

Question 1 ($\Sigma = 13$)

(a) What is thresholding?

(2 pts)



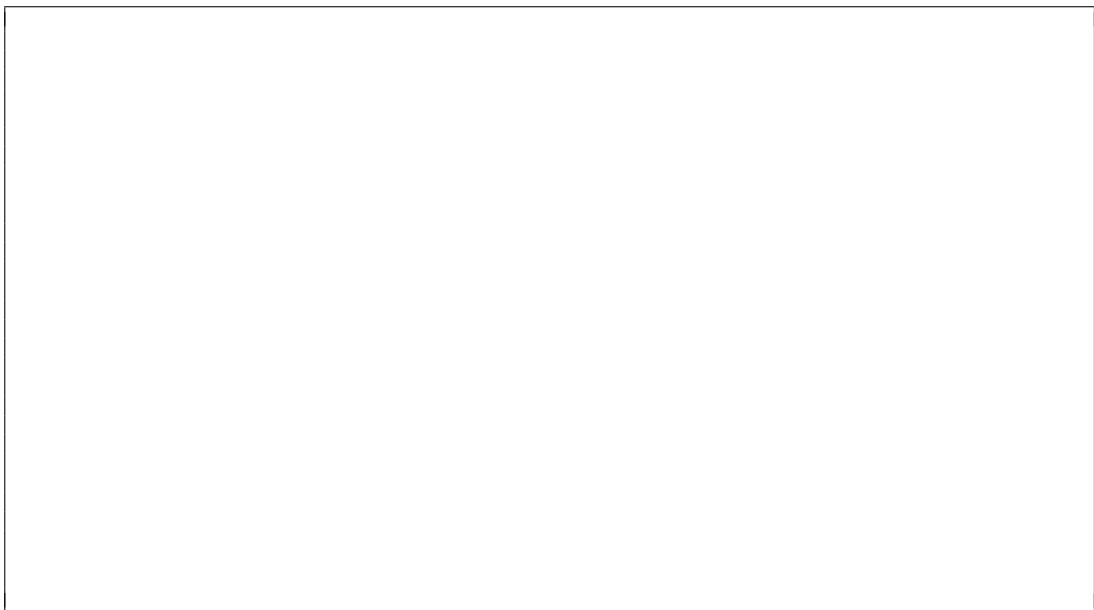
(b) Name two use-cases of thresholding.

(2 pts)

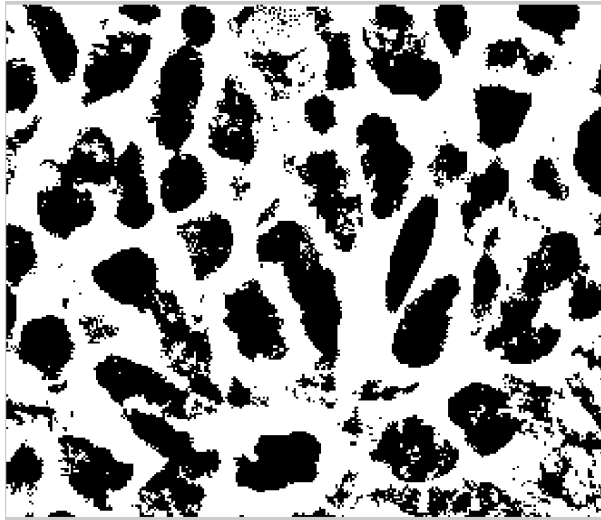


(c) Describe Otsu's thresholding algorithm.

(4 pts)



(d) You have used a thresholding algorithm and obtained the following image:



- i. We want to clean up the image using morphological operators. Explain how the morphological operators work. **(3 pts)**

- ii. Which morphological operator(s) would you use on this image and why? Remember: Foreground are the black cells. **(2 pts)**

Question 2 ($\Sigma = 16$)

- (a) List the steps of the k-Means algorithm.

(4 pts)

- (b) Properties of k-Means

(3 pts)

Will k-Means always converge?

