

Deep learning for flow observables in ultrarelativistic heavy-ion collisions

Henry Hirvonen

with Harri Niemi, Kari J. Eskola

[arXiv:2303.04517\[hep-ph\]](https://arxiv.org/abs/2303.04517)

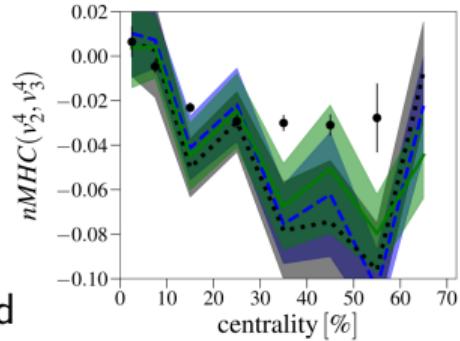
Department of Physics, University of Jyväskylä
Helsinki Institute of Physics

CoE in Quark Matter
YoctoLHC

Initial Stages 2023

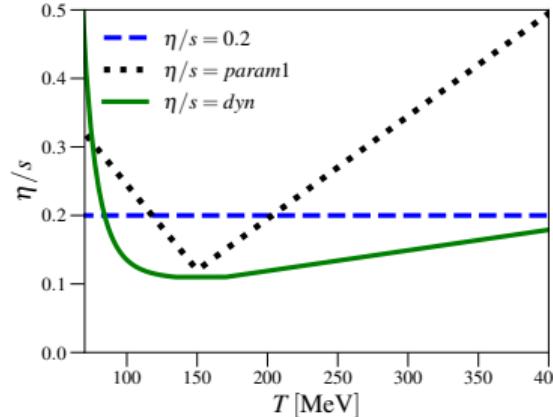


- Heavy ion collisions provide a way to probe matter properties of QGP
- Shear and bulk viscosities of QGP can be constrained from the measured data by the means of Bayesian analysis
- Measured multi-particle correlations require millions of simulated collision events to obtain enough statistics for reliable comparison with the data
- One event ~ 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

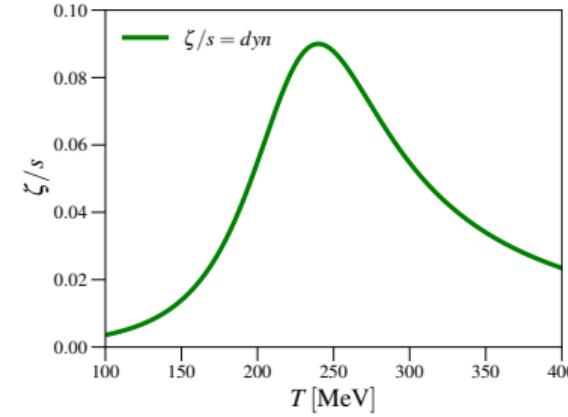


The theory framework

- 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 $\eta/s = \text{param1}$ with $T_{\text{dec}} = 100$ 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 \Rightarrow Continuous parametrization of transport coefficients across all phases of strongly interacting matter



H. Hirvonen et al. Phys.Rev.C 106, 044913 (2022)



Dynamical freeze-out

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

Knudsen number

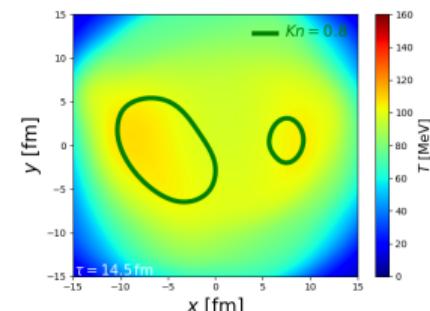
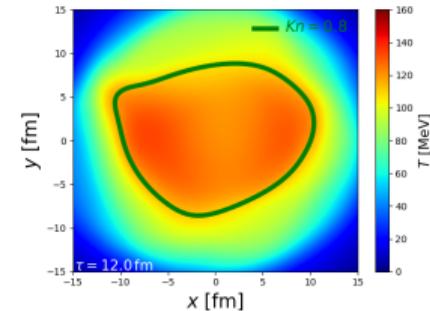
$$\text{Kn} \equiv \frac{\text{exp. rate}}{\text{scat. rate}} = \tau_\pi \theta = C_{\text{Kn}}$$

Global size of the system

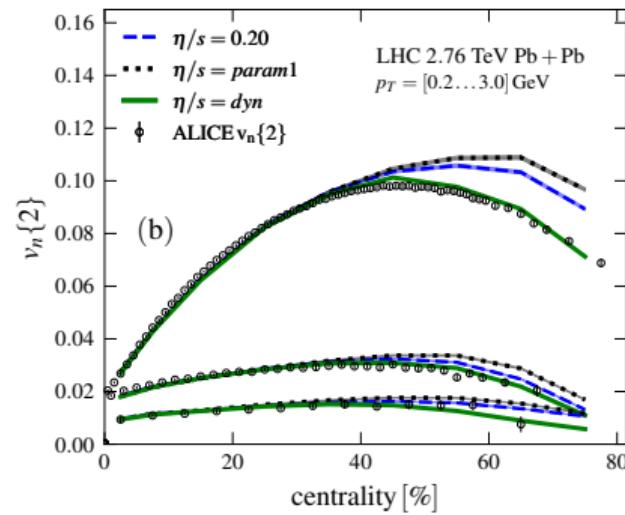
$$\frac{\gamma \tau_\pi}{R} = C_R, \quad R = \sqrt{A/\pi}$$

