CO3

DEEP LEARNING

23AD2205A

Topic:

CONTRACTIVE AUTOENCODERS AND VARIATIONAL AUTOENCODER

Session - 19

AIM OF THE SESSION

To familiarize students with the sequence prediction problems

INSTRUCTIONAL OBJECTIVES

This Session is designed to:

1. Discuss the Contractive Autoencoders and Variational autoencoder
2. Demonstrate the concept of Contractive Autoencoders and Variational autoencoder
   Discussion on Contractive Autoencoders and Variational autoencoder

LEARNING OUTCOMES

At the end of this session, you should be able to: concepts for real time applications

1. To build Contractive Autoencoders and Variational autoencoder
2. To apply different types of Contractive Autoencoders and Variational autoencoder

Contractive Autoencoder

What is a Contractive Autoencoder?

- A Contractive Autoencoder (CAE) is a specific type of autoencoder used in unsupervised machine learning.
- Autoencoders are neural networks designed to learn efficient representations of the input data, called encodings, by training the network to ignore insignificant data (“noise”).
- These encodings can then be used for tasks such as dimensionality reduction, feature learning, and more.
- The "contractive" aspect of CAEs comes from the fact that they are regularized to be insensitive to slight variations in the input data.
- This is achieved by adding a penalty to the loss function during training, which forces the model to learn a representation that is robust to small changes or noise in the input.
- The penalty is typically the Frobenius norm of the Jacobian matrix of the encoder activations with respect to the input and encourages the learned representations to contract around the training data.

Contractive autoencoders

- The objective of a contractive autoencoder

is to have a robust learned representation which

is less sensitive to small variation in the data.

- Robustness of the representation for the data

is done by applying a penalty term to the loss

function.

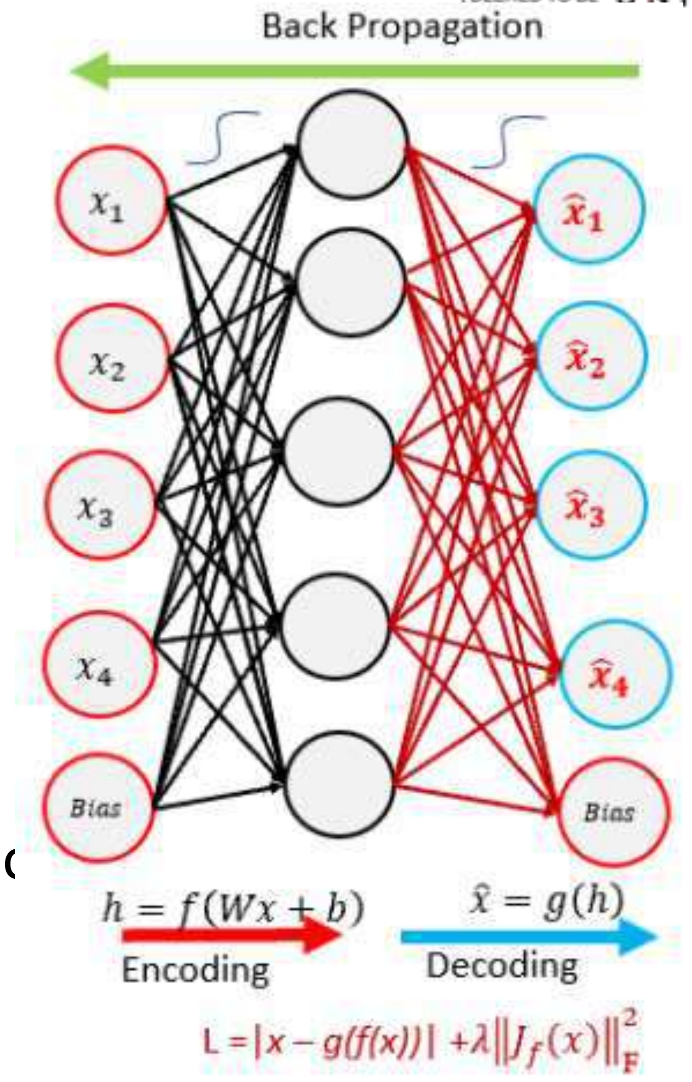
Advantages-

- Contractive autoencoder is a better choice than

denoising autoencoder to learn useful feature extractic

- This model learns an encoding in which similar

inputs have similar encodings.



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How Contractive Autoencoders Work

- A Contractive Autoencoder consists of two main components: an encoder and a decoder.
- The encoder compresses the input into a lower-dimensional representation, and the decoder reconstructs the input from this representation.
- The goal is for the reconstructed output to be as close as possible to the original input.
- The training process involves minimizing a loss function that has two terms. The first term is the reconstruction loss, which measures the difference between the original input and the reconstructed output.
- The second term is the regularization term, which measures the sensitivity of the encoded representations to the input. By penalizing the sensitivity, the CAE learns to produce encodings that do not change much when the input is perturbed slightly, leading to more robust features.

