Application of deep learning in estimating the elliptic flow coefficient in heavy-ion collisions at the RHIC and LHC

Margaret Island Symposium 2023 on Particles & Plasmas
06-09 June 2023, Budapest

Neelkamal Mallick
Indian Institute of Technology Indore, India
Neelkamal.Mallick@cern.ch

Collaborators:

Suraj Prasad, IIT Indore, India
Raghunath Sahoo, IIT Indore, India
Aditya Nath Mishra, UCRD, Mohali, India
Gergely Gábor Barnaföldi, WRCP, Budapest

Context

Based on

1. N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 105, 114022 (2022)
2. N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 107, 094001 (2023)

PHYSICAL REVIEW D **105,** 114022 (2022)

Estimating elliptic flow coefficient in heavy ion collisions using deep learning

Neelkamal Mallick,[1] Suraj Prasad,[1] Aditya Nath Mishra,[2] Raghunath Sahoo,[1,3,*] and Gergely Gábor Barnaföldi[2]

[1]*Department of Physics, Indian Institute of Technology Indore, Simrol, Indore 453552, India*
[2]*Wigner Research Center for Physics, 29-33 Konkoly-Thege Miklós Street, H-1121 Budapest, Hungary*
[3]*CERN, CH 1211, Geneva 23, Switzerland*

(Received 3 March 2022; accepted 20 May 2022; published 17 June 2022)

Machine learning techniques have been employed for the high energy physics community since the early 80s to deal with a broad spectrum of problems. This work explores the prospects of using deep learning techniques to estimate elliptic flow (v_2) in heavy-ion collisions at the RHIC and LHC energies. A novel method is developed to process the input observables from particle kinematic information. The proposed deep neural network (DNN) model is trained with Pb-Pb collisions at $\sqrt{s_{\rm NN}} = 5.02$ TeV minimum bias events simulated with a multiphase transport model. The predictions from the machine learning technique are compared to both simulation and experiment. The deep learning model seems to preserve the centrality and energy dependence of v_2 for the LHC and RHIC energies. The DNN model is also quite successful in predicting the $p_{\rm T}$ dependence of v_2. When subjected to event simulation with additional noise, the proposed DNN model still keeps the robustness and prediction accuracy intact up to a reasonable extent.

PHYSICAL REVIEW D **107,** 094001 (2023)

Deep learning predicted elliptic flow of identified particles in heavy-ion collisions at the RHIC and LHC energies

Neelkamal Mallick,[1,*] Suraj Prasad,[1,†] Aditya Nath Mishra,[2,4,‡] Raghunath Sahoo,[1,§] and Gergely Gábor Barnaföldi[3,∥]

[1]*Department of Physics, Indian Institute of Technology Indore, Simrol, Indore 453552, India*
[2]*Department of Physics, School of Applied Sciences, REVA University, Bangalore 560064, India*
[3]*Wigner Research Center for Physics, 29-33 Konkoly-Thege Miklós Str., H-1121 Budapest, Hungary*
[4]*Department of Physics, University Centre For Research & Development (UCRD), Chandigarh University, Mohali, Punjab 140413, India*

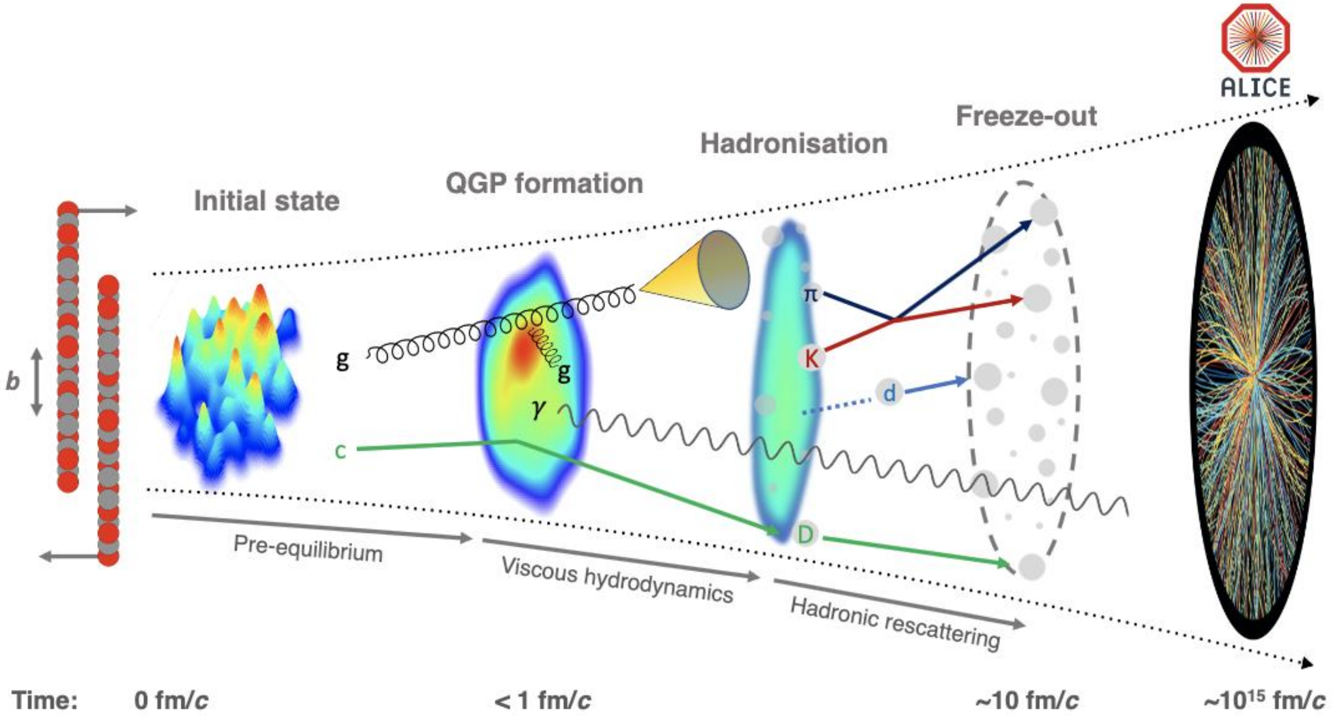
(Received 26 January 2023; accepted 29 March 2023; published 2 May 2023)

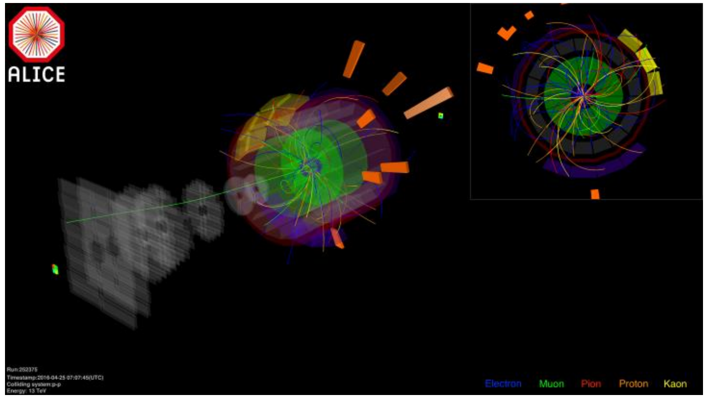
Recent developments of a deep learning feed-forward network for estimating elliptic flow (v_2) coefficients in heavy-ion collisions have shown the prediction power of this technique. The success of the model is mainly the estimation of v_2 from final-state particle kinematic information and learning the centrality and transverse momentum ($p_{\rm T}$) dependence of v_2. The deep learning model is trained with Pb-Pb collisions at $\sqrt{s_{\rm NN}} = 5.02$ TeV minimum bias events simulated with a multiphase transport model. We extend this work to estimate v_2 for light-flavor identified particles such as $\pi^{\pm}$, $K^{\pm}$, and $p + \bar{p}$ in heavy-ion collisions at RHIC and LHC energies. The number-of-constituent-quark scaling is also shown. The evolution of the $p_{\rm T}$-crossing point of $v_2(p_{\rm T})$, depicting a change in baryon-meson elliptic flow at intermediate $p_{\rm T}$, is studied for various collision systems and energies. The model is further evaluated by training it for different $p_{\rm T}$ regions. These results are compared with the available experimental data wherever possible.

