

Image Classification – COMP4423 Computer Vision

Xiaoyong Wei (魏驍勇)

x1wei@polyu.edu.hk

Department of Computing
電子計算學系



THE HONG KONG
POLYTECHNIC UNIVERSITY
香港理工大學

Opening Minds • Shaping the Future
啟迪思維 • 成就未來

New Toy



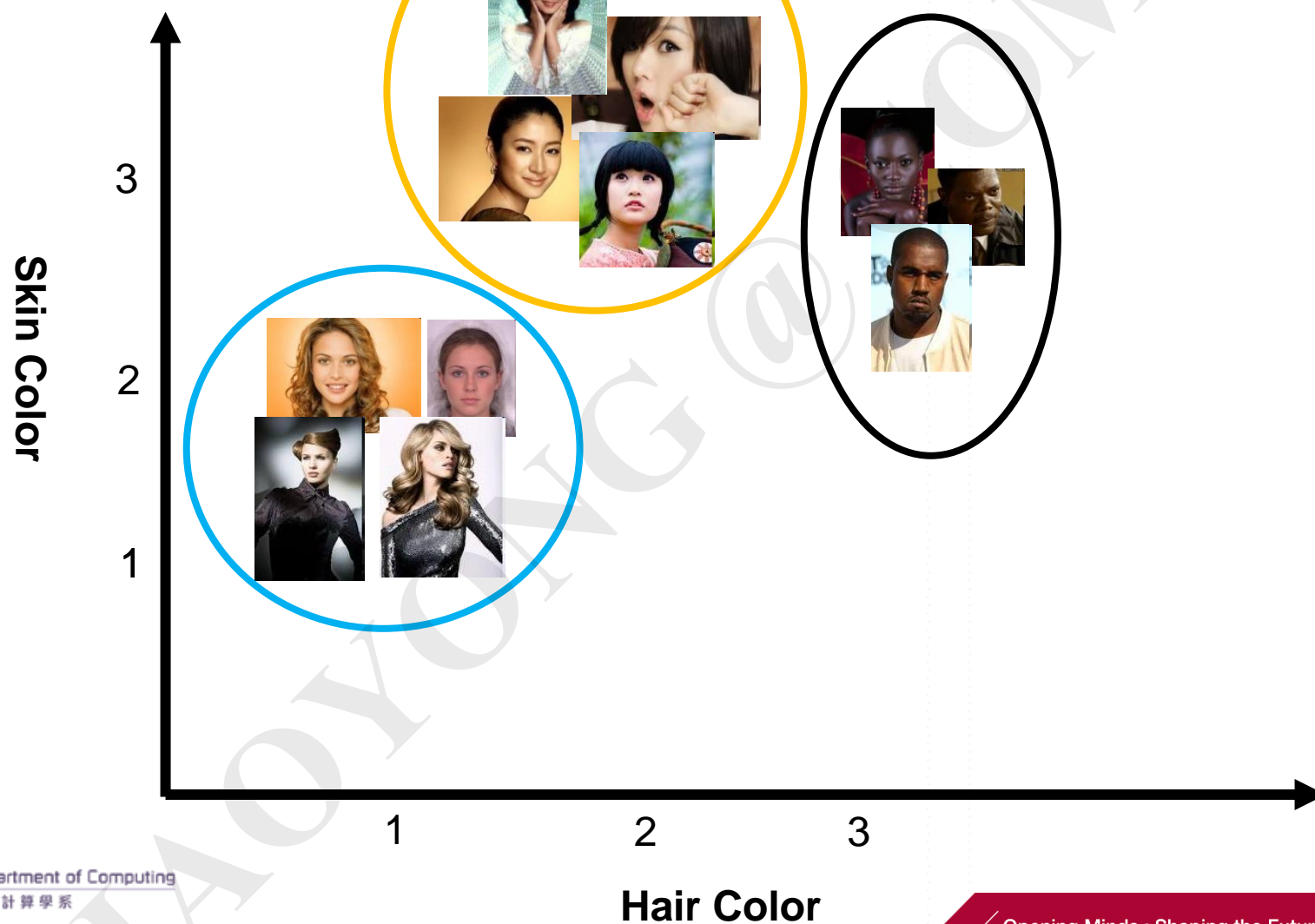
Outline

- > Classification
- > Supervised learning
- > K nearest neighbors (k-NN)
- > Bayesian classifiers
- > Support vector machines (SVM)

How do you group them?



Feature Space

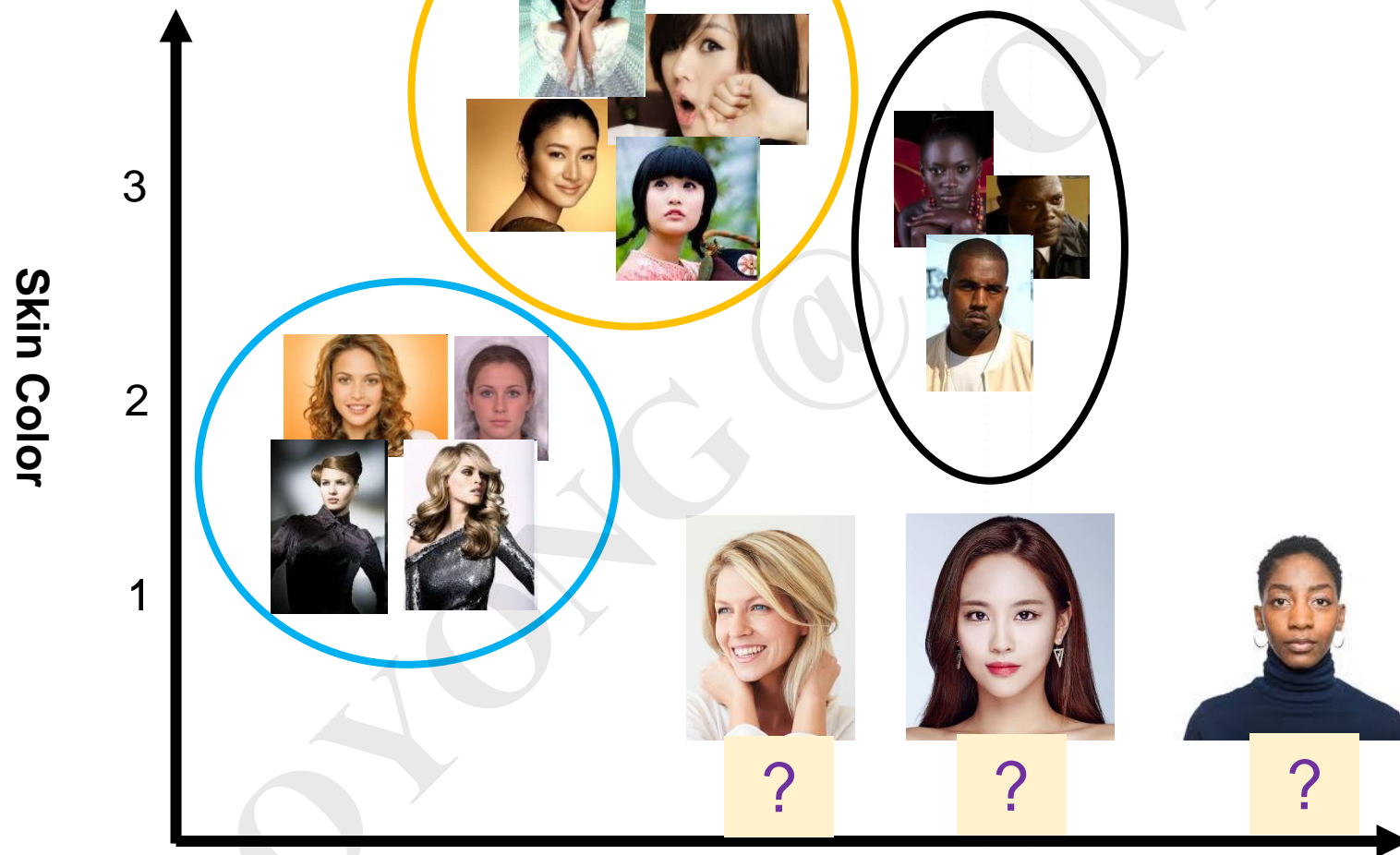


Clustering is **unsupervised learning** which means we (human) don't have to tell the computers what each group looks like. It's data-driven without using human knowledge (supervision).

Sounds good?

But ...

