Sketch to Photo Translation

Yuhang Li, Xuejin Chen, Xiangxiang Wang, Sing Bing Kang

Original idea

Sketch to Photo Translation

- Problem definition
- Why sketch?
- Characteristic of Sketch

Related works

- Sketch2Photo
- Sketch-based classification
- Sketch-based retrieval
- Image-to-image translation

Exploration

- CycleGAN
- DiscoGAN

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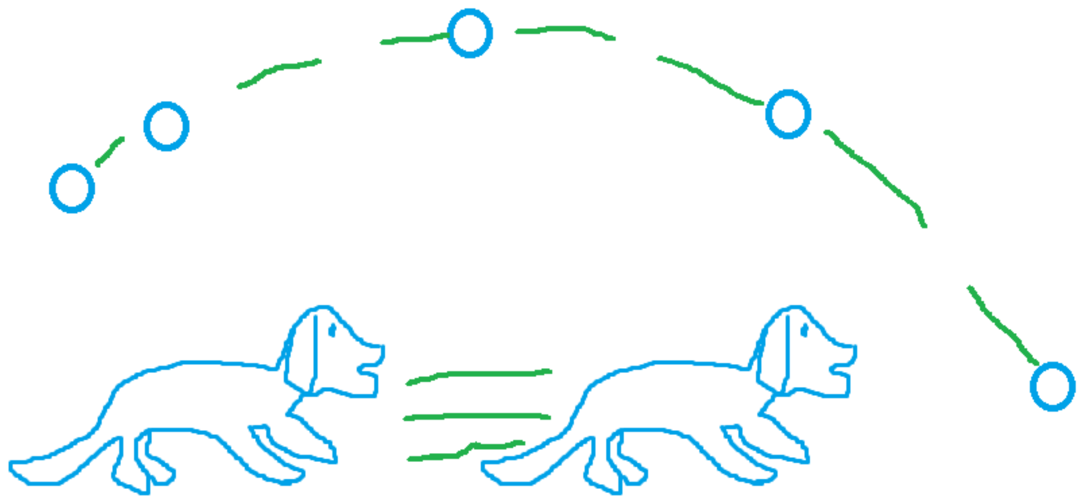
Sketch to realistic video

Two kinds of strokes in a sketch:

- Object strokes
  - What object in the scene
- Motion strokes
  - How the object moves in the scene



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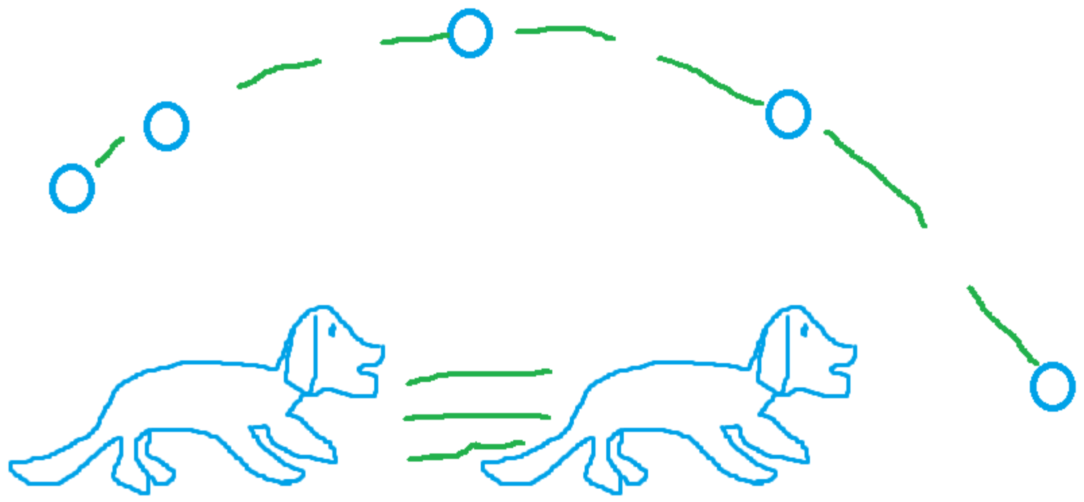

It is difficult to obtain corresponding videos that match both object strokes and motion strokes for training!

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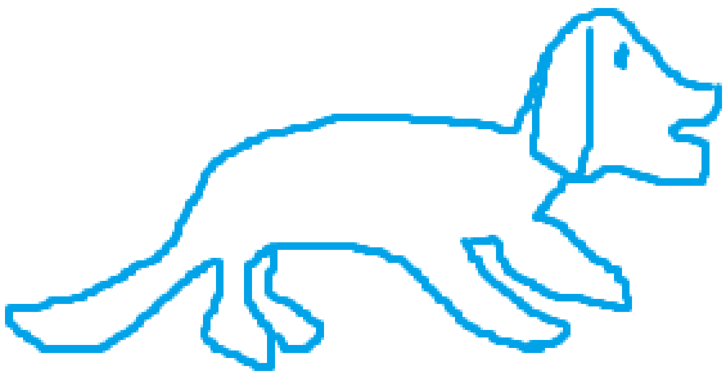

It is difficult to obtain corresponding videos that match both object strokes and motion strokes for training!

Focus on object strokes!

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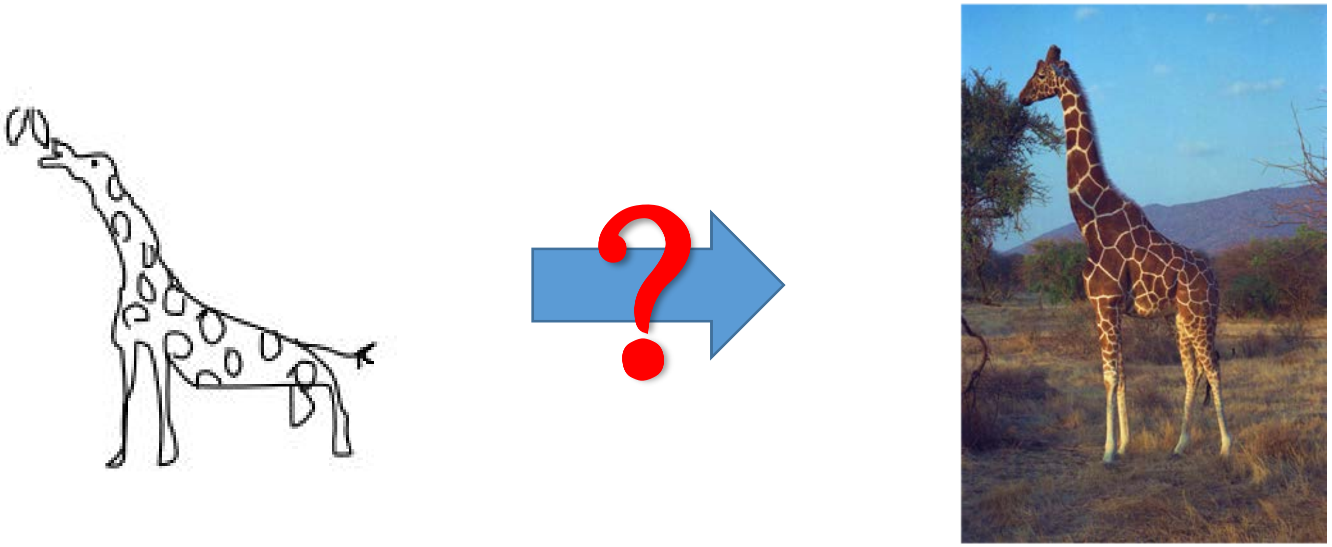
Problem definition

Sketch-based image generation

Given a sketch of **one** object, we want to generate a **new** but **realistic** image that preserves (Discuss)

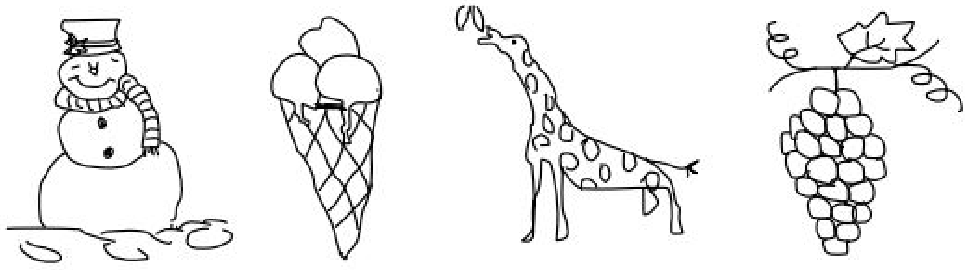
- Object class: giraffe, elephant, chair or car
- View point
- Layout: size of the object, position in the image
- Pose: standing or sitting
- Background ?

Shared information!



Sketch: why sketch?

