

Paper Review

Im2vec: Synthesizing vector graphics without vector supervision

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Im2Vec: Synthesizing Vector Graphics without Vector Supervision

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Michaël Gharbi²

Michal Lukáč²

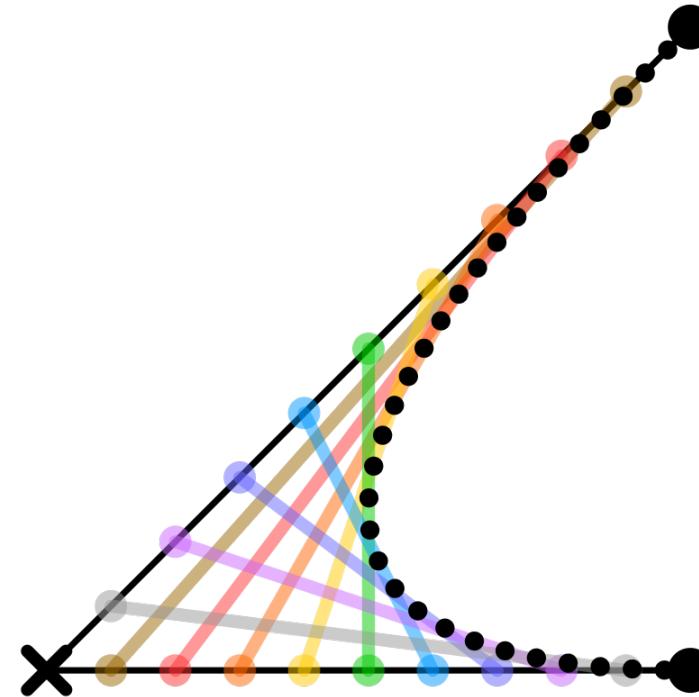
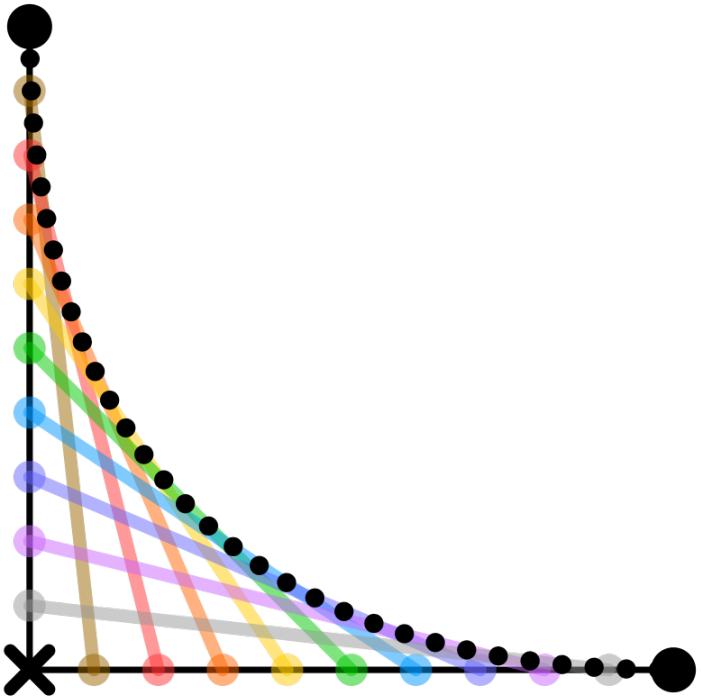
Niloy J. Mitra^{1,2}

¹University College London ²Adobe Research

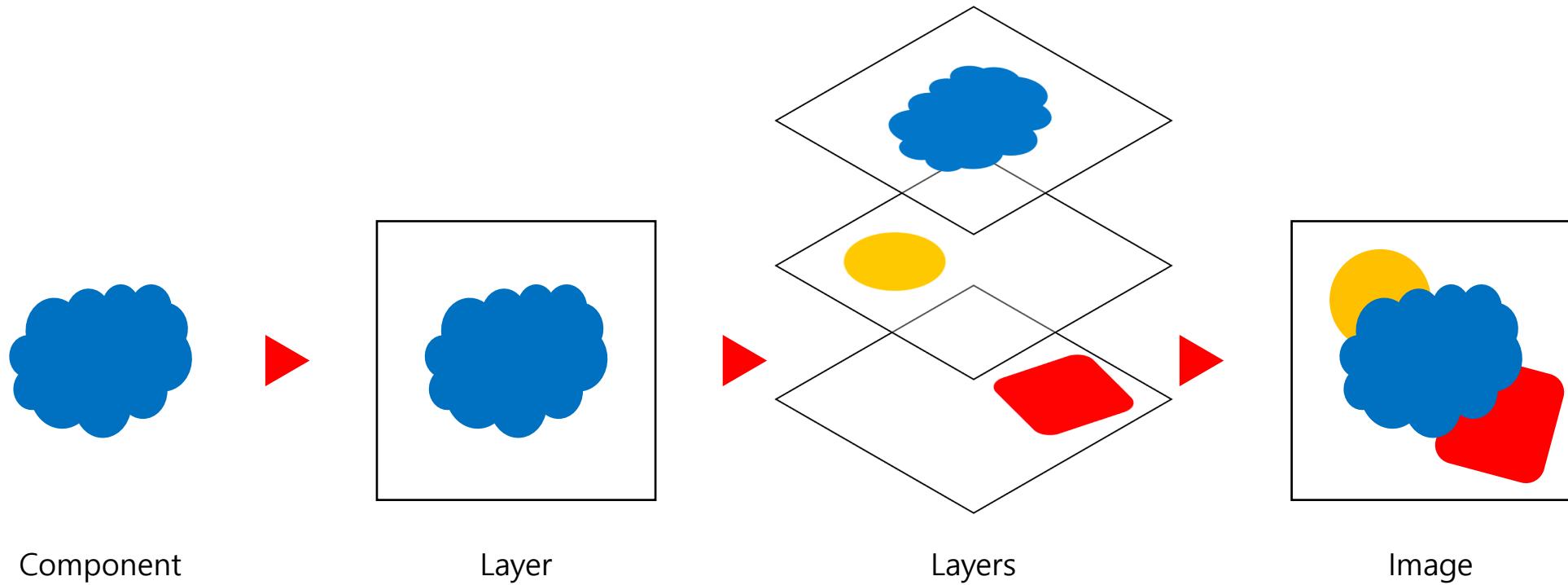


Warm-Up

Bézier Curve

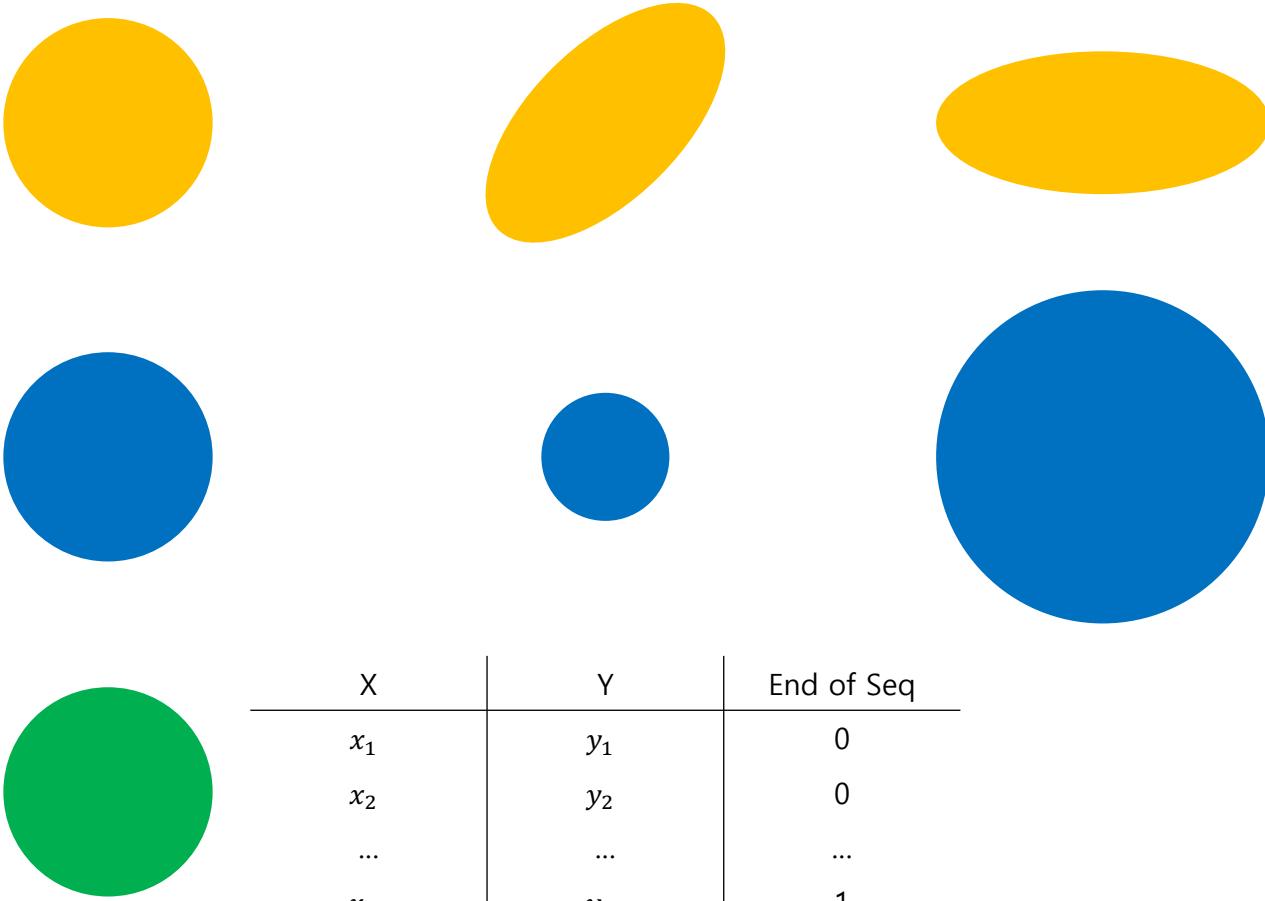


Layer Basics

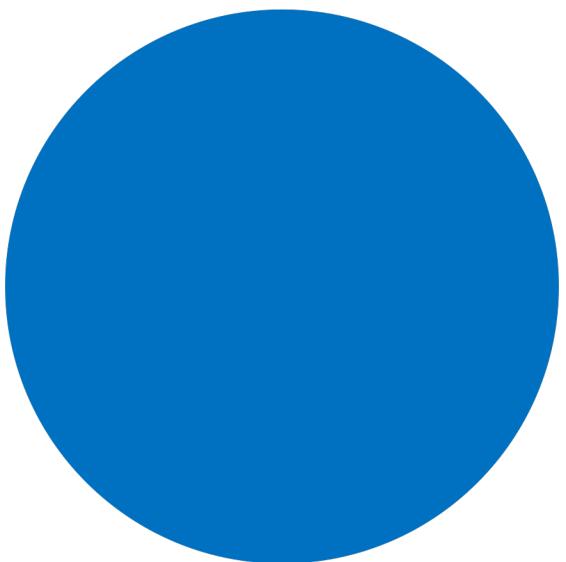


Why Vector?

