COLLIDER EVENT GENERATION WITH DEEP GENERATIVE MODELS

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Event Generation and Statistical Sampling with Deep Generative Models and a Density Information Buffer

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THE BIG PICTURE

WHAT ARE WE DOING? WHY ARE WE DOING THIS?

YES, WE WANT TO PROVIDE AN ALTERNATIVE TO MC GENERATORS

But this requires Monte Carlo! Once trained, the event generation with our ML model is several orders of magnitude faster.

ALLOW FOR MORE “FREEDOM“ FOR GENERATING EVENTS

By enabling targeted event generation and by being able to interpolate between latent space representations

USE THE EVENT GENERATOR AS AN ANOMALY DETECTOR

Train on standard model data, detect anomalous individual events AND overdensities

WE CAN CREATE META-MODELS OF THEORY SPACES

By clustering encoded observables of a theory in a latent space

WE CAN GENERATE BETTER RANDOM NUMBERS

e.g. to improve rejection efficiency for MC integration

MACHINE LEARNING METHODS

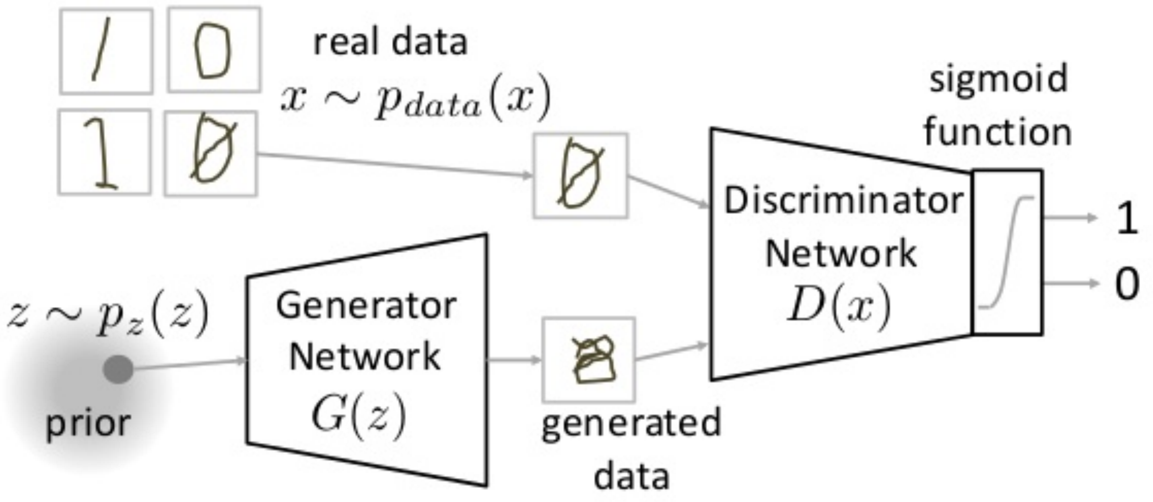
GANs and VAEs

GENERATIVE ADVERSARIAL NETWORKS

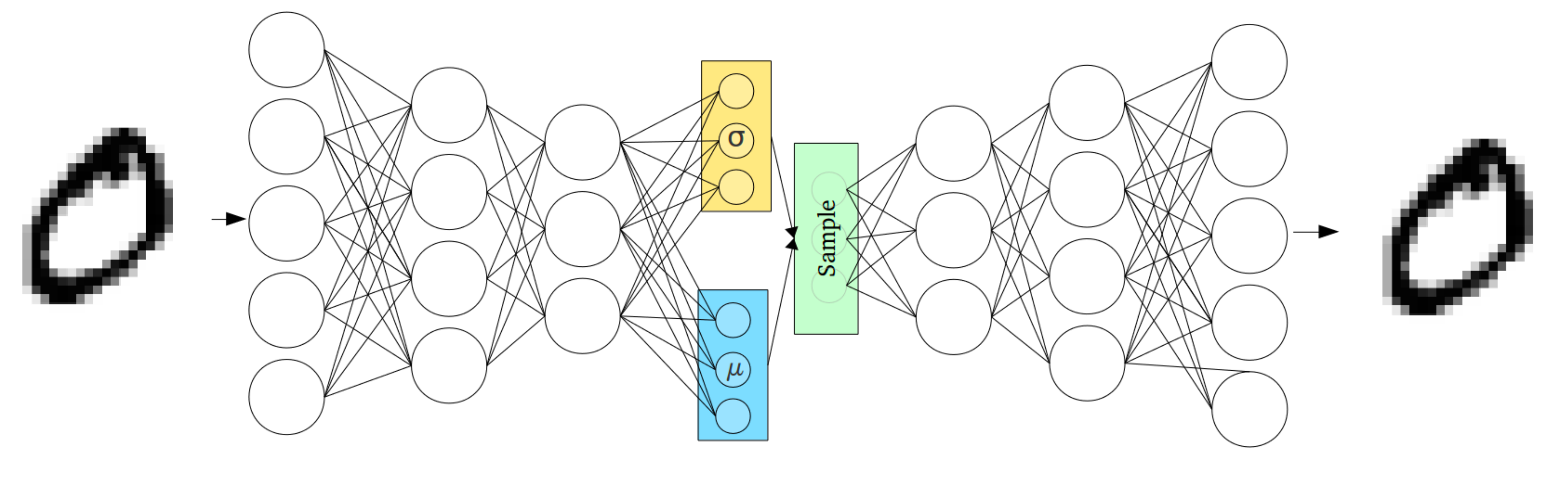
Generative Adversarial Networks

$$\min_G \max_D V(D, G)$$

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

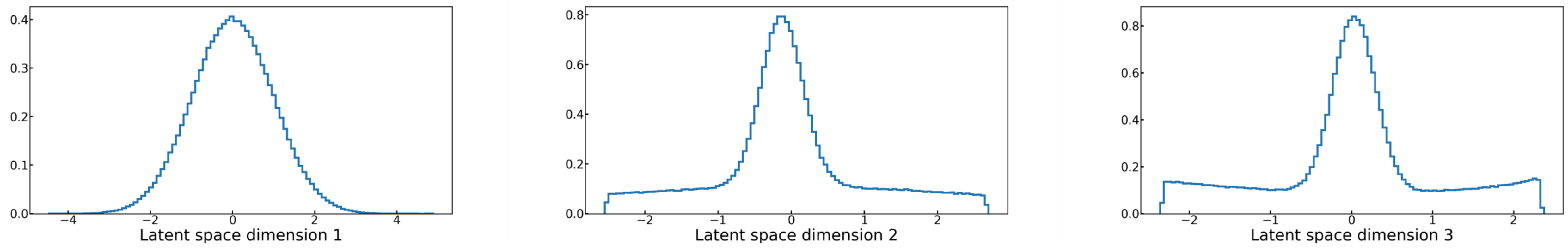


VARIATIONAL AUTOENCODER



BEYOND STANDARD VAE

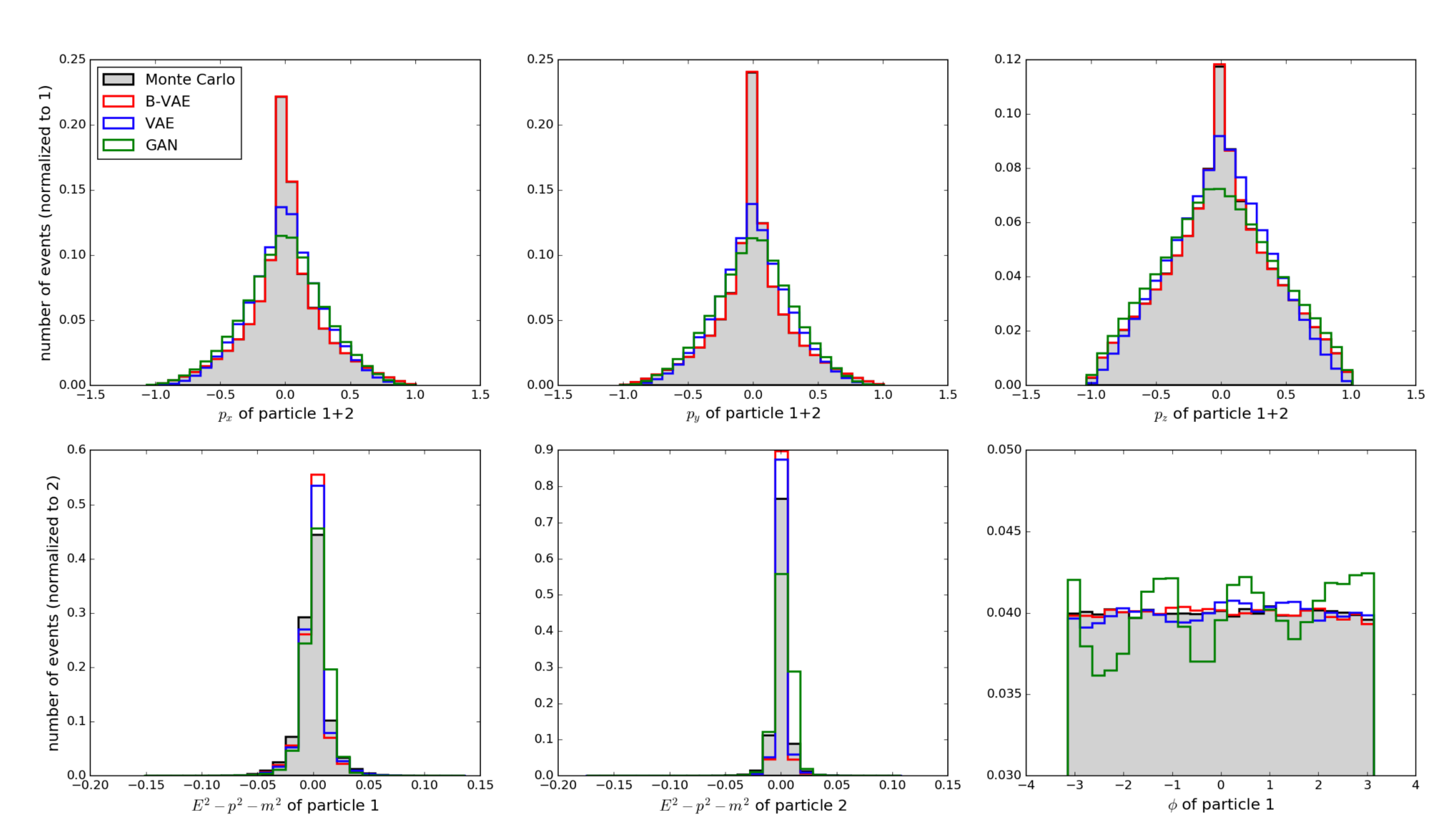
- We use the Beta-VAE
- In Addition: Density buffer in latent space and a ‘smudge factor‘
- Beta-VAE + Buffer + smudge-factor = B-VAE



