New LHC Theory Directions

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Learning from art

GANGogh [Bonafilia, Jones Danyluk (2017)]

– can networks generate something new?
– map noise vector to images
– train on 80,000 pictures [organized by style and genre]
– generate flowers

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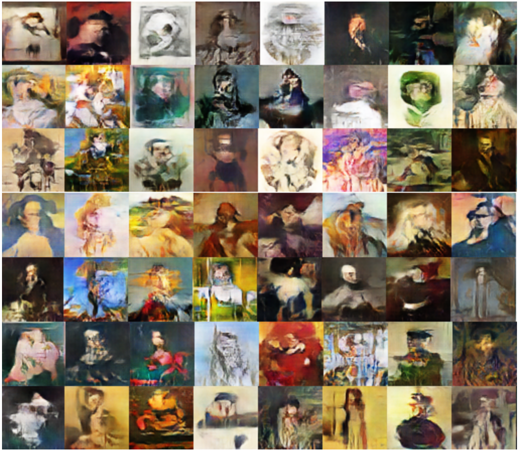

Learning from art

GANGogh [Bonafilia, Jones Danyluk (2017)]

- can networks generate something new?
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Edmond de Belamy [Caselles-Dupre, Fautrel, Vernier]

- trained on 15,000 portraits
- sold for $ 432.500

⇒ all about marketing

GAN basics

Simulations crucial for LHC physics [review: Butter & TP]

- goal: data-to-data with fundamental physics input only
- Monte Carlo challenges

  higher-order precision in bulk
  coverage of tails
  inversion to access fundamental QCD
- neural network benefits

  training on MC and/or real events
  lightning speed, once trained
  best available interpolation

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GANning events [Goodfellow etal (2014)]

- training — true events $\{x_T\}$ following P_T
  output — generated events $\{r\} \to \{x_G\}$ following P_G
- discriminator constructing $D(x)$ [$D(x) = 1, 0$ true/generated]

$$L_D = \Big\langle -\log D(x) \Big\rangle_{x \sim P_T} + \Big\langle -\log(1 - D(x)) \Big\rangle_{x \sim P_G} \to -2 \log 0.5$$

- generator producing true-looking events [D needed]

$$L_G = \Big\langle -\log D(x) \Big\rangle_{x \sim P_G}$$

$\Rightarrow$ statistically independent copy of training events

1– Jet generation

GANGogh for jet images [de Oliveira, Paganini, Nachman]

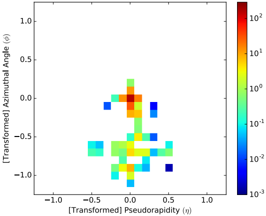
– start with calorimeter or jet images [η vs ϕ]
  sparsity the technical challenge [cf top tagging comparison]

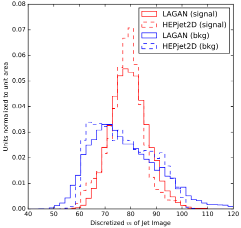
1- reproduce valid jet images from training data

2- organize them by QCD vs W-decay jets

– high-level observables m, τ_{21} as check

$\Rightarrow$ GANs generating jets





Open GAN questions

– use cases?

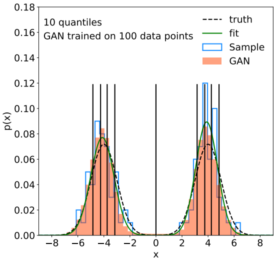
– uncertainty? [Bayesian networks?]

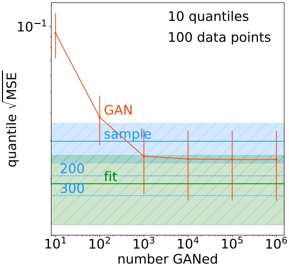
– achievable precision?

