Machine Learning for nuclear shape in heavy ion collisions

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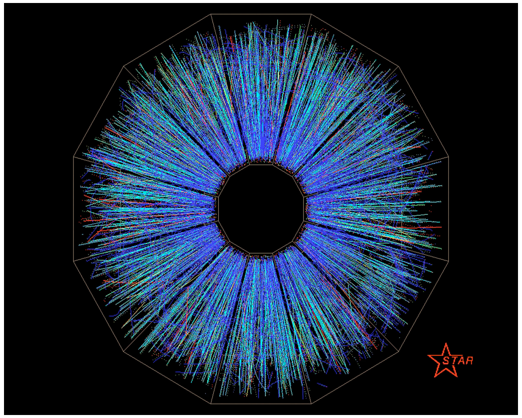
RBRC Workshop: Physics Opportunities from the RHIC Isobar Run

Motivation

- The momentum anisotropy and multi-particle correlation of final state hadrons in heavy ion collisions (HIC) is sensitive to initial state nuclear structure, e.g., nuclear radius and nuclear deformation

- Is it possible to determine the initial nuclear shape from final state output of HIC



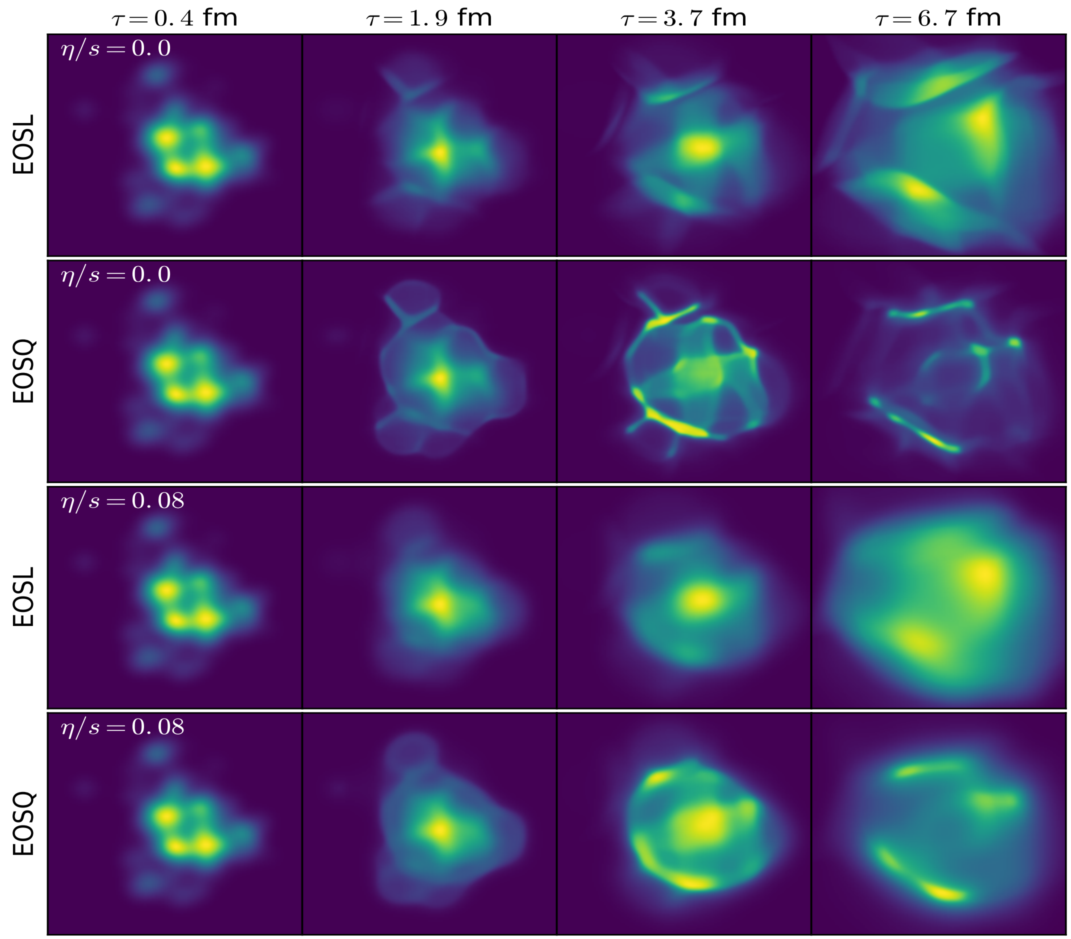
Final state

Inverse problem →

- Nuclear size
- Shape deformation
- Neutron skin
- Alpha cluster
- …

Initial state

Difficulty



CLVisc hydrodynamic simulations with 2 EoS and η/s

Information: Initial state fluctuations (nuclear structure) in coordinate space convert to final state correlations of particles in momentum space.
However, final states are also sensitive to equation of state and shear viscosity

