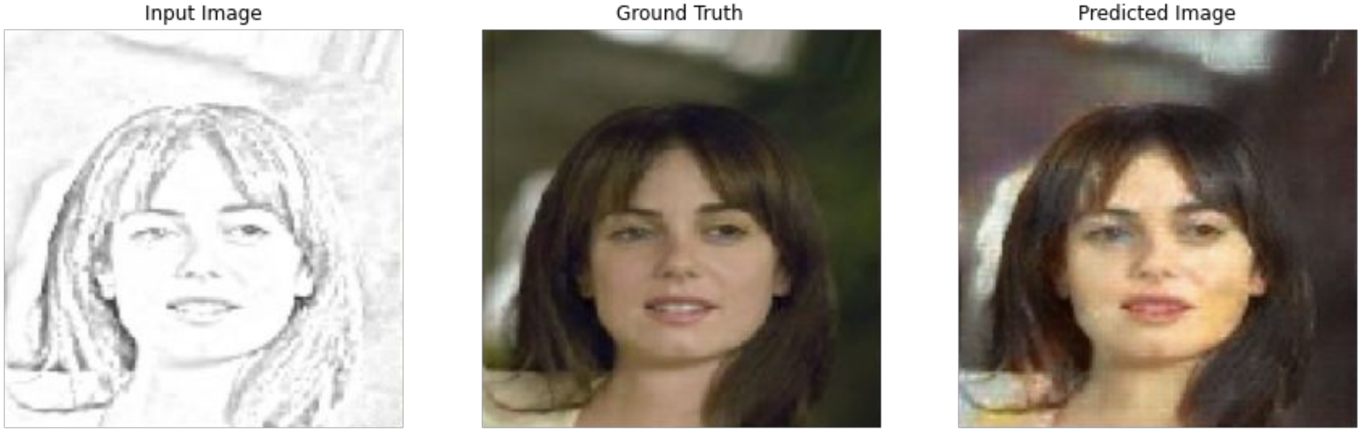
Sketch to Face Translation

Week 12/15 Final Presentation



Group 9: Joe Suzuki, Jason Li, Anthony Sokolov

Can we generate realistic faces from drawn sketches?

Problem Description

We aim to implement a model that takes a sketch of a human face and try to generate a realistic looking face conditioned with the sketch

- Can be used for rendering and animation tasks
- Useful to create new training data
- Useful for forensic purposes

Roles

Anthony explored the performance of conditional GANs cycle consistent GANS under different learning rates and generator types. He implemented a ResNet generator and set up the scaling algorithm to be used for our resolution assisted GAN. He computed the Frechet Inception Distance (FID) to measure image quality evaluation of each GAN's output.

Joe implemented markovian (PatchGAN) discriminator and a U-Net encoder-decoder generator for a conditional GAN architecture. He also implemented a conditional GAN with a U-net + residual blocks + DCGAN generator, and a loss that consists of adversarial loss, identity loss, and L1 loss.

Jason preprocessed the dataset and used OpenCV to generate sketch images. He trained conditional GAN models on different styles of input sketches to determine the ideal dataset to use. He visualized performance and evaluated training loss by using the loss log for each model to compare results.

Generative Adversarial Networks (GANs)

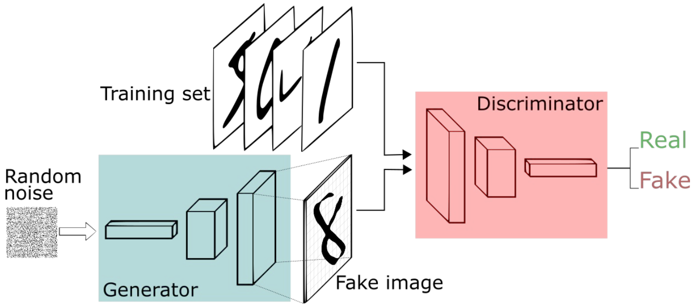
Generative Adversarial Networks (GANs) are a powerful generative model first introduced in Ian Goodfellow's 2014 paper.

GANs consist of a generator network and discriminator network

The generator tries to create images that fool the discriminator: (noise ξ, class Y | feature x)

The discriminator tries to classify whether image is real or fake: models the P(class Y | feature X))

The two networks are trained in tandem in a game like manner



How to condition a GAN model based of a sketch?

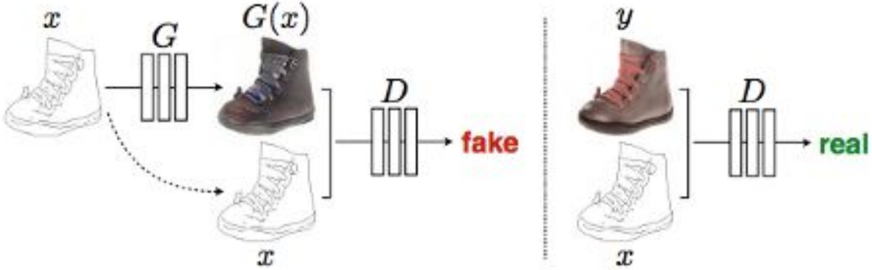
Conditional Adversarial Networks

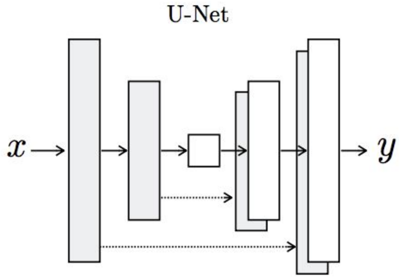
To build out conditional GAN we used the Pix2Pix architecture as our base