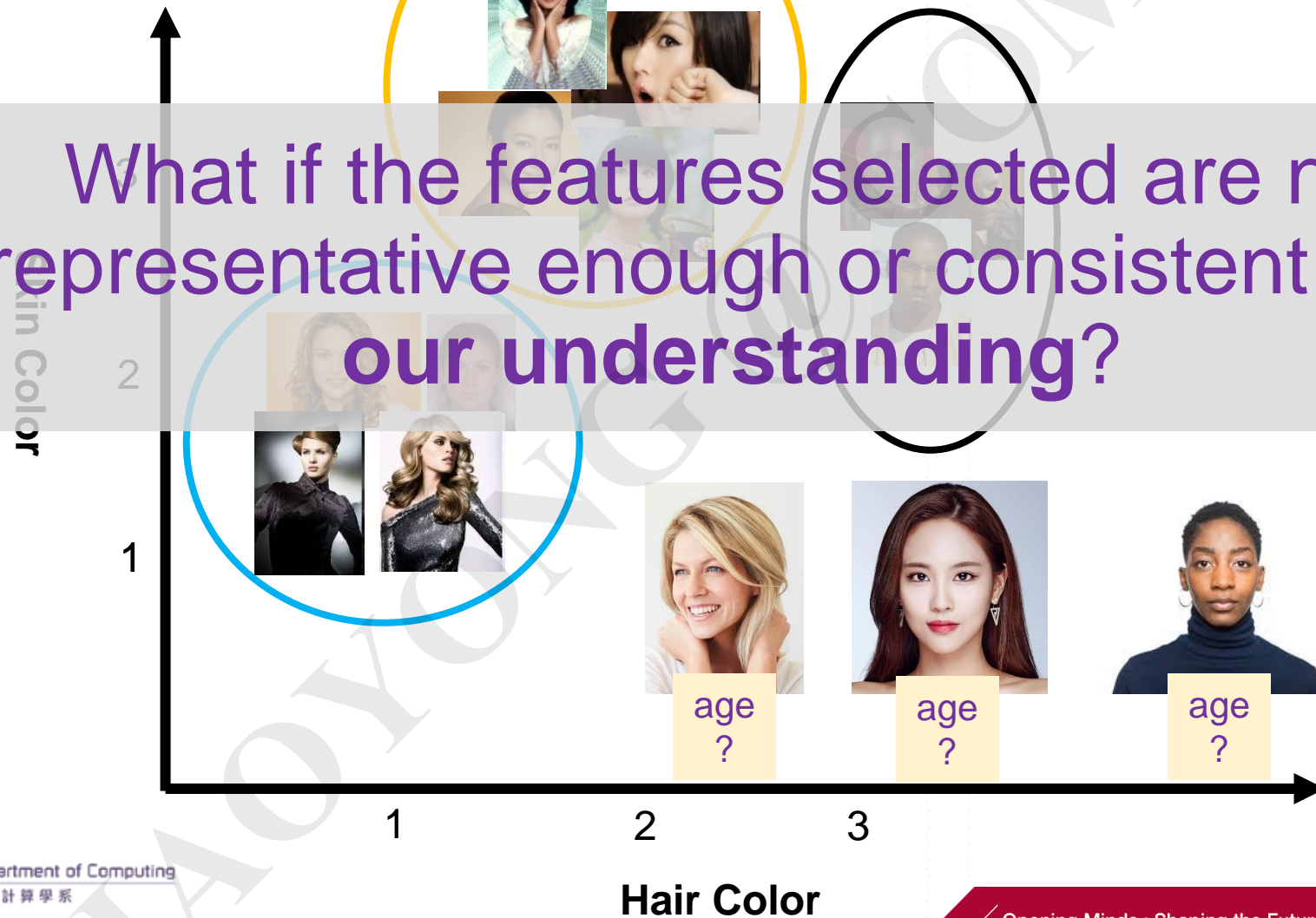
Feature Space



What if we have new examples unseen?

Feature Space

What if the features selected are not representative enough or consistent with our understanding?



We can **tell** the computers about
our understanding on the
subjects by giving **labels**.

Training Examples (Seen)

	Hair Color (H)	Skin Color (S)	Class Label (L)
	Yellow (2)	White (1)	W
	Black (3)	Yellow (2)	A
	Black (3)	Yellow (2)	A
	Yellow (2)	White (1)	W
	Black (3)	Black (3)	B

Testing Examples (Unseen)

	Hair Color (H)	Skin Color (S)	Class Label (L)
	2.2	0.8	?
	3.2	1.9	?
	3.1	2.2	?
	2.4	1.3	?
	3.1	2.9	?

Classification: to predict the labels of the testing (unseen) examples based on the knowledge learned from the training (seen) examples

Classification: to predict the labels of the testing (unseen) examples based on the knowledge learned from the training (seen) examples

We are training the computers and the processing is called **training**.
The computers are learning. This is what the term “**machine learning**” is referring to.
Our participation in learning makes it
supervised learning.

Classification: to predict the labels of the testing (unseen) examples based on the knowledge learned from the training (seen) examples

The result is the machine's understanding of the knowledge.
We call it a **model** sometimes.

Classification

Training Set

Samples	Features	Labels
1	[0.1, ...]	1
2	[0.3, ...]	-1
...

Validation Set

Samples	Features	Labels
1	[0.5, ...]	-1
2	[0.9, ...]	1
...

Model

Testing Set

Samples	Features	Labels
1	[0.8, ...]	?
2	[0.7, ...]	-?
...

Samples	Features	Labels
1	[0.8, ...]	-1
2	[0.7, ...]	1
...

Training

Testing

Then how?

Instance-based Learning



PDA



Cellphone



Desktop PC



Laptop



It looks like the
laptop I see last
time.



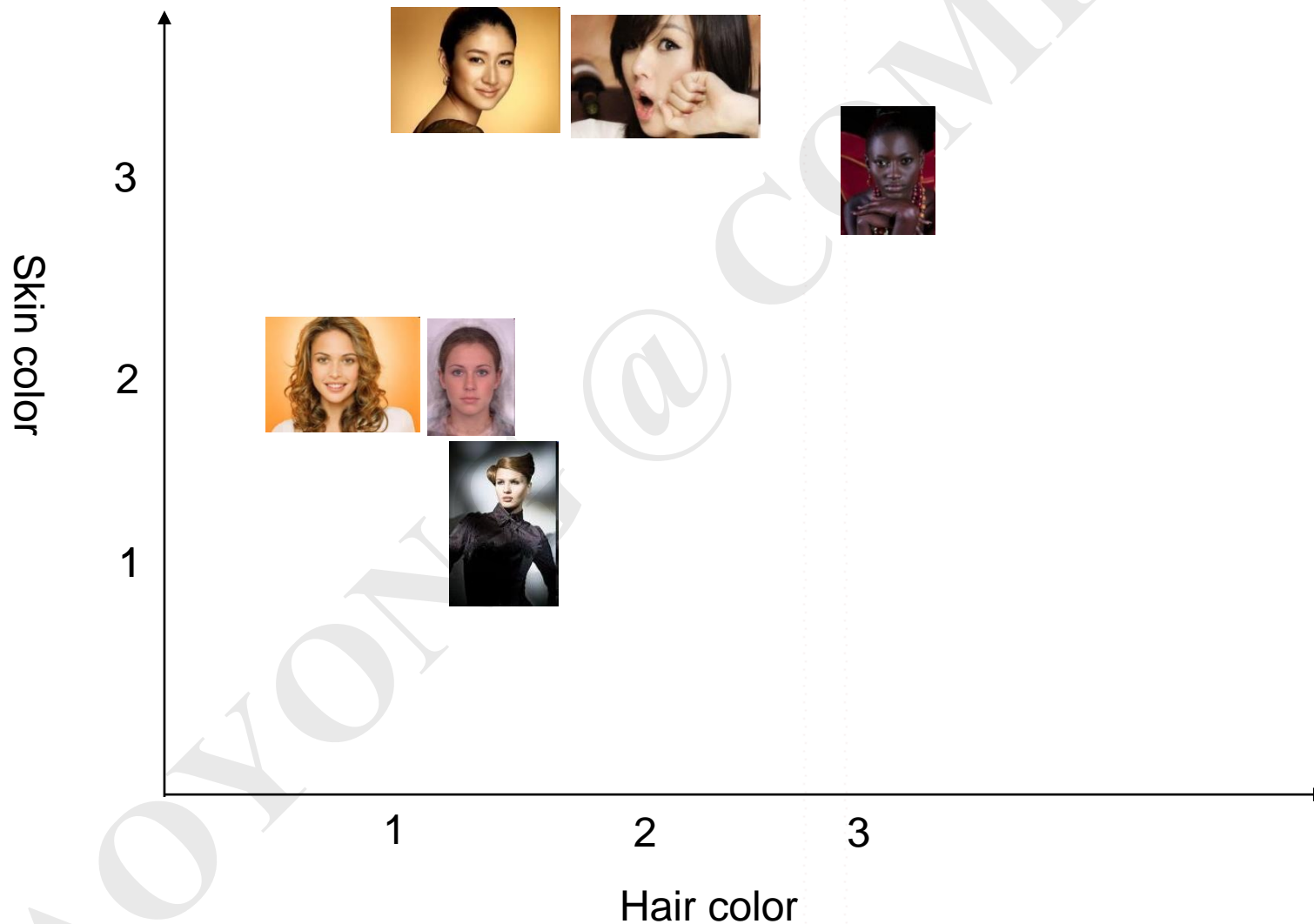
How about we use image retrieval to find the most similar ones from the seen examples for reference?

