How to GAN for LHC

Tilman Plehn

Universität Heidelberg

Milano 6/2020

Machine Learning for LHC

Fundamental understanding of LHC data

– LHC and dark matter data-driven, but never fundamental without theory

– just work with data and SM?

1. simulation from first principles [Pythia, Sherpa]
2. interpretation frameworks [SMEFT, SUSY]
3. best use of the data [using 1, 2, our brains, and ML]

– 1991 visionaries: NN-based quark-gluon tagger

USING NEURAL NETWORKS TO IDENTIFY JETS

Leif LÖNNBLAD*, Carsten PETERSON** and Thorsteinn RÖGNVALDSSON***

Department of Theoretical Physics, University of Lund, Sölvegatan 14A, S-22362 Lund, Sweden

Received 29 June 1990

A neural network method for identifying the ancestor of a hadron jet is presented. The idea is to find an efficient mapping between certain observed hadronic kinematical variables and the quark-gluon identity. This is done with a neuronic expansion in terms of a network of sigmoidal functions using a gradient descent procedure, where the errors are back-propagated through the network. With this method we are able to separate gluon from quark jets originating from Monte Carlo generated e^+e^- events with $\sim 85\%$ approach. The result is independent of the MC model used. This approach for isolating the gluon jet is then used to study the so-called string effect.

In addition, heavy quarks (b and c) in e^+e^- reactions can be identified on the 50% level by just observing the hadrons. In particular we are able to separate b-quarks with an efficiency and purity, which is comparable with what is expected from vertex detectors. We also speculate on how the neural network method can be used to disentangle different hadronization schemes by compressing the dimensionality of the state space of hadrons.

$\Rightarrow$ Not that new...

Simple classification done

SciPost Physics Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], K. Cranmer[3], D. Debnath[4], B. M. Dillon[5], M. Fairbairn[6], D. A. Faroughy[5], W. Fedorko[7], C. Gay[7], L. Gouskos[8], J. F. Kamenik[5,9], P. T. Komiske[10], S. Leiss[1], A. Lister[7], S. Macaluso[3,4], E. M. Metodiev[10], L. Moore[11], B. Nachman,[12,13], K. Nordström[14,15], J. Pearkes[7], H. Qu[8], Y. Rath[16], M. Rieger[16], D. Shih[4], J. M. Thompson[2], and S. Varma[6]

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10 Center for Theoretical Physics, MIT, Cambridge, USA
11 CP3, Universitéxx Catholique de Louvain, Louvain-la-Neuve, Belgium
12 Physics Division, Lawrence Berkeley National Laboratory, Berkeley, USA
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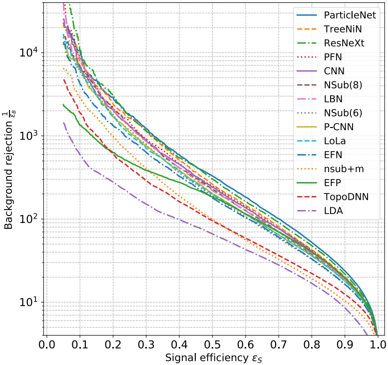
July 24, 2019

Abstract

Based on the established task of identifying boosted, hadronically decaying top quarks, we compare a wide range of modern machine learning approaches. Unlike most established methods they rely on low-level input, for instance calorimeter output. While their network architectures are vastly different, their performance is comparatively similar. In general, we find that these new approaches are extremely powerful and great fun.

