Applications of Machine Learning in Relativistic Heavy Ion Collisions

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International Workshop on Partonic & Hadronic Transport Approaches for Relativistic Heavy Ion Collisions

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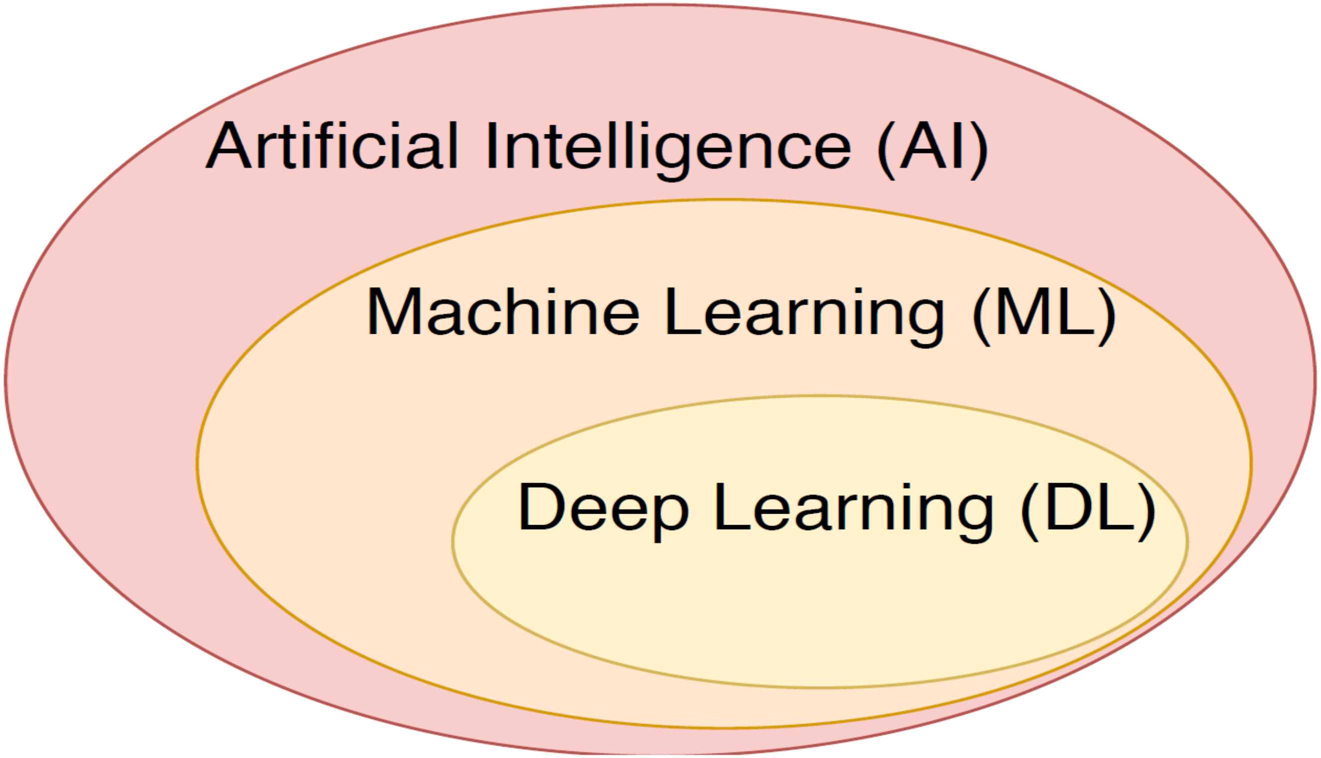
May 11, 2019

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

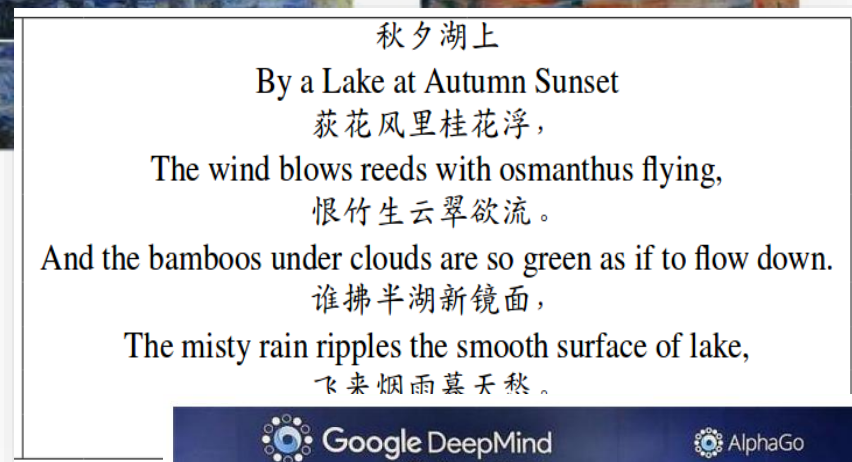
Broad Applications of Machine Learning

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,
飞来烟雨暮天秋。

-Machine translation
-Speech recognition
-Chinese poetry generation

… … … …

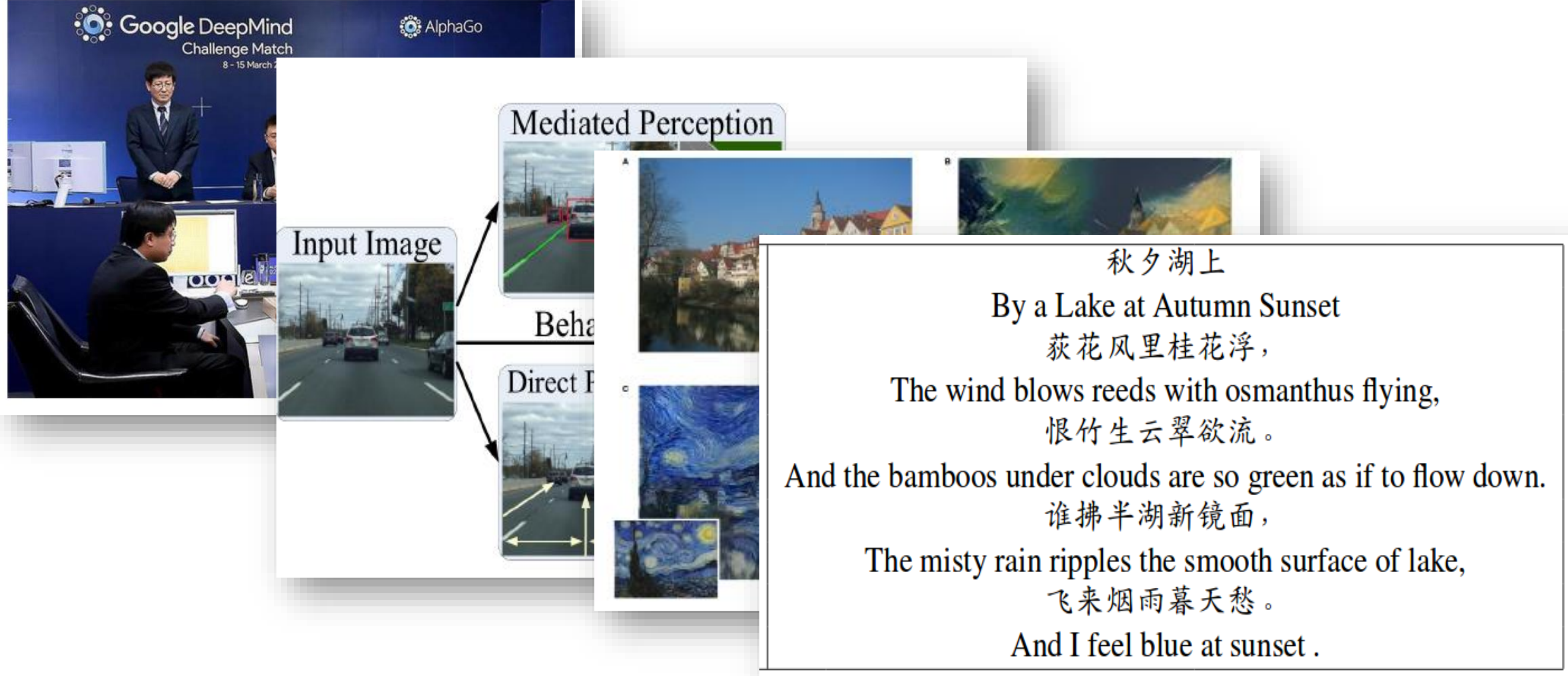
Playing Games

-AlphaGo (by Google DeepMind)

… … … …

Autonomous Driving

… … … …



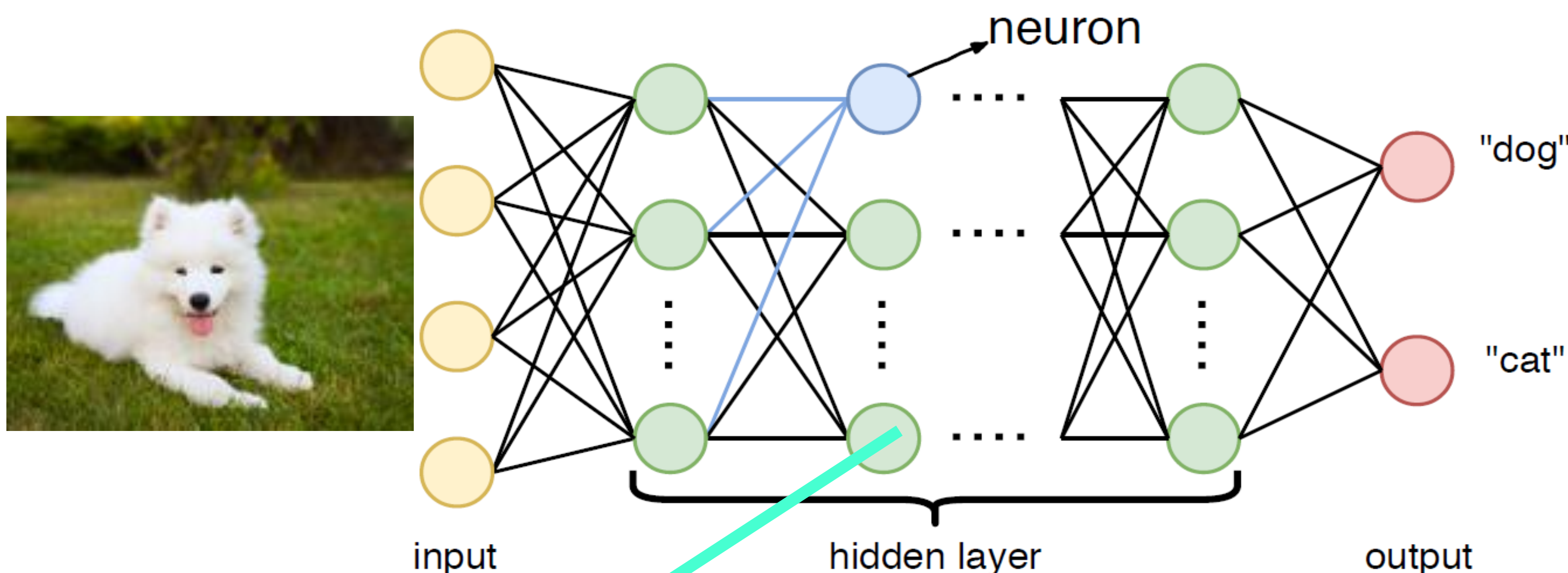
Categories:

-Supervised learning
-Unsupervised learning
-Reinforcement learning

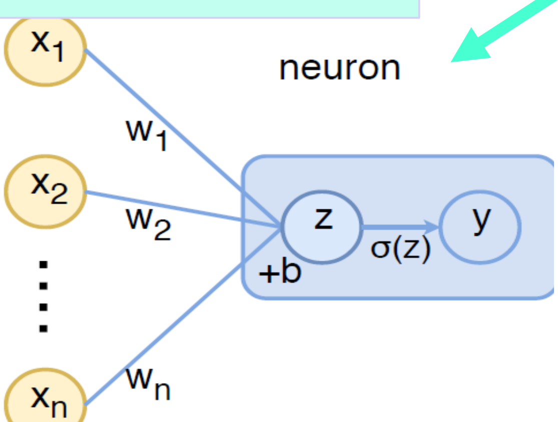
… … … …

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

Deep Neural Network



Neuron



Linear operation

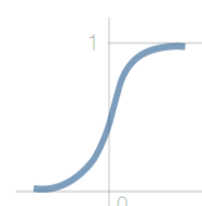
$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

