Deep Generative Modeling

used to create synthesize data

So far Supervised Learning

Data: (x, y)

x is data, y is label

Goal: Learn function to map

$x \rightarrow y$

Examples: Classification, regression, Object detection, semantic segmentation

This topic: Un Supervised Learning

Data: x

x is data, no labels!

Goal: Learn the hidden or underlying structure of data

E.g. Clustering, dimensionality reduction, allow insight to fundamental structure of data. This can be used to generate data.

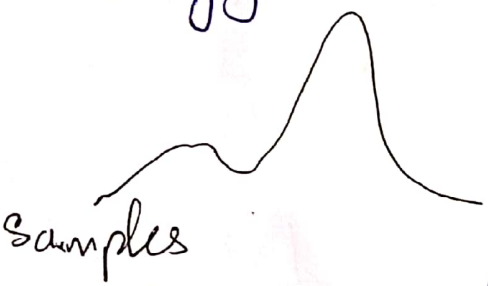
Generative Modeling (Unsupervised Learning)

Goal: Take as input training samples from some distribution and learn a model that represents distribution of the model

1) Density Estimation:

Given a set of data samples they fall according to some density.

The task of GAN is to learn the underlying PDF that describe how this data fall. along this distribution



We can understand PDF and we can use this information to generate new synthetic samples

We are considering some input examples that fall and are drawn from same training data distribution

generate synthetic examples

2) Sample Generation

Input Samples → Generated Samples

Training data ~ $P_{data}(x)$ → Generated ~ $P_{model}(x)$

How can we learn $P_{model}(x)$ similar to $P_{data}(x)$. ?

GANs enable us automatically uncover underlying features in a dataset.

How these features are distributed within a dataset.

Question: How can we learn probability distribution using our model.

GANs Applications:..

1) automatically uncover underlying features in a dataset.

given a facial dataset. We need to group according features (skin color)

dataset may be biased.

data can be sampled accordingly

GANs

2) Outlier detection:.

Self driving car:.

resultant model can be better equipped.

Problem:. How can we detect when we encounter something new

Strategy:. detect outliers using GAN

Use outliers during training.

Latent

Latent Variable:
A variable which is not directly measured but is inferred e.g. happiness or quality of life.

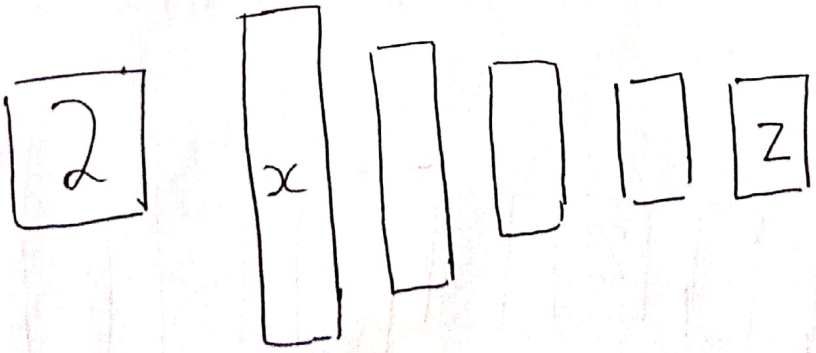
Can we learn the true explanatory factors e.g. latent variables.

Find ways of actually Learning hidden latent variables.

NN can handle multi-dimensional datasets and learn combinations of non-linear functions. That can approximate complex data distributions.

A Simple Model: which can Learn by self-encoding the input Auto Encoders

Auto Encoders:
Unsupervised approach for Learning a lower-dimensional feature representation from unlabelled training data



Encoder learns mapping from the data x, to a Low-dimensional Latent Space, Z

Latent Cave example:
shadows

Why do we need to ensure that z has low-dimensional ~~data~~ ?

