Norway grants

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UNIVERSITY OF BERGEN

Exploring the universality of jet quenching via Bayesian inference

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Konrad Tywoniuk

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ML4Jets 2023

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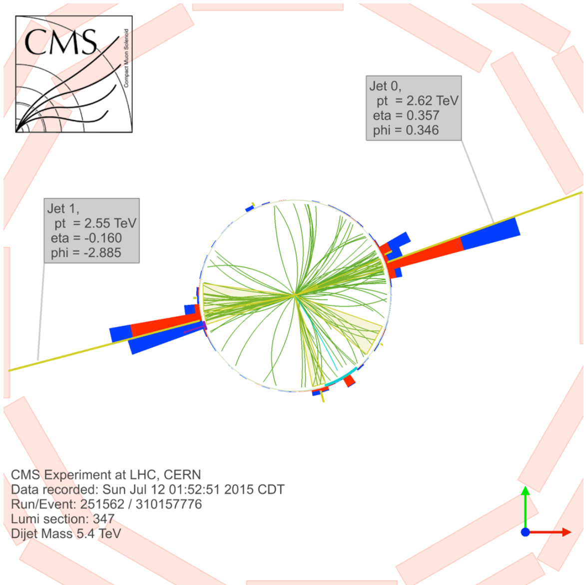
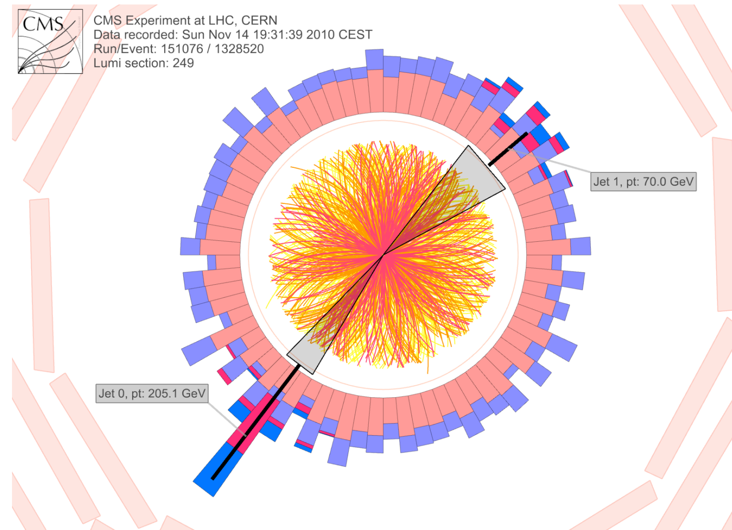
Jet quenching in heavy-ion collisions

pp event



AA event



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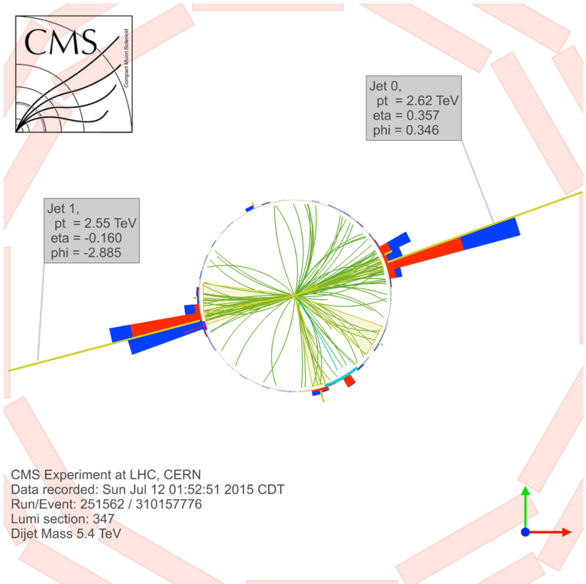

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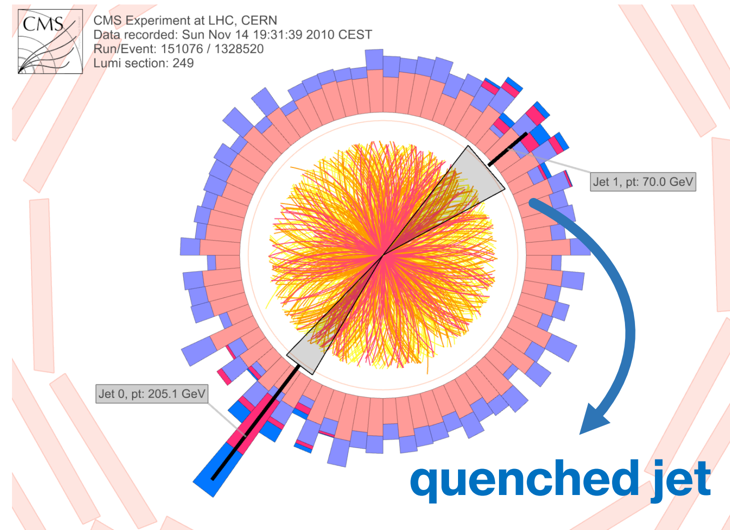

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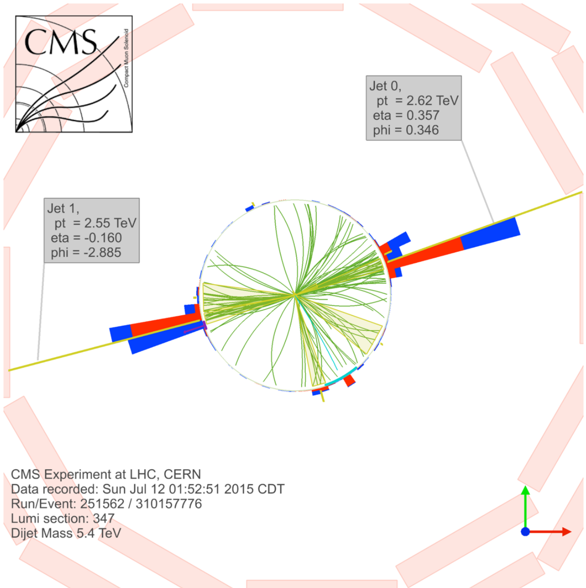

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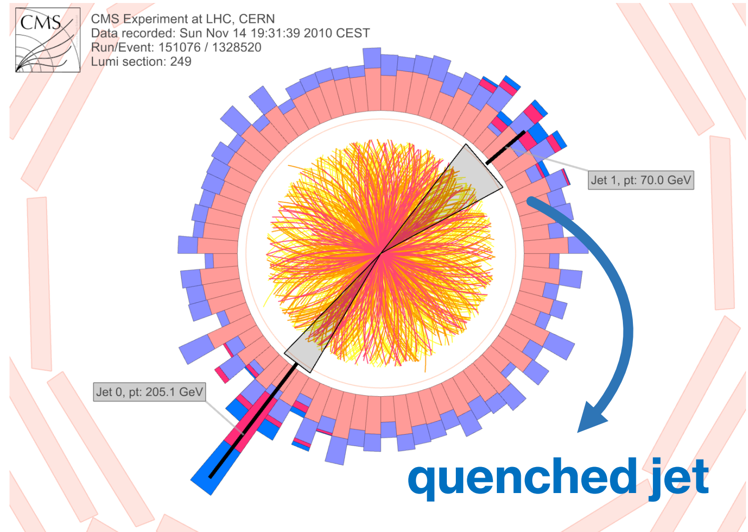
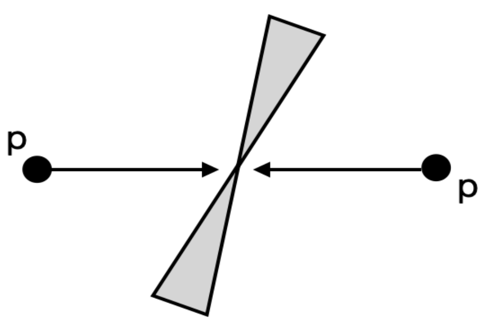
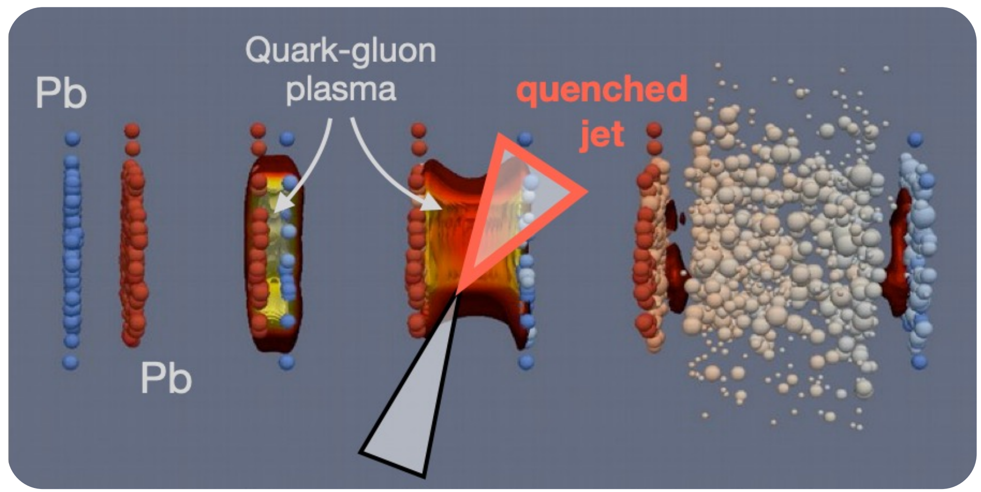


(in vacuum)





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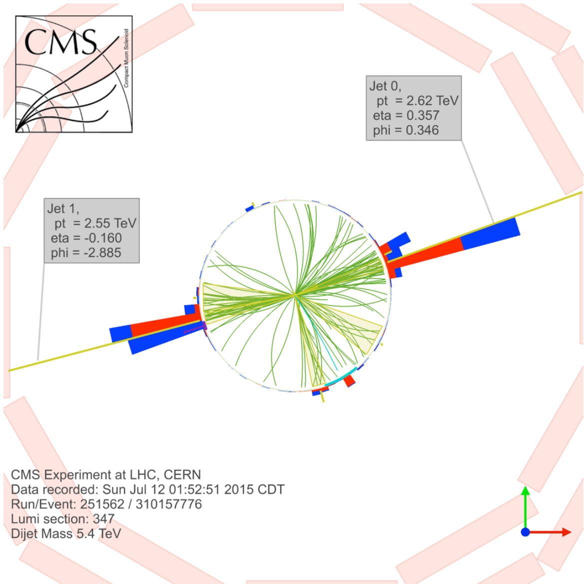

