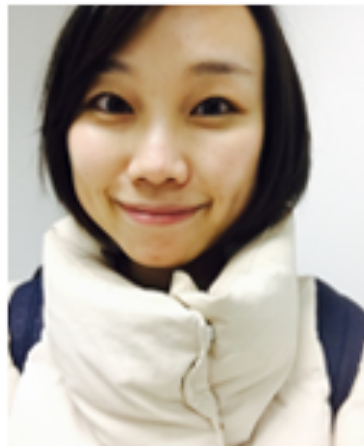




Unsupervised Sketch-to-Photo Synthesis



Runtao Liu*

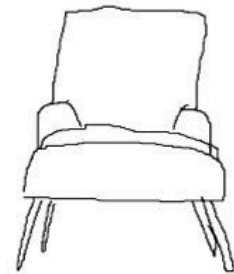
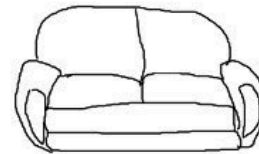
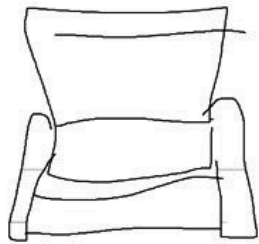
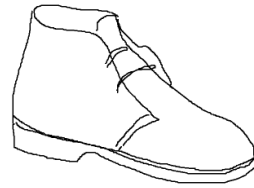
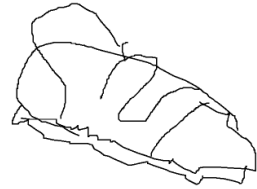
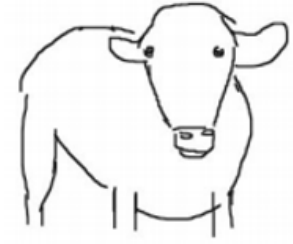
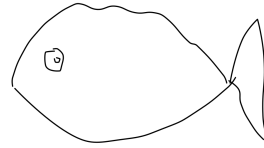
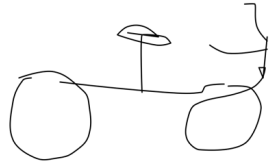


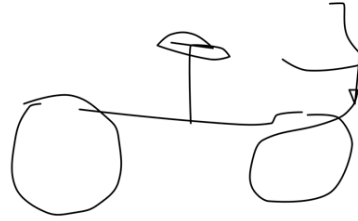
Qian Yu*



Stella Yu

<http://sketch.icsi.berkeley.edu/>



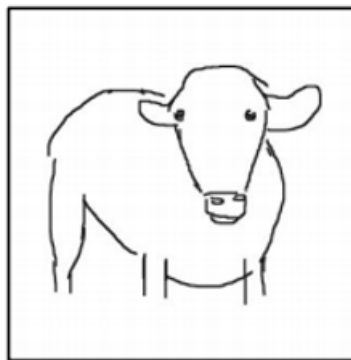


Sketch Recognition

Yu et al., BMVC 2015
Ye et al., ICMR 2016

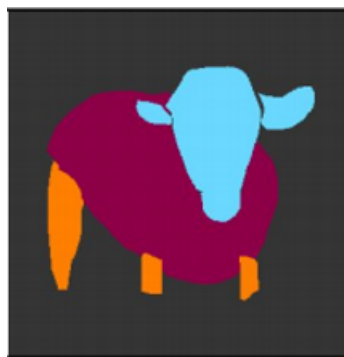


“ bicycle ”