- Deformable
- Scalable
- Compactness



Comparison



SVG



PNG

Related Works

Related Works

Discovering Pattern Structure Using Differentiable Compositing

PRADYUMNA REDDY, University College London

PAUL GUERRERO, Adobe Research

MATT FISHER, Adobe Research

WILMOT LI, Adobe Research

NILOY J. MITRA, Adobe Research and University College London

DiffComp

Differentiable Vector Graphics Rasterization for Editing and Learning

TZU-MAO LI, MIT CSAIL

MICHAL LUKÁČ, Adobe Research

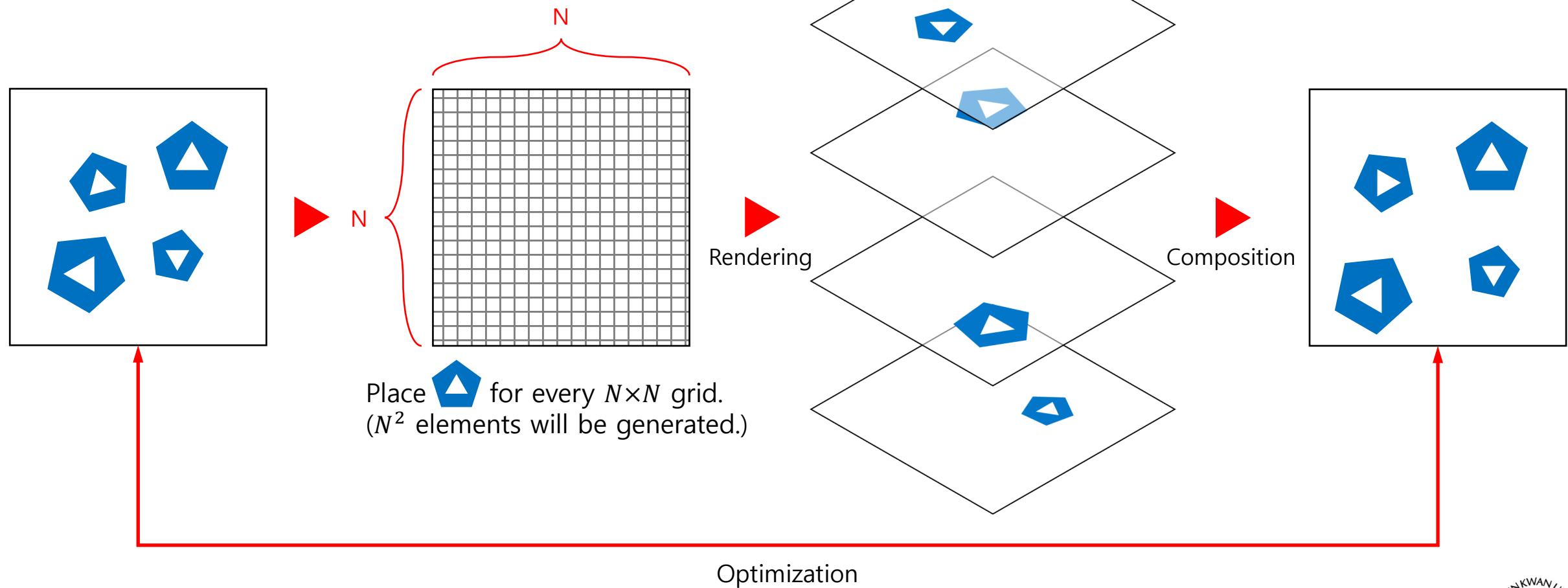
MICHAËL GHARBI, Adobe Research

JONATHAN RAGAN-KELLEY, MIT CSAIL

DiffVG



DiffComp



DiffComp

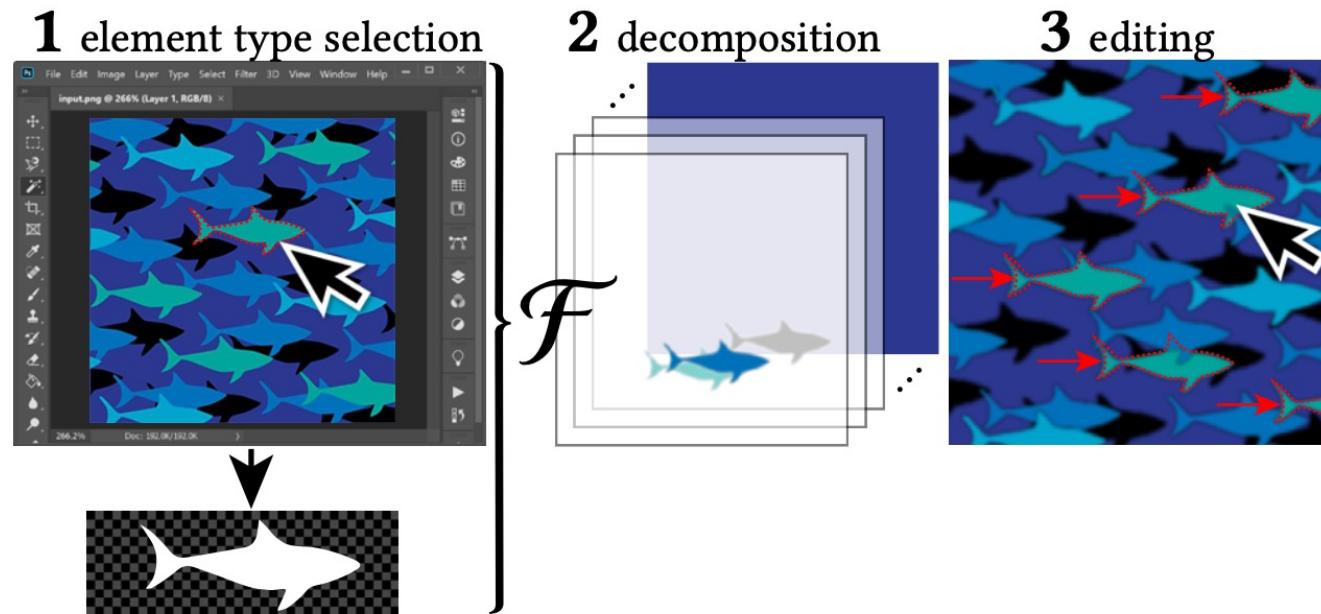
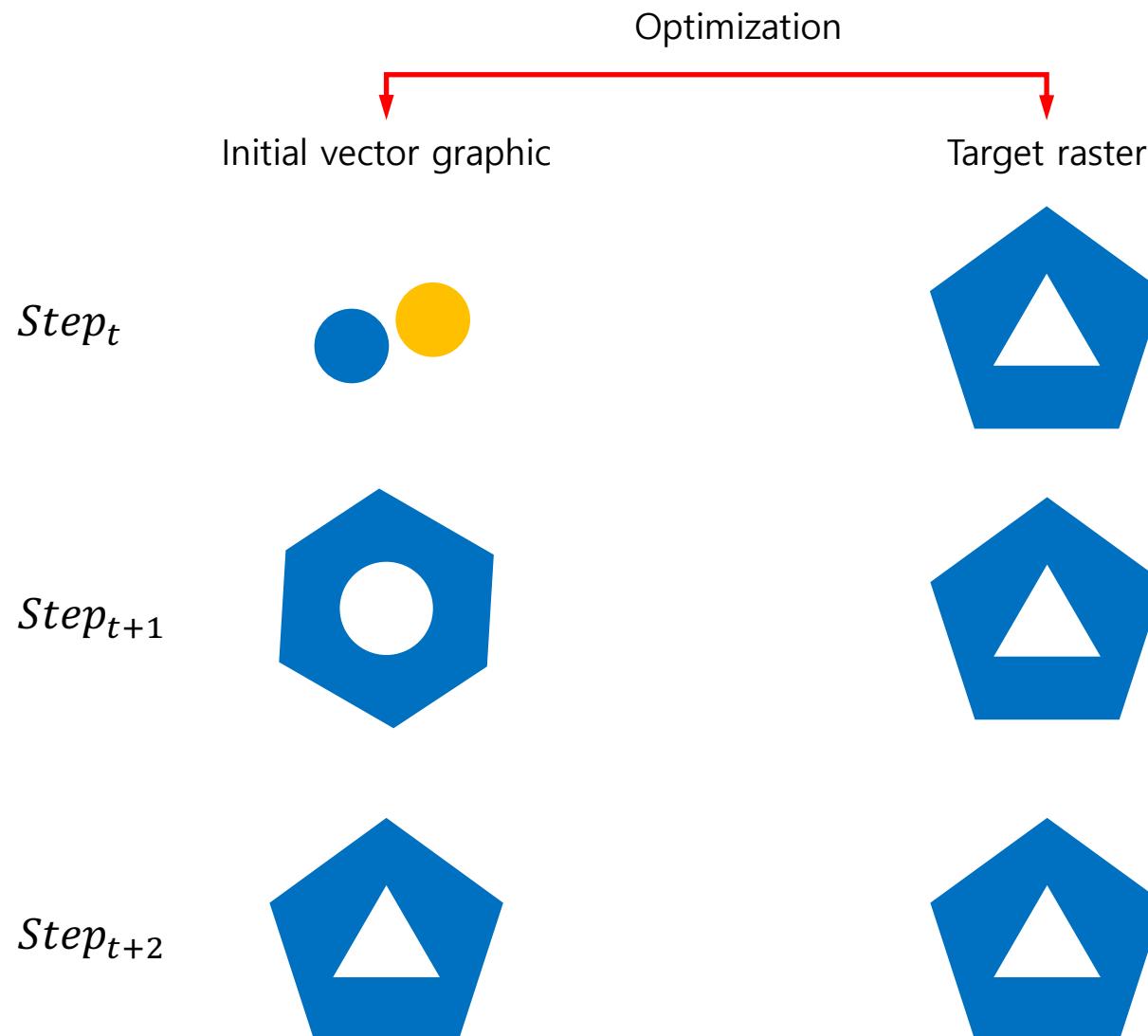


Fig. 6. Pattern decomposition workflow. Starting from a pattern image, the user selects one example of each element type. Here, we only select a single element since we optimize over element colors. The input image and the element types form the input to our differentiable compositor, resulting in discrete elements that we can edit directly or use in down-stream tasks.

