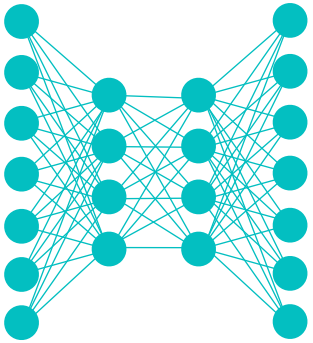
Lecture Notes for

Neural Networks and Machine Learning

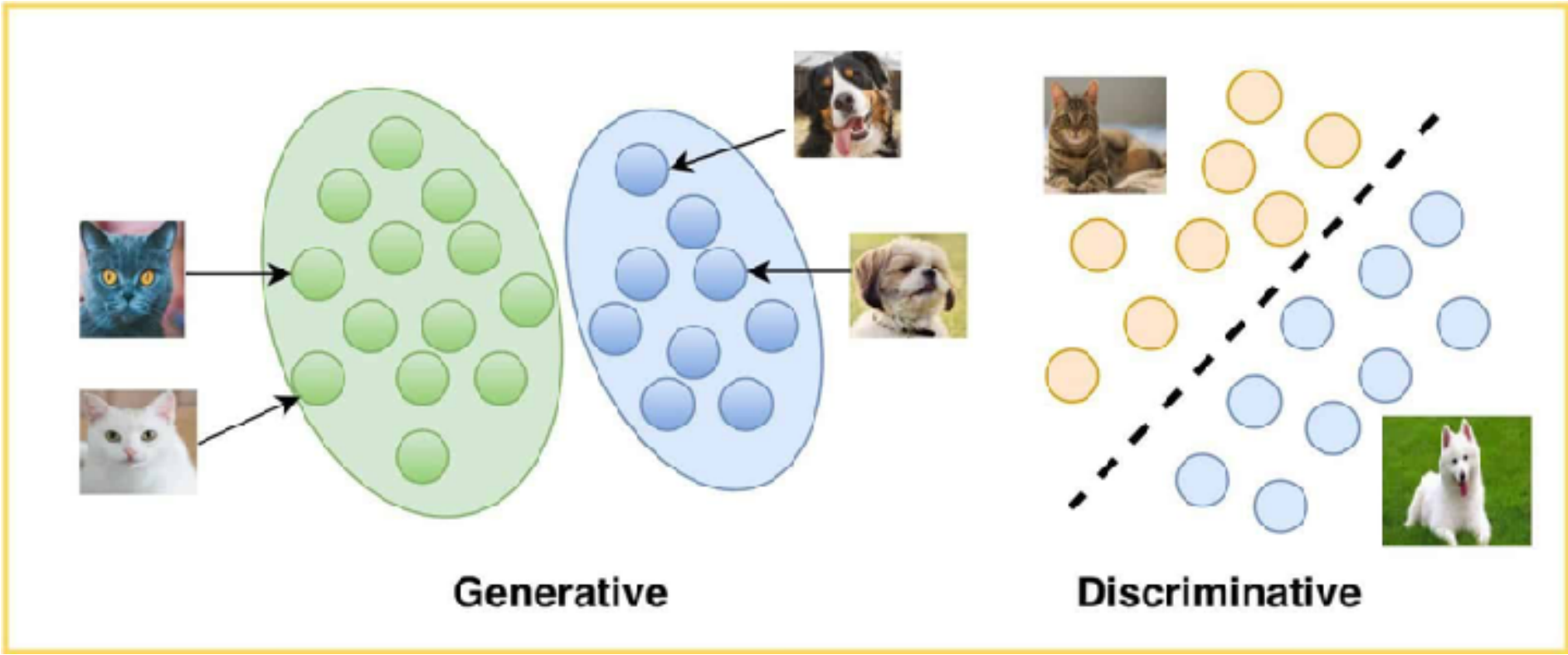
Stable Diffusion



Logistics and Agenda

- Logistics
  - Grading Update
- Agenda
  - Stable Diffusion
  - Final Project Town Hall

Generative versus Discriminative



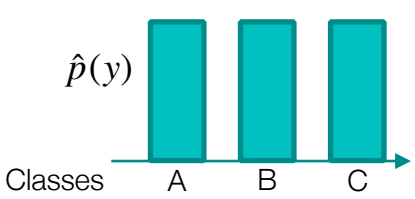
https://learnopencv.com/generative-and-discriminative-models/

An Accepted Measure: Inception Score

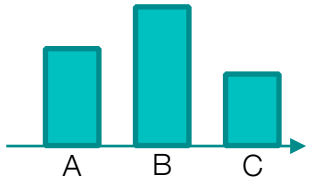
$$\hat{p}(y) = \frac{1}{N}\sum_{i} p(y \mid \mathbf{x}^{(i)}_{fake})$$

marginal

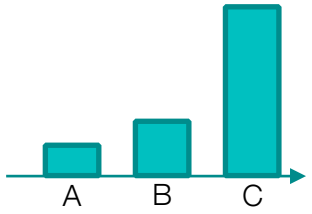
Expected class distribution through a trained CNN, like VGG/Inception should be **nearly uniform** in ideal case



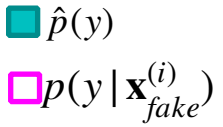
Ideal: Generator has diverse classes



Good: Generator is somewhat diverse



Bad: Generator not diverse

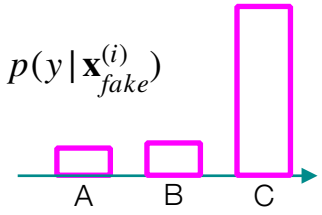


$$IS(G) \approx \exp\left(\frac{1}{N}\sum_{i} D_{KL}\left(p(y \mid \mathbf{x}^{(i)}_{fake}) \| \hat{p}(y)\right)\right)$$

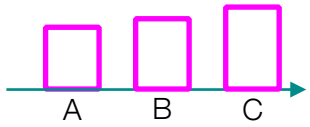
one example generated

typical generation

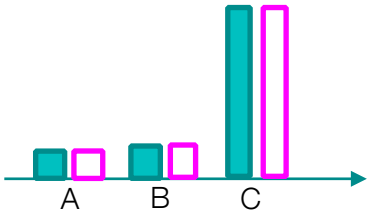
average KL Divergence of marginal of generated images with $\hat{p}$, ideally **differ dramatically**



