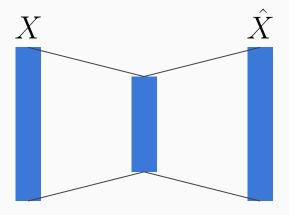
20FALL Introduction to Deep Learning Recitation 10

Variational Autoencoders

By Akshat Gupta, Jiachen Lian 11/13/2020

• Output is the input itself.

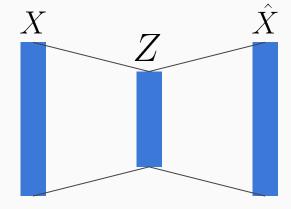
$$min \ E(||\hat{X} - X||^2)$$



• Output is the input itself.

$$min \ E(||\hat{X} - X||^2)$$

• Compressed Latent Representation.

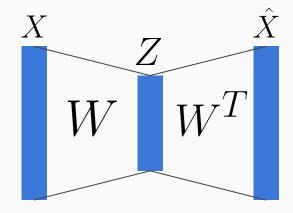


Output is the input itself.

$$min \ E(||\hat{X} - X||^2)$$

- Compressed Latent Representation.
- Linear single-layer AE performs PCA

$$\hat{X} = WW^T X$$



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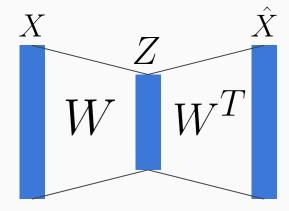
$$min \ E(||\hat{X} - X||^2)$$

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It is not PCA.

$$WW^T \neq I$$



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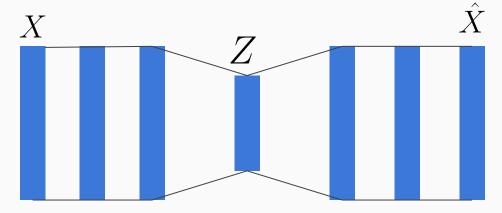
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Deep non-linear AE generates powerful representation



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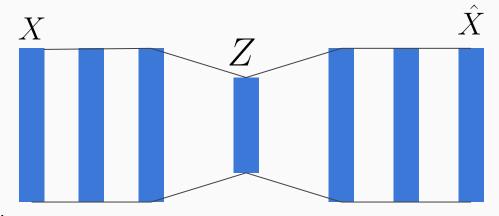
- Compressed Latent Representation.
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$$\hat{X} = WW^T X$$

It is not PCA.

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Deep non-linear AE generates powerful representation



• Why AE?

Compressed Latent Representation.

Promising Applications. E.g. Image denoising(Super Resolution), Neural Machine Translation

• Why not AE?

Zero Reconstruction loss on a limited dataset

It is difficult to generate a new datapoint

Generate an image from a distribution

$$P(X) \to X$$

$$P(X) \to X$$









$$P(X) \to X$$



 X_1



 $\overline{X_3}$



 X_2



$$X_4$$

$$X_{i} = [X_{i1}, X_{i2}, ..., X_{ik}]^{T}$$

$$X \sim N(\mu, \Sigma)$$

$$\mu = \frac{X_{1} + X_{2} + X_{3} + X_{4}}{4}$$

$$\Sigma = \sum_{i=1}^{4} \frac{(X_{i} - \mu)(X_{i} - \mu)^{T}}{4}$$

$$P(X) \to X$$



 X_1



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 X_2



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Generate an image without the image itself

$$P(X) \to X$$



 X_1



 $\overline{X_3}$



 X_2



$$X_4$$

$$X_{i} = [X_{i1}, X_{i2}, ..., X_{ik}]^{T}$$

$$X \sim N(\mu, \Sigma)$$

$$\mu = \frac{X_{1} + X_{2} + X_{3} + X_{4}}{4}$$

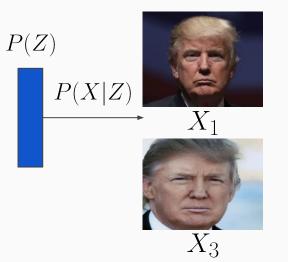
$$\Sigma = \sum_{i=1}^{4} \frac{(X_{i} - \mu)(X_{i} - \mu)^{T}}{4}$$

