深度学习与高能核物理

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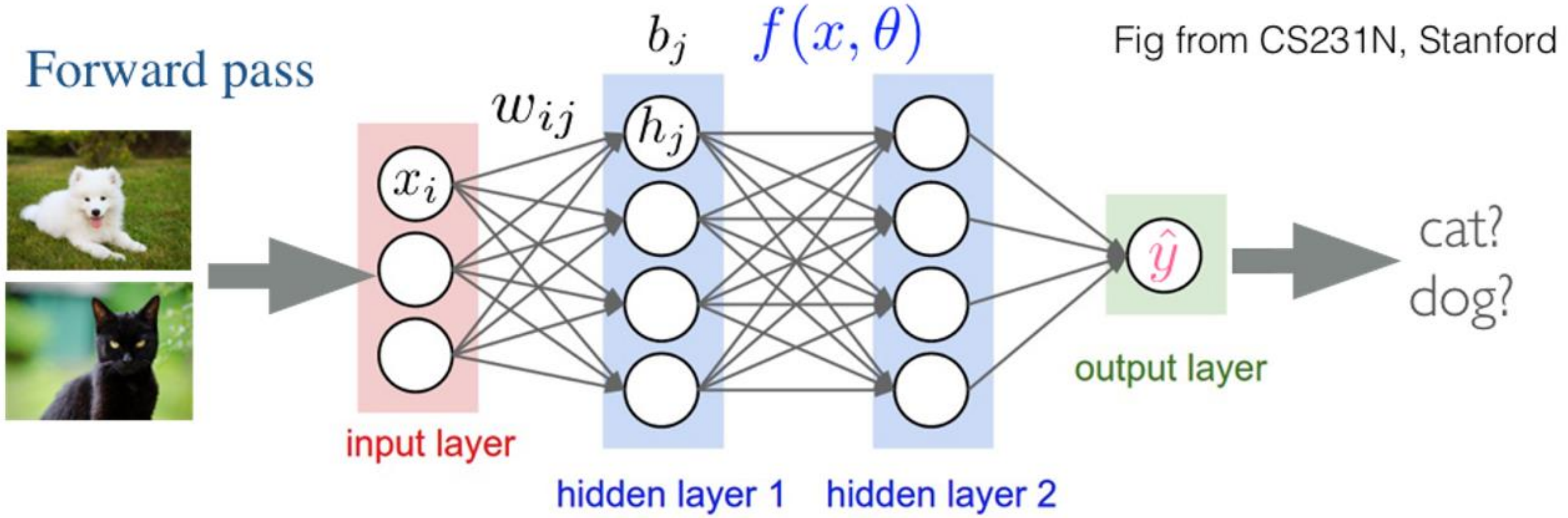
第十届华大 QCD 讲习班

深度学习是什么

Hero of deep learning: Yann LeCun

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

深度神经网络作为参数化的泛函模块



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

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

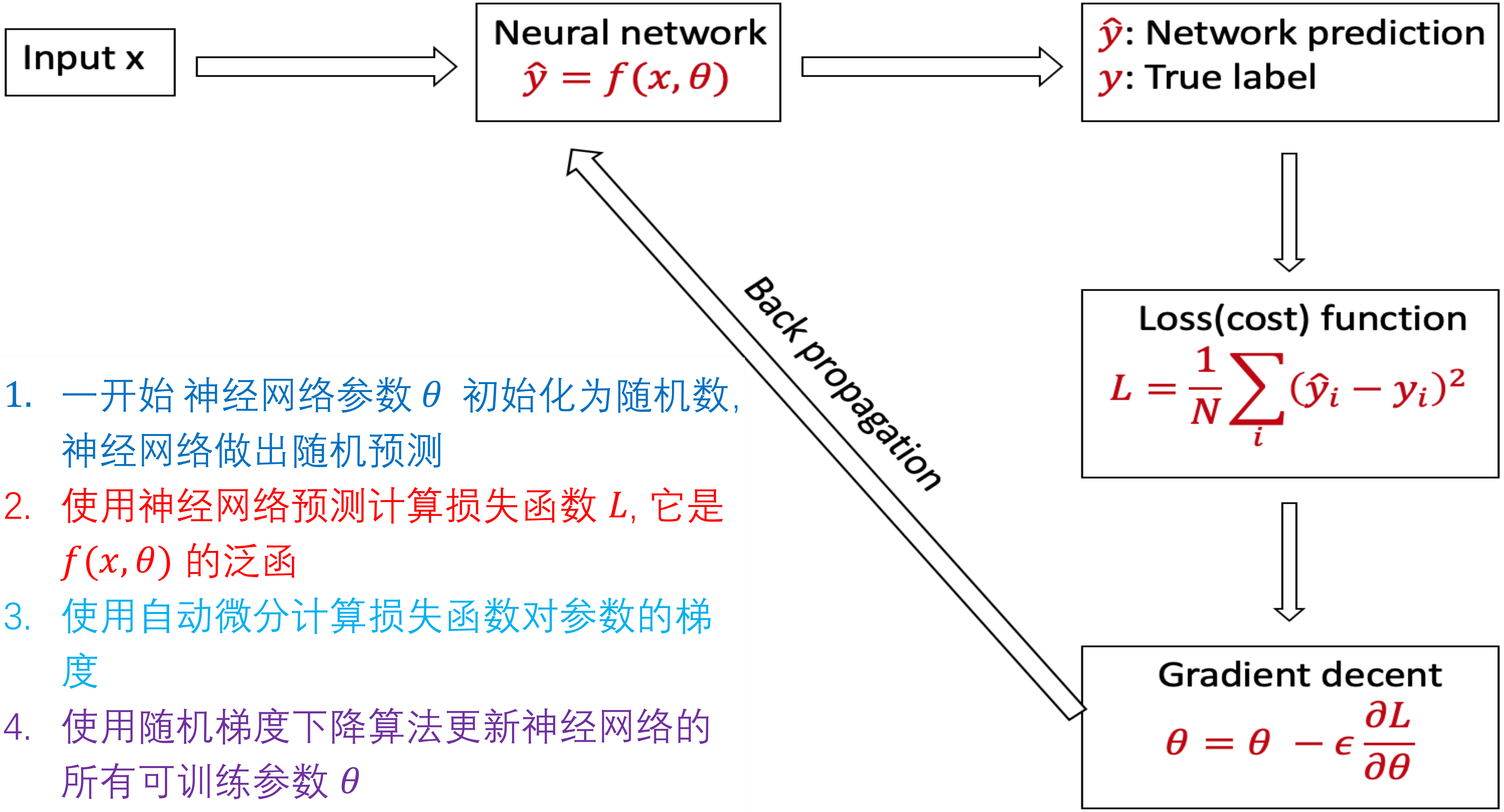
(b) ReLU

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

(c) PReLU

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

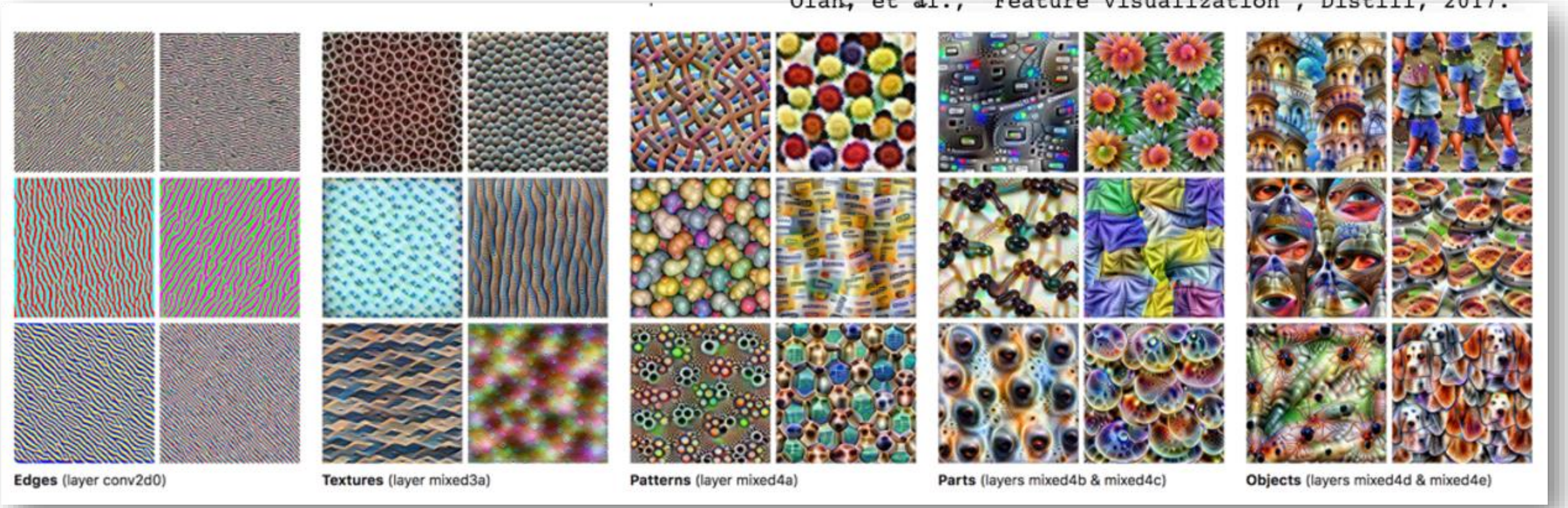
深度神经网络如何学习



1. 一开始 神经网络参数 θ 初始化为随机数，神经网络做出随机预测
2. 使用神经网络预测计算损失函数 L，它是 $f(x, \theta)$ 的泛函
3. 使用自动微分计算损失函数对参数的梯度
4. 使用随机梯度下降算法更新神经网络的所有可训练参数 θ

学习层级化的表示

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



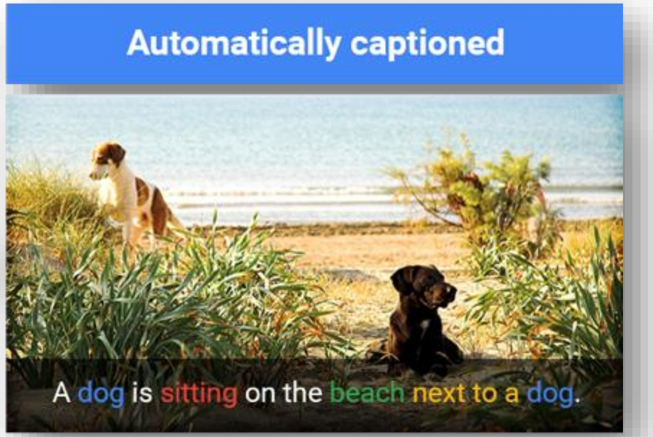
Shallow layers

Deep layers

在不同的数据之间建立映射

Google, DeepMind

Image to text



需要满足的条件

1. 映射真实存在
2. DNN 有足够的表示能力
3. 足够多的训练样本

深度学习强大的非线性映射能力

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

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

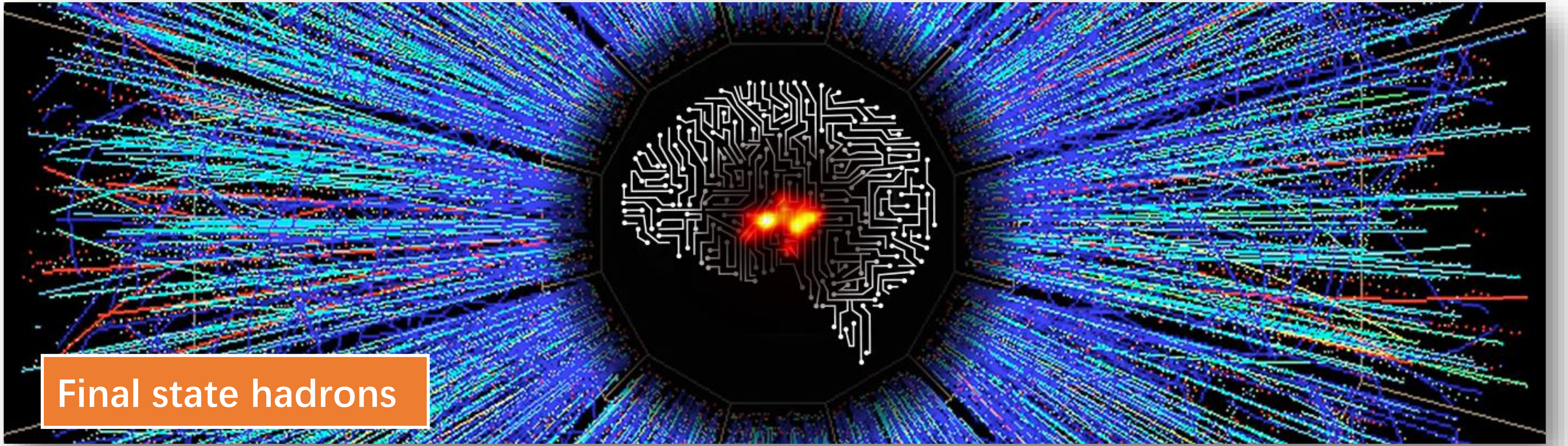
as a 1990s Saturday morning cartoon as digital art in a steampunk style

→

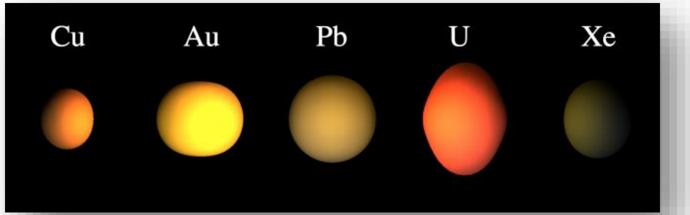
DALL·E 2 can create original, realistic images and art from a text description. It can combine concepts, attributes, and styles.

