Machine learning based estimator for elliptic flow in heavy-ion collisions

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

GPU Day 2022
Massive parallel computing for science and industrial application
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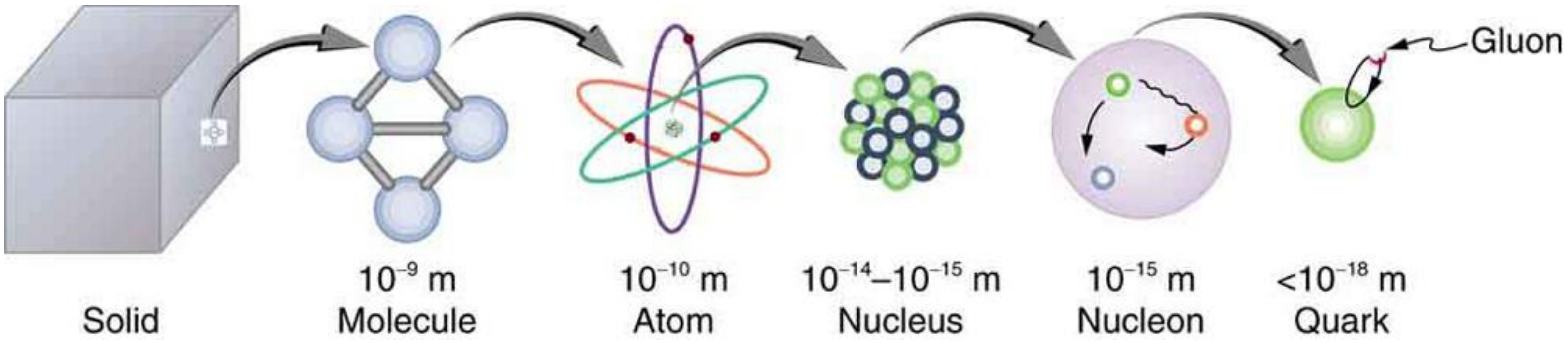
Outline

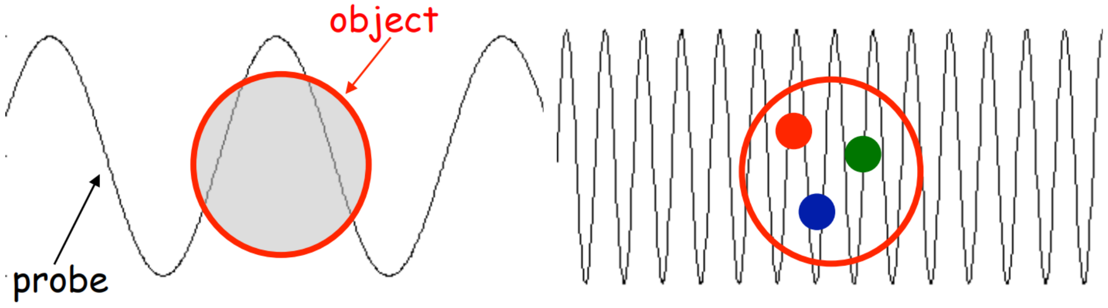
- Matter – from molecules to quarks
- Heavy-ion collisions and Quark gluon plasma
- Elliptic flow
- Deep Neural Network
- Input to the Model
- DNN Architecture
- Quality Assurance
- Results

Matter – from molecules to quarks



- Quarks – fundamental bits of matter; Gluons – mediators for strong interaction
- Quarks and gluons have color degrees of freedom and can't exist freely

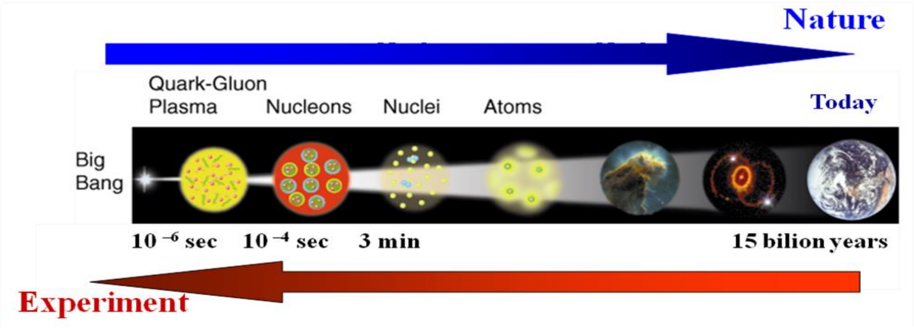
Hadrons
- Baryons (qqq)
- Mesons $(\bar{q}q)$