TWO BODY DECAY

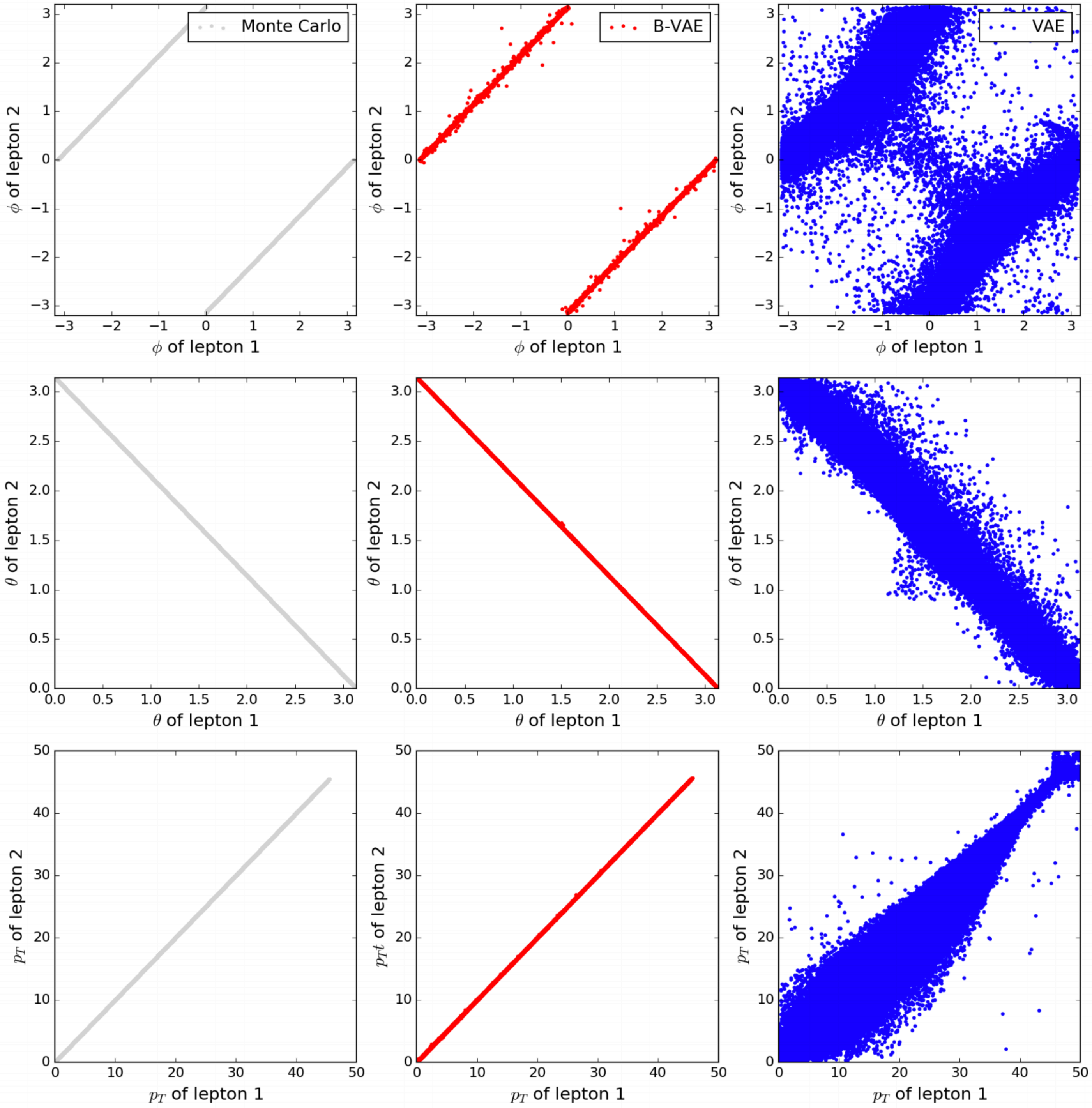
First simple toy model

GANS AND STANDARD VAES DON'T WORK WELL BUT B-VAE DOES



