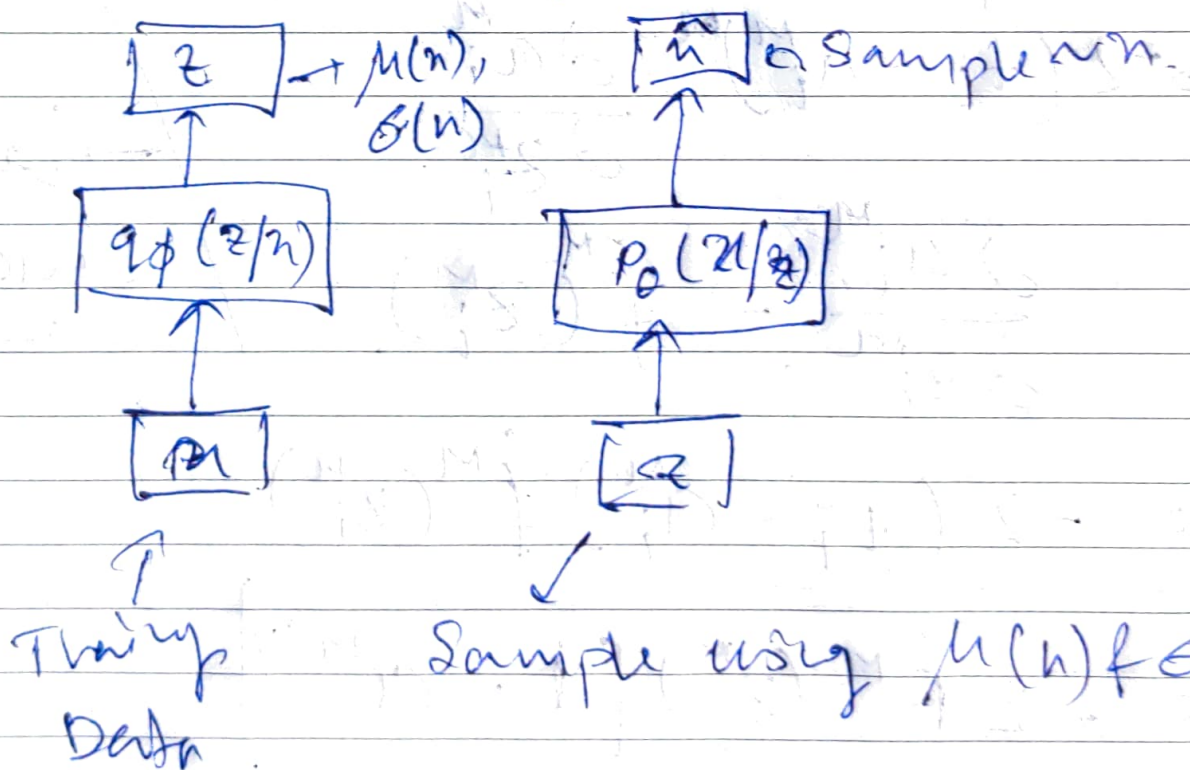
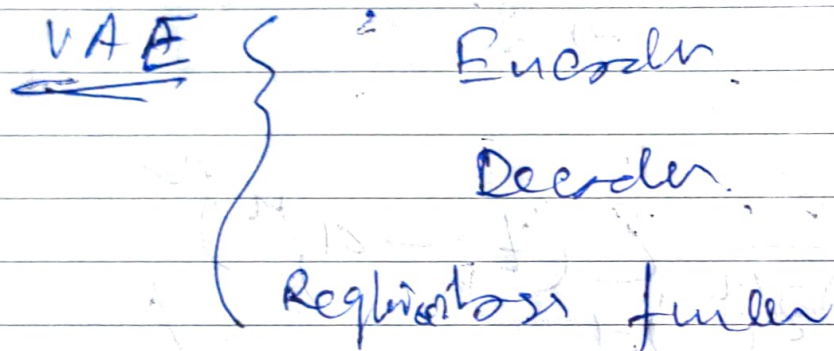
