Bayesian analyses with JETSCAPE

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MITHIG's work is supported by DOE-NP

What / Why	Problems
Recent	Future

What / Why

Problems

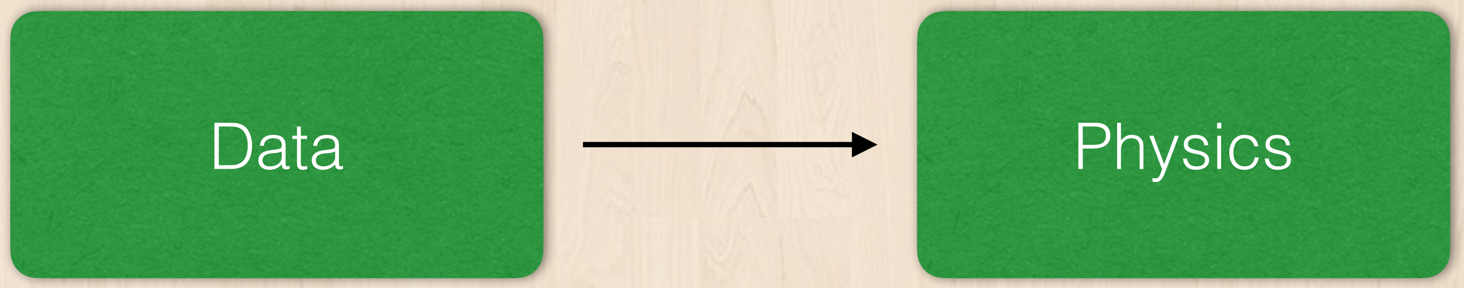
Recent

Future

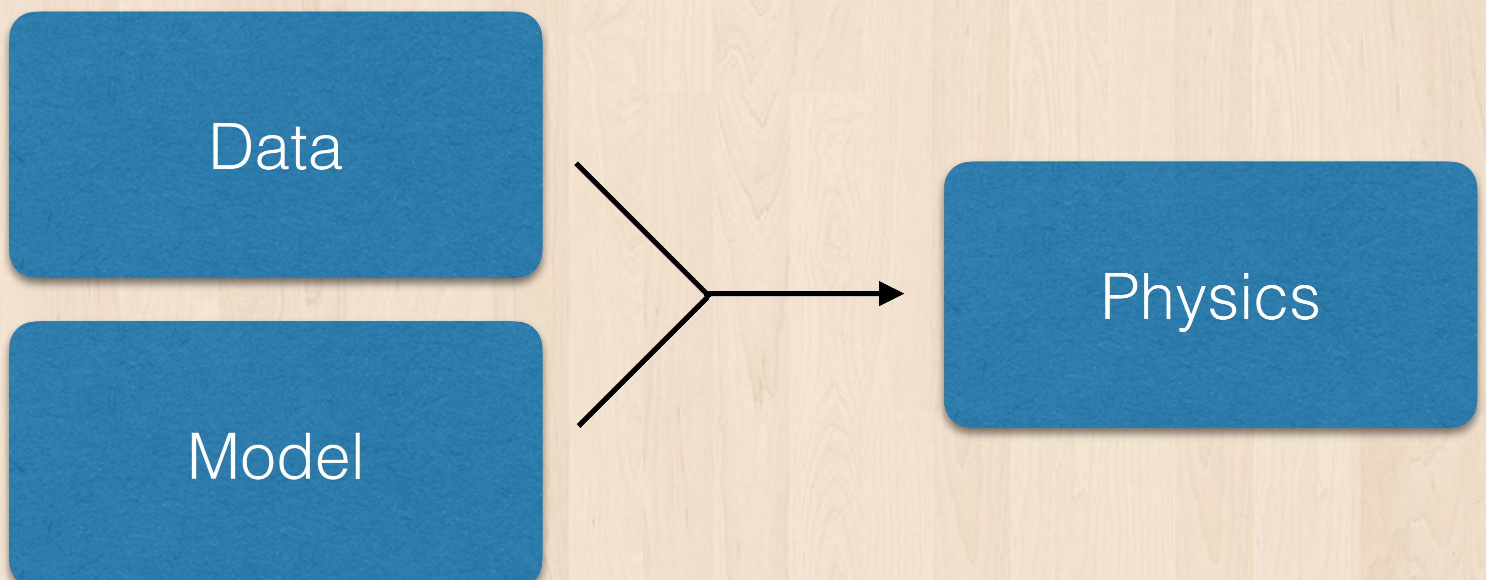
Goal: better understand heavy-ion collisions

Rigorous model-data comparison

"Silver-bullet measurements" (rarer)

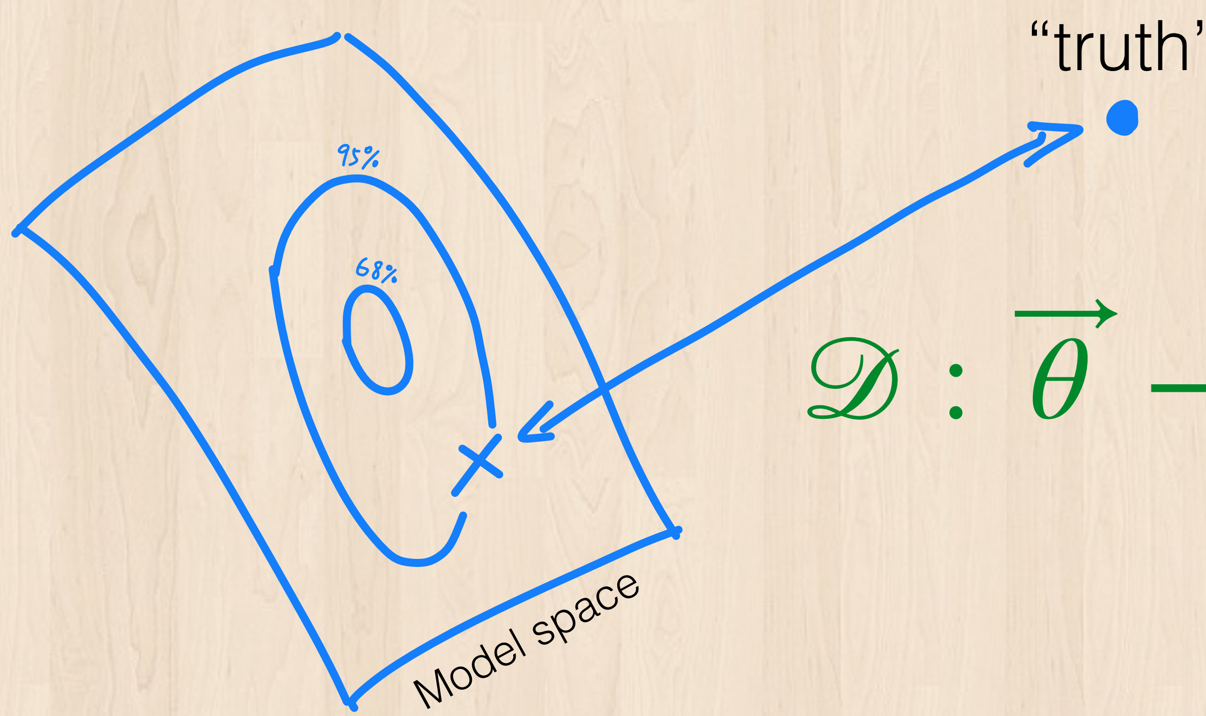


More precise data & sophisticated models

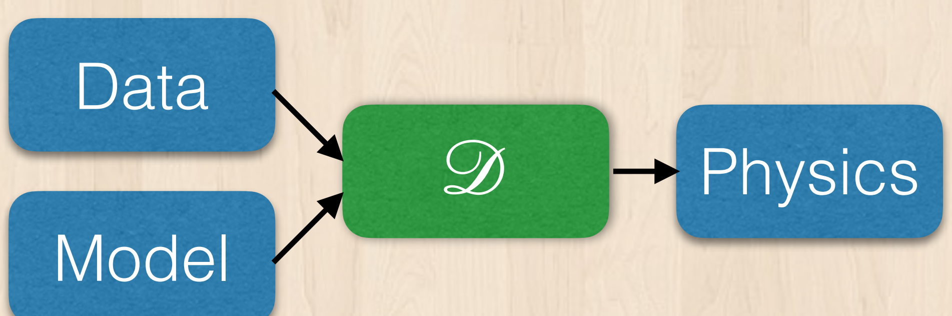


Comparing data to model

Key task: quantify “distance” between point in model space and “truth” (data = proxy of truth)



$$\mathscr{D} : \vec{\theta} \rightarrow \mathbb{R}$$



Once we have this $\mathscr{D}$ we can have fun and extract information

Candidate: Bayesian posterior

Bayesian likelihood

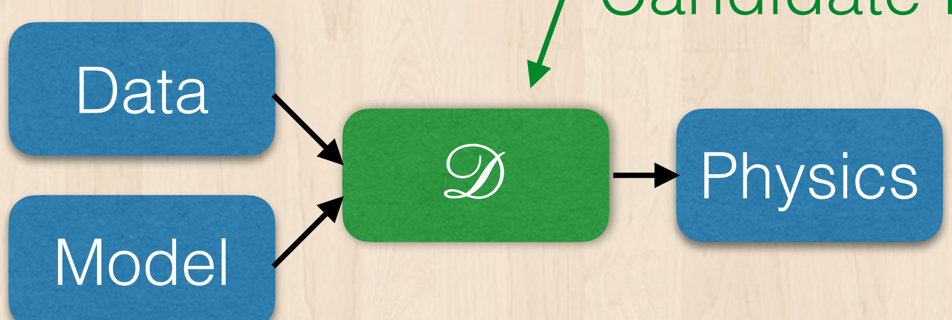
Prior knowledge

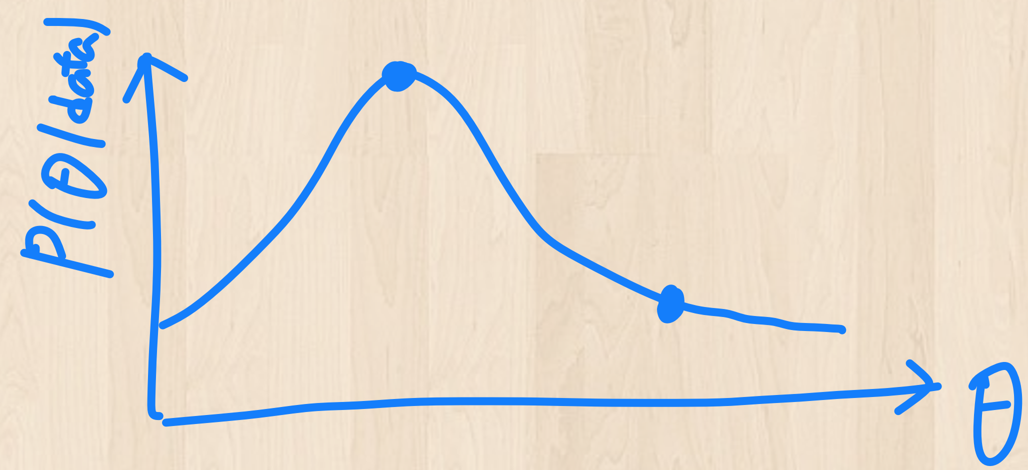
$$P(\vec{\theta} \,|\, \text{data}) = \frac{P(\text{data} \,|\, \vec{\theta})\, P(\vec{\theta})}{P(\text{data})}$$

Bayesian evidence

Posterior: probability density of parameter $\vec{\theta}$ being "best" given the observed data

Candidate for $\mathscr{D}$





What / Why

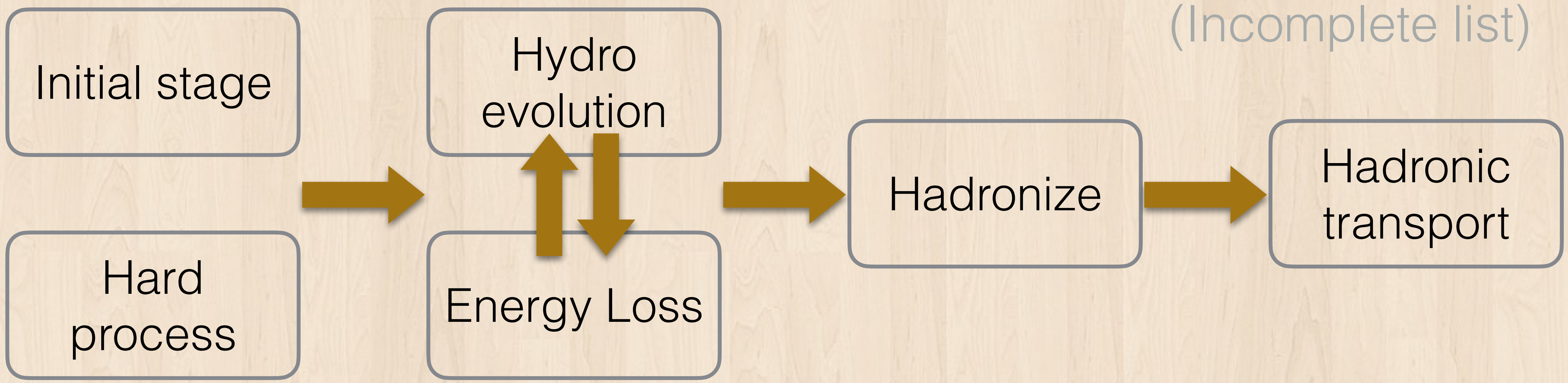
Problems

Recent

Future

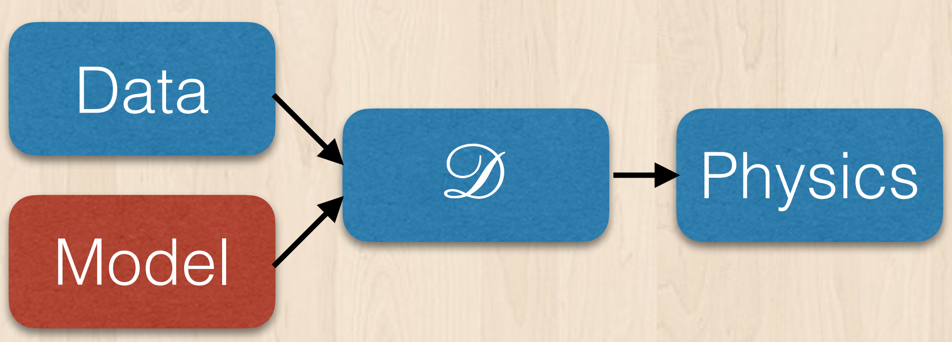
The problems of heavy ions

(Incomplete list)



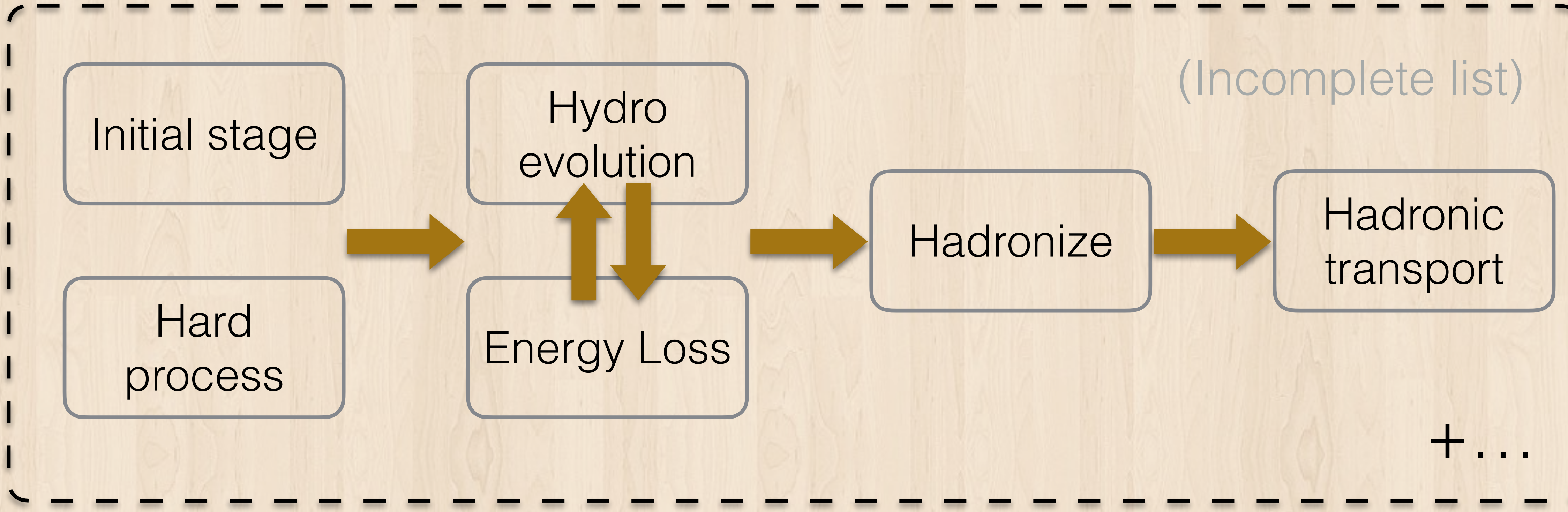
A LOT of parameters needed to specify the whole thing

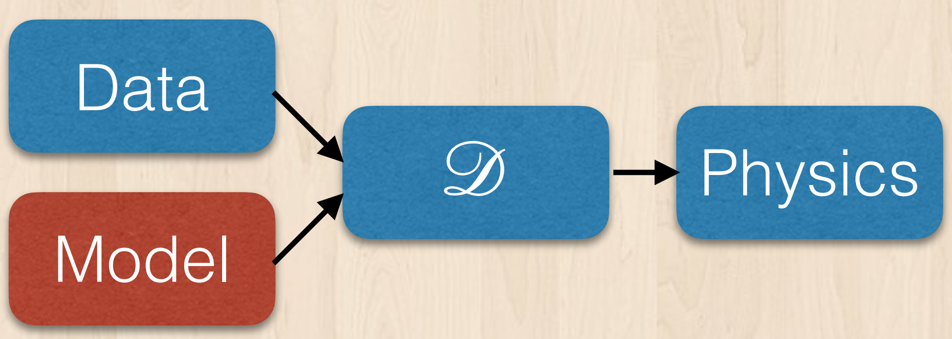
Both in each block and the interface between blocks



Usually **different code bases**

The JETSCAPE framework



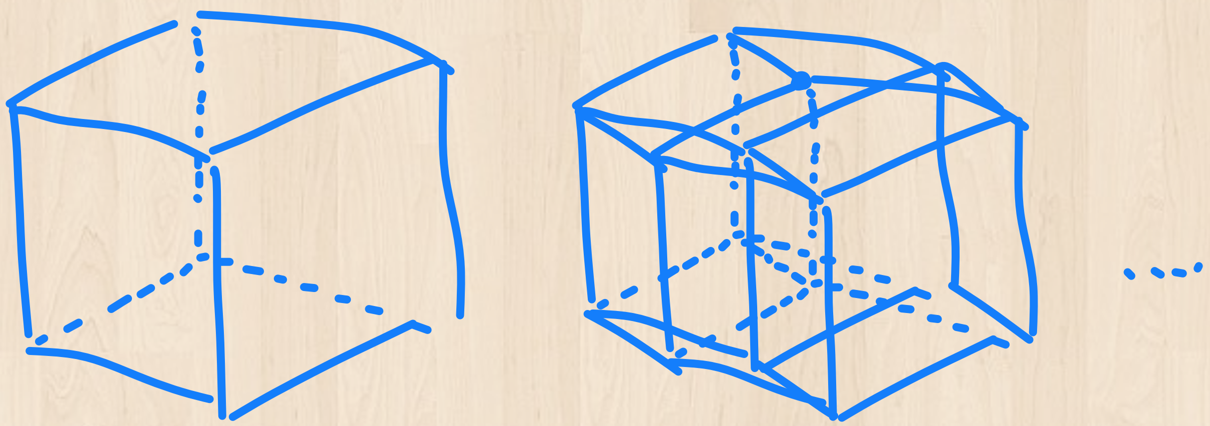


JETSCAPE framework:
- Modular design
- Easily extensible
- Unified block interface