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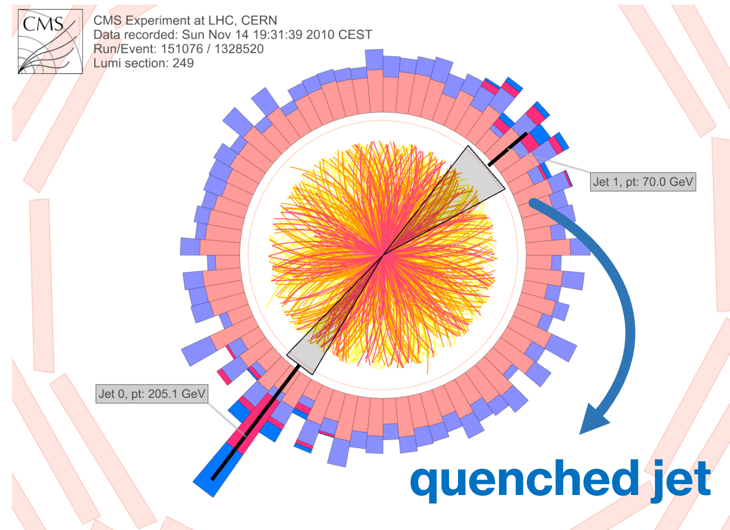

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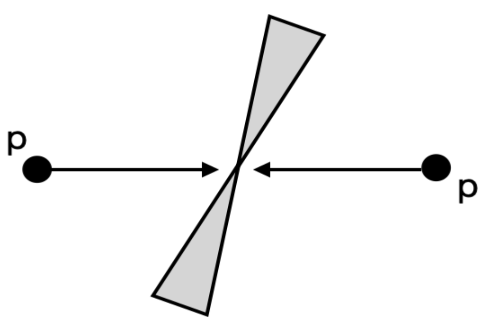
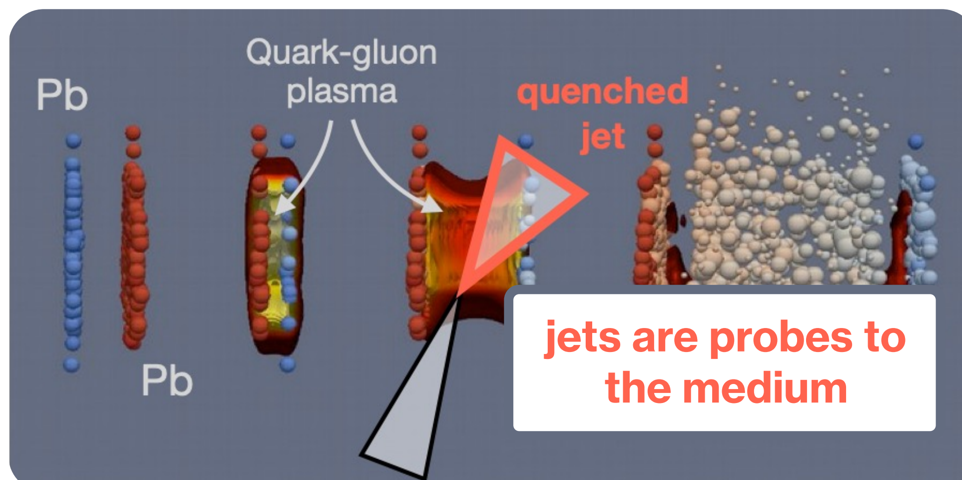
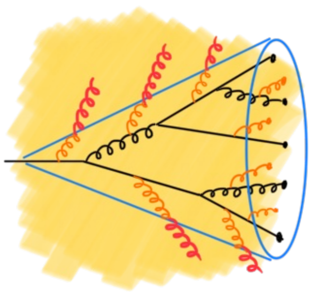




Universality of jet quenching

A complicated object in a complicated medium:



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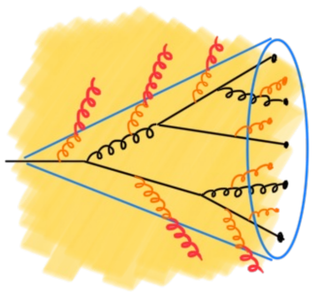
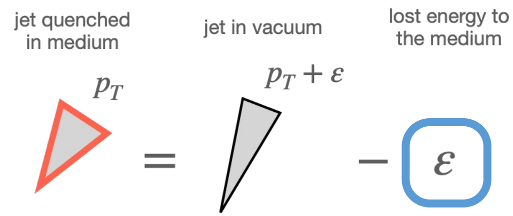


Factorization:



$$\sigma^{\text{med}} = D(\varepsilon) \otimes \sigma^{\text{vac}}$$

jet energy loss distribution $D(\varepsilon)$ contains all the information on the interaction with the medium

$$D(\varepsilon | p_T, C_R, \hat{q}(T), L, R)$$

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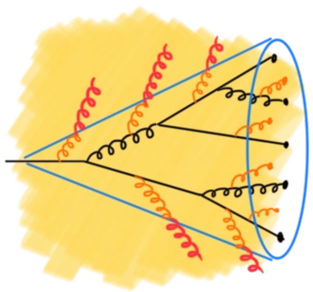
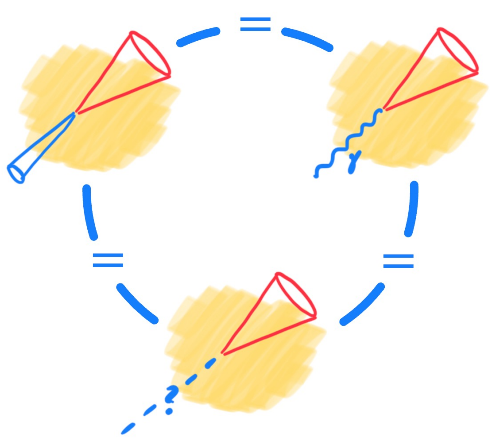


Universality of jet energy loss:

All jets lose energy to the medium in the same way



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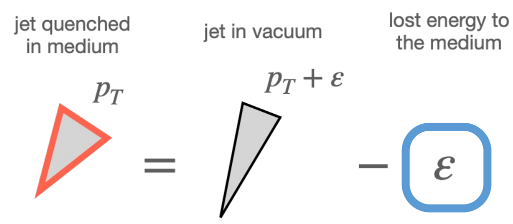

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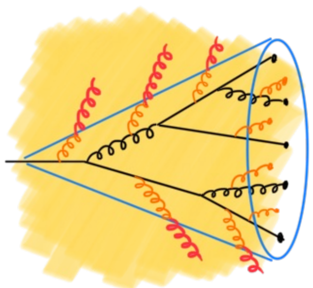

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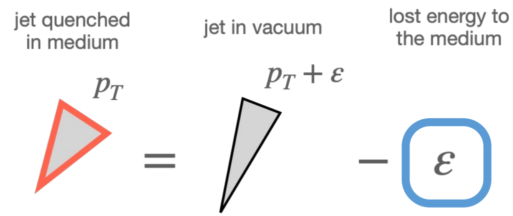

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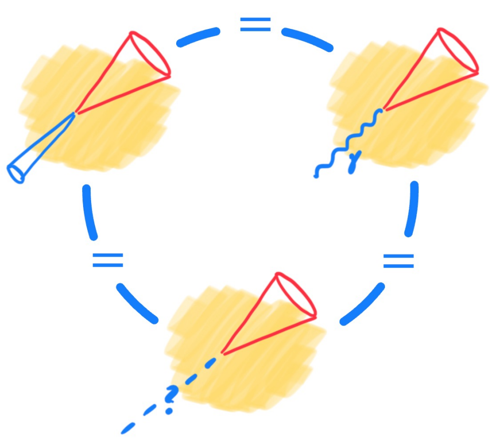
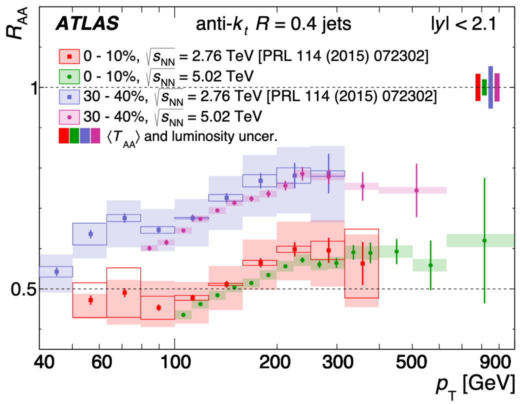


Just by looking at the data:

- **What can we learn about the jet interaction with the medium?**
- **Is the data consistent with this universality?**
- **To what extent? What minimal information de we need to keep in $D(\varepsilon)$?**

