Deep learning for high energy nuclear physics from a theoretical perspective

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Content

- Introduction to deep learning
- Deep learning for HIC
  - QCD EoS and critical end point
  - Determining nuclear structure
  - Determining in-medium heavy quark potential
  - Looking for Mach cones using DL assisted jet tomography
- Summary

What is deep learning

Hero of deep learning: Yann LeCun

Deep learning is constructing networks of parameterized functional modules & training them from examples using gradient-based optimization

DNN serve as the variational function

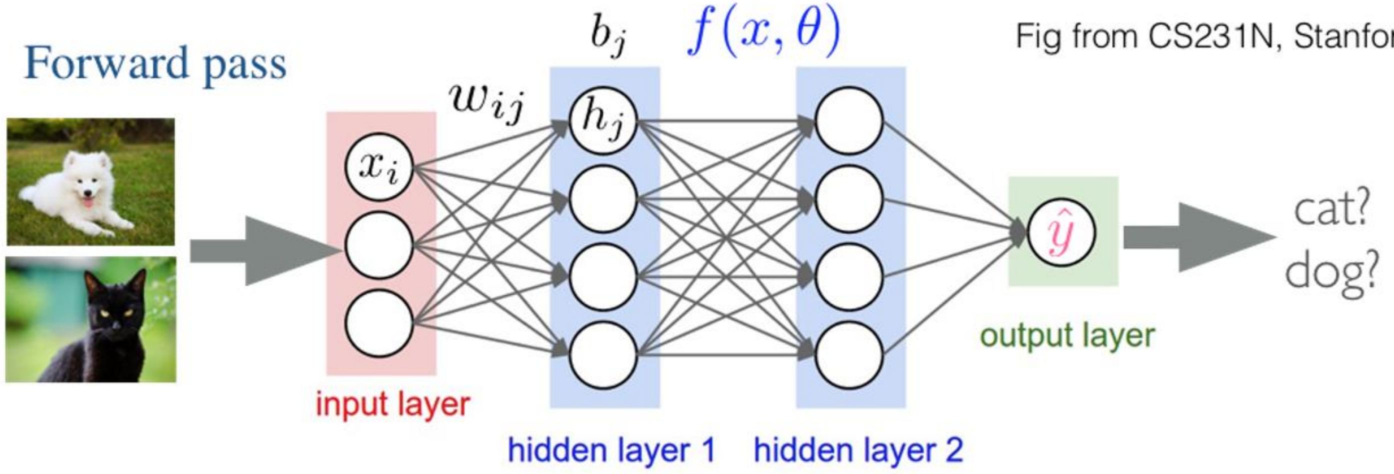


Fig from CS231N, Stanford

Linear operation

$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

scaling, rotating, boosting, changing dimensions

Non-linear activation function $h_j = \sigma(z_j)$

(a) Sigmoid

$$\sigma(z) = \frac{1}{1+\exp(-z)}$$

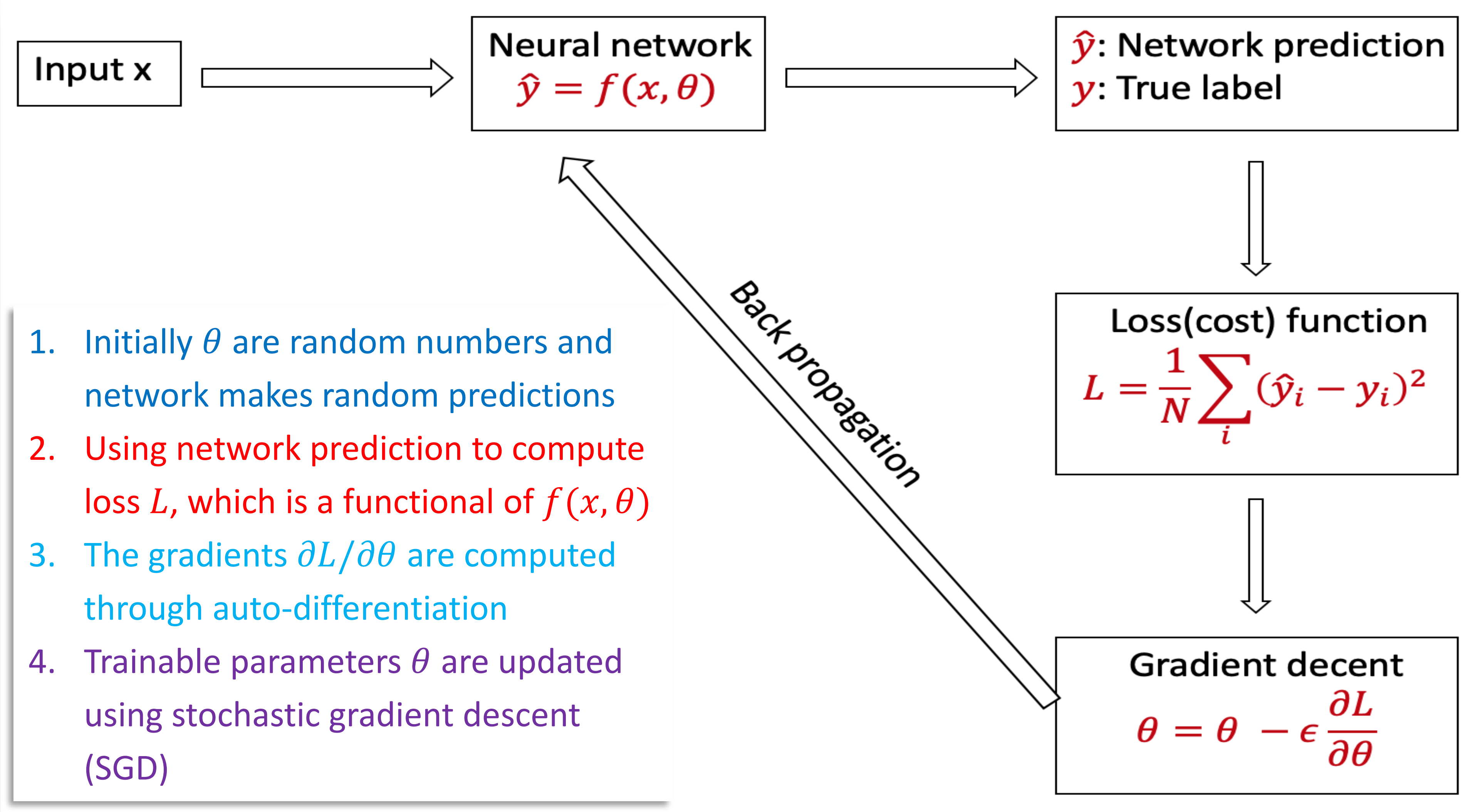
(b) ReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ 0, & z \leq 0 \end{cases}$$

(c) PReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ az, & z \leq 0 \end{cases}$$

Training process



1. Initially θ are random numbers and network makes random predictions
2. Using network prediction to compute loss L, which is a functional of $f(x, \theta)$
3. The gradients $\partial L / \partial \theta$ are computed through auto-differentiation
4. Trainable parameters θ are updated using stochastic gradient descent (SGD)

Learn Hierarchical representations

Olah, et al., "Feature Visualization", Distill, 2017.

Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

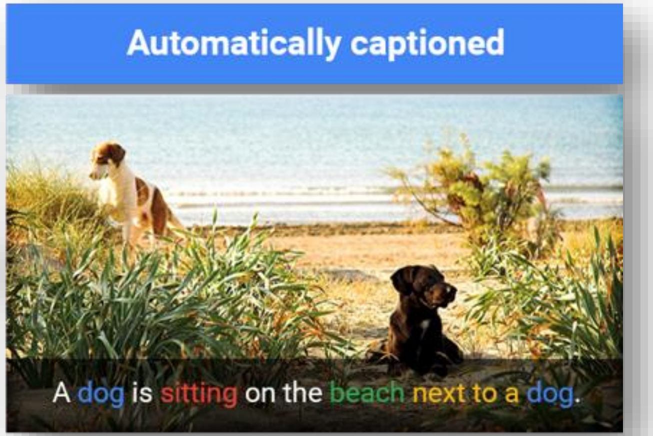
Shallow layers

Deep layers

Mapping data between two sources

Google, DeepMind

Image to text



If

1. Causality link exists
2. The used DNN has enough representation power
3. Enough training examples

Mapping data between two sources

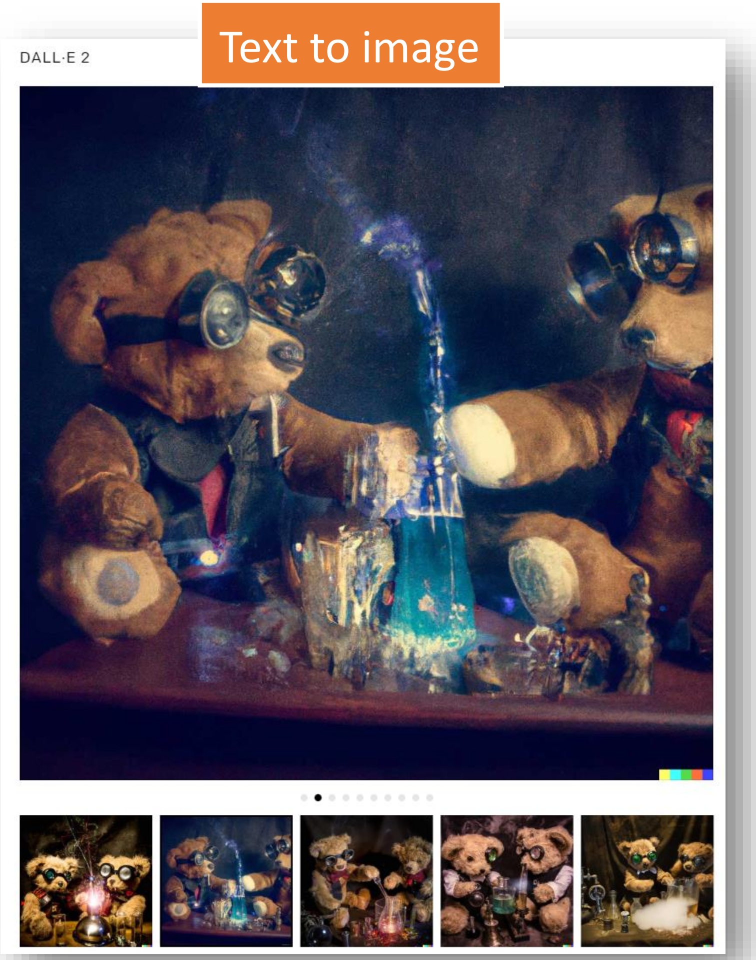
TEXT DESCRIPTION

An astronaut   Teddy bears   A bowl of soup

mixing sparkling chemicals as mad scientists   shopping for groceries   working on new AI research

as a 1990s Saturday morning cartoon   as digital art   in a steampunk style   →

DALL·E 2 can create original, realistic images and art from a text description. It can combine concepts, attributes, and styles.



Mapping data between two sources

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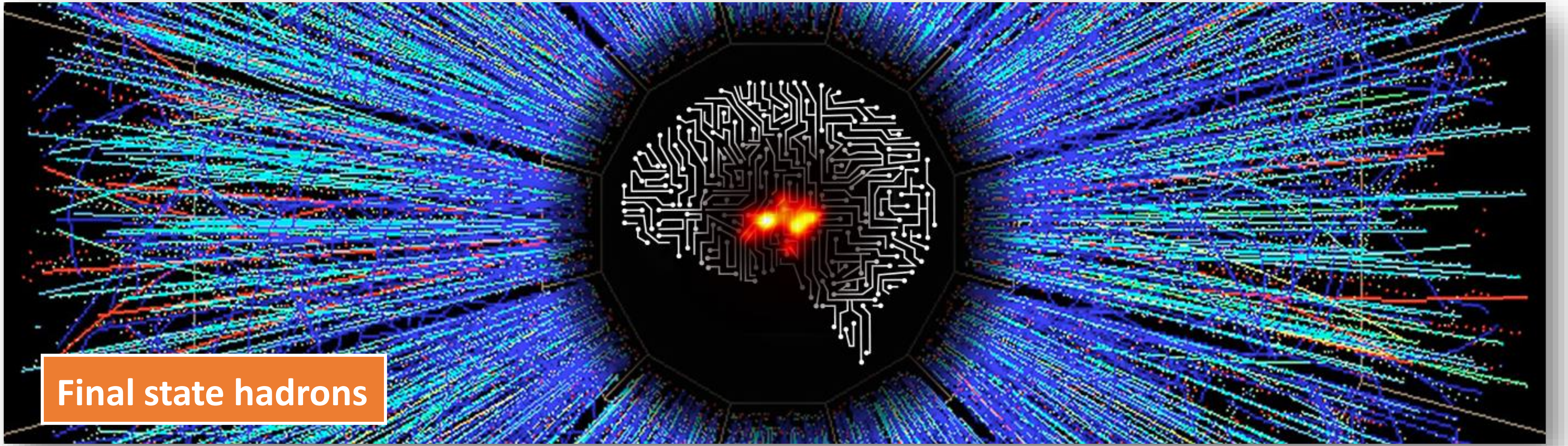
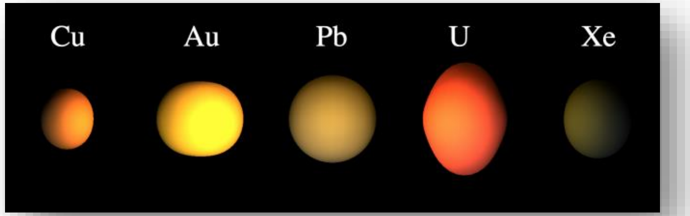
→

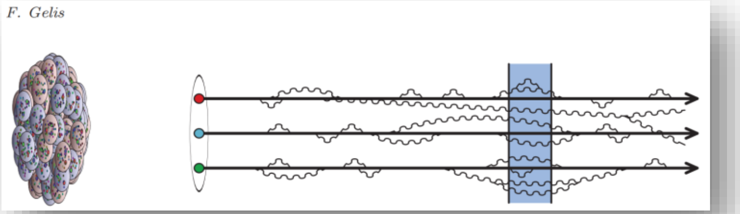
DALL·E 2 can create original, realistic images and art from a text description. It can combine concepts, attributes, and styles.