Inverse problem： decoding initial state from HIC data

Model Parameter:

eqn. of state

shear viscosity

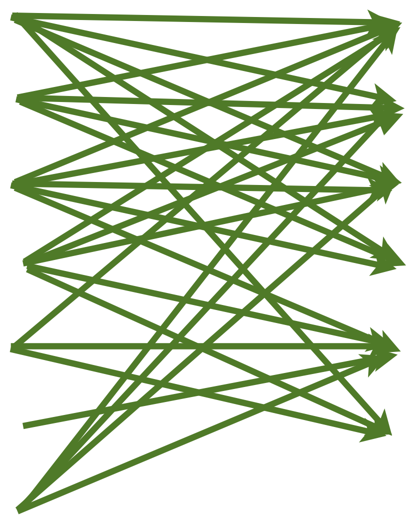
initial state

pre-equilibrium dynamics

thermalization time

quark/hadron chemistry

particlization/freeze-out



experimental data:

π/K/P spectra

yields vs. centrality & beam

elliptic flow

HBT

charge correlations & BFs

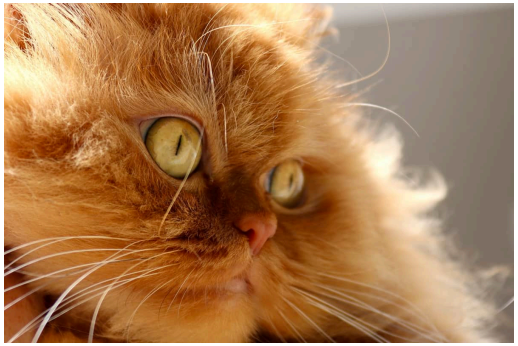
density correlations

credit: S. Bass

Problem: the non-linear transformations from initial to final states have large uncertainty.

Are there features only sensitive to nuclear structure? Can we find them?

Intelligence is robust to non-linear transformations



Non linear transformation

Are there features about nuclear structure not sensitive to the non-linear transformations from initial state to final state hadrons in HIC?

Intelligence is robust to non-linear transformations.

In HIC, non-linear transformations are pre-equilibrium, relativistic hydrodynamics as well as hadronic cascade.

