

Machine Learning-Assisted Measurement of Lepton-Jet Azimuthal Angular Asymmetries and of the complete final state in Deep-Inelastic Scattering at HERA

Vinicius Mikuni on behalf of the H1 Collaboration



The H1 Detector



One of the two multipurpose detectors at the **HERA** accelerator facility

- Data taking from 1992 to 2007 colliding electrons/positrons against protons
- Huge data preservation effort to modernize the software and preserve the data





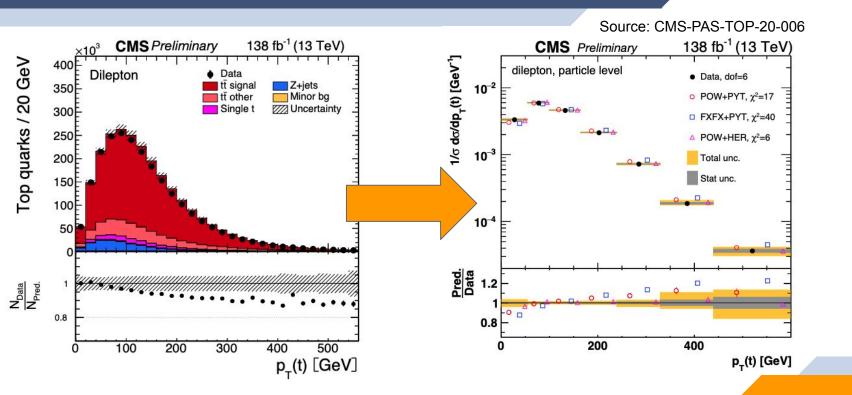
What we measure

What we want

1999999999

mmmminini mmmmmmi





4





How to define the **optimal binning**?

- Choice depends on the distribution and phase space
- Need to compromise when **combining** results from **different experiments**



How to define the **optimal binning**?

- Choice depends on the distribution and phase space
- Need to compromise when **combining** results from **different experiments**

How to include **multiple distributions**?

- Histograms are hard to scale: curse of dimensionality
- Unfolding uncertainties can be reduced using additional observables

6



How to define the **optimal binning**?

- Choice depends on the distribution and phase space
- Need to compromise when **combining** results from **different experiments**

How to include multiple distributions?

- Histograms are hard to scale: curse of dimensionality
- Unfolding uncertainties can be reduced using additional observables

How to unfold distributions that are **not** defined for each event?

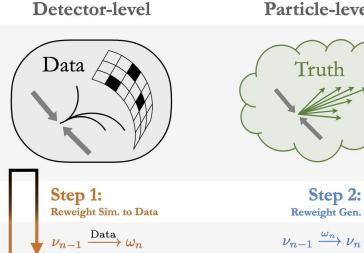
- Moments of distributions
- Energy Correlators



Natural

Synthetic

ML Based Unfolding



Pull Weights

Push Weights

Simulation



Generation

2-step iterative process

- **Step 1**: Reweight simulations to look like data
- **Step 2**: Convert learned weights into functions of particle level objects
- Use classifiers to learn the reweighting functions!

Source: Andreassen et al. PRL 124, 182001 (2020)



ML Based Unfolding

PHYSICAL REVIEW LETTERS 128, 132002 (2022)

Measurement of Lepton-Jet Correlation in Deep-Inelastic Scattering with the H1 Detector Using Machine Learning for Unfolding

