

**Tuesday 26th June 2018  
(2 hours)**

# **ADVANCED STATISTICAL INFERENCE**

**Answer all questions.**

**This examination paper includes three questions and is worth a total of 80 marks.**

1. Probabilistic Reasoning (total of [20] points)
  - (a) Consider three random variables  $A$ ,  $B$ , and  $C$ . How many ways are there to express the joint distribution as a function of the marginals/conditionals? [5]
  - (b) Write Bayes theorem to derive  $p(A|B, C)$  from  $p(B|A, C)$ . How does this simplify if  $A$  does not depend on  $C$ ? [5]
  - (c) How can you obtain  $p(A)$  from  $p(A, B, C)$ ? [5]
  - (d) Focus on  $A$  and  $B$  only, and imagine that these are binary variables and that you can obtain as many samples as you want from any of their joint/conditional/marginal distributions. How would you test whether  $A$  and  $B$  are independent? [5]
2. Bayesian Linear Regression and Gaussian Processes (total of [35] points)
  - (a) What is Linear Regression and why is it called “Linear”? [5]
  - (b) Explain how to treat Linear Regression in a Bayesian way. [5]
  - (c) Explain how to use Linear Regression for the estimation of nonlinear functions. [5]
  - (d) In Bayesian Linear Regression we usually assume that the labels are corrupted by noise. How would you reformulate Bayesian Linear Regression when assuming that the input too is affected by noise? [5]
  - (e) What is the computational complexity (space and time) of Bayesian Linear Regression with respect to number of observations  $N$  and dimensionality of the features  $D$  [5]
  - (f) Denote the  $N \times D$  input matrix by  $X$ . Interpreting Gaussian Processes as Bayesian Linear Regression, what is the “equivalent” kernel of such Gaussian Processes? [5]
  - (g) What is the computational complexity (space and time) of Gaussian Processes? [5]
3. Supervised learning (total of [25] points)
  - (a) How would you go about extending the Naïve Bayes classifier to regression? [10]

- (b) What is a kernel function in Machine Learning? Why is it useful?  
[5]
- (c) Imagine a supervised learning problem where you apply a probabilistic model based on kernels. How would you optimize kernel parameters in the two cases where the kernel is parameterized by (i) one parameter or (ii) one-hundred parameters?  
[5]
- (d) Describe an example of a probabilistic model where we need to resort to approximate inference.  
[5]