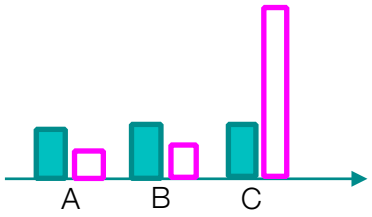
Ideal: Single Example is distinct class



Bad: Single Example is not really distinct



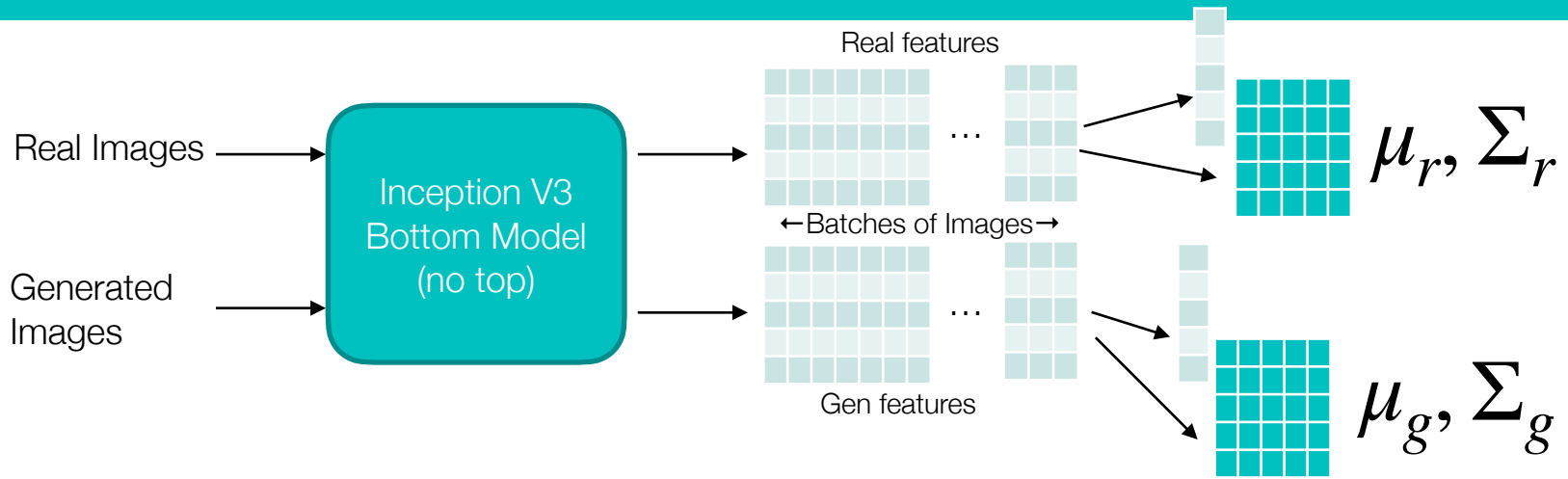
Bad: Distinct because not diverse



Ideal: Diverse and Distinct

Other Explanation: https://medium.com/octavian-ai/a-simple-explanation-of-the-inception-score-372dff6a8c7a

Another Measure: Fréchet Inception Distance



- Compare the distribution of data from Inception V3
- If distributed Gaussian, then we can use Fréchet Distance as follows:

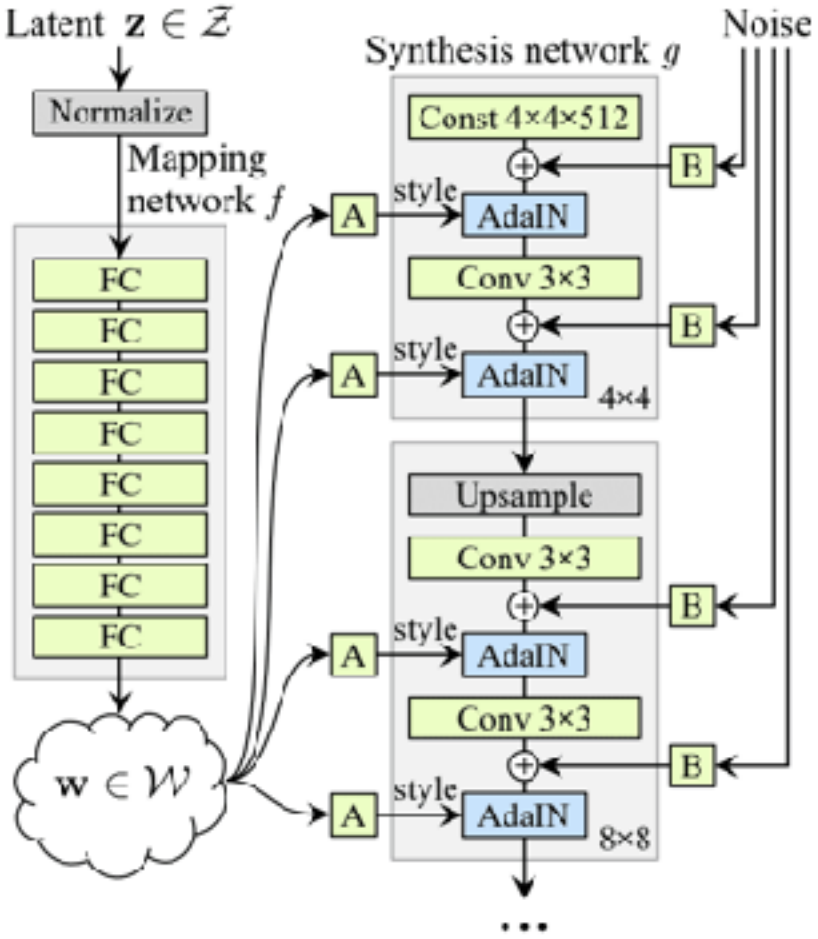
$$d_F(\mathcal{N}(\mu_r, \Sigma_r), \mathcal{N}(\mu_g, \Sigma_g))^2 = \underbrace{\|\mu_r - \mu_g\|_2^2}_{\text{diff in feature wise means}} + \text{tr}\left(\underbrace{\Sigma_r + \Sigma_g - 2\left(\Sigma_r\Sigma_g\right)^{\frac{1}{2}}}_{\text{diff in feature wise covariances}}\right)$$

"The FID compares the mean and standard deviation of the deepest layer in Inception v3. These layers are closer to output nodes that correspond to real-world objects such as a specific breed of dog or an airplane, and further from the shallow layers near the input image." Wikipedia

