Deep learning based Jet substructure at H1

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on behalf of the H1 Collaboration

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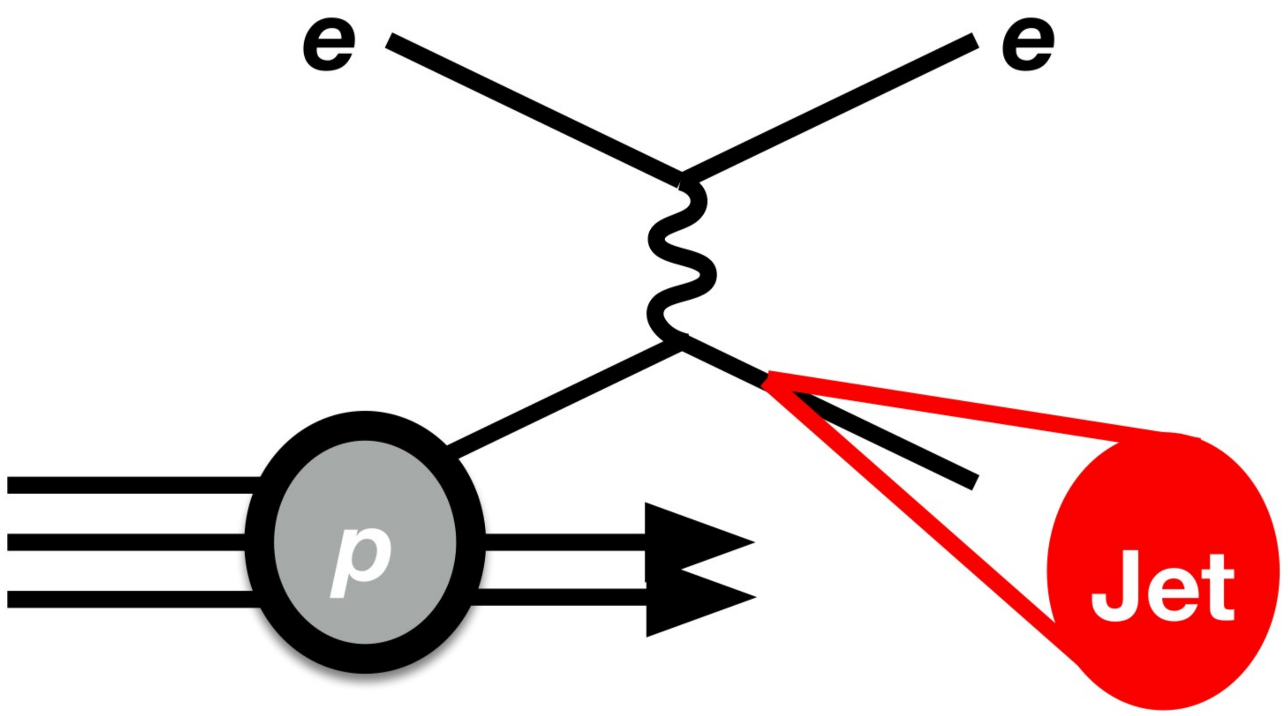
Egerszalok's stunning salt terraces

H1 @ HERA

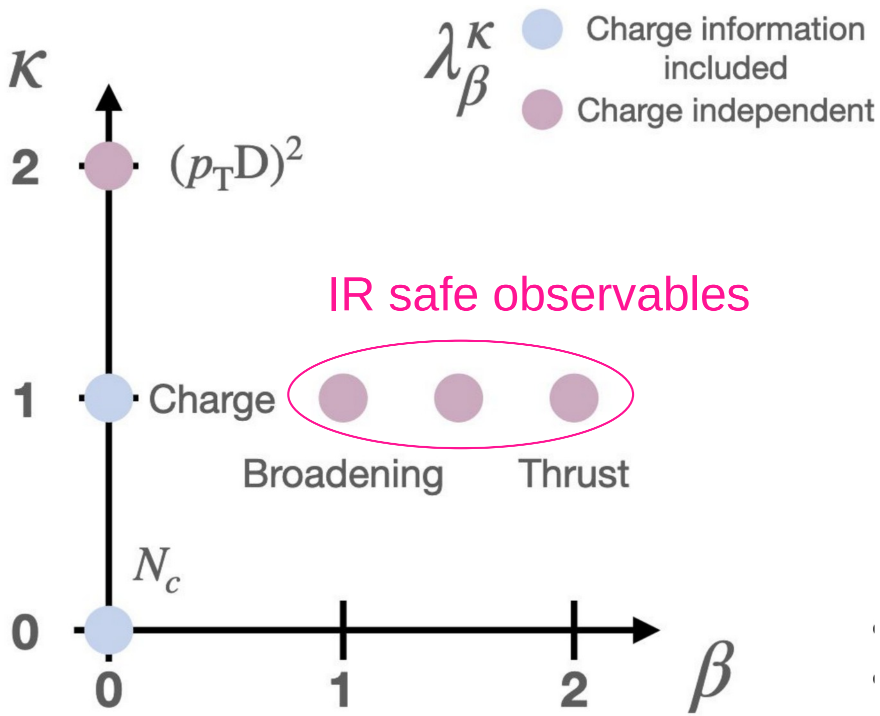
- Deep inelastic scattering: e p → e + Jet + X
  → unique environment without Underlying Event
- Crossroad between LEP (e^+e^-) and LHC (pp)
  → important input for example for MC tuning

