Deep learning for flow observables in ultrarelativistic heavy-ion collisions

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Phys. Rev. C 108, 034905 (2023)

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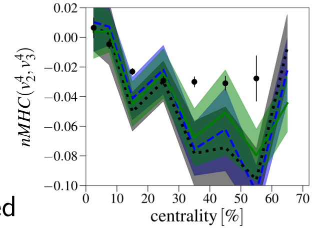
CoE in Quark Matter
YoctoLHC

STRONG-HFHF-2023 Workshop

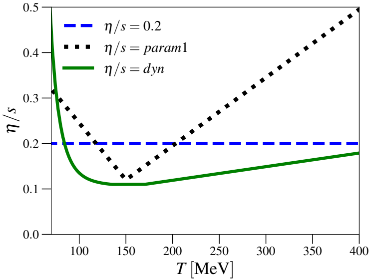
Motivation



- Heavy ion collisions provide a way to probe matter properties of QGP
- Shear and bulk viscosities of QGP can be constrained from the measured data by the means of Bayesian analysis
- Measured multi-particle correlations require millions of simulated collision events to obtain enough statistics for reliable comparison with the data
- One event $\sim$ 0.5 CPU hours $\implies \sim 10^6$ CPU hours per viscosity parametrization
- Problem: to perform Bayesian analysis one needs observables for $\sim 10^2$ parametrizations, i.e. total of $\sim 10^8$ CPU hours!
- Solution: Use machine learning to speed up the process

The theory framework

- Initial state from pQCD+saturation EKRT-framework
- 2nd-order viscous fluid dynamics with shear and bulk viscosities
  - Earlier EbyE EKRT works: $\eta/s = 0.2$ and $\eta/s = param1$ with $T_{dec} = 100$ MeV
- Here we add $\zeta/s(T)$ and convert fluid into particle spectrum by calculating Cooper-Frye integral at the decoupling surface determined by dynamical freeze-out conditions
  - Purely hydrodynamic description $\implies$ Continuous parametrization of transport coefficients across all phases of strongly interacting matter



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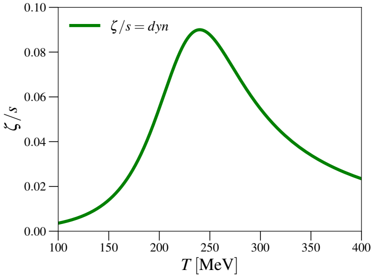

Dynamical freeze-out

- Fluid dynamics applicable when expansion rate $(\theta) \lesssim$ scattering rate $(1/\tau_\pi)$ and mean free path $(\tau_\pi) \lesssim$ size of the system (R)
  $\implies$ Dynamical decoupling conditions:

Knudsen number

$$\mathrm{Kn} \equiv \frac{\text{exp. rate}}{\text{scat. rate}} = \tau_\pi \theta = C_{\mathrm{Kn}}$$

Global size of the system

$$\frac{\gamma \tau_\pi}{R} = C_R, \quad R = \sqrt{A/\pi}$$

- C_{Kn} and C_R are free parameters, fitted from data
- A is the area in which $\mathrm{Kn} < C_{Kn}$ and T $<$ 150 MeV
- Allow multiple separate areas with different R

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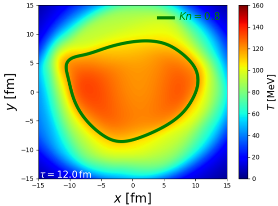
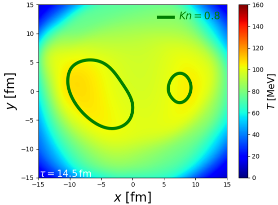
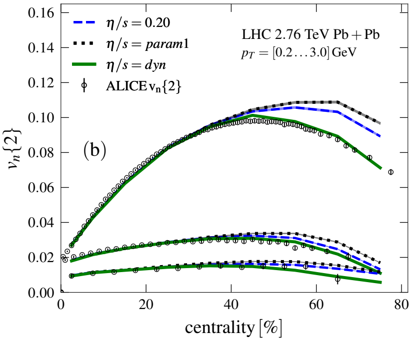