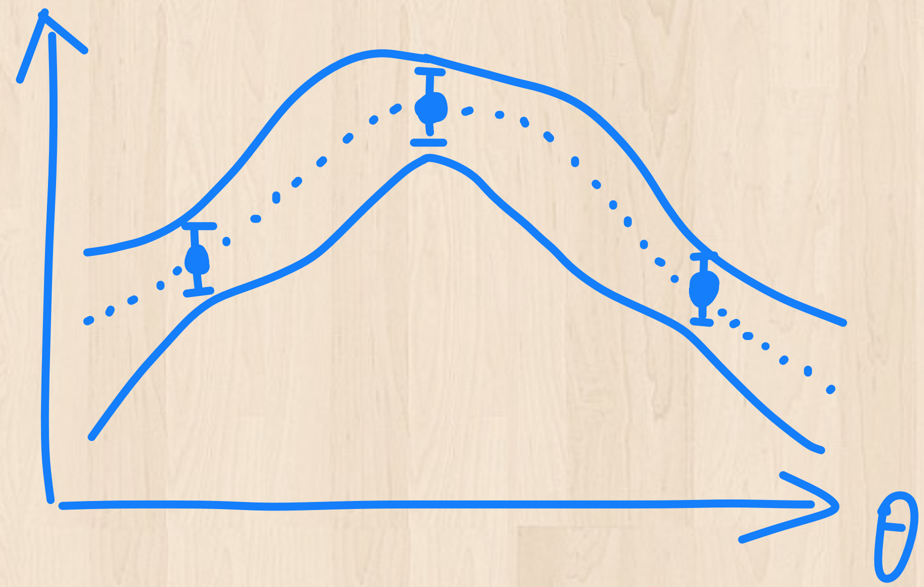
~~different code bases~~

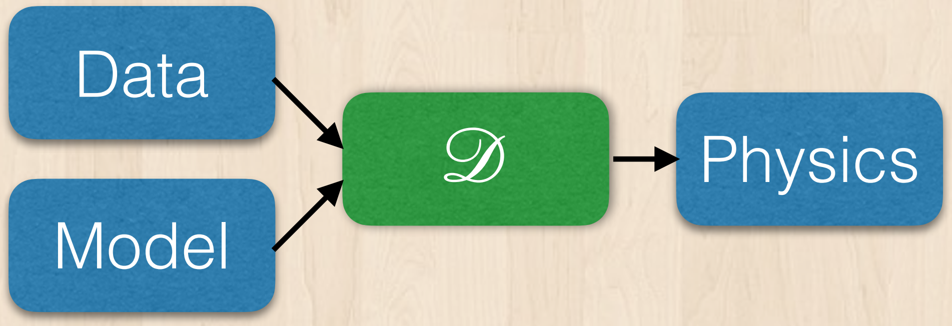
Dealing with large parameter space

Problem:
computing cost +
continuous space +
large dimensions



One solution:
strategic points +
interpolation





Still high computing
cost but doable

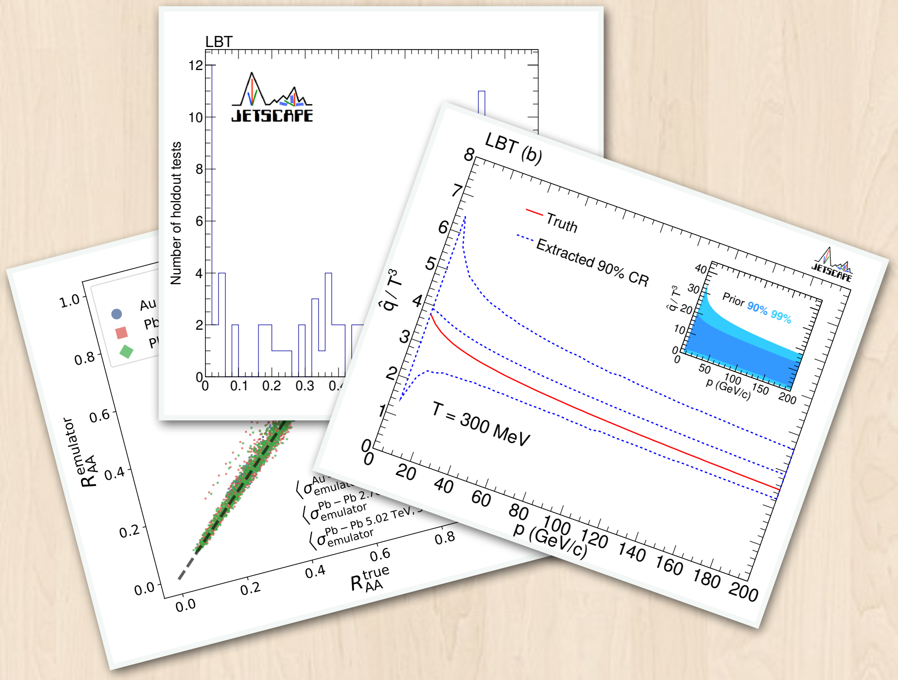
+ a lot of analysis details

Initial design points | PCA | Uncertainty propagation | Analyze posterior

Further design point[s] | … | …sterior | MCMC

Uncertainty correlation | Validation | Dealing with noise | …

Won't go into details for now



Data → $\mathscr{D}$ ← Model

$\mathscr{D}$ → Physics

A lot of care goes into making sure each step is robust

What / Why	Problems
Recent	Future

* in the context of JETSCAPE

Soft observables

$h^{\pm} : dN/d\eta$

$dE_T/d\eta$

$\pi, K, p : dN/dy, \langle p_T \rangle$

$v_2\{2\}, v_3\{2\}, v_4\{2\}$

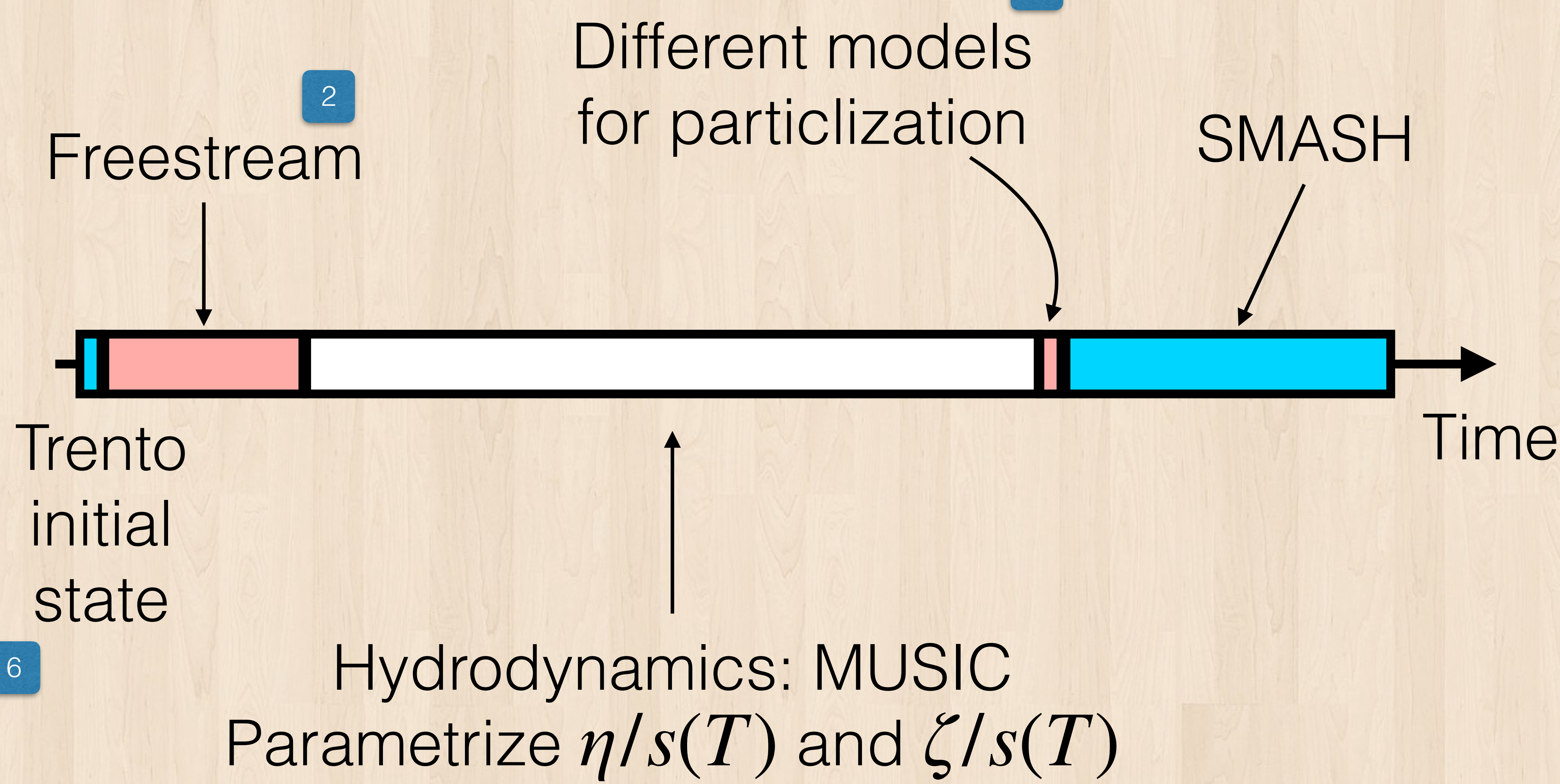
$\delta p_T / p_T$

$\longrightarrow$

Parameters in initial state hydro etc. (next page)

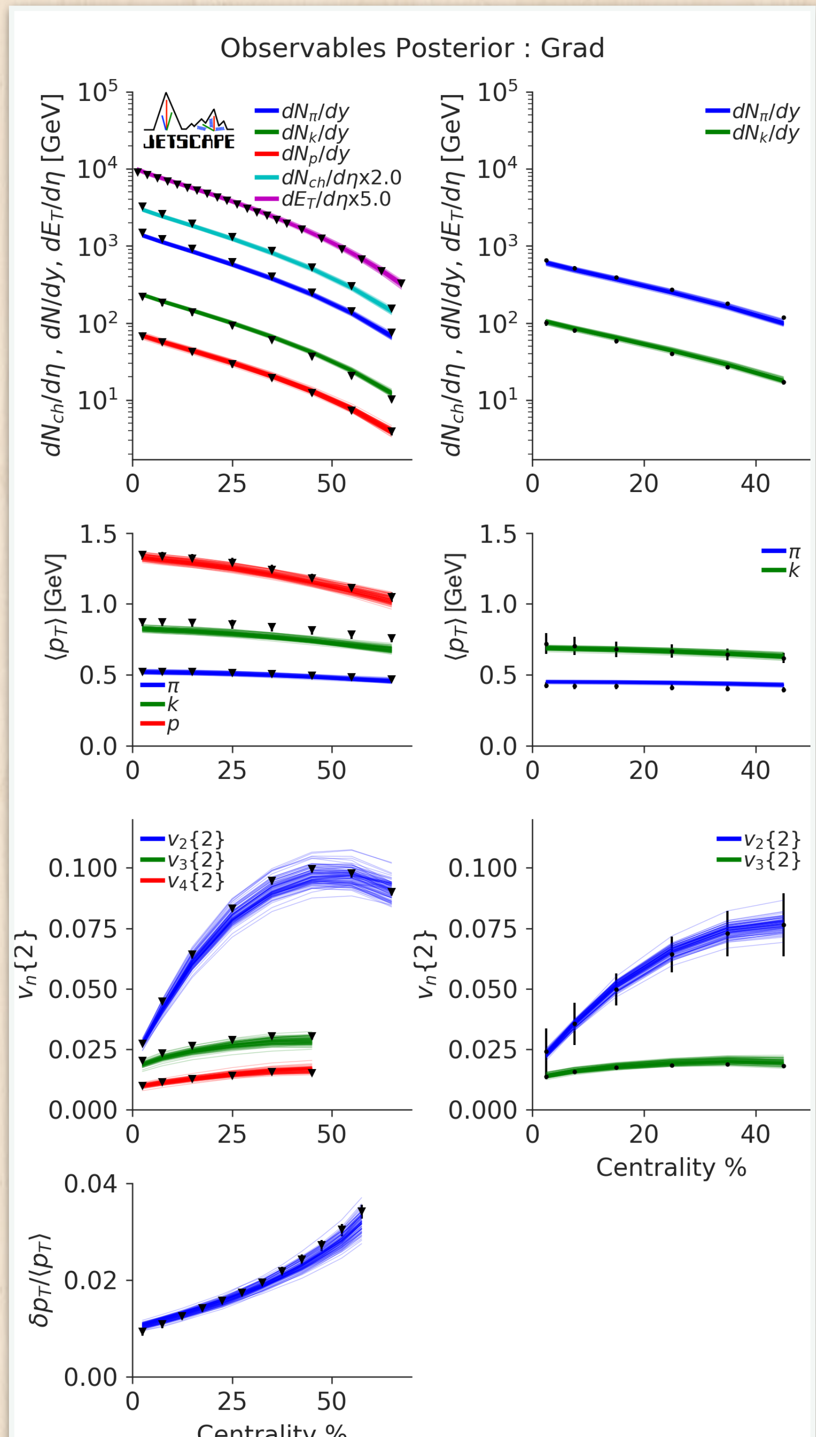
Phys. Rev. C 103, 054904 (2021)

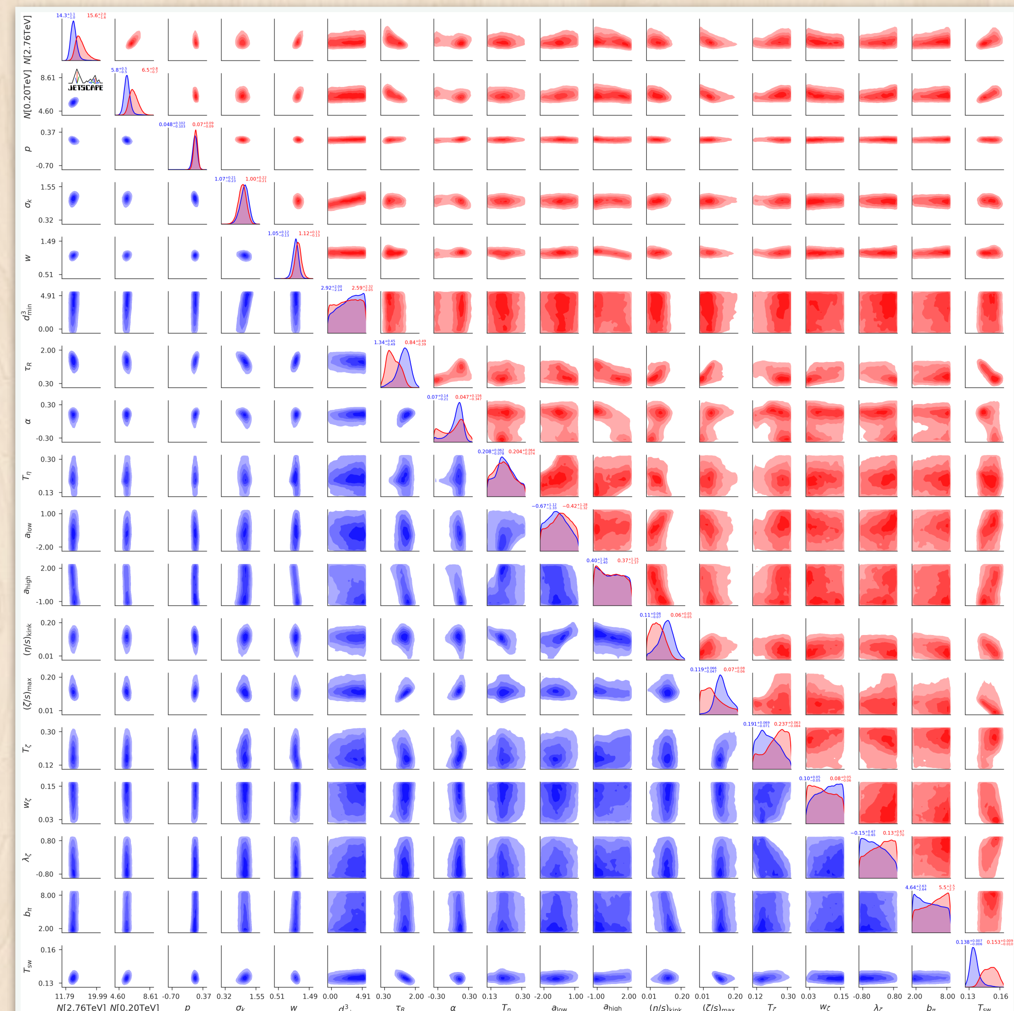
Model setup



Phys. Rev. C 103, 054904 (2021)

