[SYNTHESIS] CHAPTER 20. Generative Modelling

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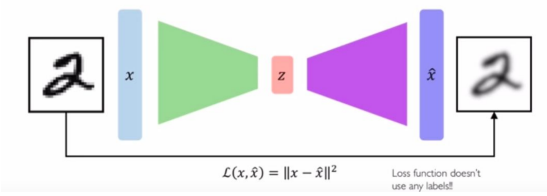
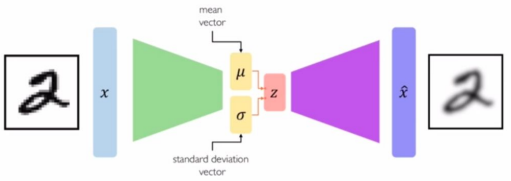
Intro:
Generative modelling is a way to learn the data distribution of images using the unsupervised manner. it helps to generate the new data points from the true data distribution from the training data set. so basically the Generative modelling is an unsupervised learning task which involves finding and learning the regularities and pattern in input data so that model can be able to learn to generate new samples which are identical and contains the important features. for this, we use the power of the neural network.

Types:
there are three approaches to the generative modelling

1. Autoencoders:- its an unsupervised approach to leaning a lower-dimensional feature representation from unlabeled training report. encoders learn a mapping from the data x, to a low dimensional latent space z. here z gives the most meaningful feature from the x. then decoder learns to map back from the latent z, to a reconstructed observation x'.

   it also uses the reconstruction loss function which has the intent to derive the model to learn the latent variable between the generated image and original image.

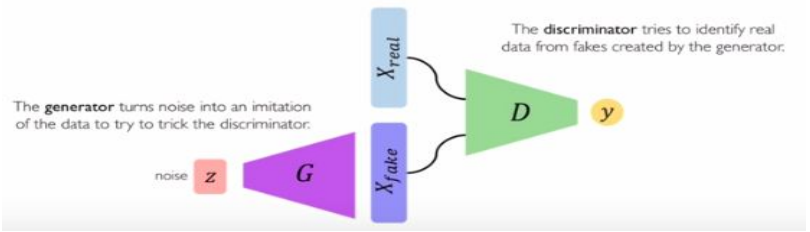




2. Variational Autoencoders: in the variation autoencoder we replacing the intermediate latent space i=from deterministic to probabilistic space we predict the mu and sigma in order to create stochastic z. so that we can get the variation of the z.
   The idea is to learn a low-dimensional latent representation of the training data called latent variables (variables which are not directly observed but are rather inferred through a mathematical model) which we assume to have generated our actual training data.

3. Generative Adversarial Networks: Generative Adversarial Networks, or GANs, are a deep-learning-based generative model. The GAN model architecture involves two sub-models: a *generator model* for generating new examples and a *discriminator model* for classifying whether generated examples are real, from the domain, or fake, generated by the generator model.

   the idea is discriminator tries to identify the real data from the fakes created by the generator and generator tries to create an imitation of data to trick the discriminator. The two models, the generator and discriminator, are trained together. The generator generates a batch of samples, and these, along with real examples from the domain, are provided to the discriminator and classified as real or fake. The discriminator is then updated to get better at discriminating real and fake samples in the next round, and importantly, the generator is updated based on how well, or not, the generated samples fooled the discriminator. At a limit, the generator generates perfect replicas from the input domain every time, and the discriminator cannot tell the difference and predicts "unsure" in every case.



Why GAN:
the gan is very useful in the field of computer vision for the data augmentation. data augmentation helps to get the better result by applying the gan technique which further increases the model result In complex domains or domains with a limited amount of data, generative modelling provides a path towards more training for modelling. GANs have seen much success in this use case in domains such as deep reinforcement learning.

Application:

- **Image Super-Resolution**. The ability to generate high-resolution versions of input images
- **Creating Art**. The ability to great new and artistic images, sketches, painting, and more
- **Image-to-Image Translation**. The ability to translate photographs across domains, such as day to night, summer to winter, and more.