AutoEncoders

MUSTAFA HAJIJ

AutoEncoder

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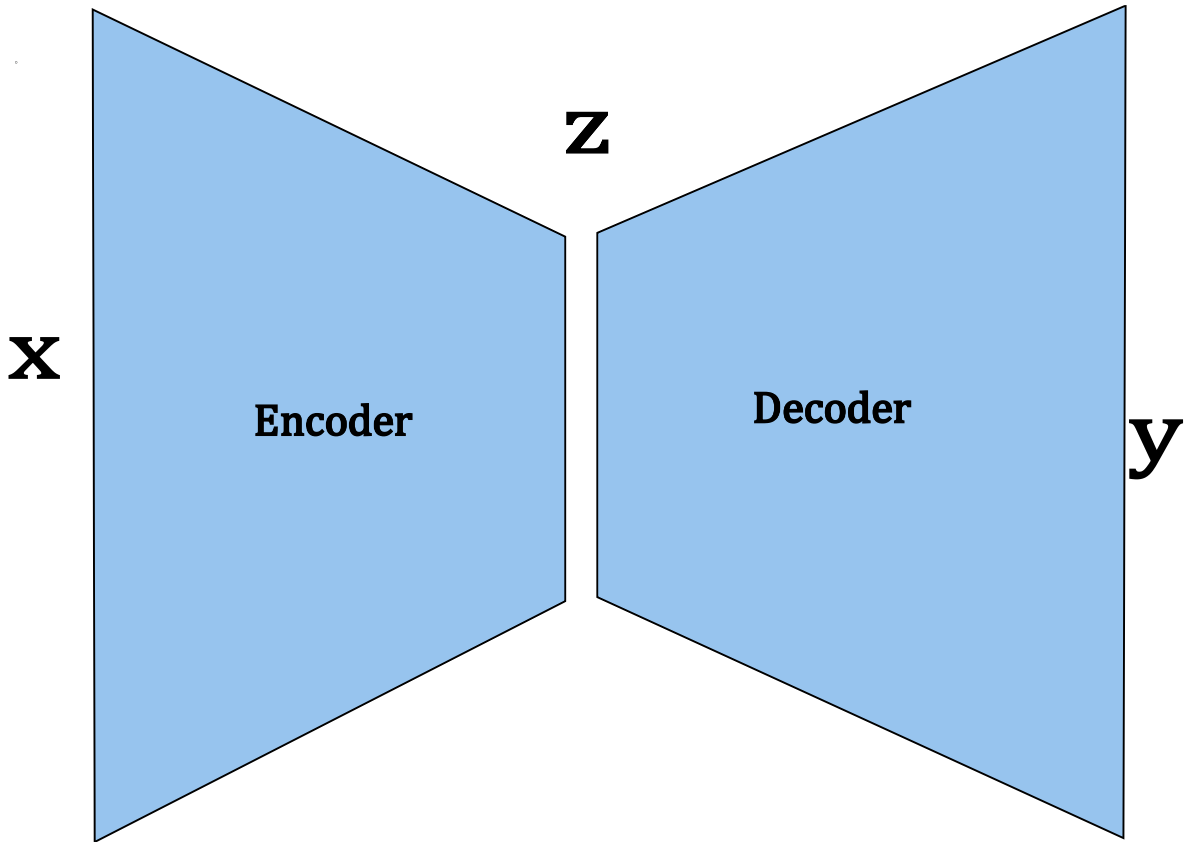