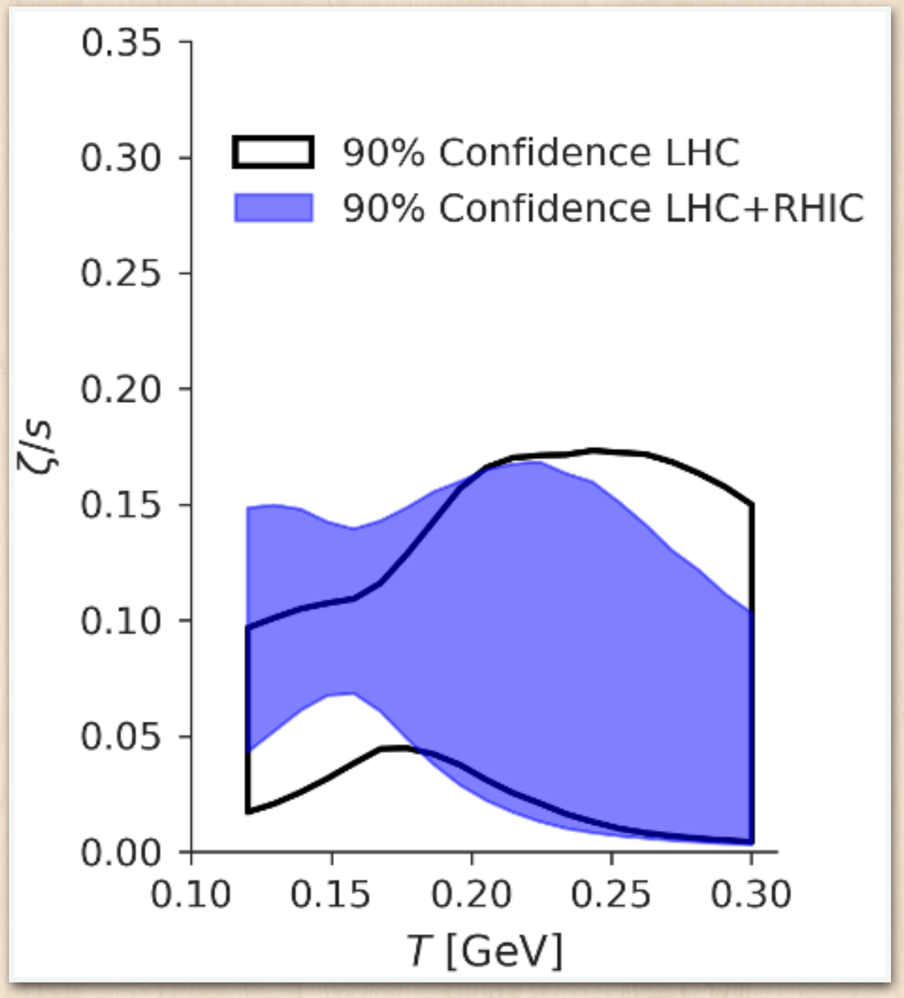
Example posterior distributions

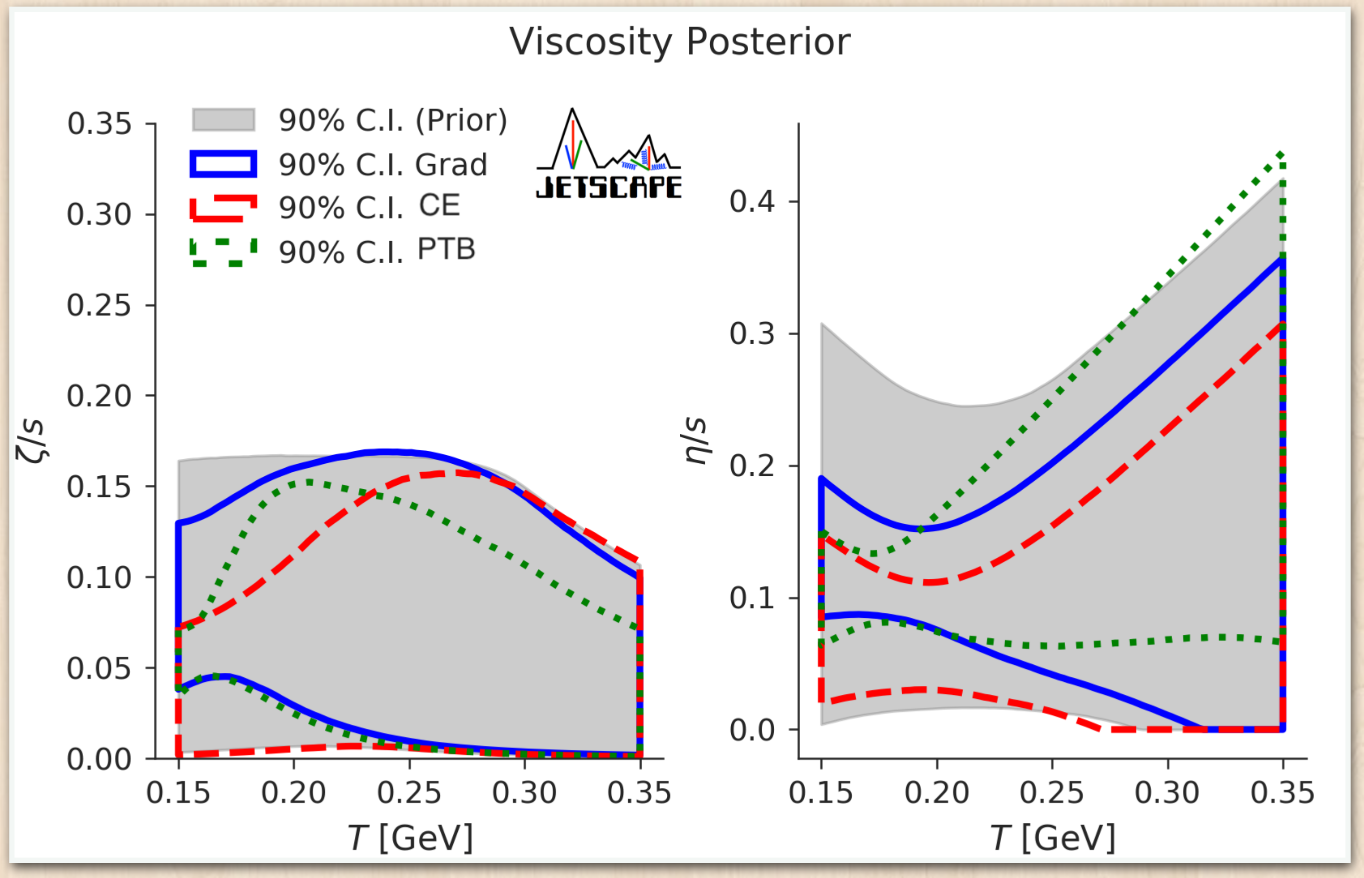




Decent agreement to both LHC and RHIC data

Extracted viscosities





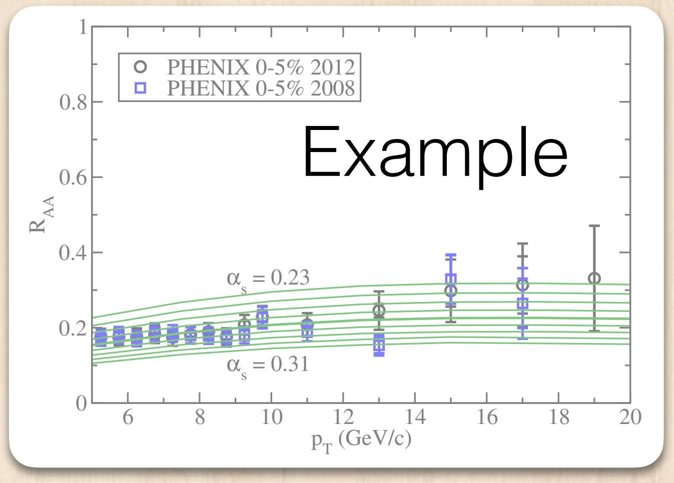
RHIC vs LHC
Complementary

Non-negligible effect
in particlization model

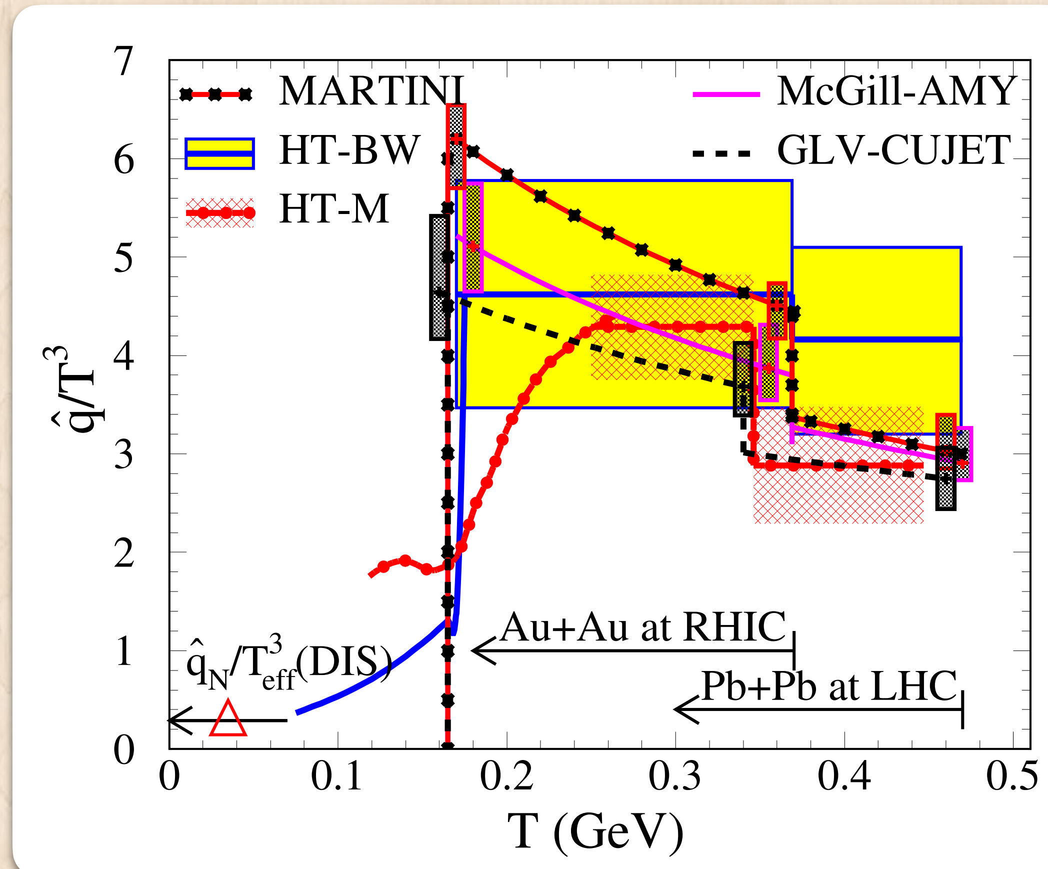
(+ many other results I don't have time to go into)

Phys. Rev. C 103, 054904 (2021)

$\hat{q}$ extraction: JET Collaboration



R_{AA} Data



Separate analyses to RHIC and LHC data from a variety of models

Can we take it one step further?

Phys. Rev. C 90, 014909 (2014)

Analysis Setup

Initial State → Hydro → E-Loss

Glauber → VISH 2+1D → MATTER / LBT / MATTER+LBT

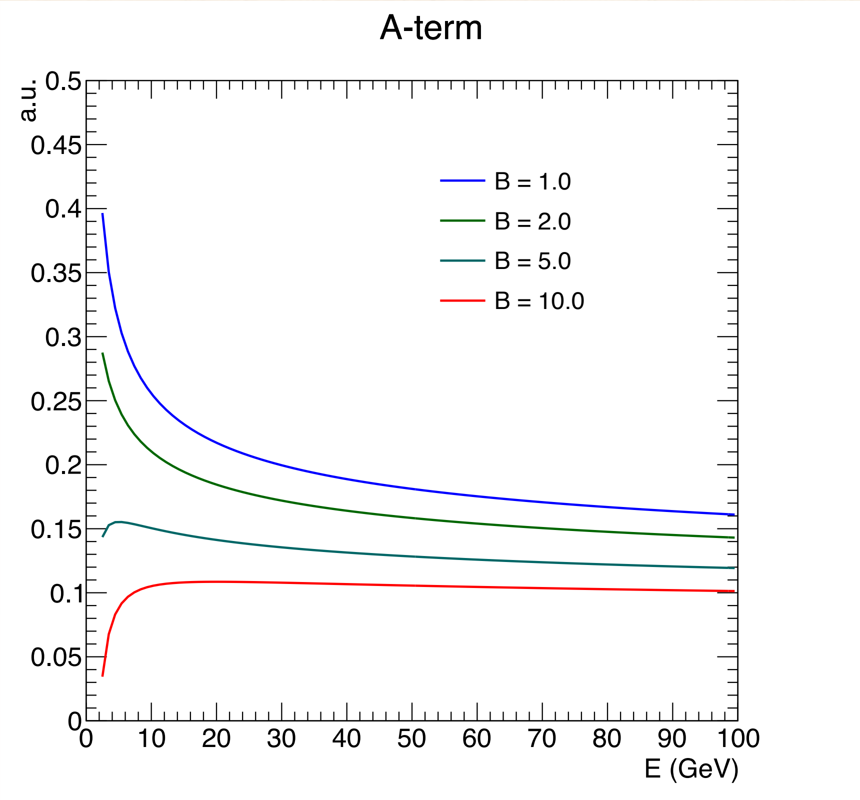
Hadron R_{AA} ⟶ $\hat{q}(T, E, Q)$

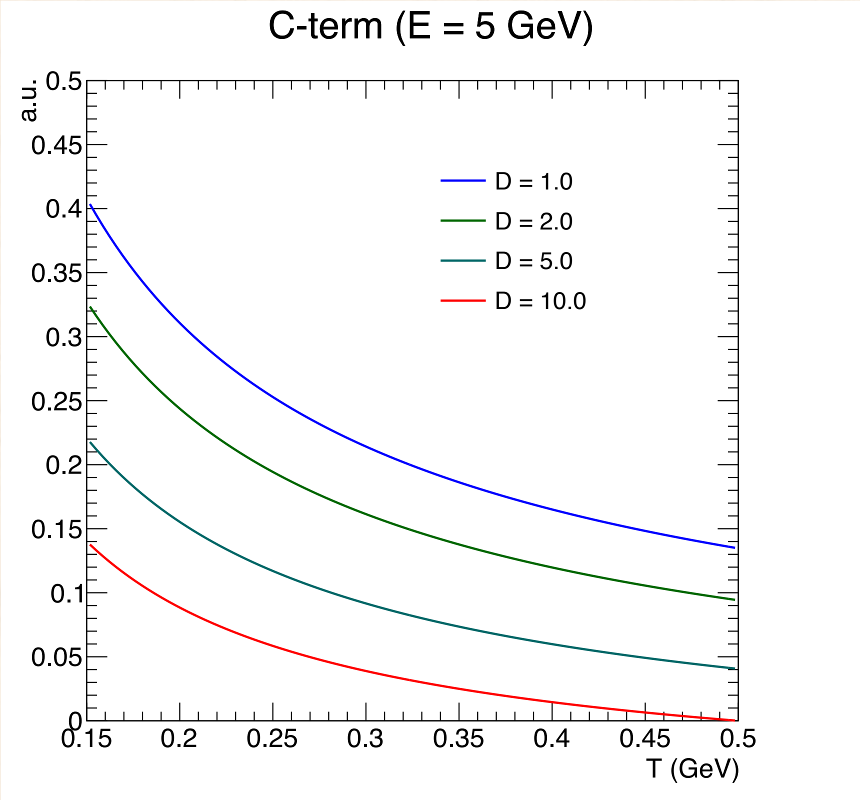
Parametrization of $\hat{q}$

$$\frac{\hat{q}}{T^3} \propto A\frac{\ln(E/\Lambda) - \ln(B)}{\ln^2(E/\Lambda)} + C\frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}$$

MATTER-inspired term

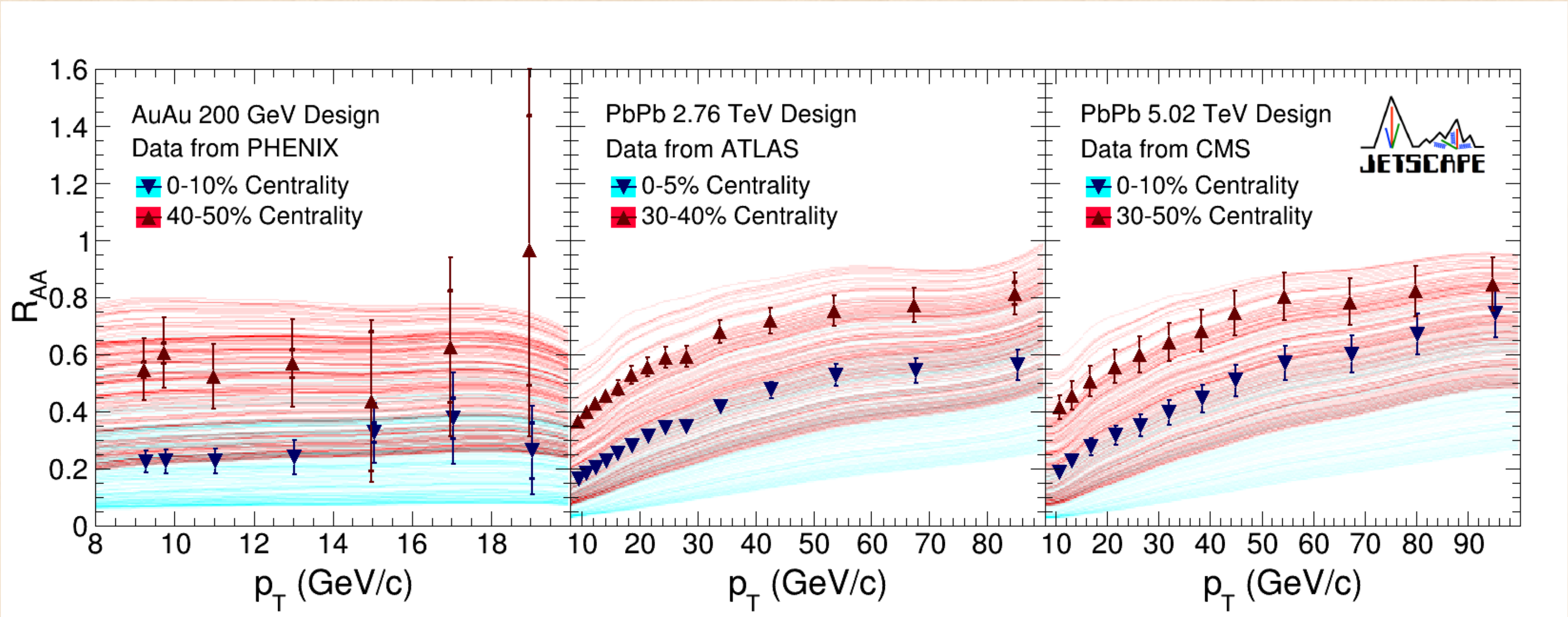
LBT-inspired term





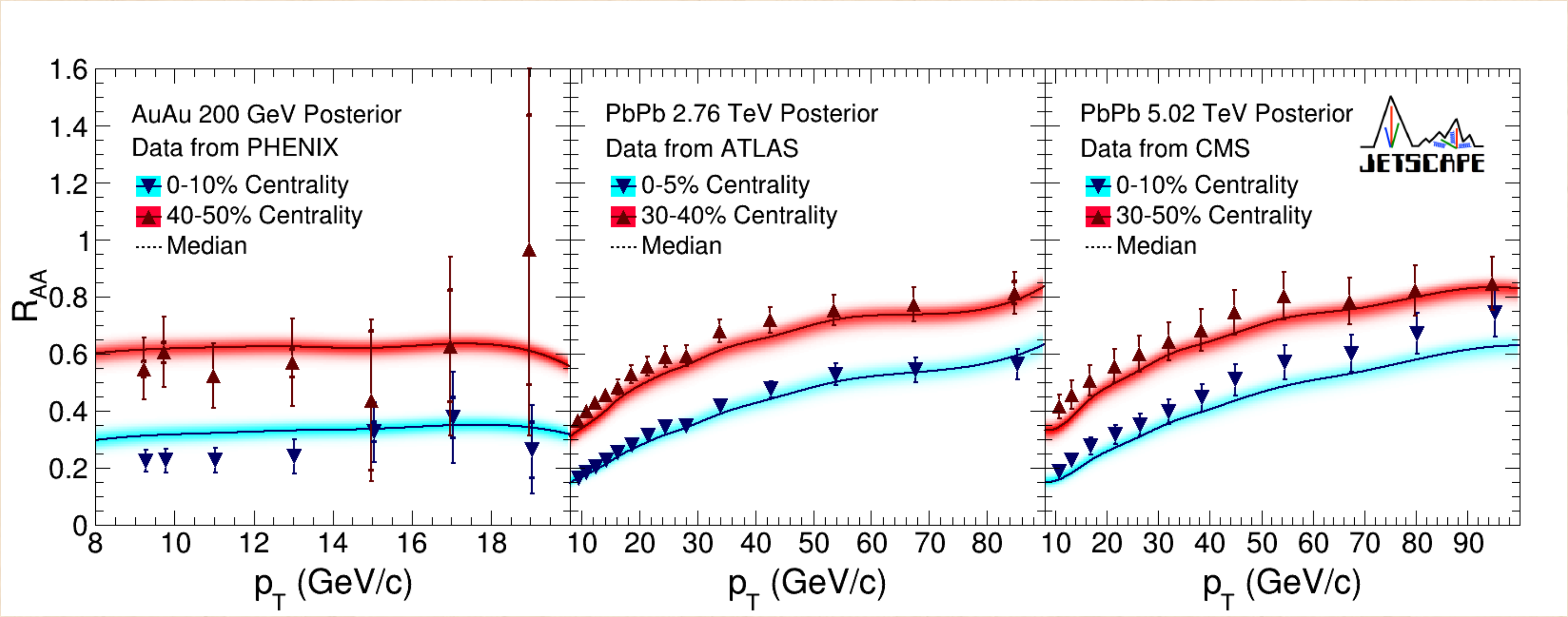
Phys. Rev. C 104, 024905 (2021)