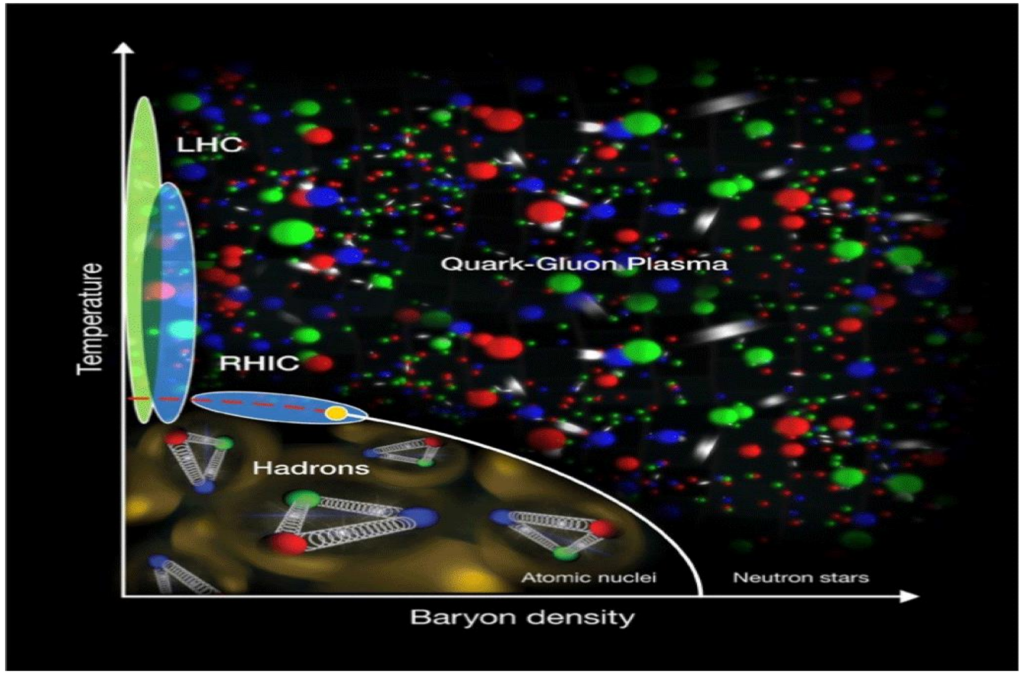


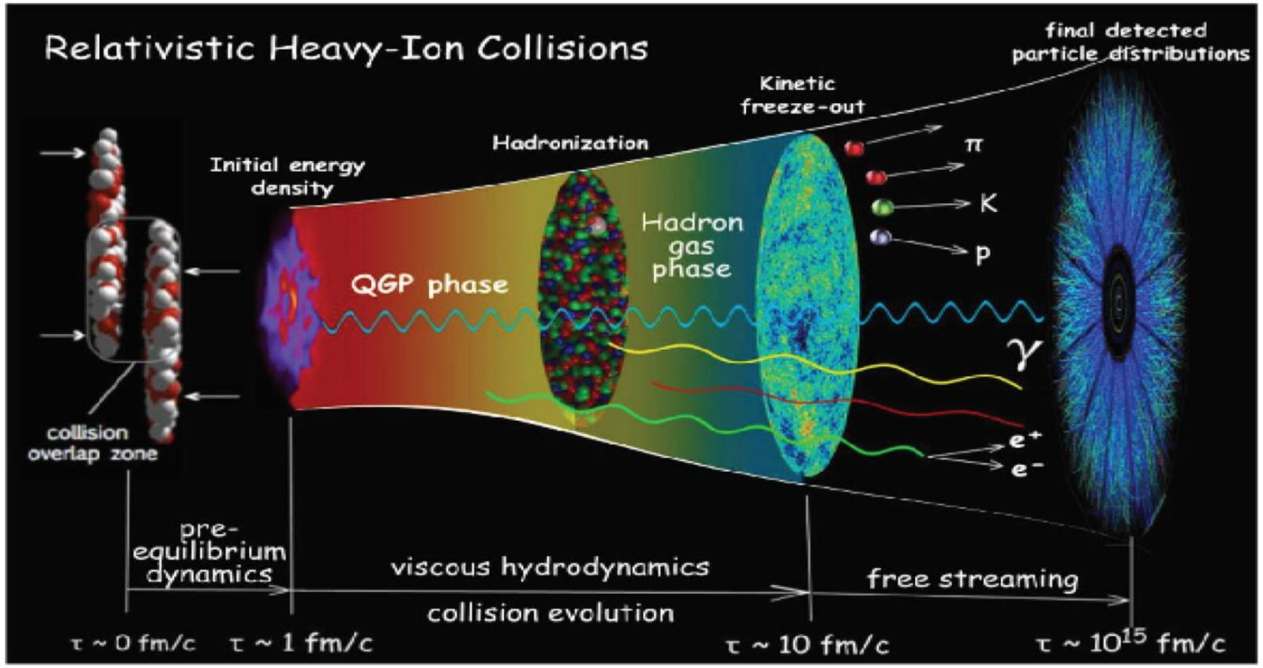
[1] R. Sahoo, "Relativistic Kinematics", [arXiv:1604.02651 [nucl-ex]]

Heavy-ion collisions (HIC) and Quark gluon plasma (QGP)

- Quark gluon plasma (QGP) is a hot and dense state of deconfined quarks and gluons in thermal equilibrium
- The value of the strong coupling constant decreases as the energy density increases: Asymptotic Freedom

