

# Face Detection

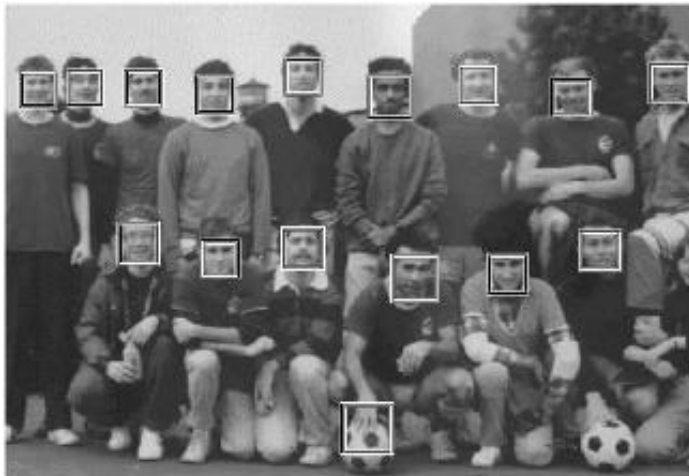
SSI Lecture Activity

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# Introduction

## Face Detection



## Face Recognition



# Challenges

- Pose



- Occlusions



# Challenges

- Facial Expressions



# Early 2000's approach

- Knowledge-based methods
- Feature invariants that characterize properties
- Template-based methods
- Appearance-based methods

# Early 2000's states of the arts

- H. Rowley et al., Neural network-based face detection. In IEEE Patt. Anal. Mach. Intell., 1998
- D. Roth et al., A snowbased face detector. Neural Information Processing, 2000
- H. Schneiderman et al., 3D object detection applied to faces and cars. Computer Vision, 2000vi
- K. Sung et al., Example-based learning for viewbased face detection. IEEE Patt. Anal. Mach. Intell., 1998

# Viola and Jones Algorithm

- P.Viola and M.Jones. Rapid object Detection. CVPR. 2001
- First face detection framework working in real time
- Requires full view frontal upright faces







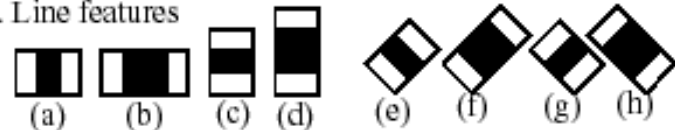
# Haar Features

- Similar to a kernel where:
  - the weight is uniform
  - the white part is positive
  - the black part is negative

1. Edge features



2. Line features



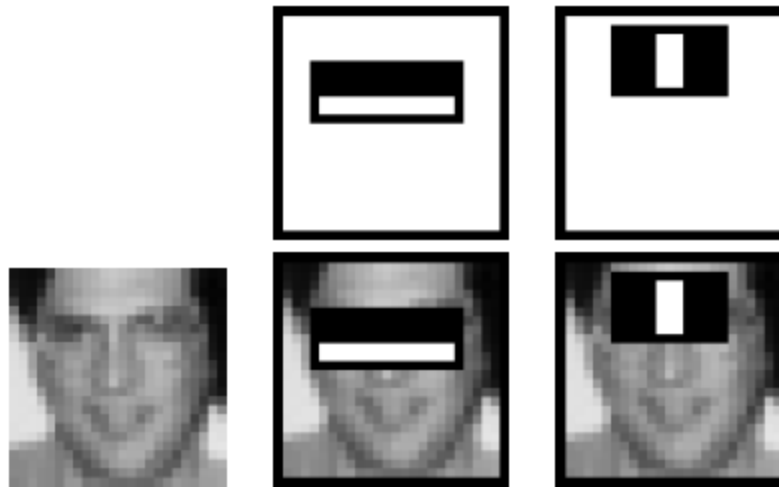
3. Center-surround features



- Each feature results in a single value

# Haar Features

- Viola jones uses a 24X24 window as the base size window to compute the features
- Considering scaling and position, over 180,000 Haar features are extractable