☐ Yes ☐ No

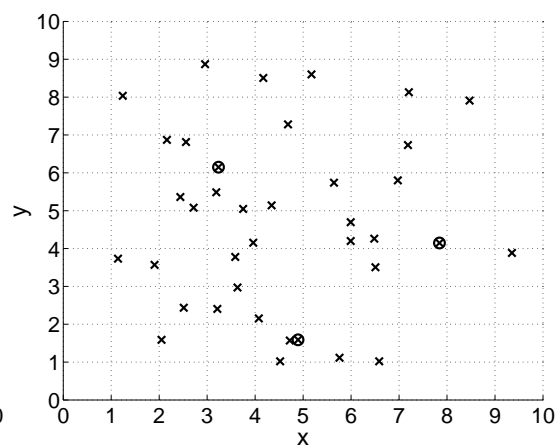
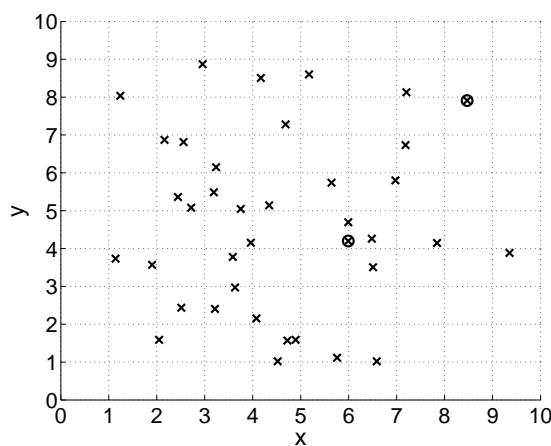
Does k-Means always find the best solution with respect to its objective function?

☐ Yes ☐ No

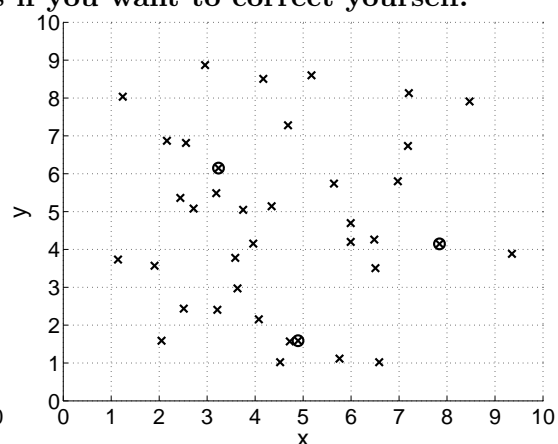
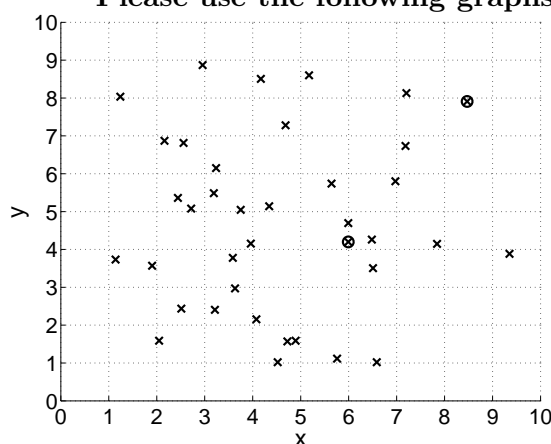
Is the problem of finding the optimal solution NP-complete?

☐ Yes ☐ No

- (c) Sketch the (approximate) cluster boundaries and their means k-Means would give for the following dataset for
- $k = 2$
- (left) and
- $k = 3$
- (right). The circled points are the initial means. (4 pts)

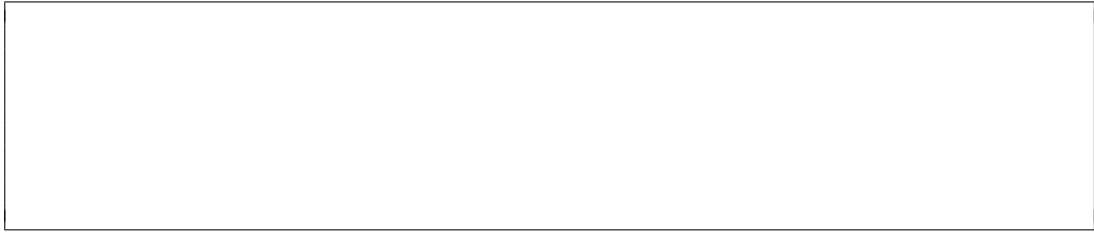


Please use the following graphs if you want to correct yourself.



