

Nan Cao, Xin Yan, Yang Shi, Chaoran Chen



Tongji University Intelligent Big Data Visualization Lab



BACKGROUND - Cave Painting



BACKGROUND - Children's Drawings





BACKGROUND - Design Drafts



Can **AI** help designers create high quality sketches and boost their productivity and creativity?





Facial Sketch Autodraw



7

Reference Pipeline for AI-Supported Sketching



Stroke Encoding

Stroke Encoding

Learning

Generating



Learning (Sketch-RNN)



Encoder: Bidirectional RNN (BRNN)

Learning (Sketch-RNN)





Generating (Sketch-RNN)



LIMITATIONS OF SKETCH-RNN

Low quality

1. generating sketches in one category (bird).



2. dealing with multi-class situations











• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

Encoder: Bidirectional RNN



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

 $X\!\!s\!\!:\!$ the sequences of strokes.

$$\boldsymbol{h}^{enc} = encode(X_s)$$



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

$$oldsymbol{h}_c ~=~ [oldsymbol{h}^{enc};oldsymbol{c}]$$

c is a k-dimensional one-hot conditional vector with k indicates the number of conditions.



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

 h_c is further transformed into two vectors to capture the distributions of the training strokes:

$$egin{aligned} oldsymbol{\mu}_s &= W_\mu oldsymbol{h}_c + oldsymbol{b}_\mu \ oldsymbol{\sigma}_s &= exp(rac{W_\sigma oldsymbol{h}_c + oldsymbol{b}_\sigma}{2}) \end{aligned}$$



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

A latent vector has been randomly sampled from the distributions for generating the next strokes:

$$oldsymbol{z}_s = oldsymbol{\mu}_s + oldsymbol{\sigma}_s \cdot oldsymbol{\lambda}$$



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

For decoding

Zs is concatenated together with the image feature vector *Zr*, the latent influence vector *Ad*, the conditional vector *C* and the last stroke vector *Si*:

$$z = [zs; zr; ad; c; si]$$

 $h^{dec} = decode(z)$



• A conditional vector is used to ensure a high quality generation of sketches from multiple categories.

predict the probabilities of the relative position of the next drawing point:

$$p(\Delta x_{i+1}, \Delta y_{i+1})$$



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.

AI-SKETCHER - Influence Layer



• An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.

AI-SKETCHER - Influence Layer



• An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.

It considers **all the previous hidden node values** until the latest drawing step in the RNN encoder.

AI-SKETCHER - Influence Layer



• An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.

The influence vector *ad* is a latent vector whose fields are sampled from these normal distributions:

$$oldsymbol{a}_d = oldsymbol{\mu}_a + oldsymbol{\sigma}_a \cdot oldsymbol{\lambda}_a$$



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.

Xr: the input raster image matrix.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.

Encoder:

- three convolutional layers with the stride size as 2.
- the other three layers with the stride size as 1.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.

Encoder:

• The last layer is a fully-connected neural network to produce the latent feature vector

Zr with 128 dimensions.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.

Decoder:

- three deconvolutional layers with stride sizes equal to 2.
- the other three layers with stride sizes equal to 1.



• A CNN-based autoencoder is employed to capture the spatial information of a training set.

ReLU is used as the activation function in both convolutional and deconvolutional layers.

tanh is used as the activation function of the fully-connected neural network.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.
- Loss function is modified.



