Sketch to Photo Translation

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

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

Sketch to Photo Translation

- Problem definition
- Why sketch?
- Characteristic of Sketch

Related works

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

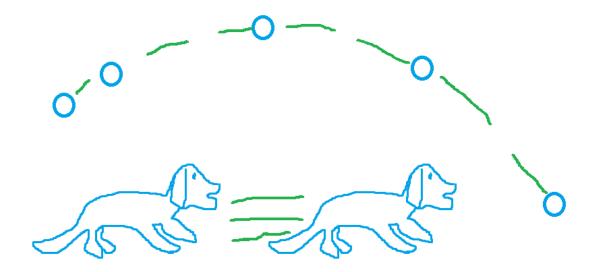
Exploration

- CycleGAN
- DiscoGAN

Sketch to realistic video

Two kinds of strokes in a sketch:

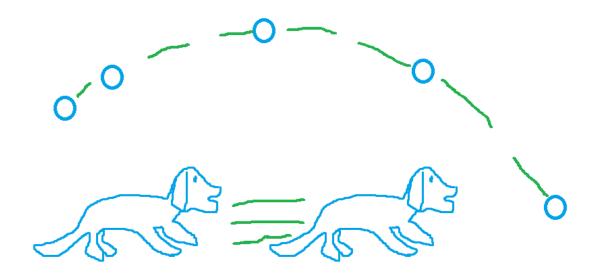
- Object strokes
 - What object in the scene
- Motion strokes
 - How the object moves in the scene



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

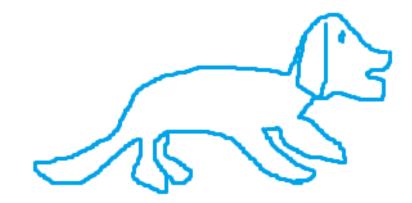


It is difficult to obtain corresponding videos that match both object strokes and motion strokes for training!

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



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

Focus on object strokes!

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

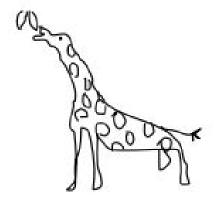
Problem definition

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!

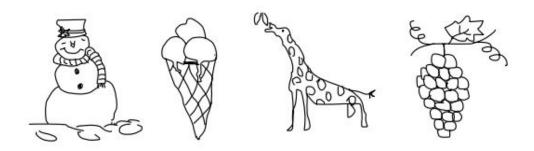




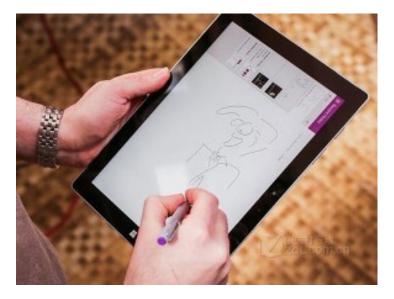


Sketch: why sketch?

- 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

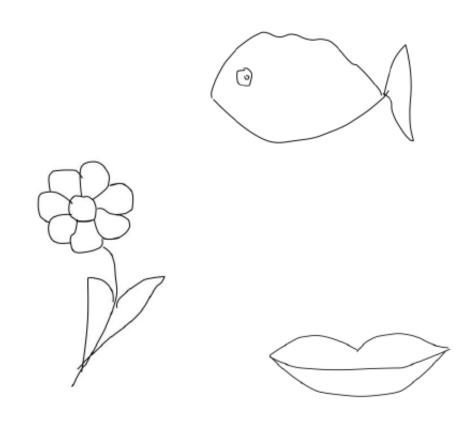






Characteristic of Sketch

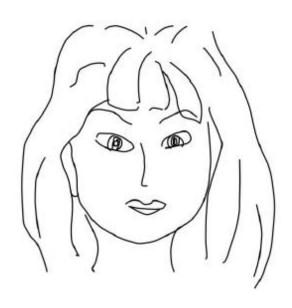
IconicSketches can be highly abstract.