LBT: design vs posterior



Before data is used

After using data



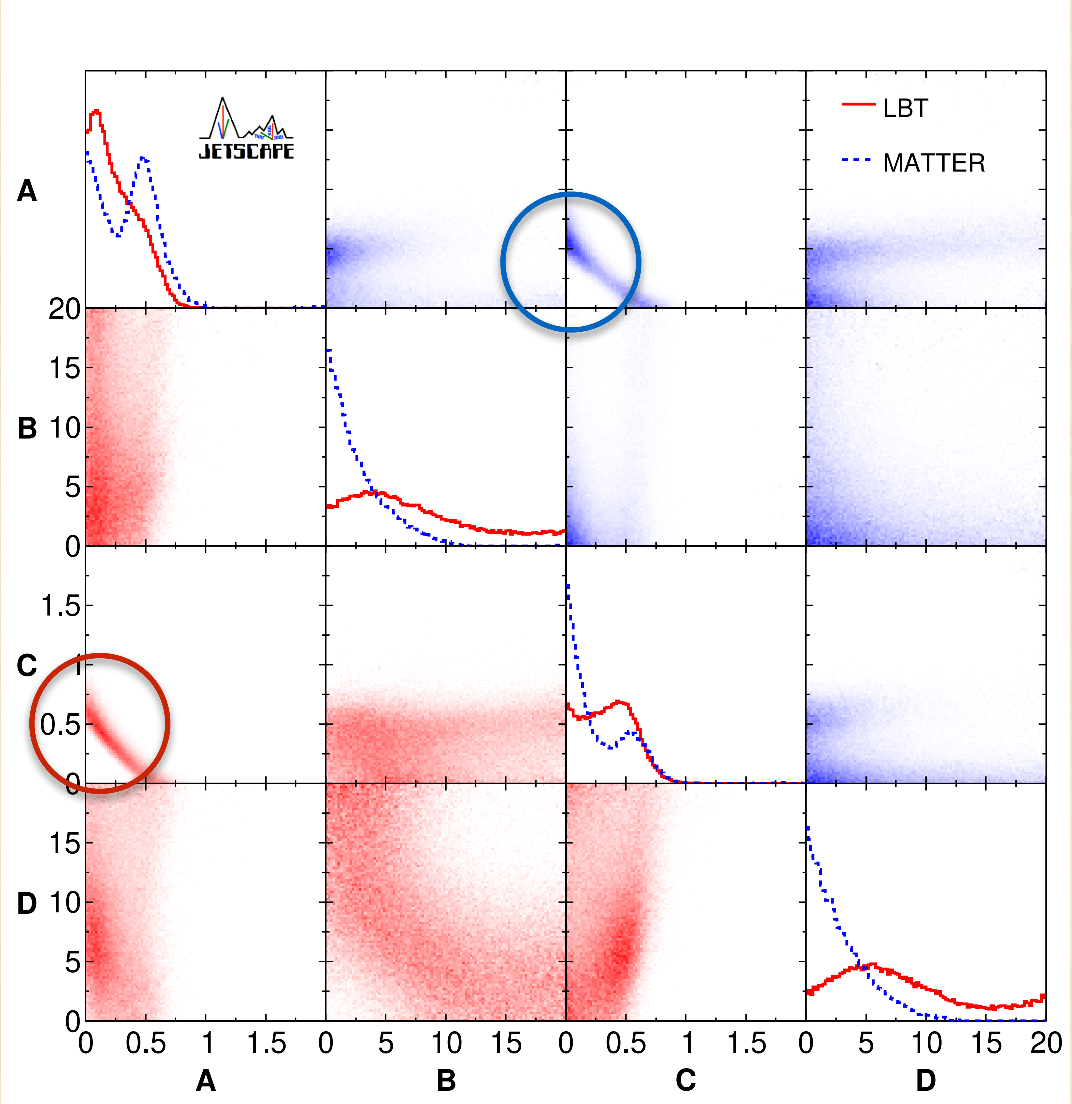
Phys. Rev. C 104, 024905 (2021)

MATTER vs LBT

$$\frac{\hat{q}}{T^3} \propto A\frac{\ln(E/\Lambda) - \ln(B)}{\ln^2(E/\Lambda)} + C\frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}$$

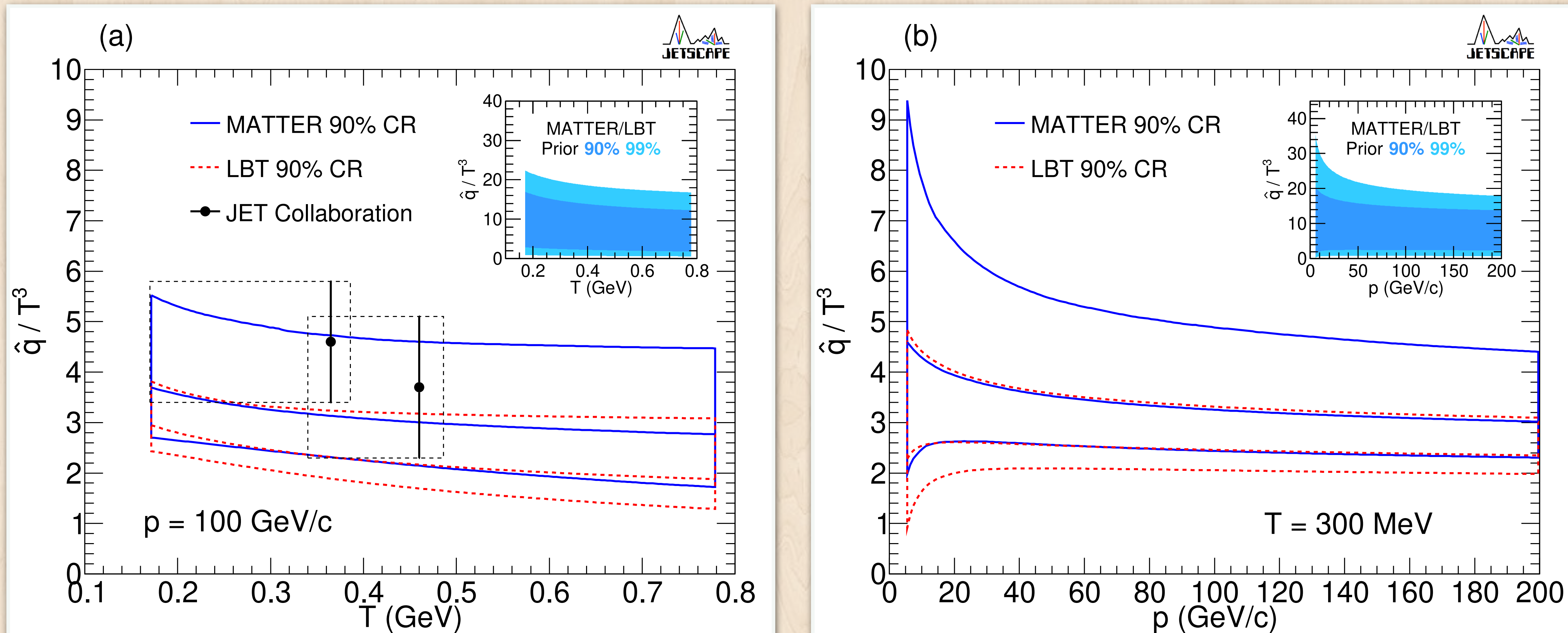
LBT prefers the C term, MATTER prefers the A term

Higher order term B & D only loosely constrained



Phys. Rev. C 104, 024905 (2021)

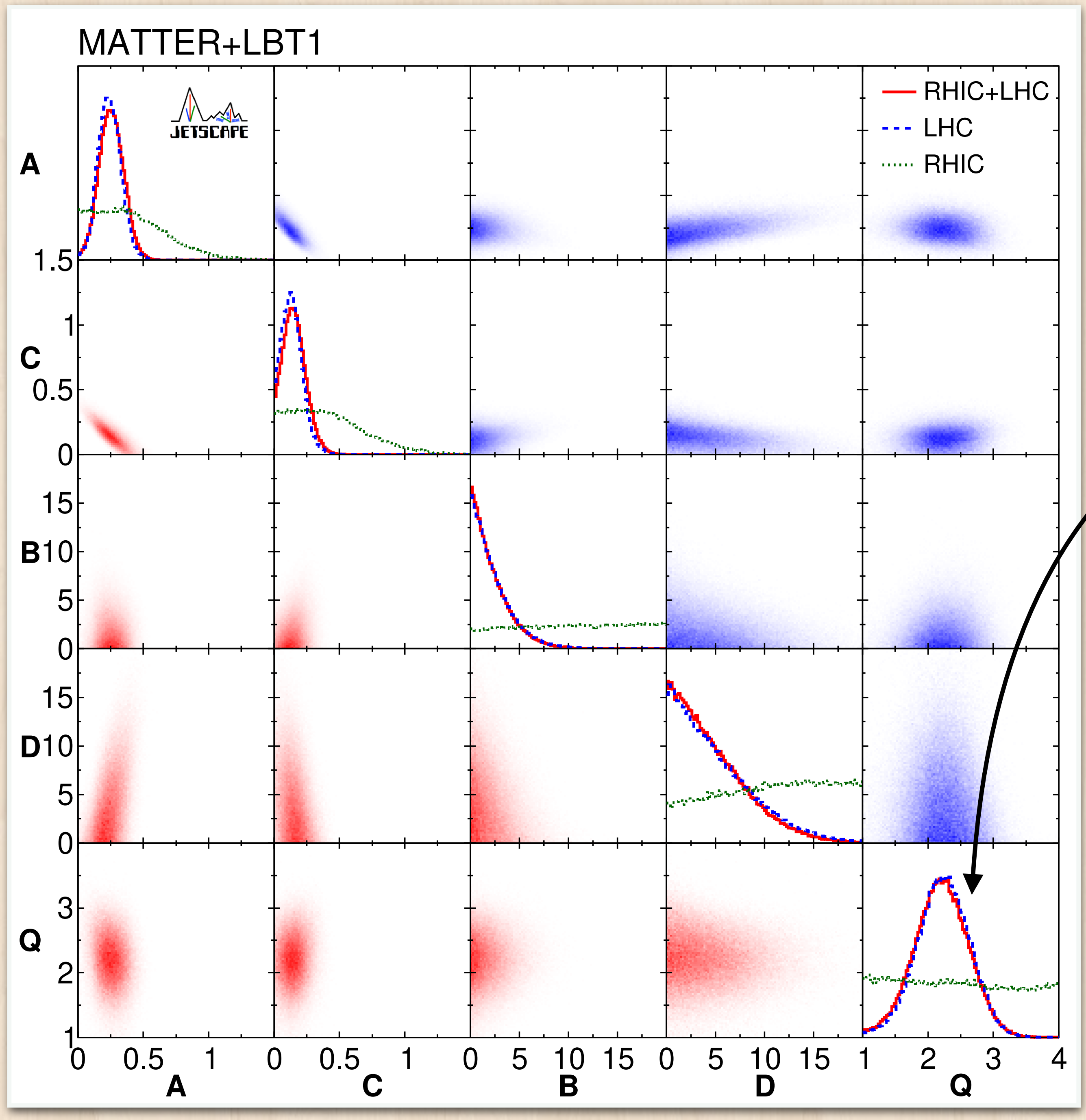
MATTER & LBT: $\hat{q}$



Compatible with JET collaboration results

Prior range » posterior range

Multi-stage approach



Use MATTER for high virtuality and LBT for low

Best switching virtuality ~ 2 GeV

Result dominated by LHC because of choice of experimental data input

Recent results: remarks

- Due to time many things not covered
- What is done so far is just the beginning! Further analyses are ongoing
  - More observables, more flexible model, …

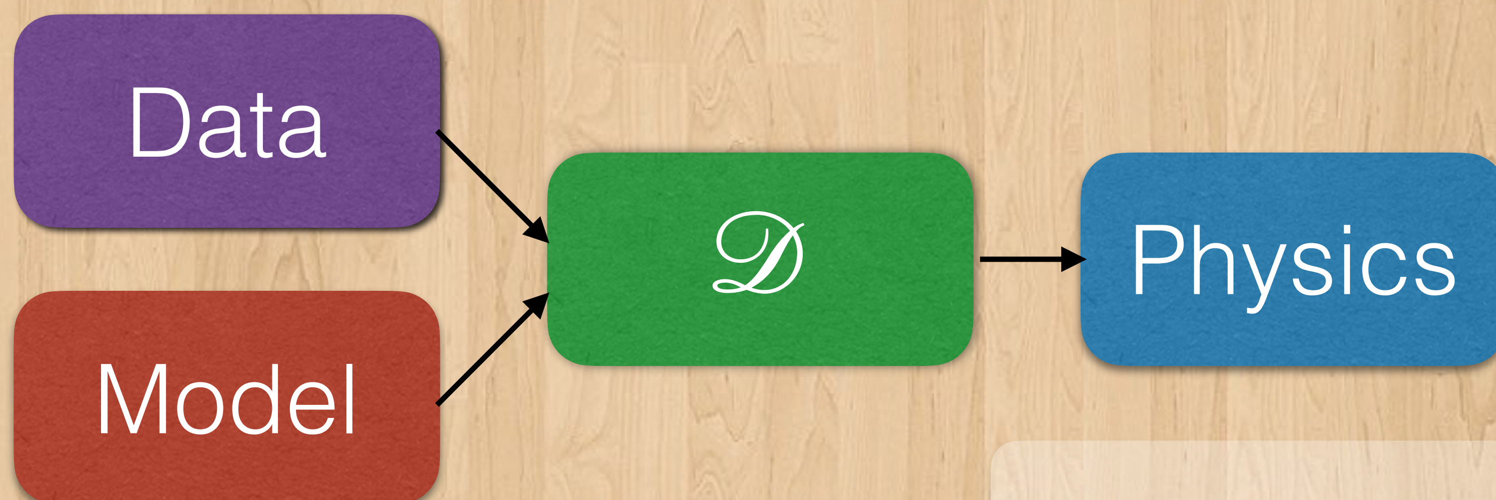
What / Why

Problems

Recent

Future

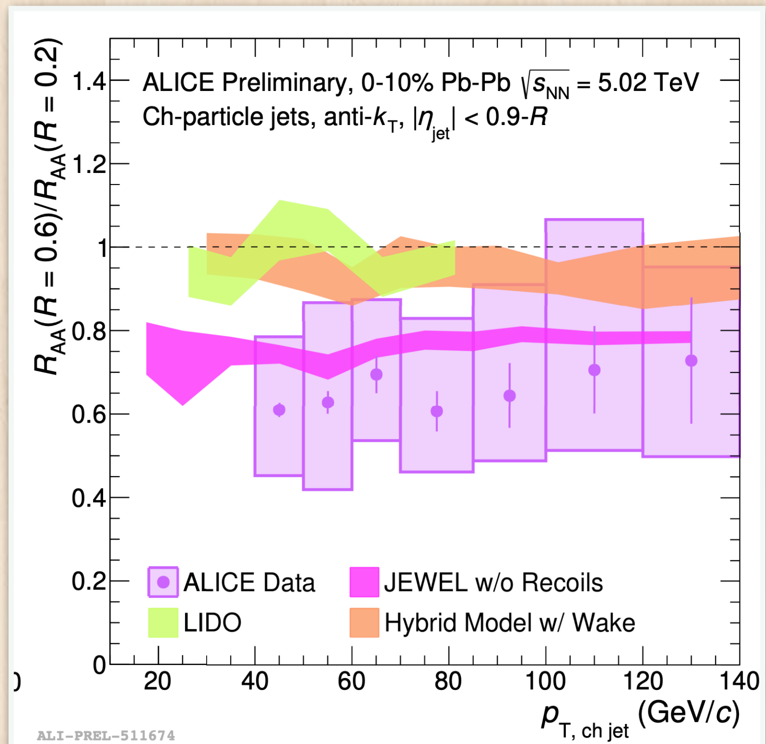
- Choice of data
- Scope of data to include
- Uncertainty treatment
- …

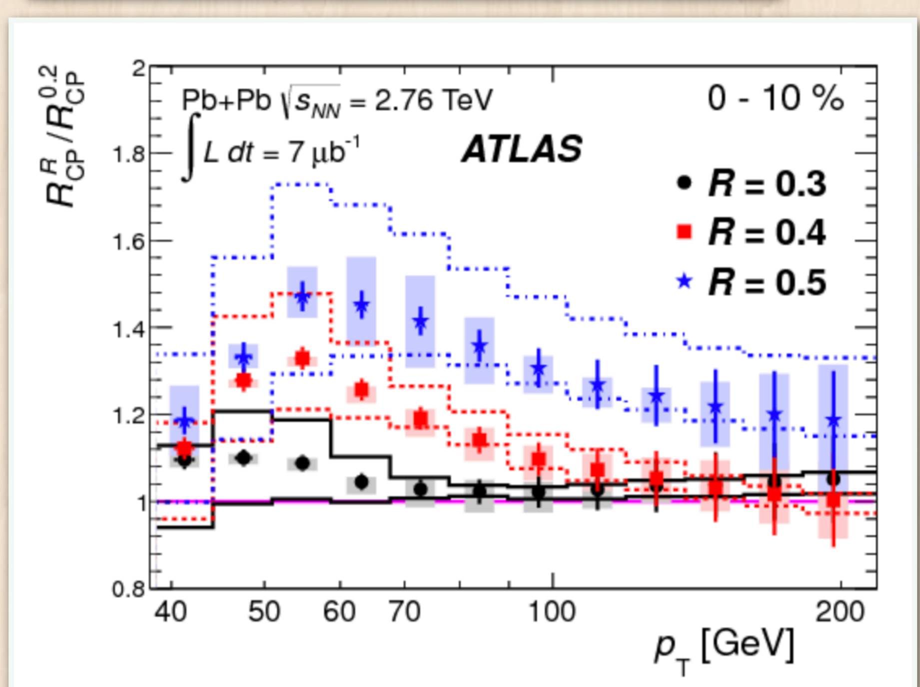


- Complexity of model
- Generators
- …

- Computational challenge
- Extensions
- …

Data choice





Important to pick a scope and include ALL eligible data

*unless there are known issues (ps. tension doesn't count)

