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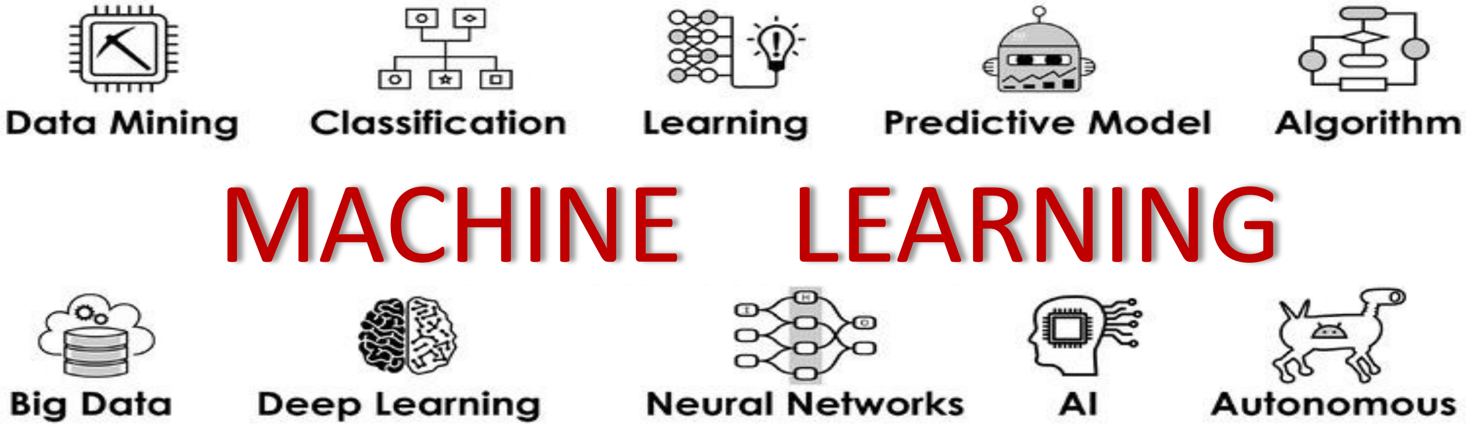

Support Vector Machine

01418496 Selected Topic in Computer Science

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Supervised Learning

Classification

Classification is about predicting a class or discrete values
Eg: Male or Female; True or False

- Logistic Regression
- Decision Tree
- Random Forest
- K-Nearest Neighbors
- Support Vector Machine Classifier
- Naïve Bayes Classifier

Regression

Regression is about predicting a quantity or continuous values
Eg: Salary; age; Price.

- Linear Regression
- Polynomial Regression
- Random Forest Regressor
- Support Vector Machine Classifier
- Bayesian Linear Regressor

Classification:

Dog

Cat

(Dog or Cat)

Regression:

Temperature

Rainfall in cm

Rainfall in cm

Unsupervised Learning

S

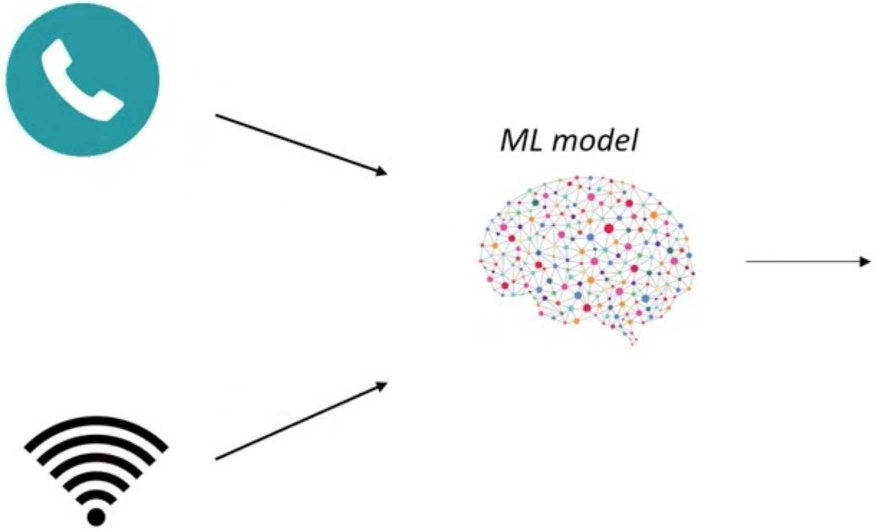
Clustering

Clustering is an unsupervised task which involves grouping the similar data points.

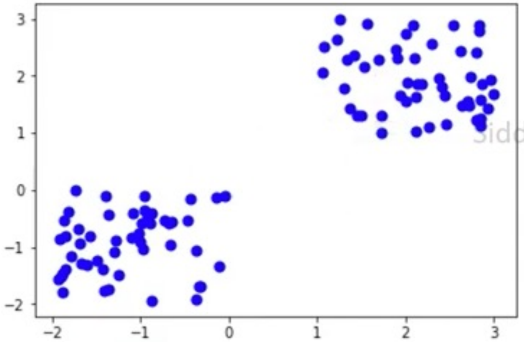
- K-Means Clustering
- Hierarchical Clustering
- Principal Component Analysis (PCA)

Association

Association is an unsupervised task that is used to find important relationship between data points



Clustering



Association

Customer 1

- *Bread*
- *Milk*
- *Fruits*
- *wheat*

Customer 2

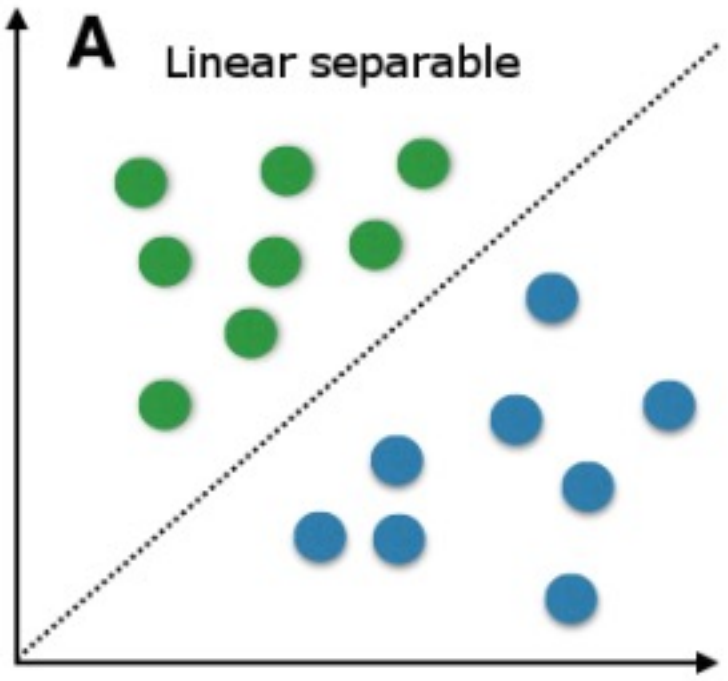
- *Bread*
- *Milk*
- *Rice*
- *Butter*

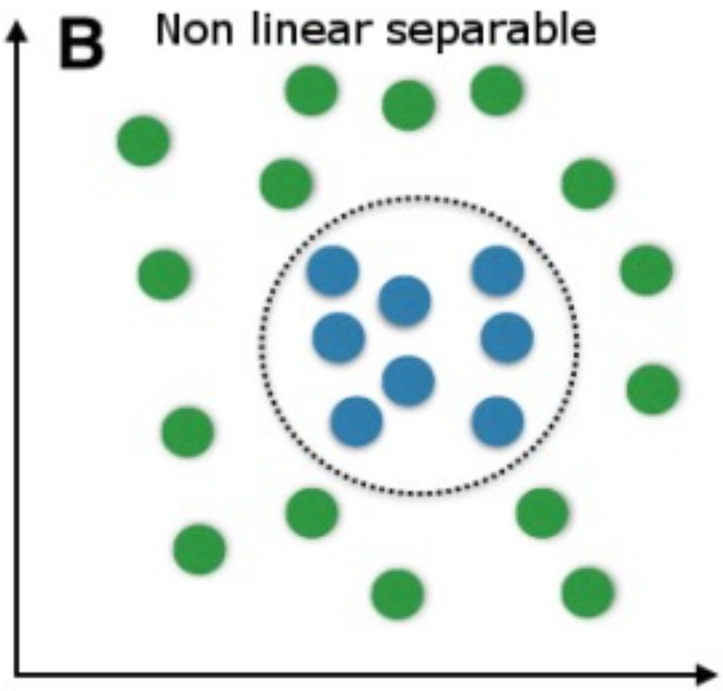
Customer 3

Now, when customer 3 goes and buys bread, it is highly likely that he will also buy milk.