Characteristic of Sketch

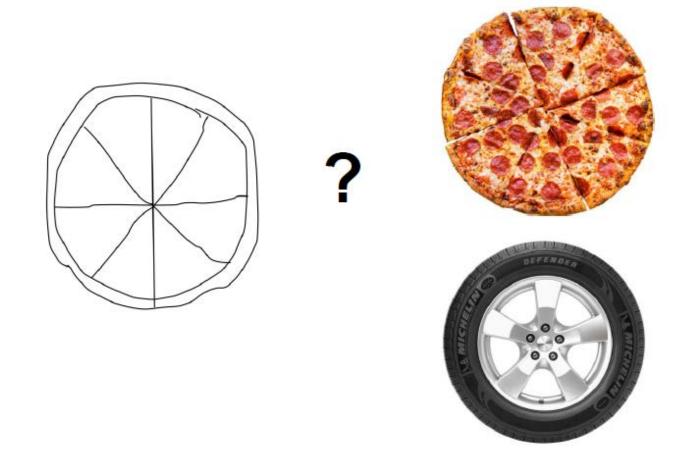
High intra-class variation
 Sketches drawn by different people vary in the level of abstraction or deformation.





Characteristic of Sketch

Lack of visual cues
 Sketches are lack of colors and textures compared to photos.

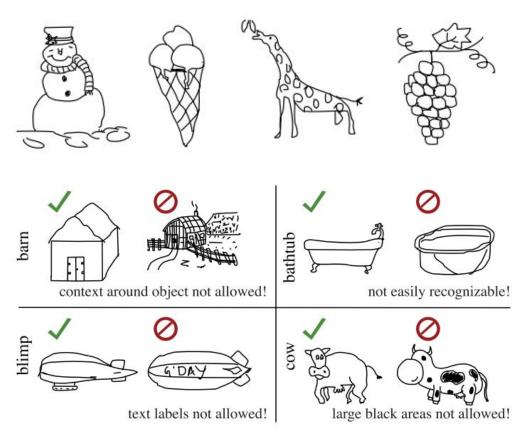


Dataset

- 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

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

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

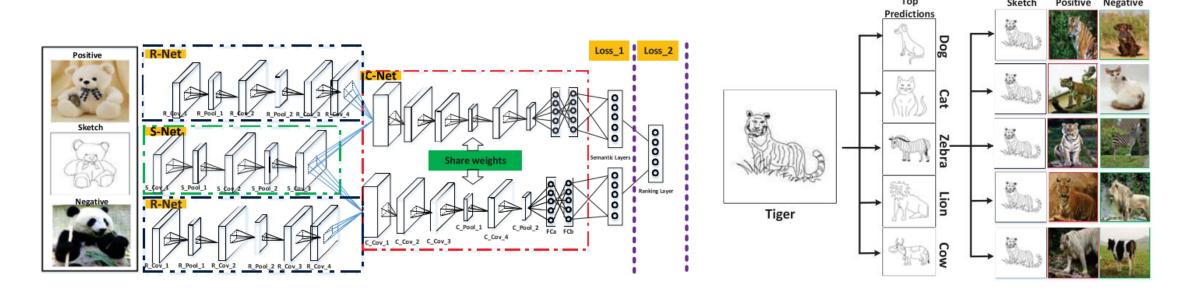
- Generate a realistic image using a simple freehand sketch annotated with text labels.
- Text labeled sketch
 - Labeling should be done automatically! (sketch classification)
- Seamlessly stitching several photograph
 - We want generate a totally **new** image, rather than a combination of existing image parts.





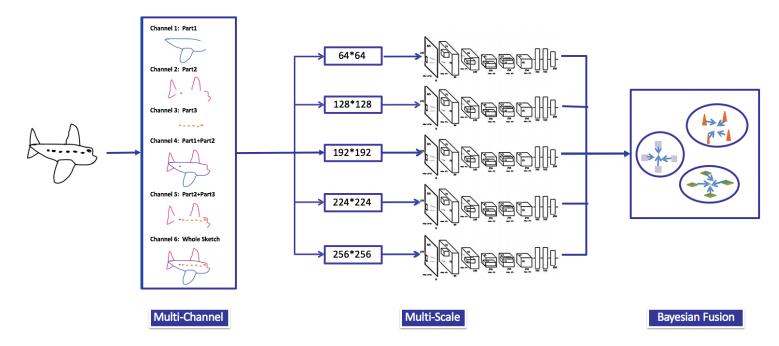
Sketch classification: SketchNet

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



Sketch classification: Sketch-a-Net

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



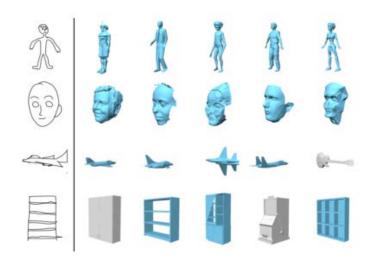
Sketch classification

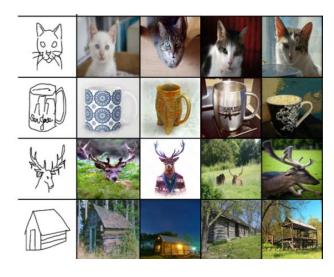
Summary and inspirations

- 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.

