

Estimating Elliptic Flow Coefficient in Heavy-ion Collisions using Deep Learning

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Support: *Hungarian OTKA grants, K135515, 2019-2.1.11-TÉT-2019-00078*

Wigner Scientific Computing Laboratory

Ref: *PRD 105, 114022 (2022) (arXiv: 2108.13938)*

Zimányi Winter School, Budapest, 6th December 2022



ELKH | Eötvös Loránd
Research Network

Outline

1) Elliptic flow & motivation

- Motivation and definition

2) Input, test & model validation

- Input data (min. bias AMPT)
- Optimization the NN
- Test with noise, epoch

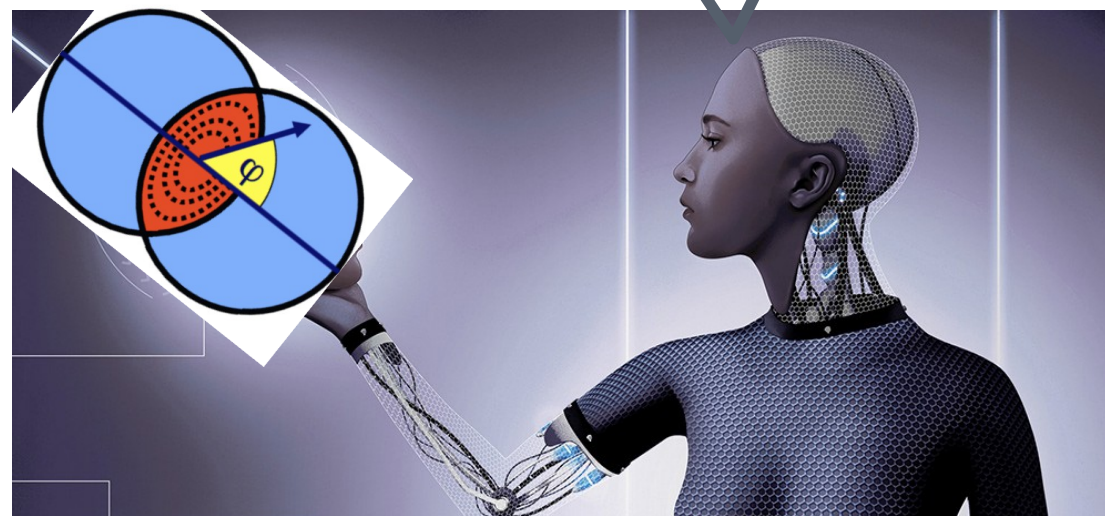
3) Results on v_2 by ML (DNN)

- Dependence on centrality, c.m. energy and p_T

Conclusions:

→ Can we estimate v_2 ex machina?

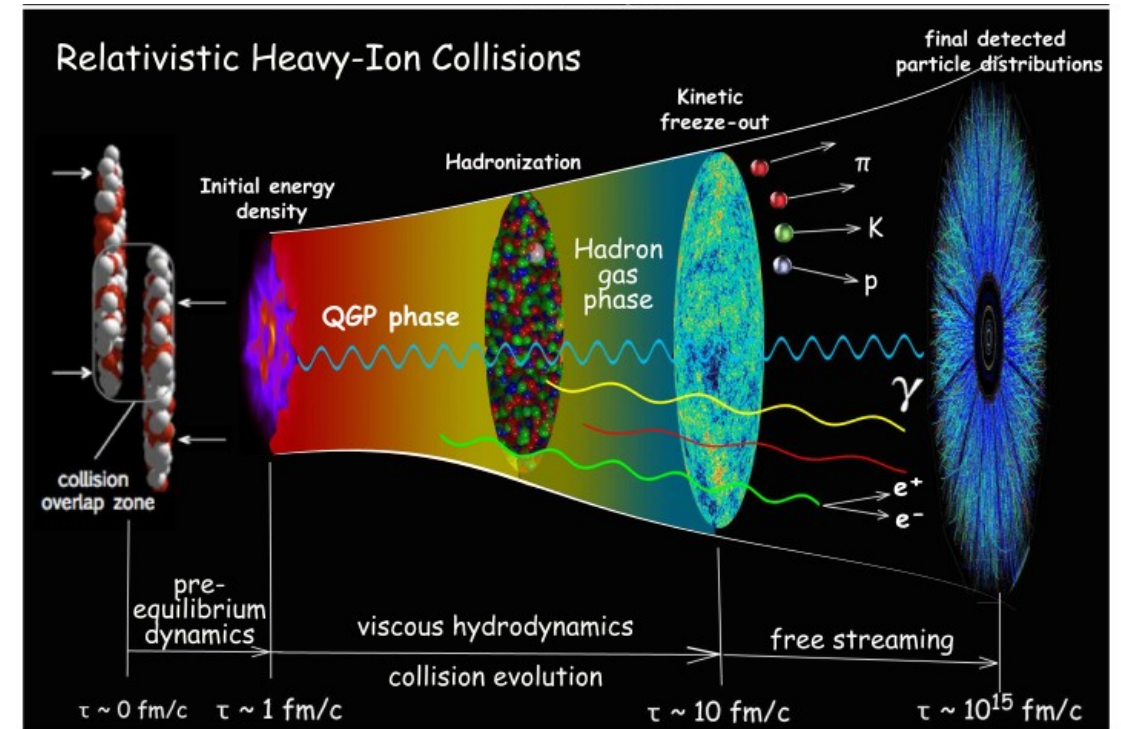
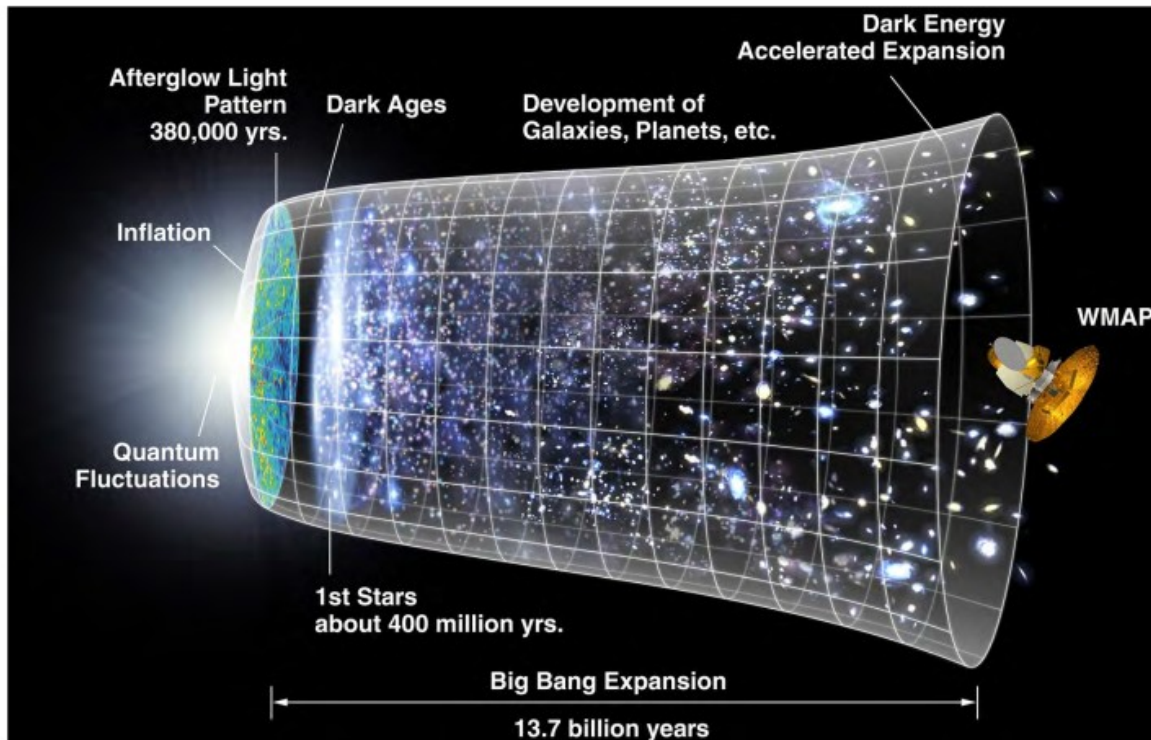
$$\frac{dN}{d\phi} = \frac{1}{2\pi} \left[1 + \sum_{n=1}^{\infty} 2v_n \cos(n(\phi - \psi_n)) \right]$$



Motivation & definitions

Primordial matter in heavy-ion collisions

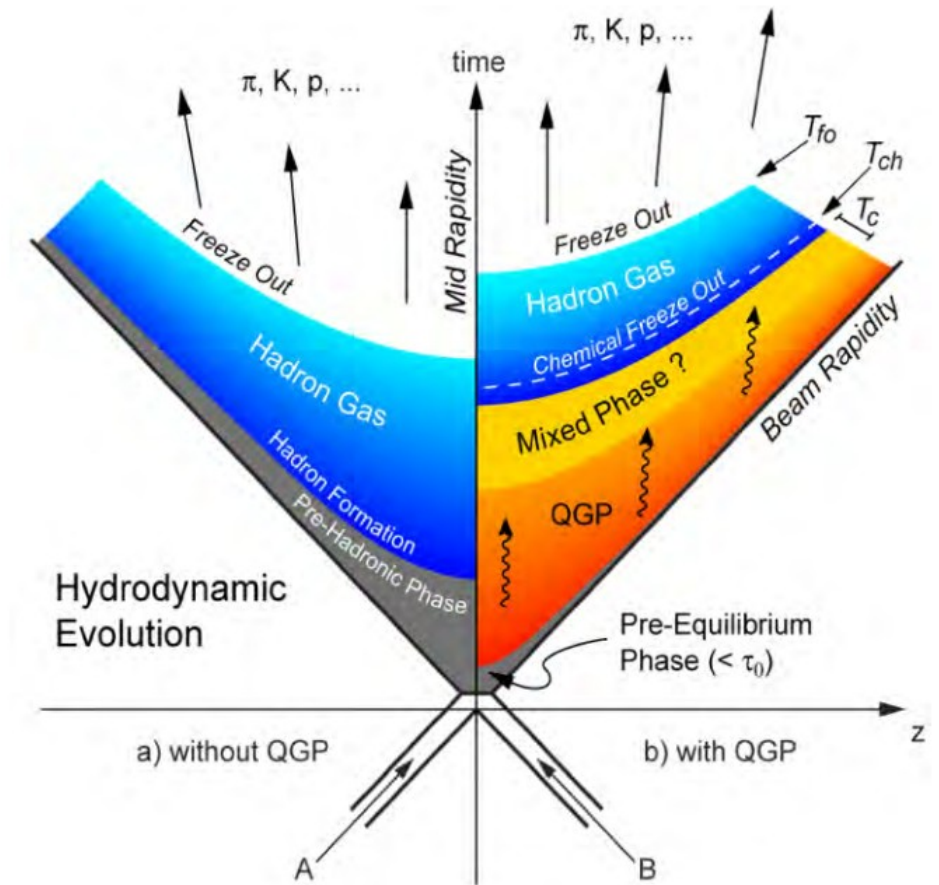
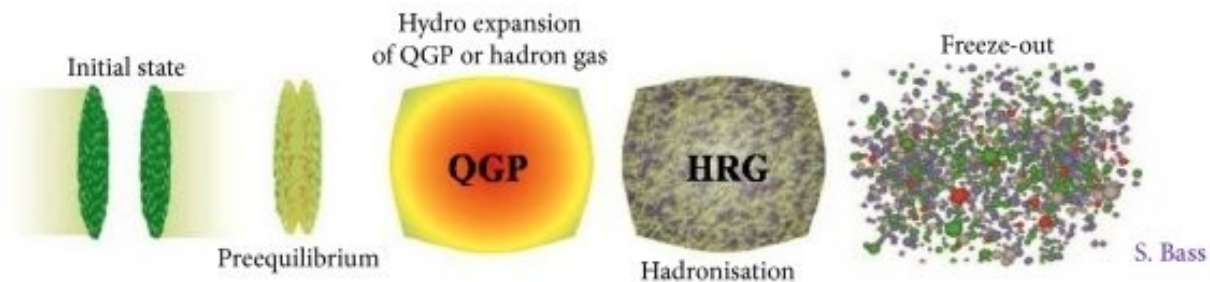
- **Quark-Gluon Plasma (QGP) research**



Primordial matter in heavy-ion collisions

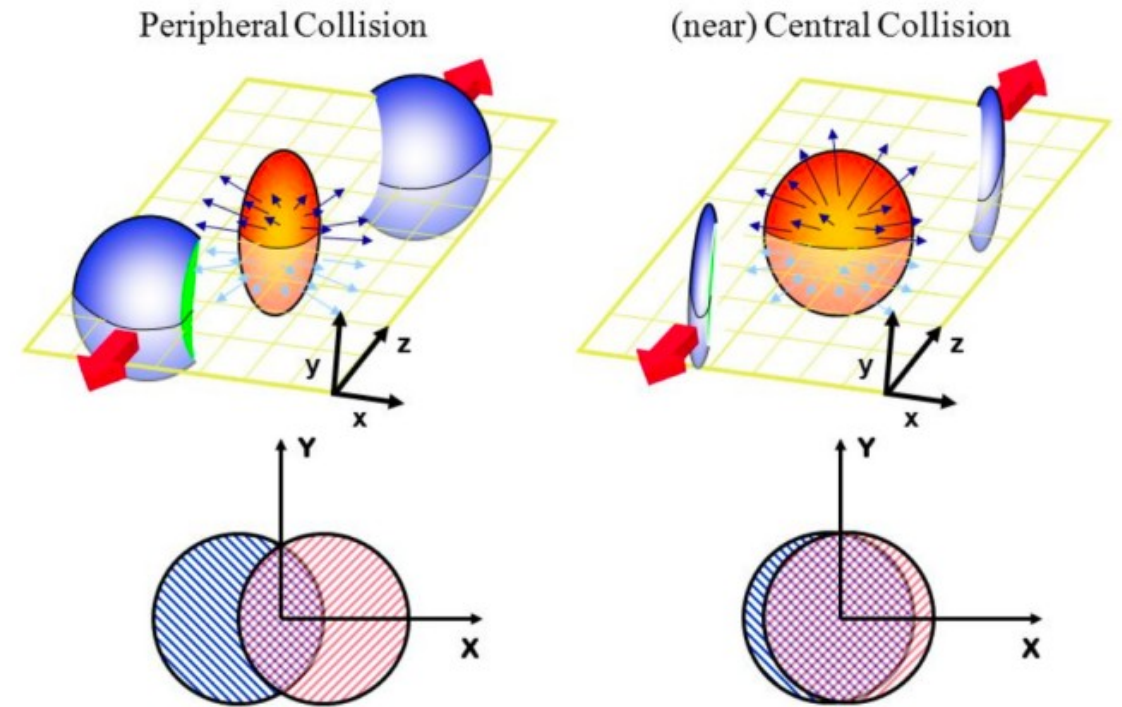
- **QGP in experimental vs theory points**

- By colliding heavy-ions we can form small drop of the hot & dense primordial matter
- No direct observations, just **signatures**: jet-quenching, correlations, collective effects, **anisotropic flow**...
- Need a complex description, including QCD phenomenology, hydrodynamics, (non-equilibrium) thermodynamics



Elliptic flow (v_2) in heavy-ion collisions

- **Experimental point:**
 - Elliptic flow describes the azimuthal momentum space anisotropy of particle emission for a non-central heavy-ion collision.