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

H. Hirvonen et al. Phys.Rev.C 106, 044913 (2022)

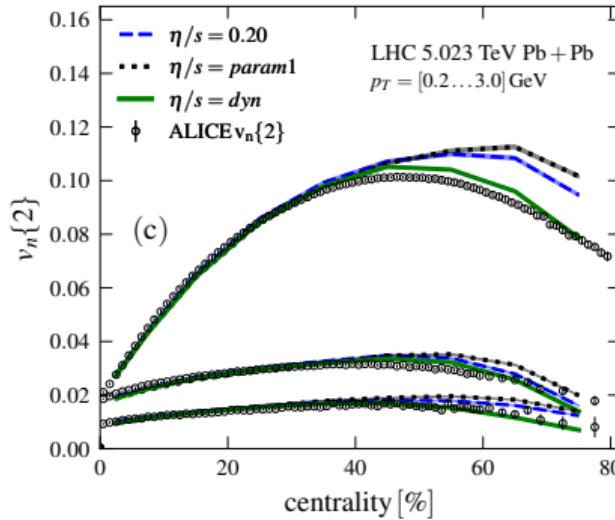


Flow coefficients



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

H. Hirvonen et al. Phys.Rev.C 106, 044913 (2022)

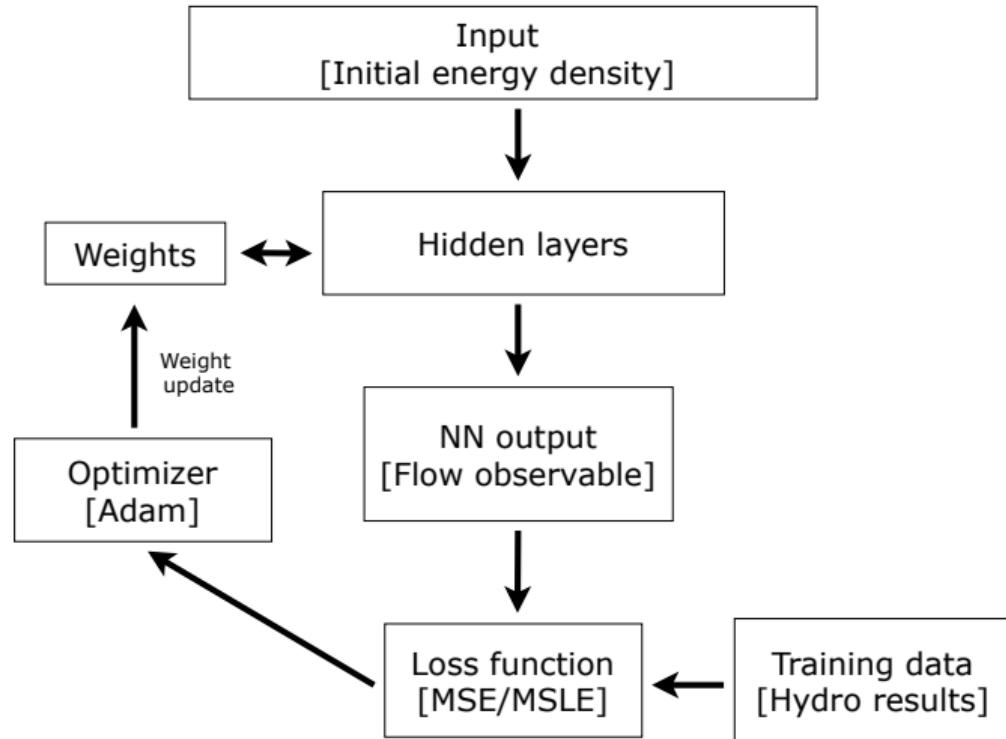


$$v_n\{2\} = \sqrt{\langle v_n^2 \rangle_{\text{ev}}}$$

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

Neural Network (NN)

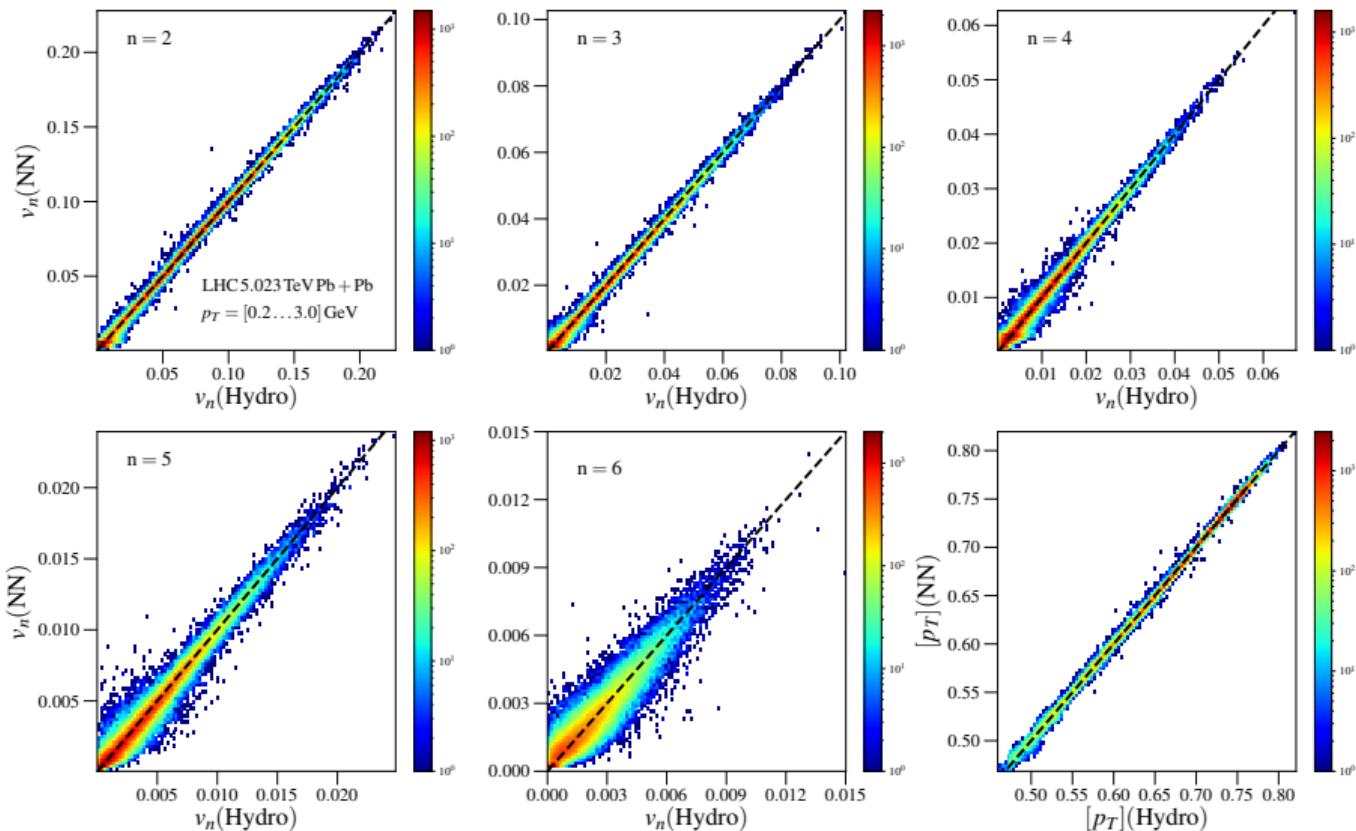
- Use NN to predict flow observables from initial $e(x, y)$ Event-by-Event
- Layers structure is implemented as a modified version of DenseNet
G. Huang et al. arXiv:1608.06993
 - Very deep network structure with 128 convolutional layers
 - In total of $\approx 5.4M$ trainable parameters
- Training data is for one fixed viscosity parametrization



- 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!