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

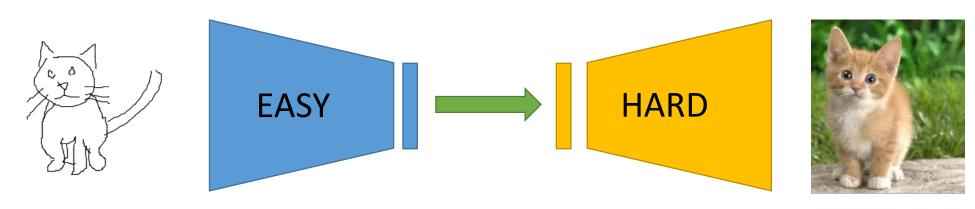
Image retrieval, P. Sangkloy et al 2016

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

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

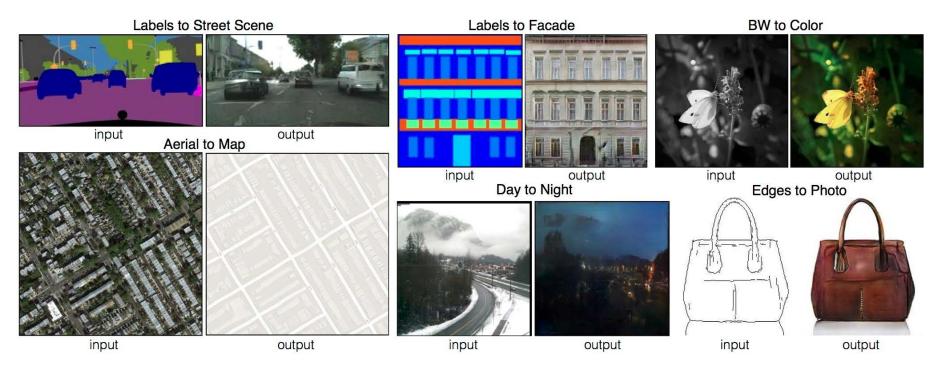


Image-to-image translation, P. Isola et al 2016

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

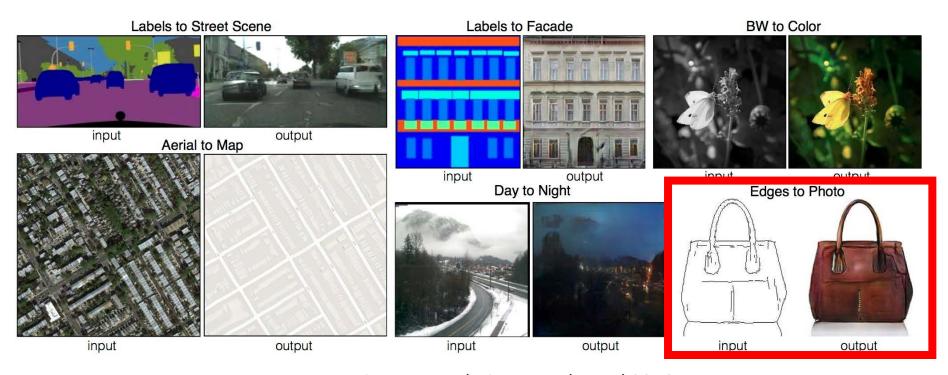


Image-to-image translation, P. Isola et al 2016



Edge map to photo, P. Isola et al 2016

- 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

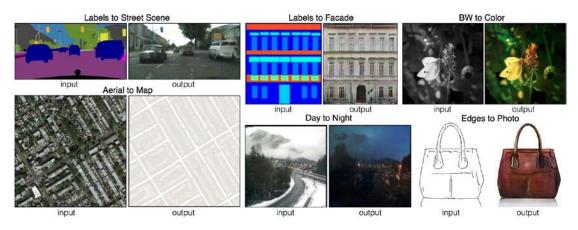


Image-to-image translation, P. Isola et al 2016



Input abstract sketch
Output image



Expected output

- 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



