syn·er·gy | ˈsinərjē |

UNIVERSITÉ DE GENÈVE
FACULTY OF SCIENCE

PIs


TG


Slava Voloshynovskiy


François Fleuret

PhD students


Tomke Schröer


Malte Algren


Jona Ackerschott


Matthew Leigh


Debajyoti Sengupta


Sam Klein


Stephen Mulligan


Guillaume Quétant


Mariia Drozdova


Ivan Oleksiyuk


Bálint Máté


Atul Kumar Sinha


Daniele Paliotta

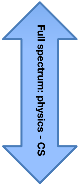
postdocs


Kinga Wozniak


Johnny Raine

This could be you !


Olga Taran



Code & publications
https://github.com/rodem-hep

Alexander von Humboldt Stiftung/Foundation

Sinergia

Swiss Government Excellence Scholarships
STUDY IN SWITZERLAND

Areas of Interest

- anomaly detection

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- anomaly detection
- kinematic reconstruction

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- anomaly detection
- kinematic reconstruction
- particle cloud generation

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- anomaly detection
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- foundation models

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- anomaly detection
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- foundation models
- decorrelation

Areas of Interest – Me

- kinematic reconstruction / unfolding
- generation
- foundation models

Anomaly Detection – CURTAINs

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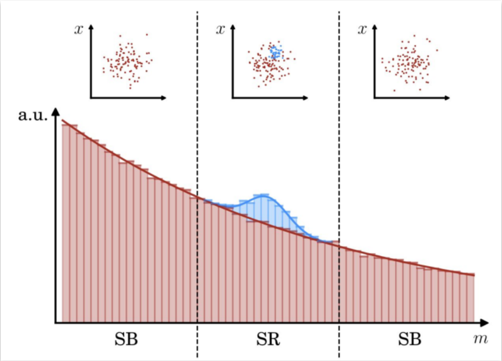
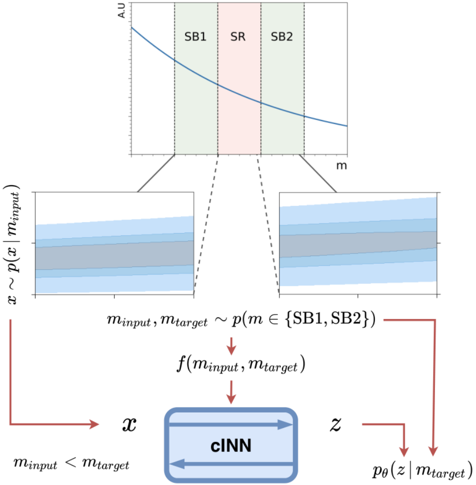
- Want to estimate background in signal region



Anomaly Detection – CURTAINs

- Want to estimate background in signal region
- Train two flows to transform $p(x \mid m_{\text{input}})$ to $p(x \mid m_{\text{target}})$



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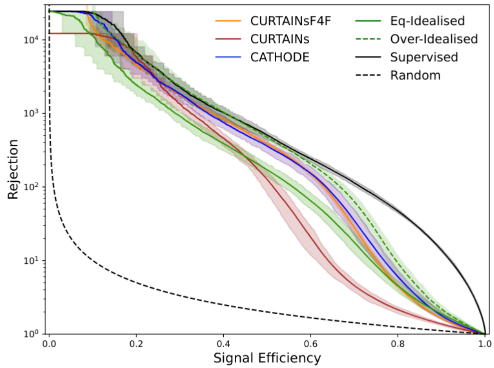