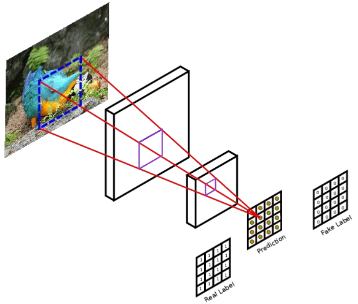
cGANs takes in an input image on which it is conditioned to make generations

The generator of the Pix2Pix GAN uses a modified encoder-decoder network called U-Net.

The Pix2Pix discriminator, called PatchGAN, outputs a matrix of classifications instead of a single value(real or fake).







Setup

Dataset: Celebrity Faces Dataset

Environment: Google Colab

Input Images:

- Face edges using Canny edge detection algorithr
- Realistic sketches using OpenCV

Experiments

We fit conditional GAN (paired images) and CycleGAN (unpaired images) architectures to our dataset

We explored the use of different learning rates, generators, and loss functions

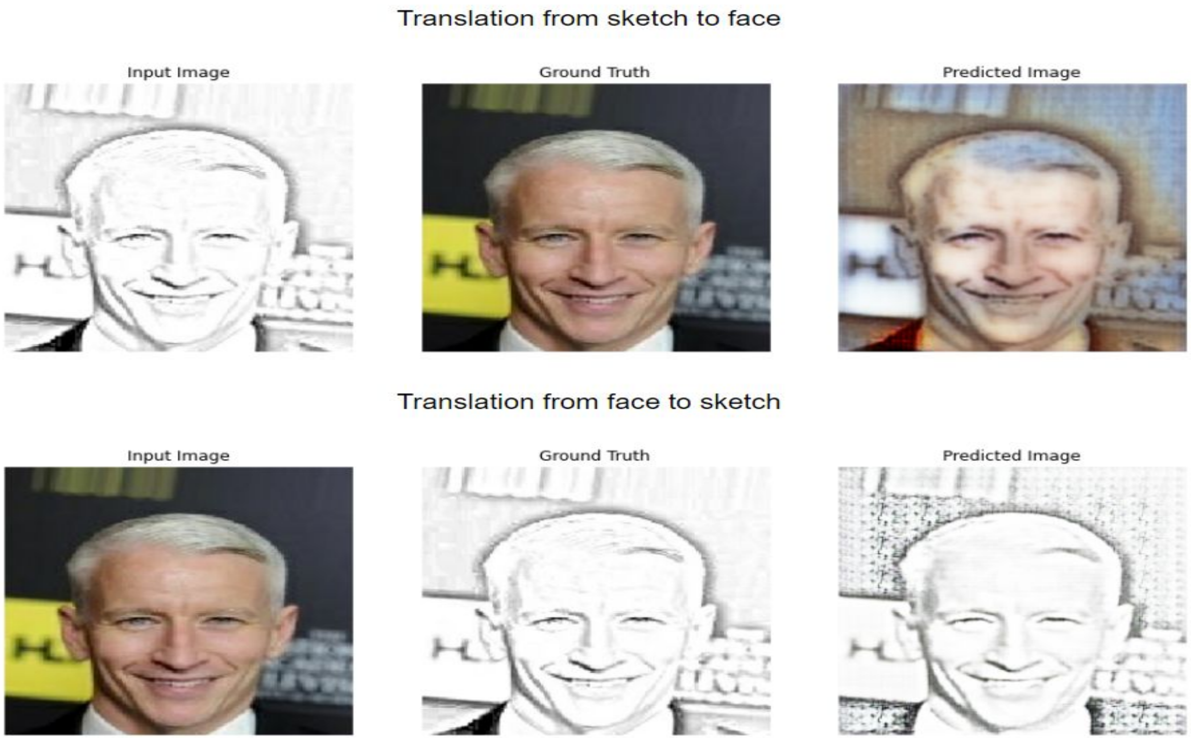
As a novel approach, we explored training lower resolution, more stable GANs and then scaling the output using deep learning

