Measurement of lepton-jet correlation in deep-inelastic scattering with the H1 detector using machine learning for unfolding

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On Behalf of the H1 Collaboration

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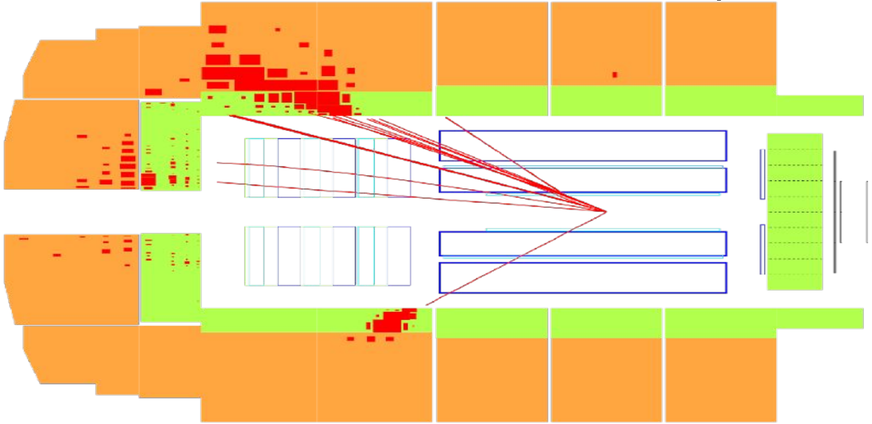
BERKELEY LAB

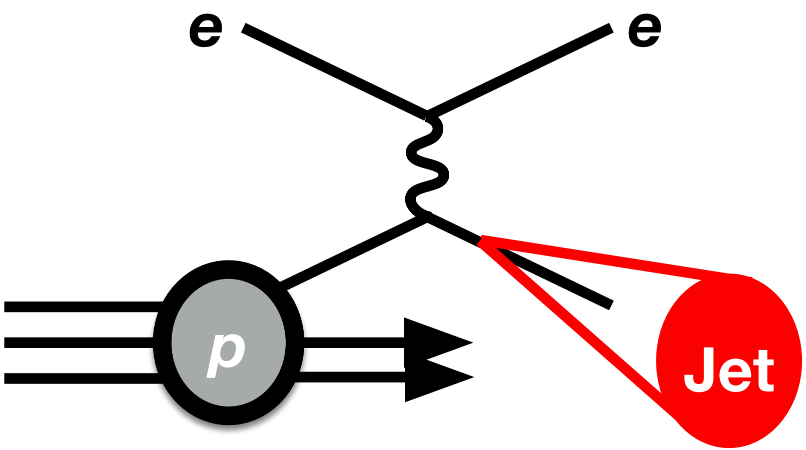
H1 @ HERA

- Deep inelastic scattering (DIS): e + p → e + jet + X
- Data from 2006-2007 run
  - L_{int} =136 pb^{-1}, $\sqrt{s}$ = 320 GeV
- This work is a measurement of the electron-jet imbalance in the transverse plane
  - Specifically exploring the momentum transfer (Q^2) dependence through multi-differential unfolding

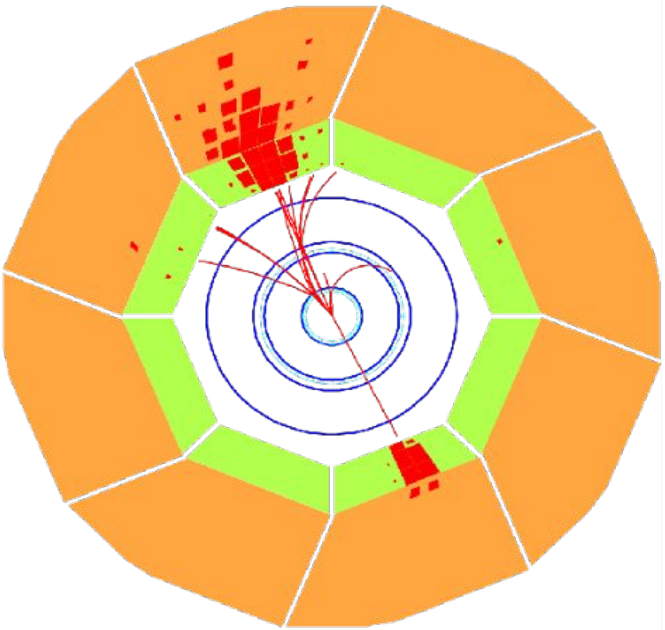
920 GeV proton



27.6 GeV positron



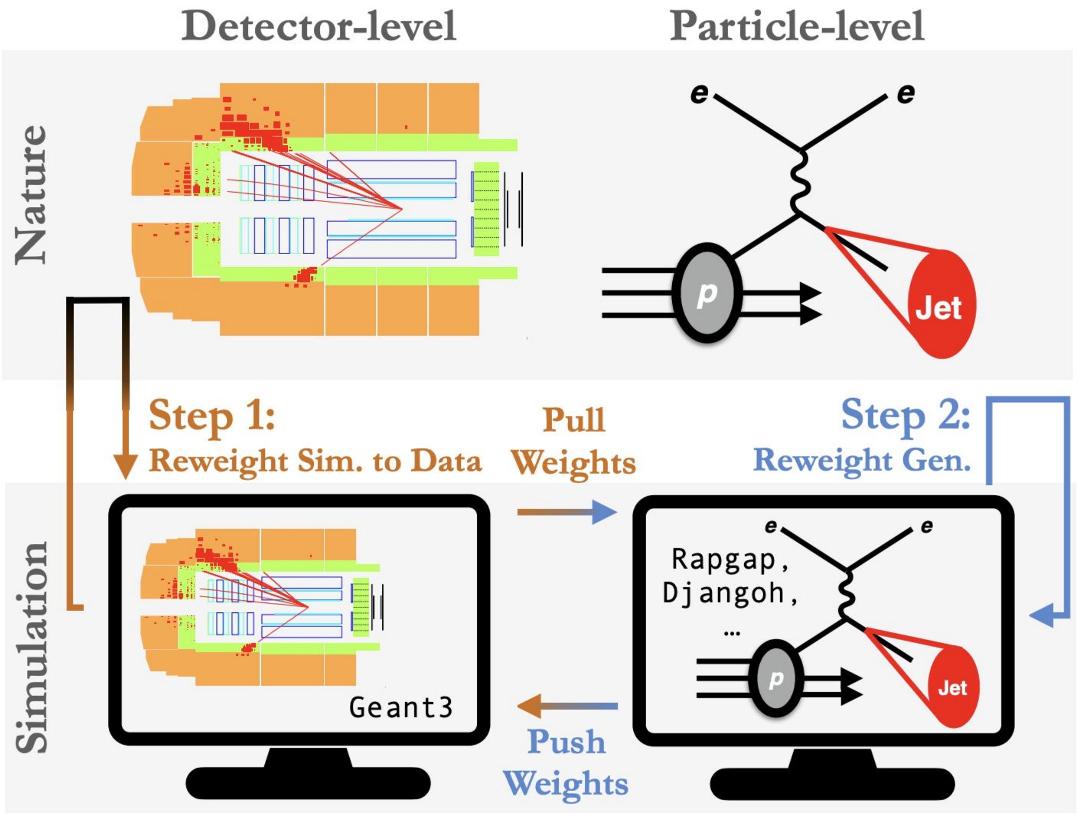
Electron-jet imbalance



- In Born-level configuration, electron and jet are back-to-back
- Studying jet production in the lab frame probes Transverse Momentum Dependent (TMD) Parton Distribution Functions (PDFs)
- Observables of interest:
  - Angular separation in the transverse plane:
    - $\Delta\phi^{jet} = |\pi - (\phi^{e} - \phi^{jet})|$
  - Relative transverse electron-jet momentum imbalance:
    - $q_T^{jet}/Q = |p_T^{e} + p_T^{jet}| / |p^{e}_{final} - p^{e}_{initial}|$

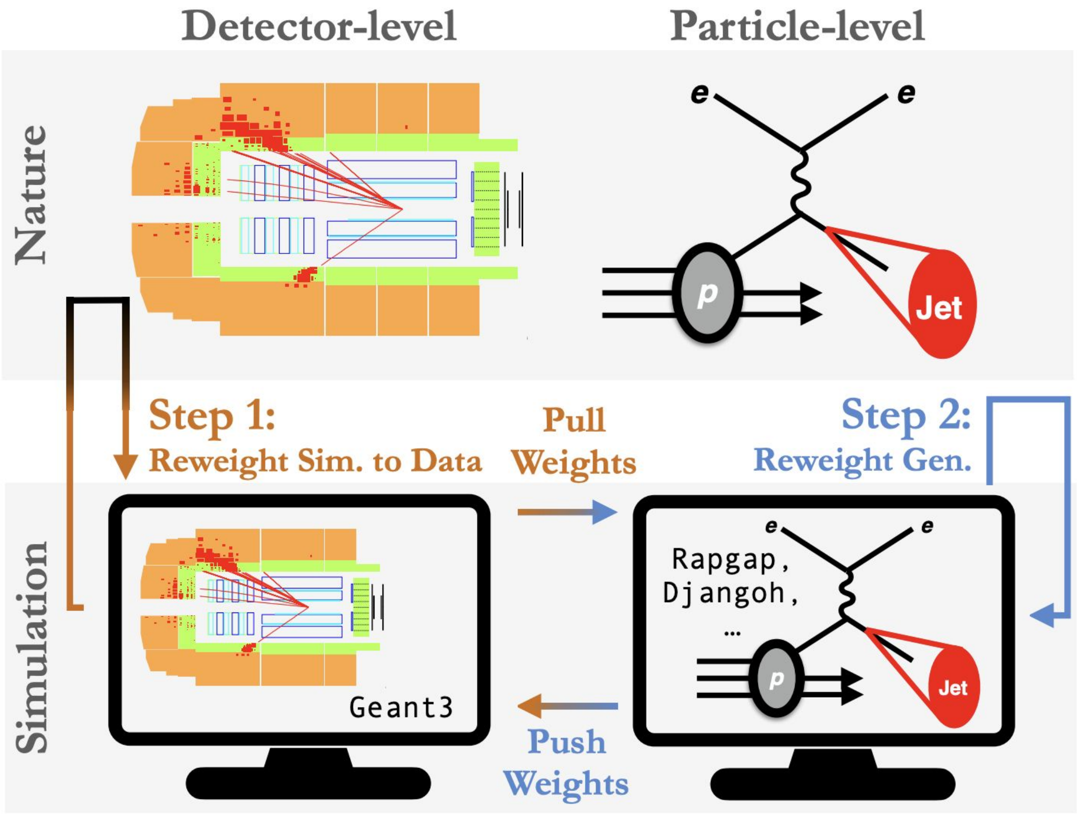
See e.g. Lieu et al. PRL (2019) 192003; Gutierrez et al. PRL (2018) 162001