This is incorrect



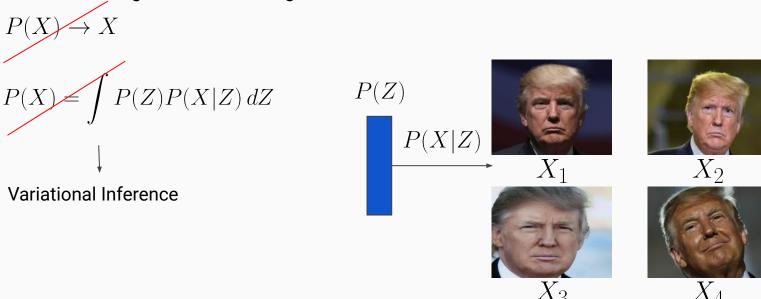
$$P(X) \to X$$

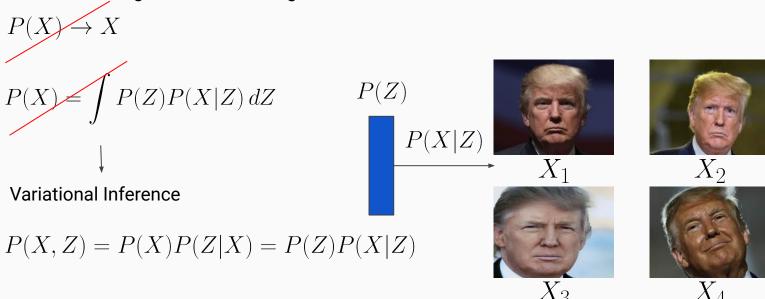
$$P(X) = \int P(Z)P(X|Z) dZ$$

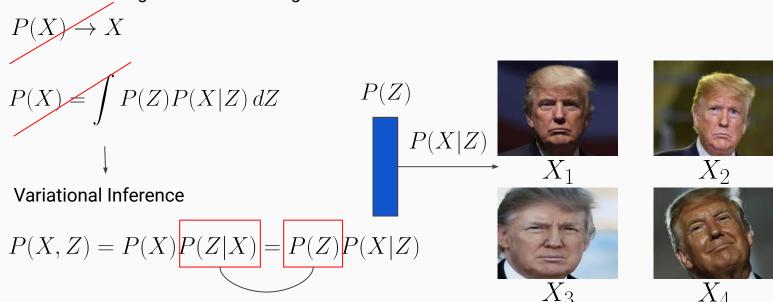


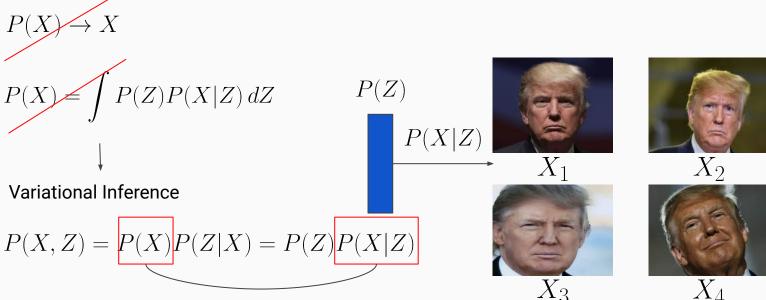


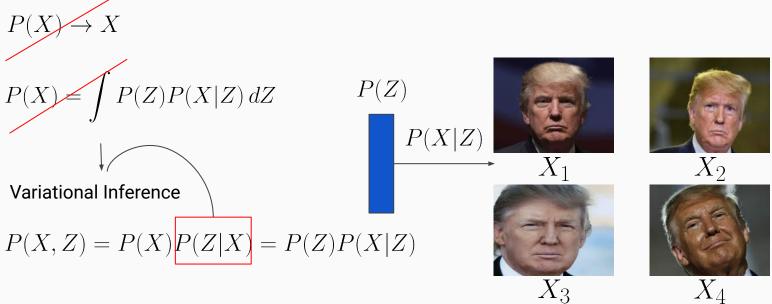


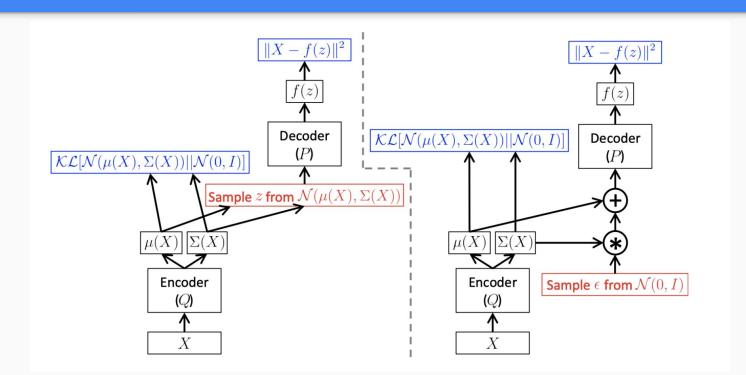


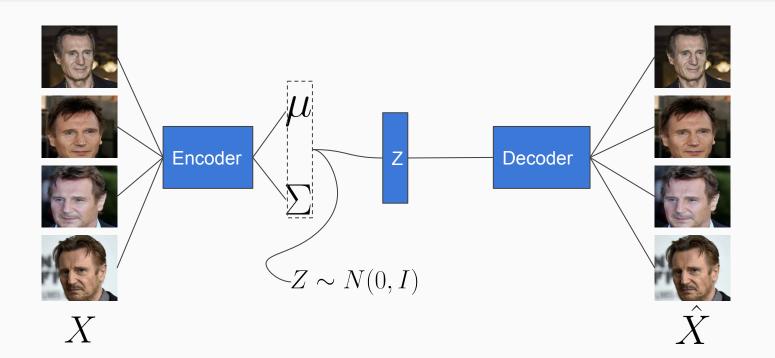


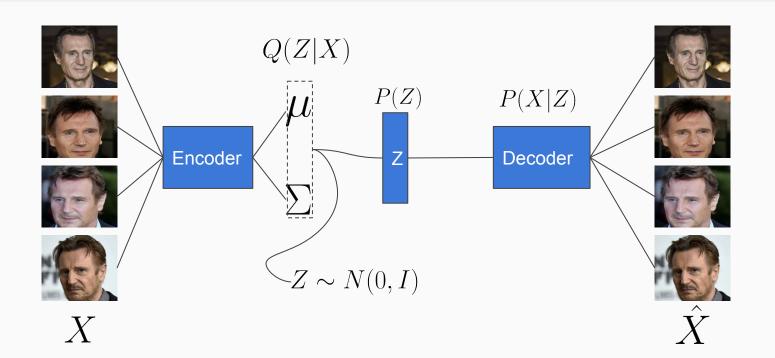


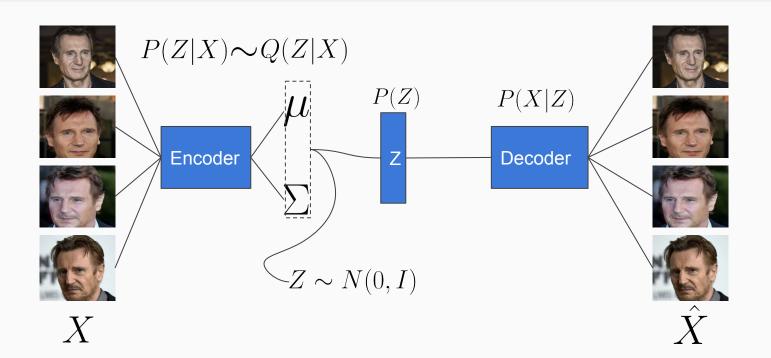


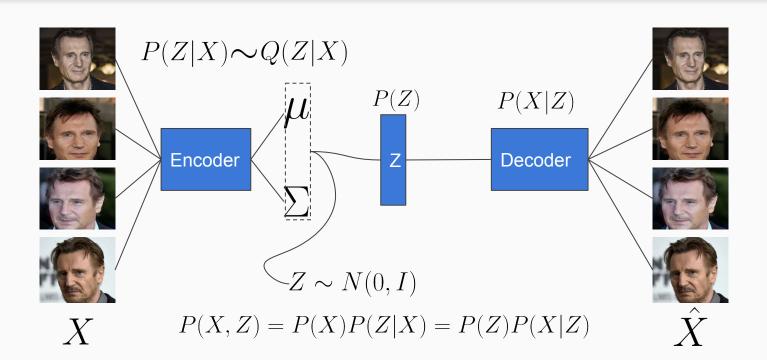


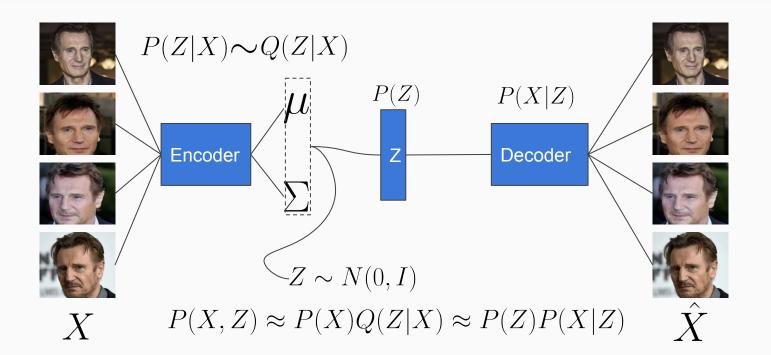


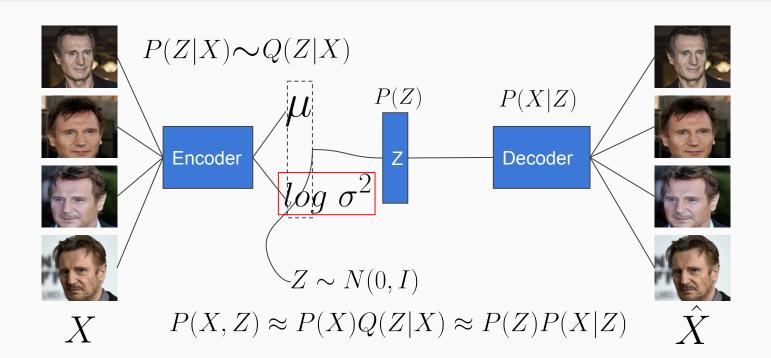












Statistical Distance between Distributions P(X) and Q(X)