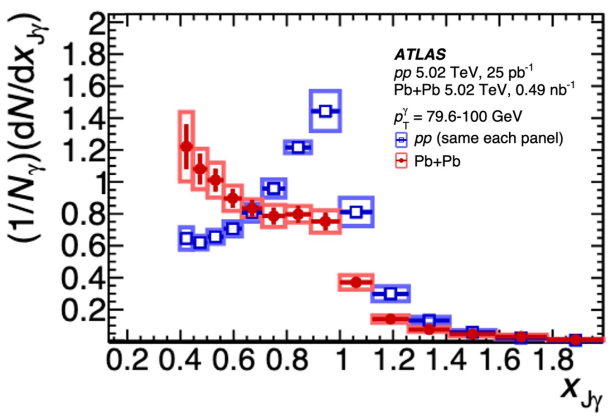
Experimental measurements

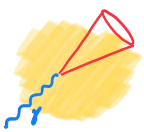
Inclusive measurements



Coincidence measurements

photon-tagged jet events





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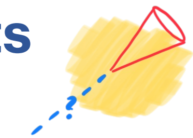
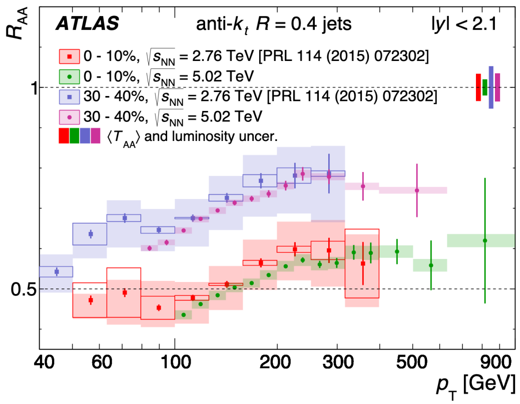
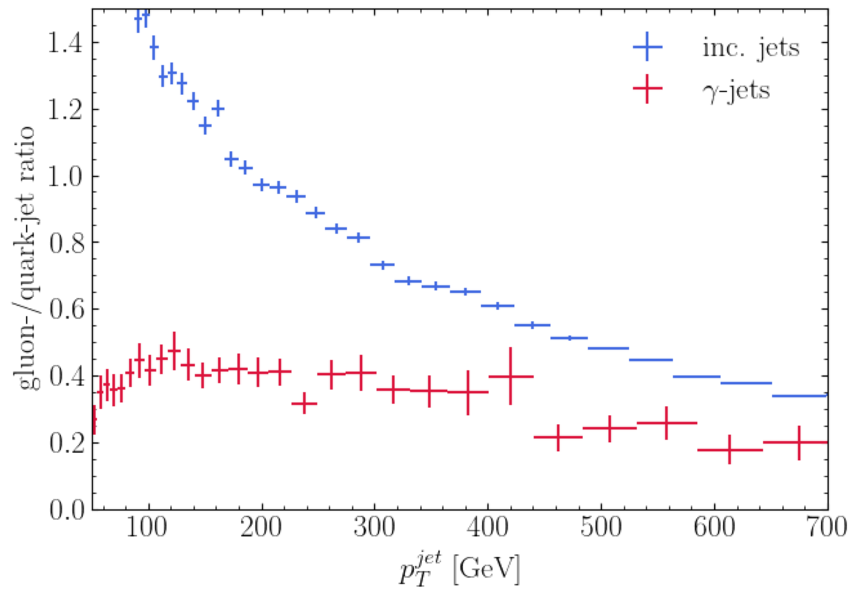




different observables

different hard processes

different quark-gluon fraction



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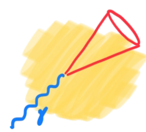

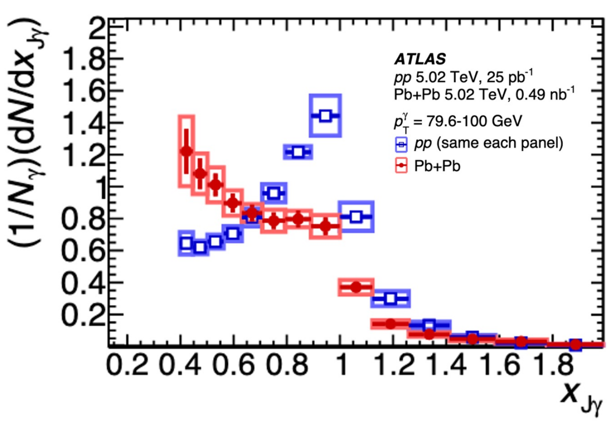

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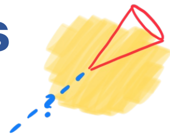

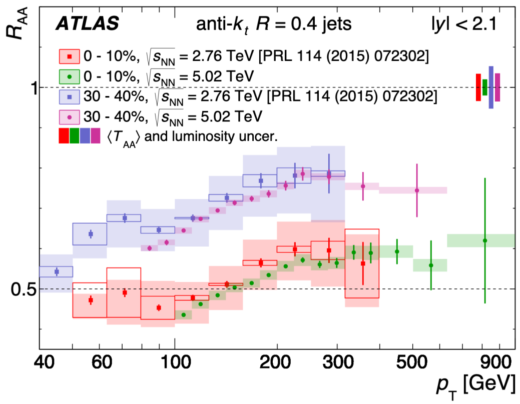

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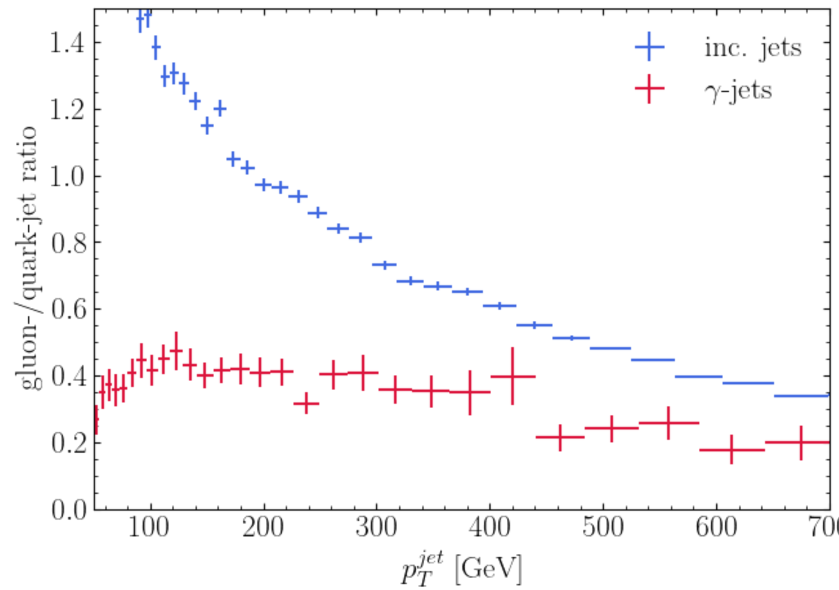

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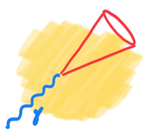

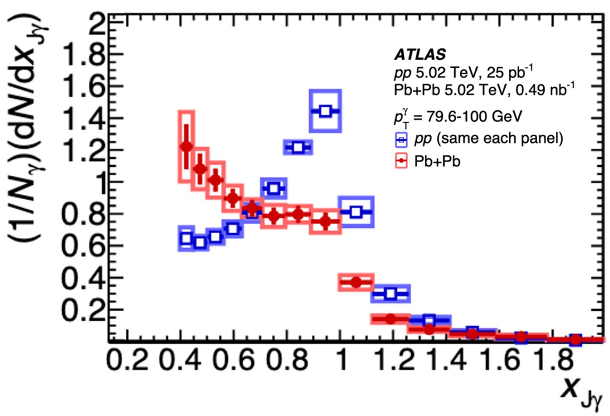

Important information to keep!

$$D_i(\varepsilon | p_T, \underline{C_R}, \hat{q}(T), L, R) = D(\varepsilon | i), \quad i = q, g$$

Bayesian parameter estimation

Model

$$\left.\frac{\mathrm{d}\sigma^{AA}}{\mathrm{d}p_T}\right|_{p_T} = \int_0^\infty \mathrm{d}\varepsilon \sum_{i=q,g} D_i(\varepsilon) \left.\frac{\mathrm{d}\sigma_i^{vac}}{\mathrm{d}p_T}\right|_{p_T+\varepsilon}$$

MODEL

DATA

Bayesian parameter estimation

Model

enrgy loss distribution

MC simulation (PYTHIA)

$$\left.\frac{\mathrm{d}\sigma^{AA}}{\mathrm{d}p_T}\right|_{p_T} = \int_0^\infty \mathrm{d}\varepsilon \sum_{i=q,g} D_i(\varepsilon) \left.\frac{\mathrm{d}\sigma_i^{vac}}{\mathrm{d}p_T}\right|_{p_T+\varepsilon}$$

observable

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observable

dependece on
jet-initiating parton

MODEL

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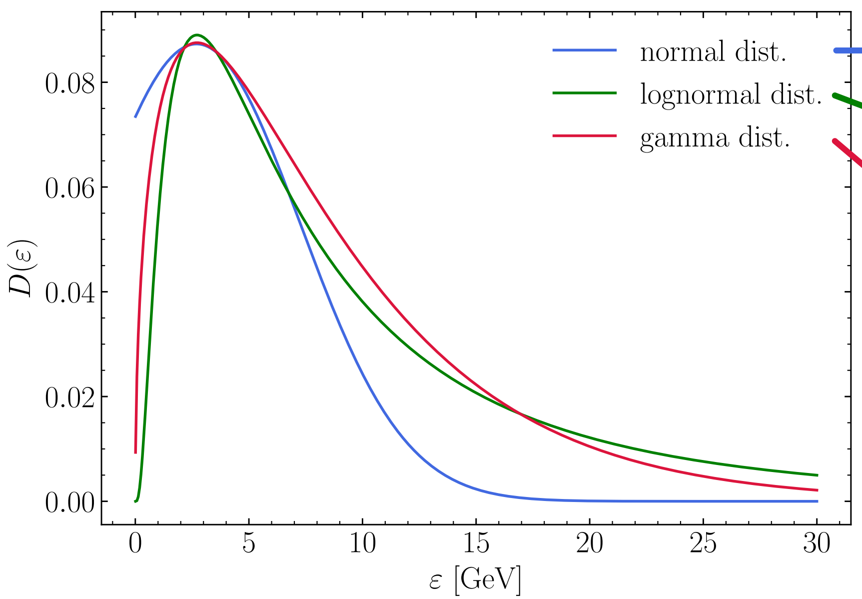
observable

dependece on jet-initiating parton

3 parameterizations:
- normal dist.
- lognormal dist.
- gamma dist.