Content



Beyond classification

Phase space networks

- MC integration [Bendavit (2017)]
- NNVegas [Klimek (2018), Carrazza (2020)]

Event generation

- parton densities [NNPDF (since 2002)]
- amplitudes [Bishara (2019), Badger (2020)]
- neural importance sampling [Bothmann (2020)]
- i-flow in SHERPA [Gao (2020)]

Generative networks

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

Learning from art

GANGogh [Bonafilia, Jones, Danyluk (2017)]

– old news: NNs turning pictures into art of a certain epoch
  but can they create new pieces of art?
– train on 80,000 pictures [organized by style and genre]
– map noise vector to images
– generate flowers

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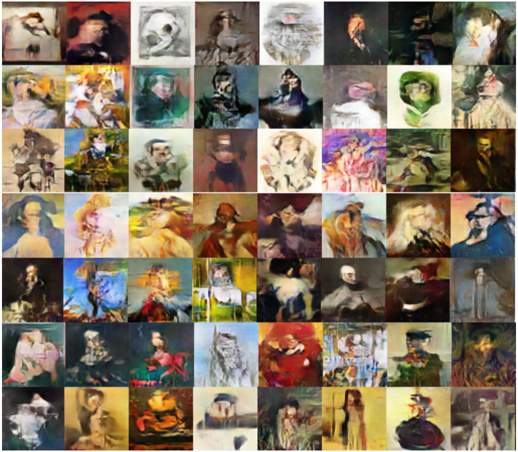
– generate portraits



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Edmond de Belamy [Caselles-Dupre, Fautrel, Vernier]

– trained on 15,000 portraits

– sold for $ 432.500

⇒ all about marketing and sales

GAN basics

MC crucial for LHC physics

– goal: data-to-data with fundamental physics input only

– MC challenges

higher-order precision in bulk
coverage of tails
inversion/unfolding to access fundamental QCD

– neural network benefits

best available interpolation
structured latent space
lightning speed, once trained
inversion solved
training on MC and/or data, anything goes

– GANs the cool kid

generator trying to produce best events
discriminator trying to catch generator
$\longrightarrow$ competing towards (Nash) equilibrium

GAN algorithm

Example: LHC events

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

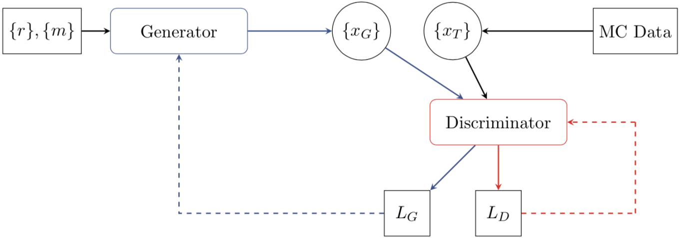
$$L_D = \big\langle -\log D(x) \big\rangle_{x\sim P_T} + \big\langle -\log(1 - D(x)) \big\rangle_{x\sim P_G} \to -2\log 0.5$$

- generator giving events [D needed]

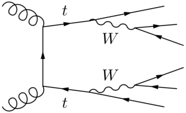
$$L_G = \big\langle -\log D(x) \big\rangle_{x\sim P_G}$$

- loss function evaluated over batch
- noise reduction/stabilization: gradient penalty [alternatively WGAN]

$\Rightarrow$ statistically independent copy of training events



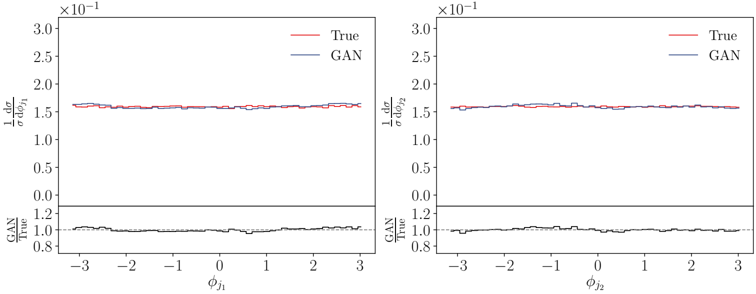
1– How to GAN LHC events



Idea: replace ME for hard process [Butter, TP, Winterhalder]

– medium-complex final state $t\bar{t} \to 6$ jets
$t/\bar{t}$ and $W^{\pm}$ on-shell with BW $6 \times 4 = 18$ dof
on-shell external states $\to$ 12 dof [constants hard to learn]

