



# Classification: Perceptron

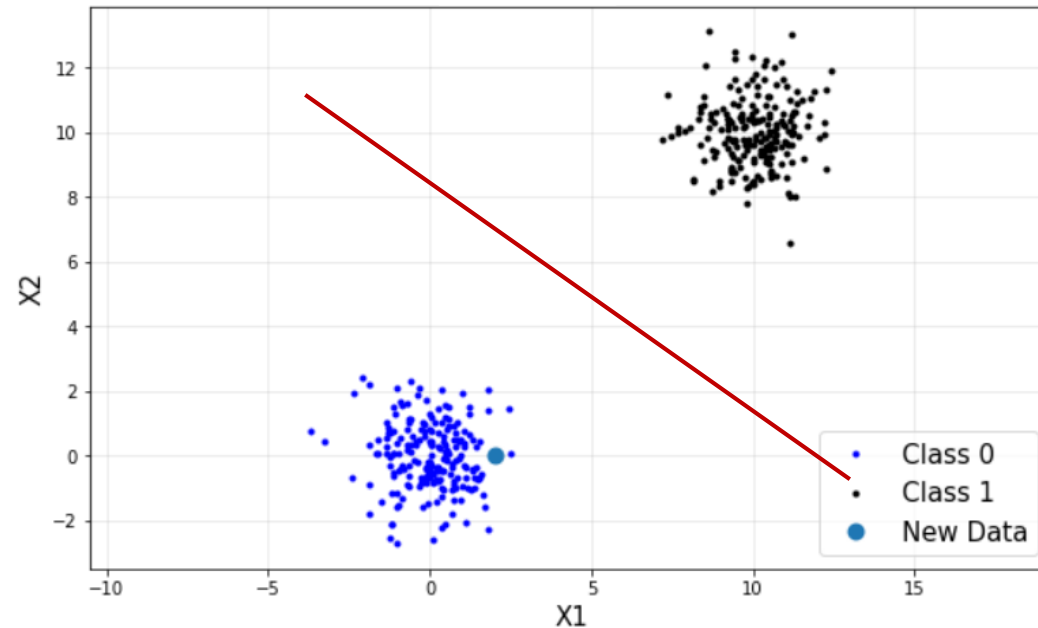
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**Industrial AI Lab.**

# Classification

- Where  $y$  is a discrete value
  - Develop the classification algorithm to determine which class a new input should fall into
- Start with a binary class problem
  - Later look at multiclass classification problem, although this is just an extension of binary classification
- We could use linear regression
  - Then, threshold the classifier output (i.e. anything over some value is yes, else no)
  - linear regression with thresholding seems to work

# Classification

- We will learn
  - Perceptron
  - Support vector machine (SVM)
  - Logistic regression
- To find a classification boundary



# Perceptron Algorithm

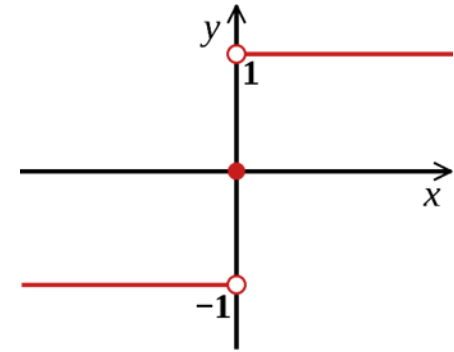
# Perceptron

- For input  $x = \begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix}$  'attributes of a customer'
- Weights  $\omega = \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_d \end{bmatrix}$

Approve credit if  $\sum_{i=1}^d \omega_i x_i > \text{threshold},$

Deny credit if  $\sum_{i=1}^d \omega_i x_i < \text{threshold}.$

$$h(x) = \text{sign} \left( \left( \sum_{i=1}^d \omega_i x_i \right) - \text{threshold} \right) = \text{sign} \left( \left( \sum_{i=1}^d \omega_i x_i \right) + \omega_0 \right)$$

