Image-to-Image Translation with Conditional Adversarial Networks

Abstract

In this paper, we explore GANs in the conditional set- ting. Just as GANs learn a generative model of data, conditional GANs (cGANs) learn a conditional generative model . This makes cGANs suitable for image-to-image translation tasks, where we condition on an input image and generate a corresponding output image.

1. Related work

Structured losses for image modeling Image-to-image translation problems are often formulated as per-pixel classification or regression.

2. Method

GANs are generative models that learn a mapping from random noise vector z to output image y: G : z → y . In contrast, conditional GANs learn a mapping from observed image x and random noise vector z, to y: G : {x, z} → y. The generator G is trained to produce outputs that cannot be distinguished from “real” images by an adversarially trained discrimintor, D, which is trained to do as well as possible at detecting the generator’s “fakes”.

2.1. Objective

The objective of a conditional GAN can be expressed as

LcGAN (G, D) =Ex,y∼pdata(x,y)[log D(x, y)]+ Ex∼pdata(x),z∼pz(z)[log(1−D(x,G(x,z))]. (1)

LGAN (G, D) =Ey∼pdata(y)[log D(y)]+ Ex∼pdata(x),z∼pz(z)[log(1−D(G(x,z))]. (2)

LL1(G)=Ex,y∼pdata(x,y),z∼pz(z)[∥y−G(x,z)∥1]. (3)

G∗ = arg min max LcGAN (G, D) + λLL1(G). (4)

2.2. Network architectures

2.3. Optimization and inference

3. Experiments

3.1. Evaluation metrics

3.2. Analysis of the objective function

3.3. Analysis of the generator architecture

4. Conclusion