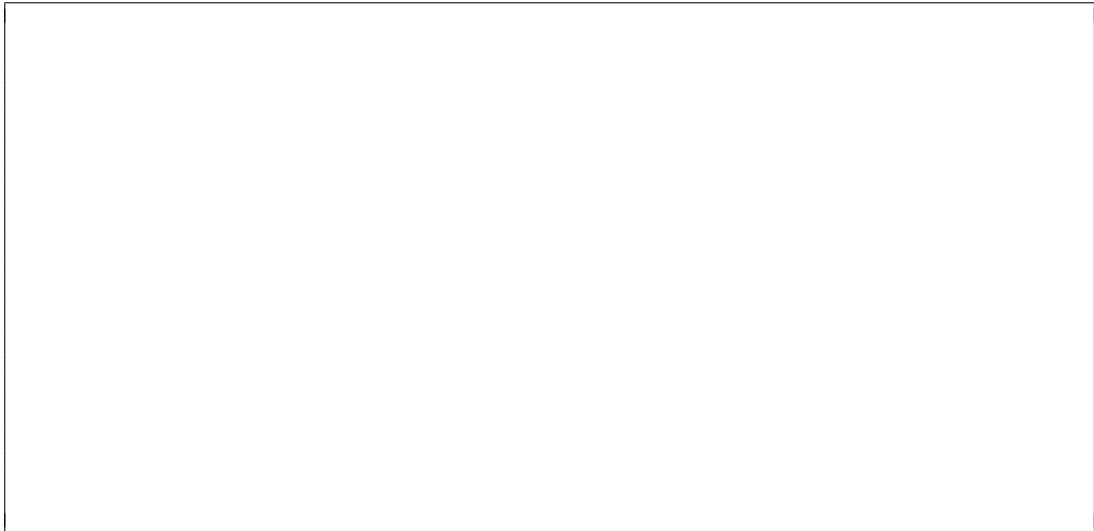
- (d) List one advantage and two disadvantages of k-Means.

(3 pts)



- (e) Describe in detail how k-Means can be used for image segmentation.

(2 pts)



Question 3 ($\Sigma = 12$)

- (a) Please fill in the following Matlab code fragment to complete the Hessian detector. (4 pts)
(Pseudo-code is sufficient, as long it is unambiguously clear what is meant.)

```

1 function [px, py] = computeHessian(filename, sigma, thresh)
2   % -----
3   % Preprocessing
4   % -----
5   I           = loadImage(filename);
6   Ig          = gaussianfilter(I, sigma); % Gaussian filter
7   [Ix, Iy]     = gaussderiv(I, sigma);    % first derivatives
8   [Ixx, Ixy, Iyy] = gaussderiv2(I, sigma); % second derivatives
9
10  % -----
11  % Compute Hessian score for each pixel
12  % -----
13  [height, width] = size(I);
14  score = zeros(height, width);
15  for y = 1:height
16      for x = 1:width
17          % Compute Hessian score for pixel I(y, x) and store it in score(y,
            % x)

```

```

18      end
19  end
20
21  % -----
22  % Postprocessing
23  % -----
24  % Extract the interest points from the computed score map.
25  [py, px] = find(score > thresh)
26 end

```

- (b) The above code is still not fully correct. There are 2 steps missing. Please point them out (A verbal explanation is sufficient). (2 pts)

(c) Details to the Hessian detector.

- i. What are the differences between the Hessian and the Harris detector? Please **(2 pts)** briefly describe.

ii. Properties of Hessian keypoints

(2 pts)

Is the Hessian detector scale-invariant?

☐ Yes ☐ No

Is the Hessian detector translation-invariant?

☐ Yes ☐ No

- iii. How can Harris be extended to detect key points with arbitrary scale automatically. **(2 pts)**

Question 4 ($\Sigma = 15$)(a) The Adaboost *training* algorithm.

i. What is the input and what is the output of this algorithm?