High chance of bias if only a subset is used

Data scope

Systematically expand the scope to probe more physics

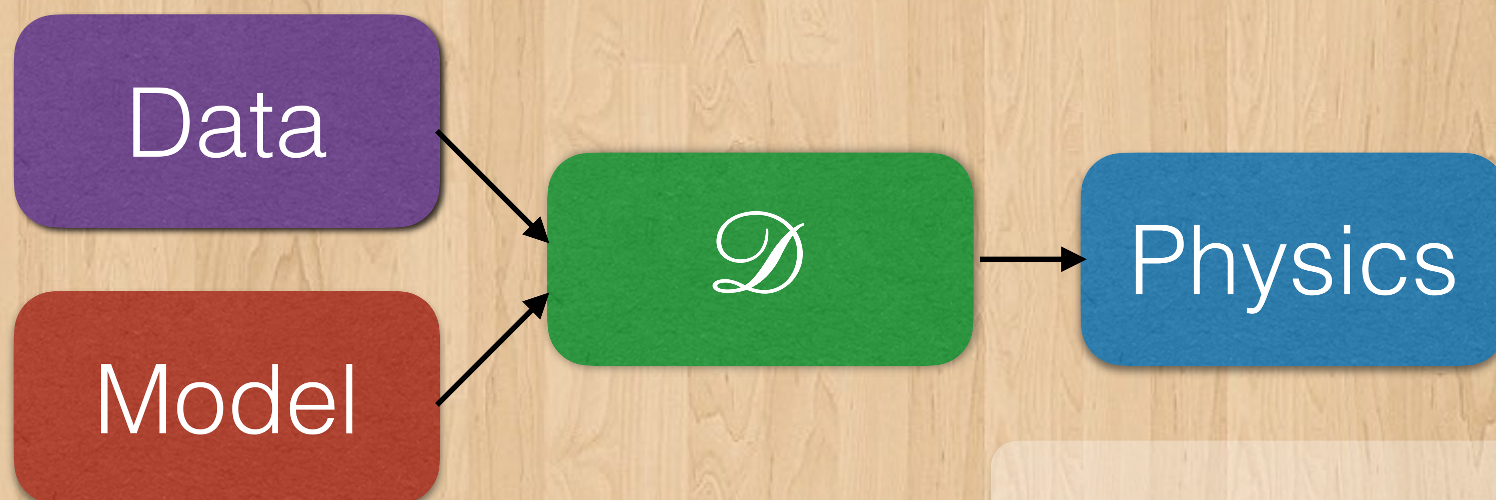
Example:

Hadron R_{AA} $\xrightarrow{+}$ Jet R_{AA} $\xrightarrow{+}$ Jet shape $\xrightarrow{+}$ …

Hadron R_{AA}	Jet R_{AA}	Jet shape
Single hard particle	Also particles in the vicinity	Shape of the softer parts

(Analogous systematic expansion of model complexity)

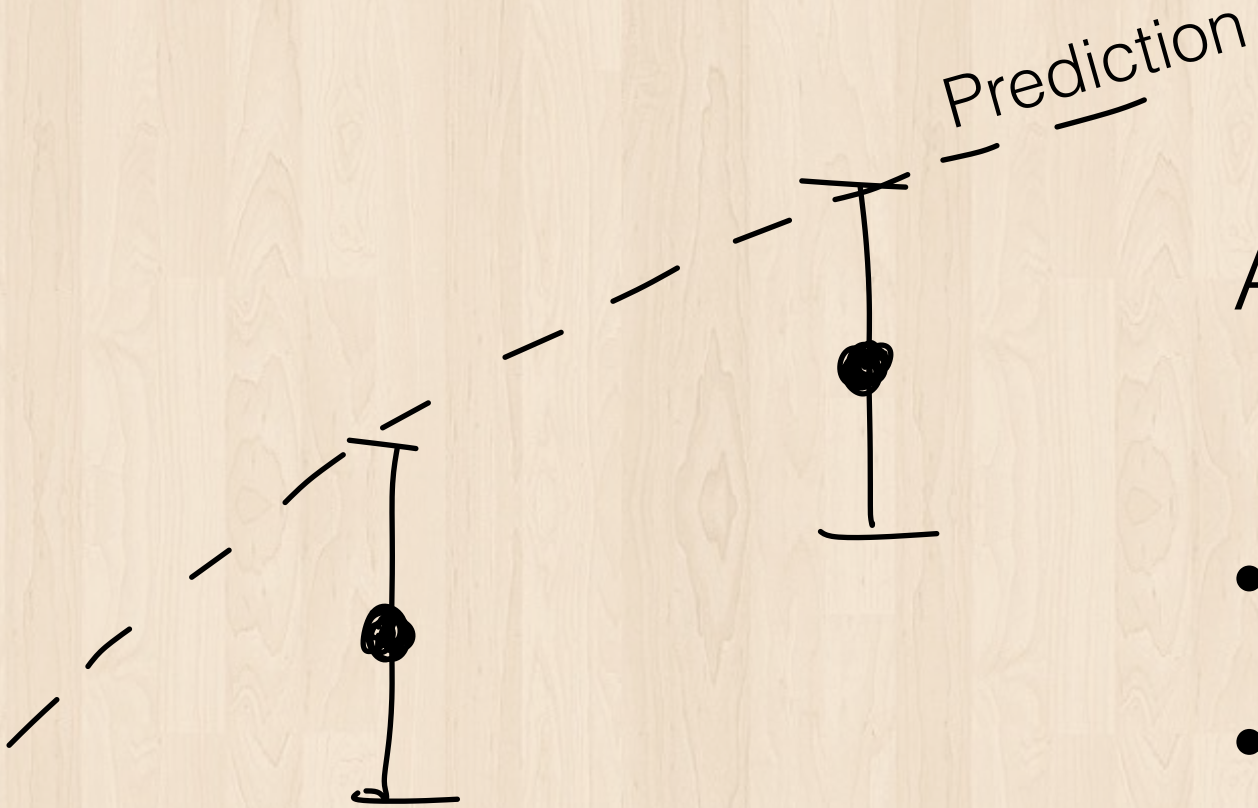
- Choice of data
- Scope of data to include
- <u>Uncertainty treatment</u>
- …



- Complexity of model
- Generators
- …

- Computational challenge
- Extensions
- …

Data uncertainty correlation



Agreement depends on uncertainty correlation

- Fully Correlated: 1σ
- Non-correlated: 2σ
- Anti-correlated: >2σ

Correlation is key!

Faithfully capturing the correlation is **crucial**

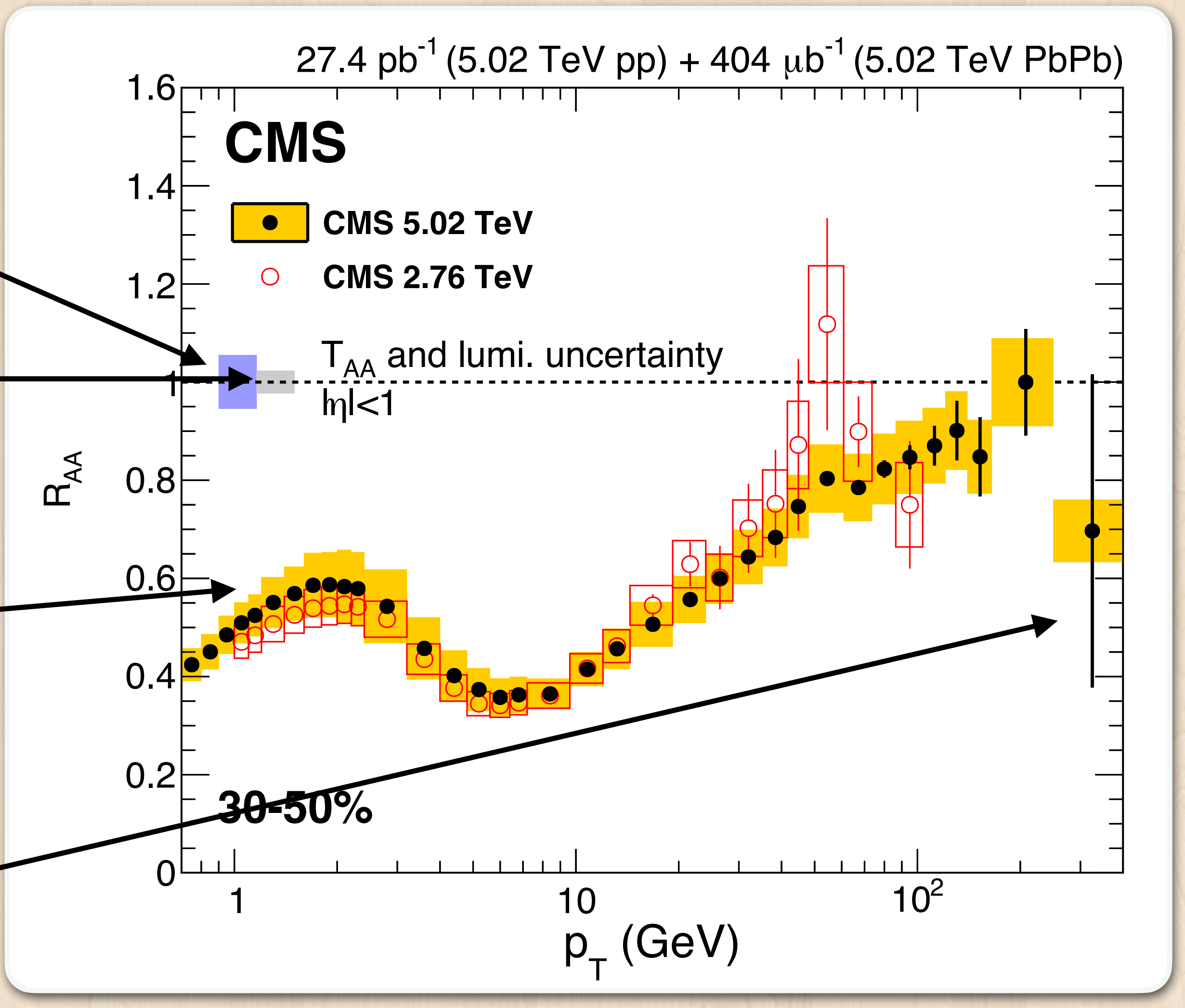
Capture Correlations

T_{AA}

Luminosity

Other Systematic Uncertainties

Statistical Uncertainty

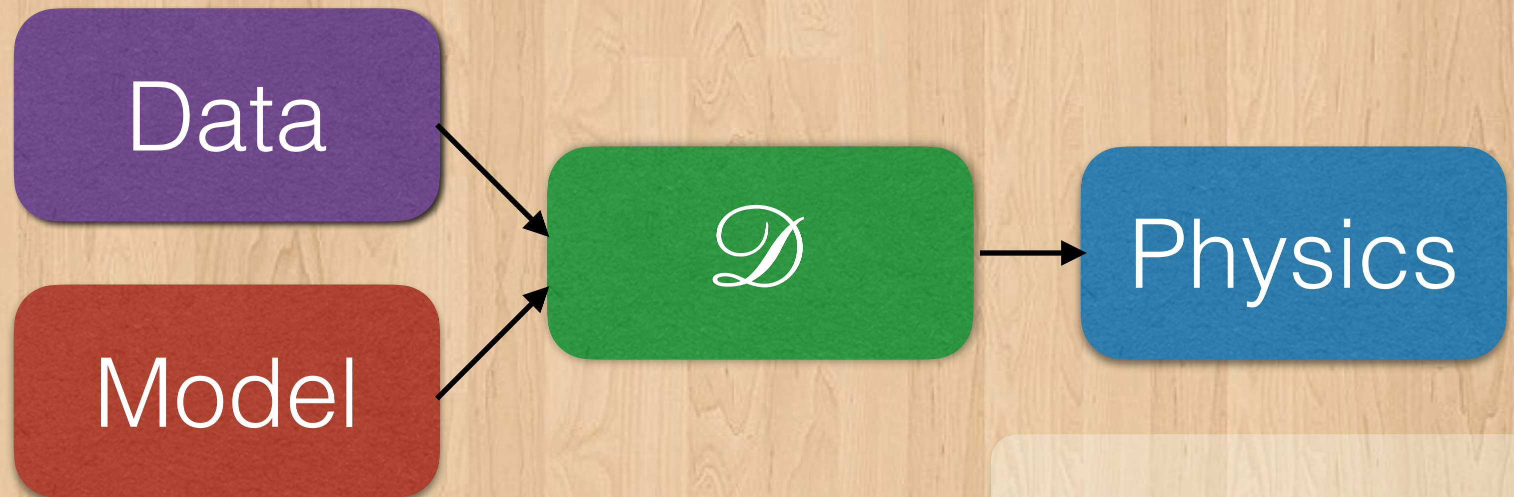


Many uncertainties with different correlations

As much as reasonably possible!

<u>More information from experiments will be nice</u>

- Choice of data
- Scope of data to include
- Uncertainty treatment
- …



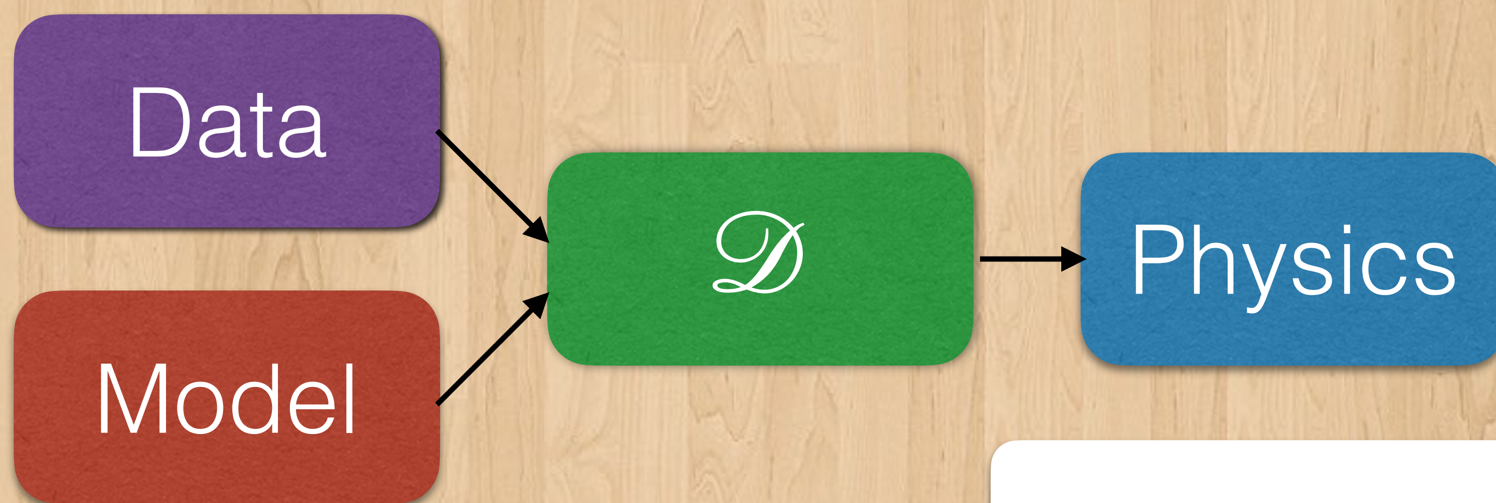
- Complexity of model
- Generators
- …

- Computational challenge
- Extensions
- …

Generators

- What Bayesian analysis does is to find the region of phase space matching the best to the data/truth
- If generator does not have required physics it's easy to misinterpret the result
    - Case for better vacuum shower modeling (for example)
- Ratios help but not everything is multiplicative

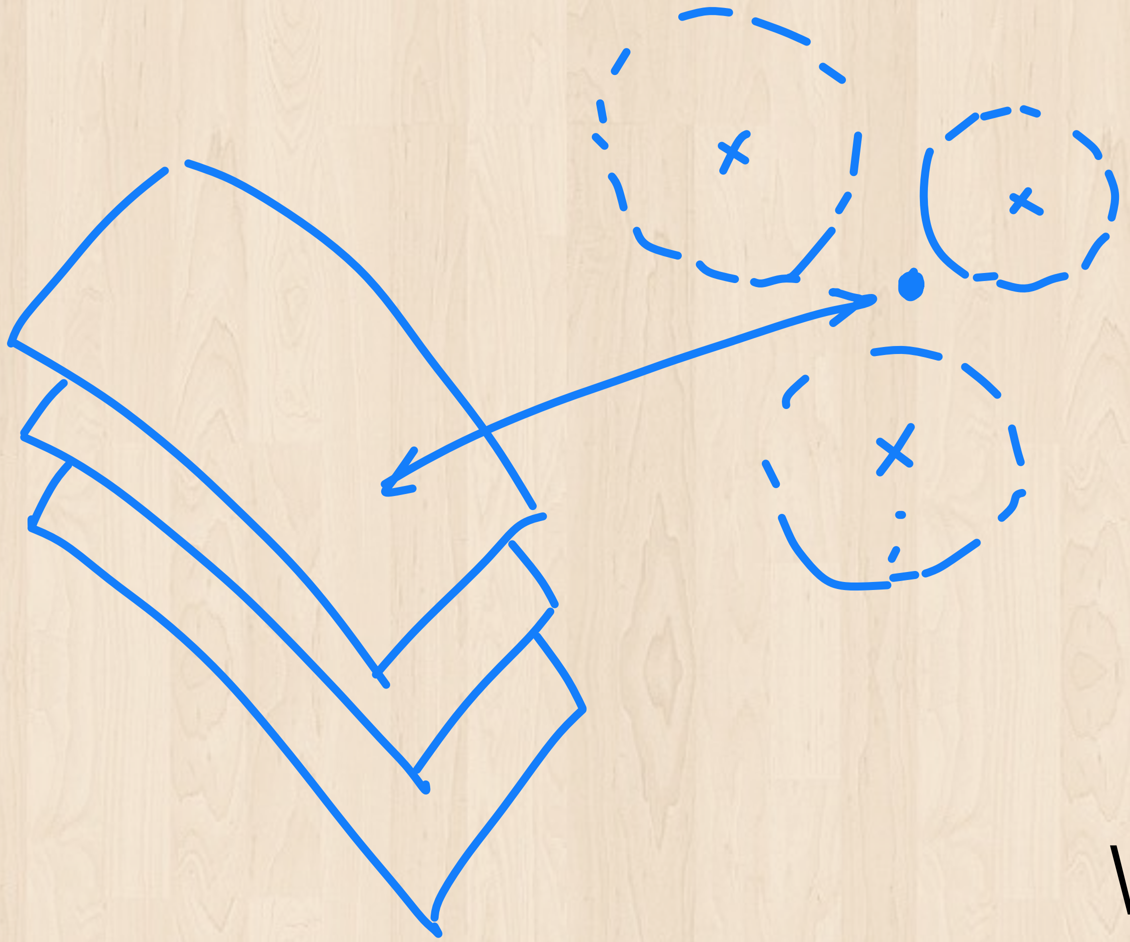
- Choice of data
- Scope of data to include
- Uncertainty treatment
- …



- Complexity of model
- Generators
- …

- Computational challenge
- Extensions
- …

Extension possibilities



Tension quantification
(in context of model)

