Deep Learning

7.3 Denoising Autoencoders

Dr. Konda Reddy Mopuri
kmopuri@iittp.ac.in
Dept. of CSE, IIT Tirupati

Besides dimensionality reduction

1. Autoencoders can capture the dependencies across signal components

Besides dimensionality reduction

1. Autoencoders can capture the dependencies across signal components
2. This can help to restore the missing components from an input

Besides dimensionality reduction

1. In this scenario, we may ignore the encoder/decoder architecture

Besides dimensionality reduction

1. In this scenario, we may ignore the encoder/decoder architecture
2. Goal in this case is not to learn a ϕ such that $\phi(X) \approx X$

Besides dimensionality reduction

1. In this scenario, we may ignore the encoder/decoder architecture
2. Goal in this case is not to learn a ϕ such that $\phi(X) \approx X$
3. It is to learn a ϕ such that $\phi(\tilde{X}) \approx X$, where $\tilde{X}$ is a perturbed version of X

Besides dimensionality reduction

1. In this scenario, we may ignore the encoder/decoder architecture
2. Goal in this case is not to learn a ϕ such that $\phi(X) \approx X$
3. It is to learn a ϕ such that $\phi(\tilde{X}) \approx X$, where $\tilde{X}$ is a perturbed version of X
4. This is referred to as a **Denoising Autoencoder**

Denoising Autoencoder

1. This can be illustrated with an additive Gaussian noise in case of a 2D signal and MSE

$$\hat{w} = \underset{w}{\operatorname{argmin}} \frac{1}{N} \sum_{n=1}^{N} \|x_n - \phi(x_n + \epsilon_n; w)\|^2 ,$$

where x_n are data samples and ϵ_n are Gaussian random noise

Denoising Autoencoder

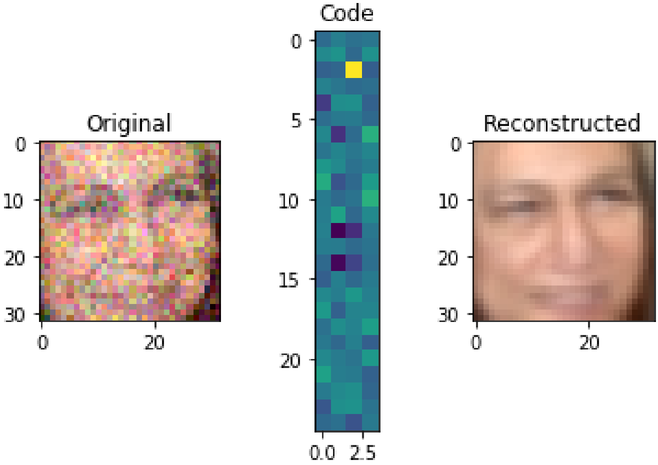

Figure credits: Ali Abdelal, https://stackabuse.com/

Weakness

1. Posterior $f_{x_n|x_n+\epsilon}$ may be multi-model

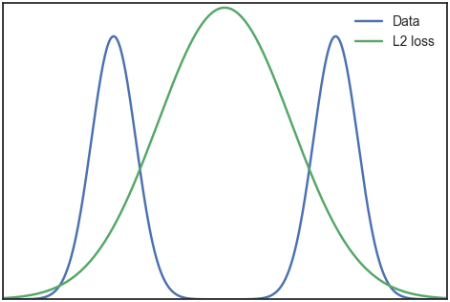

Figure credits:Patrick Langechuan Liu

Weakness

1. Posterior $f_{x_n|x_n+\epsilon}$ may be multi-model
2. L2 loss (used for training) assumes the underlying target distribution is Gaussian (thus unimodal)

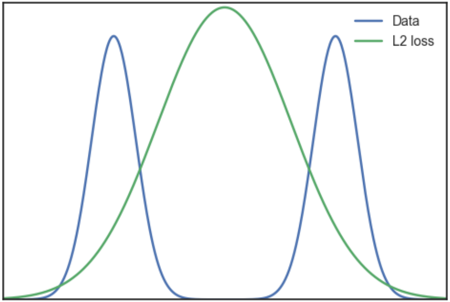

Figure credits:Patrick Langechuan Liu

Weakness

1. Posterior $f_{x_n|x_n+\epsilon}$ may be multi-model
2. L2 loss (used for training) assumes the underlying target distribution is Gaussian (thus unimodal)
3. L2 loss encourages the network to minimize loss across all modes

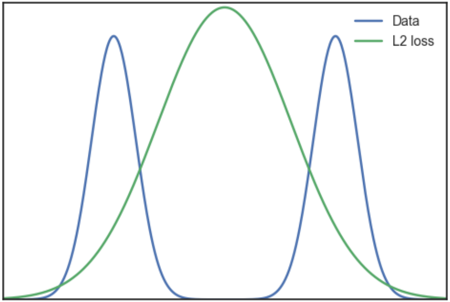

Figure credits:Patrick Langechuan Liu

Weakness

1. Posterior $f_{x_n|x_n+\epsilon}$ may be multi-model
2. L2 loss (used for training) assumes the underlying target distribution is Gaussian (thus unimodal)
3. L2 loss encourages the network to minimize loss across all modes
4. In image reconstruction applications, this leads to blurry results