2025 edition

Deep Learning for Music Analysis and Generation

Diffusion-based Text-to-music Generation

(text → audio)

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References for Diffusion Models

- References
  - Diffusion model tutorial @ ISMIR 2024 (https://sites.google.com/view/diffusion-tutorial-ismir24/materials)

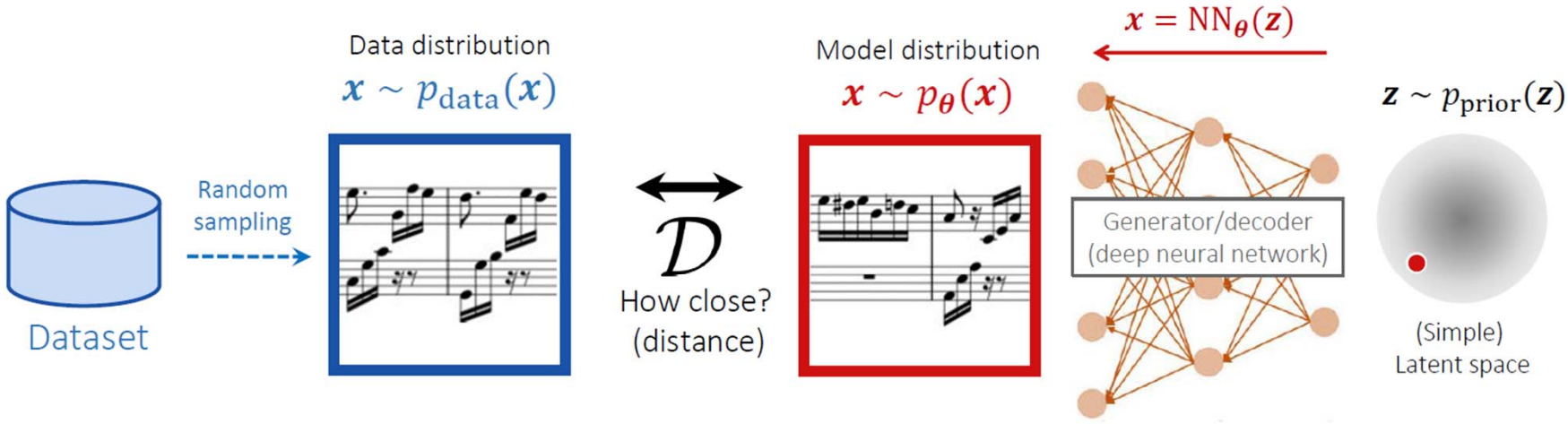
  - Prof. Hung-Yi Lee's videos (https://www.youtube.com/watch?v=ifCDXFdeaaM)

Outline

- **Diffusion models**
- Diffusion-based Text-to-music Generation
- Music ControlNet & MuseControlLite

Diffusion Models: Intro

- Learn to fit the real data distribution
- From Gaussian noises (easier to do sampling and generation)



$$\min_\theta \mathcal{D}(p_\theta(x), p_{\text{data}}(x))$$

(From: https://github.com/ChiehHsinJesseLai/ISMIR24DiffusionModelTutorial/blob/main/tutorial_diffusion_model_all.pdf)

Diffusion Models: Intro

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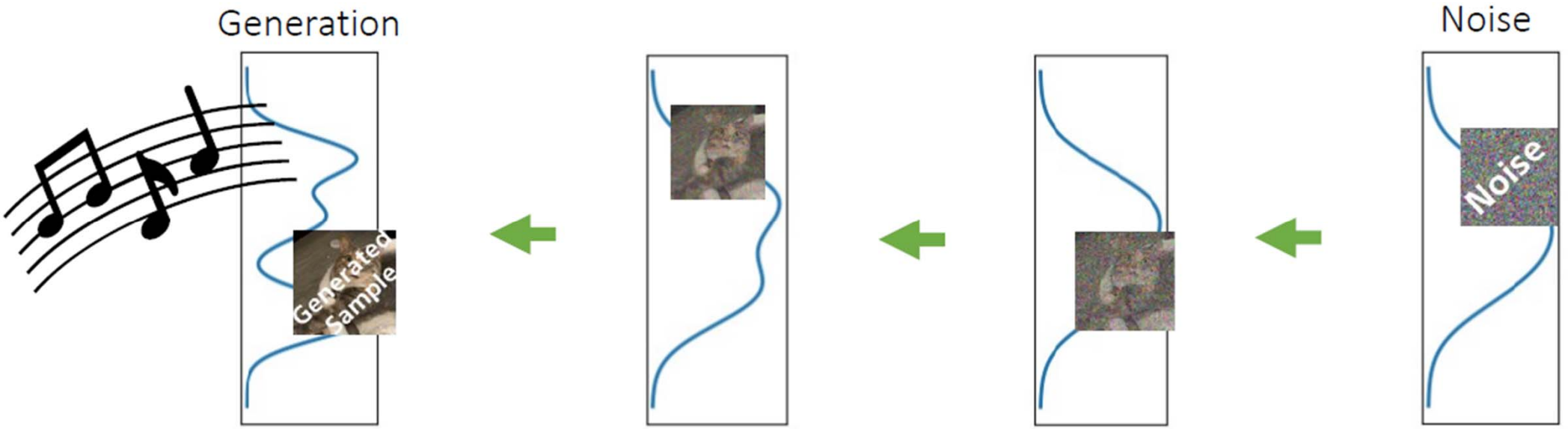
- From Gaussian noises (easier to do sampling and generation)



(From: https://github.com/ChiehHsinJesseLai/ISMIR24DiffusionModelTutorial/blob/main/tutorial_diffusion_model_all.pdf)

Diffusion Models: Learn NN to Gradually Denoise

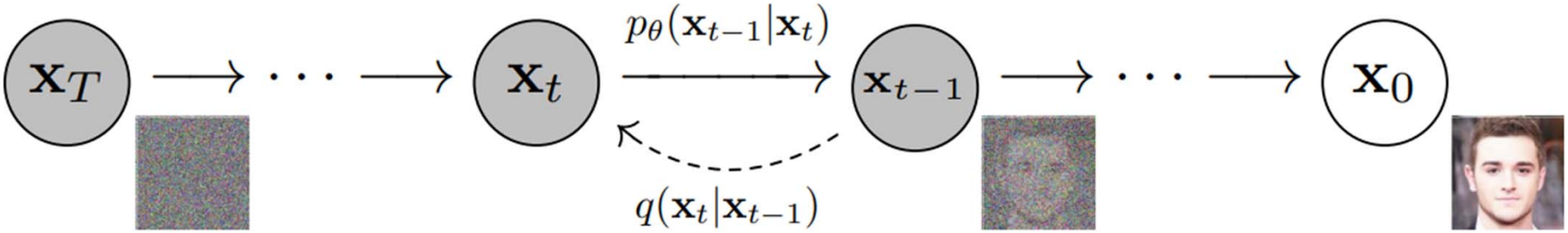


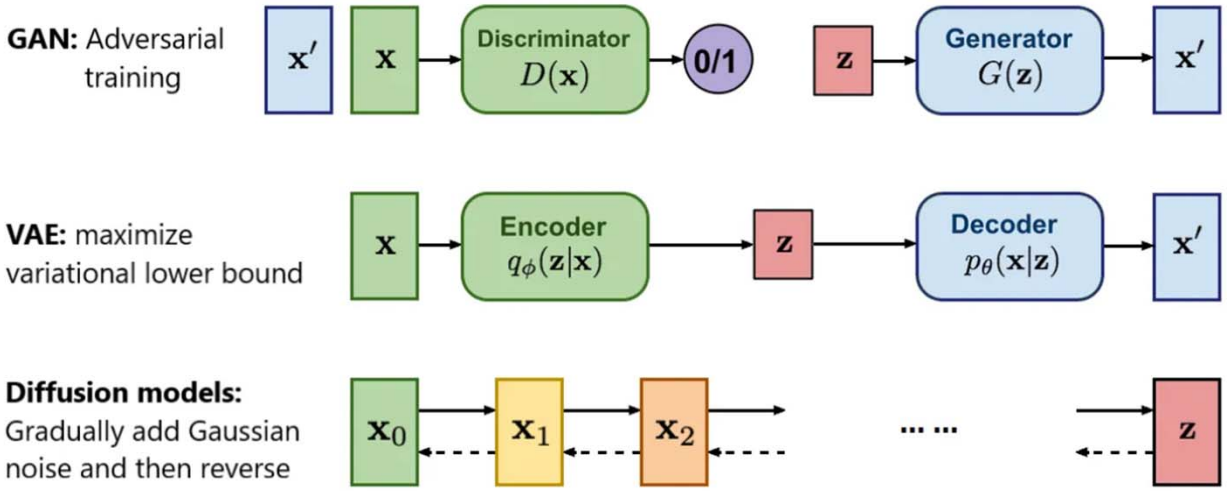
Figure 2: The directed graphical model considered in this work.

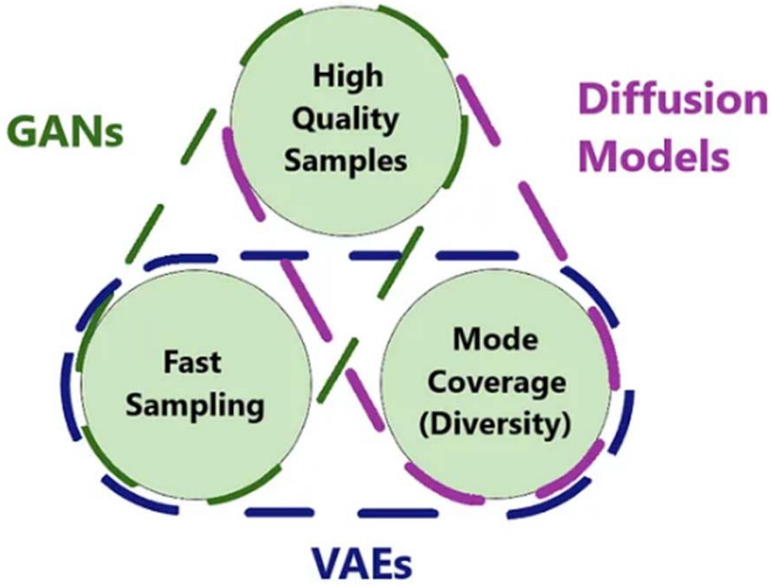
- **Forward** (or diffusion) process: $\boldsymbol{x}_0$ (real data) → $\boldsymbol{x}_T$ (Gaussian noise)
- **Reverse** process: $\boldsymbol{x}_T \rightarrow \boldsymbol{x}_0$ [denoise]
- The intermediate noisy data serve as latent codes ($\boldsymbol{z}$) and have the same size as the training data

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Diffusion Models

https://pub.towardsai.net/diffusion-models-vs-gans-vs-vaes-comparison-of-deep-generative-models-67ab93e0d9ae

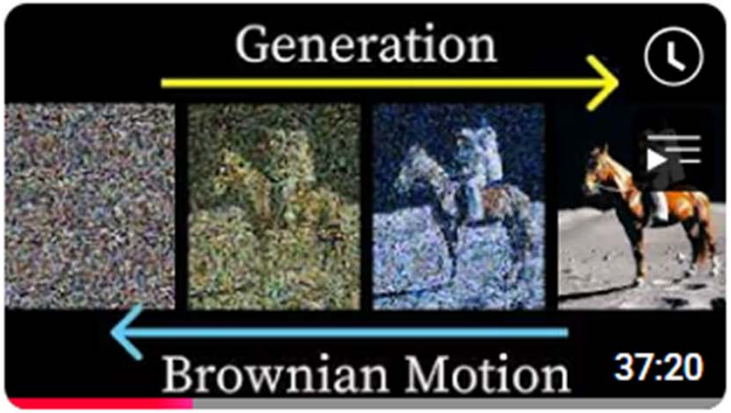




- **High-fidelity samples:** due to the nature of gradually removing noise
- **High diversity samples**: likelihood maximization covers all data modes
- **Slow sample generation**: requires multiple runs to gradually generate samples

Diffusion Models

https://www.youtube.com/watch?v=iv-5mZ_9CPY



But how do AI images and videos actually work? | Guest video by...

3Blue1Brown and Welch Labs • 1.1M views

Diffusion models, CLIP, and the math of turning text into images
Welch Labs Book: https://www.welchlabs.com/resources/imaginar...

Denoising Diffusion Probabilistic Models (DDPM)

- Add noises $\mathcal{N}(\mathbf{0}, \mathbf{I})$ during training ($\boldsymbol{\epsilon}$) and inference ($\mathbf{z}$)
  - At training, $\mathbf{x}_t = a_t \mathbf{x}_0 + b_t \boldsymbol{\epsilon}$
  - **But why at inference time?**

Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \text{Uniform}(\{1, \dots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \dots, 1$ **do**
3: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoising Diffusion Probabilistic Models (DDPM)

- The denoisier $\boldsymbol{\epsilon}_\theta(\cdot,\cdot)$ predicts the total noise added (or, equivalently, $\mathbf{x}_0$)
  - Rather than $\mathbf{x}_{t-1}$, the previous step; why?
- The denoisier has two inputs: $\mathbf{x}_t$, and the timestamp t (denoising step)

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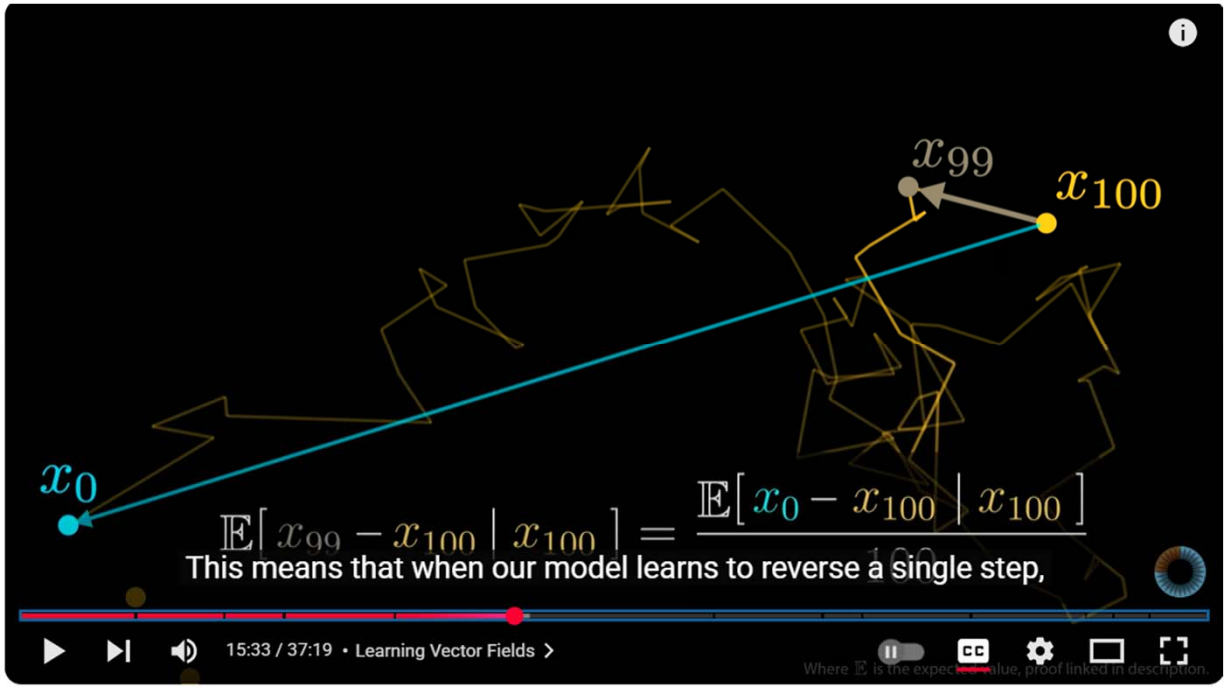
Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoising Diffusion Probabilistic Models (DDPM)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

- Predict the original input ($\mathbf{x}_0$) rather than the less noisy input ($\mathbf{x}_{t-1}$)

