



Dr. George Karraz, Ph. D.



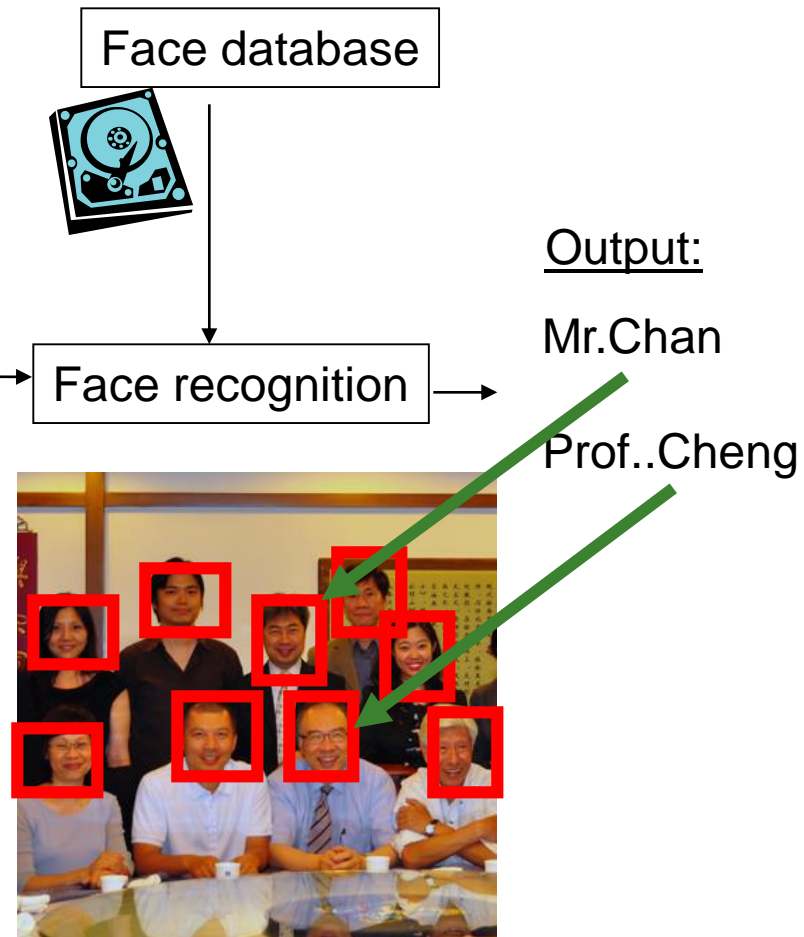
# Ch. 6: Face detection

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# Introduction

## ■ Face interface

- Face detection
- Face recognition



# Face detection [1]

- To detect faces in an image (Not recognize it yet)
- Challenges
  - A picture has 0,1 or many faces.
  - Faces are not the same: with spectacles, mustache etc.
  - Sizes of faces vary a lot.
- Available in most digital cameras nowadays
- The simple method
  - Slide a window across the window and detect faces.
    - Too slow, pictures have too many pixels.  
(1280x1024=1.3M pixels)

# Evaluation of face detection

- Detection rate
  - Total number of faces that are correctly detected/total number of faces actually exist in the picture
  - Should be high > 95%.
- False positive rate
  - The detector output is positive but it is false (there is actually no face). Definition of False positive: A result that is erroneously positive when a situation is normal. An example of a false positive: a particular test designed to detect cancer of the is positive but the person does not have cancer. (<http://www.medterms.com/script/main/art.a>)
  - Should be low  $<10^{-6}$
- A good system has
  - High detection rate,
  - Low false positive rate.



False positive result

# Example

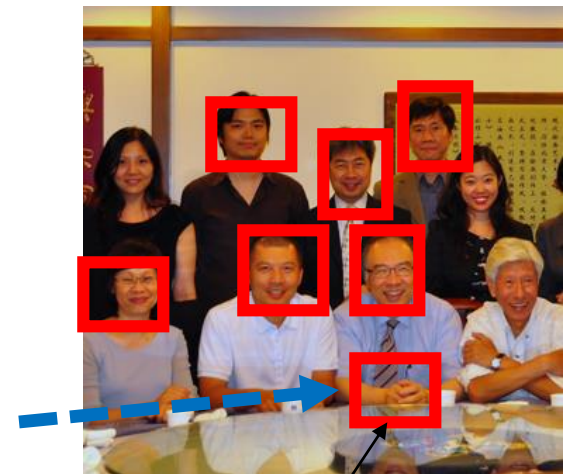
- What are the detection rate and false positive rate here?

- Answer

- detection rate= $(6/9)*100\%$
- false positive rate= $(1/7)*100\%$

6 faces correctly detected in the picture, 9 actually faces exist in the image

7 windows reported to have faces, but in 1 window it is not a face



False positive result

# The Viola and Jones method [1]

- The most famous method
- Training may need weeks
- Recognition is very fast, e.g. real-time for digital cameras.
- Techniques
  1. Integral image for feature extraction
  2. Ada-Boost for face detection
  3. Attentional cascade for fast rejection of non-face sub-windows

# Class exercise 6.1

- Detected results are in red frames
  - What are the detection rate and false positive rate here?
- Answer
- detection rate=?
  - false positive rate=?





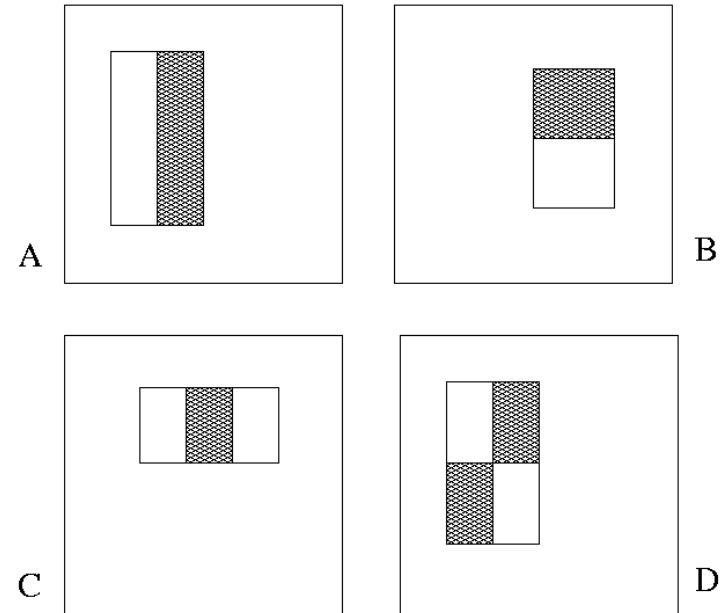
# The Viola and Jones method

## Technique 1:

Integral image for feature extraction

## Image Features ref[3]

A very simple feature calculation method  
“Rectangle filters”



*Rectangle\_Feature\_value*  $f =$

$$\sum (\text{pixels values in white area}) - \sum (\text{pixels values in shaded area})$$

# Example

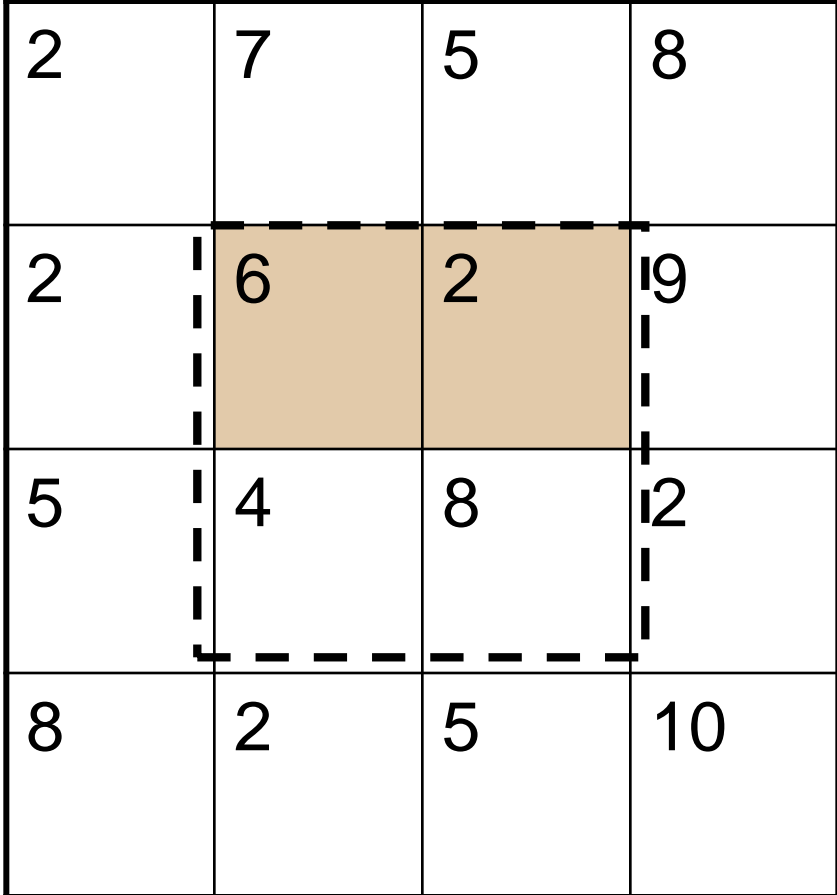
- Find the *Rectangle\_Feature\_value* (f) of the box enclosed by the dotted line
- *Rectangle\_Feature\_value*  $f =$
- $\sum (\text{pixels values in white area}) - \sum (\text{pixels values in shaded area})$
- $f = (8+7) - (0+1)$
- $= 15 - 1 = 14$

|   |   |   |   |
|---|---|---|---|
| 1 | 2 | 3 | 3 |
| 3 | 0 | 1 | 3 |
| 5 | 8 | 7 | 1 |
| 0 | 2 | 3 | 6 |

# Class exercise 6.2

- Find the *Rectangle\_Feature\_value* ( $f$ ) of the box enclosed by the dotted line
- *Rectangle\_Feature\_value*  $f =$
- $\sum (\text{pixels values in white area}) - \sum (\text{pixels values in shaded area})$
- $f =$

|   |   |   |    |
|---|---|---|----|
| 2 | 7 | 5 | 8  |
| 2 | 6 | 2 | 19 |
| 5 | 4 | 8 | 12 |
| 8 | 2 | 5 | 10 |

A 4x4 grid of numbers. The values are: Row 1: 2, 7, 5, 8; Row 2: 2, 6, 2, 19; Row 3: 5, 4, 8, 12; Row 4: 8, 2, 5, 10. A 2x2 area in the center (rows 2-3, columns 2-3) is shaded brown. A dotted line box encloses the shaded area and the cell (2,4) with value 19.

