Super resolution enhances the resolution of a low-res image. Both improve the quality of the super-resolved output. Uses a separately trained classifier to inform a ResNet about character attributes. Both improve the quality of the super-resolved output.

Related Work

Generative Adversarial Networks (GAN)

In 2014, Goodfellow et. al [1] introduced the GAN framework for deep learning, in which a generative model competes with a discriminative adversary in a two-player minimax game:

$$\min_G \max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p_z} [\log (1 - D(G(z)))]$$

Discriminative model determines whether a sample is generated or a data example.

Generative model attempts to fool the discriminative model.

GANs for Super-Resolution (SRGAN)

Ledig et al. [2] proposed a model with the capability to implement large upscaling factors (4×) with photo-realistic reconstructions of low-resolution images:

Feedforward network as the generating function

Perceptual loss as weighted combination of components

Features a deep residual network

SRGAN results are nearly indistinguishable compared to the original. [2]

Conditional GANs (CGAN)

New frameworks introduce additional information to improve the performance of GANs.

We model work on conditional GAN, introduced by Mirza et al. [3]:

- Discriminator (D) and generator (G) models are conditioned on auxiliary information y.

GANs + Auxiliary Class Information

We introduce two methods for implementing the conditional GAN framework.

1. Conditional GAN

We use a conditional predictive distribution for the discriminator and generator based on class information, y:

$$E_{x \sim p_{data}} \left[ \log D_{\theta_{D}} (x) \right] + E_{z \sim p_z} \left[ \log (1 - D_{\theta_{D}} (G_{\theta_{G}} (z) | y)) \right]$$

2. GAN + Class Loss

As another method to introduce class information, we implemented a loss function that comprises GAN loss as well as an added class loss term.

- Chose gender (Male/Female) as our conditional attribute for experiments
- Trained a gender classifier with 95.6% test accuracy, and used this checkpoineted model to compute class loss in the super-resolution model.

Class loss = cross entropy loss between predicted classes of true image and generated image.

In effect, penalize the generator for predicting an image that is not aligned with the original image’s class (gender, in this case).

Hypothesis: Penalties cause the model to maintain some of the finer class details. For example, a woman with short hair should be more likely to have feminine features than a man with short hair.

Conditional GAN (MNIST)

We trained the Conditional GAN model on the MNIST dataset.

- Concatenate class information, y, to the inputs of feed-forward G/D models

Observations

- The Vanilla GAN produces artifacts that make certain digits appear ambiguous (red highlight)
- For same examples, the C-GAN produces results that are more recognizable as digits.

GAN + Class Loss (CelebA)

We trained the GAN + class loss model with CelebA, and saw significant differences between our model and the plain GAN super-resolution model.

- Generally, both model outputs are similar in overall quality.
- When the original GAN generates an output image that has features from the opposite gender, (see image above).
- Left: GAN + class loss model produced image with feminine features
- Right: GAN model output resembles a face with male features

Our image, on the left side, has much more feminine features and face structure. This is consistent with the true gender classification of the image: female.

Takeaways

- Introducing auxiliary information into GANs for super-resolution helps maintain true attributes of images.
- GANs are notoriously difficult to train. Introducing class loss omits the need to train entirely new models. Instead, we fine-tune existing, working models.
- Would be interesting to continue exploring different methods of introducing auxiliary information to models (i.e. InfoGAN [4])

References


"Due to the pre-labeled CelebA dataset, there exists a dichotomy between faces labeled ‘masculine’/‘feminine’. We hope not to reinforce these conventions, and instead suggest that more thoughtful approaches must be taken to train real-world models based on subjective attributes.

*(Our classifier only had 4.4% error rate, so these examples are rare.)*