Higgs self-coupling sensitivity at the ILC Status and Recent Developments

ECFA meeting on e+e- to ZH angular measurements | 2024/06/18

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Agenda

- Introduction
- Part I: State-of-the-art (SOTA) Analysis Tools
- Part II: Future Analysis Tools
- Conclusion

Introduction

Physical fundamentals and methods for direct measurements of the Higgs self-coupling at future Higgs factories

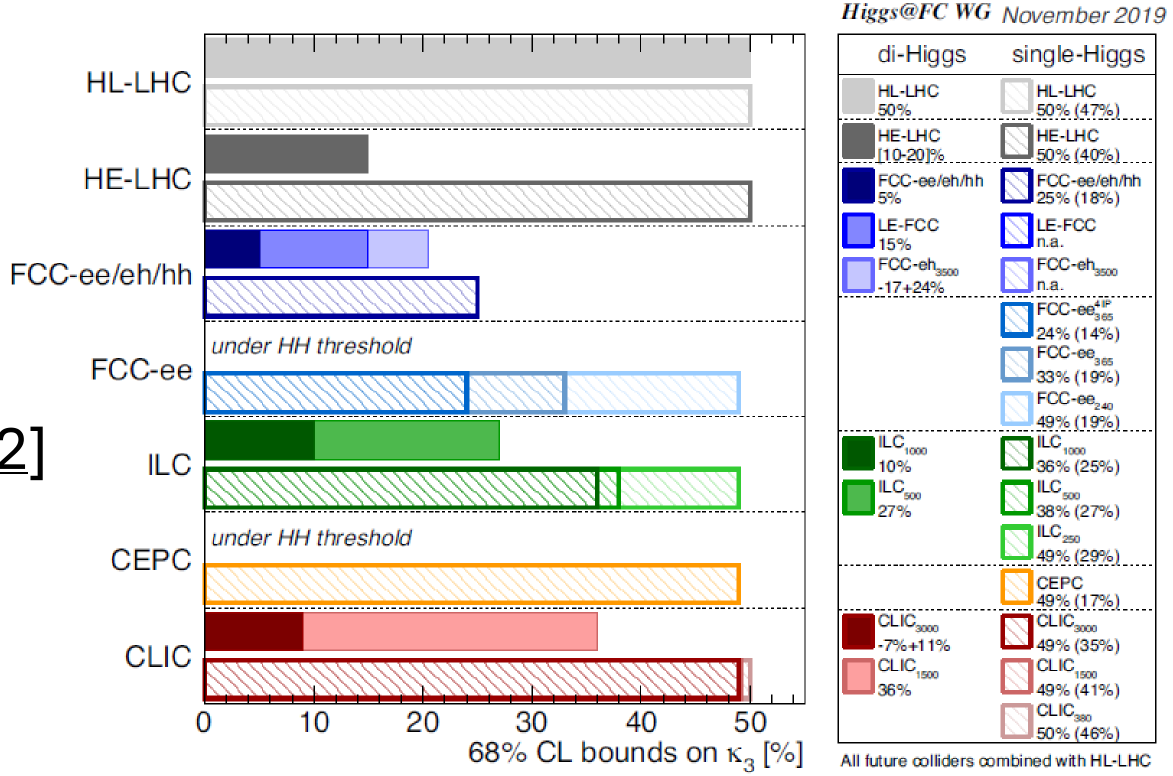
The Higgs self-coupling λ in the SM

$$V(h) = \frac{1}{2}m_H^2 h^2 + \lambda v h^3 + o(h^4); \lambda_{SM} = \frac{m_H^2}{2v^2}$$

v vacuum expectation value (vev) of Higgs field h

m_H mass of Higgs boson

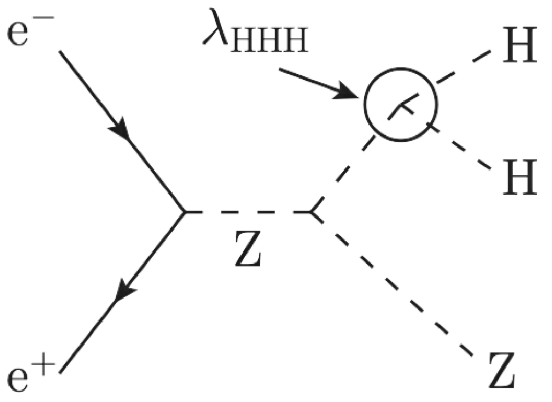
- in SM: λ_{SM} fixed since m_H is known [At/Cm12]
  - deviation from $\lambda = \lambda_{SM}$ hints at BSM physics
  - beyond SM, many values are possible
  - most projections assume $\lambda = \lambda_{SM}$

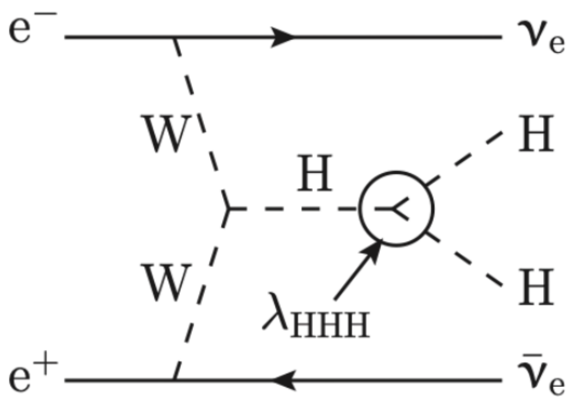


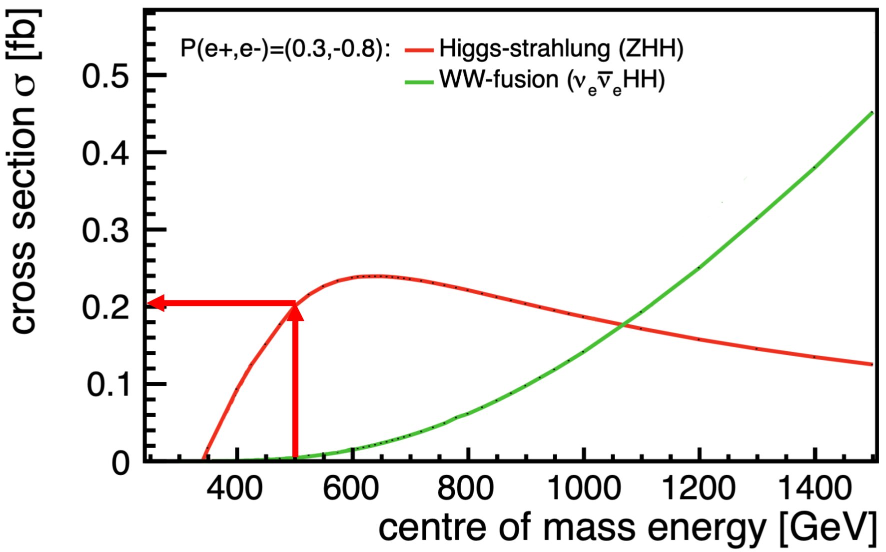
Projected sensitivity at 68% probability for k_3.
From [Db20]

Measuring the Higgs self-coupling at e+e- colliders

- *direct access* to λ through double-Higgs production
  - Di-Higgs strahlung (**ZHH**; dominant < 1 TeV)
  - vector boson fusion ($\boldsymbol{\nu\bar{\nu}}$**HH**; dominant > 1 TeV)

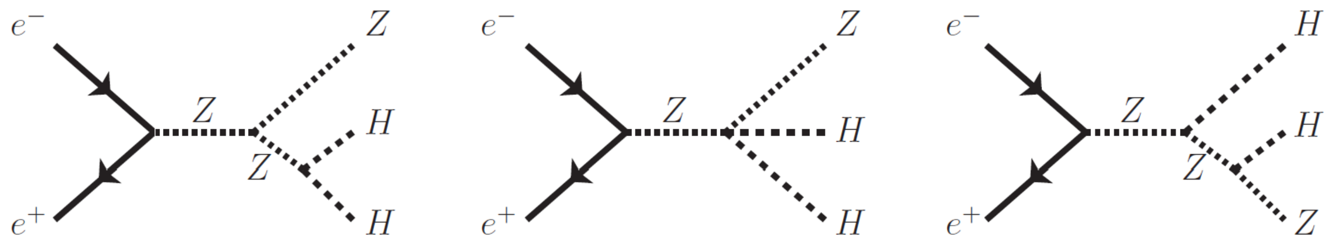






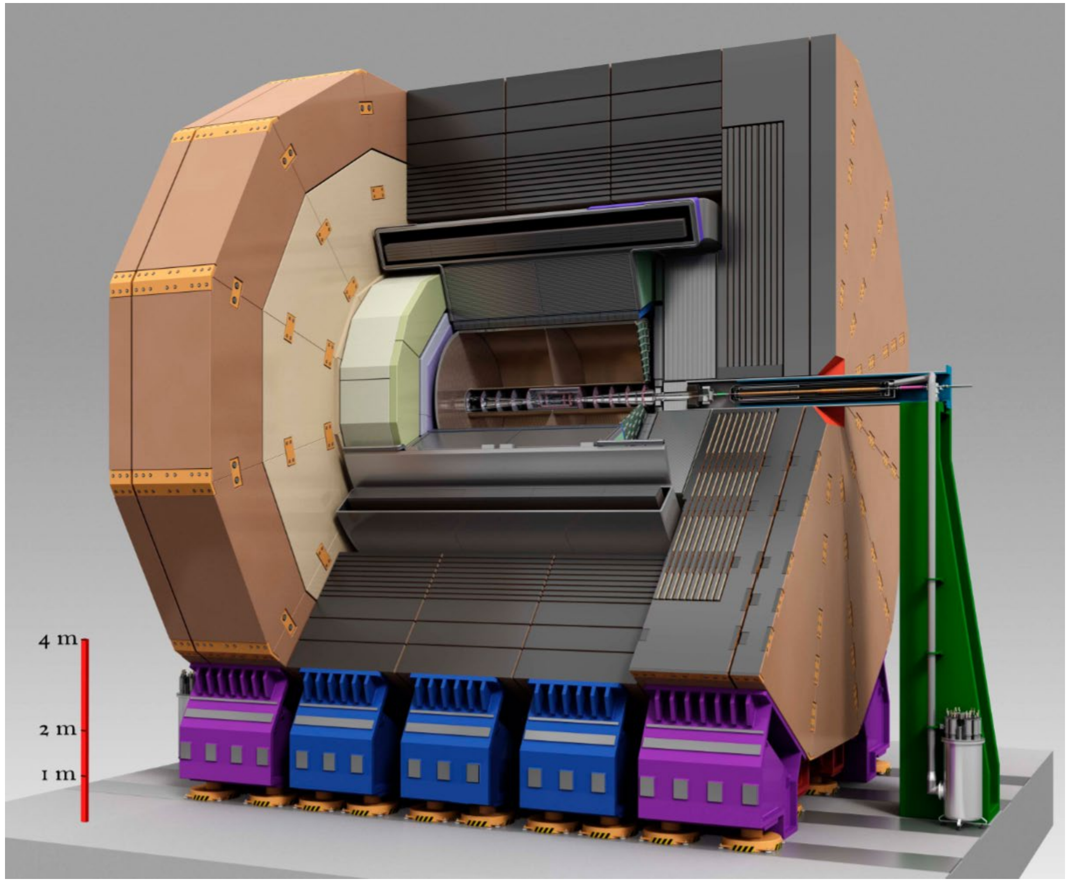
Cross-section of Di-Higgs production processes. From [Du16]

- degredation of sensitivity in ZHH by diagrams without λ



The International Large Detector (ILD)

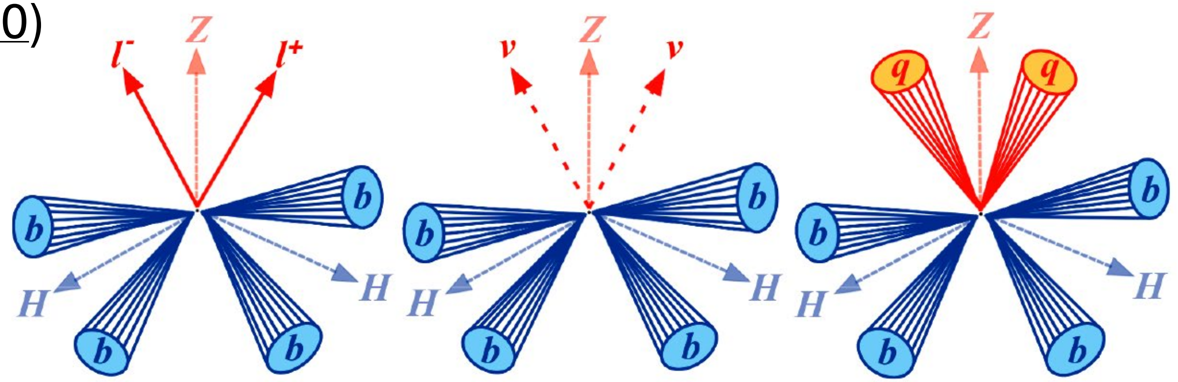
- well charatecterized, highly granular detector concept [IDR]
- designed around particle flow concept
  - allows reconstruction of individual physics objects (Particle Flow Objects, PFOs)
- full Geant4-based simulation available
  - including links between truth/reconstructed particles



Rendering of the ILD detector. From [Ba19]

The ZHH Analysis

- extensive projections at ILC500 (DESY-Thesis-16-027)
  - based on ILD detector concept (DBD2013, IDR2020)
  - 17 background and 3 signal channels considered
  - multivariate (MVA) tools for multiple steps
    e.g. lepton and flavor tagging, background rejection etc.
  - weight event counting by m_{HH}^2
    for further sensitivity enhancement



Lepton, neutrino and hadron channel of the signal process.
From [Du16]

- precision reach after running 4ab^{-1} at 500 GeV $\left(\text{HH} \to \text{b}\bar{\text{b}}\text{b}\bar{\text{b}} + \text{HH} \to \text{b}\bar{\text{b}}\text{W}^{\pm}\text{W}^{\mp}\right)$

$\Delta\sigma_{\text{ZHH}}/\sigma_{\text{ZHH}} = 16.8\%$

$\Delta\lambda_{\text{SM}}/\lambda_{\text{SM}} = 26.6\%$

$\Delta\lambda_{\text{SM}}/\lambda_{\text{SM}} = 10\%$ with additional upgrade to 1 TeV

Bottlenecks in the ZHH analysis

- jet pairing and jet misclustering: “perfect“ jet clustering → 40% improvement

  improve di-jet mass resolution

- removal of $\gamma\gamma$ overlay: 15% improvement expected

  important to tackle initial state radiation (ISR)