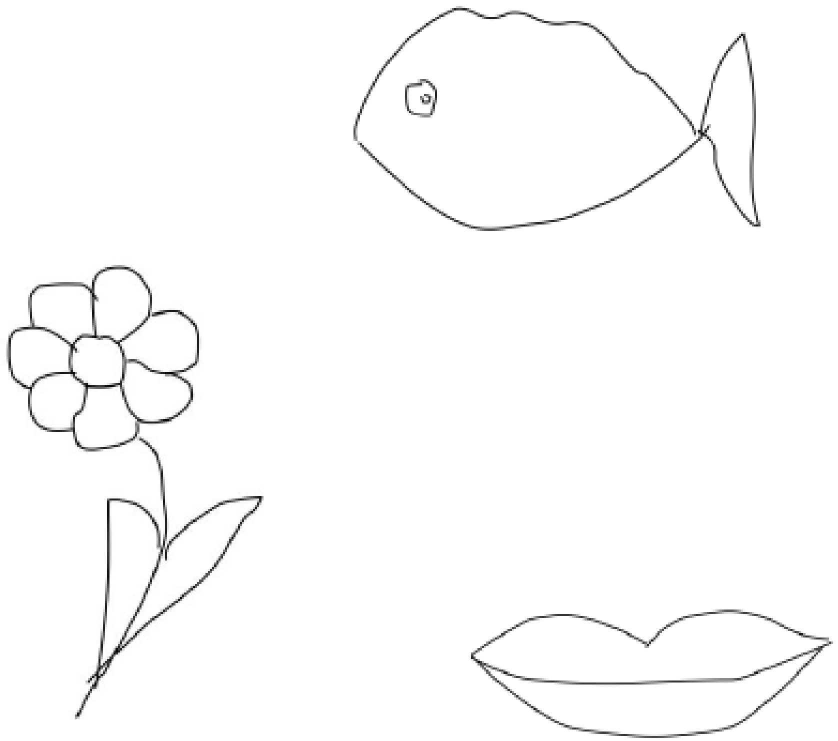
- A universal form of communication across nations and cultures
- Tracing back to prehistoric cave painting
- Conveying abstract concepts visually
- A *sketch* can speak a thousand words
- Becoming more important due to the popularity of touch devices



Characteristic of Sketch

- Iconic

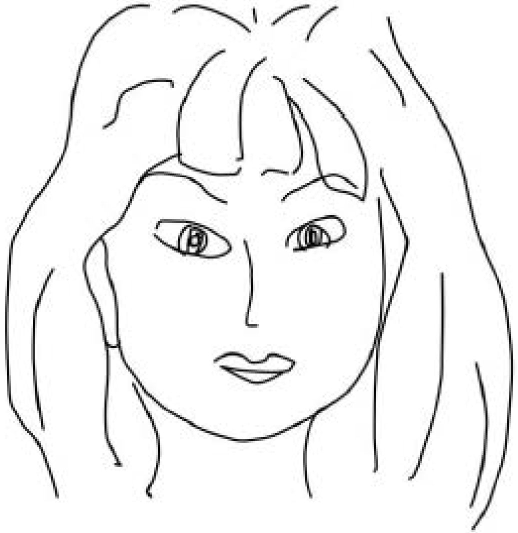
  Sketches can be highly abstract.



Characteristic of Sketch

- High intra-class variation

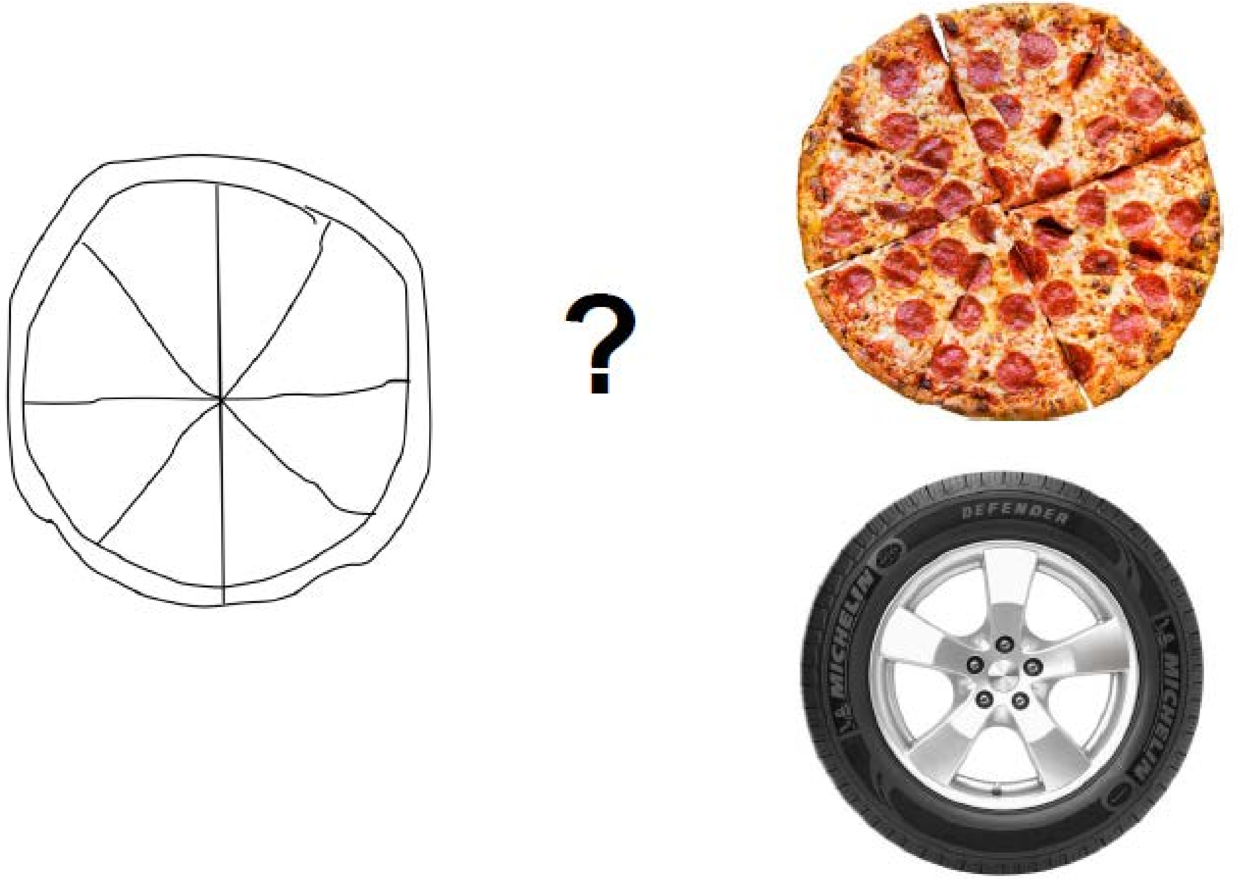
  Sketches drawn by different people vary in the level of abstraction or deformation.



Characteristic of Sketch

- Lack of visual cues

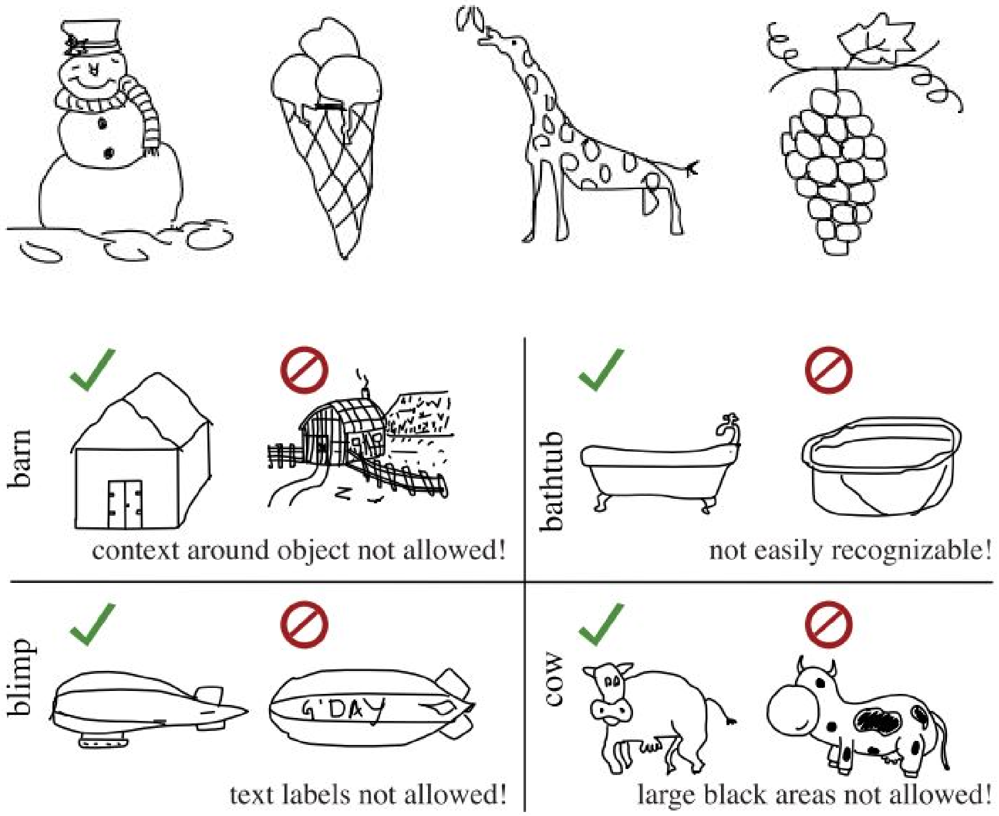
  Sketches are lack of colors and textures compared to photos.



Dataset

- TU-Berlin sketch dataset: a sketch dataset containing 250 categories and 80 sketches in each category.
- Fine-grain sketch dataset: paired fine-grain sketch and image of shoes and chairs.

Fine-grain sketch dataset



TU-Berlin sketch dataset

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Sketch2Photo: Internet Image Montage

- Generate a realistic image using a simple freehand sketch annotated with text labels.
- Text labeled sketch

- Seamlessly stitching several photograph

Sketch2Photo: Internet Image Montage

- Generate a realistic image using a simple freehand sketch annotated with text labels.
- Text labeled sketch

  We want labeling to be done automatically (sketch classification).
- Seamlessly stitching several photograph

  We want to generate a totally **new** image that every detail be generated, rather than a regional combination of existing image parts.

