

Image Analysis

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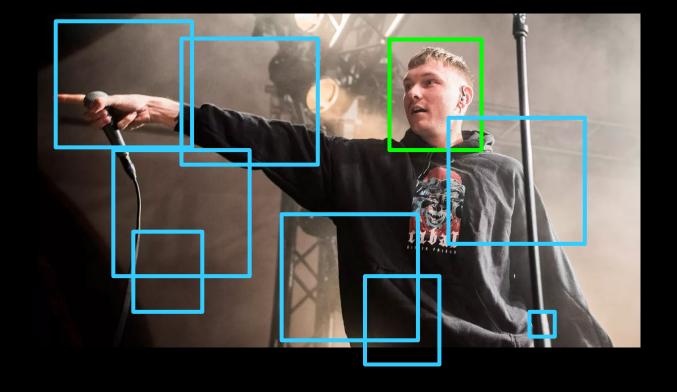
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http://www.compute.dtu.dk/courses/02502





Lecture 11 – Face detection using the Viola Jones method







What can you do after today?

- Describe the concept of face detection
- Describe the concept of Haar features
- Compute the values of 2, 3 and 4 rectangle Haar features
- Describe the integral image
- Compute the sum of pixels values in a rectangle using an integral image
- Describe the concept of a weak classifier
- Describe how several weak classifiers can be combined into a strong classifier
- Describe the attentional cascade
- Describe how faces can be detected using a moving window





Face detection

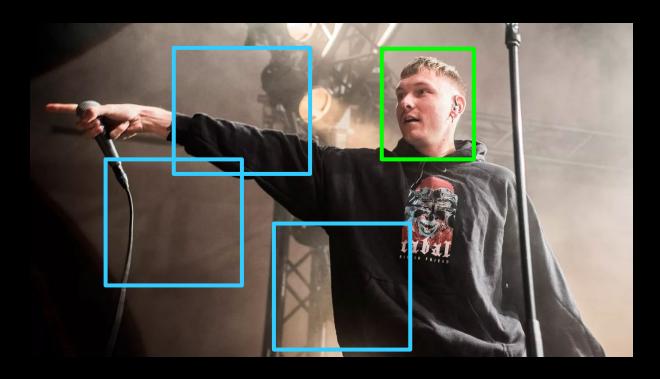


- First problem
 - Analyze a window in an image
 - Is there a face in that window?





Face detection

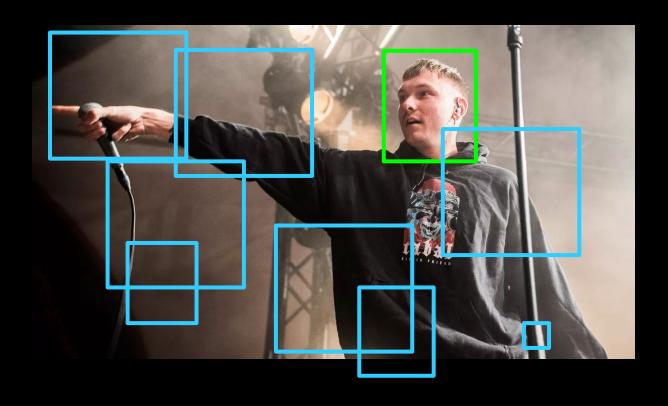


- Slightly more advanced
 - Analyze many windows in an image
 - How many (if any) windows contain faces?





Face detection



Ideal

- Analyze (almost) all possible windows in an image
- How many (if any) windows contain faces?





What is needed?