- flavor tagging: 11% improvement expected from 5% eff. increase with newer LCFIPlus

  important as $H \to b\bar{b}$ is the dominant Higgs decay channel

- adding $Z \to \tau\tau$ channel: 8% improvement expected

  include a yet unaccounted decay channel

- tagging of isolated leptons

  improves reconstruction of Z bosons

- separation of ZHH diagrams with/without the self-coupling

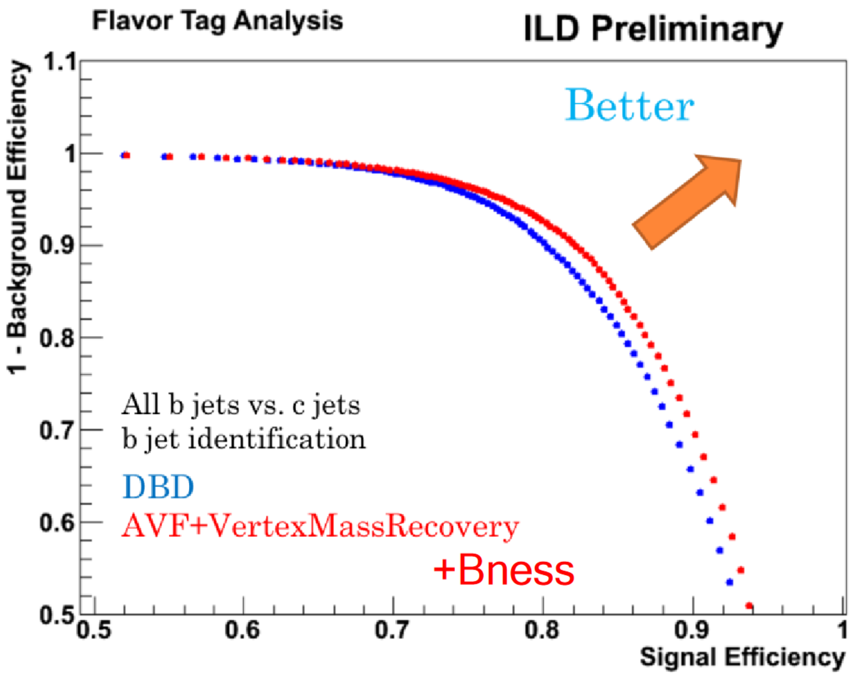
  would directly improve the sensitivity on λ (lower sensitivity factor)

Tools of Today

State-of-the-art (SOTA) tools for reconstruction and analysis expected to improve the sensitivity on λ

Flavor tagging with LCFIPlus

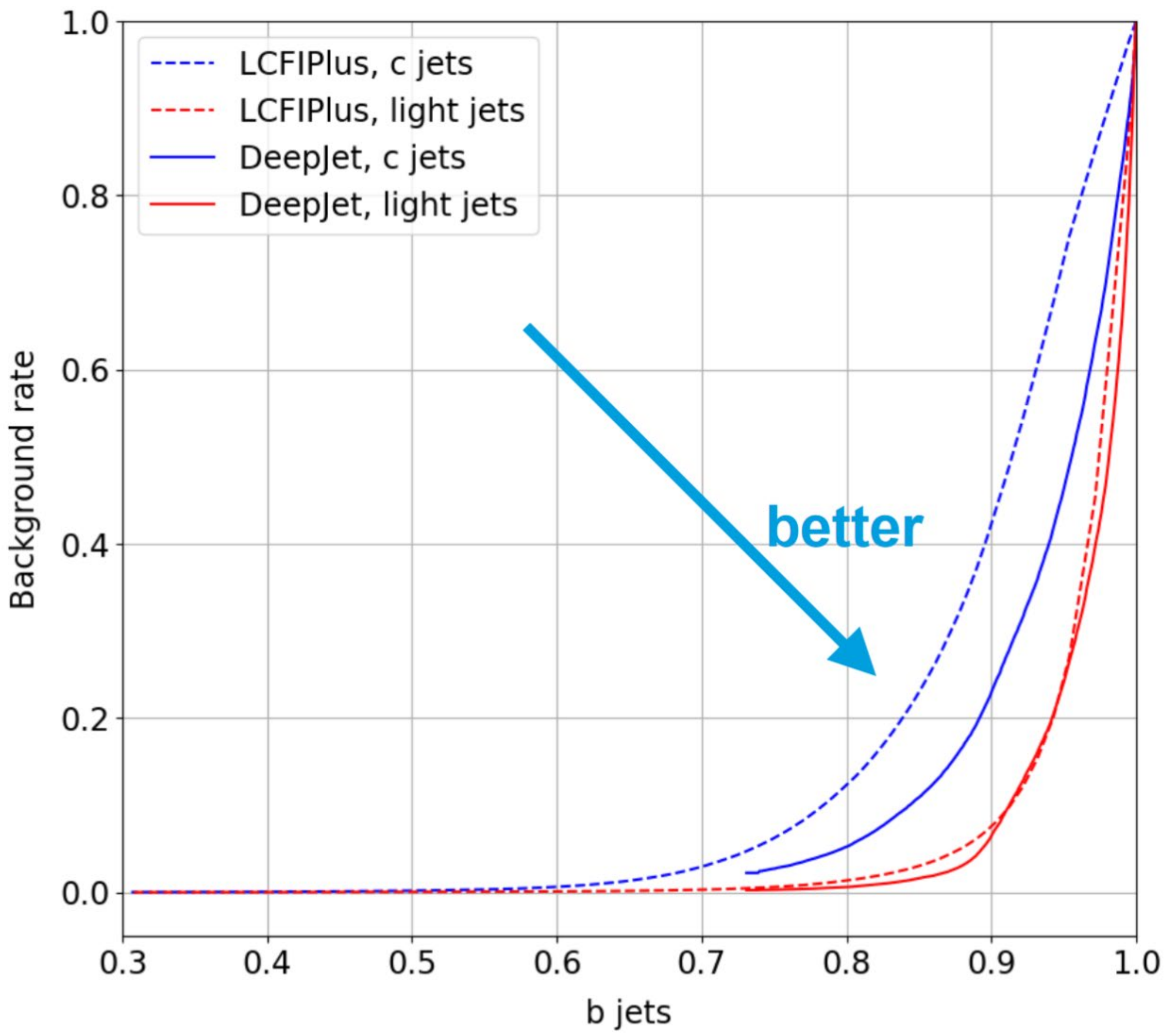
- improved b-tagging efficiency in current ILD standard LCFIPlus since SOTA projections from 2016
  - 5% relative improvement in ϵ_{b-tag} at same purity
  - 11% expected improvement in $\Delta\sigma_{\text{ZHH}}/\sigma_{\text{ZHH}}$



T. Suehara [2017]

Flavor tagging with ML (DeepJet)

- improved b-tagging efficiency since state-of-the-art projections from 2016
- ML models (DeepJet, ParticleNet, ParT) show highly improved rejection compared to LCFIPlus
- status: ready for use (in MarlinML)



Flavor tagging performance of LCFIPlus vs. DeepJet at ILD full simulation.
M. Meyer [2023]

Flavor tagging with ML (ParT)

- improved b-tagging efficiency since state-of-the-art projections from 2016
- ML models (DeepJet, ParticleNet, ParT) show highly improved rejection compared to LCFIPlus
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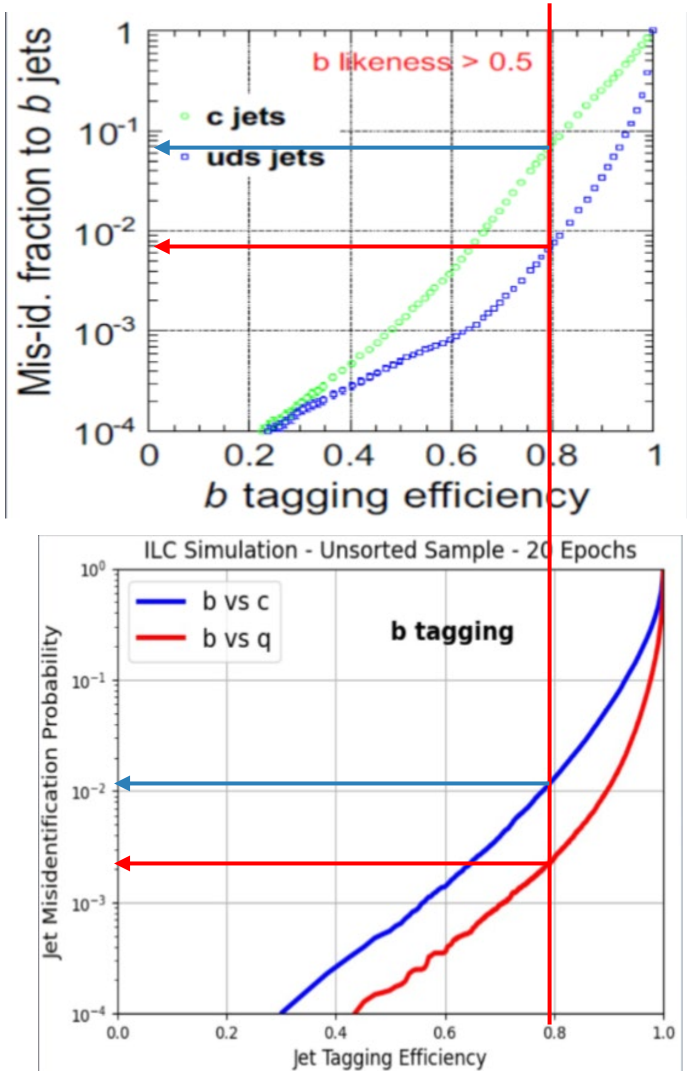


Flavor tagging performance of LCFIPlus (top) vs. ParT (bottom) at ILD full simulation. T. Suehara [2023]

ErrorFlow

- assume full parameterization of errors for individual jets

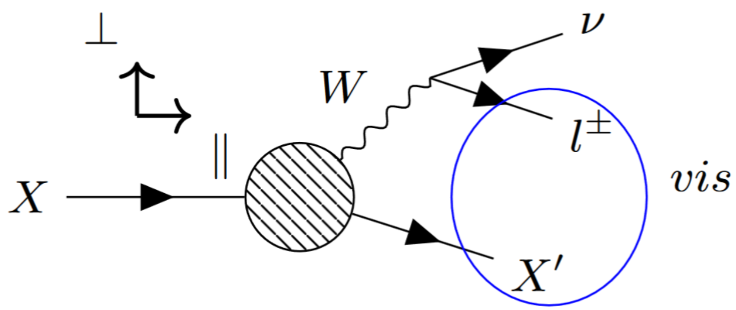
$$\sigma_{E_{jet}} = \sigma_{Det} \oplus \sigma_{Conf} \oplus \sigma_{\nu} \oplus \sigma_{Clus} \oplus \sigma_{Had} \oplus \sigma_{\gamma\gamma}$$

  - σ_{Det}: detector resolution — Y. Radkhorrami [2022]
  - σ_{Conf}: particle confusion in particle flow algorithm
  - σ_{ν}: neutrino correction

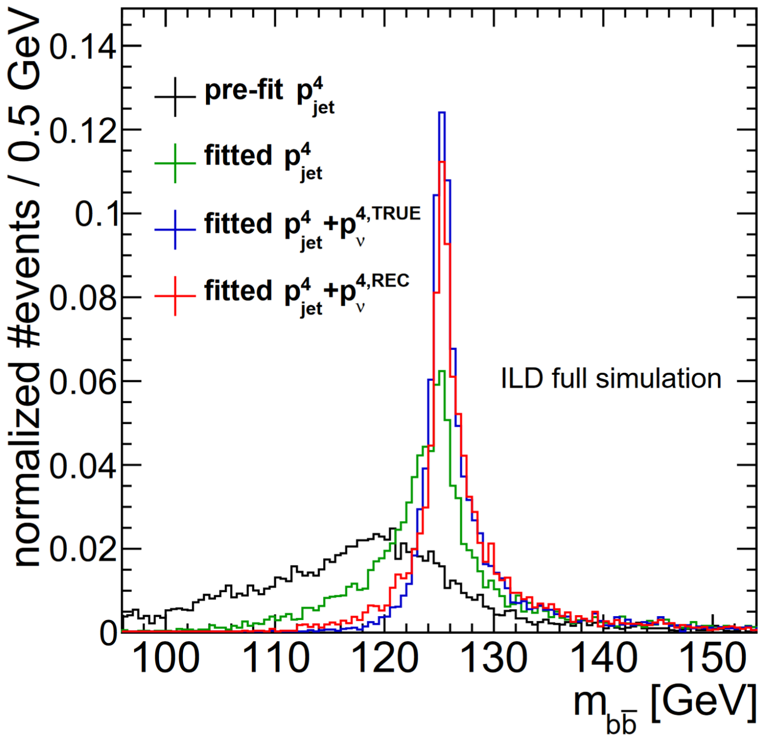
- status: in production (in MarlinReco)

Neutrino correction with kinematic fitting

- for semileptonic decay (SLD) processes
  - already in $\mathrm{ZH} \rightarrow b\bar{b}/c\bar{c}$, 66% of events include at least one SLD
- procedure:
  - identify/tag heavy quark jet
  - identify lepton in jet
  - calculate neutrino four momentum from kinematics with kinematic fitting, the best solution is selected
- status: in production (in MarlinReco)



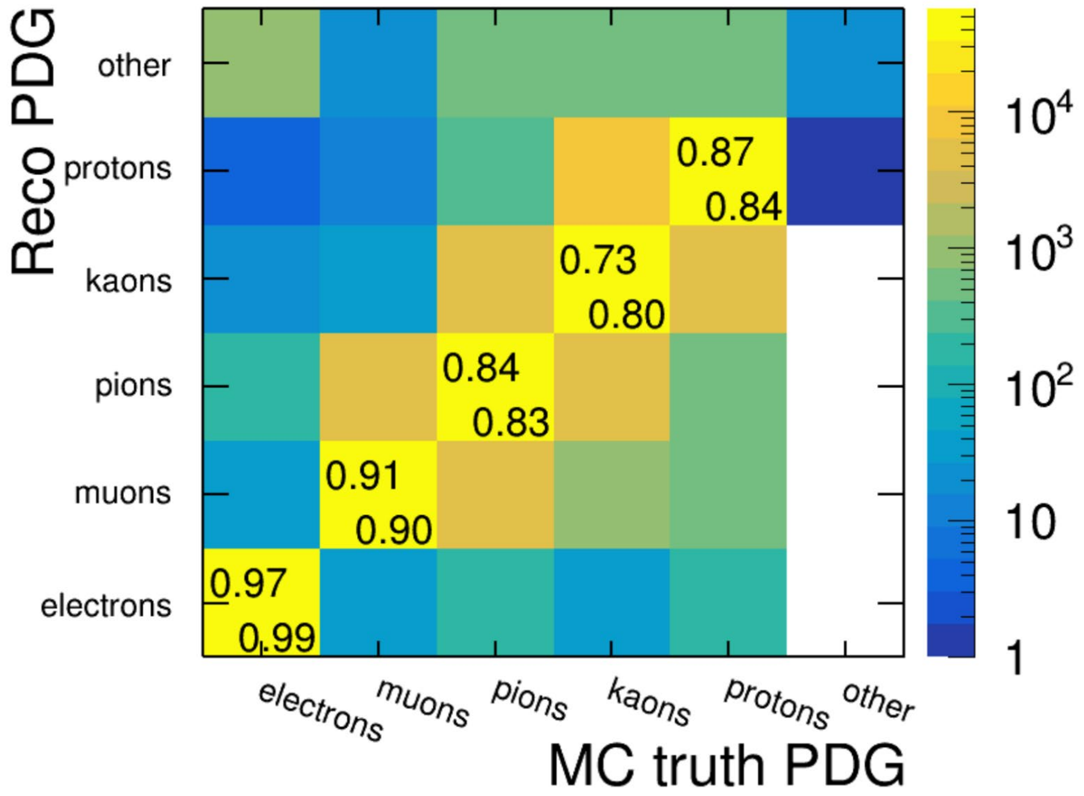
Recovering the neutrino kinematics. Y. Radkhorrami [2022]



Improved di-jet mass reconstruction. Y. Radkhorrami [2022]

Comprehensive Particle Identification (CPID)

- modular and highly configurable PID toolkit
  - "plug-and-play" of multiple data sources
    e.g. at ILD: dE/dx, TOF, cluster shape
  - extension through custom inference modules
    e.g. MVA/ML models etc.
- includes default weights for BDT model
- status: in production (in MarlinReco)



Confusion matrix for single charged partilces at ILD.
U. Einhaus (2023)

