Adversarial Variational Optimization of Non-Differentiable Simulators

Gilles Louppe[1] and **Kyle Cranmer**[1]

[1] *New York University*

In this note, ... [GL: todo.]

I. INTRODUCTION

[GL: Prescribed vs. implicit. See case of non-diff models in Balaji et al.]

II. PROBLEM STATEMENT

We consider a family of parameterized densities $p_\theta(\mathbf{x})$ defined implicitly through the simulation of a stochastic generative process, where $\mathbf{x} \in \mathbb{R}^d$ is the data and θ are the parameters of interest. The simulation may involve some complicated latent process, such that

$$p_\theta(\mathbf{x}) = \int p_\theta(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z} \tag{1}$$

where $\mathbf{z} \in \mathbb{R}^m$ is a latent variable providing an external source of randomness.

We assume that we already have an accurate simulation of the stochastic generative process that defines $p_\theta(\mathbf{x}|\mathbf{z})$, as specified through a deterministic function $g(\cdot;\theta) : \mathbb{R}^m \to \mathbb{R}^d$. That is,

$$p_\theta(\mathbf{x}) = \frac{\partial}{\partial x_1} \dots \frac{\partial}{\partial x_d} \int_{\{\mathbf{z}:g(\mathbf{z};\theta)\leq \mathbf{x}\}} p(\mathbf{z})d\mathbf{z}. \tag{2}$$

The simulator g is assumed to be a non-invertible function, that can only be used to generate data in forward mode. For this reason, evaluating the integral in Eqn. 2 is intractable. Importantly, and as increasingly found in science, we consider the additional constraint that g is a non-differentiable model, e.g. when specified as a computer program.

Given some observed data $\{\mathbf{x}_i | i = 1, \dots, N\}$ drawn from the (unknown) true distribution p_r, our goal is the inference of the parameters of interest θ^* that minimize the divergence between p_r and the modeled data distribution p_θ induced by $g(\cdot;\theta)$. That is,

$$\theta^* = \arg\min_\theta \rho(p_r, p_\theta), \tag{3}$$

where ρ is some distance or divergence.

III. BACKGROUND

A. Generative adversarial networks

Generative adversarial networks (GAN) were first proposed by [2] as a way to build an implicit generative model capable of producing samples from random noise $\mathbf{z}$. More specifically, a generative model $g(\cdot;\theta)$ is pit against an adversarial network d whose antigonistic objective is to recognize real data $\mathbf{x}$ from generated data $g(\mathbf{z};\theta)$. Both models g and d are trained simultaneously, in such a way that g learns to maximally confuse its adversary d (which happens when g produces samples comparable to the observed data), while d continuously adapts to changes in g. When d is trained to optimality before each parameter update of the generator, it can be shown that the original adversarial learning procedure amounts to minimizing the Jensen-Shannon divergence between p_r and p_θ.

More recently, ...

[GL: Explain WGAN, loss and optimum.]

B. Variational optimization

IV. ADVERSARIAL VARIATIONAL OPTIMIZATION

V. EXPERIMENTS

A. Toy problem

B. Physics example

VI. RELATED WORKS

[GL: Implicit generative models.] [GL: ABC.] [GL: carl [1].] [GL: Wood's papers.] [GL: CMA-ES.]

VII. SUMMARY

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[1] Cranmer, K., Pavez, J., and Louppe, G. Approximating likelihood ratios with calibrated discriminative classifiers. *arXiv preprint arXiv:1506.02169* (2015).

[2] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. Generative adversarial nets. In *Advances in Neural Information Processing Systems* (2014), pp. 2672–2680.