Session 33

Classification II

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Table of Content

Apa yang Akan Kita Pelajari Hari Ini?

1. SVM
2. Neural Network
3. Multiclass classification

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SVM

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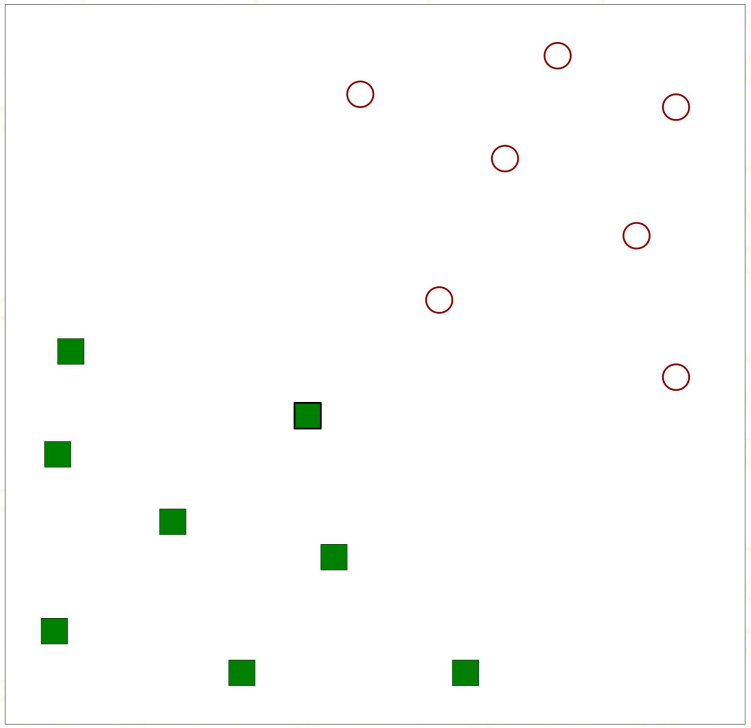
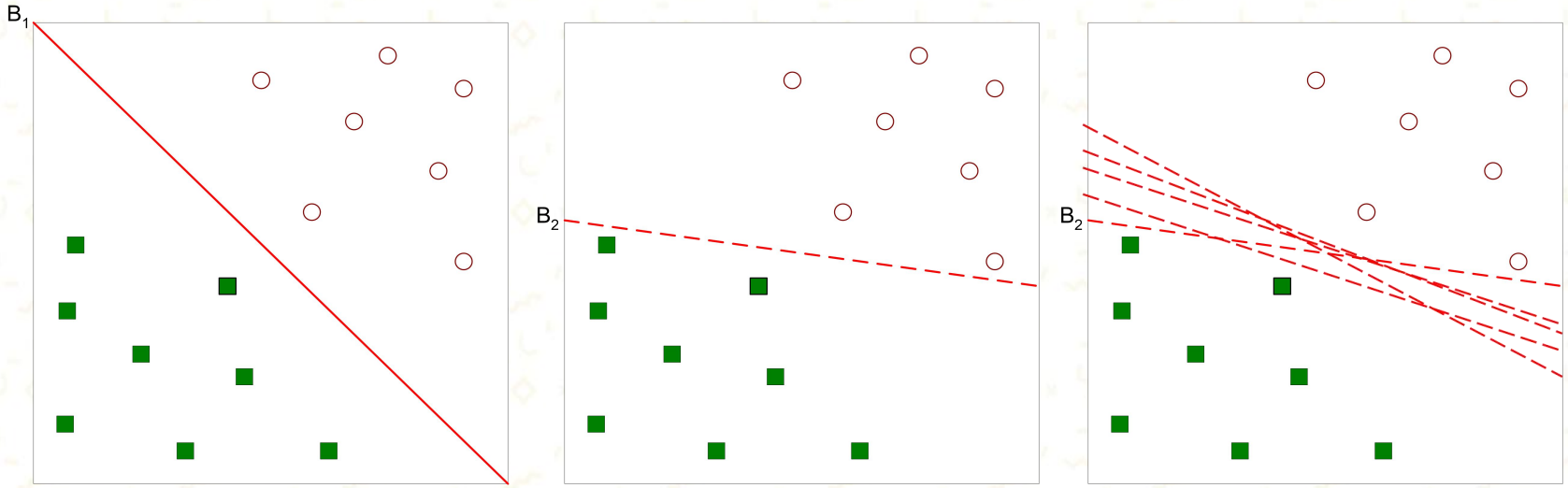
Support Vector Machines



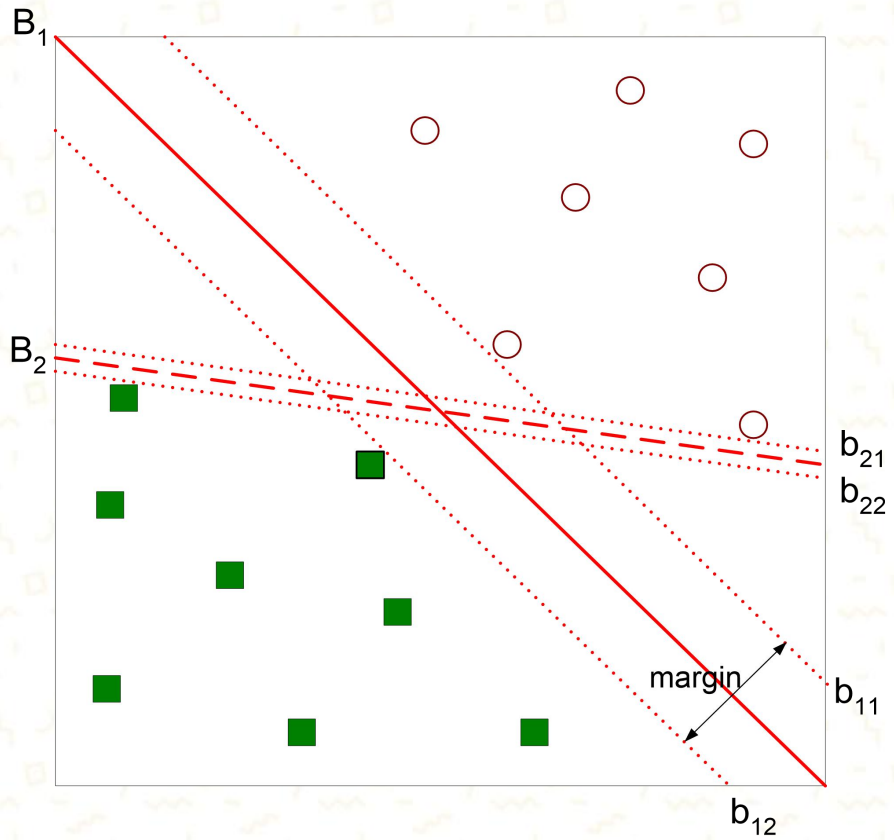
- Find a linear hyperplane (decision boundary) that will separate the data

Support Vector Machines



- There are many possible solution

Support Vector Machines



- Find hyperplane maximizes the margin => B1 is better than B2

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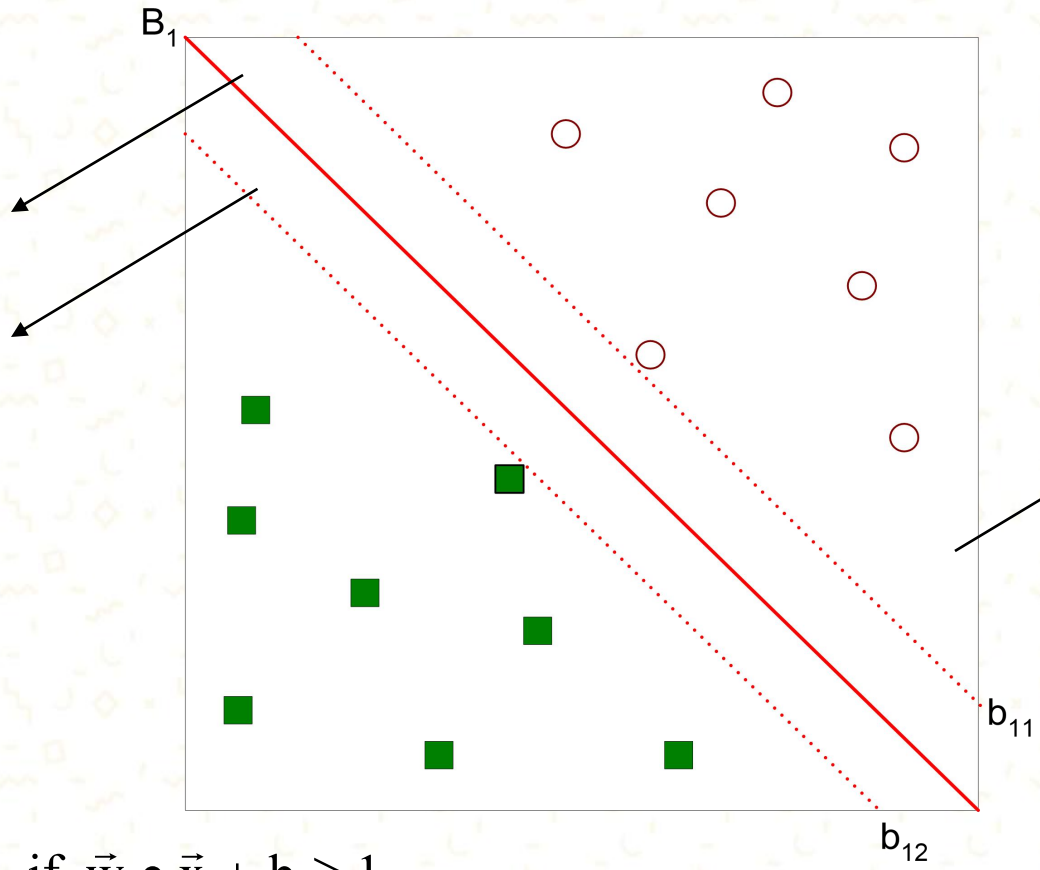
Support Vector Machines