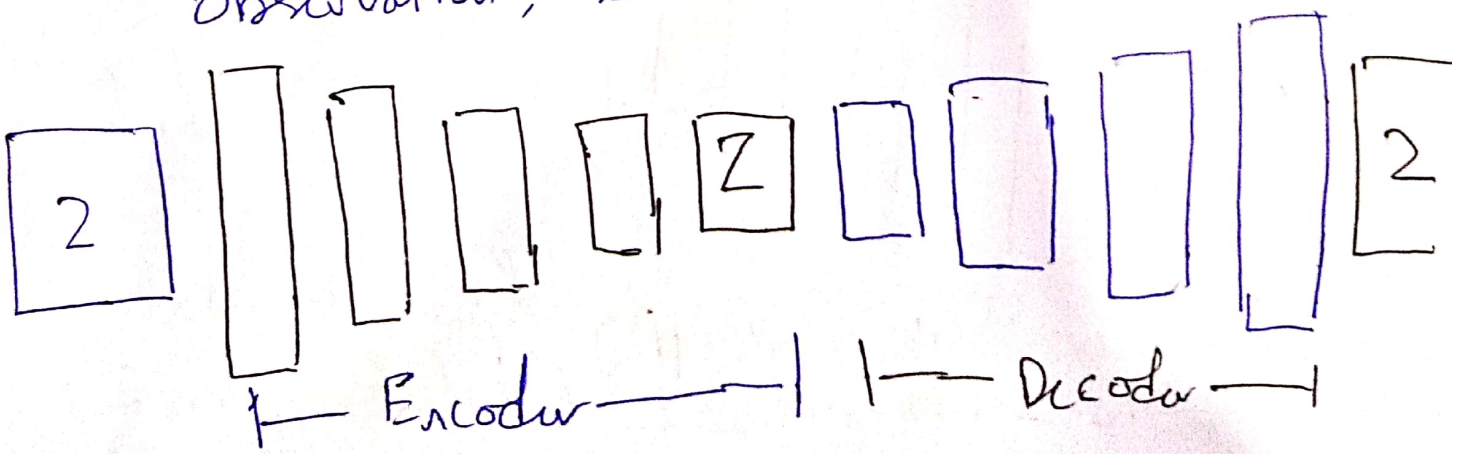
Encoder: Mapping (data) to a low-dimensional latent data z.

Low dimensions: able to compress into a small latent factor, we can learn compact feature representation.

How can we train?
Data is unlabelled.

- Use a Decoder
- Train the model to use these features to reconstruct the original data.

Decoder: Learns mapping back from latent space, z, to a reconstructed observation, $\hat{x}$



Decoder portion of the Auto Encoder is going to be a series of NN layers take this hidden layer and map it back to the hidden space.

