

Introduction

We call super-resolution (SR) the task of estimating a high-resolution (HR) image from its low-resolution (LR) counterpart.

Recent work with optimization-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).

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 distinguish. Network Architektur einfügen
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:

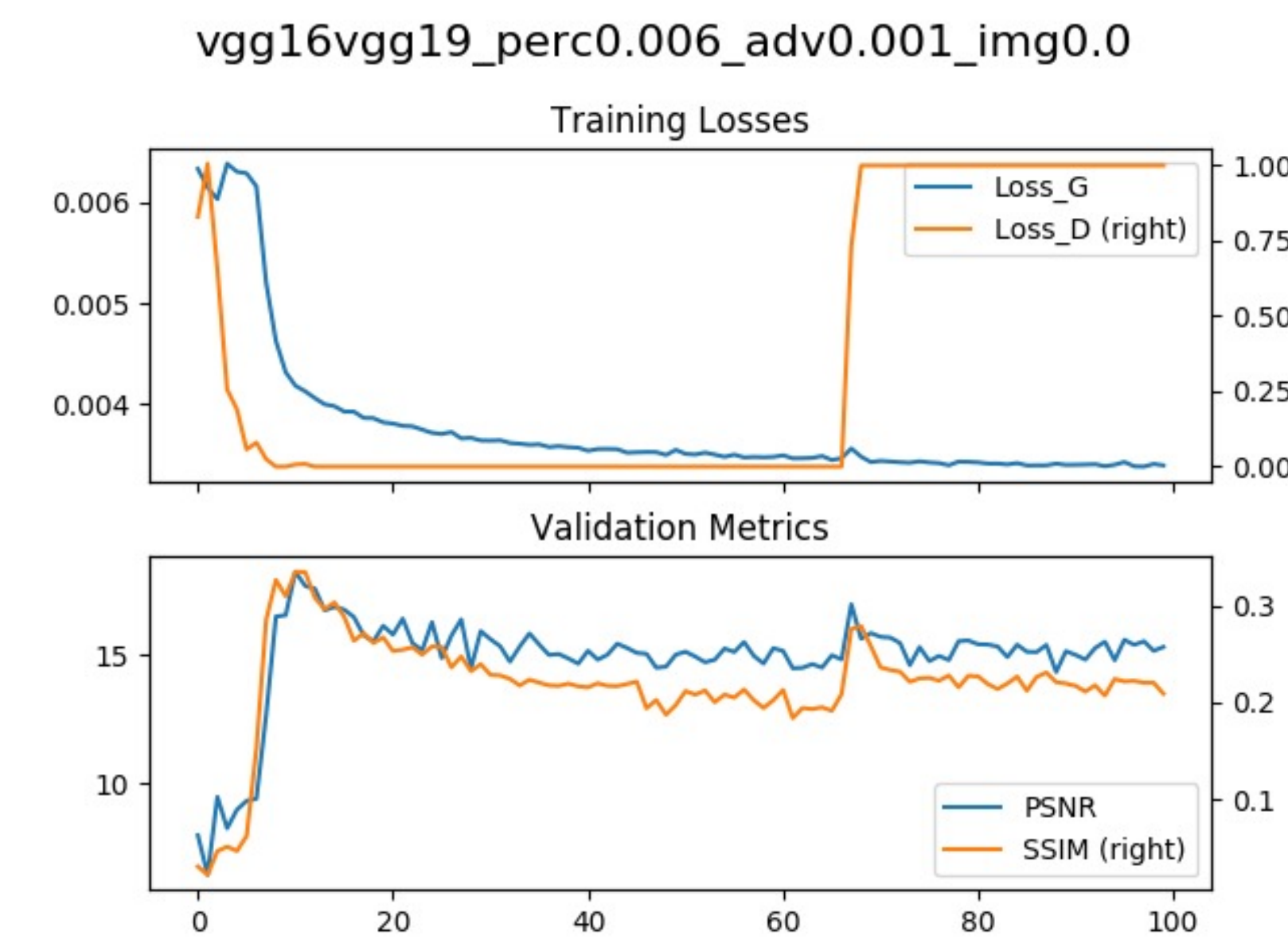
$$\min_{\Theta_G} \max_{\Theta_D} \mathbb{E}_{I^{HR} \sim p_{\text{train}}(I^{HR})} [\log D_{\Theta_D}(I^{HR})] + \mathbb{E}_{I^{LR} \sim p_G(I^{LR})} [\log(1 - G_{\Theta_G}(I^{LR}))]$$

