LIPEI DU

UC BERKELEY & LBNL

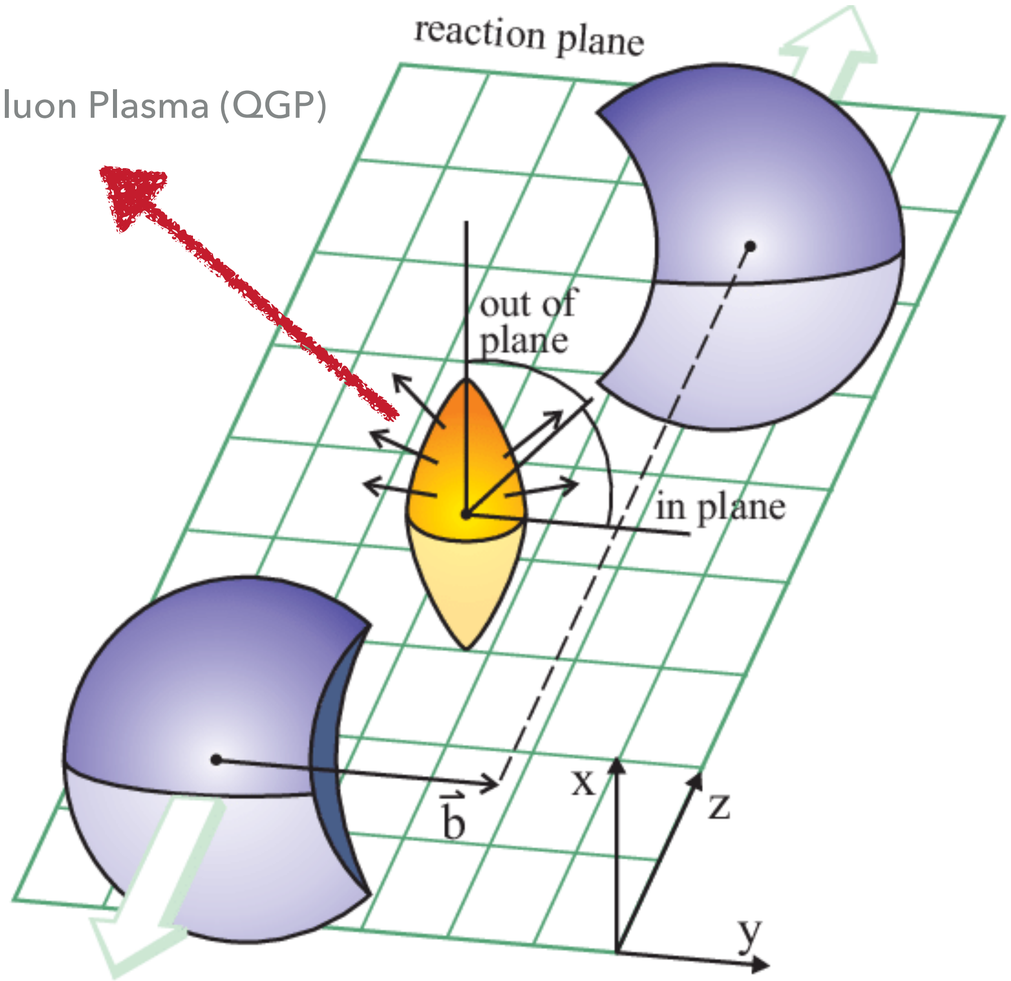
BAYESIAN EXPLORATION OF SOFT-HARD INTERPLAY IN HEAVY-ION COLLISIONS

BUQ MEETING

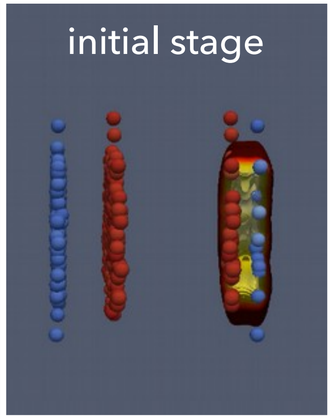
OCTOBER 22, 2025

HEAVY-ION COLLISIONS

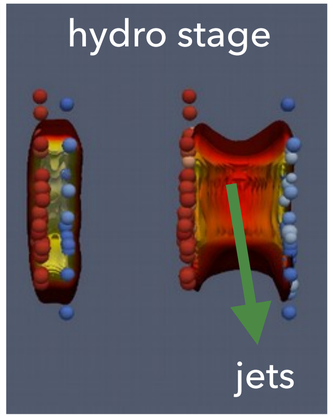
Quark-Gluon Plasma (QGP)