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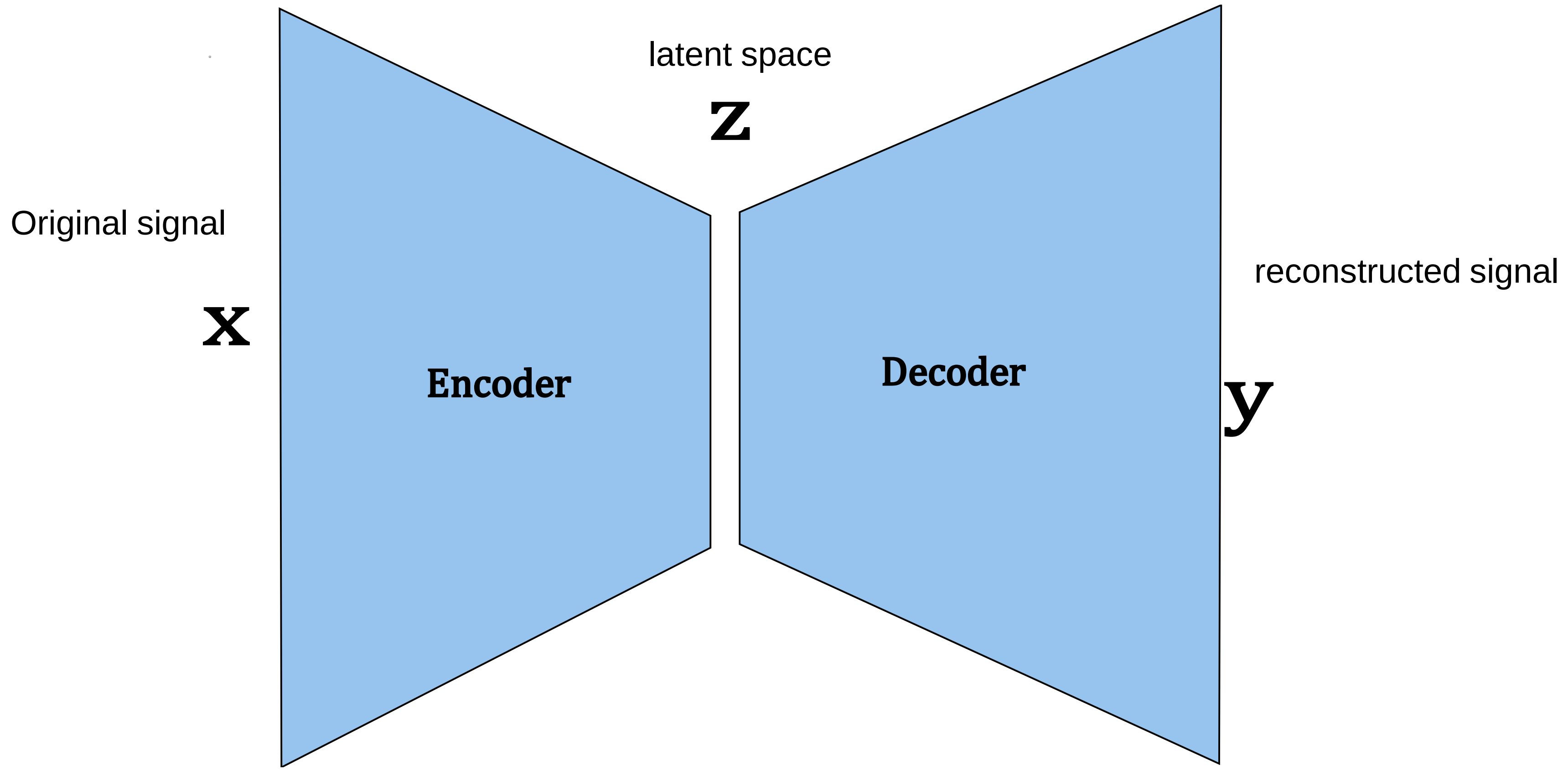

Mathematically, an autoencoder is a tuple of NNs (Encoder, Decoder) such that y=Decoder(Encoder(x))=x. In practice we realize this equation as an an MSE loss |Decoder(Encoder(x))-y| and train the tuple (Encoder, Decoder) to minimize that loss.

AutoEncoders and PCA

In the special case, an autoencoder can give us Principal Component Analysis (PCA)-like behavior when certain conditions are met.