# Example: A simple face detection method using one feature

□ *Rectangle\_Feature\_value*  $f$

□  $f = \sum (\text{pixels in white area}) - \sum (\text{pixels in shaded area})$

□ If  $f$  is large, then it is face ,i.e.

□ if  $f > \text{threshold}$ , then

□ face

□ Else

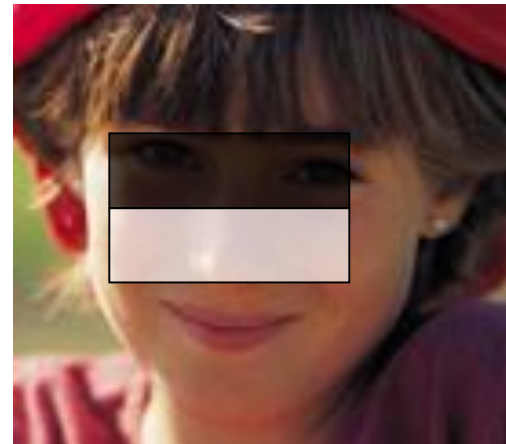
□ non-face



This is not a face.  
Because  $f$  is small



Result

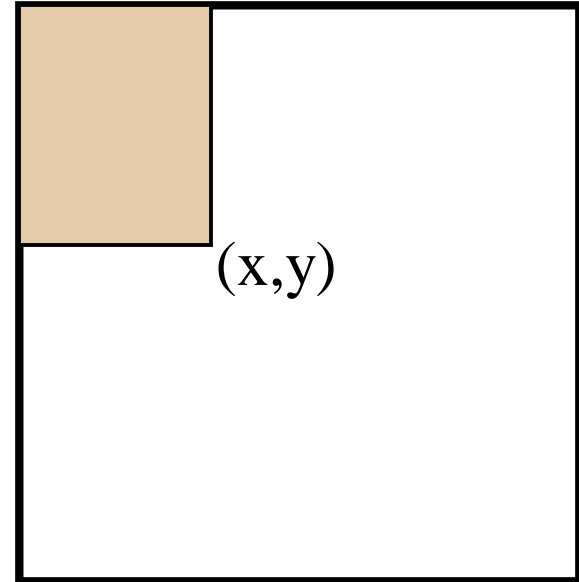


This is a face: The eye-area (shaded area) is dark, the nose-area (white area) is bright. So  $f$  is large, hence it is face

## How to find features faster?

### Integral images fast calculation method [Lazebnik09]

- The *integral image* = sum of all pixel values above and to the left of  $(x,y)$
- Can be found very quickly



# Examples

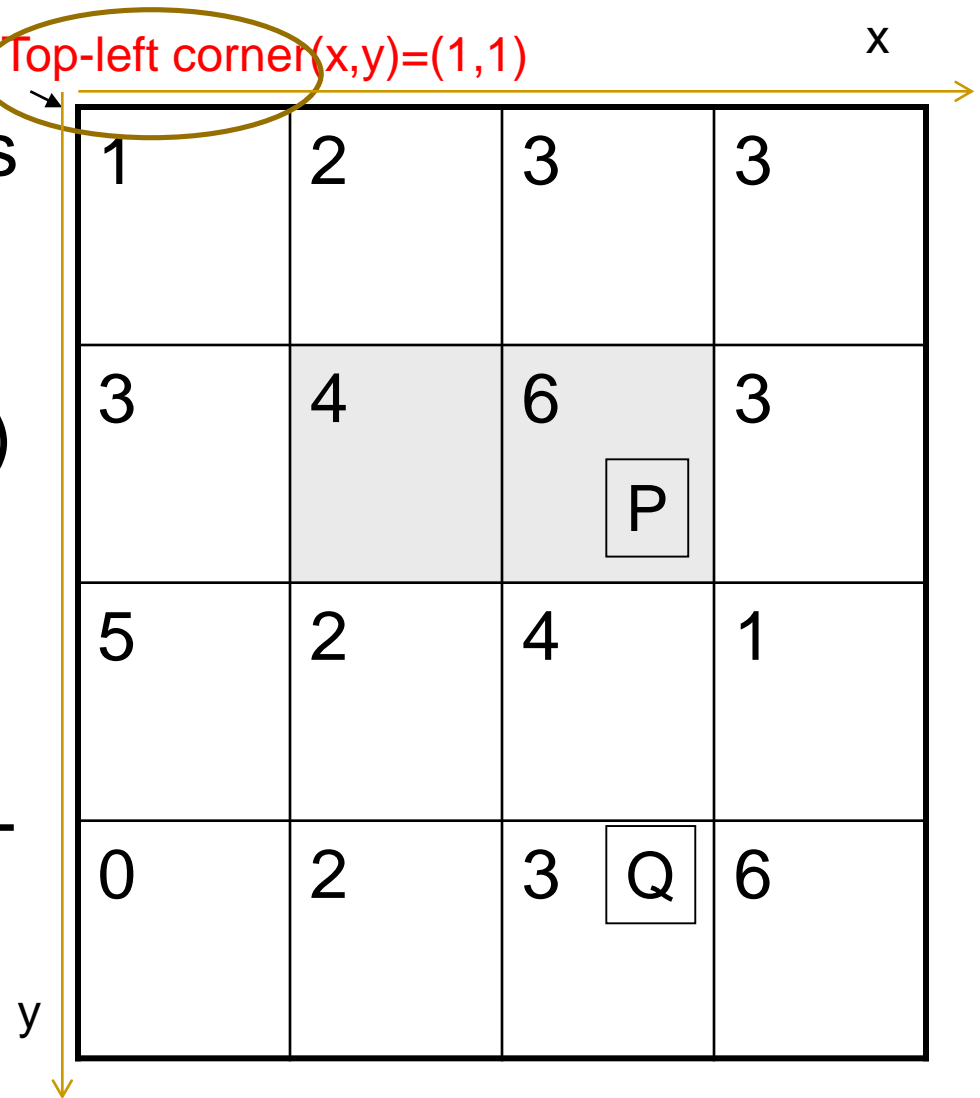
- The *integral image* = sum of all pixel values above and to the left of  $(x,y)$

- Pixel P is at  $(x=3,y=2)$

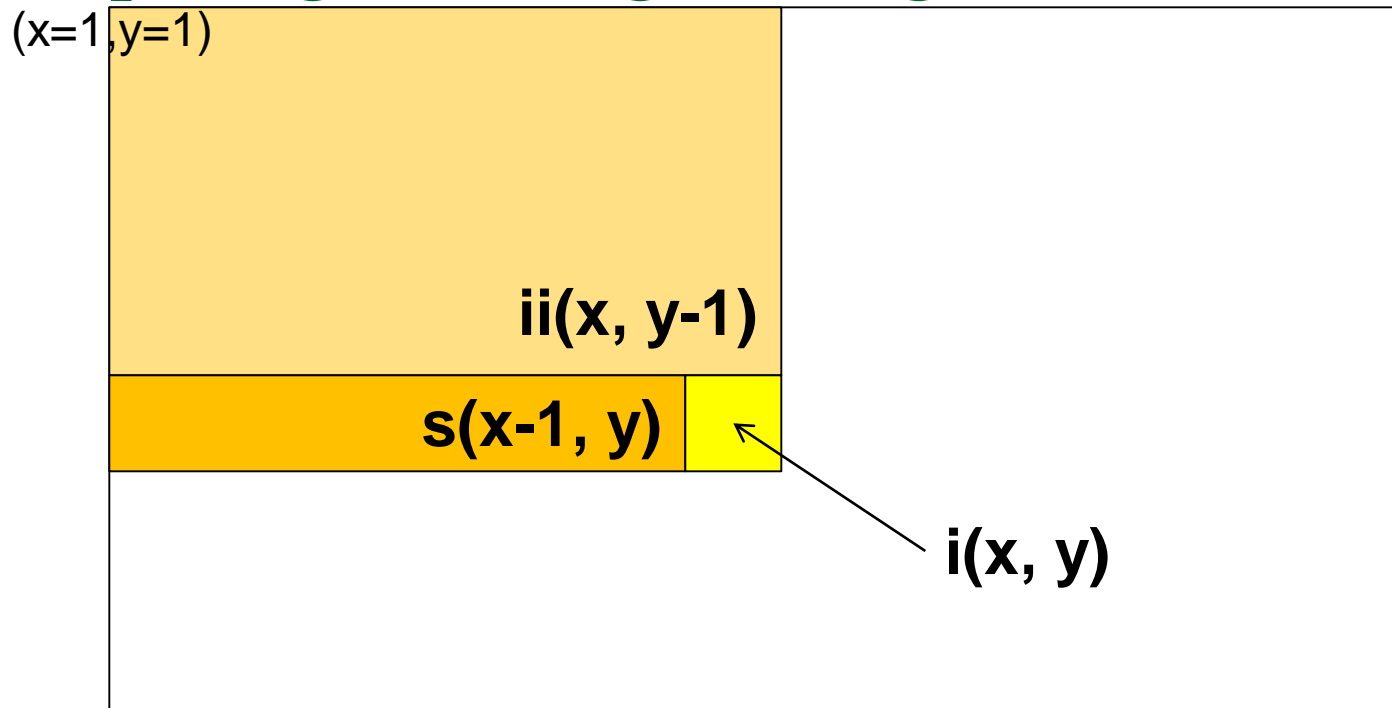
- *integral image of P* is  $=1+2+3+3+4+6$

