Pattern Classification

03. Pattern Classification Methods

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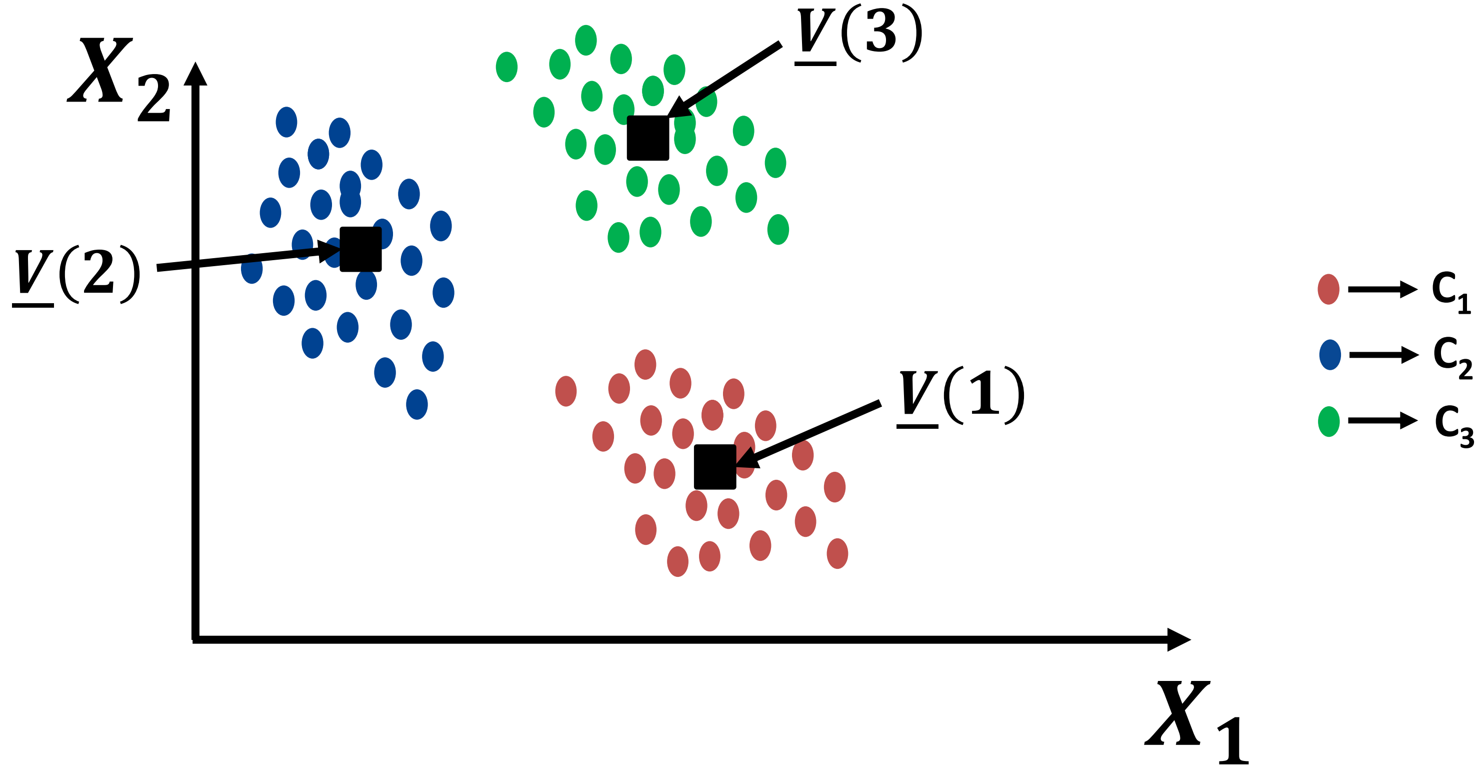
Fall 2021

Acknowledgment

- These slides have been created relying on lecture notes of Prof. Dr. Amir Atiya

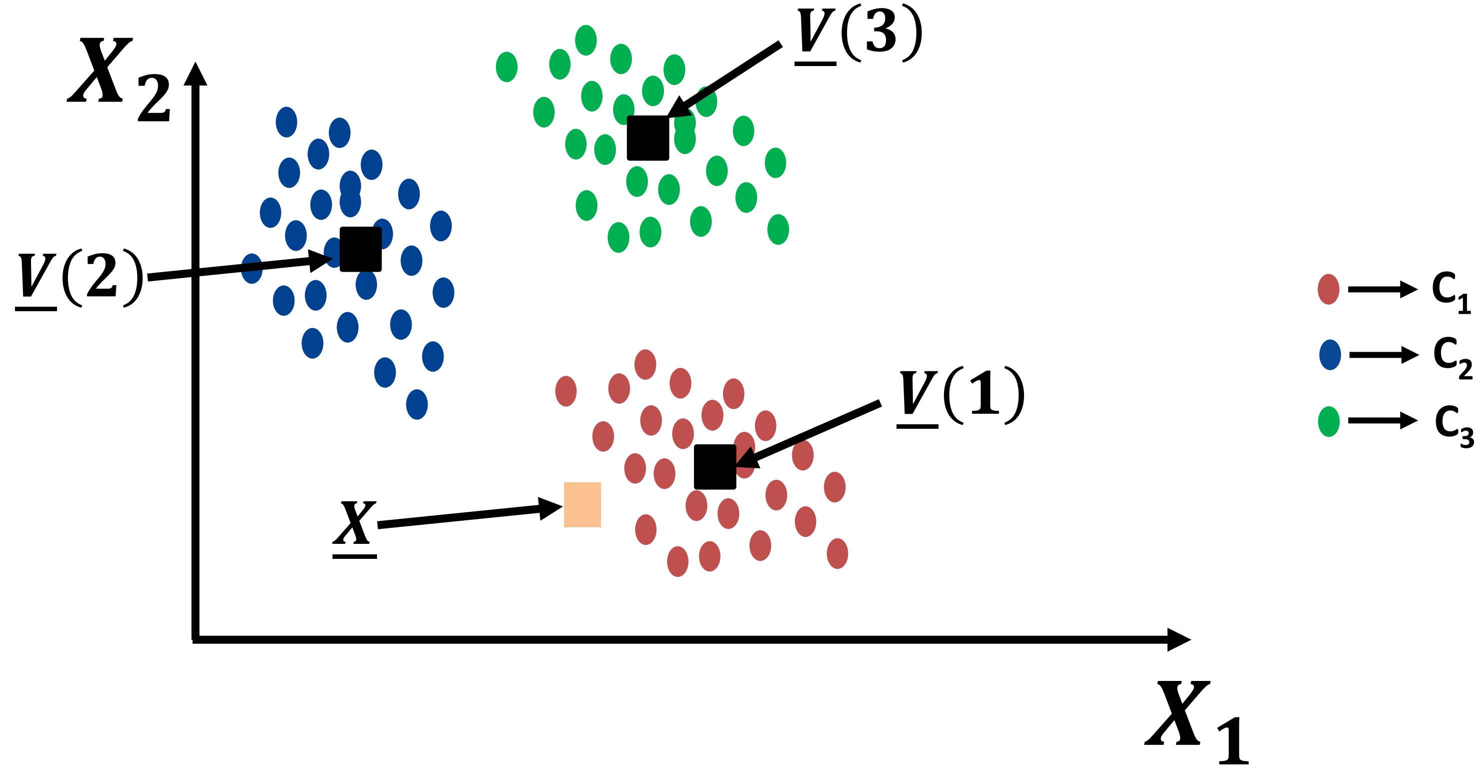
Minimum Distance Classifier

- Choose a center or a representative pattern from each class → $\underline{V}(k)$, where k is the class index