time

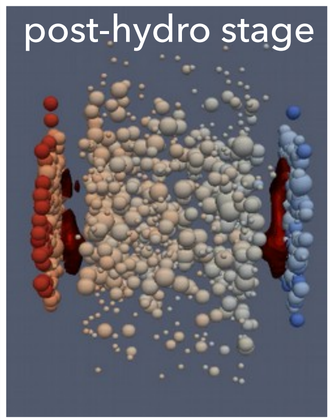


initial conditions
(Trento+free-streaming)



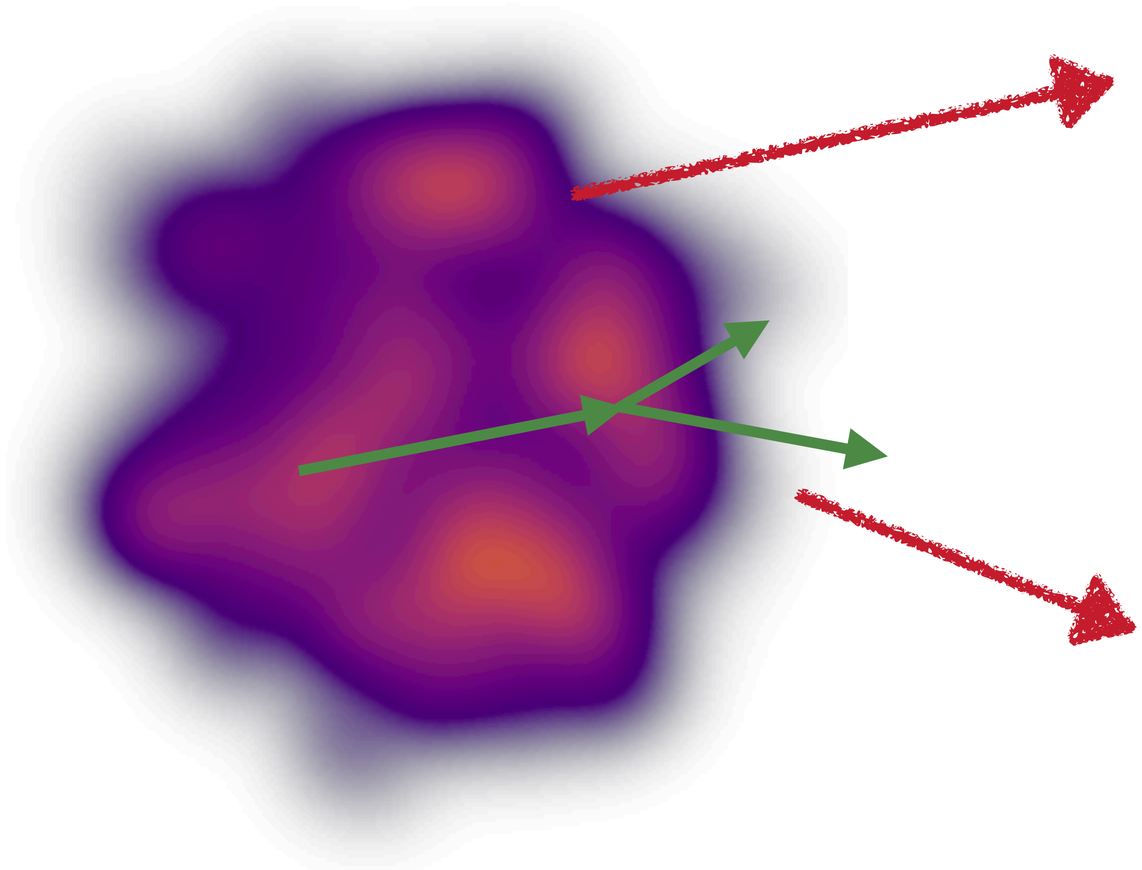
viscous hydrodynamics
(MUSIC)

particle sampler
(iSS)



hadronic transport
(SMASH)

