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Artificial Intelligence

COSC 6368

Solution Sketches Final Exam

Thursday, December 7, 2017

*Name:*

*Student-id:*

1. Reinforcement Learning and Learning in General (17 points)
2. Planning (8 points)
3. Belief Networks and Naïve Bayes (17 points)
4. Decision Trees and Learning in General (11 points)
5. Neural Networks (14 points)

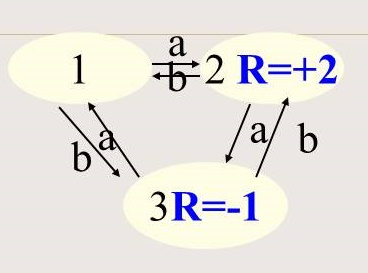
Point Total (out of 67):

Number Grade:

The exam is “open books” and you have 115 minutes to complete the exam. Please write your answers on the test papers!

1) Reinforcement Learning and Learning in General [17]

a) Assume the following world is given:



Moreover, the current Q-table contain sthe following entries:

|  |  |  |  |
| --- | --- | --- | --- |
|  | Value | QL-Update | SARSA-  Update |
| q(a,1) | 1 |  |  |
| q(b,1) | -0.5 |  |  |
| q(a,2) | -0.5 | 1 | 0.75 |
| q(b,2) | 0 |  |  |
| q(a,3) | 0 | -0.25 | -0.25 |
| q(b,3) | 1 |  |  |

Assume the agent is currently in state 2 and her policy always applies action a in every state; how does the updated Q-Table look like after the agent has applied action a the second time[[1]](#footnote-1)?

a) when Q-Learning is used?

b) when SARSA is used?  
Assume that the learning rate α and the discount rate γ are both 0.5. Do not only report the updated value, but also give the formulas for the four Q-table updates. [6]

Q:Learning:

q(a,2)=-0.5\*0.5+ 0.5\*(2+0.5\*max(0,1))=-0.25+1.25=1

q(a,3)=0\*0.5+ 0.5\*(-1+0.5\*(max(1,-0.5)=-0.25

Sarsa:

q(a,2)=-0.5\*0.5+ 0.5\*(2+0.5\*0)=-0.25+1=0.75

q(a,3)=0\*0.5+ 0.5\*(-1+0.5\*1)=-0.25

b) What **advantages** do you see in using SARSA over Q-Learning? [3]

SARSA uses the actually taken action for the update and is therefore more realistic as it uses the employed policy; Q-Learning is less realistic as it assumes a gready policy, but in most applications policies are needed that allow for some exploration.

Problem 1 continued

c) Assume an agent employs a greedy policy that always selects the action with the highest expected utility. What disadvantages do you see in using such a policy? [4]

When exploring an unknown world, the agent might receive a positive reward for applying an action a in state s, and might apply action a in state s until the end of the days without finding out that applying action a’ in state s would have led to a higher reward. [3]

When a world changes the agent is ill prepared for such a change, because she did not explore alternative routes yet; consequently, it usually takes the agent a quite long time to adapt to a change when a greedy policy is used[2]

d) How does reinforcement learning differ from supervised learning, e.g. learning decision trees? [4]

SL: static world[0.5], availability to learn from a teacher/correct answer[1]

RL: dynamic changing world[0.5]; needs to learn from indirect, sometimes delayed feedback/rewards[1]; suitable for exploration of unknown worlds[1]; temporal analysis/worried about the future/interested in an agent’s long term wellbeing[0.5], needs to carry out actions to find out if they are good—which actions/states are good is (usually) not know in advance1[0.5]

Might also use answer from the RL-Paper paragraph on that matter (page 239)!

at most 4 points.

2) Planning [8]

a) Describe 2 challenges, of your own liking, that developers of real-world planning systems face! [3]

grade using common sense; 1.5 points for any challenge they mention; conjunctive subgoals, operators have not desirable effects; need to consider cost,…

b) Assume the above state of the block’s world is given, and goal state is on(D,F). Give a brief description how a planning system of your own liking would come up with a plan to achieve **on(D,F)** for the particular world! [5].

…determine the action that makes on(D,F) true… need to mention that subgoals cleartop(D) and cleartop(F) are established, as on(D,F) is not applicable in the current, and then they come up with a plan to accomplish those two subgoals, followed by putton(D,F)

3. Belief Networks / Naïve Bayesian Systems [17]

Consider the following belief network that consists of variables A, B, C, D, E all of which have two states {true, false} and whose structure is depicted below is given.