– flat observables flat [phase space coverage okay]



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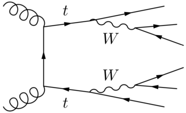

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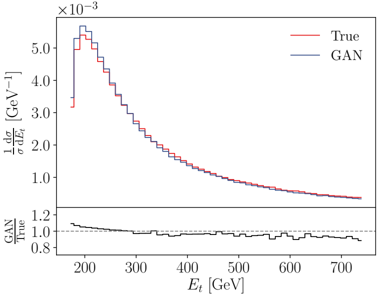
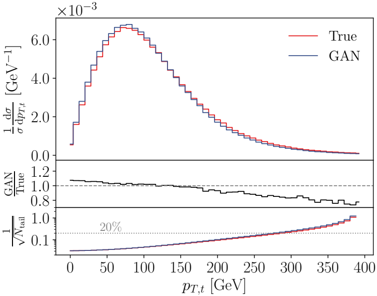
- direct observables with tails [statistical error indicated]
- constructed observables similar





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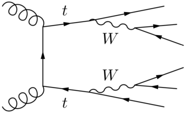

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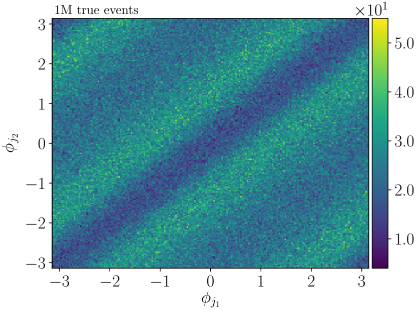
- improved resolution [1M training events]



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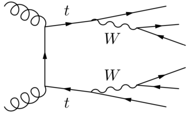

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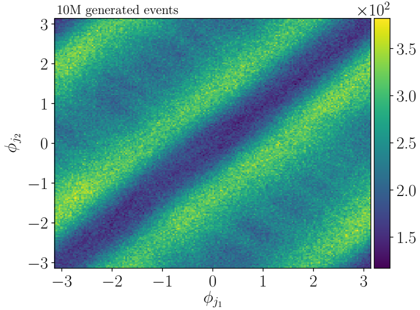
- improved resolution [10M generated events]



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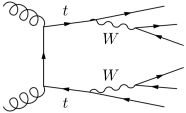

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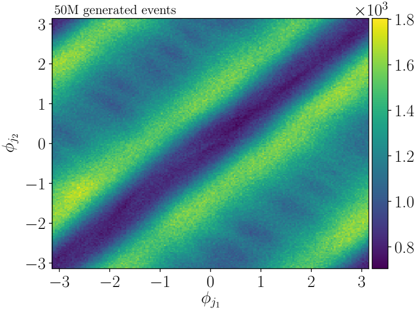
- constructed observables similar
- improved resolution [50M generated events]
- concept promising



Intermediate resonances

GAN version of adaptive sampling

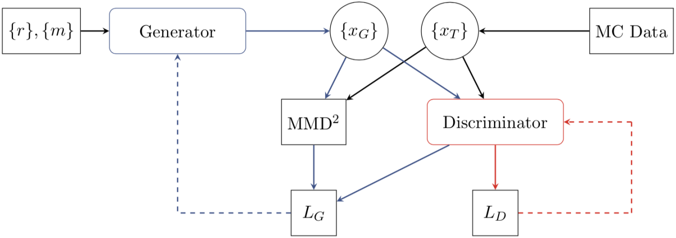
– generally 1D features

phase space boundaries
kinematic cuts
invariant masses [top, W]