Minimum Distance Classifier

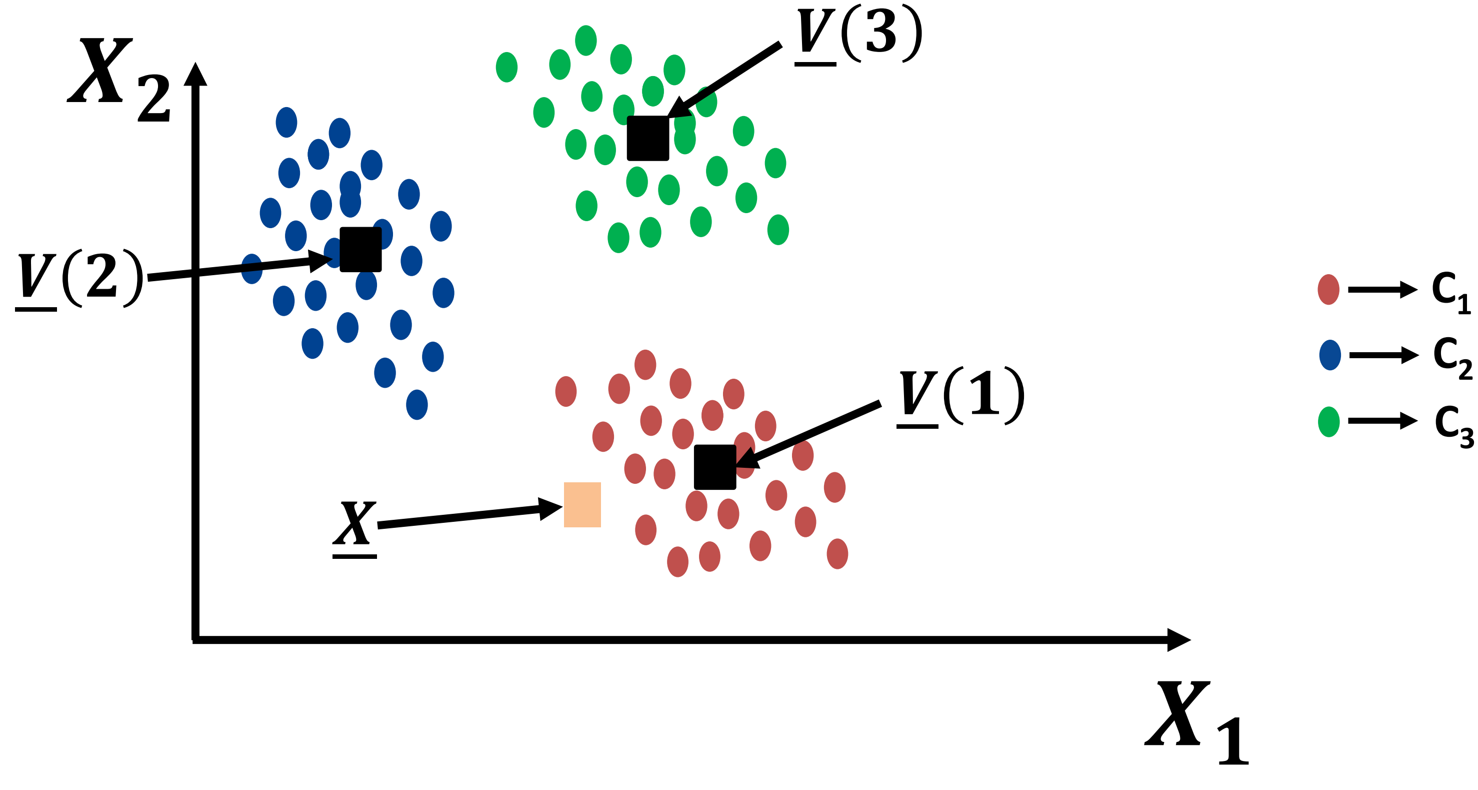
- Given a pattern $\underline{X}$ that we would like to classify



Minimum Distance Classifier

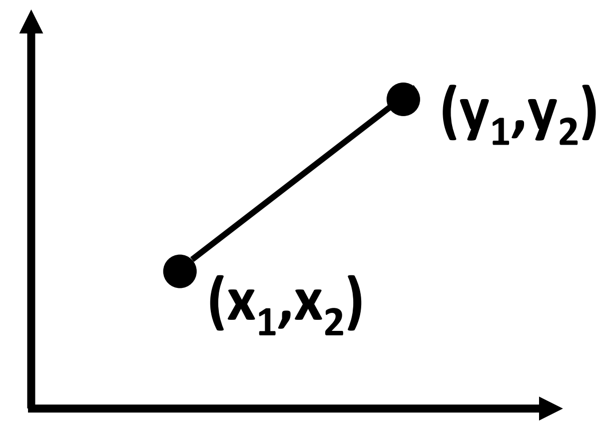
- Compute the distance from $\underline{X}$ to each center $\underline{V}(k)$:

$$\boldsymbol{d(k)} = \sum_{i=1}^{N}[\boldsymbol{V_i(k)} - \boldsymbol{X_i}]^2 \equiv \left\|\underline{\boldsymbol{V}}(\boldsymbol{k}) - \underline{\boldsymbol{X}}\right\|^2$$



Recap: Euclidean Distance

- 2D:



hence,
distance =
sqrt((x2-x1)pow2 -
(y2-y1)pow2))

$$d^2 = (y_2 - x_2)^2 + (y_1 - x_1)^2$$

- N-dimensions:

$$d^2(\underline{X}, \underline{Y}) = \sum_{i=1}^{N} (Y_i - X_i)^2$$

Minimum Distance Classifier

- Find ϰ corresponding to the minimum distance:

$$\boldsymbol{\varkappa} = \mathop{\mathbf{argmin}}_{1 \le k \le K} \boldsymbol{d(k)}$$

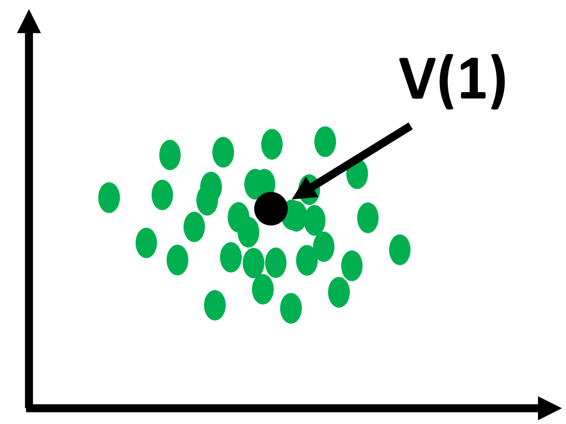
- Then our classification of is $\underline{X}$ class $C_{\varkappa}$

- $\underline{X}$ is classified as belonging to the class corresponding to the nearest class center

Class Center Estimation

- Let $\underline{X}(m) \in C_1$,

$$\underline{V}(1) = \frac{1}{M_1} \sum_{m=1}^{M_1} \underline{X}(m)$$



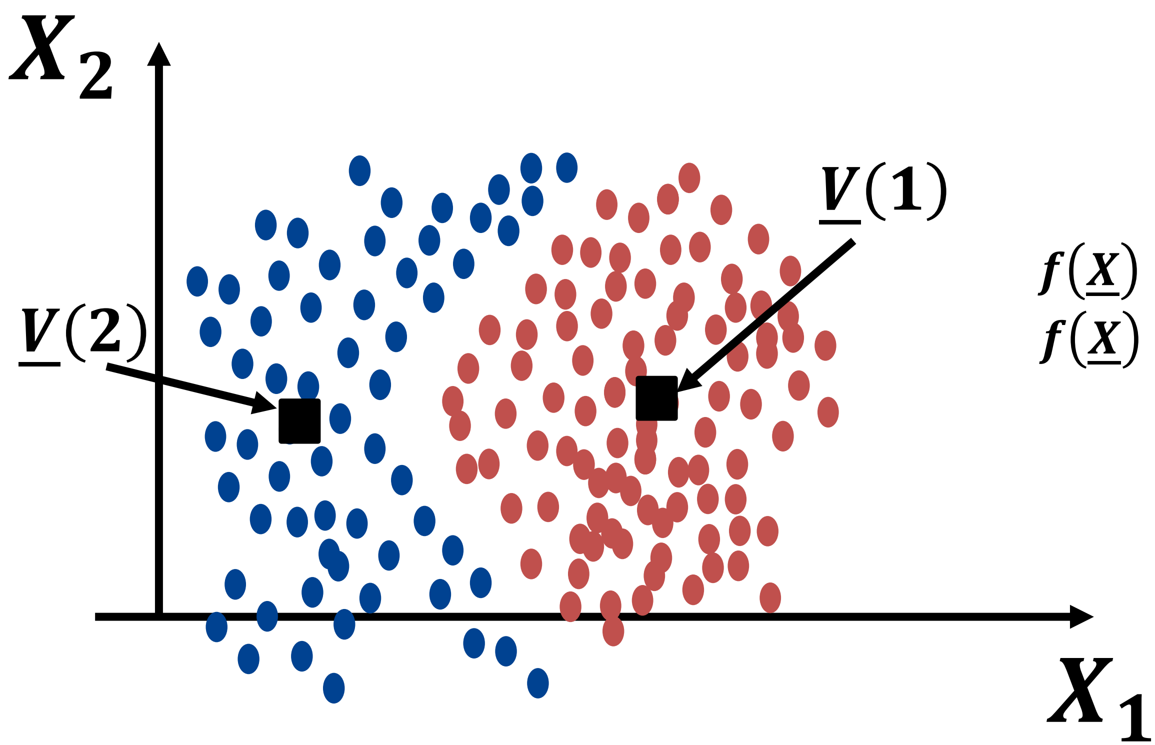
where, M1 is the number of training patterns from class C1