SOFT AND HARD SECTORS



QGP (bulk medium) → low p_T particles

transport coefficients: viscosity $\eta/s, \zeta/s, \ldots$ ← observables: anisotropic flows v_2, v_3, etc.; mean p_T

soft sector

energetic particles → high p_T particles

transport coefficients: jet transverse momentum diffusion coefficient $\hat{q}, \ldots$ ← observables: nuclear modification factor $R_{AA}, \ldots$

hard sector

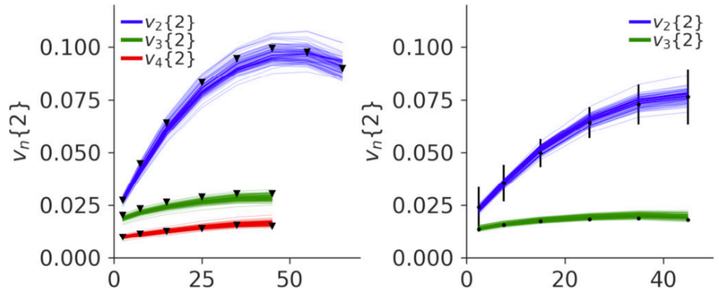
$$P(\theta_s, \theta_h \mid D_s, D_h) \propto P(D_s, D_h \mid \theta_s, \theta_h) \cdot P(\theta_s, \theta_h)$$

SEPARATE INFERENCES

soft sector

QGP (bulk medium) → low p_T particles

transport coefficients: viscosity $\eta/s, \zeta/s, \ldots$ ⇐ observables: anisotropic flows v_2, v_3, etc.; mean p_T



$$P(\theta_s \mid D_s) \propto P(D_s \mid \theta_s) \cdot P(\theta_s)$$

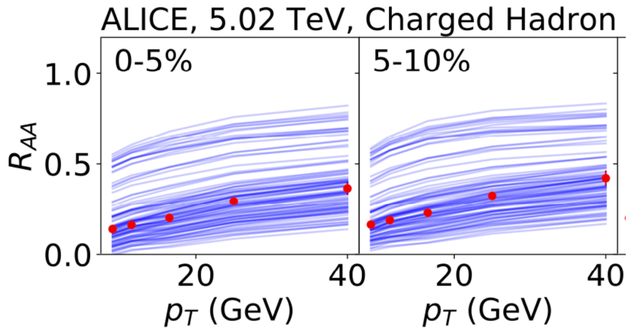
- missing constraints from D_h

hard sector

energetic particles → high p_T particles

transport coefficients: jet transverse momentum diffusion coefficient $\hat{q}, \ldots$ ⇐ observables: nuclear modification factor $R_{AA}, \ldots$

