Font Style Transfer Using Neural Style Transfer and Unsupervised Cross-domain Transfer

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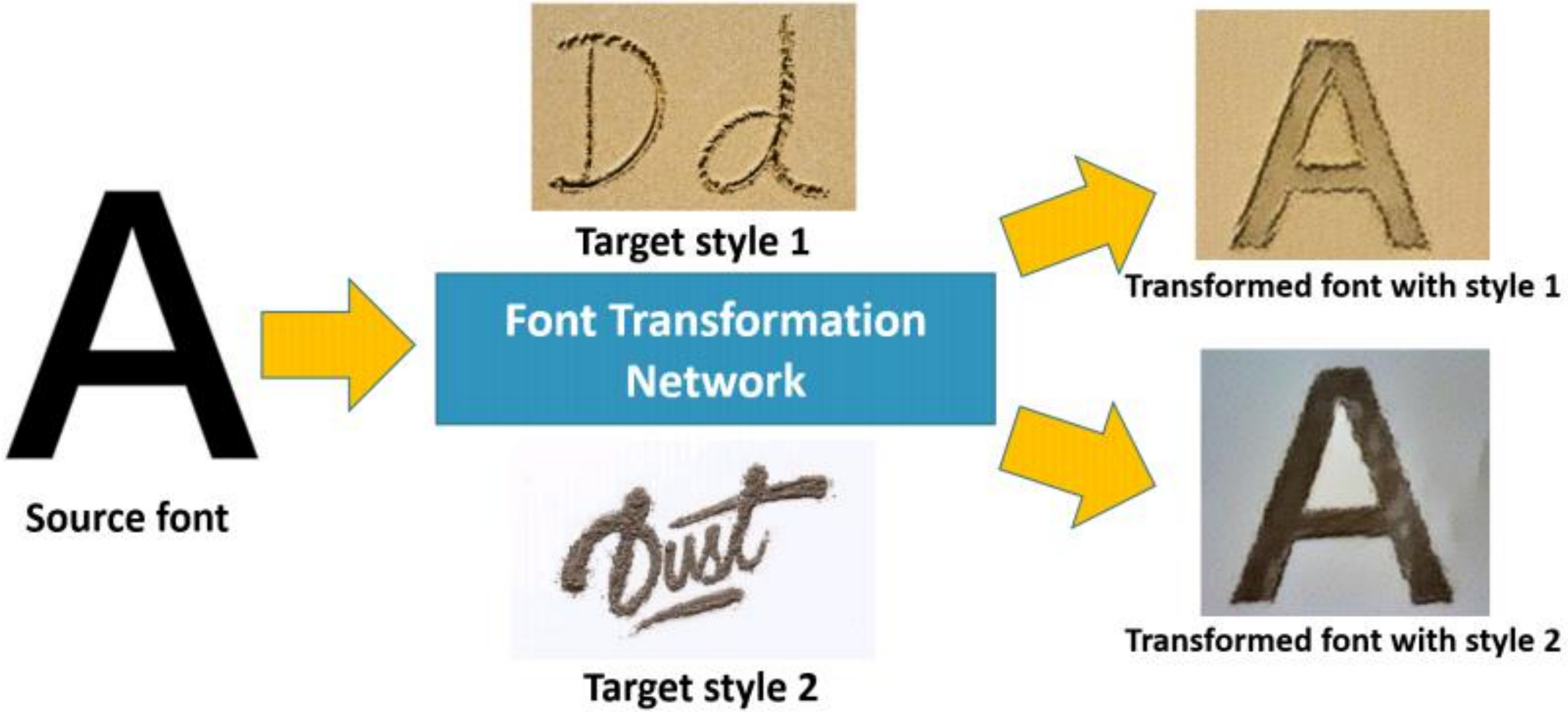
Back ground



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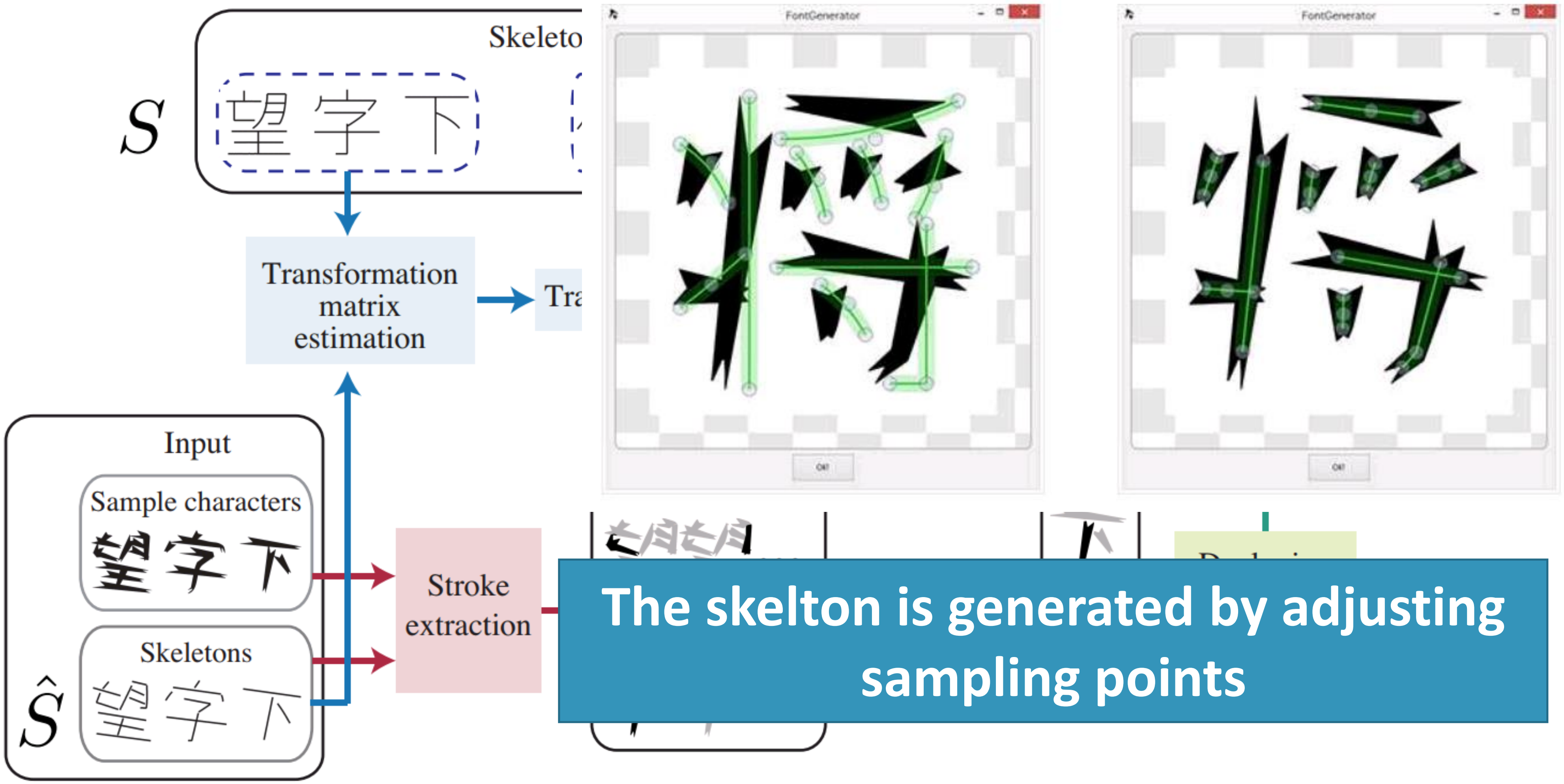
Previous works1



