Learning to generate with adversarial networks

Gilles Louppe

August 3, 2016

Problem statement

- Assume training samples $\mathcal{D} = \{\mathbf{x} | \mathbf{x} \sim p_{\text{data}}, \mathbf{x} \in \mathcal{X}\}$;
- We want a generative model p_{model} that can draw new samples $\mathbf{x} \sim p_{\text{model}}$;
- Such that $p_{\text{model}} \approx p_{\text{data}}$.

$\mathbf{x} \sim p_{\text{data}}$

$\longrightarrow$

$\mathbf{x} \sim p_{\text{model}}$

Maximum likelihood approach

- Assume some form for p_{model}, as derived from knowledge and parameterized by θ;
- Find the maximum likelihood estimator

$$\theta^* = \arg\max_{\theta} \sum_{\mathbf{x} \in \mathcal{D}} \log(p_{\text{model}}(\mathbf{x}; \theta));$$

- Draw samples from p_{θ^*} (e.g., with MCMC in case p_{model} is known only up to a constant factor).

Modern alternatives: Variational Auto-Encoders (VAEs), Generative Adversarial Networks (GANs)

Catch me if you can

Leo forges fake bank notes

Tom tries to detect them

Generative adversarial nets (Goodfellow et al., 2014)

Do not assume any form, but use a neural network to produce similar samples.

- Two-player game:
  - a generator G;
  - a discriminator D,

- G is a generator $\mathcal{Z} \mapsto \mathcal{X}$ trained to produce samples $G(\mathbf{z})$ (for $\mathbf{z} \sim p_{\text{noise}}$) that are difficult for D to distinguish from data.

- D is a classifier $\mathcal{X} \mapsto \{0, 1\}$ that tries to distinguish between
  - a sample from the data distribution ($D(\mathbf{x}) = 1$, for $\mathbf{x} \sim p_{\text{data}}$),
  - and a sample from the model distribution ($D(G(\mathbf{z})) = 0$, for $\mathbf{z} \sim p_{\text{noise}}$);

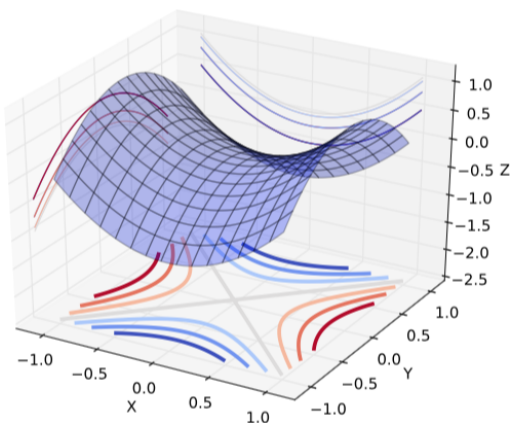
Objective

- Consider the value function

$$V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}}[\log(D(\mathbf{x}))] + \mathbb{E}_{\mathbf{z} \sim p_{\text{noise}}}[\log(1 - D(G(\mathbf{z})))];$$

