Disclaimer: This presentation is a work of fiction written from the perspective of a 2020 researcher traveling back in time to mid 2013 to share some 2020 xNN based application ideas; references to credit the actual inventors of the various ideas is provided at the end

Generative Painter

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Disclaimer!

- The main paper used for this presentation:

Auto-painter: Cartoon Image Generation from Sketch by Using Conditional Generative Adversarial Networks

By:

Yifan Liu, Zengchang Qin, Zhenbo Luo, Hua Wang

Paper link: https://arxiv.org/abs/1705.01908

Disclaimer!

- Since this work builds on conditional GANs I am going to assume that the people in 2013 are familiar with GANs and conditional GANs so as to avoid the presentation being too lengthy
- I am going to focus this presentation on key parts such as the loss functions, architecture used etc.
- The model was not readily available and I tried my best to reproduce the results from the paper using the references from here

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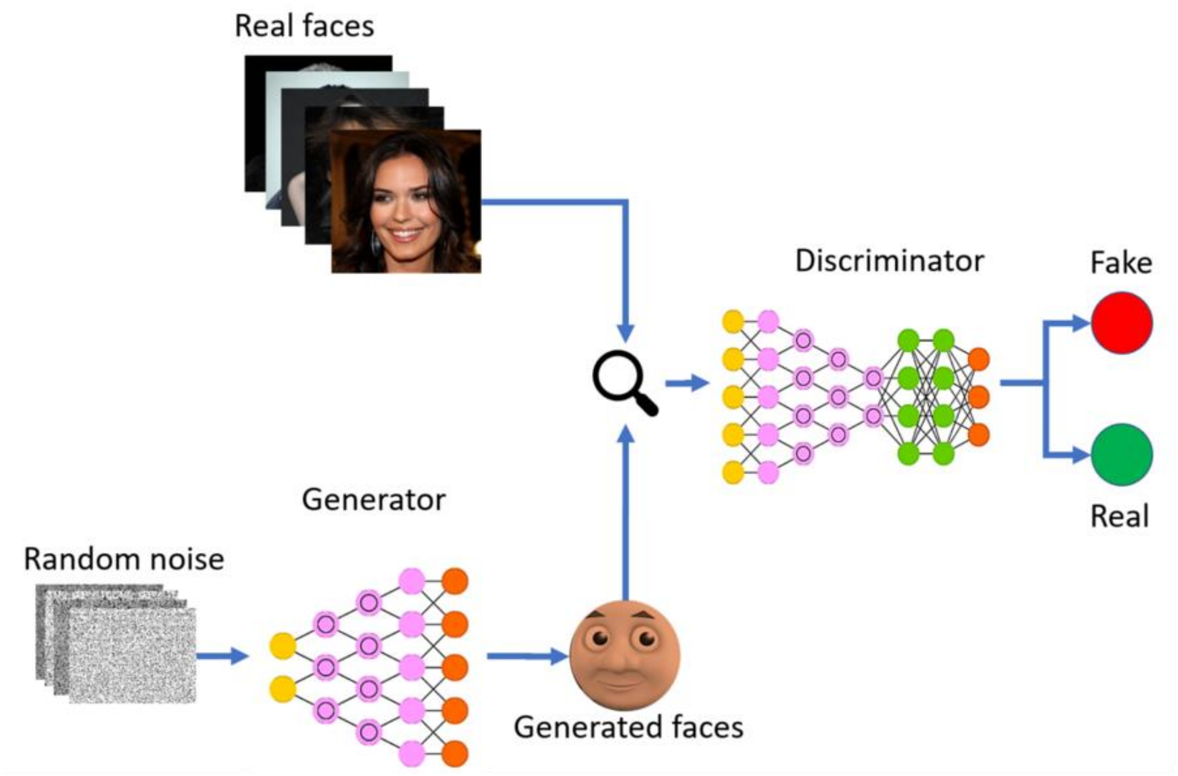
Motivation

- Coloring sketches automatically using neural networks opens a wide field of applications.
- This is especially useful to artistes and graphic designers as it helps them see the sketches from a new pair of eyes