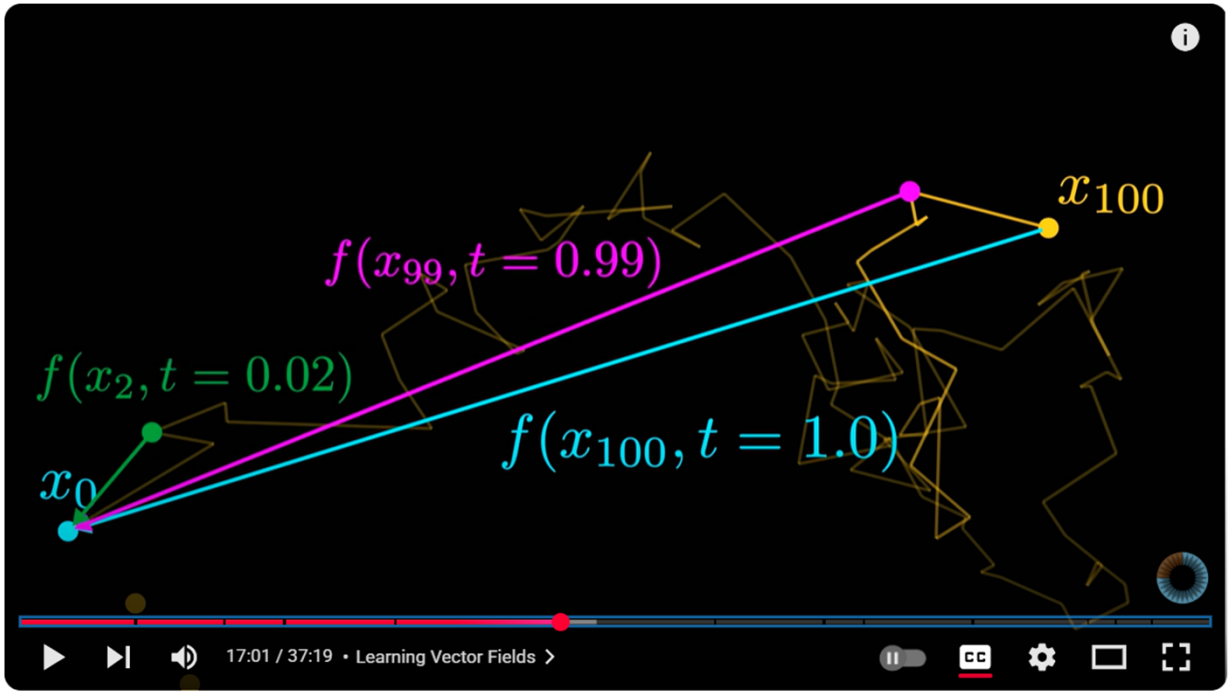


Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoising Diffusion Probabilistic Models (DDPM)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

- Add noise $\mathcal{N}(\mathbf{0}, \mathbf{I})$ during training and inference



Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoising Diffusion Probabilistic Models (DDPM)

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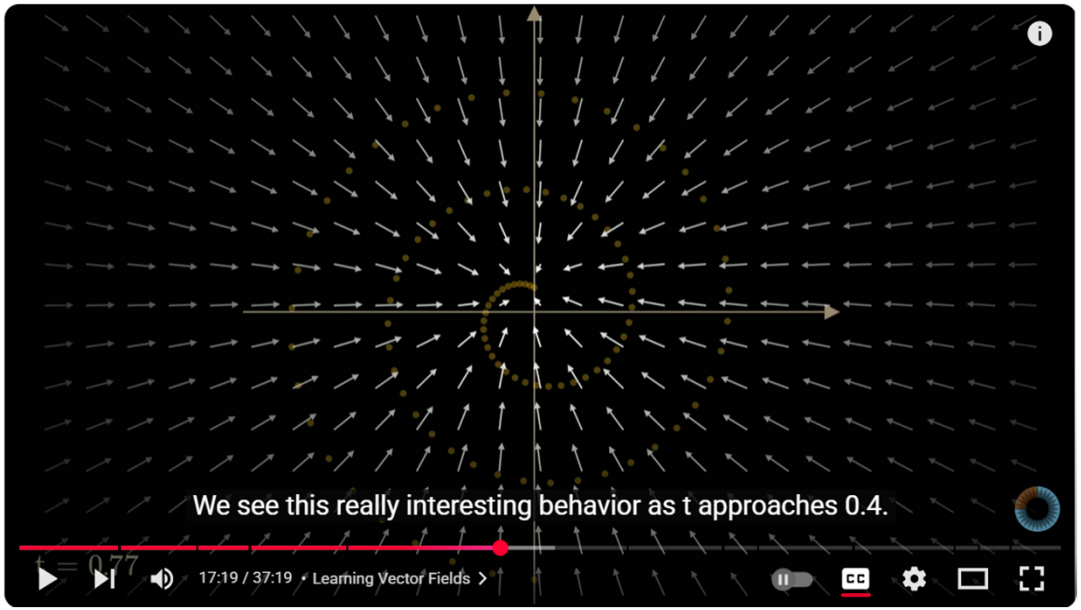

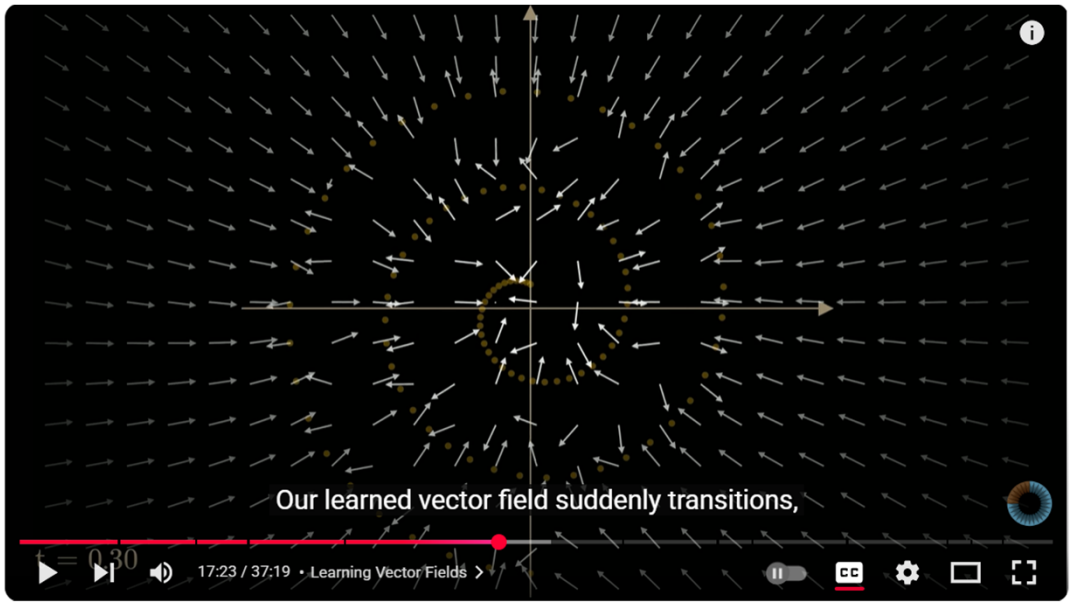

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

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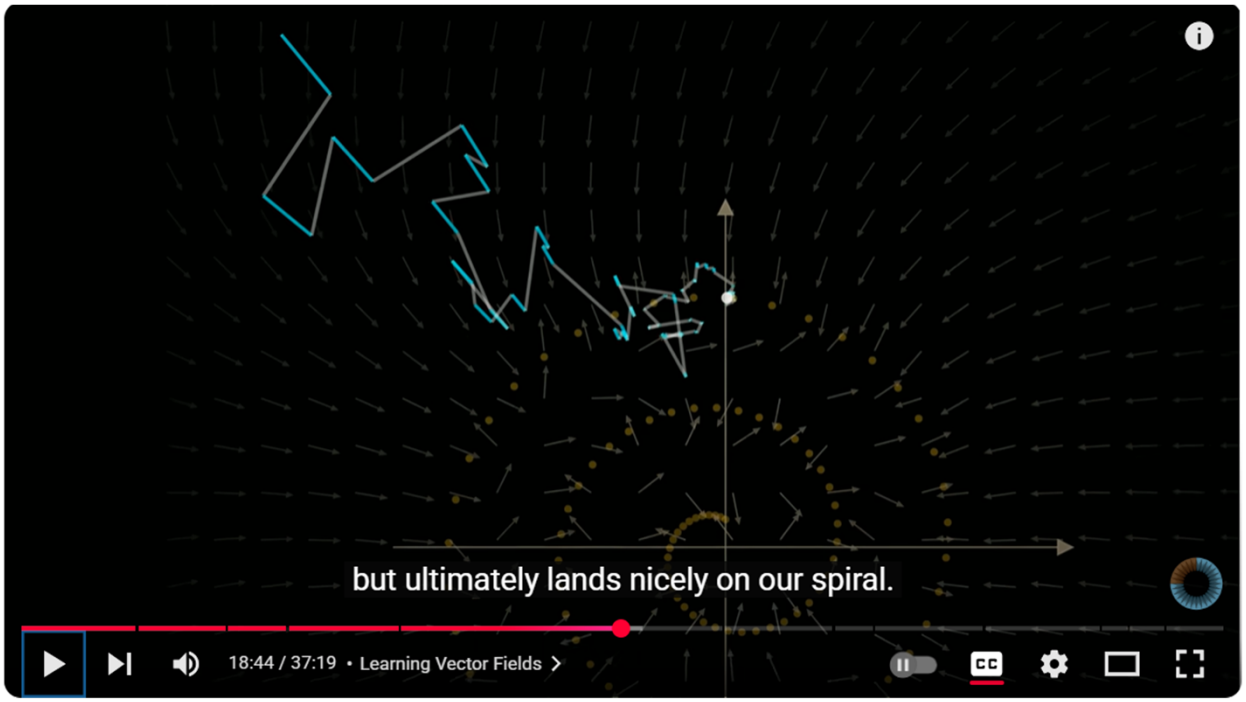

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoising Diffusion Implicit Models (DDIM)

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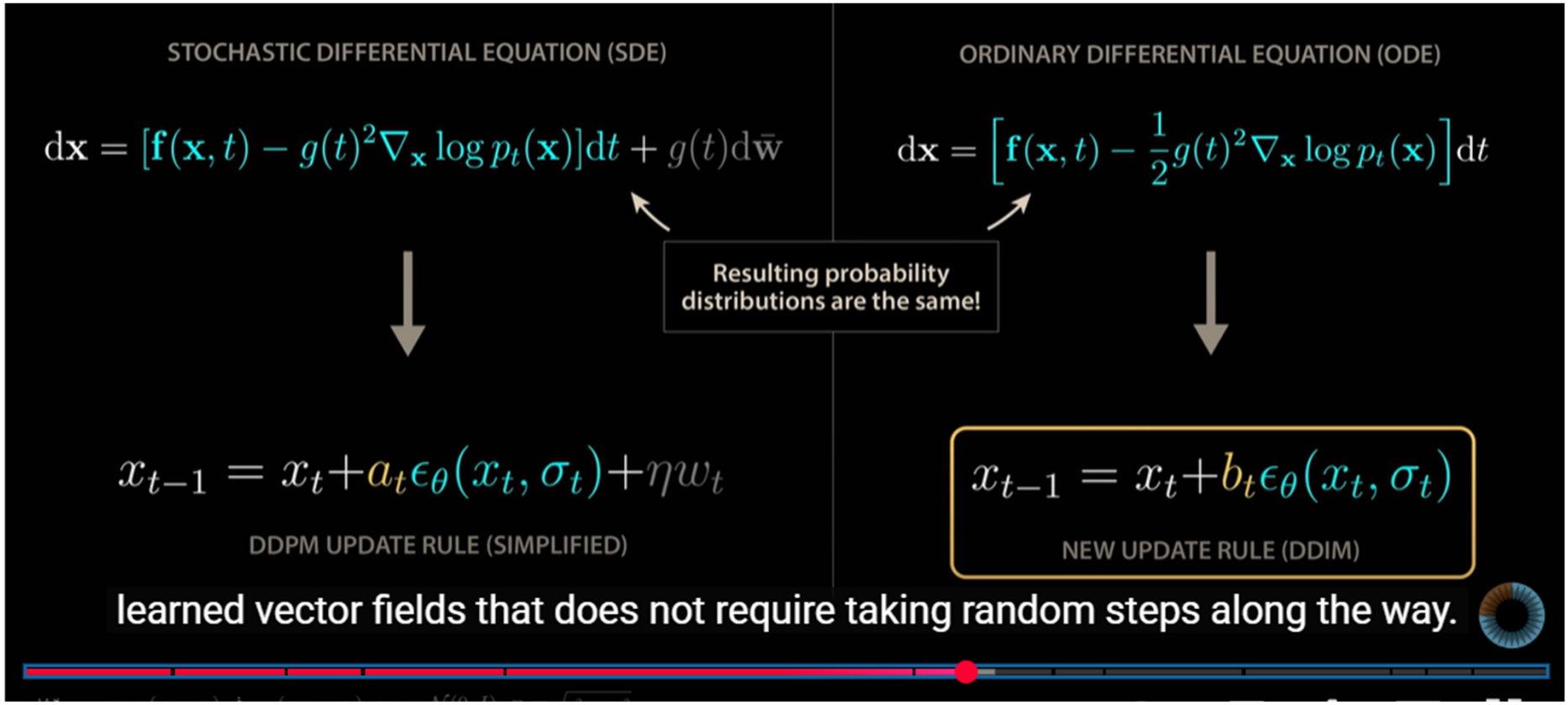
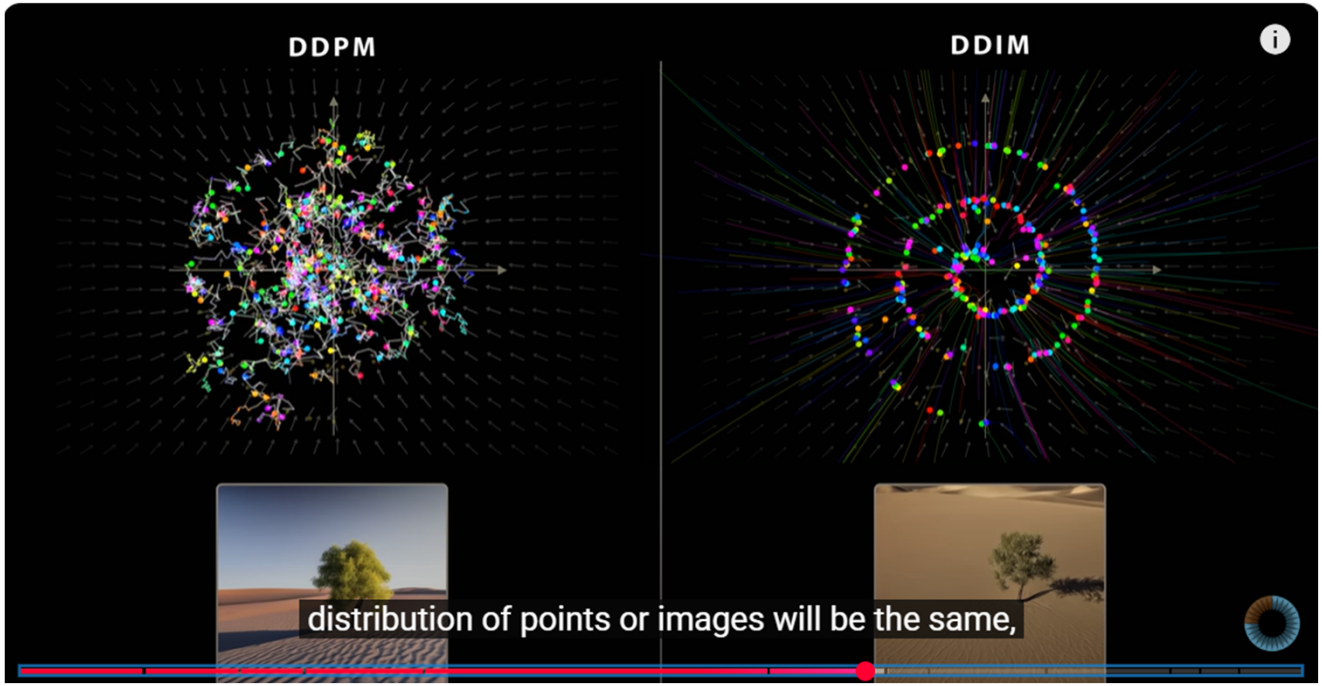