scaling, rotating, boosting, changing dimensions

Non-linear activation function

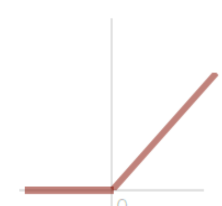
(a) Sigmoid

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



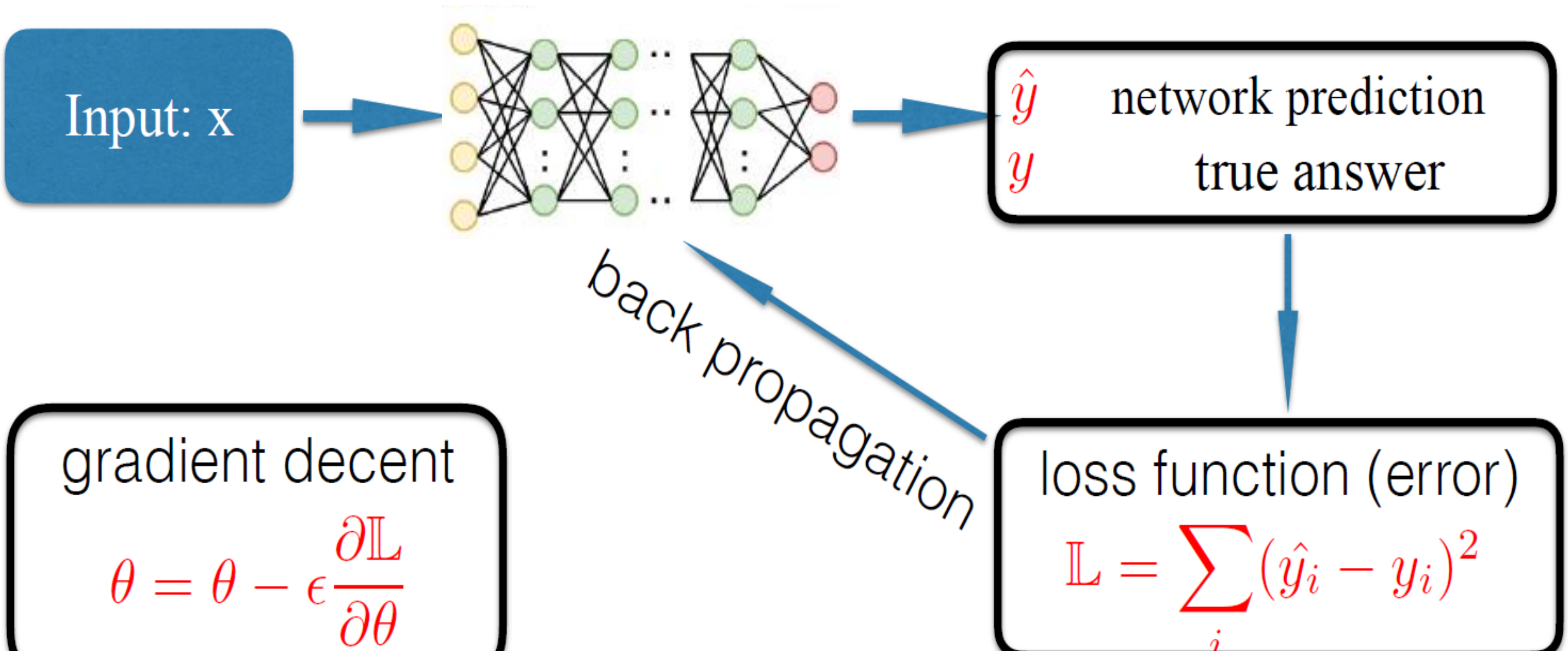
(b) ReLU

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



Deep Neural network

-Loss function, back propagation & gradient decent

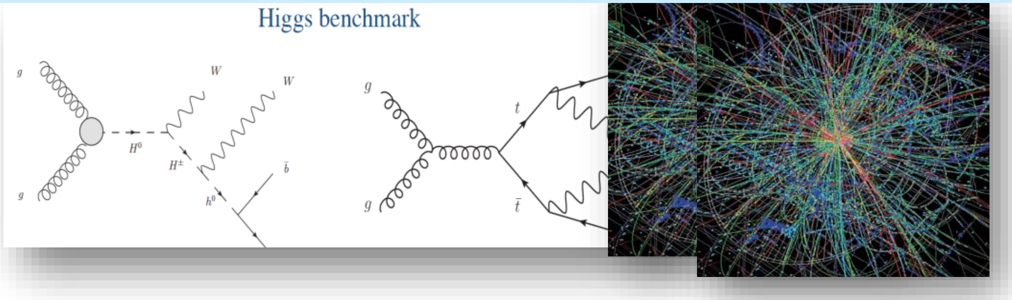


-Deep neural network can reduce fitting error by updating model parameters through back propagation and gradient decent.

Applications of Machine Learning in Physics

- 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
- . . ., . . .,
- . . .

Searching for Exotic Particles in High-Energy Physics



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

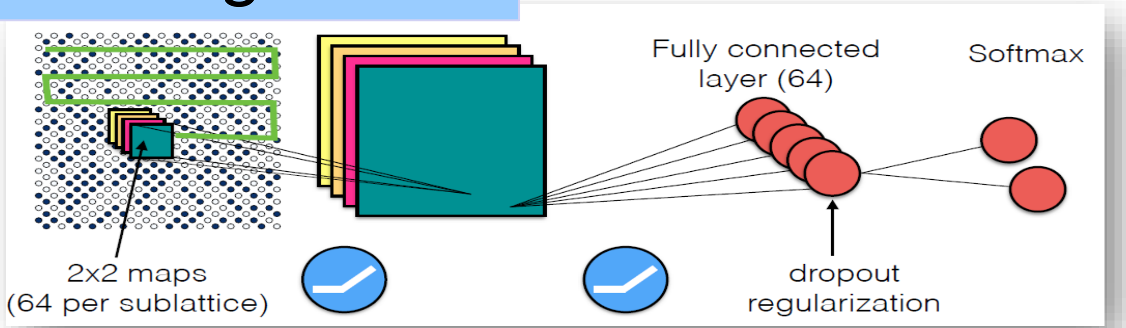
P.Baldi,P.Sadowski,& D.Whiteson Nature Commun.5, 4308 (2014)

Classifying the Phase of Ising Model

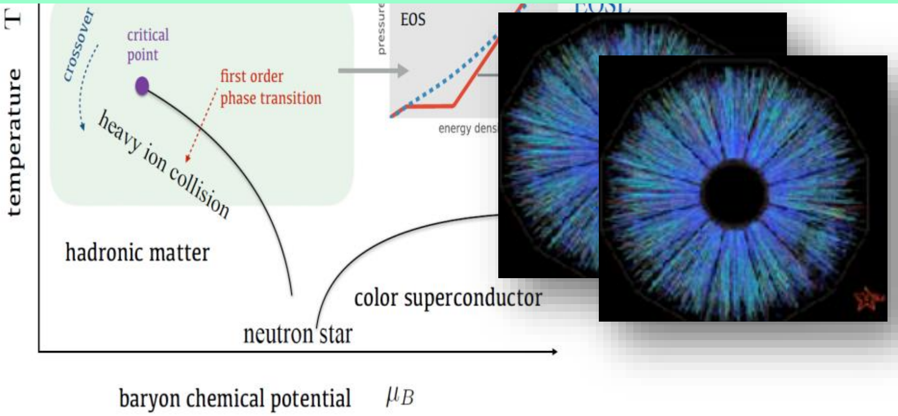
For the case of Ising gauge theory

$$H = -J \sum_p \prod_{i \in p} \sigma_i^z$$

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



Identify QCD Phase Transition with Deep Learning

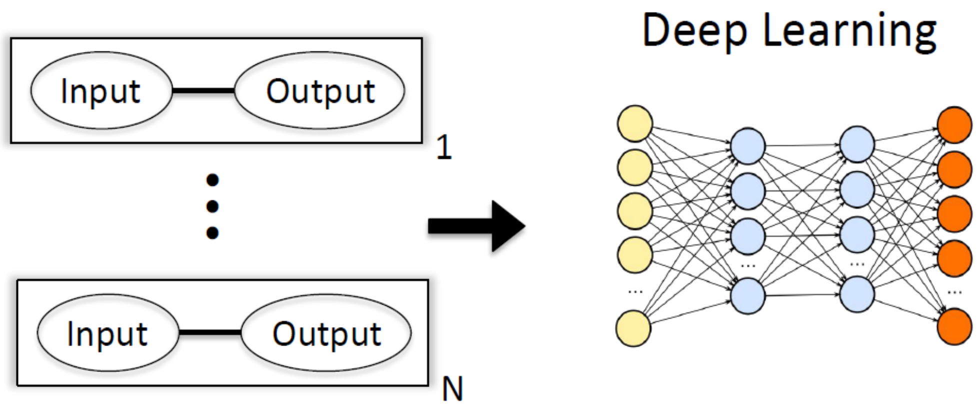


DNN efficiently decode the EOS information from the complex final particle info event by event

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

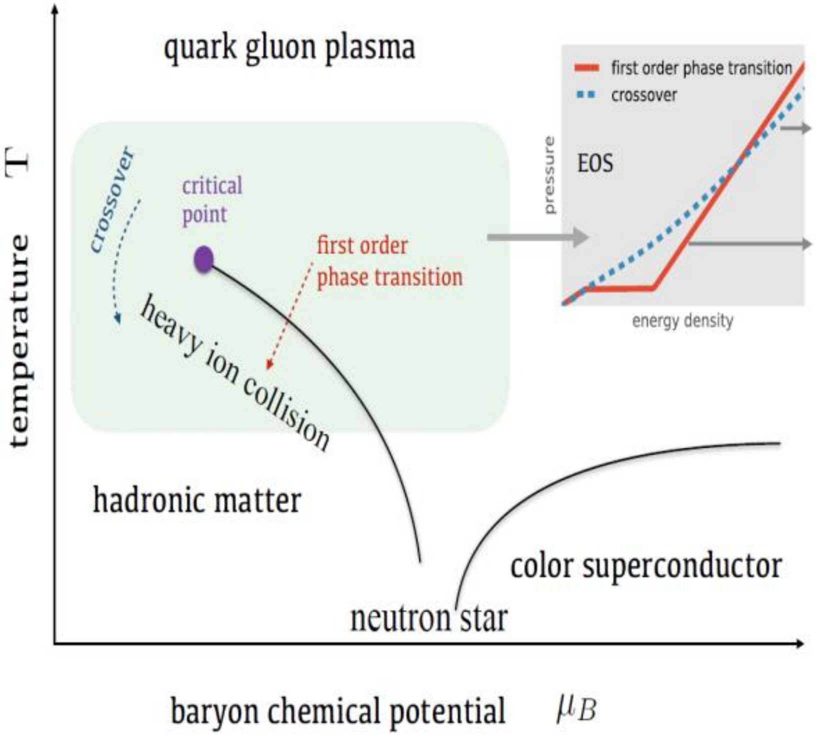
Why Machine Learning in Physics?

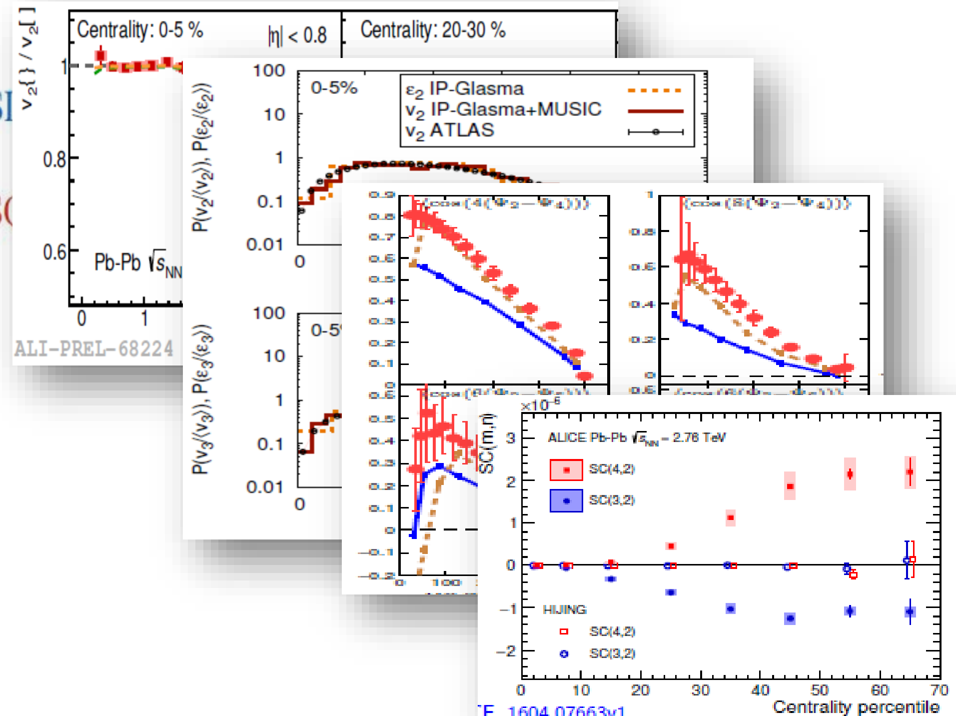
"Unlike earlier attempts … Deep Learning systems can see patterns and spot anomalies in data sets far larger and messier than human beings can cope with."

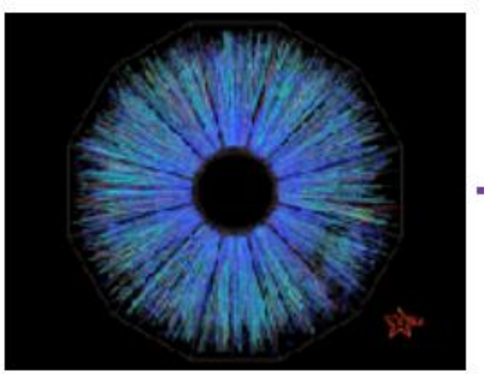


Can "**Black-box**" models learn patterns and models solely from data without relying on scientific knowledge?