The skelton is generated by adjusting sampling points

T. Miyazaki et al., arXiv:1701.05703

Previous works : without CNN

○ Good results

× Needs making skelton datasets for extracting stroke

<u>Deep learning</u>

<u>Extracting stloke automatically</u>

Previous works 2-1（Style Transfer）

+

=

Content ***Style*** ***Generated results***

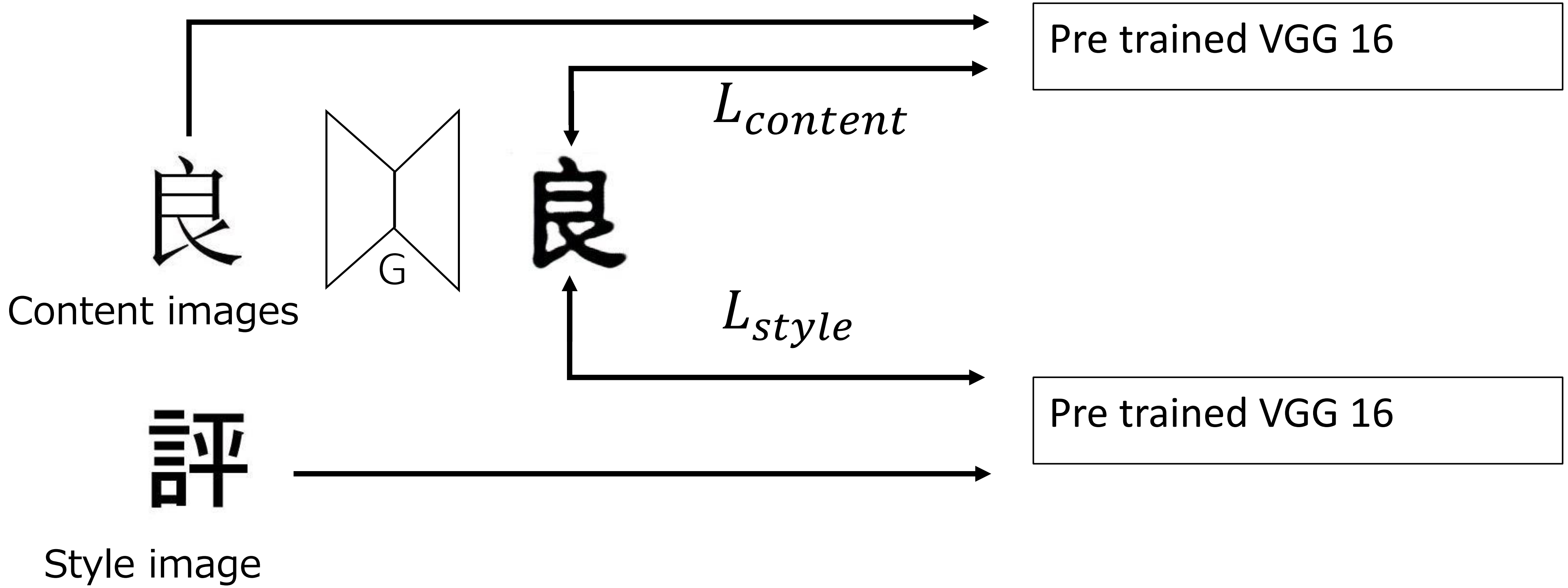
Gatys et al., CVPR2016

Font generation using Neural Style Transfer

- ○ Not requires additional training and dataset.
- ○ High quality.
- ✕ Requires large computational cost for generating an image

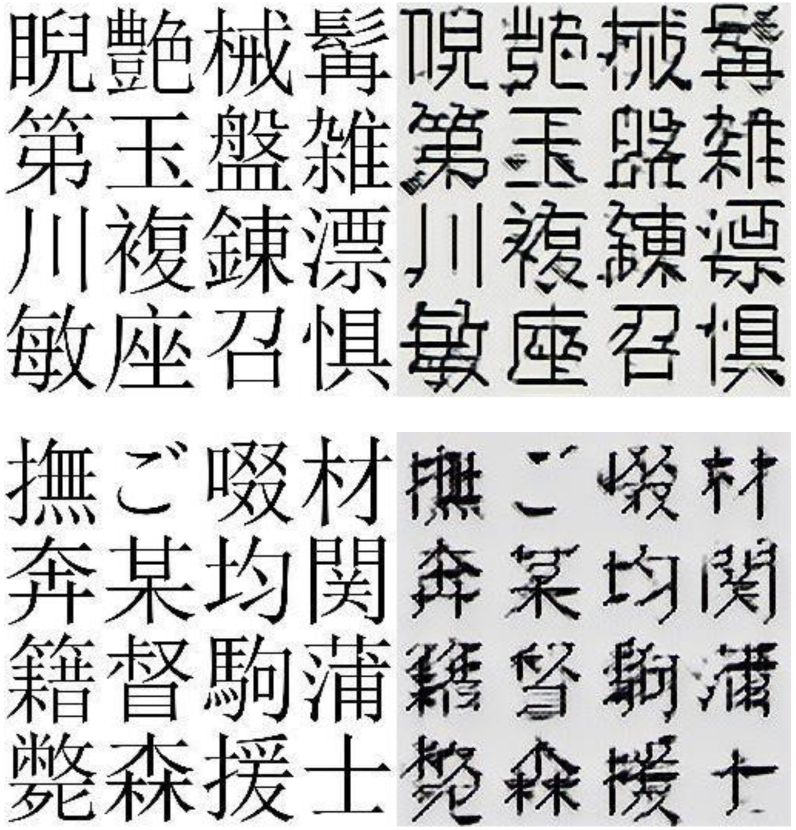
Previous works 2-2 : Fast Style Transfer