- This corresponds to component-wise averaging

$$V_i(1) = \frac{1}{M_1} \sum_{m=1}^{M_1} X_i(m)$$

Minimum Distance Classifier

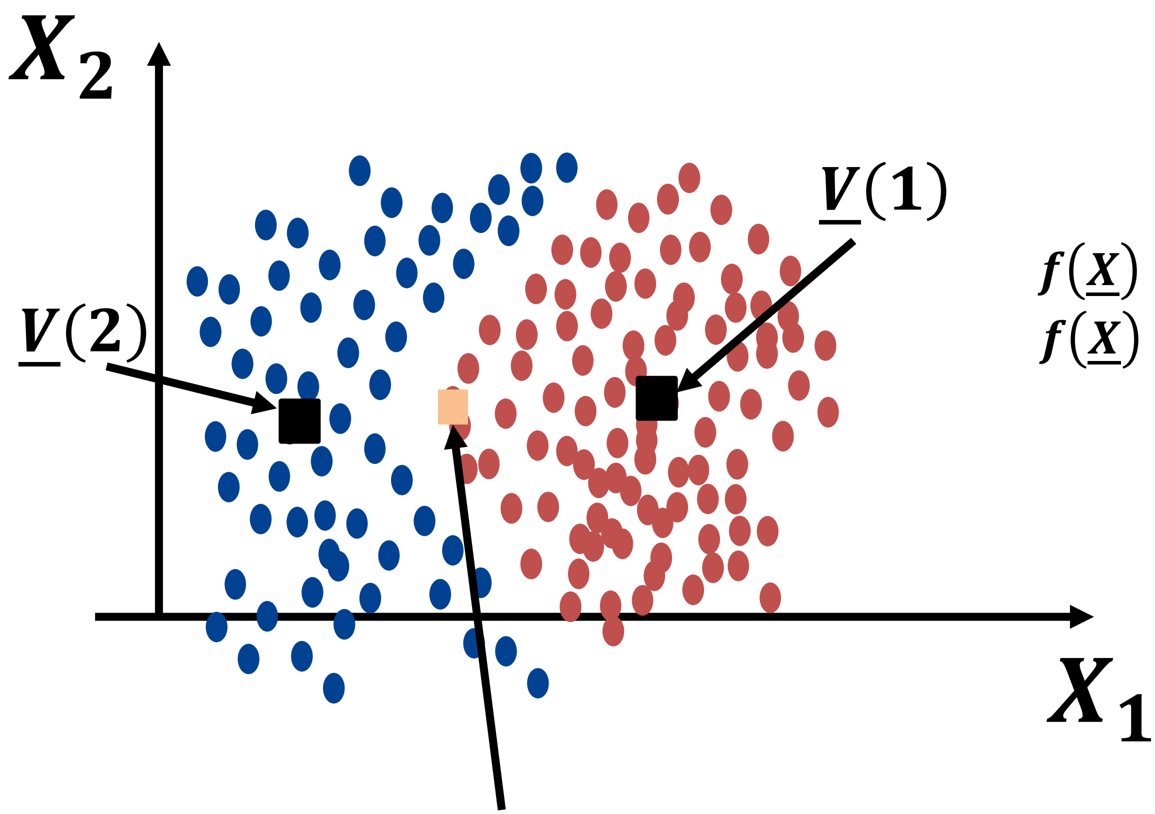
- Too simple to solve difficult problems



$f(\underline{X}) > 0 \longrightarrow c_1$
$f(\underline{X}) < 0 \longrightarrow c_2$

Minimum Distance Classifier

- Too simple to solve difficult problems

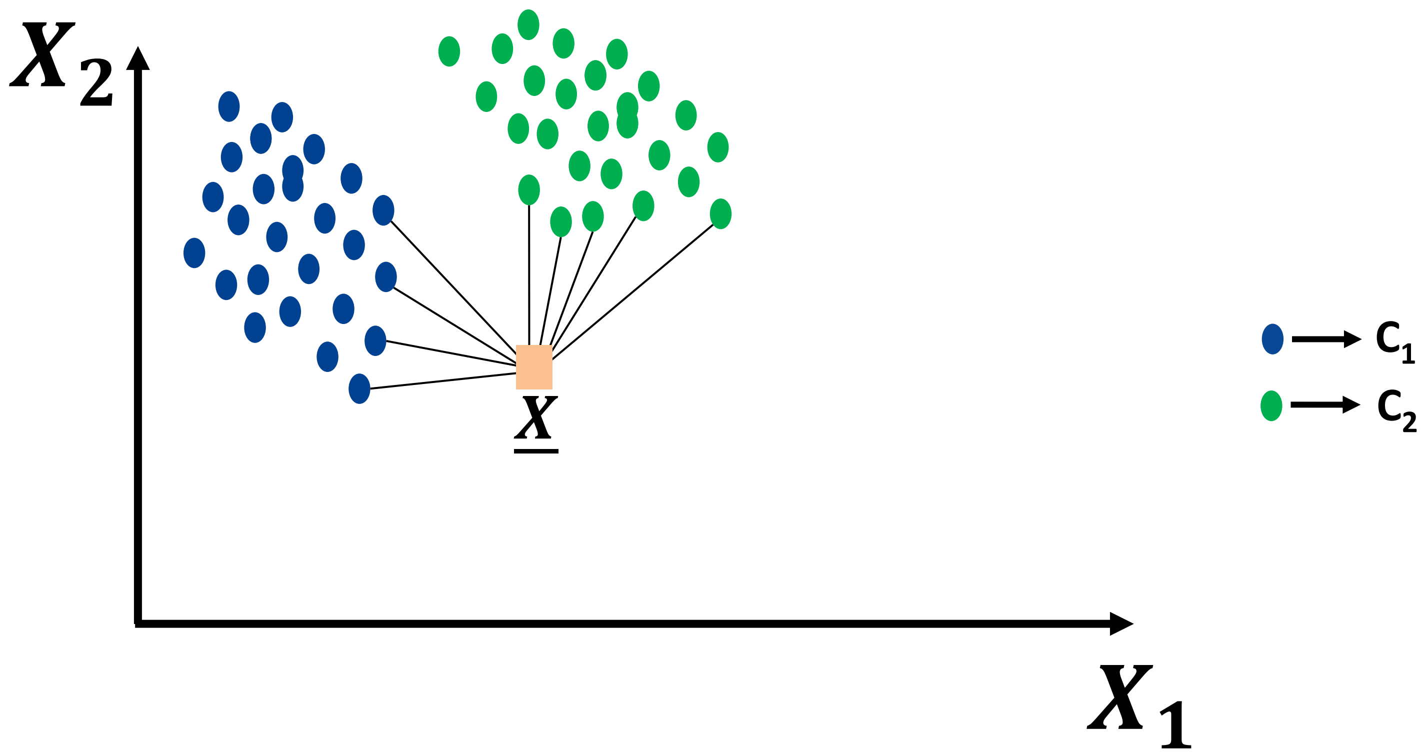


$f(\underline{X}) > 0 \longrightarrow C_1$
$f(\underline{X}) < 0 \longrightarrow C_2$

$\underline{X}$ will be classified as C_2

Nearest Neighbor Classifier

- The class of the nearest pattern to $\underline{X}$ determines its classification



Nearest Neighbor Classifier

- Compute the distance between pattern $\underline{X}$ and each pattern $\underline{X}(m)$ in the training set

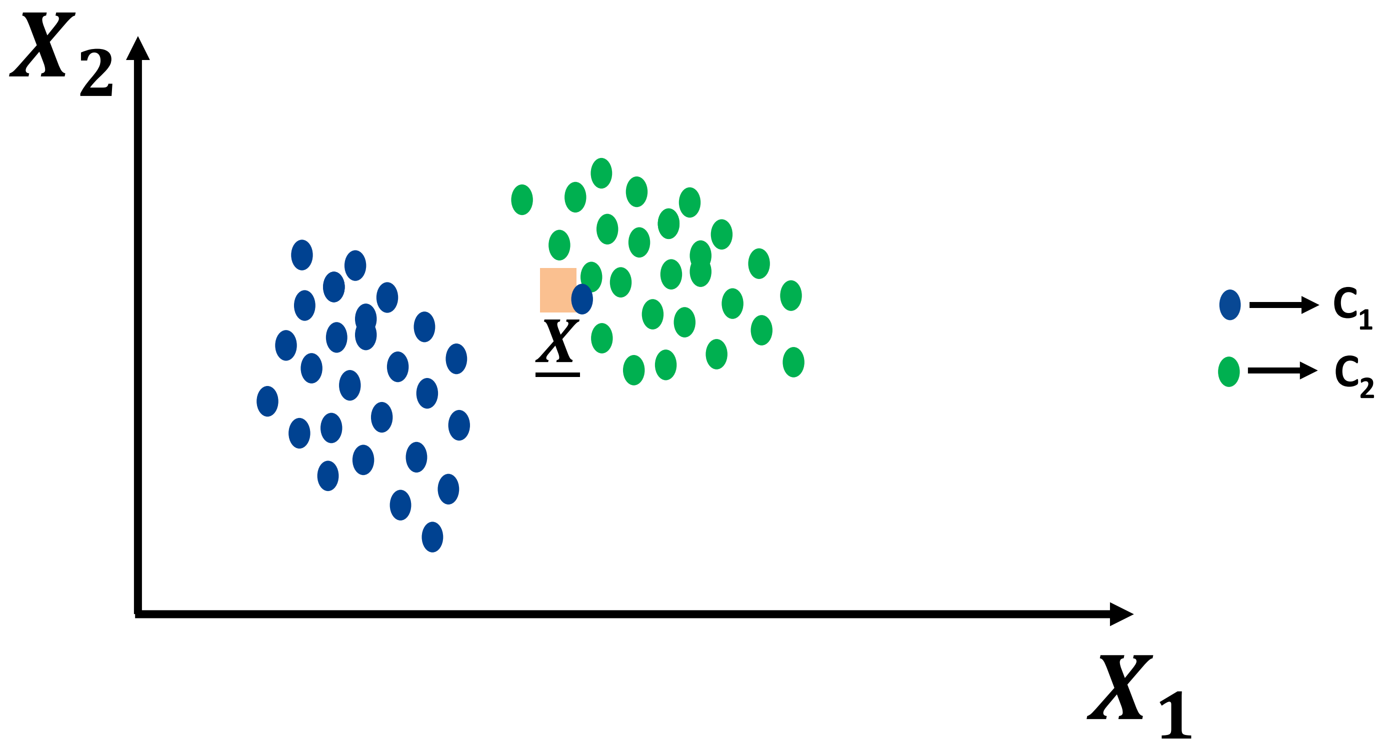
$$\boldsymbol{d}(\boldsymbol{m}) = \left\|\underline{\boldsymbol{X}} - \underline{\boldsymbol{X}}(\boldsymbol{m})\right\|^{2}$$