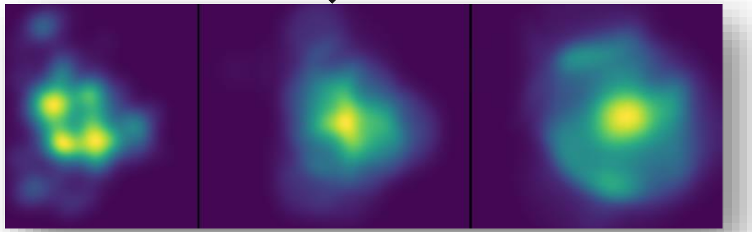
Inverse problem in HIC



Non-linear mapping

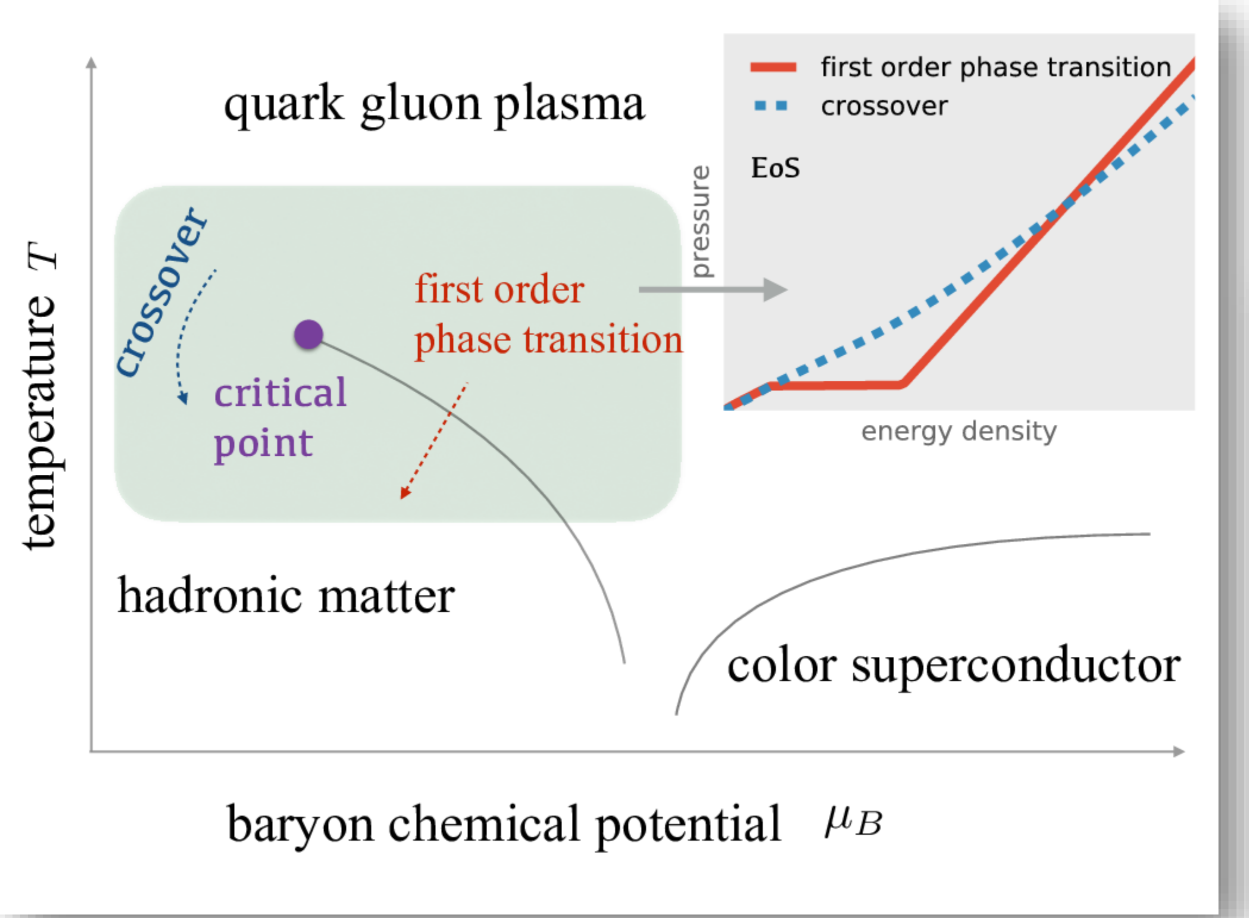




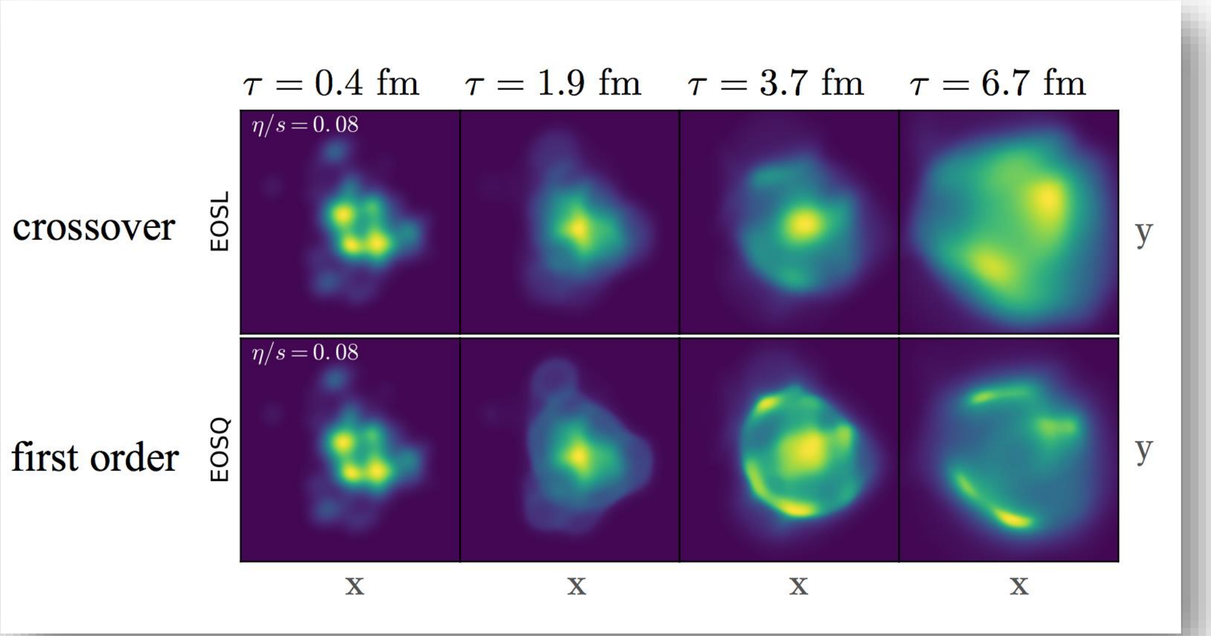


(1) Nuclear structure (2) Initial parton distribution (3) QGP properties/nuclear phase transition