Omnifold: Unfold by iterating



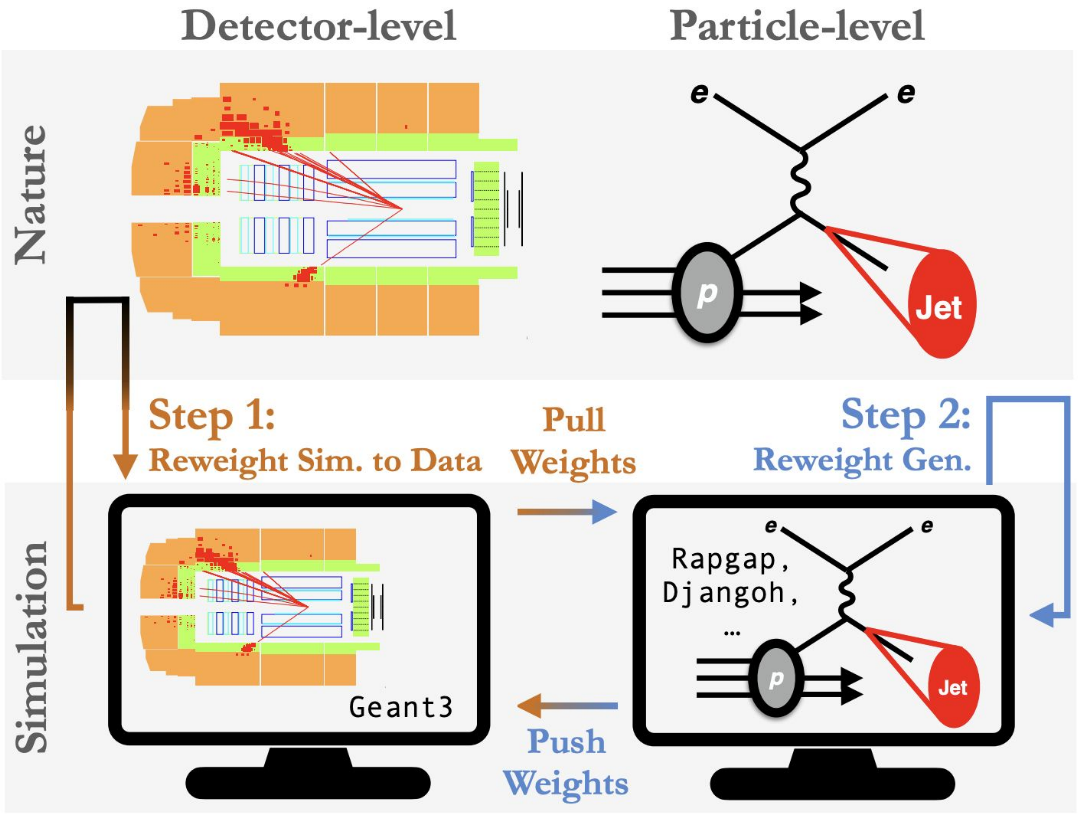
- Omnifold is a neural network based unfolding method that is:
  - Unbinned
  - Maximum likelihood method
  - High dimensional (full phase-space)
- It is a 2 step method that reweighs p_{sim} to match p_{data} at each step

Omnifold: Unfold by iterating



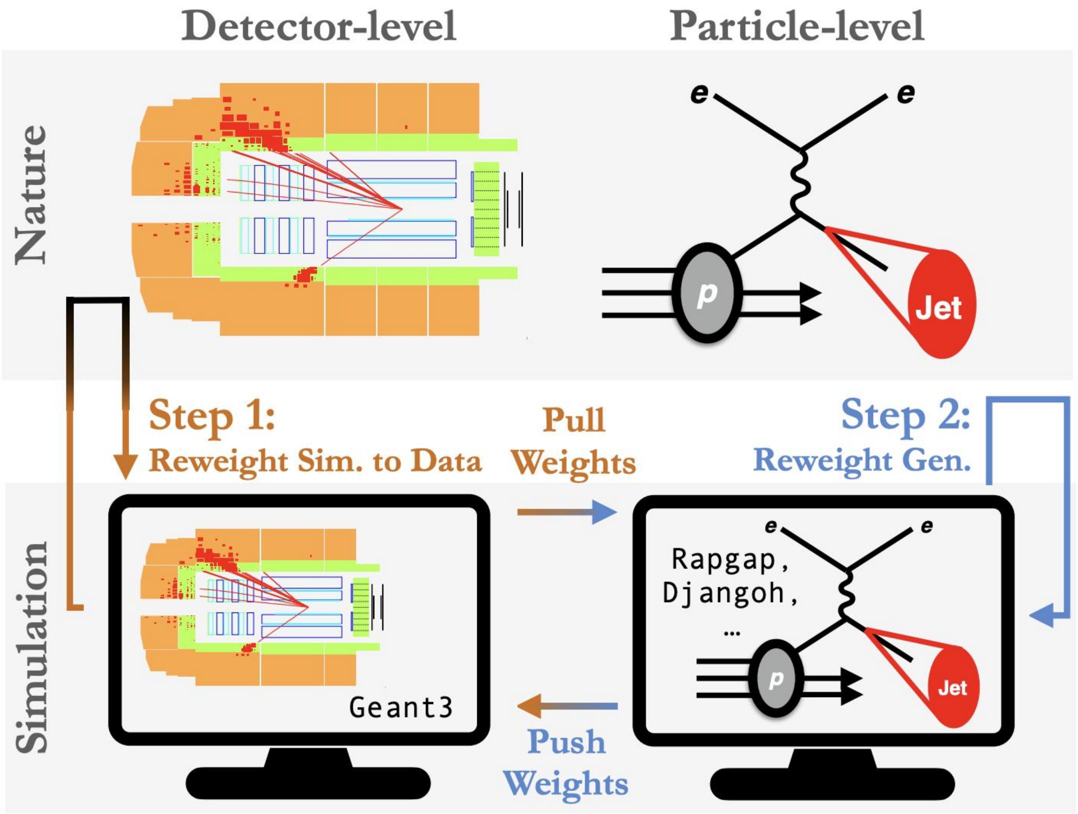
- Trains binary classifiers(NN) to distinguish events sampled from p_{sim} vs. p_{data}
- The prediction NN(x) is used to reweight p_{sim} to match p_{data} at each step
  - Obtain $w(x) = NN(x)/(1-NN(x))$ at each step

Omnifold: Unfold by iterating



- Each event has kinematics stored for:
  - Detector-level
  - Particle(generation)-level
- Step 1: reweighs detector-level simulation to H1 data, thus obtain $w_{detector}$
- Pull weights: apply $w_{detector}$ to particle level kinematics

Omnifold: Unfold by iterating



- Each event has kinematics stored for:
  - Detector-level
  - Particle(generation)-level
- Step 2: converts $w_{detector}$ to valid $w_{particle}$ because mapping from particle to detector level is stochastic
- Push weights: apply $w_{particle}$ to detector level kinematics
- Repeat Step 1

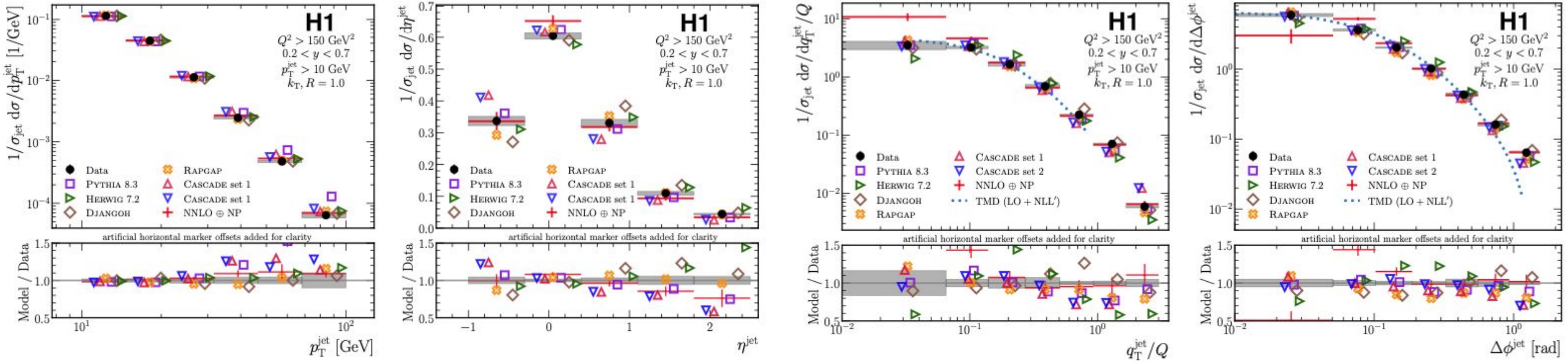
Post-training Unfolding

- We can unfold more derivative observables after the initial neural network training for weights
  - Current phase space include: p_x^e, p_y^e, p_z^e, p_T^{jet}, η^{jet}, ϕ^{jet}, $\Delta\phi^{jet}$, q_T^{jet}/Q
- We can also freely explore different regions of phase-space post-training since any function of the phase space is also unfolded for free due to the unbinned nature of the method

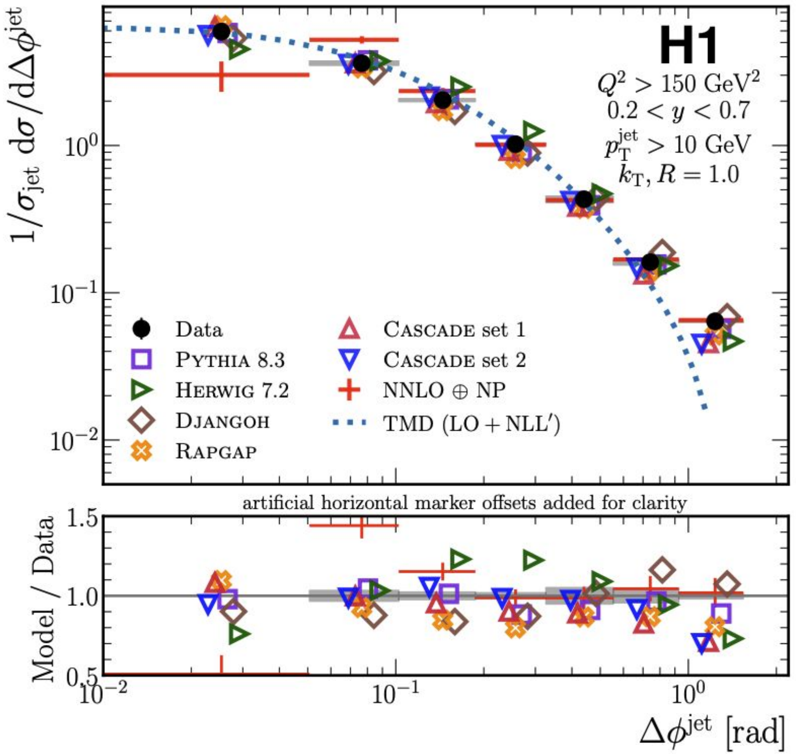
$$Q^2 = \frac{(p_x^e + p_T^{jet} cos(\phi^{jet}))^2 + (p_y^e + p_T^{jet} sin(\phi^{jet}))^2}{(q_T^{jet}/Q)^2}$$

Inclusive Q^2 binning results

- We used machine learning (OmniFold) to perform an 8-dimensional, unbinned unfolding.
- We then present four, binned results
- These azimuthal correlation results between jet and positron in the lab frame are published this year [PRL 128 (2022) 132002].