另有开源的 text2image 生成工具：Stable Diffusion

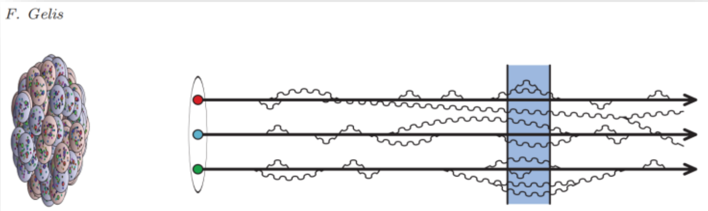
深度学习解高能核物理中的反问题



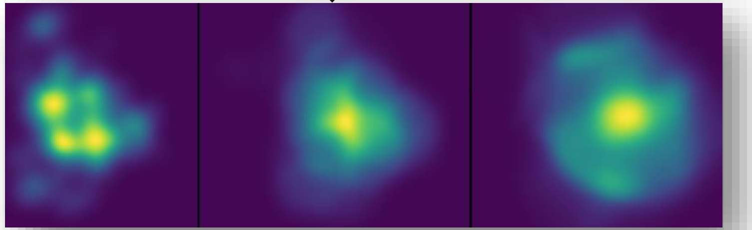
Non-linear mapping



（1）核结构

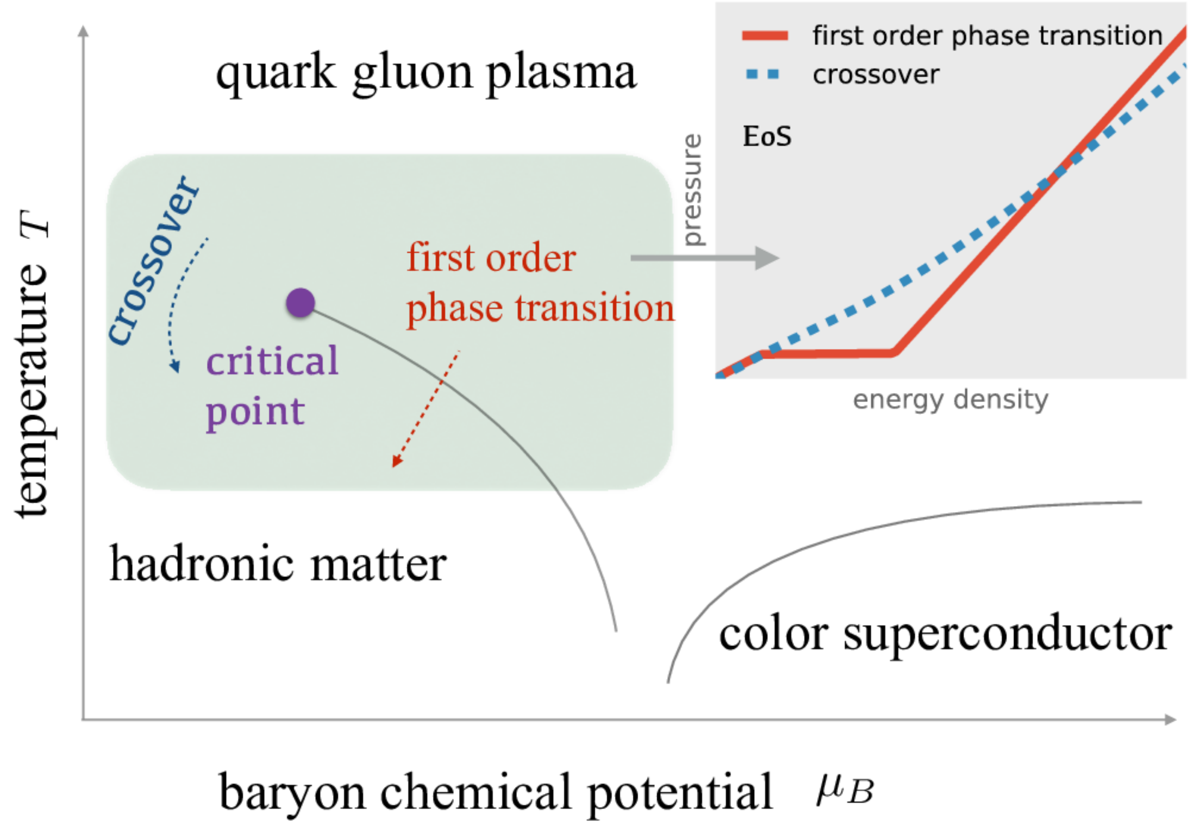


（2）初态部分子分布

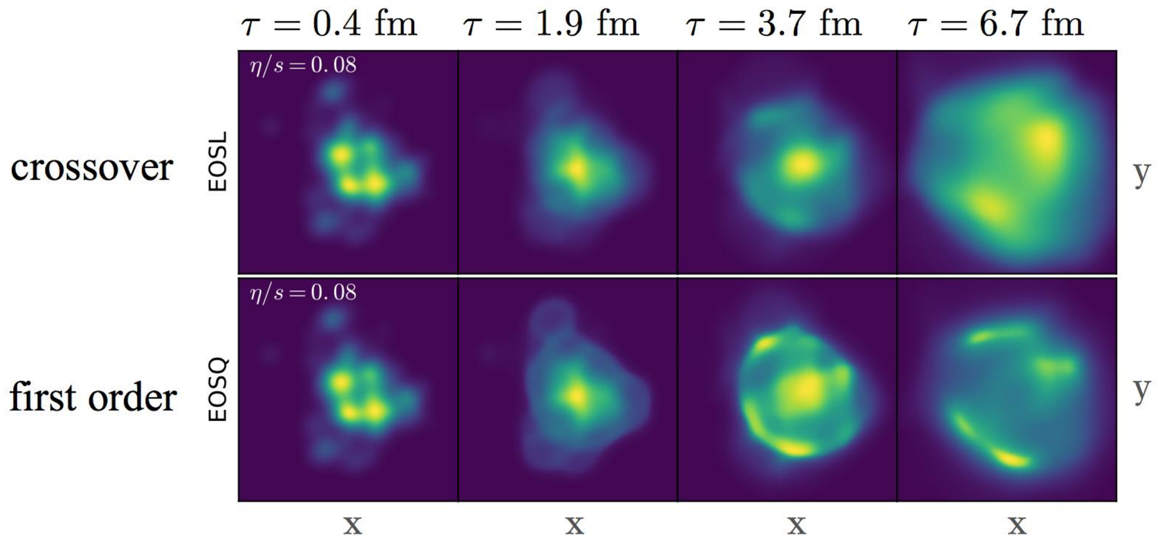


（3）QGP性质与核物质相变

深度学习研究核物质状态方程与相变

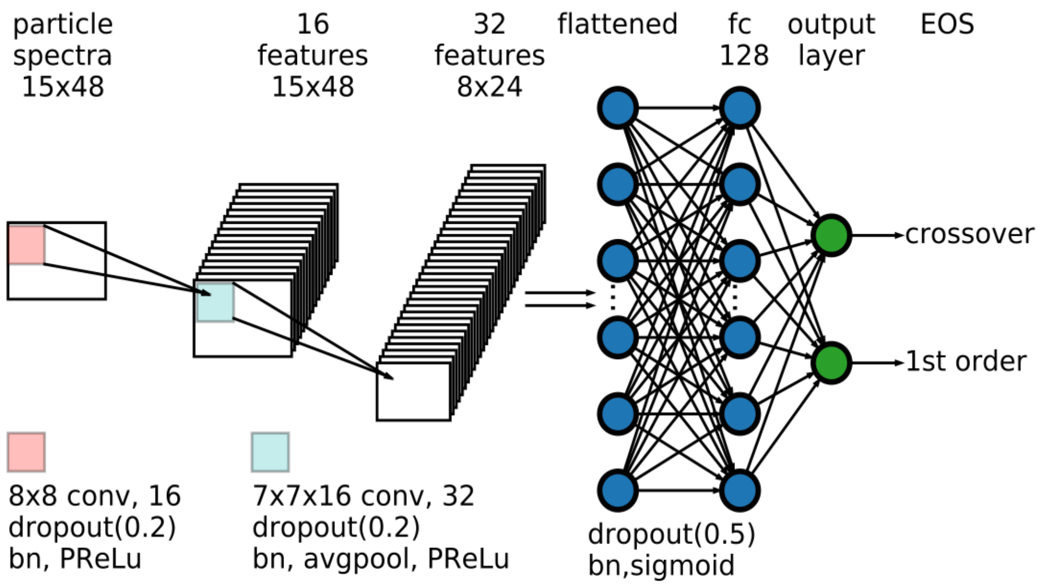


$$\nabla_\mu T^{\mu\nu} = 0$$



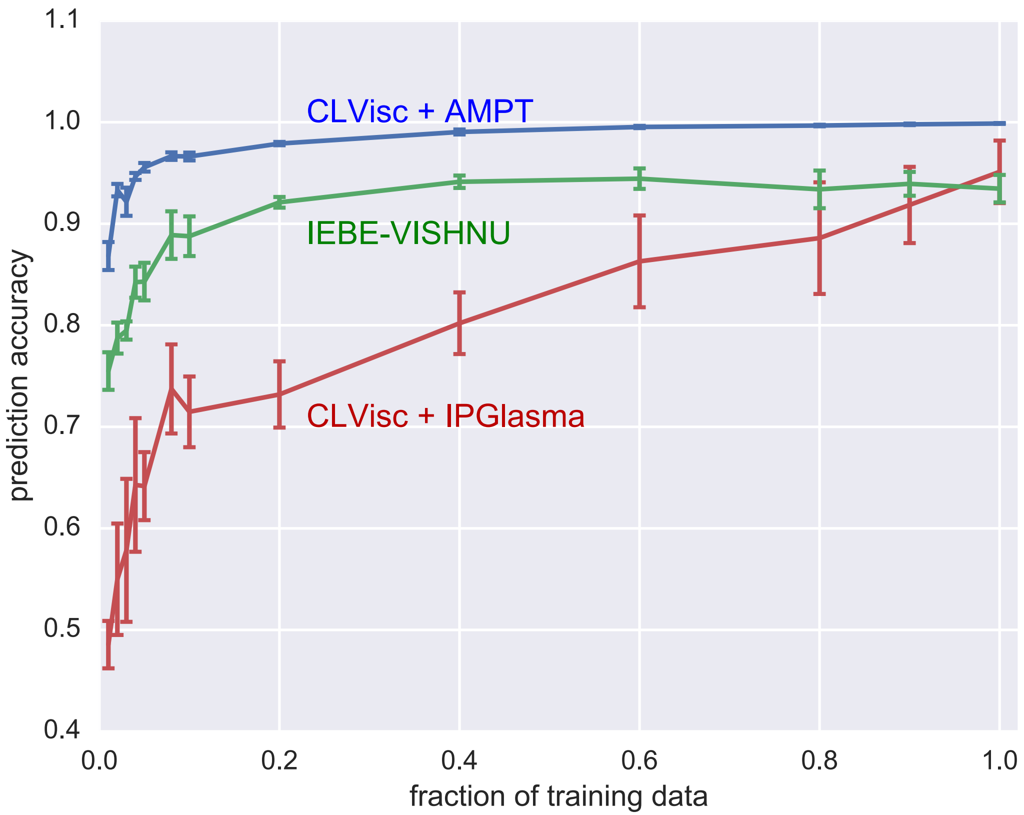
CLVisc 3+1D relativistic hydrodynamics

深度学习研究核物质状态方程与相变



$$l(\theta) = \boxed{-\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)]} + \boxed{\lambda||\theta||_2^2}$$

cross entropy loss　　L2 regularization

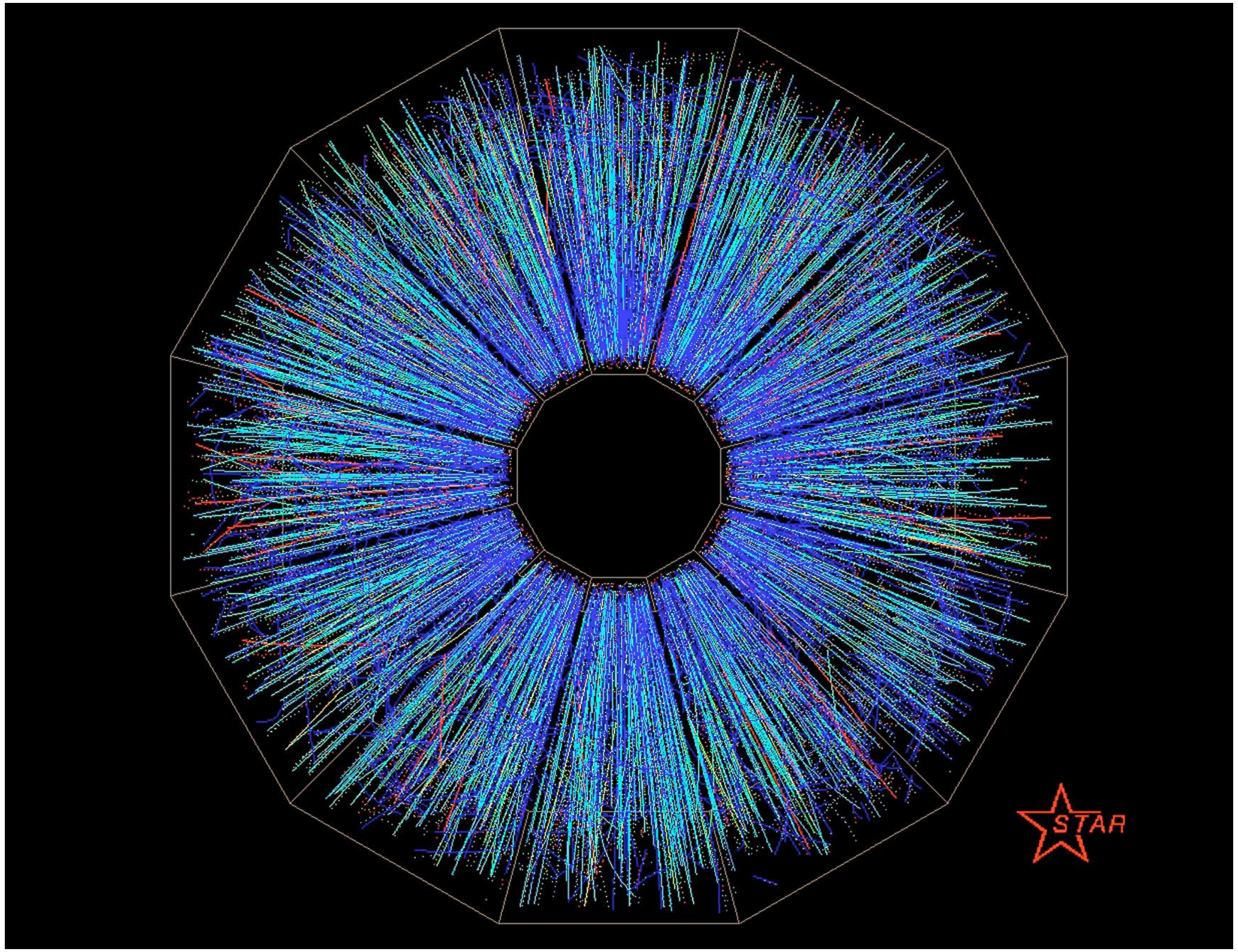


Nature Communications 2018, LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang.

