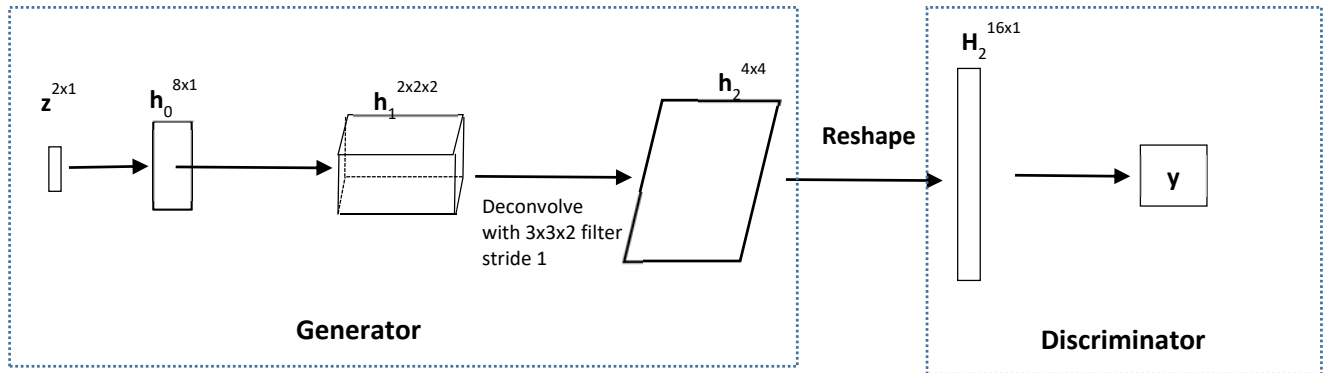


Assignment 6, due 4pm , April 12th

1. **Problem 1** Forward and backward propagation for a simple GAN below [20 points]



Generator:

Random input: $z = \begin{pmatrix} 0.4 \\ 0.8 \end{pmatrix}$

$$\text{Project: } h_0 = \text{ReLU}(w_0^T z_1 + b_0), w_0 = \begin{bmatrix} 0.1 & 0.3 \\ 0.7 & 0.9 \\ 0.5 & 0.7 \\ 0.1 & 0.9 \\ 0.3 & 0.1 \\ 0.4 & 0.6 \\ 0.7 & 0.8 \\ 0.2 & 0.1 \end{bmatrix}, b_0 = \begin{bmatrix} 0.1 \\ 0.4 \\ 0.2 \\ 0.3 \\ 0.5 \\ 0.9 \\ 0.7 \\ 0.9 \end{bmatrix}$$

$h_1 = \text{reshape}(h_0)$

$$h_2 = \text{ReLU}(\text{Deconv}(h_1, w_1, b_1)) \in R^{4 \times 4}, w_1^{3 \times 3 \times 2} = [w_1^1 \ w_1^2],$$

$$\text{Deconvolution: } w_1^1 \in \begin{bmatrix} 0.1 & 0.4 & 0.5 \\ 0.1 & 0.7 & 0.1 \\ 0.2 & 0.4 & 0.3 \end{bmatrix}, w_1^2 \in \begin{bmatrix} 0.2 & 0.1 & 0.6 \\ 0.3 & 0.9 & 0.2 \\ 0.5 & 0.2 & 0.3 \end{bmatrix}, b_1 = \begin{bmatrix} 0.1 & 0.5 & 0.6 & 0.3 \\ 0.2 & 0.4 & 0.8 & 0.1 \\ 0.1 & 0.3 & 0.7 & 0.2 \\ 0.3 & 0.1 & 0.2 & 0.1 \end{bmatrix}$$

Binary Discriminator:

$$H_2 = \text{Flatten}(h_2) \in R^{16 \times 1}$$

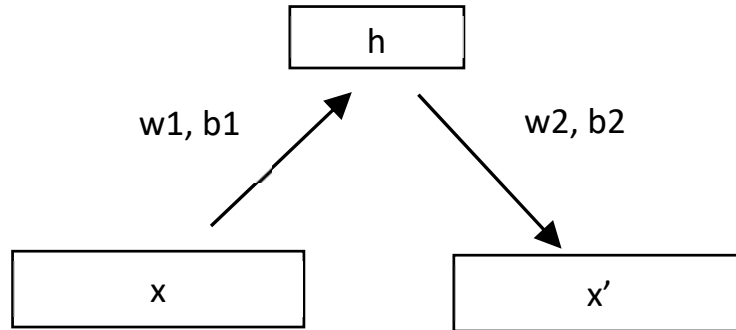
$$p(y = 0) = \sigma(w_2^t \mathbf{H}_2 + b_2), w_2 = [0.1 \ 0.2 \ 0.3 \ 0.2 \ 0.4 \ 0.6 \ 0.7 \ 0.1 \ 0.1 \ 0.2 \ 0.5 \ 0.3 \ 0.1 \ 0.2 \ 0.6 \ 0.9]^t \ b_2 = 0.3$$

Tasks:

- 1) Using the forward propagation equations and given the initial weights, produce the values for h_0 , h_1 , and h_2 from a given z .
- 2) Given the logistic regression discriminator classifier parameters $\theta^D = \{w_2, b_2\}$ above, derive the gradients for w_1 and w_0 by maximizing the $\log p(y = 0)$. Show your process.

Problem 2 Auto-encoder [20 points, only for those taking the class at 6000 level]

For the encoder and decoder below,



$$h = \text{ReLU}(w_1^t x + b_1)$$

$$x' = \sigma(w_2^t h + b_2)$$

$$w^1, w^2 = \arg \min_{w^1, w^2} \sum_{i=1}^N (x_i - x'_i)^2$$

Derive the gradient equations for w_1 and w_2 by minimizing the reconstruction errors above

3. **Problem 3** Variational Auto-encoder (VAE) [20 points, **extra credit**]

For an VAE, prove maximizing the decoder distribution $p(x|\phi)$ is equivalent to maximizing the following function, where $q(z|x, \theta)$ is the encoder function and KL the KL divergence. Hint: using Jensen's inequality

$$E_{q(z|x, \theta)}(p(x|z, \phi)) - KL(q(z|x, \theta) || p(z))$$