Lect 31 - Auto Encoders

Variational auto-encoders (VAE)

→ normally we calculate loss b/w where we are and where we want to be

- in VAE, they find distance b/w 2 probability distribution

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جہاں ہم کھڑے ہیں   جہاں ہم پہنچنا چاہتے ہیں

- we special type of loss function **KL Divergent**
- are generative models

"if we can able to find the probability distribution of any dataset we can create as many data samples as we want"

find the probability distribution of data set

then create as many sample as you want

VAE

(given data) سیمپل کی 3 طرف (variation) سامنے میں موجود ہوتا

(Auto Encoder) سے کو نکال سکتے ہیں

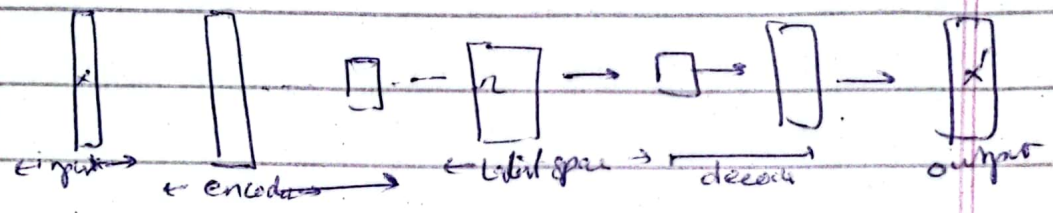
Limitations of traditional auto-encoders

↳① poor generative capabilities

② deterministic nature (No control over the distribution of latent space)

VAE

"Are probabilistic graphic model that encode data into a probabilistic latent space.



advantages of VAE

↳① Smooth latent space (Better interpolation & representation)

② Generative Capabilities (ability to generate new, diverse data)

③ Regularization (improved generalization)

① Better interpolation & Representation

latent space designed to be continuous & smooth → allowing for meaningful interpolation

② improved generalization

tend to perform better on unseen data, as capture more general patterns

Application of VAE

① image generation

② Dimensionality reduction

③ Anomaly detection

④ Data imputation

- VAE for anomaly detection in network security
- VAE in financial data computation

Practical

Simple/Vanilla Auto-Encoder

- loading dataset
- building encoder
- build decoder
stack them together
- compile → train

- autoencoder

dense layers

single 1D data

Convolutional Auto Encoder

same but with CNN

↳ build encoder & decoder

(: cov2D Transpose —)

convolutional layers

same stack

- compile — train

2D Matrix

Denoising autoencoder

- clean data
- data with noise (random func)
- train data (to noisy data as input)
- output data (clean)