Style Transfer for Chinese Fonts

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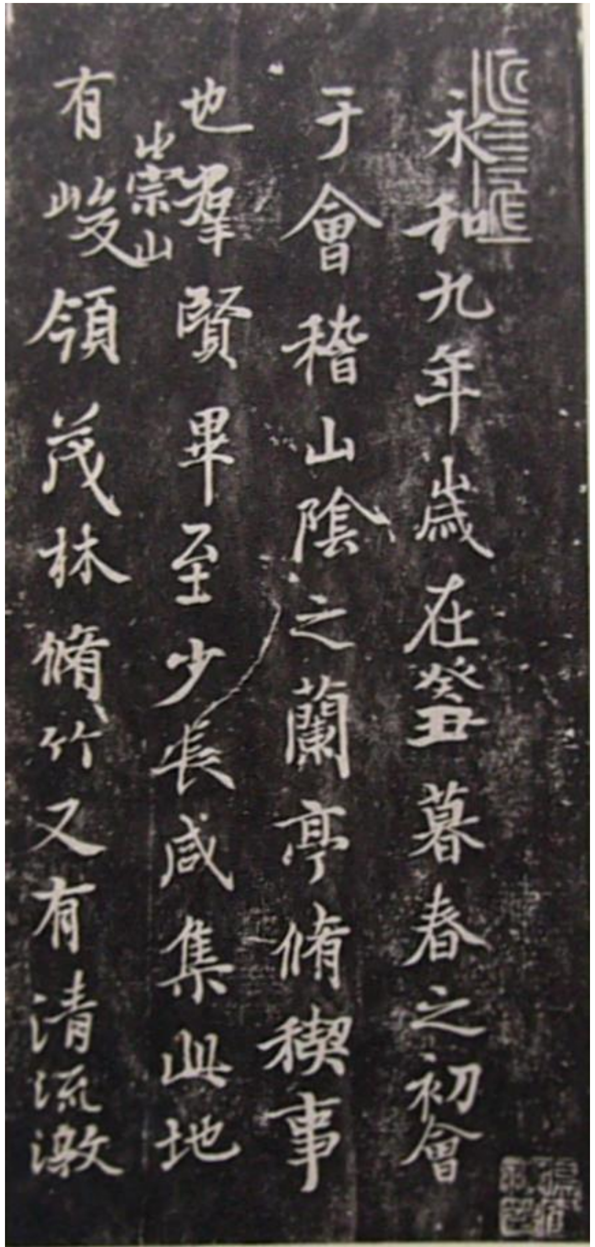
Outline

- Problem / Motivation
- Background
- Approach / Implementation
- Result
- Conclusion / Discussion

