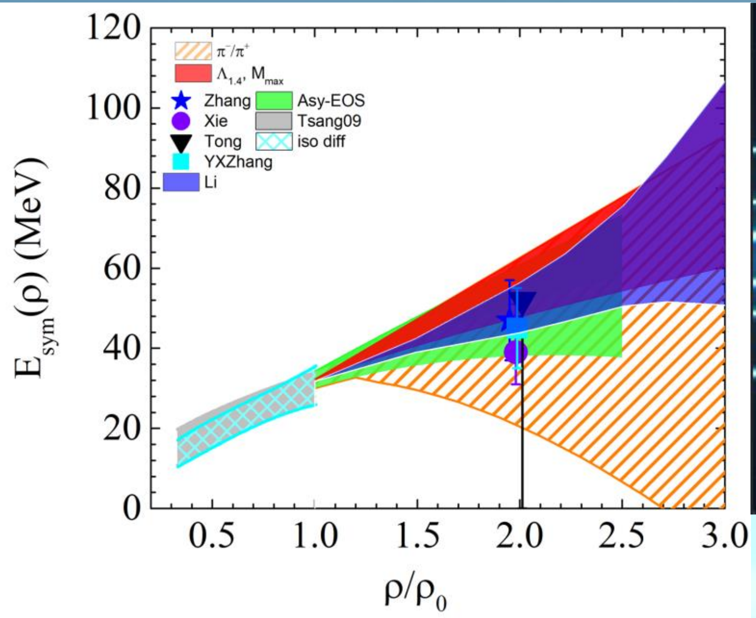
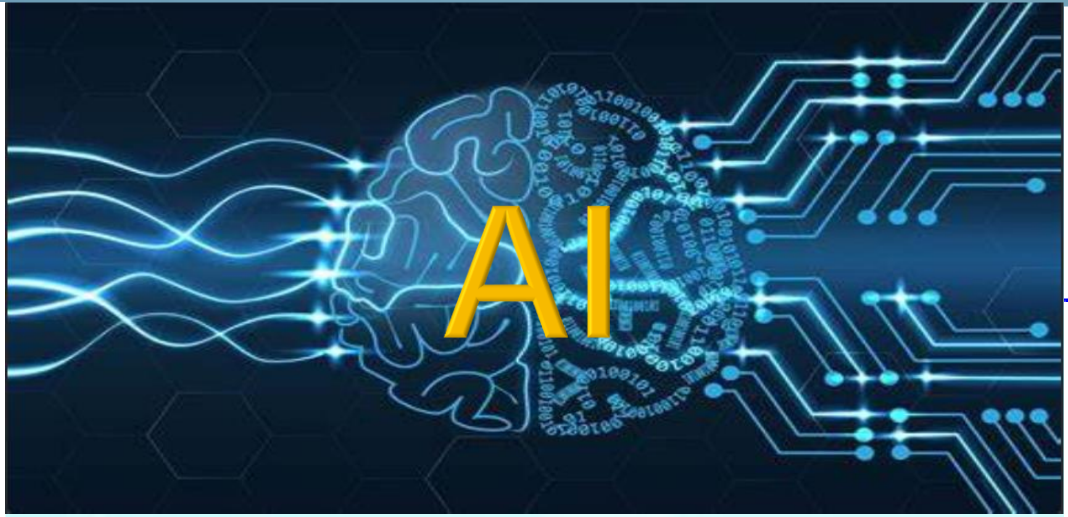
Finding signatures of the nuclear symmetry energy in heavy-ion collisions with deep learning

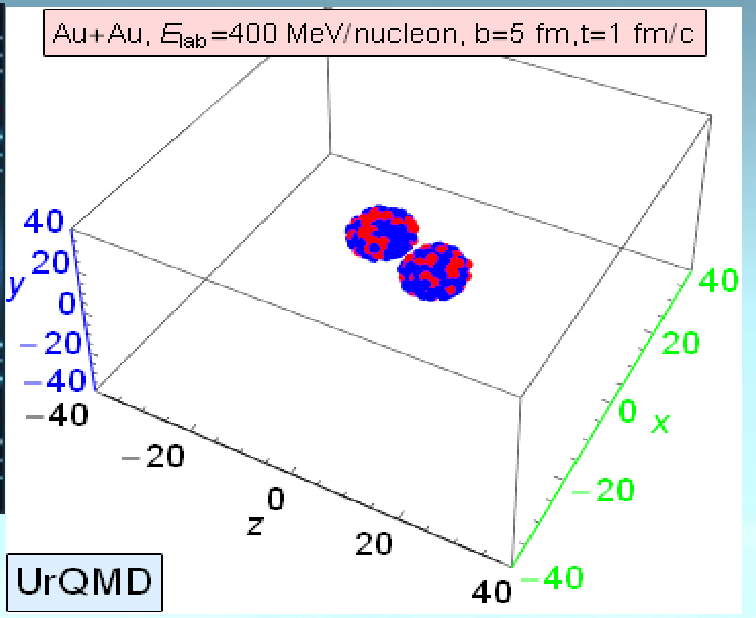
Yongjia Wang (Huzhou University)

In collaboration with Qingfeng Li (HZU), Fupeng Li (CCNU), Hongliang Lü (Huawei), Kai Zhou (FIAS)

Yongjia Wang, et al. arXiv:2107.11012, accepted by PLB







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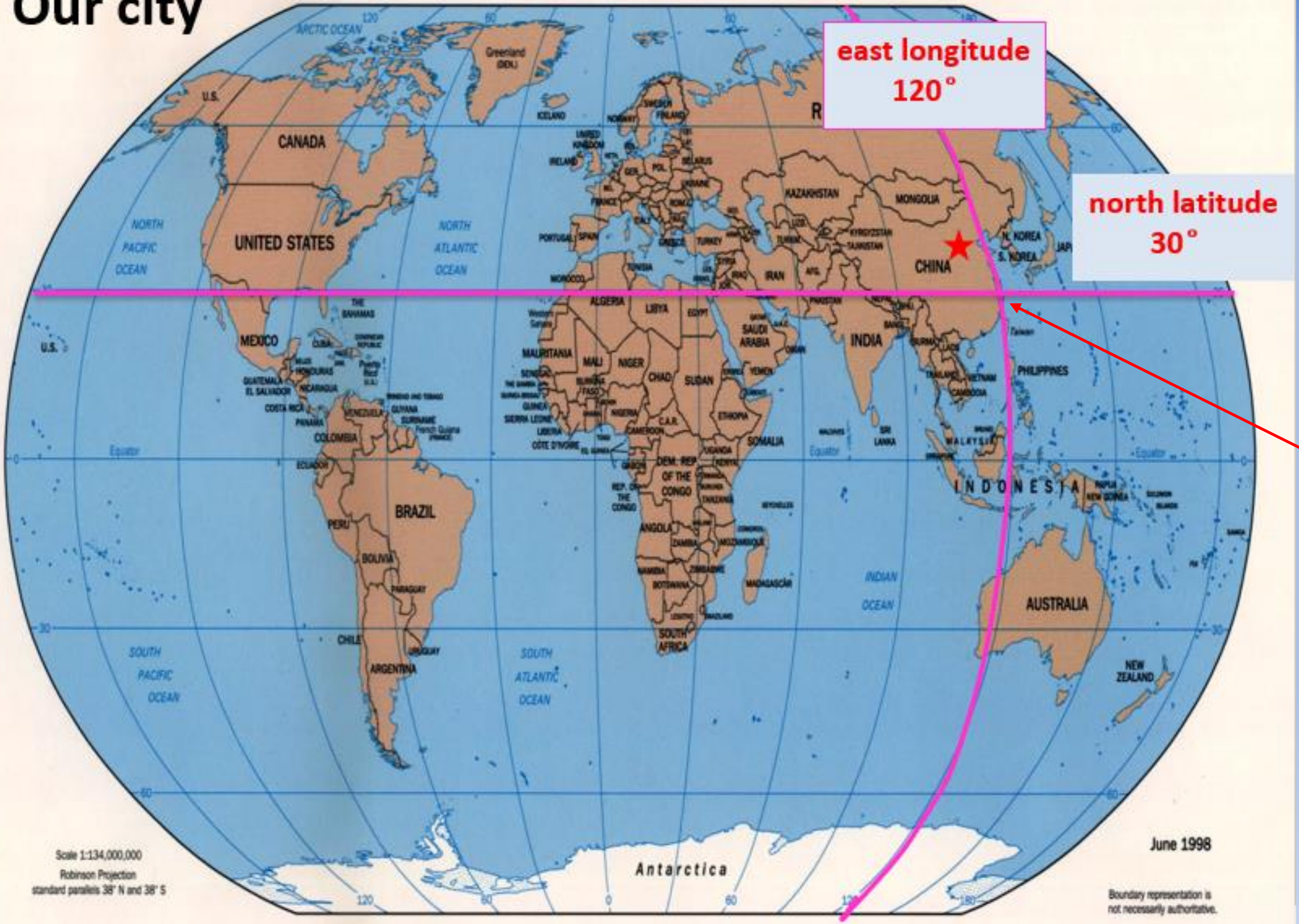
Our city



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Huzhou

Hunter (Huzhou theoretical nuclear physics Group)

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Pengcheng Li

PhD student
Xiaoqing Yue

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Master student
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Master student
Guojun Wei

Master student
Bo Gao

Master student
Zepeng Gao

Prof./Dr. Qingfeng Li

Vice president of Huzhou University

Research Interests:

Heavy-ion collisions, symmetry energy, nuclear EOS, HBT, Kaon production, machine learning…

Outline

- Background and Motivation
- Some history of the application of AI in nuclear physics
- UrQMD model and Data
- Deep learning method
- Results (classification and regression tasks)
  (1) Impact parameter (2) Nuclear symmetry energy
- Summary and outlook

ARTIFICIAL INTELLIGENCE

IS NOT NEW

ARTIFICIAL INTELLIGENCE

Any technique which enables computers to mimic human behavior

MACHINE LEARNING

AI techniques that give computers the ability to learn without being explicitly programmed to do so

DEEP LEARNING

A subset of ML which make the computation of multi-layer neural networks feasible