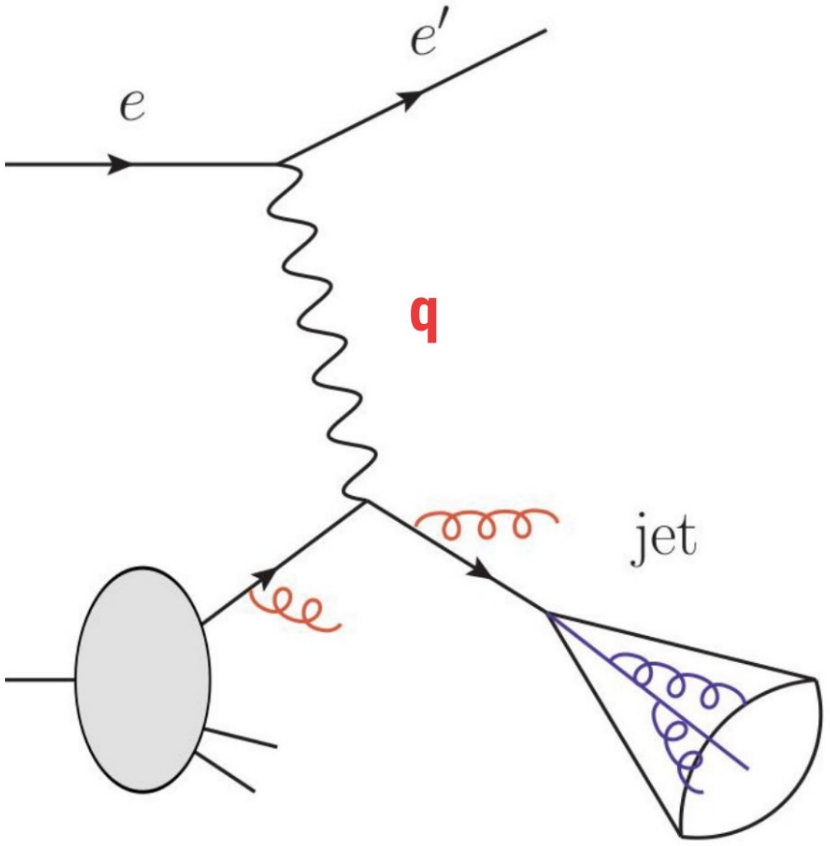


Jet angularities

- Jet constituents used to calculate several observables

$$\lambda_\beta^\kappa = \sum_{i\in\text{jet}} z_i^\kappa \left(\frac{R_i}{R_0}\right)^\beta \qquad z_i = p_{\mathrm{T},i}/p_{\mathrm{T}}^{\mathrm{jet}}$$