Deep learning

Forward pass

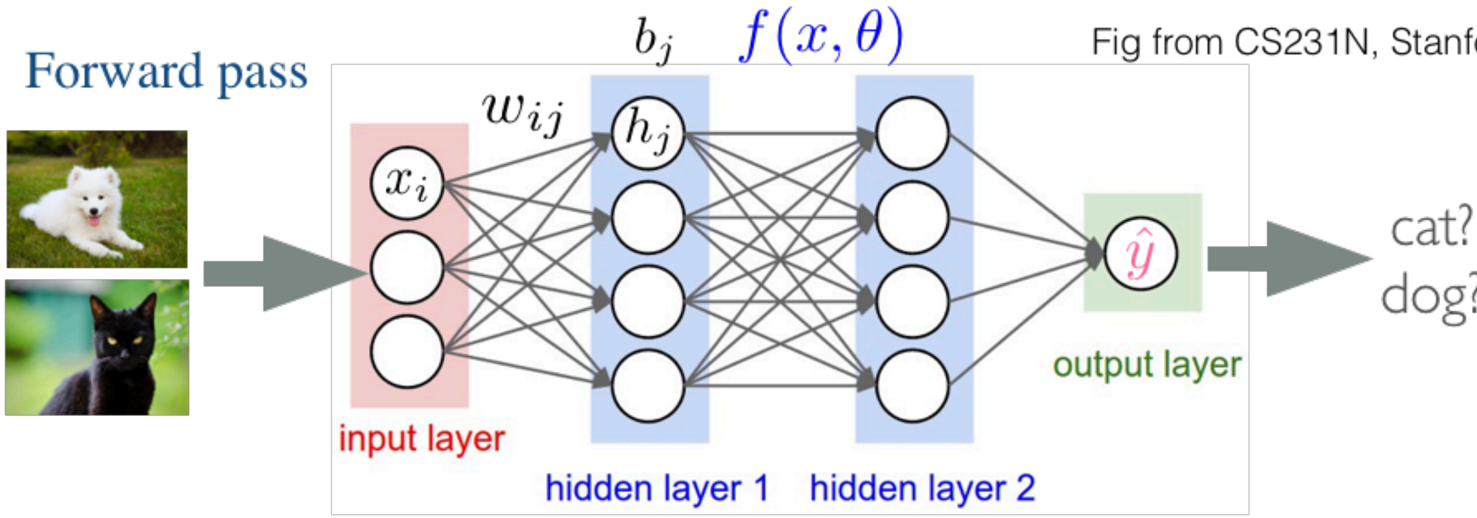


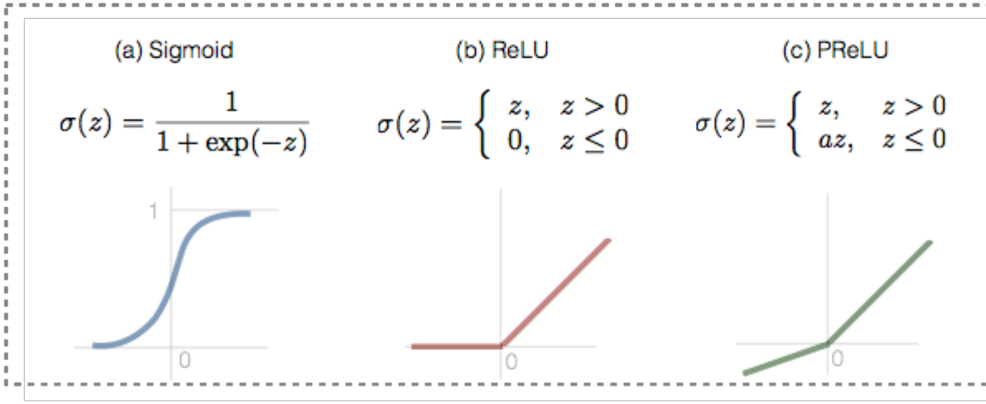
Fig from CS231N, Stanford

Linear operation

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

scaling, rotating, boosting, changing dimensions

Non-linear activation function $h_j = \sigma(z_j)$



How does deep neural network learn: back propagation

Input x

Neural network

$\hat{y} = f(x, \theta)$

$\hat{y}$: Network prediction

y: True label

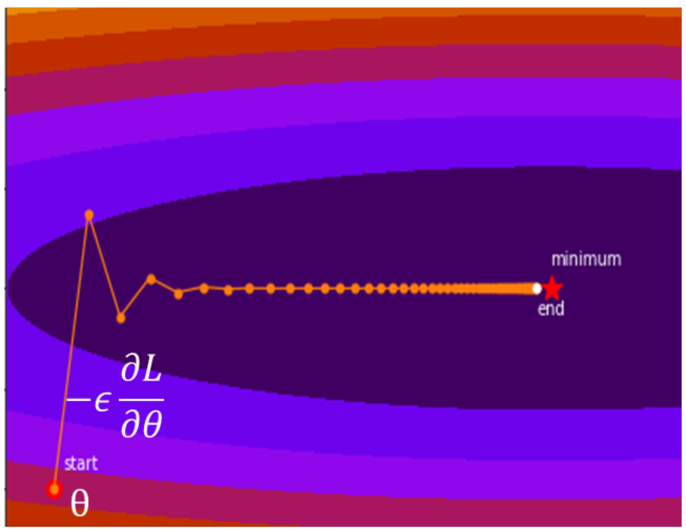
Loss(cost) function

$$L = \sum_i (\hat{y}_i - y_i)^2$$

Gradient decent

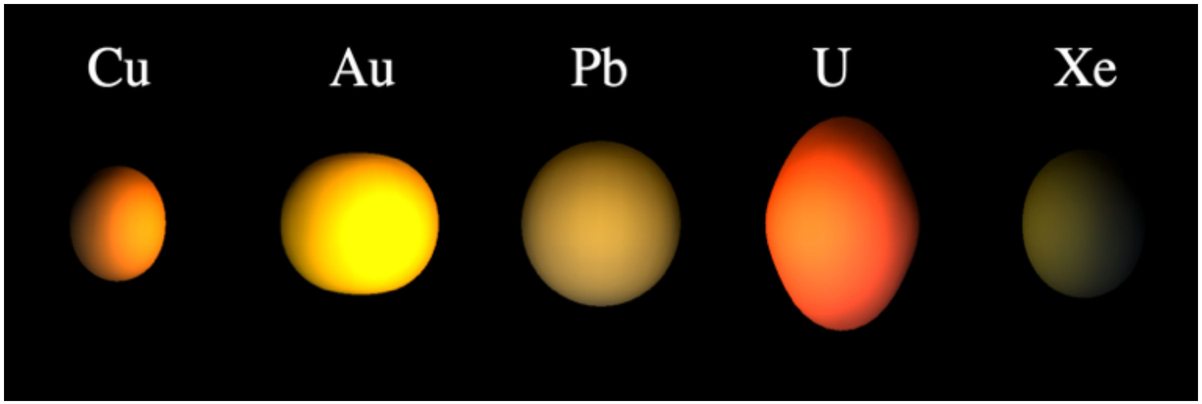
$$\theta = \theta - \epsilon \frac{\partial L}{\partial \theta}$$