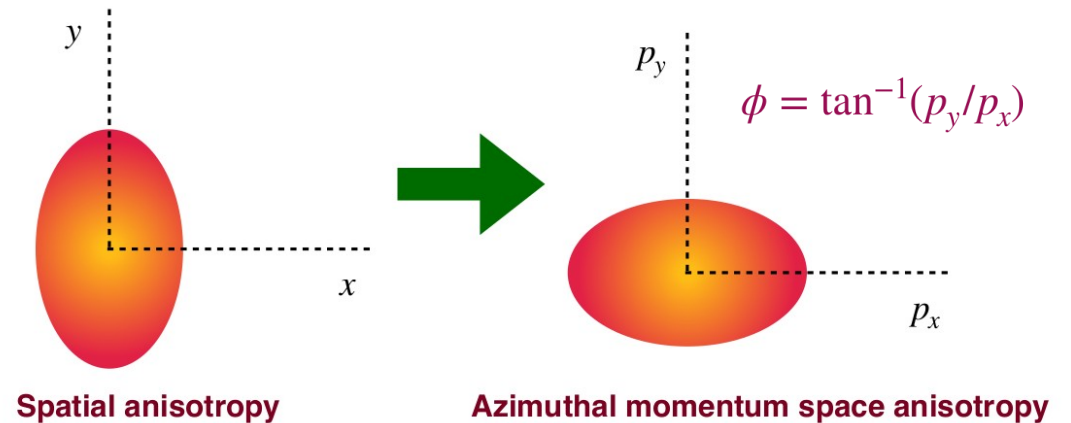


Elliptic flow (v_2) in heavy-ion collisions

- **Experimental point:**

- Elliptic flow describes the azimuthal momentum space anisotropy of particle emission for a non-central heavy-ion collision.
- The 2nd harmonic coefficient of the Fourier expansion of azimuthal momentum distribution:

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



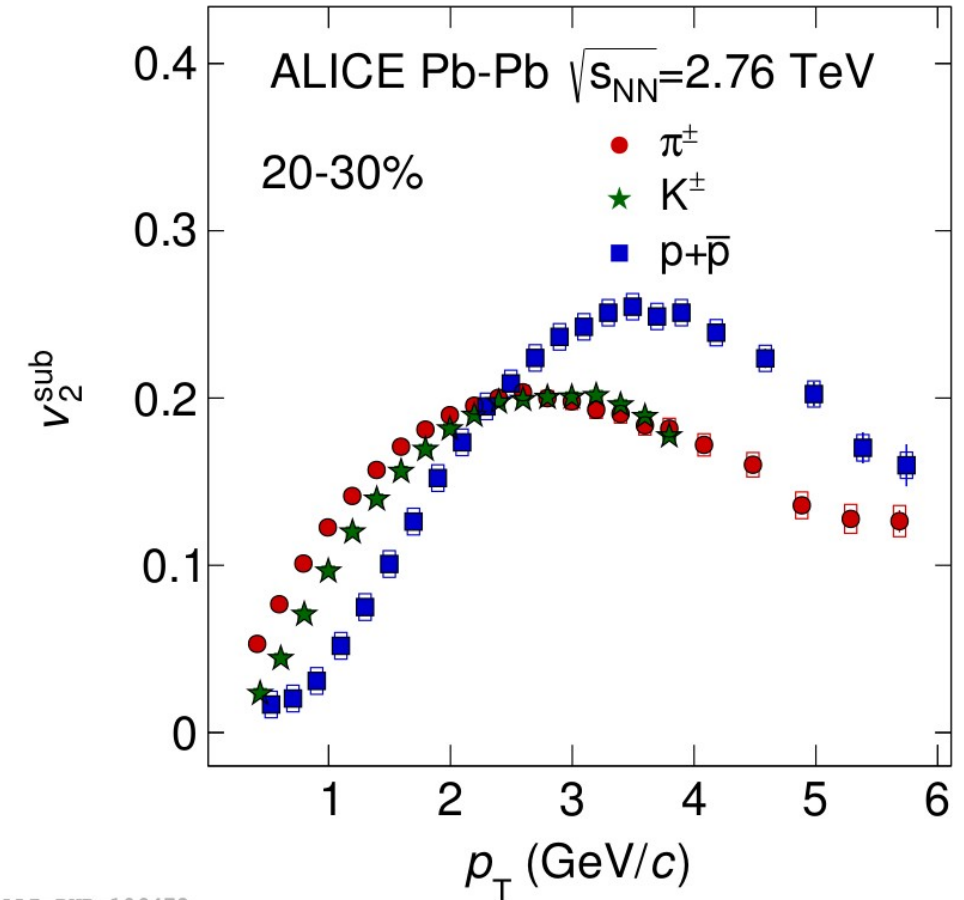
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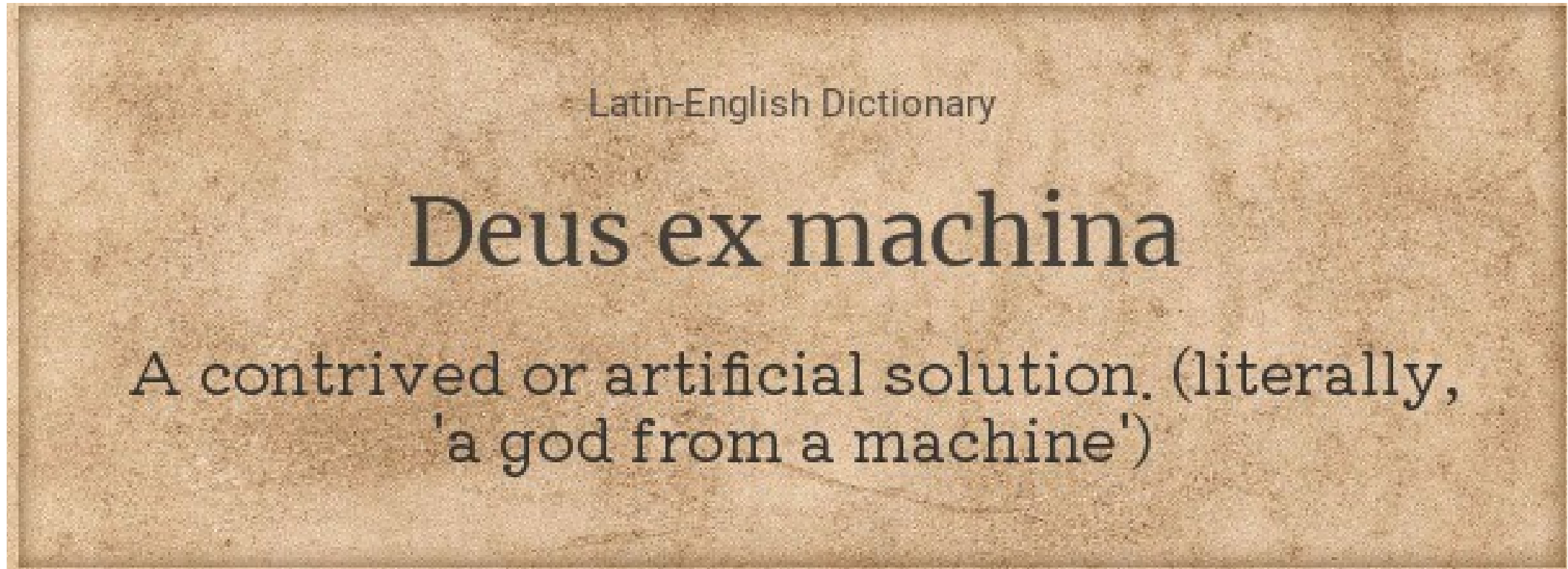
- The $v_2(p_T, y) = \langle \cos(2(\phi - \psi_2)) \rangle$ directly reflects the initial spatial anisotropy of the nuclear overlap region in the transverse plane.



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... and if the situation of calculating the v_2 is getting too problematic...

Motivation

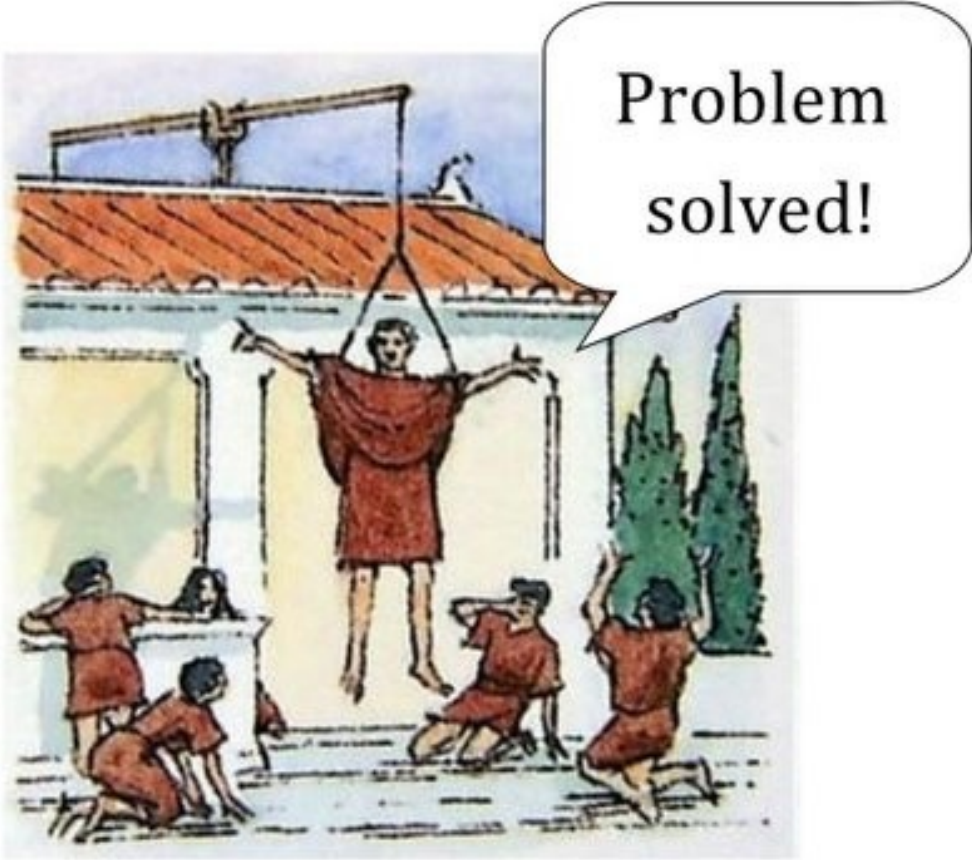


Motivation

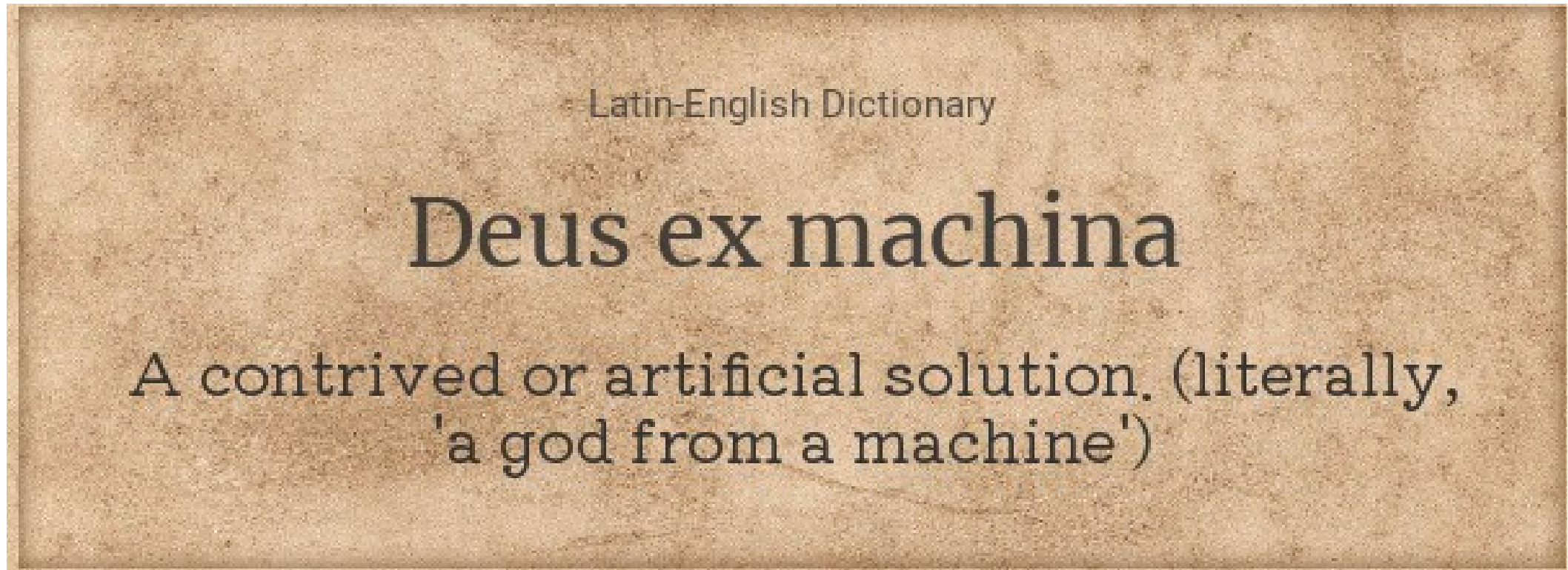
Latin-English Dictionary

Deus ex machina

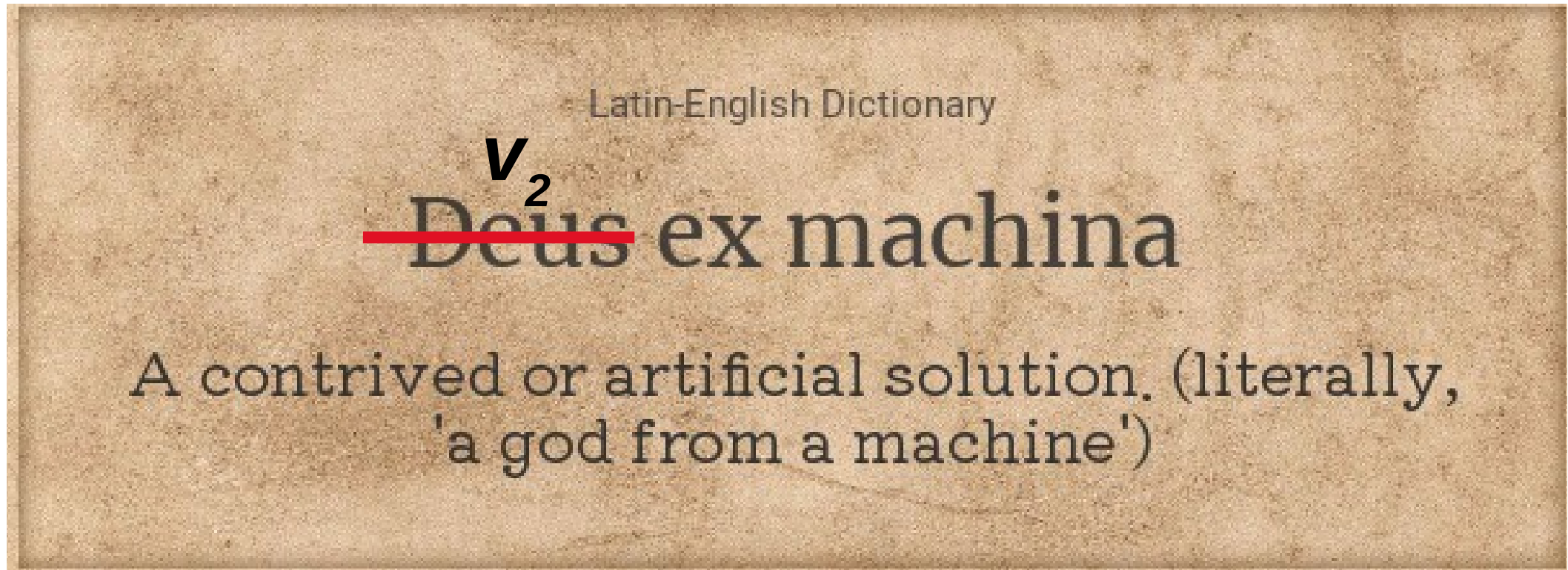
A contrived or artificial solution. (literally, 'a god from a machine')