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

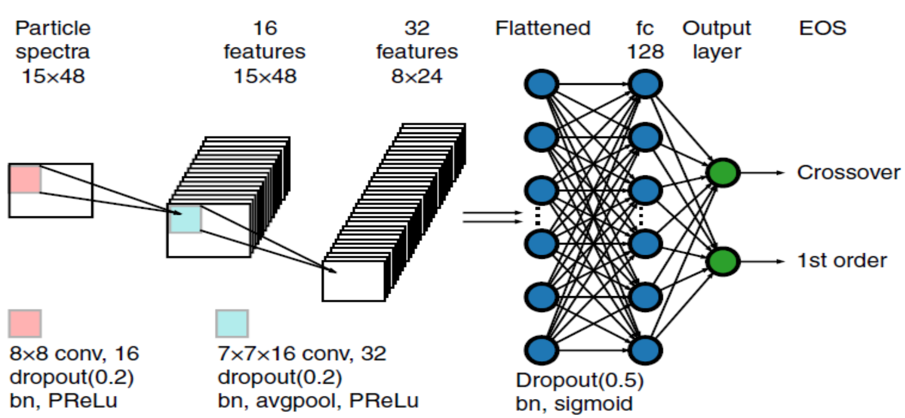
-particle spectra - image (15*48 pixels)

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

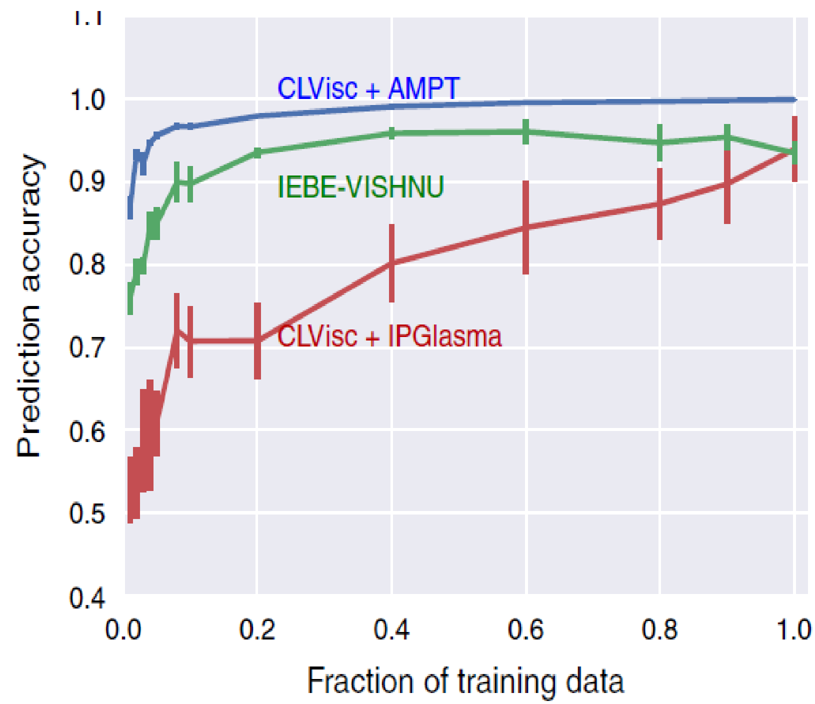
B） Training CNN

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



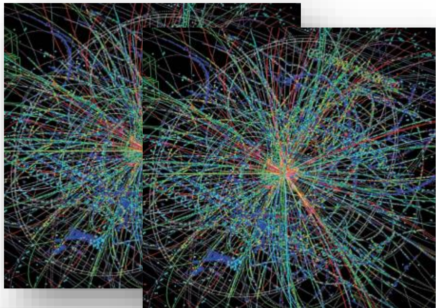
One can efficiently decode the EOS information from the complex final particle info event by event using deep learning

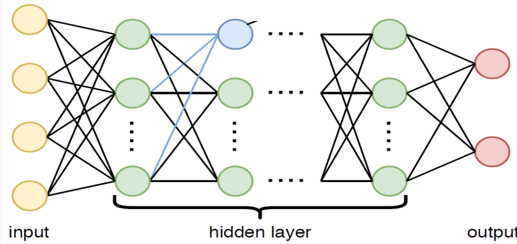
LG. Pang, K.Zhou, N.Su, H.Petersen, H. Stoecker, XN. Wang. Nature Commun.9 (2018) no.1, 210

Applications of deep learning to relativistic hydrodynamics

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

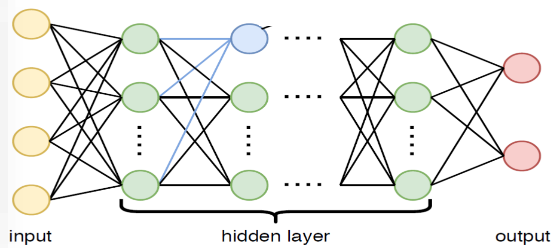
Image identification





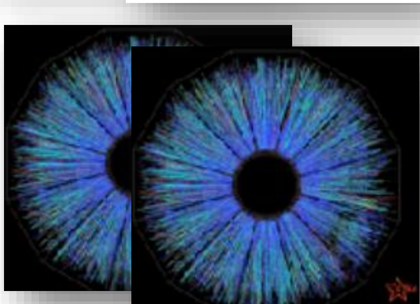
Higgs signal or background?

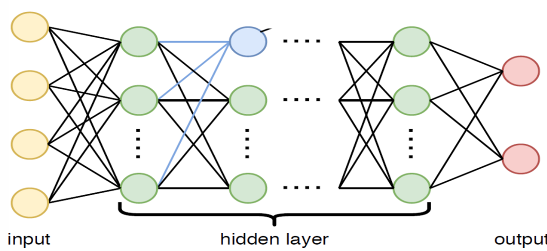
P.Baldi,et al,Nature Commun.(2014)



High temperature or low temperature phase?

Carrasquilla & Melko. Nature Physics (2017)





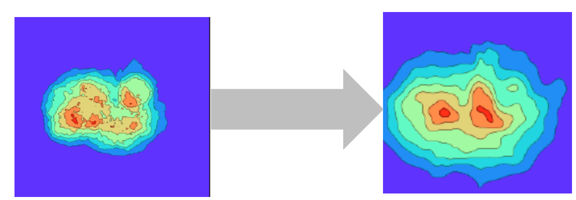
EoS L or EOSQ ?

Pang,et al Nature Commun.(2018)

Image generation

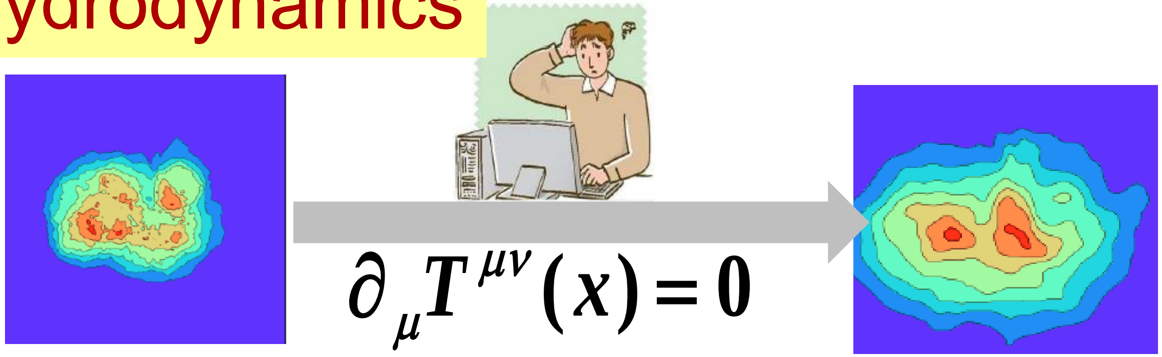
For hydrodynamics can we use deep learning to learn/predict the pattern transformation between initial and final profiles?

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



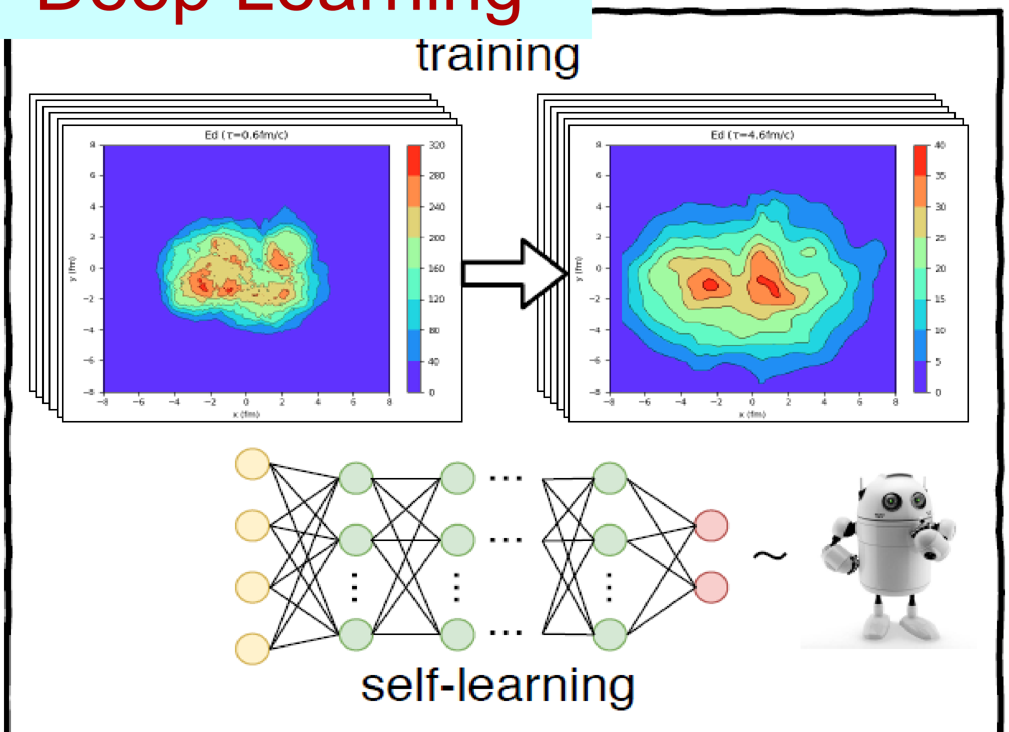
For the non-linear hydro system, can the **black-box** network could learn pattern transformations solely from data without relying on scientific knowledge?
(conservation laws)

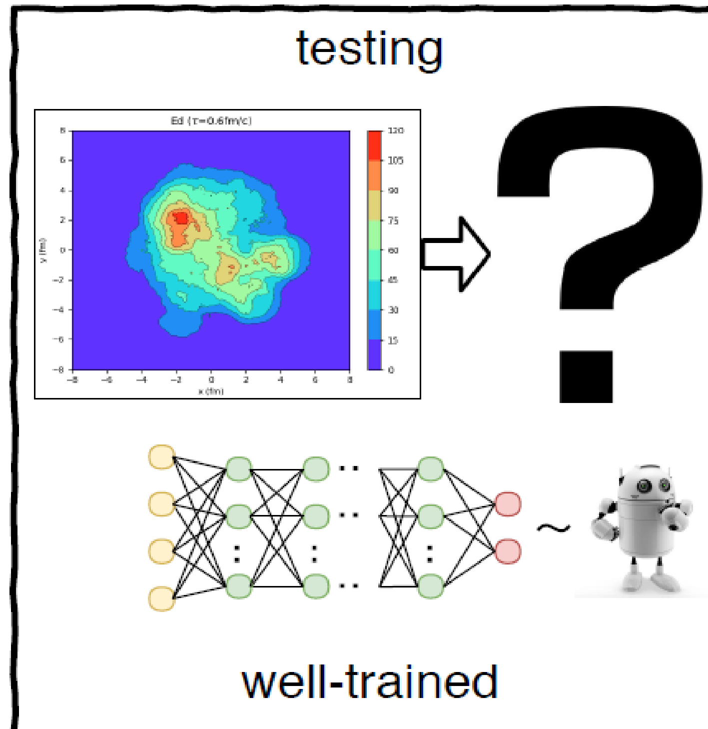
Traditional hydrodynamics



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

Deep Learning

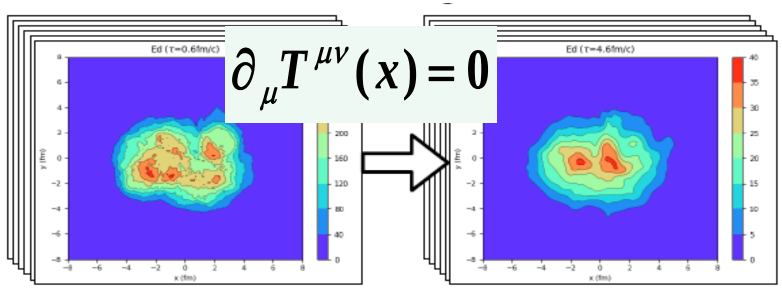




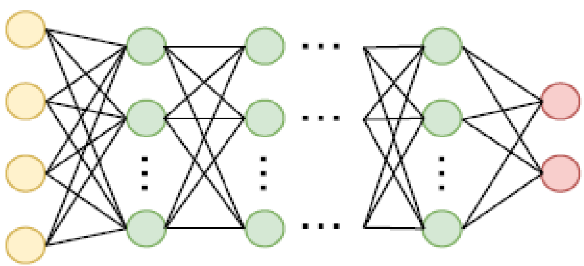
-Such deep learning systems do not need to be programmed with the hydro equation $\partial_\mu T^{\mu\nu}(x) = 0$ **Instead, they learn on their own**

Deep Learning

Step1) Generate the training/testing data sets from hydro



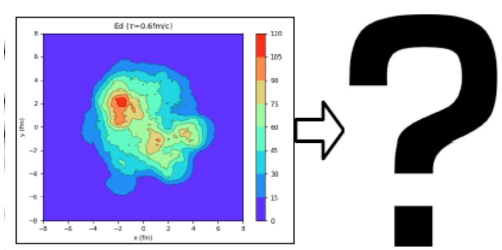
Step2) Design & train the deep neural network