Back propagation



1. Nuclear shape deformation

Widely used nucleus in heavy ion collisions at RHIC and LHC



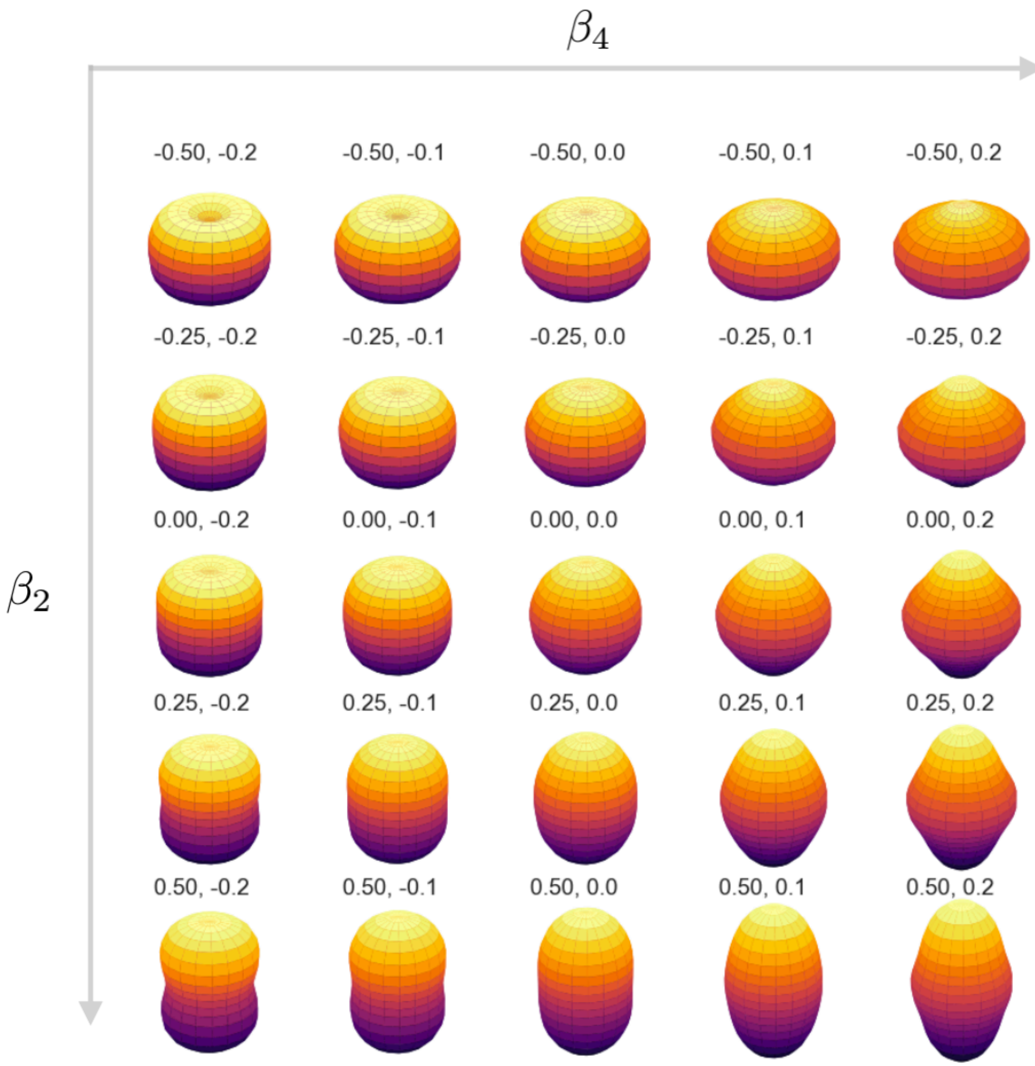
+O
+Ru
+Zr
+...

The shape of these nucleus can be approximately described by Woods-Saxon distribution:

$$\rho(r,\theta,\phi) = \frac{\rho_0}{1 + e^{(r-R_0(1+\beta_2 Y_{20}(\theta)+\beta_4 Y_{40}(\theta)))/a}}$$

Based on work: L G Pang, K Zhou, X N Wang, arXiv:1906.06429

Deformation shape scan



- 51 diff. $\beta_2 \in [-0.5, 0.5]$
- 51 diff. $\beta_4 \in [-0.2, 0.2]$
- In total there are 51x51 nucleus with different (β_2, β_4) combinations
- For each nuclear shape, we generate 0.1 million heavy ion colliding events using Trento
- The initial total entropy and spatial eccentricity ϵ_2 are used to get charged multiplicity and v_2 through simple matching