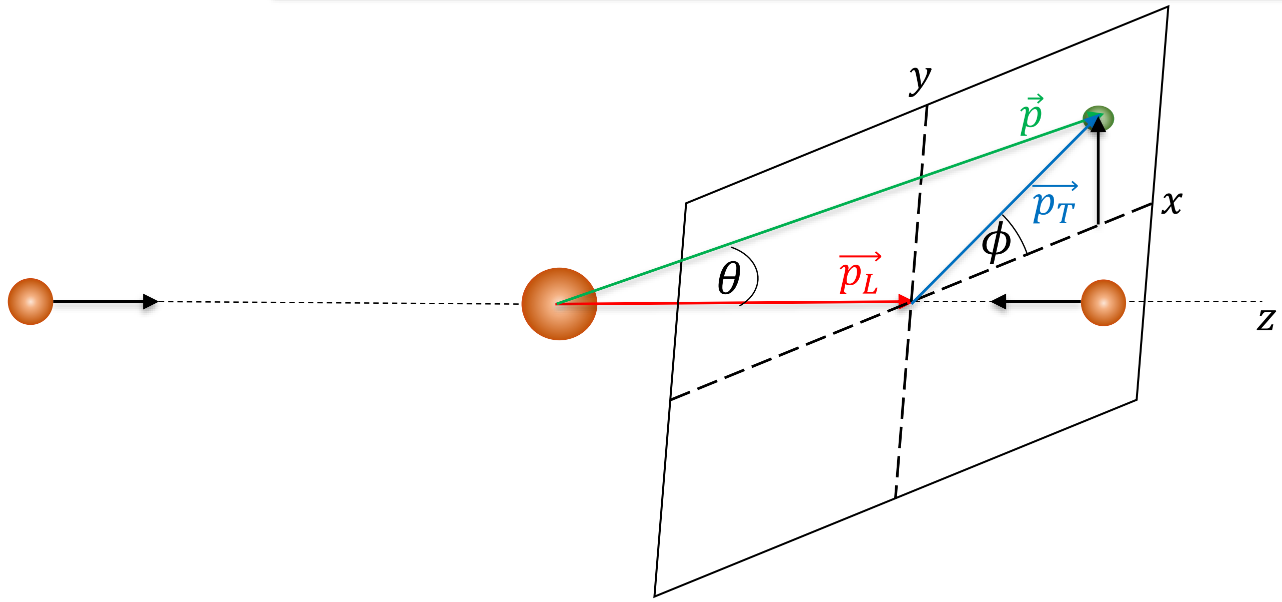


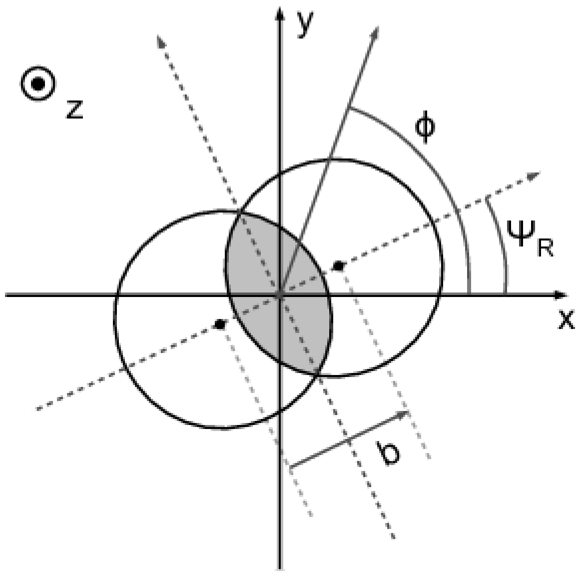




[1] R. Sahoo, AAPPS Bull. 29, 16 (2019).
[2] U. Heinz, Int. J. Mod. Phys. A 30, 1530011 (2015).
[3] R. Sahoo, and T. K. Nayak, Curr. Sci. 121, 1403 (2021).

Kinematic Observable in HIC





- Transverse Momentum, $p_T = \sqrt{p_x^2 + p_y^2}$
- Azimuthal Angle, $\phi = \tan^{-1}\left(\frac{p_y}{p_x}\right)$
- Polar angle, $\theta = \tan^{-1}\left(\frac{p_T}{p_z}\right)$
- Rapidity, $y = \frac{1}{2}\ln\left(\frac{E+p_Z}{E-p_Z}\right)$
- Pseudo-rapidity, $\eta = -\ln\left(\tan\frac{\theta}{2}\right)$
- Reaction plane angle, ψ_R: Angle made by impact parameter (b) with x-axis

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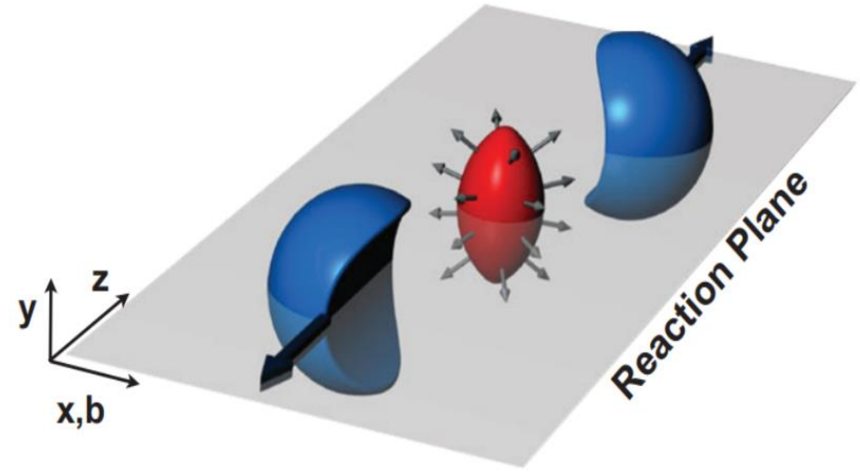
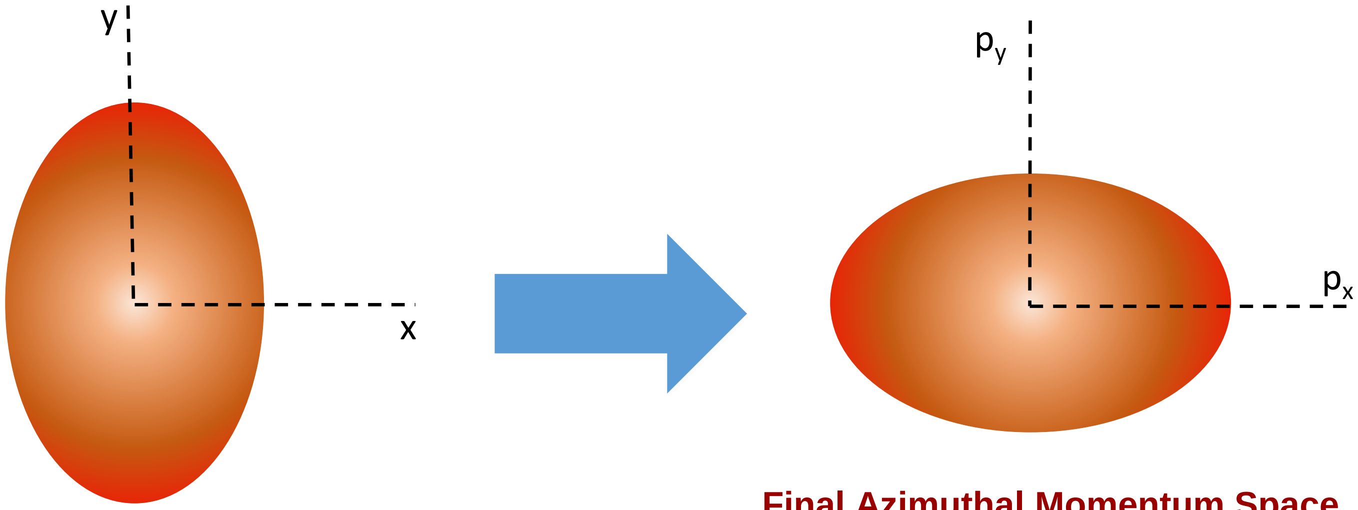
Elliptic Flow (v_2)





