MVDiffusion++: A Dense High-resolution Multi-view Diffusion Model for Single or Sparse-view 3D Object Reconstruction

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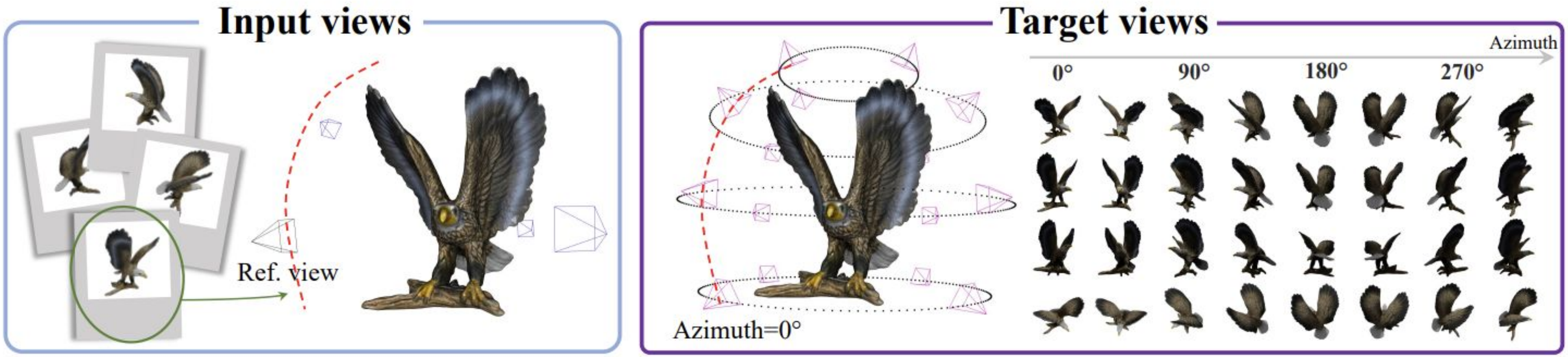
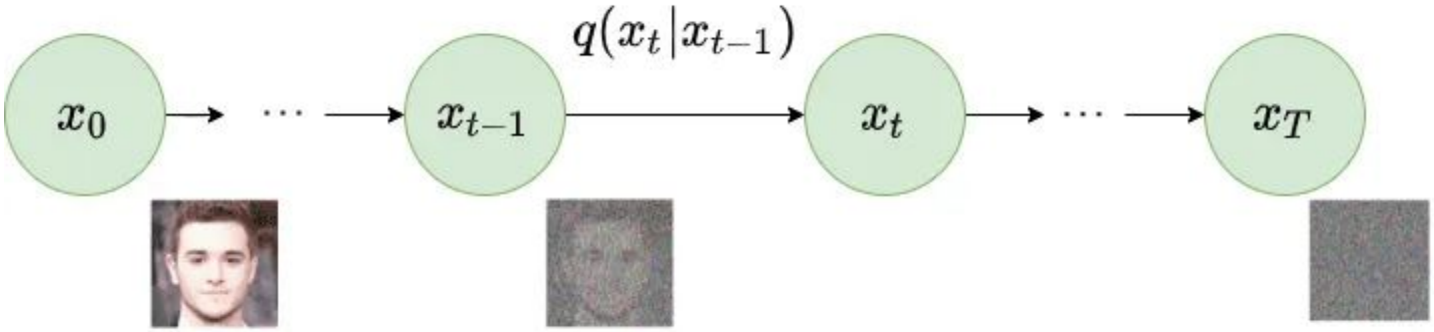
Task: Single or Sparse View Reconstruction

The 32 target images are defined in eight azimuths and four elevation levels.



Forward diffusion process:

- Sample from a basic Gaussian distribution.
- Incremental modifications via Markov chain.
- Structured noise added at each step, controlled by variance schedule.



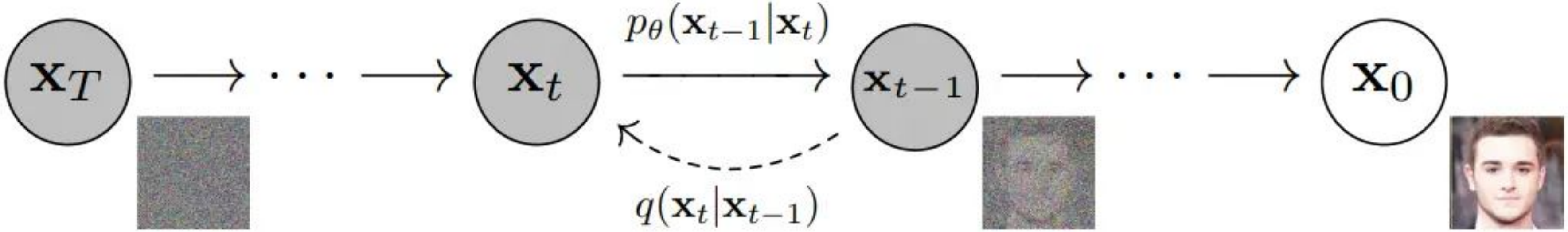
$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

"Diffusion Models," https://www.superannotate.com/blog/diffusion-models

Diffusion Model

Reverse diffusion process:

- x_T behaves like an isotropic Gaussian distribution.
- Reverse the process to create new data similar to the original dataset.
- Direct calculation of $q(x_{t-1} | x_t)$ is complex.
- Neural network estimates this, adjusting mean and variance.



$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

"Diffusion Models," https://www.superannotate.com/blog/diffusion-models

Latent Diffusion Model

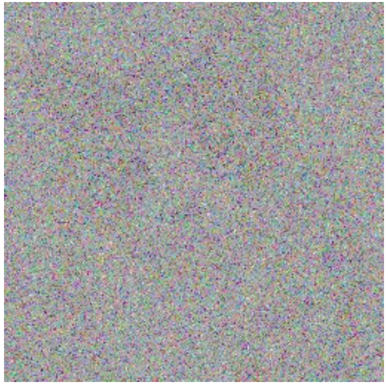
$$L_{LDM} := \mathbb{E}_{\mathcal{E}(\mathbf{x}),\mathbf{y},\epsilon\sim\mathcal{N}(0,1),t}\left[\|\epsilon - \epsilon_\theta(\mathbf{Z}_t, t, \tau_\theta(\mathbf{y}))\|_2^2\right]$$

$\mathbf{Z} = \mathcal{E}(\mathbf{x})$ where $\mathcal{E}$ is the encoder and X is the high-resolution images.