- The class of the pattern m that corresponds to the minimum distance is chosen as the classification of $\underline{X}$

Nearest Neighbor Classifier

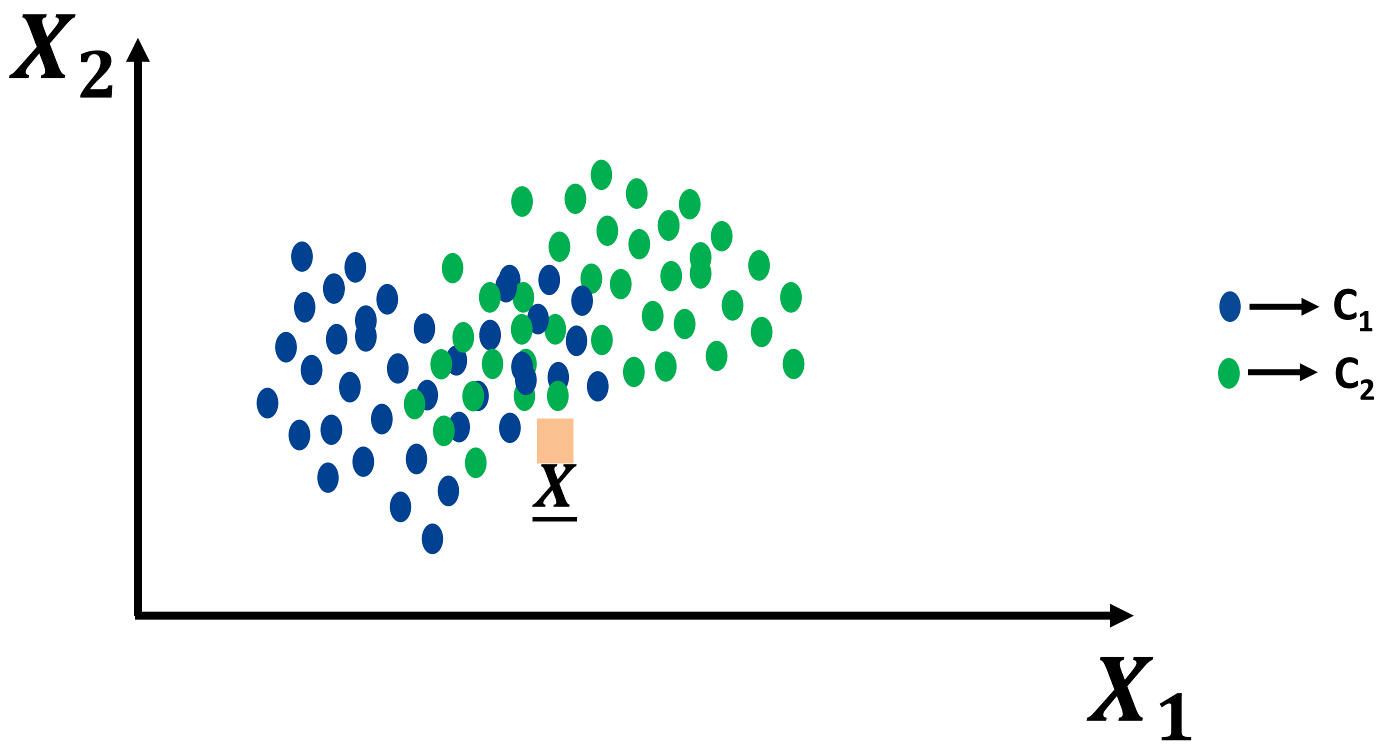
- The advantage of the nearest neighbor classifier is its simplicity

- However, a rouge pattern can affect the classification negatively



Nearest Neighbor Classifier

- Also, for patterns with large overlaps between the classes, the overlapping patterns can negatively affect performance



K-Nearest Neighbor Classifier

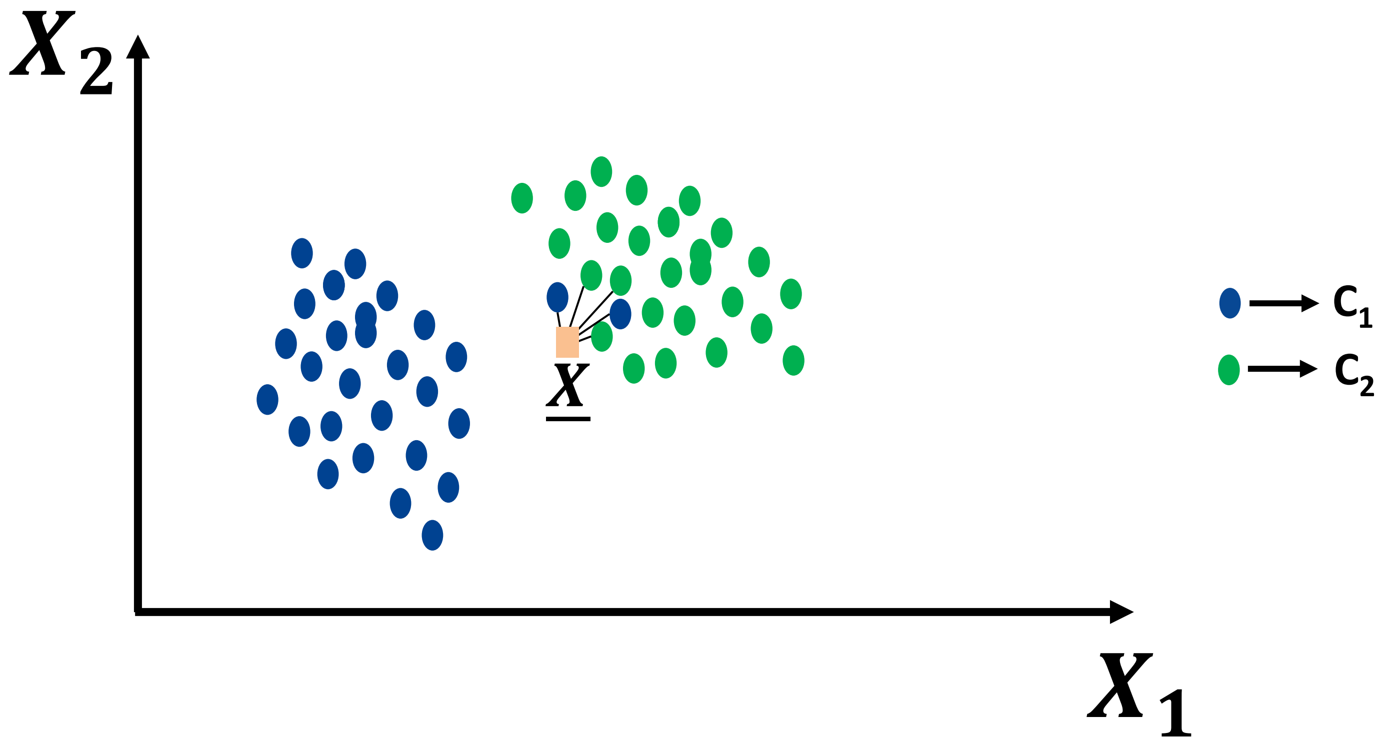
- To alleviate the problems of the NN classifier there is the k-nearest neighbor classifier

- Take the k-nearest points to point $\underline{X}$

- Choose the classification of $\underline{X}$ as the class most often represented in these k points

