KENTECH
Korea Institute of Energy Technology

Advanced Computer Vision
Week 11

Nov. 15, 2022

Seokju Lee

Parts of slides are by Prof. In So Kweon and Prof. Shree Nayar

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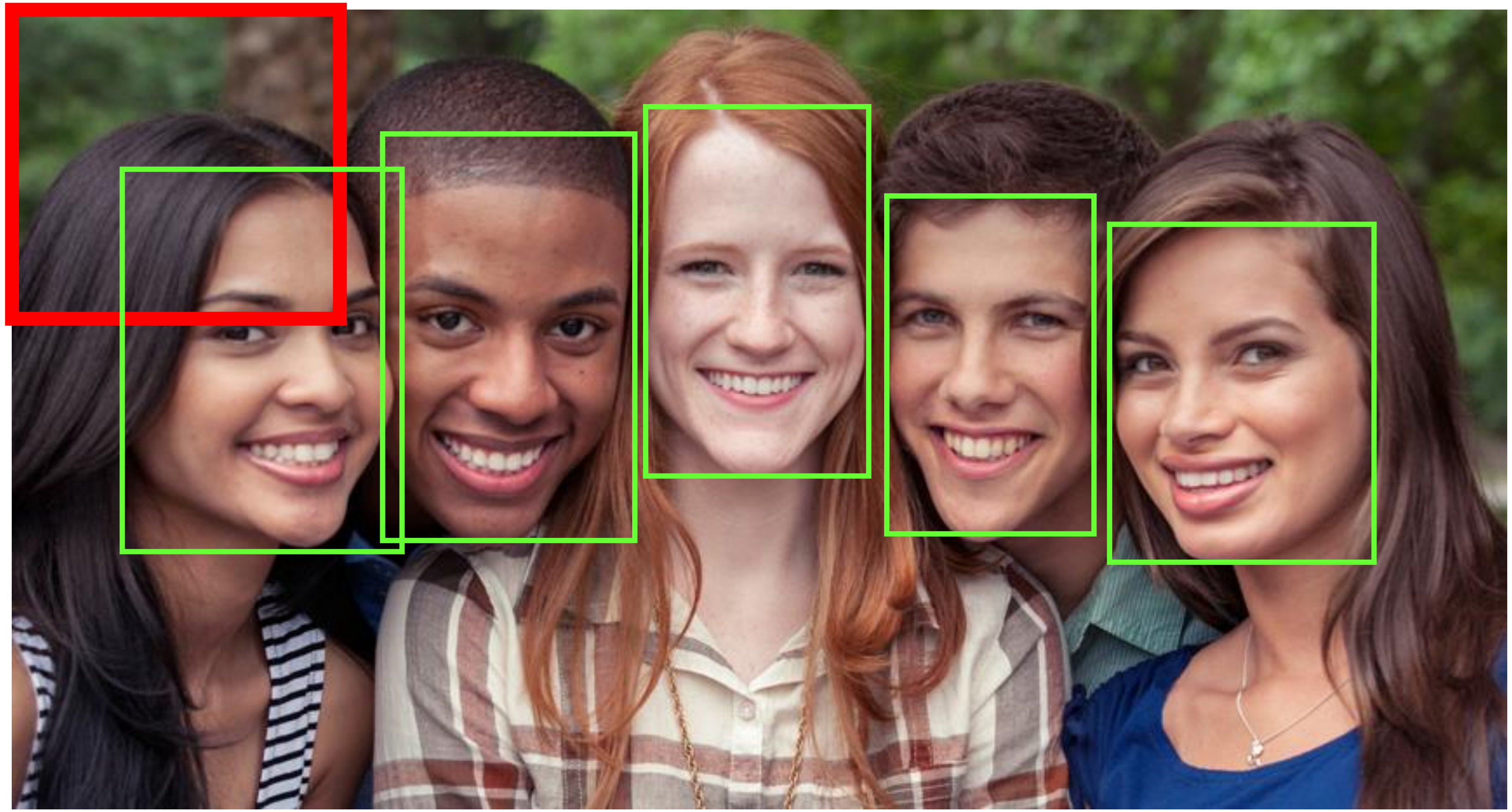
Object Recognition in the Past: Face Detection

Face Detection

Slide windows of **different** sizes across image.

At each location, **decide** the sample whether it is face or not.



Face Detection Framework

For each window:

Extract features → $\begin{bmatrix} \mathbf{f} \end{bmatrix}$ → Classify feature vector → **Yes / No**

Features: Which features represent faces well?

Classifier: How to construct a face model and efficiently classify features as face or not?

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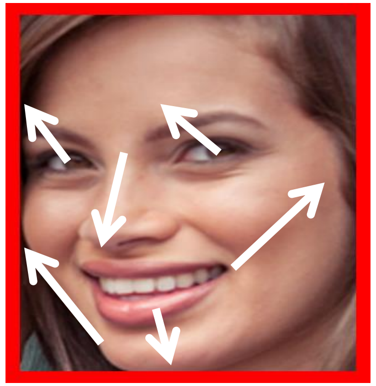
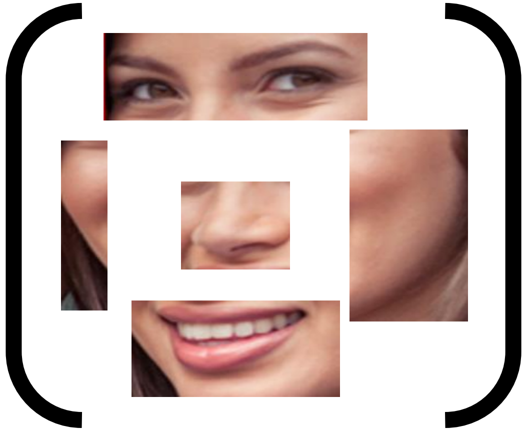
Features for Face Detection

What are Good Features?

Interest points (e.g., edges, corners, SIFT)?



Facial components (e.g., templates)?

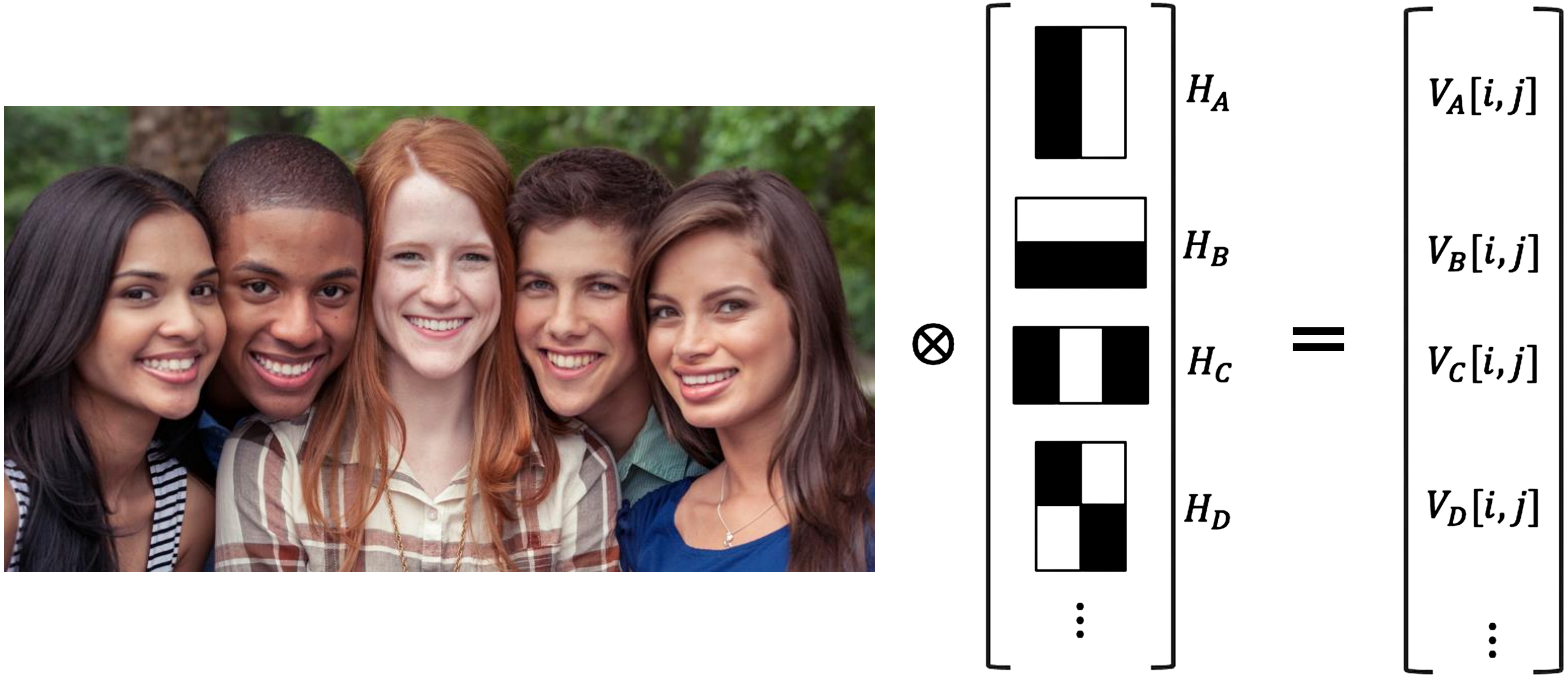


+ **Must be extremely <u>fast</u> to compute!**

(Need to process millions of windows in an image)

Haar Features

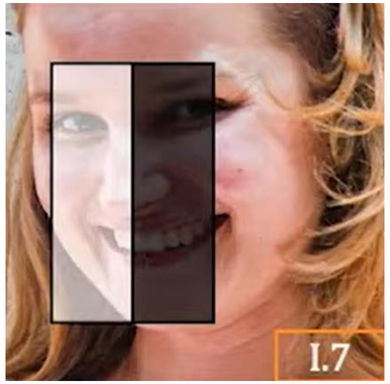
Set of correlation responses to **Haar** filters



Haar filters Haar features

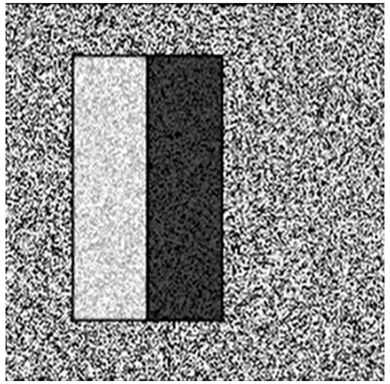
Discriminative Ability of Haar Features

Haar features are **sensitive** to **directionality** of patterns!