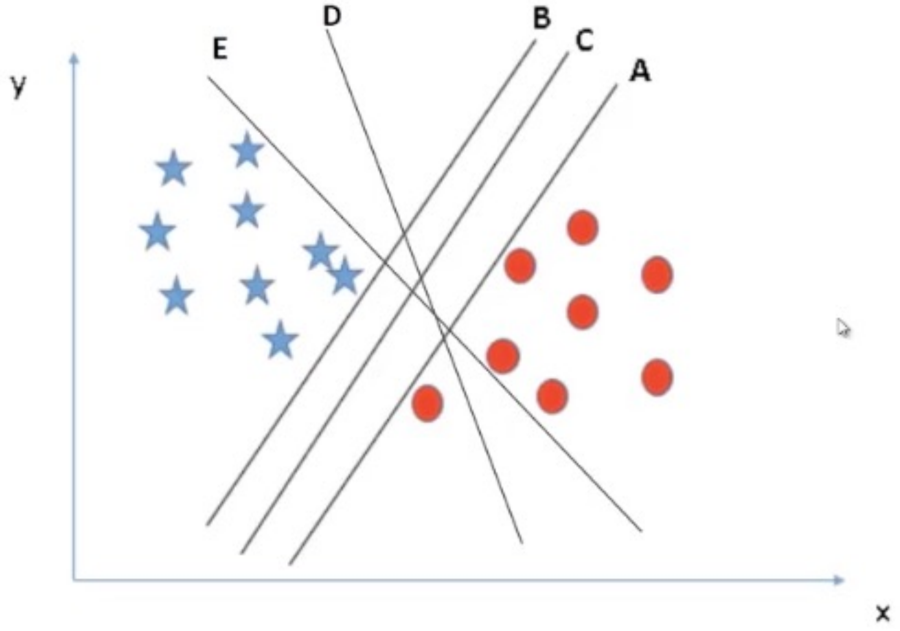
Support Vector Machines (SVM) ?

- Support Vector Machine จะเป็นการจัดกลุ่มข้อมูล Classification โดยการแบ่ง Class ของข้อมูลออกจากกัน ซึ่งสามารถใช้การแบ่งด้วยสมการเชิงเส้นได้ทั้ง Linear และ Non Linear



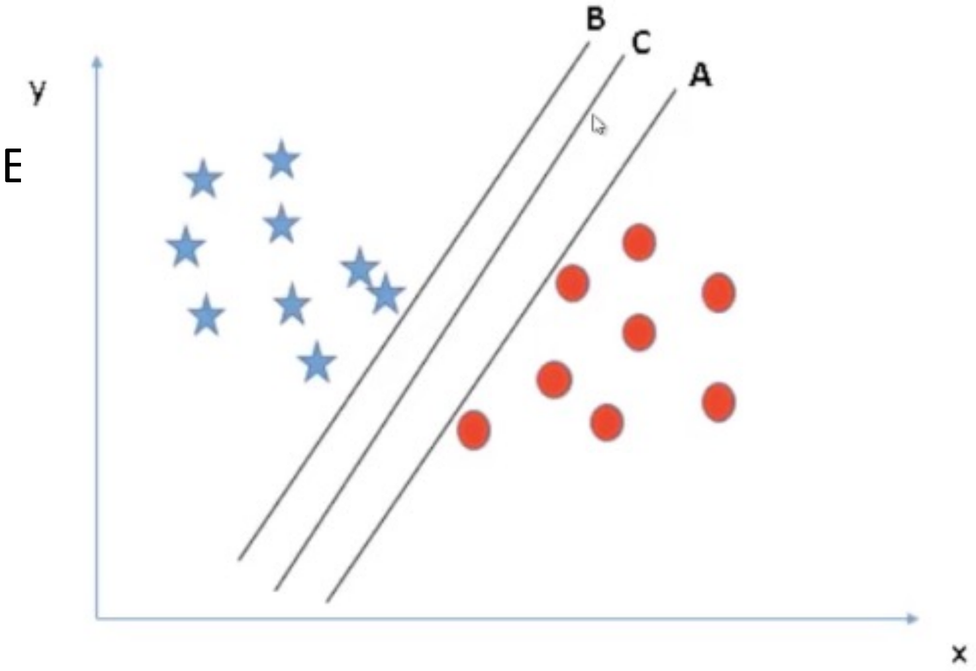


Support Vector Machines (SVM) ?

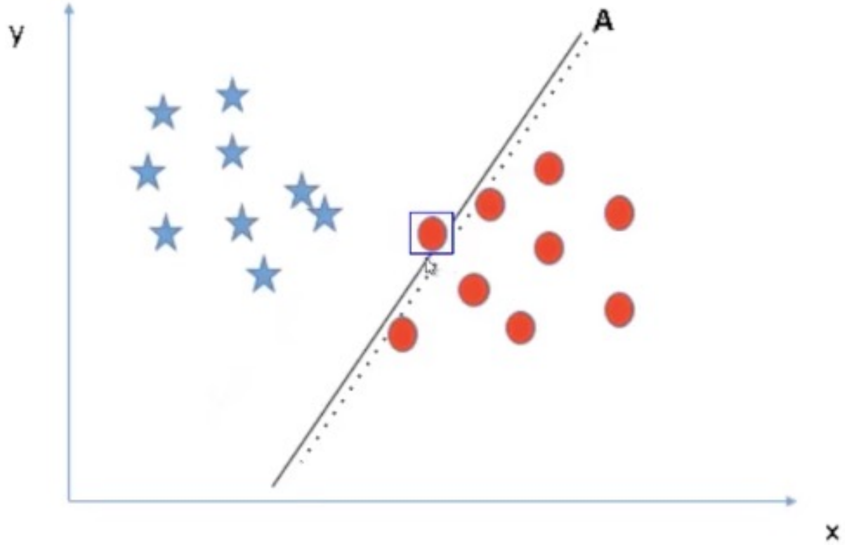


100% classification (line E and D will be removed)

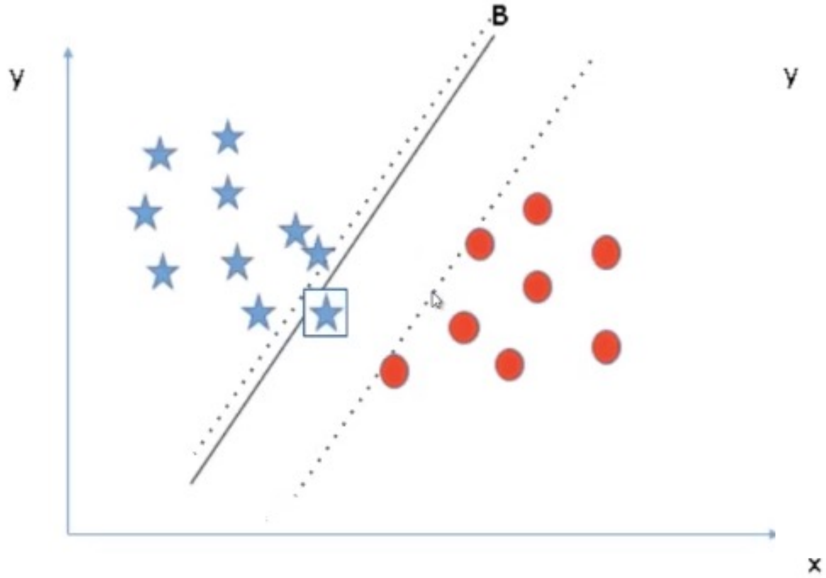
Which line is Best Separation?



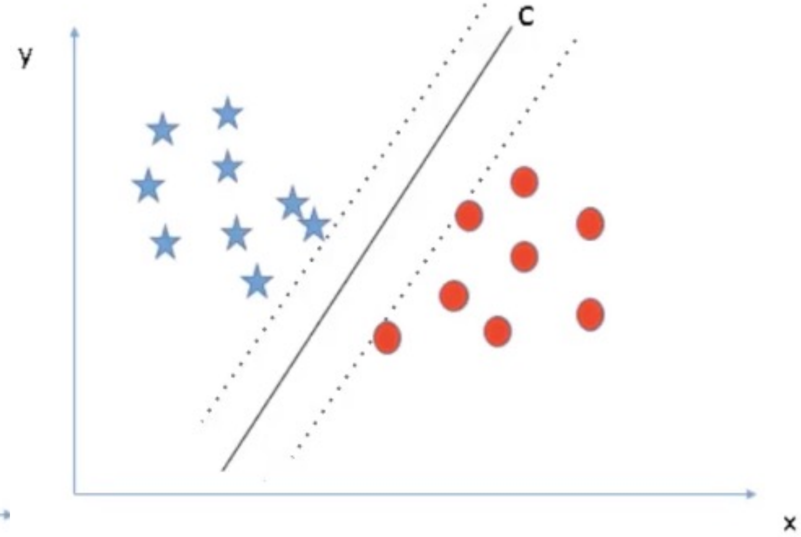
Support Vector Machines (SVM) ?



