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Learning Geometry-aware Representations by *Sketching*

THU-PM-259



Hyundo Lee



Inwoo Hwang



Hyunsung Go



Won-Seok Choi



Kibeom Kim



Byoung-Tak Zhang

Seoul National University,



SEOUL
NATIONAL
UNIVERSITY

AI Institute, Seoul National University



Brief overview

Concept



Image

Geometric concepts

ex) position, shape, distance, orientation

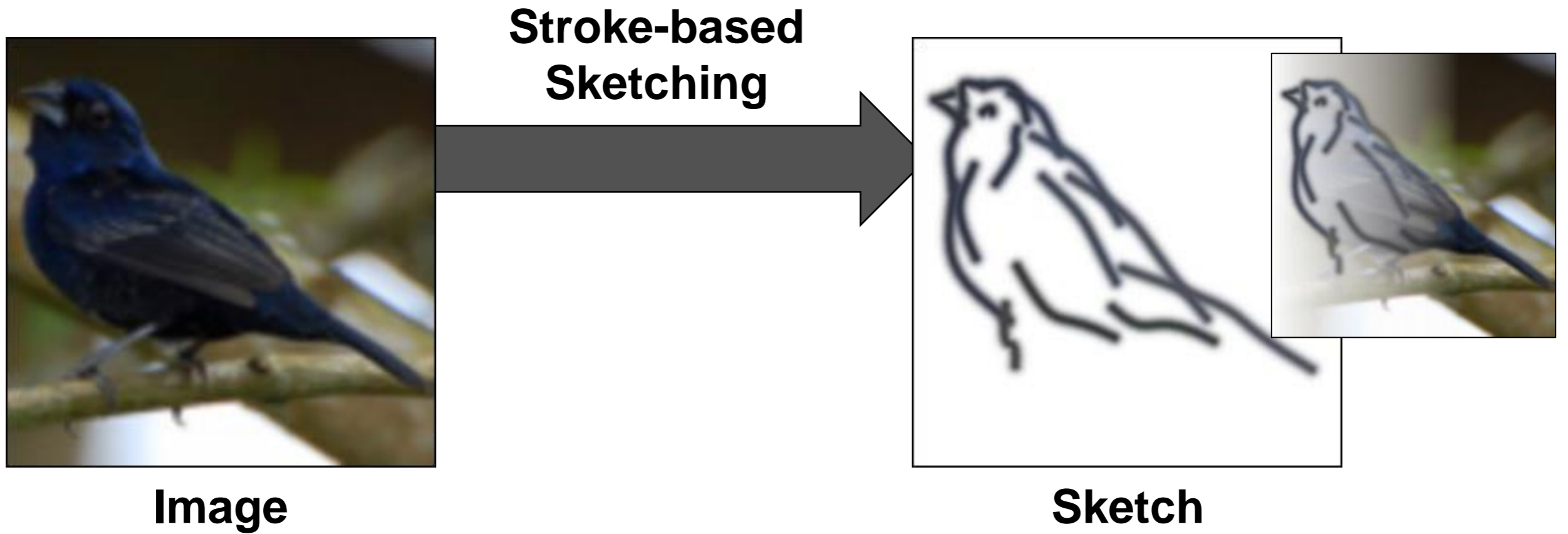


Feature (vector)