K-Nearest Neighbor Classifier

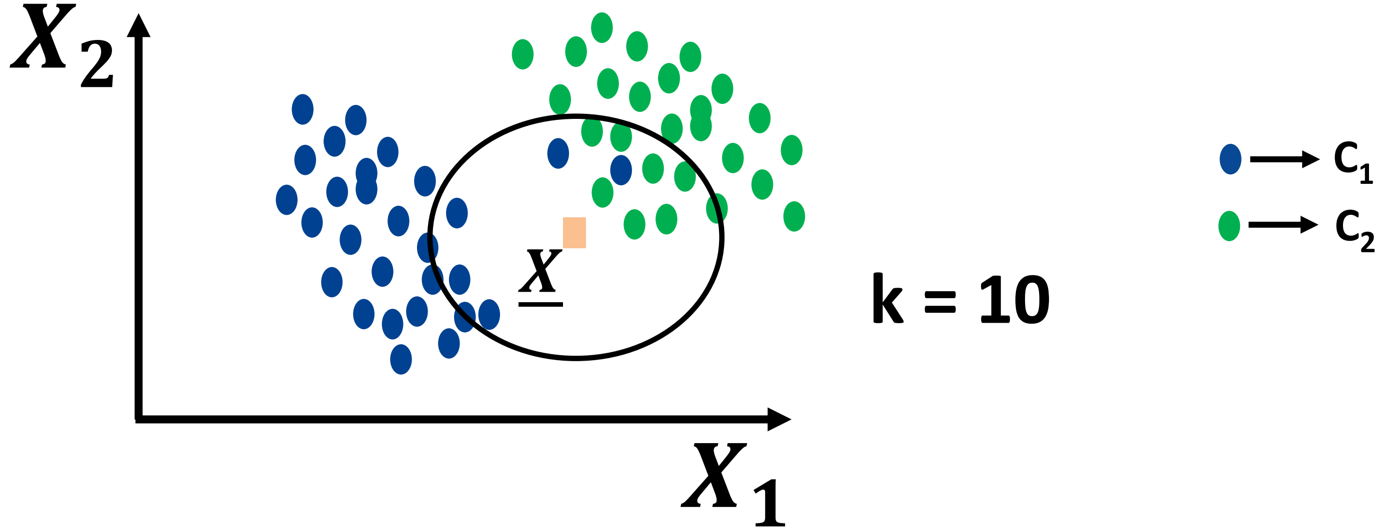
- Take k = 5



- One can see that C_2 is the majority → classify $\underline{X}$ as C_2
- The KNN rule is less dependent on strange patterns compared to the nearest neighbor classification rule

K-Nearest Neighbor Classifier

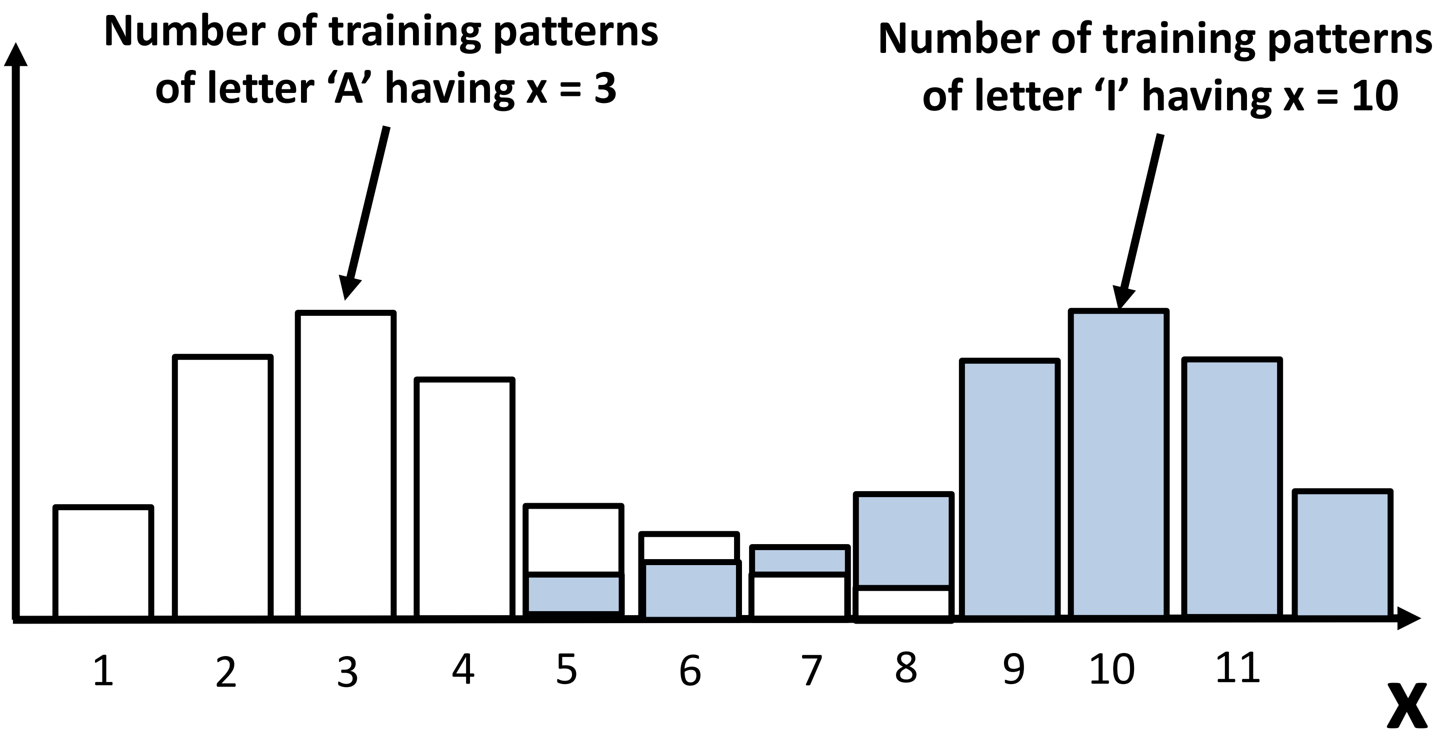
- The k-nearest neighbors could be a bit far away from $\underline{X}$



- Leading to using information that might not be relevant to the considered point $\underline{X}$

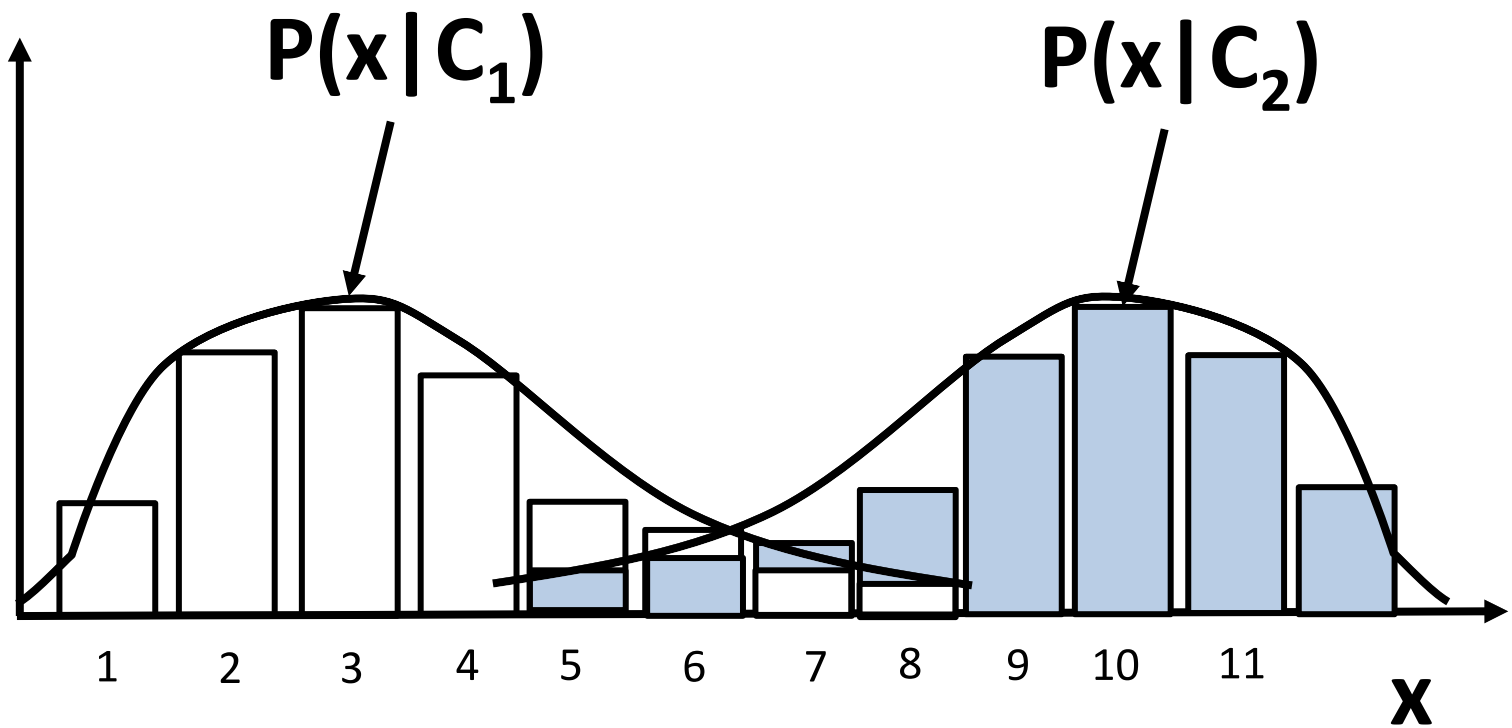
Bayes Classification Rule

- Recall: histogram for feature x from class C_1 (e.g., letter ‘A’)