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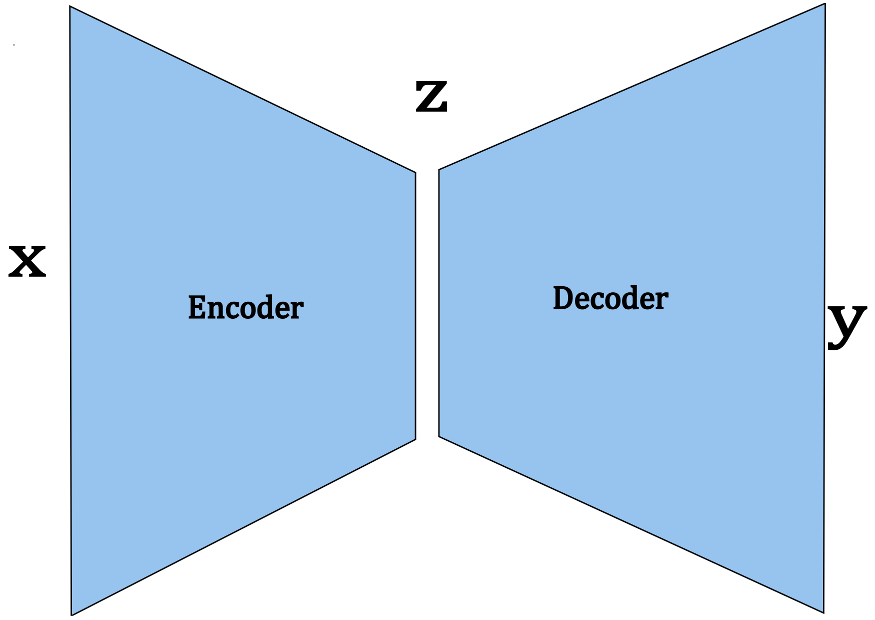

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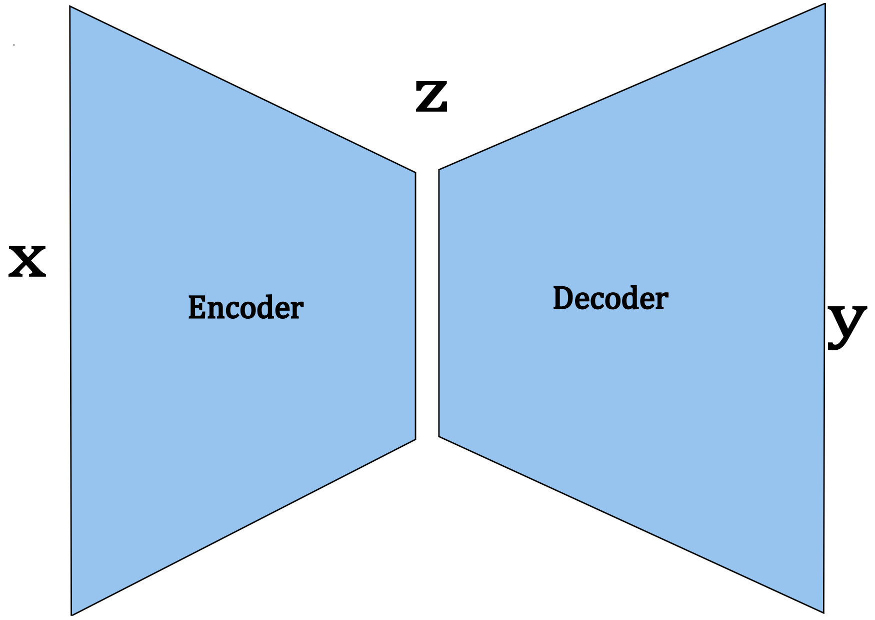