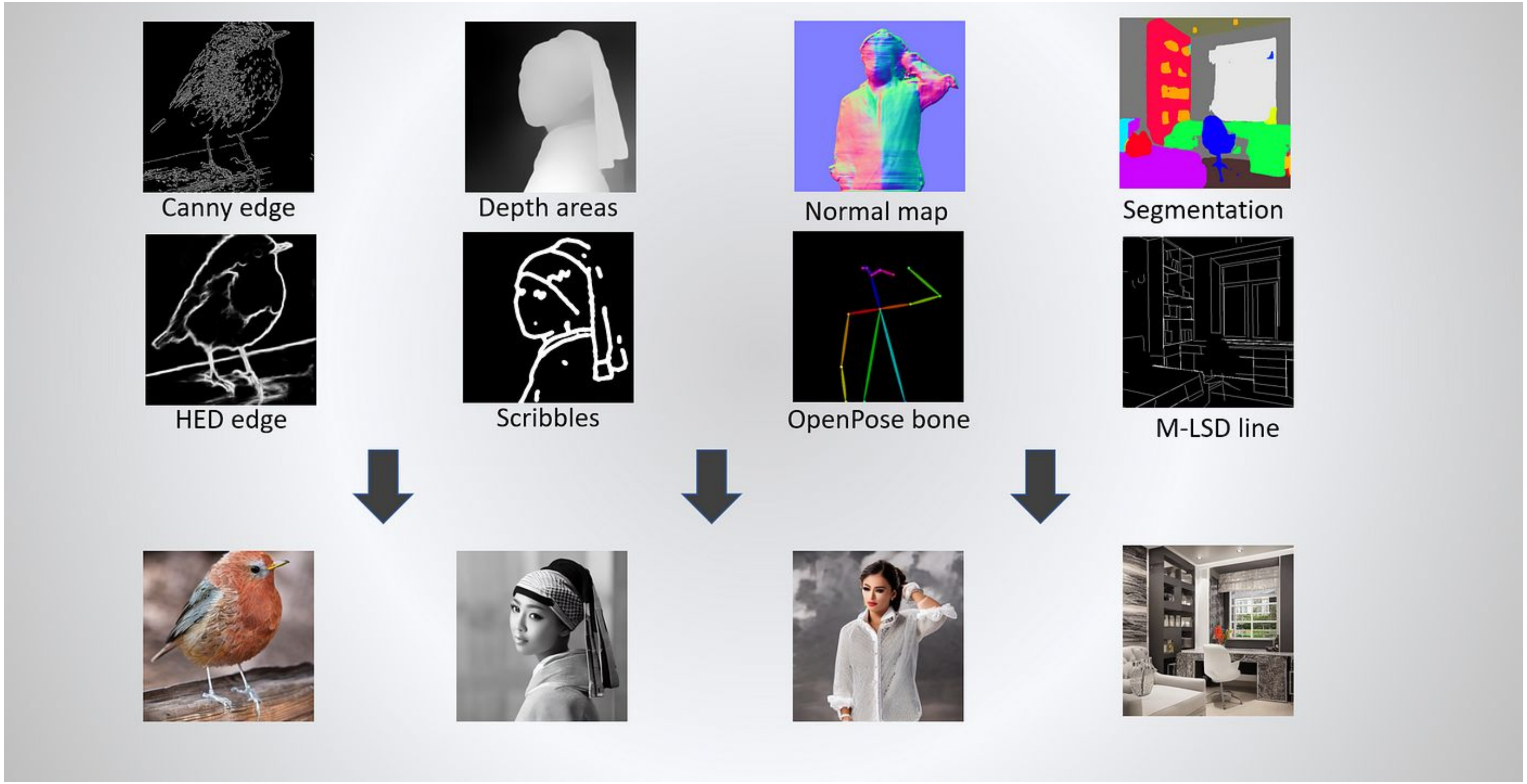
$\mathbf{Z}_t$ is the noisy latent at time step t.

τ_θ is the optional condition encoding.

$\mathbf{y}$ could be a text-prompt, an image, or any other user-specified condition.

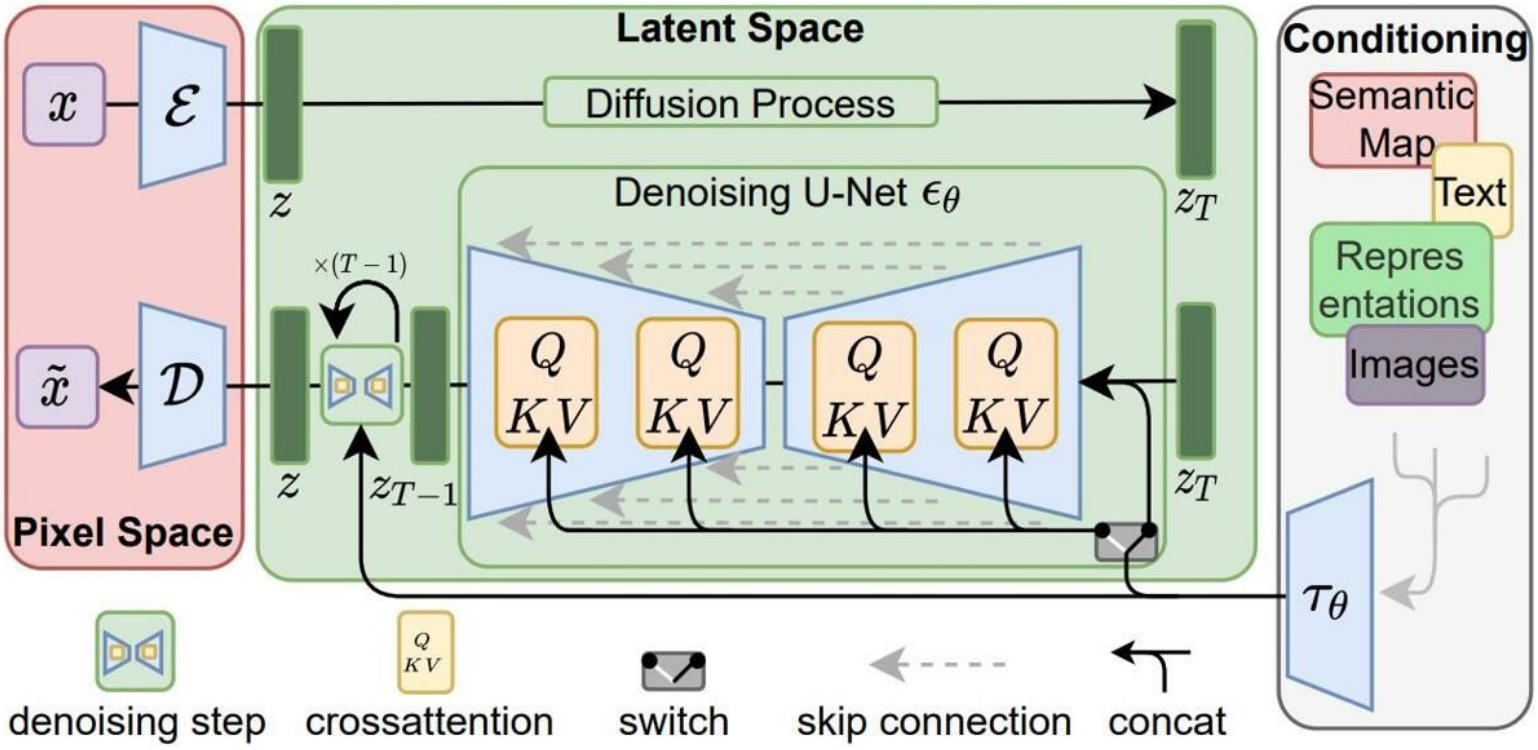


Different Conditions



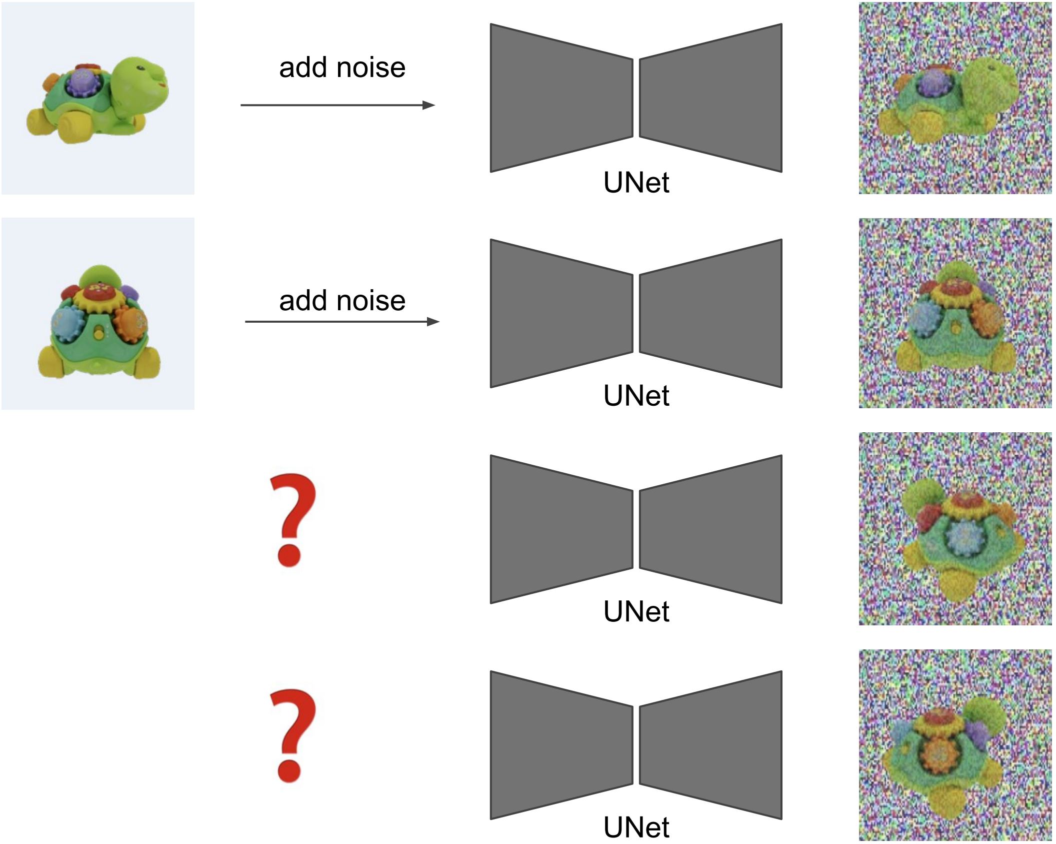
ControlNet (L. Zhang, et al - ICCV 2023)