V. Andreev,²³ M. Arratia,³⁵ A. Baghdasaryan,⁴⁶ A. Baty,¹⁶ K. Begzsuren,³⁹ A. Belousov,^{23,*} A. Bolz,¹⁴ V. Boudry,³ G. Brandt,¹³ D. Britzger,²⁶ A. Buniatvan,⁶ L. Bystritskava,²² A. J. Campbell,¹⁴ K. B. Cantun Avila,⁴⁷ K. Cerny, V. Chekelian.²⁶ Z. Chen.³⁷ J. G. Contreras.⁴⁷ L. Cunqueiro Mendez.²⁷ J. Cvach.³³ J. B. Dainton.¹⁹ K. Daum.⁴ A. Deshpande,³⁸ C. Diaconu,²¹ G. Eckerlin,¹⁴ S. Egli,⁴³ E. Elsen,¹⁴ L. Favart,⁴ A. Fedotov,²² J. Feltesse,¹² M. Fleischer,¹⁴ A. Fomenko.²³ C. Gal.³⁸ J. Gayler.¹⁴ L. Goerlich.¹⁷ N. Goerlidze.²³ M. Gouzevitch.⁴² C. Grab.⁴⁹ T. Greenshaw.¹⁵ G. Grindhammer,²⁶ D. Haidt,¹⁴ R. C. W. Henderson,¹⁸ J. Hessler,²⁶ J. Hladký,³³ D. Hoffmann,²¹ R. Horisberger, T. Hreus,⁵⁰ F. Huber,¹⁵ P. M. Jacobs,⁵ M. Jacquet,²⁹ T. Janssen,⁴ A. W. Jung,⁴⁴ H. Jung,¹⁴ M. Kapichine,¹⁰ J. Katzy,¹⁴ C. Kiesling,²⁶ M. Klein,¹⁹ C. Kleinwort,¹⁴ H. T. Klest,³⁸ R. Kogler,¹⁴ P. Kostka,¹⁹ J. Kretzschmar,¹⁹ D. Krücker,¹ K. Krüger,¹⁴ M. P. J. Landon,²⁰ W. Lange,⁴⁸ P. Laycock,⁴¹ S. H. Lee,³ S. Levonian,¹⁴ W. Li,¹⁶ J. Lin,¹⁶ K. Lipka,¹⁴ B. List,¹⁴ J. List,¹⁴ B. Lobodzinski,²⁶ E. Malinovski,²³ H.-U. Martyn,¹ S. J. Maxfield,¹⁹ A. Mehta,¹⁹ A. B. Meyer,¹⁴ J. Meyer,¹⁴ S. Mikocki,¹⁷ M. M. Mondal,³⁸ A. Morozov,¹⁰ K. Müller,⁵⁰ B. Nachman,⁵ Th. Naumann,⁴⁸ P. R. Newman,⁶ C. Niebuhr,¹⁴ G. Nowak.¹⁷ J. E. Olsson,¹⁴ D. Ozerov.⁴³ S. Park.³⁸ C. Pascaud.²⁹ G. D. Patel.¹⁹ E. Perez.¹¹ A. Petrukhin.⁴² I. Picuric.³² D. Pitzl, ¹⁴ R. Polifka, ³⁴ S. Preins, ³⁵ V. Radescu, ³⁰ N. Raicevic, ³² T. Ravdandori, ³⁹ P. Reimer, ³³ E. Rizvi, ²⁰ P. Robmann, ⁵⁰ R. Roosen.⁴ A. Rostovtsev.²⁵ M. Rotaru.⁷ D. P. C. Sankev.⁸ M. Sauter.¹⁵ E. Sauvan.^{21,2} S. Schmitten.¹⁴ B. A. Schmookler.³ L. Schoeffel,¹² A. Schöning,¹⁵ F. Sefkow,¹⁴ S. Shushkevich,²⁴ Y. Soloviev,²³ P. Sopicki,¹⁷ D. South,¹⁴ V. Spaskov,¹ A. Specka,³¹ M. Steder,¹⁴ B. Stella,³⁶ U. Straumann,⁵⁰ C. Sun,³⁷ T. Sykora,³⁴ P.D. Thompson,⁶ D. Traynor,²⁰ B. Tseepeldori,^{39,40} Z. Tu,⁴¹ A. Valkárová,³⁴ C. Vallée,²¹ P. Van Mechelen,⁴ D. Wegener,⁹ E. Wünsch,¹⁴ J. Žáček,³⁴ J. Zhang,37 Z. Zhang,29 R. Žlebčík,34 H. Zohrabvan,46 and F. Zomer29

Machine Learning-Assisted Measurement of Lepton-Jet Azimuthal Angular Asymmetries in Deep-Inelastic Scattering at HERA

