Duties and Work Allocation of Group 3

Name	Uni Number	Duties	%
Li Jiahui	3036013883	• Collecting raw data; • Find and modify source code of LAB transformation, CGAN and style transfer; • Data pre-processing (LAB converting & Re-sizing); • Hyper-parameter Tuning; • Model Interpretation; Model Testing and Evaluation; • Explore Business Implementation • Prepare Report & Slides	14.28572%
Tsang Wan Ching	3036008761		14.28575%
Lang Qing	3036021397		14.28573%
Li Moyu	3036020991		14.28573%
Huang Wantao	3036018223		14.28572%
Tang Qianmiao	3036021402		14.28573%
Yan Di	3036026206		14.28575%

Magic Brush:

Make your Vivid Photo!

— Image Colorization with CGAN

& Style transfer

Group 3:
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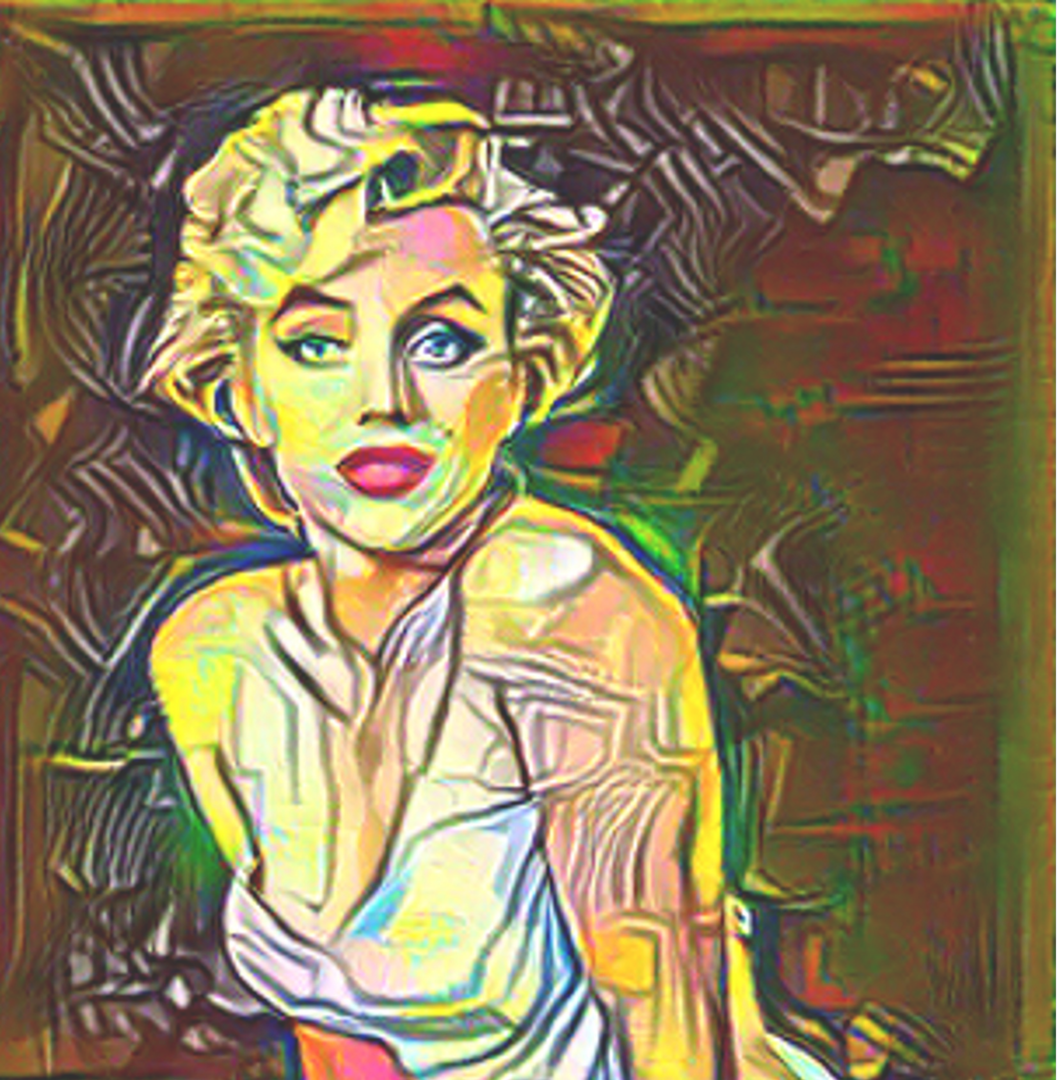