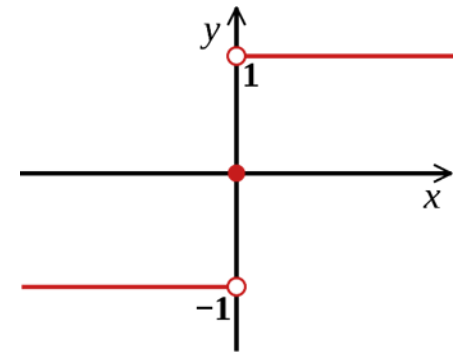


# Perceptron

$$h(x) = \text{sign} \left( \left( \sum_{i=1}^d \omega_i x_i \right) - \text{threshold} \right) = \text{sign} \left( \left( \sum_{i=1}^d \omega_i x_i \right) + \omega_0 \right)$$

- Introduce an artificial coordinate  $x_0 = 1$  :

$$h(x) = \text{sign} \left( \sum_{i=0}^d \omega_i x_i \right)$$

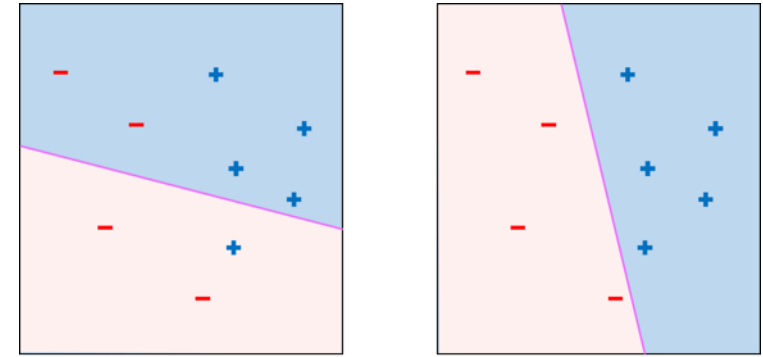


- In a vector form, the perceptron implements

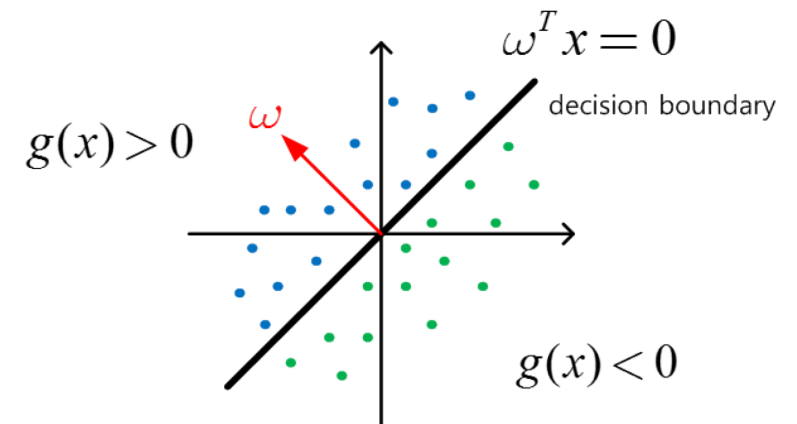
$$h(x) = \text{sign} (\omega^T x)$$

# Perceptron

- Works for linearly separable data
- Hyperplane
  - Separates a D-dimensional space into two half-spaces
  - Defined by an outward pointing normal vector
  - $\omega$  is orthogonal to any vector lying on the hyperplane
  - Assume the hyperplane passes through origin,  $\omega^T x = 0$  with  $x_0 = 1$