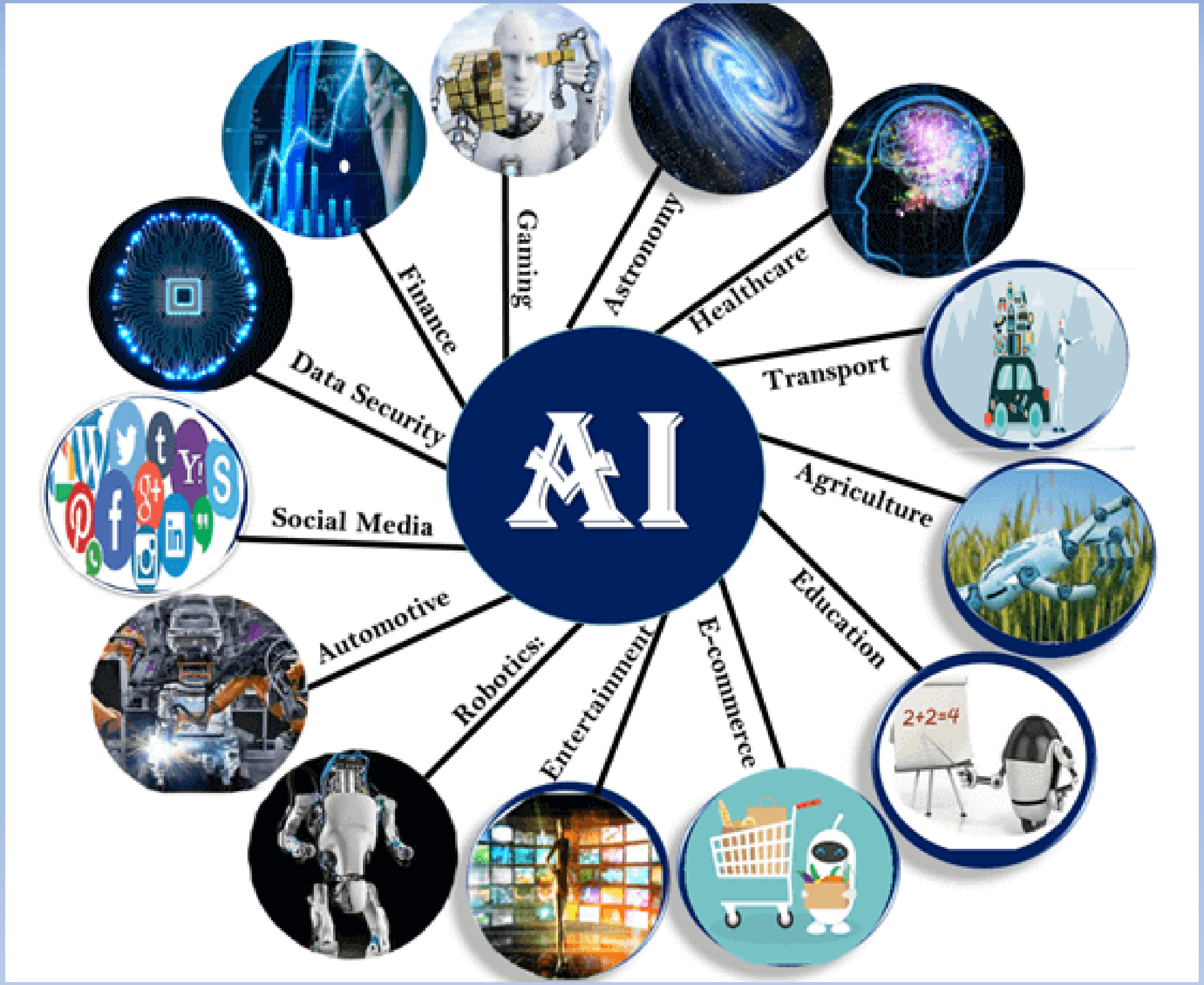
Statistical methods

Big data driven

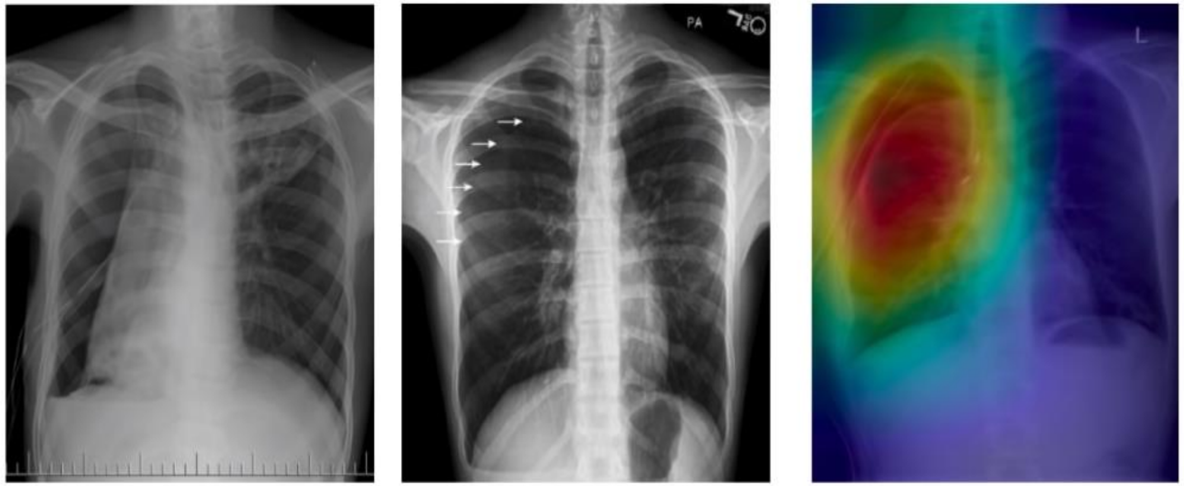
1950's 1960's 1970's 1980's 1990's 2000's 2010s

ORACLE

Application of AI in our life



Detect pneumothorax in real X-Ray scans



Application of AI in physics.
DATA & AI

nature physics

tter | Published: 13 February 2017

Machine learning phases of

an Carrasquilla & Roger G. Melko

ture Physics **13**, 431–434 (2017) | Download Cita

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RE PERSPECTIVES

Machine learning for quantum physics

el R. Hush

uthors and affiliations

2017:
25, pp. 580
e.aam6564

nature COMMUNICATIONS

Article | OPEN | Published: 15 January 2018

An equation-of-state-meter of qua
chromodynamics transition from deep
learning

Long-Gang Pang, Kai Zhou, Nan Su, Hannah Petersen, Horst Stöcker & Xin-Nian Wang

Nature Communications **9**, Article number: 210 (2018) | Download Citation

Careers Journals

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ul 2017:
e 6346, pp. 20
/science.357.6346.20

ARTICLE TOOLS

History of the application of AI in nuclear physics

Physics Letters B 300 (1993) 1–7
North-Holland

PHYSICS LETTERS B

1992 nuclear mass

Neural network models of nuclear systematics

K.A. Gernoth, J.W. Clark, J.S. Prater
McDonnell Center for the Space Sciences and Department of Physics, Washington University, St. Louis, MO 63130, USA

and

H. Bohr
Beckman Institute for Advanced Science and Technology, University of Illinois, Urbana, IL 61801, USA

Received 13 November 1992

J. Phys. G: Nucl. Part. Phys. 20 (1994) L21–L26. Printed in the UK

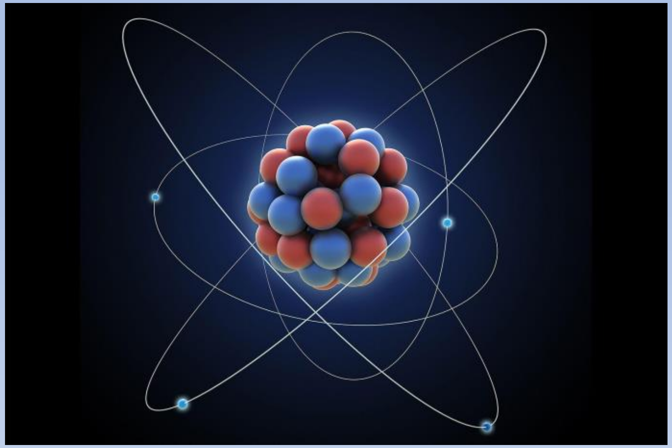
1993 impact parameter

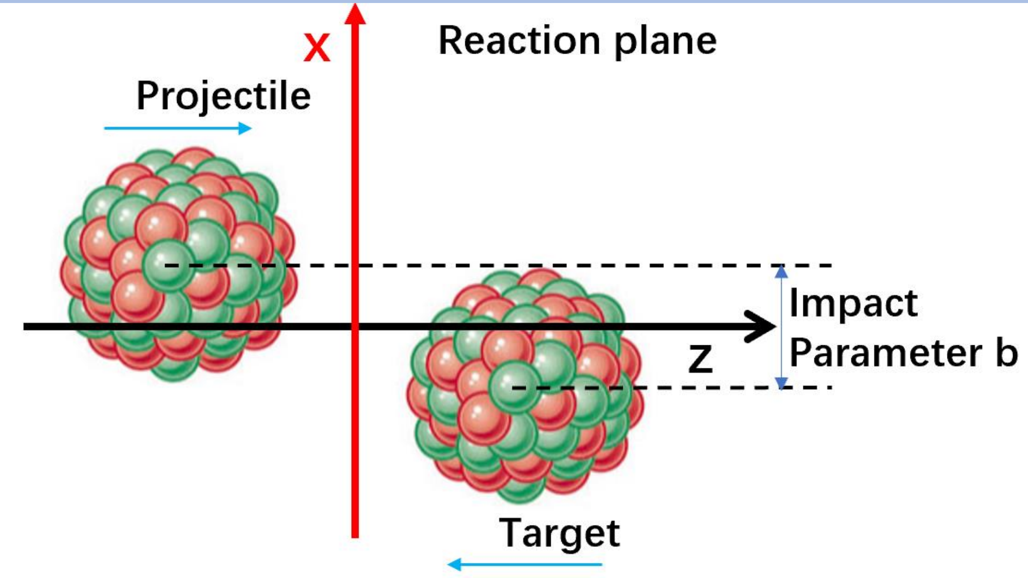
LETTER TO THE EDITOR

Neural networks for impact parameter determination*

S A Bass†‡, A Bischoff†, C Hartnack†§, J A Maruhn†, J Reinhardt†, H Stöcker† and W Greiner†
† Institut für Theoretische Physik der Universität, Postfach 111932, 60054 Frankfurt am Main, Federal Republic of Germany
‡ GSI Darmstadt, Postfach 110552, 64220 Darmstadt, Federal Republic of Germany
§ Laboratoire de Physique Nucléaire, Nantes, France

Received 8 November 1993





Recent work about the application of AI in nuclear physics

PHYSICAL REVIEW C **93**, 014311 (2016)

Nuclear mass predictions for the crustal composition of neutron stars: A Bayesian neural network approach

R. Utama,* J. Piekarewicz,† and H. B. Prosper‡

Physics Letters B 778 (2018) 48–53

Contents lists available at ScienceDirect

Physics Letters B

www.elsevier.com/locate/physletb

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PHYSICS LETTERS B

Nuclear mass predictions based on Bayesian neural network approach with pairing and shell effects

Z.M. Niu (牛中明)[a,b], H.Z. Liang (梁豪兆)[b,c,d,*]

[a] School of Physics and Materials Science, Anhui University, Hefei 230601, China
[b] Interdisciplinary Theoretical Science Research Group, RIKEN, Wako 351-0198, Japan
[c] RIKEN Nishina Center, Wako 351-0198, Japan
[d] Department of Physics, Graduate School of Science, The University of Tokyo, Tokyo 113-

PHYSICAL REVIEW C **98**, 034318 (2018)

Editors' Suggestion

Bayesian approach to model-based extrapolation of nuclear observables

PHYSICAL REVIEW LETTERS **122**, 062502 (2019)

Neutron Drip Line in the Ca Region from Bayesian Model Averaging

Léo Neufcourt,[1,2] Yuchen Cao (曹宇晨),[3] Witold Nazarewicz,[4] Erik Olsen,[2] and Frederi Viens[1]
[1]Department of Statistics and Probability, Michigan State University, East Lansing, Michigan 48824, USA
[2]FRIB Laboratory, Michigan State University, East Lansing, Michigan 48824, USA
[3]Department of Physics and Astronomy and NSCL Laboratory, Michigan State University, East Lansing, Michigan 48824, USA
[4]Department of Physics and Astronomy and FRIB Laboratory, Michigan State University, East Lansing, Michigan 48824, USA

(Received 12 September 2018; revised manuscript received 15 November 2018; published 14 February 2019)

Since 2016, more and more studies in nuclear physics using machine learning or deep learning. For example, many works focused on the nuclear mass.

R. Utama and J. Piekarewicz, Phys. Rev. C 96, 044308 (2017)
L. Neufcourt, Y. Cao, W. Nazarewicz and F. Viens, Phys. Rev. C 98, 034318 (2018)
Z. M. Niu, J. Y. Fang and Y. F. Niu, Phys. Rev. C 100, 054311 (2019)
X. H. Wu, L. H. Guo and P. W. Zhao, Phys. Lett. B 819, 136387 (2021)
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Recent work about the application of AI in nuclear physics

PHYSICAL REV

Nuclear mass predictions for th
A Bayesian neu

R. Utama,* J. Pieka

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(Received 25

Background: Be
applications, suc
Purpose: To ove
based on a Bayes
Methods: A nov
and experiment.
Results: A signi
BNN refinement
by constructing
composition of t
Conclusions: Th
systematic impr
observables is a
DOI: 10.1103/Ph

ELSEVIER

Nuclear mass pred
with pairing and sh

Z.M. Niu (牛中明)[a,b], H
[a] School of Physics and Materials Science, A
[b] Interdisciplinary Theoretical Science Rese
[c] RIKEN Nishina Center, Wako 351-0198, Ja
[d] Department of Physics, Graduate School

more and more
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ed on the nuclear

arXiv.org > nucl-th > arXiv:2105.02445

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Nuclear Theory

[Submitted on 6 May 2021]

Machine learning the nuclear mass

Zepeng Gao, Yongjia Wang, Hongliang Lü, Qingfeng Li, Caiwan Shen, Ling Liu

Background: The masses of about 2500 nuclei have been measured experimentally, however more than 7000 isotopes are predicted to exist in the nuclear landscape from H (Z=1) to Og (Z=118) based on various theoretical calculations. Exploring the mass of the remains is a hot topic in nuclear physics. Machine learning has been served as a powerful tool in learning complex representations of big data in many fields. Purpose: We use Light Gradient Boosting Machine (LightGBM) which is a highly efficient machine learning algorithm to predict the masses of unknown nuclei and to explore the nuclear landscape in neutron-rich side from learning the measured nuclear masses. Results: By using the experimental data of 80 percent of known nuclei as the training dataset, the root mean square deviation (RMSD) between the predicted and the experimental binding energy of the remaining 20% is about 0.234 MeV, 0.213 MeV, 0.170 MeV, and 0.222 MeV for the LightGBM-refined LDM, DZ, WS4, and FRDM models, respectively. These values are of about 90%, 65%, 40%, and 60% smaller than the corresponding origin mass models. The RMSD for 66 newly measured nuclei that appeared in AME2020 is also significantly improved on the same foot. One-neutron and two-neutron separation energies predicted by these refined models are in consistence with several theoretical predictions based on various physical models. Conclusions: LightGBM can be used to refine theoretical nuclear mass models so as to predict the binding energy of unknown nuclei. Moreover, the correlation between the input characteristic quantities and the output can be interpreted by SHapley Additive exPlanations (SHAP, a popular explainable artificial intelligence tool), this may provide new insights on developing theoretical nuclear mass models.

Table III. Comparison of the RMSD for the ML refined mass models. σ_{pre} denotes the RMSD of the original mass models, σ_{pre} is the result obtained with the LightGBM-refined mass models. All values are in unit of MeV.