A fast method to determine if a window contains a face





Primary task – image feature based classification

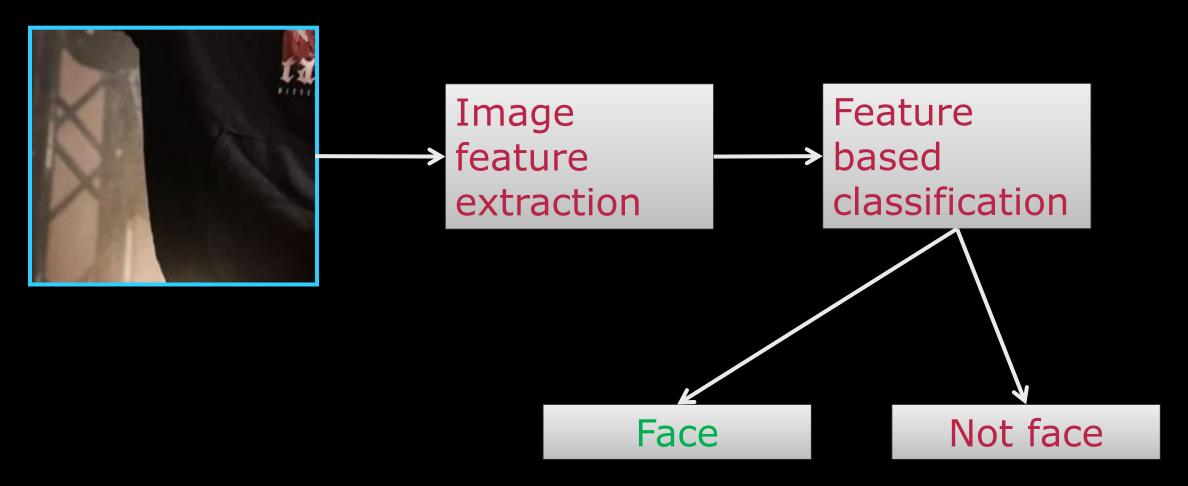






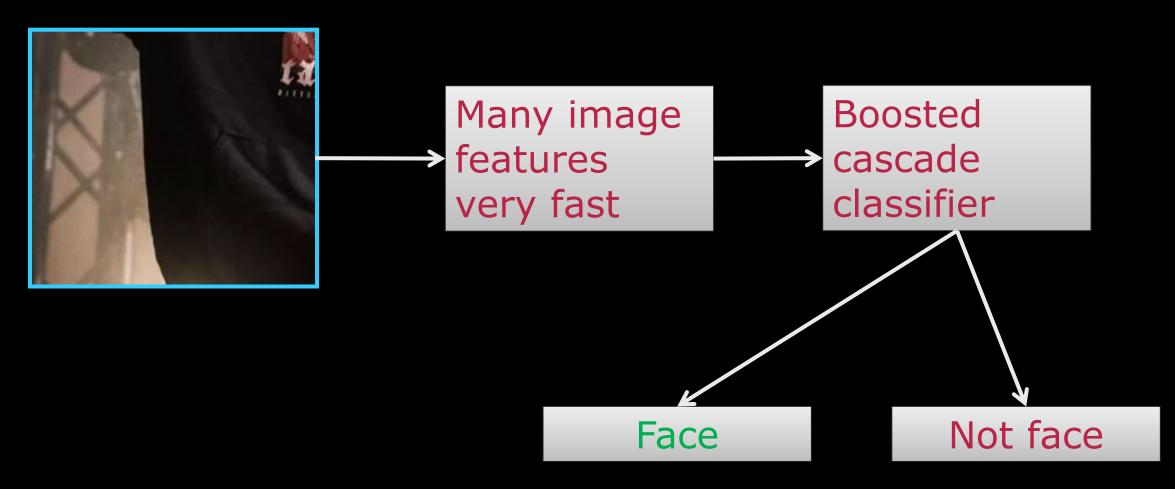
Image based features - what features can you think of?



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Viola Jones – fast features and smart classification







Training data



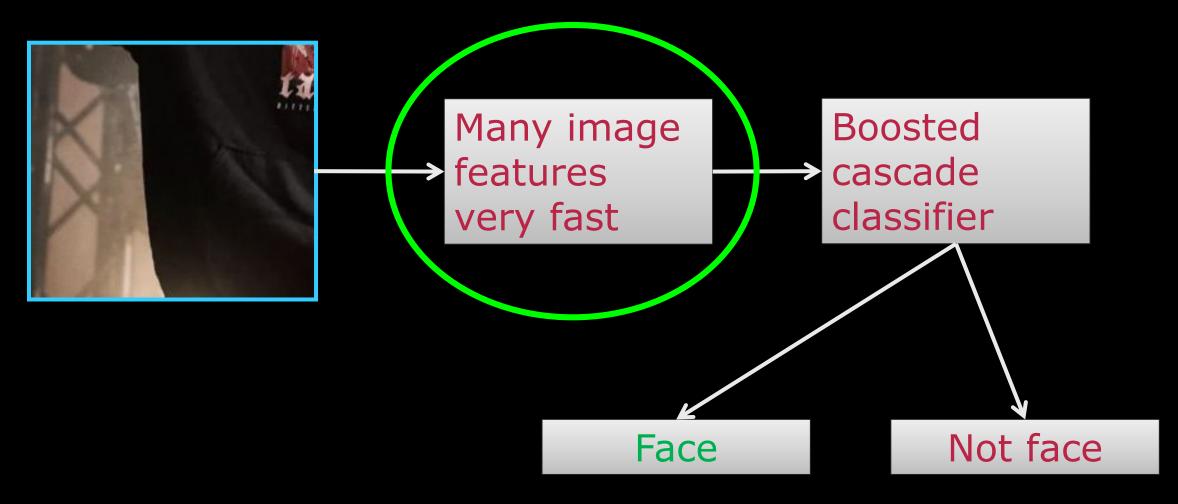
Face images:

- 4916 hand labelled faces
- Aligned and scaled to 24x24 pixels
- Non-face images:
 - 9544 images with no faces
 - 350 million sub-windows sampled from these



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Viola Jones – fast features and smart classification

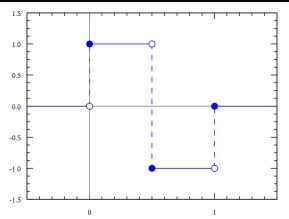






Haar features





- Alfred Haar (1885-1933)
 - Hungarian Mathematician
- Introduced the Haar wavelet in 1909
- A wavelet is a wave-like oscillation with an amplitude that begins at zero, increases or decreases, and then returns to zero one or more times.
- Simplest possible wavelet