Linearly separable data

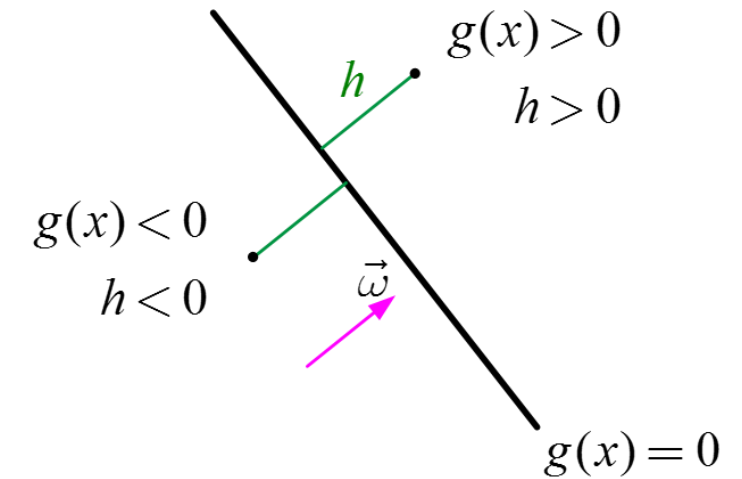


# Sign

- Sign with respect to a line

$$\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \implies g(x) = \omega_1 x_1 + \omega_2 x_2 + \omega_0 = \omega^T x + \omega_0$$

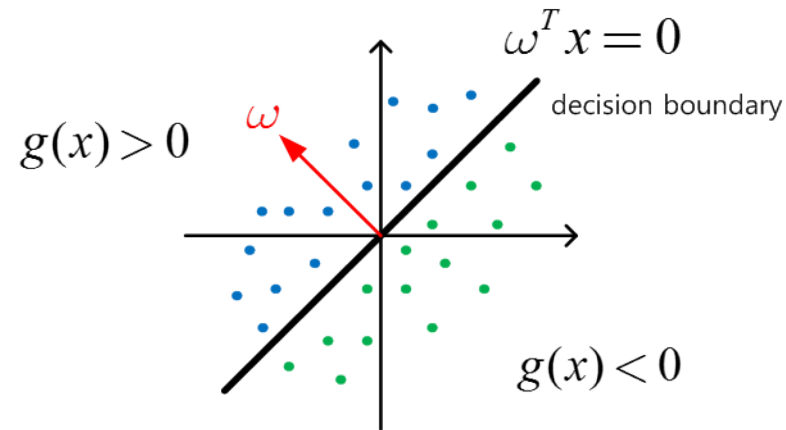
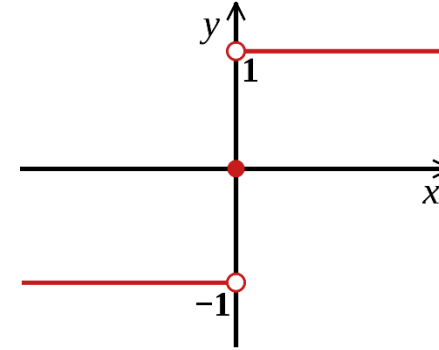
$$\omega = \begin{bmatrix} \omega_0 \\ \omega_1 \\ \omega_2 \end{bmatrix}, \quad x = \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix} \implies g(x) = \omega_0 + \omega_1 x_1 + \omega_2 x_2 = \omega^T x$$





# How to Find $\omega$

- All data in class 1 ( $y = 1$ )
  - $g(x) > 0$
- All data in class 0 ( $y = -1$ )
  - $g(x) < 0$



# Perceptron Algorithm

- The perceptron implements

$$h(x) = \text{sign}(\omega^T x)$$

- Given the training set

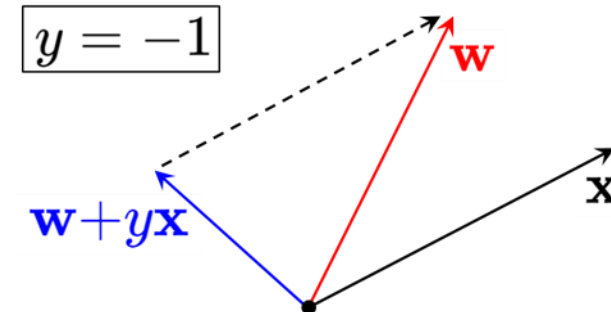
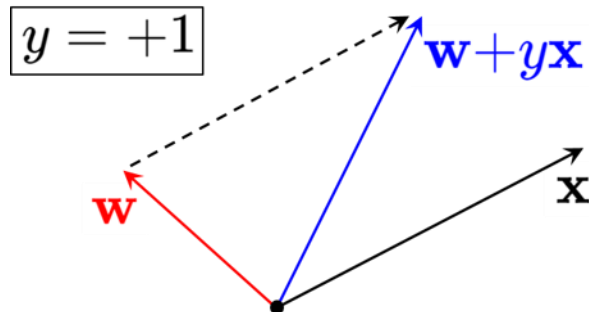
$$(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N) \quad \text{where } y_i \in \{-1, 1\}$$

