IT5005 Artificial Intelligence

Consultation – Final Exam

Miscellaneous

- will there be lots of calculations in the exam？ do we need to bring a calculator？
- may I confirm that topics tested in midterms will not be covered for the final exam? thank you!
- In prev year question - Part A is missing (20 marks), is it possible to update it? Also, will there be some MCQ like in midterm?
- Could I please confirm that first-order logic will not be covered
- How many significant figures are expected to be within error/presented in the answer when calculating the probabilities/utilities?

Propositional Logic

From the Aug 2022 past paper Q4, could you please demonstrate the process of the resolution-refutation once the KB and (negated) query have been generated, as I cannot reach an empty set

P1 :	$(\neg A \vee B \vee E)$	(from R1)
P2 :	$\neg B \vee A$	(from R1)
P3 :	$\neg E \vee A$	(from R1)
P4 :	$\neg E \vee D$	(from R2)
P5 :	$\neg C \vee \neg F \vee \neg B$	(from R3)
P6 :	$\neg E \vee B$	(from R4)
P7 :	$\neg B \vee F$	(from R5)
P8 :	$\neg B \vee C$	(from R6)

CNF of KB.

P9 :	$A \vee B$	(negation of conclusion)
P10 :	$B \vee E$	from P1 and P9 : Resolvent of P1 & P9
P11 :	B	Resolvent of P6 and P10
P12 :	C	Resolvent of P8 and P11
P13 :	$\neg F \vee \neg B$	Resolvent of P5 and P12
P14 :	$\neg B$	Resolvent of P7 and P13
P15 :	$\square$	Resolvent of P11 and P14

$\therefore$ KB $\models (\neg A \wedge \neg B)$

From the Aug 2023 past paper Q11a, would it be possible to use the inferencing rule in a single step to reach the answer (just "cancel" R and ~R)? If so, how would one demonstrate the working?

(a) Prove that the following statement is tautology. You should NOT use truth-table enumeration for the proof.

$$(\neg P \vee \neg Q \vee R) \wedge (\neg R \vee S \vee T) \Rightarrow (\neg P \vee \neg Q \vee S \vee T)$$ [5 marks]

Yes

In tutorial for Propositional Logic, Q5, why the proving end when Q and ~Q is false. Is it because Q is premise? Do you have other method like end answer is S.

5. Suppose we are given the following premises:

   - $P_1 : P \Rightarrow Q$
   - $P_2 : R \Rightarrow P$
   - $P_3 : \neg Q$
   - $P_4 : R \vee P \vee S$

   Use resolution to prove that S is always True under the premises.

The proof in tutorial is by contradiction.

Yes. Direct method can be used

In tutorial for Propositional Logic, Q6, we are proving Traffic using algorithm , the antecedent and so on, how to provide answer if we are NOT using algorithm? By writing intuitively? How would the question and answer to be for a forward and backward chaining?

- You can provide intuitive explanation.
- Alternatively, scaffolding would be provided

Probabilistic Reasoning

Can I confirm if all the content in the slides related to probabilistic reasoning is examinable? thank you!

- Approximate inference won’t be tested

IS there any difference between "probability" and "probability Distribution" when being asked? While doing tutorial on Probabilistic Reasoning Over Time Q4, the definition and understanding of ques are confused when next and next question coming up using the same word but different methodology.

- If you are asked to calculate probability distribution, then you have to calculate the probability of all values for the variable
- If you are asked to calculate the probability, then the choice is yours
  - You can calculate probability distribution and then extract the probability of a value
  - You can directly calculate the probability

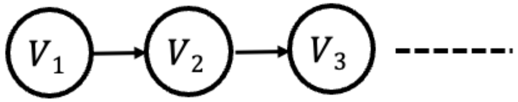
for tutorial 5, qns1, is it sufficient to show either P(toothache| catch, cavity) = P(toothache| cavity) OR P(catch|toothache,cavity) = P(catch|cavity)?

- Either of them is enough.