kNN Classifiers

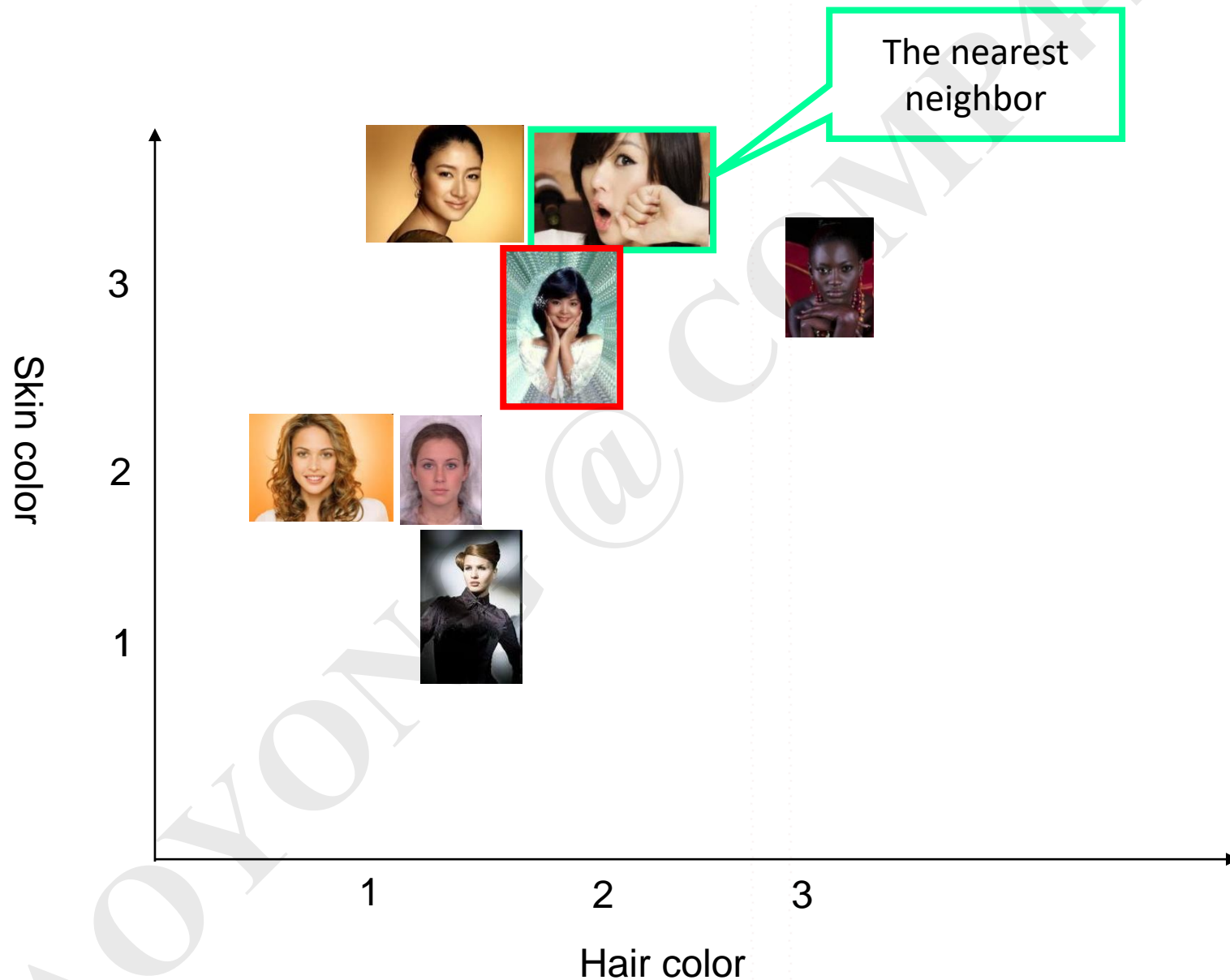
kNN Classifier

- > NN: nearest neighbors
- > k: number of nearest neighbors
- > Idea
 - When $k=1$: assign the unseen with the label of its nearest neighbor
 - 近朱者赤，近墨者黑 (If you lie down with dogs, you will get up with fleas)

$k=1$



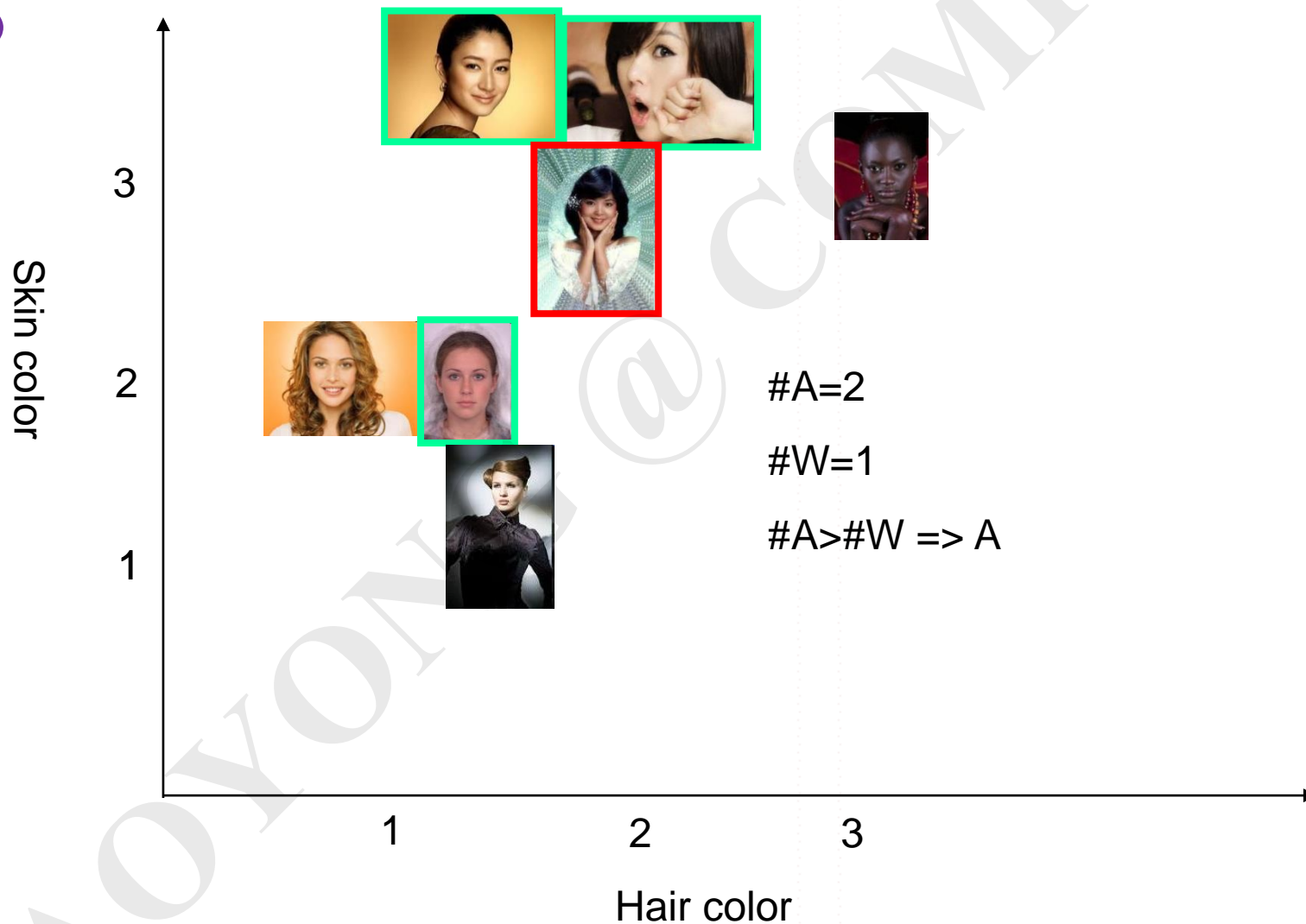
$k=1$



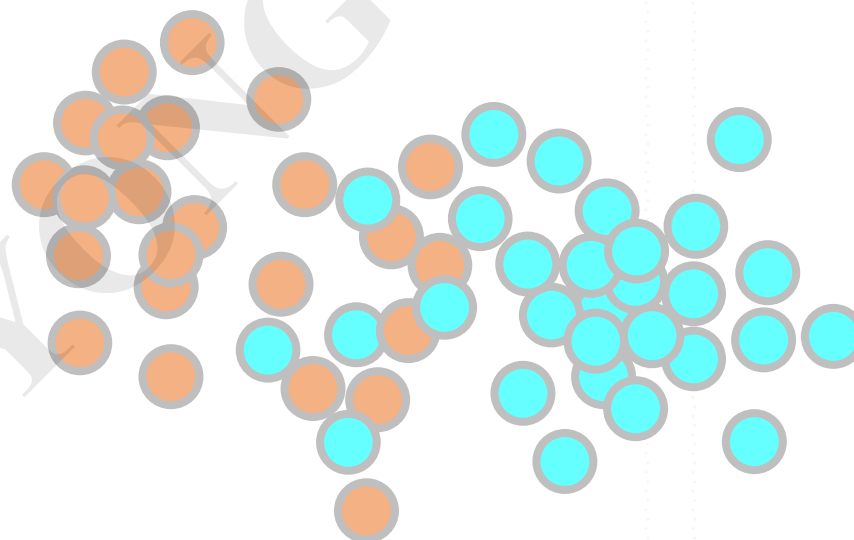
kNN Classifier

- > NN: nearest neighbors
- > k: number of nearest neighbors
- > Idea
 - $k=1$: assign the unseen with the label of its nearest neighbor
 - **$k>1$: assign the dominating label among these of the k nearest neighbors**