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

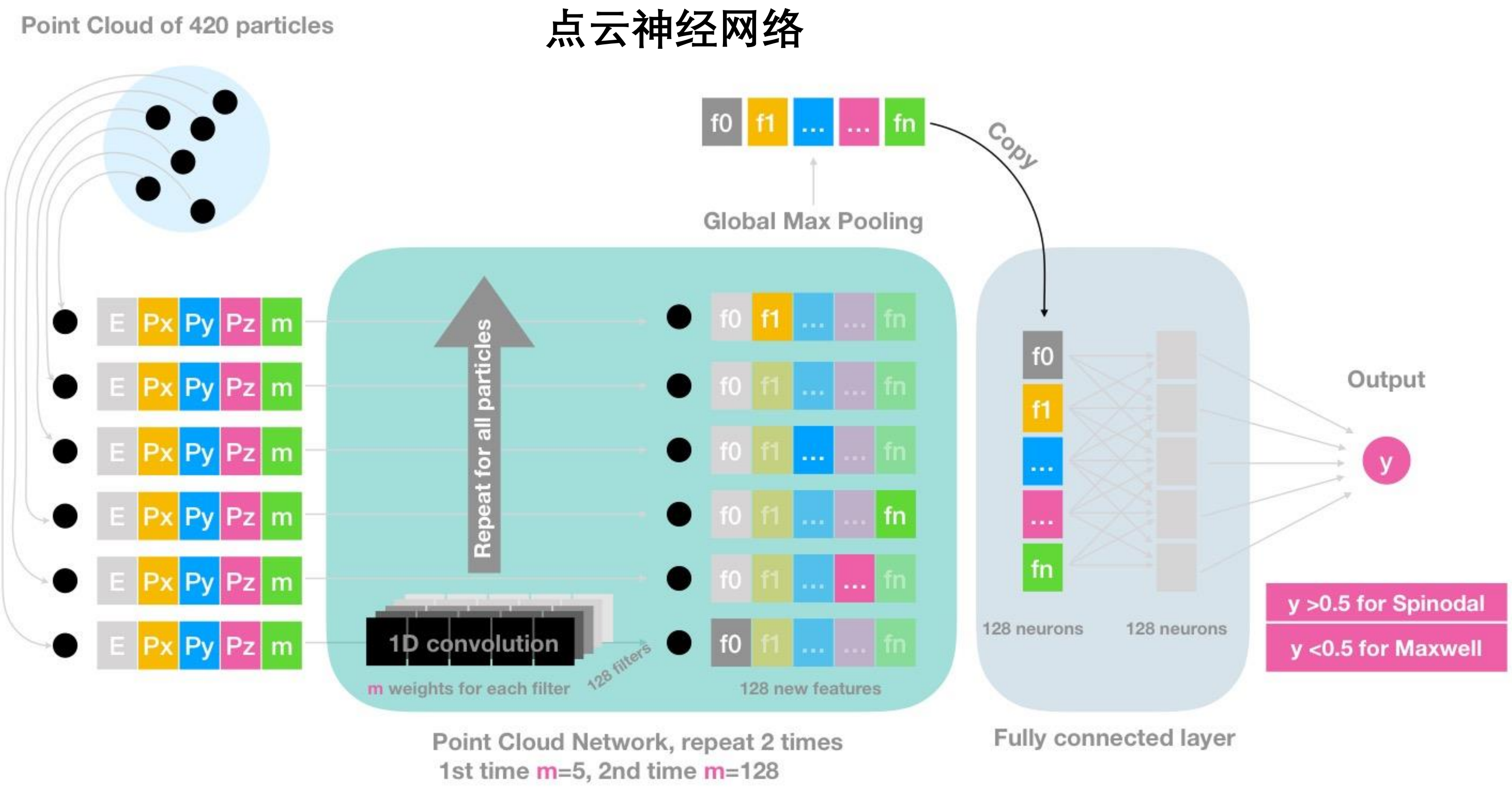
Data representation



- 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
…				

Maxwell 和 Spinodal 类型一阶相变分类

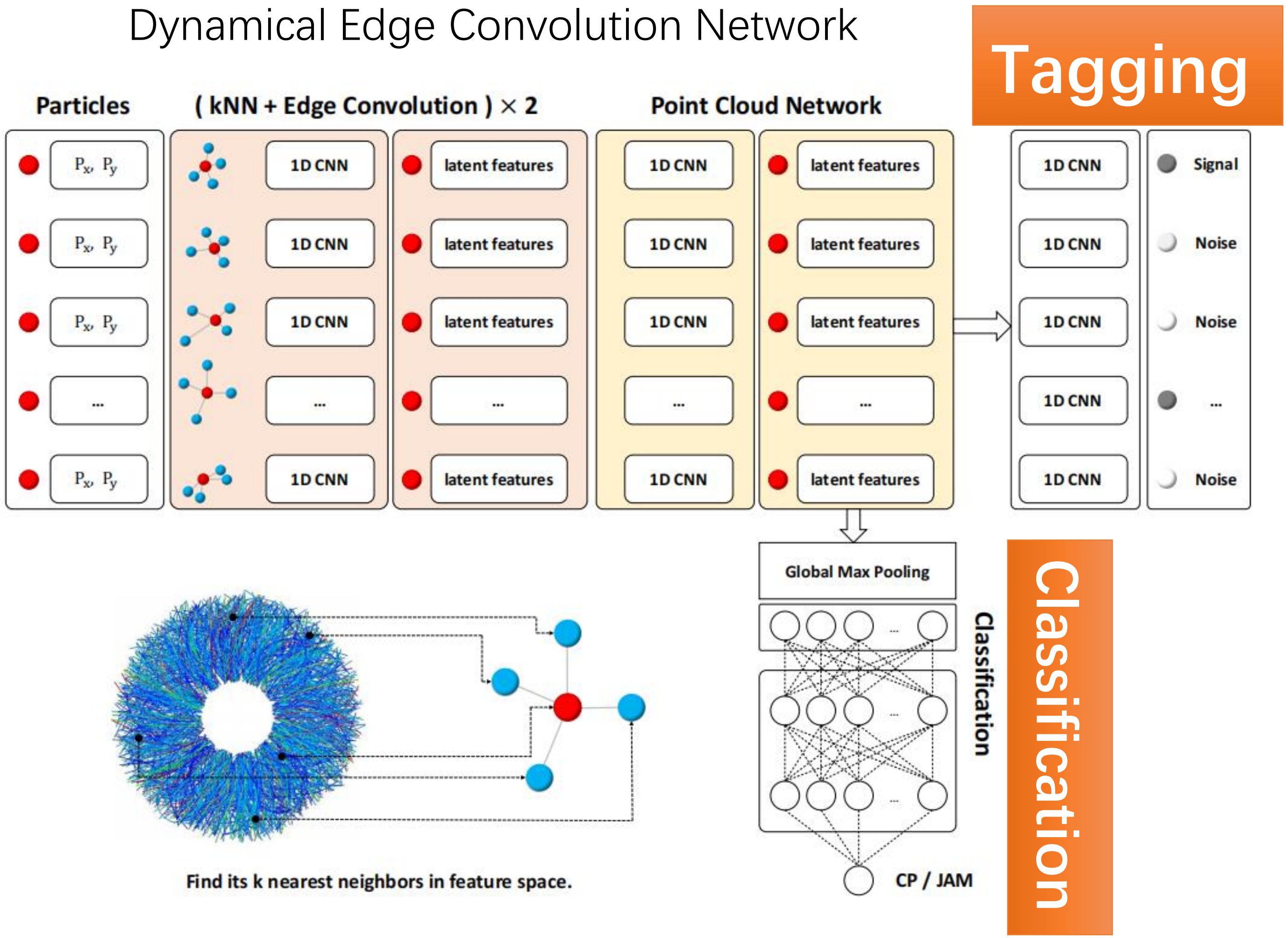


JHEP 12 (2019) 122, J. Steinheimer, L.G. Pang, K. Zhou, V. Koch and J. Randrup

通过动量空间的自相似寻找相变临界信号

分形的自相似结构

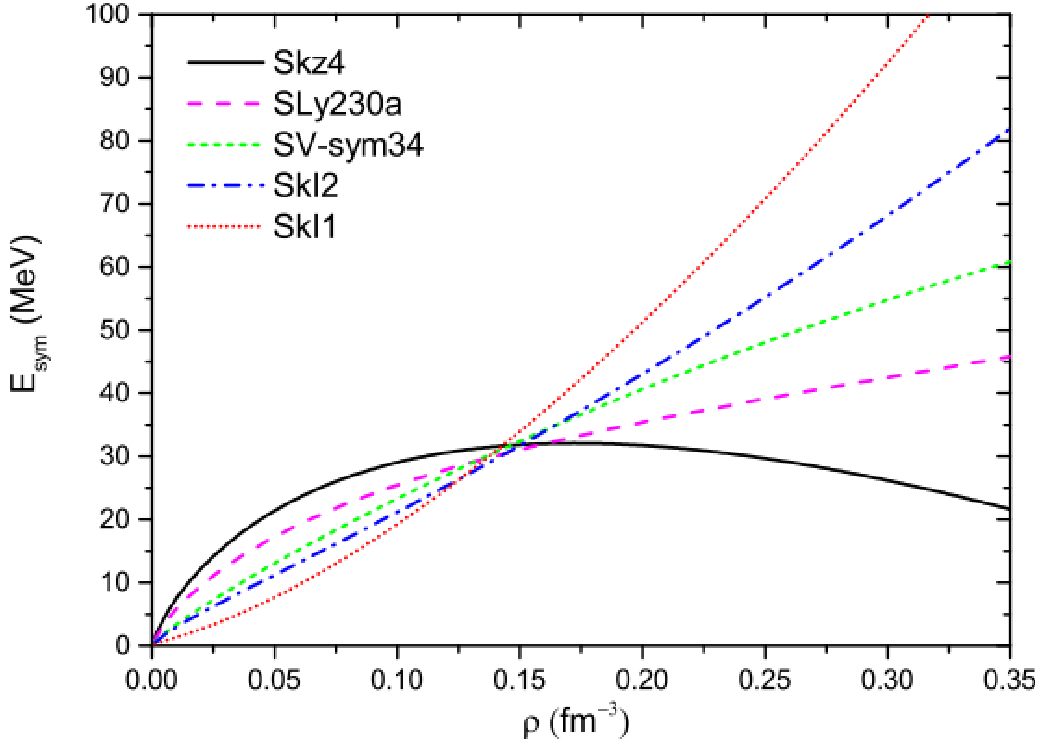
Dynamical Edge Convolution Network



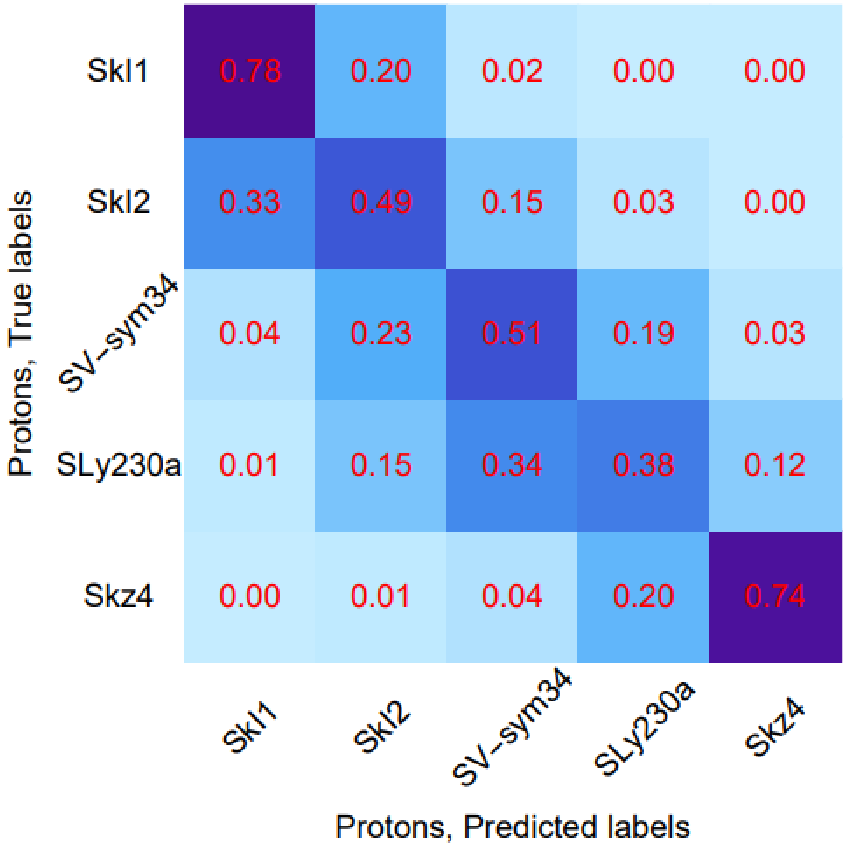
PLB 827(2022) 137001, Y.-G. Huang, L.-G. Pang, X.F. Luo and X.-N. Wang

高密区核物质状态方程

Skyrme potential + IMQMD



off-diagonal = misclassified



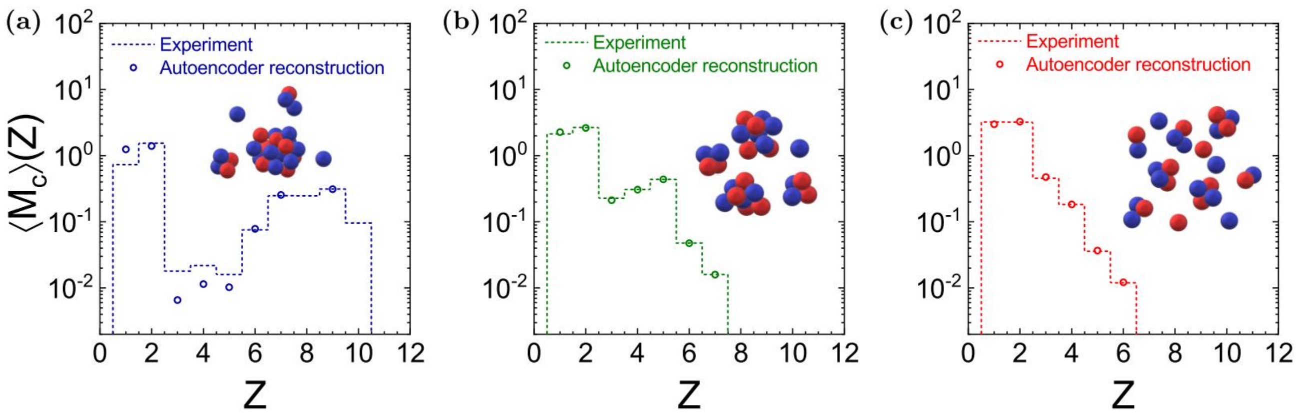
Phys.Lett.B 822 (2021) 136669, Y.J Wang, F.P. Li, Q.F. Li, H.L. L¨u, and K. Zhou