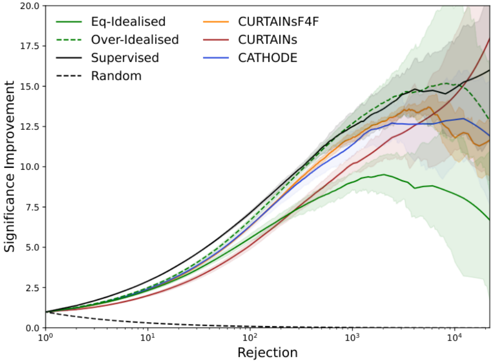

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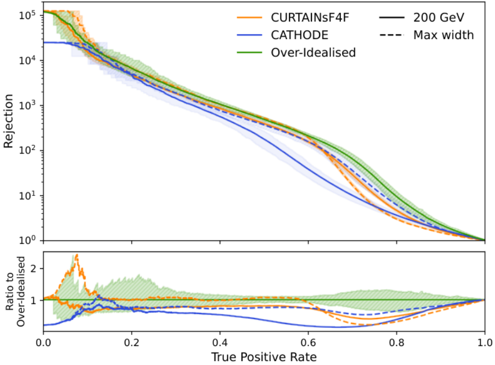
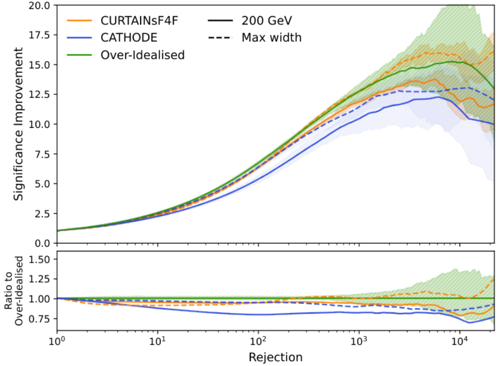
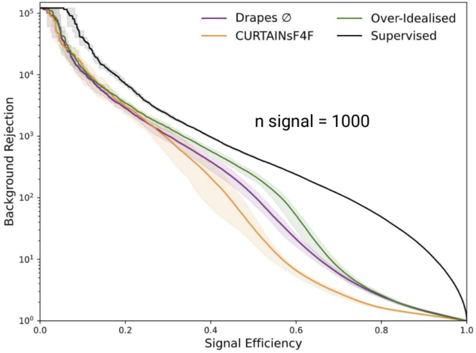


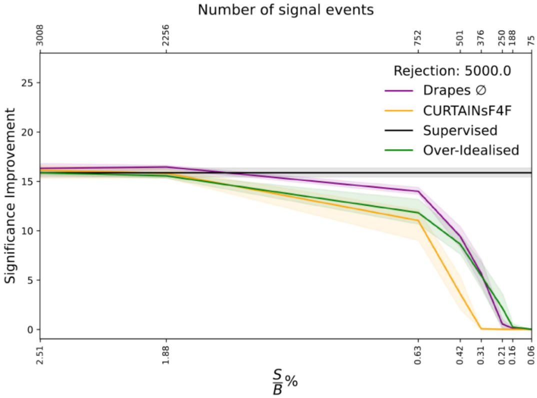


Anomaly Detection – Drapes

- Conditional density estimation using Diffusion
- Analogous to CATHODE

Anomaly Detection – Drapes





Kinematic Reconstruction – nu2-flows

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- Use cINN unfolding setup for neutrino reconstruction

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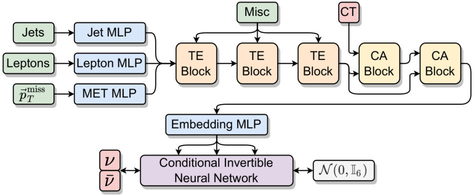

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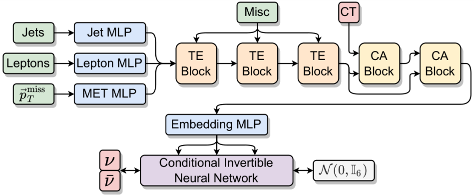
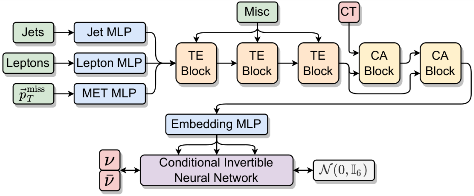


Kinematic Reconstruction – nu2-flows

- Use cINN unfolding setup for neutrino reconstruction
- preprocess reco-level information with transformer-based vision setup
- Permutation invariant
- Allows for variable number of jets



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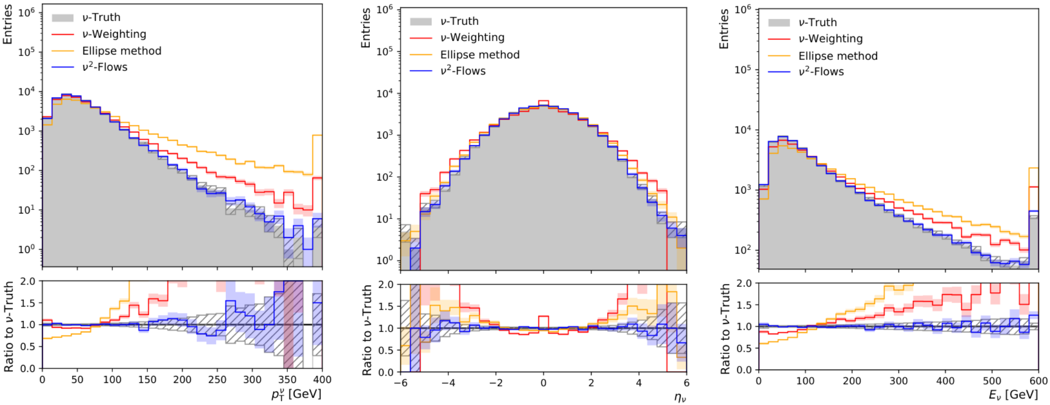
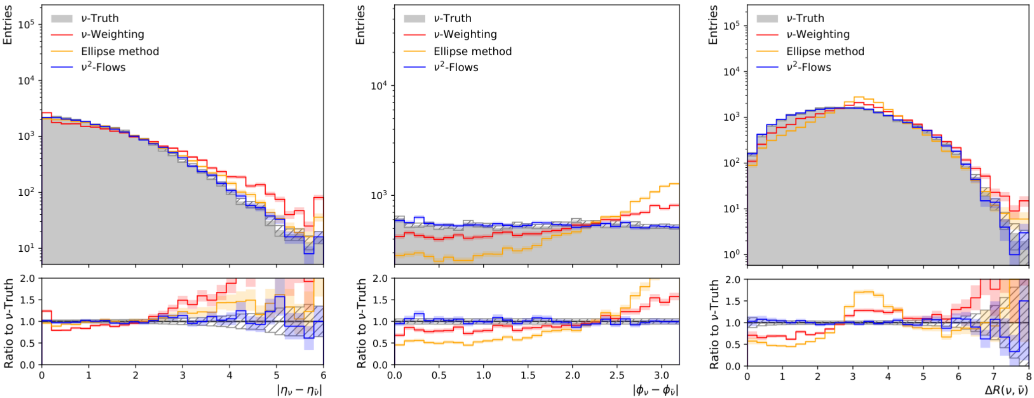