		LDM	DZ	WS4	FRDM
σ_{pre}		2.462 ± 0.023	0.613 ± 0.007	0.302 ± 0.003	0.599 ± 0.009
	RBF by N. Wang [11]	—	—	0.170	—
	KRR by X. H. Wu [40]	—	—	0.199	—
	RBFs by N. N. Ma [59]	—	—	0.130	0.209
Training set	LMNN by H. F. Zhang [39]	0.235	0.325	—	0.348
	BNN by Z. M. Niu [27]	—	—	0.176	0.187
	RBFoe by Z. M. Niu [41]	—	0.171	0.140	0.182
	NN by R. Utama [25]	0.466	0.274	—	0.342
	NN by A. Pastore [58]	—	0.324	—	—
	Trees by M. Carnini [44]	2.070	0.471	—	—
	LightGBM in this work	0.058 ± 0.011	0.066 ± 0.010	0.055 ± 0.011	0.077 ± 0.013
Test set	LMNN by H. F. Zhang	0.256	0.329	—	0.368
	BNN by Z. M. Niu	—	—	0.212	0.252
	RBFoe by Z. M. Niu	—	0.344	0.337	0.218
	NN by R. Utama	0.486	0.278	—	0.352
	NN by A. Pastore	—	0.358	—	—
	Trees by M. Carnini	2.881	0.569	—	—
	LightGBM in this work	0.234 ± 0.022	0.213 ± 0.018	0.170 ± 0.011	0.222 ± 0.016

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, 062502 (2019)

ayesian Model Averaging

z,[4] Erik Olsen,[2] and Frederi Viens[1]
y, East Lansing, Michigan 48824, USA
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e University, East Lansing, Michigan 48824, USA
e University, East Lansing, Michigan 48824, USA
vember 2018; published 14 February 2019)

R. Utama and J. Piekarewicz, Ph
044308 (2017)
L. Neufcourt, Y. Cao, W. Nazare
Phys. Rev. C 98, 034318 (2018)
Z. M. Niu, J. Y. Fang and Y. F. N
054311 (2019)
X. H. Wu, L. H. Guo and P. W. Z
819, 136387 (2021)
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Recent work about the application of AI in symmetry energy

Nuclear Physics A
Volume 958, February 2017, Pages 147-186

2017, Bayesian inference

Symmetry energy III: Isovector skins

Paweł Danielewicz [a, b, c], Pardeep Singh [a, d], Jenny Lee [e]

THE ASTROPHYSICAL JOURNAL, 883:174 (21pp), 2019 October 1
https://doi.org/10.3847/1538-4357/ab3f37

2019, Bayesian inference

Bayesian Inference of High-density Nuclear Symmetry Energy from Radii of Canonical Neutron Stars

Wen-Jie Xie[1,2] and Bao-An Li[1]
[1] Department of Physics and Astronomy, Texas A&M University–Commerce, Commerce, TX 75429, USA; Bao-An.Li@Tamuc.edu
[2] Department of Physics, Yuncheng University, Yuncheng 044000, People's Republic of China
Received 2019 July 24; revised 2019 August 19; accepted 2019 August 27; published 2019 October 3

$$P(\mathbf{x}|\mathbf{y}) \propto P(\mathbf{y}|\mathbf{x})\,P(\mathbf{x})$$

x: model parameters to be constrained
y: experimental data
P(x): prior probability, initial knowledge of x
P(x|y): posterior probability
P(y|x): Likelihood function which quantifies how well the model describes the data

Jun Xu, et al. PLB 810 (2020) 135820
Wenjie Xie, Bao-an Li, ApJ 899 (2020) 4
Wenjie Xie, Bao-an Li, PRC103 (2021) 035802
Zhen Zhang, et al. Chin. Phys. C 45 (2021) 064104
W. G. Mewton, G. Crocombe, PRC 103 (2021) 064323
S. Huth, et al. arXiv:2107.06229
……

PHYSICAL REVIEW LETTERS **125**, 202702 (2020)

2020, Gaussian processes (GPs)

How Well Do We Know the Neutron-Matter Equation of State at the Densities Inside Neutron Stars? A Bayesian Approach with Correlated Uncertainties

C. Drischler[1,2,*] R. J. Furnstahl[3,†] J. A. Melendez[3,‡] and D. R. Phillips[4,§]
[1] *Department of Physics, University of California, Berkeley, California 94720, USA*
[2] *Nuclear Science Division, Lawrence Berkeley National Laboratory, Berkeley, California 94720, USA*
[3] *Department of Physics, The Ohio State University, Columbus, Ohio 43210, USA*
[4] *Department of Physics and Astronomy and Institute of Nuclear and Particle Physics, Ohio University, Athens, Ohio 45701, USA*

Recent work about the application of AI in HICs

Physics Letters B 799 (2019) 135045

Contents lists available at ScienceDirect

Physics Letters B

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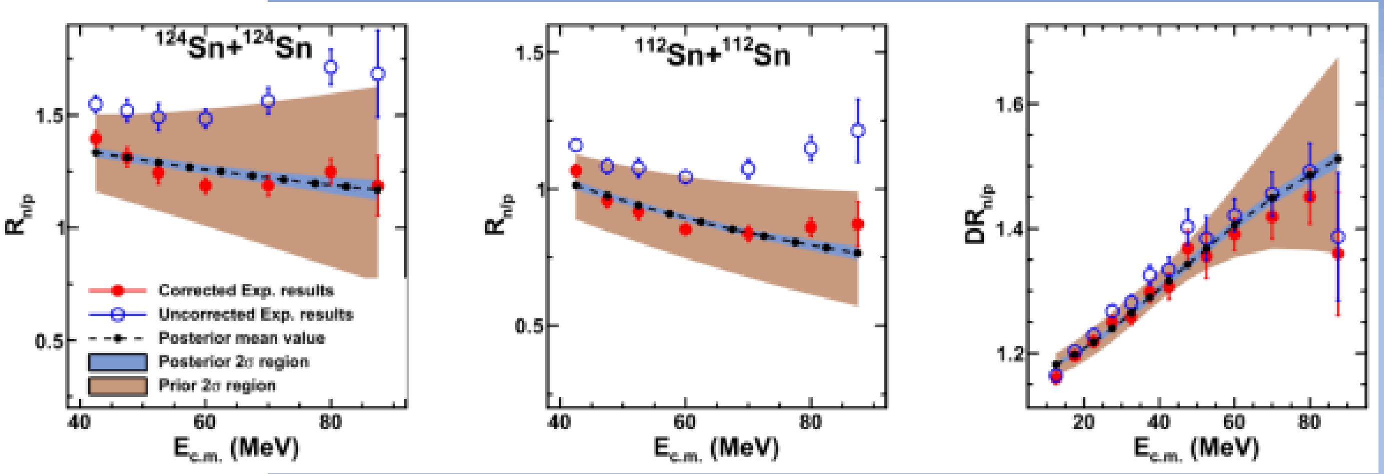
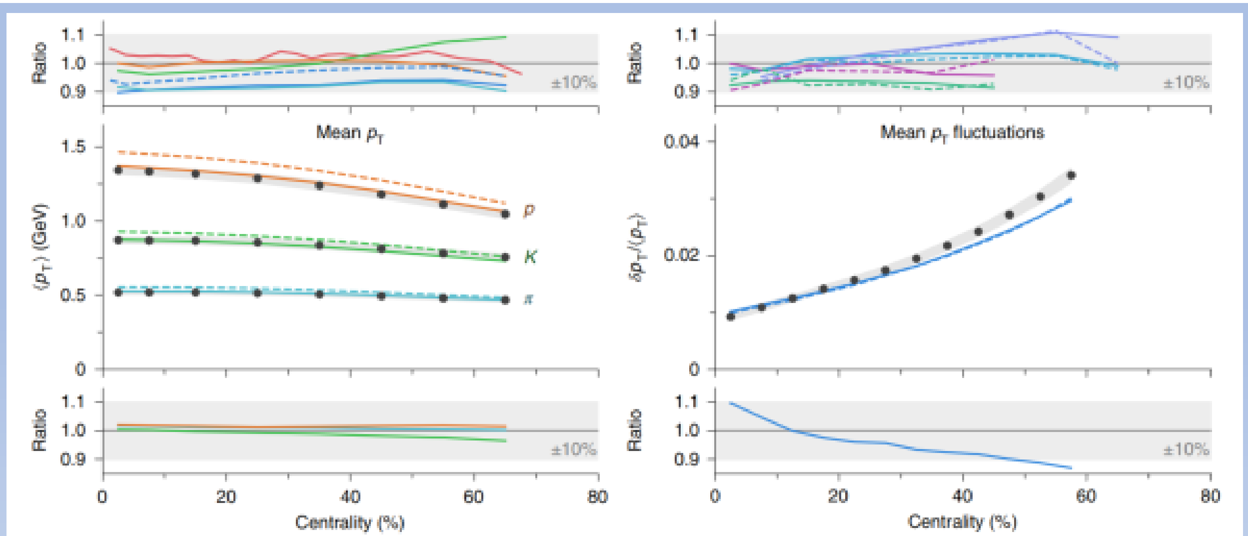
Constraining the symmetry energy with heavy-ion collisions and Bayesian analyses

P. Morfouace [a,*], C.Y. Tsang [a], Y. Zhang [b], W.G. Lynch [a], M.B. Tsang [a], D.D.S. Coupland [a], M. Youngs [a], Z. Chajecki [c], M.A. Famiano [c], T.K. Ghosh [e], G. Jhang [a], Jenny Lee [d], H. Liu [f], A. Sanetullaev [a], R. Showalter [a], J. Winkelbauer [a]





D. Everett et al. PRL 126 (2021) 242301,
G. Nijs, et al. PRC103 (2021)054909 ……

nature physics

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Letter | Published: 12 August 2019

Bayesian estimation of the specific shear and bulk viscosity of quark–gluon plasma

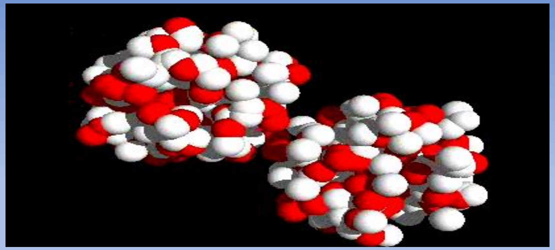
Jonah E. Bernhard, J. Scott Moreland & Steffen A. Bass

Transport model: Ultrarelativistic Quantum Molecular Dynamics Model

1).Initialization

Get the coordinate **r**

and the momentum **p**



$$\phi_i(\vec{r}_i;t) = \frac{1}{(2\pi)^{3/4}(\Delta x)^{3/2}} \exp\left\{-\frac{[\vec{r}_i - \vec{R}_i(t)]^2}{(2\Delta x)^2} + i\vec{r}_i \cdot \vec{P}_i(t)\right\}.$$

2).Propagation

Nucleon moves in the mean-field. Density, momentum, isospin-dependent.

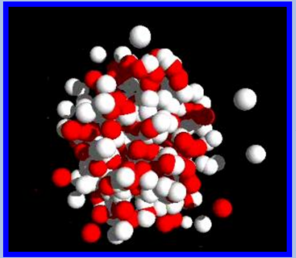
$$\dot{\mathbf{p}}_i = -\frac{\partial H}{\partial \mathbf{r}_i}, \quad \dot{\mathbf{r}}_i = \frac{\partial H}{\partial \mathbf{p}_i}.$$

Input Skyrme forces

Symmetry energy

3).Collision term

Medium modified cross section. Density, momentum, isospin-dependent. Pauli blocking.

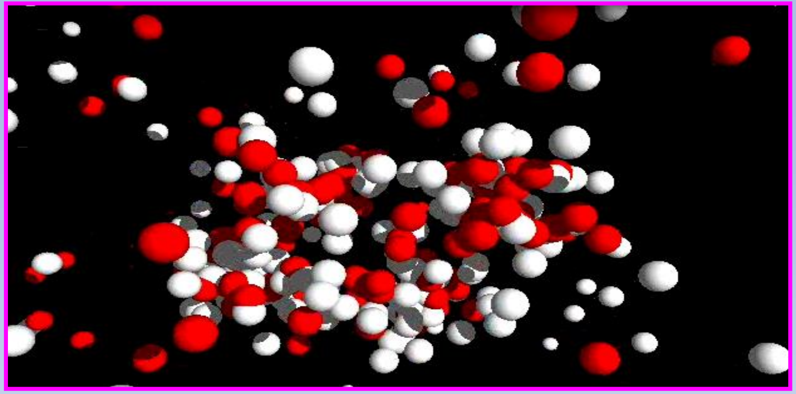


Input: $f\sigma_{pp}=f\sigma_{nn}$, and $f\sigma_{np}$

4). Cluster recognition

an isospin-dependent

Minimum Spanning Tree



Then, compare the simulated results with experimental data, one can get the information of EoS and in-medium NN cross section.

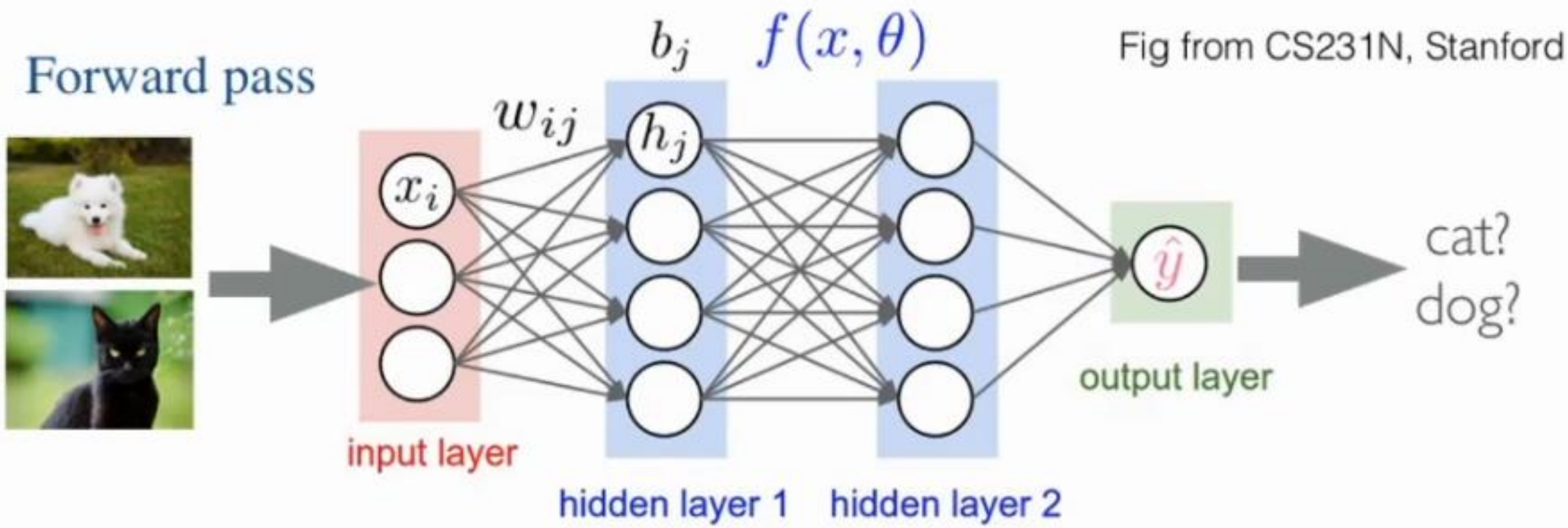
[Ref]Qingfeng Li and Yongjia Wang, et al. PRC 83, 044617 ; 89.034606;