$\vec{w} \bullet \vec{x} + b = 0$

$\vec{w} \bullet \vec{x} + b = -1$

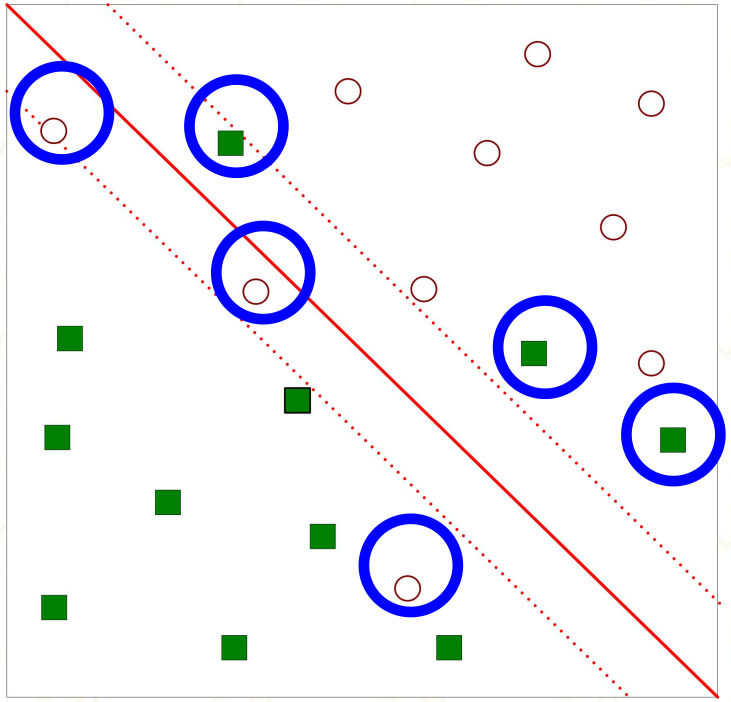
$\vec{w} \bullet \vec{x} + b = +1$

$$f(\vec{x}) = \begin{cases} 1 & \text{if } \vec{w} \bullet \vec{x} + b \geq 1 \\ -1 & \text{if } \vec{w} \bullet \vec{x} + b \leq -1 \end{cases}$$

$$\text{Margin} = \frac{2}{\|\vec{w}\|^2}$$

Support Vector Machines

- What if the problem is not linearly separable?



Support Vector Machines

- What if the problem is not linearly separable?
  - Introduce slack variables
    - Need to minimize:

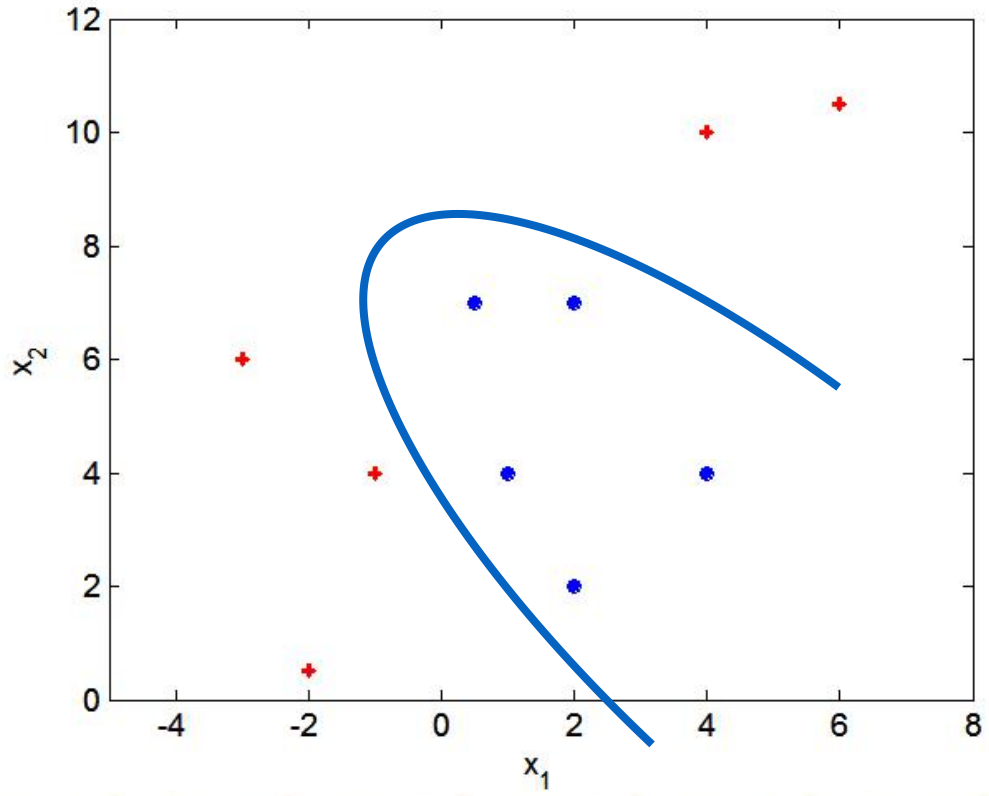
$$L(w) = \frac{\| \vec{w} \|^2}{2} + C\left(\sum_{i=1}^{N} \xi_i^k \right)$$

    - Subject to:

$$f(\vec{x}_i) = \begin{cases} 1 & \text{if } \vec{w} \bullet \vec{x}_i + b \geq 1 - \xi_i \\ -1 & \text{if } \vec{w} \bullet \vec{x}_i + b \leq -1 + \xi_i \end{cases}$$

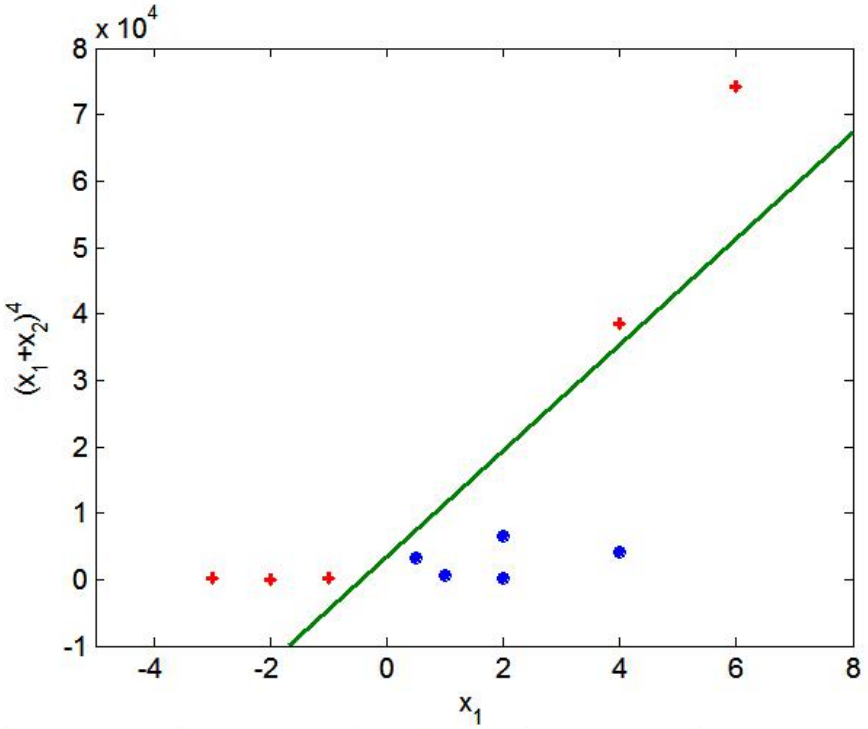
Nonlinear Support Vector Machines

- What if decision boundary is not linear?



Nonlinear Support Vector Machines

- Transform data into higher dimensional space



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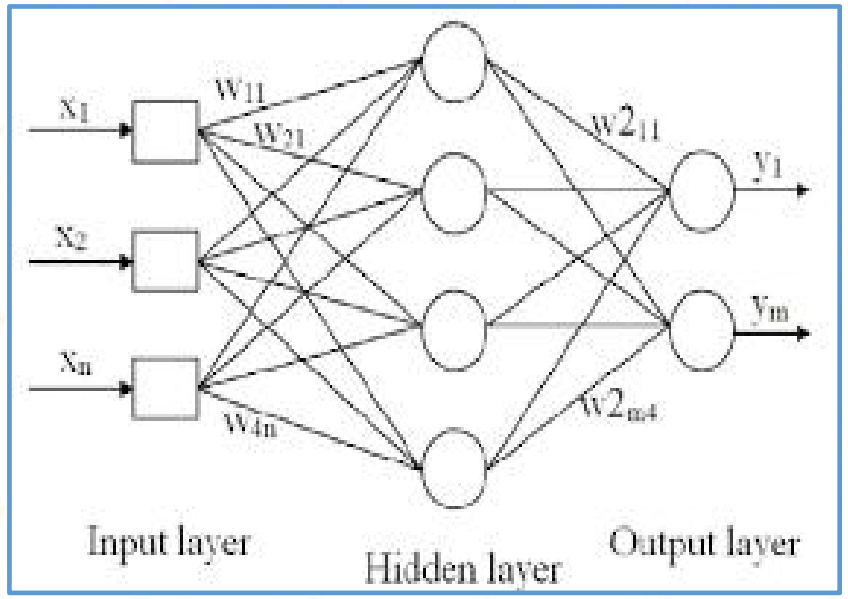
Neural Network