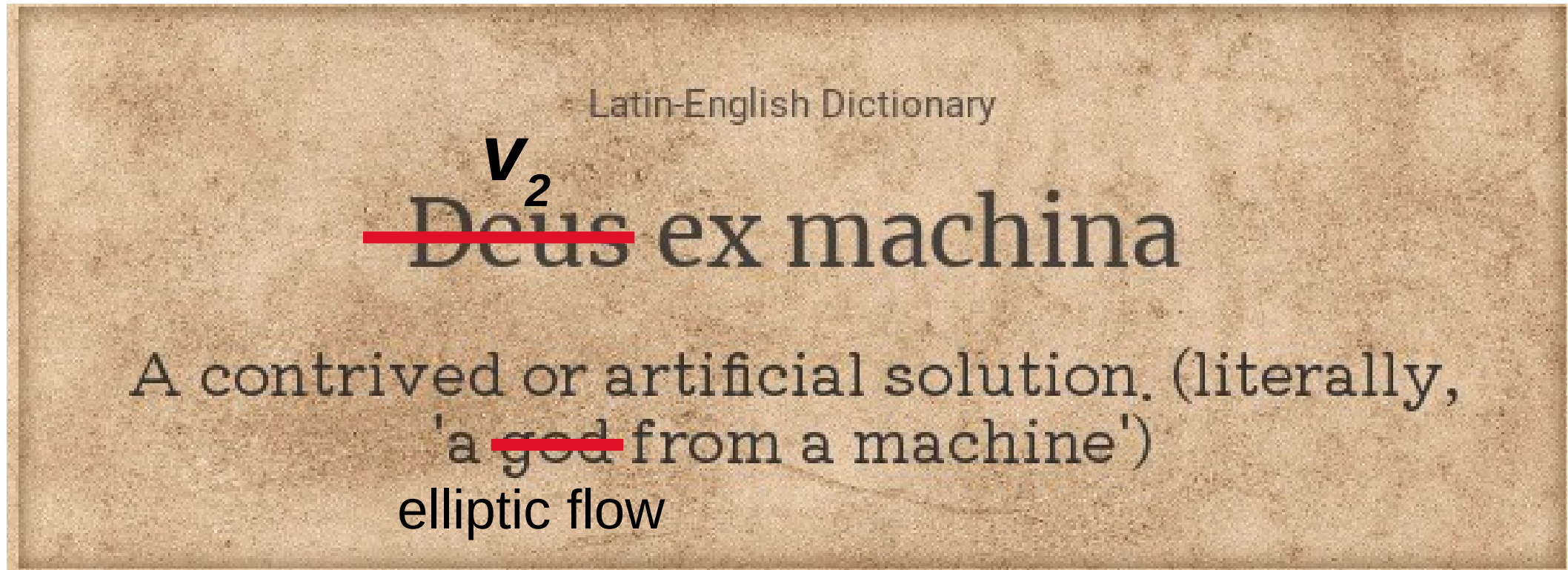
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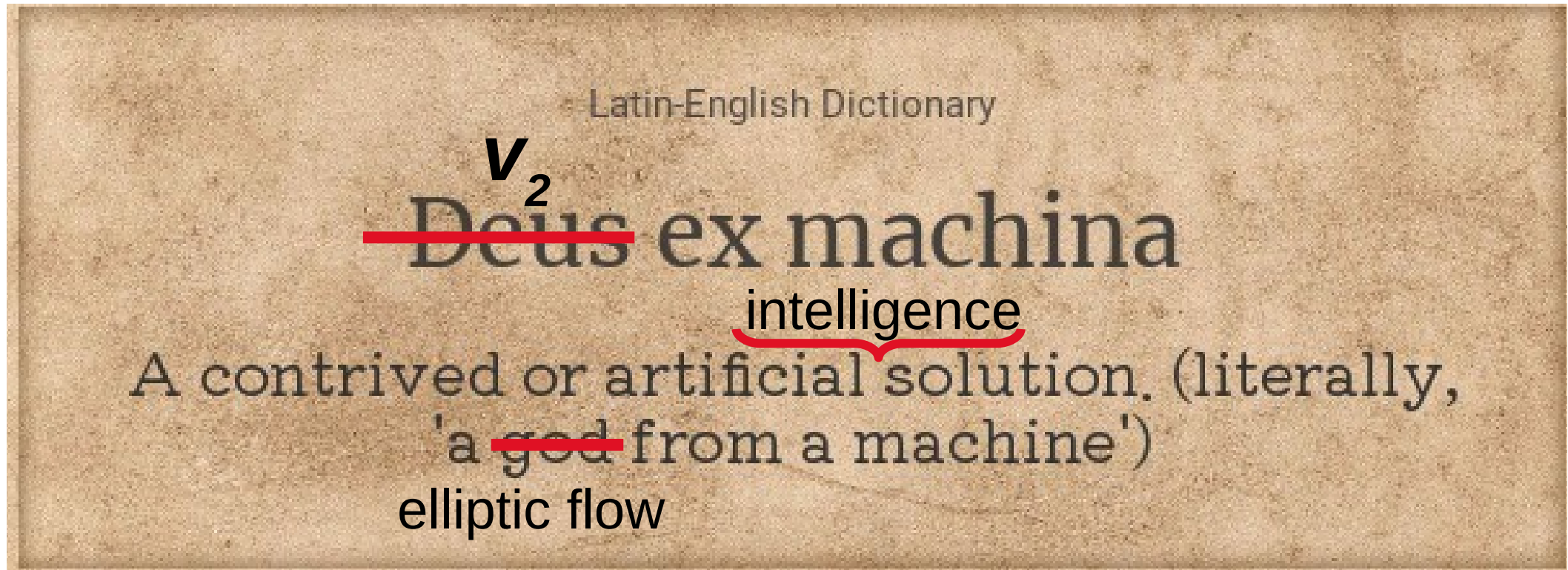
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Motivation



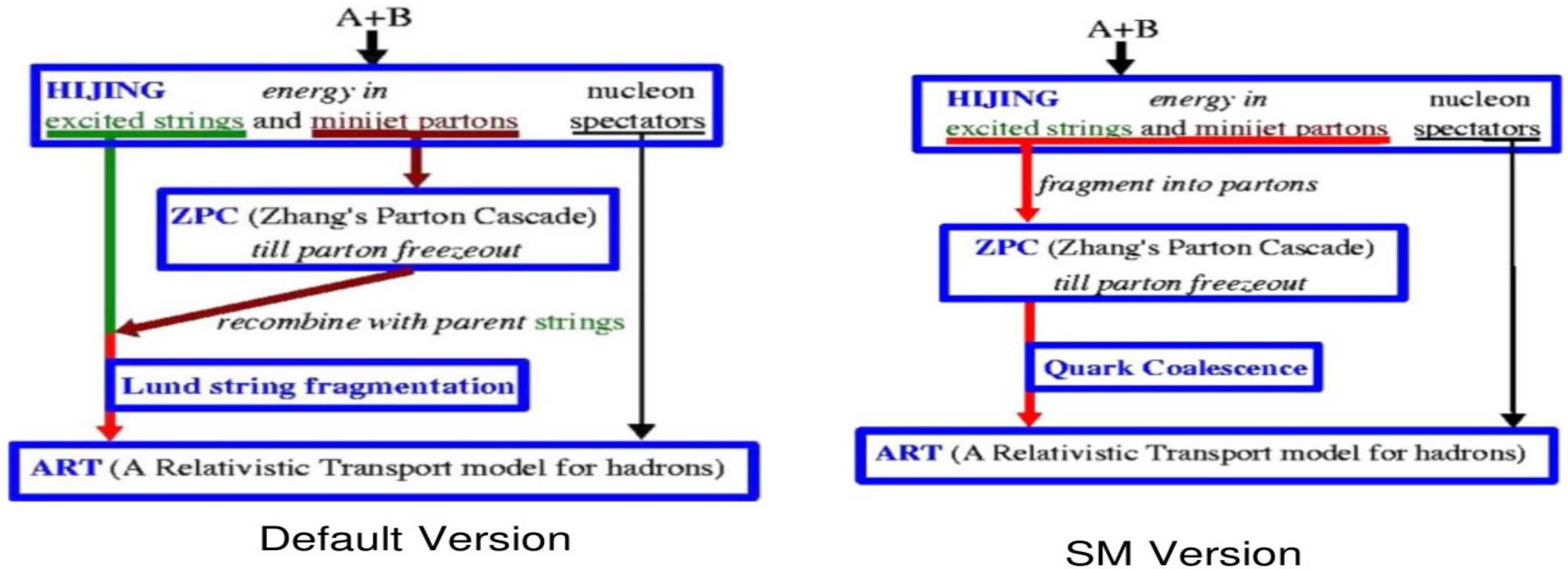
The input: MC-generated collisions

The AMPT model for Pb-Pb collisions

- **A Multi-phase transport model (AMPT):** MC event generator for simulating p-A and A-A collisions from RHIC to LHC energies.
 - **Fluctuating initial conditions:** Initialization of collision is done by obtaining the spatial and momentum distributions of the hard minijet partons and soft string excitations from the HIJING model. The inbuilt Glauber model is used to calculate and convert the cross-section of the produced mini-jets from pp to AA.
 - **Zhang's parton cascade (ZPC)** model is used to perform the partonic interactions and parton cascade which currently includes the two-body scatterings with cross-sections obtained from the pQCD with screening masses.
 - **Hadronization mechanism:** Lund string fragmentation model is used to recombine the partons with their parent strings and then the strings are converted to hadrons, whereas, in the string melting mode the transported partons are hadronized using a quark coalescence mechanism.
 - **Hadron cascade:** scattering among the produced hadrons are performed using a relativistic transport model (ART) by meson-meson, meson-baryon and baryon-baryon interactions.

The AMPT model for Pb-Pb collisions

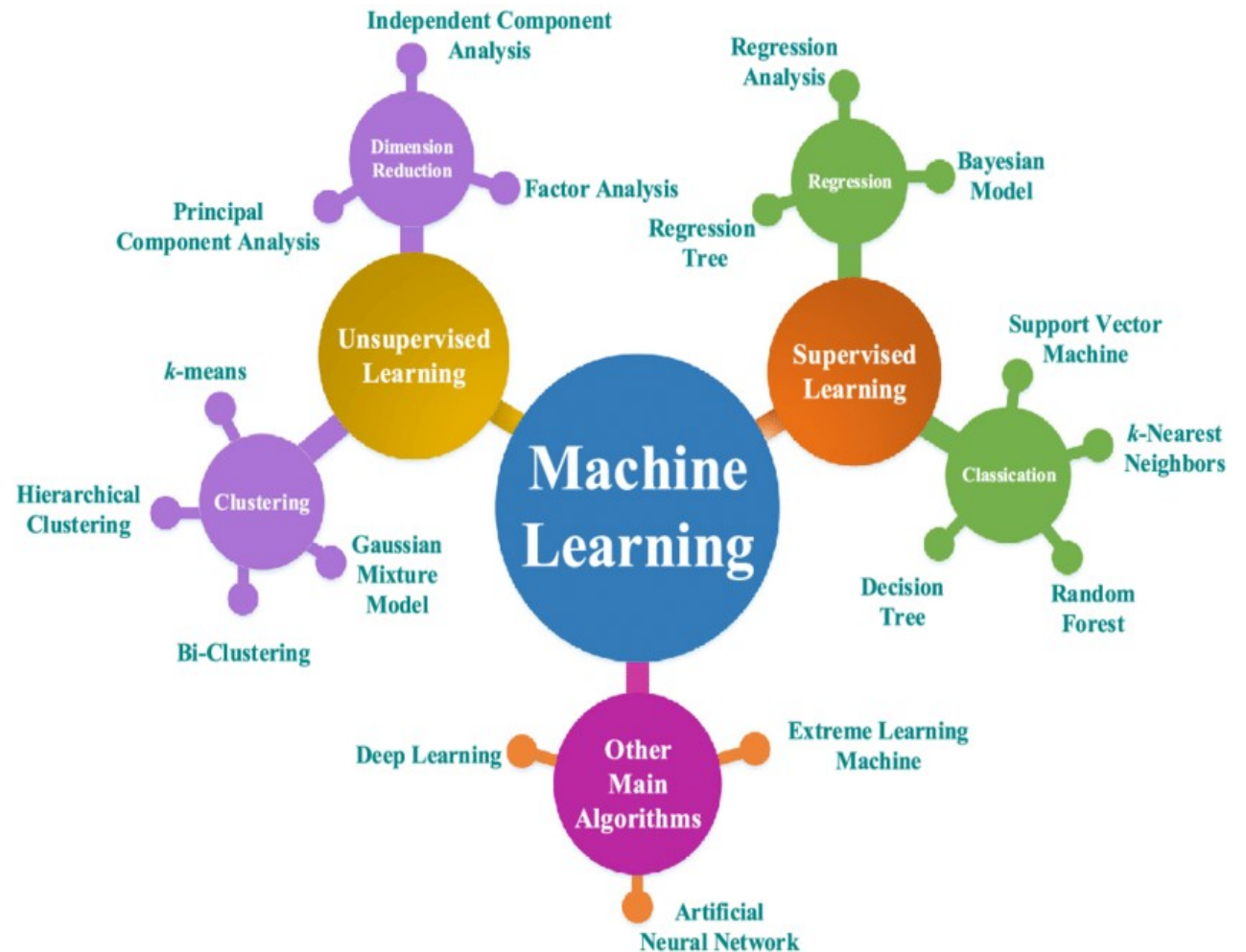
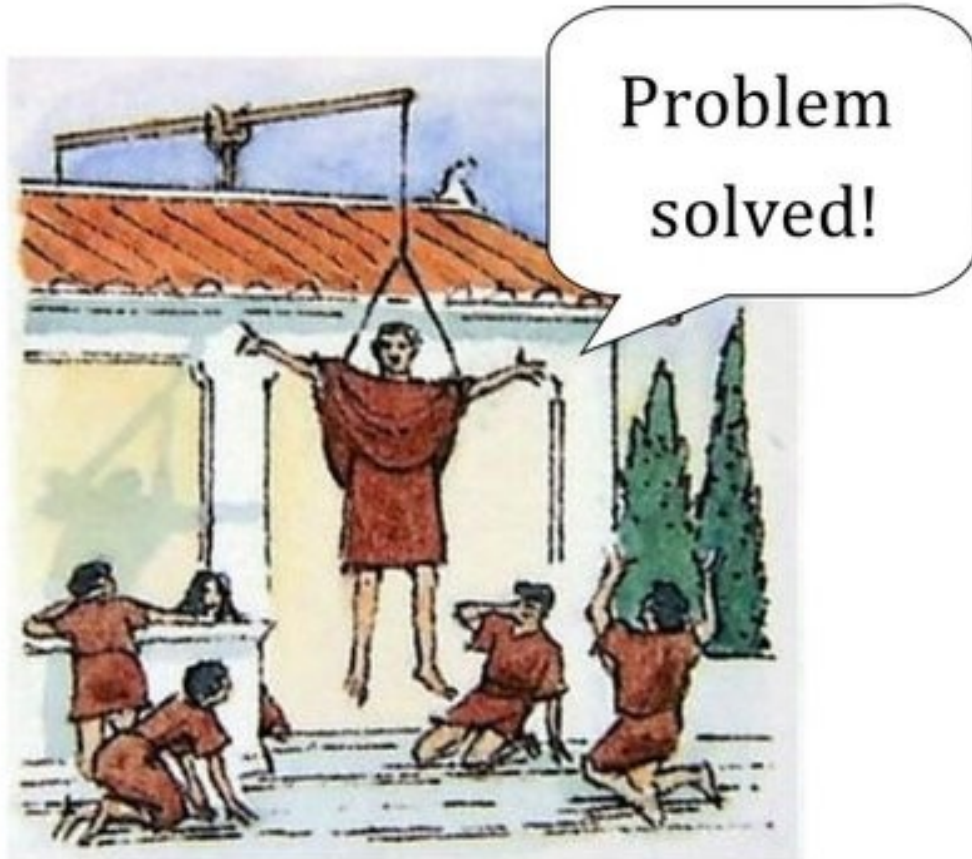
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Building up the Machine Learning: input, test, and model validation