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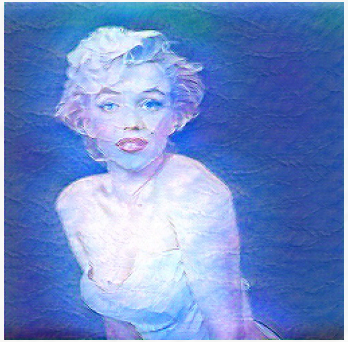


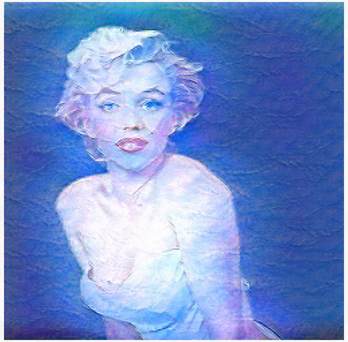

Our insights

We have great potential market !

- Restoration of old artworks/ family photos
- Design of fancy profile for fun
- Marketing & Advertising

What we do !

- AI colorizer is changing the future of art
- Digital algorithms: substitute colors into a B&W photograph by making an "informed guess"
- Mind-blowing effect, just a few seconds !



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Contents

01
Image Data

02
Image Colorization

03
Image Style Transfer

04
Application & Limitation

01 Our Image Dataset

Portrait

Scenery

Indoors

Colorization

Style Transfer

Manually-collected

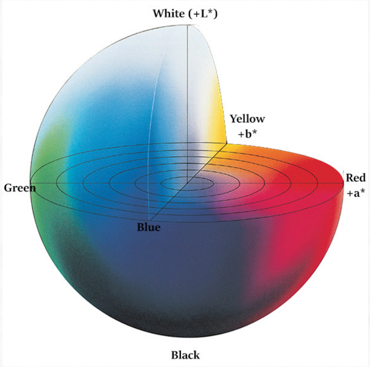
1600+

02

Image Colorization

Image Colorization —— Data Pre-processing

Step 1: Convert image from RGB to LAB color space & Split channels



LAB color space

Original Photo

=

L channel
(Black & White)

+

AB channel
(Yellow/Blue & Red/Green)

Step 2: Split images into train and test datasets

70% Training 30% Testing

1,626 photos

Image Colorization —— Generator (ResU-NET)