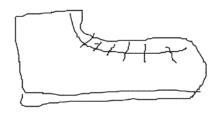
Edge map to photo, P. Isola et al 2016



Input edge map



Good result



Input abstract sketch



Bad result

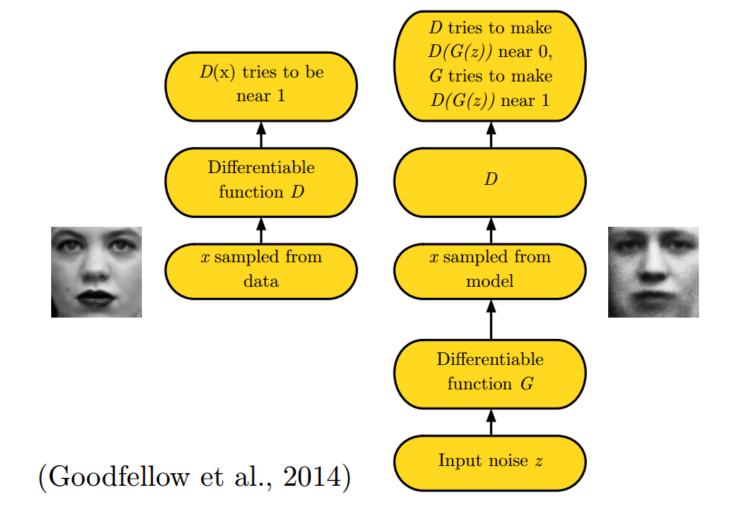
Summary and inspirations

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



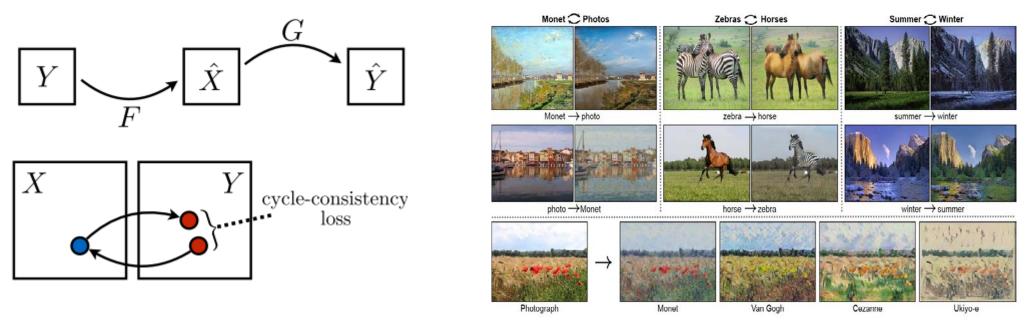
Generative Adversarial Nets (GANs)

- Generate images of a given dataset by adversarial training
- Discriminator
- Generator
- Minmax game



Unpaired image translation

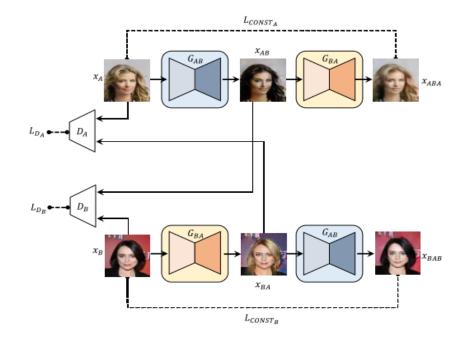
- Unpaired images datasets
- Cycle consistency
 Reconstruct the input image from generated image



CycleGAN, J. Zhu et al 2017

Unpaired image translation

- Unpaired images datasets
- Cycle consistency (same idea)
 Reconstruct the input image from generated image