Speeding up Neural Style Transfer by training a model

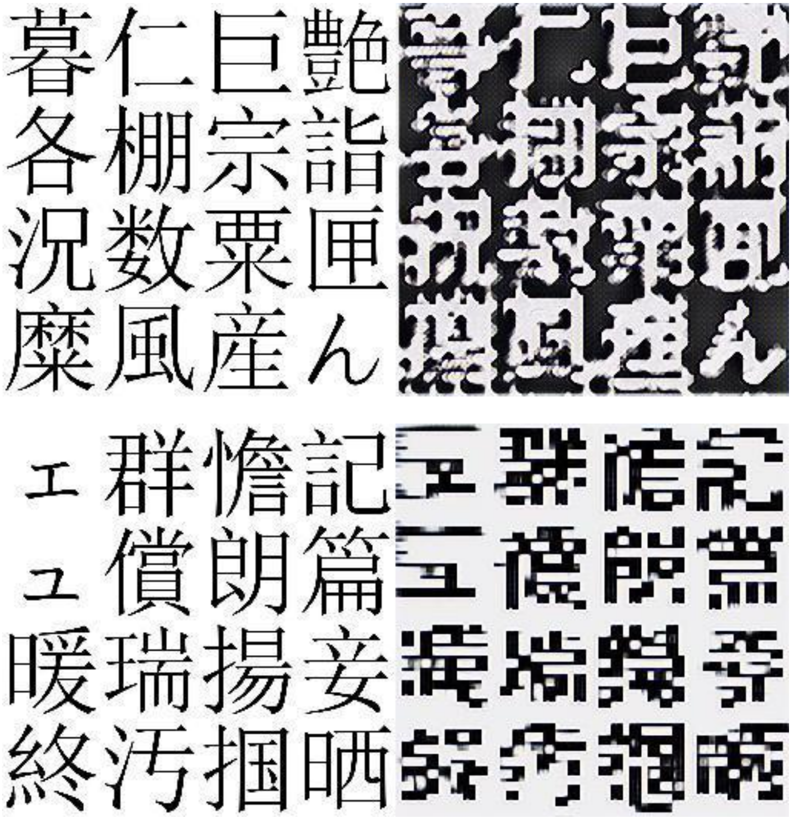


J. Johnson et al., ECCV2016

Previous works 2-2（Fast Style Transfer）



Inputs, Outputs



Inputs, Outputs

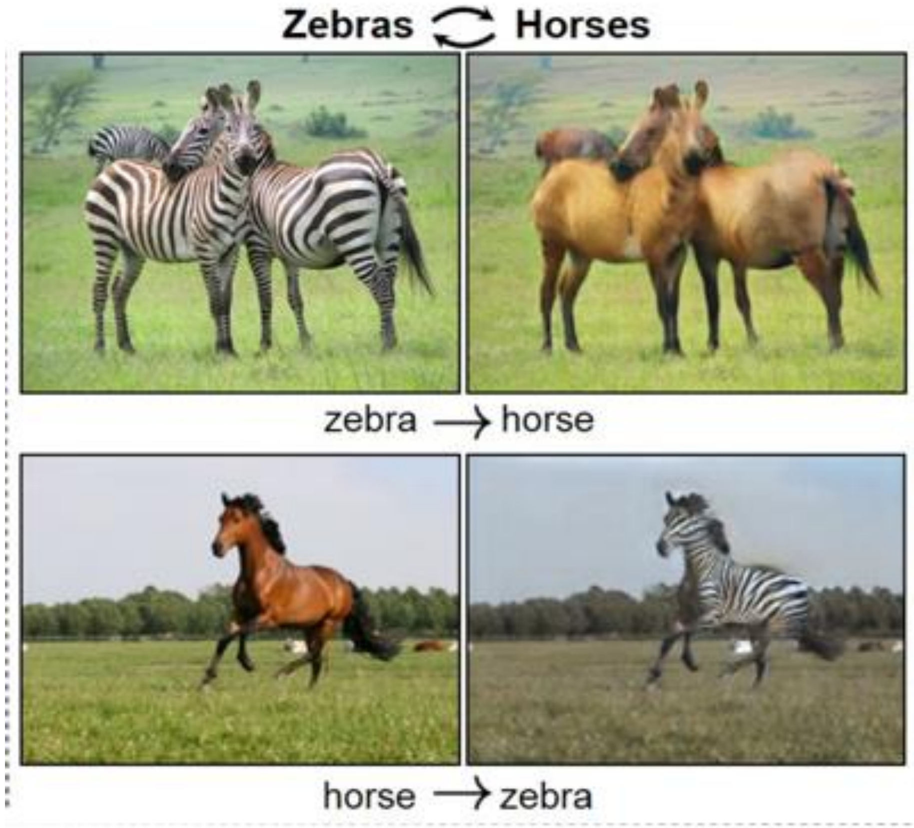
Inputs, Outputs

Fast Style Transfer

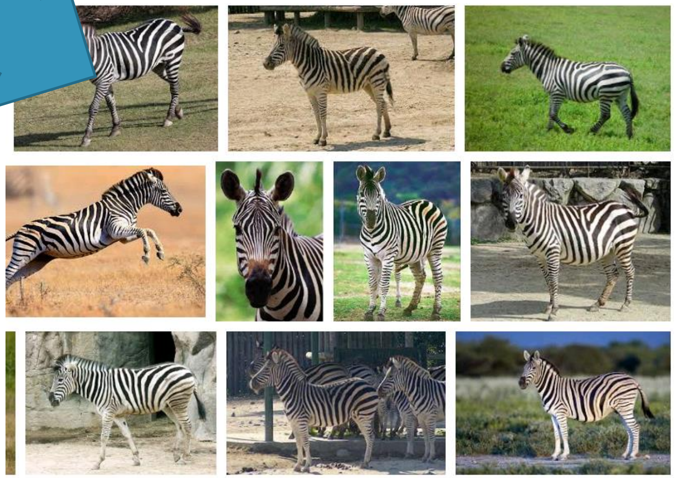
○ High readability