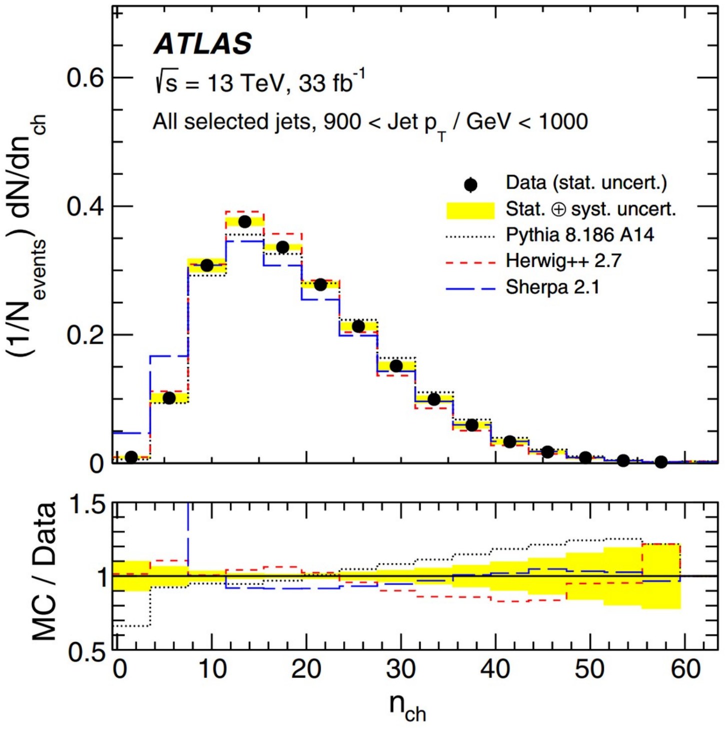


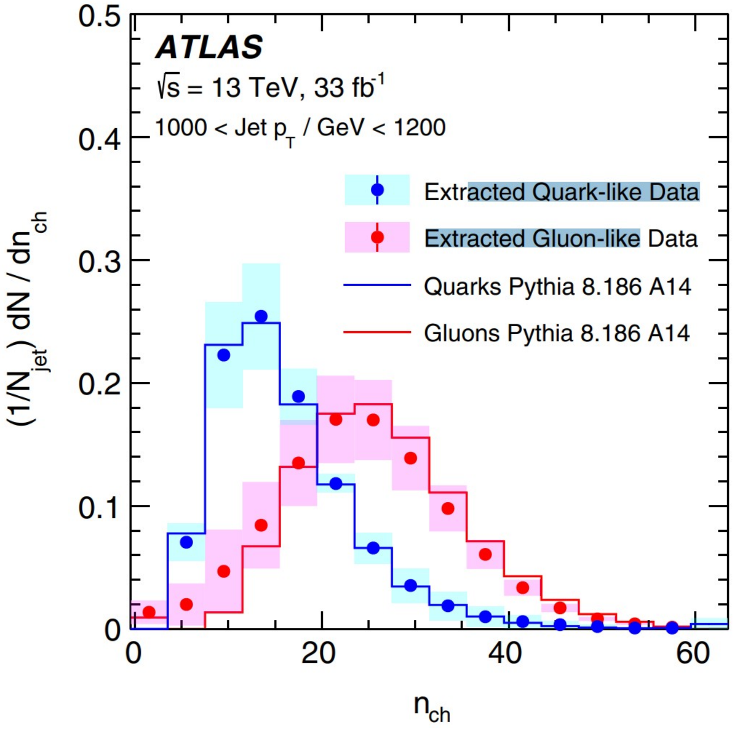


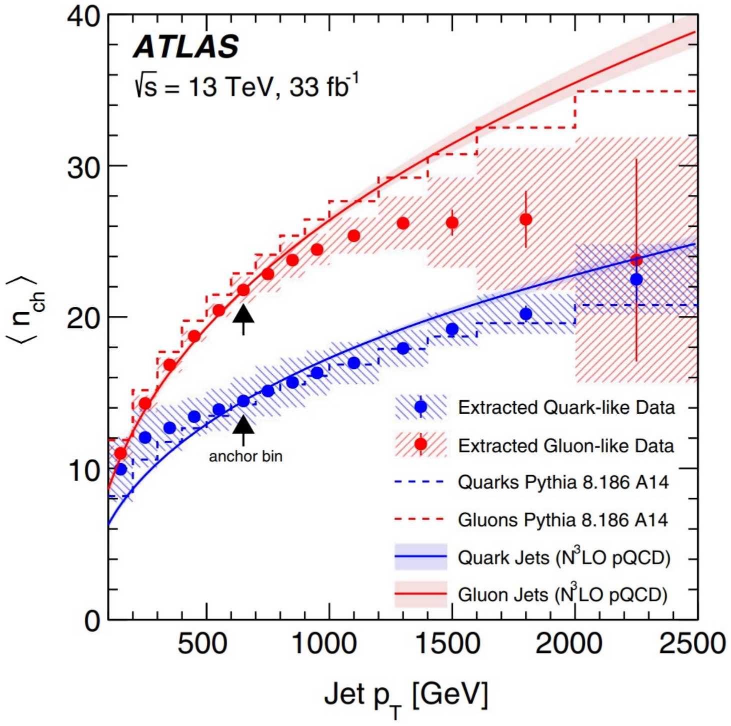
Evolution studied as a function of $Q^2 = -q^2$

Why?

- Charged particle multiplicity is sensitive to quark/gluon tagging





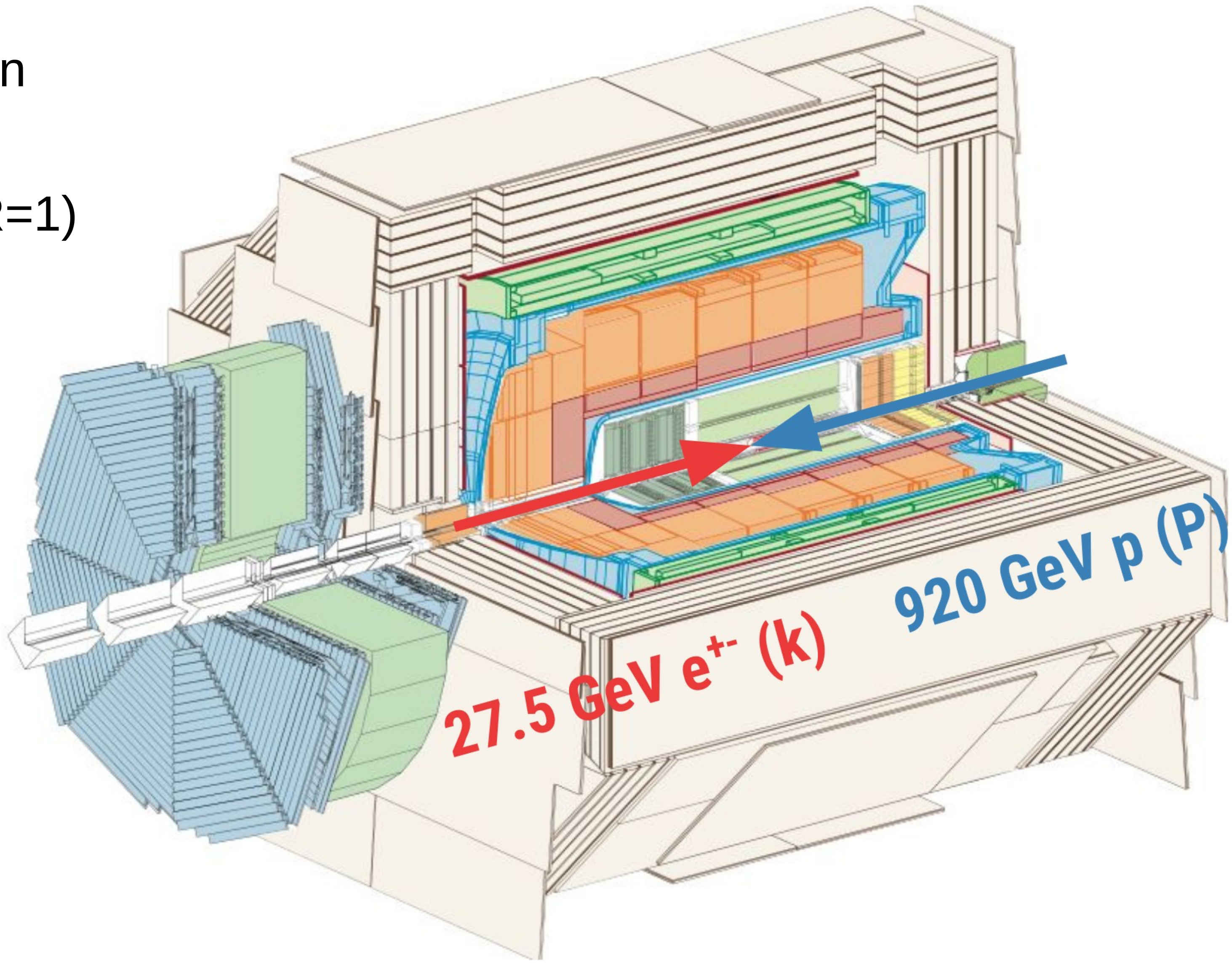


ATLAS, Phys. Rev. D 100, 052011 (2019)

HERA – the world only e$^{\pm}$p collider

Experimental setup

- 228 pb^{-1} of data collected by H1 in 2006-2007 at $\sqrt{s}$ = 319 GeV
- Phase space definition (k_T jets, R=1)
  $0.2 < y < 0.7$, $Q^2 > 150$ GeV^2
  Jet $p_T > 10$ GeV, $-1 < \eta_{lab} < 2.5$

