Collective phenomena with machine learning

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CoE in Quark Matter
YoctoLHC

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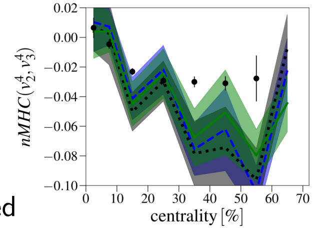
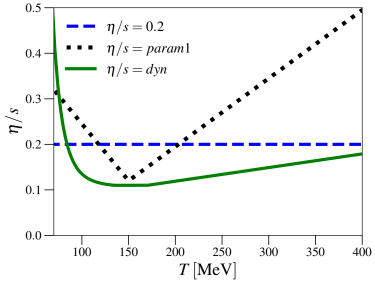
Motivation

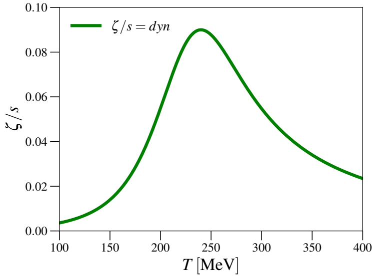


- Heavy ion collisions provide a way to probe matter properties of QGP
- Shear and bulk viscosities of QGP can be constrained from the measured data by the means of Bayesian analysis
- Measured multi-particle correlations require millions of simulated collision events to obtain enough statistics for 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
  - $\eta/s = 0.2$ and $\eta/s = param1$ from earlier EbyE EKRT works with $T_{dec} = 100$ MeV
- Here, we convert the 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





Dynamical freeze-out

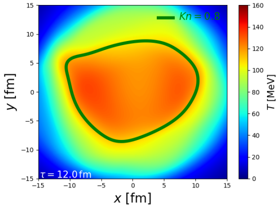
- Fluid dynamics applicable when expansion rate (θ) $\lesssim$ scattering rate ($1/\tau_\pi$) and mean free path (τ_π) $\lesssim$ size of the system (R)
  $\implies$ Dynamical decoupling conditions:

Knudsen number

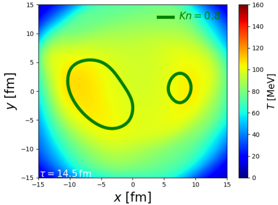
$$\mathrm{Kn} \equiv \frac{\text{exp. rate}}{\text{scat. rate}} = \tau_\pi \theta = C_{\mathrm{Kn}}$$

Global size of the system

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

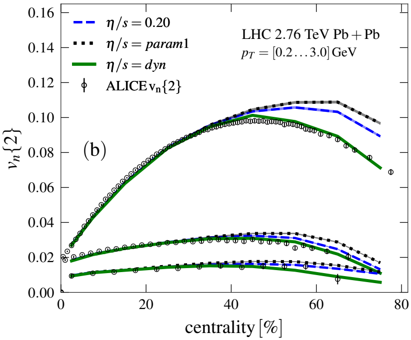


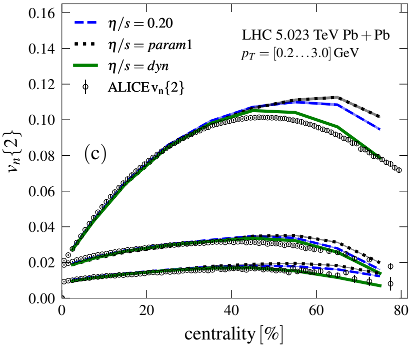
- C_{Kn} and C_R are free parameters, fitted from data
- A is the area in which $\mathrm{Kn} < C_{Kn}$ and T < 150 MeV
- Allow multiple separate areas with different R