  Current methods:
  - Most of the current approaches uses GANs and variations of it.
  - GANs are hard to train
  - We can use conditional GANs to condition our GAN outputs

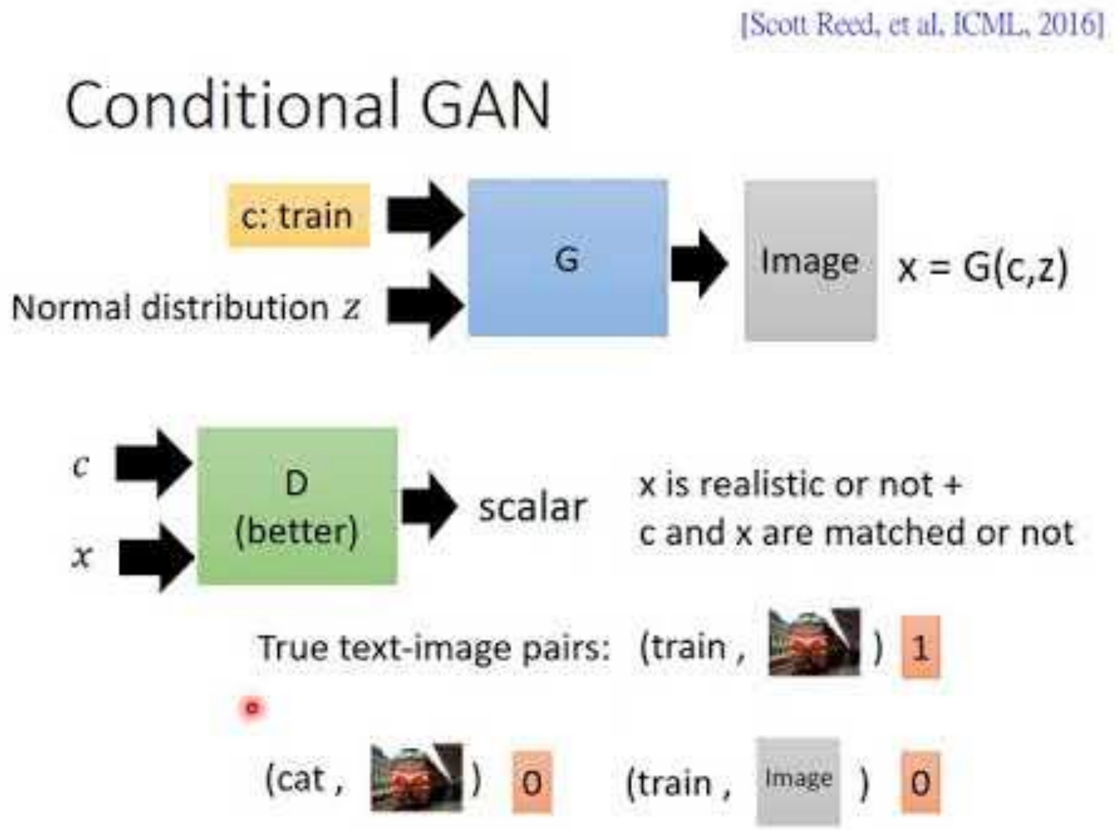
Key Insight

- Generative Modeling:
  - This can be boiled down to a classification problem when we introduce the concept of a discriminator
  - We can have two models. One generator and one discriminator (which discriminates whether the input is from the real dataset or from the generator).
  - Thus we can train the two models end to end and jointly like a classification problem using the cross entropy loss.



Proposed Approach

- Given a black & White sketch, our model can generate a painted colorful image.
- We use Conditional GANs (CGANs) to model our generative painter
- We use 4 Loss functions to train the CGAN:
  - Normal GAN loss
  - Pixel Level Loss
  - Feature Level loss
  - Total Variation loss



1. GAN Loss

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

- Objective function is a min max function (Game theory)
- Think of this as a police thief game
- The discriminator tries to maximize the above using gradient ascent
- The generator tries to minimize the above using gradient descent
- Our objective is to reach Nash Equilibrium

Ok now we have a loss function which looks just fine! so why the other 3 losses?

