JYU. Since 1863.

HELSINKI INSTITUTE OF PHYSICS

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

SUOMEN AKATEMIA
FINLANDS AKADEMI
ACADEMY OF FINLAND

CoE QM

European Research Council

JENNY JA ANTTI WIHURIN RAHASTO

Henry Hirvonen, Kari J. Eskola, Harri Niemi

Department of Physics, University of Jyväskylä, Finland
Helsinki Institute of Physics, University of Helsinki, Finland

DEEP LEARNING FOR FLOW OBSERVABLES IN ULTRARELATIVISTIC HEAVY-ION COLLISIONS

ABSTRACT

Including multi-particle flow correlations to Bayesian analyses is challenging due to a very high computational cost of simulating millions of collision events. Deep neural networks can be trained to predict final state quantities from initial energy density EbyE. This speeds up the simulations by orders of magnitude.

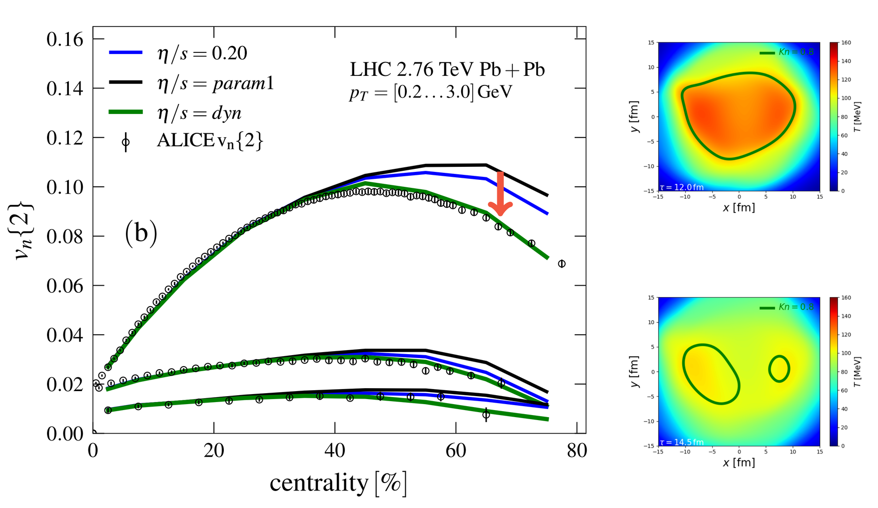
THE MODEL FRAMEWORK

- Initial state: pQCD + gluon saturation based EKRT-model
- Evolution: 2+1D second-order viscous hydrodynamics with shear and bulk viscosities
- Decoupling: Based on applicability of hydrodynamics $\Longrightarrow$ Dynamical decoupling conditions [1]:

Knudsen number	Global size of system
$\mathrm{Kn} \equiv \frac{\text{exp. rate}}{\text{scat. rate}} = \tau_\pi \theta = C_{\mathrm{Kn}}$	$\frac{\gamma \tau_\pi}{R} = C_R,\ R = \sqrt{A/\pi}$

where:

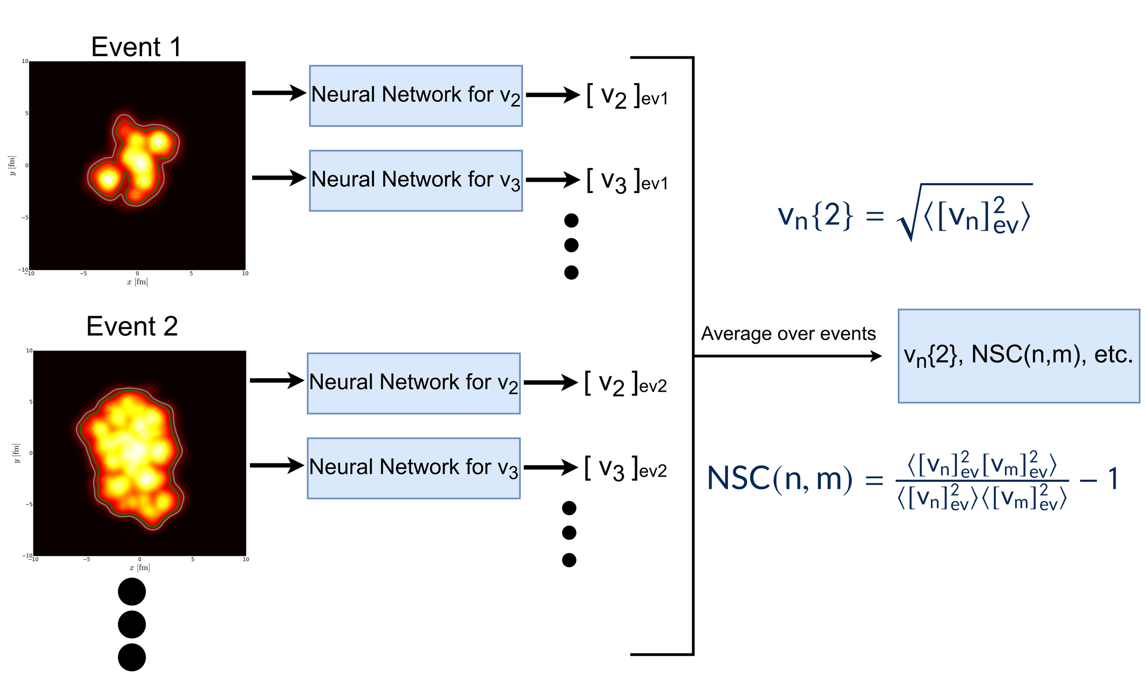
C_{Kn}, C_R are free parameters fitted from data,
τ_π = relaxation time,
θ = expansion rate,
A = area in which $\mathrm{Kn} < C_{Kn}$ and $T < 150$ MeV



Dynamical decoupling decreases lifetime of the system compared to a constant temperature decoupling in peripheral collisions $\Longrightarrow$ flow is reduced

NEURAL NETWORK

We have trained a set of neural networks to emulate heavy-ion collision simulations EbyE by taking transverse-plane initial energy densities at mid-rapidity as an input and giving a chosen set of final state observables as an output [2]. Specifically, we use deep convolutional neural networks in our implementation, which are state of the art in machine vision tasks.