# Haar Features

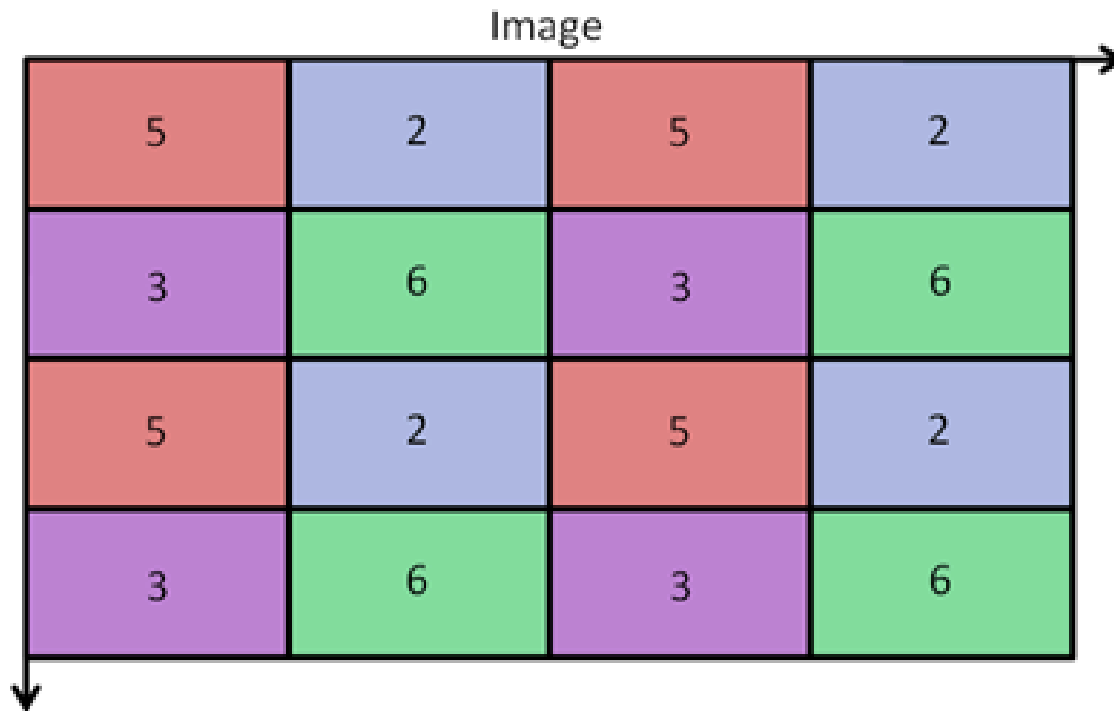
- [\*Haar features example\\_video\*](#)