$\hat{x}$ → estimated

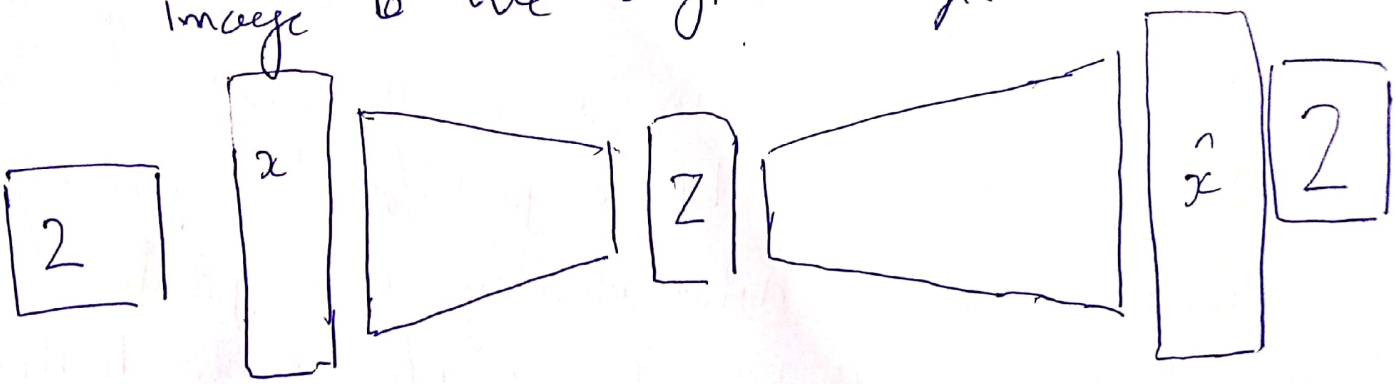
$$L(x, \hat{x}) = ||x - \hat{x}||^2$$

Loss function does not use any labels.

Loss function :: RMSE

for images, subtract one image from the another and squaring the difference pixel-wise difference of images.

Measure how close our reconstructed image to the original image.



we cannot observe z'

Dimensionality is important in re-Construction of input.

Auto encoding is a form of compression Smaller latent space will force a larger training bottleneck.

2 D Latent space might ~~be~~ have higher loss as compared to 5D

Information bottleneck

lower dimensions → poor quality

Auto Encoders for representation Learning

Auto encoder ~~Complex representation~~ can limit nodes in hidden layer

Bottleneck hidden layer: forces network to learn a ~~Compromised~~ compressed latent representation.

without presence of bottleneck Layer; network could simply learn to memorize the input values.

Reconstruction Loss: forces the latent representation to capture (or encode) as much "information" about the data as possible. Diff b/w original i/p and estimated i/p

Auto encoding = Automatically encoding data

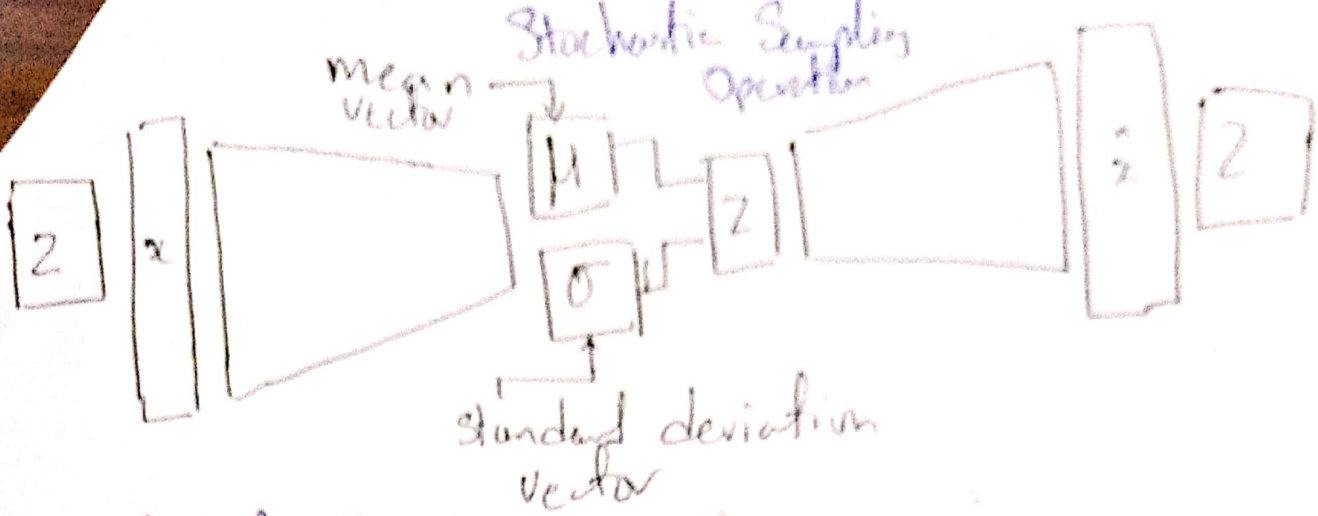
~~Used~~ autoencoder holds variations in i/p without holding to redundancies

VARIATIONAL Auto Encoders

impose a variational stochastic twist

- generate smoother representations of the input data
- improve the quality of reconstruction
- generate new images similar to the input dataset. (but not direct reconstruction of the i/p data)

stochastic sampling portion



Ideal Auto Encoders:

- Sensitive to the inputs to build reconstruction
- Insensitive to the inputs that the model does not memorize or overfit training data

$h(x, \hat{x}) +$ regularizer → discourage memorization

Instead of the latent variable directly VAEs learn the mean and variance associated with that variable. They parameterized association for that latent variable

instead of learning a vector of latent variables, we learn a vector of mean and standard deviation of latent variables.