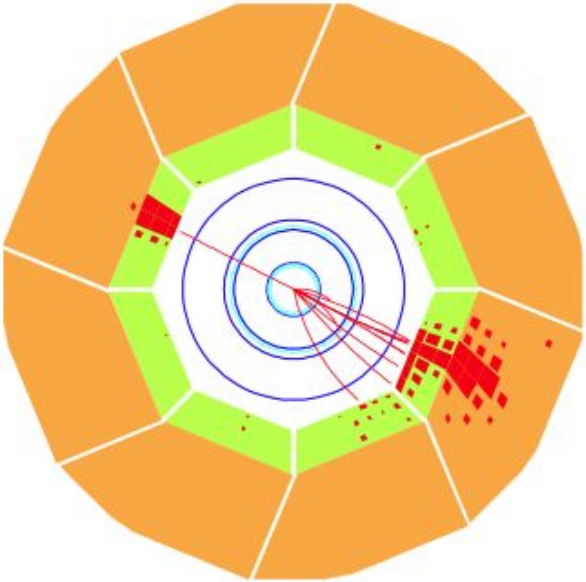
Inclusive Q^2 binning results : Δϕ



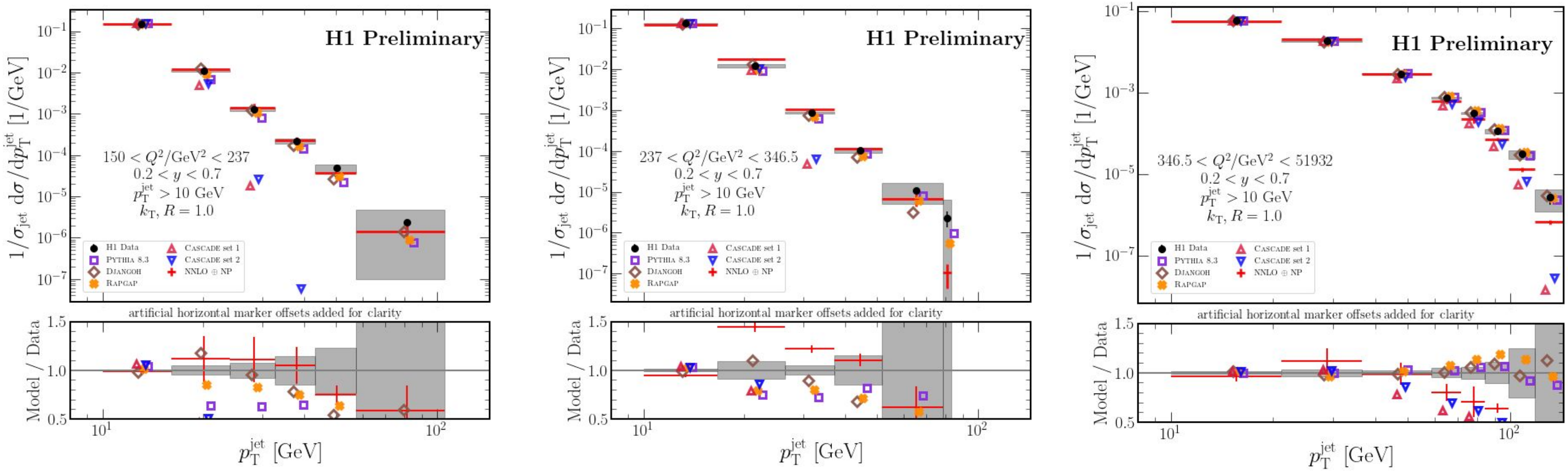
- Angular separation in the transverse plane:
  - $\Delta\phi^{jet} = |\pi - (\phi^{e} - \phi^{jet})|$
- MC predictions:
  - Rapgap (Born-level DIS)
  - Djangoh (Born-level DIS)
  - Cascade (TMD based)
- Theory predictions:
  - TMD(····) matches well at low Δϕ value
  - pQCD(+) matches well at high Δϕ value

Multi-differential binning

- The goal of this follow up work is to explore the differential nature of our previous result.
- We can use the 8-dimensional result to explore the Q^2- and y-dependence and any other observables that can be computed from the electron-jet kinematics.

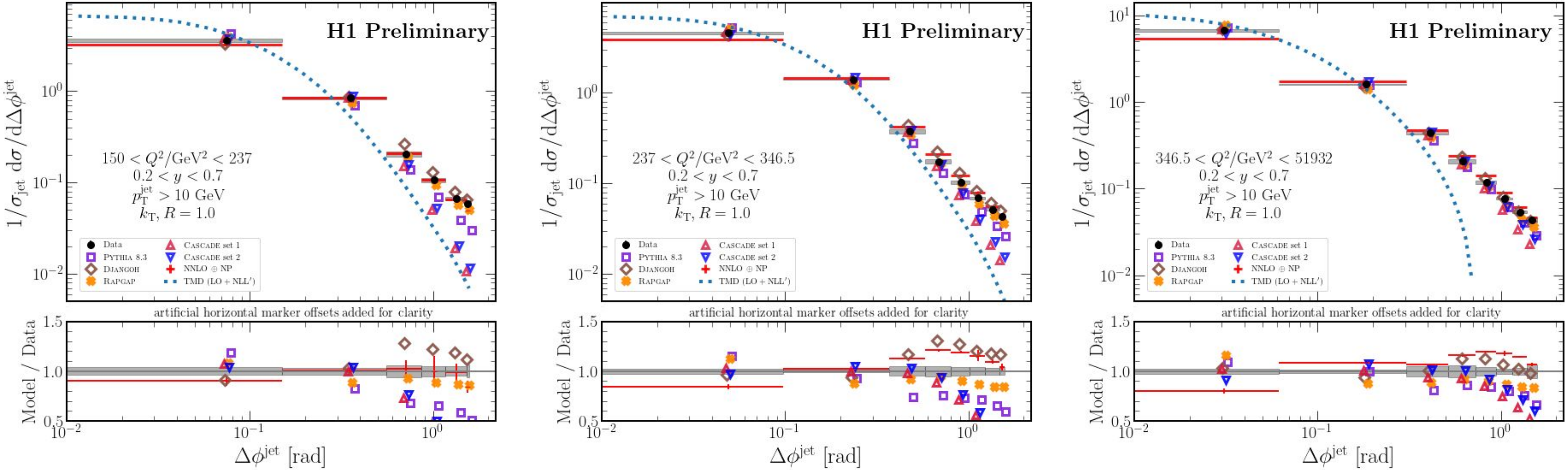


Results: Unfolded jet p_T distributions in bins of Q^2



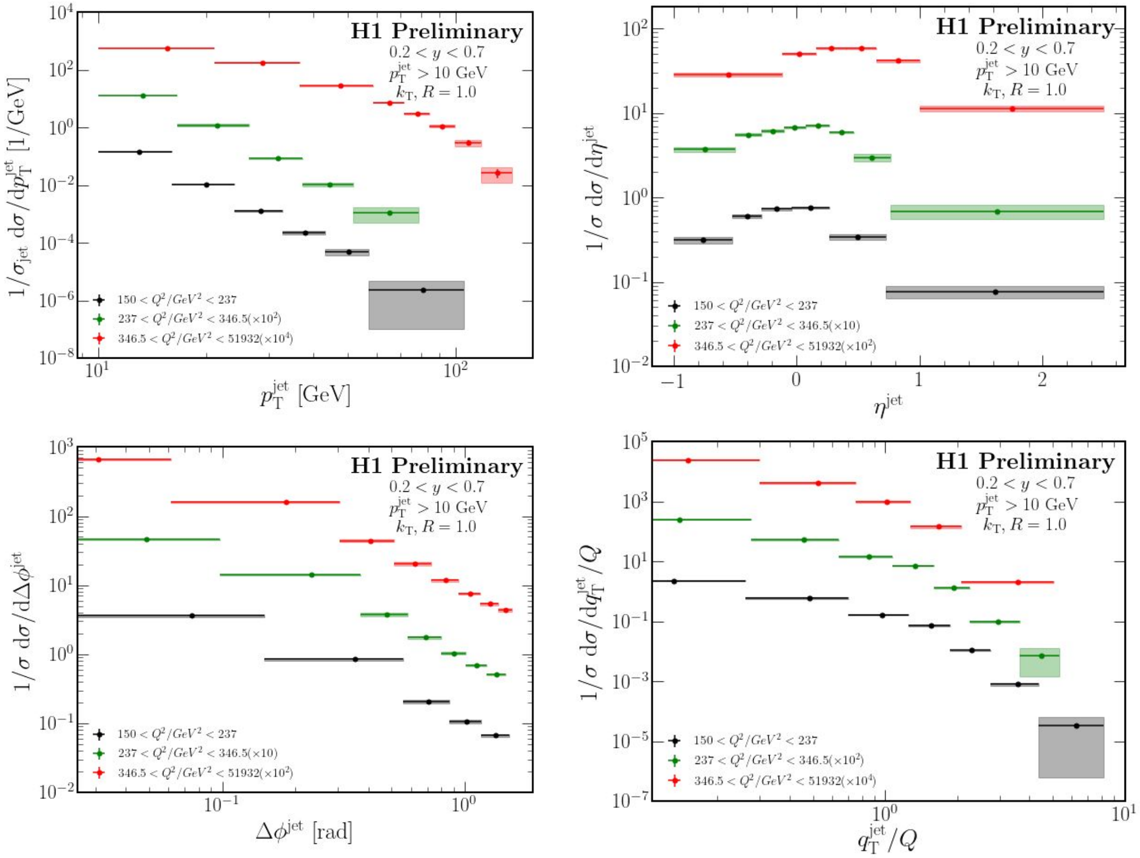
- The disagreements between data and prediction observed in the inclusive result become more pronounced as we examine the phase space differentially