Stable Diffusion Architecture



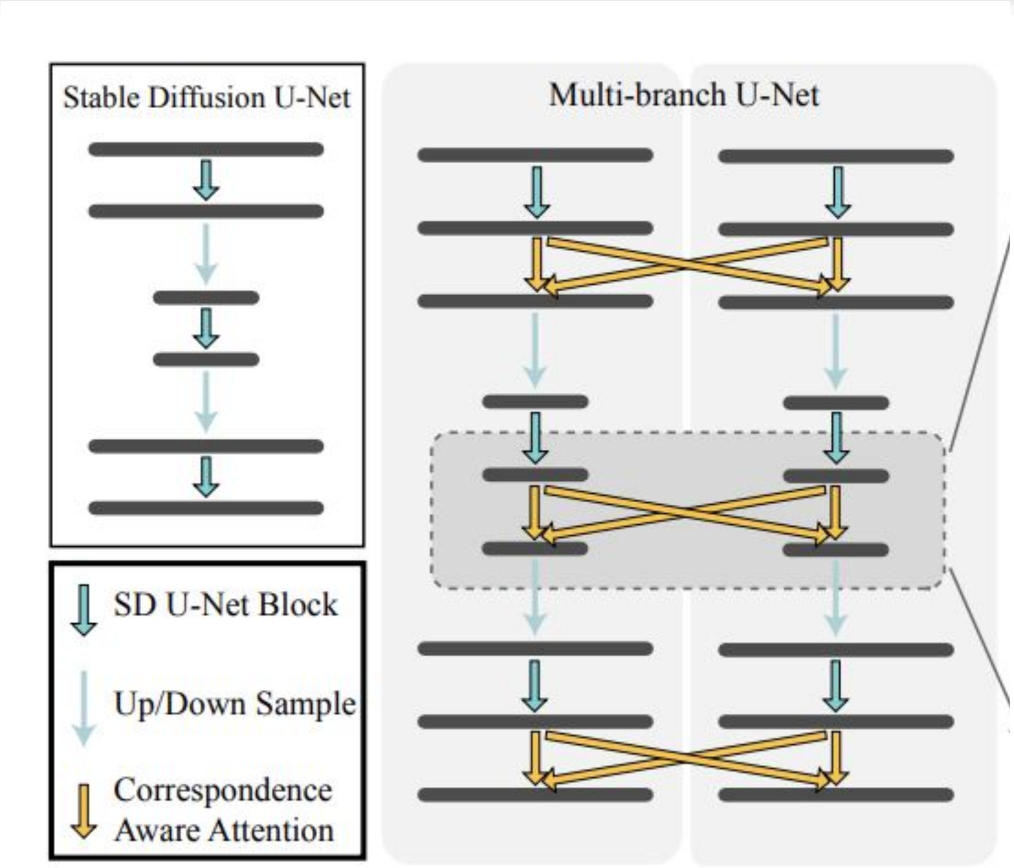
High-Resolution Image Synthesis with Latent Diffusion Models(R. Rombach, et al - CVPR 2022)

Single or Sparse View Reconstruction



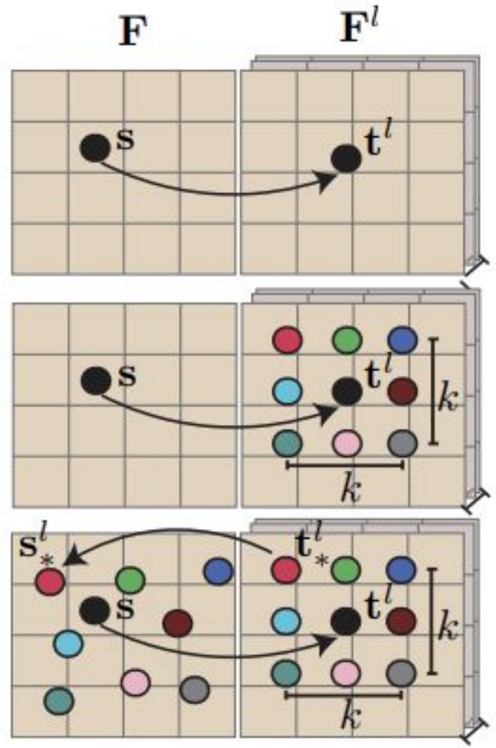
How to connect these?

Correspondence-Aware Attention (CAA)

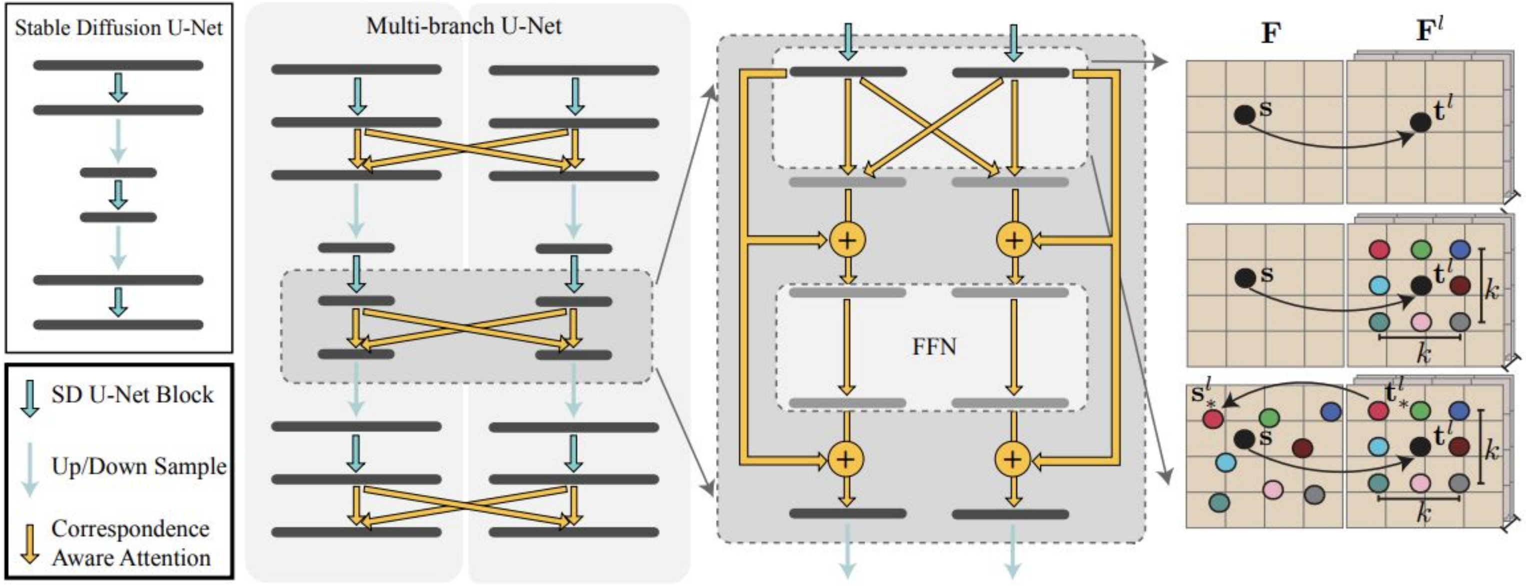


MVDiffusion: Enabling Holistic Multi-view Image Generation with Correspondence-Aware Diffusion(S. Tang, et al - NeurIPS 2023)

Correspondence-Aware Attention (CAA)