DiffVG



DiffVG

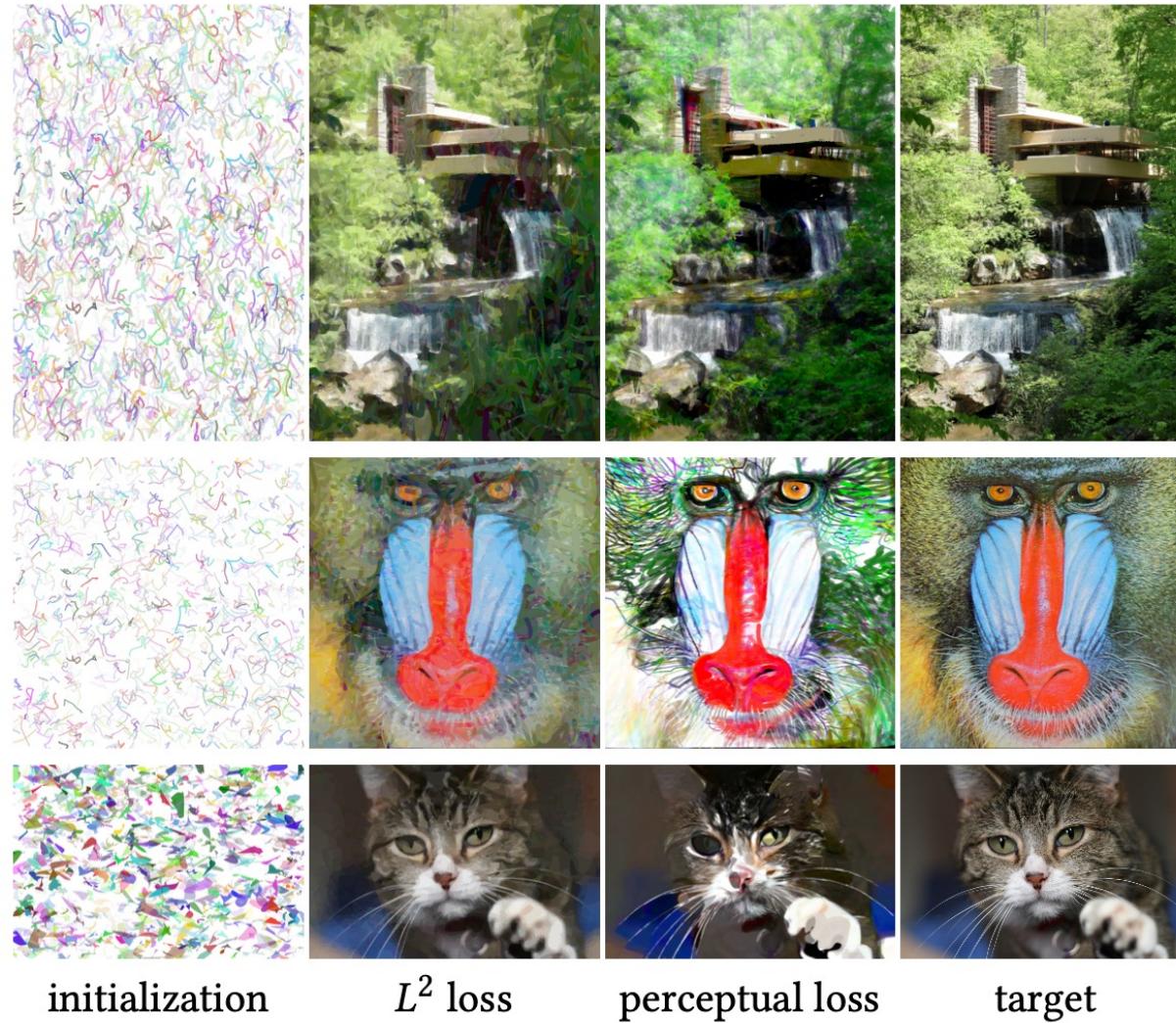


Fig. 13

Im2Vec

Summary of Im2vec

Purpose

- Generate vector graphics from raster images.
- Improve computational efficiency.
 - Computing the same component on every grid (DiffComp).
 - Limitation of active control of the number of components according to input (DiffVG).

Contributions

- Mathematical approach
 - Eliminate the cost of preparing a vector corresponding to a raster (from DiffVG).
- Neural Network Structural Approach
 - Enable active control of the number of components via RNN.
 - Ensure connectivity between Bezier components via Circular CNN.
 - Reduce the computation of redundant components via cartesian coordinate prediction.
 - Improve reconstruction accuracy within a few Bezier segments via adaptive resampler.
- Outperform the vector supervision model without vector supervision.

Limitations

- Small features are sometimes missed.
- Unnecessary features are produced among entangled vector paths.

End-to-End Variational Auto-Encoder

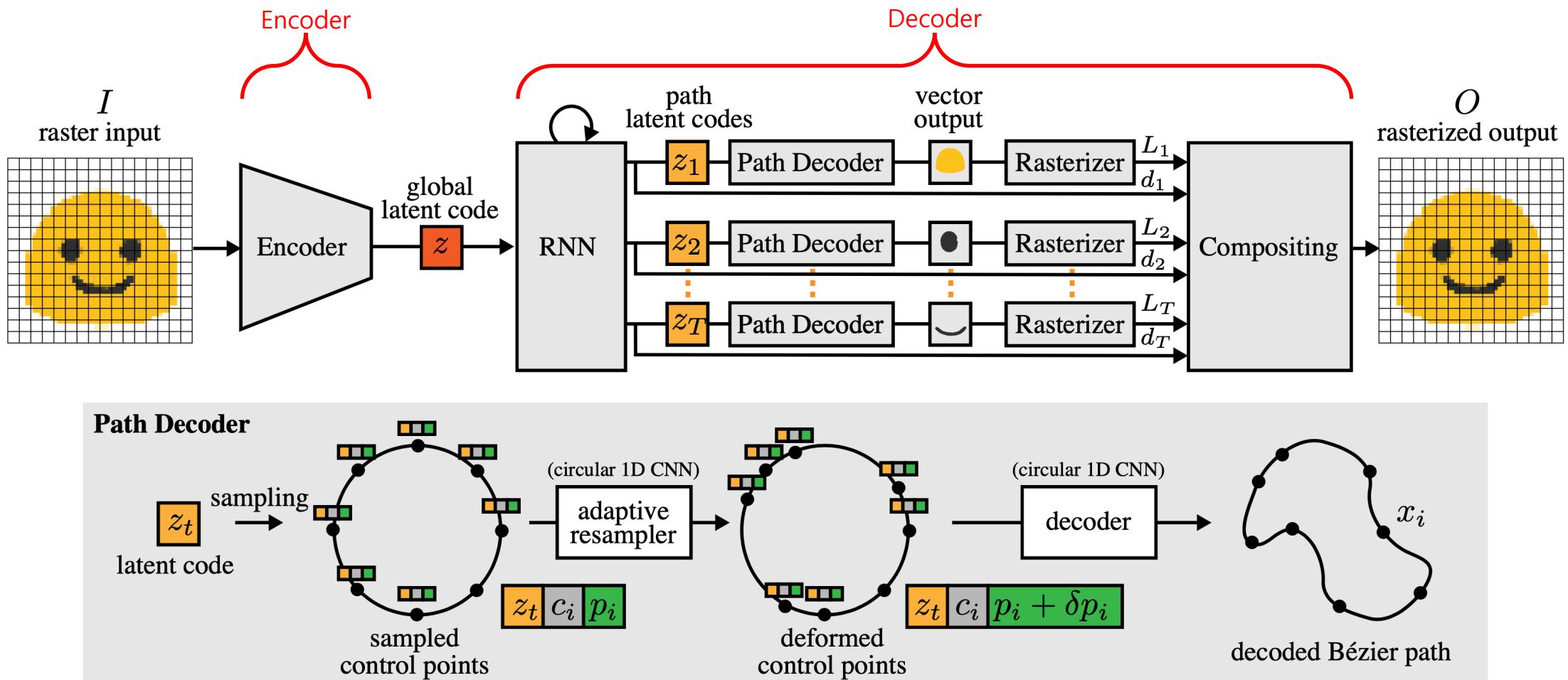
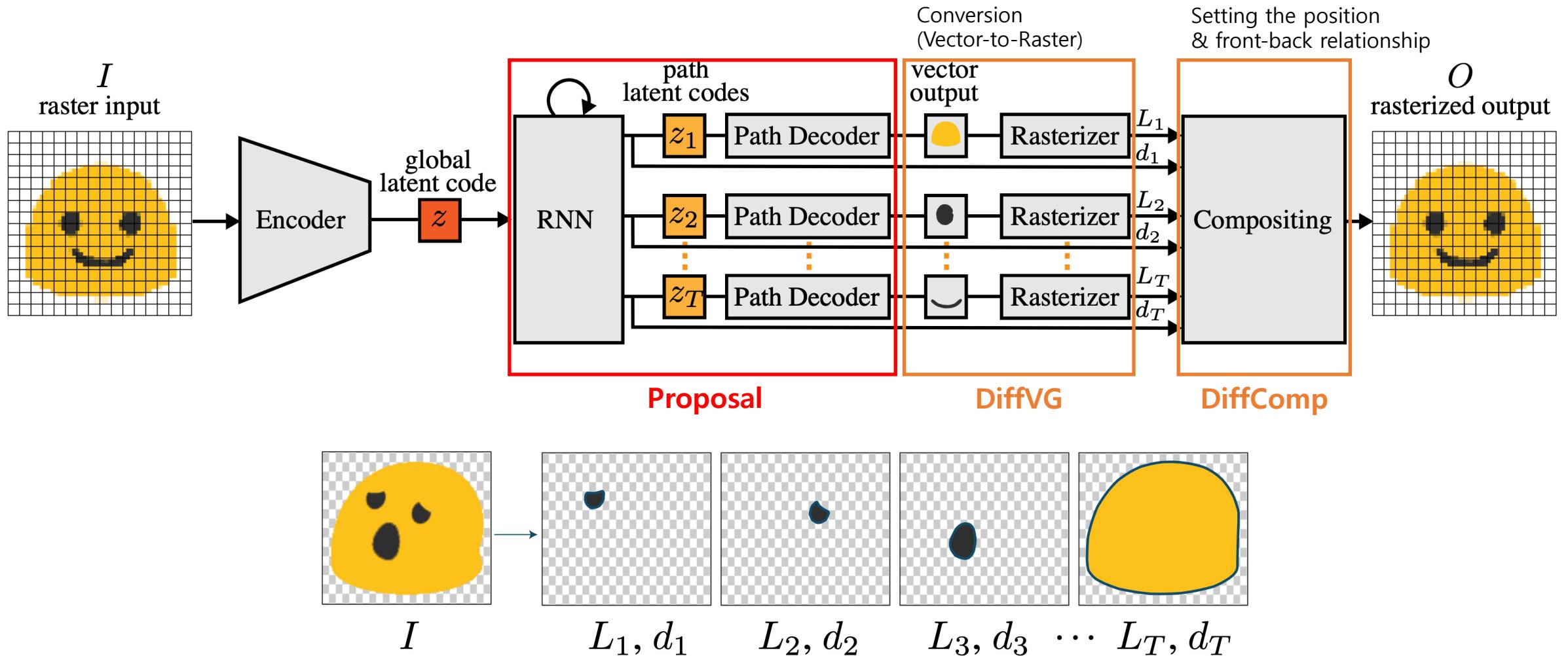
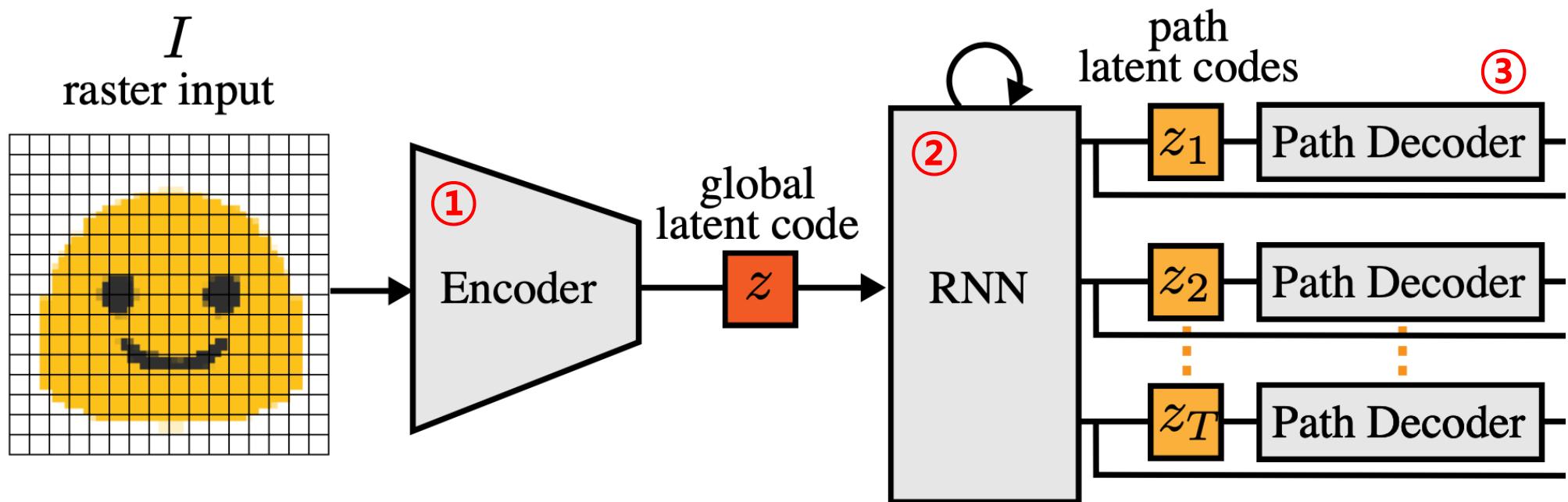