Results: Unfolded Δϕ distributions in bins of Q^2



- Probing the Q^2 scale dependence of the transition from TMD to pQCD framework

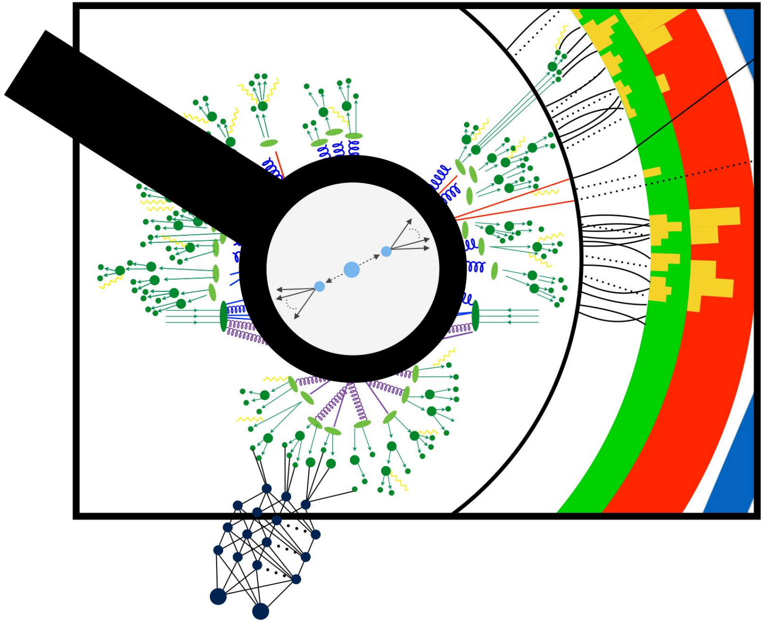
Results: Q^2 binned distributions



- Double differential measurements of lepton-jet observables in DIS over a wide range of Q^2 can be used to constrain TMD evolution effects.
- Known covariance matrix from Omnifold method.
- Similar results in y bins.

Conclusion and Outlook

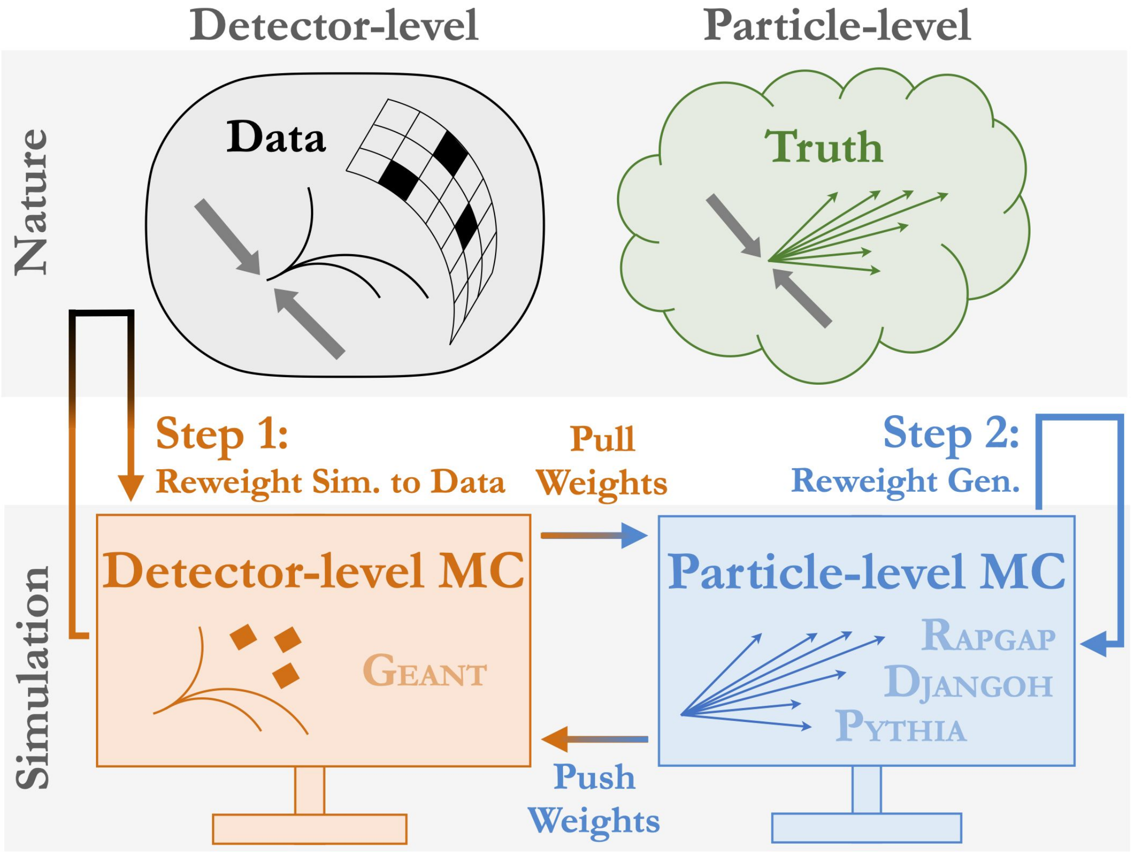
- Lepton-jet correlation measurements probe transition from TMD to pQCD framework
- First application of ML-based unbinned method (Omnifold) to unfold derived observable distributions (e.g. Q^2)
- An important methodological step towards publishing unbinned differential cross-section measurements
- Further details can be found in H1prelim-22-031



Question & Discussion

Back-up slides

Omnifold: Unfold by iterating



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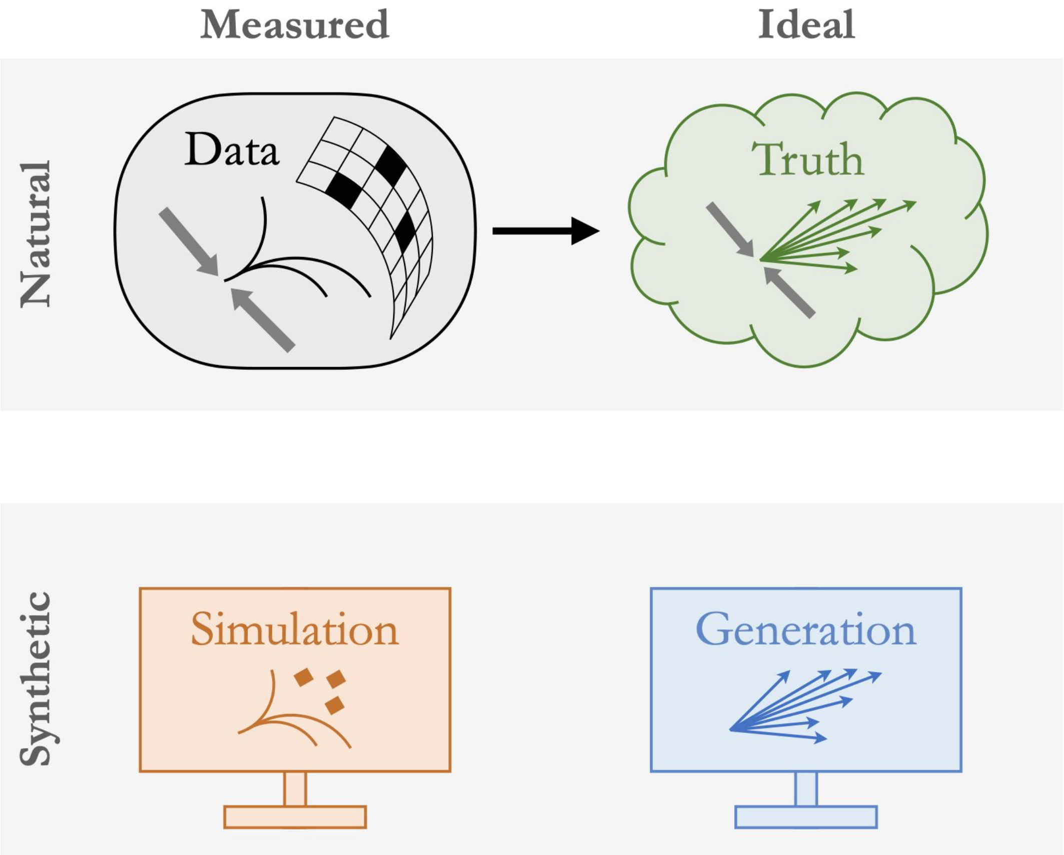
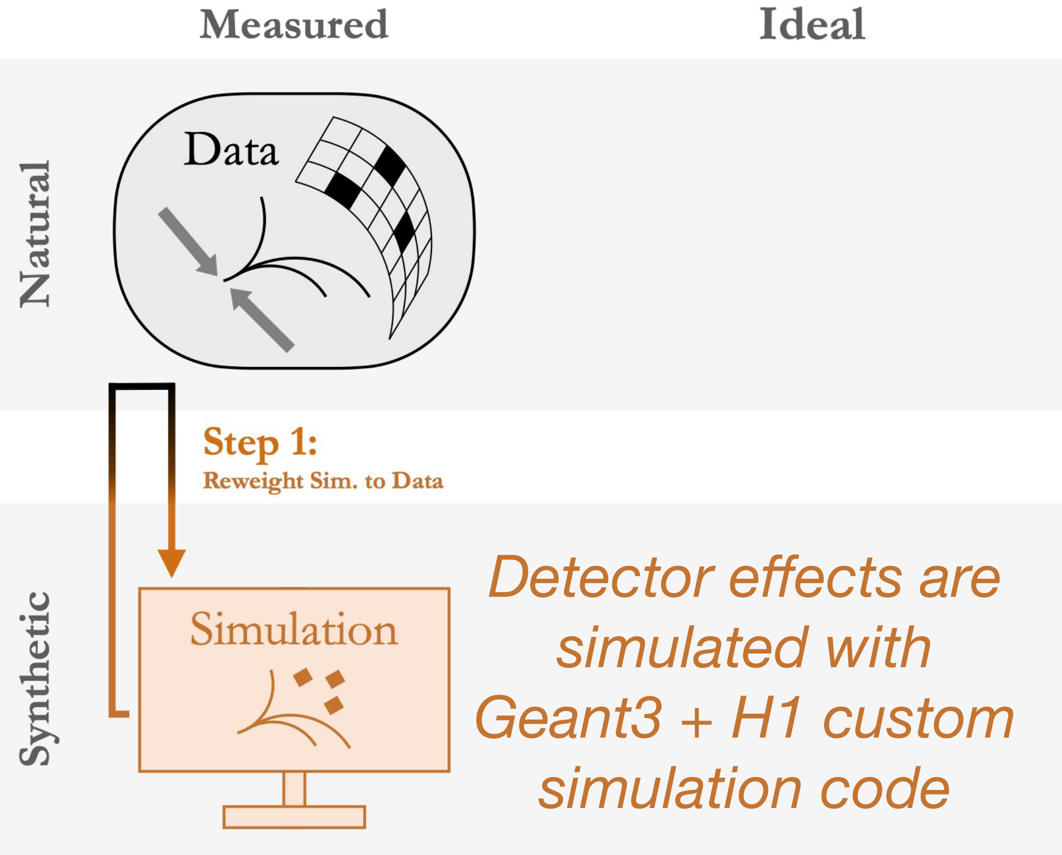