Stable Diffusion

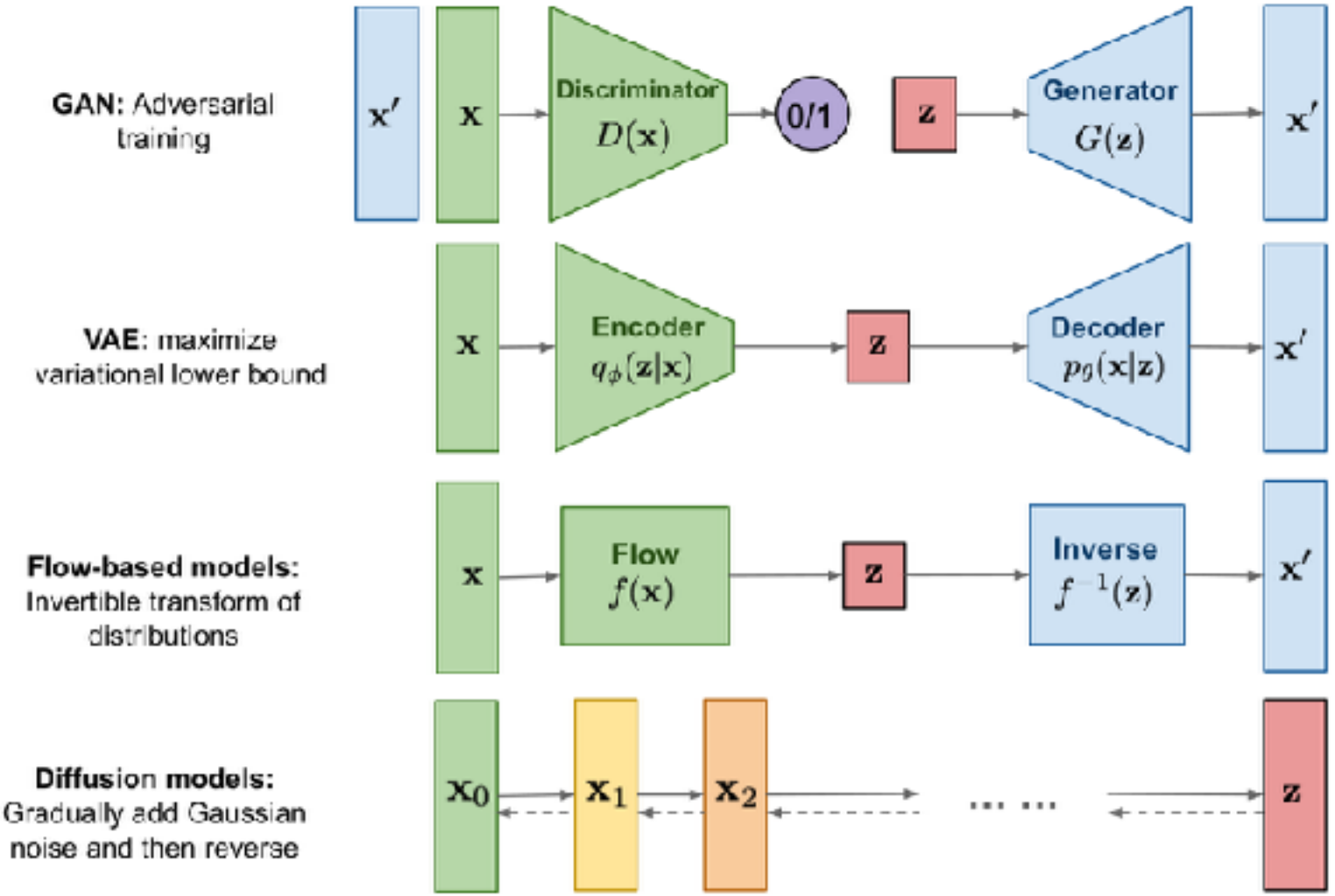
Recall StyleGAN

- A latent sample was chosen that initialized a “mapping network”
- Processing of this vector took place and representations “A” were added to a synthesis network
- Noise was systematically added to the network activations
  - Why?



Comparative Overview

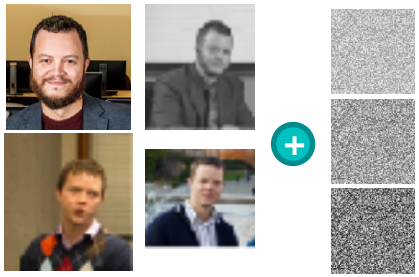
https://learnopencv.com/image-generation-using-diffusion-models/



A great resource for understanding at high level: https://jalammar.github.io/illustrated-stable-diffusion/

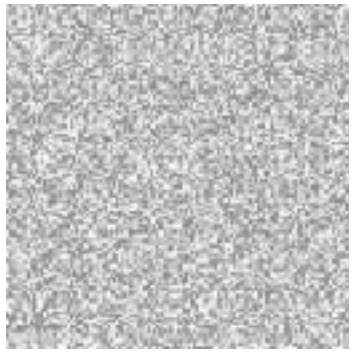
The Diffusion Process, Simplified

- ***Guiding*** Example: Predict noise sample in an image

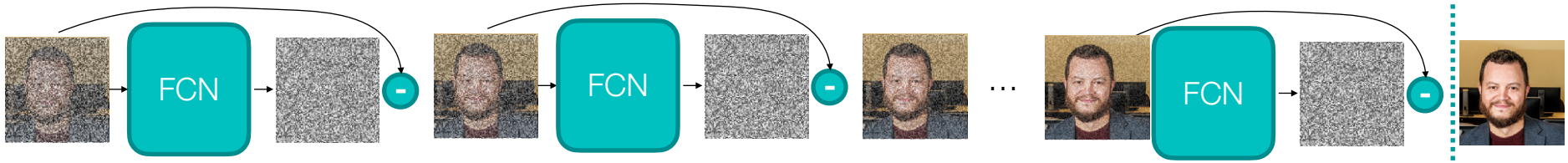


Create Dataset

Add in "t" steps of noise



Train Network on Synthetic Examples



Diffusion Process

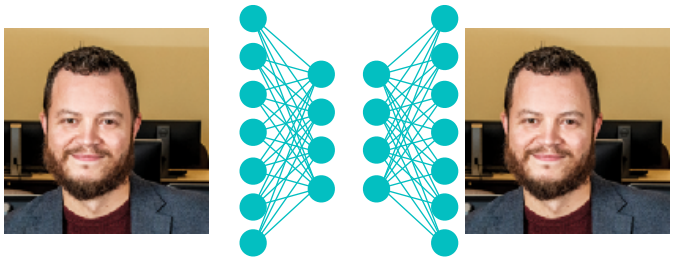
- Now we could generate great looking images from noise!!

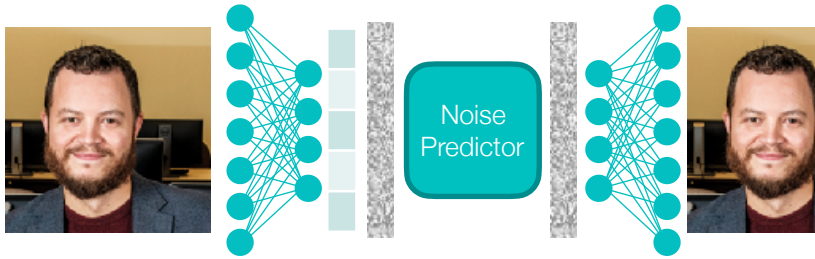
Departure to Latent Space

Departure to Latent Space Our approach starts with the analysis of already trained diffusion models in pixel space: Fig. 2 shows the rate-distortion trade-off of a trained

Rombach et al., 2022, https://arxiv.org/pdf/2112.10752.pdf

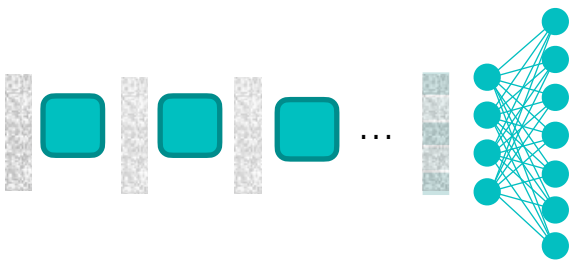
- Start with a nice auto encoder
- Train noise prediction in latent space
- Perform diffusion in latent Space
- Generate new images…