✕ Has difficulty for natural texture of generated images

Previous works 3（ Cycle GAN ）



Horse dataset



Zebra dataset

J.Zhu et al., ICCV2017

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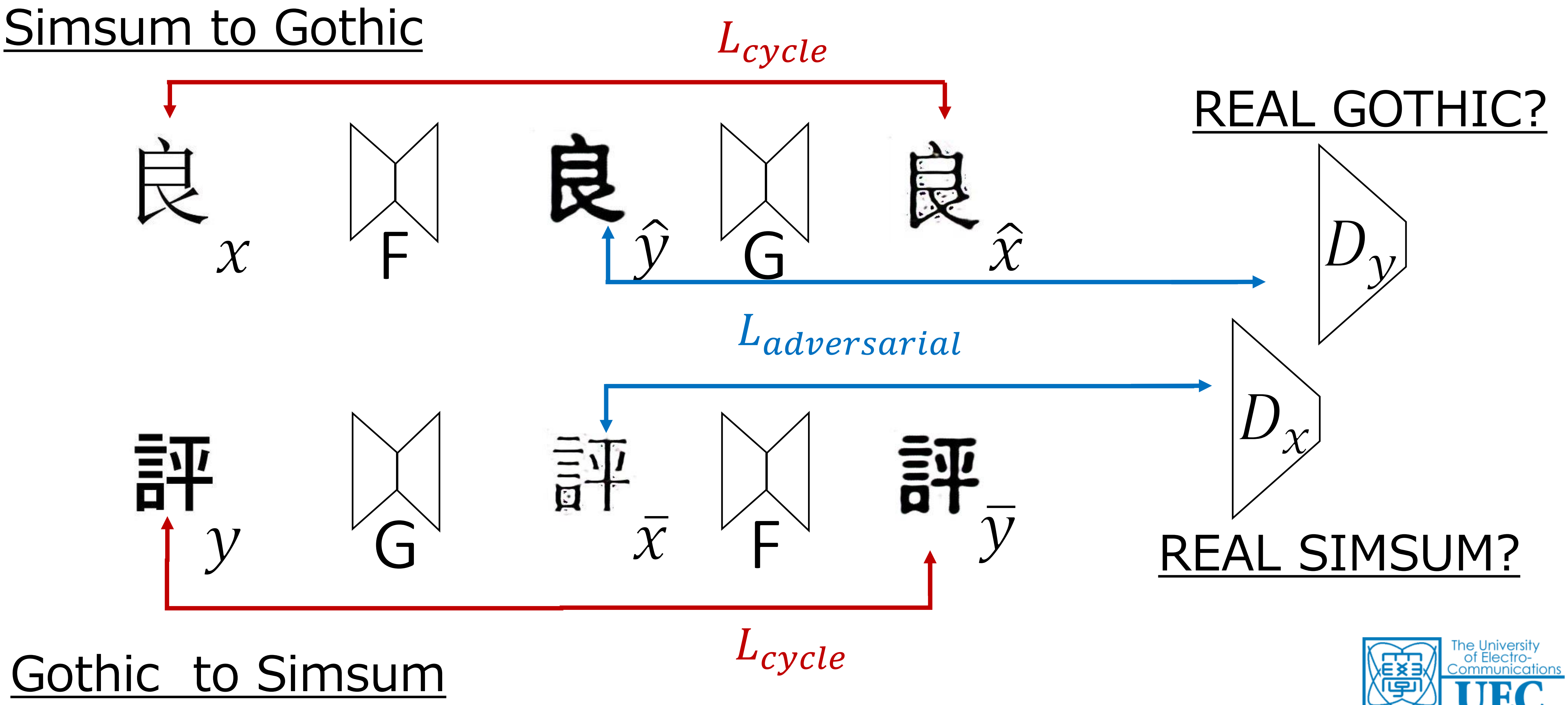
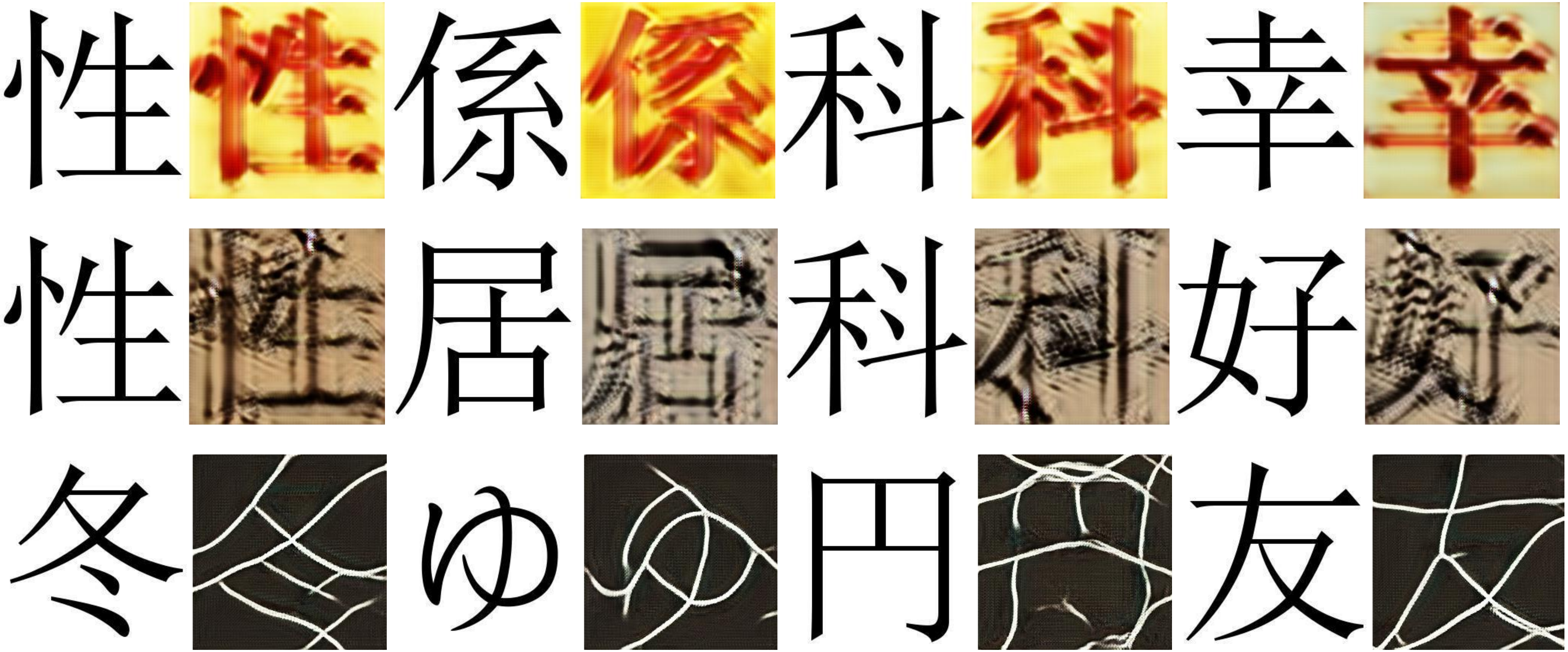
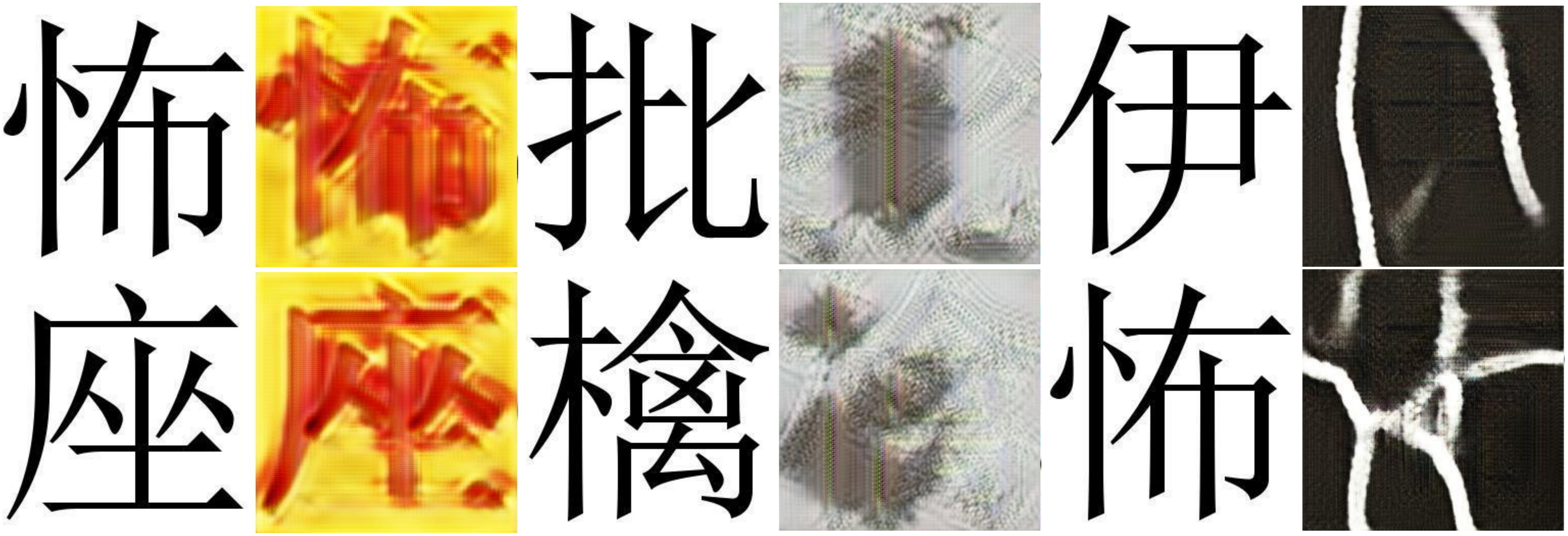
Previous works 3 (Cycle GAN)



Previous works3 (成功例)