Matching method

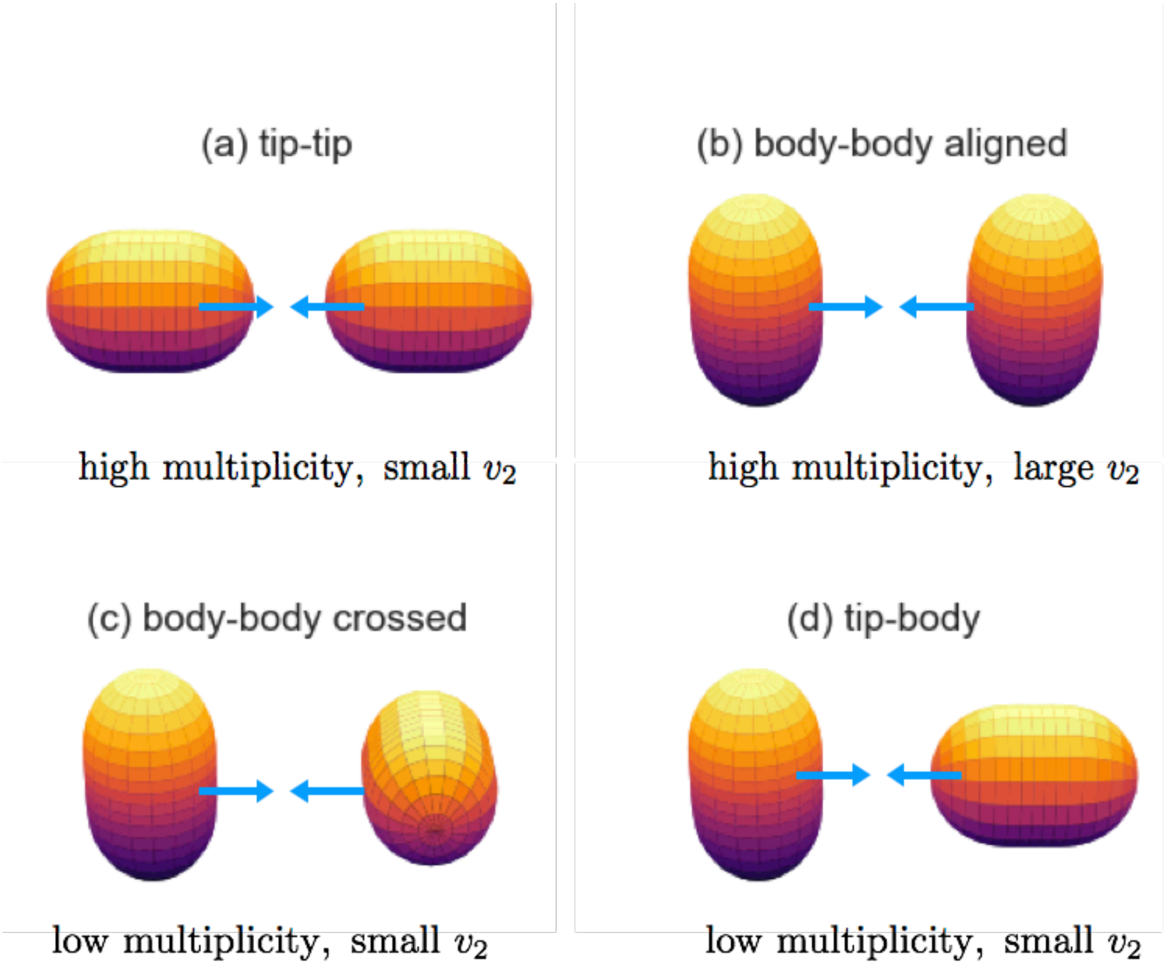
$$dN_{\rm ch}/dY\,|_{\rm normed} = \frac{dN_{\rm ch}/dY}{\langle dN_{\rm ch}/dY\rangle_{0\sim1\%}} \approx \frac{s_0}{\langle s_0\rangle_{0-1\%}}$$

where s_0 is the initial total entropy of one collision.

$$v_2 = k_2\varepsilon_2 + k_2'\varepsilon_2^3 + \delta_2$$

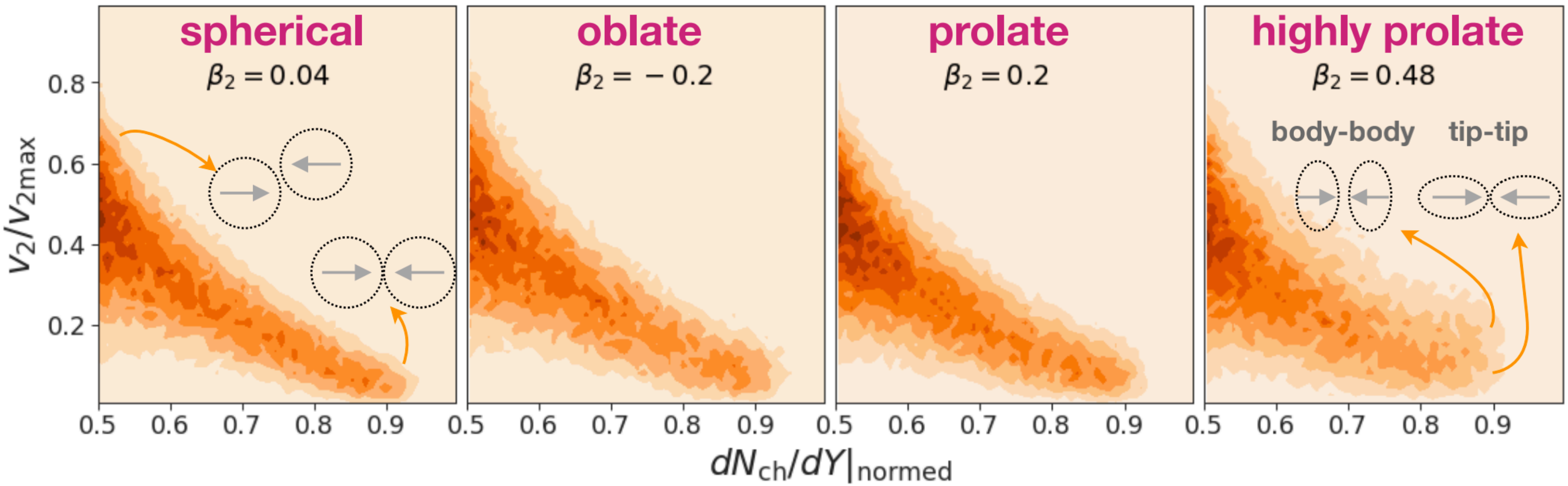
where $k_2 = 0.2,\ k_2' = 0.1$ and δ_2 is the residual that introduces additionally $\pm 10\,\%$ random fluctuations uniformly-distributed. Formula from
Jacquelyn Noronha-Hostler, Li Yan, Fernando G. Gardim, and Jean-Yves Ollitrault. **Linear and cubic response to the initial eccentricity in heavy-ion collisions.**
Phys. Rev. C93(1):014909, 2016.