- It is not as easy as it sounds to train a GAN using the above loss function
- GAN training collapses easily!
- We need to stabilize GANs
- That's the main purpose of the other 3 loss functions!

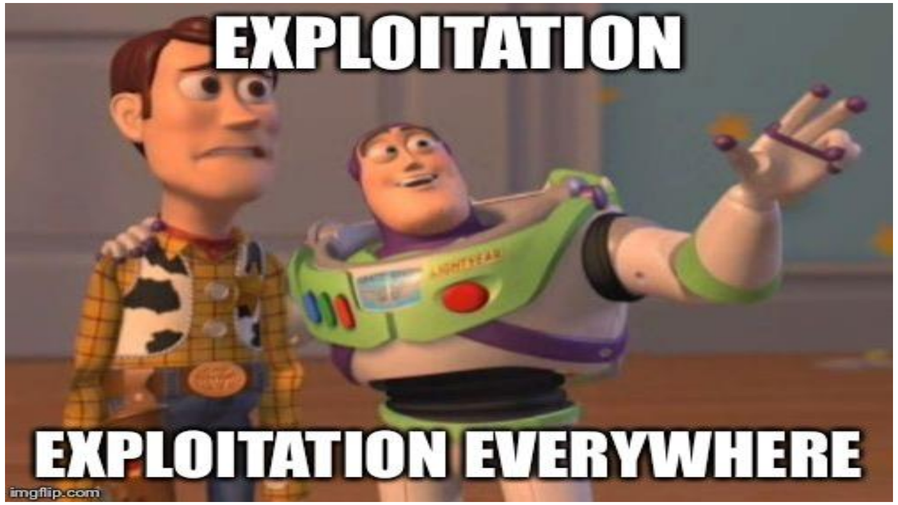
2. Pixel level Loss

$$L_p = \mathbb{E}_{x,y \sim p_{data(x,y)}, z \sim p_{data}(z)} [\|y - G(x,z)\|_1]$$

- This is just the L1 distance between each pixel of target color image and the generated color image.
- Why?: Intuitively this should help the model learn the correct color shades.
- What is missing in this?: Even though this will help the model learn the correct color shades, it doesn't correlate which features should get which color shades.
- The feature and color correspondence is not properly represented by the Pixel level Loss.

Learning the relation between image features and colors

- We know that CNNs extract features from the image
- We can exploit this fact to model the relation between image features and colors.



3. Feature Level Loss

$$L_f = \mathbb{E}_{x,y\sim p_{data(x,y)}, z\sim p_{data}(z)} \left[\|\phi_j(y) - \phi_j(G(x,z))\|_2 \right]$$

- This is similar to Pixel level loss. But we use L2 distance instead of L1
- Instead of calculating it on the images we pass the images through VGG-16 and calculate it on the 4th layer output VGG-16. This should have some information about the features in the image.
- Why 4th layer?: Well it's through experimentation we found that this works best for our case :P

4. Total Variation Loss

$$L_{tv} = \sqrt{(y_{i+1,j} - y_{i,j})^2 + (y_{i,j+1} - y_{i,j})^2}$$

- We use this loss to prevent color mutation.
- This constraints the pixel changes in the generated results and encourages smoothness.
- Think of this like a form of regularization