Outline

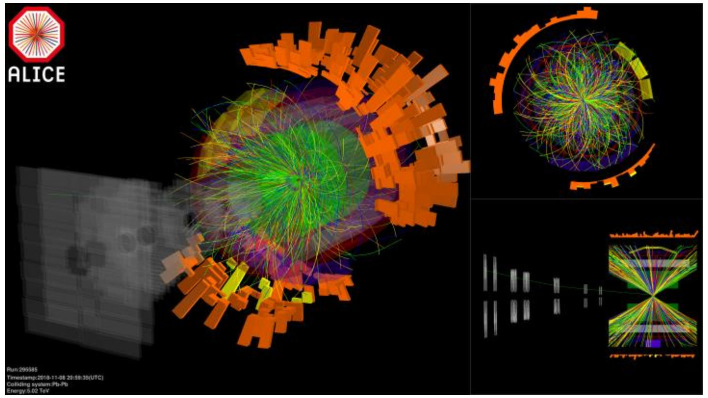
- Heavy-ion collisions
- Anisotropic flow
- Deep Neural Network
- Input, training, metrics
- Predictions
- Summary and outlook

Heavy-ion collisions





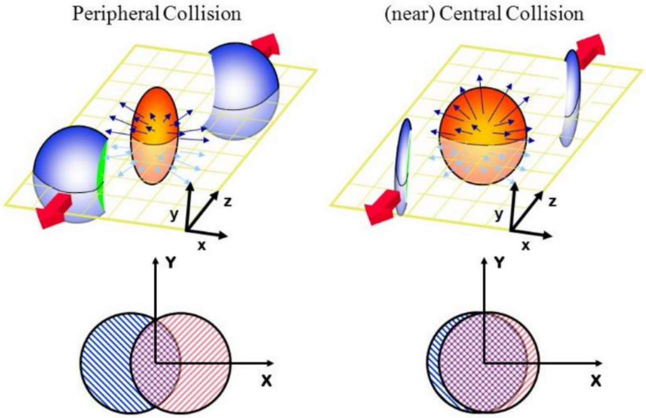
proton-proton collisions, $\sqrt{s} = 13$ TeV

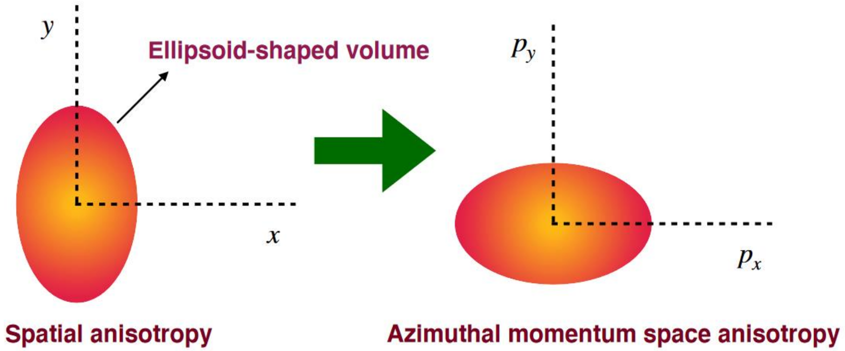


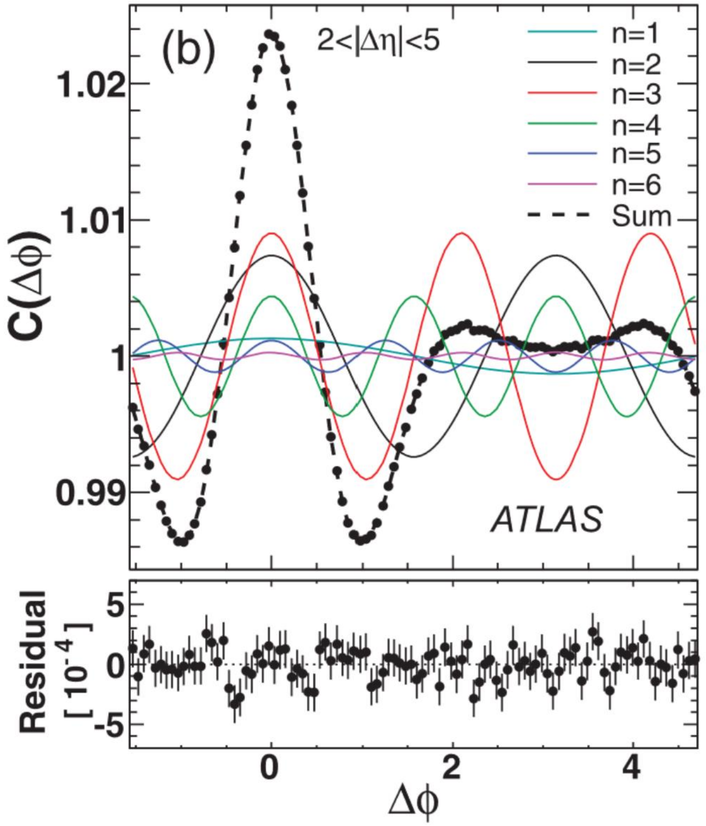
Pb-Pb collisions, $\sqrt{s_{\mathrm{NN}}} = 5.02$ TeV

- Quark-gluon plasma is a thermalized medium of deconfined QCD matter
- Heavy-ion collisions provide high temperature (T) and/or high net baryon density (μ_B)
- Asymptotic freedom: interaction weakens at large momentum transfer

Anisotropic Flow







$$E\frac{d^3N}{dp^3} = \frac{d^3N}{p_\mathrm{T}dp_\mathrm{T}dyd\phi} = \frac{d^2N}{p_\mathrm{T}dp_\mathrm{T}dy}\frac{1}{2\pi}\left(1 + 2\sum_{n=1}^{\infty} v_n \cos[n(\phi - \psi_n)]\right)$$

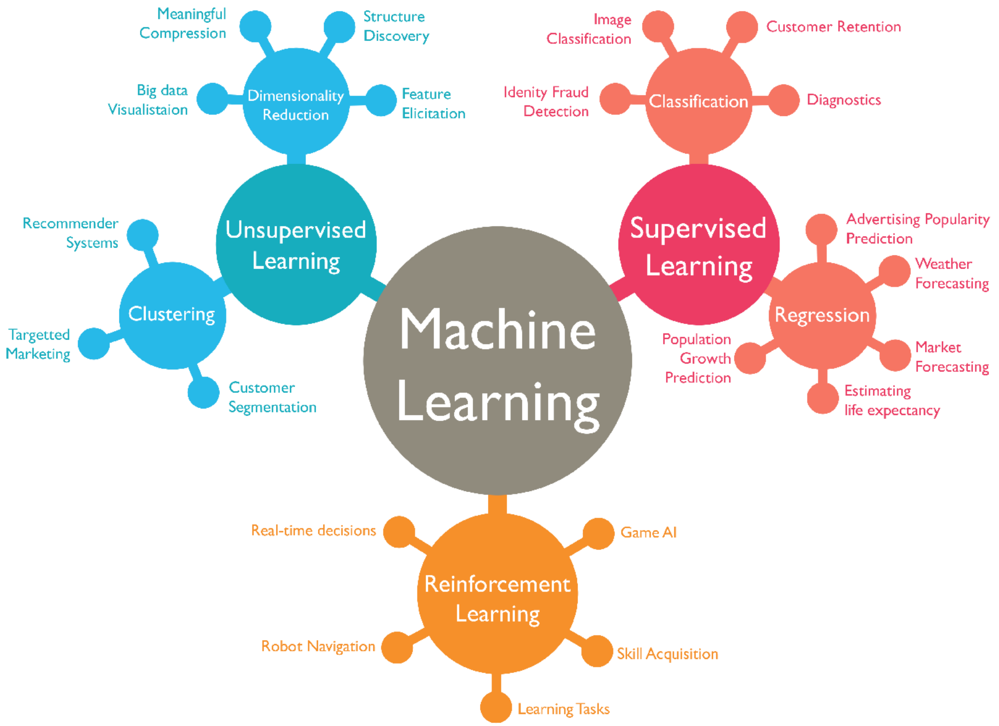
$$v_n(p_\mathrm{T}, y) = \langle \cos(n(\phi - \psi_n)) \rangle$$

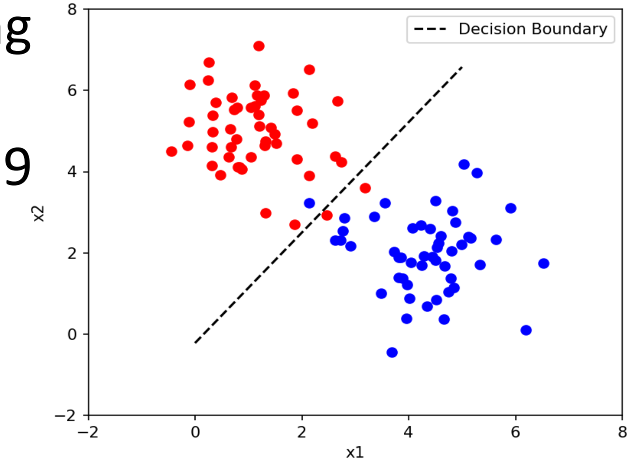
ATLAS Collaboration, Phys. Rev. C 86, 014907 (2012)