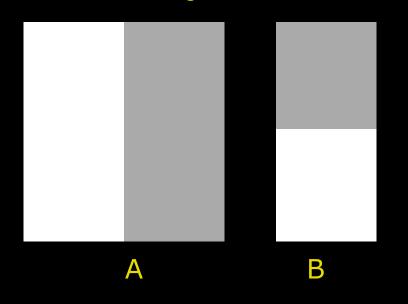
https://en.wikipedia.org/wiki/Wavelet



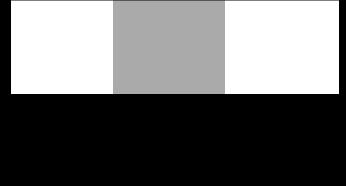


Haar features

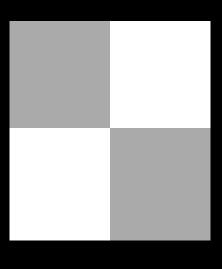
Two rectangle features



Three rectangle feature

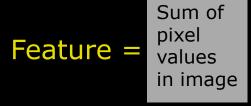


Four rectangle feature



D

Image Analysis

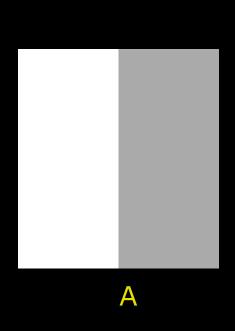


Sum of pixel values in image





One Haar feature

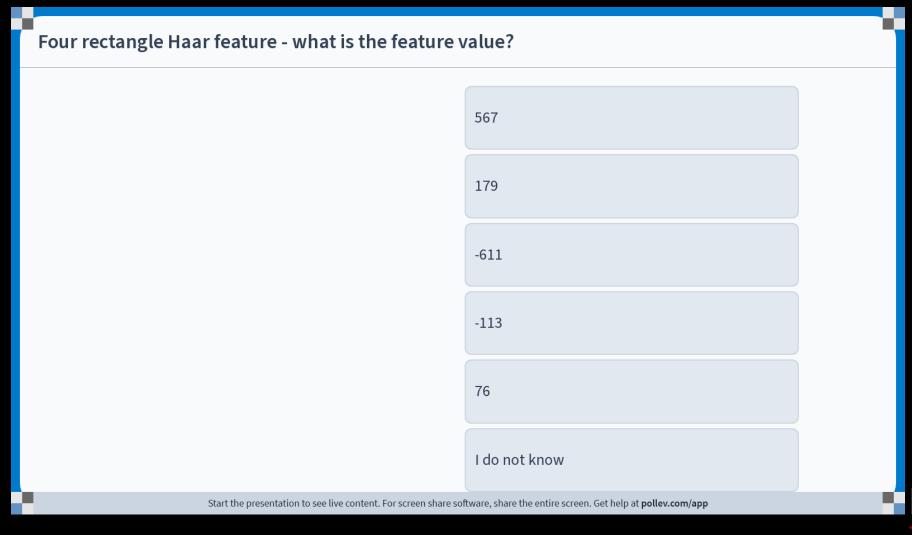




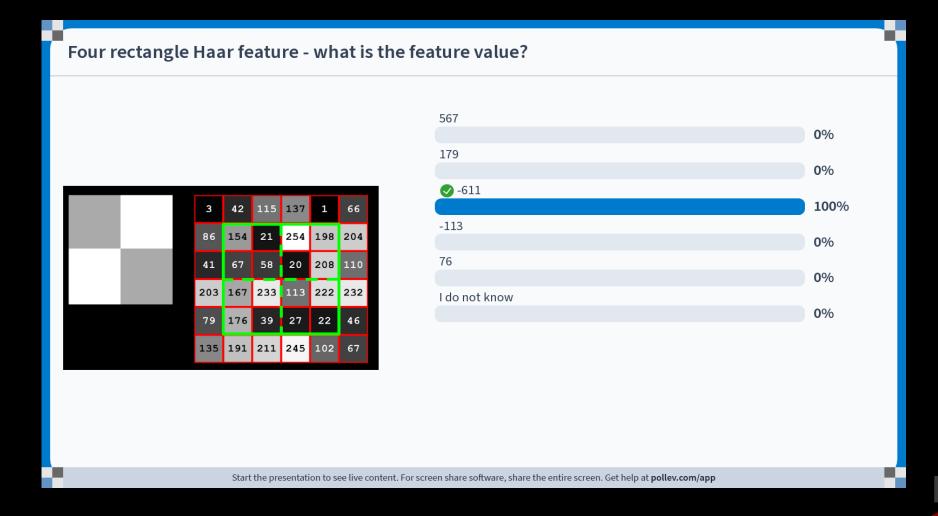
Feature = 254+198+20+208+113+222-154-21-67-58-167-233 = 1015-700 = 315