Convolutional neural network (CNN)

This is how I see

88	126	145	85	123	142	85	123	142	86	124
86	125	142	84	123	140	83	122	139	85	124
85	124	141	82	121	138	82	121	138	84	123
82	119	135	80	117	133	80	117	133	85	122
78	114	128	77	113	127	79	115	129	84	120
79	115	129	78	114	128	80	116	130	83	119
82	118	130	81	117	129	81	117	129	82	118
83	117	129	82	116	128	82	116	128	82	116
79	113	123	79	113	123	80	114	124	81	115
76	108	119	76	108	119	77	109	120	80	112
76	109	118	76	109	118	77	110	119	79	112

This is how my computer sees



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

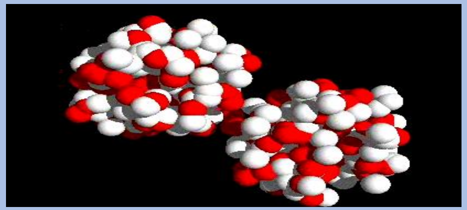
$$\sigma(z) = \begin{cases} z, & z > 0 \\ 0, & z \leq 0 \end{cases}$$

(c) PReLU

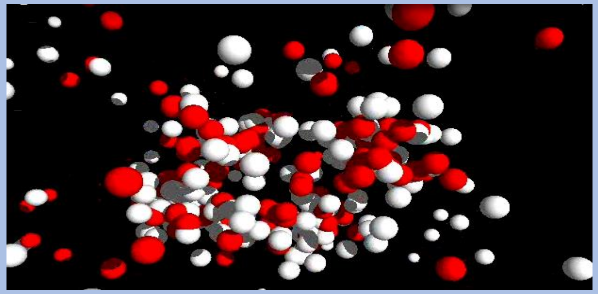
$$\sigma(z) = \begin{cases} z, & z > 0 \\ az, & z \leq 0 \end{cases}$$

Methods

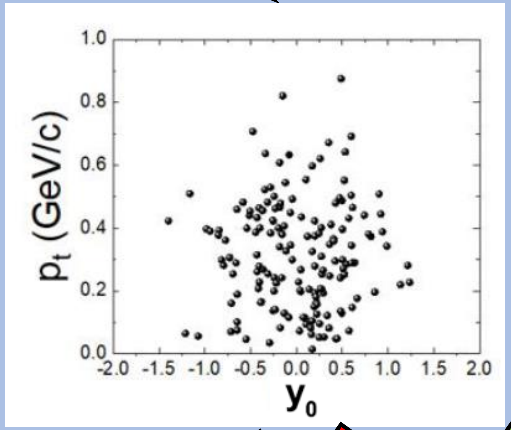
Initialization
Au+Au, E_{lab}=0.4A GeV
b=5 fm, diff sym.



Transport model simulation



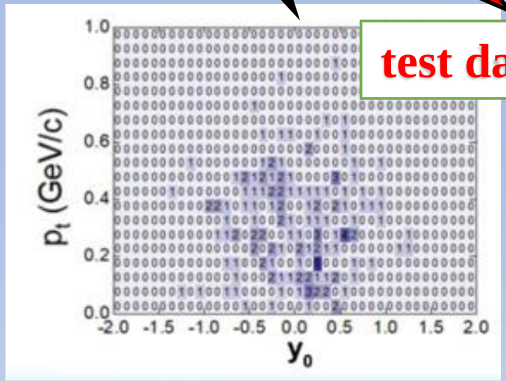
Particle distribution

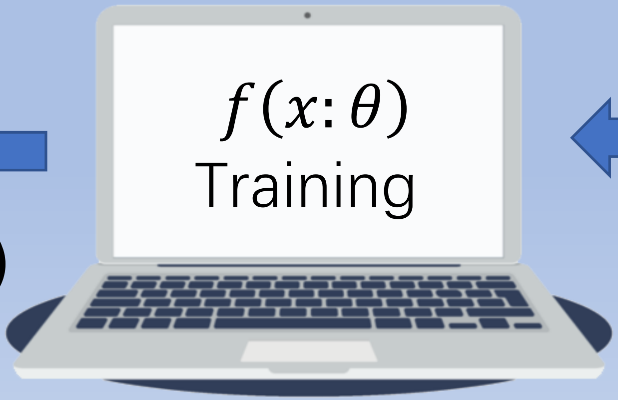


Training data

test data

validation data





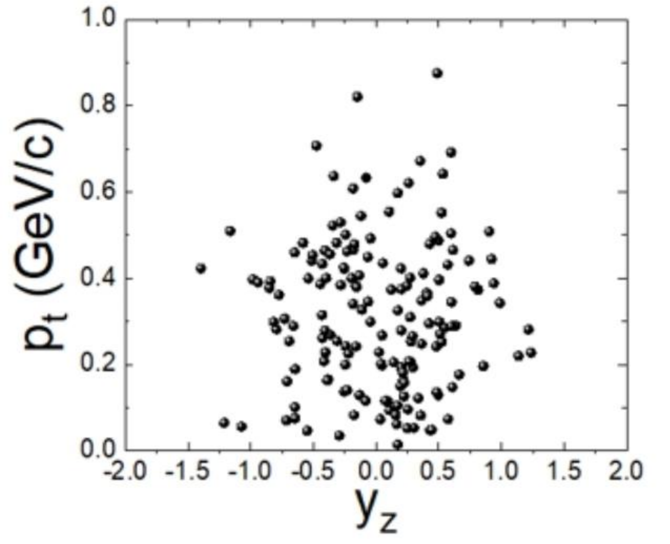
Symmetry energy

A deep convolutional neural network (CNN) is trained to learn the mapping between the symmetry energy and the particle distributions.

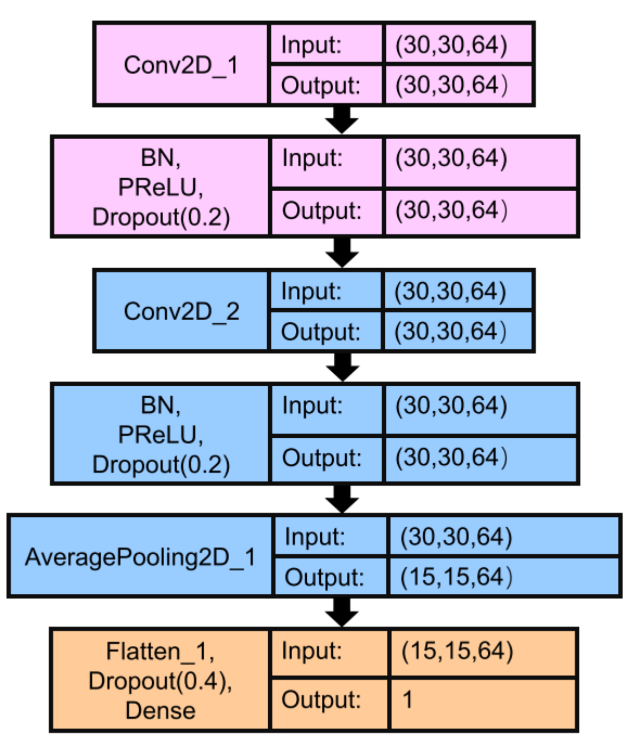
Results I: Impact parameter

$$\Delta b = \frac{1}{N_{\text{event}}} \sum_{i=1}^{N_{\text{events}}} |b_i^{\text{true}} - b_i^{\text{pred}}|.$$

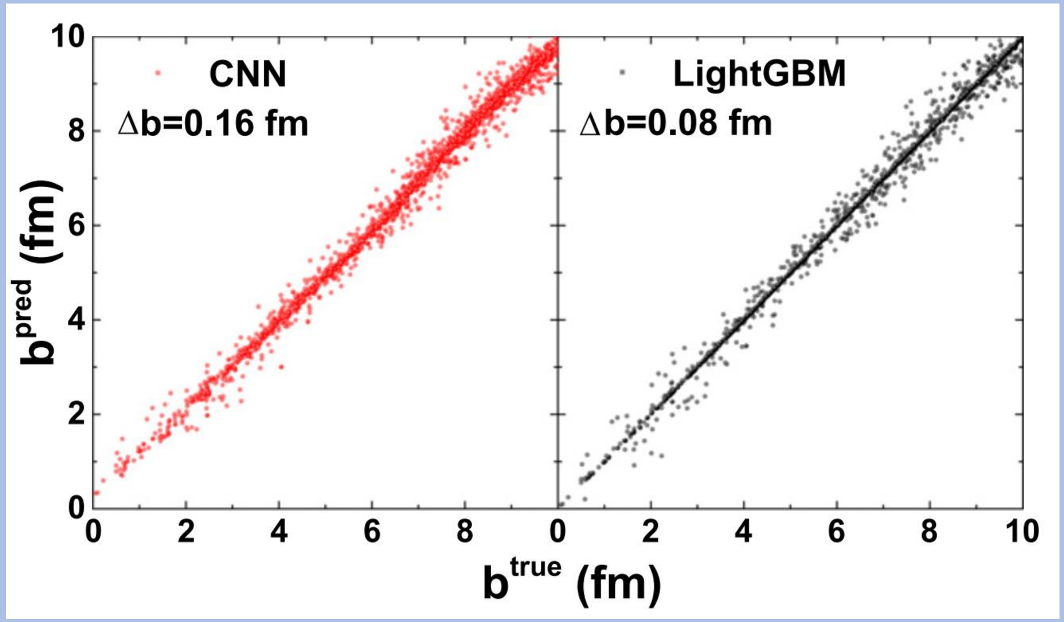
F. Li, Y. Wang, et al., J. Phys. G: Nucl. Part. Phys. 47 (2020) 115104,
Phys. Rev. C 104 (2021) 034608
C. Y. Tsang, et al. arXiv:2107.13985



Input data



Architecture of CNN

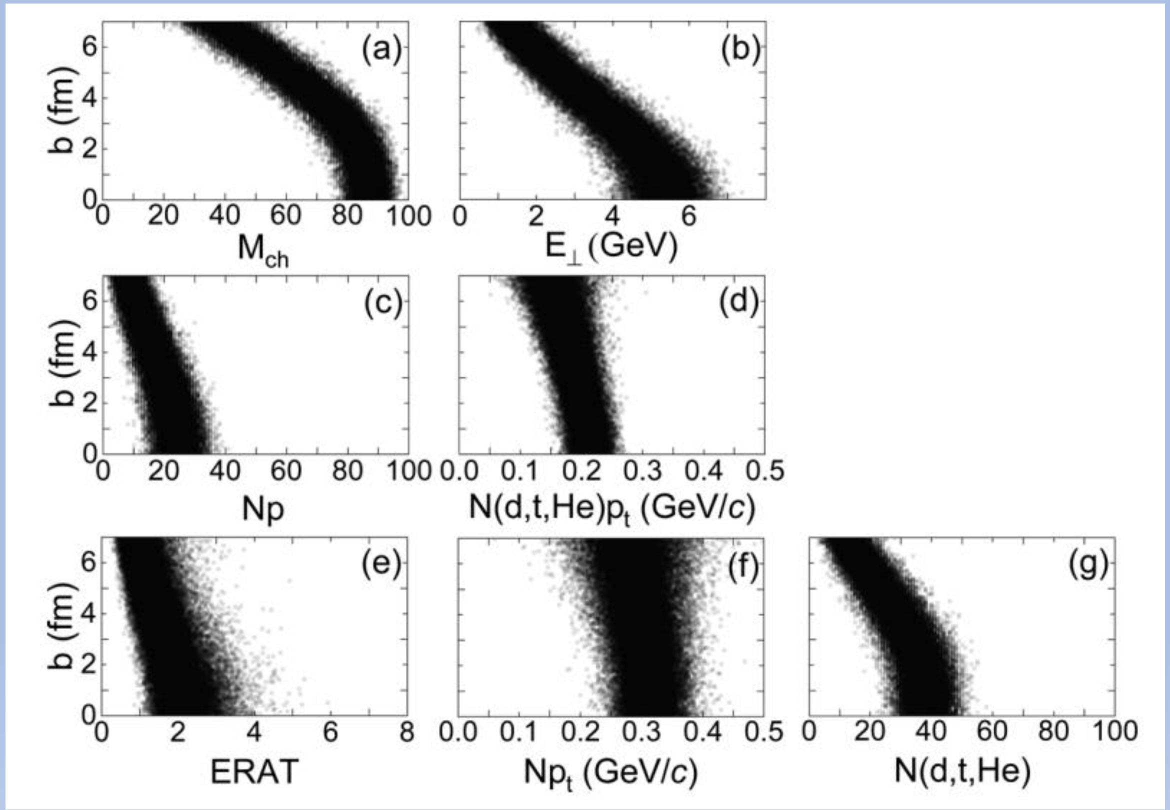


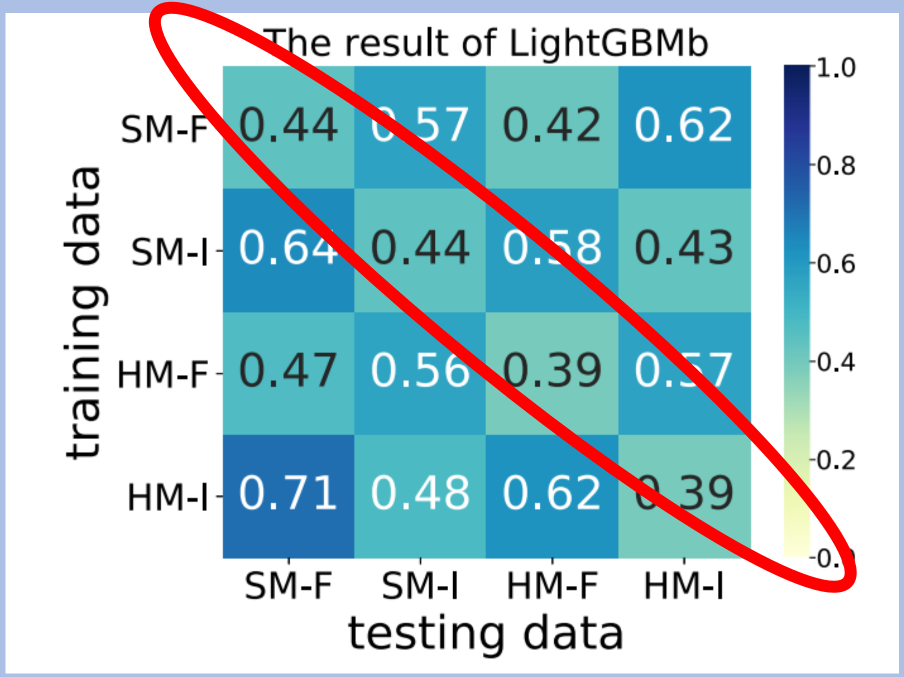
The true impact parameter vs the predicted one.