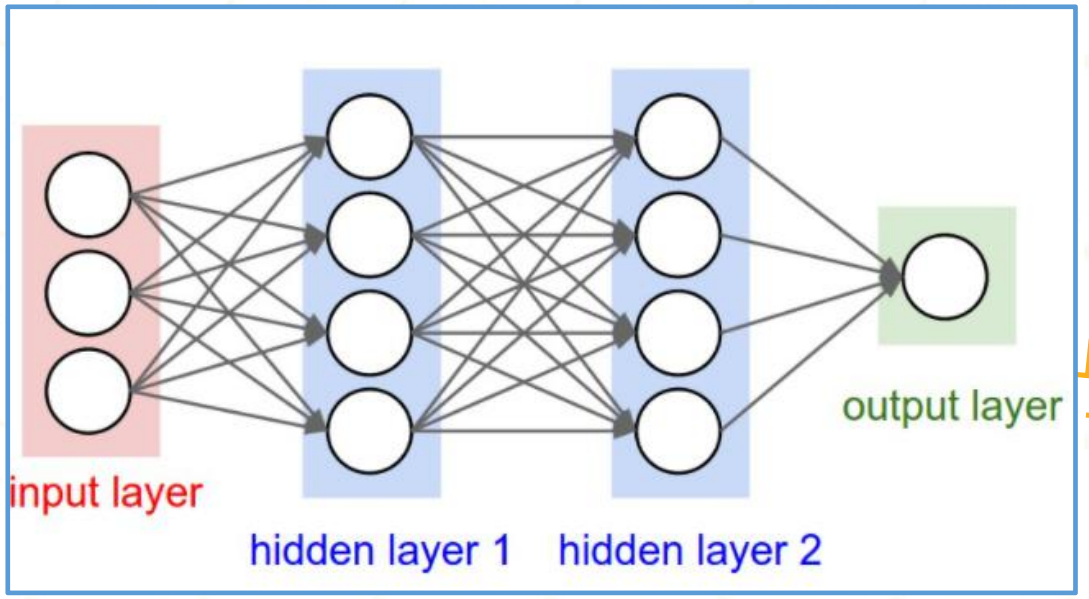
Brief History

- **History of ANN**
- 1943: McCulloch and Pitts: First mathematic model of neuron
- 1958: Rosenblatt: Perceptron - Single layer NN
- 1986: Rumelhart: Back Propagation algorithm
- 1995: Y. LeCun, Y. Bengio, et al.: Convolutional neural network
- 2006: G. E. Hinton, et al.: Deep belief nets.

Artificial Neural Network

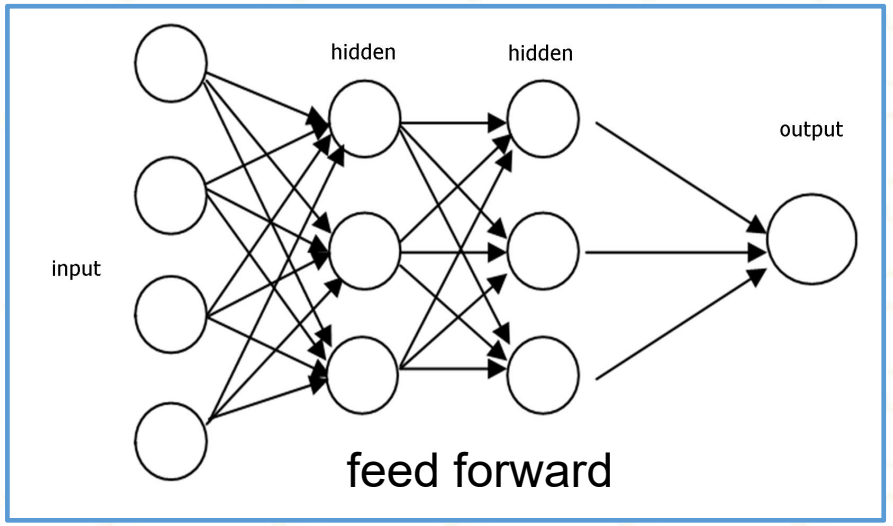
- Artificial Neural Network (Jaringan saraf tiruan) terdiri dari kumpulan unit pemrosesan sederhana yang berkomunikasi dengan mengirimkan sinyal satu sama lain melalui sejumlah besar koneksi berbobot.
- Model yang terinspirasi oleh bagaimana neuron dalam otak manusia bekerja

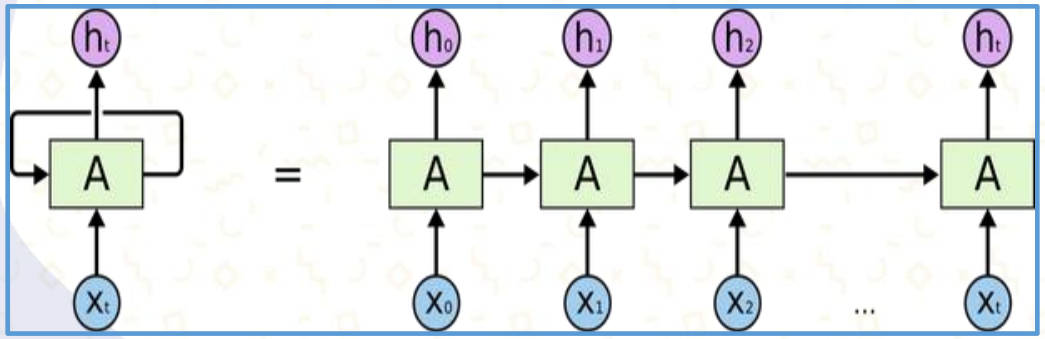




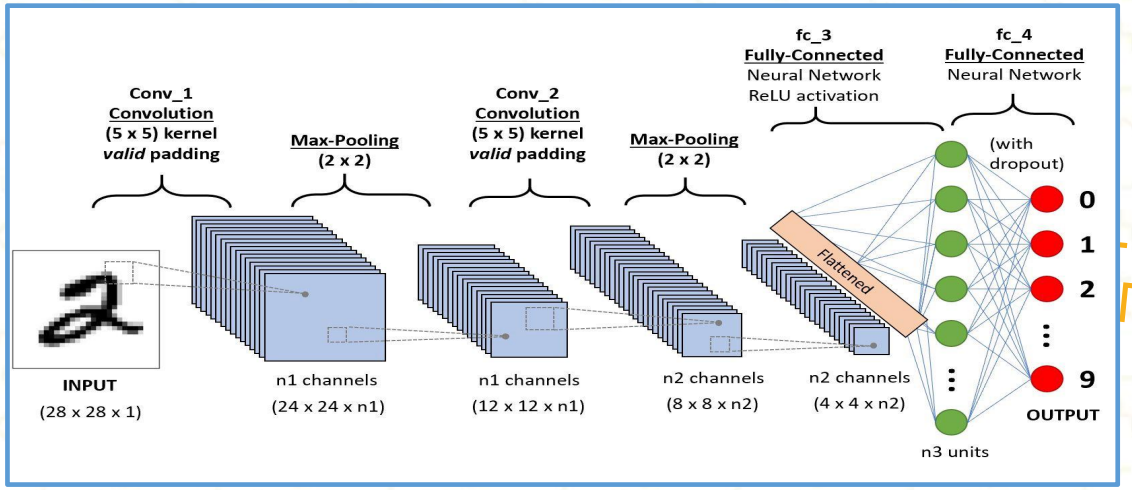
Types of ANN

- **Types of ANN**
  - Feedforward neural network
  - Recurrent neural network (RNN)
  - Convolutional neural network (CNN)
  - etc,





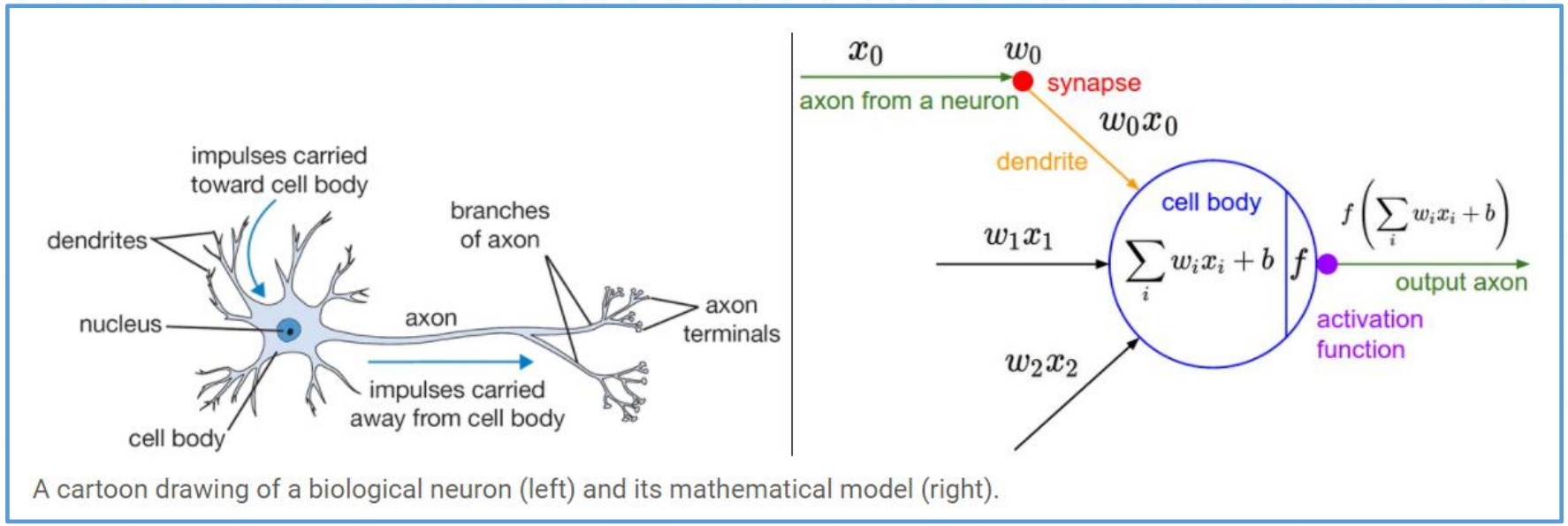
RNN



CNN

Biological motivation

- Neural Networks awalnya terinspirasi oleh tujuan pemodelan sistem saraf biologis.
- Unit komputasi dasar otak adalah neuron.
- Sekitar 86 miliar neuron dapat ditemukan di sistem saraf manusia