Kinematic Reconstruction – NU2-FLOWS



Particle Cloud Generation – PC-Droid

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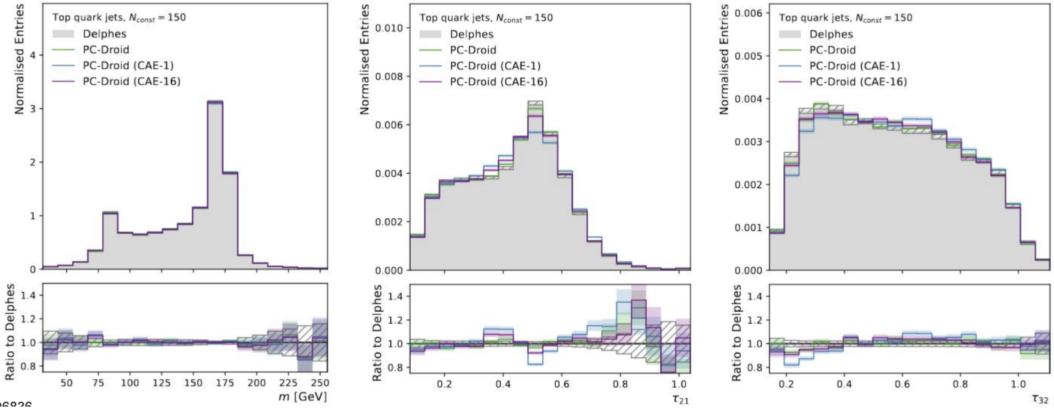
- Generation time: two orders faster than PC-JeDi, three orders faster than Delphes

Particle Cloud Generation – PC-Droid



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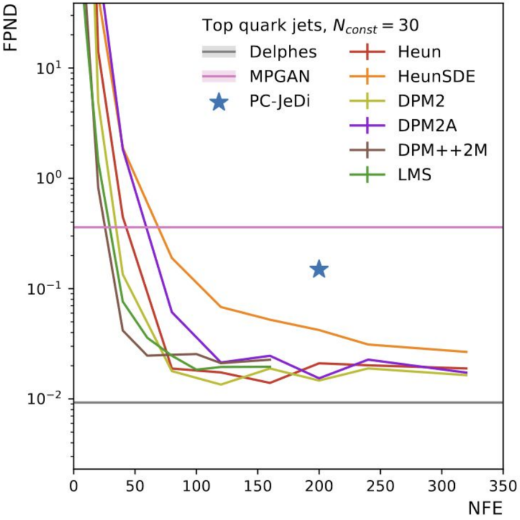

Returning CP-Observables to The Frames They Belong

Jona Ackerschott[1], Rahool Kumar Barman[2], Dorival Gonçalves[2], Theo Heimel[1], and Tilman Plehn[1]

1 Institut für Theoretische Physik, Universität Heidelberg, Germany
2 Department of Physics, Oklahoma State University, Stillwater, USA

Summary

- idea: apply ML unfolding to CP-violation detection in $pp \to ht\bar{t}$

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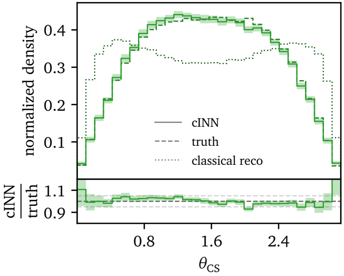
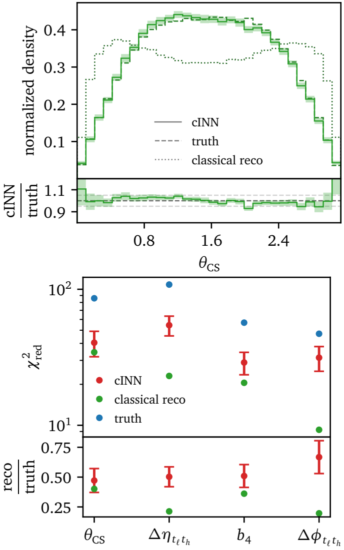