LEPTONIC Z DECAY

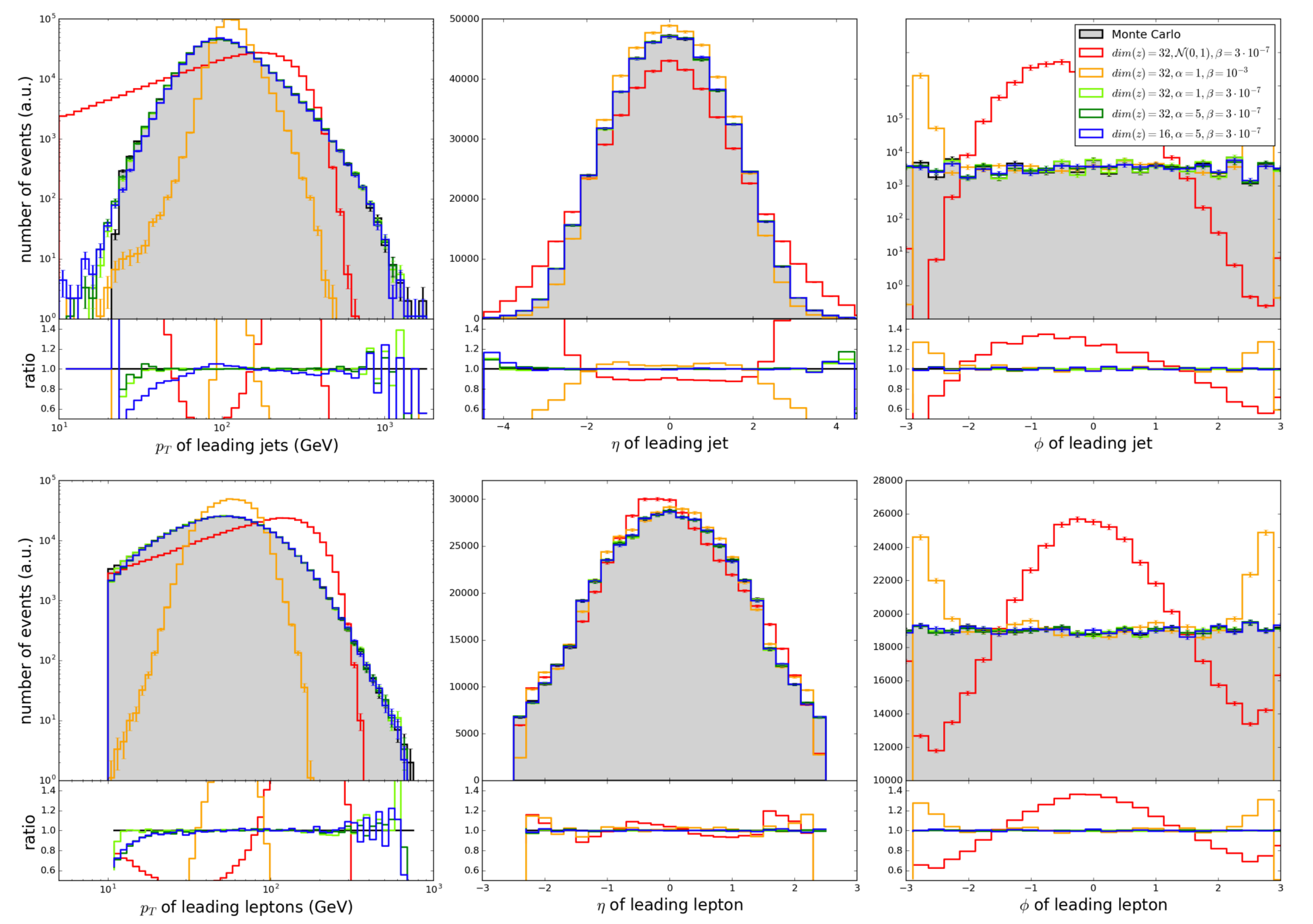
EVENTS ARE PRODUCED BACK TO BACK



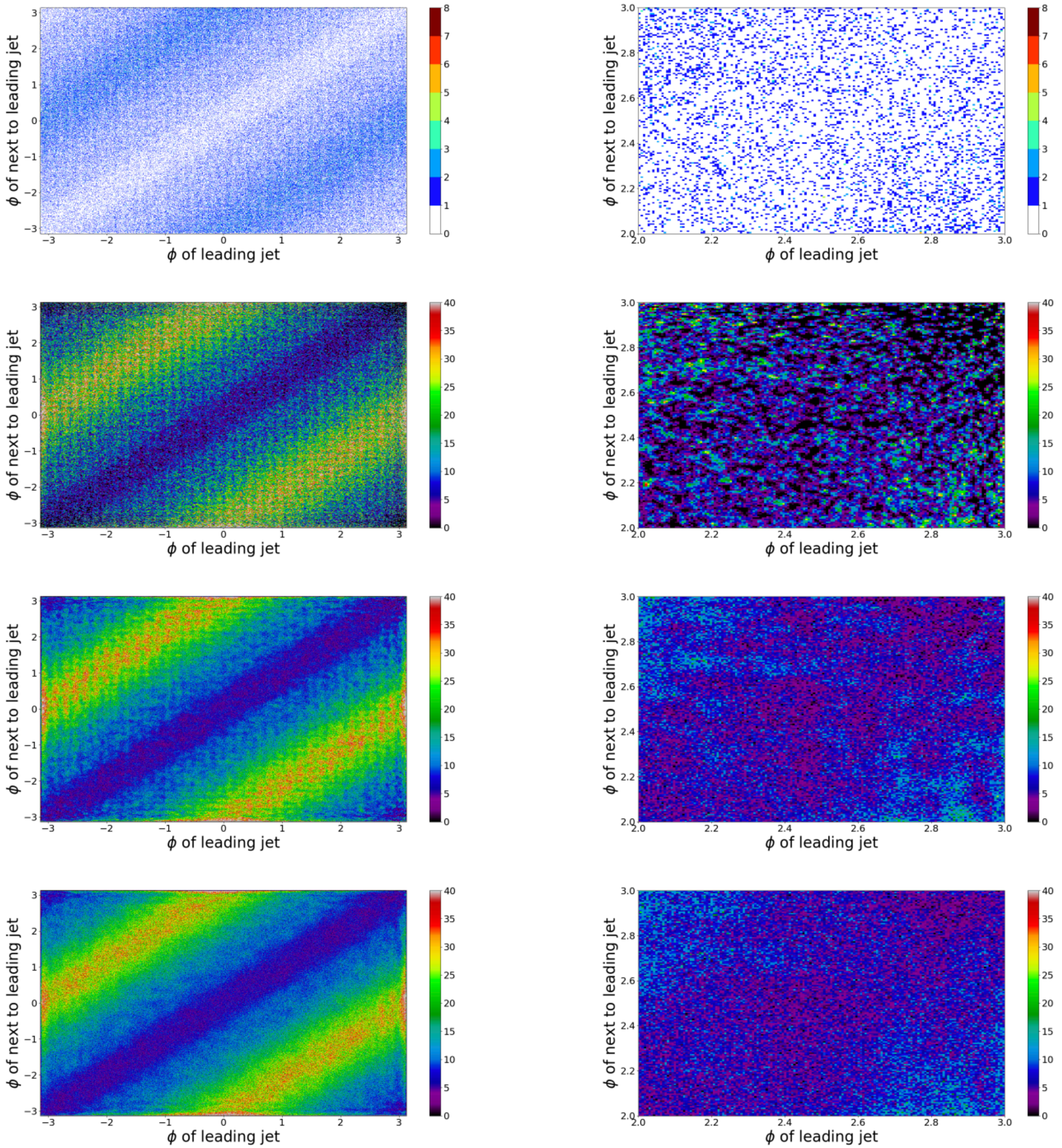