2– GANplification

Beyond training statistics? [Butter, Diefenbacher, Kasieczka, Nachman, TP]

- GAN vs sampling vs fit
- χ^2-goodness in quantiles





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Beyond training statistics? [Butter, Diefenbacher, Kasieczka, Nachman, TP]

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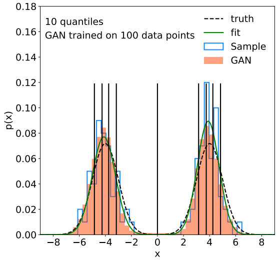
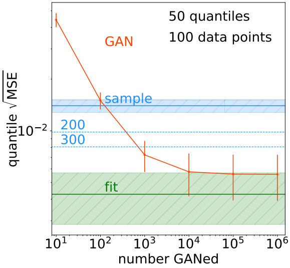
- fit like 500-1000 sampled points
  GAN like 500 sampled points [amplifictation factor 5]
  improvement up to 10,000 GANned events





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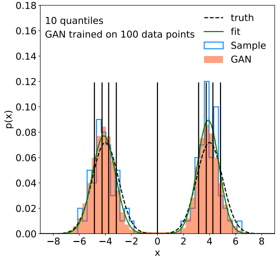
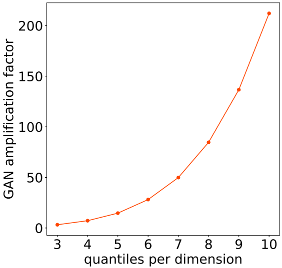
– 5-dimensional Gaussian shell
sparsely populated
amplification vs quantiles

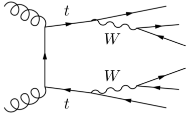
– fit-like additional information

⇒ GANs enhance training data





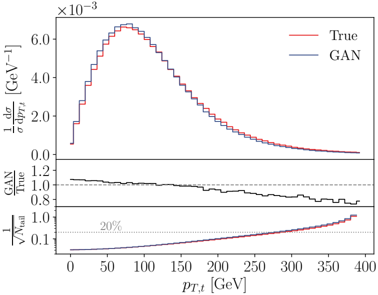
3– How to GAN LHC Events



Replace ME for hard scattering [Otten, Hashemi, Di Sipio...]

– realistic final state $t\bar{t} \to 6$ jets [Butter, TP, Winterhalder]
  on-shell external states $\to$ 12D phase space

– constructed observables with tails [statistical error indicated]



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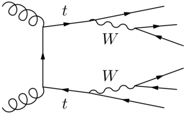

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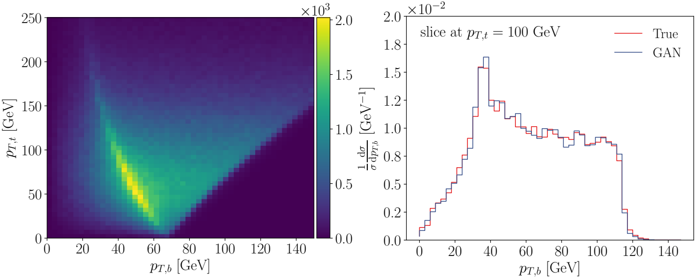
- 2D correlations



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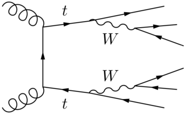

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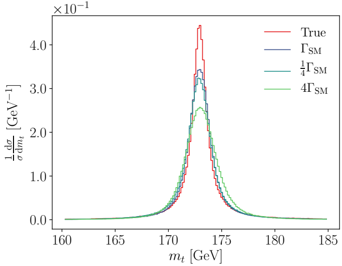
- 2D correlations
- 1D-invariant masses [top, W]
  batch-wise comparison of distributions, MMD loss with kernel k

$$\mathrm{MMD}^2 = \langle k(x, x') \rangle_{x,x' \sim P_T} + \langle k(y, y') \rangle_{y,y' \sim P_G} - 2\langle k(x, y) \rangle_{x \sim P_T, y \sim P_G}$$

$$L_G \to L_G + \lambda_G \,\mathrm{MMD}^2$$

- GANning 1.6M evts/sec on laptop



4– How to GAN event subtraction

Idea: subtract event samples without binning [Butter, TP, Winterhalder]

– statistical uncertainty

$$\Delta_{B-S} = \sqrt{\Delta_B^2 + \Delta_S^2} > \max(\Delta B, \Delta S)$$

– possible applications

soft-collinar subtraction, multi-jet merging
on-shell subtraction
background subtraction [4-body decays]

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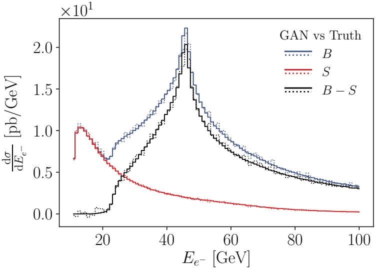
  background subtraction [4-body decays]

- event-based background subtraction

$$pp \to e^+ e^- \quad \text{(Base)} \qquad pp \to \gamma \to e^+ e^- \quad \text{(Subtracted)}$$

- Z-pole events generated

$\Rightarrow$ Why did we ever bin?