- *integral image of Q* is

- $=1+2+3+3+4+6+5+2+4+0+2+3$



# Computing the integral image [Lazebnik09]

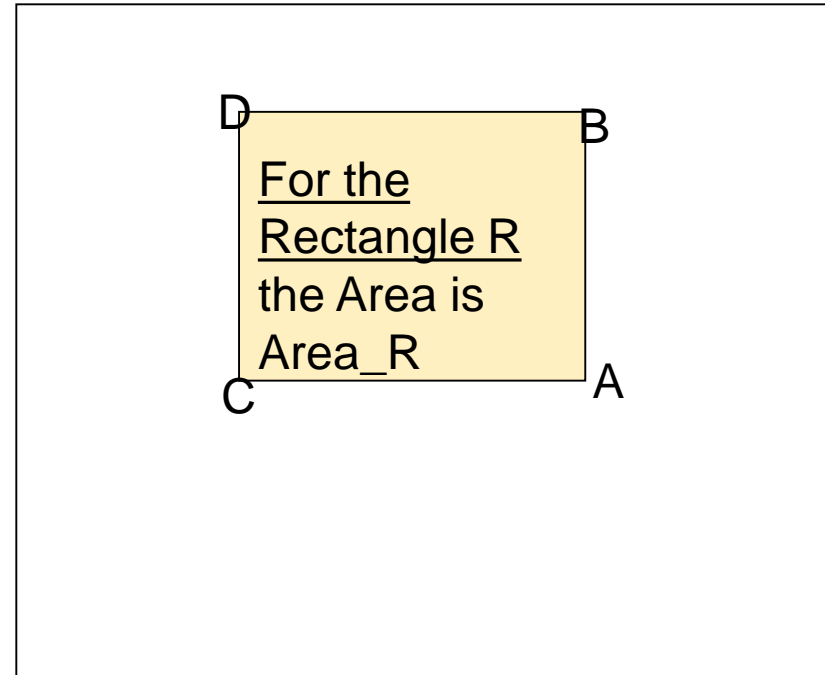


- Cumulative row sum:  $s(x, y) = s(x-1, y) + i(x, y)$
- Integral image:  $ii(x, y) = ii(x, y-1) + s(x, y)$
- MATLAB: `ii = cumsum(cumsum(double(i)), 2);`



## Calculate sum within a rectangle

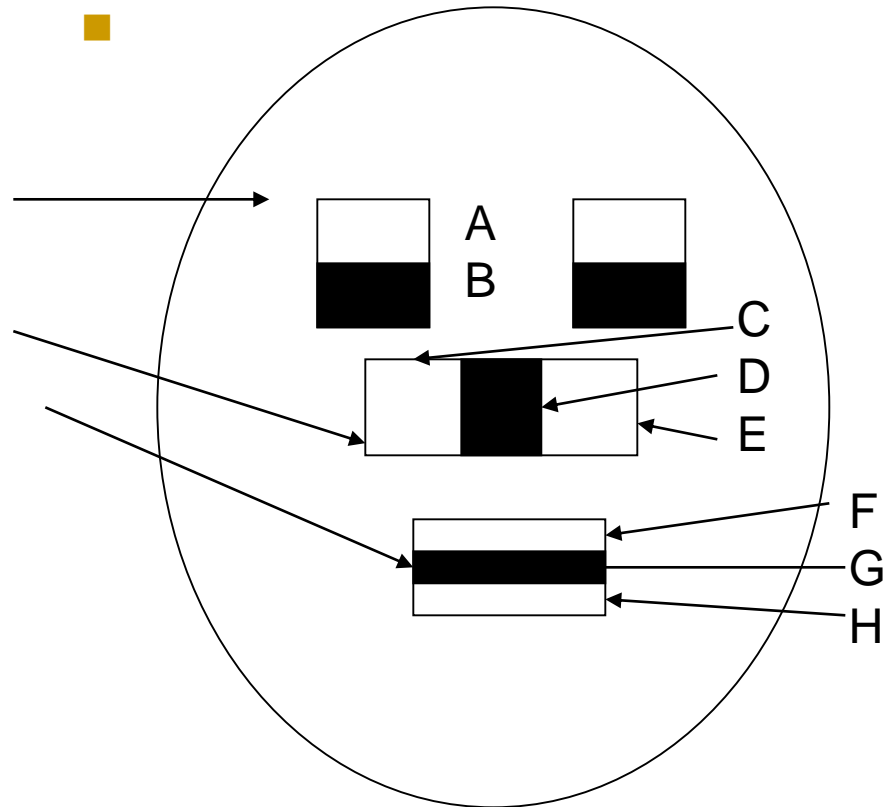
- A,B,C,D are the values of the integral images at the corners of the rectangle R.
- The sum of image values inside R is:  
$$\text{Area\_R} = A - B - C + D$$
- If A,B,C,D are found , only 3 additions are needed to find Area\_R
- Calculations of areas can reused for other windows.



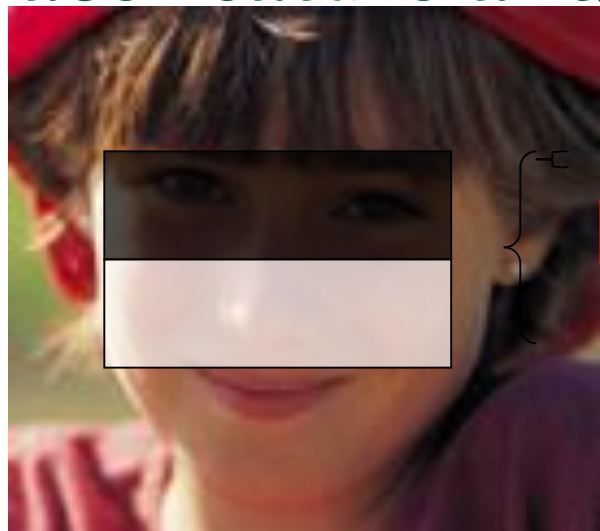
# Why do we need to find pixel sum of rectangles?

Answer: We want to get face features

- You may consider these features as face features
  - Left Eye:  $(\text{Area}_A - \text{Area}_B)$
  - Nose :  $(\text{Area}_C + \text{Area}_E - \text{Area}_D)$
  - Mouth:  $(\text{Area}_F + \text{Area}_H - \text{Area}_G)$
- They can be different sizes, polarity and aspect ratios



# Face feature and example



Pixel values inside the areas

|     |     |     |
|-----|-----|-----|
| 10  | 20  | 4   |
| 7   | 45  | 7   |
| 216 | 102 | 78  |
| 129 | 210 | 111 |

Shaded area

White area

$F = \text{Feat\_val} =$

pixel sum in white area - pixel sum in shaded area

Example

• Pixel sum in white area =  
 $216 + 102 + 78 + 129 + 210 + 111 = 846$

• Pixel sum in shaded area =  
 $10 + 20 + 4 + 7 + 45 + 7 = 93$

$\text{Feat\_val} = F = 846 - 93 = 753$

If  $F > \text{threshold}$ ,  
feature = +1

Else

feature = -1 End if;

If we can choose threshold = 700, so feature is +1.



A face

Definition:  $Area_X$  = sum of pixels in the rectangular area from the left-top corner to pixel X (including the top left corner and pixel X).

Top-left corner

- Find the feature output of this image.
- $Area_D=1$
- $Area_B=1+2+3=6$
- $Area_C = 1+3=4$
- $Area_A=1+2+3+3+4+6=19$
- $Area_E=? 1+3+5=9$
- $Area_F=? 1+2+3+3+4+6+5+2+4=30$
- Pixel sum of the area inside the box enclosed by the dotted lines=
- $Area_F - Area_B - Area_E + Area_D =? 30-6-9+1=16$

|   |   |   |   |
|---|---|---|---|
| 1 | 2 | 3 | 3 |
|   | D |   | B |
| 3 | 4 | 6 | 3 |
|   | C |   | A |
| 5 | 2 | 4 | 1 |
|   | E |   | F |
| 0 | 2 | 3 | 6 |

# Class exercise 6.3

Definition: Area at X = pixel sum of the area from top-left corner to X = Area\_X

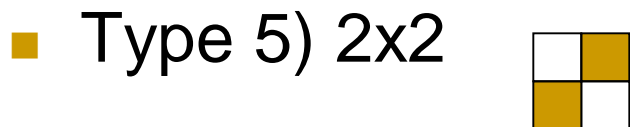
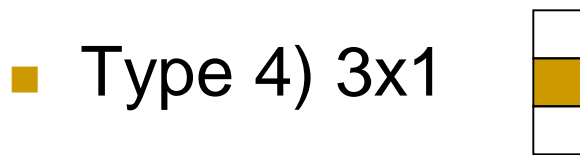
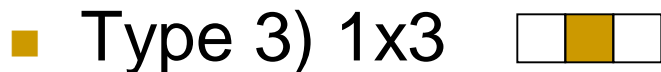
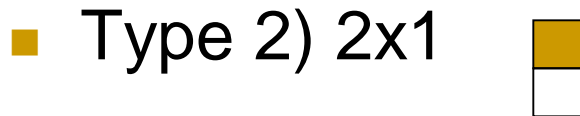
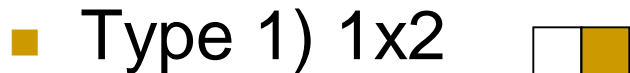
- Find the feature output of this image.
- Area\_D=1
- Area\_B=1+2+3=6
- Area\_C =1+3=4
- Area\_A=1+2+3+3+4+6=19
- Area\_E=? 1+3+5=9
- Area\_F=? 1+2+3+3+4+6+5+2+4=30
- Pixel sum of the area inside the box enclosed by the dotted lines=
- Area\_F - Area\_B - Area\_E +Area\_D =30-6-9+1=16
- WA=White area enclosed by the dotted line=?
- GA=Gray area enclosed by the dotted line=?
- (white area-shaded area)=WA-WG=?

Top-left corner

|   |   |   |   |
|---|---|---|---|
| 1 | 2 | 3 | 3 |
|   | D |   | B |
| 3 | 4 | 6 | 3 |
|   | C |   | A |
| 5 | 2 | 4 | 1 |
|   | E |   | F |
| 0 | 2 | 3 | 6 |

# 4 basic types of Rectangular Features for (white\_area)-(gray\_area)

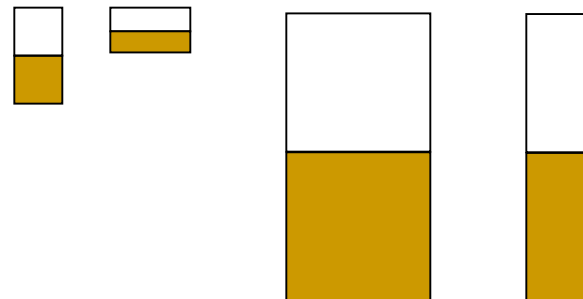
- Type) Rows x columns



- Each basic type can have different sizes and aspect ratios.

- I.e. the following feature windows are of the same type (Type2) even they have different sizes, or aspect ratios

- Each rectangle inside is of the same dimension



# Faces can be any sizes,

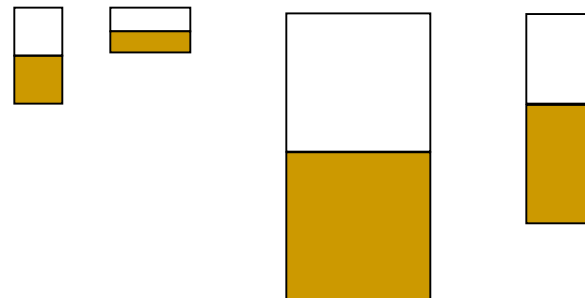
Example: a face can be big or small , from to 24 x24 to 1024x1024,

- There are faces with different sizes



So, we need feature windows with different sizes.