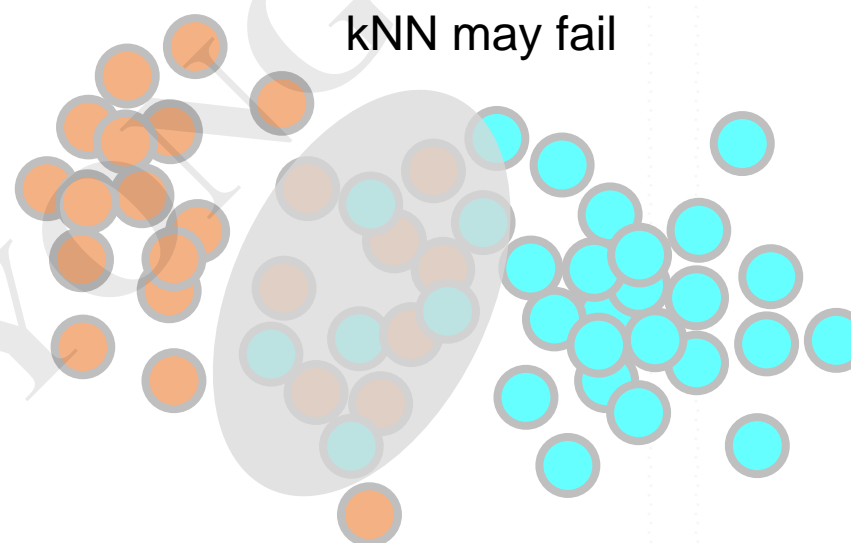
$k=3$



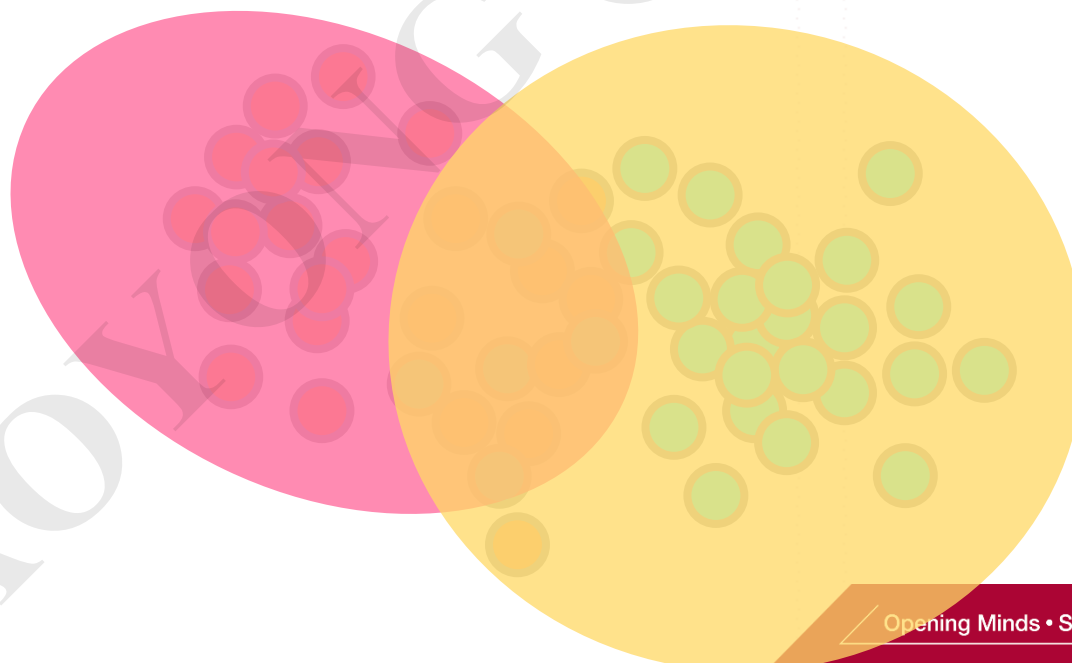
It's straightforward. But so far, we picked the simplest case (classes are well separated) for illustration purpose. In a more general sense, this is what we're going to have.



It's straightforward. But so far, we picked the simplest case (classes are well separated) for illustration purpose. In a more general sense, this is what we're going to have.



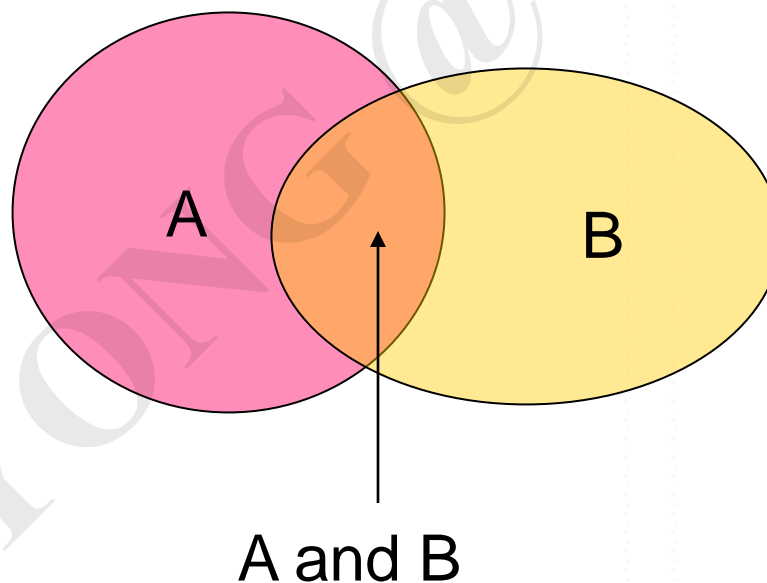
Can we teach the computer to draw a “circle” for each of the class and evaluate the membership of an example by measuring how much it falls into “circles”?



Bayesian Classifiers

Bayesian Classifiers

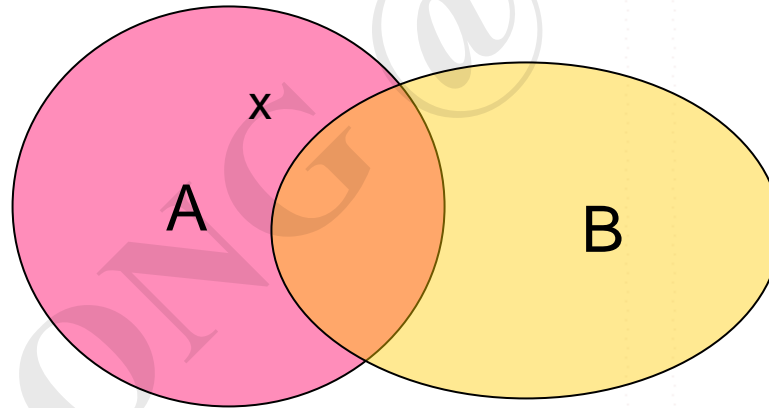
> Classes A and B as two sets



Bayesian Classifiers

> Classes A and B as two sets

- $P(A|x)$: the probability of A is observed when seeing an x
- $P(B|x)$: the probability of B is observed when seeing an x