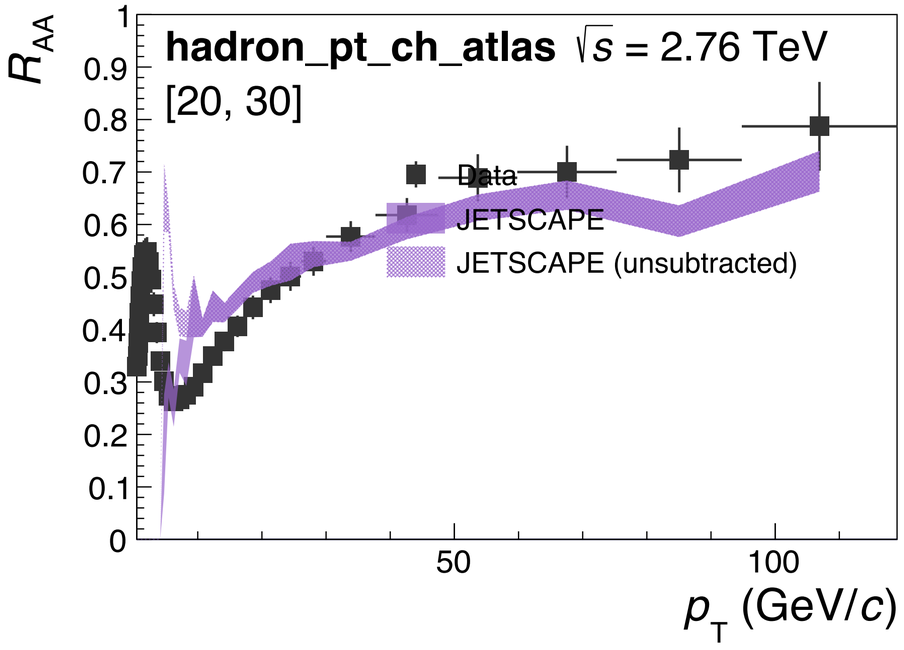
bulk medium evolution with fixed θ_s



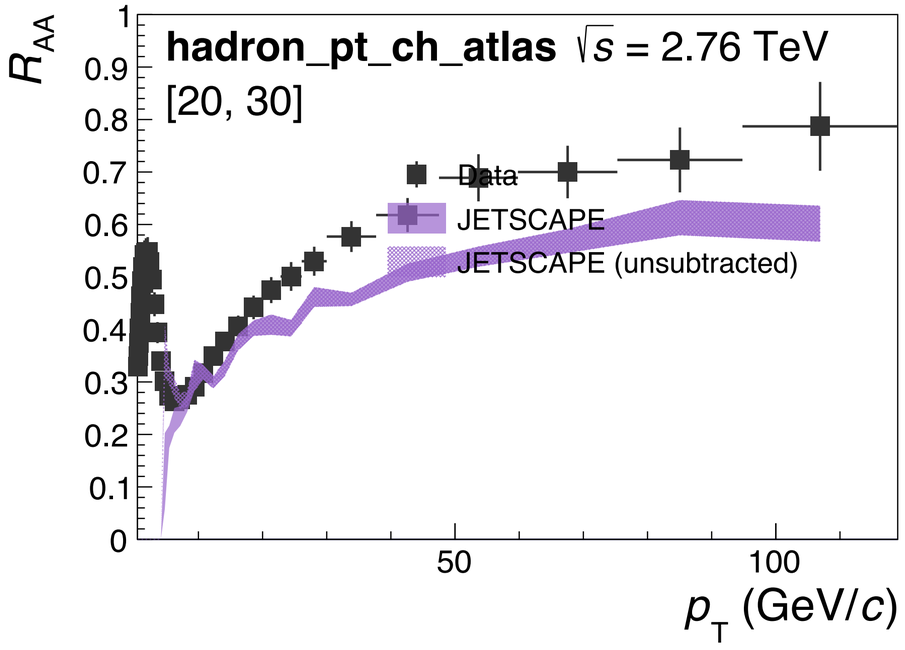
$$P(\theta_h \mid D_h) \propto P(D_h \mid \theta_h) \cdot P(\theta_h)$$

- missing uncertainties from θ_s

SOFT-HARD INTERPLAY



soft: w=0.5 fm + hard: MAP



soft: w=1.5 fm + hard: MAP

SEQUENTIAL INFERENCE

- Joint inference (fixed θ_h):

$$P(\theta_s \mid D_s, D_h) \propto P(D_s, D_h \mid \theta_s) \cdot P(\theta_s)$$

- If datasets are independent:

$$P(D_s, D_h \mid \theta_s) = P(D_h \mid \theta_s) \cdot P(D_s \mid \theta_s)$$

- Sequential inference

$$P(\theta_s \mid D_s, D_h) \propto P(D_h \mid \theta_s) \cdot P(D_s \mid \theta_s) \cdot P(\theta_s)$$

$$= P(D_h \mid \theta_s) \cdot \left[P(D_s \mid \theta_s) \cdot P(\theta_s)\right]$$

second inference — first inference

- Update knowledge of θ_s with new data D_h