- idea: apply ML unfolding to CP-violation detection in $pp \to ht\bar{t}$
  - allow for reconstruction of CP-sensitive observables

Summary

- idea: apply ML unfolding to CP-violation detection in $pp \to ht\bar{t}$
  - allow for reconstruction of CP-sensitive observables
  - improve sensitivity



arXiv:2308.00027v1

SciPost Physics Submission

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August 2, 2023

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  Higgs-top Yukawa coupling

$$\mathscr{L} \supset -\frac{m_t}{v}\kappa_t \bar{t}(\cos(\alpha)+i\gamma_5\sin(\alpha))th$$

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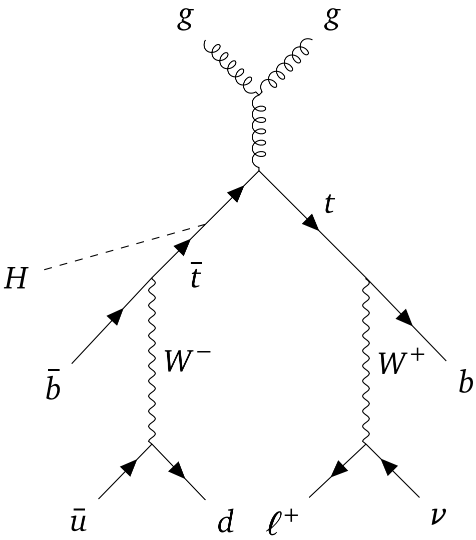
- most direct probe: $t\bar{t}h$ production



CP-sensitive Observables

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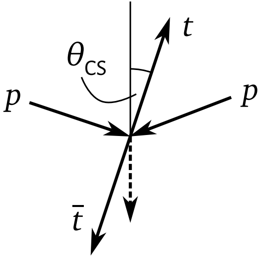

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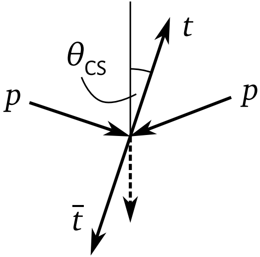

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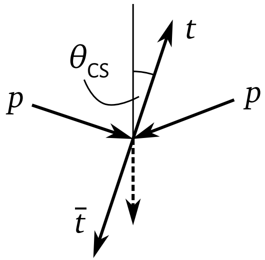

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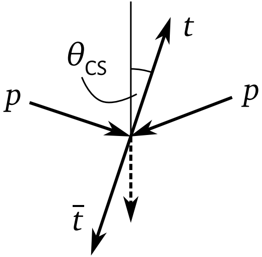

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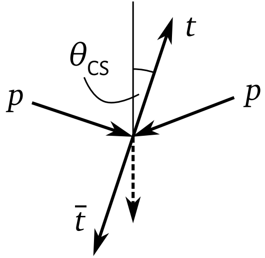
CP-sensitive Observables

- Look at four CP-sensitive observables
- Identified as most sensitive by Barman et al (arXiv:2110.07635v2)