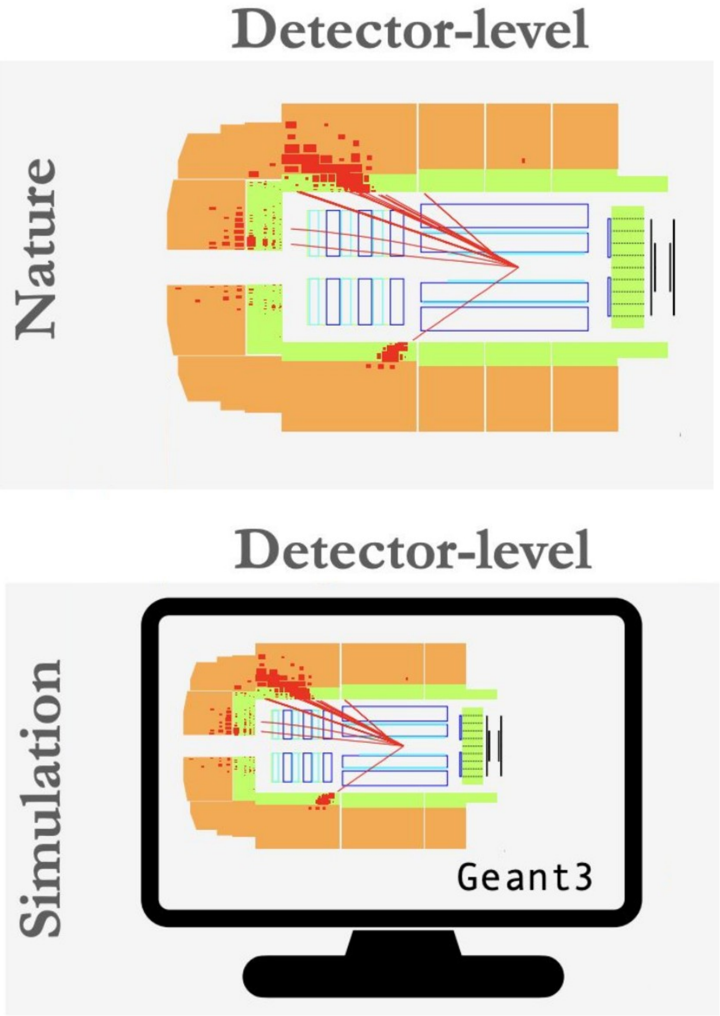


$$Q^2 = -q^2$$
$$y = Pq / pk$$

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

Omnifold: Step 1 - Detector level reweighting

- A **Binary Classifier** is trained to distinguished **Data** from **Simulation**



$$t \to d$$

OmniFold: A Method to Simultaneously Unfold All Observables, Phys.Rev.Lett. 124 (2020) 18, 182001

Binary Classifier

$$\omega = \frac{p^{\mathrm{Data}}(d)}{p^{\mathrm{MC}}(d)}$$

MC reweighted with ω weights

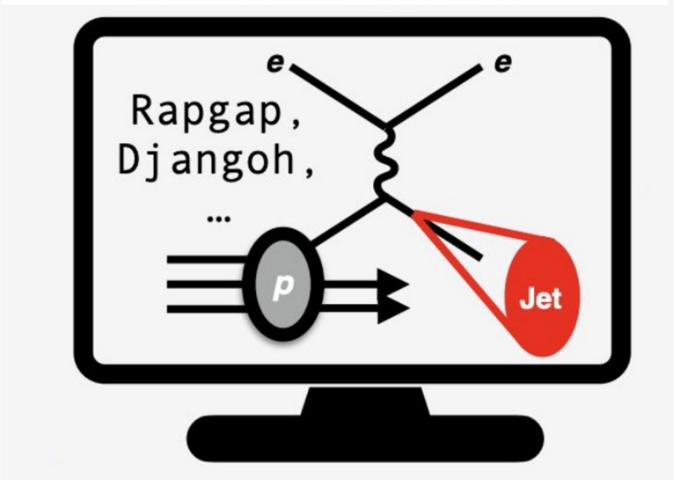
Omnifold: Step 2 - Particle level reweighting

- A **Binary Classifier** is trained to distinguished **Reweighted Simulation** from **Simulation**