Ref: Song et al, "Denoising diffusion implicit models," ICLR 2021

Denoising Diffusion Implicit Models (DDIM)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

- **Faster inference**: solving ODEs instead of SDEs



Ref: Song et al, “Denoising diffusion implicit models,” ICLR 2021

DDPM vs DDIM

https://www.youtube.com/watch?v=i2qSxMVeVLI

- DDPM outperforms DDIM with a large number of denoising steps (but slow)
- DDIM works better with fewer denoising steps
- Don’t retrain: we can take a model trained with the DDPM objective and accelerate it with the DDIM sampler

	CIFAR10 (32 × 32)					CelebA (64 × 64)				
	10	20	50	100	1000	10	20	50	100	1000
DDIM	**13.36**	**6.84**	**4.67**	**4.16**	4.04	**17.33**	**13.73**	**9.17**	**6.53**	3.51
DDPM	367.43	133.37	32.72	9.99	**3.17**	299.71	183.83	71.71	45.20	**3.26**

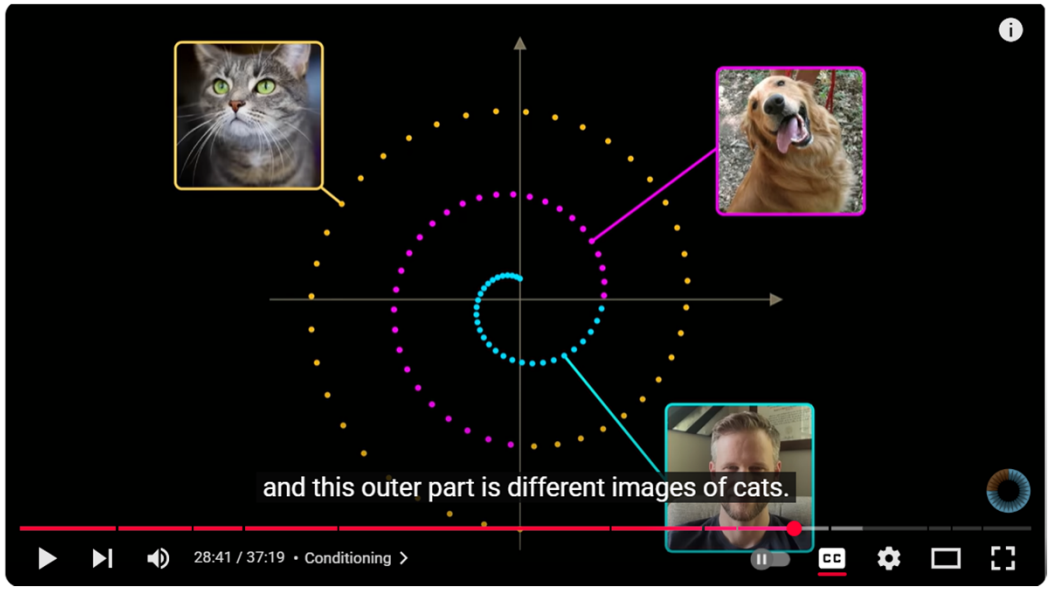
(the value here (FID) is the lower the better)

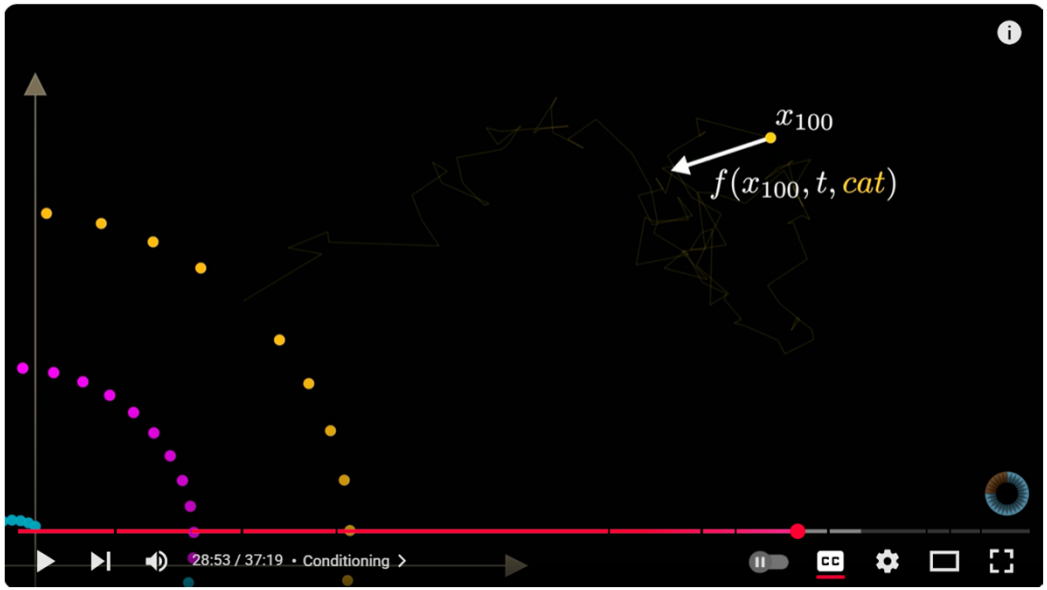
(Source: https://www.youtube.com/watch?v=i2qSxMVeVLI)

Classifier-Free Guidance (CFG)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

- Going from unconditional generation to **conditional** generation



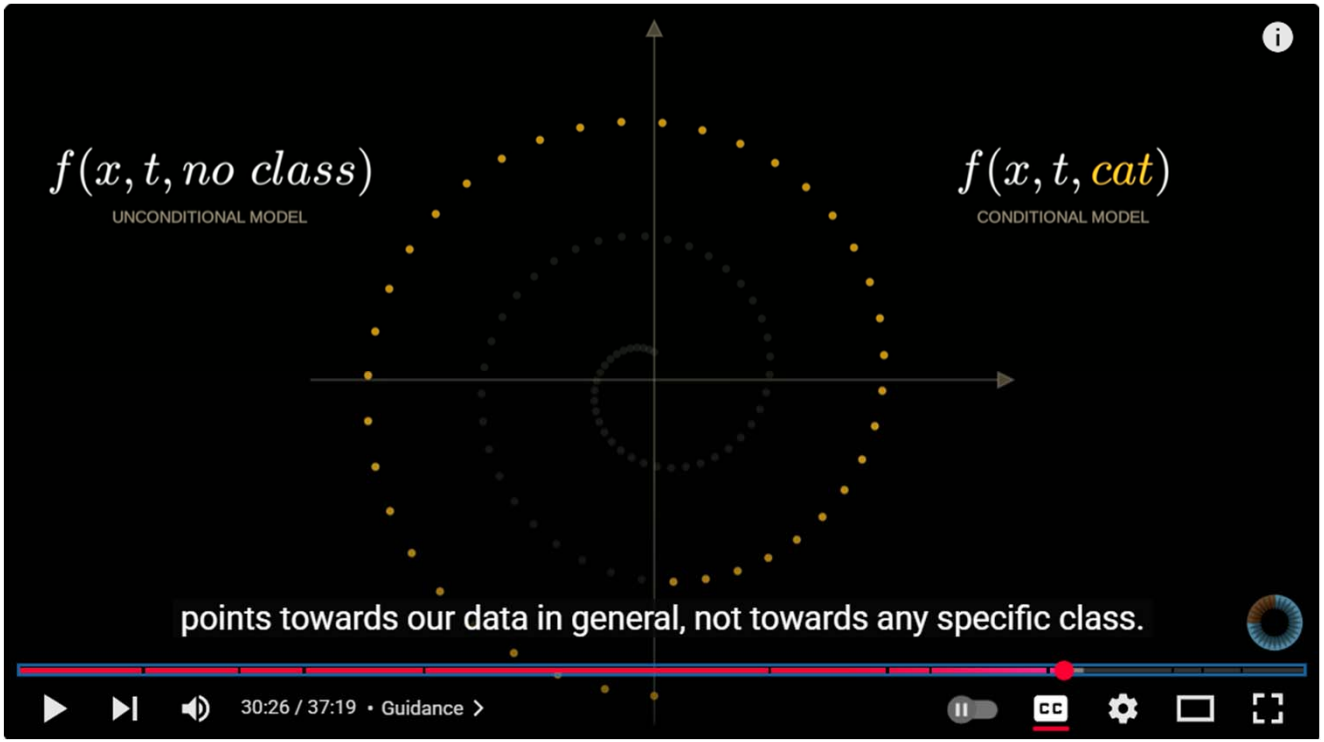


Ref: Ho & Salimans, "Classifier-free diffusion guidance," NeurIPS workshop 2021

Classifier-Free Guidance (CFG)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

- One model is sufficient: use “no class” as the dummy condition

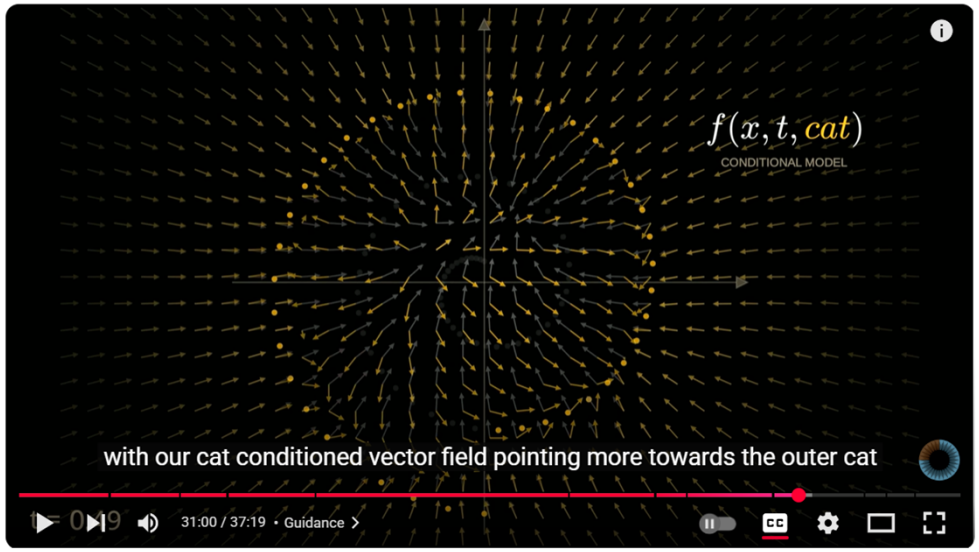


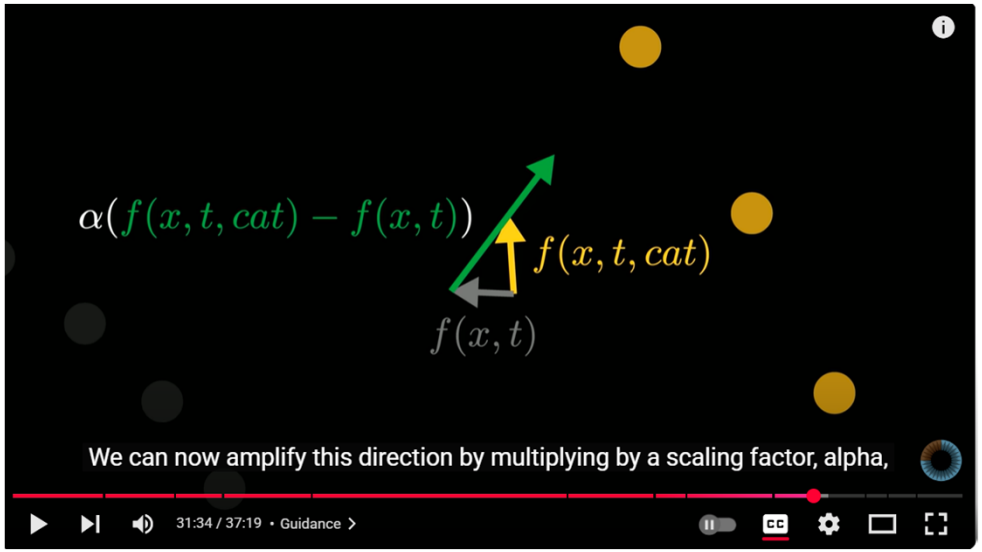
Ref: Ho & Salimans, “Classifier-free diffusion guidance,” NeurIPS workshop 2021

Classifier-Free Guidance (CFG)

https://www.youtube.com/watch?v=iv-5mZ_9CPY

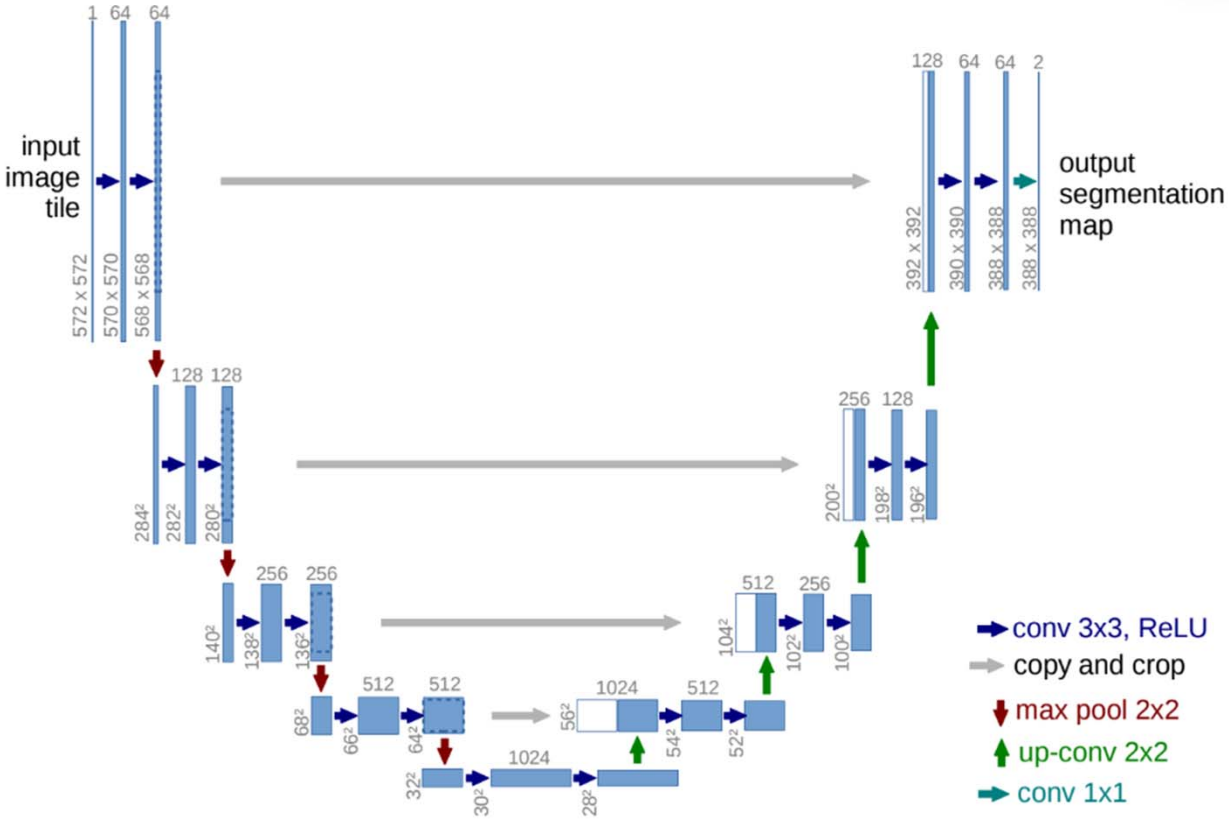
- The vector fields of the unconditional and conditional models may diverge
- Taking their difference provides a simple solution
- Moreover, we can use the "guidance scale" α as a flexible control