2

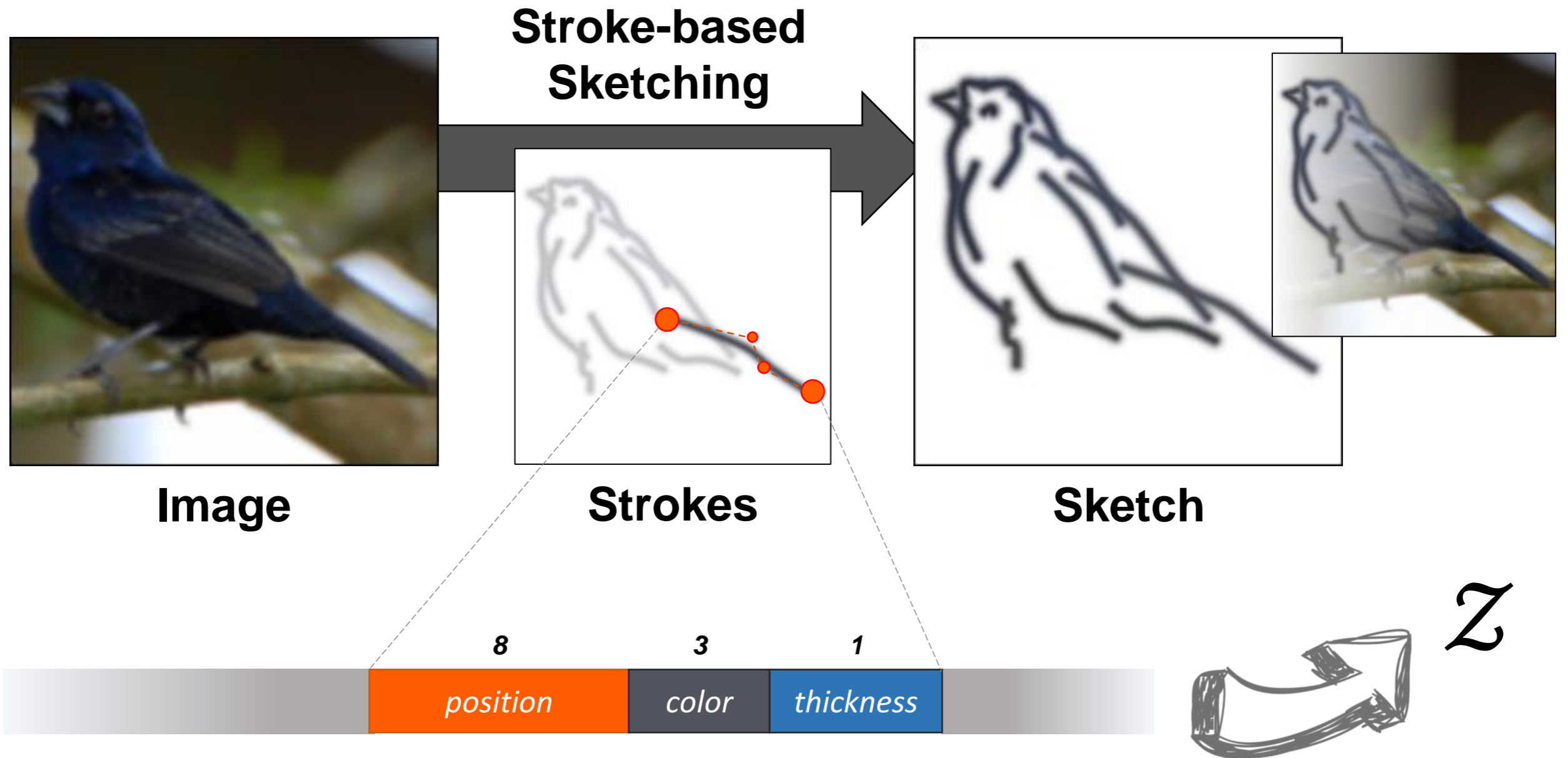
Brief overview

Concept



Brief overview

Concept



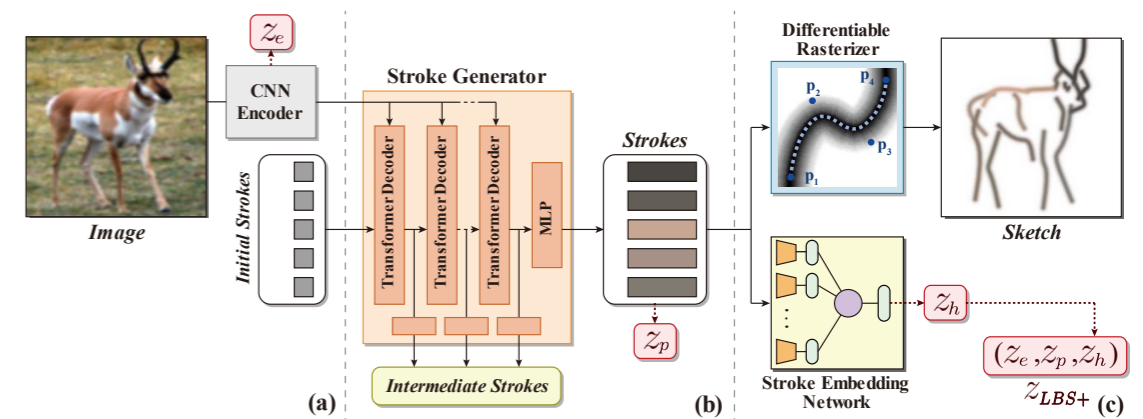
Brief overview

Contributions

- Theoretically show that **strokes can convey geometric information**

- Design a sketch-based visual representation model,

coined **LBS (Learning By Sketching)**



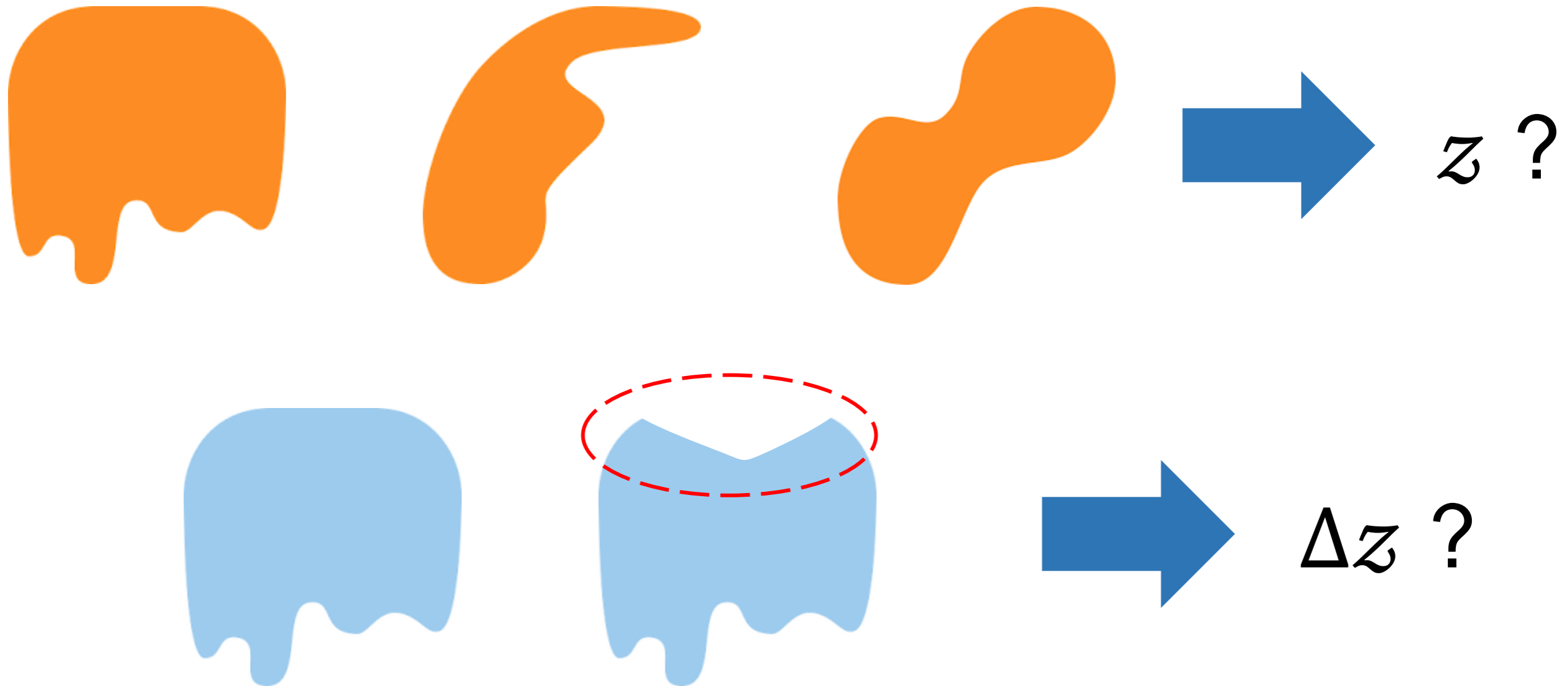
- Experiments for investigating the effectiveness of our approach in various domains and downstream tasks



Question

How do machines represent shape?