MODEL **DATA**



simple distribution

theoretical solution for one parton

used before [arXiv: 1808.05310]

Bayesian parameter estimation

Model

enrgy loss distribution

MC simulation (PYTHIA)

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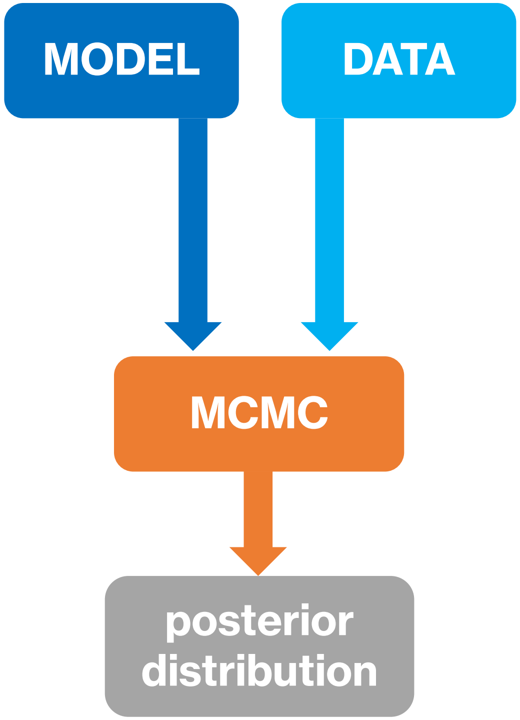

Bayesian parameter estimation

Interest is in the relative probability of different points in parameter space.

$$\mathcal{P}(\boldsymbol{\theta}|\boldsymbol{y}_{\exp}) \propto \mathcal{P}(\boldsymbol{y}_{\exp}|\boldsymbol{\theta})\mathcal{P}(\boldsymbol{\theta})$$

Markov Chain Monte Carlo (MCMC) is used to estimate the posterior. We choose:

- likelihood: multivariate normal distribution
- prior: flat

Bayesian parameter estimation

Model

enrgy loss distribution

MC simulation (PYTHIA)

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observable

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- **normal dist.**
- **lognormal dist.**
- **gamma dist.**

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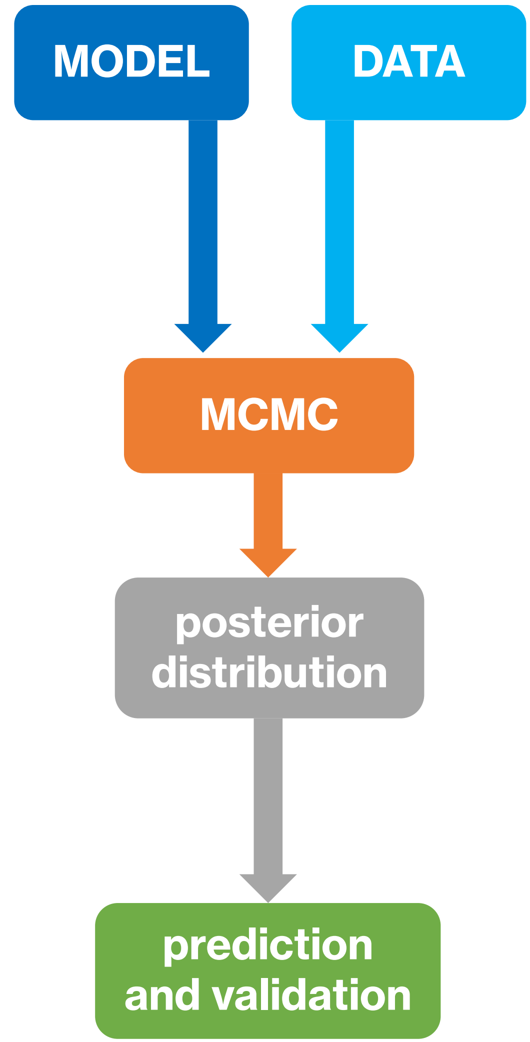
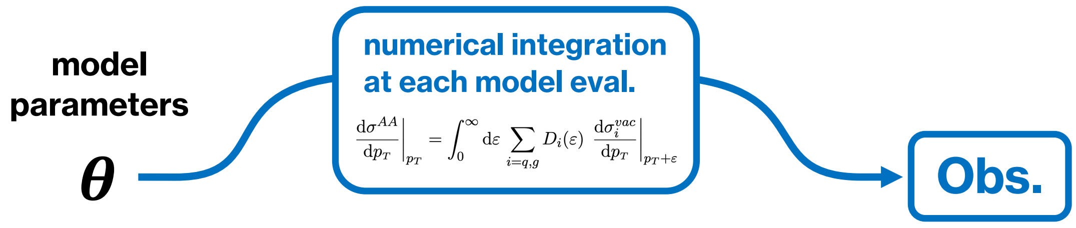
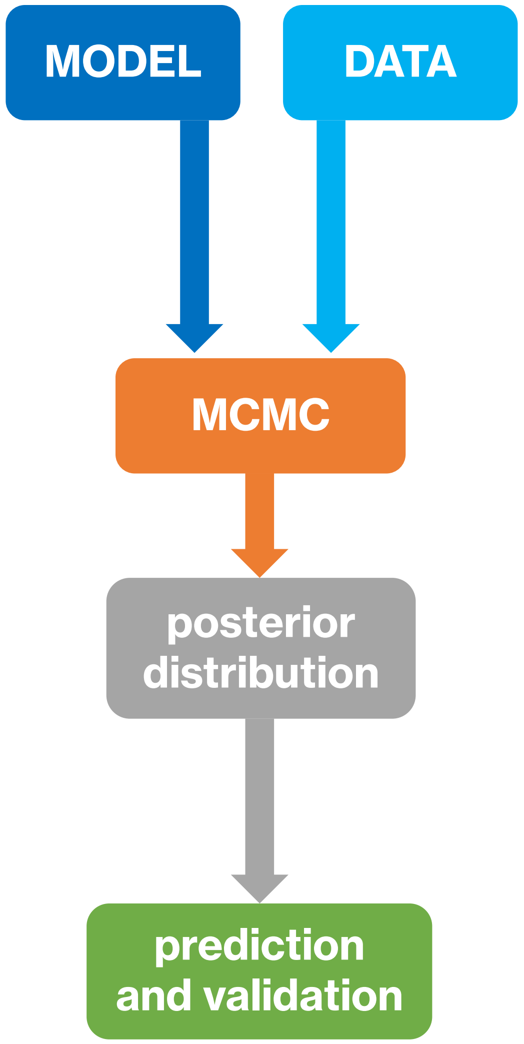


Physical model emulator (from JETSCAPE) [arXiv: 2011.01430] [arXiv: 2102.11337]





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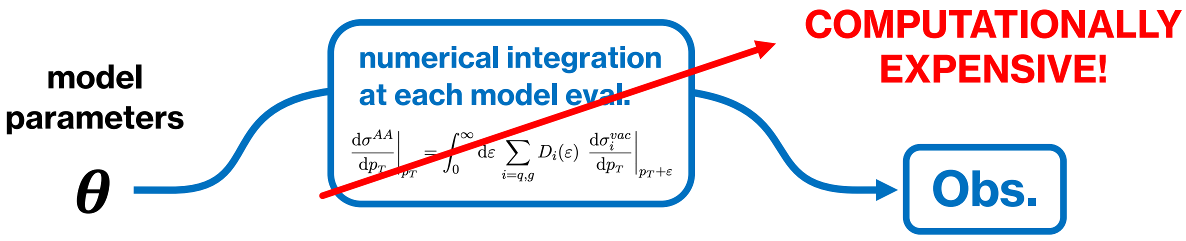

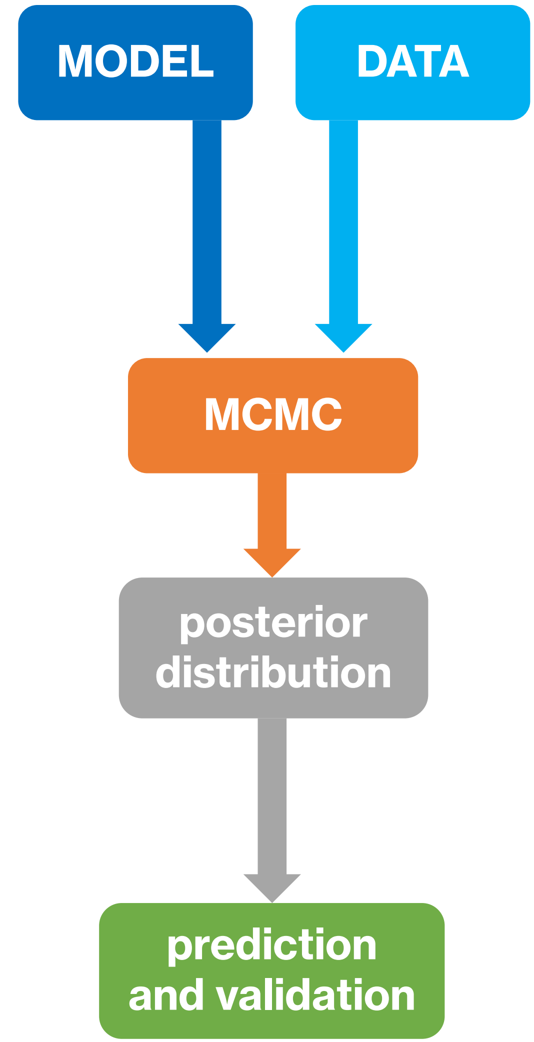

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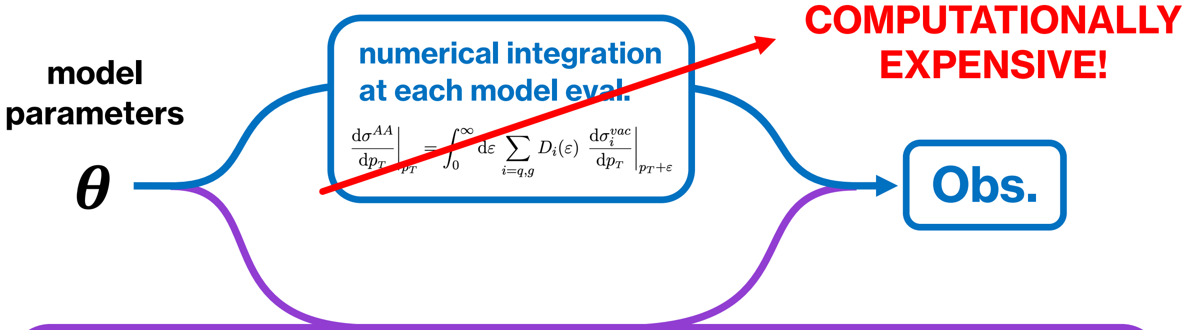


MODEL EMULATOR

Dimensionality reduction via PCA

Observbles evaluated at several **design points**, covering the parameter space.

