深度学习在
高能核物理中的应用

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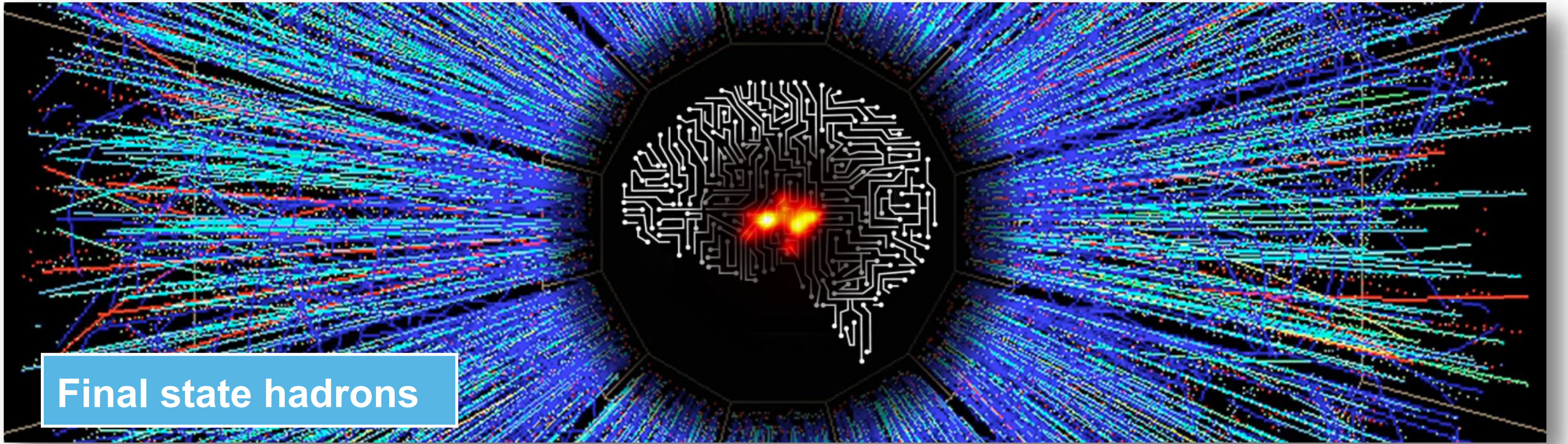
华中师范大学

2023年7月31日-8月6日

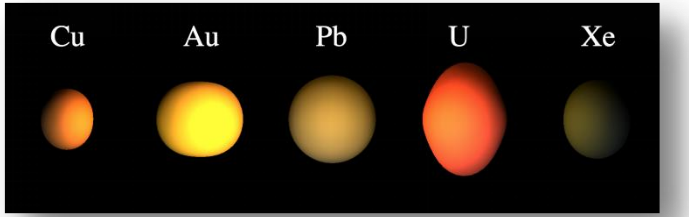
辽宁 - 大连

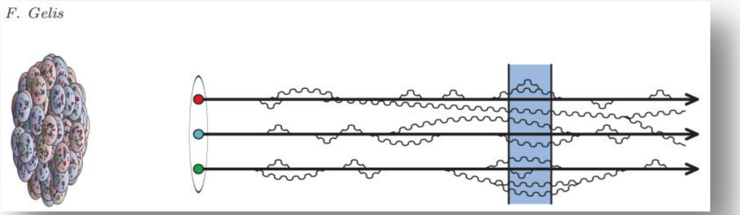
Inverse problems in HIC

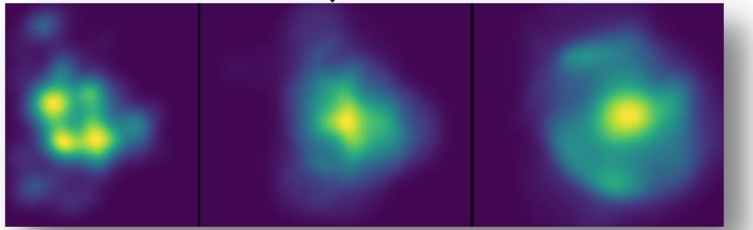


Final state hadrons

Non-linear mapping





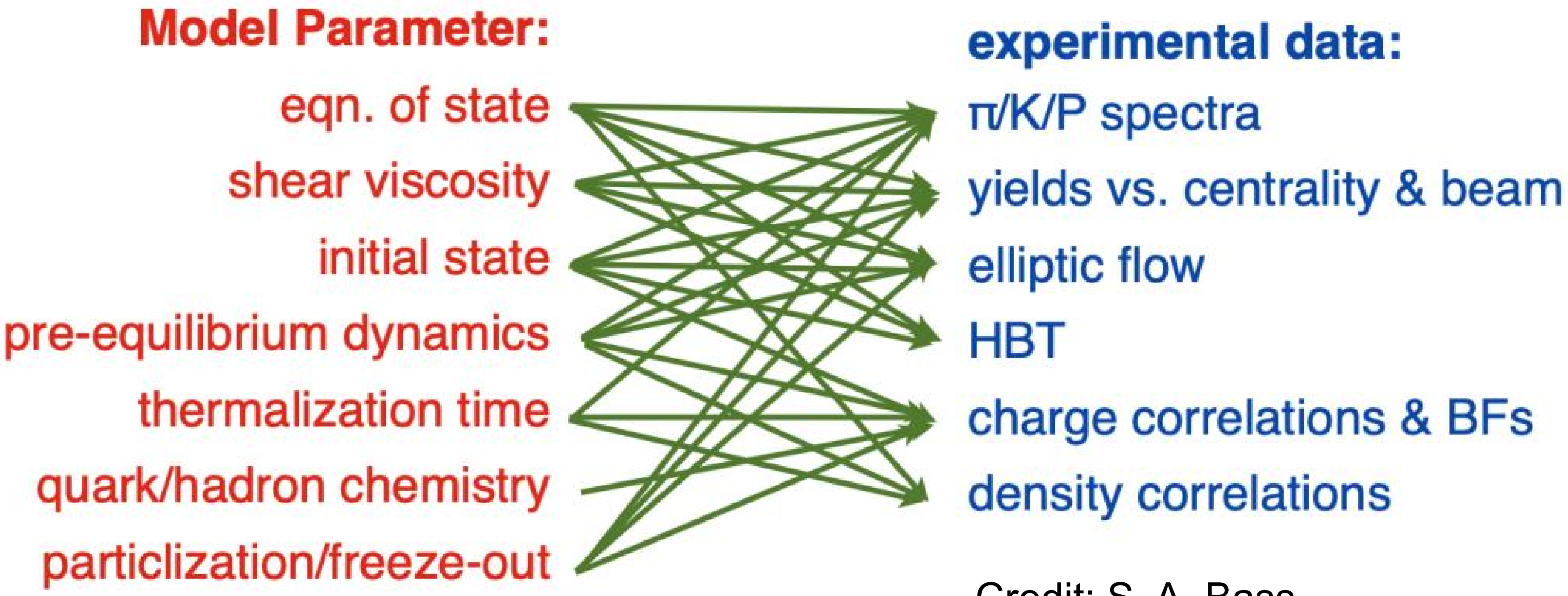


(1) Nuclear Structure

(2) Initial Parton Distribution

(3) QGP properties and EoS

Inverse Problem In HIC



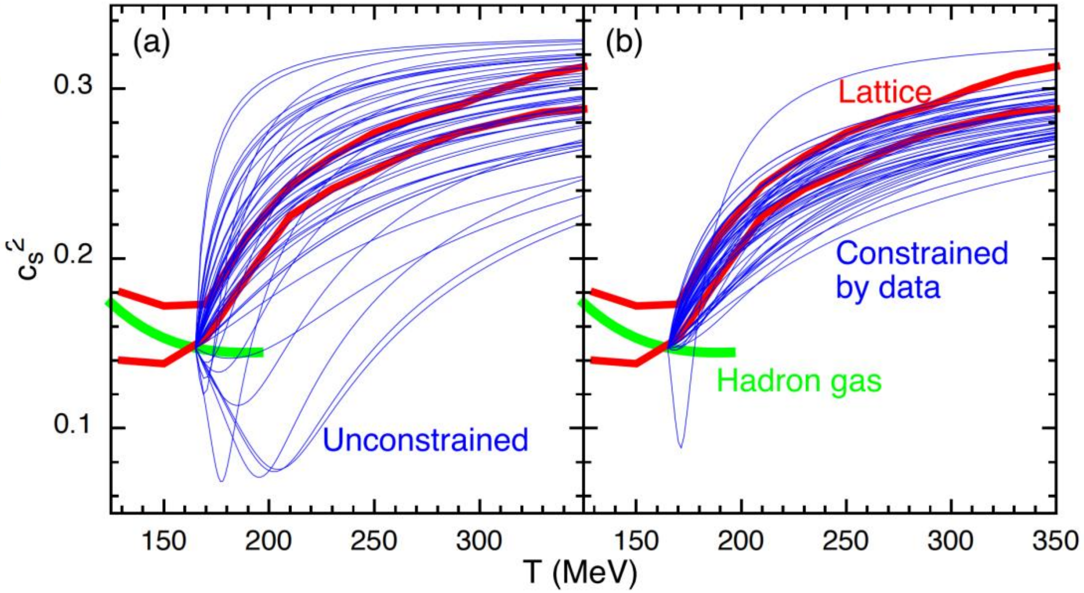
Credit: S. A. Bass

Bayesian analysis QCD EoS

The c_s^2 is parameterized as a function of energy density in the following,

$$c_s^2(\epsilon) = c_s^2(\epsilon_h) + \left(\frac{1}{3} - c_s^2(\epsilon_h)\right) \frac{X_0 x + x^2}{X_0 x + x^2 + X'^2} \tag{2.12}$$

where $X_0 = \sqrt{12} R X' c_s(\epsilon_h)$, $x \equiv \ln \frac{\epsilon}{\epsilon_h}$, ϵ_h is the energy density at $T = 165$ MeV, R and X' are the two parameters in the EoS to be determined. Randomly choosing R and X' from the range $-0.9 < R < 2$ and $0.5 < X' < 5$ generate the unconstrained EoS that varies in a large region between $c_s^2 = 0.05$ and $c_s^2 = 0.33$, as shown in Fig. 2.4-a. This corresponds to the a priori distribution of c_s^2 parameters together with other 12 parameters in the model $P(\theta)$.



Likelihood: $$P(D|\theta) = \Pi_i \exp\left(-(z_i(\theta) - z_{i,\mathrm{exp}})^2/2\right)$$

Posterior: $$P(\theta \mid D) \propto P(D \mid \theta) P(\theta)$$

S. Pratt, E. Sangaline, P. Sorensen, H. Wang, PRL. 114 (2015) 202301.

Global fitting with Bayesian analysis

Trento + iEBE-VISHNU + UrQMD

TABLE I. Input parameter ranges for the initial condition and hydrodynamic models.

Parameter	Description	Range
Norm	Overall normalization	100–250
p	Entropy deposition parameter	-1 to $+1$
k	Multiplicity fluct. shape	0.8–2.2
w	Gaussian nucleon width	0.4–1.0 fm
η/s hrg	Const. shear viscosity, $T < T_c$	0.3–1.0
η/s min	Shear viscosity at T_c	0–0.3
η/s slope	Slope above T_c	0–2 GeV^{-1}
ζ/s norm	Prefactor for $(\zeta/s)(T)$	0–2
T_{switch}	Particlization temperature	135–165 MeV

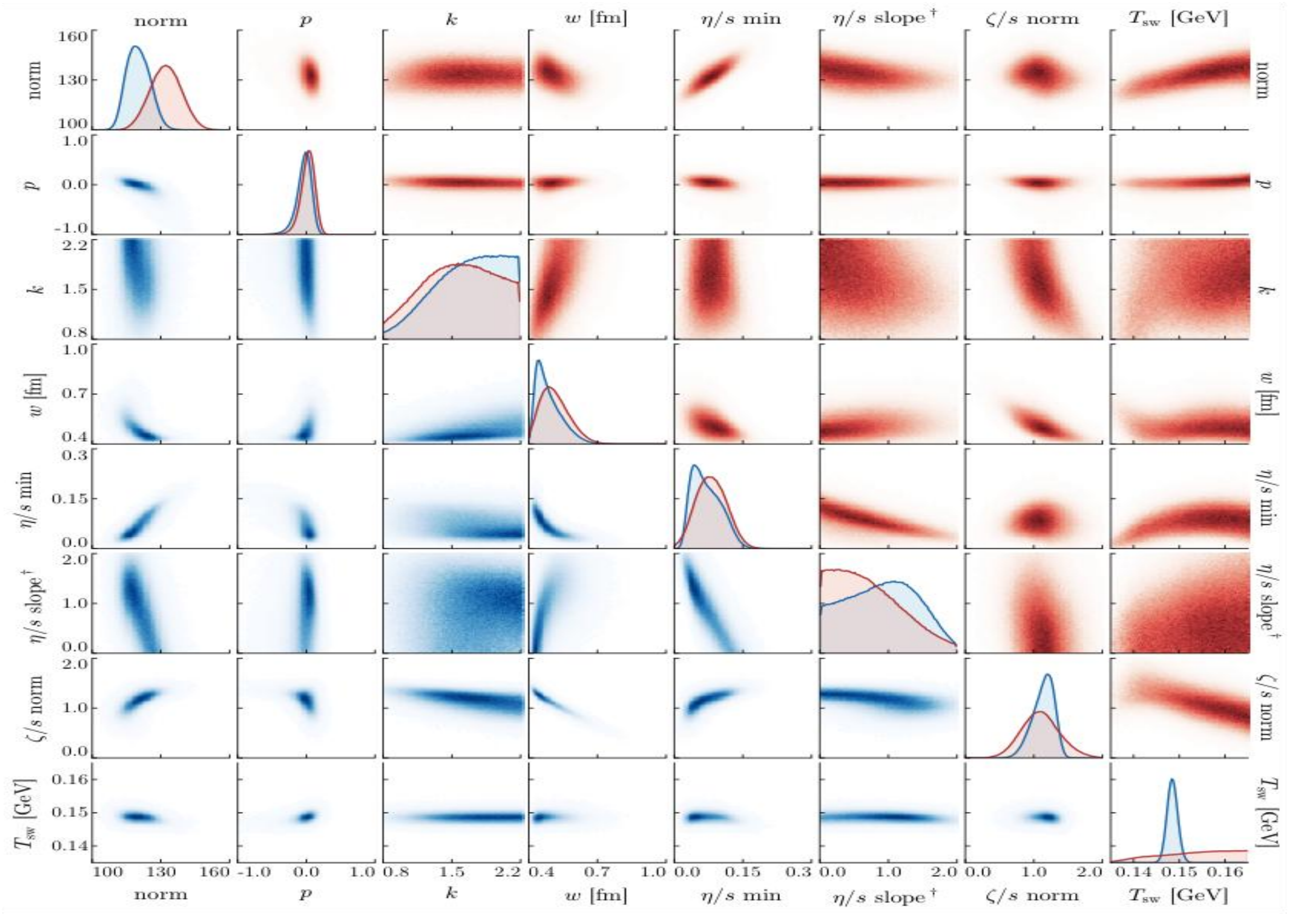


FIG. 7. Posterior distributions for the model parameters from calibrating to identified particles yields (blue, lower triangle) and charged particles yields (red, upper triangle). The diagonal has marginal distributions for each parameter, while the off-diagonal contains joint distributions showing correlations among pairs of parameters. †The units for η/s slope are [GeV^{-1}].

