Learning deep sketch abstraction

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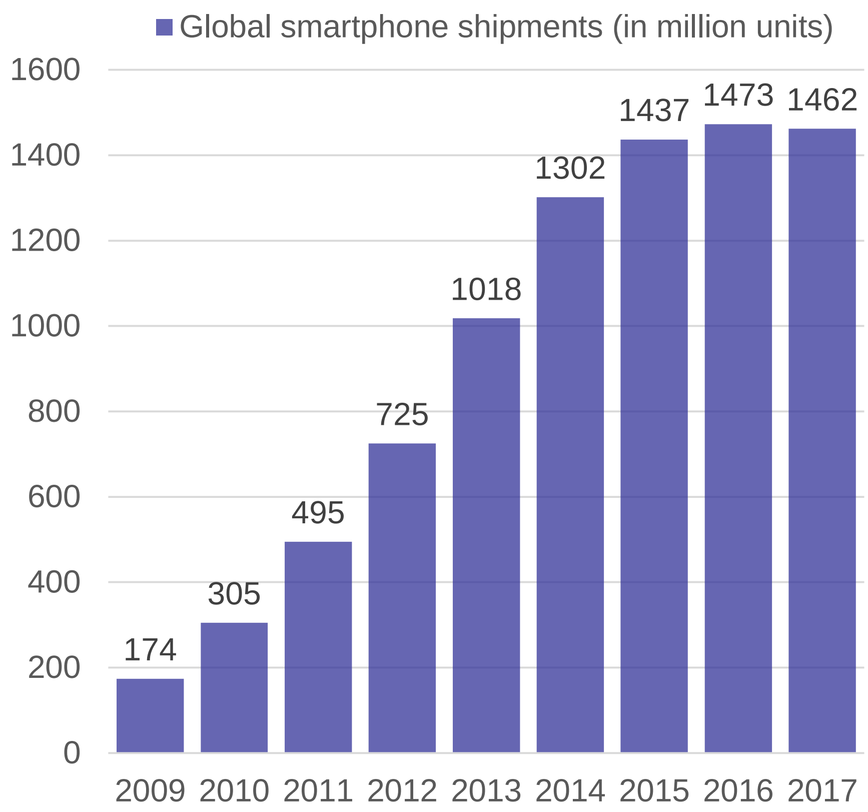
Background

Proliferation of touch-screen devices



Source: https://www.statista.com

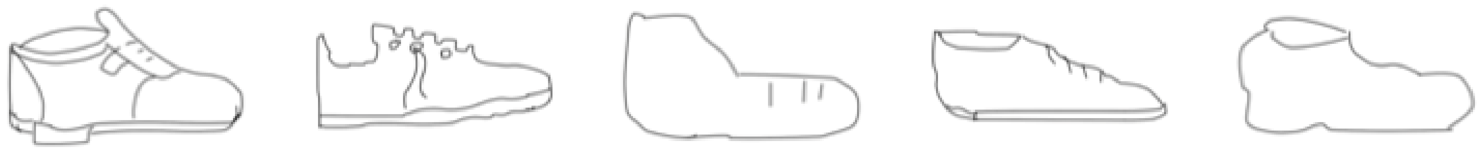
Sketch-related research

- Sketch recognition
- Sketch based image retrieval
- Forensic sketch analysis
- Sketch synthesis

Problem

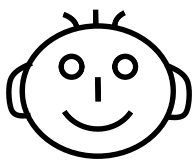
Abstraction levels in free-hand sketches