Generate the color version of the grayscale image

Encoder :
Resnet blocks + Maxpooling
Decoder:
Resnet blocks + Upsampling

Skip connections:
- Mitigate vanishing gradients
- Add valuable information

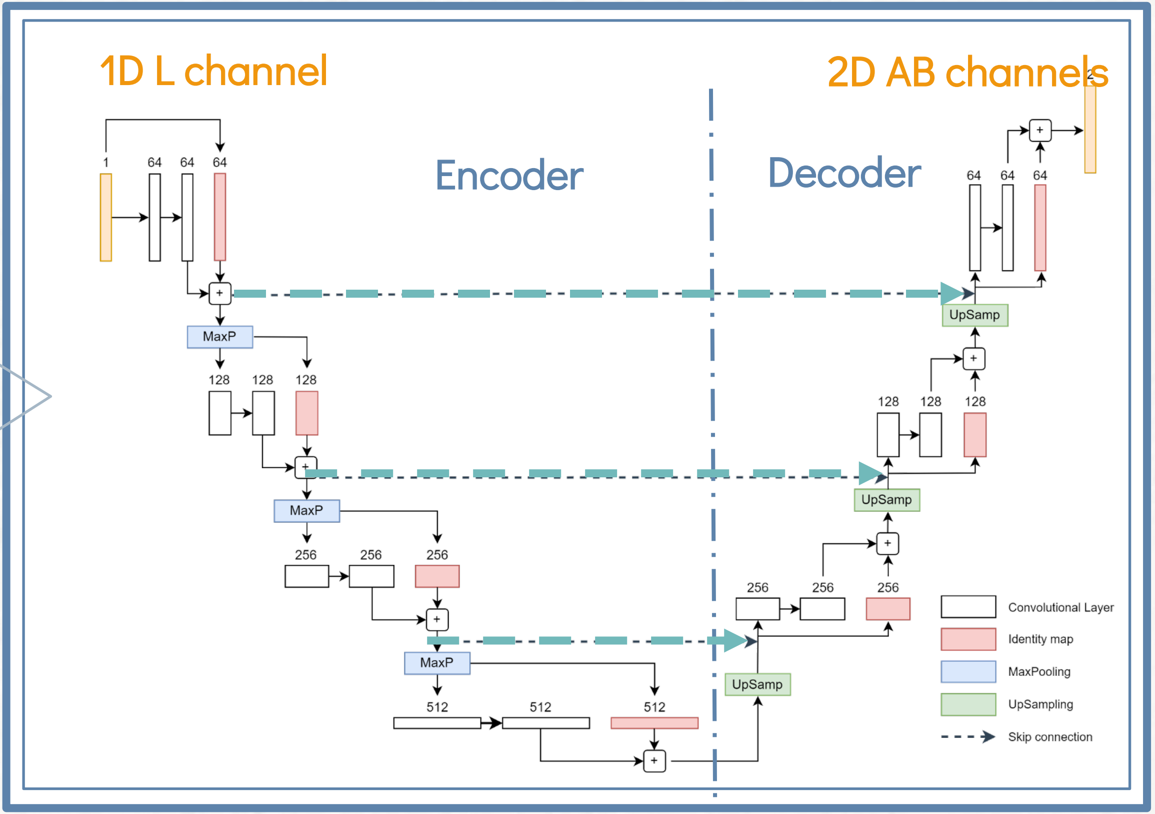


Image Colorization —— Discriminator(CNN)