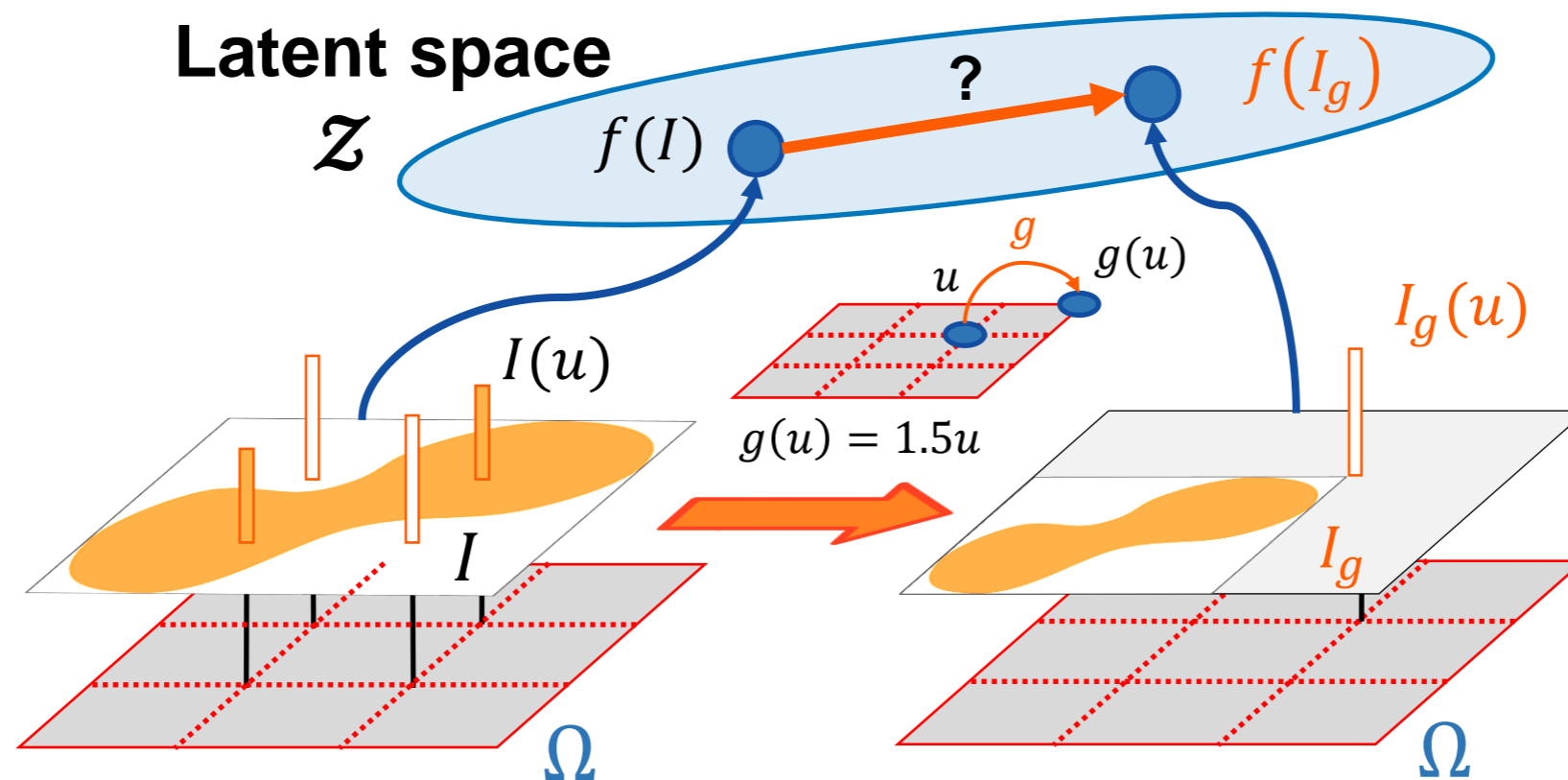
- Are they interpretable, well-aligned for downstream tasks?



Question

How do machines represent geometric concepts?

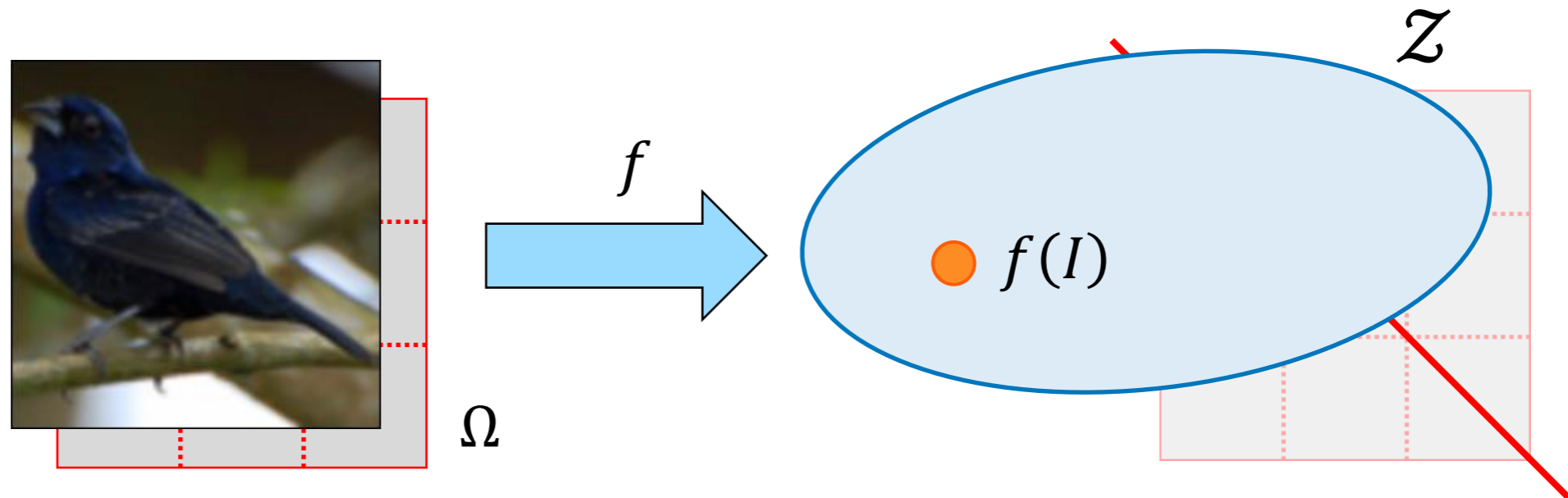
- Ex) position, shape, distance, orientation
- An image I belongs to a physical domain Ω : a 2D grid space
- For given geometric transformation $g: \Omega \rightarrow \Omega$,
 - ▶ The transformed image I_g , $I_g(u) = I(g^{-1}(u))$
- With given representations $f(I)$ and $f(I_g)$, can we predict the transformation g ?