Shoe

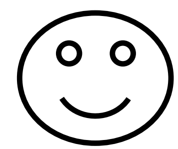


Proposed solution

Abstraction - a process of trade-off between recognizability and brevity



Sketch abstraction model



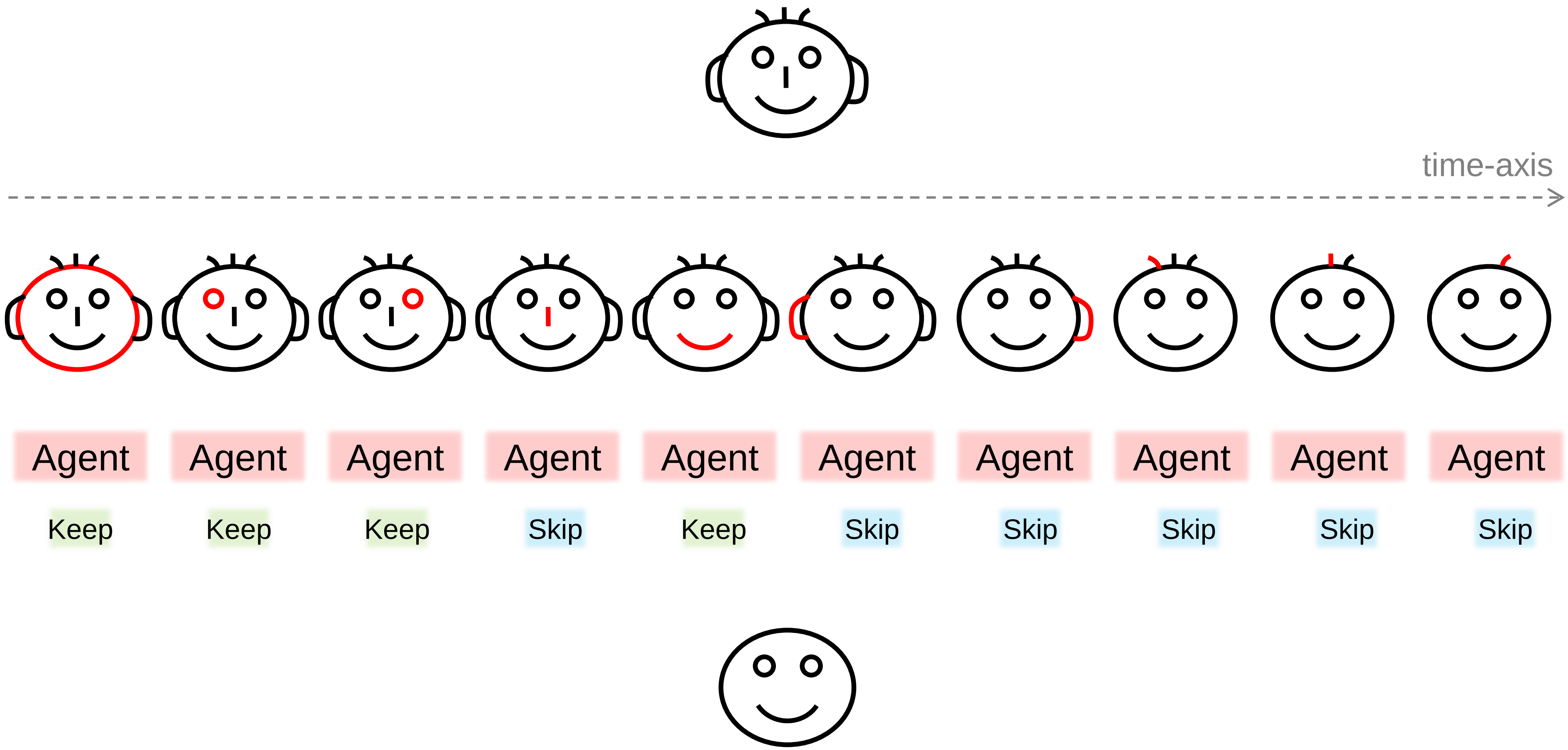
Synthesis at controllable abstraction levels