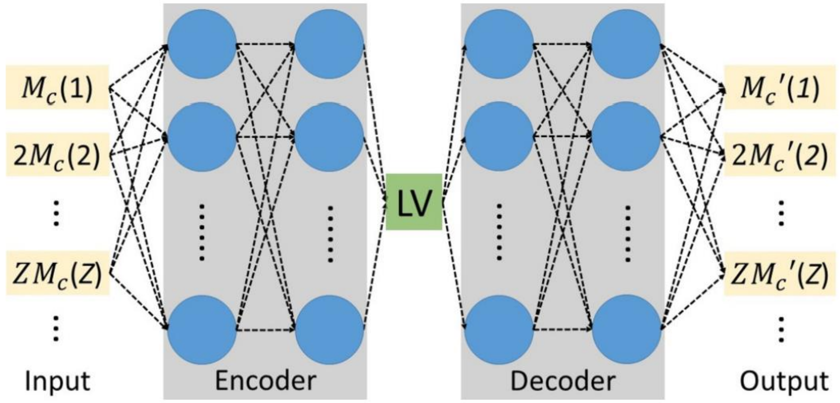
使用自编码机学习核液气相变序参数

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

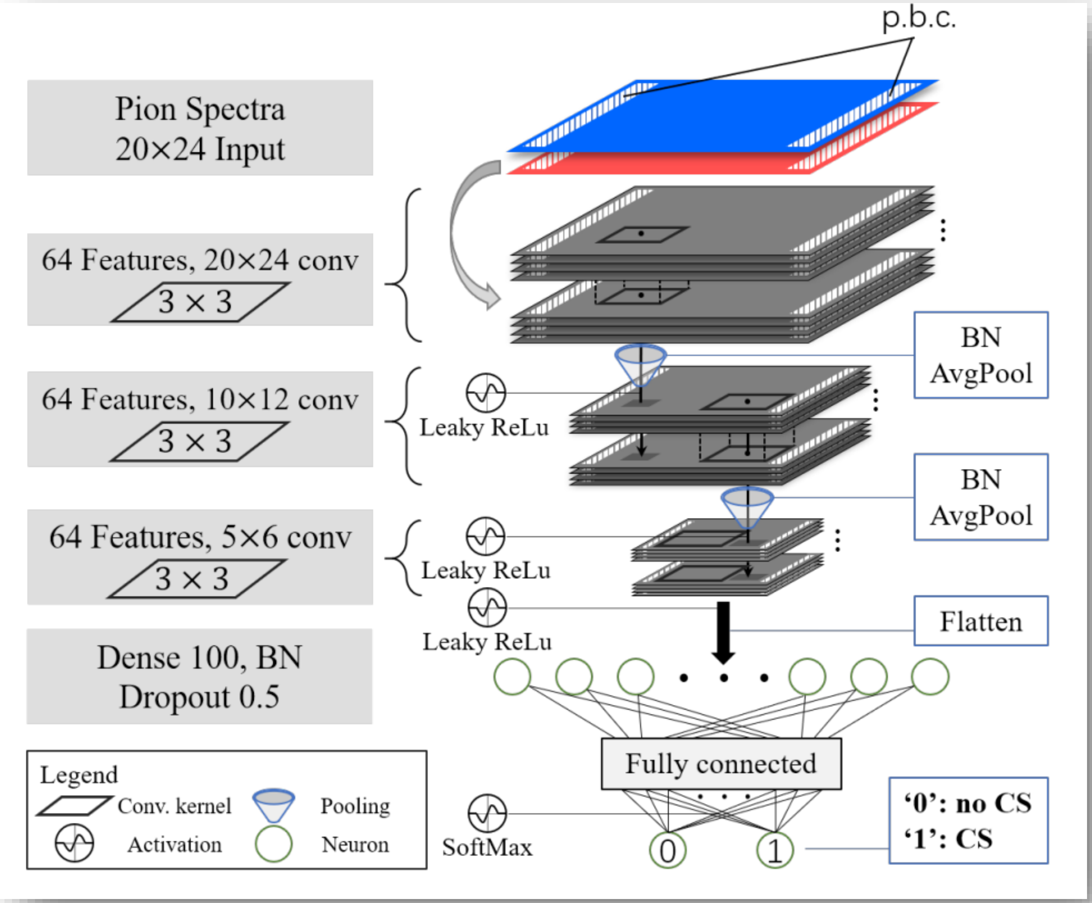
Nuclear liquid-gas phase transition with machine learning

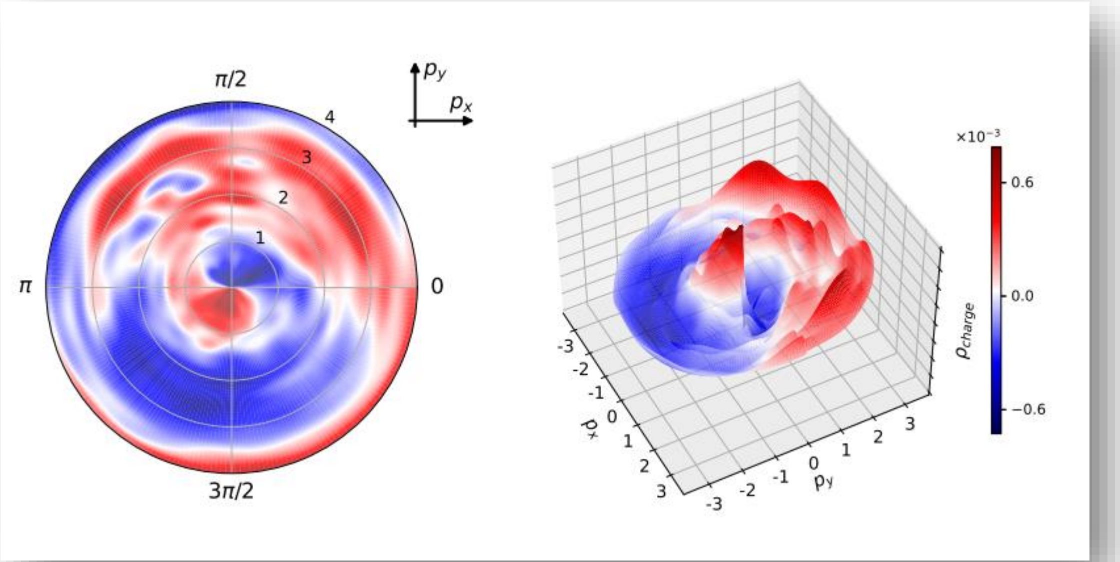
Rui Wang,[1,2,*] Yu-Gang Ma,[1,2,†] R. Wada,[3] Lie-Wen Chen,[4] Wan-Bing He,[1] Huan-Ling Liu,[2] and Kai-Jia Sun[3,5]





Detecting CME via deep learning





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

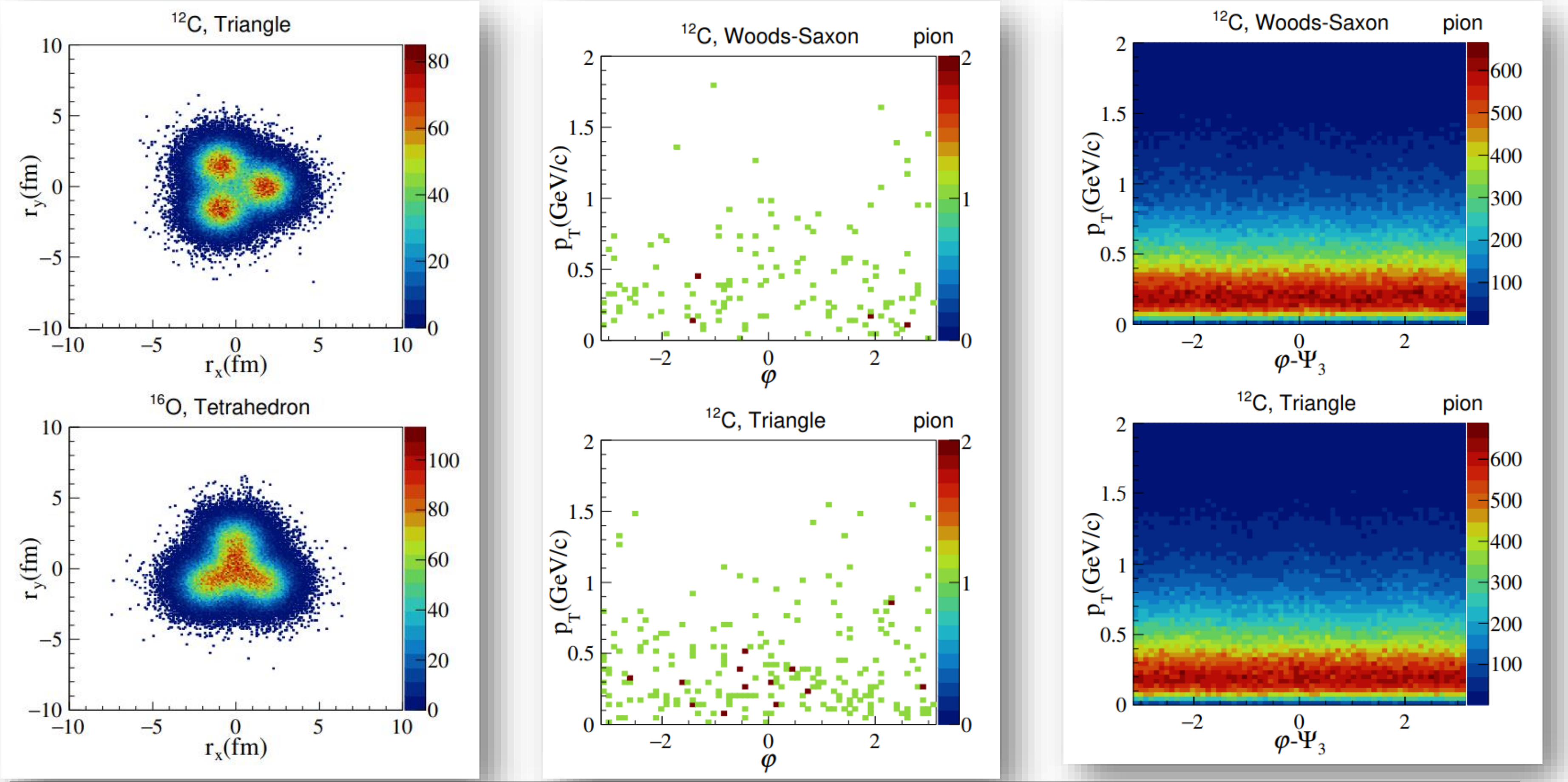
2105.13761, Y.-S. Zhao, L. Wang, K. Zhou, and X.-G. Huang (2021)

Identifying the α-clustering structure

α clusters

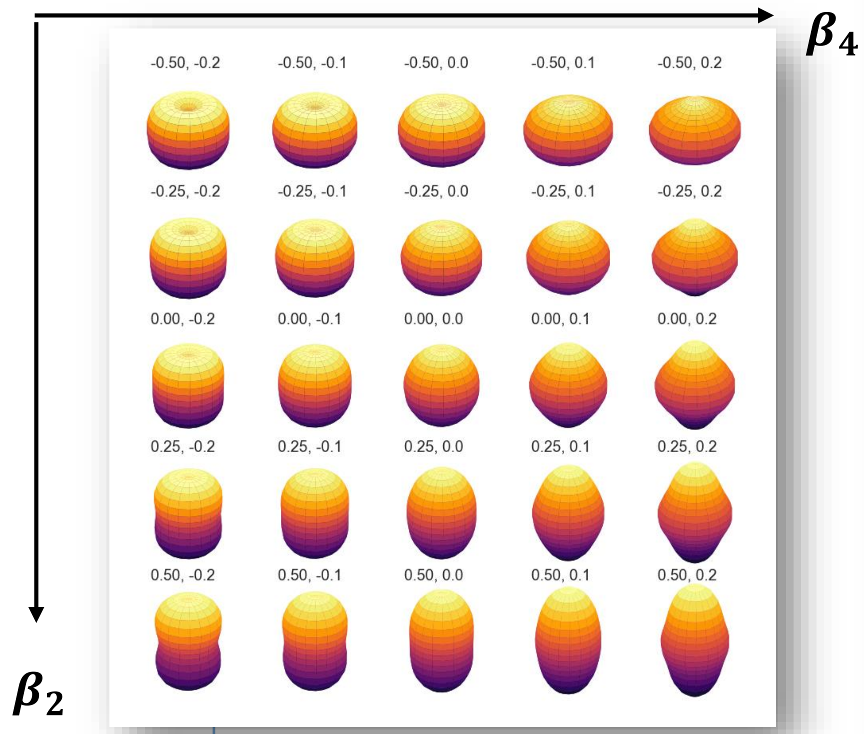
Fail in EbE

Succeed with 4000-events averag

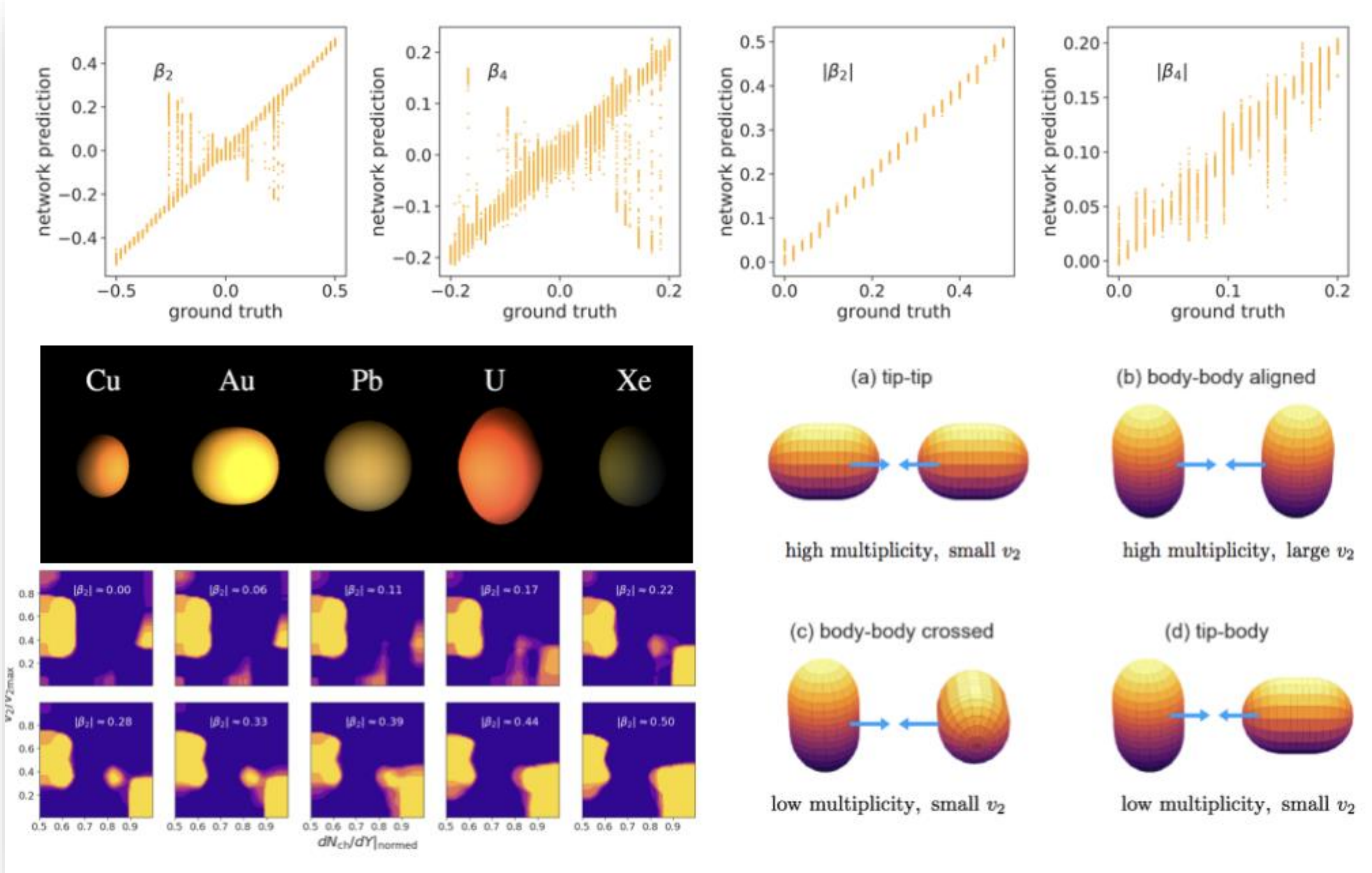


Junjie He, Wan-Bing He, Yu-Gang Ma, Song ZhangPhys. Rev. C 104, 044902 (2021)