Discriminate the generated color image and the real color image

Achitecture:
Convolutional Layers
+ Average Pooling
+ Fully Connected Layer

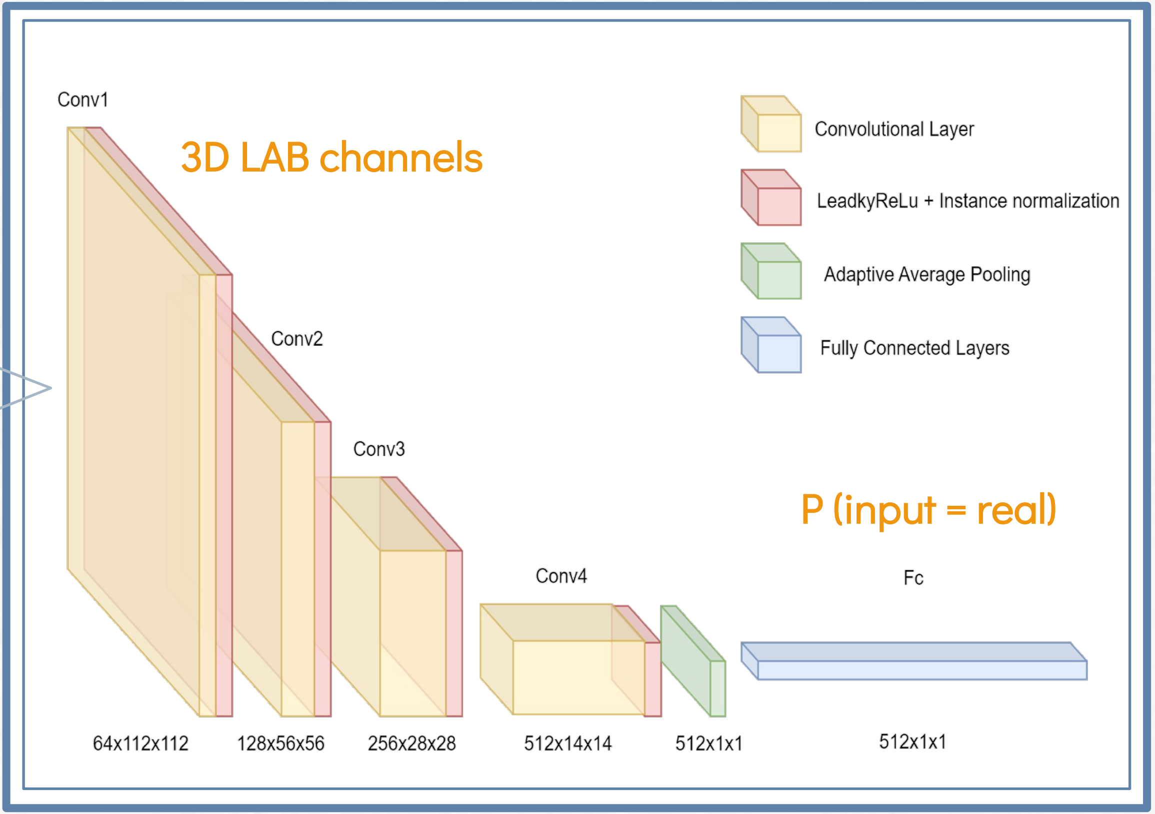


Image Colorization —— CGAN Model

Step 3: Hyper-parameters tuning (Validation set)

<u>Fréchet inception distance (FID):</u>

Compares the distribution of generated images with the distribution of real images.

$$\mathrm{FID}(x,g) = ||\mu_x - \mu_g|| + \mathrm{Tr}\left(\Sigma_x + \Sigma_g - 2\sqrt{\Sigma_x \Sigma_g}\right)$$

Discriminator_lr	Generator_lr	FID
0.001	0.0002	9.0687
0.0001	0.0003	9.156
0.002	0.0002	10.5279
0.0004	0.0002	10.6002
0.0006	0.0003	11.7109

Step 4: Model Training (Training set + Validation set)

Train for 350 epochs (around 12 hours)

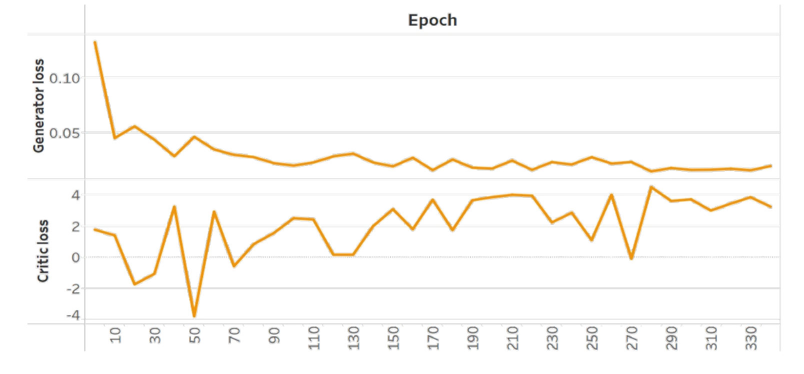


Image Colorization —— CGAN Model

Step 5: Model Testing (Testing set)

Real - Input - Output

Real - Input - Output

03

Style Transformation

Style Transfer: Data Description

train data:
(for parameter tuning)

(Selected from the train dataset of previous part)

test data:
(for final result)

(Selected from the test dataset of previous part)