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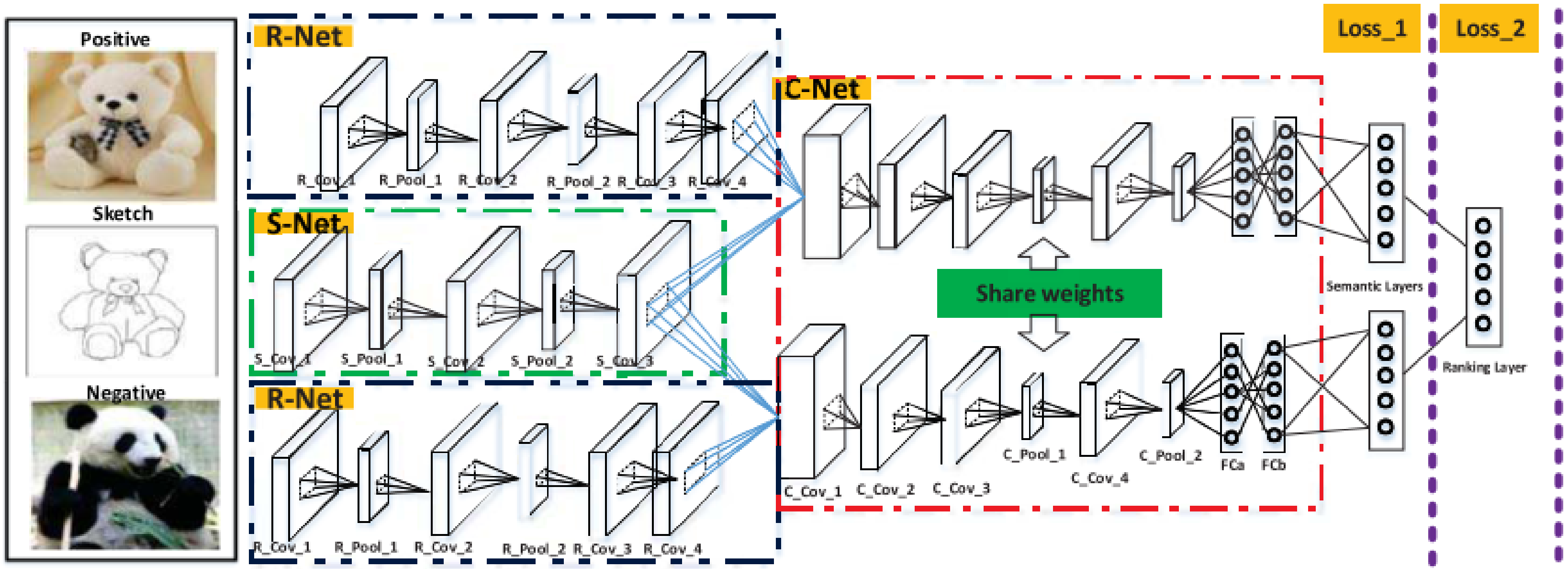
Sketch classification: SketchNet

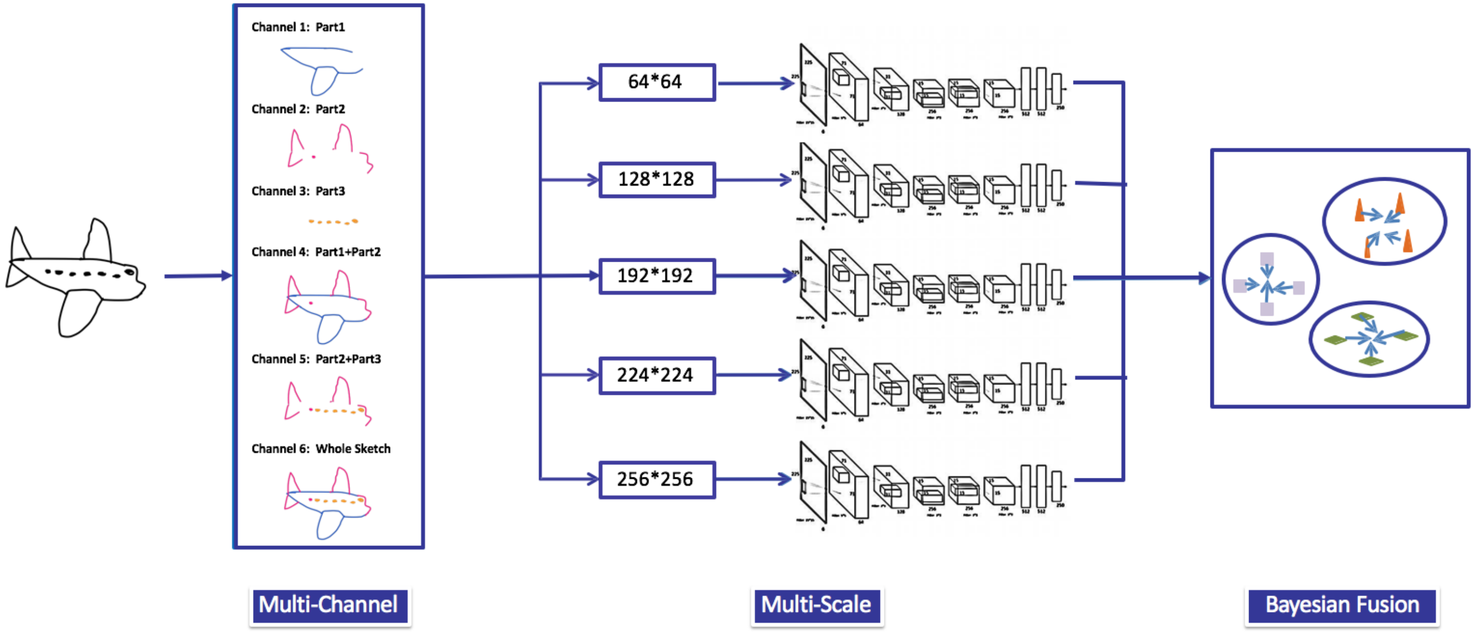
- Discover the discriminative structures of sketch images
- Triplet networks based on Siamese nets
- Weekly supervised: with the help of photo images



H. Zhang *2016*

Sketch classification: Sketch-a-Net

- A novel method of data augmentation
- Bayesian fusion
- Multiple models of different scales
- Beats human in sketch classification performance



Sketch-a-Net, Q. Yu 2016

Sketch classification

Summary and inspirations

- Deep neural networks are able to handle sketch classification.
- Sketches with high intra-class variance are still able to mapped together in specific embedding space.
- There should be no need to annotate the sketch with text label.

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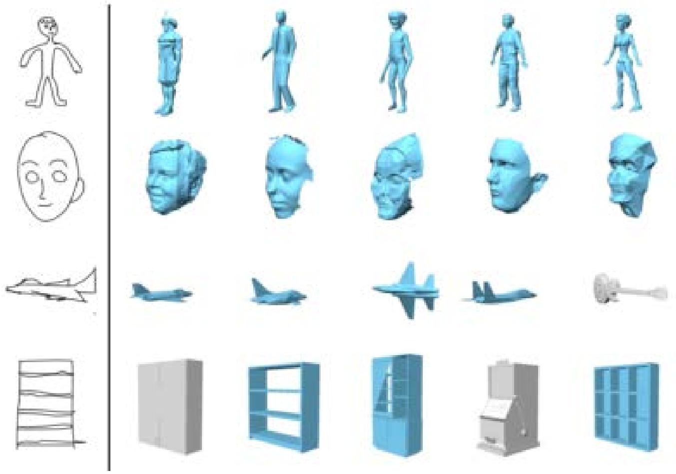
Sketch-based retrieval

- Sketch-based 3D model retrieval
- Sketch-based image retrieval
- Sketch-based fine-grain image retrieval



3D model retrieval, F. Wang et al 2015

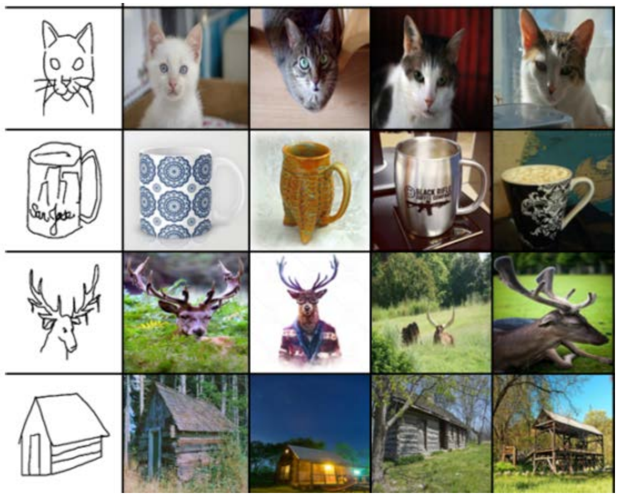


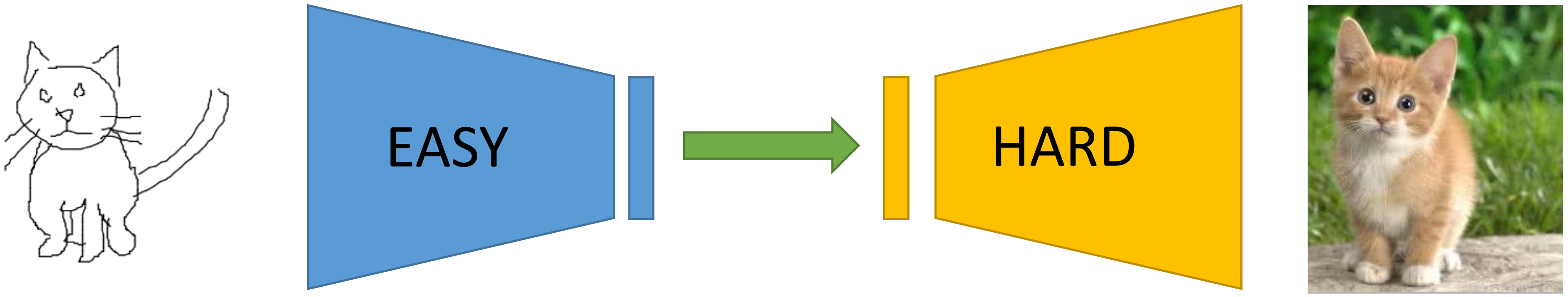
Image retrieval, P. Sangkloy et al 2016

Fine-grain image retrieval, Q. Yu et al 2016

Sketch-based retrieval

Summary and inspirations

- Minimize the distance between sketch and photo in embedding space
- A sketch and a similar photo are able to mapped close to each other in specific embedding space.