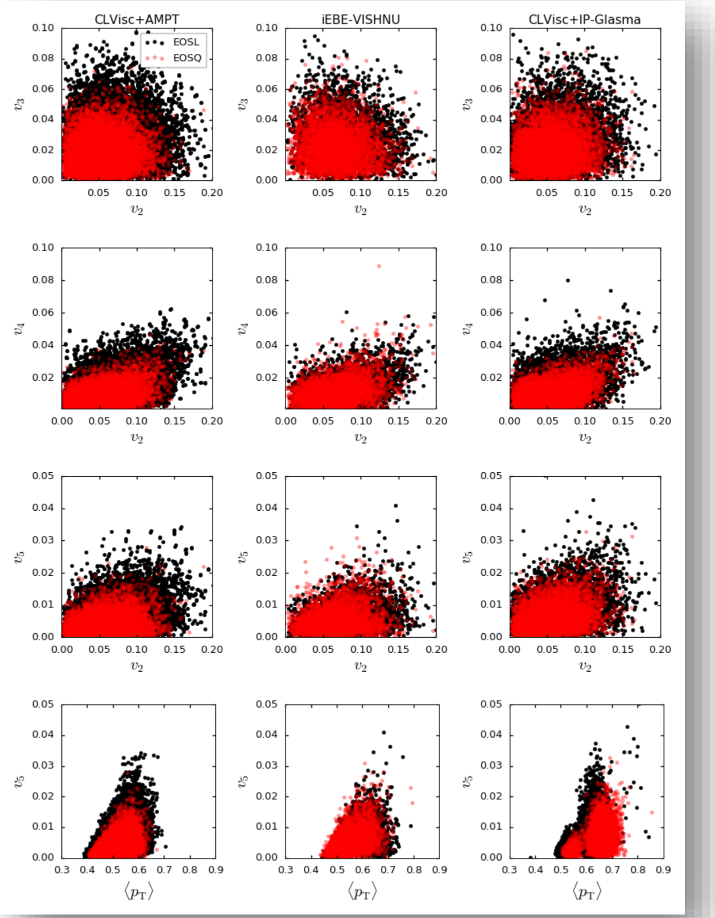
Classifying QCD EoS

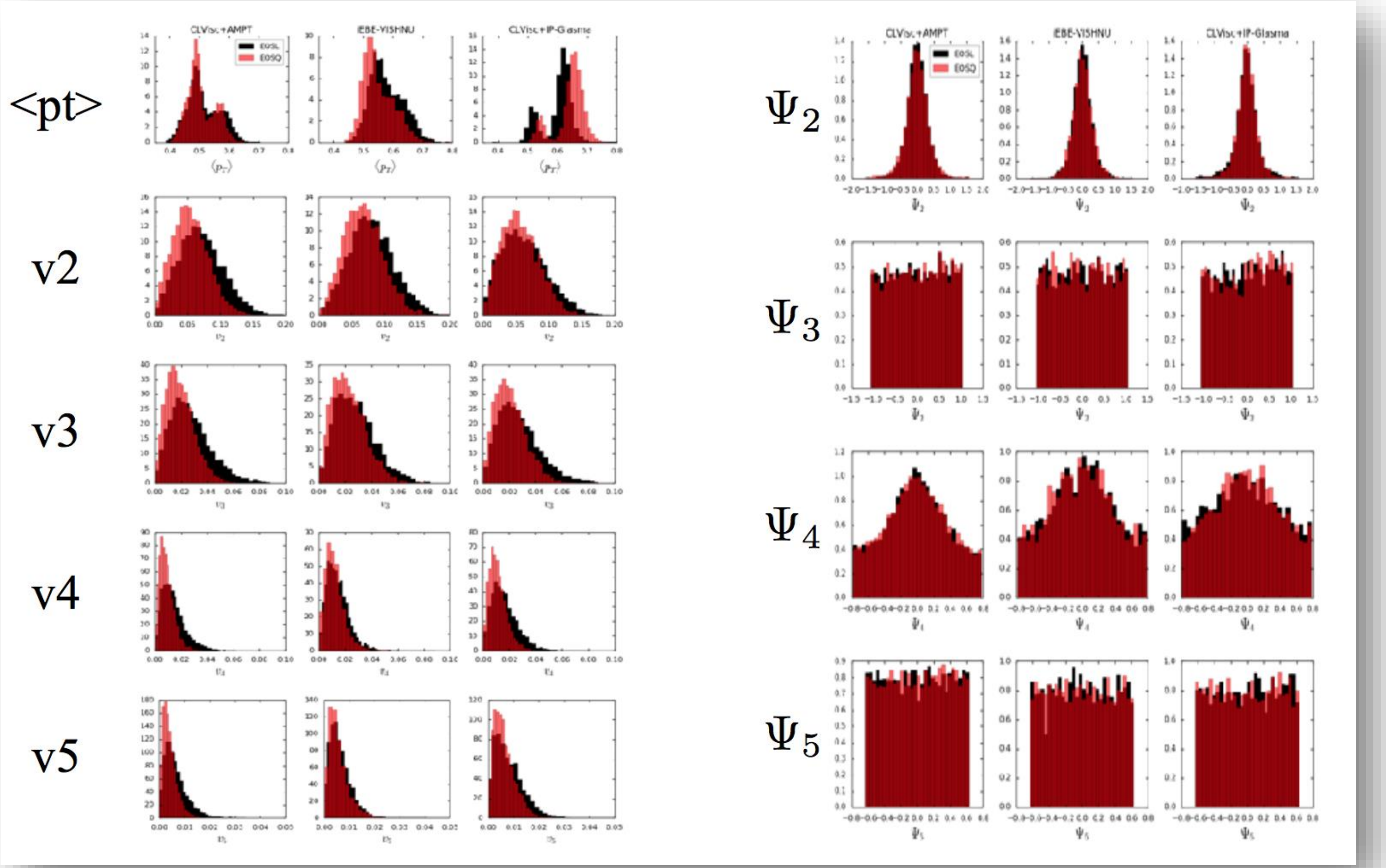


$$\nabla_\mu T^{\mu\nu} = 0$$

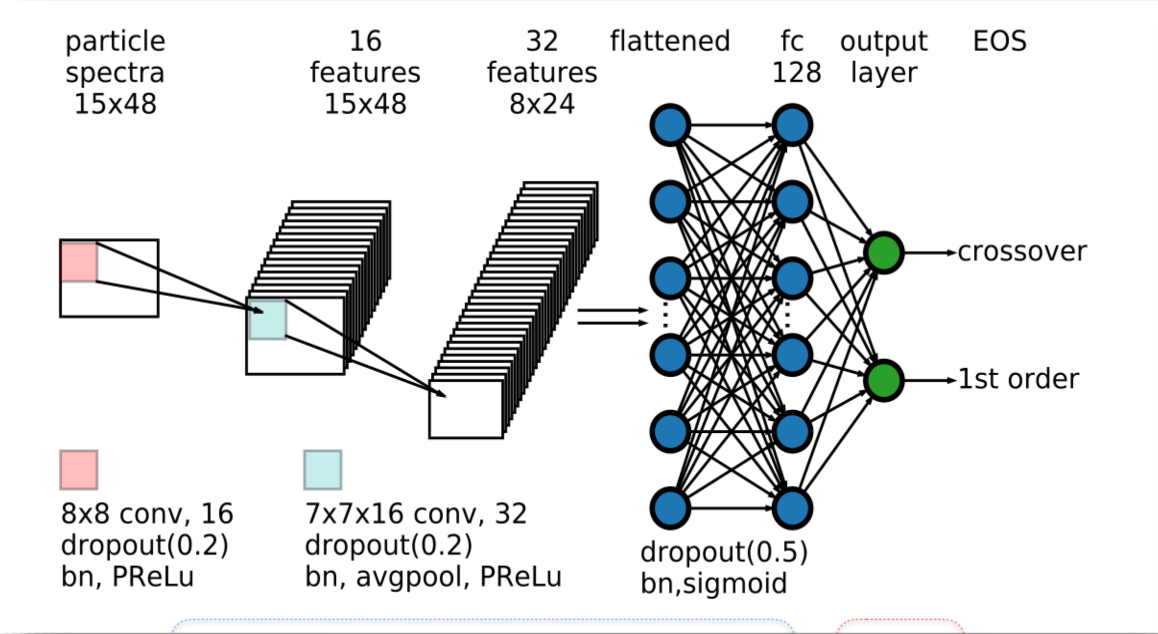


Traditional observables （EBE）

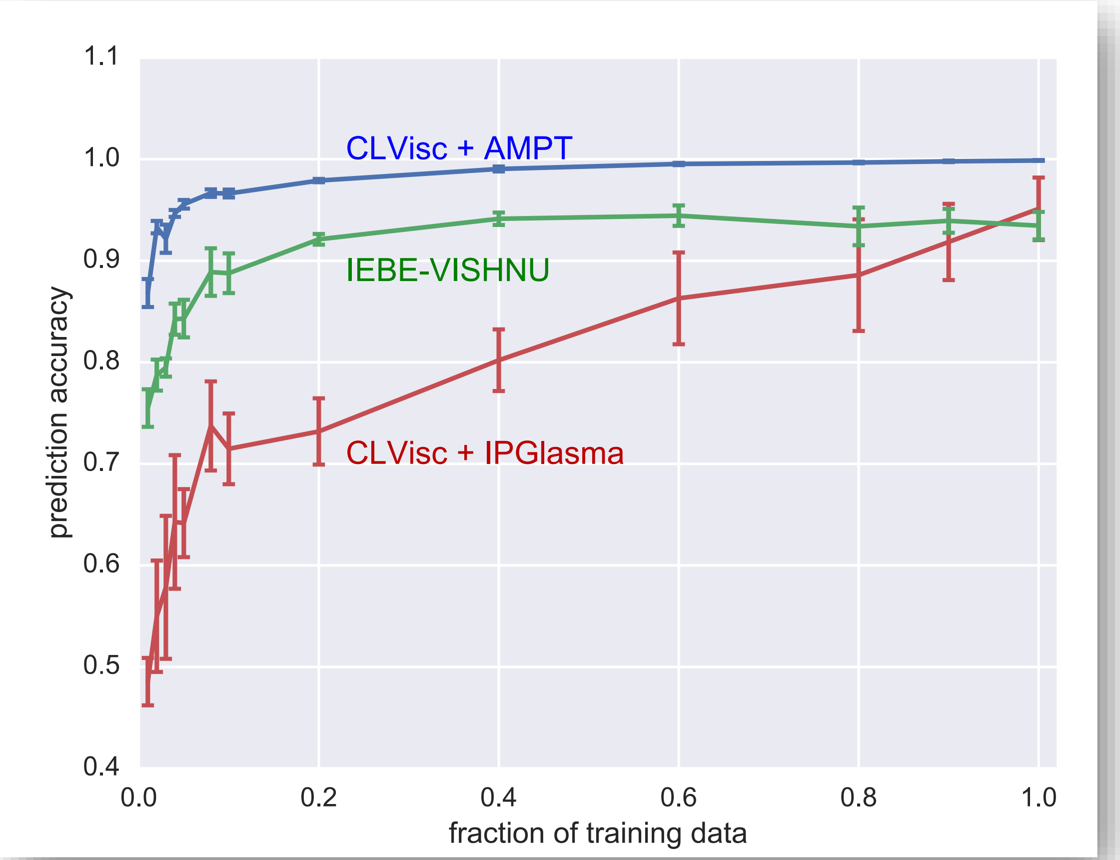




Deep learning for nuclear phase transition



$$l(\theta) = \underbrace{-\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]}_{\text{cross entropy loss}} + \underbrace{\lambda||\theta||_2^2}_{\text{L2 regularization}}$$

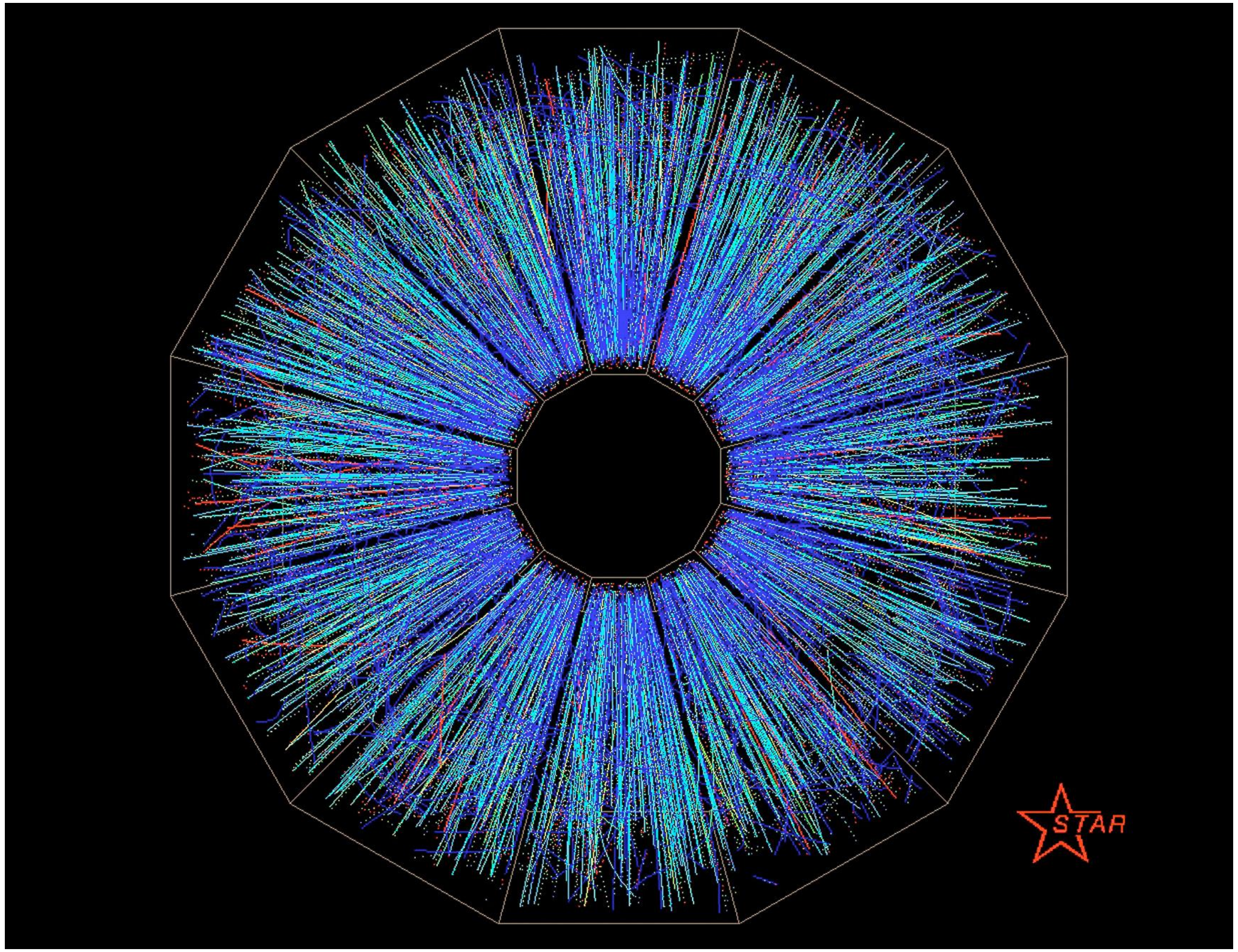


Nature Communications 2018, LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang.

Increasing list of ML for QCD EoS

- An equation-of-state-meter of quantum chromodynamics transition from deep learning, Long-Gang Pang, Kai Zhou, Nan Su, Hannah Petersen, Horst Stöcker, Xin-Nian Wang
- Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning, Yi-Lun Du, Kai Zhou, Jan Steinheimer, Long-Gang Pang, Anton Motornenko, Hong-Shi Zong, Xin-Nian Wang, Horst Stöcker
- A machine learning study to identify spinodal clumping in high energy nuclear collisions, Jan Steinheimer, LongGang Pang, Kai Zhou, Volker Koch, Jørgen Randrup, Horst Stoecker
- An equation-of-state-meter for CBM using PointNet, Manjunath Omana Kuttan, Kai Zhou, Jan Steinheimer, Andreas Redelbach, Horst Stoecker
- Classification of Equation of State in Relativistic Heavy-Ion Collisions Using Deep Learning, Yu. Kvasiuk, E. Zabrodin, L. Bravina, I. Didur, M. Frolov
- Neural network reconstruction of the dense matter equation of state from neutron star observables. Shriya Soma, Lingxiao Wang, Shuzhe Shi, Horst Stöcker, Kai Zhou
- Learning Langevin dynamics with QCD phase transition, Lingxiao Wang, Lijia Jiang, Kai Zhou
- Machine learning phase transitions of the three-dimensional Ising universality class, Xiaobing Li, Ranran Guo, Kangning Liu, Jia Zhao, Fen Long, Yu Zhou, Zhiming Li
- Extensive Studies of the Neutron Star Equation of State from the Deep Learning Inference with the Observational Data Augmentation, Yuki Fujimoto, Kenji Fukushima, Koichi Murase
- Nuclear liquid-gas phase transition with machine learning, Rui Wang, Yu-Gang Ma, R. Wada, Lie-Wen Chen, Wan-Bing He, Huan-Ling Liu, Kai-Jia Sun
- Machine learning spectral functions in lattice QCD, S.-Y. Chen, H.-T. Ding, F.-Y. Liu, G. Papp, C.-B. Yang
- Probing criticality with deep learning in relativistic heavy-ion collisions, Yige Huang, Long-Gang Pang, Xiaofeng Luo, Xin-Nian Wang
- Mapping out the thermodynamic stability of a QCD equation of state with a critical point using active learning, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