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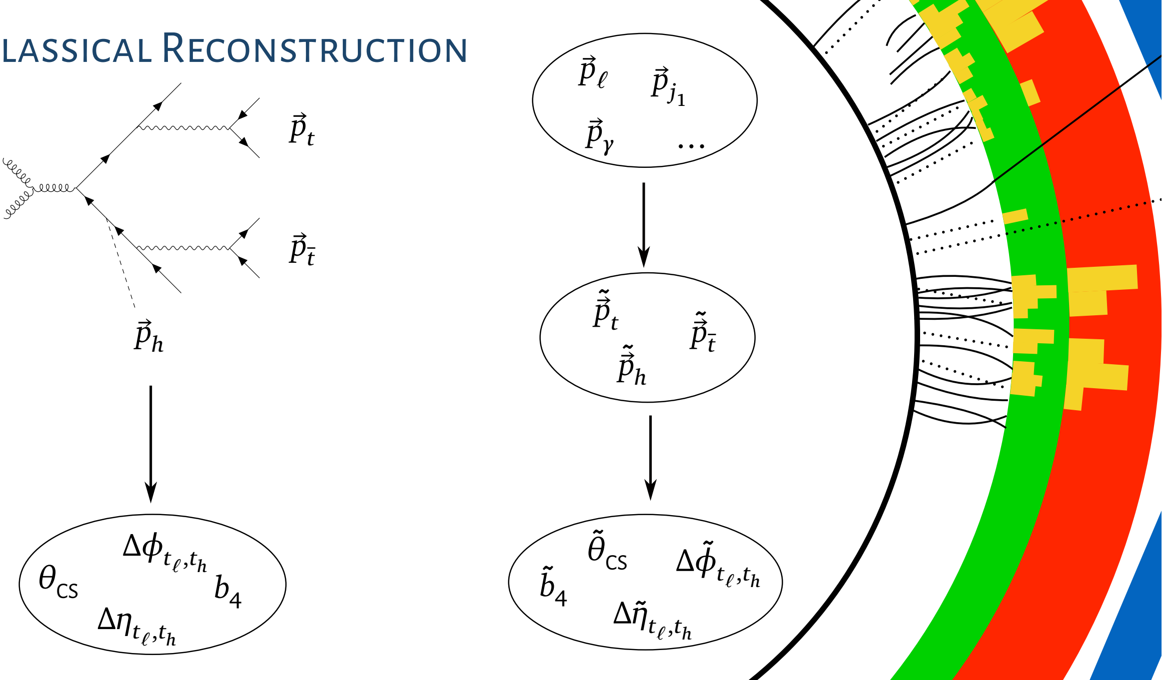
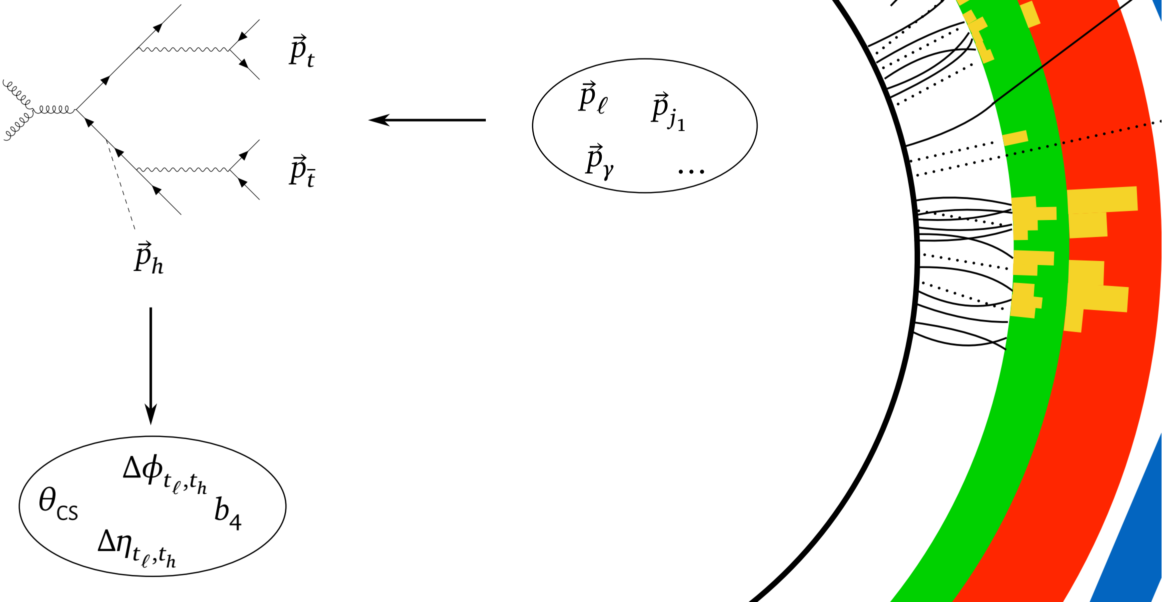
Classical Reconstruction



ML Unfolding



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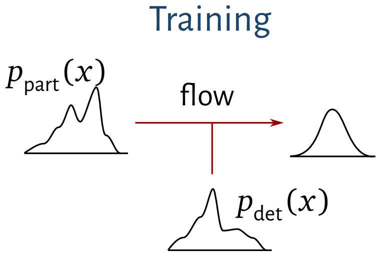
- normalize parton distribution

$$x = (p_h, p_b, p_\ell, \dots) \sim p_{\text{part}}(x)$$

conditioned on reco-level distribution

$$y = (p_{\gamma_1}, p_{\gamma_2}, p_{b_1}, \dots) \sim p_{\text{det}}(y)$$



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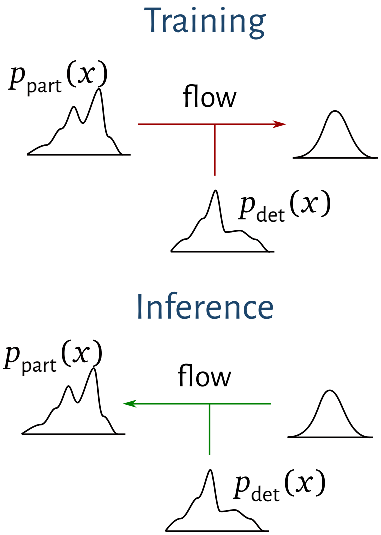

