732A96/TDDE15 ADVANCED MACHINE LEARNING

EXAM 2018-08-29

TEACHERS

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GRADES

- For 732A96 (A-E means pass):
  - A=19-20 points
  - B=17-18 points
  - C=12-16 points
  - D=10-11 points
  - E=8-9 points
  - F=0-7 points
- For TDDE15 (3-5 means pass):
  - 5=18-20 points
  - 4=12-17 points
  - 3=8-11 points
  - U=0-7 points

The total number of points is rounded to the nearest integer. In each question, full points requires clear and well motivated answers.

ALLOWED MATERIAL

Hard copy of Bishop's book, and the content of the folder given_files in the exam system.

INSTRUCTIONS

The answers to the exam should be submitted in a single PDF file using the communication client. You can make a PDF from LibreOffice (similar to Microsoft Word). You can also use Markdown from RStudio. Include important code needed to grade the exam (inline or at the end of the PDF file). Submission starts by clicking the button "Skicka in uppgift" in the communication client. Then, follow the instructions. Note that the system will let you know that the exam has been submitted, but will not tell you that it was received. This is ok and your solution has actually been received.

Do not ask question through the communication client. The teachers will be reachable by phone, and they will visit the room too.

1. Graphical Models (5 p)

- Learn a Bayesian network (both structure and parameters) from the Asia dataset that is distributed in the `bnlearn` package. To load the data, run `data("asia")`. Use any learning algorithm and settings that you consider appropriate. Use the Bayesian network learned to compute the probability distribution of a person having visited Asia given that the person has bronchitis and the X-rays came positive, i.e. $p(A|X = TRUE, B = TRUE)$. Use both the approximate and exact methods. (3 p)
- There are 29281 DAGs with five nodes. Compute approximately the fraction of the 29281 DAGs that represent an independence model that can be represented with a Markov network. You may want to use the function `skeleton` of the `bnlearn` package, which outputs the undirected graph that results from dropping the directions of the edges in the input graph. (2 p)

2. Hidden Markov Models (5 p)

- Recall Lab 2 where you were asked to build a HMM for modeling the behavior of a robot that walked around a ring. The ring was divided into 10 sectors. At any given time point, the robot was in one of the sectors and decided with equal probability to stay in that sector or move to the next sector. You did not have direct observation of the robot. However, the robot was equipped with a tracking device that you could access. The device was not very accurate though: If the robot was in the sector i, then the device reported that the robot was in the sectors [i - 2, i + 2] with equal probability.

  You are now asked to extend the HMM built in Lab 2 as follows. The observed random variable has now 11 states, corresponding to the 10 sectors of the ring plus a 11th state to represent that the tracking device is malfunctioning. If the robot is in the sector i, then the device will report that it is malfunctioning with probability 0.5 and that the robot is in the sectors [i - 2, i + 2] with probability 0.1 each. Implement the extension just described by using the `HMM` package. Moreover, consider the observations 1, 11, 11, 11, i.e. the tracking device reports sector 1 first, and then malfunctioning for three time steps. Compute the most probable path using the smoothed distribution and the Viterbi algorithm. (3 p)
- You are asked to build a HMM to model a weather forecast system. The system is based on the following information. If it was rainy (respectively sunny) the last two days, then it will be rainy (respectively sunny) today with probability 0.75 and sunny (respectively rainy) with probability 0.25. If the last two days were rainy one and sunny the other, then it will be rainy today with probability 0.5 and sunny with probability 0.5. Moreover, the weather stations that report the weather back to the system malfunction with probability 0.1, i.e. they report rainy weather when it is actually sunny and vice versa. Implement the weather forecast system described using the `HMM` package. Sample 10 observations from the HMM built. Hint: You may want to have hidden random variables with four states encoding the weather in two consecutive days. (2 p)

3. Gaussian Processes (5 p)

See attached file `Exam732A96_180829Question3.pdf`.

4. State Space Models (5 p)

- Consider the following state space model (SSM):

$$p(x_t|x_{t-1}) = \mathcal{N}(x_t|x_{t-1}+1, 1)$$
$$p(z_t|x_t) = \mathcal{N}(z_t|x_t, 5)$$
$$p(x_0) = \mathcal{N}(x_0|50, 10)$$

  Implement and simulate the SSM above for $T = 10000$ time steps to obtain a sequence of observations $z_{1:T}$ and hidden states $x_{1:T}$. Implement the Kalman filter as it appears in the course slides or in the book by Thrun et al. Note that the SSM above specifies standard deviations 1, 5 and 10 for the transition, emission and initial models. However, the Kalman filter in the slides and in the book is described in terms of variances instead.

  Run the Kalman filter on the observations $z_{1:T}$. Report the mean and standard deviation of the errors for the $T = 10000$ time steps. The error for time t is defined as $abs(x_t - E[x_t])$, where the expectation is with respect to the filtered distribution (a.k.a. belief function). (3 p)
- Repeat the exercise above with the particle filter. You may want to re-use the code you produced for the lab. (2 p)

Good luck !