Sketch Segmentation

Zou et al., ECCV 2018
Sarvadevabhatla et al., MM 2017
Qi et al., CVPR 2015



- Body
- Head
- Leg
- Tail



Sketch based
Image Retrieval

Yu et al., CVPR 2016
Hu et al., CVIU 2013
Wang et al., CVPR 2015





Challenge 1: Lack Colors and Details

Photo



Sketch



Grayscale



Edge Map



more abstract

Challenge 2: Shape Deformation & Style Variations

Photo



Sketch



Grayscale



Edge Map



more abstract

Paired / Aligned



Pix2Pix



Unpaired / Aligned



CycleGAN MUINT UGATIT



Unpaired / Unaligned



Ours



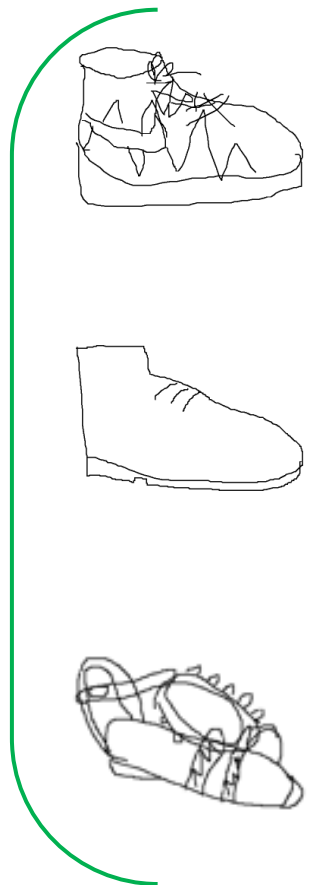
Unsupervised Sketch to Photo Synthesis



input sketch

output photo

Two-Stage Approach via Intermediate Grayscale Image



input sketch

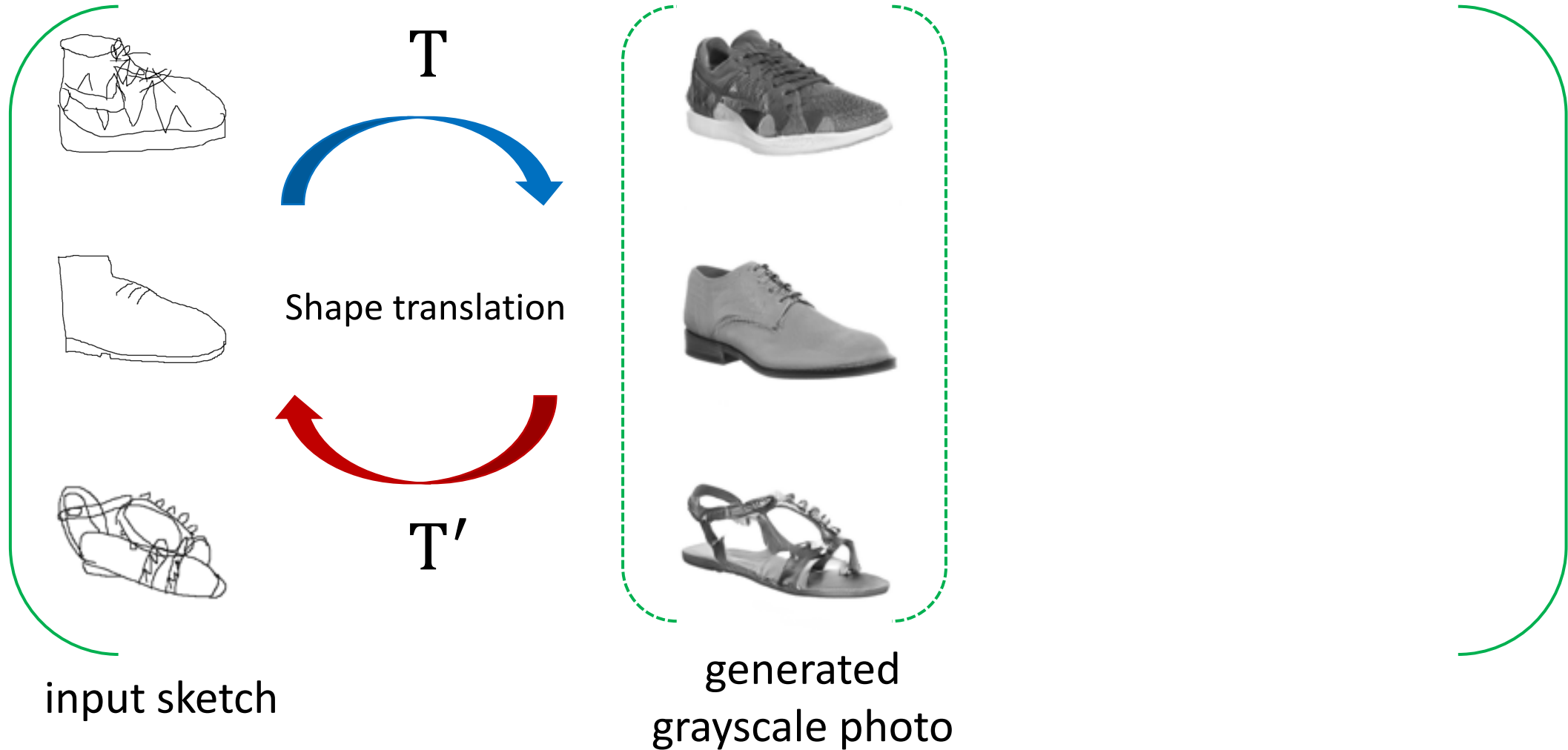


generated
grayscale photo

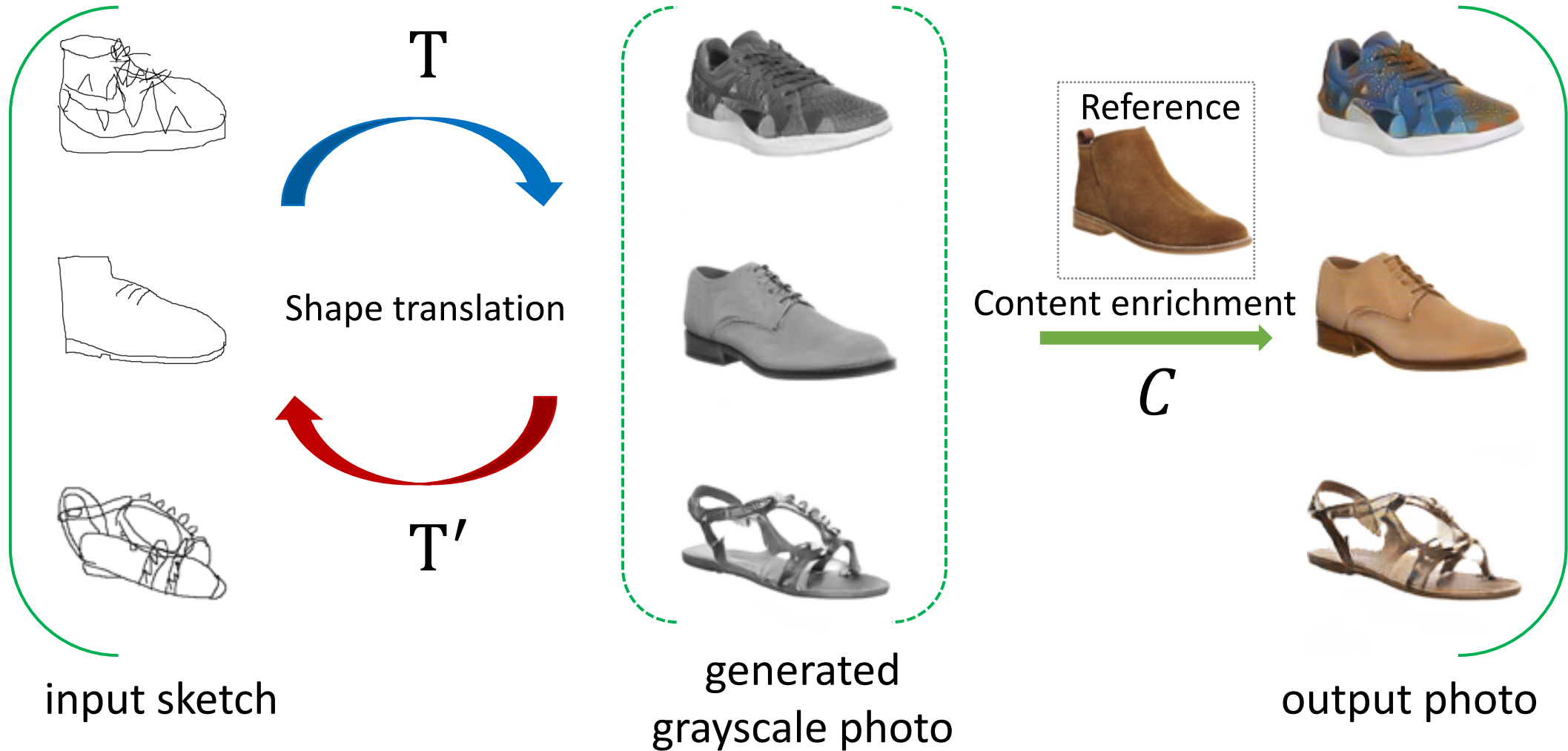


output photo

Stage 1: Shape Translation from Sketch to Grayscale



Stage 2: Content Enrichment from Grayscale to Color



Input Sketch



Synthesized Photo



Synthesized Photo Given A Reference





Pix2Pix



CycleGAN MUNIT UGATIT



Our results

Sketch \rightarrow Photo



Sketch ← Photo



Shape translation



T'



Grayscale(.)