Ref: Ho & Salimans, "Classifier-free diffusion guidance," NeurIPS workshop 2021

Denoiser: U-Net

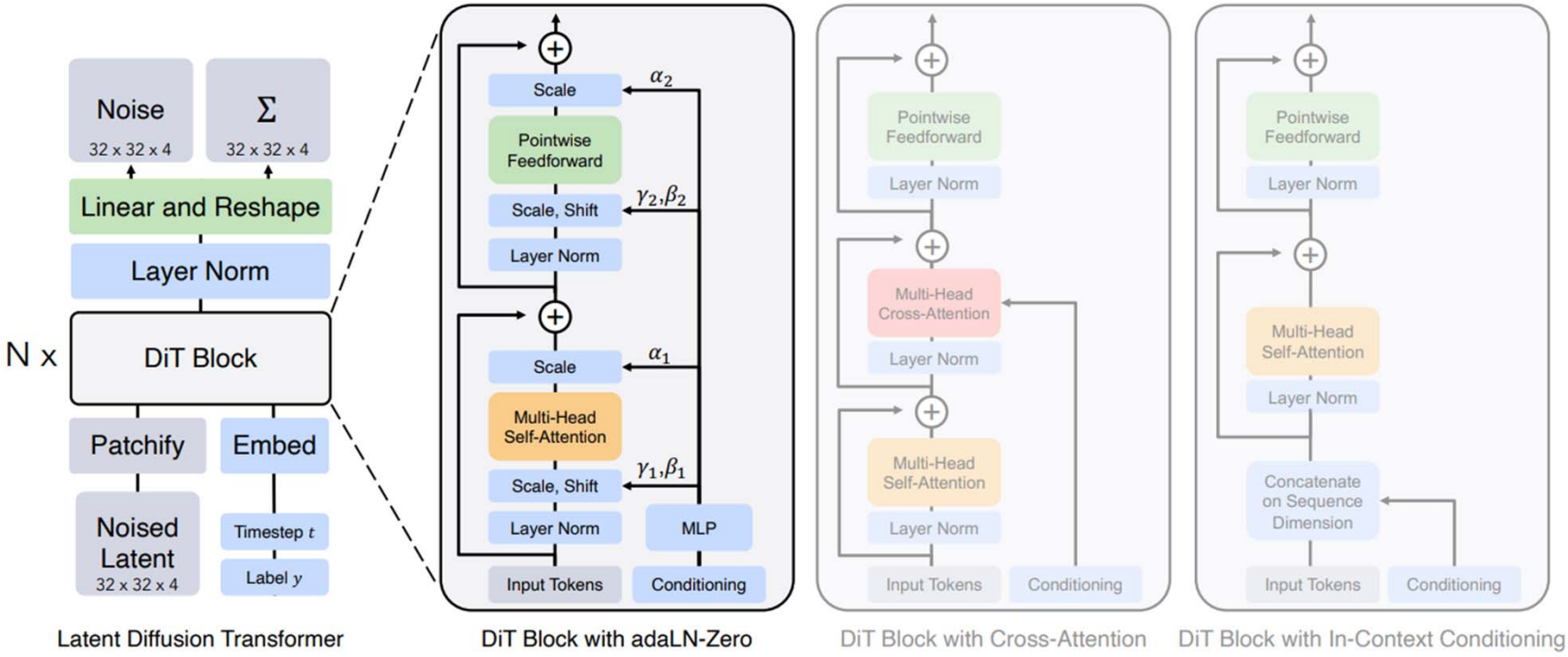


- U-net are often used in tasks where the input and output are of similar shape
  - image denoising
  - image segmentation
  - denoiser in diffusion models
- "Per-pixel" classification
- Components
  - downsampling encoder
  - upsampling decoder
  - skip connections

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Denoiser: Diffusion Transformer (DiT)

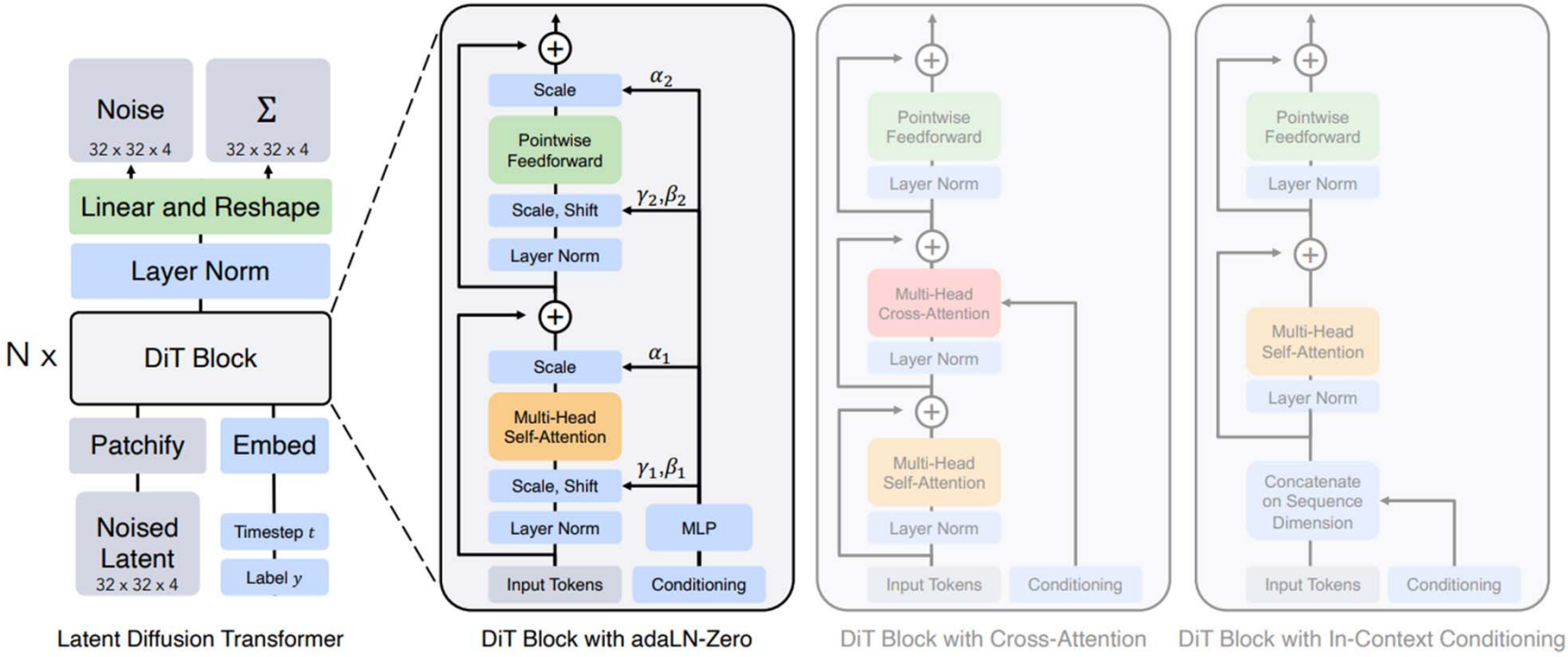
- DiT is based on the Vision Transformer (ViT) architecture which operates on sequences of patches



Ref: Peebles & Xie, “Scalable diffusion models with Transformers,” CVPR 2023

Denoiser: Diffusion Transformer (DiT)

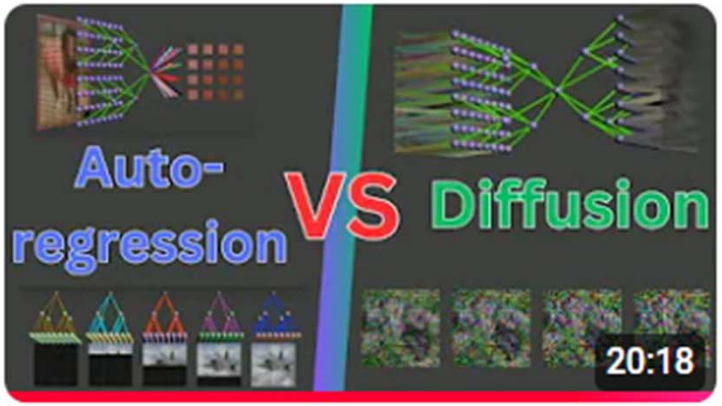
- Self-attention layers instead of convolution layers
- Use adaptive layer norm to incorporate conditioning (e.g., timestamps)



Ref: Dosovitskiy et al, "An image is worth 16x16 words: Transformers for image recognition at scale," ICLR 2020

Diffusion vs. Transformers

https://www.youtube.com/watch?v=zc5NTeJbk-k



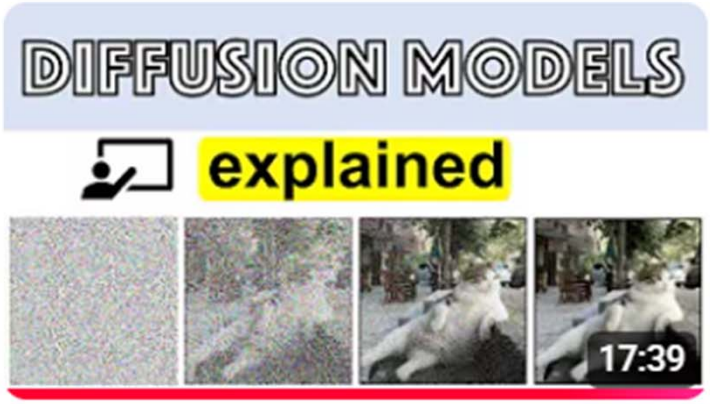
Why Does Diffusion Work Better than Auto-Regression?

Algorithmic Simplicity • 374K views

Have you ever wondered how generative AI actually works? Well the short answer is, in exactly the same as way as regular AI! In this...

Diffusion Models (from Prof. Jia-Bin Huang)

https://www.youtube.com/watch?v=i2qSxMVeVLI



How I Understand Diffusion Models

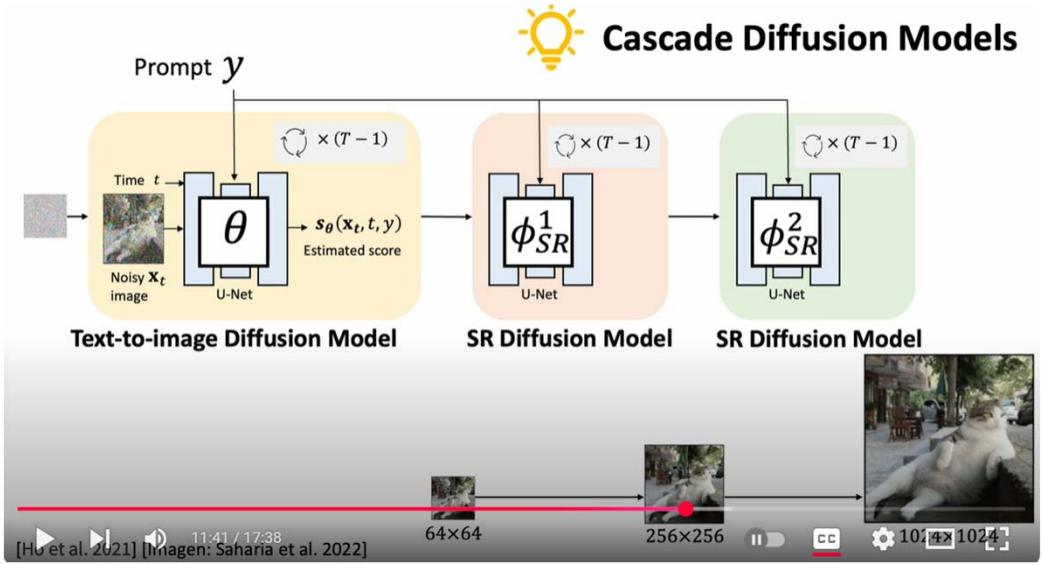
Jia-Bin Huang • 55K views

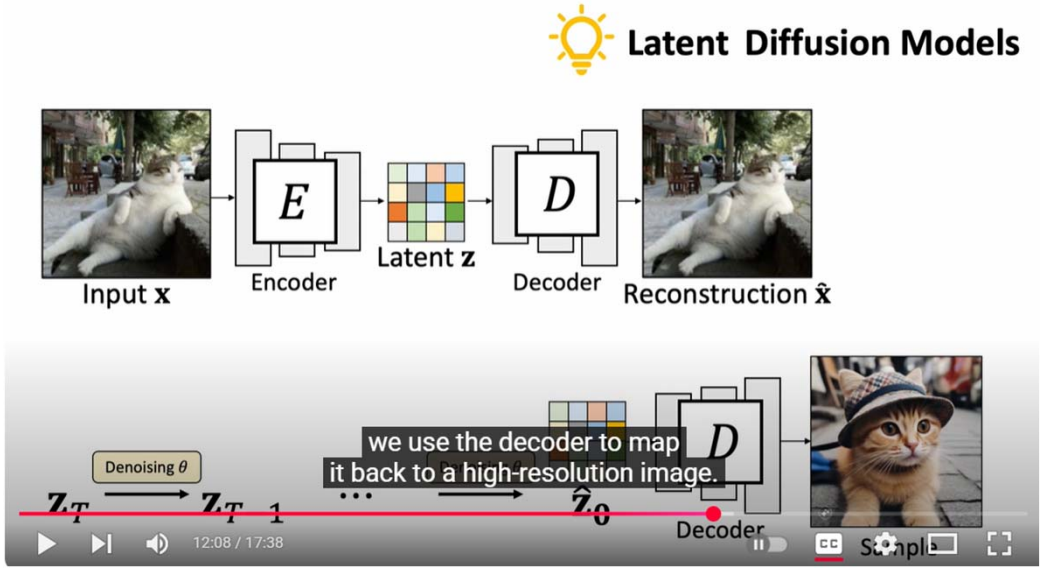
Diffusion models are powerful generative models that enable many successful applications like image, video, and 3D generation from...

Diffusion Models: Generation High-Resolution Output

https://www.youtube.com/watch?v=i2qSxMVeVLI

- Cascade diffusion models
- Latent diffusion models

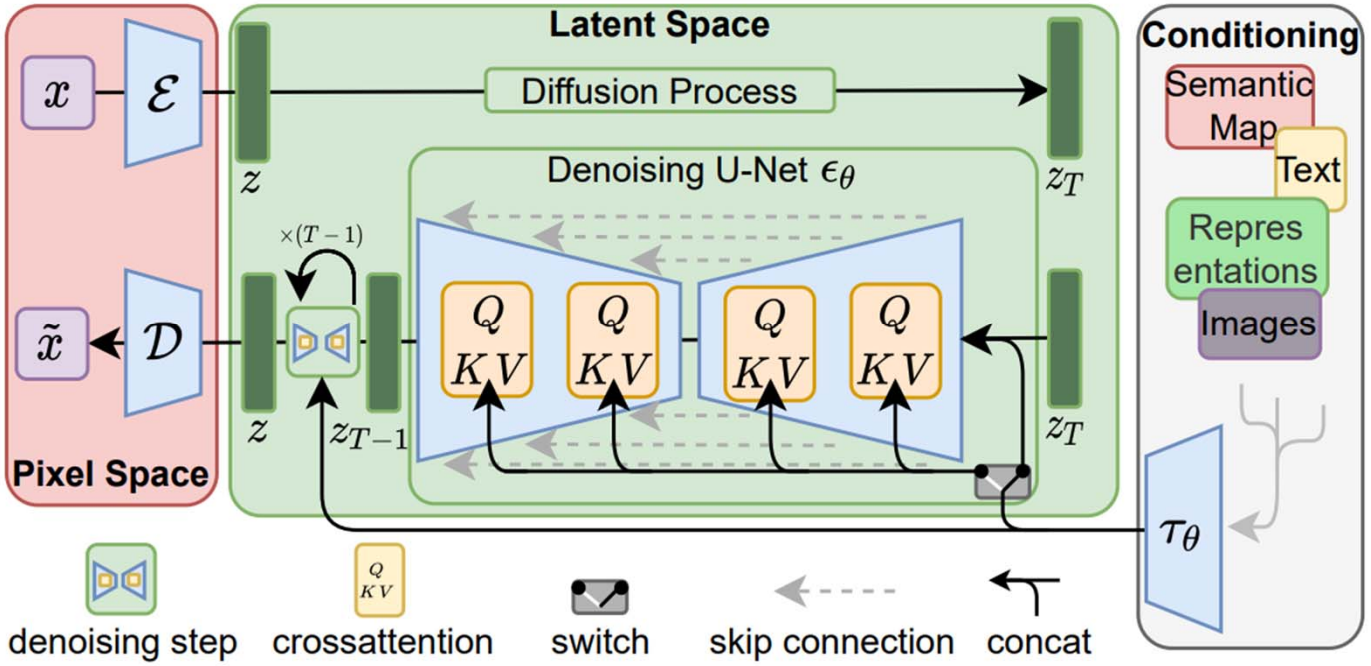




Latent Diffusion Models

$$x \in \mathbb{R}^{H \times W \times 3}$$
$$z \in \mathbb{R}^{h \times w \times c}$$