V. Andreev⁴⁷, M. Arratia³¹, A. Baghdasarvan⁴³, A. Baty⁸, K. Begzsuren³⁷, A. Bolz¹⁵, V. Boudry²⁷, G. Brandt¹⁴, D. Britzger¹¹, A. Buniatvan⁶, L. Bystritskaya⁴⁷, A.J. Campbell¹⁵, K.B. Cantun Avila⁴⁴, K. Cerny²⁵, V. Chekelian¹¹. Z. Chen³³, J.G. Contreras⁴⁴, J. Cvach²⁹, J.B. Dainton²¹, K. Daum⁴², A. Deshpande^{35,39}, C. Diaconu²³, A. Drees³⁵ G. Eckerlin¹⁵, S. Egli⁴⁰, E. Elsen¹⁵, L. Favart³, A. Fedotov⁴⁷, J. Feltesse¹³, M. Fleischer¹⁵, A. Fomenko⁴⁷, C. Gal³² J. Gayler¹⁵, L. Goerlich¹⁹, N. Gogitidze¹⁵, M. Gouzevitch⁴⁷, C. Grab⁴⁵, T. Greenshaw²¹, G. Grindhammer¹¹, D. Haidt¹⁵, R.C.W. Henderson²⁰, J. Hessler¹¹, J. Hladk⁴²⁹, D. Hoffmann²³, R. Horisberger⁴⁰, T. Hreus⁴⁶, F. Huber¹⁶ P.M. Jacobs⁴, M. Jacquet²⁶, T. Janssen³, A.W. Jung⁴¹, J. Katzy¹⁵, C. Kiesling¹¹, M. Klein^{*,21}, C. Kleinwort¹⁵, H.T. Klest¹⁸, R. Kogler¹⁵, P. Kostka²¹, J. Kretzschmar²¹, D. Krücker¹⁵, K. Krüger¹⁵, M.P.J. Landon²², W. Lange¹⁵, P. Lavcock³⁹, S.H. Lee³⁶, S. Levonian¹⁵, W. Li¹⁷, J. Lin¹⁷, K. Lipka¹⁵, B. List¹⁵, J. List¹⁵, B. Lobodzinski¹¹, O.R. Long³¹, E. Malinovski⁴⁷, H.-U. Martyn¹, S.J. Maxfield²¹, A. Mehta²¹, A.B. Meyer¹⁵, J. Meyer¹⁵, S. Mikocki¹⁹, V.M. Mikuni⁴, M.M. Mondal²⁴, K. Müller⁴⁶, B. Nachman⁴, Th. Naumann¹⁵, P.R. Newman⁶, C. Niebuhr¹⁵ G. Nowak¹⁹, J.E. Olsson¹⁵, D. Ozerov⁴⁷, S. Park³⁵, C. Pascaud²⁶, G.D. Patel²¹, E. Perez¹², A. Petrukhin³⁴ I. Picuric²⁸, D. Pitzl¹⁵, V. Radescu¹⁶, N. Raicevic²⁸, T. Ravdandori³⁷, D. Reichelt¹², P. Reimer²⁹, E. Rizvi²², P. Robmann⁴⁶, R. Roosen³, A. Rostovtsev⁴⁷, M. Rotaru⁷, D.P.C. Sankey⁹, M. Sauter¹⁶, E. Sauvan^{23,2}, S. Schmitt^{**,15}, B.A. Schmookler³⁵, G. Schnell⁵, L. Schoeffel¹³, A. Schöning¹⁶, F. Sefkow¹⁵, S. Shushkevich¹¹, Y. Soloviev¹⁵, P. Sopicki¹⁹, D. South¹⁵, A. Specka²⁷, M. Steder¹⁵, B. Stella³², U. Straumann⁴⁶, C. Sun³⁵, T. Sykora³⁰ P.D. Thompson⁶, F. Torales Acosta⁴, D. Traynor²², B. Tseepeldorj^{37,38}, Z. Tu³⁹, G. Tustin³⁵, A. Valkárová³⁰ C. Vallée²³, P. Van Mechelen³, D. Wegener¹⁰, E. Wünsch¹⁵, J. Žáček³⁰, J. Zhang³³, Z. Zhang²⁶, R. Žlebčík³⁰ H. Zohrabyan43, F. Zomer26

Contents lists available at ScienceDirect Physics Letters B **ELSEVIEI** journal homepage: www.elsevier.com/locate/physletb

Unbinned deep learning jet substructure measurement in high $0^2 ep$ collisions at HERA

