



INTRODUCTION

Composing an image, especially a photorealistic, high-resolution one, often requires hours of highly repetitive work. In addition, the complicated nature of image editing software makes the work very tedious. A solution lies with using Generative Adversarial Networks (GANs) to generate images from rough sketches. Figure 1 shows the structure of a GAN. These GANs are trained on pseudo-sketches, sketches generated using an algorithm from a real image. Unfortunately, the images generated by these GANs on human-drawn sketches are of lower quality than those generated on pseudo-sketches, hampering the application of GANs in real life. Upon analysis, we discover that this may be due to the pseudo-sketches containing too many unnatural details that are not present in human-drawn sketches.

The aim of our research project is to remove these unnatural details to enable the GAN to generate realistic images from human-drawn sketches.

> Fig 1. GAN diagram



Fig 3. Original pseudo-sketch

Improved sketch

The improved sketch does not contain as many unnatural details and resembles an actual human-drawn sketch much more closely. Training the model on these improved sketches made the model perform better on human-drawn sketches.

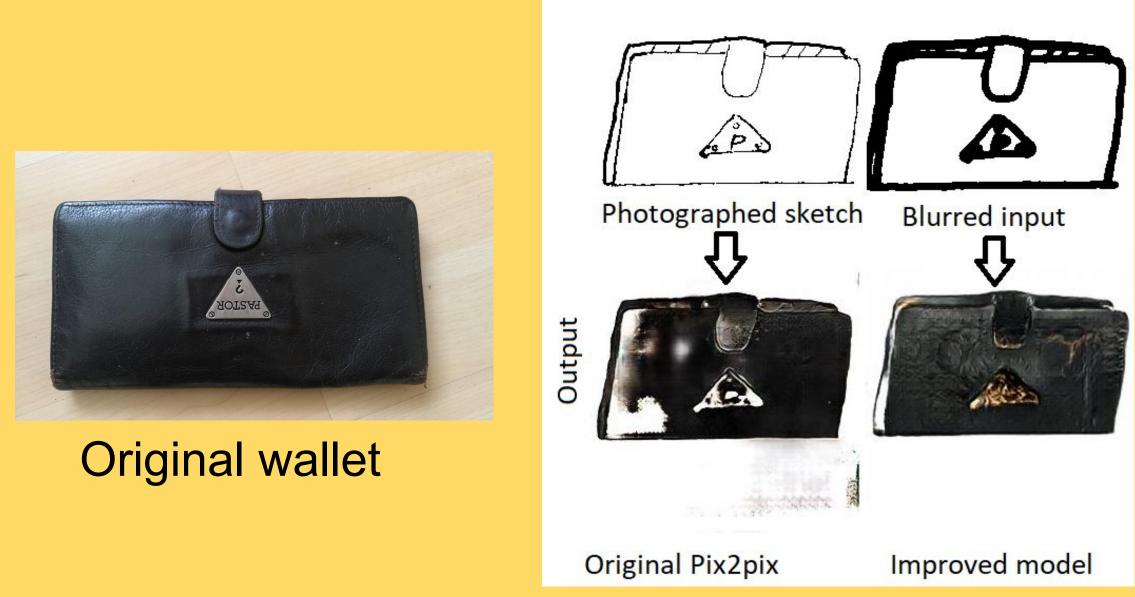
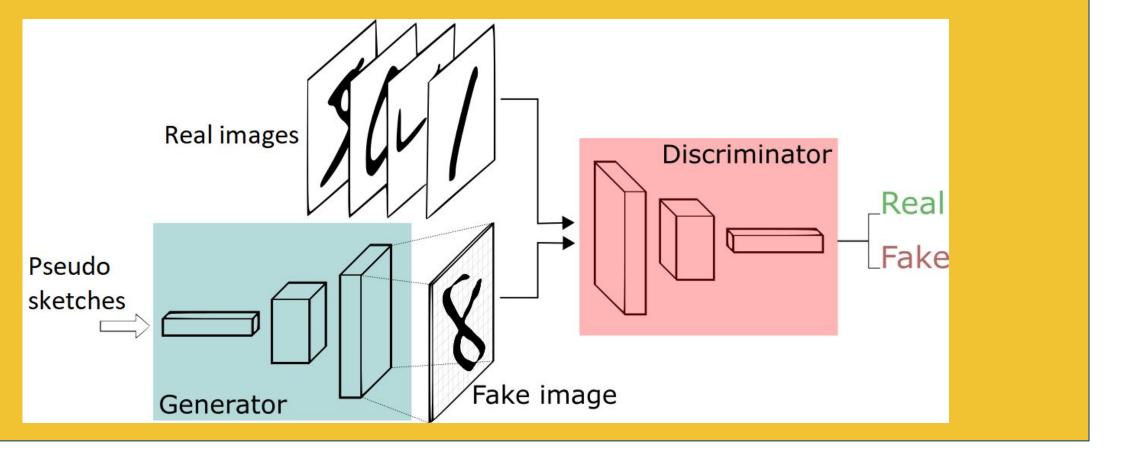


Fig 4. The improved model has substantially improved performance

The improved model generated an image with less white space and realistic use of colors, whereas the original model left the lower left portion and the triangle blank. However, the texture on the generated image leaves room for improvement.

Generating Realistic Sketch-Based Images via GANs

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Actual bag

DISCUSSION, ANALYSIS, AND EVALUATION

The output of the Sketch Based Image Synthesis (SBIS) Neural Network on human-drawn sketches is substantially naturalized.