PRC 94.024907, J. E. Bernhard, J. Scott Moreland, S. A. Bass, J. Liu, U. Heinz

Nature Physics 2019, J. E. Bernhard, J. Scott Moreland, S. A. Bass

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

DL: Neural Network with multi hidden layers

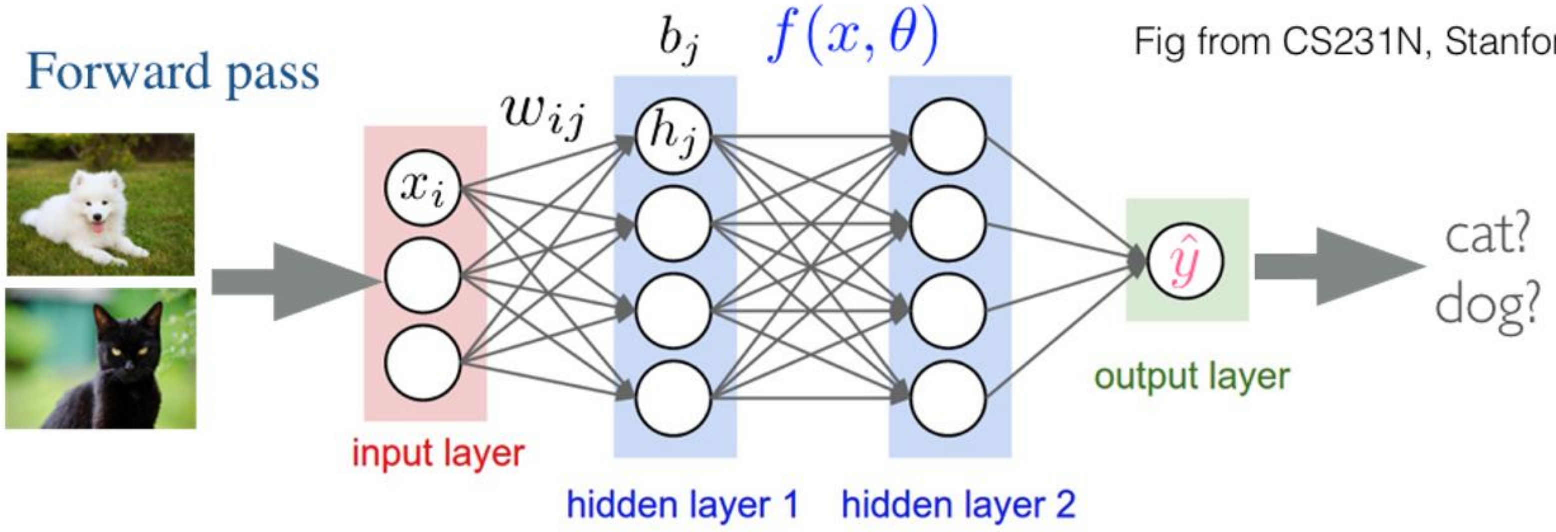


Fig from CS231N, Stanford

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

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

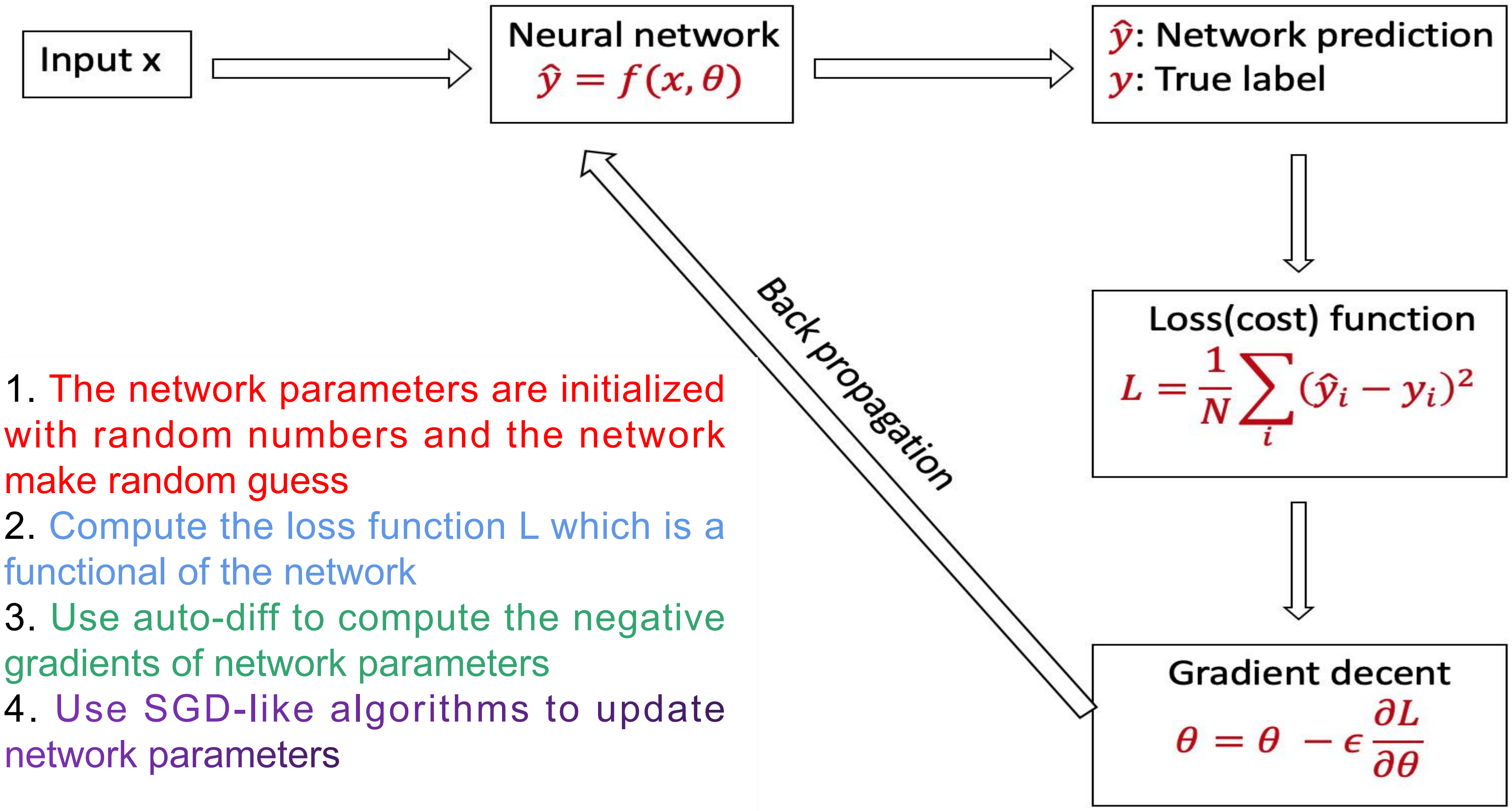
(b) ReLU

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

(c) PReLU

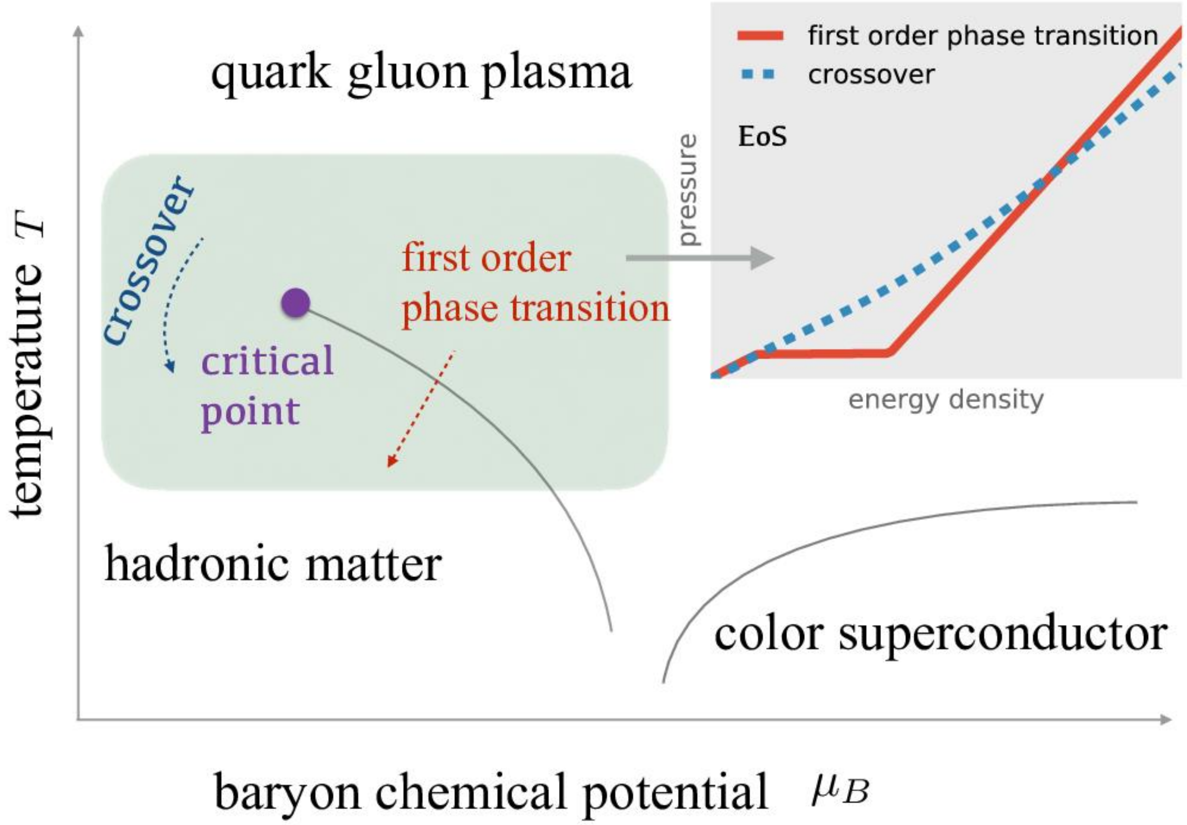
$$\sigma(z) = \begin{cases} z, & z > 0 \\ az, & z \leq 0 \end{cases}$$

How does the network learn

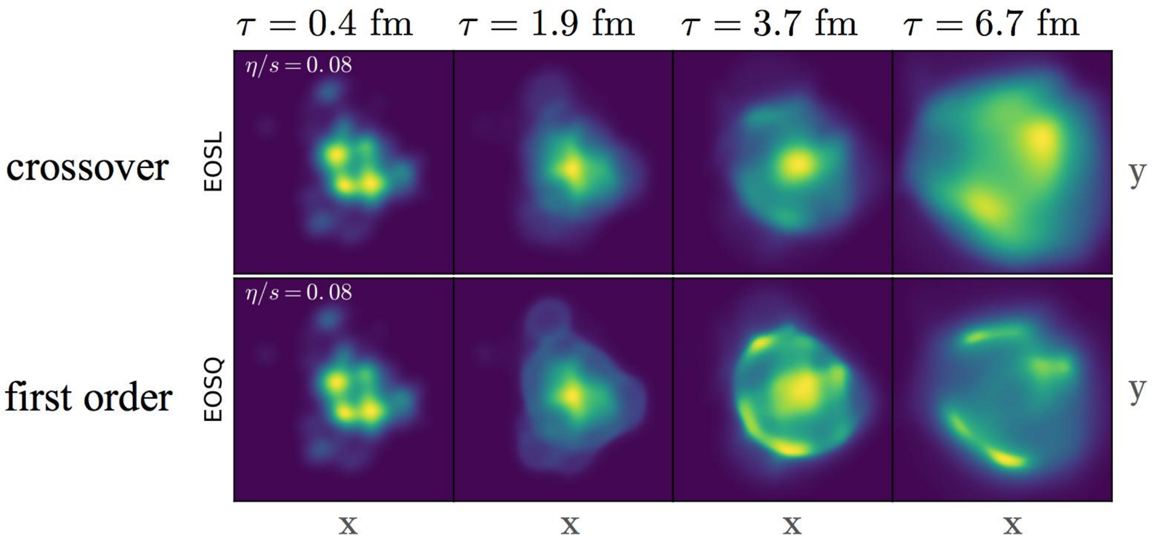


1. The network parameters are initialized with random numbers and the network make random guess
2. Compute the loss function L which is a functional of the network
3. Use auto-diff to compute the negative gradients of network parameters
4. Use SGD-like algorithms to update network parameters

Nuclear EoS and phase transition with DL

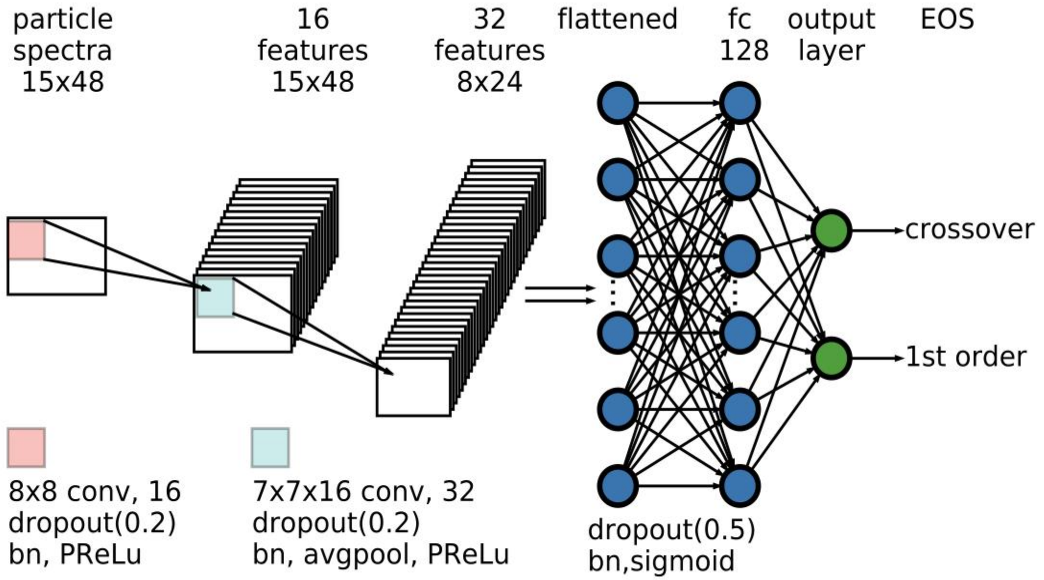


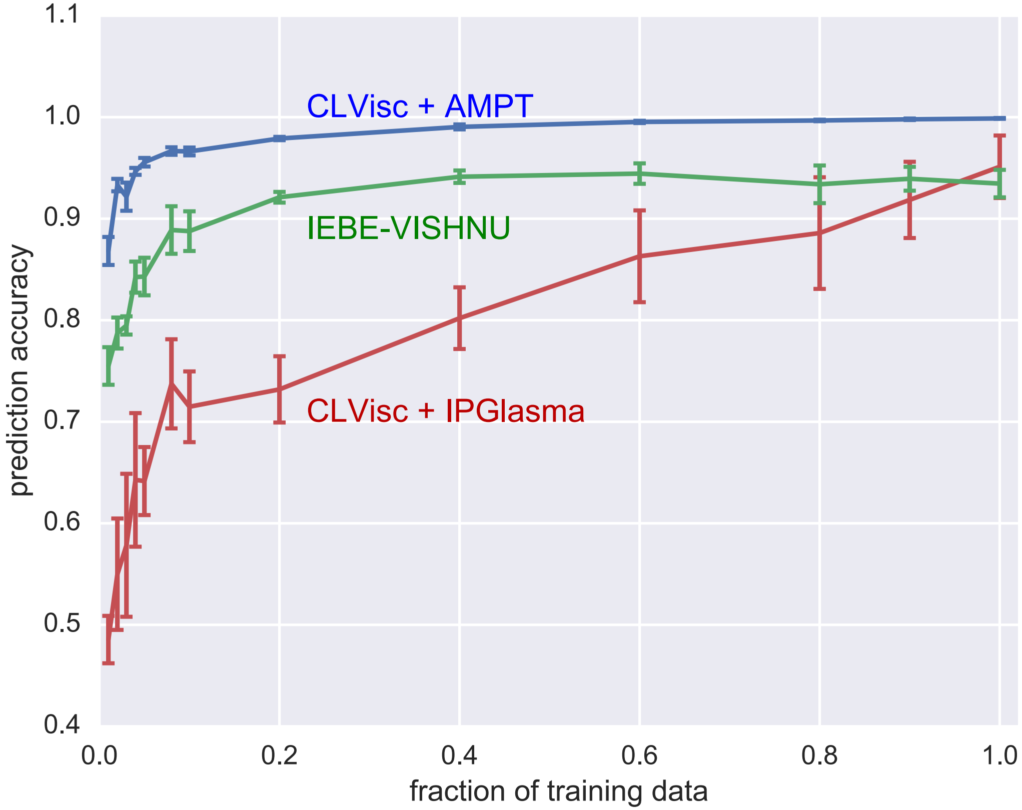
$$\nabla_\mu T^{\mu\nu} = 0$$



CLVisc 3+1D relativistic hydrodynamics

DL with CNN for EoS classification





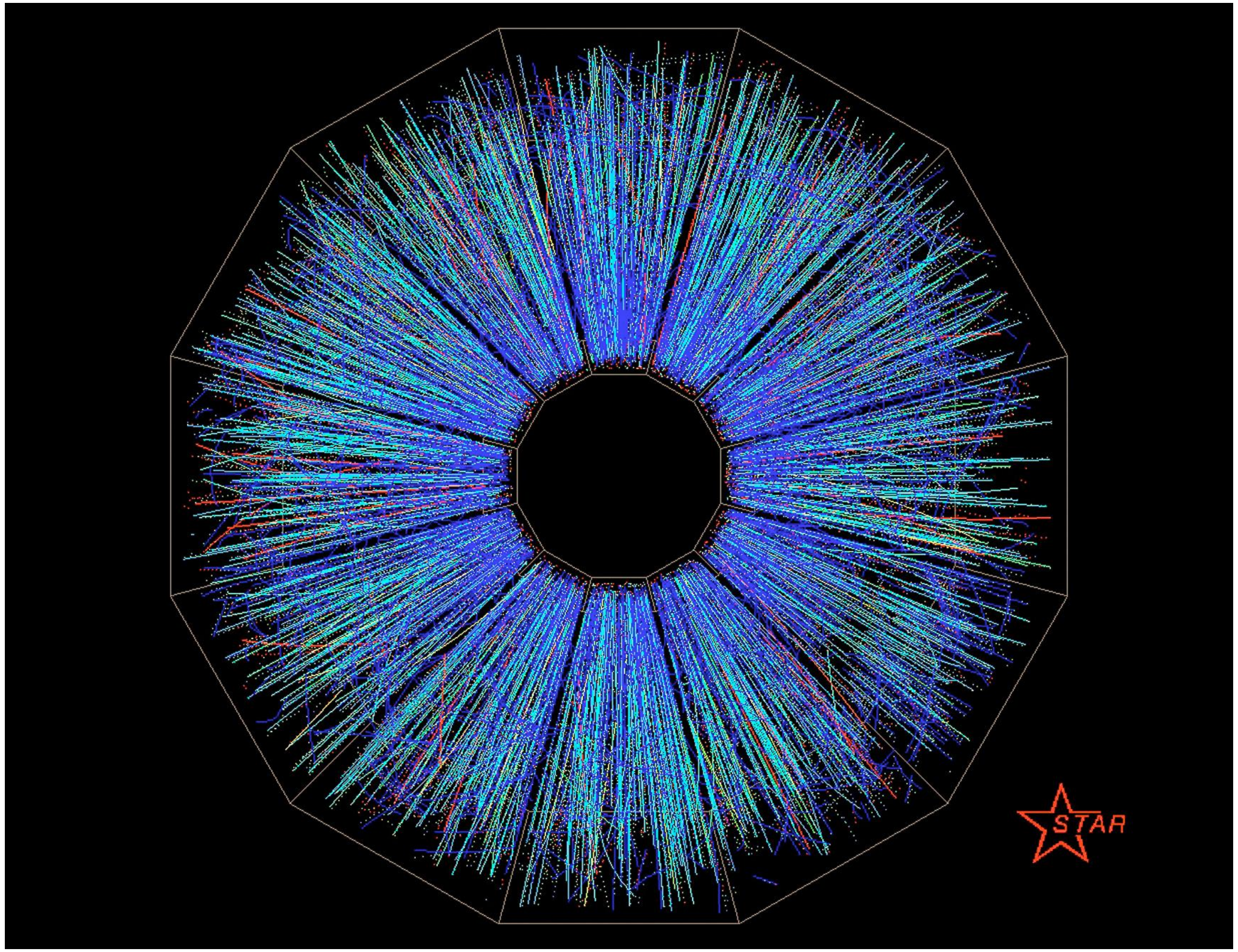
$$l(\theta) = \underbrace{-\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]}_{\text{cross entropy loss}} + \underbrace{\lambda ||\theta||_2^2}_{\text{L2 regularization}}$$

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

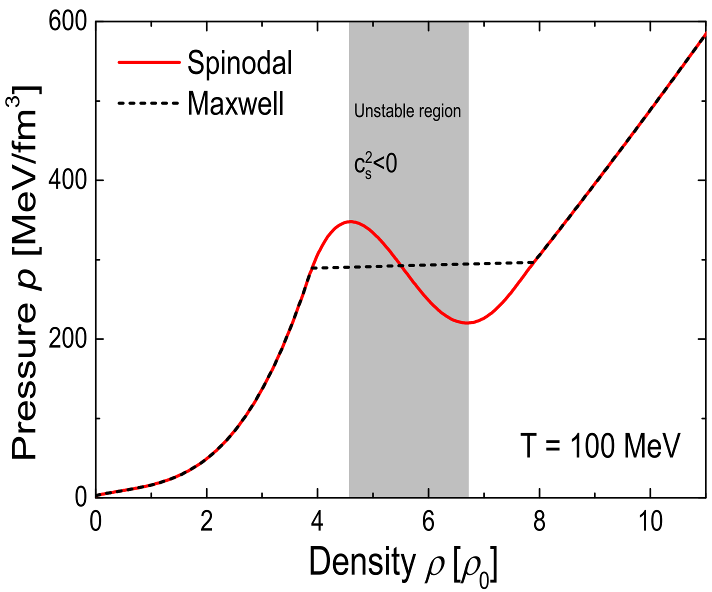
Data representation

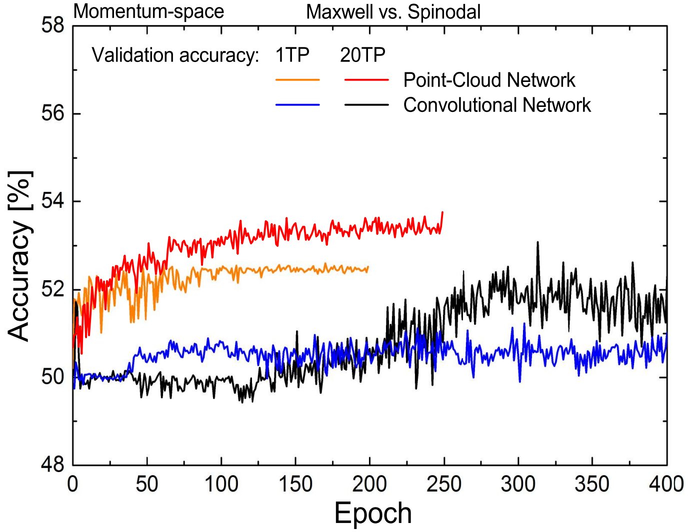


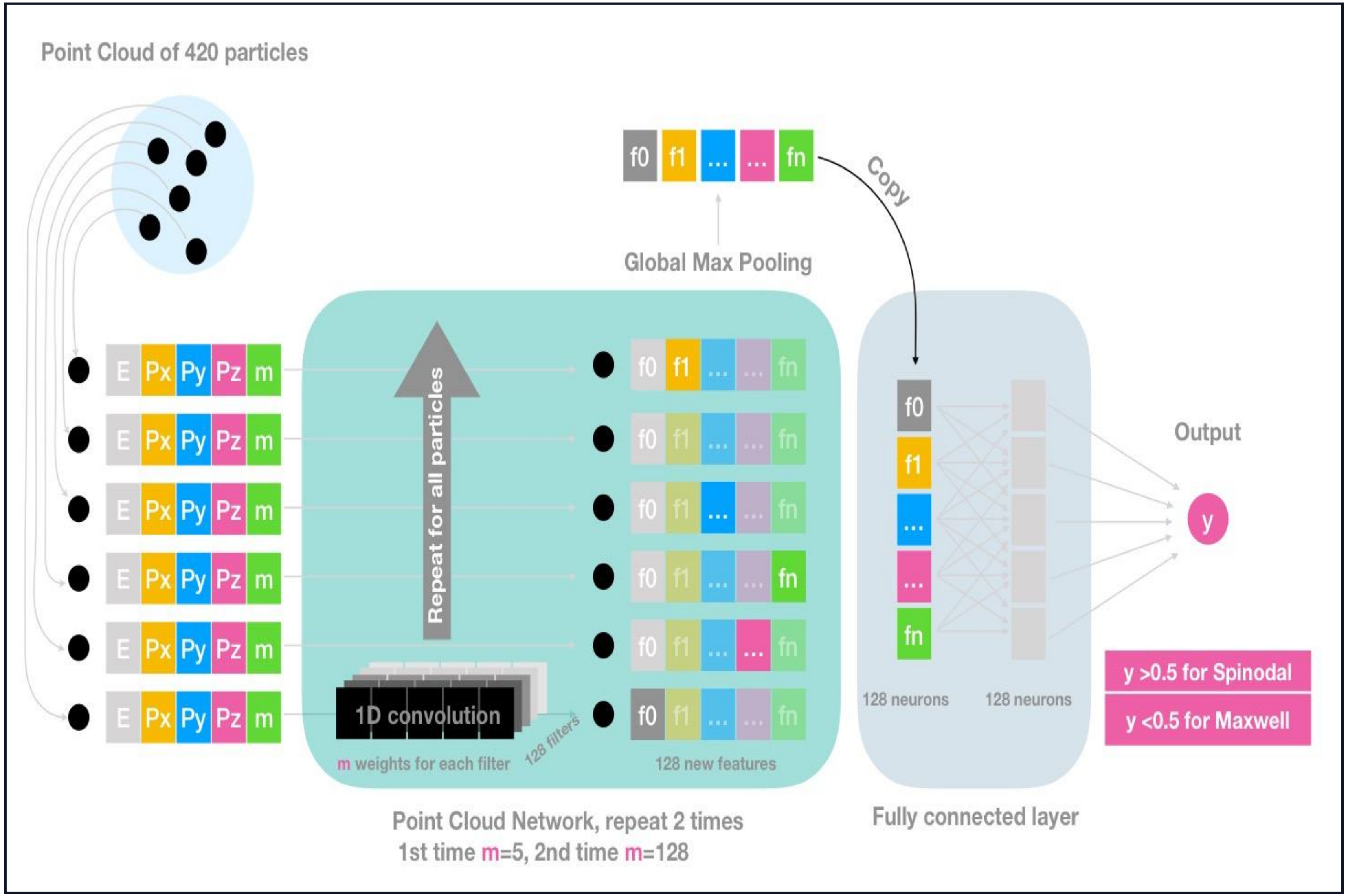
- Images: histograms
  - (px, py) or (pt, phi)
  - (px, py, pz)
  - (pt, phi, eta)
- Point cloud: particle list

