Dl LAB 7 Answers

2.

In that both methods strive to reduce the dimensionality of the data while conserving as much information as feasible, a linear autoencoder (AE) without activation functions is closely connected to Principal Component Analysis (PCA). The encoder and decoder layers of a linear AE are made up of linear transformations, which basically learn a linear mapping from the input space to a lower-dimensional latent space and back. Likewise, PCA uses a linear transformation to project data into a lower-dimensional subspace by locating the principal components (eigenvectors) of the data's covariance matrix. Both linear AEs and PCA are unsupervised dimensionality reduction approaches that might give similar results under certain scenarios. AEs, on the other hand, have the advantage of being able to learn more complicated and non-linear representations when activation functions are used.When activation functions are utilized in their layers, they become more versatile in capturing nuanced patterns in data than PCA.

4.

Because of its capacity to capture hierarchical characteristics in the input data, the second model, a convolutional autoencoder, is expected to outperform the first. The autoencoder's convolutional layers can learn to extract meaningful patterns and features from fashion MNIST photos, keeping vital information while decreasing noise. Additionally, the employment of convolutional transpose layers in the decoder aids in more successfully recreating the input data. This architecture takes advantage of spatial hierarchies and local correlations in images, making it more suitable for image reconstruction tasks than the first model's simple feedforward neural network.

6.

The capacity of the Image De-noising Autoencoder (AE) to explicitly learn and encode noise patterns in the data can be credited to the observed gains in performance between the Image De-noising AE and the Vanilla CNN (Convolutional Neural Network) AE. The De-noising AE compels itself to focus on extracting critical features while filtering out noise by training on noisy images and striving to rebuild clean versions, resulting in more effective feature representations. In comparison, the Vanilla CNN AE, which does not take noise into account during training, may be less efficient in capturing noise-related information and thus have less effective denoising capabilities. As a result of the Image De-noising AE's detailed noise modeling, denoising tasks perform better.

7.

Representation of Latent Space:

AE: Aiming to learn a deterministic mapping from input data to a fixed latent representation is the goal of AEs. The encoder network converts input data to a predetermined code or embedding.

VAEs are probabilistic models of the latent space. They encode input data into a latent space probability distribution, typically a Gaussian distribution with a mean and variance. This probabilistic technique allows for latent space sampling during both encoding and decoding.

Model of Generation:

AEs are not by definition generative models. They are concerned with rebuilding input data, and sampling from their latent space does not ensure relevant samples.

VAE stands for generative model. Not only do they encode data, but they also produce fresh data samples by sampling from the learnt latent space distribution. As a result, VAEs are well-suited for activities such as image generation.

Regularization:

To prevent overfitting, AEs employ standard regularization approaches such as dropout or weight decay.

VAEs include a regularization factor known as the Kullback-Leibler (KL) divergence in their loss function. This term helps the latent space to follow a particular probabilistic distribution, resulting in a smooth and structured latent space.

Applications:

AEs are extensively used for dimensionality reduction, feature learning, and denoising.

VAEs are particularly useful for generative tasks like as image production, data augmentation, and the generation of structured latent representations.