Written Examination

2016-07-21

Name:	Mustermann	_ First Name:	Max
Program of Study:		Informatik Master	
MatrNo.:	123456	Exam #:	123

Information:

- Write your name and matriculation number on every sheet of paper.
- Make sure that all **11 pages** are present.
- Answer each question on the provided sheet. If more space is needed, use a new sheet of paper for each question.
- If you have to draw to answer a question, multiple templates are provided. Cross out wrong answers!
- At the end of the examination this cover sheet together with the question sheets and all additionally used papers have to be returned.
- Duration of the exam: **60 minutes**.
- No additional aids (notes, calculator, ...) are allowed.
- Write **legibly**. Not readable text will not be graded.
- Use a pen with **blue or black ink** for writing down your solutions. Text written with pencils or red/green pens will not be graded.

With my signature I confirm that I have **read and understood** the information above.

C *	
Signature	

Question:	1	2	3	4	5	Total	Grade
Points:	13	10	10	14	13	60	-
Score:							
Moderation:							

(a)	For data D and hypothesis H , say whether or not the following equations must always be true. Answer in yes or no. i. $\sum_{h} p(H = h \mid D = d) = 1$	(2 pts)
	h i	
	ii. $\sum_{h} p(D = d \mid H = h) = 1$	
	h ii	
	iii. $\sum_{h} p(D = d \mid H = h)p(H = h) = 1$	
	iv. $p(H D) = \frac{p(D H)p(D)}{p(H)}$	
	iv	
(b)	In probability density estimation methods, we typically have a tuning parameter which acts as a smoothing factor. For example, in case of Histograms, bin size Δ is such a tuning parameter. Smoothing can also be interpreted in terms of 'bias' and 'variance'. Provide a very brief interpretation of bias and variance in terms of smoothing. How will bias and variance change if the bin size is increased?	(3 pts)
(c)	We want to represent the probability distribution for points x_n , $n = 1,, N$ by a univariate Gaussian distribution with parameters $\theta(\mu, \sigma^2)$. Express the likelihood $p(x_n \mid \theta)$ for a single data point using the equation for the Gaussian distribution.	(1 pt)

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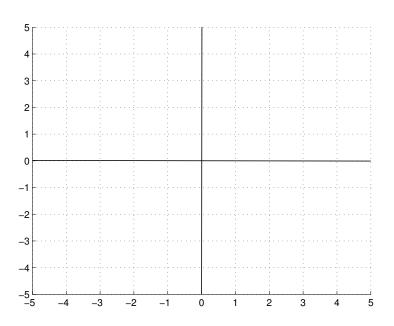
What implicit assumption did we make in this derivation?	(1]
	(2 p
What problems/limitations does Maximum Likelihood have?	(- P
What problems/limitations does Maximum Likelihood have?	

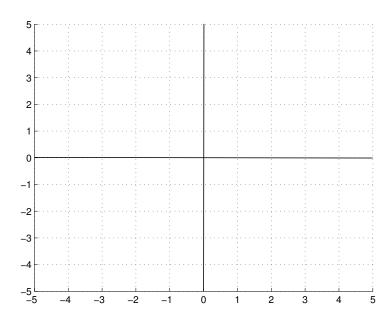
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What is the difference between	en generative and discrimi	inative methods	for classifica
tion?	on generative and discrimi	mative methods	ioi ciassilica
01011.			
Write an equation of the error b	function for a 2-dimension	al, 2-class linear l	Least-Square
Write an equation of the error be classifier and define the variab			Least-Square:
			Least-Square
			Least-Square
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			Least-Square:
			Least-Square:
			Least-Square

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(c) Plot the error function for the linear Least-Squares classifier. **Hint:** Use the second **(2 pts)** plot to correct your answer if needed. Strike out wrong answers.