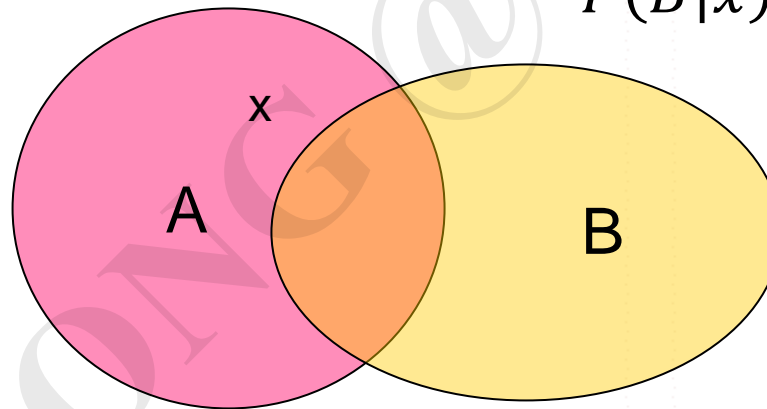
Bayesian Classifiers

> Classes A and B as two sets

- $P(A|x) \propto P(x|A)P(A)$
- $P(B|x) \propto P(x|B)P(B)$

$$P(A|x) = \frac{P(x|A)P(A)}{P(x)}$$

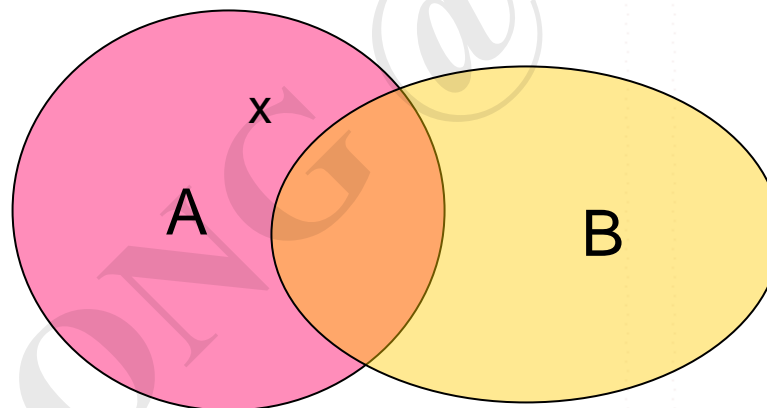
$$P(B|x) = \frac{P(x|B)P(B)}{P(x)}$$



Bayesian Classifiers

> Classes A and B as two sets

- $P(A|x) \propto P(x|A)P(A)$
- $P(B|x) \propto P(x|B)P(B)$



$$P(A) = \#A / (\#A + \#B)$$

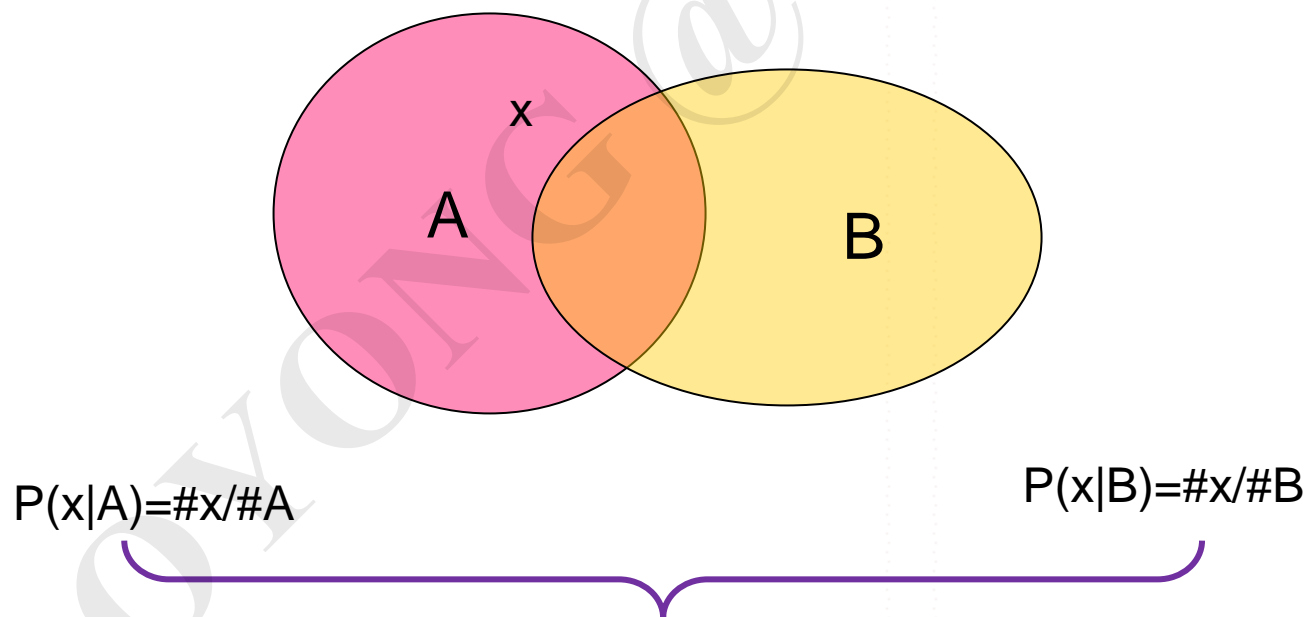
$$P(B) = \#B / (\#A + \#B)$$

The Prior Probability

Bayesian Classifiers

> Classes A and B as two sets

- $P(A|x) \propto P(x|A)P(A)$
- $P(B|x) \propto P(x|B)P(B)$

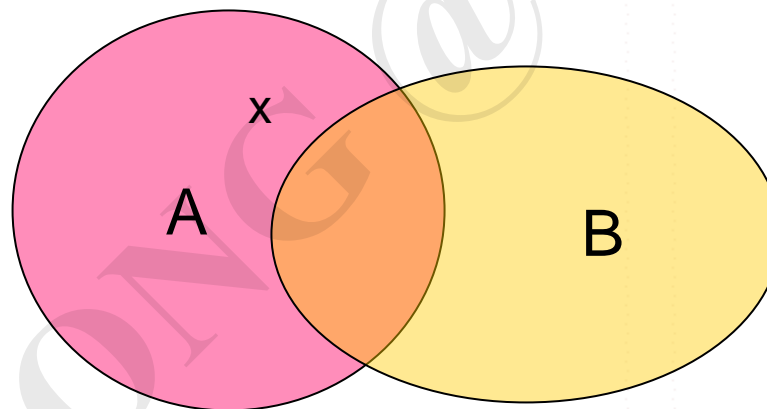


The Conditional Probability (Likelihood)

Bayesian Classifiers

> Classes A and B as two sets

- $P(A|x) \propto P(x|A)P(A)$
- $P(B|x) \propto P(x|B)P(B)$



Decision function: x is A if $P(A|x) > P(B|x)$,
 B otherwise

Naive Bayesian

> Advantages:

- Fast
- Extendable to multi-class problems
- Requires less training examples
- Works well for categorical data

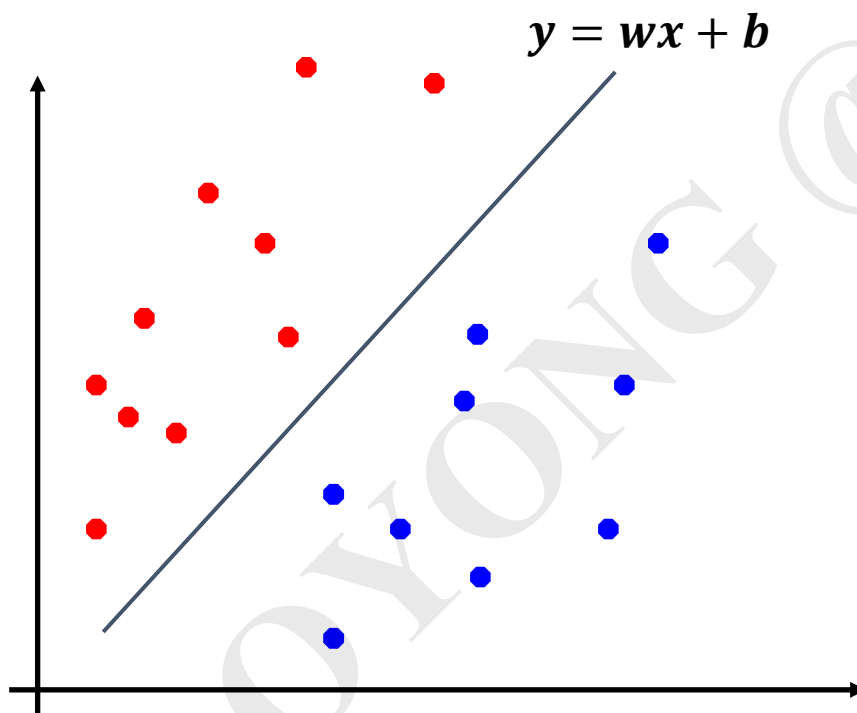
> Disadvantages:

- **Features are assumed to be independent to each other** (not true in real-world applications)
- Zero-frequency problem

Support Vector Machines

Linear Separators

> Binary classification can be viewed as the task of separating classes in feature space:



$$-y + wx + b = 0$$



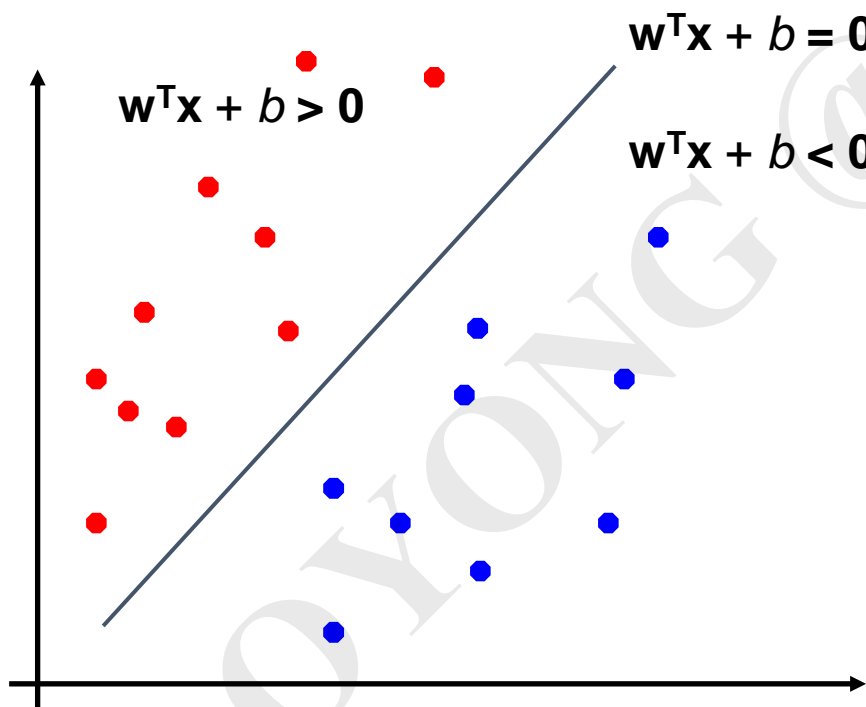
$$\begin{bmatrix} w \\ -1 \end{bmatrix} \begin{bmatrix} x & y \end{bmatrix} + b = 0$$



