Applications of Machine Learning in Relativistic Heavy Ion Collisions

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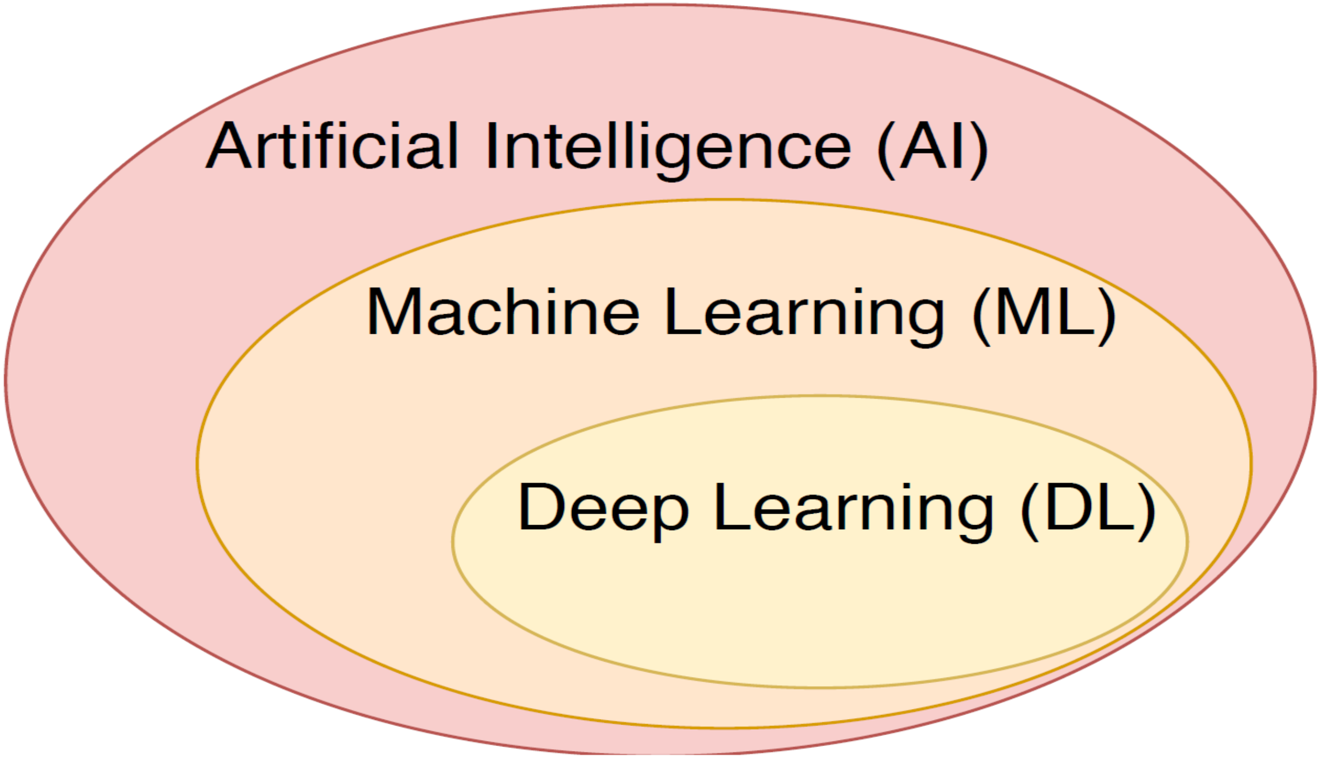
What is Machine Learning / Deep Learning?



AI： the broadest term, applying to any technique that enables computers to mimic human intelligence.

ML： A subset of AI aiming at optimizing a performance criterion using example data or past experience, but without explicit instruction.

DL： A subset of ML aiming at understanding high-level representations of data using a deeper structure of multiple processing layers

Broad Applications of Machine Learning

Computer vision

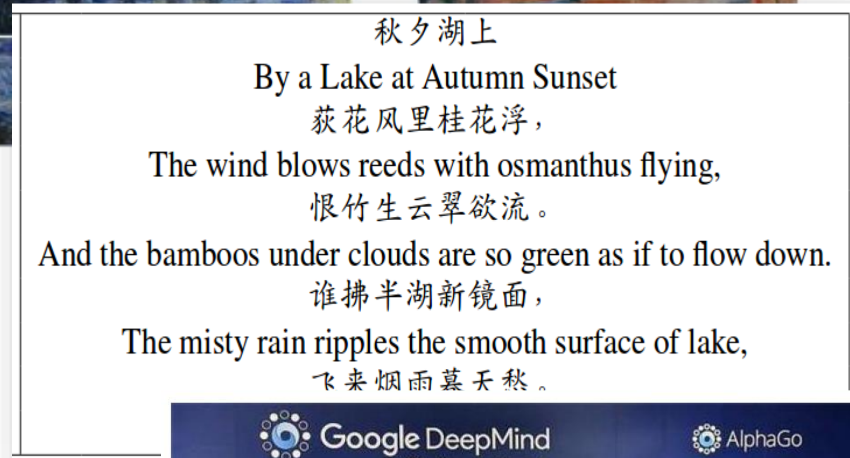
-**Image identification**

-**Image style transition**

-**Image generation**

… … … …

Language processing



秋夕湖上

By a Lake at Autumn Sunset

荻花风里桂花浮，

The wind blows reeds with osmanthus flying,

恨竹生云翠欲流。

And the bamboos under clouds are so green as if to flow down.

谁拂半湖新镜面，

The misty rain ripples the smooth surface of lake,

飞来烟雨暮天愁。

-**Machine translation**

-**Speech recognition**

-**Chinese poetry generation**

… … … …

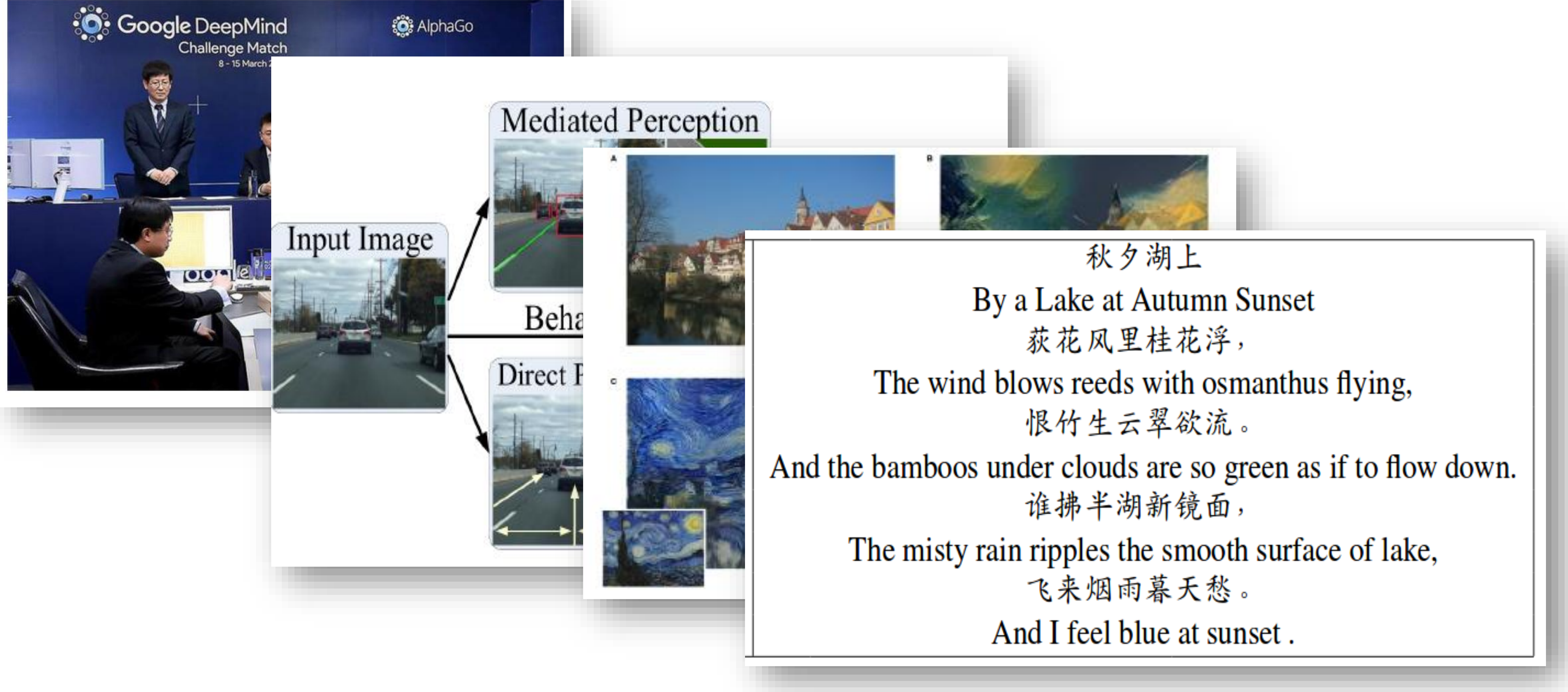
Playing Games

-**AlphaGo (by Google DeepMind)**

… … … …

Autonomous Driving

… … … …



Categories:

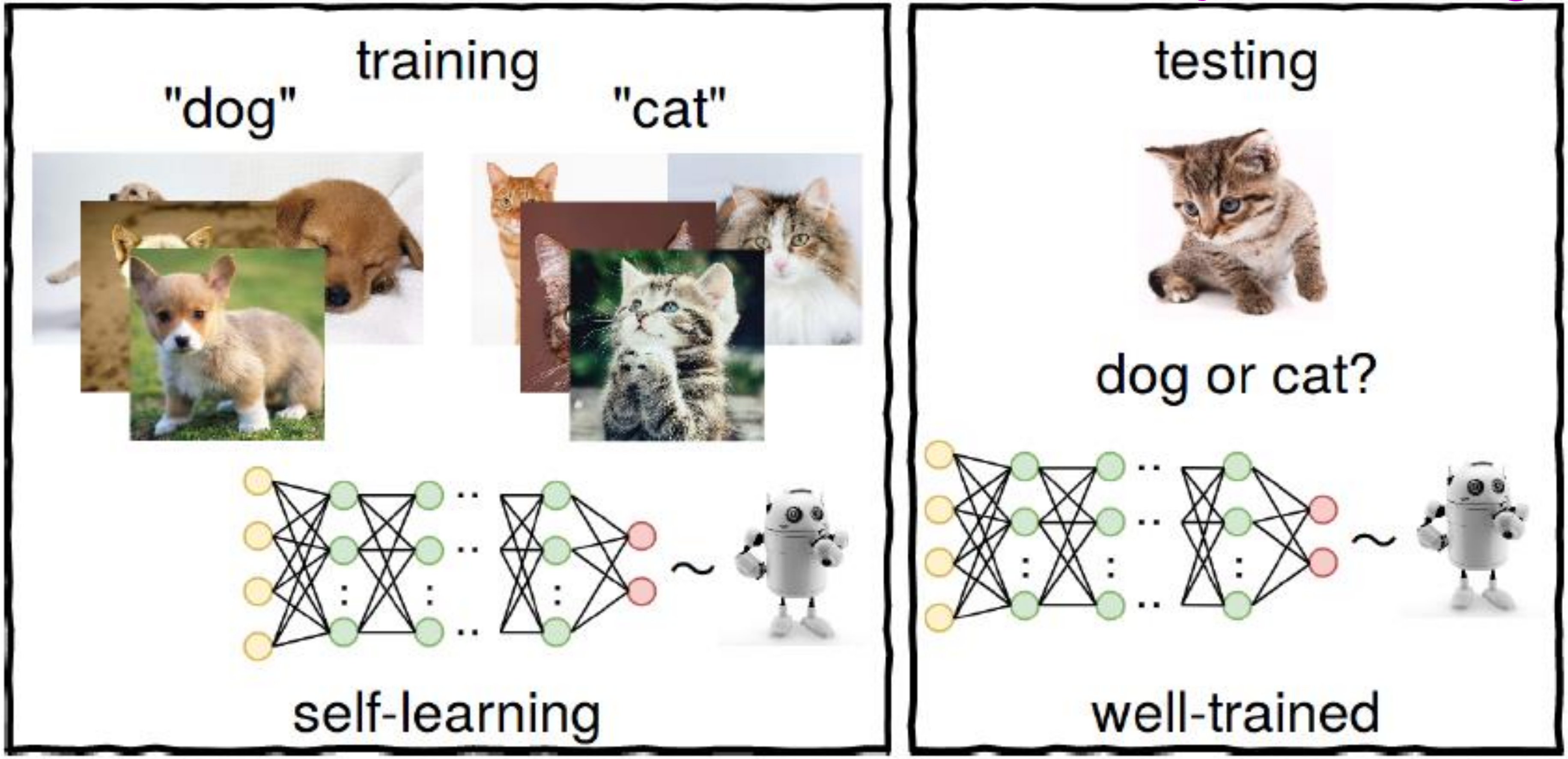
-Supervised learning
-Unsupervised learning
-Reinforcement learning

… … … …

Ian Goodfellow, Yoshua Bengio, and Aaron Courville, http://www.deeplearningbook.org MIT Press, 2016

An example of Supervised Learning

-Identify cats and dogs

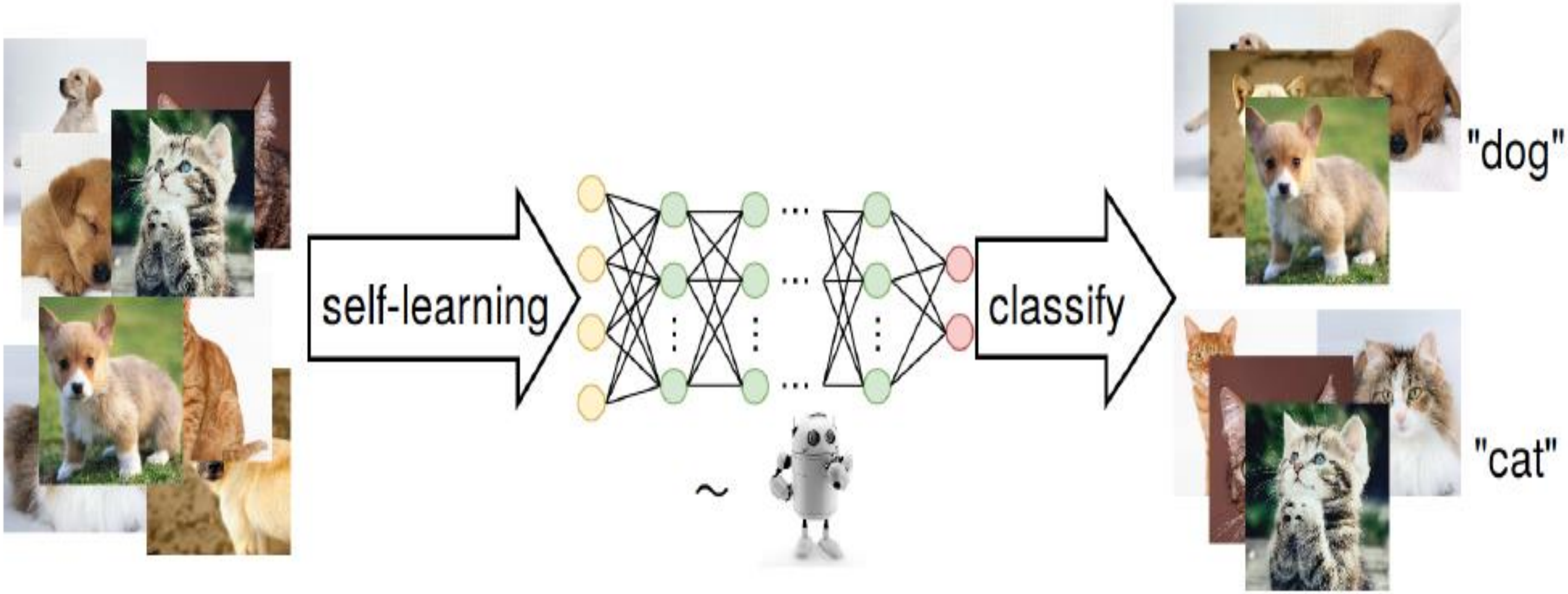


Supervised learning:

Training on a dataset contains many features and associated with **a label or target.**