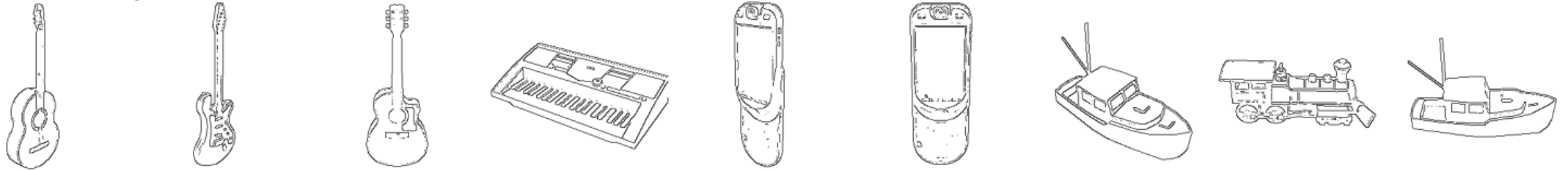


Photo → Sketch





Canny – Hand-crafted edge detector



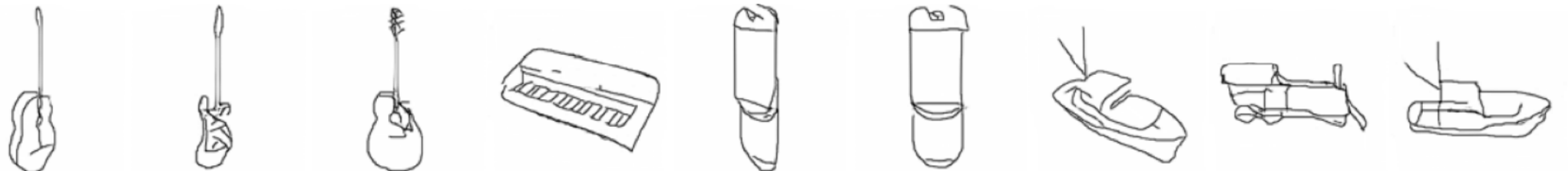
HED – Deep-learning-based edge detector





PhotoSketching – Deep-learning-based contour drawing





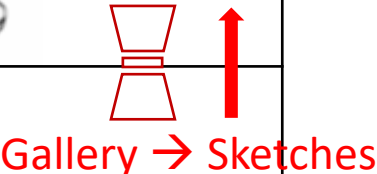

Ours – Automatic universal sketcher






Application: Sketch-based Image Retrieval

Domain	Query	Gallery
Sketch		
Photo		

Application: Sketch-based Image Retrieval

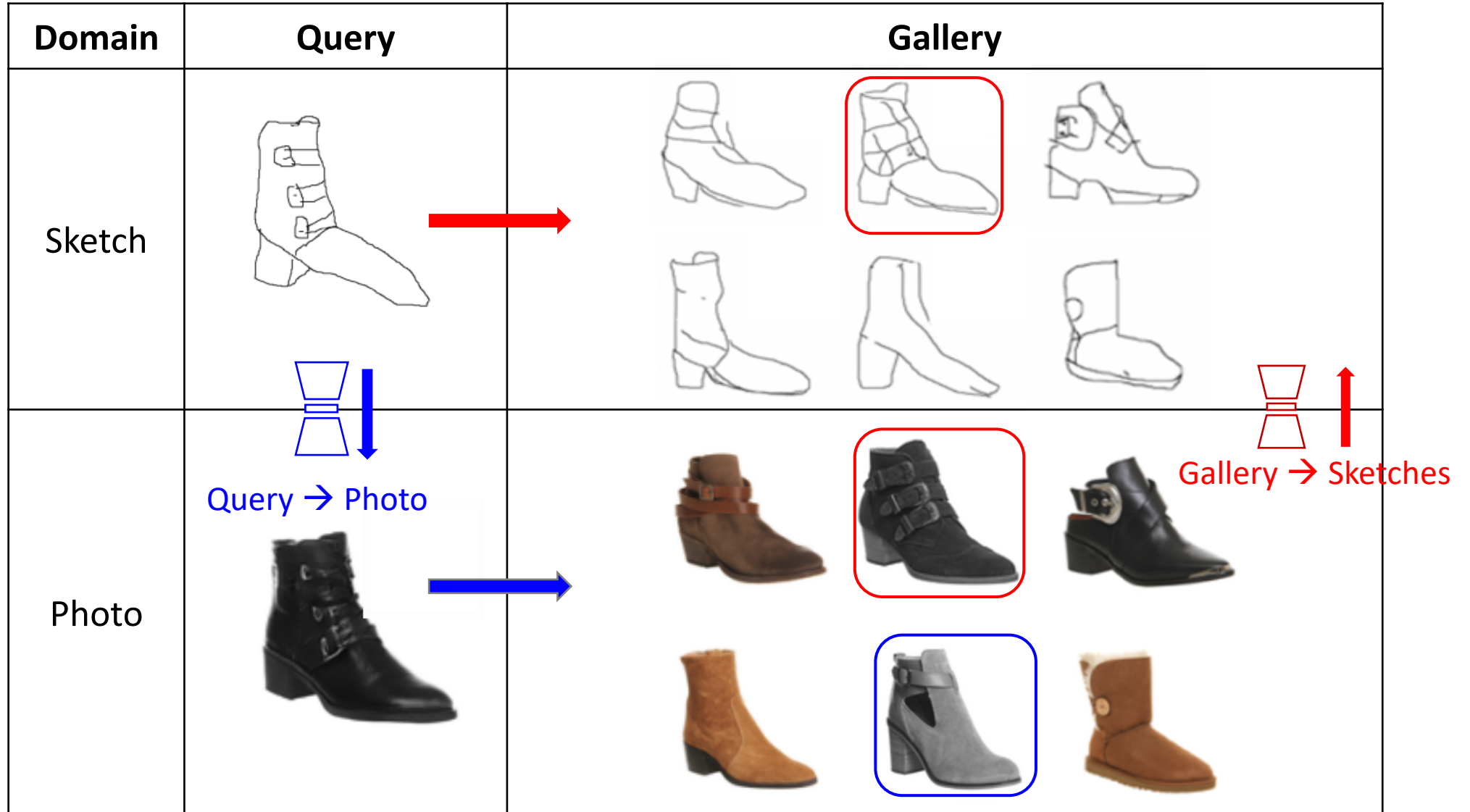
Domain	Query	Gallery
Sketch		 
Photo		

Application: Sketch-based Image Retrieval

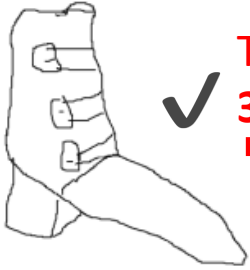



Domain	Query	Gallery
Sketch	 A red arrow points from the query sketch to the gallery.	 A red arrow points from the query sketch to the gallery.
Photo		 A red arrow points from the gallery to the sketches.

Gallery → Sketches

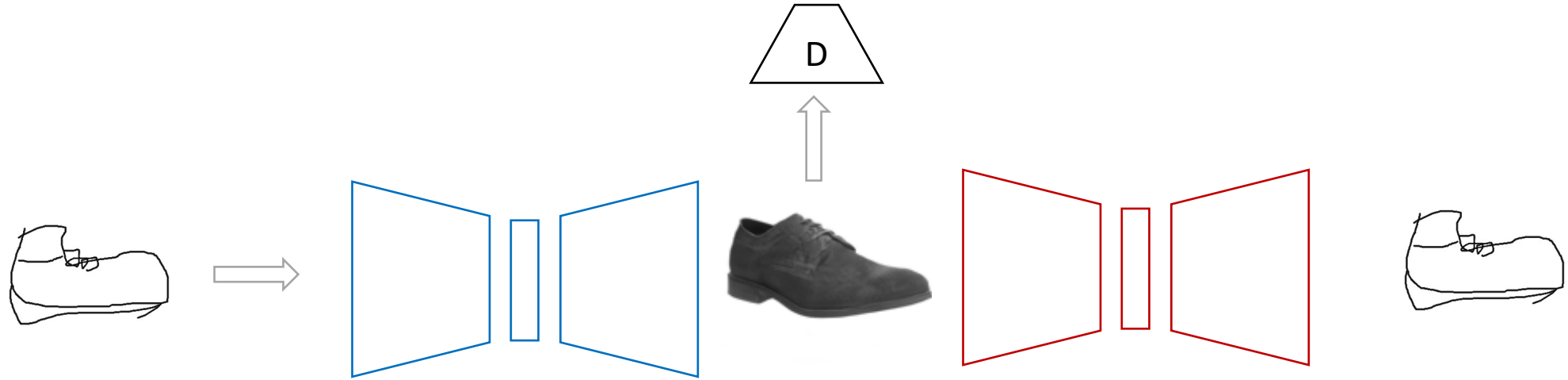
Application: Sketch-based Image Retrieval



Application: Sketch-based Image Retrieval

Domain	Query	Gallery
Sketch	 <p>✓ Top 5: 37%</p> <p>Top 5: 27%</p>	 <p>Top 5: 27%</p>
Photo		 <p>Top 5: 27%</p>