Contractive Auto Encoders

Loss Function of Contactive AutoEncoder

Contractive autoencoder adds an extra term in the loss function of autoencoder, it is given as:

$$\|J_h(X)\|_F^2 = \sum_{ij} \left(\frac{\partial h_j(X)}{\partial X_i} \right)^2$$

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Applications of Contractive Autoencoders

Contractive Autoencoders have several applications in the field of machine learning and artificial intelligence:

- **Feature Learning:** CAEs can learn to capture the most salient features in the data, which can then be used for various downstream tasks such as classification or clustering.
- **Dimensionality Reduction:**

  Like other autoencoders, CAEs can reduce the dimensionality of data, which is useful for visualization or as a preprocessing step for other algorithms that perform poorly with high-dimensional data.
- **Denoising:** Due to their contractive property, CAEs can be used to remove noise from data, as they learn to ignore small variations in the input.
- **Data Generation:** While not their primary application, autoencoders can generate new data points by decoding samples from the learned encoding space.

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Advantages of Contractive Autoencoders

Contractive Autoencoders offer several advantages:

- **Robustness to Noise:** By design, CAEs are robust to small perturbations or noise in the input data.
- **Improved Generalization:** The contractive penalty encourages the model to learn more general features that do not depend on the specific noise or variations present in the training data.
- **Stability:** The regularization term helps to stabilize the training process by preventing the model from learning trivial or overfitted representations.

Variational Auto Encoders

What is a Variational Autoencoder?

- Variational autoencoder was proposed in 2013 by Diederik P. Kingma and Max Welling at Google and Qualcomm. A variational autoencoder (VAE) provides a probabilistic manner for describing an observation in latent space.
- Thus, rather than building an encoder that outputs a single value to describe each latent state attribute, we'll formulate our encoder to describe a probability distribution for each latent attribute. It has many applications, such as data compression, synthetic data creation, etc.
- Variational autoencoder is different from an autoencoder in a way that it provides a statistical manner for describing the samples of the dataset in latent space. Therefore, in the variational autoencoder, the encoder outputs a probability distribution in the bottleneck layer instead of a single output value.

Architecture of Variational Auto Encoders

Architecture of Variational Autoencoder

The encoder-decoder architecture lies at the heart of Variational Autoencoders (VAEs), distinguishing them from traditional autoencoders. The encoder network takes raw input data and transforms it into a probability distribution within the latent space.

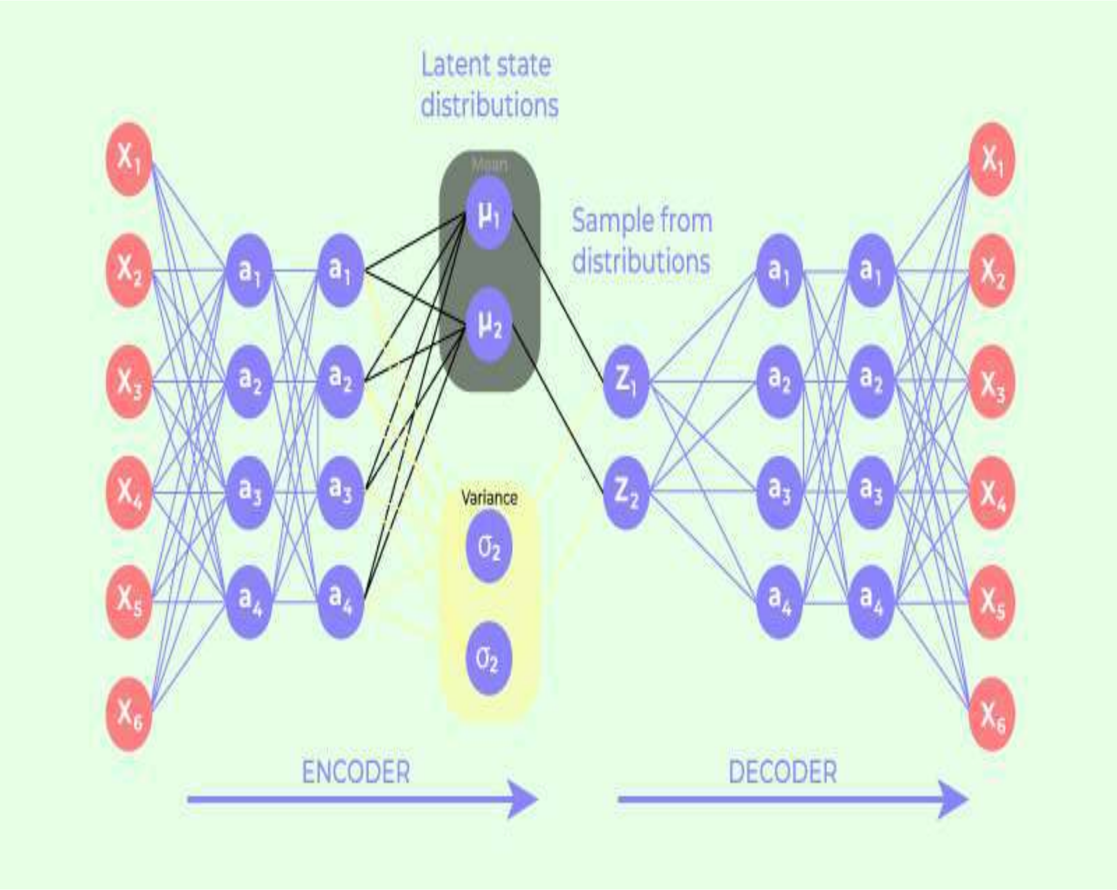
The latent code generated by the encoder is a probabilistic encoding, allowing the VAE to express not just a single point in the latent space but a distribution of potential representations.