Building up the ML structure

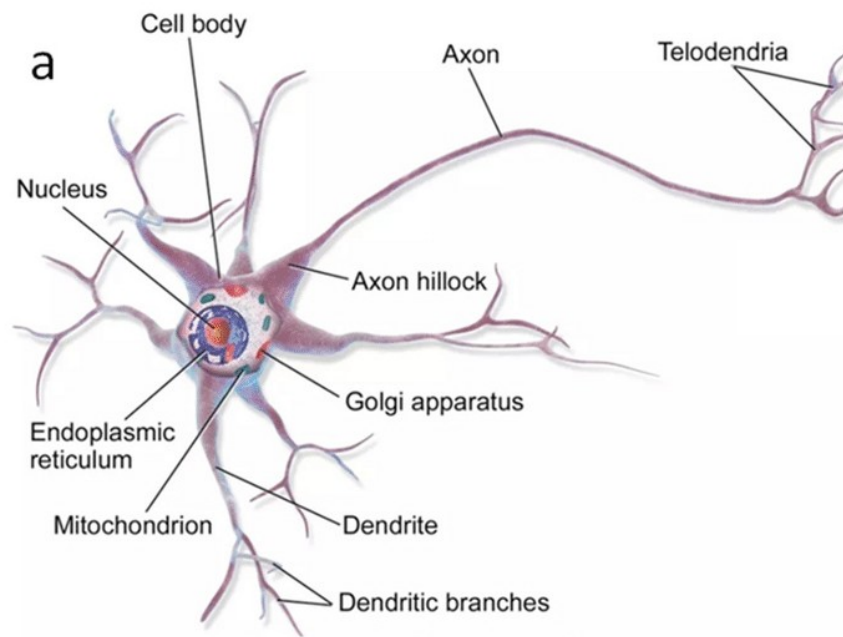
Machine Learning Basics



Building up the ML structure

Machine Learning Basics

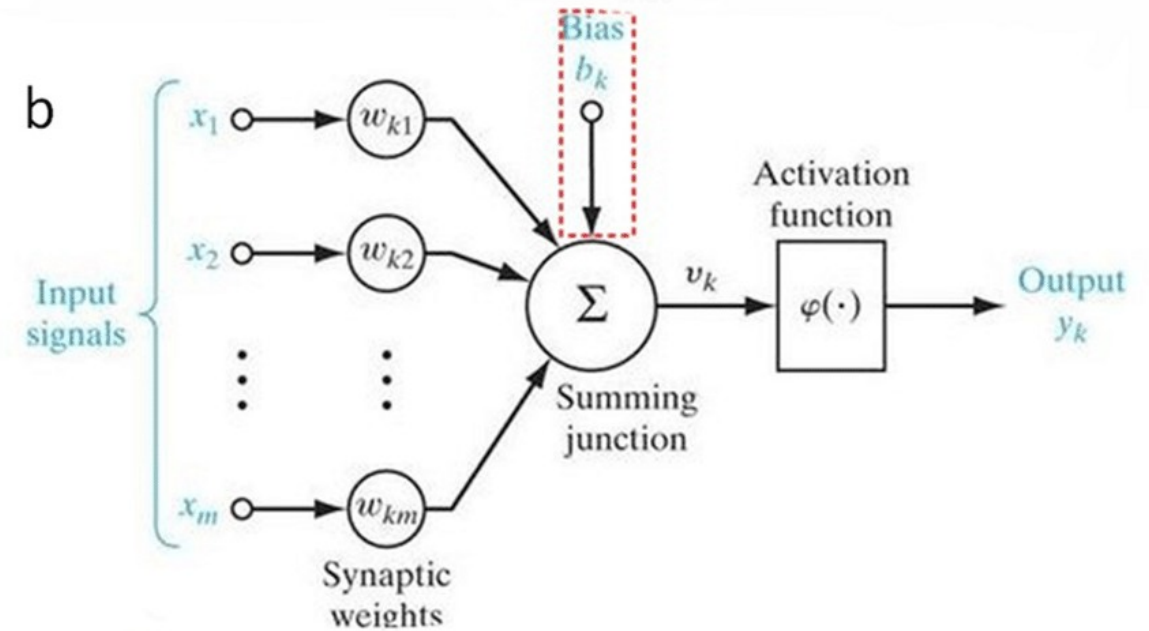
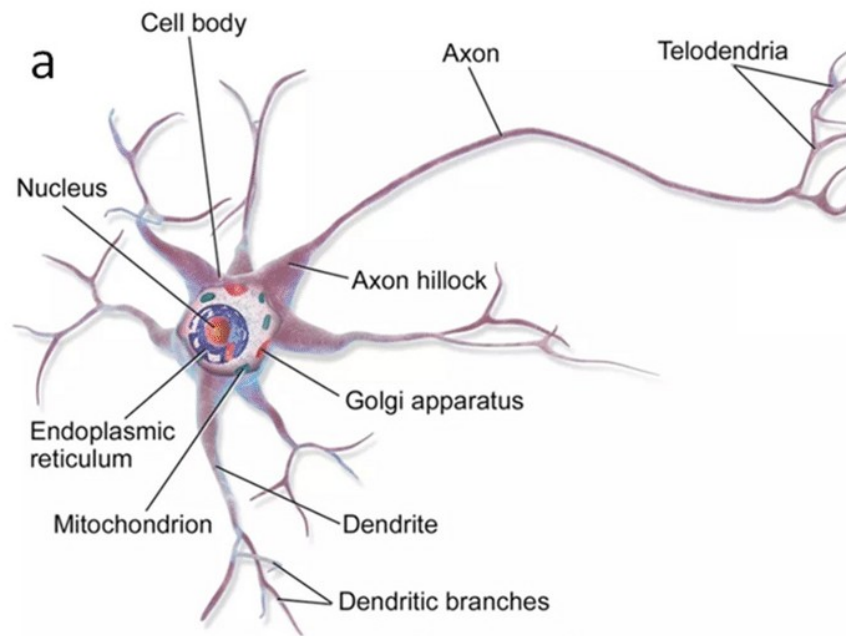
- **Neuron:** Biological



Building up the ML structure

Machine Learning Basics

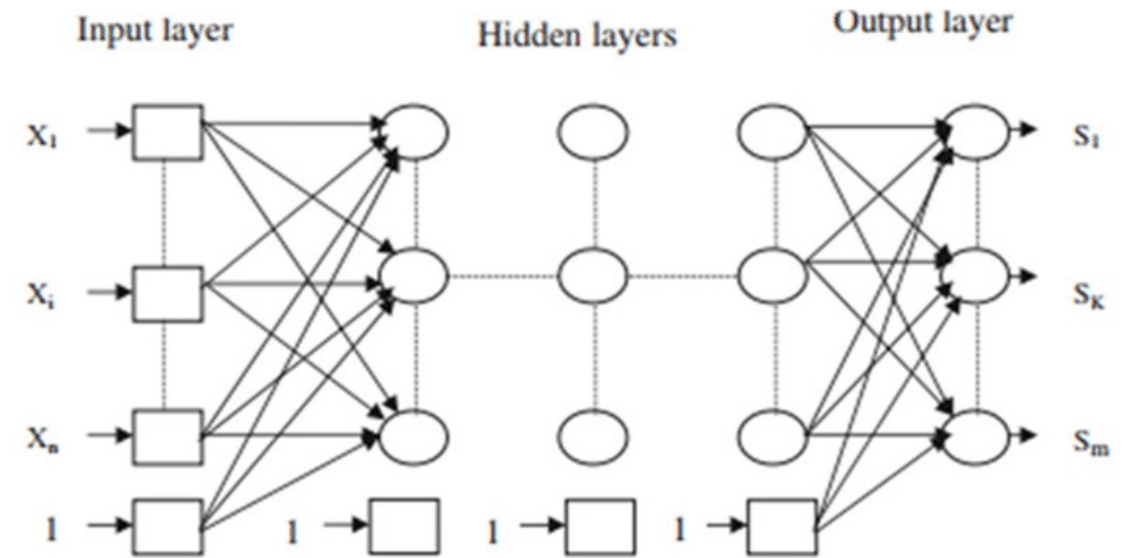
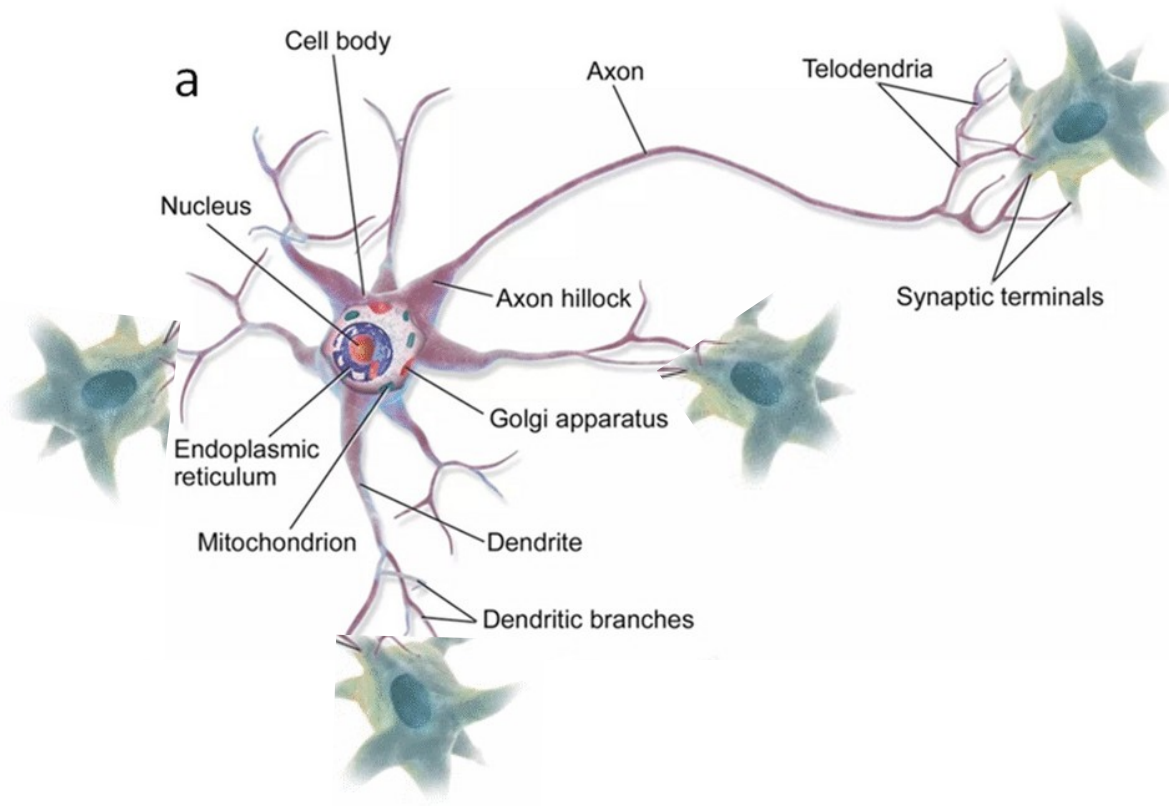
- **Neuron:** Biological vs. artificial



Building up the ML structure

Machine Learning Basics

- **ANN**: Artificial Neural Network



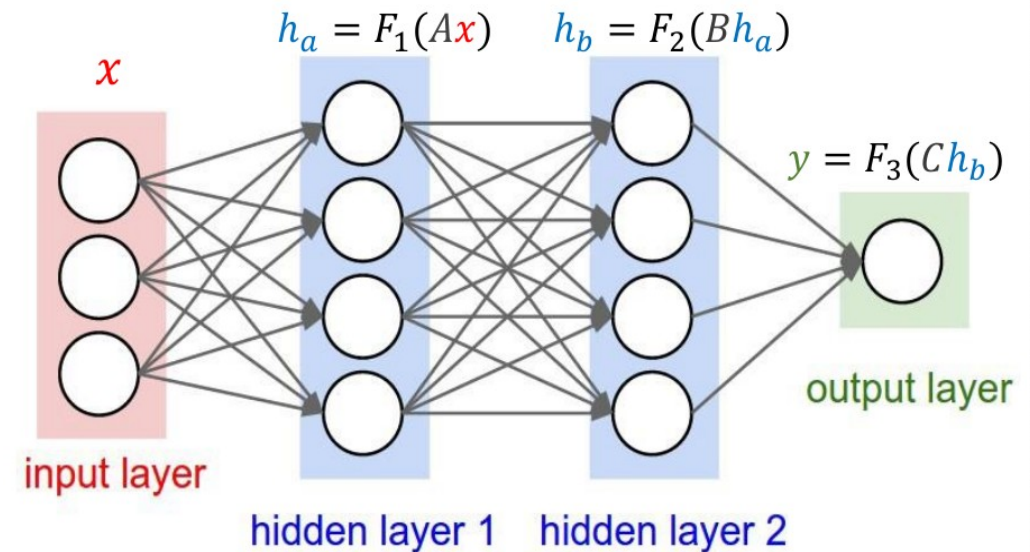
Building up the ML structure

Example: DNN with 2 layers

- **Input:** Takes the features as inputs
- **Hidden layers:** Connects to each neuron through different weights
- **Output:** Gives the result as a number or class

$$y = F_3 \left(C F_2 \left(B F_1 (Ax) \right) \right)$$

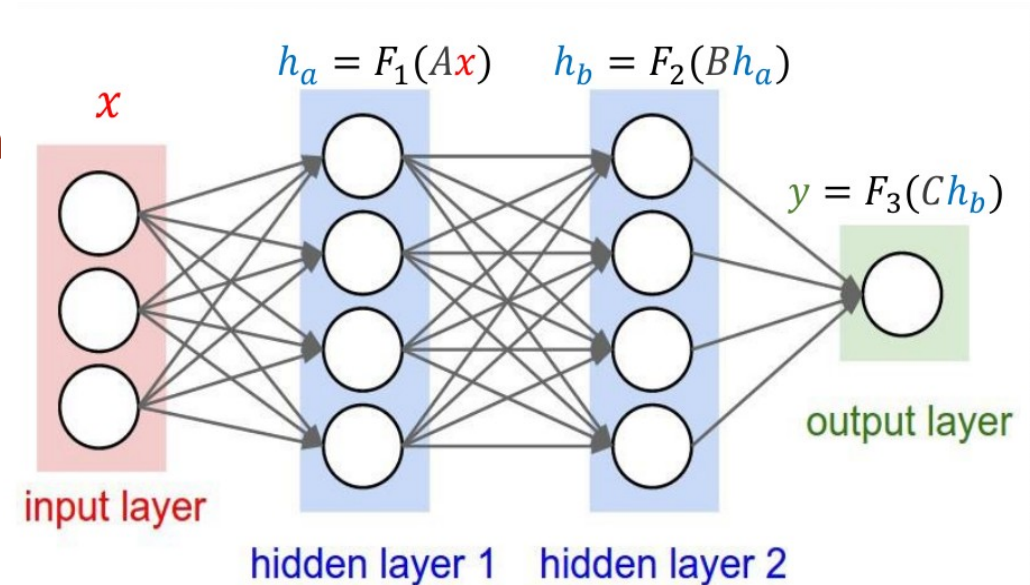
A, B, C represent the weight matrices
 F_1, F_2, F_3 represent the activation functions



Building up the ML structure

Math & algorithms behind

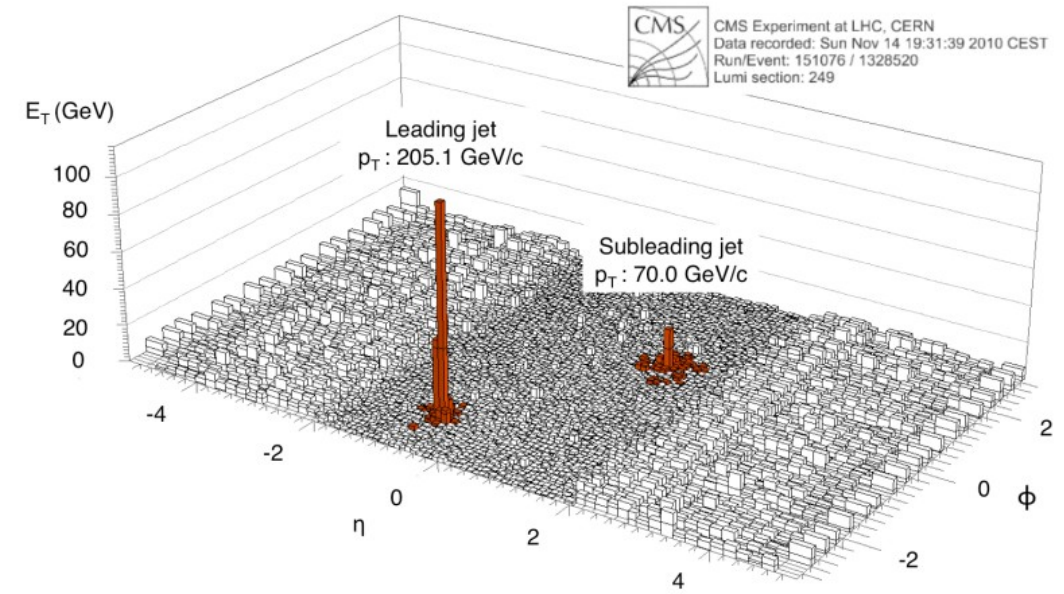
- **Weights** dictate the importance of an input
→ more important features get more weights
- **Activation function**: mathematical function that guides the outcome at each node
→ Standardize the values
- **Cost function**: Evaluates the accuracy between machine prediction and true value
- **Optimizer**: Method (or algorithm) that minimizes the cost function by automatically updating the weights