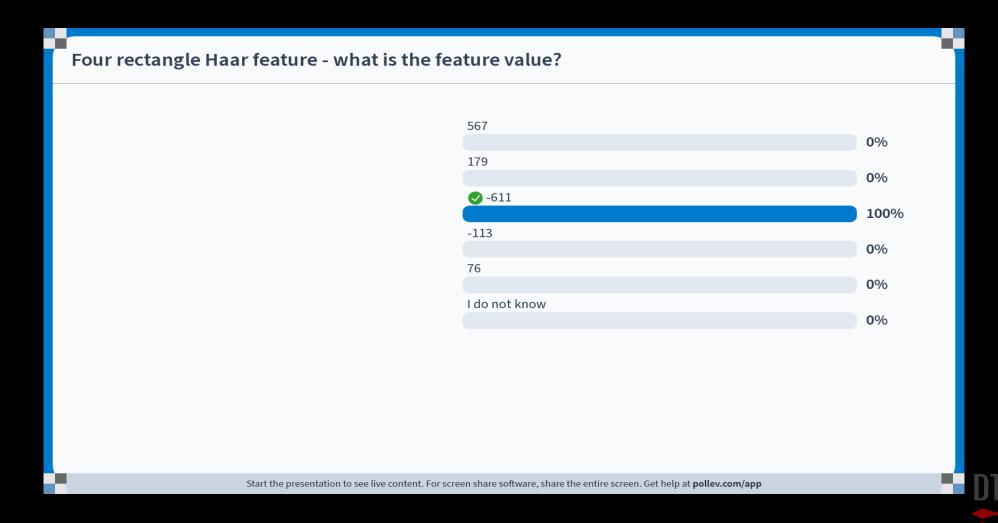










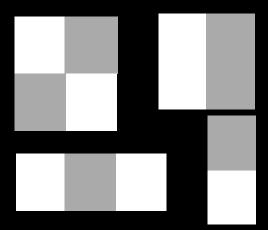




Fast computing of Haar features



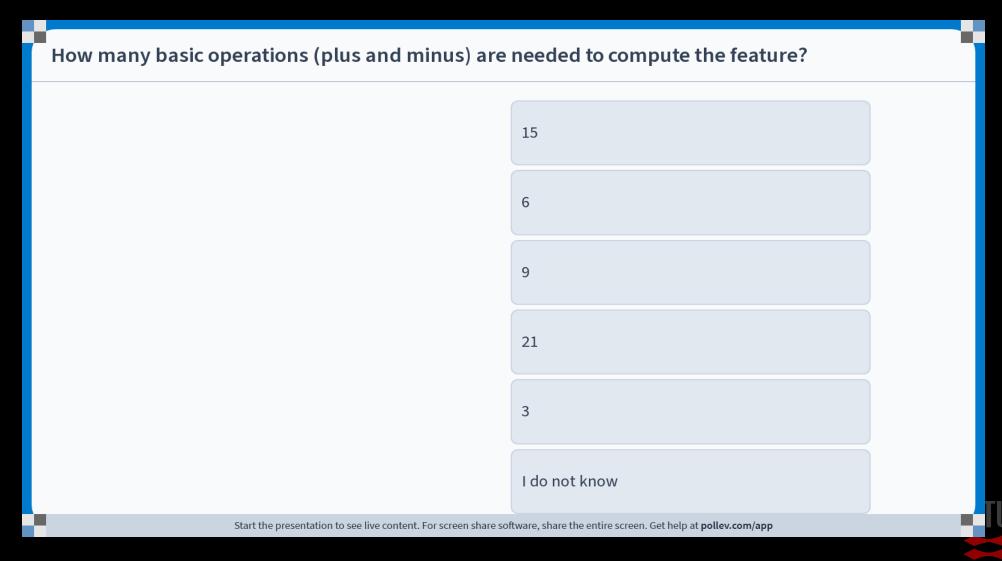
24 x 24 pixels



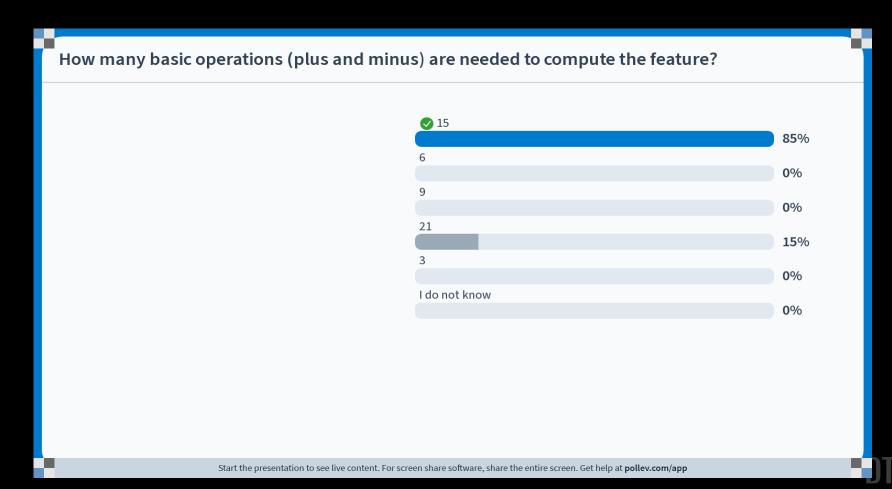
- Even for small Haar features, there are quite a lot of basic operations
- The larger the Haar feature, the more operations
- We need a fast way to compute Haar features