Principal Component Analysis (PCA):

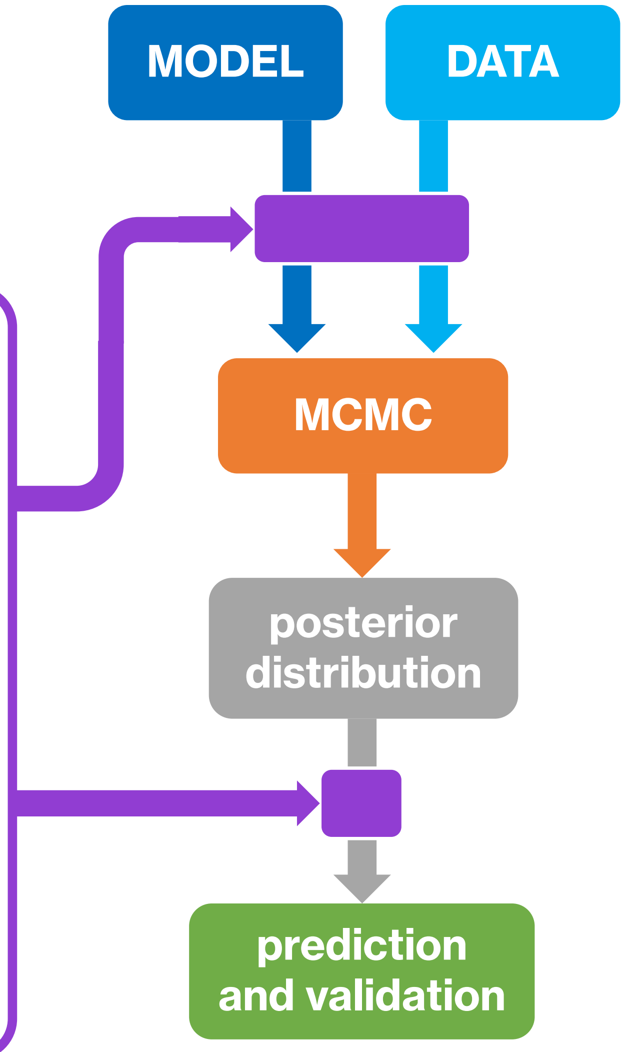
- data is reduced to the first 4 principal components
- $\sim 99.5\ \%$ of explained variance

Interpolation with Gaussian process

Principal componets interpolated with **Gaussian processes**

Reconstruction of observables

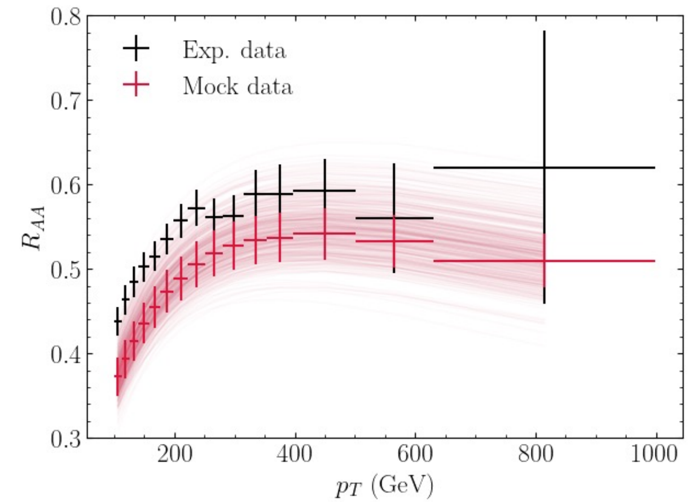
Predictions via inverse PCA transformation

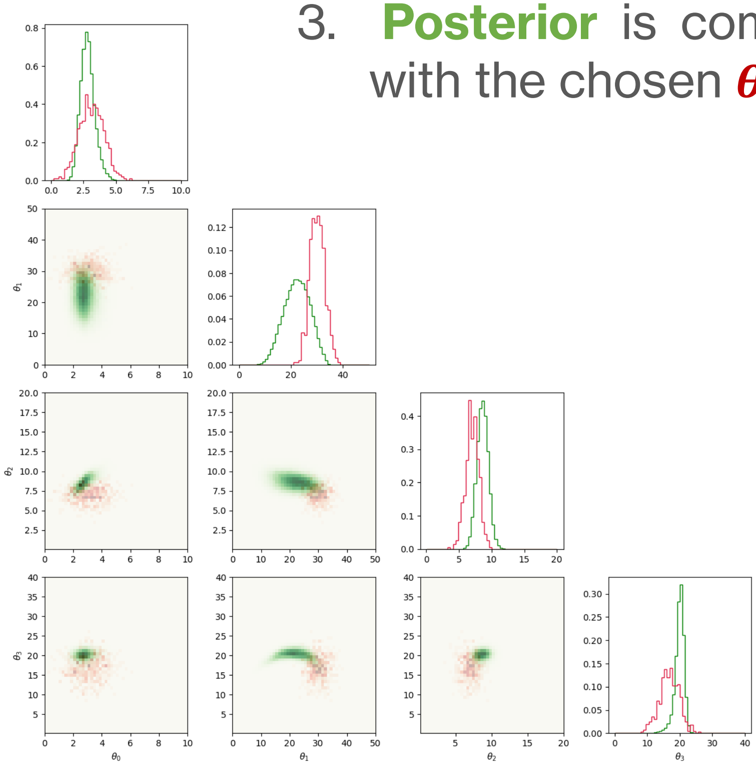


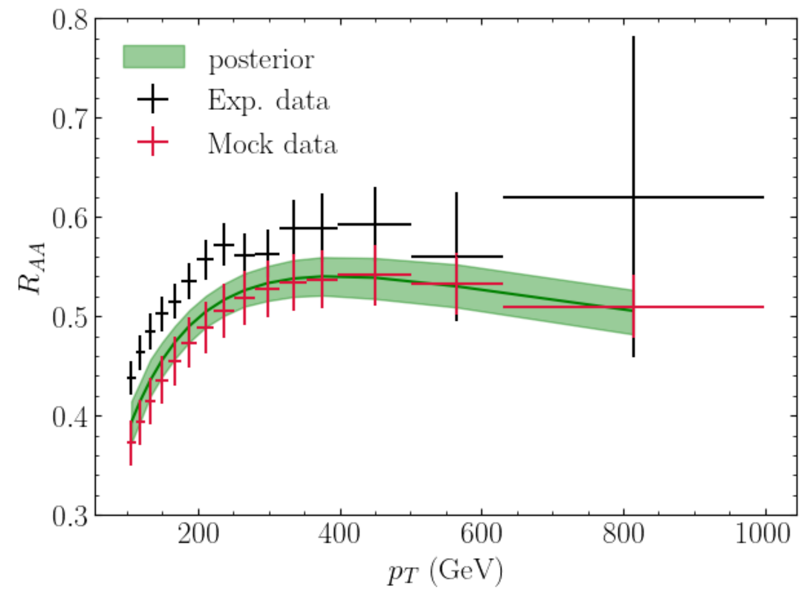
Setup validation

Closure tests

1. **Mock data** generated from chosen parameters $\boldsymbol{\theta}_{\mathrm{true}}$;
2. Bayesian inference on **Mock data**;
3. **Posterior** is compared with the chosen $\boldsymbol{\theta}_{\mathrm{true}}$.



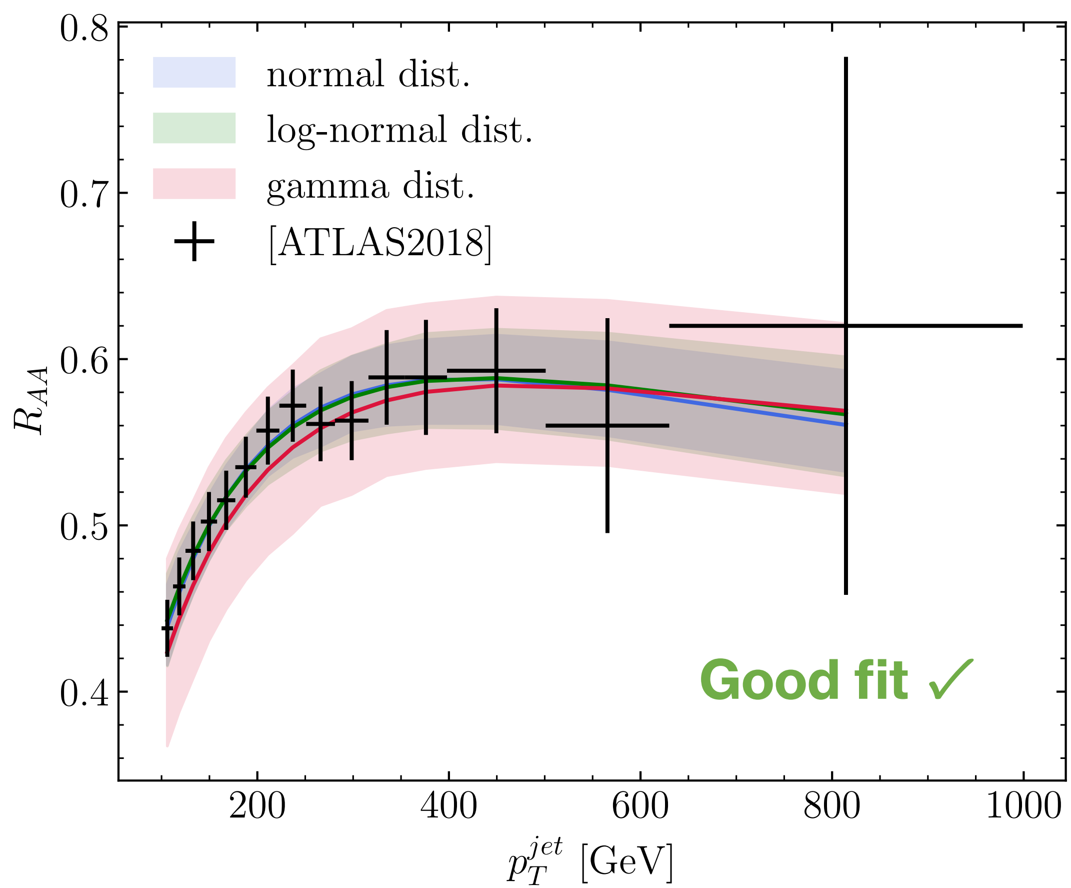


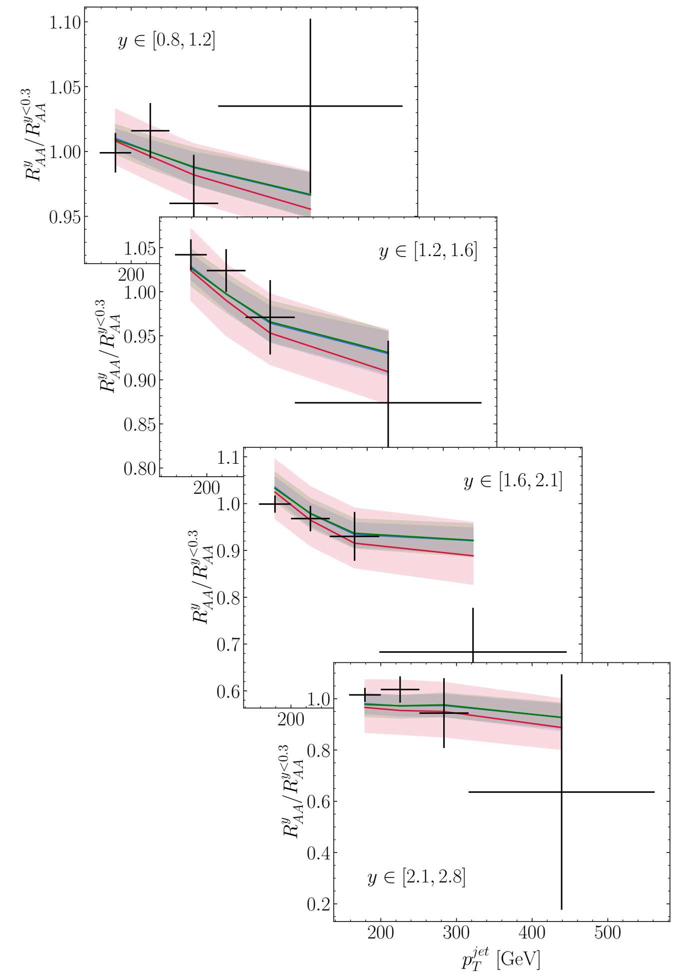


Results: the fit

Inclusive jets are fitted:

leaving photon-tagged jets for validation

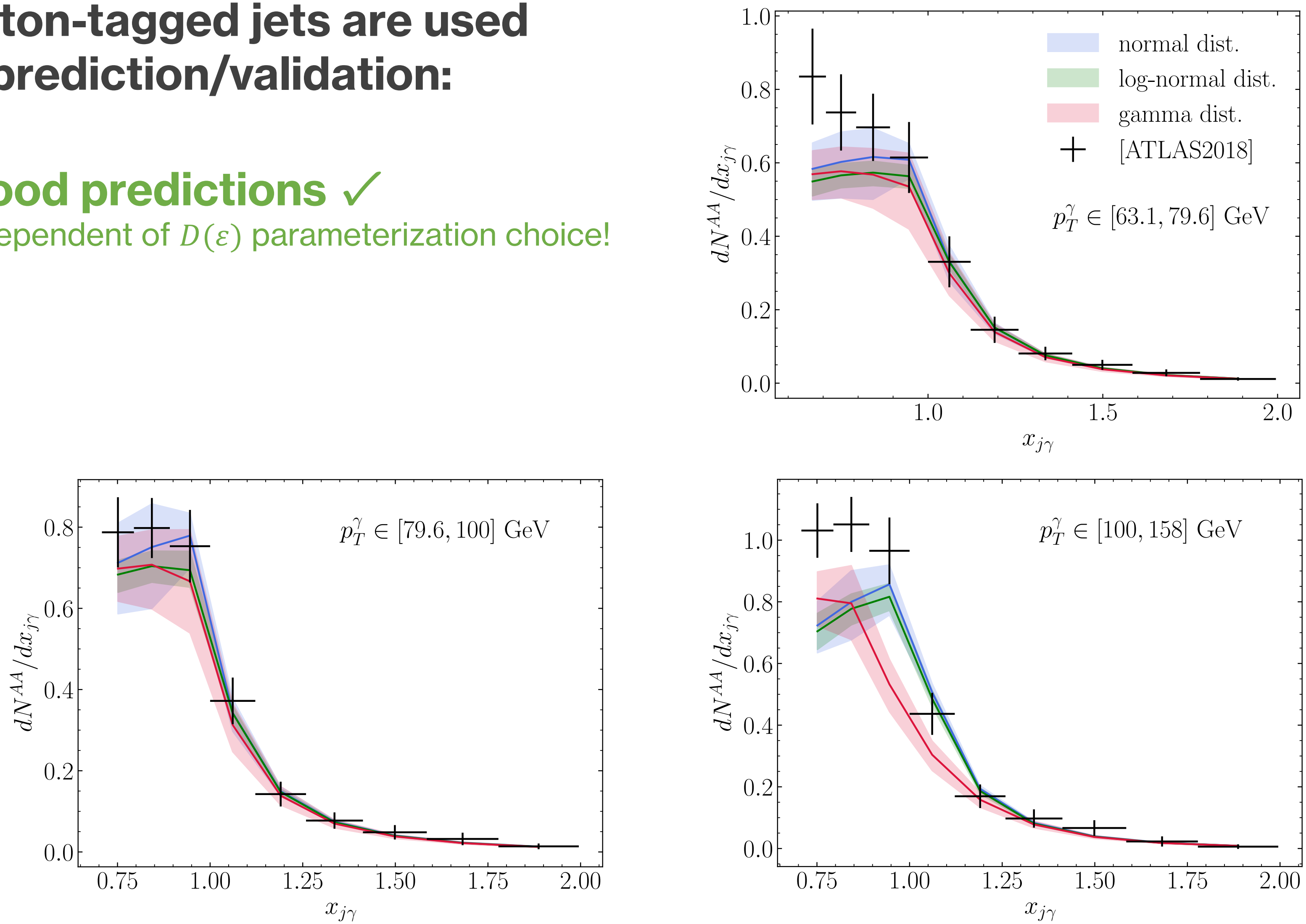




Results: the prediction

Photon-tagged jets are used for prediction/validation:

Good predictions ✓
independent of $D(\varepsilon)$ parameterization choice!



Results: the prediction

Photon-tagged jets are used for prediction/validation:

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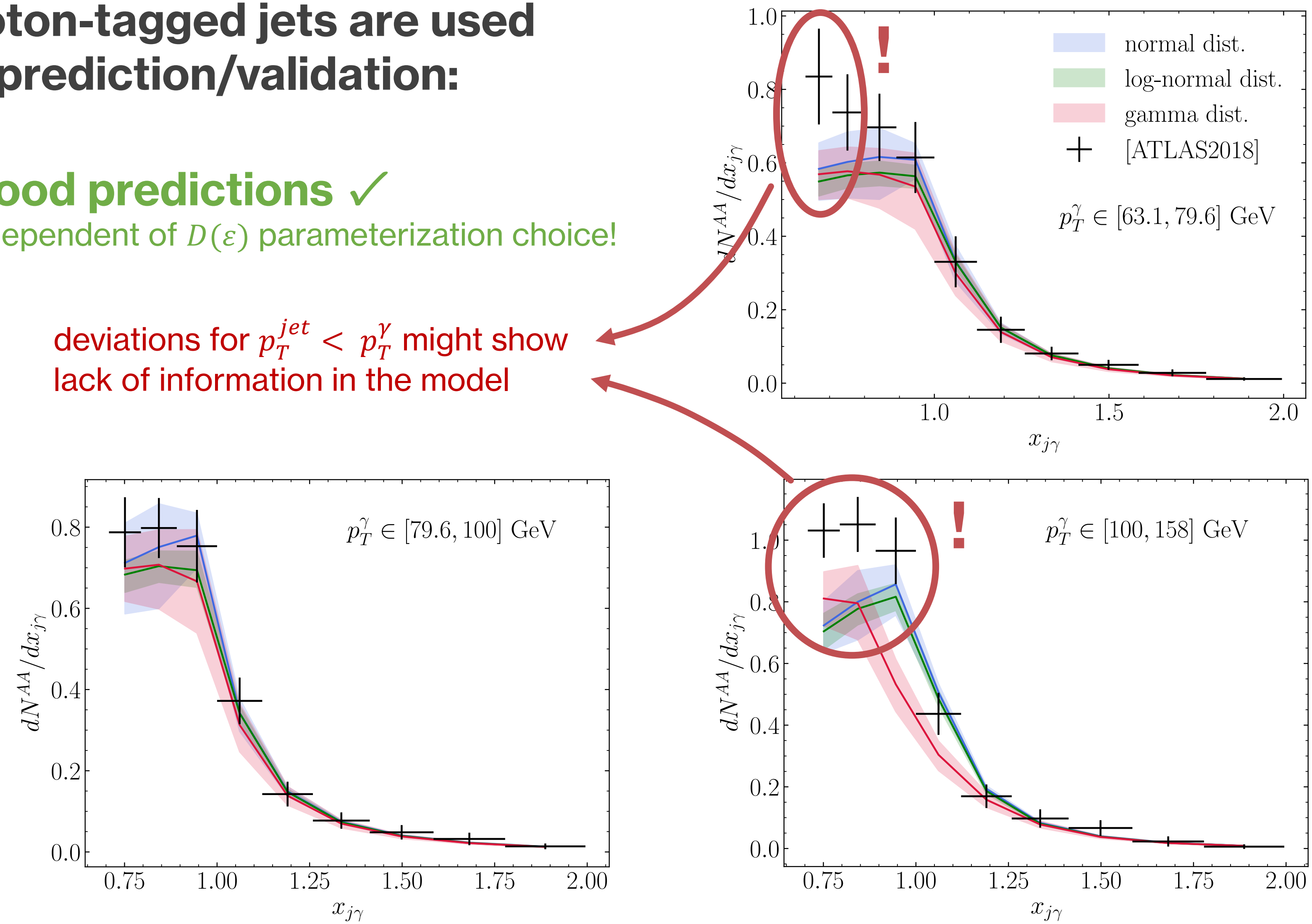
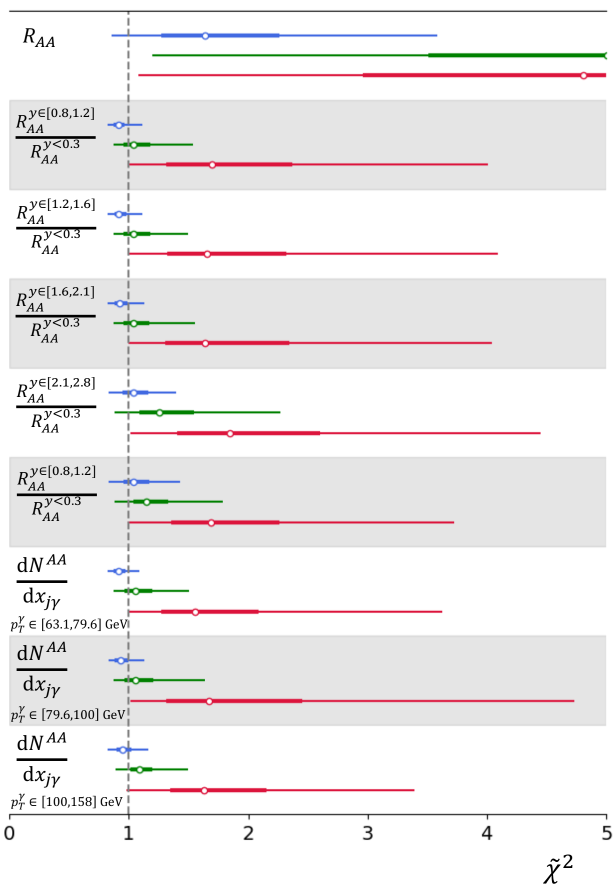
deviations for $p_T^{jet} < p_T^{\gamma}$ might show lack of information in the model



Leave-one-out cross-validation

- Bayesian inference on the whole data **except one observable**.
- The data that was set aside is predicted, and the **reduced chi squared** is evaluated for the whole data.