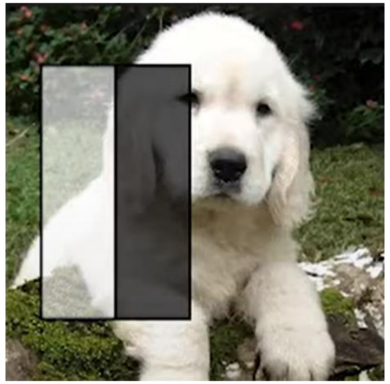


$V_A = 64$

$V_A = 16$



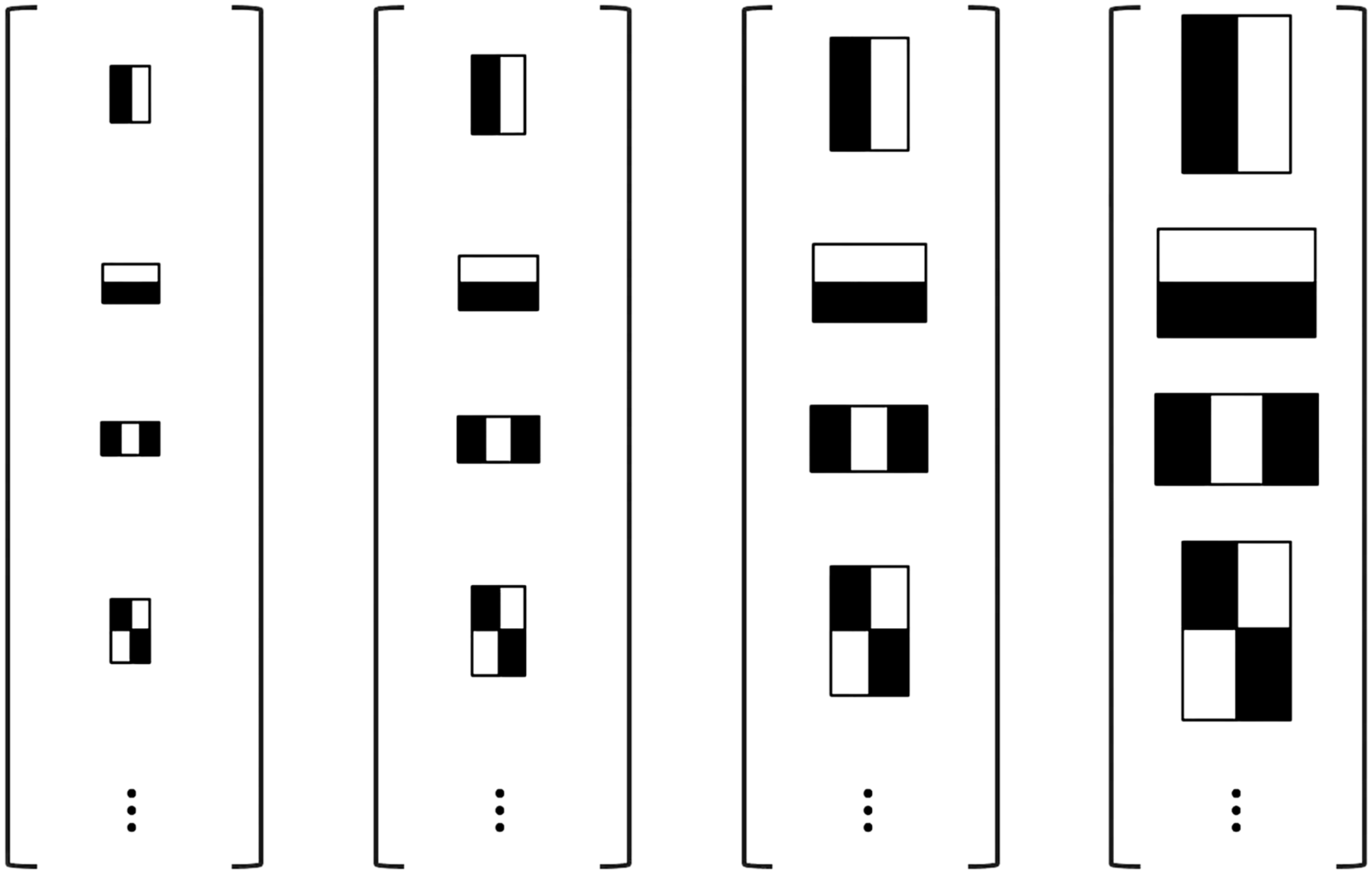
$V_A = 0$



$V_A = -127$

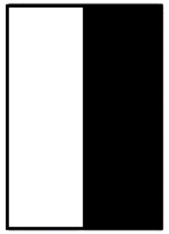
Detecting Faces of Different Size

Compute Haar features at **different scales** to detect faces of different sizes!



Computing a Haar Feature

$\otimes$



H_A

White = 1, Black = -1

Response to Filter H_A at location (i, j):

$$V_A[i,j] = \sum_m \sum_n I[m-i, n-j] H_A[m,n]$$

$$V_A[i,j] = \sum (\text{pixel intensities in white area}) - \sum (\text{pixels intensities in black area})$$

Computing Integral Image

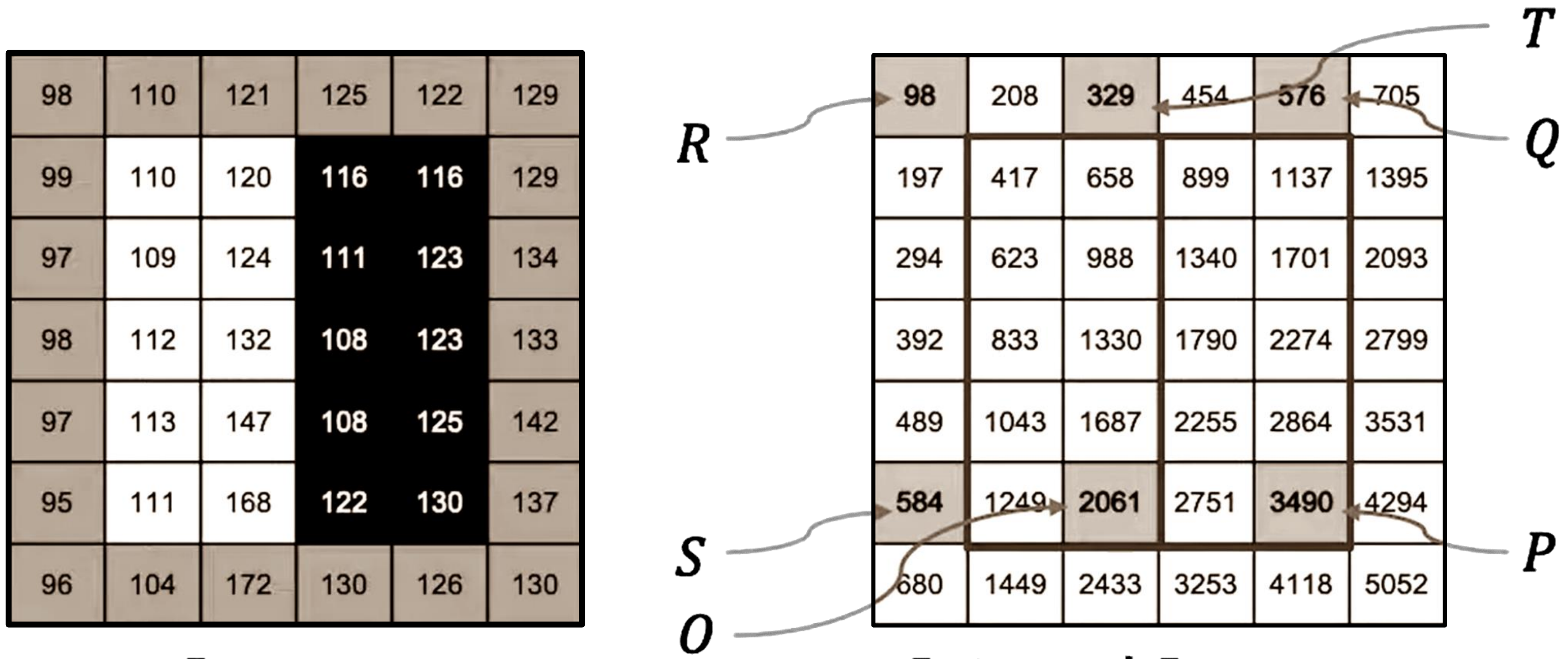


Image I Integral Image II

$$V_A = \sum(\textit{pixel intensities in white}) - \sum(\textit{pixel intensities in black})$$

$$= (II_O - II_T + II_R - II_S) - (II_P - II_Q + II_T - II_O)$$

$$= (2061 - 329 + 98 - 584) - (3490 - 576 + 329 - 2061) = 64$$

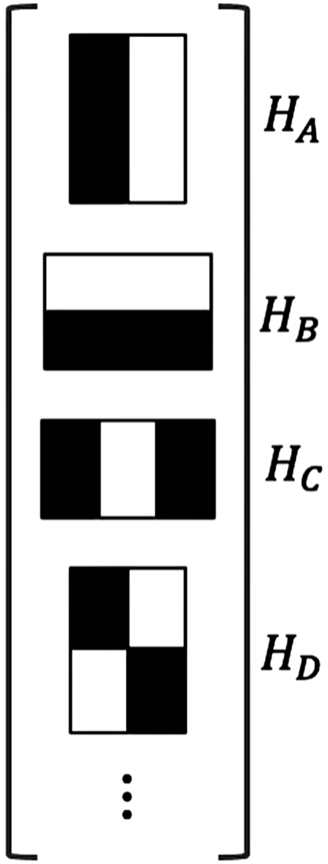
Computational Cost: Only 7 additions

Haar Features Using Integral Images

Integral image needs to be computed **once** per test image.

Allows **fast** computations of Haar features.

$\otimes$



$$=$$

$$\begin{bmatrix} V_A[i,j] \\ V_B[i,j] \\ V_C[i,j] \\ V_D[i,j] \\ \vdots \end{bmatrix}$$

Haar filters

Haar features

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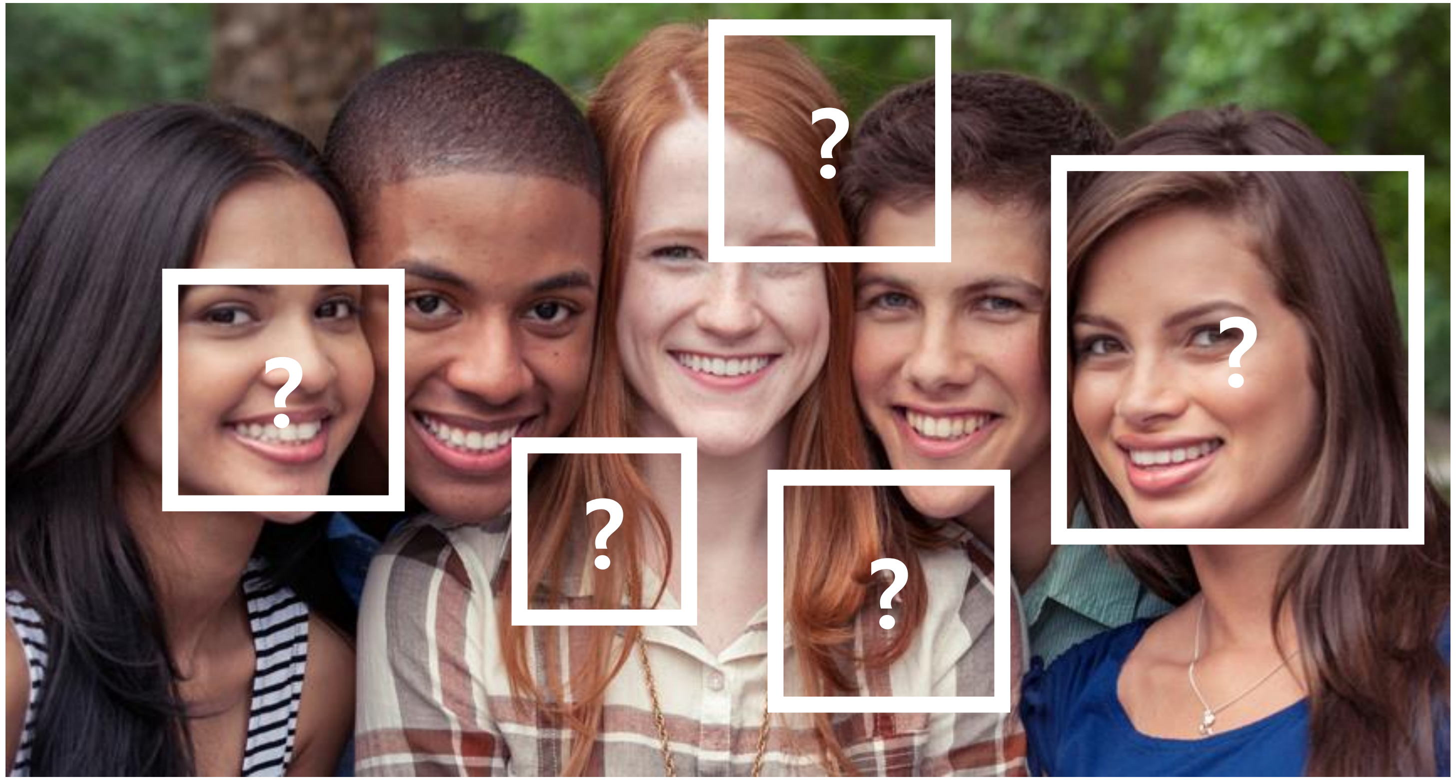
Classifier for Face Detection