Bayes Classification Rule

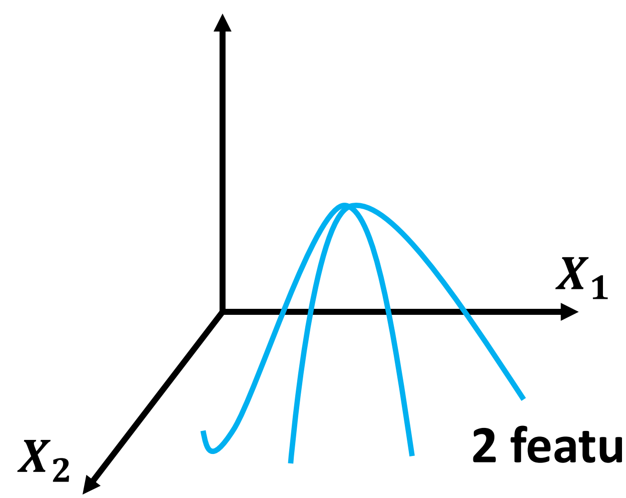
P(x|class C_i) ≡ class conditional probability function
≡ probability density of feature x, given that x comes from class C_i



Bayes Classification Rule

- If $\underline{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix}$ is a feature vector then:

$$\boldsymbol{P}(\underline{\boldsymbol{X}} | \boldsymbol{C_i}) = \boldsymbol{P}(\boldsymbol{X_1}, \boldsymbol{X_2}, \cdots, \boldsymbol{X_N} | \boldsymbol{C_i})$$



2 features!

Bayes Classification Rule

- Given a pattern $\underline{X}$ (with unknown class) that we wish to classify:
  - Compute $P(C_1|\underline{X})$, $P(C_2|\underline{X})$, … , $P(C_K|\underline{X})$
  - Find the k giving maximum $P(C_k|\underline{X})$
- This is our classification according to the Bayes classification rule
- We classify the data point (pattern) as belonging to the ***most likely*** class

Bayes Classification Rule

- To compute $P(C_i|\underline{X})$, we use Bayes rule:

$$P(C_i|\underline{X}) = \frac{P(C_i, \underline{X})}{P(\underline{X})}$$

$$= \frac{P(\underline{X}|C_i)\,P(C_i)}{P(\underline{X})}$$

Bayes Rule:
P(A,B) = P(A|B)P(B) = P(B|A)P(A)

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)\,P(A)}{P(B)}$$

Bayes Classification Rule

- To compute $P\left(C_i \middle| \underline{X}\right)$, we use ***Bayes rule***:

$$P\left(C_i \middle| \underline{X}\right) = \frac{P\left(\underline{X} | C_i\right) P(C_i)}{P(\underline{X})}$$

- $P\left(\underline{X} | C_i\right) \equiv$ Class-conditional density (***defined before***)

- $P(C_i) \equiv$ Probability of class C_i before or without observing the features $\underline{X}$
  $\equiv$ a priori probability of class C_i

Bayes Classification Rule

- The a priori probabilities represent the frequencies of the classes irrespective of the observed features

- For example in OCR, the a priori probabilities are taken as the frequency or fraction of occurrence of the different letters in a typical text
  - For the letters E & A → $P(C_i)$ will be higher
  - For letters Q & X → $P(C_i)$ will be low because they are infrequent

Bayes Classification Rule

- Find C_k giving max $P(C_k|\underline{X})$

$$P(C_k|\underline{X}) = \frac{P(\underline{X}|C_k)\, P(C_k)}{P(\underline{X})}$$

  - $P(C_k|\underline{X}) \equiv$ posterior prob.
  - $P(C_k) \equiv$ a priori prob.
  - $P(\underline{X}|C_k) \equiv$ class-conditional densities

- $P(\underline{X}) = \sum_{i=1}^{K} P(\underline{X}, C_i) = \sum_{i=1}^{K} P(\underline{X}|C_i) P(C_i)$

Recap: Marginalization

- Discrete case:

da el kanon bta3 el shghra.

$$P(A) = \sum_{i=1}^{N} P(A, B = B_i)$$

- Continuous case:

$$P(x) = \int_{-\infty}^{\infty} P(x, y)\, dy$$

Law of total probability

- So:

$$P(\underline{X}) = \underbrace{\sum_{i=1}^{K} P(\underline{X}, C_i)}_{\text{Marginalization}} = \underbrace{\sum_{i=1}^{K} P(\underline{X} \mid C_i) P(C_i)}_{\text{Bayes rule}}$$

Bayes Classification Rule

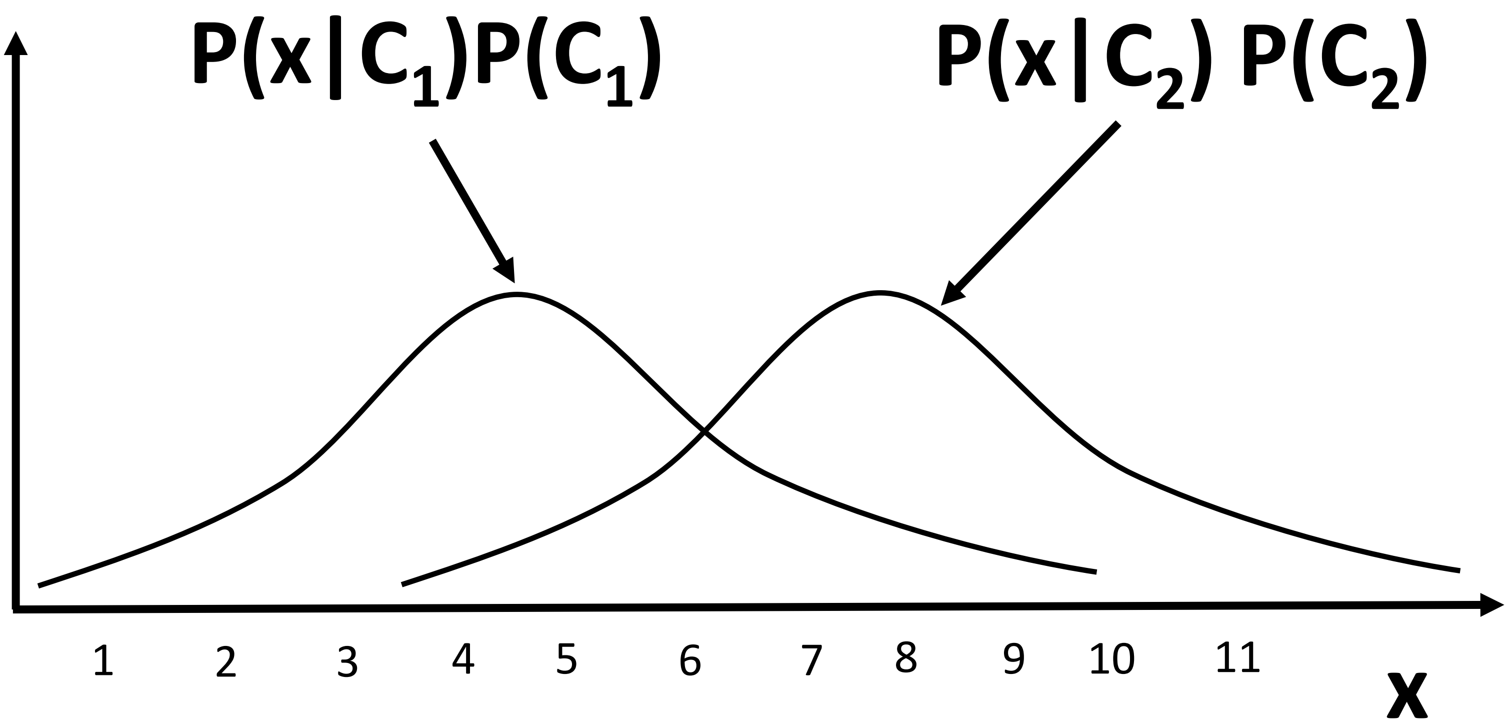
$$P\left(C_k \middle| \underline{X}\right) = \frac{P\left(\underline{X} | C_k\right) P(C_k)}{\sum_{i=1}^{K} P\left(\underline{X} \middle| C_i\right) P(C_i)}$$

- In reality, we do not need to compute $P\left(\underline{X}\right)$ because it is a common factor for all the terms in the expression for $P\left(C_k \middle| \underline{X}\right)$
- Hence, it will not affect which terms will end up being maximum

Bayes Classification Rule

- Classify $\underline{X}$ to the class corresponding to max $P\left(\underline{X}|C_k\right)P(C_k)$