Complex collision patterns using Trento Monte Carlo simulations



Correlations between multiplicity and elliptic flow are quite different for deformed nucleus and spherical nucleus.

Training data



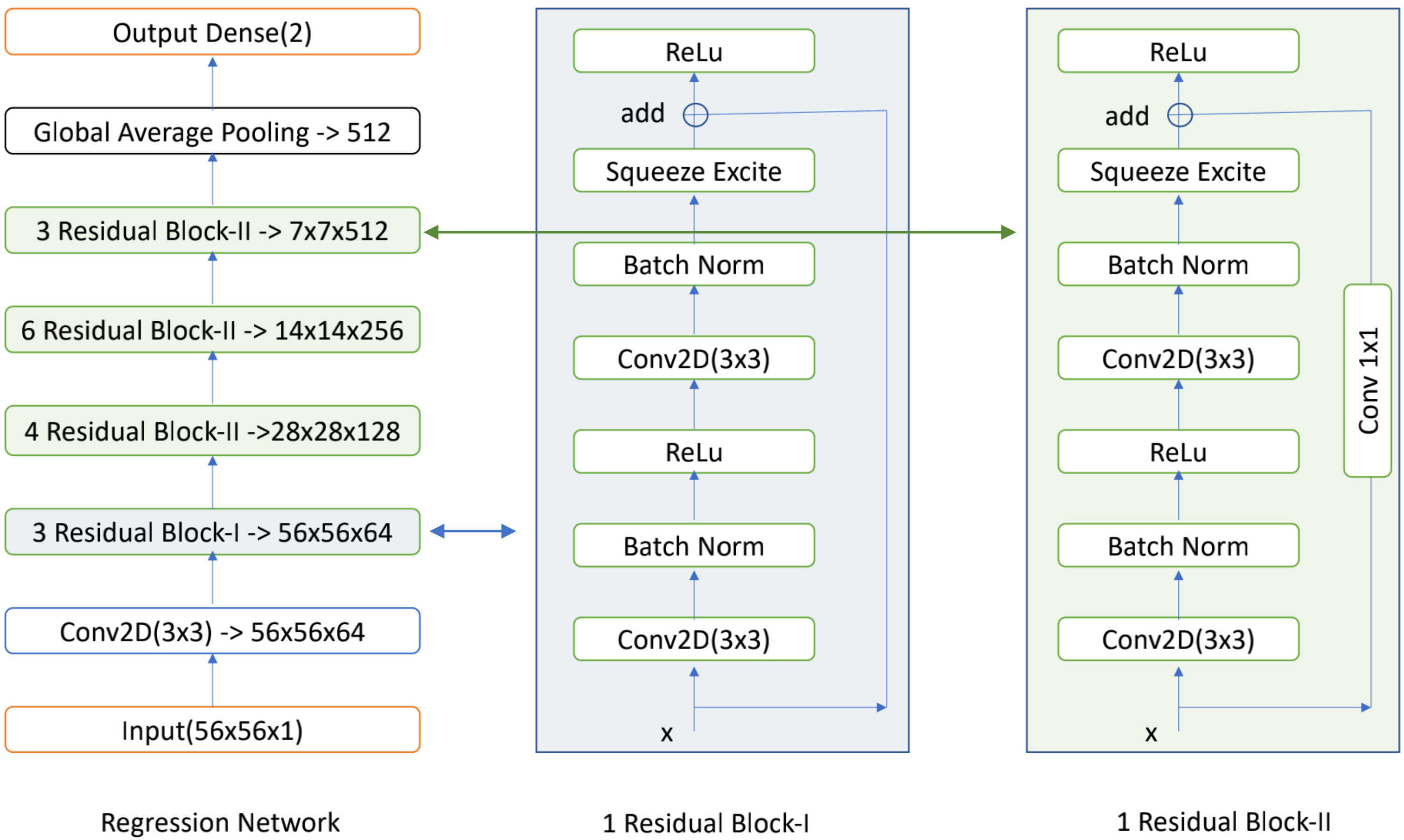
Known features

- More peripheral collisions than central collisions
- Large v2 and small multiplicity for peripheral collisions
- Small v2 and large multiplicity for central collisions
- v2 fluctuations are larger in most central collisions for deformed nucleus than spherical nucleus

Are there unknown patterns important for $(\beta_2,\ \beta_4)$ regression?