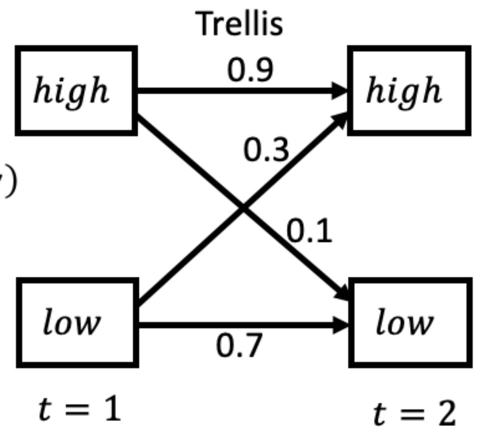
Markov Chains and HMMs

Why exactly do we need to transpose the transition matrix in markov chain probability distribution?

Example: Stock Value of a Firm



- Given $\boldsymbol{P}(V_1)$ and $\boldsymbol{P}(V_t|V_{t-1})$, What is $\boldsymbol{P}(V_2)$?



$$P(V_2 = high) = P(V_2 = high|V_1 = high)P(V_1 = high) + P(V_2 = high|V_1 = low)P(V_1 = low)$$

$$P(V_2 = low) = P(V_2 = low|V_1 = high)P(V_1 = high) + P(V_2 = low|V_1 = low)P(V_1 = low)$$

$$\begin{bmatrix} P(V_2 = high) \\ P(V_2 = low) \end{bmatrix} = \begin{bmatrix} P(V_2 = high|V_1 = high) & P(V_2 = high|V_1 = low) \\ P(V_2 = low|V_1 = high) & P(V_2 = low|V_1 = low) \end{bmatrix} \begin{bmatrix} P(V_1 = high) \\ P(V_1 = low) \end{bmatrix}$$

$$\boxed{\boldsymbol{P}(V_2) = \boldsymbol{T}^T \boldsymbol{P}(V_1)}$$

$$where\ \boldsymbol{P}(V_2) = \begin{bmatrix} P(V_2 = high) \\ P(V_2 = low) \end{bmatrix}$$

$$\boldsymbol{P}(V_1) = \begin{bmatrix} P(V_1 = high) \\ P(V_1 = low) \end{bmatrix}$$

$$\boldsymbol{T} = \begin{bmatrix} P(V_2 = high|V_1 = high) & P(V_2 = low|V_1 = high) \\ P(V_2 = high|V_1 = low) & P(V_2 = low|V_1 = low) \end{bmatrix}$$

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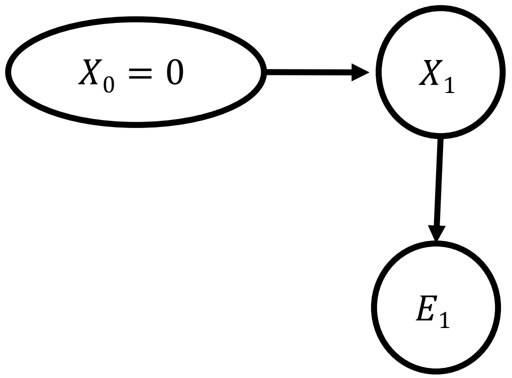
a. Calculate $\boldsymbol{P}(X_1 | E_1 = c)$



- $\boldsymbol{P}(X_1|E_1 = c) = \begin{bmatrix} P(X_1 = 0|E_1 = c) \\ P(X_1 = S|E_1 = c) \\ P(X_1 = A|E_1 = c) \\ P(X_1 = B|E_1 = c) \\ P(X_1 = C|E_1 = c) \end{bmatrix} =?$

$$\boldsymbol{P}(X_1|E_1) = \boldsymbol{f}_{1:1} = \alpha \boldsymbol{O}_1 \boldsymbol{T}^T \boldsymbol{f}_0$$