Margin of line A



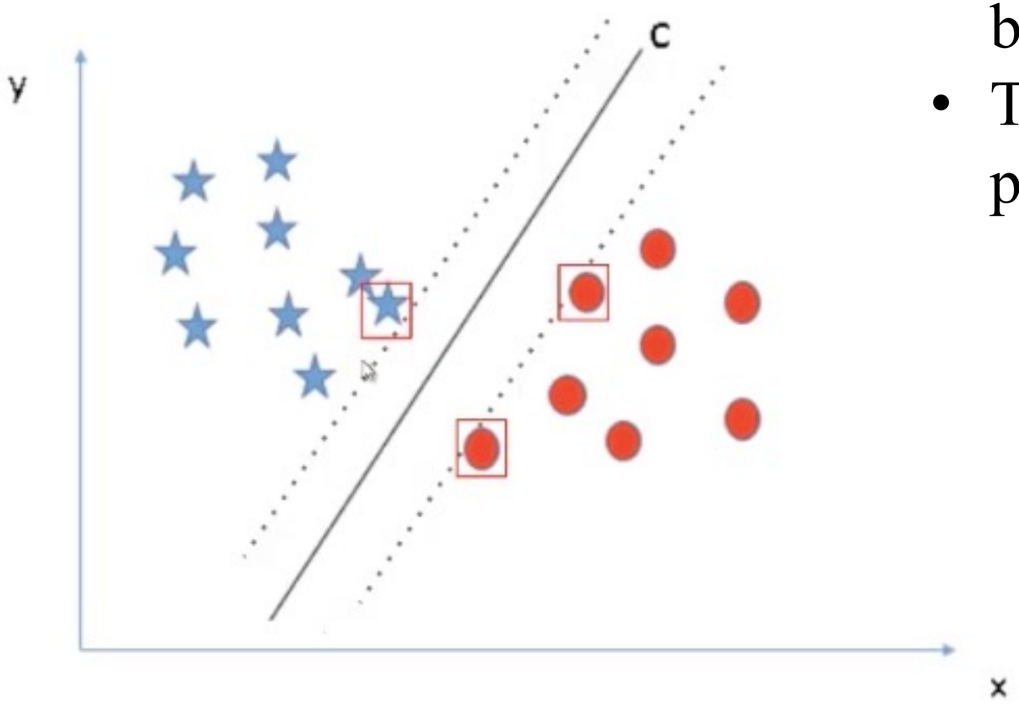
Margin of line B



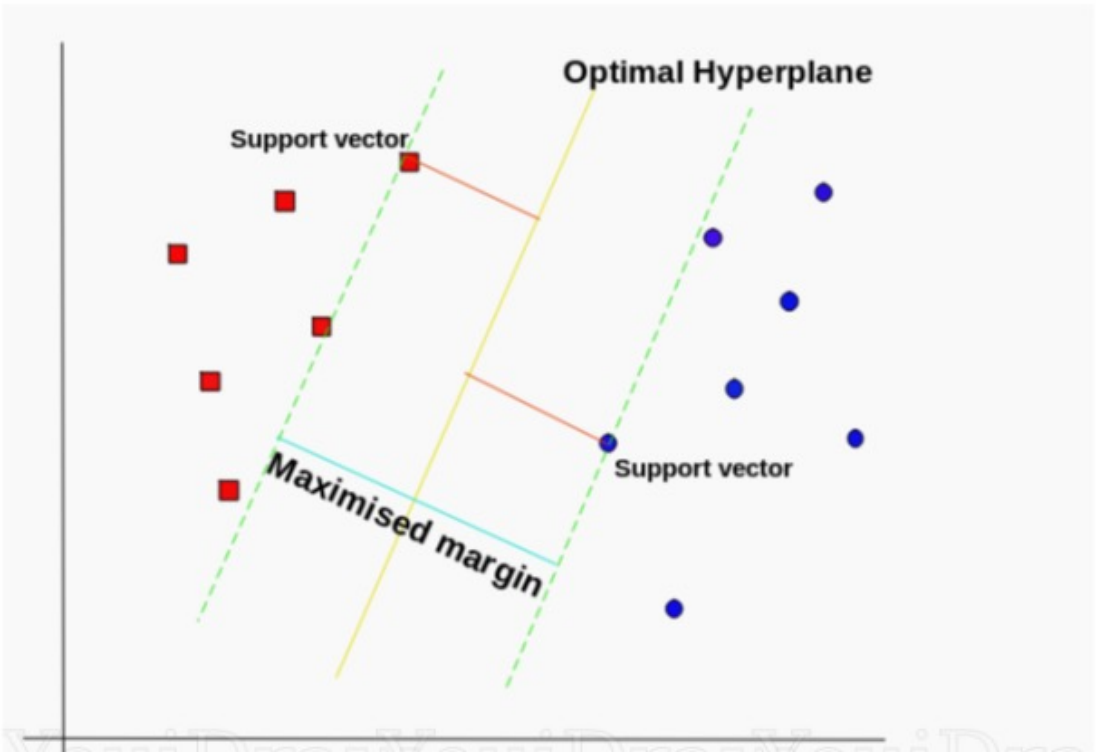
Margin of line C

So Line C present the maximum margin

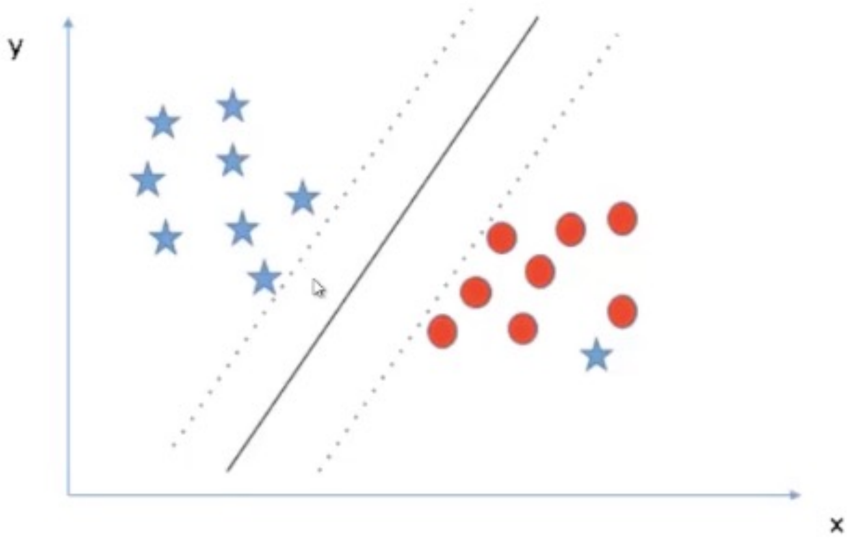
Support Vector Machines (SVM) ?