- A conditional vector is used to ensure a high quality generation of sketches from multiple categories.
- An influence layer is introduced to estimate how the previous strokes will influence on the next stroke.
- A CNN-based autoencoder is employed to capture the spatial information of a training set.





$$Loss = l_r + \alpha \cdot max(l_{kl}, \epsilon)$$

• Loss function is modified.

$$Loss = l_r + \alpha \cdot max (l_{kl} \epsilon)$$

the reconstruction loss

estimates the differences between the generated strokes and the training samples. estimates the distribution differences between the generated strokes and the strokes in the training set modeled by the standard normal distribution.

$$Loss = l_r + \alpha \cdot max(l_{kl}, \epsilon)$$

$$l_{z} = -\frac{1}{2n_{z}} \sum_{i=1}^{n_{z}} (1 + \boldsymbol{\sigma}_{s_{i}} - exp(\boldsymbol{\sigma}_{s_{i}}) - \boldsymbol{\mu}_{s_{i}}^{2})$$

$$l_{a} = -\frac{1}{2n_{a}} \sum_{j=1}^{n_{a}} (1 + \boldsymbol{\sigma}_{a_{j}} - exp(\boldsymbol{\sigma}_{a_{j}}) - \boldsymbol{\mu}_{a_{j}}^{2})$$

$$l_{kl} = l_{z} + \beta l_{a}$$



We performed three experiments in purpose of validating the AI-Sketcher's

• drawing quality

- capability of generating sketches from **multiple classes**
- generation **diversity**

EVALUATION - Dataset

The QuickDraw dataset contains over 50 million sketches in 75 object categories and originally used for training Sketch-RNN.

Qvick, Draw! The Data 🥩 Play the game <															
	Þ	G	<u> </u>	(Å)	، ، ,	Same and		G	(Lan	N. M.	P	ŒÐ	D	Ø	
A	and the second	ſ		\otimes		ð	Ŧ	E K		P	SH	\bigcirc		940	
PG	G	æ	۲			Ð	m	D	No.	T)	I	<u>}</u>	6		
0	H		ß	ЗB	發		000 000 000	3. MP	R		(F)	Å.	â		
Ľ	£3-	AN S	M	(in the second	¥	${\gg}$		A	ŲĮ	t.	\bigcirc	O'TTOOM	L	\bigcirc	

EVALUATION - Dataset

The FaceX dataset consists of 5 million sketches of both male's and female's facial expressions showing seven different types of emotions.



A Dataset Containing 5,240,088 Hand-Drawing Sketches

The dataset contains over 5 million labeled facial sketches categorized by genders (male, female), viewing angles (frontal, mid-profile left view), emotions (neutral, happy, sad, angry, fearful, surprised, disgusted), and artistic styles (realistic, cartoon, abstract styles).









Two genders

0 6

Suprised



Disgusted









e Left View Frontal View

Abstract Style Cartoon Style Realistic Style______



EVALUATION - Dataset



Drawing quality



Drawing quality

ୖୢୖୖ	<u>کَ</u> ج	input
		Conditional Sketch-RNN
		AI-Sketcher Influence Layer Only)
		AI-Sketcher (Autoencoder Only)
		AI-Sketcher
angry disgusted fearful happy sad surprised neutral	angry disgusted fearful happy sad surprised neutral	

Drawing quality



Drawing quality



Drawing quality



Drawing quality

A within-subject user study

- 20 participants (10 females)
- The repeated measures one way ANOVA analysis showed that the generation quality of AI-Sketcher had an average rating of **3.9** and was significantly better than that of the baseline models (with all *p*<.01).