Particle-level

MC reweighted
with ω weights

Particle-level



Binary Classifier

$$\nu = \frac{p^{\mathrm{MC}'}(t)}{p^{\mathrm{MC}}(t)}$$

MC reweighted
with ν weights

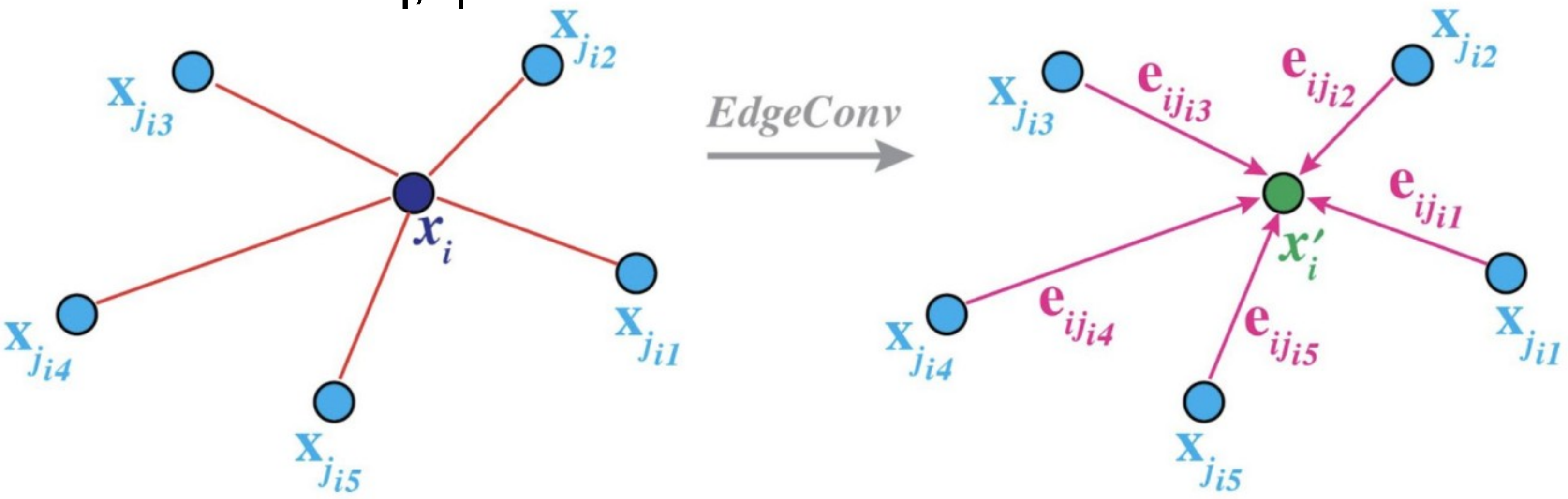
Omnifold: Detector level Classifier

- All jet particles used as input to the NN Model
  → (p_T, η, φ, charge) for each particle + (p_T^{jet}, η^{jet}, φ^{jet}) + Q^2
  up to (30x4 + 3 + 1) features at detector level

- Point Cloud Transformer architecture
  → exploiting success of Transformers in LLM