Conclusion I: The ZHH Analysis with SOTA-Tools

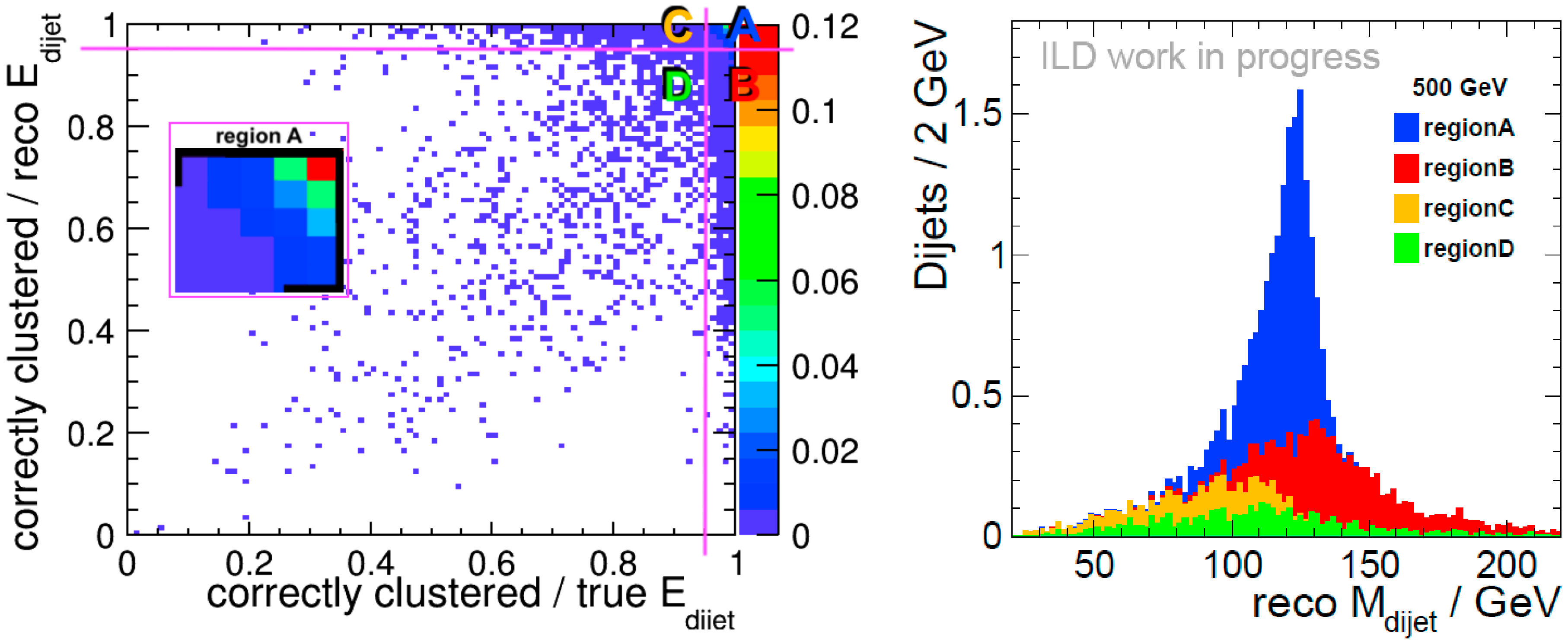
- major advancements in key aspects since last ZHH analysis [Du16]
  - flavor tagging efficiency improved by at least 5% ($\approx 10\%$ with ML tools)
  - kinematic fits benefit substantially from full ErrorFlow paramterization
  - neutrino correction has greatly improved di-jet mass resolution in events with SLDs
  - particle identification now aware of multiple detector systems
- **better than 20% sensitivity of $\Delta\lambda_{SM}$ / λ_{SM}** expected with SOTA tools [To24b]

Tools of Tomorrow

Potential future tools for reconstruction and analysis

Motivation: Misclustering in the ZHH analysis

- misclustering of PFOs to jets deteriorates the sensitivity to λ by ≈ 2 [Du16]
- quantification: purity vs efficiency of energy in reconstructed di-jets
- classify di-jets into 4 regions (A, B, C, D) based on threshold: $> 95\%$ on both axes
  - e.g. 45.5% of dijets in region A

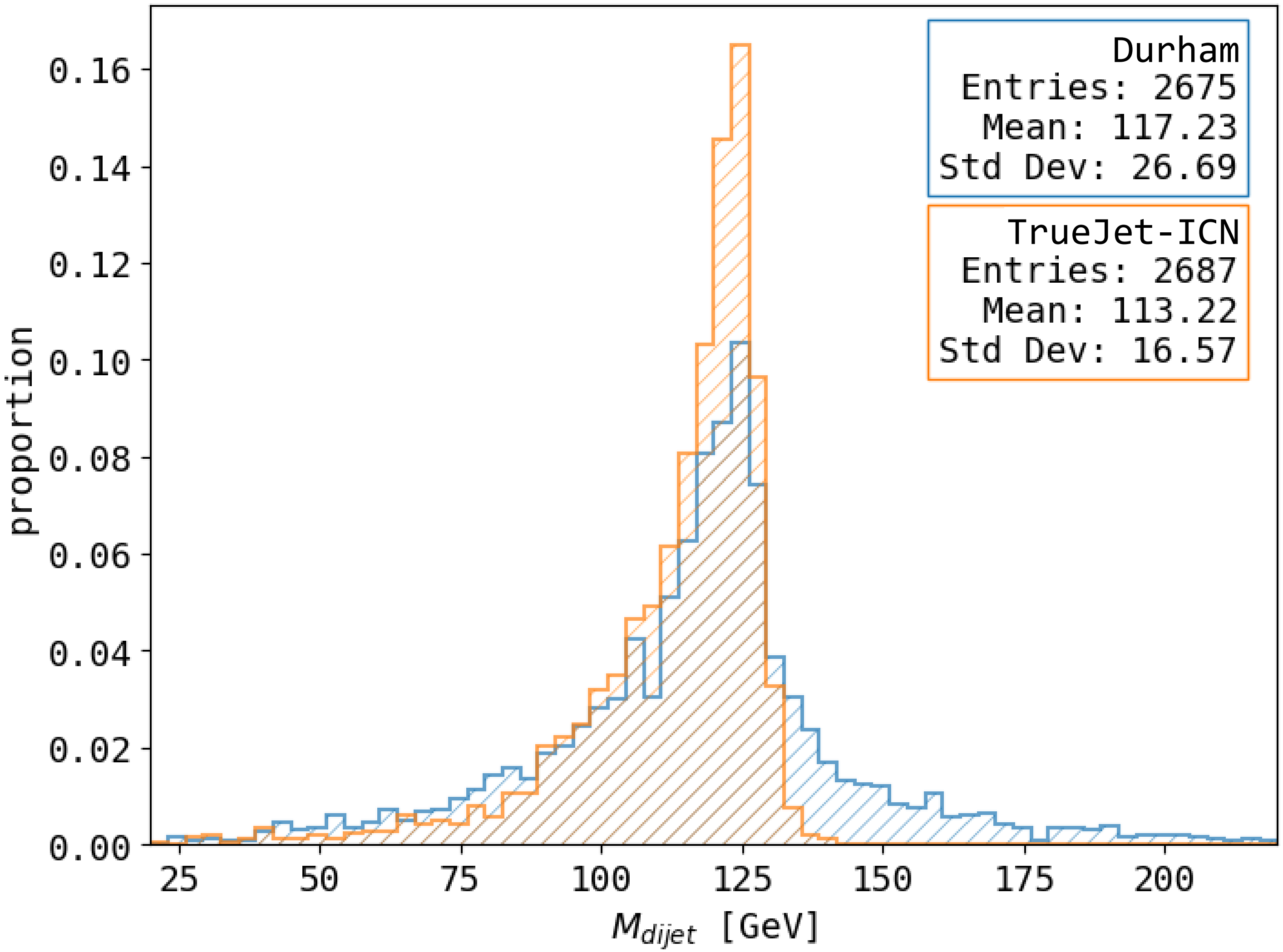


Misclustering in ZHH events at ILC500. From [To23b]

Misclustering in the ZHH analysis
J. Torndal, J. List (2023)

Supervised Jet Clustering

- idea: learn from truth-reco links to cluster PFOs into jets
  - upper performance bar given by TrueJet-ICN jet clustering
  - realistic target performance bounded by Durham and TrueJet



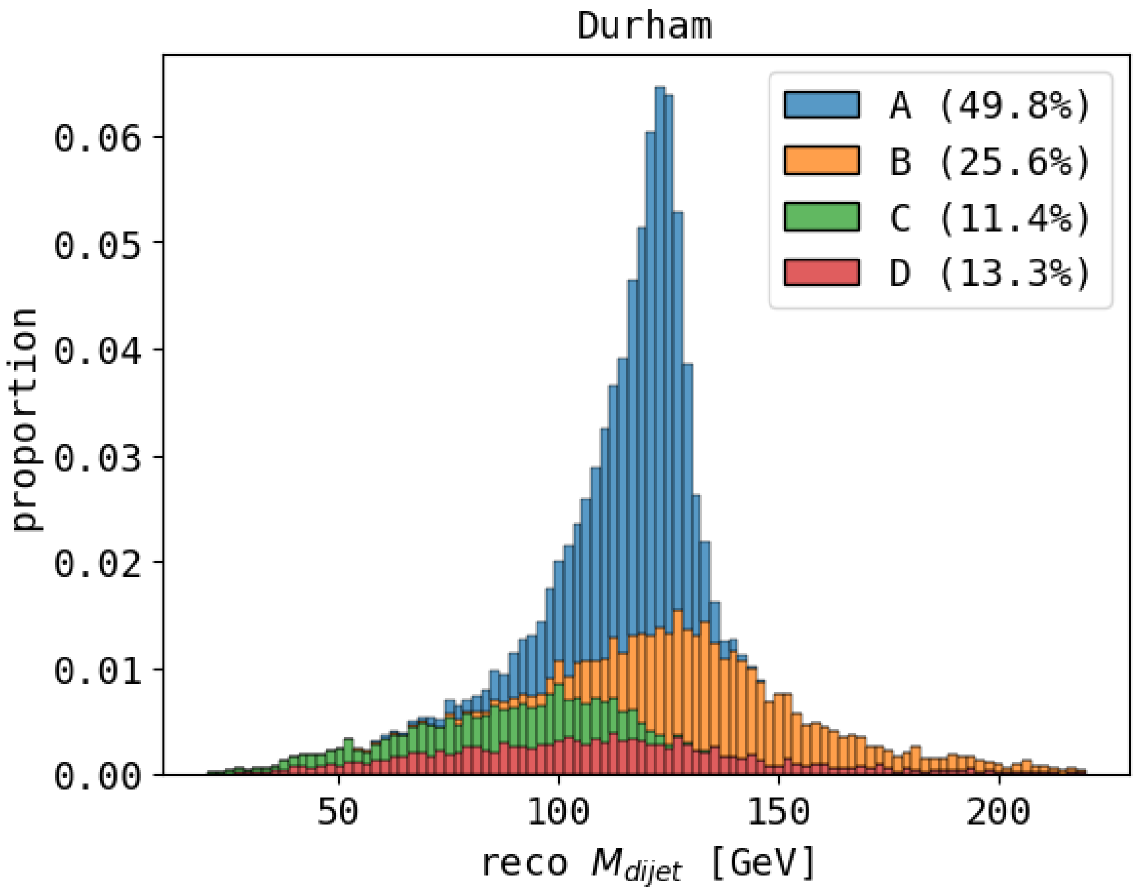
Di-jet mass reconstruction using Durham algorithm and TrueJet

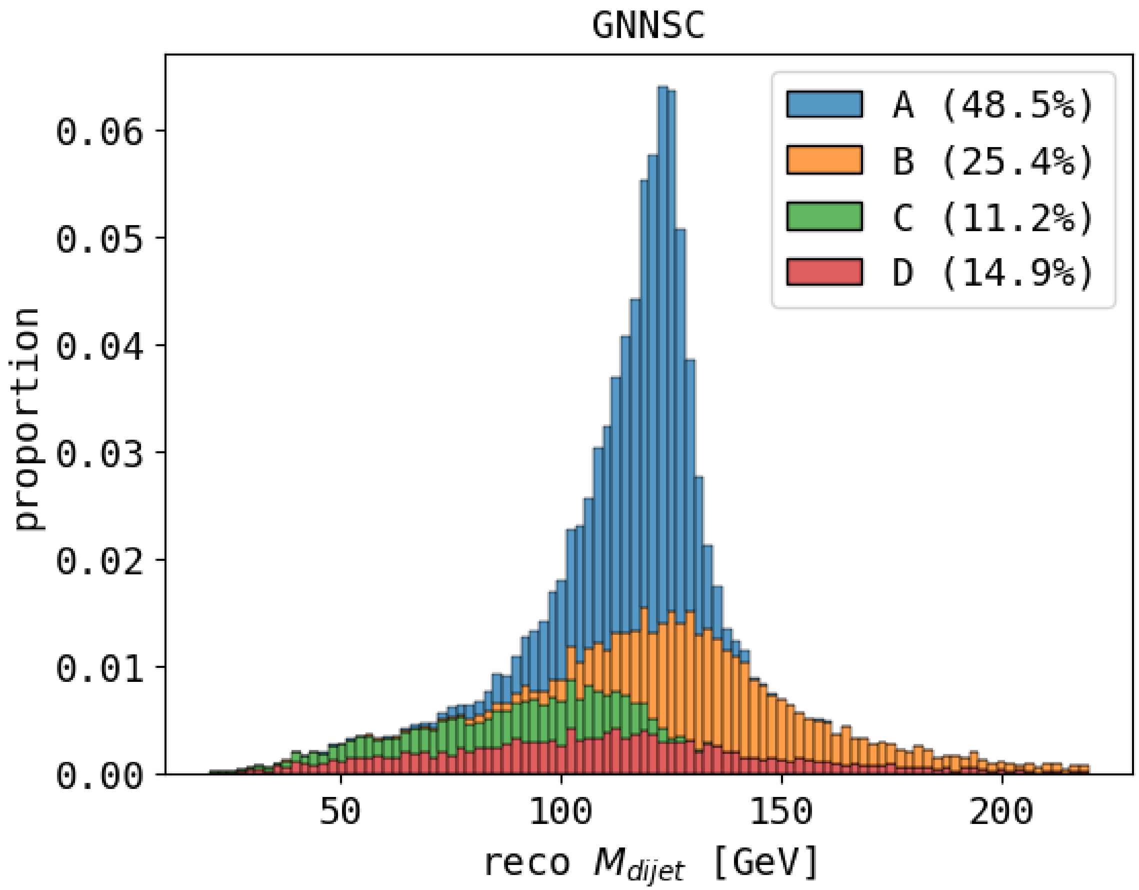
Inspired by: *Supervised jet clustering with graph neural networks for Lorentz boosted bosons*. Nachman et al. [Na20]

TrueJet: M. Berggren (2018)

Supervised Jet Clustering

- proof-of-concept ML model (GNNSC) shows performance on par with Durham
  - status: proof-of-concept (Marlin processor available)
  - in the future: investigate more powerful architectures





The Matrix Element Method (MEM)

- method for calculating event-likelihoods, i.e. $p(\text{event } \boldsymbol{x} | \text{channel i}) = p_i(\boldsymbol{x})$
  - example use case: separate ZHH vs. $\mathrm{ZZH} \rightarrow \mu^- \mu^+ b\bar{b}b\bar{b}$ using likelihood ratio lr

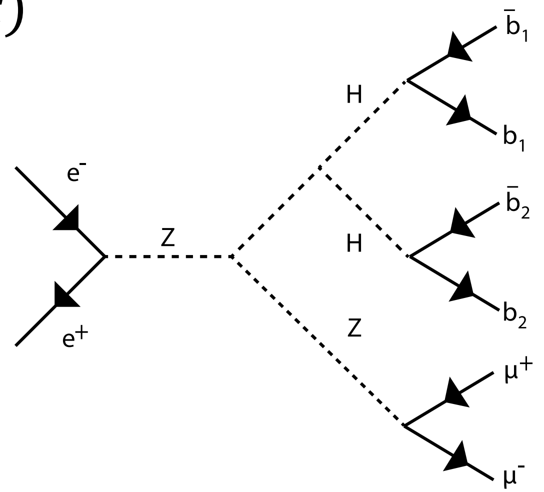
$$\mathrm{lr} = \frac{p_{ZHH}}{p_{ZZH}}$$