The Training Data Sets

hydro VISH2+1	MC-Gl
	10000

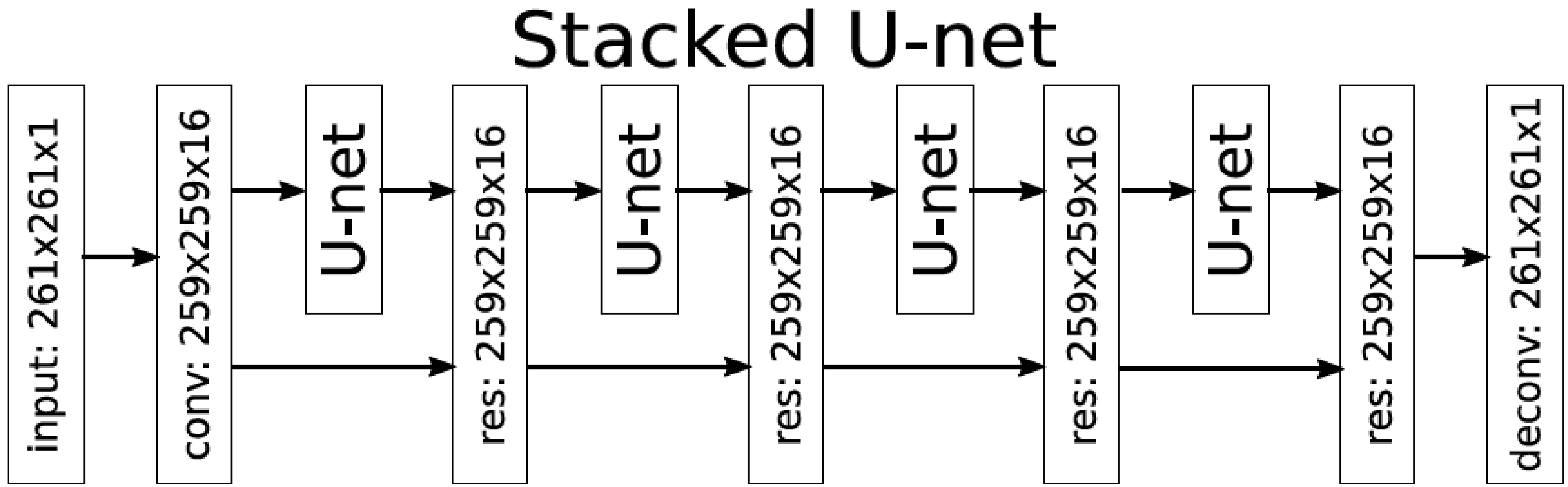
Step3) Test the deep neural network

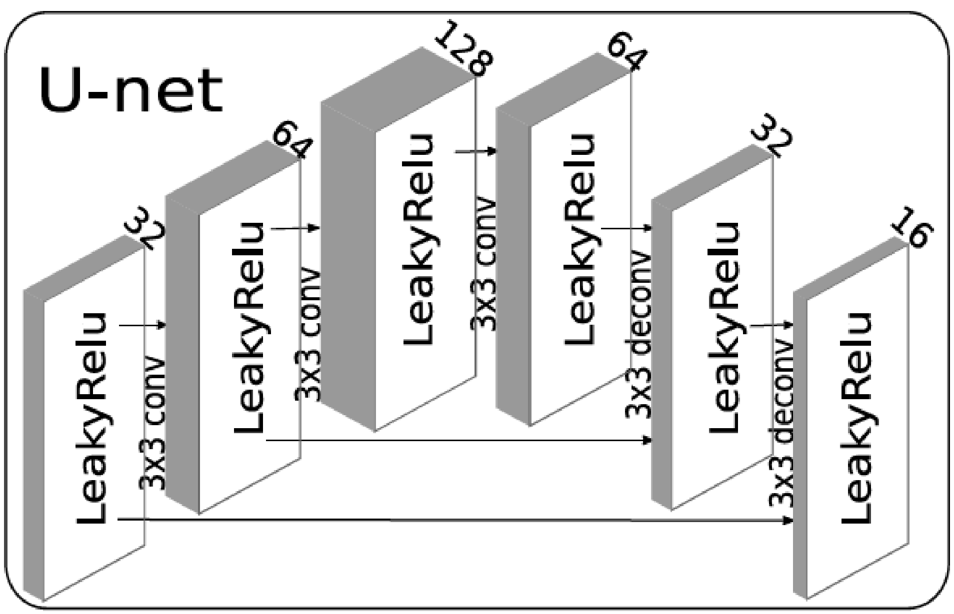


The Testing Data Sets

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

Training / Testing data sets from 2+1-d hydro

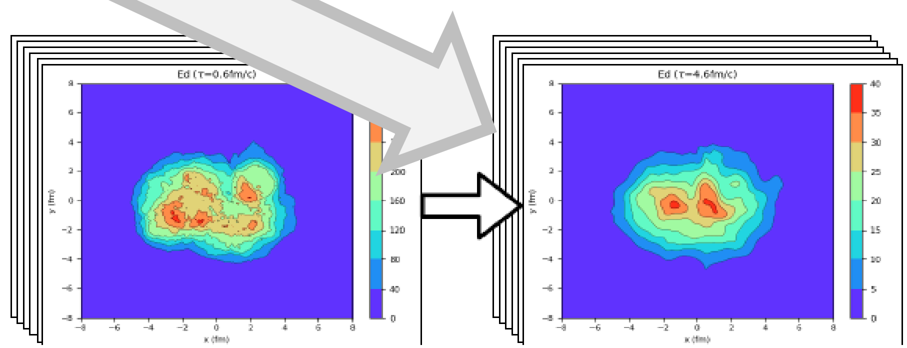
$$T^{\tau\tau}{}_{,\tau} + (\bar{v}_x T^{\tau\tau})_{,x} + (\bar{v}_y T^{\tau\tau}) = -\frac{p+T^{\tau\tau}}{\tau} - (p\,\bar{v}_x)_{,x} - (p\,\bar{v}_y)_{,y}$$

$$T^{\tau x}{}_{,\tau} + (\bar{v}_x T^{\tau x})_{,x} + (\bar{v}_y T^{\tau x})_{,y} = -p_{,x} - \frac{T^{\tau x}}{\tau}$$

$$T^{\tau y}{}_{,\tau} + (\bar{v}_x T^{\tau y})_{,x} + (\bar{v}_y T^{\tau y})_{,y} = -p_{,y} - \frac{T^{\tau y}}{\tau}$$

Initial conditions: MC-Glauber, MC-KLN, AMPT, Trento   EoS: p=e/3,

hydro evolution time: $\tau - \tau_0 = 2.0,\ 4.0,\ 6.0\ \mathrm{fm/c}$



The Training Data Sets

2+1-d hydro VISH2+1	MC-Glauber
	10000 events

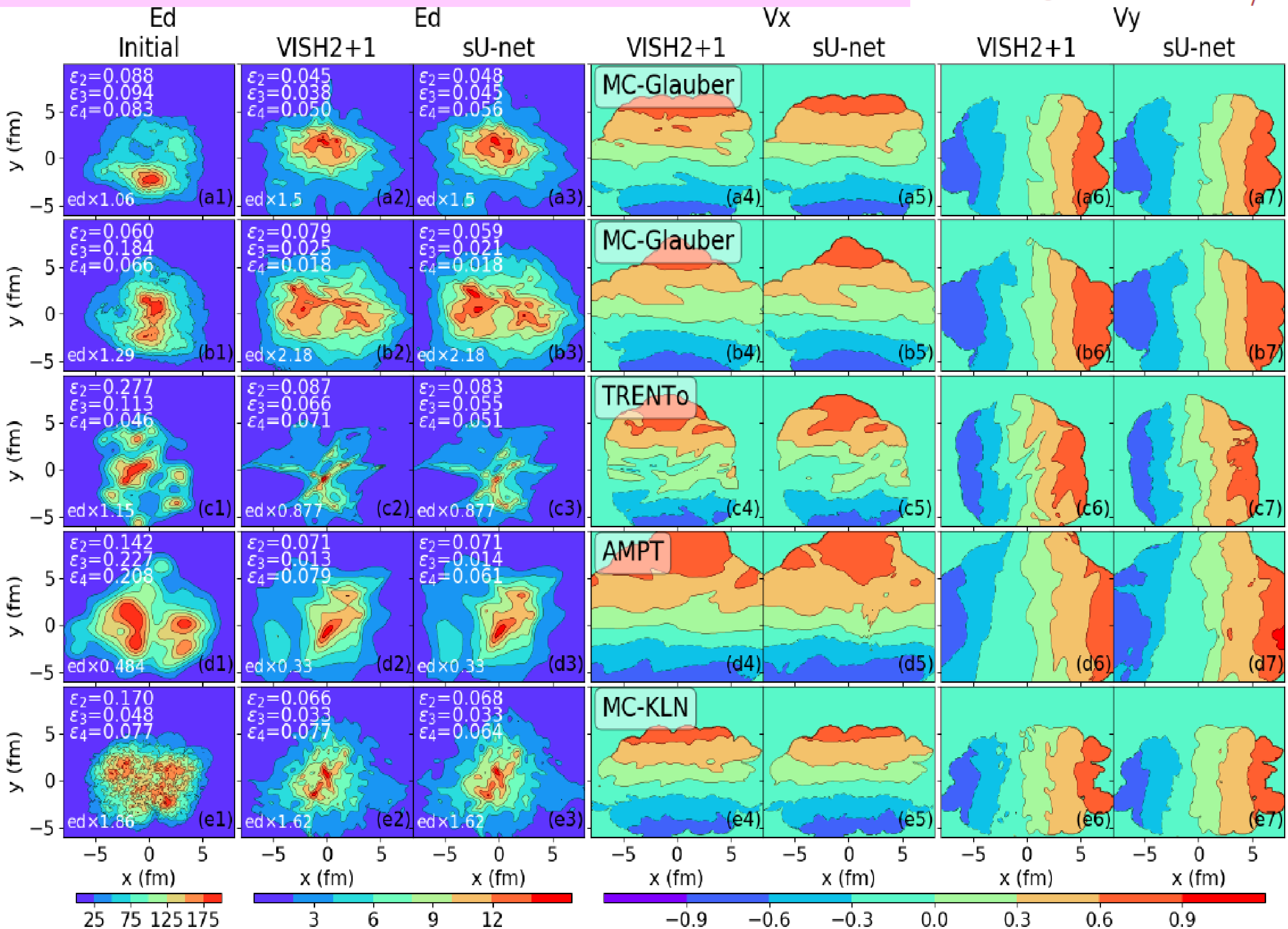
The Testing Data Sets

2+1-d hydro VISH 2+1	MC-Glauber	MC-KLN	AMPT	Trento
	10000 events	10000 events	10000 events	*10000 events*