- 1) pick a misclassified point

$$\text{sign}(\omega^T x_n) \neq y_n$$

- 2) and update the weight vector

$$\omega \leftarrow \omega + y_n x_n$$



# Perceptron Algorithm

- Why perceptron updates work ?
- Let's look at a misclassified positive example ( $y_n = +1$ )
  - Perceptron (wrongly) thinks  $\omega_{old}^T x_n < 0$
  - Updates would be

$$\omega_{new} = \omega_{old} + y_n x_n = \omega_{old} + x_n$$

$$\omega_{new}^T x_n = (\omega_{old} + x_n)^T x_n = \omega_{old}^T x_n + x_n^T x_n$$

- Thus  $\omega_{new}^T x_n$  is **less negative** than  $\omega_{old}^T x_n$

# Iterations of Perceptron

1. Randomly assign  $\omega$
2. One iteration of the PLA (perceptron learning algorithm)

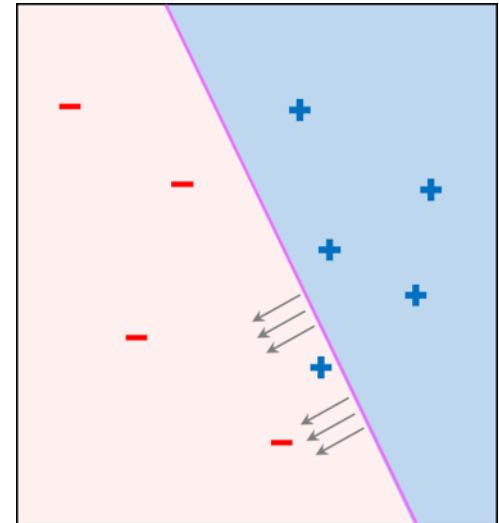
$$\omega \leftarrow \omega + yx$$

where  $(x, y)$  is a misclassified training point

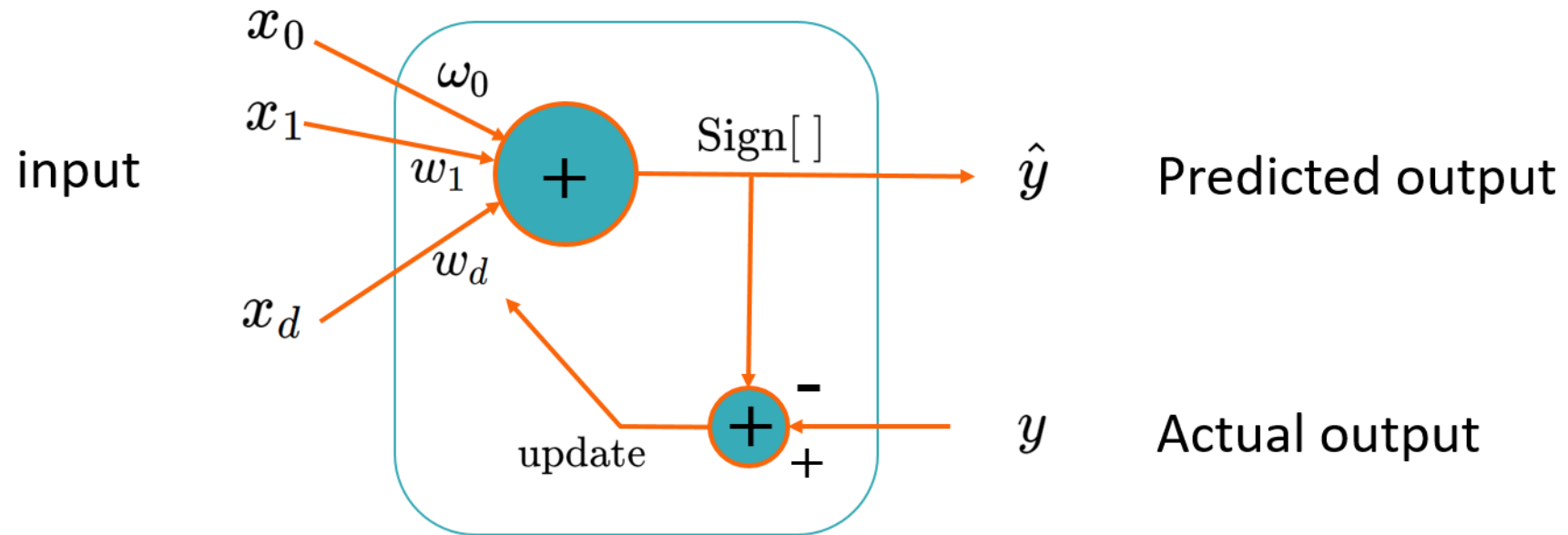
3. At iteration  $i = 1, 2, 3, \dots$ , pick a misclassified point from