B

A D E

C

1. Which of the following statements are implied by the indicated network structure; answer yes and no; and give reasons for your answers! [6]
2. P(A,D|C) = P(A|C)\*P(D|C)—is A[[2]](#footnote-2) d-separable from D

No[1]There are two paths ABD and ACD consider; however, path ACD is not blocked, because C is in evidence[[3]](#footnote-3); therefore, they are not d-separable[2].

1. P(A,E|B,C,D)=P(A|B,C,D)\*P(E|B,C,D) is A|B,C,D d-separable from E|B,C,D

Yes[1]There are two paths to consider ABDE and ACDE; however, both paths are blocked in D is D is in evidence and the path matches patterns; as both paths are blocked A|B,C,D d-separable from E|B,C,D[2]

b) Using the information in the probability table of the above belief network (P(A),P(B|A),P(B|~A),P(C|A), P(C|~A),P(D), P(E|D), P(E|~D)) compute **P(E|A)**; give reasons for non-obvious steps in your computations! [6]

P(E|A)=P(E)=P(E,D)+P(E,~D)= P(D)\*P(E|D)+P(~D)\*P(E|~D)

As E and A are d-seperable; the two paths are blocked in C and D (pattern3); therefore,

We are done as all probabilities in the formula P(D)\*P(E|D)+P(~D)\*P(E|~D)

c) What capabilities do Bayesian Belief Networks provide to its users? [2]

They allow to specify evidence E and compute the probabilities of the other nodes N in the network

Problem 3 continued

d) Naïve Bayesian Systems make conditional independence assumptions; why do they do that? [3]

to reduce knowledge acquisition cost [3]; to simplify computations[1]

4) Decision Tree Learning / Entropy [11]

a) What are the characteristics of overfitting? [3]

training set accuracy is usually good [0.5], but testing set accuracy is not optimal [2] due to too high model complexity; a less complex model would have lead to higher accuracies. [2.5]; training set size too small [0.5]

at most 3 points

b) Assume we like to predict the ethnicity of a group of 32 students 16 of which are white, 8 are African American and 8 are Asian[[4]](#footnote-4); compute the information gain of the attribute ‘gender’ for predicting ethnicity, assuming that all white students are male and all students of the other 2 ethnicities are female. Do not only give the formula in your answer, but compute the exact numerical value of the information gain of the attribute ‘gender’! [5]

InformationGain(Gender)=H(1/2,1/4,1/4)-(1/2\*H(1,0,0)+1/2\*(H(0,1/2,1/2)) [3]

At most1 point for an almost correct formula

=1/2Log2(2)+2\*1/4\*log2(4)-1/2\*(2\*1/2\*log2(2))= 1.5-0.5=1 [2]

At most 0.5 point for partially correct computations.

c) How do decision tree learning algorithms select tests involving numerical attributes? [3]

They obtain the different values for the numerical attribute A for the example in the training set associated with the particular node, and compute the information gain/GINI/ for all tests A≥θ where θ is a value of A that occurs in those training examples, and determine the value θ’ for which information gain/… is maximal, and then use the test A≥’θ to compete with tests involving other attributes to be considered to be chosen for a test for the decision tree node in question.

5. Neural Networks [14]

a. Assume a 2-layer neural network with a given structure and activation functions is given and a training set is given as well. How do neural networks learn/update weights from this information—how do they search for the “best” set of weights? [6]

Things that should be mentioned include: Iterate over the training examples, and use steepest decent hill climbing over the error function for updating weights; weight updates follow the steepest gradient of the error function; how much a particular weight is updated depends on the learning rate α, the error in the previous layer (|T-O| in the output layer or the back propagated error, otherwise) and the input activation of the node associated with the particular weight…This process continues…until…

b. What factors determine the value of back-propagated errors in multi-layer NNs? [4].

The error at the node belonging to the next layer[1.5], the weight of the connection of the previous layer to the next layer[1], and the derivative of the activation function applied to the weighted, linear input[[5]](#footnote-5) of the node whose back-propagated error is computed[1.5].

c. List 2 deep learning recipes, of your own choice; also briefly explain why the particular recipe is important for the successful deployment of deep learning systems. [4]

take a look at deep learning slides; 1 point for the recipe and 1 point for mentioning why it is important!

1. —after applying a-a [↑](#footnote-ref-1)
2. No evidence! [↑](#footnote-ref-2)
3. It would be blocked if C is not in evidence [↑](#footnote-ref-3)
4. That is, the classification problem has 3 classes! [↑](#footnote-ref-4)
5. Need to be precise on that factor! [↑](#footnote-ref-5)