- Work on a **latent** space instead of pixel space
  - **noisy latents → clean latents**
  - focus on the important, semantic bits of data
  - computational efficiency
- Latent space regularization
  - KL-reg
  - VQ-reg

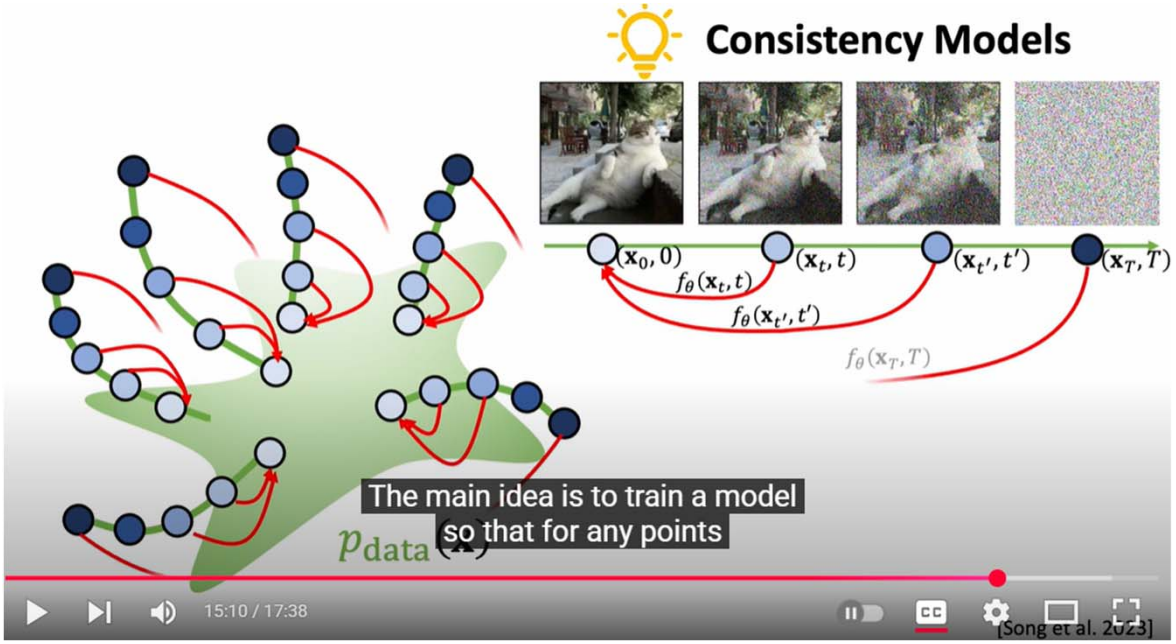


Ref: Rombach et al, "High-resolution image synthesis with latent diffusion models," CVPR 2022

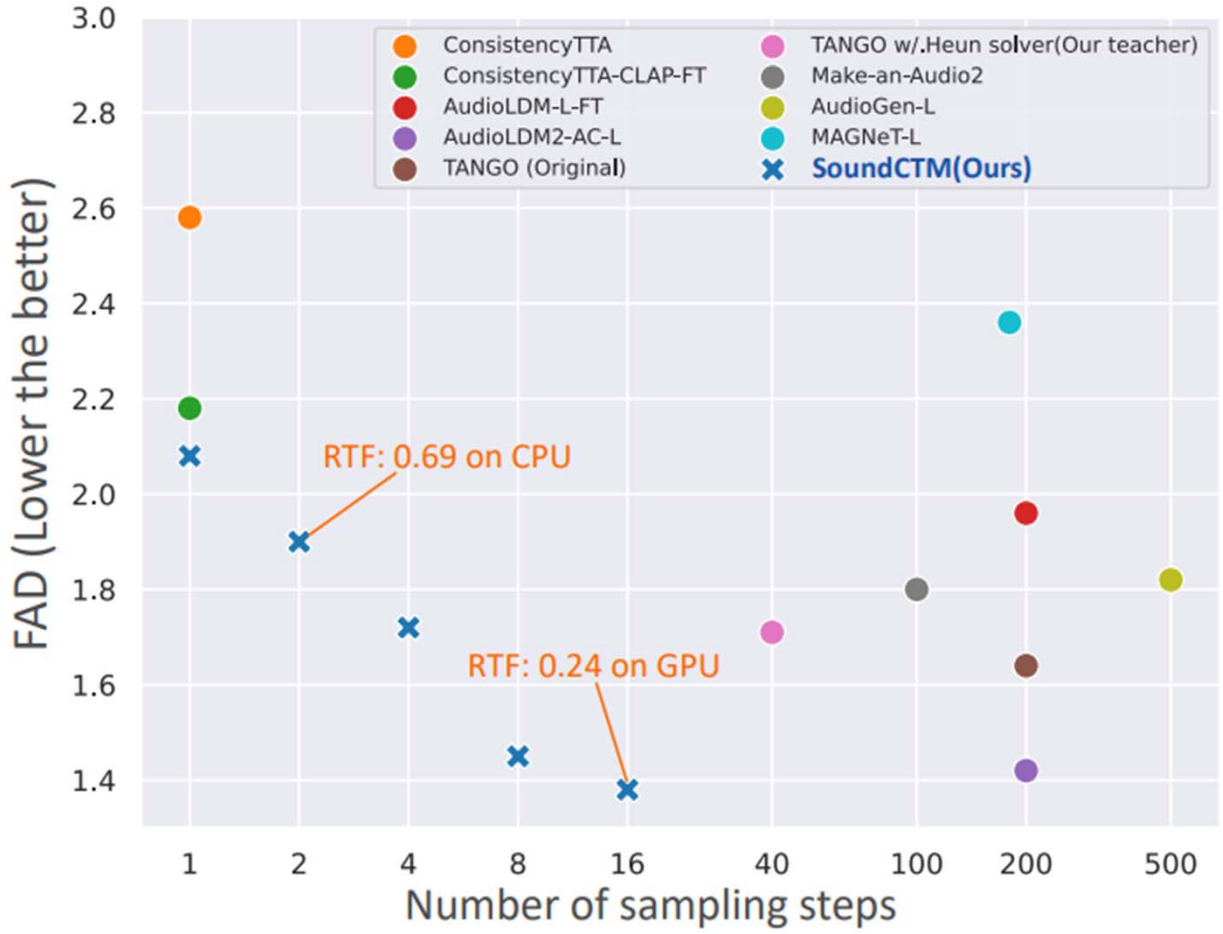
Diffusion Models: Faster Inference

https://www.youtube.com/watch?v=i2qSxMVeVLI

- Progressive distillation / guided distillation
- Consistency models / latent consistency models



Consistency Model: One-Step Generation

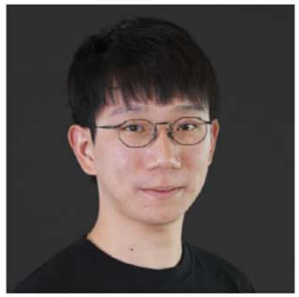


Ref: Saito et al, “SoundCTM: Uniting score-based and consistency models for text-to-sound generation,” arXiv 2024

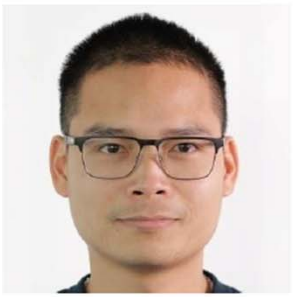
Consistency Model: One-Step Generation

https://sites.google.com/view/diffusion-tutorial-ismir24/materials

MEET OUR SPEAKERS



Chieh-Hsin (Jesse) Lai



Bac Nguyen

Koichi Saito

Yuki Mitsufuji

Mean Flows (from Prof. Jia-Bin Huang)

https://www.youtube.com/watch?v=swKdn-qT47Q

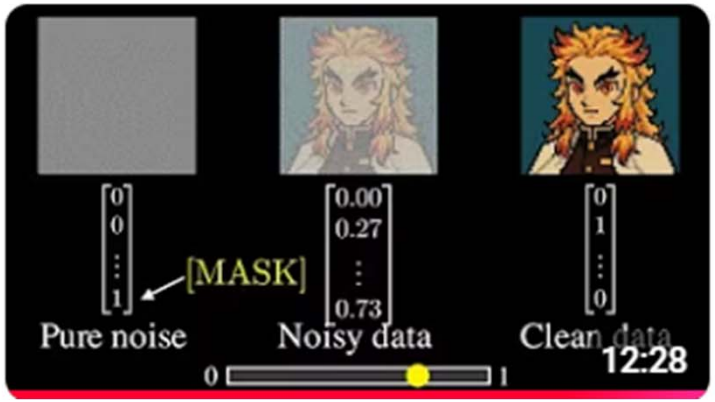
The Rise of Single-Step Generative Models

Jia-Bin Huang • 7.5K views

Diffusion and flow-matching models are key techniques for the current generative AI boom. However, their fundamental limitation i...

Diffusion LM (from Prof. Jia-Bin Huang)

https://www.youtube.com/watch?v=8BTOoc0yDVA



But how do Diffusion Language Models actually work?

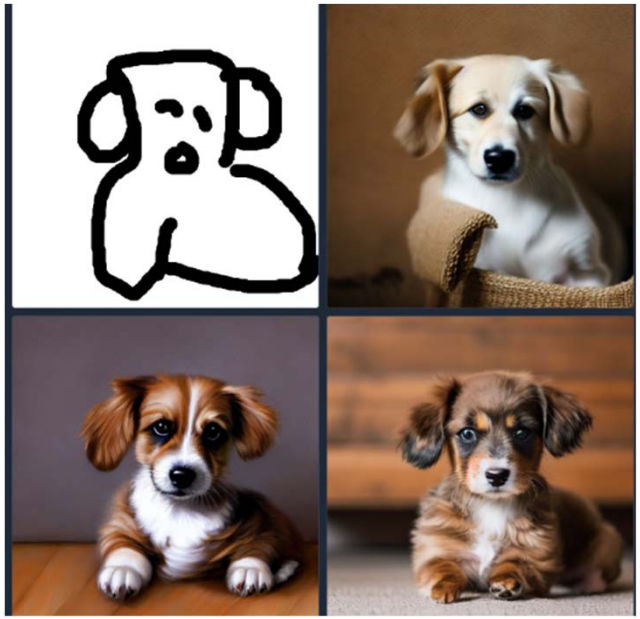
Jia-Bin Huang • 13K views

Most Large Language Models (LLMs) today are based on Autoregressive models (i.e., they predict texts in a left-to-right order...

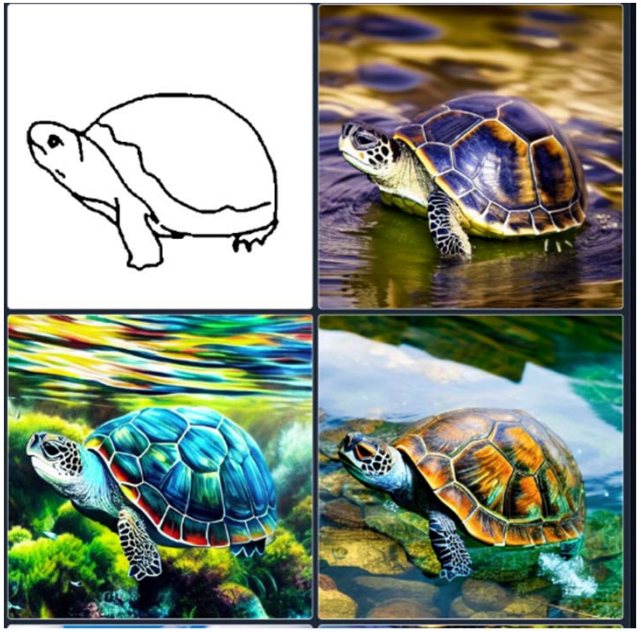
Not Just Text: “ControlNet” for Adding More Controls

https://github.com/lllyasviel/ControlNet

scribble map



scribble map



anime line drawing

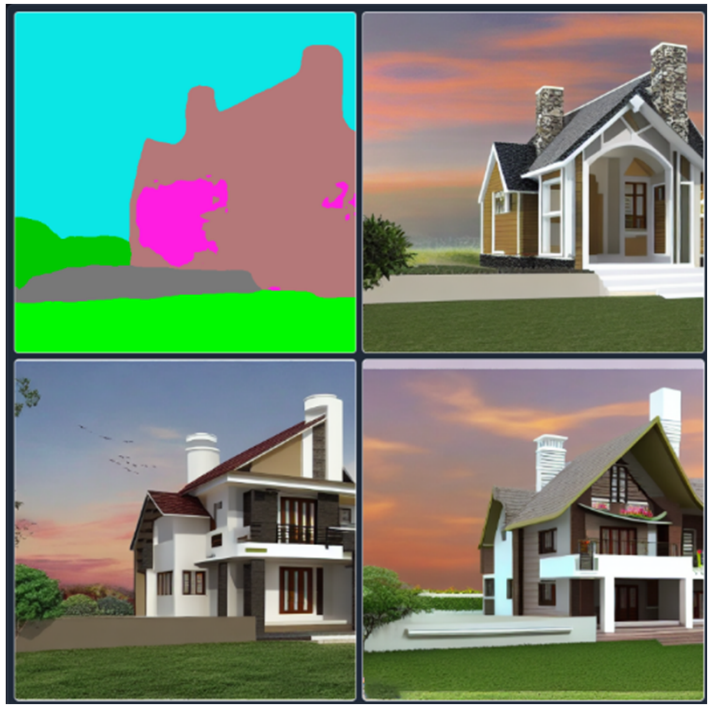
Ref: Zhang et al, “Adding conditional control to text-to-image diffusion models,” ICCV 2023

Not Just Text: “ControlNet” for Adding More Controls

https://github.com/lllyasviel/ControlNet

human pose

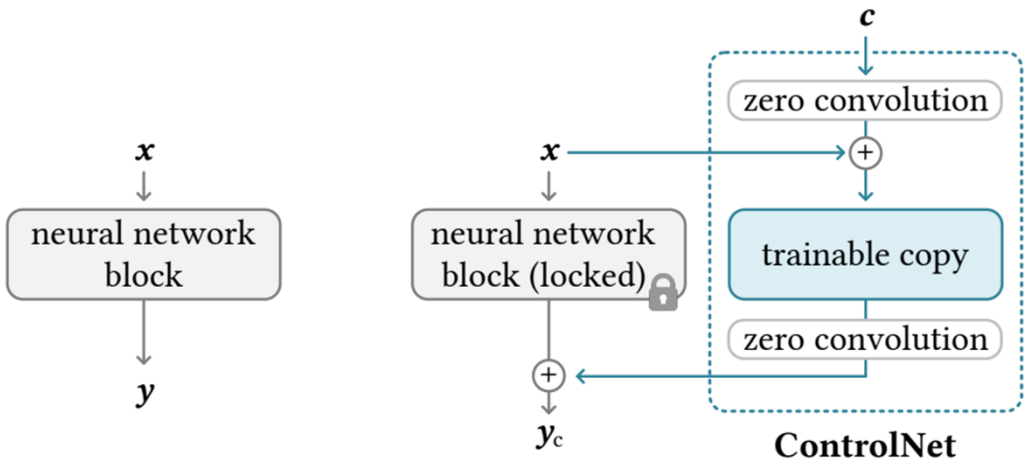
segmentation map



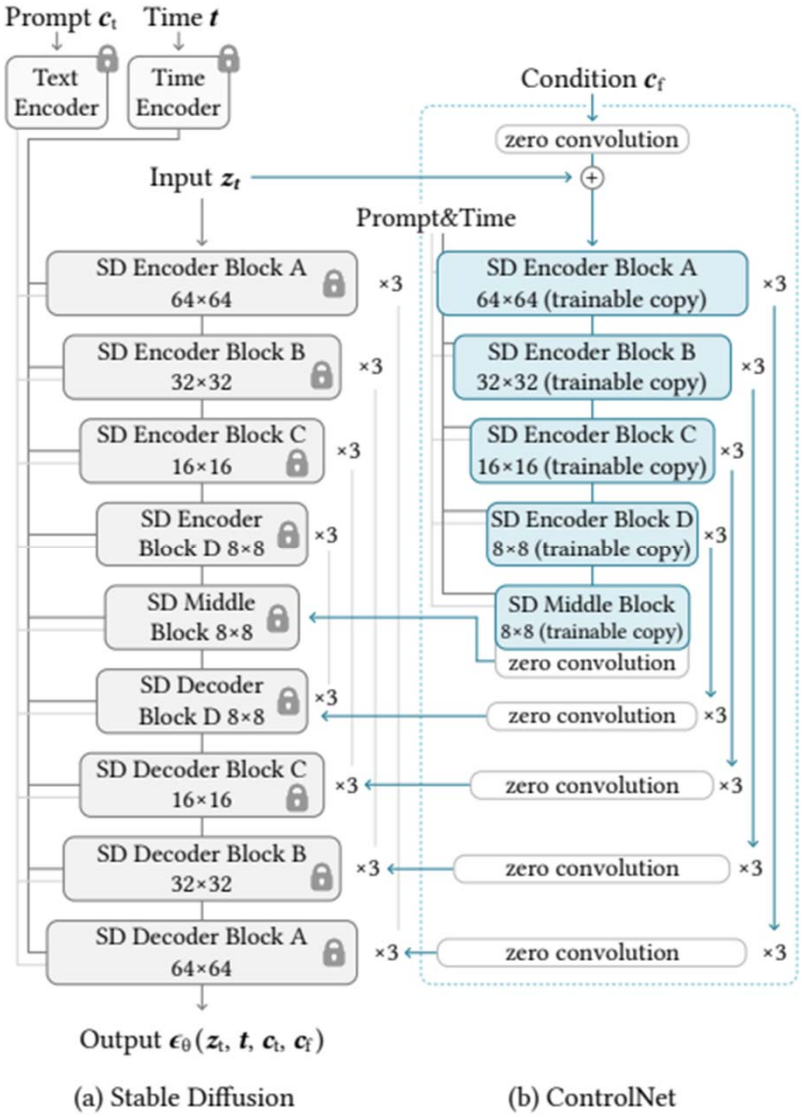
depth map

Ref: Zhang et al, “Adding conditional control to text-to-image diffusion models,” ICCV 2023