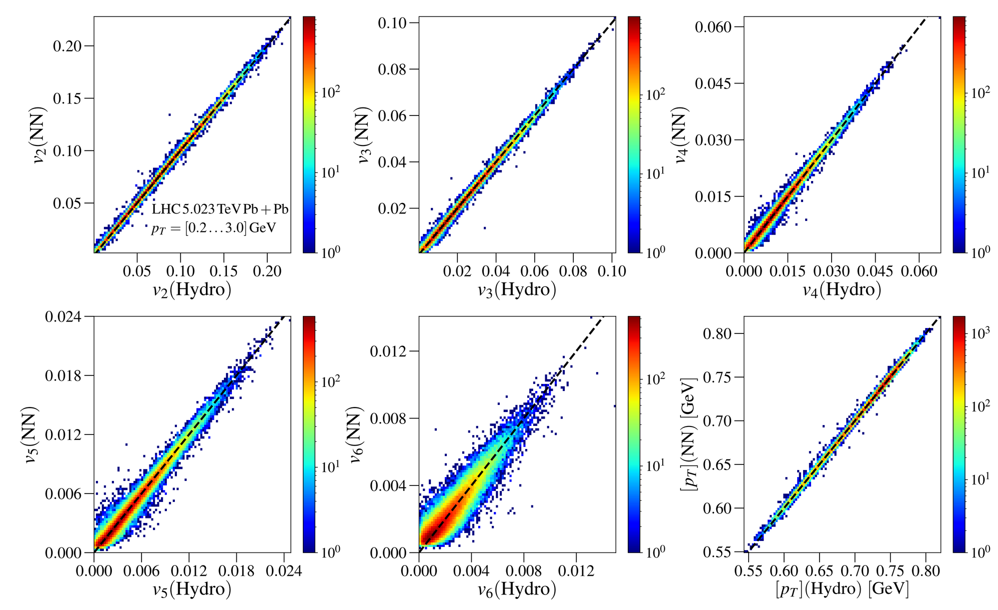


TRAINING AND VALIDATION

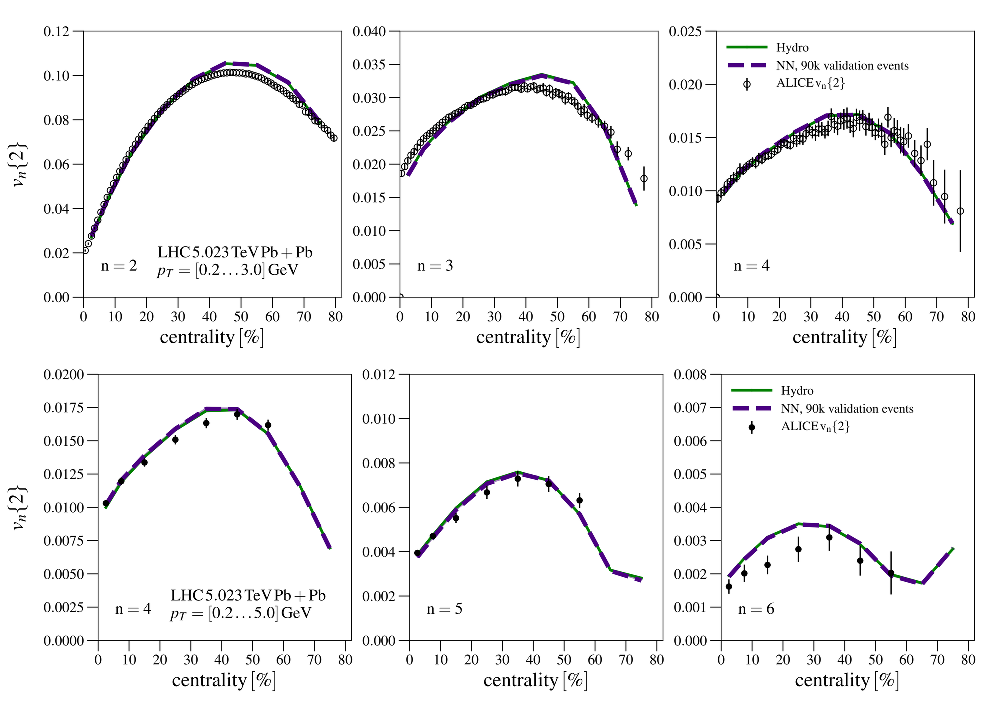
Here the neural networks are trained to predict p_T-integrated flow observables v_2, v_3, v_4, v_5, v_6, $[p_T]$ and $dN_{ch}/d\eta$. The training for each neural network takes around one hour with NVIDIA V100 32GB GPU. As training data, we have used 5k events for each collision system:

- 200 GeV Au+Au
- 2.76 TeV Pb+Pb
- 5.023 TeV Pb+Pb
- 5.44 TeV Xe+Xe (deformed nuclei)

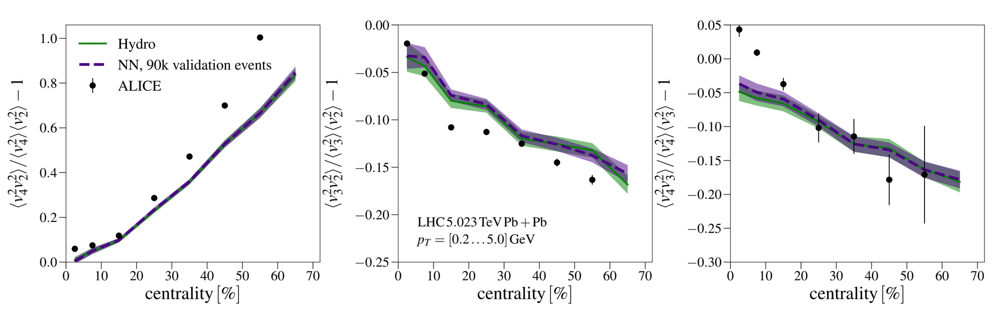
Validation of the neural networks is done by generating 90k independent initial energy density profiles and comparing results between the full simulations (Hydro) and neural network predictions (NN).