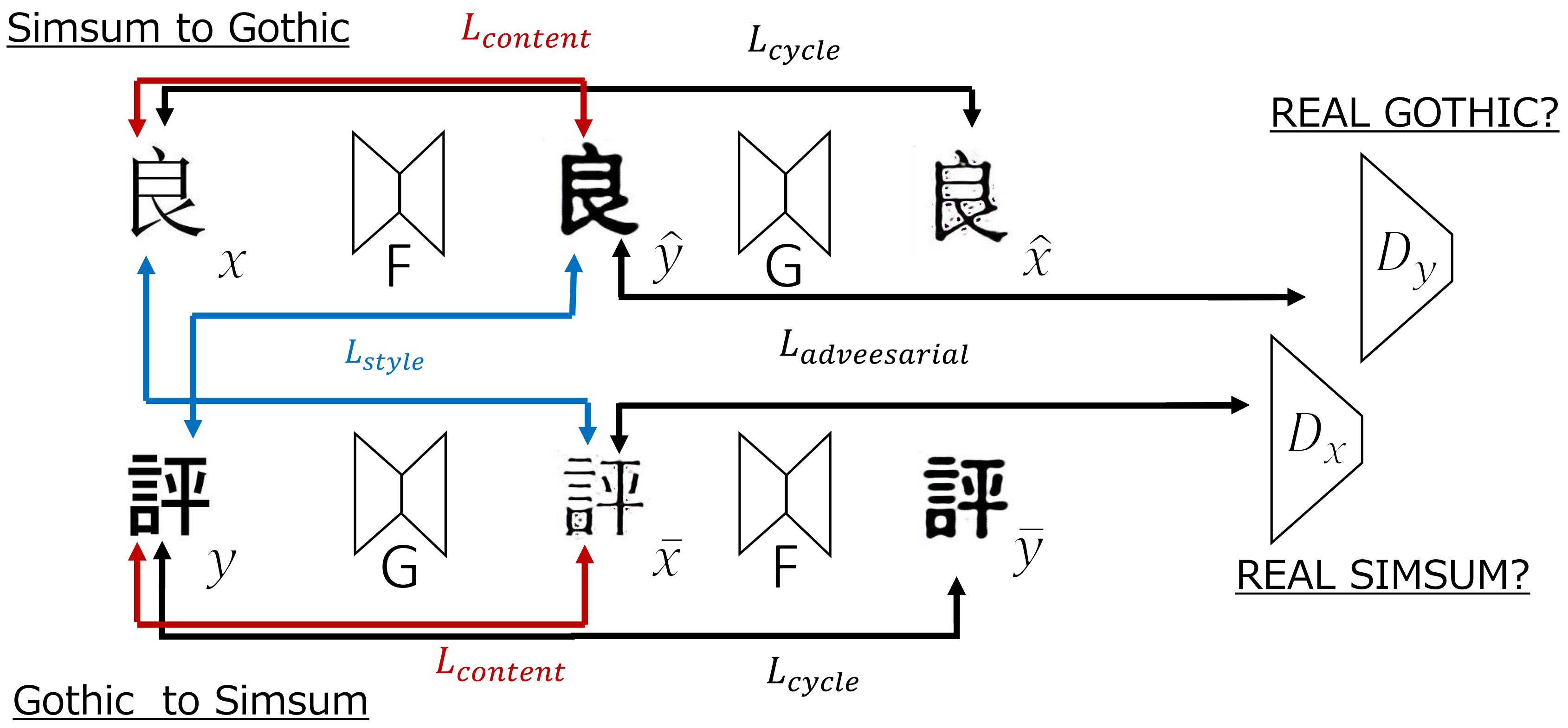
Previous works 3 (失敗例)



Unsupervised cross domain learning using Cycle GAN

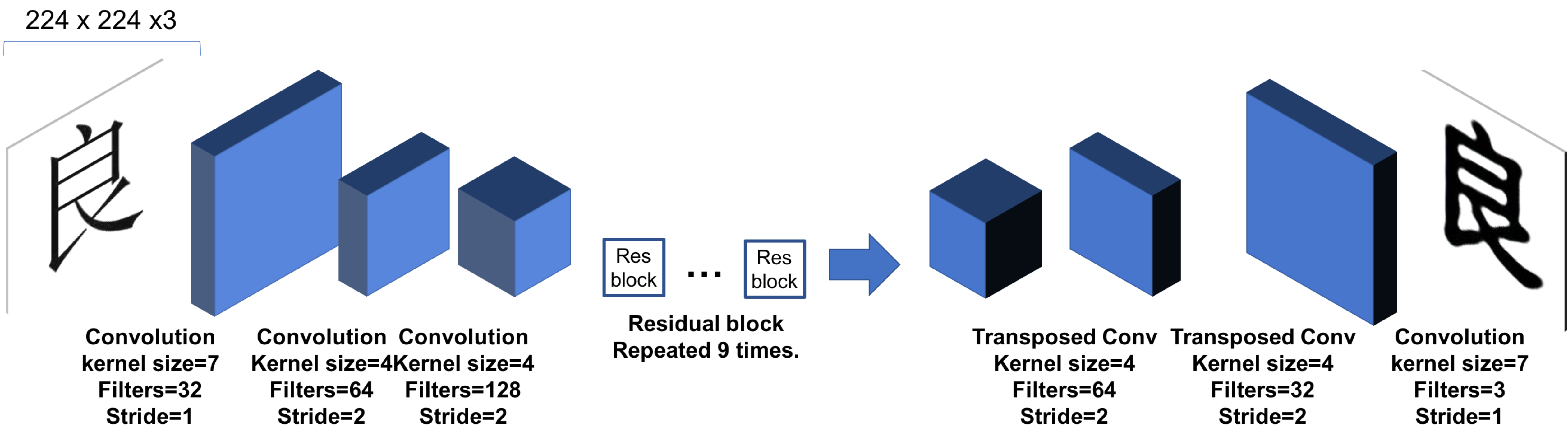
- ○ Unsupervised learning
- ○ superiority on transferring complexed style
- × The readability of generated image is low

Proposed method :
Cycle GAN With Style Loss + Content Loss



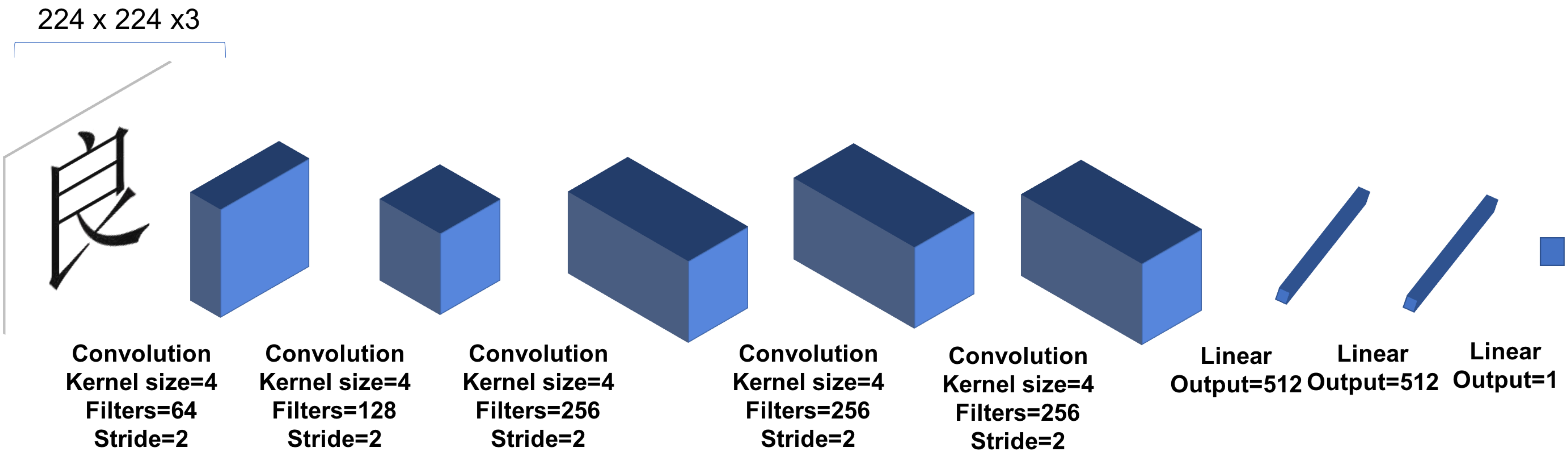
$$L_{total} = \alpha\, L_{adversarial} + \beta\, L_{cycle} + \gamma\, L_{style} + \delta\, L_{content}$$