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

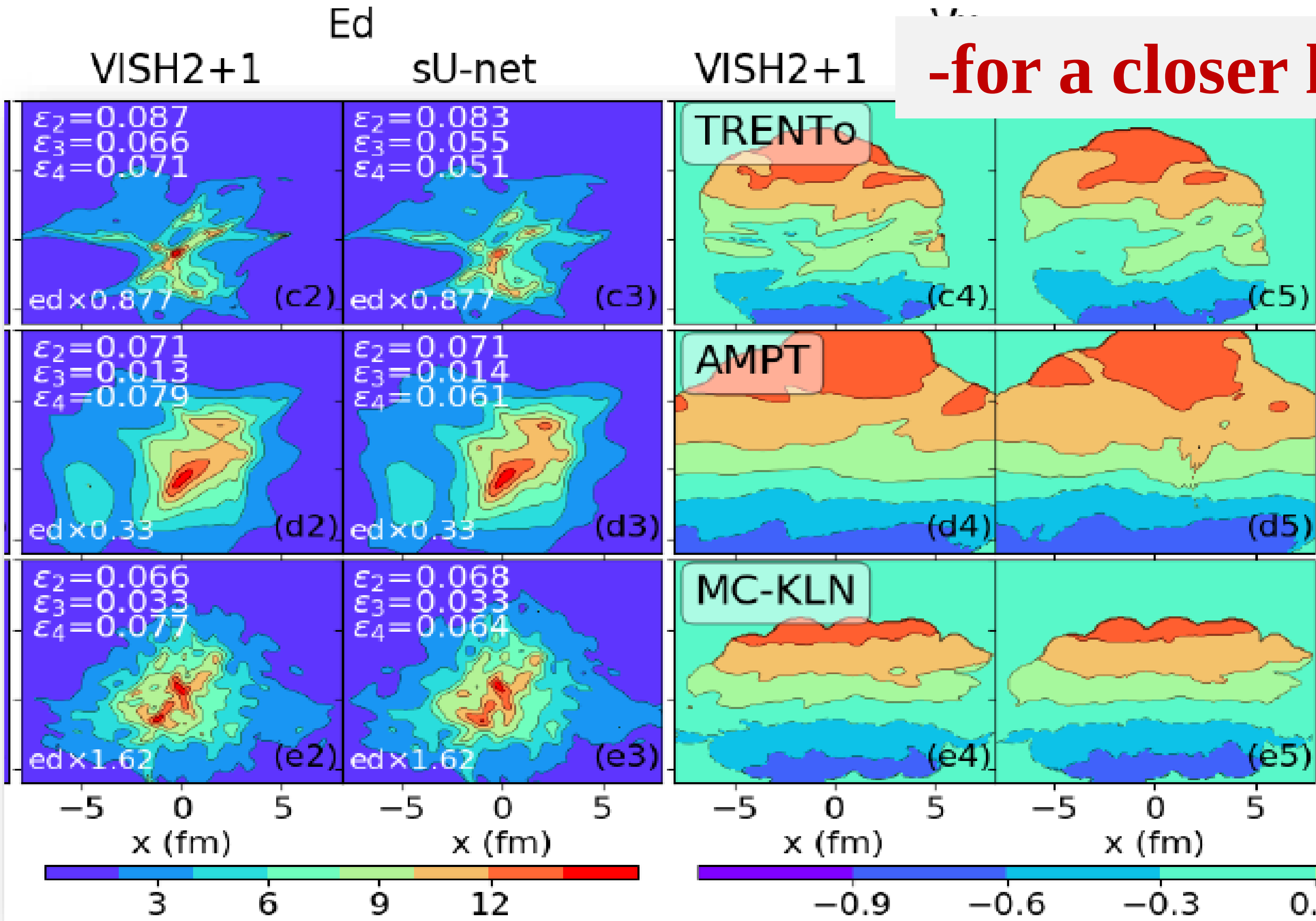
sUnet prediction vs. hydro simulations

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



sUnet prediction vs. hydro simulations

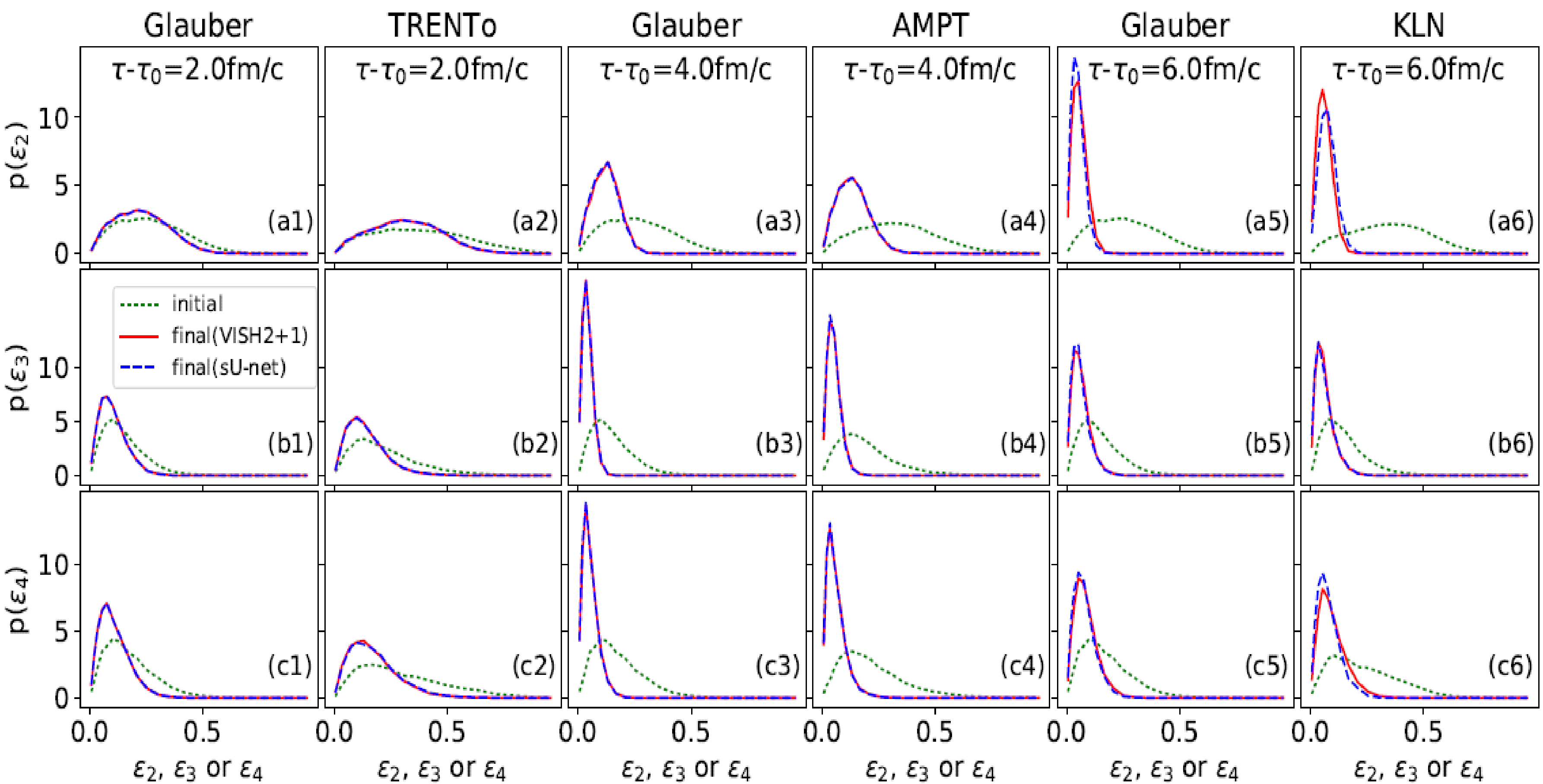
$\tau - \tau_0 = 6.0fm/c$



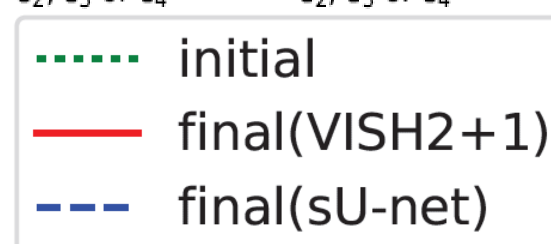
-for a closer look

sUnet prediction vs. hydro simulations

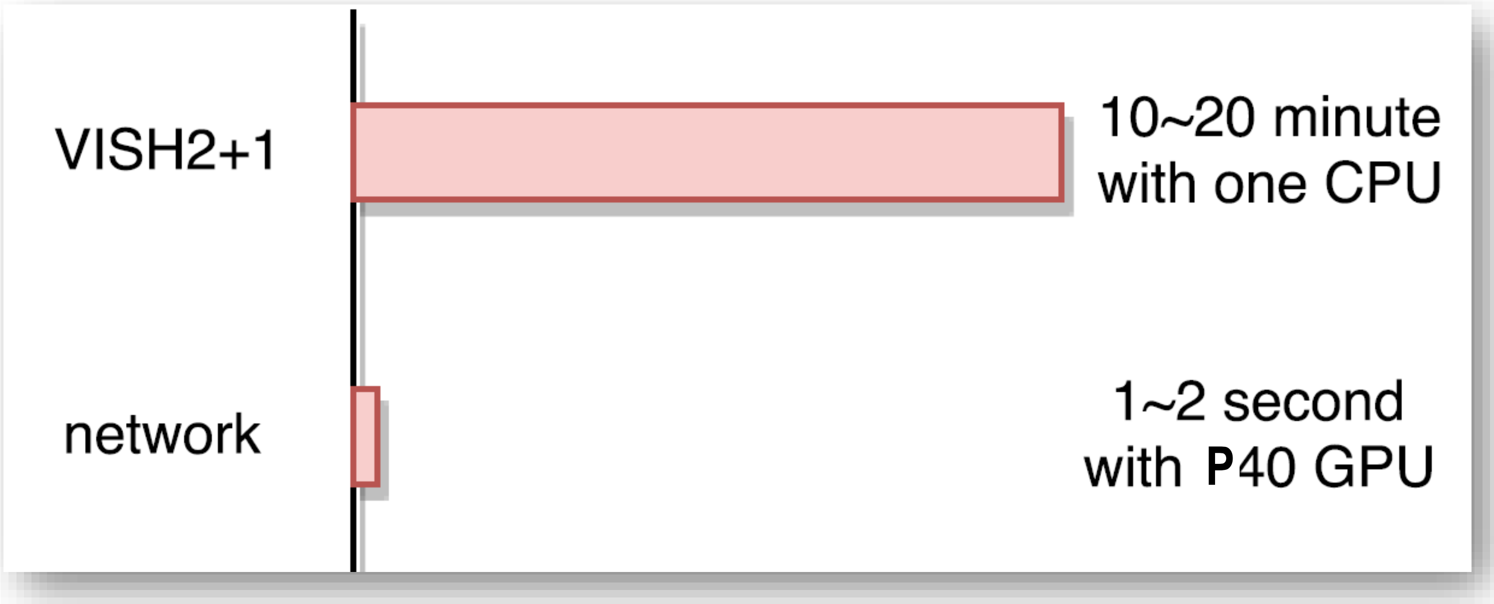
Eccentricity distributions:

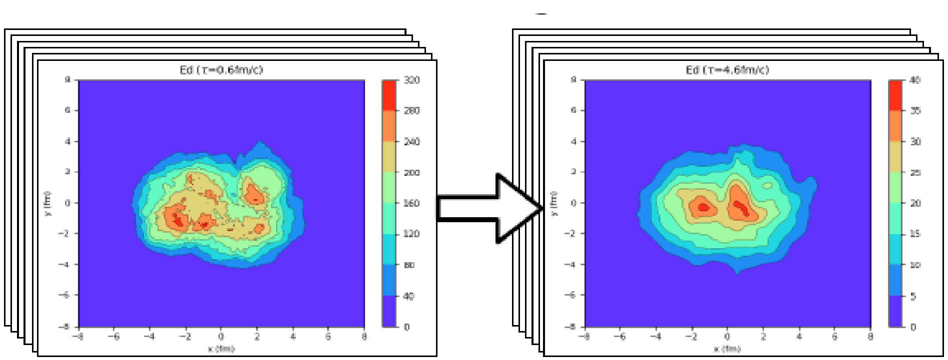


$$\varepsilon_n e^{in\Phi_n} = -\frac{\int dxdyr^2 e^{in\phi} e(x,y)}{\int dxdyr^2 e(x,y)}$$



Simulation time: sUnet vs. hydro

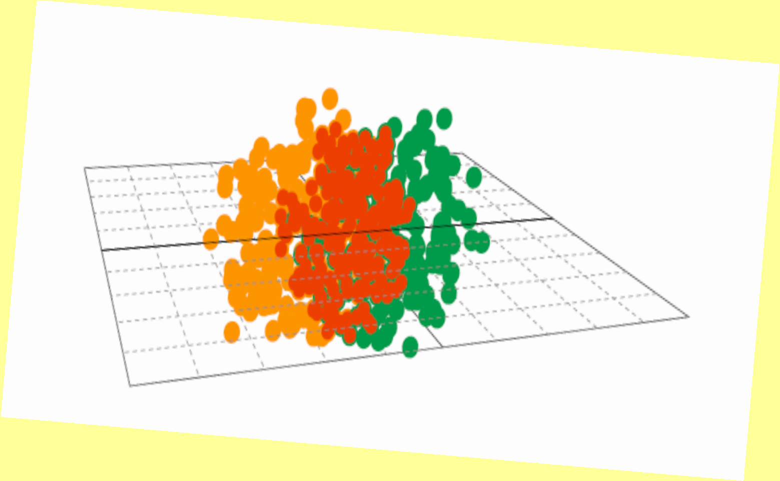


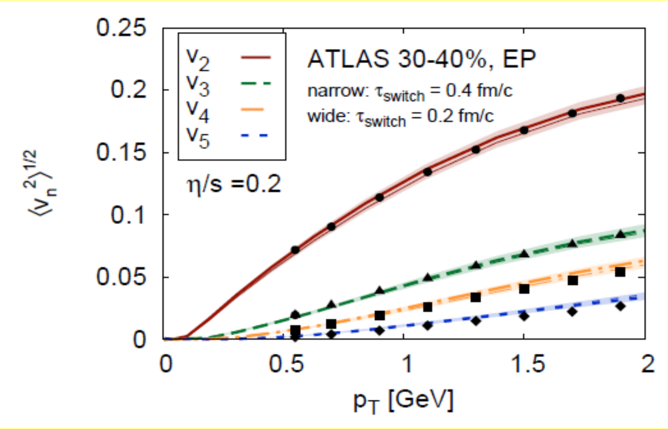


With the well trained network, the final state profiles can be quickly generated from the initial profiles. (5-10 times faster for GPU based calculations)

Principal Component Analysis for Flow

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





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

$$+2v_3(p_T,b)\cos(3\varphi)......]$$ -flow definition from human being

-- Can Machine Learning directly discover flow harmonics from complex data sets?

What is Principal Component Analysis (PCA)

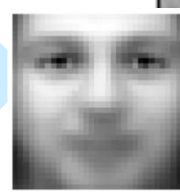
-a statistical procedure that uses an <u>orthogonal transformation</u> to convert a set of observations into a set of values of <u>linearly uncorrelated</u> variables called principal components.

PCA for FACE analysis

Data sets: many many faces

PCA

mean μ



top eigenvectors: μ_1, μ_2, μ_3 … …

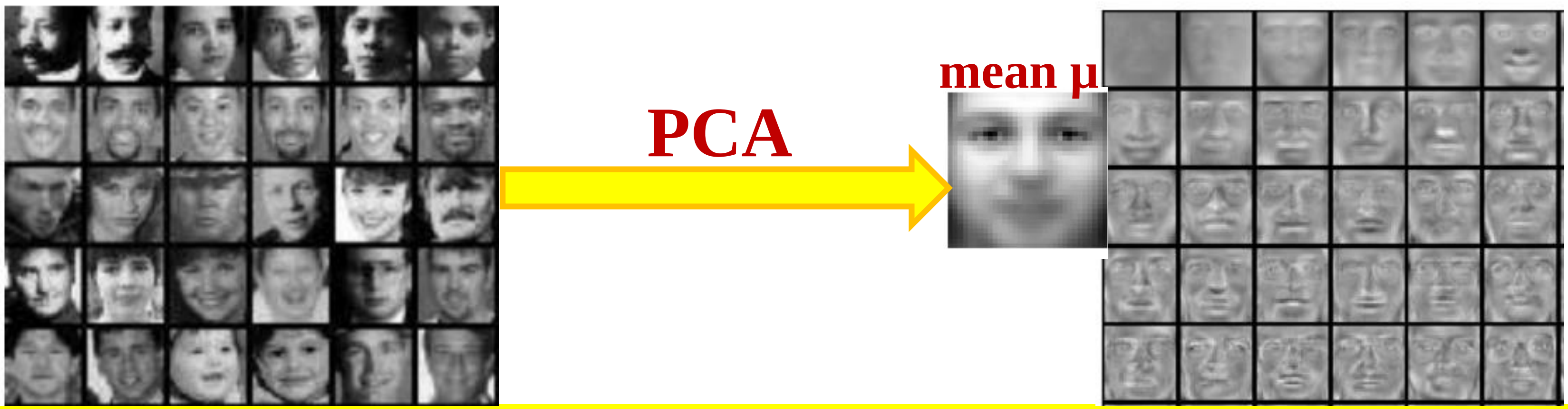
With PCA, each face is decomposed into superposition of eigenfaces.