Determining nuclear deformation



Data: Trento + Matching



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

Stacked U-net for relativistic hydrodynamics

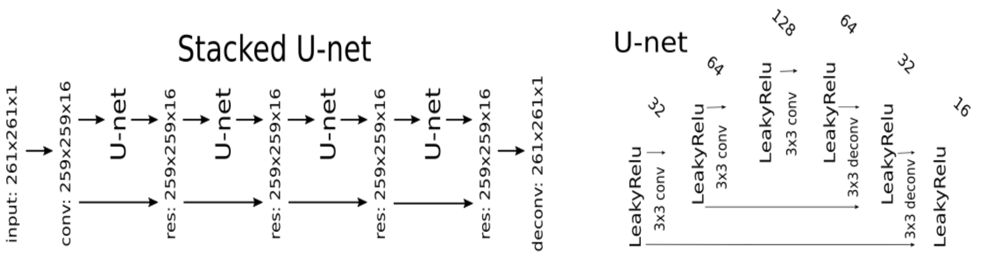
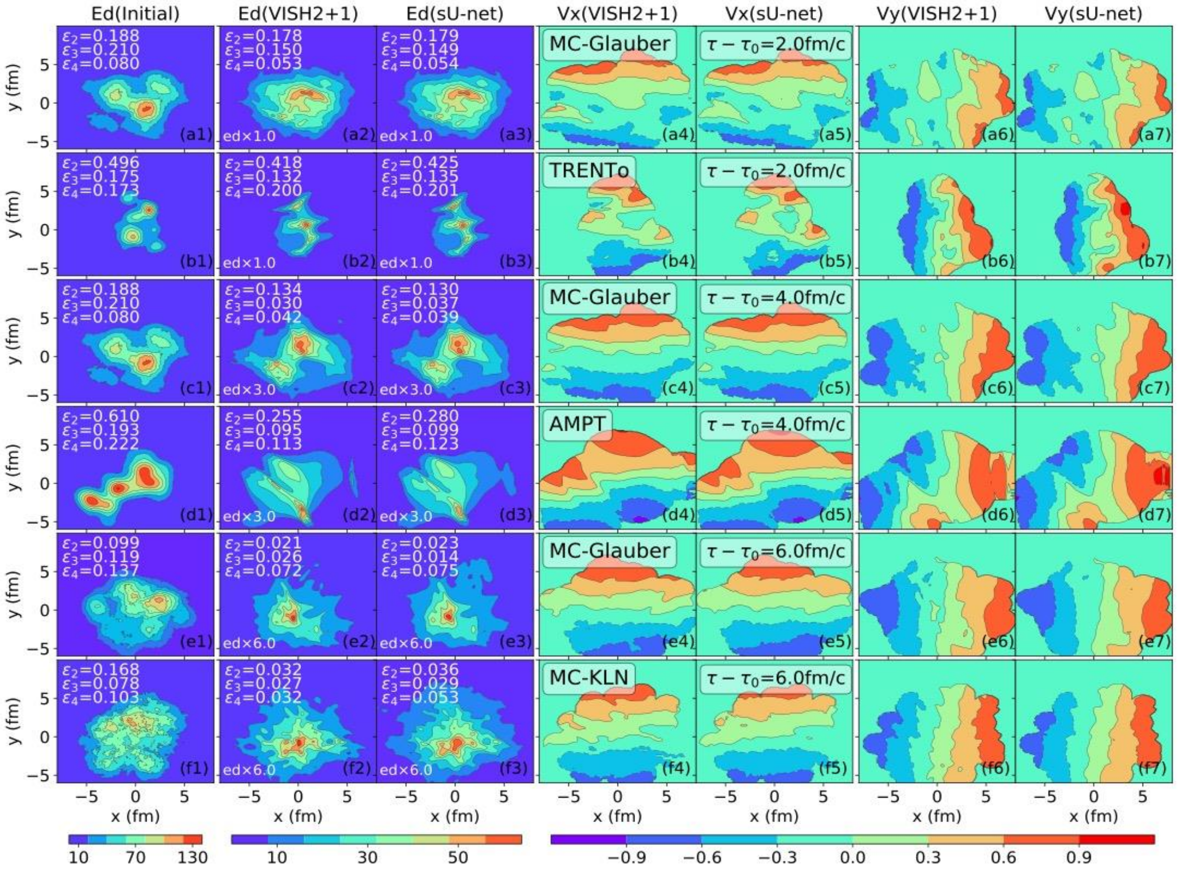


FIG. 1: An illustration of the encode-decode network, **stacked U-net**, which consists of the input and out layers and four residual U-net blocks. The right figure shows the U-net structure, and the depth of the hidden layer is written on the top of them.

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; Phys. Rev. Research **3**, 023256, H.Huang, B.Xiao, H.Xiong, Z.Liu, Z.Wu, Y. Mu and H.Song

使用主动学习排除非物理的状态方程

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

4 parameters from 3D Ising mode

QCD EoS

Lables for classification

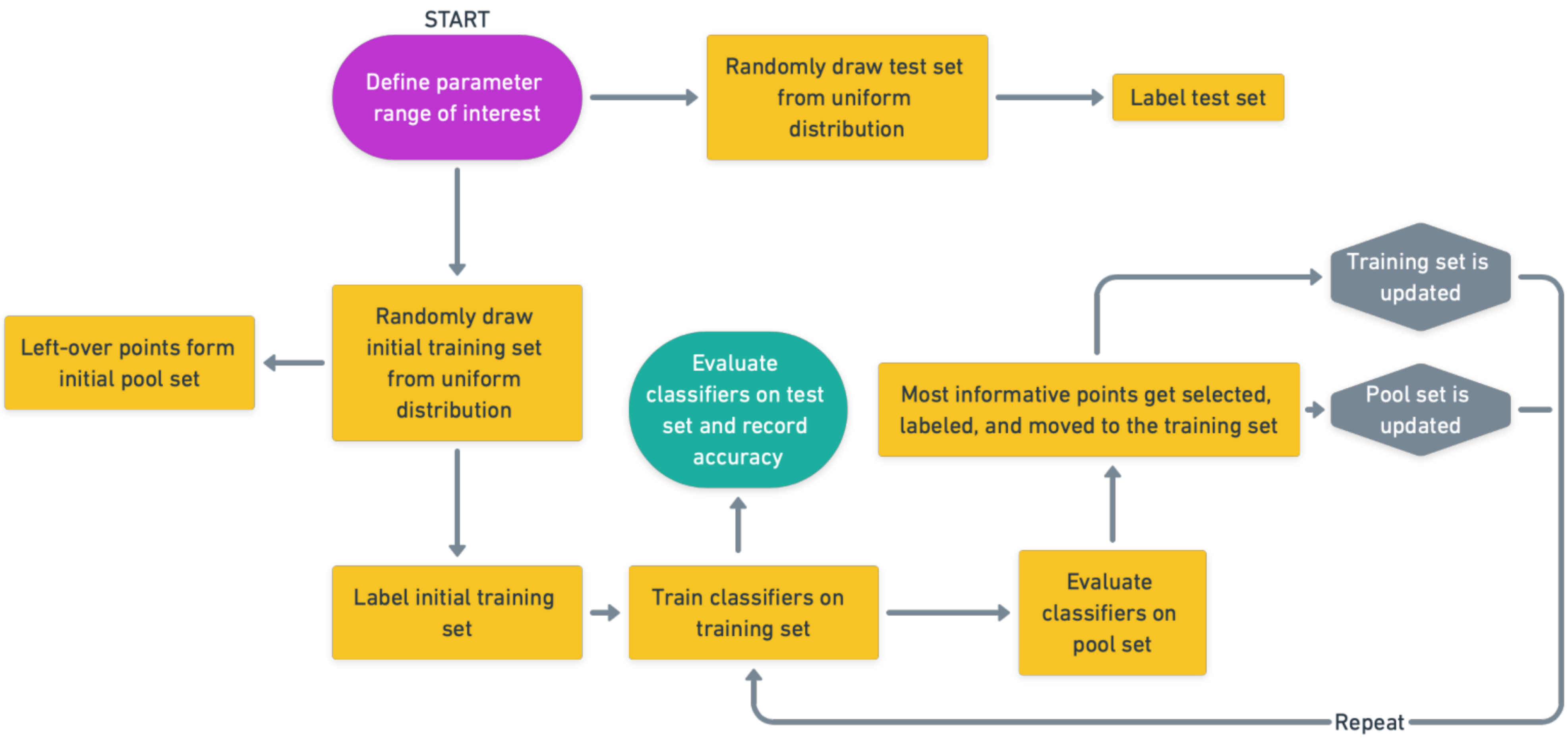
$\boxed{\text{Acceptable = Stable + Causal}}$

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

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

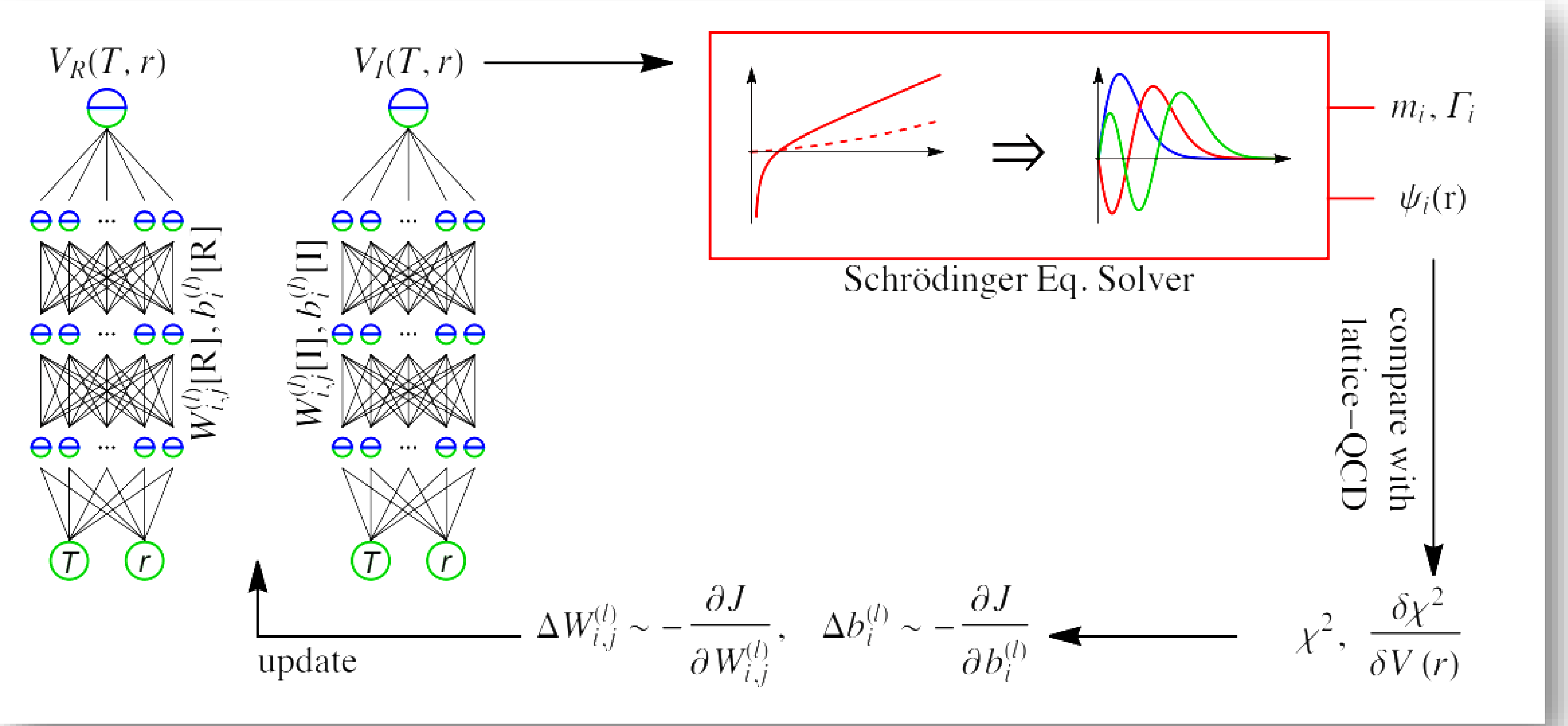
2203.13876, D. Mroczek, M. Hjorth-Jensen, J. Noronha-Hostler, P. Parotto, C. Ratti, and R. Vilalta

使用主动学习排除非物理的状态方程



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

将神经网络用作多体量子计算的波函数

Tu fully include spin-isospin correlations, we have introduced a generalized back-flow ansatz

$$\hat{\psi}(X) = \det \begin{pmatrix} \phi_1(x_1; x_{j\neq 1}) & \phi_1(x_2; \{x_{j\neq 2}\}) & \dots & \phi_1(x_A; \{x_{j\neq A}\}) \\ \phi_2(x_1; x_{j\neq 1}) & \phi_2(x_2; \{x_{j\neq 2}\}) & \dots & \phi_2(x_A; \{x_{j\neq A}\}) \\ \vdots & \vdots & \dots & \vdots \\ \phi_A(x_1; x_{j\neq 1}) & \phi_A(x_2; \{x_{j\neq 2}\}) & \dots & \phi_A(x_A; \{x_{j\neq A}\}) \end{pmatrix},$$

Each of the $\phi_i(x_j; x_{k\neq j})$ must be permutation invariant must be invariant under the exchange of the order of $x_{k\neq j}$. We have achieved this using the Deep-Sets architecture;

This approach scales polynomially with A and allows us to treat larger nuclei than currently possible with the GFMC and AFDMC methods;

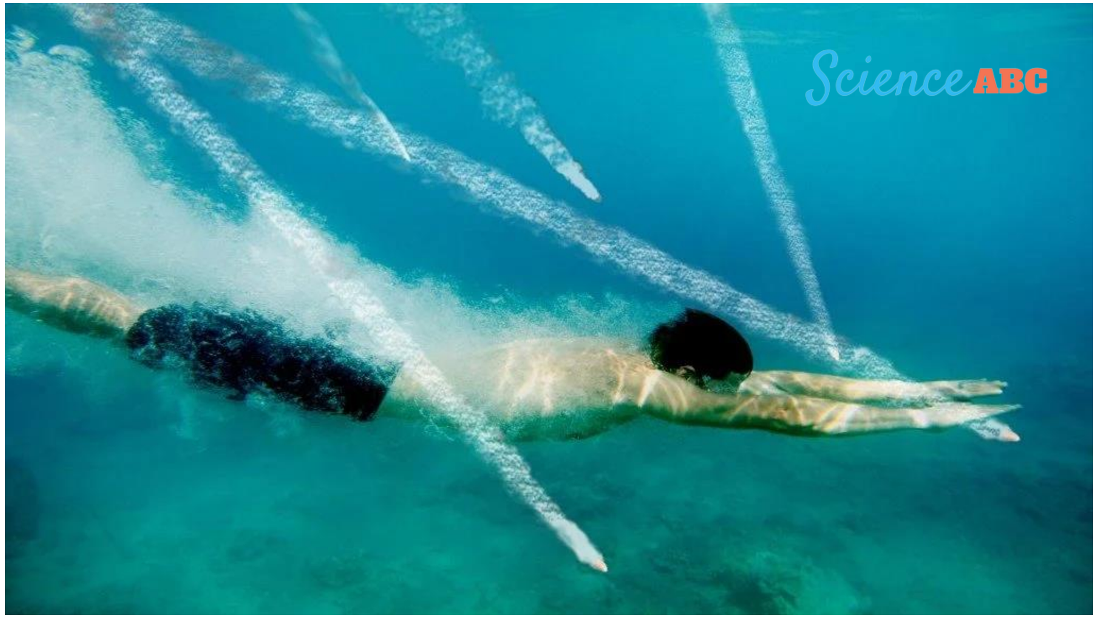
Nothing prevents from using the ANN ansatz as a trial wave function for AFDMC calculations;

DL for jets in HIC

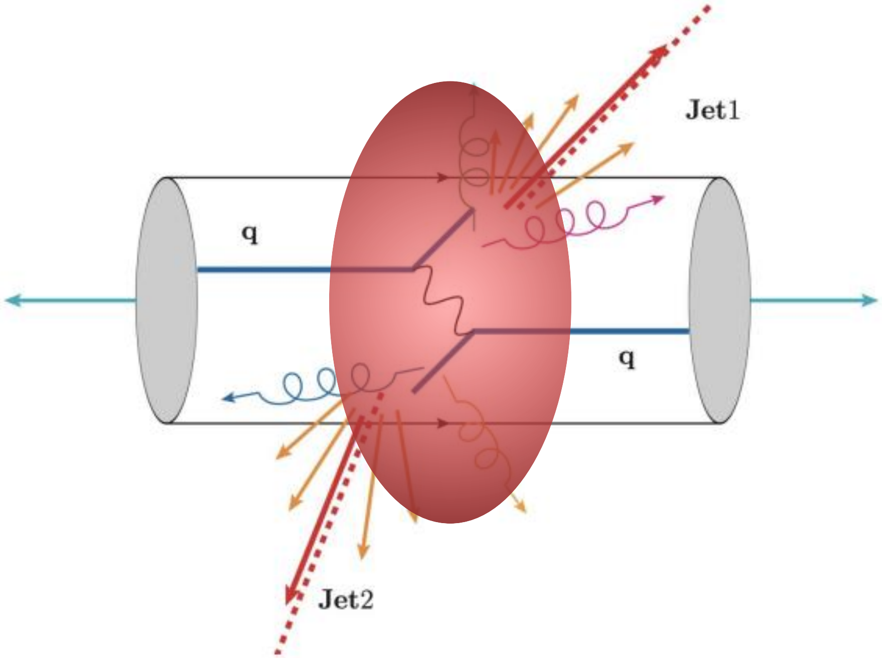
- Probing heavy ion collisions using quark and gluon jet substructure, Yang-Ting Chien, Raghav Kunnawalkam Elayavalli
- Data-driven extraction of the substructure of quark and gluon jets in proton-proton and heavy-ion collisions, Yueyang Ying, Jasmine Brewer, Yi Chen, Yen-Jie Lee
- Data-driven quark 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
- ...