Sketch to Photo Translation

- Problem definition
- Why sketch?
- Characteristic of Sketch

Related works

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

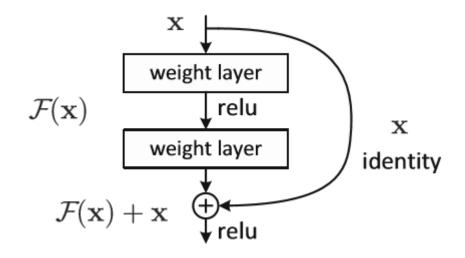
Exploration

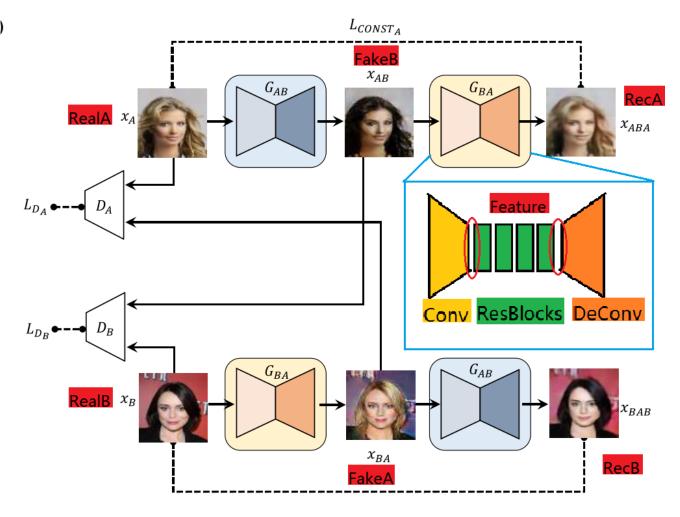
- CycleGAN
- DiscoGAN



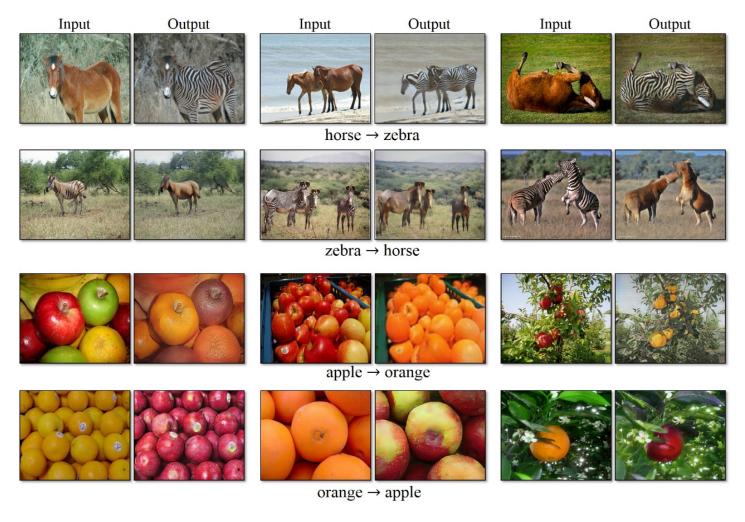
Architecture details

- Residual blocks
- Instance normalization
- Generated image pool

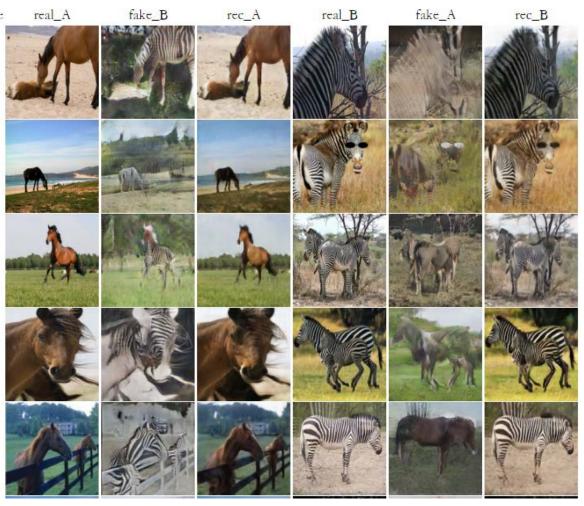




Reported results

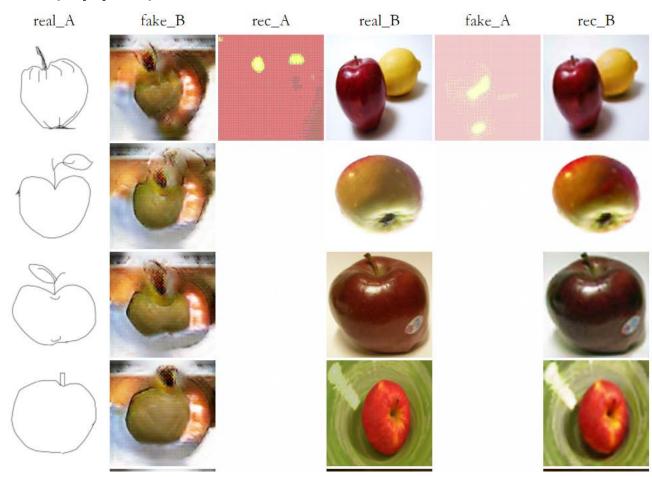


Results by training after 200 epochs with the official torch implementation. Horse to zebra dataset.



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

- Mode collapse (sketch to photo)
- All white (photo to sketch)



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