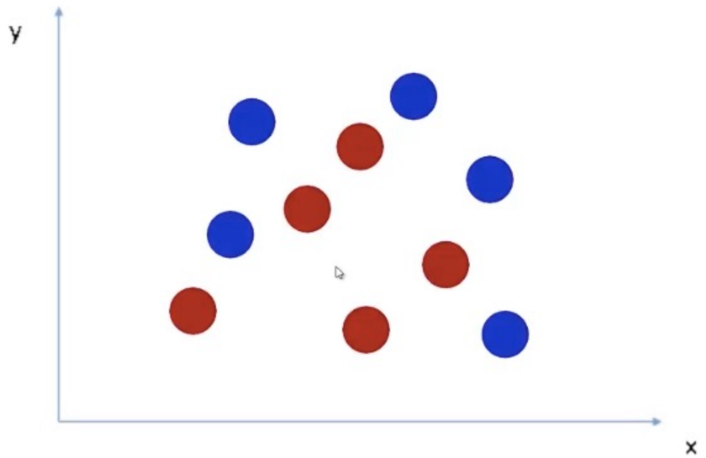


- the margin for hyper-plane C is high as compared to both A and B
- The point that help us to identify the right hyper-plane they are called "Support Vector"



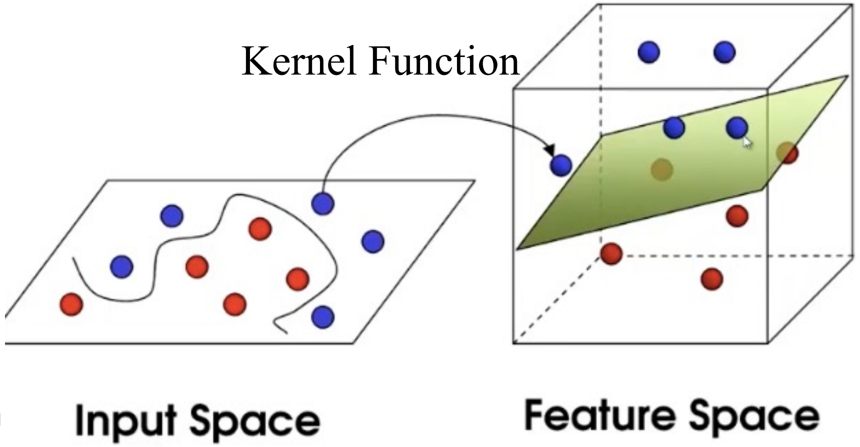
100% classification → Maximum Classification





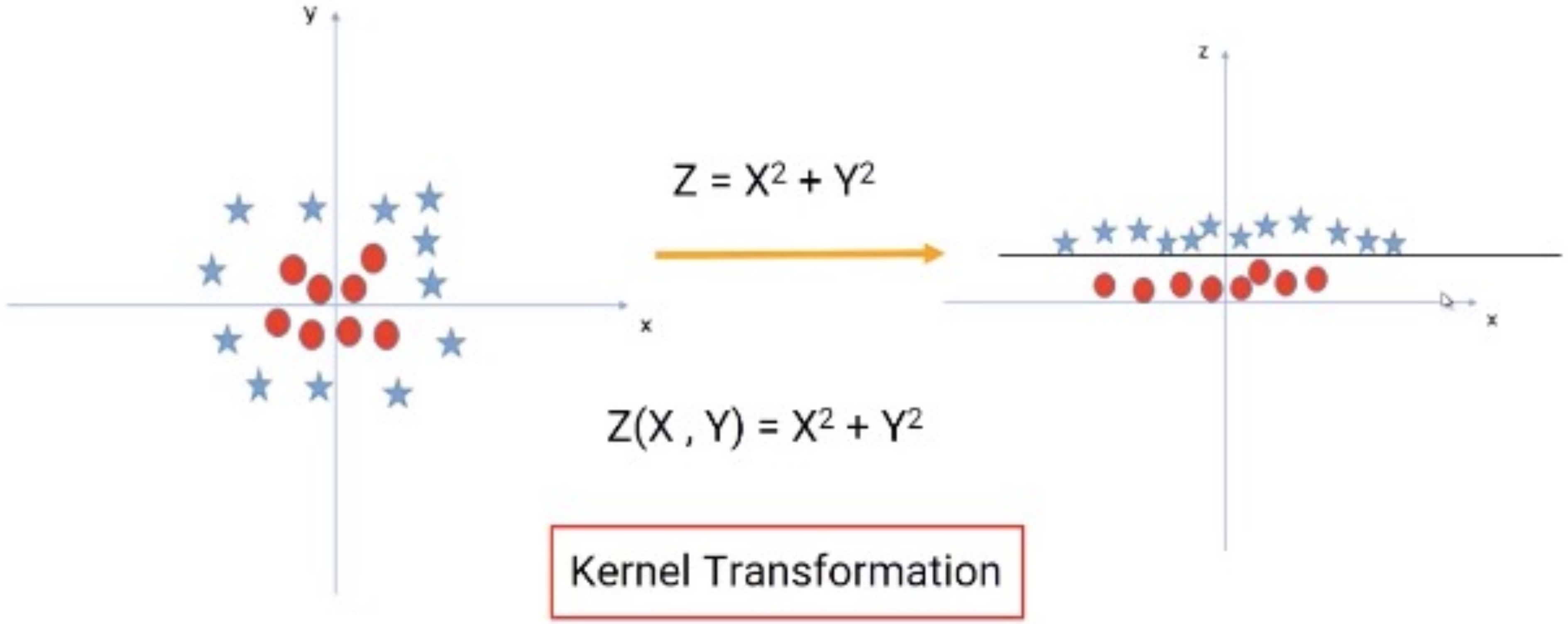
- In the scenario below, we can't have linear hyperplane between the two classes,
- How does SVM classify these two classes?

- SVM can solve this problem
- It solves this problem by introducing an additional feature.



Projecting to Higher Dimension

- An additional feature ($z = x^2+y^2$)



SVM with python

```
import pandas as pd
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
………

model = SVC( )
model.fit(train_x,train_y)
```

How to tune Parameters of SVM?

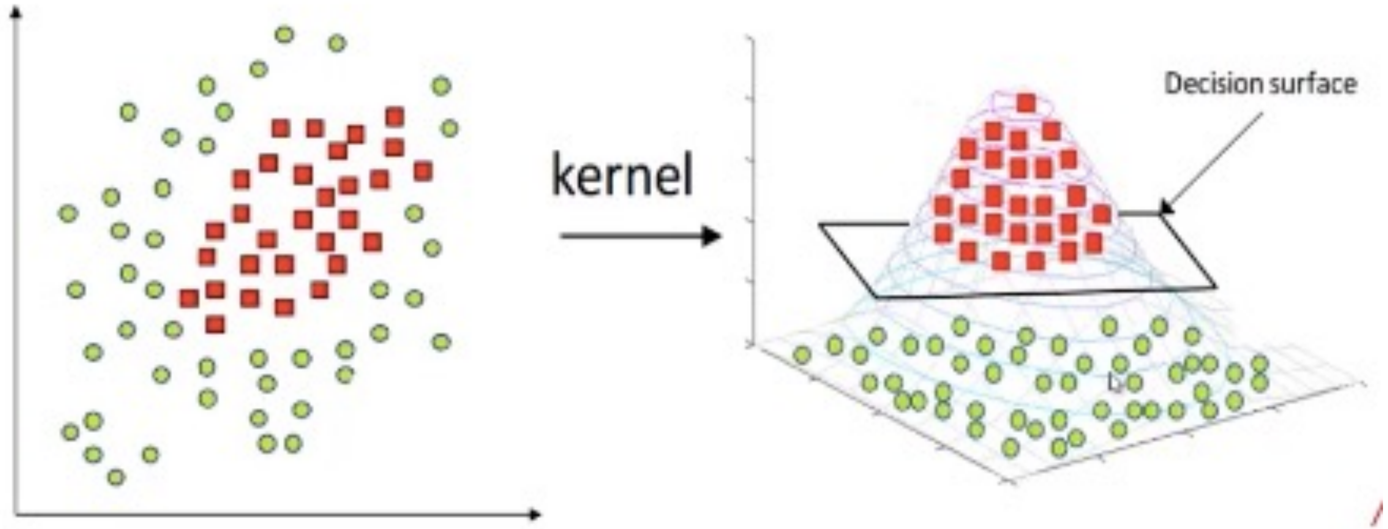
sklearn.svm.SVC(***C=1.0*, *kernel='rbf'*, *degree=3*, *gamma=0.0***, *coef0=0.0*, *shrinking=True*, *probability=False*,*tol=0.001*, *cache_size=200*, *class_weight=None*, *verbose=False*, *max_iter=-1*, *random_state=None*)

