# Accelerating Stable Diffusion-based Video Generation

程煜格 22/08/2024

# Accelerating Stable Diffusion-based Video Generation

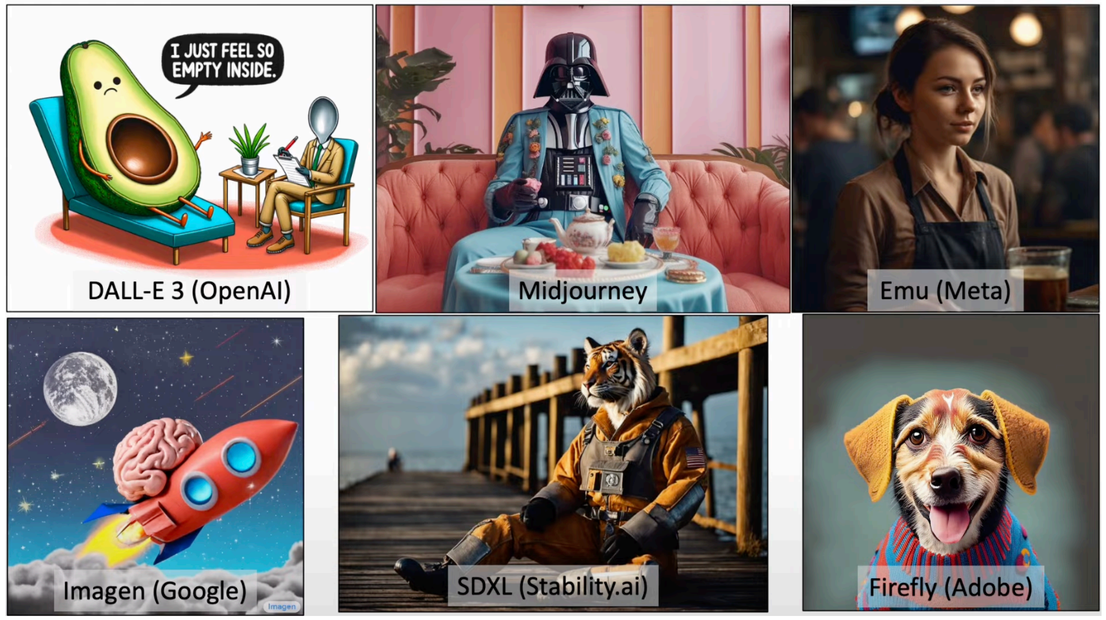
## Outlines

- Foundations - diffusion model & stable diffusion
- **Accelerations**
  - (ISCA’24) Cambricon-D: Full-Network Differential Acceleration for Diffusion Models
  - (CVPR’24) DeepCache: Accelerating Diffusion Models for Free
- Open-sourced video generation models
  - Open-sora: spatial and temporal attention

# Foundations

## Diffusion models

- What can diffusion models do?
  - Image generation




  - Video generation

“A flock of paper airplanes flutters through a dense jungle, weaving around trees as if they were migrating birds. ”

  - And more!

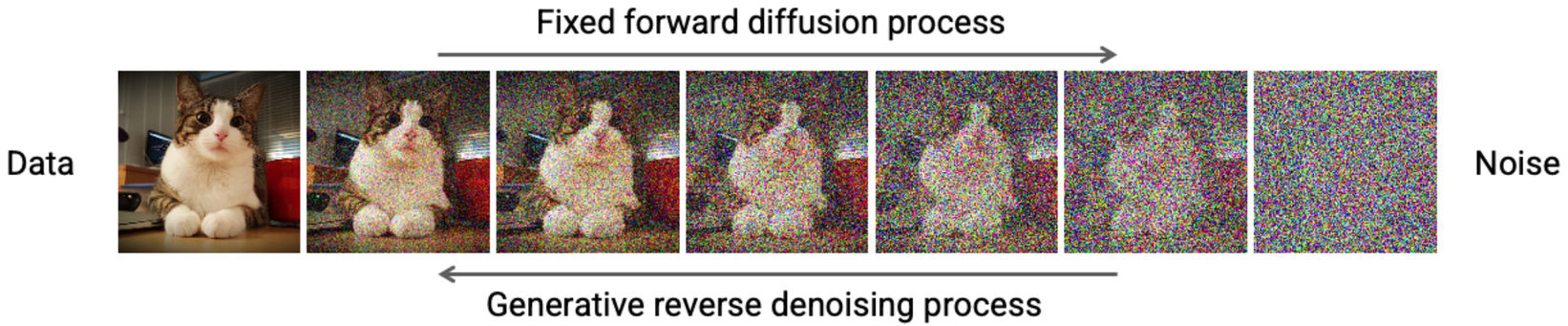
https://openai.com/index/sora/

# Foundations

## Diffusion models

Diffusion models consist of two processes:

- **Forward** diffusion process that gradually adds noise to input
- **Reverse** denoising process that learns to generate data by denoising

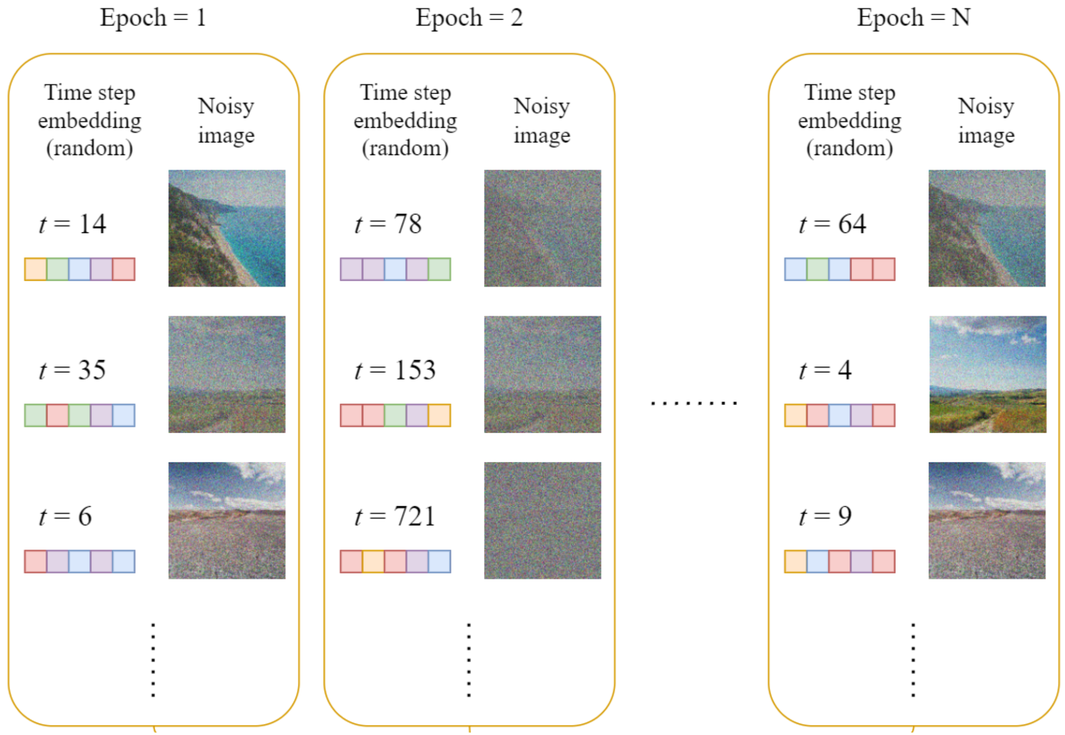


# Foundations

## Diffusion models

**1. Forward process (training)**: **predicts the noise**, given the current timestep **t** and image **Xt**

Each diffusion step is called a *timestep*.



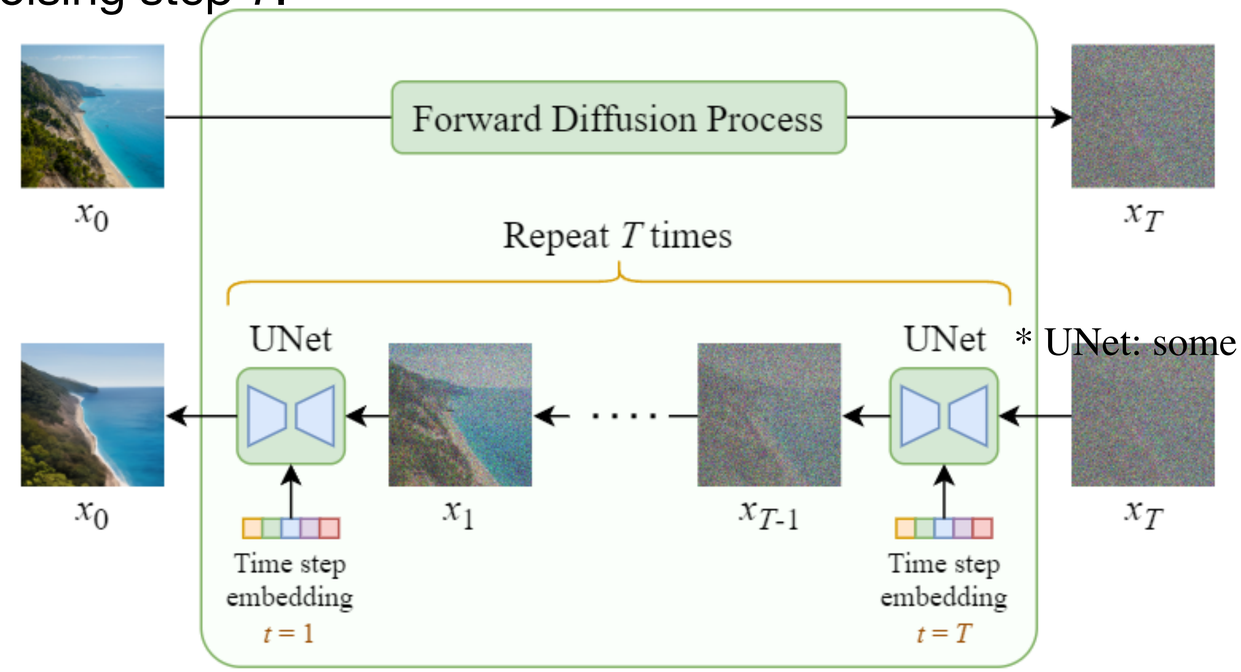

https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

# Foundations

## Diffusion models

**2. Backward process (inferencing)**: denoises step-by-step to **generate samples**, given the pure noise **$x_T$**

First define the total denoising step $T$.