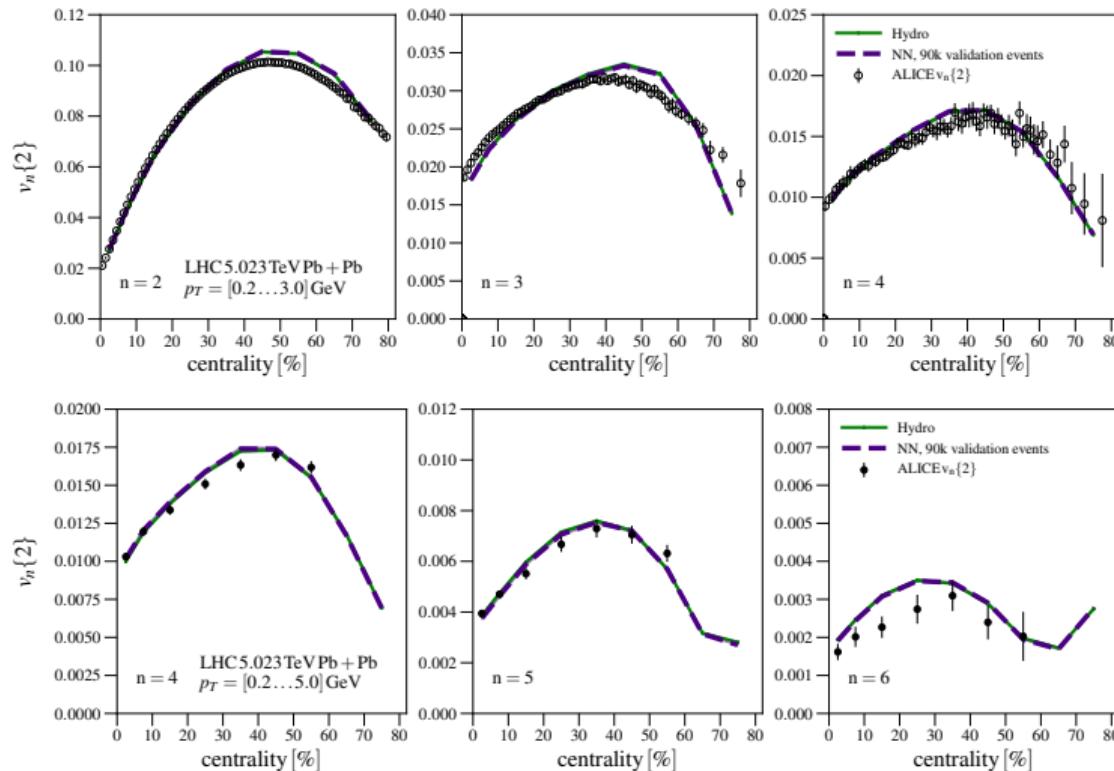
Validation tests: Errors with 90k validation events

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



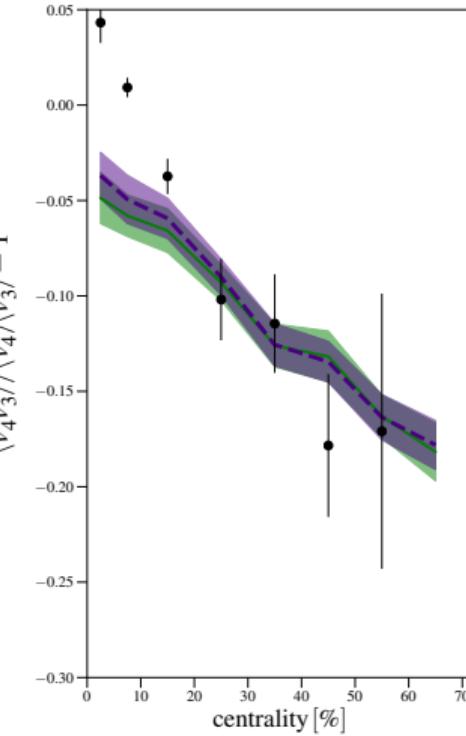
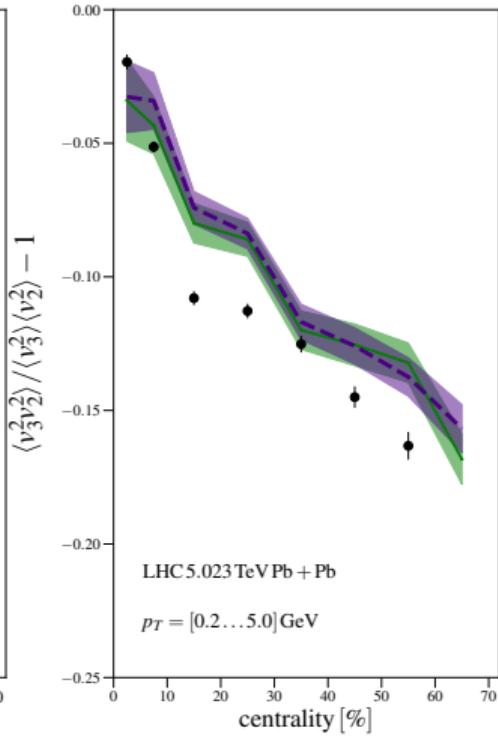
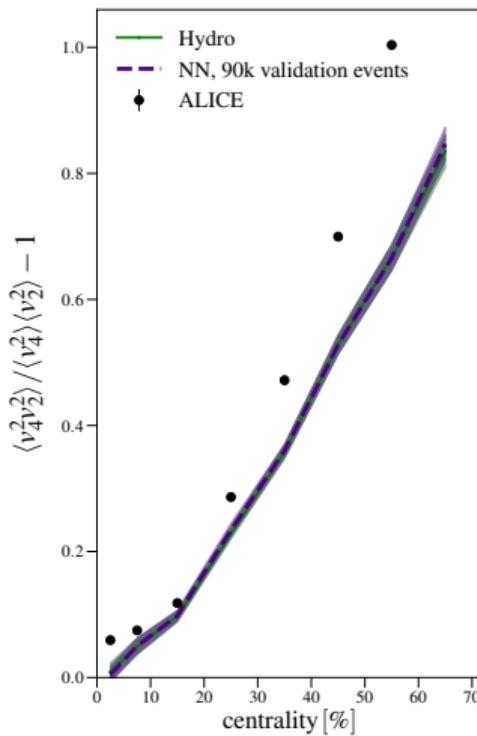
Validation tests: Flow coefficients

