732A96/TDDE15 ADVANCED MACHINE LEARNING

EXAM 2021-10-27

Teacher

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Grades

- For 732A96 (A-E means pass):
  - A=19-20 points
  - B=17-18 points
  - C=14-16 points
  - D=12-13 points
  - E=10-11 points
  - F=0-9 points
- For TDDE15 (3-5 means pass):
  - 5=18-20 points
  - 4=14-17 points
  - 3=10-13 points
  - U=0-9 points

In each question, full points requires clear and well motivated answers and commented code.

Instructions

- The exam will be made available via Teams at 8.00 am. Hand in your answers before 12.15 pm via LISAM/Submissions. If you have the right to extended examination time, then hand in by e-mail to `jose.m.pena@liu.se`.
- This is an individual exam. No help from others is allowed. No communication with others regarding the exam is allowed. Answers to the exam questions may be sent to Urkund.
- This is an anonymous exam. Do not write your name on it.
- The answers to the exam should be submitted in a single PDF file. 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).

Allowed help

Everything on the course webpage. Your individual and group solutions to the labs.

1. Graphical Models (5 p)

- In the course, you have seen how to perform exact and approximate inference with a Bayesian network (BN). Approximate inference consists essentially in sampling from the joint distribution and, then, counting relative frequencies. Sampling is easy thanks to the directed acyclic graph (DAG) of the BN: You sample the nodes in any ordering, as long as the parents of a node are sampled before the node itself. That is, you sample from the distribution of the child conditioned on the values previously sampled for the parents.

  Your task is to load the Asia data, build the true Asia DAG, learn the parameters from the data, and sample 1000 points from the resulting BN using the algorithm outlined above. Use the sample obtained to approximate $p(S|D = yes)$. Compare the approximation with the result you obtain using exact inference.

  Help: If your BN is called `net`, you can access the conditional probability distributions of the node A by doing `net$A$prob`. Recall that you used the true Asia DAG in the lab.

2. Hidden Markov Models (5 p)

- You are asked to use a hidden Markov model (HMM) to model the following domain. The probability that a healthy person remains healthy the day after is 0.9. The probability that an infected person remains infected the day after is 0.8. However, there is an exception to this: When a person gets infected, he/she remains infected for at least two days. Moreover, we never know for sure if a person is infected. Luckily, there is a lab test that gives us information about the true health status of a person. The test is not perfect, though. The sensitivity of the test (i.e., the true positive rate) is 0.6, whereas the specificity of the test (i.e., the true negative rate) is 0.7.

  Your task is to build a HMM from the description above, simulate it for 100 time steps, and confirm that the HMM really models the fact that the infection lasts for at least two days.

3. Reinforcement Learning (5 p)

- In the course, you have learned about the roles that ϵ and γ play in Q-learning. Although typically selected by the user, their values can also be selected via validation. For instance, consider the values $\epsilon = 0.1, 0.25, 0.5$ and $\gamma = 0.5, 0.75, 0.95$. For each pair of values for ϵ and γ, run Q-learning 30000 episodes. Freeze the resulting Q-table, i.e. do not update it anymore. Run Q-learning 1000 additional episodes (without updating the Q-table). Compute the average reward in these 1000 episodes. The first 30000 episodes learn the policy (training), whereas the last 1000 evaluate the policy (validation). Now, simply select the pair of values for ϵ and γ that performed best in the validation phase.

  Your task is to implement the validation framework described above for the environment B in the lab. Discuss your results.

4. Gaussian Processes (5 p)

- In the course, you have learned about the roles that σ_f and l play in Gaussian processes (GPs) for regression. Now, you are asked to elaborate on the role of σ_n. Specifically, you are asked to repeat the exercises 2.1.4 and 2.1.5 from the lab with $\sigma_n = 1$. In other words, update the prior GP with the five points in the lab exercises using $\sigma_f = 1$, $l = 0.3, 1$ and $\sigma_n = 0.1, 1$. Plot the posterior mean and probability bands for each of the four combinations of hyperparameter values. Use the plots to draw conclusions about the role of σ_n.