- As long as white/gray areas have the relations
- The followings are Type2 Rectangular Features
  - The white rectangle is above the shaded rectangle
  - White and shaded rectangle are of same dimension



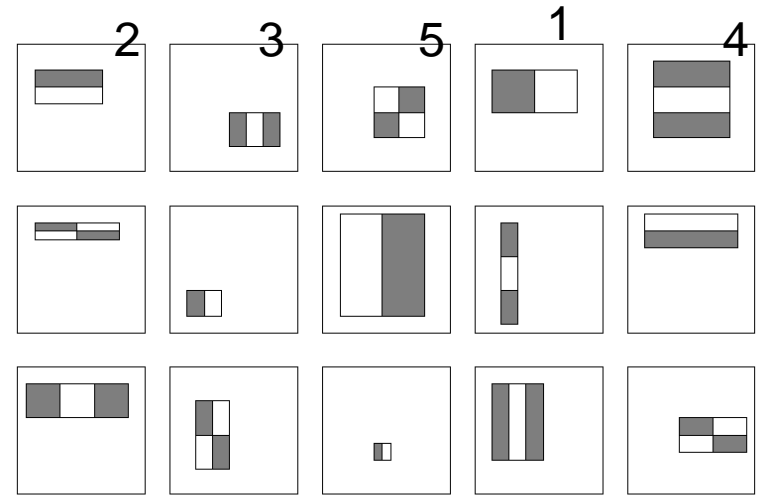
# Class exercise 6.4

## Feature selection [Lazebnik09]

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- Name the types (type 1,2,3,4,5) of the rectangular features in the figures.

Some examples and their types

Fill in the types for the 2nd, 3rd rows



Standard Rectangular Feature Types

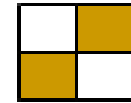
- |    |  |
|----|--|
| 1) |  |
| 2) |  |
| 3) |  |
| 4) |  |
| 5) |  |



## Class exercise 5: Features in a 24x24 (pixel) window

- Exercise 5a : How many rectangular features of all 5 types can be found a 24x24 pixel window?
- Answer: 162,336 (explain)
- Exercise 5b : How many type 1 features in a 24x24 (pixel) window?
- Answer: 43200 (explain)

Type 5)



# Class exercise 6.6?

- Still keeping the 5 basic rectangular features types (1,2,3,4,5) (5 types: 2x1, 1x2, 3x1, 1x3, 2x2)
  - Find the number of rectangular features for a resolution of 36 x36 windows
  - Answer: 816264, explain your answer.



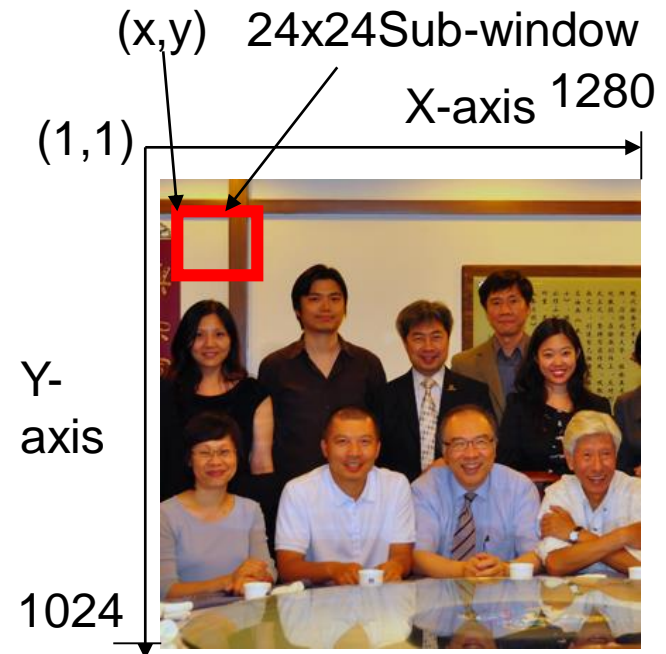
# The Viola and Jones method

## Technique 2:

AdaBoost for face detection

# Class exercise 7: The detection challenge

- Use 24x24 base window
- For  $y=1; y \leq 1024; y++$   
{For  $x=1; x \leq 1024; x++$ {
  - Set  $(x,y)$  = the left top corner of the 24x24 sub-window, different scales are needed to be considered too.
  - For the 24x24 sub-window, extract 162,336 features and see they combine to form a face or not.
- }
- Exercise 7 : Discuss the number of operations required.
- Conclusion : too slow, solution use boosting



Answer 7:

# Solution to make it efficient

- The whole 162,336 feature set is too large
  - Solution: select good features to make it more efficient.
  - Use: “Boosting”
- Boosting
  - Combine many small weak classifiers to become a strong classifier.
  - Training is needed.

# Boosting for face detection

- Define weak learners based on rectangle features

$$h_t(x) = \begin{cases} 1 & \text{if } p_t f_t(x) < p_t \theta_t \\ 0 & \text{otherwise} \end{cases}$$

Annotations:

- value of rectangle feature (points to  $f_t(x)$ )
- threshold (points to  $\theta_t$ )
- $p_t$  (points to  $p_t$ )
- polarity  $\{+1, -1\}$  (points to  $p_t$ )
- window (points to  $x$ )

# Face detection using Adaboost

## ■ AdaBoost training

- ❑ E.g. Collect 5000 faces, and 9400 non-faces. Different scales.
- ❑ Use AdaBoost for training to build a strong classifier.
- ❑ Pick suitable features of different scales and positions, pick the best few. (Take months to do , details is in [Viola 2004] paper)

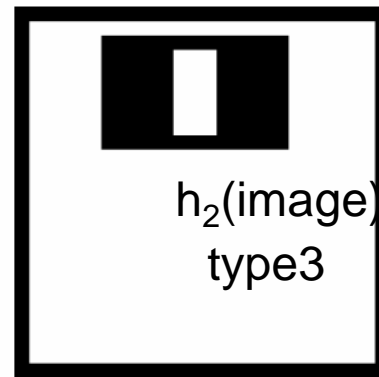
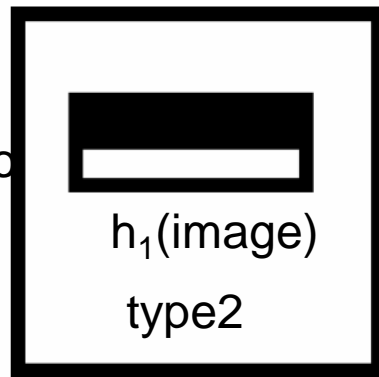
## ■ Testing

- ❑ Scan through the image (any where), pick a window (any size  $\geq 24 \times 24$ ) and rescale it to  $24 \times 24$ ,
- ❑ Pass it to the strong classifier for detection.
- ❑ Report face, if the output is positive

# Boosting for face detection [viola2004]

- In the paper it shows that the following two features (obtained after training) in cascaded picked by AdaBoost have 100% detection rate and 50% false positive rate
- But 50% false positive rate is not good enough
- Approach [viola2004] :Attentional cascade

Pick a window in the image and rescale it to 24x24 as "image"



I.e. Strong classifier  
 $H(\text{face}) = \text{Sign}\{\alpha_1 h_1(\text{image}) + \alpha_2 h_2(\text{image})\}$

$H(\text{face}) = +1 \rightarrow \text{face}$   
 $H(\text{face}) = -1 \rightarrow \text{non-face}$

Standard Types

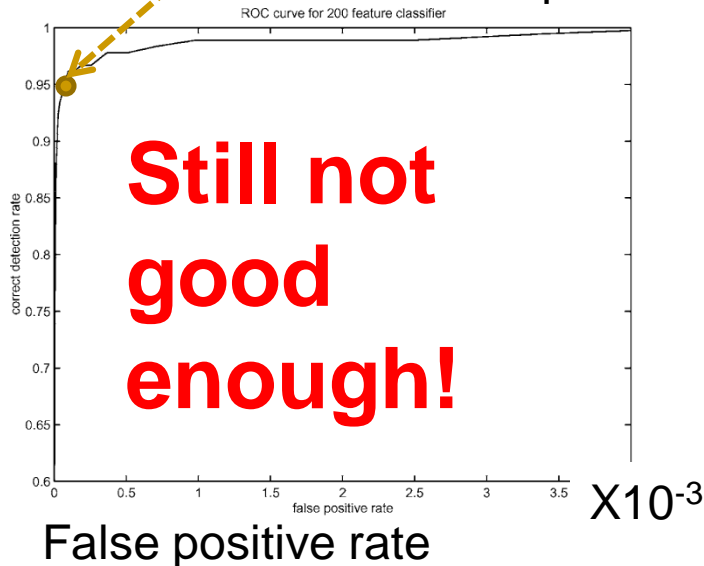
- 1)
- 2)
- 3)
- 4)
- 5)



# Boosting for face detection

- An experiment shows: A 200-feature classifier can yield 95% detection rate and a false positive rate of 1 in 14084 ( $7.1 \times 10^{-5}$  Still not good enough)
- Recall: False positive rate
  - The detector output is positive but it is false (there is actually no face).  
*Definition of False positive: A result that is erroneously positive when a situation is normal. An example of a false positive: a particular test designed to detect cancer of the toenail is positive but the person does not have toenail cancer.*  
(<http://www.medterms.com/script/main/art.asp?articlekey=3377>)