Classifier for Face Detection

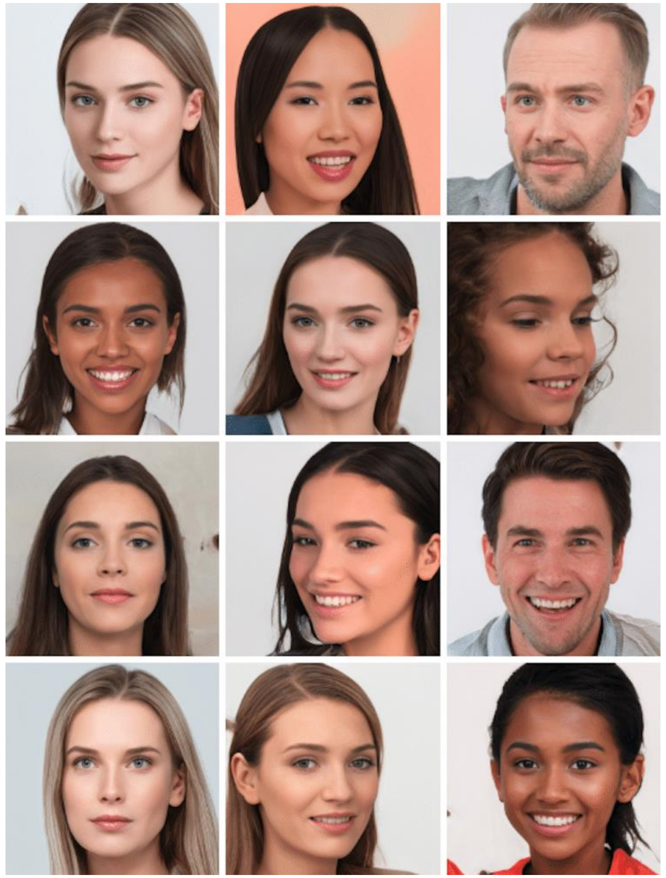
Given the **features** for a window,

How to **decide** whether it contains a face or not?

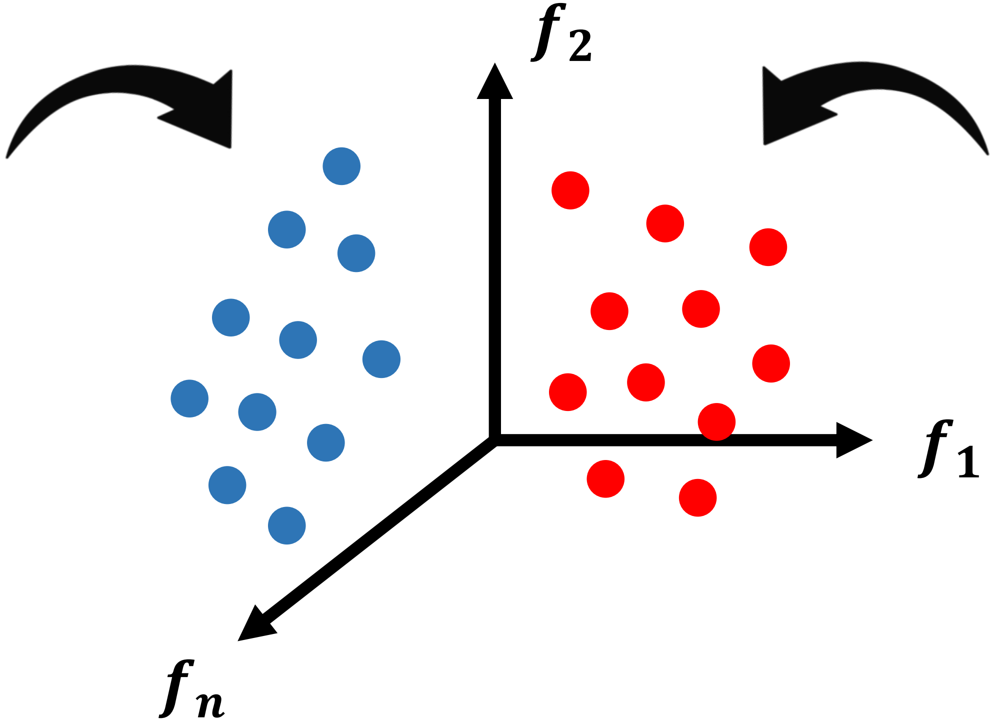


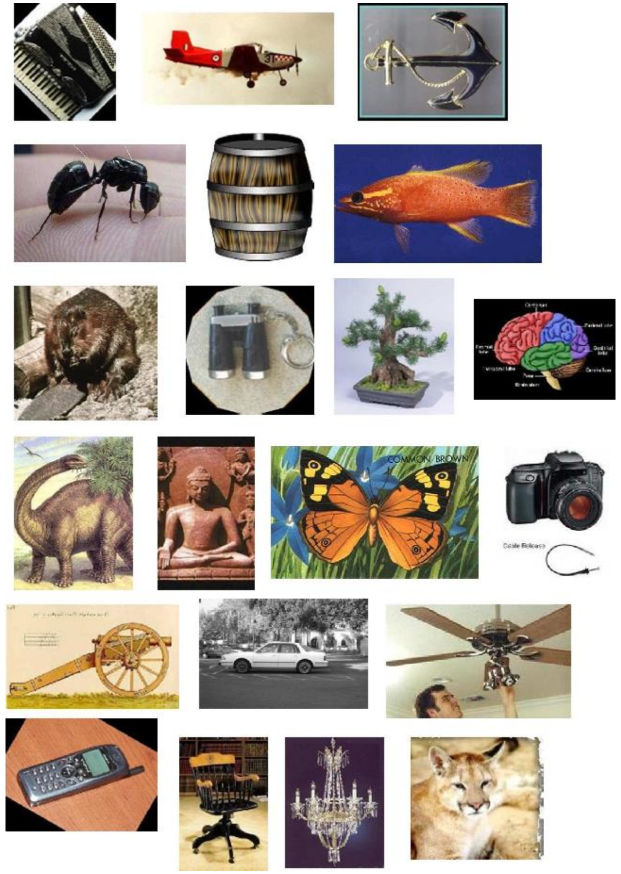
Feature Space

Haar features $\mathbf{f}$ (a vector) at a pixel is a point in an n-D space, $\mathbf{f} \in \mathbb{R}^n$



Training data of **face**

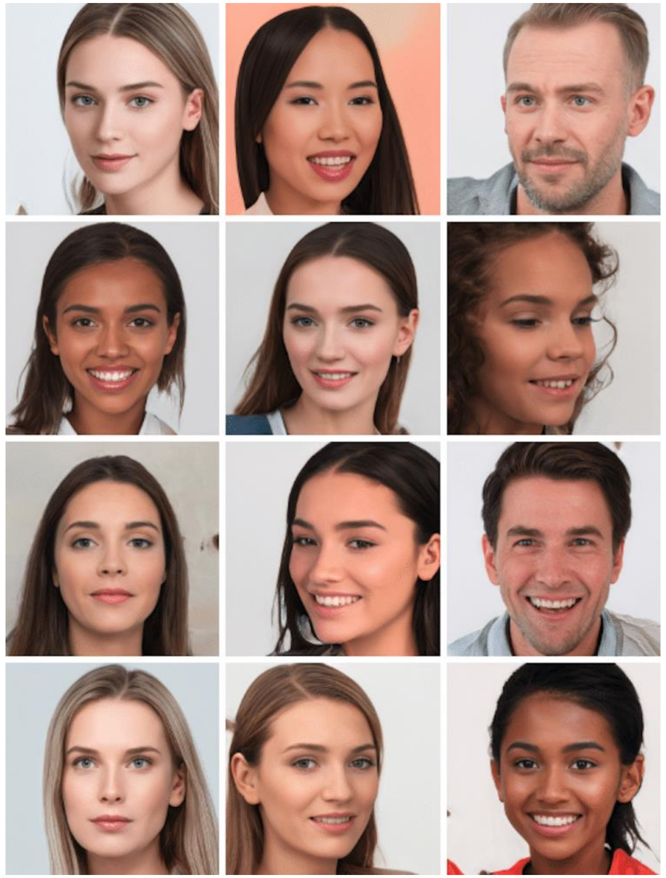




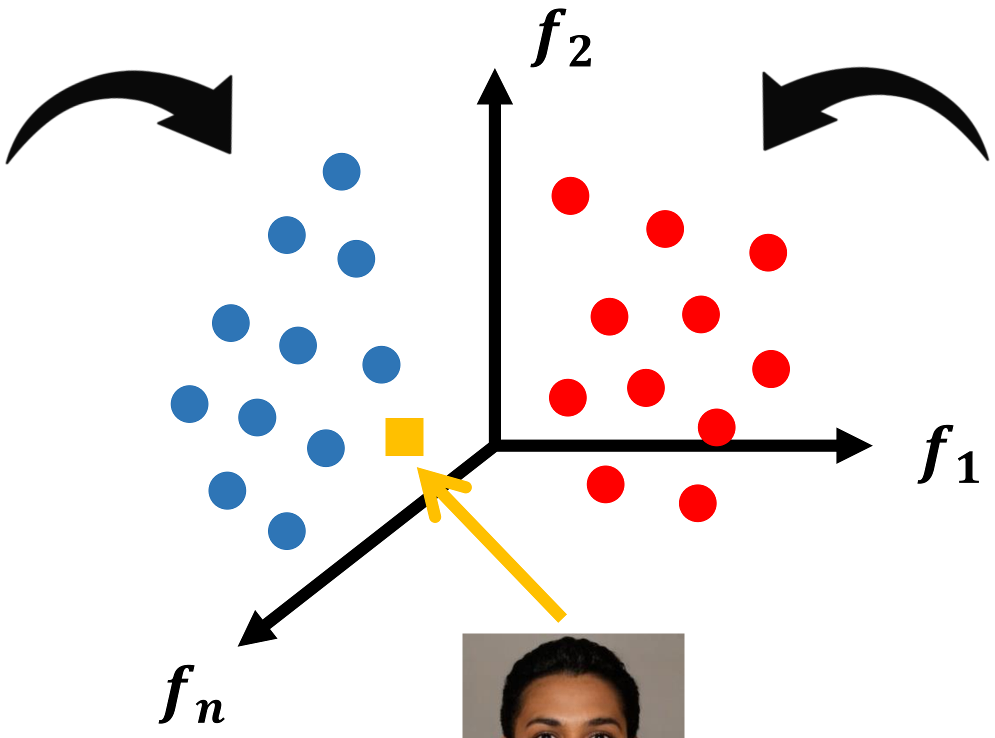
Training data of **non-face**
(Caltech 101)

Nearest Neighbor Classifier

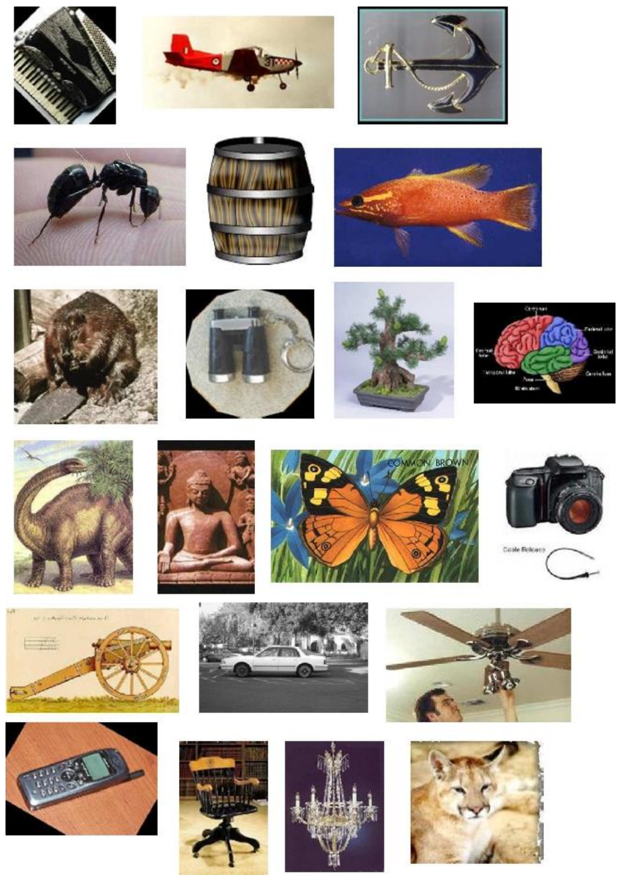
Find the **nearest** training sample using $\boldsymbol{L^2}$ distance and assign its label.