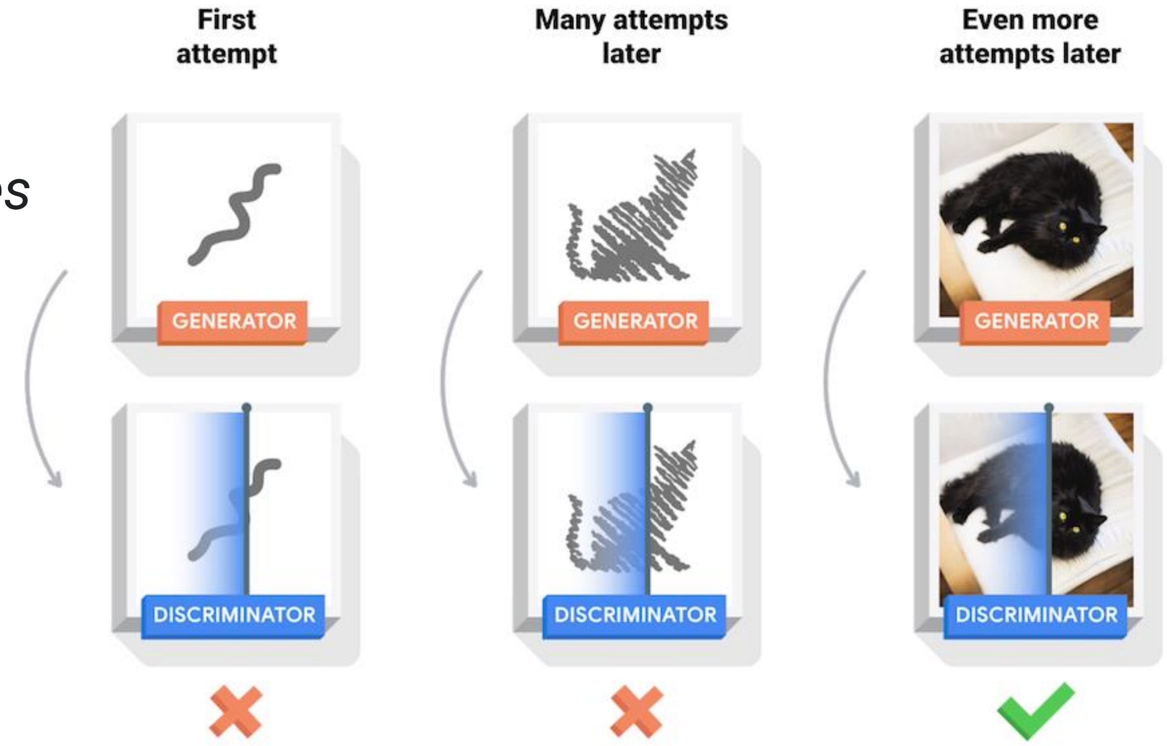
Problem / Motivation

- Good handwriting have visual arts value and commercial values
- Need to learn for years to simulate the handwriting from famous calligraphists
- However, there are more than 80,000 Chinese characters



Background (style transfer / GAN)

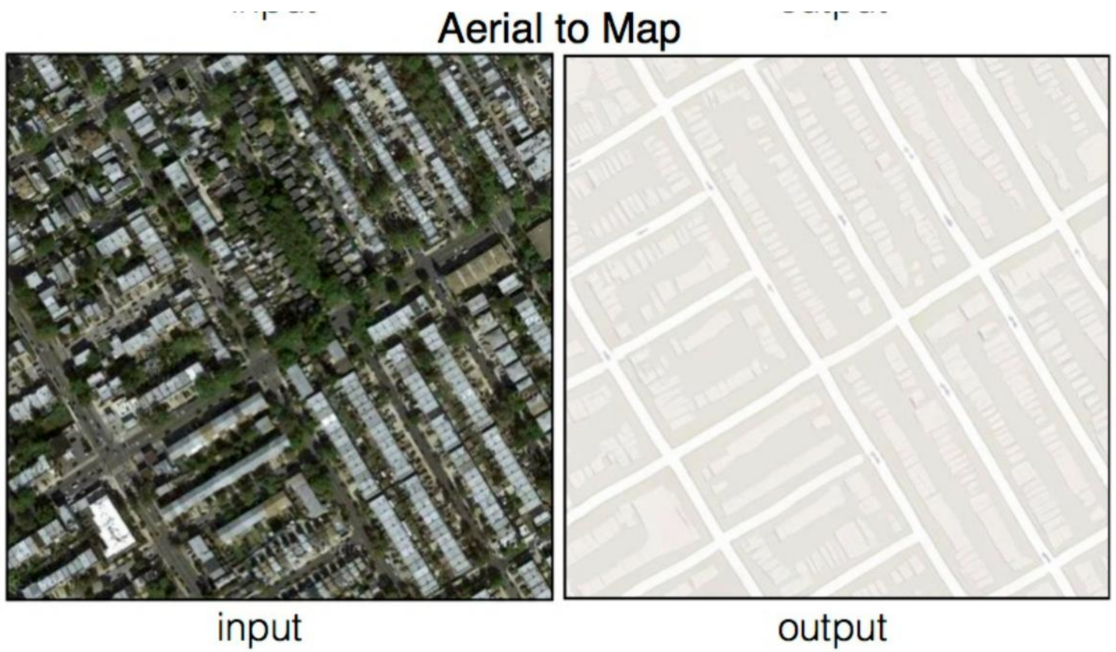
- Style Transfer – Adopt destination's appearance to source's image.
- Existed Approaches – GAN
- Train two models simultaneously
  - *Generator: create fake images*
  - *Discriminator: tell reals apart from fakes*
- Notable variants
  - DCGan
  - Pix2pix
  - CycleGAN
  - …