 =  + 

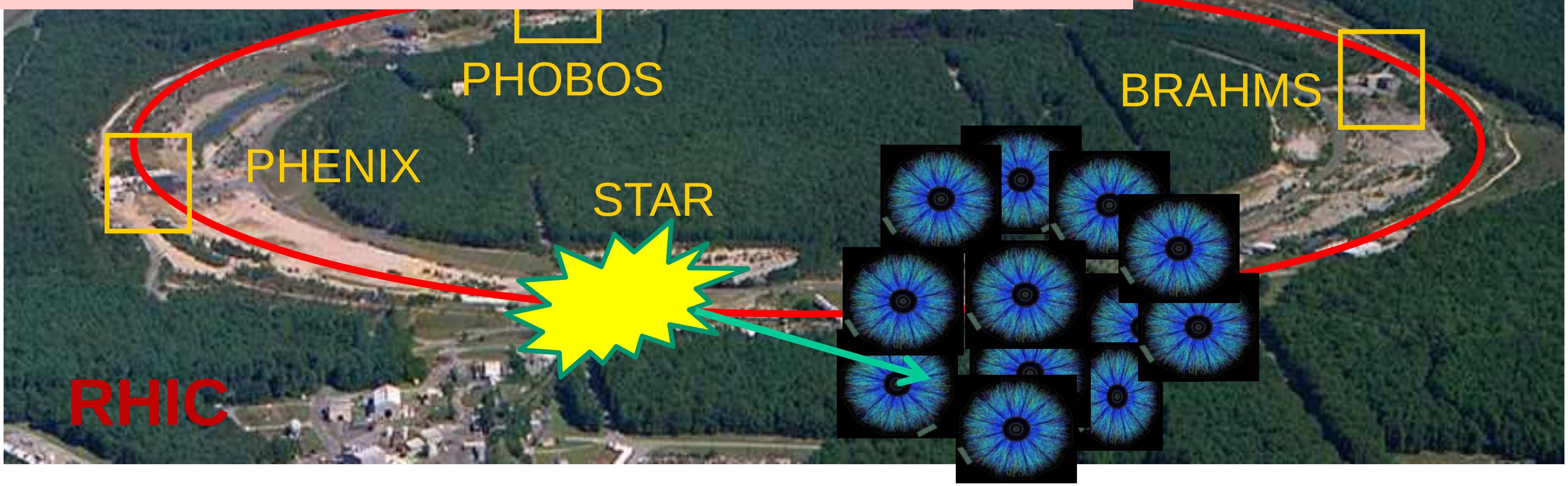
$$\hat{x} = \mu + w_1 u_1 + w_2 u_2 + w_3 u_3 + w_4 u_4 + \dots$$

PCA for FACE analysis

Data sets: many many faces — **top eigenvectors: μ_1, μ_2, μ_3 …**



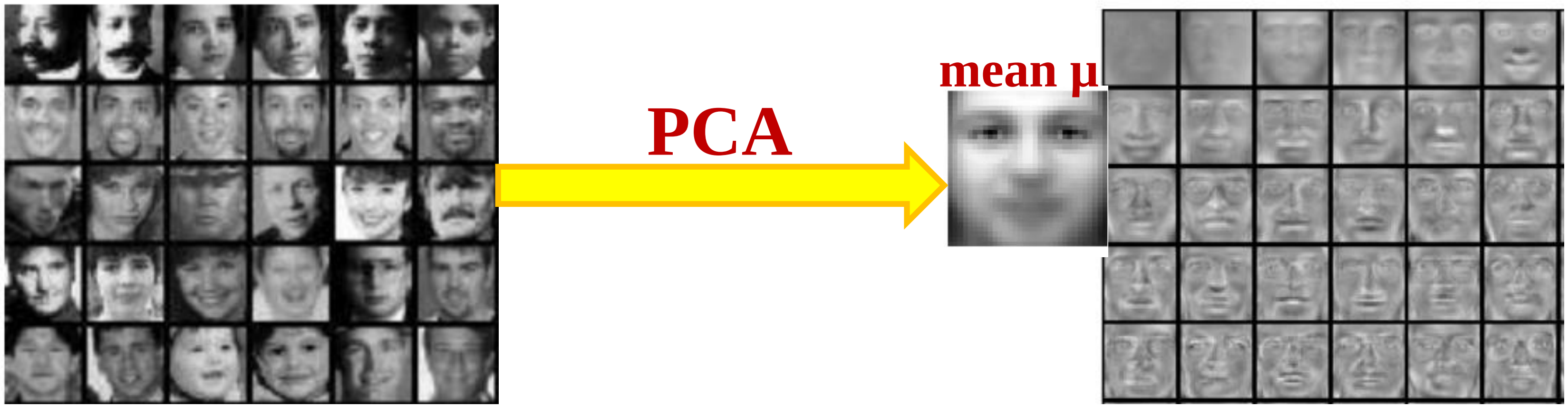
PCA for Relativistic Heavy Ion Collisions?



Can PCA (machine) directly identify the different configurations behind the massive heavy ion data?

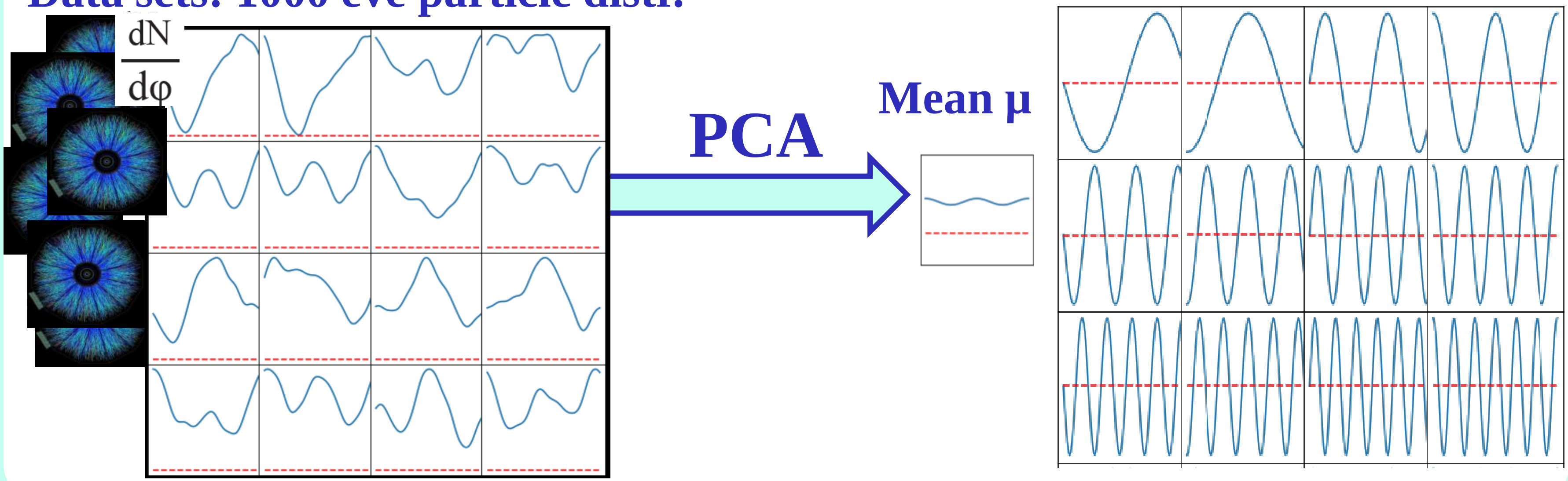
PCA for FACE analysis

Data sets: many many faces **top eigenvectors: μ_1, μ_2, μ_3 …**



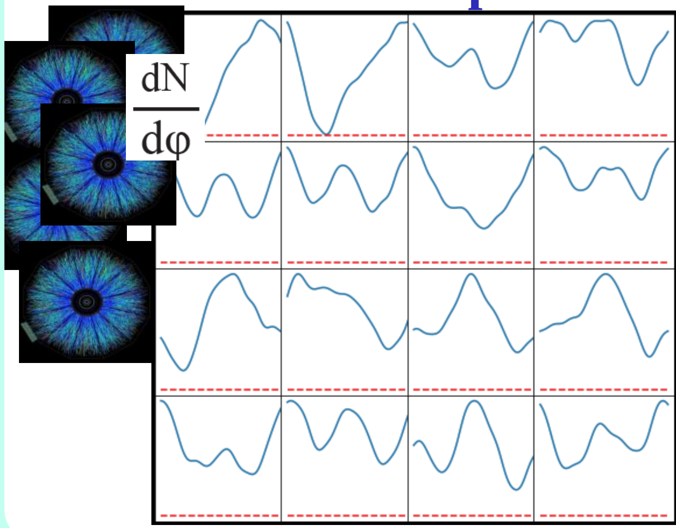
PCA for flow analysis –**basic idea**

Data sets: 1000 eve particle distr. **top eigenvectors: $\sigma_1, \sigma_2, \sigma_3$ …**



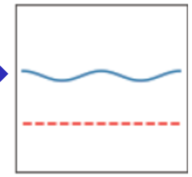
PCA for flow analysis –**basic idea**

Data sets: 1000 eve particle distr.

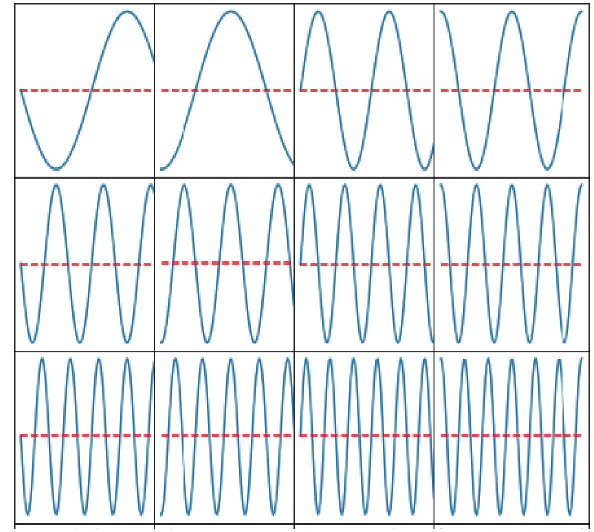


PCA

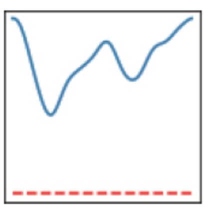
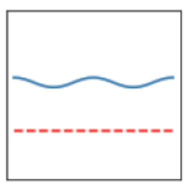
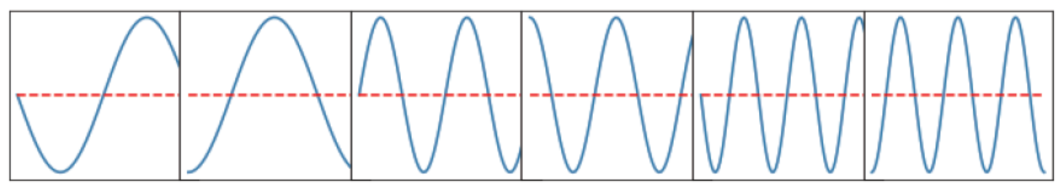
Mean μ



top eigenvectors:σ1,σ2,σ3 …



With PCA, particle distributions in each events also decomposed into superpositions of eigenmodes

 =  + 

$$\frac{dN}{d\varphi} = \mu + x_1 z_1 + x_2 z_2 + x_3 z_3 + \ldots\ldots$$

In the next few slides, I will SHOW

-PCA define its own flow harmonics (eigenmodes)

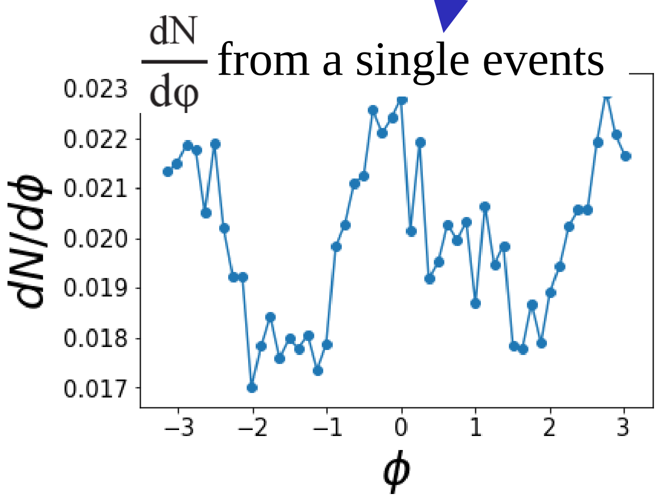
-PCA could analyze flow with event average/ event-by-event