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



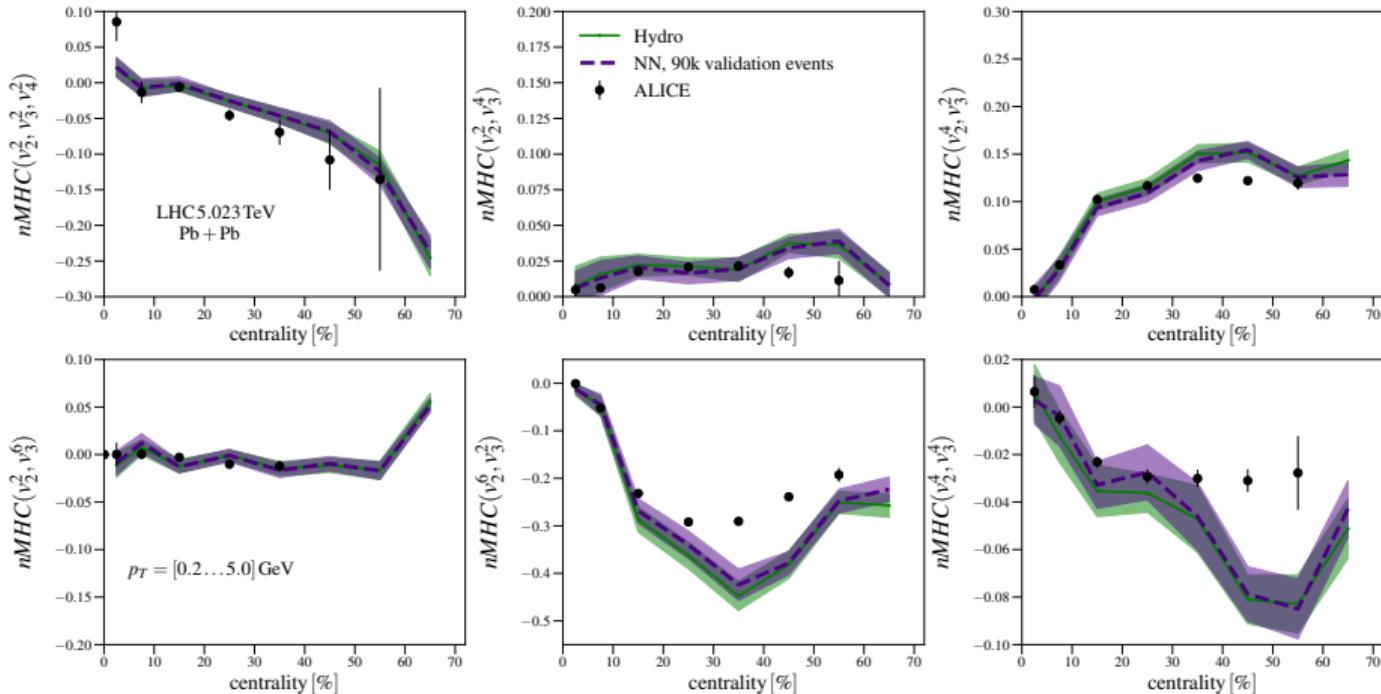
Validation tests: Four-particle flow correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



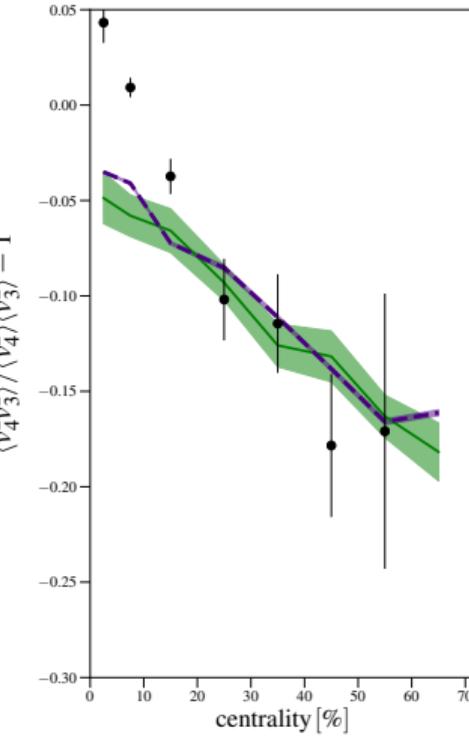
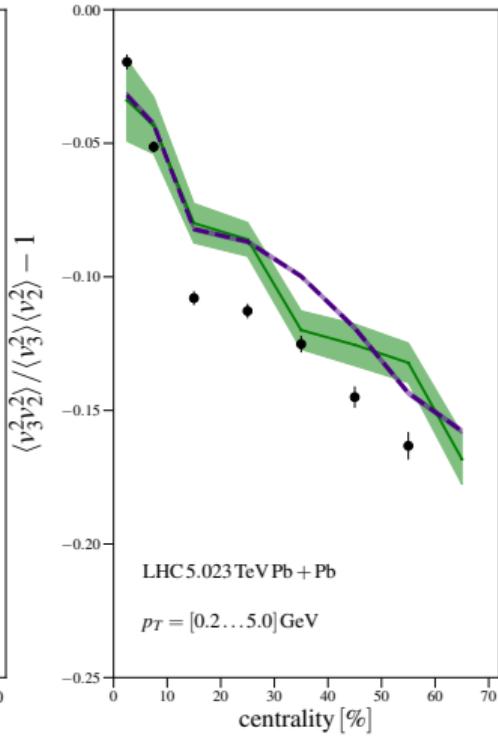
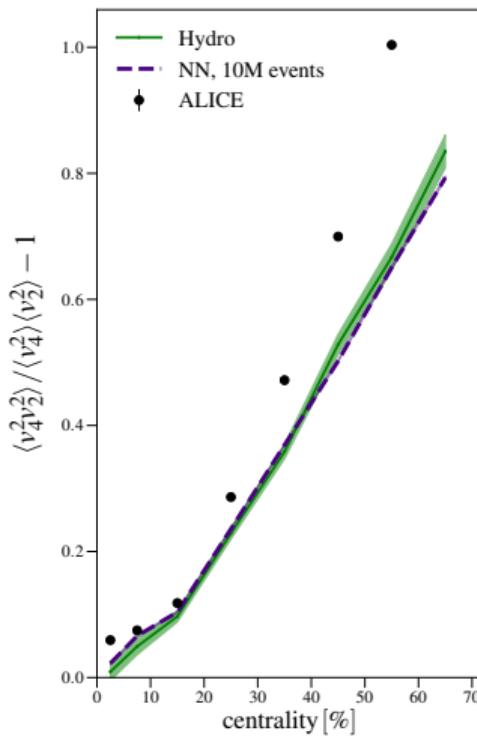
Validation tests: Six- and eight-particle flow correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