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KL-Divergence

Information: $I(p(X)) = -log \ p(X)$

Statistical Distance between Distributions P(X) and Q(X)

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Entropy:
$$H = \Sigma_i p(X_i) I(p(X_i)) = \Sigma_i - p(X_i) log \ p(X_i)$$

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 $-\int p \ log \ p \ dx$

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$$KL(P||Q) = -\Sigma_i P(X_i) log \frac{Q(X_i)}{P(X_i)}$$
 $-\int p \, log \frac{q}{p} \, dx$

Statistical Distance between Distributions P(X) and Q(X)

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$$I(p(X)) = -\log p(X)$$
 Entropy:
$$H = \Sigma_i p(X_i) I(p(X_i)) = \Sigma_i - p(X_i) \log p(X_i) \qquad -\int p \log p \ dp$$

$$KL(P||Q) = -\Sigma_i P(X_i) \log \frac{Q(X_i)}{P(X_i)} \qquad -\int p \ \log \frac{q}{p} \ dx$$

$$KL(Q||P) = -\Sigma_i Q(X_i) \log \frac{P(X_i)}{Q(X_i)} \qquad -\int q \ \log \frac{p}{q} \ dx$$

Statistical Distance between Distributions P(X) and Q(X)

KL-Divergence

$$\ \, \hbox{Information:} \ \, I(p(X)) = -log \,\, p(X)$$

$$KL(P||Q) = -\Sigma_i P(X_i) log \frac{Q(X_i)}{P(X_i)}$$

$$KL(Q||P) = -\Sigma_i Q(X_i) log \frac{P(X_i)}{Q(X_i)}$$

$$KL(Q||P) \neq KL(P||Q)$$

You can pick either!