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
…				

Spinodal vs Maxwell 1st order phase transition

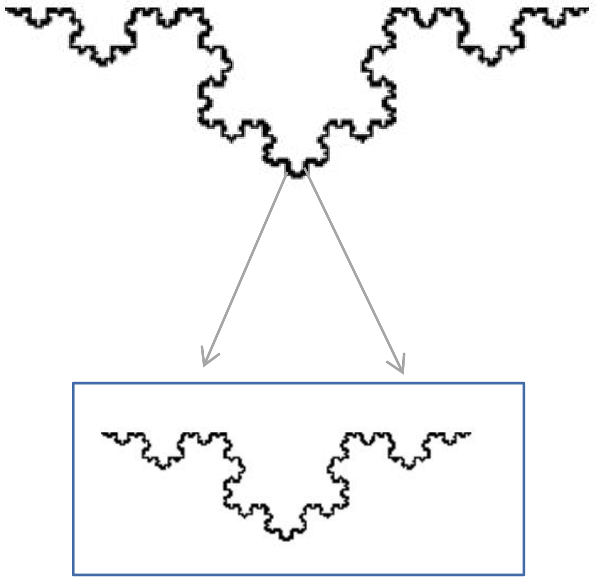






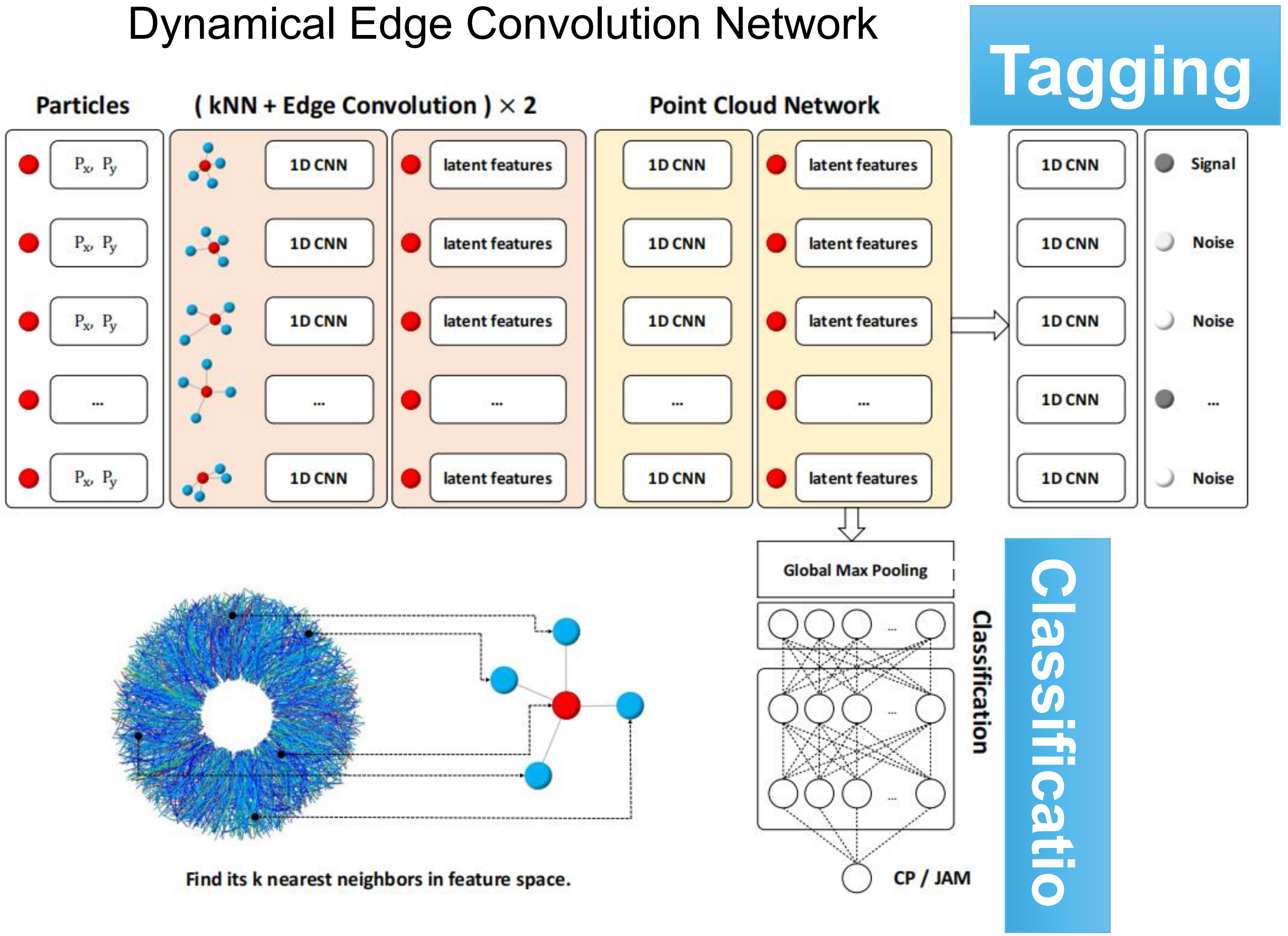
J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup, JHEP 12 (2019) 122

Looking for self similarity in momentum space



Self similarity, scaling invariance

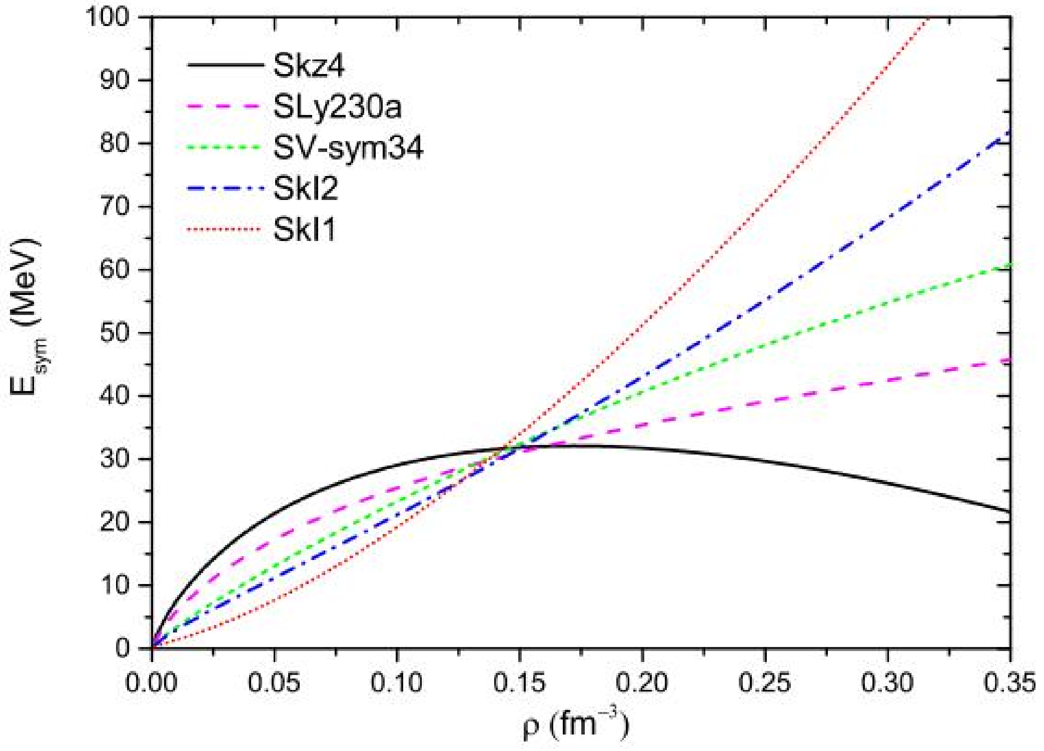
Dynamical Edge Convolution Network



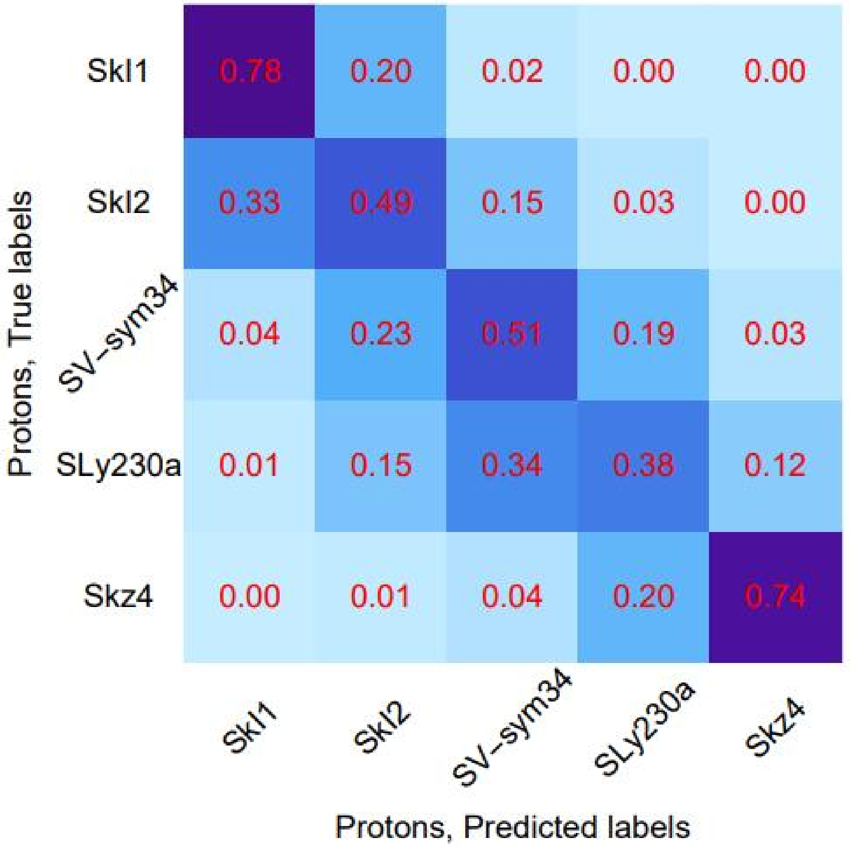
PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

Nuclear EoS at high density region

Skyrme potential + IMQMD



off-diagonal = misclassified



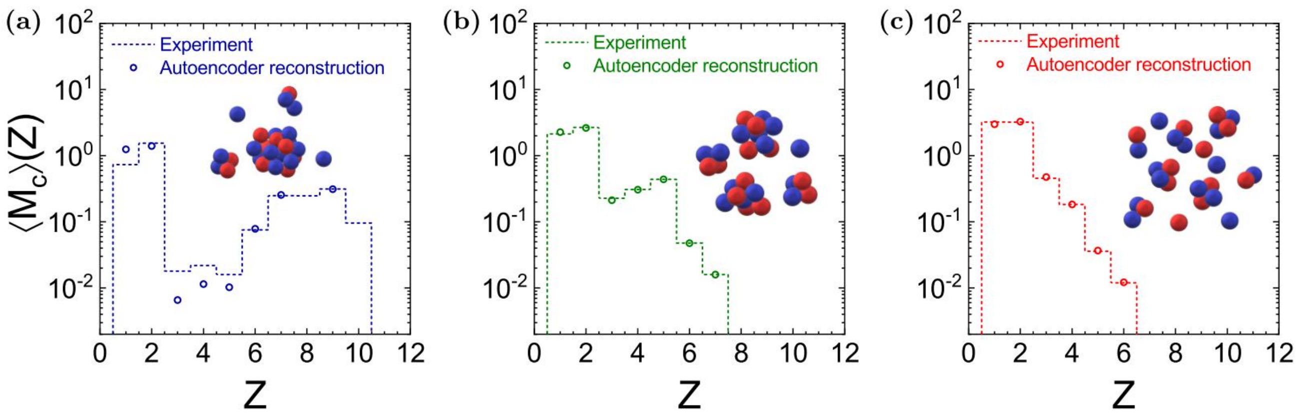
PLB 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

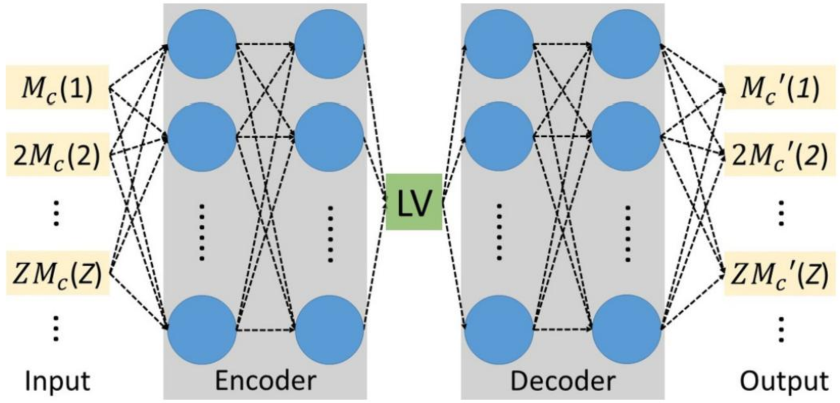
Auto Encoder for order parameter

PHYSICAL REVIEW RESEARCH **2**, 043202 (2020)

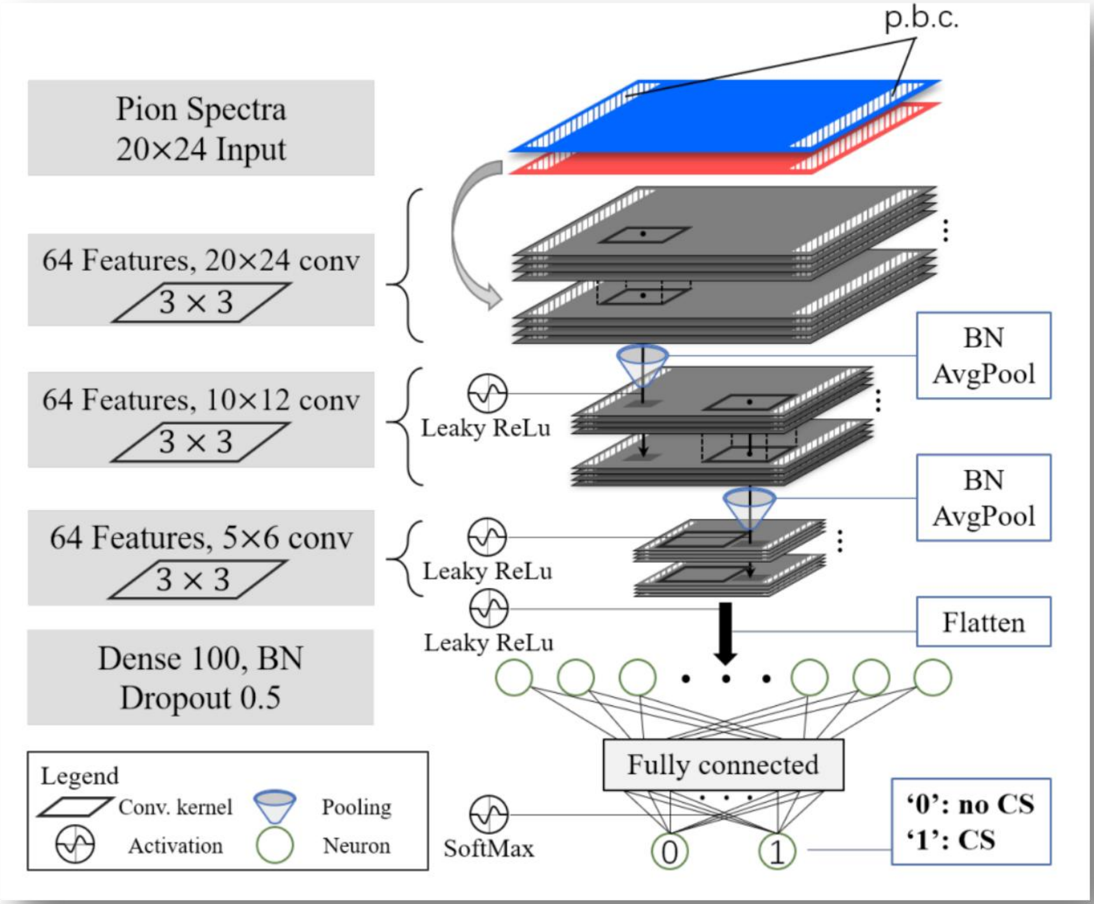
Nuclear liquid-gas phase transition with machine learning

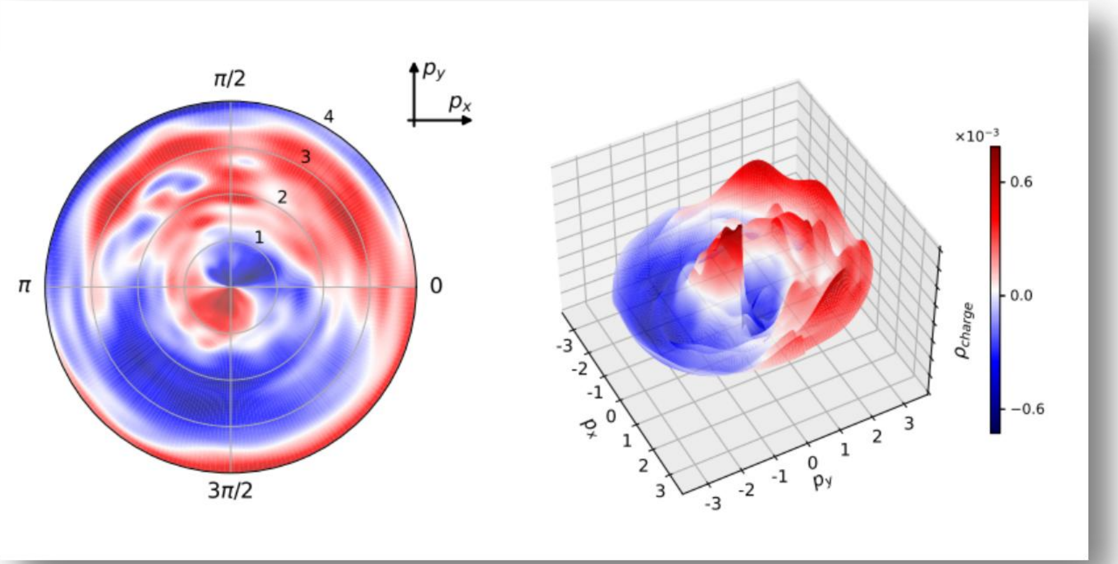
Rui Wang,[1,2,*] Yu-Gang Ma,[1,2,†] R. Wada,[3] Lie-Wen Chen,[4] Wan-Bing He,[1] Huan-Ling Liu,[2] and Kai-Jia Sun[3,5]





Detecting CME via deep learning





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

Y.-S. Zhao, L. Wang, K. Zhou, and X.-G. Huang PRC 106 (2022) 5, L051901

Active learning to mapping out unphysical regions in nuclear 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

