Instructions:

- Verify your name and Andrew ID above.

- This exam contains 5 pages (including this cover page).
  The total number of points is 14.

- 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 5 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!

Question	Points
1. Deep Models for Vision	3
2. GANs	4
3. Diffusion Models	4
4. VAEs	3
Total:	14

1 Deep Models for Vision (3 points)

1.1. (1 point) **True or False:** As we go deeper into a CNN, the weights of *later* convolutional layers learn to detect features of *larger* patches of the input images.

○ True

○ False

1.2. (1 point) **Select one:** Consider a 2D convolution layer with input image size $M \times M$ with C_{in} channels. Let N_W be the original number of weight parameters. If we double the input image width and height to be $2M \times 2M$ and change nothing else about the layer, what is total number of weights in this layer?

○ $N_W/2$

○ $N_W/4$

○ $\sqrt{2}N_W$

○ $2N_W$

○ $4N_W$

○ None of the above

1.3. (1 point) **Select all that apply:** Which aspects of an encoder-only Transformer model need to be substantially changed to convert it to a basic Vision Transformer (ViT) model?

Select as few options as necessary.

☐ Tokenization

☐ Position embedding

☐ Attention blocks

☐ Transformer blocks

☐ Optimization algorithm

☐ None of the above

2   GANs (4 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

    ○ False

2.2. (2 points) **Select all that apply:** GANs learn by trying to find a θ and ϕ that optimize a minimax problem for a generator G_θ and a discriminator D_ϕ:

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

$\mathbf{x}^{(i)}$ 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?

    □ Alternate between a step in the direction of $\nabla_\phi J(\theta, \phi)$ and a step opposite the gradient of $\nabla_\theta J(\theta, \phi)$.

    □ Alternate between a step opposite the direction of $\nabla_\phi J(\theta, \phi)$ and a step in the gradient of $\nabla_\theta J(\theta, \phi)$.

    □ Jointly step in the direction $(\nabla_\phi J(\theta, \phi), -\nabla_\theta J(\theta, \phi))$

    □ Jointly step in the direction $(-\nabla_\phi J(\theta, \phi), \nabla_\theta J(\theta, \phi))$

    □ 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.

    ○ 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.

3   Diffusion Models (4 points)

3.1. (1 point) **True or False:** To train a diffusion model, we find the parameters for the reverse process model that maximize the sum of the log-likelihoods of the training images, i.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 $\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(N)}$ are the N training images.

- ○ True

- ○ False

3.2. (1 point) **True or False:** The forward process of a diffusion model *and* the (learned) reverse process are both stochastic.

- ○ True

- ○ False

3.3. (2 points) **Select all that apply:** Why does the Denoising Diffusion Probabilistic Model (DDPM) use a UNet model? Recall that the structure of the exact reverse process $q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0)$ 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 (3 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 $\hat{\mathbf{x}}^{(i)} \sim p_\theta(\mathbf{x} \mid \mathbf{z}^{(i)})$.

- ☐ $\frac{1}{N} \sum_{i=1}^{N} \|\mathbf{x}^{(i)} - \hat{\mathbf{x}}^{(i)}\|_2^2 - KL\left(q_\phi(\mathbf{z} \mid \mathbf{x}) \| \mathcal{N}(\mathbf{0}, \mathbf{I})\right)$

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

- ☐ $-\text{ELBO}(q_\phi)$

- ☐ 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

- ◯ False