A. Andreassen, P. Komiske, E. Metodiev, BPN, J. Thaler, PRL 124 (2020) 182001

Omnifold: Unfold by iterating



Detector effects are simulated with Geant3 + H1 custom simulation code

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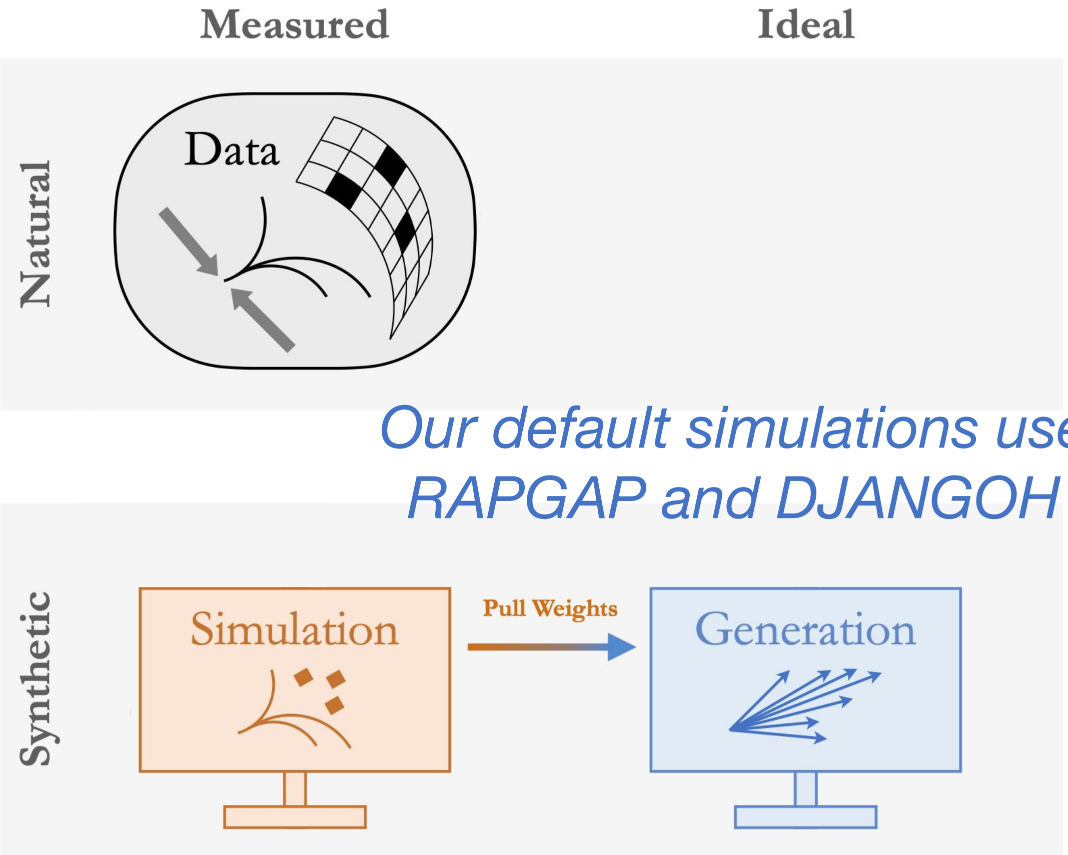
Omnifold: Unfold by iterating



Our default simulations use RAPGAP and DJANGOH

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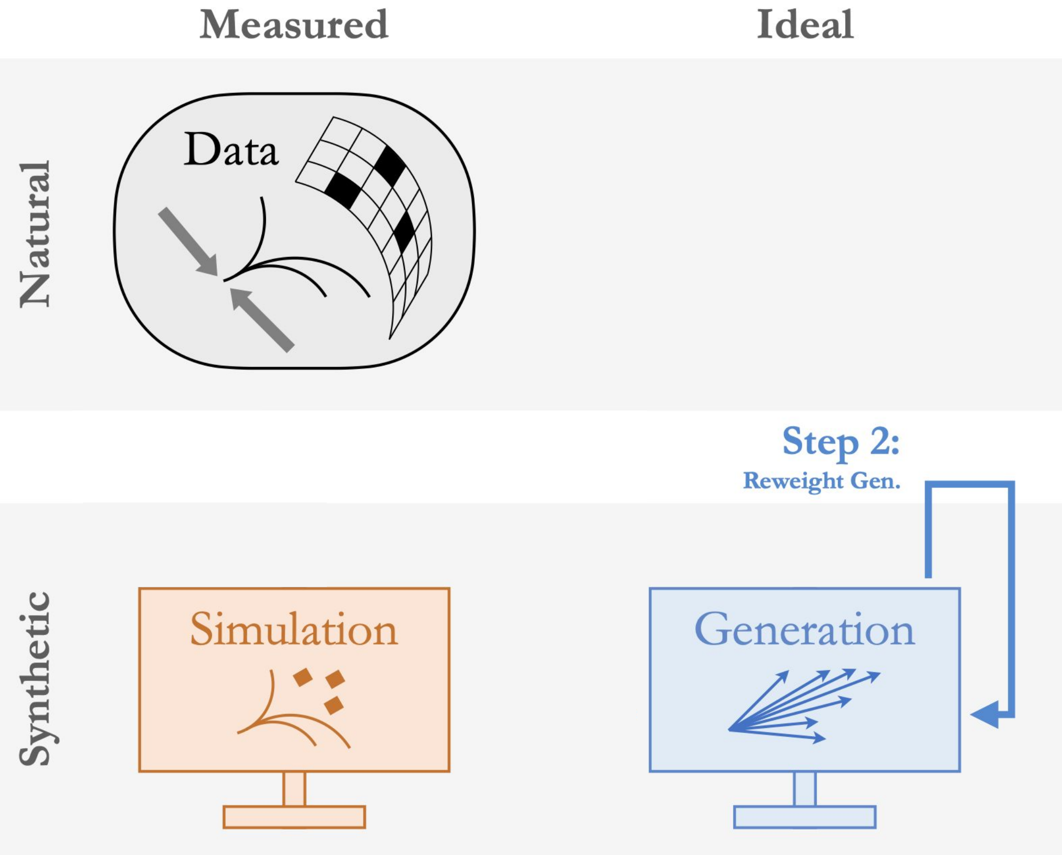

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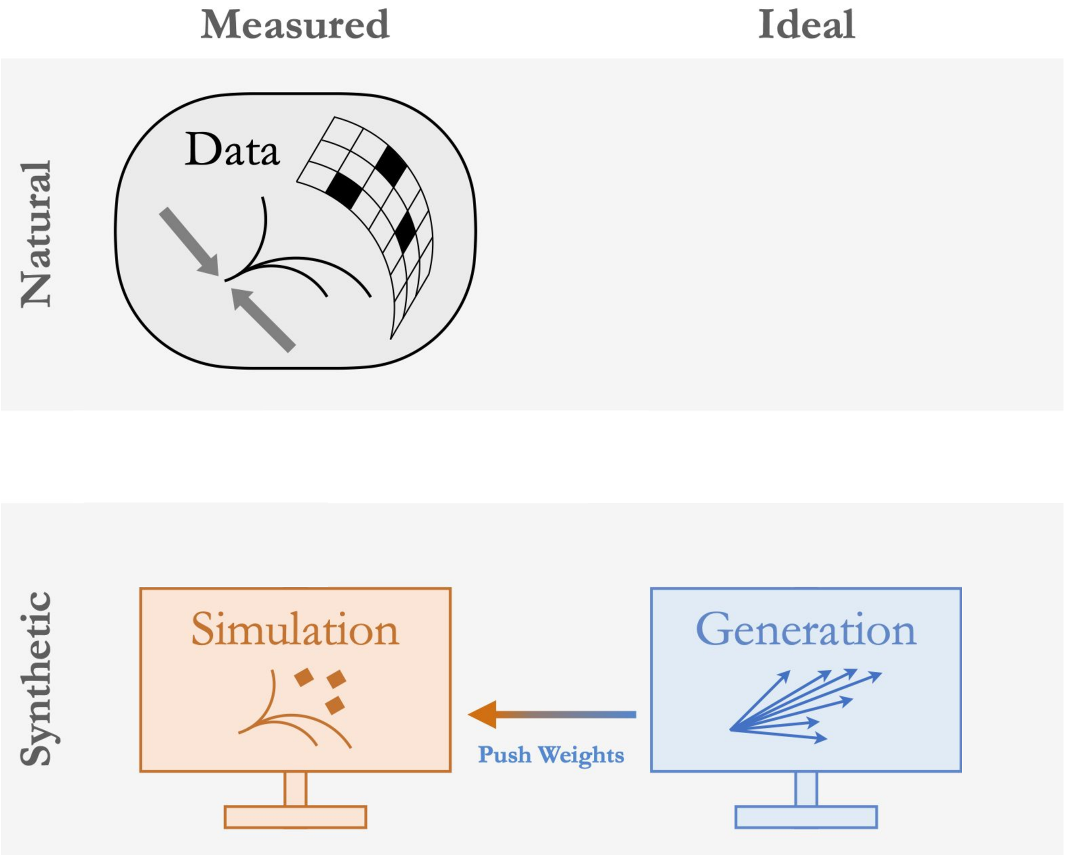