– batch-wise comparison of distributions, MMD loss with kernel k

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

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



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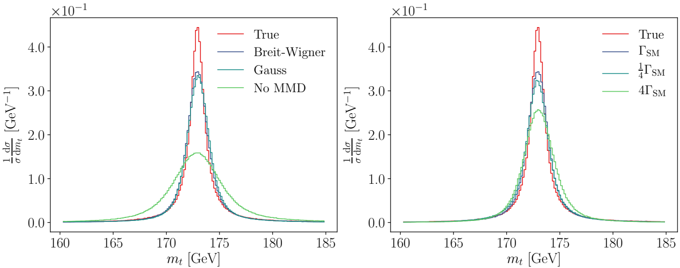


⇒ minor impact of kernel function and width

2– How to GAN event subtraction

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

– statistical uncertainty

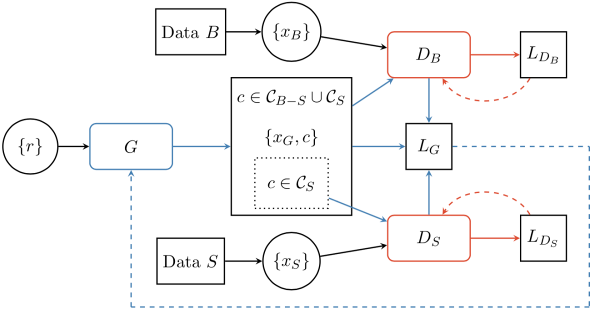
$$\Delta_{B-S} = \Delta_{n_B N_B - n_S N_S} = \sqrt{\Delta^2_{n_B N_B} + \Delta^2_{n_S N_S}} = \sqrt{n_B^2 N_B + n_S^2 N_S} > \max(B, S)$$

– applications in LHC physics

soft-collinar subtraction, multi-jet merging
on-shell subtraction
background/signal subtraction

– GAN setup

1. differential, steep class label
2. sample normalization



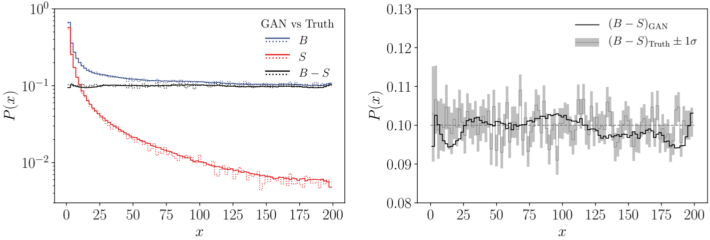
Subtracted events

How to beat statistics by subtracting

1– 1D toy example

$$P_B(x) = \frac{1}{x} + 0.1 \qquad P_S(x) = \frac{1}{x} \qquad \Rightarrow \qquad P_{B-S} = 0.1$$

– statistical fluctuations reduced (sic!)



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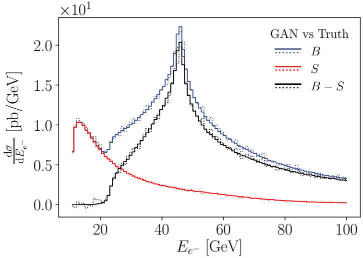
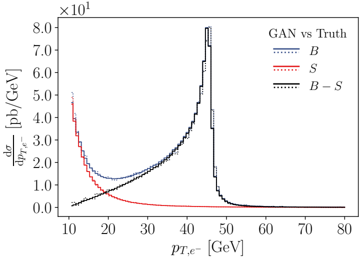
2– event-based background subtraction [weird notation, sorry]

$$pp \to e^+e^- \quad \text{(B)} \qquad pp \to \gamma \to e^+e^- \quad \text{(S)} \qquad \Rightarrow \qquad pp \to Z \to e^+e^- \quad \text{(B-S)}$$