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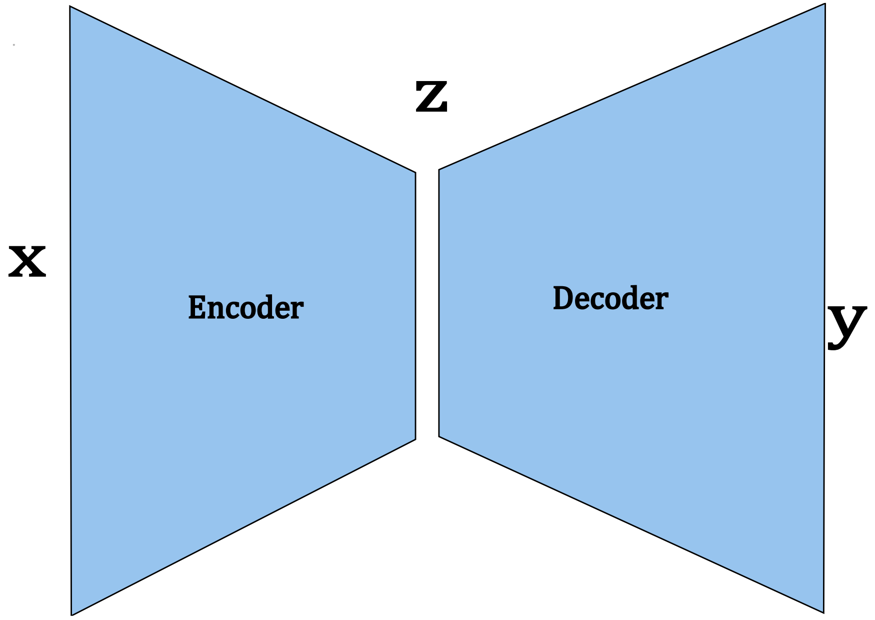

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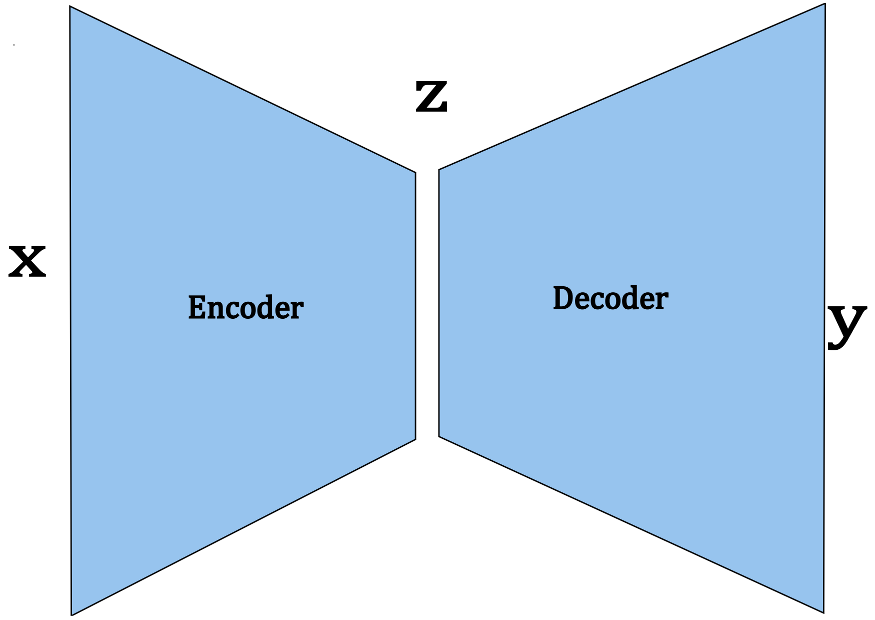
This process encourages the autoencoder to find a low-dimensional representation of the data that preserves the most important information, similar to how PCA finds the directions of maximum variance. The latent space of the autoencoder can be considered as the principal components, and the encoder weights can be interpreted as the loading vectors of the principal components.



