Adversarial training for density estimation: a case study in collider physics

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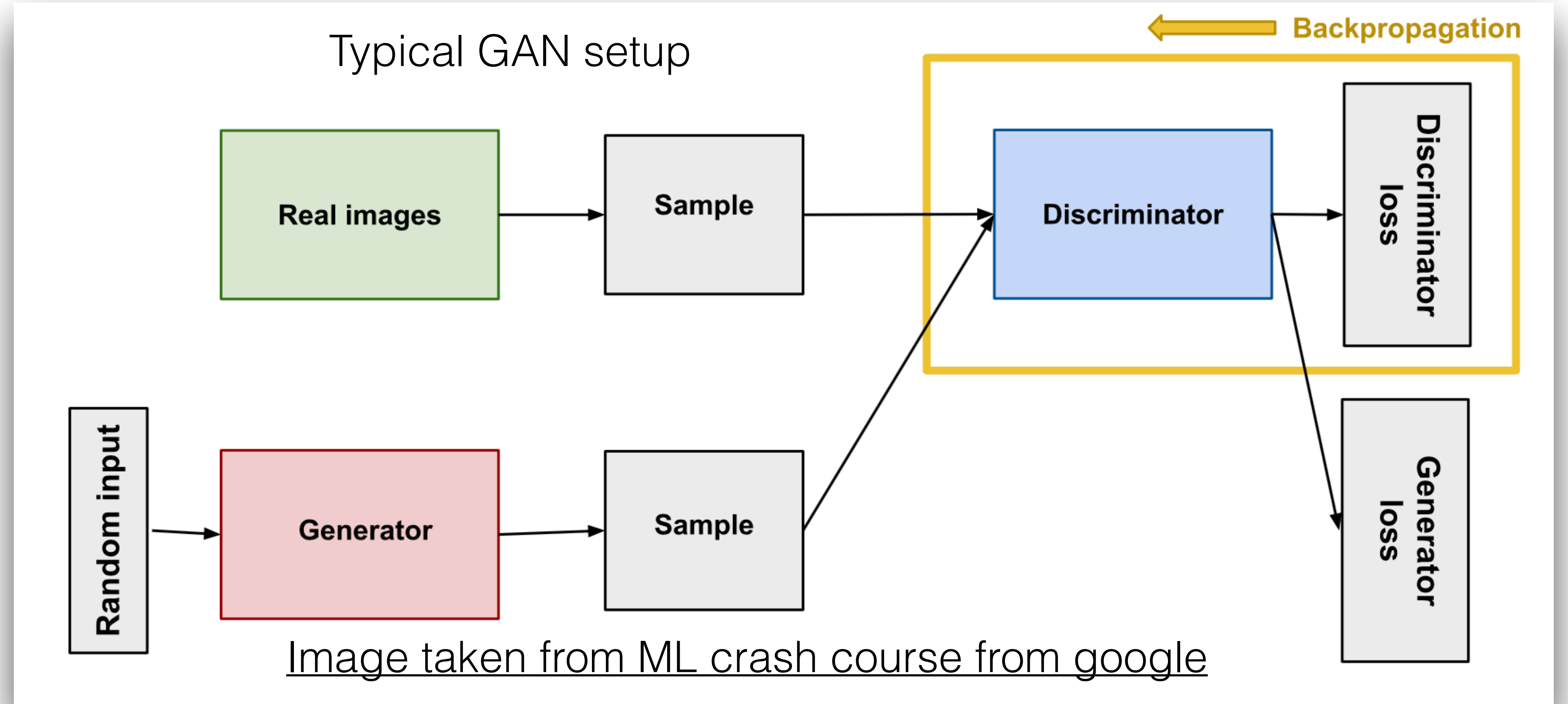
Formulation