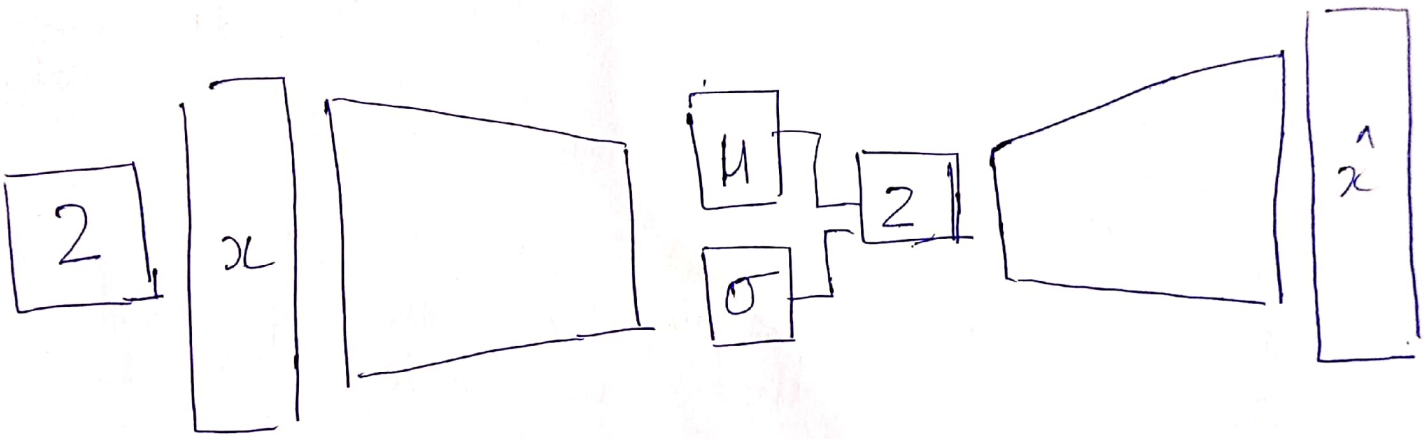
They parameterized probability distribution for that variable.

Traditional Auto Encoders are deterministic. O/P is single value for each encoding dimension.

Variational autoencoders are a probabilistic twist on autoencoders. A probability distribution for each latent attribute. Sample from the mean and standard deviation to compute the latent sample.

probabilistic twist to compute sample information

Encoder and decoder are now probabilistic



Encoder computes $q_\phi(z|x)$ Decoder computes $p_\theta(x|z)$

Performing sampling information to sample each of the latent variable

Encoder is now try to learn a PDF of latent distribution z given the data x.

Decoder ~~will try to learn~~ is going to take that learned representation and compute a new PDF of input x given the latent distribution z.

Encoder and decoder are defined by separate sets of weights (ϕ, θ)

$$L(\phi, \theta, x) = (\text{reconstruction loss}) + (\text{regularization term})$$

reconstruction loss is going to capture the difference between the input and reconstructed output.
e.g. log likelihood $\cdot \|x - \hat{x}\|^2$ For image data MSE b/w o/p and i/p

regularization loss (VAE loss):

$q_\phi(z|x)$ is a distribution on the latent space z given the data x.
As part of this learning process, we are going to place a prior on latent ~~learning~~ space z.
Some initial hypothesis what z will look like.