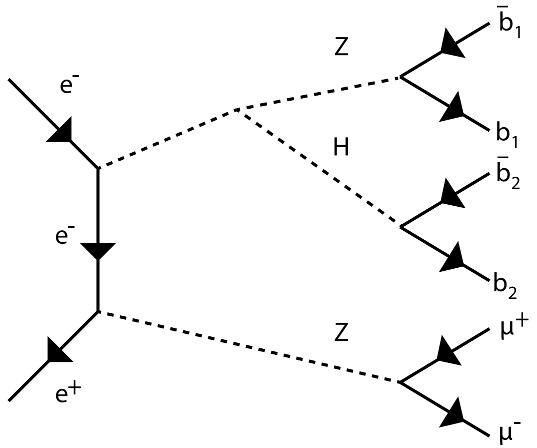
  - binary classification by cutting on lr

- for each event $\boldsymbol{y}$ and process i (ZHH, ZZH), solve integral

$$p_i\,(\boldsymbol{y}\,) = \frac{1}{\sigma_i \cdot A_i} \int |M_i(\boldsymbol{x})|^2 W_i(\boldsymbol{y} \mid \boldsymbol{x}) \epsilon_i(\boldsymbol{x}) d\boldsymbol{\Phi}_n(\boldsymbol{x})$$

  - $M_i(\boldsymbol{x})$ LO matrix element
  - $W_i(\boldsymbol{y}|\boldsymbol{x})$ transfer function (TF): PDF for measuring $\boldsymbol{y}$ given $\boldsymbol{x}$; fit from ILD full-simulation samples



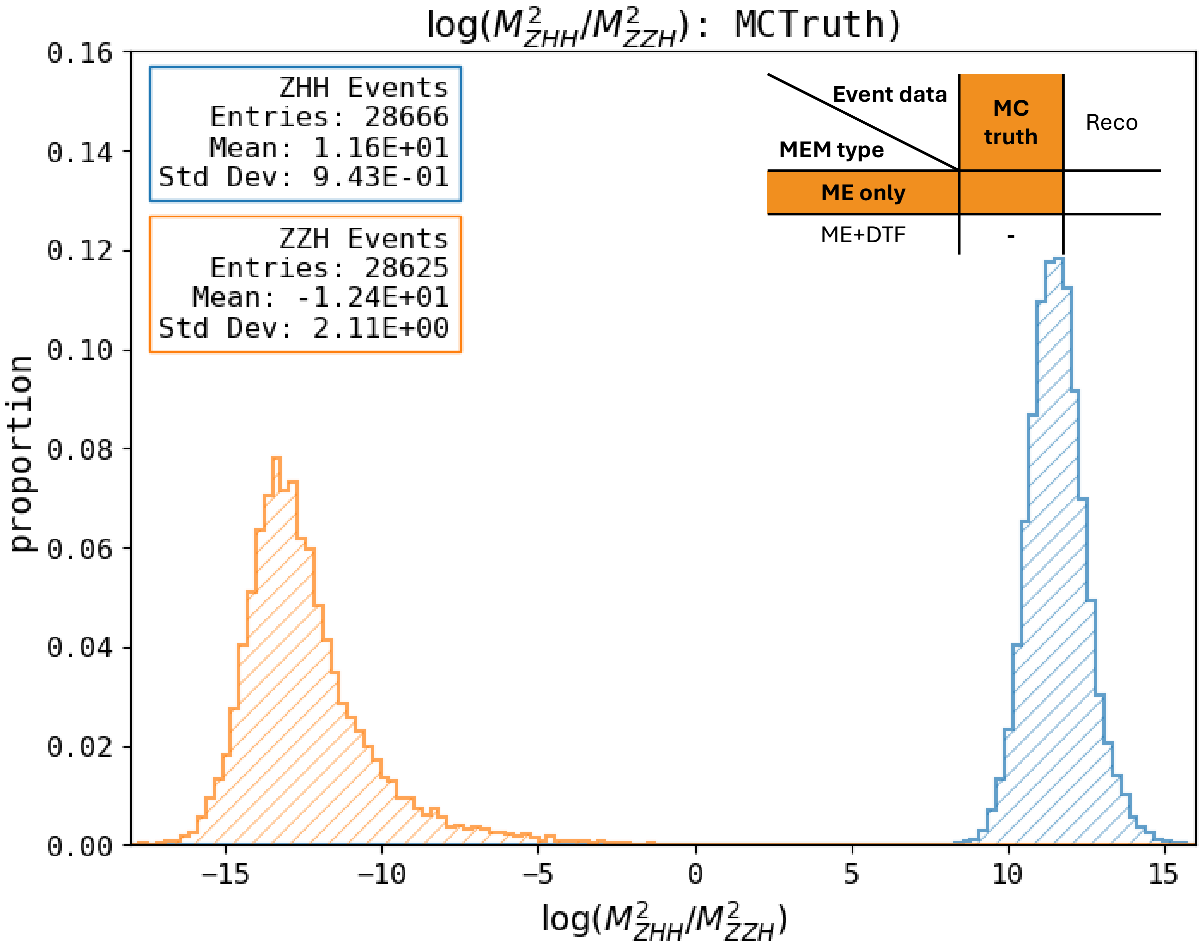


A_i : acceptance of channel i
$\epsilon_i(\boldsymbol{x})$: detector efficiency

MEM Introduction with Examples

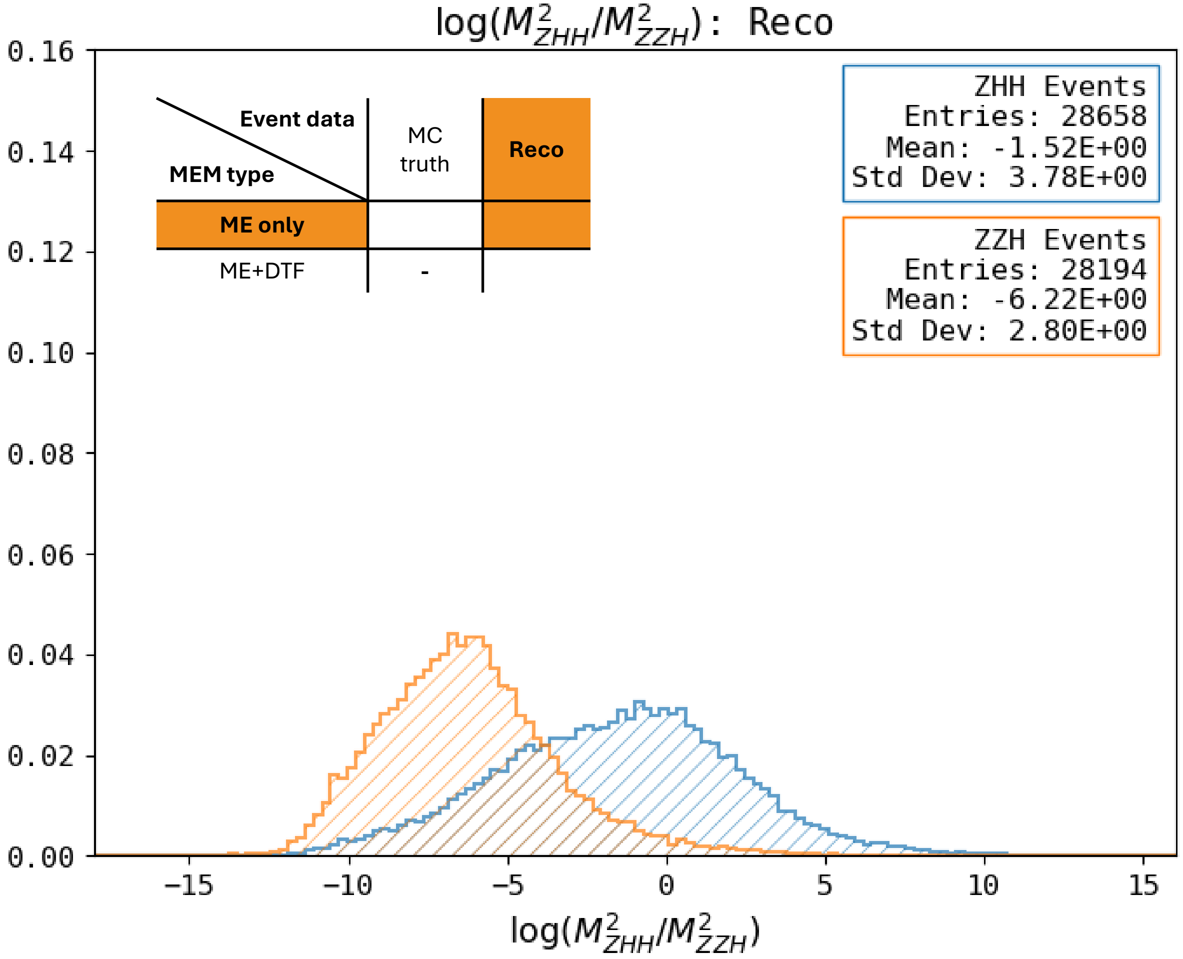
generator level check

- excellent separation



naive MEM

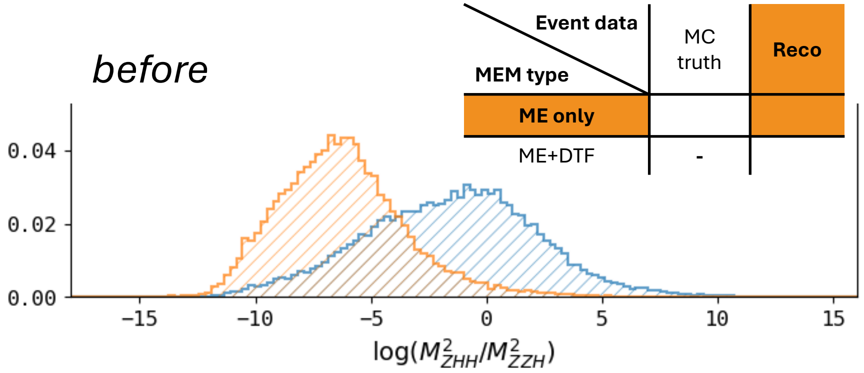
- significant separation power lost

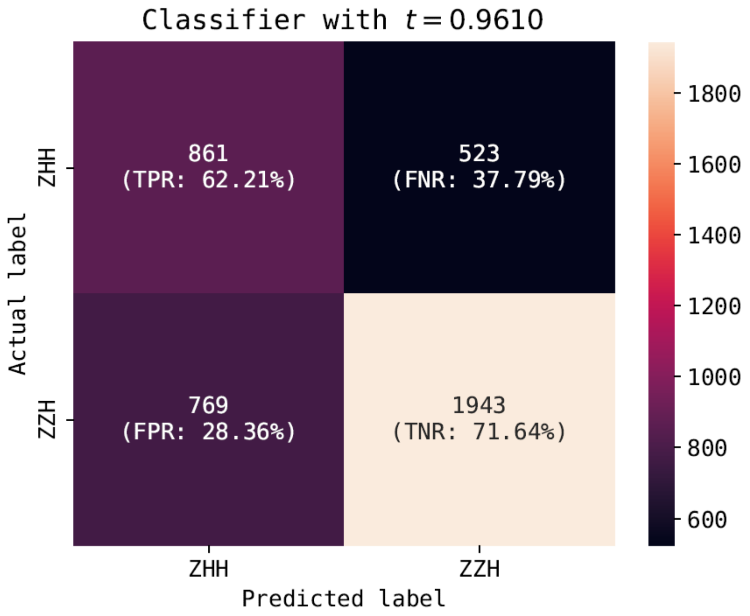


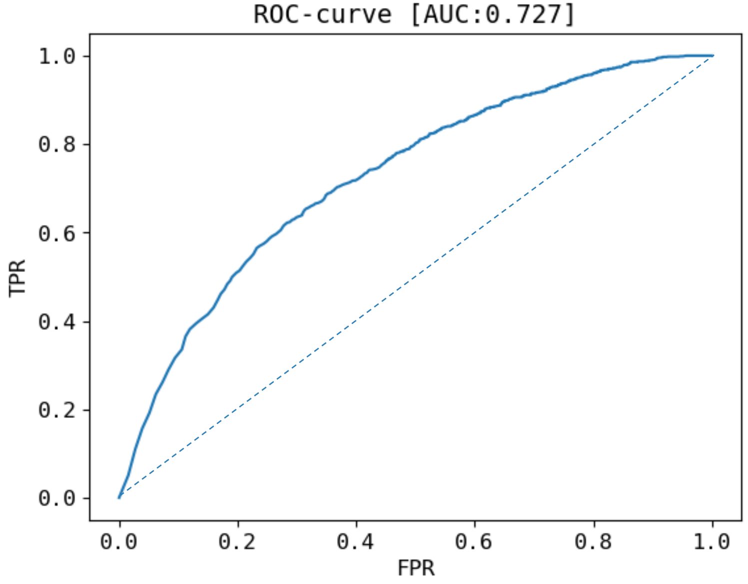
➔ need to describe smearing with TFs

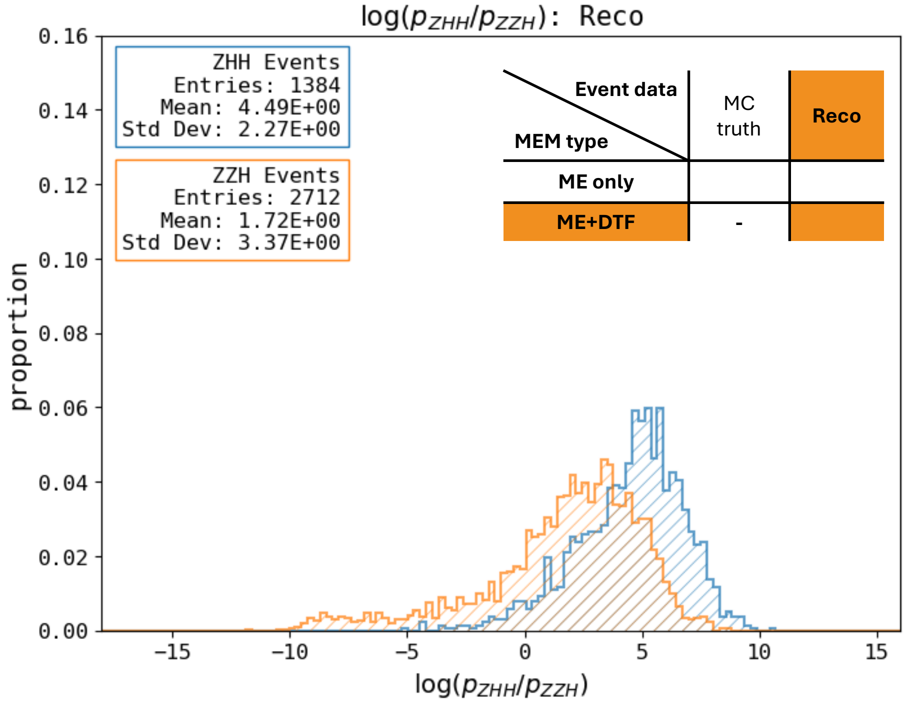
MEM Results

- obtained using VEGAS algorithm
- by including integration over transfer functions, some separation power is regained; $\mathrm{AUROC} = 0.73$