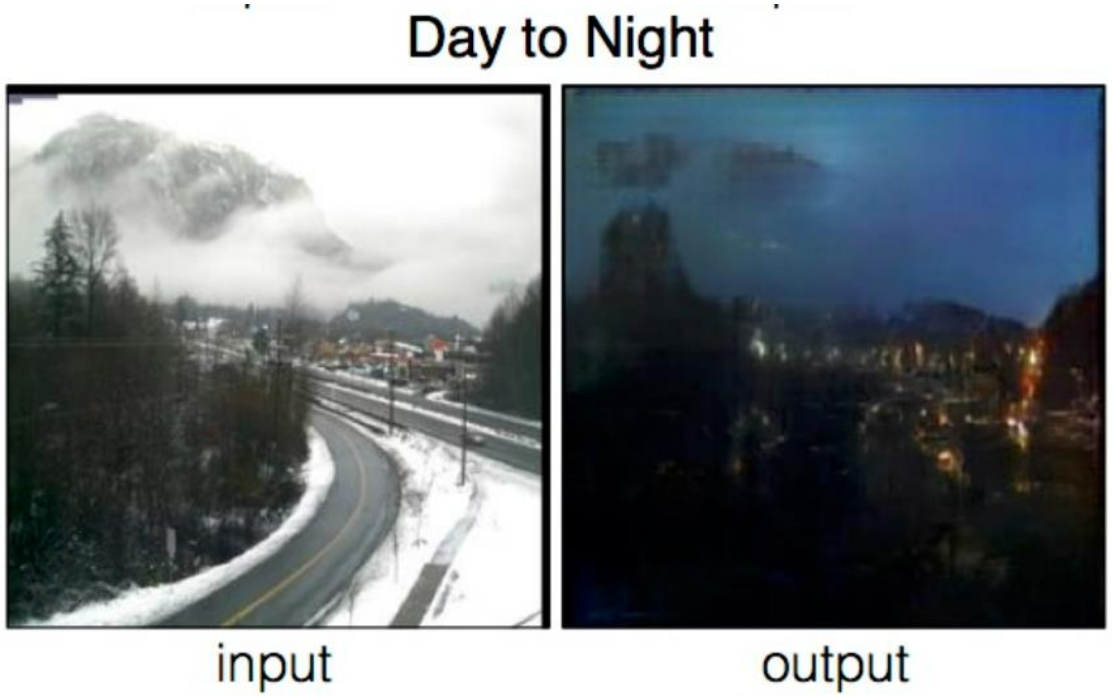


Source: [TensorFlow Core]

Pix2pix (1/2)

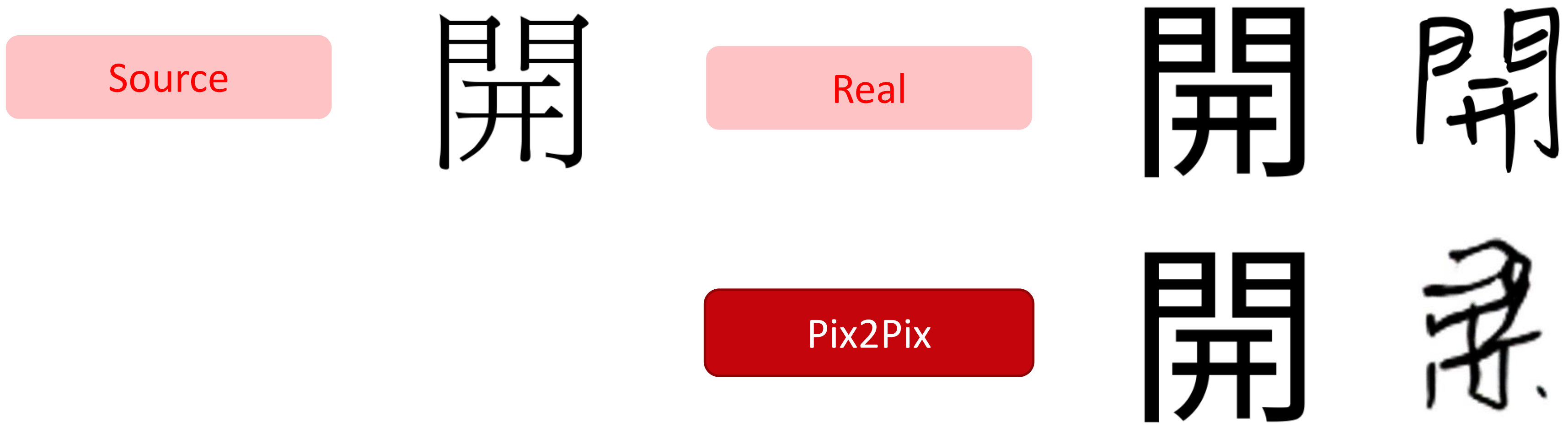
- Image-to-image translation with a conditional GAN(cGAN)
- Paired