- Good EbyE agreement for lower order flow coefficients and mean transverse momentum



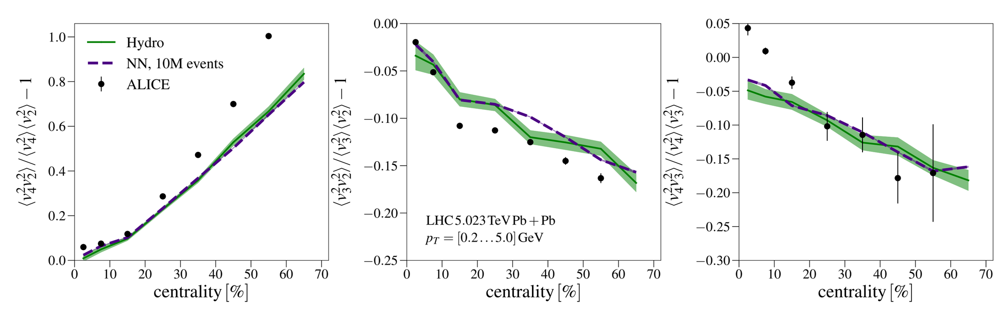
- The agreement nearly exact for all event averaged flow coefficients



- Great agreement also for multi-particle correlations!

HIGH-STATISTICS PREDICTIONS

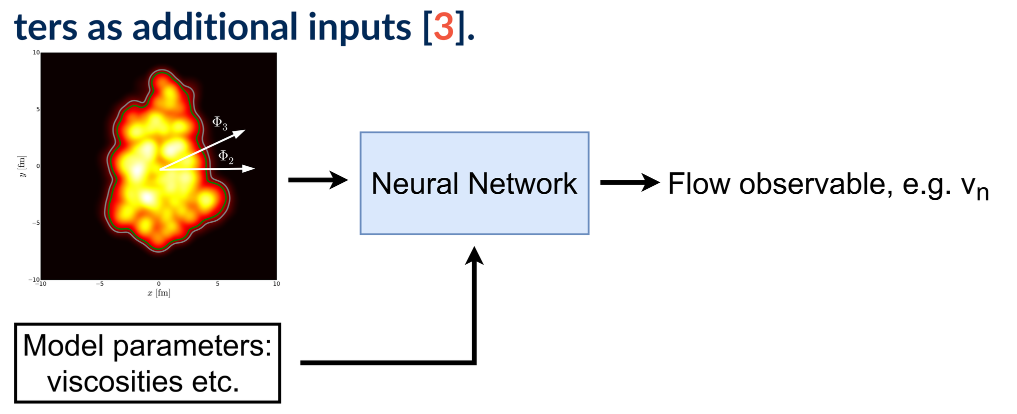
Generating 10 million events with the trained neural networks takes around 20 hours with GPU, which is five orders of magnitude faster than doing full simulations using the CPU.