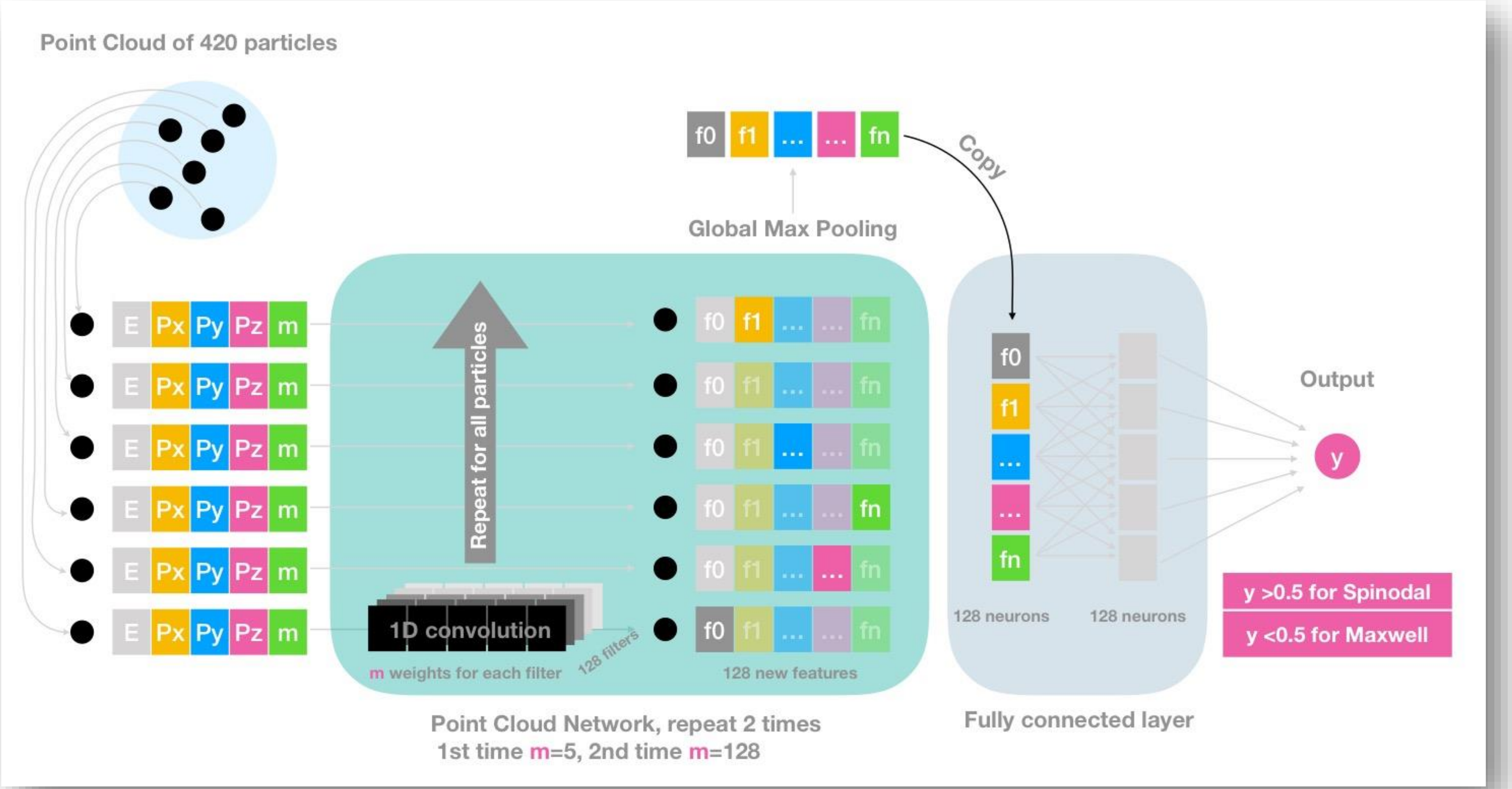
Data representation



- Images: histograms
  - (px, py) or (pt, phi)
  - (px, py, pz)
  - (pt, phi, eta)
- Point cloud: particle list

E	Px	Py	Pz	pid
6.84	1.07	4.5	6.83	211
68.92	0.75	0.64	68.91	2212
40.4	0.06	0.54	40	321
…				

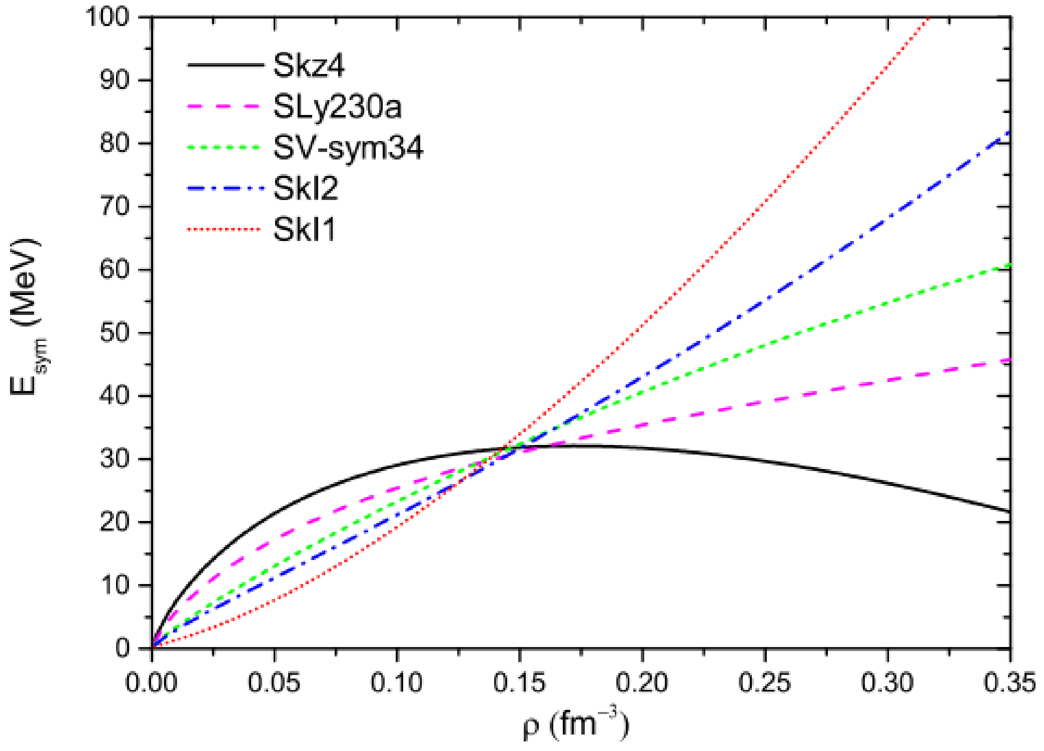
Point cloud network for HIC



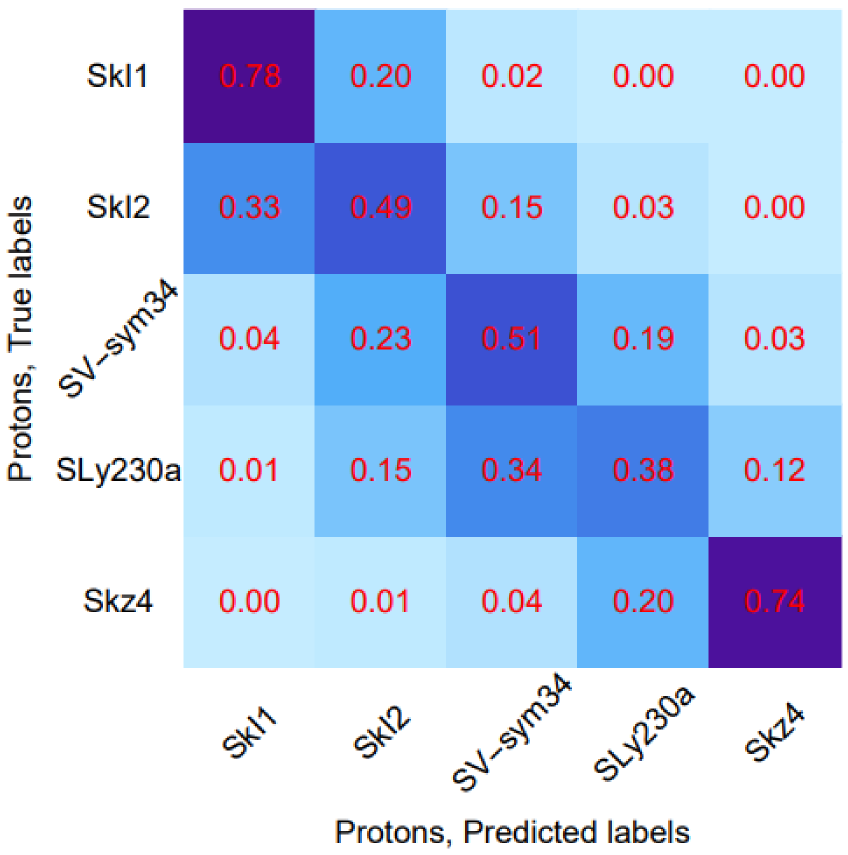
JHEP 12 (2019) 122, J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and Jørgen Randrup

CNN for symmetry energy

Skyrme potential + IMQMD



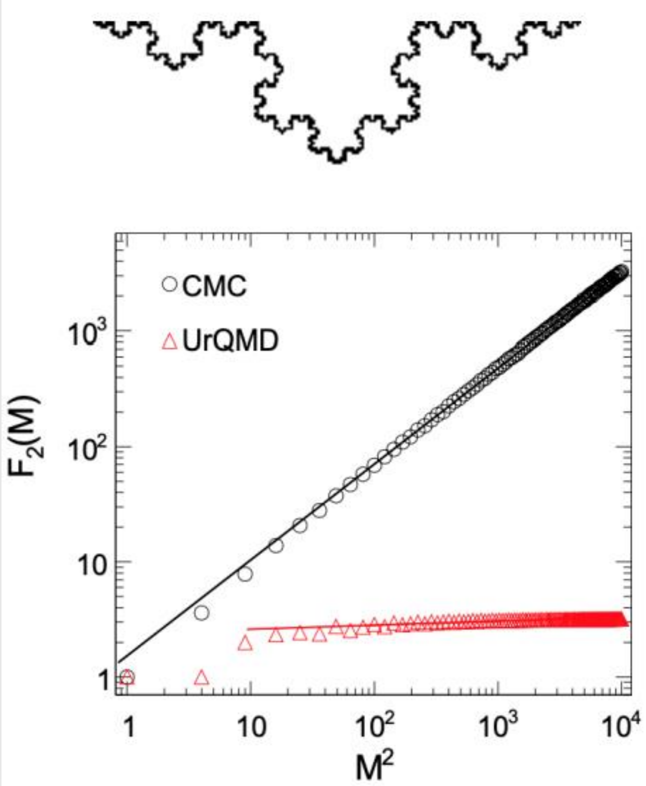
off-diagonal = misclassified



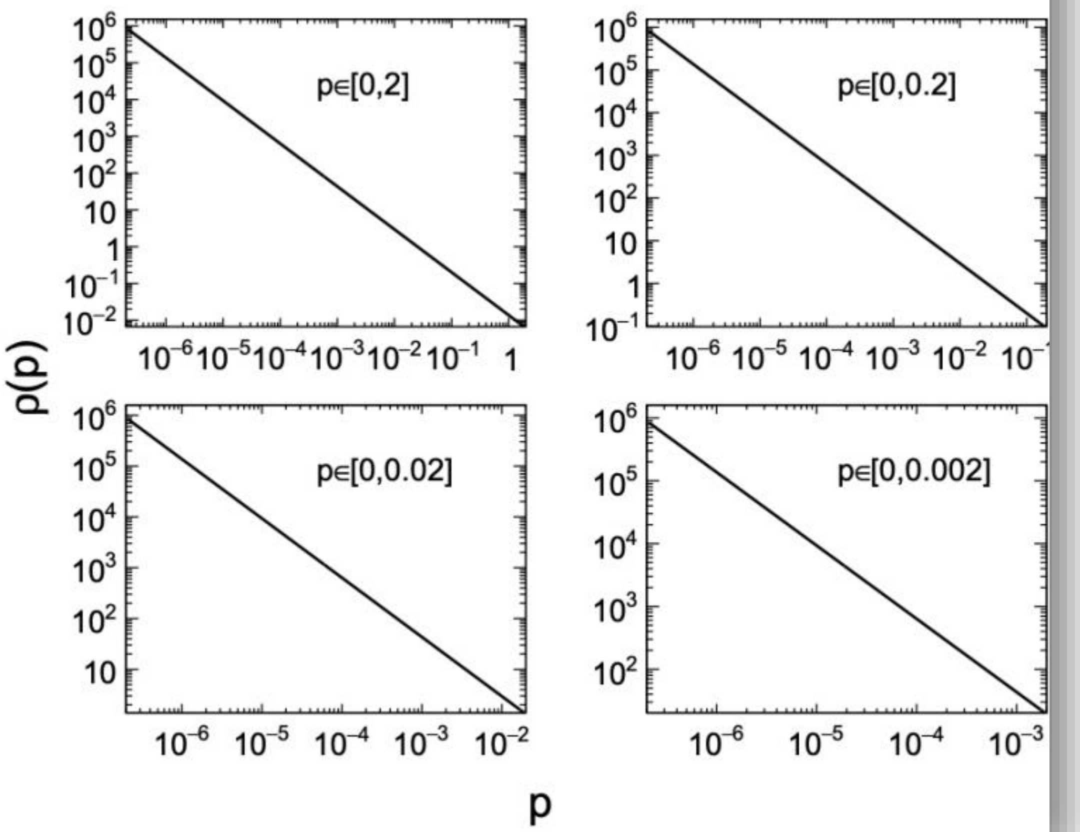
Phys.Lett.B 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