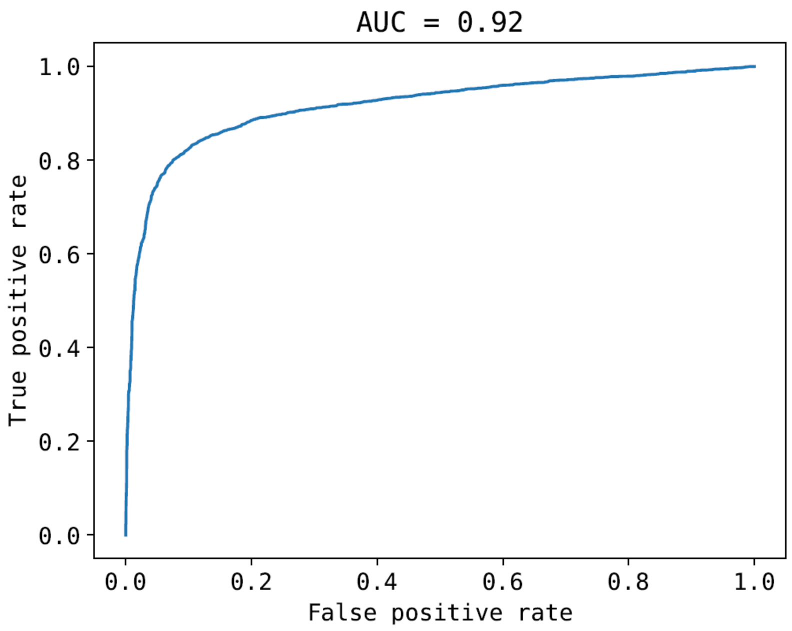




Direct S/B Separation with ML models

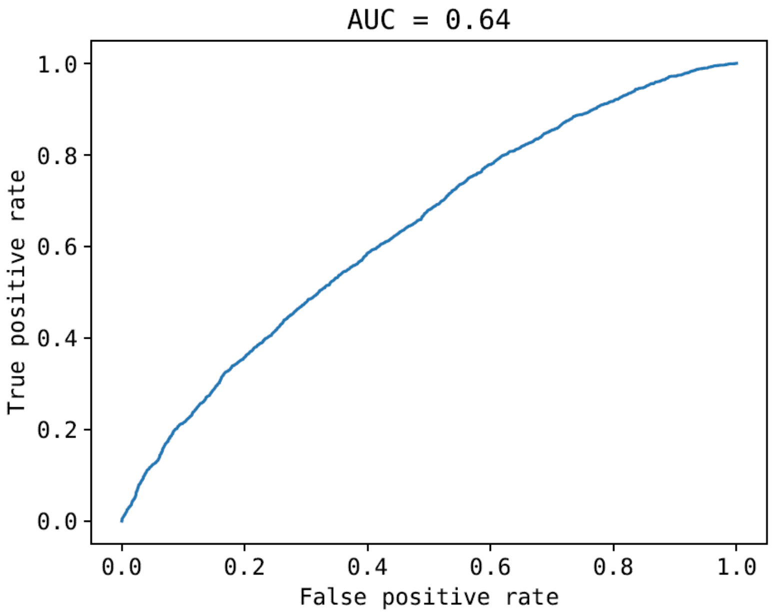
- using different architectures, a binary classifier is learned to again separate ZHH/ZZH
- input data: sets of four-momenta of the muons and b-jets; train/test ratio: 80/20

Benchmark



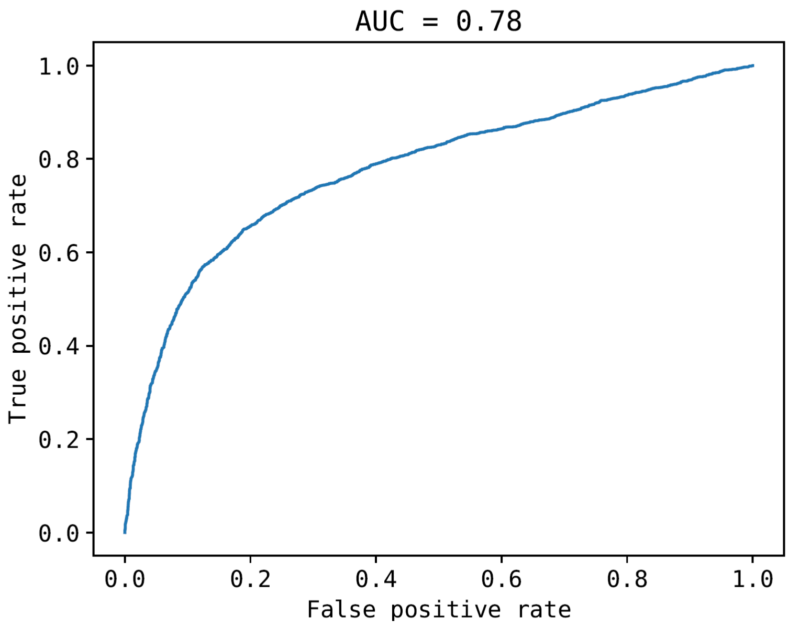
- **model: transformer encoder**
- **data : cheated jet-parton matching**

Realistic Model I



- **model: permutation invariant (DeepSet)**
- **data : jets randomly permuted**

Realistic Model II



- **model: transformer encoder**
- **data : jets sorted by energy**

Conclusion II: The ZHH Analysis with potential future tools

- in existing ZHH analysis: jet clustering as one leading source of uncertainty [Du16]
  - "proof-of-concept" supervised ML model for jet clustering implemented
  - performance approximately on par with current reconstruction (Durham algorithm)
- MEM implemented with example use case of process separation
  - time-complexity remains an issue due to phase space integration
  - in theory, gives access to perfect discriminator
- ML models for direct separation of ZHH/ZZH:
  - demonstrated that jet-parton matching is key information for separation power
  - best separation ($\mathrm{AUROC} = 0.78,\ \mathrm{AvgPrecision} = 67\%$)

General Conclusion

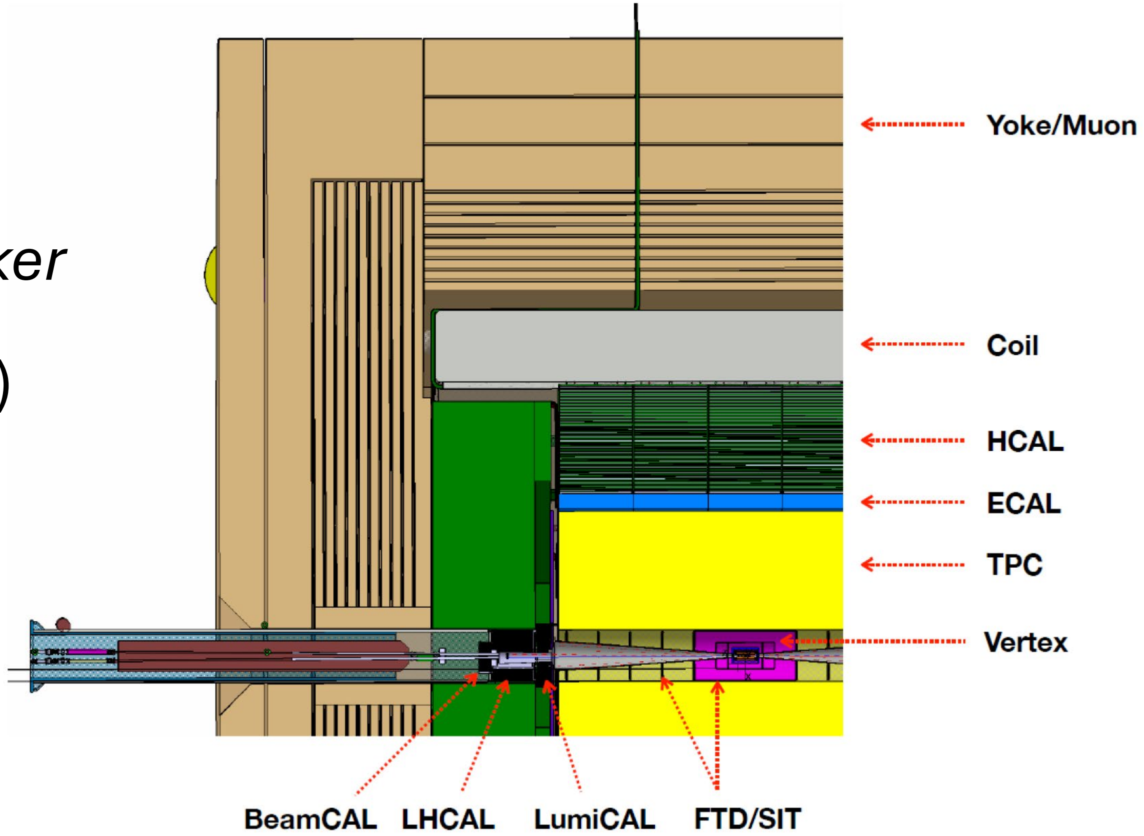
- major improvements in key analysis tools since last ZHH study [Du16]
  - existing SOTA are expected to improve the sensitivity on $\Delta\lambda_{SM}$ / λ_{SM} to better than 20%
- jet clustering and process separation identified as leading sources of error [Du16]
  - proof-of-concept ML jet clustering on par with Durham with potential for improvement
  - MEM implementation and ML models demonstrated to improve channel separation
- true/reco links unique to ILD full simulation allow supervised learning approaches
- outlook:
  - new estimates on $\Delta\lambda/\lambda$ with current SOTA reconstruction and analysis
  - ever more complex ML architectures can be expected to further improve reconstruction and analysis

Thank you for listening!

Backup

The International Large Detector (ILD)

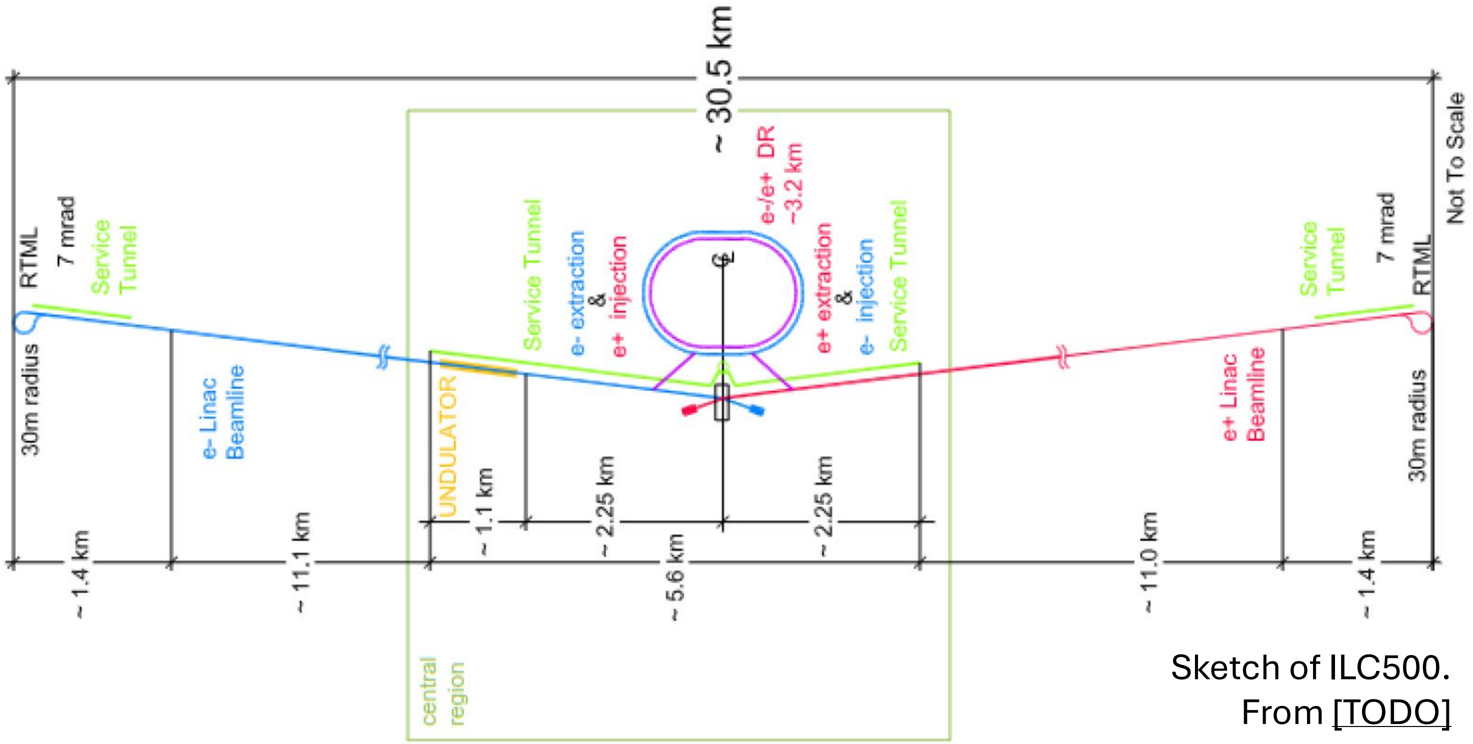
- Inner and Forward tracker (**SiT**, **FTD**)
- Identification of decay vertices of long-lived particles
- Time-projection chamber (**TPC**) as main *tracker*
- Electromagnetic (**ECAL**) and hadronic (**HCAL**) calorimeters inside magnetic coil to reduce material budget
- Iron yoke, muon detector



Quarter-slice through the ILD detector. From [TODO]

The International Linear Collider (ILC)

- linear collider concept with multiple energy stages $\left(\frac{\sqrt{s}}{\text{GeV}} = 250, \mathbf{500}, 1000\right)$
  - $500\ \text{GeV}$ stage allows direct measurements of λ through di-Higgs production
- mature concept (TDR), technologies available (superconducting RF-cavities etc.)