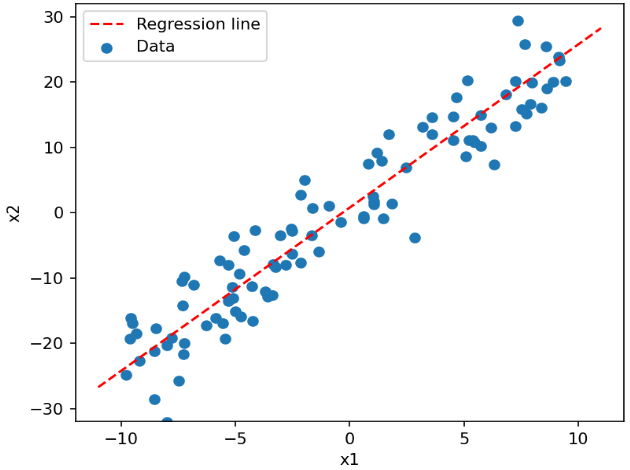
Machine learning

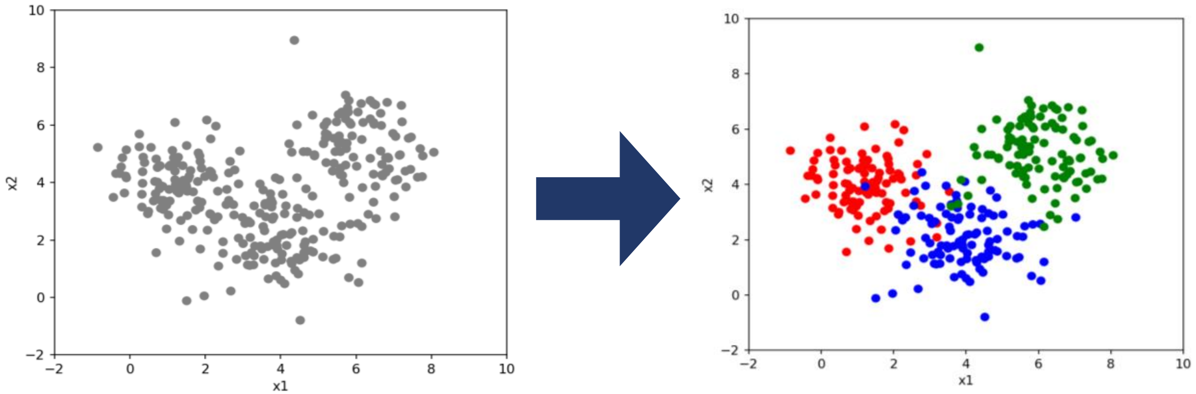
“Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed.”

-Arthur Samuel, 1959



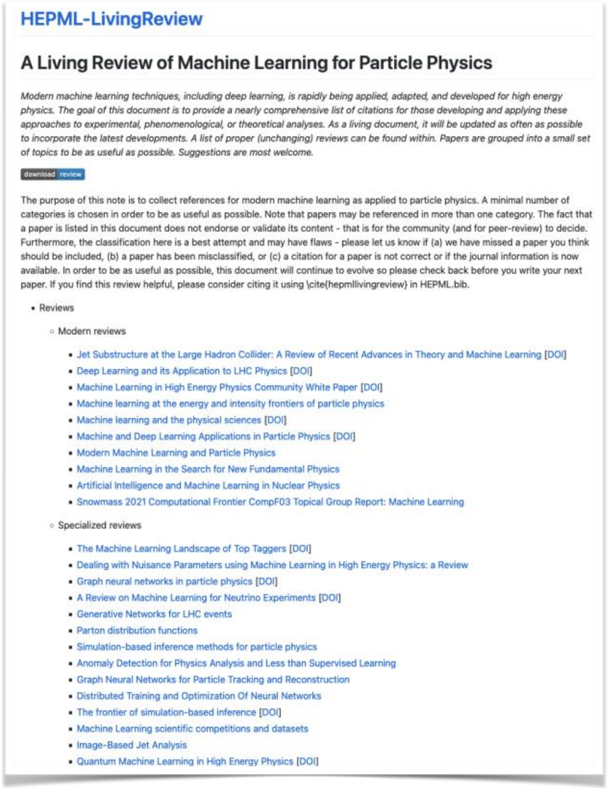






Machine learning in HEP

- Particle Identification
- Track reconstruction
- Triggering
- Fast Simulation
- Data Quality Monitoring
- Unfolding Techniques
- Signal and background classification
- Jet identification and tagging
- Beyond standard model physics
- **Heavy-ion physics and QGP phenomenology**



HEPML-LivingReview

A Living Review of Machine Learning for Particle Physics

Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

download review

The purpose of this note is to collect references for modern machine learning as applied to particle physics. A minimal number of categories is chosen in order to be as useful as possible. Note that papers may be referenced in more than one category. The fact that a paper is listed in this document does not endorse or validate its content - that is for the community (and for peer-review) to decide. Furthermore, the classification here is a best attempt and may have flaws - please let us know if (a) we have missed a paper you think should be included, (b) a paper has been misclassified, or (c) a citation for a paper is not correct or if the journal information is now available. In order to be as useful as possible, this document will continue to evolve so please check back before you write your next paper. If you find this review helpful, please consider citing it using \cite{hepmllivingreview} in HEPML.bib.

- Reviews
  - Modern reviews
    - Jet Substructure at the Large Hadron Collider: A Review of Recent Advances in Theory and Machine Learning [DOI]
    - Deep Learning and its Application to LHC Physics [DOI]
    - Machine Learning in High Energy Physics Community White Paper [DOI]
    - Machine learning at the energy and intensity frontiers of particle physics
    - Machine learning and the physical sciences [DOI]
    - Machine and Deep Learning Applications in Particle Physics [DOI]
    - Modern Machine Learning and Particle Physics
    - Machine Learning in the Search for New Fundamental Physics
    - Artificial Intelligence and Machine Learning in Nuclear Physics
    - Snowmass 2021 Computational Frontier CompF03 Topical Group Report: Machine Learning
  - Specialized reviews
    - The Machine Learning Landscape of Top Taggers [DOI]
    - Dealing with Nuisance Parameters using Machine Learning in High Energy Physics: a Review
    - Graph neural networks in particle physics [DOI]
    - A Review on Machine Learning for Neutrino Experiments [DOI]
    - Generative Networks for LHC events
    - Parton distribution functions
    - Simulation-based inference methods for particle physics
    - Anomaly Detection for Physics Analysis and Less than Supervised Learning
    - Graph Neural Networks for Particle Tracking and Reconstruction
    - Distributed Training and Optimization Of Neural Networks
    - The frontier of simulation-based inference [DOI]
    - Machine Learning scientific competitions and datasets
    - Image-Based Jet Analysis
    - Quantum Machine Learning in High Energy Physics [DOI]

ROOT Data Analysis Framework

scikit learn machine learning in Python

TMVA

TensorFlow

Keras

*TensorFlow, the TensorFlow logo and any related marks are trademarks of Google Inc.

https://root.cern/
https://root.cern/manual/tmva/
Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825, 2011
https://keras.io/https://www.tensorflow.org/

A living review of ML in Particle Physics:
https://iml-wg.github.io/HEPML-LivingReview/