Critical behavior

Self Similarity

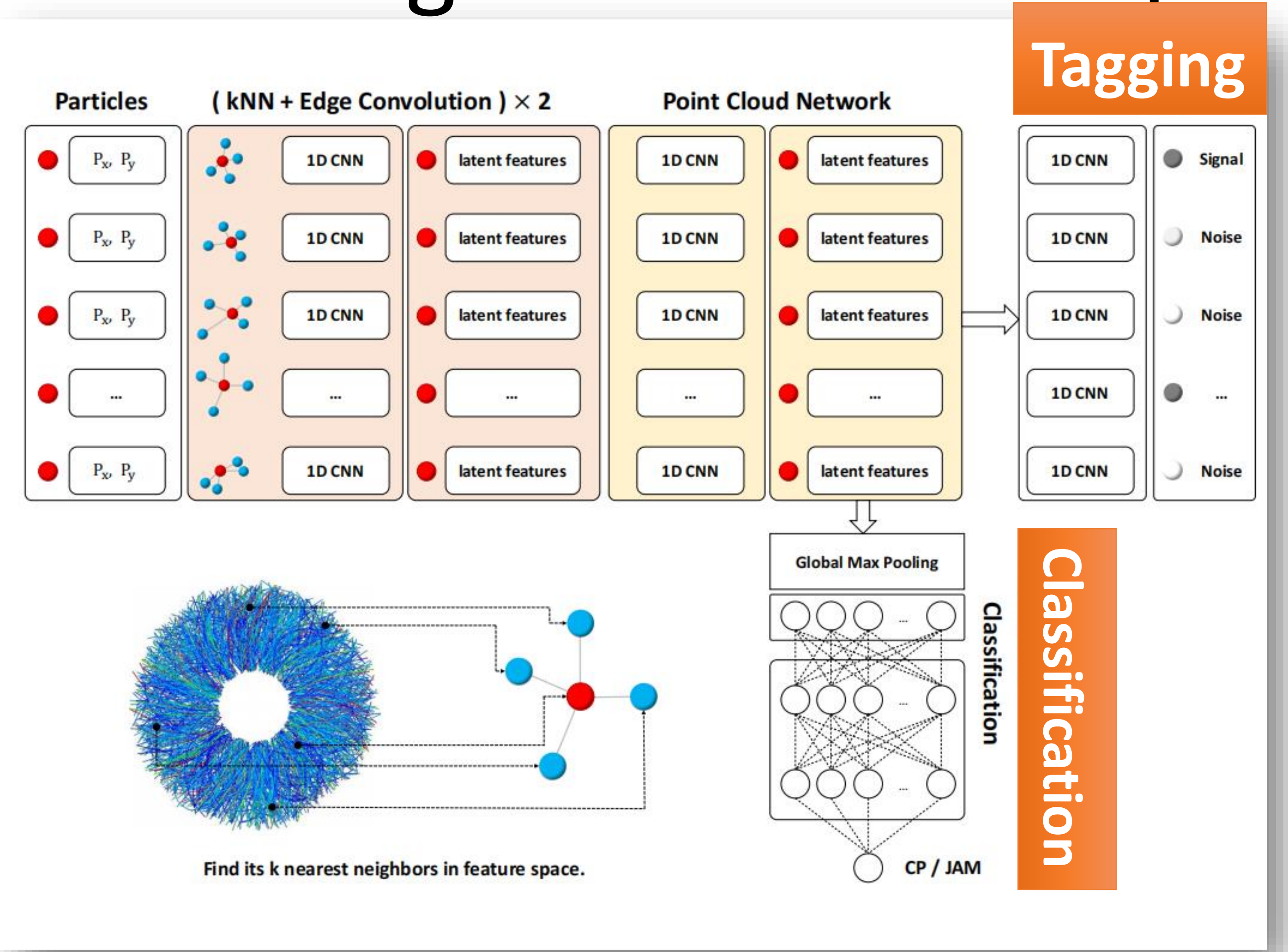


Self Similarity in momentum space



PLB 801(2020) 135186, J. Wu, Y.F. Wu, Z.M. Li

Looking for critical end point



Technique:

Point cloud network,

Dynamical edge convolution neural network

Two tasks:

1. Tagging: label each particle
2. Classification: label each event

PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

Active learning to rule out unphysical EoS

$$(\mu_{BC}, \alpha_{\text{diff}}, w, \rho) \mapsto P(T, \mu_B) \mapsto \{\text{acceptable, unstable, acausal}\}.$$

4 parameters from 3D Ising model

QCD EoS

Lables for classification

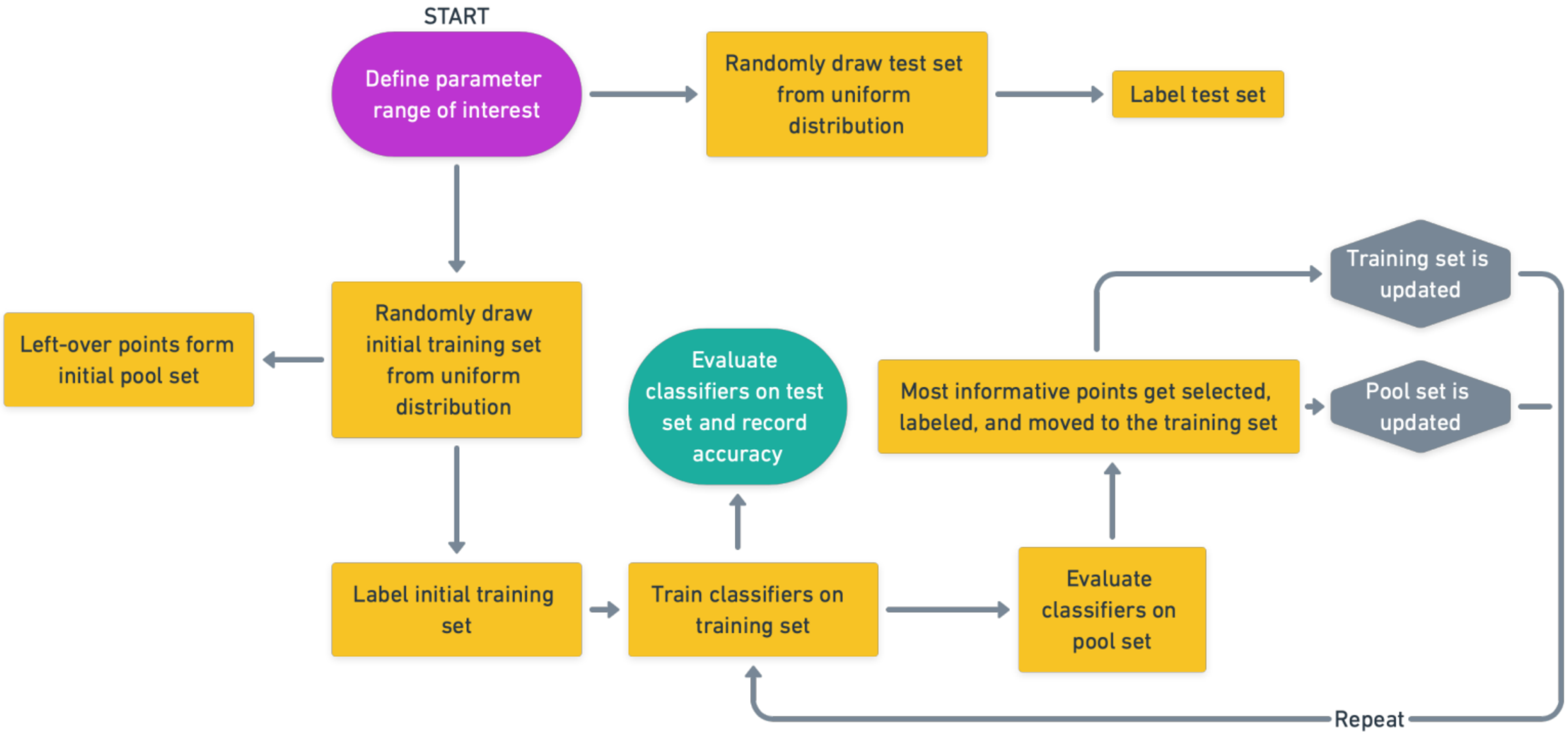
Acceptable = Stable + Causal

$$P, s, \varepsilon, n_B, \chi_2^B, \left(\frac{\partial S}{\partial T}\right)_{n_B} > 0 \ ,$$

$$0 \leq c_s^2 \leq 1.$$

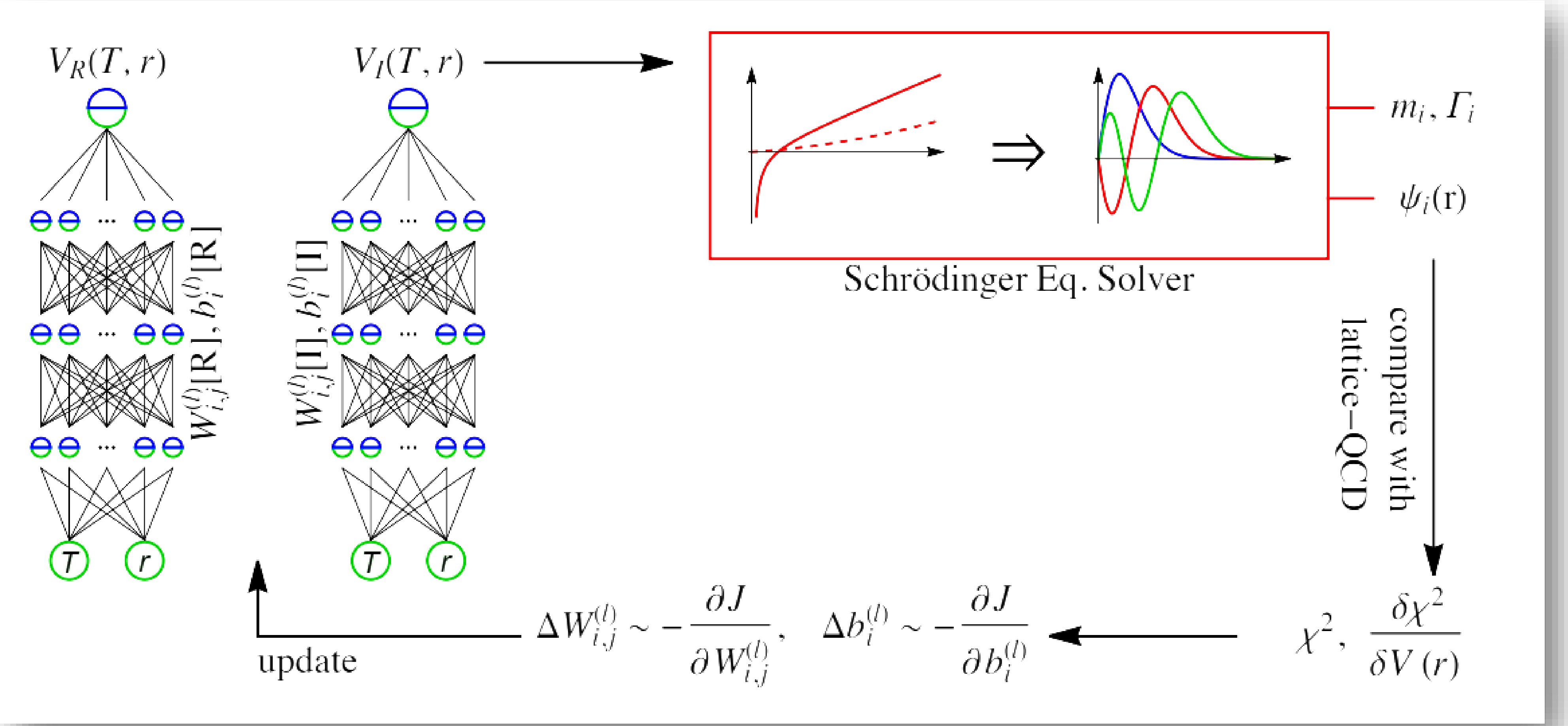
2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

Active learning to rule out unphysical EoS



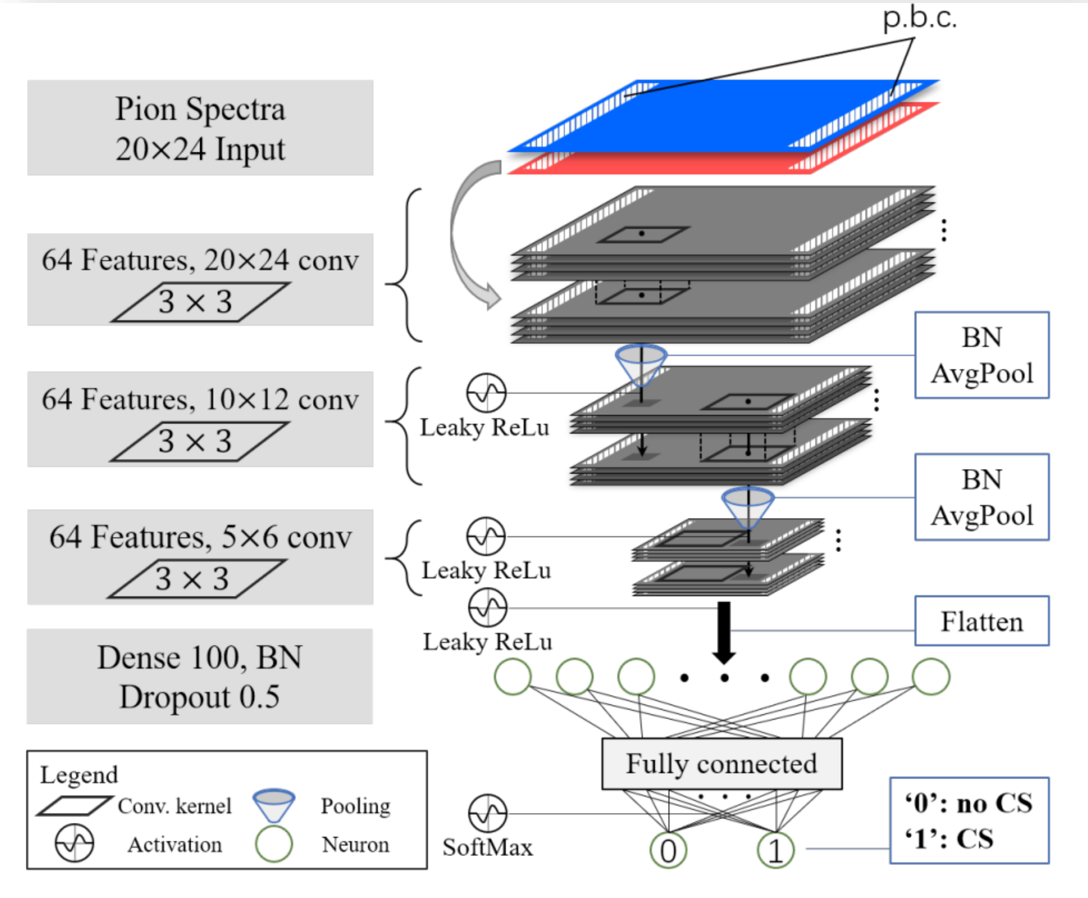
2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

