### **Perceptron algorithm**

The Perceptron algorithm is a **binary classification** machine learning algorithm.

A perceptron is a classification model that consists of a set of weights, or scores, one for every feature, and a threshold.

The weighted sum of the input of the model is called the activation.

Activation = Weights \* Inputs + Bias

If the activation is above 0.0, the model will **output 1.0**; otherwise, it will **output 0.0**.

Predict 1: If Activation > 0.0

Predict 0: If Activation <= 0.0

The Perceptron is a **linear classification algorithm**. This means that it learns a decision boundary that separates two classes using a line (**called a hyperplane**) in the feature space.

The coefficients of the model are referred to as **input weights** and are trained using the **stochastic gradient descent** optimization algorithm.

The weights of the model are then updated to reduce the errors for the example. This is called the **Perceptron update rule**. This process is repeated for all examples in the training dataset, called an **epoch**.

Model weights are updated with a small proportion of **the error each batch**, and the proportion is controlled by a hyperparameter called **the learning rate**, typically set to a small value.

```
weights (t + 1) = weights(t) + learning_rate * (expected_i - predicted_) * input_i
```

Training is stopped when the error made by the model falls to a low level or no longer improves, or a maximum number of epochs is performed.

The learning rate and number of training epochs are hyperparameters of the algorithm that can be set using **heuristics or hyperparameter tuning.** 

#### Pseudocode:

# Algorithm 5 PerceptronTrain(D, MaxIter)

```
w_d \leftarrow o, for all d = 1 \dots D
                                                                              // initialize weights
2: b ← o
                                                                                  // initialize bias
_{3:} for iter = 1 ... MaxIter do
      for all (x,y) \in \mathbf{D} do
         a \leftarrow \sum_{d=1}^{D} w_d x_d + b
                                                     // compute activation for this example
         if ya \leq o then
          w_d \leftarrow w_d + yx_d, for all d = 1 \dots D
                                                                               // update weights
            b \leftarrow b + y
                                                                                    // update bias
         end if
      end for
... end for
12: return w_0, w_1, ..., w_D, b
```

# Algorithm 6 PerceptronTest( $w_0, w_1, \ldots, w_D, b, \hat{x}$ )

```
:: a \leftarrow \sum_{d=1}^{D} w_d \ \hat{x}_d + b // compute activation for the test example :: return sign(a)
```

- 1. Initialize our weight vector w with small random values
- 2. Until Perceptron converges:
- (a) Loop over each feature vector xj and true class label di in our training set D
- (b) Take x and pass it through the network, calculating the output value:  $yj = f(w(t) \cdot xj)$
- (c) Update the weights w: wi(t +1) = wi(t) + $\alpha$ (dj -yj)xj,i for all features 0 <= i <= n

### B. Code:

```
import matplotlib.pyplot as plt
```

```
plt.scatter(df['0.3'],df['class-1'])
X = df[['5.0', '3.5', '1.3']]
y = df['0.3']
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3)
y_test
from sklearn.linear model import LinearRegression
clf = LinearRegression()
clf.fit(X_train, y_train)
```

```
X_test
# In[17]:
clf.predict(X_test)
# In[18]:

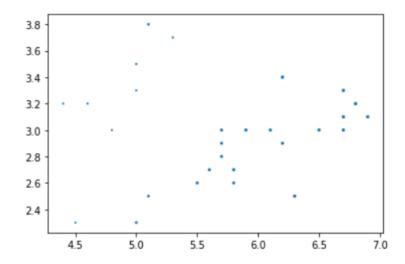
y_test
# In[19]:
clf.score(X_test, y_test)
# In[20]:

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=10)
X_test
# In[]:
```

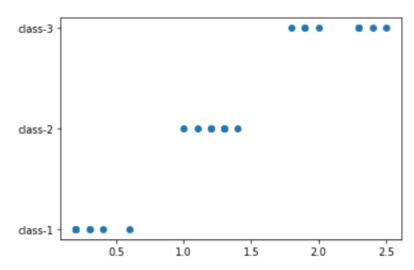
# C: Classes:

```
In [5]: plt.scatter(df['5.0'],df['3.5'],df['1.3'])
```

Out[5]: <matplotlib.collections.PathCollection at 0x20cadca8d00>



Out[7]: <matplotlib.collections.PathCollection at 0x20cafe719c0>



# D. train and test:

```
clf.score(X_test, y_test)
```

```
0.8668918391902904 --→ 0.3
```

0.9265018393202821 --→ 0.1 is better score