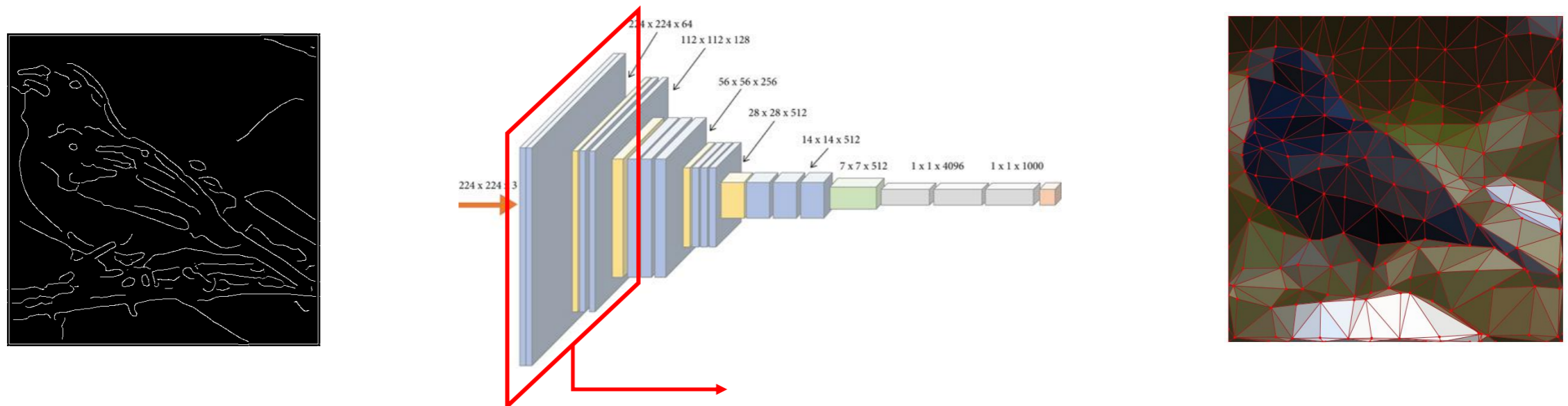
Background

Previous studies

- Representations on semantic latent space



- Representations with same domain Ω



Motivation

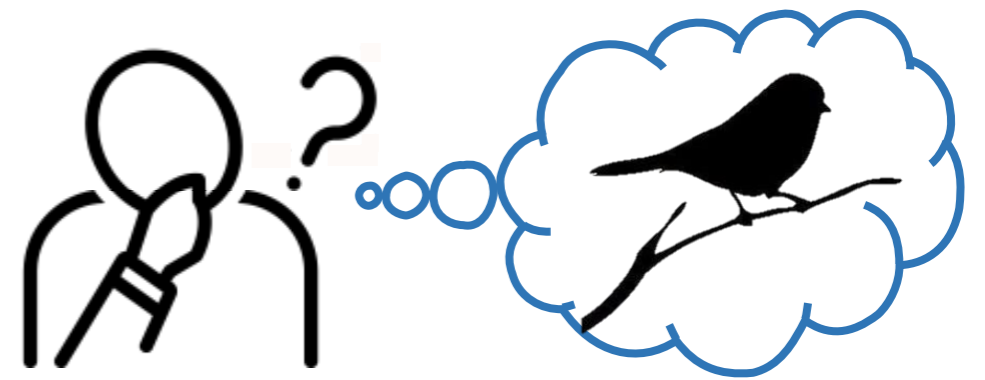
How do human represent image?

- Language



Language

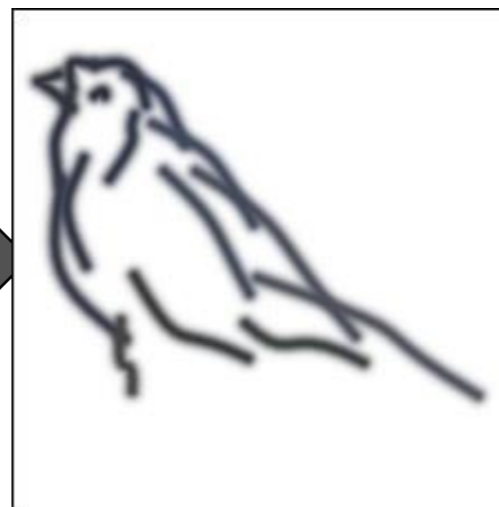
“A black bird
sitting on a branch”



- Drawing/sketching



Image



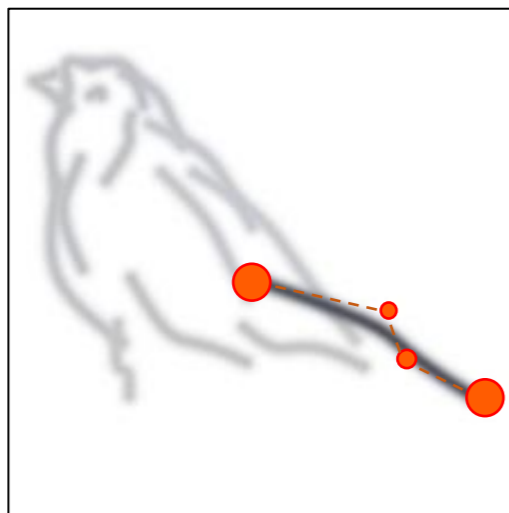
Sketch



Motivation

Core properties

- Sketching
 - ▶ salient features of an image \Rightarrow abstract image based on set of colored strokes
 - ▶ **Preserving geometry**: shares the same physical domain Ω
 - ▶ **Abstraction**: representation with limited # of strokes
 - ▶ **Compactness**: can be represented as a set of parametric curves