Flow coefficients



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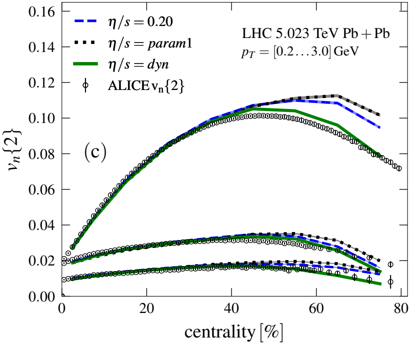


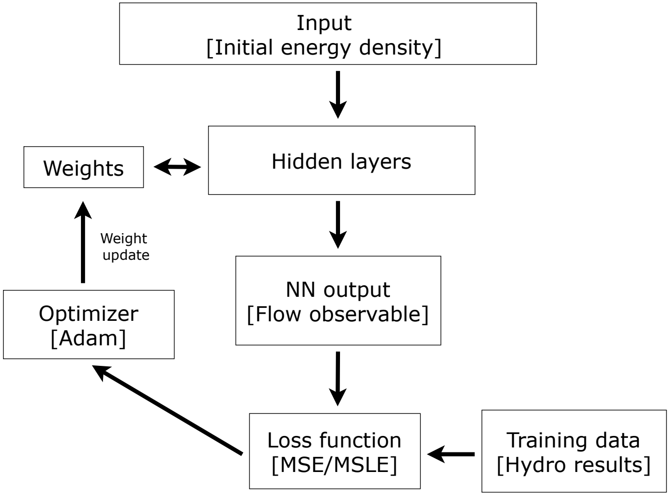
$$\frac{dN}{dyd\phi} = \frac{1}{2\pi}\frac{dN}{dy}\left(1 + \sum_{n=1}^{\infty} v_n \cos[n(\phi - \Psi_n(p_T))]\right)$$

$$v_n\{2\} = \sqrt{\langle v_n^2 \rangle_{\mathrm{ev}}}$$

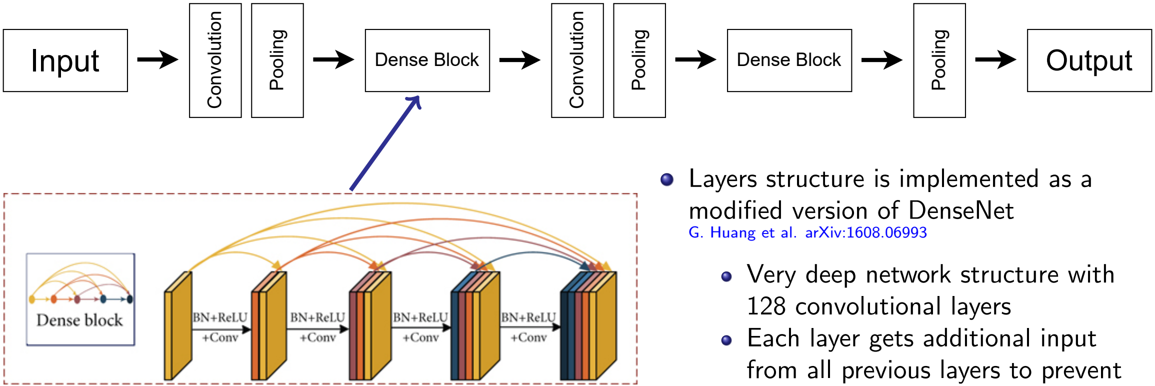
- Dynamical freeze-out decreases amount of flow in peripheral collisions and improves agreement with the measurements

Neural Network (NN)

- Use NN to predict flow observables from initial $e(x, y)$ Event-by-Event
- The weights in the hidden layers are trained to minimize the loss function
- Training data is for one fixed viscosity parametrization