An example of Unsupervised Learning

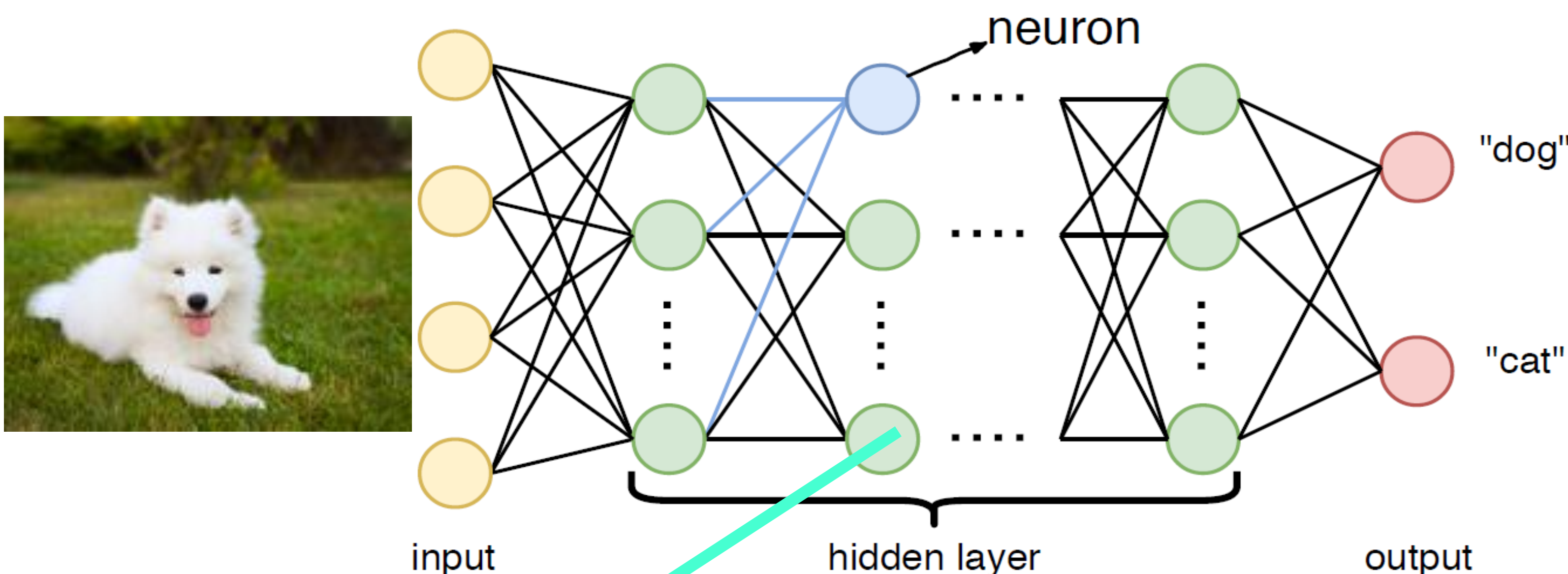
-Classify cats and dogs



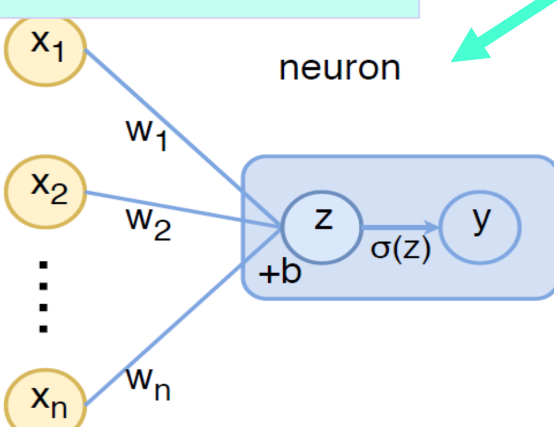
Unsupervised learning

-experience a dataset contains many features but **without labels**, and learn useful properties of the structure of this dataset.

Deep Neural Network



Neuron



Linear operation

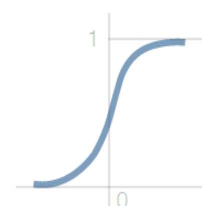
$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

scaling, rotating, boosting, changing dimensions

Non-linear activation function

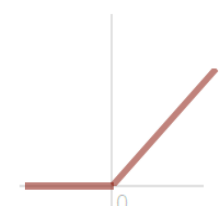
(a) Sigmoid

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



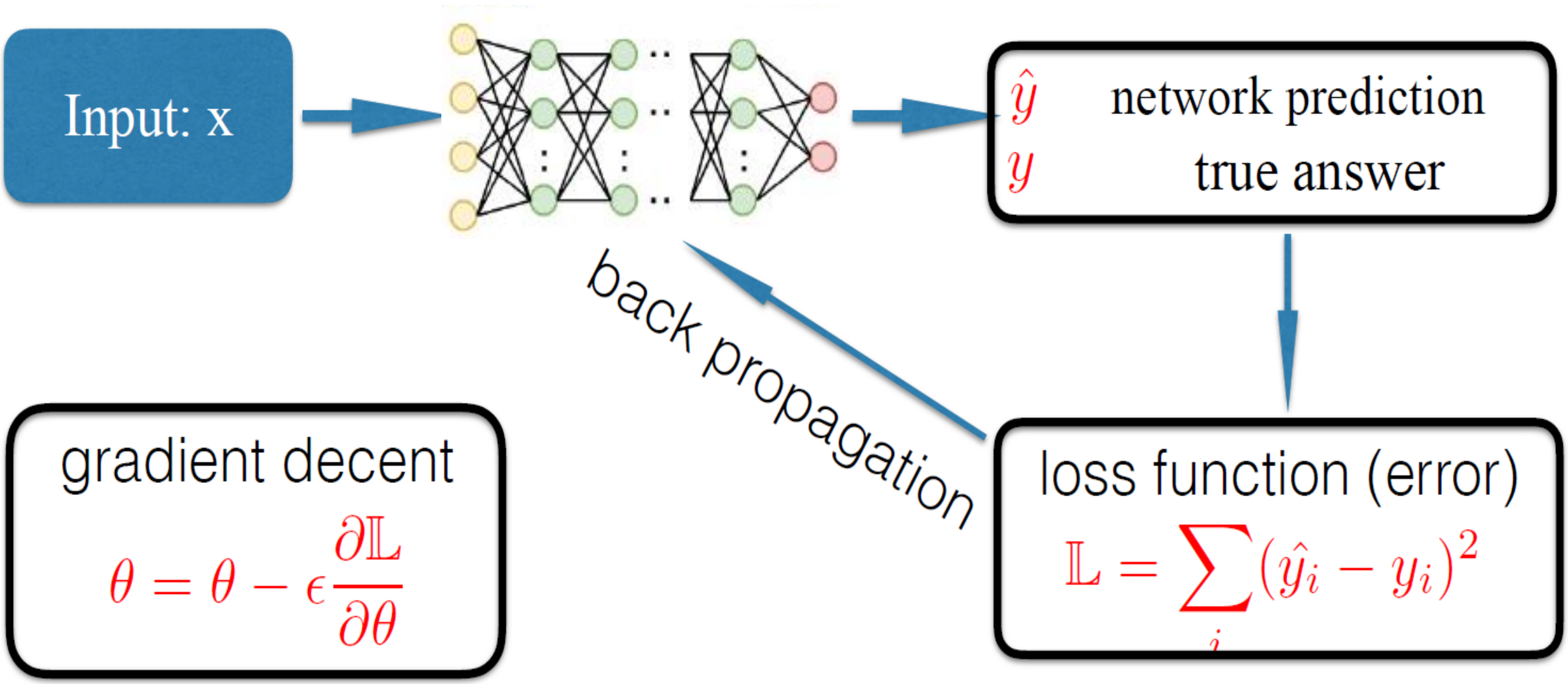
(b) ReLU

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



Deep Neural network

-Loss function, back propagation & gradient decent

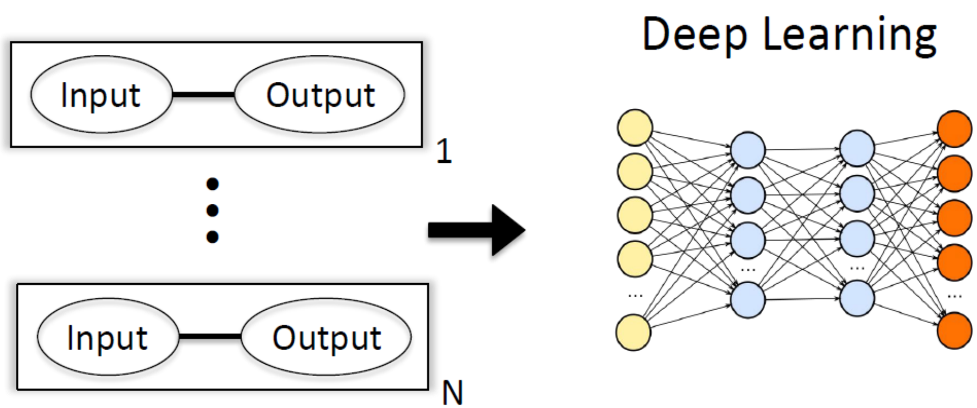


-Deep neural network can reduce fitting error by updating model parameters through back propagation and gradient decent.

Applications of Machine Learning in Physics

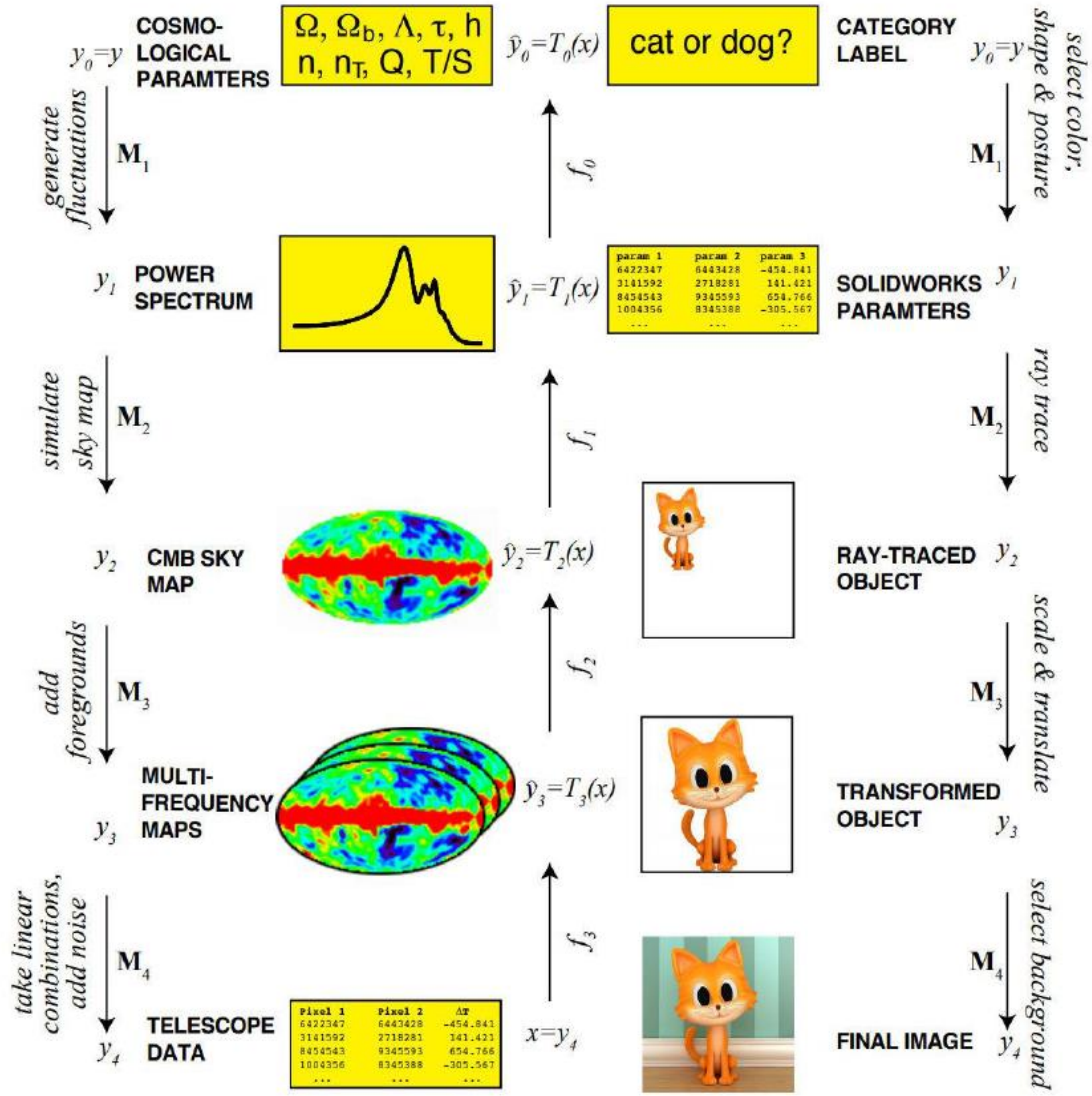
Why Machine Learning in Physics?

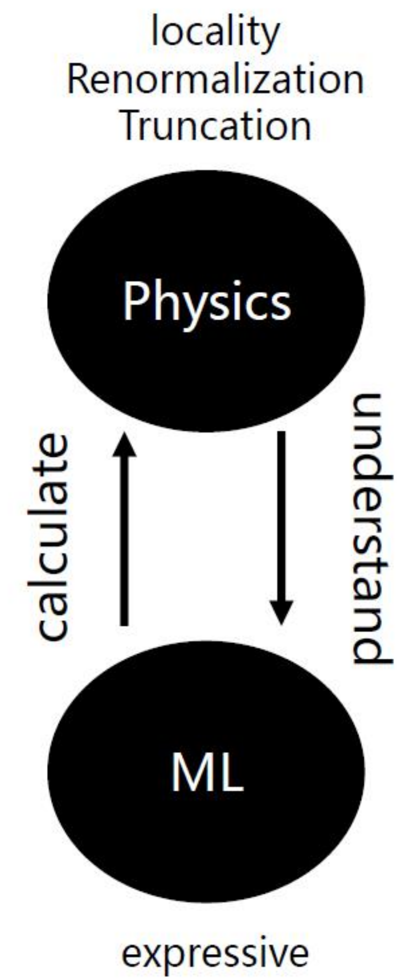
"Unlike earlier attempts … Deep Learning systems can see patterns and spot anomalies in data sets far larger and messier than human beings can cope with."



Can "**Black-box**" models learn patterns and models solely from data without relying on scientific knowledge?

A win-win game





Why does deep and cheap learning work so well? arXiv:1608.08225

Applications of Machine Learning in Physics

- Y. D. Hezaveh, L. Perreault Levasseur and P. J. Marshall, Nature 548, 555 (2017)
- J. Carrasquilla and G. R. Melko, Nature Phys. 13, 431 (2017)
- Carleo et al., Science 355, 602-606 (2017)
- E. P. L. van Nieuwenburg, Y. H. Liu, S. Huber, Nature Phys. 13, 435 (2017)
- Pierre Baldi, Peter Sadowski, and Daniel Whiteson, Nature Commun. 5 (2014) 4308
- Luke de Oliveira, Michela Paganini, and Benjamin Nachman, Comput Softw Big Sci (2017) 1: 4
- Long-Gang Pang et al., Nature Commun. 9 (2018) no.1, 210
- ..., ...,
- ...

$\langle Physics|Machine\ learning\rangle$

https://physicsml.github.io/pages/papers.html

PAPERS

The following are recent papers combining the fields of physics - especially quantum mechanics - and machine learning. Please email Anna Go if you would like to see a paper added to this page.