Building up the ML structure

Estimation of elliptic flow using DNN

- Elliptic flow \rightarrow Event property
- Inputs \rightarrow Track properties
- $(\eta-\phi)$ space is the primary input space

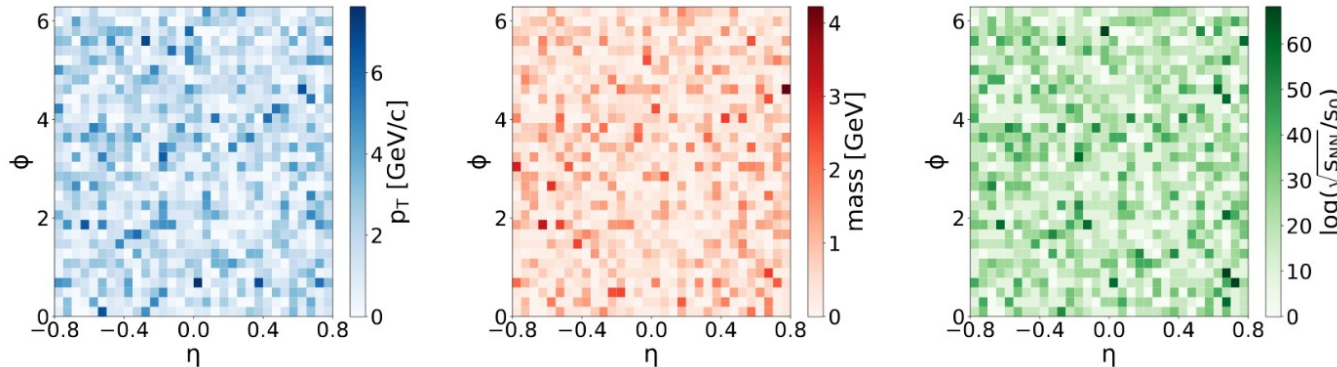
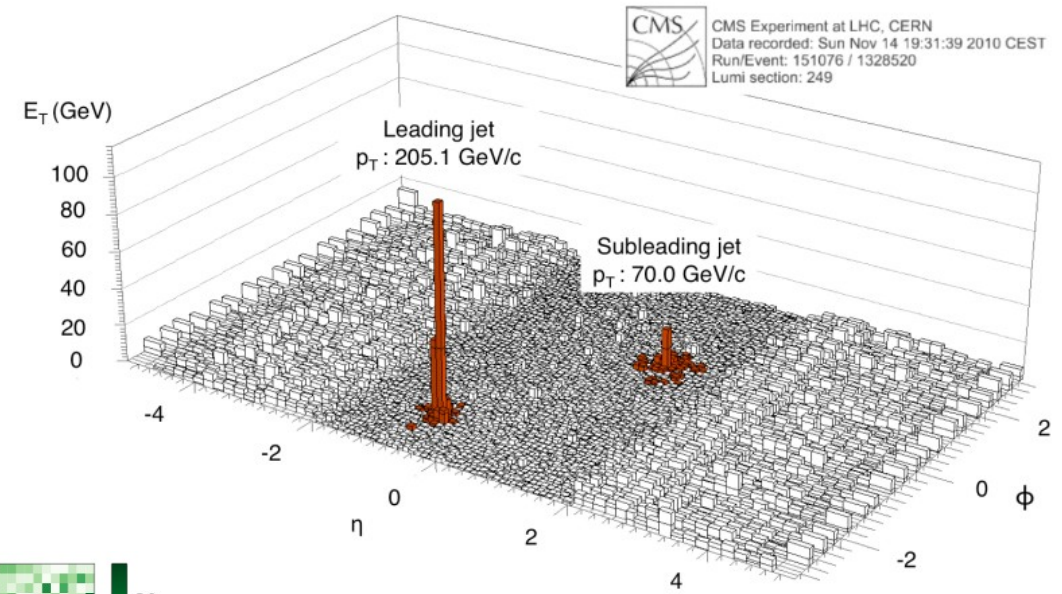


Serguei Chatrchyan et al., [Phys.Rev.C 84 \(2011\), 024906](#)

Building up the ML structure

Estimation of elliptic flow using DNN

- Elliptic flow \rightarrow Event property
- Inputs \rightarrow Track properties
- $(\eta-\phi)$ space is the primary input space
- Three layers having different weights: p_T , mass and $\log(s_{NN}/s_0)$ weighted layers serve as the secondary input space



Pb-Pb, $\sqrt{s_{NN}} = 5.02$ TeV, AMPT Simulation

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

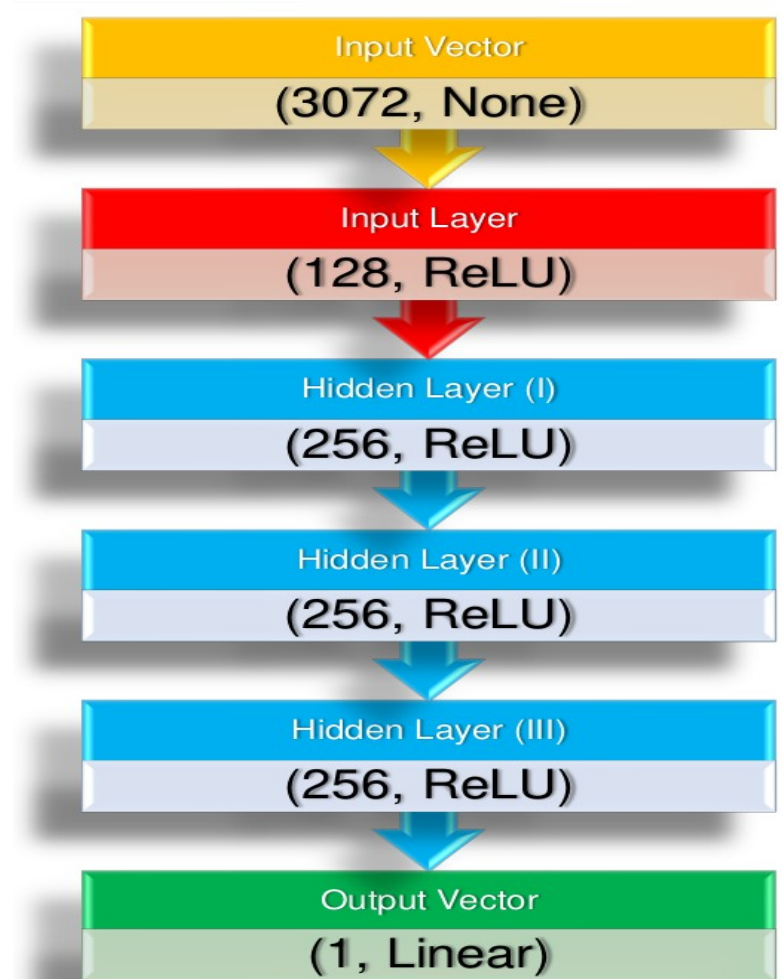
Building up the ML structure

Input “pictures” for DNN

- Each space has 32×32 pixels (grids)
- Total number of pixel points = $32 \times 32 \times 3 = 3072$ for each event

DNN with the following architecture

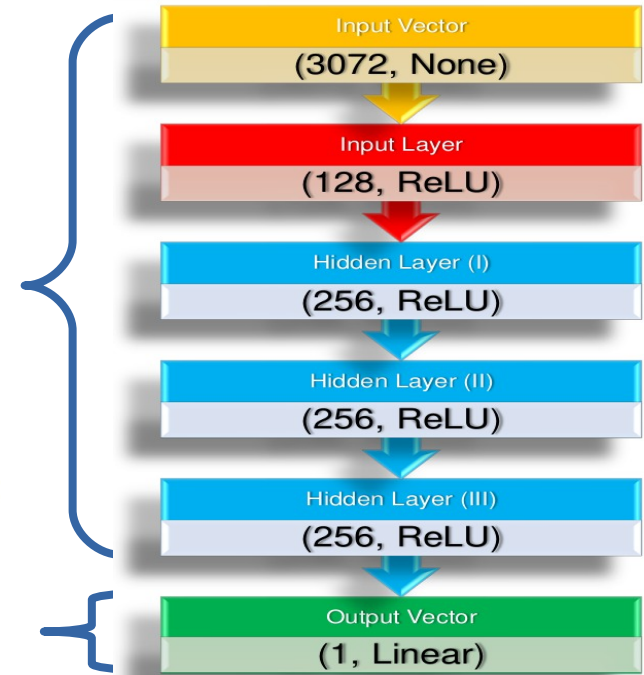
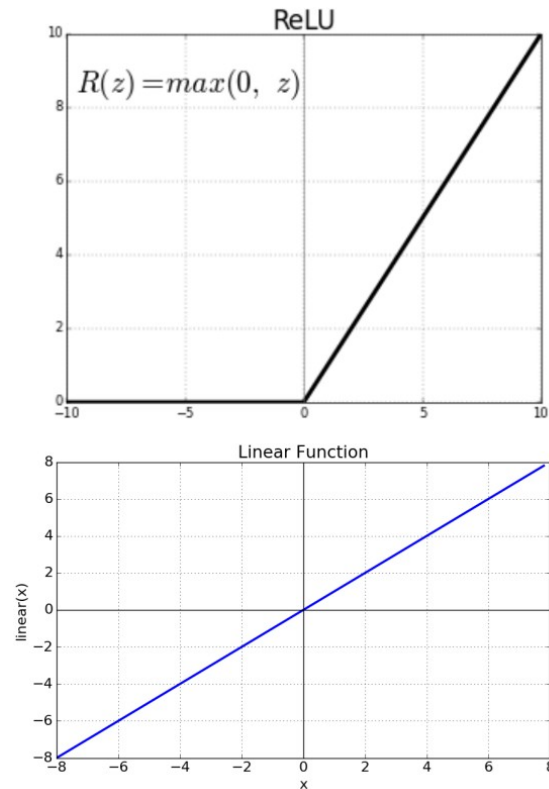
- Input Layer: 128 Nodes
- Three hidden layers: 256 Nodes each
- Final layer : 1 node (v_2)



Building up the ML structure

Activation, optimization, validation

- Input and hidden layers have ReLU Activation
- Output layer has Linear activation
- Optimizer: adam , Loss function: mse

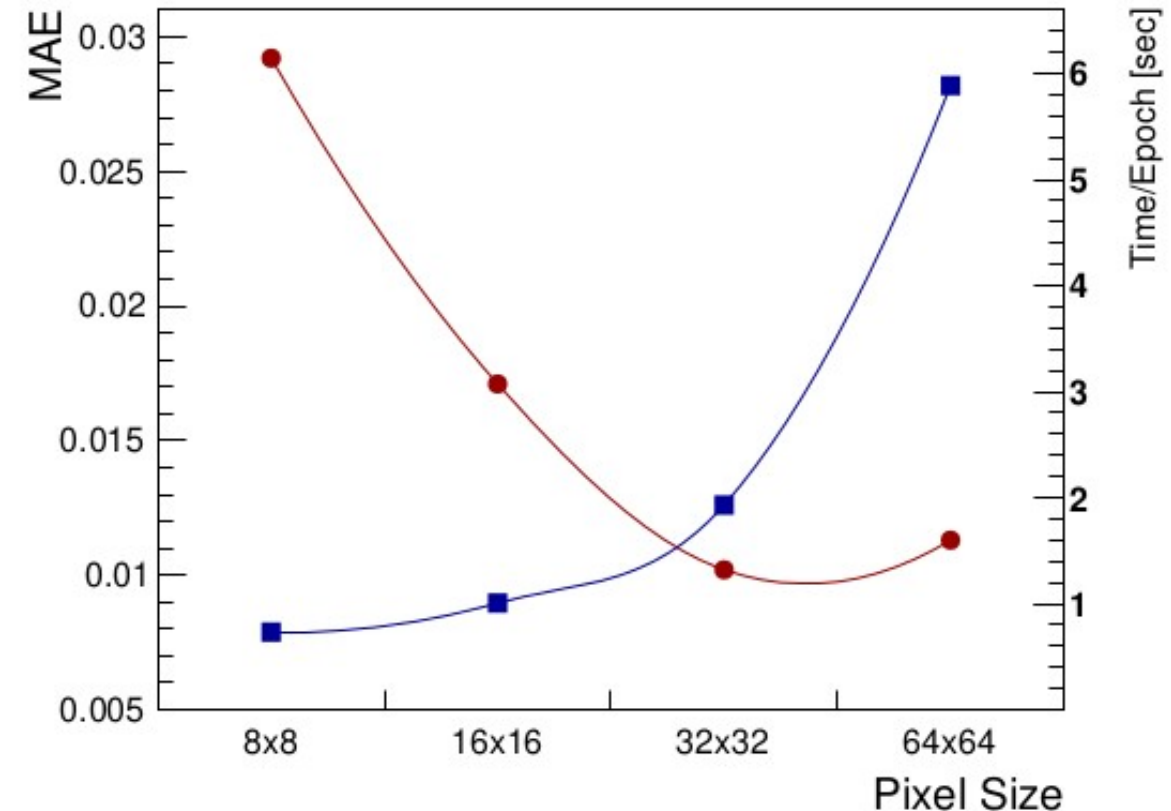


Optimizing the ML structure

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- Epoch: 30, Batch Size: 32x32
- Training: 10^8 Events (~ 25 GB)

Bin size	Input neurons	MAE	Epoch	$\frac{\text{Time (sec)}}{\text{Epoch}}$	Trainable parameters
8×8	192	0.0292	18	1.679	189,569
16×16	768	0.0171	28	1.909	263,297
32×32	3072	0.0102	30	2.684	558,209
64×64	12288	0.0113	60	6.001	1,737,857