Stroke-level saliency

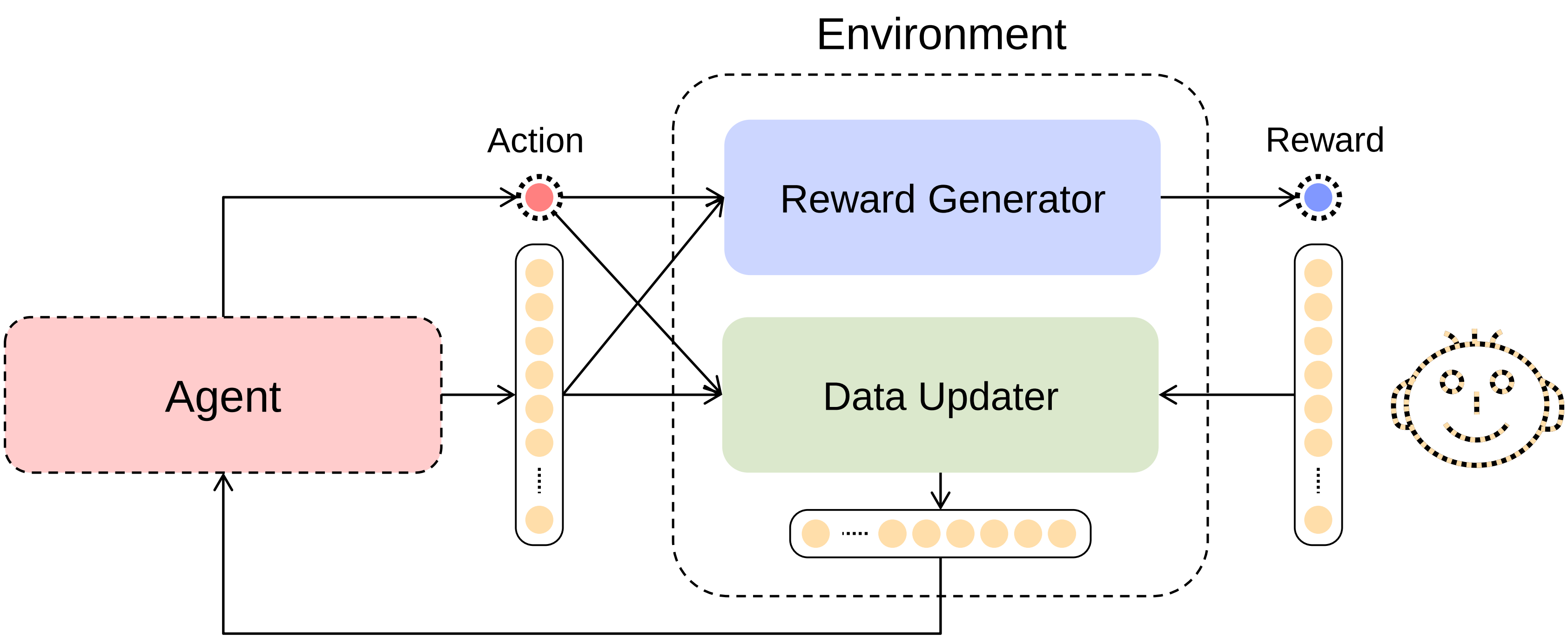
Fine-grained SBIR

Photo to sketch synthesis

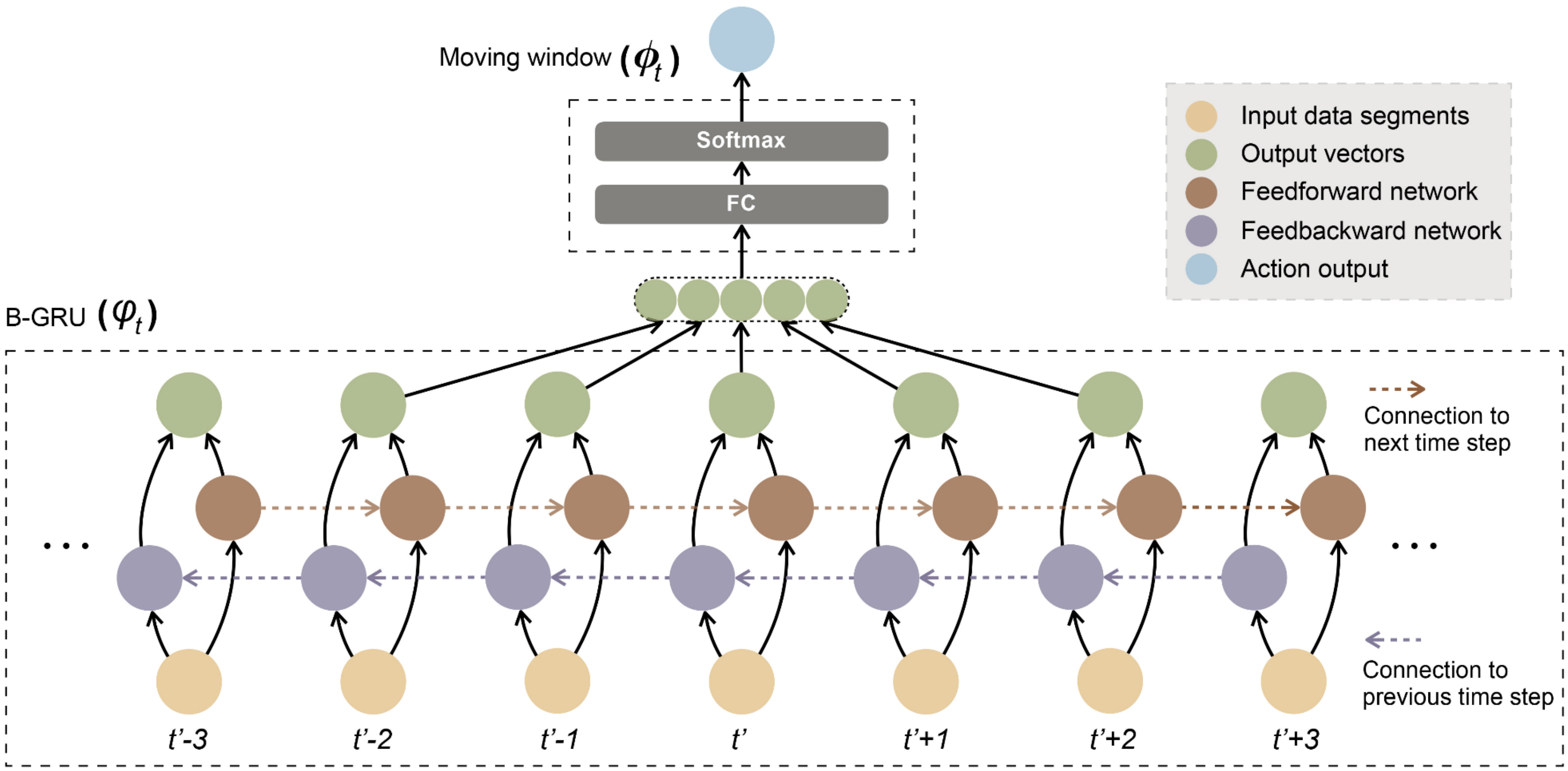
Abstraction formulation



Reinforcement learning



Agent



Moving window (ϕ_t)
Softmax
FC
B-GRU (φ_t)
Input data segments
Output vectors
Feedforward network
Feedbackward network
Action output
Connection to next time step
Connection to previous time step
t'-3
t'-2
t'-1
t'
t'+1
t'+2
t'+3

Basic reward scheme

$$R_t = b_t$$

$$b_t = \begin{cases} +1, & \text{if } t < M \text{ and } a_t = 0 \ \text{(skip)} \\ -5, & \text{if } t < M \text{ and } a_t = 1 \ \text{(keep)} \\ +100 & \text{if } t = M \text{ and Class}(s_t) \ = \ \text{G} \\ -100 & \text{if } t = M \text{ and Class}(s_t) \ \neq \ \text{G} \end{cases}$$