(d) Discuss the behavior of Least-Squares classification in the presence of outliers. (2 pts)



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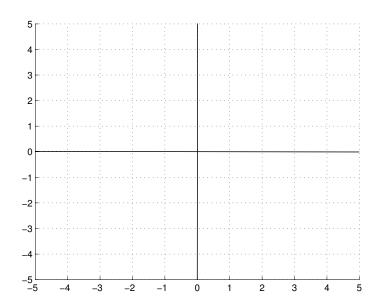
(e) Name two other methods that use linear discriminants and draw their corresponding error functions.

i. Name of the classification method:

(1 pt)

i.

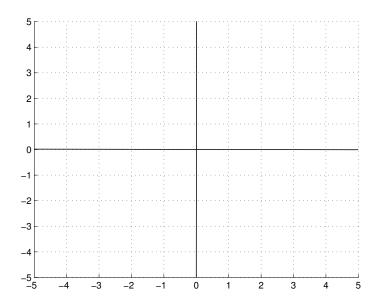
Error function:



ii. Name of the classification method:

(1 pt)

Error function:



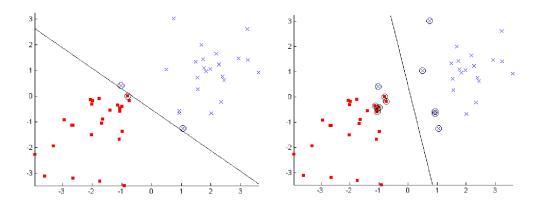
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are	t H be the set of all oriented lines in the (x, y) -plane. Points on one side of the line x classified as positive and on the other side as negative. What is the VC-dimensions x
Fo	r each of the following cases, state whether it would be best to use the primal or
	al SVM formulation. Briefly explain your answer. . We apply a feature transformation that maps the input data into a feature space with infinite dimension.
ii	. We apply a feature transformation that doubles the dimension of the input data.
	The input data has millions of training examples and is linearly separable.

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(c) _____

(d) You trained a linear SVM on the toy problem below and obtained the solution shown (2 pts) on the left. Your friend also trained a linear SVM on the same problem, but obtained the solution shown on the right.



What happened here? How can the difference be explained?



(e) In general explain which data points will be selected as support vectors by an SVM. (2 pts)



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${ m Question \ 4: \ Adaboost} \ (\Sigma=14)$	/
(a) Write down the steps of Adaboost algorithm below and provide the corresponding for mulas. Given a candidate pool of weak classifiers $\{h_k\}$ and training samples $\{(\mathbf{x}_n, t_n)\}$ $n = 1 \dots N$ (where $\mathbf{x}_n \in \mathbb{R}^d$ are data points in d -dimensional space and $t_n \in \{-1, +1\}$ are class labels), the AdaBoost algorithm for the two-class problem is:	},
i. Initialize the weights:	(1 pt
ii. For $m = 1, \ldots, M$	(6 pts
	_
iii. Resulting classifier:	_ (1 pt
	\- P *

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ii. AdaB	post can model non-linear decision boundaries.	(2 p
	Boost work better with strong base classifier or with weak ones? Why?	_ (2 p
Does Adal		7
Does Adal		

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Question 5: Graphical Models $(\Sigma=13)$

Consider the following Bayesian Network

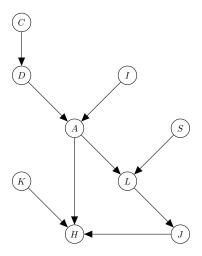


Figure 1: Bayesian Network

(a)	Write down	the set of	variables whi	ch forms the	e Markov	blanket of	'A' in Fig.	1?	(2 pts)
-----	------------	------------	---------------	--------------	----------	------------	-------------	----	---------

- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	
- 1	

- (b) For each of the following independence assumptions, please state whether it is true or (2 pts) false:

i. _____

ii. $D \perp \!\!\! \perp S \mid L$.

.. 11

iii. $C \perp \!\!\!\perp J \mid H$.

iii. _____

iv. $C \perp \!\!\!\perp J \mid A$.

V.

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	work given ab						
	the given Baw the resultin	ayesian Networ 1g graph.	rk in Figure	1 into an un	directed grap	phical model	(3
Specify sulting	the factorizat undirected mo	tion of the joir odel.	nt probabilit	y p(A, C, D, I)	I,S,L,J,K,I	I) of the re-	(3

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