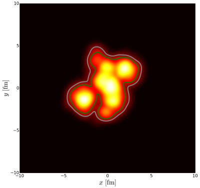
Network structure



- Layers structure is implemented as a modified version of DenseNet
  G. Huang et al. arXiv:1608.06993
  - Very deep network structure with 128 convolutional layers
  - Each layer gets additional input from all previous layers to prevent feature loss and vanishing gradients
  - In total of $\approx$ 5.4M trainable parameters

Workflow

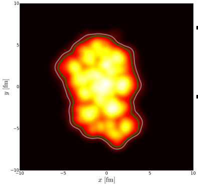
Event 1



Neural Network for v_2 → $[\, v_2 \,]_{ev1}$

Neural Network for v_3 → $[\, v_3 \,]_{ev1}$

Event 2



Neural Network for v_2 → $[\, v_2 \,]_{ev2}$

Neural Network for v_3 → $[\, v_3 \,]_{ev2}$

Average over events → $v_n\{2\}$, NSC(n,m), etc.

$$\mathrm{NSC(n,m)} = \frac{\langle [\mathrm{v_n}]^2_{\mathrm{ev}} [\mathrm{v_m}]^2_{\mathrm{ev}} \rangle}{\langle [\mathrm{v_n}]^2_{\mathrm{ev}} \rangle \langle [\mathrm{v_m}]^2_{\mathrm{ev}} \rangle} - 1$$

$$\mathrm{v_n}\{2\} = \sqrt{\langle [\mathrm{v_n}]^2_{\mathrm{ev}} \rangle}$$

Implementation

- Separate network trained for each p_T-integrated observable: $v_2, v_3, v_4, v_5, v_6, [p_T], dN_{ch}/d\eta$
- Each network trained with multiple different p_T ranges for an observable
- In total of 20000 training events: 5000 from each collision system
  - 200 GeV Au+Au
  - 2.76 TeV Pb+Pb
  - 5.023 TeV Pb+Pb
  - 5.44 TeV Xe+Xe (deformed nuclei)
- Training data augmented using random flips, rotations and translations
- Training one network takes ≈ 1 GPU hour with NVIDIA V100 32GB GPU
- After training, NN can generate $\sim 10^6$ events/hour with GPU
  - Factor of 10^5 faster than doing full simulations using CPU!

Validation tests: Errors with 90k validation events

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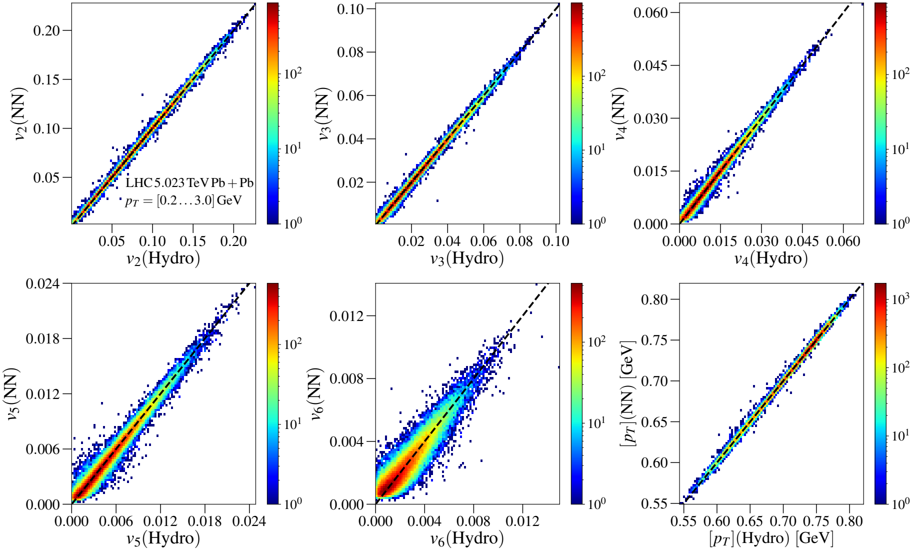

