Image Super Resolution for Facial Recognition

Corey Shih
ctshih@stanford.edu

Abstract

The problem of super resolution entails artificially enhancing the resolution of a low resolution image to obtain a plausible corresponding higher resolution image. This is of particular use to images used for facial recognition, as higher resolution inputs can improve the performance of facial recognition systems. In this project, I train two conditional generative adversarial networks (cGANs) to output 250 × 250 images from 50 × 50 and 25 × 25 input images of human faces. The resulting outputs are clearer than those obtained from bicubic interpolation, but still leave room for improvement.

1. Introduction

Facial recognition systems are becoming increasingly common in day-to-day life; however, one of the biggest detractors from the performance of such technology is blurry or low resolution images. Traditional techniques for increasing image resolution, such as interpolation, usually result in blurry images. Being able to produce accurate estimates of high resolution images from low resolution ones would greatly improve the performance of facial recognition systems, and is the goal of the field of image super resolution. Image super resolution in general proves to be a challenging problem since there can be many plausible high resolution images corresponding to the same low resolution image.

This project attempts to generate 250 × 250 color images of human faces from 25 × 25 and 50 × 50 color image inputs of faces. The inputs are fed into a cGAN, which take either the 25 × 25 or 50 × 50 image as input, and generate a higher resolution 250 × 250 output image.

2. Related Work

This project was inspired by work done by Ryan Dahl, Mohammad Norouzi, and Jonathon Shlens at Google Brain on pixel recursive super resolution.[1] In the paper, they implement an extension of PixelCNN using a new probabilistic network architecture that is trained end-to-end using a log-likelihood objective. The model is capable of generating 32 × 32 color face images from mere 8 × 8 color inputs. Instead of utilizing a CNN, I attempt to tackle a similar problem using a cGAN instead.

3. Dataset and Features

Images were taken from the Labeled Faces in the Wild (LFW) database, which provides 13233 images of 5749 different people from the web.[2] The database consists of color images that are 250 × 250 in resolution. I used TensorFlow to downscale these images to 25 × 25 and 50 × 50 resolution using nearest-neighbor interpolation for use in training two separate models. The low resolution and corresponding original resolution image are fed into the GAN as an input/target pair. The image pairs were split into training and test sets with 10586 and 2647 images, respectively. Figure 1 shows an example of an image from the dataset, as well as its lower resolution versions that are used as inputs to the model.

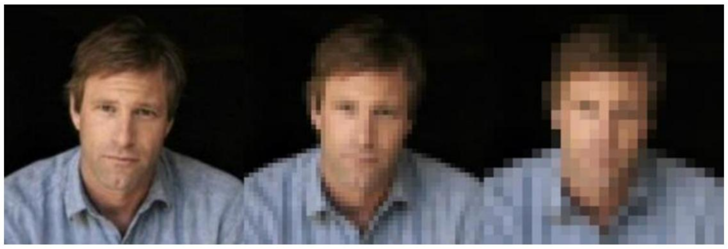


Figure 1. Example of image in dataset. From left to right: original 250 × 250 image, 50 × 50 input, 25 × 25 input.

4. Methods

Two cGAN models were implemented using the pix2pix architecture by Isola et al. for 25 × 25 inputs and 50 × 50 inputs.[3]

GANs consist of two major components, the generator and the discriminator. The generator takes in the low resolution input (25 × 25 or 50 × 50) and outputs a 250 × 250 resolution image. The discriminator takes in the input/target and input/output image pairs and attempts to determine which pair is real and which is generated. The generator's parameters are then updated based on the gradients from the loss of the discriminator. By training in this way, the generator is learning to beat the discriminator, and ideally by the end of training will be capable of generating plausible images capable of fooling the discriminator or a human.

