#### **Instructions:**

• Verify your name and Andrew ID above.

- This exam contains ?? pages (including this cover page). The total number of points is ??.
- Clearly mark your answers in the allocated space. If you have made a mistake, cross out the invalid parts of your solution, and circle the ones which should be graded.
- Look over the exam first to make sure that none of the ?? pages are missing.
- No electronic devices may be used during the exam.
- Please write all answers in pen or darkly in pencil.
- You have 15 minutes to complete the exam. Good luck!

Run LaTeX again to produce the table

# 1 Deep Models for Vision (?? points)

1.1.	(1 point) <b>True or False:</b> As we go deeper into a CNN, the weights of <i>later</i> convolutional layers learn to detect features of <i>larger</i> patches of the input images.		
	$\bigcirc$	True	
	$\circ$	False	
1.2.	M with C double th	<b>Select one:</b> Consider a 2D convolution layer with input image size $M \times C_{in}$ channels. Let $N_W$ be the original number of weight parameters. If we enjut image width and height to be $2M \times 2M$ and change nothing else e layer, what is total number of weights in this layer?	
	$\bigcirc$	$N_W/2$	
	$\bigcirc$	$N_W/4$	
	$\bigcirc$	$\sqrt{2}N_W$	
	$\bigcirc$	$2N_W$	
	$\bigcirc$	$4N_W$	
	$\bigcirc$	None of the above	
1.3.	` - /	Select all that apply: Which aspects of an encoder-only Transformer ed to be substantially changed to convert it to a basic Vision Transformer edel?	
	Select as	few options as necessary.	
		Tokenization	
		Position embedding	
		Attention blocks	
		Transformer blocks	
		Optimization algorithm	
		None of the above	

### 2 GANs (?? points)

2.1. (1 point) **True or False:** The discriminator's role in a GAN is to determine whether the noise vector was obtained by adding noise to a real image or by sampling noise from the generator model.

○ True

O False

2.2. (2 points) Select all that apply: GANs learn by trying to find a  $\theta$  and  $\phi$  that optimize a minimax problem for a generator  $G_{\theta}$  and a discriminator  $D_{\phi}$ :

$$\min_{\theta} \max_{\phi} J(\theta, \phi), \quad \text{where } J(\theta, \phi) = \log \left( D_{\phi}(\mathbf{x}^{(i)}) \right) + \log \left( 1 - D_{\phi}(G_{\theta}(\mathbf{z}^{(i)})) \right),$$

- $\mathbf{x}^{(i)}$  is a random training image, and  $\mathbf{z}^{(i)}$  is a random noise vector. Which of the following techniques could be used to optimize this learning problem?
  - $\square$  Alternate between a step in the direction of  $\nabla_{\phi}J(\theta,\phi)$  and a step opposite the gradient of  $\nabla_{\theta}J(\theta,\phi)$ .
  - $\square$  Alternate between a step opposite the direction of  $\nabla_{\phi} J(\theta, \phi)$  and a step in the gradient of  $\nabla_{\theta} J(\theta, \phi)$ .
  - $\Box$  Jointly step in the direction  $(\nabla_{\phi}J(\theta,\phi), -\nabla_{\theta}J(\theta,\phi))$
  - $\square$  Jointly step in the direction  $(-\nabla_{\phi}J(\theta,\phi), \nabla_{\theta}J(\theta,\phi))$
  - $\square$  None of the above
- 2.3. (1 point) **Select one:** Which of the following best describes how an image is generated from a trained GAN?
  - A neural network creates the mean and covariance parameters of a Gaussian, and an image is sampled from that Gaussian.
  - O Gaussian noise is repeatedly subtracted away from a randomly sampled noise vector until an image is left remaining.
  - A noise vector is sampled from a Gaussian, then a deterministic neural network transforms the noise vector into an image.
  - A noise vector is constructed by a neural network and then an image is sampled from a nonlinear distribution that conditions on that noise vector.

### Diffusion Models (?? points) 3

3.1.	reverse primages, i	<b>True or False:</b> To train a diffusion model, we find the parameters for the rocess model that maximize the sum of the log-likelihoods of the training e. $\hat{\boldsymbol{\theta}} = \arg \max \sum_{i=1}^{N} \log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)})$ where $p_{\boldsymbol{\theta}}$ is the reverse process, and $\mathbf{x}^{(N)}$ are the $N$ training images.
	$\bigcirc$	True
	$\bigcirc$	False
3.2.	,	<b>True or False:</b> The forward process of a diffusion model <i>and</i> the (learned rocess are both stochastic.
	$\bigcirc$	True
	$\bigcirc$	False
3.3.	Model (I	Select all that apply: Why does the Denoising Diffusion Probabilistic DPM) use a UNet model? Recall that the structure of the exact reverse $(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0)$ is a Gaussian of the form $\mathcal{N}(\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0), \sigma_t^2 \mathbf{I})$ .
		Because a UNet is a parameter efficient encoder-only Transformer model.
		Because the inputs and outputs of a UNet can be of the same dimension.
		In order to approximate $\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0)$ through various parameterizations.
		In order to approximate $\sigma_t^2 \mathbf{I}$ through various parameterizations.
		None of the above

## 4 VAEs (?? points)

4.1. (2 points) Select all that apply. Which of the following would we like to minimize when training a variational autoencoder, where  $q_{\phi}(\mathbf{z} \mid \mathbf{x})$  is the encoder,  $p_{\theta}(\mathbf{x} \mid \mathbf{z})$  is the decoder,  $\mathbf{z}^{(i)} \sim q_{\phi}(\mathbf{z} \mid \mathbf{x}^{(i)})$ , and  $\hat{\mathbf{x}}^{(i)} \sim p_{\theta}(\mathbf{x} \mid \mathbf{z}^{(i)})$ .

$$\Box \frac{1}{N} \sum_{i=1}^{N} \|\mathbf{x}^{(i)} - \hat{\mathbf{x}}^{(i)}\|_{2}^{2} - KL\left(q_{\phi}(\mathbf{z} \mid \mathbf{x}) \mid\mid \mathcal{N}(\mathbf{0}, \mathbf{I})\right)$$

$$\square \ \mathbb{E}_{\mathbf{z} \sim q_{\phi}(\mathbf{z} \mid \mathbf{x})} \left[ -\log p_{\theta}(\mathbf{x} \mid \mathbf{z}) \right] - KL \left( q_{\phi}(\mathbf{z} \mid \mathbf{x}) \mid\mid p_{\theta}(\mathbf{z}) \right)$$

 $\Box$  -ELBO $(q_{\phi})$ 

 $\square$  None of the above

4.2. (1 point) **True or False:** The reparameterization trick is used to avoid having a random function on the computation path between the generator network weights and the objective.

○ True

O False