By imposing these regularization terms the model will ~~achieve~~ try to enforce z that it learns to follow this prior distribution ($p(z)$)

$$D\left(q_\phi(z|x) \,||\, p(z)\right)$$

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regularization term will try to enforce ~~this diversion~~.

minimization of this diversion b/w what encoder is trying to infer the probability distribution of $z|x$ and the prior on the latent variable $P(z)$.

avoid overfitting on latent space

encourage latent variables to adopt a distribution which is similar to $P(z)$; prior.

Regularization: or pricing (prior) is important

consider the ~~divergence~~ divergence b/w inferred latent distribution and fixed prior.

$$D\left(q_\phi(z|x) \,\|\, p(z)\right)$$

Inferred latent distribution

Fixed prior on latent distribution

Choice of prior:

Common choice of prior — Normal Gaussian

$$p(z) = N(\mu = 0, \sigma^2 = 1)$$

S.D and variance = 1

Normal distribution centered around mean 0

- Encourages encodings to distribute encodings evenly around the center of the latent space
- Penalize the network when it tries to cheat by clustering points in specific regions. (i.e. by memorizing the data).

encoder
↑ VAE will distribution learned by be distributed evenly around the center of each latent variable. outside the region far away will be penalized.

Inferred latent distribution ↓ $q_\phi(z|x)$ → Fixed prior on latent distribution $p(z)$

$$D(q_\phi(z|x) \,||\, p(z)) = -\frac{1}{2}\sum_{j=0}^{k-1}(\sigma_j + \mu_j^2 - 1 - \log\sigma_j)$$

KL-divergence b/w the two distributions

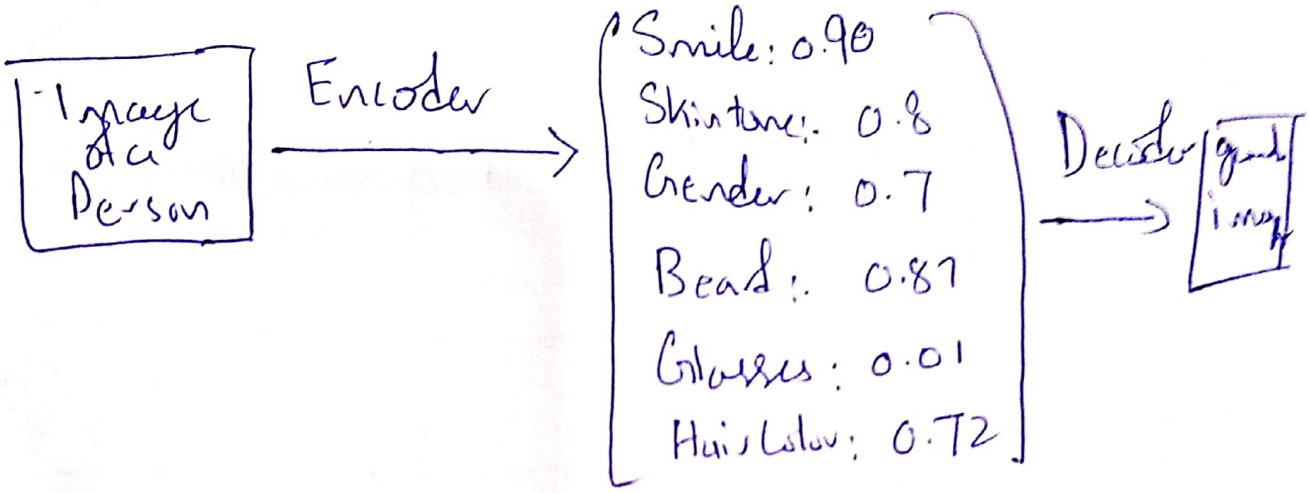
KL-Divergence:

A measure that how one probability distribution is different from another.