# Integral Image

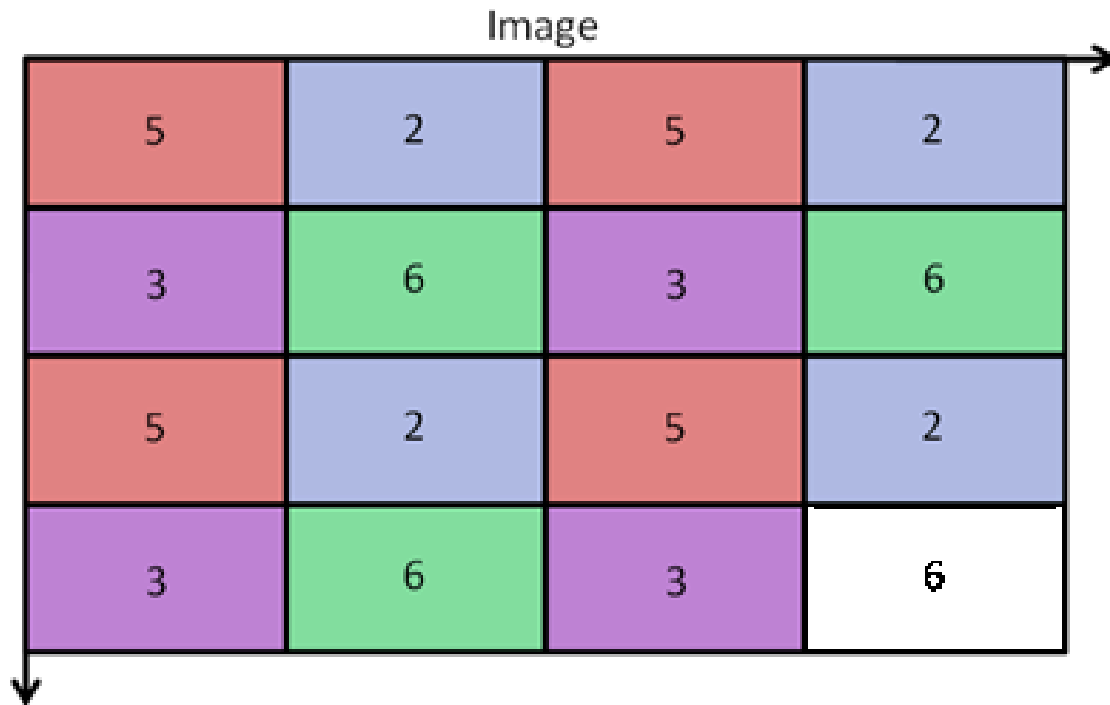
- Naive approach :

Summing all the pixel of a region



# Integral Image

$1^2=1$  Pixel wide regions



# Integral Image

$2^2=4$  Pixels wide regions

Image

5	2	5	2
3	6	3	6
5	2	5	2
3	6	3	6

# Integral Image

$3^2=9$  Pixels wide regions

Image →

5	2	5	2
3	6	3	6
5	2	5	2
3	6	3	6

↓

# Integral Image

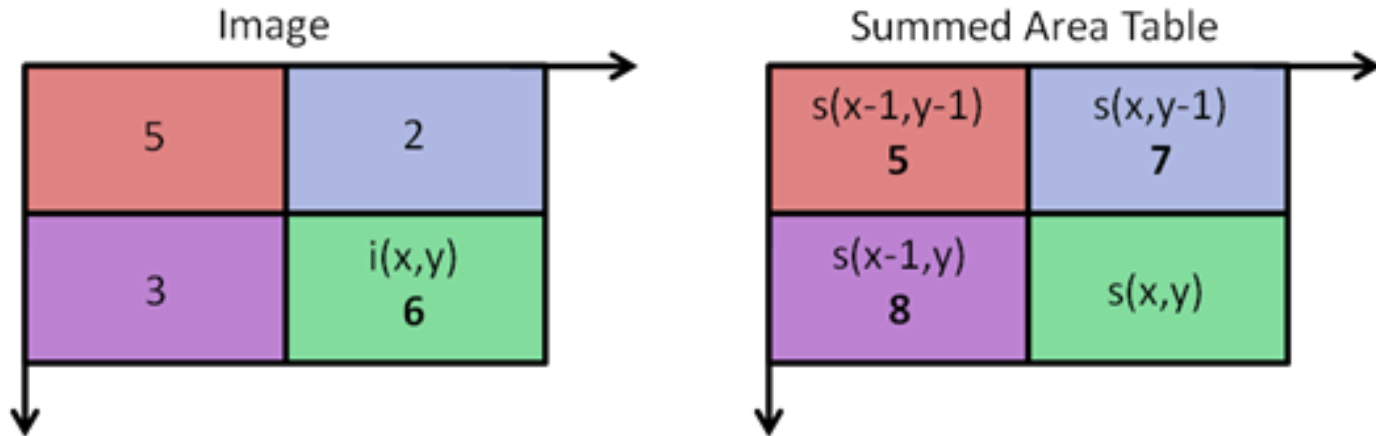
Complexity :  $O(N^2)$  !!