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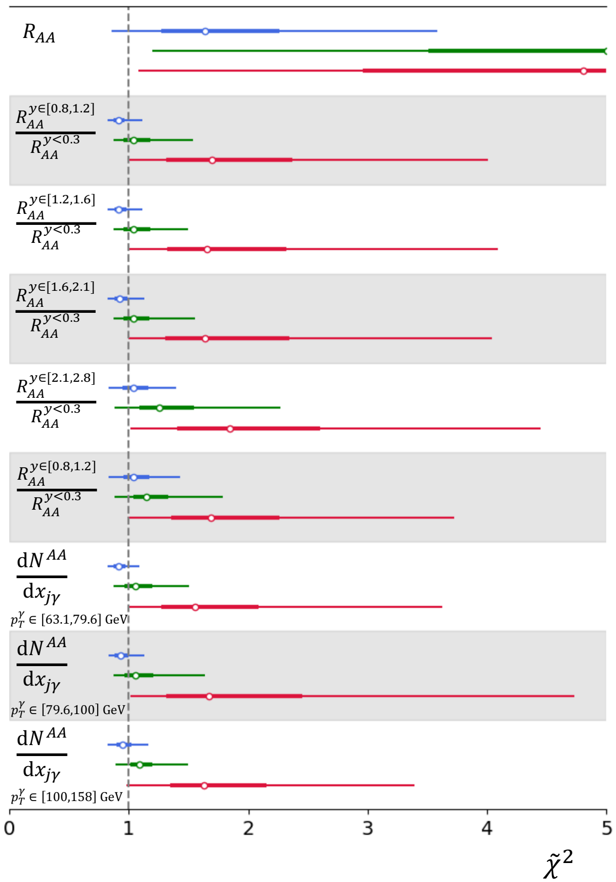
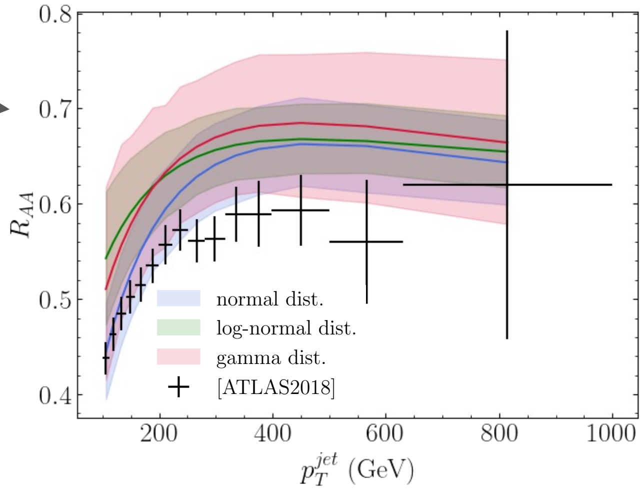


the inclusive R_{AA} contains more information

prediction from other observables fit



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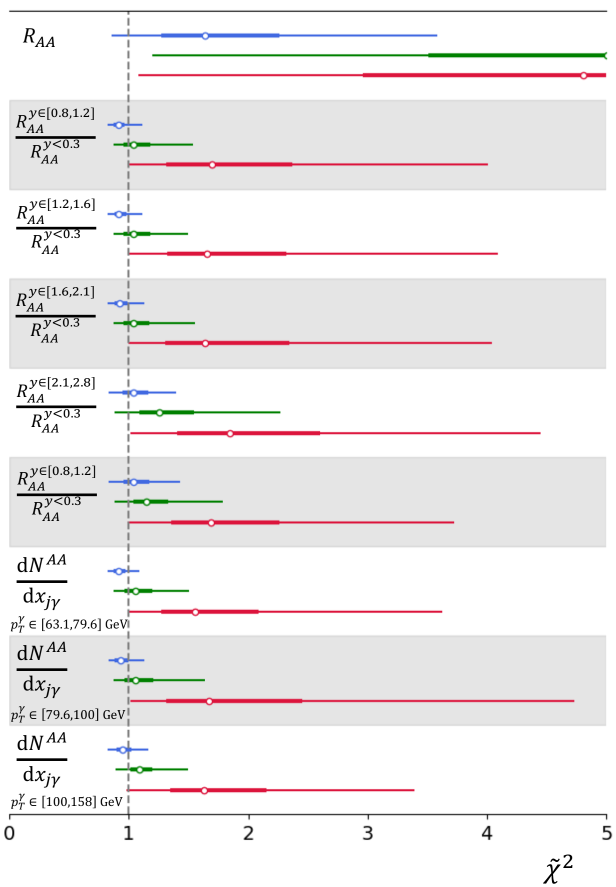
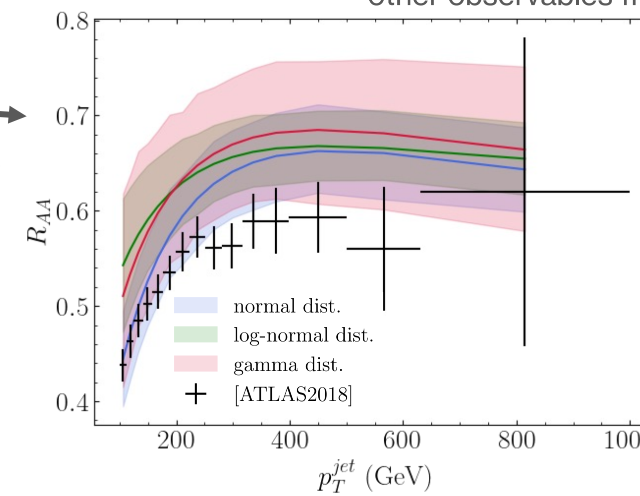
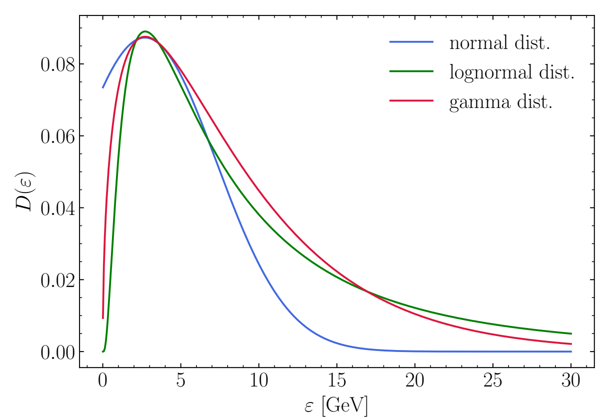


the inclusive R_{AA} contains more information

normal distribution better describes the data

prediction from other observables fit



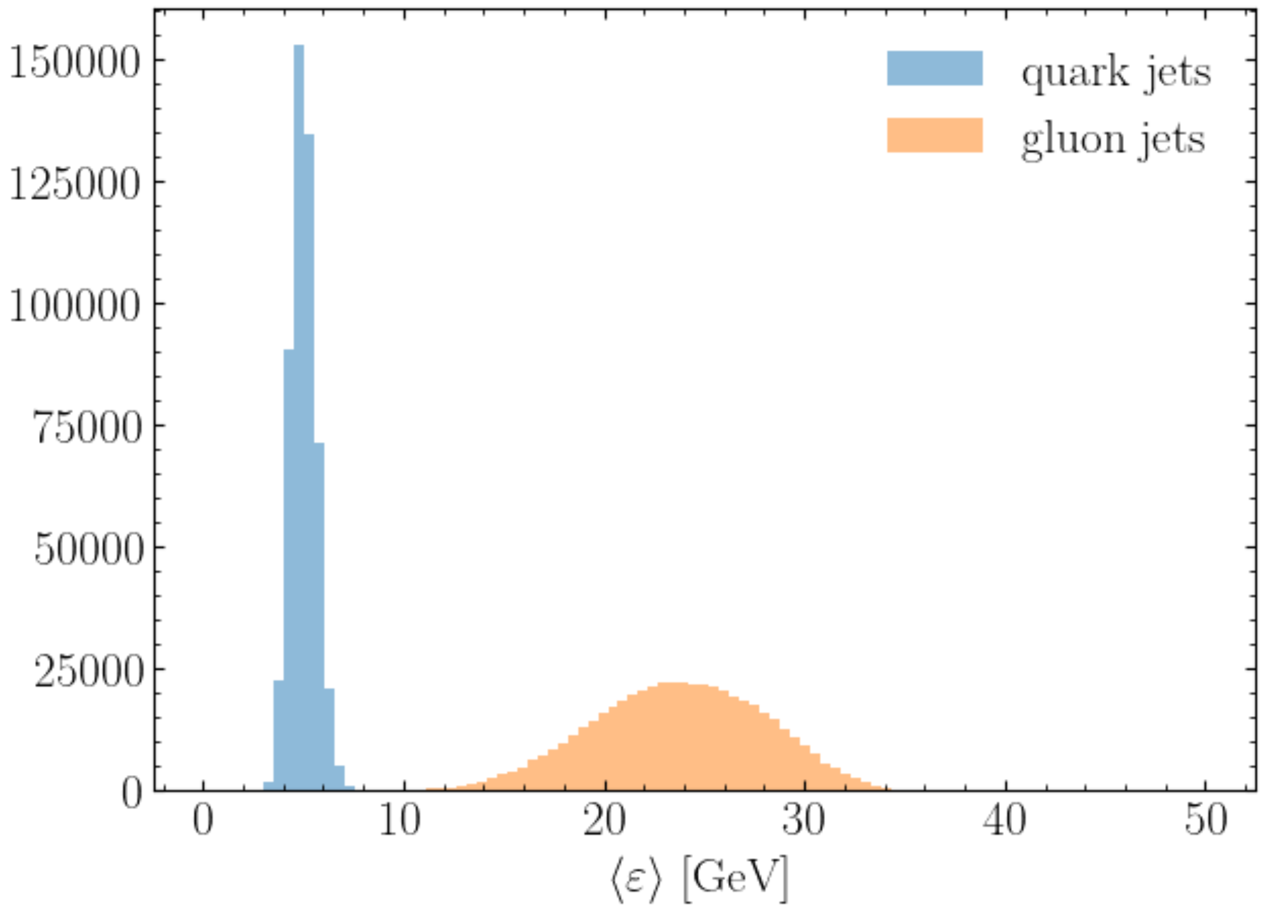


From normal distribution shape:

- energy loss distribution that goes faster to zero seems to be prefered
- less probability of high energy loss to the medium

Results: quark- Vs. gluon-jet energy loss

From the posterior distributions, we can access the distribution for the mean energy loss of the quark- and gluon-jets:



posterior for the mean energy loss using normal dist.