Figure 3: Architecture overview.

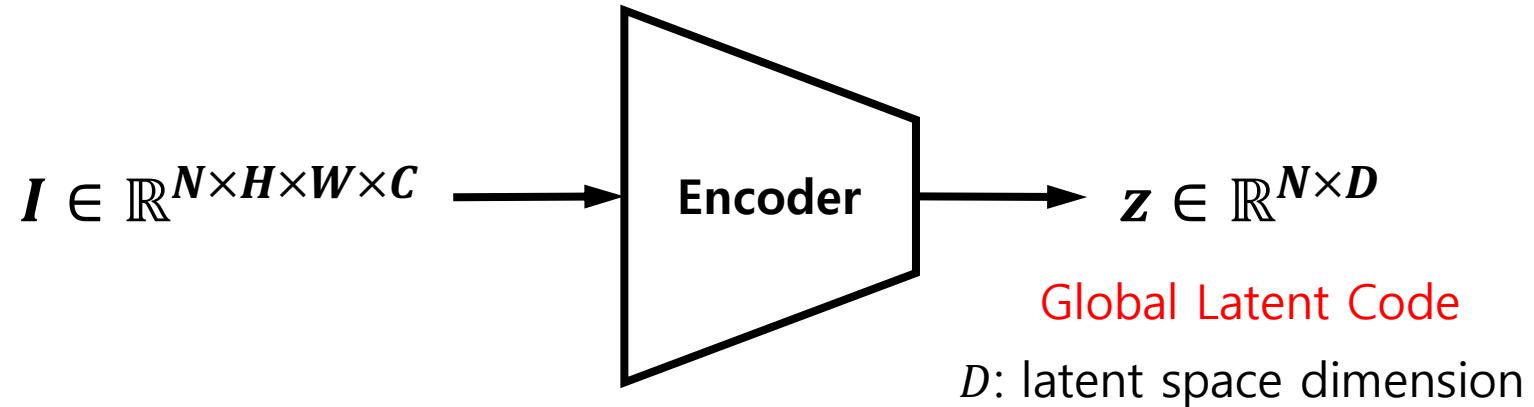
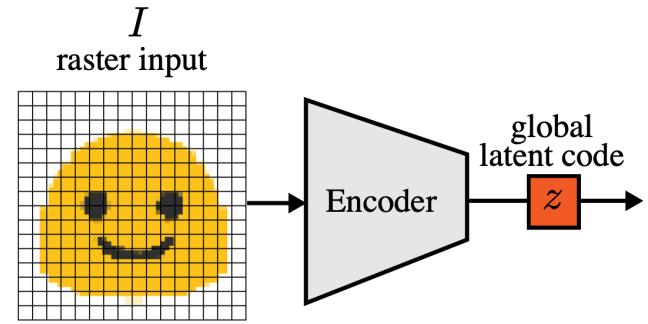
End-to-End Variational Auto-Encoder



Vector Generation

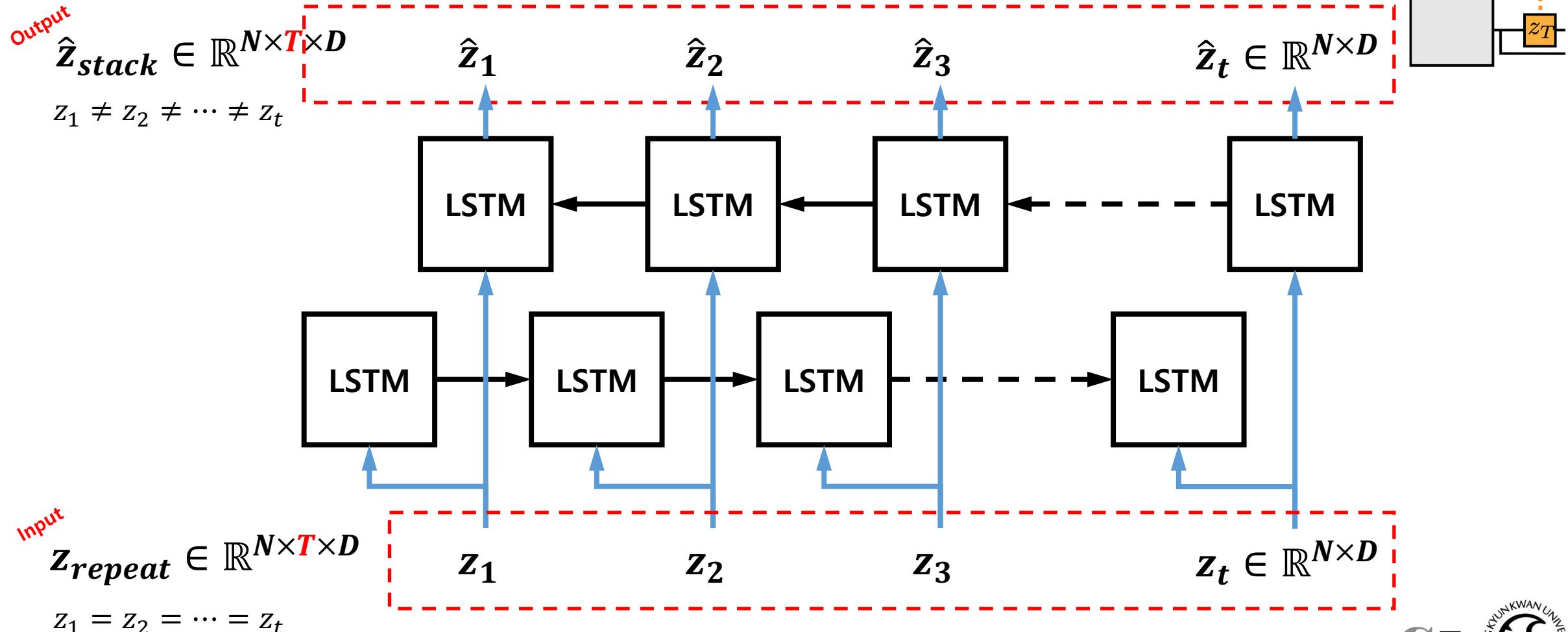


Step 1 – Convolutional Encoder



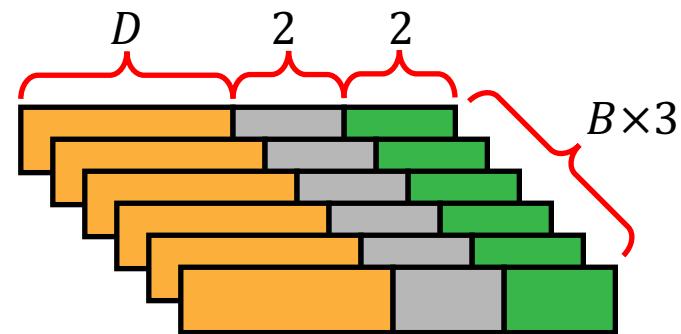
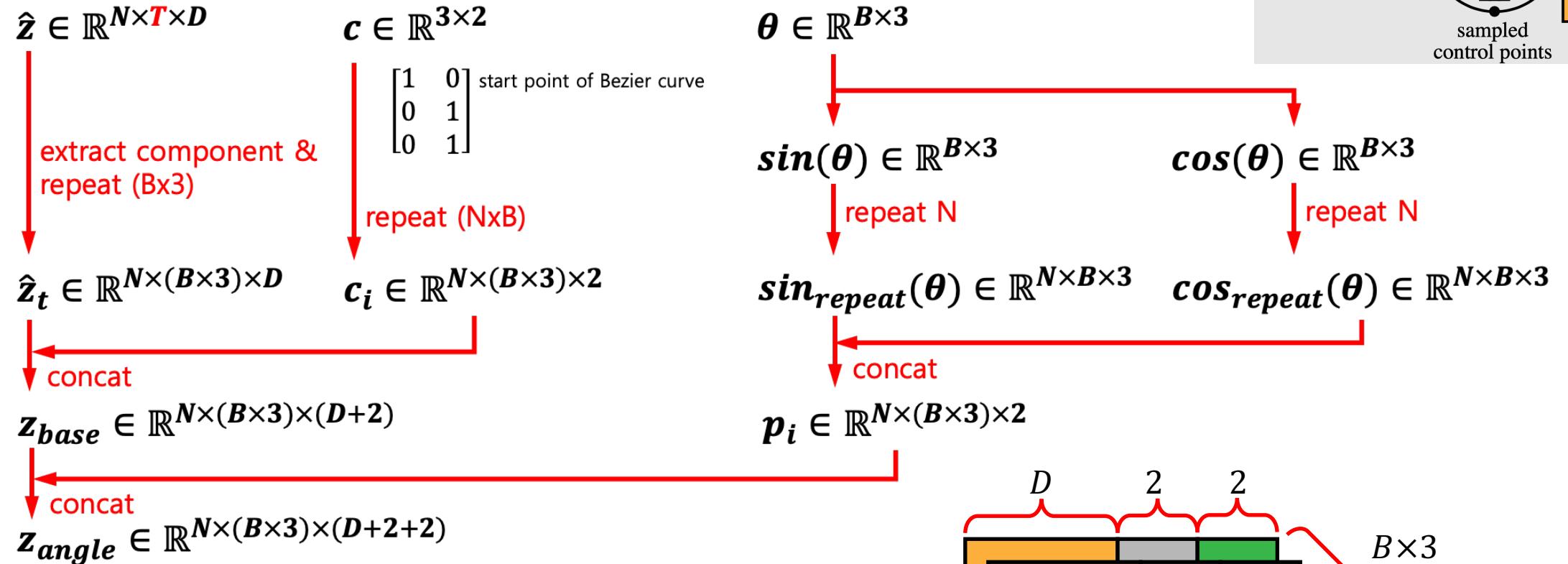
T : number of vector components