# Integral Image

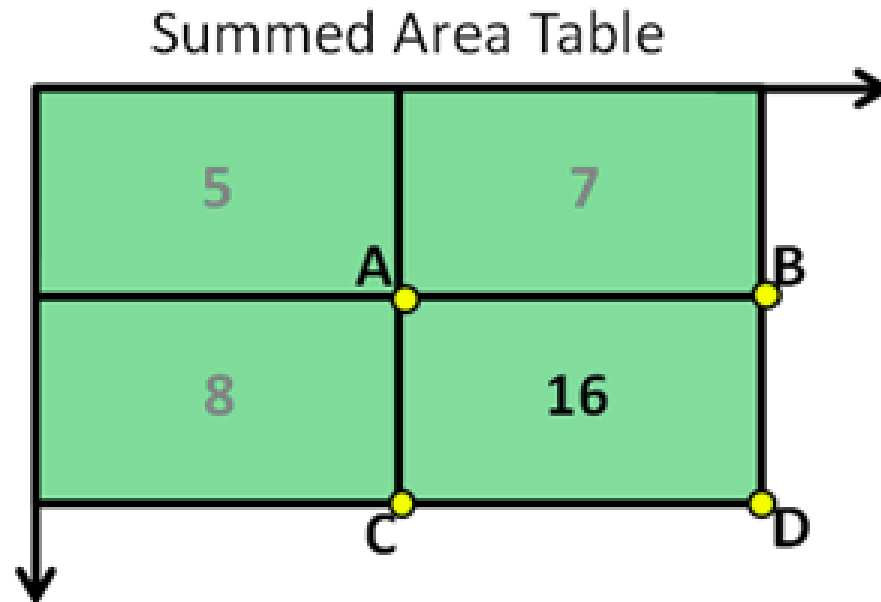
- Complexity :  $O(1)$  constant

$$s(x,y) = i(x,y) + s(x-1,y) + s(x,y-1) - s(x-1,y-1)$$



# Integral Image

$$\begin{aligned} I(x', y') &= S(A) + S(D) - S(B) - S(C) \\ &= 5 + 16 - 7 - 8 = 6 \end{aligned}$$



# Integral Image

Working with bigger example

Image

5	2	5	2
3	6	3	6
5	2	5	2
3	6	3	6

Summed Area Table

5	7	12	14
8	16	24	32
13	23	36	46
16	32	48	64

# Integral Image

$$I(x', y') = S(A) + S(D) - S(B) - S(C)$$
$$= 64 + 16 - 32 - 32 = 16$$

Summed Area Table

5	7	12	14
8	16	24	32
13	23	36	46
16	32	48	64

The diagram shows a 4x4 grid of cells. The first two rows and the first two columns are gray. The last two rows and the last two columns are green. The values in the cells are as follows:

- Row 1: 5, 7, 12, 14
- Row 2: 8, 16, 24, 32
- Row 3: 13, 23, 36, 46
- Row 4: 16, 32, 48, 64

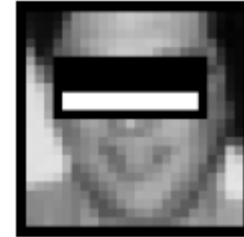
Points A, B, C, and D are marked at the intersections of the third and fourth rows with the second and fourth columns:

- A is at the intersection of the third row and the second column.
- B is at the intersection of the third row and the fourth column.
- C is at the intersection of the fourth row and the second column.
- D is at the intersection of the fourth row and the fourth column.



# AdaBoost Algorithm

- Learning Algorithm
- Introduced by Freund and Schapire in 1999
- To know the relevant and irrelevant features
- It produces a strong classifier based on simple classifiers by linear combination



$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \dots$$

# AdaBoost Algorithm

- Given Example Image
- Initialize the weights
- Normalize the weights
- Train the classifier and Choosing the classifier
- Update the weights and Construct the strong classifier





# The Attentional Cascade

- Observations:

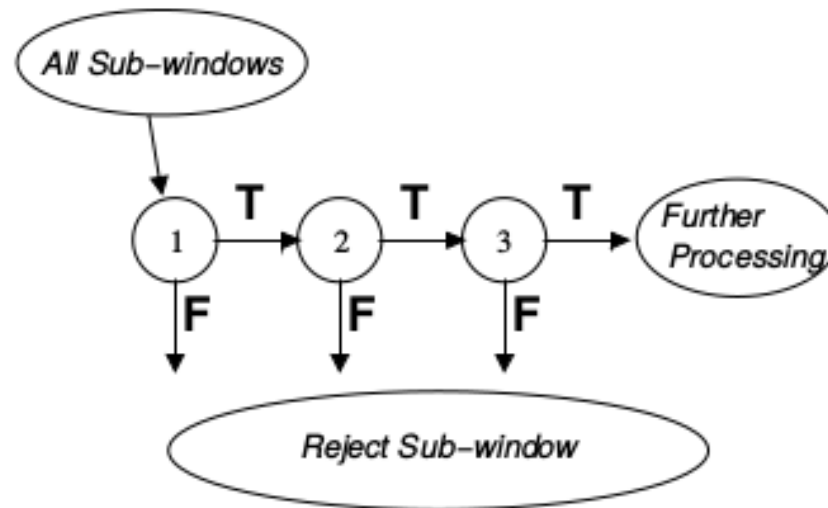
- Within any single image an overwhelming majority of sub\_window doesn't contain faces
- Recognizing faces is computationally expensive

# The Attentional Cascade

- Viola and Jones Solution :

Cascade Implementation:

A series of classifiers, each ones “harder” than the previous ones



# The Attentional Cascade

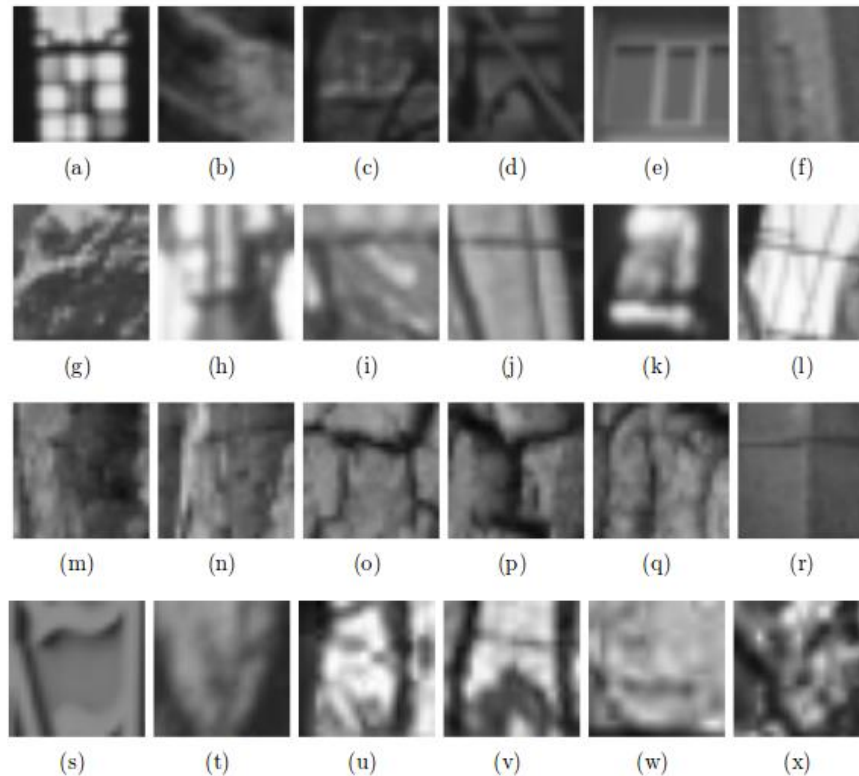


Figure 5: A selection of negative training examples at round 21 (a) (b) (c) (d) (e) (f), round 26 (g) (h) (i) (j) (k) (l), round 27 (m) (n) (o) (p) (q) (r), round 28 (s) (t) (u) (v) (w) (x). Observe how the negative training examples become increasingly difficult to discriminate from real faces.