Physics Letters B 844 (2023) 138101

V. Andreev^{ar}, M. Arratia^{ac}, A. Baghdasaryan^{an}, A. Baty^p, K. Begzsuren^{ah}, A. Bolzⁿ, V. Boudry^y, G. Brandt^m, D. Britzger^v, A. Buniatyan^g, L. Bystritskaya^{ar}, A.J. Campbellⁿ, K.B. Cantun Avila^{ao}, K. Cerny^W, V. Chekelian^V, Z. Chen^{ae}, I.G. Contreras^{ao}, I. Cvach^{aa}, I.B. Dainton^s, K. Daum^{am}, A. Deshpande^{ag,aj}, C. Diaconu^u, A. Drees^{ag}, G. Eckerlinⁿ, S. Egli^{ak}, E. Elsenⁿ, L. Favart^d, A. Fedotov^{ar}, J. Feltesse¹, M. Fleischerⁿ, A. Fomenko^{ar}, C. Gal^{ag}, J. Gavlerⁿ, L. Goerlich^q, N. Gogitidzeⁿ, M. Gouzevitch^{ar}, C. Grab^{ap}, T. Greenshaw^s, G. Grindhammer^v, D. Haidtⁿ, R.C.W. Henderson^r, J. Hessler^v, J. Hladký^{aa}, D. Hoffmann^u, R. Horisberger^{ak}, T. Hreus^{aq}, F. Huber^o, P.M. Jacobs^e, M. Jacquet^x, T. Janssen^d, A.W. Jung^{al}, J. Katzyⁿ, C. Kiesling^v, M. Klein^s, C. Kleinwortⁿ, H.T. Klest^{ag}, R. Koglerⁿ, P. Kostka^s, I. Kretzschmar^s, D. Krückerⁿ, K. Krügerⁿ, M.P.I. Landon^t, W. Langeⁿ, P. Lavcock^{a]}, S.H. Lee^b, S. Levonianⁿ, W. Li^p, I. Lin^p, K. Lipkaⁿ, B. Listⁿ J. Listⁿ, B. Lobodzinski^v, O.R. Long^{ac}, E. Malinovski^{ar}, H.-U. Martyn^a, S.J. Maxfield^s, A. Mehta^s, A.B. Meverⁿ, I. Meverⁿ, S. Mikocki^q, V.M. Mikuni^e, M.M. Mondal^{ag}, K. Müller^{aq}, B. Nachman^e, Th. Naumannⁿ, P.R. Newman^g, C. Niebuhrⁿ, G. Nowak^q, J.E. Olssonⁿ, D. Ozerov^{ar}, S. Park^{ag}, C. Pascaud^x, G.D. Patel^s, E. Perez^k, A. Petrukhin^{al} I. Picuric², D. Pitzlⁿ, R. Polifka^{ab}, S. Preins^{ac}, V. Radescu^o, N. Raicevic², T. Ravdandori^{ah}, P. Reimer^{aa}, E. Rizvi^t, P. Robmann^{aq}, R. Roosen^d, A. Rostovtsev^{ar}, M. Rotaru^h, D.P.C. Sankey¹, M. Sauter⁰, E. Sauvan^{u,c}, S. Schmitt^{n,*}, B.A. Schmookler^{ag}, G. Schnell^f, L. Schoeffel¹, A. Schöning⁰, F. Sefkowⁿ, S. Shushkevich^v, Y. Solovievⁿ, P. Sopicki^q, D. Southⁿ, A. Specka^y, M. Stederⁿ, B. Stella^{ad}, U. Straumann^{aq}, C. Sun^{ag}, T. Sykora^{ab}, P.D. Thompson^g, F. Torales Acosta^e, D. Traynor^t, B. Tseepeldorj^{ah,ai}, Z. Tu^{aj}, G. Tustin^{ag}, A. Valkárová ab, C. Vallée^u, P. Van Mechelen^d, D. Wegener^j, E. Wünschⁿ, J. Žáček^{ab}, I. Zhang^{ae}, Z. Zhang^x, R. Žlebčík^{ab}, H. Zohrabyan^{an}, F. Zomer^x