In general, the losses of the discriminator and generator are the standard cross-entropy losses for classification problems. The discriminator loss is given by:

$$J^{(D)} = -\frac{1}{m_{real}} \sum_{i=1}^{m_{real}} y_{real}^{(i)} \log\left(D\left(x^{(i)}\right)\right) - \frac{1}{m_{gen}} \sum_{i=1}^{m_{gen}} (1 - y_{gen}^{(i)}) \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)$$

The generator loss is given by:

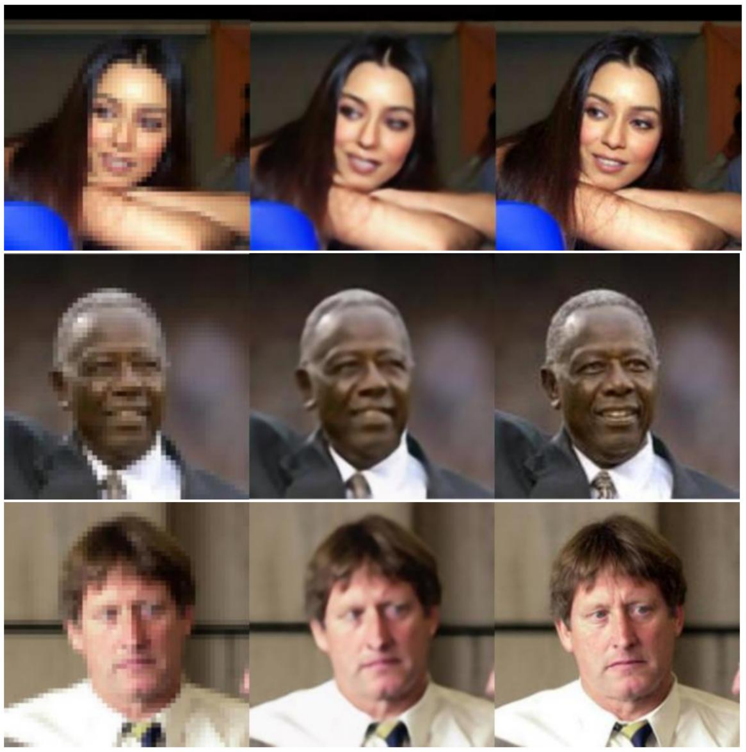
$$J^{(G)} = -\frac{1}{m_{gen}} \sum_{i=1}^{m_{gen}} \log\left(D\left(G\left(z^{(i)}\right)\right)\right)$$

Here, D and G represent the discriminator and generator outputs, respectively. For this implementation, I also added a L1 loss term to the generator loss, which measures the difference between the output image and target image. In doing so, the generator is incentivized to generate images similar to the target image.

For this project, I used TensorFlow to train both cGAN models on a Tesla K80 GPU for 10 epochs, taking roughly 10 hours each. An Adam optimizer was used with a learning rate of 0.0005, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 10^{-8}$. A mini-batch size of 128 was used for training.

5. Results and Discussion

Some results from both the 25 × 25 and 50 × 50 models are shown in the figures below.



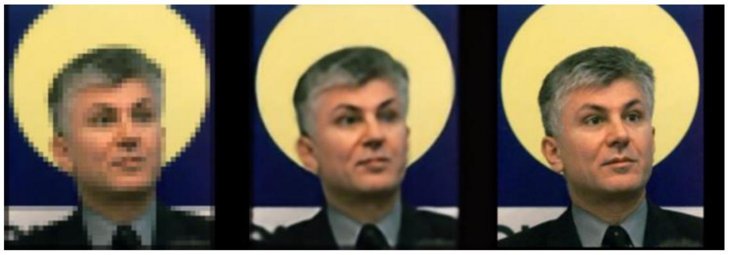


Figure 2. Example results from 50 × 50 model. From left to right: 50 × 50 input, 250 × 250 output, 250 × 250 target.