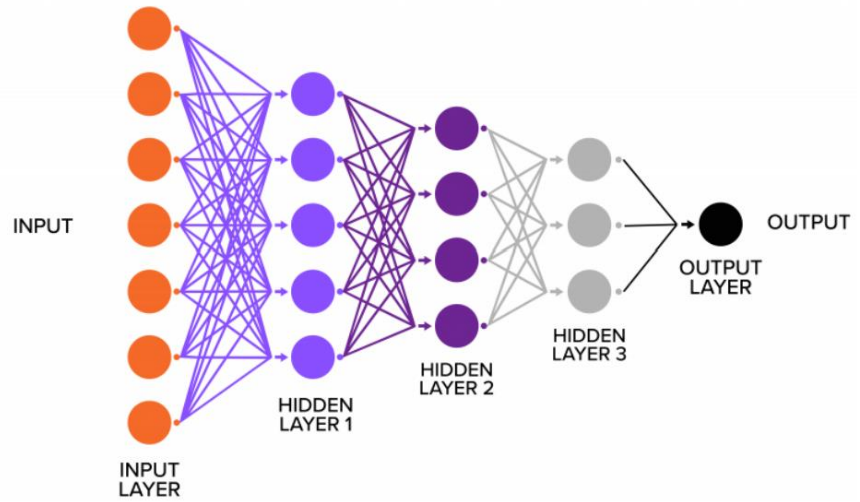
Deep Neural Network

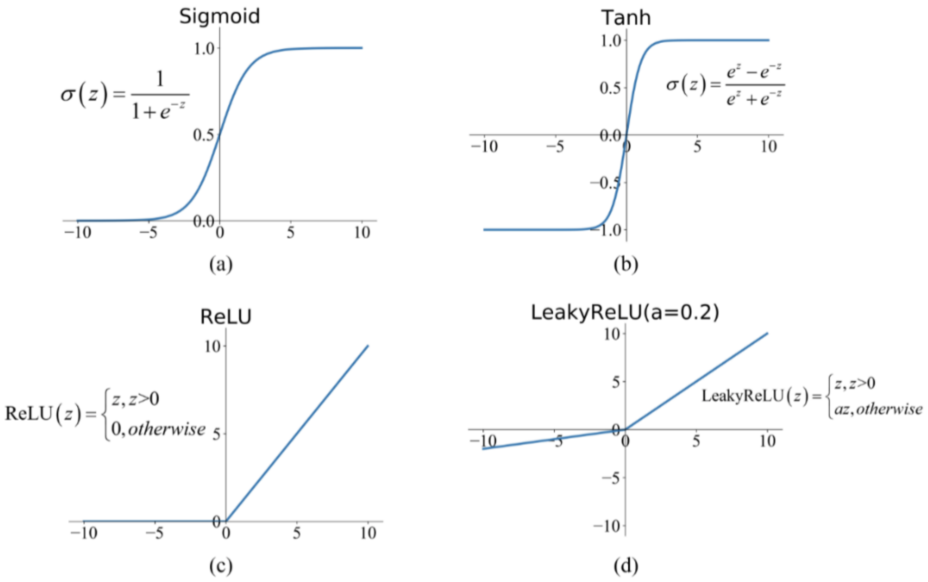
- Neural network as Universal function approximator
- Goal: Learn the mapping function $\boldsymbol{y} = f^*(\boldsymbol{x})$ or $\boldsymbol{y} = f(\boldsymbol{x}; \boldsymbol{w})$
- **Input:** Takes the features as input
- **Hidden layers:** Connects to each node through different weights
- **Output:** Gives the result as a number or class

  Weights dictate the importance of an input more important features get more weights
- **Activation function**: Includes nonlinearity in the model
- **Cost function**: Evaluates the accuracy between machine prediction and true value
- **Optimizer**: Method (or algorithm) that minimizes the cost function by automatically updating the weights

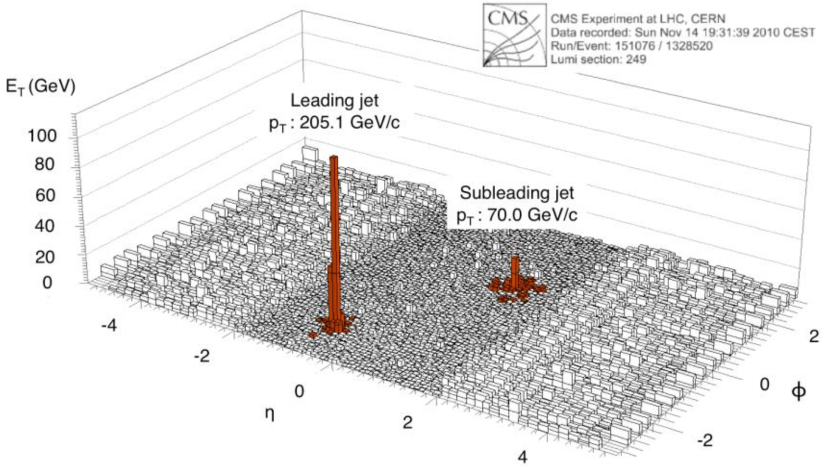
$$\mathbf{y} = f(\langle \mathbf{x}, \mathbf{W} \rangle + b) \qquad \mathbf{y} = \mathbf{f}^{(3)}(\mathbf{f}^{(2)}(\mathbf{f}^{(1)}(\,.\,)))$$

Junxi Feng et al. , Phys. Rev. E 100, 033308 (2019).

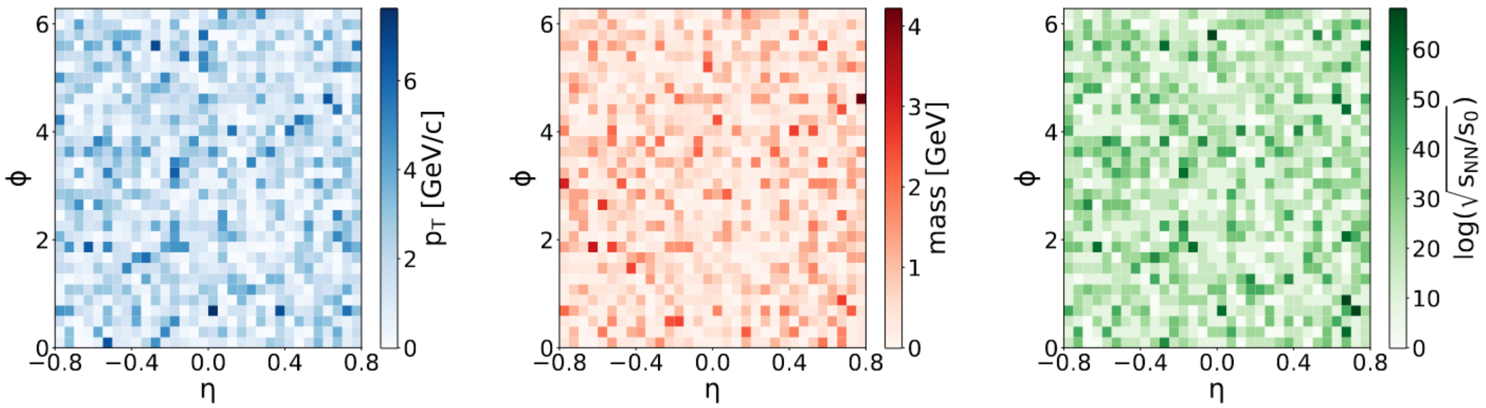




Input and Output



Pb-Pb collisions, $\sqrt{s_{\mathrm{NN}}} = 5.02$ TeV, AMPT simulation



- First deep neural network based estimator for flow estimation
- $(\eta - \phi)$ space as the primary input space
- p_T, mass, and $\log\sqrt{s_{NN}/s_0}$ weighted layers serve as the secondary input space
- Model trained on Pb-Pb, $\sqrt{s_{NN}}$ = 5.02 TeV (Minimum Bias)

Basic kinematics observables

$$\eta = -\log\left(\tan\left(\frac{\theta}{2}\right)\right) \qquad p_T = \sqrt{p_x^2 + p_y^2}$$

$$\phi = \tan^{-1}\frac{p_y}{p_x} \qquad \theta = \cos^{-1}\frac{p_z}{|\vec{p}|}$$

Serguei Chatrchyan et al., Phys.Rev.C 84, 024906 (2011)

N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 105, 114022 (2022)

