CMPT 419 Graphical Models/ Recurrent Neural Networks

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Fall 2018

1 Question 1: Graphical Models

- 1. See Appendix section
- 2. P(A, L, G, E, T) = P(T) * P(A|T) * P(E|L, G) * P(L)
- 3. At Node T it is simply a Linear Gaussian $\frac{1}{\sqrt{2*\pi*\sigma^2}}*e^{\frac{-(x-\mu)^2}{2*\sigma^2}}$ At Node A it is a sigmoidal distibution with the following form $\frac{1}{1+exp(g+\sum_{n=1}^K w_n*z_n)}$ where the parents are T and E

At Node E it is a Gaussian as follows, we use L=0 to denote non-university and L=1 to denote u and the same analogy applies for the current provincial government random variable G,

$$L(E|L = 0, G = 0) \sim N(A, B)$$

 $L(E|L = 0, G = 1) \sim N(C, D)$
 $L(E|L = 1, G = 0) \sim N(E, F)$

$$L(E|L = 1, G = 0) \sim N(E, F)$$

 $L(E|L = 1, G = 1) \sim N(G, H)$

As for the values of the respective parameters, it can be guessed that one would assign a larger

 μ for the Node T as it can be argued that there is more emphasis on the Tuition distribution when deciding whether or not to enroll in SFU. Furthermore, larger weighting

will be given to the T parent in the Sigmoidal distribution as despite economy size, tuition becomes a larger deciding factor and the parameters for the Gaussian can be arbitary.

Some example values I'd use A=10, B=4, C=8,D=3, E=5, F=9, G=10, H=15.

4. We need to moralize our graph and realize that the only elements that are relevant are the intermediate parents at each of the nodes.

2 Question 2: KL Divergence

- 1. This is essentially the case when the two distributions are equal i.e p(x) = q(x) As such when both distributions are equal the log inside the KL formula i.e $\frac{log(p(x))}{log(p(x))}$
- 2. No

3. We take the proof outlined in this Stats Stack Exchange post and change the "+" sign to a minus sign and change it to a "-" sign and since our mu terms equal they also zero out plus our

$$log(\frac{\sigma_2}{\sigma_1}) + \frac{\sigma_1^2}{2*\sigma_2^2} - log(\frac{\sigma_1}{\sigma_2}) - \frac{\sigma_2^2}{2*\sigma_1^2}$$

$$log(\frac{\sigma_2^2}{\sigma_1^2}) + \frac{\sigma_1^2}{2*\sigma_2^2} - \frac{\sigma_2^2}{2*\sigma_1^2}$$

0.5 terms zero out $log(\frac{\sigma_2}{\sigma_1}) + \frac{\sigma_1^2}{2*\sigma_2^2} - log(\frac{\sigma_1}{\sigma_2}) - \frac{\sigma_2^2}{2*\sigma_1^2}$ $log(\frac{\sigma_2^2}{\sigma_1^2}) + \frac{\sigma_1^2}{2*\sigma_2^2} - \frac{\sigma_2^2}{2*\sigma_1^2}$ We then use the above equation and make the term inside the log our Х

3 Question 3: Gated Recurrent Unit

- 1. When both are zero.
- 2. The hidden state at that time step will be also zero, i.e that GRU forgets everything.

4 Appendix