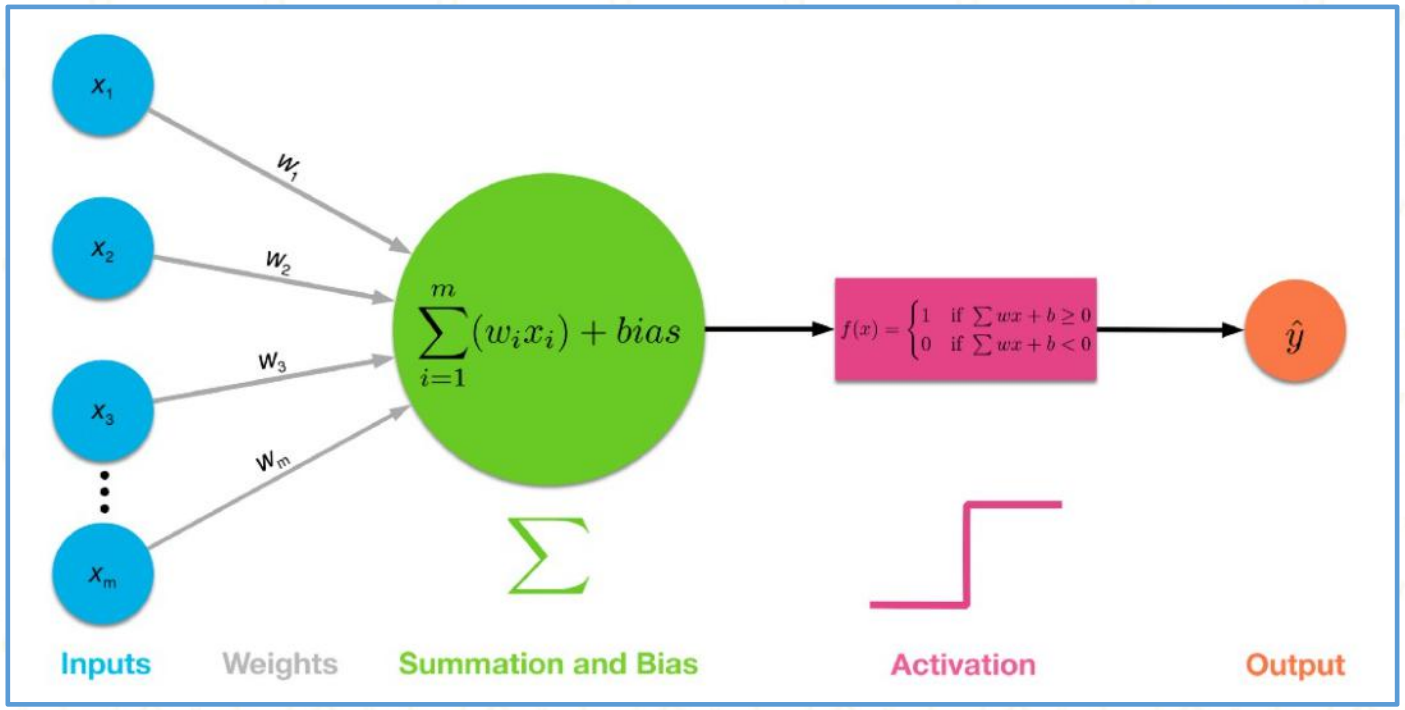


A cartoon drawing of a biological neuron (left) and its mathematical model (right).

https://cs231n.github.io/neural-networks-1/

Perceptron

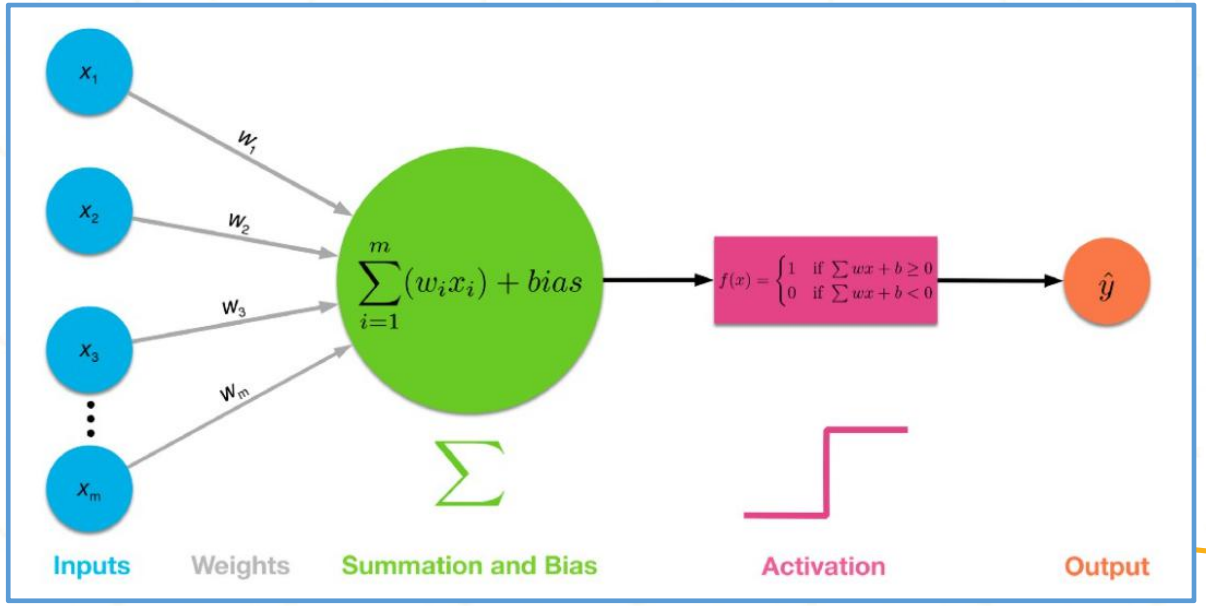
- Perceptron adalah pengklasifikasi linier (linear classifier).
- Frank Rosenblatt, seorang psikolog Amerika, mengusulkan model perceptron klasik pada tahun 1958



https://towardsdatascience.com/multi-layer-neural-networks-with-sigmoid-function-deep-learning-for-rookies-2-bf464f09eb7f

Perceptron

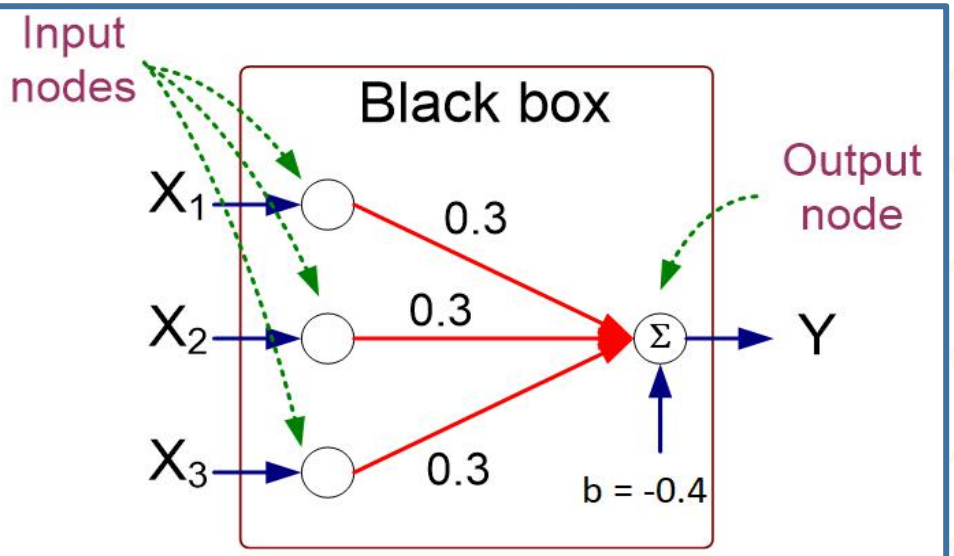
- Digunakan untuk mengklasifikasikan data input yang diberikan.
- The perceptron terdiri dari 4 bagian
  - Input values atau one input layer
  - Weights dan Bias
  - Net sum
  - Activation Function



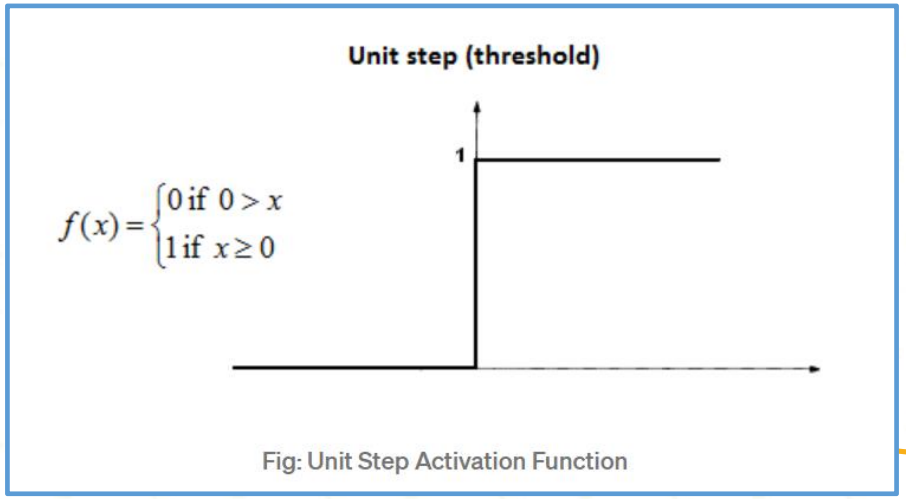
Perceptron (how does it work?)