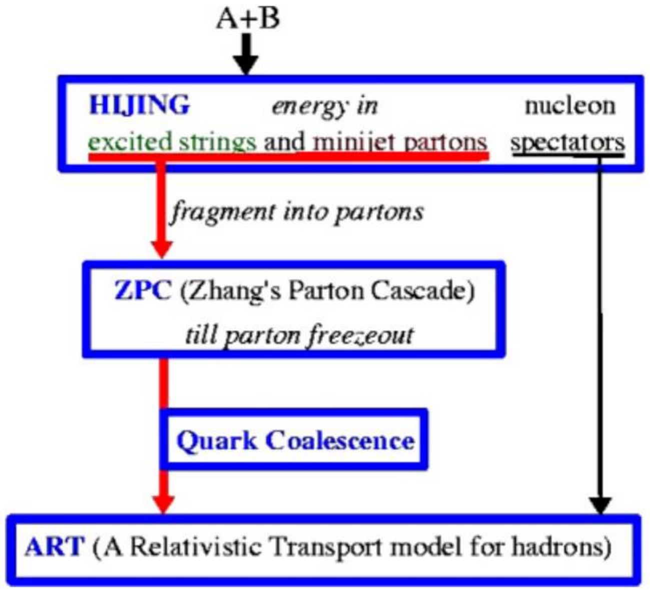
Model architecture

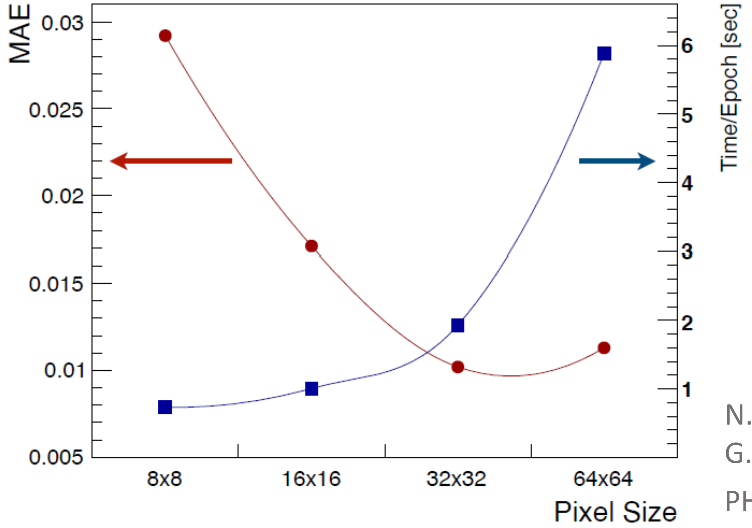
A multiphase transport model (AMPT)

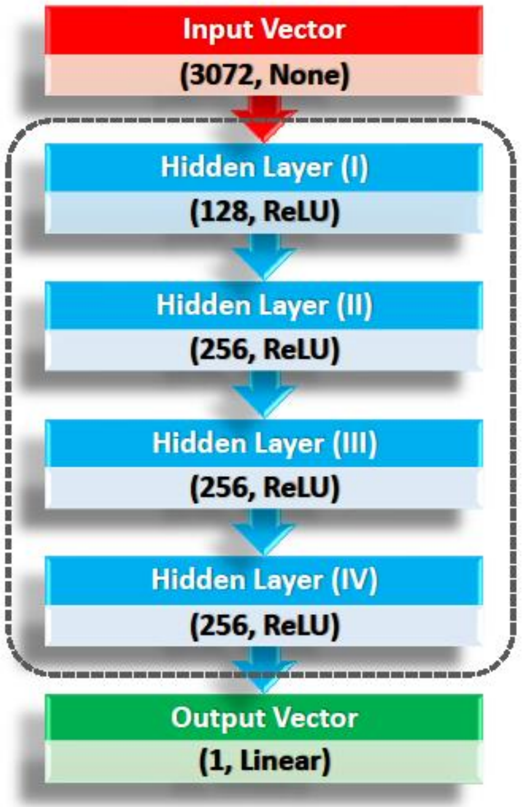
1. Initialization: Glauber MC with HIJING
2. Parton Cascade: Zhang's Parton Cascade
3. Hadronization: Quark Coalescence Model
4. Hadron Cascade: A Relativistic Transport Model (ART)

Model parameters

- Feature size = $32 \times 32 \times 3 = 3072$ per event
- Increasing sparsity and model parameters with pixel size
- Optimzer: *adam* , Loss function: *mse*
- Max epoch: 100
  Batch Size: 32, callback = *early_stopping*
- Training: 2×10^5 events (~60 GB)
- Validation: 10% Events





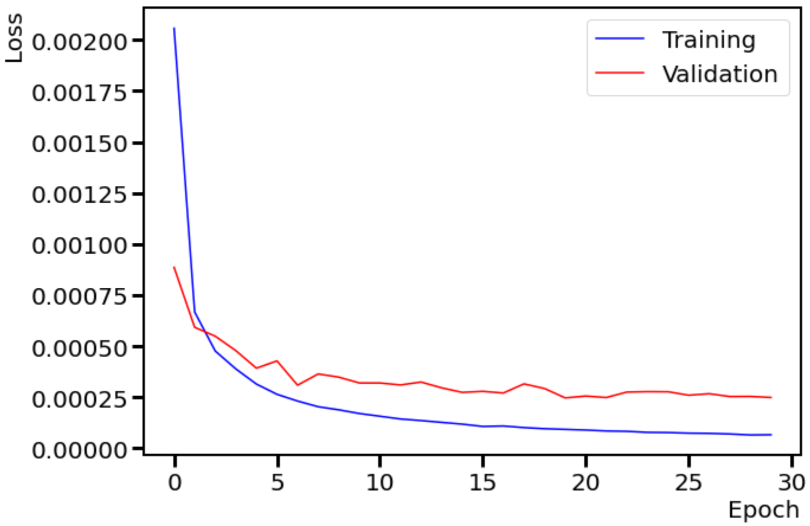


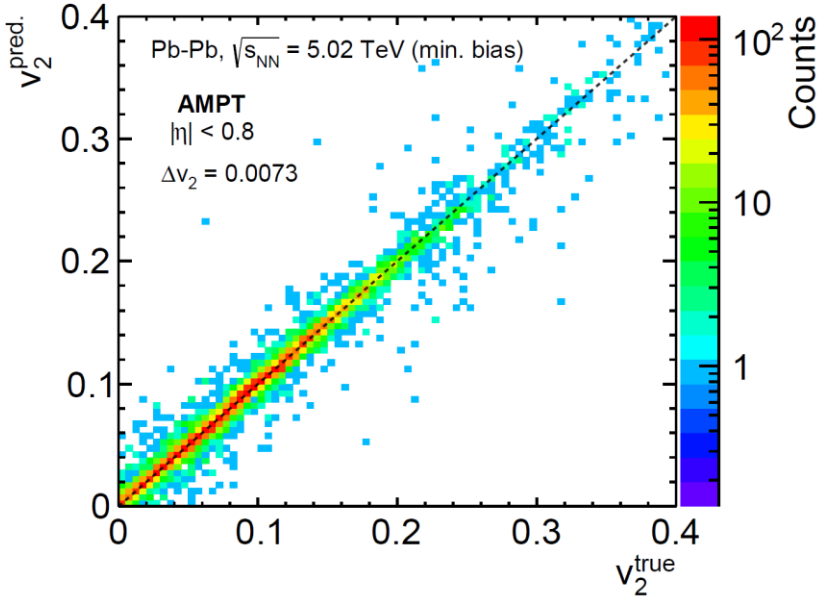
$$\Delta v_2 = \frac{1}{N_{\text{events}}} \sum_{n=1}^{N_{\text{events}}} | v_{2_n}^{true} - v_{2_n}^{pred.} |$$

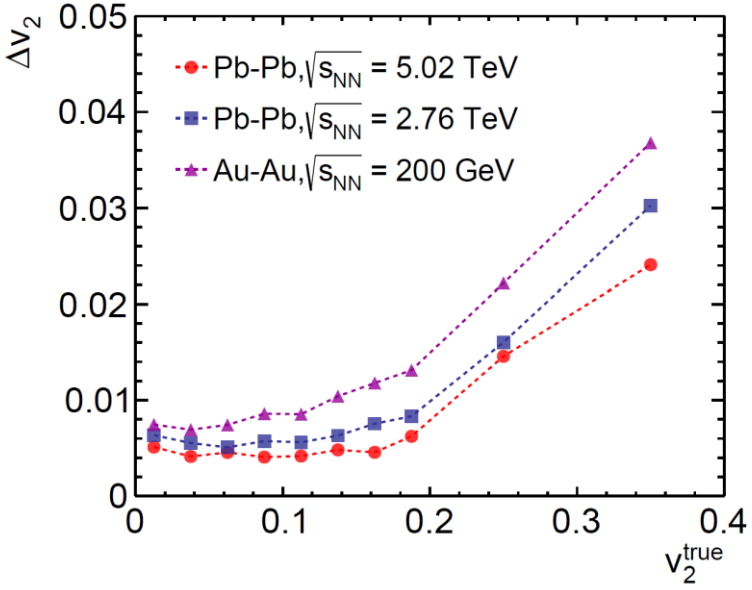
N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 105, 114022 (2022)

PHYSICAL REVIEW C 72, 064901 (2005)