Model selection
Model combination

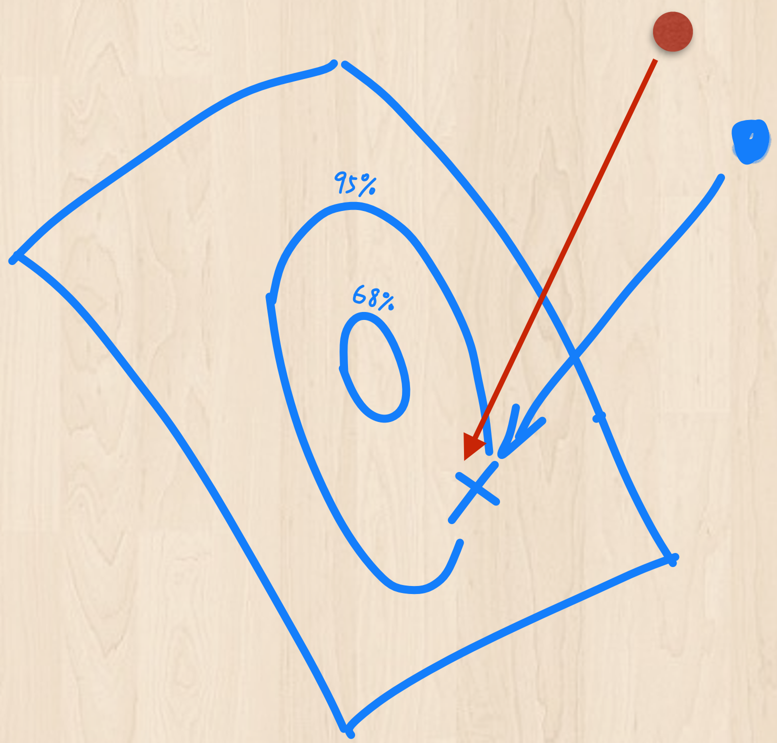
Event generation with
full posterior (not just MAP)
…

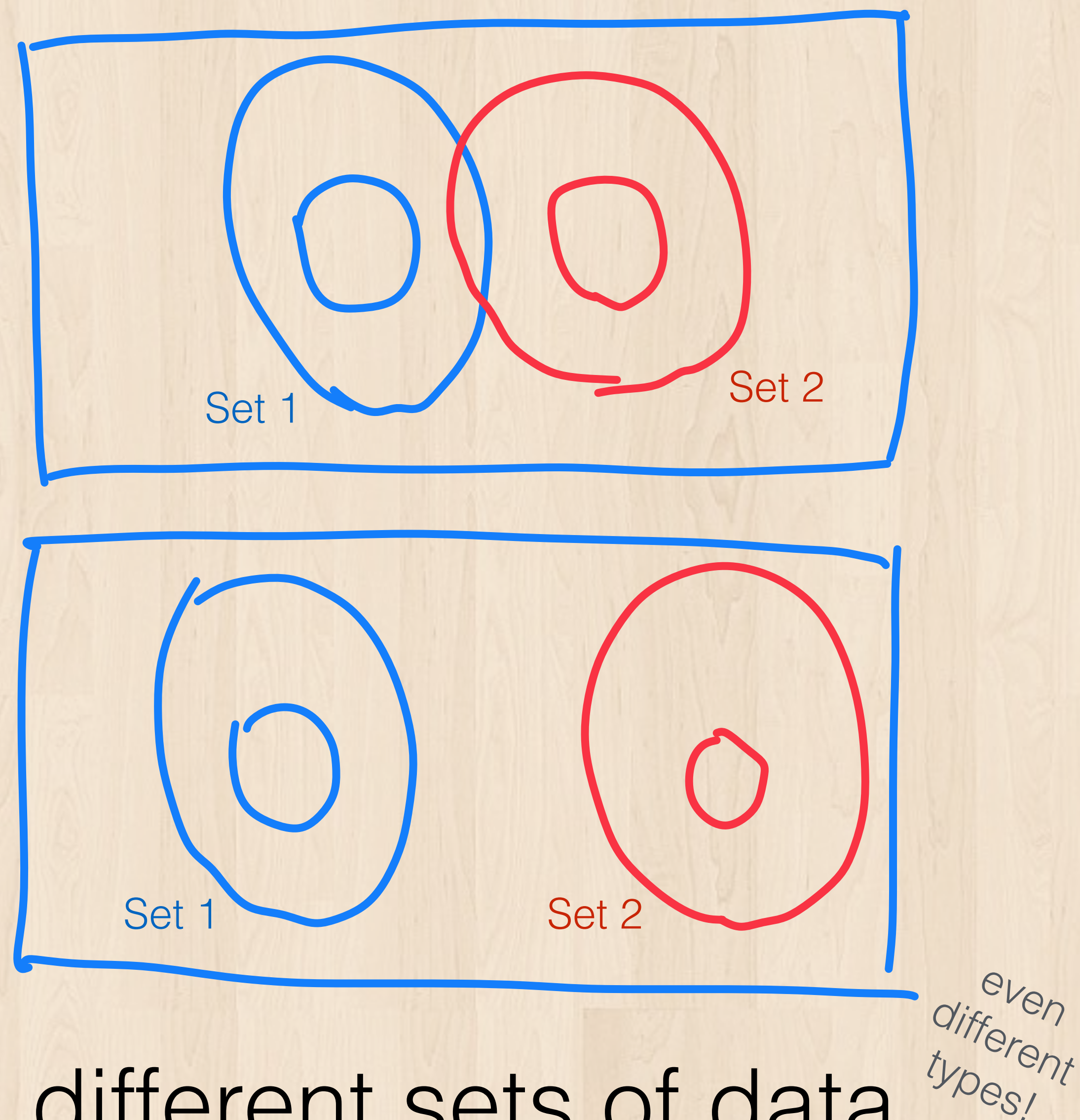
We're just getting started:

Many possibilities with **using the Bayesian analysis as a tool** to probe different things

Tension quantification

Bayesian posterior = data vs. model point compatibility

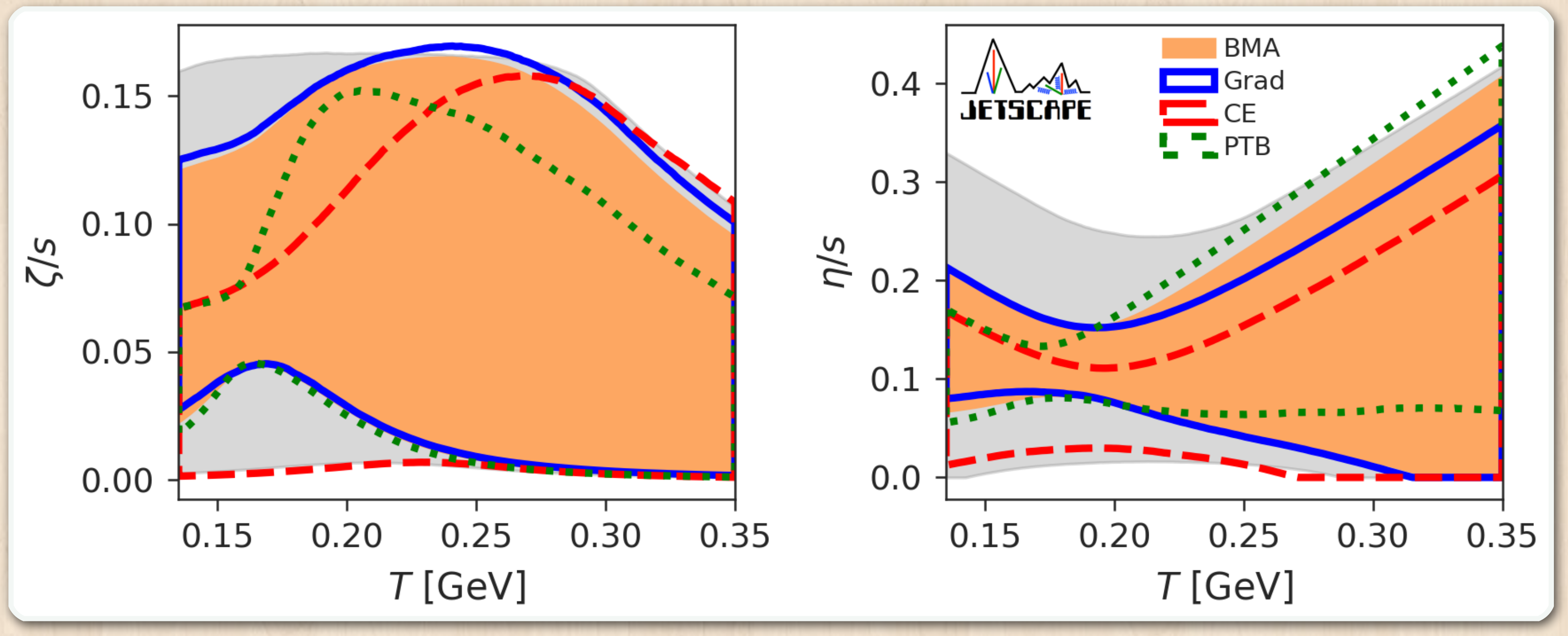




Bayesian analysis with different sets of data
=> controlled way to study compatibility

Combining: model averaging

Application of Bayesian model averaging



Grad/CE/PTB: different particlization models

Combine using the Bayesian evidence

Rigorous data-driven way to combine the models

Phys. Rev. Lett. 126, 242301 (2021)

Concluding remarks

What / Why	Problems
Recent	Future

Rigorous data-model comparison

Data-model "distance": Bayesian posterior

Problems

Recent

Future

Rigorous data-model comparison

Data-model “distance”: Bayesian posterior

Different code => JETSCAPE framework

Large parameter space => design point + interpolation

Recent

Future

Rigorous data-model comparison

Data-model “distance”: Bayesian posterior

Different code => JETSCAPE framework

Large parameter space => design point + interpolation

Soft sector: bulk properties

Hard sector: first step $\hat{q}$

Future

Rigorous data-model comparison

Data-model “distance”: Bayesian posterior

Different code => JETSCAPE framework

Large parameter space => design point + interpolation

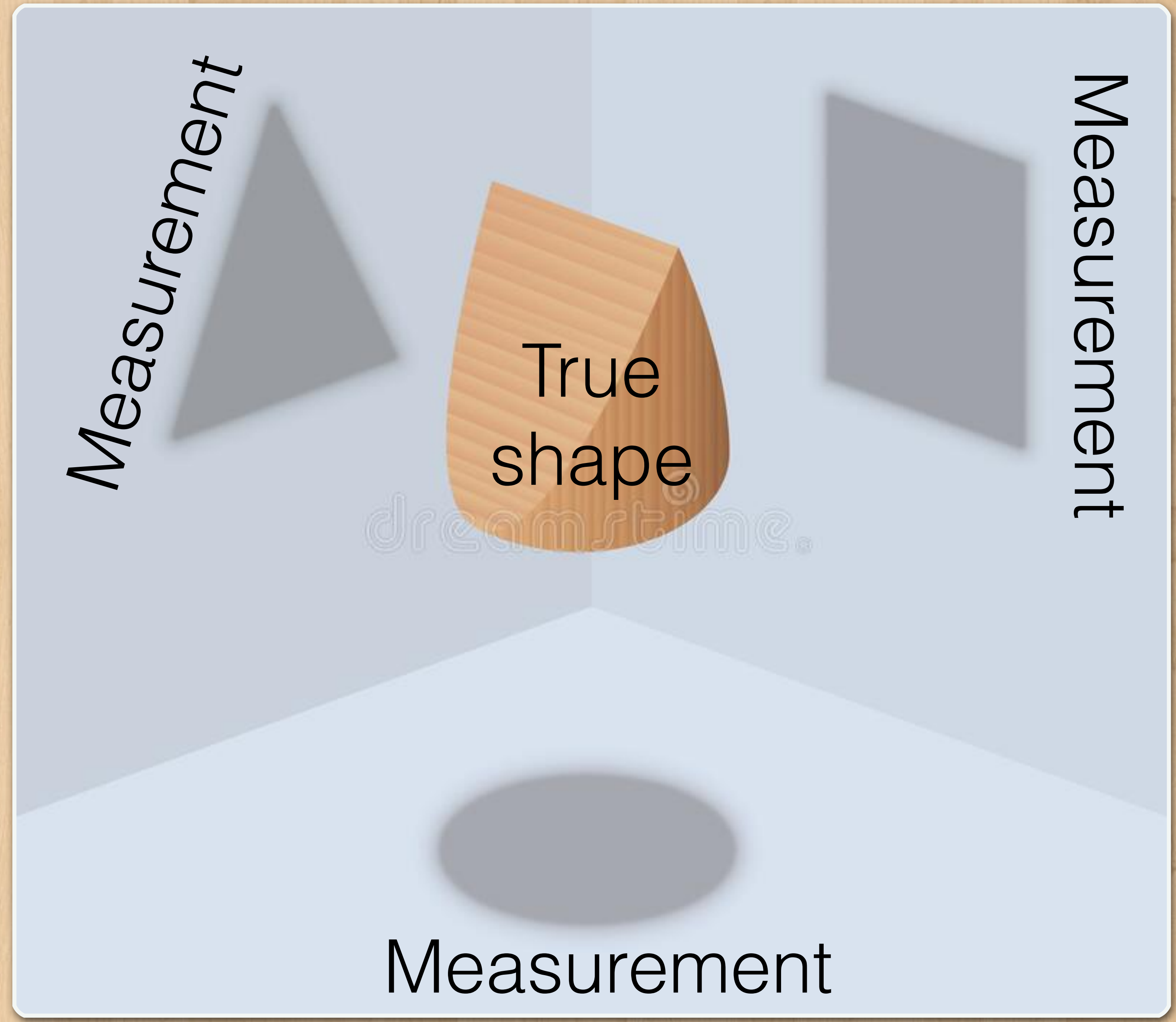
Soft sector: bulk properties

Hard sector: first step $\hat{q}$

Better data handling

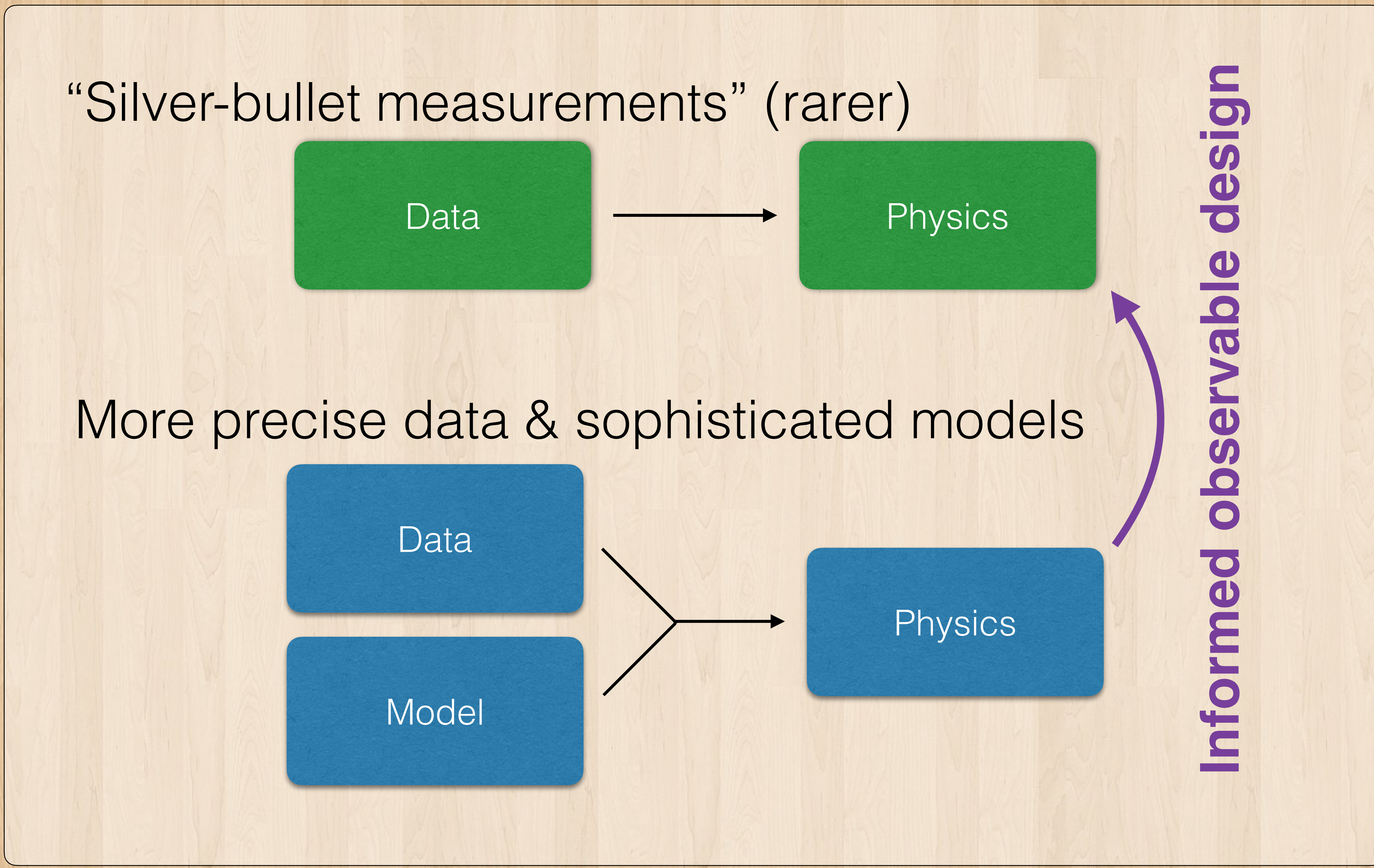
Progressively more data and model complexity

Many extensions possible


Measurement
True
shape
Measurement
Measurement

Backup Slides Ahead

Rigorous model-data comparison



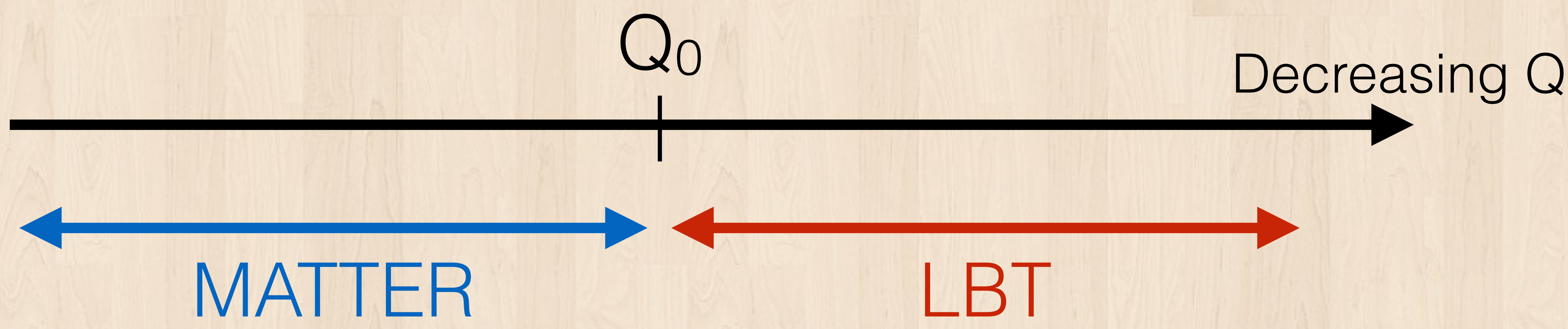
Computational challenge

- Complex parameter space & more precise data
  - More calculation needed both in precision and number of points to run over
- Challenge in organizing large-scale calculation: highly non-trivial task, operate more similar to large experiment collaborations
  - Placement of design points more important than ever
- Challenge in speeding things up

Simulation Setup

Label	Comment	Parameters
MATTER	MATTER all the way	A, B, C, D
LBT	LBT all the way	A, B, C, D
MATTER+LBT1	Same formula as above, but just switch at Q_0	A, B, C, D, Q_0
MATTER+LBT2	Virtuality Q used instead of E in the MATTER-only term	A, C, D, Q_0