V. Mikuni and F. Canelli 2021 Mach. Learn.: Sci. Technol. 2 035027

η, φ



Trained at 50M jets using 128 GPUs of Perlmutter supercomputer

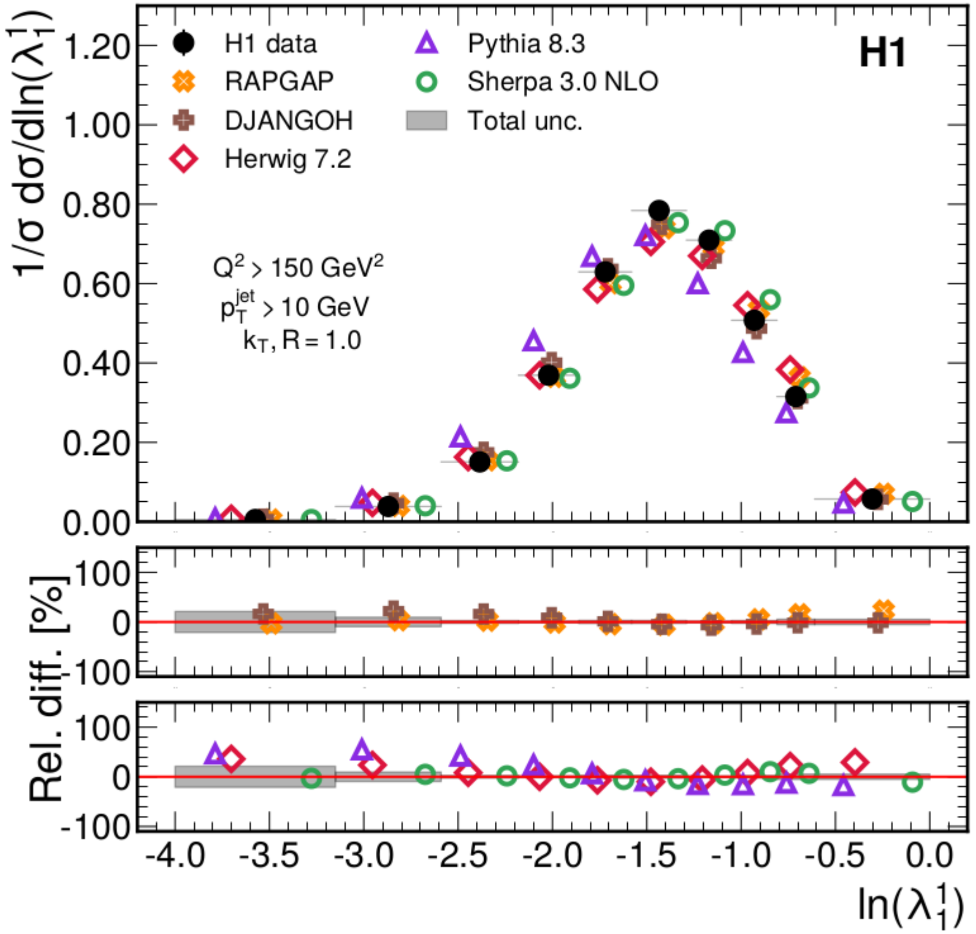
MC Models

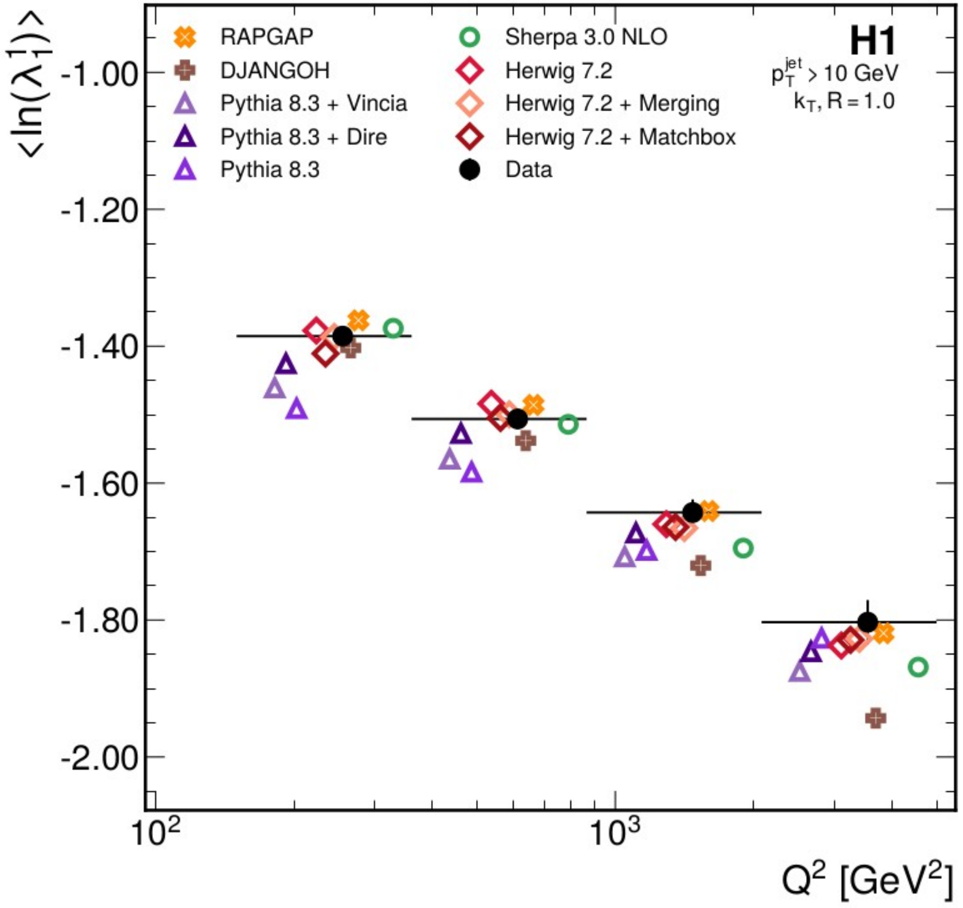
- **Legacy ep models** (Lund string hadr., CTEQ6L PDF set)
  → Rapgap: Py6-like shower
  → Djangoh: Dipole shower from Ariadne
- **Pythia 8.3**: default NNPDF3.1 PDF
  → Vincia: p_T ordered antenna showering
  → Dire: NLL dipole model, MMHT14 PDF
- **Herwig 7.2**: Shower with angular ordering,
  cluster hadronization, CT14 PDF
- **Sherpa 3.0**: NLO pQCD for 2 jets,
  cluster hadronization

Jet broadening

$$\lambda_1^1 = \sum_{i \in \text{jet}} z_i \frac{R_i}{R_0}$$

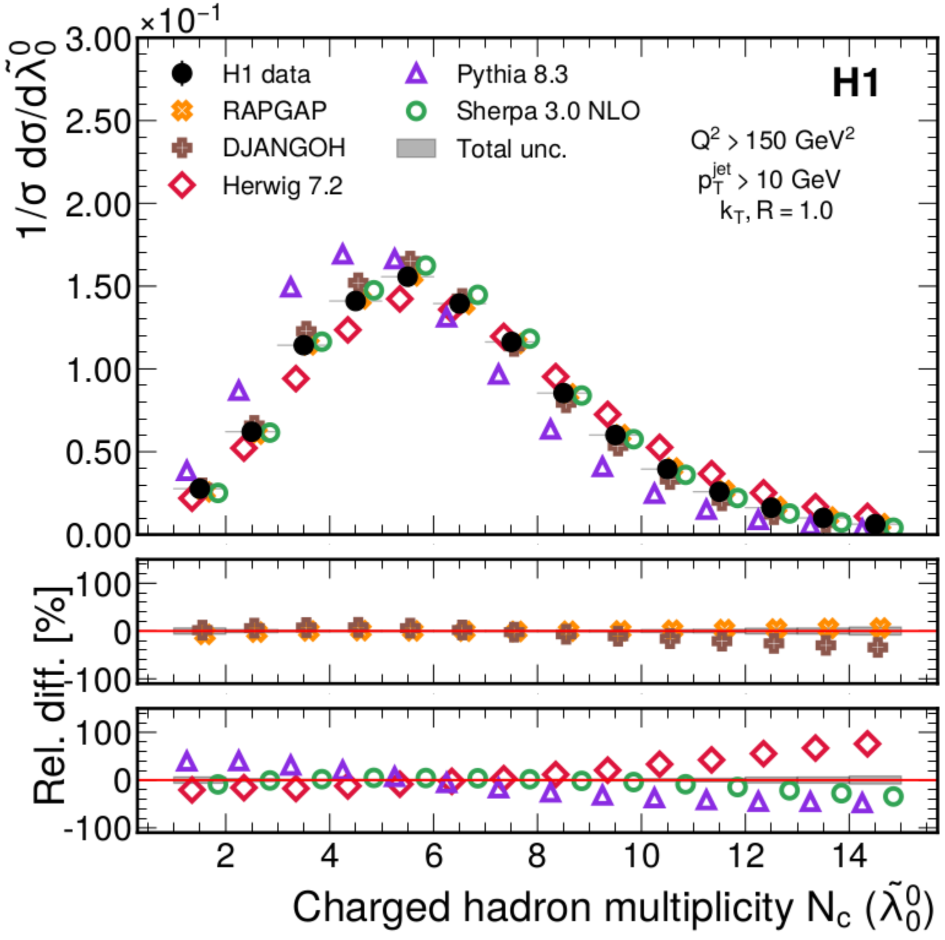
- **Herwig** describes best the Q^2 dependence
- **Pythia** underestimates the broadening