Encoder-Decoder Network



Encoder-Decoder Net with Res blocks

Discriminator Network



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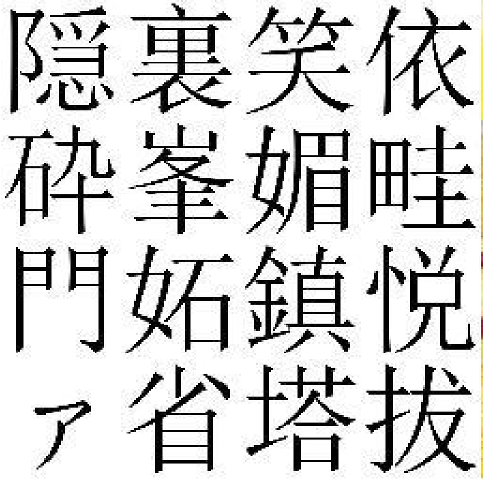
Datasets



Source

Target

Dtasets	Number of image
SimSun font	893
ketchup character	445
Sand character	483
rope pattern	796

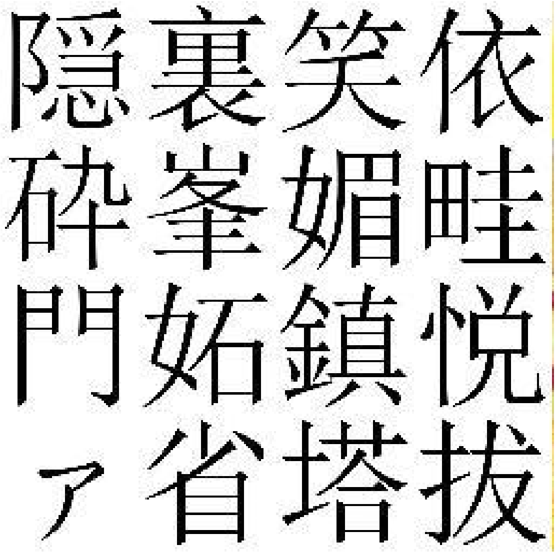
Examples of datasets

Character

Art

Random pattern

A format of input image



Input image size
(256x256)

Target images

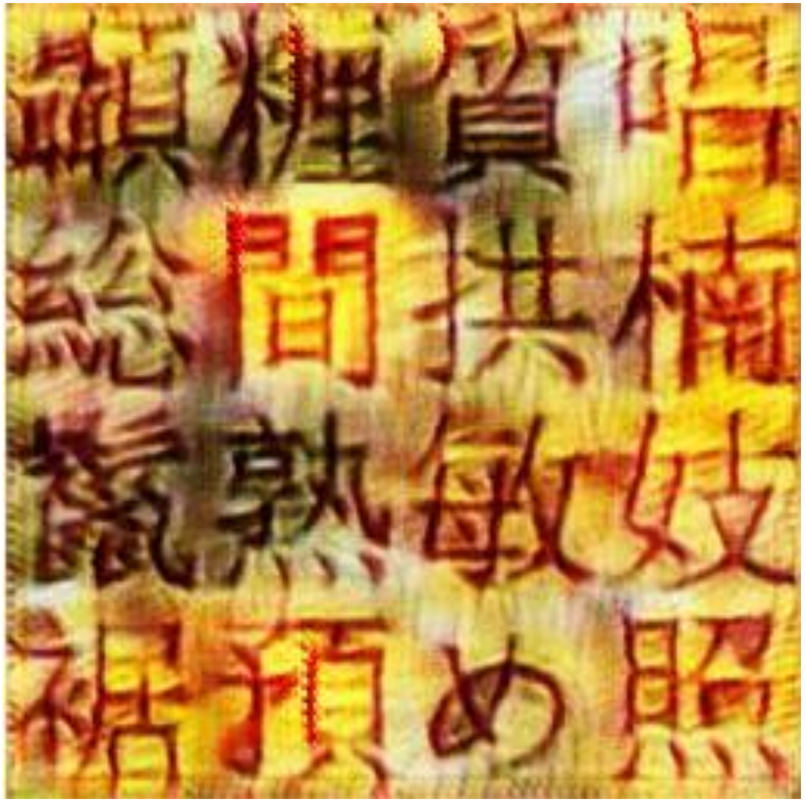
Setting 16 characters in a training image

Training: 450 , Validation : 50

Comparison on ketchup character dataset

Style Transfer

Cycle GAN



Ours

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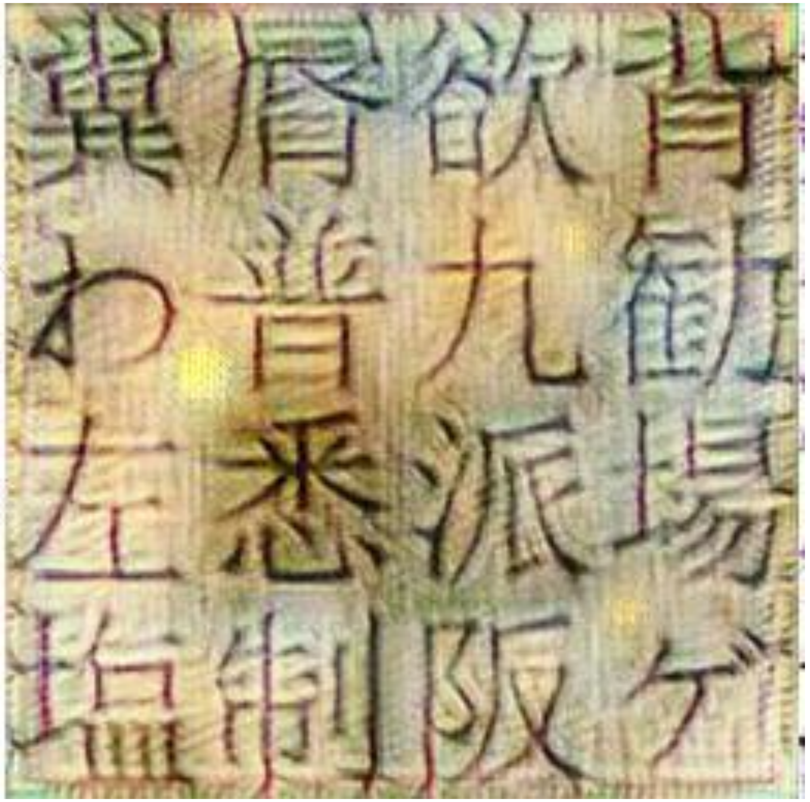
Comparison on sand character dataset

Style Transfer

Cycle GAN



Ours

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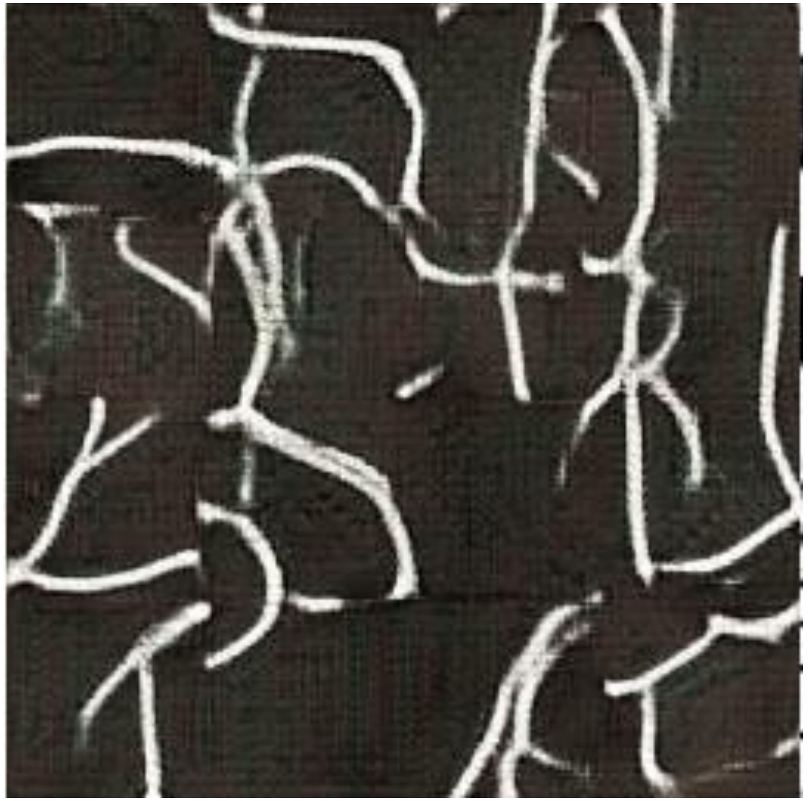
Comparison on rope character dataset