Results I: Impact parameter

$$\Delta b = \frac{1}{N_{\text{event}}} \sum_{i=1}^{N_{\text{events}}} |b_i^{\text{true}} - b_i^{\text{pred}}|.$$

F. Li, Y. Wang, et al., J. Phys. G: Nucl. Part. Phys. 47 (2020) 115104,
Phys. Rev. C 104 (2021) 034608
C. Y. Tsang, et al. arXiv:2107.13985





Data are generated with different model parameter sets.

Generalizability

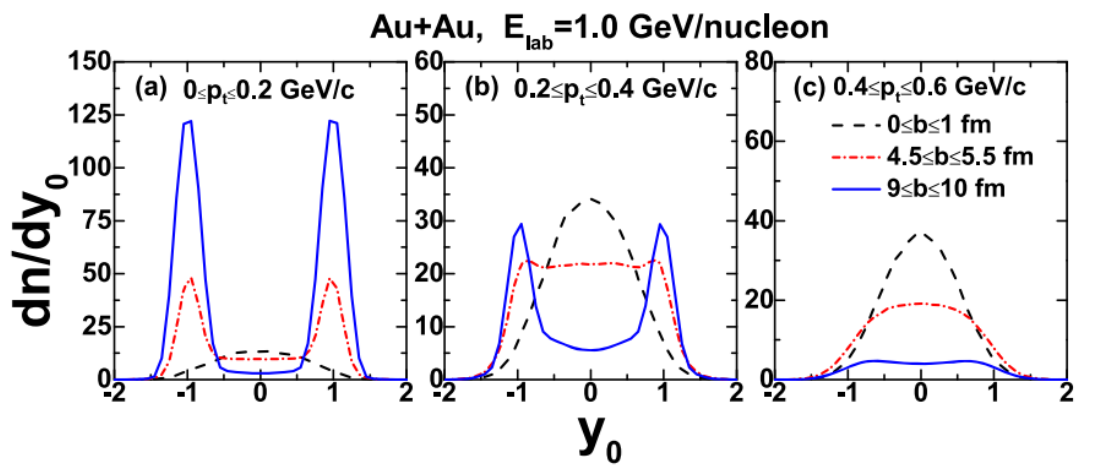
We hope the trained AI model is robust enough, i.e., it works when testing data are obtained from different model parameter sets or from different models, or from experimental data.

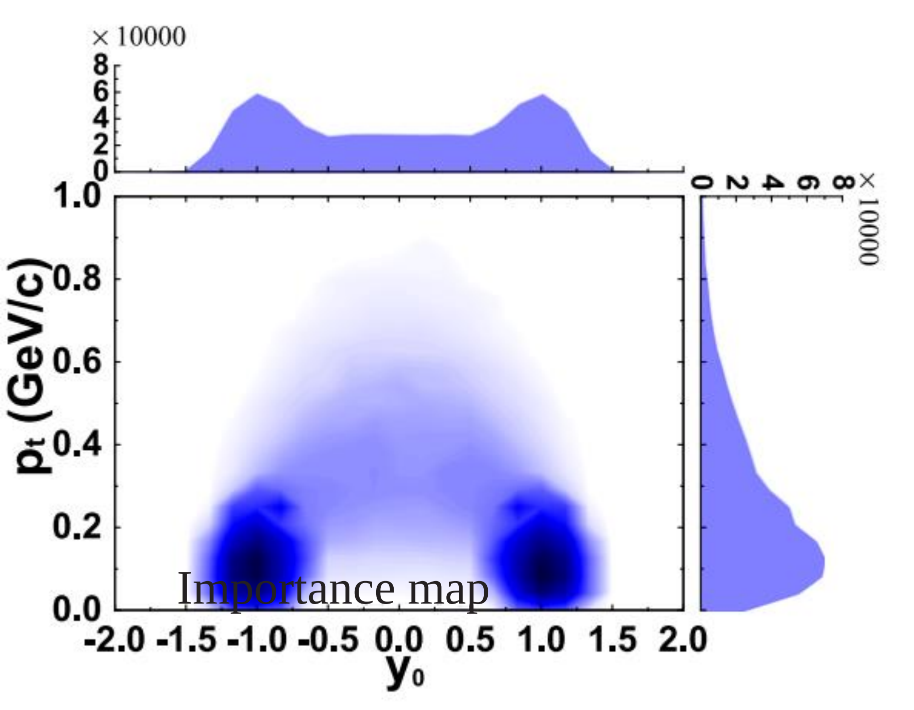
Results I: Impact parameter

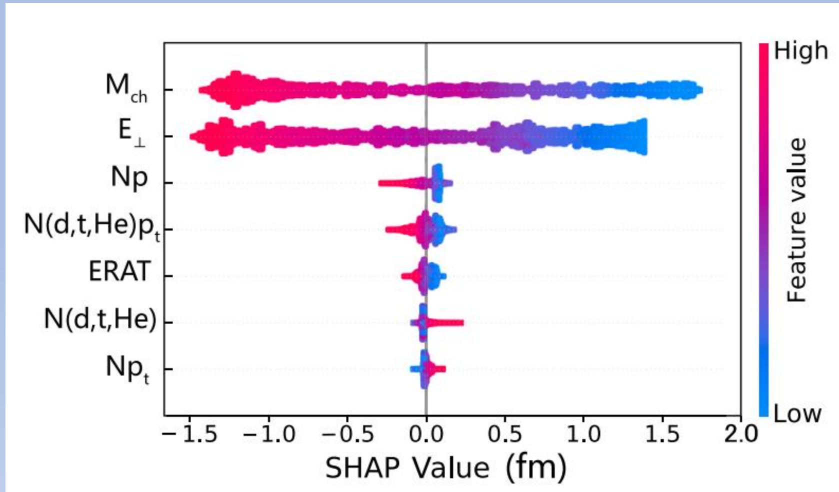
$$\Delta b = \frac{1}{N_{\mathrm{event}}} \sum_{i=1}^{N_{\mathrm{events}}} |b_i^{\mathrm{true}} - b_i^{\mathrm{pred}}|.$$

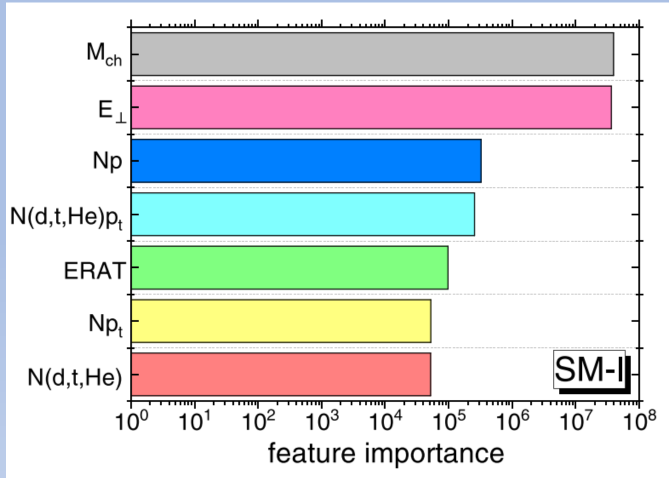
F. Li, Y. Wang, et al., J. Phys. G: Nucl. Part. Phys. 47 (2020) 115104,
Phys. Rev. C 104 (2021) 034608
C. Y. Tsang, et al. arXiv:2107.13985

Explainability
What can we get from AI?





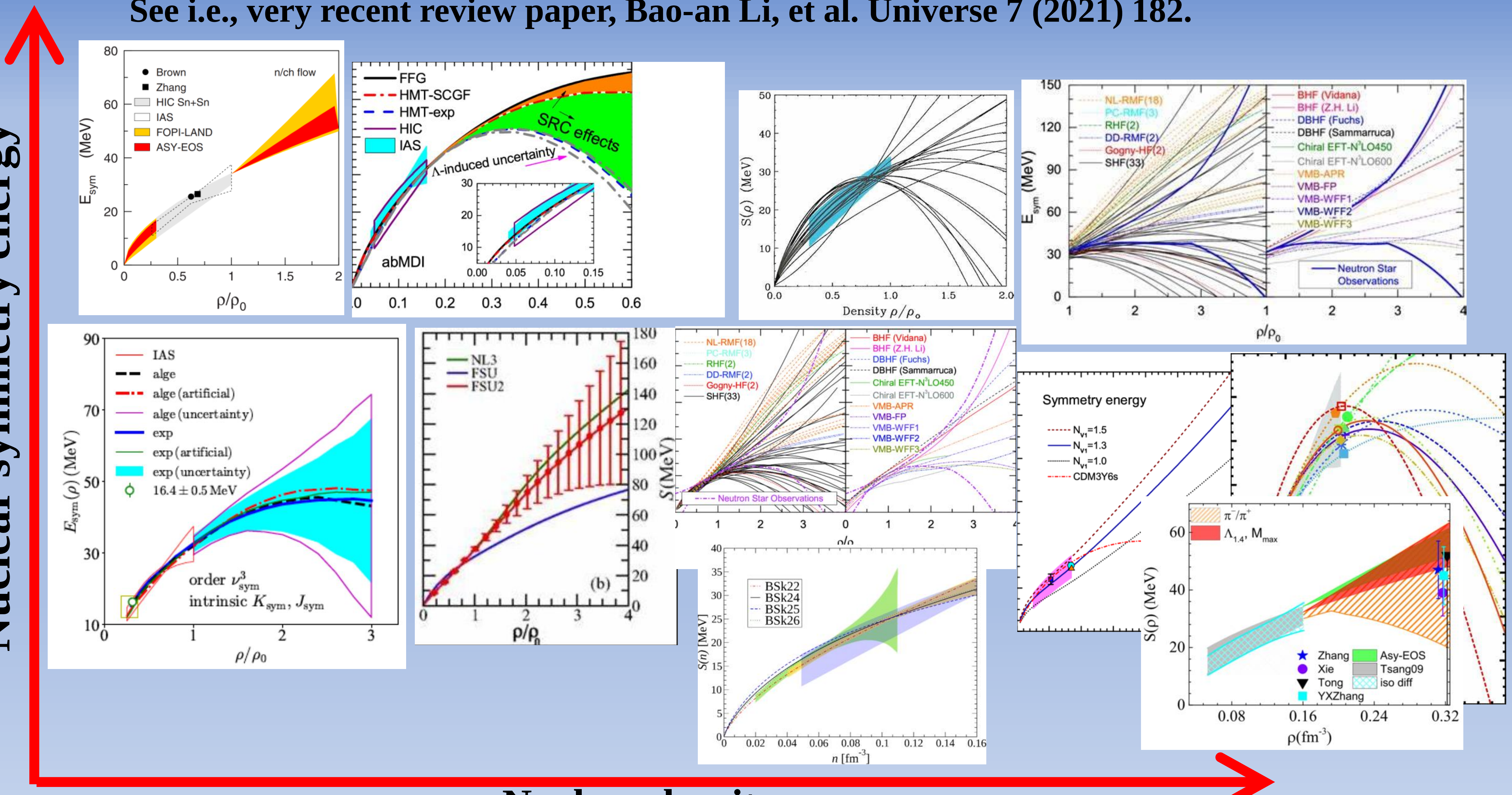




Results II: Symmetry energy

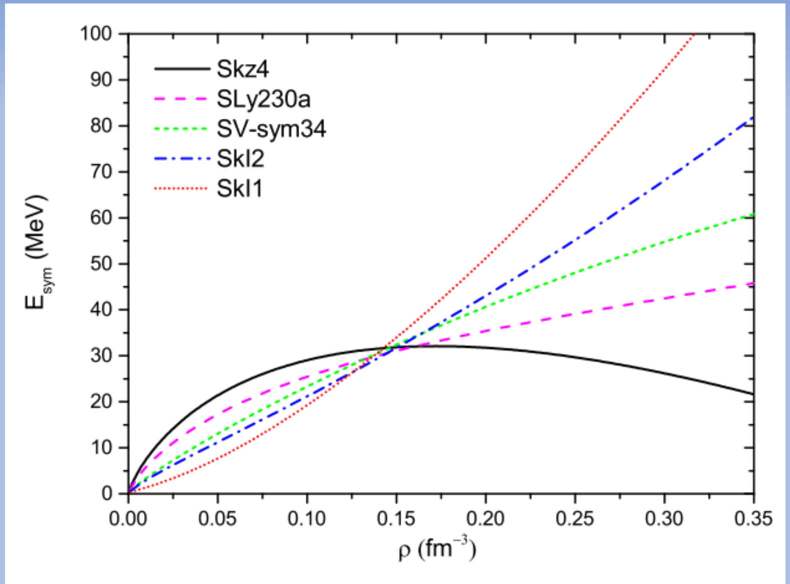
See i.e., very recent review paper, Bao-an Li, et al. Universe 7 (2021) 182.