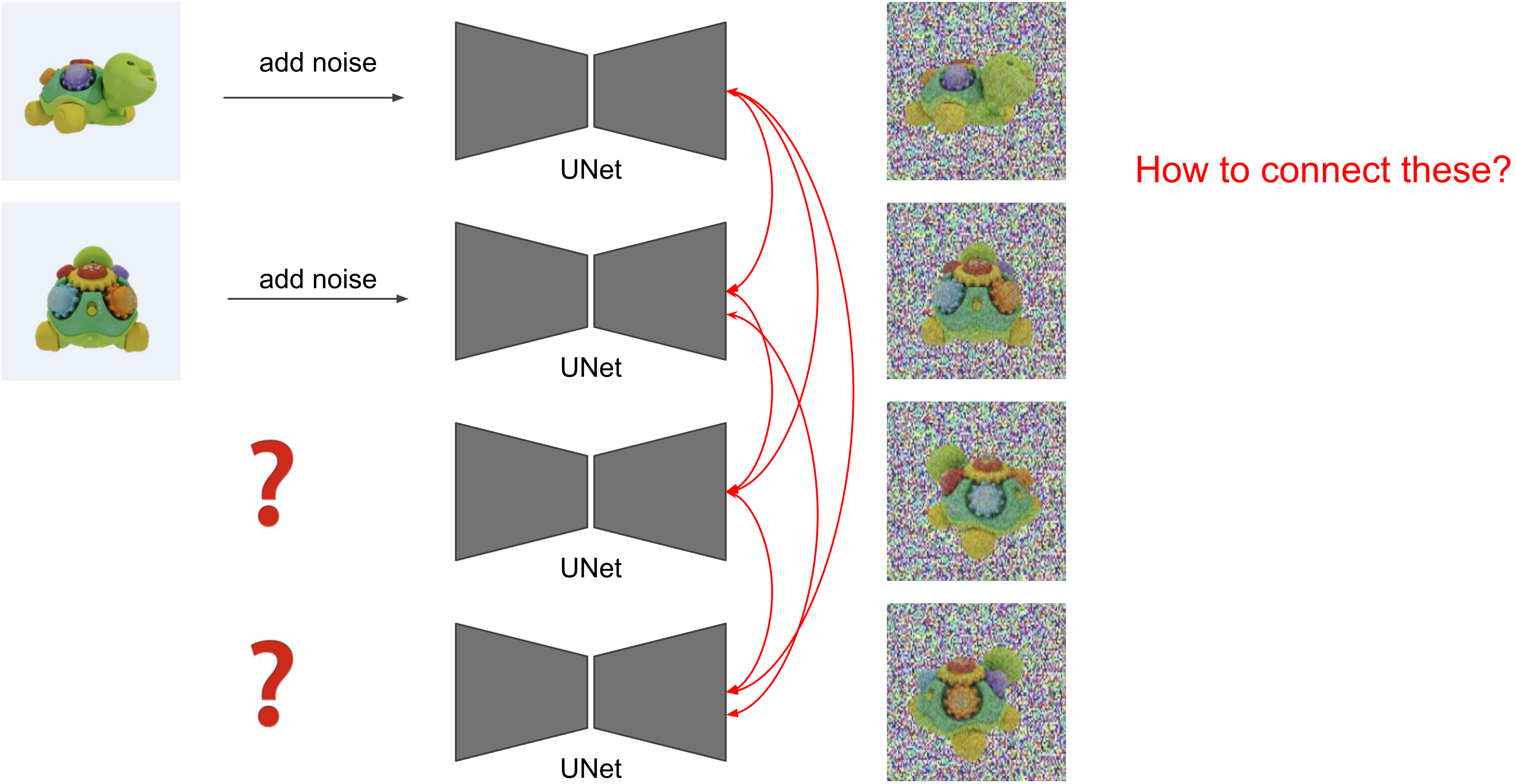
Correspondence-Aware Attention (CAA)



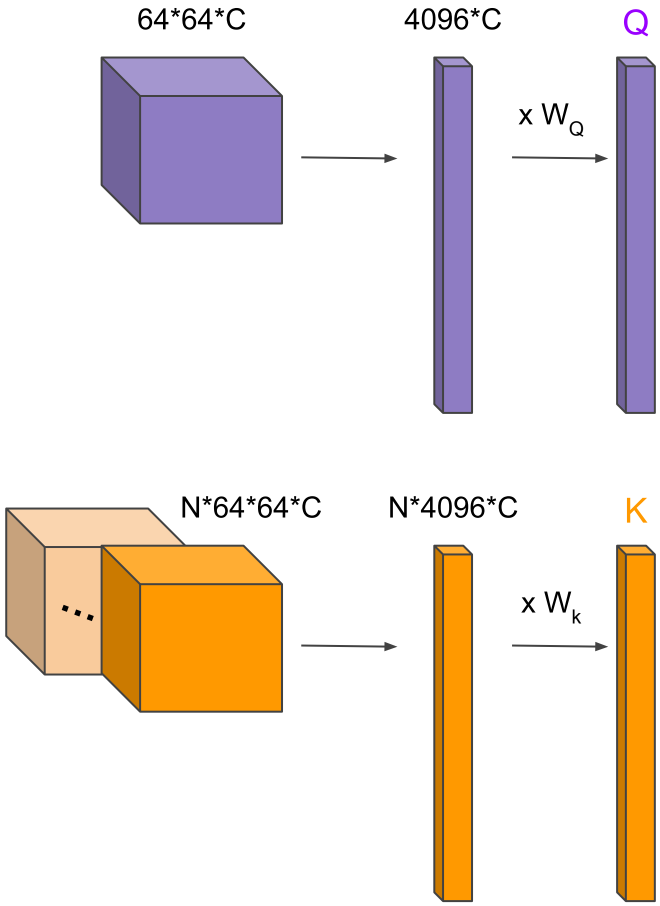
$$\mathbf{M} = \sum \sum \mathrm{SoftMax}\left(\left[\mathbf{W_Q}\bar{\mathbf{F}}(\mathbf{s})\right] \cdot \left[\mathbf{W_K}\bar{\mathbf{F}}^l(t^l_*)\right]\right) \mathbf{W_V}\bar{\mathbf{F}}^l(t^l_*)$$

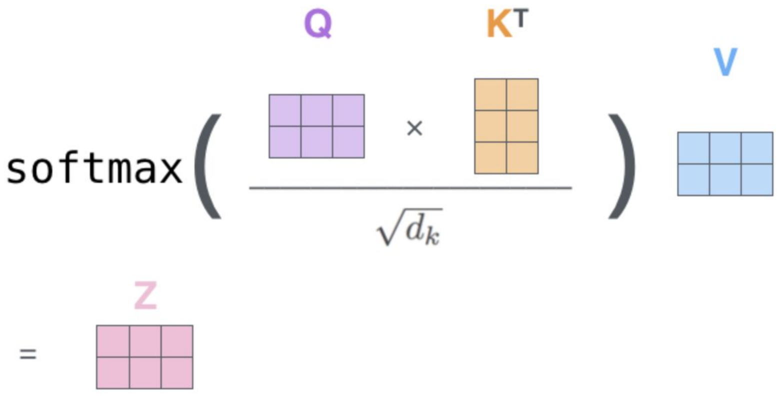
$$\bar{\mathbf{F}}(\mathbf{s}) = \mathbf{F}(\mathbf{s}) + \gamma(0), \quad \bar{\mathbf{F}}^l(t^l_*) = \mathbf{F}^l(t^l_*) + \gamma(\mathbf{s}^l_* - \mathbf{s})$$