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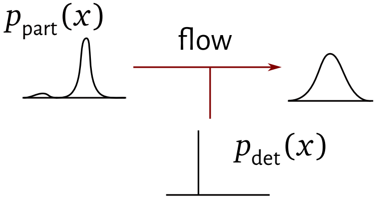
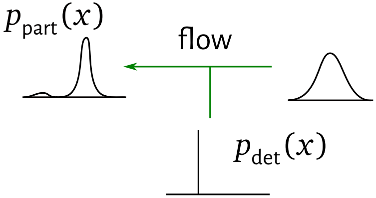
Training



Inference



Unfolding Method

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- Main idea of generative models

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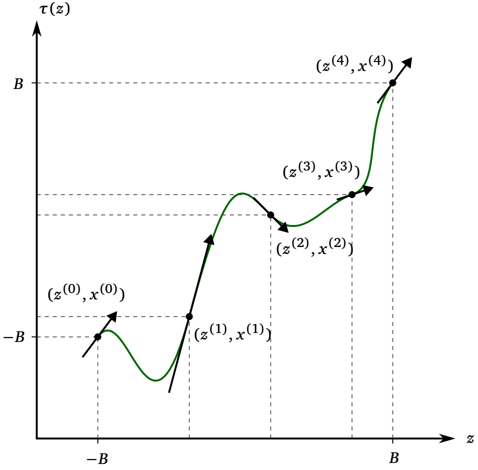
- Invertible NN allows for change of variable formula

$$p_\phi(x_{\text{part}}) = q(f_\phi(x_{\text{part}}))\,\left|\det(Df_\phi(x_{\text{part}}))\right|$$

Unfolding Method

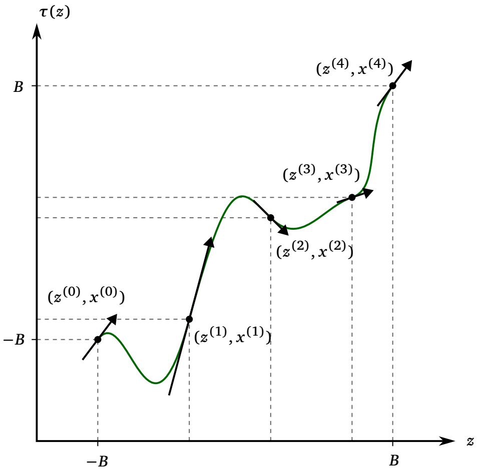
Unfolding Method

- Use feature transformation that is invertible and flexible

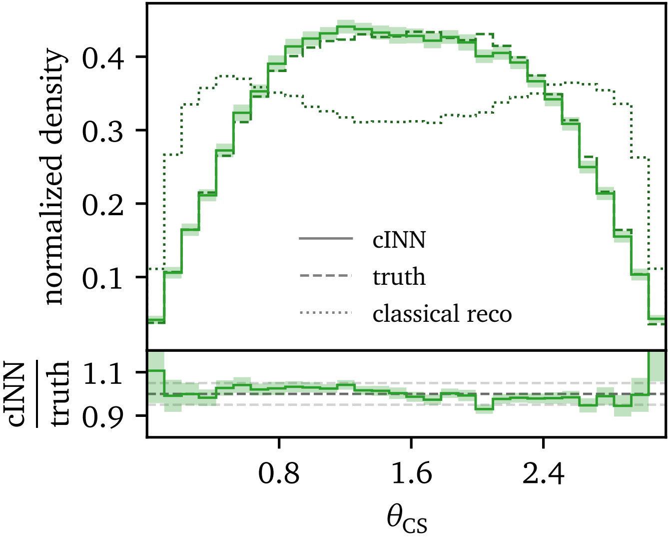


Unfolding Method

- Use feature transformation that is invertible and flexible
- Predict parameters of transformation with NN