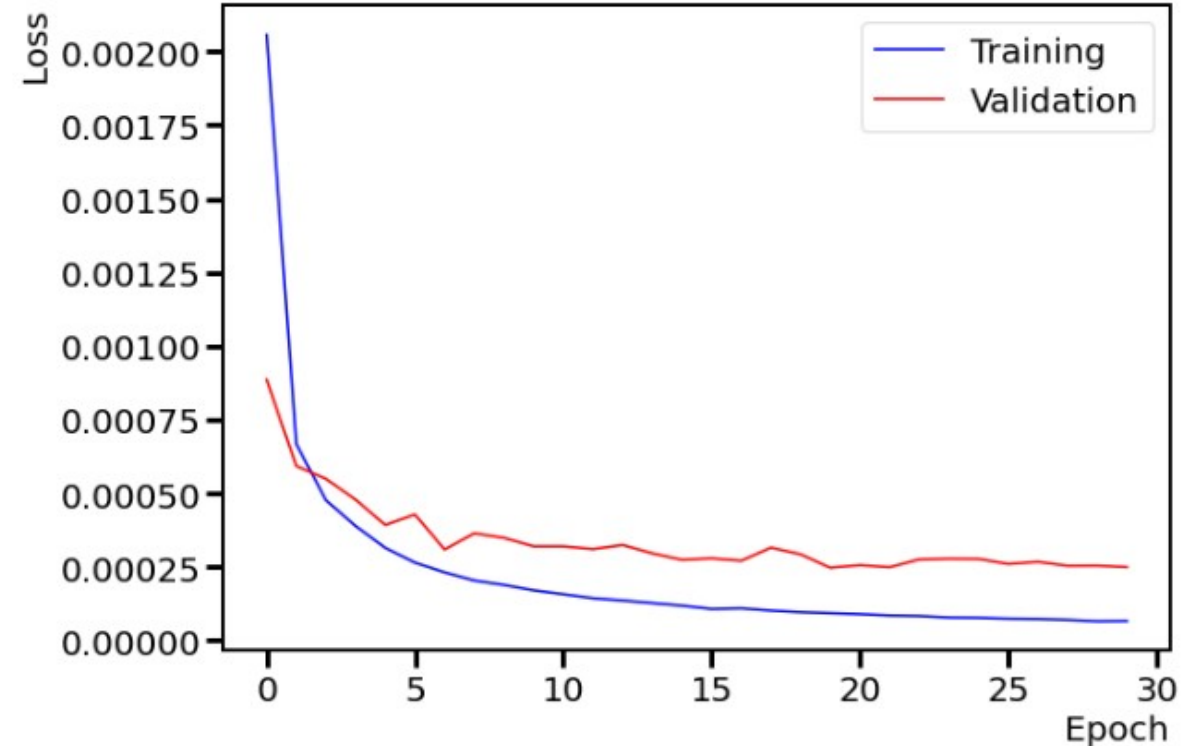


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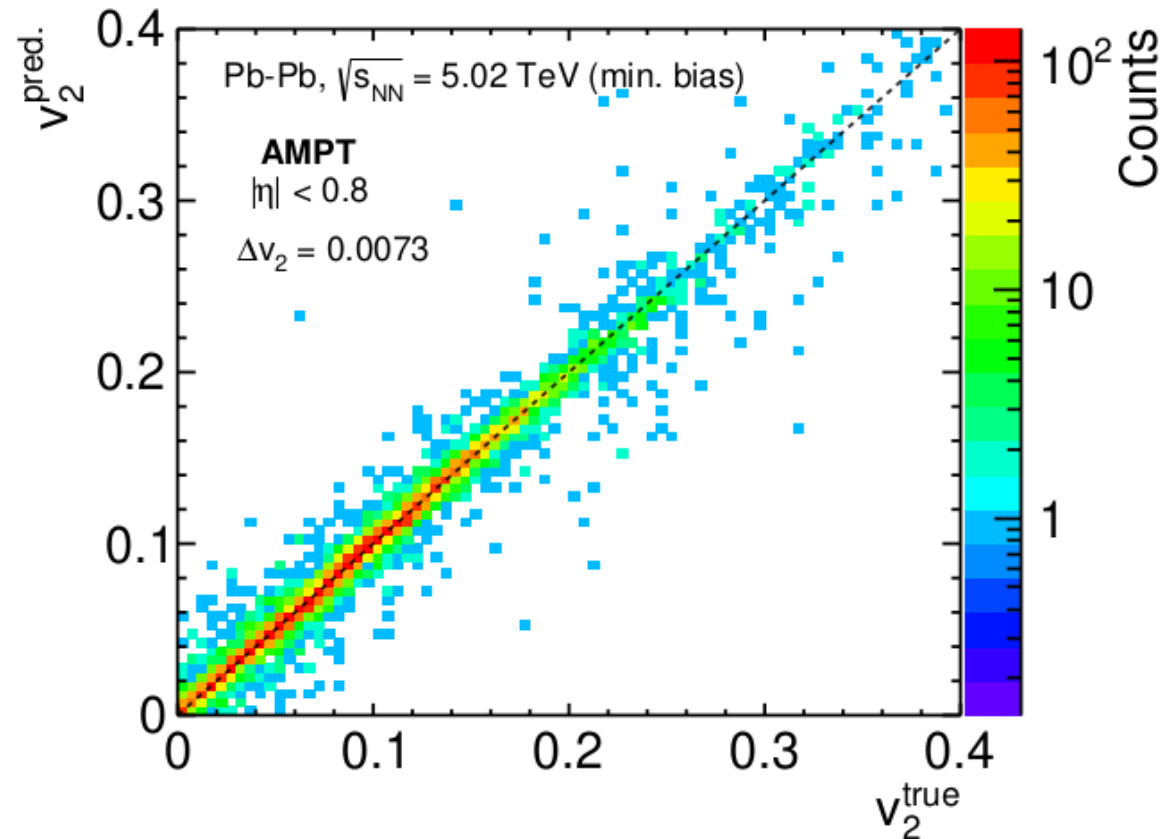


Testing the ML structure

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

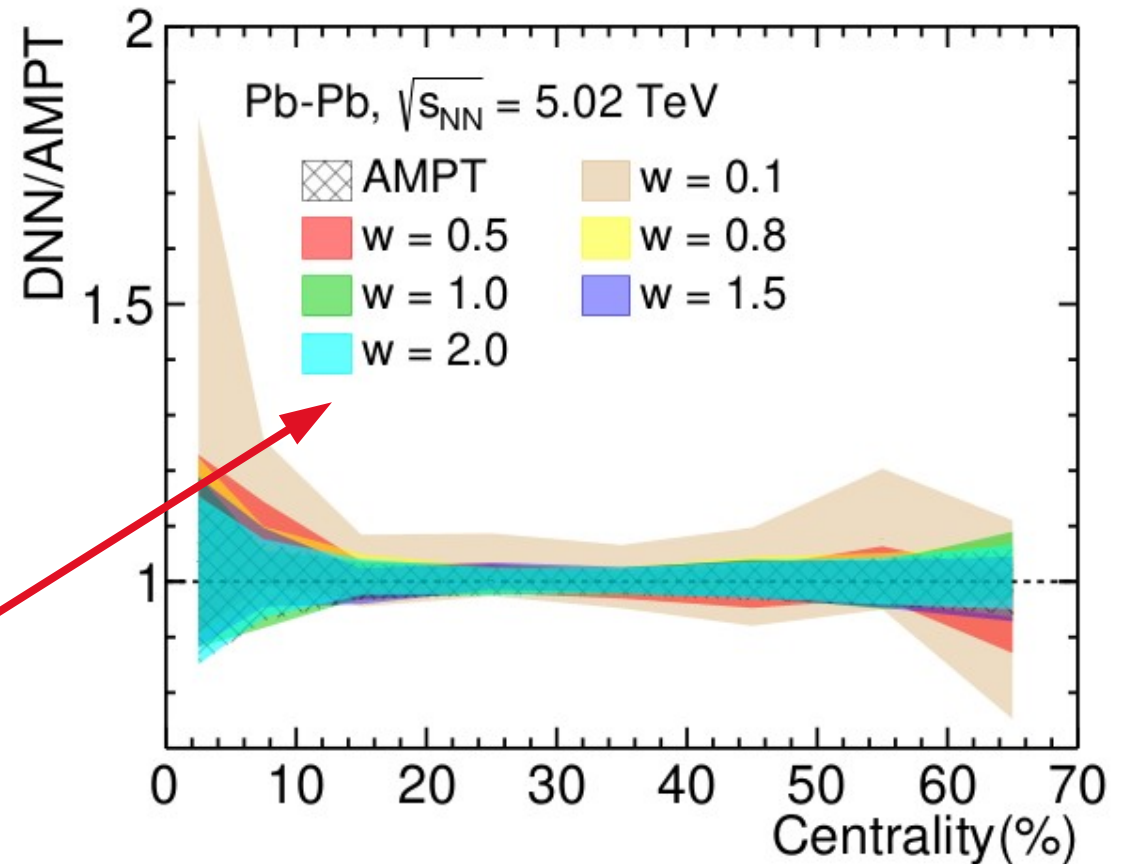


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- Error: effect of uncorrelated noise

$$F_{i,j} = F_{i,j} + X_{i,j}/w$$

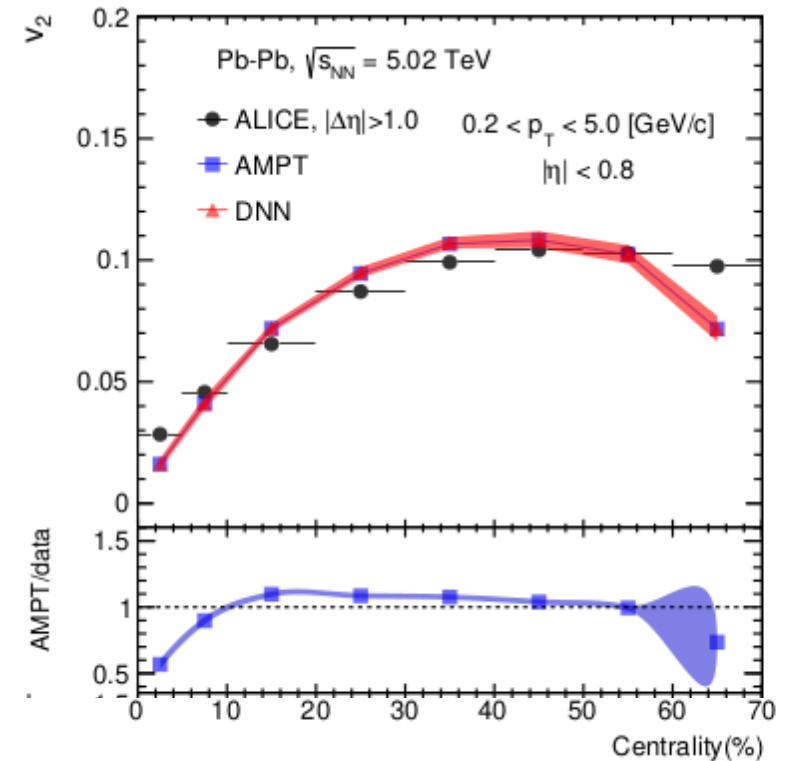


v_2 *ex machina*

Results on v_2 vs centrality

Results on the training data & sets

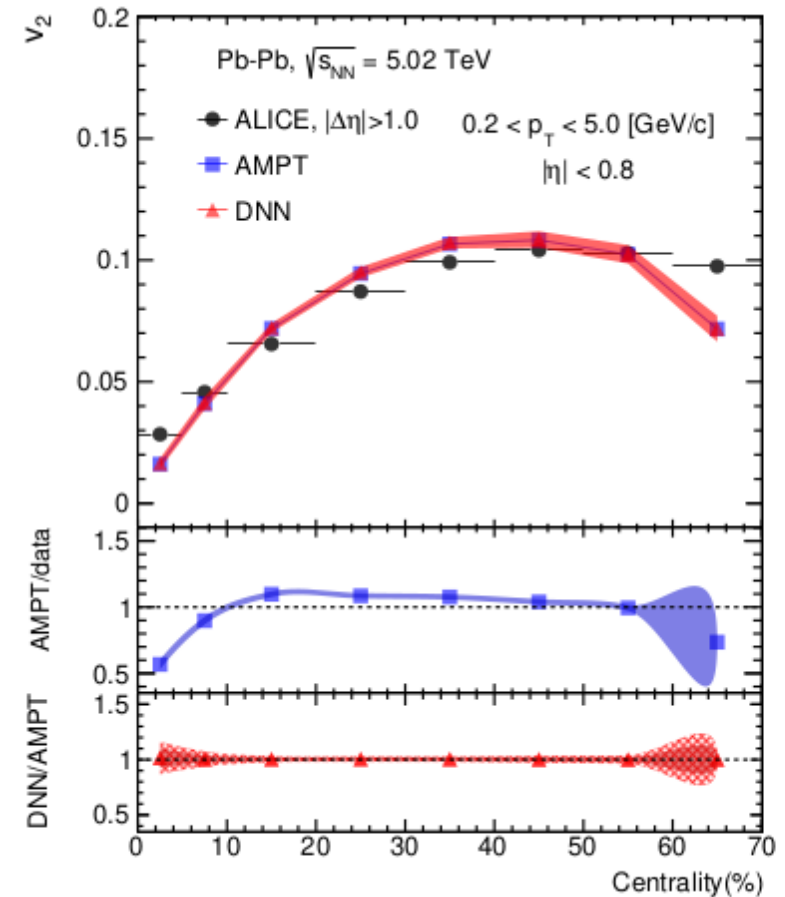
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 - works well [10%:60%] centrality
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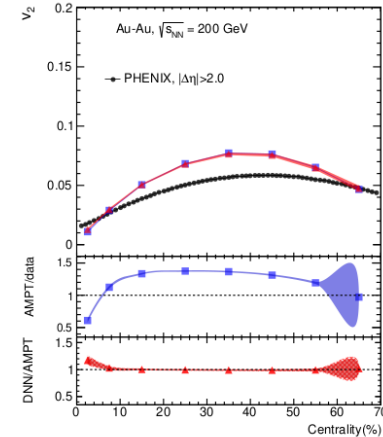
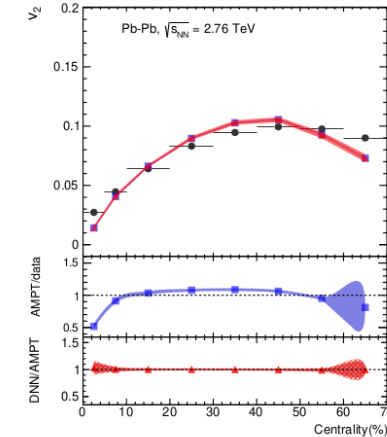
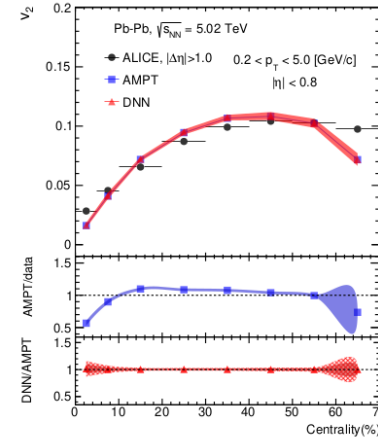
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Results on v_2 vs c.m. energy

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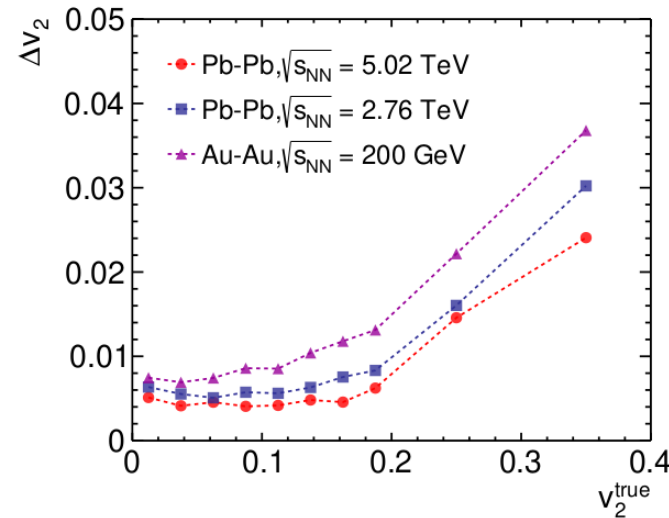
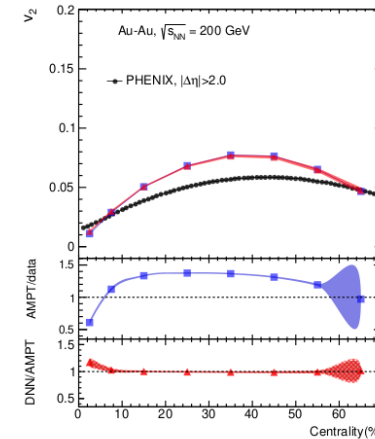
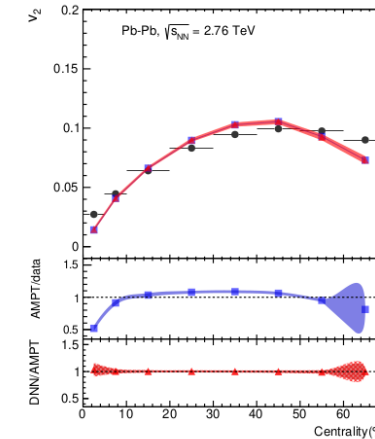
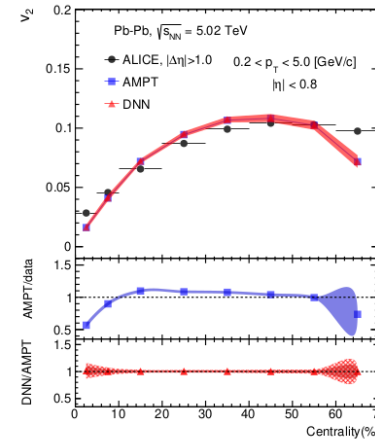
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 - similar trends as on the training
 - AMPT tune for 200 GeV is different