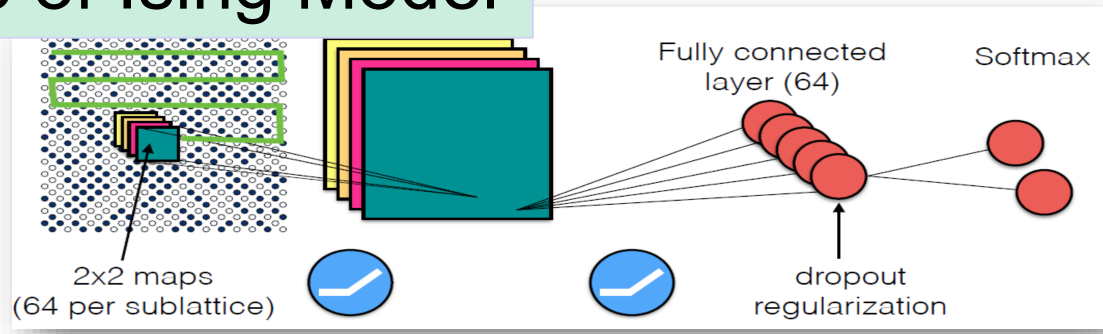
APPLYING MACHINE LEARNING TO PHYSICS

- "QuCumber: wavefunction reconstruction with neural networks", Matthew J. S. Beach, Isaac De Vlugt, Anna Golubeva, Patrick Huembeli, Bohdan Kulchytskyy, Xiuzhe Luo, Roger G. Melko, Ejaaz Merali, Giacomo Torlai, arXiv: 1812.09329, 12/2018
- "Deep ToC: A New Method for Estimating the Solutions of PDEs", Carl Leake, arXiv: 1812.08625, 12/2018
- "Optimizing Quantum Error Correction Codes with Reinforcement Learning", Hendrik Poulsen Nautrup, Nicolas Delfosse, Vedran Dunjko, Hans J. Briegel, Nicolai Friis, arXiv: 1812.08451, 12/2018
- "Parameters optimization and real-time calibration of Measurement-Device-Independent Quantum Key Distribution Network based on Back Propagation Artificial Neural Network", Feng-Yu Lu, Zhen-Qiang Yin, Chao Wang, Chao-Han Cui, Jun Teng, Shuang Wang, Wei Chen, Wei Huang, Bing-Jie Xu, Guang-Can Guo, Zheng-Fu Han, arXiv: 1812.08388, 12/2018
- "Machine Learning for Optimal Parameter Prediction in Quantum Key Distribution", Wenyuan Wang, Hoi-Kwong Lo, arXiv: 1812.07724, 12/2018
- "Machine Learning as a universal tool for quantitative investigations of phase transition", Cinzia Giannetti, Biagio Lucini, Davide Vadacchino, arXiv: 1812.06726, 12/2018

Classifying the Phase of Ising Model

Deep neural net work can identify the phase transition of Ising Model

J. Carrasquilla and R. G. Melko. Nature Physics 13, 431–434 (2017)

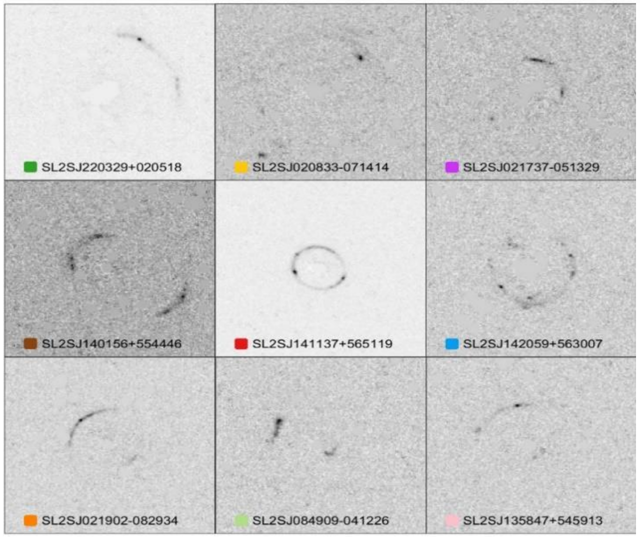


Gravitational Lensing

Parameter estimation with Neural network

10^7 times faster than traditional method

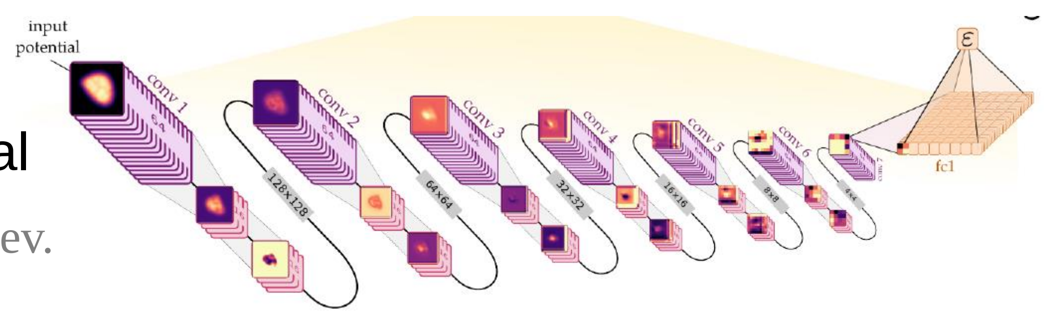
Y. D. Hezaveh, L. P. Levasseur, P. J. Marshall Nature volume548, pages555–557



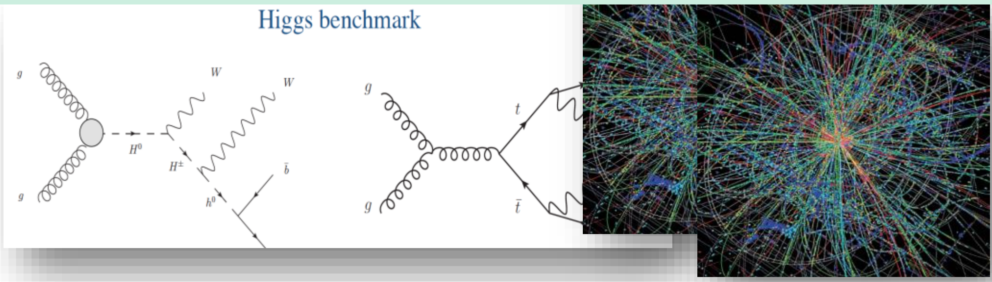
Solving Schrodinger Equation

A trained deep neutral network could successfully predict the ground state energy of 2-d potential

K. Mills, M. Spanner, I. Tamblyn, Phys. Rev. A 96, 042113 (2017)



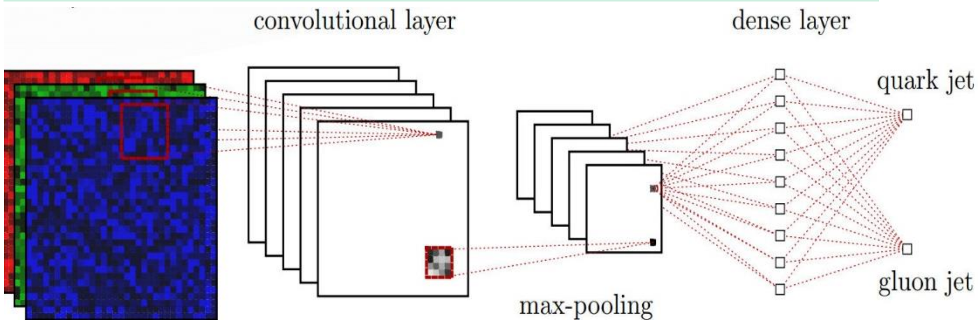
Searching for Exotic Particles in High-Energy Physics



Deep learning can improve the power for the collider search of exotic particles

P.Baldi,P.Sadowski,& D.Whiteson Nature Commun.5, 4308 (2014)

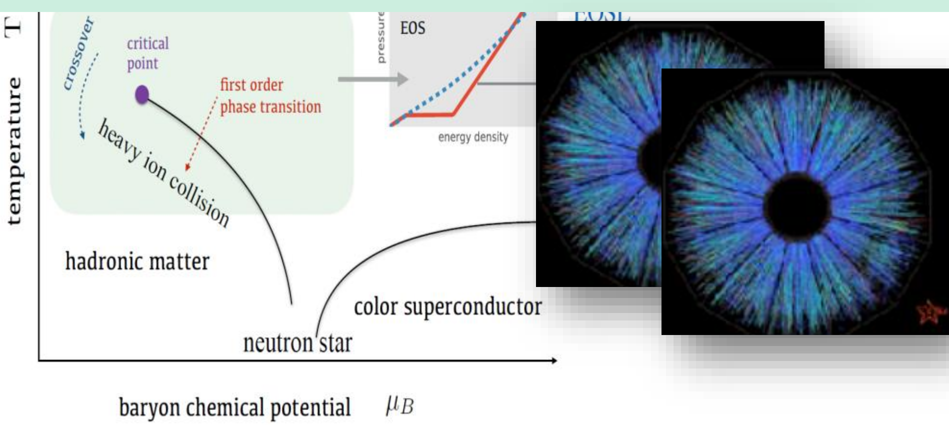
Gluon / quark jet tagging



Deep learning can outperform traditional methods in discriminating between quark jet and gluon jet

P. T. Komiske, E. M. Metodiev, M. D. Schwartz JHEP 1701 (2017) 110

Identify QCD Phase Transition with Deep Learning



DNN efficiently decode the EOS information from the complex final particle info event by event

LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang. Nature Commun.9 (2018) no.1, 210

Applications of Machine Learning for Relativistic Heavy Ion Collisions & hot QCD matter

-Identify QCD Phase Transition with Deep Learning

LG. Pang, et. al Nature Commun.9 no.1, 210 (2018)

-Applications of deep learning to relativistic hydrodynamics

H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song arXiv: 1801.03334; NPA2019

-Principle Component Analysis for Flow

Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

-Identify gluon /quark jet of hot QCD matter

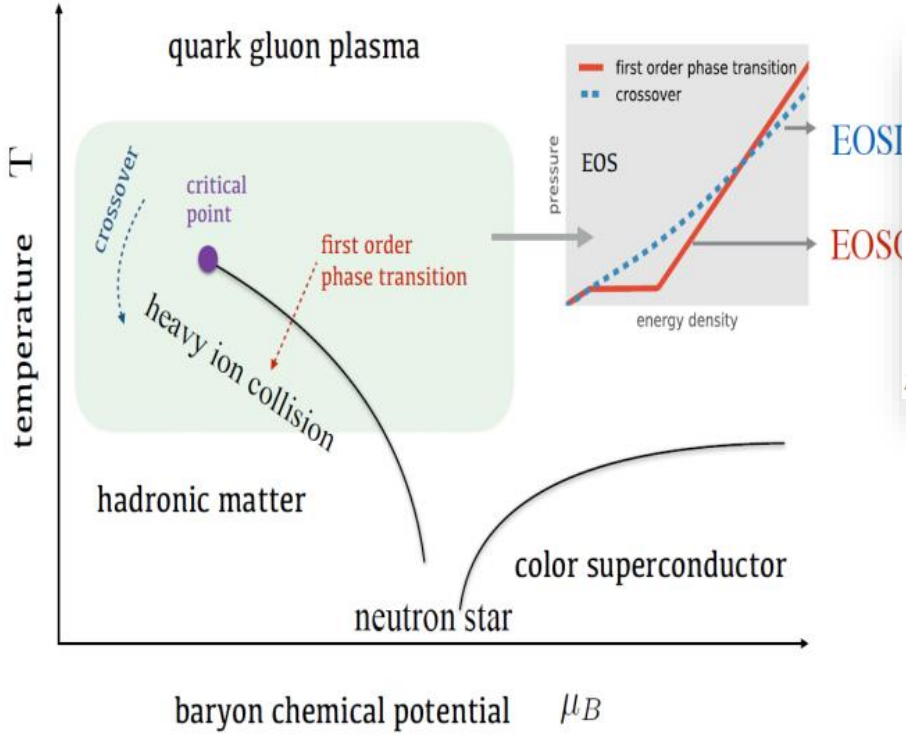
Y.T.Chien and R.K. Elayavalli, arXiv:1803.03589 [hep-ph], NPA 2019

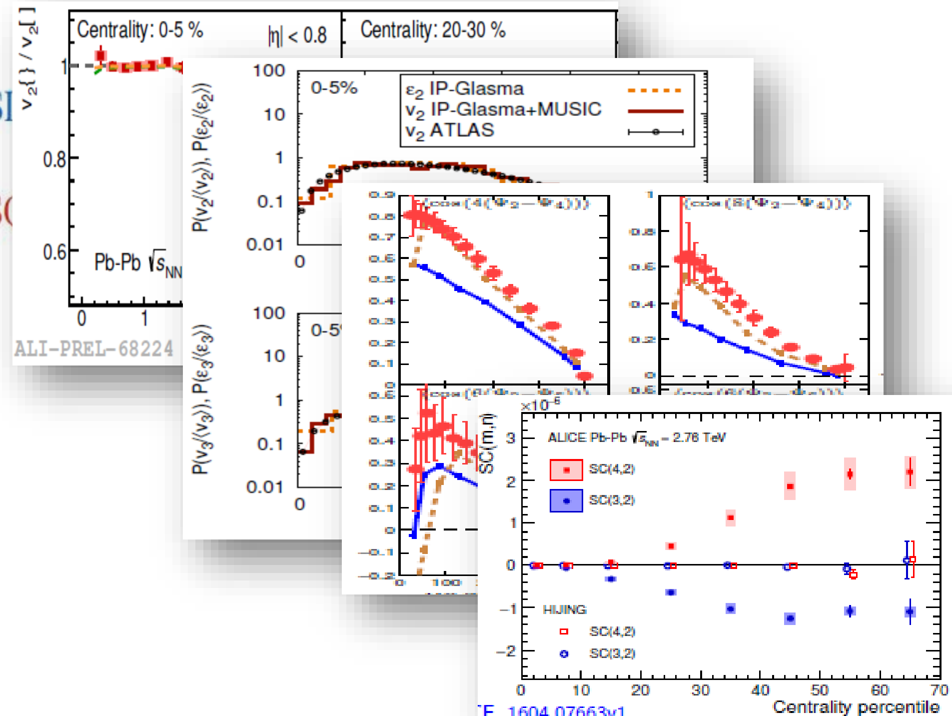
-Lattice Scalar Field Theory with finite T & μ

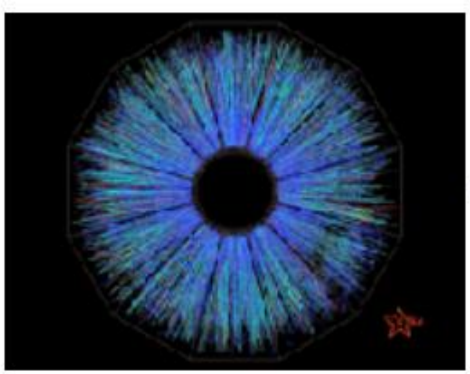
K. Zhou, G. Endrődi, L. G. Pang and H. Stöcker, arXiv:1810.12879 [hep-lat].

… … … …

Identify QCD Phase Transition with Deep Learning







$$\rho(p_T, \Phi)$$

Motivation:

-Traditionally, the properties of the QCD matter are extracted from the event averaged observables

-Can deep learning identify different EoS from the raw data of heavy ion collisions?

LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang. Nature Commun.9 (2018) no.1, 210

Identify QCD Phase Transition with Deep Learning

A） Generating training/testing data:

-Run Hydro with EOS L and EOS Q

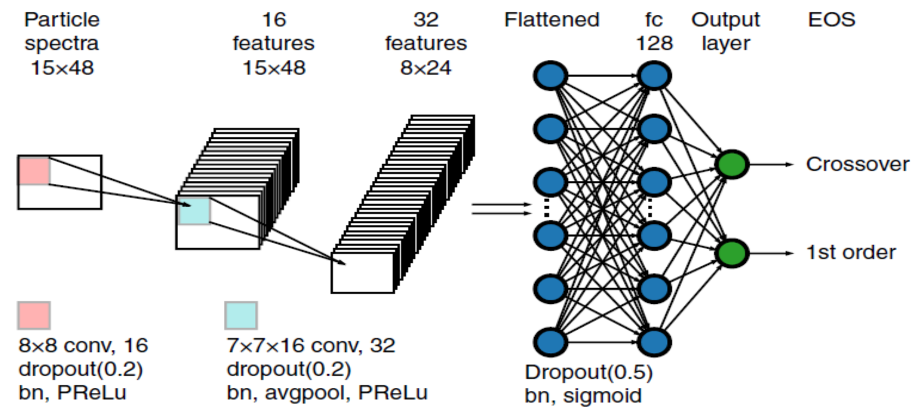
-particle spectra - image (15*48 pixels)

$$\rho(p_T,\phi) \equiv \frac{dN_i}{dY p_T dp_T d\phi} = g_i \int_\sigma p^\mu d\sigma_\mu f_i,$$

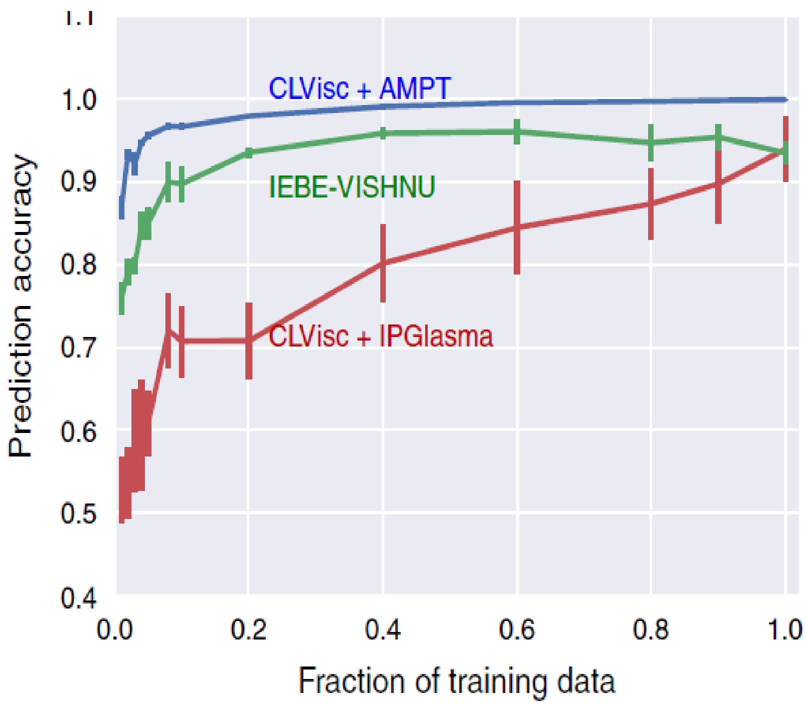
B） Training CNN

Table 1 The training data set Hydro CLVis (AMPT)