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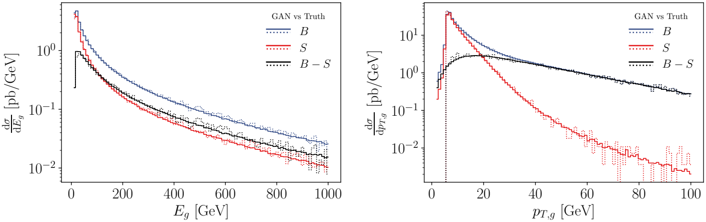
3– collinear subtraction [assumed non-local]

$$pp \to Zg \qquad \text{(B: matrix element, S: collinear approximation)}$$



$\Rightarrow$ applications in theory and analysis

3– How to GAN away detector effects

Bottom line from SFitter etc [e.g. global SMEFT analyses]

– total rates without necessary information
  STXS model-dependent
  unfolded distributions extremely convenient [$t\bar{t}$ results]

– benefits

  access to hard matrix element/first-principles QCD
  matrix element method

– challenges

  non-invertible detector simulation
  model dependence

General: invert Markov processes [Bellagente, Butter, Kasiczka, TP, Winterhalder]

– detector simulation typical Markov process

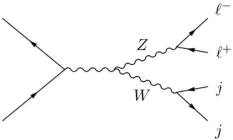
– inversion possible, in principle [entangled convolutions]

– GAN task

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

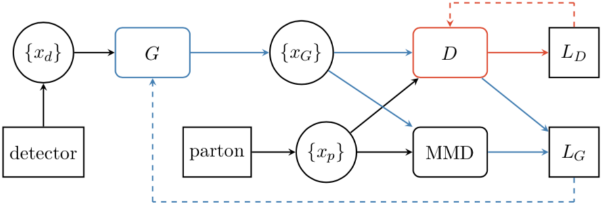
$\Rightarrow$ full phase space unfolded

Standard GAN



Reconstructing the parton level

- $pp \to ZW \to (\ell\ell)\ (jj)$
- broad jj mass peak
  narrow $\ell\ell$ mass peak
  modified $2 \to 2$ kinematics
  fun phase space boundaries
- GAN same as event generation [with MMD]



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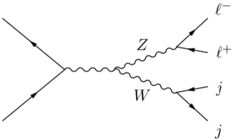

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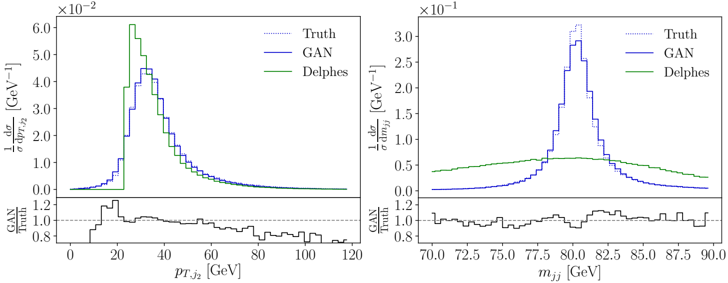
- full inversion fine



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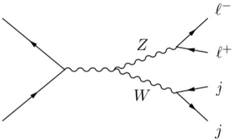

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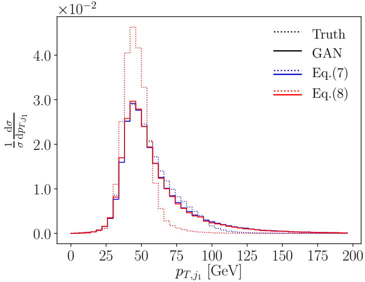
- GAN same as event generation [with MMD]
- full inversion fine
- problem: kinematics cuts in test data [88%, 38% events]

$$p_{T,j_1} = 30 \dots 100\ \text{GeV} \tag{7}$$

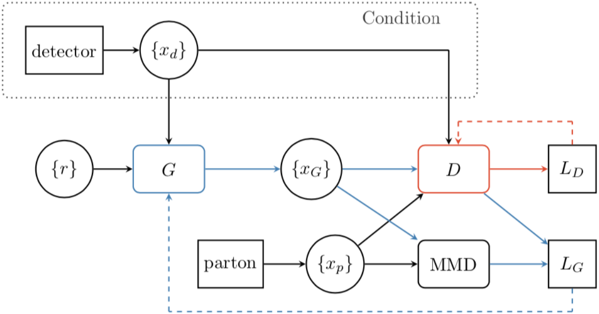
$$p_{T,j_1} = 30 \dots 60\ \text{GeV} \quad \text{and} \quad p_{T,j_2} = 30 \dots 50\ \text{GeV} \tag{8}$$