Initial Spatial Anisotropy

Final Azimuthal Momentum Space Anisotropy

- Anisotropic flow: hydrodynamic response to spatial deformation of the initial density profile.

$$E\frac{d^3N}{dp^3} = \frac{d^2N}{2\pi p_T dp_T dy}\left(1 + 2\sum_{n=1}^{\infty} v_n \cos[n(\phi - \psi_n)]\right) = \frac{d^2N}{2\pi p_T dp_T dy}\left(1 + \underbrace{2v_1 \cos(\phi - \psi_1)}_{\text{Directed flow}} + \underbrace{2v_2 \cos[2(\phi - \psi_2)]}_{\text{Elliptic flow}} + \underbrace{2v_3 \cos[3(\phi - \psi_3)}_{\text{Triangular flow}} + \ldots]\right)$$

$$\boxed{v_2 = \langle \cos[2(\phi - \psi_2)] \rangle}$$

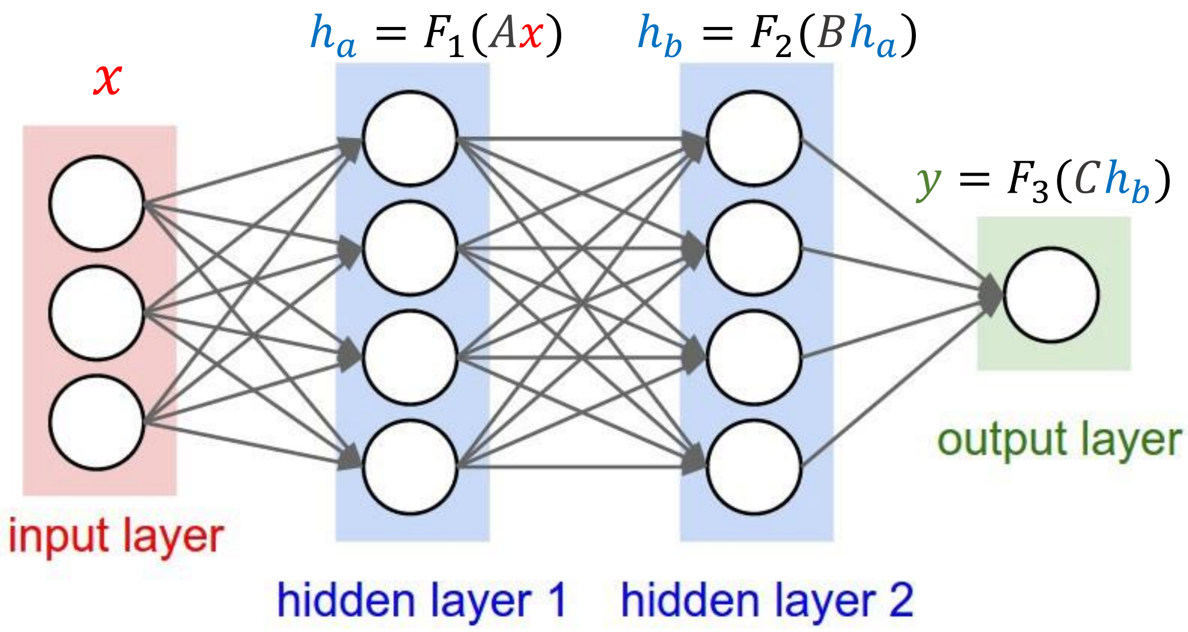
N. Mallick, R. Sahoo and S. Tripathy, and A. Ortiz, J. Phys. G 48, 045104 (2021)
B. B. Abelev et al. [ALICE Collaboration], JHEP 1506, 190 (2015)

Deep Neural Network (DNN)

- It is an ML algorithm inspired by the structure of the neurons in the animal brain
- Three key layers

  Input layer: Takes different features as input
  Hidden layer: Connects to different neurons to weights
  Output layer: gives the result as a number or class

- Weights: represents the importance of a neuron
- Activation function: Guides the outcome of each node
- Cost function: Evaluates the accuracy of the prediction
- Optimizer: Methods/Algorithms used to minimize the cost function by updating the weights



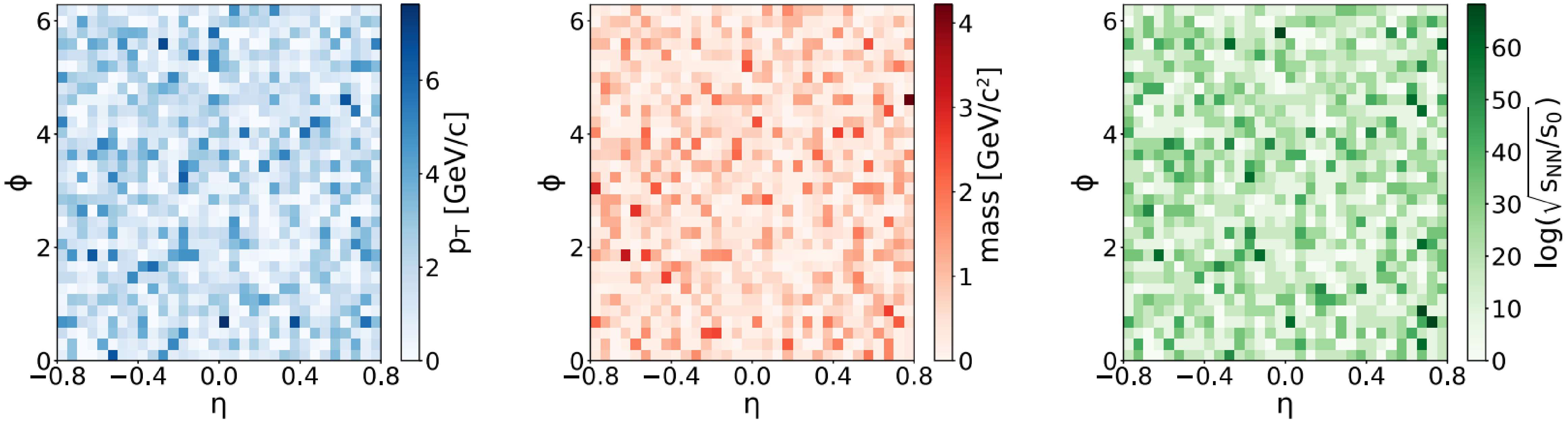
- For an input layer x, two hidden layers, the output y can be represented as:

$$y = F_3\left(CF_2\left(BF_1(Ax)\right)\right)$$

A, B, C represent the weight matrices
F_1, F_2, F_3 represent the activation functions