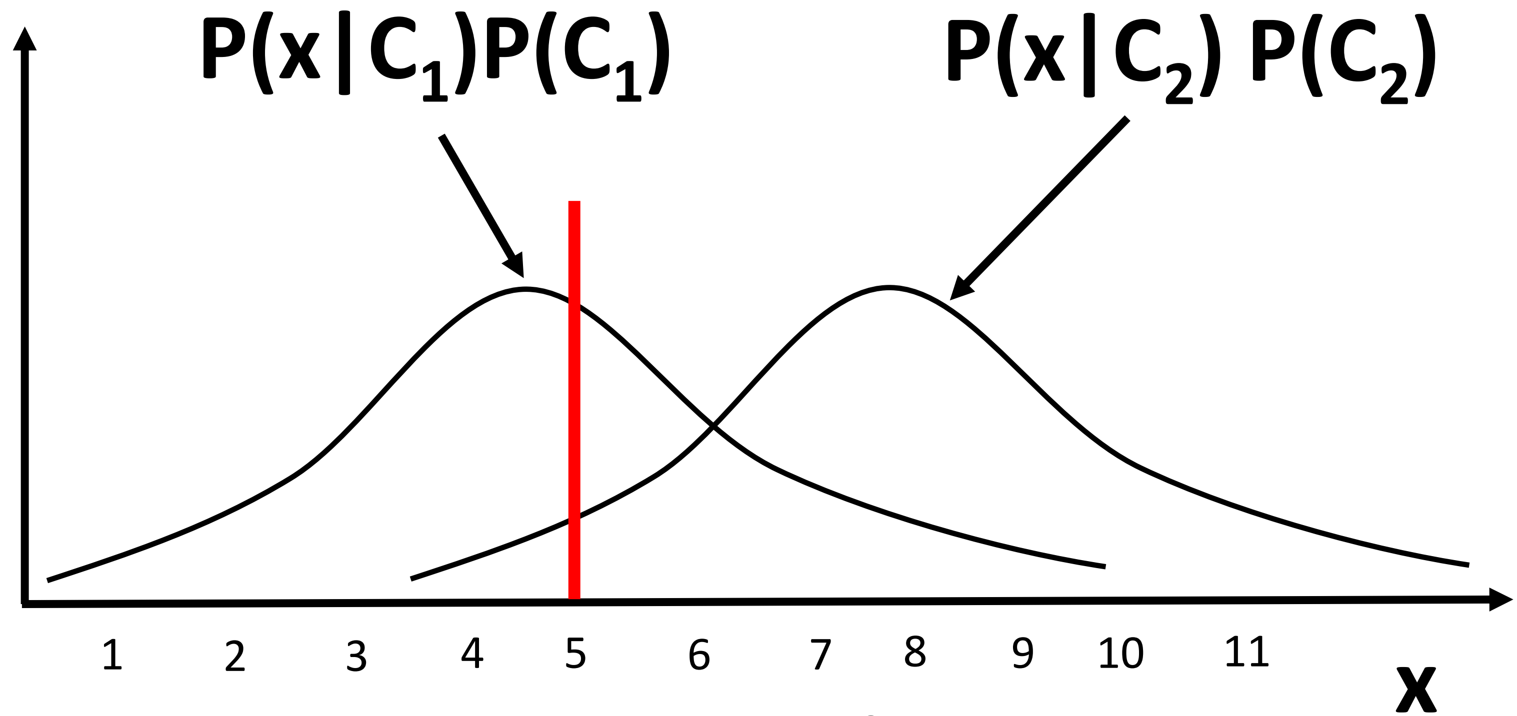
b3d ma t7sb el classification, edrbhom baa fe e7tmalyt 7doshom fl 72e2a, 34an te3rf e7tmalythom el wak3ya bkam.



1-D example

Bayes Classification Rule

- Classify $\underline{X}$ to the class corresponding to max $P(\underline{X}|C_k)\,P(C_k)$



1-D example

- For x=5, $P(x|C_1)P(C_1)$ has a higher value compared to $P(x|C_2)P(C_2)$
  → classify as C_1

Classification Accuracy

$$\boldsymbol{P\left(correct\ classification \middle| \underline{X}\right) = \max_{1 \le i \le K} P(C_i | \underline{X})}$$

- Example: 3-class case:
  - $P\left(C_1 \middle| \underline{X}\right) = 0.6,\ P\left(C_2 \middle| \underline{X}\right) = 0.3,\ P\left(C_3 \middle| \underline{X}\right) = 0.1$
  - You classified $\underline{X}$ as C_1 → it has highest $P(C_i | \underline{X})$
  - The probability that your classifier is correct equals to the probability that $\underline{X}$ belongs to the same class of the classification (which is 0.6)

e7tmalyt en el classification bt3tk tkon s7 hya e7tmalyt en X tkon f3ln btntmy lel class da

Classification Accuracy

- Overall P(correct) is:

$$P(correct) = \int P(correct, \underline{X})\, d\underline{X}$$ **Marginal prob.**

$$= \int P(correct|\underline{X}) P(\underline{X})\, d\underline{X}$$ **Bayes rule**

$$= \int \max_k \left[\frac{P(\underline{X}|C_k)\, P(C_k)}{\cancel{P(\underline{X})}} \right] \cancel{P(\underline{X})}\, d\underline{X}$$

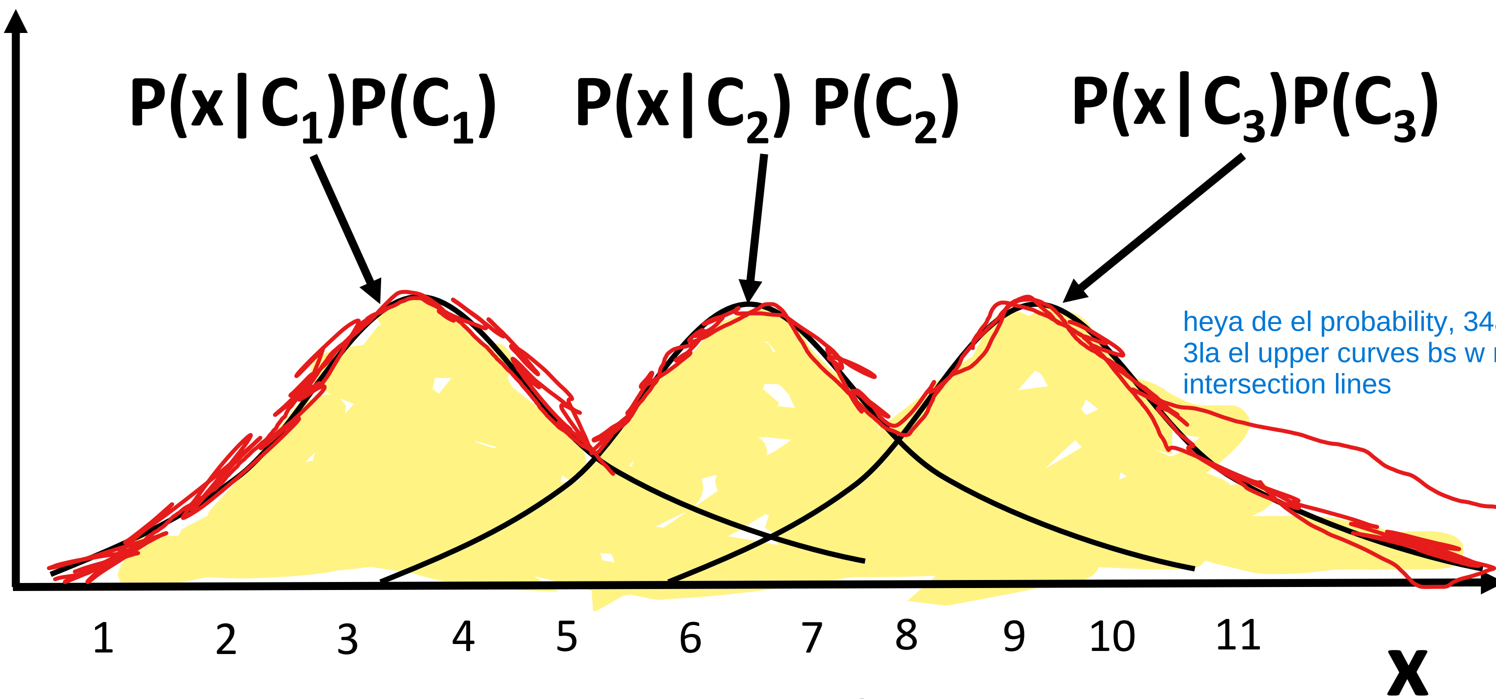
$$= \int \max_k P(\underline{X}|C_k)\, P(C_k)\, d\underline{X}$$

bmshy 3la el shape diagram bta3y, w bakhod el upper points lel rsma kolaha, w 34an t3rf el probability hatro7 t7sb el area under the whole curve

Classification Accuracy

- Overall P(correct) is:

$$P(correct) = \int \max_k P\left(\underline{X} | C_k\right) P(C_k)\, d\underline{X}$$



heya de el probability, 34an enta htmshy 3la el upper curves bs w msh bt-consider el intersection lines