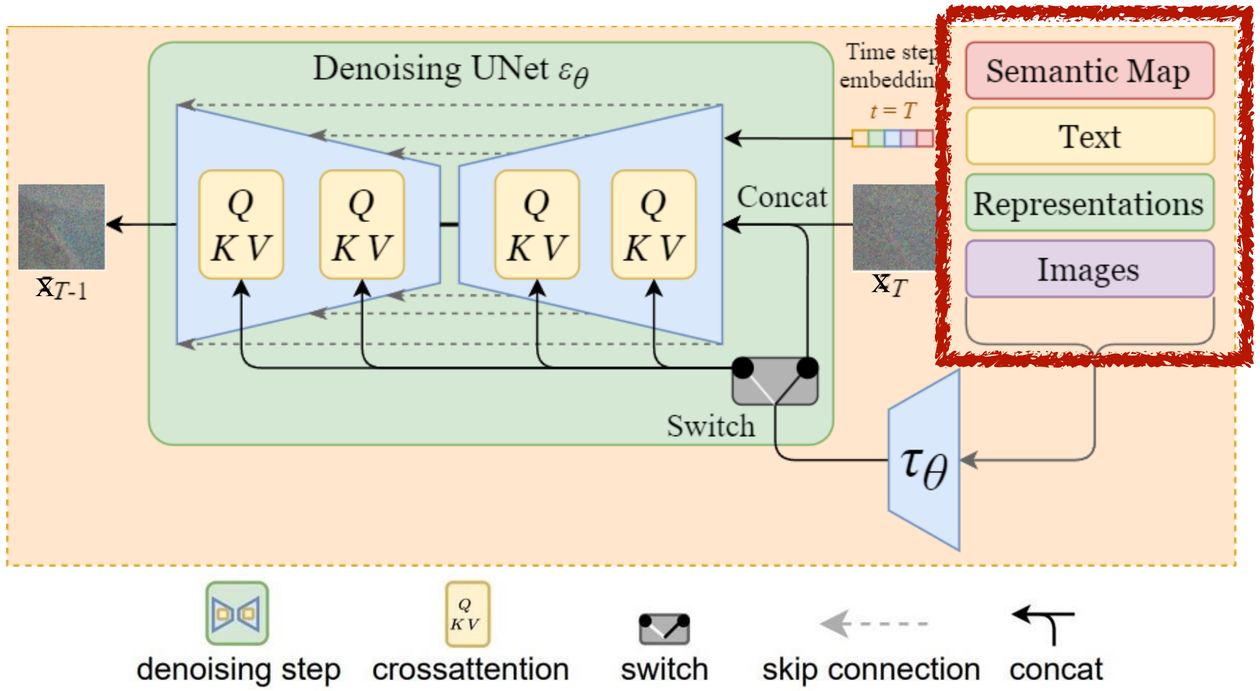

* UNet: some Convolutional Neural Networks (CNN)

https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

# Foundations

## Diffusion models

Conditioning




e.g. “A smiling cat.”

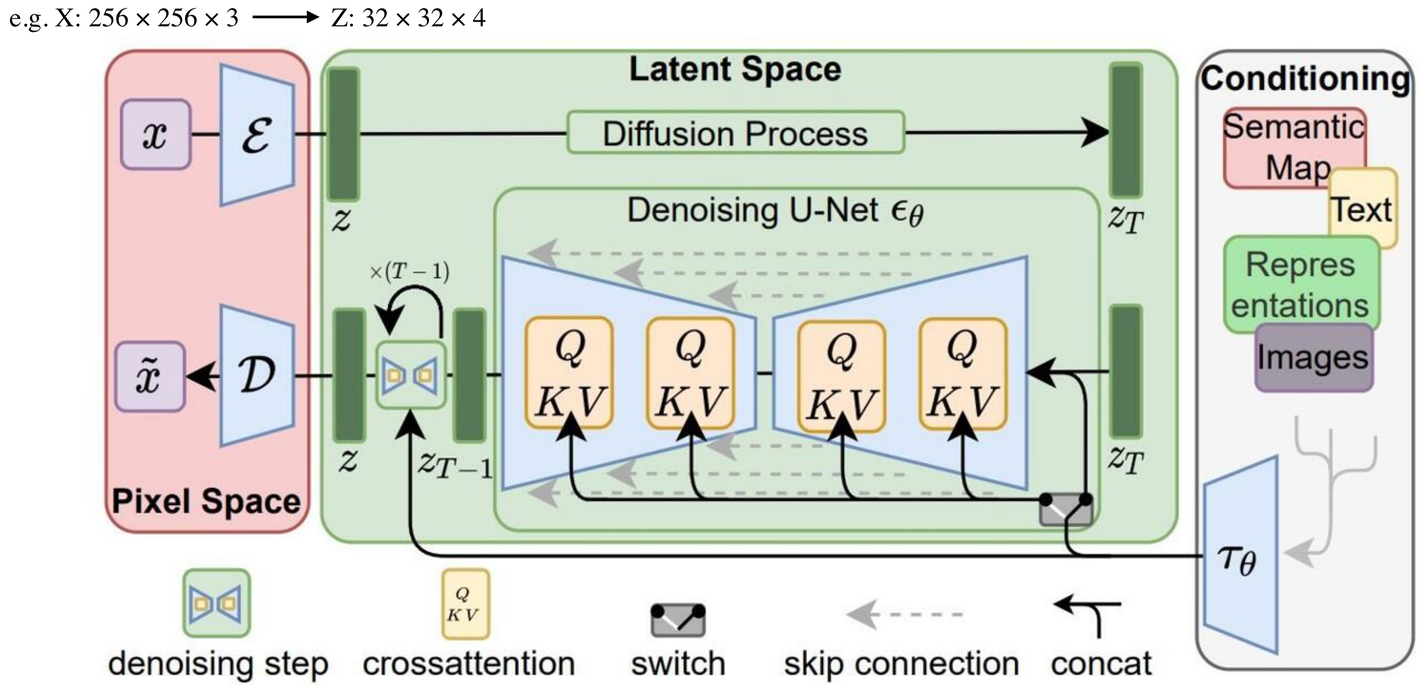


https://cvpr2022-tutorial-diffusion-models.github.io/

# Foundations

## Stable Diffusion / Latent Diffusion Models

The diffusion process happens within the **latent space (a lower-dimensional representation of data).**