$$\mathbf{w}^T \mathbf{x} + b = 0$$

Linear Separators

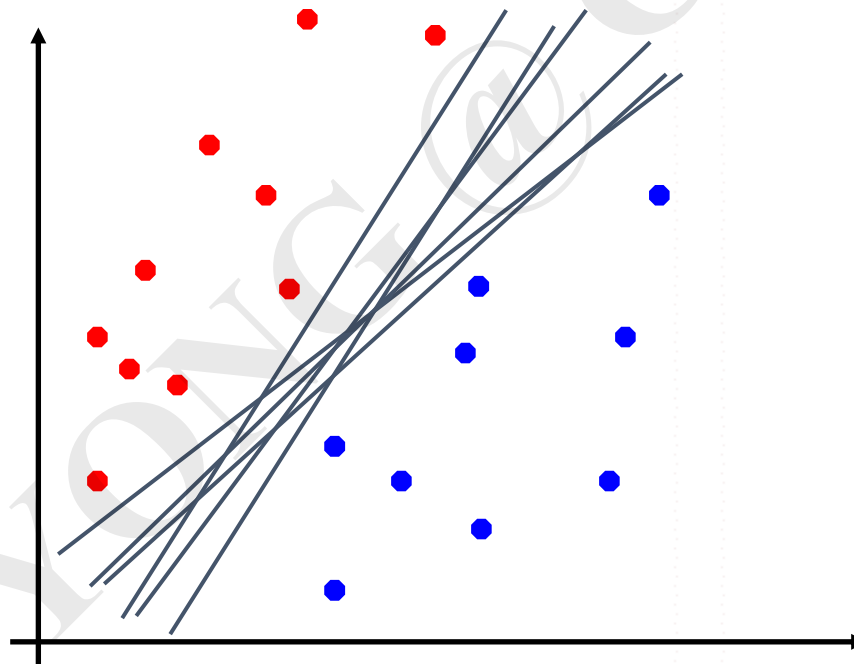
> Binary classification can be viewed as the task of separating classes in feature space:



$$f(\mathbf{x}) = \text{sign}(w^T \mathbf{x} + b)$$

Linear Separators

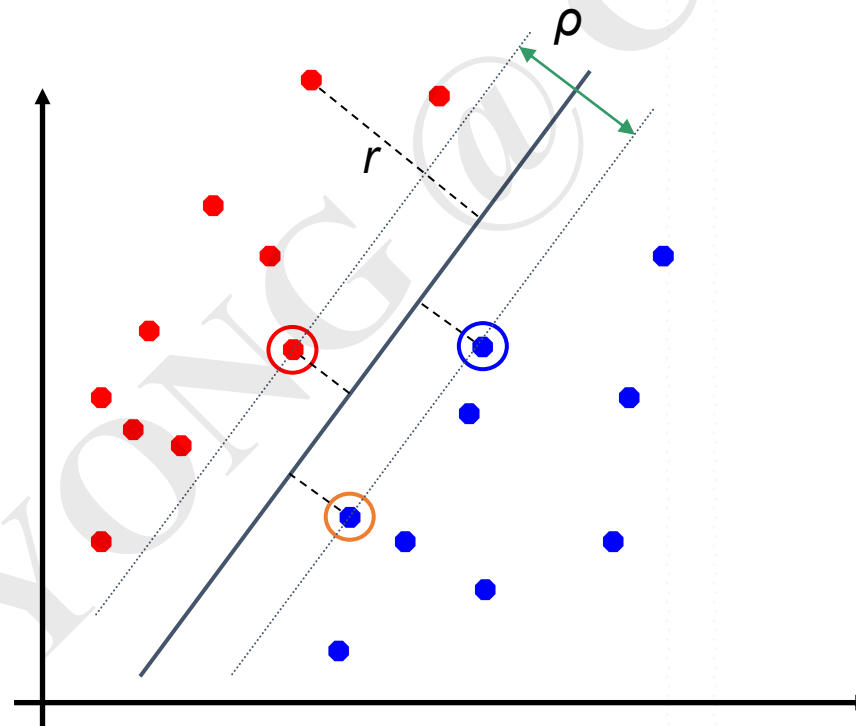
> Binary classification can be viewed as the task of separating classes in feature space:



> Which one is the best?

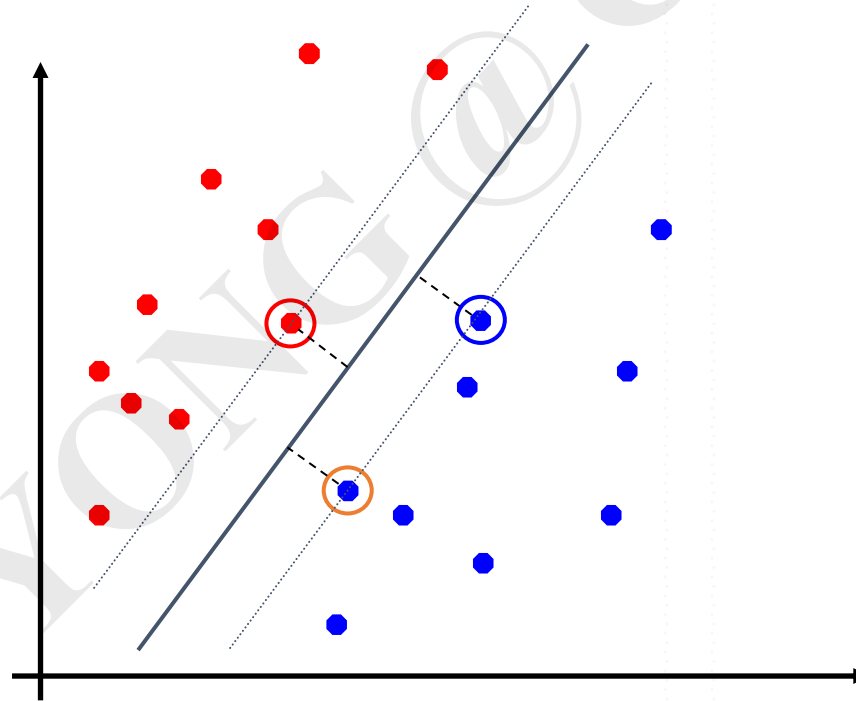
Margin

- > Distance from example \mathbf{x}_i to the separator is $r = \frac{\mathbf{w}^T \mathbf{x}_i + b}{\|\mathbf{w}\|}$
- > Examples closest to the hyperplane are **support vectors**.
- > **Margin** ρ of the separator is the distance between support vectors.



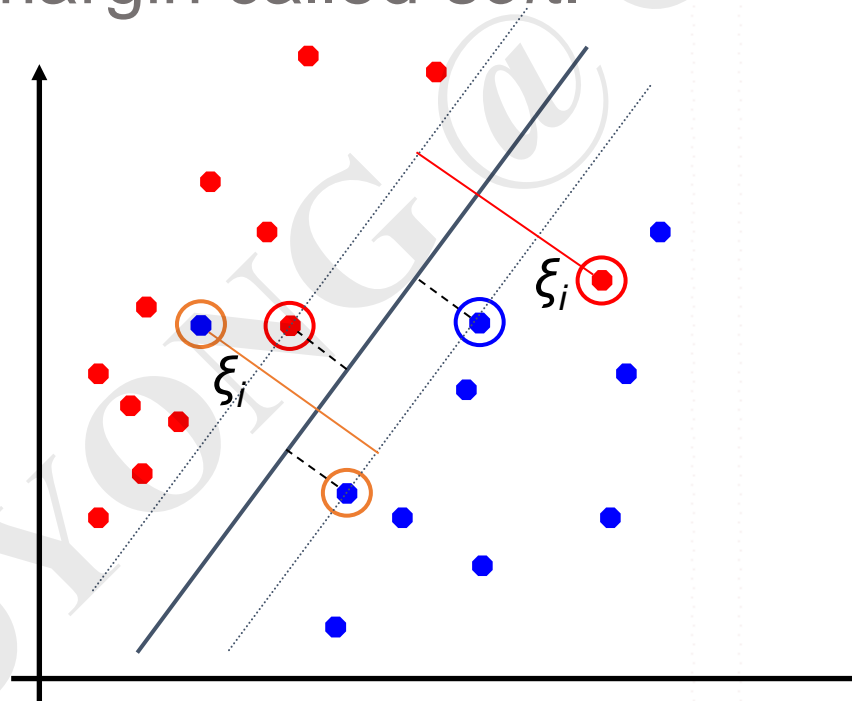
Maximum Margin Classification

- > Maximizing the margin is good according to intuition and PAC theory (Probably Approximately Correct).
- > Implies that only support vectors matter; other training examples are ignorable.



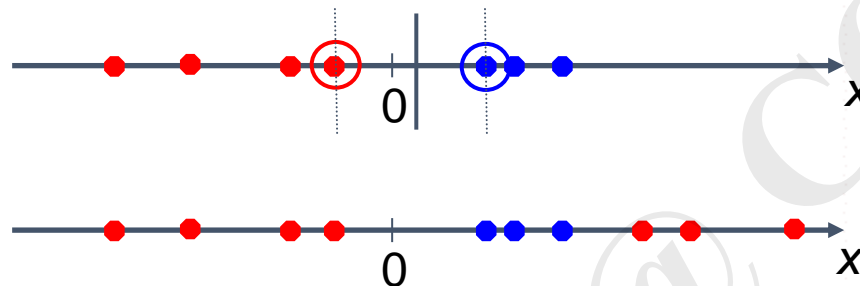
Soft Margin Classification

- > What if the training set is not linearly separable?
- > *Slack variables* ξ_i can be added to allow misclassification of difficult or noisy examples, resulting margin called *soft*.