Sketch of ILC500.
From [TODO]

Future Higgs Factories

- goal: high production of Higgs bosons
- e^+e^- colliders for precision measurements
- different concepts proposed:
  - linear (ILC, CLIC, C^3):
    - maximum energy constrained by length
    - *direct* measurements of λ possible
    - measurements with polarized beams possible
  - circular (FCC-ee, CEPC):
    - maximum energy limited by synchrotron radiation
    - higher luminosities through beam reuse

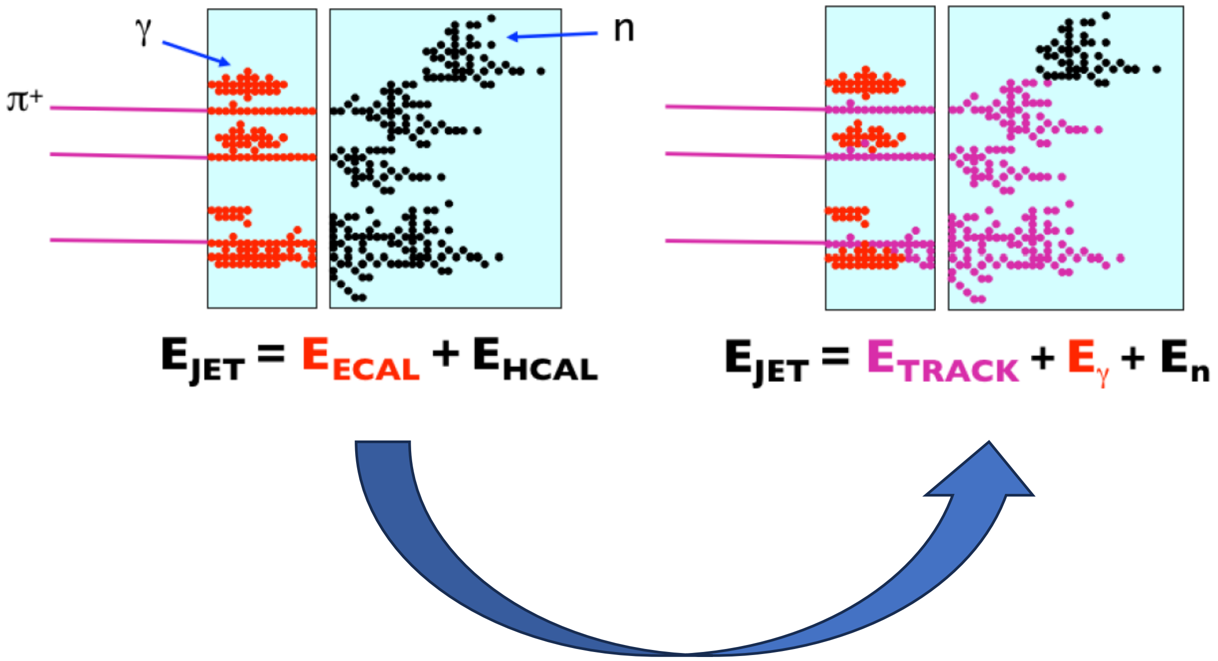
Collider	$\sqrt{s}$	$\mathcal{P}(e^-/e^+)[\%]$	N_{det}	$\mathcal{L}[\text{abarn}^{-1}\text{s}^{-1}]$
ILC	250 GeV	$\pm 80/\pm 30$	1	2.0
	500 GeV	$\pm 80/\pm 30$	1	4.0
	1000 GeV	$\pm 80/\pm 30$	1	8.0
CLIC	380 GeV	$\pm 80/0$	1	1.0
	1.5 TeV	$\pm 80/0$	1	2.5
	3.0 TeV	$\pm 80/0$	1	5.0
C^3	250 GeV	$\pm x/0$	?	1.3
	550 GeV	$\pm x/0$	?	2.4
FCC-ee	M_Z	0/0	2	150
	$2M_W$	0/0	2	10
	240 GeV	0/0	2	5
	$2m_{top}$	0/0	2	1.5
CEPC	M_Z	0/0	2	16
	$2M_W$	0/0	2	2.6
	240 GeV	0/0	2	5.6
HALHF	250 GeV	0/0	1	≈ 2

Comparison of selected physics programs at the proposed accelerators ILC, CLIC, FCCee, CEPC, C^3 and HALHF. From [Db20]

Particle Flow

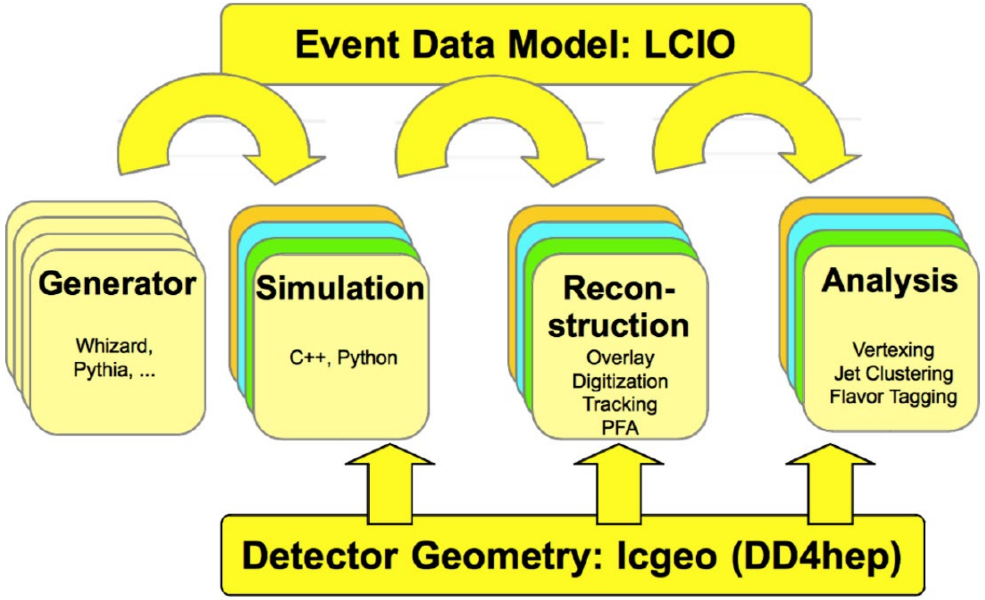
- use best combined information between detectors for highest energy resolution (**Particle Flow objects, PFOs**)
- goal: best jet energy resolution

From traditional to particle flow calorimetry. From [Du16]



Software

- iLCSoft software stack
- Marlin for reconstruction;
  important in existing ZHH-analysis:
  - TrueJet: jet-clustering of PFOs using truth information
  - isolated lepton tagging: decision trees for tagging leptons



Event flow in the iLCSoft stack. From [TODO]

Durham jet clustering

- Durham algorithm: common jet-clustering method at e^+e^--colliders
  - sequential algorithm: cluster objects (here: PFOs) i and j together by lowest test variable y_{ij} until either a cut $y_{ij} > y_{cut}$ or a number of jets is reached; in Durham:

$$y_{ij} = \frac{M_{ij}^2}{Q^2}$$

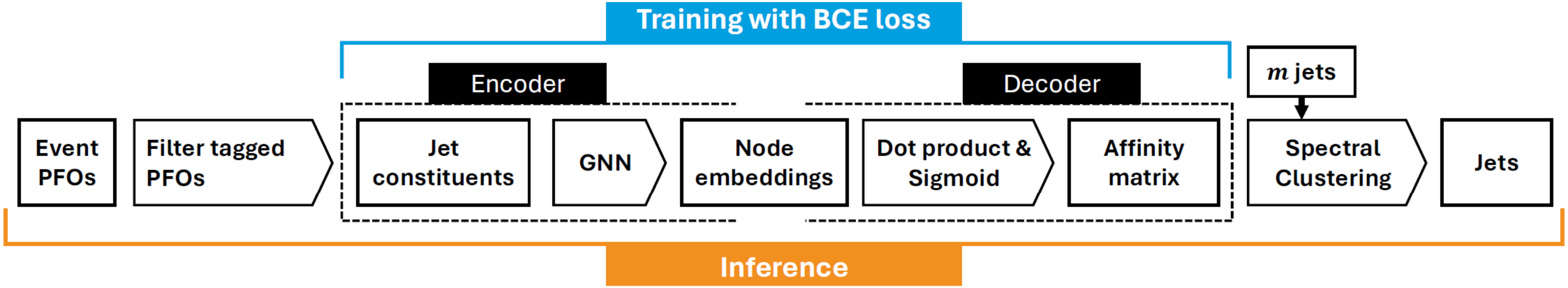
$$M_{ij}^2 = k_\perp^2 = 2\min\left(E_i, E_j\right)^2 \cdot \left(1 - \cos\theta_{ij}\right)$$

  - is **IRC-safe**: same result when arbitrarily soft/colinear input objects are added

Architecture: Supervised Jet Clustering with GNNs

TransformerConv operator from the paper *Masked Label Prediction: Unified Message Passing Model for Semi-Supervised Classification* [Sh20].

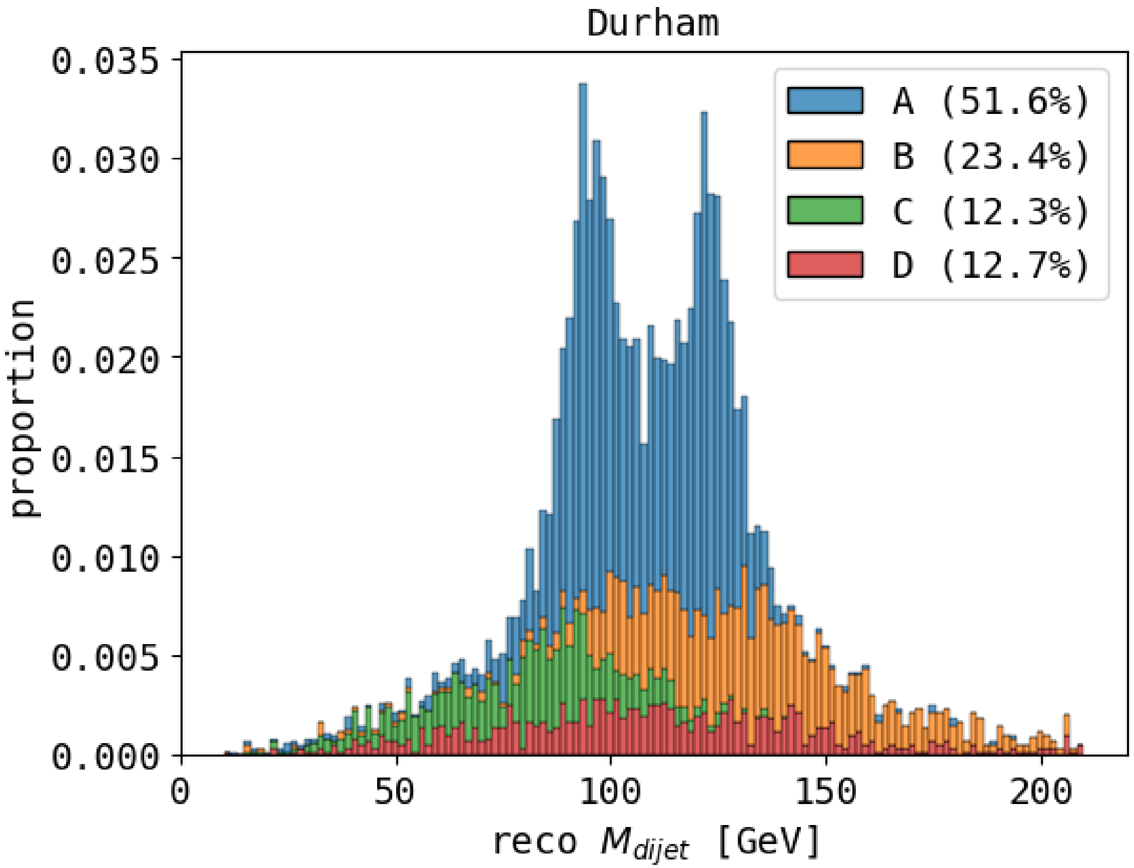
- here: implemented as hybrid model (**GNNSC**)
  - training a GNN in supervised manner to calculate edge scores
    here: using TransformerConv layer (implements message-passing and graph attention)
  - spectral clustering (SC) to build "jets"

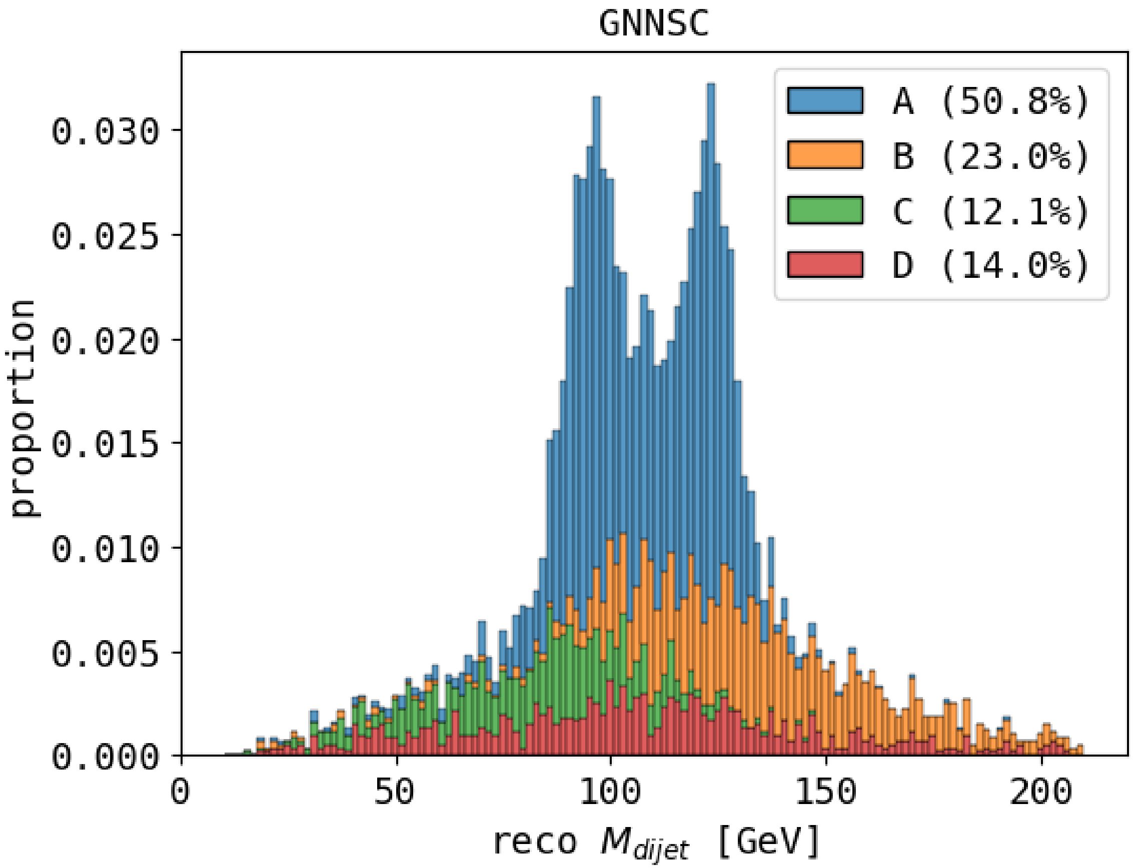


- advantages:
  - permutation invariant by construction
  - straightforward implementation
- disadvantages:
  - not fully differentiable
  - no inherent IRC-safety

Jet Clustering on ZZH events

- model was learned on ZHH events; how well does it generalize to ZZH events?
  - again, nearly identical performance of Durham and GNNSC model

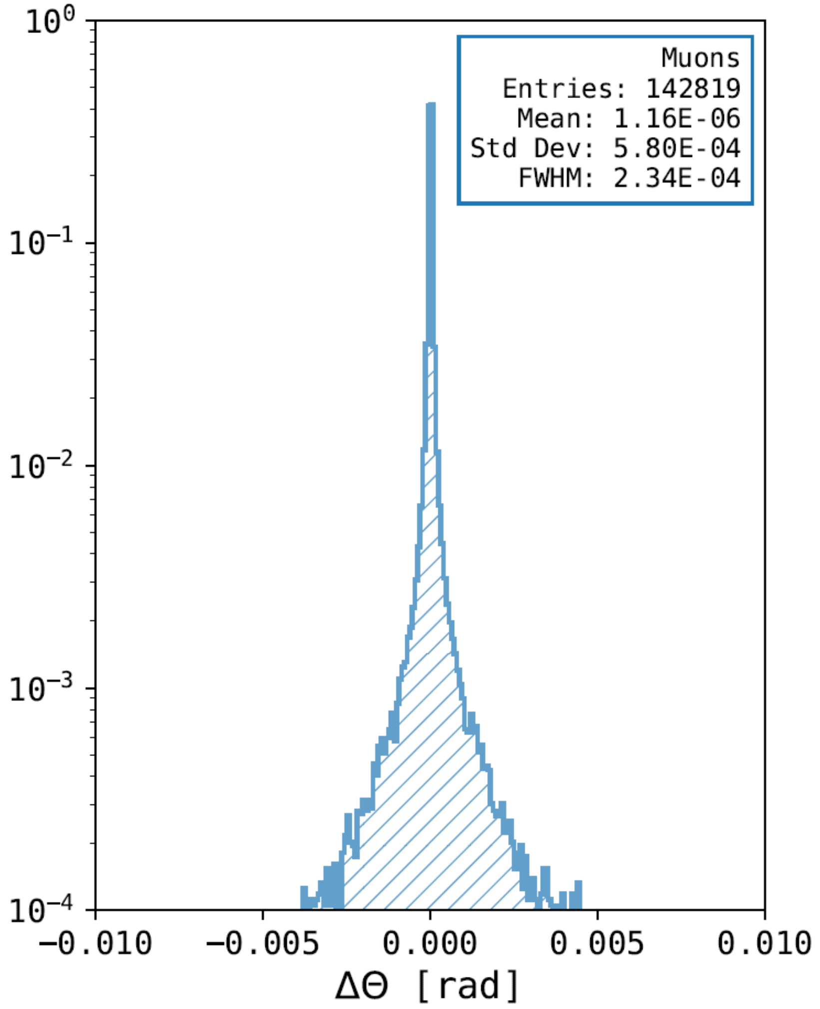




Assumptions for the MEM

- assumptions:
  - same acceptance A_i for $i = \mathrm{ZHH}, \mathrm{ZZH}$ hypotheses
  - ignore efficiency $\epsilon_i(\boldsymbol{x})$
  - TF factorizes: $W_i(\boldsymbol{y}|\boldsymbol{x}) = \prod_{j=\text{final state particles}} W_{ij}(\boldsymbol{y_j}|\boldsymbol{x_j})$
  - components of TF can be parameterized in differences e.g. $W_{ij}(\boldsymbol{E^{reco}}|\boldsymbol{E^{true}}) = \widehat{W}(\Delta E = \boldsymbol{E^{reco}} - \boldsymbol{E^{true}})$
  - muon kinematics (energy + angles) perfectly measured
  - narrow width approximation (NWA): Higgs boson width is small w.r.t. mass <-> propagator delta peaked
- dimensionality of integral reduced from 18 to 11
  - further reduction to 7 by integrating out four momentum conserv.