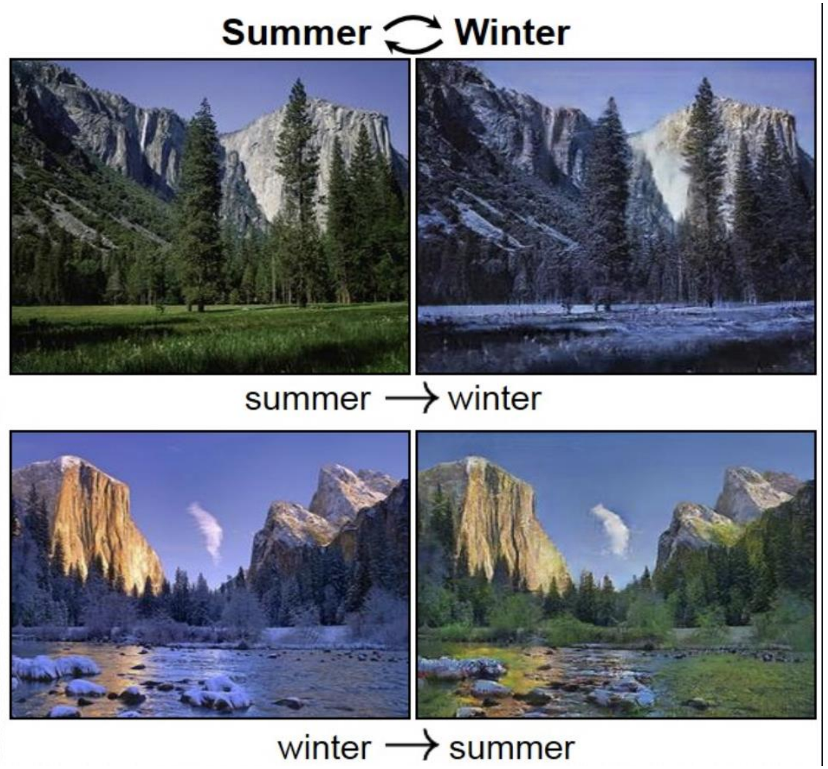
Pix2pix (2/2)

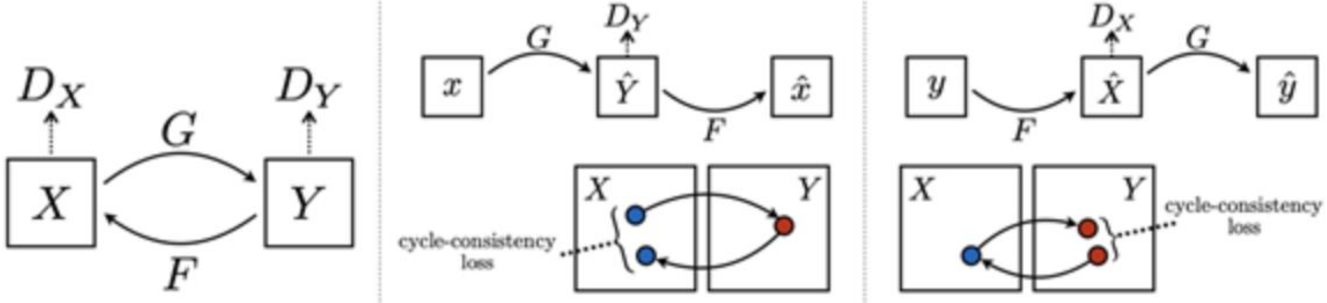
- Require "pixel to pixel" mapping
- Work well if the style is not significantly different
- Unusable in the writing style case



Approach – Implement Cycle GAN

- Image-to-image translation
- Unpaired

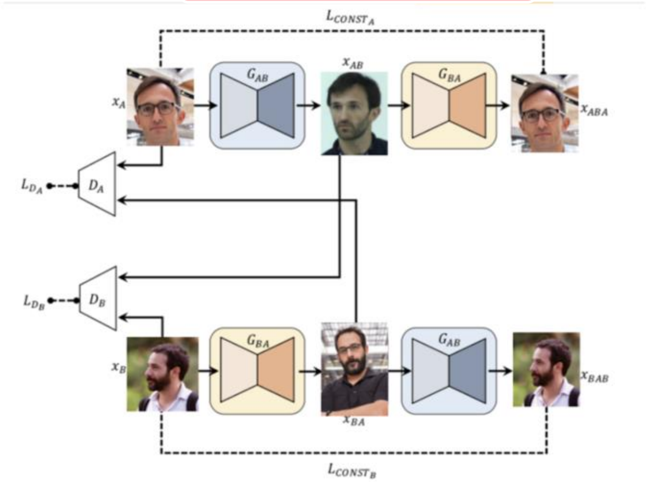




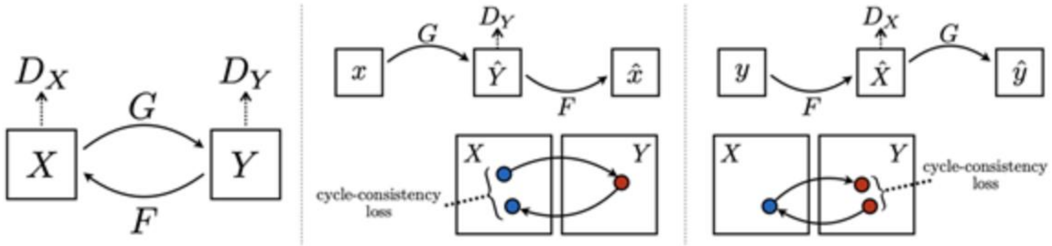
Approach – Implement Disco GAN and Cycle GAN