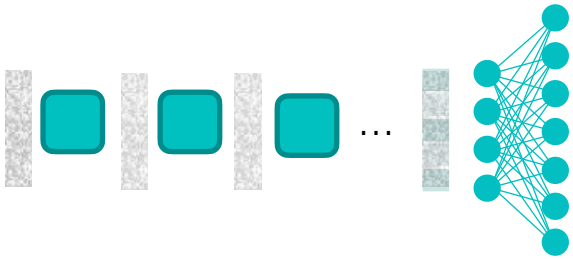


Random Noise

$z \sim \mathcal{N}(0,I)$



$z \sim \mathcal{N}(0,I)$



Eric Larson, Brown University

Eric Larson, Disney Animator

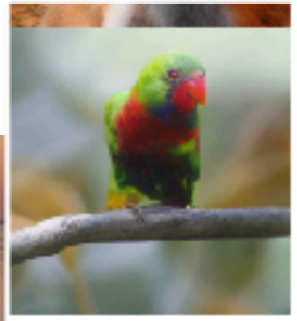
Examples of Diffusion in Latent Space

CelebA-HQ 256 × 256				FFHQ 256 × 256			
Method	FID ↓	Prec. ↑	Recall ↑	Method	FID ↓	Prec. ↑	Recall ↑
DC-VAE [63]	15.8	-	-	ImageBART [21]	9.57	-	-
VQGAN+T. [23] (k=400)	10.2	-	-	U-Net GAN (+aug) [77]	10.9 (7.6)	-	-
PGGAN [39]	8.0	-	-	UDM [43]	5.54	-	-
LSGM [93]	7.22	-	-	StyleGAN [41]	4.16	0.71	0.46
UDM [43]	7.16	-	-	ProjectedGAN [76]	**3.08**	0.65	0.46

Method	FID↓	IS↑	Precision↑	Recall↑	N_{params}	
BigGan-deep [3]	6.95	203.6±2.6	**0.87**	0.28	340M	-
ADM [15]	10.94	100.98	0.69	**0.63**	554M	250 DDIM steps
ADM-G [15]	4.59	186.7	0.82	0.52	608M	250 DDIM steps
LDM-4 (ours)	10.56	103.49±1.24	0.71	0.62	400M	250 DDIM steps
LDM-4-G (ours)	**3.60**	**247.67**±5.59	**0.87**	0.48	400M	250 steps, c.f.g [32], $s = 1.5$

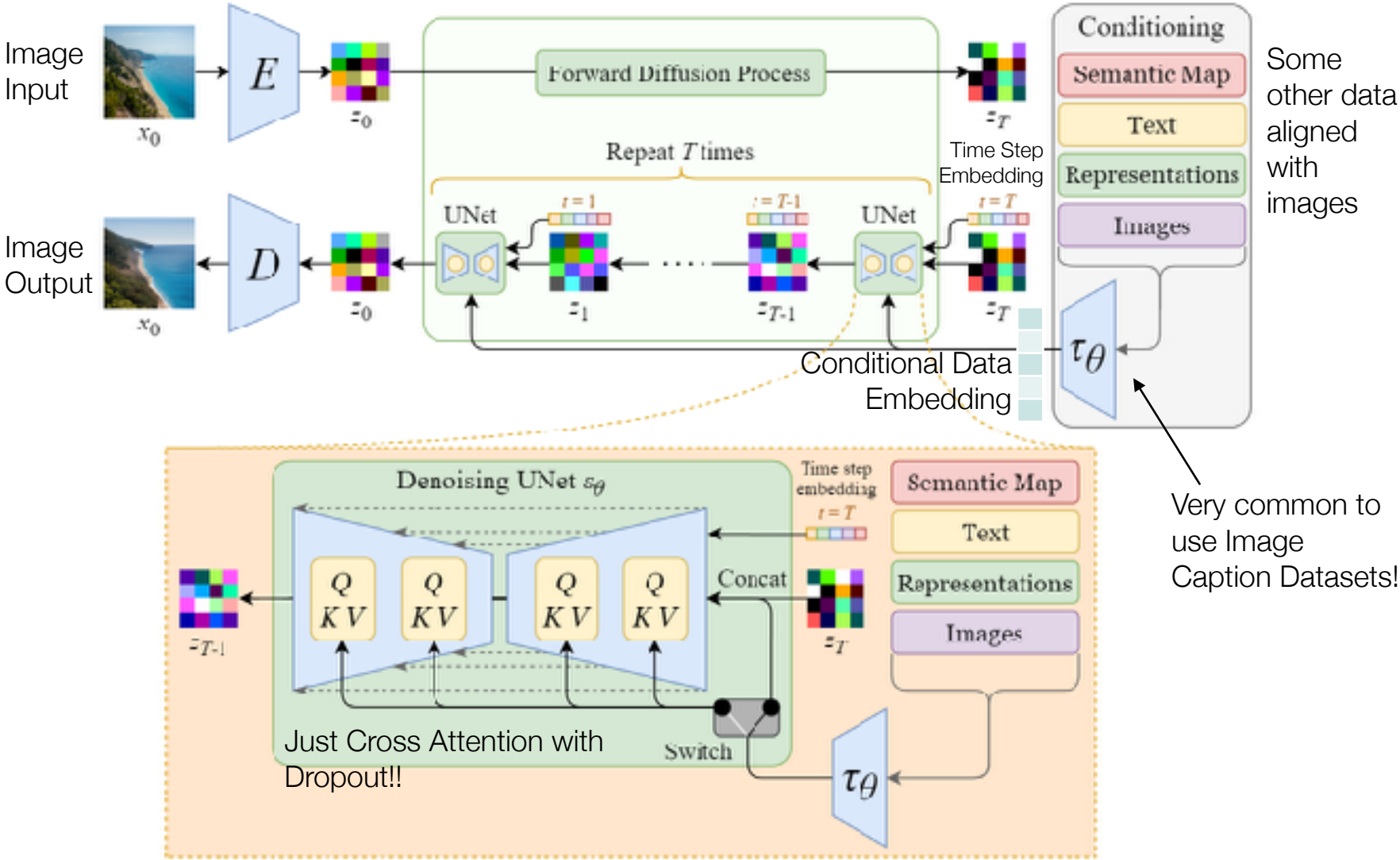
LDM-8 (ours, 200 s) 4.02 0.64 0.52 *LDM-4* (ours, 200 s) 2.95 0.66 0.46

Table 1. Evaluation metrics for unconditional image synthesis.