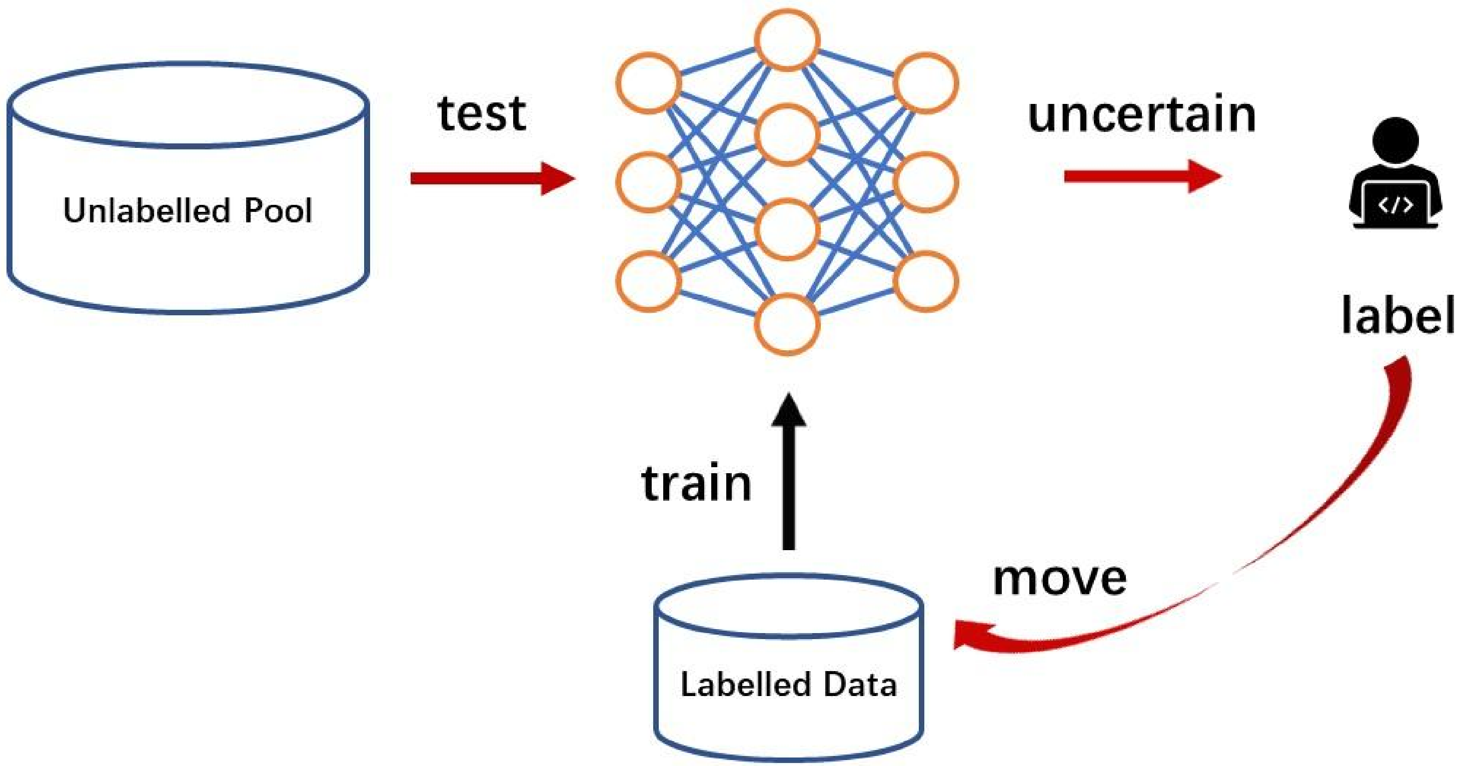
Acceptable = Stable + Causal

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

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

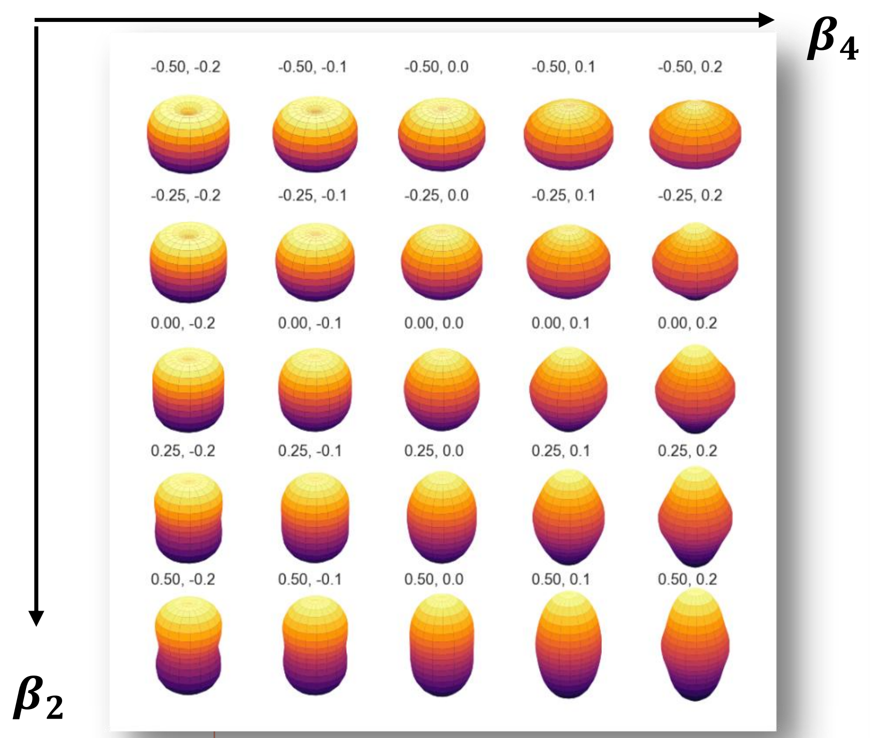
2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

Active learning procedure

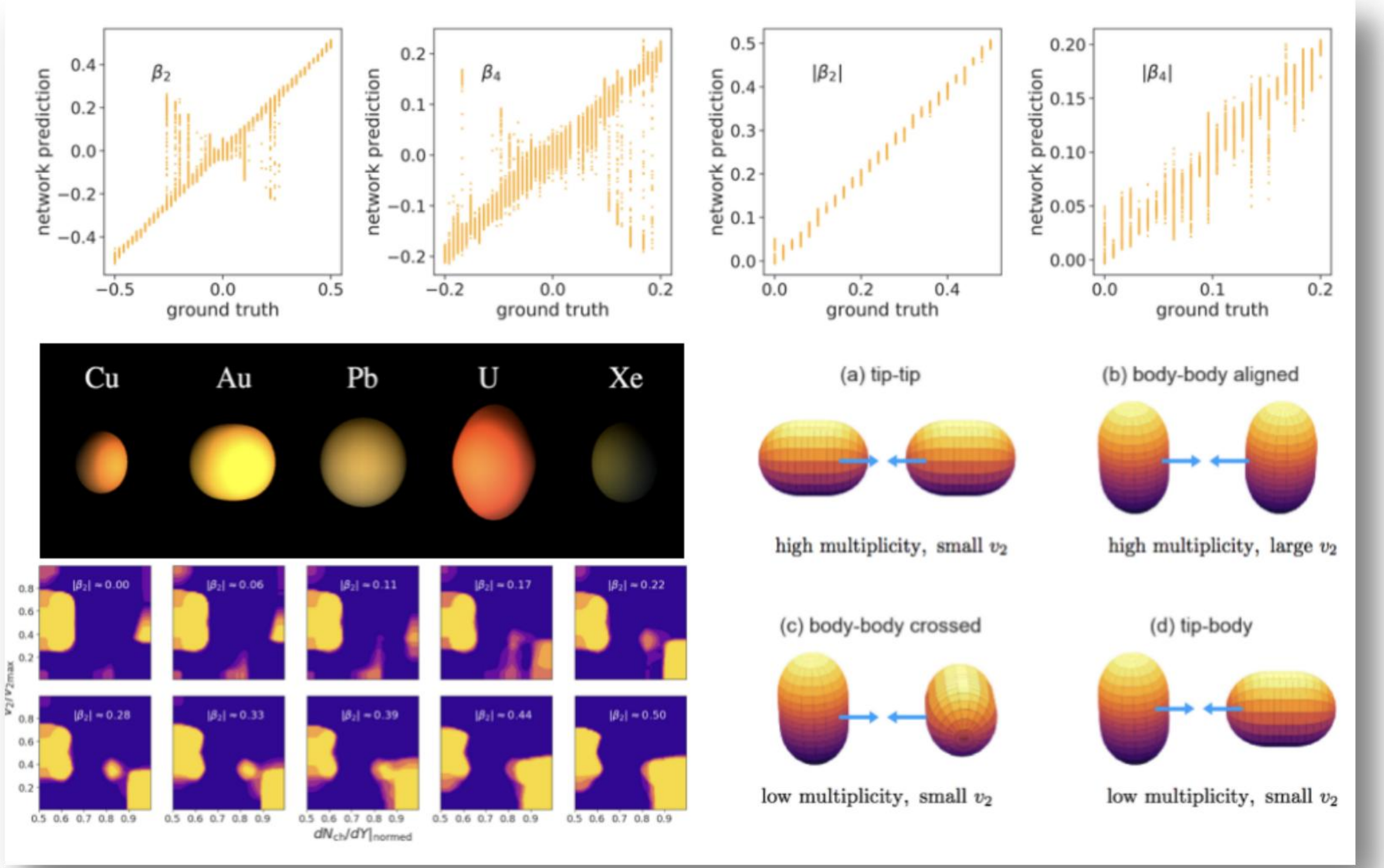


2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

Determining nuclear deformation



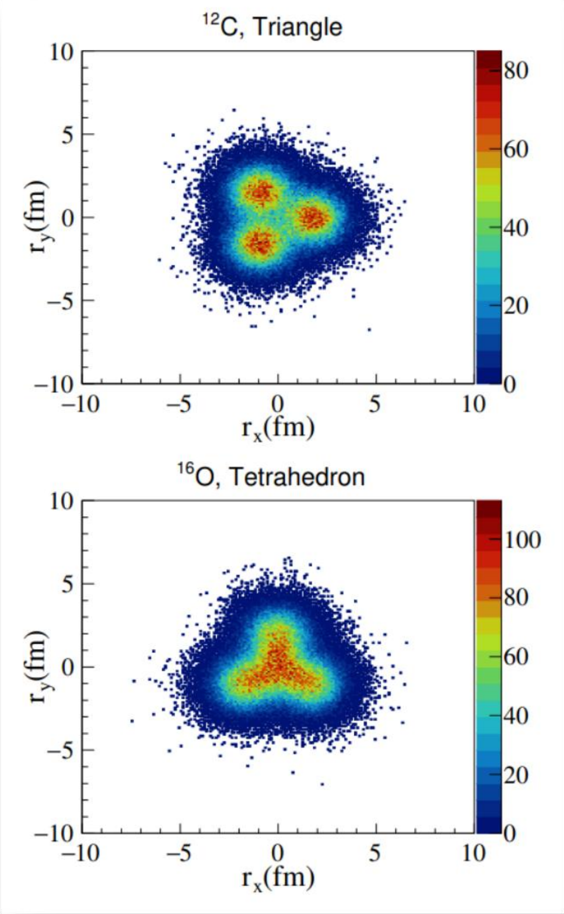
Data: Trento + Matching



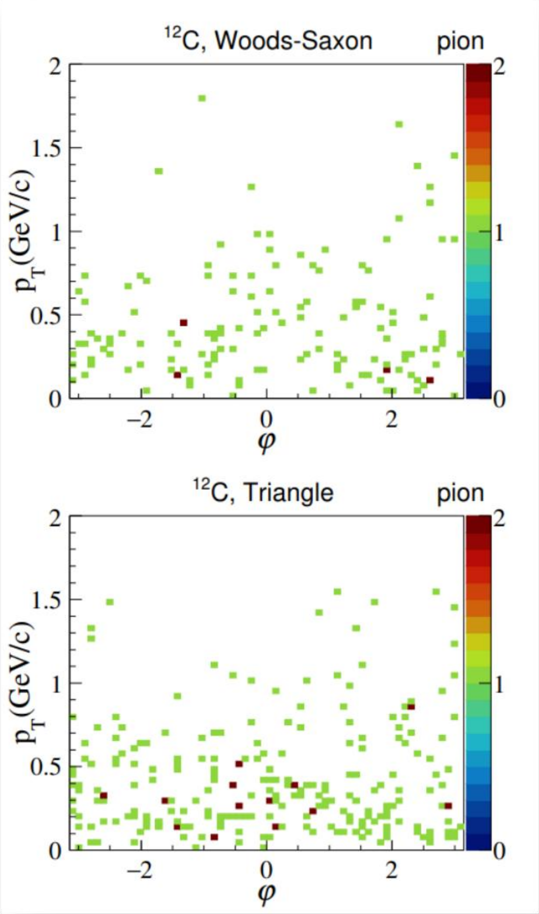
L.-G. Pang, K. Zhou and X.-N. Wang, arXiv:1906.06429

Identifying the α-clustering structure

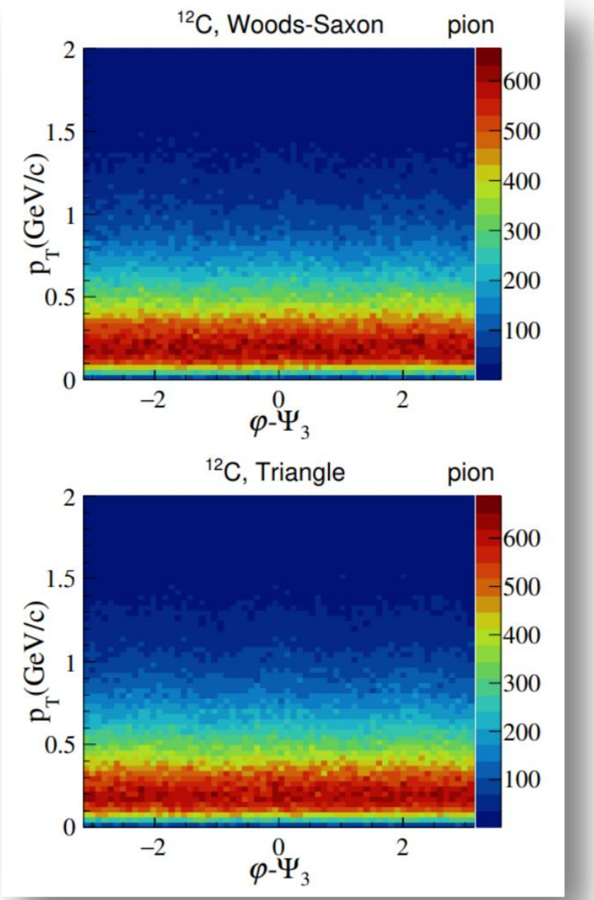
α clusters



Fail in EbE



Succeed with 4000-events average



JJ He, WB He, YG Ma, S Zhang, Phys. Rev. C 104, 044902 (2021)

Stacked U-net for relativistic hydrodynamics

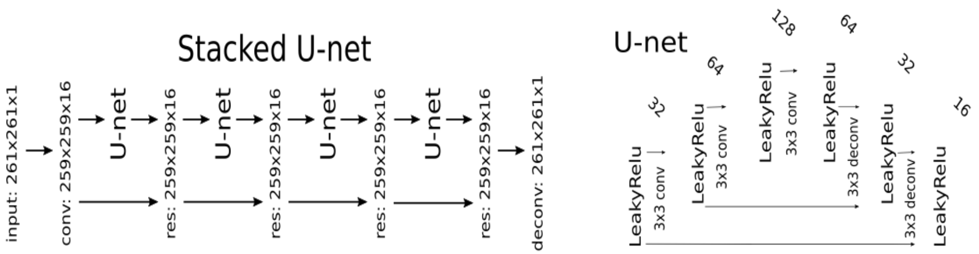
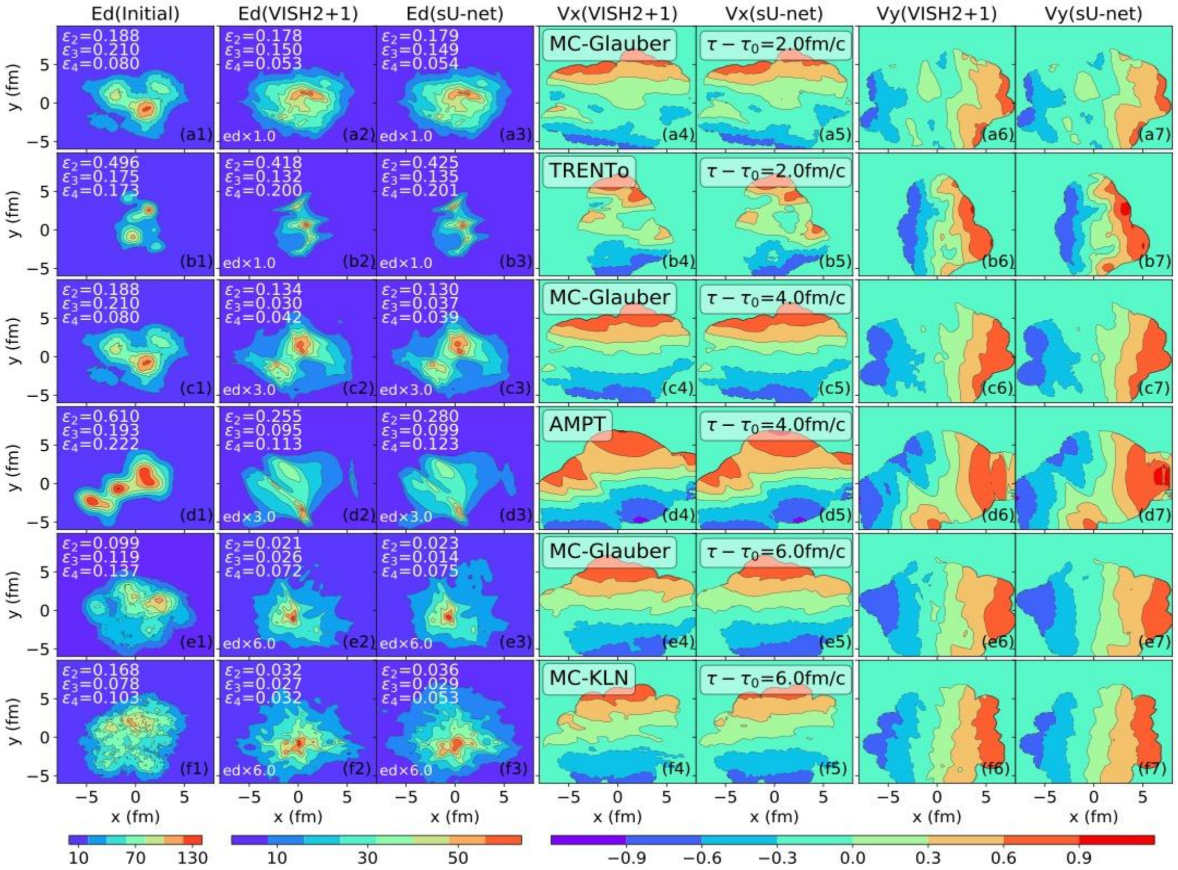


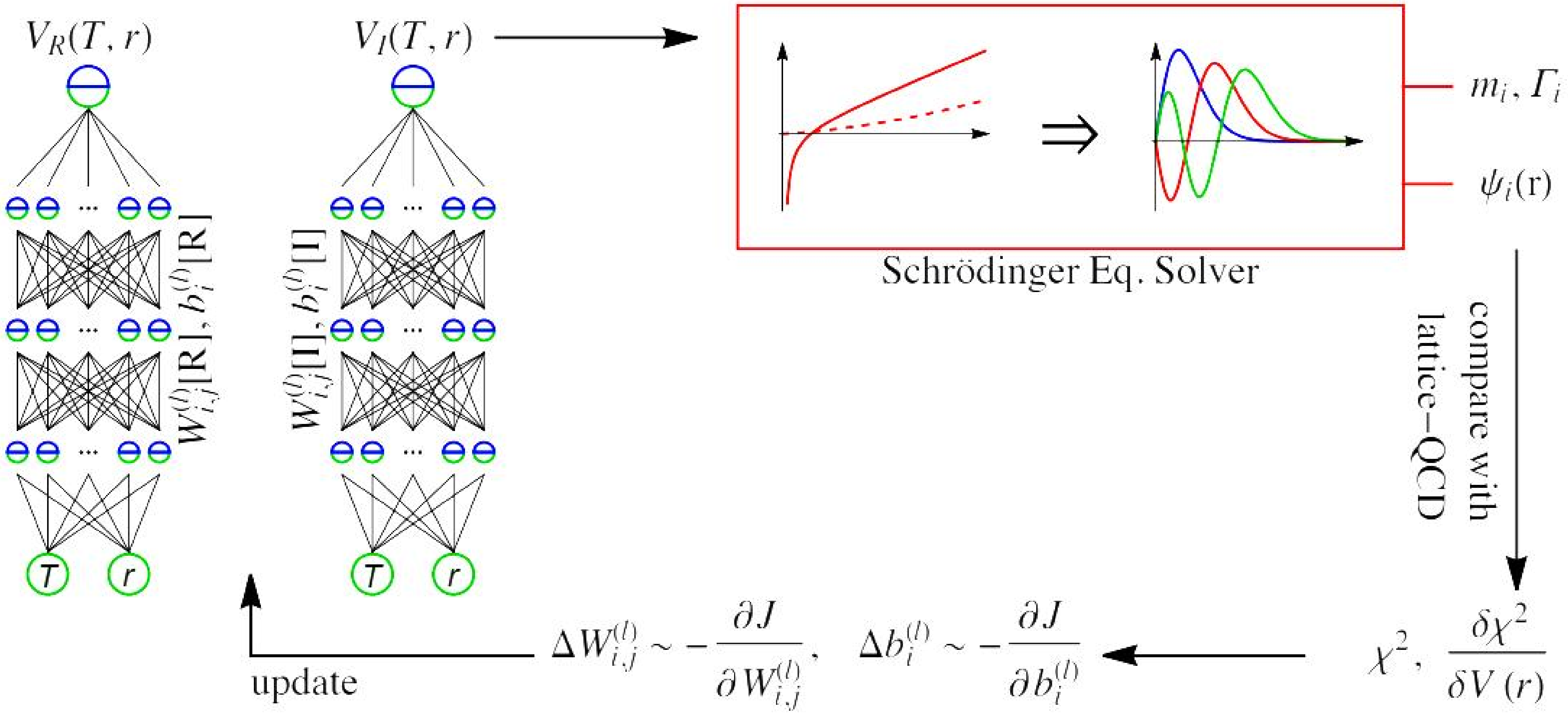
FIG. 1: An illustration of the encode-decode network, **stacked U-net**, which consists of the input and out layers and four residual U-net blocks. The right figure shows the U-net structure, and the depth of the hidden layer is written on the top of them.