Flow coefficients

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





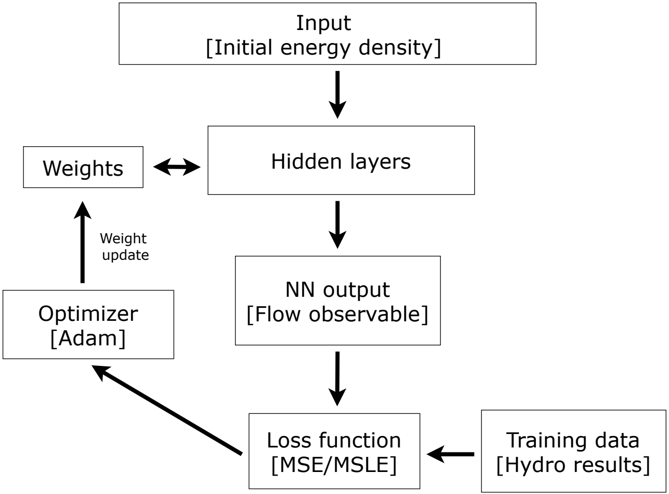
$$\frac{dN}{dyd\phi} = \frac{1}{2\pi}\frac{dN}{dy}\left(1 + \sum_{n=1}^{\infty} v_n \cos[n(\phi - \Psi_n(p_T))]\right)$$

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

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

Neural Network (NN)

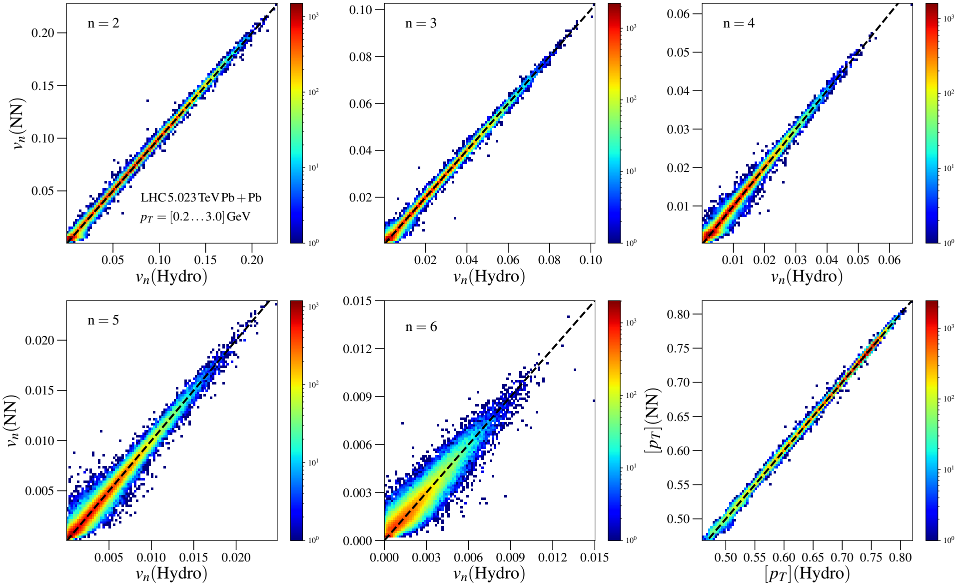
- Layers structure is implemented as a modified version of DenseNet G. Huang et al. arXiv:1608.06993
  - Very deep network structure with 128 convolutional layers
  - In total of $\approx$ 5.4M trainable parameters
- Training data is for one fixed viscosity parametrization

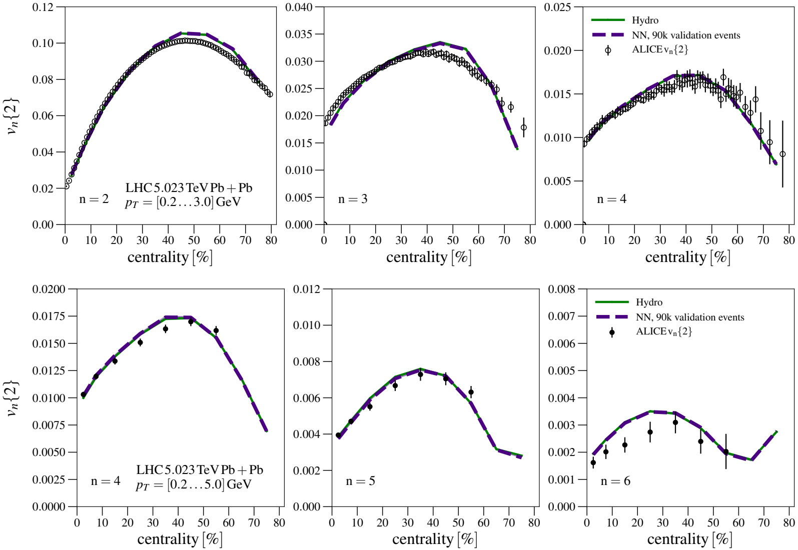


Neural Network

- Separate network trained for each p_T-integrated observable: $v_2, v_3, v_4, v_5, v_6, [p_T], dN_{ch}/d\eta$
- Single 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 $\approx$ 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!