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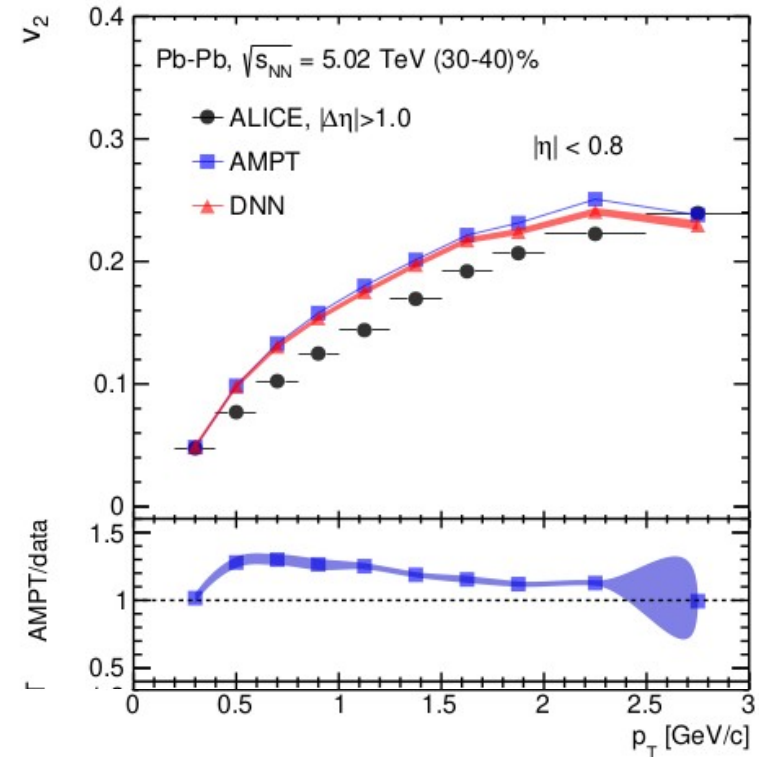


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Results on v_2 vs p_T

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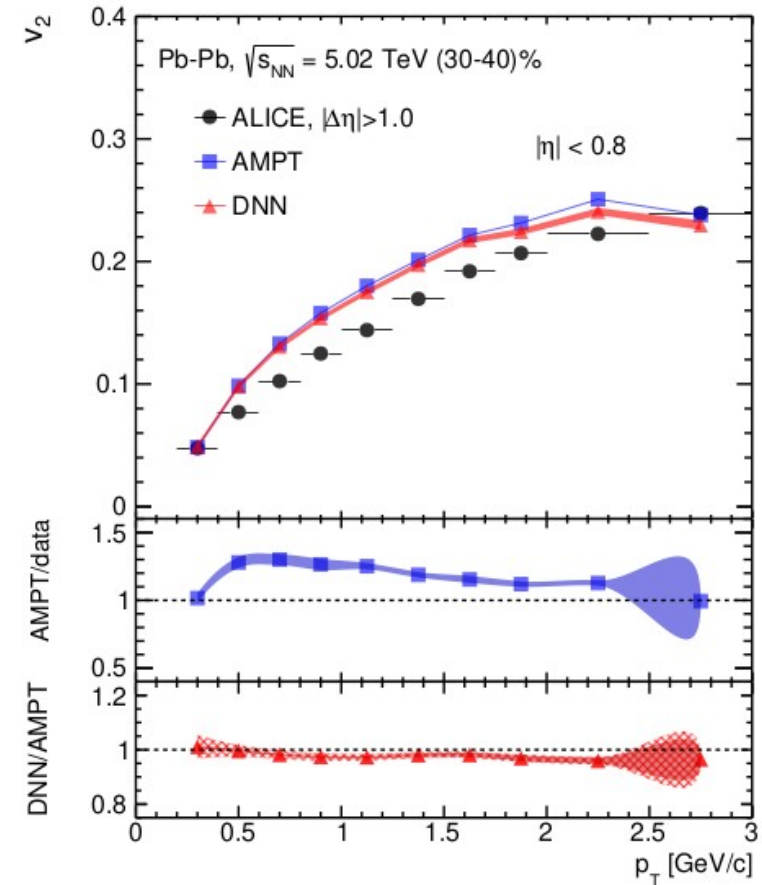
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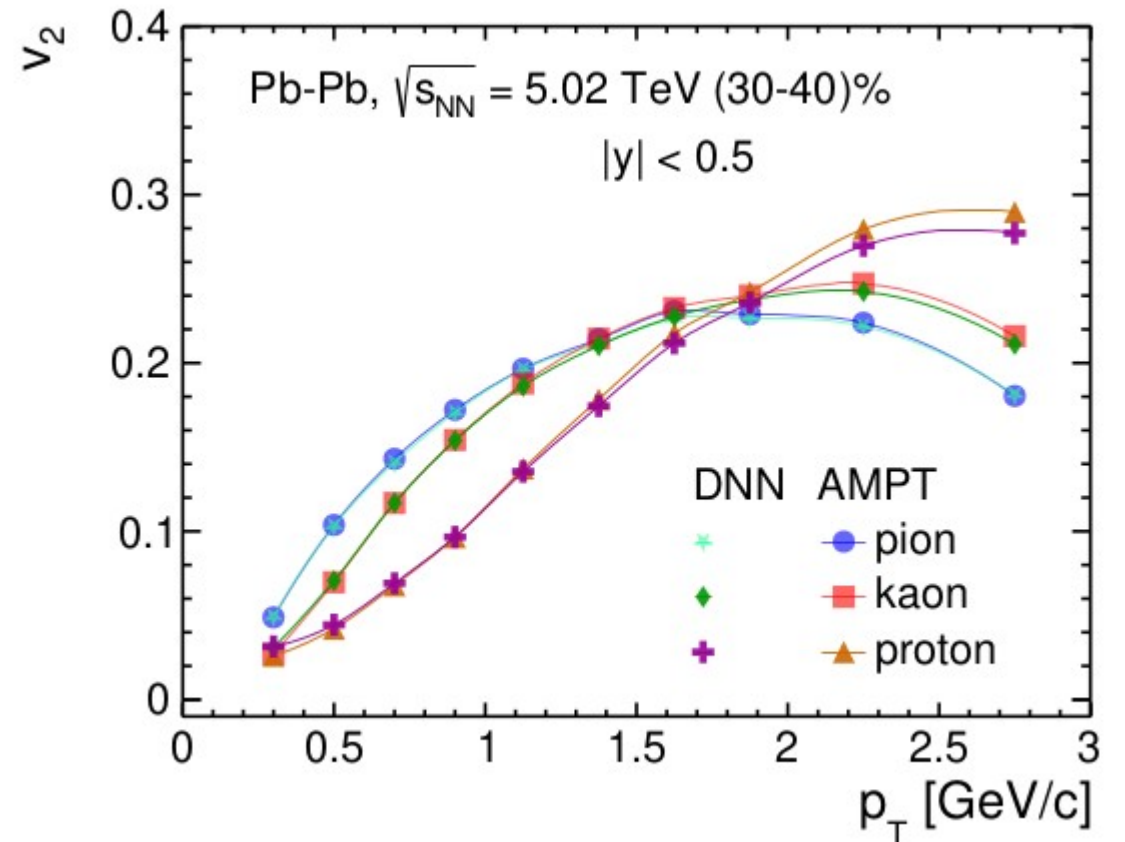
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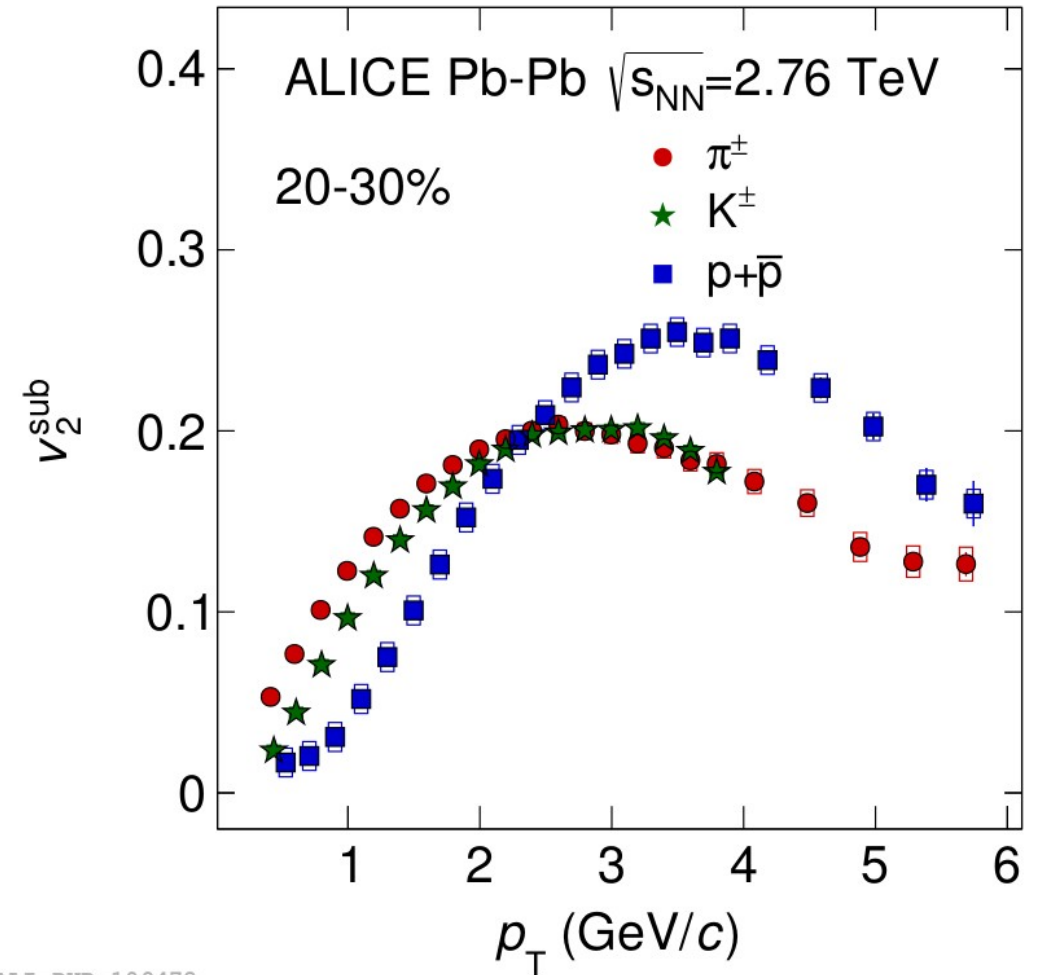
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 - DNN/AMPT=1 satisfied at low p_T
 - Interesting feature: turning point
 - Coalescence scaling



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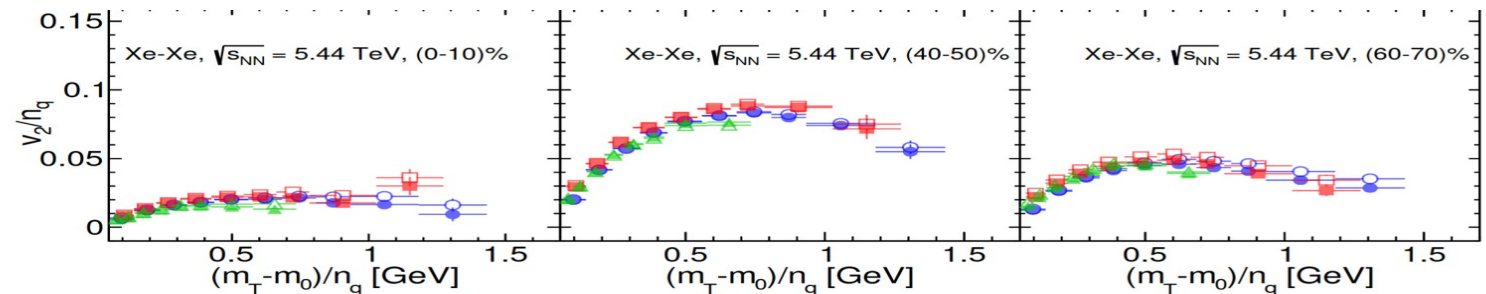


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Scaling properties are in the DNN

- **Centrality**

The largest in case 30%-40% mid-central



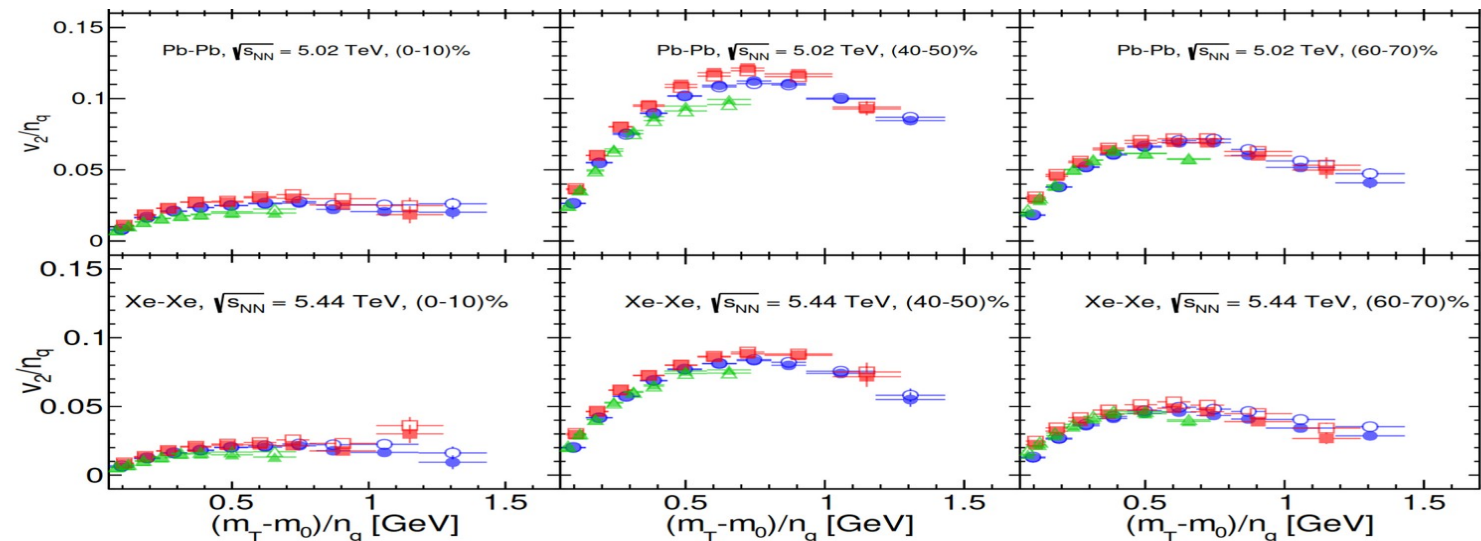
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- **Collision energy**

The higher the energy higher effect.



