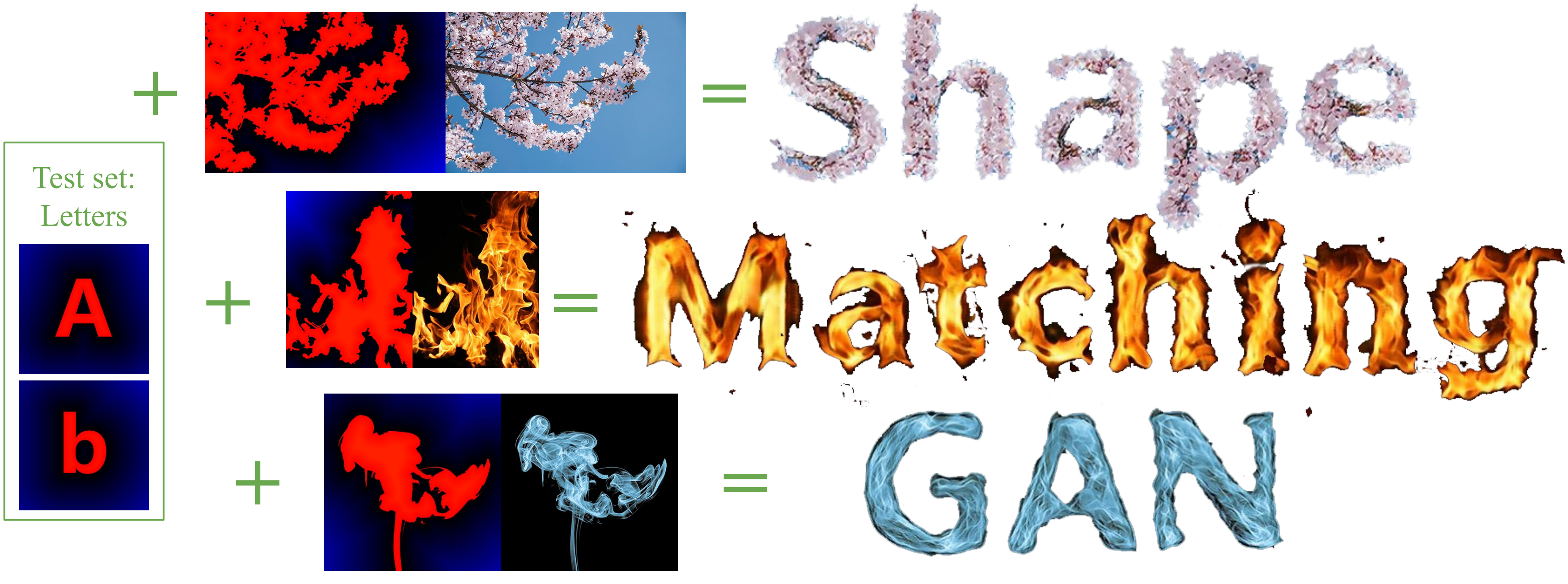
Shape Matching GAN

Intro to CV Final Project Presentation

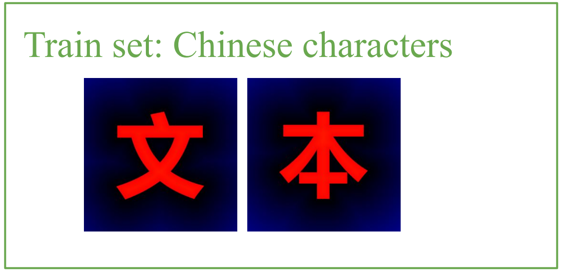
by Binfang Ye & Xinyue Chen



Raw text

Style (structure & texture)

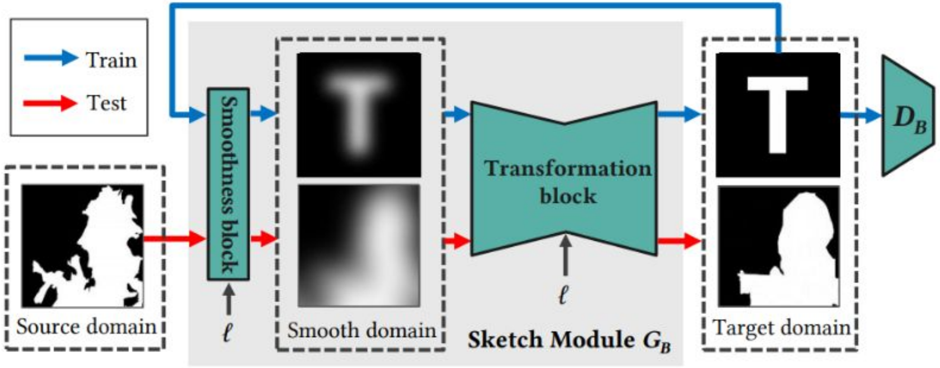
(Yang et al. "Controllable Artistic Text Style Transfer via Shape-Matching GAN." *ICCV*. 2019.)