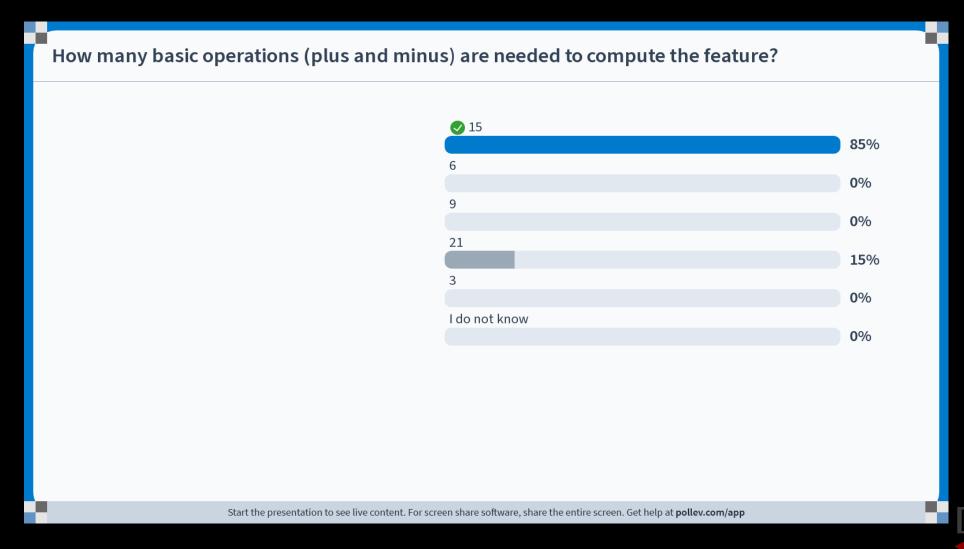






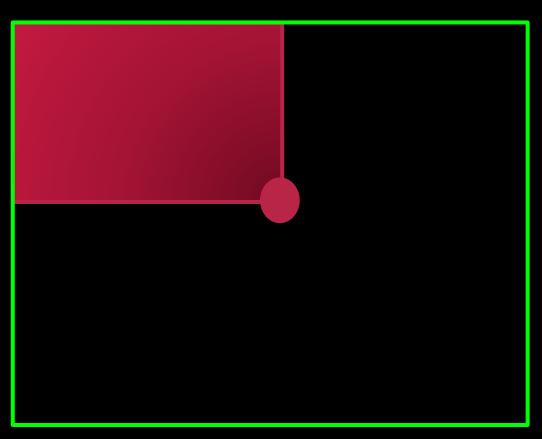








Fast computation of Haar features – the integral image



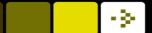
- In an integral image the pixel value is:
 - The sum of pixel above it and to the left of it in the original image

- Including the pixel itself
- Can be computed very fast







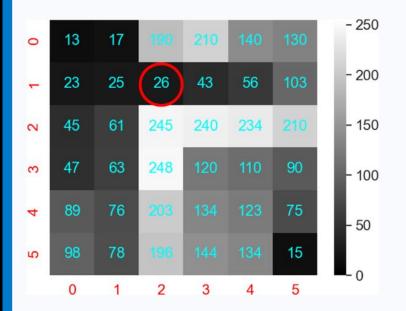


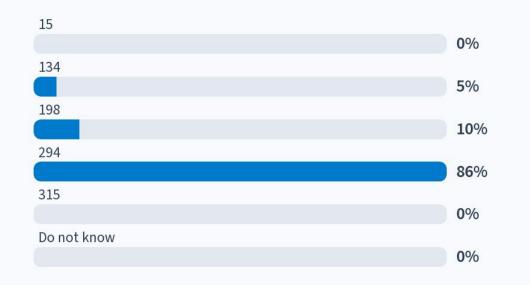






Computing the integral image - what is the value in the marked pixel?

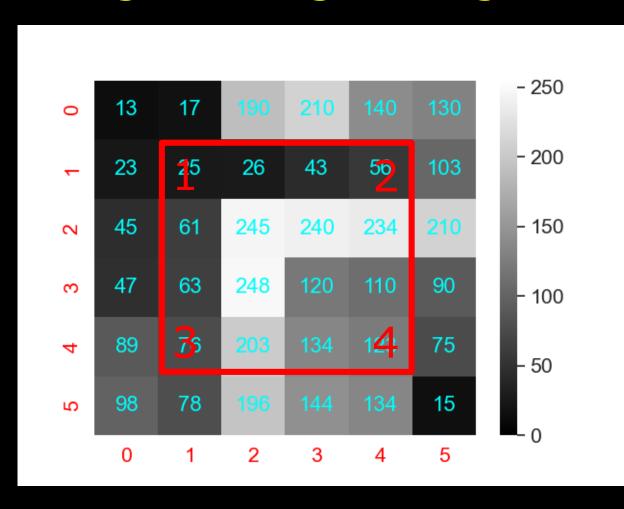




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Using the integral image

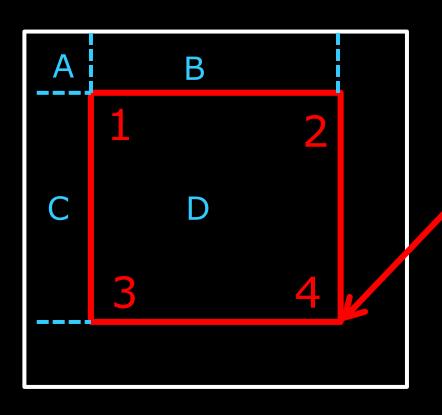


- We want to compute the pixel sum in the rectangle
- Defined by four corners: 1, 2, 3, 4





