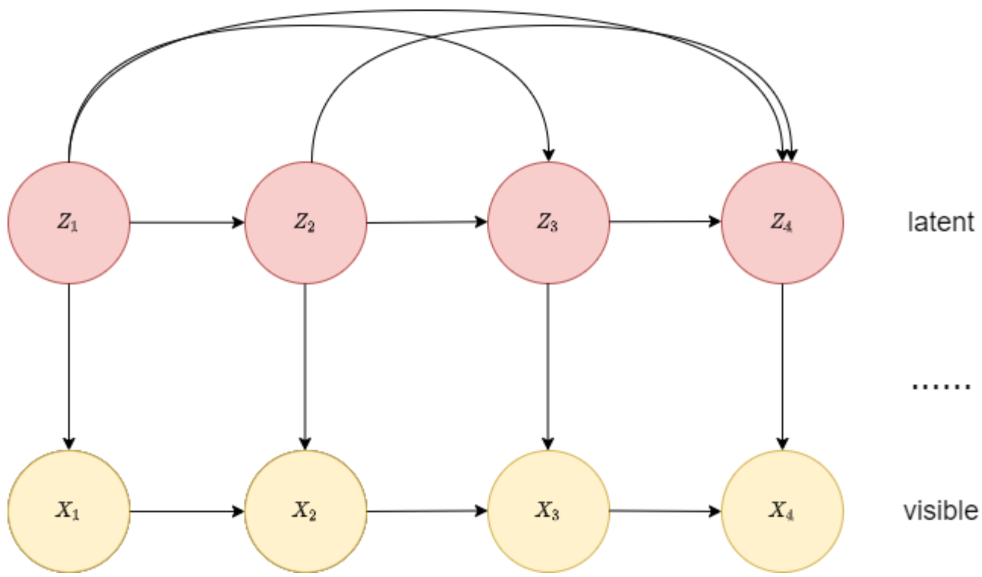
Deep Learning and Practice — Final Exam

Date: Thursday, September 2, 2021
Time: 01:20pm – 04:20pm (180 minutes)
Format: Open book
Instructions:
1) You may give your answers in Chinese or English.
2) Please give your answers in succinct phrases or point form.
3) Please write your answers clearly (with explicit denotation of labels and symbols used).

1. (25 pts) Consider the following latent factor model, where $Z_i, i = 1, 2, \ldots, T$ are latent variables and $X_i, i = 1, 2, \ldots, T$ are visible variables.



(a) (8 pts) Design an inevitable mapping from X_i's to their latent representations Z_i's using the flow model idea. Use $T = 3$ as an example. Think about how you should convert each of the X_i's into the corresponding Z_i's and what the conditioning variable should be utilized in each of these conversions. The conversions may involve coupling layers as fundamental building blocks.

(b) (2 pts) According to the graphical model, factorize the joint distribution $p(Z_{1-T})$.

(c) (5 pts) Describe how you would evaluate the probability $p(X_1, X_2, X_3)$ of one specific sample X_1, X_2, X_3 once the model is trained.

(d) (5 pts) How would you train the flow model in (a)?

(e) (5 pts) Describe how you would sample X_i's from Z_i's using the designed flow model.

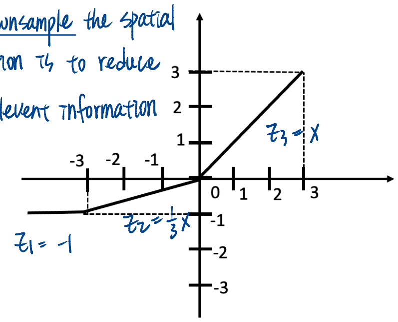
2. (20 pts) Convolution, Pooling, Activation function, CNN

   (a) (4 pts) What is the output feature map size for an 256 x 256 input image after convolution with kernel (3,3), padding (2,2), and stride (2,2) ?

   (b) (4 pts) Describe the function of pooling layer.

   (c) (3 pts) Use the maxout unit to design the activation function below.

(b) The pooling layer is a component in CNN that helps to downsample the spatial dimensions of the input feature maps. Its primary function is to reduce the spatial size of feature maps while retaining the relevent information (or extracting features).