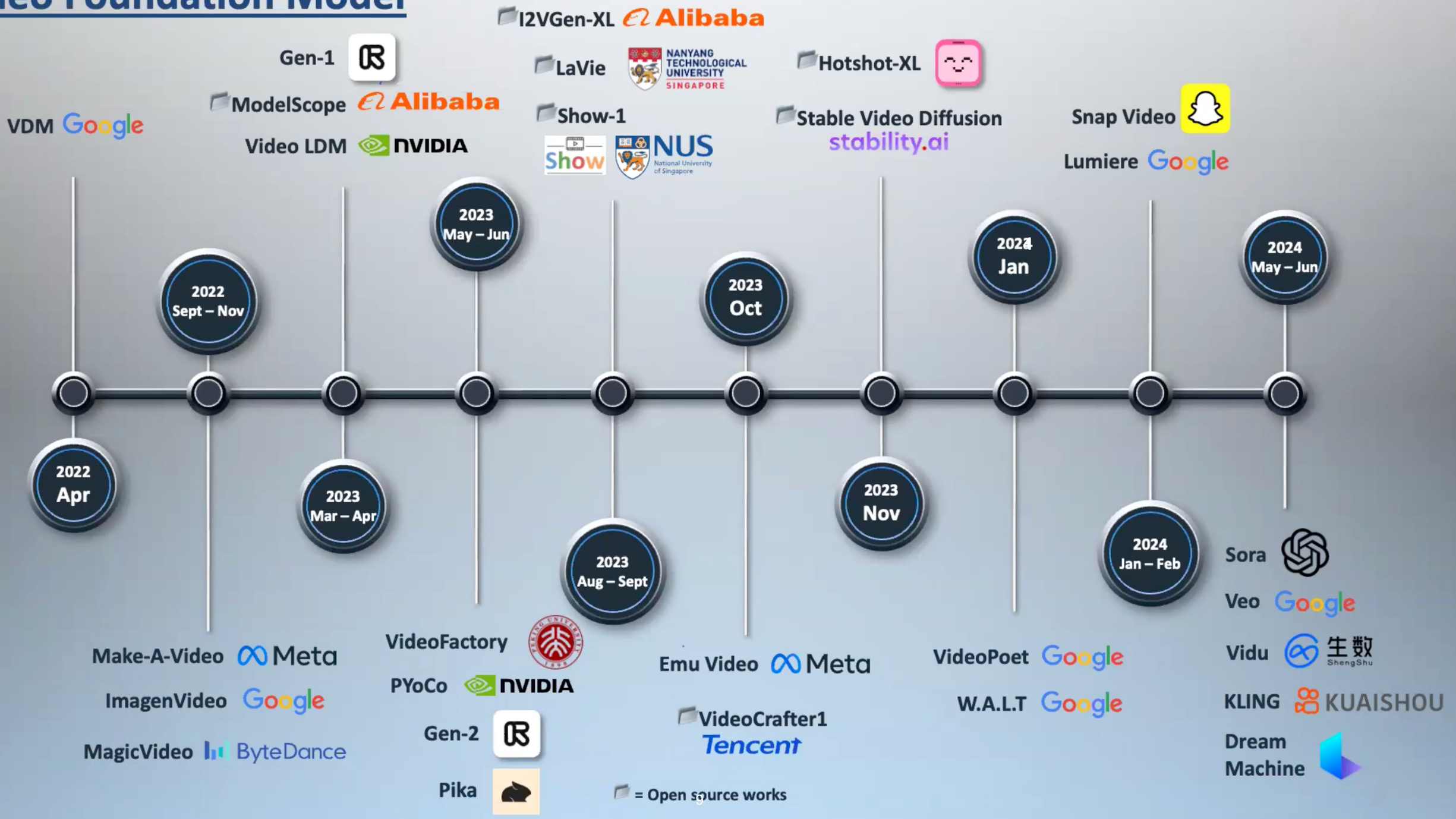



Everything else stays the same :D



https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

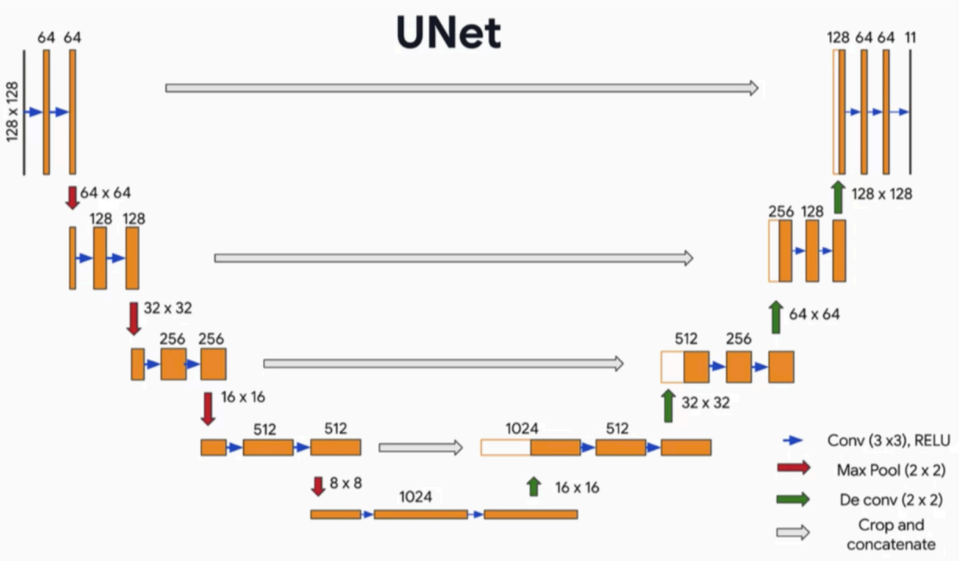
# Video Foundation Model



# Overview

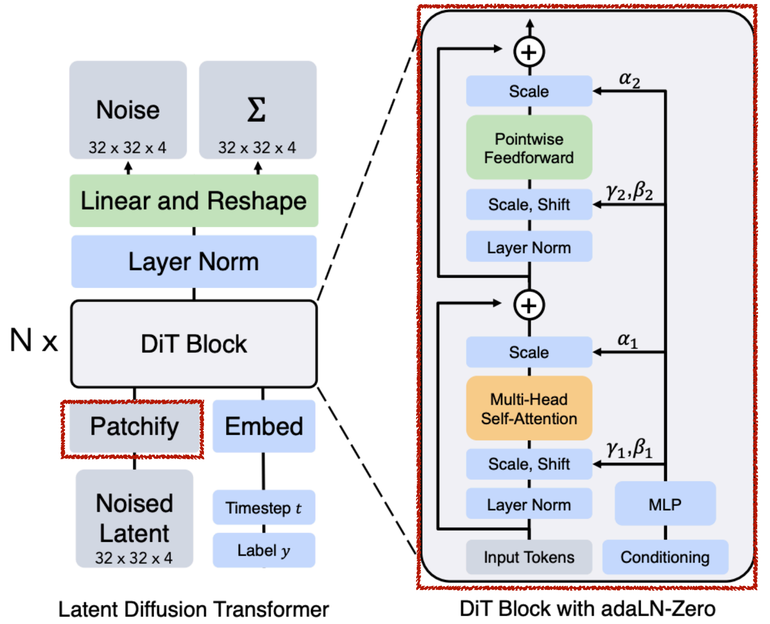
## Stable diffusion models evolution

- Two main backbones used




The diffusion process is performed **on image latent**.

**Transformer**




The diffusion process is performed **on image latent tokens**.

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**Observation**: input data is slightly altered across timesteps.

Therefore, the iterative process of diffusion models implies a remarkable computational redundancy.

(a) (b) (c)

Example of two images in neighboring timesteps and their delta. Pixels with no difference are grey (128,128,128).

Kong, Weihao, et al. "Cambricon-D: Full-Network Differential Acceleration for Diffusion Models." *2024 ACM/IEEE 51st Annual International Symposium on Computer Architecture (ISCA)*. IEEE, 2024.

# Acceleration of Diffusion Models Inference

## Cambricon-D

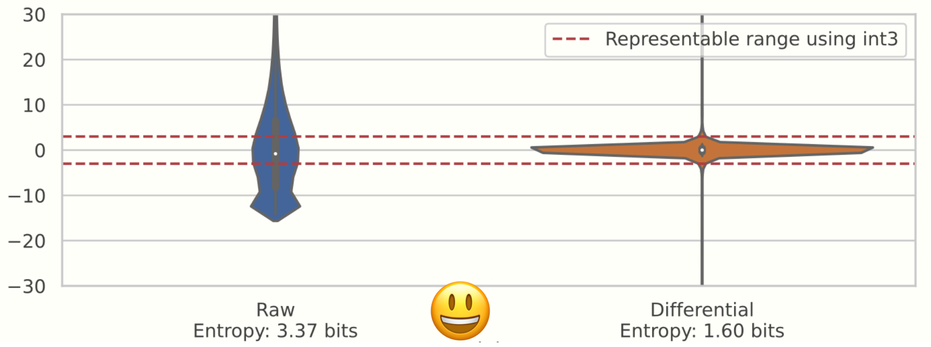
full-network differential acceleration with concise memory access

**Observation**: input data is slightly altered across timesteps.

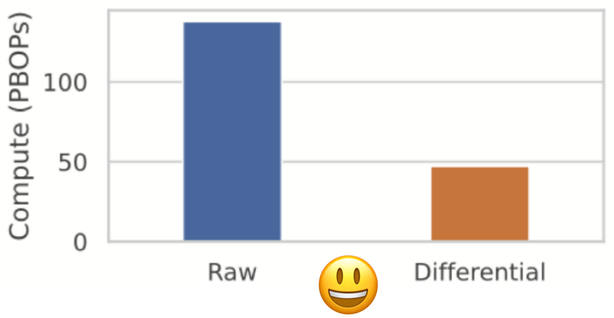
Therefore, the iterative process of diffusion models implies a remarkable computational redundancy.

**Differential computing**: focuses the computation on these input variations (aka. deltas).

- leveraging the narrower data range of deltas (compared to raw input) -> representation with fewer bits




Distributions and entropy of raw and delta input values for a typical layer. Raw activations often fall outside quantizable range.




Execution time reduction from using differential computing compared to raw valued computing.

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**Observation**: input data is slightly altered across timesteps.