$$(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)$$

4. And run a PLA iteration on it
5. That's it!



# Diagram of Perceptron



# Perceptron Loss Function

$$L(\omega) = \sum_{n=1}^m \max \{0, -y_n \cdot (\omega^T x_n)\}$$

- Loss = 0 on examples where perceptron is correct,  
*i.e.*,  $y_n \cdot (\omega^T x_n) > 0$
- Loss > 0 on examples where perceptron is misclassified,  
*i.e.*,  $y_n \cdot (\omega^T x_n) < 0$
- Note:
  - $\text{sign}(\omega^T x_n) \neq y_n$  is equivalent to  $y_n \cdot (\omega^T x_n) < 0$

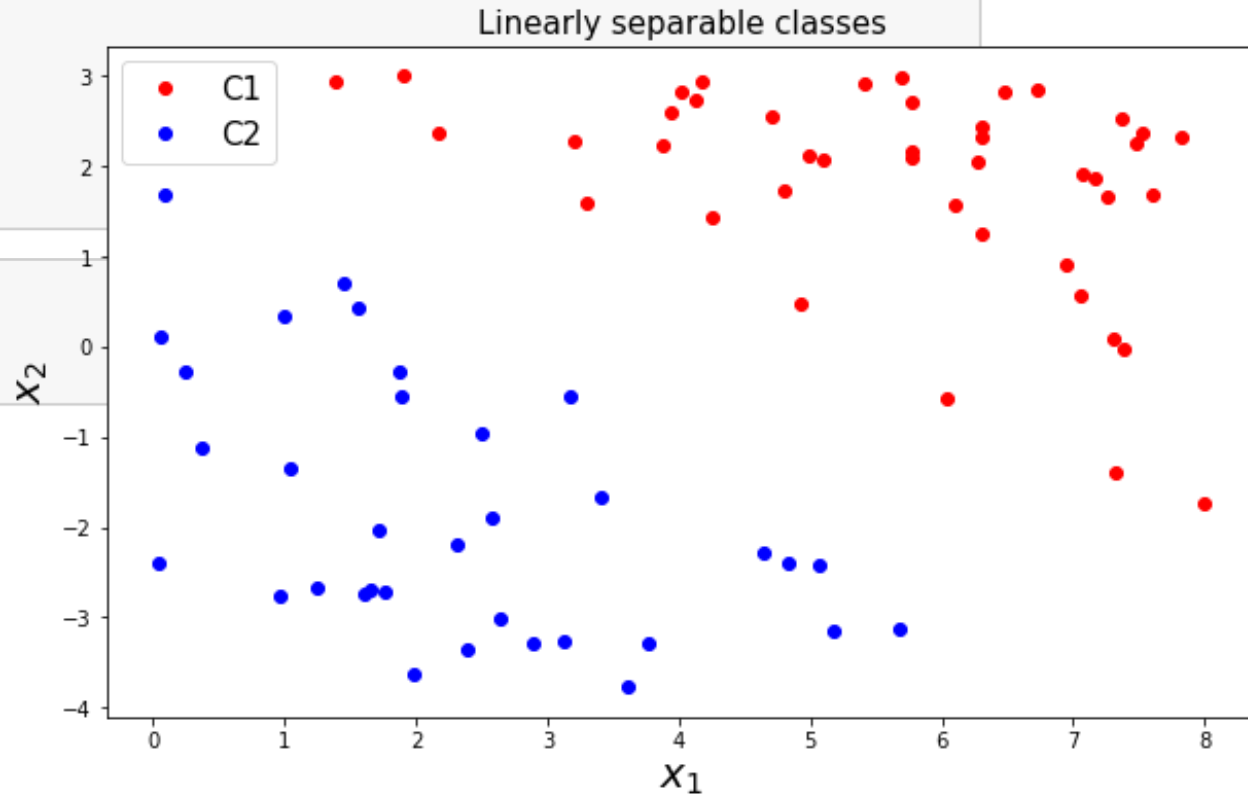
# Perceptron Algorithm in Python

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
#training data generation
m = 100
x1 = 8*np.random.rand(m, 1)
x2 = 7*np.random.rand(m, 1) - 4

g = 0.8*x1 + x2 - 3
```

```
C1 = np.where(g >= 1)
C2 = np.where(g < -1)
print(C1)
```



# Perceptron Algorithm in Python

- Unknown parameters  $\omega$

$$g(x) = \omega_0 + \omega^T x = \omega_0 + \omega_1 x_1 + \omega_2 x_2 = 0$$

$$\omega = \begin{bmatrix} \omega_0 \\ \omega_1 \\ \omega_2 \end{bmatrix}$$

$$x = \begin{bmatrix} (x^{(1)})^T \\ (x^{(2)})^T \\ (x^{(3)})^T \\ \vdots \\ (x^{(m)})^T \end{bmatrix} = \begin{bmatrix} 1 & x_1^{(1)} & x_2^{(1)} \\ 1 & x_1^{(2)} & x_2^{(2)} \\ 1 & x_1^{(3)} & x_2^{(3)} \\ \vdots & \vdots & \vdots \\ 1 & x_1^{(m)} & x_2^{(m)} \end{bmatrix}$$

$$y = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ y^{(3)} \\ \vdots \\ y^{(m)} \end{bmatrix}$$

```
X1 = np.hstack([np.ones([C1.shape[0],1]), x1[C1], x2[C1]])
X2 = np.hstack([np.ones([C2.shape[0],1]), x1[C2], x2[C2]])
X = np.vstack([X1, X2])

y = np.vstack([np.ones([C1.shape[0],1]), -np.ones([C2.shape[0],1])])

X = np.asmatrix(X)
y = np.asmatrix(y)
```



# Perceptron Algorithm in Python

$$\omega = \begin{bmatrix} \omega_0 \\ \omega_1 \\ \omega_2 \end{bmatrix}$$

$\omega \leftarrow \omega + yx$       where  $(x, y)$  is a misclassified training point

```
w = np.ones([3,1])
w = np.asmatrix(w)

n_iter = y.shape[0]
for k in range(n_iter):
    for i in range(n_iter):
        if y[i,0] != np.sign(X[i,:]*w)[0,0]:
            w += y[i,0]*X[i,:].T