研究QGP性质的另一种方法：喷注淬火

Can Being Underwater Protect You From Bullets?

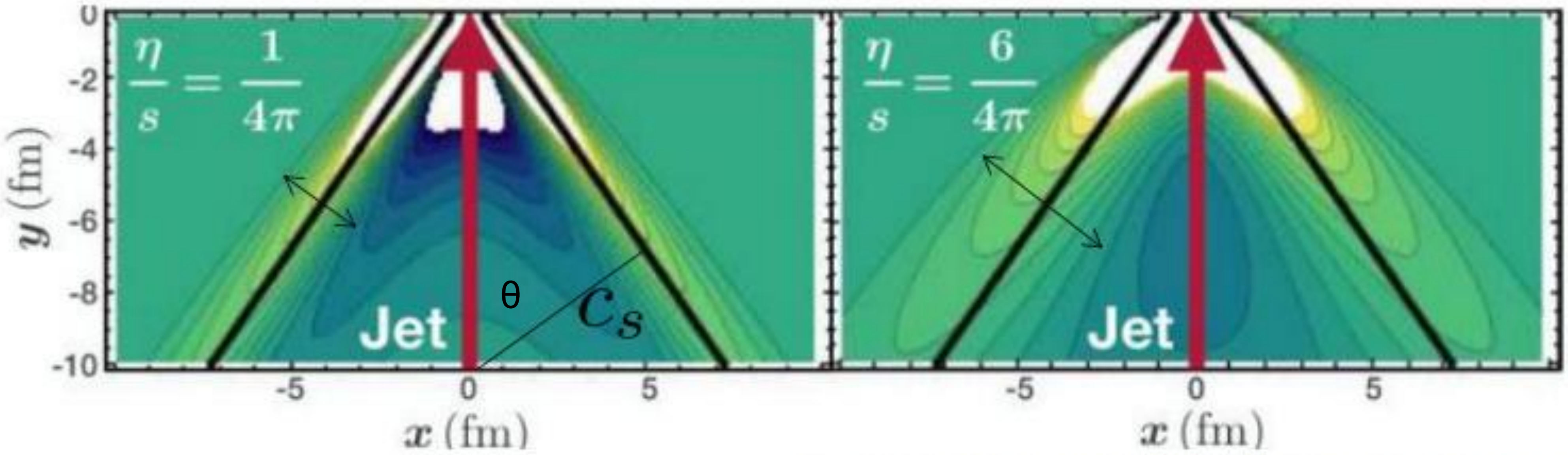


If the bullet is shot from an angle of 30 Degrees, then being underwater in the range of 3-5 feet (0.9-1.5 meters) can ensure safety from most guns.



高能部分子喷注穿过热密 QGP 时损失能量

马赫锥与核物质状态方程



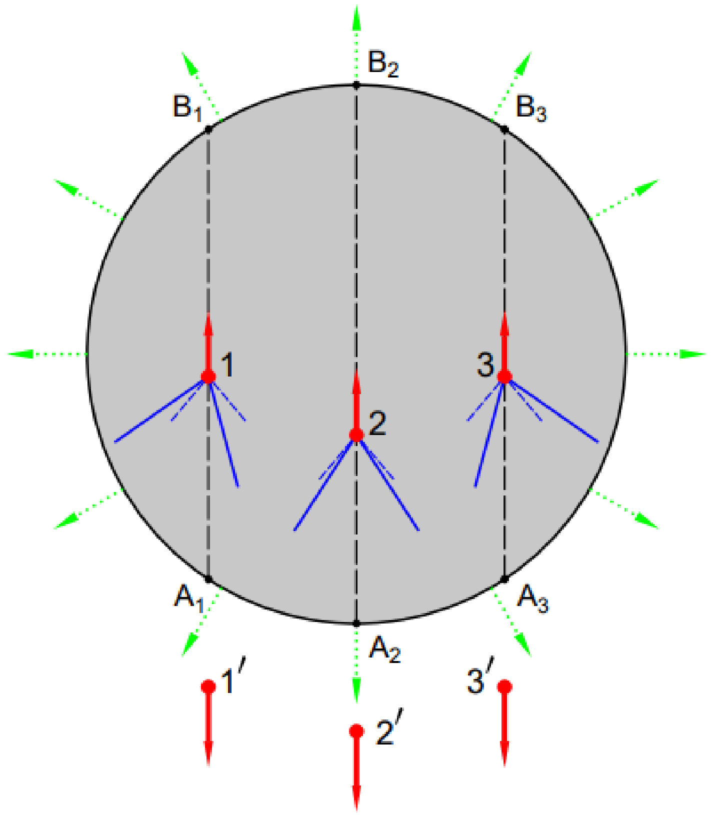
R.B.Neufeld. PRC79,054909(09')

核物质状态方程：$c_s^2 = \frac{dP}{d\epsilon} = cos^2\,\theta$

核物质剪切粘滞：马赫锥锥前宽度

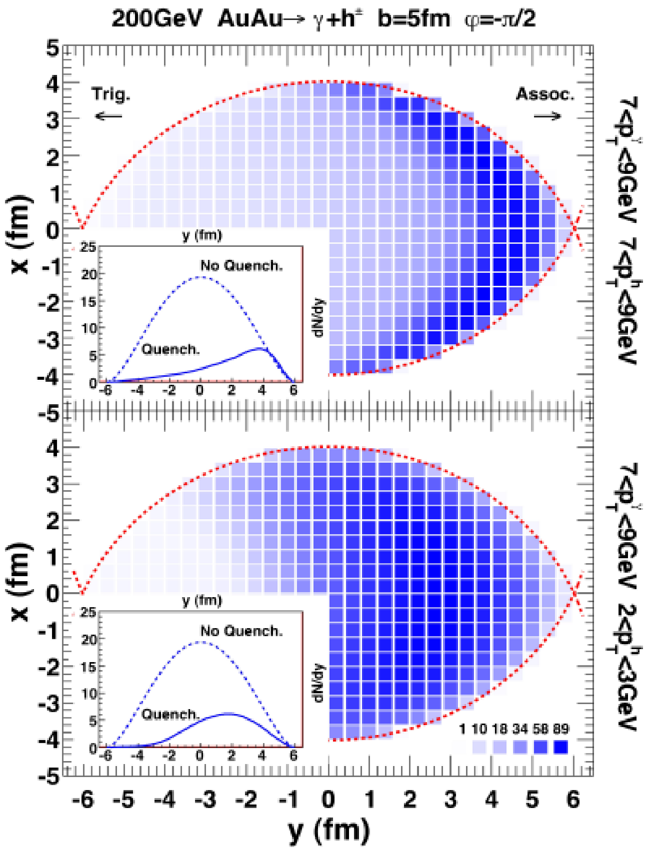
在核液滴中寻找马赫锥的难点

- 喷注产生位置与出射方向随机，Path Length dependence
- 马赫锥受到集体流影响，形状改变
- 研究动机：如果能定位喷注产生位置，可根据马赫锥形状的改变来推断状态方程与 QGP 输运系数



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

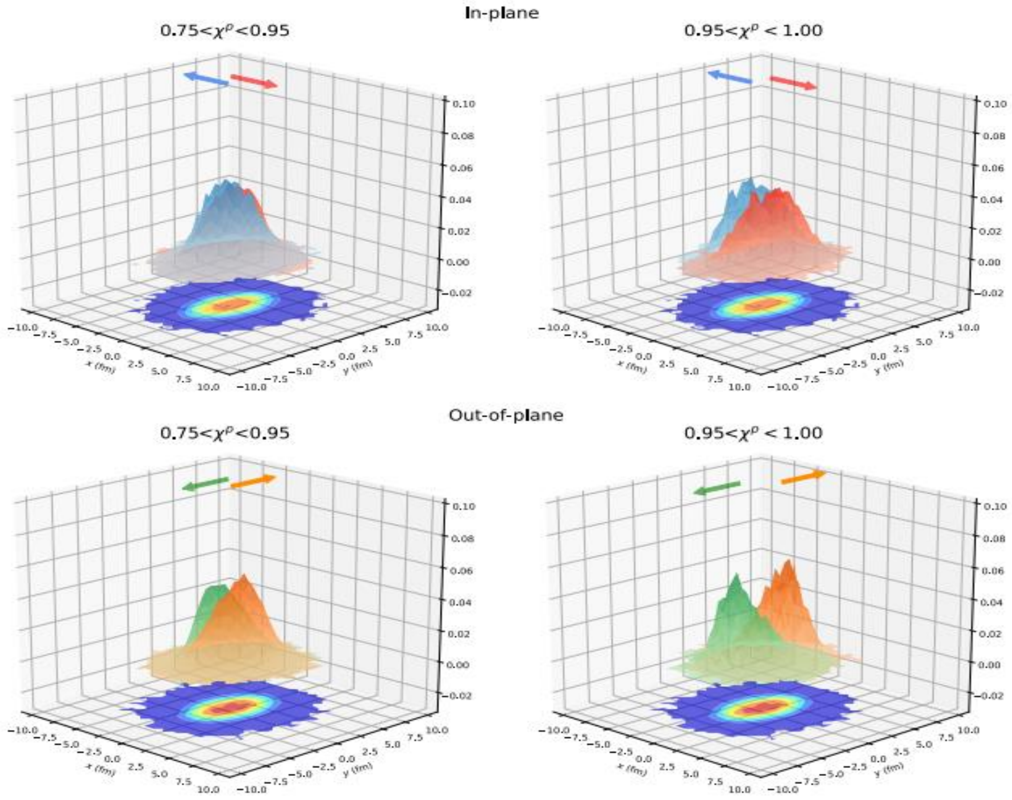
喷注纵向定位： Path Length Dependence



Short path length
能损小

Long path length
能损大

深度学习喷注能损，确定喷注纵向分布

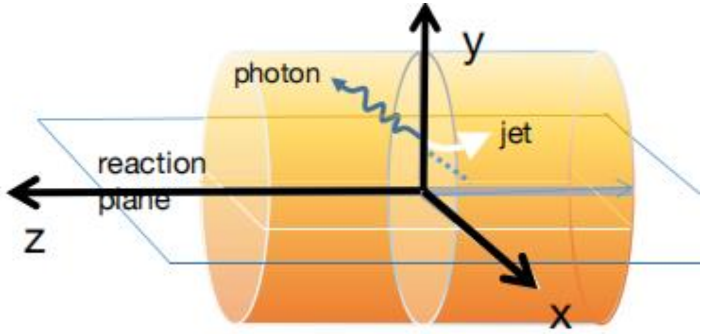


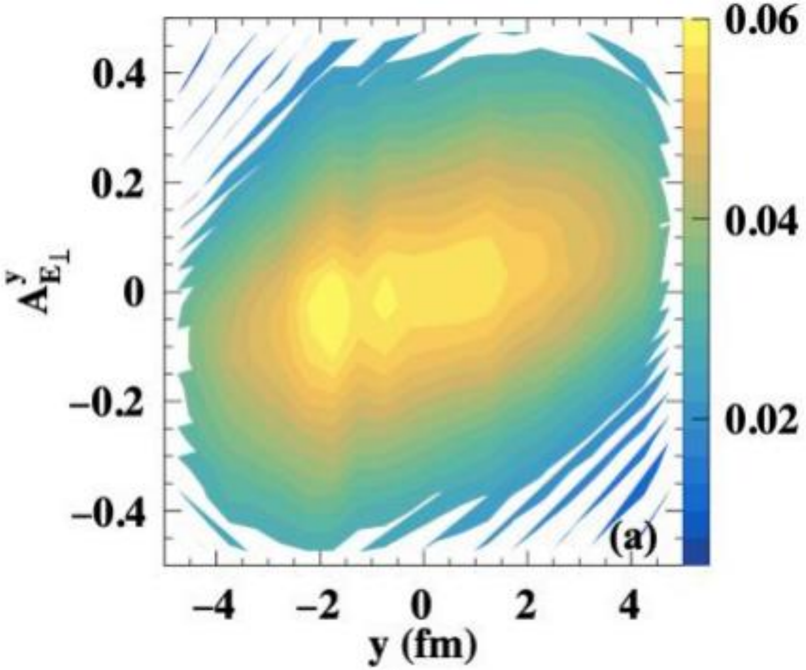
zhang, Owens, Wang and XNW, PRL 103, 032302, (2009)

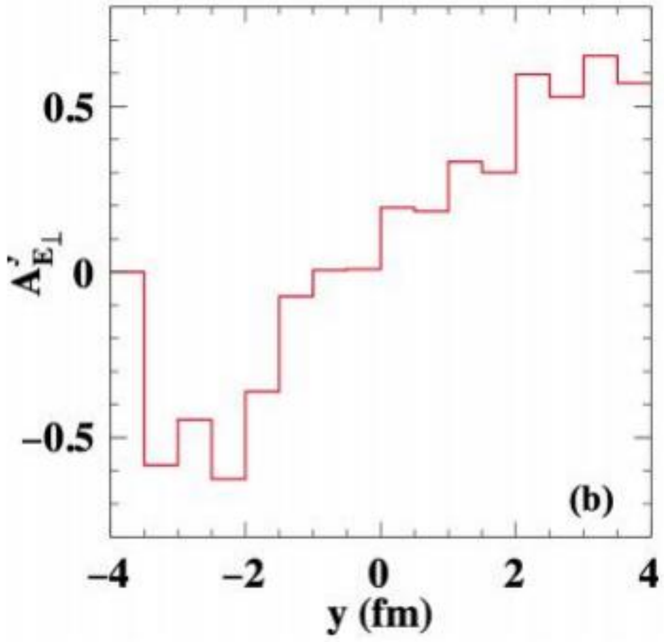
Yi-Lun Du, D. Pablos, K. Tywoniuk, PRL 2022