Therefore, the iterative process of diffusion models implies a remarkable computational redundancy.

$$delta^t_{out} \neq f_{non-linear}(delta^t_{in})$$

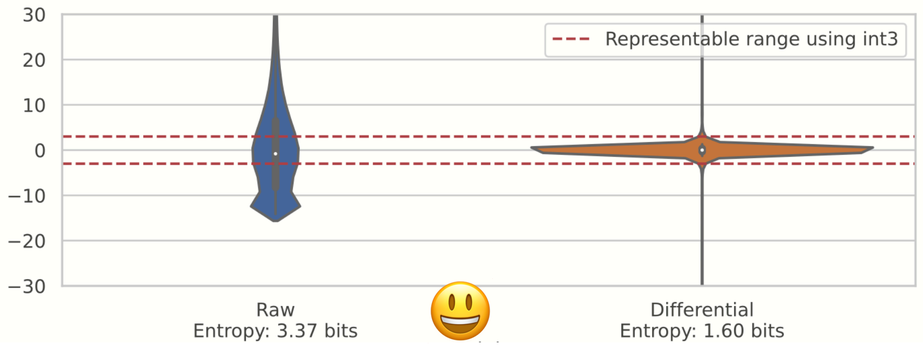
$$raw^t_{out} = f_{non-linear}(raw^{t-1}_{in} + delta^t_{in})$$

$$raw^t_{in}$$

**Differential computing**: focuses the computation on these input variations (aka. deltas).

- leveraging the narrower data range of deltas (compared to raw input) -> representation with fewer bits

$$delta^t_{out} = raw^t_{out} - raw^t_{in}$$

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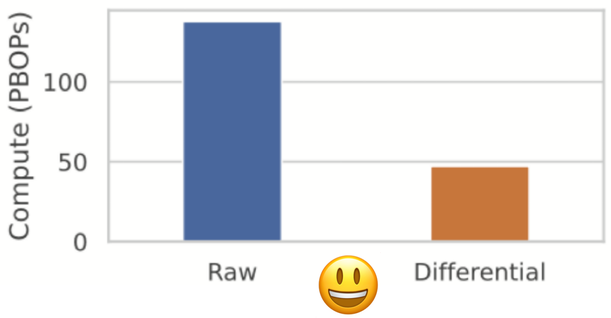
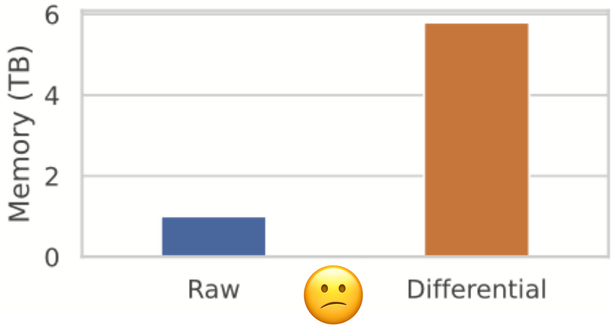



Execution time reduction from using differential computing compared to raw valued computing.




Memory traffic overhead from differential computing compared to raw valued computing.

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**Solutions**:

- a sign-mask dataflow, achieving an efficient *full-network* differential computation
- an outlier-aware PE array, dealing with delta outliers effectively

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**1. The sign-mask dataflow**

- Approximates the non-linear ReLU function **using the narrower delta values**

$\text{sgn}(Y_t) \approx \text{sgn}(Y_{t-1})$ because $\Delta Y_t$ is relatively small.

$$\text{ReLU}(Y_t) = \begin{cases} 0, & \text{if } Y_t < 0 \\ Y_t, & \text{if } Y_t \geq 0 \end{cases} = Y_t \cdot \text{sgn}(Y_t) \qquad (1)$$

$$\begin{aligned} \Delta Y'_t &= \text{ReLU}(Y_t) - \text{ReLU}(Y_{t-1}) \\ &= Y_t \cdot \text{sgn}(Y_t) - Y_{t-1} \cdot \text{sgn}(Y_{t-1}) \qquad (2) \\ &\approx \Delta Y_t \cdot \text{sgn}(Y_{t-1}) \qquad (3) \end{aligned}$$

$$\text{where} \quad Y_t := Y_{t-1} + \Delta Y_t.$$

- **Key insight: only read the sign bits of the tensor sgn(Y)** from the off-chip memory, instead of the entire raw tensor Y

# Acceleration of Diffusion Models Inference

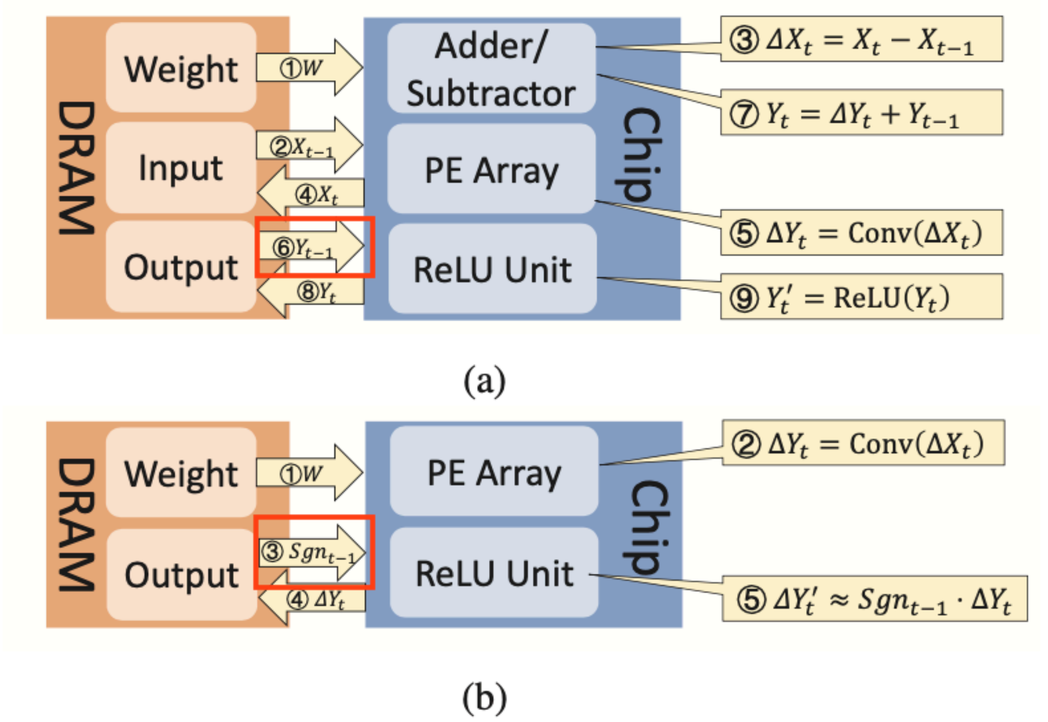
## Cambricon-D

full-network differential acceleration with concise memory access

**The sign-mask dataflow consists of mainly 5 steps:**

1) Load weights W
2) Compute tensor multiplication (using W and delta_X)
3) Load sign bits
4) Store output delta_Y
5) Compute ReLU with sign masking

A **full-network differential** methed!




Comparison of dataflows of Diffy (a) and the sign-mask dataflow of Cambricon-D (b).

Mahmoud, Mostafa, Kevin Siu, and Andreas Moshovos. "Diffy: A Déjà vu-free differential deep neural network accelerator." *2018 51st Annual IEEE/ACM International Symposium on Microarchitecture (MICRO)*. IEEE, 2018.

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**Accessing and Maintaining the Sign Bit**:

- Maintain a tensor of sign bits for each raw input tensor in a separate memory location in DRAM
- Update the sign bits tensor utilizing a **NDP (near-data-processing) engine**
  - read the raw input tensor and update the sign bits tensor in the off-chip memory devices

1. Fetching the entire raw input tensor on-chip
2. Adding deltas for the incremental update
3. Writing updated data tensor off-chip

**only transmit the deltas off-chip**

$$
\begin{aligned}
\Delta Y_t' &= \mathrm{ReLU}(Y_t) - \mathrm{ReLU}(Y_{t-1}) \\
&= Y_t \cdot \mathrm{sgn}(Y_t) - Y_{t-1} \cdot \mathrm{sgn}(Y_{t-1}) \\
&\approx \Delta Y_t \cdot \mathrm{sgn}(Y_{t-1})
\end{aligned}
$$

$$
\text{where} \quad Y_t := Y_{t-1} + \Delta Y_t.
$$

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**Differential computation of other operators:**

- Group normalization (non-linear) $\mathrm{GN}(G) = \frac{G - \mu_G}{\sqrt{\sigma_G^2 + \epsilon}}$
- Attention mechanism (non-linear) $\mathrm{Attn}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$
- The rest: residual connections, dropouts, upsampling, and downsampling. (linear)

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**2. The outlier-aware PE array**

- Outliers: delta values that overflow in the *fp-to-int* quantization
- PE array: processing elements that performs differential computing
- Problems
  - Increasing the bitwidth to incorporate all outliers is unrealistic
  - Throwing them away will also incur a significant precision penalty

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**2. The outlier-aware PE array**

- Solutions

  Each PE is a multiplier group. In each multiplier group,

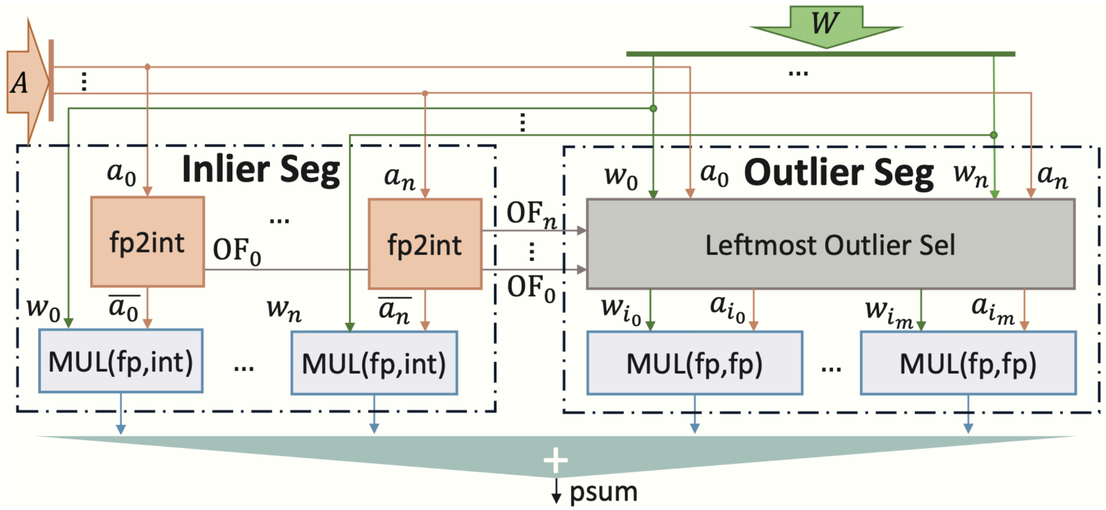
  1. n *int-and-fp* multipliers to multiply the **quantized inliers** with the **floating point weights**
  2. m *fp-and-fp* multipliers to multiply the **floating point outliers** with the **floating point weights**

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**2. The outlier-aware PE array**




Architecture details of a multiplier group in a PE.