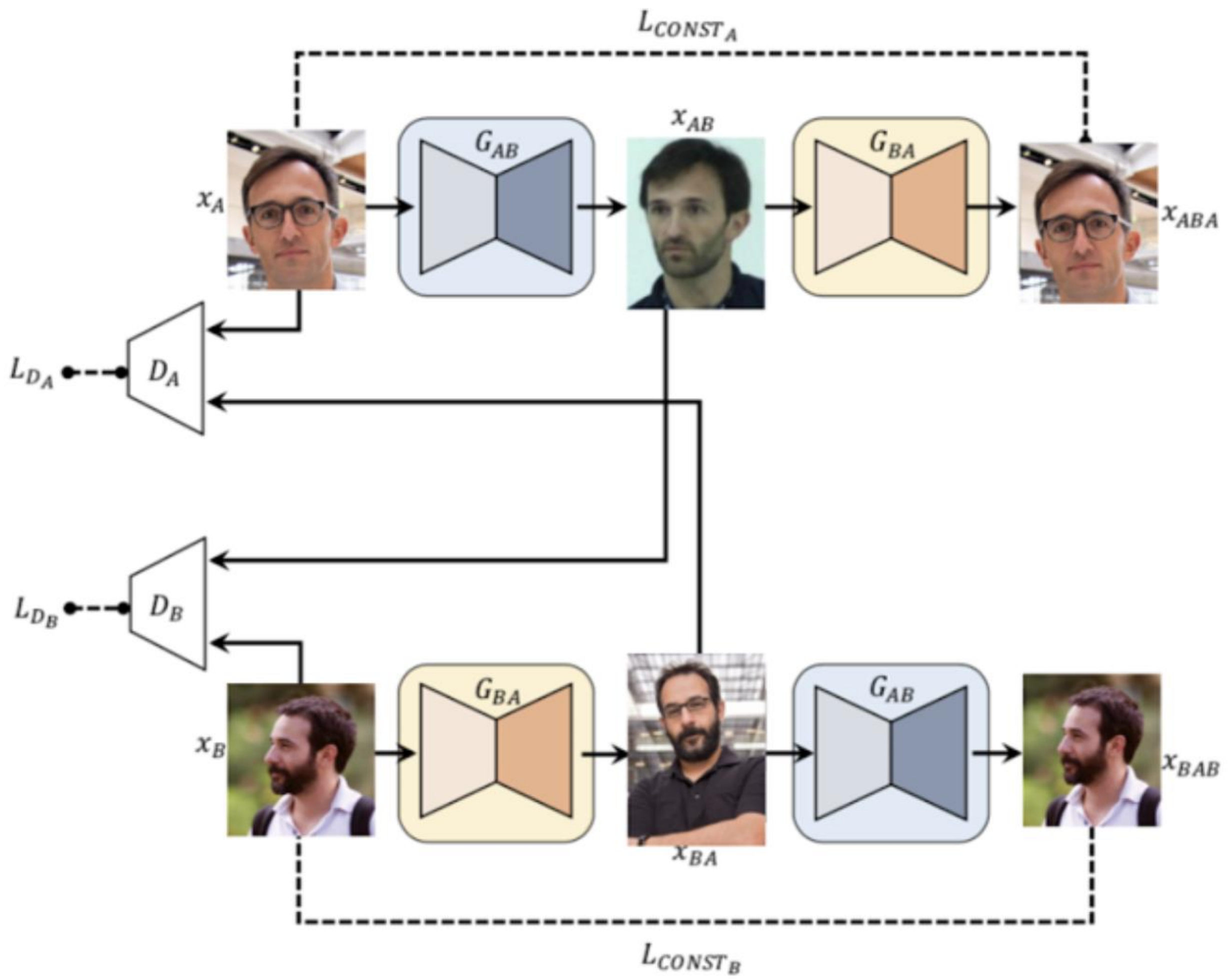
- Same:
  - Learn cross-domain relations given unpaired data
  - trained on the fundamentals of reconstruction loss and use forward, backward cycle consistency loss to achieve bijective mapping
- Difference:
  - Different model structure
  - Different loss function (mse vs l1)