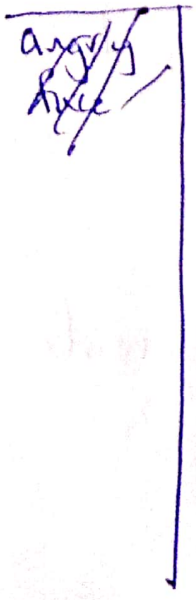
~~Latent vs.~~

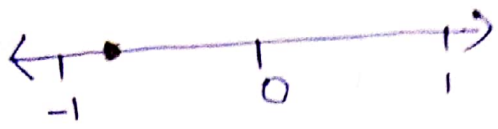
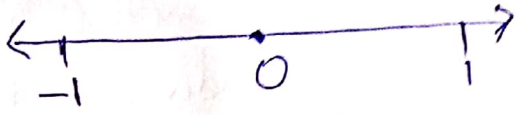
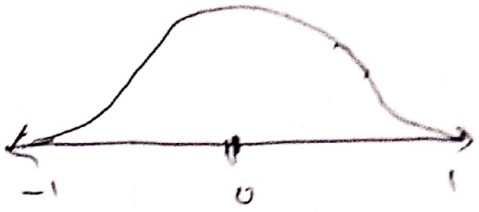
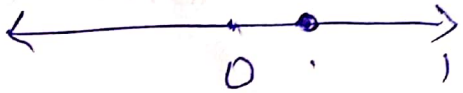
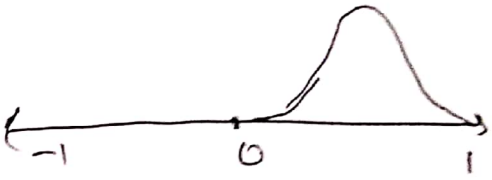
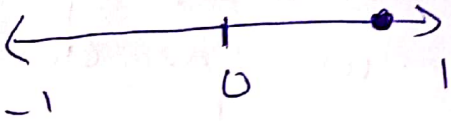
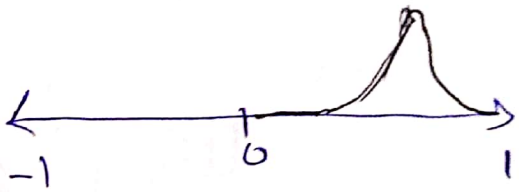
Auto Encoder Vs. VAE

Auto encoder will learn descriptive attributes.
Example



- A single value to describe each attribute
How about representing each attribute as a range of values.
Using VEA, we can describe using probabilistic terms.



Type	Smile Discrete Value	Smile Probability Distribution
Angry face		
gentle Smile		
Happy face		
Very Happy face		

Each latent attribute is represented as probability distribution.

When decoding: randomly sample from each latent state distribution to generate a vector as input.

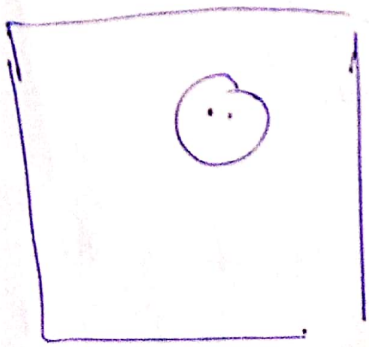
Why we want to regularize?
What is regularization.

What properties do we want from regularization.?

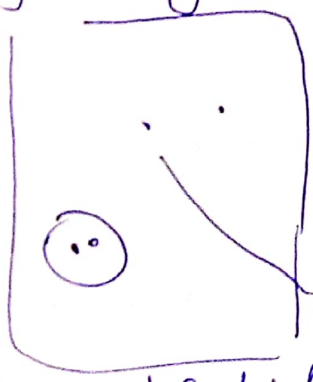
1- Continuity: Points that are close in latent space → similar content after decoding

2. Completeness: sampling from latent space → meaningful content after decoding

Without regularization: Points in latent space could be close but they may not get decoded correctly or they may be ~~far~~ at a distance in the latent space



Points close in latent space are meaningful decoded.



distant points during decoding

does not result in meaningful content.