(2 pts)

ii. Briefly explain the steps of the Adaboost *training* algorithm (no formulas required). (3 pts)

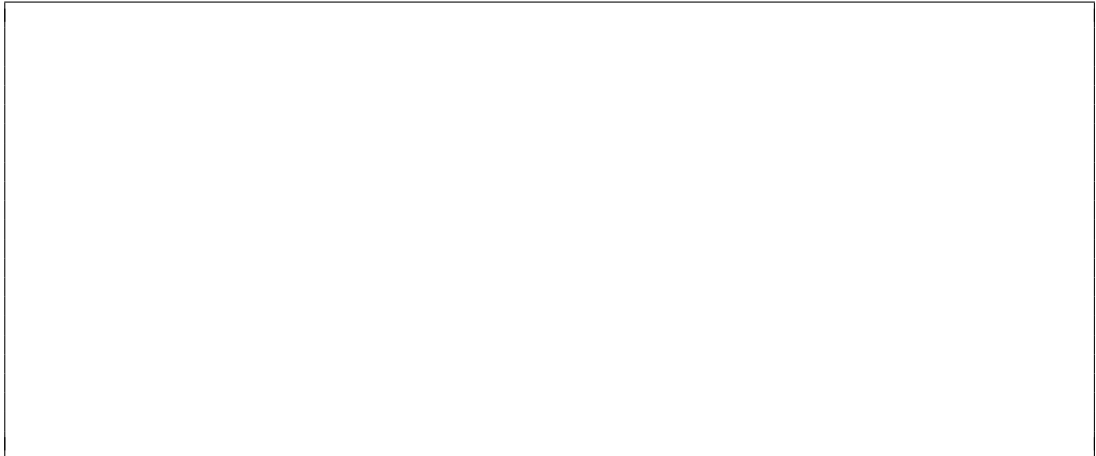
(b) Which property has to be fulfilled by the weak classifiers?

(1 pt)

(c) How is a test point classified? Give the equation.

(2 pts)

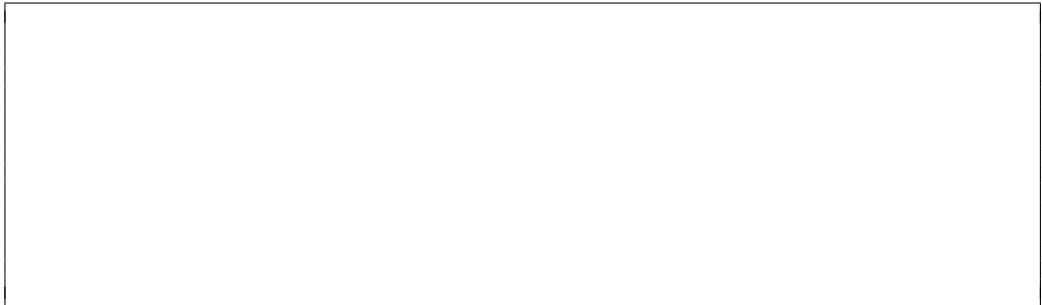
- (d) What are the weak classifiers that are used for Viola-Jones face detection? (You may **(2 pts)** sketch to support your answer.)



(e) Integral Images

- i. What is an integral image?

(1 pt)



- ii. Why and how are integral images used for Viola-Jones face detection? (You may **(2 pts)** sketch to support your answer.)



- (f) Briefly explain how cascading classifiers for detection works.

(2 pts)



Question 5 ($\Sigma = 13$)

(a) Briefly explain the following concepts

i. Fundamental Matrix

(1 pt)

ii. Epipolar plane

(1 pt)

(b) Eight-point algorithm

(4 pts)

i. Fill in the first row of the following matrix in order to complete the Eight-point algorithm. Assume that the point correspondence is called (\mathbf{x}, \mathbf{y}) where $\mathbf{x} = (x_1, x_2, 1)$ is located in the left image and $\mathbf{y} = (y_1, y_2, 1)$ in the right image. (**Hint:** Use the derivation of the algorithm).

$$\begin{bmatrix} \boxed{} & \boxed{} & \boxed{} & \boxed{} & \boxed{} & \boxed{} & \boxed{} & \boxed{} & \boxed{} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \cdot \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{bmatrix} = 0$$

ii. How do we solve this equation? What exactly is the solution?

(1 pt)

- iii. Solving this equation directly usually leads to very inaccurate results in presence of noise. Please explain why. **(1 pt)**

- iv. What can we do to about this issue in order to get more accurate results, and how? **(1 pt)**

(c) Rank constraints of the Fundamental Matrix.

- i. What is the rank of the Fundamental matrix? Why? **(2 pts)**

- ii. What would happen if F had full rank? **(1 pt)**

- iii. How do we enforce the rank constraint when estimationg F ? **(1 pt)**