ControlNet



(a) Before (b) After



(a) Stable Diffusion (b) ControlNet

Ref: Zhang et al, "Adding conditional control to text-to-image diffusion models," ICCV 2023

ControlNet: Zero-init Convolutions

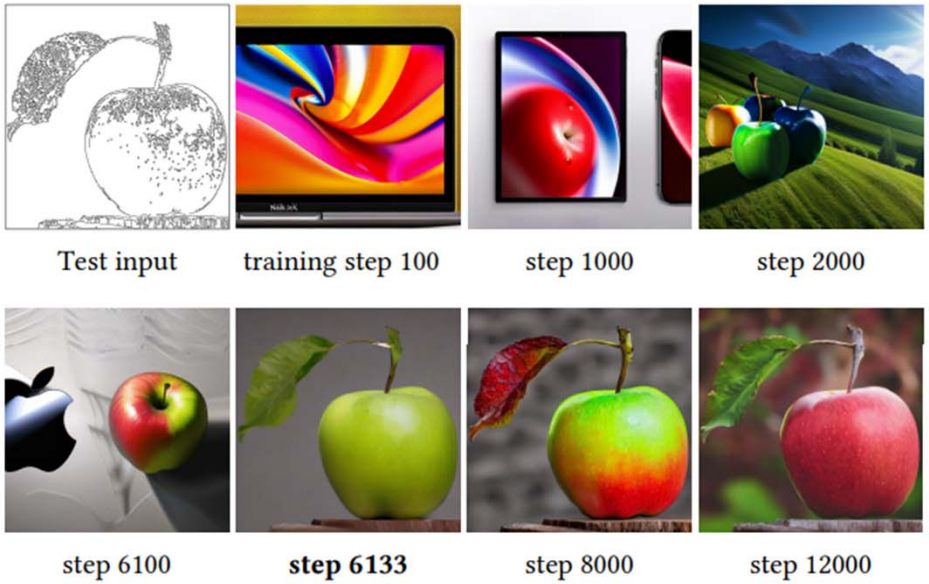
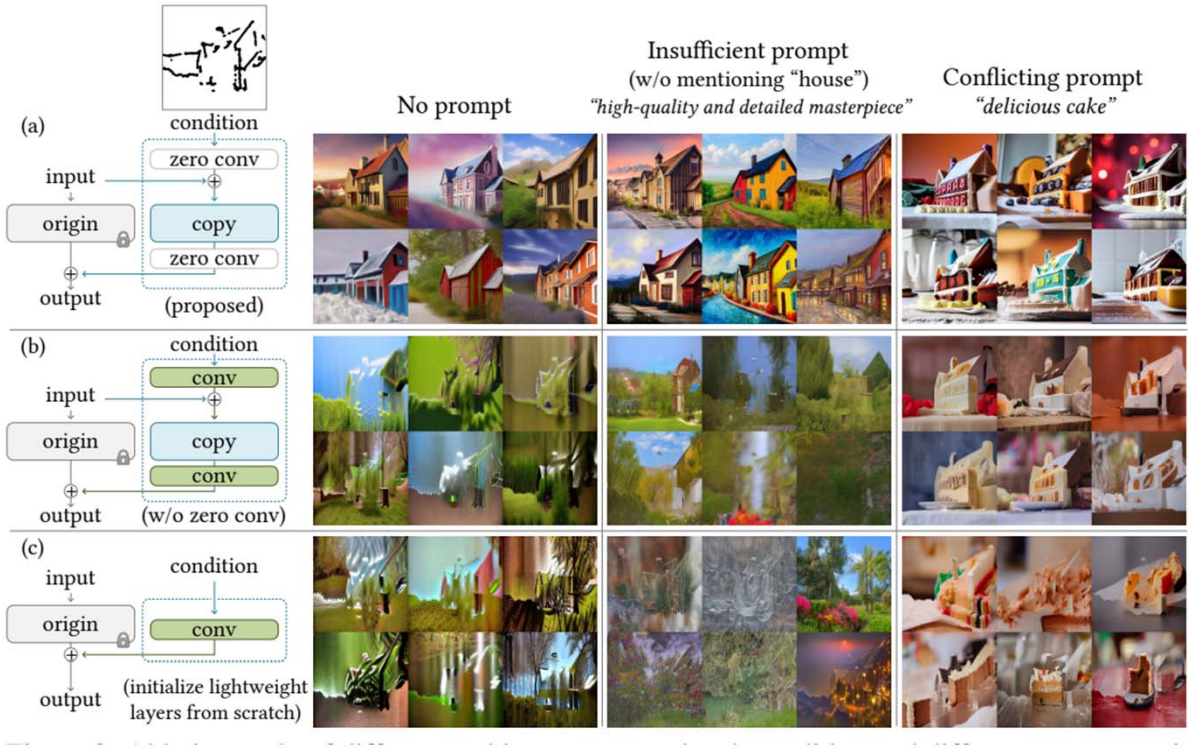


Figure 4: The sudden convergence phenomenon. Due to the zero convolutions, ControlNet always predicts high-quality images during the entire training. At a certain step in the training process (*e.g.*, the 6133 steps marked in bold), the model suddenly learns to follow the input condition.



Ref: Zhang et al, "Adding conditional control to text-to-image diffusion models," ICCV 2023

Diffusers

https://github.com/huggingface/diffusers

Task	Pipeline	🤗 Hub
Unconditional Image Generation	DDPM	google/ddpm-ema-church-256
Text-to-Image	Stable Diffusion Text-to-Image	stable-diffusion-v1-5/stable-diffusion-v1-5
Text-to-Image	unCLIP	kakaobrain/karlo-v1-alpha
Text-to-Image	DeepFloyd IF	DeepFloyd/IF-I-XL-v1.0
Text-to-Image	Kandinsky	kandinsky-community/kandinsky-2-2-decoder
Text-guided Image-to-Image	ControlNet	lllyasviel/sd-controlnet-canny
Text-guided Image-to-Image	InstructPix2Pix	timbrooks/instruct-pix2pix
Text-guided Image-to-Image	Stable Diffusion Image-to-Image	stable-diffusion-v1-5/stable-diffusion-v1-5
Text-guided Image Inpainting	Stable Diffusion Inpainting	runwayml/stable-diffusion-inpainting
Image Variation	Stable Diffusion Image Variation	lambdalabs/sd-image-variations-diffusers
Super Resolution	Stable Diffusion Upscale	stabilityai/stable-diffusion-x4-upscaler
Super Resolution	Stable Diffusion Latent Upscale	stabilityai/sd-x2-latent-upscaler

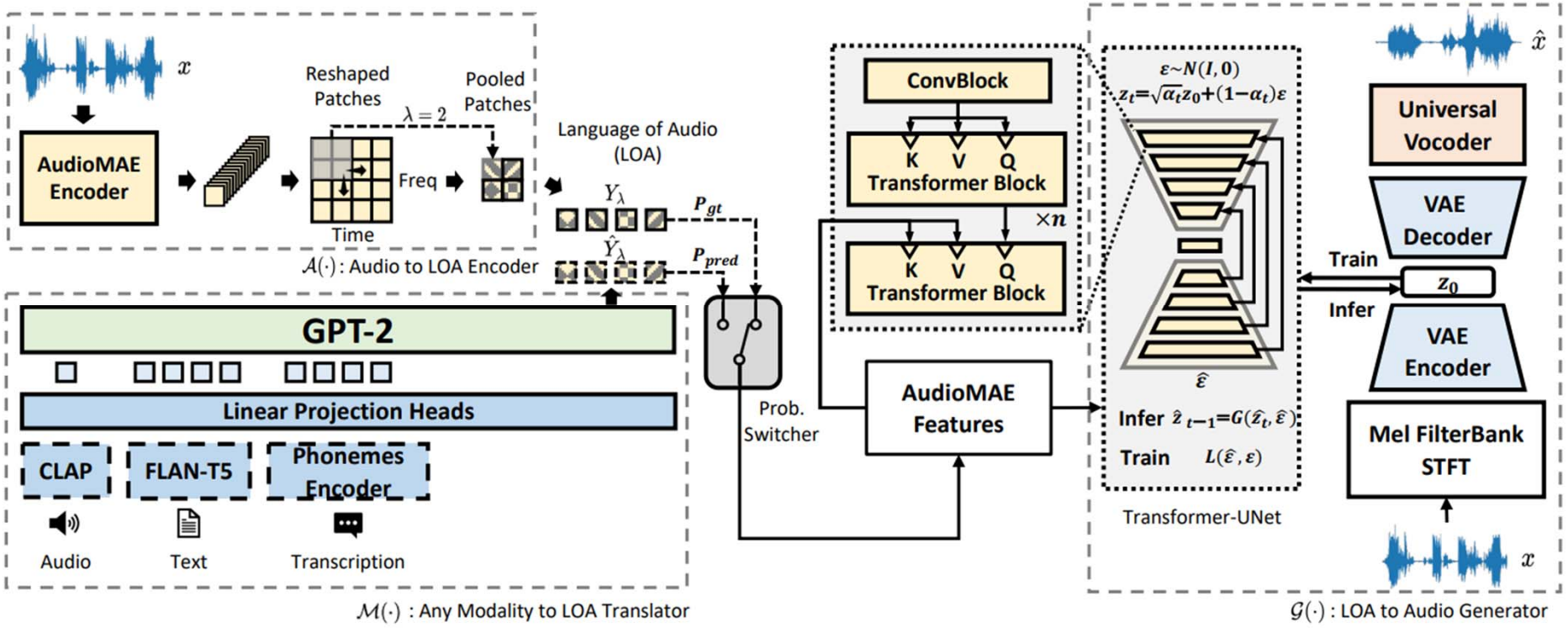
Outline

- Diffusion models
- **Diffusion-based Text-to-music Generation**
- Music ControlNet & MuseControlLite

AudioLDM2

https://github.com/haoheliu/AudioLDM2

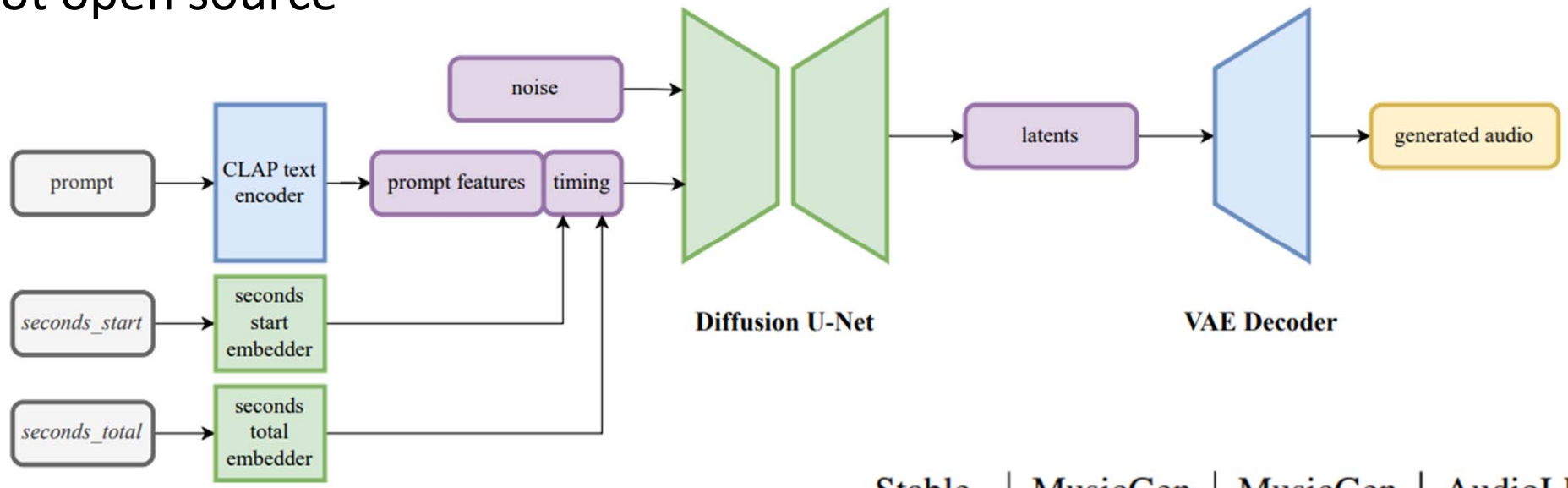
- Open source!
- Latent diffusion + Transformer U-Net



Ref: Liu et al, "AudioLDM 2: Learning holistic audio generation with self-supervised pretraining," TASLP 2024

Stable Audio

- Not open source



	Stable Audio	MusicGen large	MusicGen stereo	AudioLDM2 48kHz
Audio Quality	**3.0**±0.7	2.1±0.9	2.8±0.7	1.2±0.5
Text Alignment	**2.9**±0.8	2.4±0.9	2.4±0.9	1.3±0.6
Musicality	**2.7**±0.9	2.0±0.9	**2.7**±0.9	1.5±0.7