Our Stage 1 Model is Built upon Basic CycleGAN



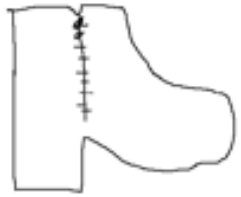
CycleGAN Works Well for Simple Sketches



CycleGAN Fails with Complex Stroke Patterns



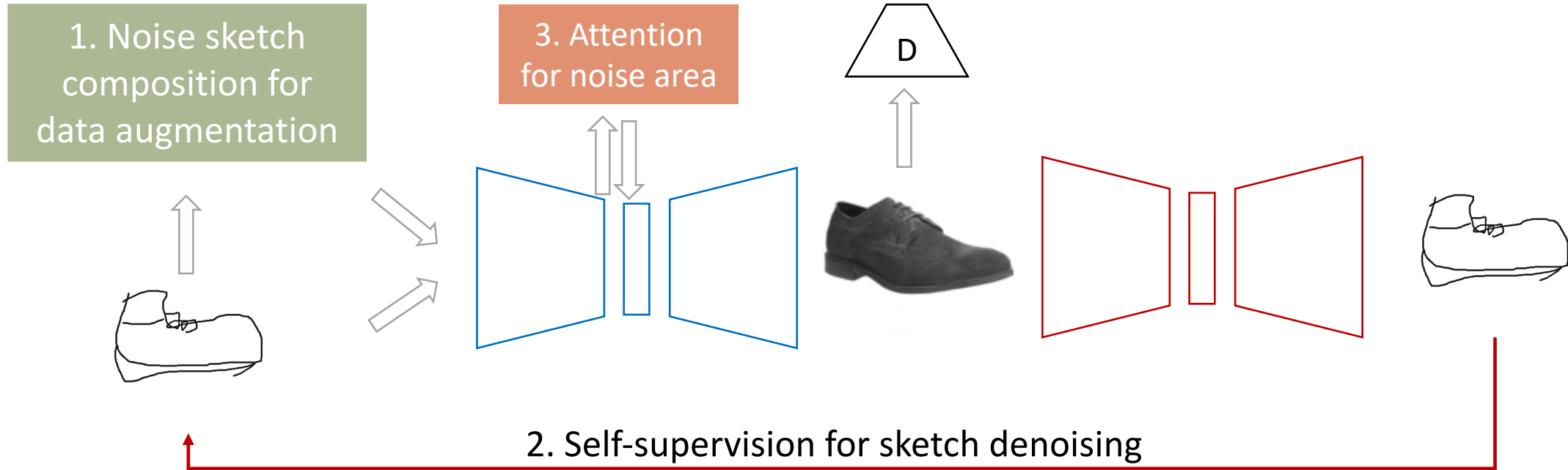
CycleGAN Fails with Noise Sketch



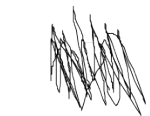
Noise



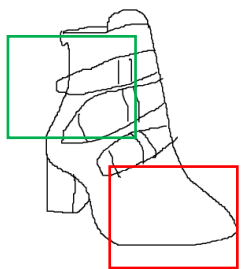
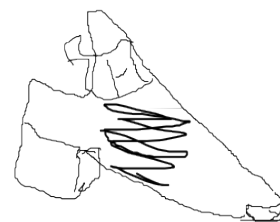
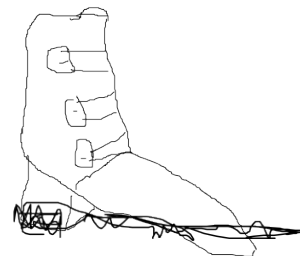
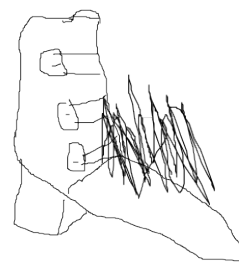
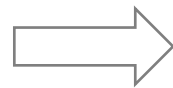
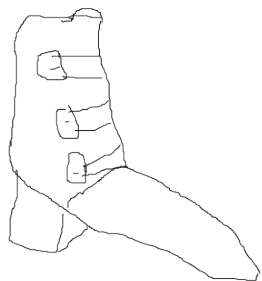
Stage 1: Key Sketch-Specific Technical Novelties



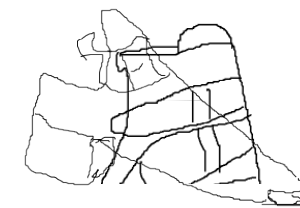
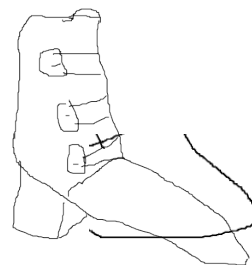
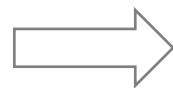
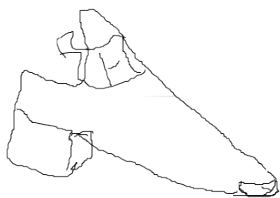
Noise Sketch Composition