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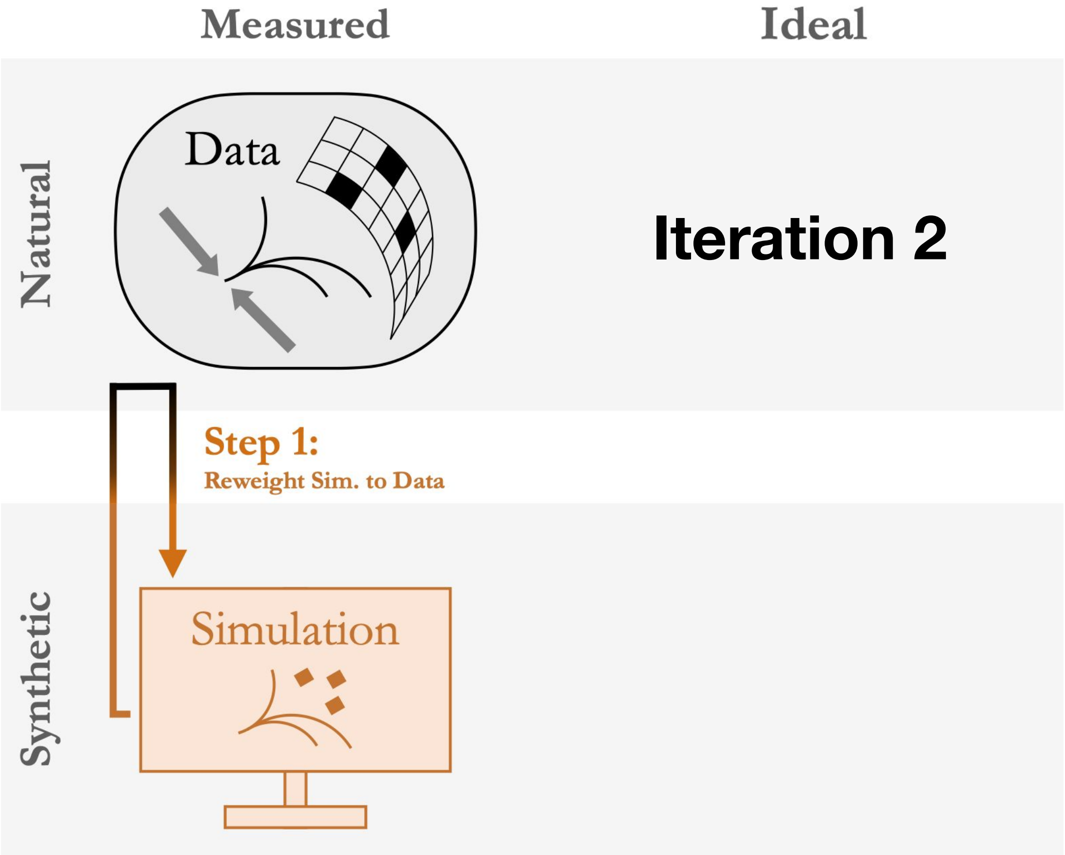

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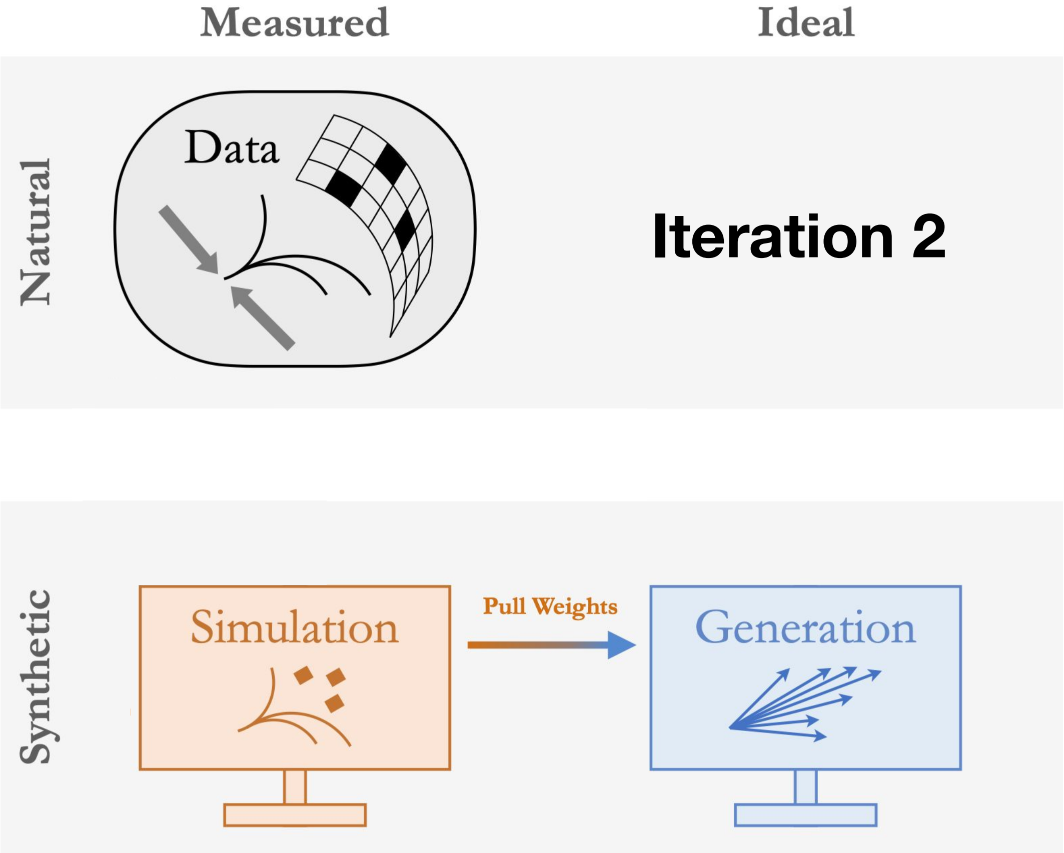

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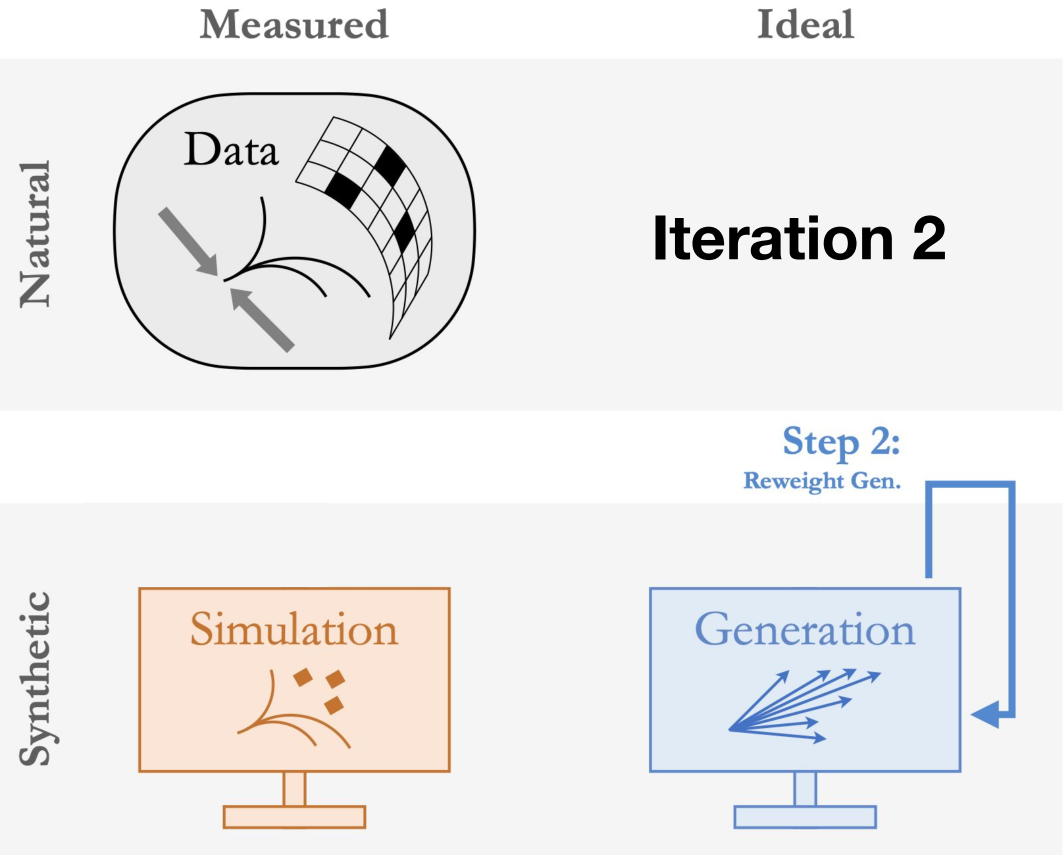