SVM with python

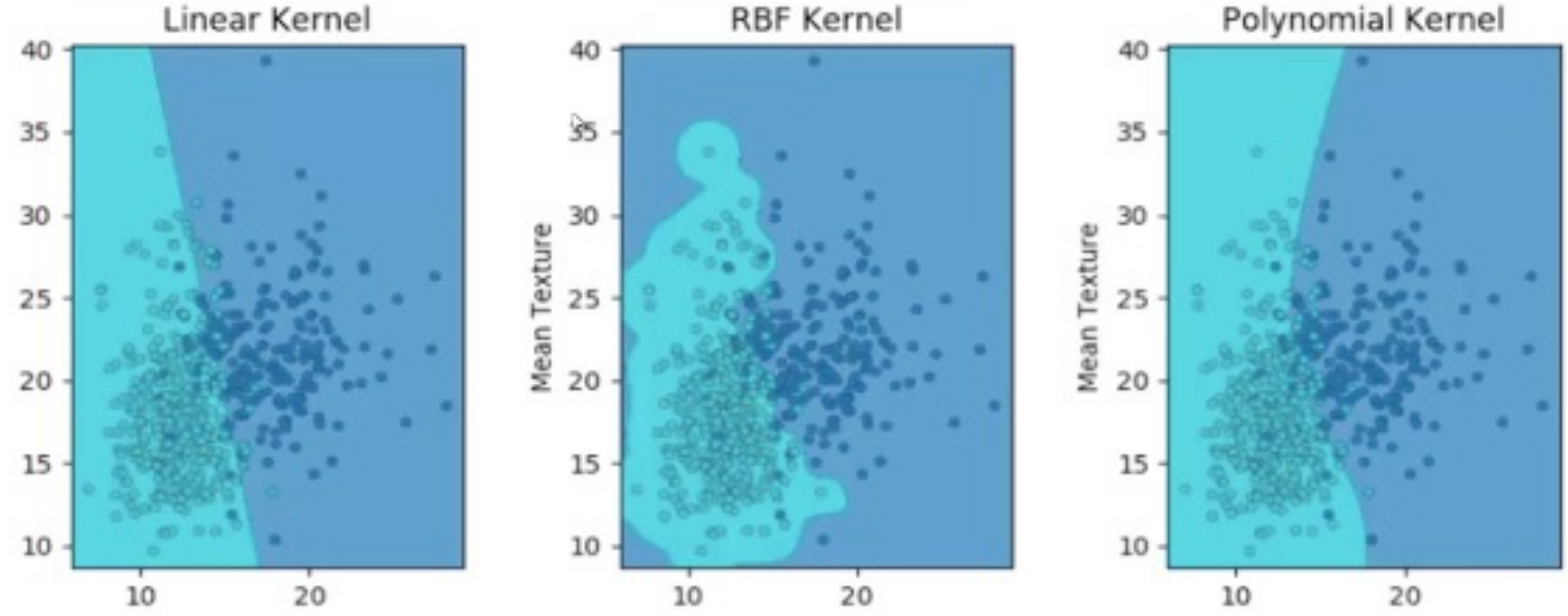
- *Kernel*
  - There are various options available with kernel: “linear”, “rbf”,”poly” and others (default value is “rbf”).
  - “rbf” and “poly” are useful for non-linear hyper-plane.

- **Radial Basic Function (rbf):**

$$Z(X, Y) = \exp\left(-\frac{\| X - Y \|^2}{2\sigma^2}\right)$$



The example shape of each kernel type

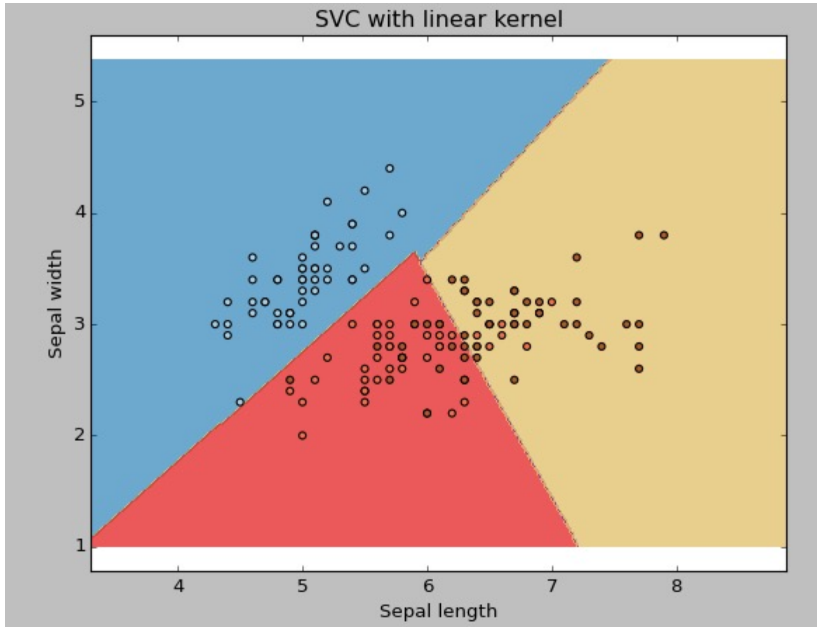


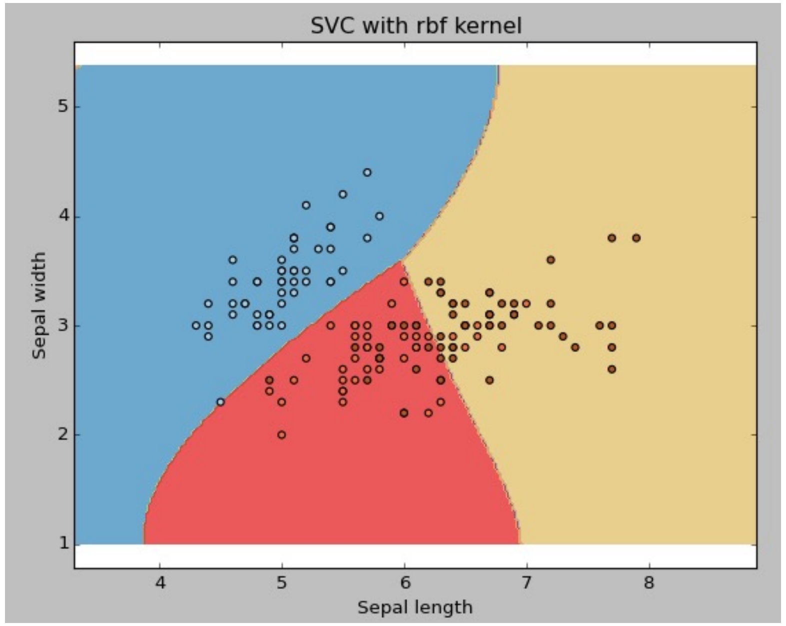
https://youtu.be/3liCbRZPrZA

SVM with python

```
svc = svm.SVC(kernel='linear', C=1,gamma=0)
scv.fit(X, y)
```

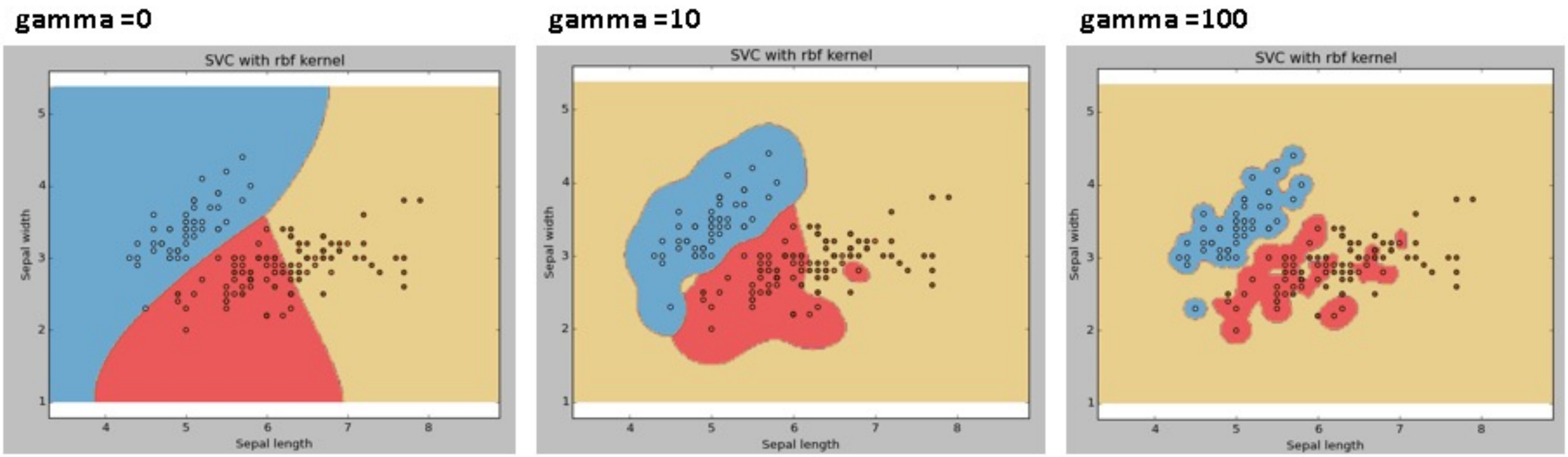
```
svc = svm.SVC(kernel='rbf', C=1,gamma=0)
Svc.fit(X, y)
```





SVM with python

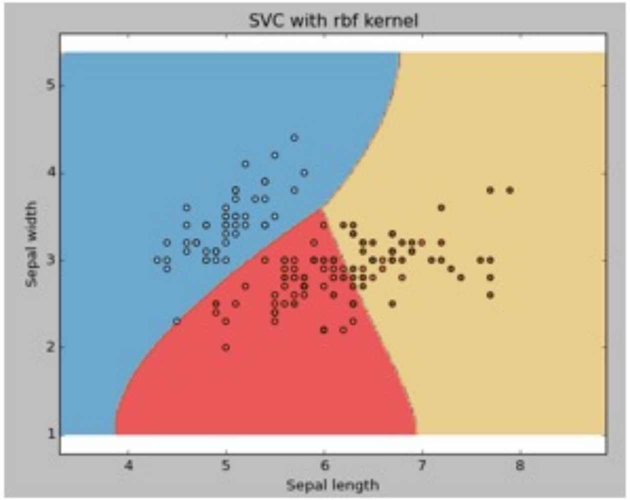
- **gamma:** Higher the value of gamma, will try to exact fit the as per training data set.