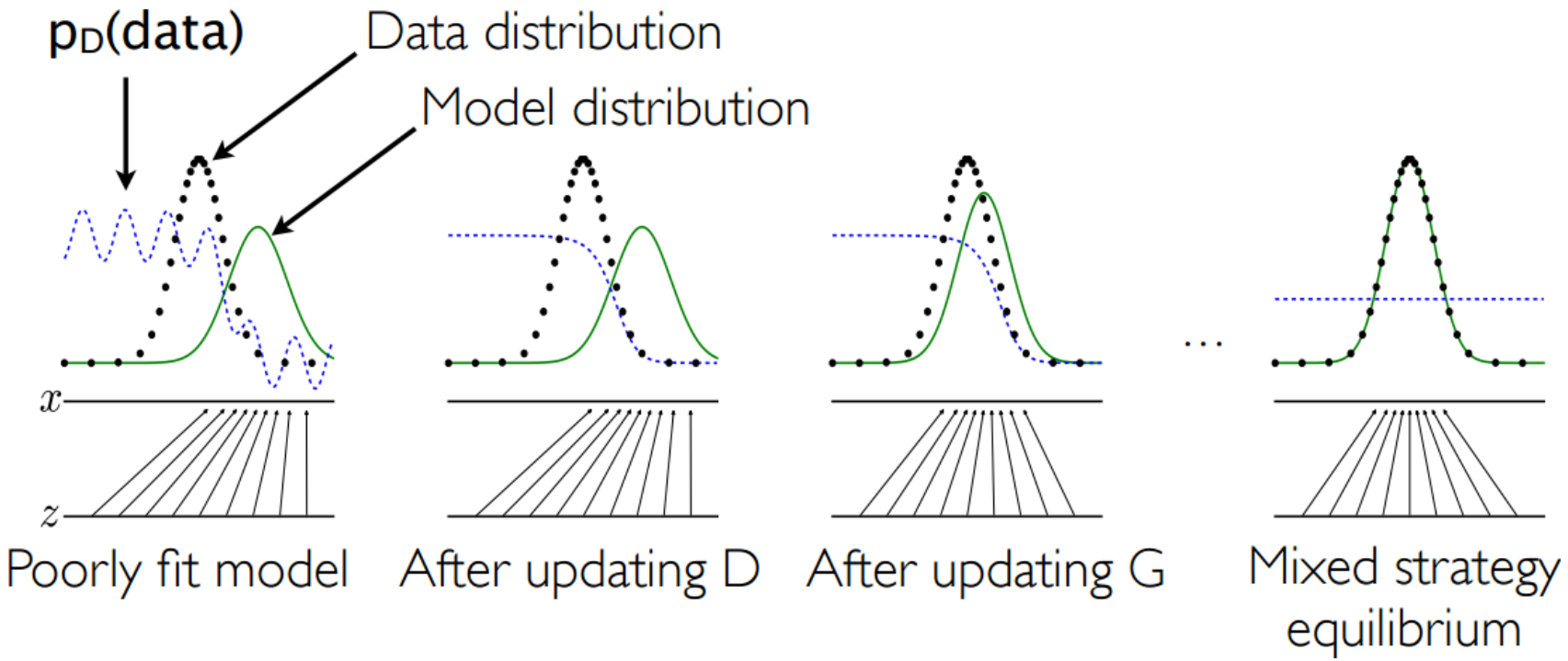
- We want to
  - Find D which maximizes $V(D, G)$,
  - Find G which minimizes $V(D, G)$;
- In other words, we are looking for the *saddle point*

$$(D^*, G^*) = \max_D \min_G V(D, G).$$



Learning process

Assuming D and G are neural networks parameterized by θ_D and θ_G, backpropagation can be used to optimize D's and G's objectives *alternatively* until convergence.



Theoretical guarantees

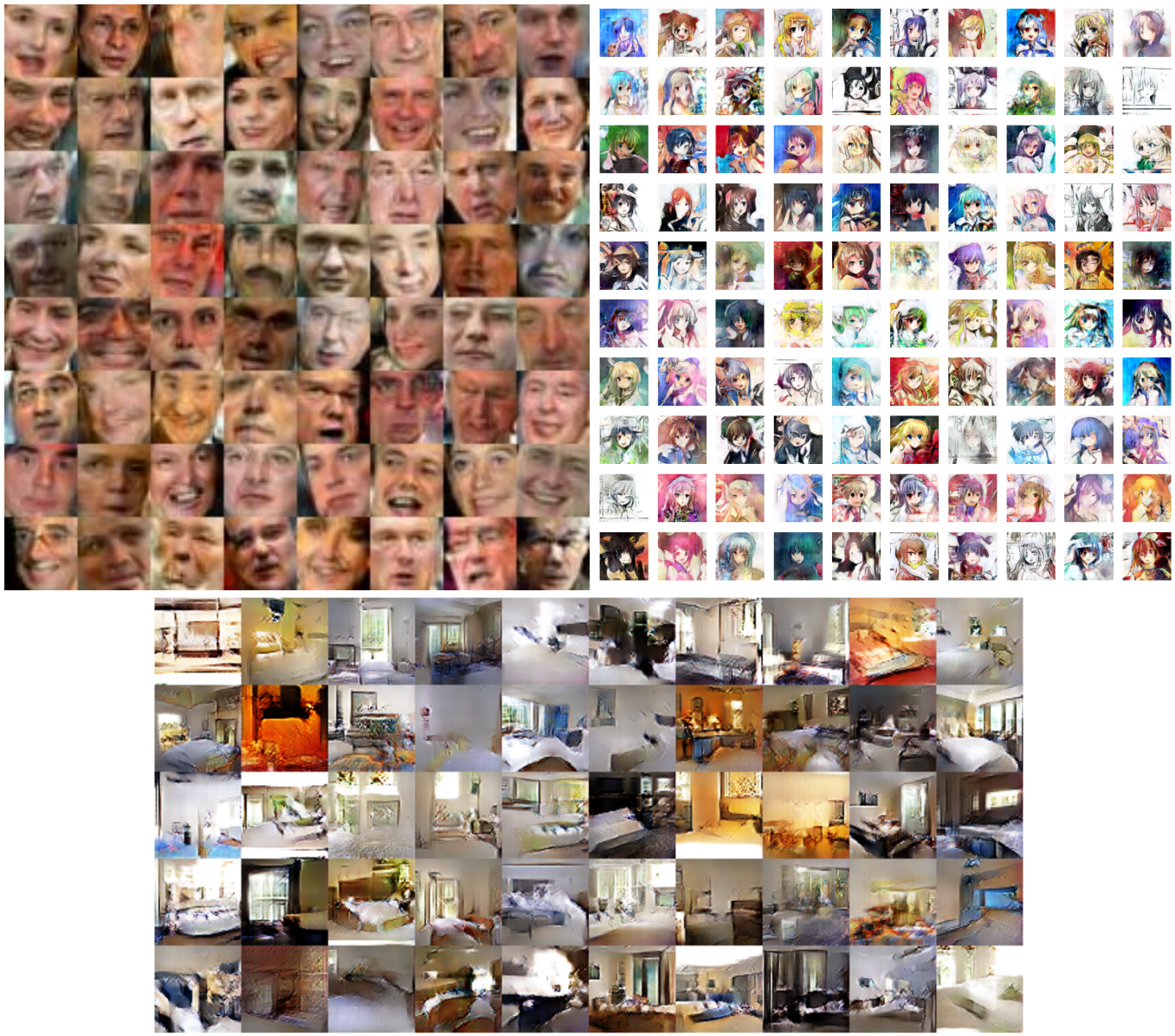
- Unique global optimum ;
- At the optimum, $p_{\text{model}} = p_{\text{data}}$;
- Convergence guaranteed.