Sparse View Reconstruction



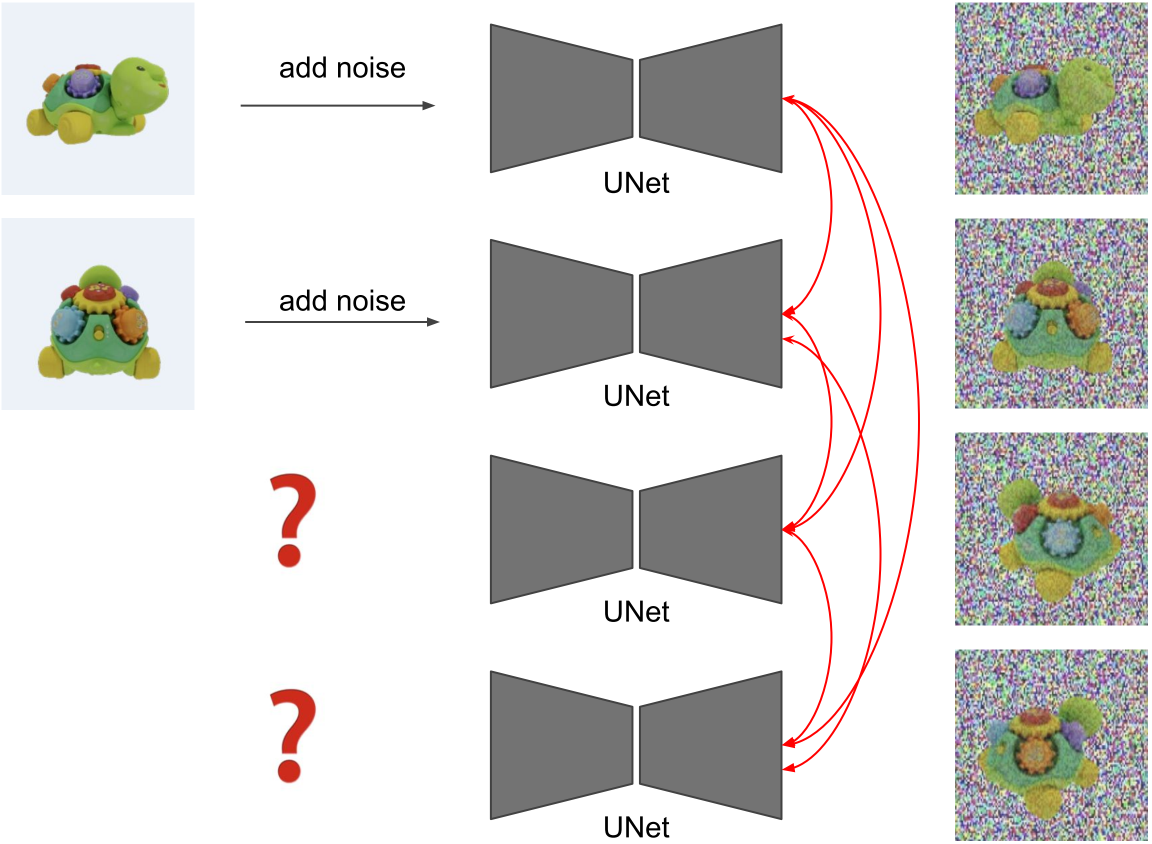
Global Self Attention





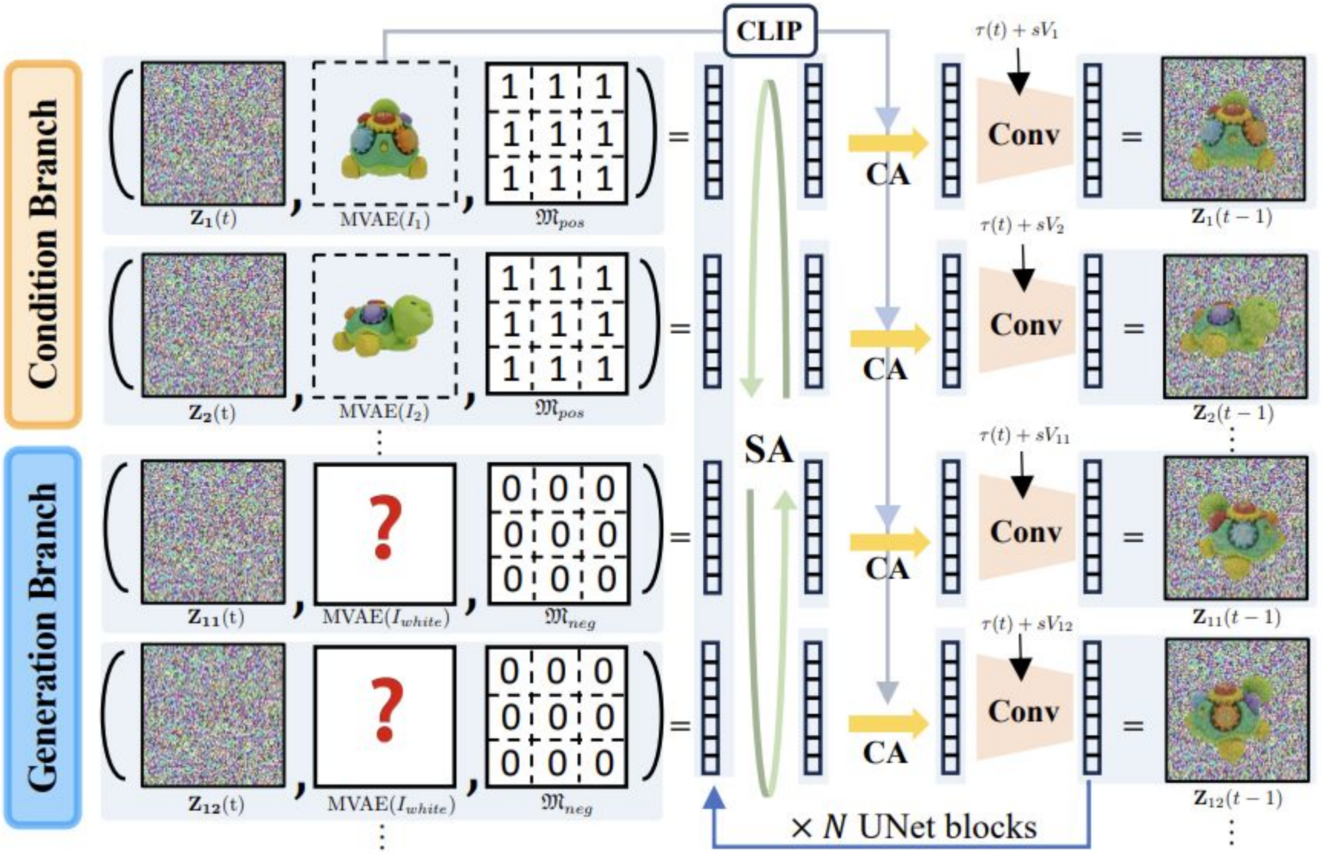
The self-attention calculation in matrix form

Sparse View Reconstruction

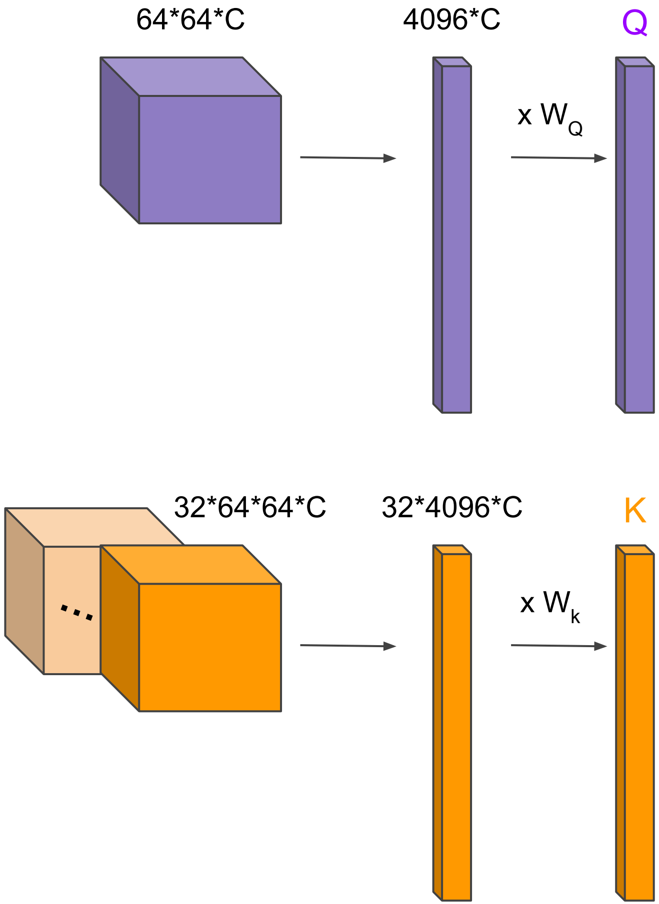


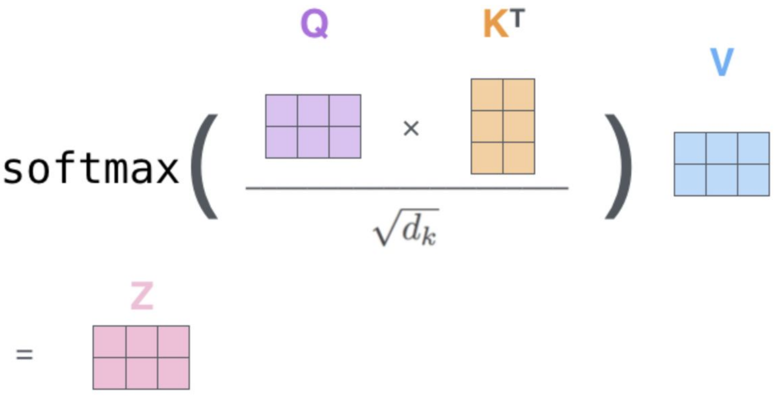
How to connect these?

