Generative Networks for the LHC

and Some News on Symmetries

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Universität Heidelberg

SUSY 8/2021

LHC goals

Fundamental questions

– particle nature of dark matter?

– origin of the Higgs mechanism?

– matter-antimatter asymmetry?

– Standard Model all there is? — No!

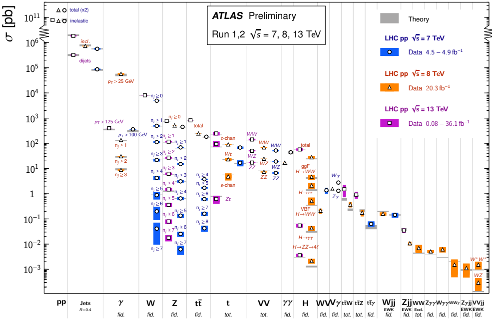
Show-off measurements

– many processes

– vastly different rates

– high precision

– in agreement with theory



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Show-off measurements

– many processes

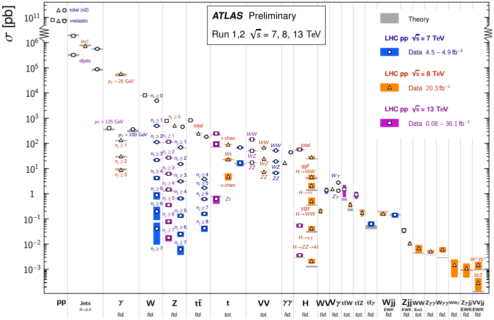
– vastly different rates

– high precision

– in agreement with theory

– but completely useless

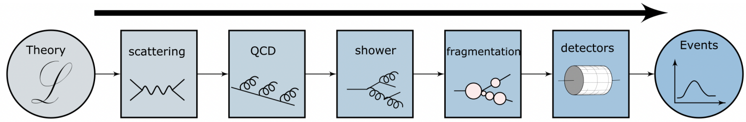
$\Rightarrow$ Kinematics all we care about



LHC simulations

Simulation-based inference [likelihood-free inference]

– start with Lagrangian
– calculate scattering in perturbative QFT
– simulate events [theory: Sherpa, Madgraph, Pythia]
– simulate detectors [experiment: ATLAS, CMS, Delphes]
$\Rightarrow$ LHC events in virtual worlds



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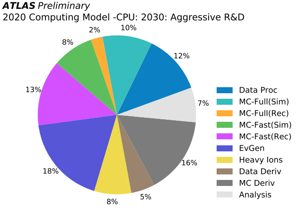
HL-LHC: preparing for 25-fold data set

- simulated event numbers $\sim$ expected events
- statistics requiring 1%-2% uncertainty [NNLO/N^{3}LO]
- flexible signal hypotheses [time-dependent]
- low-rate high-multiplicity backgrounds



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Three ways to use ML

- improve current tools: iSherpa, ML-MadGraph...
- new tools: fast ML-generator-networks...
- conceptual progress: invertible simulations, inference...

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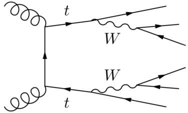
Generative network studies [hyperlinked]

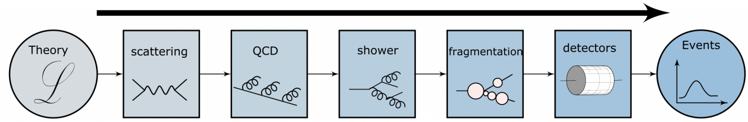
- Basics [GANplification (2020), Diefenbacher (2020), Winterhalder (2021)]
- Jets [de Oliveira (2017), Andreassen (2018), Carrazza-Dreyer (2019), Dohi (2020)]
- Superresolution [DiBello (2020), Baldi (2020)]
- Phase space [Bothmann (2020), Gao (2020), Klimek (2020), I-Kai Chen (2020), Carrazza (2020), Krause (2021)]
- Detectors [Paganini (2017), Musella, Erdmann, Ghosh, Salamani (2018), Belayneh (2019) Buhmann (2020,2021)]
- Events [Otten (2019), Hashemi, DiSipio, Butter (2019), Martinez (2019), Alanazi (2020), Chen (2020), Kansal (2020)]
- Event subtraction & unweighting [Butter (2019), Stienen (2020), Backes (2020)]
- Unfolding [Datta (2018), Omnifold, Bellagente (2019), Bellagente, Vandegar, Howard (2020), Komiske (2021)]
- QCD factorization [Lin (2019)]
- EFT models [Erbin (2018)]
- Inference [Brehmer (2020), Park (2020), Bieringer (2020)]
- Parton densities [Carrazza (2021)]
- Uncertainties [Bellagente (2021)]