- Semua inputs x dikalikan dengan weights w
- Jumlahkan semua hasil perkalikan tersebut (kita sebut *Weighted Sum*)
- Mengaplikasikan activation function ke weighted sum

X_1	X_2	X_3	Y
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	0
0	1	0	0
0	1	1	1
0	0	0	0

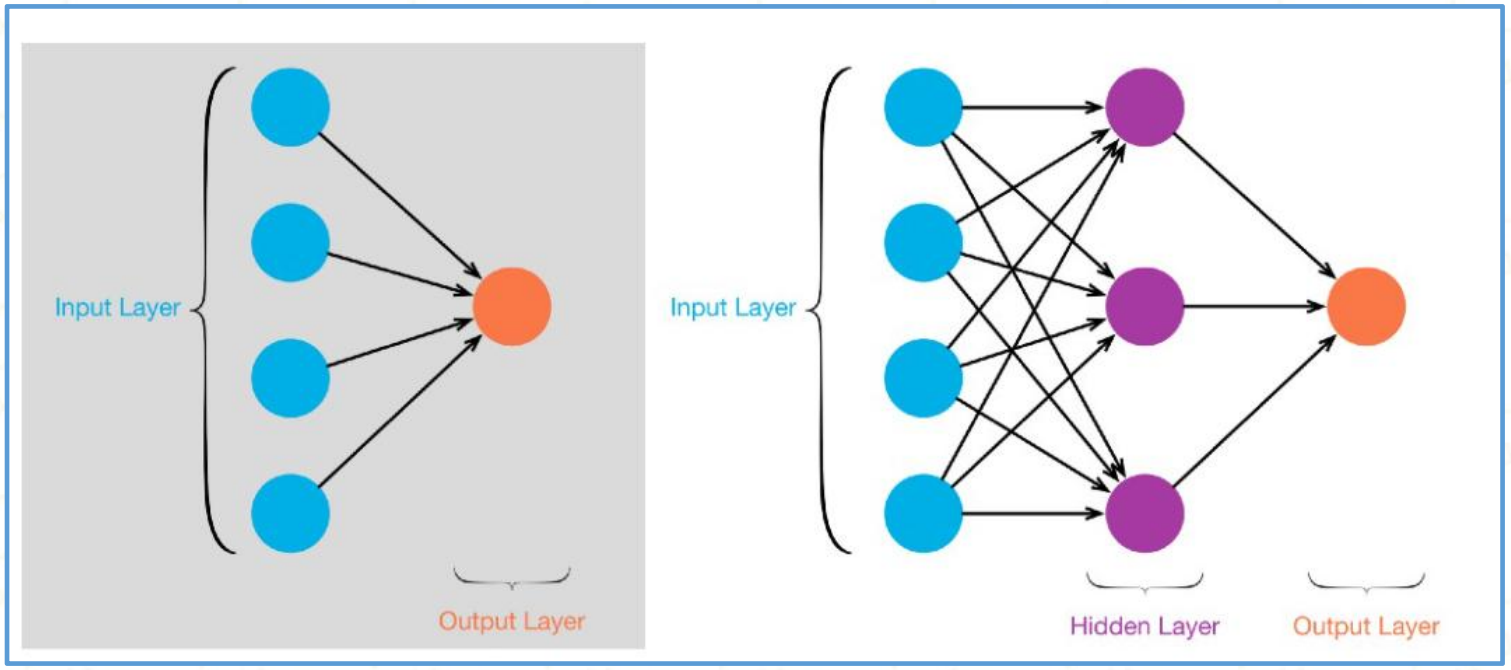


y = f(0.3*x1 + 0.3*x2 + 0.3*x3 - 0.4)

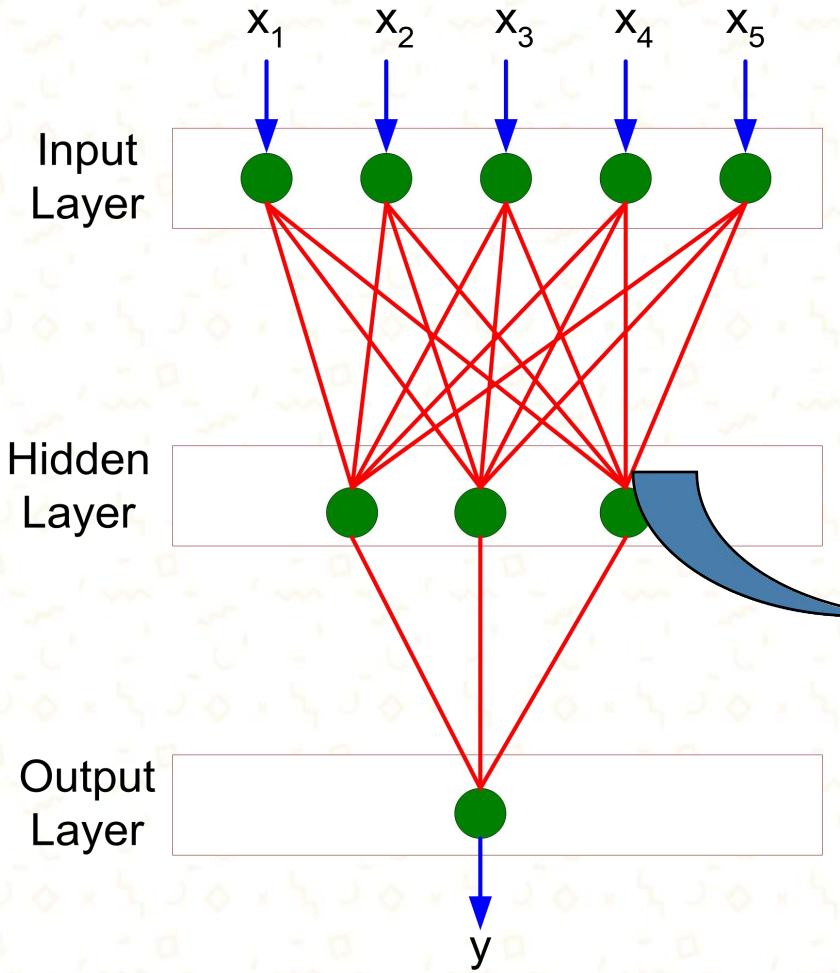


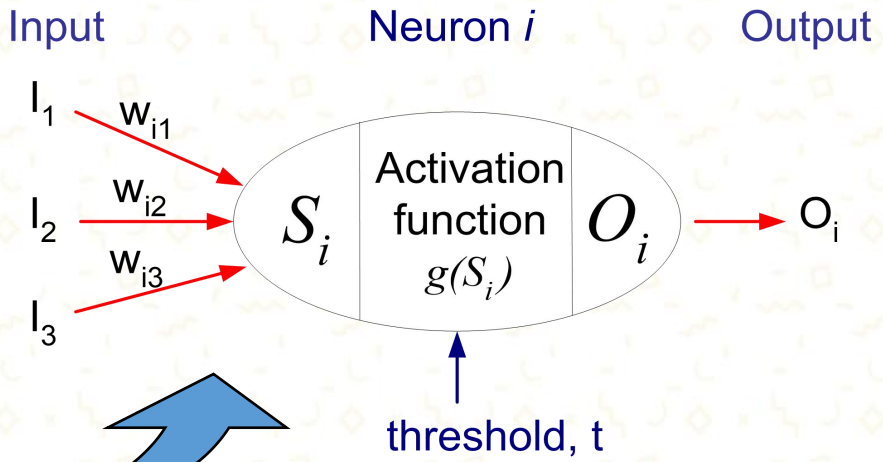
Multilayer perceptron

- Model ini terdiri dari tiga jenis layer — input layer, hidden layer, output layer.
- Kecuali node input, setiap node adalah neuron yang menggunakan fungsi aktivasi nonlinier.
- MLP menggunakan backpropagation untuk training-nya.



General Structure of MLP



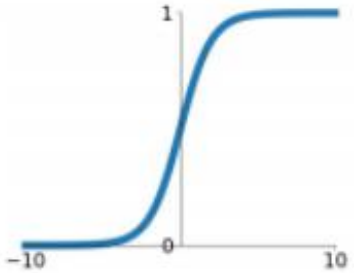


Training ANN means learning the weights of the neurons

Activation function

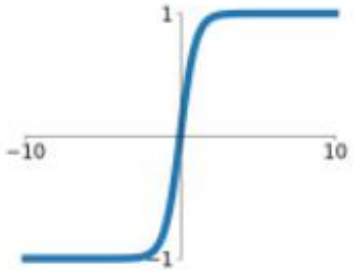
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