Training data set	$\eta/s=0$		$\eta/s=0.08$	
	EOSL	EOSQ	EOSL	EOSQ
Au-Au $\sqrt{s_{NN}}=200$ GeV	7435	5328	500	500
Pb-Pb $\sqrt{s_{NN}}=2.76$ TeV	4967	2828	500	500



C) testing the trained net work



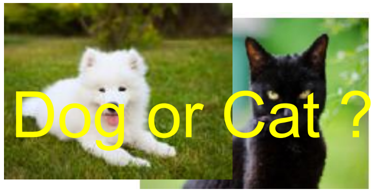
One can efficiently decode the EOS information from the complex final particle info event by event using deep learning

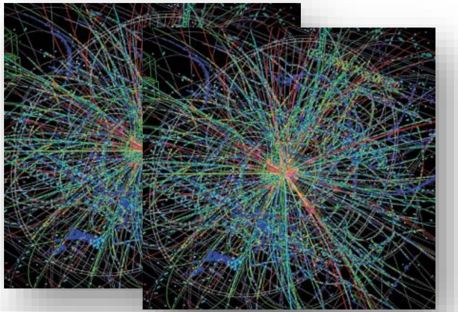
LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang. Nature Commun.9 (2018) no.1, 210

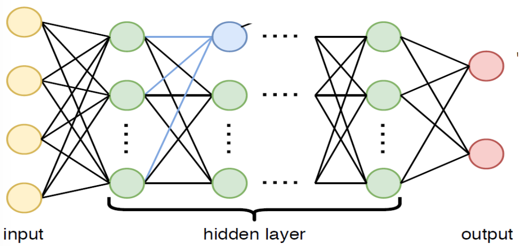
Applications of deep learning to relativistic hydrodynamics

H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song arXiv: 1801.03334; NPA2019

Image identification

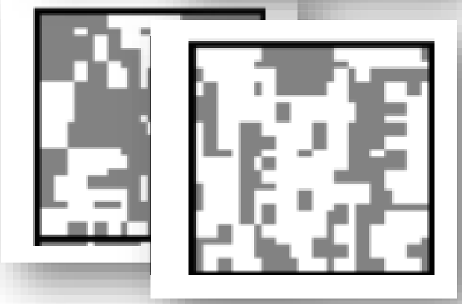


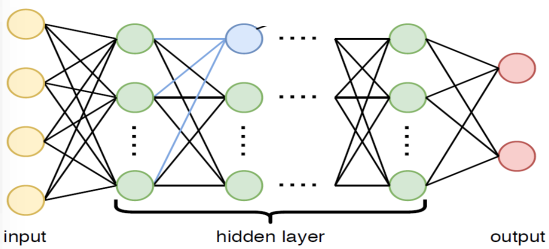




Higgs signal or background?

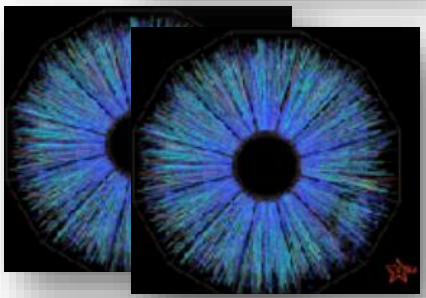
P.Baldi,et al,Nature Commun.(2014)

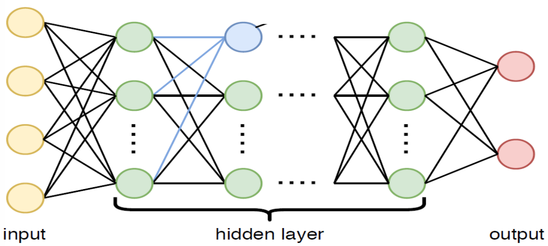




High temperature or low temperature phase?

Carrasquilla & Melko. Nature Physics (2017)





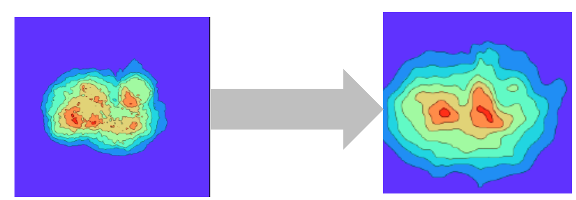
EoS L or EOSQ ?

Pang,et al Nature Commun.(2018)

Image generation

For hydrodynamics can we use deep learning to learn/predict the pattern transformation between initial and final profiles?

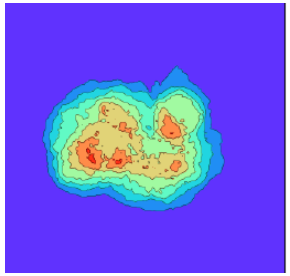
Initial energy density profiles
-------- > final energy density velocity profiles



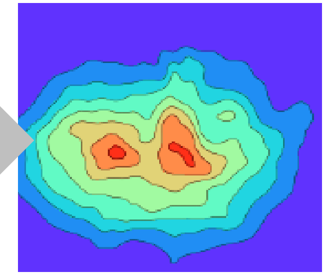
For the non-linear hydro system, can the **black-box** network could learn pattern transformations solely from data without relying on scientific knowledge?

(conservation laws)

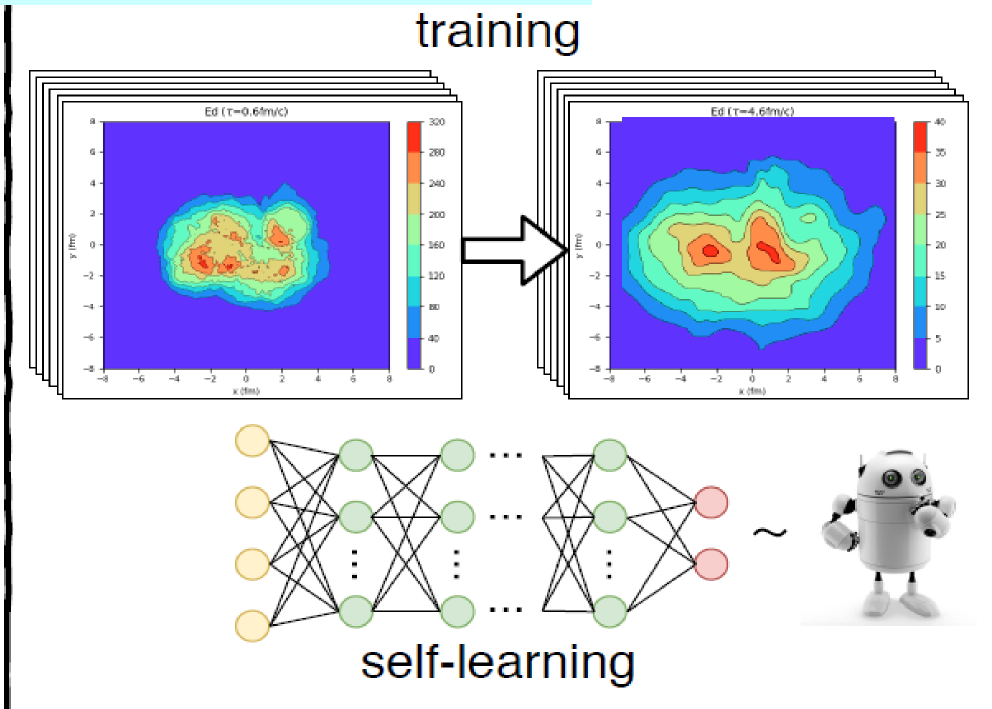
Traditional hydrodynamics

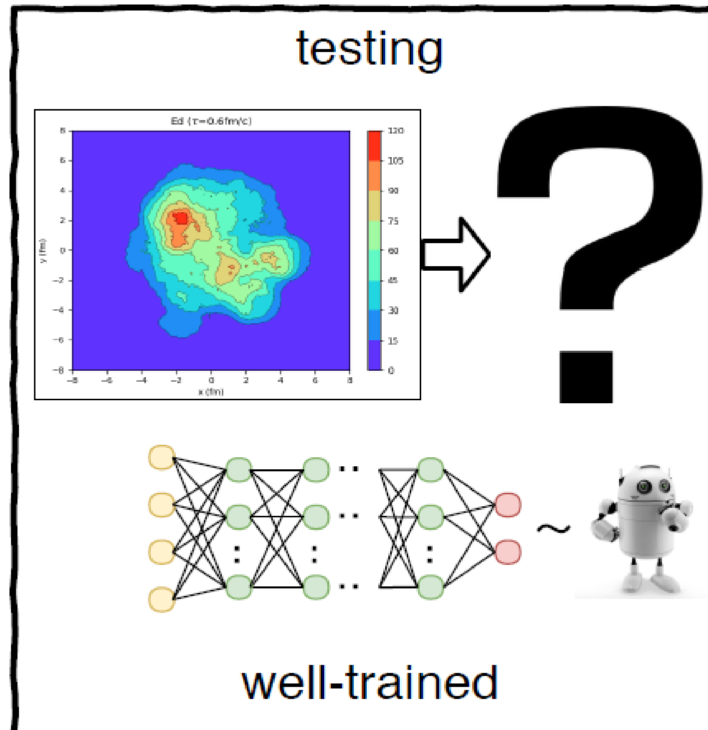


$$\partial_\mu T^{\mu\nu}(x) = 0$$



Deep Learning

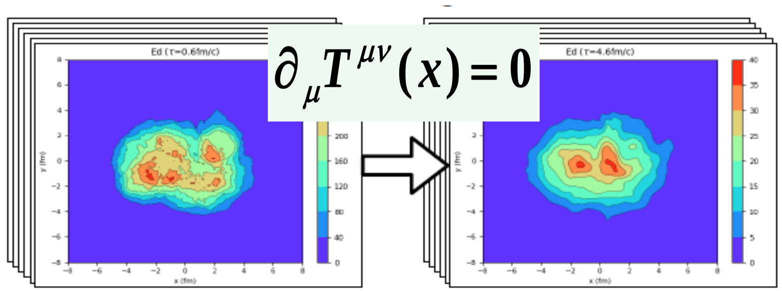




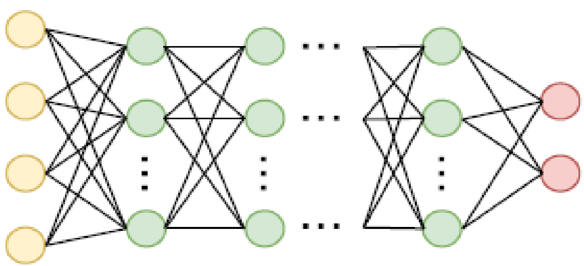
-Such deep learning systems do not need to be programmed with the hydro equation $\partial_\mu T^{\mu\nu}(x) = 0$ **Instead, they learn on their own**

Deep Learning

Step1) Generate the training/testing data sets from hydro



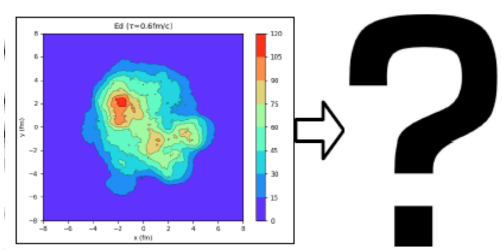
Step2) Design & train the deep neural network



The Training Data Sets

hydro VISH2+1	MC-Gl
	10000

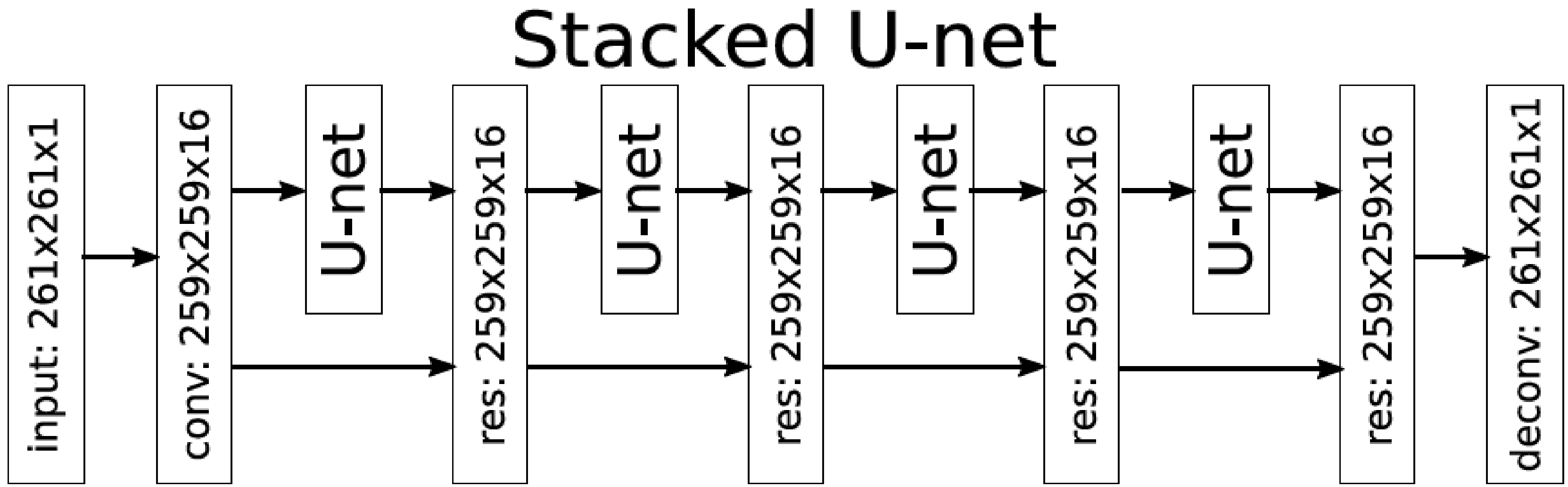
Step3) Test the deep neural network

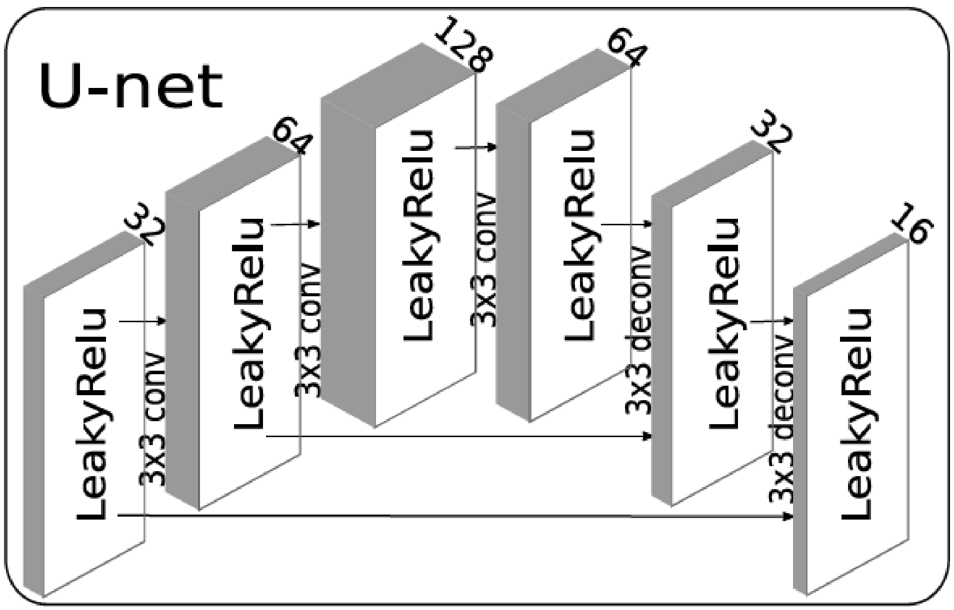


The Testing Data Sets

hydro VISH 2+1	MC-Gl	MC-KLN	AMPT	Trento
	10000	10000	10000	10000

Stacked U-net for 2+1-d hydro





The activation function:

$$Leaky\ ReLU\quad f(x) = \max\{x, 0.03x\}$$

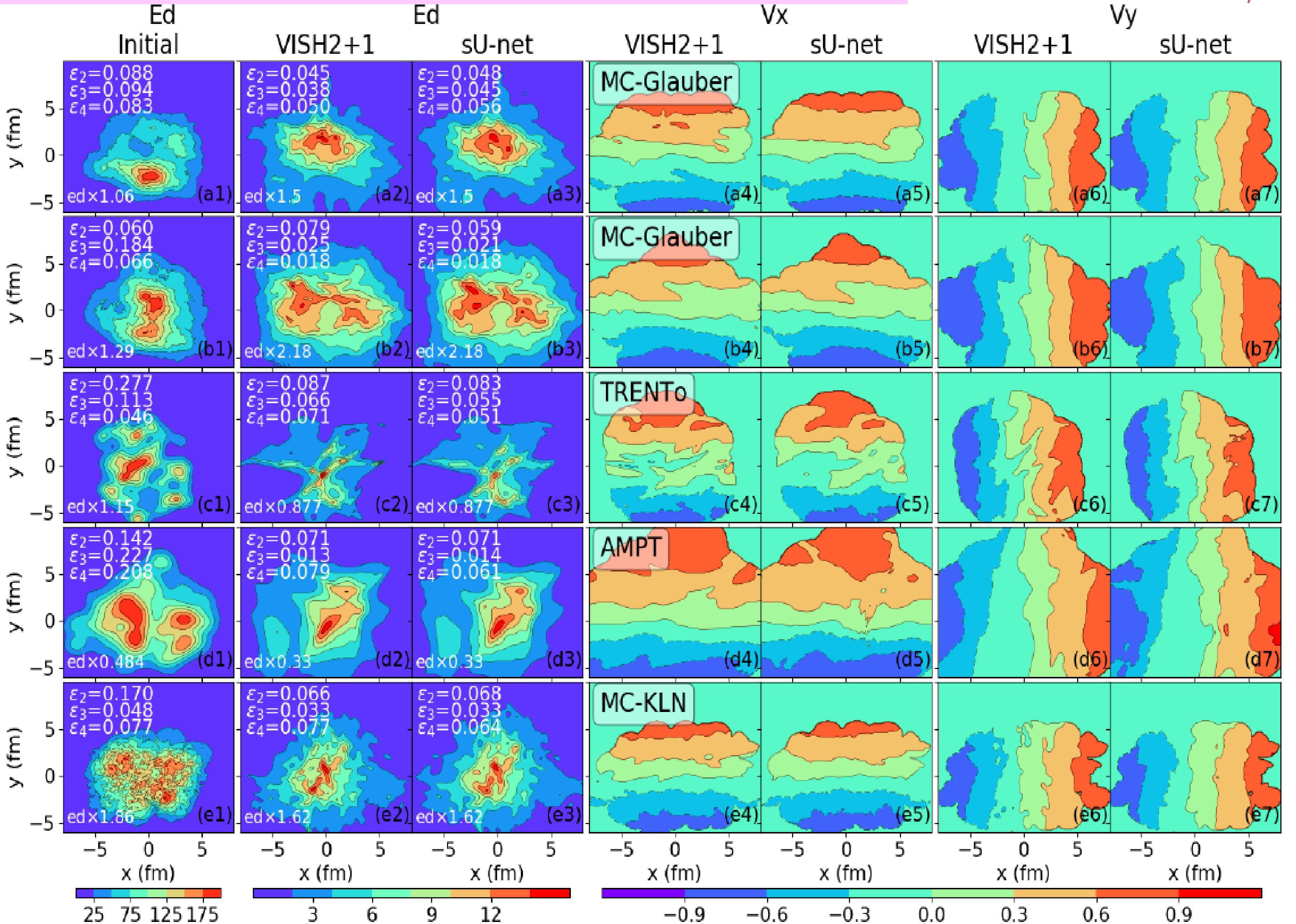
The loss function:

normalized MAE loss $\quad Loss = \frac{|y_1 - y_0|}{|y_0|}$

H.Huang, B.Xiao, H.Xiong, Z.Wu, Y. Mu and H.Song arXiv: 1801.03334, NPA 2018

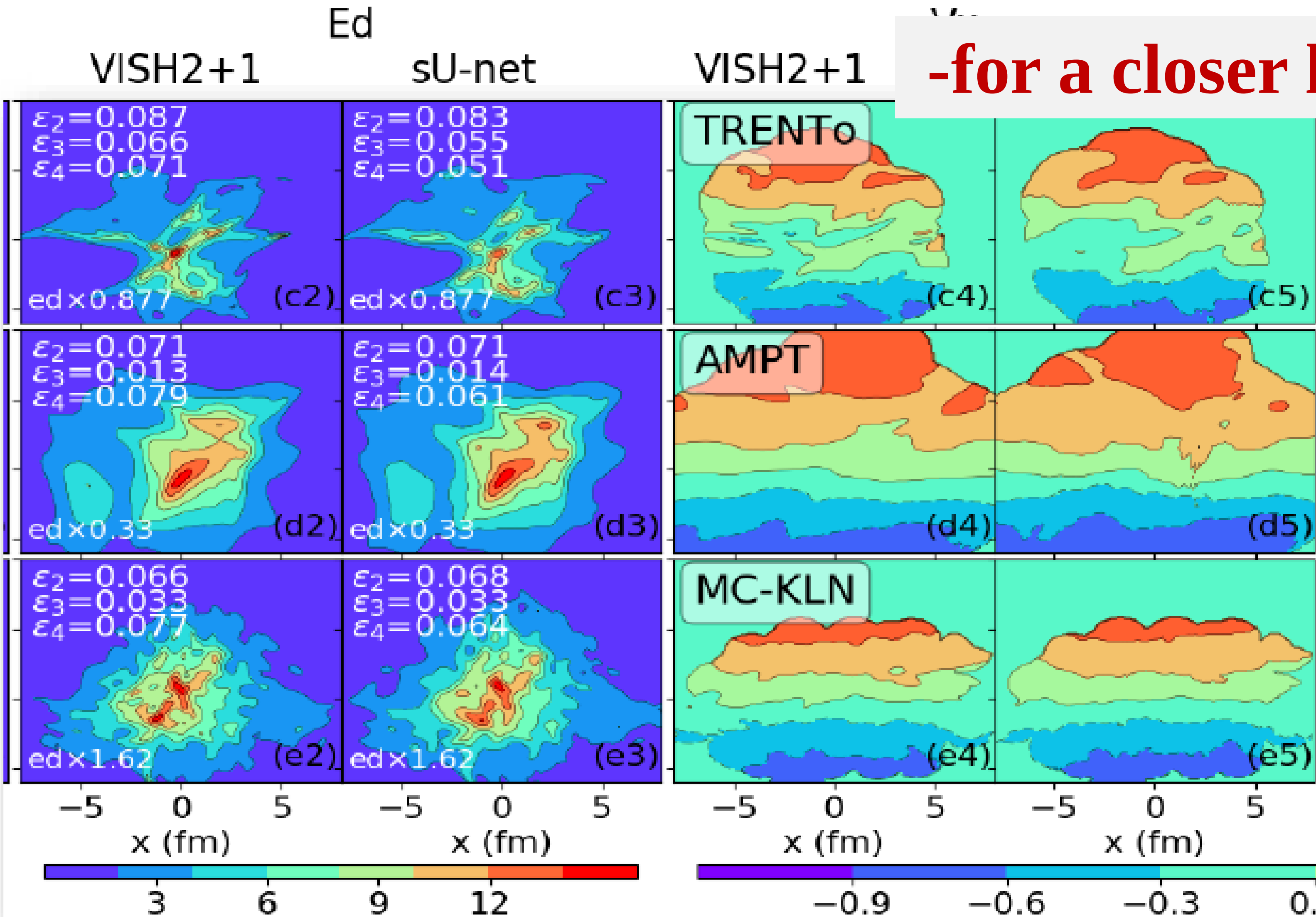
sUnet prediction vs. hydro simulations

$\tau - \tau_0 = 6.0 fm/c$



sUnet prediction vs. hydro simulations

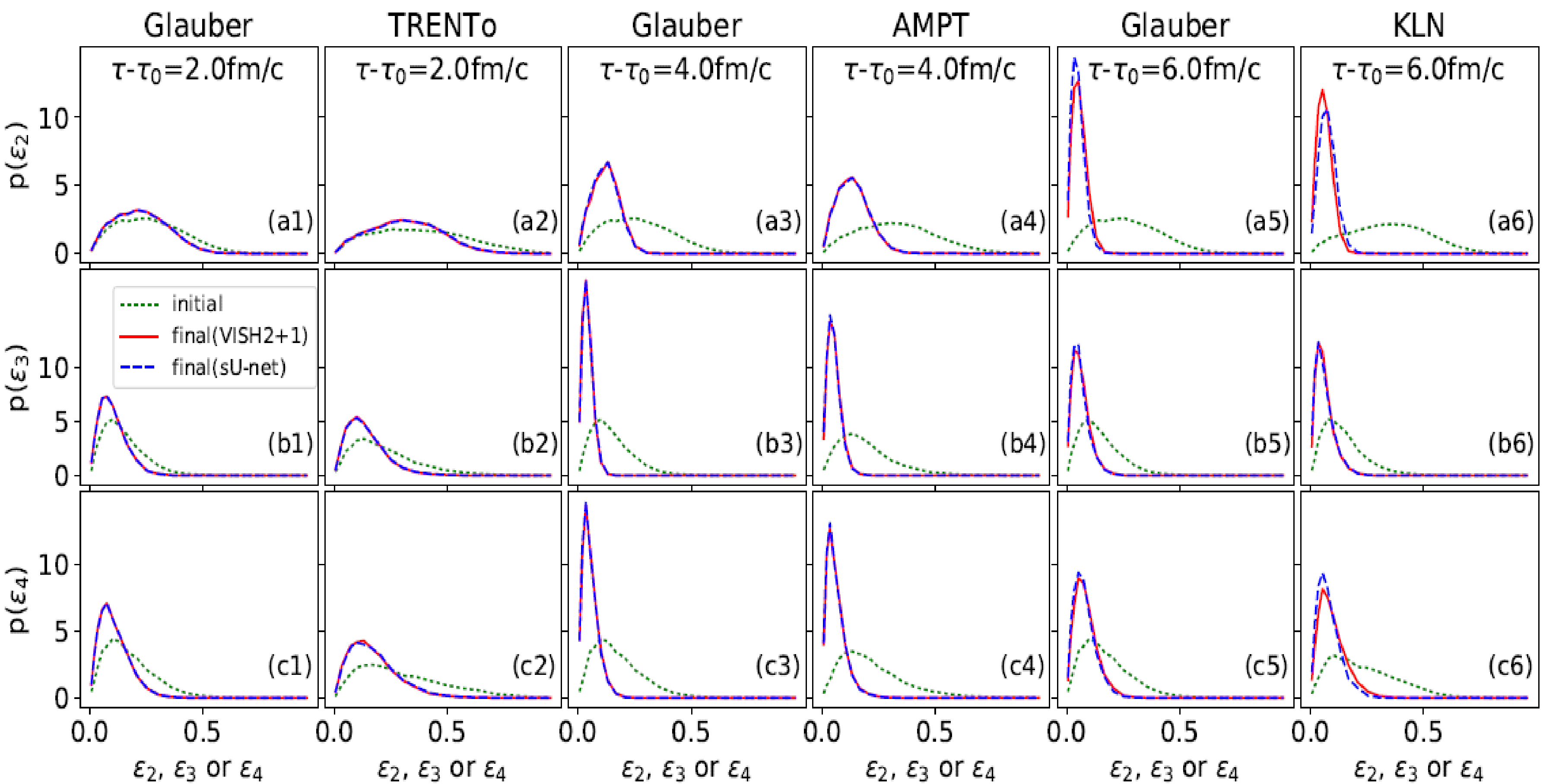
$\tau - \tau_0 = 6.0fm/c$



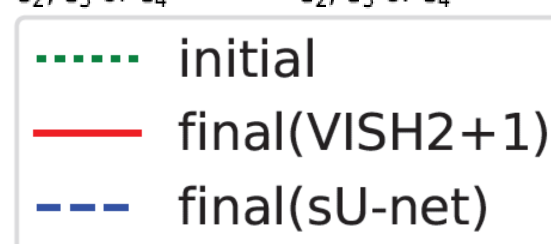
-for a closer look

sUnet prediction vs. hydro simulations

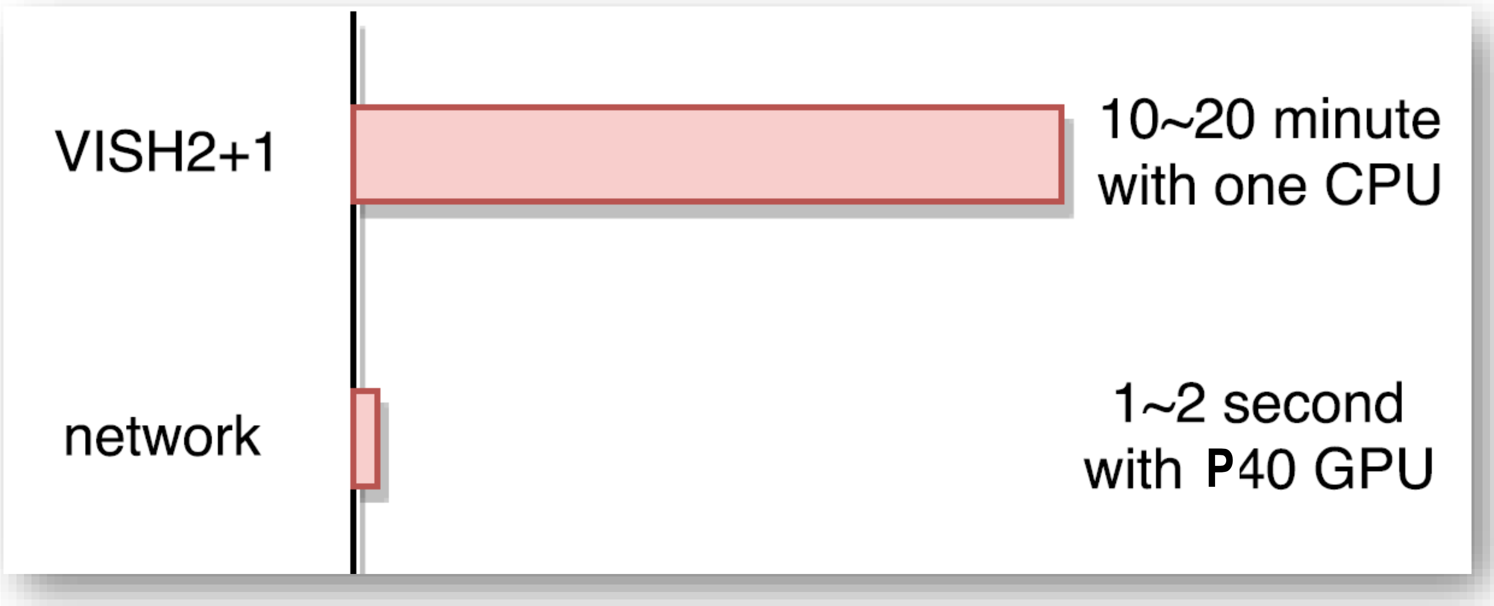
Eccentricity distributions:

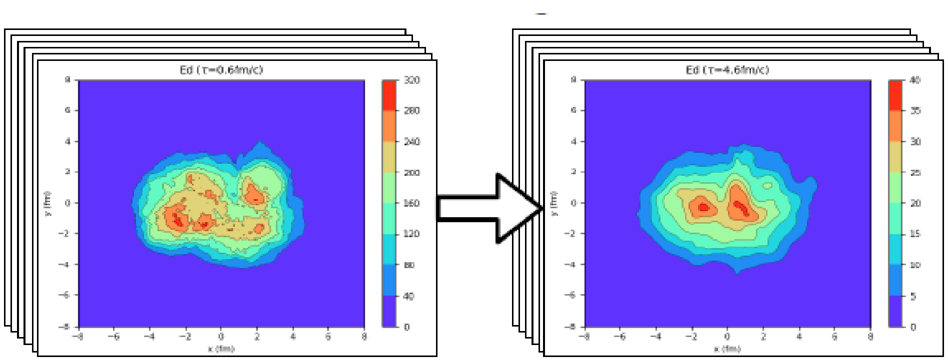


$$\varepsilon_n e^{in\Phi_n} = -\frac{\int dxdyr^2 e^{in\phi} e(x,y)}{\int dxdyr^2 e(x,y)}$$