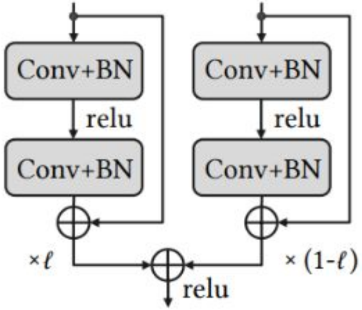
- Our results on style transfer for artistic texts

The Shape-Matching GAN Algorithm

- Backward structure transfer (from text image to source image)
  - Smoothness block
  - Transformation block

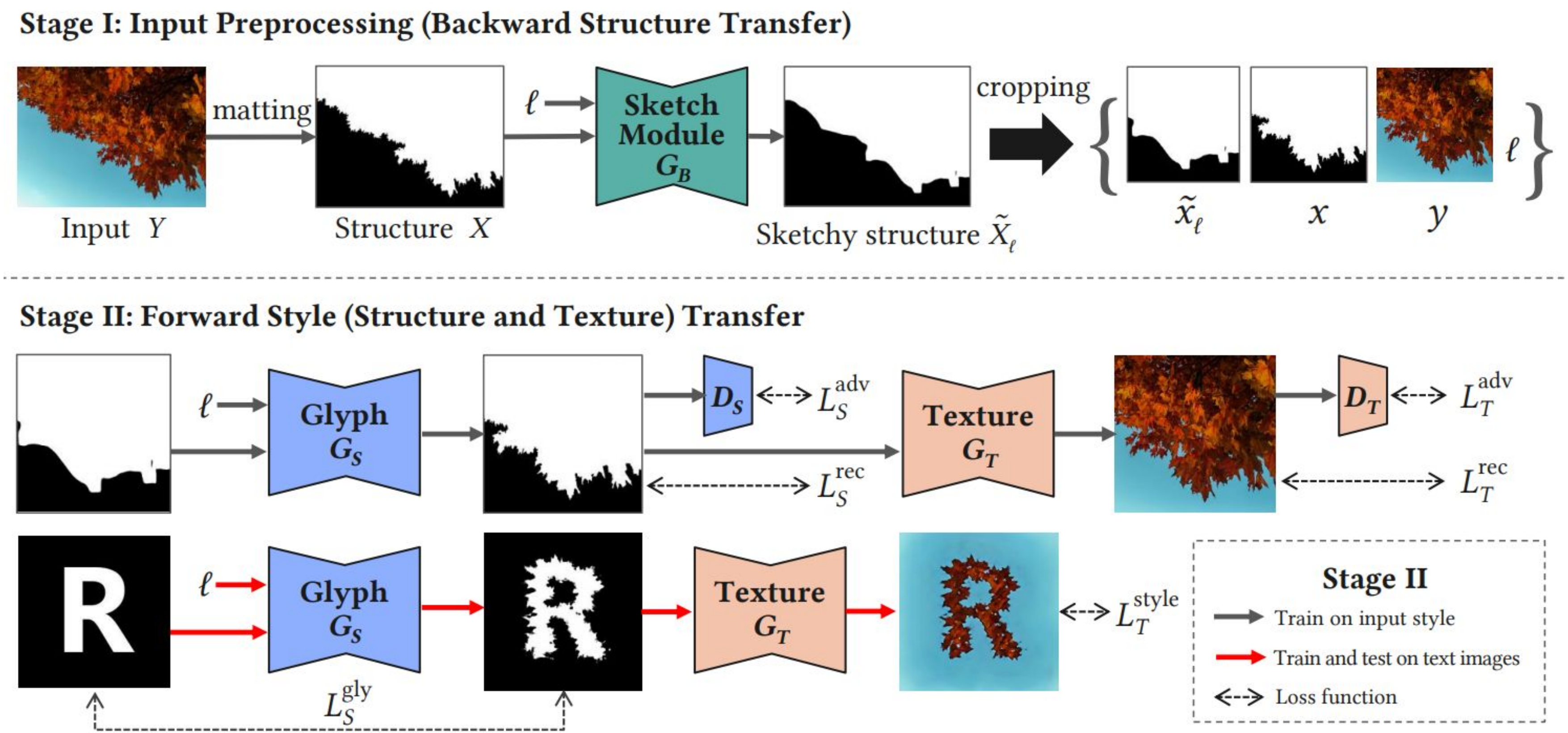


- Forward transfer (from source image to text image)
  - Structure transfer
    - Controllable Resblock



  - Texture Transfer

The Shape-Matching GAN Algorithm



Ablation study

In the Shape Matching GAN paper, the authors already did an ablation study on some components of the algorithm.