# The Attentional Cascade

- Key Point of the classifiers:

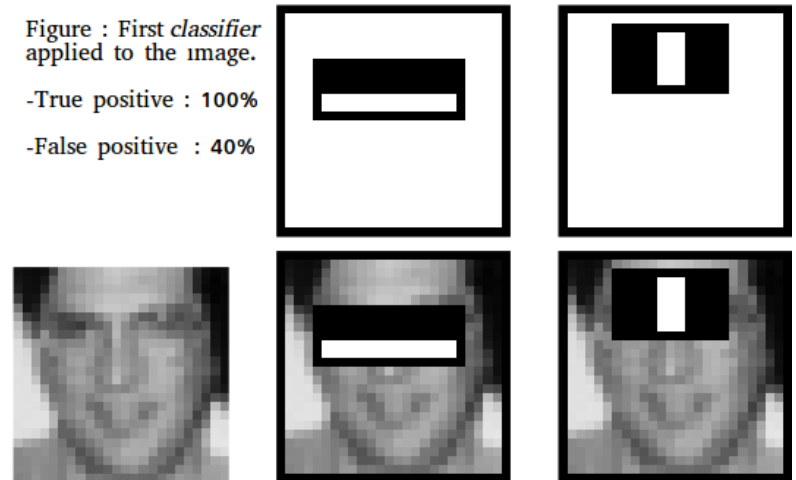
- Reduce: False Positive

- Minimize : False negative

Figure : First *classifier* applied to the image.

-True positive : 100%

-False positive : 40%



# The Attentional Cascade

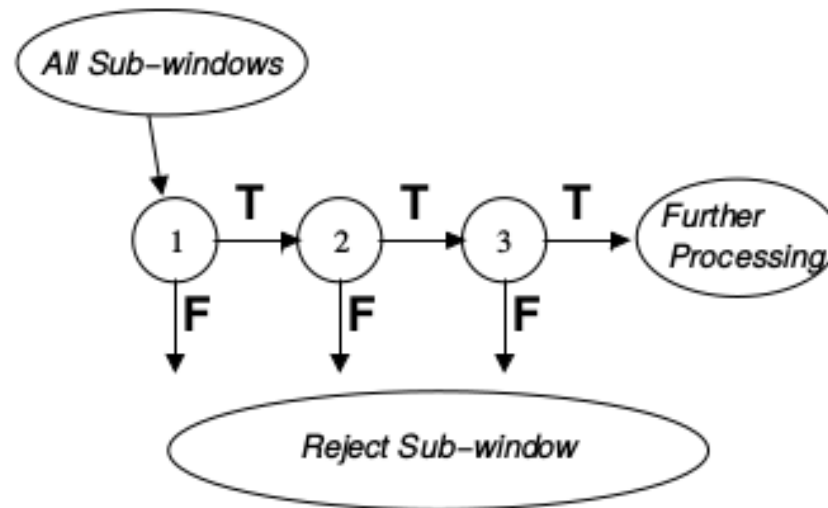
- Optimization in Theory:
  - The number of classifier stages
  - The number of features in each stage
  - The threshold of each stage

# The Attentional Cascade

- Optimization in Practices:
  - Set a Detection rate
  - Set a False Positive rate
  - Add features to classifiers until they meet those threshold

# The Attentional Cascade

- Overall:
  - 38 stages with 6061 features
  - An average of 10 features used by sub-windows



# The Attentional Cascade



Figure 6: How the trained cascade performs with (a) 16 layers, (b) 21 layers, (c) 26 layers and (d) 31 layers: the more layers, the less false positives.