Validation tests: Flow coefficients

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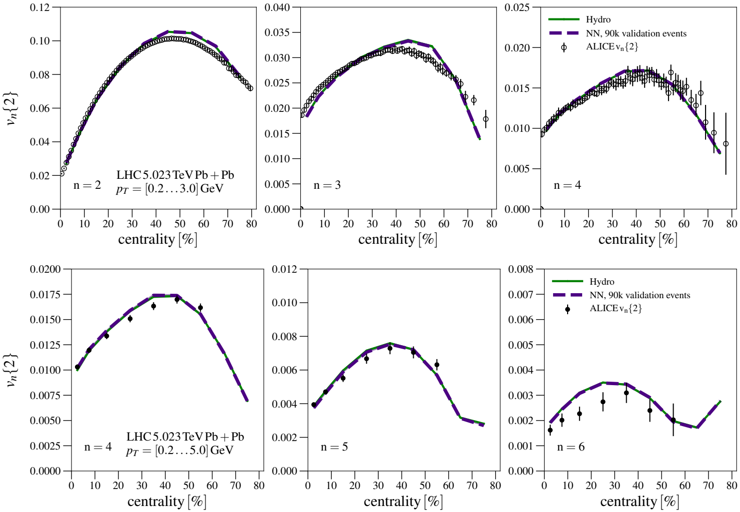

Validation tests: Four-particle flow correlations

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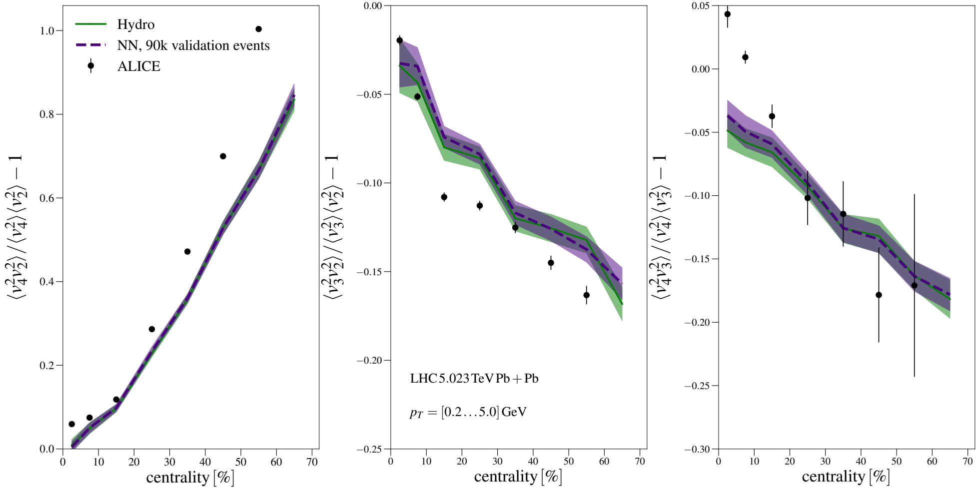

Validation tests: Six- and eight-particle flow correlations

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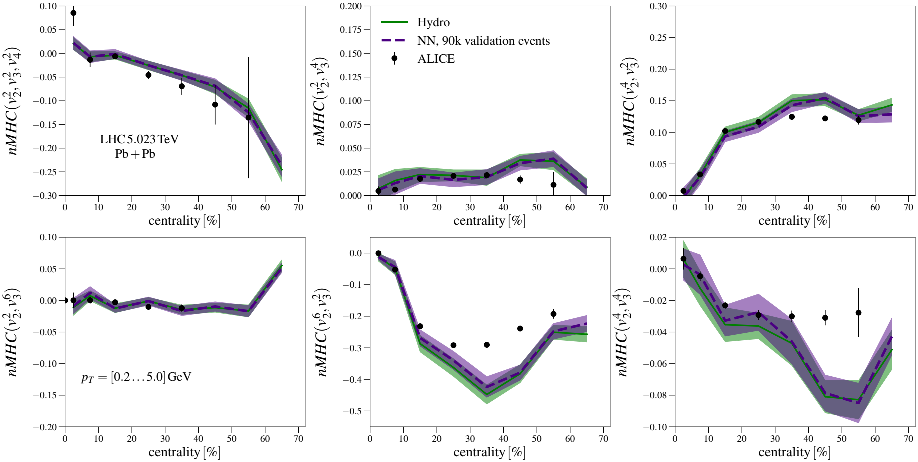