Disco



Cycle

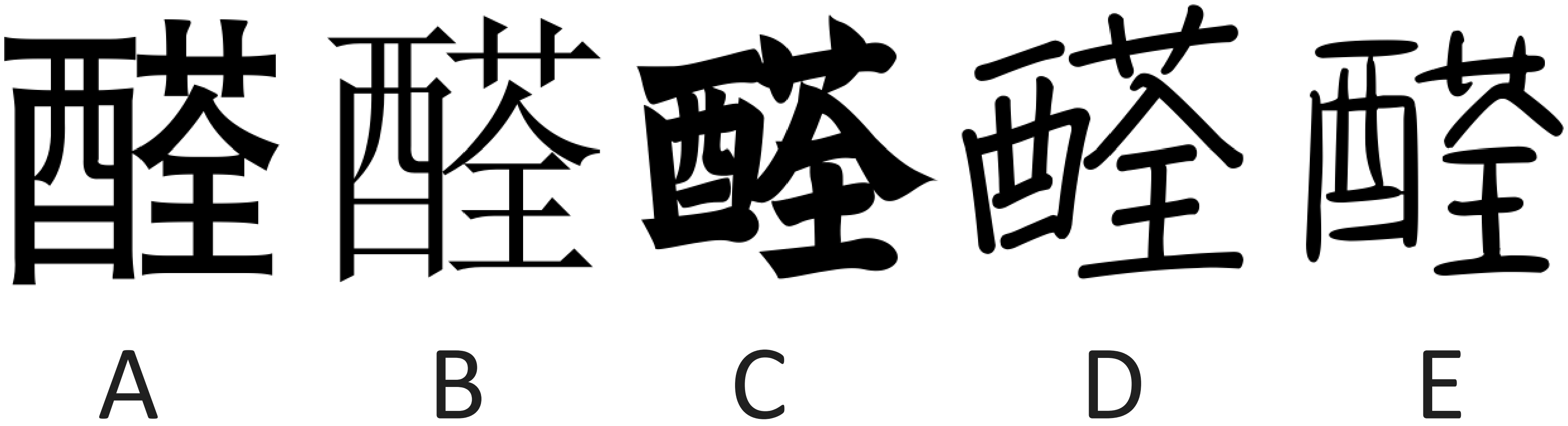




L_{CONST_A}
x_A
G_{AB}
x_{AB}
G_{BA}
x_{ABA}
L_{D_A}
D_A
L_{D_B}
D_B
x_B
G_{BA}
x_{BA}
G_{AB}
x_{BAB}
L_{CONST_B}

Dataset

- We prepared 5 different style of fonts
- Each contains the same ~1500 characters
- All tests attempt to transfer from style A to others



Result – Cycle / Disco

Source Style: 客 汉 杉 材 役 渡

Dual GAN

- Generator adopt U-shaped net structure.
  - Share low-level information
  - Keep the alignment of image structures

- Discriminator: employ Markovian PatchGAN
  - Keep independence between pixels distanced beyond a specific patch size
  - Effective in capturing local high-frequency