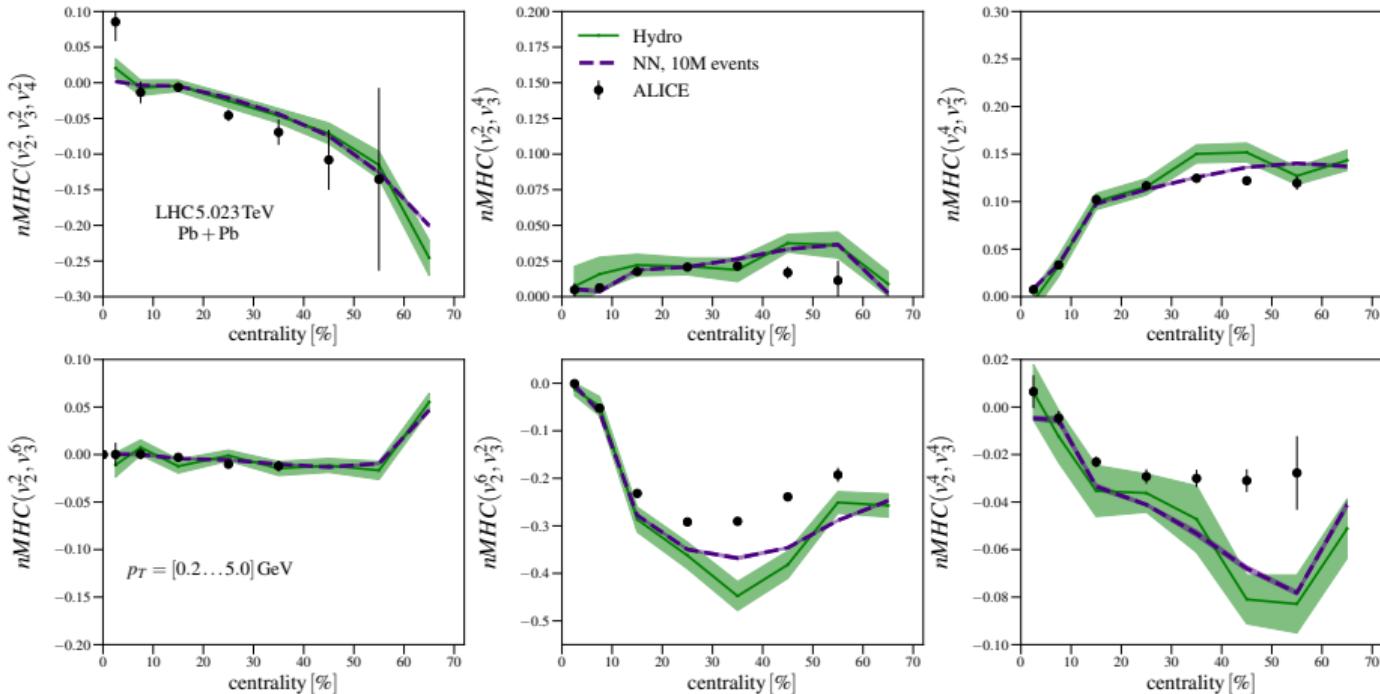
NN predictions: Four-particle flow correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



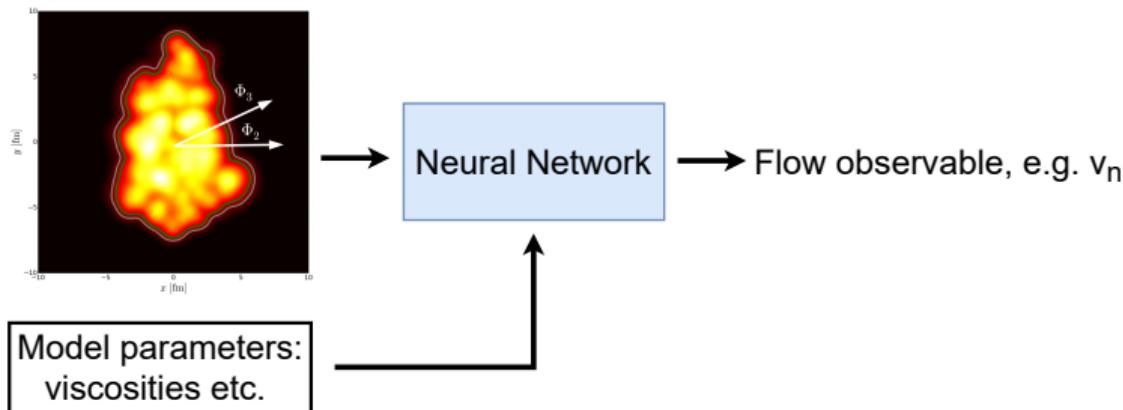
NN predictions: Six- and eight-particle flow correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]

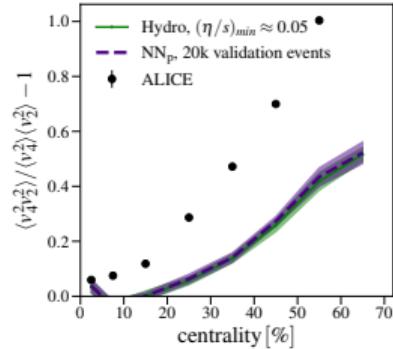
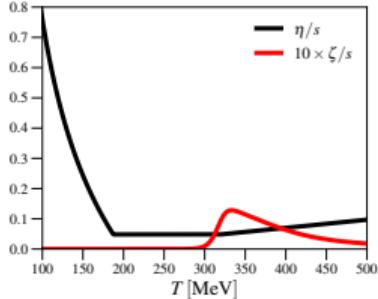


Model parameters as an input (NN_p)