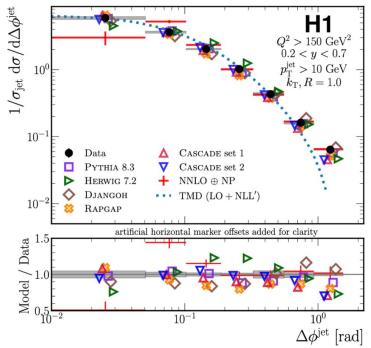
3 papers on ML-based unfolding using H1 data



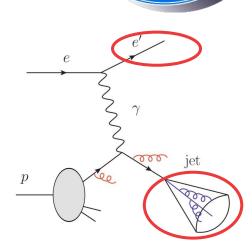
Q



Azimuthal Asymmetries



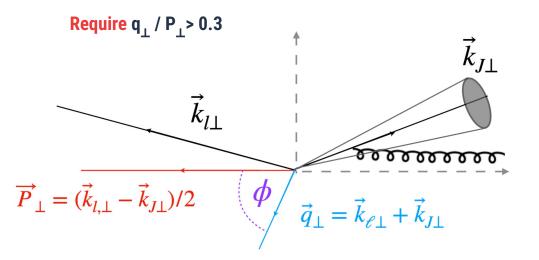
Study of correlations between the scattered lepton and jet



Phys.Rev.Lett. 128 (2022) 13, 132002



Azimuthal Asymmetries



- k_{LL} : transverse momentum of the scattered lepton
- k_{JL} : transverse momentum of the jet

Measure: $cos(\phi)$, $cos(2\phi)$, $cos(3\phi)$

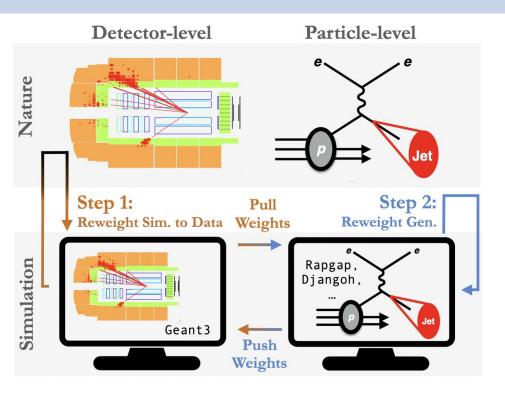
Final state lepton and jet are **mostly** back-to-back

- Imbalance can arise from perturbative initial/final state radiation
- Target the region where the asymmetry is dominated by soft gluon emissions: P₁ >> q₁
- Provide information for TMD PDF measurements where the soft gluon contribution can be factorized

11



Azimuthal Asymmetries



Reuse the results presented at PRL. 128, 132002 on the measurement of lepton-jet correlations

Quantities previously unfolded

COS

 $p_x^e, p_y^e, p_z^e, p_T^{\text{jet}}, \eta^{\text{jet}}, \phi^{\text{jet}}, \Delta \phi^{\text{jet}}, q_T^{\text{jet}}/Q$

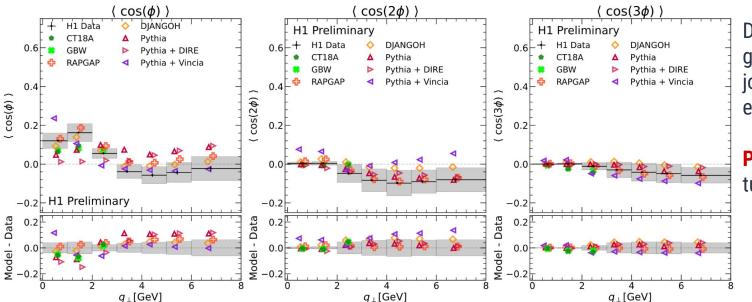
 $\frac{q_{\perp}\cdot P_{\perp}}{|\vec{q_{\perp}}|\cdot |P_{\perp}|}$



Results



arXiv:2412.14092, submitted to PLB



Dedicated DIS generators do a good job **everywhere**, especially **Rapgap**

Pythia predictions not tuned to this data

GBW Includes gluon saturation effects while **CT18A** uses NLO TMD calculations with collinear PDFs, both currently available only for low q

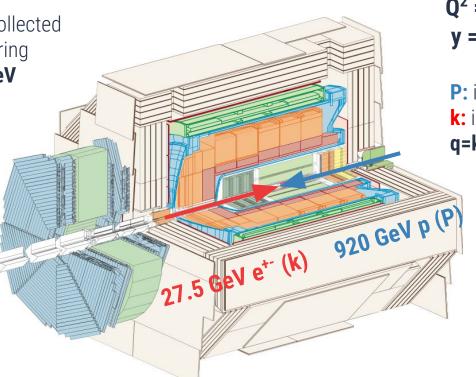
What if we unfolded everything?