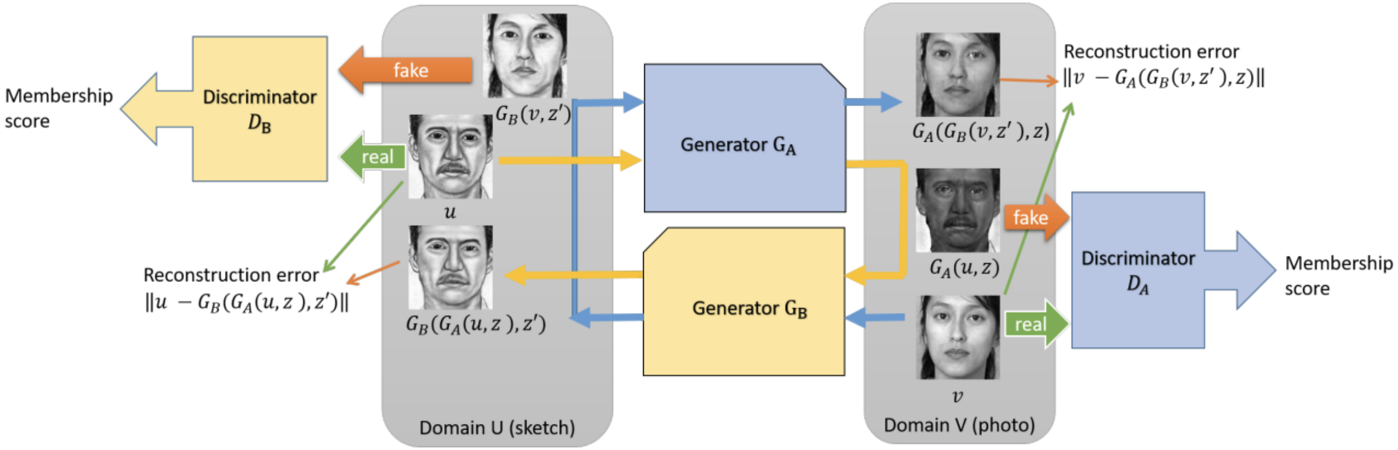
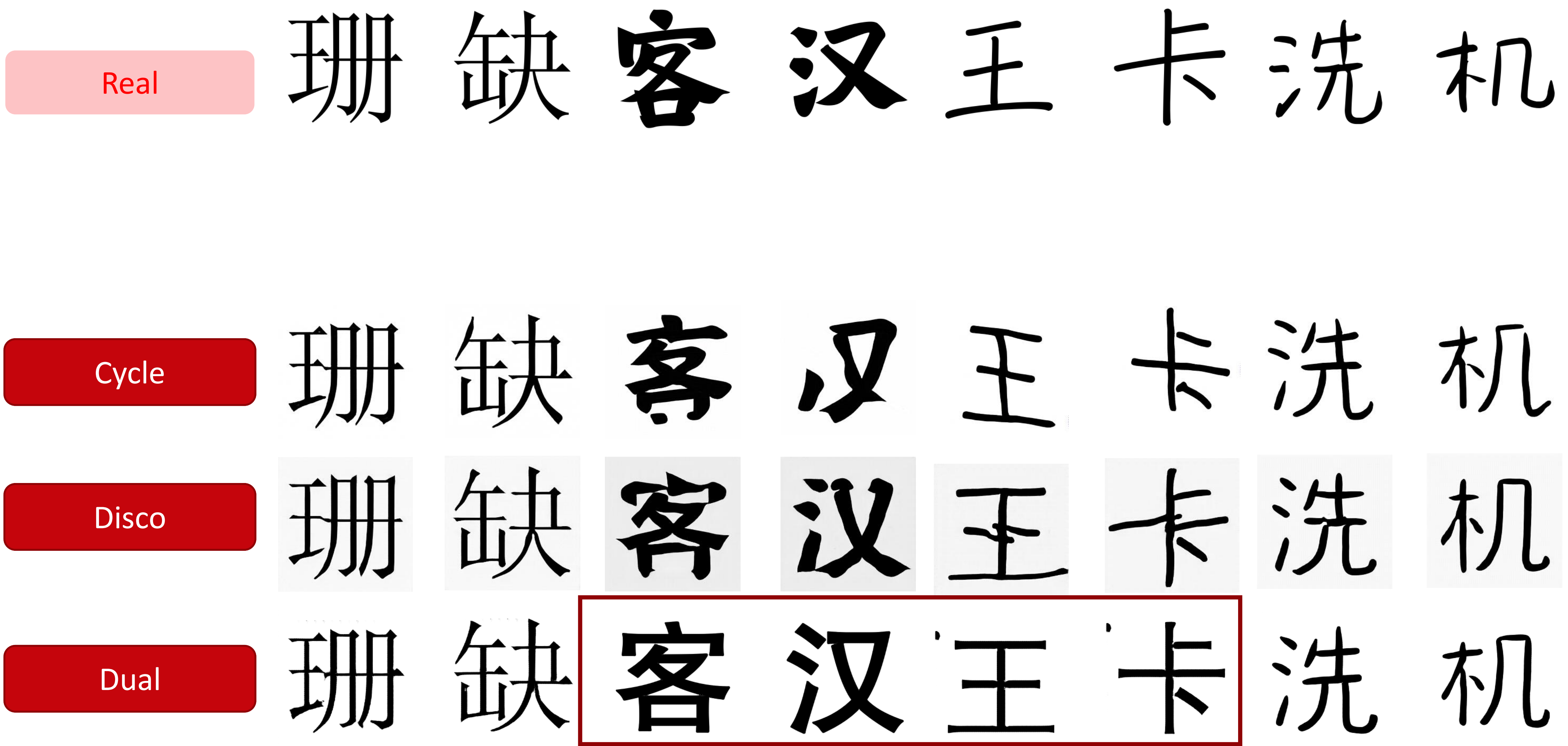


Figure 1: Network architecture and data flow chart of DualGAN for image-to-image translation.