Training data of **face**



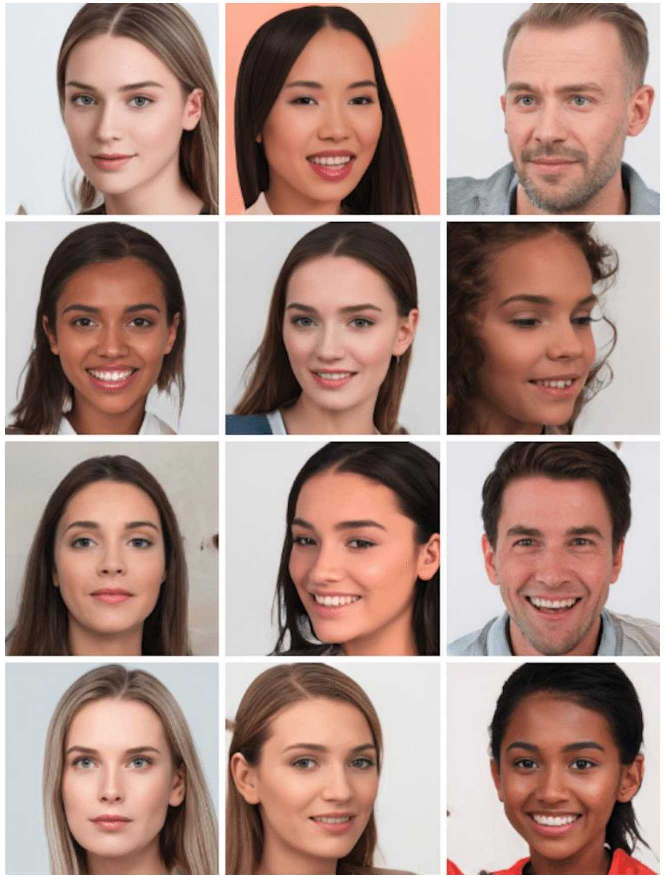
Test image
(true positive)



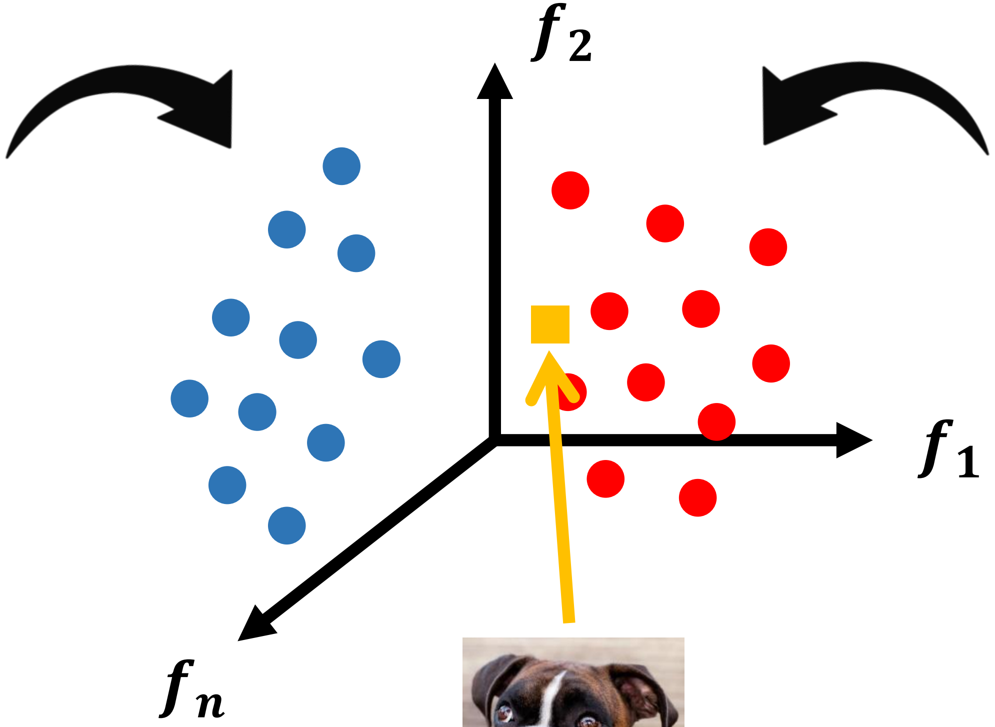
Training data of **non-face**
(Caltech 101)

Nearest Neighbor Classifier

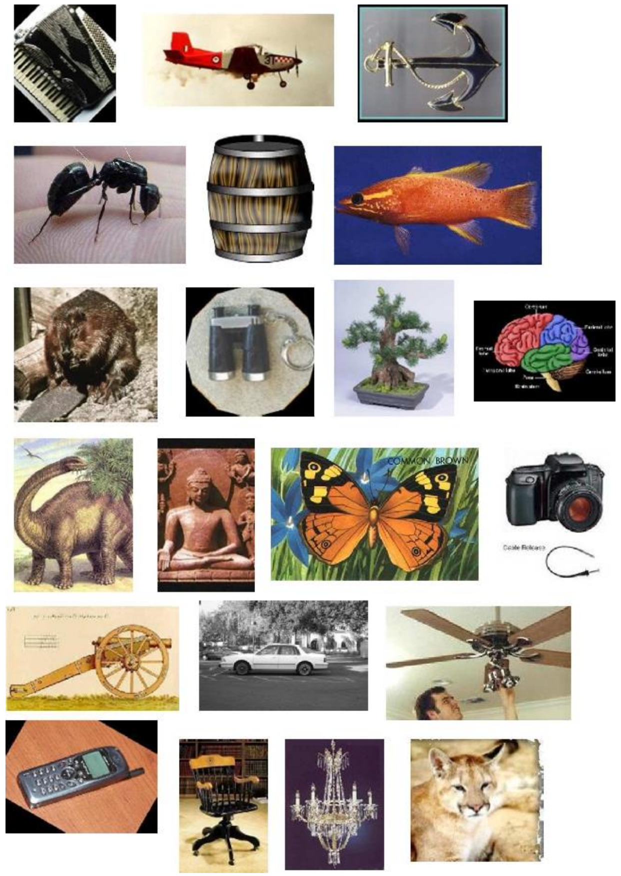
Find the **nearest** training sample using L^2 distance and assign its label.



Training data of **face**



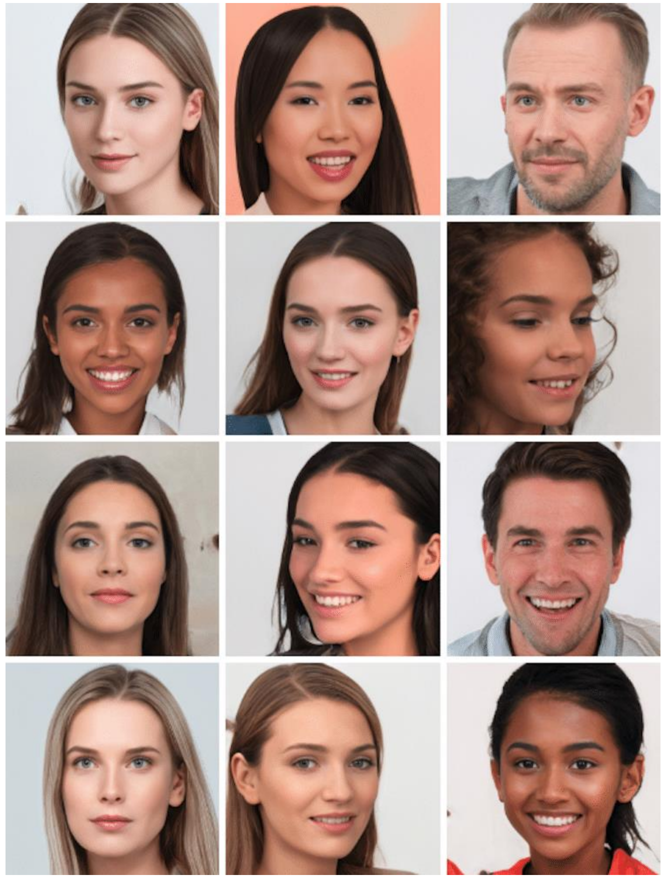
Test image
(true negative)



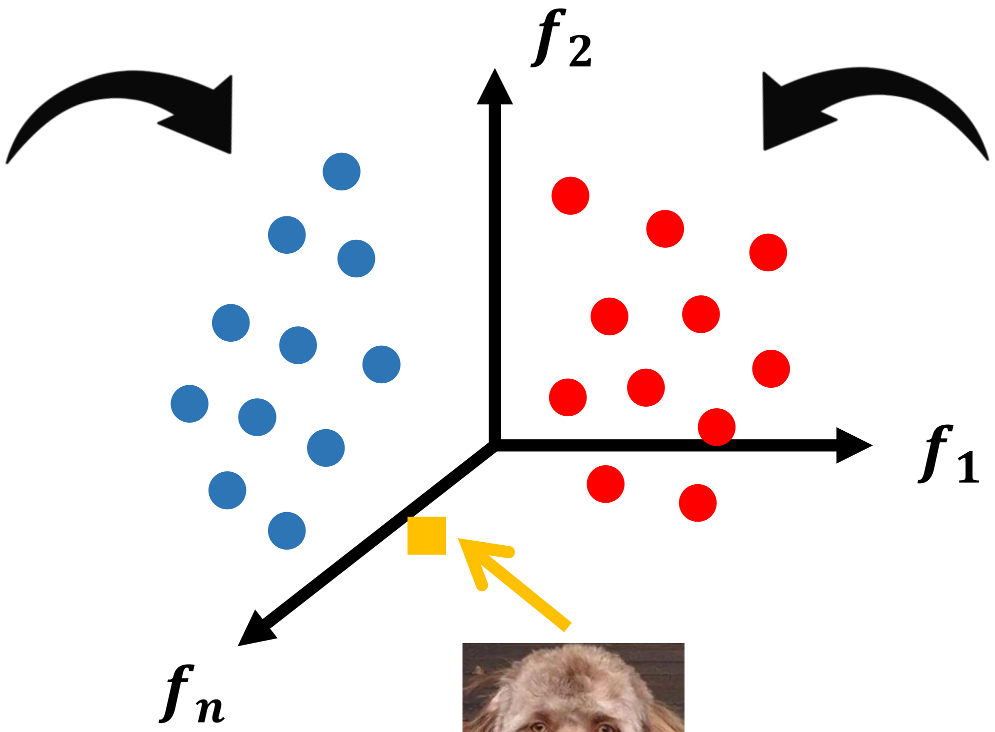
Training data of **non-face**
(Caltech 101)

Nearest Neighbor Classifier

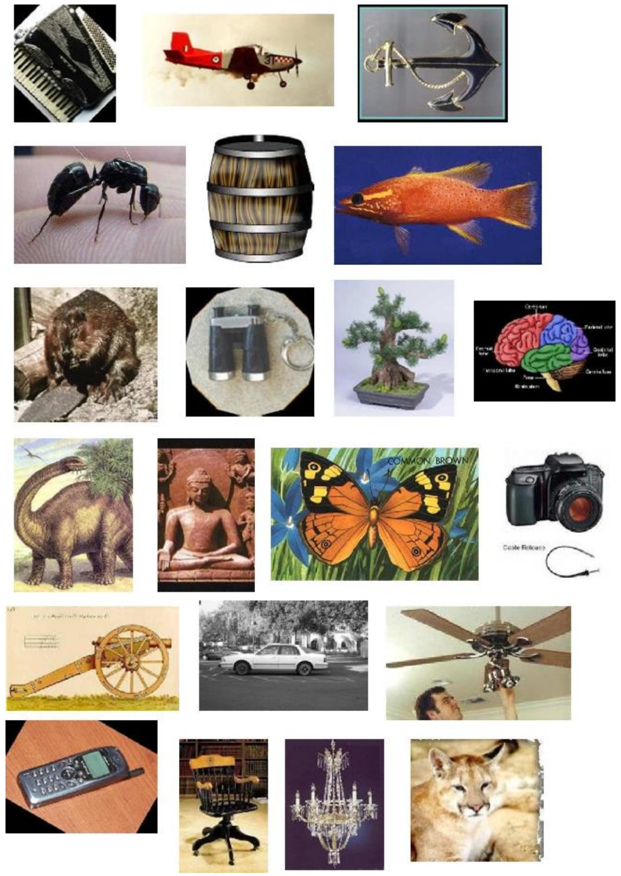
Find the **nearest** training sample using L^2 distance and assign its label.