MVDiffusion++ Architecture



Global Self Attention





The self-attention calculation in matrix form

View dropout training strategy

High Token Count:

- 32 copies of UNet features produce over 130,000 tokens.

Self-Attention Limitation:

- Global self-attention becomes infeasible due to memory constraints, even with advanced memory-efficient transformers.

Solution:

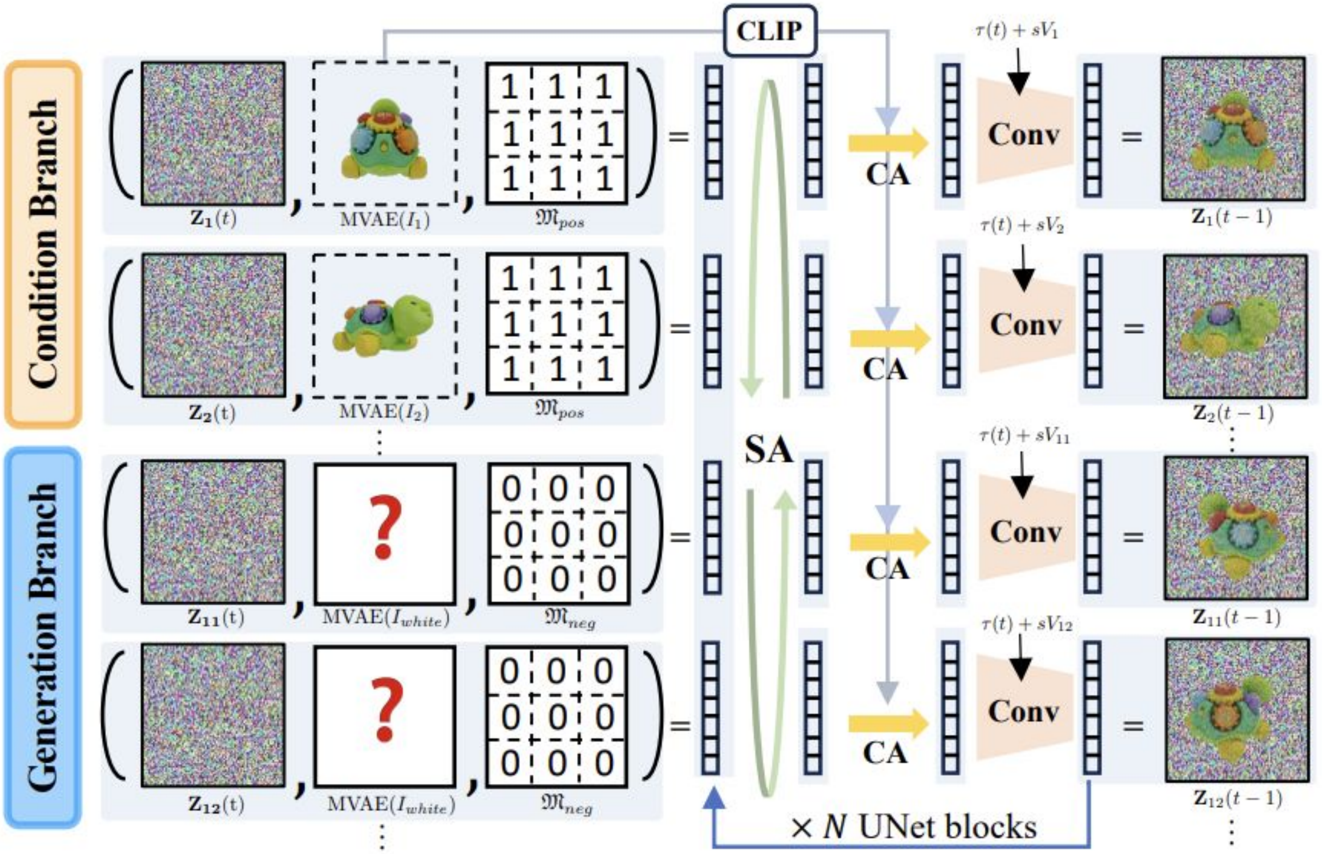
During Training:

- Randomly drop 24 out of 32 views for each object in every iteration.
- Results in significant memory reduction.

At Test Time:

- Utilize full architecture to generate 32 views, ensuring comprehensive output.

MVDiffusion++ Architecture



Key Functions in Each Block

Global Self-Attention:

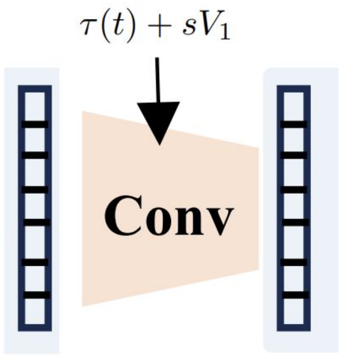
Maintains 3D consistency across all images.

Cross-Attention:

Incorporates CLIP embeddings from the condition images to enhance contextual relevance.

CNN Processing:

Manages per-image features and integrates timestep frequency encoding and image index embeddings.



$Z(t)$: Noisy latent
U : Feature map
I : Image
M : Background/Foreground mask
$\mathfrak{M}_{neg}$: Zero-mask
$\mathfrak{M}_{pos}$: One-mask
CAA : CAA attention
SA/CA : Self/Cross attention
CLIP : CLIP encoder
CNN : Convolution network
MVAE : Mask-aware VAE

MVDiffusion Block

[At first block]

$\forall i\; U_i^0 \leftarrow \mathbf{CNN}(Z_i(t))$

[For each block]

$\forall i\; U_i^b \leftarrow \mathbf{CAA}(U_i^b, \{U_{i-1}^b, U_{i+1}^b\})$

$\forall i\; U_i^b \leftarrow \mathbf{SA}(U_i^b)$

$\forall i\; U_i^b \leftarrow \mathbf{CA}(U_i^b, \mathbf{CLIP}(T_{text}))$

$\forall i\; U_i^{b+1} \leftarrow \mathbf{CNN}([U_i^b, \tau(t)+s\,\tau(V_i)])$

[At last block]

$\forall i\; Z_i(t-1) \leftarrow \mathrm{DDPM}(\mathbf{CNN}(U_i^{bmax}))$

MVDiffHD Block

[At first block]

$$\forall i\; U_i^0 \leftarrow \begin{cases} \mathbf{CNN}([Z_i(t), \mathbf{MVAE}(I_i, M_i), \mathfrak{M}_{pos}]), \text{ conditional branch,} \\ \mathbf{CNN}([Z_i(t), \mathbf{MVAE}(I_{white}, \mathfrak{M}_{neg}), \mathfrak{M}_{neg}]), \text{ generation branch.} \end{cases}$$

[For each block]

$\forall i\; U_i^b \leftarrow \mathbf{SA}(\{U_*^b\})$

$\forall i\; U_i^b \leftarrow \mathbf{CA}(U_i^b, \mathbf{CLIP}(I_i \in I_{cond}))$