Stroke



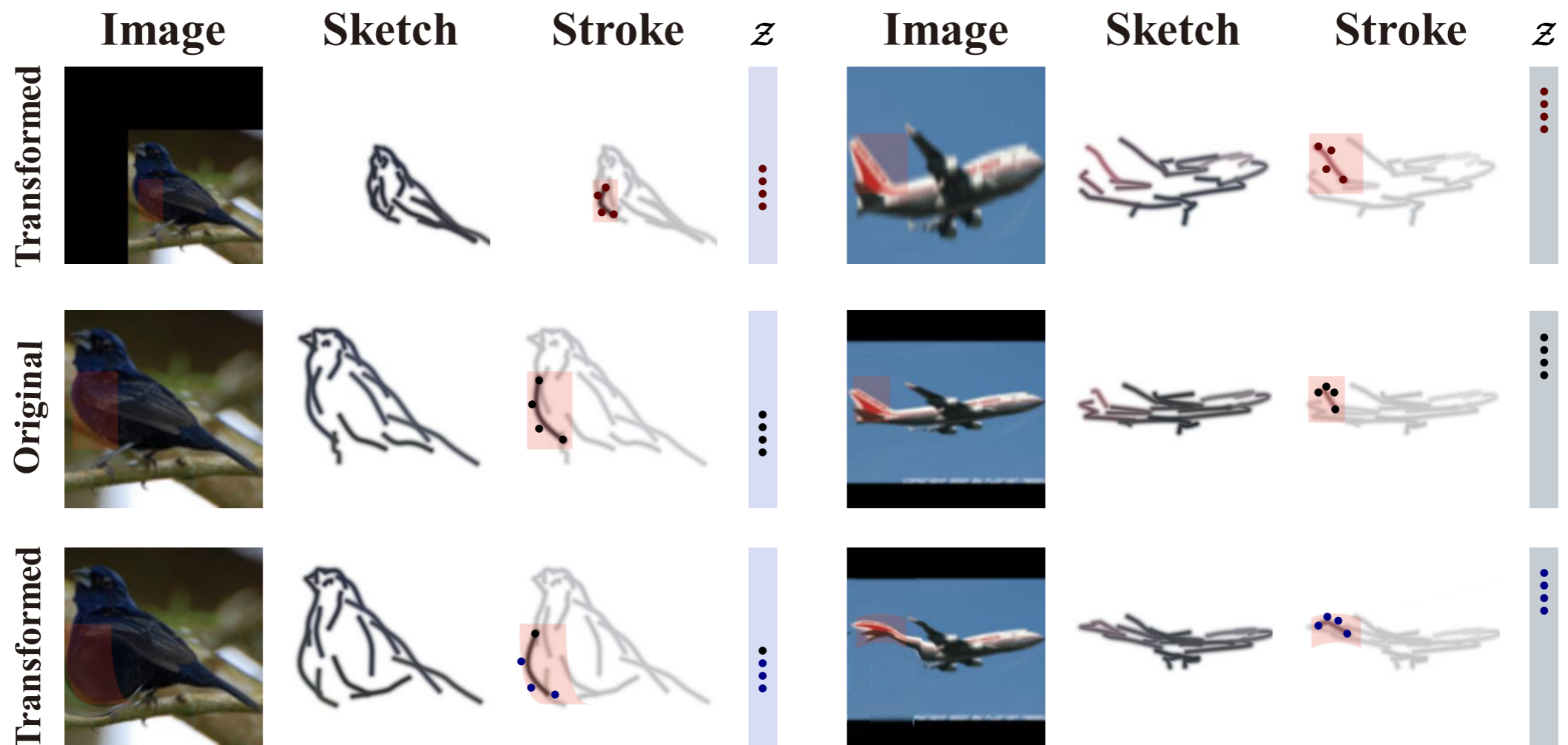
Parameterization

\Rightarrow Based on these properties,
we use **strokes** as a **geometry-aware representation** for various downstream tasks

Mathematical framework

Does sketches & strokes represent geometric information?

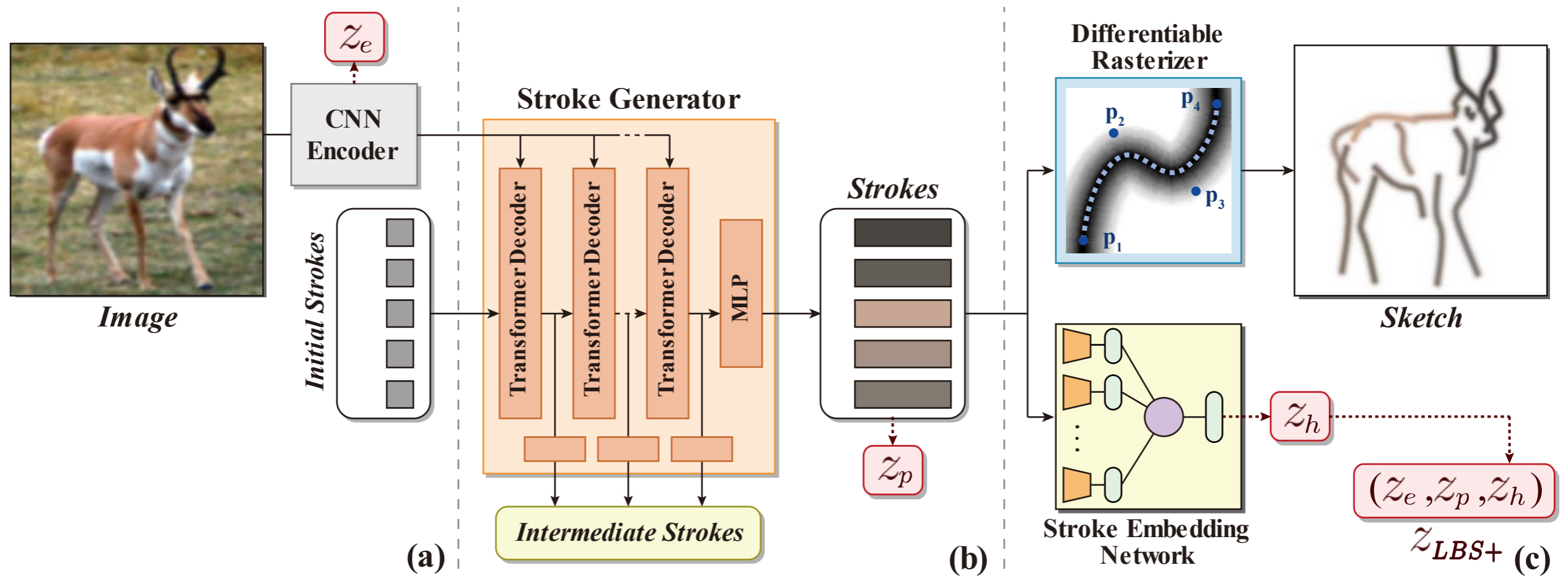
- With given representations $f(I)$ and $f(I_g)$, can we predict the transformation g ?
- **\mathcal{G} -equivariance**: $\exists \rho'$ s.t. $f(\rho(g) \cdot I) = \rho'(g) \cdot f(I)$
 - ▶ Sketching is equivariant to arbitrary geometric transformation $g \in \mathcal{G}$ ($\rho' = \rho$)
 - ▶ Converting into stroke is equivariant to affine transformation $a \in \mathcal{A}$



Architecture

Learning By Sketching (LBS)

- Abstraction & reflecting geometric information in a short inference time
- Without using explicit sketch dataset.