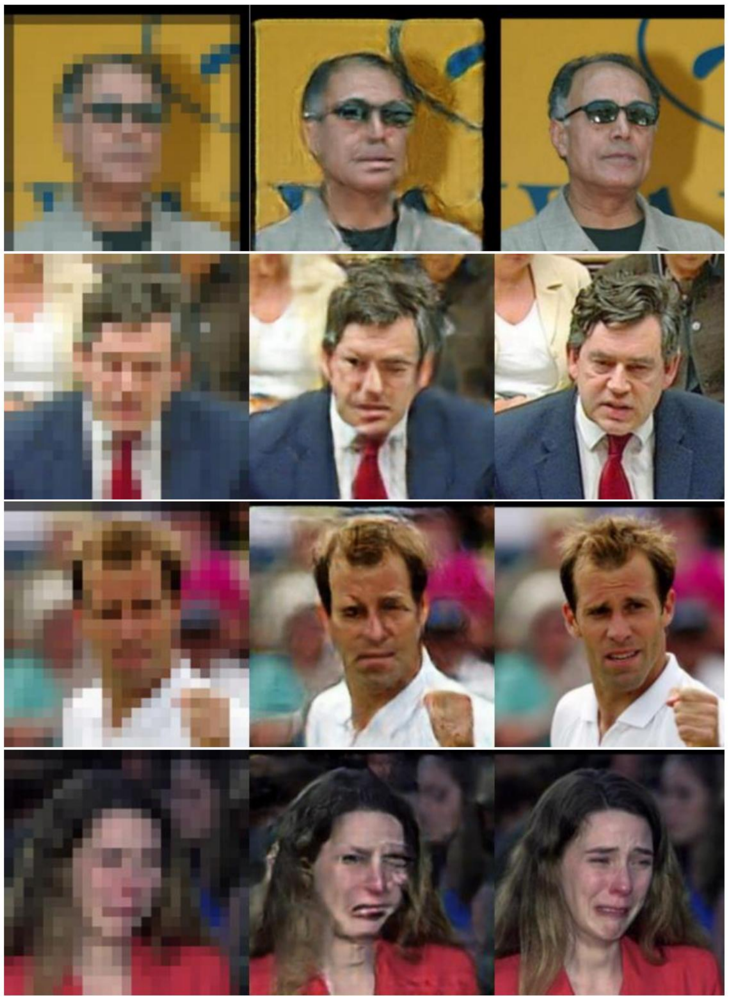


Figure 3. Example results from 25 × 25 model. From left to right: 25 × 25 input, 250 × 250 output, 250 × 250 target.

From Figure 2, the outputs from the 50 × 50 model generally look very reasonable, although they are still quite blurry when compared to the target images. The results from the 25 × 25 model in Figure 3 show that the outputs are much more distorted and have more artifacts, likely due to the fact that there is much less information to work with in such low resolution input images. For the most part, the cGAN seems to do a reasonable job of simulating higher resolution images, but the results are still far behind that of Dahl et al. One reason for this is due to the fact that the authors of the Google Brain paper worked with 8 × 8 inputs and 32 × 32 targets, which is a factor of 16 increase in the number of pixels. For comparison, going from 50 × 50 inputs to 250 × 250 targets is a factor of 25 increase in pixel count, and 25 × 25 inputs to 250 × 250 targets is a factor of 100 increase. The models implemented in this project need to simulate many more pixels, making the overall task more difficult.

Both models perform significantly worse on images of people with their face at an angle, likely due to the fact that there simply are not as many images of angled faces in the database. Incorporating more of such images into the training set may improve performance on such examples.

Figures 4 shows a comparison between the output images from the 50 × 50 model and the corresponding result from bicubic interpolation. While still a bit blurry, the outputs from the 50 × 50 model are noticeably clearer than the images obtained from bicubic interpolation. Edges in particular are much sharper in the model output, and jagged edges are not present. The overall level of detail in both images is still significantly less than that of the target image.