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

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



In medium heavy quark potential

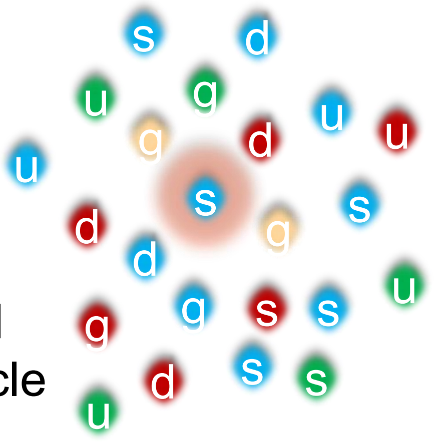


SZ Shi, K Zhou, JX Zhao, S Mukherjee, and PF Zhuang, PRD 105, 014017

Mass of Quasi Partons for QGP EoS

$$\ln Z(T) = \ln Z_g(T) + \ln Z_{u,d}(T) + \ln Z_s(T),$$

Screened
Dressed
Regularized
Quasi Particle



Fermi-Dirac distributions,

$$\ln Z_g(T) = -\frac{16V}{2\pi^2}\int_0^\infty p^2 dp$$
$$\ln\left[1-\exp\left(-\frac{1}{T}\sqrt{p^2+m_g^2(T)}\right)\right], \qquad (2)$$

$$\ln Z_{q_i}(T) = +\frac{12V}{2\pi^2}\int_0^\infty p^2 dp$$
$$\ln\left[1+\exp\left(-\frac{1}{T}\sqrt{p^2+m_{q_i}^2(T)}\right)\right], \qquad (3)$$

quarks, $m_s(T,\theta_2)$ for strange quark and $m_g(T,\theta_3)$ for gluons, where θ_1, θ_2 and θ_3 are the parameters in DNN shown in Fig. 1.

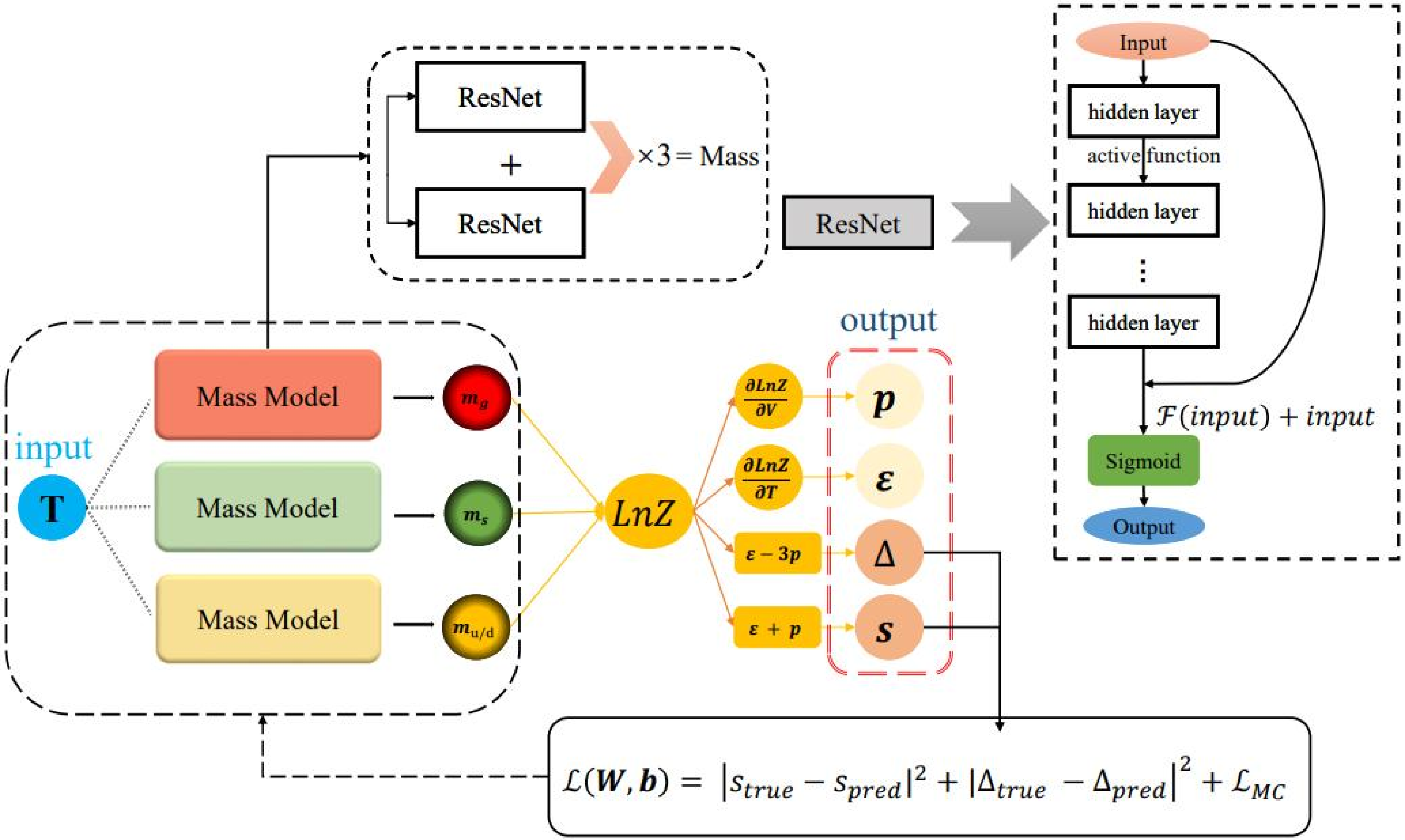
The resulting pressure and energy density are computed using the following statistical formulae,

$$P(T) = T\left(\frac{\partial \ln Z(T)}{\partial V}\right)_T, \qquad (5)$$

$$\epsilon(T) = \frac{T^2}{V}\left(\frac{\partial \ln Z(T)}{\partial T}\right)_V, \qquad (6)$$

FuPeng Li, HongLiang Lu, LongGang Pang, GuangYou Qin, PLB 2023

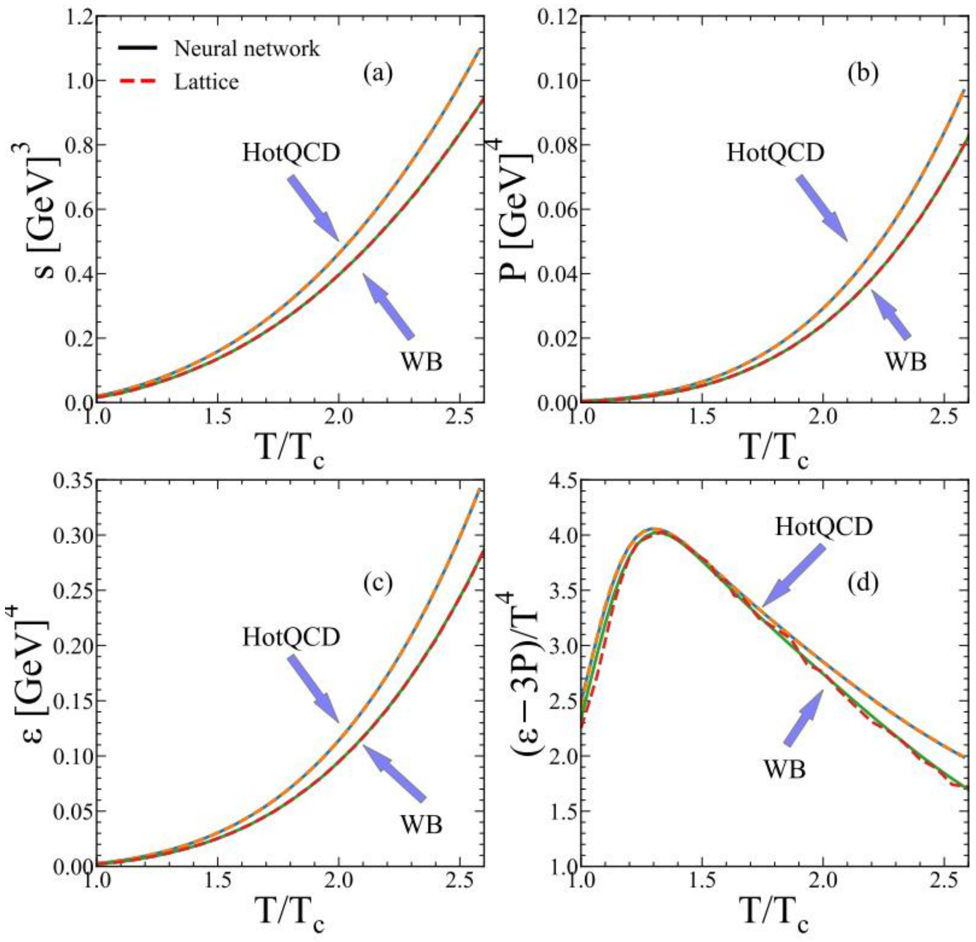
DL and auto-diff for quasi partons



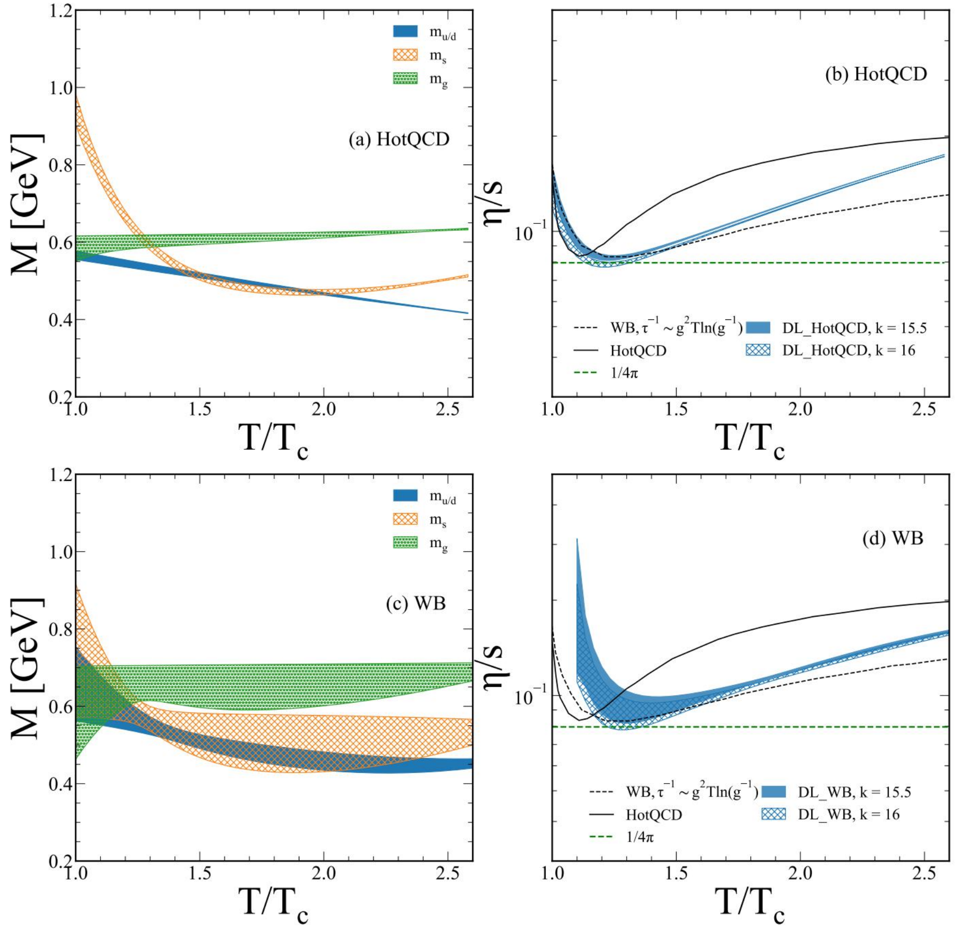
FuPeng Li, HongLiang Lu, LongGang Pang, GuangYou Qin, PLB 2023

The learned quasi parton mass

EoS vs Lattice QCD



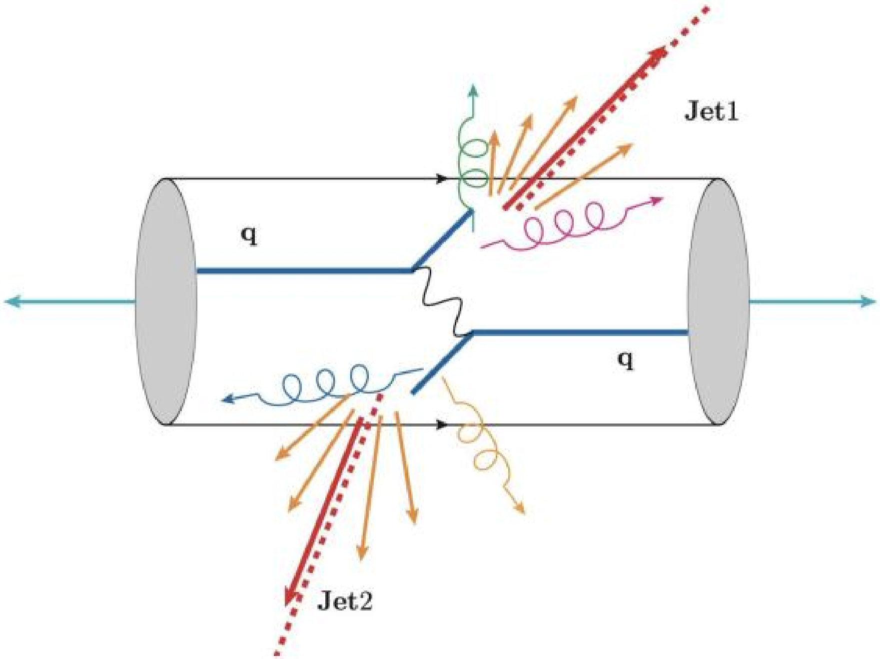
Learned Mass η/s



Jet quecnhing

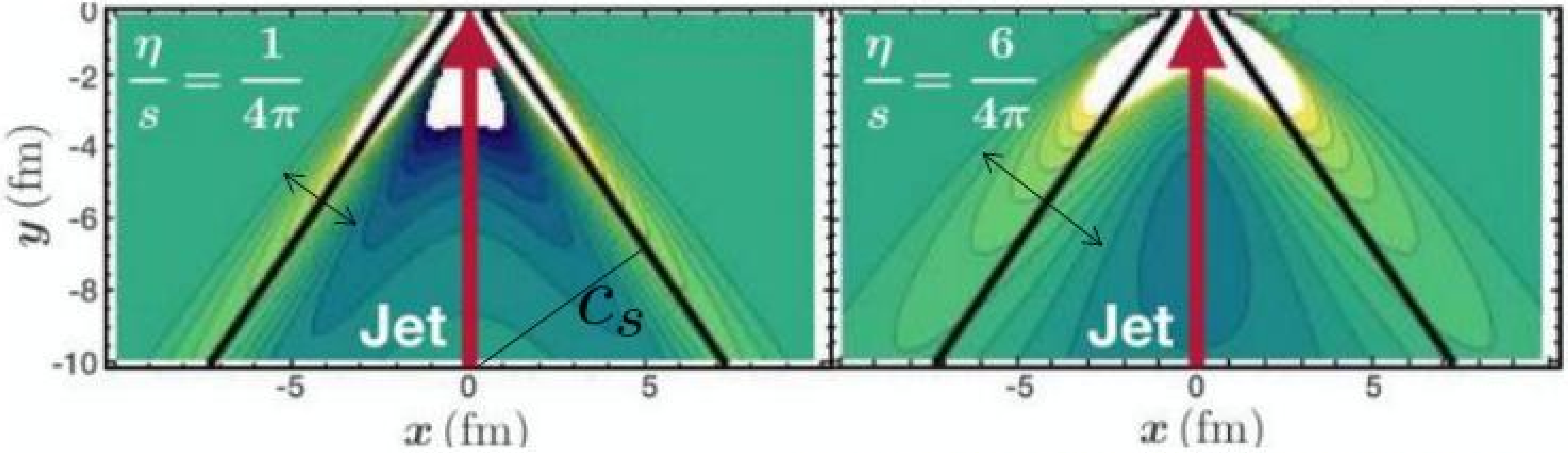
Can Being Underwater Protect You From Bullets?

❝ *If the bullet is shot from an angle of 30 Degrees, then being underwater in the range of 3-5 feet (0.9-1.5 meters) can ensure safety from most guns.*



Jet quenching in hot QGP

The nuclear EoS and Mach Cone



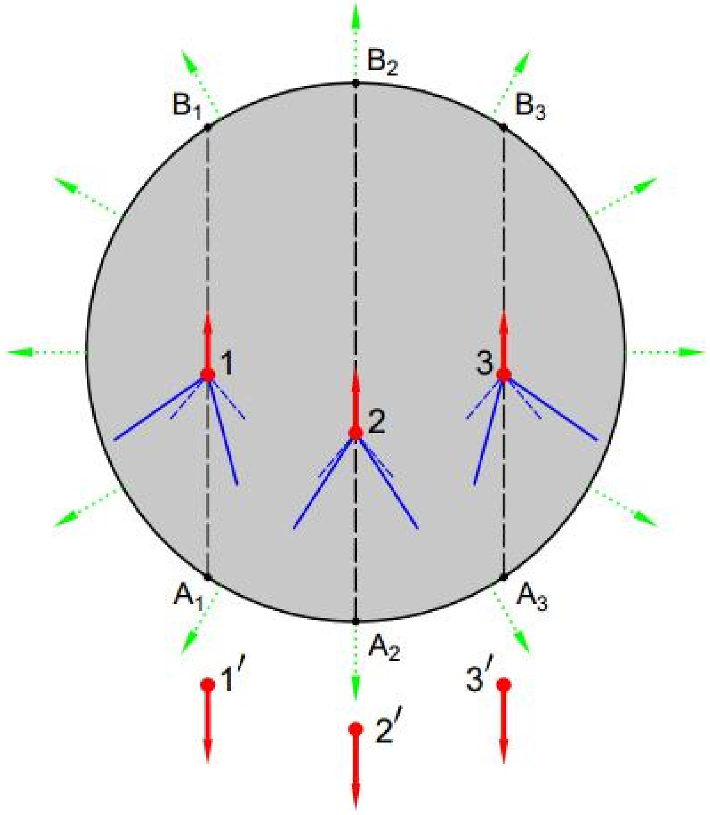
R.B.Neufeld. PRC79,054909(09')

Nuclear EoS： $c_s^2 = \frac{dP}{d\epsilon} = \sin^2\theta$

Shear Viscosity： width of the shock wave

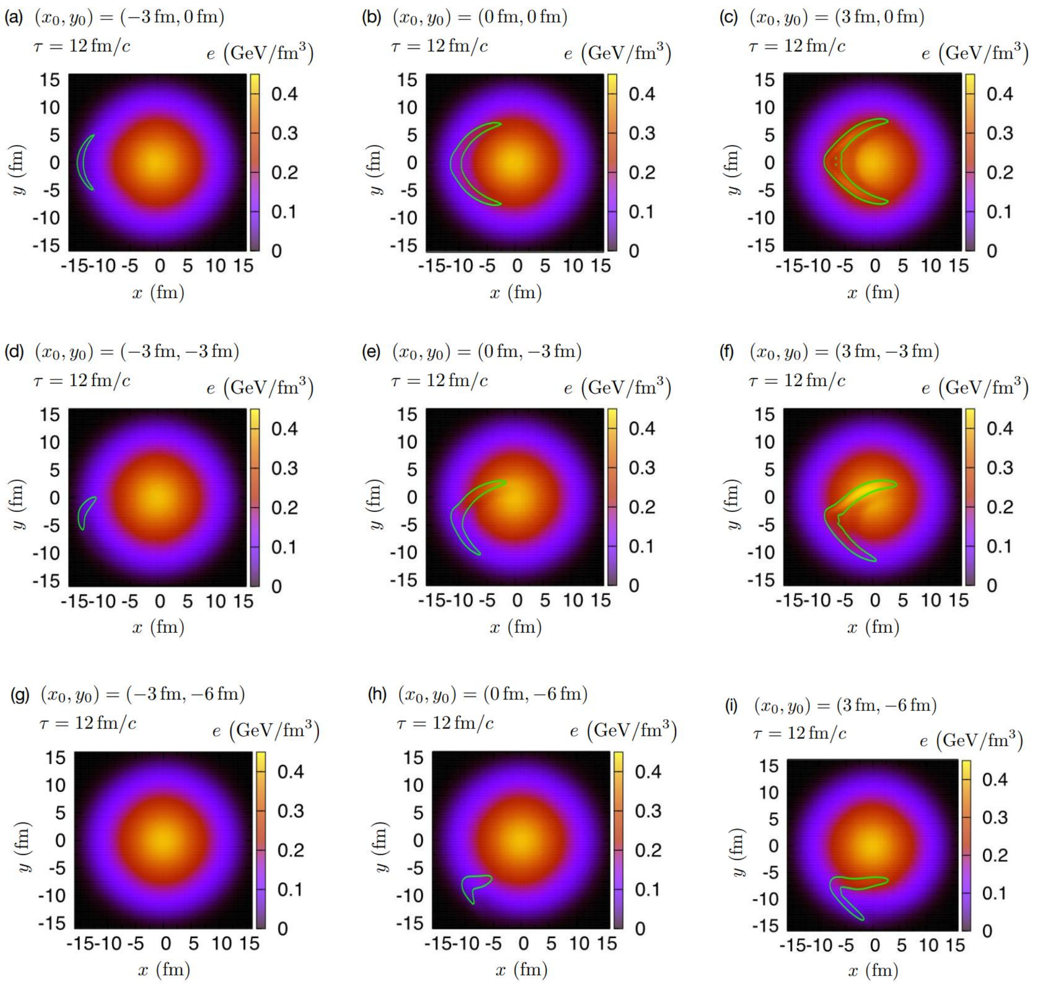
Difficulties in looking for Mach Cones in HIC