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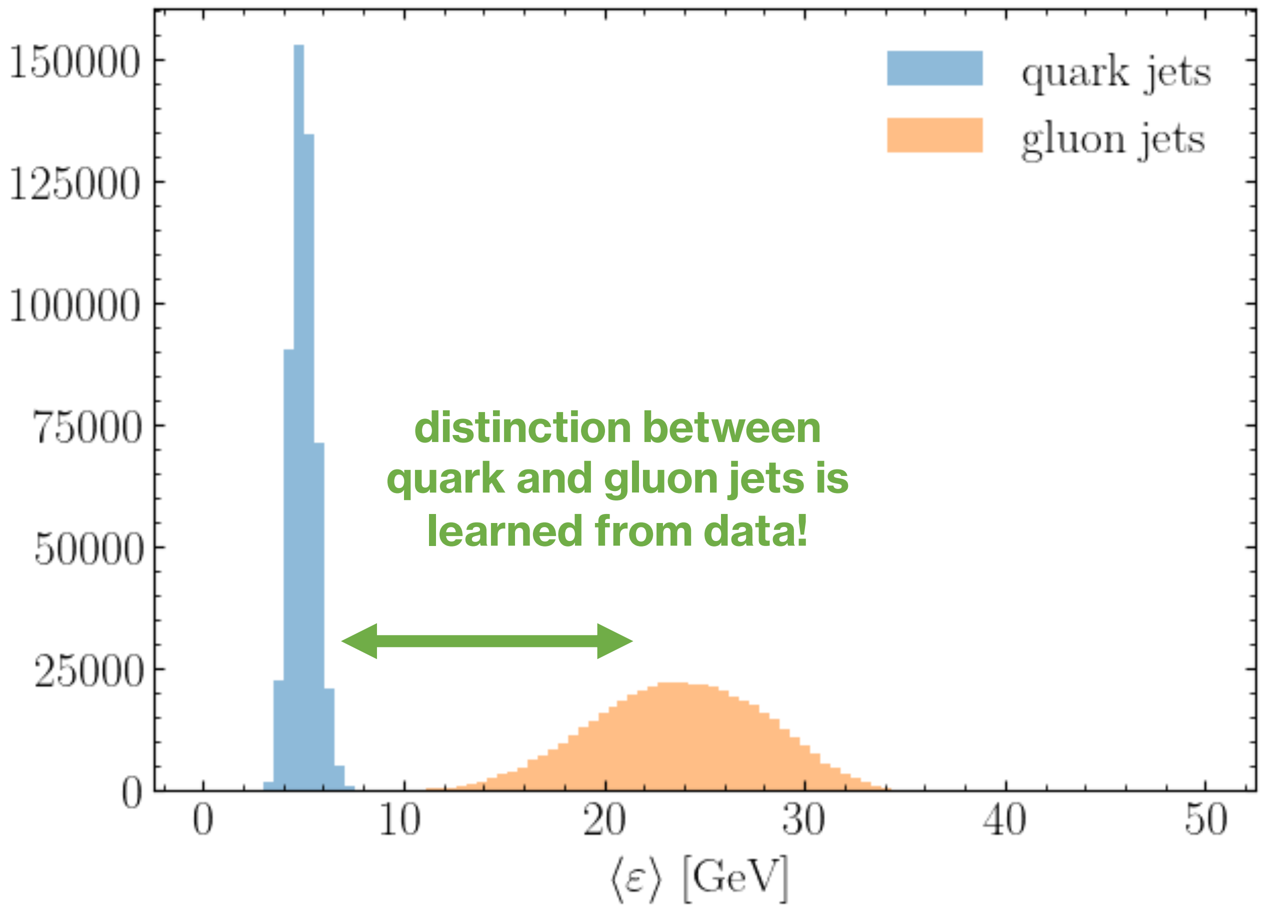

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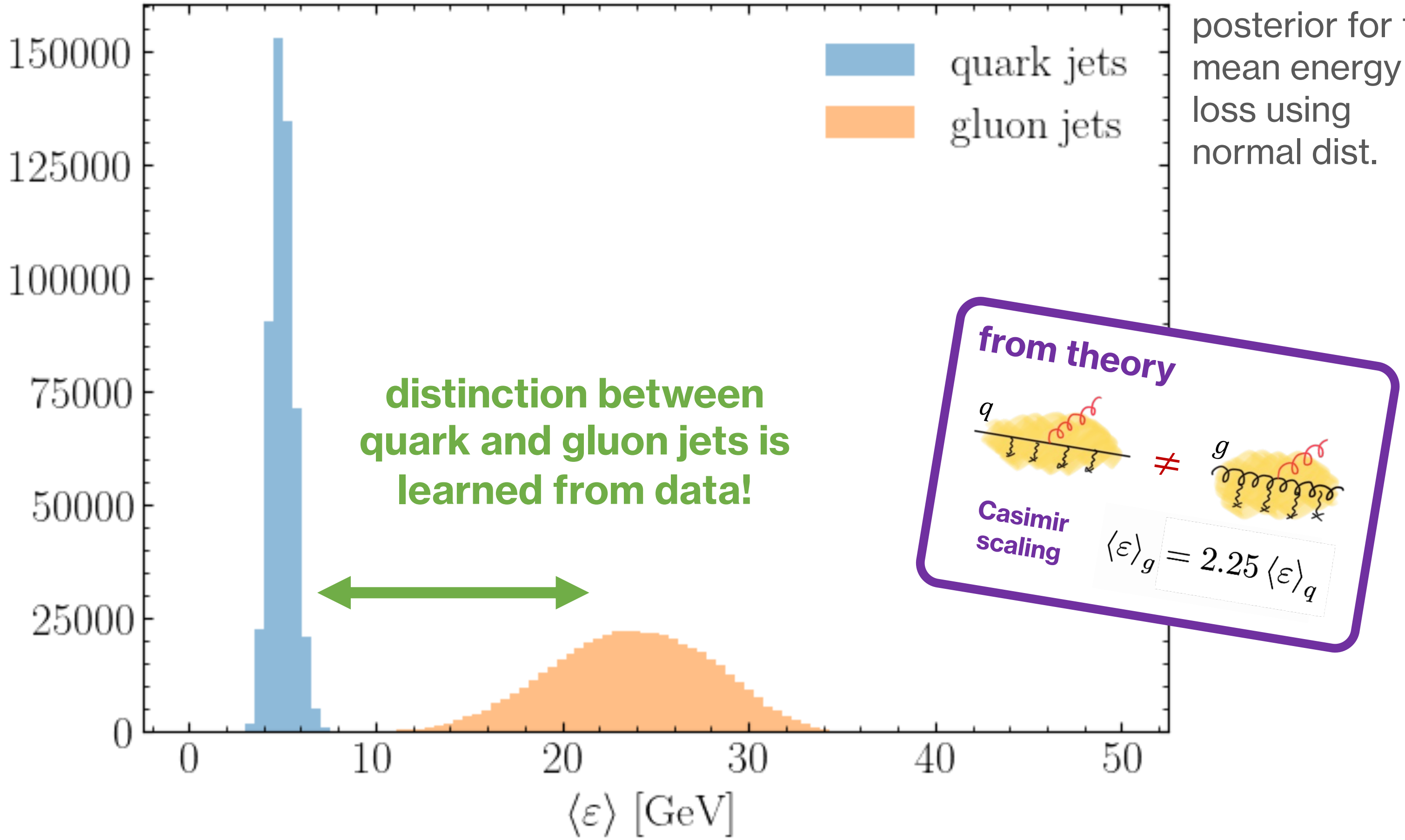
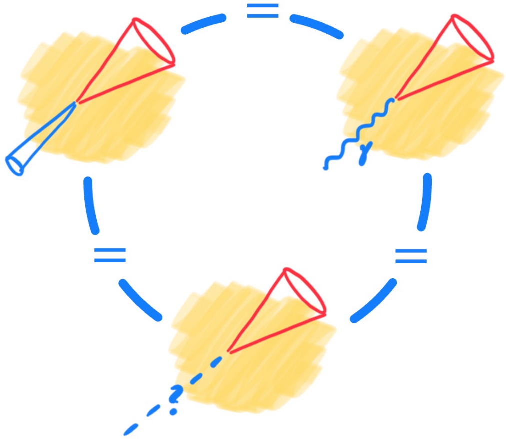


posterior for the mean energy loss using normal dist.

Outlook

Universality of jet quenching:

- Factorization holds with only the information about the jet-initiating parton;
- Low sensitivity to the energy loss distribution parameterization;

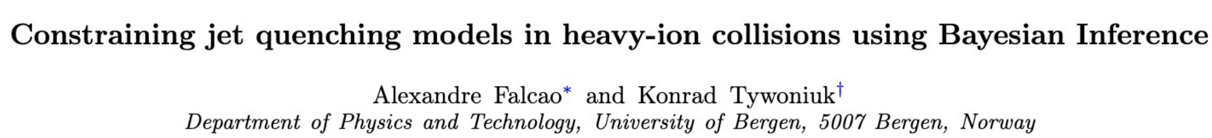


Theory insight:

- Clear separation between the energy loss of quark-jets from gluon-jets.
- ML can have a crucial role in developing the theoretical understating of jet quenching and the QGP itself.

Coming soon:

[arXiv: 23xx.xxxxx]



Constraining jet quenching models in heavy-ion collisions using Bayesian Inference

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