喷注横向定位：梯度层析

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





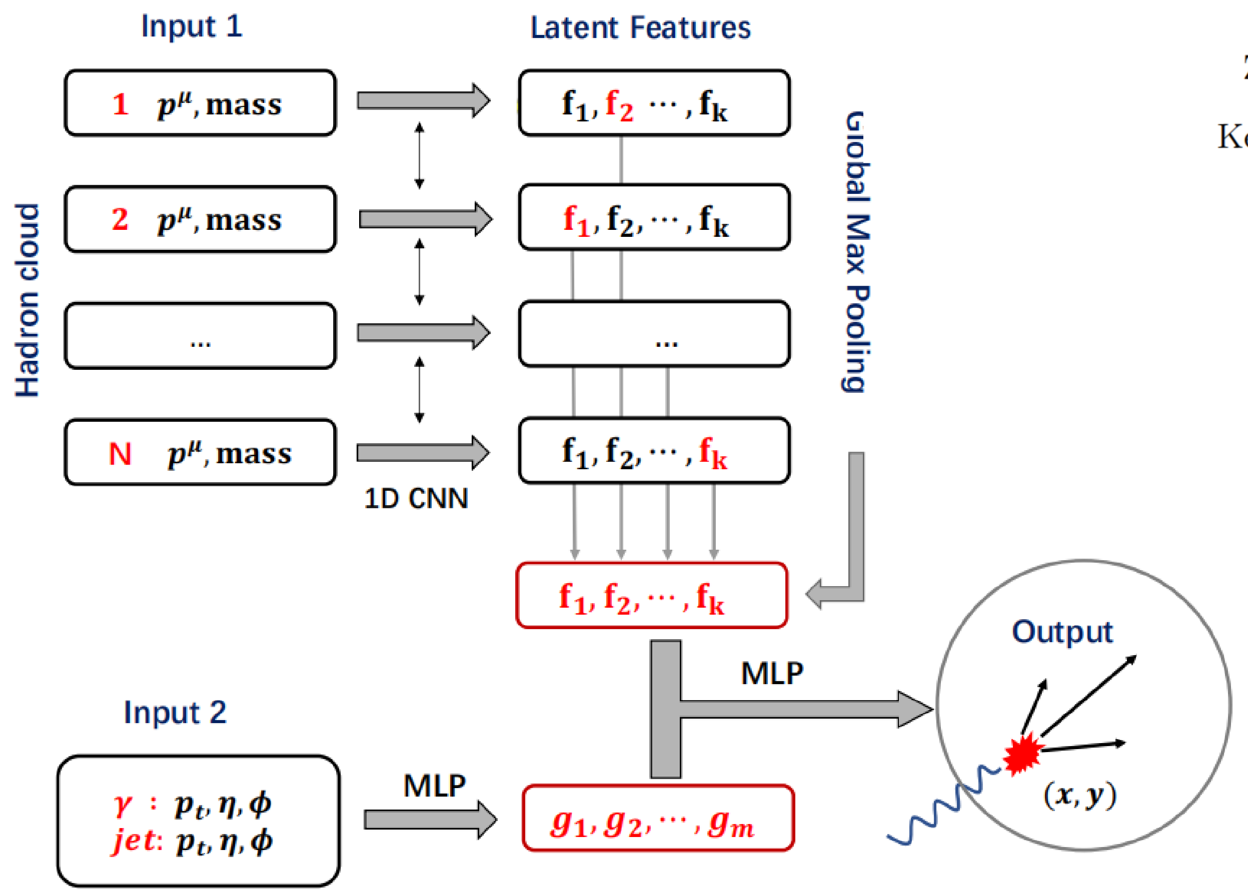


He, Pang & Wang, PRL 125 (2020) 12, 122301

深度学习辅助喷注定位

Deep learning assisted jet tomography for the study of Mach cones in QGP

Zhong Yang[1], Yayun He[2,3], Wei Chen[4], Wei-Yao Ke[5,6,7], Long-Gang Pang[1a] and Xin-Nian Wang[1,5,6b]



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

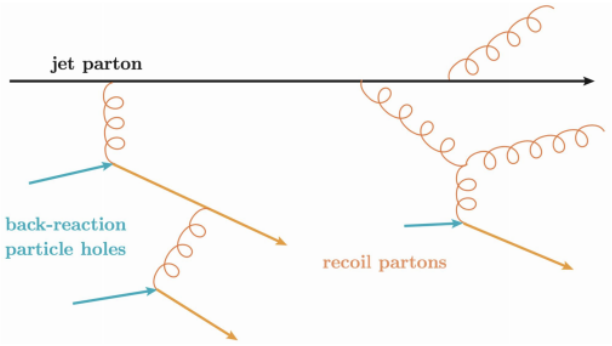
- γ-triggered jet 事件
- 使用点云神经网络架构
- 输入数据：
  - 1. 喷注锥角内所有横动量大于 2 GeV 的末态强子的四动量与质量
  - 2. γ 与喷注的整体信息
- 任务目标：使用蒙特卡洛模拟产生的数据训练，根据输入数据判断喷注产生位置

训练数据: CoLBT-hydro: LBT + CLVisc

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

Medium-induced gluon(HT):

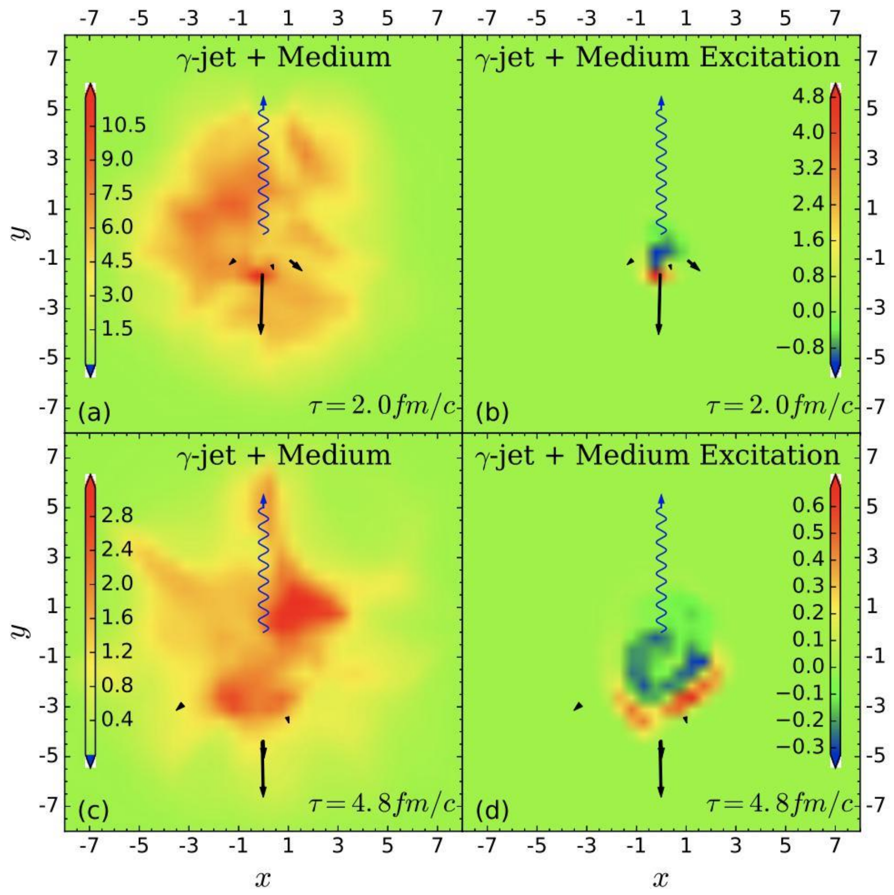
$$\frac{dN_g}{dz d^2 k_\perp dt} \approx \frac{2 C_A \alpha_s}{\pi k_\perp^4} P(z) \hat{q} (\hat{p} \cdot u) sin^2 \frac{k_\perp^2 (t - t_0)}{4z(1-z)E}$$



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

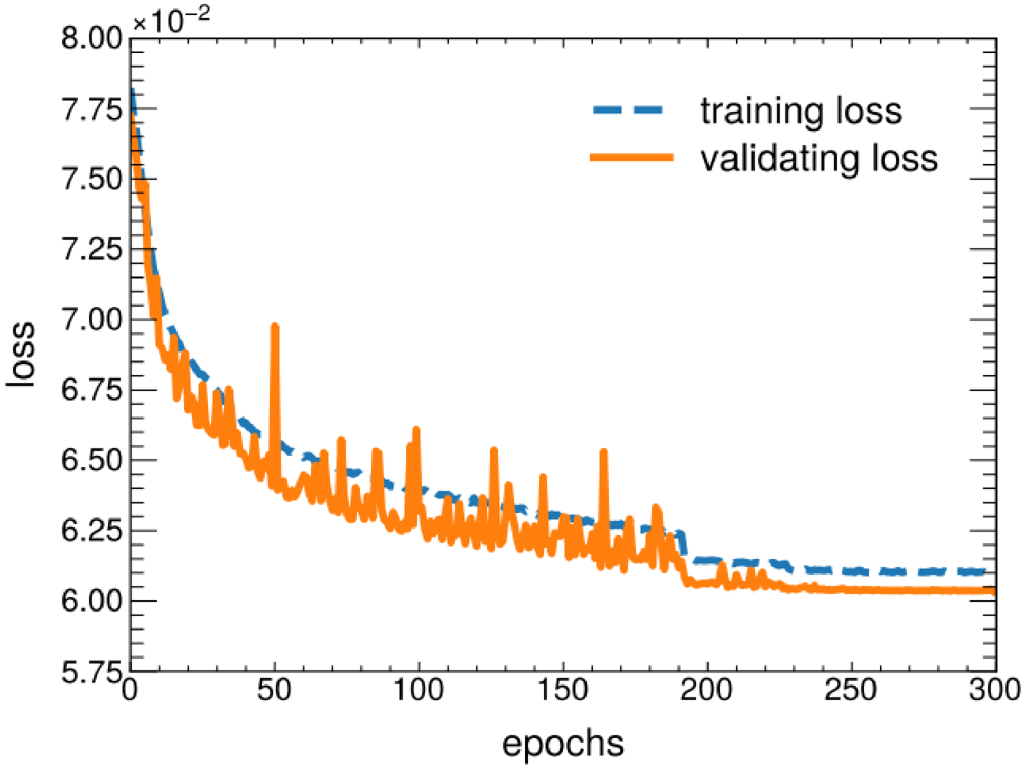
$$\partial_\mu T^{\mu\nu}(x) = j^\nu(x)$$

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

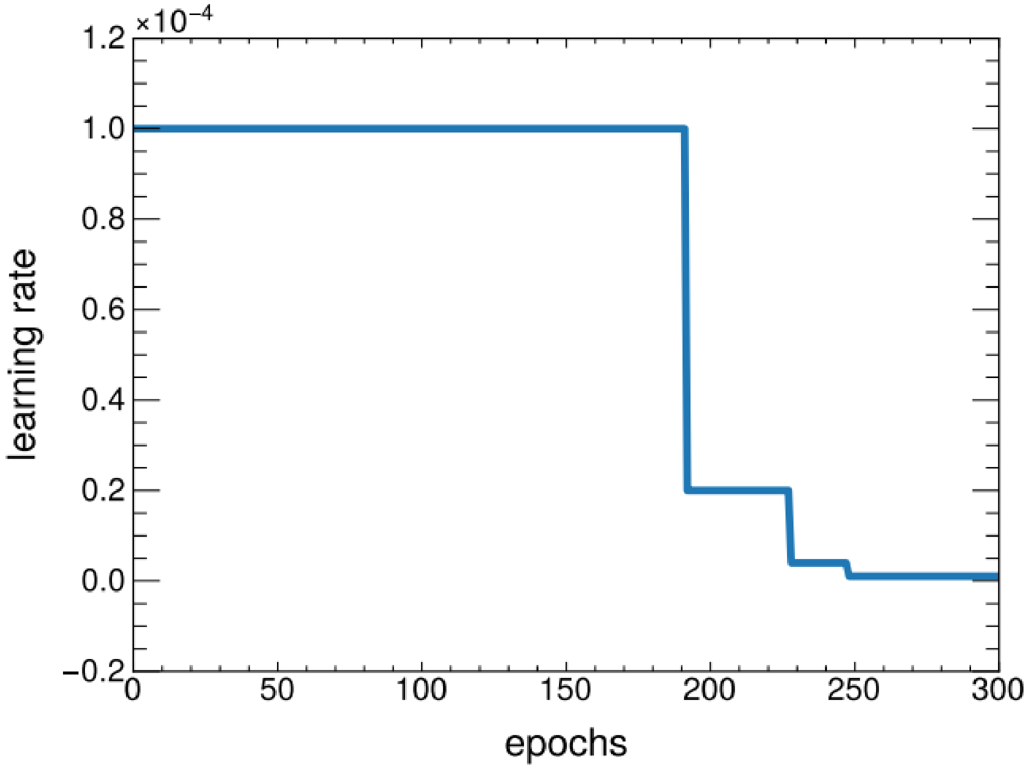


W. Chen, S.S Cao, T. Luo, L.G Pang, X.N Wang, PLB 2017

训练进程与验证精度

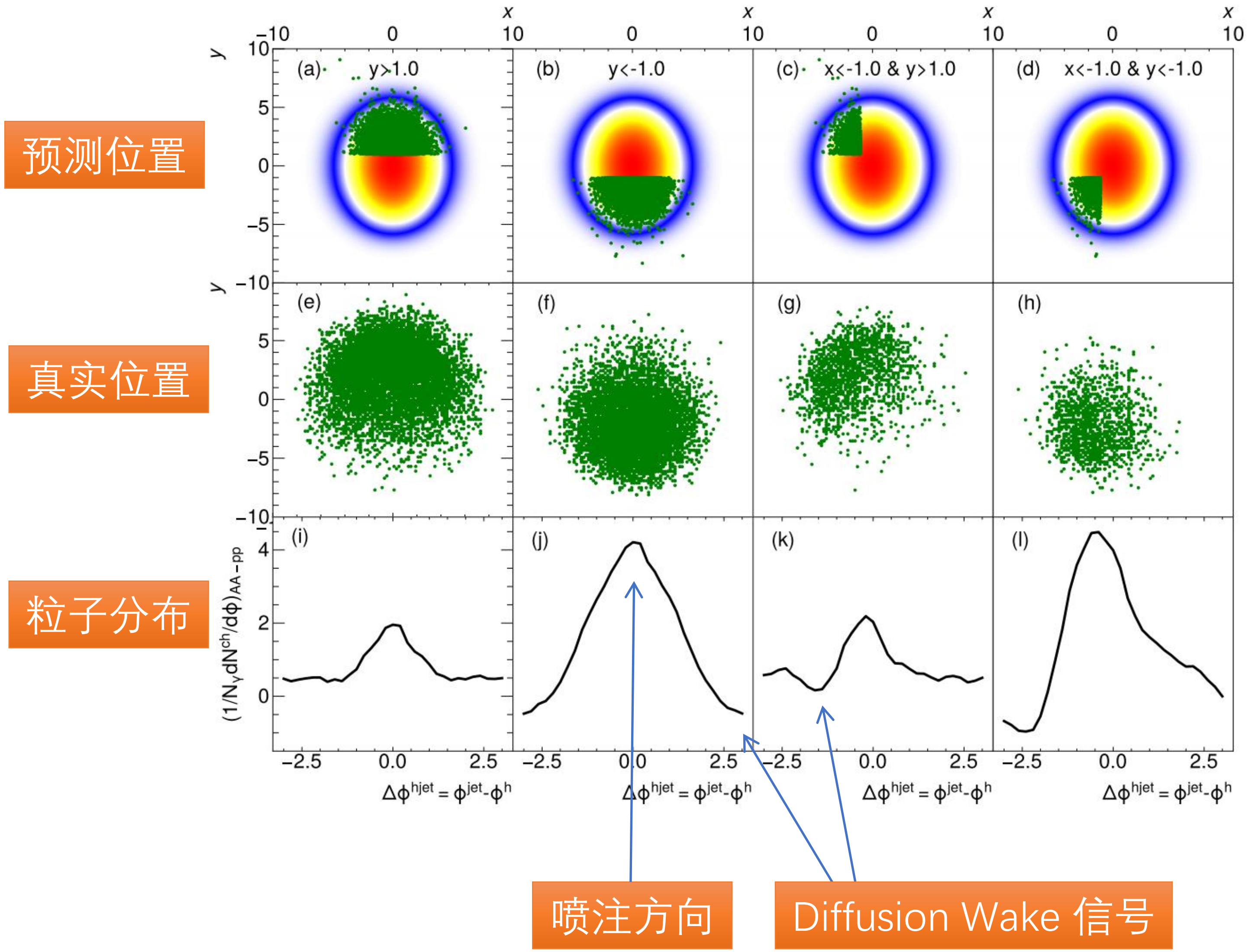


×10⁻²
8.00
7.75
7.50
7.25
7.00
6.75
6.50
6.25
6.00
5.75
loss
0
50
100
150
200
250
300
epochs
training loss
validating loss