TTBAR PRODUCTION

With up to four jets + leptons

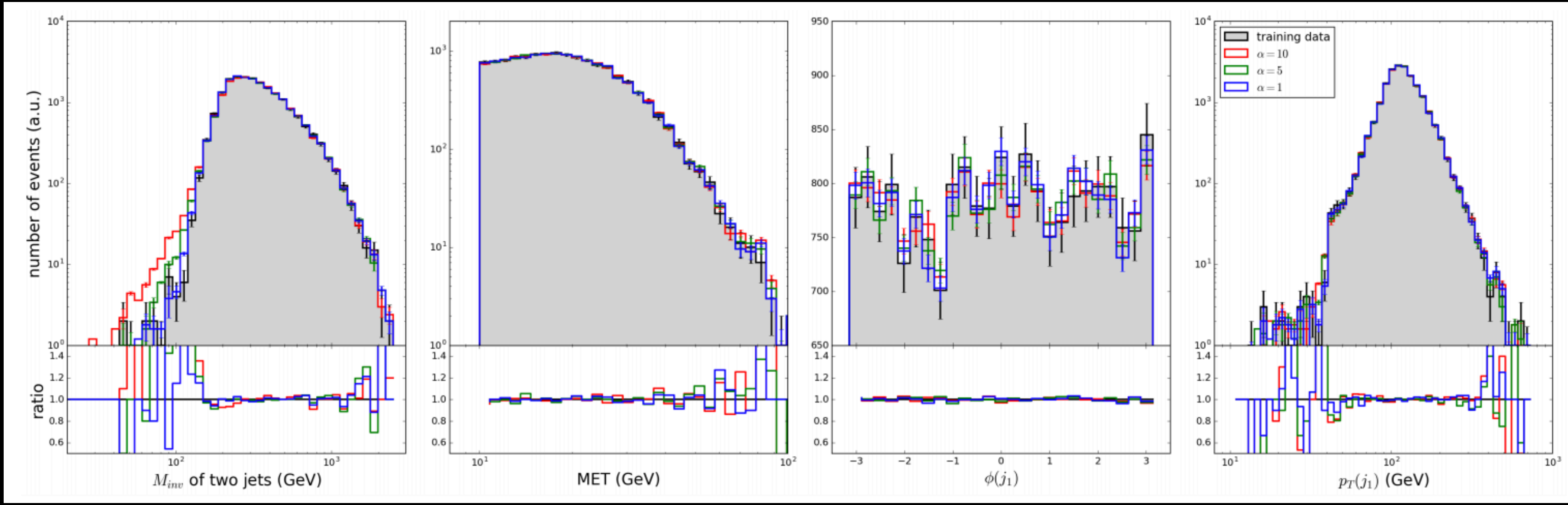
ALSO WORKS WELL FOR COMPLICATED PROCESSES