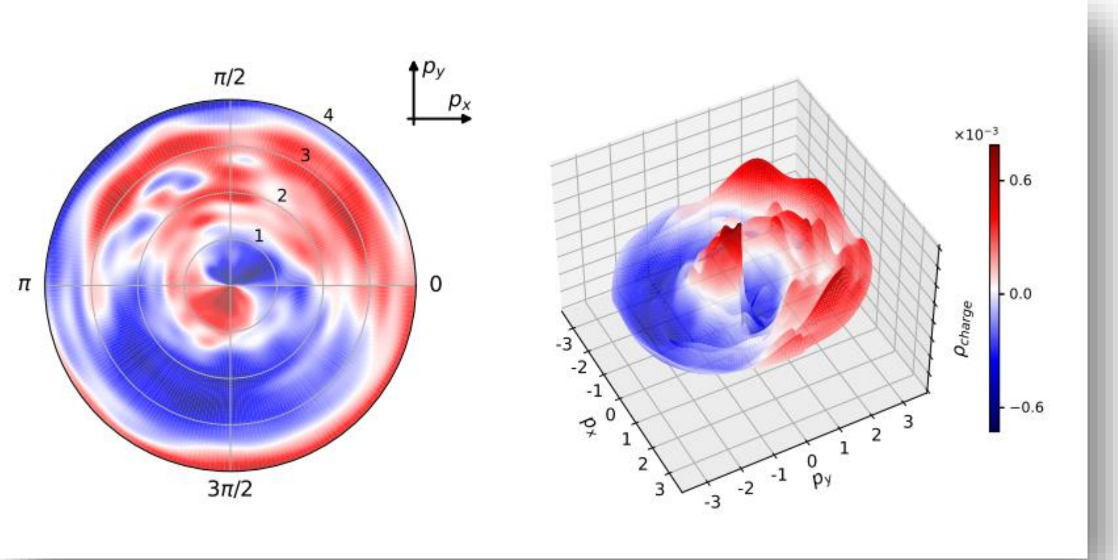
In medium heavy quark potential



S.Z. Shi, K. Zhou, J.X. Zhao, S. Mukherjee, and P.F. Zhuang Phys. Rev. D 105, 014017

Detecting CME via deep learning

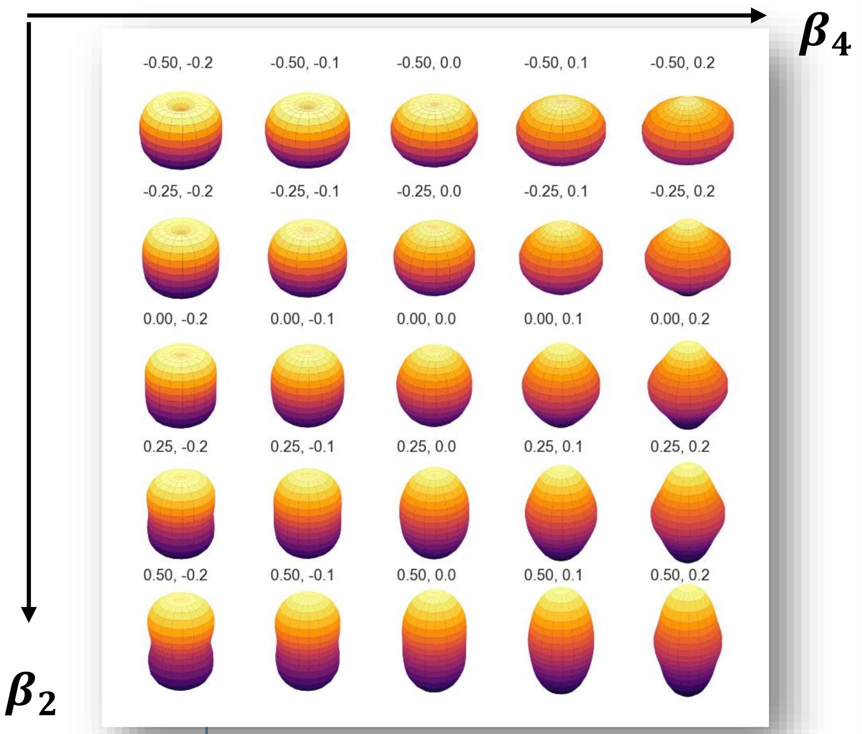




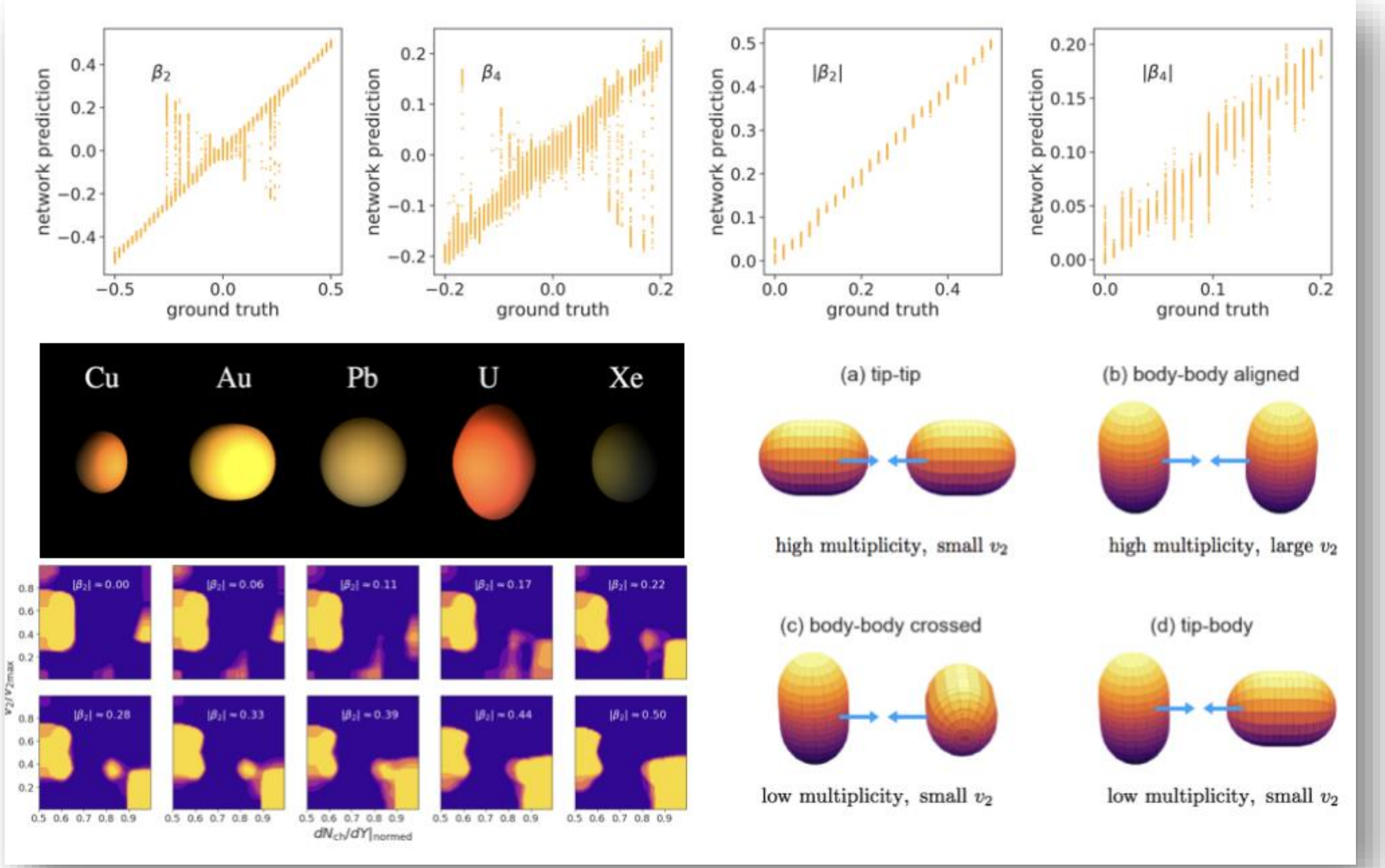
Gradient ascent to get the most responsive CME-spectra that demonstrates what has been learned by the machine.

2105.13761, Y.-S. Zhao, L. Wang, K. Zhou, and X.-G. Huang (2021)

Determining nuclear deformation



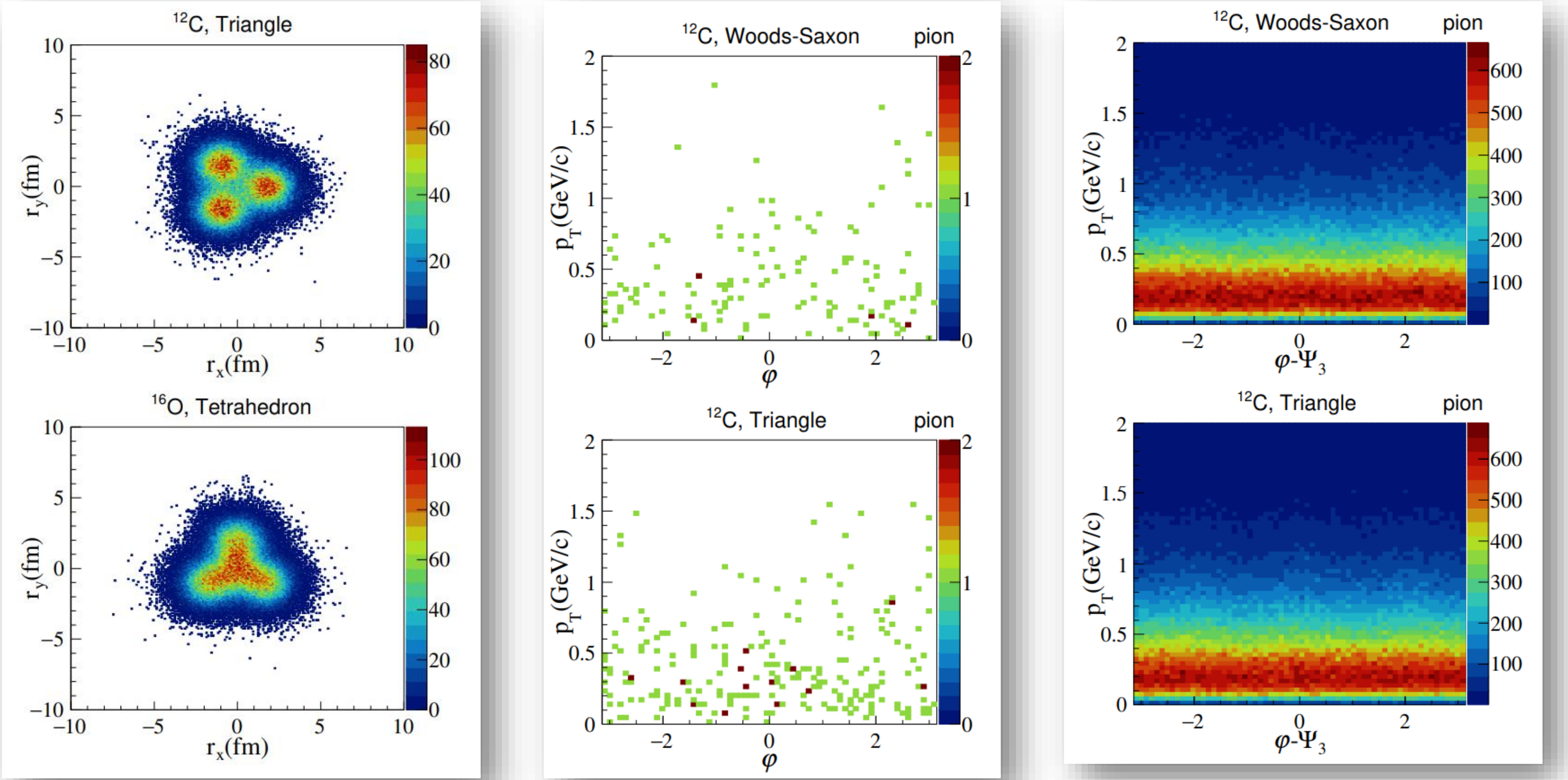
Data: Trento + Matching



arXiv:1906.06429, L.-G. Pang, K. Zhou and X.-N. Wang

Identifying the α-clustering structure

α clusters | Fail in EbE | Succeed with 4000-events average



Junjie He, Wan-Bing He, Yu-Gang Ma, Song ZhangPhys. Rev. C 104, 044902 (2021)