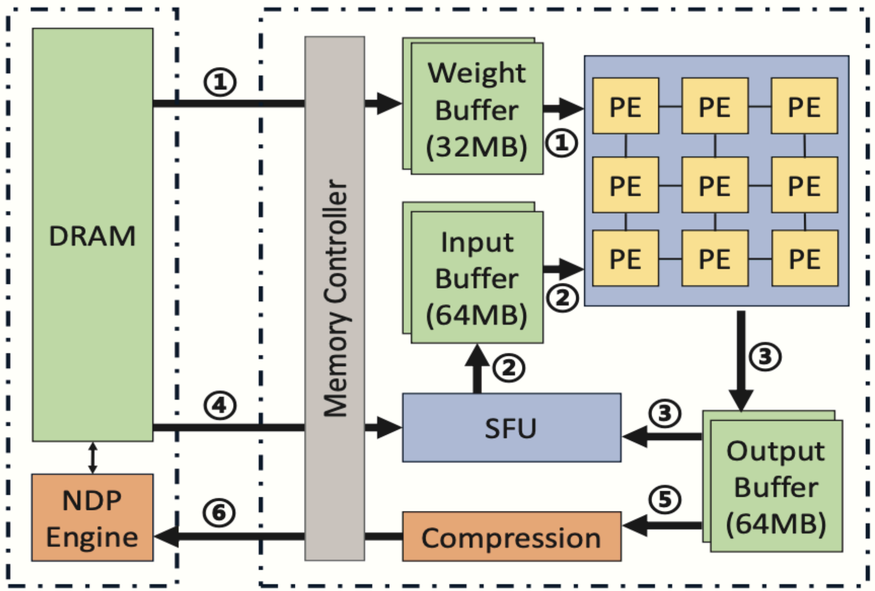
1) Each input delta (fp) is first attempted to be quantified into int.
2) Those who failed to quantize give a overflow flag (OF).
3) A leftmost outlier selection circuit gather the first m outliers according to OFs.

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**The overall architecture of Cambricon-D**




**The PE array**: differential computing.

**The SFU**: other functions besides the tensor multiplication (e.g. ReLU).

**The Compression Unit**: compresses the delta values before writing off-chip.

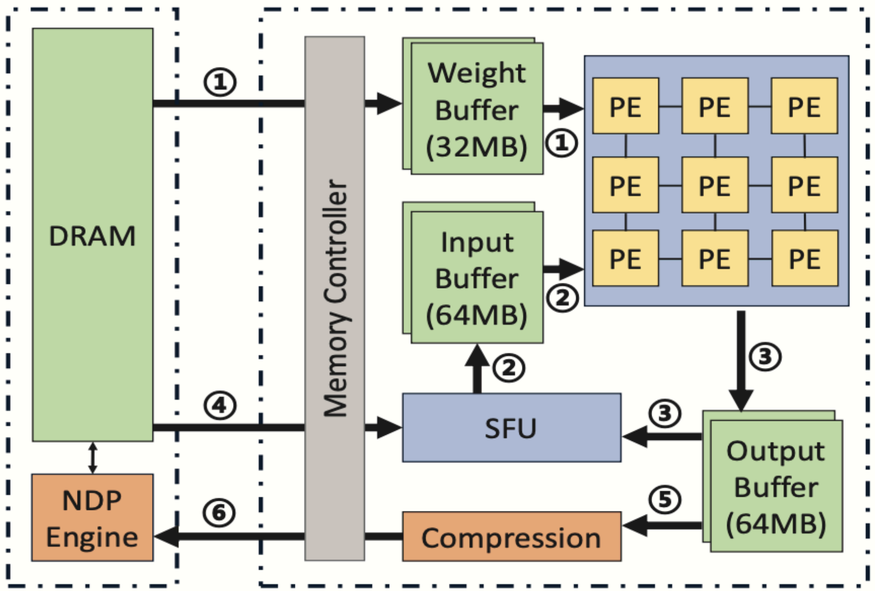
**The NDP engine** (on the DRAM side)

# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**The overall architecture of Cambricon-D**




**The dataflow of Cambricon-D of 6 kinds:**

1) Weights: DRAM -> on-chip buffer -> PE array
2) Input deltas: on-chip buffer -> PE array
3) Output deltas: PE array -> on-chip buffer -> SFU

**The PE array**: differential computing.

**The SFU**: other functions besides the tensor multiplication (e.g. ReLU).

**The Compression Unit**: compresses the delta values before writing off-chip.

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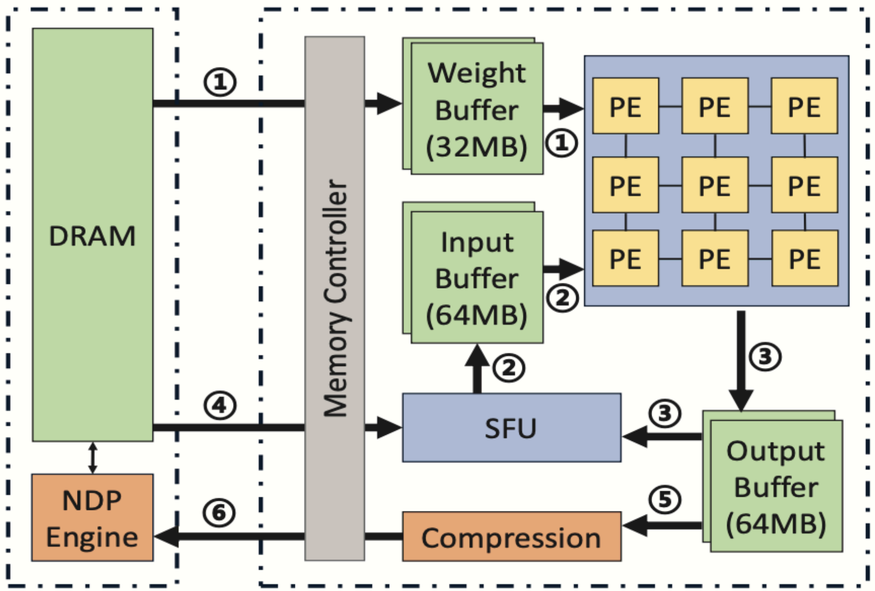
# Acceleration of Diffusion Models Inference

## Cambricon-D

full-network differential acceleration with concise memory access

**The overall architecture of Cambricon-D**




**The dataflow of Cambricon-D of 6 kinds:**

1) Weights: DRAM -> on-chip buffer -> PE array
2) Input deltas: on-chip buffer -> PE array
3) Output deltas: PE array -> on-chip buffer -> SFU
4) Sign bits: DRAM -> SFU
5) Output deltas: PE array -> on-chip buffer -> Compression
6) Compressed output deltas: Compression -> NDP Engine

**The PE array**: differential computing.

**The SFU**: other functions besides the tensor multiplication (e.g. ReLU).

**The Compression Unit**: compresses the delta values before writing off-chip.

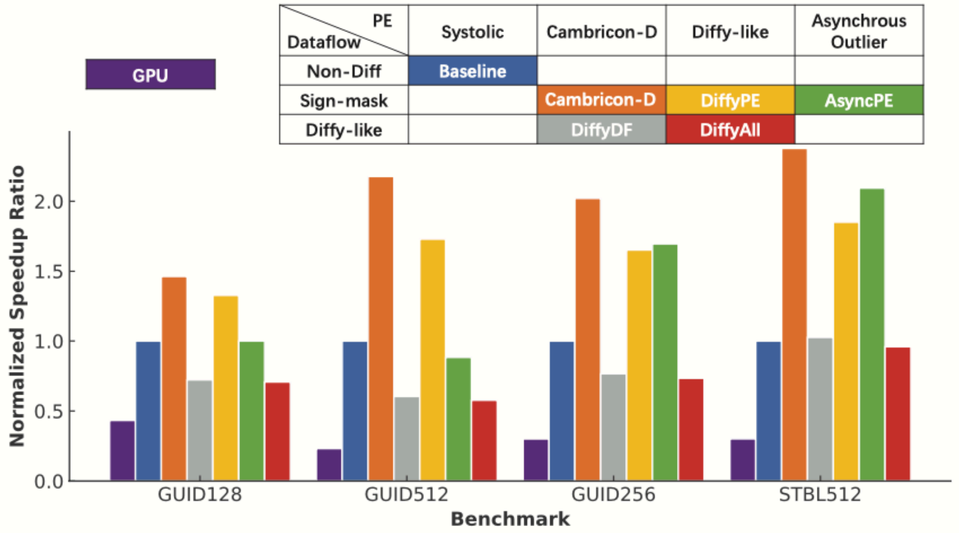
**The NDP engine** (on the DRAM side)