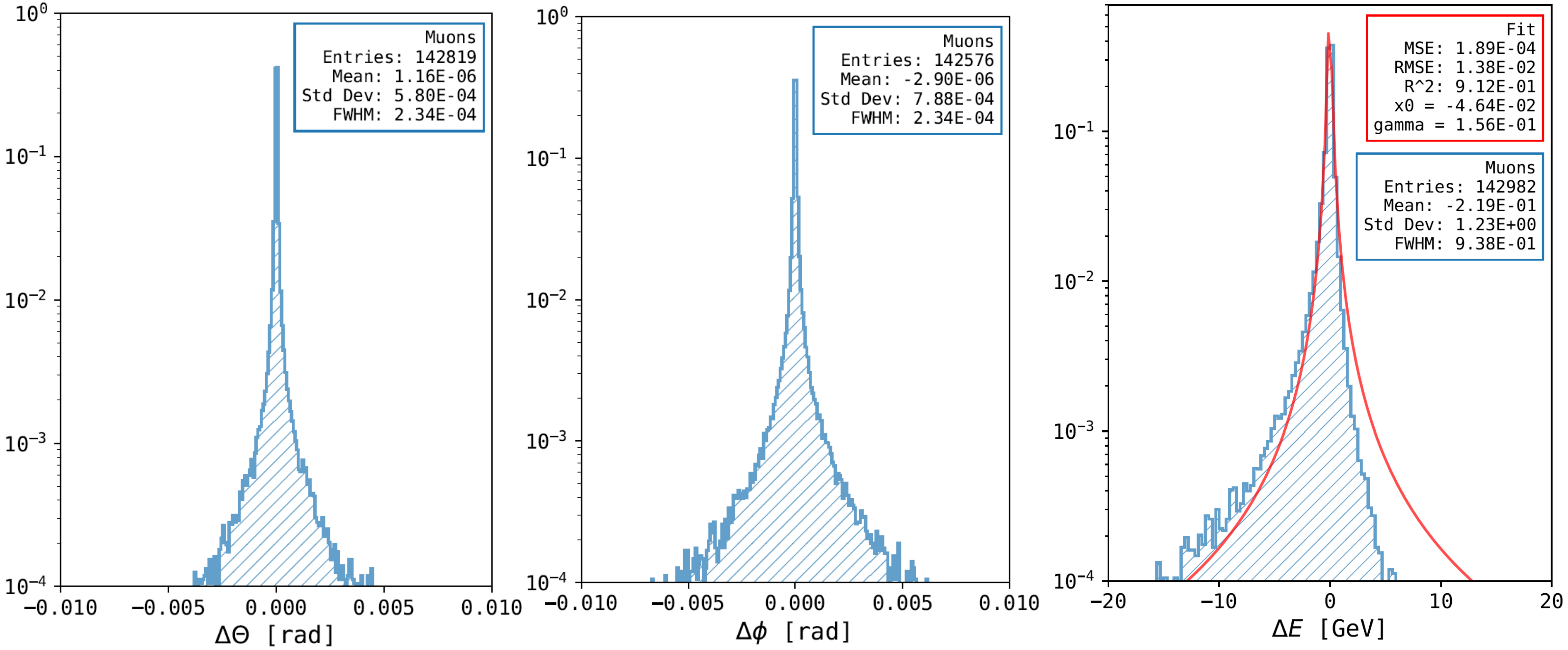
Example TF : $W_{\mu^\pm,(\theta,\phi)} = \theta^{Reco}_{\mu^\pm} - \theta^{True}_{\mu^\pm}$



MEM Transfer Functions – Muons

Angles $W_{\mu^\pm,(\theta,\phi)} = (\theta,\phi)^{Reco}_{\mu^\pm} - (\theta,\phi)^{True}_{\mu^\pm}$

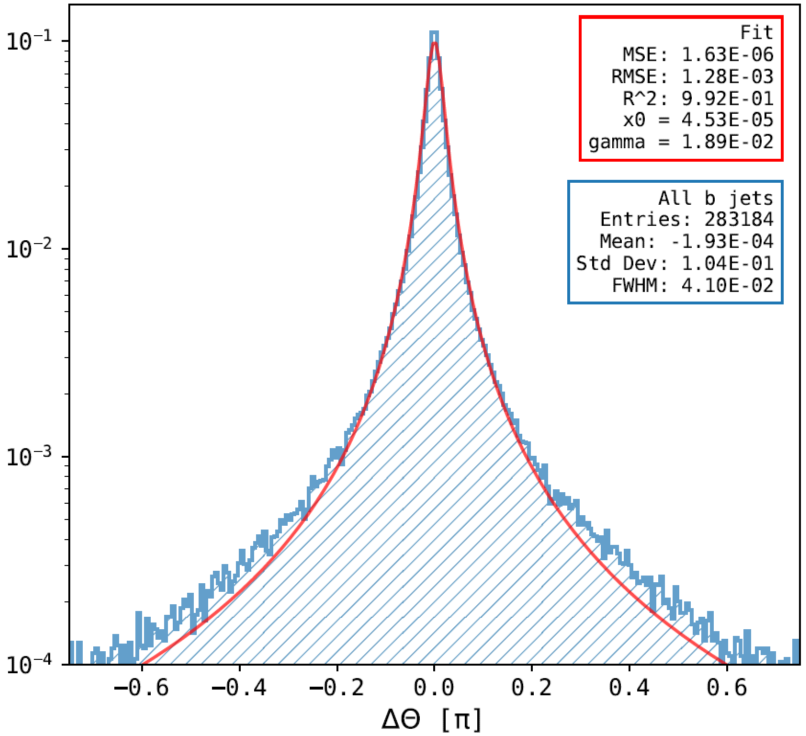
Energy: $W_{\mu^\pm,E} = E^{Reco}_{\mu^\pm} - E^{True}_{\mu^\pm}$

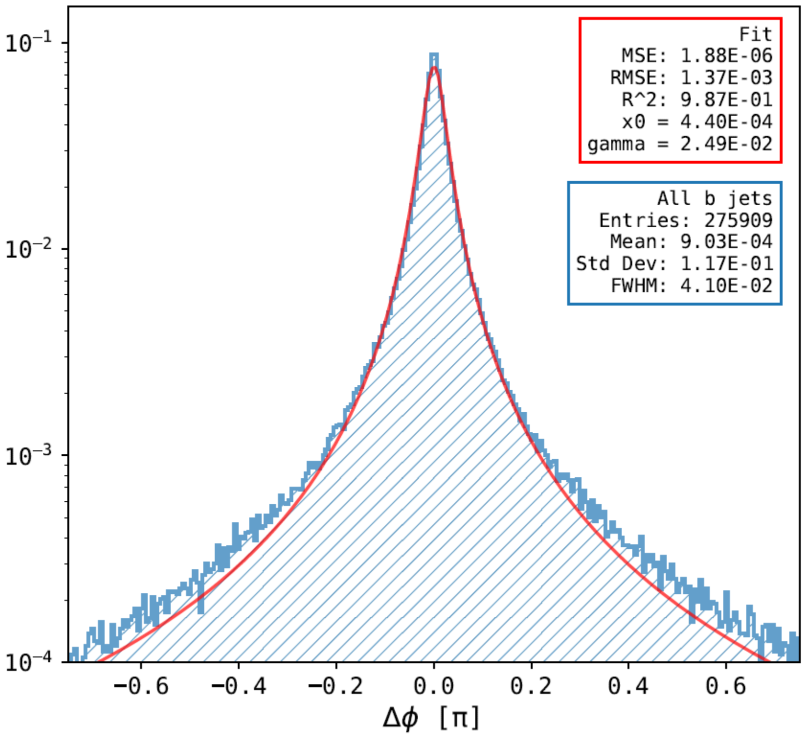


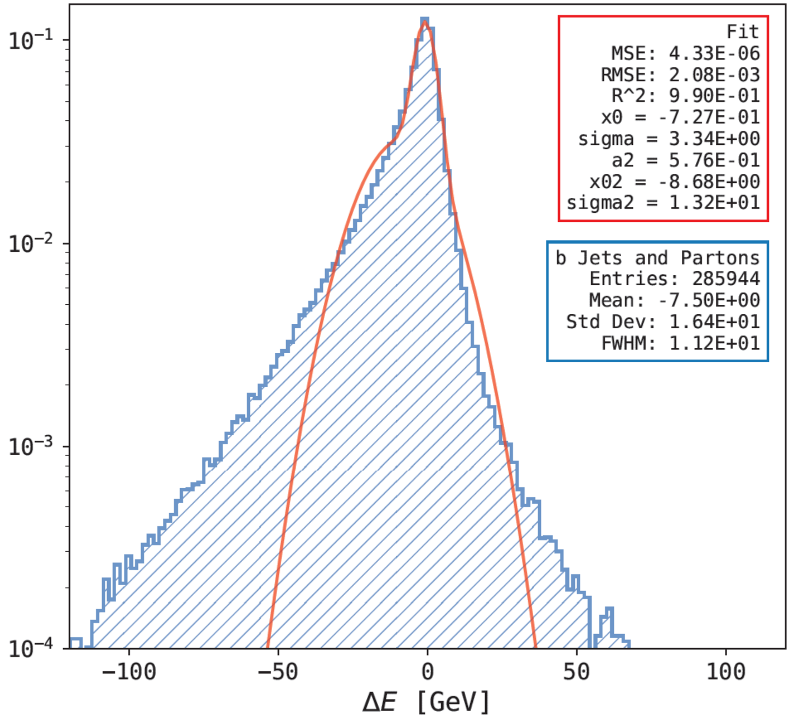
MEM Transfer Functions – Jets/b and $\bar{b}$ quarks

Angles $W_{b,(\theta,\phi)} = (\theta,\phi)_b^{Reco} - (\theta,\phi)_b^{True}$

Energy: $W_{b,E} = E_b^{Reco} - E_b^{True}$







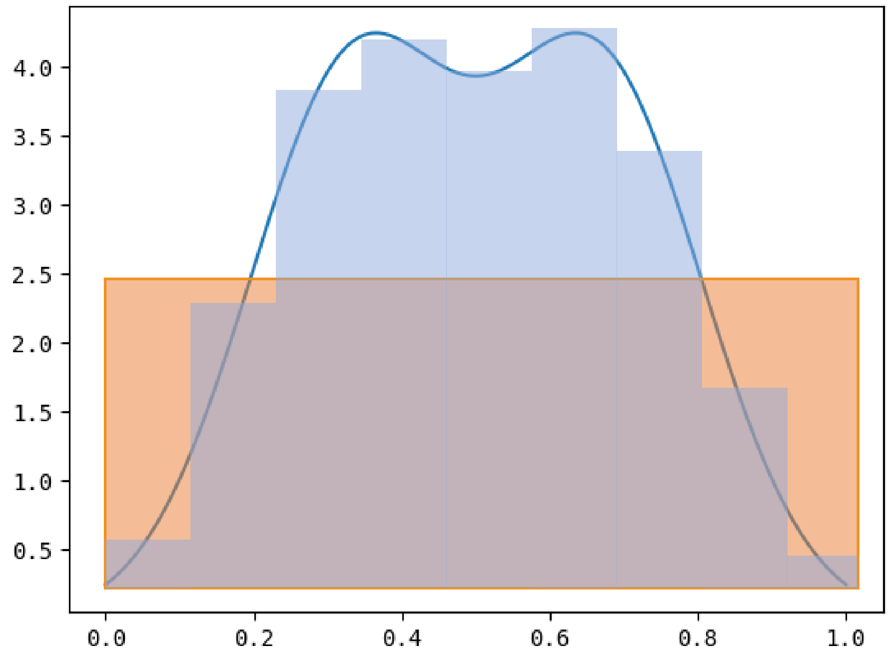
Solving the MEM integral

- problem: the chosen phase space parametrization is 7-dim.: efficient evaluation?
- solution: Monte Carlo (MC) integration

$$E_{p(x)}[I(f)] = \frac{1}{n}\sum_{i}^{n} f(x_i);\; x \sim p(X)$$

$$\sigma = \frac{\sqrt{E[(f - E[f])^2]}}{\sqrt{n}}$$

  - crude MC: uniform sampling; in every dim: $p(x) = \frac{1}{a-b}$
  - importance sampling: sample from proposal $x \sim q(x)$
    - need to find proposal dist. $q(x)$ that fits integrand without knowing integral
    - the "better" q, the faster the variance decreases
    - many approaches: e.g. VEGAS algorithm, neural importance sampling (NIS)



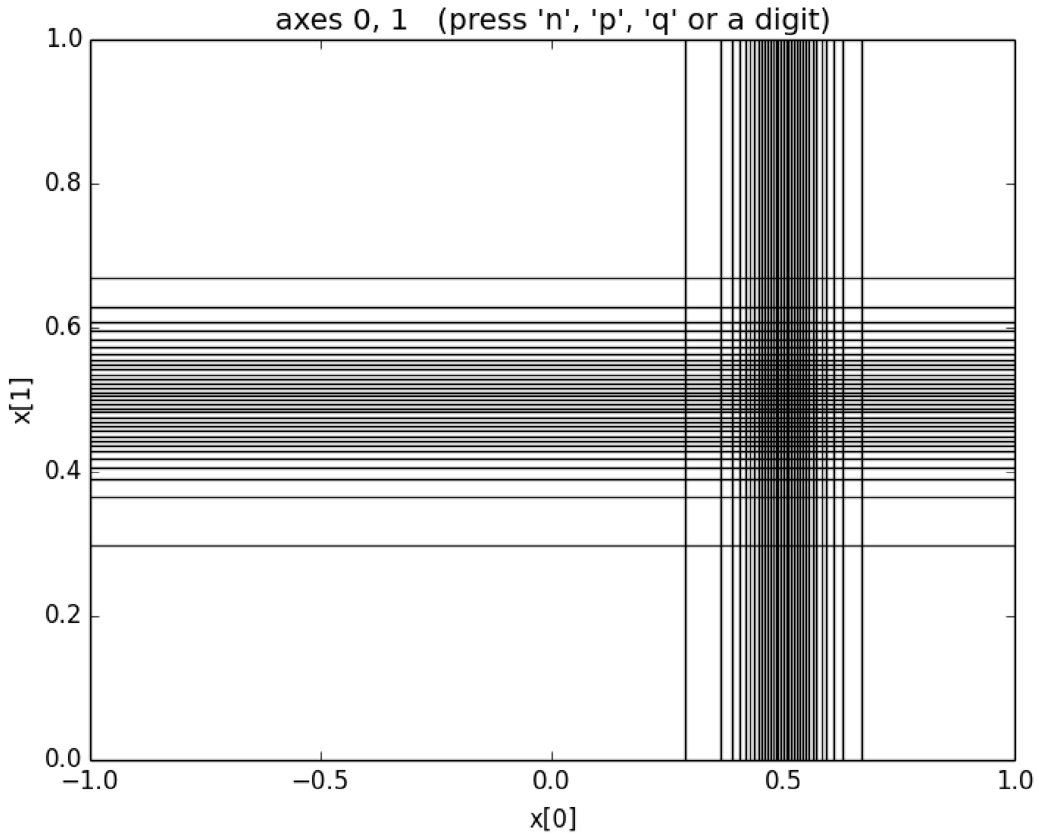
VEGAS Importance Sampling MC

- assume the integrand factorizes

$$f(x) = \prod_{i}^{n} f_i(x_i)$$

- divide each dimension into n bins with equal probability
- adjust the **bin widths** to sample more often in the more important regions