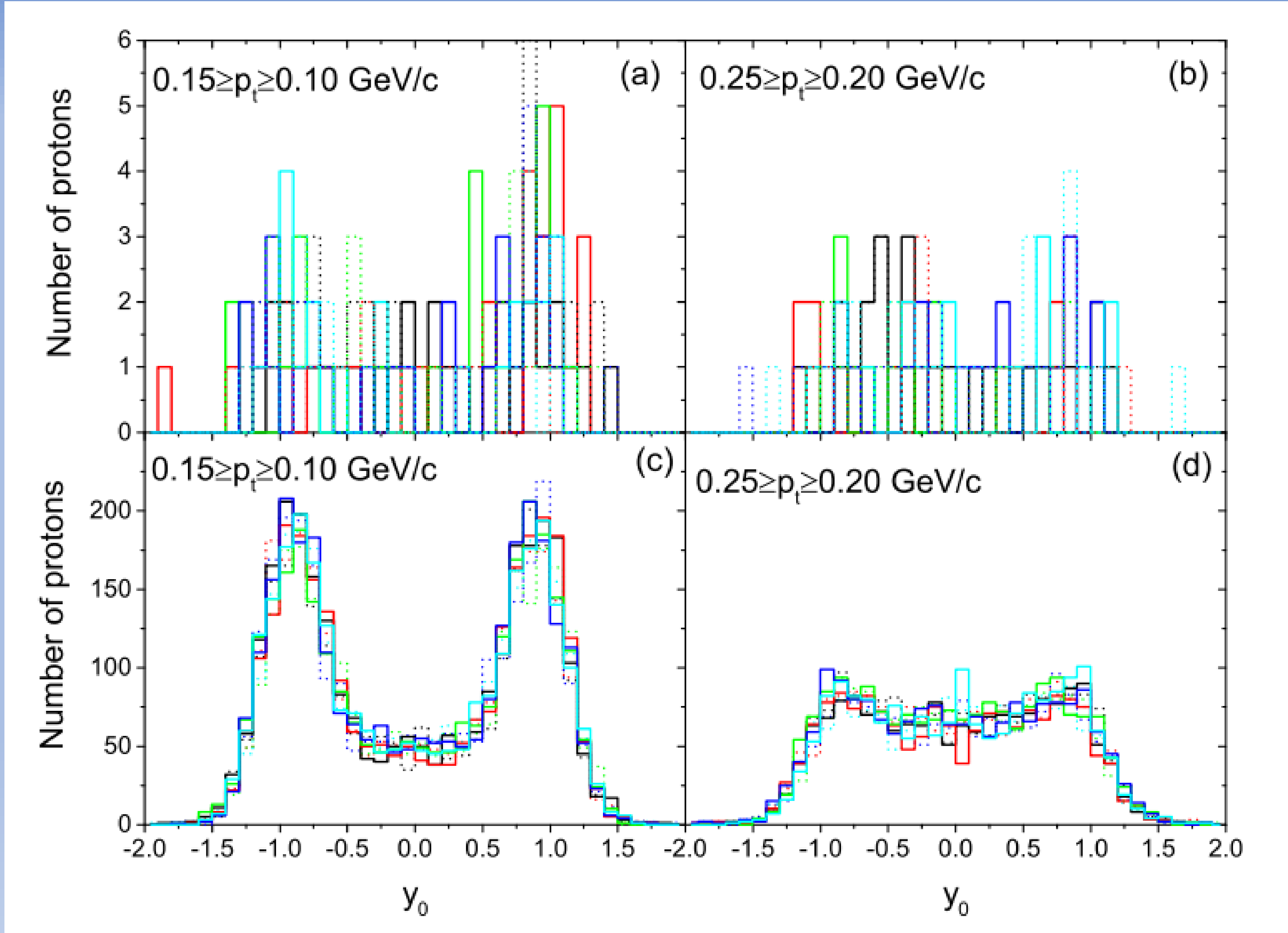
Nuclear symmetry energy



Nuclear density

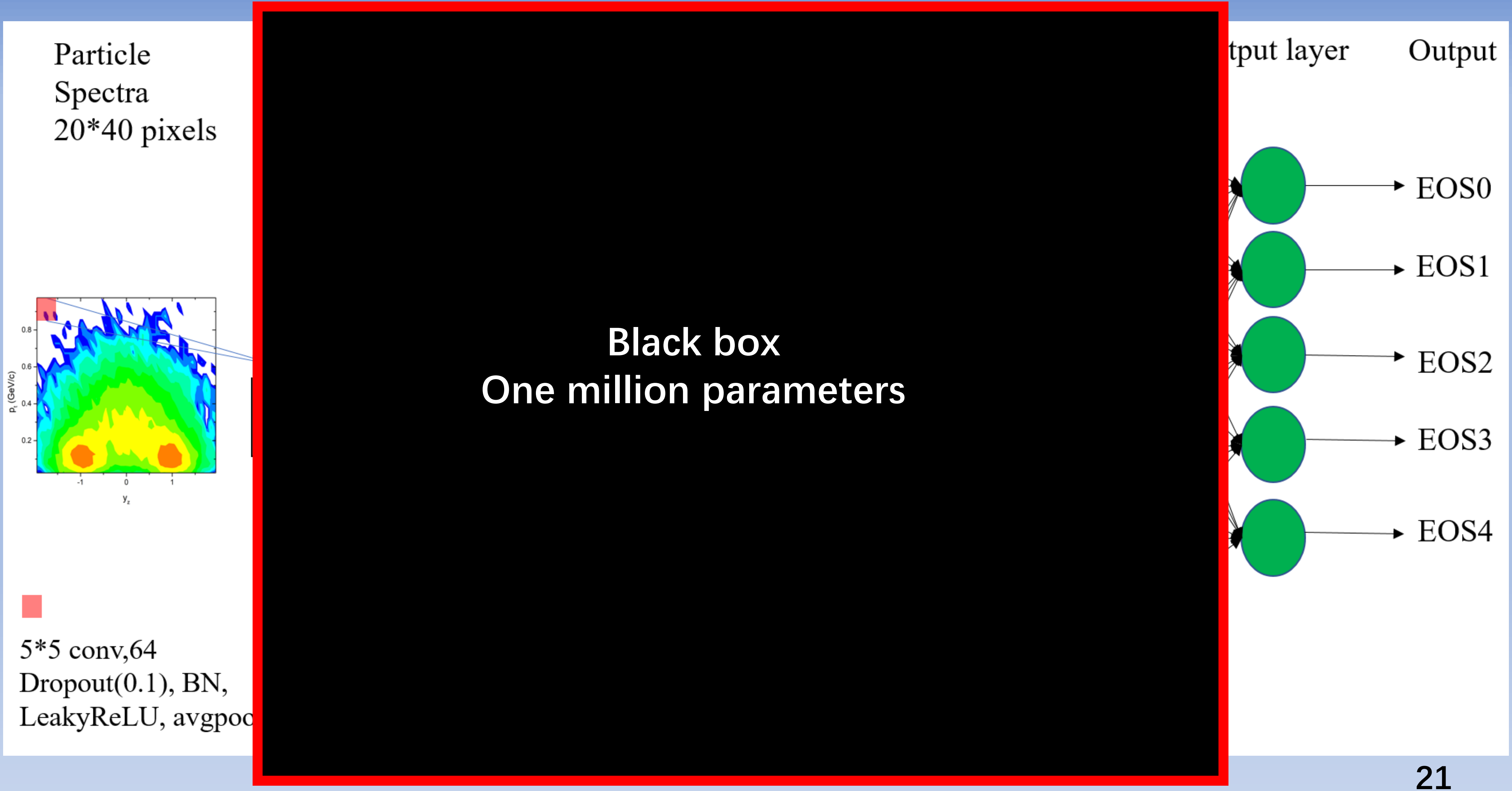
Results II: Symmetry energy





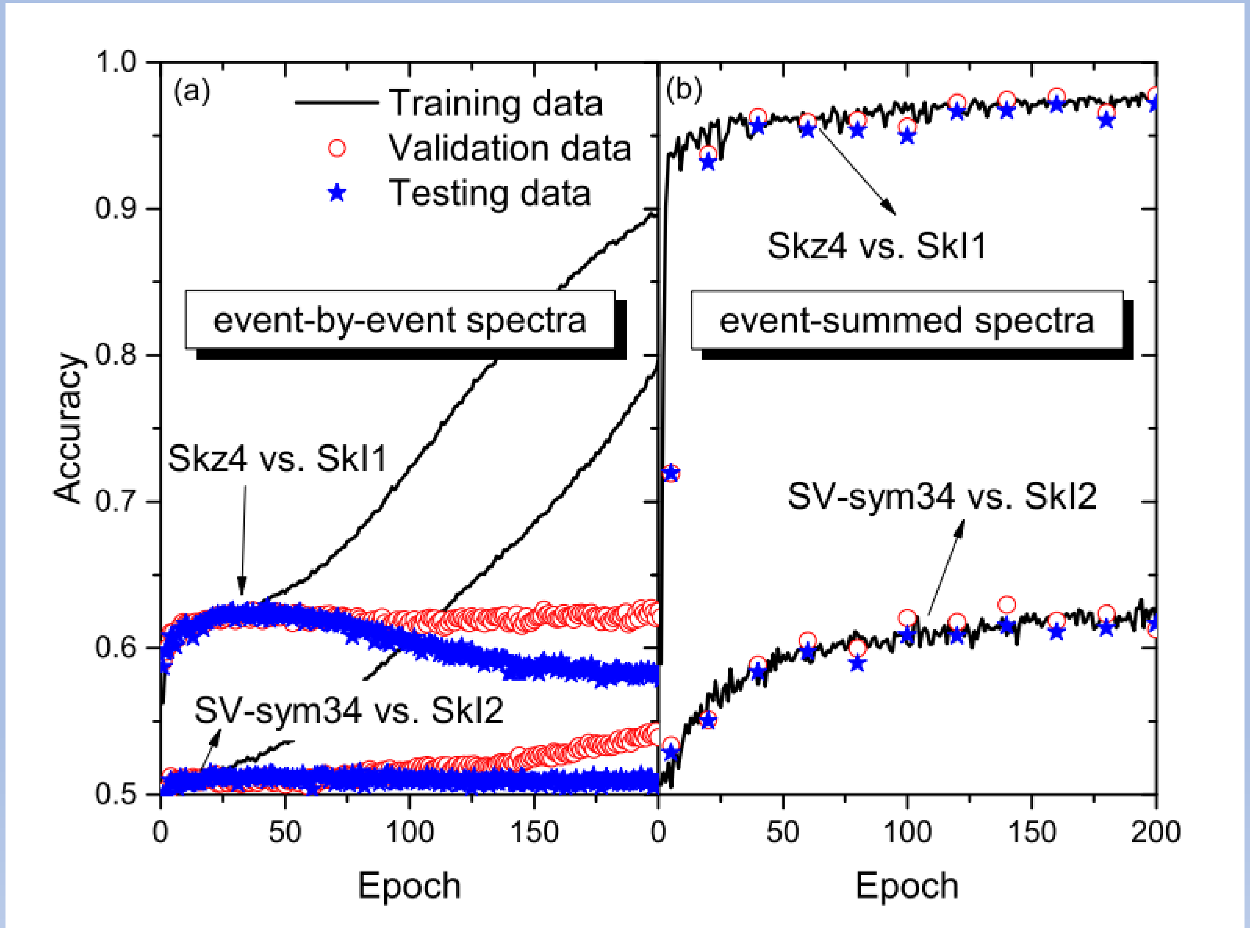
Due to **initial fluctuations** and **the random nucleon-nucleon collisions**, fluctuations on the rapidity and transverse momentum distributions are very large, consequently, the effects of symmetry energy on the distributions are hidden.