Ref: Evans et al, "Fast timing-conditioned latent audio diffusion," ICML 2024

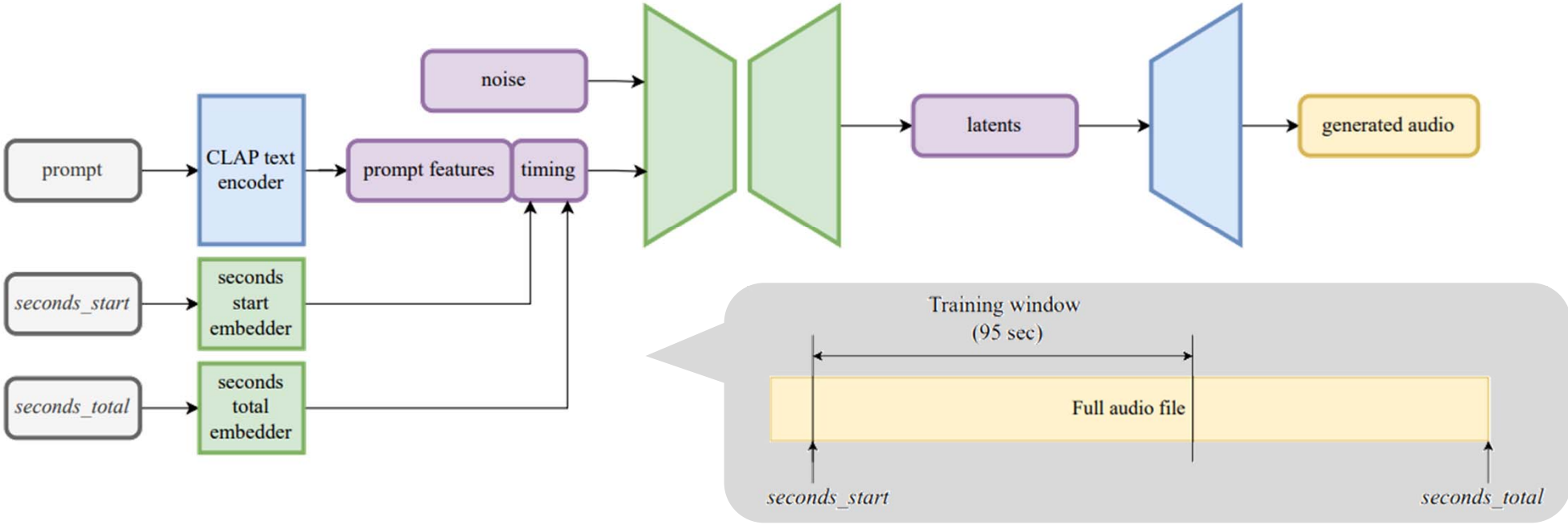
Stable Audio

- Better latent representation
  - based on **DAC** but no VQ
    - “To allow for arbitrary-length audio encoding and decoding, we use a fully-convolutional architecture (133M parameters) that follows the Descript Audio Codec (Kumar et al., 2023) encoder and decoder (without the quantizer). We found that the **Snake activations** (Ziyin et al., 2020) in the Descript Audio Codec architecture improved audio reconstruction at high compression ratios compared to alternatives such as EnCodec (Défossez et al., 2022), at the expense of increased VRAM consumption.”
  - **sequence of latents**: maps a 2×L input into 64× (L/1024) latents
    - “The VAE is trained from scratch on our dataset and downsamples the input stereo audio sequence **by a factor of 1024**, with the resulting latent sequence having a **channel dimension of 64**.”
- Diffusion model
  - **U-Net** with 4 levels of down/upsampling, residual conv layers, self/cross-attention

Ref: Evans et al, “Fast timing-conditioned latent audio diffusion,” ICML 2024

Stable Audio

- Conditioning
  - CLAP as the text encoder
  - **Timing embeddings:** `seconds_start` & `seconds_total` (for both training/inference)
    - represented as sinusoidal embeddings
    - this method allows the user generating **variable-length** music and sound effects



Stable Audio

	channels/sr	output length	$FD_{openl3} \downarrow$	$KL_{passt} \downarrow$	$CLAP_{score} \uparrow$	inference time
Training data (upper bound)	2/44.1kHz	full songs	101.47	-	-	-
Autoencoded training data	2/44.1kHz	full songs	117.52	-	-	-
Stable Audio w/ $CLAP_{ours}$	2/44.1kHz	23 sec	<u>118.09</u>	<u>0.97</u>	<u>0.44</u>	4 sec
Stable Audio w/ $CLAP_{LAION}$	2/44.1kHz	23 sec	123.30	1.09	0.43	4 sec
Stable Audio w/ T5	2/44.1kHz	23 sec	126.93	1.06	0.41	4 sec
AudioLDM2-music	1/16kHz	95 sec	354.05	1.53	0.30	38 sec
AudioLDM2-large	1/16kHz	95 sec	339.25	1.46	0.30	37 sec
AudioLDM2-48kHz	1/**48kHz**	95 sec	299.47	2.77	0.22	242 sec
MusicGen-small	1/32kHz	95 sec	205.65	0.96	0.33	126 sec
MusicGen-large	1/32kHz	95 sec	197.12	0.85	0.36	242 sec
MusicGen-large-stereo	**2**/32kHz	95 sec	216.07	1.04	0.32	295 sec
Stable Audio	**2**/44.1kHz	95 sec	**108.69**	**0.80**	**0.46**	**8** sec

Ref: Evans et al, “Fast timing-conditioned latent audio diffusion,” ICML 2024

Stable Audio 2

- Not open source

	DiT	AE	CLAP	Total
Parameters	1.1B	157M	125M	1.3B

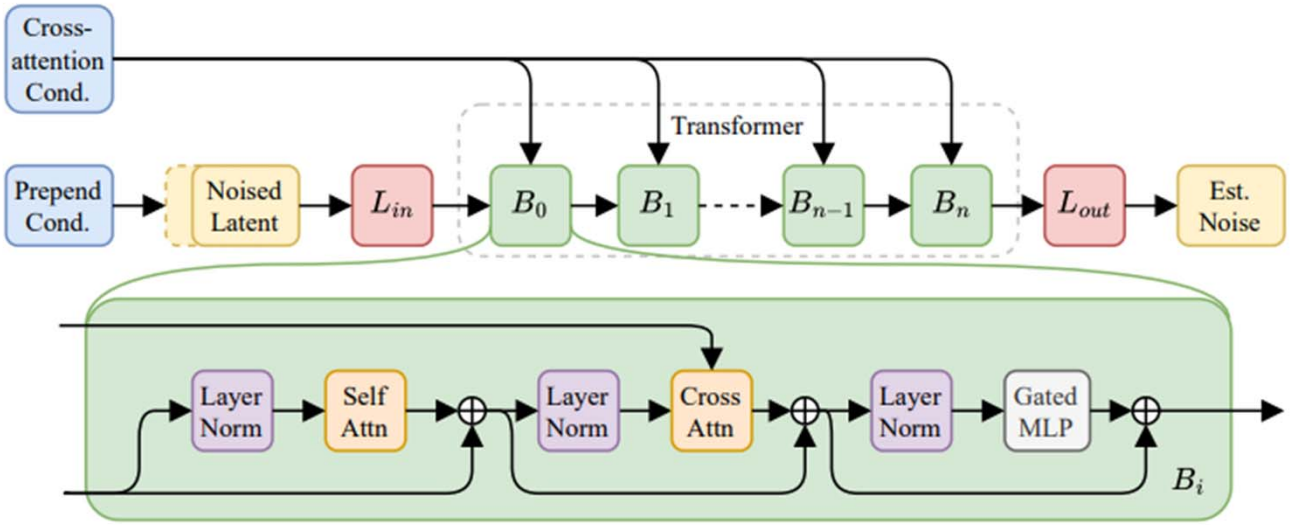
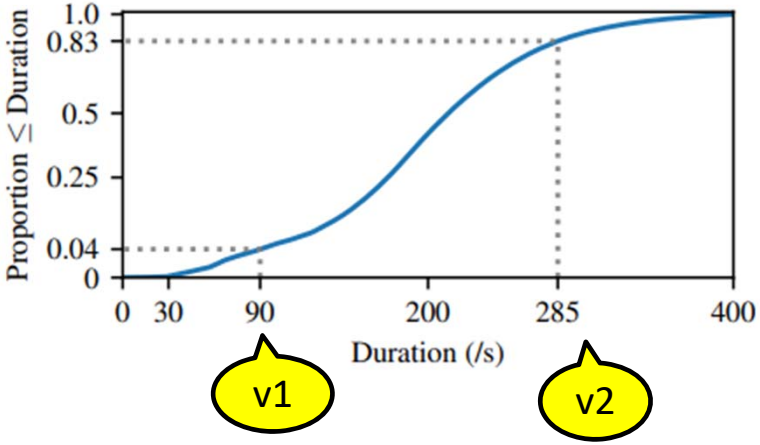


Figure 2: Architecture of the diffusion-transformer (DiT).



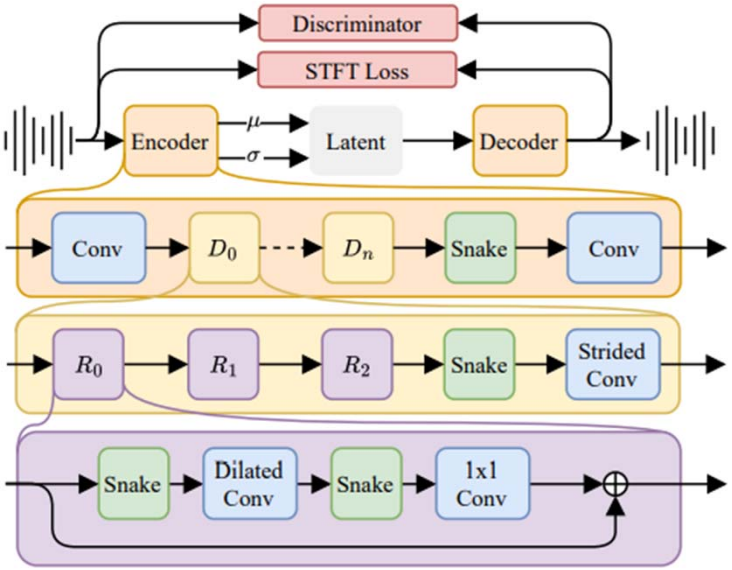


Figure 3: Architecture of the autoencoder.

Ref: Evans et al, “Long-form music generation with latent diffusion,” ISMIR 2024

Stable Audio 1 vs Stable Audio 2

- U-Net → DiT
- 95 seconds → up to 4m 45s
- Reduced latent rate (43 Hz → 21.5 Hz)

	sampling rate	STFT distance ↓	MEL distance ↓	SI-SDR ↑	latent rate	latent (channels)
DAC [23]	44.1kHz	0.96	0.52	10.83	86 Hz	discrete
AudioGen [24]	48kHz	1.17	0.64	9.27	50 Hz	discrete
Encodec [8, 22]	32kHz	1.82	1.12	5.33	50 Hz	discrete
AudioGen [24]	48kHz	1.10	0.64	8.82	100 Hz	continuous (32)
Stable Audio [14]	44.1kHz	1.19	0.67	8.62	43 Hz	continuous (64)
Ours	44.1kHz	1.19	0.71	7.14	21.5 Hz	continuous (64)

Stable Audio 2 vs MusicGen-large

	channels/sr	output length	$FD_{openl3} \downarrow$	$KL_{passt} \downarrow$	$CLAP_{score} \uparrow$	inference time
MusicGen-large-stereo [8]	2/32kHz	2m	204.03	0.49	0.28	6m 38s
Ours (fully-trained)	2/44.1kHz	2m†	79.09	0.35	0.40	13s
MusicGen-large-stereo [8]	2/32kHz	4m 45s	218.02	0.50	0.27	12m 53s
Ours (fully-trained)	2/44.1kHz	4m 45s	81.96	0.34	0.39	13s

Results with the fully-trained model:	2m long			4m 45s long	
	Stable Audio 2	MusicGen-large-stereo	ground truth	Stable Audio 2	MusicGen-large-stereo
Audio Quality	4.0±0.6	2.8±0.8	4.6±0.4	4.5±0.4	2.8±0.8
Text Alignment	4.3±0.7	3.1±0.8	4.6±0.5	4.6±0.4	2.9±1.0
Structure	3.5±1.3	2.4±0.7	4.3±0.8	4.0±1.0	2.1±0.7
Musicality	4.0±0.8	2.7±0.9	4.6±0.5	4.3±0.7	2.6±0.7
Stereo correctness	96%	61%	96%	100%	57%

Stable Audio Open

https://stability-ai.github.io/stable-audio-open-demo/

- Open source!
  - trained on data from Freesound and FMA (about 500K recordings; or 7,300 h)
  - all licensed under CC-0, CC-BY, or CC-Sampling+

	channels/sr	output length	$FD_{openl3} \downarrow$	$KL_{passt} \downarrow$	$CLAP_{score} \uparrow$
MusicGen-large-stereo [8]	2/32kHz	47	190.47	0.52	0.31
Stable Audio 1.0 [5]	2/44.1kHz	95 sec †	142.50	0.40	0.38
Stable Audio 2.0 [6]	2/44.1kHz	190 sec †	**71.25**	**0.37**	**0.42**
Stable Audio 2.0 [6]	2/44.1kHz	285 sec †	81.05	0.39	0.42
Stable Audio Open	2/44.1kHz	47	96.51	0.55	0.41

Ref: Evans et al, “Stable Audio Open,” arXiv 2024

Stable Audio Open

- Sequence length **47 sec**
  - It's actually a sequence of 1024 latents (47×21.5)
- T5 as the text encoder
- DiT-based denoiser

	sampling rate	STFT distance ↓	MEL distance ↓	SI-SDR ↑	latent rate	latent (channels)
DAC [21]	44.1kHz	0.96	0.53	11.30	86Hz	discrete
AudioGen [20]	48kHz	1.16	0.66	9.64	50Hz	discrete
Encodec [22, 8]	32kHz	1.70	1.09	5.75	50Hz	discrete
AudioGen [20]	48kHz	1.10	0.65	9.21	100Hz	continuous (32)
Stable Audio 1.0 [5]	44.1kHz	1.20	0.67	9.12	43Hz	continuous (64)
Stable Audio 2.0 [6]	44.1kHz	**1.21**	**0.72**	**7.65**	21.5Hz	continuous (64)
Ours	44.1kHz	1.29	0.77	6.28	21.5Hz	continuous (64)

Ref: Evans et al, "Stable Audio Open," arXiv 2024

Stable Audio Tools

https://github.com/Stability-AI/stable-audio-tools

Start training

To start a training run, run the `train.py` script in the repo root with:

```
$ python3 ./train.py --dataset-config /path/to/dataset/config --model-config /path/to/model/config --na
```

Fine-tuning

Fine-tuning a model involves continuning a training run from a pre-trained checkpoint.

To continue a training run from a wrapped model checkpoint, you can pass in the checkpoint path to `train.py` with the `--ckpt-path` flag.

To start a fresh training run using a pre-trained unwrapped model, you can pass in the unwrapped checkpoint to `train.py` with the `--pretrained-ckpt-path` flag.

Stable Audio Tools

https://github.com/Stability-AI/stable-audio-tools

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Stable Audio Open Small

https://stability.ai/news/stability-ai-and-arm-release-stable-audio-open-small-enabling-real-world-deployment-for-on-device-audio-control

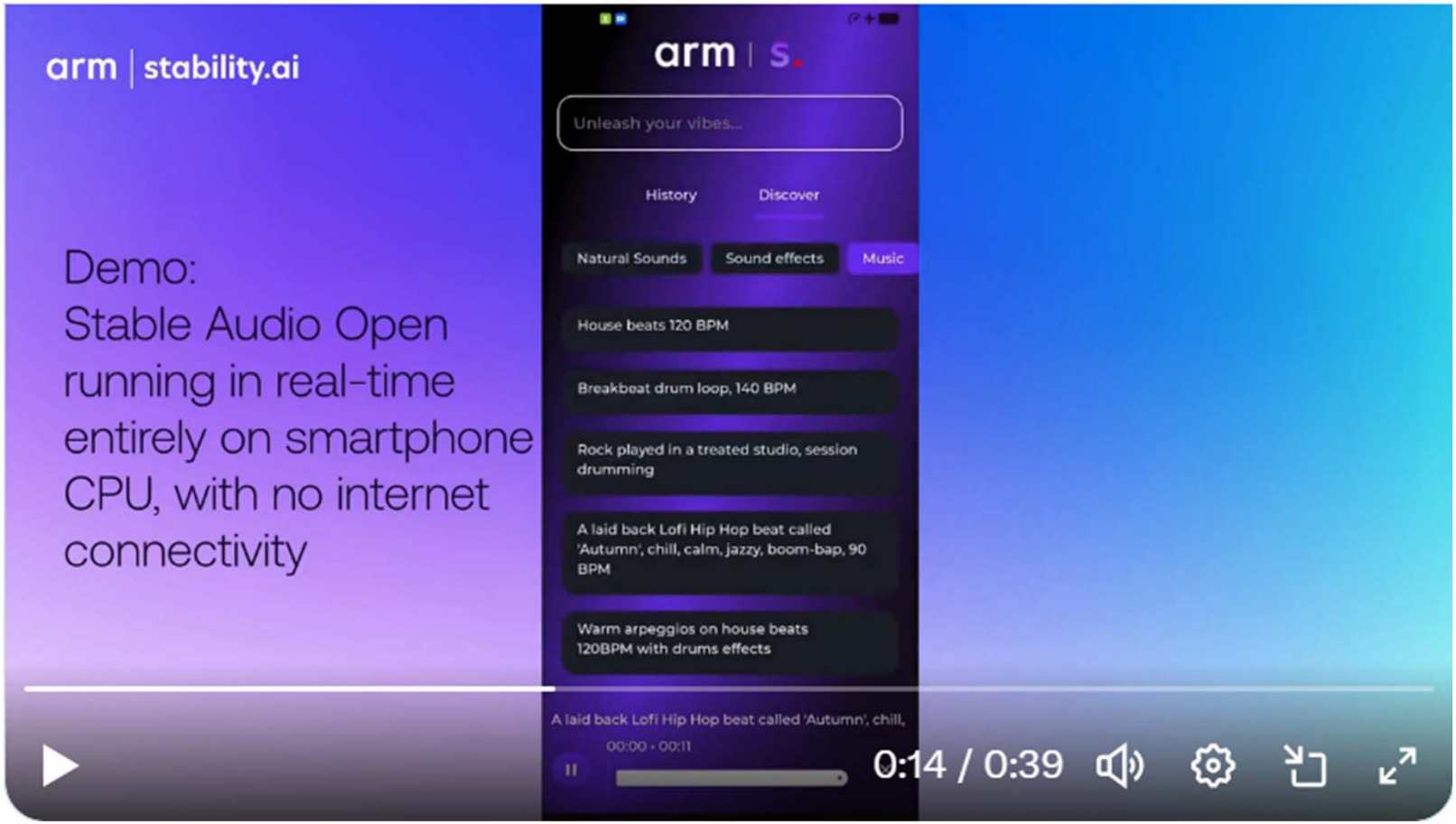
2025年5月14日

Key Takeaways:

- We're open-sourcing Stable Audio Open Small, a 341 million parameter text-to-audio model optimized to run entirely on Arm CPUs. Designed for quickly generating short audio samples, it can produce up to 11 seconds of audio on a smartphone in less than 8 seconds.
- This release builds on our collaboration with Arm to bring generative audio creation to smartphones, following our recent announcement at Mobile World Congress.