print(w)
```

# Perceptron Algorithm in Python

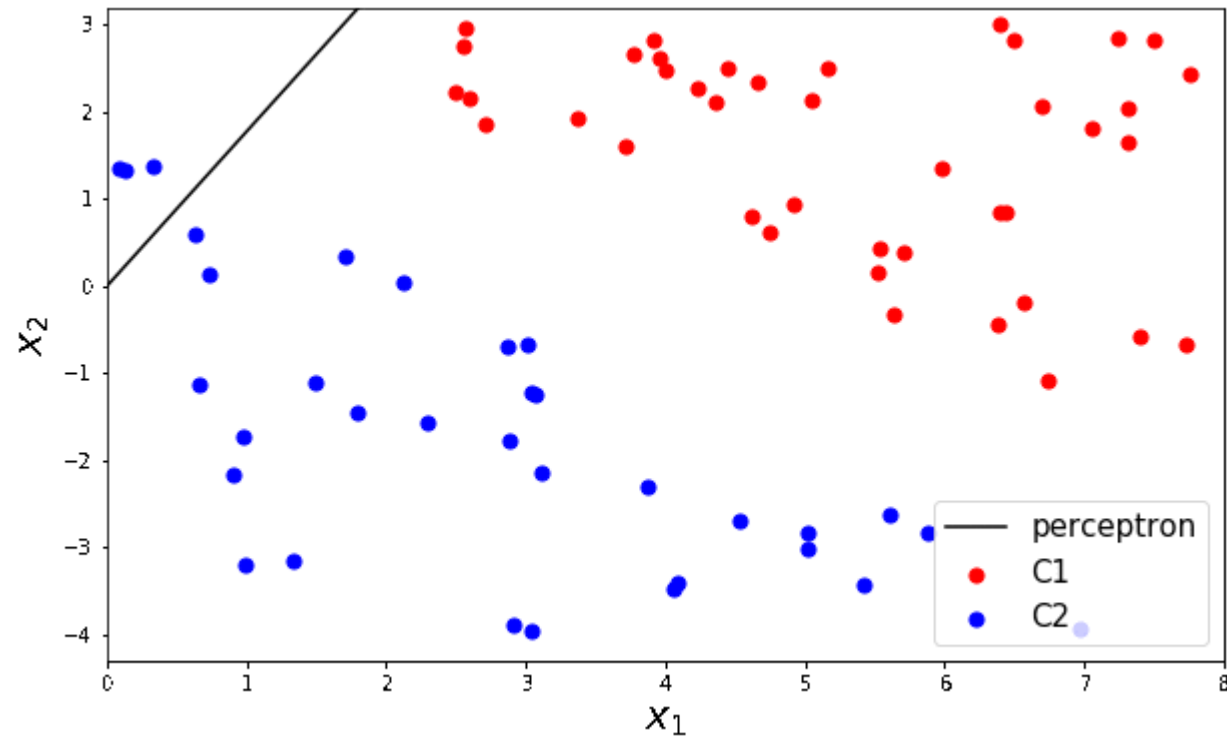
$$g(x) = \omega_0 + \omega^T x = \omega_0 + \omega_1 x_1 + \omega_2 x_2 = 0$$