Convolutional neural network (CNN)

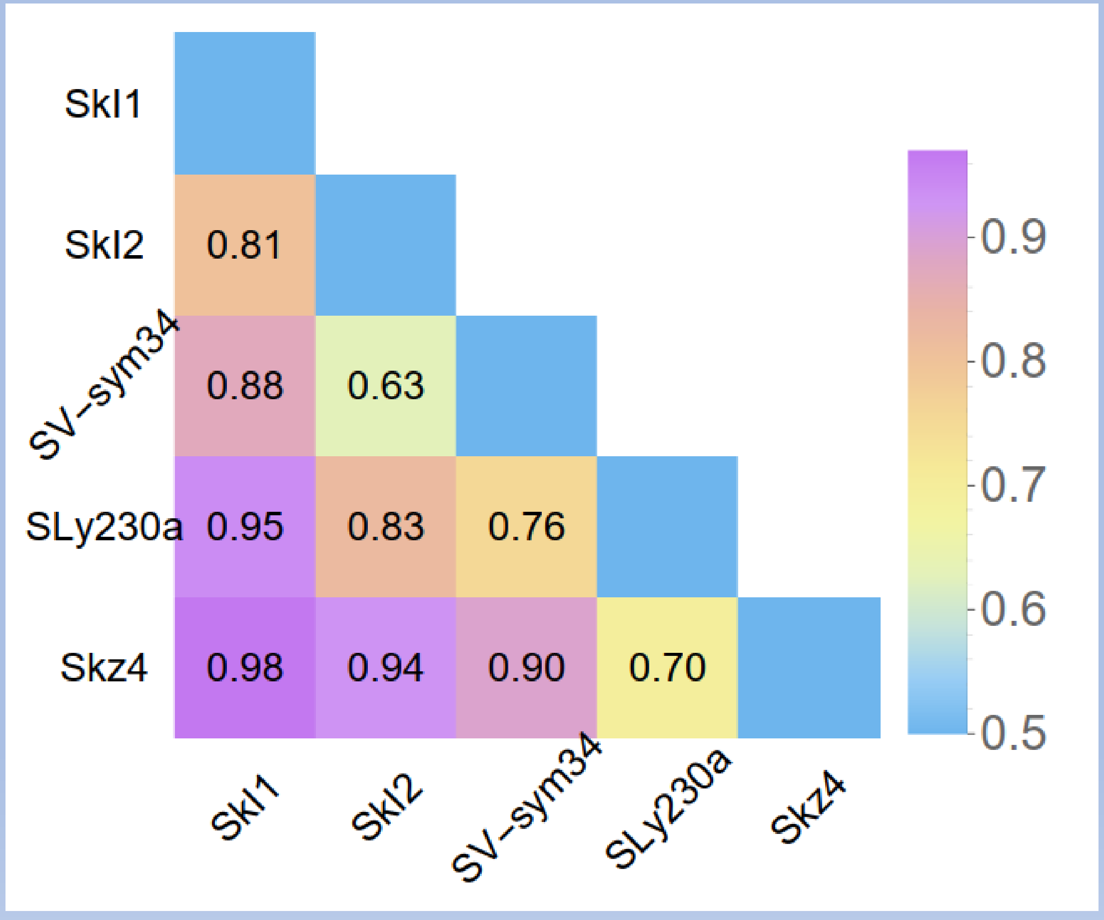


Results II: Symmetry energy

Result of two-class classification task

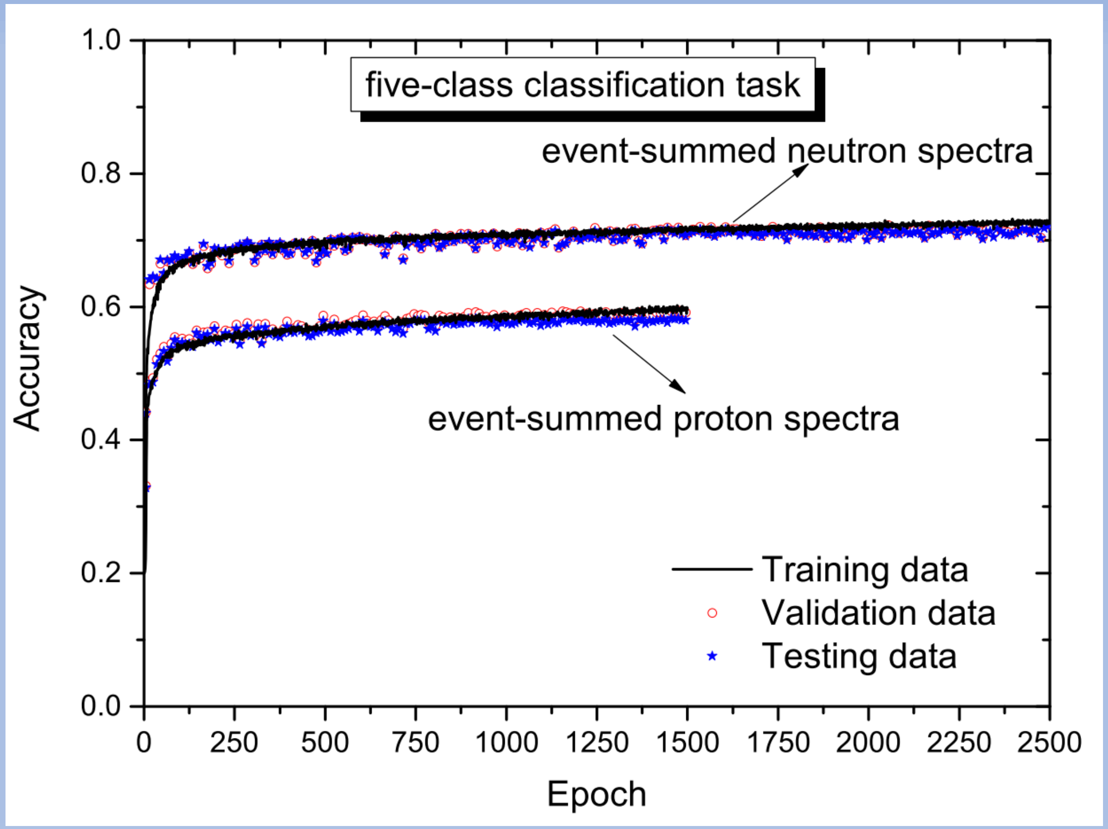


Accuracy increases with increasing difference in L.

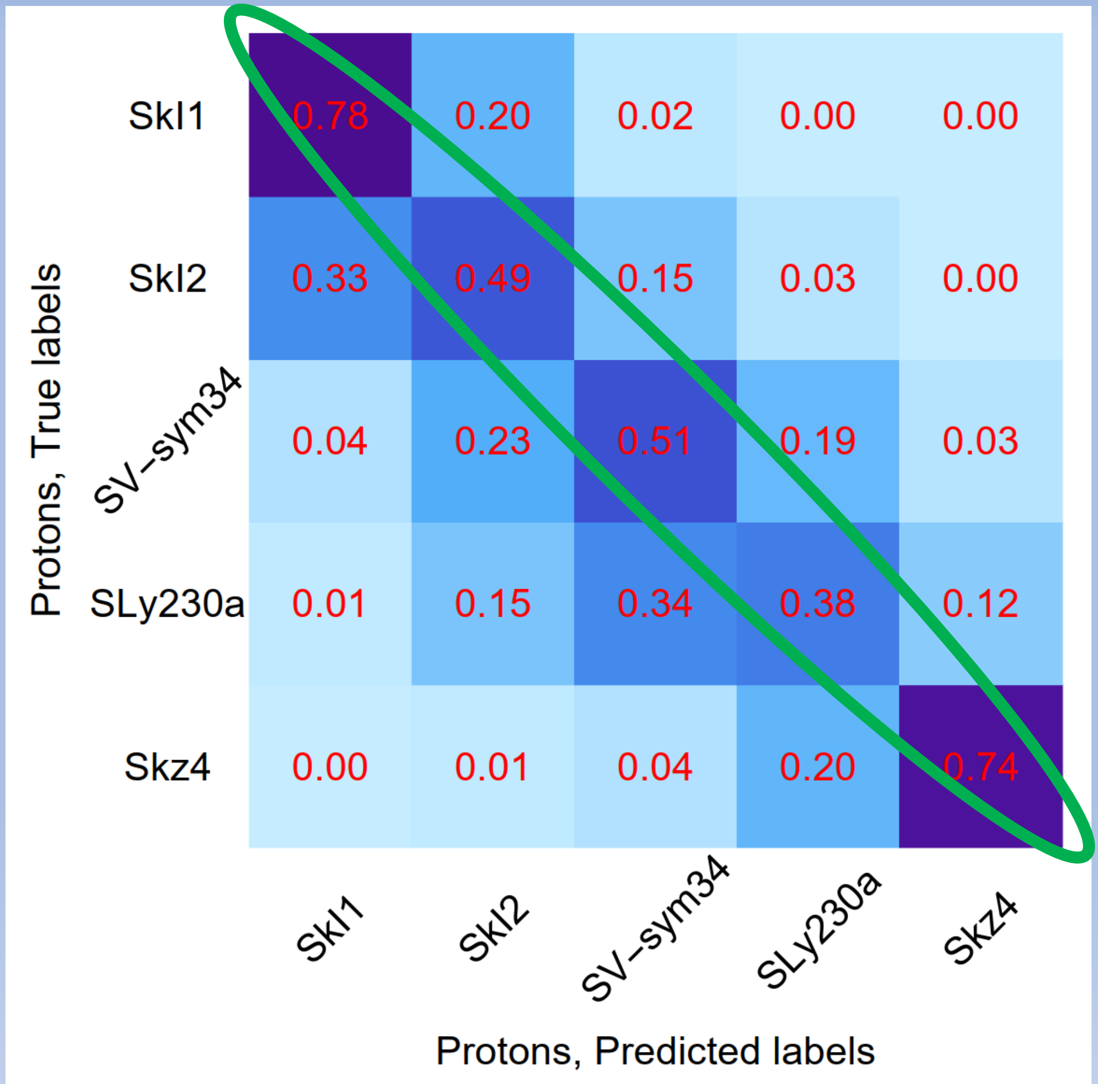


Results II: Symmetry energy

Result of five-class classification task



The confusion matrix for five-class classification task



The diagonal entries show the fraction of correctly classified testing data.

Off-diagonal cell: the probability that the object of the symmetry energy (vertical label) being misclassified as the horizontal labelled symmetry energy.

Results II: Symmetry energy

Result of regression task

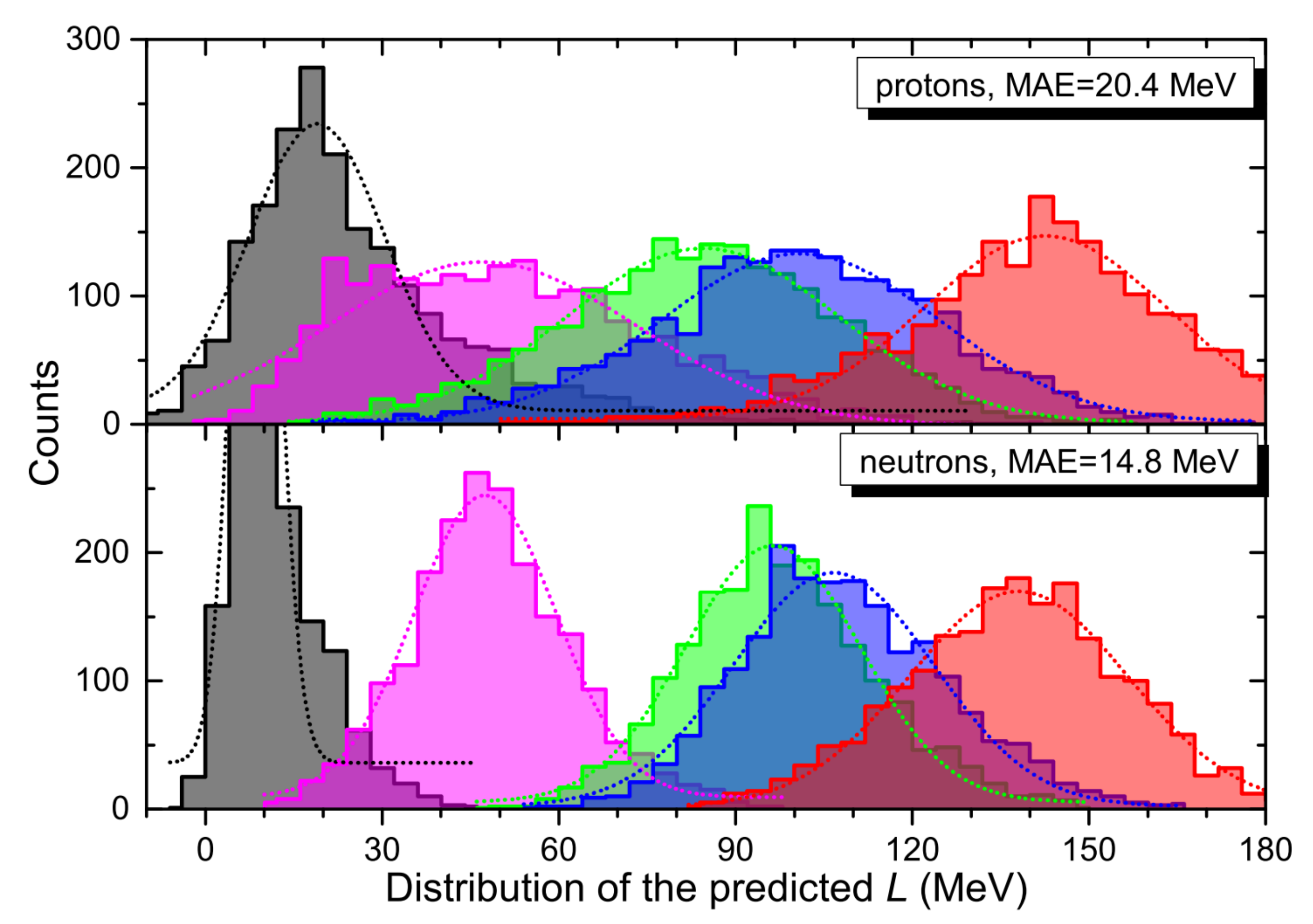


TABLE II: The mean values of predicted L and its standard deviation σ obtained with Gaussian fit, in units of MeV.

		Proton spectra		Neutron spectra	
	L_{true}	L_{pred}	σ	L_{pred}	σ
Skz4	5.8	18.9	11.5	8.5	3.7
SLy230a	44.3	46.9	26.5	47.5	12.1
SV-sym36	81.2	84.5	23.3	96.4	14.8
SkI2	106.4	100.9	23.6	106.7	17.0
SkI1	159.0	142.6	20.7	138.1	18.5

Summary and outlook

- AI can be used to deduced impact parameter with high accuracy.
- On event-by-event basis as input, the accuracy for classifying the very soft and stiff Esym(ρ) is about 60%, while by setting event-summed proton spectra as input, the classification accuracy increases to 98%.
- By combining 100 events = 1 samples, accuracy is about 55% and 70% with proton and neutron data, respectively, for five-classification task.
- For regression task, mean absolute error are about 20.4 and 14.8 MeV for proton and neutron data, respectively.