Rambach et al., 2022, High-Resolution Image Synthesis with Latent Diffusion Models https://arxiv.org/pdf/2112.10752.pdf

Conditioning for Denoising, Overview

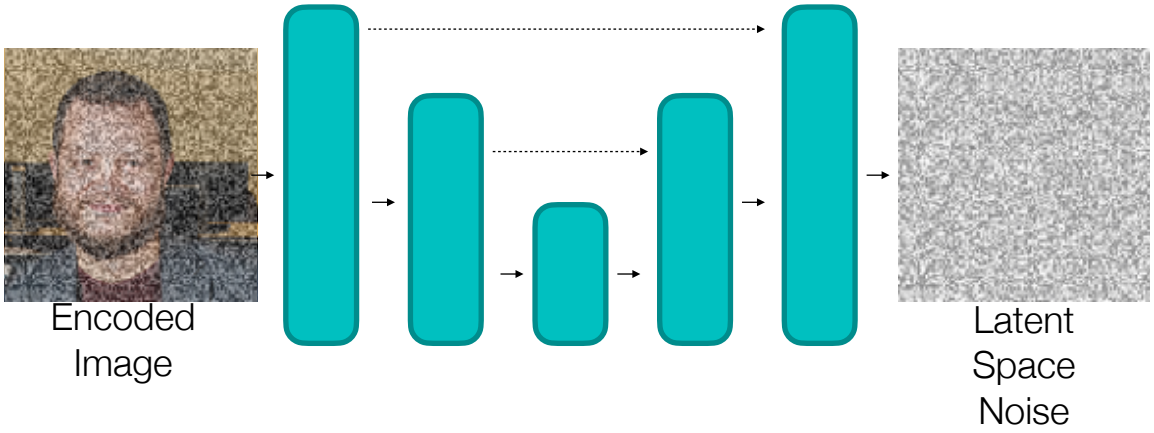


Rambach et al., 2022, High-Resolution Image Synthesis with Latent Diffusion Models https://arxiv.org/pdf/2112.10752.pdf

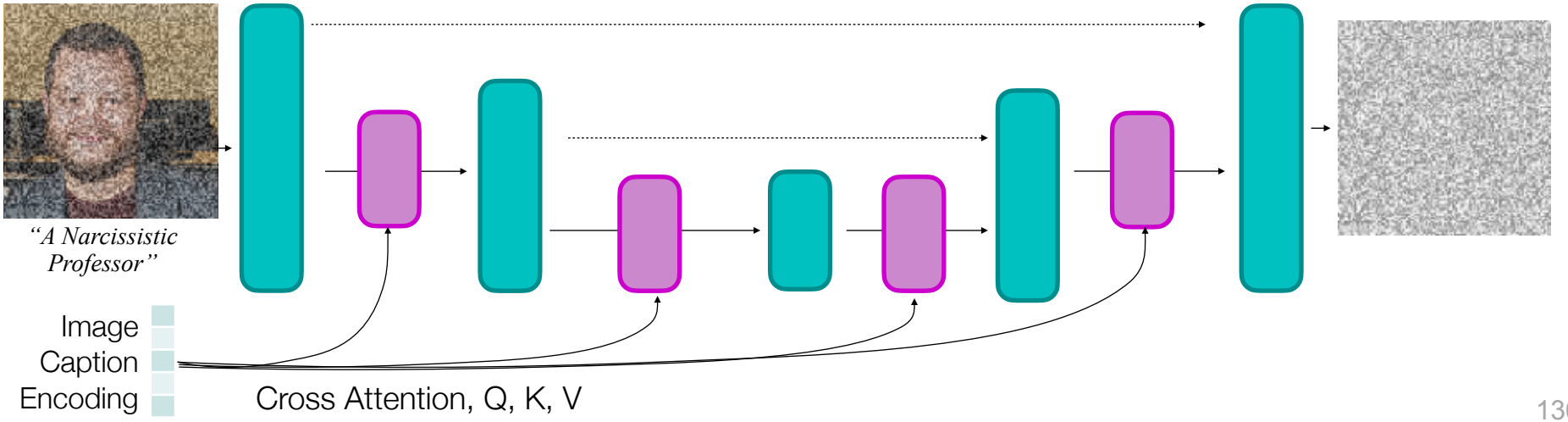
Unpacking "Text Conditioning"

- Employ text embeddings in model denoising

Full Convolutional Network, Noise Predictor



Model denoising is sensitive to the content within it…
Model learns how to De-noise specific objects!



Are all text embeddings created equal?

- No! We need embeddings that are good for images…

Image Encoder Pre-trained

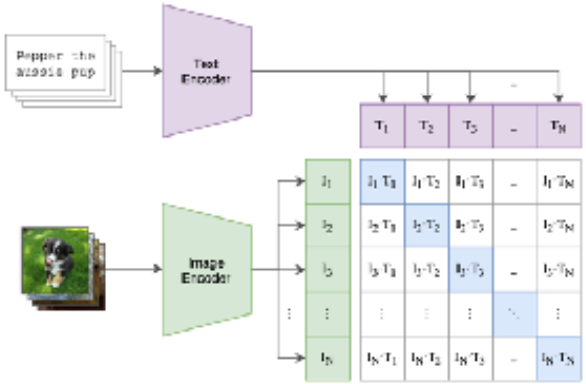
W_i

"A Narcissistic Professor"

Text Encoder Pre-trained

W_t

Positive Examples: Make similar
Negative Examples: Make dissimilar



Contrastive Language-Image Pre-training

CLIP

Radford et al. 2021, Learning Transferable Visual Models From Natural Language Supervision, https://arxiv.org/pdf/2103.00020.pdf

Many questions remaining…

- How to add noise in the latent space?
  - Does it even matter?
- How many time steps to add noise before training denoising algorithm?
- How many time steps are good for diffusion?
- What architecture to use for denoising?
  - And what about its depth, parameters, etc. ?
- What size images or mixture of images to use?
- What conditioning embeddings are most versatile?
- What labels are most valuable for conditioning?
- …And many other questions for research community to investigate…

Stable Diffusion 3

Scaling Rectified Flow Transformers for High-Resolution Image Synthesis

Patrick Esser * **Sumith Kulal** **Andreas Blattmann** **Rahim Entezari** **Jonas Müller** **Harry Saini** **Yam Levi**
Dominik Lorenz **Axel Sauer** **Frederic Boesel** **Dustin Podell** **Tim Dockhorn** **Zion English**
Kyle Lacey **Alex Goodwin** **Yannik Marek** **Robin Rombach** *
Stability AI

Prompt: Epic anime artwork of a wizard atop a mountain at night casting a cosmic spell into the dark sky that says "Stable Diffusion 3" made out of colorful energy

https://stability.ai/news/stable-diffusion-3

https://arxiv.org/pdf/2403.03206.pdf

Stable Diffusion 3

- Released March 5, 2024
- 28 Pages of background, explanation, methods, results—maybe the definitive paper in the field?
- Lots of ablation studies on parameter choices
- Evaluated in the right way. I love this paper!

an old rusted robot wearing pants and a jacket riding skis in a supermarket.

smiling cartoon dog sits at a table, coffee mug on hand, as a room goes up in flames. "This is fine," the dog assures himself.