# **Results**

# Results

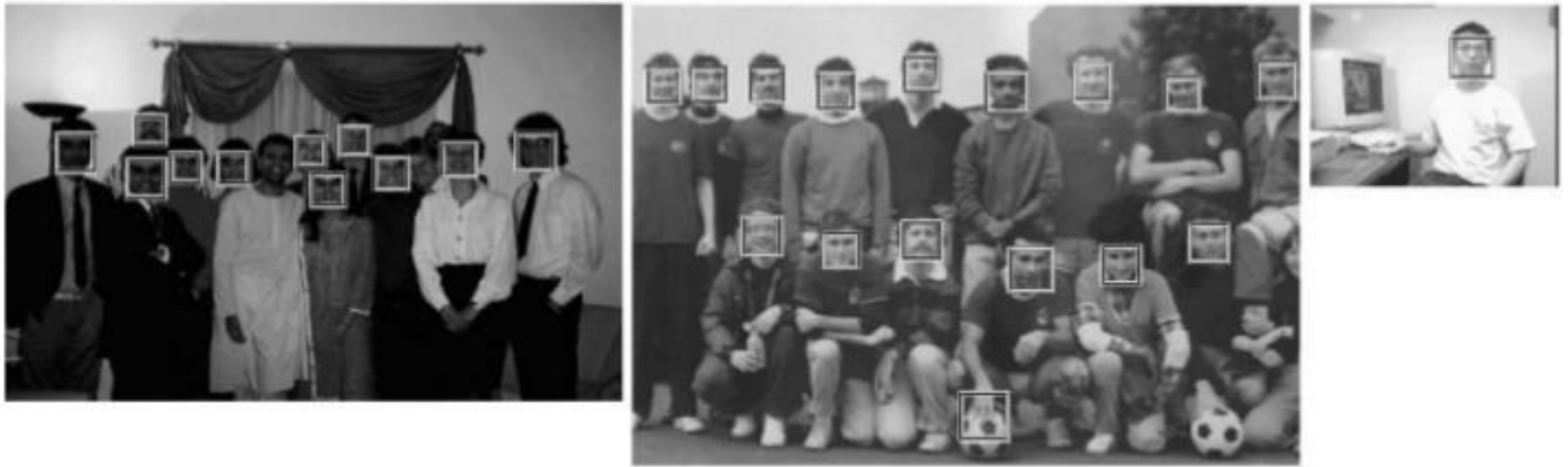


Figure 7: Output of our face detector on a number of test images from the MIT+CMU test set.

# Results

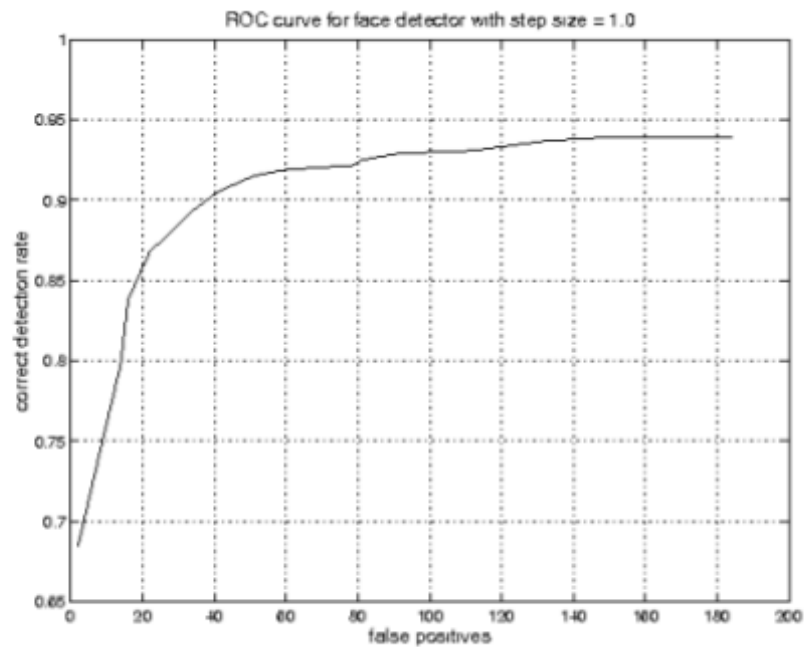


Figure 6: ROC curve for our face detector on the MIT+CMU test set. The detector was run using a step size of 1.0 and starting scale of 1.0 (75,081,800 sub-windows scanned).