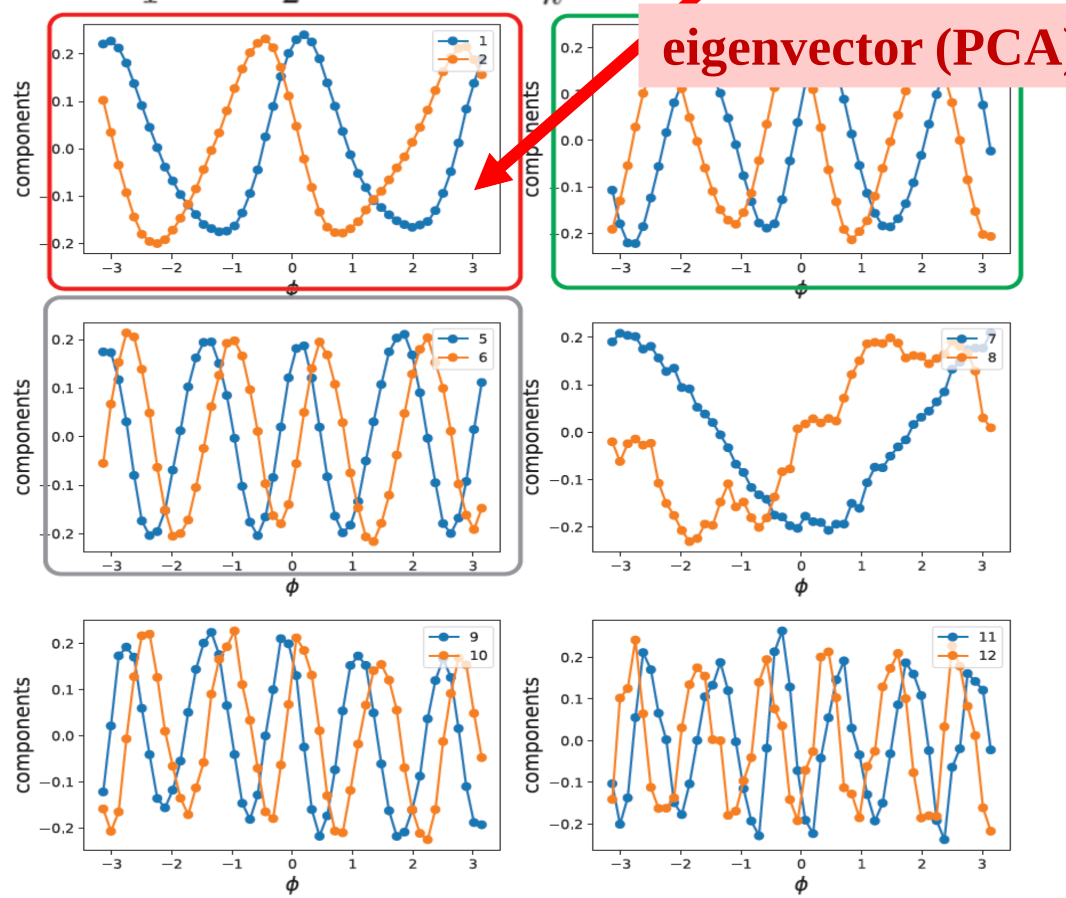
PCA for flow analysis –results(I)

Components

events

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



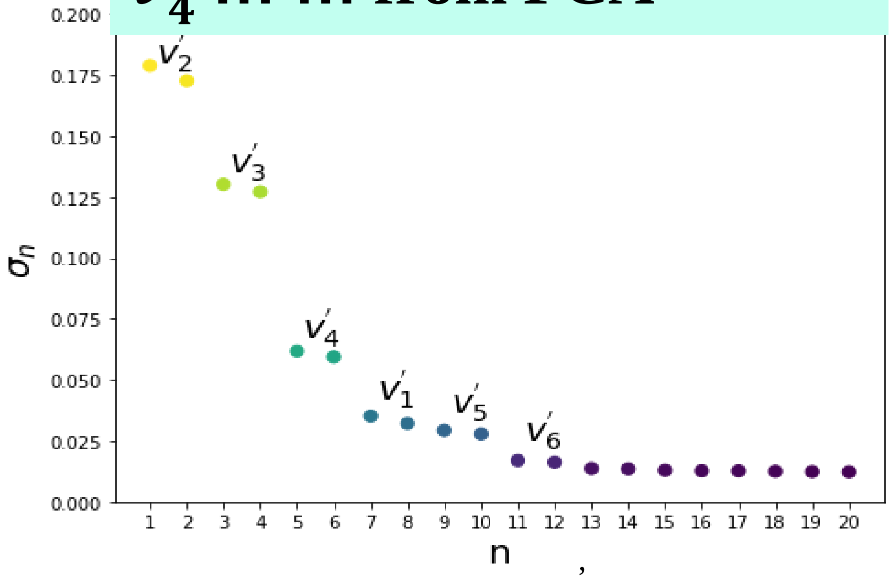


The eigenvector (PCA) is similar to the Fourier ones

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

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

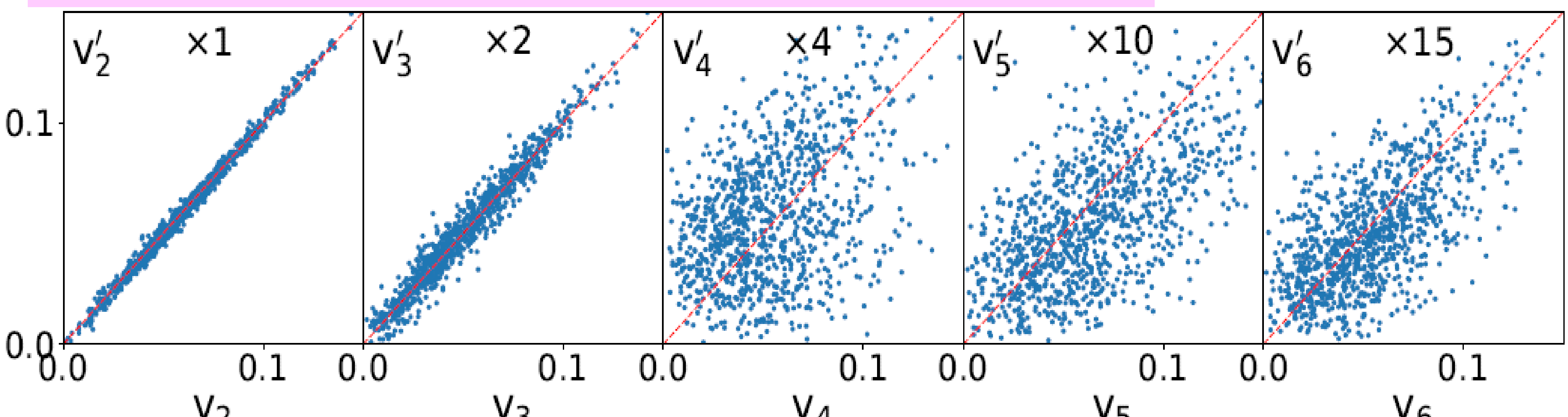
Event averaged $\overline{v'_2}$, $\overline{v'_3}$, $\overline{v'_4}$ … … from PCA



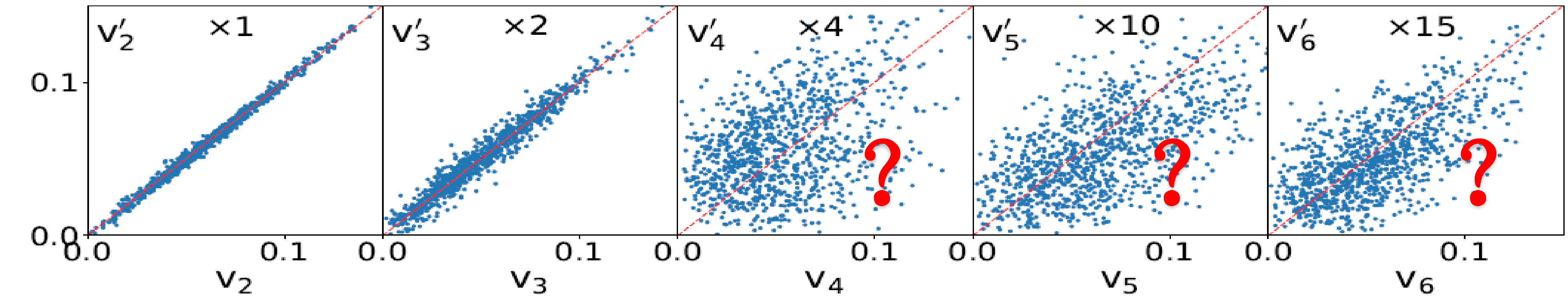
-PCA gives the event averaged flow harmonics $\overline{v'_2}$, $\overline{v'_3}$, $\overline{v'_4}$ … … and the event-by-event v'_2, v'_3, v'_4 … … Results of elliptic and triangular flow are similar to the ones from traditional Fourier transform, but show deviations for higher order flow harmonics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

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

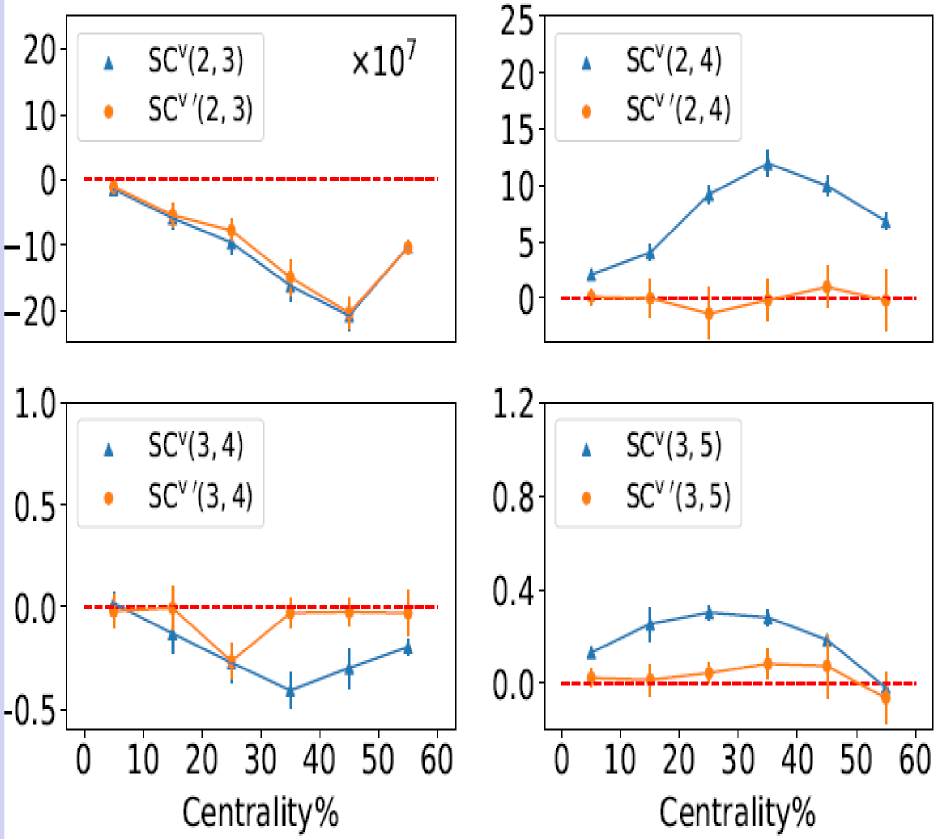
Event-by-event v'_n (PCA) vs. v_n (Fourier)



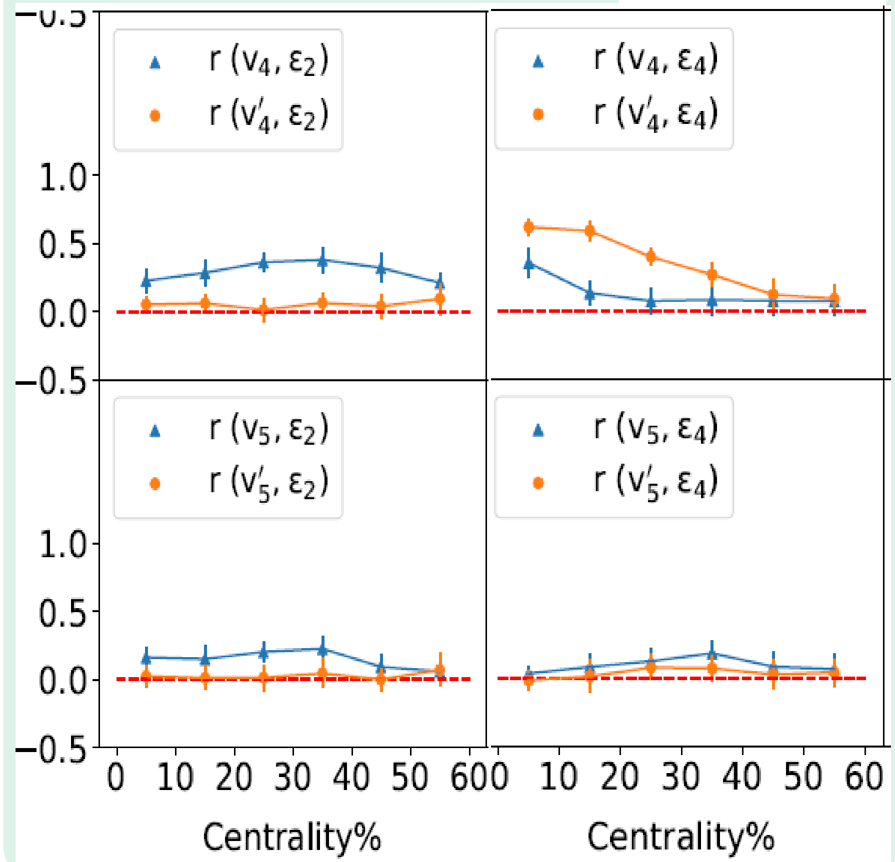
v'_n (PCA) vs. v_n (Fourier)



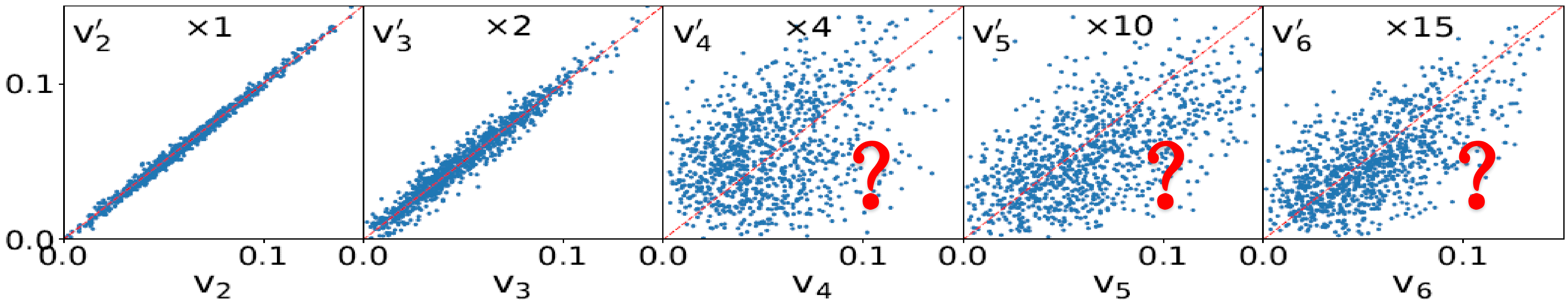
Symmetric Cumulants



Pearson Coefficients



v_n' (PCA) vs. v_n (Fourier)