Result – DualGAN

Source Style: 客 汉 杉 材 役 渡



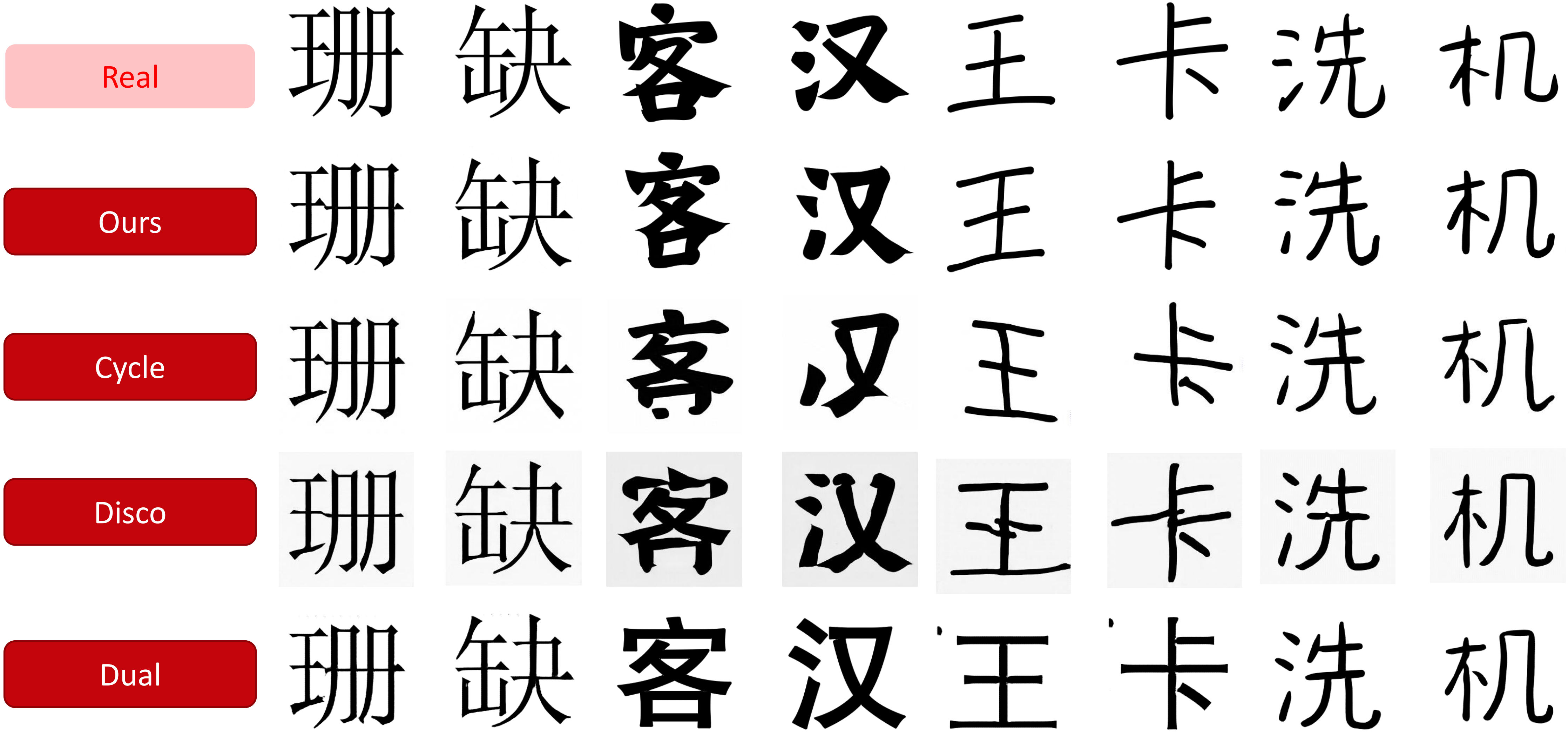
Doesn’t work well in these two fonts

Ours

- Still use the basic structure and models of CycleGAN
- Use DiscoGAN’s mse lost function
  - since it’s more sensitive to shape changes
- Introduce “true loss” to the lost function
  - True loss: MSE compared to the ground truth
- Preprocessing
  - Random Flip
  - Convert to gray scale

Result - Ours

Source Style: 客 汉 杉 材 役 渡



Conclusion

- Our goal: Transfer style in the Chinese font domain
- Test on well-known algorithm pix2pix – does not perform well
- Implement CycleGAN and DiscoGAN – Acceptable performance
- Modify CycleGAN to get the best result in our case

Future Work

- Quickly learn new style by using existing model
- Transfer font style from one language to another

Thanks!