Style Transfer **Cycle GAN** **Ours**

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Difference between combination of losses

Adversarial
+Cycle
(Cycle GAN)

Style
+ Content
+Cycle

Adversarial
+Style
+Cycle

Adversarial
+Style
+ Cycle
+Content

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Difference between combination of losses

Adverial
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Adversarial
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Difference between combination of losses

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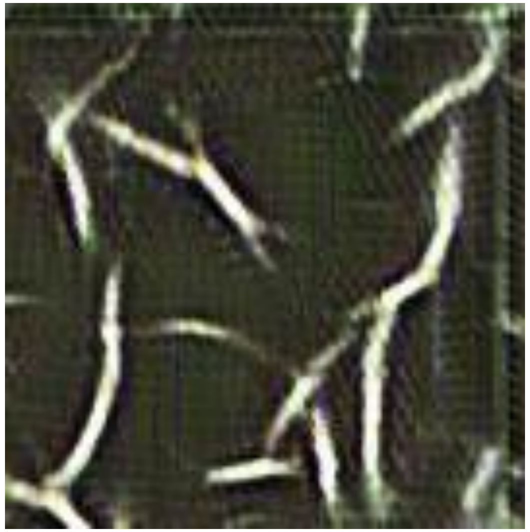
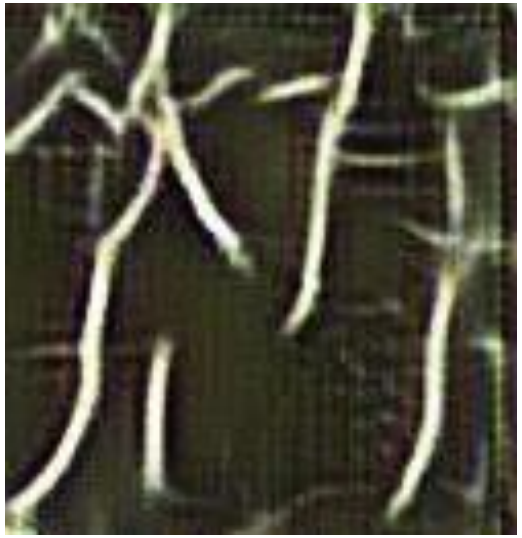


Adversarial
+Style
+Cycle



Adversarial
+Style
+ Cycle
+Content

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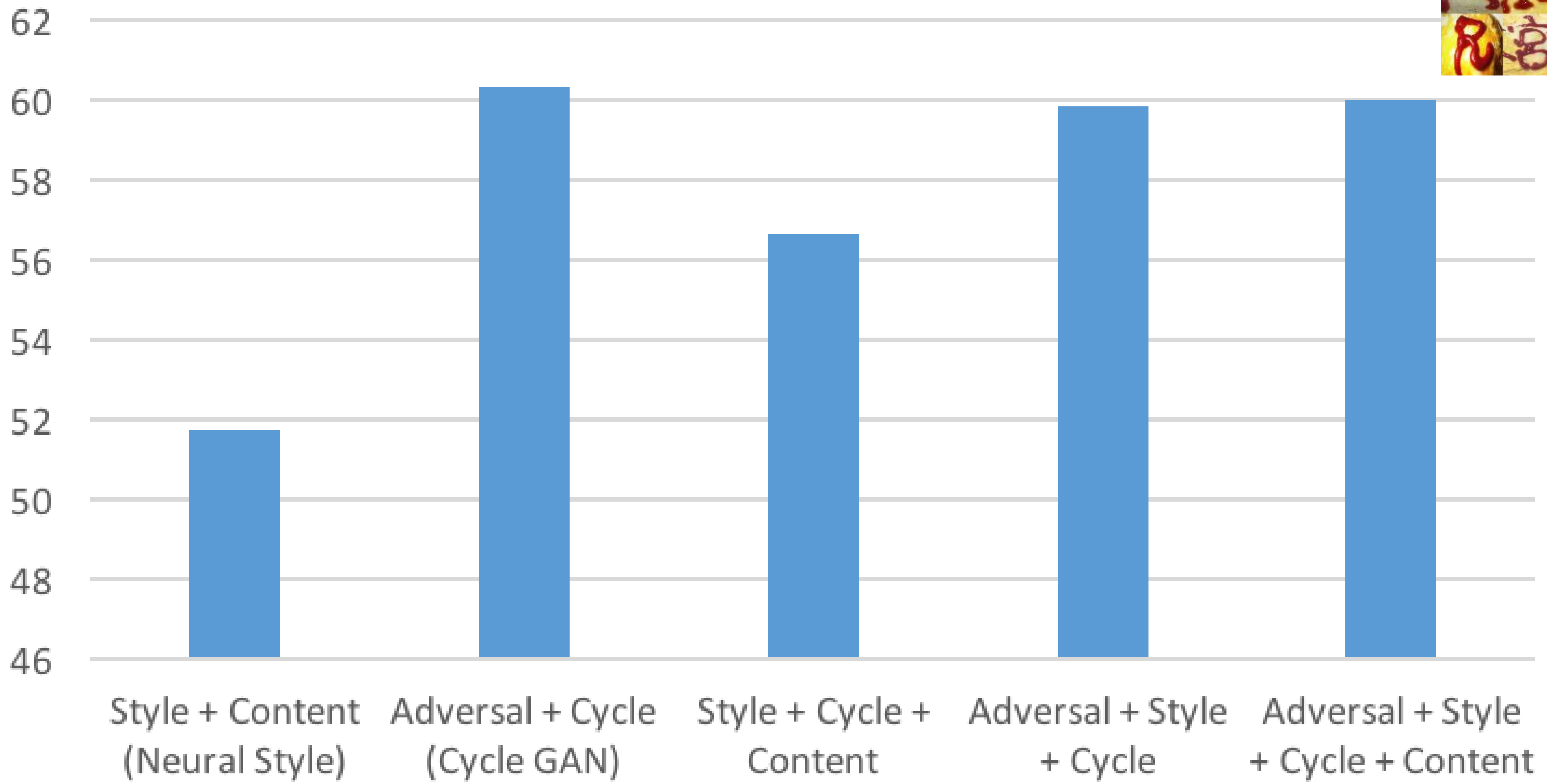
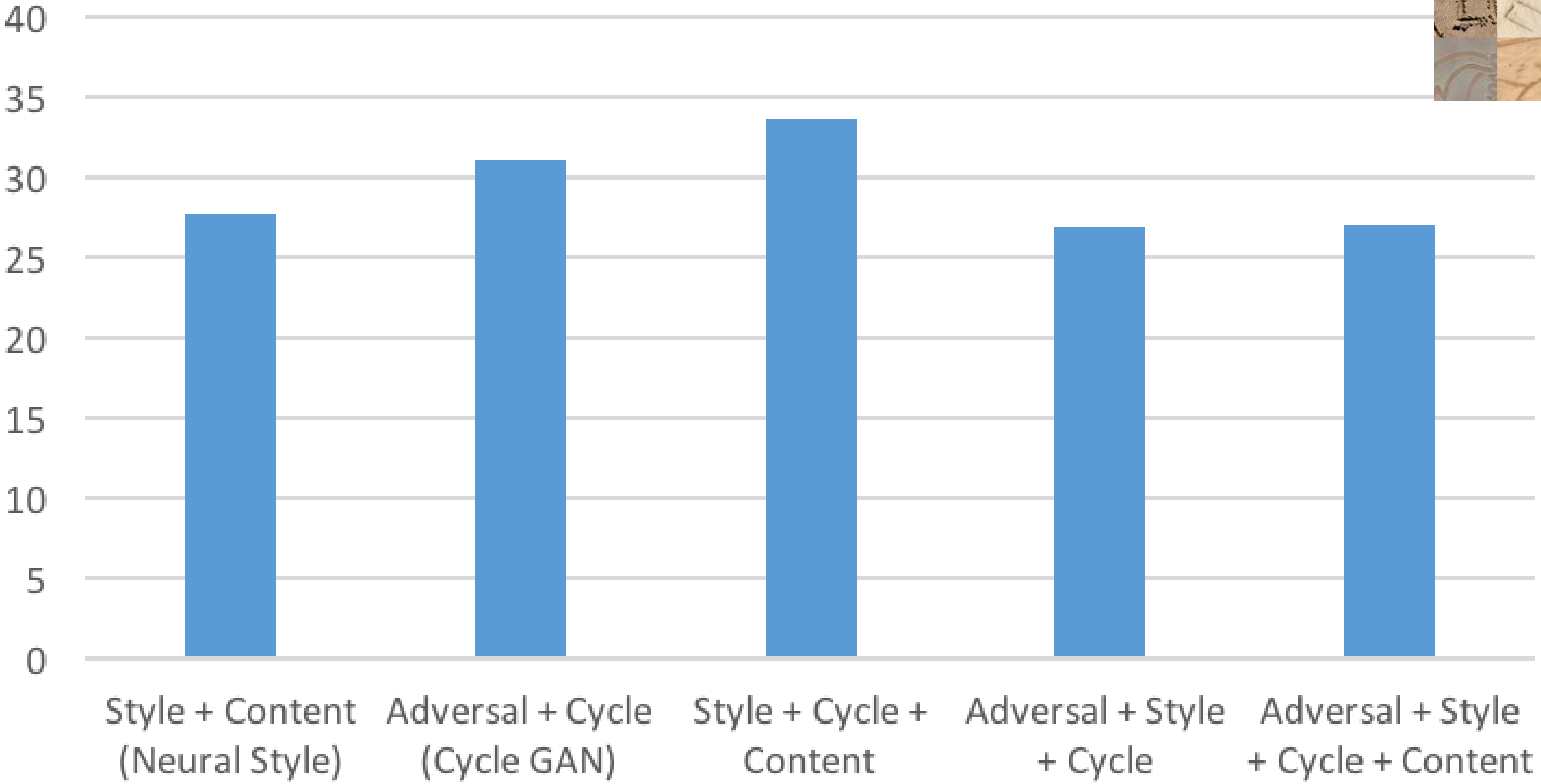
Mean of style loss on ketchup character dataset