Step 2 – Bi-directional LSTM (Component Generator)

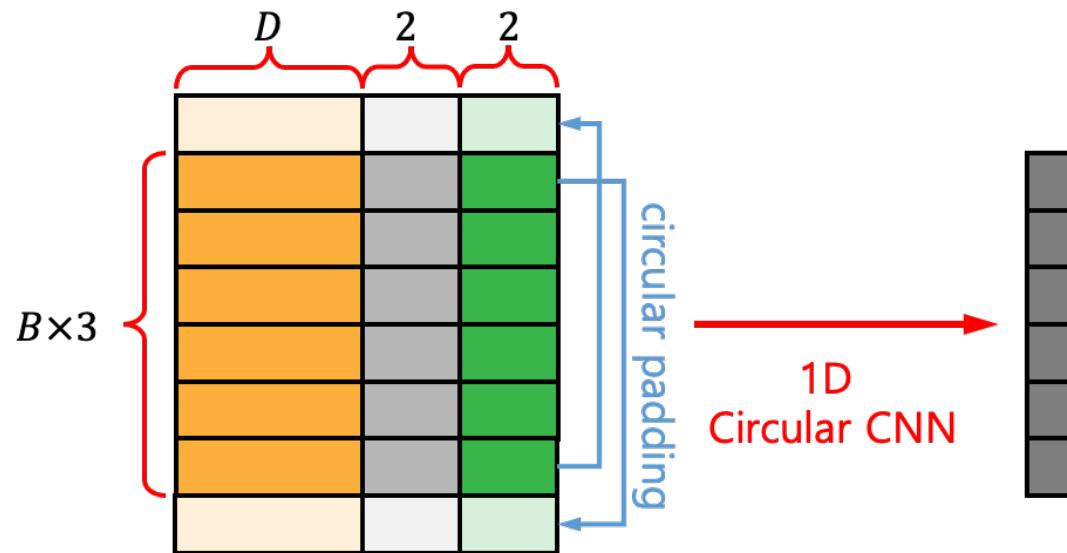
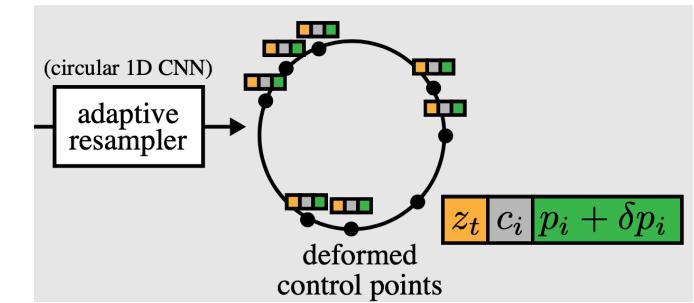


B : number of Bezier curve

Step 3 – Path Decoder (1)



Step 3 – Path Decoder (2) / Adaptive Resampler



$$\mathbf{z}_{angle} \in \mathbb{R}^{N \times (B \times 3) \times (D+2+2)}$$

$$\boldsymbol{\delta} \in \mathbb{R}^{N \times (B \times 3)}$$

$$\begin{aligned}
 & \theta + \boldsymbol{\delta} \in \mathbb{R}^{B \times 3} \\
 & \downarrow \text{sin, cos, repeat, concat} \\
 & \hat{\mathbf{p}}_i \in \mathbb{R}^{N \times (B \times 3) \times 2} \\
 & \mathbf{z}_{base} \in \mathbb{R}^{N \times (B \times 3) \times (D+2)} \\
 & \downarrow \text{concat} \\
 & \mathbf{z}_{deform} \in \mathbb{R}^{N \times (B \times 3) \times (D+2+2)}
 \end{aligned}$$

Step 3 – Path Decoder & Rasterizer

$$z_{deform} \in \mathbb{R}^{N \times (B \times 3) \times (D+2+2)}$$

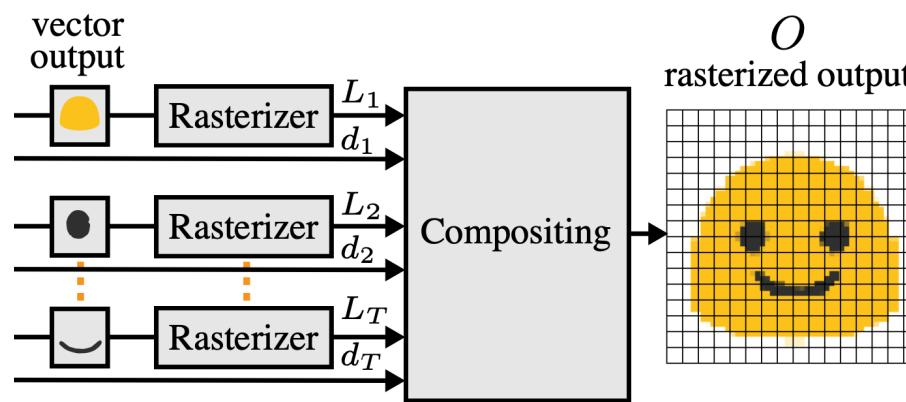
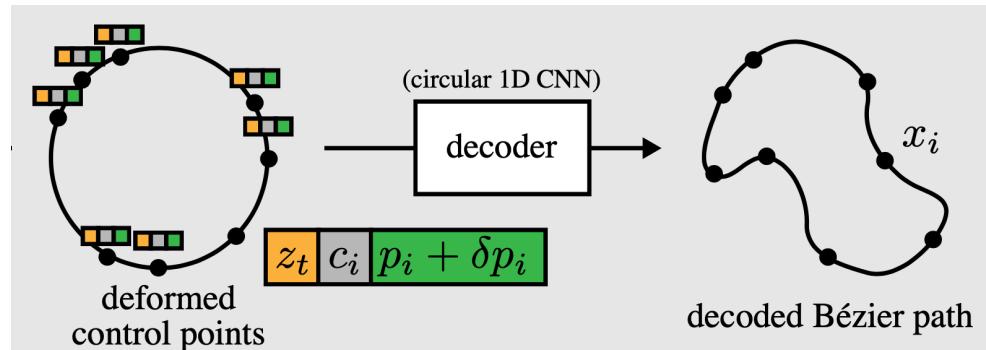
↓
1D
Circular CNN

$$x_t \in \mathbb{R}^{N \times (B \times 3) \times 2}$$

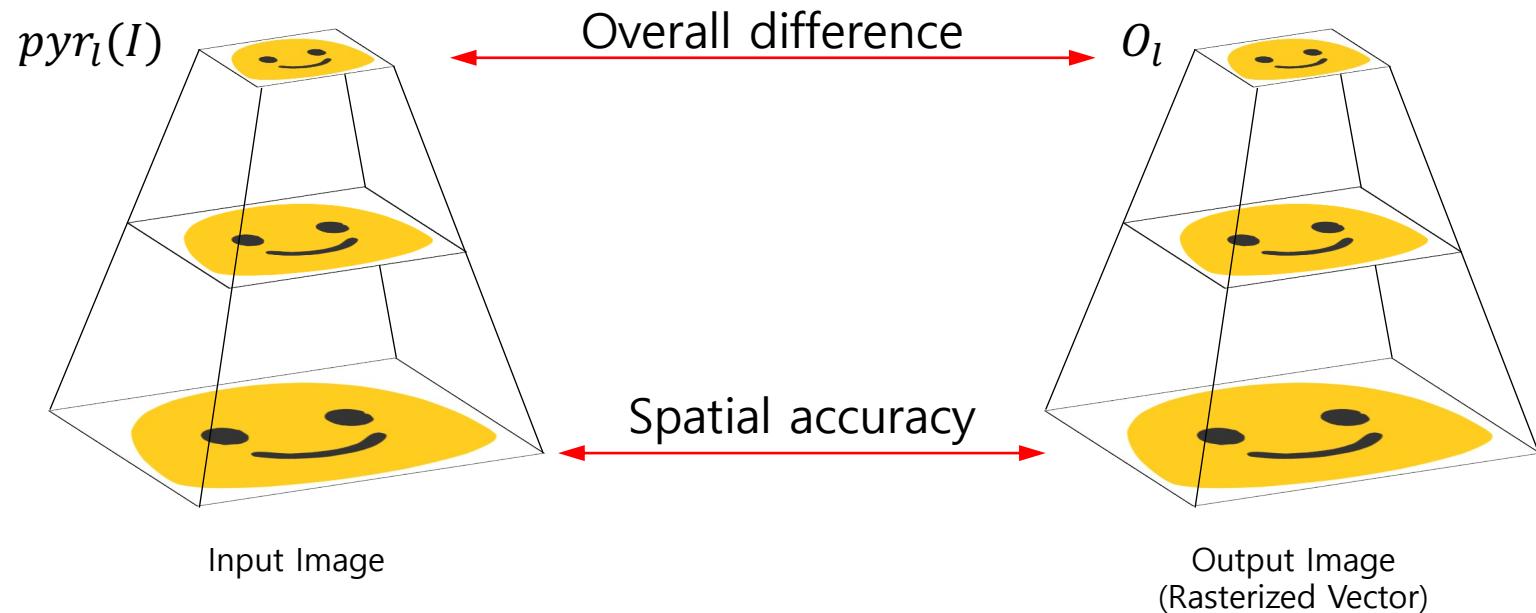
↓
Vector component

↓
Rasterizing

↓
Compositing



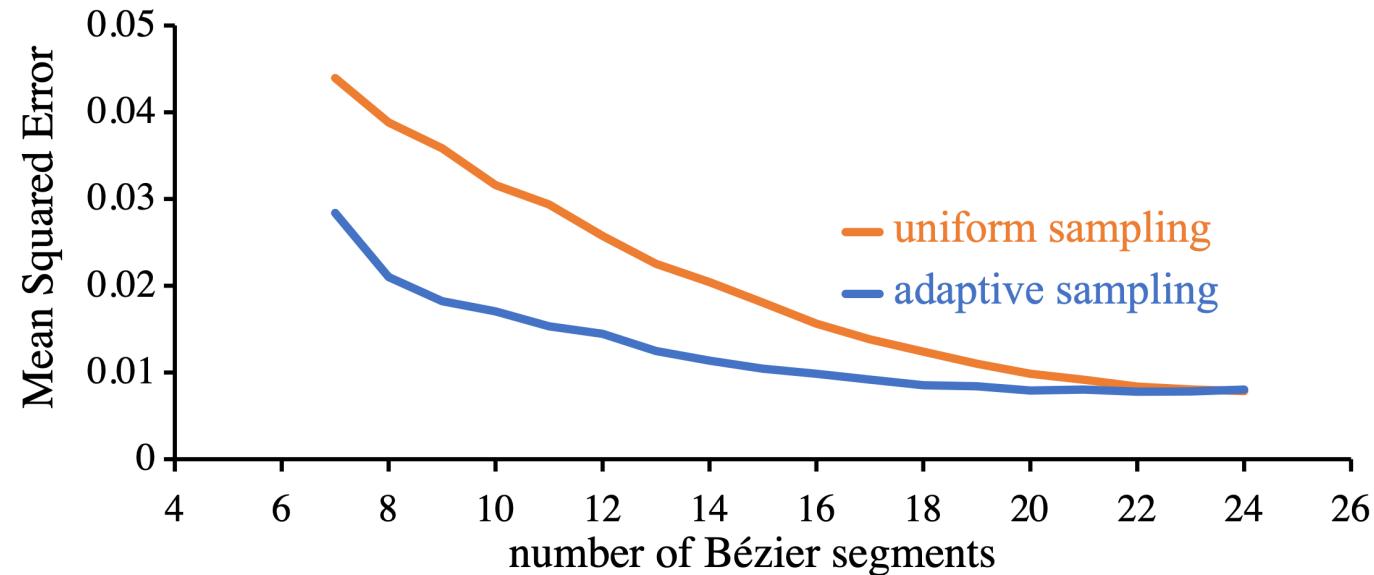
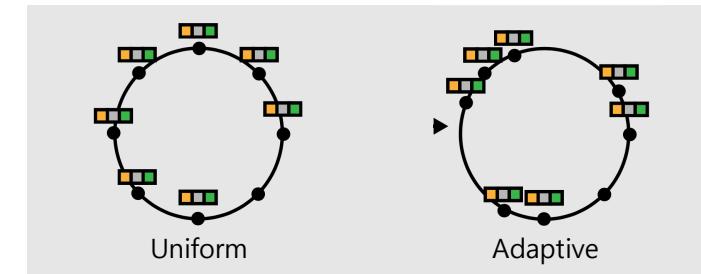
Loss Function / Multi-resolution Raster Loss