NN predictions: Four-particle flow correlations

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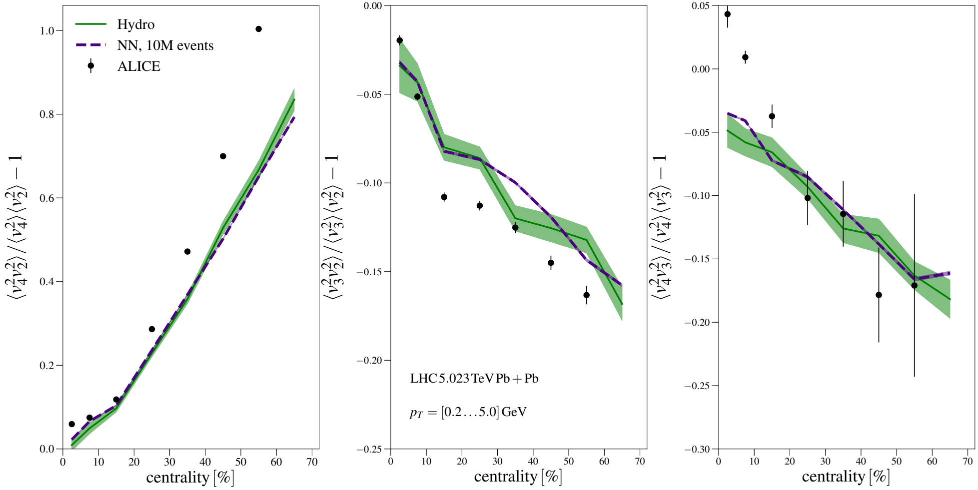

NN predictions: Six- and eight-particle flow correlations

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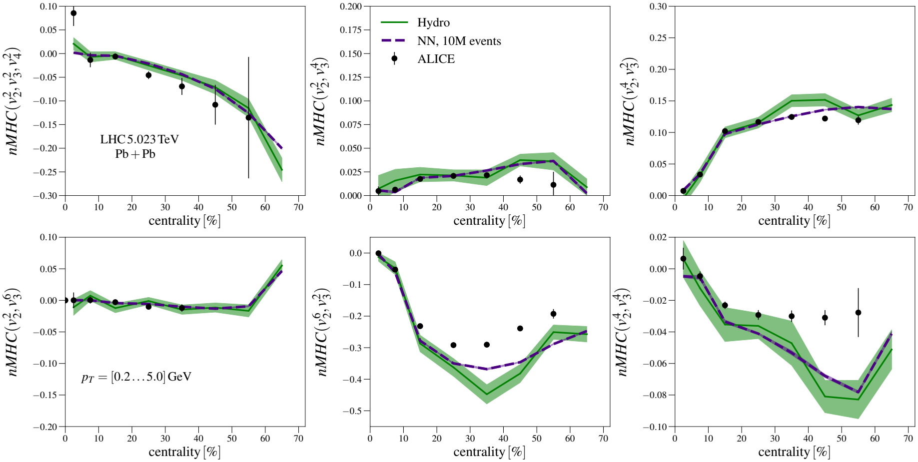
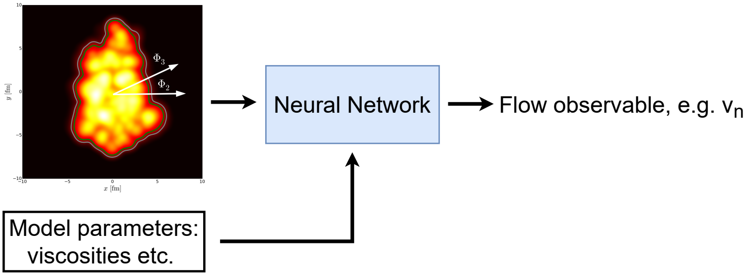