1-D example

Classification Accuracy

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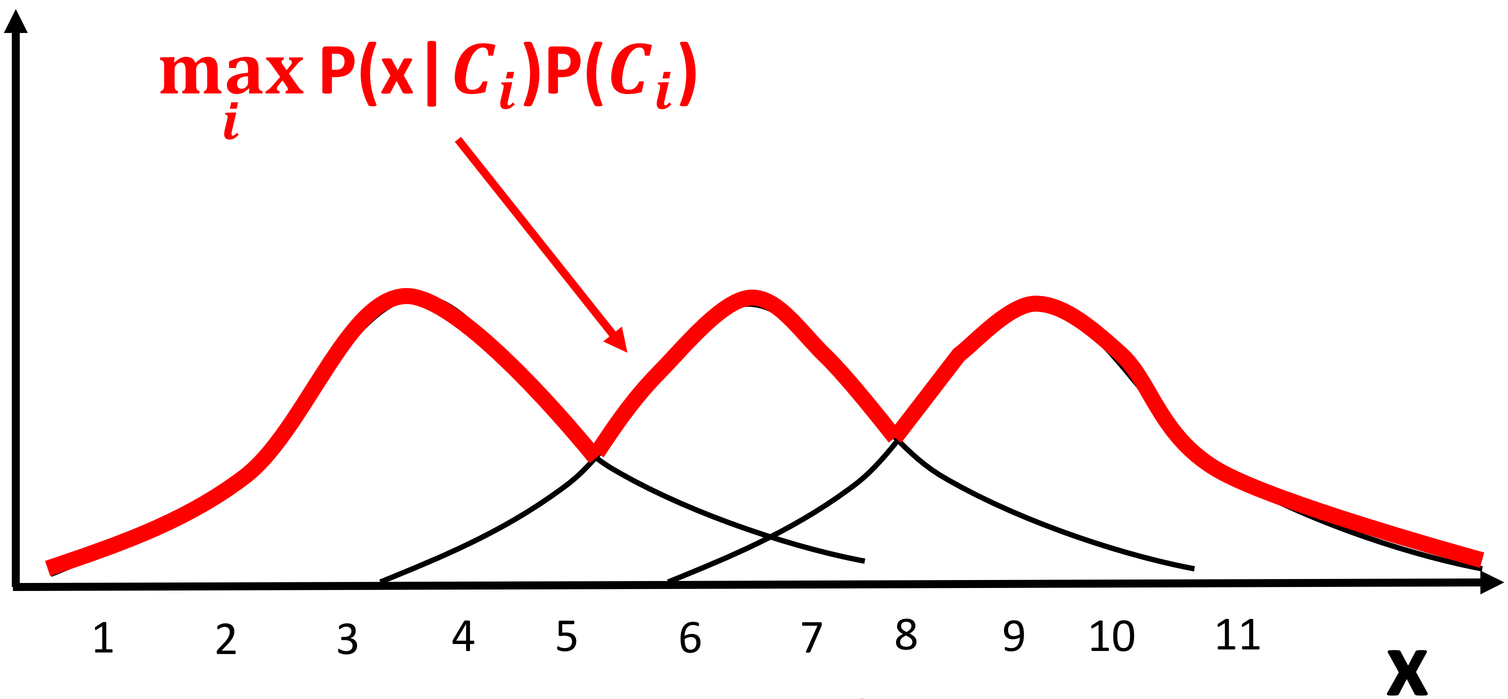

1-D example

Classification Accuracy

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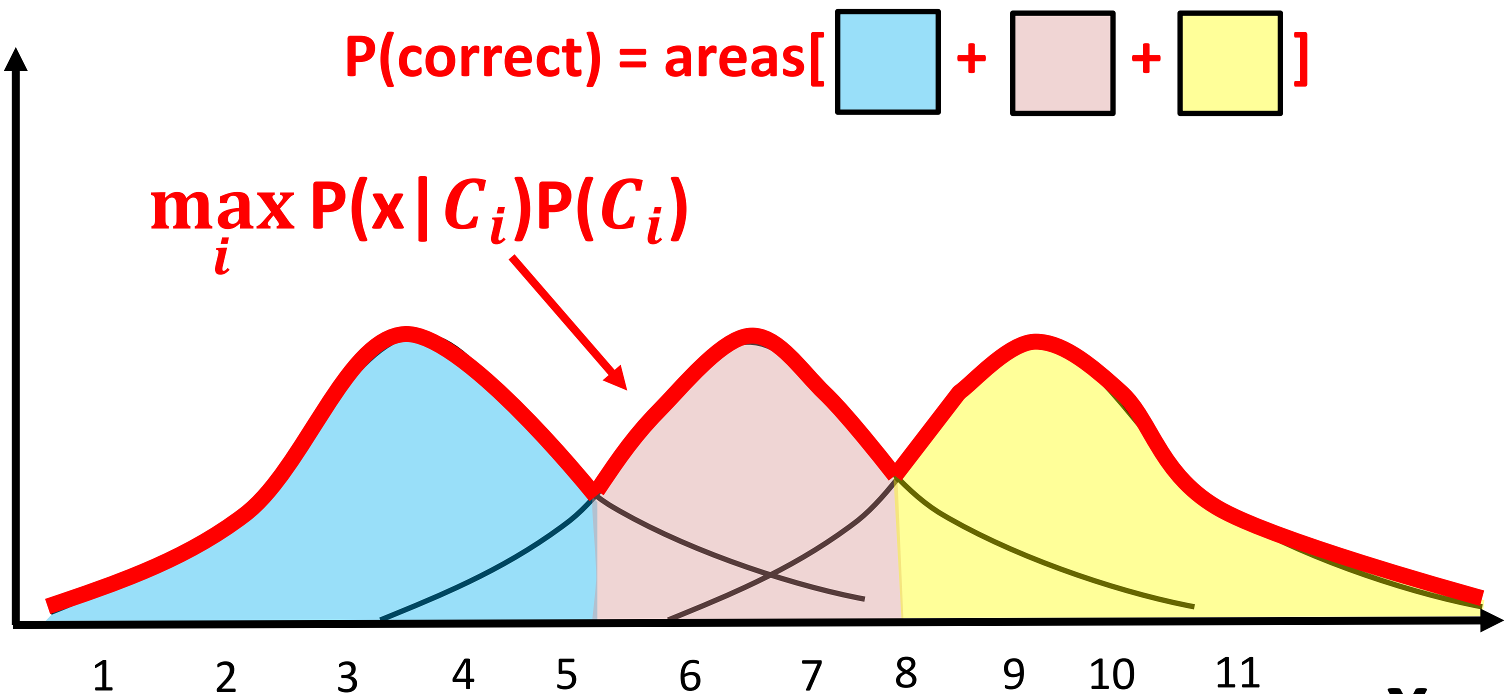


1-D example

lama 3dd el features byzed, byb2a s3b ne7sb el P(err) 3la toul, fa lama bnege n7sb, bn7sb el area under curve, w b3den bn2ol el P(err) = 1 - P(correct)

Classification Accuracy

$$P(correct) = \int \max_k P(\underline{X}|C_k)\, P(C_k)\, d\underline{X}$$

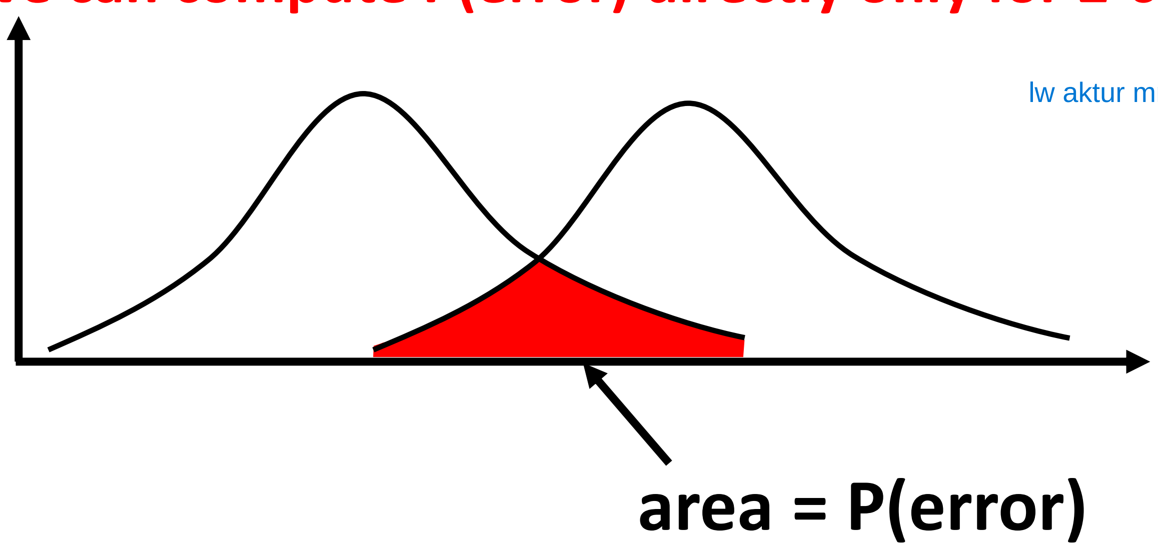
$$P(error) = 1 - P(correct)$$

Classification Accuracy

$$P(correct) = \int \max_k P(\underline{X}|C_k)\, P(C_k)\, d\underline{X}$$

$$P(error) = 1 - P(correct)$$

We can compute P(error) directly only for 2-class case!



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