Simulation time: sUnet vs. hydro

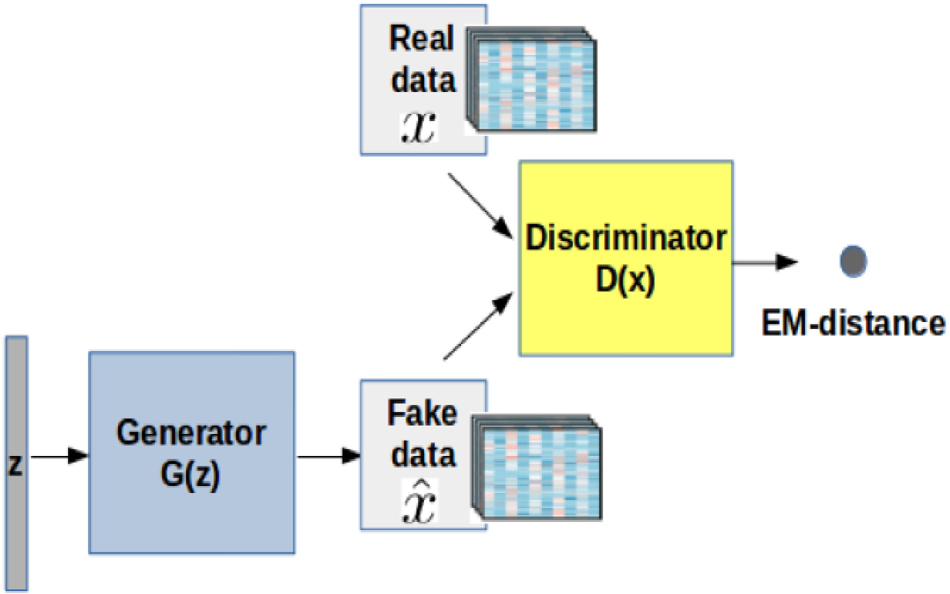




With the well trained network, the final state profiles can be quickly generated from the initial profiles. (5-10 times faster for GPU based calculations)

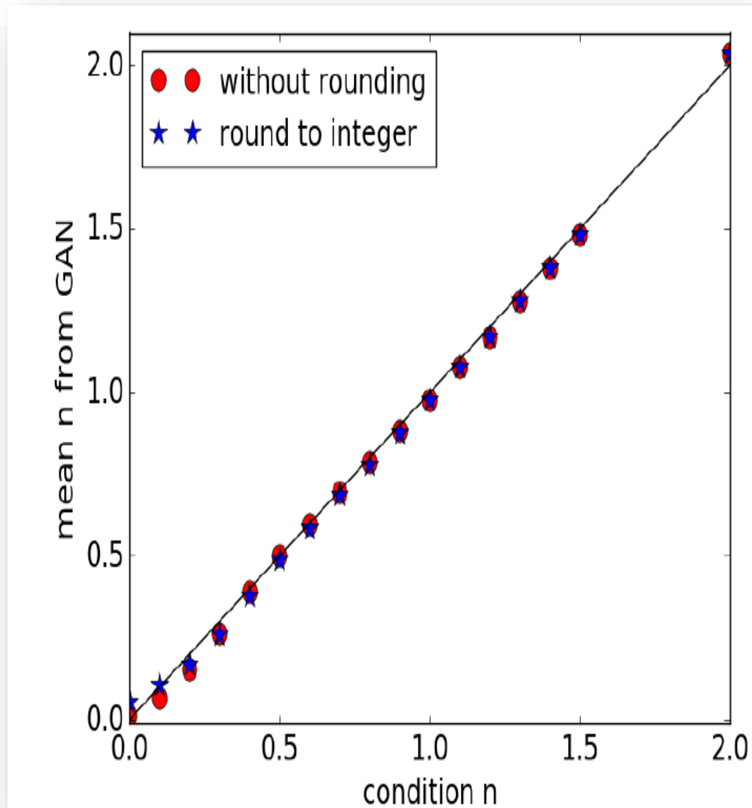
1+1-d Lattice Scaler Field Theory with finite T & μ -Configuration production using GAN

K. Zhou, G. Endrődi, L. G. Pang and H. Stöcker, arXiv:1810.12879 [hep-lat].



-Phase diagram generated by c-GAN on mu with limited ensemble of training set

-The potential uses of such a generative approach for sampling outside the training region, but near the critical point?



training sample: n= 0.4, 0.5, 0.6, 0.7

Principal Component Analysis for Flow

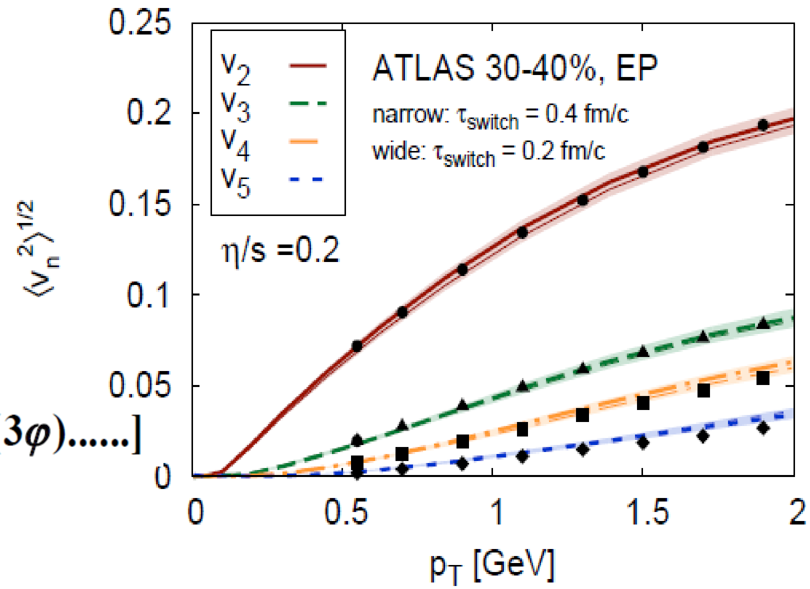
Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

Flow definition： human-being vs. Machine

Flow definition since 1992

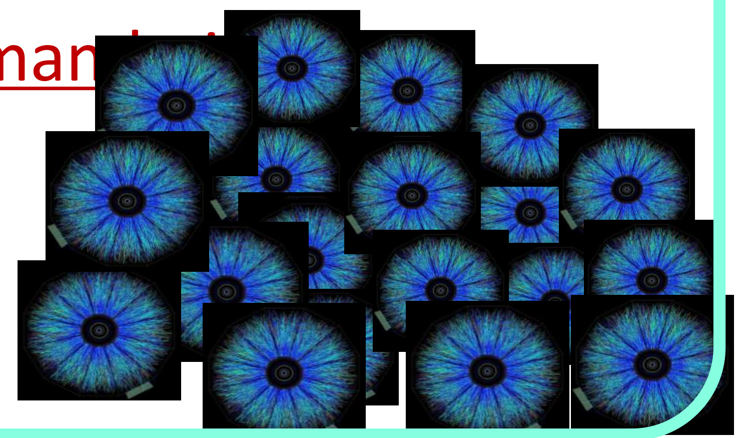
Fourier
Transformation?

$$E\frac{dN}{d^3p}=\frac{1}{2\pi}\frac{dN}{dyp_Tdp_T}[1+2v_1(p_T,b)\cos(\varphi)$$
$$+2v_2(p_T,b)\cos(2\varphi)\ +2v_3(p_T,b)\cos(3\varphi)......]$$



Can machine directly discover flow from data
without explicit instructions from Human

??? flow



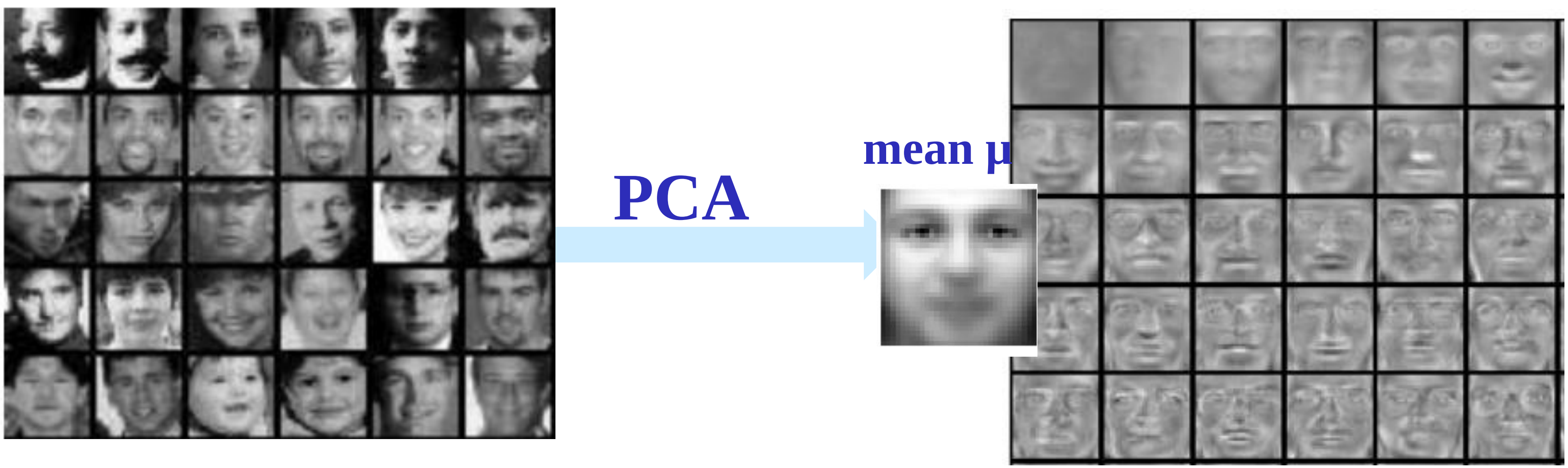
What is Principal Component Analysis (PCA)

-a statistical procedure that uses an <u>orthogonal transformation</u> to convert a set of observations into a set of values of <u>linearly uncorrelated</u> variables called principal components.

PCA for FACE analysis

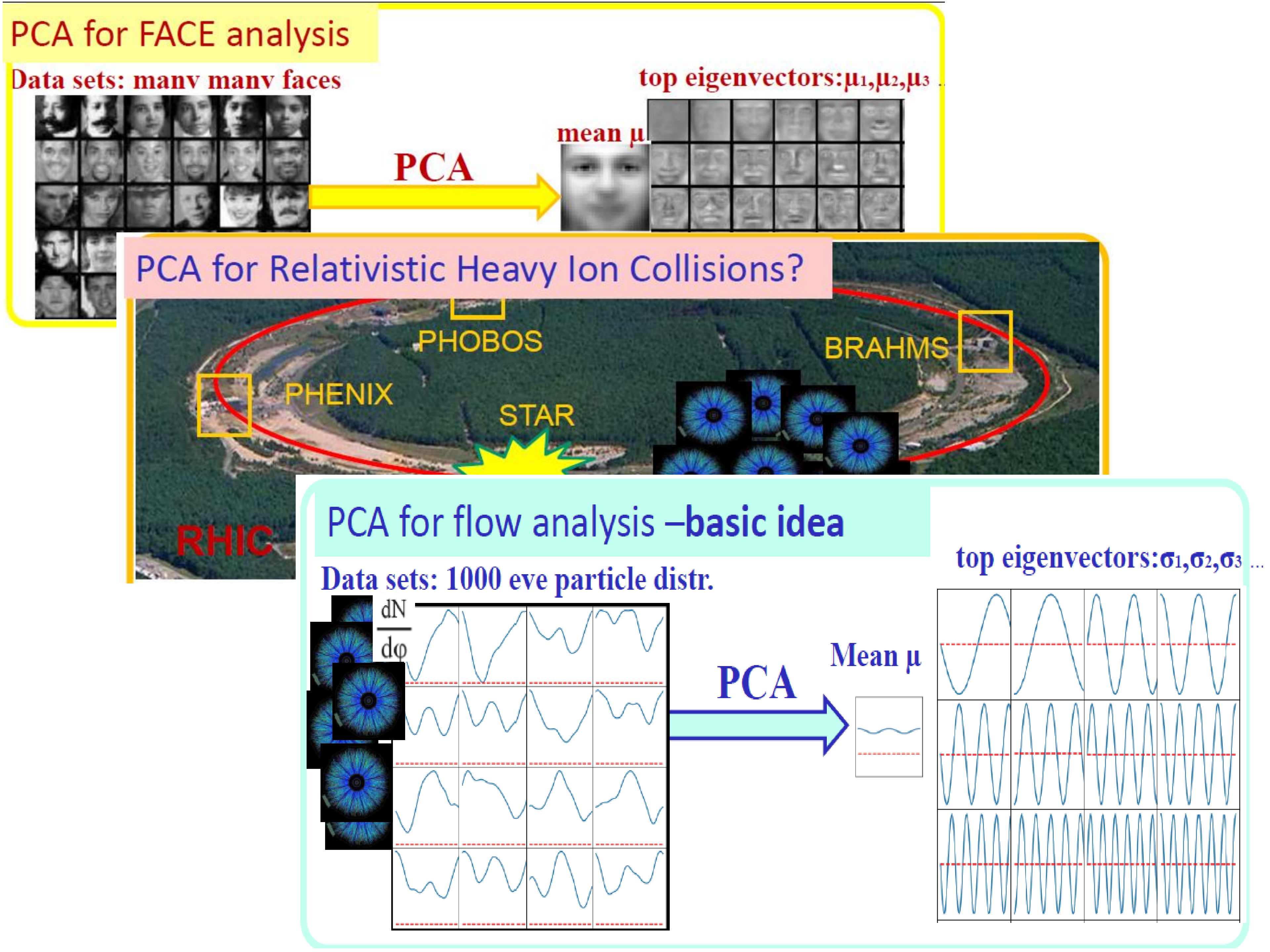
Data sets: many many faces

top eigenvectors:μ_1,μ_2,μ_3 … …



With PCA, each face is decomposed into superposition of eigenfaces.

$$\hat{x} = \mu + w_1u_1 + w_2u_2 + w_3u_3 + w_4u_4 + \ldots$$



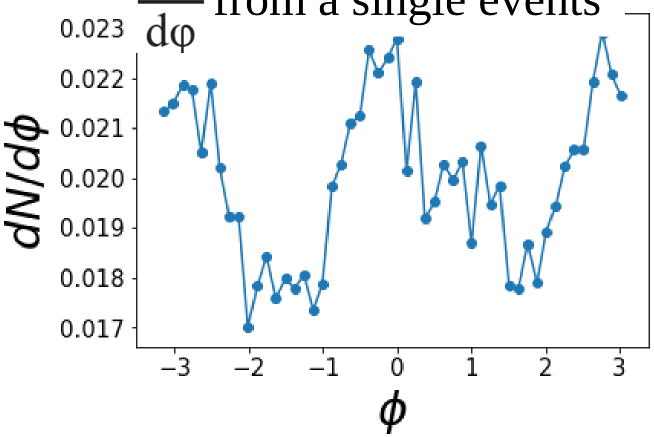
PCA for FACE analysis
Data sets: many many faces
PCA
mean μ
top eigenvectors: μ1,μ2,μ3 ...
PCA for Relativistic Heavy Ion Collisions?
PHOBOS
BRAHMS
PHENIX
STAR
RHIC
PCA for flow analysis –basic idea
Data sets: 1000 eve particle distr.
dN/dφ
PCA
Mean μ
top eigenvectors: σ1,σ2,σ3 ...