Model parameters as an input ($\mathrm{NN_p}$)

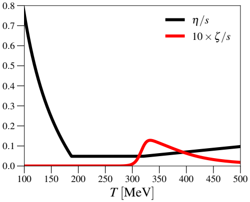
- Neural network can be extended to take model parameters as additional input:
  - 6 parameters describing $\eta/s(T)$
  - 4 parameters describing $\zeta/s(T)$
  - 3 parameters describing chemical and kinetic decoupling
- Training data consist of 160000 events
  - 2000 different parameter points sampled from Latin hypercube
  - 4 collision systems

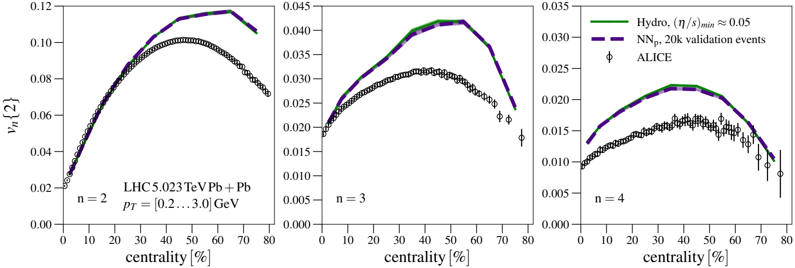
$\Longrightarrow$ Very efficient: only 80 training events for each parameter point

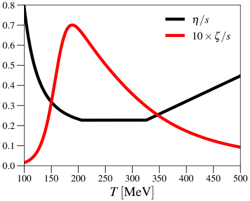


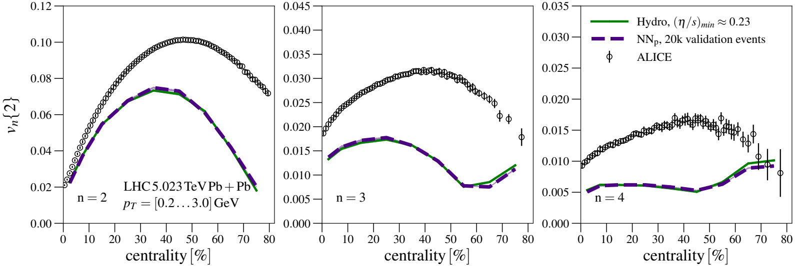
Validation: Flow coefficients

Work in progress!