Inspired architecture of sketch-to-photo translation

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Image-to-image translation

- Based on generative adversarial nets (GANs)
- Paired images for training
- A framework for multiple applications, only switching the training sets.

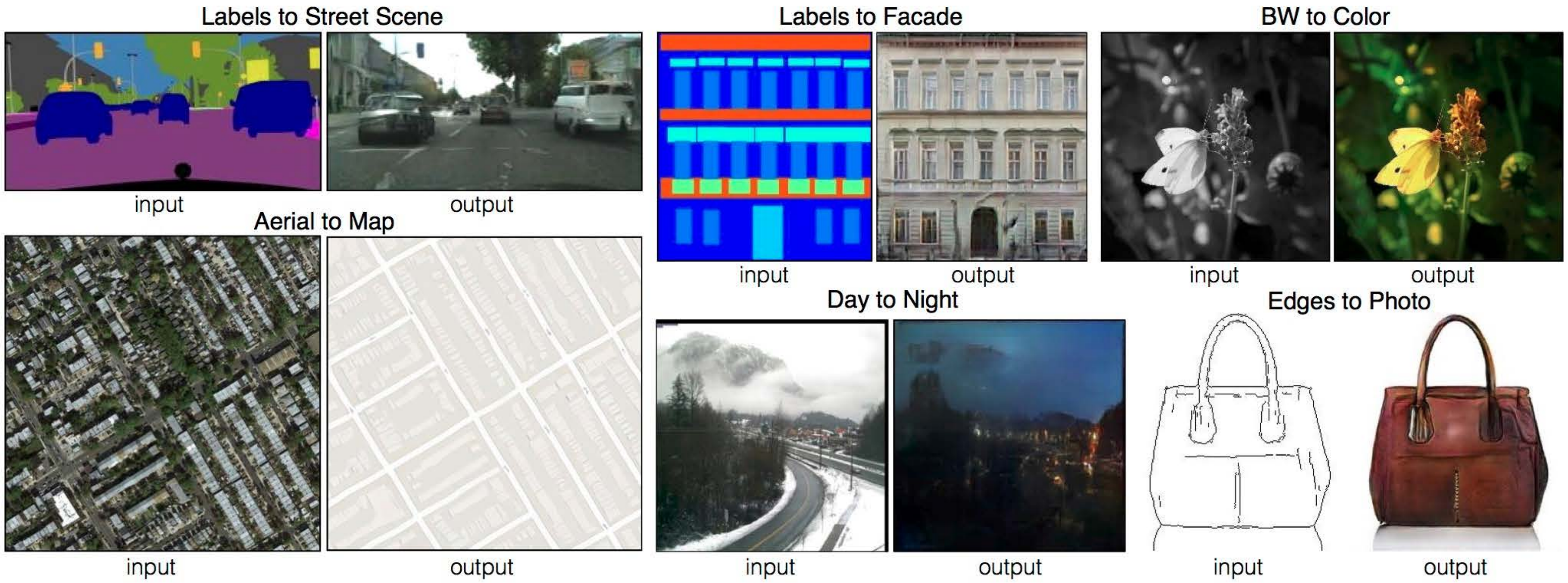

Image-to-image translation, P. Isola et al 2016

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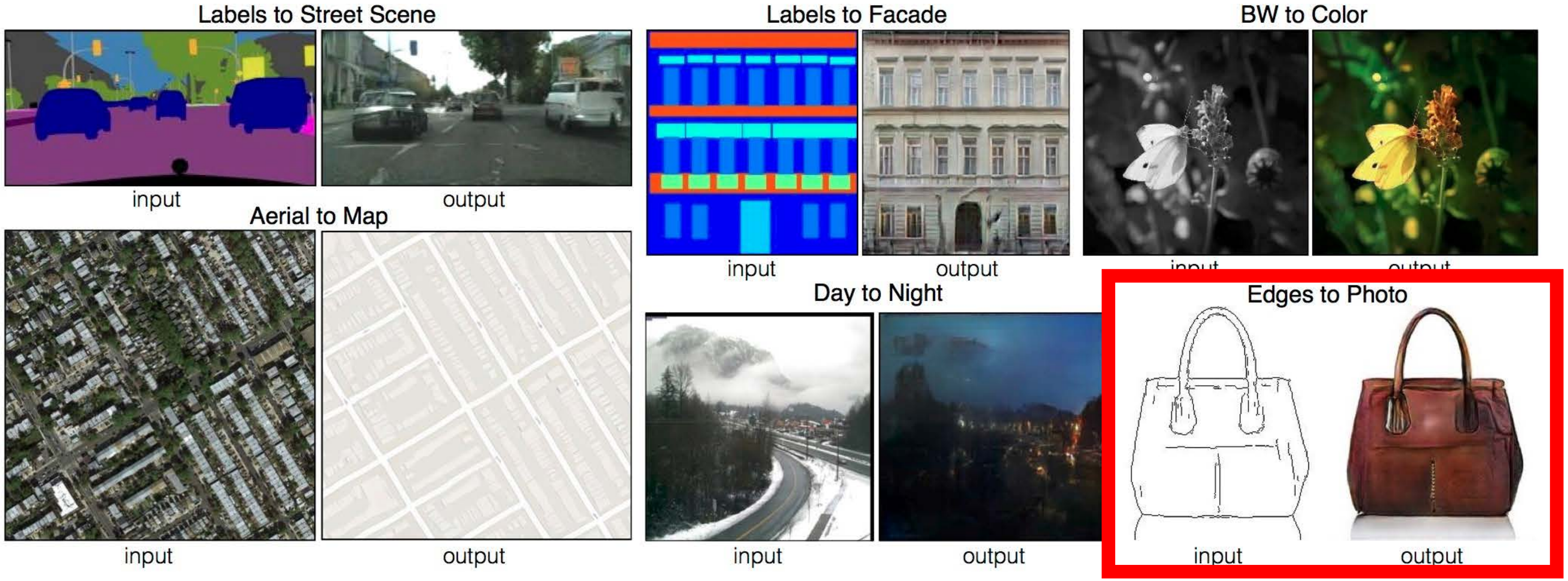
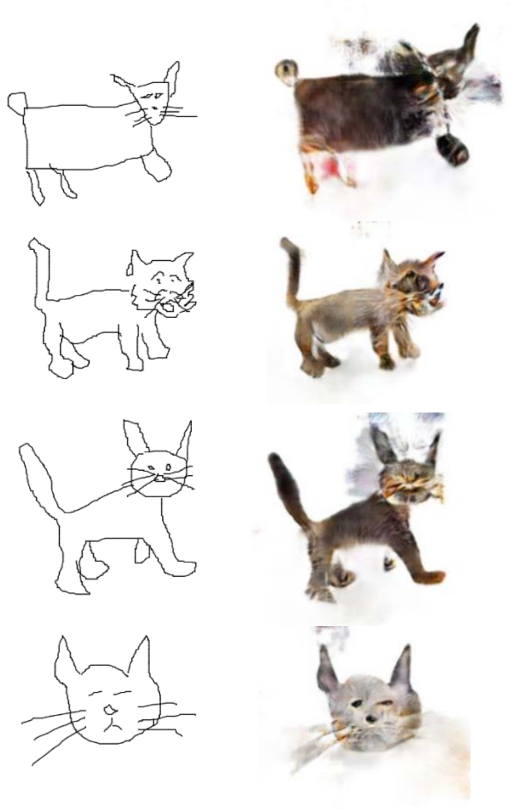


Image-to-image translation, P. Isola et al 2016

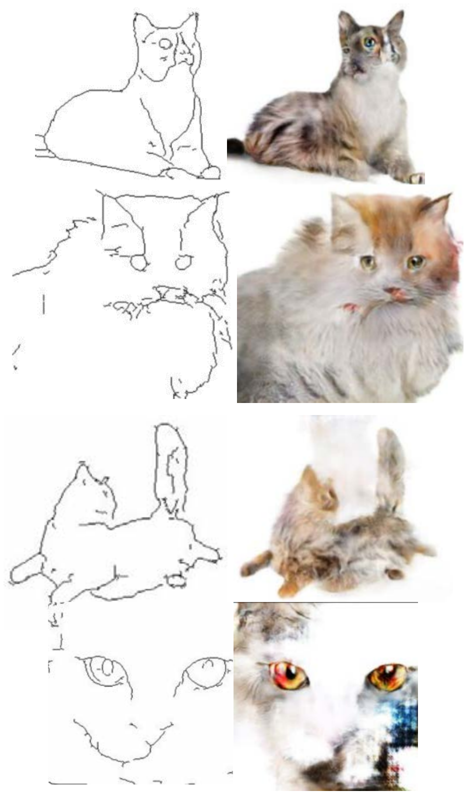
Image-to-image translation

Edge map to photo, P. Isola et al 2016

Image-to-image translation



Abstract sketch (cat) and corresponding results



Edge maps (cat) and corresponding results

Abstract sketch (shoe) and corresponding results

Edge maps (cat) and corresponding results

Results tested with a pre-trained model.