$$\implies x_2 = -\frac{\omega_1}{\omega_2} x_1 - \frac{\omega_0}{\omega_2}$$

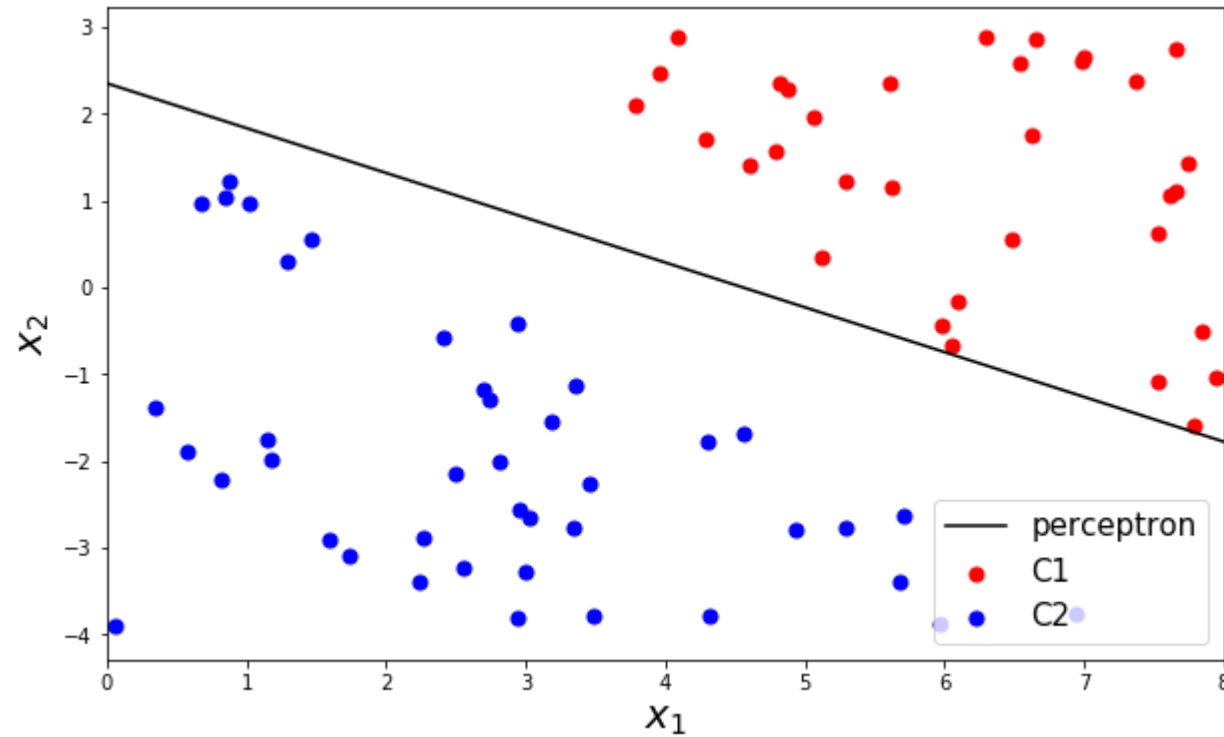
```
x1p = np.linspace(0,8,100).reshape(-1,1)
x2p = - w[1,0]/w[2,0]*x1p - w[0,0]/w[2,0]