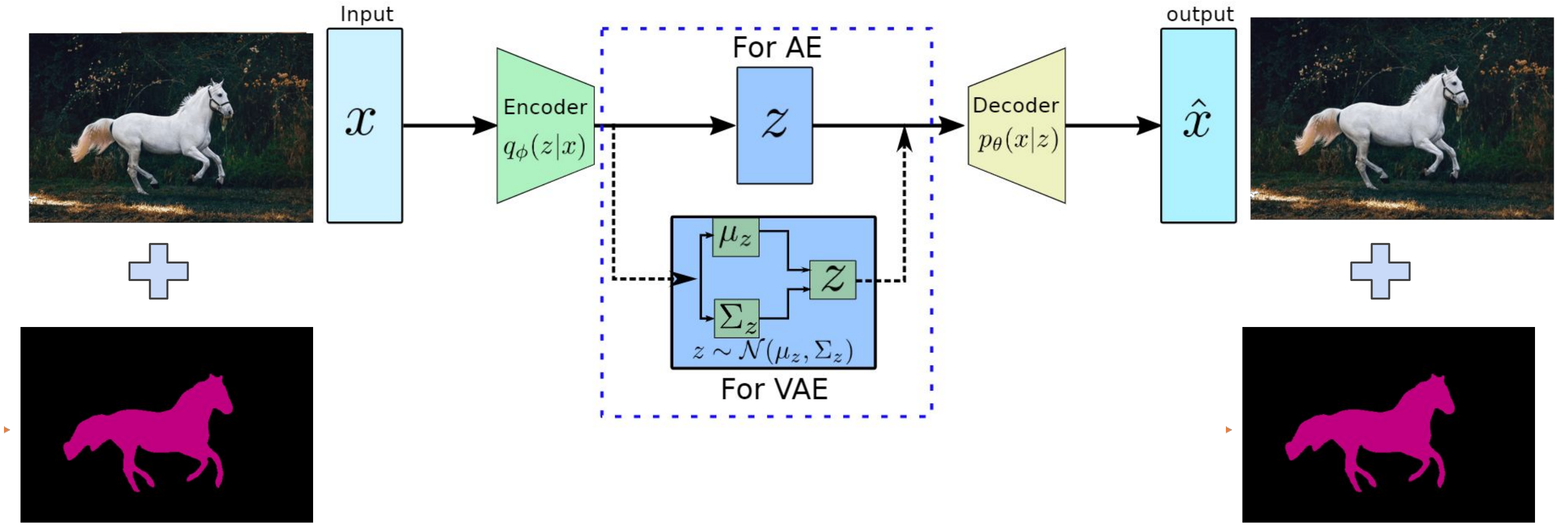
$\forall i\; U_i^{b+1} \leftarrow \mathbf{CNN}([U_i^b, \tau(t)+s\,\tau(V_i)])$

[At last block]

$\forall i\; Z_i(t-1) \leftarrow \mathrm{DDPM}(\mathbf{CNN}(U_i^{bmax}))$

Mask-aware VAE pre-fine-tuning

- Adapts VAE to process object images with segmentation masks.
- Dataset Used: Approximately 3 million RGBA images from the Objaverse dataset.
- Enhances PSNR from 36.6 to 41.2, improving quality of generated 3D models.



Training Resource

Hardware Used:

- Utilized 128 Nvidia H100 GPUs.

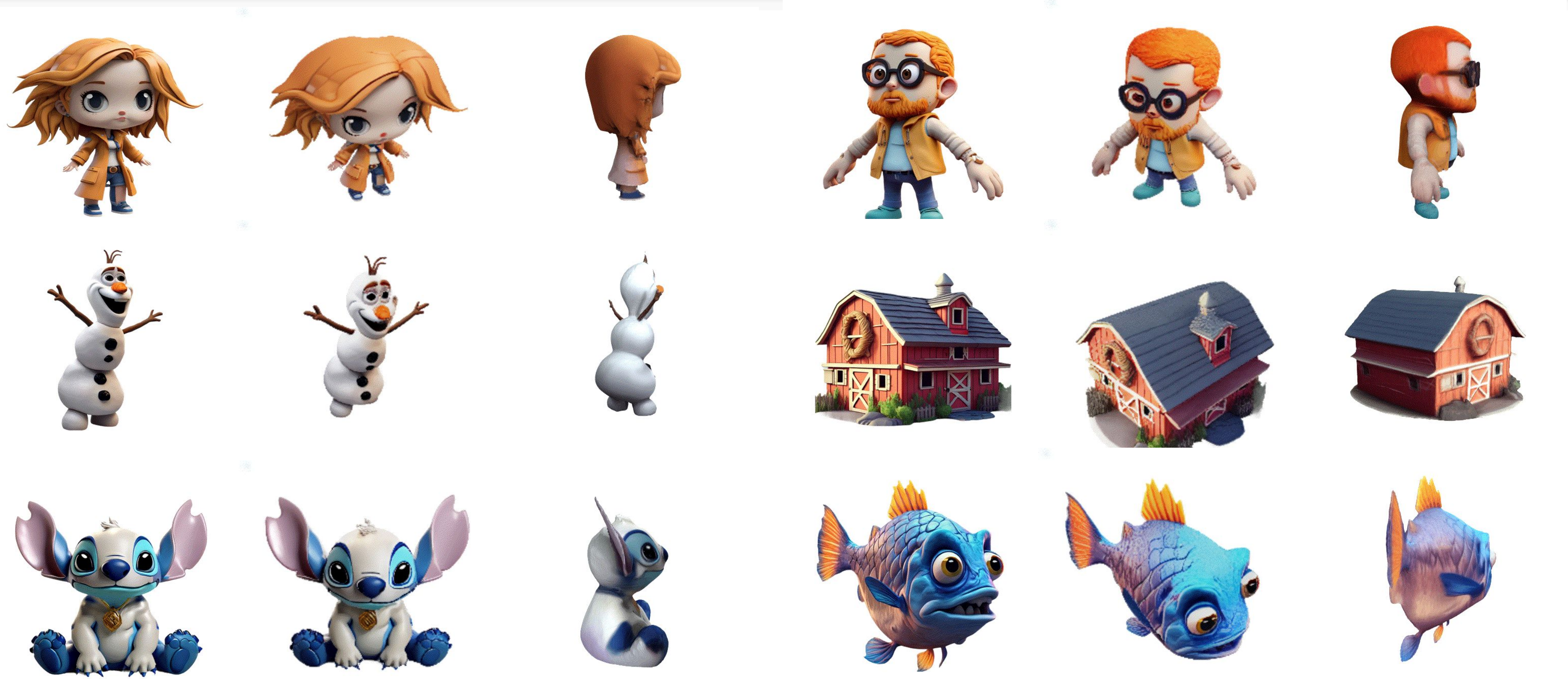
Duration of Training:

- Training conducted continuously for approximately one week.