$$\mathbb{E}_{I \sim \mathcal{D}} \sum_{l=1}^L \|pyr_l(I) - O_l\|^2$$

Experiments

Comparison – Sampling Method



(b) error vs. number of segments

Figure 4: Uniform vs. adaptive sampling.

Comparison – Font / Reconstruction

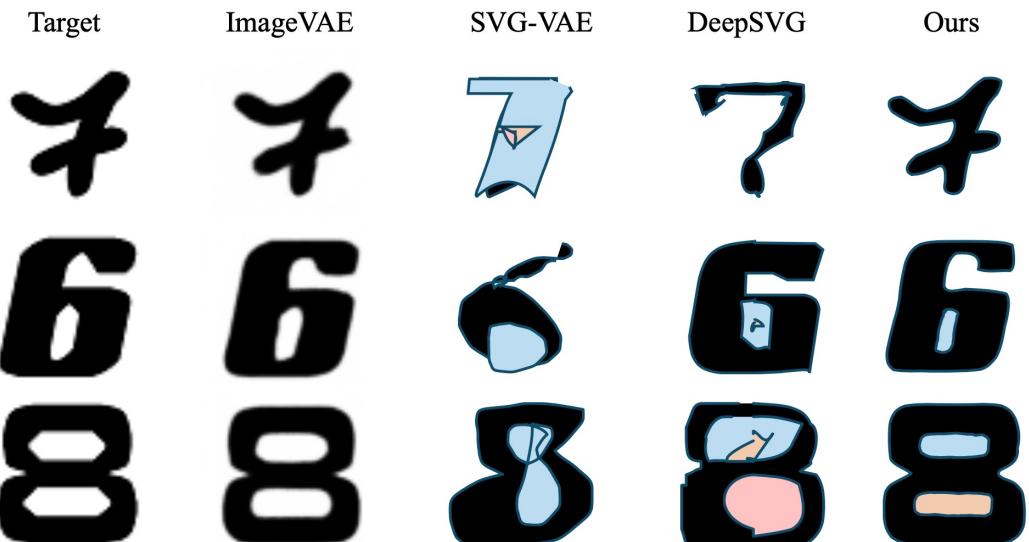


Figure 6: **Reconstructions on Fonts.** ■ Componant-1
■ Componant-2
■ Componant-3
■ Componant-4

Table 1: **Reconstruction quality.** Comparison of pixel-space reconstruction losses for various methods and datasets. Note that neither SVG-VAE nor DeepSVG operate on datasets without vector supervision.

	FONTS	MNIST	EMOJIS	ICONS
ImageVAE	0.0116	0.0033	0.0016	0.0002
SVG-VAE	0.1322	X	-	-
DeepSVG	0.0938	X	-	-
Im2Vec (Ours)	0.0284	0.0036	0.0014	0.0003

Comparison – Font / Interpolation



(b) Comparison to baselines on FONTS

Comparison – MNIST

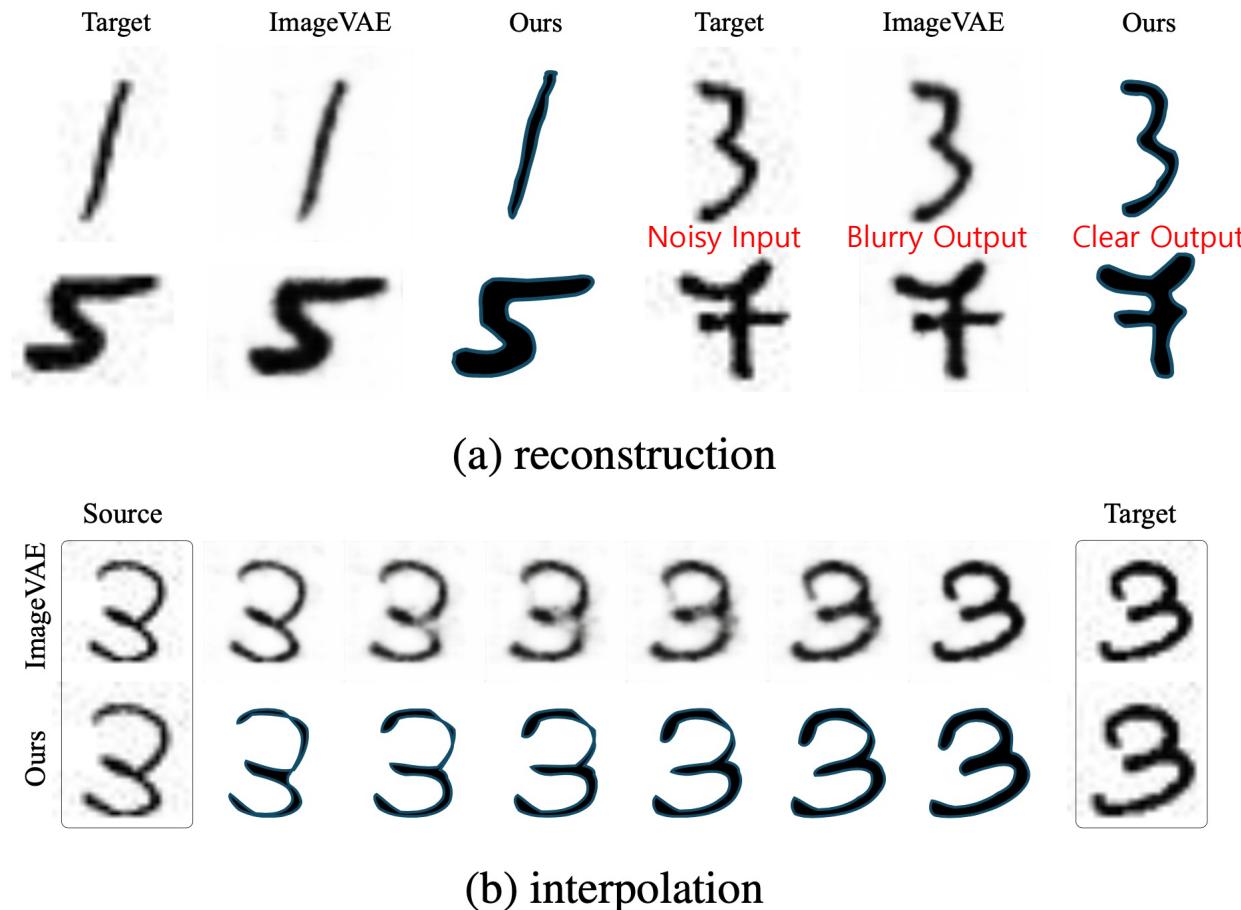
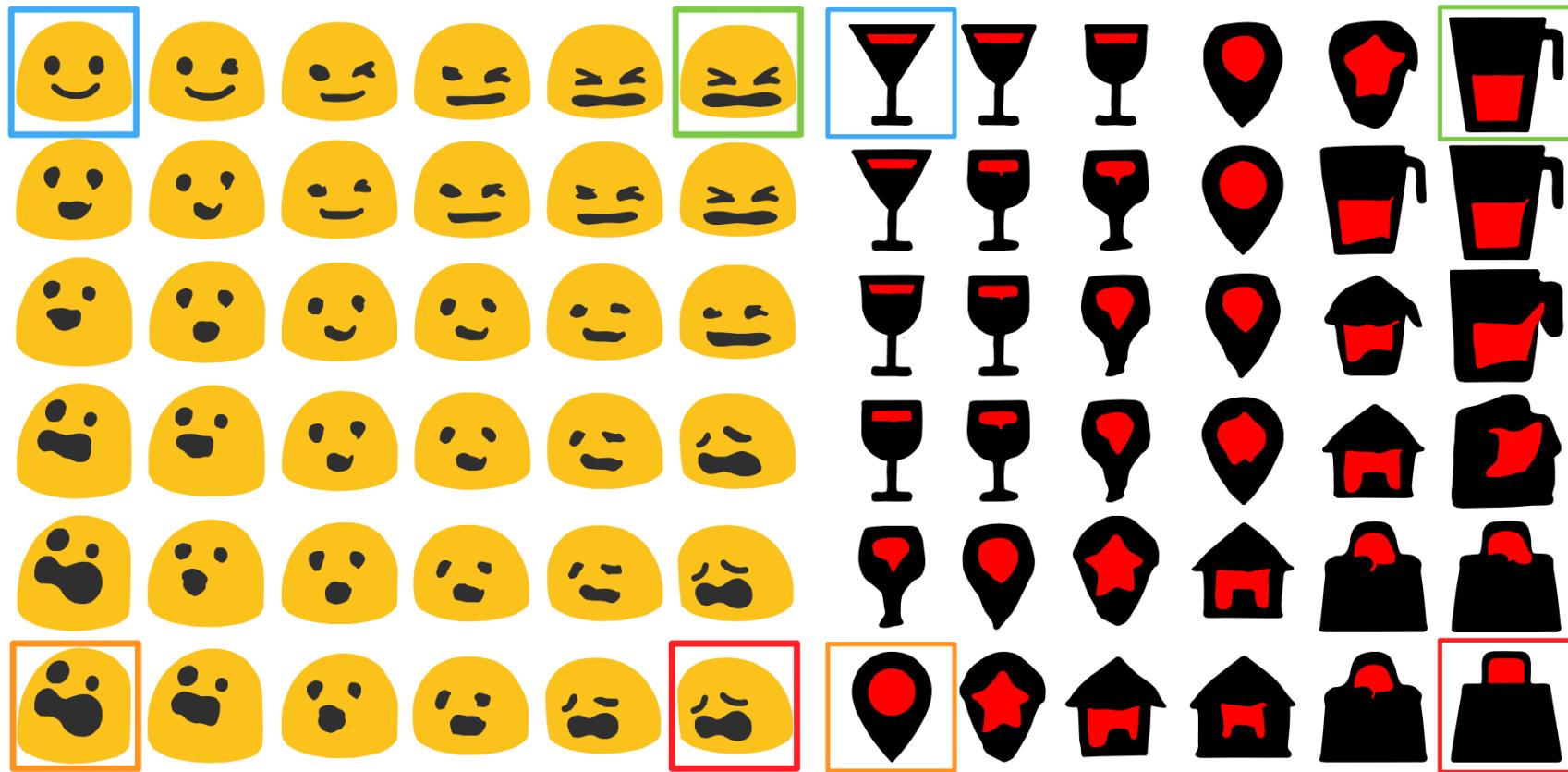


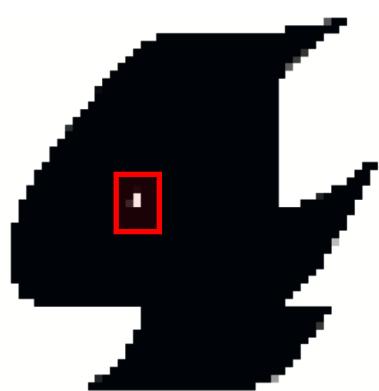
Figure 7: MNIST results.