Conditional GAN Learning Rates Comparison

Sample outputs using different learning rates

0.01 | 0.001 | 0.0001 | 0.00001

CycleGAN Translations



CycleGAN Learning Rates Comparison

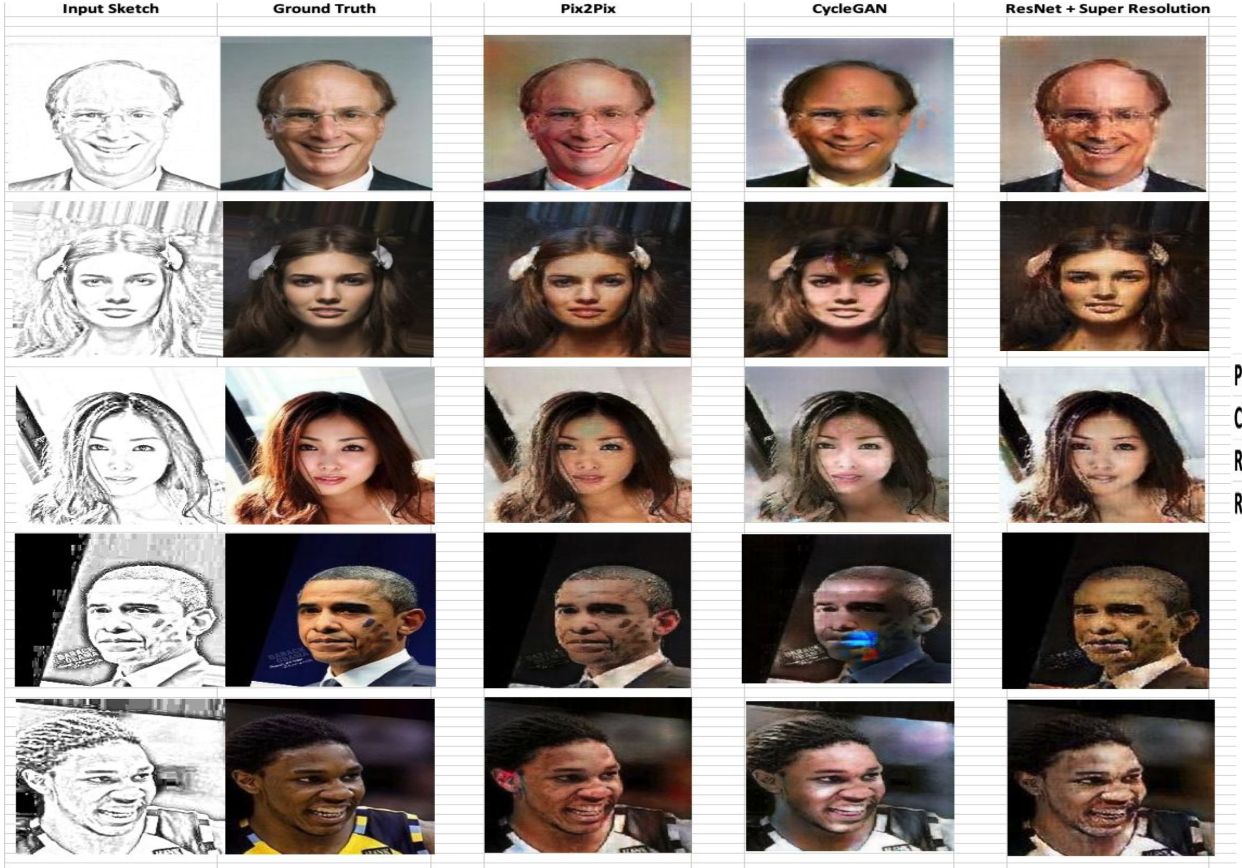
Equal learning rates

Generator learns twice as fast

Smaller Conditional GAN + Super Resolution

We trained a smaller Conditional GAN that outputs 128x128 images

We used a pretrained CNN to scale the outputs from the GAN to 256x256



Final Outputs

	Frechet Inception Distance	Average Pixel Difference
Pix2Pix	142.44	0.9
CycleGAN	143.18	0.96
ResNet + Bicubic Interpolation	142.05	0.91
ResNet + Super Resolution	139.07	0.91

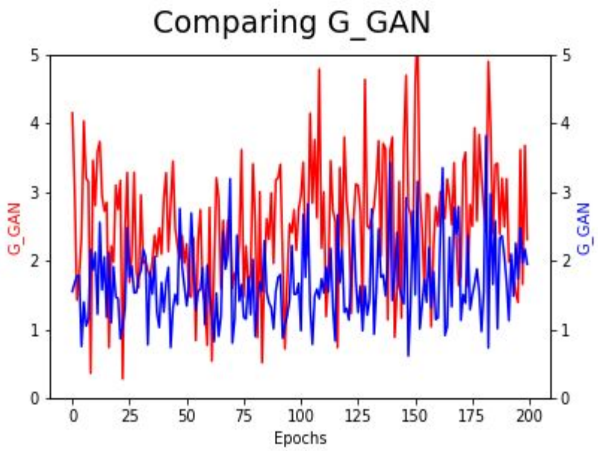
Initial Testing

- Tested the model using face edges
- Tested the model using realistic sketches

Face Edges Input	Face Edges Output	Realistic Sketch Input	Realistic Sketch Output	Actual Image

Evaluations

- Loss is uninformative of performance as values often oscillated which does not give us a clear indication of how well the model is performing.
- We used the FID(Frechet Inception Distance) score



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Lessons Learned

- GANs for image translation
- Importance of tuning
- GANs complications

Challenges faced

- Data preprocessing
- Time constraint
- Environment Crashing

Goals not achieved

- Used FID(Frechet Inception Distance) instead of other types of evaluation metric due to time constraint
- Test models for certain biases