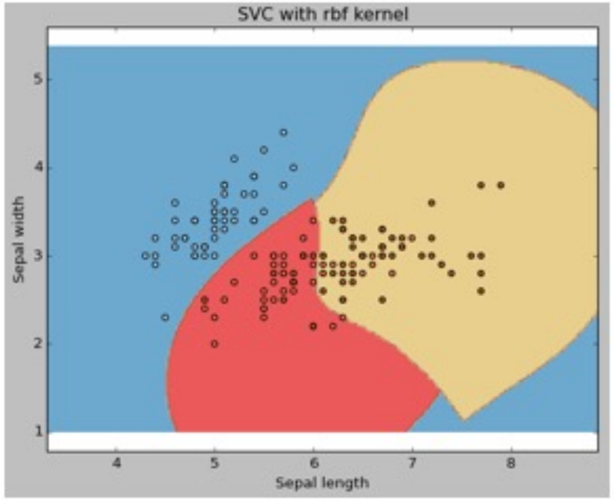
SVM with python

- **C:** Penalty parameter C of the error term. It also controls the trade-off between smooth decision boundaries and classifying the training points correctly.

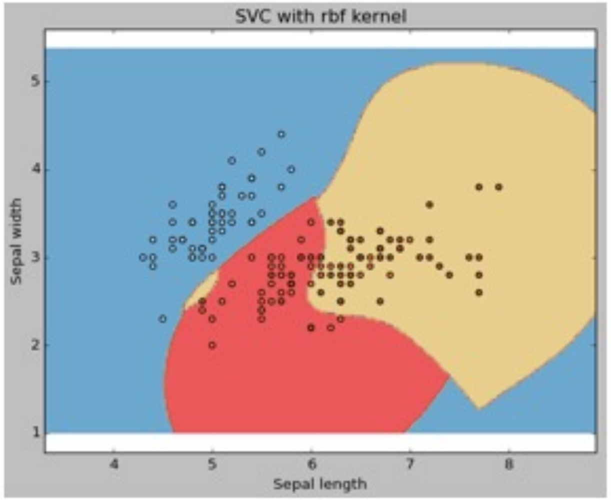
c =1



C =100



c =1000



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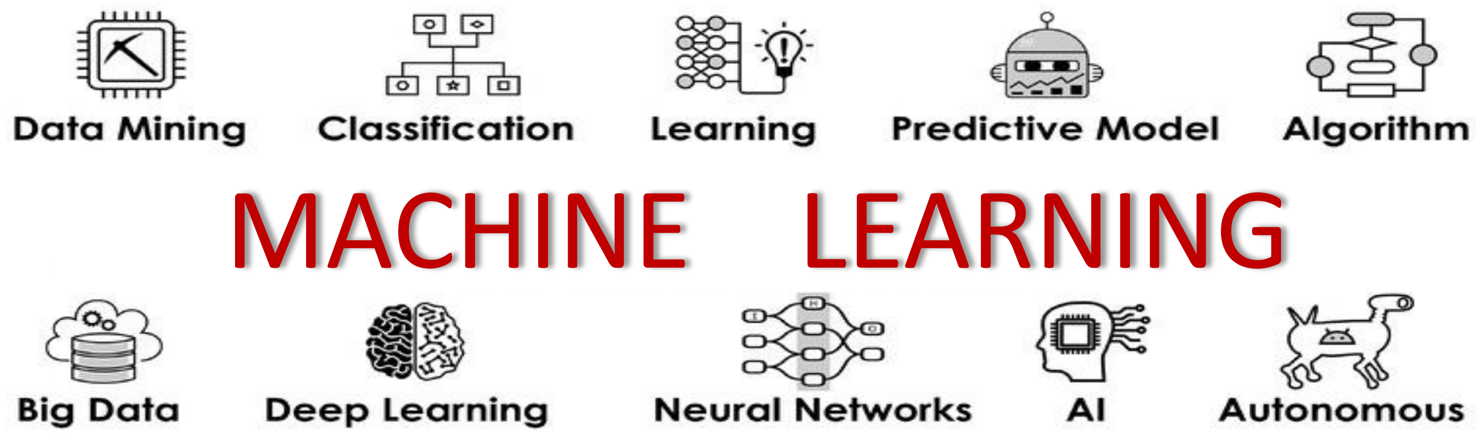

Naïve Bay / Neural Network

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Naive Bayes

- Naive Bayes is a simple but surprisingly powerful algorithm for predictive modelling.
- Selecting the best hypothesis (h) given data (d).
- The easiest ways of selecting the most probable hypothesis given the data is using Bayes' Theorem.

$$P\left(\frac{H}{D}\right) = \frac{P(D|H) * P(H)}{P(D)}$$

P(H): คือค่าความน่าจะเป็นที่สมมุติฐาน H จะเป็นจริง

P(D): คือค่าความน่าจะเป็นของข้อมูล D

P(D|H): คือค่าความน่าจะเป็นของข้อมูล D ที่จะทำให้สมมุติฐาน H เป็นจริง

P(H|D): คือค่าความน่าจะเป็นของสมมุติฐาน ที่ทำให้ข้อมูล D เป็น จริง

Naive Bayes Classifier

- Prediction of membership probabilities is made for every class.
- Calculate the probability of data points that associate to a particular class.
- The class having maximum probability is appraised as the most suitable class.
- This is also referred as Maximum A Posteriori (MAP).
  - This can be written as:

★ $$\text{MAP}(h) = \max(P(h|d))$$

Or $$\text{MAP}(h) = \max((P(d|h) * P(h)) / P(d))$$

Or $$\text{MAP}(h) = \max(P(d|h) * P(h))$$

P(d) ใช้สำหรับการ Normalization โดยเราสามารถตัดทิ้งได้ ถ้าเราให้ความสนใจที่ สมมุติฐาน H อย่างเดียว

Representation Used By Naive Bayes Models

- A list of probabilities are stored to file for a learned Naive Bayes model:
  - Class Probabilities: The probabilities of each class in the training dataset.
  - Conditional Probabilities: The conditional probabilities of each input value given each class value.

- **Calculating Class Probabilities**, For example in a binary classification, the probability of class 1 can find by

$$P_{class(1)} = \frac{Count_{class(1)}}{Count_{calss(0)} + Count_{class(1)}}$$

Representation Used By Naive Bayes Models

- **Calculating Conditional Probabilities**
  - If a "*weather*" attribute had the values "*sunny*" and "*rainy*" and the class attribute had the class values "*go-out*" and "*stay-home*",
  - then the conditional probabilities of each weather value for each class value could be calculated as:

$$P_{(weather=sunny|class=go-out)} = \frac{Count_{weather=sunny\ and\ class=go-out}}{Count_{class=go-out}}$$

$$P_{(weather=sunny|class=stay-home)} = \frac{Count_{weather=sunny\ and\ class=stay-home}}{Count_{class=stay-home}}$$

Make Predictions With a Naive Bayes Model

- If we had a new instance with the *weather of sunny*, we could make predictions for new data using Bayes theorem.

MAP(h) = max(P(d|h) * P(h))

$$Class_{(go\_out)} = \frac{P(weather = sunny|class = go\_out)}{P(class = go - out)}$$

$$Class_{(stay\_home)} = \frac{P(weather = sunny|class = stay\_home)}{P(class = stay\_home)}$$

$$P(go\_out|weather = sunny) = \frac{go\_out}{(go\_out + stay\_home)}$$

$$P(stay\_home|weather = sunny) = \frac{stay\_home}{(go\_out + stay\_home)}$$

We can choose the class that has the largest calculated value.