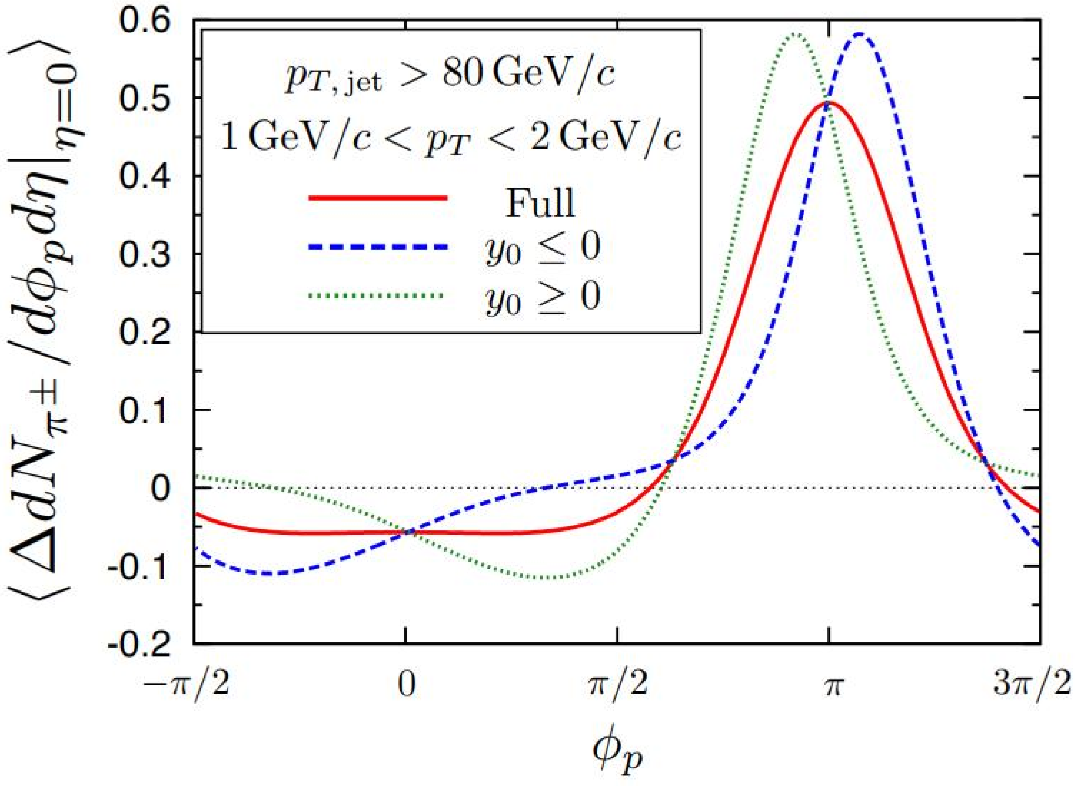
- Random production locations and propagating directions relative to collective flow
- Tilted by different path length and collective flow



L.M. Satarov, H. Stoecker, I.N. Mishustin, PLB 627 (2005) 64-70

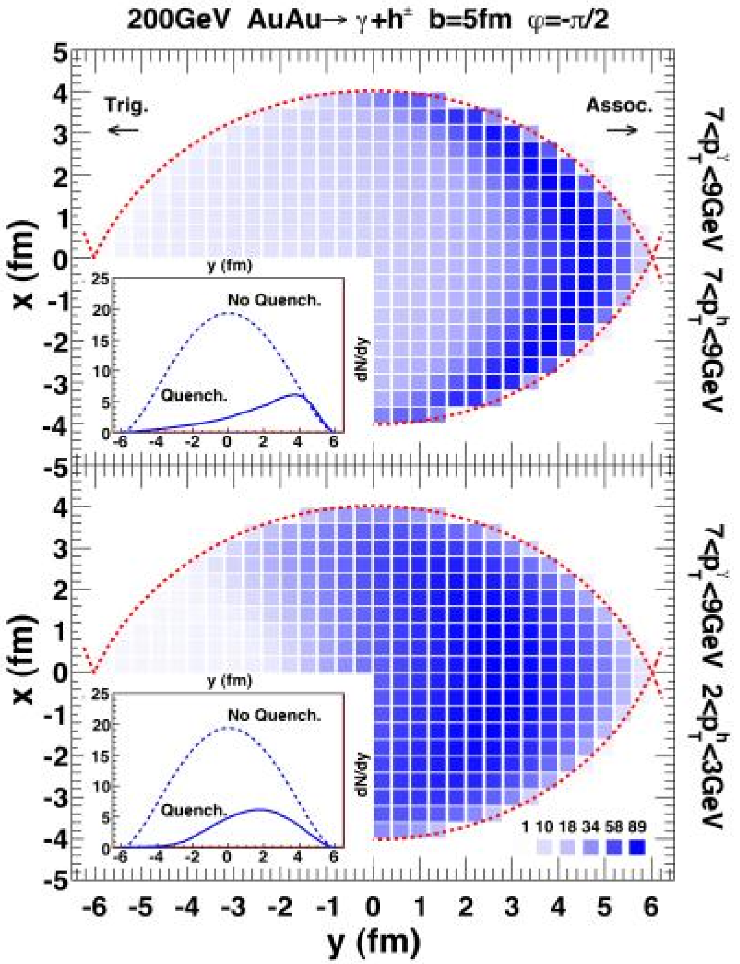
If it is possible to locate the initial jets





Y Tachibana, T Hirano, PRC 93 (2016) 5, 054907

Longitudinal location: path length dependence



$$p_T^h/p_T^\gamma \sim 1$$

Surface emission less energy loss.

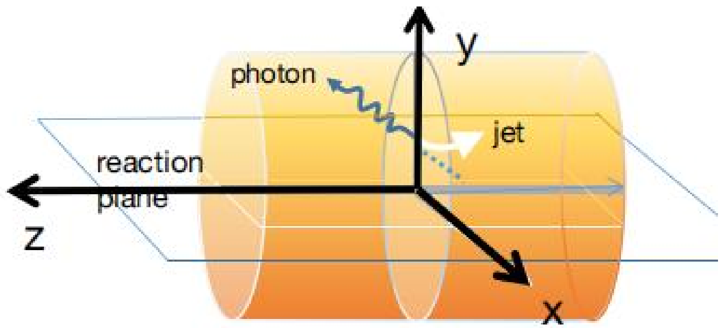
$$p_T^h/p_T^\gamma \sim 0.3$$

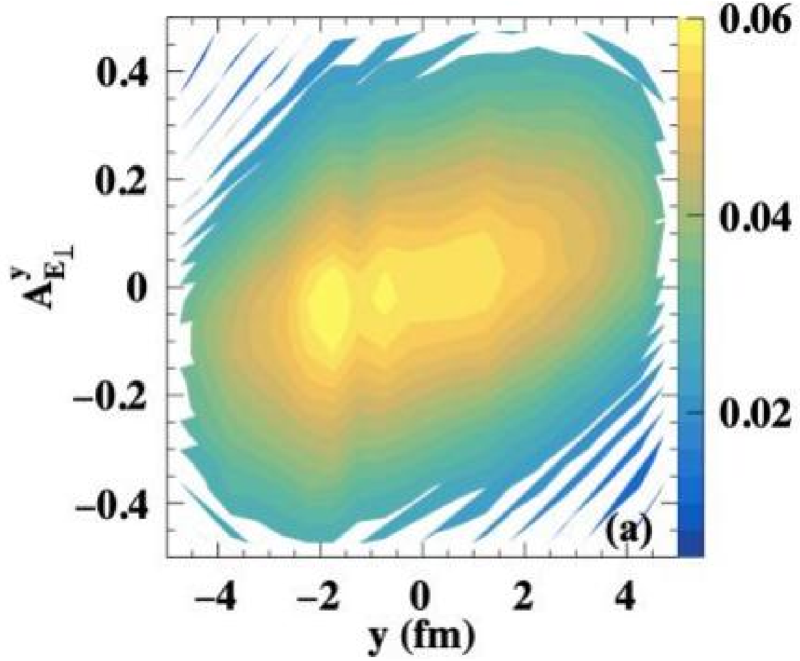
Volume emission more energy loss.

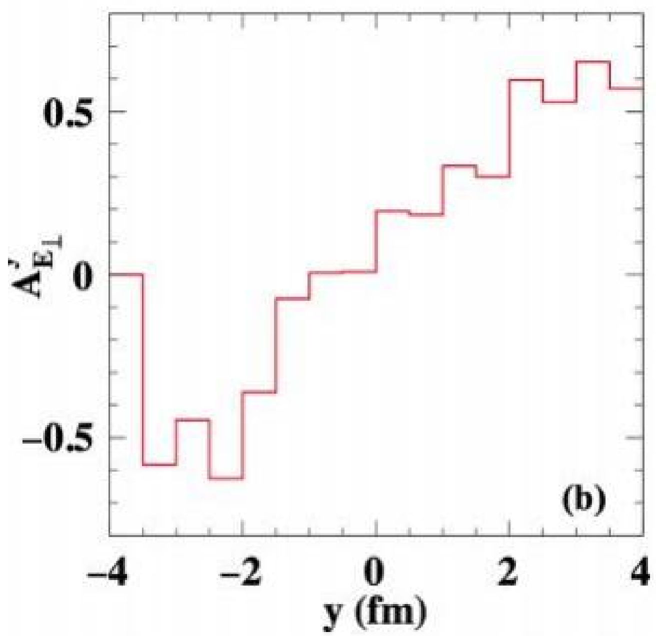
Zhang, Owens, Wang and XNW, Phys. Rev. Lett. 103, 032302 (2009)

Transverse location: gradient tomography

$$A_N^{\vec{n}} = \frac{d^3 r d^3 k f_a(\vec{k}, \vec{r}) \mathrm{Sign}(\vec{k} \cdot \vec{n})}{\int d^3 r d^3 k f_a(\vec{k}, \vec{r})}$$

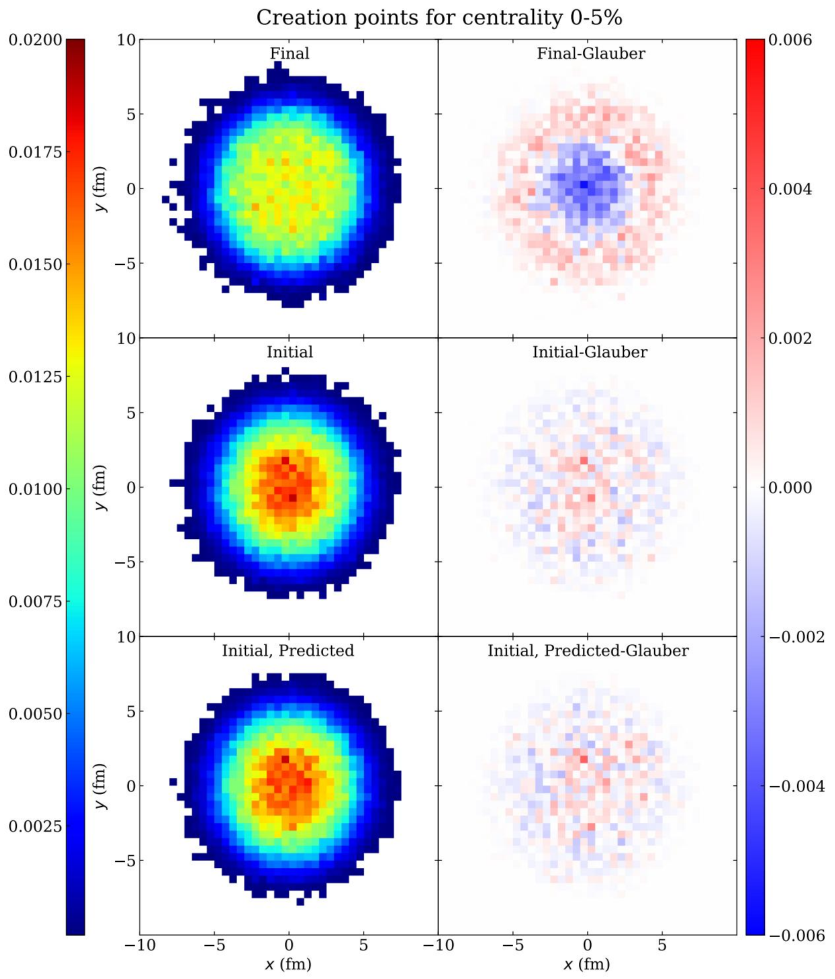






He, Pang & Wang, PRL 125 (2020) 12, 122301

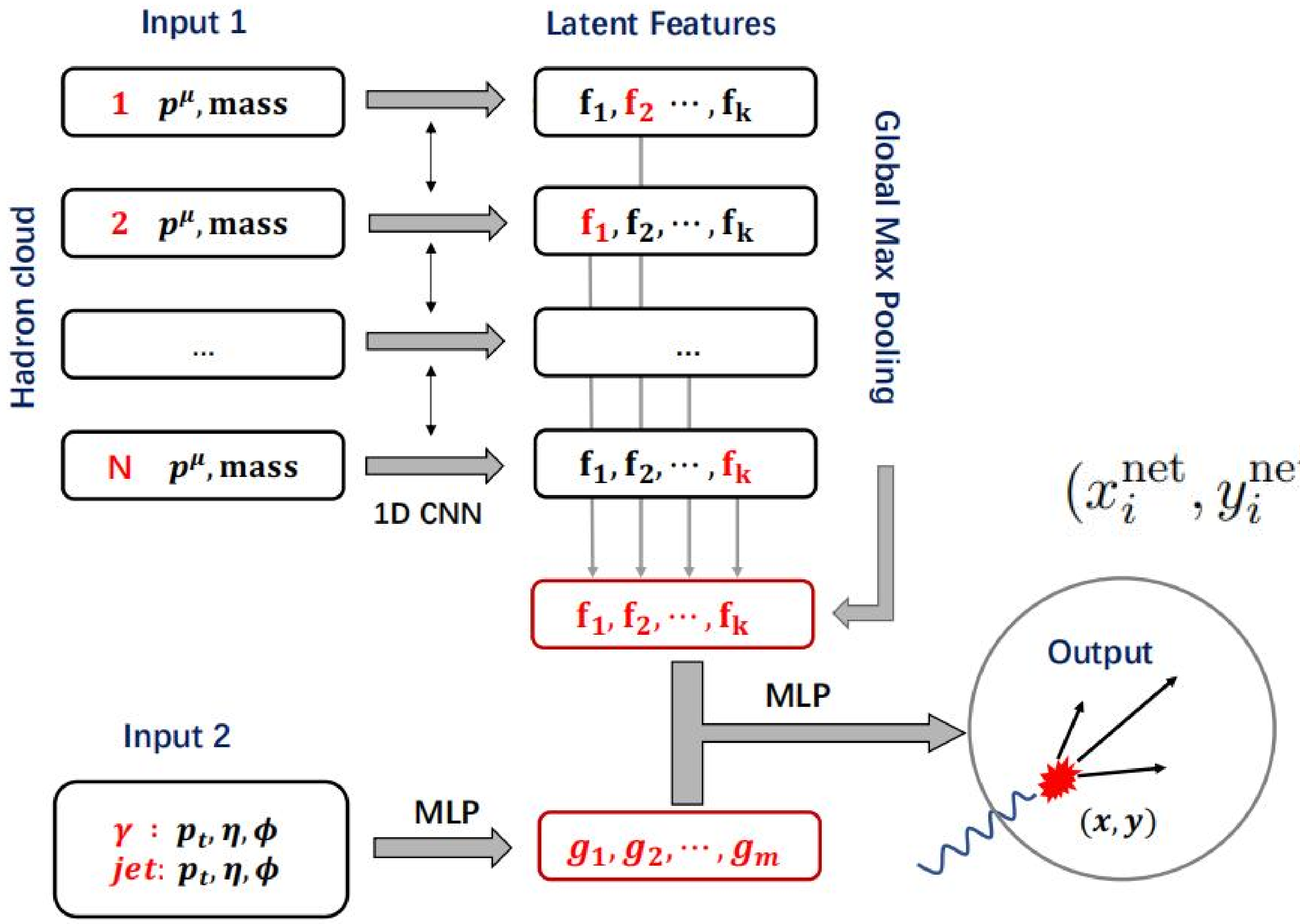
Jet tomography with deep learning (di-jet)



- Top: using final energy selection (**FES**), the estimated di-jet production point deviate from Glauber model a lot
- Middle: initial energy selection, ground truth
- Bottom: initial energy selection using predicted energy loss and initial jet energy with deep learning

YL Du, D Pablos and K Tywoniuk, PRL128, no.1, 012301 (2022)

DL assisted jet tomography (gamma-jet)



$$(x_i^{\text{net}}, y_i^{\text{net}}) = f(\{\vec{p}\}_i, \theta),$$

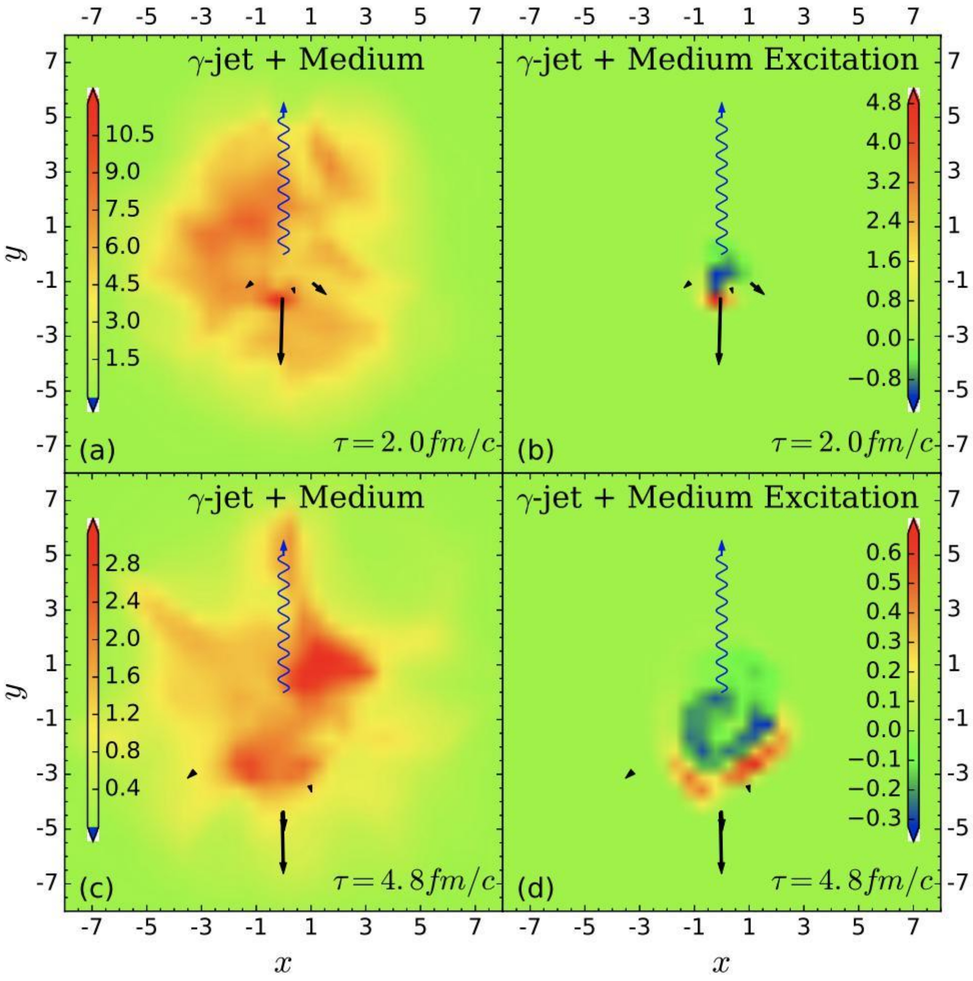
Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652