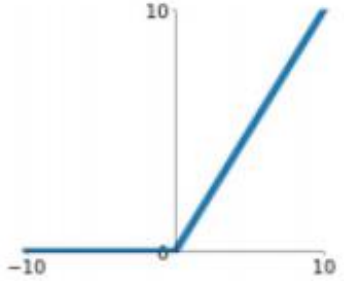
tanh

$$\tanh(x)$$

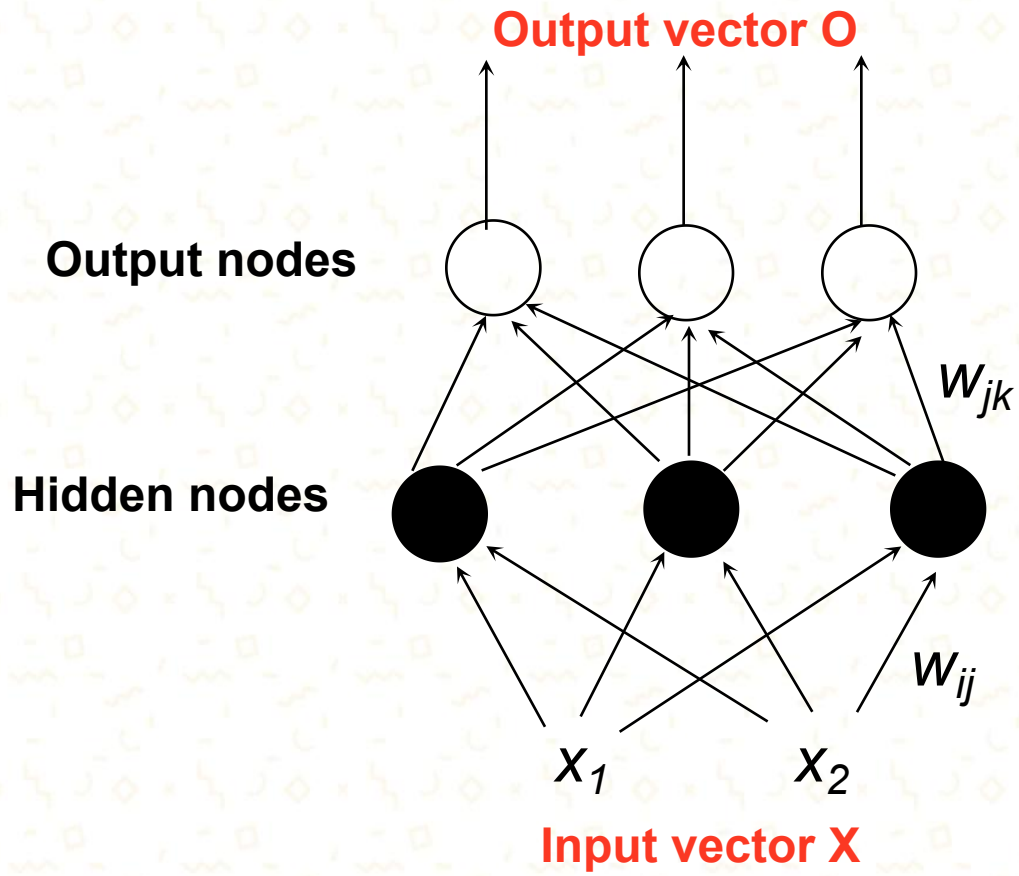


ReLU

$$\max(0, x)$$



Multilayer perceptron



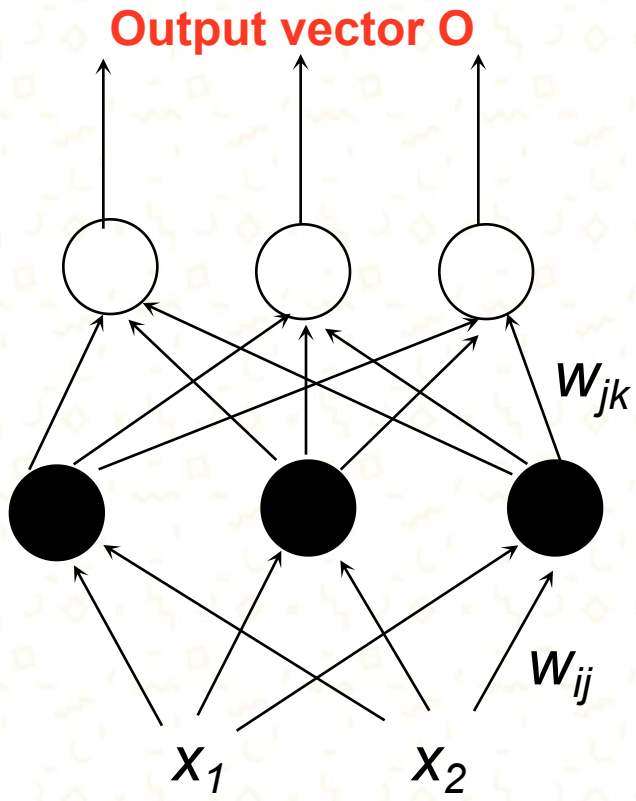
$$O_k = \frac{1}{1+e^{-\sum h_j w_{jk} + \theta_k}}$$

$$h_j = \frac{1}{1+e^{-\sum x_i w_{ij} + \theta_j}}$$

Network Training

- Tujuan dari training
  - Mendapatkan weights yang membuat hampir semua sampel dalam training data dapat diklasifikasikan dengan benar
- Langkah-langkah
  - Inisialisasi weights w_{ij} dengan nilai acak(random)
  - Masukkan (feed) sample training ***X*** ke dalam jaringan satu persatu
  - Untuk setiap unit
    - Hitung output value ***O*** dengan mengaplikasikan activation function
    - Hitung error ***E***
    - Update weights w_{ij} dan biases

Backpropagation Learning



$$Err_k = (T_k - O_k)$$

O_k

h_j

Given (X, T)

$$\delta_k = O_k(1-O_k)(T_k - O_k)$$

$$w_{jk} = w_{jk} + (l)\delta_k O_k$$

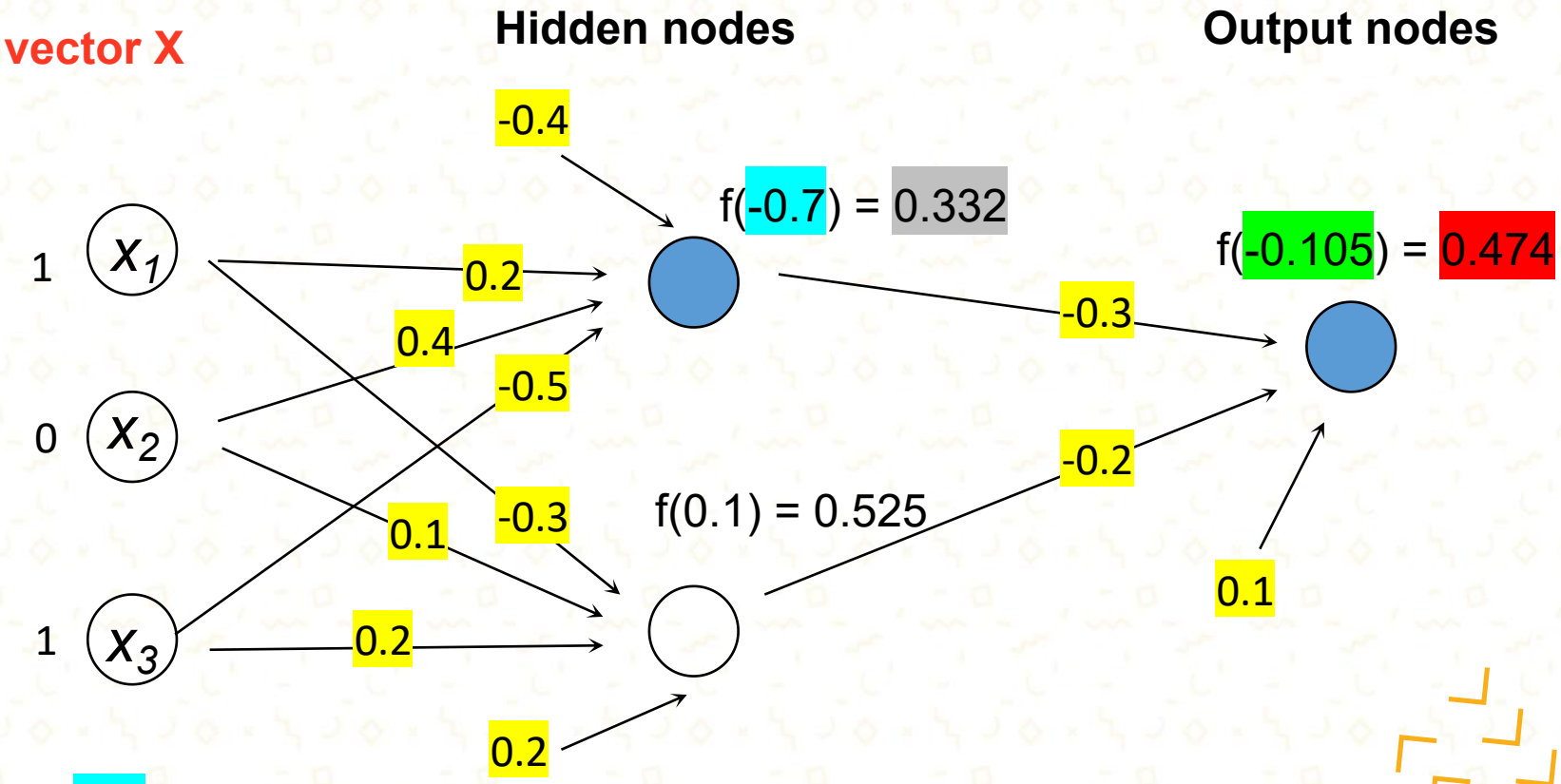
$$\delta_j = h_j(1-h_j)\sum_k \delta_k w_{jk}$$

$$w_{ij} = w_{ij} + (l)\delta_j h_j$$

Contoh

Input vector X

X_1	X_2	X_3	Y
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	0
0	1	0	0
0	1	1	1
0	0	0	0