Metrics





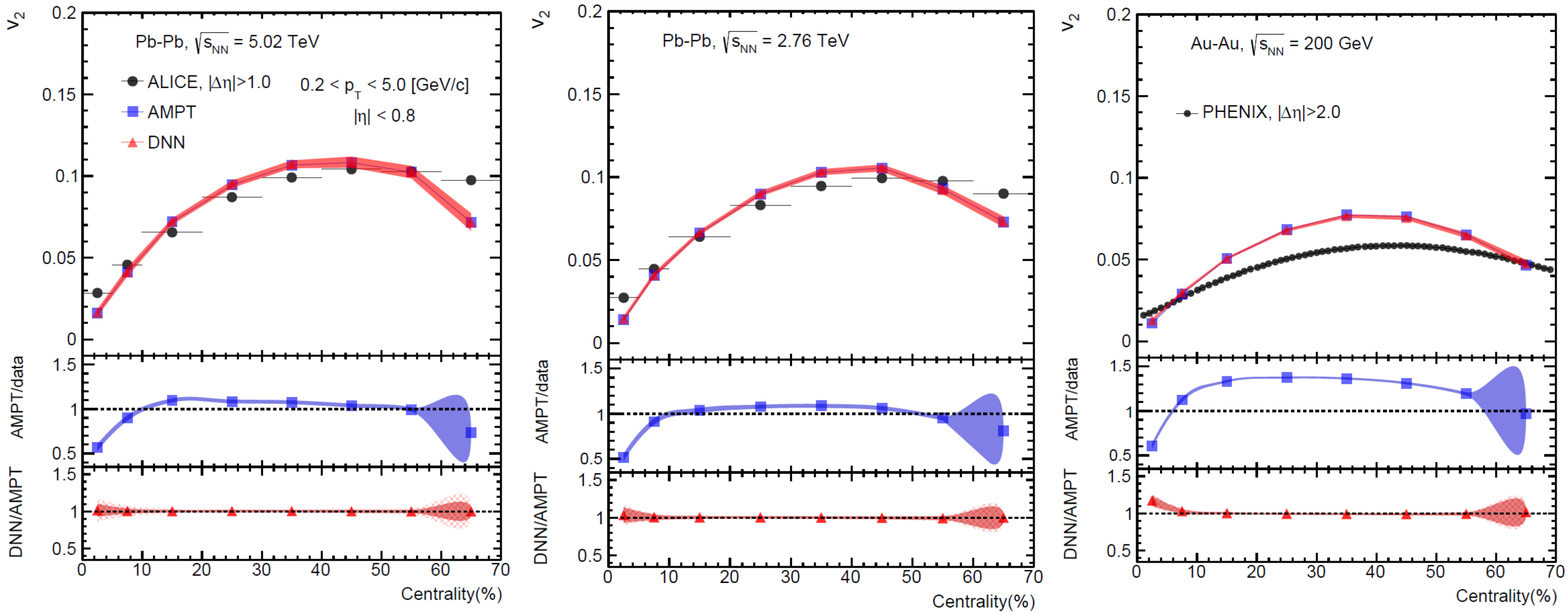


- Loss is measure of the deviation of prediction from the true value
- $E = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$: mean-squared-loss
- Training and validation curves are fairly smooth and approaches zero
- Training on Pb—Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV
- Applied on Pb—Pb collisions, $\sqrt{s_{NN}} = 2.76$ TeV,
  and Au—Au collisions, $\sqrt{s_{NN}} = 200$ GeV

$$\Delta v_2 = \frac{1}{N_{\text{events}}} \sum_{n=1}^{N_{\text{events}}} |v_{2_n}^{true} - v_{2_n}^{pred.}|$$

N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 105, 114022 (2022)

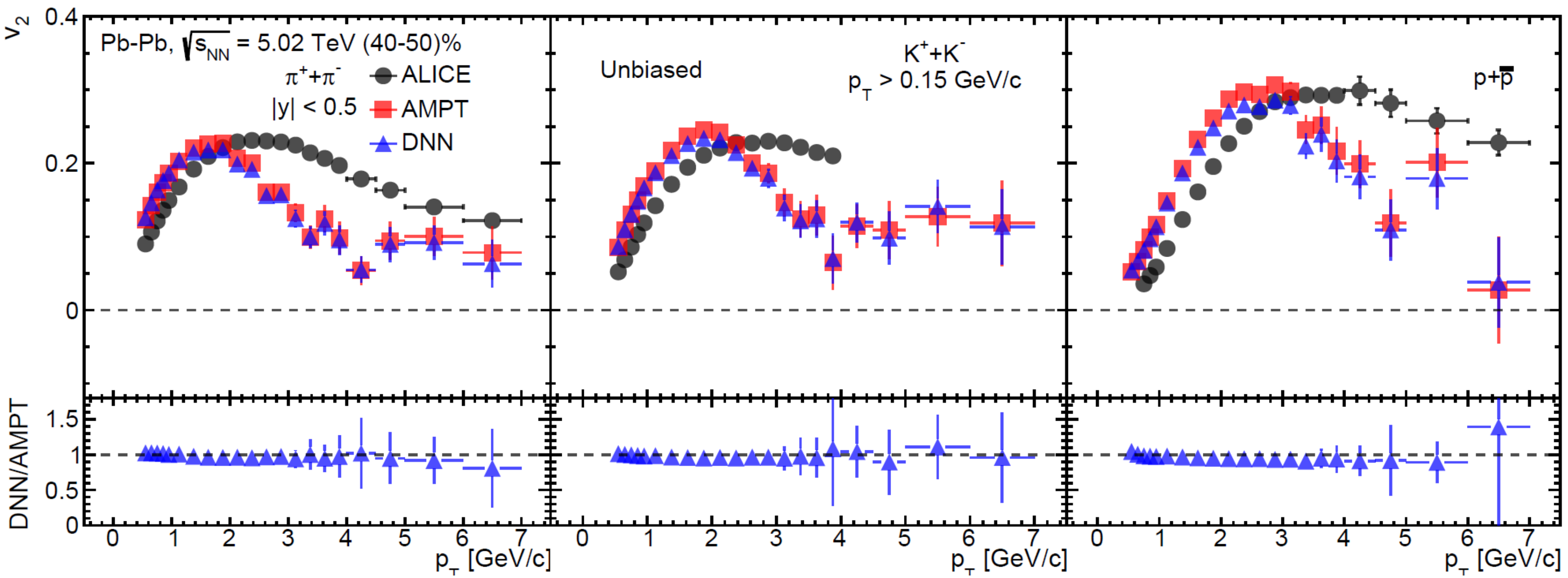
Centrality dependence of v_2



- Good agreement between the simulated and predicted values
- **DNN preserves centrality, and collision system dependence of v_2**

ALICE, Phys. Rev. Lett. 116, 132302 (2016)
PHENIX, Phys. Rev. C 99, 024903 (2019)
N. Mallick et al., Phys. Rev. D 105, 114022 (2022)