Experimental setup

Using **228 pb⁻¹** of data collected by the **H1 Experiment** during **2006** and **2007** at **318 GeV** center-of-mass energy

Goal: Include the information of **all reconstructed particles + scattered lepton** in the collision





Q² = - q² y = Pq / pk

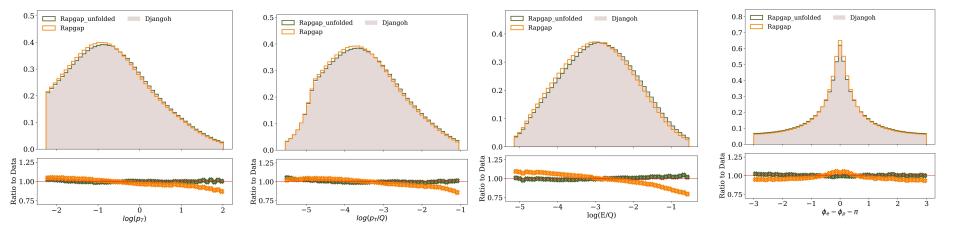
P: incoming proton 4-vector
k: incoming electron 4-vector
q=k-k' : 4-momentum transfer

Reconstructed hadrons using combined detector information: **energy flow algorithm**





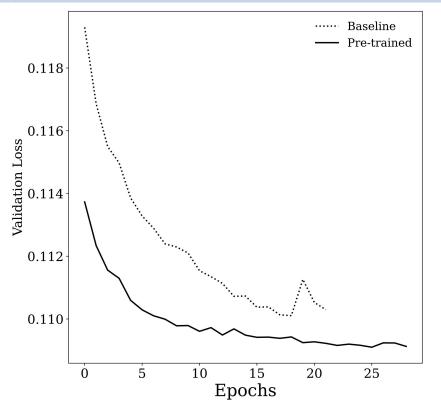
Use Djangoh as the pseudo-data and unfold Rapgap



- Features used during the unfolding:
 - Kinematic information of all hadrons and scattered lepton



Pretraining

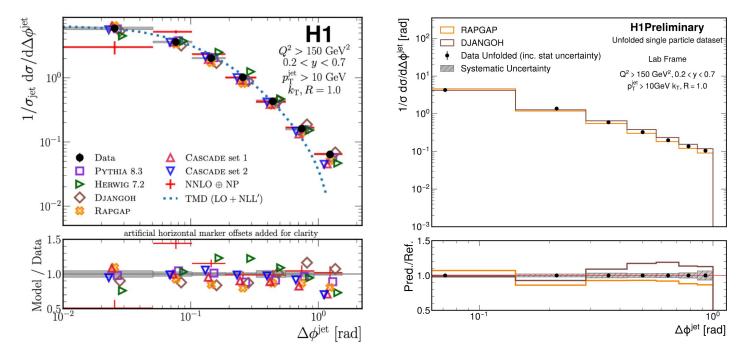


We would like to unfold up to 130*3 = 390 features simultaneously: **requires lots of data**

- Our data size is around 500k events, but we have 20M simulations for 2 different simulators
- Idea: Pretrain a model using only simulations and then fine-tune this model with data
- Use this model as the starting point for the rest of all trainings needed for the unfolding



Cluster unfolded jets using kT algorithm with radius of 1.0 We are able to re-derive **past results**