Training data: CoLBT(LBT + CLVisc)

$$p\partial f(p) = -C(p) \quad (p \cdot u > p^0_{cut})$$

$$\partial_\mu T^{\mu\nu}(x) = j^\nu(x)$$

$$j^\nu = \sum_i p_i^\nu \delta^{(4)}(x - x_i)\theta(p^0_{cut} - p \cdot u)$$

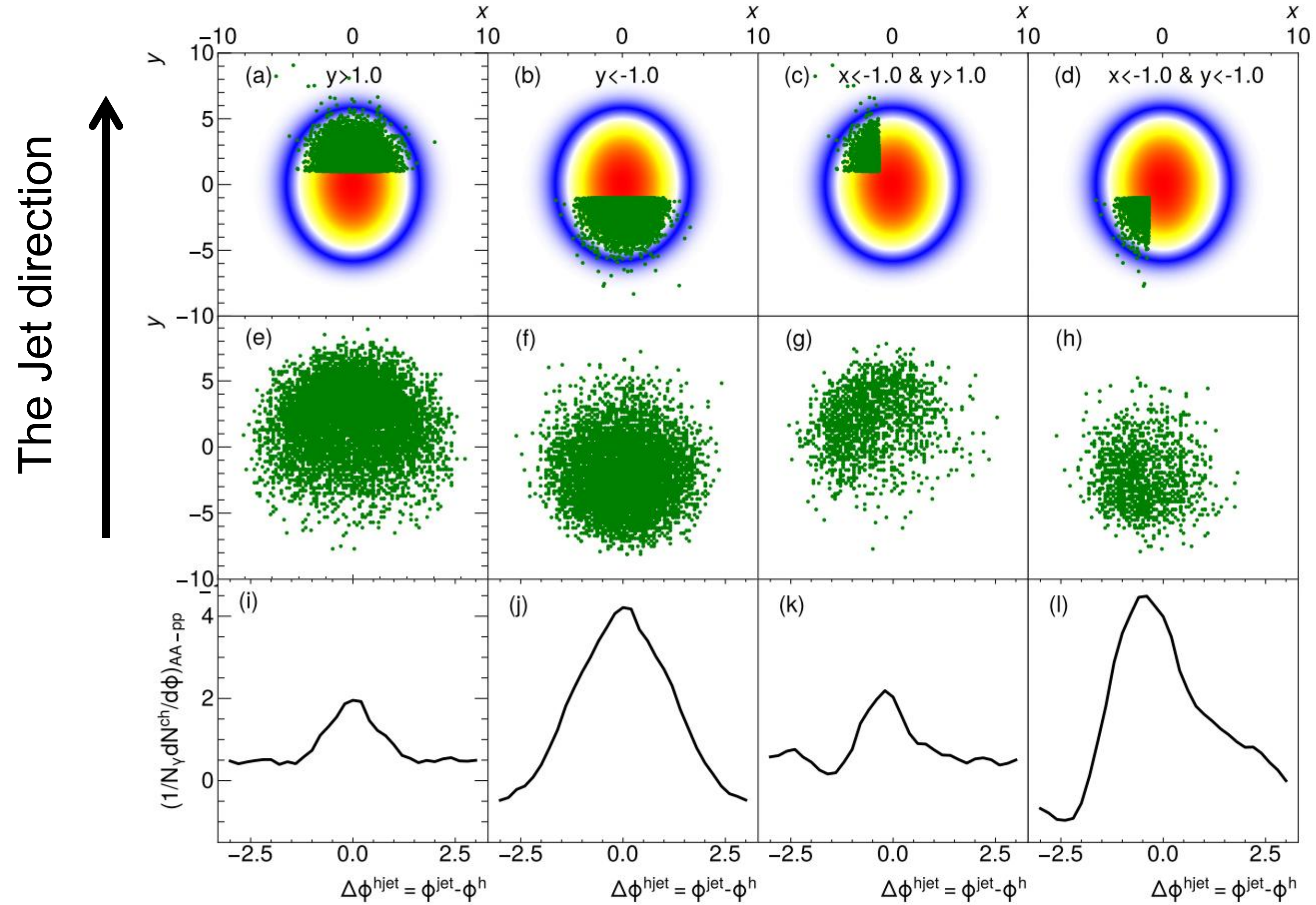


LBT: YY He, T Luo, XN Wang, Y Zhu,
PRC 91 (2015) 054908, PRC 97 (2018) 1, 019902

CLVisc:
LG Pang, Q Wang, XN Wang, PRC 86 (2012) 024911
LG Pang, H Petersen, XN Wang, PRC 97 (2018) 6, 064918
XY Wu, GY Qin, LG Pang, XN Wang,PRC 105 (2022) 3, 034909

CoLBT:
W Chen, T Luo, SS Cao, LG Pang, XN Wang, PLB 777 (2018) 86-90

Jet hadron correlation with DL assisted jet tomography



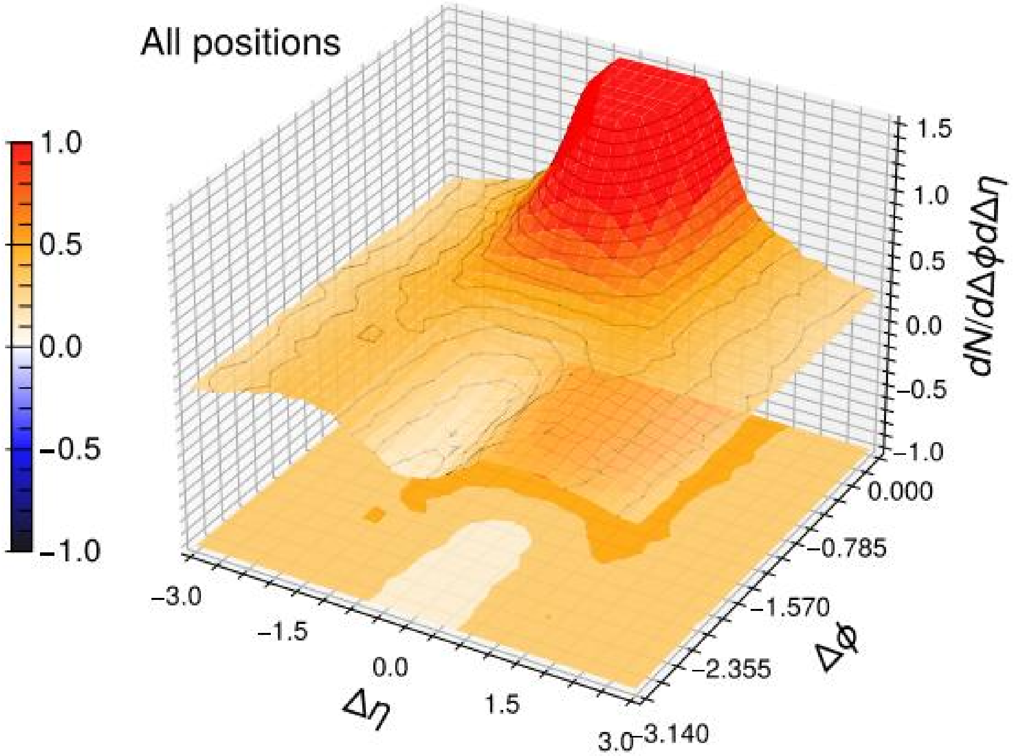
network predictions

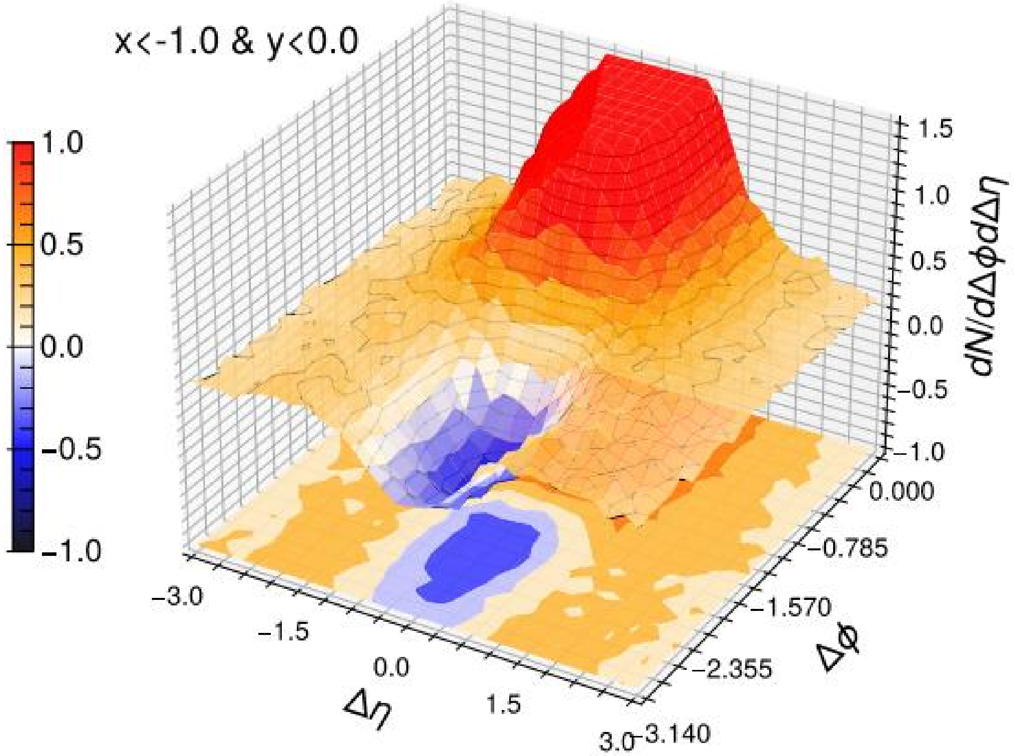
true locations

jet hadron correlation for selected events whose locations are constrained to specific regions using DL assisted jet tomography

Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652

Enhance the Diffusion Wake signal





Z Yang, YY He, W Chen, WY Ke, LG Pang, XN Wang, EPJC 83 (2023) 7, 652

Z Yang, T Luo, W Chen, LG Pang, XN Wang, PRL 130 (2023) 5, 052301

Summary

- DL is widely used in HIC to determine the nuclear EoS and many other QGP properties
- The network can be used as variational functions
- DL is used in the regression task to locate the jet production positions, which helps to study the QCD EoS through mach cones
- In the future, the DL will also be an important tool for nuclear structure studies

综述文章或学习资料

第九届华大 QCD 讲习班，主题：

《深度学习与粒子物理核物理》

讲习班PPT和视频下载地址：

https://pan.baidu.com/s/1IGITolwDoOm0LyRMbgx7pw

提取码：ccnu

第九届华大 QCD 讲习班（The 9th HuaDa QCD School）

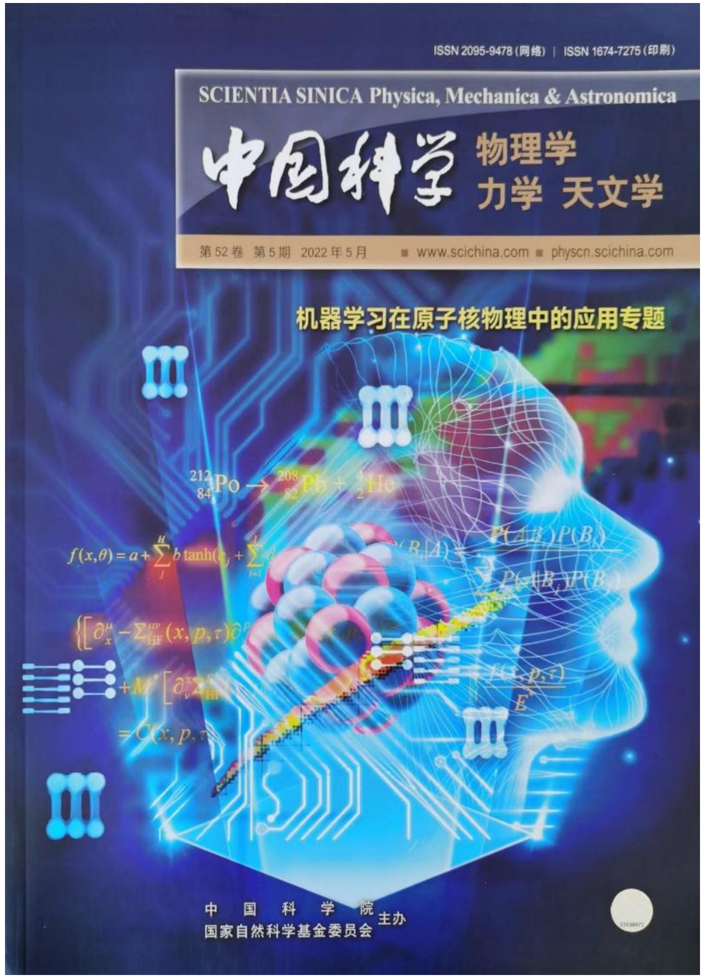
深度学习与粒子物理/核物理（Deep learning for particle and nuclear physics）

时间：2021 年 10 月 11-15 日
线下地点：华中师范大学粒子物理研究所 9409 会议室
线上链接： https://meeting.tencent.com/dm/t0fqqGFBorE5
腾讯会议 ID：967 8555 3730；密码：2021
最新信息见讲习班网站： https://indico.ihep.ac.cn/event/14735/

	10 月 11 日	10 月 12 日	10 月 13 日	10 月 14 日	10 月 15 日
8:30-9:00	开幕	Discussion	Discussion	Discussion	Discussion
9:00-10:30	**武雷** **南京师大** 机器学习简介	**张潘** **中科院理论物理所** 张量网络与统计物理	**牛中明** **安徽大学** 贝叶斯神经网络与核物理	**王琪瑞** **华为** MindSpore 图神经网络及生物制药	**张林峰** **北京大数据研究院** DeePMD **陆路** **UPenn** Physics Informed NN
10:30-11:00	茶歇	茶歇	茶歇	茶歇	茶歇
11:00-12:30	**武雷** **南京师大** 机器学习简介	**张潘** **中科院理论物理所** 张量网络与统计物理	**牛中明** **安徽大学** 贝叶斯神经网络与核物理	**刘红升** **华为** Mindspore 与电磁仿真	**王磊** **中科院物理所** 自动微分编程 **符世园** **中科院高能所** 智能无损压缩算法
12:30-2:00	午餐	午餐	午餐	午餐	午餐
2:00-3:30	**吴昊** **同济大学** 流模型与 MCMC	**任杰** **北京理工大学** 机器学习实操	**张振** **中山大学** 贝叶斯分析与核物理	**柯伟尧** **UCB** 贝叶斯分析与高能核物理	**李紫源** **中山大学** 深度学习与大型液基探测器 **李钊** **中科院高能所** Jet & CNN
3:30-4:00	茶歇	茶歇	茶歇	茶歇	茶歇
4:00-5:30	**吴昊** **同济大学** 流模型与 MCMC	**任杰** **北京理工大学** 机器学习实操	**曲慧麟** **CERN** 图神经网络与粒子物理	**曲慧麟** **CERN** 图神经网络与粒子物理	**方文兴** **中科院高能所** 生成网络和高能物理 **周凯** **FIAS** 机器学习量子力学反问题
5:30-6:00	Q&A	Q&A	Q&A	Q&A	闭幕

组织者：庞龙刚，秦广友，张本威，尹伊　　**秘书：马亚，袁强**

综述文章或学习资料



李庆峰，马余刚

我国首届核物理及核数据中的机器学习应用研讨会在赣召开

来源：中国核电信息网　发布日期：2022-08-17

8月4日至7日，由中国原子能科学研究院主办，原子能院瑞昌核物理应用研究院、江西核学会承办的我国首届核物理及核数据中的机器学习应用研讨会在江西瑞昌召开。**这是国内首次举办该主题会议，对于促进机器学习在核物理中的发展和应用，以及核物理、核天体、核数据、核工程等领域的交叉融合起到了积极的促进作用。**

原子能院

综述文章或学习资料

Colloquium: Machine learning in nuclear physics

Amber Boehnlein, Markus Diefenthaler, Nobuo Sato, Malachi Schram, Veronique Ziegler, Cristiano Far
Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostroumo
Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang

Rev. Mod. Phys. **94**, 031003 – Published 8 September 2022

Article | References | No Citing Articles | PDF | HTML | Export Citation

ABSTRACT

Advances in machine learning methods provide tools that have broad applicability in scientific research. These techniques are being applied across the diversity of nuclear physics research topics, leading to advances that will facilitate scientific discoveries and societal applications. This Colloquium provides a

#1

High energy nuclear physics meets Machine Learning

Wan-Bing He (Fudan U., Shanghai and Fudan U.), Yu-Gang Ma (Fudan U., Shanghai and Fudan U.), Long-Gang Pang, Huichao Song (CCNU, Wuhan, Inst. Part. Phys. and Hua-Zhong Normal U., LQLP and Peking U.), Kai Zhou (Frankfurt U., FIAS) (Mar 12, 2023)

e-Print: 2303.06752 [hep-ph]

pdf

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
be as useful as possible, this document will continue to evolve so please check back before you write your next paper.
helpful, please consider citing it using \cite{hepmllivingreview} in HEPML.bib.

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- earning and its Application to LHC Physics [DOI]
- e Learning in High Energy Physics Community White Paper [DOI]
- e learning at the energy and intensity frontiers of particle physics
- e learning and the physical sciences [DOI]
- e and Deep Learning Applications in Particle Physics [DOI]
- Machine Learning and Particle Physics
- e Learning in the Search for New Fundamental Physics
- l Intelligence and Machine Learning in Nuclear Physics

Exploring QCD matter in extreme conditions with Machine Learning

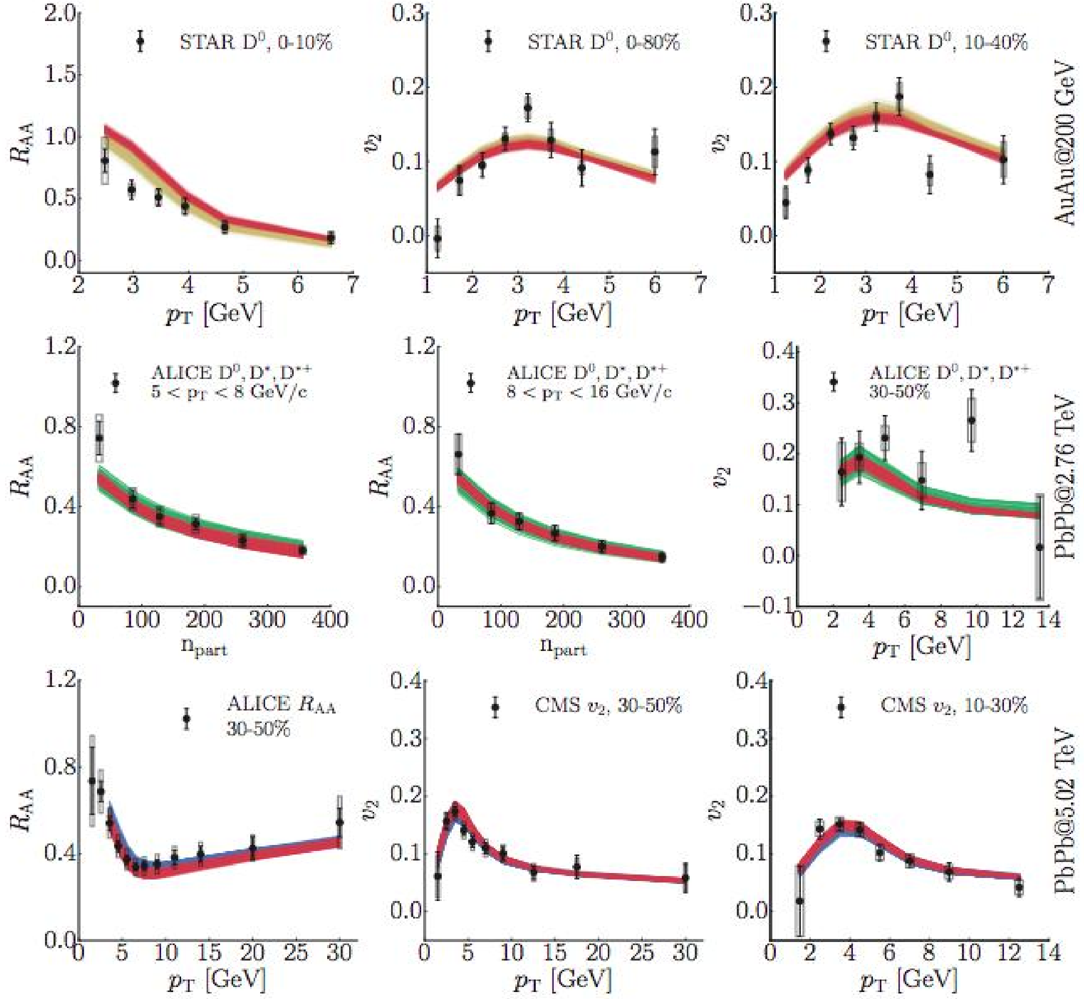
Kai Zhou (Frankfurt U., FIAS), Lingxiao Wang (Frankfurt U., FIAS), Long-Gang Pang (CCNU, Wuhan, Inst. Part. Phys.), Shuzhe Shi (Stony Brook U.)

Mar 27, 2023

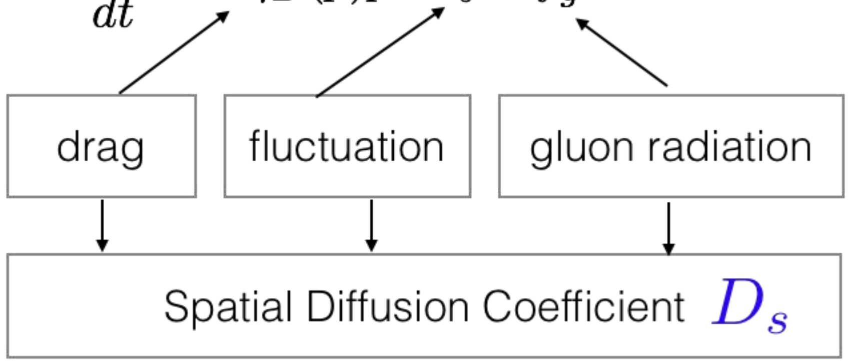
146 pages

e-Print: 2303.15136 [hep-ph]

Bayesian analysis heavy quark diffusion coefficients



$$\frac{d\vec{p}}{dt} = -\eta_D(p)\vec{p} + \vec{\xi} + \vec{f}_g.$$



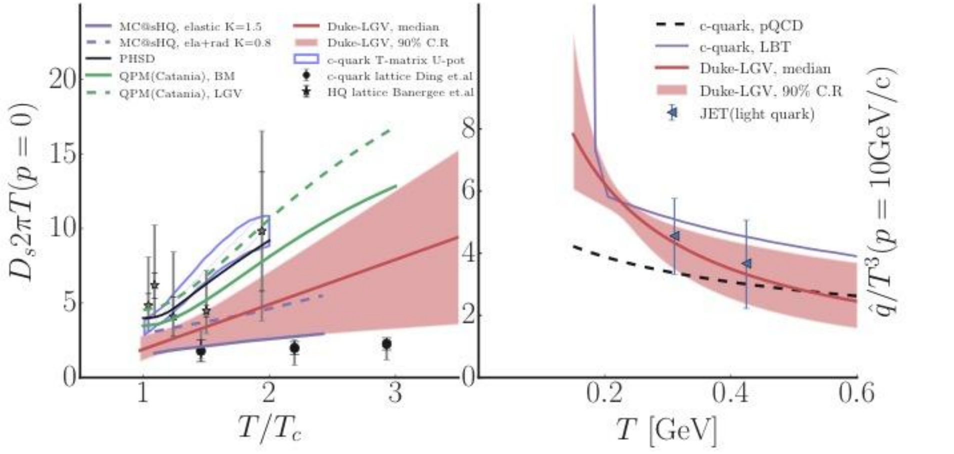


FIG. 12. (Color online) Comparison of the heavy quark diffusion coefficients across multiple approaches available in the literature. (**left**) spatial diffusion coefficient at zero momentum $D_s 2\pi T(p=0)$. (**right**) momentum diffusion coefficient $\hat{q}/T^3$ at $p = 10$ GeV.