Stable Audio Open Small: On-Device Generation

https://x.com/zacknovack/status/1896602380244054168



Stable Audio 2.5

https://stability.ai/news/stability-ai-introduces-stable-audio-25-the-first-audio-model-built-for-enterprise-sound-production-at-scale

2025年9月10日

Key Takeaways:

- We're launching Stable Audio 2.5, the first audio generation model designed specifically for enterprise-grade sound production.
- Stable Audio 2.5 is purpose-built for this challenge of creating customizable, high-quality audio at scale. That includes elevated musical composition, fast inference at less than two seconds on a GPU, and support for more control with audio inpainting.
- You can try Stable Audio 2.5 now at StableAudio.com or seamlessly deploy through the Stability AI API; partner platforms such as fal, Replicate, and ComfyUI; and on-premises with an enterprise license.

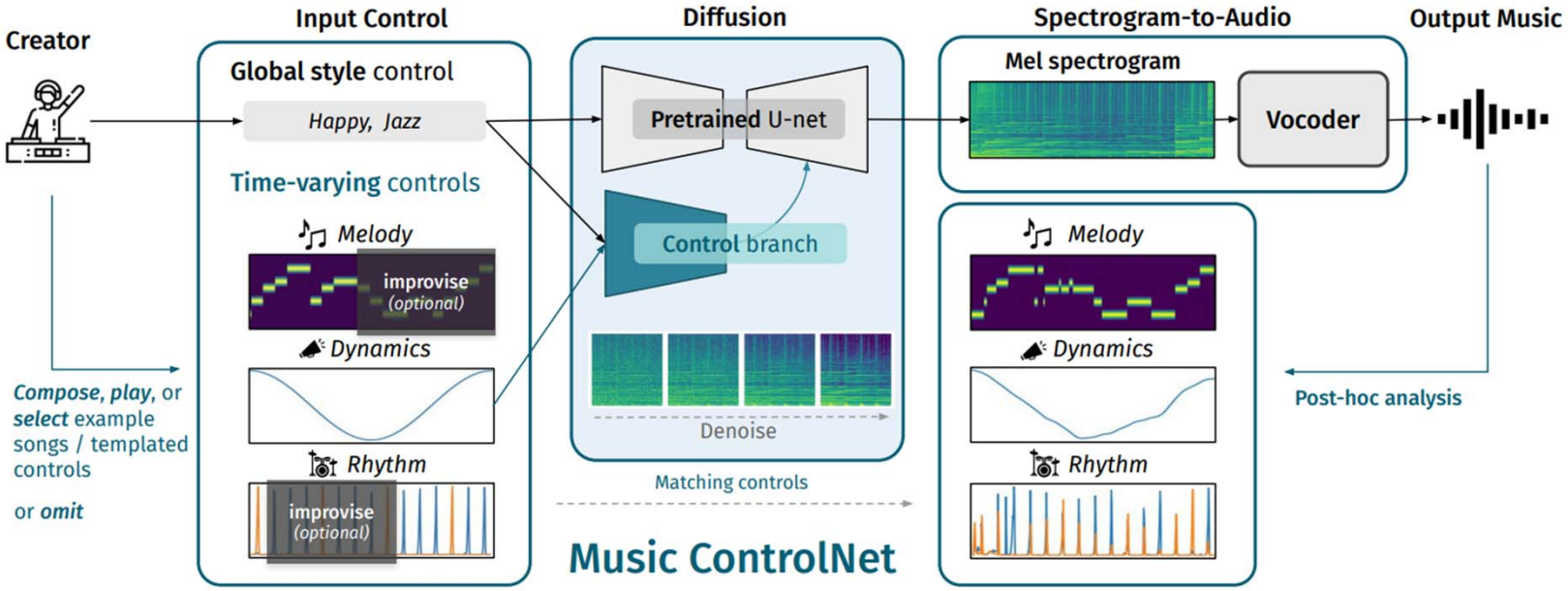
Outline

- Diffusion models
- Diffusion-based Text-to-music Generation
- **Music ControlNet & MuseControlLite**

Music ControlNet (for Attribute Control)

https://musiccontrolnet.github.io/web/

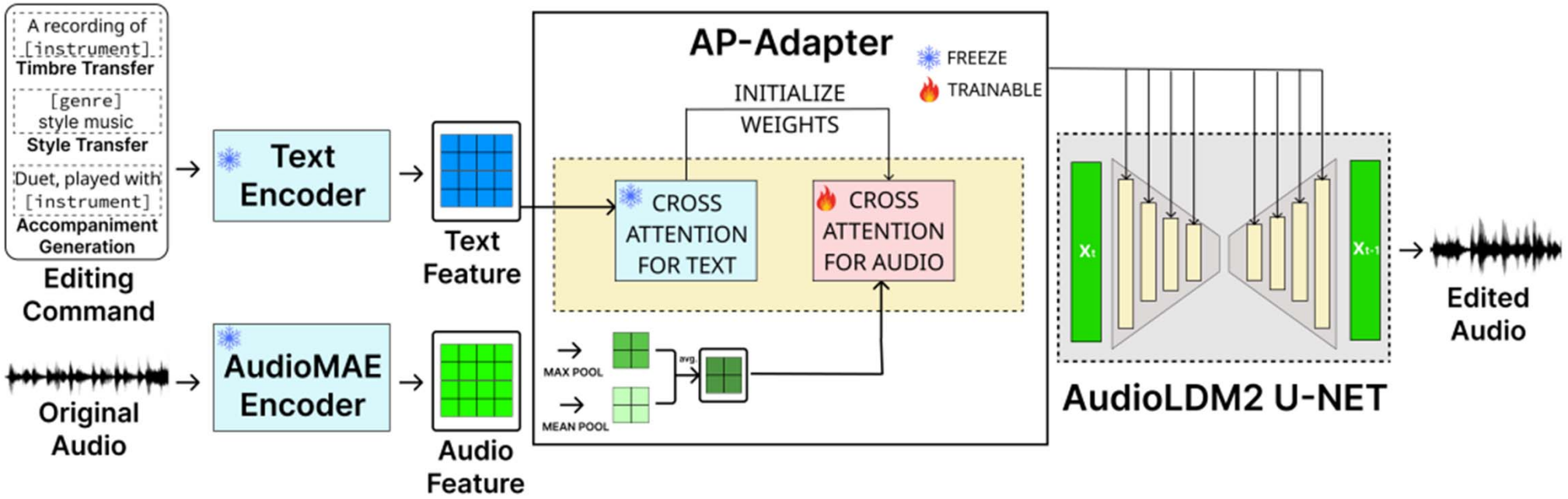
- Work in the “pixel” domain
- Not open source



Ref: Wu et al, “Music ControlNet: Multiple time-varying controls for music generation,” TASLP 2024

AP-Adapter (for Text+Audio Control)

https://young-almond-689.notion.site/Audio-Prompt-Adapter-Unleashing-Music-Editing-Abilities-For-Text-To-Music-with-Lightweight-Finetuni-fbbfeb0608664f61a6bf894d56e85820



Ref: Tsai et al, “Audio Prompt Adapter: Unleashing music editing abilities for text-to-music with lightweight finetuning,” ISMIR 2024

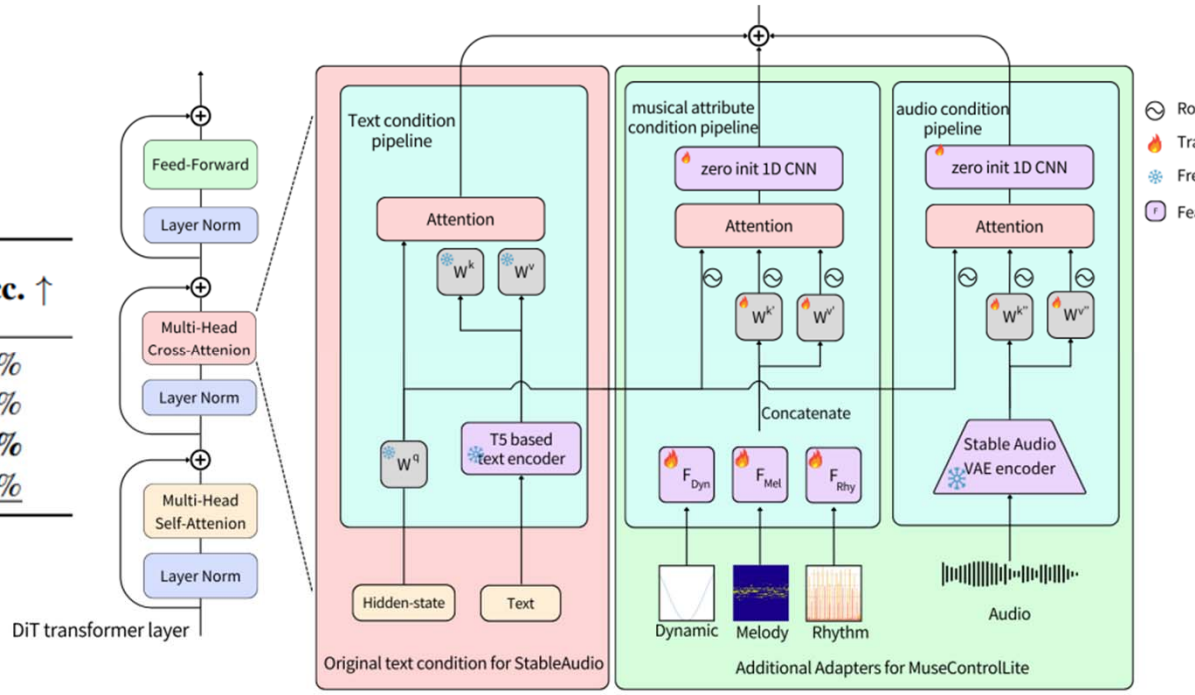
MusicControlLite (for Attribute & Audio Control)

https://musecontrollite.github.io/web/

https://colab.research.google.com/drive/1rR-Ncng_gSeb6hX0LY20SA4O9RCF-ZF3

- Latent diffusion
- Open source

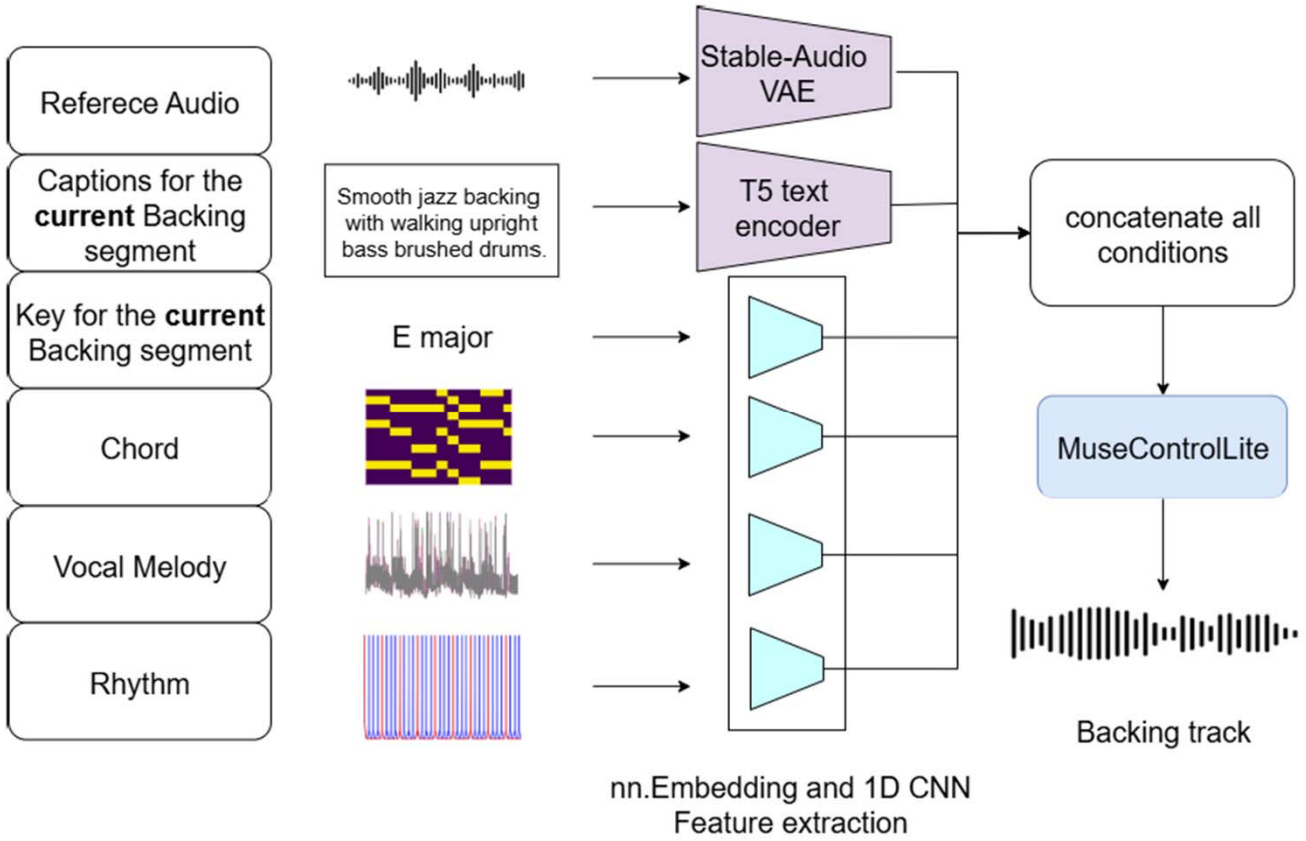
Model	FD ↓	KL ↓	CLAP ↑	Mel acc. ↑
MusicGen-Stereo-Large-Melody	193.66	0.436	0.354	43.1%
Stable Audio Open ControlNet	97.73	**0.265**	**0.396**	56.6%
Ours (MuseControlLite-Melody)	**76.42**	0.289	0.372	**61.1%**
Ours (MuseControlLite-Attr)	80.79	0.271	0.373	60.6%



Ref: Tsai et al, "MuseControlLite: Multifunctional music generation with lightweight conditioners," ICML 2025

MusicControlLite (for Singing Accompaniment Generation)

https://musecontrollite.github.io/web/



Ref: Tsai et al, “Demonstrating singing accompaniment capabilities for MuseControlLite,” AI4music Workshop 2025