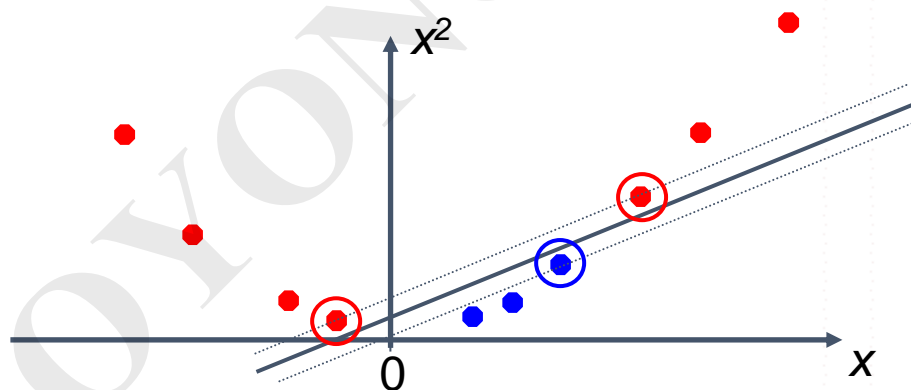
Non-linear SVMs

> Datasets that are linearly separable with some noise work out great:



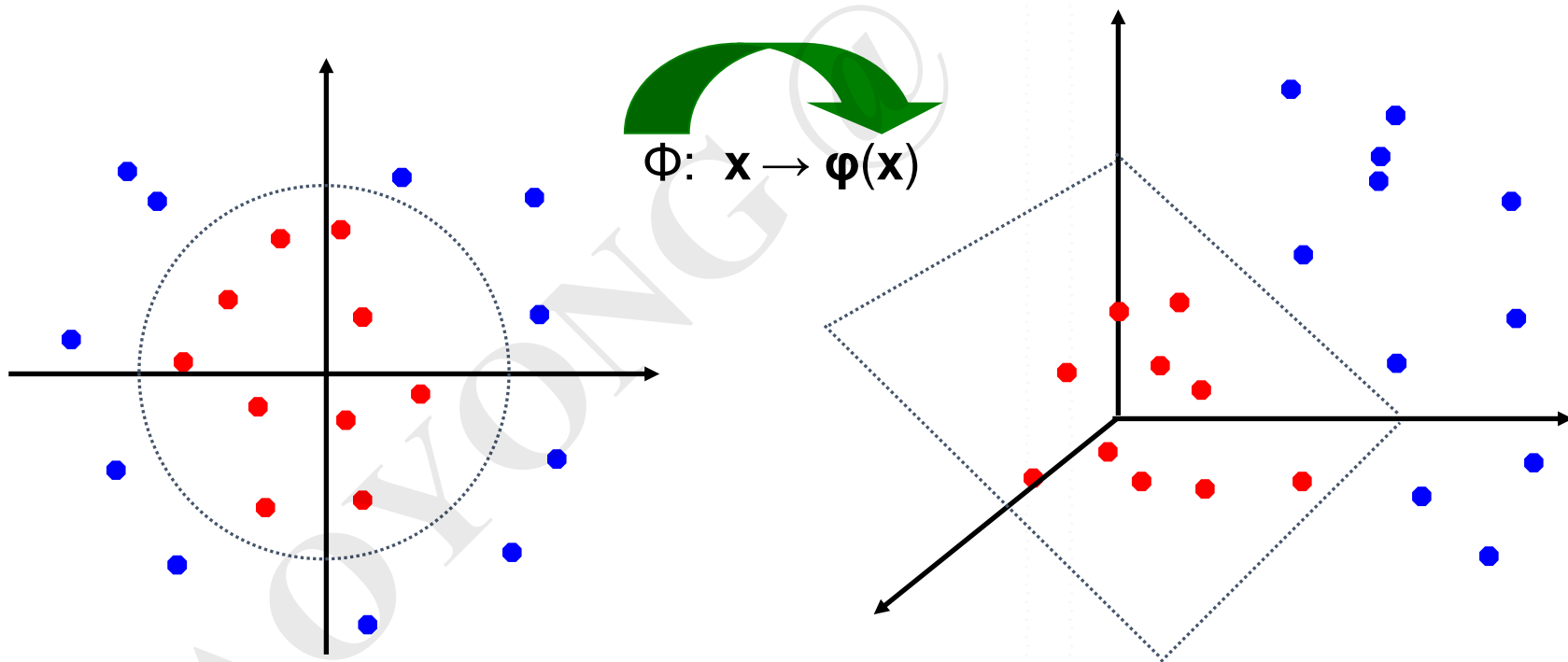
> But what are we going to do if the dataset is just too hard?

> How about... mapping data to a higher-dimensional space:



Non-linear SVMs: Feature spaces

> General idea: the original feature space can always be mapped to some higher-dimensional feature space where the training set is separable:



The “Kernel Trick”

- > The linear classifier relies on inner product between vectors $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$
- > If every datapoint is mapped into high-dimensional space via some transformation $\Phi: \mathbf{x} \rightarrow \phi(\mathbf{x})$, the inner product becomes:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$$

- > A *kernel function* is a function that is equivalent to an inner product in some feature space.
- > Example:

2-dimensional vectors $\mathbf{x} = [x_1 \ x_2]$; let $K(\mathbf{x}_i, \mathbf{x}_j) = (1 + \mathbf{x}_i^T \mathbf{x}_j)^2$,

Need to show that $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$:

$$\begin{aligned} K(\mathbf{x}_i, \mathbf{x}_j) &= (1 + \mathbf{x}_i^T \mathbf{x}_j)^2 = 1 + x_{i1}^2 x_{j1}^2 + 2 x_{i1} x_{j1} x_{i2} x_{j2} + x_{i2}^2 x_{j2}^2 + 2 x_{i1} x_{j1} + 2 x_{i2} x_{j2} = \\ &= [1 \ x_{i1}^2 \ \sqrt{2} x_{i1} x_{i2} \ x_{i2}^2 \ \sqrt{2} x_{i1} \ \sqrt{2} x_{i2}]^T [1 \ x_{j1}^2 \ \sqrt{2} x_{j1} x_{j2} \ x_{j2}^2 \ \sqrt{2} x_{j1} \ \sqrt{2} x_{j2}] = \\ &= \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j), \quad \text{where } \phi(\mathbf{x}) = [1 \ x_1^2 \ \sqrt{2} x_1 x_2 \ x_2^2 \ \sqrt{2} x_1 \ \sqrt{2} x_2] \end{aligned}$$

- > Thus, a kernel function *implicitly* maps data to a high-dimensional space (without the need to compute each $\phi(\mathbf{x})$ explicitly).

Examples of Kernel Functions

- > Linear: $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$
 - Mapping Φ : $\mathbf{x} \rightarrow \boldsymbol{\varphi}(\mathbf{x})$, where $\boldsymbol{\varphi}(\mathbf{x})$ is \mathbf{x} itself
- > Polynomial of power p : $K(\mathbf{x}_i, \mathbf{x}_j) = (1 + \mathbf{x}_i^T \mathbf{x}_j)^p$
 - Mapping Φ : $\mathbf{x} \rightarrow \boldsymbol{\varphi}(\mathbf{x})$, where $\boldsymbol{\varphi}(\mathbf{x})$ has $\binom{d+p}{p}$ dimensions
- > Gaussian (radial-basis function): $K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}}$
 - Mapping Φ : $\mathbf{x} \rightarrow \boldsymbol{\varphi}(\mathbf{x})$, where $\boldsymbol{\varphi}(\mathbf{x})$ is *infinite-dimensional*: every point is mapped to *a function* (a Gaussian); combination of functions for support vectors is the separator.
- > Higher-dimensional space still has *intrinsic* dimensionality d (the mapping is not *onto*), but linear separators in it correspond to *non-linear* separators in original space.

Classification

Training Set

Samples	Features	Labels
1	[0.1, ...]	1
2	[0.3, ...]	-1
...

Validation Set

Samples	Features	Labels
1	[0.5, ...]	-1
2	[0.9, ...]	1
...

Model

Testing Set

Samples	Features	Labels
1	[0.8, ...]	?
2	[0.7, ...]	-?
...

Samples	Features	Labels
1	[0.8, ...]	-1
2	[0.7, ...]	1
...