Generating sketches from multiple classes

	Sketch-RNN	Sketch-pix2seq	AI-Sketcher	
				5 classes
5 classes	face crab rabbit pig bird	Image: Second	face crab rabbit pig bird	1 Sketch-RNN 0 Sketch-pix2seq -1 Al-Sketcher
isses				-2 -3 -4
cla	face crab rabbit pig bird	face crab rabbit pig bird	face crab rabbit pig bird	-5 -
10			\$\$ \$ G \$ @	0 10000 20000 30000 10 classes
	cat dolphin door flower eye	cat dolphin door flower eye	cat dolphin door flower eye	Sketch-pix2seq
	@ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~	C R Y B P	0 2 2 8 6 4	-1 - Al-Sketcher
	face crab rabbit pig bird	face crab rabbit pig bird	face crab rabbit pig bird	-4-
5 classes	\$ \$ \$ \$ \$ \$			-5- -6- U 10000 20000 30000
ij	cat dolphin door flower eye	cat dolphin door flower eye	cat dolphin door flower eye	15 classes
	1 MB BR		N P O B m	2 - Sketch-RNN Sketch-pix2seq Al-Sketcher
	pencil table purse cup shorts	pencil table purse cup shorts	pencil table purse cup shorts	0-
				2-
	face crab rabbit pig bird	face crab rabbit pig bird	face crab rabbit pig bird	-6-
sses	FR B B P	$\mathbf{E} = \mathbf{E} \neq \mathbf{C}$		0 10000 20000 30000 20 classes
clas	cat dolphin door flower eye	cat_dolphin_door_flowereye	cat_dolphin_door_flowereye	Sketch-RNN
20			N M B B M	o- -z
	pencil table purse cup shorts	pencil table purse cup shorts	pencil table purse cup shorts	-4-
	$\bigcirc \bigcirc $	O \square \square \textcircled{O} \textcircled{O}		-6-
	apple tooth spoon lion ball	apple tooth spoon lion ball	apple tooth spoon lion ball	D 60000 20000 30000

Generating sketches from multiple classes



Generating sketches from multiple classes



Generating sketches from multiple classes

			Sketch-pix2seq					AI-Sketcher					
classes								Ci Sear Mi	(i)	Ð			
								face crab rabbit	pig	bird	-44		
ses										47			
clas								face crab rabbit	pig	bird			
10								83C	- Cop	6			
								cat dolphin door	flower	eye	2		
								9 H 8	6	47			
s								face crab rabbit	pig	bird			
classe									E.	Ø			
15								cat dolphin door	flower	eye			
									B	\square			
								pencil table purse	cup	shorts			
								(j) 44 (j)	6	Ļ			
								face crab rabbit	pig	bird			
ses								戦う日	S S	Ø			
clas								cat dolphin door	flower	eye			
20									Þ	\Box			
								pencil table purse	cup	shorts			
								$\bigcirc \mathbb{R} \sim$	翻	Ð			
			apple				ball	apple tooth spoon	lion	ball		63	000

Generating sketches from multiple classes

Experiments based on QuickDraw Dataset

face

cat

pencil

apple

classes

20



Generation Diversity

In each set, the pairwised distances between sketches were calculated based on the **perceptual hash**.

The unpaired t-test showed that AI-Sketcher and Sketch-RNN had no significant difference.

Input								T-D			
Model											
Mean	30.66	30.97	29.76	29.87	28.98	28.82	29.23	29.45	29.66	30.00	
SD	5.18	5.54	5.79	5.84	5.93	6.20	6.08	5.87	5.37	5.83	
t(198)	-1.42		-0.53		0.65		-0.	92	-1.53		
p	0.16 >.05		0.56	> .05	0.51	> .05	0.35	> .05	0.13 > .05		

AI-Sketcher Sketch-RNN

POTENTIAL APPLICATION





We introduced **AI-Sketcher,** a hybrid deep learning model to automatically generate high quality sketch drawings .

Our model improves drawing quality by

- employing **a CNN-based autoencoder** to capture the positional information.
- introducing an influence layer to more precisely guide the generation of each stroke.
- provideding **a conditional vector** to support multi-class sketch generation.

Thank You

Nan Cao, Xin Yan, Yang Shi, Chaoran Chen







Tongji University

Intelligent Big Data Visualization Lab



F@ceX

A Dataset Containing 5,240,088 Hand-Drawing Sketches

The dataset contains over 5 million labeled facial sketches categorized by genders (male, female), viewing angles (frontal, mid-profile left view), emotions (neutral, happy, sad, angry, fearful, surprised, disgusted), and artistic styles (realistic, cartoon, abstract styles).



https://facex.idvxlab.com/





68.