Input to the Model

- Elliptic flow (v_2) is an event property, depends upon: η, mass, p_T, centrality, etc.
- v_2 is calculated using the event plane method and ψ_R is set to zero in AMPT. ($\Rightarrow\ v_2 = \langle\cos(2\phi)\rangle$)
- $(\eta - \phi)$ space is considered as primary input space, divided into (32x32) bin space
- Weighted p_T, mass and $\log(\sqrt{(s_{NN}/s_0)})$ are taken as input to the DNN architecture.
- $32 \times 32 \times 3\ (= 3072)$ features per event
- Trained with 150K minimum bias events of Pb-Pb collisions at $\sqrt{s_{NN}} = 5.02$ TeV simulated with AMPT.



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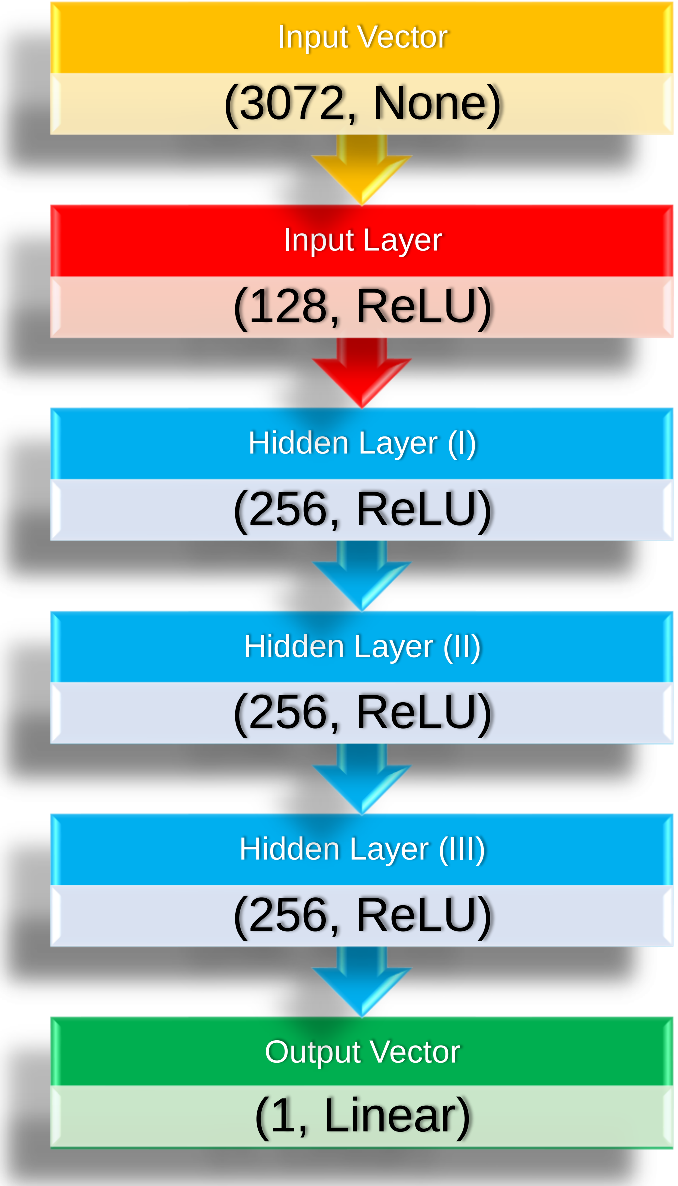
DNN Architecture

- Each event has 3072 input features mapped into the first dense layer with 128 nodes and ReLU activation function
- 3 hidden layers with 256 nodes and ReLU activation function
- The final layer has single node as v_2 and linear activation function is used
- ReLU (x) = max$(0, x)$
- Cost Function: mean squared error
- Optimiser: adam
- Early stopping mechanism is used to stop the training
- Early stopping patience level of maximum 10 epochs
- Max Epoch=60, batch size = 32



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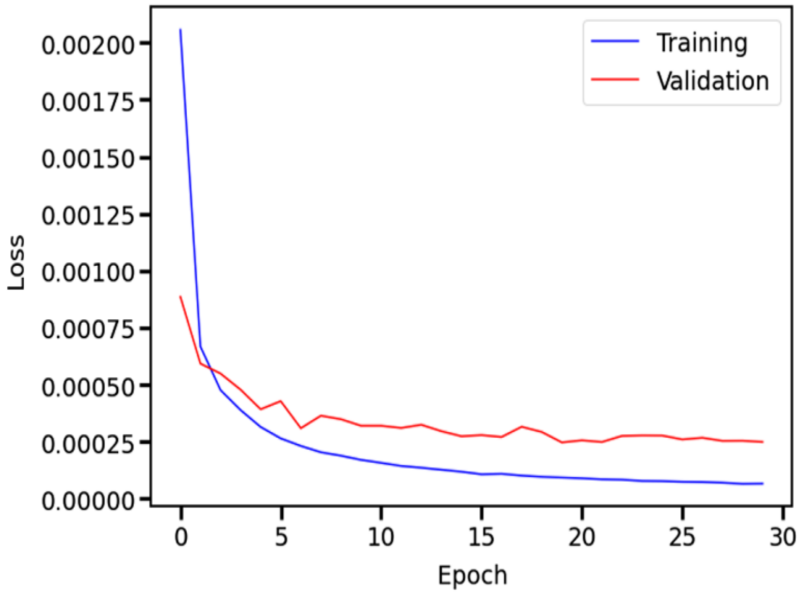
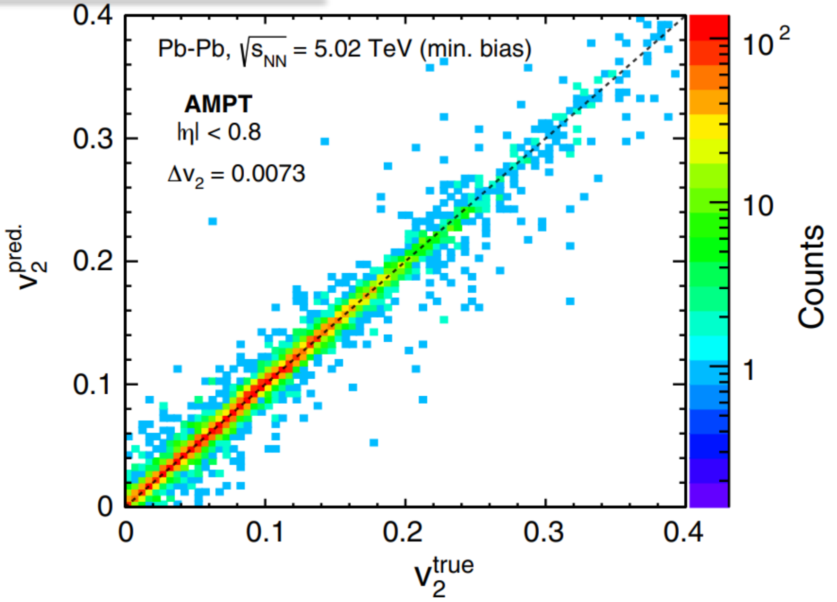
Quality Assurance