Image-to-image translation

- Paired images are required
  - Highly complex, expensive to obtain
  - Sometimes, not even well–defined
- Generated images are aligned to the edges. (Not only in the application of edge-to-photo)
- Not able to generate good results from abstract sketches

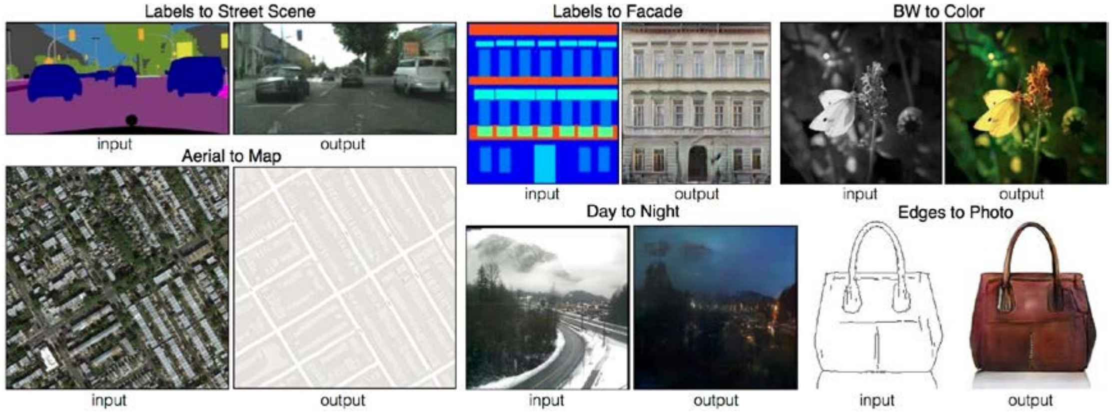


Image-to-image translation, P. Isola et al 2016

Input abstract sketch

Output image

Expected output

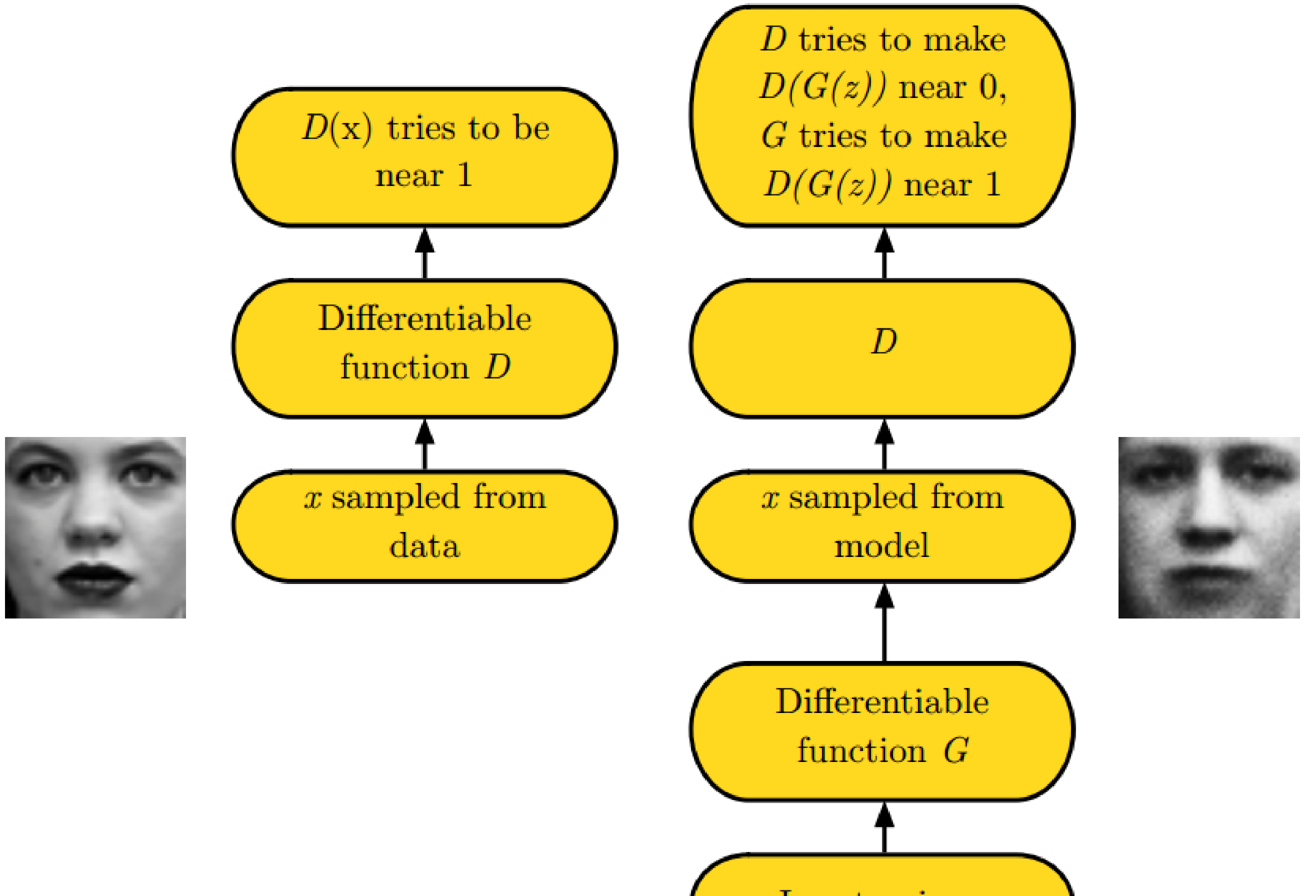
Image-to-image translation

Summary and inspirations

- GAN is a powerful framework to generate images.
- Images generated by image-conditional GANs tend to remember the edge maps of the input images.

Generative Adversarial Nets (GANs)

- Generate images of a given dataset by adversarial training
- Discriminator
- Generator
- Minmax game
- Problems
  - Unstable in training (sensitive to hyper parameters)
  - Mode collapse

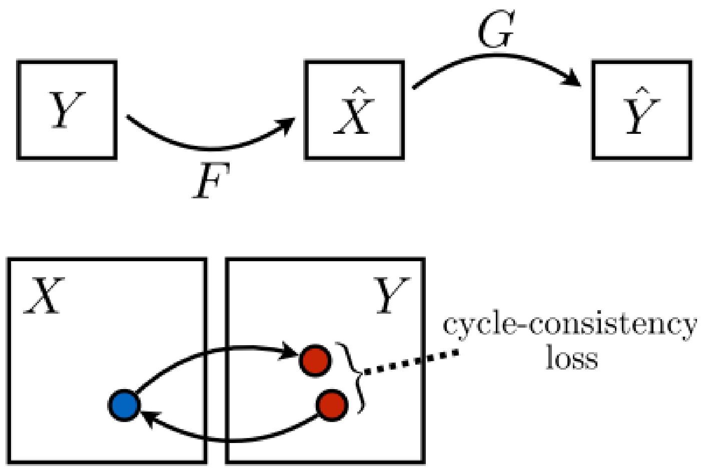


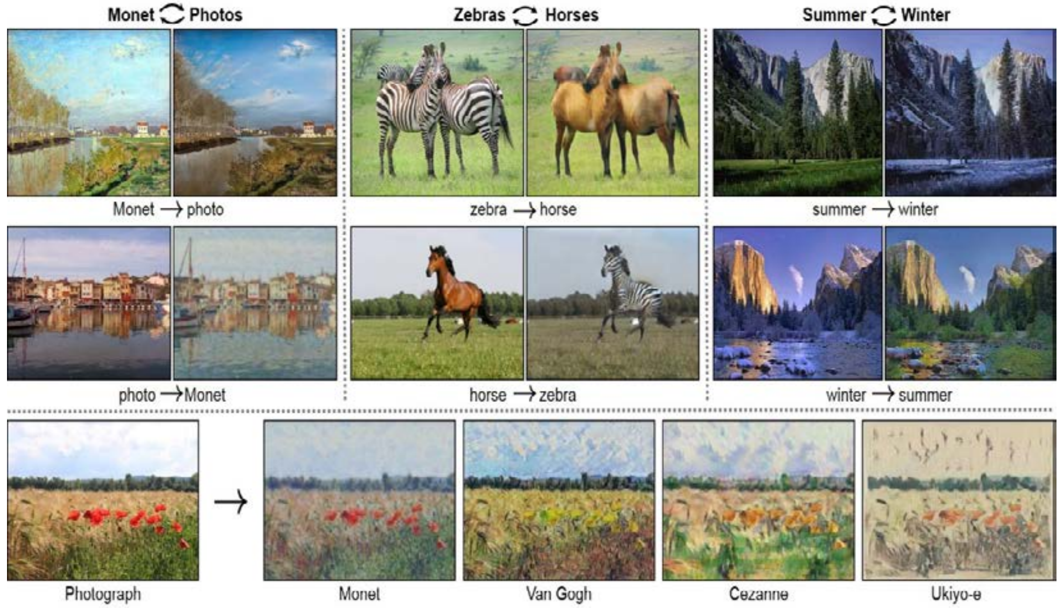
(Goodfellow et al., 2014)

Unpaired image translation

- Unpaired images datasets
- Generate images from one domain to another
- Cycle consistency