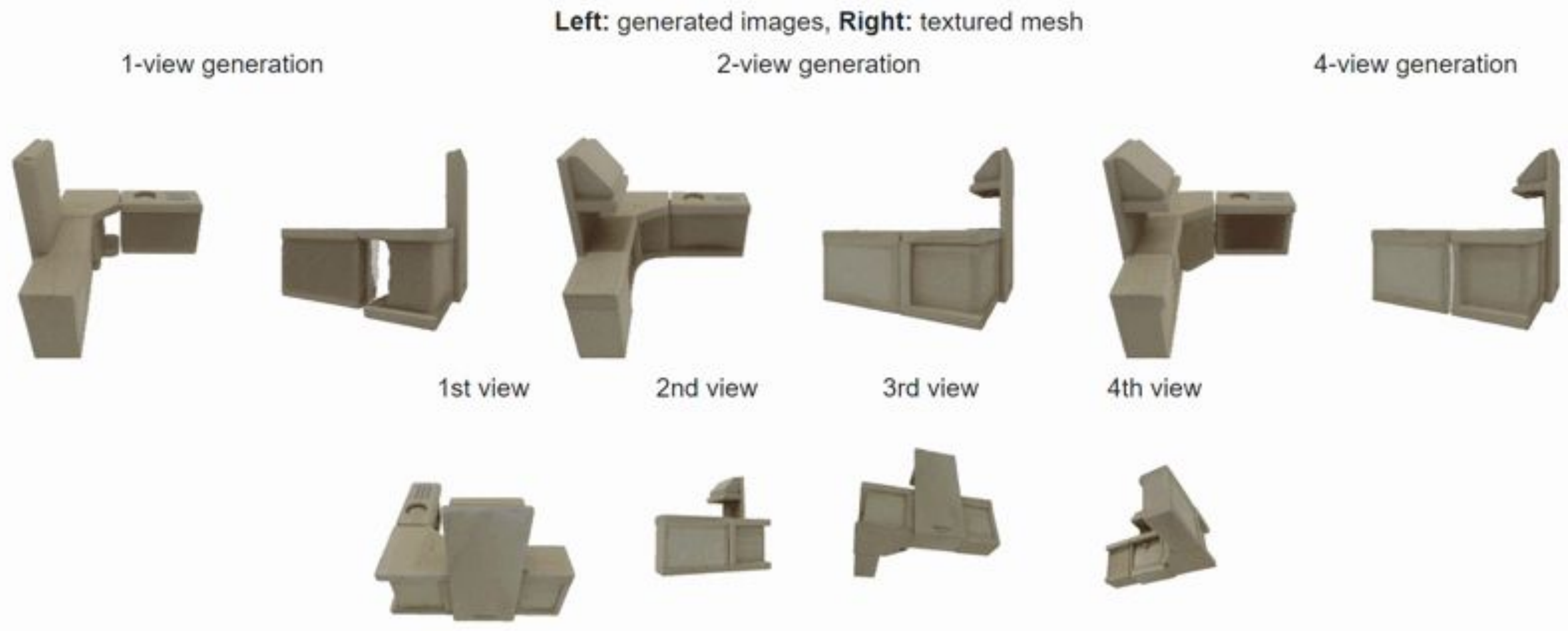
Results

Task →	3D reconstruction		Novel view synthesis		
Method	Chamfer Dist.↓	Vol. IoU↑	PSNR↑	SSIM↑	LPIPS↓
Realfusion [20]	0.0819	0.2741	15.26	0.722	0.283
Magic123 [26]	0.0516	0.4528	-	-	-
One-2-3-45 [16]	0.0629	0.4086	-	-	-
Point-E [24]	0.0426	0.2875	-	-	-
Shap-E [13]	0.0436	0.3584	-	-	-
Zero123 [17]	0.0339	0.5035	18.93	0.779	0.166
SyncDreamer [18]	0.0261	0.5421	20.05	0.798	0.146
Wonder3D [19]*	0.0329	0.5768	-	-	-
Open-LRM [9]*	0.0285	0.5945	-	-	-
Ours	**0.0165**	**0.6973**	**21.45**	**0.844**	**0.129**

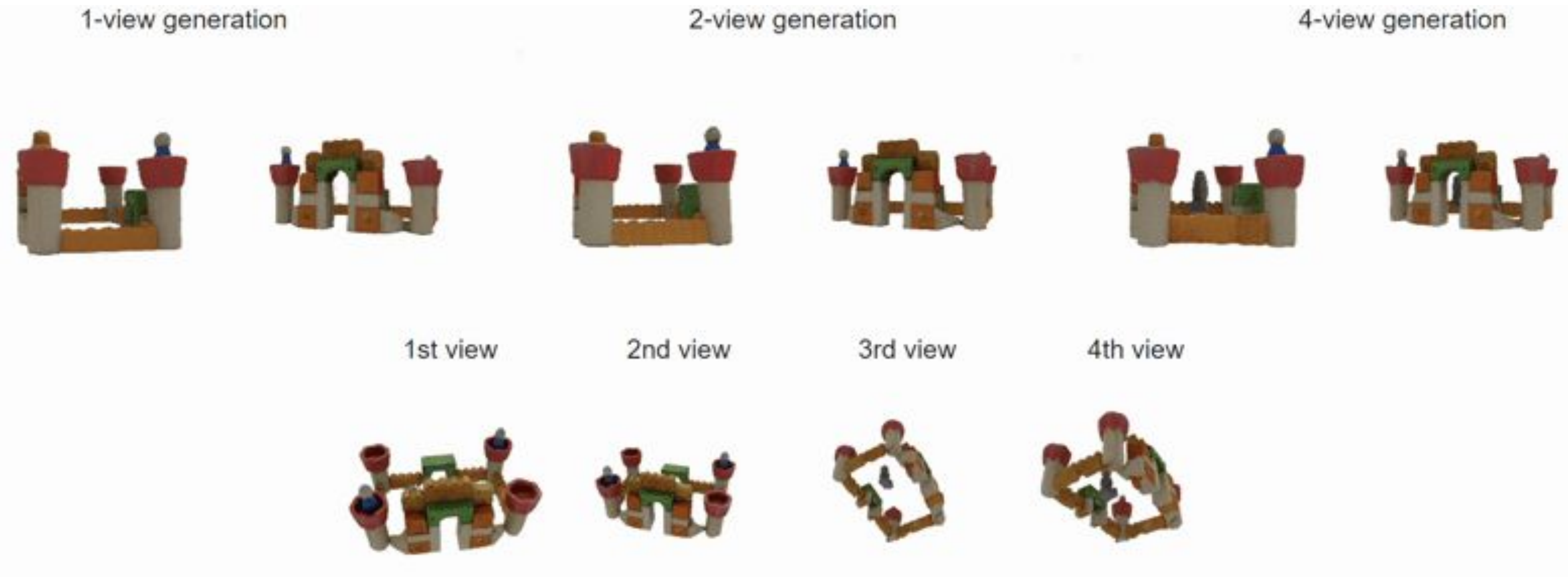
Single view reconstruction



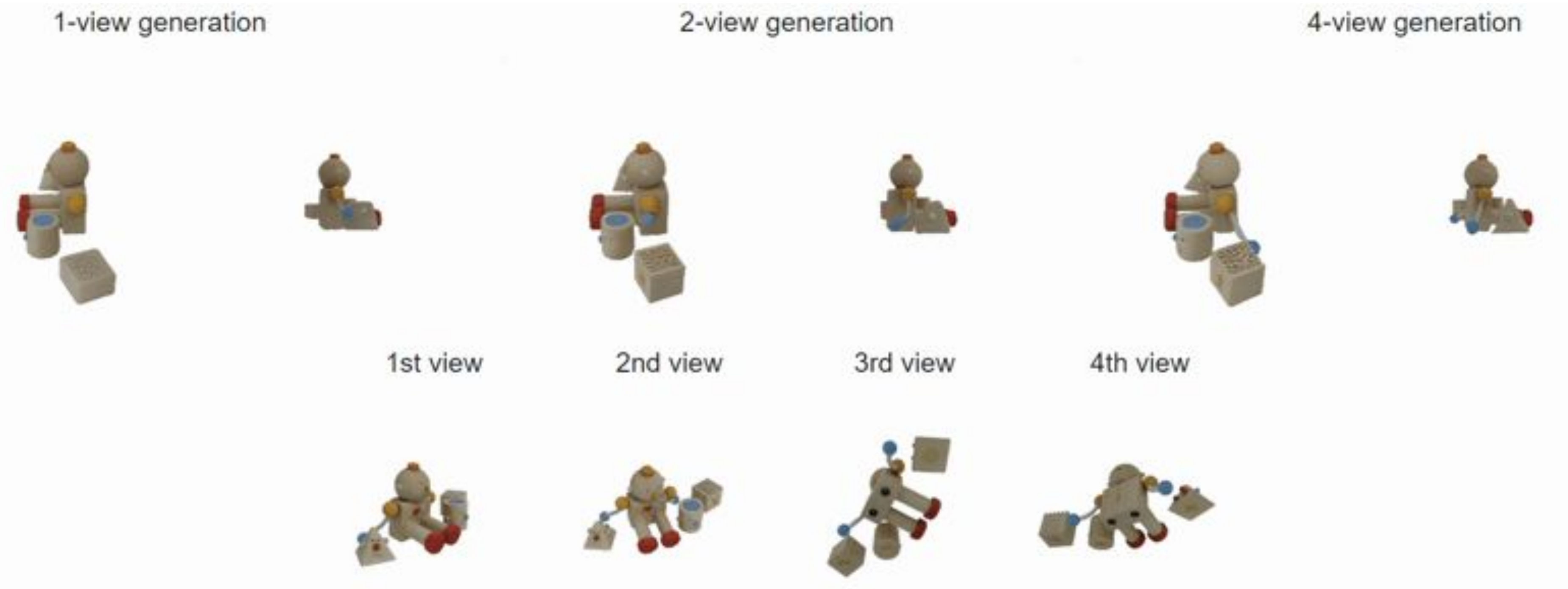
Sparse view reconstruction



Sparse view reconstruction



Sparse view reconstruction



Thank you!

- Thank you for your attention!
- I appreciate your time and interest.
- If you have any questions, please feel free to ask.
- Contact information: alimohammadiamirhossein@gmail.com