732A96/TDDE15 ADVANCED MACHINE LEARNING

EXAM 2022-10-26

Teacher

Jose M. Peña. Questions can be asked via the exam system. If this does not work satisfactorily, then I will visit the room. I will also be available by phone.

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

- This is an individual exam. No help from others is allowed. No communication with others 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 (no support is provided though). 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. This help is available on the corresponding directories of the exam system.

1. Bayesian networks (5 p)

This exercise is an extension of lab 1 and, thus, you may want to reuse your code. Consider the Asia dataset. Consider the true Asia BN structure. Use the dataset to estimate the BN parameter values. Let us call these parameter values the true ones. Now, assume that only the 10 first cases of the dataset are complete, i.e. they include values for all the variables. The rest of the cases contain no values for the variables B and E. This is rather common in practice as some variables may be difficult or expensive to measure. Use the 10 complete cases to estimate the BN parameter values. Now that you have a BN, you can perform inference to impute the missing values of B and E for the remaining 4990 cases: For each case with missing values, (i) compute the posterior distribution of B conditioned on the values for the rest of the variables, (ii) do the same for E, (iii) impute the value for B by sampling the posterior distribution for B, and (iv) do the same for E. Now you have a completed dataset with 5000 cases. Use it to estimate the BN parameter values.

Consider the conditional distribution of D given its parents that you obtained from the 10 complete cases, and the one that you obtained from the 5000 cases with imputed values. Which of the two is closer to the true one?

2. Hidden Markov Models (5 p)

This exercise is a modification of lab 2 and, thus, you may want to reuse your code. The ring the robot walks has now only five sectors. If the robot is in the sector i, then the tracking device will report that the robot is in the sectors $[i-1, i+1]$ with equal probability. The rest of the sectors receive zero probability. The robot must now spend at least two time steps in sector 1, three time steps in sector 2, two time steps in sector 3, one time step in sector 4, and two time steps in sector 5. The different durations correspond to the robot having to perform different tasks in different sectors. You are asked to implement this modification. In particular, the regime's minimum duration should be implemented implicitly by duplicating hidden states and the observation model, i.e. do not use increasing or decreasing counting variables.

Simulate the HMM model built above to confirm that it behaves as expected.

3. Reinforcement Learning (4 p)

This exercise is an extension of lab 3 and, thus, you may want to reuse your code. In that lab, you looked at the sensitivity of your results with respect to several hyperparameters. The learning rate was always $\alpha = 0.1$. You are now asked to study the effect of the learning rate. Specifically, you are asked to run Q-learning on environment A, 500 episodes, $\gamma = 1$ and $\alpha = 0.001, 0.01, 0.1$. The rest of the hyperparameters should be set to the same values as in the lab. Report and analyze the results that you obtain.

4. Gaussian Processes (2.5 + 3.5 p)

- This exercise is an extension of lab 4 and, thus, you may want to reuse your code. Specifically, you are asked to fit a GP for regression to the data below.

```
X<-seq(0,10,.1)
Yfun<-function(x){
  return (x*(sin(x)+sin(3*x))+rnorm(length(x),0,2))
}
plot(X,Yfun(X),xlim=c(0,10),ylim=c(-15,15))
```

  Use the squared exponential kernel, a prior mean equal to 0, $\sigma_n = 2$, and $\sigma_f = 0.5$. Plot the posterior mean as well as the 95 % probability bands. Choose the value of ℓ that you deem appropriate by visual inspection, i.e. do not perform a grid search or optimization of the log marginal or any other score. Motivate your choice for the value of ℓ. Now, you are free to choose the values for both σ_f and ℓ by visual inspection. Motivate your choices.

- In this second exercise, you are asked to fit a GP for regression to the data below (note that it is not the same code as before).

```
X<-seq(0,10,2)
Yfun<-function(x){
  return (x*(sin(x)+sin(3*x))+rnorm(length(x),0,.2))
}
plot(X,Yfun(X),xlim=c(0,10),ylim=c(-15,15))
```

  Now, you are free to select the next x-value for which you would like to observe its y-value, in order to update the GP with it. This is common in many domains. One reasonable strategy is to choose the x-value for which there is most uncertainty about its y-value. We can assess this uncertainty with the help of the 95 % probability bands, i.e. as the difference between the upper and lower bands. Implement this strategy to choose the next x-value. Run the `Yfun` function above for this x-value. Update the previous GP with the new point, i.e. learn a GP for regression with the previous points and the new point. Repeat this process for the updated GP, i.e. select point and update. Repeat it once more.