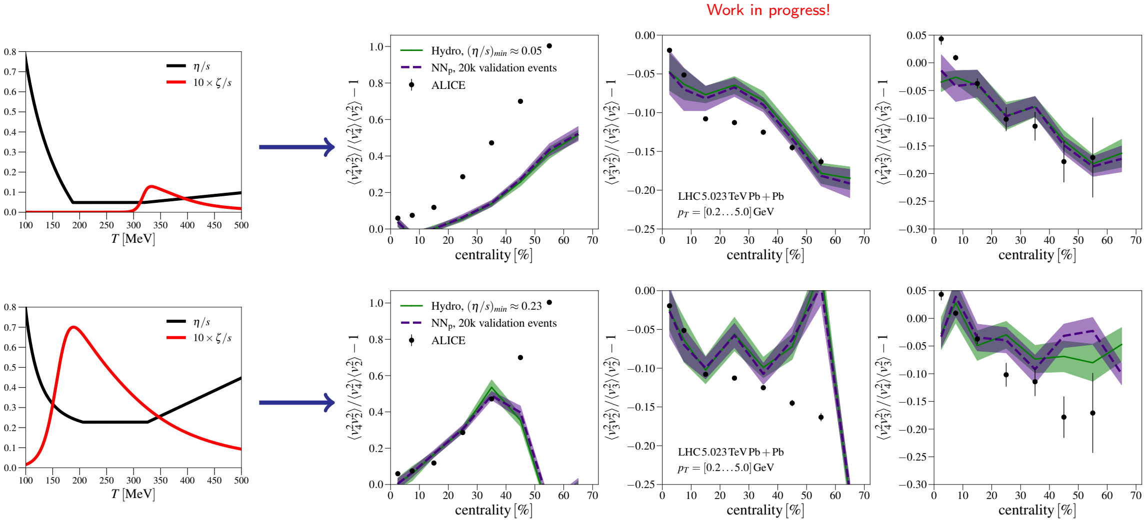








Validation: Normalized symmetric cumulants



Summary

- Dynamical decoupling $\implies$ Clear improvement in centrality dependence of flow coefficients
- Using neural network to predict flow observables from initial energy density reduces computation time by many orders of magnitude
  - Speedup achieved while maintaining good accuracy, even for multi-particle correlations
  - Can be extended to take model parameters as additional input
- In future: use neural networks in Bayesian analysis

Backup:

Validation: Flow-transverse-momentum correlations

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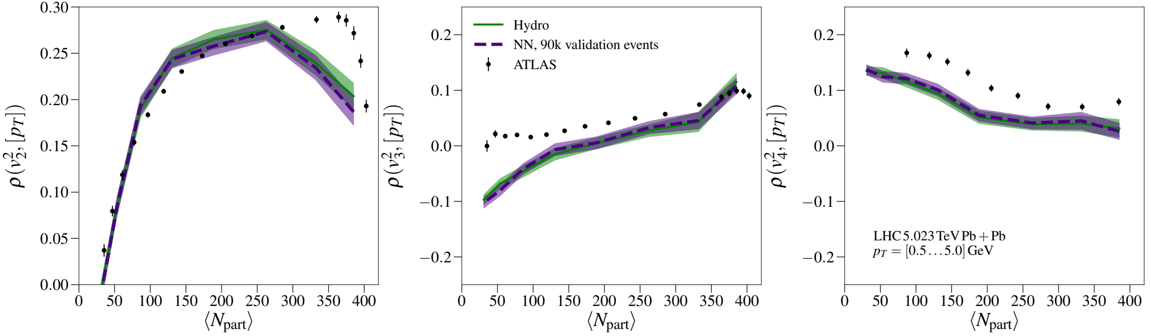