Using the integral image

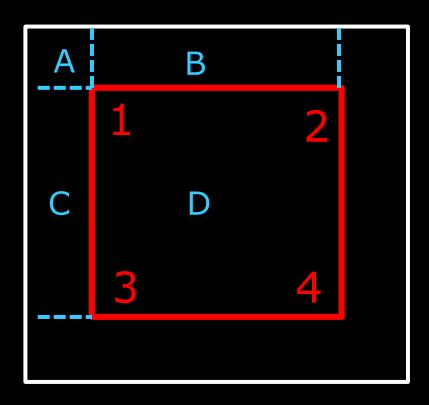


- Define four regions:
 - A, B, C, D
- The sum of pixels in the area
 - A+B+C+D is the value of the integral image at point 4





Using the integral image

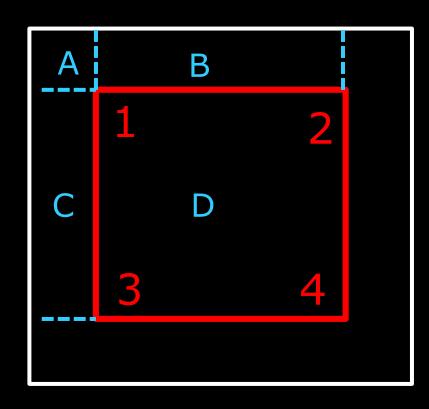


- The sum of pixels in the area
 - A+B is the value of the integral image at point 2
 - A+C is the value of the integral image at point 3





Using the integral image – short notation



The sum of pixels in the area

$$-ii(2) = A+B$$

$$- ii(3) = A+C$$

$$-ii(4) = A+B+C+D$$

$$-ii(1) = A$$

$$-ii(4)-ii(3)-ii(2) = D - A$$

$$-ii(4)-ii(3)-ii(2)+ii(1) = D$$





Course evaluation

- Very important to get your feedback on the course
- Please do it now log into DTU Inside and fill in the evaluation
- What works well so we should keep it and strengthen that part
- What can be improved and how?
- The question about "The teacher gave me feedback on my progress"
 - Very hard with large courses
 - We try with quizzes, TAs, exercise solutions

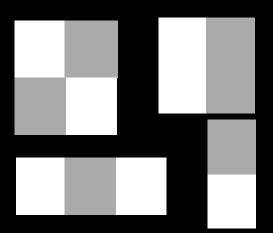




Haar features in an image window



24 x 24 pixels



- Image window of 24 x 24 pixels
- All possible sizes and shapes of Haar features
- More than 180.000 features according to Viola and Jones
- They are overcomplete meaning there is a very high redundancy
- We need feature selection





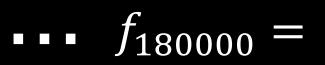
Possible features

$$f_1 = \mathbf{I} \qquad f_5 = \mathbf{I}$$

$$f_2 = \mathbf{I} \qquad f_6 = \mathbf{I}$$

$$f_2 = \mathbf{I} \qquad f_6 = \mathbf{I}$$

$$f_4 = \begin{bmatrix} f_8 \end{bmatrix}$$







Feature selection – from the article









- There are over 180,000 rectangle features associated with each image subwindow, a number far larger than the number of pixels.
- Even though each feature can be computed very efficiently, computing the complete set is prohibitively expensive.
- Our hypothesis, which is borne out by experiment, is that a very small number of these features can be combined to form an effective classifier.
- The main challenge is to find these features





Learning Classification Functions



$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$





24 x 24 subwindow

$$f_j = \blacksquare$$

Feature value computed on the sub-window

$$p_j \in [-1, 1]$$

Parity – determines if the feature value should be positive or negative

$$\theta_j$$

Feature threshold



$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$

Weak classifier

$$f_j(\square) = \square = 2049$$

Learnt by training: $p_j = 1$ $\theta_j = 456$

$$\rightarrow 1 * 2049 < 1 * 456 \rightarrow h_j(\square) = 0$$





What is this parity?



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$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$

Weak classifier

$$x =$$

$$f_j(\square) = \square = 2049$$

Learnt by training:

$$p_j = -1 \quad \theta_j = 456$$

$$\rightarrow -1 * 2049 < -1 * 456 \rightarrow h_j(\square) = 1$$





Creating a strong classifier from weak classifiers

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

$$h_1(\square) =$$

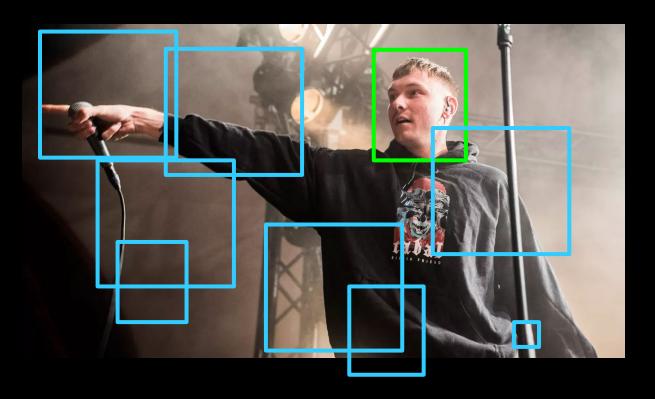
$$h(\square) = \alpha_1 h_1 + a_2 h_2 + \dots + a_T h_T$$