Fully conditional GAN

Proper sampling

– map random numbers to parton level
  hadron level as condition [matched event pairs]



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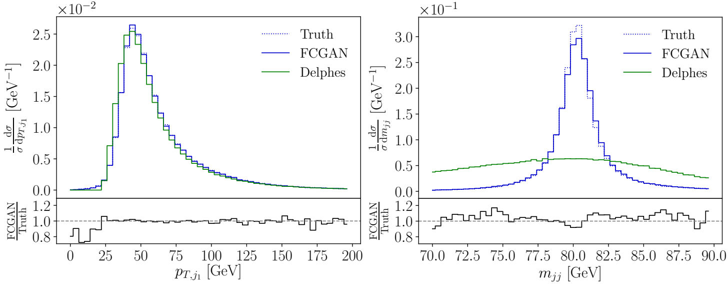

Fully conditional GAN

Proper sampling

- map random numbers to parton level
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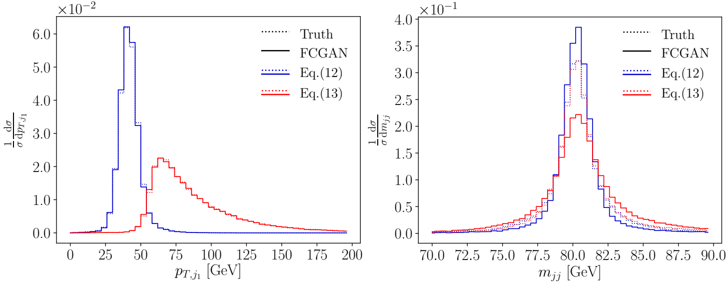
- full inversion fine [again]
- tougher cuts challenging m_{jj} [14%, 39% events, no interpolation, MMD not conditional]

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

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



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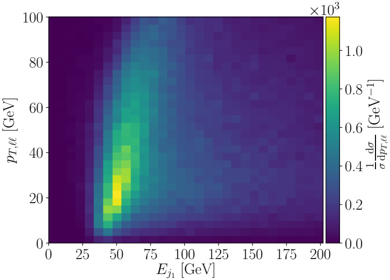
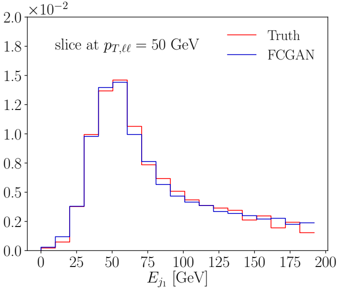
- pretty pictures in 2D





$\Rightarrow$ 1.FCGAN unfolding works!

BSM injection

Different training (MC) and actual data... [not in v1, thank you to Ben Nachman]

...or model dependence of unfolding

...or localization in latent space

– train: SM events
  test: 10% events with W' in s-channel $\Rightarrow$ any guesses?

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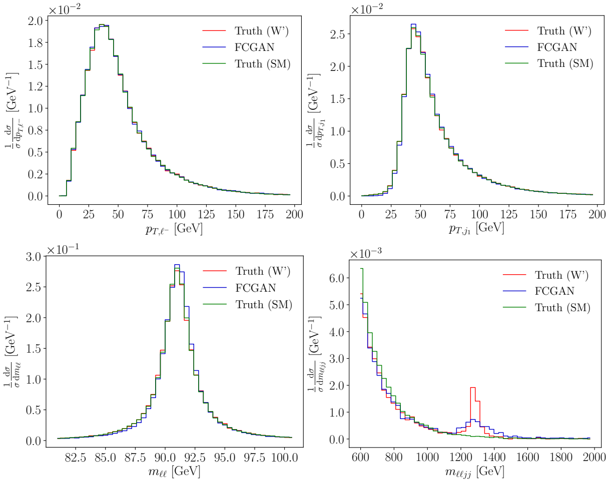
– train: SM events
  test: 10% events with W' in s-channel $\Rightarrow$ any guesses?