The example

Type	Long	Not Long	Sweet	Not Sweet	Yellow	Not Yellow	**Total**
Banana	400	100	350	150	450	50	500
Orange	0	300	150	150	300	0	300
Other	100	100	150	50	50	150	200
Total	500	500	650	350	800	200	1000

- Out of 1000 records in training data, you have 500 Bananas, 300 Oranges and 200 Others.
  - P(Y=Banana) = 500 / 1000 = 0.50
  - P(Y=Orange) = 300 / 1000 = 0.30
  - P(Y=Other) = 200 / 1000 = 0.20
- Compute the probability of evidence
  - P(x1=Long) = 500 / 1000 = 0.50
  - P(x2=Sweet) = 650 / 1000 = 0.65
  - P(x3=Yellow) = 800 / 1000 = 0.80

Type	Long	Not Long	Sweet	Not Sweet	Yellow	Not Yellow	**Total**
Banana	400	100	350	150	450	50	500
Orange	0	300	150	150	300	0	300
Other	100	100	150	50	50	150	200
Total	500	500	650	350	800	200	1000

- Compute the probability of likelihood of evidences
  - P(x1=Long | Y=Banana) = 400 / 500 = 0.80
  - P(x2=Sweet | Y=Banana) = 350 / 500 = 0.70
  - P(x3=Yellow | Y=Banana) = 450 / 500 = 0.90

So, the overall probability of Likelihood of evidence for Banana = 0.8 * 0.7 * 0.9 = 0.504

- If fruit is ‘long’, ‘sweet’, and ‘yellow’, what fruit is it?

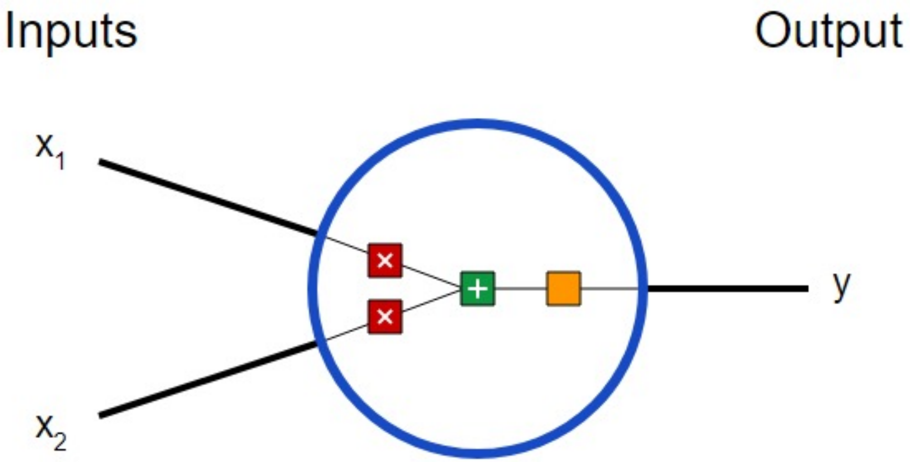
$$P(Banana|Long, Sweet\ and\ Yellow) = \frac{P(Long|Banana) * P(Sweet|Banana) * P(Yellow|Banana) * P(Banana)}{P(Long) * P(Sweet) * P(Yellow)}$$

$$= \frac{0.8*0.7*0.9*0.5}{P(Evidence)} = \frac{0.252}{P(Evidence)}$$

$$P(Orenge|Long, Sweet\ and\ Yellow) = 0\ , because\ P(Long|Orange) = 0$$

$$P(Other\ Fruit|Long, Sweet\ and\ Yellow) = \frac{0.01875}{P(Evidence)}$$

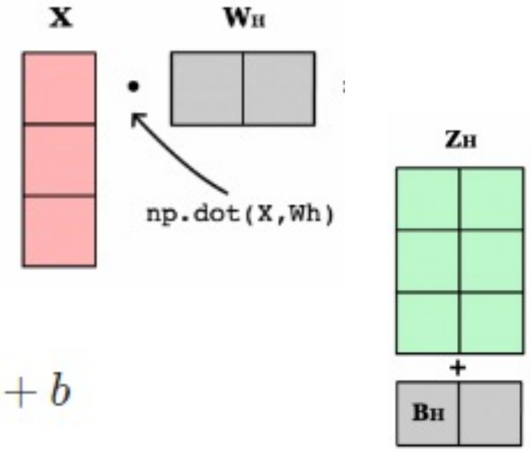
Basic Neural Networks



- Neural Network หรือ Artificial Neural Network คือ โครงข่ายประสาทเทียม เป็นแนวคิดที่ออกแบบระบบโครงข่ายคอมพิวเตอร์ ให้เลียนแบบการทำงานของสมองมนุษย์
- ถ้า เรามี 2 input, neural network ก็จะมีลักษณะดังภาพ
  - แต่ละ input จะถูกคูณกับ weight

$$x_1 \rightarrow x_1 * w_1$$

$$x_2 \rightarrow x_2 * w_2$$



  - จากนั้นจะถูกบวกกับ bias

$$(x_1 * w_1) + (x_2 * w_2) + b$$

  - จากนั้นหาผลรวมและส่งไปยัง Activation Function

$$y = f(x_1 * w_1 + x_2 * w_2 + b)$$

Activation Function เป็นฟังก์ชันที่รับผลการประมวลผลจากทุก input ภานใน 1 neural แล้วคำนวณว่าจะส่งเป็น Output เท่าไหร่ Activation Function นิยม ได้แก่ ReLU และ Sigmoid

Basic Neural Networks

- Example:
  - กำหนดให้ input x = [2,3] Network จะทำการ คำนวณค่าอย่างไร ถ้า weight เท่ากับ w = [0,1] bias = 0

$$\begin{aligned} h_1 = h_2 &= f(w \cdot x + b) \\ &= f((0 * 2) + (1 * 3) + 0) \\ &= f(3) \\ &= 0.9526 \end{aligned}$$

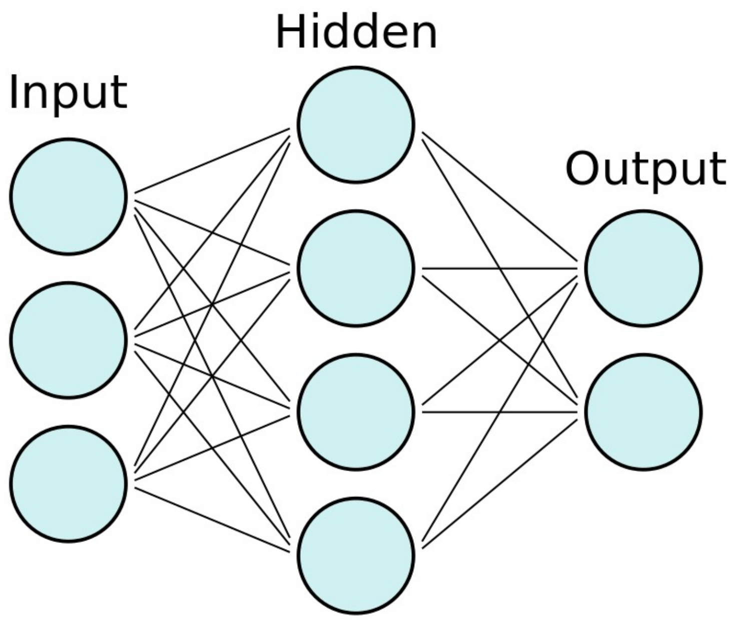
$$\begin{aligned} o_1 &= f(w \cdot [h_1, h_2] + b) \\ &= f((0 * h_1) + (1 * h_2) + 0) \\ &= f(0.9526) \\ &= \boxed{0.7216} \end{aligned}$$

Sentiment Analysis

- **Basic Neural Networks**

$$o_j = f\left(\sum_i w_{i,j} a_i + b_i\right)$$

Neural network formula




```python
#For Neural Network
from keras.models import Sequential
from keras import layers
```

```python
model = Sequential()
model.add(layers.Dense(10, input_dim=input_dim, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='Adam', metrics=['accuracy'])
model.summary()
```