Observable Reconstruction



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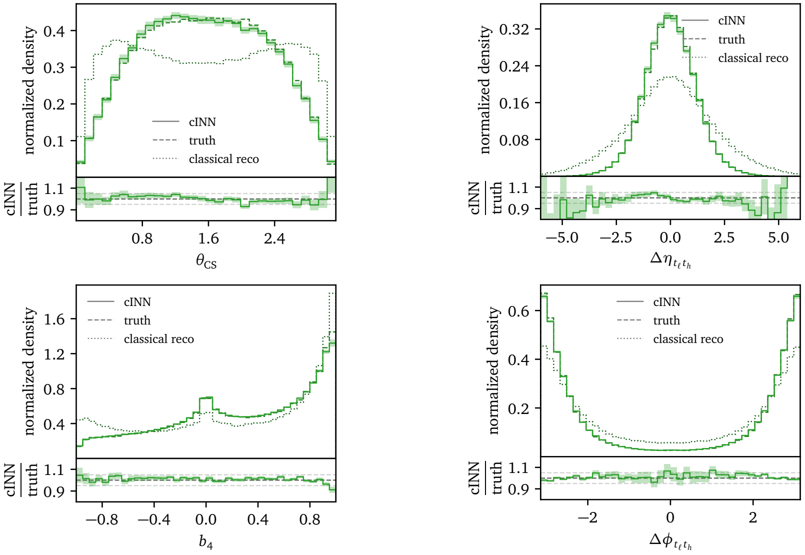
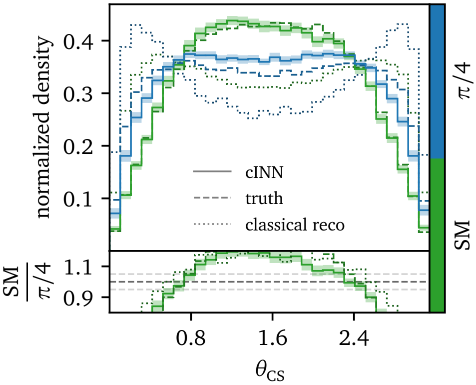


Sensitivity



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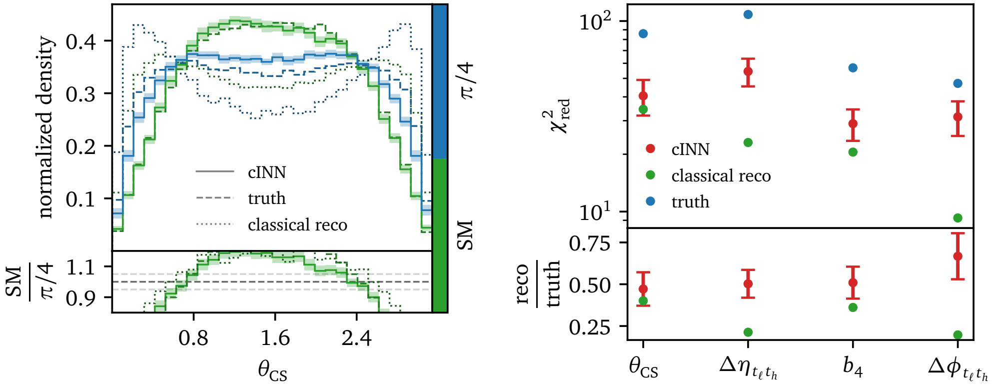

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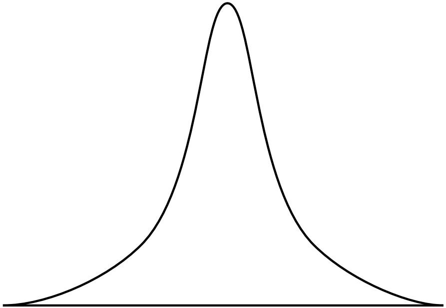

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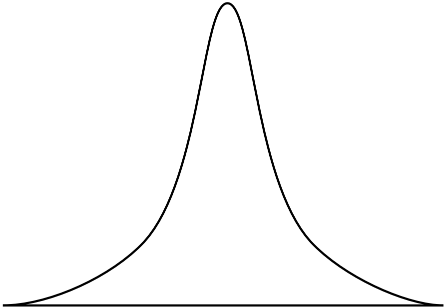
→ use phase space parameterization that includes intermediate masses



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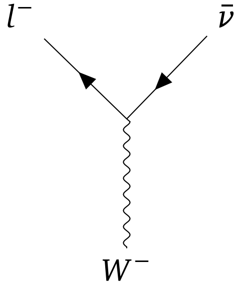
Example



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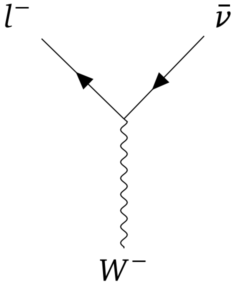

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- Use $(m_W, \vec{p}_W, \phi_l^W, \theta_l^W)$
- From on-shell conditions

$$E_\ell^W = |\vec{p}_\ell^W| = m_W$$

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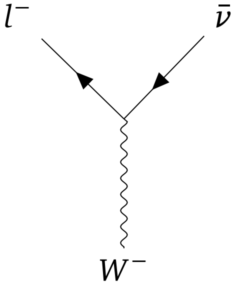