Training data of **face**



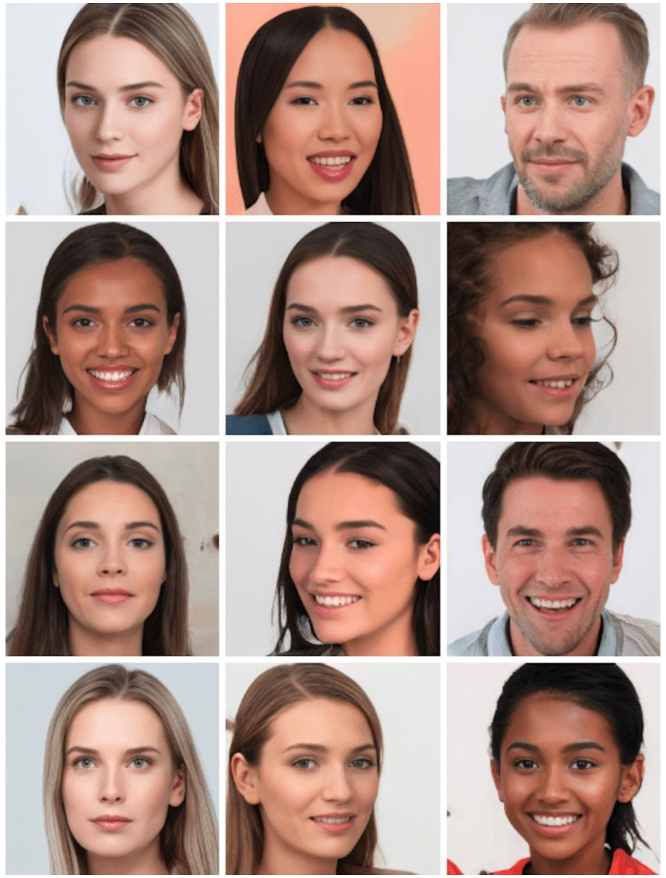
Test image
(false positive)



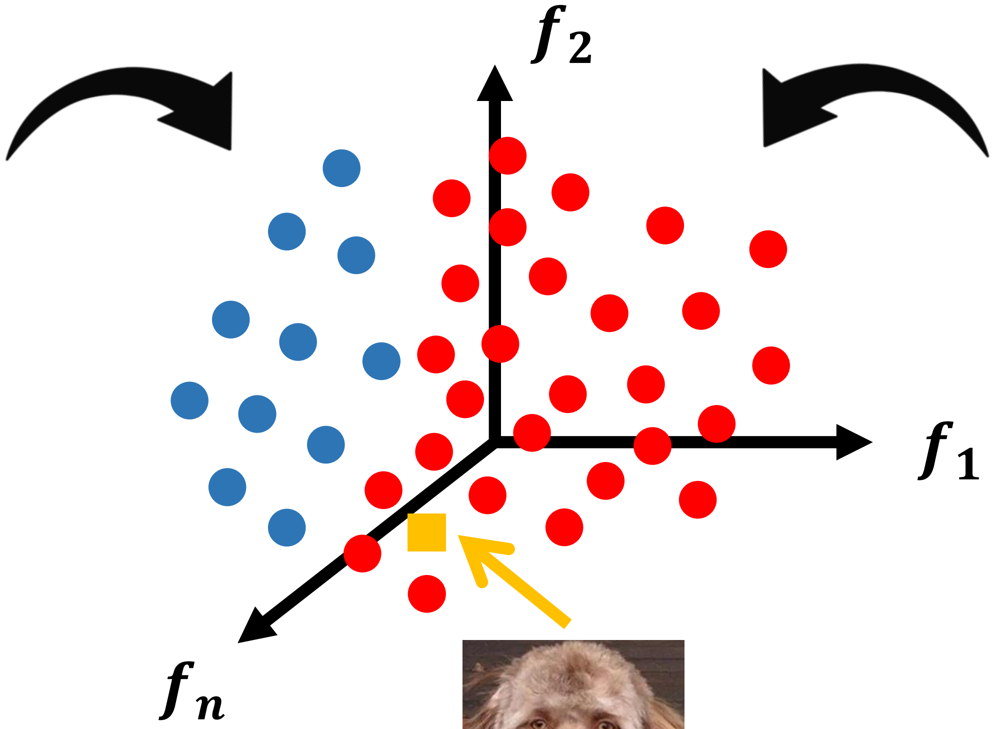
Training data of **non-face**
(Caltech 101)

Nearest Neighbor Classifier

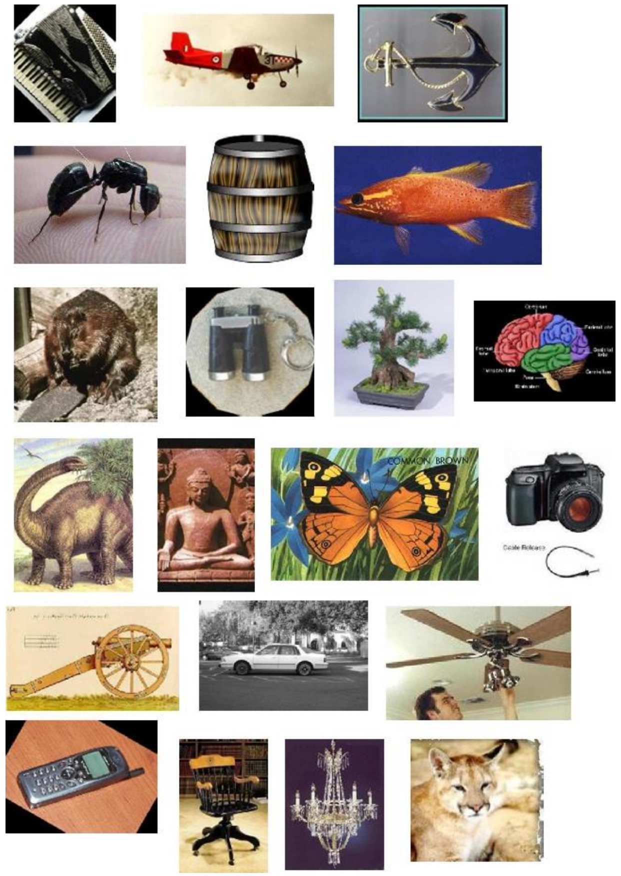
Larger the training set, **more robust** the NN classifier!



Training data of **face**



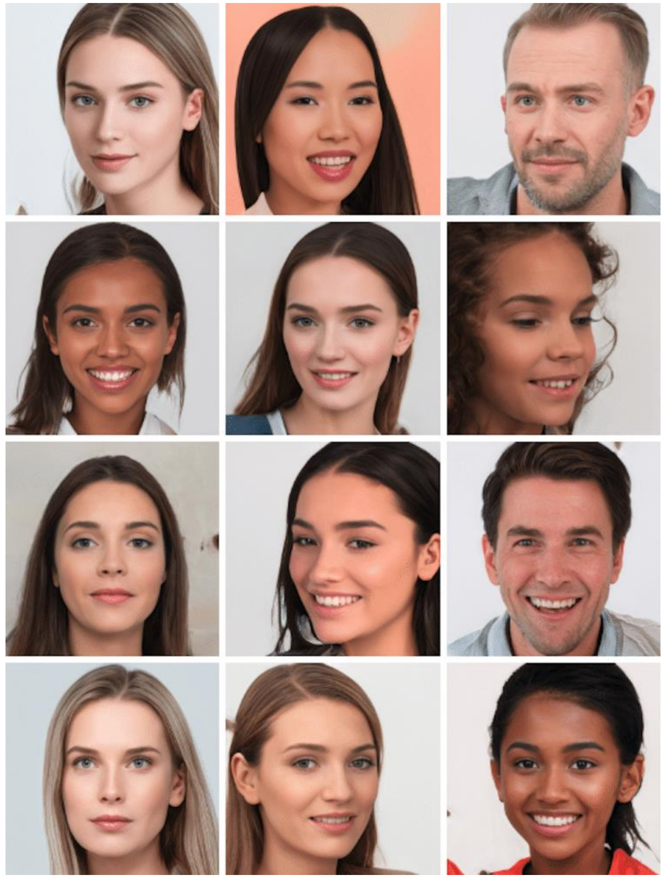
Test image
(false positive)



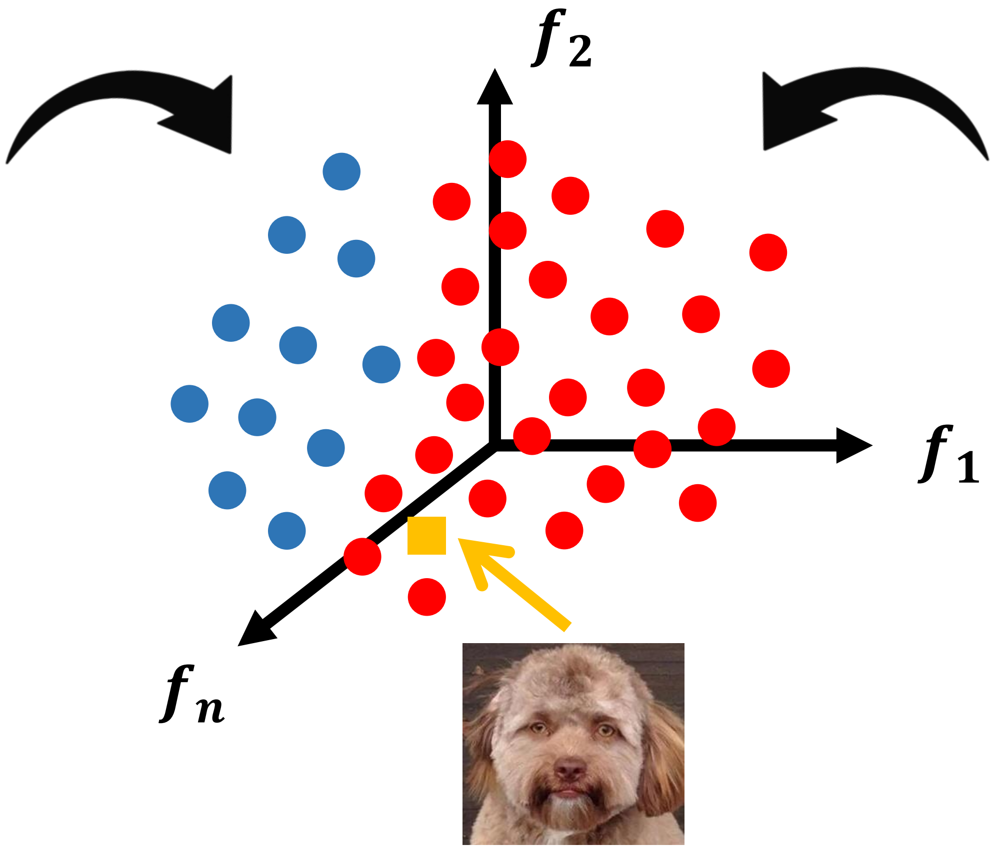
Training data of **non-face**
(Caltech 101)

Nearest Neighbor Classifier

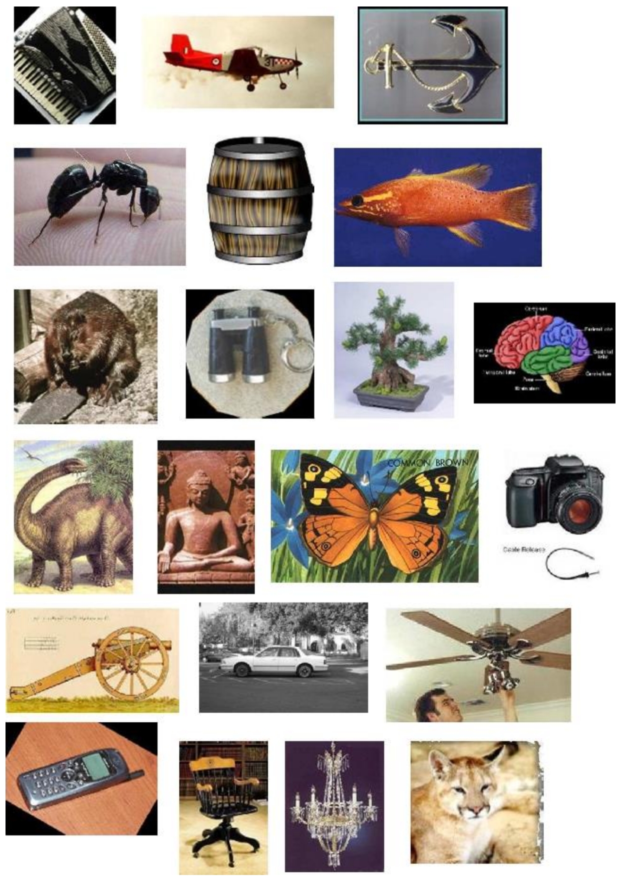
Larger the training set, **slower** the NN classifier!