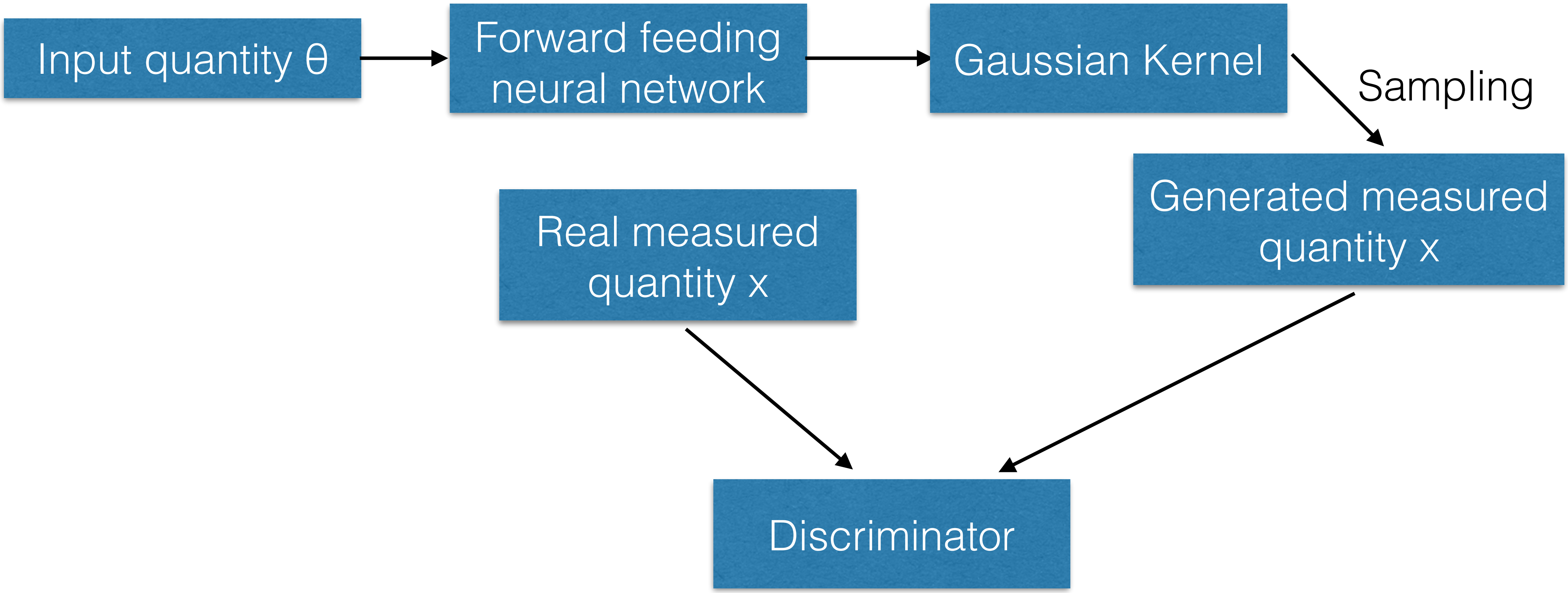
- Fast MC simulation with ML
  - GAN: CaloGAN, Z→μμ, di-jets, jets, MEM
  - Variational inference
- MC simulation as condition probability density $p(x|\theta)$
  - θ as generator-level quantities, x as reco-level quantities
  - Given any θ, we would like to have a good approximation $q(x|\theta)$ to $p(x|\theta)$
- Common density estimation technique usually involves likelihood model
- Density estimation with adversarial training
- A case study with a simple example of muon reconstruction in with Delphes simulation

Adversarial training for density estimation: a case in collider physics



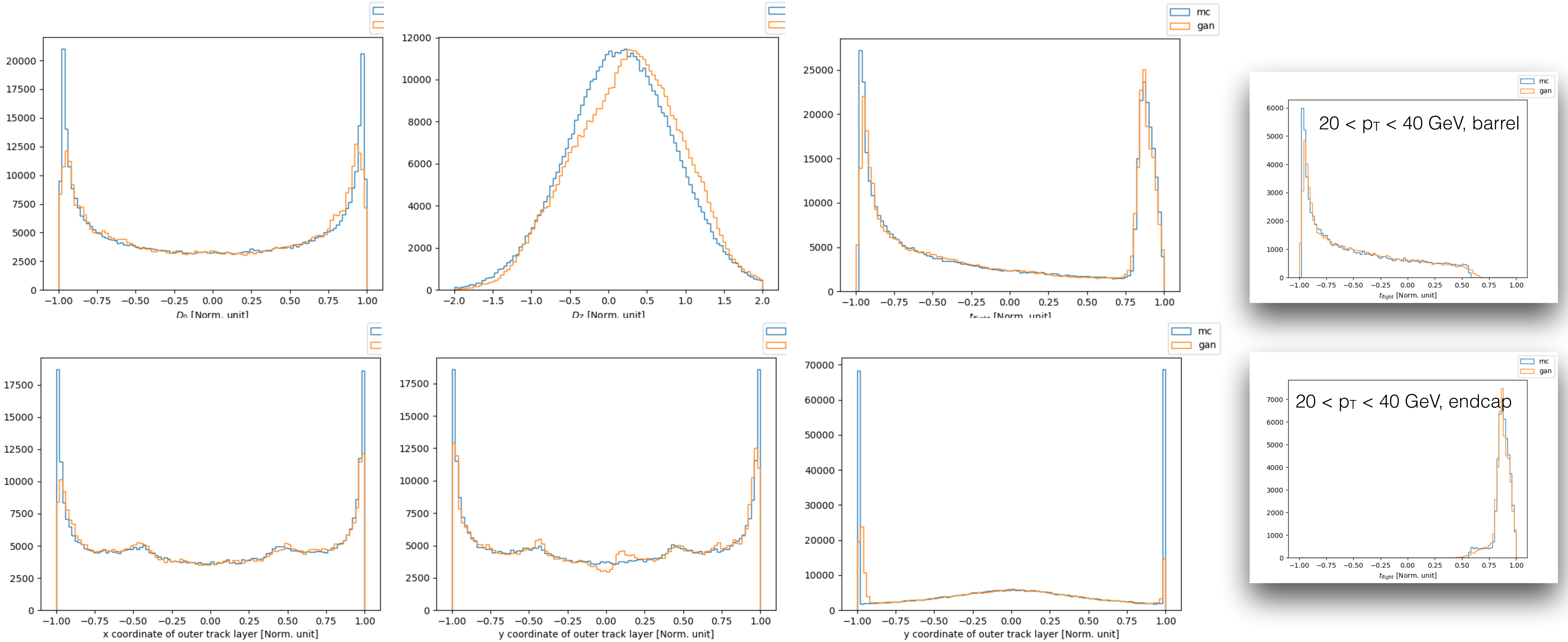
- Generator as $g(z\,|\,\theta) : z \to x$
  - Sometimes the latent variable z is of little interest
- Density estimation: approximate $p(x\,|\,\theta)$ with $q_\phi(x\,|\,\theta)$, then do sampling in x
- Commonly-used $q_\phi(x\,|\,\theta)$: mixture density network
- Need to enable back-propagation by “reparametisation trick” or other techniques