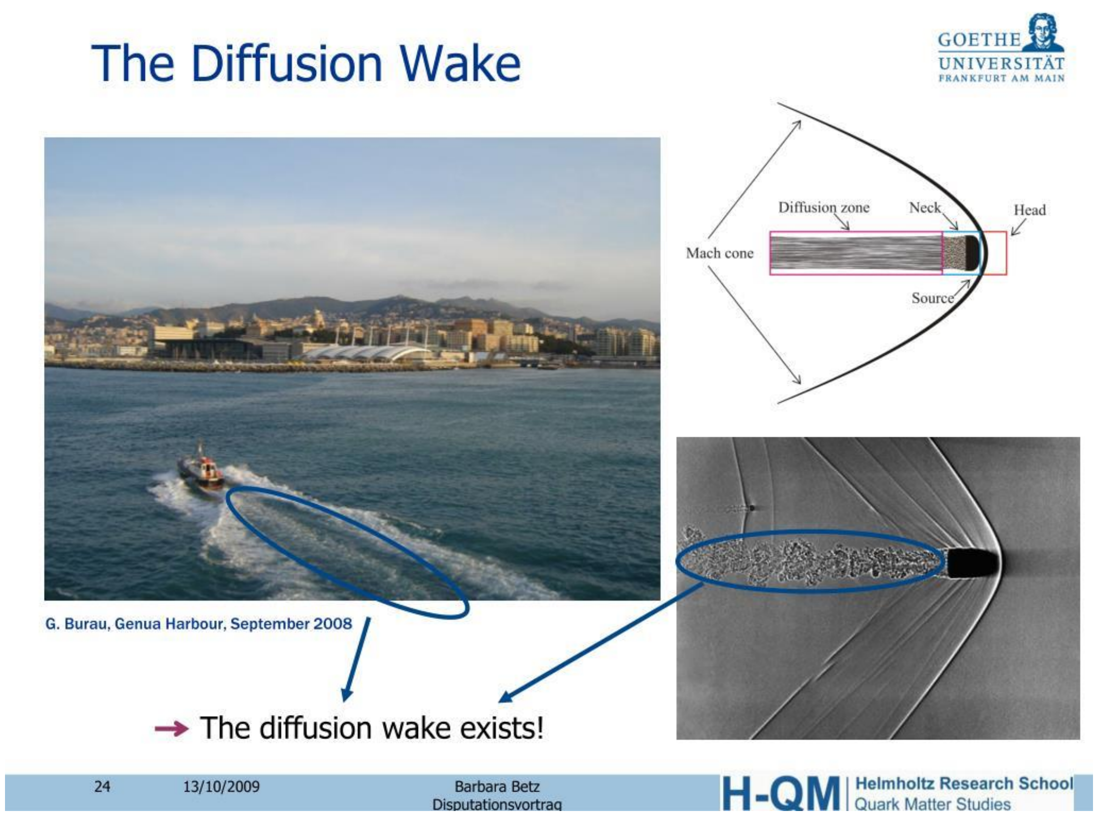
×10⁻⁴
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
learning rate
0
50
100
150
200
250
300
epochs

喷注产生位置筛选与粒子方位角分布统计



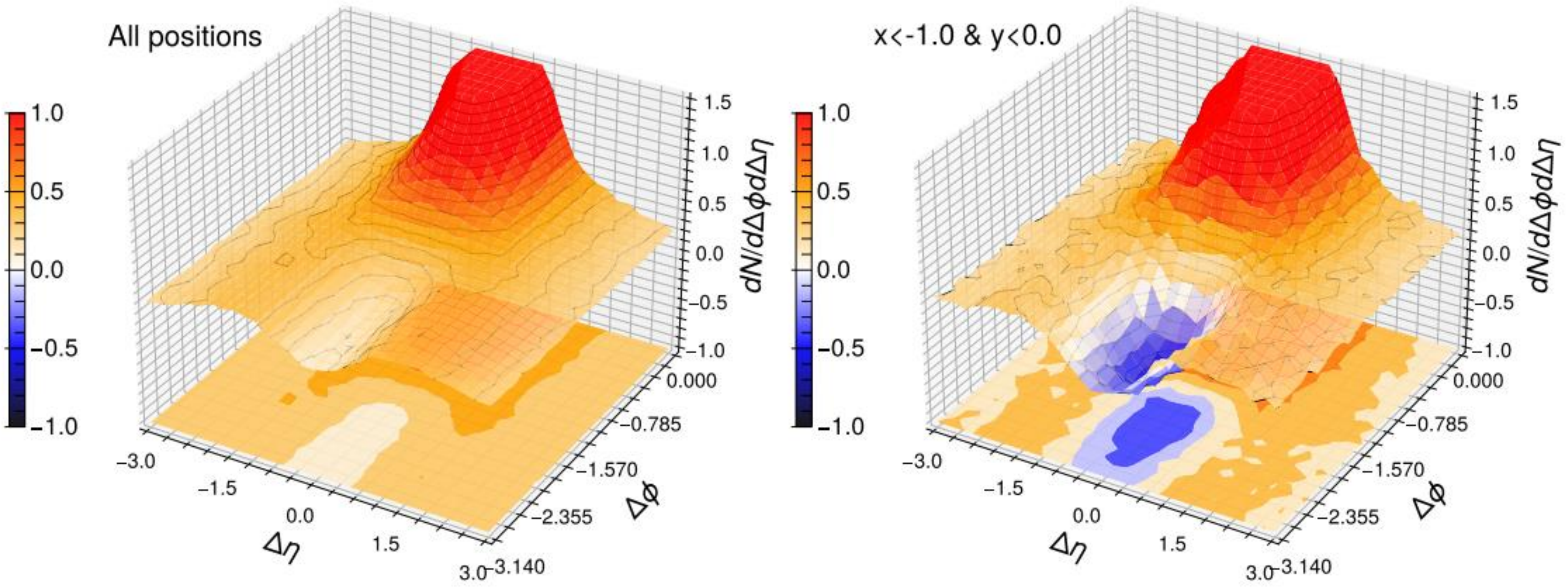
- 1. 数据存在涨落，预测结果存在误差性。
- 2. 神经网络可以帮助选择从一个区域出射的喷注
- 3. 因为路径长度依赖和集体流的影响，从不同位置出射的喷注其 diffusion wake 的位置和深度不同

马赫锥伴生信号：Diffusion Wake



- 马赫锥前方与喷注方向重合，难以区分喷注与QGP介质响应的信号
- 马赫锥后方存在 Diffusion Wake，它对粒子方位角分布的影响是寻找核液滴中马赫锥的更好信号

喷注定位对 Diffusion Wake 信号的增强



综述文章或学习资料

第九届华大 QCD 讲习班，主体《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/1lGITolwDoOm0LyRMbgx7pw

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

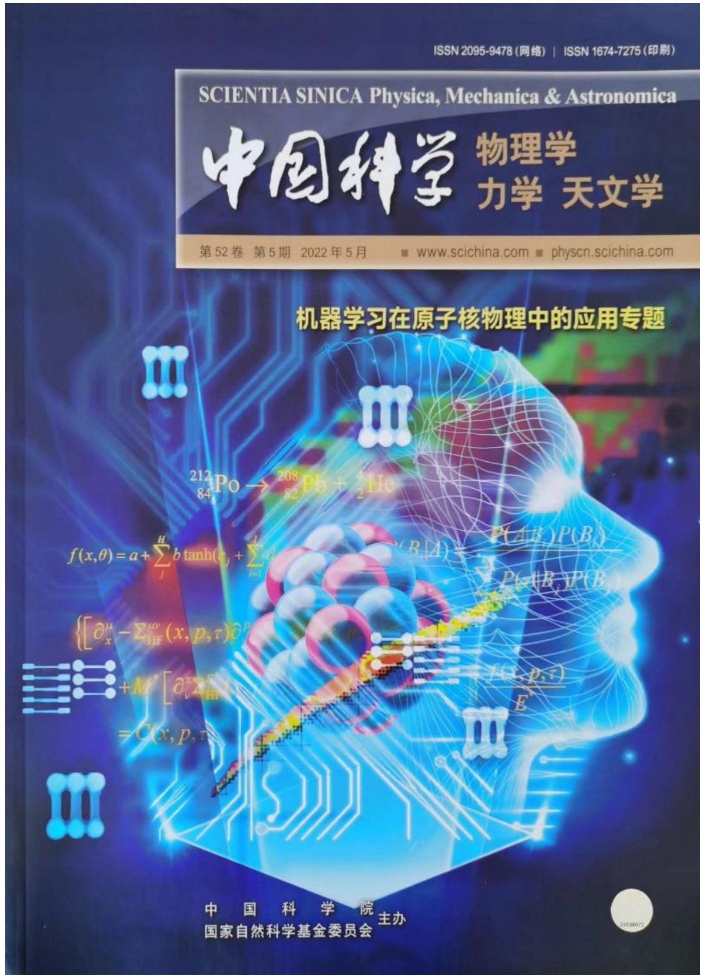
腾讯会议 ID：967 8555 3730；密码：2021

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 Fanelli, Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostroumov, Kostas Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang

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

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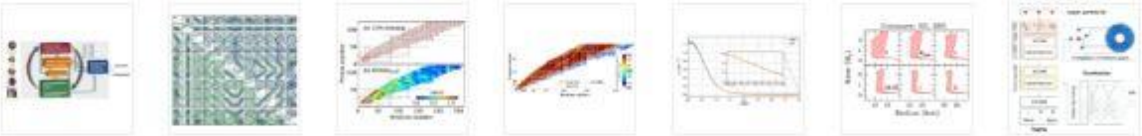
ABSTRACT

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 snapshot of nuclear physics research, which has been transformed by machine learning techniques.



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Received 19 January 2022

DOI: https://doi.org/10.1103/RevModPhys.94.031003

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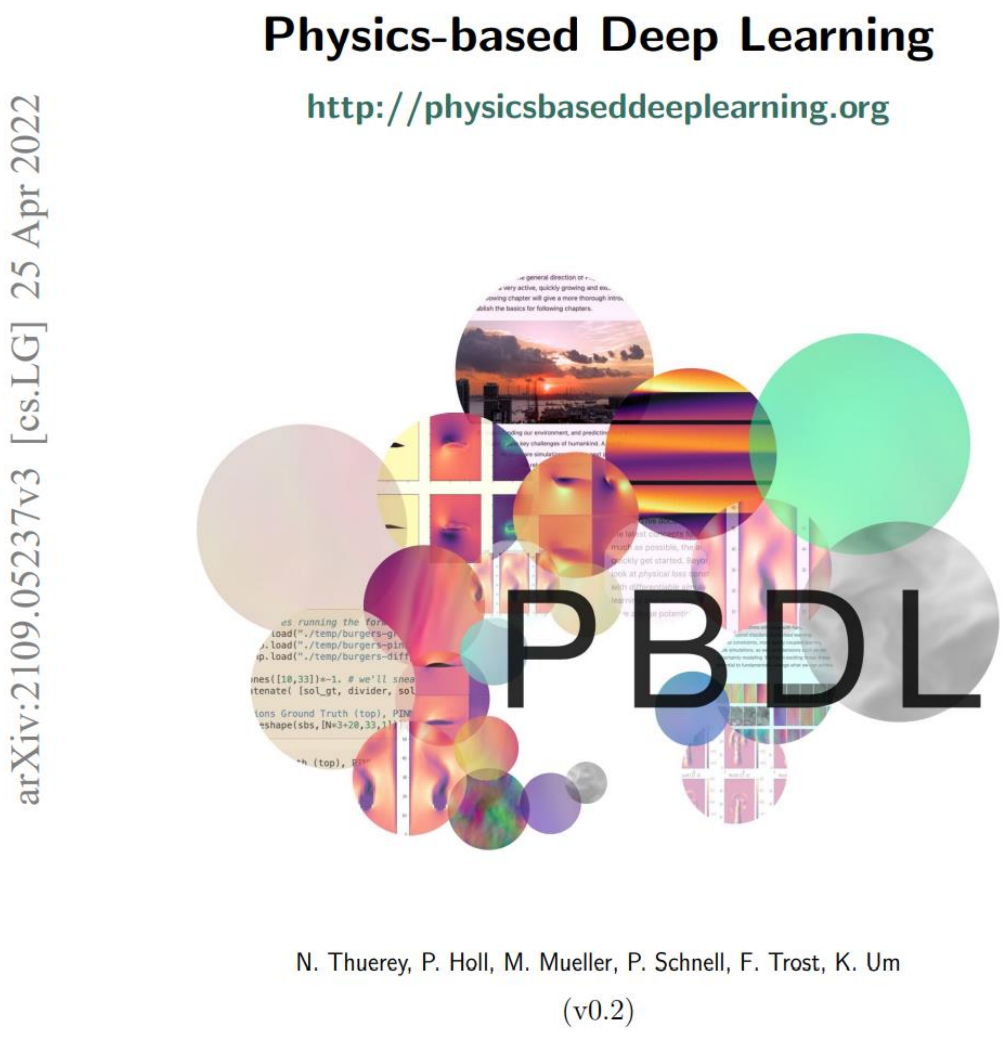
arXiv:2109.05237v3 [cs.LG] 25 Apr 2022

Physics-based Deep Learning

http://physicsbaseddeeplearning.org

PBDL

N. Thuerey, P. Holl, M. Mueller, P. Schnell, F. Trost, K. Um

(v0.2)