Comparison – Emoji & Icons

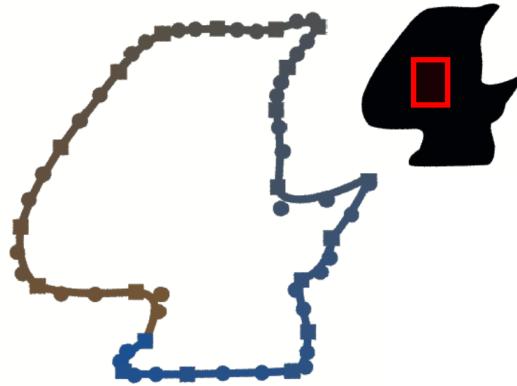


(a) EMOJIS and ICONS interpolations using Im2Vec

Limitations



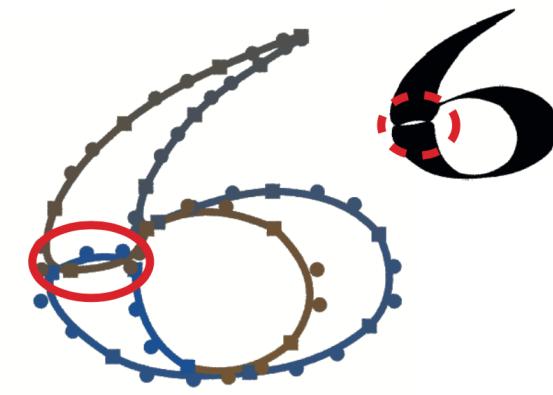
Input



Reconstruction



Input



Reconstruction

Figure 11: Limitations.

Recap. Im2vec

Purpose

- Generate vector graphics from raster images.
- Improve computational efficiency.
 - Computing the same component on every grid (DiffComp).
 - Limitation of active control of the number of components according to input (DiffVG).

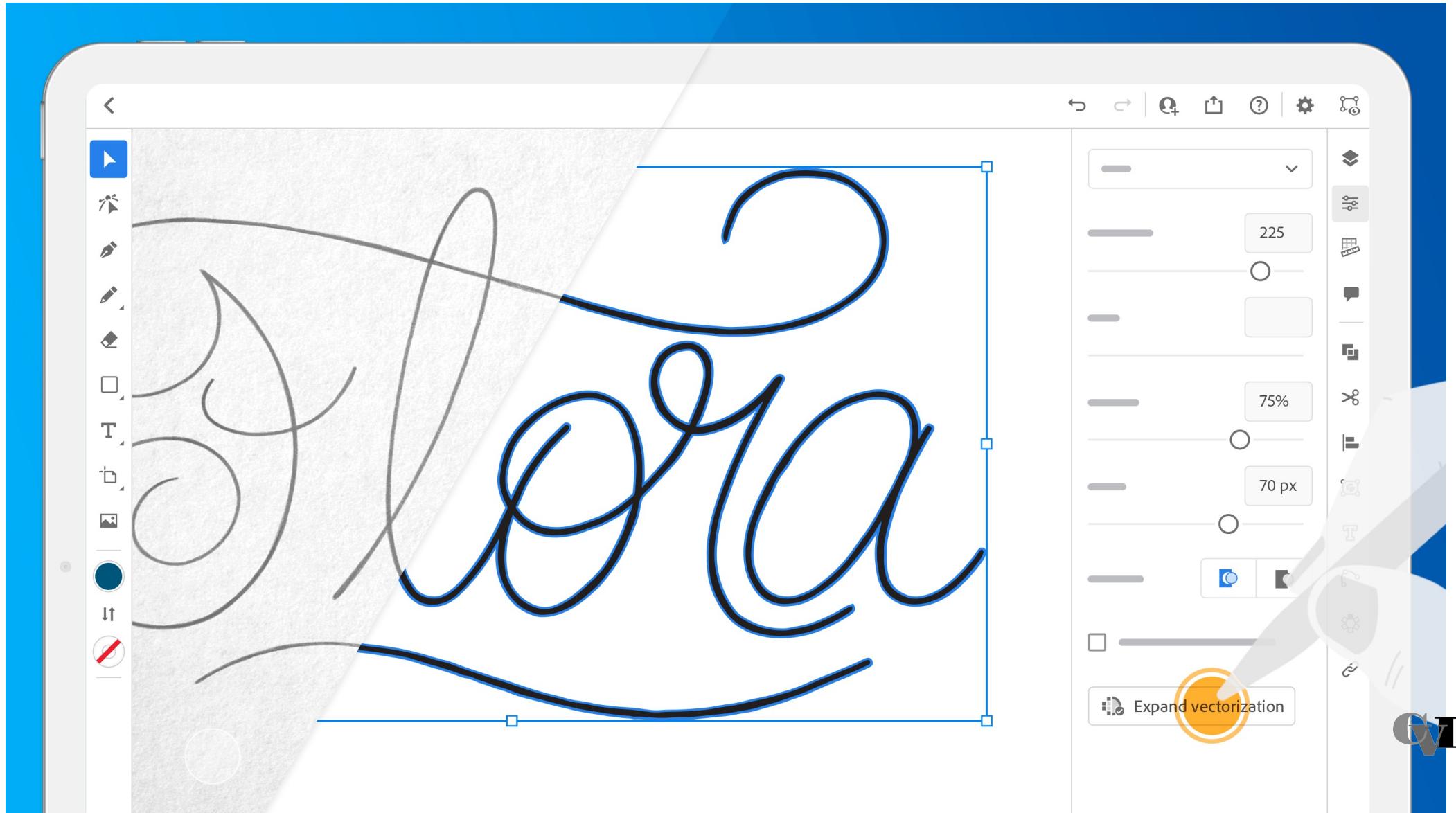
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Limitations

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Where to Use?