Variational Autoencoders

$AutoEncoders \qquad x \rightarrow z = e(x) \rightarrow y = d(z)$

Image source

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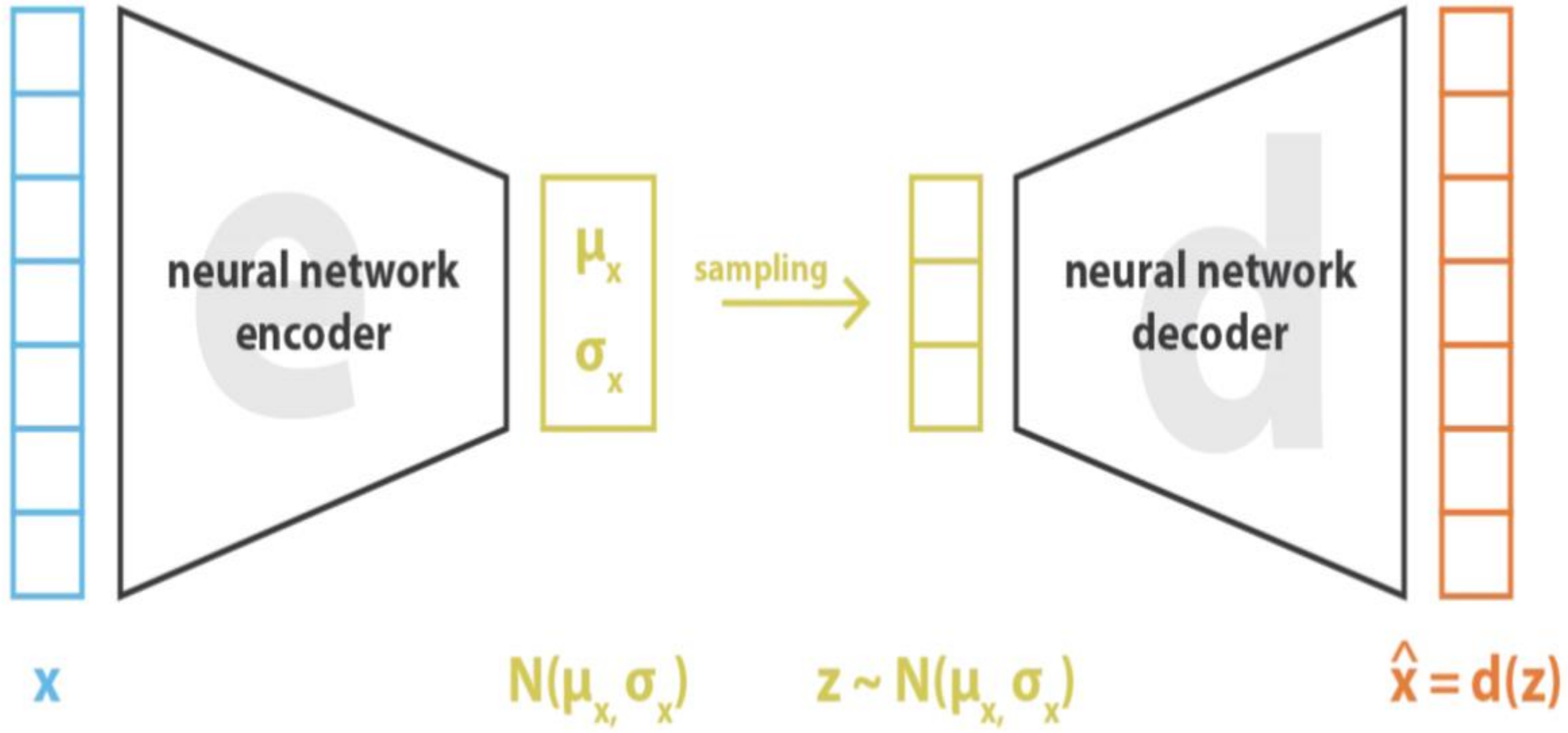
Rather than encoding the input as a single point, we encode it as a distribution over the latent space.

$$Variational\ AutoEncoders \qquad x \rightarrow \underbrace{p(z|x)}_{latent\ distribution} \rightarrow \underbrace{z \sim p(z|x)}_{sample\ from\ latent\ distribution} \rightarrow \underbrace{d(z)}_{reconstruction}$$

Image source

Variational Autoencoders



$$\text{loss} = \| x - \hat{x} \|^2 + KL[N(\mu_x, \sigma_x), N(0, I)] = \| x - d(z) \|^2 + KL[N(\mu_x, \sigma_x), N(0, I)]$$

Image source

Variational Autoencoders

1.Encoding Variational Distribution: The VAE framework assumes that the encoder network learns to map the input data to a distribution in the latent space. This distribution is usually assumed to be a multivariate Gaussian with a mean and a diagonal covariance matrix.