(assuming infinite data and enough model capacity)

Conditional generative adversarial nets (Mirza and Osindero, 2014)

- The GAN framework can be extended to learn a parameterized generator $p_{\text{model}}(\mathbf{x}|\theta)$;
  - D is trained on $(\mathbf{x}, \theta)$ pairs,
  - G gets $(\mathbf{z}, \theta)$ as inputs;
- Useful to obtain a *single* generator object for all θ configurations;
- Can be used to interpolate between distributions.

In practice



None of these are real pictures!

Software

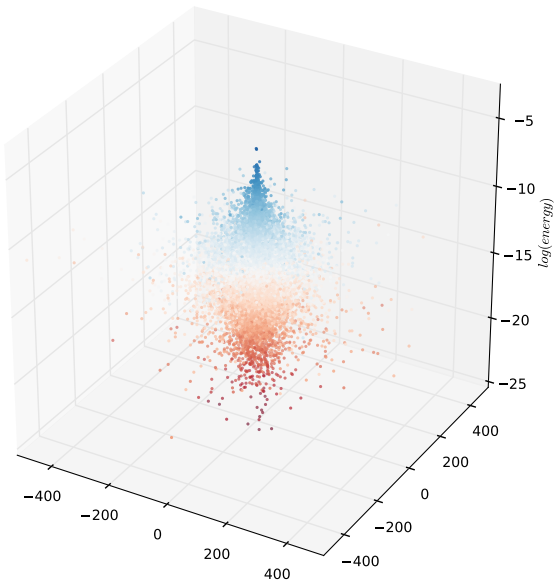
- Generative adversarial nets are good old neural nets;
- Therefore, the deep learning software stack can be leveraged
  - E.g. TensorFlow
    - Python and C++ compatible,
    - Compatible with single/multi/distributed CPUs/GPUs,
    - Active and strong community, backed by Google and others;
- Disentangle training from predictions for easier integration.
  - E.g. Using lwtnn to integrate a trained NN into any C++ framework, with minimal dependencies.

Generative models for simulation?

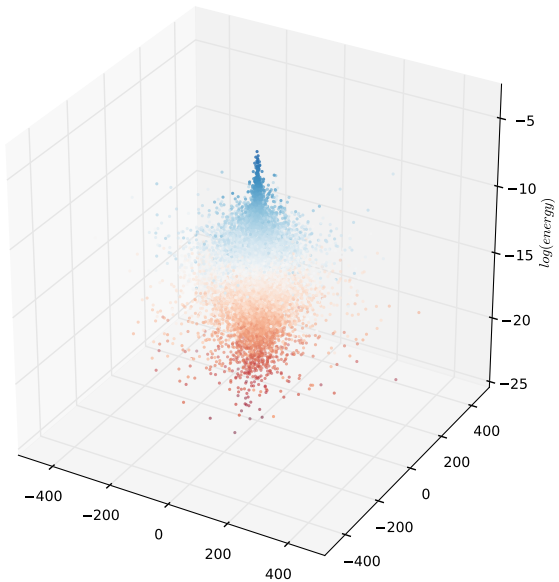
- For fast approximations of otherwise heavy computations;
  - for either small or longer steps in the simulation pipeline (e.g. a generator for hits in a calorimeter, across one or several layers)
- For unknown processes for which we only have data
  - e.g. some old equipment for which no simulator was ever written;
- For interpolating between parameterized distributions.