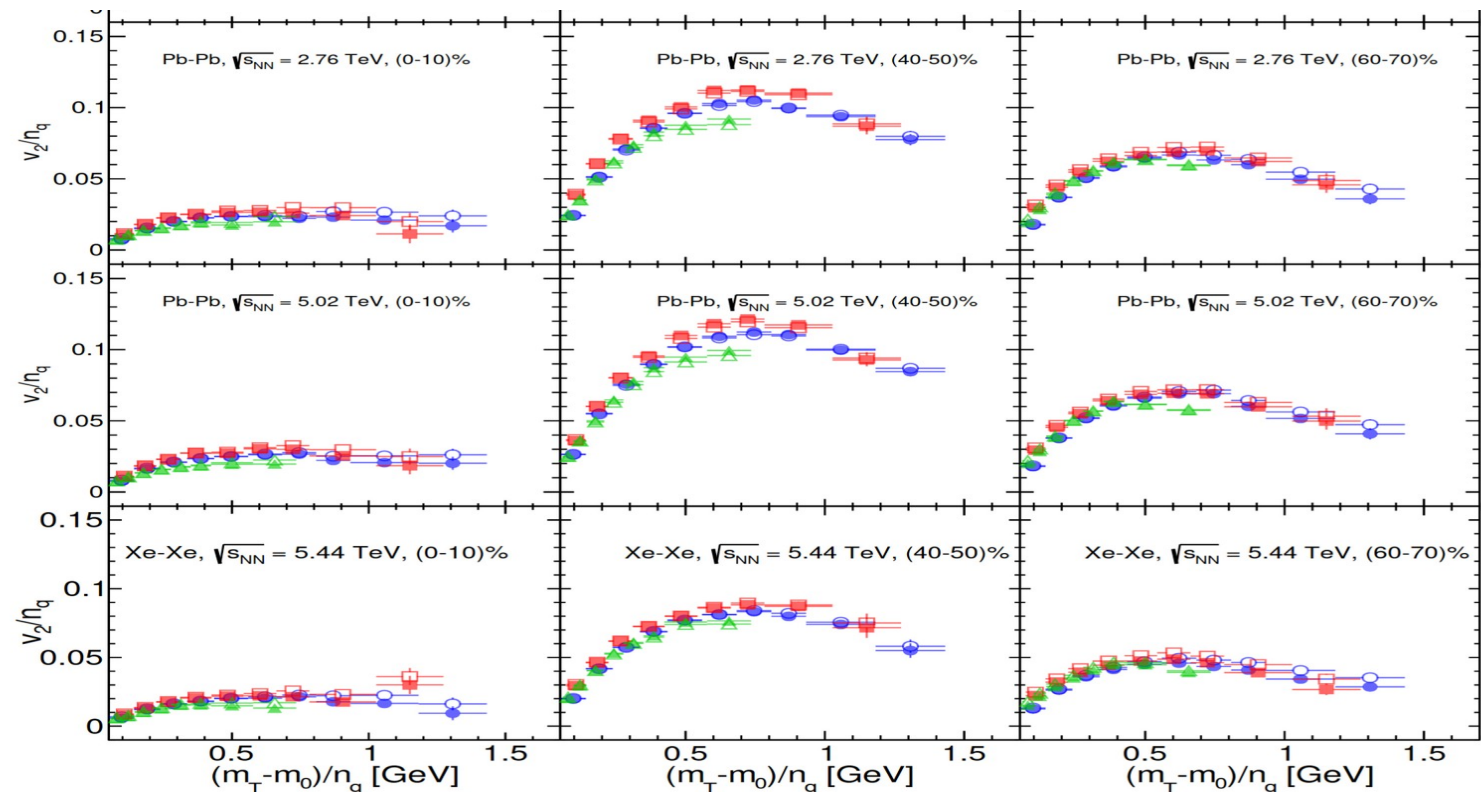
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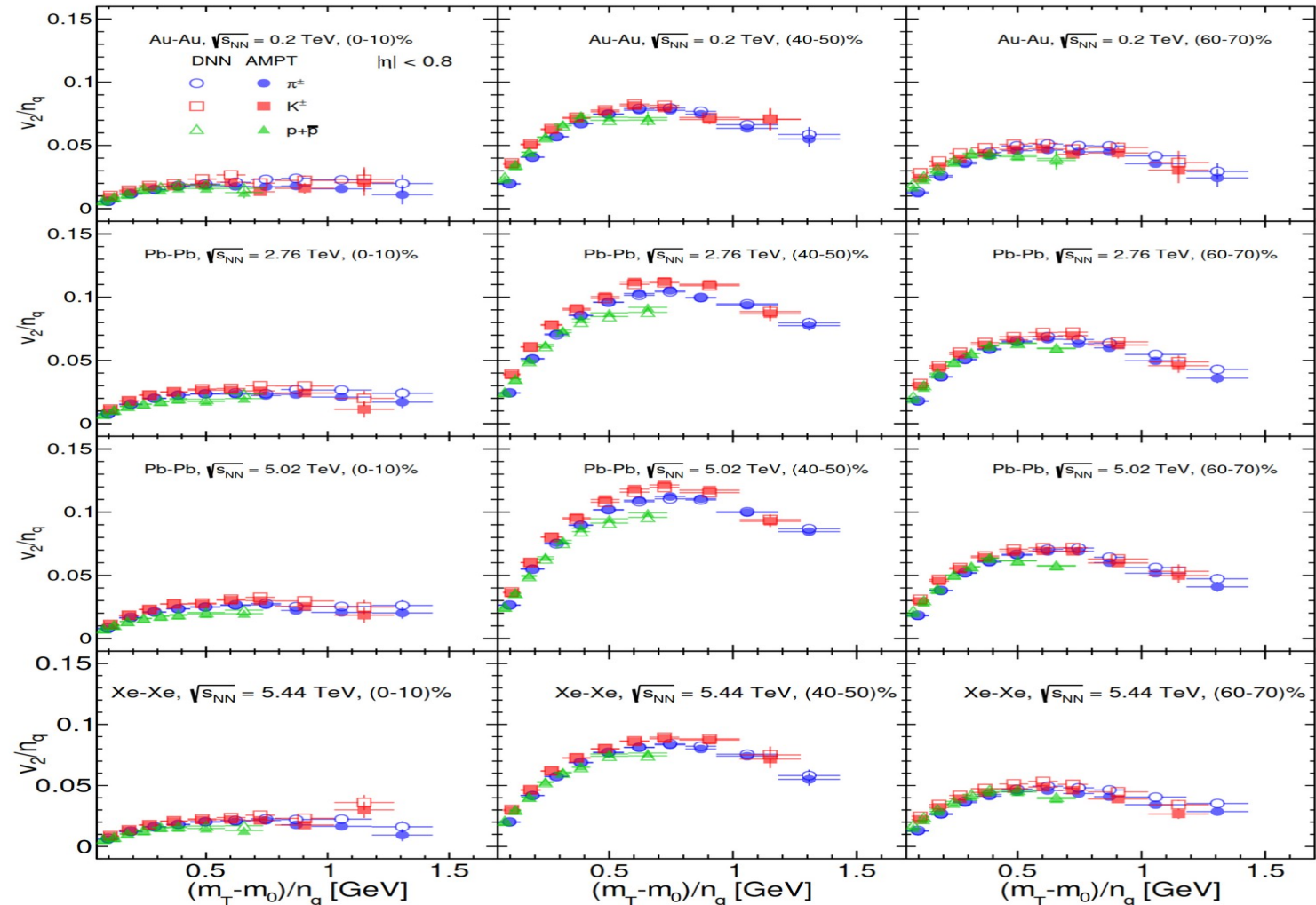
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- **Collision energy**

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- **DNN**

Follows well the trends \rightarrow scaling is encoded.



Conclusions

- **Is it possible to estimate the elliptic flow by ML?**
 - Get best Min. Bias. Monte Carlo simulation data and train the well-designed DNN system...
 - More sophisticated NN, the less epoch needs
 - Un-correlated noise can be even $w=1$
 - AMPT & DNN correlates well for all centrality
 - Best correlation is for the highest statistic
 - Energy scaling is well preserved (non-linear)
 - The $v_2(p_T)$ is also preserved with PID



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 - AMPT & DNN correlates well for all centrality
 - Best correlation is for the highest statistic
 - Energy scaling is well preserved (non-linear)
 - The $v_2(p_T)$ is also preserved with PID
- **What is missing...**
 - Test of correlated noise (detector setup, etc)
 - Train with real data from ALICE



Thank You!

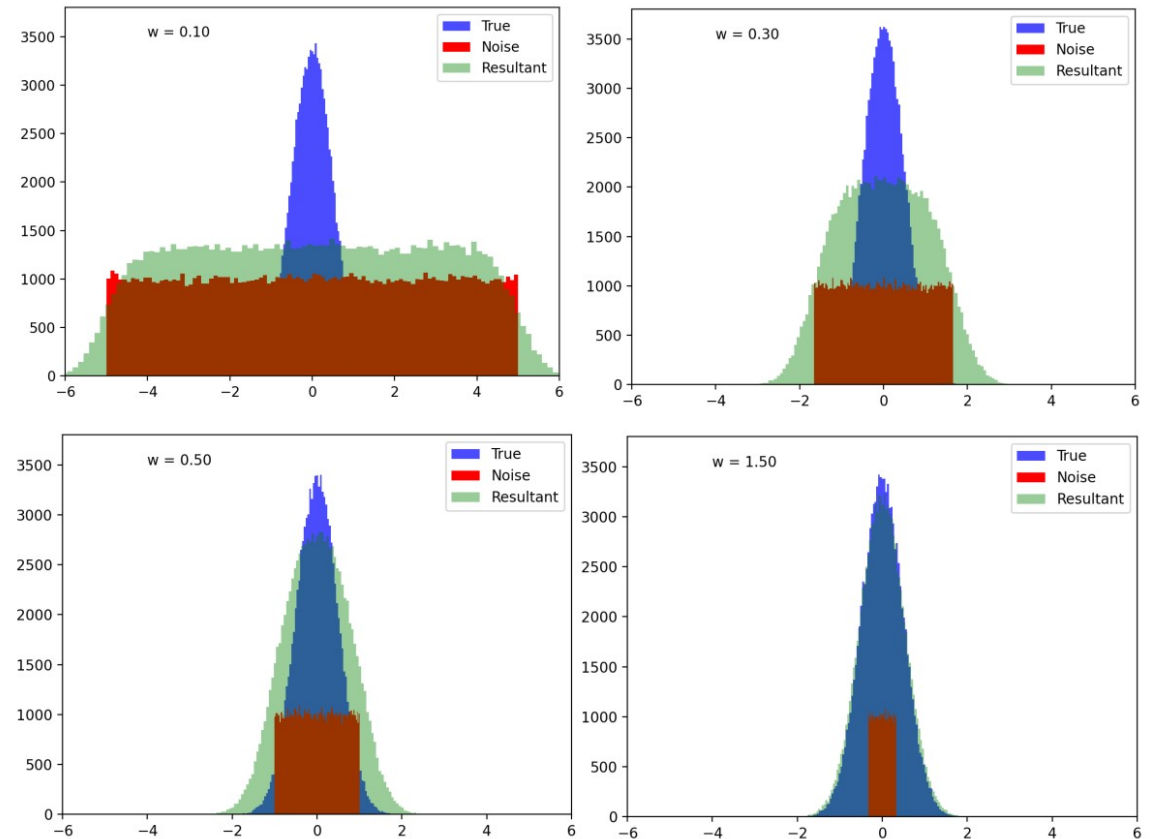
BACKUP

Testing the ML structure

Activation, optimization, validation

- Input and hidden layers have ReLu Activation
- Output layer has Linear activation
- Optimizer: adam , Loss function: mse
- Epoch: 30, Batch Size: 32x32
- Training: 10^8 Events (~ 25 GB)
- Validation: 10^4 Events
- Error: effect of uncorrelated noise

$$F_{i,j} = F_{i,j} + \tilde{X}_{i,j}/w$$



Scaling properties are in the DNN

- **Centrality**

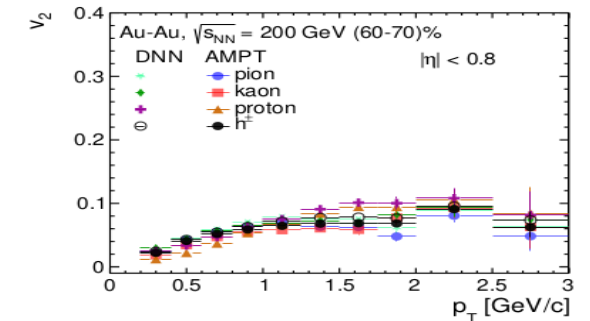
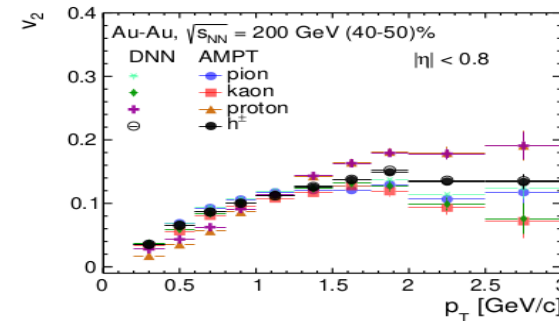
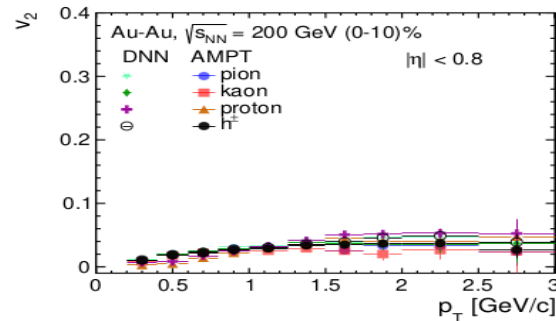
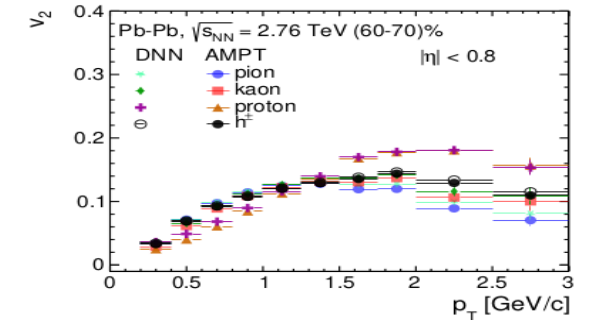
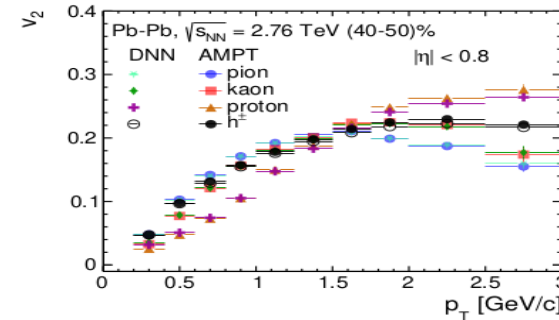
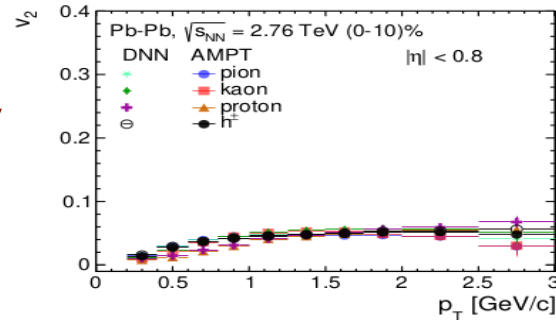
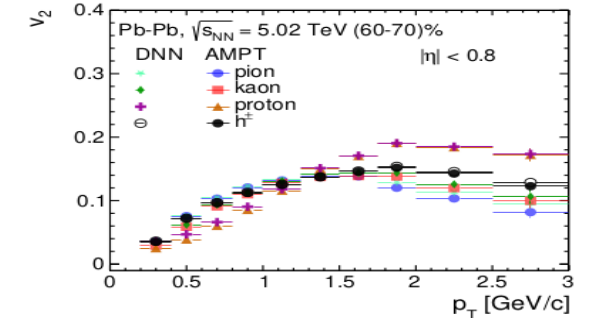
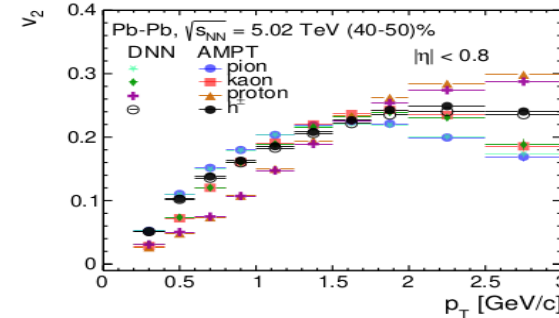
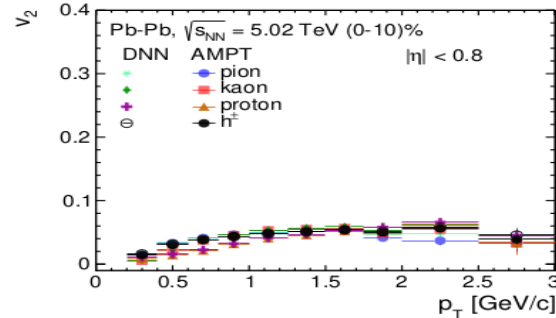
The largest in case 30%-40% mid-central

- **Collision energy**

The higher the energy higher effect.

- **DNN**

Follows well the trends \rightarrow scaling is encoded.



Preliminary: results at higher p_T

- **AMPT vs Data**

→ Does not fit well above than few p_T
Best at 30%-40% mid-central.

→ Need for more statistics

- **AMPT vs DNN**

→ DNN follows well the AMPT at any energy & centrality.

- **DNN**

Follows well AMPT but NOT the high p_T data
→ need to improve!