The decoder network, in turn, takes a sampled point from the latent distribution and reconstructs it back into data space. During training, the model refines both the encoder and decoder parameters to minimize the reconstruction loss – the disparity between the input data and the decoded output. The goal is not just to achieve accurate reconstruction but also to regularize the latent space, ensuring that it conforms to a specified distribution.

The process involves a delicate balance between two essential components: the reconstruction loss and the regularization term, often represented by the Kullback-Leibler divergence. The reconstruction loss compels the model to accurately reconstruct the input, while the regularization term encourages the latent space to adhere to the chosen distribution, preventing overfitting and promoting generalization.

Variational Auto Encoders

By iteratively adjusting these parameters during training, the VAE learns to encode input data into a meaningful latent space representation. This optimized latent code encapsulates the underlying features and structures of the data, facilitating precise reconstruction. The probabilistic nature of the latent space also enables the generation of novel samples by drawing random points from the learned distribution.



Variational Auto Encoders

Mathematics behind Variational Autoencoder

Variational autoencoder uses KL-divergence as its loss function, the goal of this is to minimize the difference between a supposed distribution and original distribution of dataset.

Suppose we have a distribution z and we want to generate the observation x from it. In other words, we want to calculate $p(z|x)$

We can do it by following way:

$$p(z|x) = \frac{p(x|z)p(z)}{p(x)}$$

But, the calculation of p(x) can be quite difficult

$$p(x) = \int p(x|z)\, p(z)\, dz$$

Variational Auto Encoders

This usually makes it an intractable distribution. Hence, we need to approximate p(z|x) to q(z|x) to make it a tractable distribution. To better approximate p(z|x) to q(z|x), we will minimize the KL-divergence loss which calculates how similar two distributions are:

$$\min KL\left(q\left(z|x\right)||p\left(z|x\right)\right)$$

By simplifying, the above minimization problem is equivalent to the following maximization problem :

$$E_{q(z|x)} \log p\left(x|z\right) - KL\left(q\left(z|x\right)||p\left(z\right)\right)$$

The first term represents the reconstruction likelihood and the other term ensures that our learned distribution q is similar to the true prior distribution p.

Variational Auto Encoders

Thus our total loss consists of two terms, one is reconstruction error and other is KL-divergence loss:

$$Loss = L(x, \hat{x}) + \sum_{j} KL(q_j(z|x) || p(z))$$

Conclusion

- Contractive Autoencoders are a powerful tool in unsupervised learning, providing a way to learn robust and stable representations of data.
- They are particularly useful when the goal is to learn features that are invariant to small changes in the input.
- While they come with some computational overhead and require careful tuning, their ability to improve generalization makes them a valuable asset in the machine learning practitioner's toolkit.
- Variational Autoencoders (VAEs) are a type of generative model that learns a probabilistic representation of input data, allowing for the creation of new, similar data points. They achieve this by mapping inputs to a distribution in the latent space and using a reparameterization trick to enable backpropagation through stochastic nodes. VAEs are widely used in applications such as image generation, anomaly detection, and data imputation due to their ability to produce smooth and interpretable latent spaces.

SELF-ASSESSMENT QUESTIONS

1. An autoencoder is ________ learning model.

Unsupervised

2. Autoencoder is a dimentionality reduction algorithm?

True

3 . Sequence prediction involves predicting the next value for a given input sequence

True

TERMINAL QUESTIONS

- List out the applications of contractive autoencoder.
- Demonstrate the working of variational autoencoder.
- Illustrate the architecture of and Contractive and variational autoencoders

REFERENCES FOR FURTHER LEARNING OF THE SESSION

Books:

1 Ian Goodfellow and Yoshua Bengio and Aaron Courville (2016) Deep Learning Book
2.Deep Learning Book. eep Learning with Python, Francois Chollet , Manning publications, 2018

Resources

- https://www.tensorflow.org/tutorials/generative/autoencoder
- https://www.linkedin.com/company/autoencoder?originalSubdomain=in
- https://www.simplilearn.com/tutorials/deep-learning-tutorial/what-are-autoencoders-in-deep-learning
- https://blog.keras.io/building-autoencoders-in-keras.