Correct  
Detection  
rate



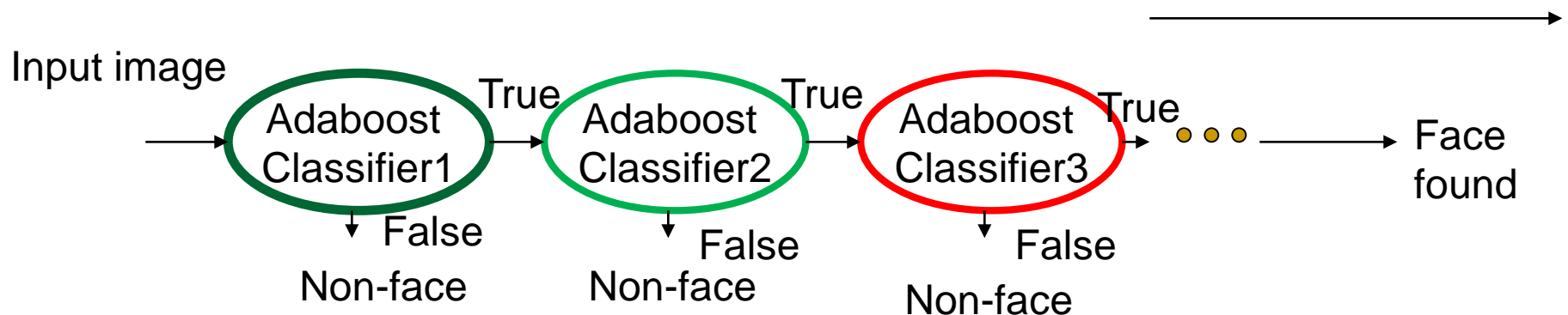
# The Viola and Jones method

## Technique 3:

Attentional cascade for fast rejection of non-face sub-windows

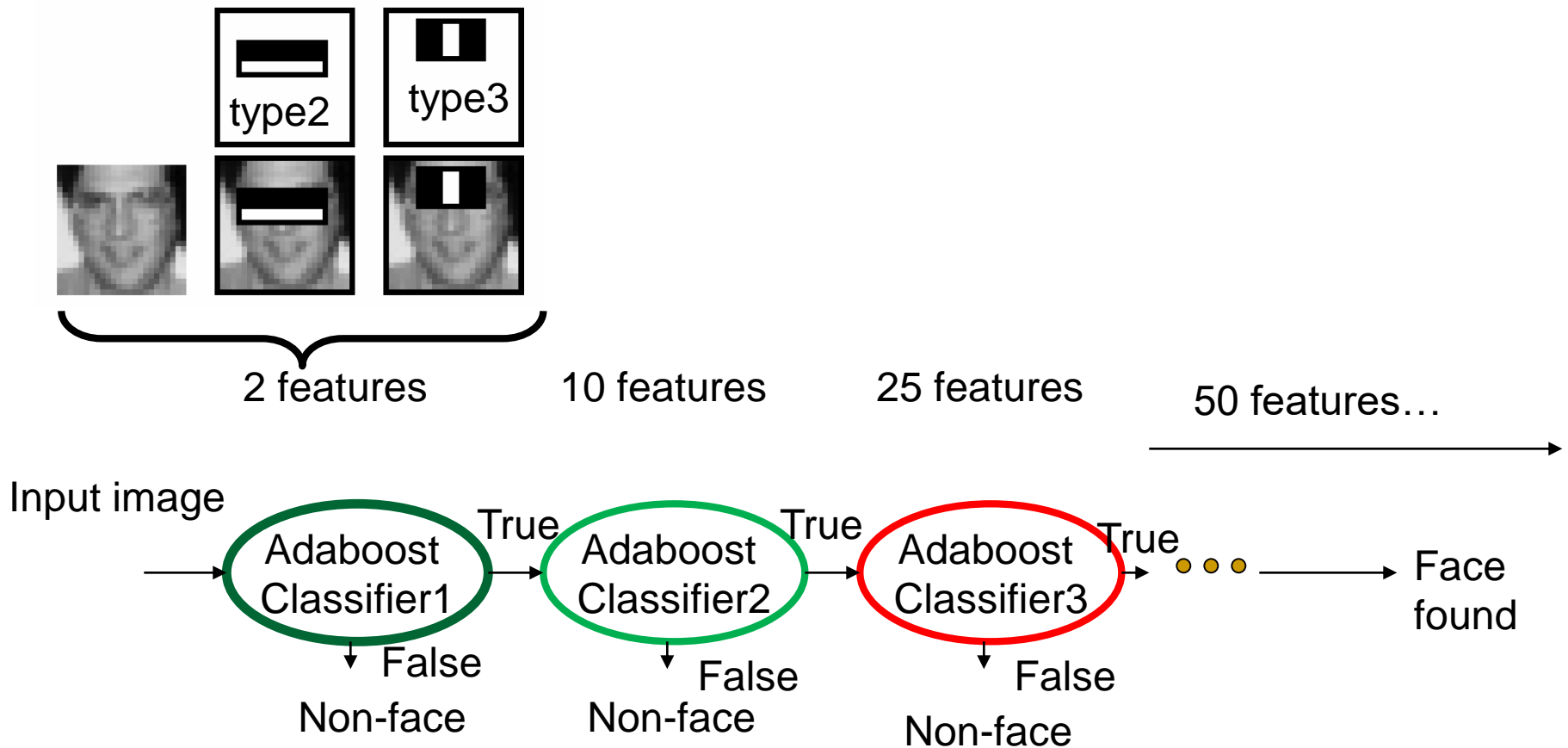
# To improve false positive rate: Attentional cascade

- Cascade of many AdaBoost strong classifiers.
- Begin with simple classifiers to reject many negative sub-windows.
- Many non-faces are rejected at the first few stages.
- Hence the system is efficient enough for real time processing.



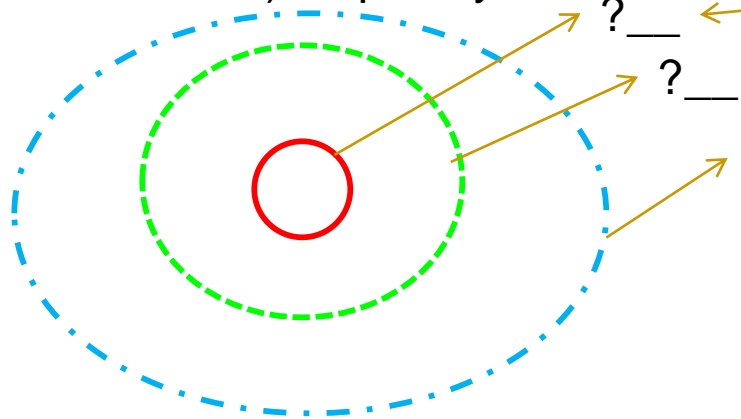
# An example

- More features for later stages in the cascade [viola2004]

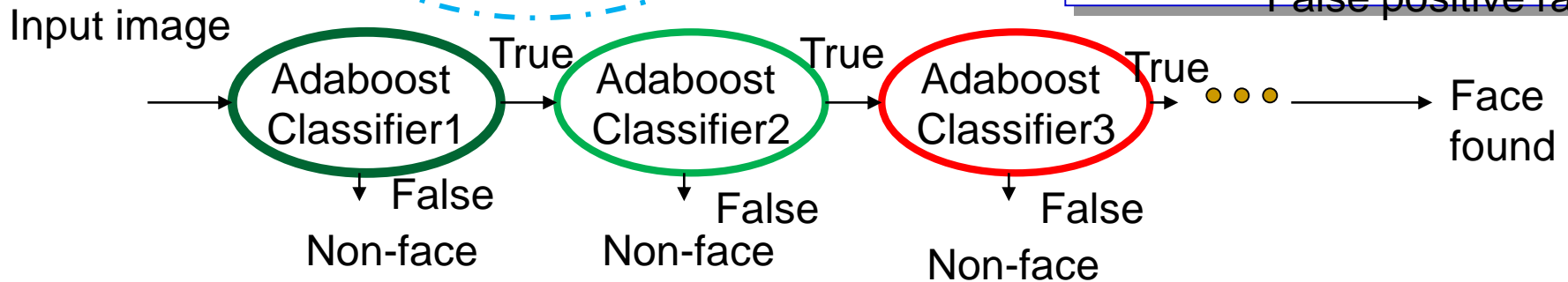
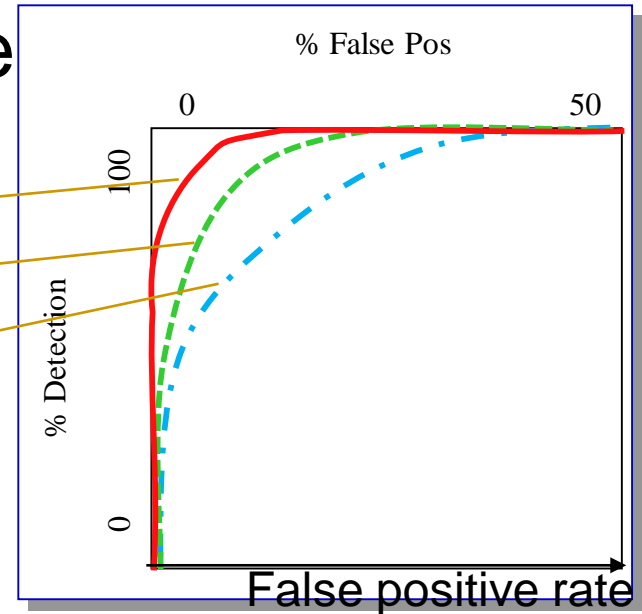


# Class exercise 6.8: Attentional cascade

- Chain classifiers that are progressively more complex and have lower false positive rates:
- Fill in ?: Name the classifier (1 or 2 or 3), explain your answer

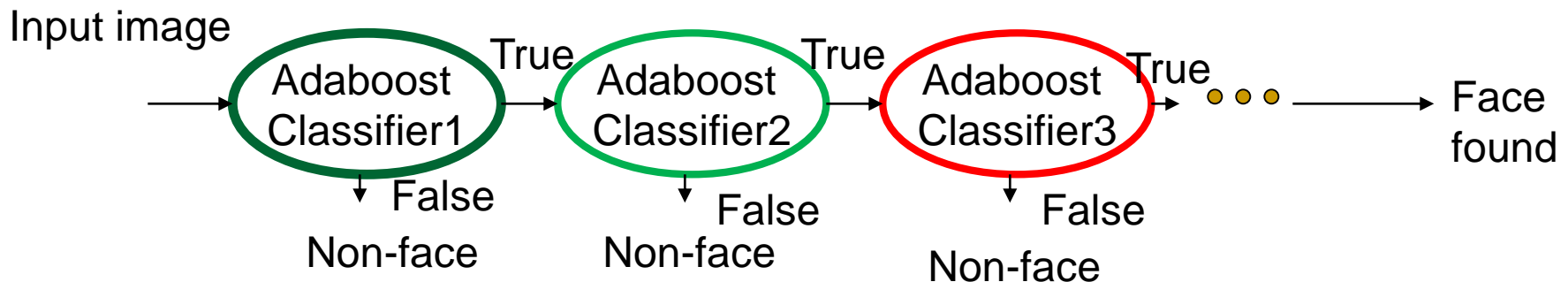


Receiver operating characteristic



# Attentional cascade [Viola2004]

- Detection rate for each stage is 0.99 , for 10 stages,
  - overall detection rate is  $0.99^{10} \approx 0.9$
- False positive rate at each stage is 0.3, for 10 stages
  - false positive rate =  $0.3^{10} \approx 6 \times 10^{-6}$



# Detection process in practice [smyth2007]

- Use 24x24 sub-window
- Scaling
  - scale the detection (not the input image)
  - Features evaluated at scales by factors of 1.25 at each level
  - Location : move detector around the image (1 pixel increments)
- Final detections
  - A real face may result in multiple nearby detections (merge them to become the final result)

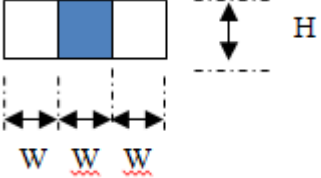
# Summary

- Learned
  - How to extract face feature
  - How to apply adaboost for face detection
  - How to train up the system and how to detect face



# Additional Exercise A1

- Definition: = Area\_X = sum of pixels in the area from left-top corner to pixel X
- Based on the window in image1, answer the following questions.
- i) Find Area\_A, Area\_B, Area\_C, Area\_D, Area\_E, Area\_F
- In image1, calculate the number of Type-3 features found in each of the following different cases :
- W=1 pixel, H=1 pixel,
- W=2 pixels, H=2 pixels.