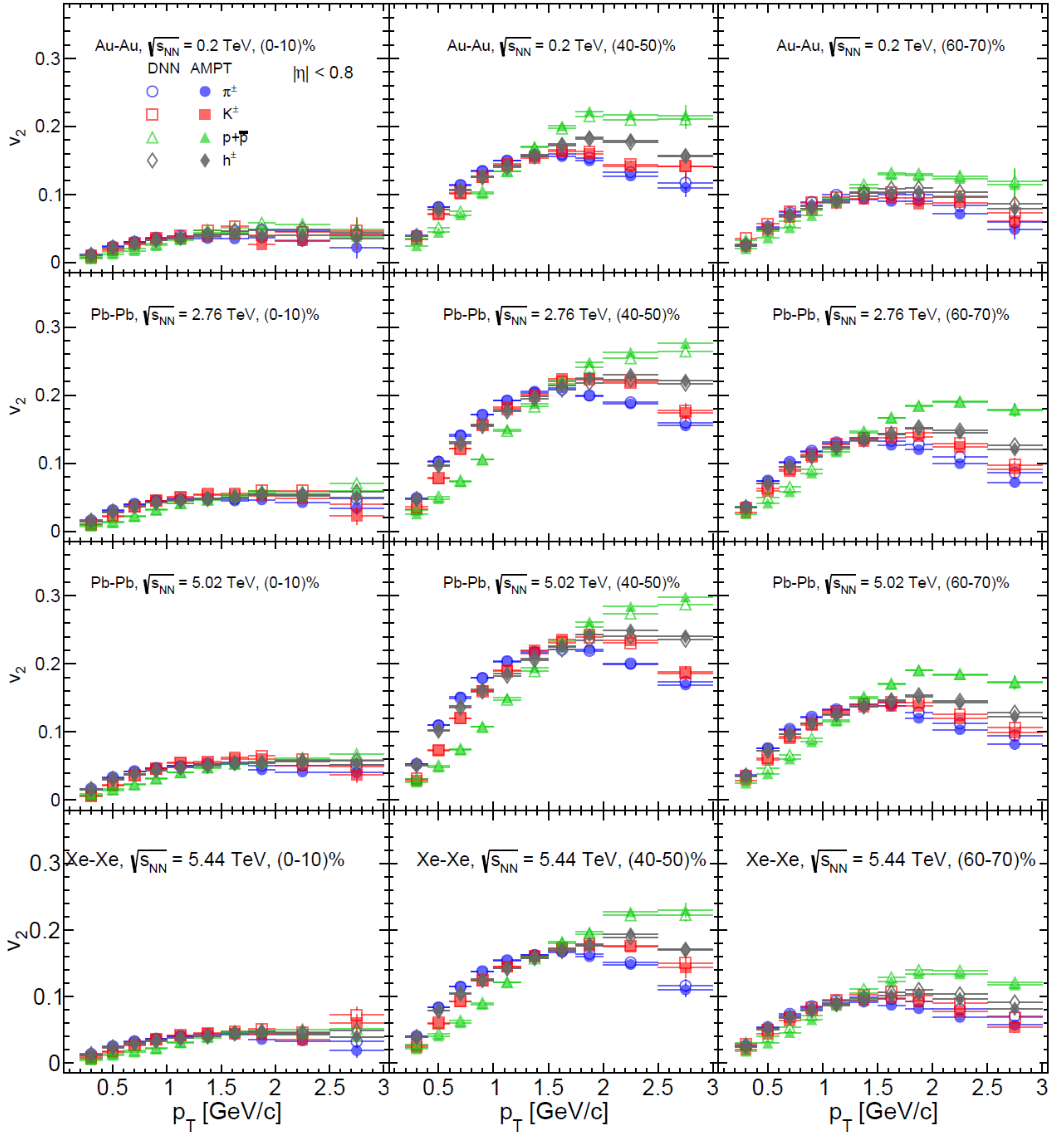
Light-flavor hadrons

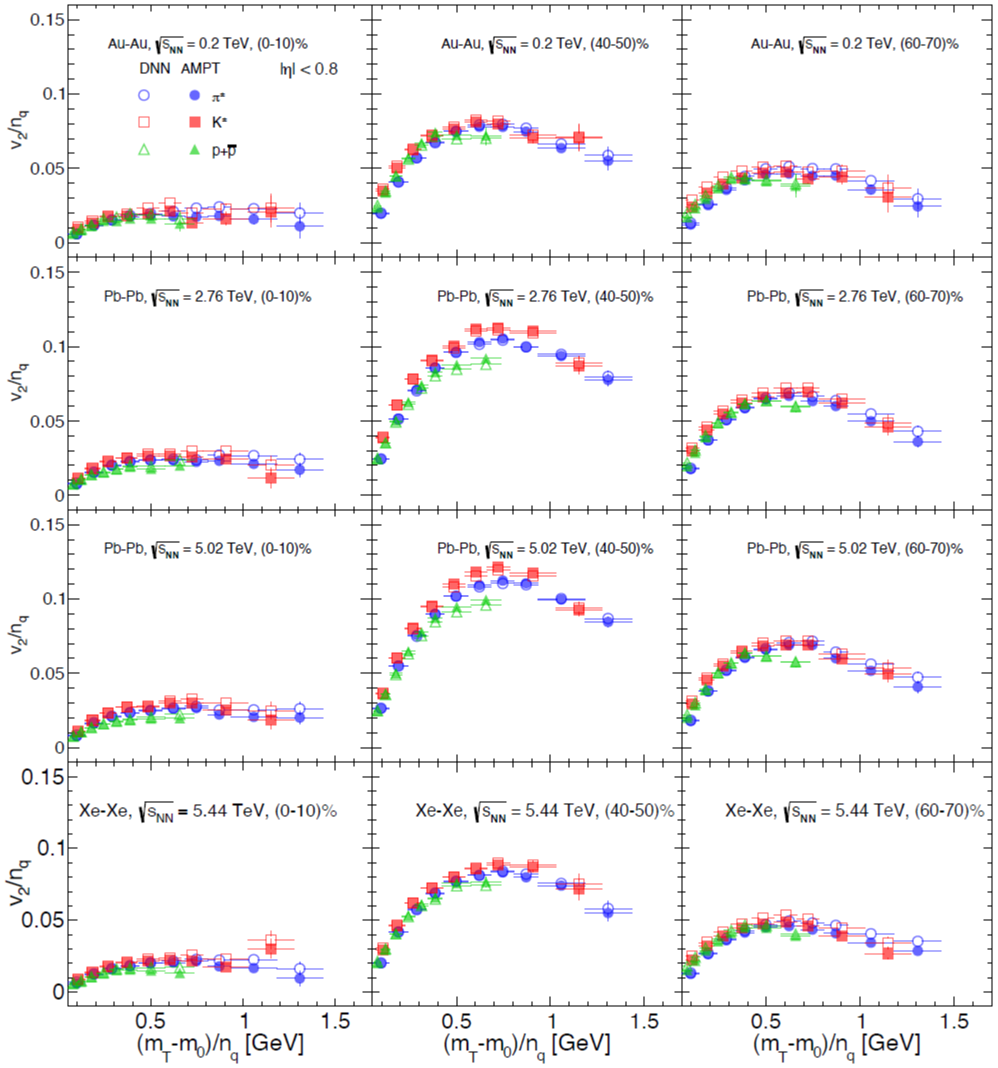


- Estimation of elliptic flow for pion, kaon, and proton
- DNN is trained with Pb-Pb, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias)
- **DNN preserves the p_T dependence of v_2**
- **Meson-Baryon level elliptic flow is preserved with DNN**

