, Length: 1372, dtype: int64
```

In [10]:
```
scaled_data = pd.DataFrame(scaled_data)
print(scaled_data)
```

```
             0         1
0     1.121806  1.149455
1     1.447066  1.064453
2     1.207810 -0.777352
3     1.063742  1.295478
4    -0.036772 -1.087038
...        ...       ...
1367 -0.009711 -0.097693
1368 -0.641313 -1.158984
1369 -1.472357 -2.621646
1370 -1.406693 -1.756471
1371 -1.047122 -0.439822

[1372 rows x 2 columns]
```

In [11]:
```
plt.scatter(scaled_data.iloc[:, 0], scaled_data.iloc[:, 1],c=target)
plt.show()
```



In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(scaled_data, target , tes
```

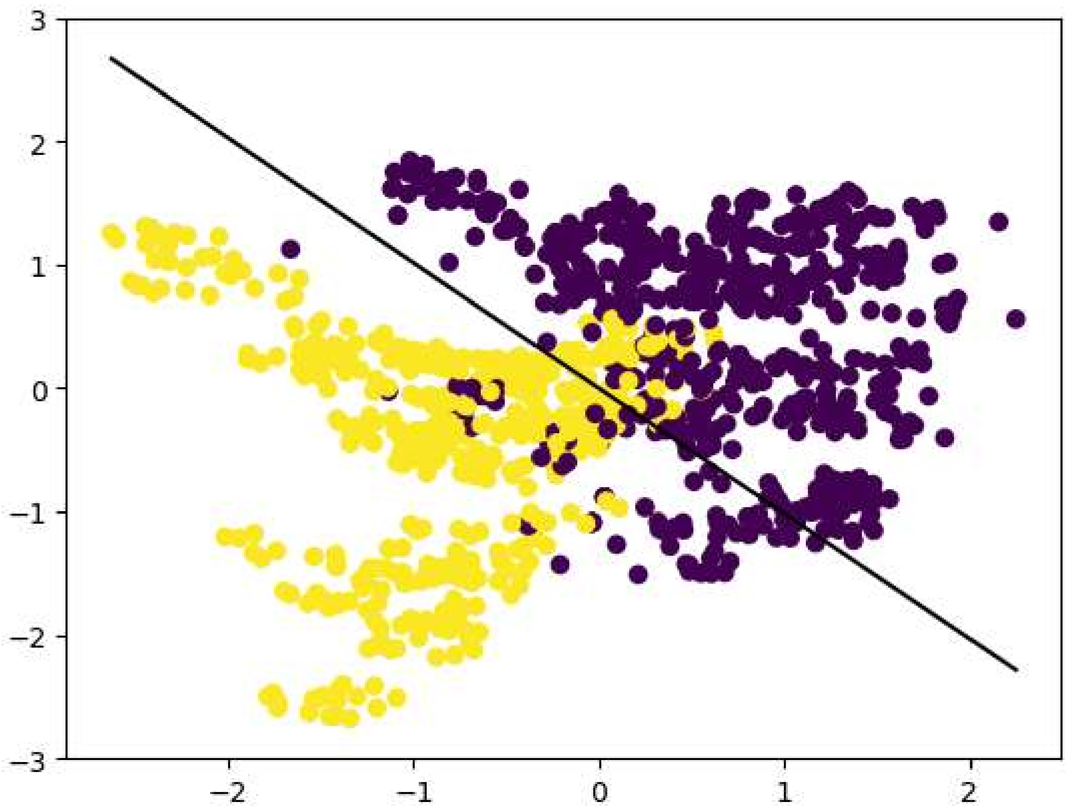
Perceptron

In [13]:
```
percept = Perceptron(learning_rate=0.0001, epochs=1000)
percept.fit(X_train, y_train)
percept_predictions = percept.predict(X_test)
```

In [14]:
```
print("Perceptron classification accuracy:", accuracy(y_test, percept_predict
print("-"*50)
print("Perceptron classification MSE:", MSE(percept_predictions , y_test)*100
```

```
Perceptron classification accuracy: 86.9090909090909
--------------------------------------------------
Perceptron classification MSE: 13.090909090909092
```