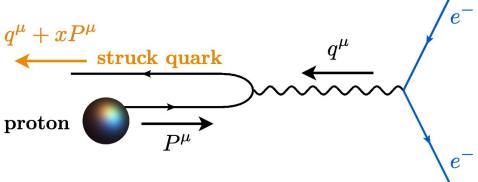
Phys. Rev. Lett.(128) 132002

Results

18

Results



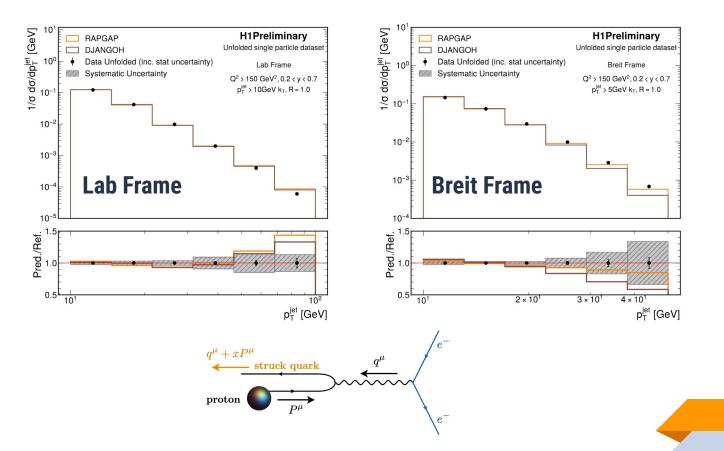


Breit Frame provides a natural frame to study ep collisions, where the struck quark forms a jet opposite from the proton beam: useful for jet and TMD studies

• Starting from the Lab frame, we need to boost the system: not trivial in terms of unfolding

Cluster jets using kT algorithm with radius of 1.0 We can study observables in **different frames**!

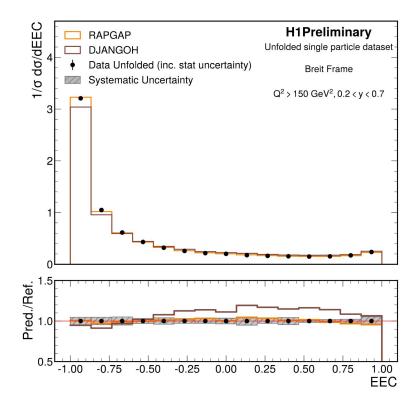
Results





Unfold observables that are hard to unfold without machine learning: **Energy Correlators**





Results

Sensitive to transverse momentum dependent parton distribution functions and fragmentation functions

$$\operatorname{EEC}_{\mathrm{DIS}} = \sum_{a} \int \frac{\mathrm{d}\sigma_{ep \to e+a+X}}{\sigma} \, z_a \, \delta(\cos\theta_{ap} - \cos\theta) \,,$$

$$z_a \equiv rac{P \cdot p_q}{P \cdot (\sum_i p_i)},$$

Eq. from Phys.Rev.D 103 (2021) 9, 094005



Conclusions and Next steps



- Unfolding is the task of removing detector effects from physics observables
- Building on previous results, we unfold the information of all reconstructed hadrons and scattered lepton in high Q² DIS events at the H1 experiment
- Preliminary results with more details available at: <u>https://www-h1.desy.de/h1/www/publications/htmlsplit/H1prelim-25-0</u> <u>31.long.html</u>
- Working on the publication draft with more details, observables, and comparisons with predictions!

Backup



Systematic uncertainties



Systematic uncertainties

- HFS energy scale: +- 1%
- HFS azimuthal angle: +- 20 mrad
- **Lepton energy:** +- 0.5%
- Lepton azimuthal angle: +- 1 mrad
- Model uncertainty: differences in unfolded results between Djangoh and Rapgap
- Non-closure uncertainty: Differences between the expected and obtained values of the closure test

Unfolding uncertainties



Phi dependence

Cross Section & ϕ



$\frac{d^5 \sigma^{ep \to e'qX}}{dy_\ell d^2 P_\perp d^2 q_\perp} = \sigma_0^{eq} x f_q(x) \delta^{(2)}(q_\perp)$