Vector Gradient Flow Scalers

- Define Loss as a vector field, after lots of simplifications:

$$\mathcal{L}_w(x_0) = -\frac{1}{2}\mathbb{E}_{t\sim\mathcal{U}(t),\epsilon\sim\mathcal{N}(0,I)}\left[w_t\lambda_t'\|\epsilon_\Theta(z_t,t)-\epsilon\|^2\right]$$

x0 is latent of original image

sampling at time step t

with noise added to image latent

defines different scaling factors, depends on how noise added and time steps

Predicted Noise at time t

Actual Noise

- In paper, they compare lots of different scaling variations with different noise models:

Rectified flow: $z_t = (1-t)x_0 + t\epsilon \qquad w_t^{\text{RF}} = \frac{t}{1-t}$

EDM: $z_t = x_0 + b_t\epsilon \qquad b_t = \exp F_{\mathcal{N}}^{-1}(t|P_m, P_s^2) \qquad w_t^{\text{EDM}} = \mathcal{N}(\lambda_t|-2P_m,(2P_s)^2)(e^{-\lambda_t}+0.5^2)$

Cosine: $z_t = \cos(\frac{\pi}{2}t)x_0 + \sin(\frac{\pi}{2}t)\epsilon \qquad w_t = e^{-\dot{\lambda}_t/2}$

LDM Linear: $z_t = a_t x_0 + b_t\epsilon \qquad b_t = \sqrt{1-a_t^2}, \qquad a_t = (\prod_{s=0}^{t}(1-\beta_s))^{\frac{1}{2}} \qquad \beta_t = \left(\sqrt{\beta_0} + \frac{t}{T-1}(\sqrt{\beta_{T-1}} - \sqrt{\beta_0})\right)^2$

Sampling t

- In paper, look at lots of ways to sample the t across the various distributions:

Uniform Distribution: $\mathcal{U}(t)$

Logit-normal: $$\pi_{\ln}(t; m, s) = \frac{1}{s\sqrt{2\pi}} \frac{1}{t(1-t)} \exp\left(-\frac{(\text{logit}(t) - m)^2}{2s^2}\right),$$

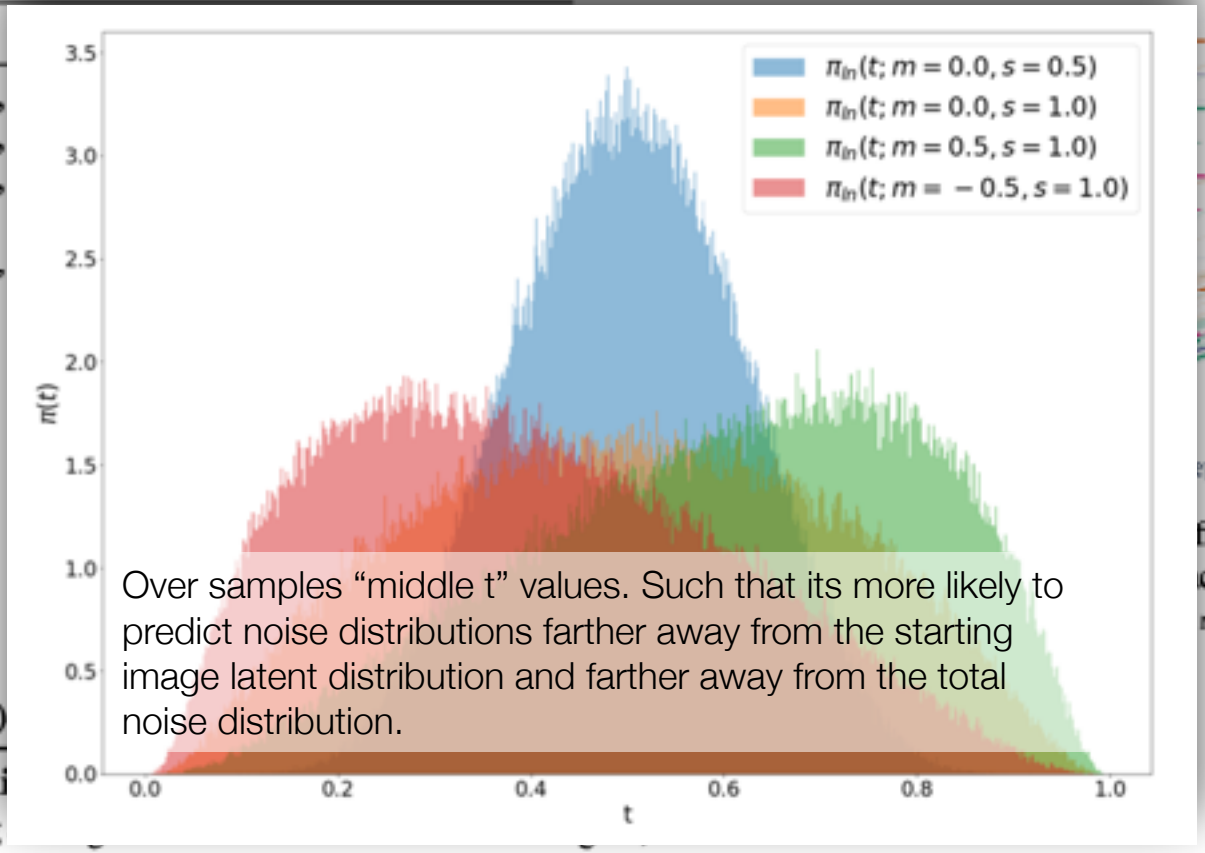
Heavy Tailed Mode: $$f_{\text{mode}}(u; s) = 1 - u - s \cdot \left(\cos^2\left(\frac{\pi}{2}u\right) - 1 + u\right)$$

CosMap: $$\pi_{\text{CosMap}}(t) = \left|\frac{d}{dt} f^{-1}(t)\right| = \frac{2}{\pi - 2\pi t + 2\pi t^2}.$$

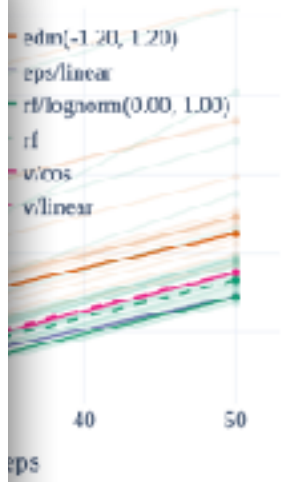
Ablation for Variant and Sampling

variant	rank averaged over
rf/lognorm(0.00,	
rf/lognorm(1.00,	
rf/lognorm(0.50,	
rf/mode(1.29)	
rf/lognorm(0.50,	
eps/linear	
rf/mode(1.75)	
rf/cosmap	
edm(0.00, 0.60)	
rf	
v/linear	
edm(0.60, 1.20)	
v/cos	
edm/cos	
edm/rf	
edm(-1.20, 1.20)	

Table 1. **Global ranki**
non-dominated sorting
two datasets and different sampling settings.