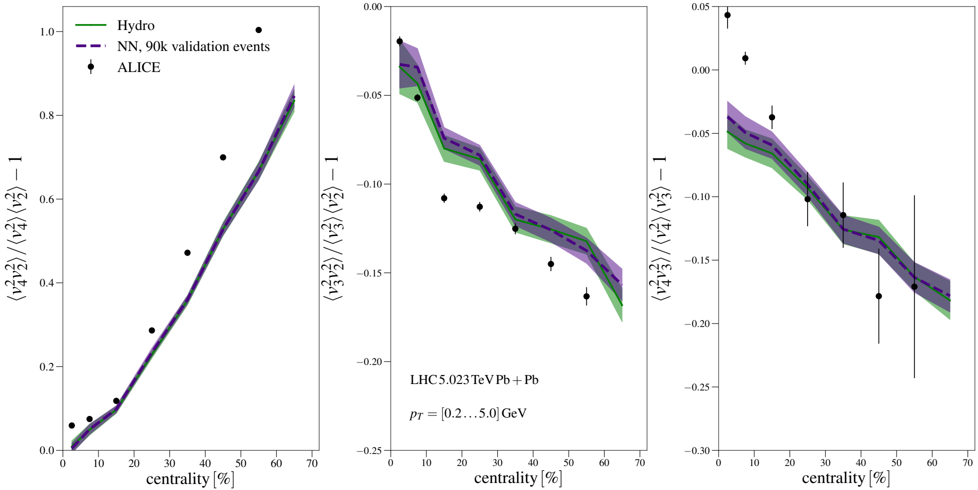
Validation tests: Errors with 90k validation events



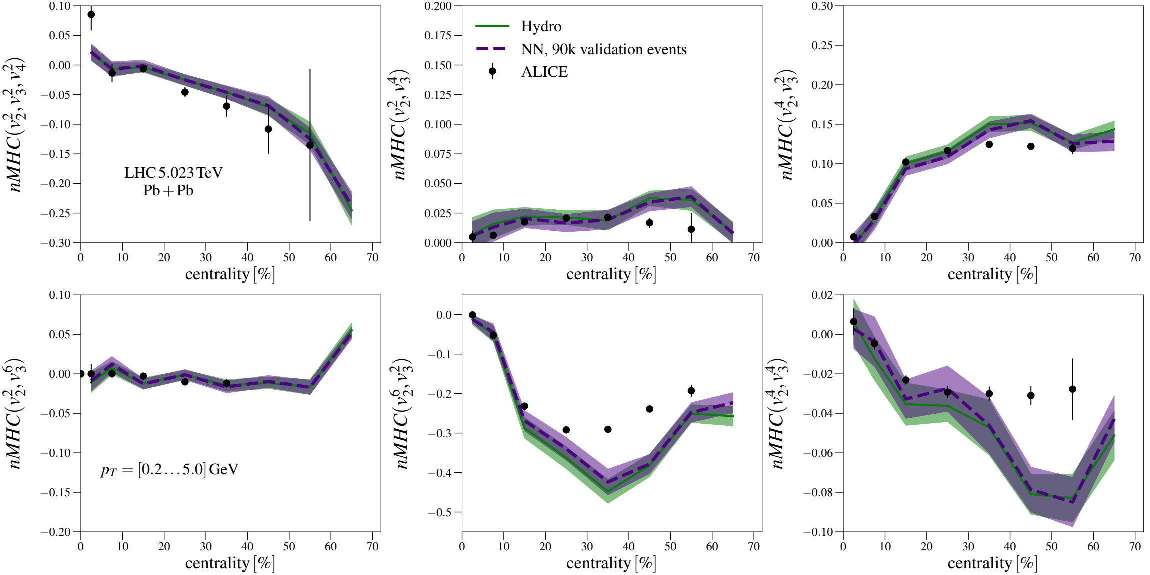


Hydro
NN, 90k validation events
ALICE $v_n\{2\}$
LHC 5.023 TeV Pb + Pb
$p_T = [0.2 \ldots 3.0]$ GeV
n = 2
n = 3
n = 4
LHC 5.023 TeV Pb + Pb
$p_T = [0.2 \ldots 5.0]$ GeV
n = 4
n = 5
n = 6
$v_n\{2\}$
centrality [%]