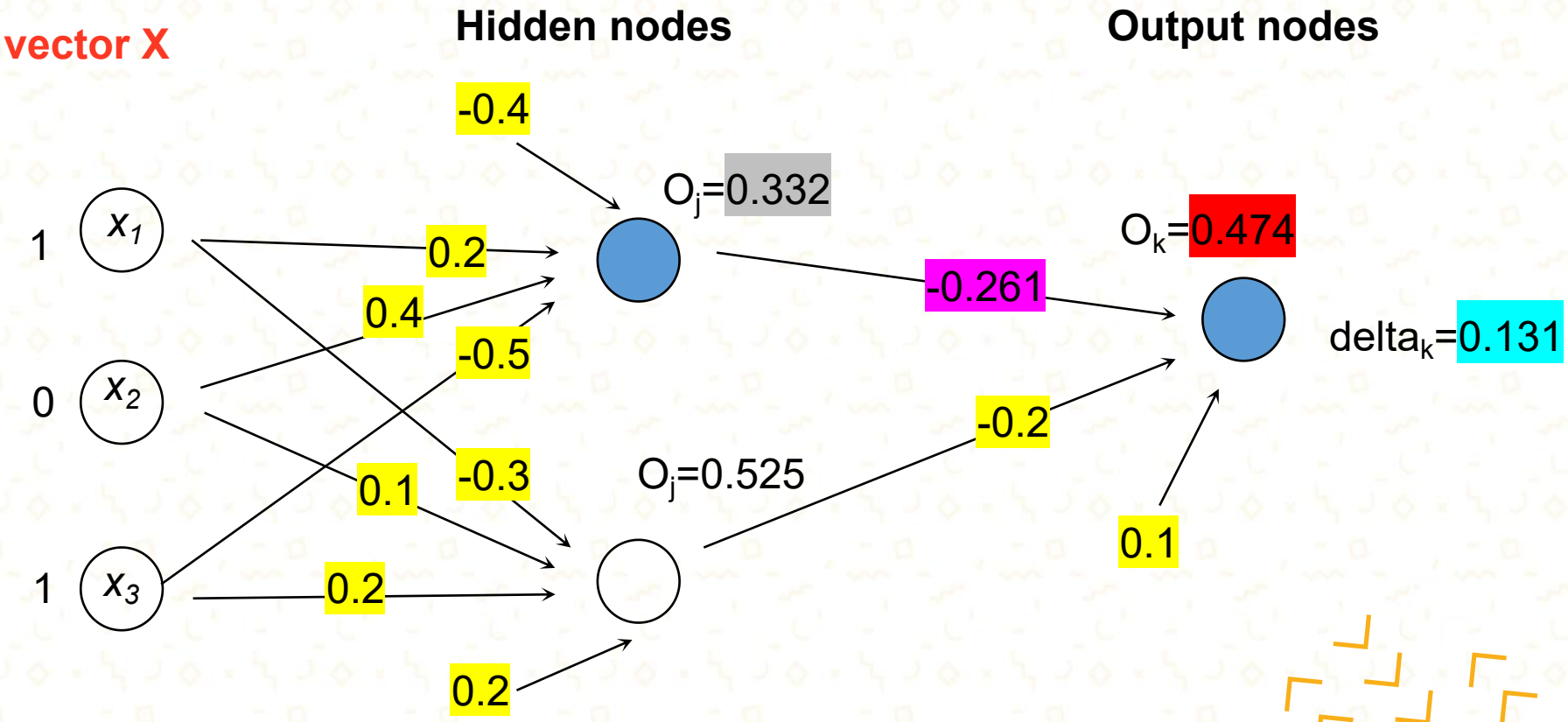


- Net Input I_j = 0.2 + 0 + -0.5 -0.4 = -0.7
- Output O_j = $(1/(1+e^{0.7})$=0.332

- Net Input I_k = -0.3(0.332) - (0.2)(0.525) + 0.1 = -0.105
- Output O_k = $(1/(1+e^{0.105})$ = 0.474

Contoh

X_1	X_2	X_3	Y
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	0
0	1	0	0
0	1	1	1
0	0	0	0



- $delta_k$=(0.474)(1-0.474)(1-0.474)=0.131
- w_{jk} = -0.3+(0.9)(0.1311)(0.332)=-0.261

- Dan seterusnya..

Discussion on NN

- Keuntungan
  - **Robust** -berfungsi baik ketika training set mengandung error
  - Output bisa discrete, real-valued, atau vector
- Criticism
  - Waktu yang lama saat training
  - Sulit untuk dipahami

MLP in Sklearn

- Sklearn menyediakan class MLPClassifier

```
class sklearn.neural_network.MLPClassifier(hidden_layer_sizes=(100), activation='relu', *, solver='adam', alpha=0.0001,
batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5, max_iter=200, shuffle=True, random_state=None,
tol=0.0001, verbose=False, warm_start=False, momentum=0.9, nesterovs_momentum=True, early_stopping=False,
validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08, n_iter_no_change=10, max_fun=15000)   [source]
```

Hyperparameter	Description
hidden_layer_sizes	Jumlah hidden layer dan node-nya
activation	Activation function
max_iter	Jumlah iterasi

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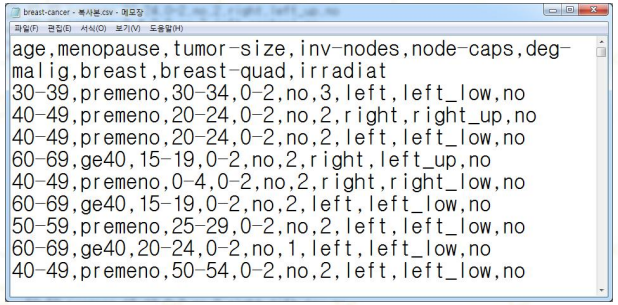
Multiclass

Basic Classification in ML

Input $\mathbf{x} \in \mathcal{X}$	Output $y \in \mathcal{Y}$

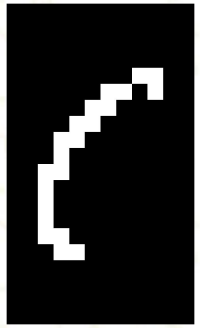
Cancer detection



Binary

- Cancer
- Not cancer

Character recognition

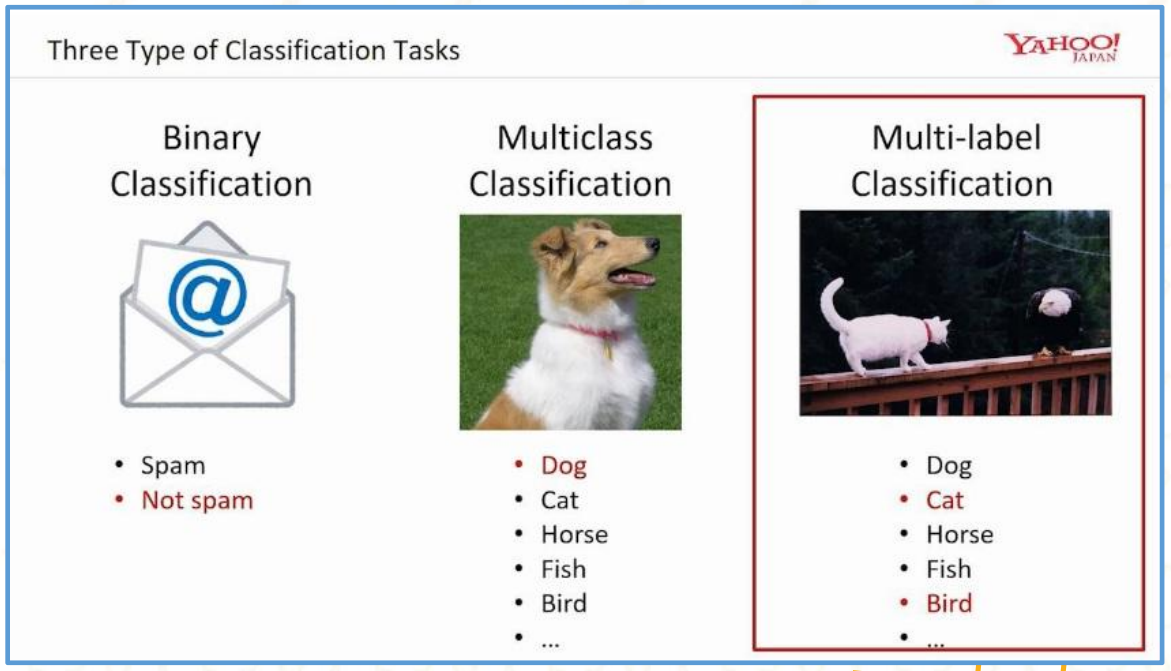


Multi-Class

- A
- B
- C
- …

Multiclass classification

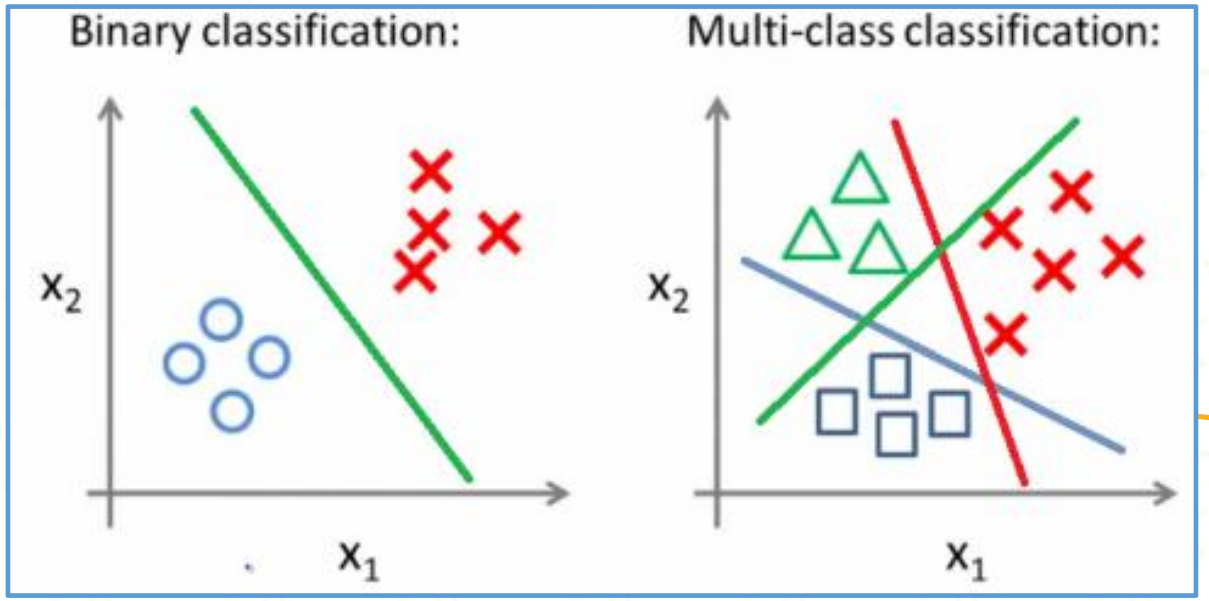
- Multiclass classification
  - Klasifikasi yang melibatkan lebih dari dua Class
  - Setiap data hanya dapat dimiliki oleh satu Class
- Multilabel classification
  - Klasifikasi yang melibatkan lebih dari dua Class
  - Setiap data dapat dimiliki oleh beberapa Class



