Super-Resolution with GANs

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1. Introduction

We call super-resolution (SR) the task of estimating a high-resolution (HR) image from its low-resolution (LR) counterpart. Recent work with optmizition-based methods largely focuses on minimizing the mean squared reconstruction error. This results in high peak signal–to–noise ratios, but they often have problems with modelling high–frequency details. The results are often too smooth. In our work we tried to tackle this problem using generative adversarial networks (GANs).

2. GANs

GANs consist of two different networks, a Generator Network and a Discriminator Network. The concept behind this is that the generative network estimates a super-resolved image from its LR version with the goal to become highly similar to real images that the discriminator network fails to distiguish.

Therefore we optimize the discriminator network D_{Θ_D} in an alternating manner along with the generative network G_{Θ_G} to solve the adversarial min-max problem:
G_{Θ_G} to solve adversarial min-max problem:

$$min_{\Theta_G} max_{\Theta_G} \mathbb{E}_{I^{HR} \backsim p_{\text{train}}(I^{HR})}[\log D_{\Theta_D}(I^{HR})] \\ + \mathbb{E}_{I^{HR} \backsim p_G(I^{LR})}[\log(1 - G_{\Theta_G}(I^{LR}))]$$

The perceputal loss l^{SR} we defined as weighted sum of a content loss and an discriminative loss component:

$$l^{SR} = \alpha l^{SR}_{MSE} + \beta l^{SR}_{VGG16_19/i.j} + \gamma l^{SR}_D$$

More precisely, the content loss components are defined as follows:

$$l^{SR}_{MSE} = \frac{1}{r^2 WH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I^{HR}_{x,y} - G_{\theta_G}(I^{LR})_{x,y})^2$$

$$l^{SR}_{VGG1619/i,j} = \frac{1}{W_{i,j} H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\Phi_{i,j}(I^{HR})_{x,y} - \Phi_{i,j}(G_{\Theta_G}(I^{LR}))^2_{x,y}$$

with downsampling factor r and W, H defining the tensor size. Finally the discriminative loss is defined as follows

$$l^{SR}_D = \sum_{n=1}^{N} -\log D_{\Theta_D}(G_{\Theta_G}(I^{LR}))$$

3. Setup

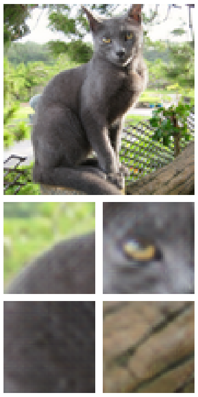
For training we used the PASCAL VOC Dataset[3] with more than 10,000 images as well as the NITRE Dataset[1] with 800 images.

We used pretrained VGG networks in different configurations. The best results were obtained when we used a VGG1619 network. We also considered a VGG16 network. Although faster at training it did not yield results of equal quality.

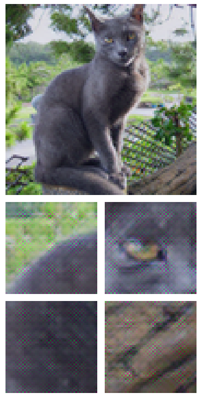
4. Results

We observed that the widely used metrics, SSIM and PSNE, i. e., structural similarity and peak signal to noise ratio respectively, are not sufficient for our purposes. This observation was also made by other authors dealing with image super resolution. Therefore, in addtion to the numerical values of the metrics, we also had to trust our perception of the images. This is similar to the mean opinion score (MOS) used in [7].

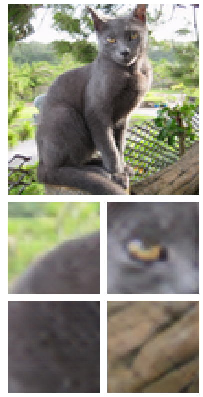
For comparison we include some samples of a image, that has been super–resolved by our methods.



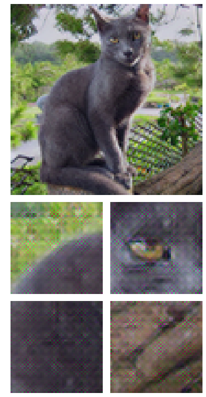
(a) VGG1619 perceptual, adversarial, image loss



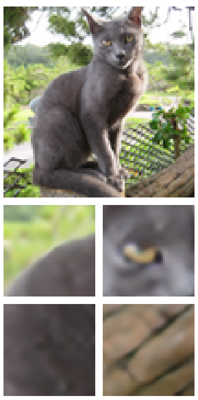
(b) VGG1619 perceptual, adversarial loss



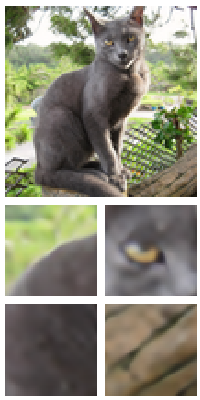
(c) VGG1619 perceptual, image loss



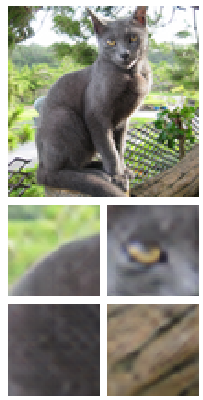
(d) VGG1619 perceptual loss



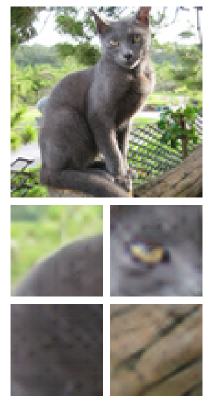
(e) VGG1619 adversarial, image loss



(f) VGG1619 image loss



(g) VGG19 perception, adversarial, image loss



(h) VGG16 perception, adversarial, image loss

5. Conclusion

One main point is, the training. It was very hard to keep the dicriminator and the generator in line. Often we killed our discriminator sucht that it could not contribute anymore.

We also observed that super resolution works even without any discriminator activated, as was suggested by the paper we started with.

Another key learning point is the quality of the produced images. The metrics don't change much from some point on but the visual impression of the generated images still improves.

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