noise mask



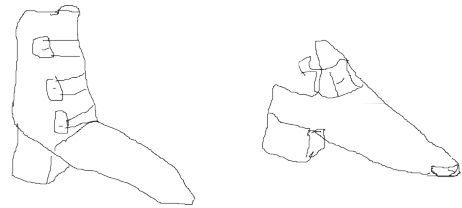
random patch



original sketch

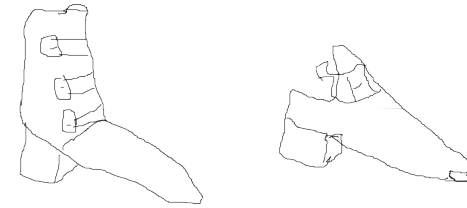
composed sketch

Self-Supervised Objective

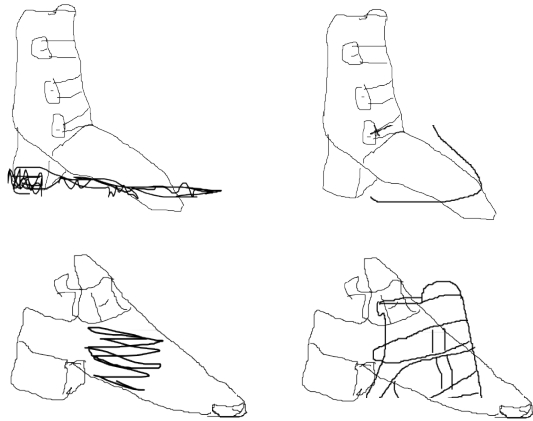


input sketch

Cycle-consistency

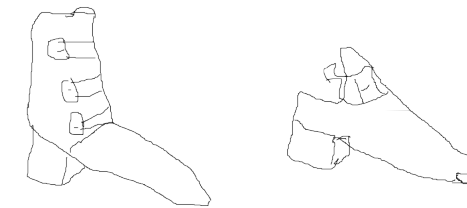


target



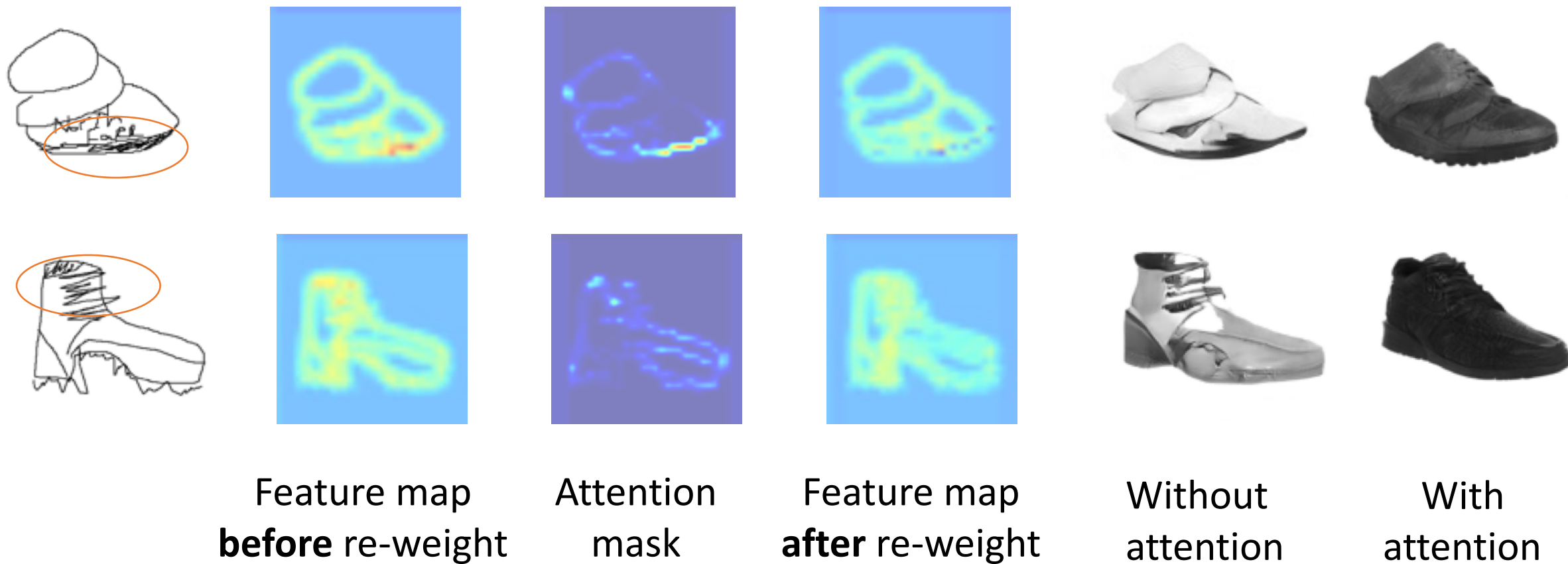
composed sketch

Self-supervised
Denoising

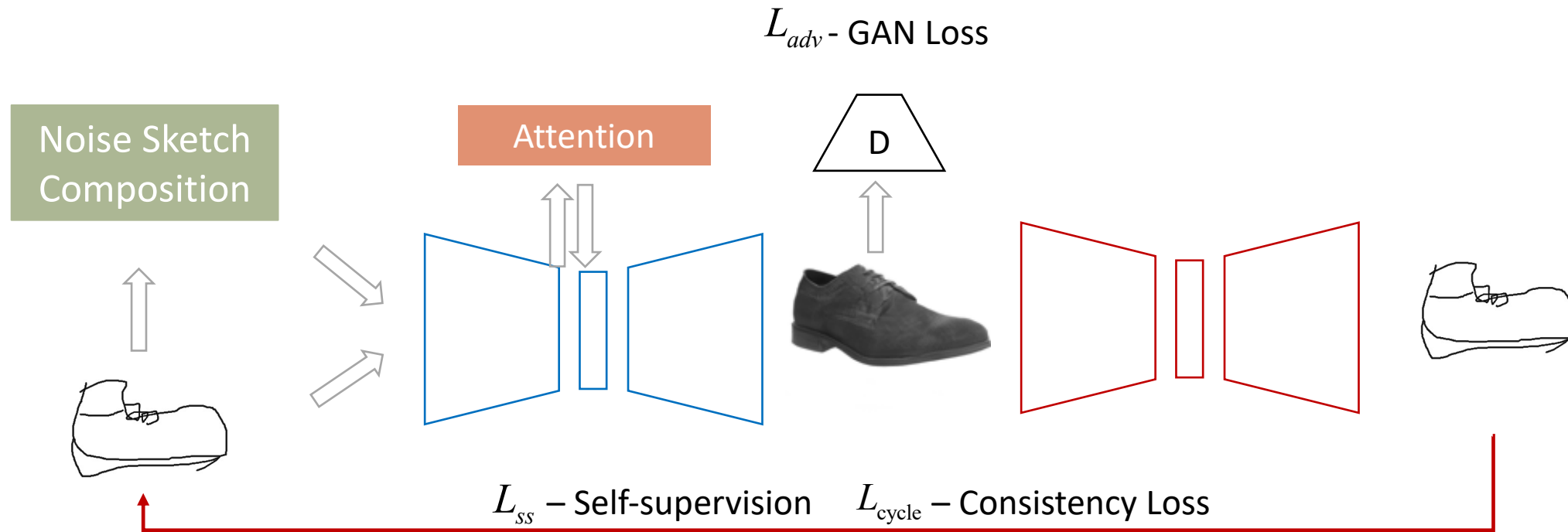


target

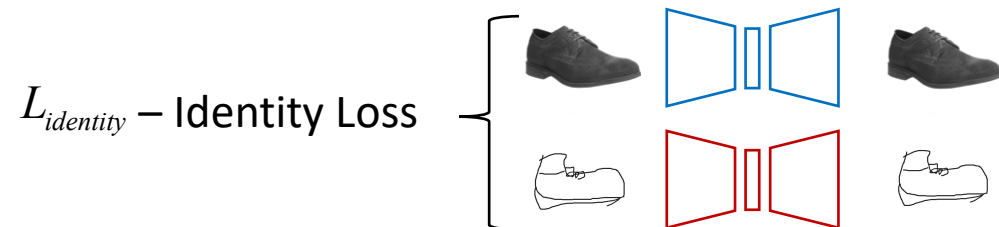
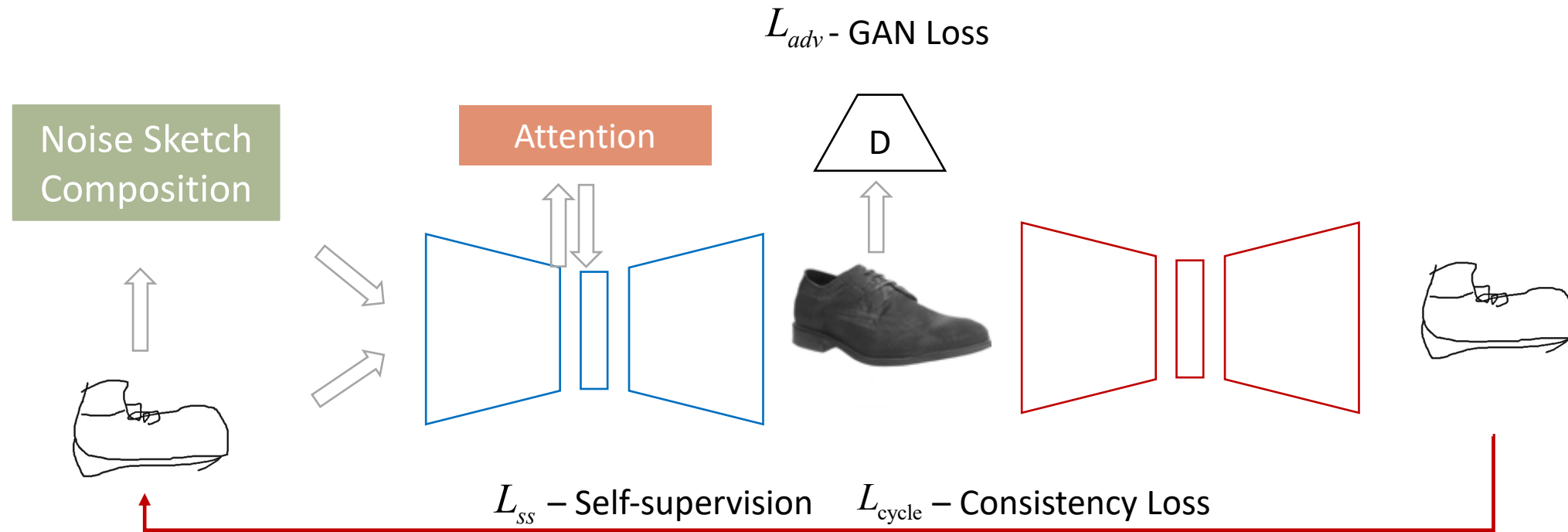
Attention - Ignore Distractions