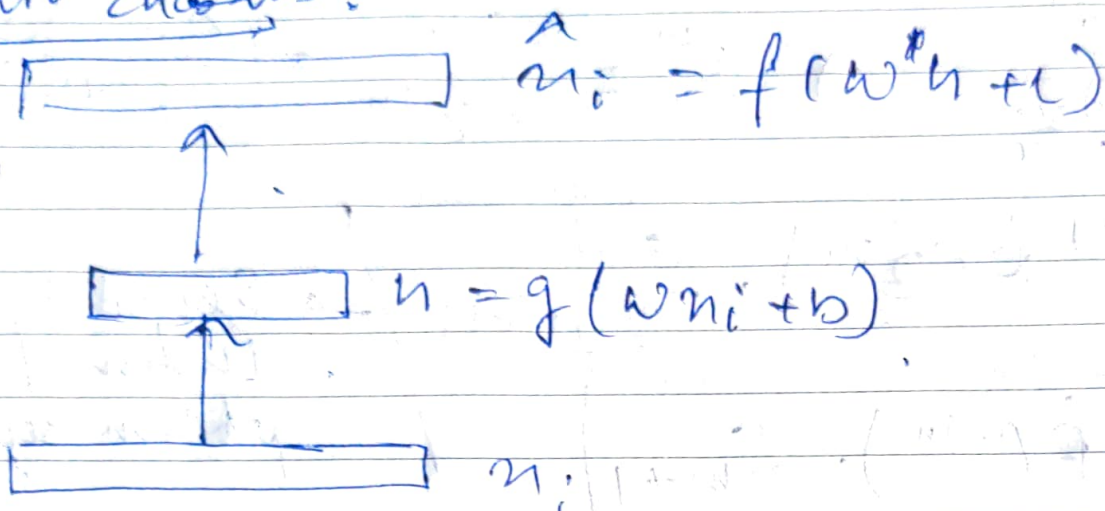