# Results

- Performance :

~ 15 times faster than the fastest alternative (Rowley Baluja Kanade)

False detections Detector	10	31	50	65	78	95	167
Viola-Jones	76.1%	88.4%	91.4%	92.0%	92.1%	92.9%	93.9%
Viola-Jones (voting)	81.1%	89.7%	92.1%	93.1%	93.1%	93.2 %	93.7%
Rowley-Baluja-Kanade	83.2%	86.0%	-	-	-	89.2%	90.1 %
Schneiderman-Kanade	-	-	-	94.4%	-	-	-
Roth-Yang-Ahuja	-	-	-	-	(94.8%)	-	-

Table 2: Detection rates for various numbers of false positives on the MIT+CMU test set containing 130 images and 507 faces.

# **Conclusion**

# Advantages

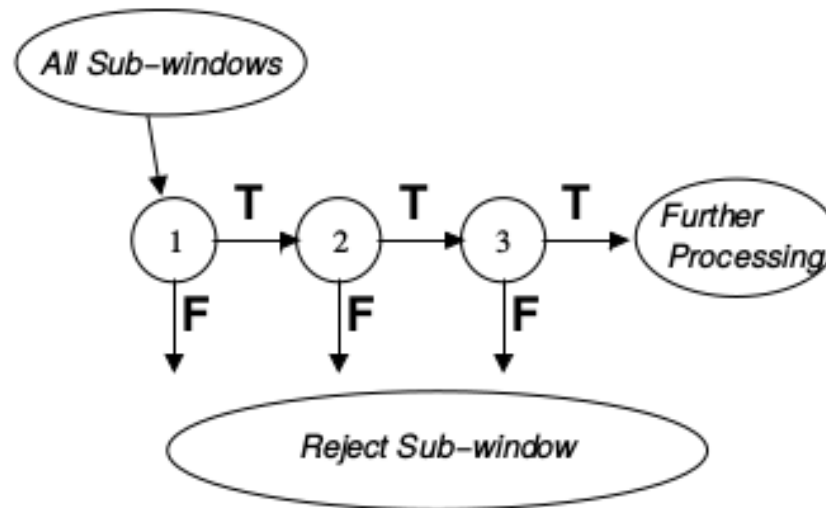
- Efficient features selections
- Scales and locations invariant detector
- Scale the features instead of the image
- Can be trained to detect other types of objects (e.g. cars, hands)

# Disadvantages

- Requires full view frontal upright faces
- Hardly cope with 45° face rotation both around the vertical and horizontal axis
- Sensitive to lighting conditions
- Might get multiple detections of the same face, due to overlapping sub-windows

# Paper's Contributions

- Integral Images
- Constructing a classifiers with Adaboost
- Cascade Structure





# References

- S.R. Arashloo et al., *Pose-invariant Face Recognition by Matching on Multi-resolution MRFs linked by Supercoupling Transform*, CVIU. 2011
- P.Viola and M.Jones. *Rapid Object Detection using a Boosted Cascade of Simple Features*, CVPR. 2001
- L.Lopez, *Local Binary Patterns applied to Face Detection and Recognition*, UPC 2010

# References

- <https://computersciencesource.wordpress.com/2010/09/03/computer-vision-the-integral-image/>
- [https://en.wikipedia.org/wiki/Viola%E2%80%93Jones\\_object\\_detection\\_framework](https://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework)
- <http://www.ipol.im/pub/art/2014/104/article.pdf>
- [http://docs.opencv.org/2.4/modules/objdetect/doc/cascade\\_classification.html](http://docs.opencv.org/2.4/modules/objdetect/doc/cascade_classification.html)
- [http://docs.opencv.org/trunk/d7/d8b/tutorial\\_py\\_face\\_detection.html](http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detection.html)

MOLTES  
GRÀCIES!!