SMUDGING SMOOTHES THE DISTRIBUTION AND FILLS HOLES



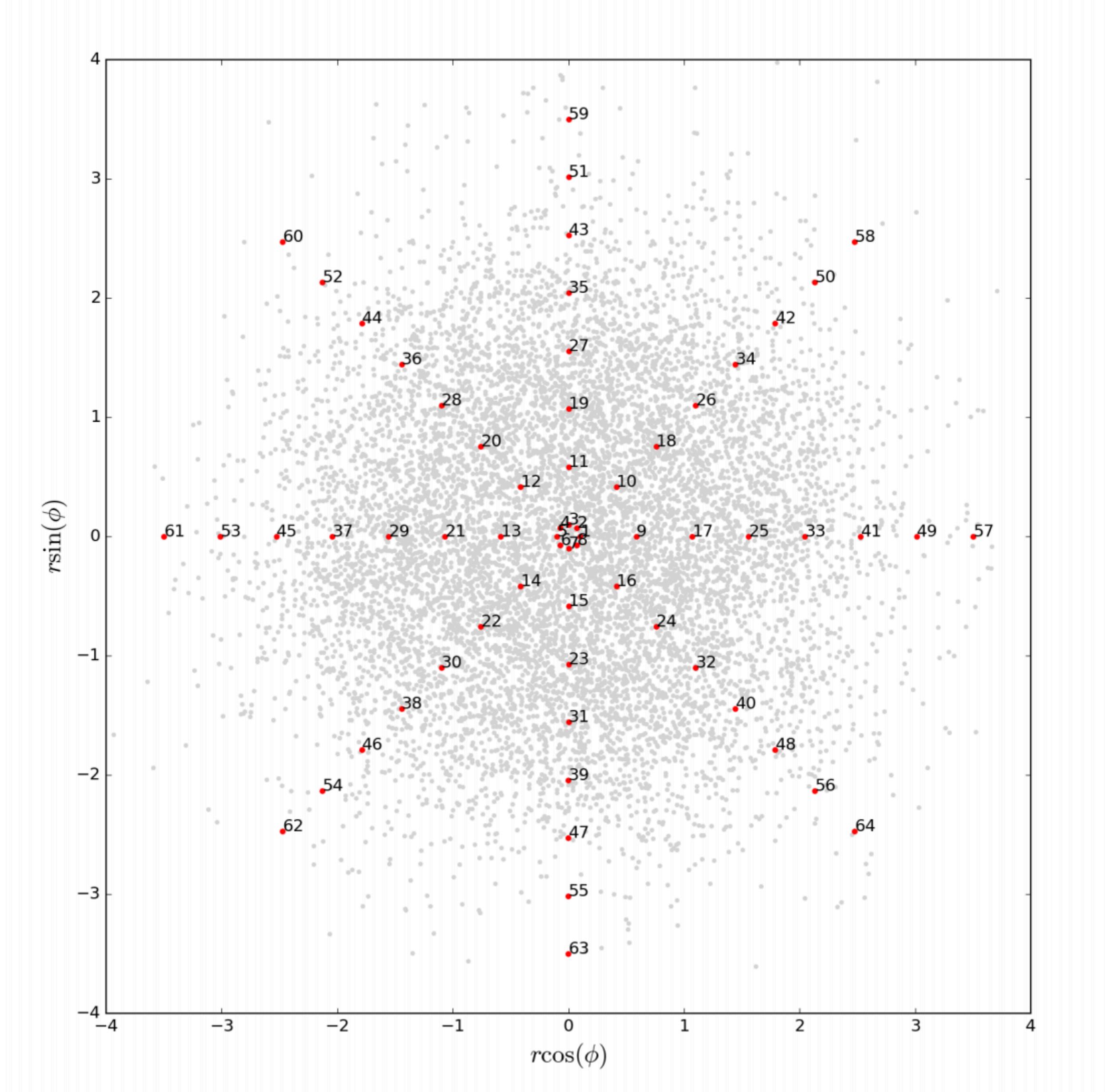
FIRST LHC GENERATOR FROM REAL EXPERIMENTAL DATA