Gluon Matrix Element

Integration over emitted gluon

phase space

$$\begin{array}{l} & \left. \begin{array}{c} \int P(2\pi)^{\mu} \langle 2\pi \rangle^{\mu} \\ \times \langle P|F_{a}^{+\mu}(\xi^{-},\xi_{\perp})\mathcal{L}_{vab}^{\dagger}(\xi^{-},\xi_{\perp})\mathcal{L}_{vbc}(0,0_{\perp})F_{c}^{\nu+}(0)|P\rangle \\ \hline g^{2}\int \frac{d^{3}k_{g}}{(2\pi)^{3}2E_{k_{g}}}\delta^{(2)}(q_{\perp}+k_{g\perp})C_{F}S_{g}(k_{J},p_{1}) \\ & = \frac{\alpha_{s}C_{F}}{2\pi^{2}q_{\perp}^{2}}\left[\ln\frac{Q^{2}}{q_{\perp}^{2}}+\ln\frac{Q^{2}}{k_{\ell\perp}^{2}}+c_{0}+2c_{1}\cos(\phi)+2c_{2}\cos(2\phi)+\cdots\right], \end{array}$$

 $\mathcal{M}^{\mu\nu}(x,k_{\perp}) = \int \frac{d\xi^- d^2 \xi_{\perp}}{P^+ (2\pi)^3} e^{-ixP^+ \xi^- + i\vec{k}_{\perp} \cdot \vec{\xi}_{\perp}}$

$$c_n = \ln \frac{1}{R^2} + f(n) + g(nR),$$

Fourier Coefficient (Introduces ϕ dependance)

$$f(n) = \frac{2}{\pi} \int_0^{\pi} d\phi(\pi - \phi) \frac{\cos \phi}{\sin \phi} (\cos n\phi - 1) ,$$

$$g(nR) = \frac{4}{\pi} \int_0^1 \frac{d\phi}{\phi} \tan^{-1} \frac{\sqrt{1 - \phi^2}}{\phi} [1 - \cos(nR\phi)]$$

$$= \frac{n^2 R^2}{4} {}_2F_3\left(1, 1; 2, 2, 2; -\frac{n^2 R^2}{4}\right).$$

See more in this talk given by Fernando Torales



Experimental setup

Fiducial Phase space definition:

- 0.2 < y < 0.7
- $Q^2 > 150 \text{ GeV}^2$

Particle selection:

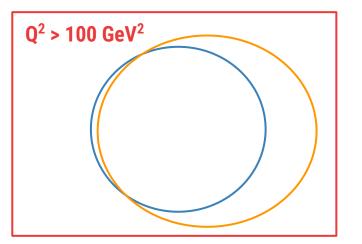
- p_T > 0.1 GeV
- $-1 < \eta_{\text{lab}} < 2.75$
- Charge information used if $\eta_{\rm lab}$ < 2

Reco Phase space definition:

- 0.08 < y < 0.7
- $Q^2 > 150 \text{ GeV}^2$
- p_{T} miss < 10 GeV,
- 45 < em/p₇ < 65

Particle selection:

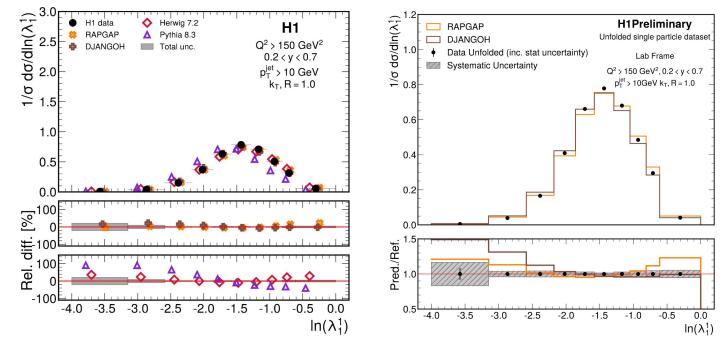
- $p_T > 0.1 \text{ GeV}$ ■ $-1 < \eta_{\text{lab}} < 2.75$
- Pass reco selection: Red -> Orange: 77%
- Pass fiducial selection: Red -> Blue: 58%
- Pass fiducial and reco selection: Blue -> Orange: 96%
- Don't pass fiducial but pass reco: Red -> Orange (without blue): 50%





Cluster unfolded jets using kT algorithm with radius of 1.0

We are able to re-derive **past results**



Phys.Lett.B 844 (2023) 138101

Results

$$\lambda_eta^\kappa = \sum_{i\in ext{jet}} z^\kappa_i \left(rac{R_i}{R_0}
ight)^eta$$

27