Training data of **face**



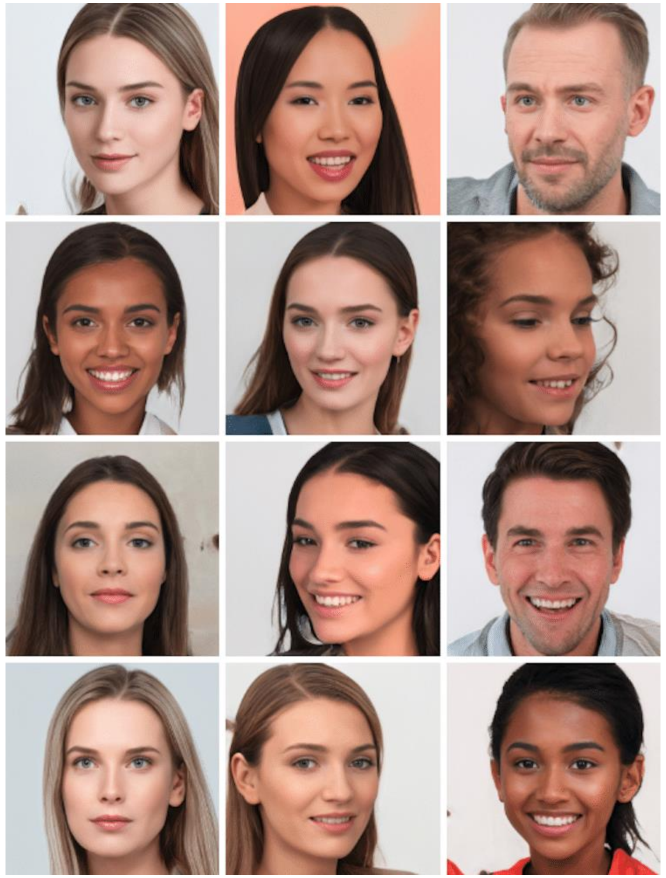
Test image
(false positive)



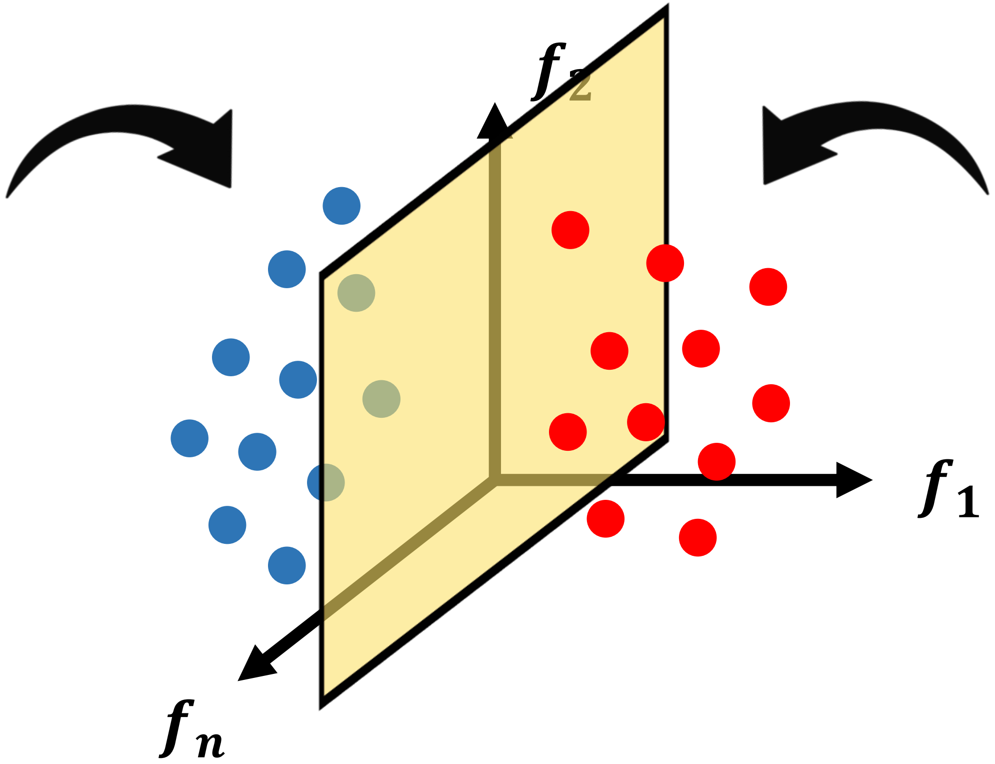
Training data of **non-face**
(Caltech 101)

Decision Boundary

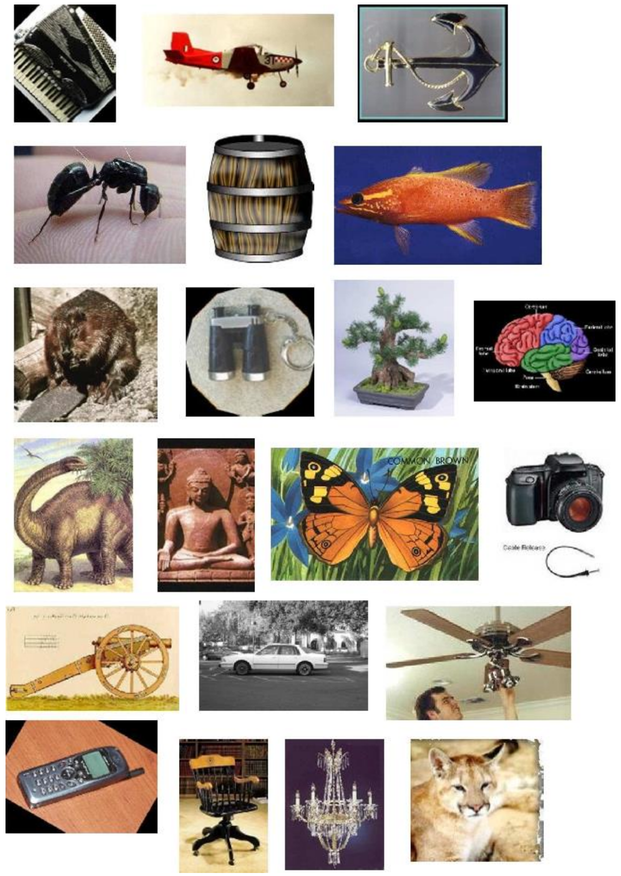
A simple decision boundary **separates** face and non-face.



Training data of **face**



→ **How to design it?**



Training data of **non-face**
(Caltech 101)

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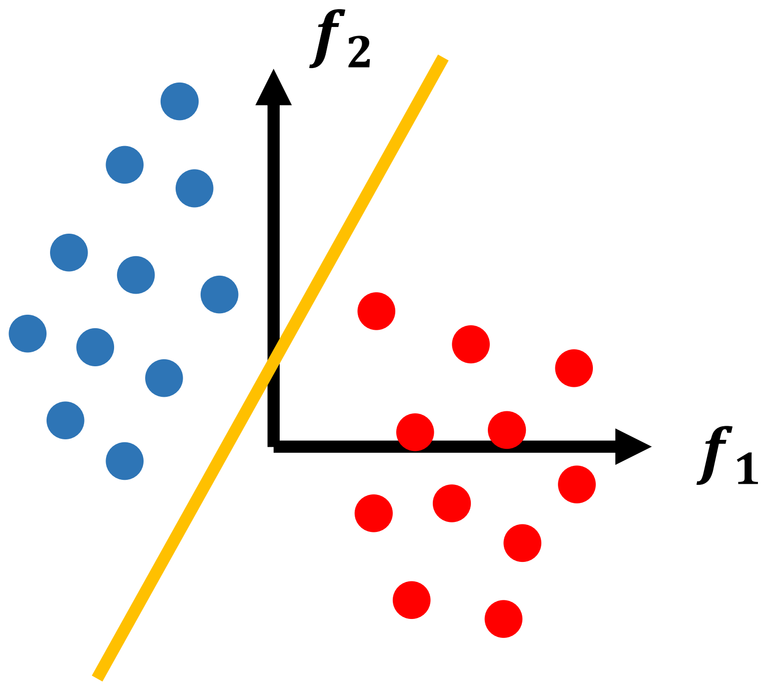
Support Vector Machine (SVM)

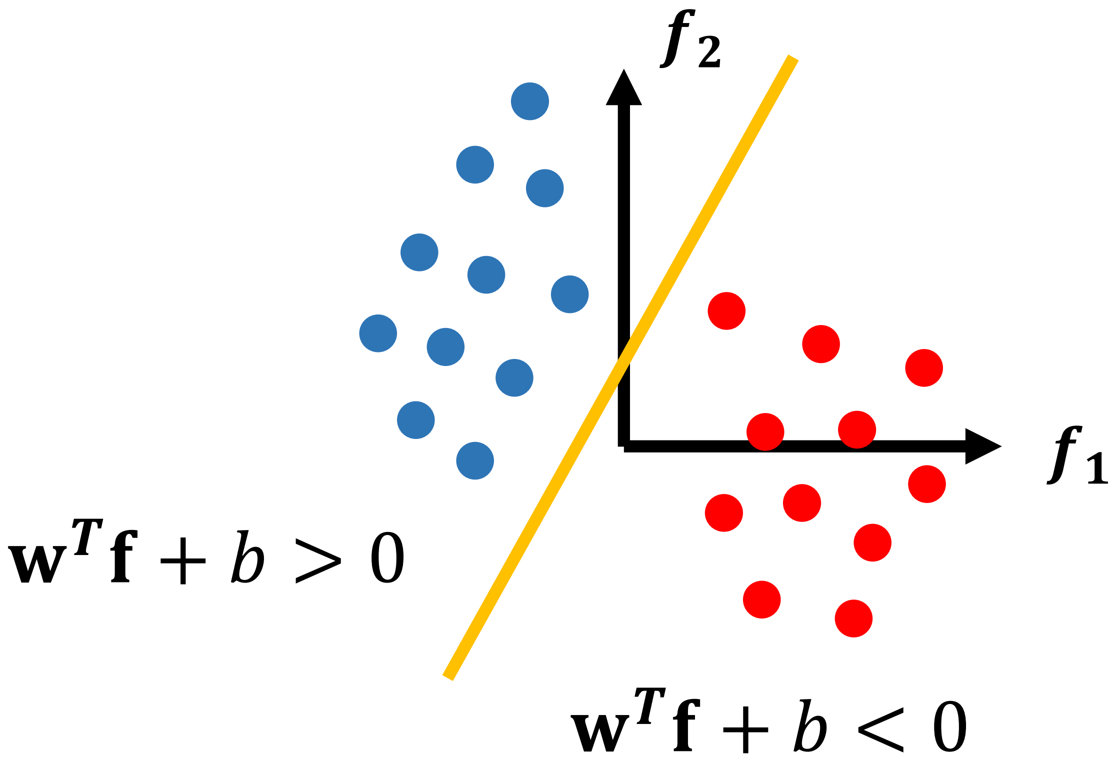
Linear Decision Boundaries

A linear decision boundary in 2D space is a 1D line.