# Acceleration of Diffusion Models Inference

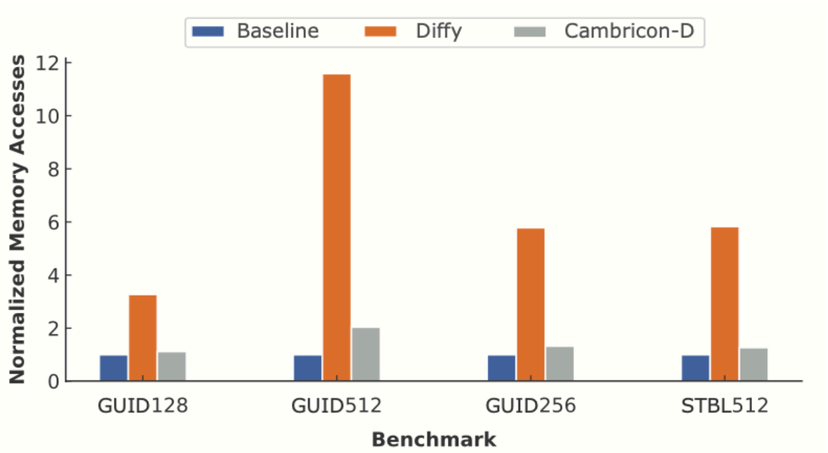
## Cambricon-D

full-network differential acceleration with concise memory access

- **Experiments**




Speedup of Cambricon-D compared with baseline as well as alternative designs.



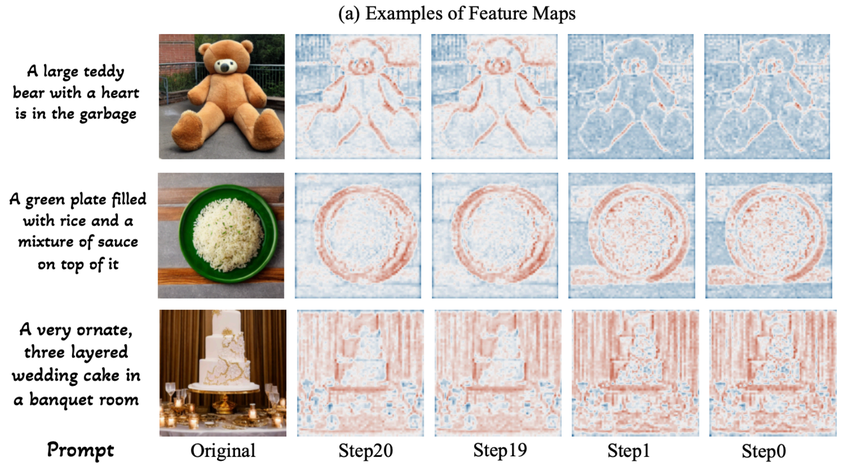

Total memory traffic of Cambricon-D compared with baseline as well as DiffyDF design.

# Acceleration of Diffusion Models Inference

## DeepCache

reduce the computational overhead at each denoising step without additional training

- **Feature redundancy in sequential denoising**
  Adjacent steps in the denoising process exhibit significant temporal similarity in high-level features.




Ma, Xinyin, Gongfan Fang, and Xinchao Wang. "Deepcache: Accelerating diffusion models for free." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2024.

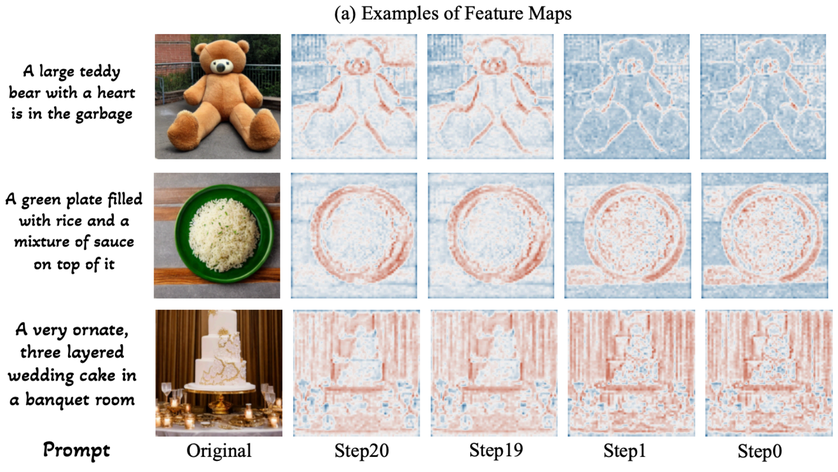
# Acceleration of Diffusion Models Inference

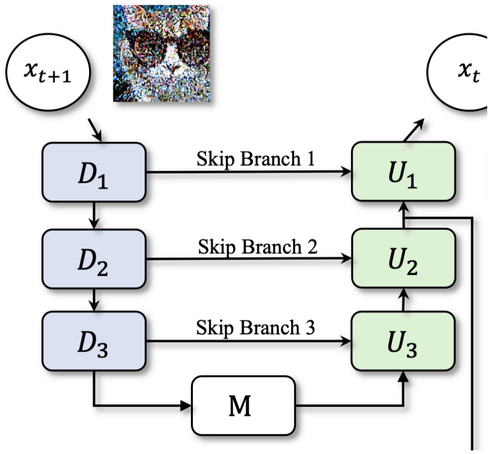
## DeepCache

reduce the computational overhead at each denoising step without additional training

- **Feature redundancy in sequential denoising**
  Adjacent steps in the denoising process exhibit significant temporal similarity in high-level features.

- **Leveraging the structural property of U-Net**
  i.e. a concatenation of :
  1) low-level features from the skip branch
  2) high-level features from the main branch



# Acceleration of Diffusion Models Inference

## DeepCache

reduce the computational overhead at each denoising step without additional training

At each denoising step:

- strategically **cache** slowly evolving high-level features to skip connections with U-Net
- by substituting the compute of the main branch with a retrieving operation from the cache
- while maintaining the low-level features updated

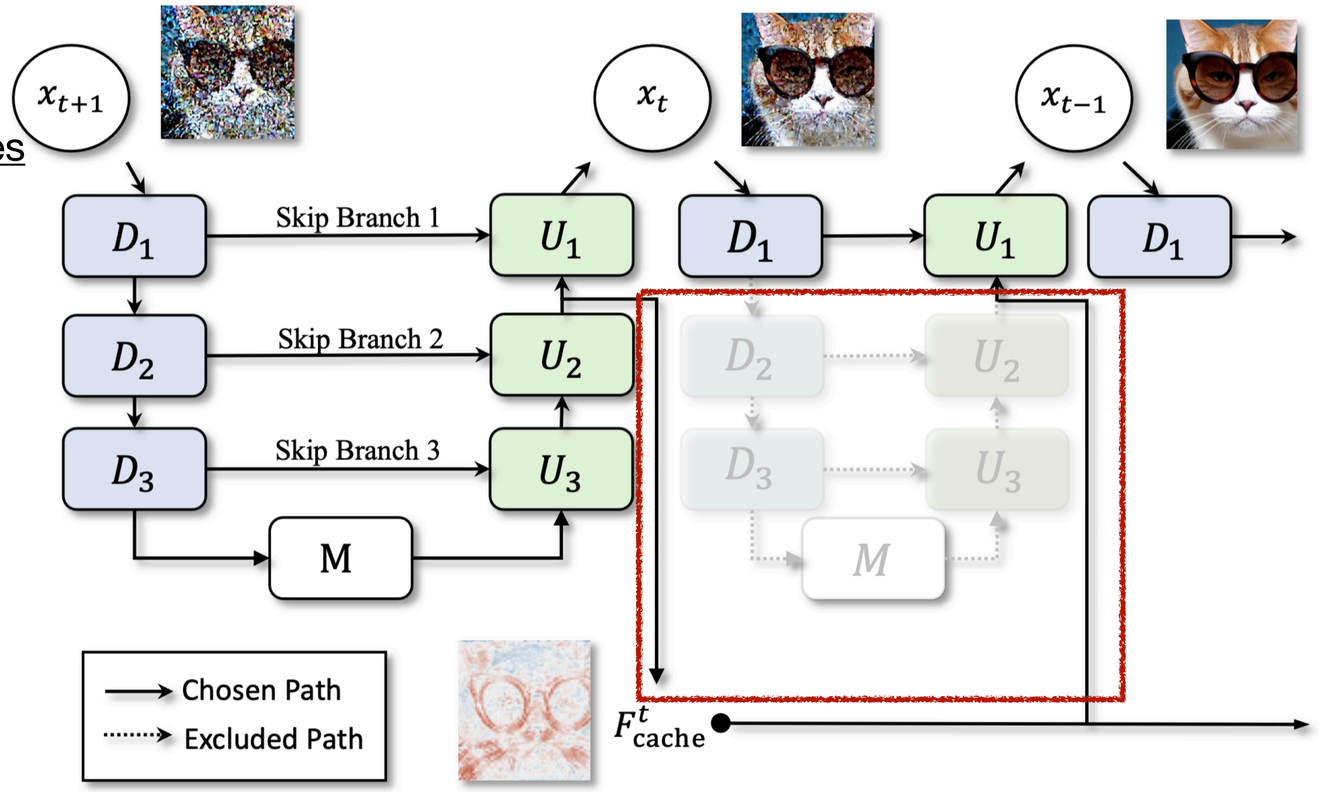



Illustration of DeepCache.