Yingru Xu, J.E. Bernhard, S.A. Bass and M. Nahrgang and S.S. Cao, PRC. **97 (2018)**, 014907

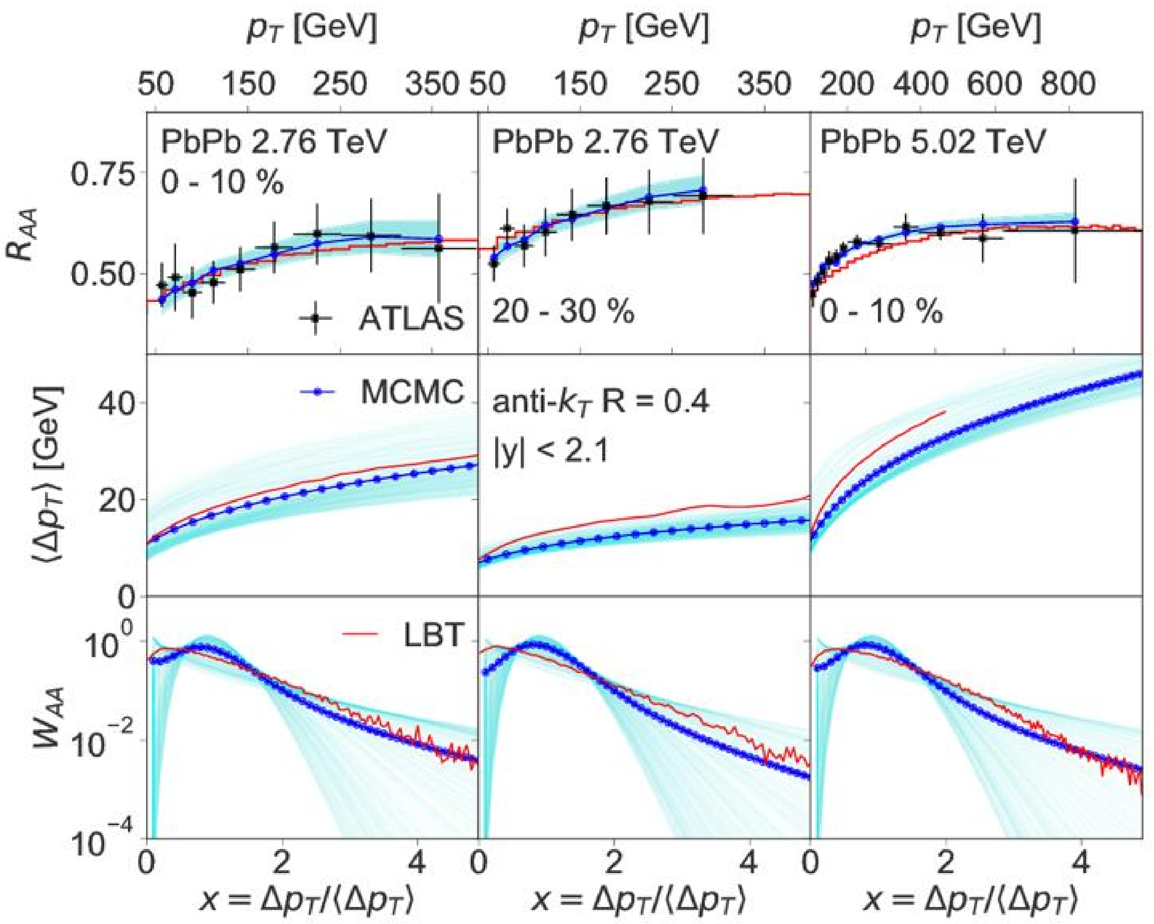
Bayesian extraction of jet energy loss distribution

LBT: Linear Boltzmann Transport model

$$p_a \cdot \partial f_a = \int \sum_{bcd} \prod_{i=b,c,d} \frac{d^3 p_i}{2E_i (2\pi)^3} (f_c f_d - f_a f_b) |\mathcal{M}_{ab \to cd}|^2 \times \frac{\gamma_b}{2} S_2(\hat{s}, \hat{t}, \hat{u}) (2\pi)^4 \delta^4 (p_a + p_b - p_c - p_d) + \text{inelastic}, \quad (1)$$

Modification factor for Bayesian analysis

$$R_{AA}(p_T) \approx \frac{\int d\Delta p_T d\sigma_{pp}^{\text{jet}}(p_T + \Delta p_T) W_{AA}(p_T + \Delta p_T \to p_T, R)}{d\sigma_{pp}^{\text{jet}}(p_T)}.$$



Yayun He, L.G. Pang and X.N. Wang, PRL2019

Temperature dependent $\hat{q}$ from multistage jet energy loss model

LBT | MATTER

MATTER + LBT_1:

$$\frac{\hat{q}}{T^3} = 42 C_R \frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2 \left[\frac{A\left[\ln(\frac{E}{\Lambda}) - \ln B\right]}{\left[\ln(\frac{E}{\Lambda})\right]^2}\theta(Q-Q_0) + \frac{C\left[\ln(\frac{E}{T}) - \ln(D)\right]}{\left[\ln(\frac{ET}{\Lambda^2})\right]^2}\right]$$

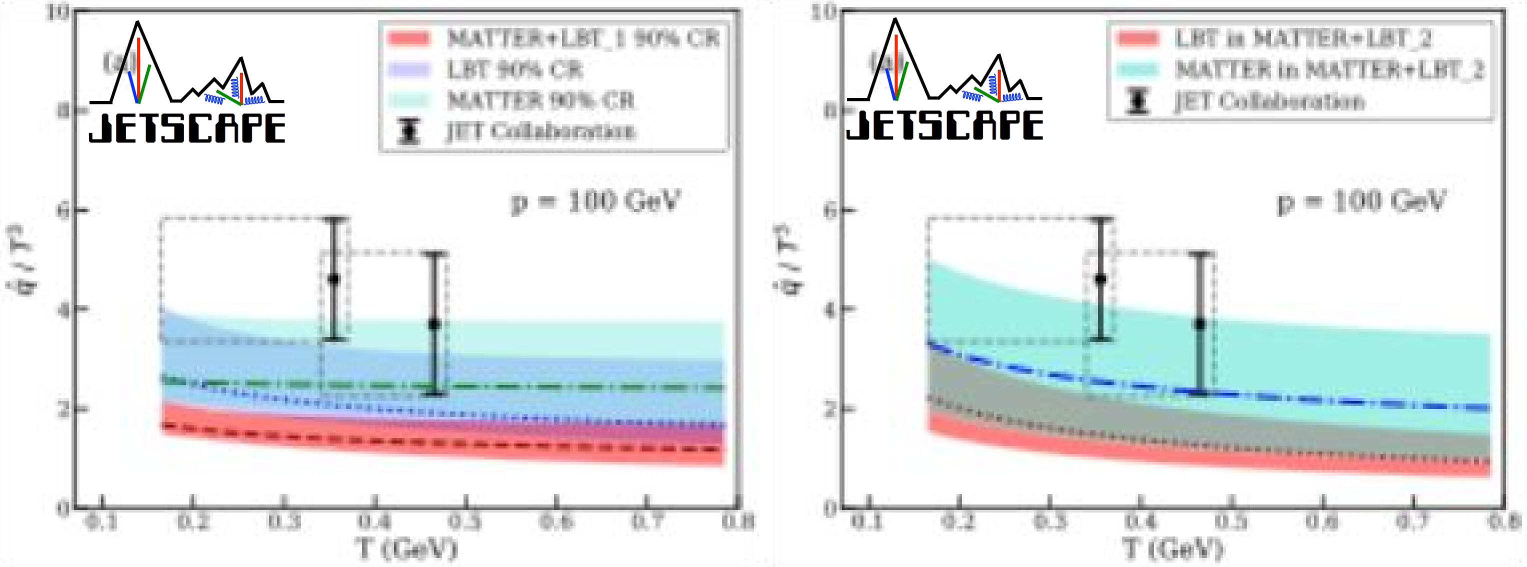
MATTER + LBT_2:

$$\frac{\hat{q}}{T^3} = 42 C_R \frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2 \left\{\frac{A\left[\ln\left(\frac{Q}{\Lambda}\right) - \ln\left(\frac{Q_0}{\Lambda}\right)\right]}{\left[\ln\left(\frac{Q}{\Lambda}\right)\right]^2}\theta(Q-Q_0) + \frac{C\left[\ln\left(\frac{E}{T}\right) - \ln(D)\right]}{\left[\ln\left(\frac{ET}{\Lambda^2}\right)\right]^2}\right\}$$

$$\hat{q} = \frac{\langle \Delta k_T^2 \rangle}{L}$$

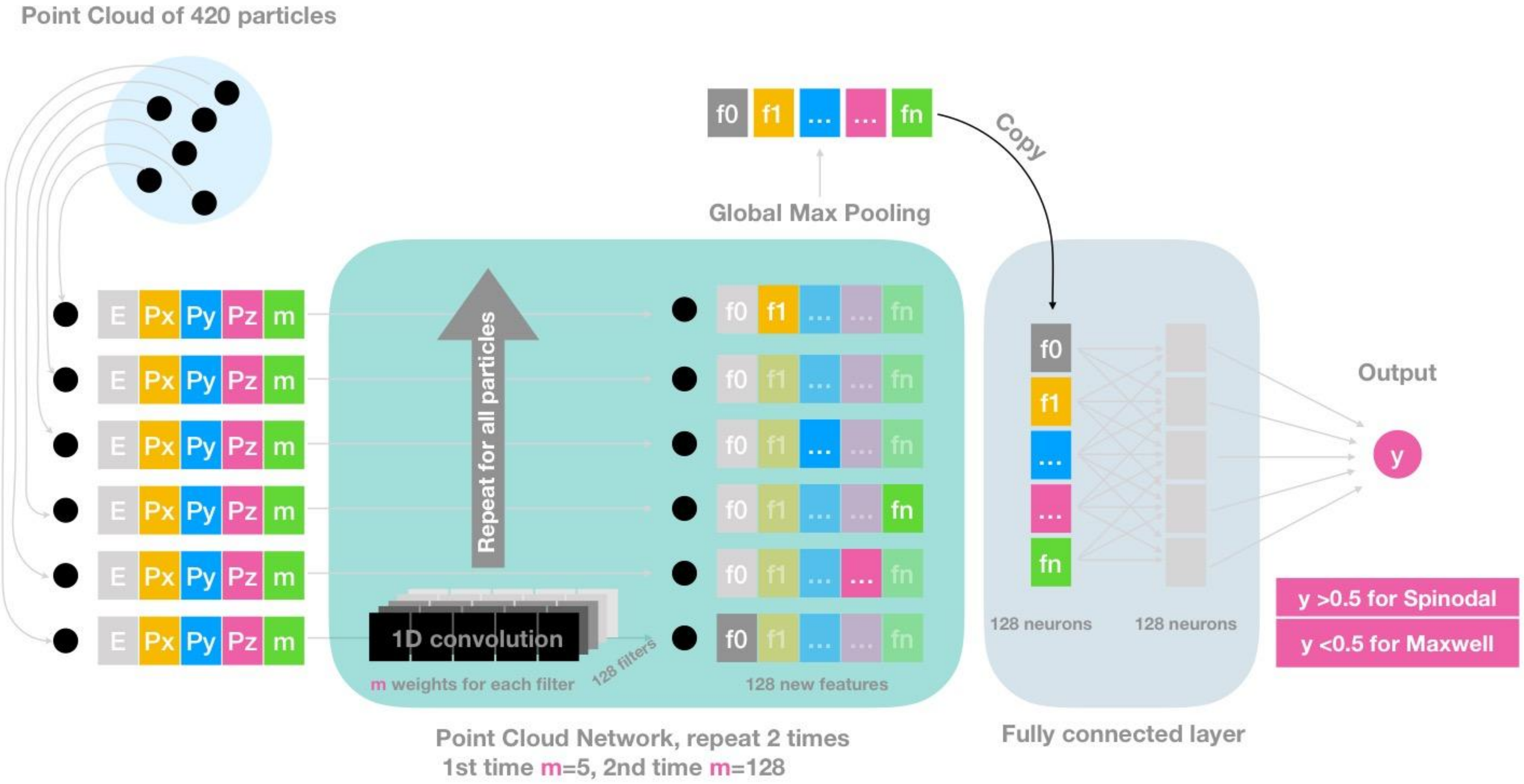
Switching virtuality

$Q_0 \sim 2.09$, 2.86 GeV



HardProbe2018, Ron Soltz for the JETSCAPE collaboration

Point Cloud Net for Maxwell and Spinodal



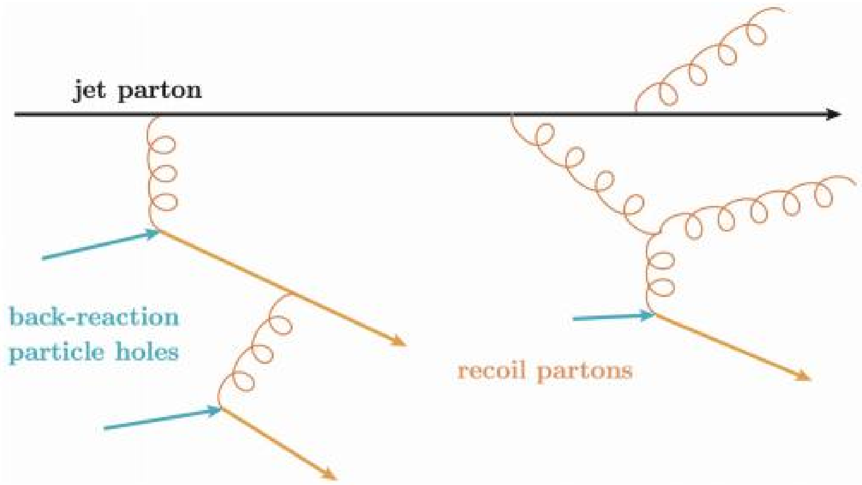
JHEP 12 (2019) 122, J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup

LBT: Linear Boltzmann Transport

$$p_1 \partial f_1 = - \int dp_2 dp_3 dp_4 (f_1 f_2 - f_3 f_4) \left| M_{12 \to 34} \right|^2 (2\pi)^4 \delta^4 (\sum_i p^i) + inelastic$$

Medium-induced gluon(HT):

$$\frac{dN_g}{dz d^2 k_\perp dt} \approx \frac{2 C_A \alpha_s}{\pi k_\perp^4} P(z) \hat{q} (\hat{p} \cdot u) sin^2 \frac{k_\perp^2 (t - t_0)}{4z(1-z)E}$$

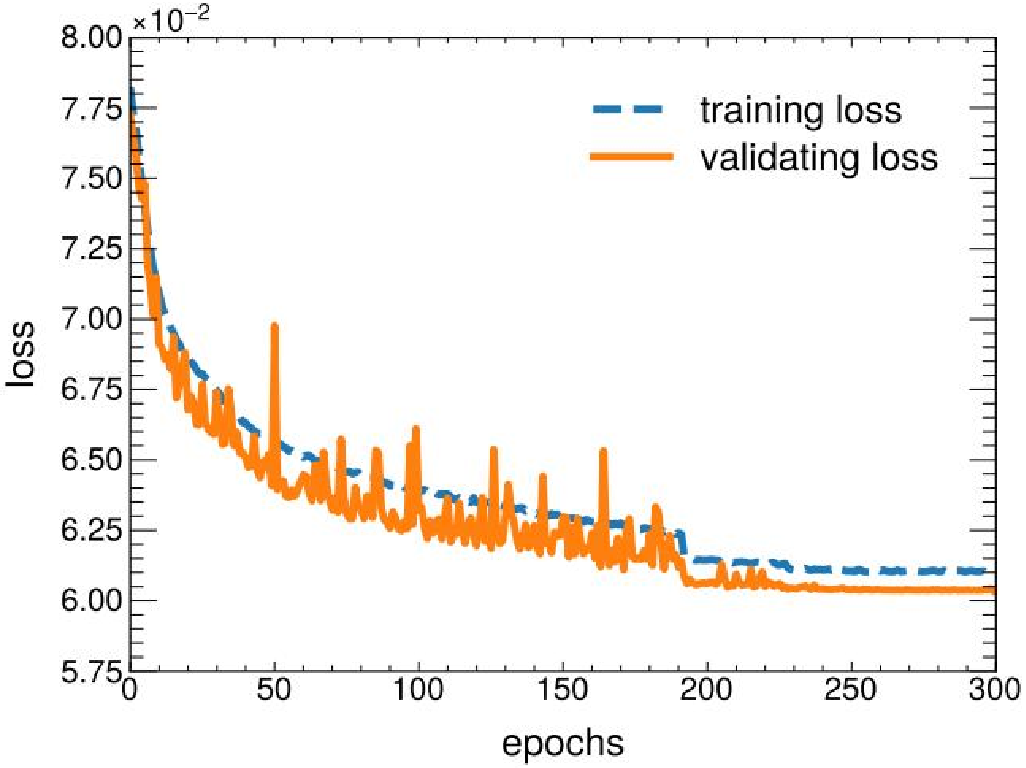


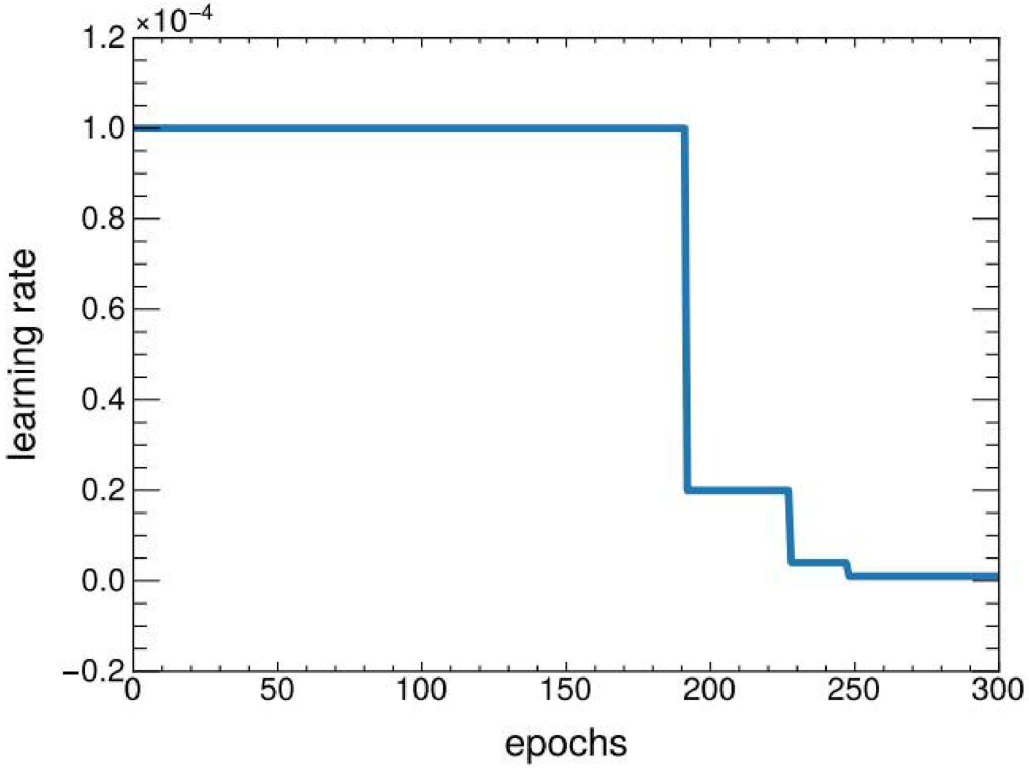
Tracked partons:

- Jet shower partons
- Thermal recoil partons
- Radiated gluons
- Negative partons(Back reaction induced by energy-momentum conservation)

YY He, T Luo, XN Wang, Y Zhu, PRC 91 (2015) 054908, PRC 97 (2018) 1, 019902

Training process





The shape of mach cones for selected events