Traditional Fourier Transform

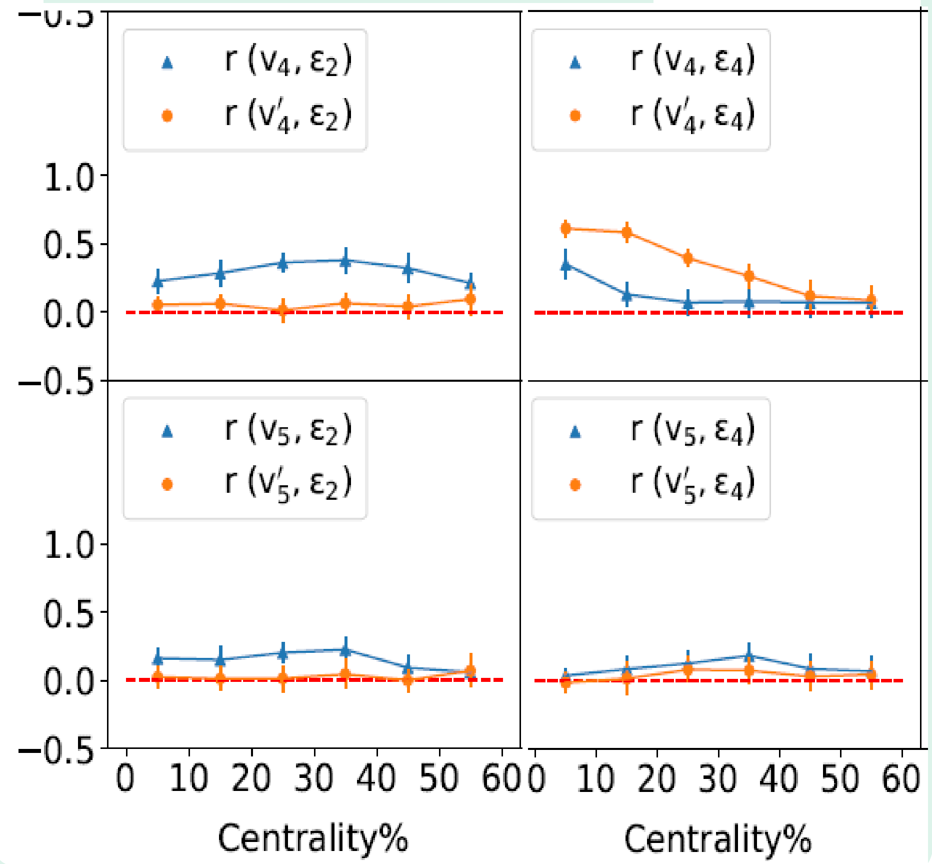
-Strong mode couplings between v_4 and v_2
-interoperated as highly non-linear hydro evolution that mix v_4 and ε_2^2

PCA:

-Reduce the correlations between v_4' and ε_2
-increase correlations between v_4' and ε_4

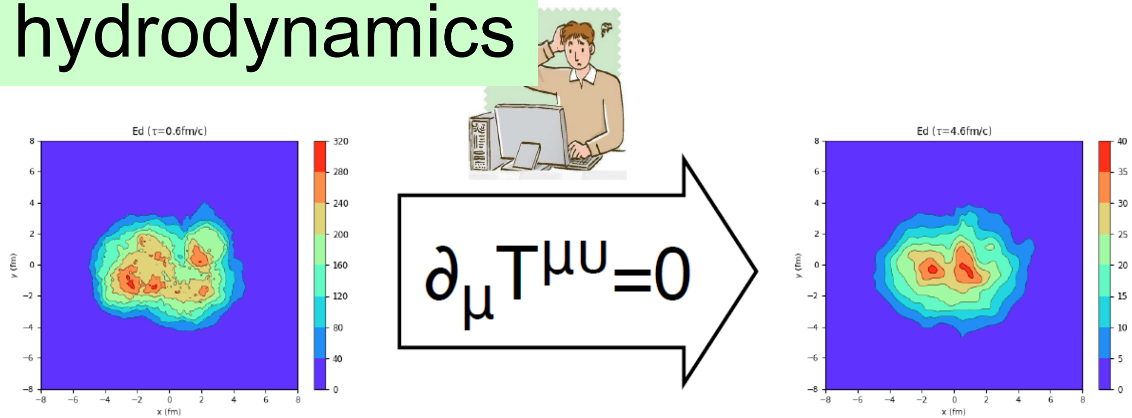
Z. Liu, W. Zhao, and H. Song, arXiv: 1903.09833

Pearson Coefficients

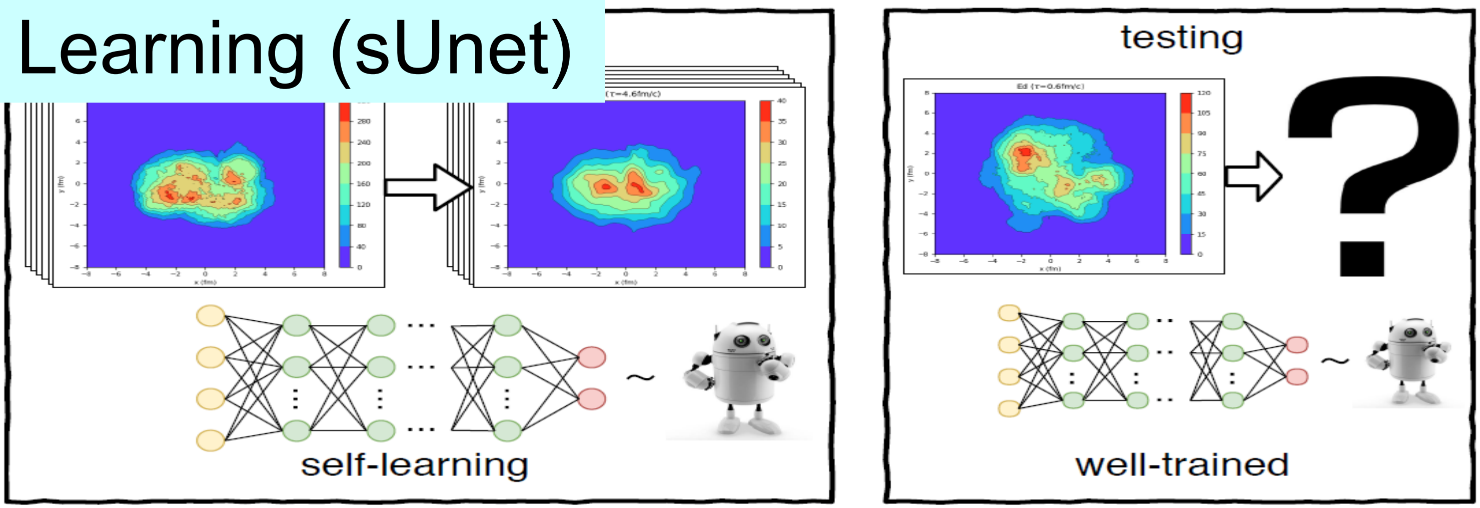


Summary & outlook

Traditional hydrodynamics



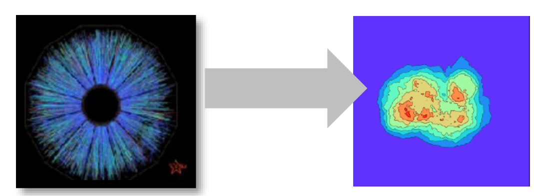
Deep Learning (sUnet)



Outlook

Final particle profiles

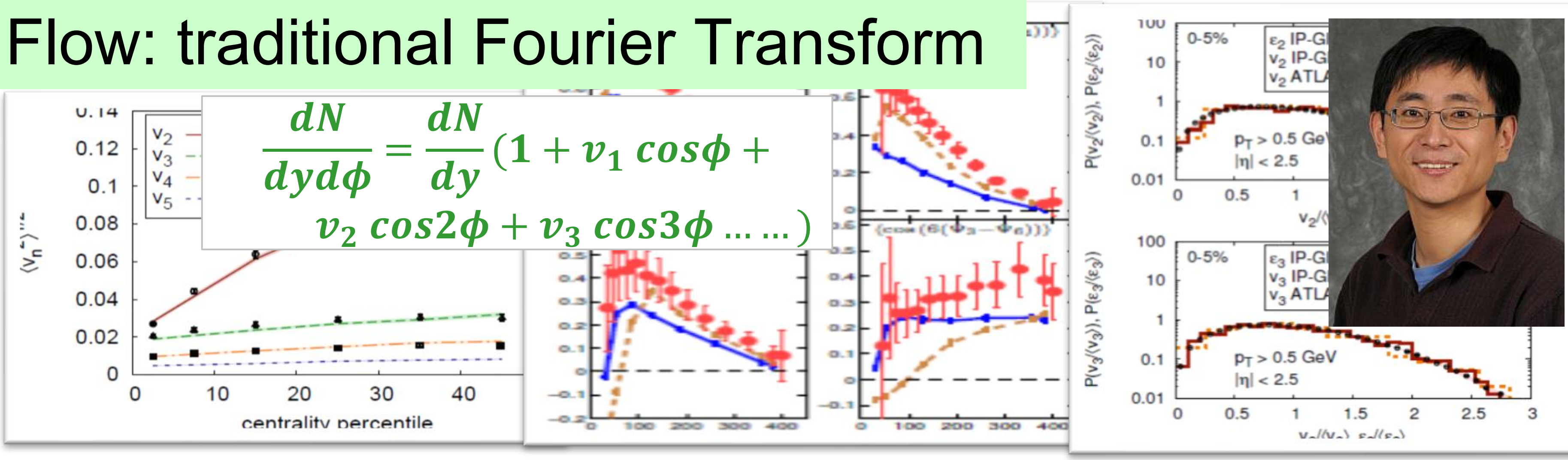
-------- > Initial energy density profiles



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

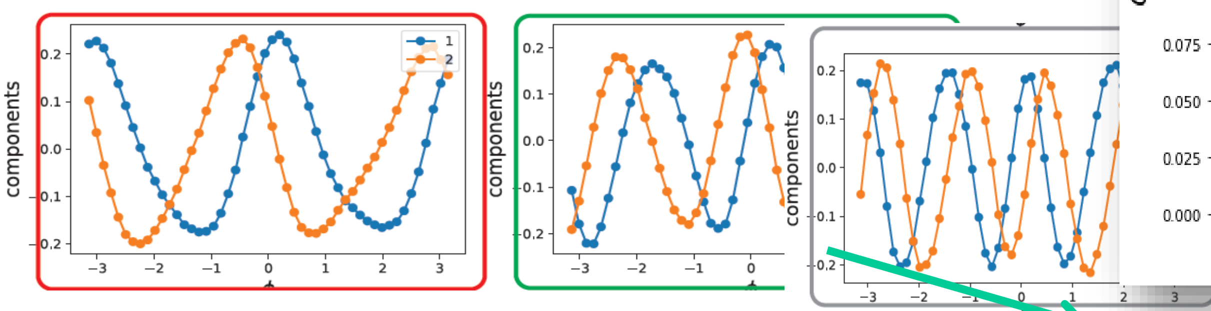
Flow: traditional Fourier Transform

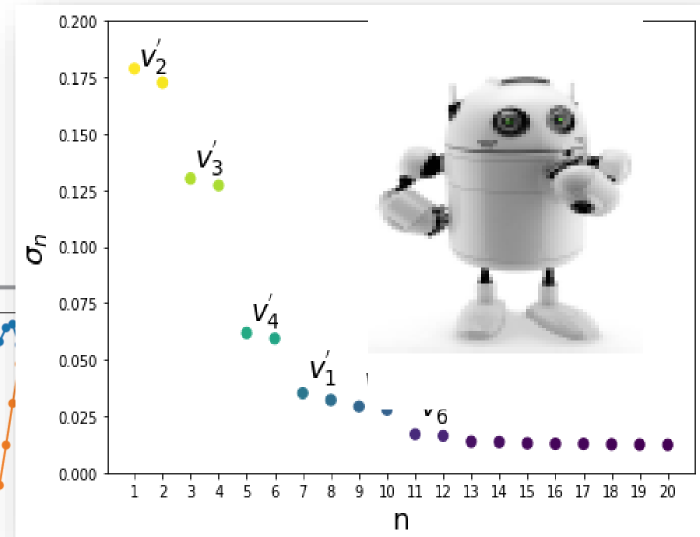
$$\frac{dN}{dyd\phi} = \frac{dN}{dy}(1 + v_1 \cos\phi + v_2 \cos 2\phi + v_3 \cos 3\phi \ldots \ldots)$$



Unsupervised Learning (PCA)

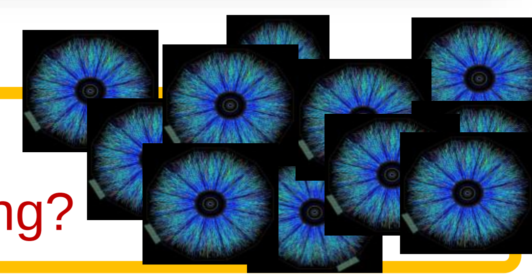
It independently discovered the flow harmonics without explicit instructions from human being!





Outlook

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



Thank You