Training

Testing



The New Toy

New Toy



Feature Extraction

```

15 import cv2
16 import requests
17 from requests_toolbelt.multipart.encoder import MultipartEncoder
18 import numpy as np, random
19
20 cap = cv2.VideoCapture(0)
21 WindName = "Toy Program @ COMP 4423"
22 cv2.namedWindow(WindName)
23 cv2.resizeWindow(WindName, 1024, 768)
24
25 #polysmart_svr_url = 'http://127.0.0.1:8000/'
26 polysmart_svr_url = 'http://158.132.255.32:8088/'
27
28 polysmart_facerecg_svr = polysmart_svr_url+'handdetect/'
29
30 def detect(pic):
31     _, im_buf = cv2.imencode(".jpg", pic)
32     byte_im = im_buf.tobytes()
33
34     data = MultipartEncoder(fields={'file': ('img.jpg', byte_im)})
35     response = requests.post(polysmart_facerecg_svr, data=data, headers={
36         'Content-Type': data.content_type})
37     # print((response.status_code,response.json()))
38     retJson = response.json()
39     return retJson['results'] if retJson['code'] >= 0 else []
40
41 connections = [[4, 3, 2, 1, 0],# thumb
42                [8, 7, 6, 5],# index
43                [12, 11, 10, 9],# middle
44                [16, 15, 14, 13],# ring
45                [20, 19, 18, 17, 0], #pinky
46                [3, 5, 9, 13, 17]# palm
47                ]
48

```



```

50 def draw_landmarks(image, landmarks):
51     h, w, c = image.shape
52     # print([h, w, c])
53     id2cords = {}
54     for lm in landmarks:
55         idx, ftx, fty = lm['idx'], int(lm['x']*w), int(lm['y']*h)
56         id2cords[idx] = [ftx, fty]
57     for line in connections:
58         pts = [[id2cords[idx][0], id2cords[idx][1]] for idx in line]
59         pts = np.array(pts, np.int32)
60         pts = pts.reshape((-1, 1, 2))
61         image = cv2.polylines(image, [pts], False, (0, 128, 128), 4)
62     for idx in id2cords:
63         image = cv2.circle(
64             image, (id2cords[idx][0], id2cords[idx][1]), 10, (224, 224, 0), 5)
65     image = cv2.circle(
66         image, (id2cords[8][0], id2cords[8][1]), 15, (0, 0, 128), 5)
67     return image, id2cords
68
69 def extrac_feature(id2cords):
70     feat=[]
71     for id in range(21):
72         a=np.array(id2cords[id])
73         for tag in range(id+1,21):
74             b=np.array(id2cords[tag])
75             dist=np.linalg.norm(a-b)/800 # normalize the distane in the range of [0,1] by assuming the 800 is the maximum dist possible
76             feat.append(dist)
77     print('sum feat=',sum(feat))
78     return feat
79

```

```

80 feat_x,feat_y=[],[]
81 while True:
82     success, image = cap.read()
83     if not success:
84         continue
85     image = cv2.flip(image, 1)
86     imageRGB = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
87
88     results = detect(imageRGB)
89     id2cords = {}
90     #print(['len=', len(results)])
91     if len(results) == 0:
92         print("Nothing detected ...")
93     else:
94         image, id2cords = draw_landmarks(image, results[0]['landmarks'])
95
96     cv2.imshow(WindName, image)
97
98     key=cv2.waitKey(1) & 0xFF
99     if key == ord('q') or key==27:
100         break
101
102     if key == ord('p') and not id2cords =={}:
103         # capture a sample for the class 'paper'
104         feat=extrac_feature(id2cords)
105         feat_x.append(feat)
106         feat_y.append(1)
107     if key == ord('r') and not id2cords =={}:
108         # capture a sample for the class 'rock'
109         feat=extrac_feature(id2cords)
110         feat_x.append(feat)
111         feat_y.append(2)
112     if key == ord('x') and not id2cords =={}:
113         # capture a sample for the class 'rock'
114         feat=extrac_feature(id2cords)
115         feat_x.append(feat)

```

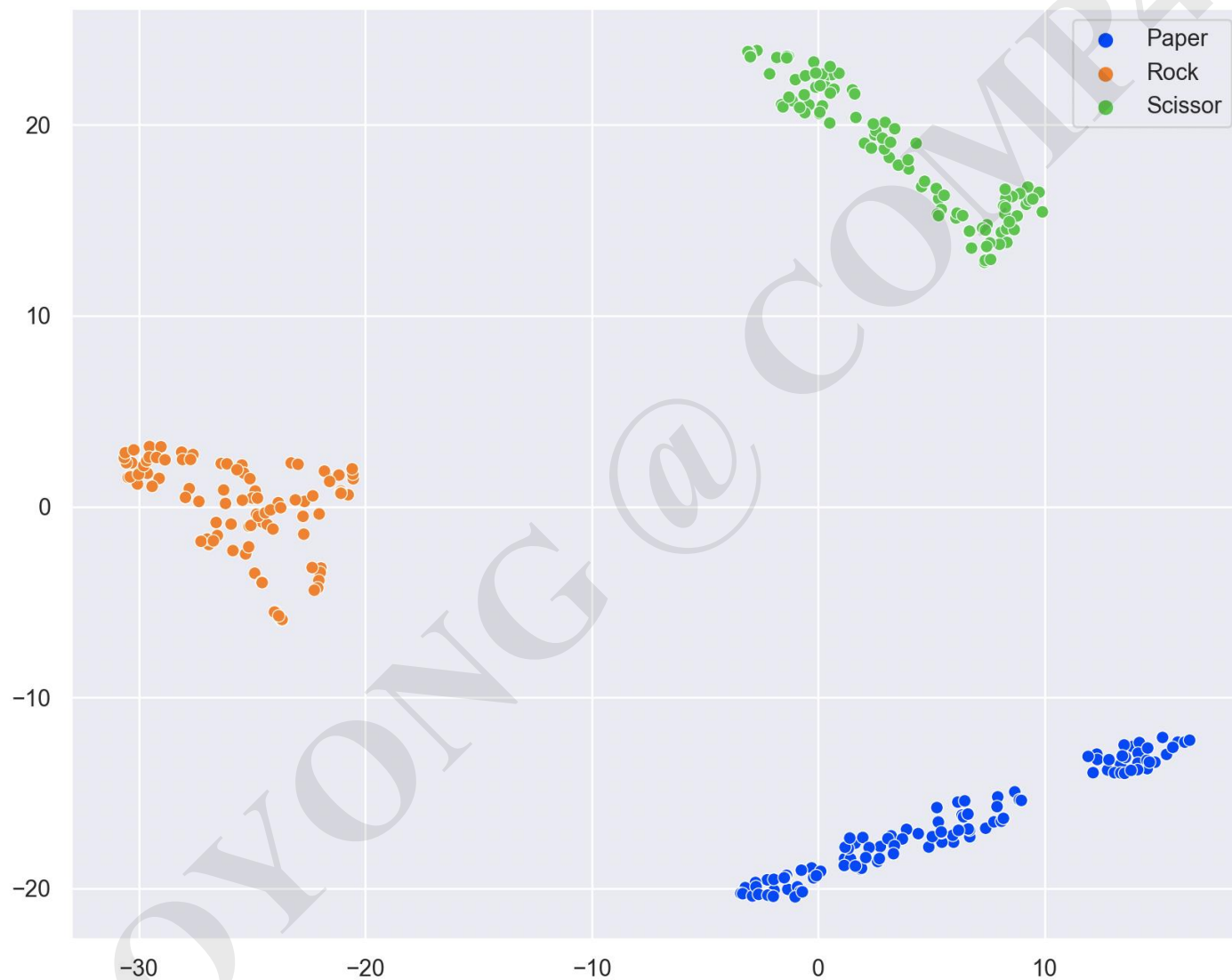
Training & Testing

```
84 feat_x,feat_y=np.load('feat_x.npy'),np.load('feat_y.npy')
85
86 ##### run cross-validation #####
87 from sklearn import svm
88 from sklearn.model_selection import cross_val_score
89 model = svm.SVC(kernel='rbf')
90 scores = cross_val_score(model, feat_x, feat_y, cv=10)
91 print('cross validation scores: ',scores)
92 #print(feat_x.shape)
93
94 ##### visualize the data #####
95 from sklearn.manifold import TSNE
96 import seaborn as sns
97 import matplotlib.pyplot as plt
98 sns.set(rc={'figure.figsize':(10,8)})
99 palette = sns.color_palette("bright", 3)
100 tsne = TSNE()
101 X_embedded = tsne.fit_transform(feat_x)
102 label2str={1:'Paper',2:'Rock',3:'Scissor'}
103 markers=[label2str[feat_y[i]] for i in range(len(feat_y))]
104 sns.scatterplot(x=X_embedded[:,0], y=X_embedded[:,1], markers=markers, hue=markers, legend='full', palette=palette)
105 plt.show()
106
107 ##### fit the model #####
108 model.fit(feat_x,feat_y)
```

```

131 # show status text
132 if status_id>0: # in game mode
133     dur=time.time()-game_start_time
134     status_id=next((i for i in range(len(status_check_points)) if dur < status_check_points[i]),-1)
135     if status_id==-1:
136         status_id, game_start_time, votes = 1, time.time(), {} # restart a game
137 overlay=cv2.rectangle(overlay, (125,40),(1500,120),color=(213, 231, 242),thickness=-1)
138 image=cv2.addWeighted(overlay, 0.5, image, 0.5, 0)
139 image=cv2.putText(image,status_texts[status_id],(150,100),cv2.FONT_HERSHEY_SIMPLEX,1,(70, 62, 57),2)
140
141 id2cords = {}
142 if status_id in [0,4]:
143     results = detect(imageRGB)
144
145     if len(results) == 0:
146         print("Nothing detected ...")
147     else:
148         image, id2cords = draw_landmarks(image, results[0]['landmarks'])
149         feat=np.array([extrac_feature(id2cords)])
150         print(feat.shape)
151         label=model.predict(np.array(feat))[0]
152         print('label=',label)
153         votes[label]=votes[label]+1 if label in votes else 1
154         if status_id==0:
155             image=cv2.putText(image,label2str[label],(250,120),cv2.FONT_HERSHEY_TRIPLEX,5,(134, 152, 109),3)
156         if status_id==4:
157             computer_move=random.randint(1,3)
158

```





THE HONG KONG
POLYTECHNIC UNIVERSITY
香港理工大學

Department of Computing
電子計算學系

Thank you!