# Acceleration of Diffusion Models Inference

## DeepCache

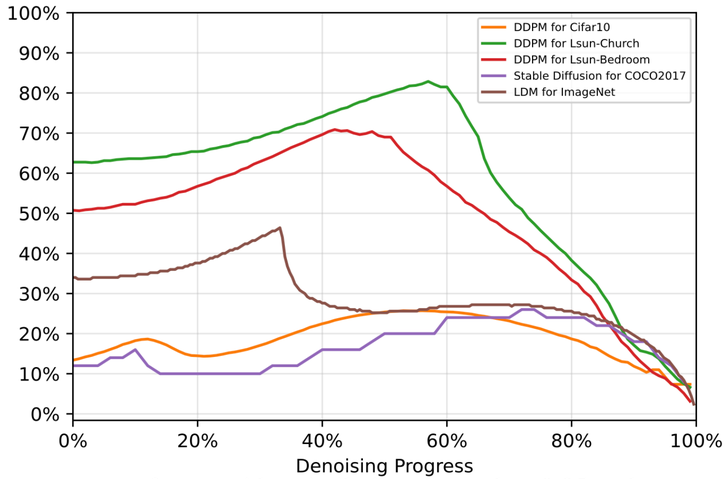
reduce the computational overhead at each denoising step without additional training

Extending to **1:N** Inference:

- The mechanism can be extended to cover more steps
- with the cached features calculated once and reused in the consecutive N-1 steps.

**Non-uniform 1:N** Inference:

- As the similarity of the features does not remain constant across all steps
- sample more on those steps with relatively small similarities.



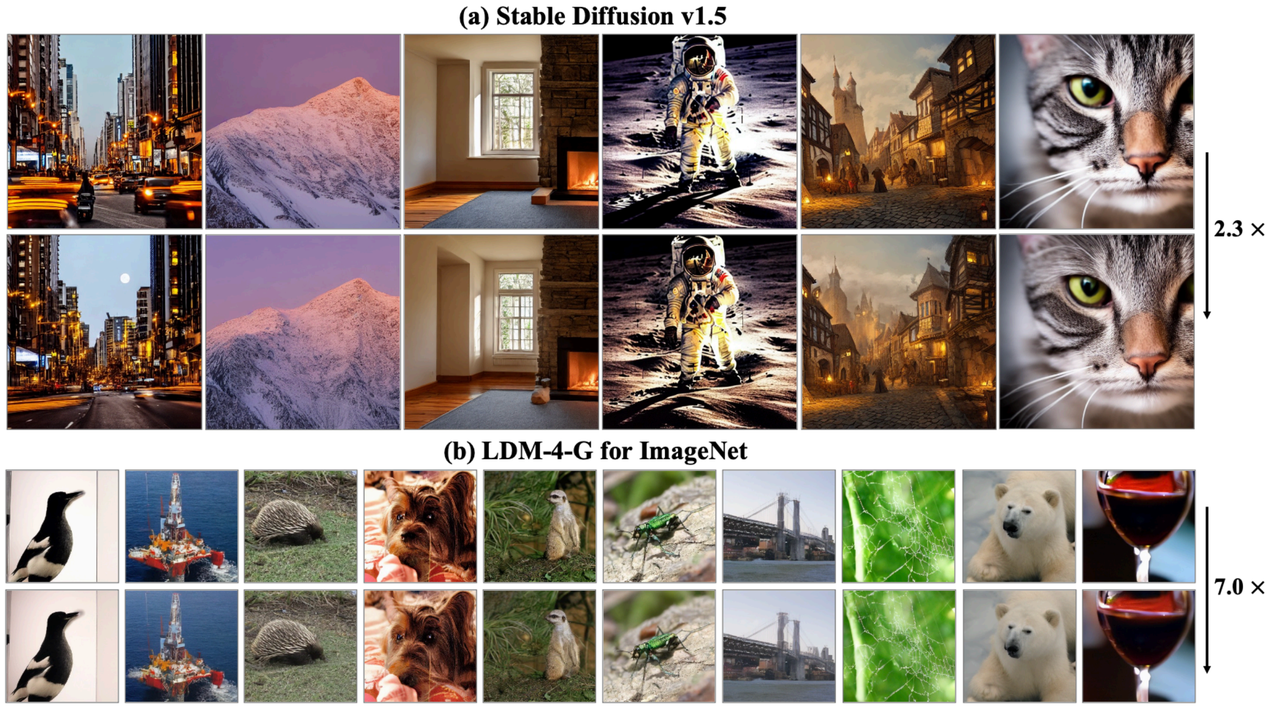

The percentage of steps with a similarity greater than 0.95 to the current step

# Acceleration of Diffusion Models Inference

## DeepCache

reduce the computational overhead at each denoising step without additional training

- Experiments




**Accelerating** Stable Diffusion V1.5 and LDM-4-G by **2.3** and **7.0**, with 50 PLMS steps and 250 DDIM steps respectively.

# Acceleration of Diffusion Models Inference

## DeepCache

reduce the computational overhead at each denoising step without additional training

- Experiments: the effectiveness of the non-uniform 1:N strategy

| Method | MACs ↓ | Throughput ↑ | Speed ↑ | Retrain | FID ↓ | sFID ↓ | IS ↑ | Precision ↑ | Recall ↑ |
|---|---|---|---|---|---|---|---|---|---|
| | ImageNet 256 × 256 | | | | | | | | |
| IDDPM [44] | 1416.3G | - | - | ✗ | 12.26 | 5.42 | - | 70.0 | 62.0 |
| ADM-G [9] | 1186.4G | - | - | ✗ | 4.59 | 5.25 | 186.70 | 82.0 | 52.0 |
| LDM-4 [49] | 99.82G | 0.178 | 1× | ✗ | 3.60 | - | 247.67 | 87.0 | 48.0 |
| LDM-4* | 99.82G | 0.178 | 1× | ✗ | 3.37 | 5.14 | 204.56 | 82.71 | 53.86 |
| Spectral DPM [68] | 9.9G | - | - | ✓ | 10.60 | - | - | - | - |
| Diff-Pruning [10]* | 52.71G | 0.269 | 1.51× | ✓ | 9.27(9.16) | 10.59 | 214.42(201.81) | 87.87 | 30.87 |
| **Uniform - N=2** | 52.12G | 0.334 | 1.88× | ✗ | 3.39 | 5.11 | 204.09 | 82.75 | 54.07 |
| **Uniform - N=3** | 36.48G | 0.471 | 2.65× | ✗ | 3.44 | 5.11 | 202.79 | 82.65 | 53.81 |
| **Uniform - N=5** | 23.50G | 0.733 | 4.12× | ✗ | 3.59 | 5.16 | 200.45 | 82.36 | 53.31 |
| **Uniform - N=10** | 13.97G | 1.239 | 6.96× | ✗ | 4.41 | 5.57 | 191.11 | 81.26 | 51.53 |
| **Uniform - N=20** | 9.39G | 1.876 | 10.54× | ✗ | 8.23 | 8.08 | 161.83 | 75.31 | 50.57 |
| **NonUniform - N=10** | 13.97G | 1.239 | 6.96× | ✗ | 4.27 | 5.42 | 193.11 | 81.75 | 51.84 |
| **NonUniform - N=20** | 9.39G | 1.876 | 10.54× | ✗ | 7.11 | 7.34 | 167.85 | 77.44 | 50.08 |

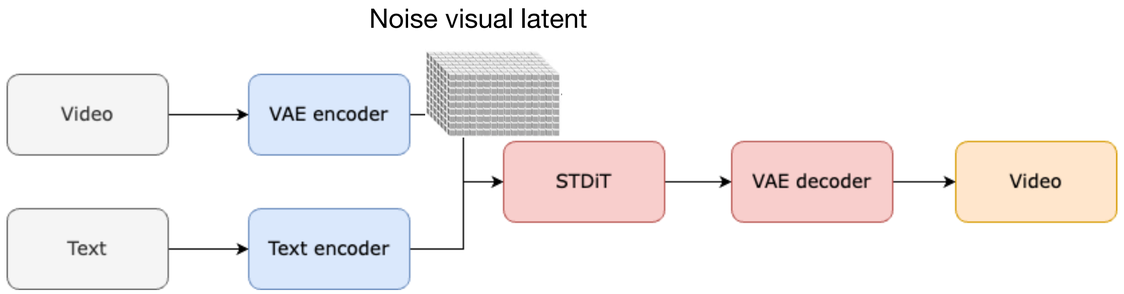
Class-conditional generation quality on ImageNet using LDM-4-G with 250 DDIM steps.