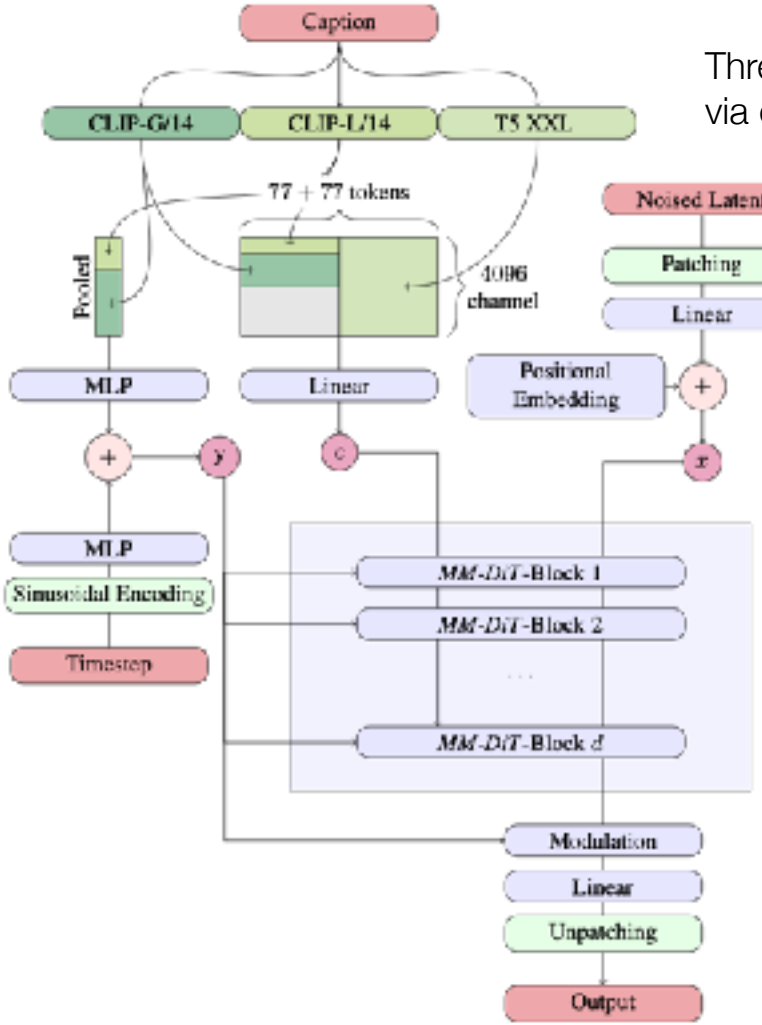
Over samples "middle t" values. Such that its more likely to predict noise distributions farther away from the starting image latent distribution and farther away from the total noise distribution.



ficient. Rectified Flows
cn sampling fewer steps.
m(0.00, 1.00) re-

Rectified flow is always one of the better performers, especially using logit-normal sampling m=0, s=1

The Architecture



(a) Overview of all components.

Three Conditioning Language and Image encoders used, via concatenation

Input Modality Dropout used to ensure "good" results on any of the encoders at deployment time Drop out T5, or Dropout CLIP, etc.

Separate text modality and image modality before feeding into the noise prediction network.

Each MM-DiT is just a transformer working on the concatenated modalities

In paper, investigated many "depth scaling" techniques, found bigger is always better. An that there was no saturation, so could probably get even better results, but the GPUs are not big enough…

Architecture: X-former block

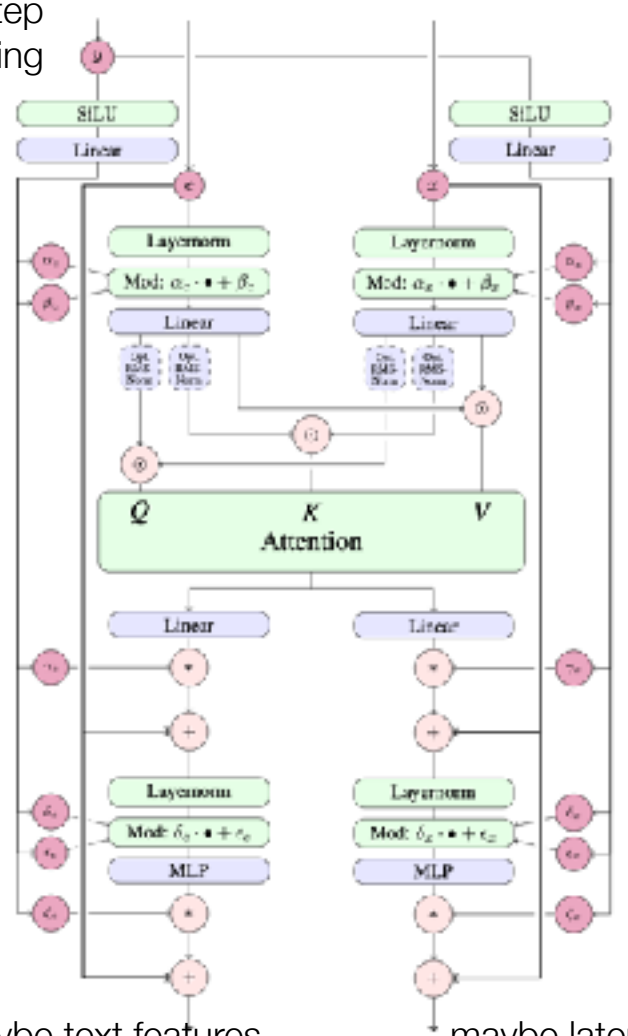
Other Misc Things:

When Training:
Do not use only human generated captions. Humans tend to not describe things like background, colors, etc.

Solution: Use trained models for generating captions of high quality. Then use a mix of "human captions" and "augmented captions" while training.

Make Encoder/Decoder large dimensionality.

Use as many x-formers as possible.



(b) One *MM-DiT* block

Concatenate each modality and run in standard x-former (multi-headed)

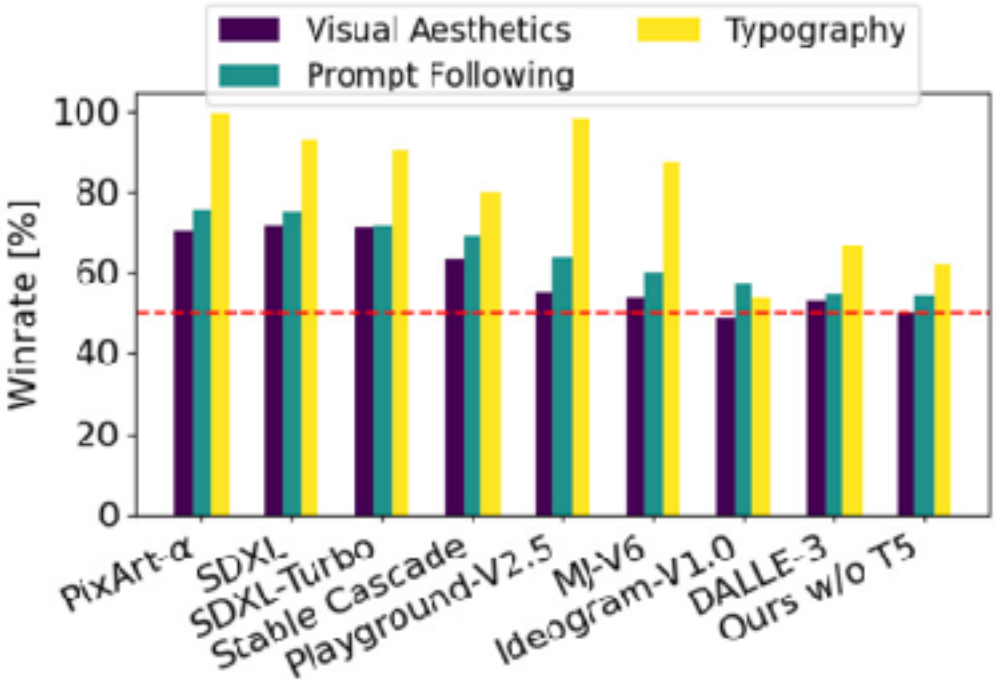
Branch into two MLPs to separate out into two modalities