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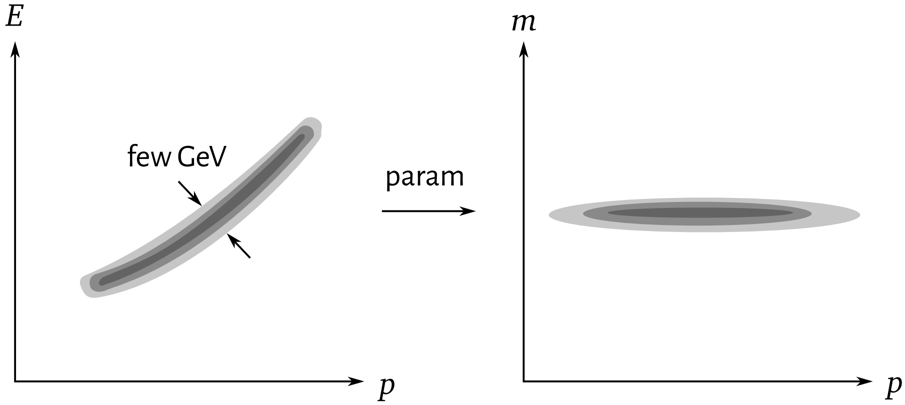

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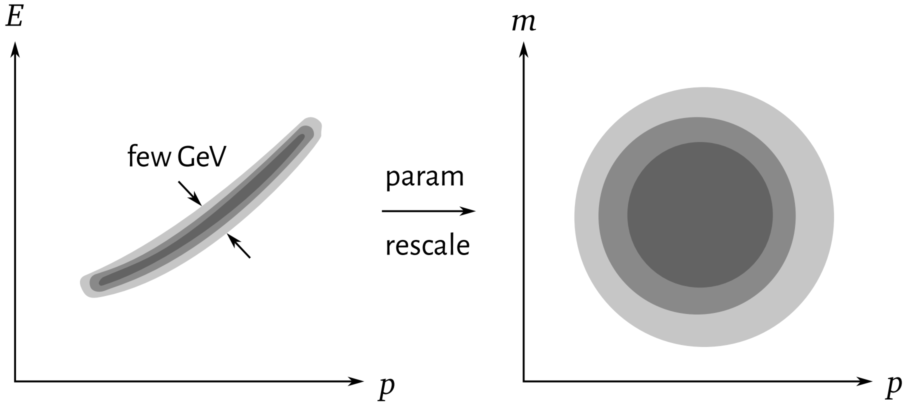

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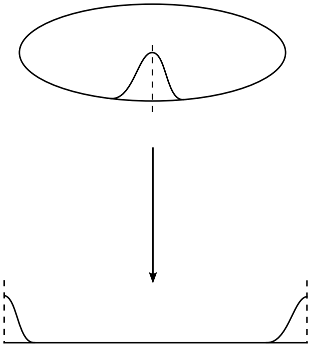

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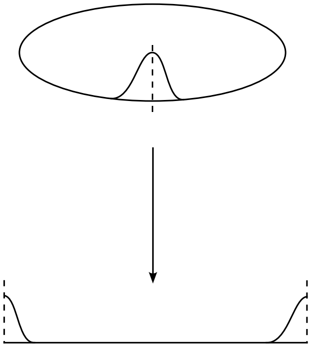
→ adapt flow architecture with periodic coupling blocks



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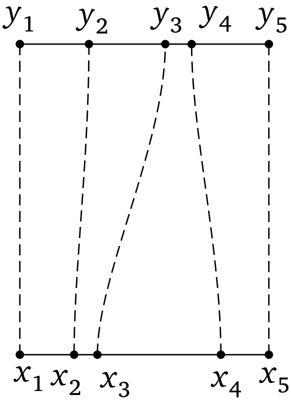

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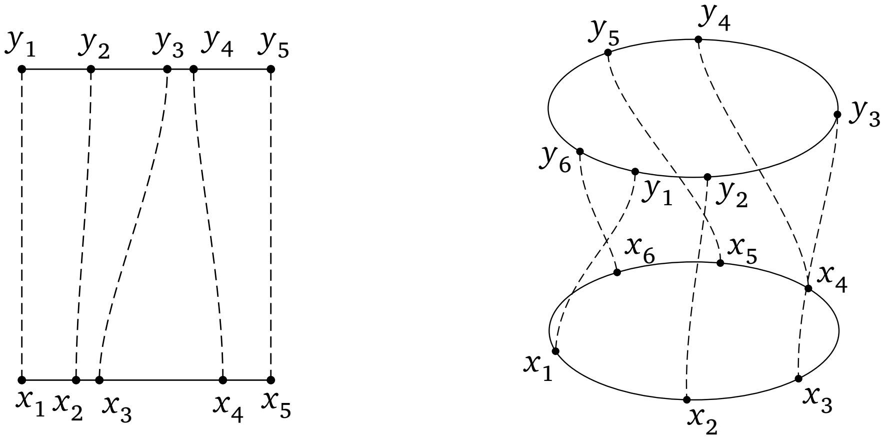

Outlook

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- proper treatment of experimental limitations