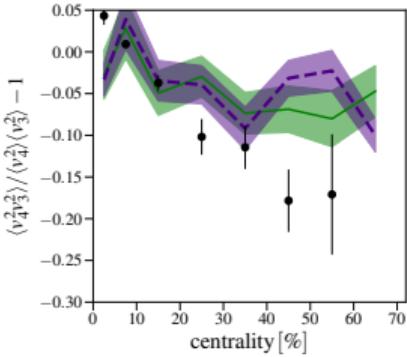
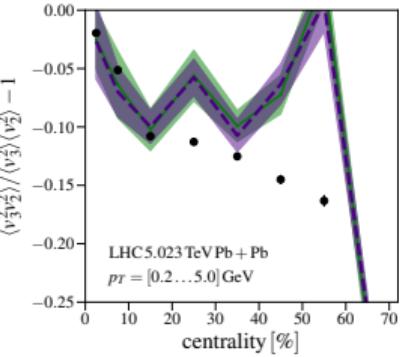
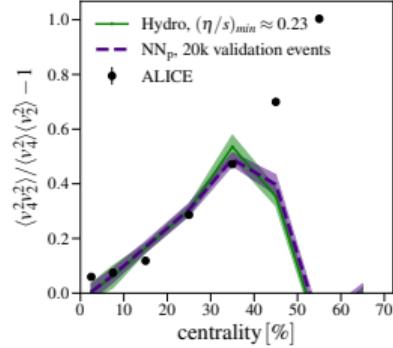
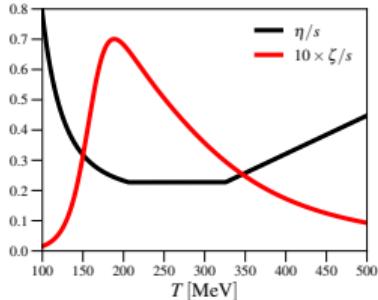
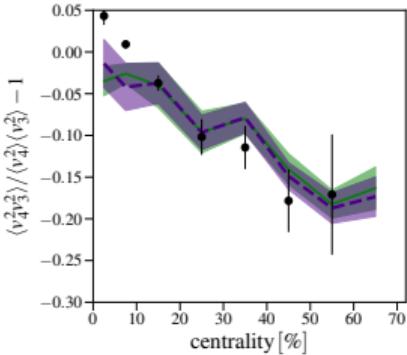
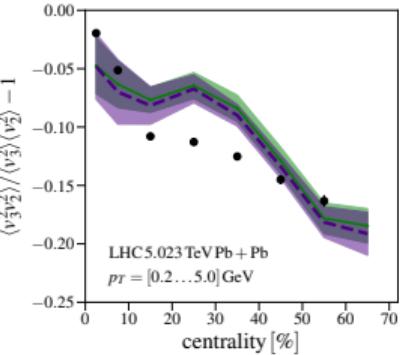
- Neural network can be extended to take model parameters as additional input:
 - 6 parameters describing $\eta/s(T)$
 - 4 parameters describing $\zeta/s(T)$
 - 3 parameters describing chemical and kinetic decoupling
 - Training data consist of 160000 events
 - 2000 different parameter points sampled from Latin hypercube
 - 4 collision systems
- ⇒ Very efficient: only 80 training events for each parameter point



Validation: Normalized symmetric cumulants



Work in progress!

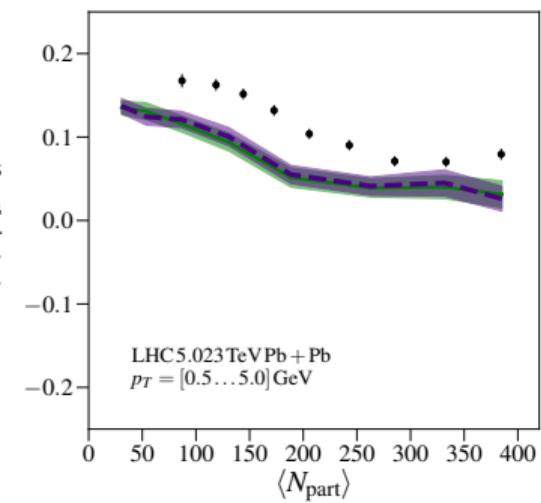
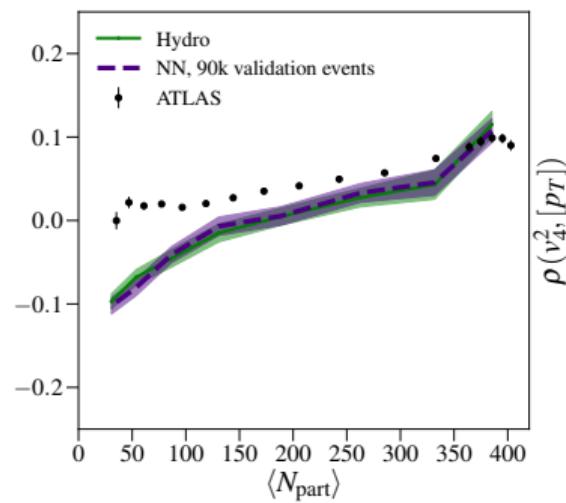
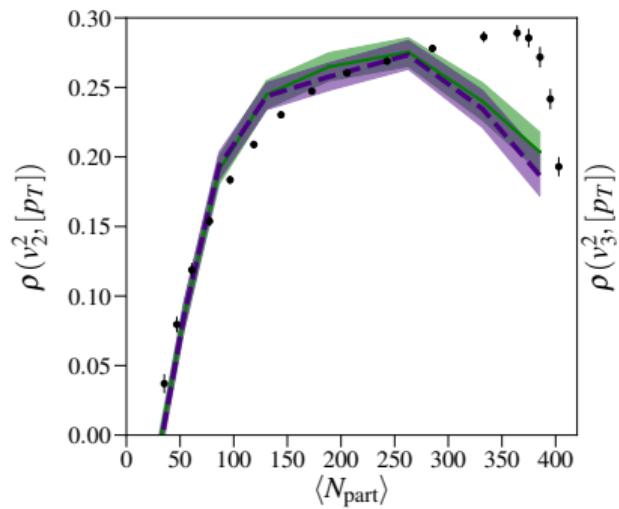


- Dynamical decoupling \implies Clear improvement in centrality dependence of flow coefficients
- Using neural network to predict flow observables from initial energy density reduces computation time by many orders of magnitude
 - Speedup achieved while maintaining good accuracy, even for multi-particle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

Backup:

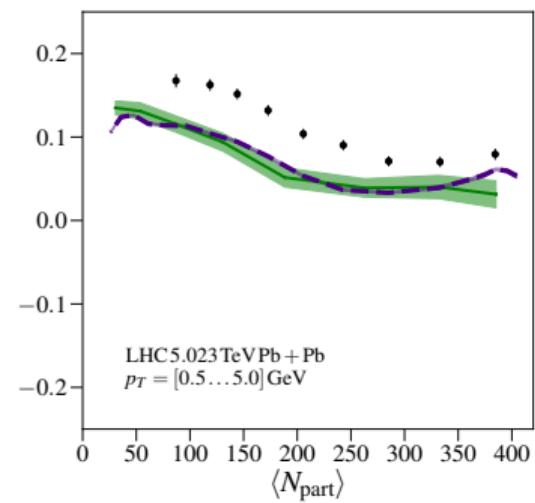
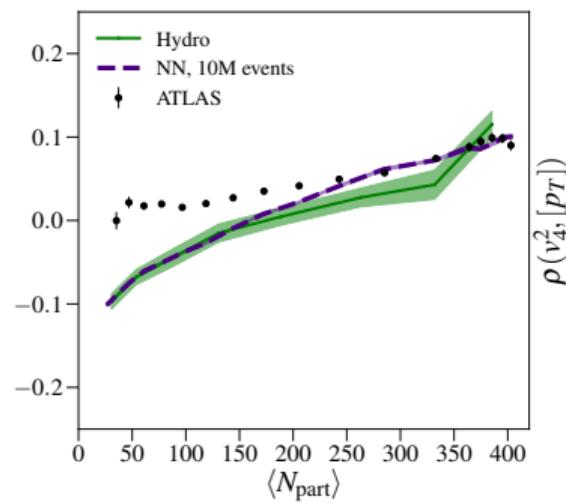
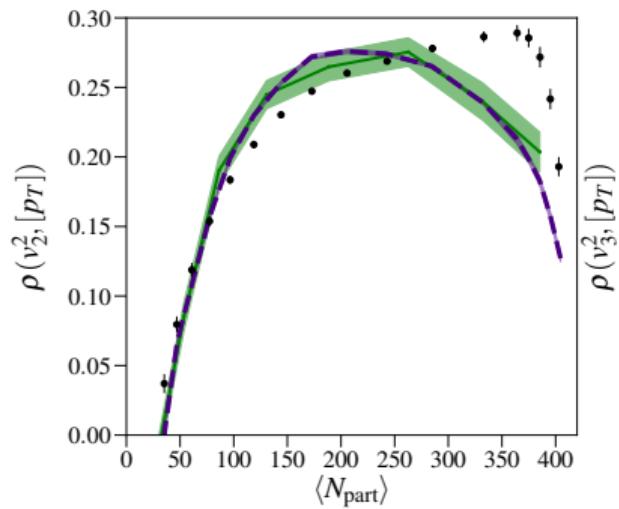
Validation: Flow-transverse-momentum correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



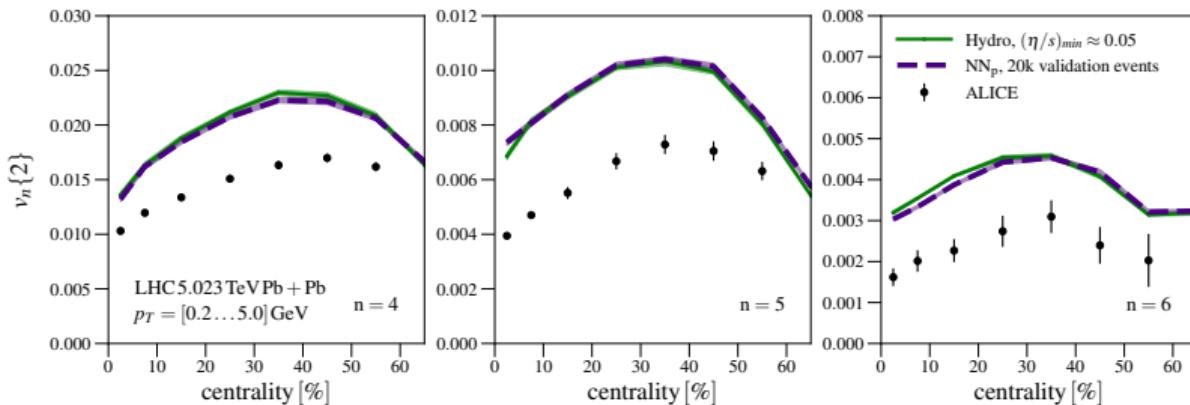
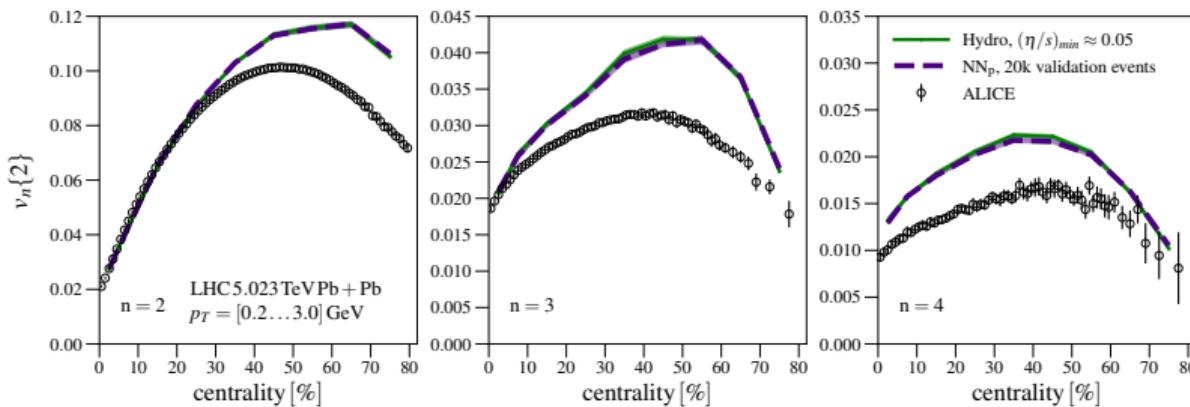
NN predictions: Flow-transverse-momentum correlations