These feed into next layer

Next Layer: maybe text features maybe latent image features

Evaluation

- Conducted large scale human subjects rating study
- Generate images from top models from same prompt
- Ask humans which version they prefer.
- What is the probability of their model winning?



Asked preference based on:
1. Simple Aesthetics (looks)
2. Following of the prompt
3. Accuracy of text and typography

A whimsical and creative image depicting a hybrid creature that is a mix of a waffle and a hippopotamus. This imaginative creature features the distinctive, bulky body of a hippo, but with a texture and appearance resembling a golden-brown, crispy waffle. The creature might have elements like waffle squares across its skin and a syrup-like sheen. It's set in a surreal environment that playfully combines a natural water habitat of a hippo with elements of a breakfast table setting, possibly including oversized utensils or plates in the background. The image should evoke a sense of playful absurdity and culinary fantasy.

All text-encoders *w/o T5 (Raffel et al., 2019)*

"A burger patty, with the bottom bun and lettuce and tomatoes. "COFFEE" written on it in mustard"

"A monkey holding a sign reading "Scaling transformer models is awesome!"

"A mischievous ferret with a playful grin squeezes itself into a large glass jar, surrounded by colorful candy. The jar sits on a wooden table in a cozy kitchen, and warm sunlight filters through a nearby window"

Detailed pen and ink drawing of a happy pig butcher selling meat in its shop.

a massive alien space ship that is shaped like a pretzel

A kangaroo holding a beer, wearing ski goggles and passionately singing silly songs.

An entire universe inside a bottle sitting on the shelf at walmart on sale.

A cheesburger surfing the vibe wave at night

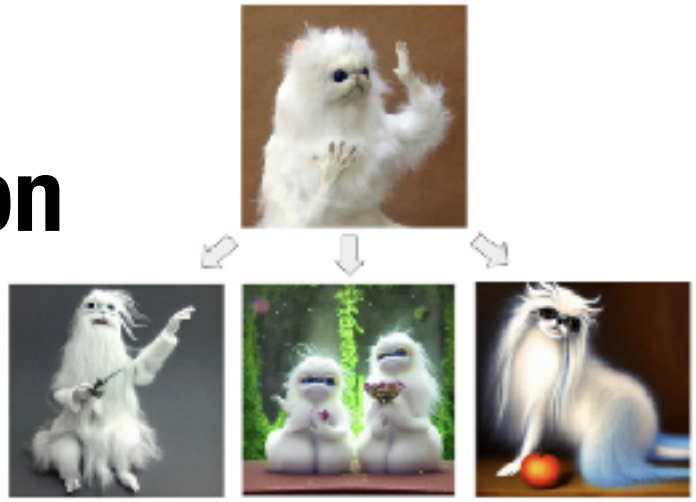
A swamp ogre with a pearl earring by Johannes Vermeer

A car made out of vegetables.

heat death of the universe, line art

if time

Stable Diffusion



High-performance image generation using Stable Diffusion in KerasCV

Authors: fchollet, lukewood, divamgupta
Date created: 2022/09/25
Last modified: 2022/09/25
Description: Generate new images using KerasCV's StableDiffusion model.

View in Colab • GitHub source

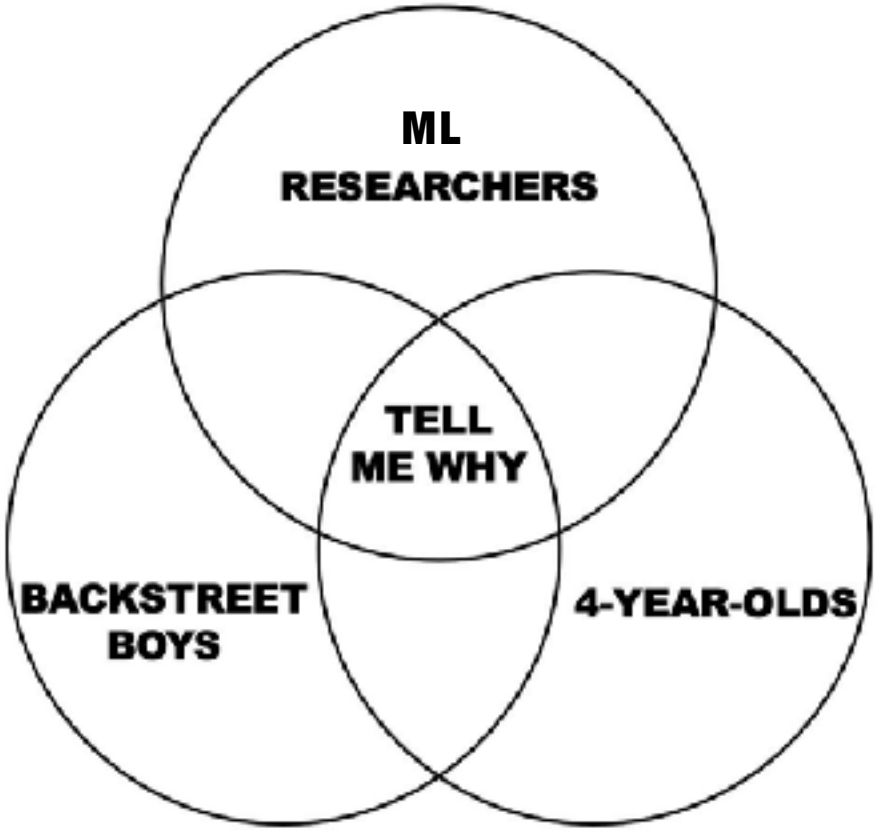
Sponsor Follow

LukeWood Luke Wood

KerasCV Author, Full Time Keras team member & Machine Learning researcher @ Google, Part Time UCSD Ph.D student

PRO

Final Project Draft Town Hall



Lecture Notes for

Neural Networks and Machine Learning

Stable Diffusion

Next Time:
Reinforcement Learning

Reading: None