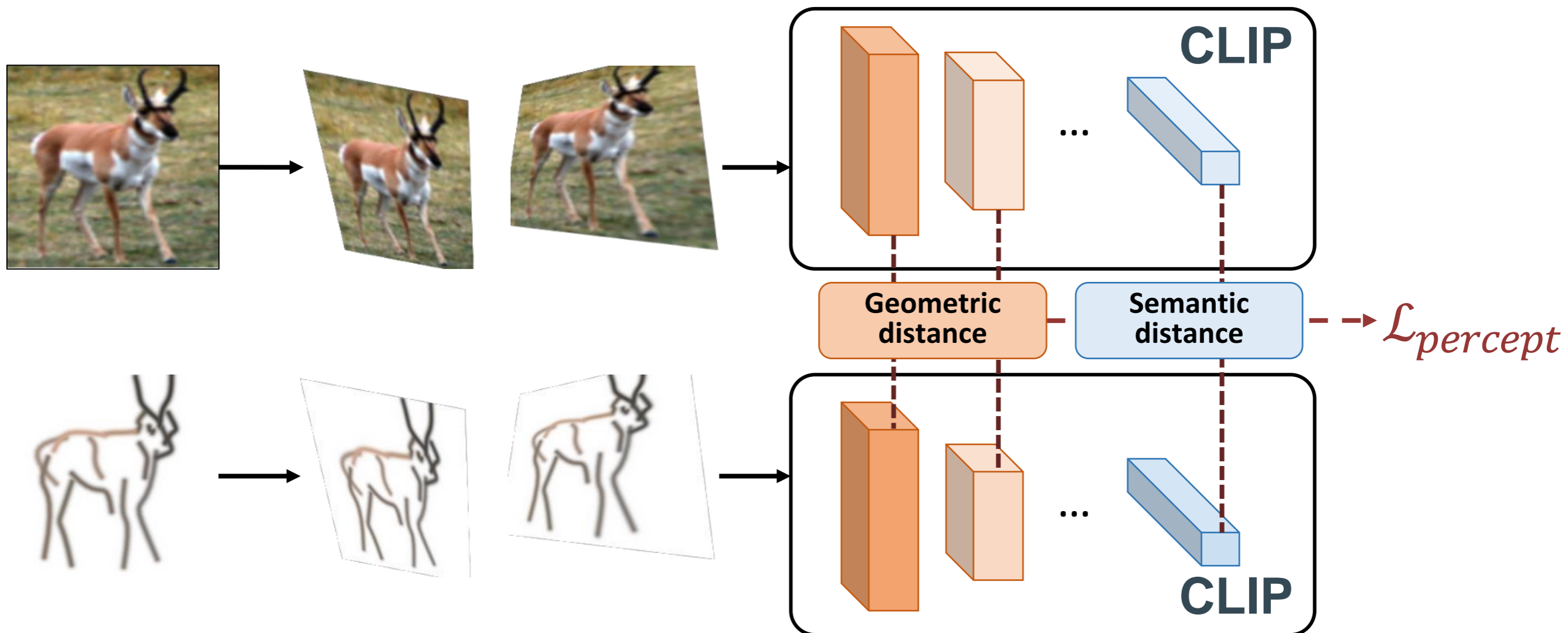


$$\mathcal{L}_{LBS} = \mathcal{L}_{percept} + \lambda_g \cdot \mathcal{L}_{guide} + \lambda_e \cdot \mathcal{L}_{embed}$$

Architecture

Learning By Sketching (LBS)

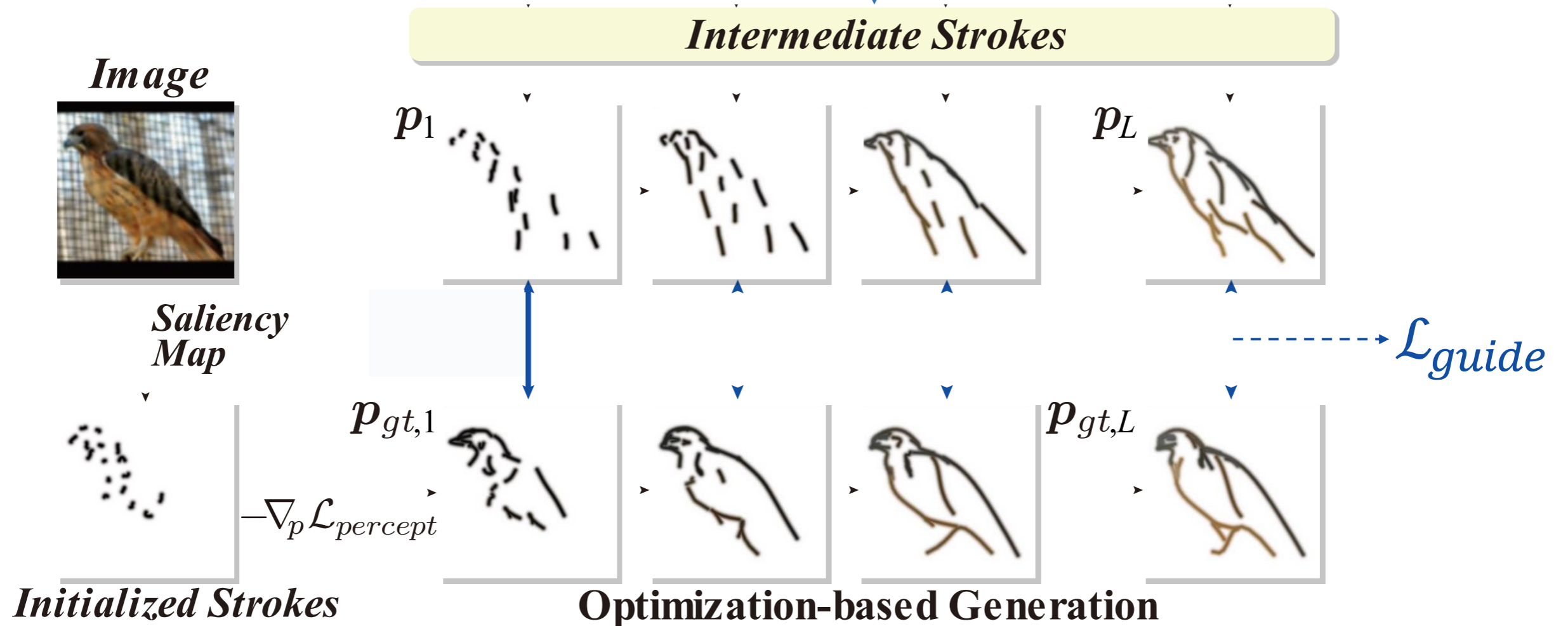
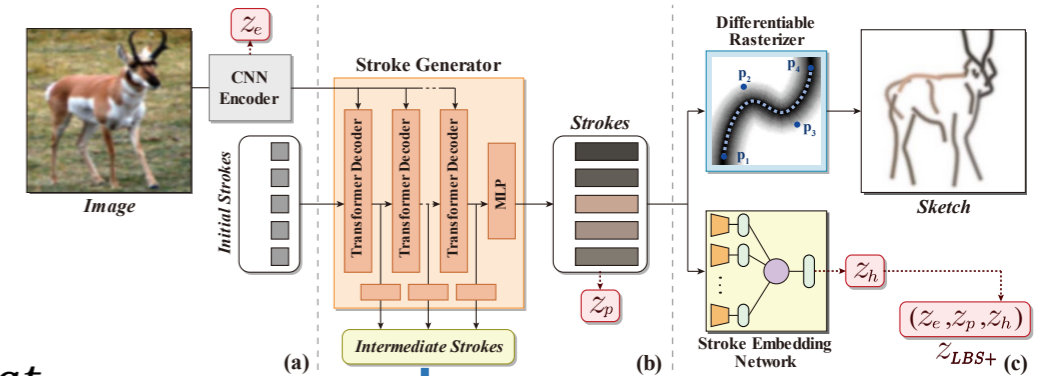
- $\mathcal{L}_{percept}$: CLIP-based perceptual loss [1]



Architecture

Learning By Sketching (LBS)