Sentiment Analysis

- **Basic Neural Networks**
  - **Training model**

```
history = model.fit(X_train, y_train,
                    epochs=10,
                    verbose=1,
                    validation_data=(X_test, y_test),
                    batch_size=10)
```

```
Train on 800 samples, validate on 200 samples
Epoch 1/10
800/800 [==============================] - 1s 2ms/step - loss: 0.6863 - accuracy: 0.5725 - val_loss: 0.6716 - val_accuracy:
0.6850
Epoch 2/10
800/800 [==============================] - 0s 606us/step - loss: 0.6187 - accuracy: 0.8200 - val_loss: 0.6259 - val_accurac
y: 0.7550
Epoch 3/10
800/800 [==============================] - 0s 601us/step - loss: 0.5141 - accuracy: 0.8963 - val_loss: 0.5668 - val_accurac
y: 0.7750
Epoch 4/10
800/800 [==============================] - 0s 610us/step - loss: 0.4020 - accuracy: 0.9337 - val_loss: 0.5195 - val_accurac
y: 0.8000
Epoch 5/10
800/800 [==============================] - 0s 610us/step - loss: 0.3091 - accuracy: 0.9563 - val_loss: 0.4875 - val_accurac
y: 0.8050
```

```python
#plot graph
import matplotlib.pyplot as plt
plt.style.use('ggplot')

def plot_history(history):
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    x = range(1, len(acc) + 1)

    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(x, acc, 'b', label='Training acc')
    plt.plot(x, val_acc, 'r', label='Validation acc')
    plt.title('Training and validation accuracy')
    plt.legend()
    plt.subplot(1, 2, 2)
    plt.plot(x, loss, 'b', label='Training loss')
    plt.plot(x, val_loss, 'r', label='Validation loss')
    plt.title('Training and validation loss')
    plt.legend()

plot_history(history)
```

Save, Load and Use model

Save

Load

Use

```
from keras import models

model.save('NN_Sentiment_model')

trained_model = models.load_model("NN_Sentiment_model")

predicted_class = trained_model.predict(X_test[10])
actual_class = y_test[10]
print(predicted_class, actual_class)
```

Neural Networks with Embedded Layer

- Create Model

```
from keras.models import Sequential
from keras import layers
```

```
embedding_dim = 50
model = Sequential()
model.add(layers.Embedding(input_dim=vocab_size,
                           input_length=maxlen,
                           output_dim=embedding_dim
                           ))
model.add(layers.Flatten())
model.add(layers.Dense(10, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
model.summary()
```

Neural Networks with Embedded Layer

- Train Model

```
history = model.fit(X_train, y_train,
                    epochs=20,
                    verbose=1,
                    validation_data=(X_test, y_test),
                    batch_size=10)
```

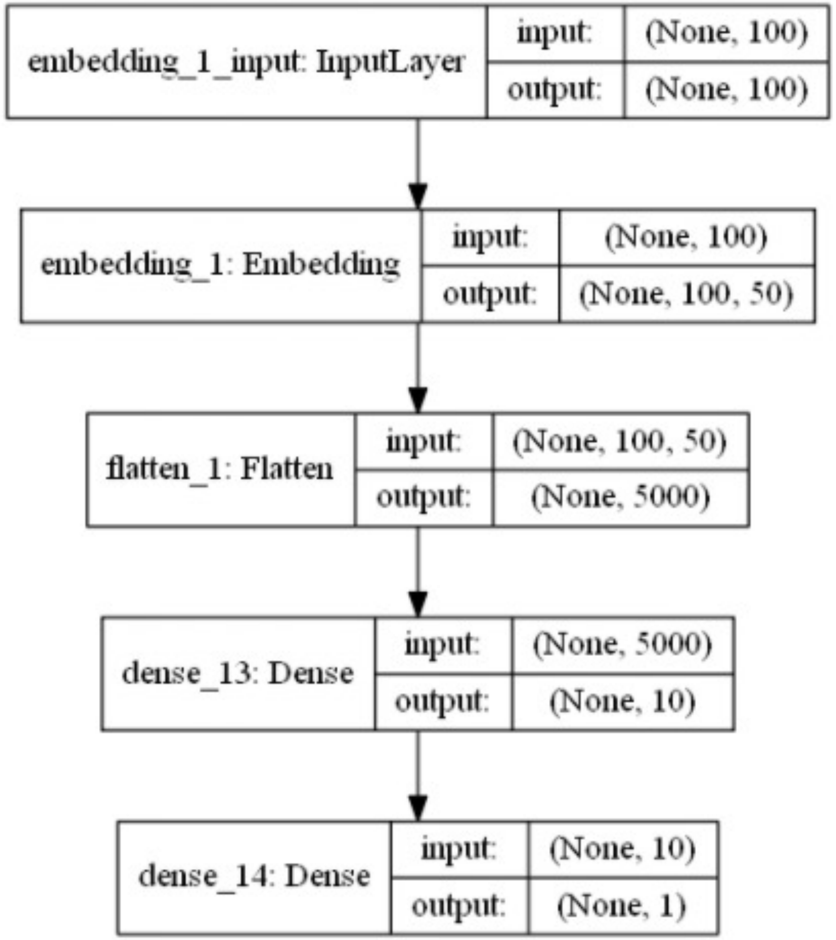
- Print Accuracy and Plot Graph

```
loss, accuracy = model.evaluate(X_train, y_train, verbose=False)
print("Training Accuracy: {:.4f}".format(accuracy))
loss, accuracy = model.evaluate(X_test, y_test, verbose=False)
print("Testing Accuracy:  {:.4f}".format(accuracy))
```

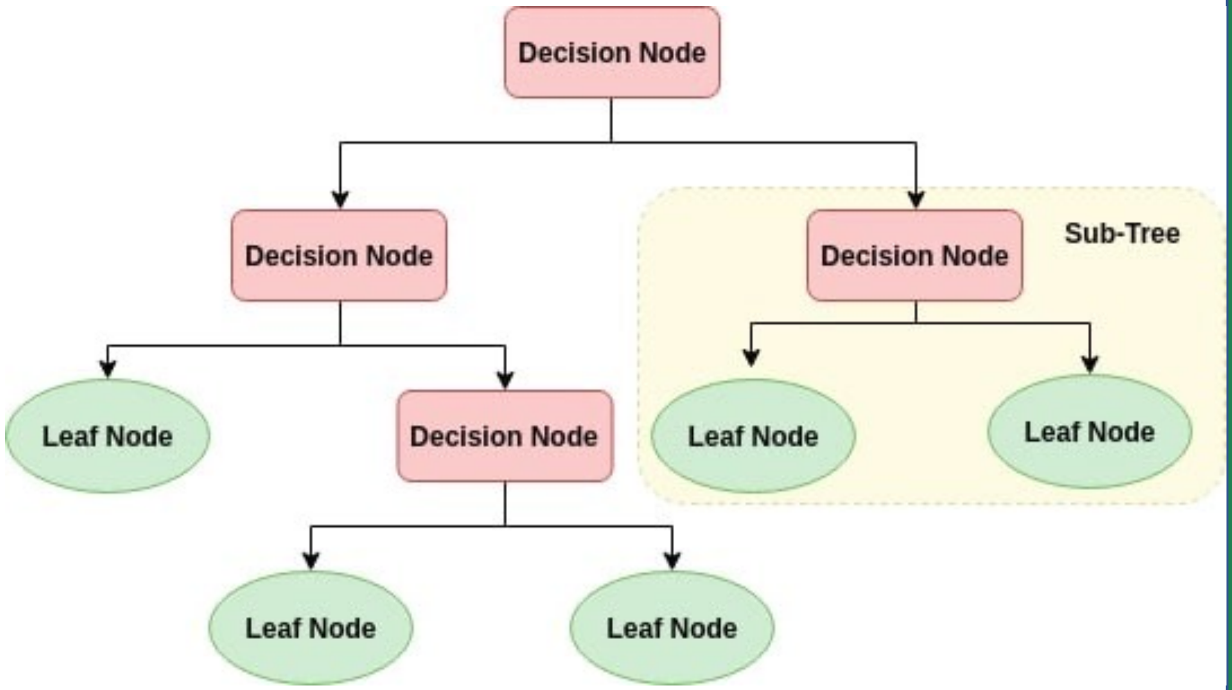
```
plot_history(history)
```

Model Structure

```
from keras.utils import plot_model
plot_model(model, show_shapes=True, to_file='model_structure.png')
```



Decision Tree Algorithm



- A decision tree is a flowchart-like tree structure
  - An internal node represents feature(or attribute)
  - The branch represents a decision rule
  - Each leaf node represents the outcome.
- It learns to partition on the basis of the attribute value.

Decision Tree Algorithm

- Decision Tree is a white box type of ML algorithm. It shares internal decision-making logic.
- Its training time is faster compared to the neural network algorithm.
- The decision tree is a distribution-free or non-parametric method, which does not depend upon probability distribution assumptions.
- There are two types of Decision Tree:
  - Regression Tree
  - Classification Tree