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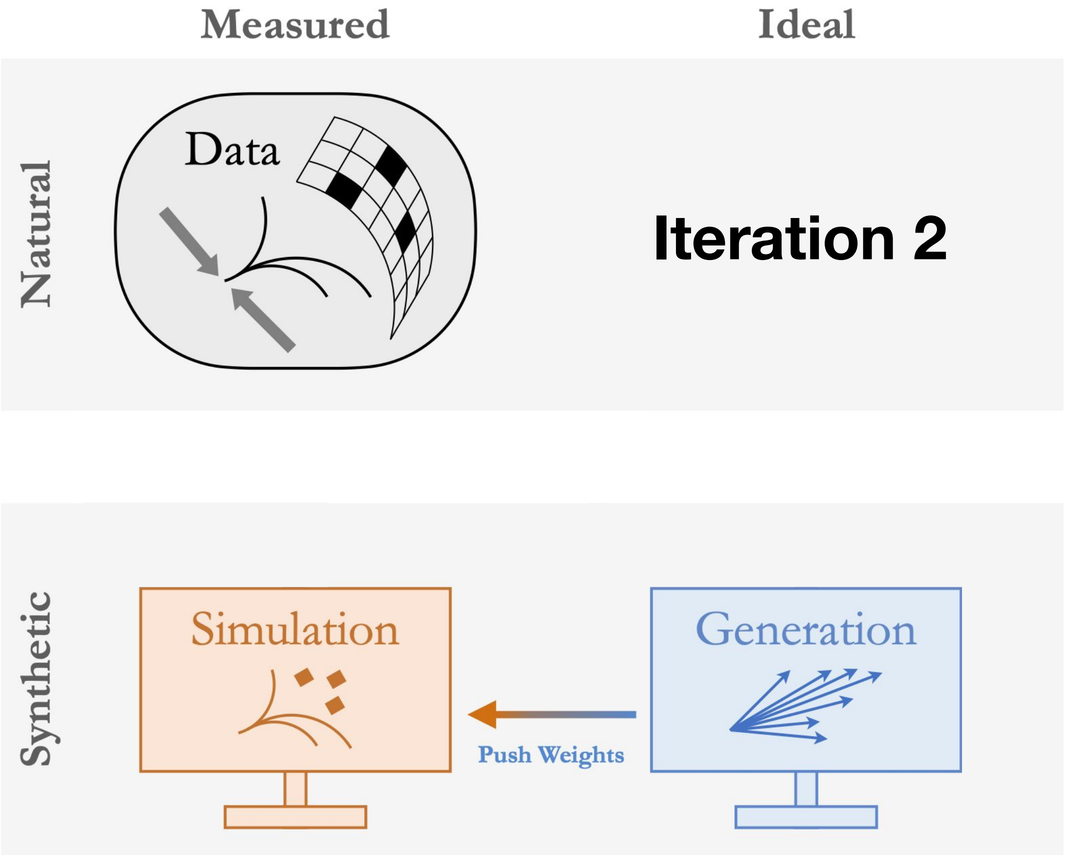

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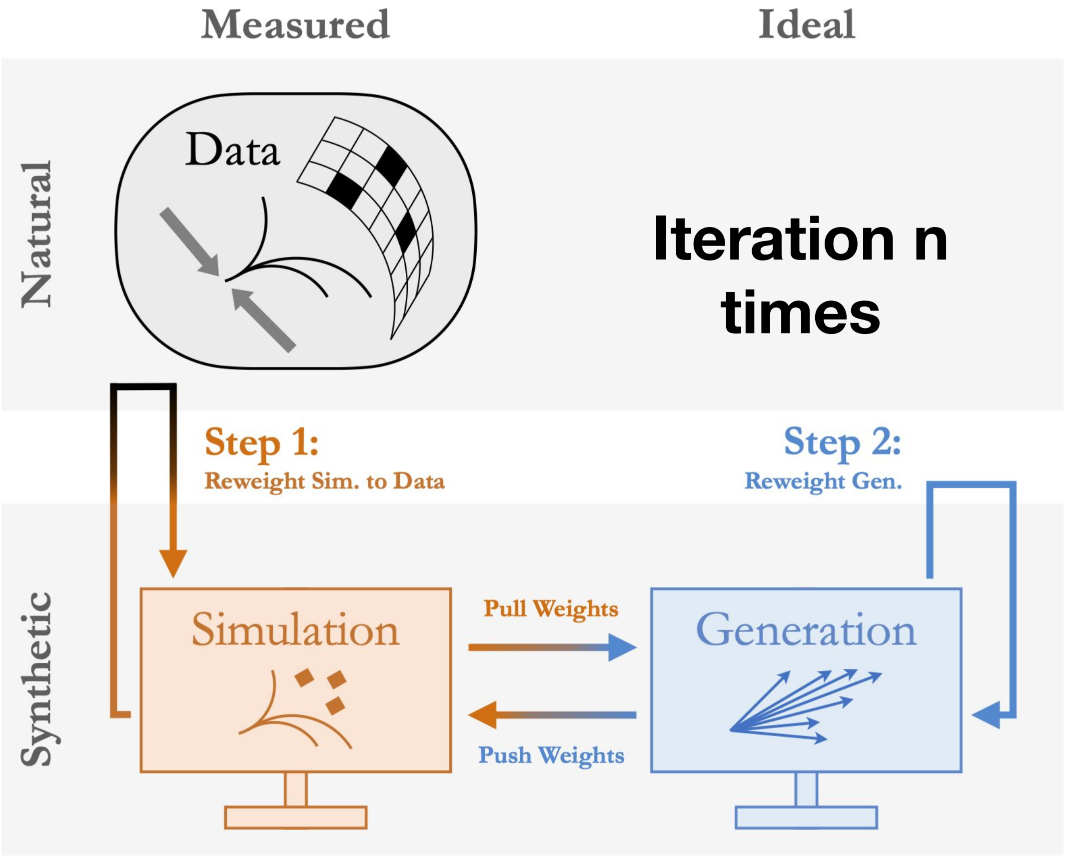

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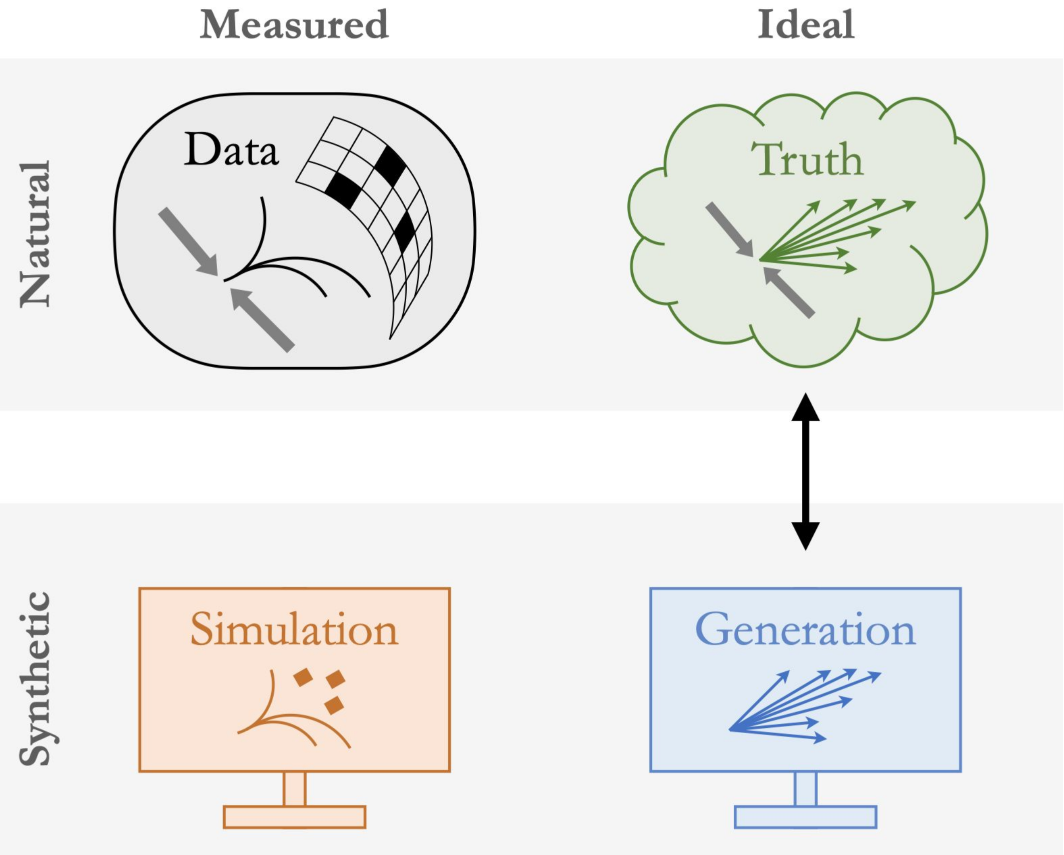