In [15]:
```
X_train=X_train.to_numpy()
fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)
plt.scatter(X_train[:, 0], X_train[:, 1], marker="o", c=y_train)
x0_1 = np.amin(X_train[:, 0])
x0_2 = np.amax(X_train[:, 0])
x1_1 = (-percept.weights[0] * x0_1 - percept.bias) / percept.weights[1]
x1_2 = (-percept.weights[0] * x0_2 - percept.bias) / percept.weights[1]
ax.plot([x0_1, x0_2], [x1_1, x1_2], "k")
ymin = np.amin(X_train[:, 1])
ymax = np.amax(X_train[:, 1])
ax.set_ylim([ymin - 3, ymax + 3])
plt.ylim(-3,3)
plt.show()
```



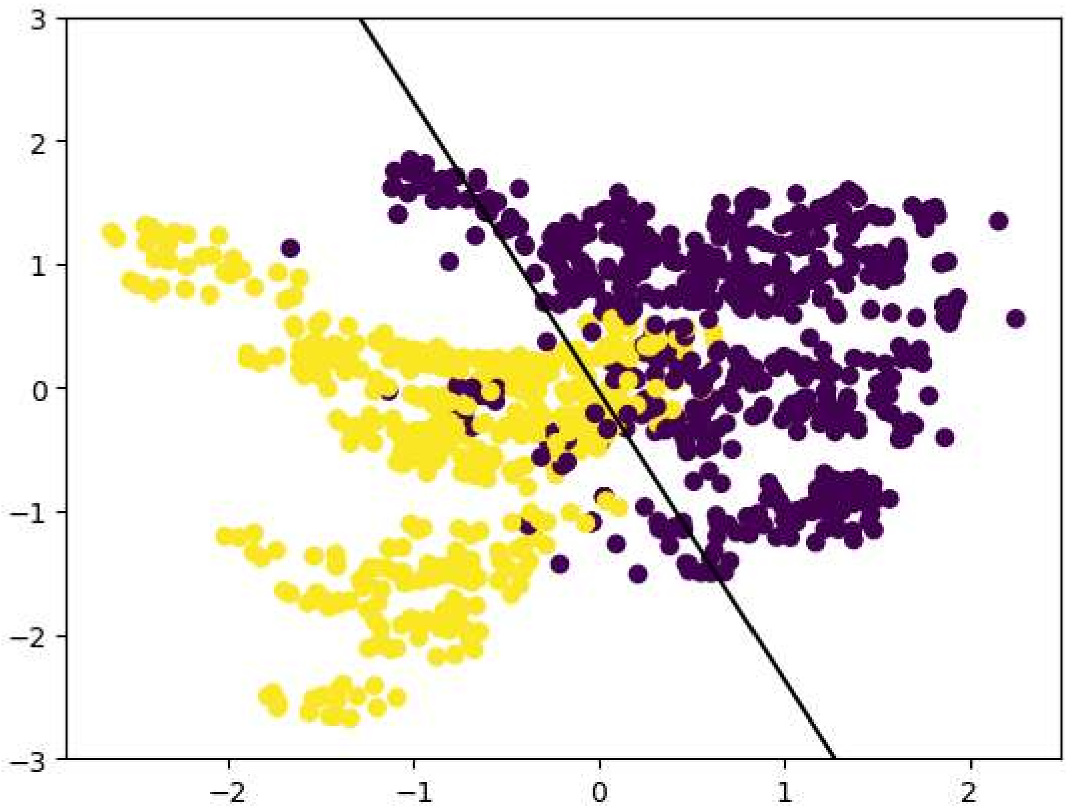
Adaline

In [16]:
```
ada = Adaline()
w, b =ada.fit(X_train,y_train)
ada_predictions = ada.predict(X_test)
```

In [17]:
```
print("Adaline classification accuracy:", accuracy(y_test, ada_predictions)*1(
print("-"*50)
print("Adaline classification MSE:", MSE(ada_predictions , y_test)*100)
```

```
Adaline classification accuracy: 69.45454545454545
--------------------------------------------------
Adaline classification MSE: 30.545454545454547
```

In [18]:
```
fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)
plt.scatter(X_train[:, 0], X_train[:, 1], marker="o", c=y_train)
x0_1 = np.amin(X_train[:, 0])
x0_2 = np.amax(X_train[:, 0])
x1_1 = (-w[0] * x0_1 - b) / w[1]
x1_2 = (-w[0] * x0_2 - b) / w[1]
ax.plot([x0_1, x0_2], [x1_1, x1_2], "k")
ymin = np.amin(X_train[:, 1])
ymax = np.amax(X_train[:, 1])
ax.set_ylim([ymin - 3, ymax + 3])
plt.ylim(-3,3)
plt.show()
```



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