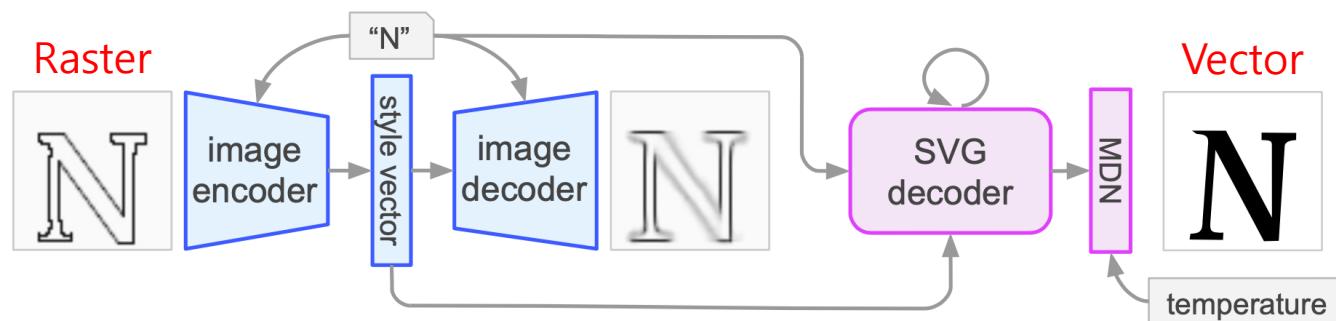


Appendix-A

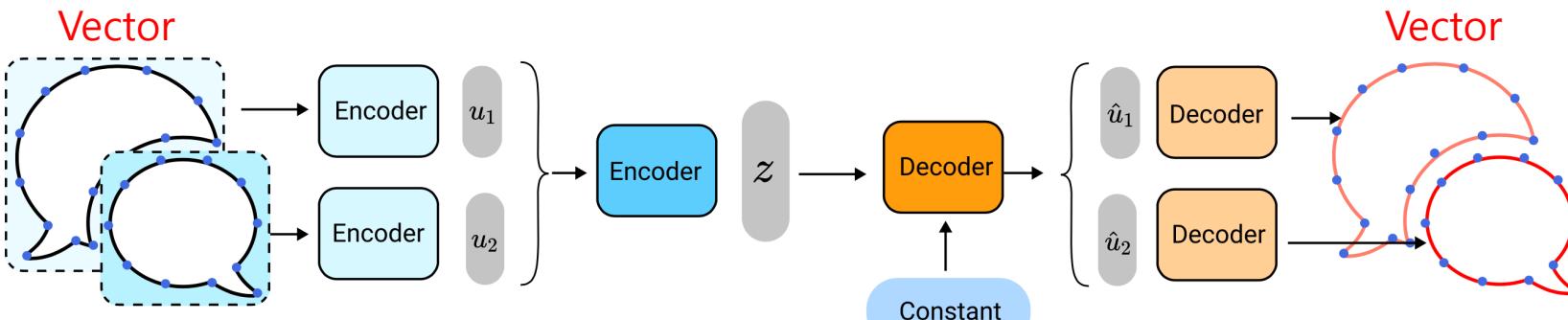
Vector Supervised Models

SVG-VAE

Image Autoencoder



DeepSVG



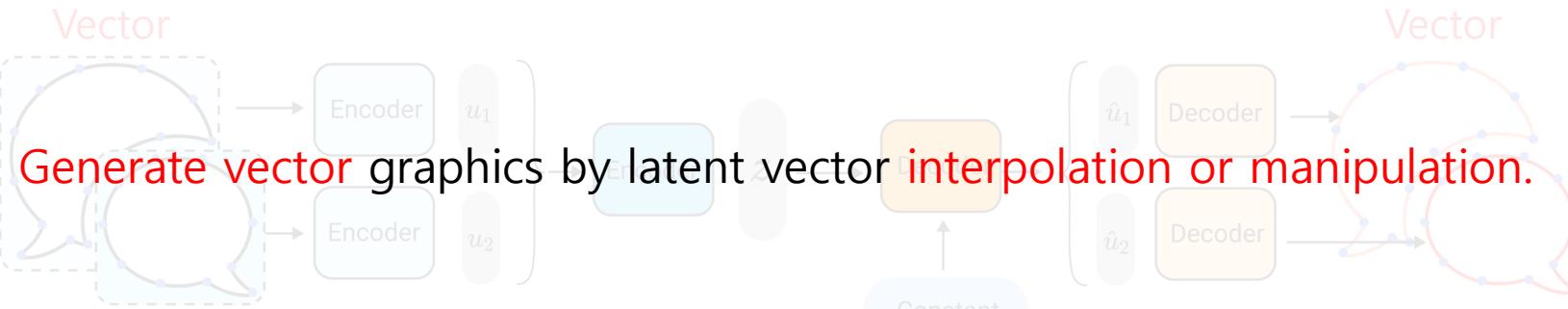
Vector Supervised Models

SVG-VAE

Image Autoencoder



DeepSVG

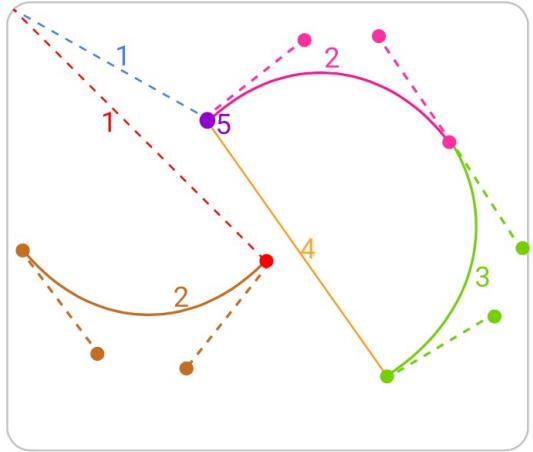


Scalable Vector Graphics (SVG) Representation

Table 1: List of the SVG draw-commands, along with their arguments and a visualization, used in this work. The start-position (x_1, y_1) is implicitly defined as the end-position of the preceding command.

Command	Arguments	Description	Visualization
<SOS>	\emptyset	'Start of SVG' token.	
M (MoveTo)	x_2, y_2	Move the cursor to the end-point (x_2, y_2) without drawing anything.	
L (LineTo)	x_2, y_2	Draw a line to the point (x_2, y_2) .	
C (Cubic Bézier)	q_{x1}, q_{y1} q_{x2}, q_{y2} x_2, y_2	Draw a cubic Bézier curve with control points (q_{x1}, q_{y1}) , (q_{x2}, q_{y2}) and end-point (x_2, y_2) .	
z (ClosePath)	\emptyset	Close the path by moving the cursor back to the path's starting position (x_0, y_0) .	
<EOS>	\emptyset	'End of SVG' token.	

SVG Visualization

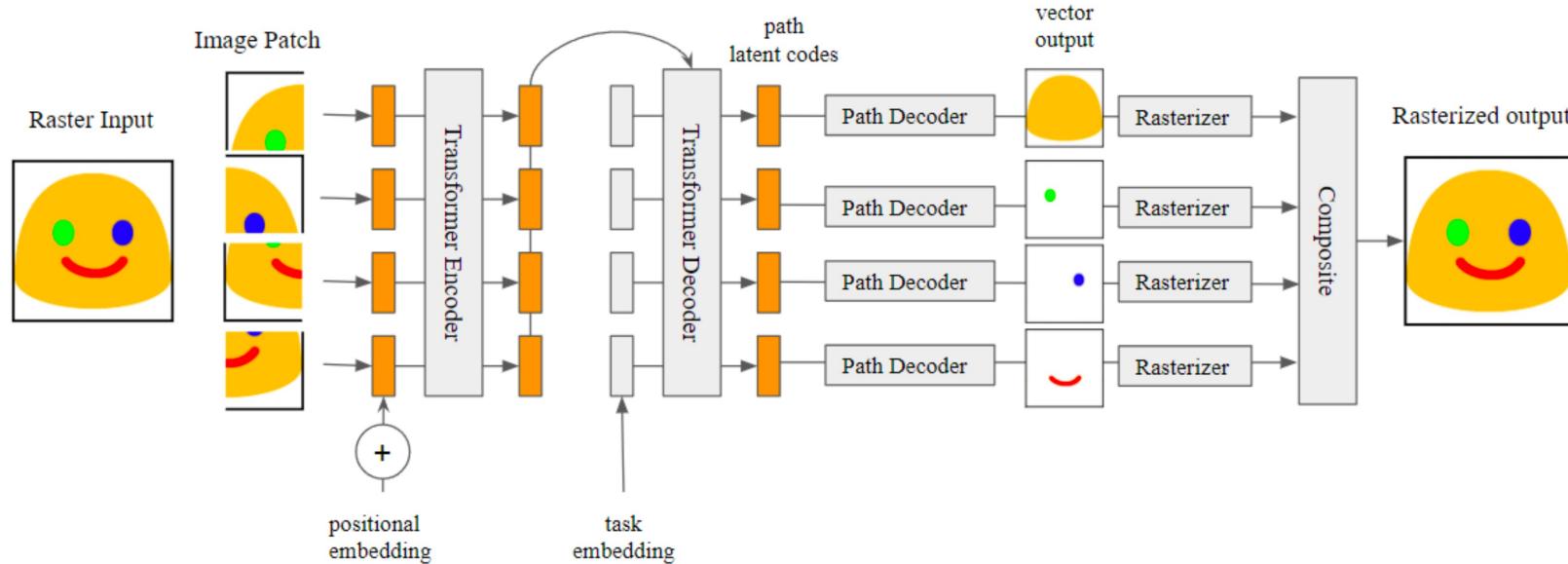


Index	Command	Arguments	P_1	P_2
0	<SOS>	-1 -1 -1 -1 -1 -1		
1	m	-1 -1 -1 -1 95 54		
2	c	143 16 180 14 215 66		
3	c	255 118 244 152 191 181		
4	l	-1 -1 -1 -1 95 54		
5	z	-1 -1 -1 -1 -1 -1		
6	<EOS>	-1 -1 -1 -1 -1 -1		

Figure 10: Example of SVG representation. Left: Input SVG image. Right: Corresponding tensor representations with 2 paths and 7 commands ($N_P = 2$, $N_C = 7$). Commands in the image and the corresponding tensor are color-coded for a better visualization. The arguments are listed in the order $q_{x1}, q_{y1}, q_{x2}, q_{y2}, x_2$ and y_2 . Best viewed in color.

Appendix-B

트랜스포머를 이용한 래스터 이미지 벡터화 자기 지도학습



장점

- CNN 대신 ViT로 latent code 형성 (global feature)

단점

- Latent code의 수 (컴포넌트 수)가 패치 개수에 의존성을 가짐

Appendix-C

Appendix

Official Source Code

- Im2Vec: <https://github.com/preddy5/Im2Vec>  PyTorch
- DiffComp: <https://github.com/preddy5/DiffCompositing>  PyTorch
- DiffVG: <https://github.com/BachiLi/difvg>  PyTorch

DiffComp

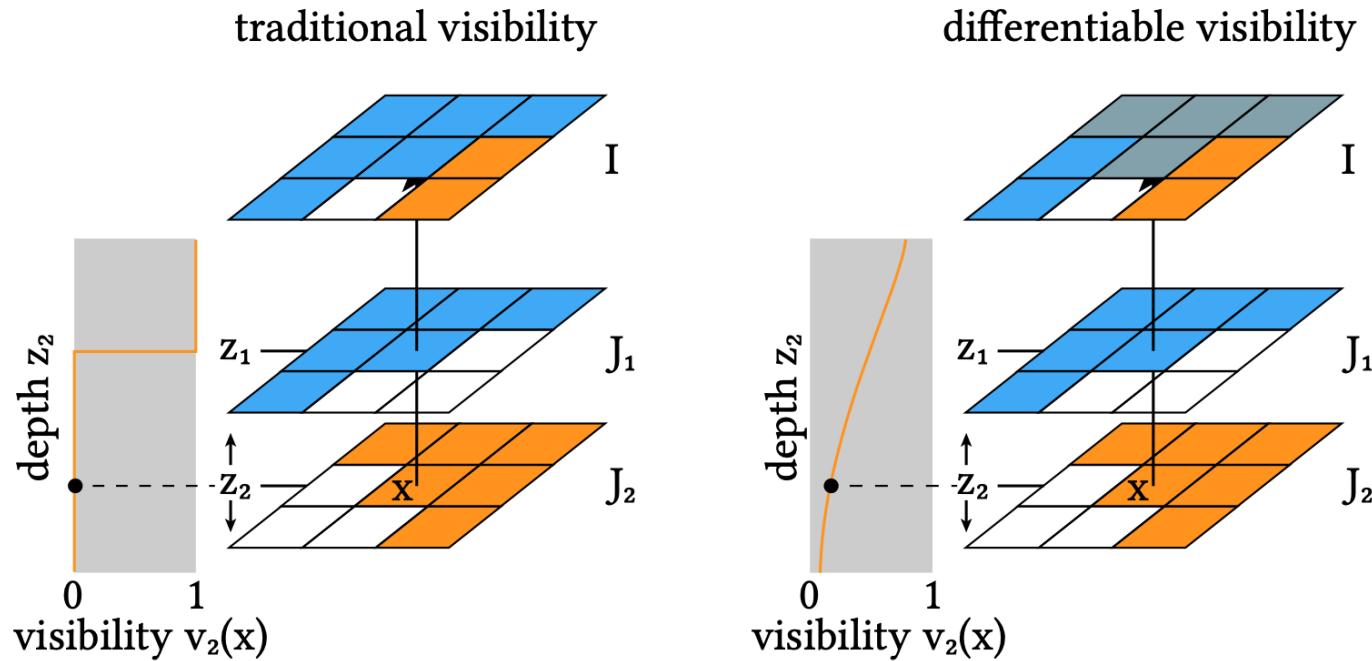


Fig. 5. Differentiable visibility. The traditional visibility function is not differentiable due to C^0 discontinuities at disocclusions. In our differentiable formulation, each layer contributes to the final image with a weight that decreases exponentially with distance from the top-most layer.

DiffVG

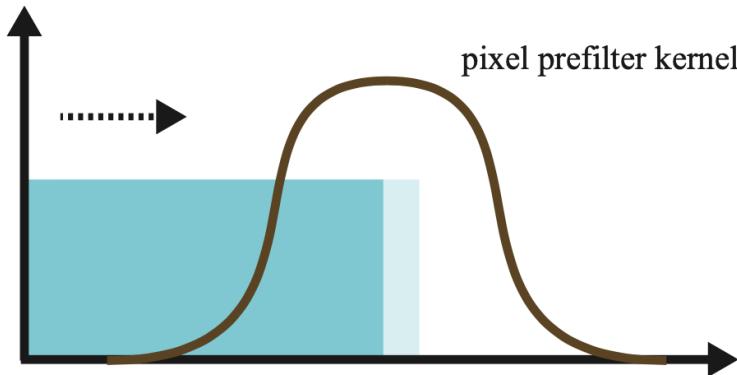


Fig. 2. Pixel prefiltering using a convolution makes a discontinuous function smooth. We illustrate this using a box function in 1D. To rasterize this discontinuous box function with anti-aliasing, we convolve the box with a kernel centered at the pixel center. Moving the box causes a continuous change of the area under the filtering kernel, and therefore, of the anti-aliased signal.