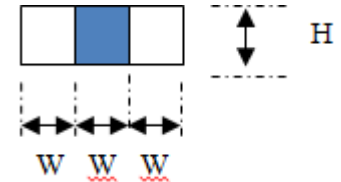
| Type    | Rows × Columns | Feature value   | Features   |
|---------|----------------|---|--|
| Type -3 | 1 × 3          | (Sum of pixels in shaded area)<br>- (Sum of pixels in white area) |  <p>Three rectangular blocks in a row.<br/>Width of each rectangle =W pixels.<br/>Height of each rectangle =H pixels.</p> |

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 2 | 7 | 3 | 8 | 2 | 4 |
| A |   |   |   |   | B |
| 0 | 4 | 2 | 3 | 5 | 5 |
| C |   |   |   |   | D |
| 1 | 3 | 6 | 8 | 2 | 8 |
| E |   |   |   |   | F |
| 8 | 0 | 3 | 5 | 3 | 2 |
| 1 | 3 | 5 | 7 | 4 | 1 |

Image 1

# Answer A1

- Definition: = Area\_X = sum of pixels in the area from left-top corner to pixel X
- Based on the window in Figure 1, answer the following questions.
- i) Find Area\_A, Area\_B, Area\_C, Area\_D, Area\_E, Area\_F



- Answer:
- Area\_A=2
- Area\_B=2+7+3+8+2+4=26
- Area\_C=2
- Area\_D=AreaB+4+2+3+5+5=26+4+2+3+5+5=45
- Area\_E=3
- Area\_F=Area\_D+1+3+6+8+2+8=45+73

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 2 | 7 | 3 | 8 | 2 | 4 |
| A |   |   |   |   | B |
| 0 | 4 | 2 | 3 | 5 | 5 |
| C |   |   |   |   | D |
| 1 | 3 | 6 | 8 | 2 | 8 |
| E |   |   |   |   | F |
| 8 | 0 | 3 | 5 | 3 | 2 |
| 1 | 3 | 5 | 7 | 4 | 1 |

- ii) Find the area inside the box CDFE based on the result in (i).
- Answer: Area\_F-Area\_B=73-26=47
- iii) Calculate the type 3 feature value in the area CDFE.
- Answer: (2+3+6+8)-(0+4+1+3)-(5+5+2+8)= -9
- iv) Calculate the number of features found in each of the following cases if W and H are the features are :
- W=1 pixel,H=1 pixels, answer=5x4=20
- W=2 pixels,H=2 pixels, Answer:4x1= 4

# References

1. [viola2004] Paul A. Viola, Michael J. Jones: Robust Real-Time Face Detection. International Journal of Computer Vision 57(2): 137-154 (2004) (PDF: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.137.4879&rep=rep1&type=pdf>)
2. [viola2001] Paul A. Viola, Michael J. Jones, Rapid object detection using a boosted cascade of simple features CVPR 2001 (PDF: [http://research.microsoft.com/en-us/um/people/viola/Pubs/Detect/violaJones\\_CVPR2001.pdf](http://research.microsoft.com/en-us/um/people/viola/Pubs/Detect/violaJones_CVPR2001.pdf))
3. [Lazebnik09] [www.cs.unc.edu/~lazebnik/spring09/lec23\\_face\\_detection.ppt](http://www.cs.unc.edu/~lazebnik/spring09/lec23_face_detection.ppt)
4. [stackoverflow] <http://stackoverflow.com/questions/1707620/viola-jones-face-detection-claims-180k-features>
5. [Jensen 2008] Ole Helvig Jensen, "Implementing the Viola-Jones Face Detection Algorithm "Kongens Lyngby 2008", IMM-M.Sc.-2008-93, Technical University of Denmark Informatics and Mathematical Modeling
6. [smyth2007] Face detection using the viola Jones method ppt, UL Irvine (lecture notes of CS175 Fall 2007)
7. [yu tm] [http://aimm02.cse.ttu.edu.tw/class\\_2009\\_1/PR/Lecture%207/Adaboost.ppt](http://aimm02.cse.ttu.edu.tw/class_2009_1/PR/Lecture%207/Adaboost.ppt)
8. [stackoverflow] <http://stackoverflow.com/questions/1707620/viola-jones-face-detection-claims-180k-features>

# Appendix 1

Advanced topics

# Training

The face Adaboost detection system

Given :  $(x_1, y_1), \dots, (x_n, y_n)$ , where  $x_i \in X, Y = \{-1, +1\}$  for negative and positive examples

• Initialize weights :

–  $w_{1,i} = 1/2M, M = \text{number of positive example}$

–  $w_{1,i} = 1/2L, L = \text{number of negative example}$

For  $t = 1, 2, \dots, T$

Adaboost face detection  
Training algorithm [Jensen  
2008 ]

■ { Step1 : Normalize weights  $w_{t,i} \leftarrow \frac{w_{t,j}}{\sum_{j=1}^n w_{t,j}}$

Step2 : Select the weak classifier with smallest weighted error

$$\text{find } \varepsilon_t = \min_{f,p,\theta} \sum_i w_i |h(x_i, f, p, \theta) - y_i|$$

Step3 : Define  $h_t(x) = h(x, f_t, p_t, \theta_t)$ , where  $f_t, p_t, \theta_t$  are minimizer of  $\varepsilon_t$  at stage  $t$

Step4 : update weights

update the weights :  $w_{t+1,i} = w_{t,i} \beta^{1-e_i}$

where  $e_i = 0$  if example  $x_i$  is classified correctly and  $e_i = 1$  otherwise ,

$$\text{and } \beta = \frac{\varepsilon_t}{1 - \varepsilon_t}$$

}

The final strong classifier is :  $C(x) = \begin{cases} 1 & \text{if } \sum_{t=1}^T \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^T \alpha_t \\ 0 & \text{otherwise} \end{cases}$ , where  $\alpha_t = \log \frac{1}{\beta_t}$

# Inside the main loop for training

For  $t=1, \dots, T$

- Step1
  - Init all weights
  - *Same weights all for samples at  $t=1$*

Inside the main loop for training

For  $t=1, \dots, T$

-assume at stage  $t$

- Step2: select the best weak classifier (weak learner) find  $\varepsilon_t = \min_{f,p,\theta} \sum_i^n w_i |h(x_i, f, p, \theta) - y_i|$
- For all  $f$  (1,2,3,... 162,336 feature set)
- For all  $p$  ( $p=+1$  or  $-1$ )
  - For different  $\theta$ , ( $\theta$  as low as possible to produce good result)

- {
- $$\varepsilon_{f,p,\theta} = \sum_i^n w_i \overbrace{|h(x_i, f, p, \theta) - y_i|}^{\text{Mistakenly classified}}$$
- }

$$\{f, p, \theta\}_{best\_weak\_classifier} = \text{arguments}(\min\{\varepsilon_{f,p,\theta}\})$$



## Step2 : more explanation

-assume at stage  $t$

- Test every feature in the feature set  $\{1,2,3,\dots, 162,336 \text{ feature set}\}$
- Test different polarity  $\{+1,-1\}$ : dark/white reversed.
- Try different  $\theta$  (for simplicity start from 0.4), make it lower to see if performance (recognition, false-positive rates are improved.
- Output=  $\{f_t$  (type of feature),  $p_t$  (polarity),  $\theta_t$  (threshold) $\}$  which give the minimum error  $\varepsilon_t$
- $\{f_t, p_t, \theta_t\} = (\text{minimizer of } \varepsilon_t) \text{ at stage } t$

Inside the main loop for training

For  $t=1, \dots, T$

-assume at stage  $t$

■ Step3

$$h_t(x) = h(x, f_t, p_t, \theta_t)$$

$f_t, p_t, \theta_t$  are minimizer of  $\varepsilon_t$  at stage  $t$

Inside the main loop for training

For  $t=1, \dots, T$

-assume at stage  $t$

■ **step4**

update the weights :

$$w_{t+1,i} = w_{t,i} \beta^{1-e_i}$$

where  $e_i = 0$  if example  $x_i$  is classified correctly and  $e_i = 1$  otherwise,

$$\text{and } \beta = \frac{\varepsilon_t}{1 - \varepsilon_t}$$

Inside the main loop for training

For  $t=1, \dots, T$

-assume at stage  $t$

■ step5

$$C(x) = \begin{cases} 1 & \text{if } \sum_{t=1}^T \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^T \alpha_t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{where } \alpha_t = \log \frac{1}{\beta_t}$$

# Appendix2

- Answers to exercises

# Answer: Class exercise 6.1

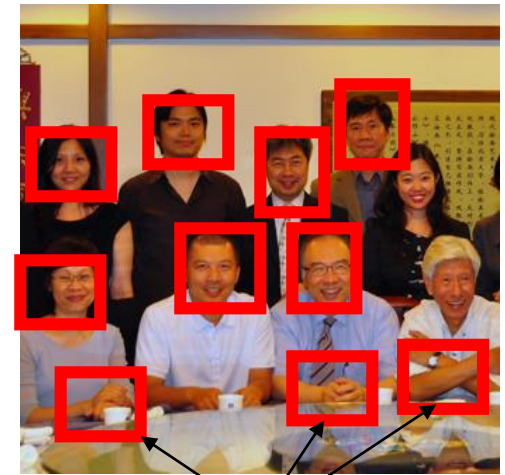
- Detected results are in red frames
- What are the detection rate and false positive rate here?