Linear Decision Boundaries

A linear decision boundary in 2D space is a 1D line.



Equation of Line:

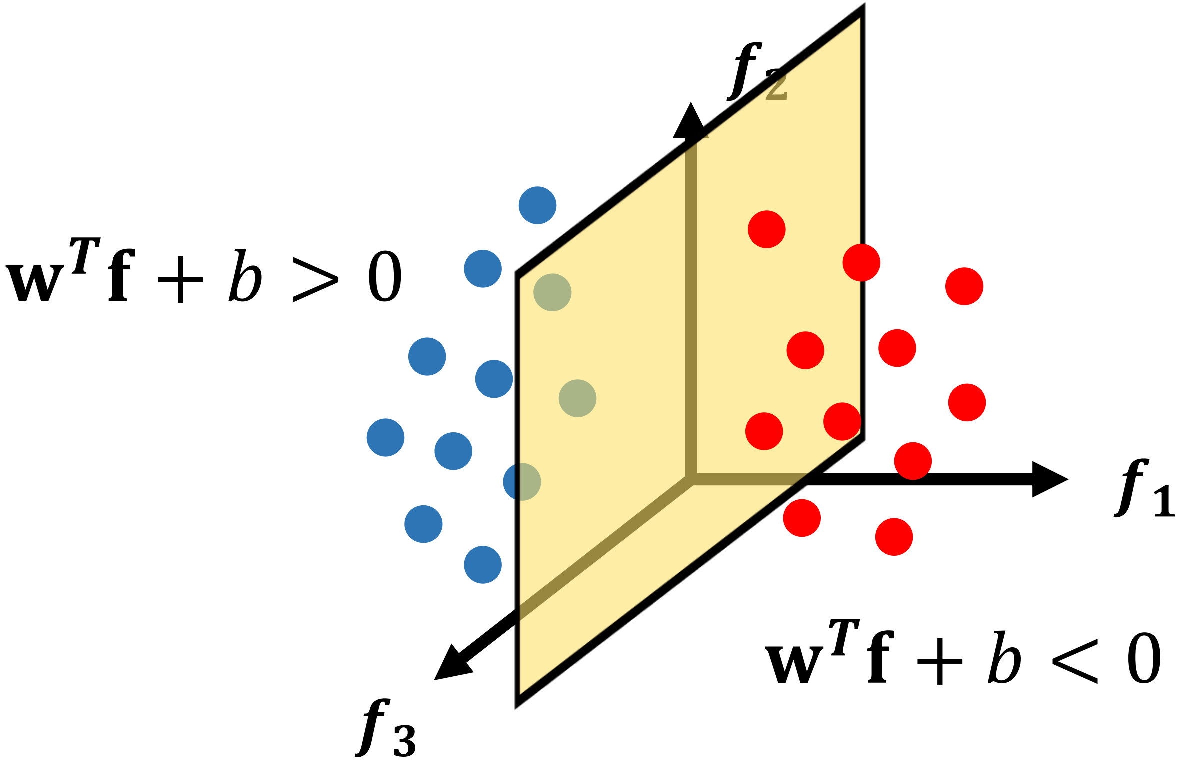
$$w_1 f_1 + w_2 f_2 + b = 0$$

$$\begin{bmatrix} w_1 & w_2 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \end{bmatrix} + b = 0$$

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

Linear Decision Boundaries

A linear decision boundary in 3D space is a 2D plane.



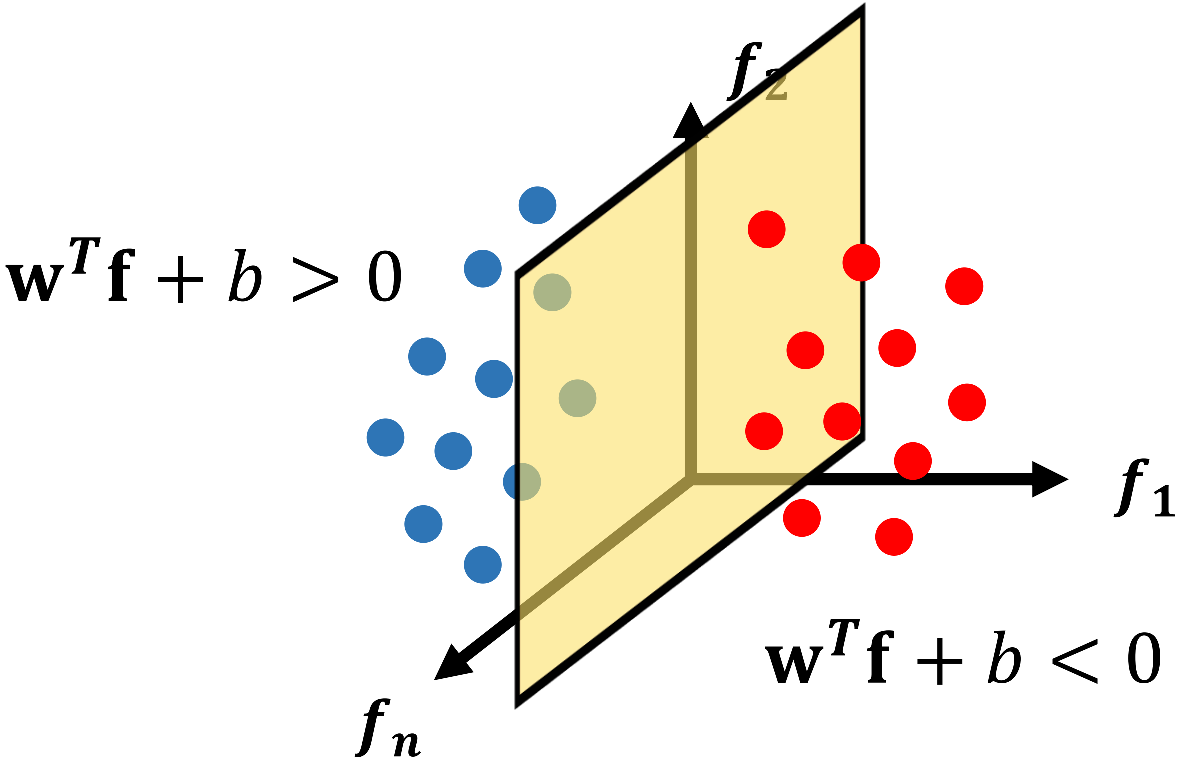
Equation of Plane:

$$w_1 f_1 + w_2 f_2 + w_3 f_3 + b = 0$$

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

Linear Decision Boundaries

A linear decision boundary in n-D space is a $(n-1)$-D hyperplane.



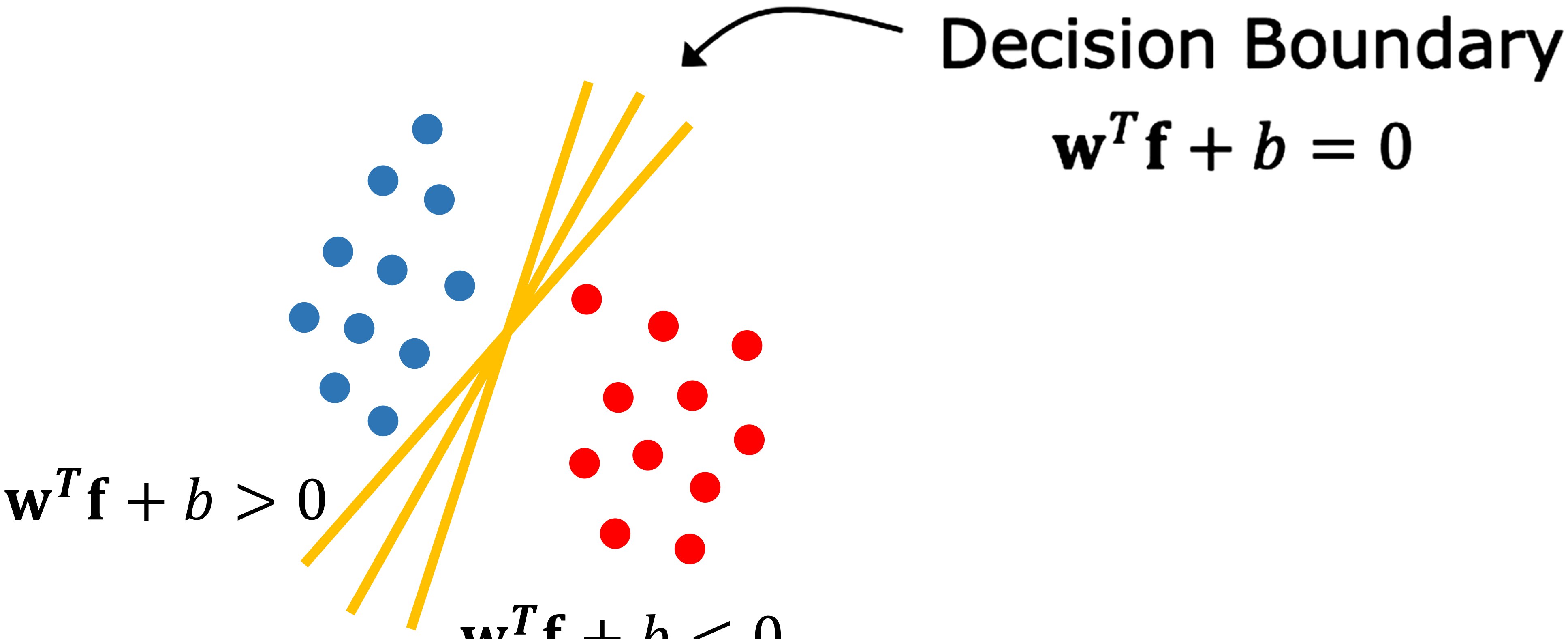
Equation of Hyperplane:

$$w_1 f_1 + w_2 f_2 + \cdots + w_n f_n + b = 0$$

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

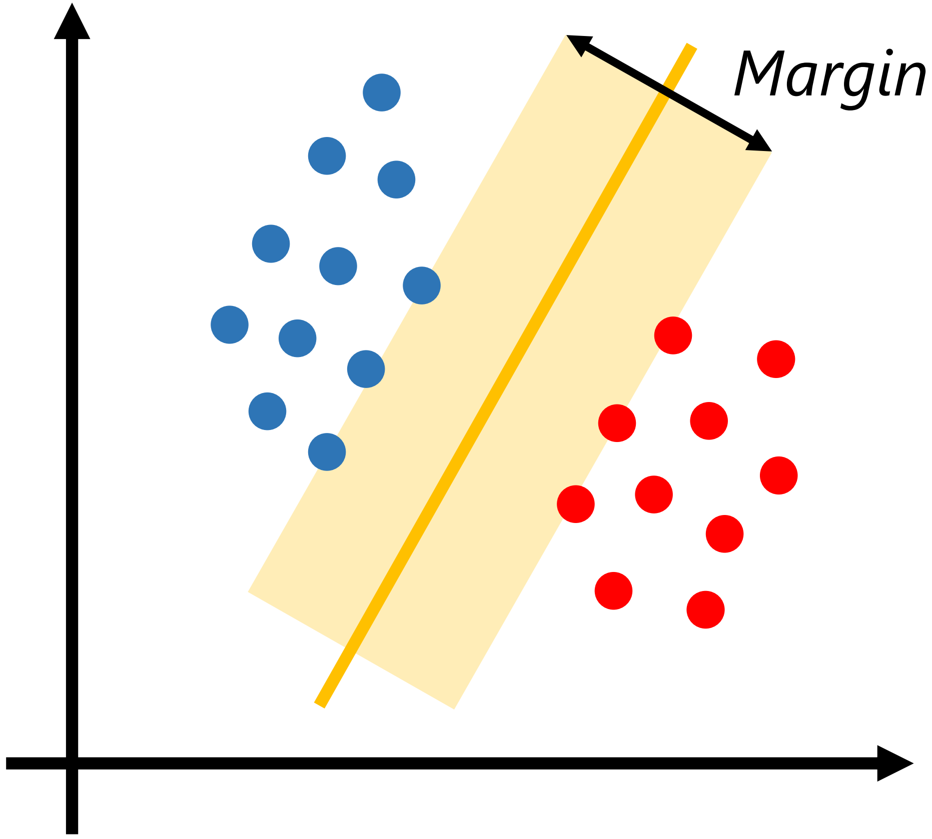
Decision Boundary ($\mathbf{w}$, b)

What is the **optimal** decision boundary?



