https://arxiv.org/pdf/2112.10752.pdf
Stable diffusion based on this! https://github.com/CompVis/stable-diffusion

Background
Decomposing image formation process into sequential application of denoising autoencoders (diffusion), image synthesis

- Guiding mechanism to control image generation process without retraining

Currently

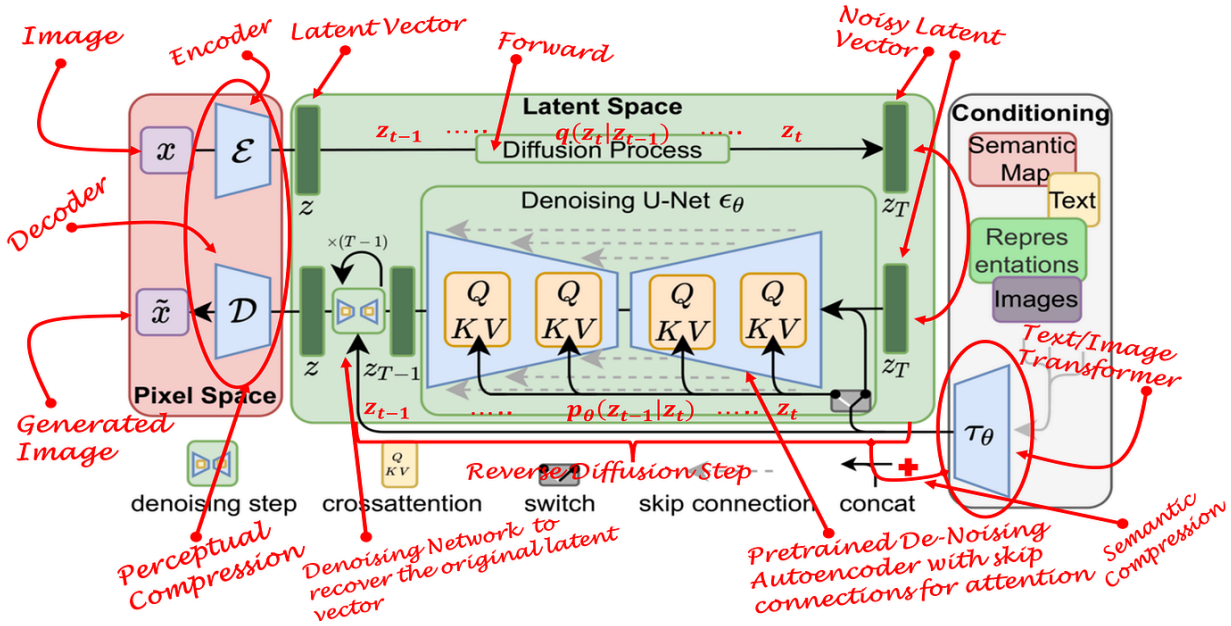
- Large likelihood based models (ARM) in autoregressive transformers, billions of parameters -> low resolution
    - mode covering behavior makes them spend excessive amounts of capacity modeling imperceptible details -> High computational cost
- Also likelihood: VAE and flow based sample quality is worse than GANs but can render multi modal
- GAN confined to data with limited variability due to adversarial learning not easily scaling to model complex, multi modal distributions
- Democratizing High Resolution Image Synthesis for DMs
    - Diffusion probabilistic models are also likelihood based models
    - No mode collapse and instability in GANs
    - Parameter sharing so doesn't need billions of parameters
    - Training in pixel space is hard because high computational cost
- Two stage image synthesis which combines the strengths of different methods into more efficient and performant models
    - VQ- VAE: autoregressive to learn prior in latent space
    - VQGANs: first stage with adversarial and perceptual objective to scale autoregressive transformer
        - Computationally expensive scaling

Idea (Latent Diffusion Models)
Training in pixel space is expensive and requires sequential evaluation

- Perceptual compression: removes high frequency details and a bit of semantic variation
    - Theirs is lower dimensional than data space
    - Do not need to rely on excessive spatial compressions
    - Efficient image generation with single network pass as a result
    - "Universal autoencoding stage": reuse for multiple DM trainings
    - Perceptual loss + patch based adversarial objective
        - Confined to image manifold by enforcing local realism and avoid blurriness introduced by relying solely on pixel space losses
    - KL regularization to avoid high variance latent spaces
        - Mild compression with 2D latent space (previous used 1D, ignored spatial structure)

- Semantic compression: Generative model learns semantic and conceptual composition of data
    - Connects transformers to DM's Unet backbone
    - Denoising Unet with transformers (combine conditioning info with noisy latent space)
- Find a perceptually equivalent but computationally more suitable space (latent)
- Latent space instead with pre trained autoencoders
    - Complexity reduction and detail preservation -> better visual fidelity (focus on semantics)
    - Does not require delicate weighting of reconstruction (autoencoding) and generative (diffusion) abilities
        - Prior work needs to learn encoder/ decoder and score based prior

Cross attention layers for general conditioning inputs (text, bounding boxes) + synthesis can be possible in a convolutional manner



Explicit separation of compressive from generative learning phase

- Autoencoding model which learns a space perceptually equivalent to image space but reduced complexity
- Exploit inductive bias of DMs (UNet architecture): effective for data with spatial structure and alleviate need for compression

Isn't VQ regularized latent space the 1D space?

- LDMs in VQ latent space achieve better sample quality even though reconstruction quality is worse

Tasks

- Image inpainting

- Class conditioned image synthesis
- Text to image, super resolution, etc.

Limitations

- Still require sequential sampling but does reduce computational requirements
- Use of LDMs questionable when high precision is required
    - Table 5 (section 4.4)