□ Answer

- detection rate= $(7/9)*100\%$
- false positive rate= $(3/10)*100\%$

7 faces correctly detected in the picture, 9 actually faces exist in the image

10 windows reported to have faces, but in 3 windows they are not faces.

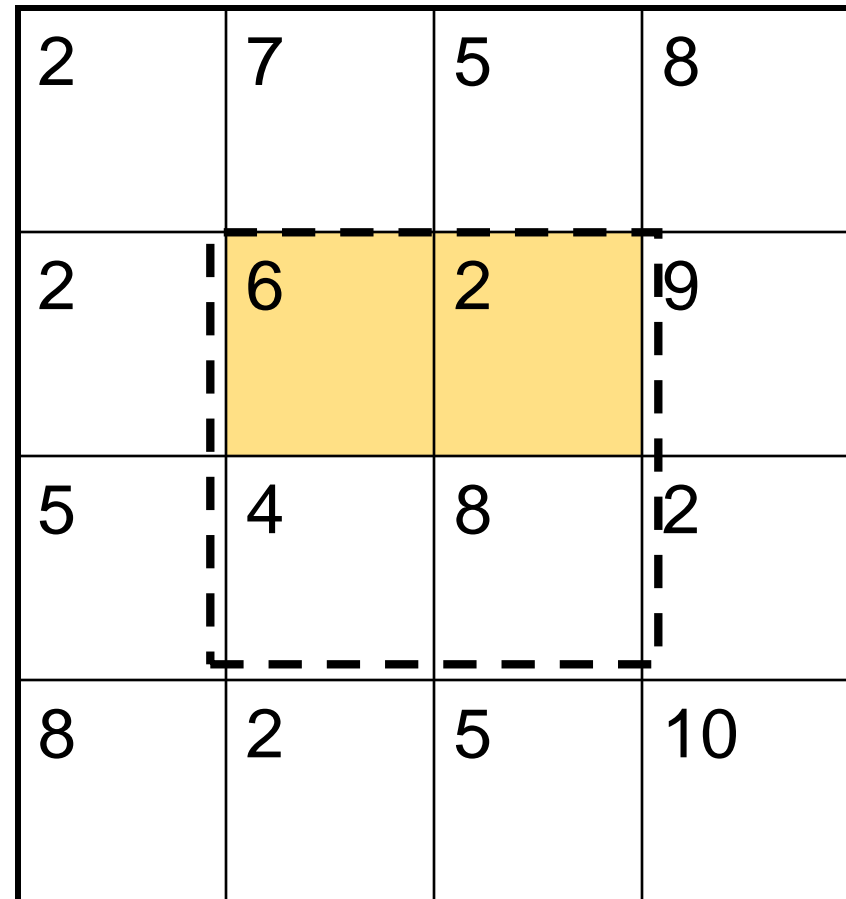


False positive results

# Answer: Class exercise 6.2

- Find the *Rectangle\_Feature\_value* (f) of the box enclosed by the dotted line
- *Rectangle\_Feature\_value*  $f =$
- $\sum (\text{pixels values in white area}) - \sum (\text{pixels values in shaded area})$
- $f = (4+8) - (6+2) = 12 - 8 = 4$

|   |   |   |    |
|---|---|---|----|
| 2 | 7 | 5 | 8  |
| 2 | 6 | 2 | 9  |
| 5 | 4 | 8 | 2  |
| 8 | 2 | 5 | 10 |

A 4x4 grid of numbers. The values are: Row 1: 2, 7, 5, 8; Row 2: 2, 6, 2, 9; Row 3: 5, 4, 8, 2; Row 4: 8, 2, 5, 10. A 2x2 area in the center (rows 2-3, columns 2-3) is shaded yellow. A dotted line encloses this shaded area, with its corners at the intersections of the grid lines.

# Answer: Class exercise 3

Definition: Area at X = pixel sum of the area from top-left corner to X = Area\_X

- Find the feature output of this image.
- Area\_D=1
- Area\_B=1+2+3=6
- Area\_C =1+3=4
- Area\_A=1+2+3+3+4+6=19
- Area\_E=? 1+3+5=9
- Area\_F=? 1+2+3+3+4+6+5+2+4=30
- Pixel sum of the area inside the box enclosed by the dotted lines=
- Area\_F - Area\_B - Area\_E +Area\_D =? 30-6-9+1=16
- WA=White area enclosed by the dotted line= Area\_F - Area\_A - Area\_E +Area\_C=30-19-9+4= 6
- GA=Gray area enclosed by the dotted line= Area\_A - Area\_B - Area\_C +Area\_D=19-6-4+1=10
- (white area-shaded area)=WA-WG=6-10=-4

Top-left corner

|   |   |   |   |
|---|---|---|---|
| 1 | 2 | 3 | 3 |
|   | D |   | B |
| 3 | 4 | 6 | 3 |
|   | C | A |   |
| 5 | 2 | 4 | 1 |
|   | E | F |   |
| 0 | 2 | 3 | 6 |



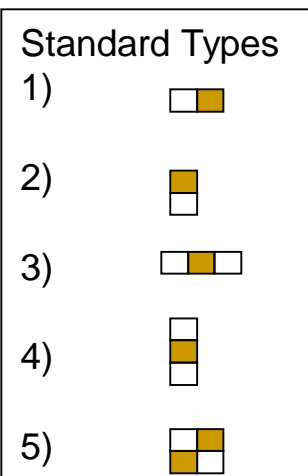
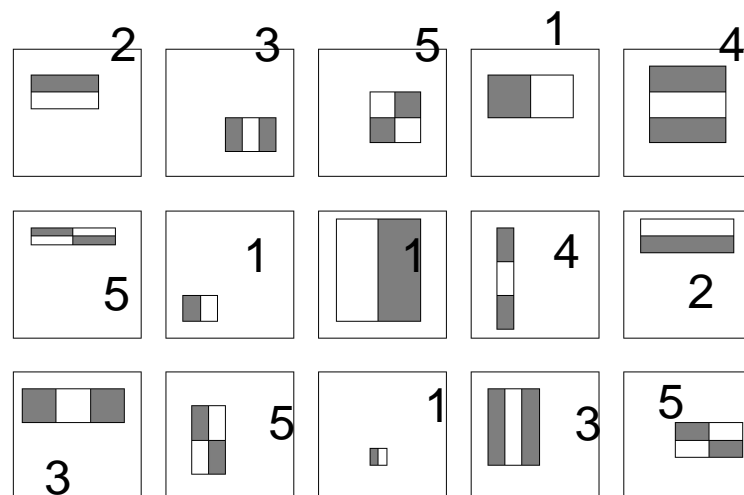
# Answer: class exercise 4

## Feature selection [Lazebnik09]

Some examples and their types

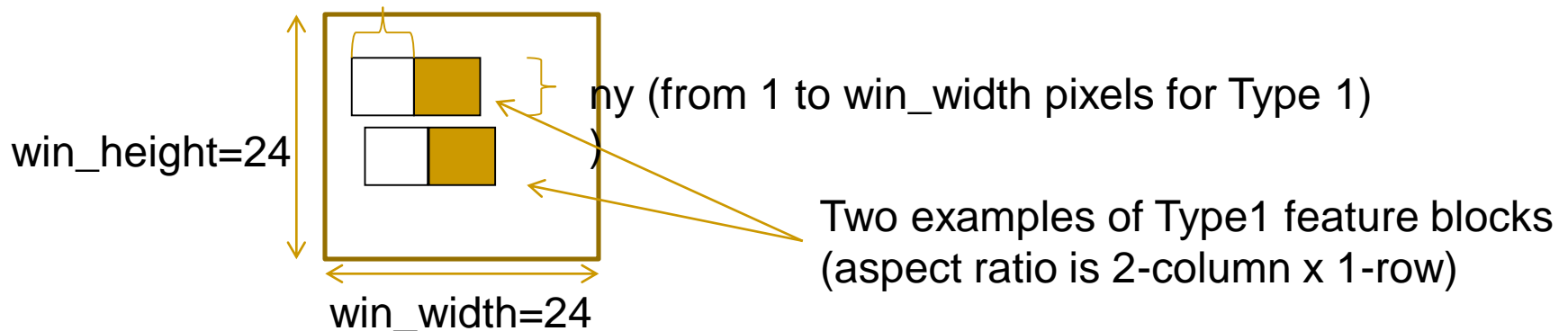
Fill in the types for the 2nd, 3rd rows

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- Name the types (type 1,2,3,4,5) of the rectangular features in the figures .
- Answer: see the labels in the diagram.



# Answer5a1: Class exercise 5a : How many type 1 features in a 24x24 (pixel) window?

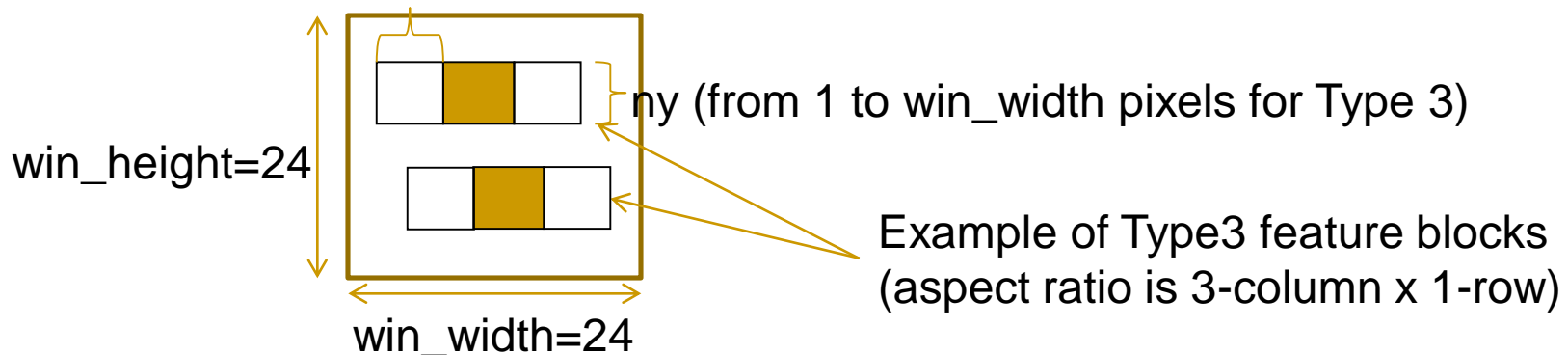
- `temp=0; %Type1 feature: block aspect ratio is width=2 units, height=1 unit`
- `for nx=1:win_width/2%nx=no. of x pixels in white area. Min =1,max=win_width/2`
- `for ny=1:win_height%ny=no. of x pixels in white area. Min =1,max=win_width`
- `number_of_blocks_x=(win_width-2*nx+1);%no.of x Blocks fit in win_width`
- `number_of_blocks_y=(win_height-ny+1);%no.of y Blocks fit in win_height`
- `temp=number_of_blocks_x*number_of_blocks_y+temp;`
- `end`
- `end`
- `temp %is the total= 43200`  
`nx (from 1 to win_width/2 pixels for Type1)`