Evaluating a Decision Boundary

Margin or **safe zone**: The width that the boundary could be increased by, before hitting a feature point.

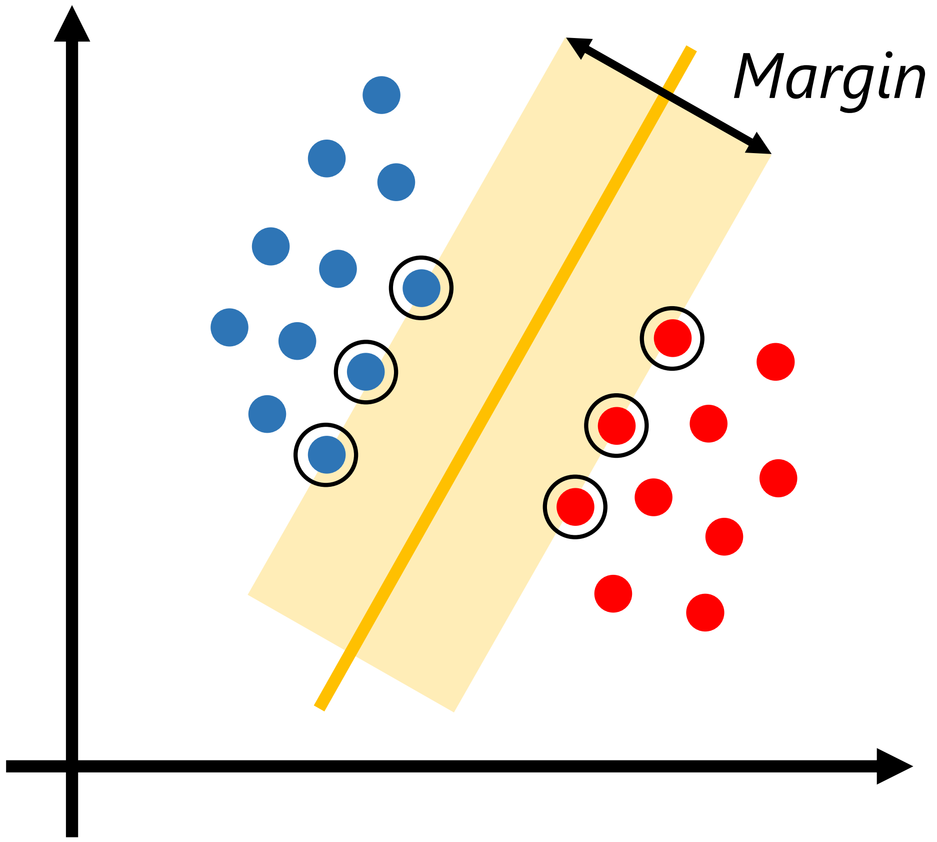


→ Choose decision boundary with **maximum** margin!

Support Vector Machine (SVM)

Classifier optimized to **maximize** margin.

Support vectors: **Closest** data samples to the boundary.



→ Decision boundary & margin are **only** dependent on support vectors!

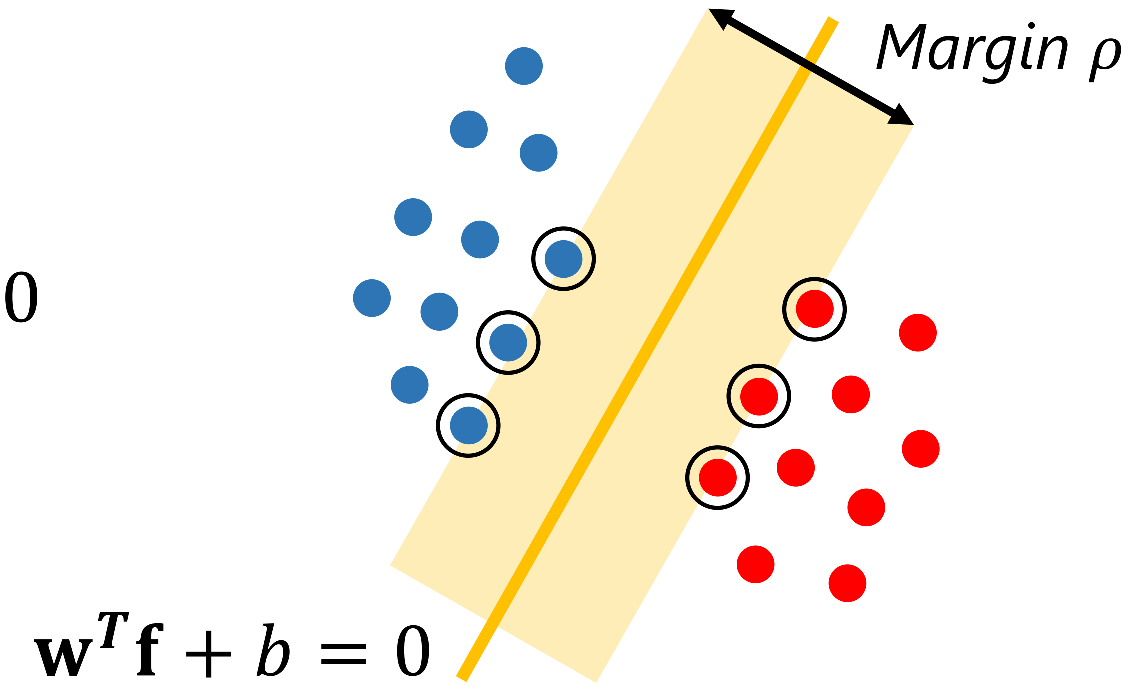
Support Vector Machine (SVM)

Given:

- k training images $\{I_1, I_2, \dots, I_k\}$ and their Haar features $\{\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_k\}$.
- k corresponding labels $\{\lambda_1, \lambda_2, \dots, \lambda_k\}$, where $\lambda_j = +1$ if I_j is a face and $\lambda_j = -1$ if I_j is a face.

Find:

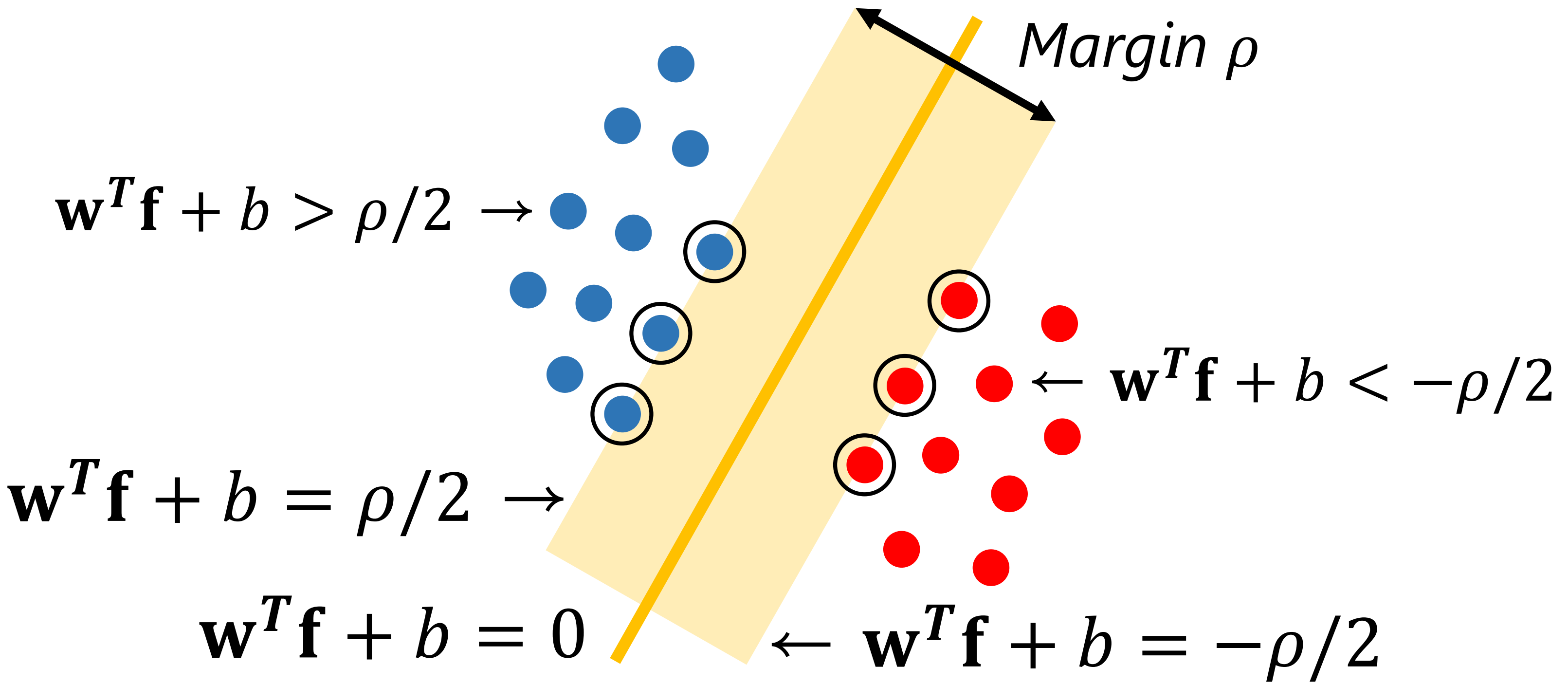
- Decision boundary $\mathbf{w}^T\mathbf{f} + b = 0$
- with maximum margin ρ



Finding Decision Boundary $(\mathbf{w}, b)$

For each training sample $(\mathbf{f}_i, \lambda_i)$:

$$\left.\begin{array}{ll} \text{If } \lambda_i = +1: & \mathbf{w}^T\mathbf{f}_i + b \geq \rho/2 \\ \text{If } \lambda_i = -1: & \mathbf{w}^T\mathbf{f}_i + b \leq -\rho/2 \end{array}\right\} \quad \boxed{\lambda_i(\mathbf{w}^T\mathbf{f}_i + b) \geq \rho/2}$$



Finding Decision Boundary ($\mathbf{w}$, b)

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If $\mathcal{S}$ is the set of support vectors,

Then for every support vector $s \in \mathcal{S}$: $\boxed{\lambda_s(\mathbf{w}^T\mathbf{f}_s + b) = \rho/2}$

Numerical methods exist to find
$\mathbf{w}, b$ and $\mathcal{S}$ that maximize ρ

Classification Using SVM

Given: Haar features $\mathbf{f}$ for an image window and SVM parameters $\mathbf{w}, b, \rho, \mathcal{S}$

Classification:

Compute $d = \mathbf{w}^T\mathbf{f} + b$

If:
$$\begin{cases} d \geq \rho/2 & \text{Face} \\ d > 0 \; and \; d < \rho/2 & \text{Probably face} \\ d < 0 \; and \; d > -\rho/2 & \text{Probably non-face} \\ d \leq -\rho/2 & \text{Non-face} \end{cases}$$

Experiments

Face detection & SVM

Updated codes are available in https://view.kentech.ac.kr/f088fa7f-874e-44bc-bd6d-6084b42dfdf7

```
$ python face.py
```

```
$ python svm.py
```