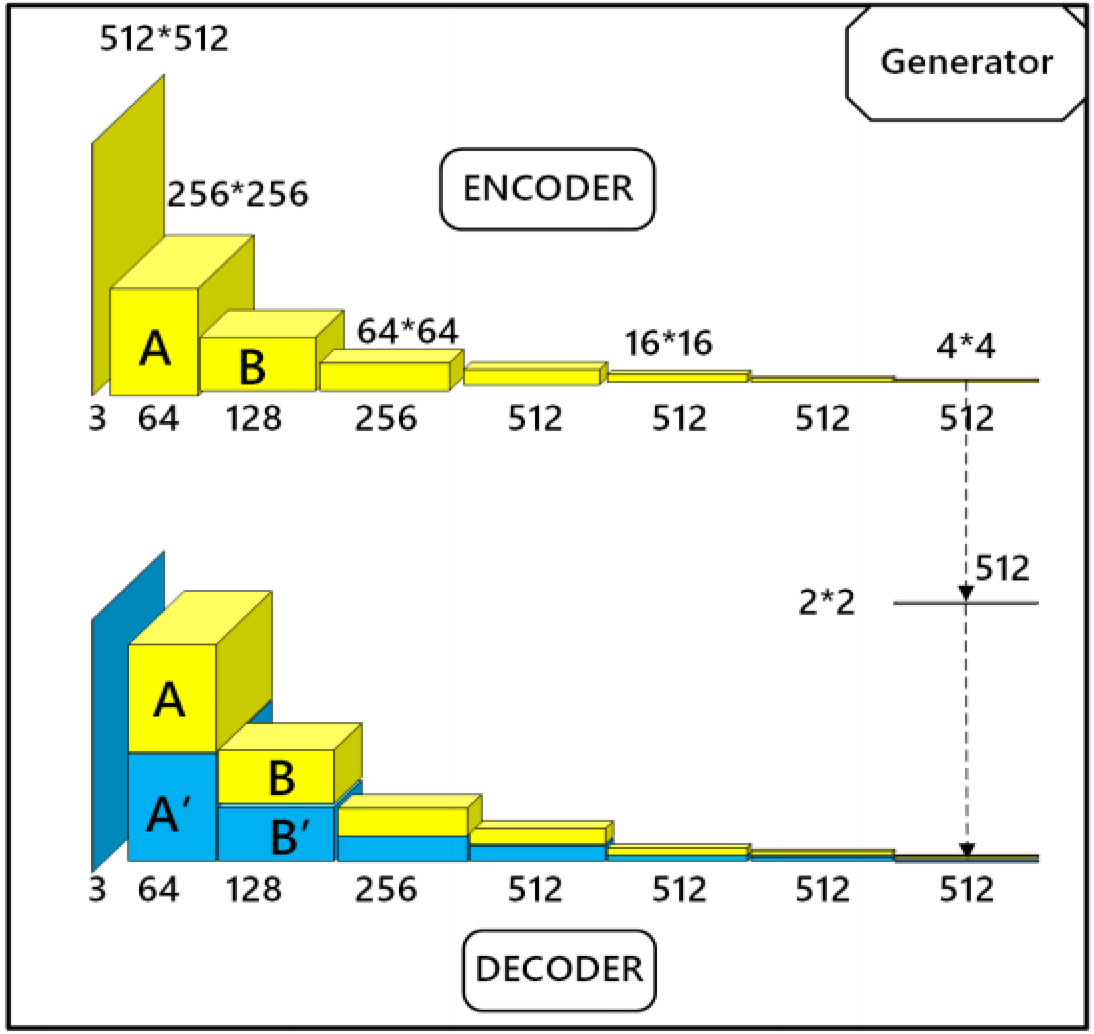
Combining the 4 losses

$$L = w_p L_P + w_f L_f + w_G L_G + w_{tv} L_{tv}$$

- We train the CGAN using a weighted combination of the 4 losses mentioned
- The weights are adjusted according to how important each loss is.
- We use the following weights:
  - Pixel Level Loss weight: 100
  - Feature Level Loss weight: 0.01
  - Total Variation Loss weight: 0.0001
  - Normal Gan Loss weight: 1.0