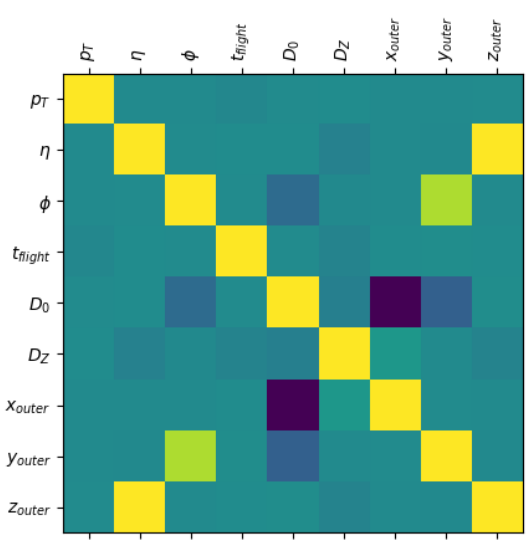
A case study in collider physics



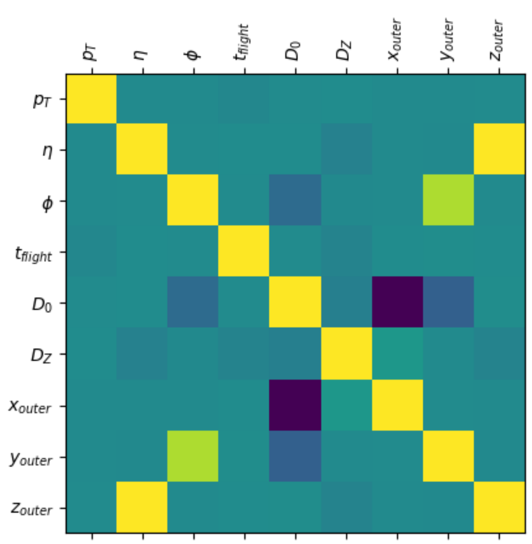
- Muon reconstruction with $pp \to Z \to \mu\mu$ in Delphes simulation in CMS detector setup
- A sample of 5 million events
  - θ: p_T, η, ϕ, charge
  - x: p_T, η, ϕ, t_{flight}, D_0, D_z, positions of hits in outer tracker
- $q_\phi(x \mid \theta) : \theta \to x$ as a "samplable" forward feeding neural network

Comparison of results





Generated sample



Original sample

- Reasonable performance in 1D distribution, except at sharp edges
- Reproduce underlaying relationship between variables, such as correlation, to a good level
    - Not necessarily true in some cases, such as arXiv:1901.05282

Summary

- Density estimation more akin to standard Monte Carlo simulation used in collider physics
- Possible to perform density estimation with adversarial training
- Demonstrated a test case of muon reconstruction in a simple setup with Delphes simulation
  - Observed reasonably good performance
  - Possibility to re-use the discriminator information when generating synthetic samples
- Complicated $p(x \mid \theta)$, such as actual ATLAS/CMS reconstruction software, will require advanced $q_\phi(x \mid \theta)$, back-propagation and sampling techniques