Ranked reward scheme

$$R_t = w_b \, b_t + w_r \, r_t$$

$$b_t = \begin{cases} +1, & \text{if } t < M \text{ and } a_t = 0 \;\; \text{(skip)} \\ -5, & \text{if } t < M \text{ and } a_t = 1 \;\; \text{(keep)} \\ +100 & \text{if } t = M \text{ and } \mathrm{Class}(s_t) \; = \; \mathrm{G} \\ -100 & \text{if } t = M \text{ and } \mathrm{Class}(s_t) \; \neq \; \mathrm{G} \end{cases}$$

$$r_t = \begin{cases} (w_c \, c_t + w_v \, v_t) \, b_t & \text{if } t < M \\ 0 & \text{if } t = M \end{cases}$$

$$c_t = 1 - \left(\frac{\mathrm{K} - C_t}{\mathrm{K}} \right)$$

$$v_t = 1 - \left(\frac{\mathrm{K} - (C_t - C_{t-1})}{2 \cdot \mathrm{K}} \right)$$

Extensions

- Controlling abstraction level
- Sketch stroke saliency
- Category-level sketch synthesis
- Photo to sketch synthesis
- Fine-grained SBIR

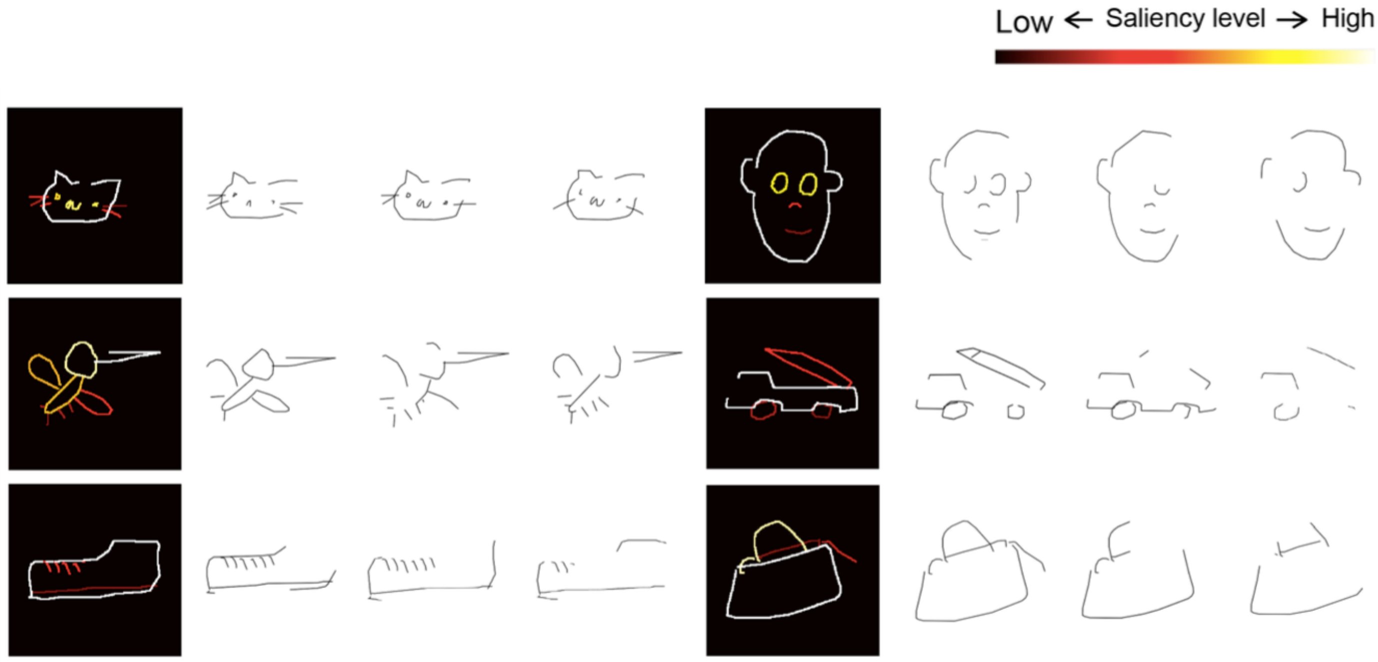
Controlling abstraction levels

$$\phi_t^* = (\phi_t(a_t = 0) + \delta,\ \phi_t(a_t = 1) - \delta)$$

		#DataSegments	Accuracy
Full Sketch		64.79	97.00%
1st Level Abstraction ($\delta = -0.1$)	Baseline	51.00	85.00%
	Basic Reward	51.12	87.60%
	Ranked Reward	51.31	**88.20%**
2nd Level Abstraction ($\delta = 0.0$)	Baseline	43.00	74.60%
	Basic Reward	43.09	78.80%
	Ranked Reward	43.33	**80.80%**
3rd Level Abstraction ($\delta = +0.1$)	Baseline	39.00	64.20%
	Basic Reward	39.37	68.00%
	Ranked Reward	39.48	**70.40%**

Saliency

$$\mathbb{S}_l = \frac{\sum_{t=l_{min}}^{l_{max}} \phi_t(a_t = 1)}{l_{max} - l_{min}}$$



