Solution Sketches

Review2 for Final Exam COSC 6368 Fall 2017

1) D-Separability and Computation of Probabilities

Assume that the following belief network is given, consisting of nodes A, B, C, D, and E that can take values of true and false.

a) Are C and E independent; is C|∅ and E|∅ d-separable? Give a reason for your answer! ∅ denotes “no evidence given”[2]

b) Is E|CD d-separable from A|CD? Give a reason for your answer! [3]

c) Compute P(C|D) from the probabilities that are given for the above Belief Network (P(A),P(B), P(C|A,B), …P(C|~A,~B),…P(D|E), P(D|~E), P(E|B,D), P(E|~B,D),…!

P(C|D)= P(D|C)\*P(C)**/**P(D) *Bayes’ Theorem*

P(C )=P(C,A,B)+P(C,~A,B)+P(C, A,~B) )+P(C,~A,~B)

P(A,B,C)= P(A,B)\*P(C|AB)=P(A)\*P(B)\*P(C|A,B)

*As A no evidence is d-separable from B no evidence.*

P(A,B,~C)= P(A,B)\*P(~C|AB)=P(A)\*P(B)\*P(~C|A,B)

Compute the other 2 probabilities similarly…

P(D)=P(D,C)+P(D,~C)= P(C)\*P(D|C) + P(~C)\*P(D|~C)

*As P(D|C) and P(D|~C) are in a probability table of the BNN and we just computed P(C), we are done.*

1. Learning

a) What is the main differences between reinforcement learning and inductive learning, also called learning from examples?

b) We would like to predict the gender of a person based on two binary attributes: leg-cover (pants or skirts) and beard (beard or bare-faced). We assume we have a data set of 20000 individuals, 10000 of which are male and 10000 of which are female. 75% of the 10000 males are barefaced. Skirts are present on 50% of the females. All females are bare-faced and no male wears a skirt.

Compute the information gain of using the attribute leg-cover for predicting gender! [4]

c) What is the key contribution of the backpropagation algorithm? What problems does it solve? Why is there no backpropagation algorithm for 2-layer perceptron?

d) Your observe overfitting for a decision tree learning algorithm; what could you do to reduce overfitting?

3) Reinforcement Learning

Assume you have a policy that always selects the action that leads to the state with the highest expected utility. Present arguments that this is usually not a good policy by describing scenarios in which this policy leads to suboptimal behavior of the agent!

4) Naïve Bayes

Naïve Bayesian systems make the conditional independence assumption when for example computing P(D|S1,S2,S4). What assumptions are exactly made? What advantages do you see in the approach? What are the drawbacks of making the conditional independence assumption?

P(D|S1,S2,S3)= P(D)\*P(S1,S2,S3|D)/P(S1,S2,S3)≈P(D)\*P(S1|D)/P(S1)\*P(S2|D)/P(S2)\*P(S3|D)/P(S3)

1) D-Separability

Assume that the following belief network is given, consisting of nodes A, B, C, D, and E that can take values of true and false.

a) Are C and E independent; is C|∅ and E|∅ d-separable? Give a reason for your answer! ∅ denotes “no evidence given”[2]

There are two paths from C to E

C-B-E

C-D-E

Neither path is blocked —it would only be blocked if both arrows would be pointing to B, and both arrow would be pointing to D respectively; consequently, C and E are not d-separable.

b) Is E|CD d-separable from A|CD? Give a reason for your answer! [3]

There are 2 paths between A and E:

A-C-B-E neither node C(in evidence) satisfies patterns 1a,1b or 2 nor node B (not in evidence) satisfies pattern 3; therefore this path is not blocked

A-C-D-E node D(in evidence) satisfies pattern 1a; consequently, this path is blocked.

However, as not all paths are blocked between E and A, A|CD is not d-separable from E|CD

2a) What are the main differences between supervised learning and reinforcement learning? [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]

2b)

H(1/2,1/2)-1/4\*H(0,1)-3/4\*H(2/3,1/3)= 1-3/4\*H(2/3,1/3)=13/4\*(2/3\*log2(1.5)+1/3\*log2(3))

Side discussion—how to compute the entropy function H

H(1/2,1/4.1/8,1/8)= ½\*log2(2)+ 1/4\*log2(4)+2\*1/8\*log2(8)=1/2+1/2+3/4=1.75

2c) computes an error for the intermediate layer by backpropagating the errors from the previous layer—nodes that contribute more to errors in the next layer will have higher errors compared to nodes that contributed less towards the error;this is not necessary for output nodes as the error in output nodes is known; consequently, 2 layer perceptrons do not need a back propagation algorithm.

2d) increase the number of training examples; reduce the size of the learnt decision tree by using decision tree pruning.

3a)

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.

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.

4) We have to assume that S1|D, S2|D, S3|D are independent and if the exact probability of P(D|S1,S2,S3) needs to be computed we additionally have to assume that S1, S2, and S3 are independent. If Naïve Bayes is just used for a classification problem, it is not necessary to know P(S1,S2,S3) as we are only interested in know if P(D|S1,S2,S3) is larger/smaller than P(D’|S1,S2,S3); consequently the exact value for P(S1,S2,S3) is not relevant!