DATS_6203_10: Final Project

Photo Coloring
by: Group 4

Introduction

- Photo Coloring

gray pictures   **color pictures**

- Applications: restoring old images, 2D animation..

- Main method: Generative Adversarial Network

- Additional method: Conditional Adversarial Networks

Dataset Description

- Flickr1024 - A large-scale stereo image dataset consisting 1024 high-quality image pairs and covering diverse scenarios like animals, building, lands, plants.

- https://yingqianwang.github.io/Flickr1024/

- size: 2.64GB

Literature Review

Image colorization: https://arxiv.org/abs/1803.05400

Deep Convolutional GAN: https://arxiv.org/abs/1511.06434

Image to Image translation:
https://openaccess.thecvf.com/content_cvpr_2017/papers/Isola_Image-To-Image_Translation_With_CVPR_2017_paper.pdf

GANs - Method based on color space

- GAN: G: Generative; A: Adversarial(discriminator); N: network.

- Photo transformation: LAB color space

❖ L: Lightness - gray photo

❖ A: Green-Red tradeoff

❖ B: Blue-Yellow tradeoff

❖ Input: L channel sequence, Output: A, B channel sequence

Data Preprocessing

Package - Open CV

- Use cv2.imread() to read to photo

- Resize to (256, 256) - Due to computation power limation and training time

- Tranform color space for BGR to LAB

Model

Conv2d(1, 32)
BatchNorm2d(32)
ReLU()

Conv2d(32, 64)
BatchNorm2d(64)
ReLU()

Conv2d(64, 128)
BatchNorm2d(128)
ReLU()

Conv2d(128, 128)
BatchNorm2d(128)
ReLU()

Conv2d(128, 128)
BatchNorm2d(128)
ReLU()

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ReLU()

Conv2d(128, 128)
BatchNorm2d(128)
ReLU()

Conv2d(128, 128)
BatchNorm2d(128)
ReLU()

ConvTranspose2d(128, 64)
BatchNorm2d(64)
ReLU()
ConvTranspose2d(64, 32)
BatchNorm2d(32)
ReLU()
Conv2d(32,2)
Tanh()

Training process

- Loss function - Cross entropy
  - Generator loss: cross entropy loss of generated images + MSE of ab channels
  - Discirmation loss: (loss of generated images + loss of real images) / 2
- Flip label generated images - 1 and real images - 0 (works)
- Soft and Noisy label: Using a random number between 0 and 0.1 to represent 0 labels (real images) and a random number between 0.9 and 1.0 to represents 1 labels (generated images) when training the discriminator. (works)
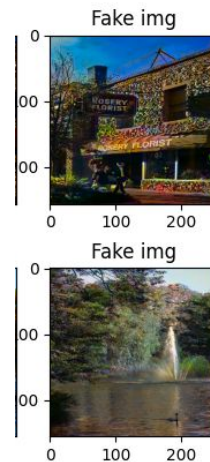
Results

training of 100 epochs:
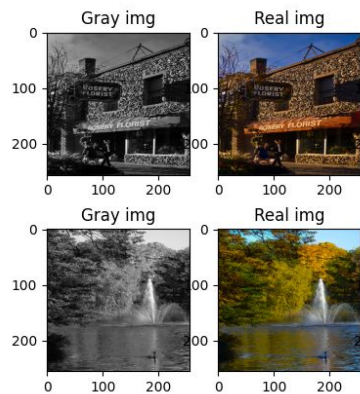
training of 200 epochs:
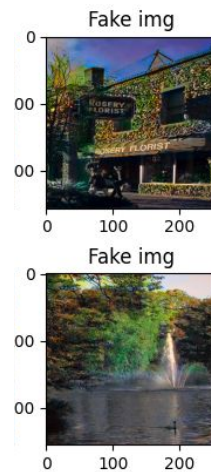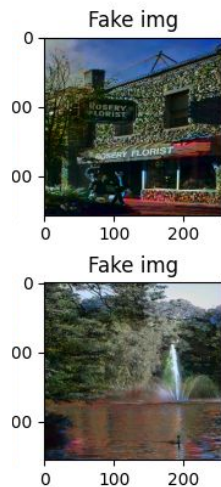
training of 300 epochs:

Conditional GANs

- predict pixels from pixels

- learn a mapping from observed image x and random noise vector z

- The objective of a conditional GAN:

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \\ \mathbb{E}_{x,z}[\log(1 - D(x, G(x,z)))],$$

- Markovian discriminator(PatchGAN): only penalizes structure at the scale of patches

Data Preprocessing

- Read the image from google drive

- Use cv2.cvtColor to convert BGR to RGB.

- To get the color image, so we turn the data into image format. We used Image.fromarray() to get the image-format RGB dataset.

- Use cv2.cvtColor again to finish the process from BGR-RGB-Gary (make sure it has three channels).