Mean of style loss on sand character dataset



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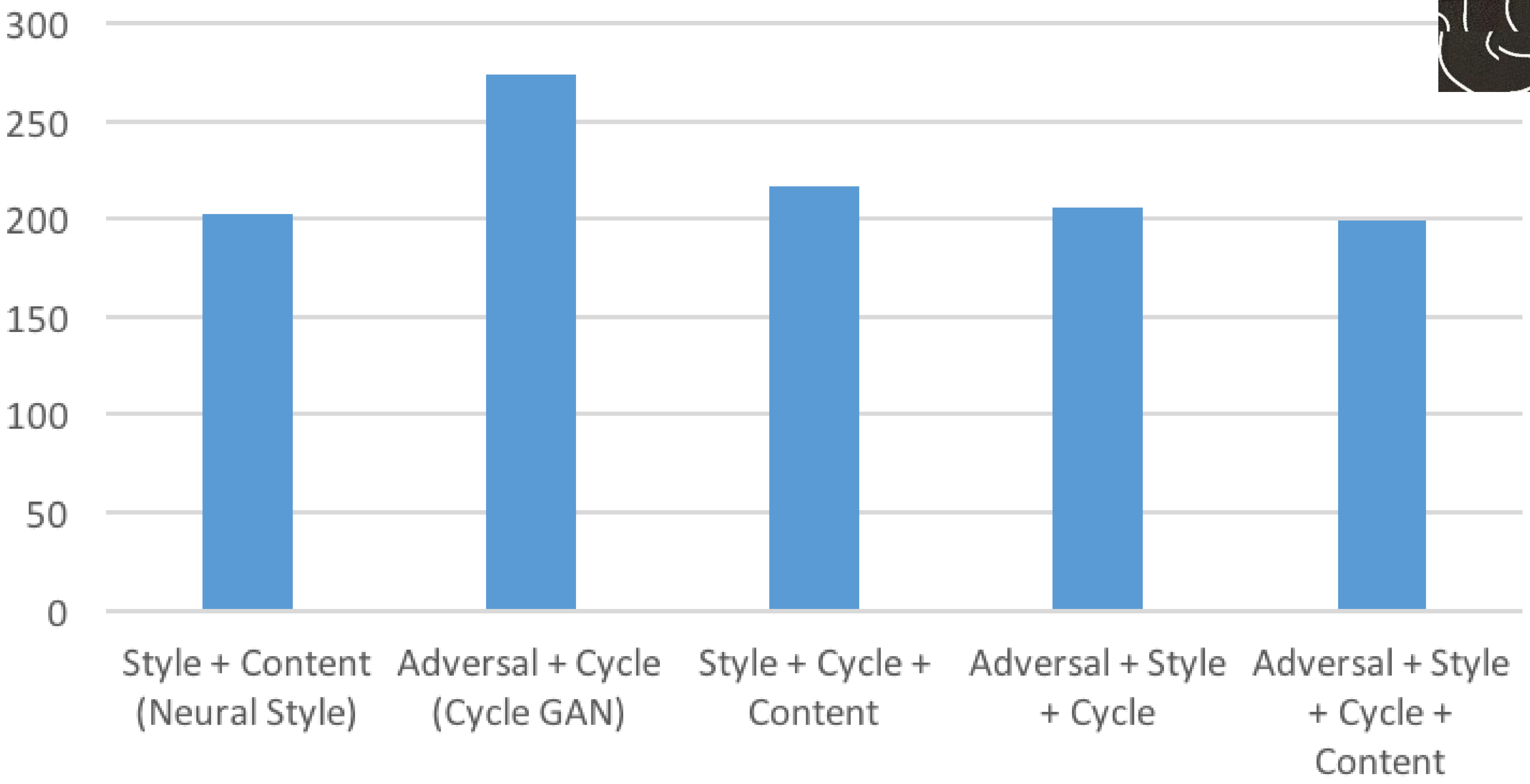
Mean of style loss on rope pattern dataset



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Conclusion

- we proposed a method to combine neural style network with CycleGAN
- We optimized four types of loss adversarial loss, cycle loss, style loss and content loss
  - the effective combinations differed in each dataset
  - content loss keeps original image character structure
- Future works
  - perturb the shape of input image to make it easy to find correspondence between sources and targets
  - introduce a patch-based approach

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