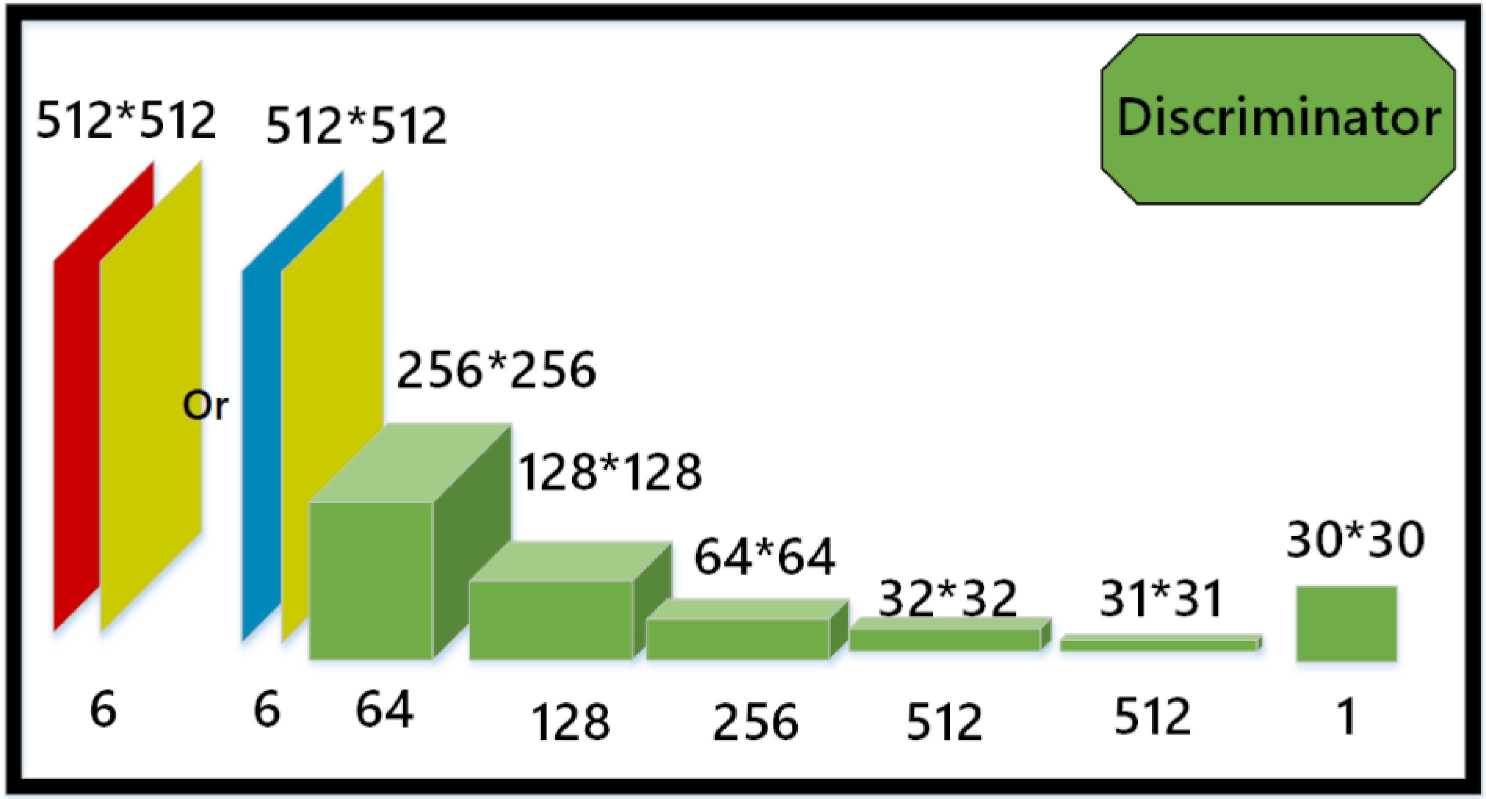
Generator Architecture Inspiration: U-Net

- It consists of an Encoder which reduces the 512 x 512 x 3 image to a latent dimension of 2 x 2x 512 using comvolution operations
- The decoder takes this latent dimension as input and upsamples it to 512 x 512 x 3 using Transposed convolution operation
- To improve the performance of the decoder, we concatenate the corresponding layers of the encoder with the decoder
- The generator is conditioned on the input sketch (obviously :P)



Discriminator Architecture

- The discriminator takes a 512 x 512 x 3 image (either from the training set or the generator output)
- This maps this input to a latent dimension of 30x30x1
- Each element of that gives the probability of being real for a pair of corresponding patches from the input sketch and the colored image.