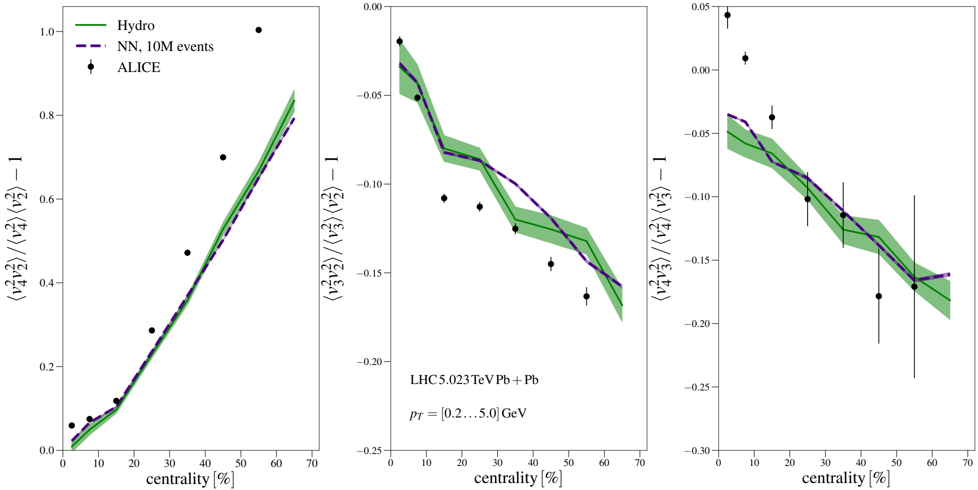
Validation tests: Four-particle flow correlations



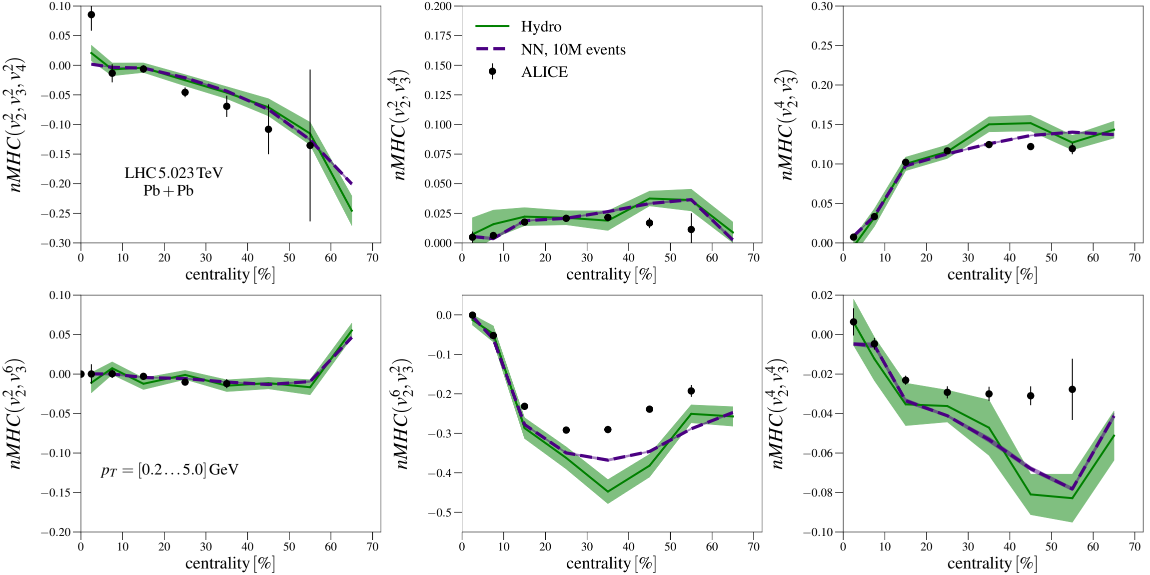
Validation tests: Six- and eight-particle flow correlations



NN predictions: Four-particle flow correlations



NN predictions: Six- and eight-particle flow correlations



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
  - Currently works only for fixed viscosity parametrization
- In future: extend the neural network for arbitrary viscosity parametrizations and use it to perform Bayesian analysis