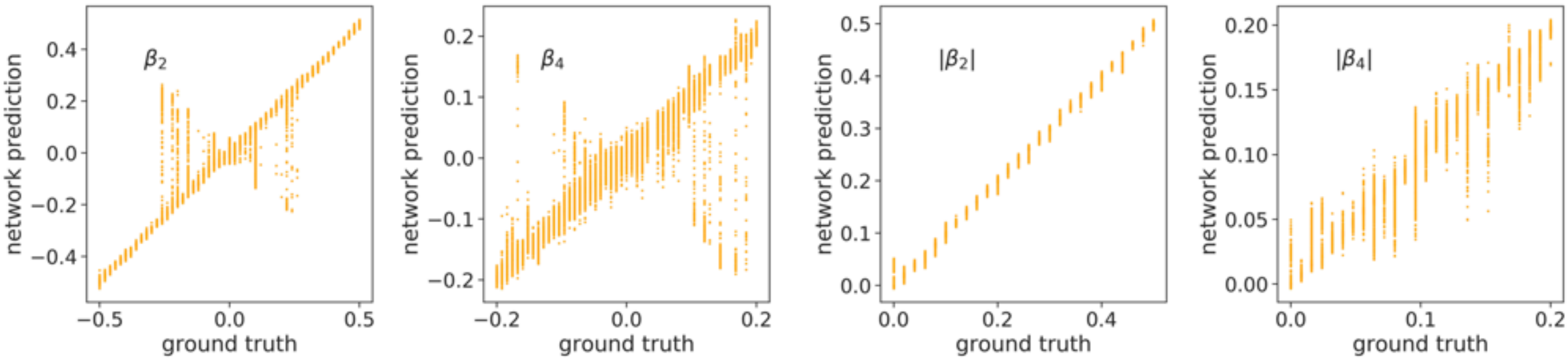
Deep Convolution Neural Network

Output: (β_2, β_4)