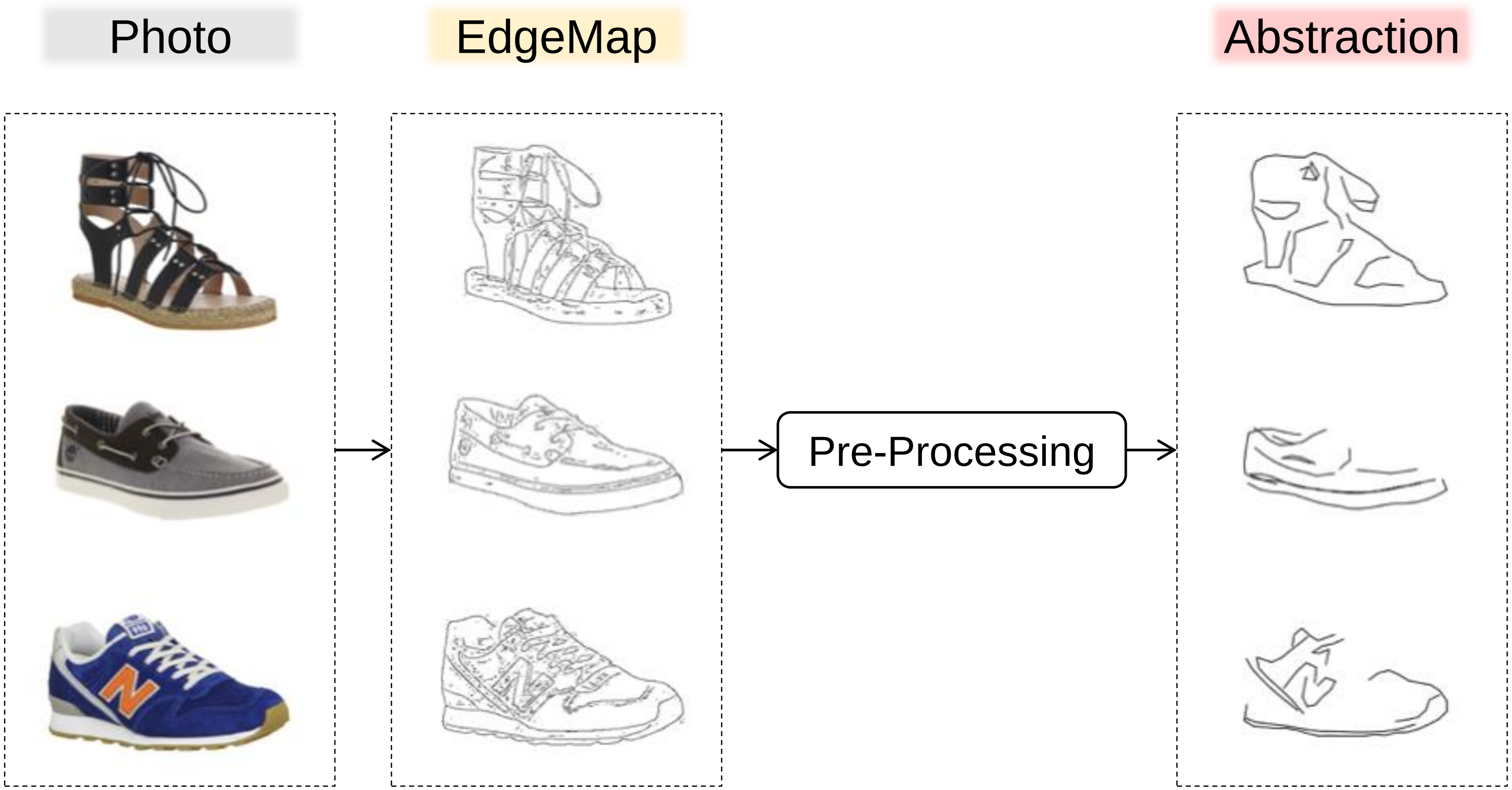
Category-level synthesis

Sketch synthesis [*] + Abstraction model

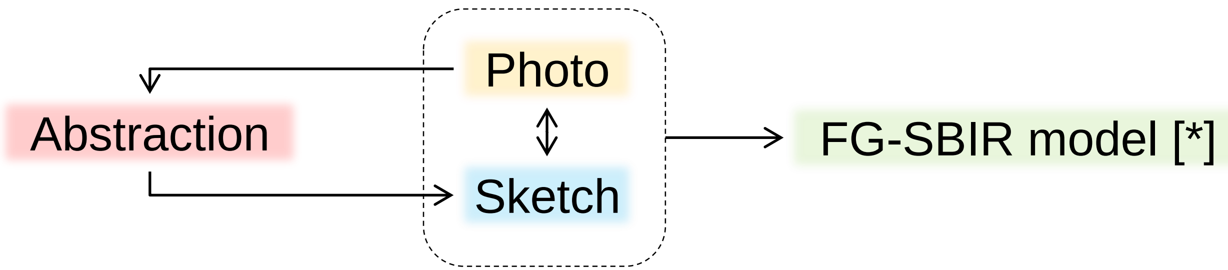
		#DataSegments	Accuracy
Full Sketch		69.61	99.6%
1st Level Abstraction ($\delta = -0.1$)	Baseline	50.00	89.96%
	Basic Reward	50.43	92.60%
	Ranked Reward	50.08	**94.20%**
2nd Level Abstraction ($\delta = 0.0$)	Baseline	44.00	80.20%
	Basic Reward	44.13	88.40%
	Ranked Reward	44.32	**90.80%**
3rd Level Abstraction ($\delta = +0.1$)	Baseline	37.00	69.20%
	Basic Reward	37.15	73.20%
	Ranked Reward	37.56	**79.40%**

[*] D. Ha and D. Eck. A neural representation of sketch drawings. *arXiv preprint arXiv:1704.03477*, 2017.

Photo to sketch synthesis



Fine-grained SBIR



	Shoe-V2		Chair-V2	
Method	Top1	Top10	Top1	Top10
Baseline1 [**]	8.86%	32.28%	31.27%	78.02%
Baseline2	16.67%	50.90%	34.67%	73.99%
Ours	**21.17%**	**55.86%**	**41.80%**	**84.21%**
Upper Bound	34.38%	79.43%	48.92%	90.71%

[*] Q.Yu,F.Liu,Y.-Z.SonG,T.Xiang,T.Hospedales,andC.C. Loy.
Sketch me that shoe. In CVPR, 2016
[**] P. Sangkloy, J. Lu, C. Fang, F. Yu, and J. Hays.
Scribbler: Controlling deep image synthesis with sketch and color. CVPR, 2017

Conclusion

Summary

- Sketch abstraction is studied for the first time.
- RL framework with a novel rank-reward to enforce stroke saliency.
- The model can address a number of sketch analysis tasks.

Future plans

- Make this model more practical by extending it to work with edge-maps in the wild.
- Develop an end-to-end trained abstraction model which could directly sample a variable abstraction-level sketch.