A deep introspection on Generative Adversarial Networks

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***Abstract*—GANs, namely Generative Adversarial Networks, are a hot topic nowadays.**

I. INTRODUCTION

Since its rise, deep learning had a great impact on discriminative models. Generative models instead were not affected by this innovation at first, but this trend changed with the introduction of Generative Adversarial Networks (GAN), a powerful framework first introduced in [1]. Since then, GAN gained more and more momentum because of the ability of training *deep generative models*, avoiding some of the difficulties encountered in other frameworks [2].

GAN is a sub-class of generative models where a probability density function (pdf) is implicitly defined; since GAN makes use of, generally two, *neural networks*, the pdf is induced by their architecture and parameters design: given a training set of sample data, distributed according to an unknown pdf p_d, the purpose of GAN is indeed to generate samples according to a distribution p_g, that mimics p_d, without explicitly defining it. As suggested by the name, this is achieved by putting in competition two entities: a generator and a discriminator. The task of the generator (G) is to generate data that can be regarded as true by the discriminator, while the discriminator (D) has the purpose of correctly distinguishing real from fake data. The classical real-life analogy with this process involves counterfeiters trying to produce fake currency and the police trying to detect it. This kind of interaction between the two entities can naturally be modeled with a game theoretical approach, where each player has its ownstrategies and payoffs, but in this paper we will rather talk about costs, as will be discussed in II. The major drawback of this framework anyway, is that the training of the model requires to compute the Nash Equilibrium (NE) of the game involving the two entities, which is not as simple as optimizing an objective function: without the guarantee of a NE, results obtained by the model could be different fom the ones desired.

In this paper we review some of the literature and explain our need to go back to the origins of GAN, implementing our own version of the code and simulating different scenarios, where in each one the discriminator is passed a different fake-to-true ratio of images.

The remainder of the paper is organized as follows: a brief overview of the literature is presented in II; a description of our work is then presented in III; the obtained results are presented in IV; finally we discuss our conlcusions in V.

II. RELATED WORK

Since their appearance in literature, GANs have been successfully applied to problems of image generation, editing and semi-supervised learning [5] [6]. *The results obtained with this technique were so good that they captured the attention of a great number of researchers, leading to a proliferation of various flavors of GAN, each performing better than the others on a specific domain.* It's difficult anyway to understand how to compare different GAN models, because of the lack of a consistent metric and the different architectures with which networks can be designed, which for each project are related to the corresponding computational budget. A tentative to define some guidelines to avoid these problems, together with a fair and comprehensive comparison of state-of-the-art GANs, is discussed in [3][MISSING ACCENTS ON REF]. From there it can be evinced that there is no variation to the original GAN model that really improve the performances on a neutral field. Thus we present here a formalization of the original problem [1], modeling it with a game theory approach in a more precise way, as partially done in [4].

Deep Convolutional GAN (DCGAN) can be naturally represented as a 2-player zero-sum game:

III. EXPERIMENTAL SETTING

IV. RESULTS

V. CONCLUSIONS

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