Multi-stage approach



Implement a "switching scale" Q_0,
where we switch from MATTER to LBT

Use the same $\hat{q}$ parameterization on both models

"MATTER+LBT1": same $\hat{q}$ formula as before

$$\frac{\hat{q}}{T^3} \propto A \frac{\ln(E/\Lambda) - \ln(B)}{\ln^2(E/\Lambda)} + C \frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}$$

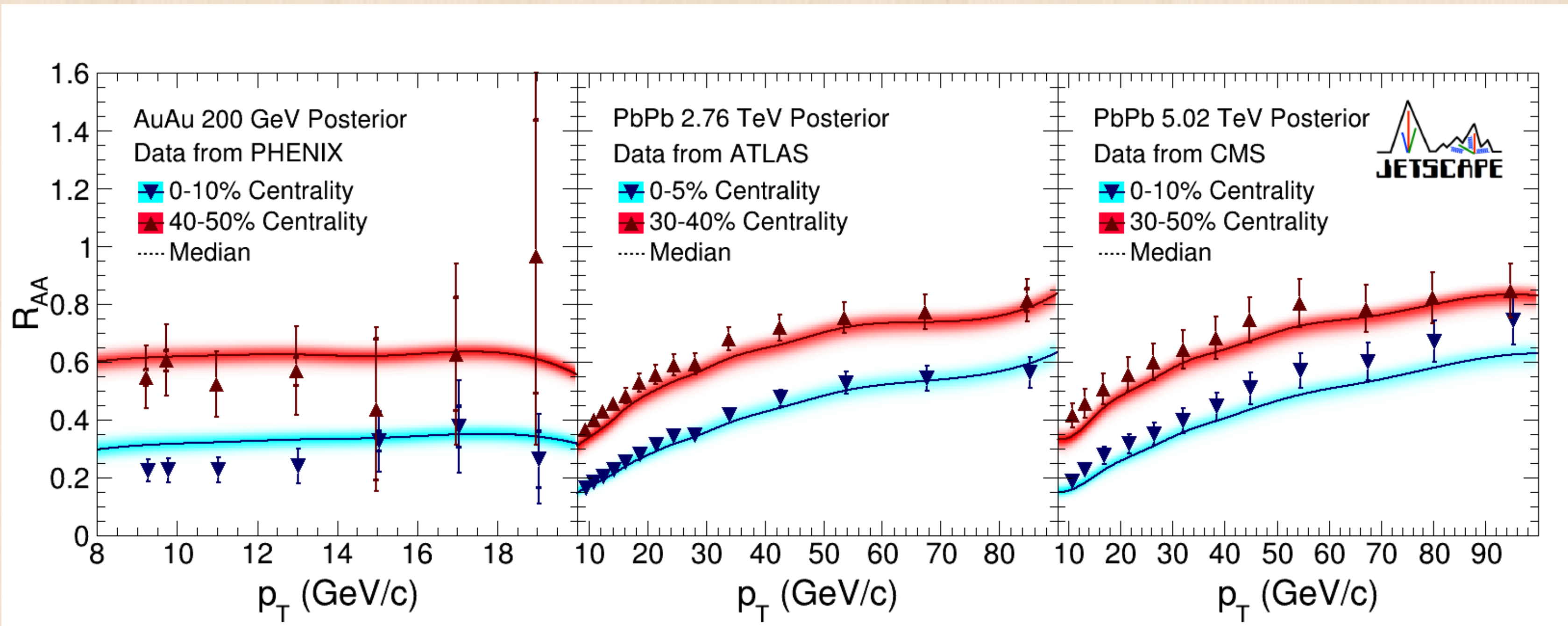
Multi-stage approach

MATTER+LBT2 parameterization

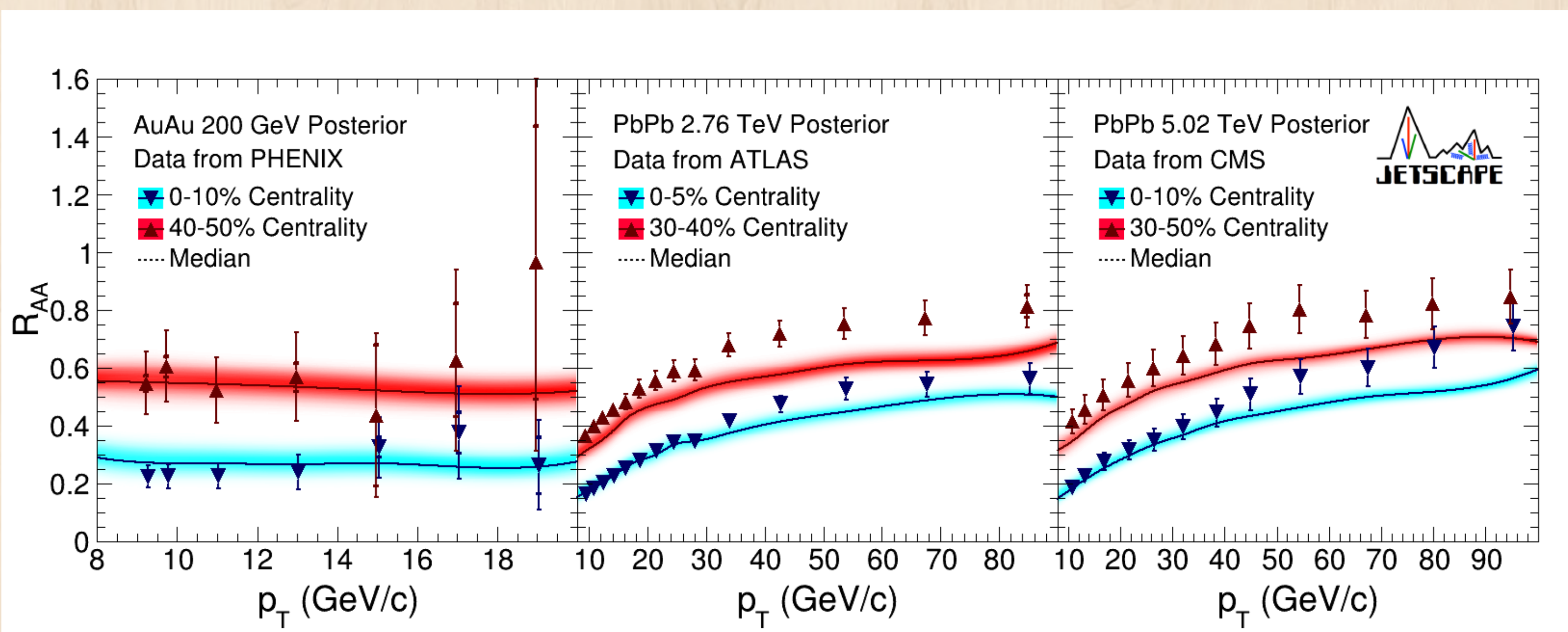
$$\frac{\hat{q}}{T^3} \propto \underbrace{A\frac{\ln(Q/\Lambda) - \ln(Q_0/\Lambda)}{\ln^2(Q/\Lambda)}\theta(Q - Q_0)}_{\text{MATTER-only term}} + \underline{C\frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}}$$

Switch to virtuality instead of energy to better capture the nature of virtuality evolution in MATTER

Multi-stage approach: (1)



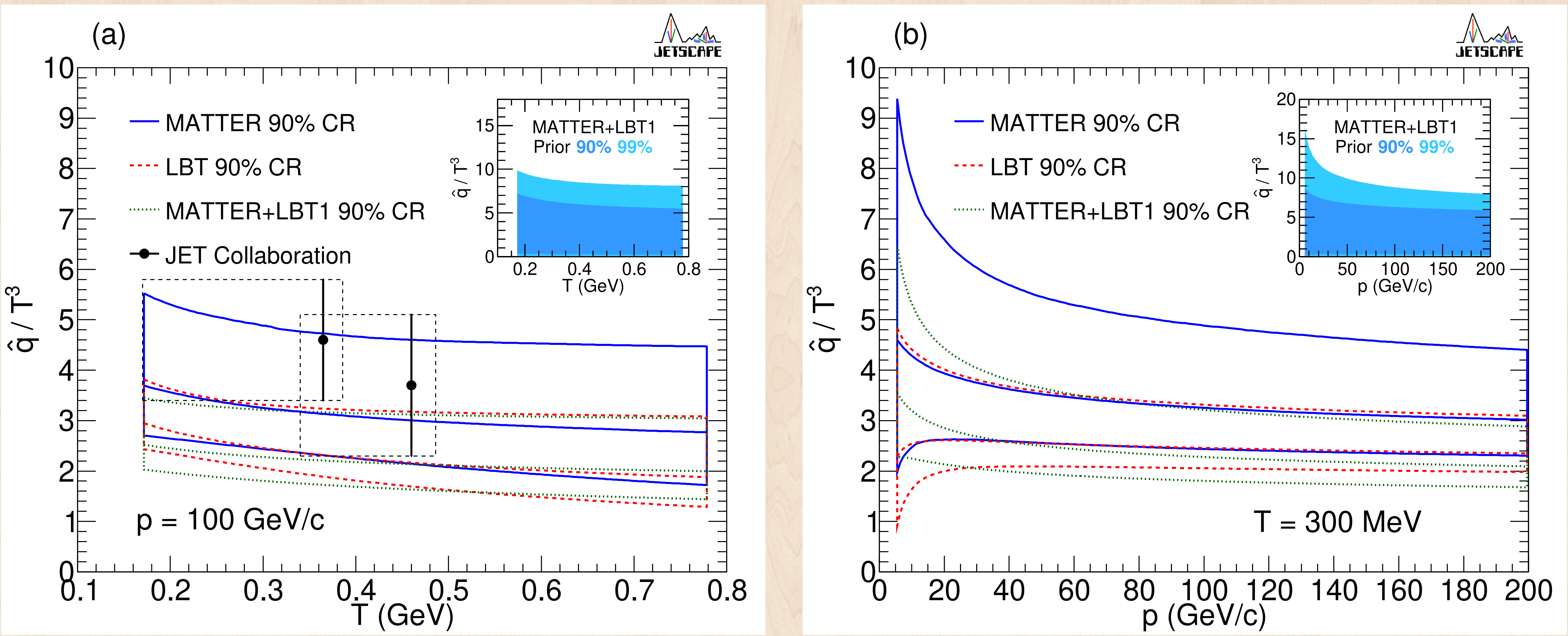
LBT-only



MATTER+LBT1

Inclusion of Q_0 does not improve agreement much

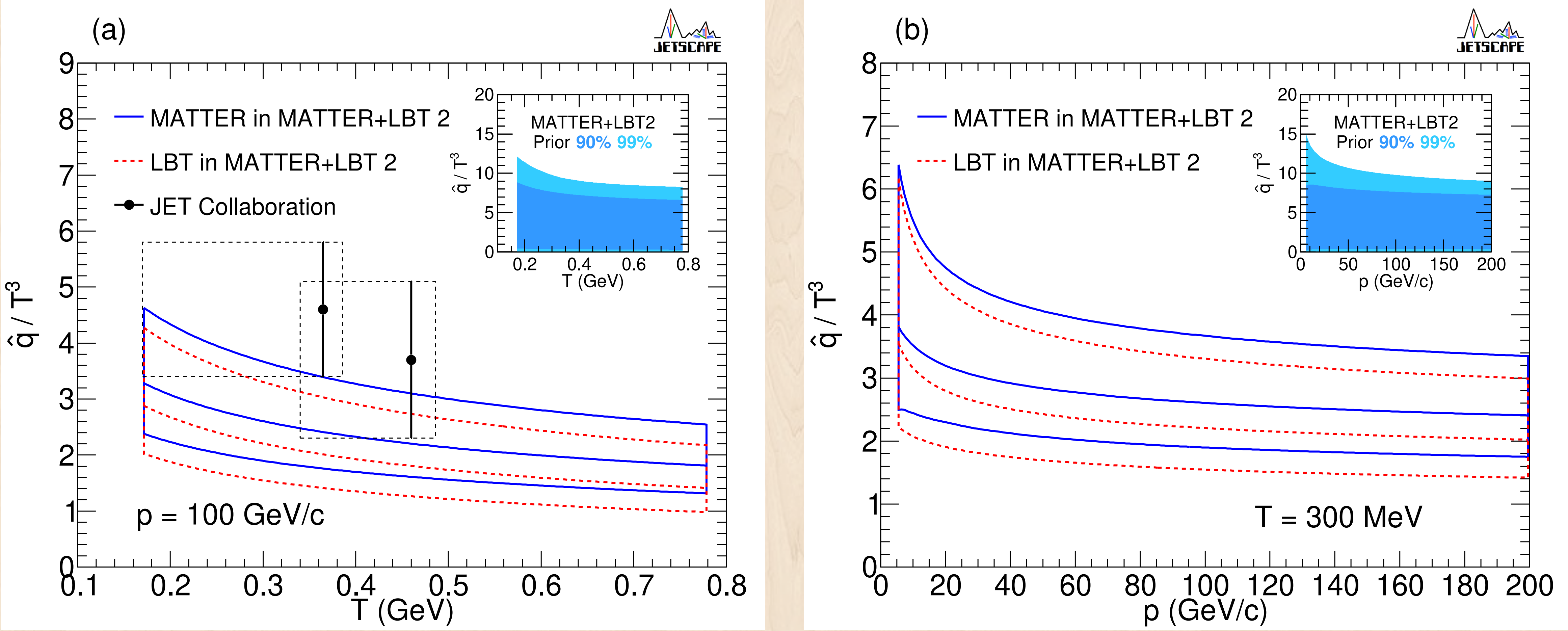
Multi-stage approach: (1)



MATTER+LBT1 ≲ MATTER or LBT alone

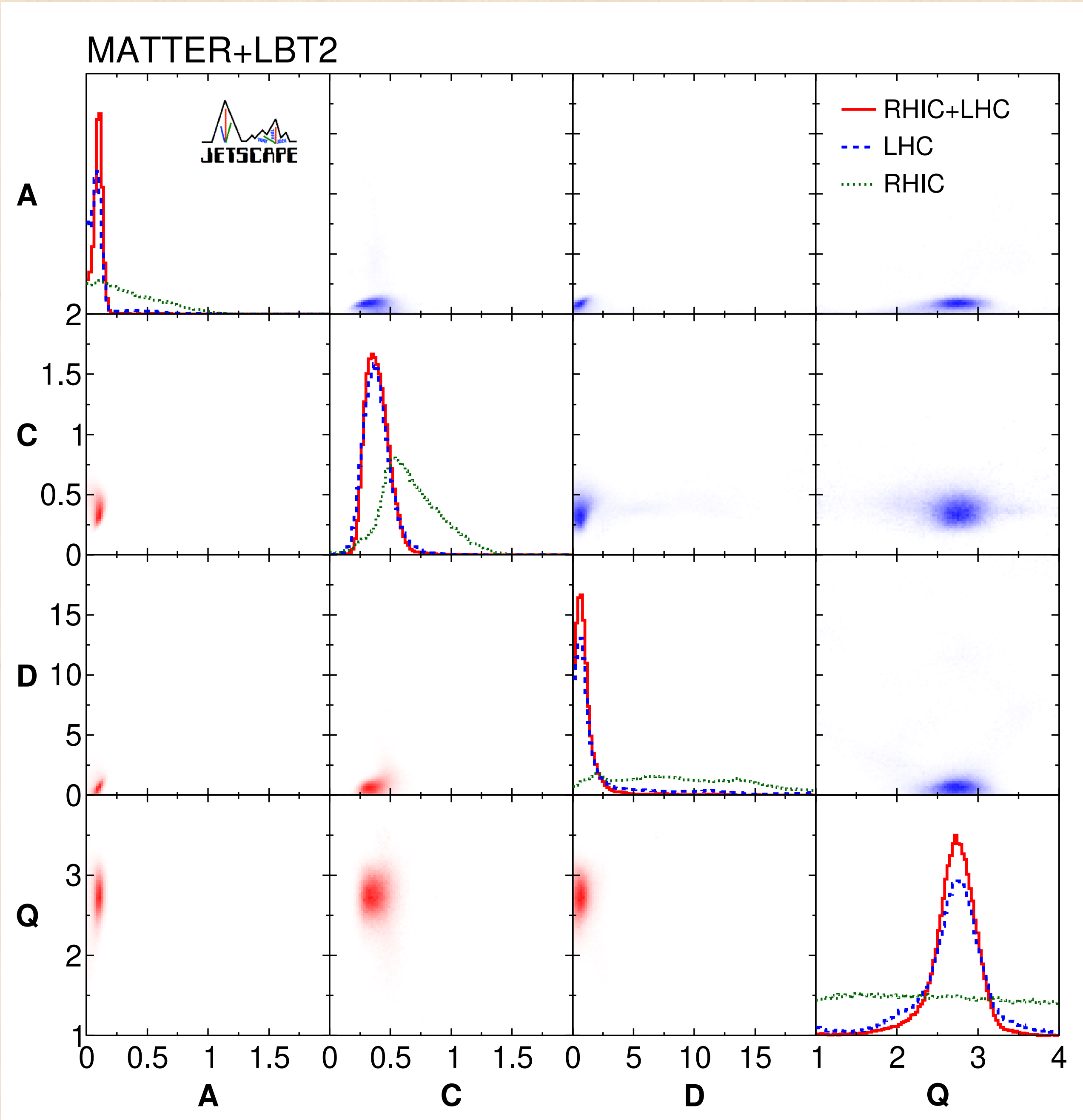
Multi-stage approach: (2)

$$\frac{\hat{q}}{T^3} \propto A \frac{\ln(Q/\Lambda) - \ln(Q_0/\Lambda)}{\ln^2(Q/\Lambda)} \theta(Q - Q_0) + C \frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}$$



MATTER > LBT ~ by construction ($\theta(Q - Q_0)$)