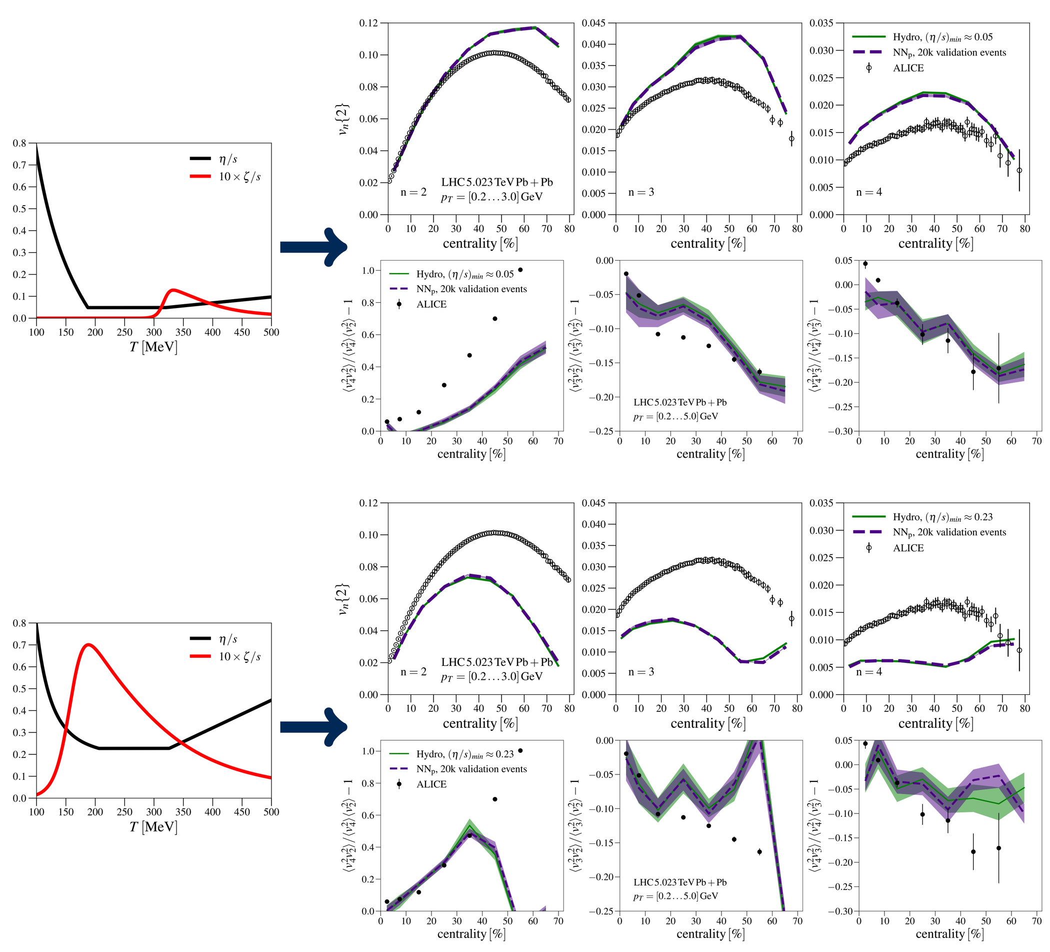
- Increasing statistic from 90k to 10M events is very significant for rare flow correlators

ADDITIONAL INPUTS

To make neural networks more versatile and suitable for Bayesian analyses, it is necessary to add all model parameters as additional inputs [3].



The training with additional inputs uses a total of 160k events, which are distributed evenly between 2k parameter points. We now only use 80 training events for each parameter point, which is 250 times less than in the previous case with 20k training events.



- NN can predict Hydro results quite well for both viscosities

APPLICATION TO BAYESIAN ANALYSIS

Neural networks presented here are still not directly usable to perform Bayesian analysis since it is too slow to generate ~ 1M events in every MCMC random walk step. However, neural networks can be used to generate training data for a Gaussian process emulator in a fraction of the time compared to conventional methods.

CONCLUSIONS

We have trained neural networks to predict flow observables from initial energy density EbyE and shown that they can predict the results from full hydrodynamical simulations quite reliably. This method can be used in the future to perform Bayesian analyses that take into account multi-particle flow correlations with immensely reduced computational time.

REFERENCES

[1] H. Hirvonen, K. J. Eskola and H. Niemi, *Phys. Rev. C* 106 (2022) no. 4 044913.

[2] H. Hirvonen, K. J. Eskola and H. Niemi, arXiv:2303.04517 [hep-ph]. To appear in Phys. Rev. C.

[3] H. Hirvonen, J. Auvinen, K. J. Eskola and H. Niemi, work in progress.