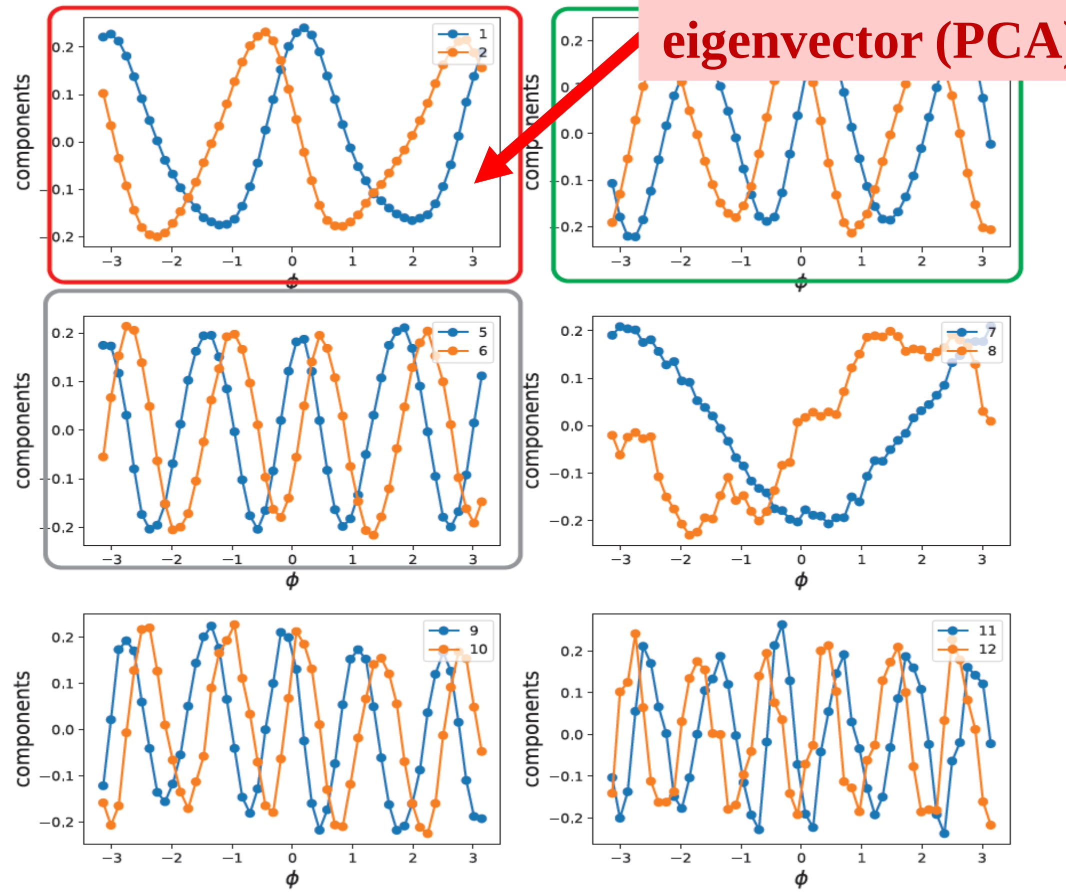
PCA for flow analysis –results(I)

Components

$$\begin{array}{c|cccc} \text{events} & 1 & 2 & \cdots & m \\ \hline 1 & a_1^{(1)} & a_2^{(1)} & \cdots & a_m^{(1)} \\ 2 & a_1^{(2)} & a_2^{(2)} & \cdots & a_m^{(2)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ n & a_1^{(n)} & a_2^{(n)} & \cdots & a_m^{(n)} \end{array} = \begin{array}{c|cccc} & 1 & 2 & \cdots & k \\ \hline 1 & x_1^{(1)} & x_2^{(1)} & \cdots & x_k^{(1)} \\ 2 & x_1^{(2)} & x_2^{(2)} & \cdots & x_k^{(2)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ n & x_1^{(n)} & x_2^{(n)} & \cdots & x_k^{(n)} \end{array} * \begin{array}{c|c} & m \\ \hline 1 & z_1 \\ 2 & z_2 \\ \vdots & \vdots \\ k & z_k \end{array}$$

$\frac{\mathrm{dN}}{\mathrm{d}\varphi}$ from a single events



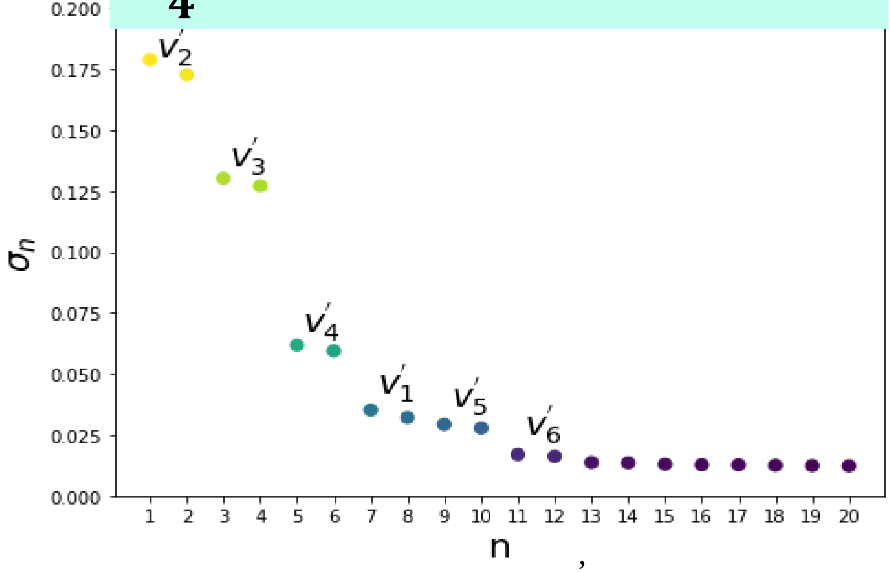


The eigenvector (PCA) is similar to the Fourier ones

$$\frac{dN}{dy d\phi} = \frac{dN}{dy}(1 + v_1 \cos\phi + v_2 \cos 2\phi + v_3 \cos 3\phi \ldots\ldots)$$

Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

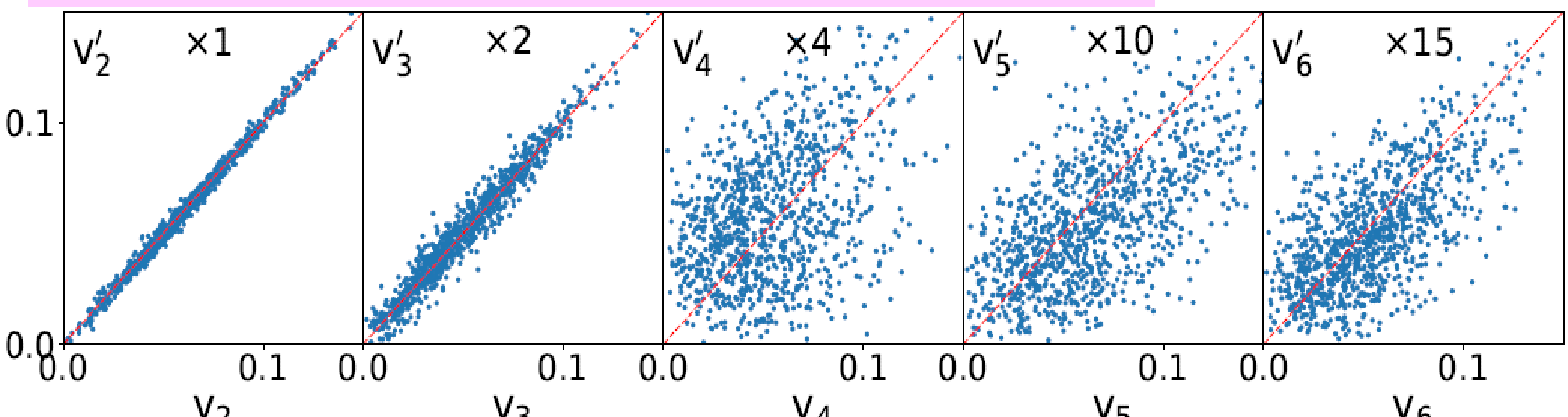
Event averaged $\overline{v'_2}$, $\overline{v'_3}$, $\overline{v'_4}$ … … from PCA



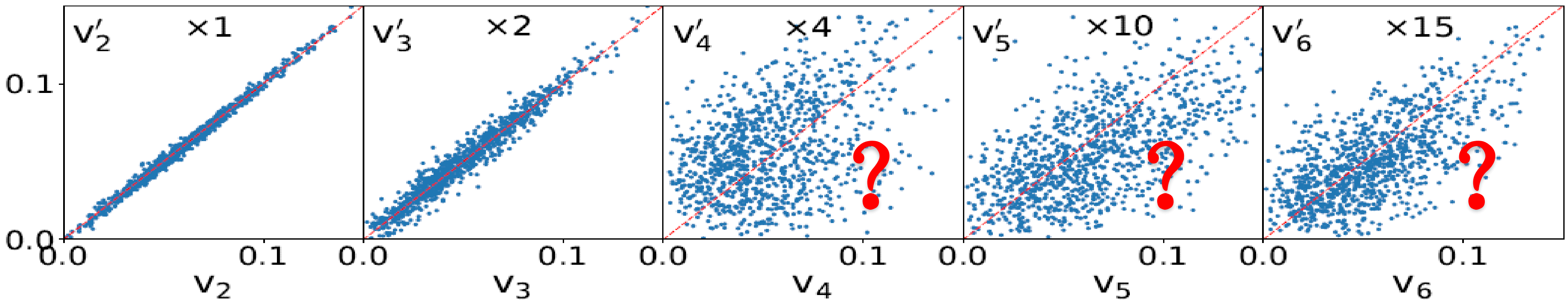
-PCA gives the event averaged flow harmonics $\overline{v'_2}$, $\overline{v'_3}$, $\overline{v'_4}$ … … and the event-by-event v'_2, v'_3, v'_4 … … Results of elliptic and triangular flow are similar to the ones from traditional Fourier transform, but show deviations for higher order flow harmonics with $n \geq 4$

Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

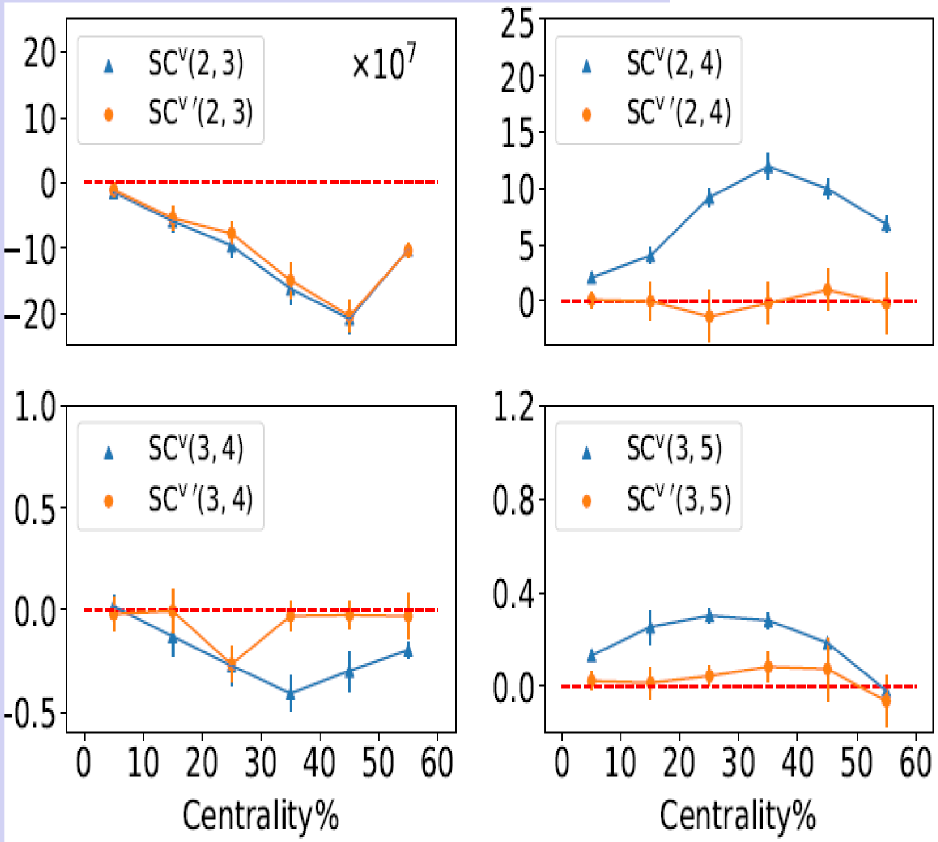
Event-by-event v'_n (PCA) vs. v_n (Fourier)



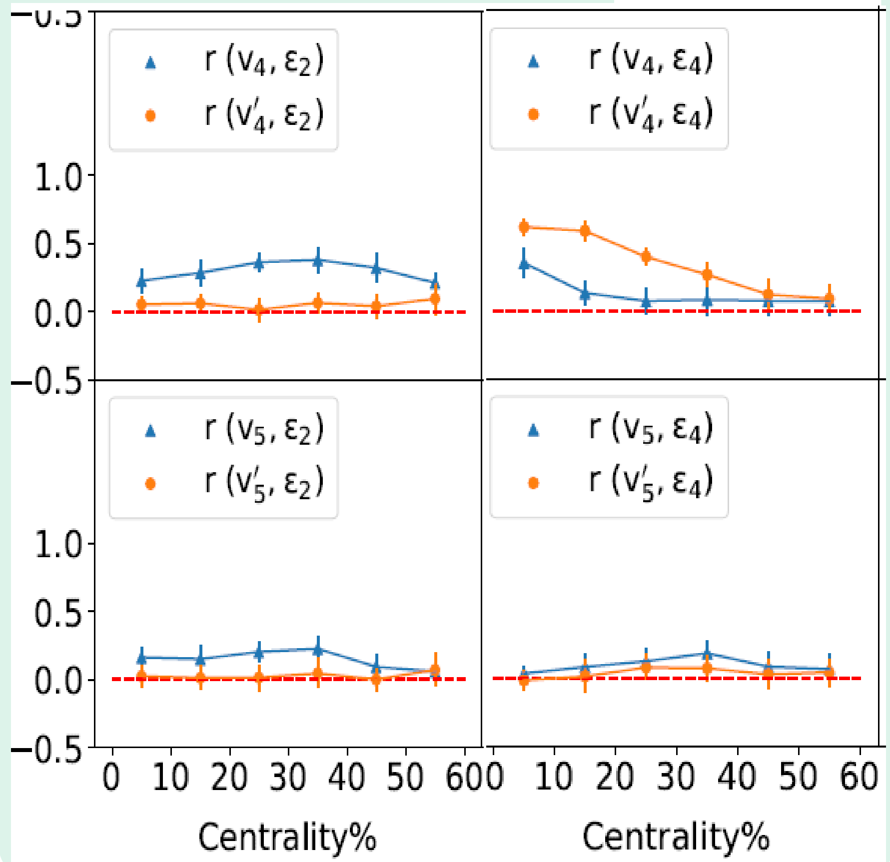
v_n' (PCA) vs. v_n (Fourier)



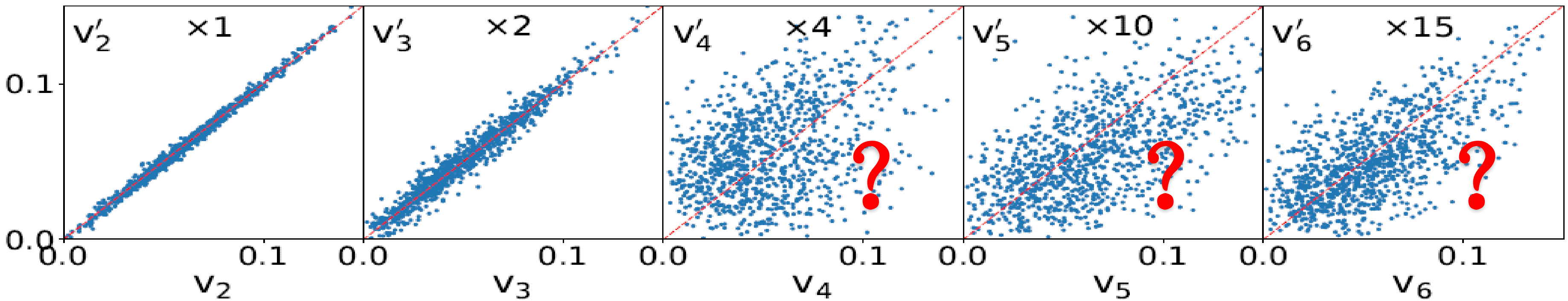
Symmetric Cumulants



Pearson Coefficients



v_n' (PCA) vs. v_n (Fourier)



