GNR638 200050103

Quiz 2

1) RoI pooling and RoI align is a technique to convert the Region of Interest proposal of different sizes to appropriate dimensions for further processing / classification.

incorrect asked so $\boxed{\text{Ans: a, b, d}}$

2) Regression Layer in Faster RCNN is dependent on output of classification layer is true $\boxed{\text{Ans: d}}$

3) Precision = $\frac{TP}{TP+FP}$ =

TP: true positive

FN: False negative

FP: False Positive

Recall = $\frac{TP}{TP+FN}$ =

TP: exists and correctly detected = 1 (horse that correctly detected)

FP: wrongly detected (exists or not) = ~~1~~ 3 (wrongly detected zebras)

(exists → Gtruth)

Precision = $\frac{1}{3+1}$ = 0.25

FN: ~~ex~~ exists but undetected / wrongly classified : $\underbrace{4}_{\text{undetected horses}} + \underbrace{3}_{\text{undetected zebras}} + \underbrace{3}_{\text{wrongly classified zebras}}$ = 10

Recall = $\frac{1}{10+1} = \frac{1}{11} = 0.09$

$\boxed{\text{Ans: none of the above}}$

4) reset gate act as forget + input gate in GRUs

update gate act as $\underbrace{\text{update}}_{\text{of LSTMs}}$ ~~gate~~ in GRUs

GRU's don't have forget gates

~~False~~

∴ Short-term → reset

$\boxed{\text{Ans: Long-term → update}}$

5) Forget gate gives output in [0,1] and tanh = $\frac{e^x - e^{-x}}{e^x + e^{-x}}$

$\frac{1}{1+e^{-x}}$

$0 \le \frac{1}{\infty} \le \frac{1}{e^{-x}+1} \le \frac{1}{\infty}$

range is [-1, 1]. ∴ Forget gate doesn't use tanh, it uses $\underbrace{\sigma()}_{\text{sigmoid}}$

∴ 2 is incorrect

⇒ option b, c are incorrect.

~~4~~ 1) is true ~~False~~ (vacuosly, all options have 1)

P.T.O

4: forget gates uses σ, so it decides which value to pass and tanh decides weightage.

So 4 is true

$\boxed{\text{Ans: d}}$

6) Sigmoid can cause vanishing gradients problem

grad of $\sigma(x)$ when $x \to \infty$ or $x \to -\infty$ is very small leading to vanishing grads

TanH also has a similar graph to σ (curve appearances)

and can lead to vanishing grad problem.

Since only one option, i choose first option TanH

$\boxed{\text{Ans: a}}$

7) GRU uses less parameters and has 2 gates rather than 3 in LSTM making vanishing grads / exploding grads problem occurrance smaller and reduces training time in

Ans: d

8) Sigmoid best for gating mechanisms. eg. gives 0 if not worthy to be remembered and 1 if must be kept.

9) ~~a) $i = \sigma(U_i h_{t-1})$ & $f = U$~~

b) sigmoid gives non-neg. output. So f_t, i_t, o_t are ≥ 0

$\boxed{\text{Ans: b}}$

10) learning underlying $P(x)$ is difficult, so generator needs more training steps than discriminator (intuition) thus

K steps for generator and 1 step for discriminator

(from slides generator training then disc. training was given)

11) a) property and training of C-GAN done that way.

d) training done using backprop.

c) semi-supervised GANs exist

↳ (output as real or fake and classification output)

12) G's aim is to

a) * maximize classification error for D

$$\underset{G_\phi, D_\theta}{\text{Loss}} = \max_{\theta} \min_{\phi} \left[E_{x \sim P_{real}} [\log(D_\theta(x))] + \underbrace{E_{z \sim P(z)_{gen}} [\log(1 - D_\theta(G_\phi(z)))]}_{\text{generator tries to minimize this}} \right]$$

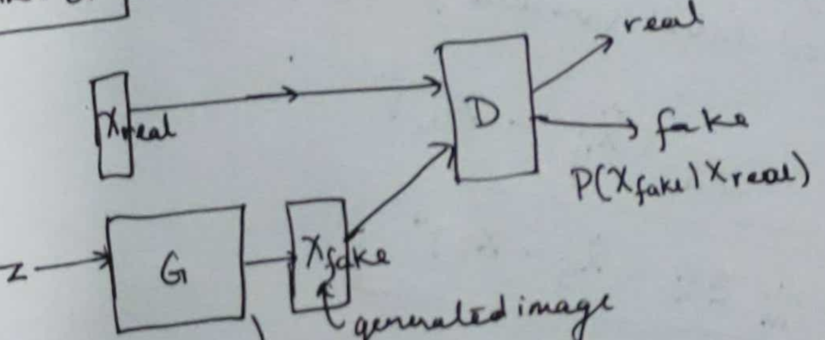
$D_\theta(G_\phi(z))$ ↑ prob of generated image is real

13) Generator tries to maximise $\log(D(G(z)))$. So when G is poor, D easily rejects with high confidence, so G is updated / trained to become better more rapidly (the whole idea of adversarials / adversarial nets)

thus $\log(D(G(z)))$ will not saturate.

$\boxed{\text{Ans: d}}$

14)



$P(X_{real})$ (G tries estimating this) Learns both prior and posterior

$\boxed{\text{Ans: d) A or B}}$

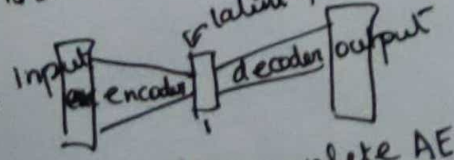
15) d is false

$\boxed{\text{Ans: d}}$

compressed rep of input data may be further compressed.

First 3 statements are true.

16) A)



undercomplete AE

Constraining # of nodes does help implement an UAE.

True

B) ~~UAE are meant to do this~~

True

$\boxed{\text{Ans: a}}$

17) ~~Allows mean and log variance as learnable parameter but μ as a hyperparameter.~~

$Z = \mu + \epsilon\sigma^2$ $\quad \epsilon \rightarrow N(0,1)$

$\therefore$ mean 0 centred and log variance as 1 so sampling is super easy $\sigma \rightarrow 2$

$\boxed{\text{Ans: b}}$

18) $z = \mu + \epsilon\sigma^2$

$z_1 = 0.2 + 0.5(0.2)^2 = 0.2 + \cancel{0.5}\ \cancel{0.04}\ 0.02\ \text{vals} = 0.22 \approx 0.2$

$z_2 = 0.3 + 0.2(0.1)^2 = 0.3 + 0.2(0.01) = 0.302 \approx 0.3$

$z_3 = 0.1 + 0.8(0.1)^2 = 0.1 + 0.8(0.01) = 0.108 \approx 0.1$

$\boxed{\text{Ans: c}}$

19) Intractability of the evaluation of $P(x)$ leads to variational inference in VAE

Ans: c

20) For each sample we need good latent representation.

$\therefore \frac{1}{m}$ in objective fxn.

and we want good latent variables for X, not $\tilde{X}$ (corrupted),

So MSE must be $\sum_m \sum_n (\hat{x}_{ij} - x_{ij})^2$

$\boxed{\text{Ans: b) } \arg\min_x \frac{1}{m} \sum_m \sum_n (\hat{x}_{ij} - x_{ij})^2}$