H. Hirvonen et al. arXiv:2303.04517[hep-ph]



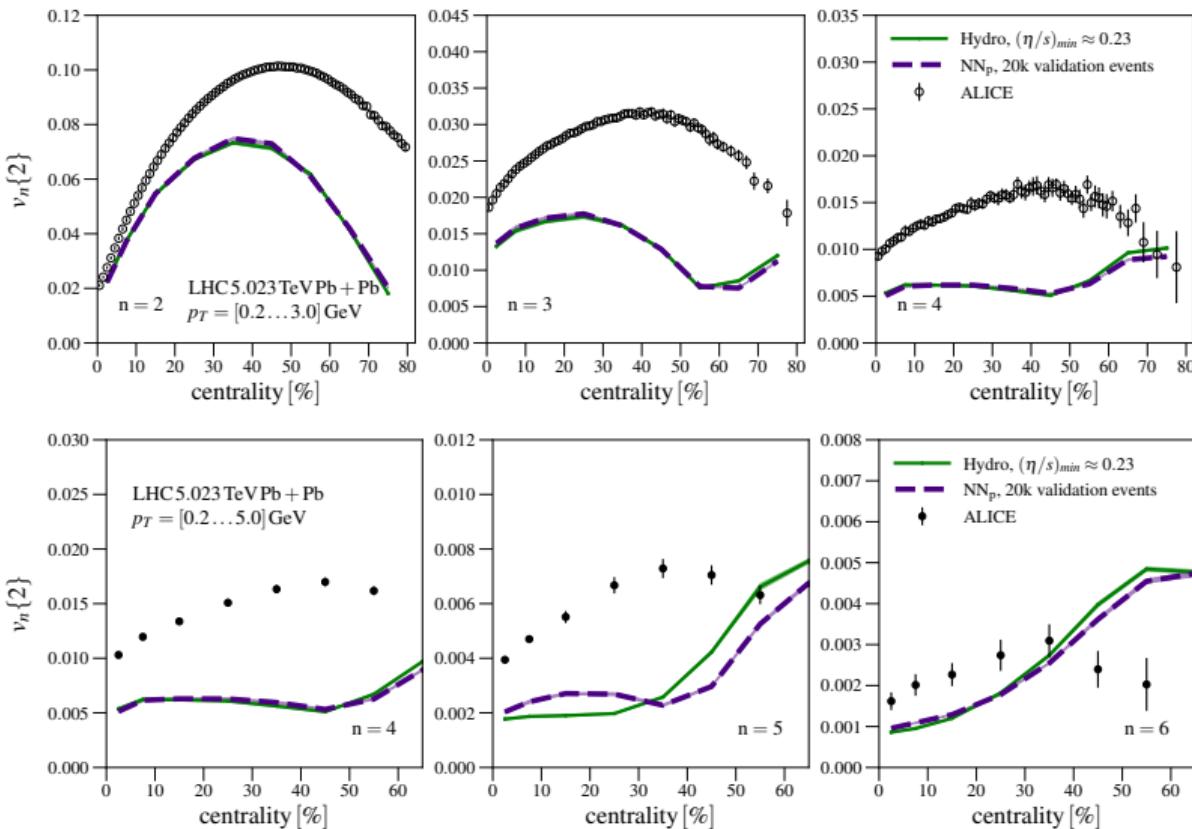
Validation: flow coefficients, low viscosity

Work in progress!



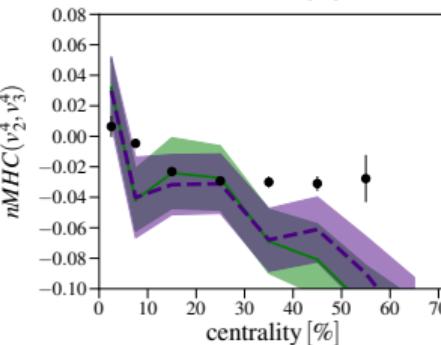
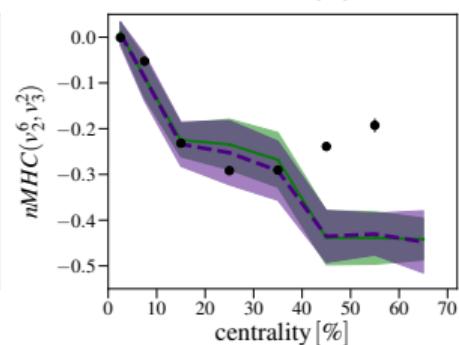
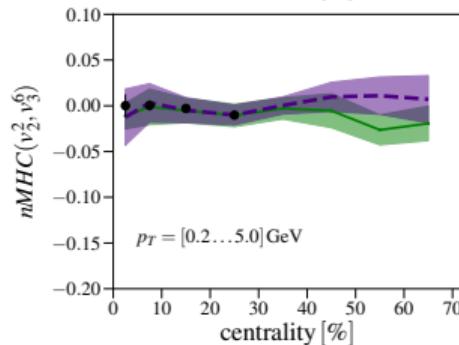
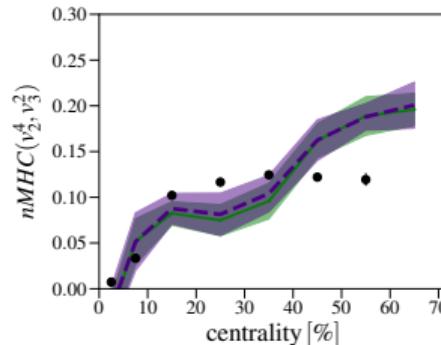
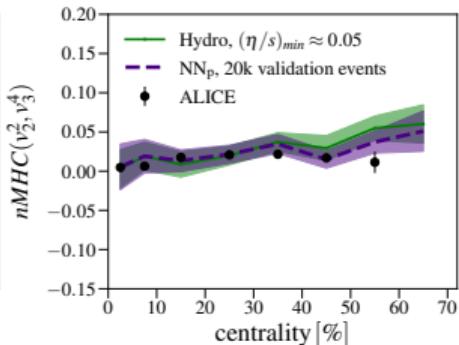
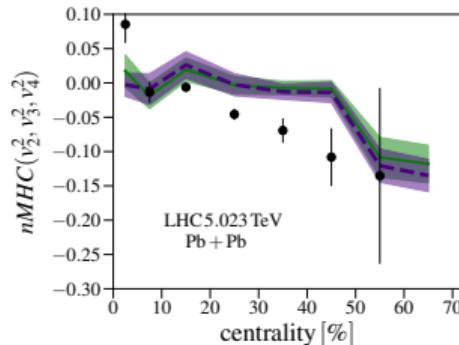
Validation: flow coefficients, high viscosity

Work in progress!



Validation: nMHC, low viscosity

Work in progress!



Validation: nMHC, high viscosity

Work in progress!