  Reconstruct the input image from generated image



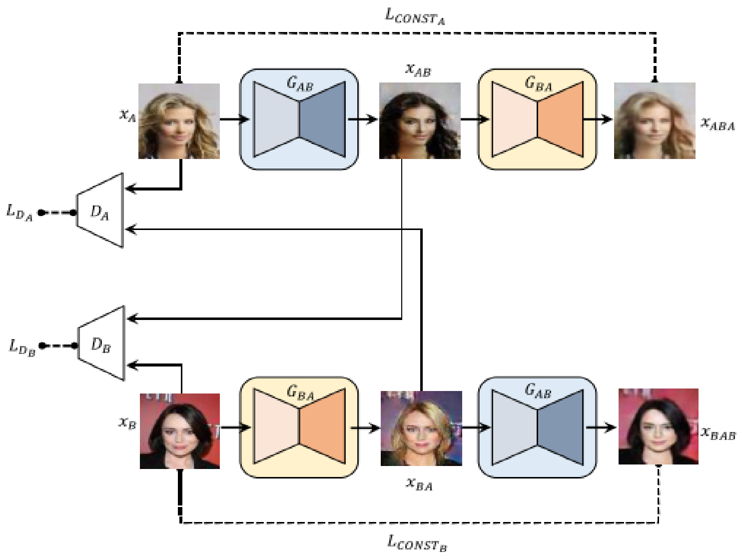


CycleGAN, J. Zhu et al 2017

Unpaired image translation

- Unpaired images datasets
- Generate images from one domain to a
- Cycle consistency (same idea)

  Reconstruct the input image from generated image



(a) Learning cross-domain relations **without any extra label**

(b) Handbag images (input) & **Generated** shoe images (output)

(c) Shoe images (input) & **Generated** handbag images (output)

DiscoGAN, T. Kim et al 2017

Unpaired image translation

Summary and inspirations

- Unpaired image datasets
  - Easy to obtain
- Not necessary to be edge aligned
- Preserve shared attributions

(b) Handbag images (input) & **Generated** shoe images (output)

DiscoGAN, T. Kim et al 2017

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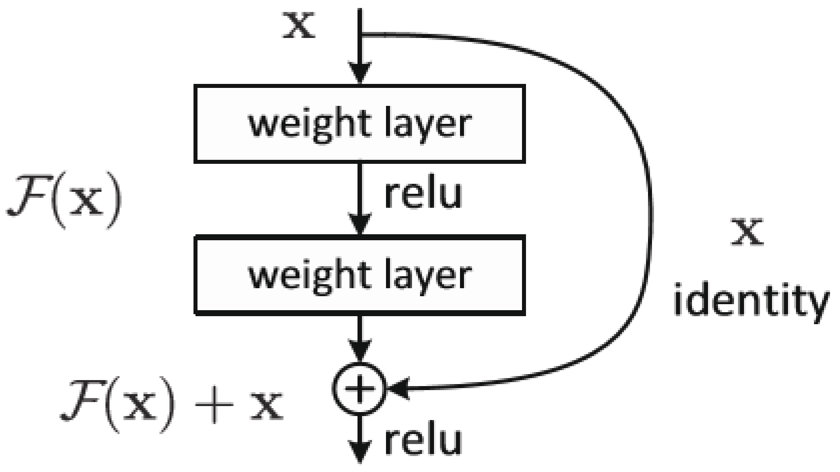
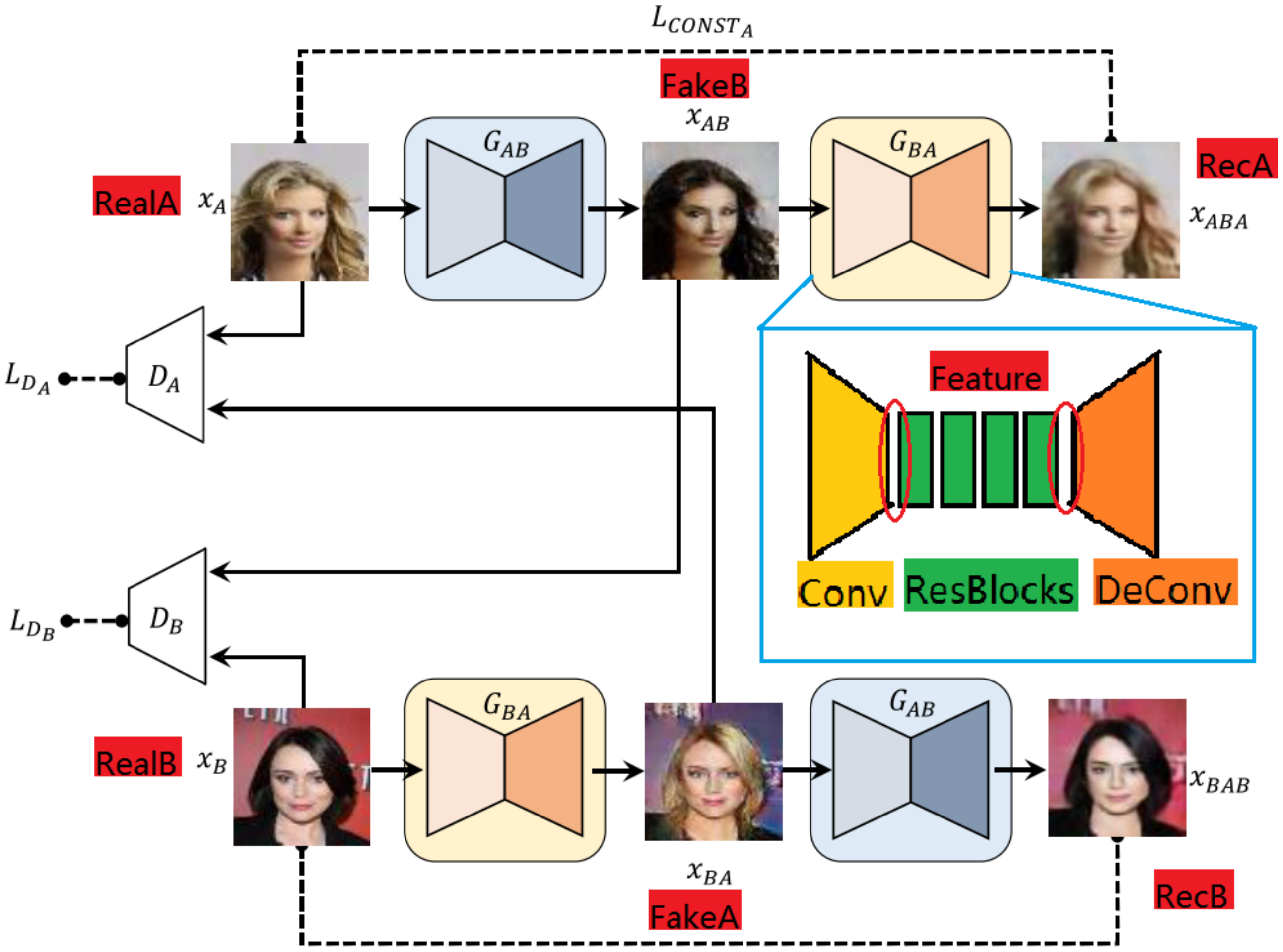
Exploration: CycleGAN

Architecture details

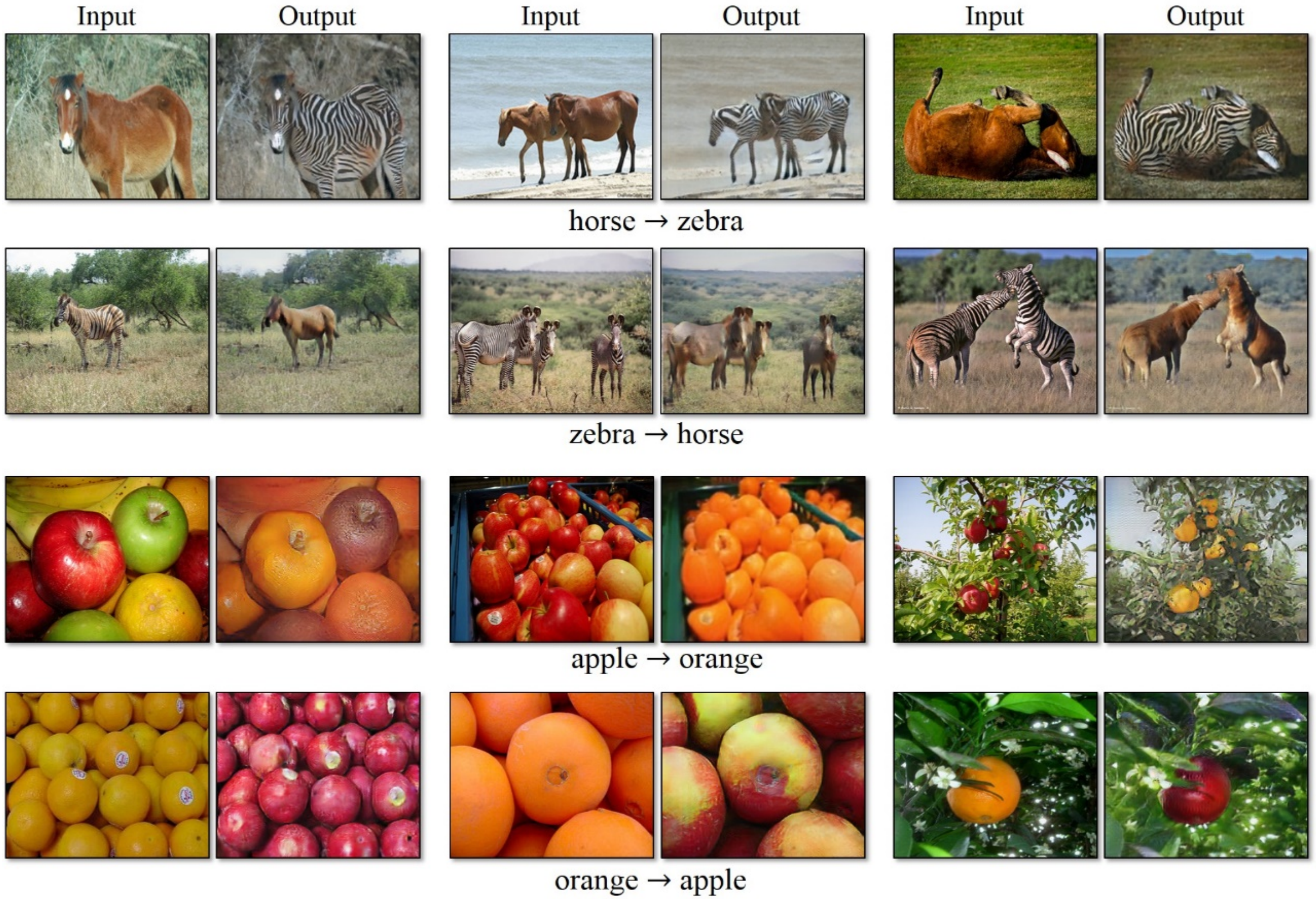
- Residual blocks
- Instance normalization
- Generated image pool