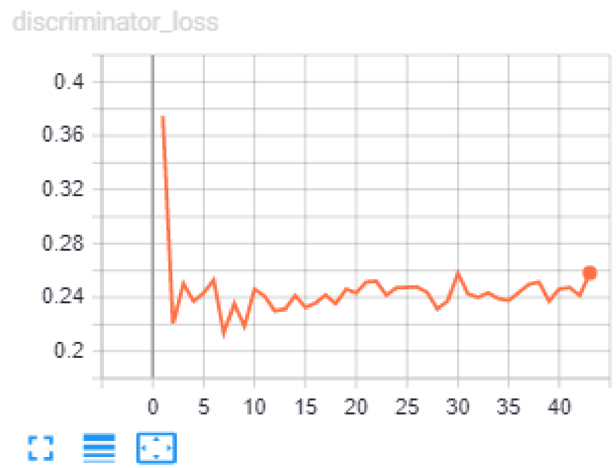


Dataset details

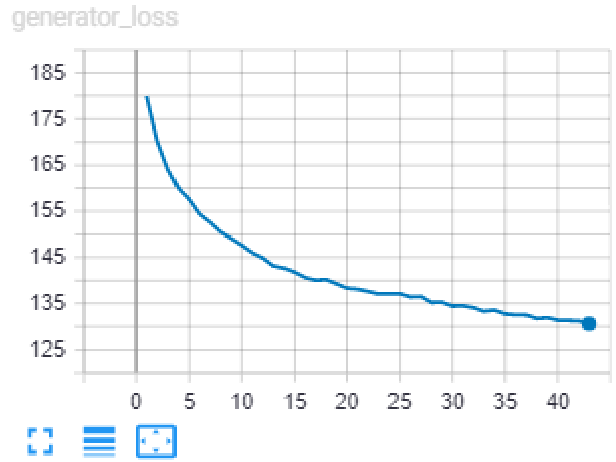
- Anime Sketch Colorization Pair from Kaggle
- This Dataset consists of Anime sketches and their corresponding image after colorization
- This dataset is perfect for our case
- This dataset has 14,224 pairs of training sketches and colored images
- 3545 pairs of test sketches and colored images

Training progress

discriminator_loss



generator_loss



Took approximately 12 hrs to train!