<u>**Traditional Fourier Transform**</u>

-Strong mode couplings between v_4 and v_2

-interoperated as highly non-linear hydro evolution that mix v_4 and ε_2^2

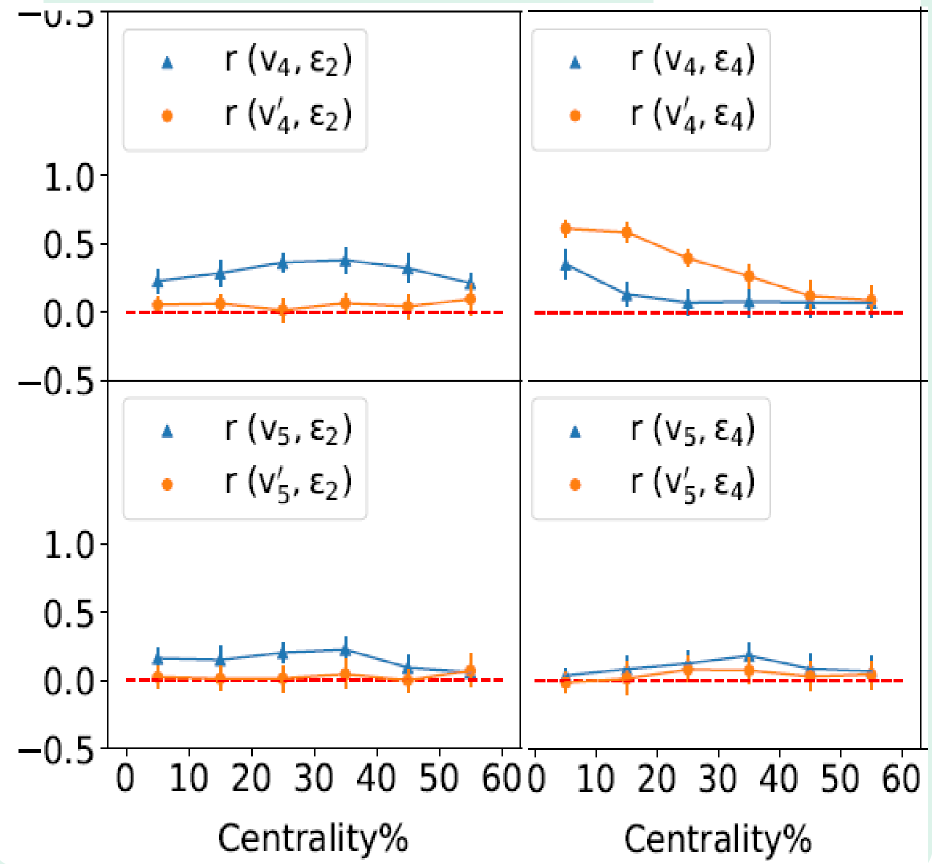
<u>**PCA:**</u>

-Reduce the correlations between v_4' and ε_2

-increase correlations between v_4' and ε_4

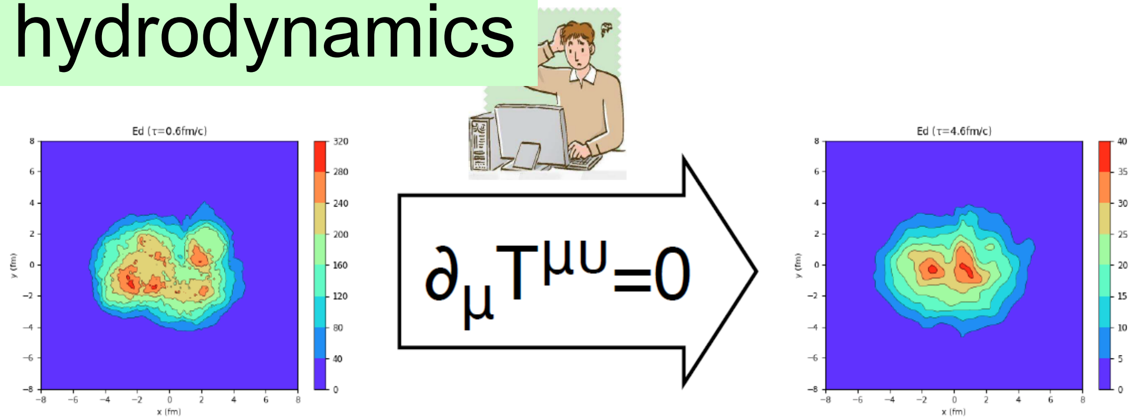
Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

Pearson Coefficients

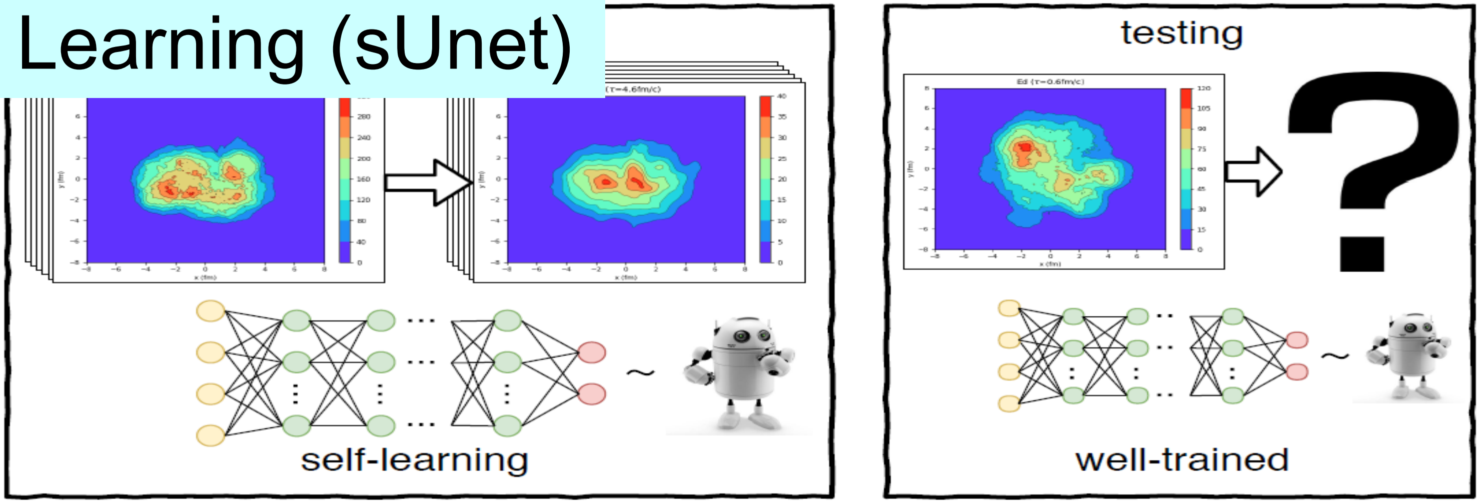


Summary & outlook

Traditional hydrodynamics



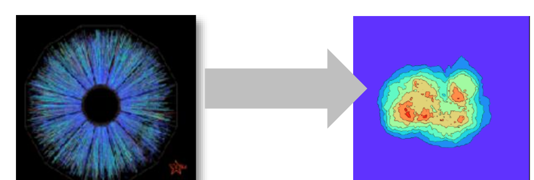
Deep Learning (sUnet)



Outlook

Final particle profiles

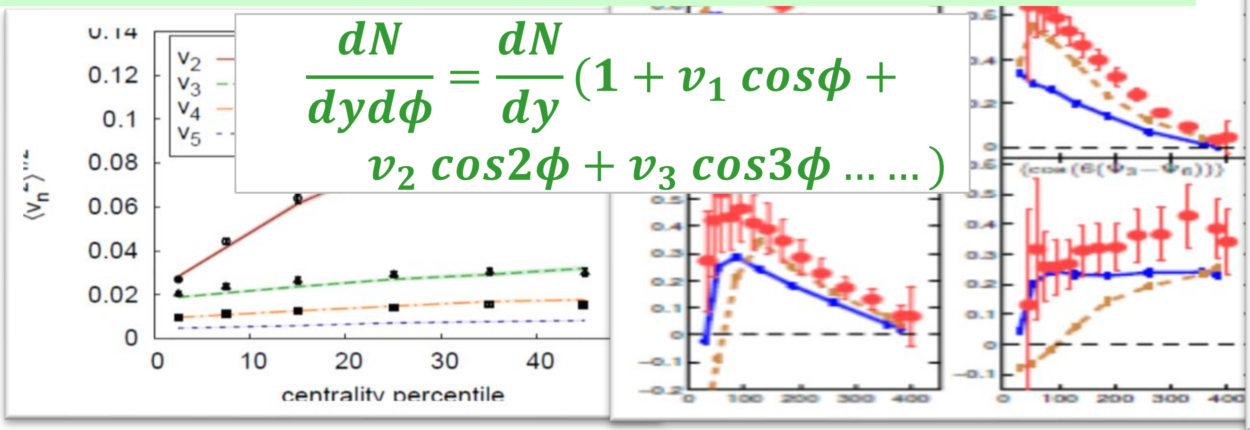
-------- > Initial energy density profiles

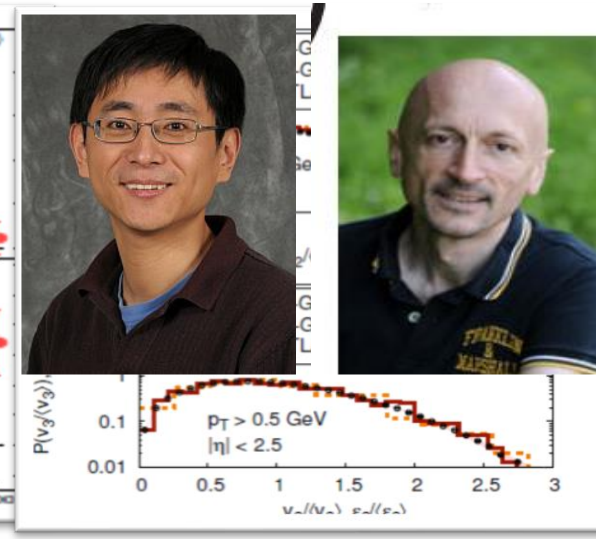


Can deep learning discover knowledge (conservation laws) from the massive data generated from hydrodynamics?

Flow: traditional Fourier Transform

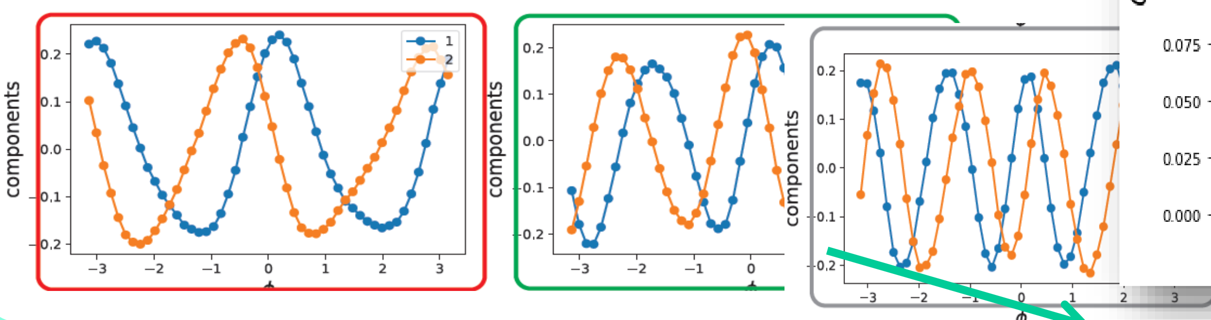
$$\frac{dN}{dyd\phi} = \frac{dN}{dy}(1 + v_1\, cos\phi + v_2\, cos2\phi + v_3\, cos3\phi \,\ldots\ldots)$$

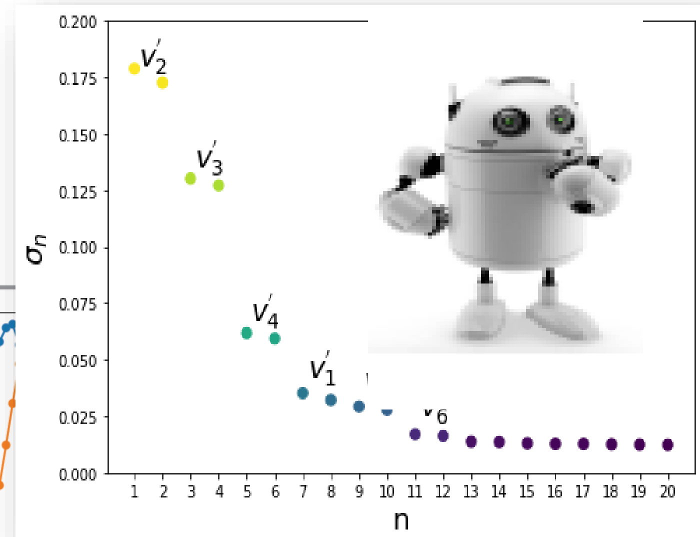




Unsupervised Learning (PCA)

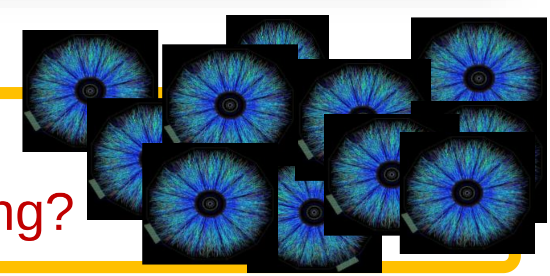
It independently discovered the flow harmonics without explicit instructions from human being!



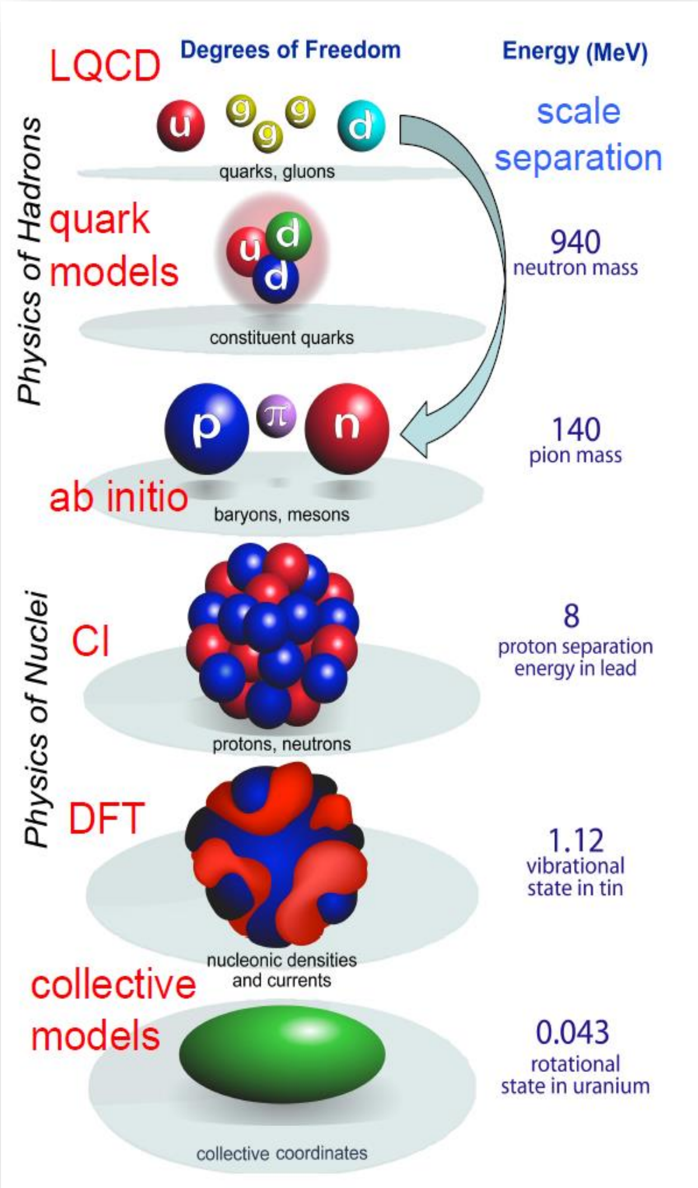


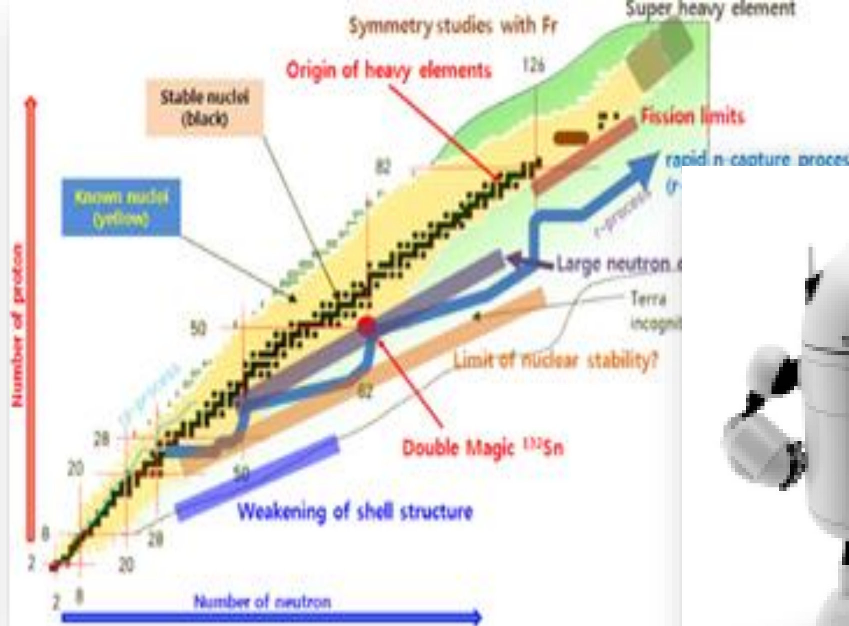
Outlook

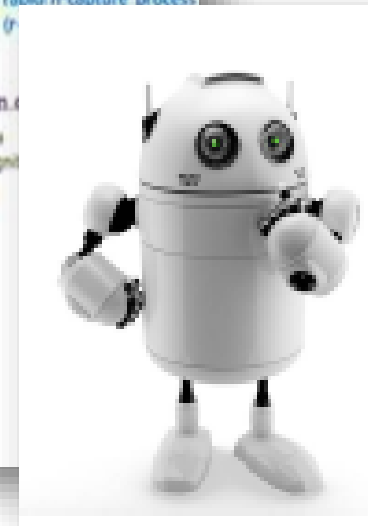
Can PCA detect modes or structures from the massive data that is not realized or easily defined by human being?



Outlook







Machine Learning for Nuclear Physics

-- A proper field for Machine Learning
-- It is jut beginning
-- Many many more to explore … …
-- What ML can bring us after 10 years?

Enjoy it! have fun!

Thank You