# Answer5a2: Class exercise 5a : How many type 3 features in a 24x24 (pixel) window?

- temp=0;
- %Type3: aspect ratio of the feature block, width=3 units, height=1unit
- for nx=1:win\_width/3 %nx=no. of x pixels in white area.Min =1,max=win\_width/3
- for ny=1:win\_height %ny=no. of y pixels in white area.Min =1,max=win\_width
- number\_of\_blocks\_x=(win\_width-3\*nx+1);%no.of x Blocks fit in win\_width
- number\_of\_blocks\_y=(win\_height-ny+1);%no.of y Blocks fit in win\_height
- temp=number\_of\_blocks\_x\*number\_of\_blocks\_y+temp;
- end
- end
- N\_Type3=temp %answer= 27600

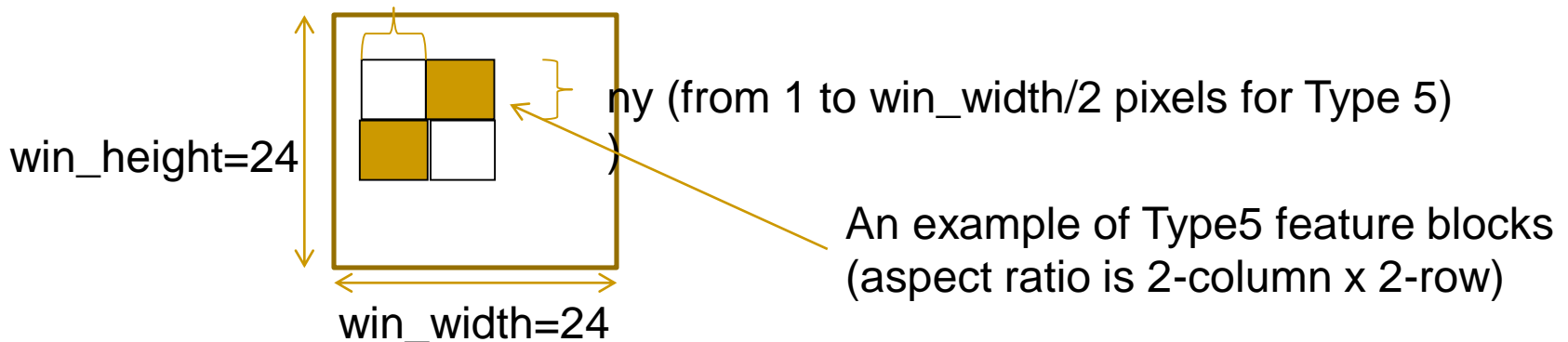
nx (from 1 to win\_width/2 pixels for Type3)



# Answer5a3 Exercise 5a : How many type 5 features in a 24x24 (pixel) window?

- temp=0; %-----
- %type5: aspect ratio of the feature block, width=2 units, height=2unit
- for nx=1:win\_width/2%nx=no. of x pixels in white area.Min =1,max=win\_width/2
- for ny=1:win\_height/2%ny=no. of y pixels in white area.Min =1,max=win\_width/2
- number\_of\_blocks\_x=(win\_width-2\*nx+1);%no.of x Blocks fit in win\_width
- number\_of\_blocks\_y=(win\_height-2\*ny+1);%no.of y Blocks fit in win\_height
- temp=number\_of\_blocks\_x\*number\_of\_blocks\_y+temp;
- end
- end
- N\_Type5=temp % =20736

nx (from 1 to win\_width/2 pixels for Type5)



# Answer for Exercise 5 and 6: Matlab: for a 24x24 windows, add all types

$$N\_type1 \times 2 + N\_type3 \times 2 + N\_type5 = (43200 \times 2 + 27600 \times 2 + 20736) = 162336$$

```

clear; temp=0;
%--matlab program to find number of features %(5 types (columns x rows):
%type1: 2x1; type2: 1x2; type3: 3x1; type 4: 1x3; type 5: 2x2)
%in Viola-Jones face detection cascaded Adaboost algorithm-
%%%% 2x1 shape : (2 rows x 1 column, same as 1 row x 2 columns) , 2 types
%win_width=24%(you may choose 36 or 24 etc.)
win_width=24%(you may choose 36 or 24 or 12etc.)

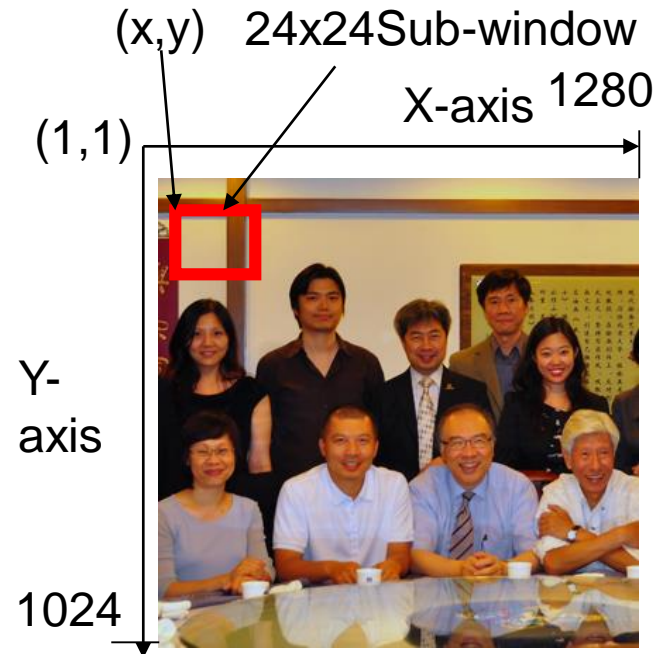
win_height=win_width;%x=horizontal direction; y=vertical direction
%Type1: aspect ratio of the feature block, width=2 units, height=1 unit
for nx=1:win_width/2%nx=no. of x pixels of each square. Min =1,max=win_width/2
    for ny=1:win_height%ny=no. of y pixels of each square. Min =1,max=win_width
        number_of_blocks_x=(win_width-2*nx+1);%no.of x Blocks fit in win_width
        number_of_blocks_y=(win_height-ny+1);%no.of y Blocks fit in win_height
        temp=number_of_blocks_x*number_of_blocks_y+temp;
    end
end
N_Type1=temp
N_Type2=N_Type1 % same as 2 rows x 1 column
pause

temp=0;
%Type3: aspect ratio of the feature block, width=3 units, height=1 unit
for nx=1:win_width/3%nx=no. of x pixels of each square.Min =1,max=win_width/3
    for ny=1:win_height%ny=no. of y pixels of each square.Min =1,max=win_width
        number_of_blocks_x=(win_width-3*nx+1);%no.of x Blocks fit in win_width
        number_of_blocks_y=(win_height-ny+1);%no.of y Blocks fit in win_height
        temp=number_of_blocks_x*number_of_blocks_y+temp;
    end
end
N_Type3=temp
N_Type4=N_Type3 % same as 3 rows x 1 column
pause
%
temp=0;%-----
%type5: aspect ratio of the feature block, width=2 units, height=2 unit
for nx=1:win_width/2%nx=no. of x pixels of each square.Min =1,max=win_width/2
    for ny=1:win_height/2%ny=no. of y pixels of each square.Min =1,max=win_width/2
        number_of_blocks_x=(win_width-2*nx+1);%no.of x Blocks fit in win_width
        number_of_blocks_y=(win_height-2*ny+1);%no.of y Blocks fit in win_height
        temp=number_of_blocks_x*number_of_blocks_y+temp;
    end
end
N_Type5=temp
'total'
N_ALL=N_Type1+N_Type2+N_Type3+N_Type4+N_Type5
%Result= 162336 if width =24
%Result= : 816264 if width =36 ( ??or 704004??)

```

# Answer 7: The detection challenge

- Use 24x24 base window
- For  $y=1; y \leq 1024; y++$ 
  - {For  $x=1; x \leq 1024; x++$ {
    - Set  $(x,y)$  = the left top corner of the 24x24 sub-window, different scales are needed to be considered too.
    - For the 24x24 sub-window, extract 162,336 features and see they combine to form a face or not.
    - } }
- Exercise 7 : Discuss the number of operations required.
- Conclusion : too slow, solution use boosting



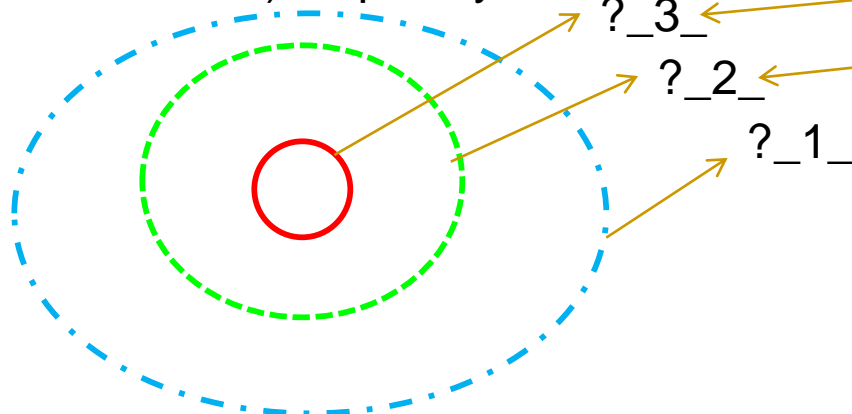
## Answer 7:

- possible locations of  $(x,y)=1024 \times 1280$ .
- Each  $(x,y)$  location, for  $i=1,2,3..$  obtain sub-images: each has size  $(24i \times 24i)$  with left-top corner at  $(x,y)$  as long as  $x+24i < 1024$
- For a sub-image, shrink it to a 24x24 window.
- For each 24x24 window, it has 162336 features to be calculated.

# Answer: Class exercise 6.8: Attentional cascade

- Chain classifiers that are progressively more complex and have lower false positive rates:

Fill in ?: Name the classifier (1 or 2 or 3), explain your answer



Receiver operating characteristic