Datasets

PASCAL VOC¹ over 10 000 images for classification in 20 categories

NITRE² 800 high resolution images

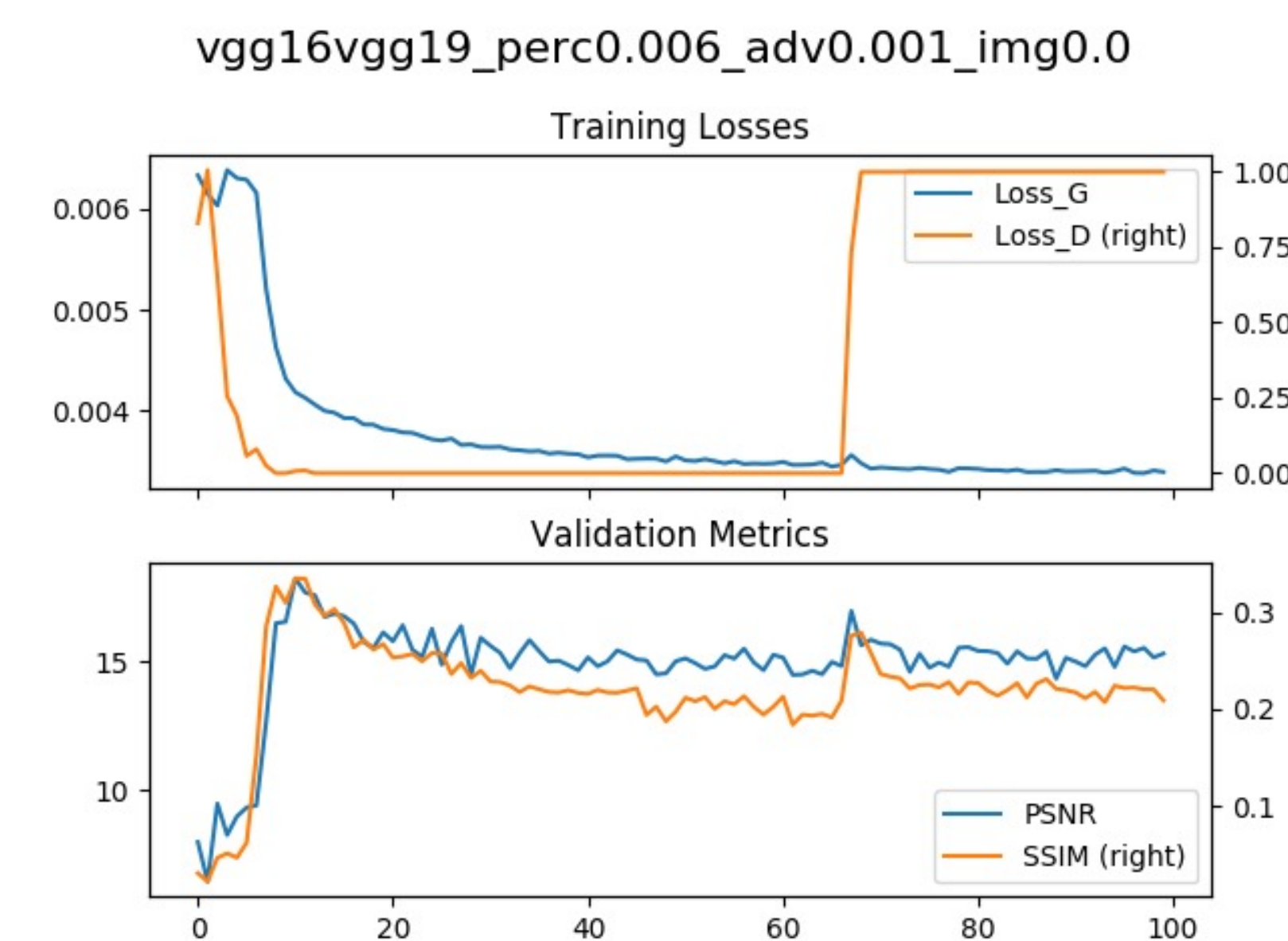
Statistics



Results



Statistics2



Results2



Main Results

- Networks learn even without discriminator
- Seemingly the training is faster with the use of a discriminator.
- Metrics do not change significantly after some training but the images get better
- In some settings the discriminator “dies” but images still improve
- Discriminator loss is extreme, either very low or very large; the transition is rapid
- Training the networks is tricky; discriminator “dies” often