Statistical Distance between Distributions P(X) and Q(X)

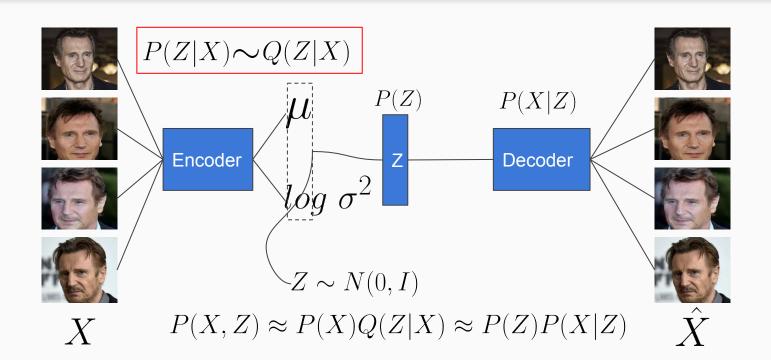
KL-Divergence

 $lemma\ 1: KL(P||Q) \ge 0$

Statistical Distance between Distributions P(X) and Q(X)

$$lemma\ 1: KL(P||Q) \ge 0$$

$$lemma~1: KL(P||Q) \geq 0$$
 Proof:
$$KL(P||Q) = -\Sigma Plog\frac{Q}{P} \geq log(\Sigma P\frac{Q}{P}) = 0$$



 $P(Z|X) \sim Q(Z|X)$

$$P(Z|X) \sim Q(Z|X)$$

$$P(Z|X) \sim Q(Z|X)$$

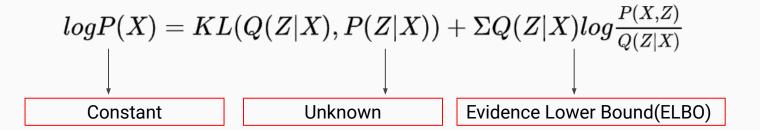
$$KL(Q(Z|X), P(Z|X)) = -\Sigma Q(Z|X) log \frac{P(Z|X)}{Q(Z|X)}$$

$$\begin{split} P(Z|X) \sim &Q(Z|X) \\ KL(Q(Z|X), P(Z|X)) = - \Sigma Q(Z|X) log \frac{P(Z|X)}{Q(Z|X))} \\ &= - \Sigma Q(Z|X) log \frac{P(X,Z)}{P(X)Q(Z|X)} \end{split}$$

$$\begin{split} P(Z|X) \sim &Q(Z|X) \\ KL(Q(Z|X), P(Z|X)) = -\Sigma Q(Z|X)log \frac{P(Z|X)}{Q(Z|X))} \\ &= -\Sigma Q(Z|X)log \frac{P(X,Z)}{P(X)Q(Z|X)} \\ &= -\Sigma Q(Z|X)log \frac{P(X,Z)}{Q(Z|X)} + log P(X) \end{split}$$

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$$log P(X) = KL(Q(Z|X), P(Z|X)) + \Sigma Q(Z|X)log rac{P(X,Z)}{Q(Z|X)}$$



$$log P(X) = KL(Q(Z|X), P(Z|X)) + \Sigma Q(Z|X)log rac{P(X,Z)}{Q(Z|X)}$$
 Constant Unknown Evidence Lower Bound(ELBO)

$$Max~L = \Sigma Q(Z|X)lograc{P(X,Z)}{Q(Z|X)}$$

$$\begin{split} &P(X,Z) = P(X)P(Z|X) = P(Z)P(X|Z) \\ &P(Z|X) \sim Q(Z|X) \\ &log P(X) = KL(Q(Z|X), P(Z|X)) + \Sigma Q(Z|X)log \frac{P(X,Z)}{Q(Z|X)} \\ &Max \; L = \Sigma Q(Z|X)log \frac{P(X,Z)}{Q(Z|X)} \end{split}$$

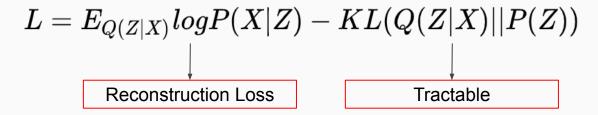
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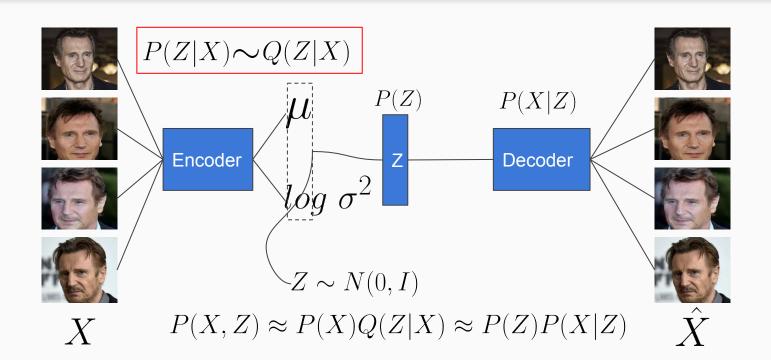
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$$Loss = -E_{Q(Z|X)}logP(X|Z) + KL(Q(Z|X)||P(Z))$$