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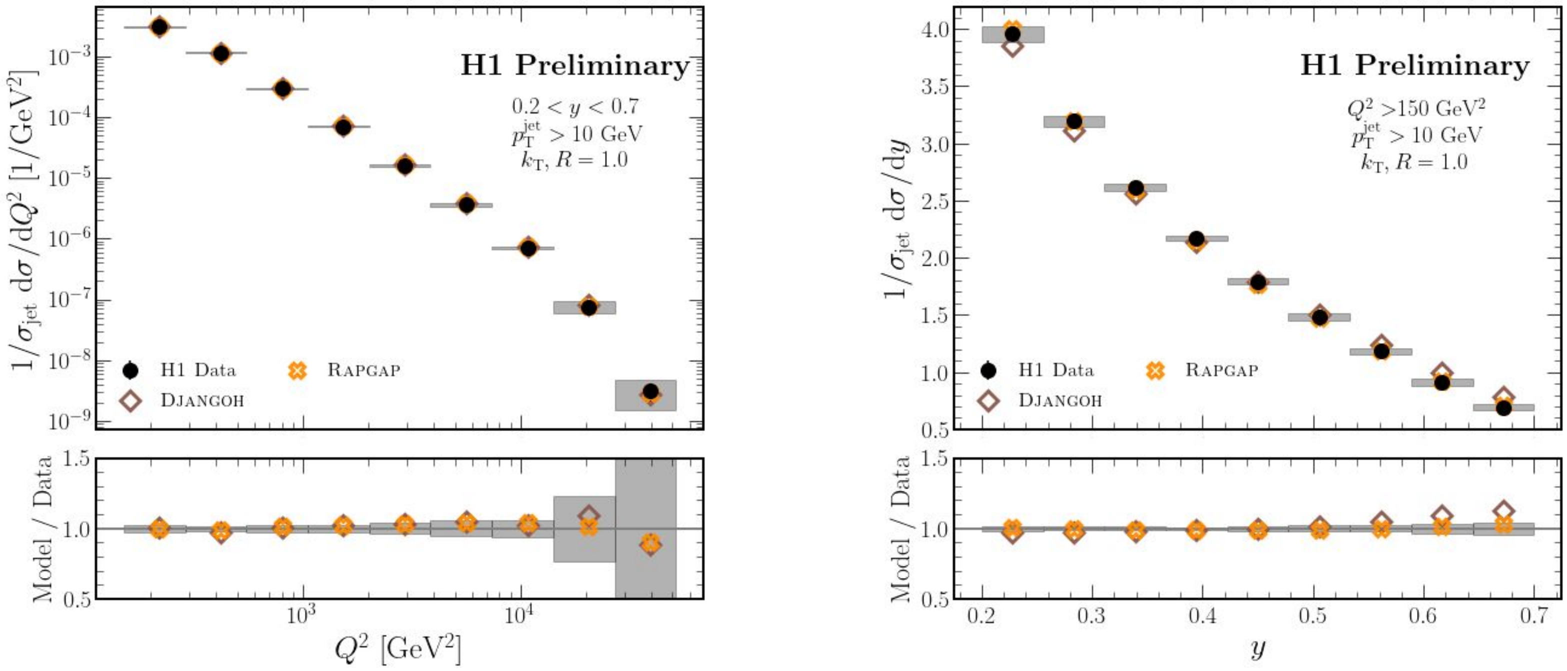
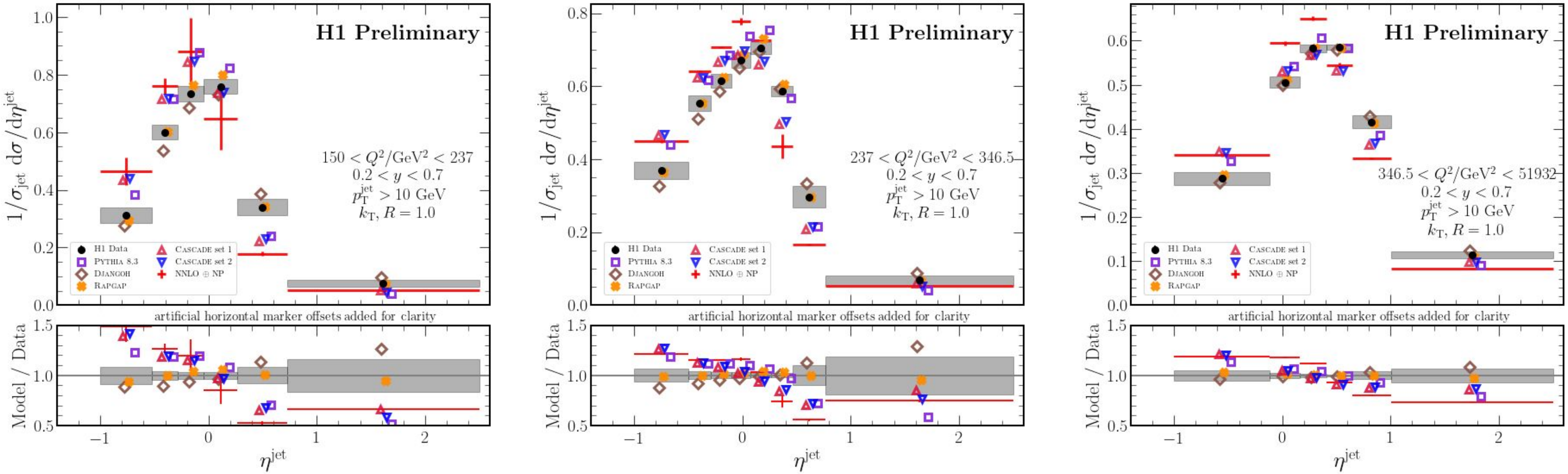
Results: Unfolded Q^2 and y distributions(back up)



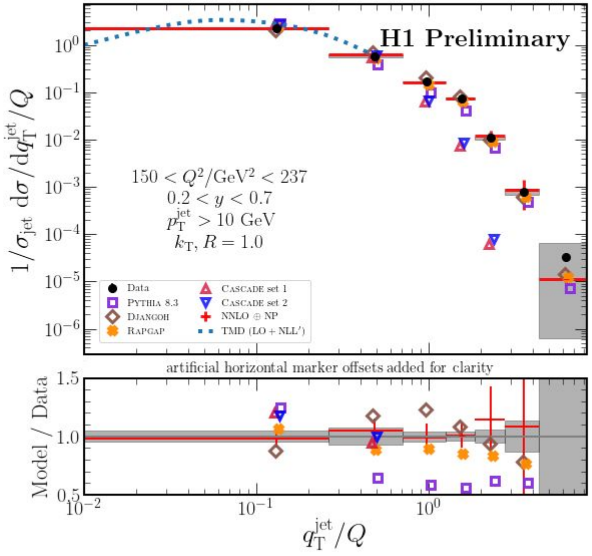
- Both Q^2 and y exhibit steeply falling distributions that are well-described by RAPGGAP and DJANGOH.

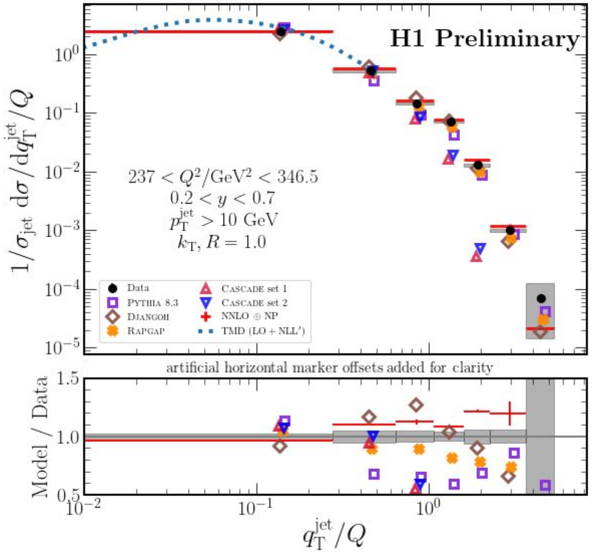
Results: Unfolded jet η distributions(back up)

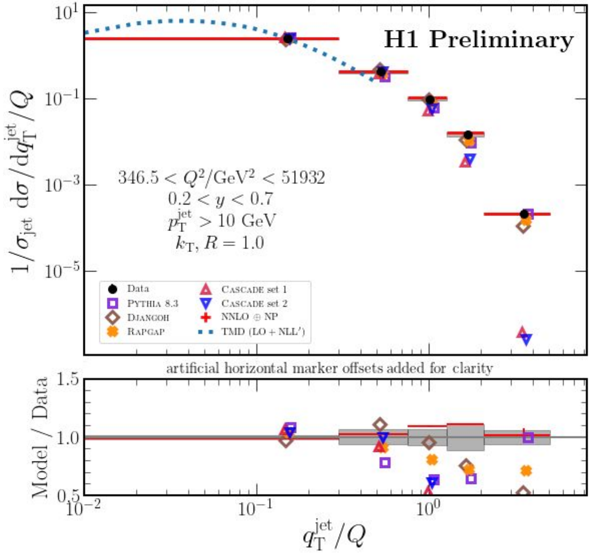


- The jet η peaks near 0 and is asymmetric due to the asymmetry of the colliding beams.

Results: Unfolded qT/Q distributions (back up)

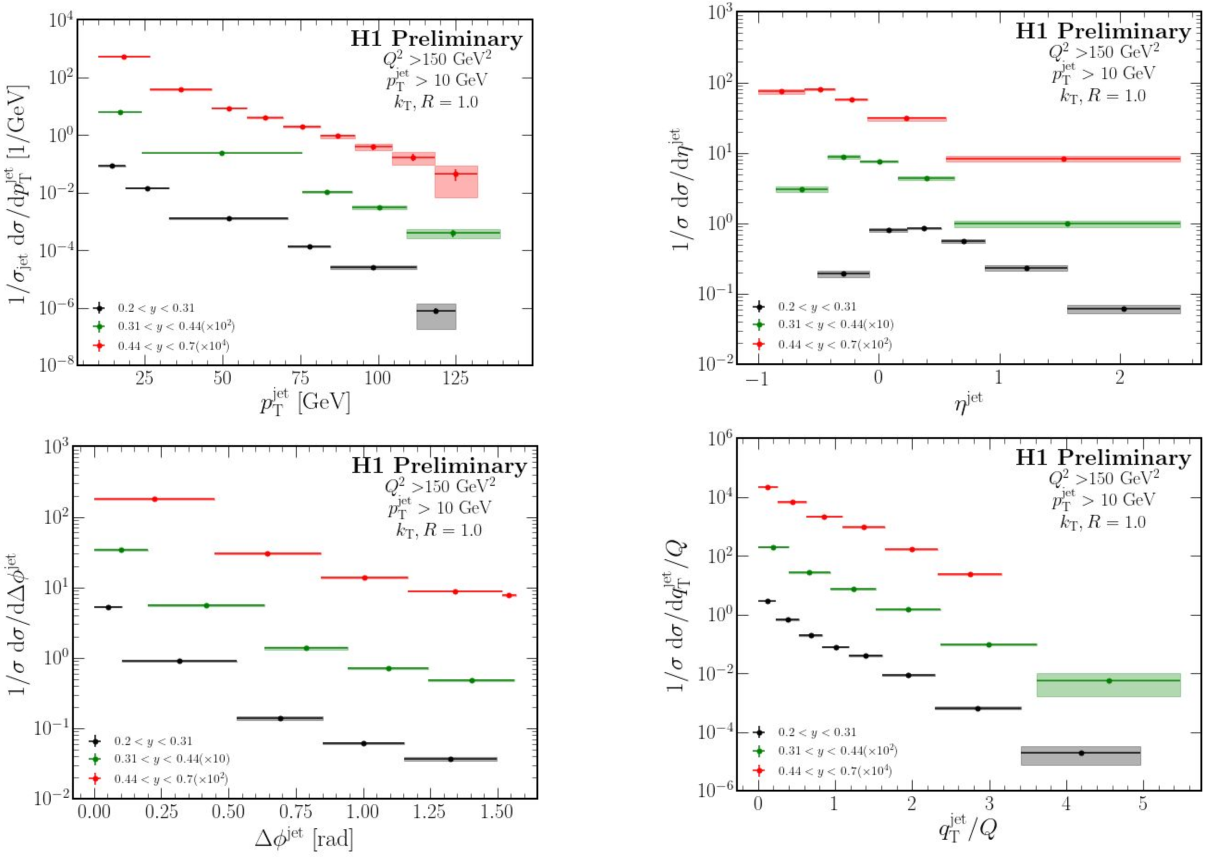






- Transition from TMD to pQCD
- Probing the Q^2 scale dependence

Results: y binned distributions (back up)



$$y = 1 - \frac{E_e^2 \sin^2\theta_e}{Q^2}$$

$$= 1 - \frac{\left((p_x^e)^2 + (p_y^e)^2 + (p_z^e)^2 + m_e^2\right)\left(\frac{(p_x^e)^2+(p_y^e)^2}{(p_x^e)^2+(p_y^e)^2+(p_z^e)^2}\right)^2}{Q^2}$$