

Deep Learning

Variational Autoencoders

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Variational Autoencoders

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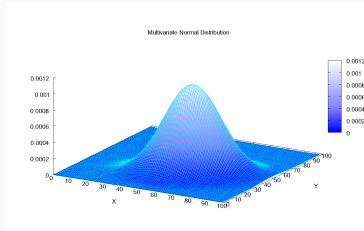
- The autoencoder itself works well in a task.
- What about encoders?
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- The autoencoder itself works well in a task.
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 - The size of the output is defined by model.
 - The representation follows the needs of the encoder.
- What about decoder?
 - Decoder decodes the encoded representation into an original form (with some modification).
 - The representation is defined as an "agreement" between encoder and decoder.
 - May it be used for generation of new images?

- The representation produced by encoder is too specific to be directly generated.
- A major modification need to be designed¹
- The encoder process tries to create a latent representation that contains all the information that are needed to reconstruct it.
- Latent representation may be imagined as the object, thickness of the line, color, etc...
- When we have these parameters, we may reconstruct the originals.

¹Kingma DP, Welling M. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114. 2013 Dec 20.

Variational Autoencoders - Idea



- VAE model the process of the latent representation generation and the reconstruction using the Law of Total Probability:

$$P(x) = \int P(x|z)P(z)dz$$

- z is a candidate latent vector.
- $P(x|z)$ represents the probability that input x may be generated using the z .
- $P(z)$ represents the probability that the z exists in the latent space.

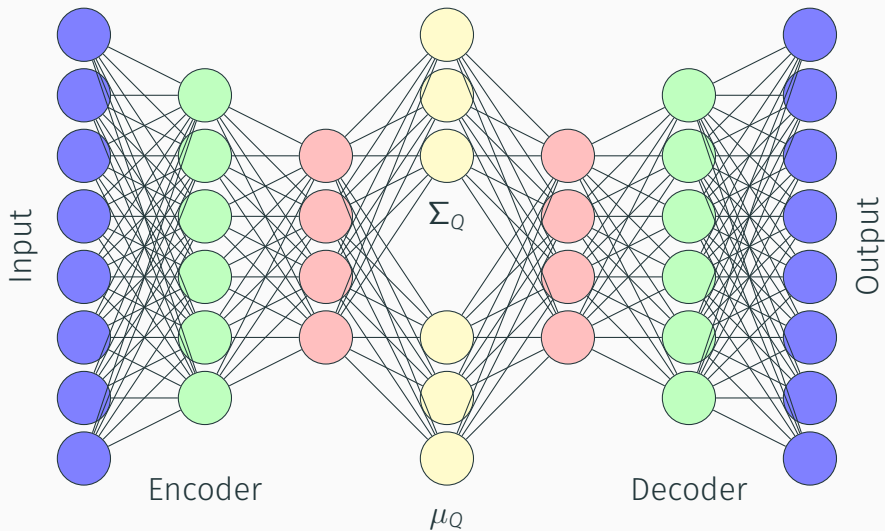
- VAE training objective is to maximize $P(x)$.
- $P(x|z)$ is modeled as a multi-variate Gaussian $\mathcal{N}(f(x), \sigma^2 \cdot I)$
- The f is what is modeled using the Neural network.
- The σ is a hyper-parameter.

- The latent space itself is very complex and hard to define or determine.
- Interpretation of each dimension is very hard.
- Latent dimension may be correlated.
- Reconstruction from the latent space is also very complex task.
- We need to define the function that maps from latent space into $P(x|z)$.

- Lets choose $P(z)$ to be standard multivariate Gaussian.
- Deep learning/Neural networks solves the problem of finding f using the following decomposition:
 1. Defines the encoder that maps the Gaussian to the true distribution over latent space.
 2. Defines the decoder that map the latent space to $P(x|z)$.

- It is difficult to derive the latent representation directly even using NN - not all samples has meaning to $P(x)$.
- We may substitute it with a different distribution $Q(z, x)$ that increases the likelihood of usability of z .
- Solution is to replace latent space with something that is easier, e.g. parameterless Gaussian.
- The input is the summarized using the mean μ_Q and diagonal covariance matrix Σ_Q - these are the encoded parameters.

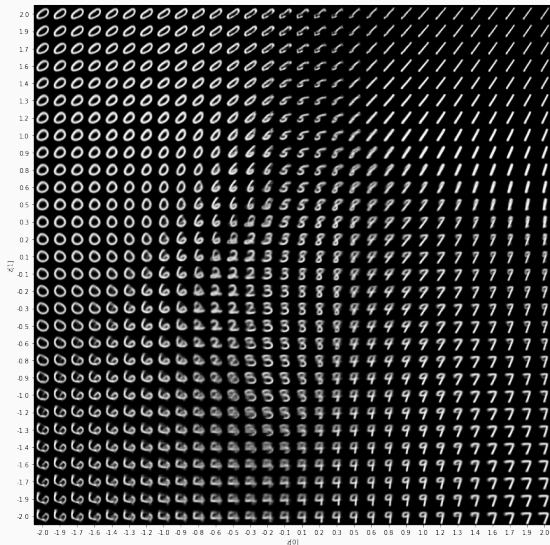
Variational Autoencoder



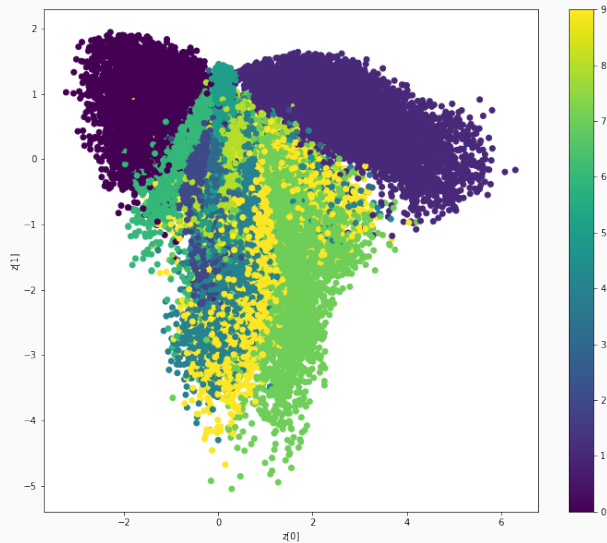
1. The input image is passed through an encoder network.
2. The encoder outputs parameters μ_Q and Σ_Q of the distribution $Q(z|x)$.
3. The latent vector z is sampled from $Q(z|x)$.
4. The decoder decodes the z into an image.

- The VAE learn how to set the distribution properly.
- The mean values should group similar objects and spread different objects across the latent space.
- The encoder complexity as well as decoder complexity may be large.
- Again, any type of network may be used (Dense, CNN, ...).

Variational Autoencoder



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Questions?