$$\begin{split} &P(X,Z) = P(X)P(Z|X) = P(Z)P(X|Z) \\ &P(Z|X) \sim Q(Z|X) \\ &logP(X) = KL(Q(Z|X), P(Z|X)) + \Sigma Q(Z|X)log\frac{P(X,Z)}{Q(Z|X)} \\ &Max \ L = \Sigma Q(Z|X)log\frac{P(X,Z)}{Q(Z|X)} \\ &L = E_{Q(Z|X)}logP(X|Z) - KL(Q(Z|X)||P(Z)) \\ &Loss = -E_{Q(Z|X)}logP(X|Z) + KL(Q(Z|X)||P(Z)) \end{split}$$



Discussion 1

$$Q(Z|X) \sim P(Z) \sim P(Z|X)$$

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$$egin{aligned} Q(Z|X) &\sim P(Z) \sim P(Z|X) \ KL(N(\mu,\sigma^2)||N(0,1)) = rac{1}{2}(-log\sigma^2 + \mu^2 + \sigma^2 - 1) \ KL(p||q) = -\int p \ lograc{q}{p} \ dx \end{aligned}$$

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$$Loss = E(||X-\hat{X}||^2) + rac{1}{2}(-log\sigma^2 + \mu^2 + \sigma^2 - 1)$$

• Discussion 2

$$Q(Z|X) \sim P(Z) \sim P(Z|X)$$

$$Loss = -E_{Q(Z|X)}logP(X|Z) + KL(Q(Z|X)||P(Z))$$

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$$P(Z) = P(Z|X) \rightarrow P(Z,X) = P(Z)P(X)$$

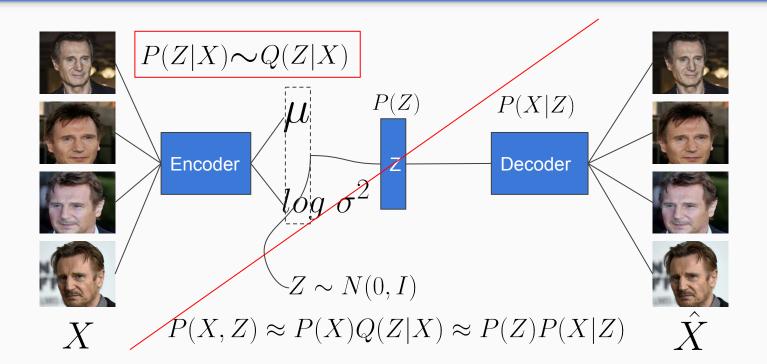
• Discussion 2

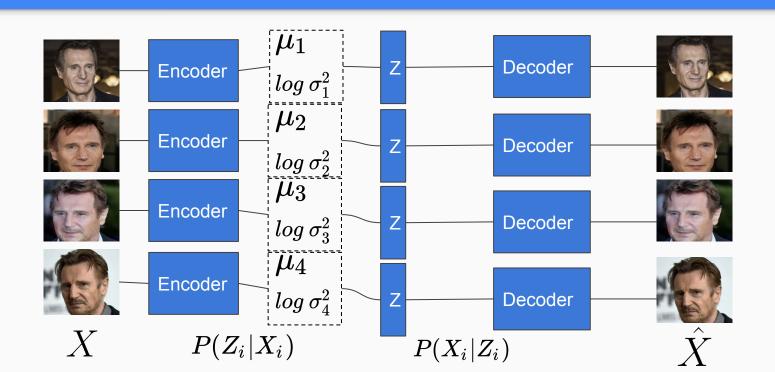
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$$P(Z) = P(Z|X) \rightarrow P(Z,X) = P(Z)P(X)$$

Undesired!





Discussion 3

Reparameterization

$$Z = \mu + \epsilon \sigma \ \sim N(\mu, \sigma^2)$$

$$\epsilon \sim N(0,1)$$