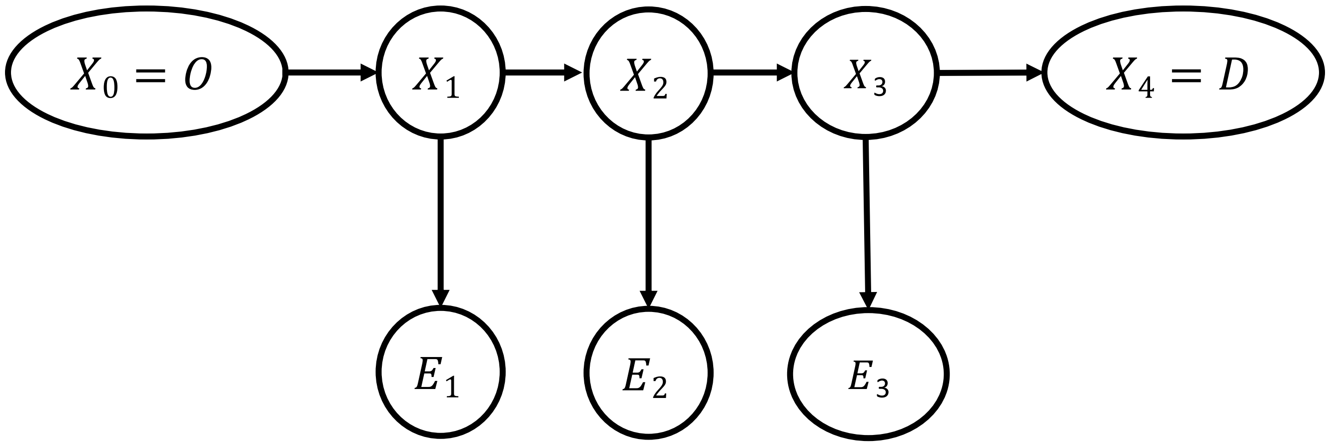
$$\boldsymbol{O}_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0 & 0.3 \end{bmatrix} \qquad \boldsymbol{T} = \begin{array}{c} \\ O \\ S \\ A \\ B \\ C \end{array} \!\!\begin{array}{c} \begin{array}{ccccc} O & S & A & B & C \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0.3 & 0.2 & 0.1 & 0.1 \\ 0 & 0.25 & 0.1 & 0.05 & 0.15 \\ 0 & 0.05 & 0.4 & 0.15 & 0.2 \\ 0 & 0.5 & 0.2 & 0.2 & 0.05 \end{bmatrix} \end{array} \qquad \boldsymbol{f}_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\boldsymbol{f}_{1:1} = \alpha \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0 & 0.3 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0.3 & 0.2 & 0.1 & 0.1 \\ 0 & 0.25 & 0.1 & 0.05 & 0.15 \\ 0 & 0.05 & 0.4 & 0.15 & 0.2 \\ 0 & 0.5 & 0.2 & 0.2 & 0.05 \end{bmatrix}^T \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \alpha \begin{bmatrix} 0 \\ 0.6 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Why we skipped last column?

Table 1: Transition Probabilities

T_{ij}	$x_j = S$	$x_j = A$	$x_j = B$	$x_j = C$	$x_j = D$
$x_i = S$	0.3	0.2	0.1	0.1	0.3
$x_i = A$	0.25	0.1	0.05	0.15	0.25
$x_i = B$	0.05	0.4	0.15	0.2	0.2
$x_i = C$	0.5	0.2	0.2	0.05	0.05



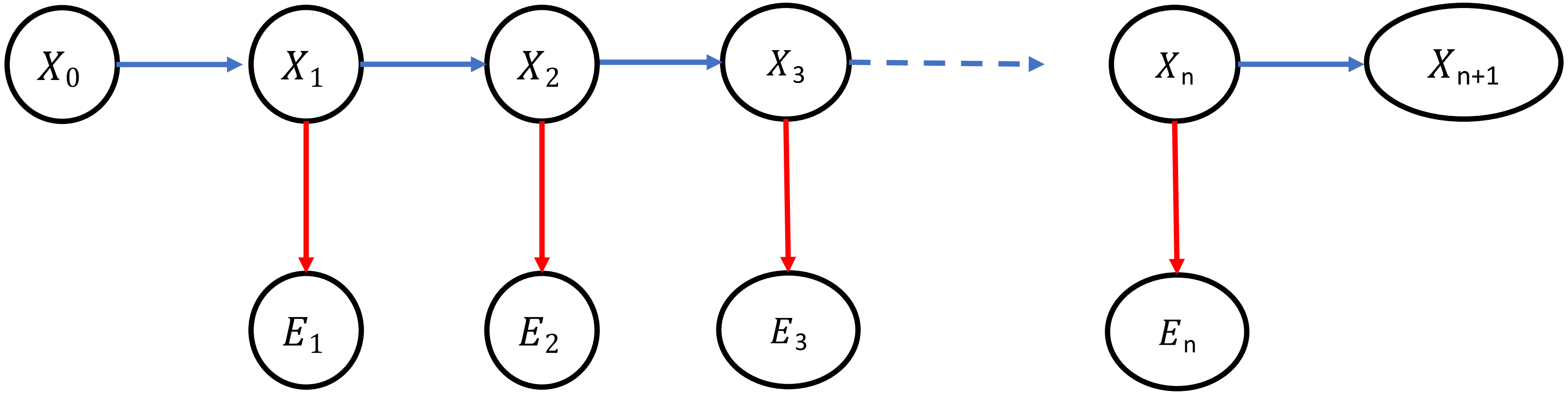
$$\boldsymbol{T} = \begin{array}{c} \\ O \\ S \\ A \\ B \\ C \end{array} \begin{array}{c} \begin{array}{ccccc} S & A & B & C & D \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.3 & 0.2 & 0.1 & 0.1 & 0.3 \\ 0.25 & 0.1 & 0.05 & 0.15 & 0.25 \\ 0.05 & 0.4 & 0.15 & 0.2 & 0.2 \\ 0.5 & 0.2 & 0.2 & 0.05 & 0.05 \end{bmatrix} \end{array}$$

