1. VAE vs. Diffusion Models

Differences:

1. VAEs use an encoder-decoder structure, where the encoder compresses data into a latent space, and the decoder reconstructs it from this representation. Diffusion Models start from pure noise and progressively refine it through a learned reverse diffusion process to generate realistic data.
2. VAEs generate samples in a single forward pass, making them efficient, but they often struggle with producing highly detailed images due to blurriness from variational constraints. Diffusion Models typically yield higher-quality samples but require multiple steps of denoising, making them computationally expensive and slower than VAEs.

Similarities:

1. Both methods uses probability distributions and likelihood-based training to learn data representations.
2. Both methods are used for generating new data **(**e.g., images, text, or audio) by learning the underlying data distribution.

2. Dequantization

Dequantization helps generative models handle discrete data by converting it into a continuous form. Many models like VAEs and diffusion models assume continuous probability distributions, but real-world data (e.g., pixel values or text) is often discrete. To address this, dequantization adds small random noise to discrete values, smoothing the data and making it more suitable for continuous modeling. This improves likelihood estimation, enables gradient-based optimization, and reduces artifacts in generated outputs.
For example, in images, adding uniform noise to pixel values transforms them into continuous variables, allowing the model to learn more effectively and produce realistic generations.

3. The Coupling Network

The Coupling Network plays a crucial role in enabling efficient, invertible transformations for generative modeling. It splits the input, keeping one part fixed while applying a learnable transformation to the other, ensuring computational efficiency and stability. This structure maintains a simple Jacobian determinant, allowing efficient likelihood estimation. Additionally, it supports scalable deep normalizing flows without excessive costs, making it ideal for high-dimensional tasks like image generation and speech synthesis. By ensuring efficient invertibility, expressive transformations, and stable learning, the coupling network

enables normalizing flows to model complex probability distributions while remaining computationally feasible.

4.Reverse Diffusion: Why Intermediate Steps Are Needed

In reverse diffusion, intermediate steps are crucial because they help the model incrementally denoise the input, gradually reconstructing the original data from a noisy version. If we tried to reconstruct the original input directly from the noisy image, the problem would be too complex due to the high level of randomness in the noise. Intermediate steps break this process into manageable stages, allowing the model to progressively refine its predictions and improve the quality of the output.

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5. Self-Supervised Learning (SSL): Idea and Purpose

Self-Supervised Learning (SSL) is a machine learning paradigm where a model learns to generate labels from the data itself, eliminating the need for manually labeled datasets. The goal is to learn meaningful representations of data by solving pretext tasks, such as predicting missing parts of an image or identifying relationships between parts of text.

SSL is particularly useful for downstream tasks (e.g., classification or object detection) because the learned representations capture essential features of the data. These features can then be fine-tuned with smaller labeled datasets, saving time and resources while improving model performance.

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6. Contrastive Learning: Application and Triplet Loss Function

When It Can Be Applied:
Contrastive learning is applied when we aim to learn embeddings that group similar data points closer together and push dissimilar points further apart. It's commonly used in tasks like face recognition, image retrieval, and representation learning.

Idea of the Triplet Loss Function:
The triplet loss function works by training on sets of three samples:

1. **Anchor (A):** The reference sample.
2. **Positive (P):** A sample similar to the anchor (e.g., an image of the same person as the anchor).
3. **Negative (N):** A sample dissimilar to the anchor (e.g., an image of a different person).

The goal of triplet loss is to ensure that the distance between the anchor and the positive is smaller than the distance between the anchor and the negative by at least a predefined margin.

This encourages the model to learn embeddings where similar samples are clustered together in the feature space, while dissimilar samples are far apart.

Loss Function Formula:

L= max(0, d(A, P) d(A, N) + margin)

Where d is the distance function and the margin is a small positive value ensuring separation between classes