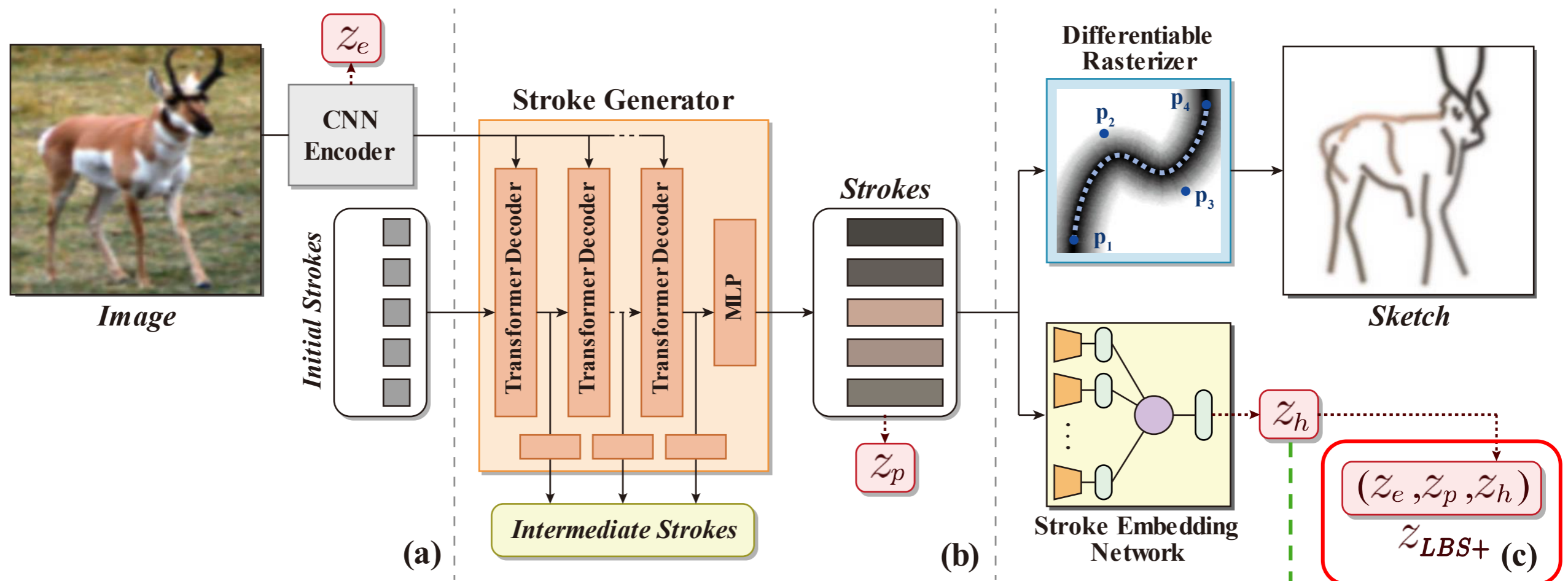
- Guidance loss \mathcal{L}_{guide}
 - ▶ Optimization-based generation with $\mathcal{L}_{percept}$: \mathbf{p}_{gt}
 - ▶ Predicting $\Delta \mathbf{p}_{gt}$ for each layer



Architecture

Learning By Sketching (LBS)

- Stroke embedding loss \mathcal{L}_{embed}
 - z_h : combines the information of all strokes through a stroke embedding network

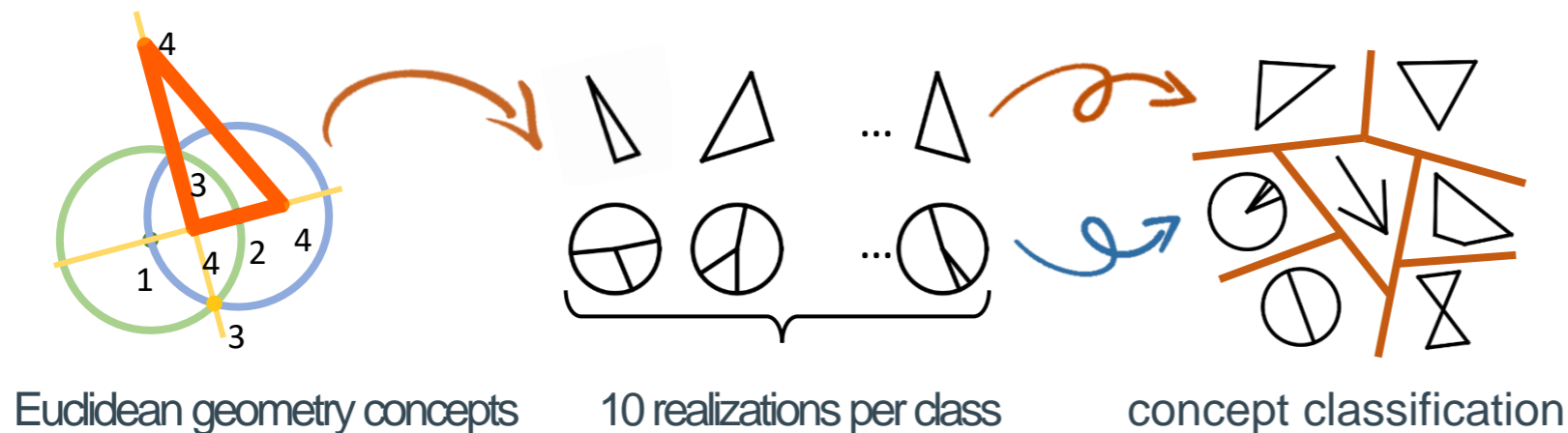


Supervised/unsupervised loss
Ex) CE, InfoNCE, ...

Experiments

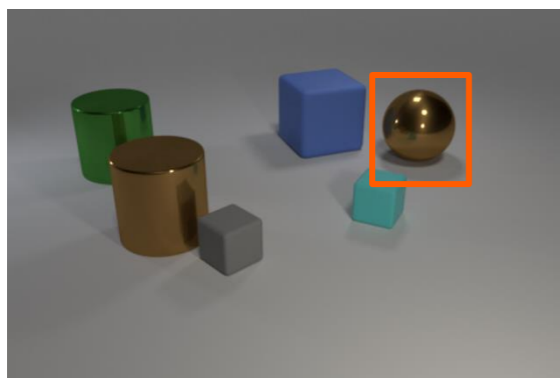
Quantitative results

- Understanding geometric primitives & concepts



Label	Method	Geoclidean	
		Constraints	Elements
✓	CE	53.89±1.58	70.57±4.29
	SupCon [38]	42.41±3.16	55.83±4.28
	LtD-diff [54]	57.26±2.19	69.47±2.11
	E(2)-CNN [73]	71.03 ±1.94	69.28±1.46
	LBS (CE)	50.01±1.58	81.06 ±3.14
✗	SimCLR [9]	32.04±0.64	65.14±4.11
	β-TCVAE [8]	17.18±1.35	33.82±1.64
	GeoSSL [55]	18.66±3.33	33.47±2.80
	HoG [14]	23.82	52.05
	LBS	47.43 ±1.34	81.34 ±0.16

- Local geometric information & Simple spatial reasoning

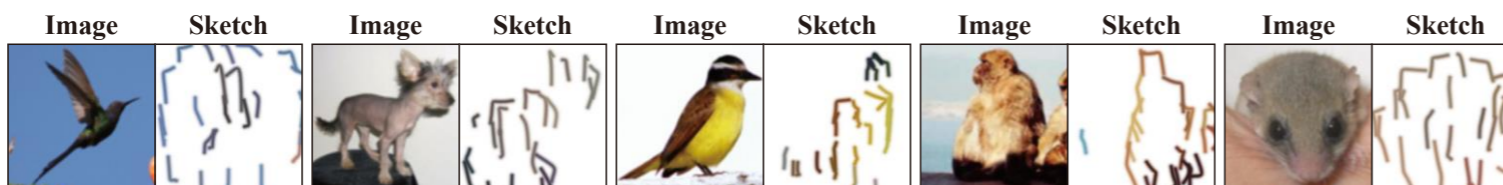


- Q) Color of the leftmost object?
- Q) Shape of the rightmost object?
- Q) Results after shifting the rightmost object?
- ...