# Open-sora

## Leveraging pretrained T2I models for video generation

In the inference stage

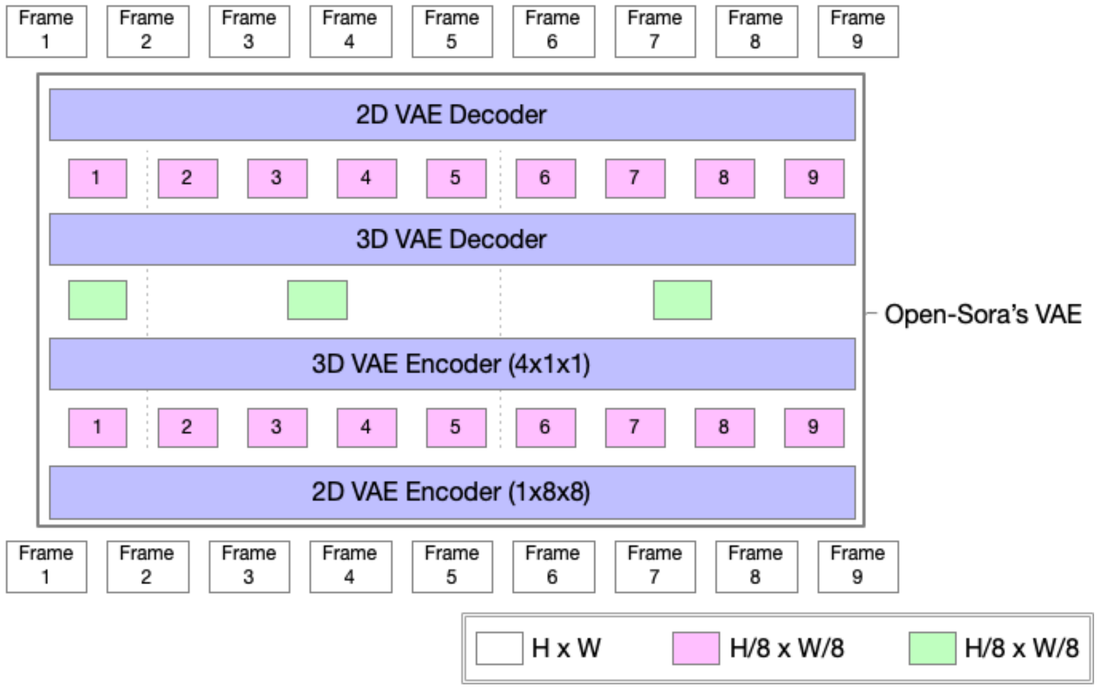
- Randomly sample a Gaussian noise from the latent space of the VAE
- Input noise into the STDiT (Spatial Temporal Diffusion Transformer) model together with the prompt embedding for denoising
- Input denoised features into the VAE decoder to get the video



# Open-sora

## Leveraging pretrained T2I models for video generation

Video Compression Network



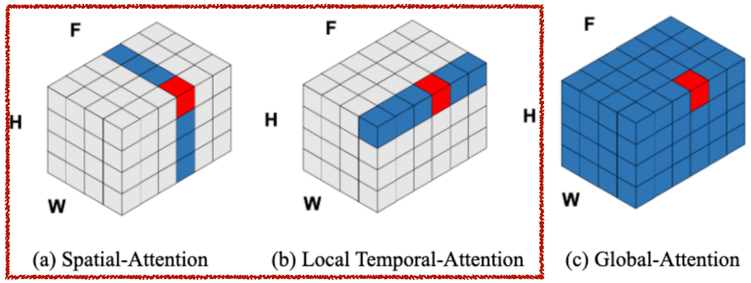

- first compress the video in the spatial dimension by 8x8 times
- then compress the video in the temporal dimension by 4x times

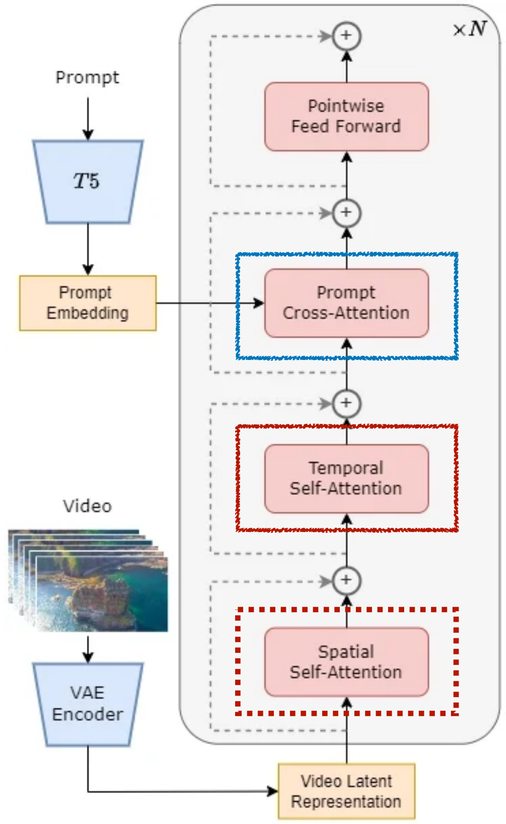
# Open-sora

## Leveraging pretrained T2I models for video generation

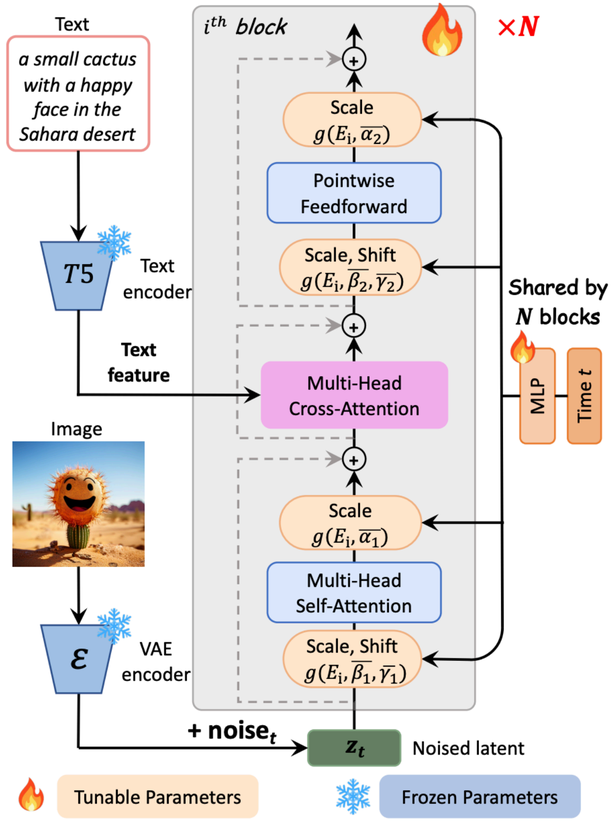
STDiT Model Structure

- The **cross-attention** module is used to align the semantics of the text
- Add a **temporal attention** layer for modeling temporal relationships



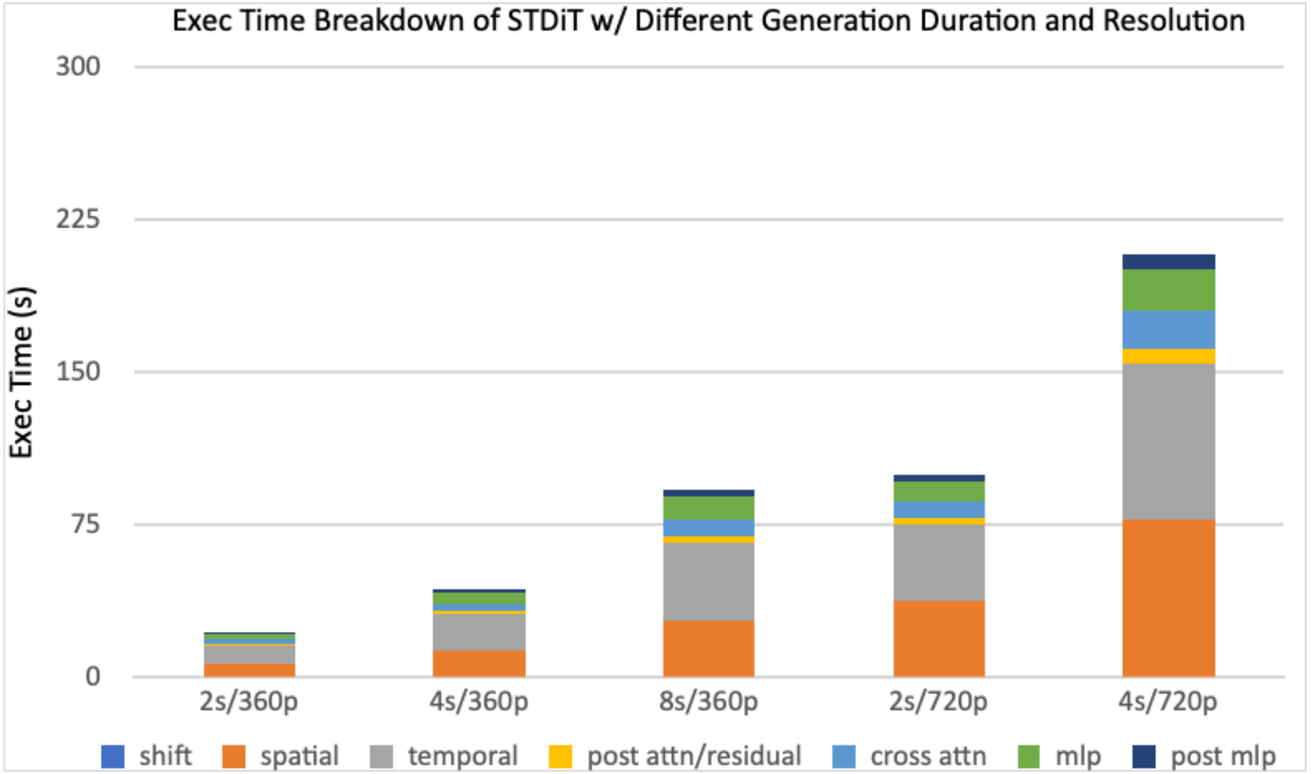

STDiT Model Structure Schematic




Model architecture of PIXART-α

# Our Findings

- Attention computation takes up most of the exec time



# Discussion

**Thanks for listening!**