Proof of concept: generating shower shape data

$$\mathcal{D} = \{\mathbf{x} | \mathbf{x} = (\text{radius}, \text{angle}, \log(\text{energy})), \mathbf{x} \in \mathbb{R}^+ \times [0; 2\pi] \times \mathbb{R}\}$$

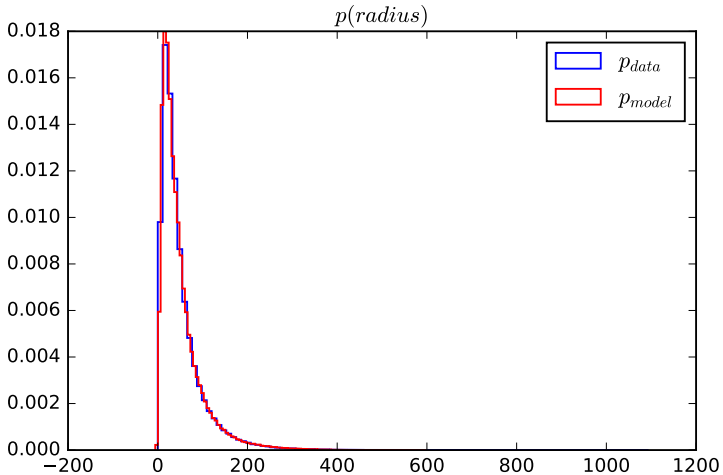


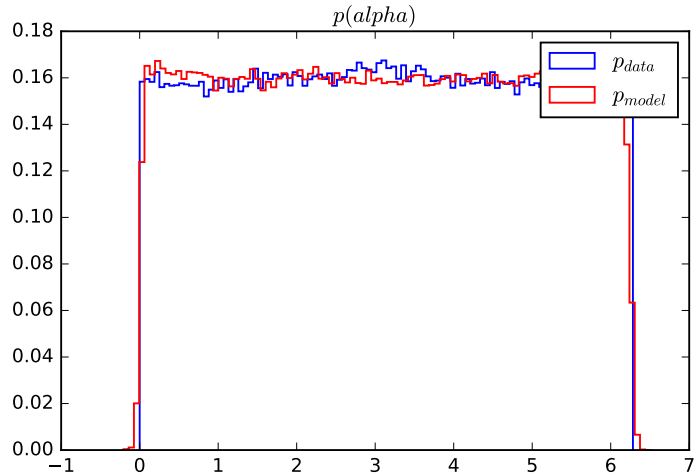
$\mathbf{x} \sim p_{\text{data}}$

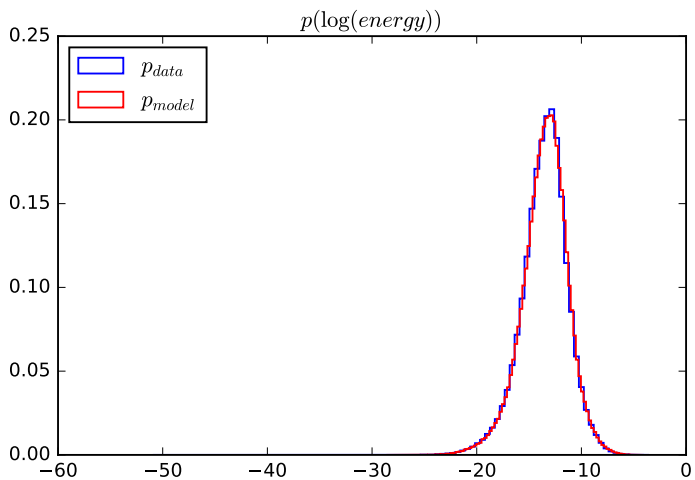


$\mathbf{x} \sim p_{\text{model}}$

Proof of concept: generating shower shape data







Summary

- GANs can be used to learn a generator, from data only;
- GANs come with theoretical guarantees;
- GANs can be used to learn to sample from conditional distributions;

References

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

Mirza, M. and Osindero, S. (2014). Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*.