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3. Learning the Latent Space Distribution: The goal of the VAE is to learn the parameters (mean and covariance) of the distribution in the latent space that best represents the training data. This is achieved by minimizing the reconstruction error (reconstruction loss) and simultaneously regularizing the distribution in the latent space using the KL loss.

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5.Balancing Reconstruction and Regularization: By including the KL loss in the training objective, the VAE strikes a balance between accurate data reconstruction (minimizing reconstruction loss) and ensuring the learned distribution in the latent space follows the desired prior distribution (minimizing KL loss).

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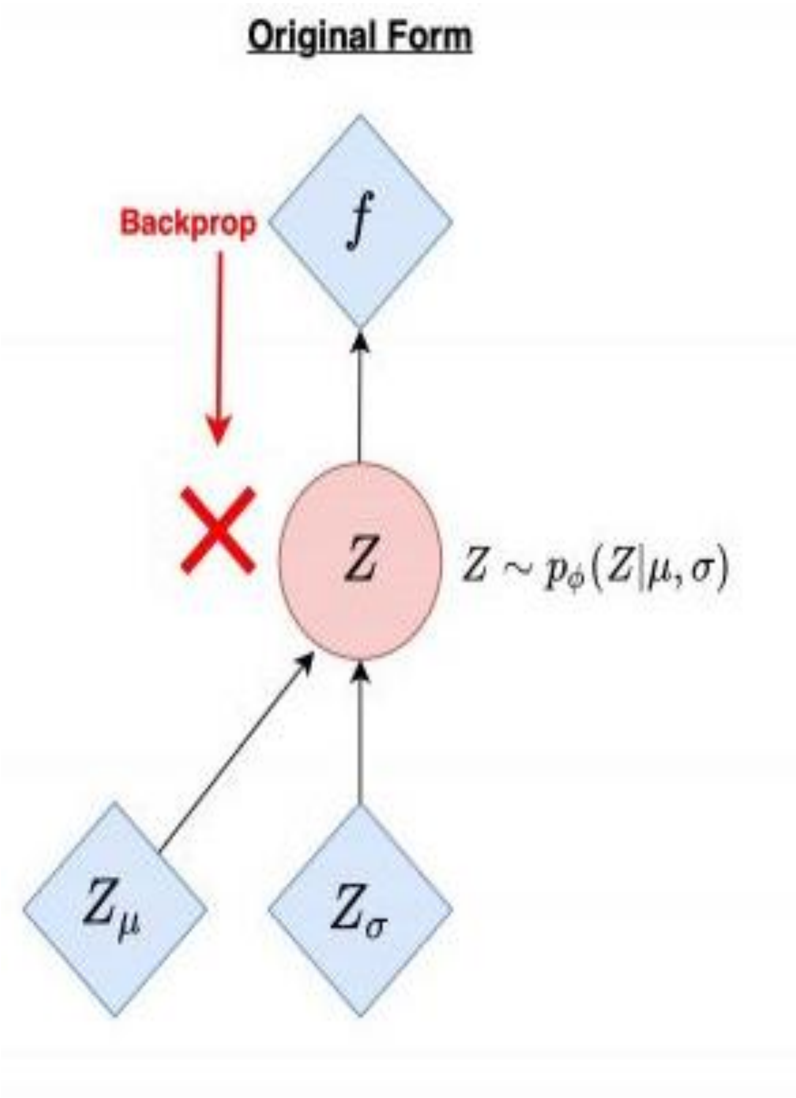