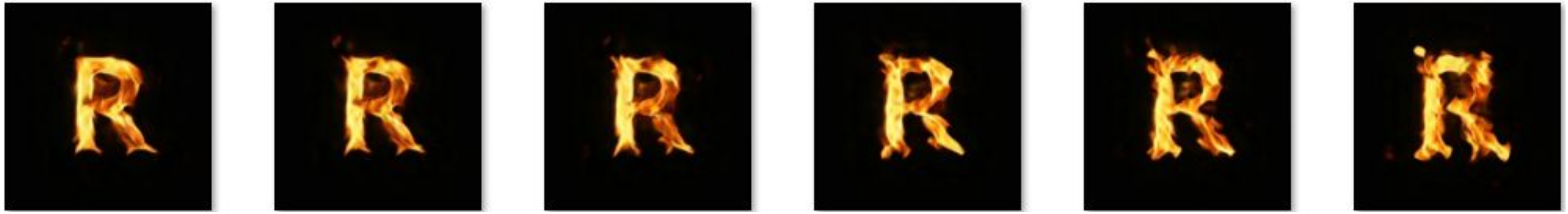
Additionally, we consider 2 components that are not studied in their paper:

- Image augmentation
- Glyph preserve loss

Ablation study

ℓ = 0.0 0.2 0.4 0.6 0.8 1.0

- Full model



- w/o Image augmentation

- w/o Glyph preserve loss

Extension to other types of images

We consider the *easy-drawing* images.

Challenges:

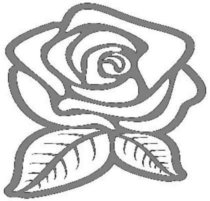
- **Complexity** of the glyph are higher.
- **Stroke width** is typically smaller than texts.
- **Multiple** objects

Question:

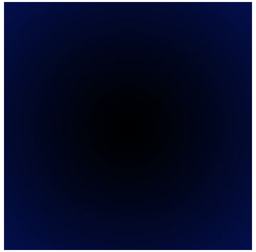
Does features learnt on text images generalize to easy-drawing images?

Data Generation

- Easy-drawing pictures after applying the mean shift algorithm



- Gradient background

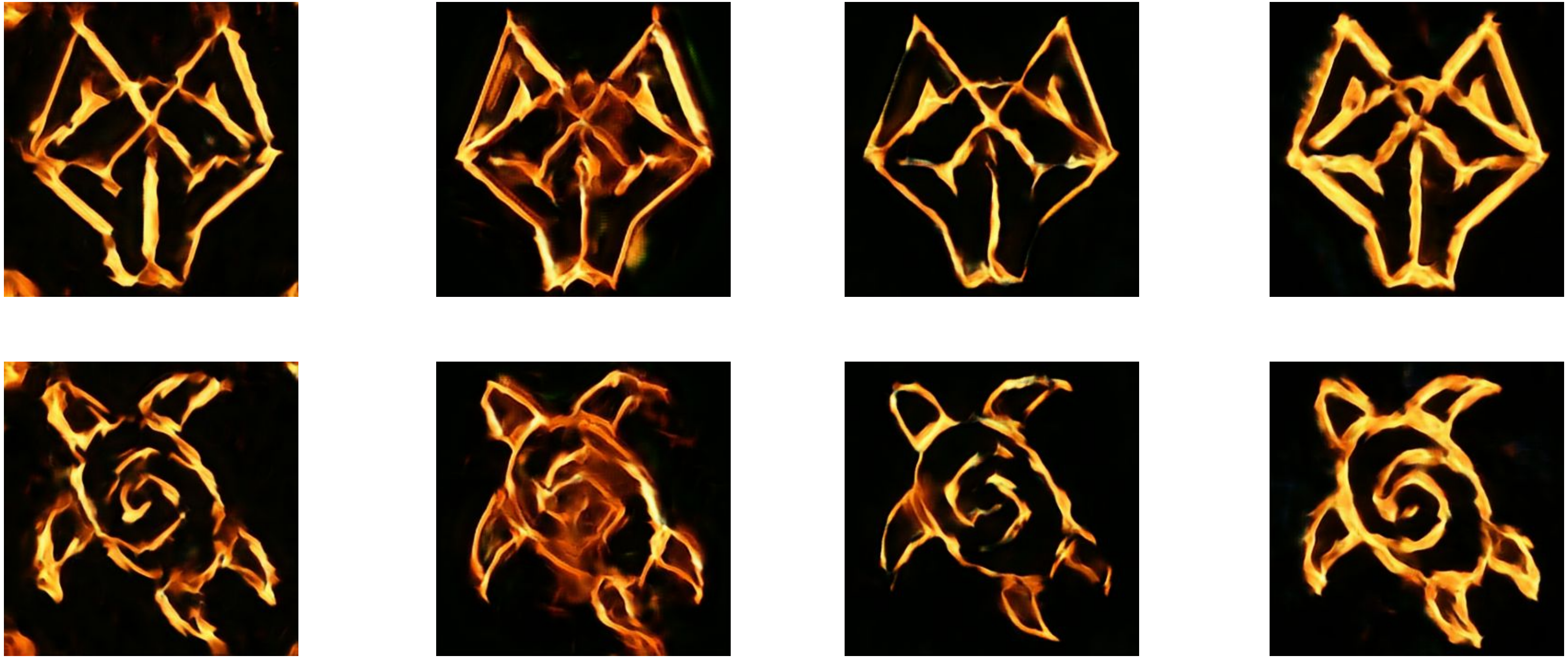


- Changed the stroke color to red

Results on Test set (ℓ=0.4)

Train set distribution

text data	text data+drawing data	text data+drawing data	drawing data
(~700)	(~700+30)	(70+30)	(30)



Thank you!