4– Unfolding as inverting

Invertible networks? [Bellagente, Butter, Kasieczka, TP, Rousselot, Winterhalder (soon)]

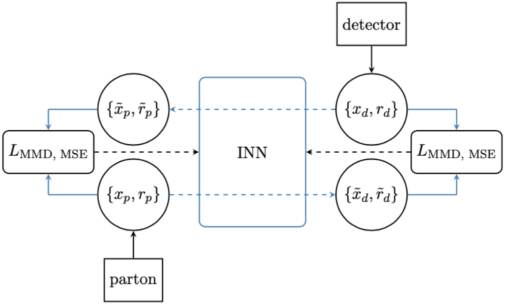
– network as bijective transformation — normalizing flow
  Jacobian tractable — normalizing flow
  evaluation in both directions — INN [Ardizzone, Kruse, Rother, Köthe]

– building block: coupling layer

$$x_d \sim g(x_p) \qquad \text{with} \qquad \frac{\partial g(x_p)}{\partial x_p} = \begin{pmatrix} \text{diag } e^{s_2(x_{p,2})} & \text{finite} \\ 0 & \text{diag } e^{s_1(x_{d,1})} \end{pmatrix}$$

– dimensions padded by random numbers

$$\begin{pmatrix} x_p \\ r_p \end{pmatrix} \xleftrightarrow[\leftarrow\ \text{unfolding:}\bar{g}]{\text{PYTHIA,DELPHES:}g\rightarrow} \begin{pmatrix} x_d \\ r_d \end{pmatrix}$$



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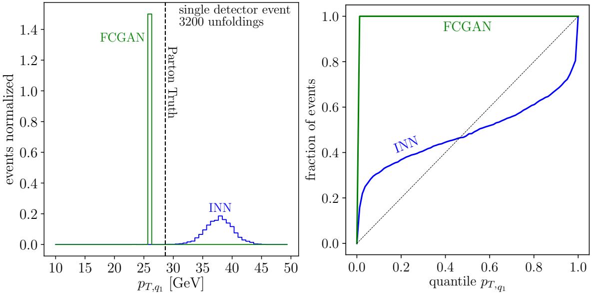
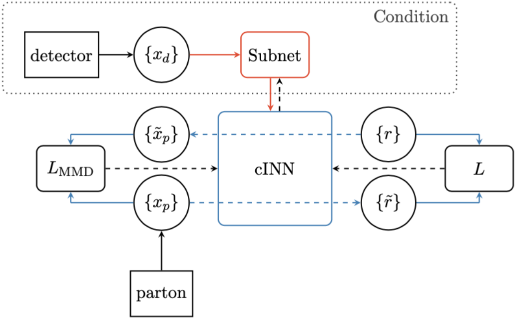
⇒ statistically promising



Conditional INN

Further improvement: conditional network

- same procedure as for GAN
- sampling parton level events from random numbers



Conditional INN

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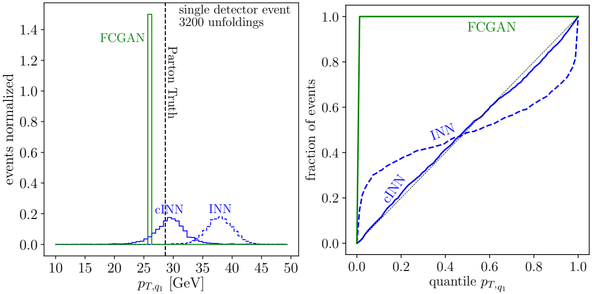
- calibration for statistical unfolding