NN-generating LHC events



LHC scattering benchmarks

- n-particle phase space $\quad n \times 3$ d.o.f.
  training from event samples [optimal transport vs likelihoods]
  energy-momentum conservation learned
  no detector effects [smoother structures]
- top-quark pairs $\quad t\bar{t} \to 6$ jets
  $t/\bar{t}$ and $W^\pm$ on-shell [Breit-Wigner $\Gamma/m \sim \mathcal{O}(\%)$]
- n-jets/WZ+jets
  variable number of particles
  topology through jet-jet separation



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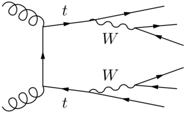

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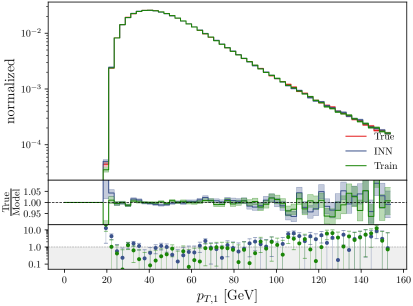
INN-generator [Butter, Heimel, TP,... (prelim)]

- normalizing flow to phase space
  bijective, stable mapping
  Jacobian known
- training on 2M n-jet events
- goal $\quad$ 1% precision



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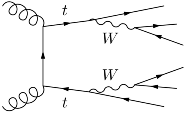

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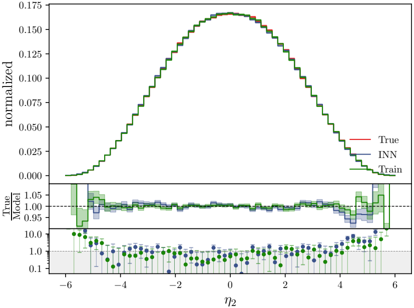

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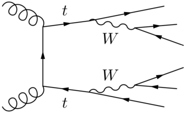

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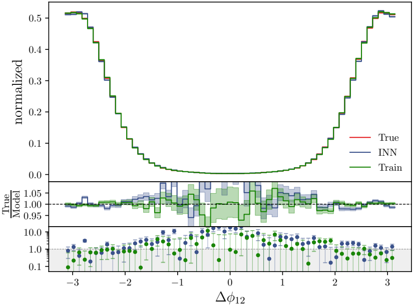

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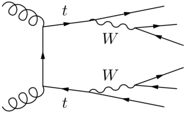

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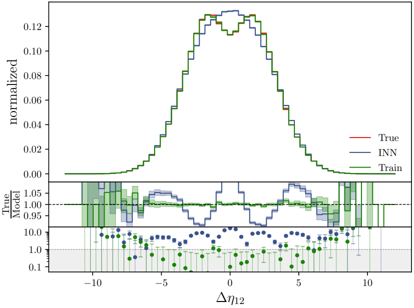

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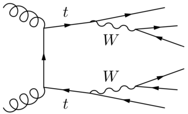

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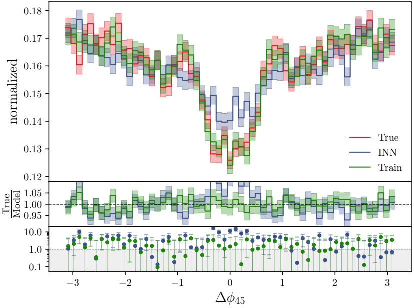
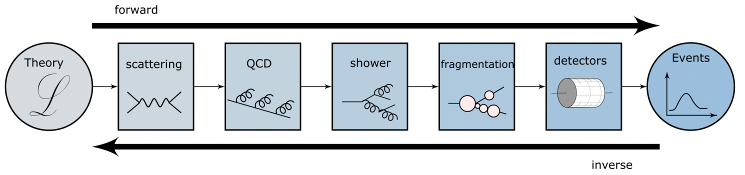