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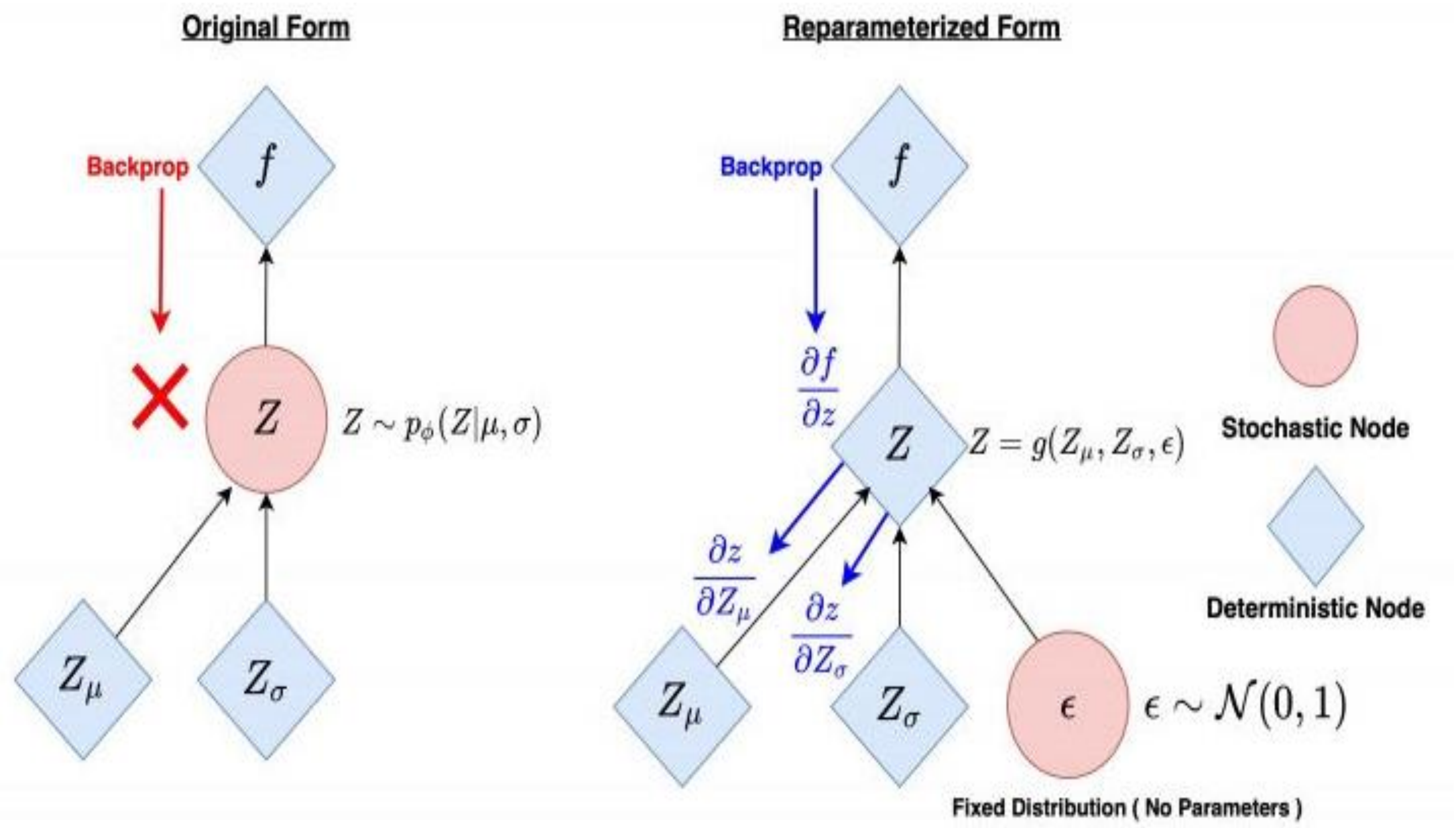

$$Z = Z_\mu + Z_\sigma^2 \odot \varepsilon$$

Here, $\varepsilon \sim \mathcal{N}(0,1)$ and $\odot$ is element-wise multiplication.

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Refs

[Variational Autoencoder in TensorFlow (Python Code) (learnopencv.com)]