Learnt using AdaBoost





Boosted features – good performance but not enough



- Frontal face classifier with
 - T=200 features
 - Detection rate 95%
 - False positives 1 in 14084
 - 0.7 seconds for a 384 x 288

$$h_1(\mathbf{n}) = \alpha_1 h_1 + a_2 h_2 + \dots + a_T h_T$$





The Attentional Cascade



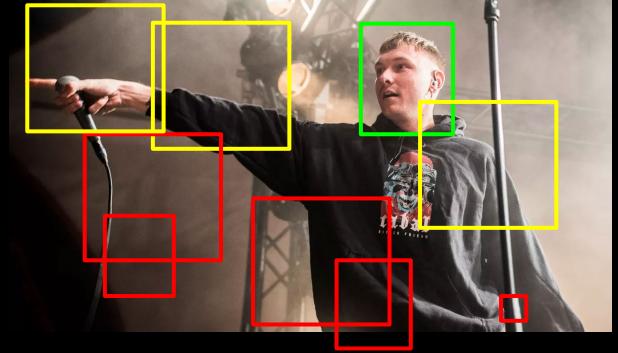






Image Attention

- The process of focusing on specific parts of an image
 - Followed by fine grained analysis of selected windows



Focusing on potential face regions



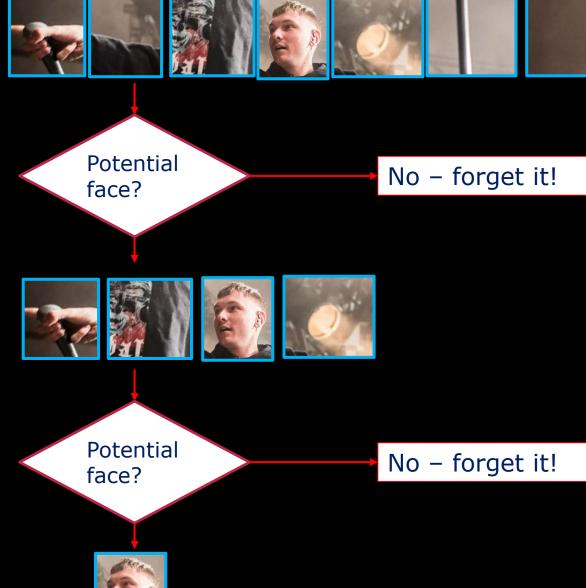
Input image windows



Cascaded classifier



Also called a *degenerate decision* tree





What is a false negative?

A face window classifed as face window

A background window classified as a face window

A face window classified as a background window

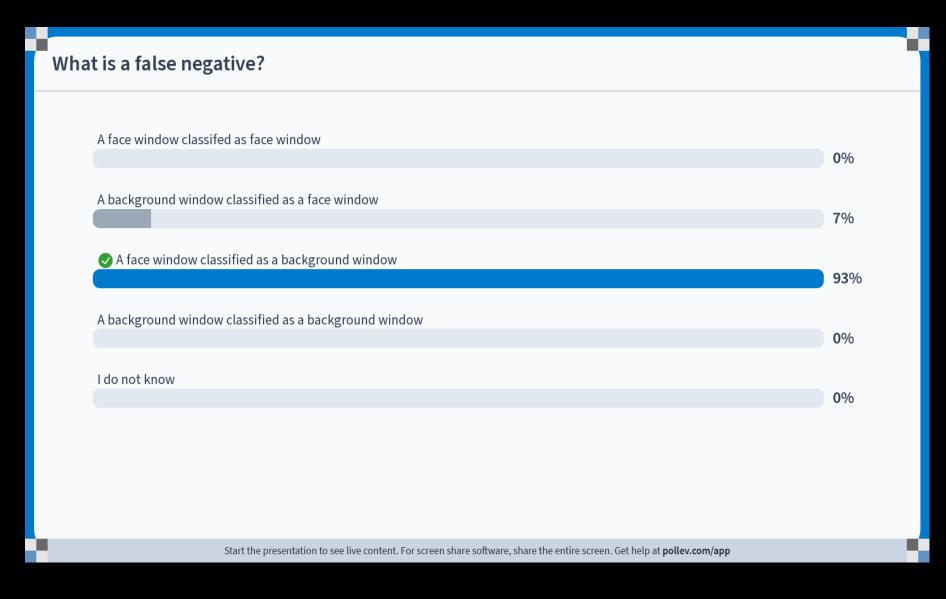
A background window classified as a background window