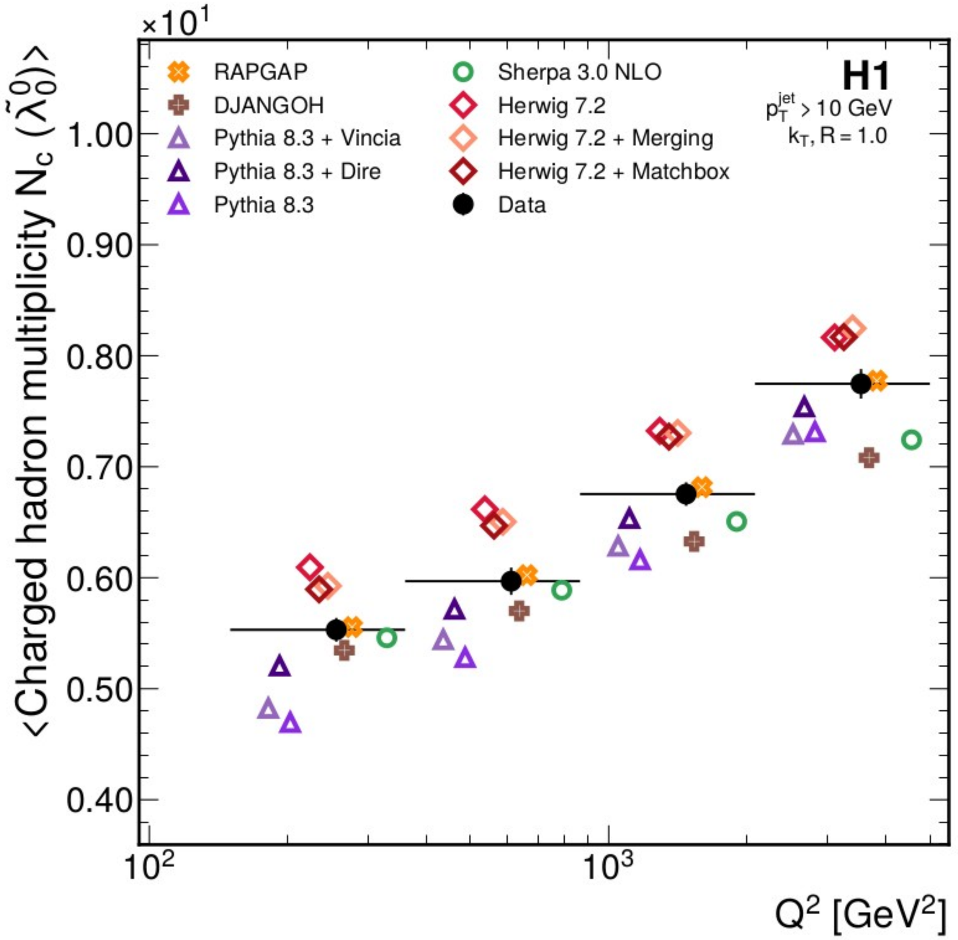




Charged hadron multiplicity in the jet

- **Sherpa** does good job in describing the shape
- **Pythia** predicts lower multiplicities