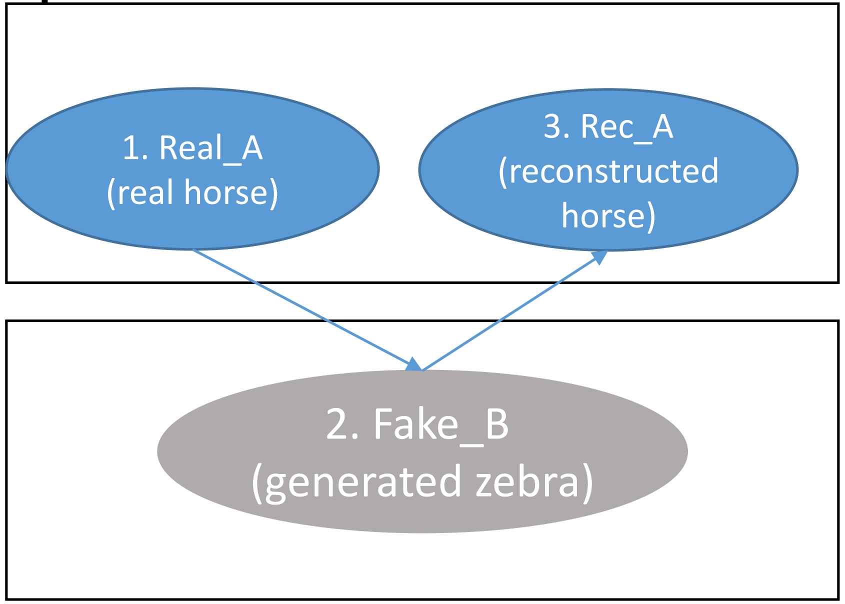
Exploration: CycleGAN

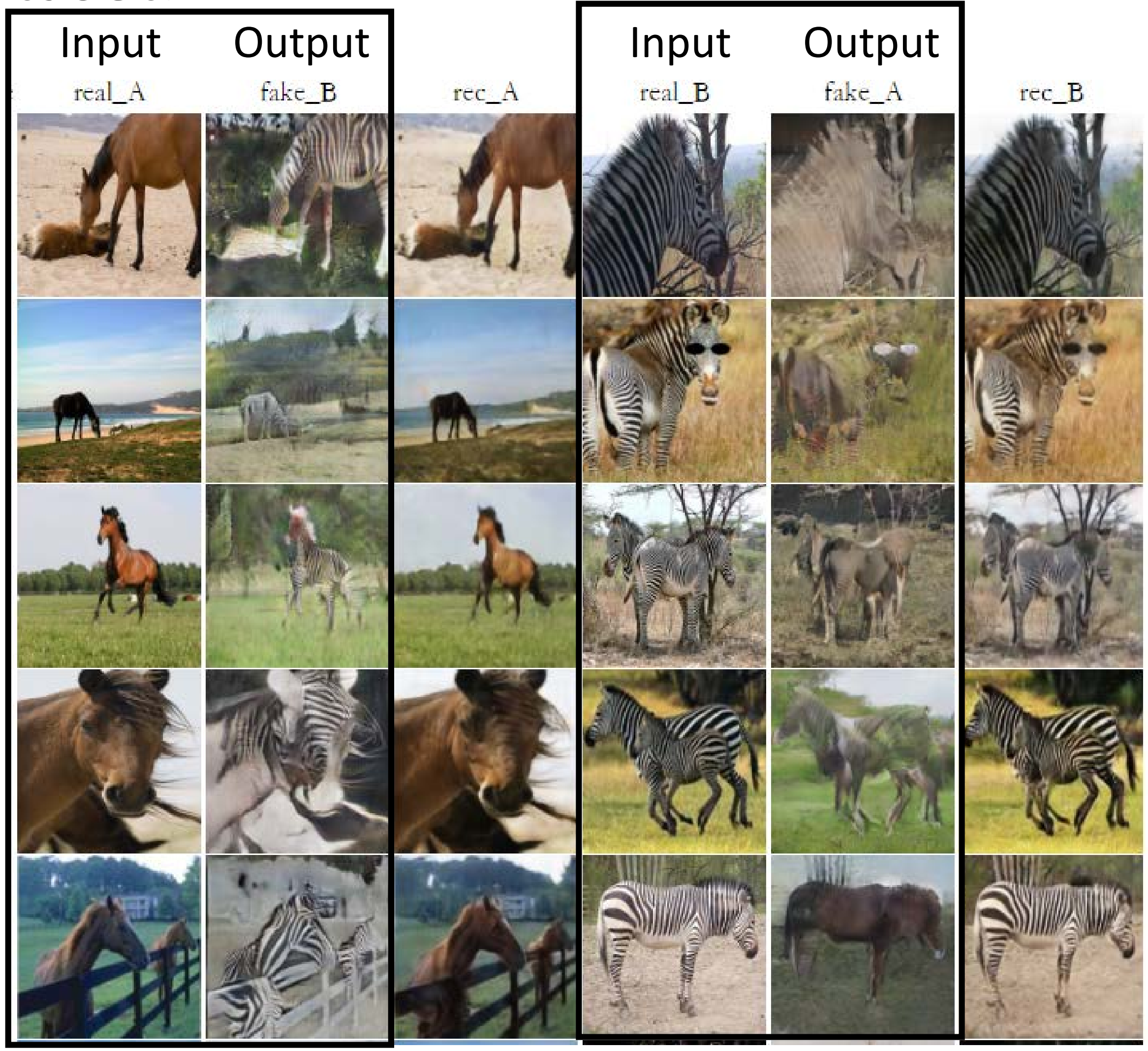
Reported results



Exploration: CycleGAN

Results by training after 200 epochs with the official torch implementation. Horse to zebra dataset.



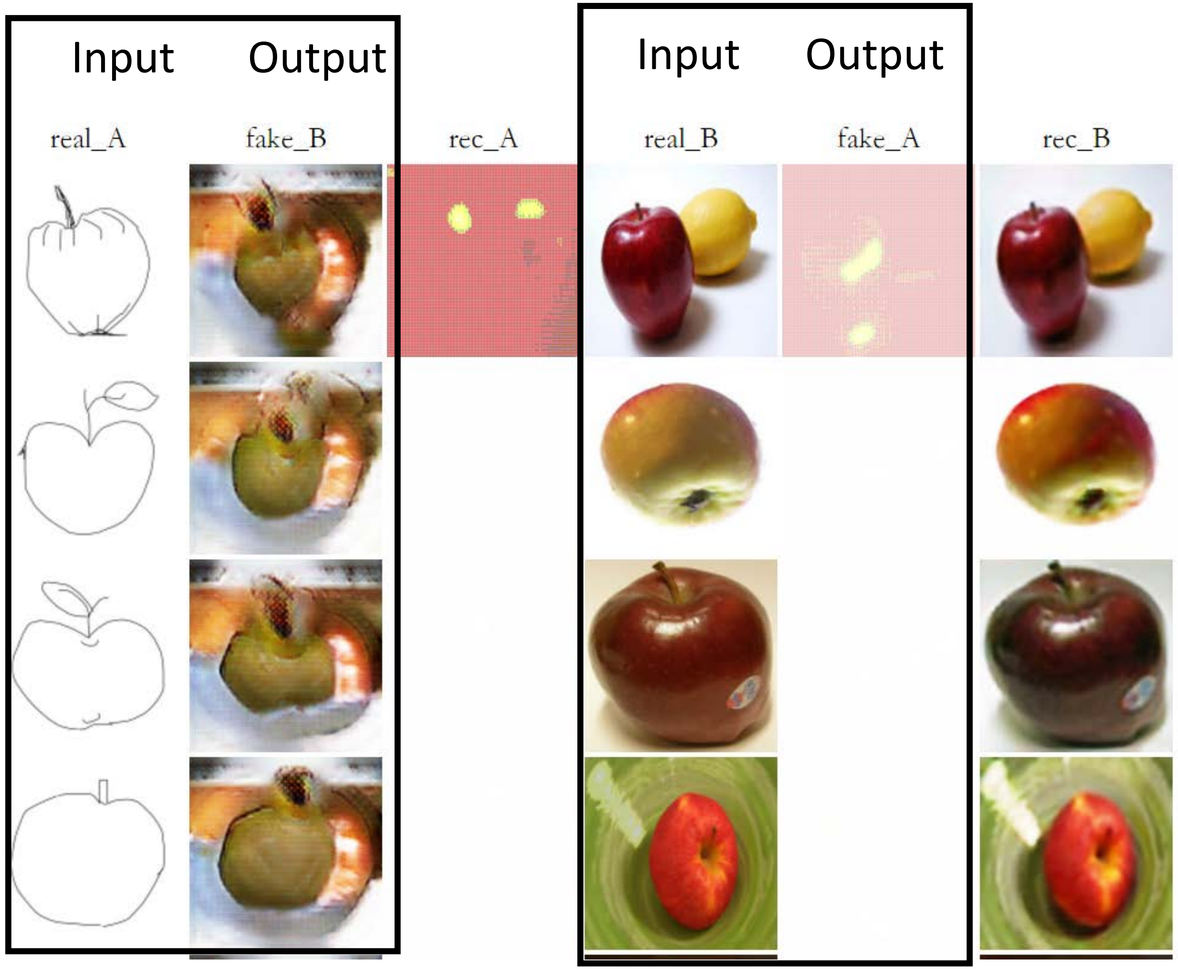


Exploration: CycleGAN

Results by training after 200 epochs with the official torch implementation. Sketch to photo (apple) dataset.