Stacked U-net for relativistic hydrodynamics

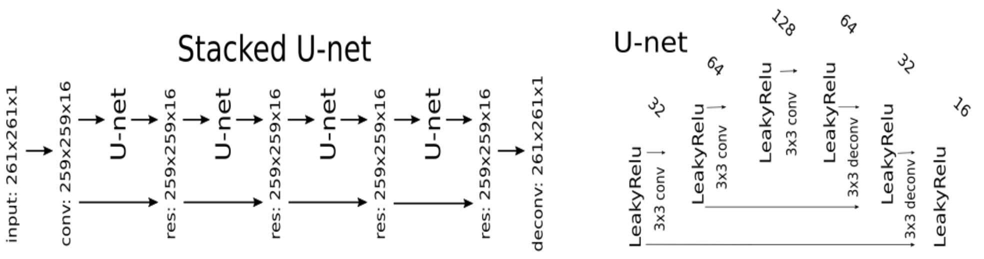
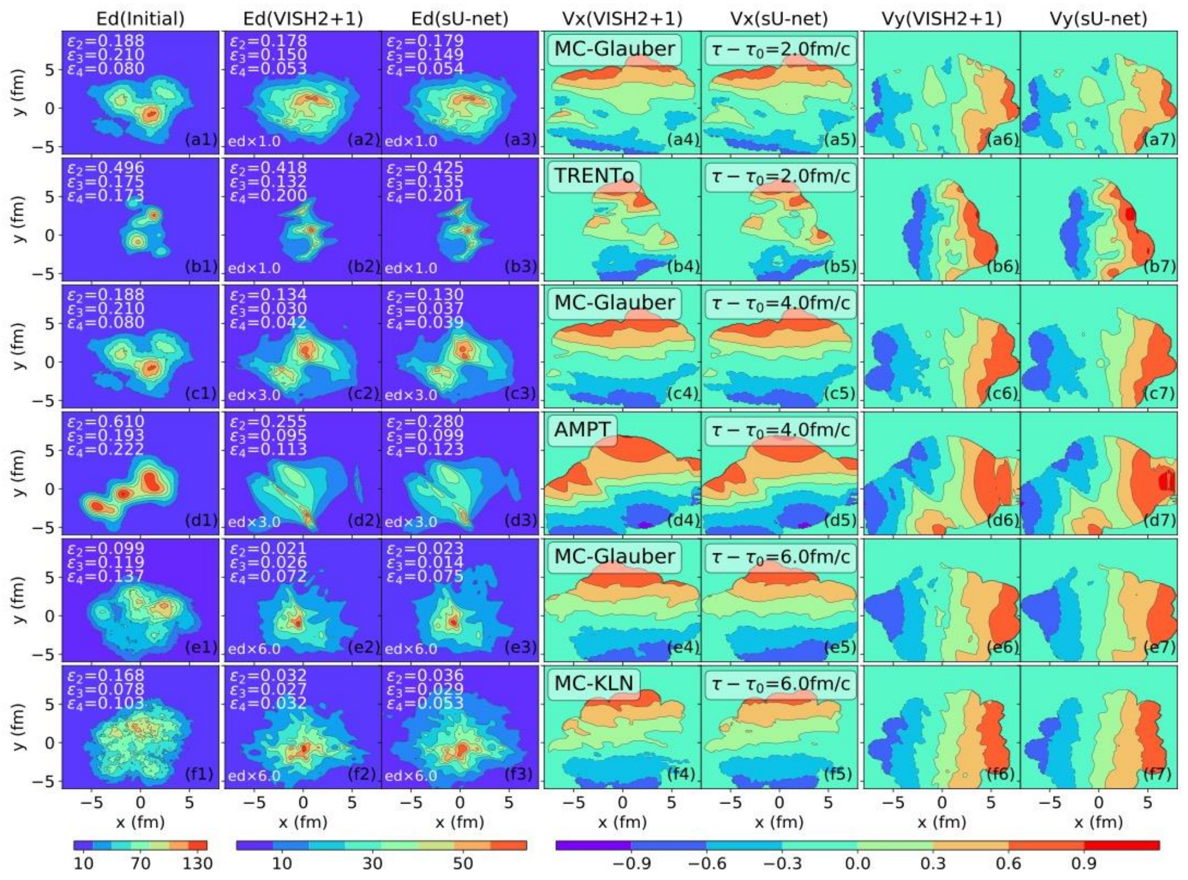


FIG. 1: An illustration of the encode-decode network, `stacked U-net`, which consists of the input and out layers and four residual U-net blocks. The right figure shows the U-net structure, and the depth of the hidden layer is written on the top of them.

The expansion of quark gluon plasma is learned in the image translation task using stacked UNET.

$$\nabla_\mu T^{\mu\nu} = 0$$

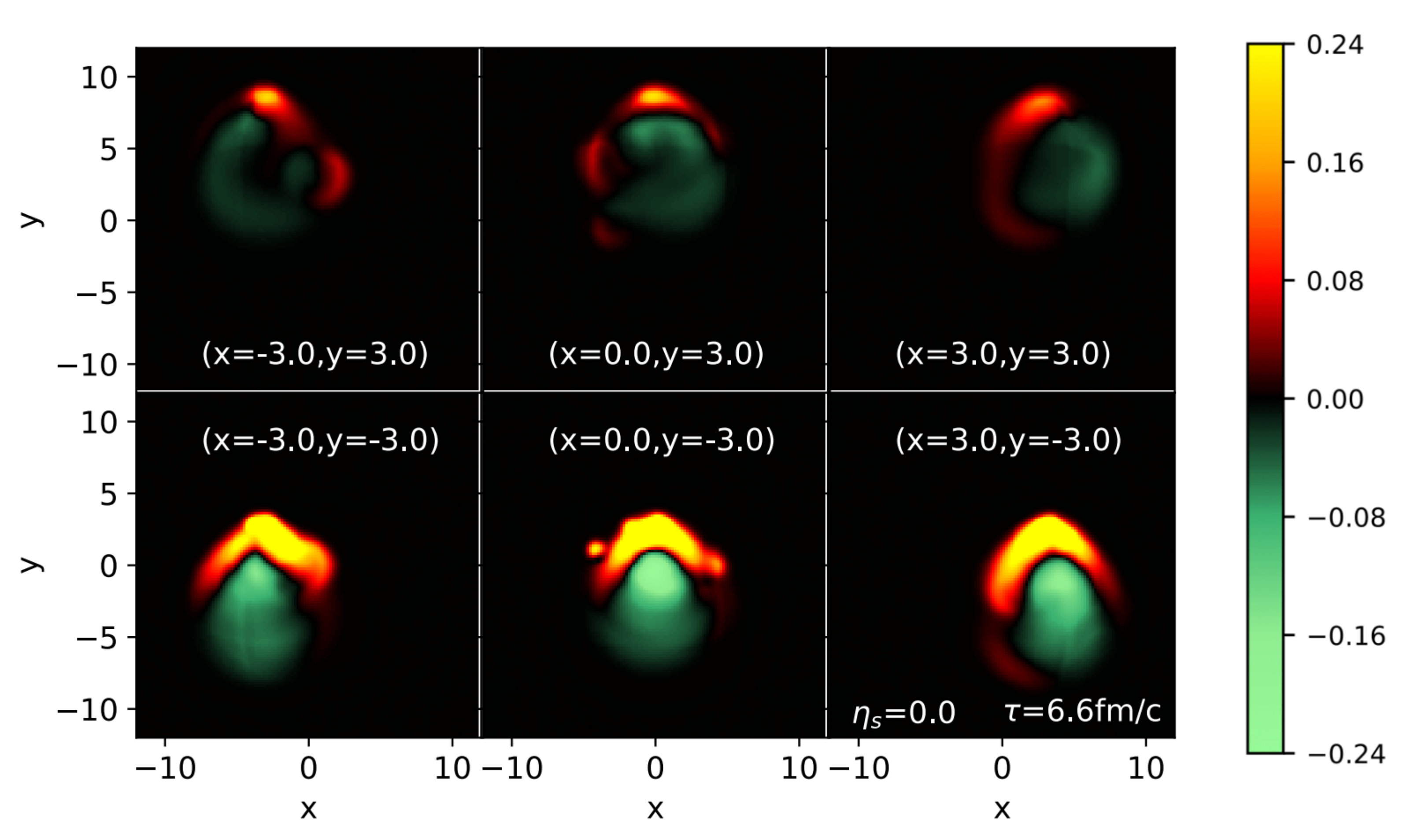


arXiv: 1801.03334; NPA2018, H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song

Increasing list of DL for jets in HIC

- Probing heavy ion collisions using quark and gluon jet substructure, Yang-Ting Chien, Raghav Kunnawalkam Elayavalli
- Data-driven extraction of the substructure of quark and gluon jets in proton-proton and heavy-ion collisions, Yueyang Ying, Jasmine Brewer, Yi Chen, Yen-Jie Lee
- Data-driven quark and gluon jet modification in heavy-ion collisions, Jasmine Brewer, Jesse Thaler and Andrew P. Turner
- Classification of quark and gluon jets in hot QCD medium with deep learning, Yi-Lun Du, Daniel Pablos, Konrad Tywoniuk
- Deep learning jet modifications in heavy-ion collisions, Yi-Lun Du, Daniel Pablos, Konrad Tywoniuk
- Jet Tomography in Heavy-Ion Collisions with Deep Learning, Yi-Lun Du, Daniel Pablos, Konrad Tywoniuk
- The information content of jet quenching and machine learning assisted observable design, Yue Shi Lai, James Mulligan, Mateusz Płoskoń, Felix Ringer
- Deep Learning for the classification of quenched jets, Liliana Apolinário, Nuno F. Castro, M. Crispim Romão, Jose Guilherme Milhano, Rute Pedro
- Deep learning assisted jet tomography for the study of Mach cones in QGP, Zhong Yang, Yayun He, Wei Chen , Wei-Yao Ke, Long-Gang Pang and Xin-Nian Wang
- ...

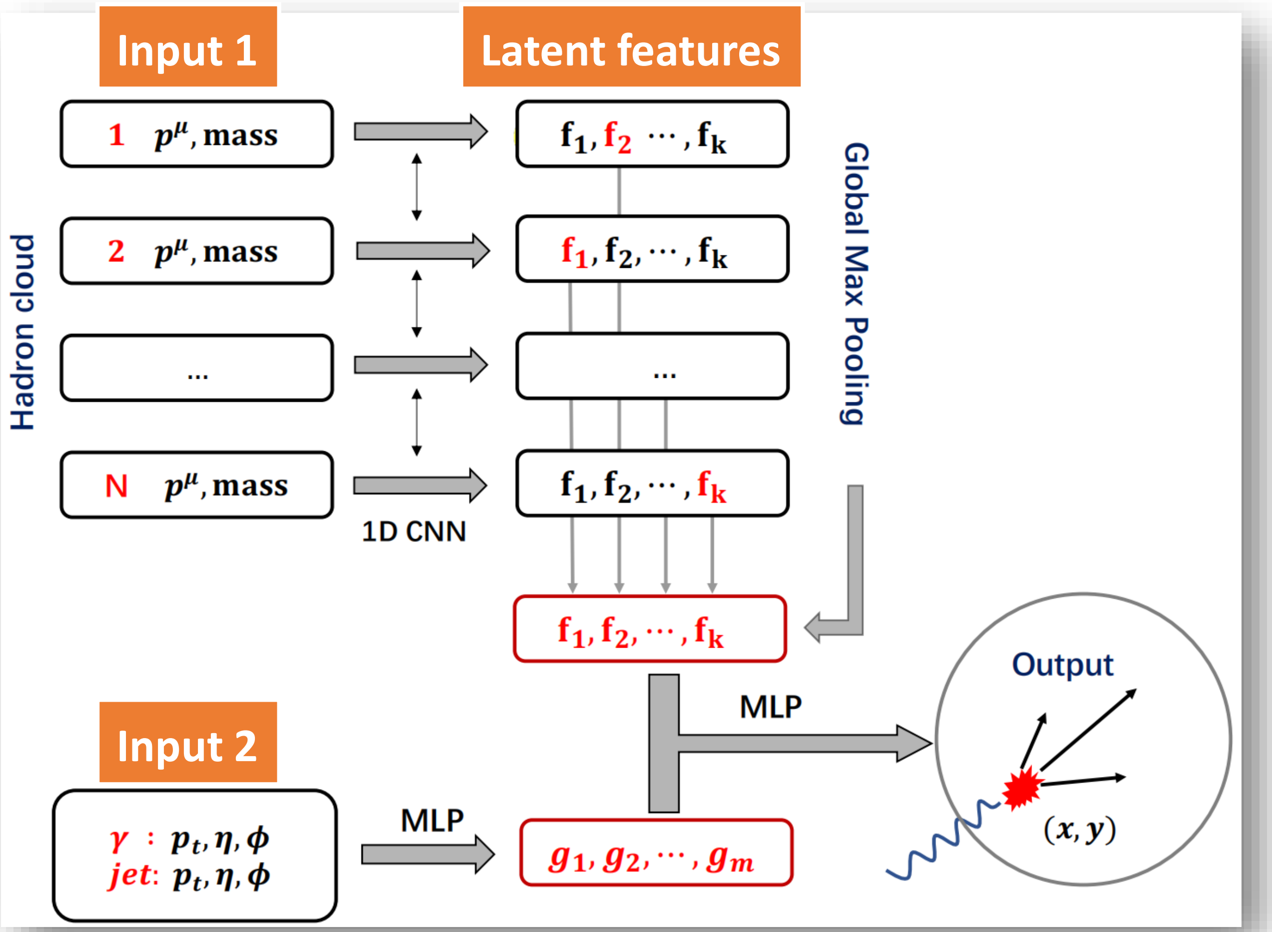
DL assisted jet tomography for Mach Cones