INNverting event generation

Inverting LHC simulations [Bellagente, Butter, Kasieczka... (2020)]

– unfolding QCD-shower to hard parton standard [jet algorithm]
unfolding detector common
unfolding top-quark decays useful
matrix element method for hypothesis test

$\Rightarrow$ systematic approach through generative network



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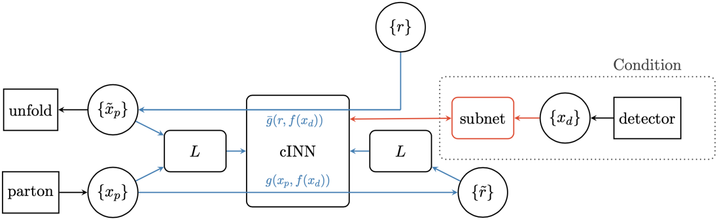
Conditional INN

– standard INN/cINN setup: parton-level events from $\{r\}$

– maximum likelihood loss

$$\begin{aligned} L &= -\left\langle \log p(\theta|x_p, x_d) \right\rangle_{x_p, x_d} \\ &= -\left\langle \log p(g(x_p, x_d)) + \log \left| \frac{\partial g(x_p, x_d)}{\partial x_p} \right| \right\rangle_{x_p, x_d} - \log p(\theta) + \text{const.} \end{aligned}$$

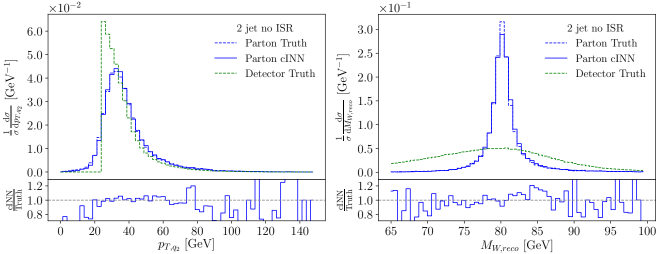


INNverting event simulations

Hard process $q\bar{q} \to ZW \to (\ell\ell)\ (jj)$

– stochastic inverse problem
model assumption like in forward direction

– invert detector effects



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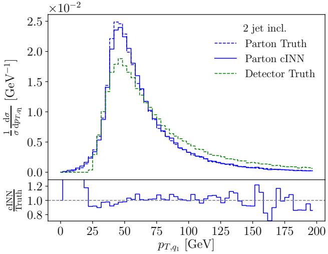

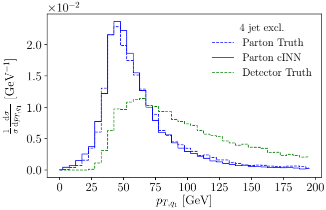

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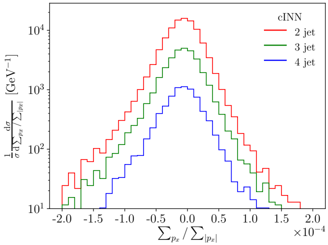

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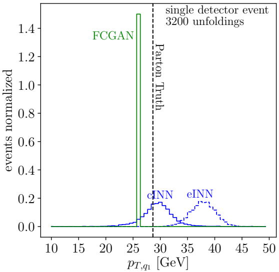
Proper statistical inversion

- distribution
  single detector event
  3200 unfoldings to partonic phase space



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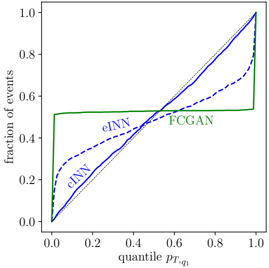
Proper statistical inversion

- distribution
  single detector event
  3200 unfoldings to partonic phase space
- calibration
  1500 detector-parton event pairs
  60 unfoldings per pair, in quantiles
  truth within given quantile for fraction of pairs