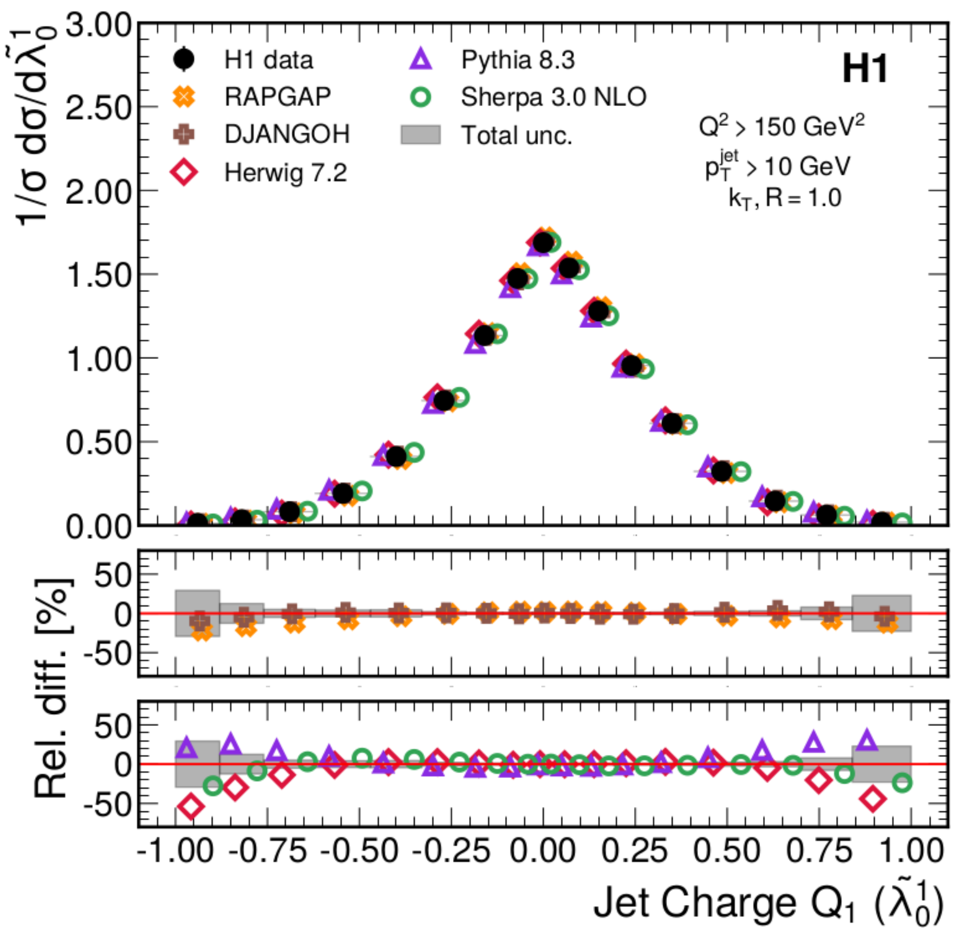


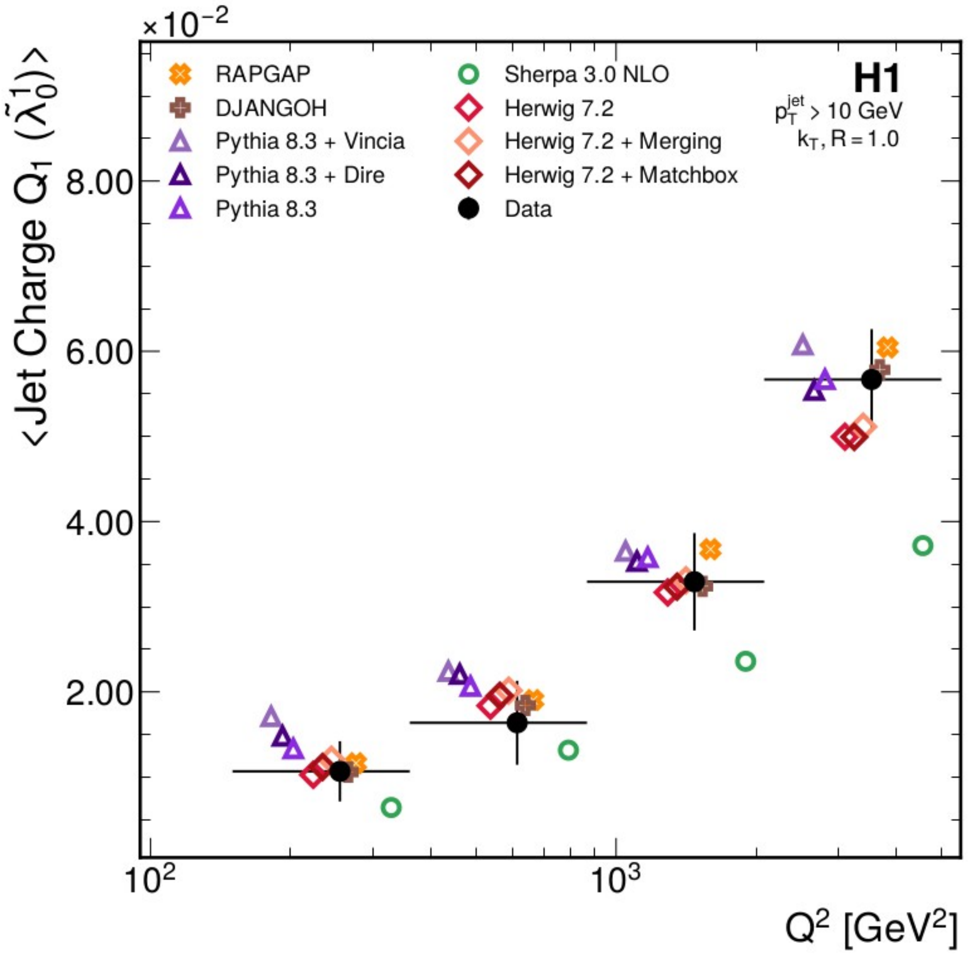


Jet charge

- **Sherpa** underestimates jet charge at higher Q2
- **Pythia** & **Herwig** do comparable job

High Q2 jets are more quark-like





Conclusions

- Revival of H1 data using state-of the art statistical methods
- Substructure of jets in ep can help to disentangle underlying event contribution and better understand of the QCD dynamics

Backup

Systematic uncertainties currently considered

- **HFS energy scale:** +- 1%
- **HFS azimuthal angle:** +- 20 mrad
- **Lepton energy:** +- 0.5% (mainly affects Q^2)
- **Lepton azimuthal angle:** +- 1 mrad (mainly affects Q^2)
- **Model uncertainty:** differences in unfolded results between Djangoh and Rapgap
- **Non-closure uncertainty:** Differences between the expected and obtained values of the closure test
- **QED uncertainty**: Use the variation of measured quantities when radiation is turned off in the simulation
- **Statistical uncertainty:** Standard deviation of 100 bootstrap samples with replacement

Backup

- Example of results with uncertainties

Q^2 [GeV^2]	$<\tilde{\lambda}_0^0>$	Stat.	Tot.	HFS(jet)	HFS(other)	HFS(ϕ)	Lepton(E)	Lepton(ϕ)	Model	Closure
[150.00, 360.42]	5.531	0.019	0.019	0.010	0.020	0.047	0.006	0.041	0.012	0.081
[360.42, 866.03]	5.969	0.024	0.021	0.021	0.023	0.020	0.020	0.036	0.070	0.081
[866.03, 2080.90]	6.753	0.035	0.016	0.012	0.028	0.032	0.048	0.006	0.037	0.066
[2080.90, 5000.00]	7.747	0.056	0.017	0.053	0.056	0.050	0.050	0.028	0.019	0.050
Q^2 [GeV^2]	$<\tilde{\lambda}_0^1>$	Stat.	Tot.	HFS(jet)	HFS(other)	HFS(ϕ)	Lepton(E)	Lepton(ϕ)	Model	Closure
[150.00, 360.42]	0.011	0.001	0.332	0.001	0.001	0.001	0.001	0.001	0.001	0.001
[360.42, 866.03]	0.016	0.001	0.302	0.001	0.001	0.002	0.003	0.001	0.001	0.001
[866.03, 2080.90]	0.033	0.002	0.174	0.001	0.001	0.003	0.004	0.001	0.001	0.001
[2080.90, 5000.00]	0.057	0.003	0.104	0.002	0.003	0.002	0.001	0.001	0.002	0.002
Q^2 [GeV^2]	$<\sqrt{\lambda_0^2}>$	Stat.	Tot.	HFS(jet)	HFS(other)	HFS(ϕ)	Lepton(E)	Lepton(ϕ)	Model	Closure
[150.00, 360.42]	0.449	0.001	0.009	0.001	0.001	0.002	0.001	0.002	0.001	0.001
[360.42, 866.03]	0.441	0.001	0.011	0.001	0.001	0.002	0.001	0.003	0.001	0.001
[866.03, 2080.90]	0.429	0.001	0.009	0.001	0.001	0.001	0.001	0.003	0.001	0.001
[2080.90, 5000.00]	0.419	0.002	0.010	0.002	0.002	0.002	0.001	0.001	0.002	0.001
Q^2 [GeV^2]	$<\ln(\lambda_1^1)>$	Stat.	Tot.	HFS(jet)	HFS(other)	HFS(ϕ)	Lepton(E)	Lepton(ϕ)	Model	Closure
[150.00, 360.42]	-1.385	0.004	0.007	0.004	0.004	0.004	0.002	0.002	0.002	0.002
[360.42, 866.03]	-1.506	0.005	0.009	0.003	0.000	0.004	0.002	0.004	0.007	0.009
[866.03, 2080.90]	-1.643	0.006	0.012	0.006	0.005	0.000	0.014	0.005	0.004	0.005
[2080.90, 5000.00]	-1.803	0.010	0.018	0.008	0.009	0.010	0.020	0.008	0.009	0.014