Binary to multiclass

- Can we use a binary classifier to construct a multiclass classifier?
  - Decompose the prediction into multiple binary decisions

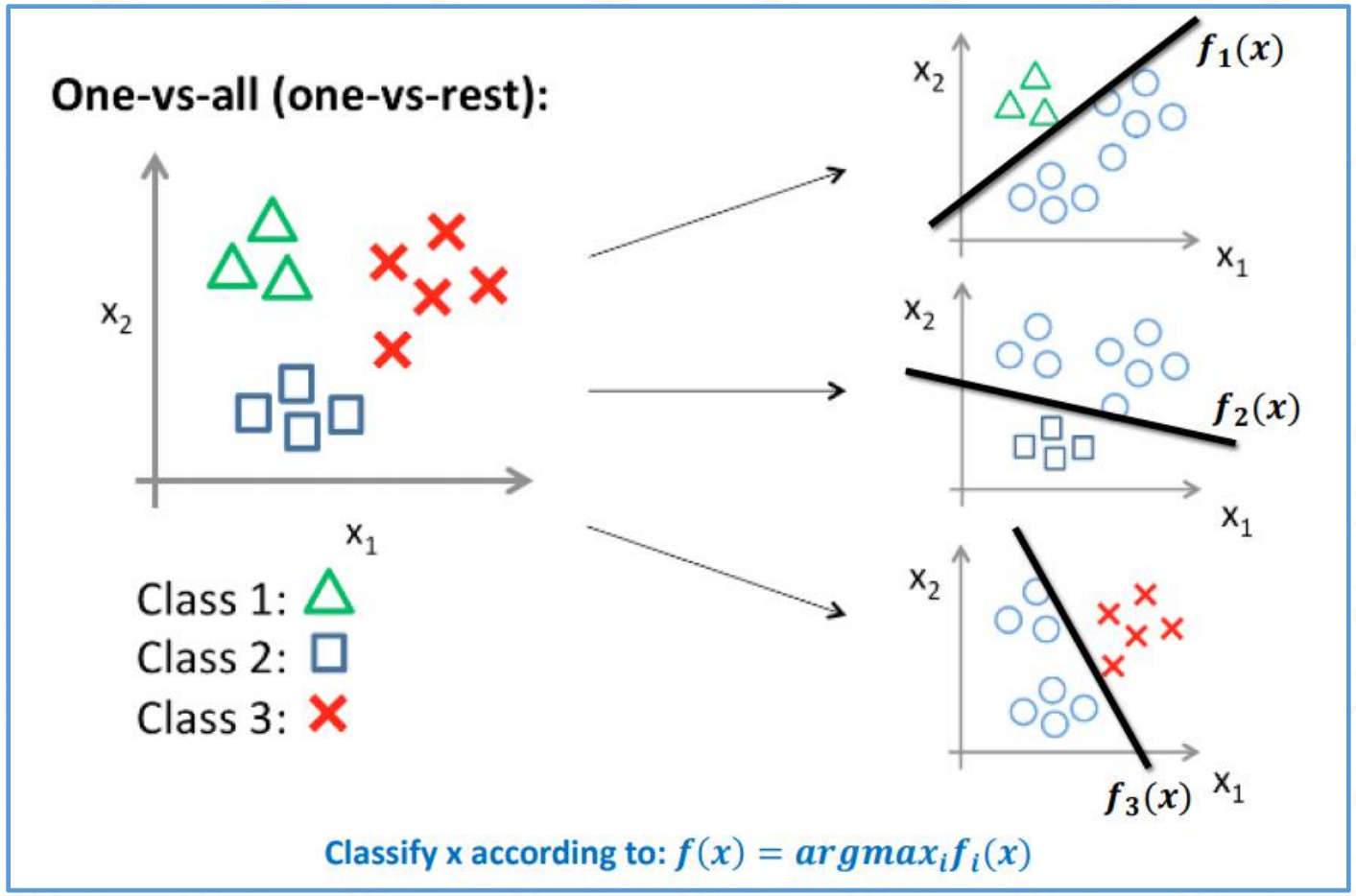
- How to decompose?
  - One-vs-all (One vs Rest/ OvR)
  - One vs One (OvO)



One vs Rest (OvR)

- Learn a classifier one at a time
- Given m classes, train m classifiers: one for each class
- Classifier j: treat tuples in class j as positive & all others as negative
- To classify a tuple X, choose the classifier with maximum value

Visualizing one vs rest



One vs Rest learning algorithm

- Learning: Given a dataset $D = \{(x_i, y_i)\}$
  $x_i \in R^n$, $y_i \in \{1,2,3, \ldots K\}$
- Decompose into K binary classification tasks
  - Learn K models: $w_1, w_2, w_3, \ldots w_K$
  - For class k, construct a binary classification task as:
    - Positive examples: Elements of D with label k
    - Negative examples: All other elements of D
  - The binary classification can be solved by any algorithm we have seen

One vs Rest inference algorithm

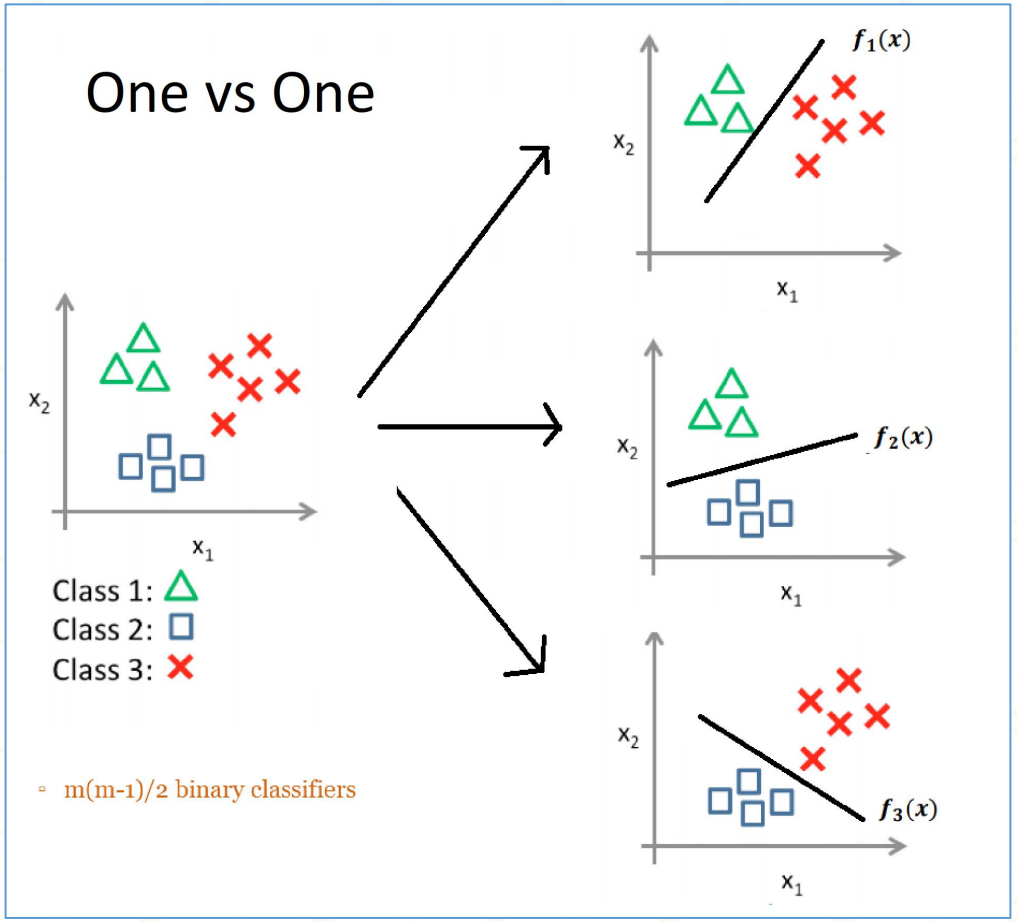
- Inference: “Winner takes all”
  - $\hat{y} = \text{argmax}_{y \in \{1,2,\ldots K\}} \, w_y^T \, x$

For example: $\text{y} = \text{argmax}(w_{red}^T \, x \, , \; w_{blue}^T \, x, \; w_{green}^T \, x)$

One vs One (OvO)

- Learn a classifier for each pair of classes
- Given m classes, construct *m(m-1)/2* binary classifiers
- A classifier is trained using tuples of the two classes
- To classify a tuple X, each classifier votes.
- X is assigned to the class with maximal vote

One vs One (OvO)



Classify x according to majority voting

One vs One learning algorithm

- Learning: Given a dataset $D = \{(x_i, y_i)\}$
  $x_i \in R^n,\ y_i \in \{1,2,3, \ldots K\}$
- Decompose into K(K-1)/2 binary classification tasks
  - Learn K(K-1)/2 models: $w_1,\ w_2,\ w_3, \ldots w_{K*(K-1)/2}$
  - For each class pair (i,j), construct a binary classification task as:
    - Positive examples: Elements of D with label i
    - Negative examples Elements of D with label j
    - The binary classification can be solved by any algorithm

One vs One Inference algorithm

- Prediction:
    - Majority: Pick the label with maximum votes

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Lets Practice!

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Thank YOU