Example of a VEGAS grid after adaption



Source

Neural Importance Sampling MC

- principle
  - from a known base distribution u $\sim \pi(u)$
  - use ML to learn a **bijective and differentiable function** g to transform u to a more complex distribution

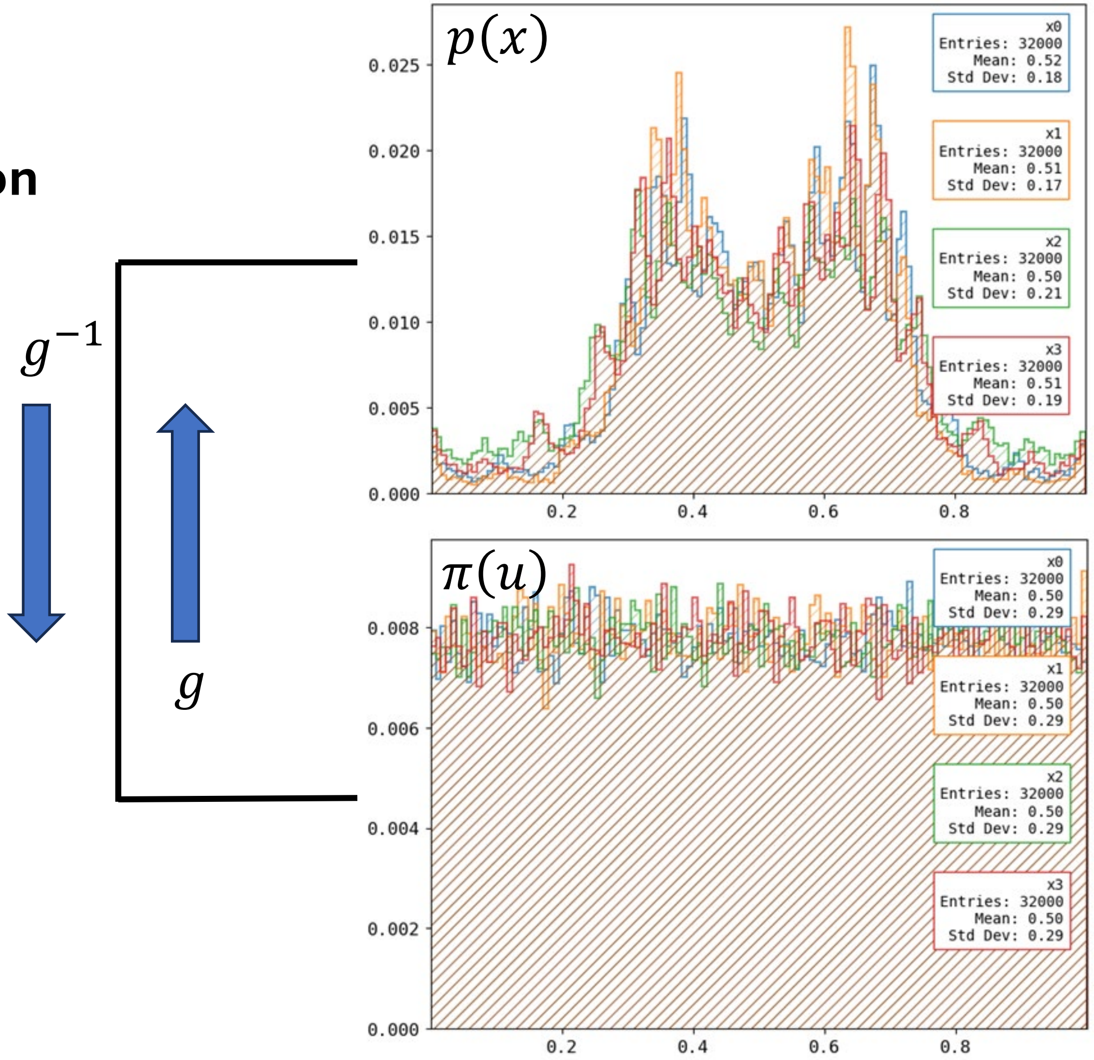
$$x = g(u)$$

- PDF of x given by change of variables formula

$$p(x) = \pi(g^{-1}(x)) \left| \det\left(\frac{\partial g^{-1}}{\partial x} \right) \right|$$

- here: transformation using piecewise rational quadratic spline

Before/after the flow: Example marginal distribution



[arXiv:1410.8516] : NICE: Non-linear Independent Components Estimation
[arXiv:1808.03856] :Neural Importance Sampling
[arXiv:1906.04032] : Neural Spline Flows
[arXiv:2001.05486] : i-flow

Monte-Carlo integration for the MEM

$$P_i\,(\boldsymbol{y}\mid\boldsymbol{a}) = \frac{1}{\sigma_i(\boldsymbol{a})\cdot A_i(\boldsymbol{a})}\int W_i(\boldsymbol{y}\mid\boldsymbol{x},\boldsymbol{a})|M_i(\boldsymbol{x},\boldsymbol{a})|^2 T_i(\boldsymbol{x},\boldsymbol{a})\,d\boldsymbol{\Phi}_n$$

$$d\boldsymbol{\Phi}_n = \prod_i^{\mu^-,\mu^+,b_1,\overline{b_1},b_2,\overline{b_2}} \frac{d^3\boldsymbol{p_i}}{(2\pi)^3 2E_i}$$

- leptons well measured ➔ no integration for μ^-, μ^+
- conservation of four momentum and narrow-width-approximation ➔ reduction of integration to 7 dimensions
- integration variables: $\Theta_{b1}, \phi_{b1}, \rho_{b1}, \theta_{b1b}, \phi_{b1b}, \rho_{b2}, \Theta_{b2}$
- with VEGAS+ and integrand in C++, computation time 1-2 minutes per process (including setup of integration grid)

itn	integral	wgt average	chi2/dof	Q
1	4.2(3.6)e-09	4.2(3.6)e-09	0.00	1.00
2	6.7(2.7)e-10	6.9(2.7)e-10	0.94	0.33
3	6.0(2.1)e-10	6.4(1.7)e-10	0.50	0.60
4	2.69(55)e-10	3.05(52)e-10	1.81	0.14
5	3.49(58)e-10	3.24(39)e-10	1.44	0.22
6	2.96(43)e-10	3.12(29)e-10	1.20	0.31
7	5.0(1.2)e-10	3.23(28)e-10	1.42	0.20
8	4.78(94)e-10	3.35(27)e-10	1.58	0.14
9	8.6(2.2)e-10	3.43(27)e-10	2.11	0.03
10	5.9(1.8)e-10	3.48(26)e-10	2.07	0.03

result = 3.48(26)e-10 Q = 0.03

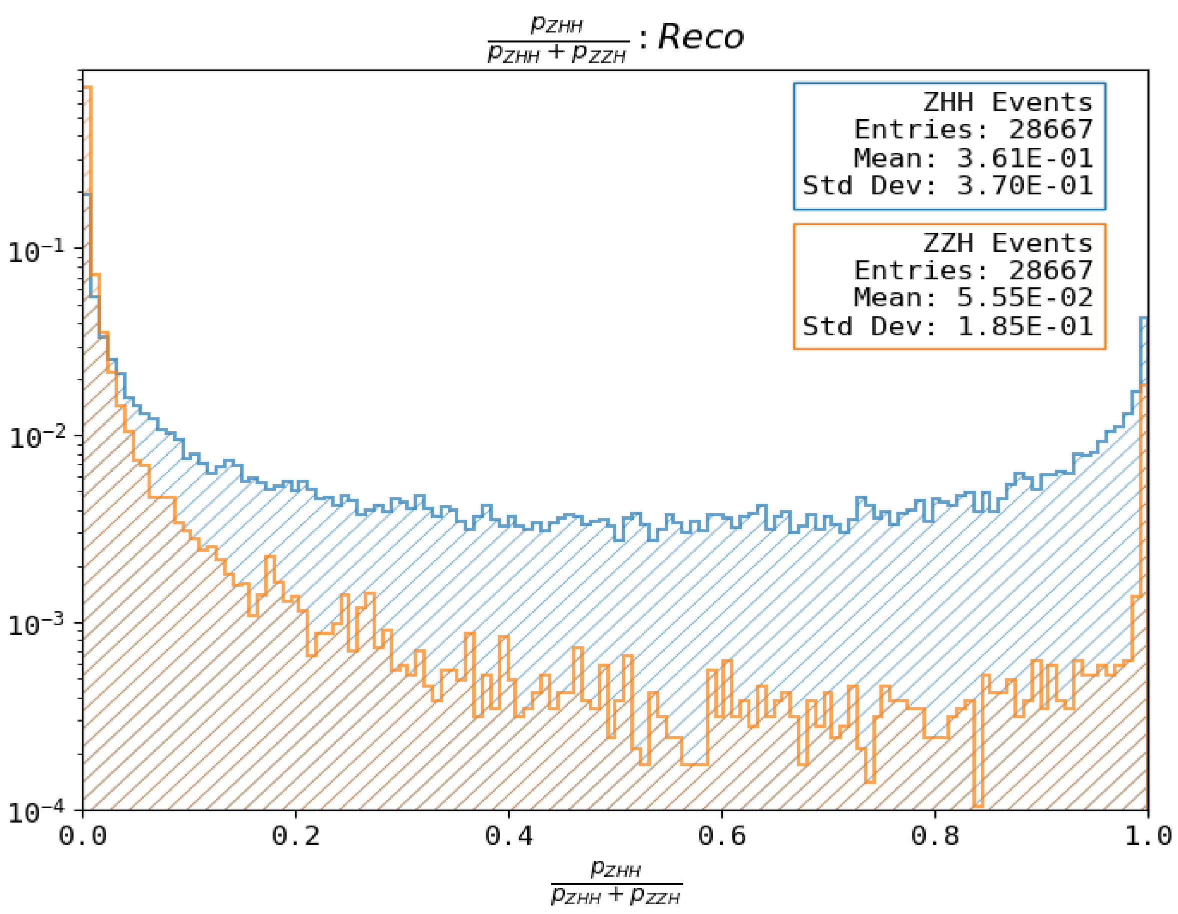
itn	integral	wgt average	chi2/dof	Q
1	1.58(18)e-09	1.58(18)e-09	0.00	1.00
2	1.68(19)e-09	1.63(13)e-09	0.13	0.72
3	1.94(19)e-09	1.72(11)e-09	0.96	0.38
4	1.91(13)e-09	1.800(82)e-09	1.04	0.37
5	1.98(27)e-09	1.815(79)e-09	0.88	0.48
6	2.73(99)e-09	1.821(78)e-09	0.88	0.50
7	1.78(10)e-09	1.807(62)e-09	0.74	0.61
8	2.03(17)e-09	1.834(59)e-09	0.86	0.54
9	1.72(13)e-09	1.816(54)e-09	0.82	0.58
10	1.813(83)e-09	1.815(45)e-09	0.73	0.68

result = 1.815(45)e-09 Q = 0.68

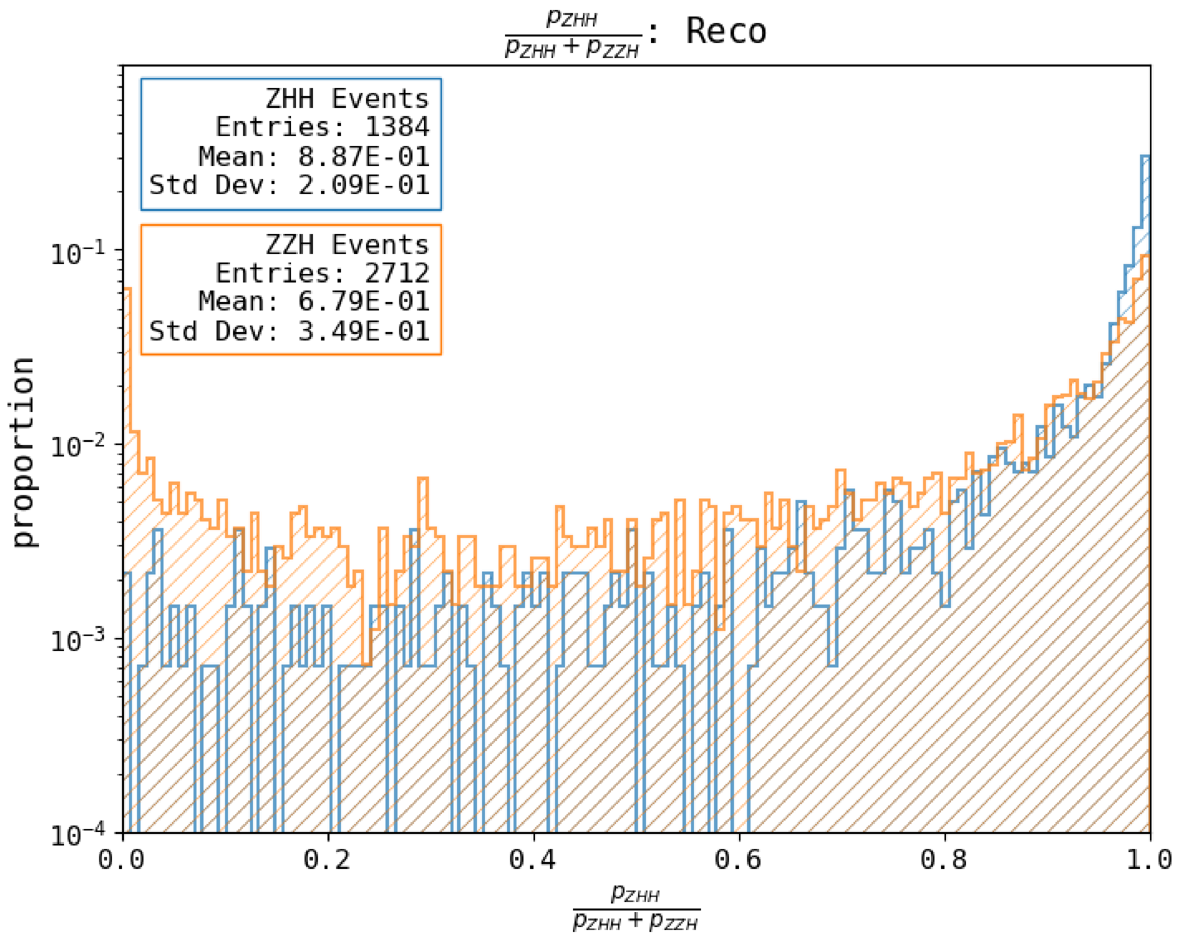
MEM results for example ZHH (top) and ZZH (bottom) event

MEM Results

Generator level: cross-x normalized ME only



VEGAS full MEM



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