$$\boldsymbol{T} = \begin{array}{c} \\ S \\ A \\ B \\ C \end{array} \begin{array}{c} \begin{array}{cccc} S & A & B & C \end{array} \\ \begin{bmatrix} 0.3 & 0.2 & 0.1 & 0.1 \\ 0.25 & 0.1 & 0.05 & 0.15 \\ 0.05 & 0.4 & 0.15 & 0.2 \\ 0.5 & 0.2 & 0.2 & 0.05 \end{bmatrix} \end{array}$$

Because we are not interested in finding the probability of STOP state in filtering in filtering, which is an online algorithm

It is needed when we are doing reasoning offline reasoning such as Viterbi algorithm or smoothing
where you consider future evidence

For Bayesian Recursive Filtering, I don't quite understand why it needs to be a 2-step process of prediction + update; could you run us through the intuition?



$$\boldsymbol{P}(E_1, \dots, E_n, X_0, X_1, \dots, X_n, X_{n+1}) = \underbrace{\boldsymbol{P}(X_0)}_{\text{Initial Probability}} \prod_{i=1}^{n+1} \overset{\text{Prediction}}{\underbrace{\boldsymbol{P}(X_i | X_{i-1})}_{\text{Transition Distribution}}} \prod_{i=1}^{n} \overset{\text{Correction}}{\underbrace{\boldsymbol{P}(E_i | X_i)}_{\text{Emission Distribution}}}$$

MDP

will we be required to do value/policy iteration by hand for the exam?

- Yes

When we write the Bellman update equations, do we include the terminal state in the equation, or should we assume/assign it an utility value (e.g., 0)?

- Depends on the model
- It would be either explicitly stated in the question or you can infer it from the problem statement

Introduction to Learning

Will we be expected to know equations for various functions, e.g. for ellipse, circle, hyperbola for classification problems?

- No

Will we be expected to know derivaties of various activation functions, e.g., tanh, sigmoid functions, etc.

- Yes, but if the derivatives involve non-standard functions, it would be provided in the question

From Aug 2023 Q15b, which values of w_1 and w_2 should we be substituting once we have the (correct) expression for the partial derivative dy/dw? In 15a it we are given x = 0 and x = 1 and the expression does not require w, but in 15b substituting 1 for w_1 and w_2 does not give the correct answer.

- Weight parameters are initialized as 1 and bias is initialized as 0 and x = 1

$$\frac{\partial \hat{y}}{\partial w_2} = \frac{\partial g^{[2]}}{\partial f^{[2]}} \frac{\partial f^{[2]}}{\partial w_2}$$

$$= \left(1 - \left[\tanh\left(w_2 \tanh(w_1 x)\right)\right]^2\right) \tanh(w_1 x)$$

$$= 0.4477$$

$$\tanh(1) = 0.76159$$
$$\tanh(\tanh(1)) = 0.6420$$
$$(1 - 0.6420^2)0.76159 = 0.4477$$