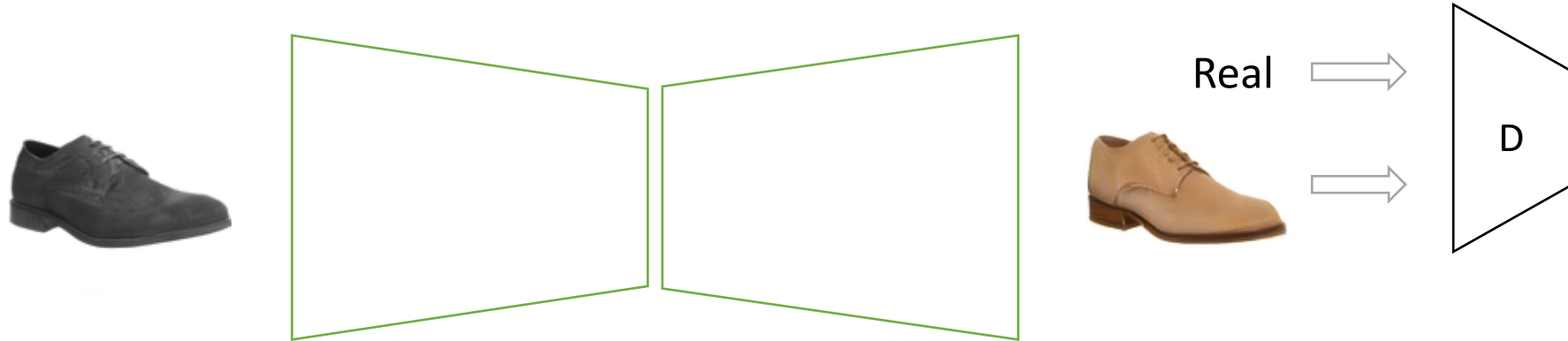
Stage 1: Shape Translation



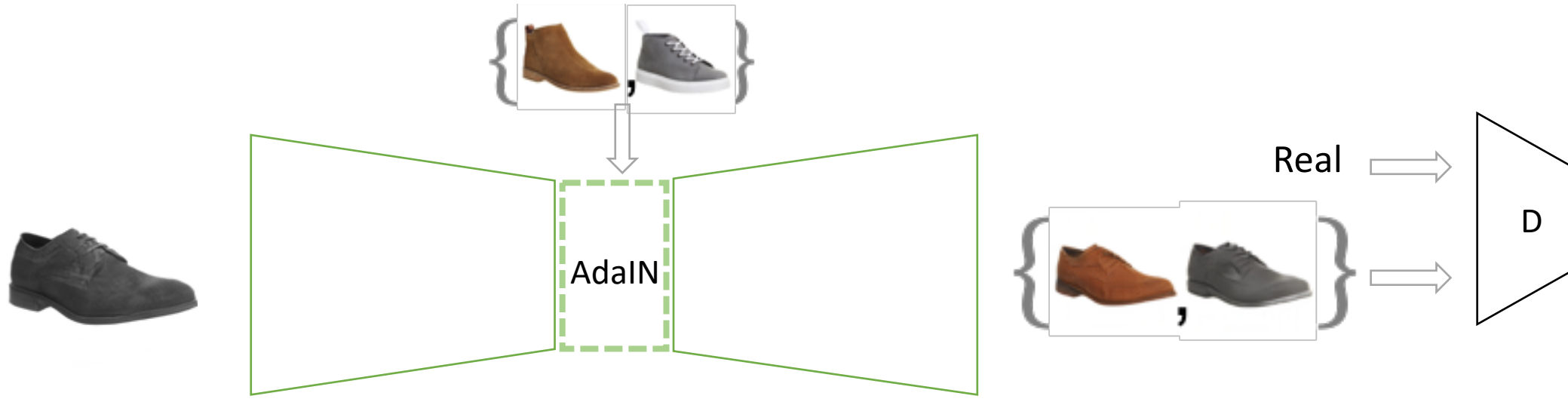
Stage 1: Shape Translation



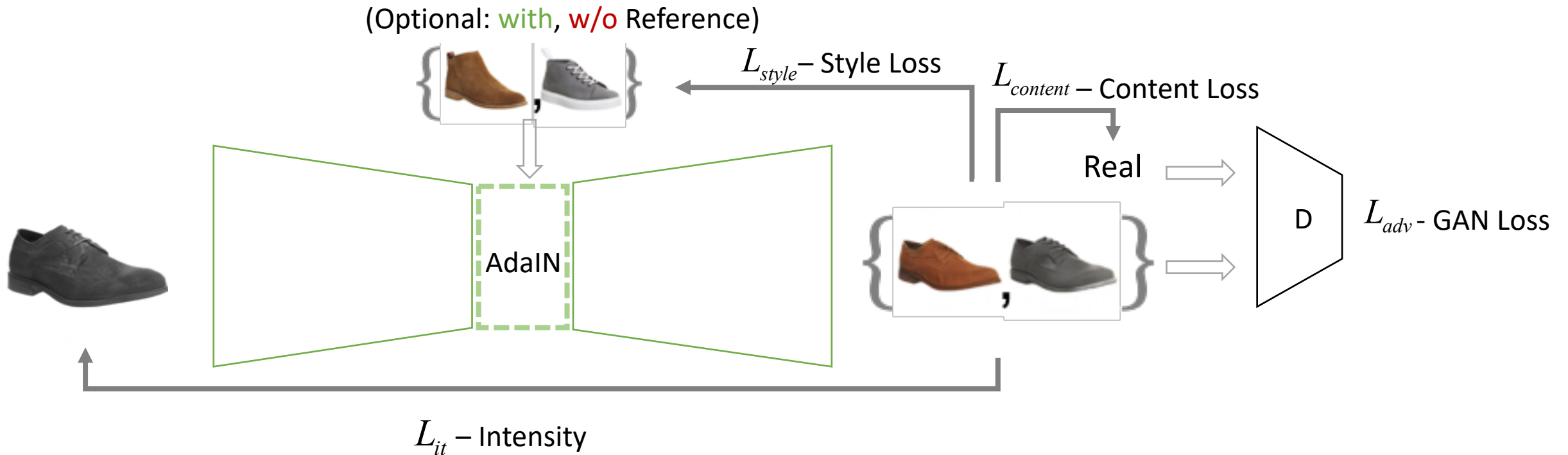
Stage 2: Content Enrichment without Reference



Stage 2: Content Enrichment with Reference



Stage 2: Content Enrichment with Optional Reference



Ours Are More Photo-Realistic, Sketch-Faithful, Diverse

Model	ShoeV2			ChairV2		
	FID ↓	Quality ↑	LPIPS ↑	FID ↓	Quality ↑	LPIPS ↑
Pix2Pix*	65.09	27.0	0.071	177.79	13.0	0.096
CycleGAN	79.35	12.0	0.0	124.96	20.0	0.0
MUNIT	92.21	14.5	0.248	168.81	6.5	0.264
UGATIT	76.89	21.5	0.0	107.24	19.5	0.0
Ours	48.73	50.0	0.146	100.51	50.0	0.156