After colorization

Content Data

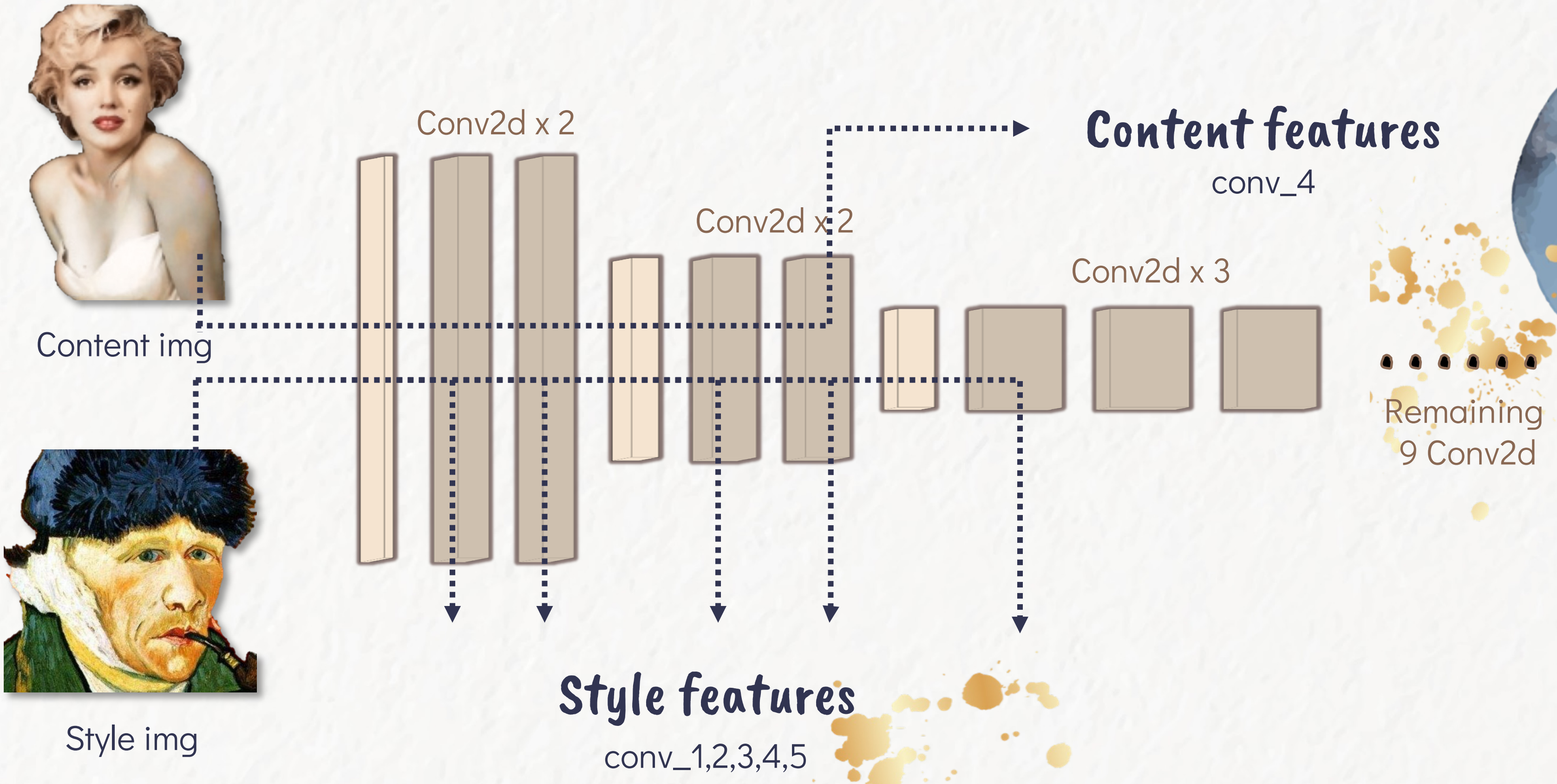
+

(Collected from Internet)

Style Data

= ?

Style Transfer: Model—Structure(VGG19)



Style Transfer: Model – Loss Function

- **Total Loss Function:**

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

p: content input a: style input X: generated

- **Content Loss Function:**

$$L_{content}(\vec{p}, \vec{x}, \vec{l}) = \frac{1}{2} \sum_{i,j} (F_{ij}^{l} - P_{ij}^{l})^2$$