$$\frac{\partial \hat{y}}{\partial w_1} = \frac{\partial g^{[2]}}{\partial f^{[2]}} \frac{\partial f^{[2]}}{\partial g^{[1]}} \frac{\partial g^{[1]}}{\partial f^{[1]}} \frac{\partial f^{[1]}}{\partial w_1}$$

$$= \left(1 - \left[\tanh\left(w_2 \tanh(w_1 x)\right)\right]^2\right) w_2 \left(1 - \left(\tanh(w_1 x)\right)^2\right) x$$

$$= 0.2469$$

$$(1 - 0.6420^2)(1 - 0.76159^2) = 0.2469$$

For the introduction to learning tutorial, do we need to compute the normal equation manually during exam? $\boldsymbol{w}$ = ($X^{T}X$)^-1$X^{T}Y$

- No, matrix inversions with more than two/three dimensions are time consuming and they usually wont be tested in the exam

For the multi-class logistic regression in tutorial 8 Question 5, why is the hypothesis for each class z1^(i) = wcat*x(i)? why is it not z=w^Tx? In the code, it was Z = np.dot(W, X.T).

- Both are same
- The rows of the matrix W corresponding to each hypothesis

```
w_cat = np.array([4.2, -0.01, -0.12])
w_horse = np.array([-20, -0.08, 35])
w_elephant = np.array([-1250, 0.82, 0.9])
W = np.array([w_cat, w_horse, w_elephant])

print("The weight matrix is:")
print(W)

X = np.array([[1, 4.2, 0.4], [1, 720, 2.4], [1, 2350, 5.5]])
print("The data matrix is:")
print(X)

# Calculate the Z matrix
Z = np.dot(W, X.T)
print("Z matrix:")
print(Z)
```

Do we need to hand compute softmax?

- Yes, you need scientific calculator

Neural Networks

For Aug 2023 Q15a, could you demonstrate how g(f(x))[1 - g(f(x))] was derived?

- Derivative of Sigma function:
- $g(f) = \frac{1}{1+e^{-f}}$
- $g'(f) = \frac{e^{-f}}{(1+e^{-f})^2} = \frac{1}{1+e^{-f}}\left(1 - \frac{1}{1+e^{-f}}\right) = g(f)[1 - g(f)]$

Reinforcement Learning

Could you go through for Aug 2022 finals how was the answer for T(S1,Ri, S2) and T(S2,Ri, S3) was derived in question 8a?

8. Consider an environment whose MDP model is unknown. It is known to the agent that there are three states: $\mathbf{S_1}$, $\mathbf{S_2}$, and $\mathbf{S_3}$. The agent also knows the actions that need to be taken. Specifically, only action Ri can be taken at state S_1 and actions Le and Ri can be taken at States S_2 and S_3. The agent acted in the environment and an episode of the recorded information is provided below:

S	A	R	S'
$\mathbf{S_1}$	Ri	0	$\mathbf{S_2}$
$\mathbf{S_2}$	Ri	0	$\mathbf{S_3}$
$\mathbf{S_3}$	Le	0	$\mathbf{S_2}$
$\mathbf{S_2}$	Le	0	$\mathbf{S_1}$
$\mathbf{S_1}$	Ri	0	$\mathbf{S_2}$
$\mathbf{S_2}$	Ri	0	$\mathbf{S_1}$
$\mathbf{S_1}$	Ri	0	$\mathbf{S_2}$
$\mathbf{S_2}$	Ri	0	$\mathbf{S_3}$
$\mathbf{S_3}$	Ri	1	$Exit$

In the above table, S indicates the current state, A indicates the action, R indicates the reward, and S' indicates the resulting state after taking action A at state S. The agent repeated the actions infinite number of times. The same sequence of (S, A, R, S') are observed.

(a) Estimate the following quantities: $T(S_1, Ri, S_2)$, $T(S_2, Ri, S_3)$, $R(S_3, Ri, Exit)$, where $T(S, a, S')$ indicates the probability of moving from state S to S' with action a and $R(S, a, S')$ indicate the reward for the transition from state S to S' with action a. [6 Marks]

$$T(S_1, R_i, S_2) = \frac{3}{3}$$
$$T(S_2, R_i, S_3) = \frac{2}{3}$$
$$R(S_3, R_i, Exit) = 1$$