Not Regularized

Stochastic Sampling:
Every point in the signal has a non-zero probability of being sampled.

How can we achieve this

VAEs try to encode inputs as distribution which are defined by mean and variance.

Mean and S.D alone are not sufficient

Recall: Loss = Reconstruction + Regularization

Without regularization: the model will try to minimize the reconstruction loss

means could be converged or totally diverged.

Normal prior will encourage learned latent distributions to overlap in latent space.

Normal prior based regularization helps enforce information gradient in the latent space.

Points and distances in the latent space have some relationship with the content reconstructed

Trade off between regularizing and reconstructing. The more we generalize there is a risk of suffering w.r.t quality

How do we back propagate?

It requires deterministic approach.

idea:-

Reparameterizing the sampling layer.

$$z \sim N(\mu, \sigma^2)$$ — variance

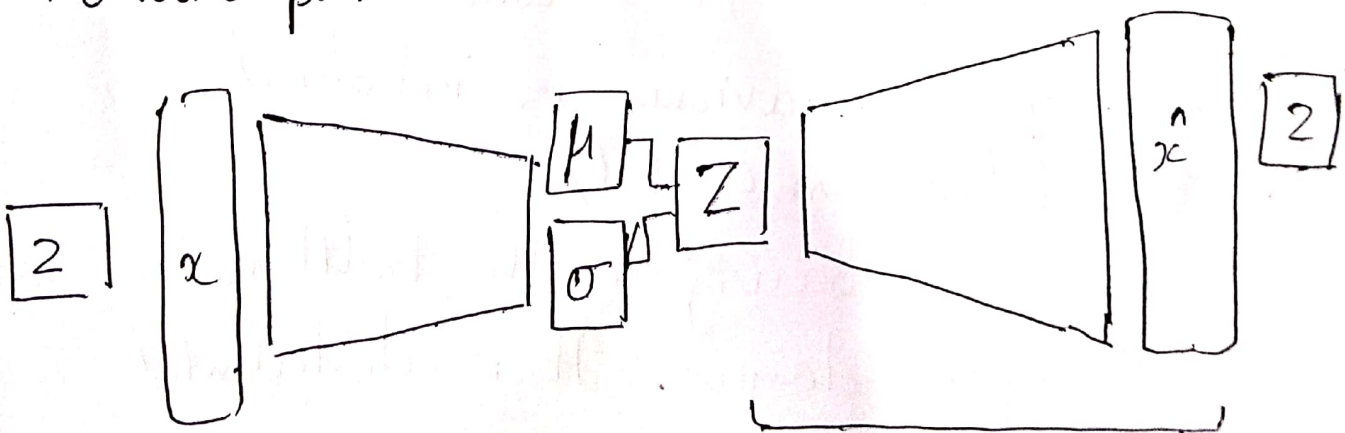
We cannot compute gradients through stochastic sampling.

Consider the sampled latent vector z as a sum of

- a fixed vector μ
- a fixed σ vector scaled by random constants from the prior distribution

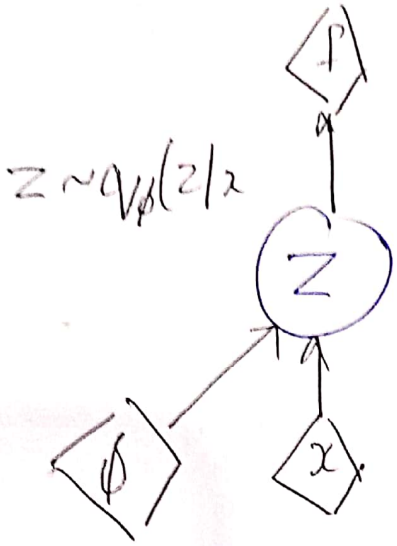
$$\Rightarrow z = \mu + \sigma \odot \epsilon$$ where $\epsilon \sim N(0, 1)$

