Perceptrons - Training

Note for 717005@ Hallym University !

- Make a prediction with weights

In [1]:

```
def predict(X, w):
    bias = w[0]
    activation = bias + w[1]* X[0] + w[2]* X[1]
    if activation >= 0.0:
        return 1.0
    else:
        return 0.0
```

- Estimate Perceptron weights using stochastic gradient descent

In [2]:

```
def train_weights(train, l_rate, n_epoch):
    #weights = [0.0 for i in range(len(train[0]))]
    weights = [0, 0, 0]
    print(weights)
    print('----------------------')

    vb = []
    vw0 = []
    vw1 = []

    for epoch in range(n_epoch):
        sum_error = 0.0
        for row in train:
            prediction = predict(row, weights)
            jd = row[-1]
            error =  jd - prediction
            sum_error += error**2

            weights[0] = weights[0] + l_rate * error
            for i in range(len(row)-1):
                weights[i + 1] = weights[i + 1] + l_rate * error * row[i]

            vb.append(weights[0])
            vw0.append(weights[1])
            vw1.append(weights[2])

        print('epoch={}, error={}'.format(epoch, sum_error))
    return weights, vb, vw0, vw1
```

In [3]:

```
# training set
dataset = [[2.7810836,2.550537003,0],
    [1.465489372,2.362125076,0],
    [3.396561688,4.400293529,0],
    [1.38807019,1.850220317,0],
    [3.06407232,3.005305973,0],
    [7.627531214,2.759262235,1],
    [5.332441248,2.088626775,1],
    [6.922596716,1.77106367,1],
    [8.675418651,-0.242068655,1],
    [7.673756466,3.508563011,1]]
```

- Hyperparameters

In [4]:

```
l_rate = 0.1
n_epoch = 5
```

In [5]:

```
weights, vb, vw0, vw1 = train_weights(dataset, l_rate, n_epoch)
```

```
[0, 0, 0]
----------------------
epoch=0, error=2.0
epoch=1, error=1.0
epoch=2, error=0.0
epoch=3, error=0.0
epoch=4, error=0.0
```

In [6]:

```
print(weights)
```

```
[-0.1, 0.20653640140000007, -0.23418117710000003]
```

In [7]:

```
pred = predict([3.8, 3], weights)
print(pred)
```

```
0.0
```

In [8]:

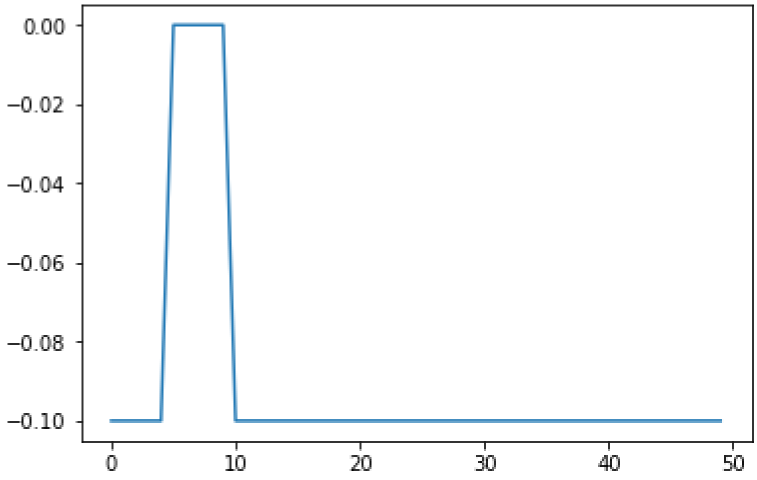
```
import matplotlib.pyplot as plt
```

In [9]:

```
plt.plot(vb)
```

Out[9]:

```
[<matplotlib.lines.Line2D at 0x10bd95fd0>]
```

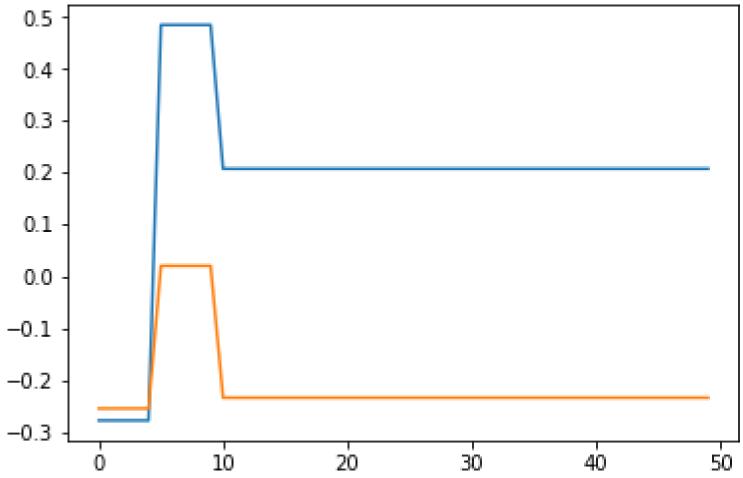


In [10]:

```
plt.plot(vw0)
plt.plot(vw1)
```

Out[10]:

```
[<matplotlib.lines.Line2D at 0x10be32a90>]
```



- Why ?

partial derivative with respect to m (a.k.a weight)

$$
\begin{aligned}
\frac{\partial J(m,b)}{\partial m} &= \frac{1}{n}\sum_{i=1}^{n} -2x^{(i)}(y_i - (mx^{(i)} + b)) \\
&= \frac{2}{n}\sum_{i=1}^{n} x^{(i)}((mx^{(i)} + b) - y^{(i)}) \\
&= \frac{2}{n}\sum_{i=1}^{n} x^{(i)}(\hat{y}^{(i)} - y^{(i)})
\end{aligned}
$$

partial derivative with respect to b (a.k.a bias)

$$
\begin{aligned}
\frac{\partial J(m,b)}{\partial b} &= \frac{1}{n}\sum_{i=1}^{n} -2(y^{(i)} - (mx^{(i)} + b)) \\
&= \frac{-2}{n}\sum_{i=1}^{n}(y^{(i)} - (mx^{(i)} + b)) \\
&= \frac{2}{n}\sum_{i=1}^{n}(\hat{y}^{(i)} - y^{(i)})
\end{aligned}
$$

Partial derivatives : https://www.mathsisfun.com/calculus/derivatives-partial.html (https://www.mathsisfun.com/calculus/derivatives-partial.html)

- References

```
https://machinelearningmastery.com/implement-perceptron-algorithm-scratch-py
thon/
```