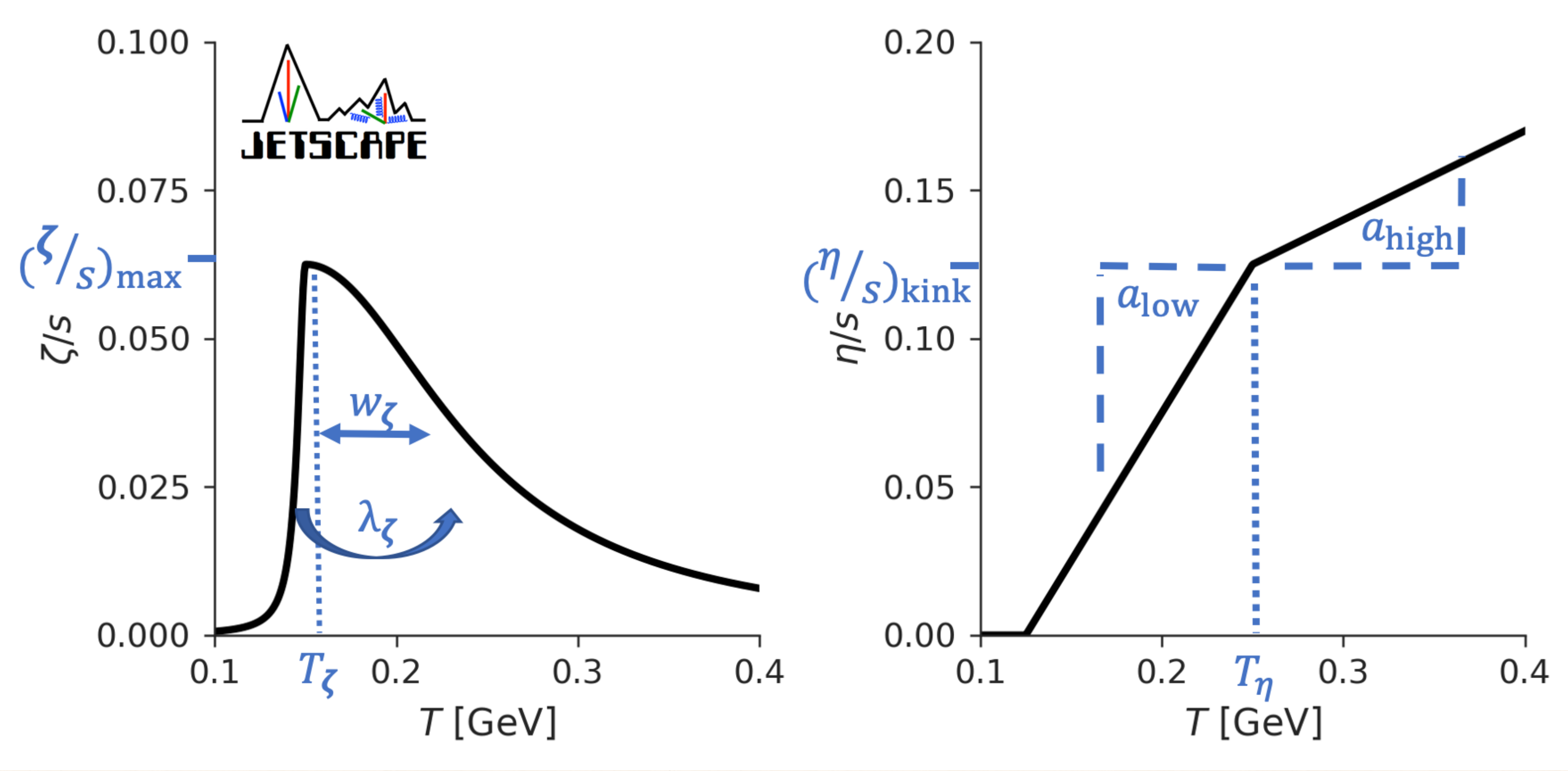
Multi-stage approach: (2)



Consistent picture compared to MATTER+LBT1 setting

Q_0 slightly higher but consistent

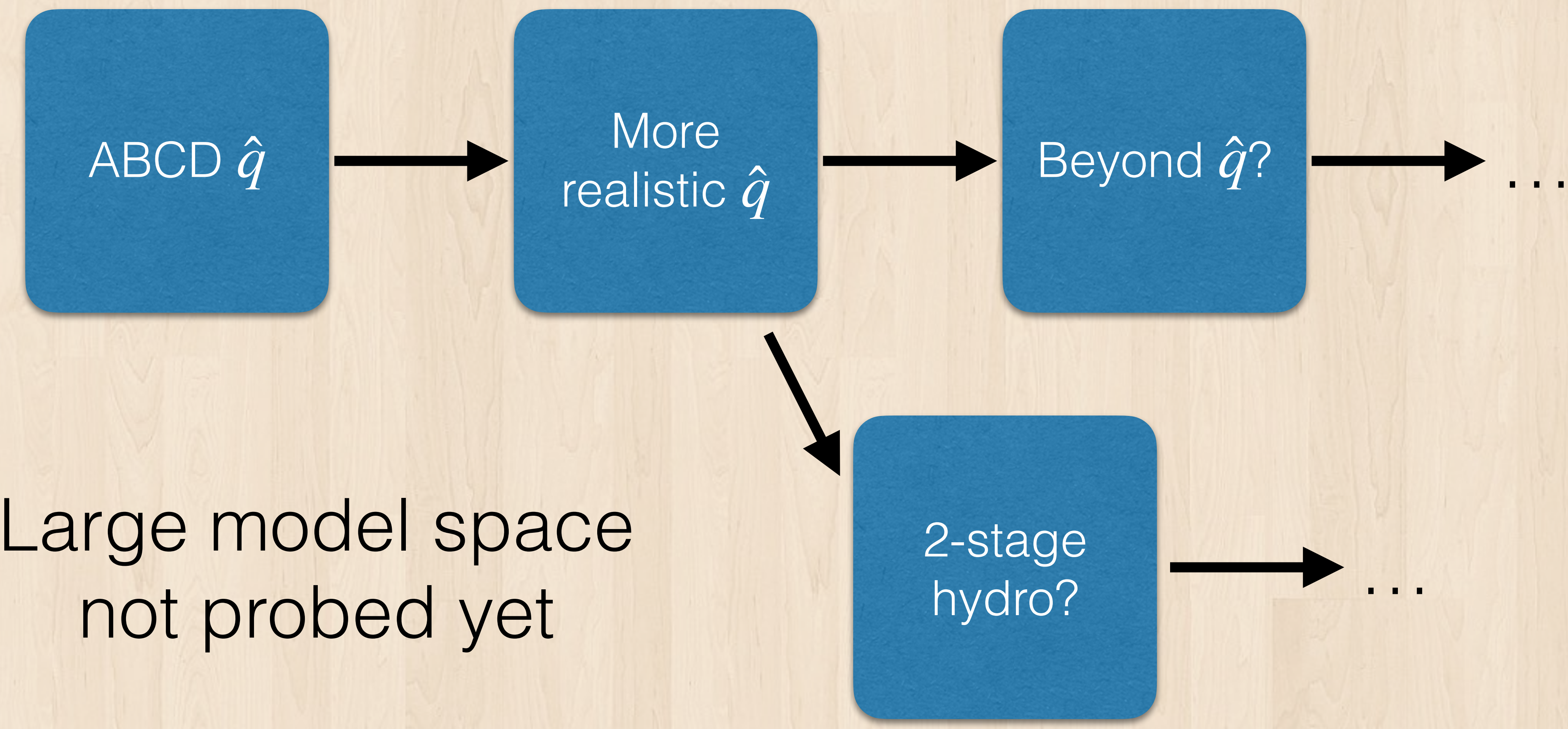
Viscosity parameterization



Model complexity

As the data scope expands we also need
to expand on the modeling side

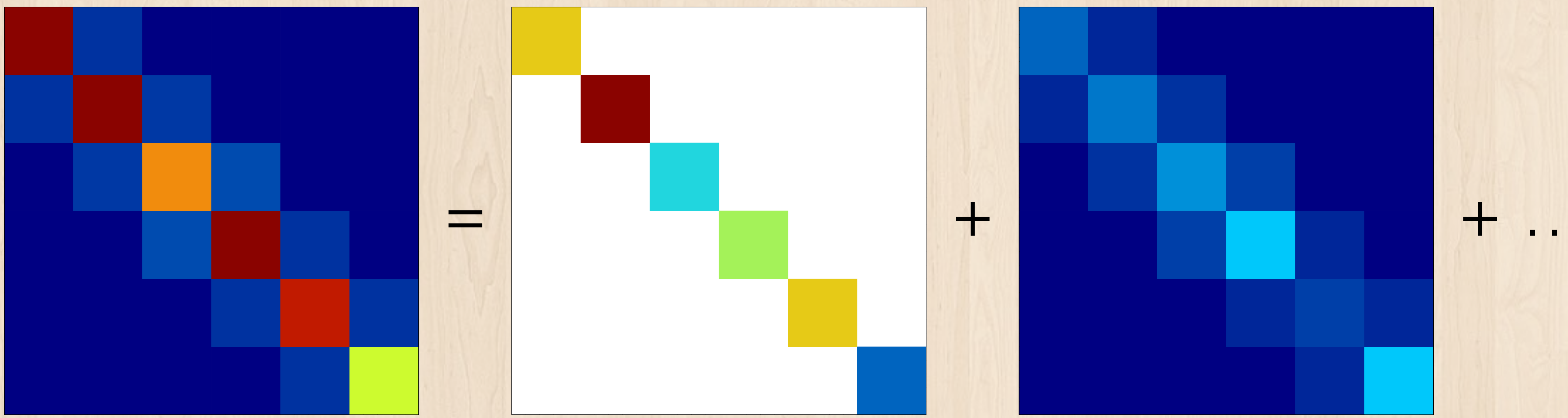
Example:



Large model space
not probed yet

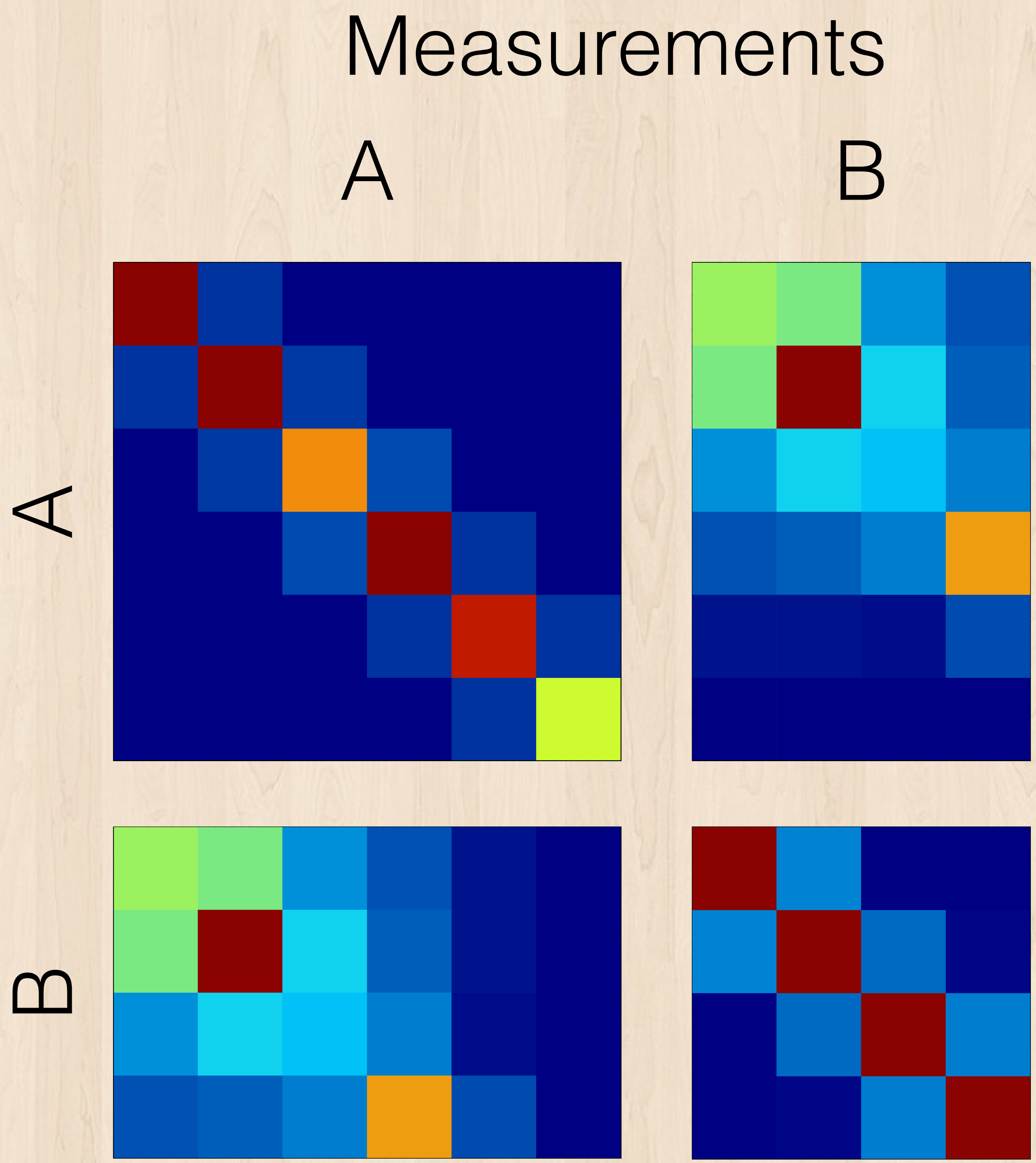
Capture Correlations

Full Covariance Uncorrelated Somewhat correlated



Add up the covariance matrices source-by-source

Capture Correlations



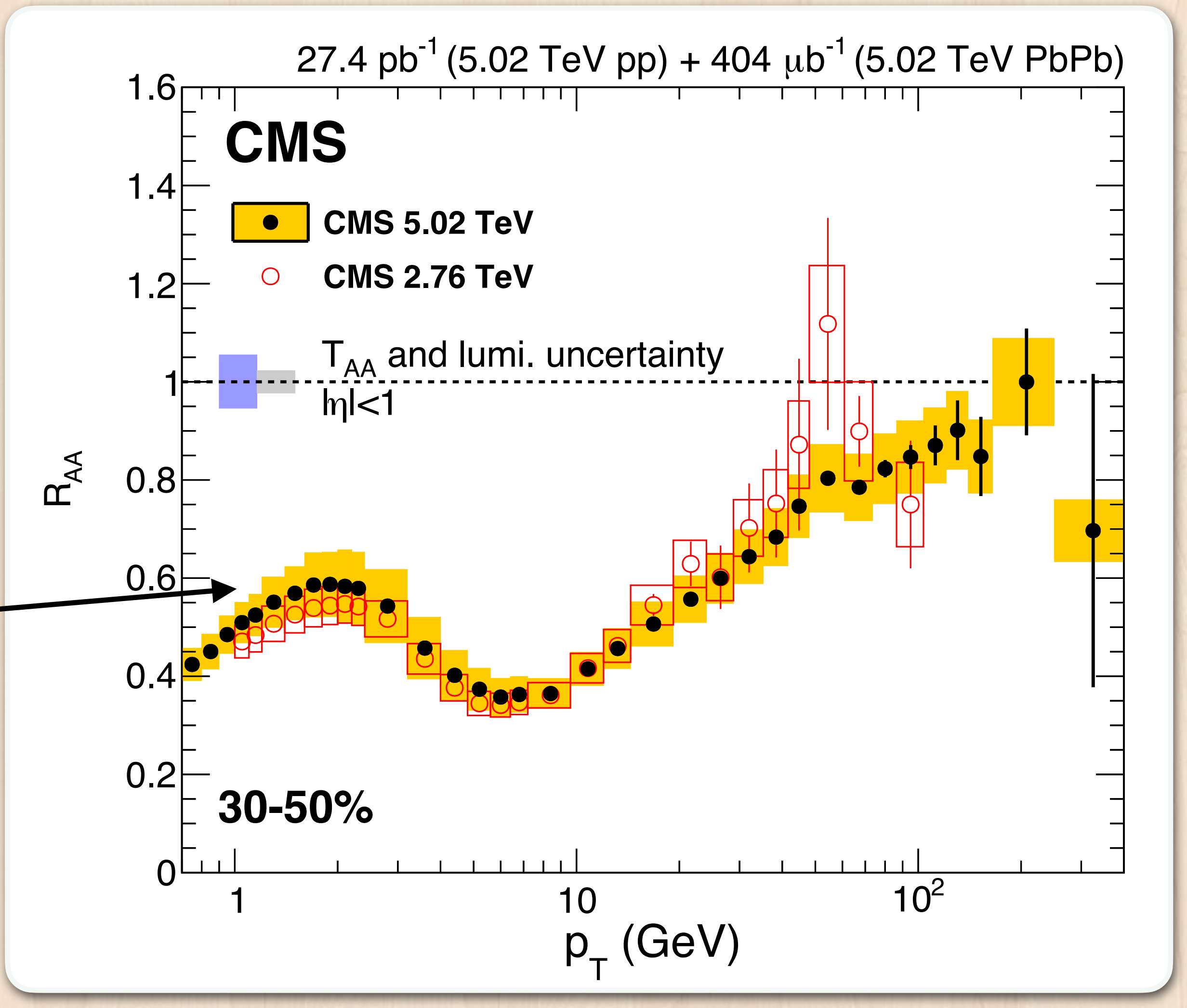
Some uncertainties are correlated across measurements

For example luminosity uncertainty from the same experiment

T_{AA} across experiment

Capture Correlations

Unfortunately, experiments do not provide full correlation matrix 😢



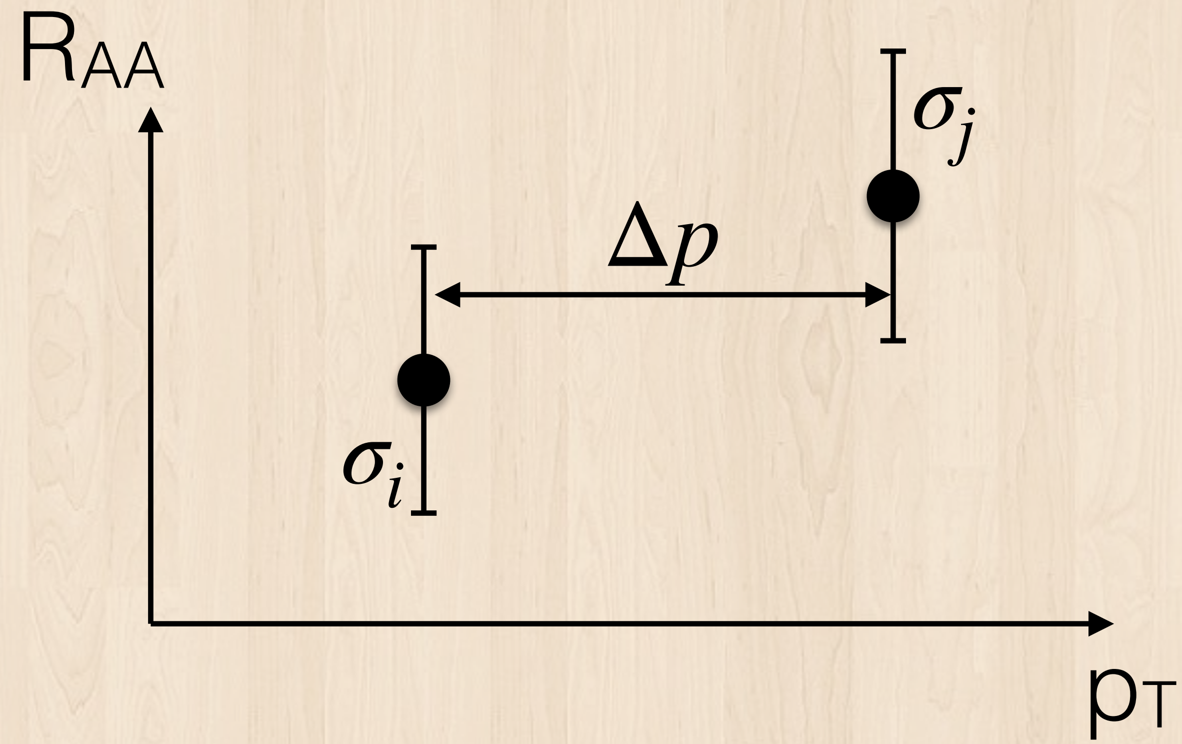
Other Systematic Uncertainties

= “Everything else”

Capture Correlations

…and we are forced to make guesses

$$\Sigma_{ij} \sim \sigma_i \sigma_j \exp\left(- \left| \frac{\Delta p}{\ell} \right|^{1.9} \right)$$



In the $\hat{q}$ case, we guess the correlation using a correlation length ℓ = 0.2 x (max p_T range) for the “catch-all” uncertainty*

* cross check with ℓ = 10