5– How to GAN away detector effects

Idea: invert Monte Carlos [Datta; Bellagente, Butter, Kasiczka, TP, Winterhalder]

– detector simulation — unfolding established use case

– inversion possible, in principle [entangled convolutions]

– GAN task

$$\text{partons} \xrightarrow{\text{DELPHES}} \text{detector} \xrightarrow{\text{GAN}} \text{partons}$$

$\Rightarrow$ Full phase space unfolding

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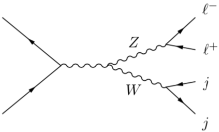
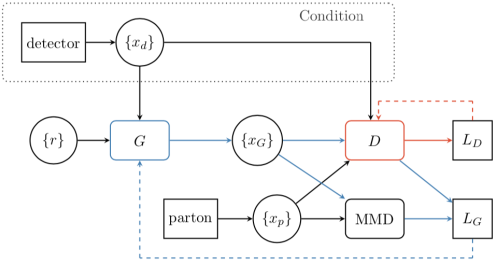


Reconstructing parton-level $pp \to ZW \to (\ell\ell)\ (jj)$

– broad jj mass peak
narrow $\ell\ell$ mass peak
modified $2 \to 2$ kinematics

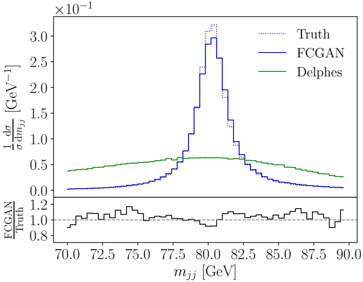
– (conditional) GAN like for event generation



Fully conditional GAN

Test data modified from training data

– full inversion no point in showing...



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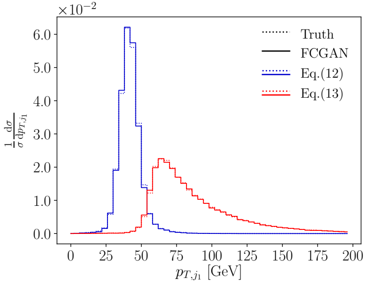
– test cuts [14%, 39% events]

$$p_{T,j_1} = 30 \dots 50\ \text{GeV} \quad p_{T,j_2} = 30 \dots 40\ \text{GeV} \quad p_{T,\ell-} = 20 \dots 50\ \text{GeV} \tag{12}$$

$$p_{T,j_1} > 60\ \text{GeV} \tag{13}$$

⇒ Phase space unfolding working



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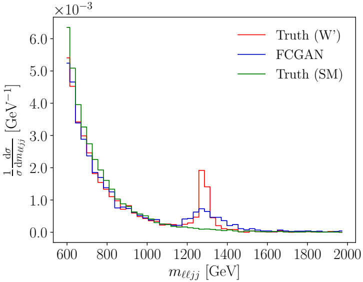
⇒ Phase space unfolding working

New physics in data [model dependence]

- train: Standard Model events
  test: 10% events with W' in s-channel
- nightmare: unfold W' onto Standard Model?

⇒ Statistical model: cINN



Concluding...

LHC physics really is big data

- NN best interpolation [Butter (2020)]
- training on MC and/or data
- latent space structured

GAN studies

- Jet Images [de Oliveira (2017), Carazza (2019)]
- Detector simulations [Paganini (2017), Musella (2018), Erdmann (2018), Ghosh (2018), Buhmann (2020)]
- Events [Otten(2019), Hashemi (2019), Di Sipio (2019), Butter (2019), Martinez (2019), Alanazi (2020)]
- Unfolding [Datta (2018), Bellagente (2019)]
- Templates for QCD factorization [Lin (2019)]
- EFT models [Erbin (2018)]
- Event subtraction [Butter (2019)]

Event generators

- neural importance sampling [Bothmann (2020)]
- i-flow in SHERPA [Gao (2020)]
- statistical unfolding [Bellagente (2020)]