- Loss is the mean squared error of predicted v_2 w.r.t true v_2
- Loss is in the order of 10^{-4} : Good training
- Less to no overfitting/underfitting.
- Mean absolute error (MAE) of v_2 is defined as:

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

- $v_2^{true} = v_2^{pred}$ straight line is well populated
- 32x32 bin size is faster and has optimum performance compared to other bin size
- Model is quite sturdy and less sensitive to noise of different weights

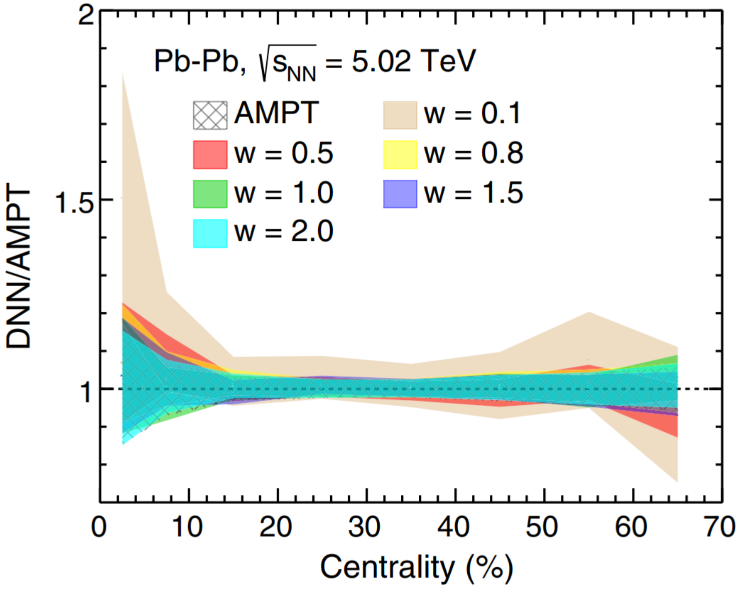




- Modified j^{th} feature of i^{th} event:

$$F'_{ij} = F_{ij} + X_{ij}/w$$

w: weight
$X_{ij} \in (-\sigma_j, \sigma_j)$ is a random number



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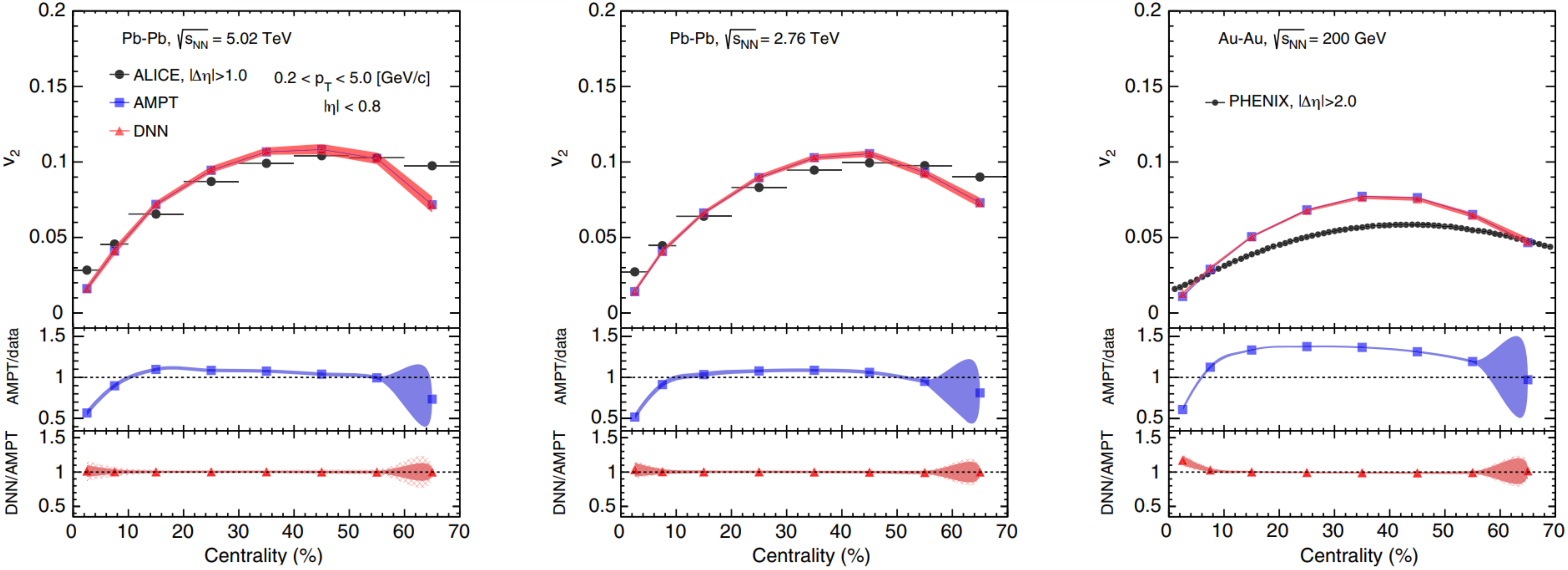
Results and Discussions