I do not know

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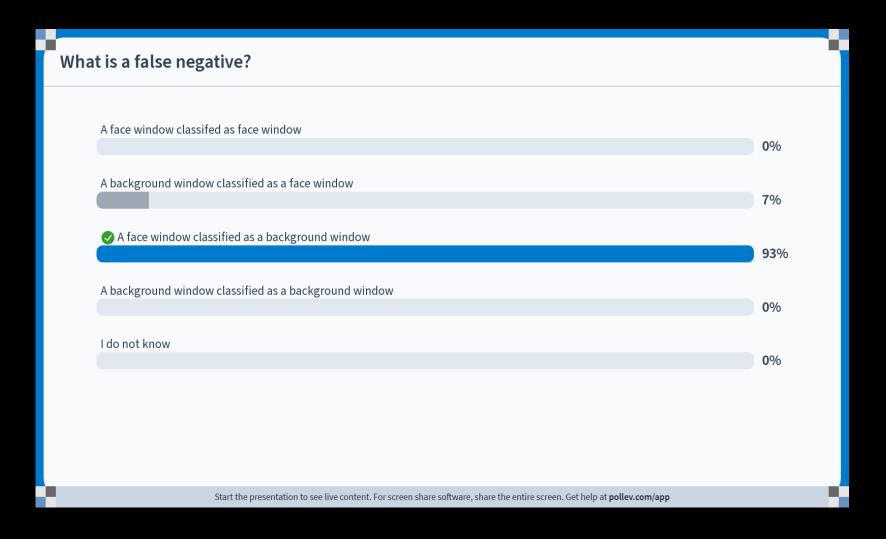












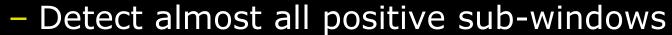




The attentional cascade

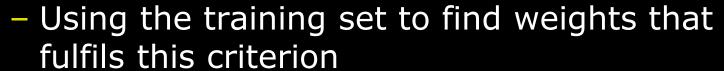














- Later more complex classifier
 - Low false positive rate













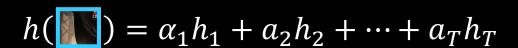




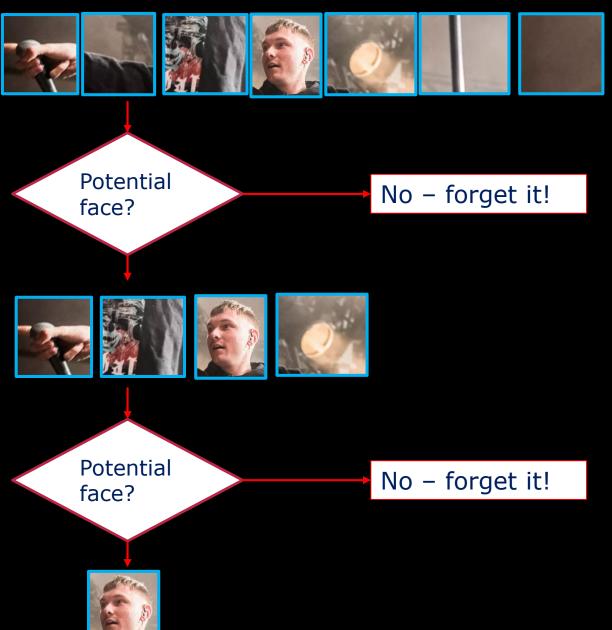
Training a cascade

$$h(\blacksquare) = \alpha_1 h_1 + a_2 h_2 + \dots + a_T h_T$$

Learnt using AdaBoost



Learnt using AdaBoost







First stage classifier











Final classifier

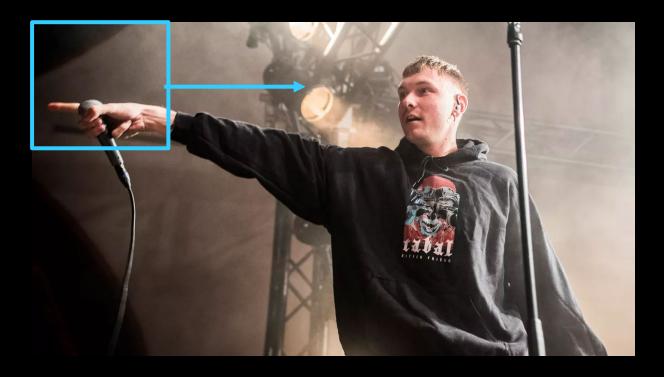


- 38 stages (step in the cascade)
- Total 6000 features (over the entire cascade)
- Faces are detected using on average 10 features per sub-window





Finding all faces in an image

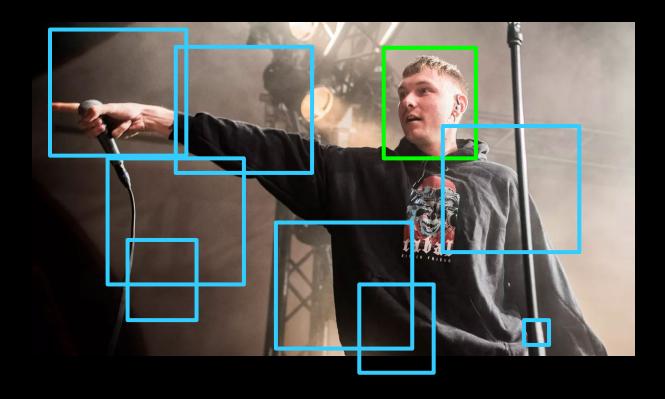


- Slide a sub-window over the entire image
- Do a face detection for all positions
- Scale the features in a certain interval
 - To find faces of different sizes





Conclusion



- One of the most important algorithms before deep learning
- Uses many interesting concepts
 - Attention
 - Boosted weak classifiers
 - Very fast feature computation





Demo





Next week(s)

- Advanced topics
- Statistical models of shape and appearance