Conditional INN

Further improvement: conditional network

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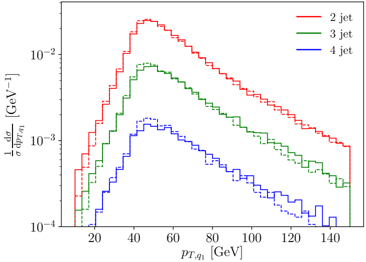
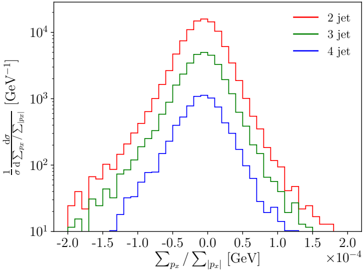
- calibration for statistical unfolding

Unfolding extra jets

- detector-level process $pp \to ZW$+jets [variable number of objects]
- parton-level hard process chosen $2 \to 2$ [whatever you want]
- ME vs PS jets decided by network [including momentum conservation]





$\Rightarrow$ proper inversion, all working!

Outlook

Machine learning a great tool box

LHC physics really is big data

imagine classification was a starting point

jet classification largely established

generative networks exciting for theory

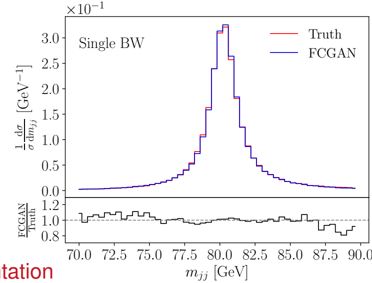
advantage 1: NN interpolation

advantage 2: latent space structures

advantage 3: training on MC and/or data

Any ideas?

Dynamic MMD



Technical side-remark: dynamic MMD

– minimal input

functional form of correlation m_{ij}
kernel shape (irrelevant) and resolution

– Adaptive resolution?

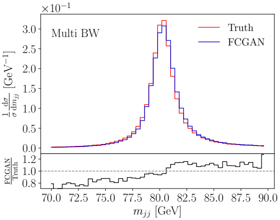
Technical side-remark: dynamic MMD implementation

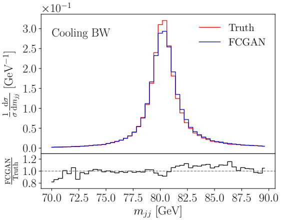
– multiple fixed-width kernels

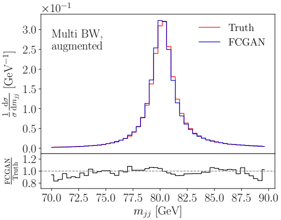
– multiple kernels for conditional input

– cooling kernel [from SD of generator m_{ij}]

$\Rightarrow$ Technical implementation still open...



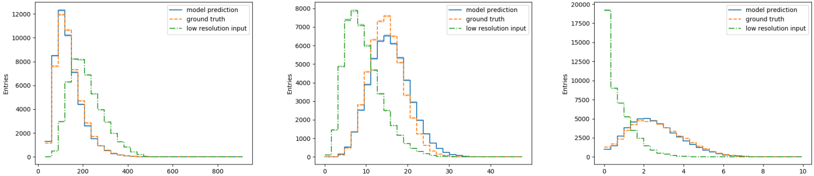




Superresolution GANs (preview)

Getting inspired [Blecher, Butter, Keilbach, TP + Irvine]

- take high-resolution calorimeter images
  down-sample to 1/8th 1D resolution
  GAN inversion
- works because the GAN learn structure [showers are QCD]
- start from low-resolution calorimeter images
  GAN high-resolution images
- energy of constituents no.1,10,30



$\Rightarrow$ GANs are kind of magic