Summary and outlook

- What benefit can we get from AI?

  Importance map, accelerate calculations, estimate uncertainties……
- How AI can help us constrain symmetry energy in multi-messenger ear?

  Bayesian inference and more……
- How can physics-guided neural networks (PGNN) and physics-informed neural networks (PINN) in the study of symmetry energy?
- Can we open the black box of AI?

Physics-informed neural networks: A deep learning framework fo...

https://www.sciencedirect.com/science/article/pii/S0021999118307125

Feb 01, 2019 · We introduce physics-informed neural networks – neural networks that are trained **to solve supervised learning tasks while respecting any given laws of physics described by general nonlinear partial differential equations.** In this work, we present our developments in the context of solving two main classes of problems: data-driven solution and data-driven discovery of partial ...

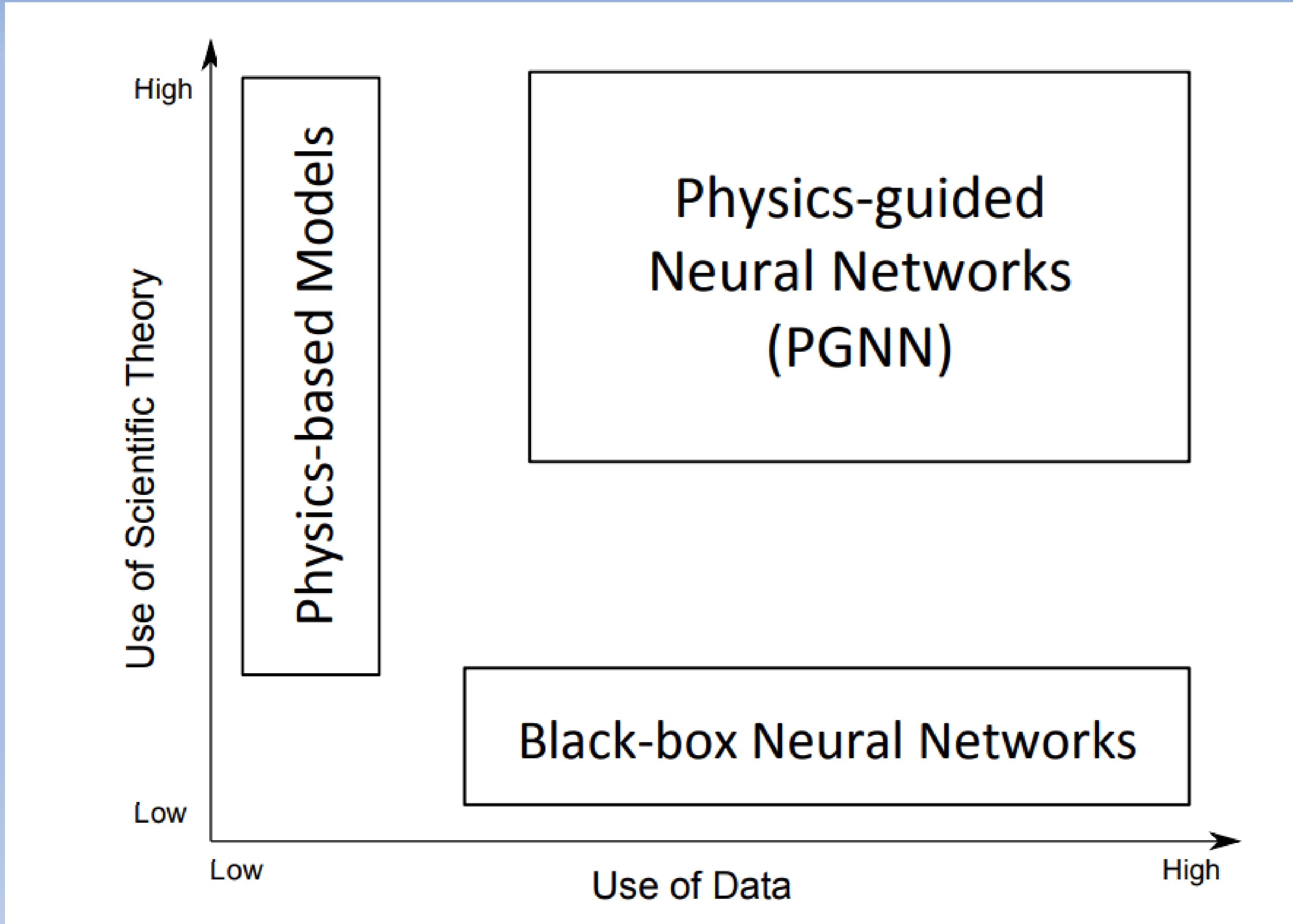
Cited by: 1441 **Author:** Maziar Raissi, Paris Perdikaris, George E. K...

Publish Year: 2019

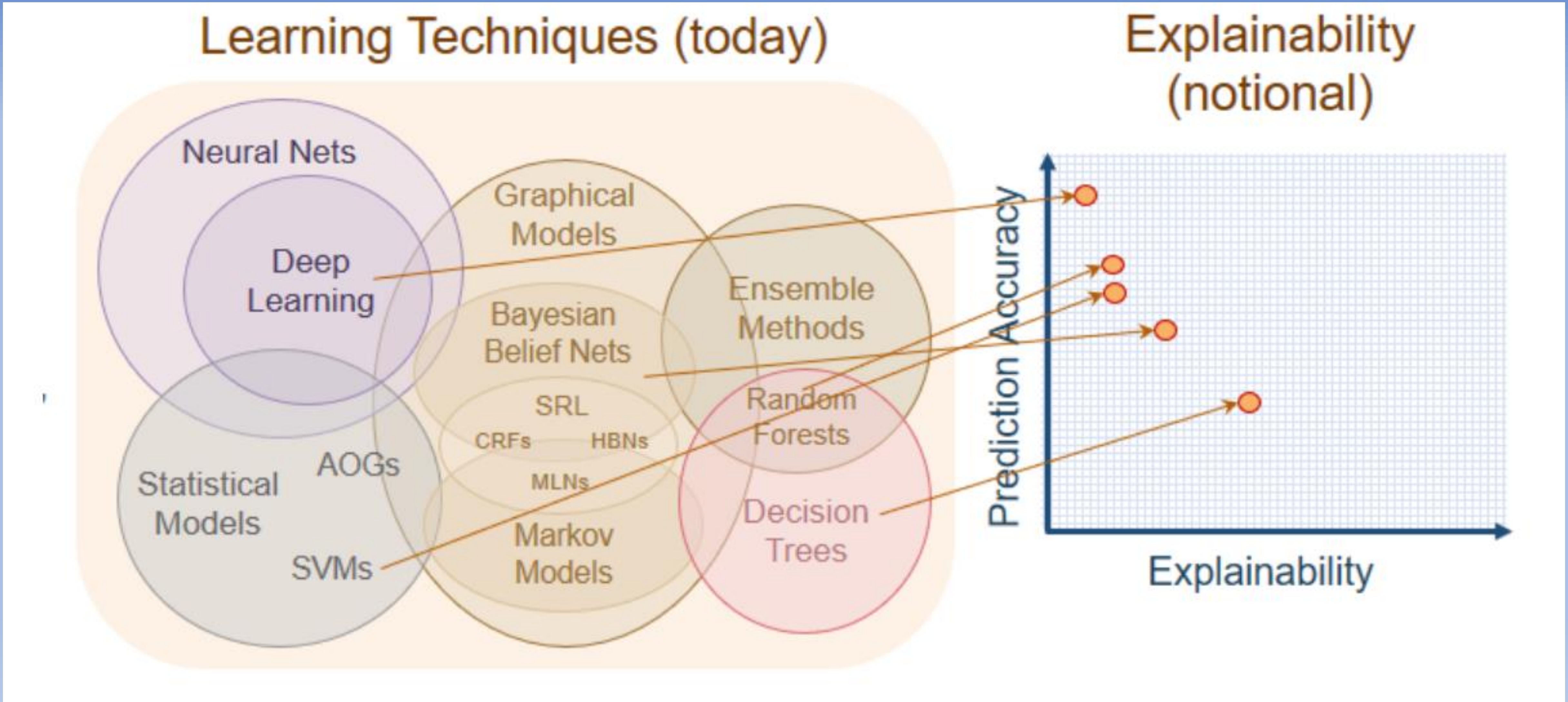
Thanks a lot!

Summary and outlook

arXiv:1710.11431v2



A schematic representation of physics-guided neural networks in the context of other knowledge discovery approaches that either use physics or data. The X-axis measures the use of data while the Y –axis measures the use of scientific knowledge.



Explainability of machine learning models appear inverse to their prediction accuracy.

F. Y. Xu, H. Uszkoreit, Y. Z. Du *et al.*, in *Natural Language Processing and Chinese Computing, NLPCC 2019*, Lecture Notes in Computer Science, Vol. 11839 (Springer, Cham, 2019), pp. 563–574

F. Emmert-Streib, O. Yli-Harja, and M. Dehmer, WIREs Data Mining Knowl. Discovery **10**, e1368 (2020)

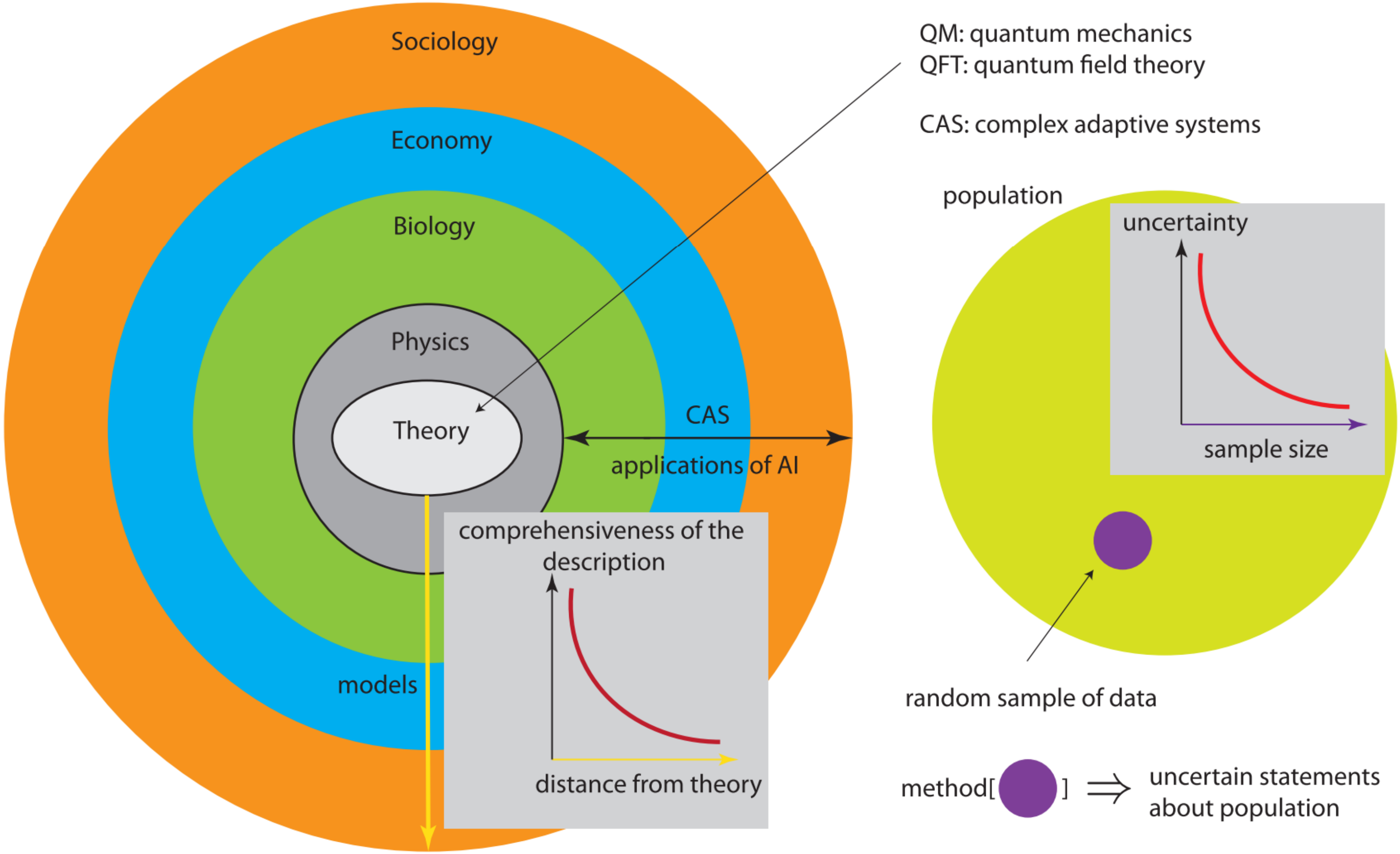


FIGURE 1 An overview describing the limitations of explainable artificial intelligence (AI) with respect to attainable goals. (Left) Different scientific fields are arranged according to their increasing complexity (Anderson, 1972) starting from the best (most comprehensive) theories of physics in the center. The further the distance from these theories the less comprehensive are the models describing subjects of complex adaptive systems (left coordinate system). (Right) Any AI system analyzes a random sample of data drawn from a population. One source of uncertainty is provided by the sample size of the data (right coordinate system) that translates directly into uncertain statements about the population