(c) Activation Function $f(x)$

$\Rightarrow f(x) = \max\{z_1(x), z_2(x), z_3(x)\}$,

where $z_1 = -1$, $z_2 = \frac{1}{3}x$, $z_3 = x$

   (d) (6 pts) What may cause gradient vanish problem and how to solve it? Explain your answer.

   (e) (3 pts) What are the major reasons that contribute to the success of convolutional neural networks?

(e) L7. CNN - p.8

3. (15 pts) Training the VAE.

   (a) (3 pts) In training the VAE, we try to maximize a variational lower bound on the data log-likelihood. Explain the main idea and provide the exact objective function to be maximized.

   (b) (3 pts) What distribution does the approximate posterior $q(z|x)$ take for training VAE? Is this an assumption?

   (c) (3 pts) Explain the notion of the re-parameterization trick.

   (d) (3 pts) True or False: In maximizing the variational lower bound, the approximate posterior $q(z|x)$ should ideally be identical to the prior $p(z)$ when the variational lower bound is maximized. Explain your answer.

   (e) (3 pts) How would you evaluate the KL divergence $KL(q(z|x)||p(z))$ if the prior $p(z)$ is replaced with a Gaussian Mixture distribution?

4. (10 pts) Compare VAE, GAN, WGAN, and Flow Models in terms of (a) their generator/decoder outputs (stochastic or deterministic) and (b) training objectives. (c) Which models allow you to evaluate the probability of a specific data sample? (d) Which models allow you to generate the latent code of a specific data sample. (e) From their training losses, how do you evaluate the generator quality for these models? Which models cannot you decide the generator quality?

M3.

(a) The main idea of maximizing a variational lower bound on the data log-likelihood:

① Learn a generative model that can capture the underlying distribution of data.

② Learn an approximate inference model that can infer the latent variables given the observed data.

The objective function is the Evidence Lower Bound (ELBO), which is given by:

$$ELBO = \underbrace{E[\log p(x|z)]}_{\text{reconstruction term}} + \underbrace{KL[q(z|x) \| p(z)]}_{\text{regularization term}}$$

(b) The approximate posterior $q(z|x)$ typically takes the form of a Gaussian distribution, which is not an assumption but a modeling choice.

(c) The reparameterization trick is a techique used in training VAE to enable the backpropagation of gradients through the stochastic sampling process.

Instead of directly sampling z, the reparameterization trick allows sampling ϵ from $N(0,1)$, and then transform it to obtain a sample from $q(z|x)$ like following:

$q(z|x) \sim N(\mu, \sigma)$

$\Rightarrow z = \mu + \sigma \cdot \epsilon$

(d) False. In maximizing ELBO, the objective is not to minimize the regularization term.

The goal is to find a balance between $\underbrace{E[\log p(x|z)]}_{\text{encourages the model to accurately reconstruct data}}$ and $\underbrace{KL[q(z|x) \| p(z)]}_{\text{encourages the } q(z|x) \text{ close to } p(z)}$.

(e) When $p(z)$ is replaced with a GMM distribution model is challenging because the KL divergence does not have a closed-form solution in this case.

要估計KL divergence，我們可以從 $q(z|x)$ 中抽多個樣本，並分別計算每個樣本的 KL divergence.

最終以平均值作為我們的估計值

M4.

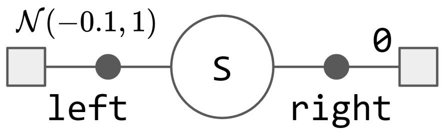
(a)

5. (14 pts)

(a) (7 pts) Prove the following theorem: For any ε-greedy policy π, the ε-greedy policy π' with respect to q_π is an improvement, that is $v_{\pi'}(s) \geq v_\pi(s)$.

(b) (7 pts) Show how ε-greedy policy improvement will converge to the optimal.

6. (18 pts) Consider the undiscounted MDP shown below.



Episodes start in S with a choice between two actions, left and right. The right action transitions immediately to the terminal state with a reward of zero. The left action also transitions to the terminal state but with a reward drawn from a normal distribution with mean -0.1 and variance 1.0.

(a) (2 pts) What is the optimal state-action value $Q^*(S, \text{left})$ and $Q^*(S, \text{right})$?

(b) (2 pts) What is the probability of taking the left action using the ε-greedy policy ($\varepsilon = 0.1$) with respect to Q^*?

(c) (14 pts) What problem will you encounter when training with Deep Q-learning (DQN)? In order to avoid the problem, what method can we apply?