plt.figure(figsize=(10, 6))
plt.scatter(x1[C1], x2[C1], c='r', s=50, label='C1')
plt.scatter(x1[C2], x2[C2], c='b', s=50, label='C2')
plt.plot(x1p, x2p, c='k', label='perceptron')
plt.xlim([0,8])
plt.xlabel('$x_1$', fontsize = 20)
plt.ylabel('$x_2$', fontsize = 20)
plt.legend(loc = 1, fontsize = 15)
plt.show()
```

# Perceptron Algorithm in Python



# Perceptron Algorithm in Python



# Scikit-Learn for Perceptron

```
X1 = np.hstack([x1[C1], x2[C1]])
X2 = np.hstack([x1[C2], x2[C2]])
X = np.vstack([X1, X2])

y = np.vstack([np.ones([C1.shape[0],1]), -np.ones([C2.shape[0],1])])
```

```
from sklearn import linear_model

clf = linear_model.Perceptron(tol=1e-3)
clf.fit(X, np.ravel(y))
```

```
clf.predict([[3, -2]])
```

```
array([-1.])
```

$$x = \begin{bmatrix} (x^{(1)})^T \\ (x^{(2)})^T \\ (x^{(3)})^T \\ \vdots \\ (x^{(m)})^T \end{bmatrix} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} \\ x_1^{(2)} & x_2^{(2)} \\ x_1^{(3)} & x_2^{(3)} \\ \vdots & \vdots \\ x_1^{(m)} & x_2^{(m)} \end{bmatrix}$$

$$y = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ y^{(3)} \\ \vdots \\ y^{(m)} \end{bmatrix}$$

# The Best Hyperplane Separator?

- Perceptron finds one of the many possible hyperplanes separating the data if one exists
- Of the many possible choices, which one is the best?
- Utilize distance information
- Intuitively we want the hyperplane having the maximum **margin**
- Large margin leads to good generalization on the test data
  - we will see this formally when we discuss Support Vector Machine (SVM)
- Utilize distance information from all data samples
  - We will see this formally when we discuss the logistic regression
- **Perceptron will be shown to be a basic unit for neural networks and deep learning later**