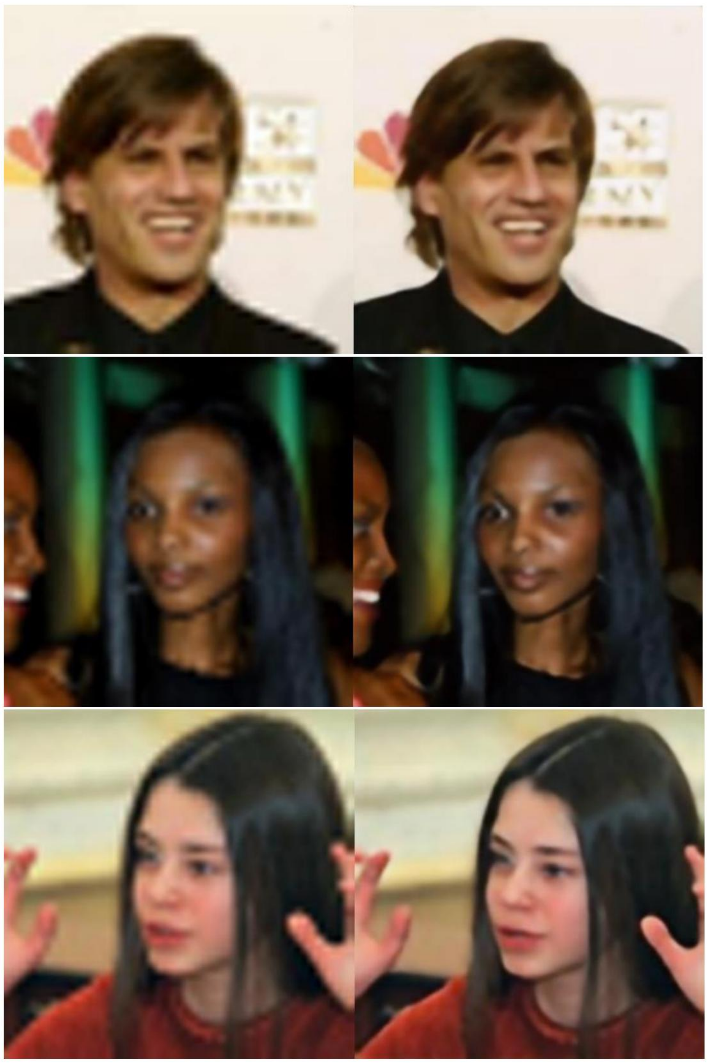


Figure 4. Bicubic vs. Ouput for 50 × 50 model. The bicubic interpolation image is on the left, and the output of the model on the right.

The blurriness of the output images from both models is potentially due to the L1 loss term incorporated into the generator loss. Such a term attempts to minimize the difference between the output and target images, but in doing so, also tends towards blurrier images, as such images are easy to generate and tend to have low L1 losses when compared to the target image. Adjusting the weight of this term in the generator loss could lead to clearer images at the cost of some accuracy. Overall, GANs can be notoriously hard to train, and hyperparameter tuning proved to be difficult. Increasing the learning rate or training for too many epochs led to the discriminator becoming too powerful, leaving the generator without useful gradients to train on. Handicapping the discriminator by updating it less frequently or adding Gaussian noise to the data could help with this issue, although it may still prove finicky.

6. Conclusion and Future Work

Using images from the LFW database, I trained a cGAN based on the pix2pix architecture to generate 250 × 250 output images of human faces from 50 × 50 and 25 × 25 inputs. Both models resulted in clearer images than those obtained from interpolation, but were still blurry when compared to the target images. The 25 × 25 model exhibited significant distortion due to the lack of information in the low resolution image. Additional hyperparameter tuning and/or handicapping the discriminator may be useful in training a better model.

A number of additional methods could also be implemented to improve the performance of the models trained in this project. Additional data preprocessing such as cropping or deep funneling could improve network performance. Exploring larger alternative datasets, such as the VoxCeleb dataset, might also yield better results. Furthermore, trying alternative network architectures or perhaps simpler CNN models could also be worthwhile.

7. Contributions

All work on this project was done by Corey Shih.

8. References

1) Dahl, R.; Norouzi, M.; Shlens, J. Pixel Recursive Super Resolution, *arXiv,* **2017.**

2) Huang, G.B.; Ramesh, M.; Berg, T.; Learned-Miller, E. Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments, *University of Massachusetts,* **2007,** *Amherst, MA, USA.*
3) Isola, P.; Zhu, J.; Zhou, T.; Efros, A.A. Image-to-Image Translation with Conditional Adversarial Networks, *arXiv,* **2016.**