- AMPT results do not match with experimental data, which can be optimised with different settings available in AMPT
- DNN predictions almost match with the v_2 value from the AMPT, not only at LHC but also at RHIC energies, which is new to DNN

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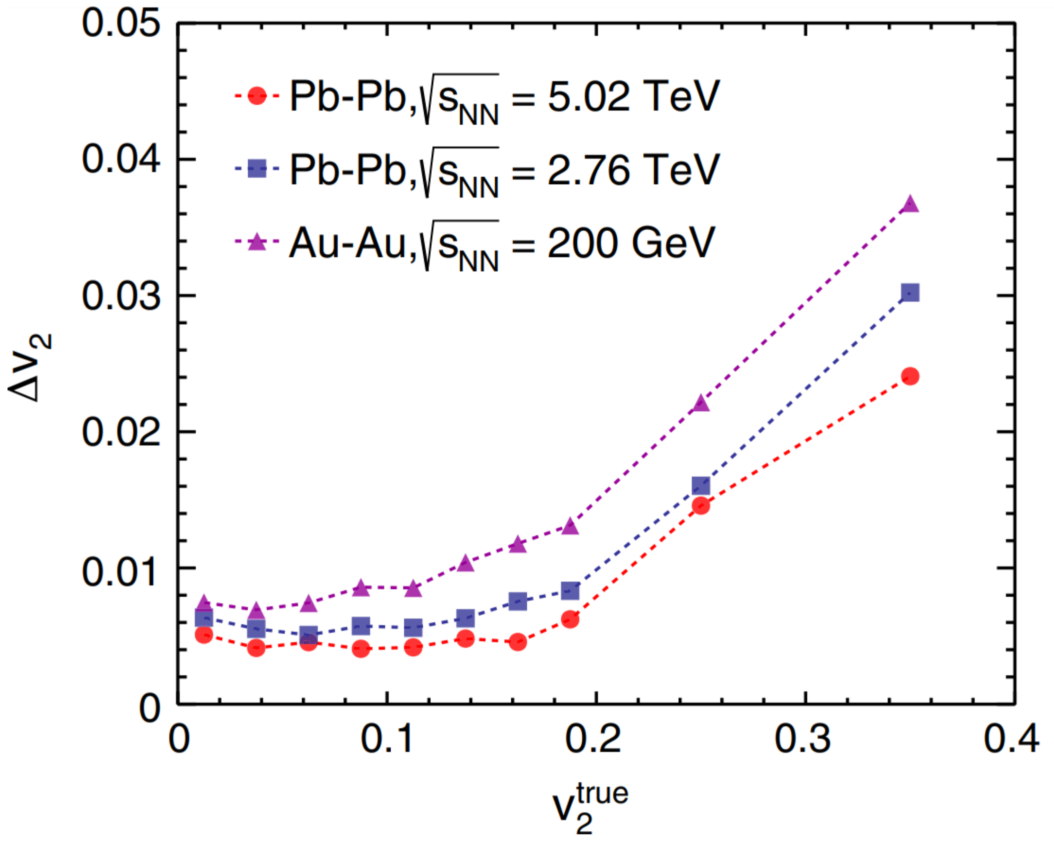