Auto Encoders:



loss function:

$$-D_{KL} [q_\phi(z|x) \parallel p_\theta(z)] + \mathbb{E}_{q_\phi(z|x)} [\log(p_\theta(z|x))]$$

regularizer $\rightarrow N(0, I)$ loss

$q_\phi(z|x) \rightarrow \mu(x), \sigma(x)$ Gaussian

\downarrow
continuous to be
discrete

$$\mathbb{E} \log(p_\theta(z|x))$$

\rightarrow output of decoder.

$$KL[N(\mu(x), \sigma(x)) \parallel N(0, I)]$$

$$+ \|x - f(z)\|^2.$$

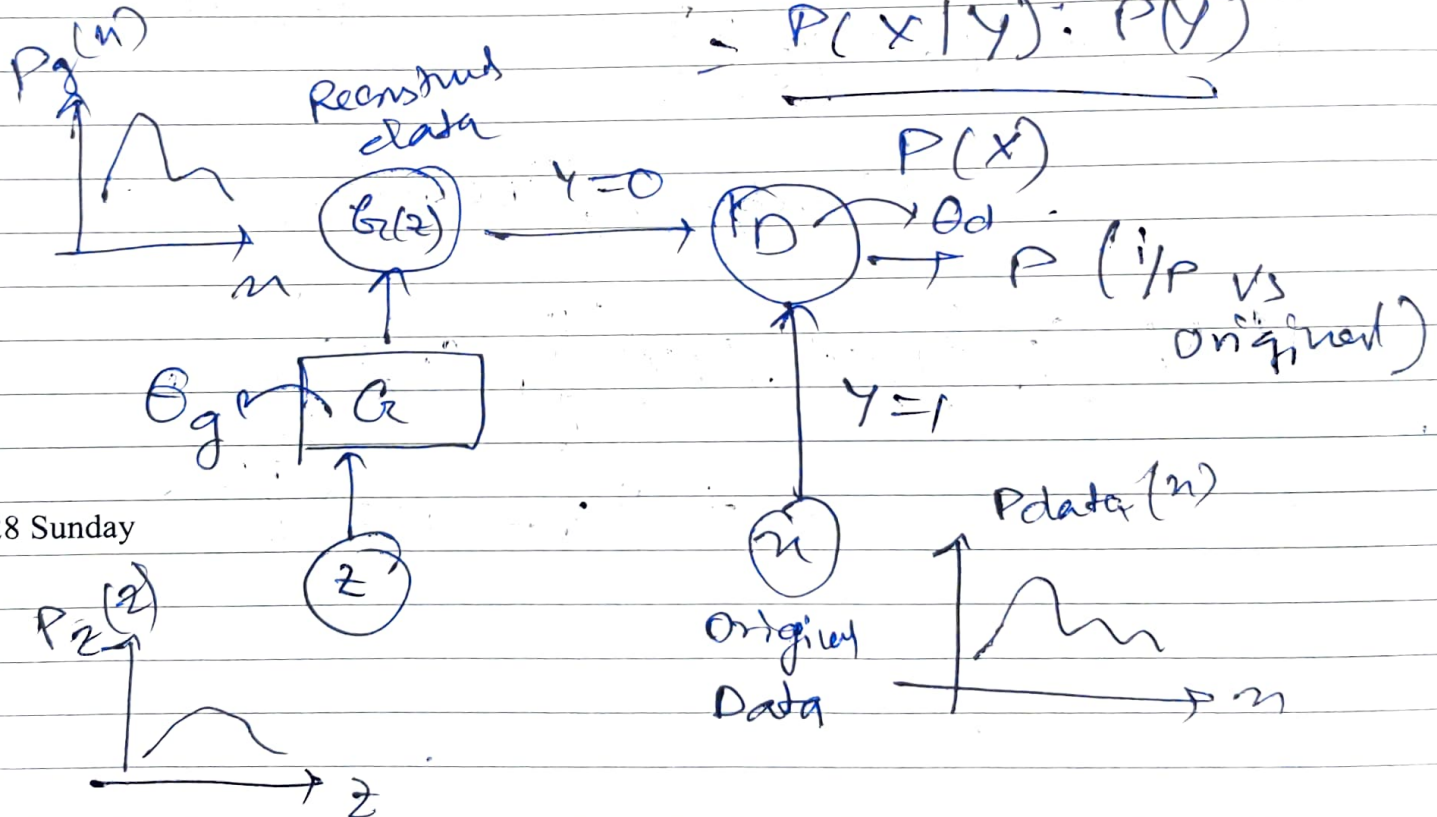
GANs

Generator: $P(X, Y) = P(X|Y) \cdot P(Y)$

Discriminator: $P(Y|X=x)$

Bayes term $\rightarrow P(Y|X) = \frac{P(X, Y)}{P(X)}$

$= \frac{P(X|Y) \cdot P(Y)}{P(X)}$



28 Sunday

Minimax Game:

Value function:

$$\min_{G_2} \max_D V(G, D) = E_{n \sim P_{data}} [\ln(D(n))] + E_{z \sim P_2} [\ln(1 - D(G(z)))]$$

Binary Cross Entropy:

$$\mathcal{L} = - \sum y \ln \hat{y} + (1-y) \ln(1-\hat{y})$$

where, $y=1, \hat{y}=D(n) \Rightarrow \mathcal{L} = -\ln[D(n)]$

$y=0, \hat{y}=D(G(z)) \Rightarrow \mathcal{L} = -\ln[1-D(G(z))]$

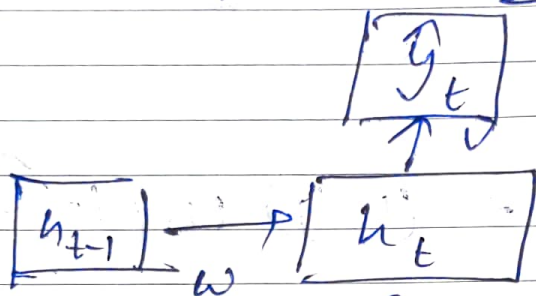
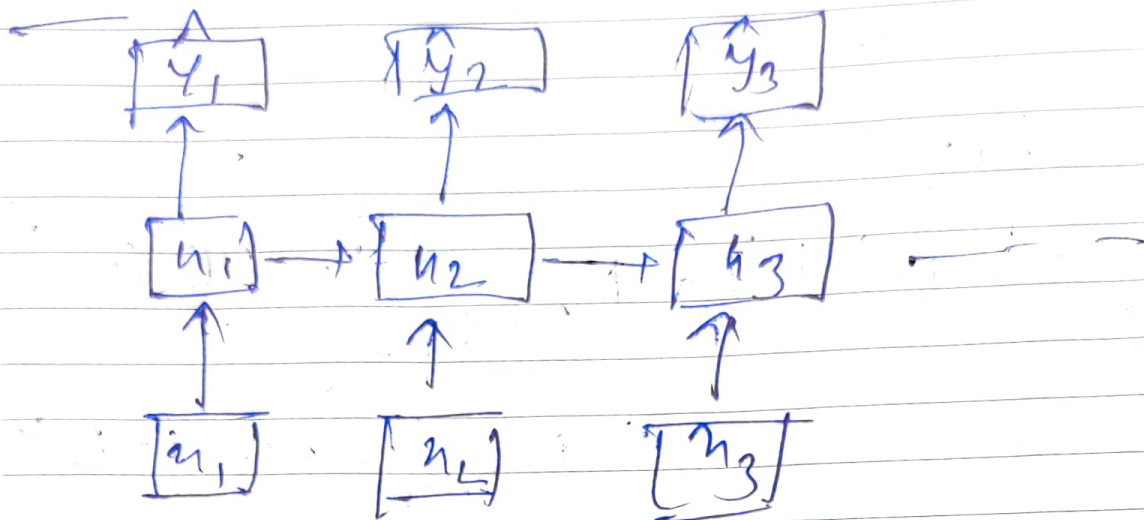
Adding, $\mathcal{L} = -\ln[D(n)] + \ln[1-D(G(z))]$

$$E(\mathcal{L}) = E[-\ln D(n)] + E[\ln[1-D(G(z))]]$$

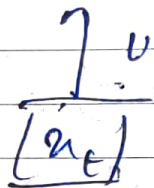
$$= \sum P_{data}(n) \ln[D(n)] + \sum_z P_2(z) \ln[1-D(G(z))]$$

$$= \int P_{data}(n) \ln(D(n)) dn + \int P_2(z) \ln(1-D(G(z))) dz$$

RNN.



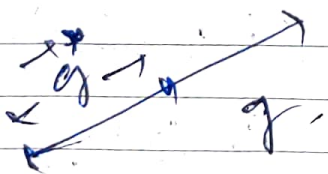
$$h_t = f_w(h_{t-1}, x_t)$$



$$h_t = \tanh(\overset{w}{\omega_{hh}} h_{t-1} + \overset{w}{\omega_{hx}} x_t + b_h)$$

$$y_t = g(\omega_{hy} h_t)$$

Expressing Grad: Grad Clipping:



$$\hat{g} = \frac{g}{\|g\|} \cdot \text{Gmax}$$

Vanishing Gradient: GRU, LSTM.

LSTM:

$$\text{from GRU: } h_t = f \odot h_{t-1} + (1-f) \odot g$$

Vanilla
RNN-

Memory cell:

$\hookrightarrow c_t$ forget input

$$c_t = f \odot c_{t-1} + \bar{i} \odot g$$

$$h_t = o \odot \tanh(z_h)$$

output $o \in [0, 1]$

$$o = \sigma(z_o)$$

$$f = \sigma(z_f)$$

$$\bar{i} = \sigma(z_{\bar{i}})$$

$$g = \tanh(z_g)$$

$$z_o = w_o h_{t-1} + u_o a_t$$

$$z_h = w_h h_{t-1} + u_h a_t$$