$\Rightarrow$ Probability distribution in parton phase space

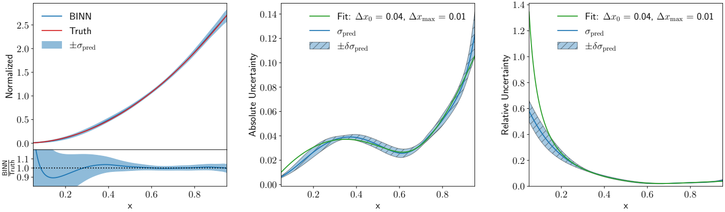


One number is not a prediction

Bayesian generative network [Bellagente, Luchmann, Haußmann, TP (2021)]

- generate events with error bars
  i.e. learn density and uncertainty maps over phase space
- normalizing flow/INN [Köthe etal]
- 2D toy models: wedge ramp, kicker ramp, Gaussian ring

$\Rightarrow$ Error estimate works...



...and we see how the network learns!

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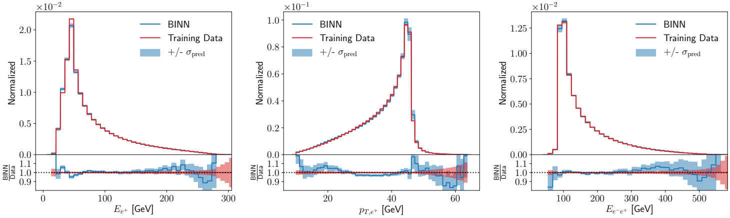
Simple LHC process

- 1D kinematic distributions with errors

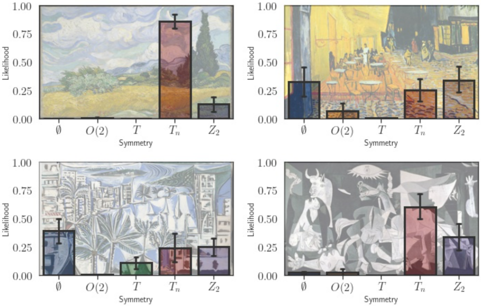


$\Rightarrow$ Key step in NN-simulations

SUSY Conference — Symmetries in ML

Symmetries key concept in particle physics

– analyze symmetries [Barenboim, Hirn, Sanz (2021)]



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– taggers: Lorentz symmetries [Butter (2018), Erdmann (2019), Bogatskiy (2020)]
permutation symmetries [graphs (2020), Komiske (2018), Dolan (2020)]
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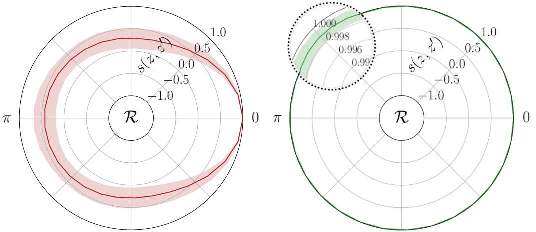
Particle-physics symmetries in latent space [JetCLR (Dillon 2021)]

– for instance anomaly searches: analysis in latent space [Dillon (2021)]
means: equivalent jets/events in same latent-space point [$s(z, z') \to 1$]

– jet symmetries: rotation, translation, permutation
jet augmentations: collinear merging, soft noise



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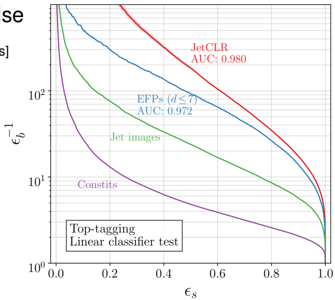
  jet augmentations: collinear merging, soft noise
- self-supervised learning [implicit: images, explicit: EFPs]
- test: linear classifier in latent space

$\Rightarrow$ Symmetries putting theory into ML-tools



Machine learning for LHC theory

On the way to the numerics mainstream

- ML standard for classification/regression/generation
- neural network benefits

  best available interpolation
  training on MC and/or data, anything goes
  lightning speed, once trained
- GANs the cool kid

  generator trying to produce best events
  discriminator trying to catch generator
- INNs my theory hope

  flow networks for control
  condition for inversion
- precision still an issue
  reliability crucial
  uncertainties from BayesianNNs
- symmetries the current challenge
- Progress needs new and fun ideas!