Before, there were significant problems with the generated images. There are still some differences, but the biggest discrepancies have vanished.

We have vastly improved the resilience of SBIS algorithms to variations in the quality of input sketches. original model only accepted thin lines. image processing methods can be highly successful.

Special thanks to Dave Shen for giving helpful feedback on our milestones. Works Cited:

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... Bengio, Y. (2014). Generative adversarial nets. Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., ... Shi, W. (2017). Photo-realistic single image super-resolution using a generative adversarial network.

Goodfellow, I., Salimans, T., Zaremba, W., Cheung, V., Radford, A., Chen, X., (2016) Improved Techniques for training GANs. Isola, P., Zhu, J., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. Güçlütürk, Y., Güçlü, U., Van Lier, R., & Van Gerven, M. A. (2016). Convolutional sketch inversion. Jin, Y., Zhang, J., Li, M., Tian, Y., Zhu, H., & Fang, Z. (2017). Towards the automatic anime characters creation with generative adversarial networks.

Karpathy, A. (n.d.). Generative adversarial networks.

Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., ... Shi, W. (2017). Photo-realistic single image super-resolution using a generative adversarial network.

Liu, Y., Qin, Z., Luo, Z., & Wang, H. (2017). Auto-painter: Cartoon image generation from sketch by using generative adversarial networks. Osokin, A., Chessel, A., Carazo Salas, R. E., & Vaggi, F. (2017). GANs for biological image synthesis. Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. (2016). Generative adversarial text to image synthesis.

RESEARCH METHODOLOGIES

- We use a GAN hosted on a GPU server to create our Real photos of handbags sketch-based image synthesis program. Our main focus is to improve the program by feeding higher-quality test data that the GAN can use.
- We apply Gaussian blurring with a kernel size of 9X9 pixels, followed by thresholding. These two steps merge the lines that are close together but originally separate, eliminating unnecessary and unnatural details. The GAN is then trained on these images with batch size 1 and 40 epochs of 10000 training examples each.
- Our goal is to collect both quantitative and qualitative data: quantitative data in the form of image statistics for every trial and qualitative data in the from of the images themselves.

- For example, the performance of the model does not differ much between sketches drawn with thicker lines and thinner lines. The
- As a result, real life application of SBIS is now much more viable. We also proved that augmenting Neural Networks with conventional

CONCLUSIONS, IMPLICATIONS, AND NEXT STEPS

By combining our SBIS network with augmented test data, the quality of our generated images have substantially improved. However, some issues more dependent on the nature of the neural network still remain. For example, computation of the mean power spectrum for computer-generated images fail to match distributions of ones generated using natural images.

Future work: 1. Generalized SBIS program animal pictures.

2. Color-hints

3. Additional augmentation

We have shown that augmenting advanced neural networks with conventional image processing algorithms can result in great improvements. More methods of augmentation should be explored to discover more of the potential of this strategy.





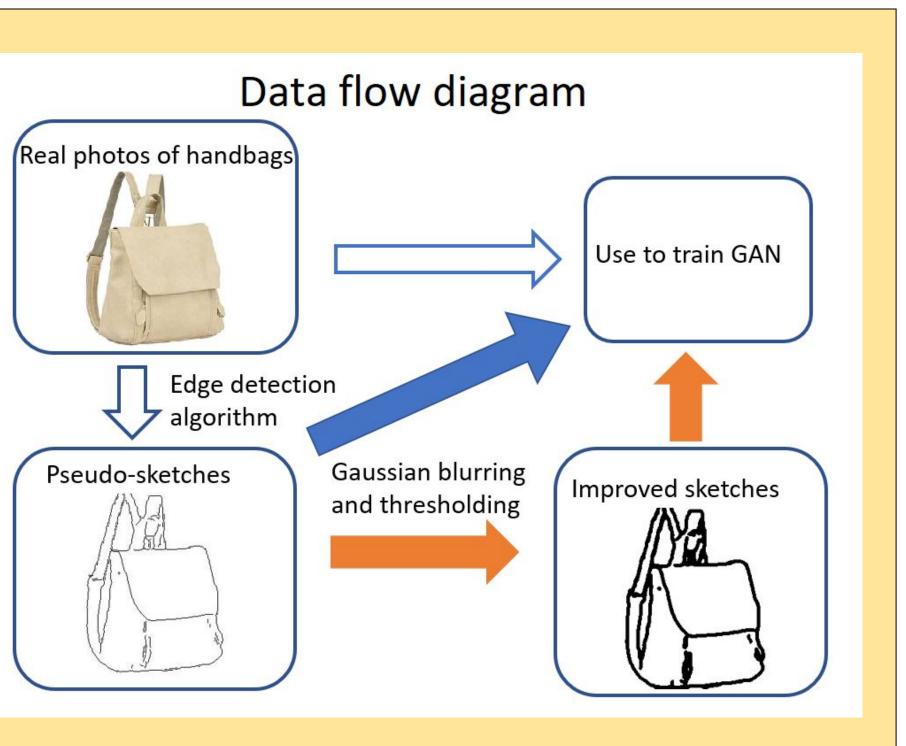


Fig 2. Research Methodology Visualized

Right now, our program mainly focuses on handbags. We can see if our results hold if we replicate our experiment using different types of test data, such as

The author can currently only control the shape, not the color, of the generated image. We can work toward enabling color-control by placing blots of the desired color in parts of the sketch.