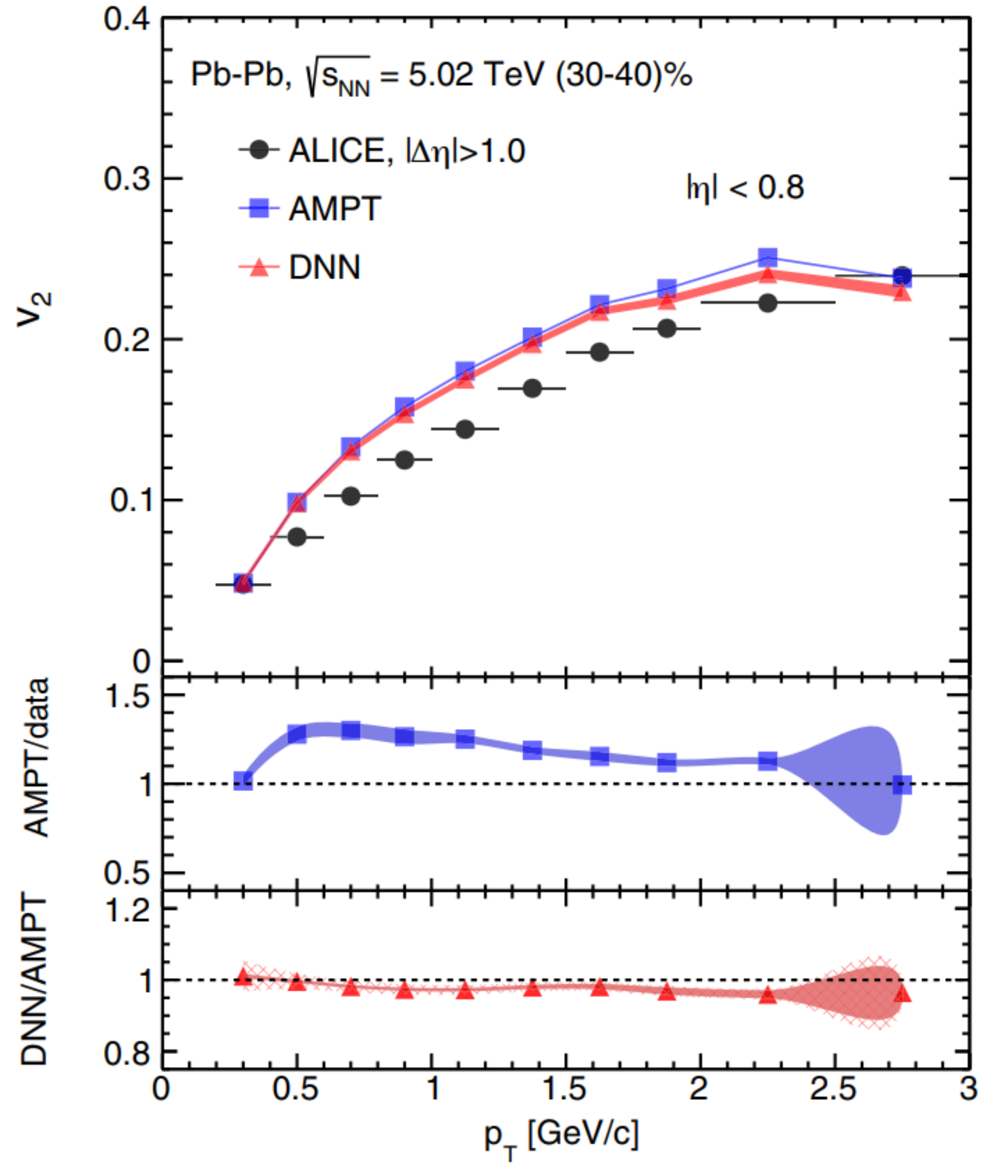

- Δv_2, is less than 10% of the true v_2
- Δv_2 is least for the case where it's trained
- DNN retains the p_T dependence, and matches with v_2 from AMPT in low p_T region.

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Summary

- Elliptic flow is one of the important observables to understand the physics of QGP, and it can be successfully predicted with machine learning based DNN algorithm
- The DNN model retains the centrality, energy and p_T dependence and predicts with accuracy
- The DNN model is quite robust and it’s less sensitive to input data with uncorrelated noise

Outlook

- The DNN model is yet to be tested for particle dependence (mass dependence).
- In AMPT, we have set $\psi_R = 0$, The model is yet to be tested for random orientation of ψ and its dependence
- This DNN model takes nonflow effects into account while calculating v_2, which can be improved.

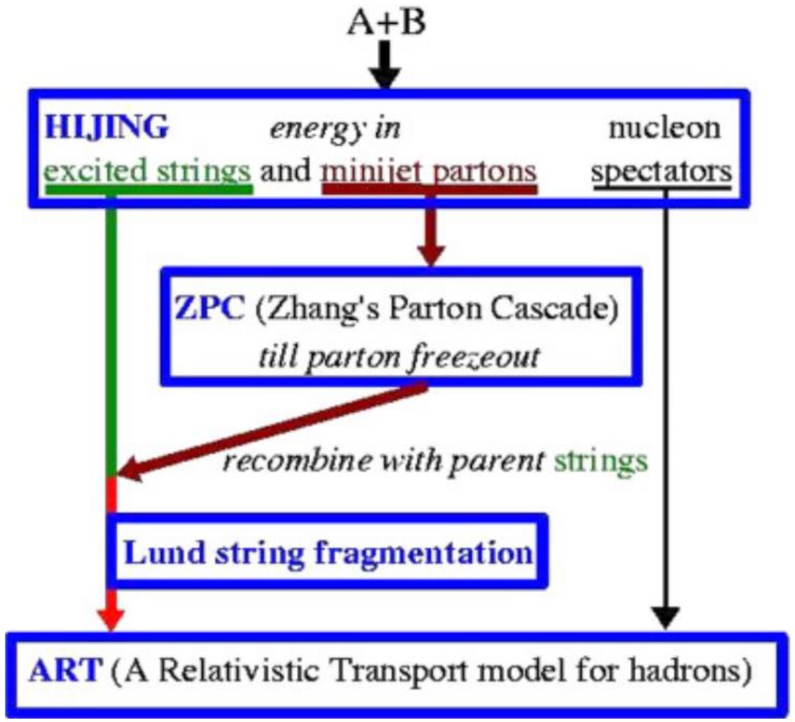
Thank You

For the attention

Backup Slides

A Multi-phase Transport Model (AMPT)

- Initialisation of collisions (HIJING)
- Parton Transport (ZPC)
- Hadronisation (Lund string fragmentation / Quark coalescence)
- Hadron Transport (ART)



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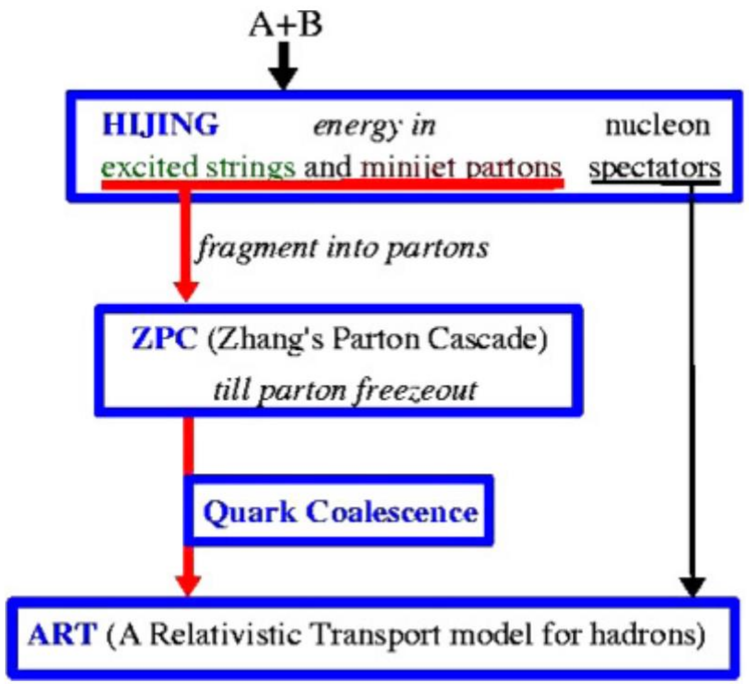

SM Version

Zi-Wei Lin, Che Ming Ko, Bao-An Li, Bin Zhang, and Subrata Pal, Phys. Rev. C 72, 064901 (2005)