F: feature map coming from the generated image

P: feature map coming from the content image

Style Transfer: Model – Loss Function

- **Style Loss Function – Gram Matrix**

$$G = \begin{pmatrix} (\alpha_1, \alpha_1) & (\alpha_1, \alpha_2) & \cdots & (\alpha_1, \alpha_k) \\ (\alpha_2, \alpha_1) & (\alpha_2, \alpha_2) & \cdots & (\alpha_2, \alpha_k) \\ \vdots & \vdots & \vdots & \vdots \\ (\alpha_k, \alpha_1) & (\alpha_k, \alpha_2) & \cdots & (\alpha_k, \alpha_k) \end{pmatrix}$$

$$G^l_{ij} = \sum_{i,j} F^l_{ik} F^l_{jk}$$

Gij can reflect the relationship between feature map *i* and *j*

- The diagonal reflect information of feature maps themselves
- The other part reflect relationships between feature maps

➡ Gram matrix can help record the overall style of image

Style Transfer: Model – Loss Function

- **Style Loss Function – Gram Matrix**

For each layer:

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l - A_{ij}^l)^2$$

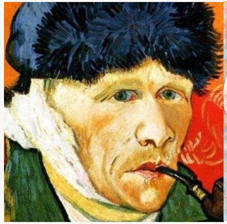
Total style loss:

$$L_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l$$

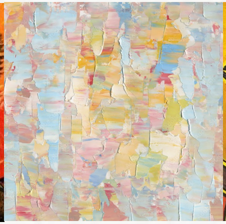
Style Transfer: Outputs

Original Input

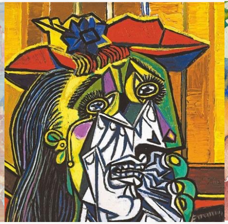
Style weight = 999
Content weight = 1



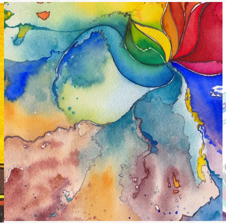
Van Gogh



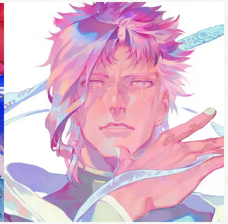
Oil Painting



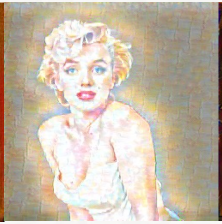
Picasso



Watercolor



Comic



	Van Gogh	Oil Painting	Picasso	Watercolor	Comic
Style loss	0.4039	0.2187	3.8189	0.3383	0.4484
Content loss	3.3713	1.4705	7.8161	2.1918	2.9617
Total loss	3.7752	1.6891	11.6350	2.5301	3.4101

04

Application & Limitation

Applications

- Photography

Old photo restoration

- Be useful for businesses in the photography or film preservation industries
- Be useful for individuals who want to preserve family memories

Applied as filters

- Be applied to the short video platforms (Facebook, TikTok...) as a filter for users to take photos or videos
- Picasso filter, animation filter, etc.

- Other industries

Medical imaging

- To highlight specific areas of an medical image (MRI or CT scan)
- To differentiate between different types of tissue

Marketing & advertising

- Businesses can use style transfer techniques to create unique and eye-catching visuals for social media or display ads

Limitation

Greyer than original photo

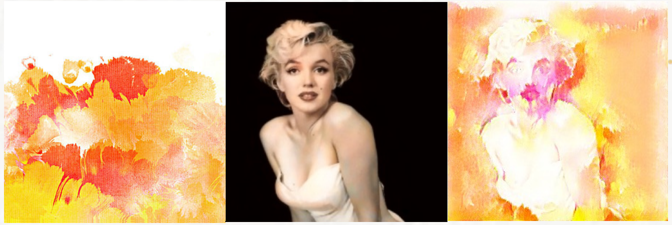
Frequent wrong color on lips and clothes

Transfer model limitation

-Clear brush strokes
-Strong style

Input Output Real

Style Content Transferred



Improvement

More epochs

Add suitable photos in training dataset

Combine transfer with GAN

AnimeGAN :

-grayscale style loss

-color reconstruction loss

- Load style datasets
- Grayscale and Gaussian filtering of style photos
- Input real photos in G
- Input generated photos and style photos in D
- Calculate loss and train
- **Final generator**

Thanks!

If you have questions,
please feel free to reach us!

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