Code link

https://github.com/Abhijit-2592/cnn_project3

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Resulting good images

Input

Output

Resulting good images

Input

Output

Resulting good images

Input

Output

Resulting bad image

Input

Output

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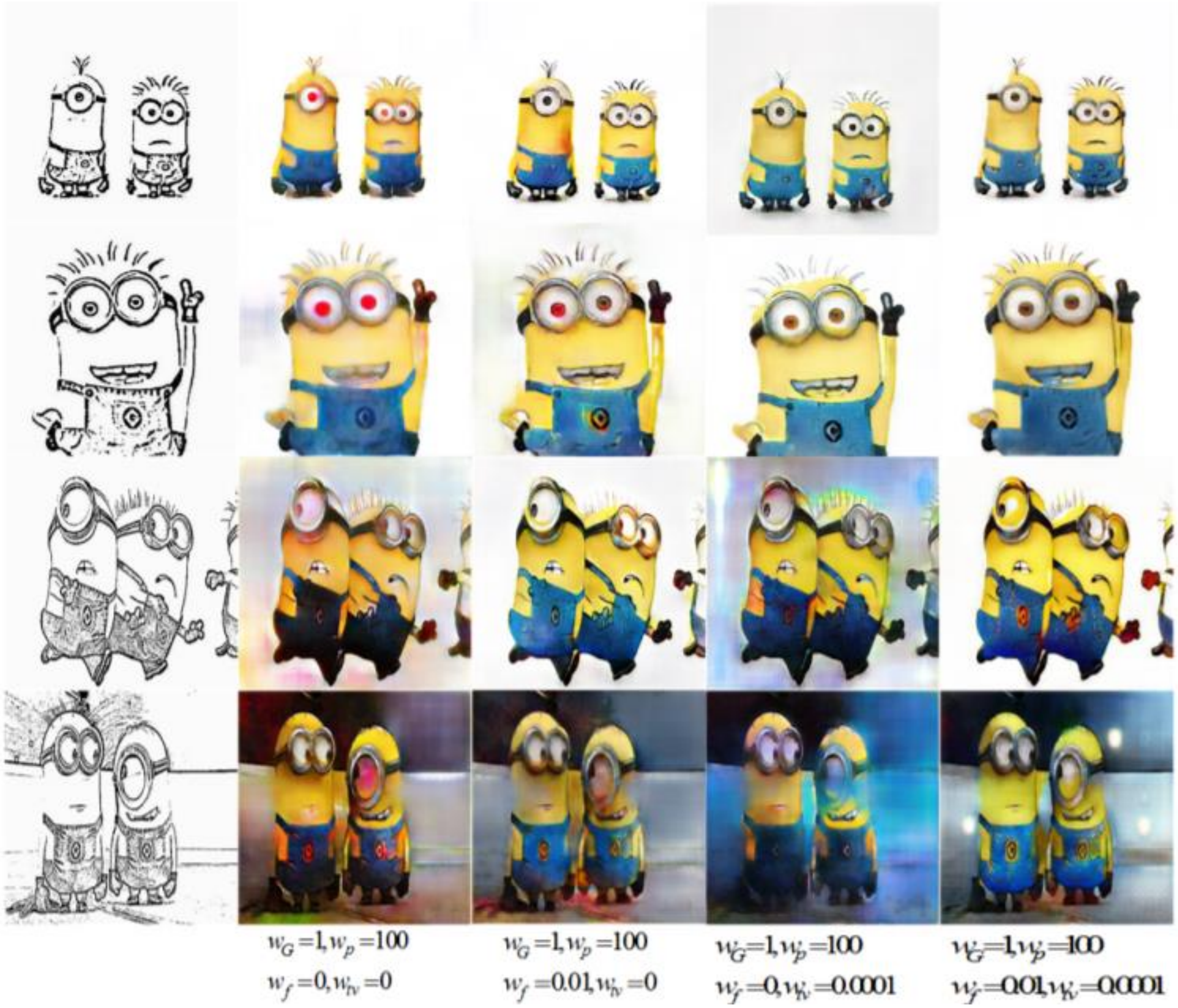
Results

Results of Ablation experiments on Different values of weights for the loss function



Next Steps

- The generative painter even though performs fairly on some sketches it fails in others.
- The color looks kind of washed away in most generated images and sometimes look unnatural.
- In future we will try to improve this work by increasing the stability of the generated color image so that the images look as natural as possible

References

- Note: As stated above, this presentation is a work of fiction; the following are the actual inventors of the ideas described in this presentation

- Liu, Yifan, Zengchang Qin, Zhenbo Luo and Hua Wang. “Auto-painter: Cartoon Image Generation from Sketch by Using Conditional Generative Adversarial Networks.” *ArXiv* abs/1705.01908 (2017): n. pag.
- Ronneberger, Olaf, Philipp Fischer and Thomas Brox. “U-Net: Convolutional Networks for Biomedical Image Segmentation.” *MICCAI* (2015).
- Goodfellow, Ian J., Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville and Yoshua Bengio. “Generative Adversarial Networks.” *ArXiv* abs/1406.2661 (2014): n. pag.
- Radford, Alec, Luke Metz and Soumith Chintala. “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.” *CoRR* abs/1511.06434 (2016): n. pag.
- Mirza, Mehdi and Simon Osindero. “Conditional Generative Adversarial Nets.” *ArXiv* abs/1411.1784 (2014): n. pag.
- Code reference: https://github.com/sanjay235/Sketch2Color-anime-translation
- Other references: https://machinelearningmastery.com/

Thank You!