Quality: User study on forced choice per photo quality w.r.t. sketch

1. Trained on ShoeV2, Generalize to Other Datasets

Sketchy

TU-Berlin

Quick Draw

Trained on
ShoeV2



2. Trained on ShoeV2, Test on Other Categories

Training



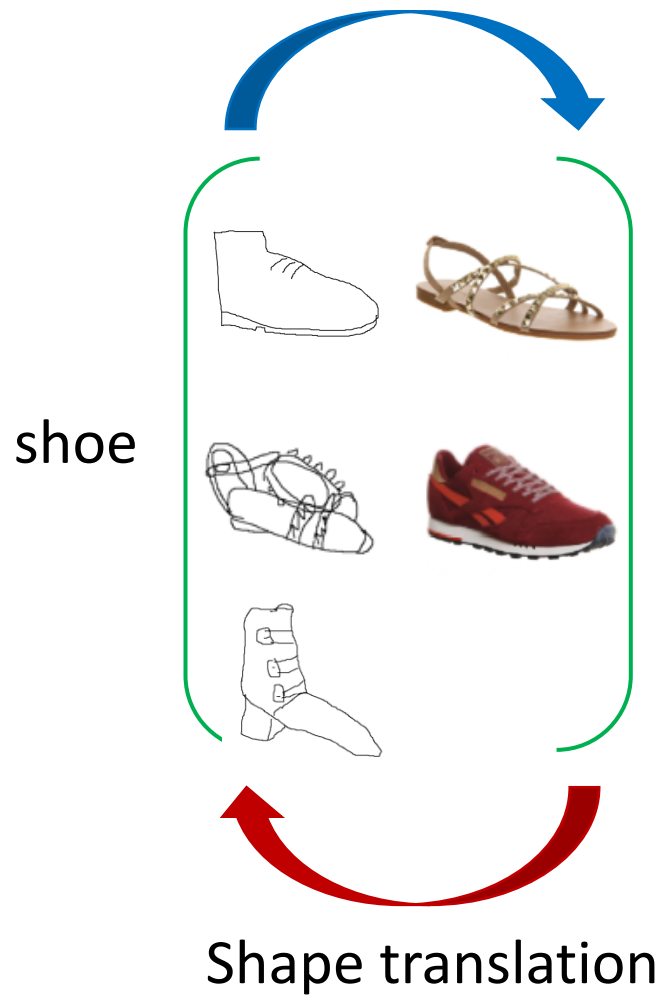
Shape translation

Testing

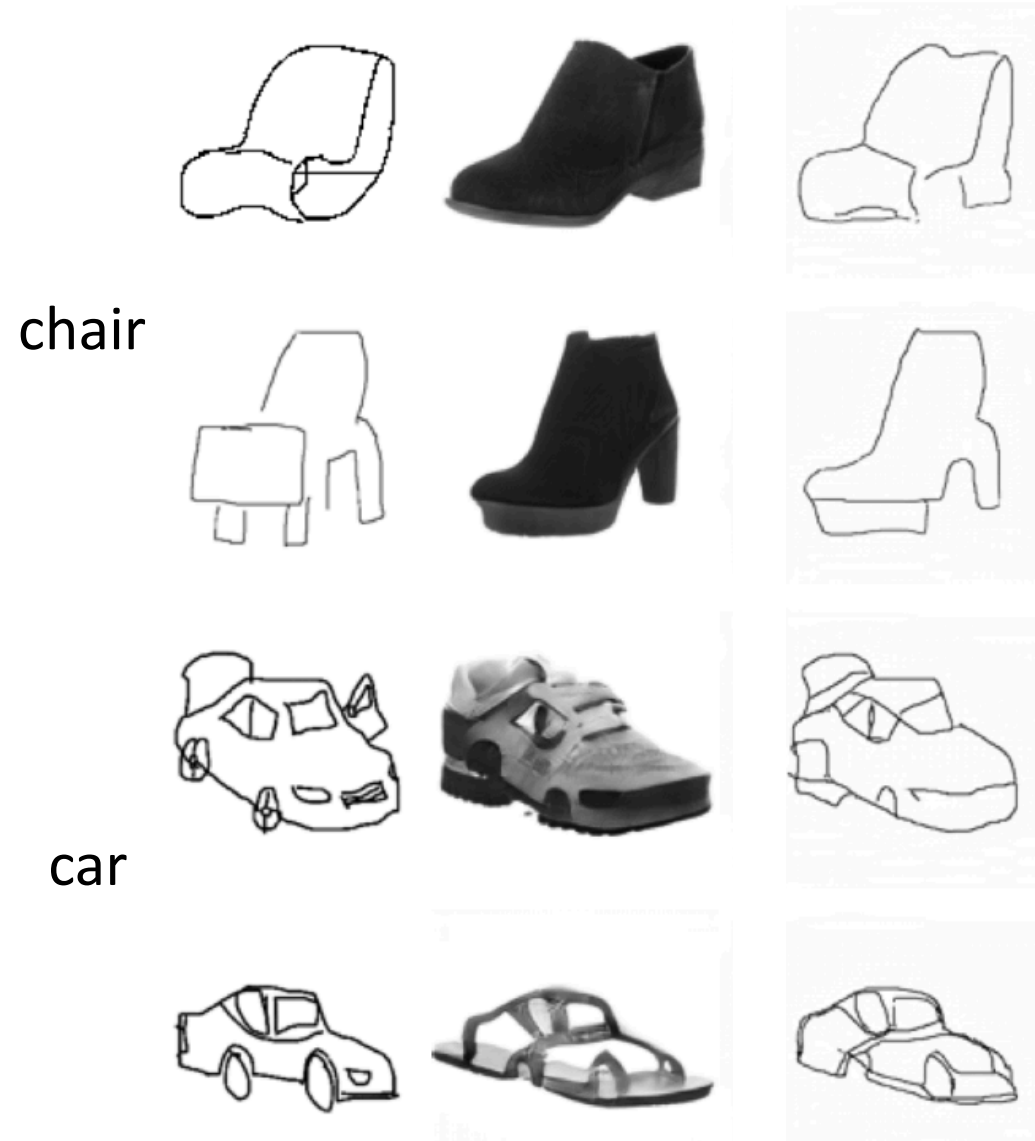


2. Trained on ShoeV2, Test on Other Categories

Training



Testing

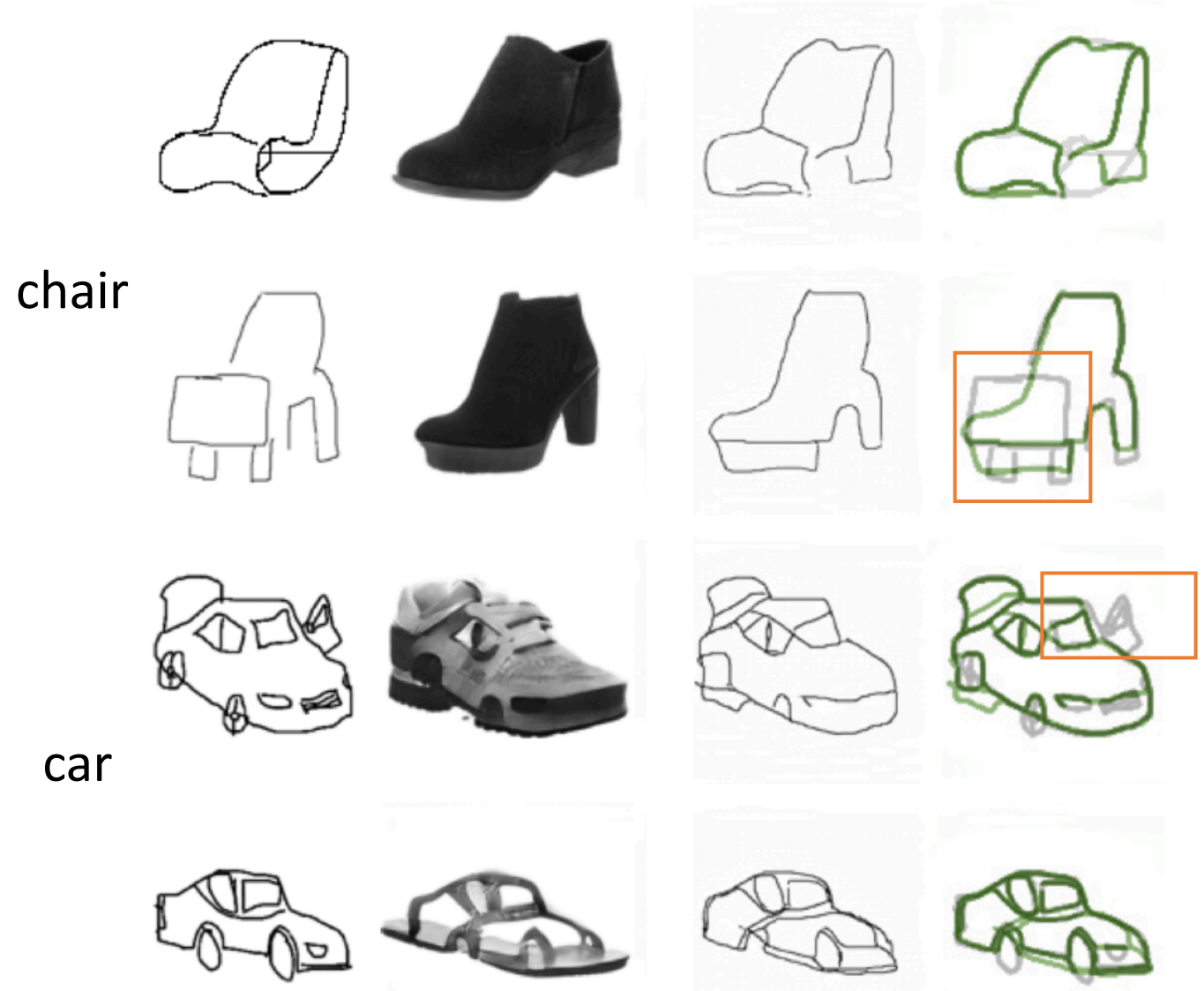


2. Trained on ShoeV2, Test on Other Categories

Training

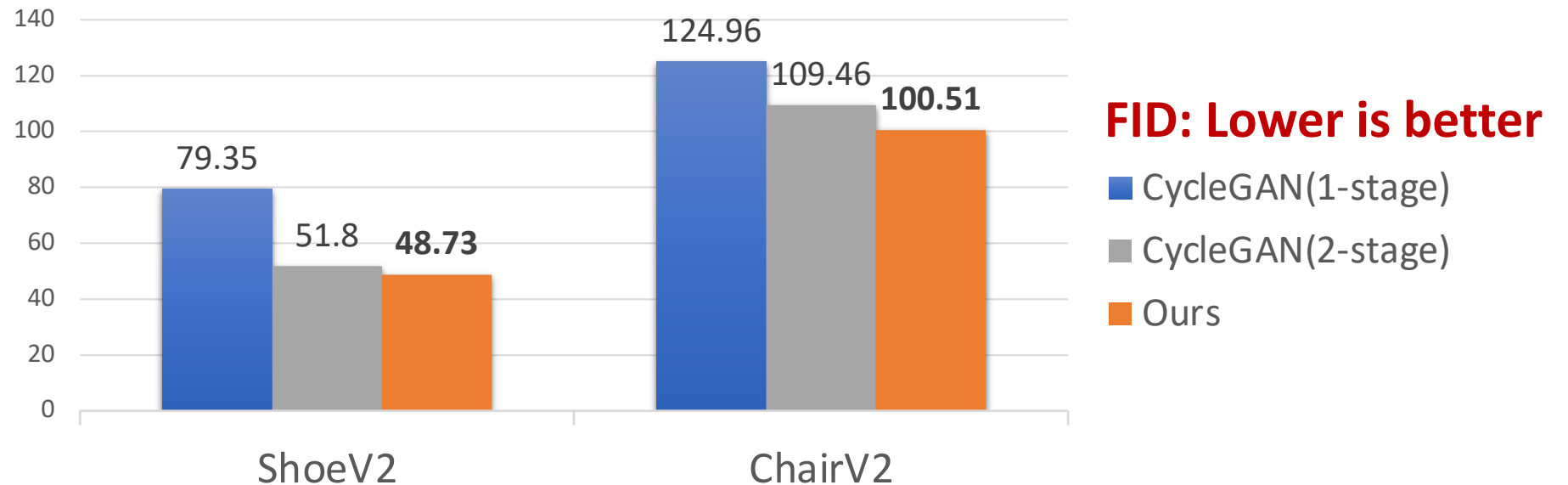


Testing