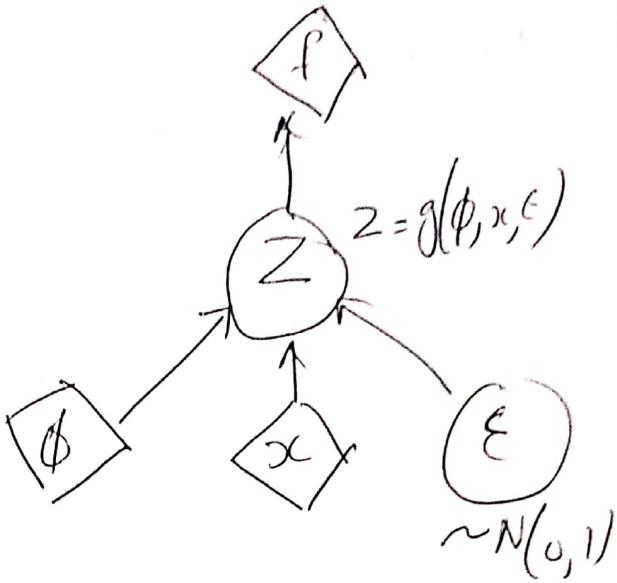
Forward pass:



$$L(\phi, \theta, x) = (\text{reconstruction loss}) + (\text{regularization term})$$

Deterministic node





Stochastic node

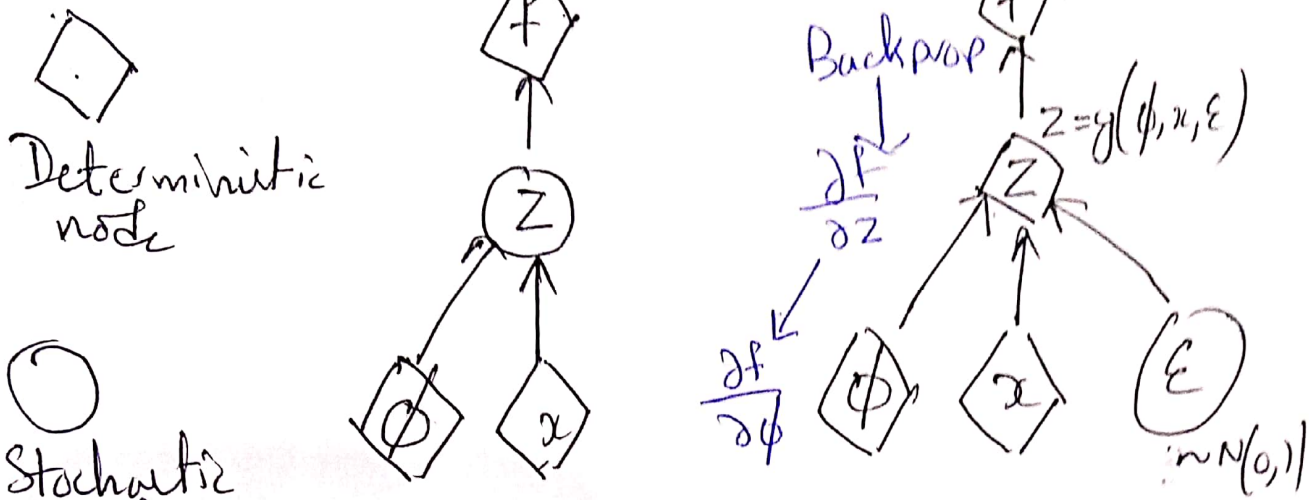
Original form

Back propagation requires deterministic nodes.

reparameterizing use $z = \mu + \sigma \odot \epsilon$ where $\epsilon \sim N(0,1)$

stochastic behaviour is introduced by ϵ (random constant).

ϵ is not occuring in the bottleneck sampling layer. It is distributed elsewhere.



Original form

Reparametrized form

We can directly backpropagate through z. ε is constant & it is re-parameterized elsewhere.