Label: brown

Label	Method	RC	BC	Size	Shape	Third	Shift
✓	CE	98.71±0.10	76.02±0.90	92.51±0.40	49.97±0.29	40.66±0.20	62.06 ±1.62
	SupCon [38]	98.75 ±0.08	66.04±2.65	91.88±0.37	49.15±0.85	37.93±0.27	56.05±2.56
	LtD-diff [54]	62.29±0.48	15.84±0.43	63.98±3.38	43.96±3.05	16.47±0.59	17.21±0.29
	E(2)-CNN [73]	98.50±0.10	73.51±2.50	89.84±0.46	45.85±0.93	41.95 ±0.18	59.29±0.91
	LBS (CE)	97.49±0.22	84.09 ±0.84	93.22 ±0.29	70.03 ±0.68	38.23±0.25	51.56±0.16
✗	SimCLR [9]	60.61±1.24	63.77±2.29	83.35±0.60	41.95±0.33	33.42±0.55	43.05±0.55
	E(2)-CNN [73]	53.50±7.30	55.52±7.60	83.52±1.56	42.06±1.12	30.74±2.84	38.03±4.44
	β-TCVAE [8]	17.09±0.20	20.04±0.71	71.27±0.10	36.30±0.10	15.38±0.19	16.35±0.18
	GeoSSL [55]	20.16±0.63	21.61±0.67	73.79±0.78	44.08±1.10	15.39±0.16	16.94±0.34
	DefGrid [21]	73.81±0.91	73.38±0.80	81.50±0.22	46.34±0.77	24.90±0.27	36.28±0.13
LBS	84.31 ±0.08	83.00 ±0.39	92.66 ±0.41	70.01 ±0.53	37.41 ±0.29	49.32 ±0.17	
	CLIP [59]	37.39	54.98	77.51	66.91	34.75	34.80
	HoG [14]	56.83	58.69	81.73	61.14	24.28	33.25

- Domain transfer

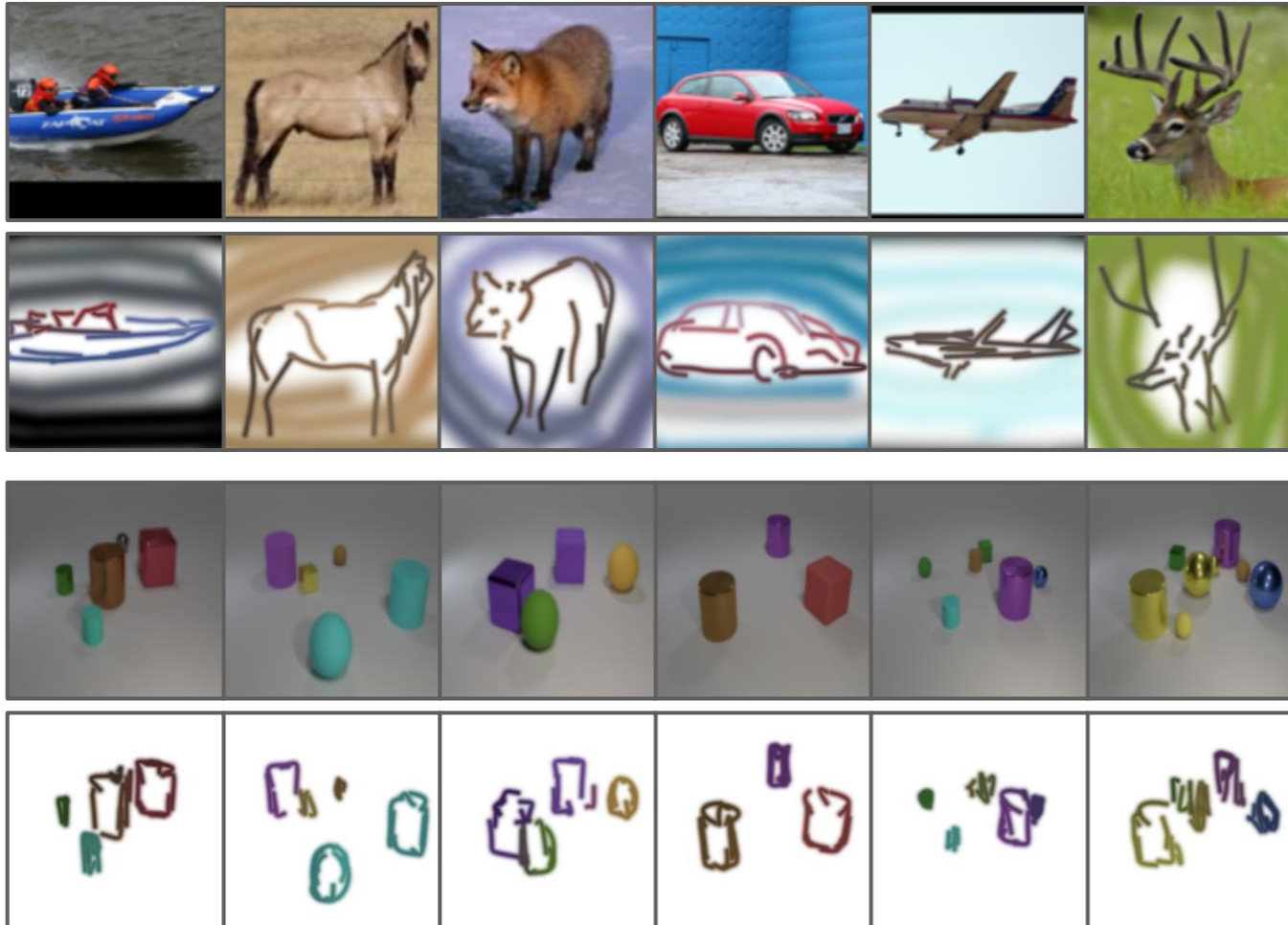


(b) CLEVR → STL-10

Dataset	Method	Labeled	Unlabeled	
		Accuracy	Method	Accuracy
CLEVR	CE	46.15±0.12	SimCLR [9]	41.68±0.05
	SupCon [38]	43.41±0.36	β-TCVAE [8]	27.35±0.38
	LtD-diff [54]	50.81±0.67	GeoSSL [55]	35.93±0.96
	E(2)-CNN [73]	45.19±0.84	E(2)-CNN [73]	38.50±0.49
STL-10	LBS (CE)	56.48 ±0.89	DefGrid [21]	33.13±0.17
	LBS		LBS	55.35 ±0.18

Experiments

Qualitative results



- Progressive optimization process



Thank you