N. Mallick et al., Phys. Rev. D 107, 094001 (2023)
ALICE, Phys. Rev. Lett. 116, 132302 (2016)

Other collision systems

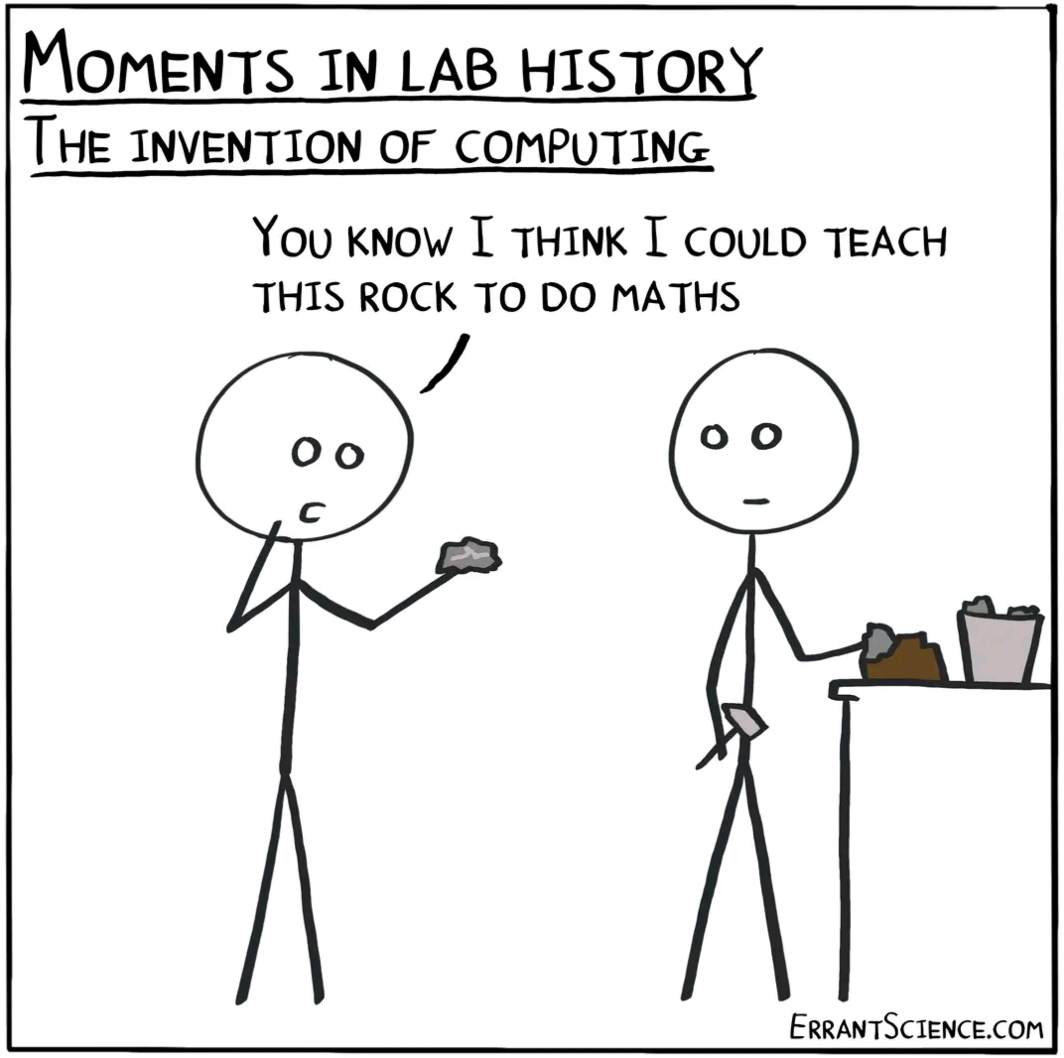




N. Mallick et al., Phys. Rev. D 107, 094001 (2023), ALICE, Phys. Rev. Lett. 116, 132302 (2016)

Summary and outlook

- Deep learning estimator for flow measurements
- DNN preserves the centrality, transverse momentum dependence
- Meson-Baryon level elliptic flow is also preserved
- The prediction is much faster and accurate
- Simultaneous prediction of higher order coefficients
- Extraction of transport coefficients, or prediction for initial energy density
- A full hydrodynamic simulation based on NN


MOMENTS IN LAB HISTORY
THE INVENTION OF COMPUTING
YOU KNOW I THINK I COULD TEACH THIS ROCK TO DO MATHS
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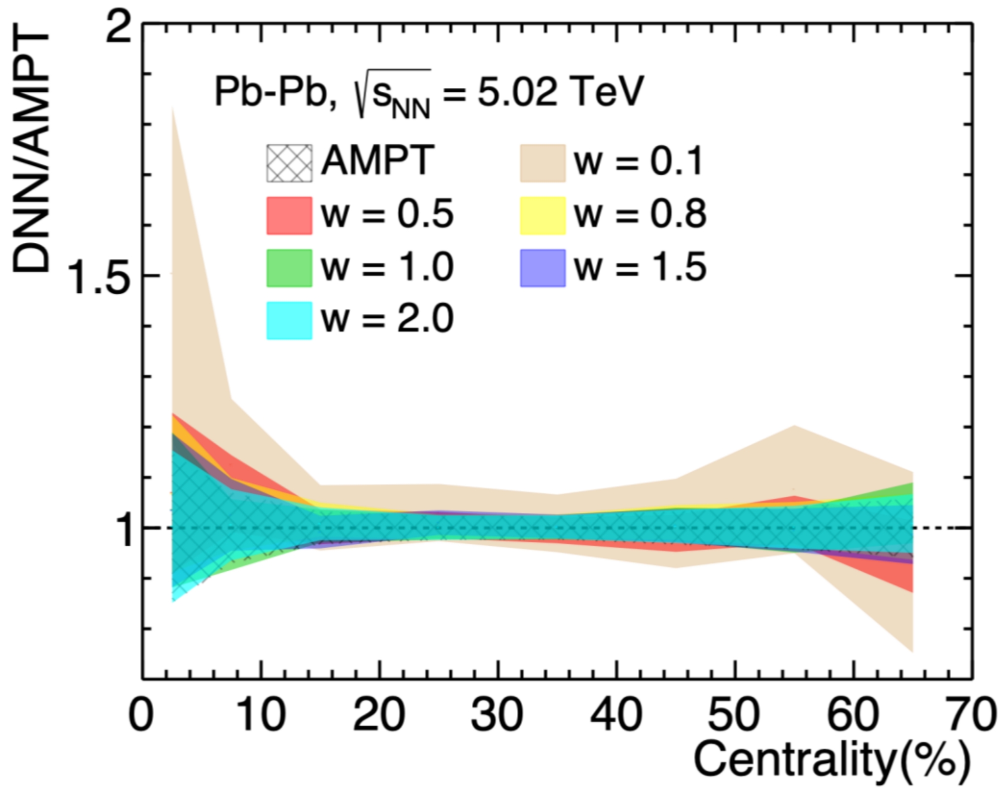
Thank you

Systematic Uncertainty

- Introduce uncorrelated and random noise to simulation
- For i^{th} event, and j^{th} feature, the feature value,

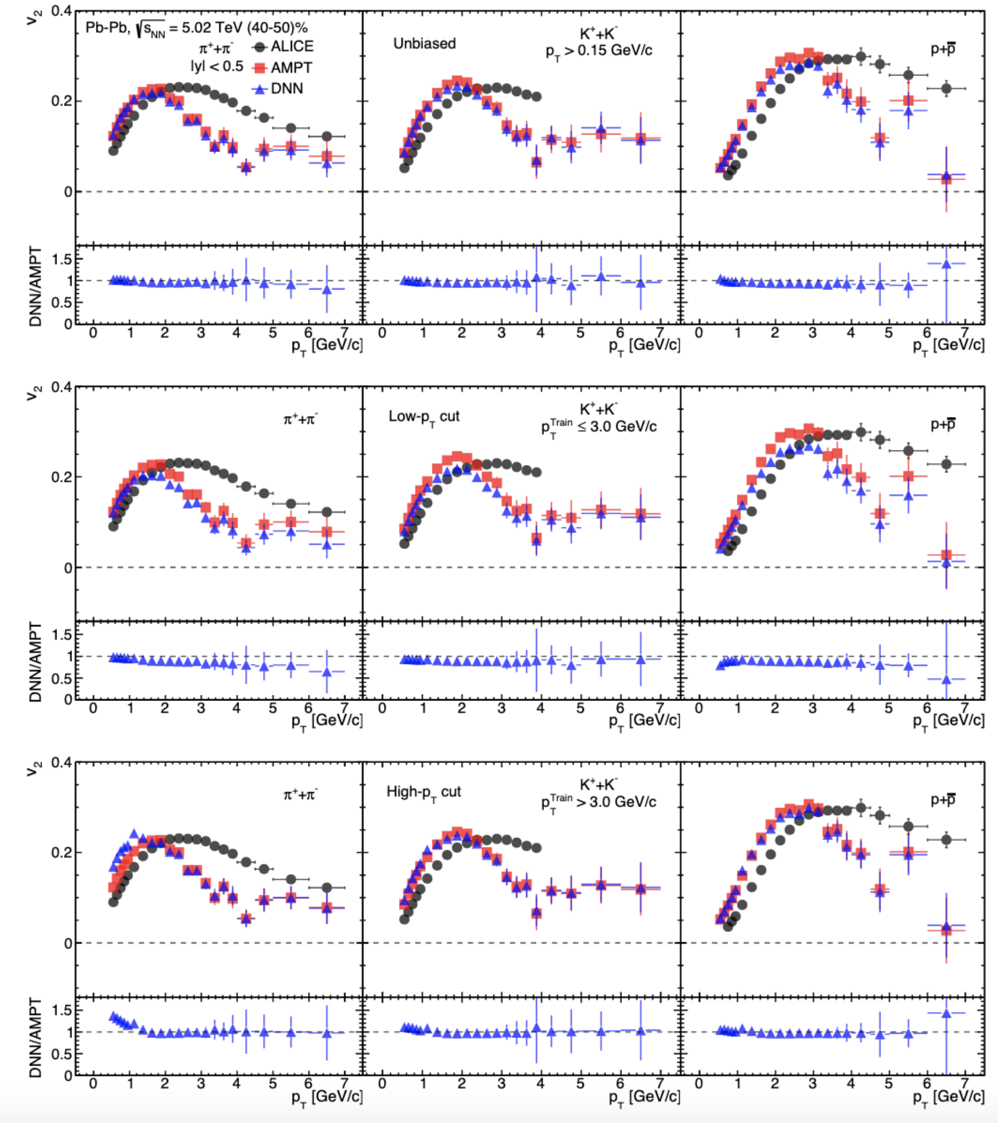
  $F_{i,j} \leftarrow F_{i,j} + X_{i,j}/w$,where $X_{i,j} \in (-\sigma_j, \sigma_j)$.

  σ_j = standard deviation, w = noise parameter
- Large $w \rightarrow$ small noise and *vice versa.*
- *Stable and accurate prediction* $\rightarrow$ *robust model*
- Systematic Uncertainty



N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo, and G.G. Barnaföldi, Phys. Rev. D 105, 114022 (2022)

Effect of p_T dependent training



N. Mallick et al., Phys. Rev. D 107, 094001 (2023)