Problems

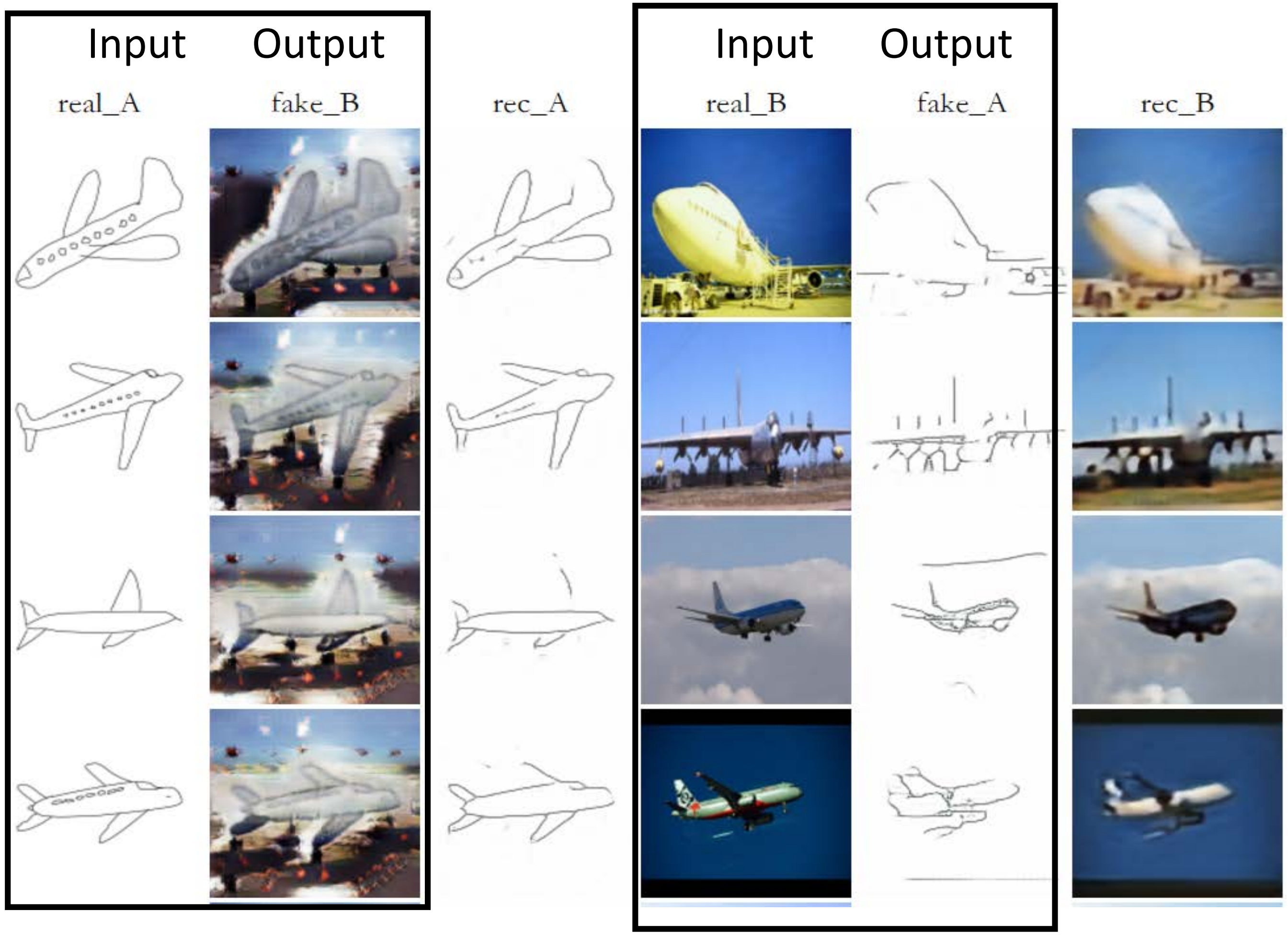
- Mode collapse (sketch to photo) every input is mapped to the same result.
- All white (photo to sketch)



Exploration: CycleGAN

Results by training after 200 epochs with the official torch implementation. Sketch to photo (airplane) dataset.

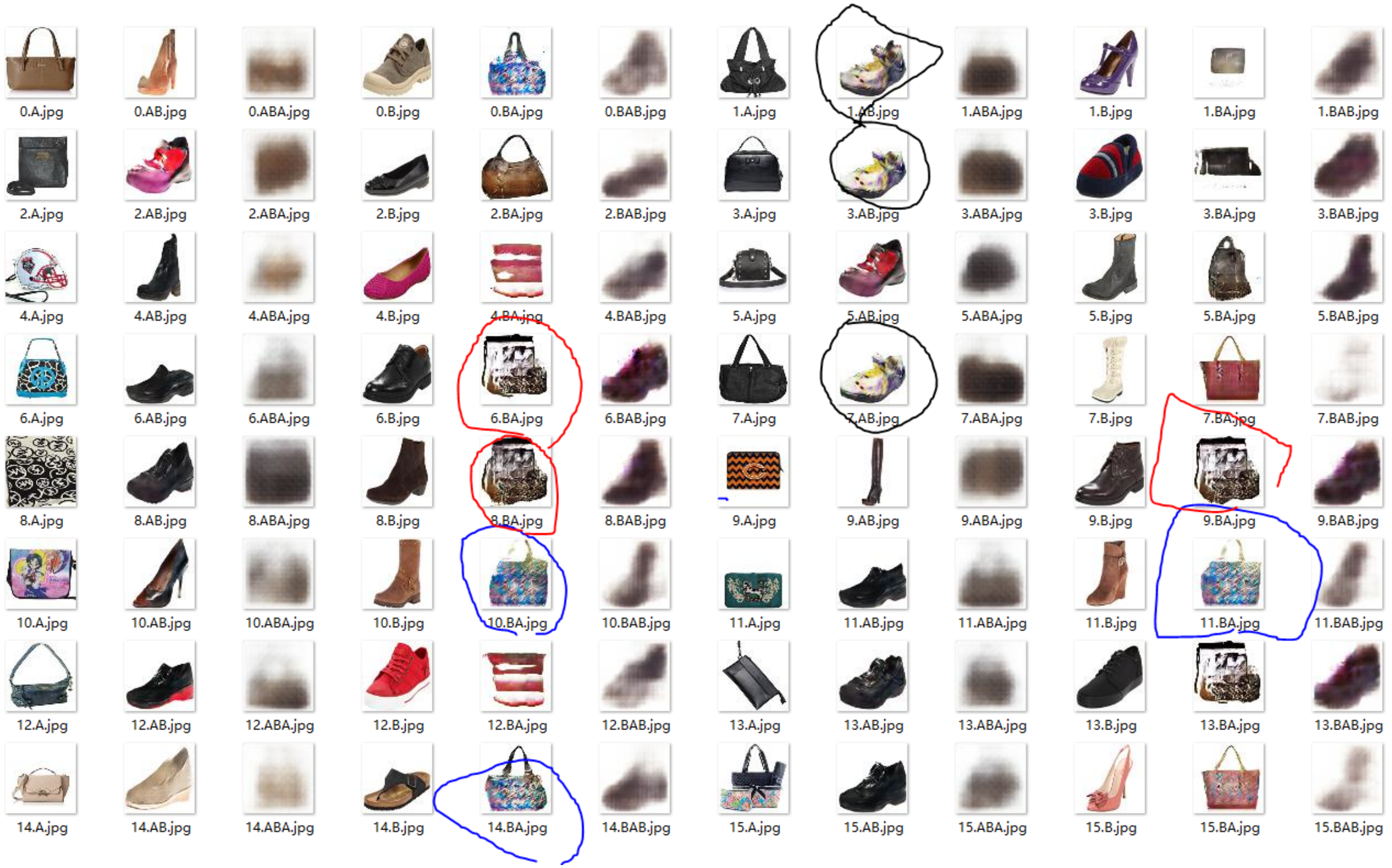
- Unexpected edge-aligned
- Not able to distinguish sketches from edge maps.
- Severe mode collapse.



Exploration: DiscoGAN

Results by training after 200 epochs with the official torch implementation. Shoe to handbag dataset.

- A light mode collapse (marked in different colors)
- Not able to reconstruct input images (3rd column)



Exploration: DiscoGAN

Results by training after 200 epochs with the official torch implementation. Sketch to photo (shoe) dataset.

Insights and plan

- Edge aligned issue
  - Need an additional mechanism to help the model to distinguish sketch from edge maps
  - Try to add negative samples (edge maps) to the training procedure
- An image is composed of ***content*** and ***appearance***.
  - Content is the shared information between photos and sketches; appearances vary from photos to sketches.
  - Content information is represented by the feature maps of neural networks; appearance information is stored in the weights of the convolution layers (J.Johnson et al 2016).
  - The deeper the network is, the higher level semantic information is extracted.
  - Try a deeper network to focus on classification (high level) instead of edge (low level).