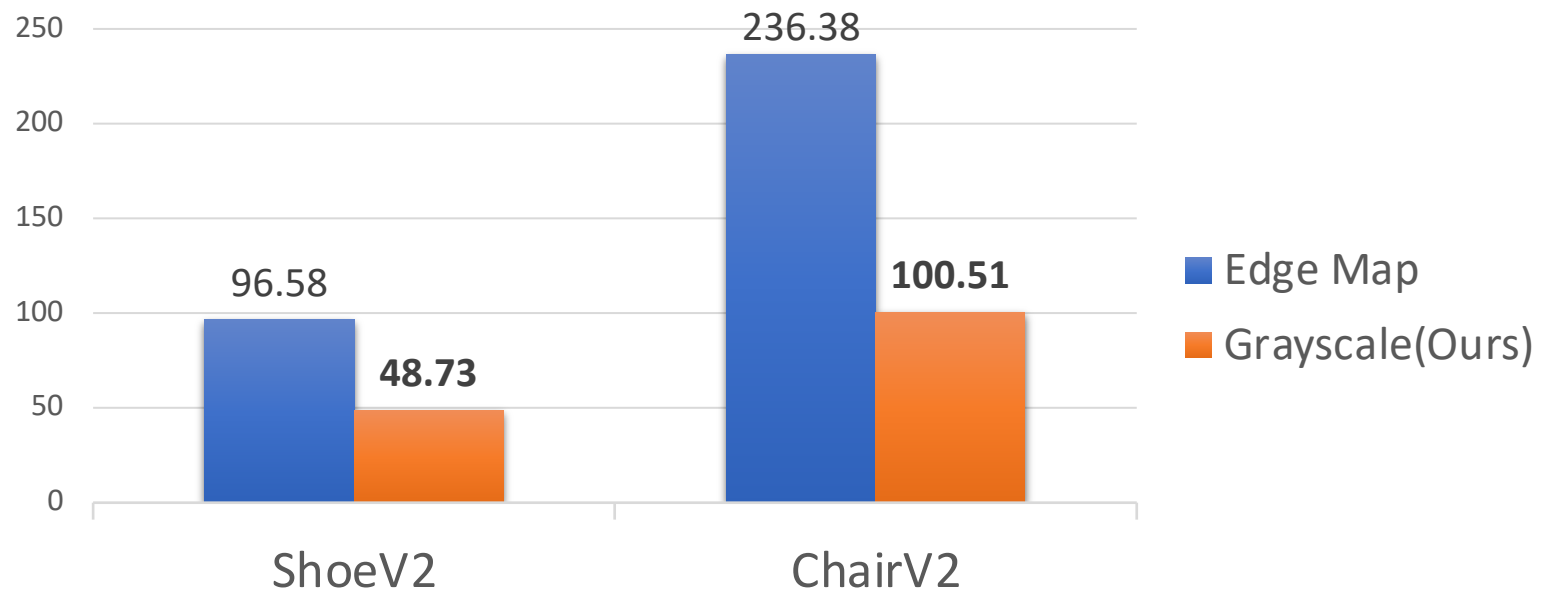
Ablation Study: Three Insights

	Alternative	Our Choice
Architecture Choice	One-Stage	Two-Stage ✓



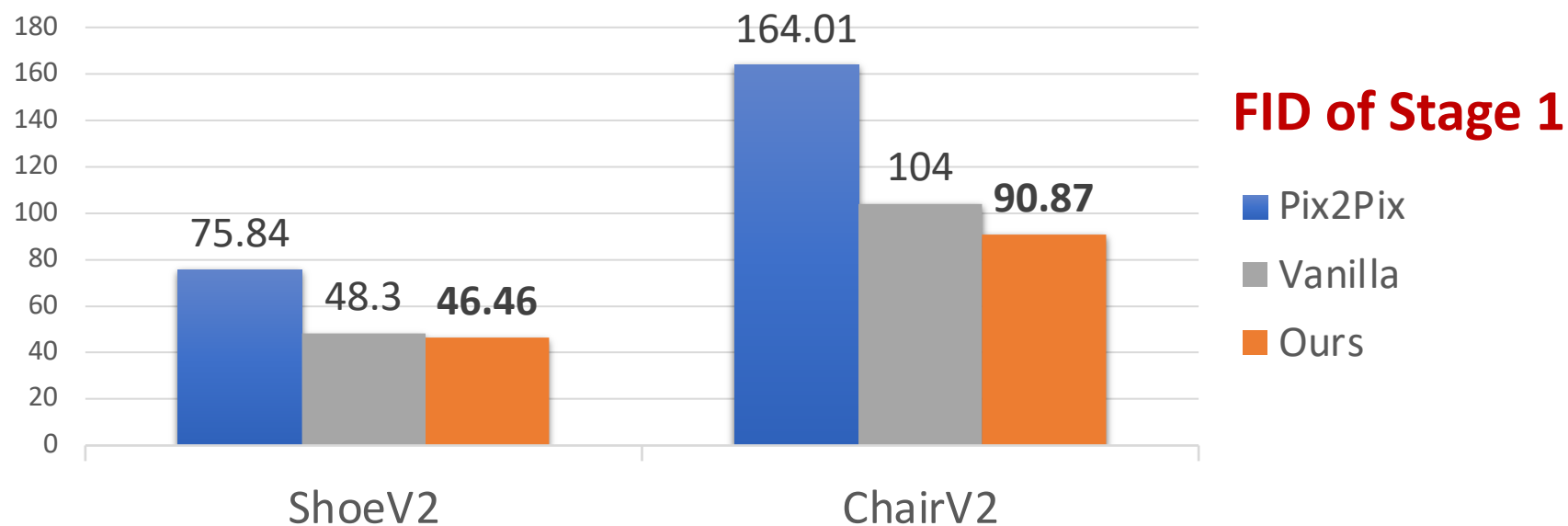
Ablation Study: Three Insights

	Alternative	Our Choice	
Architecture Choice	One-Stage	Two-Stage	✓
Intermediate Synthesis Goal	Edge-Map	Grayscale	✓



Ablation Study: Three Insights

	Alternative	Our Choice
Architecture Choice	One-Stage	Two-Stage ✓
Intermediate Synthesis Goal	Edge-Map	Grayscale ✓
Training Setting	Paired	Unpaired ✓



Code / Model / Demo



<http://sketch.icsi.berkeley.edu/>