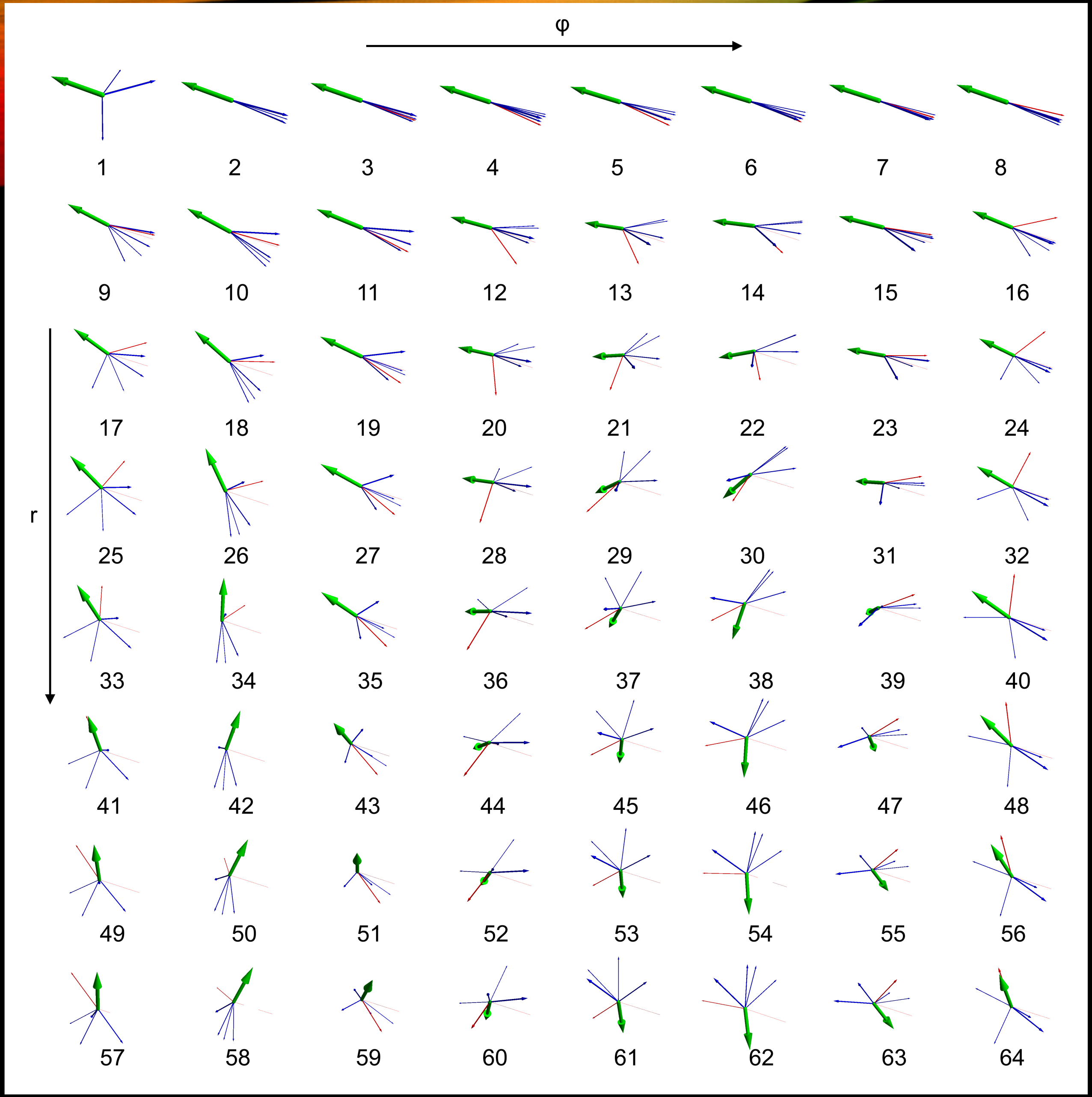


EXPLORING LATENT SPACE

With a principal component analysis

SAMPLING IN PCA SPACE





ALLOWS US TO STEER EVENT GENERATION!

CONCLUSION

- Basically we can learn any relevant probability distribution from data
- In particular we can learn to generate complicated events with the correct frequency of occurence
- Has many applications:
  - An 82-dimensional event generator case including many sparse entries worked reasonably well
  - More efficient MC sampling e.g. for integrating matrix elements
  - Learn generator directly from experimental data
  - Create an anomaly detector for new physics
  - Learn the detector response (and its inverse)
  - Applications beyond particle physics

THANK YOU FOR YOUR ATTENTION!