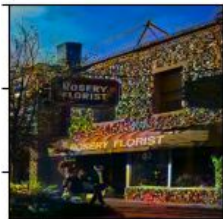- Transformed both of them into tensors.
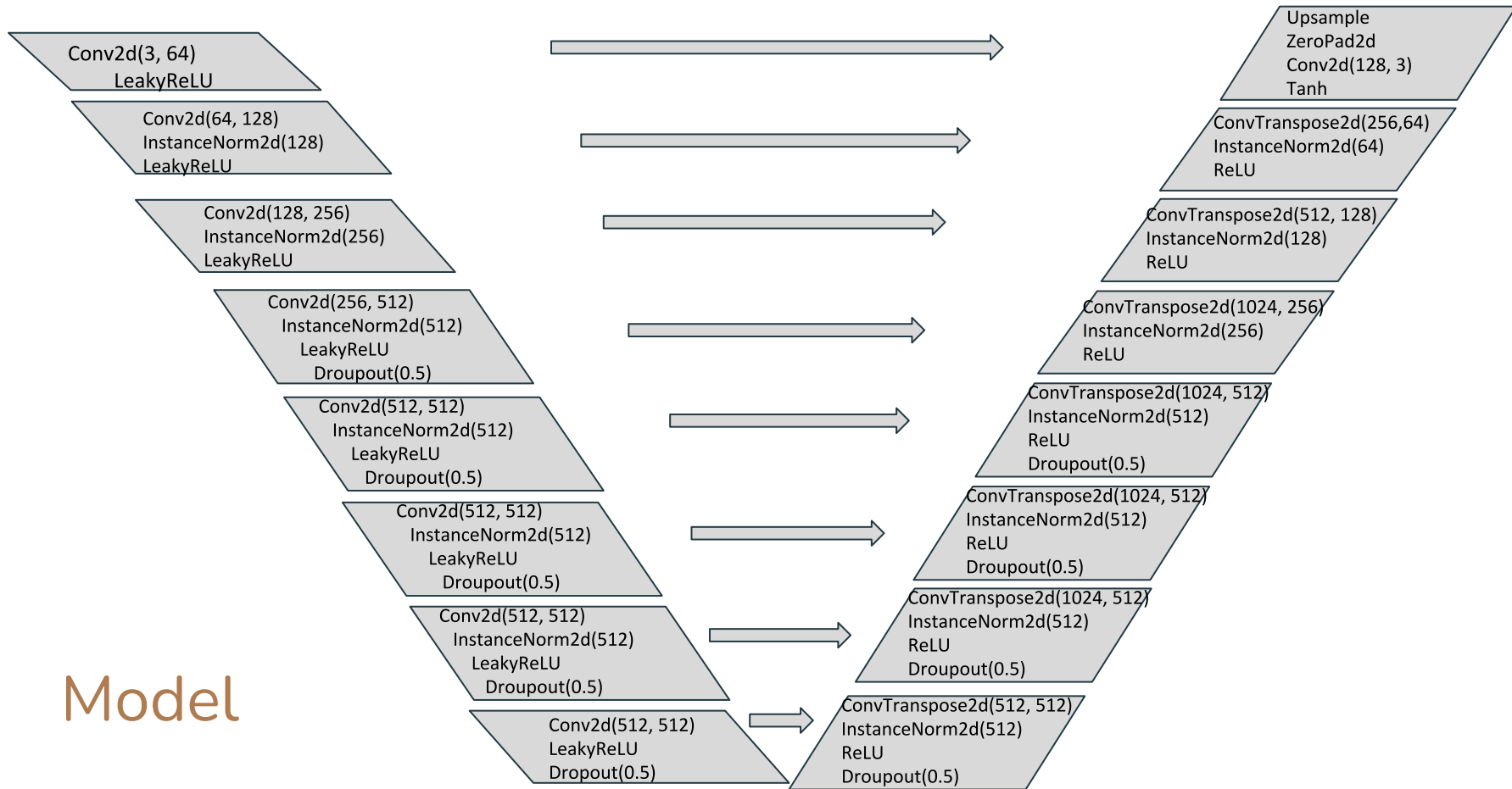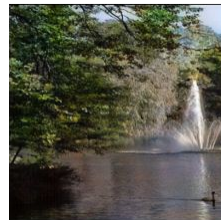
Model

Results
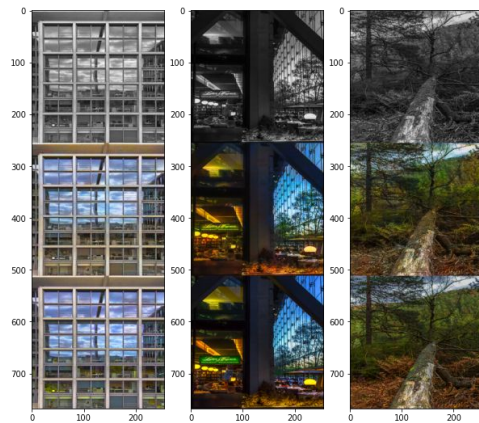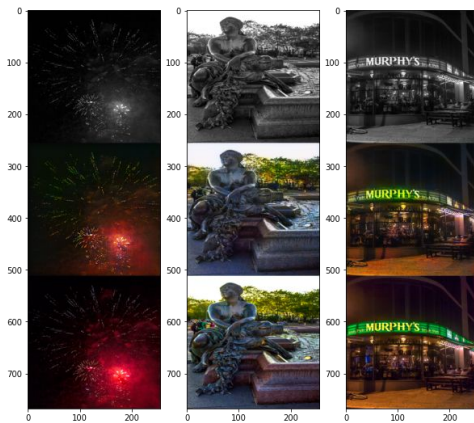
Performance Comparison

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L*a*b* GAN

Pix2Pix GAN

Conclusion

- Automatically colorizing grayscale images using GAN to an acceptable visual degree

- The model was able to consistently produce better looking (qualitatively) images than real images

- Mis-colorization was a frequent occurrence with images containing high levels of textured details-- didn't learn enough from human photos

Limation

- The dataset does not include enough person images. The result is not good on person.

- The training process is very slow.

- And the game between Generator and Discriminator is not balance. Usually, D perform better.

Improvement

- Adding person images into training

- Speeding the training process

- Changing generator structures to be banlanced with discriminator

- seeking a better quantitative metric to measure performance -- all evaluations were qualitative

- Application in coloring videos: With further training and improvement, we can turn the black

  and white movies into color movies.