NN predictions: Flow-transverse-momentum correlations

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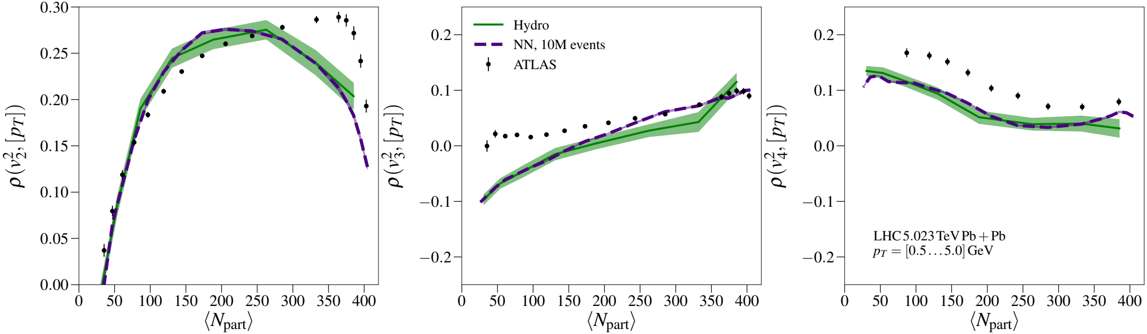
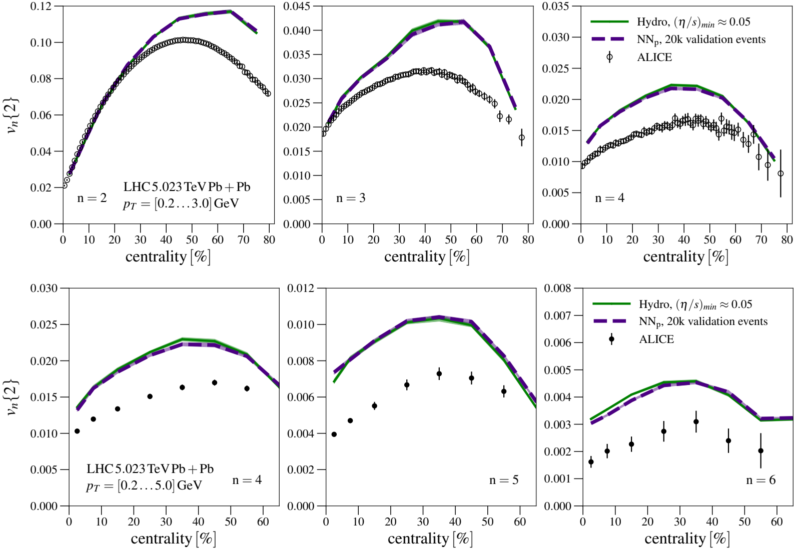
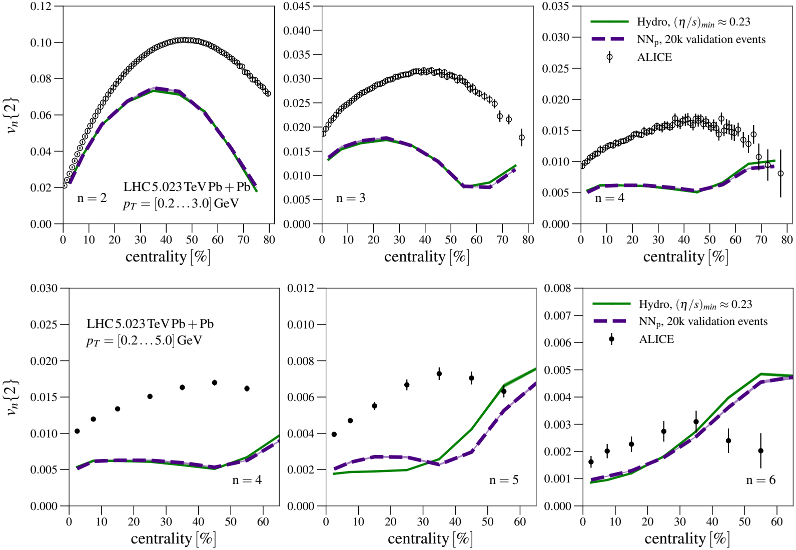


Validation: flow coefficients, low viscosity

Work in progress!

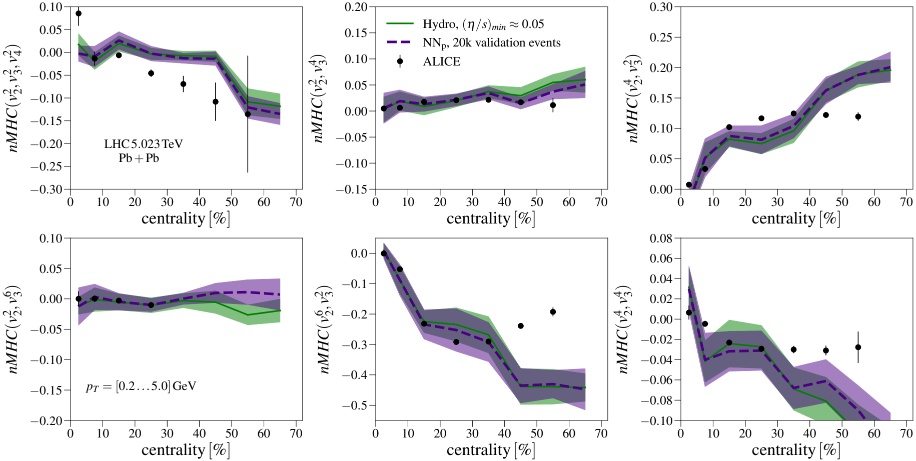


Work in progress!



Validation: nMHC, low viscosity

Work in progress!



Validation: nMHC, high viscosity

Work in progress!