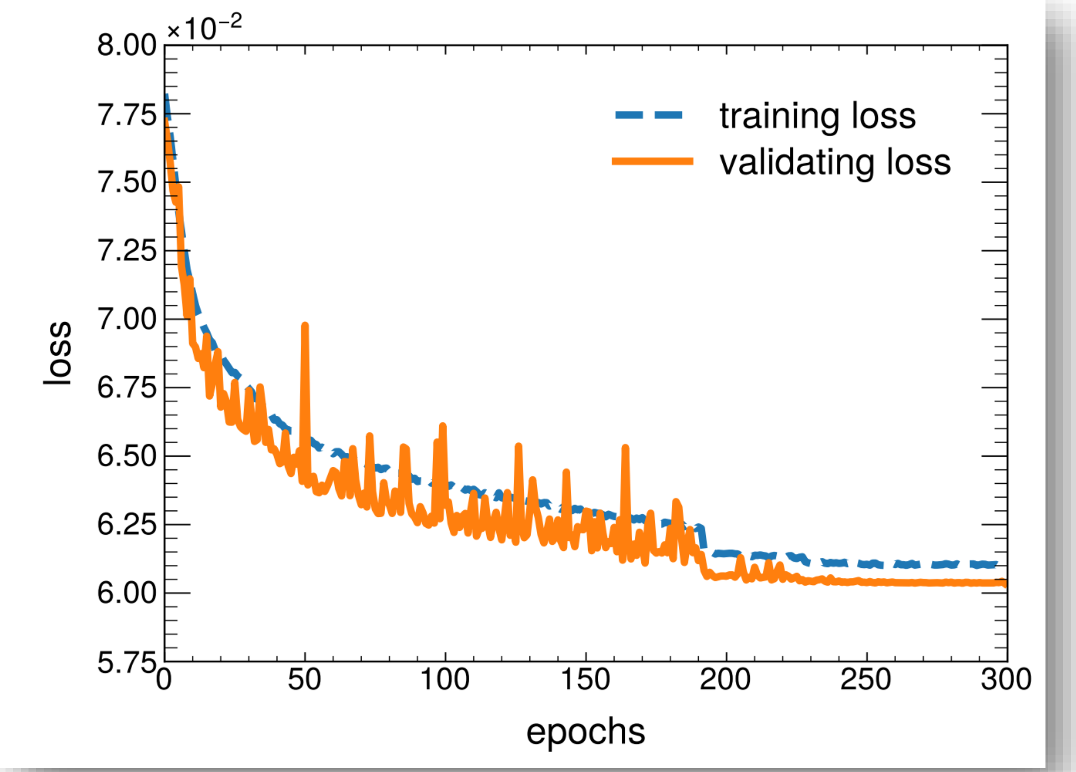
1. Jets start from different positions are distorted differently due to different path length, temperature gradient and radial flow.
2. Locating jets will help differential studies on Mach cones and jet energy loss.

arXiv:2206.02393v1 , Z. Yang, Y.-Y. He, W. Chen , W.-Y. Ke, L.-G. Pang and X.-N. Wang

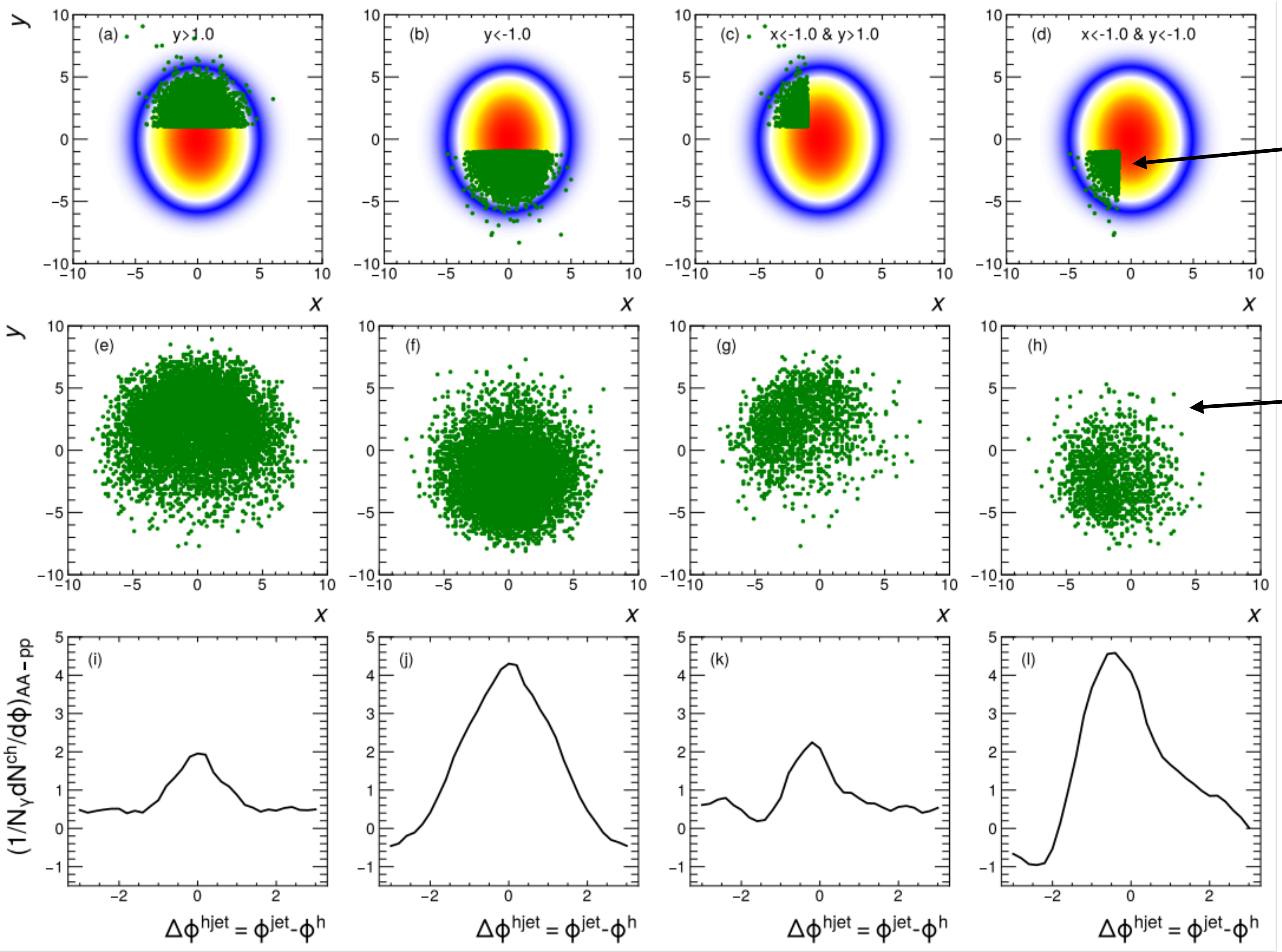
DL assisted jet tomography for Mach Cones



RMS Error ≈ 2.4 fm



DL assisted jet tomography for Mach Cones



Network prediction

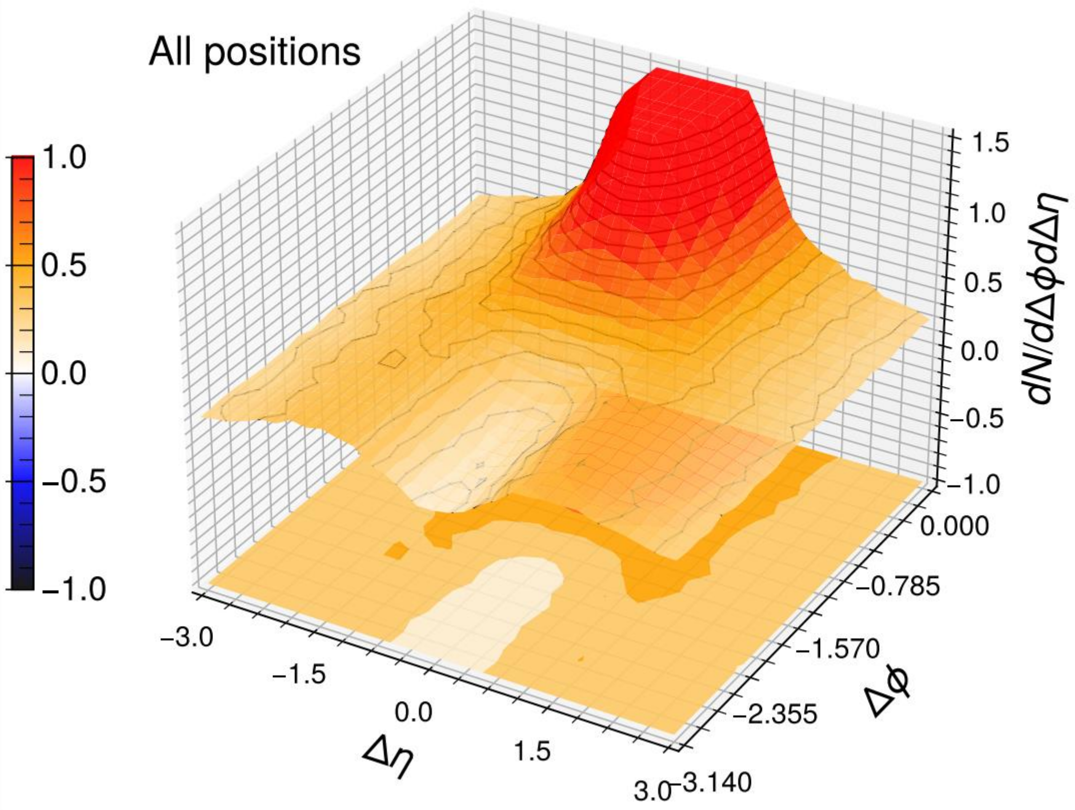
True positions

Azimuthal angular distributions of jet hadrons with pt>2 GeV are shown for events selected by deep-learning assisted jet-tomography, which shows

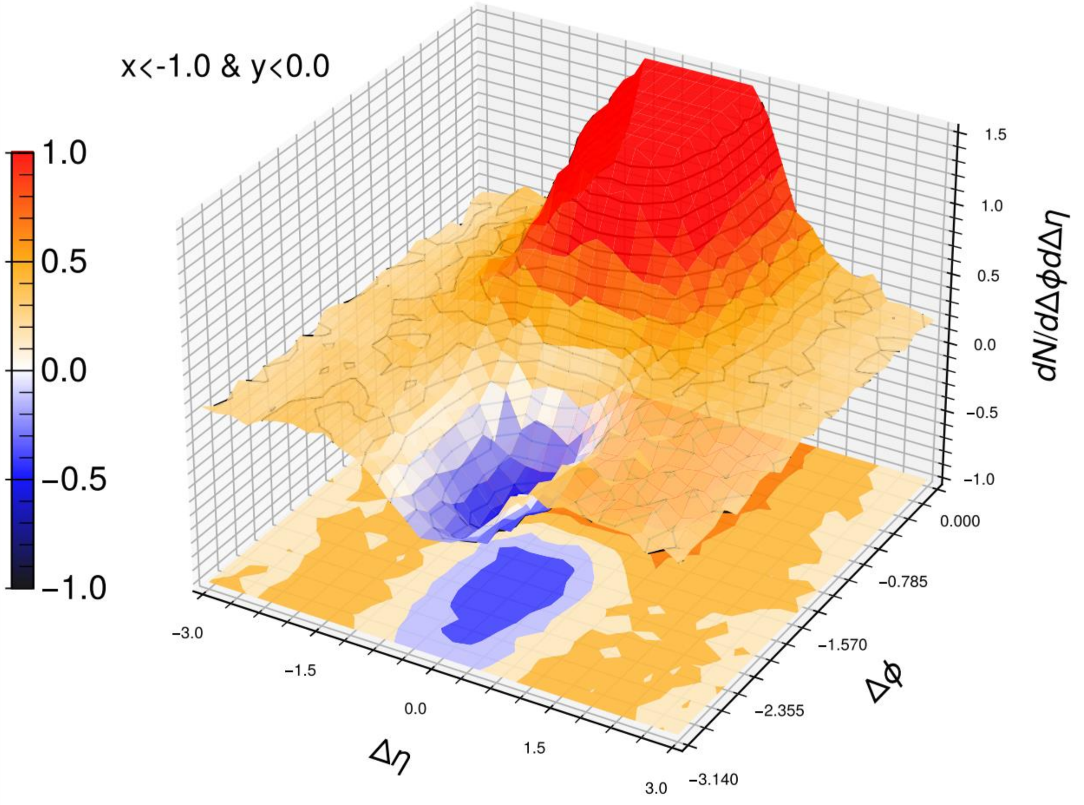
1. **Path length dependence**
2. **Effect of temperature gradient**
3. **Effect of radial flow**

Deep learning assisted jet tomography

Not selected



DL assisted selection



3D structure of Mach cones using DL assisted jet tomography

Summary

- DL can build the non-linear map between two groups of data as long as there is causality link between them
- DL is widely used in the inverse problem of HIC to extract
  1. the initial nuclear structure
  2. the QCD equation of state
  3. the in-medium heavy quark potential
  4. the jet modification in QGP
  5. …
- Deep learning assisted jet tomography helps to locate jet production positions for differential studies of Mach cones