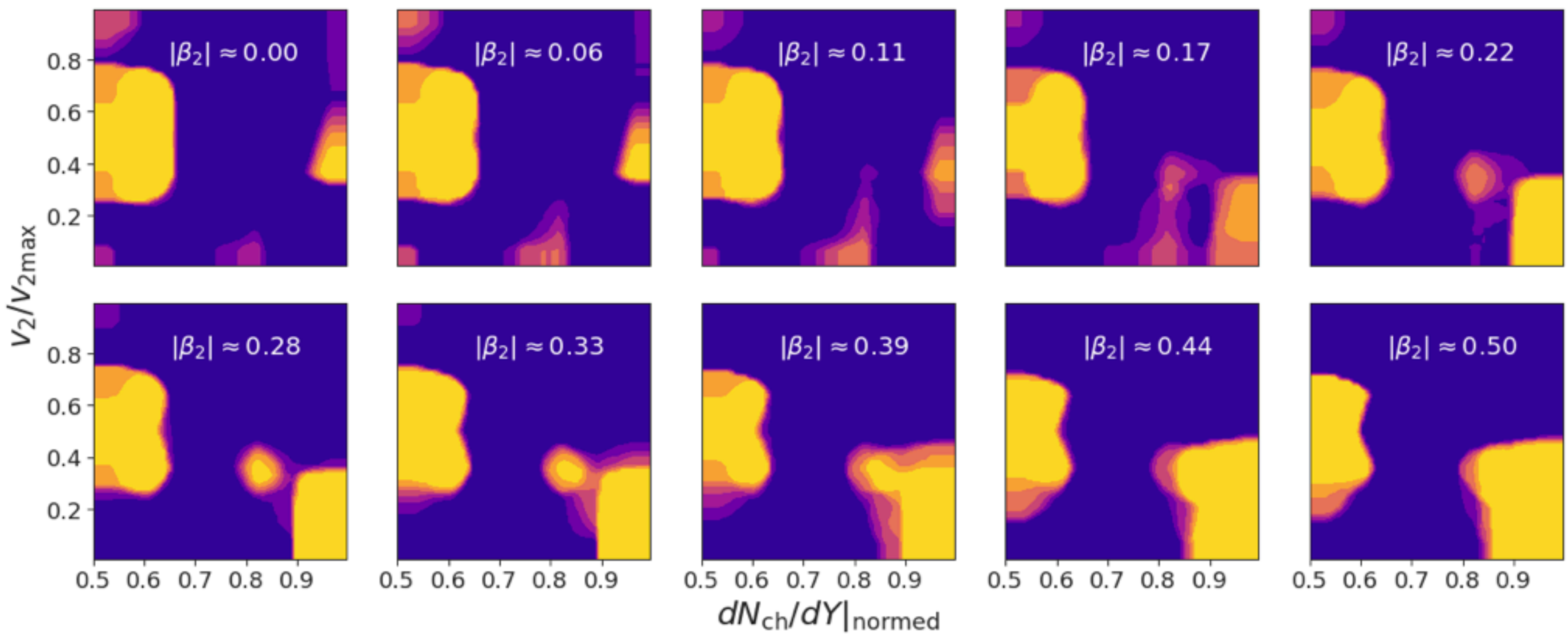
Input: $(v_2, dN/dy)$ images

Results

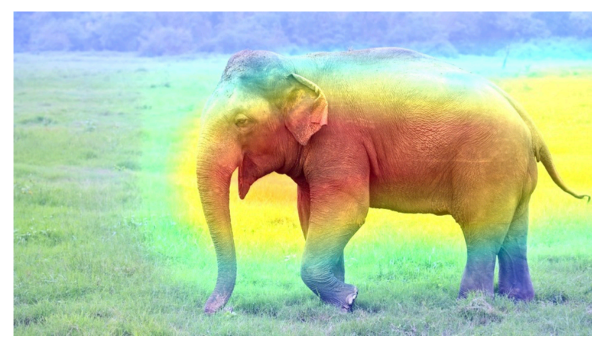


- For small deformation:
  - The network predicts $|\beta_2|$ well
  - Degeneracy between β_2 and $-\beta_2$ in high energy HIC using Trento due to Lorentz contraction along beam direction
- For large deformation, the network predicts β_2 correctly

What has been learned by the network



- Class Activation Map method roughly locate the regions used for regression (the same algorithm is tested to find the attention of the trained network for elephant recognition)
- For small $|\beta_2|$, network uses semi-peripheral collisions
- For large $|\beta_2|$, network uses both most central and semi-peripheral collisions



1. Prototype study on extracting nuclear deformation using Monte carlo simulations of HIC and deep learning
2. The patterns in the 2D images of charged multiplicity and elliptic flow encoded the information of β_2 and β_4
3. Deep neural network can extract the absolute values of β_2 and β_4 if the non-linear transformations from initial to final state is known
4. Right now we did not succeed in getting β_2 and β_4 using the trained network with data from different matching parameters. Maybe higher resolution will help.

2. Neutron skin types

The charge distribution is easier to measure than neutron distribution.
Motivation: prototype study to determine the neutron distribution in ^{208}Pb from final state of heavy ion collisions

Table 1 Parameters for two neutron skin types and one nucleon distribution without neutron skin

Types	r_{p0} [fm]	r_{n0} [fm]	d_{p0} [fm]	d_{n0} [fm]
skin	6.70	6.84	0.56	0.56
halo	6.70	6.70	0.56	0.63
noskin	6.70	6.70	0.56	0.56

$$\rho(r) = \frac{\rho_0}{\exp(\frac{r - r_0}{d}) + 1}$$

- skin type: $r_{p0} < r_{n0}$, $d_{p0} = d_{n0}$
- halo type: $r_{p0} = r_{n0}$, $d_{p0} < d_{n0}$
- no skin: $r_{n0} = r_{p0}$, $d_{n0} = d_{p0}$

Determining the neutron skin types using deep learning and nuclear collisions, an attempt

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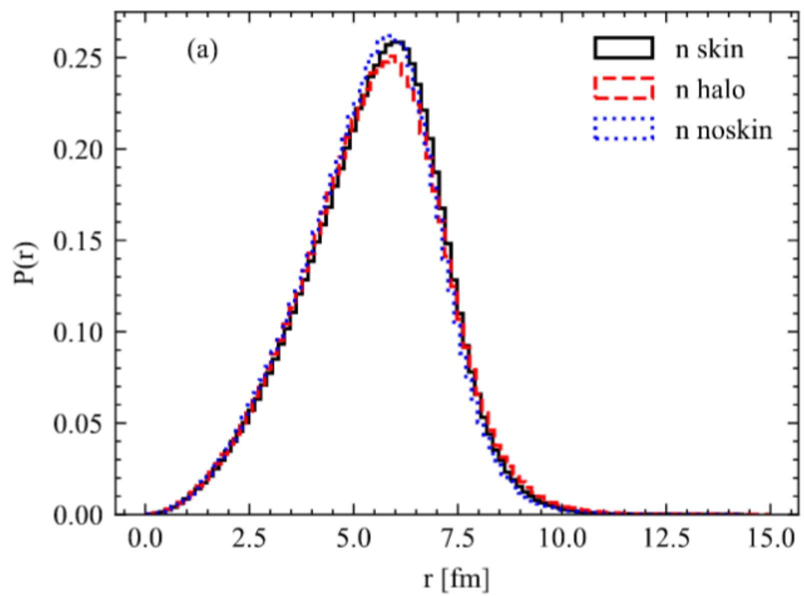
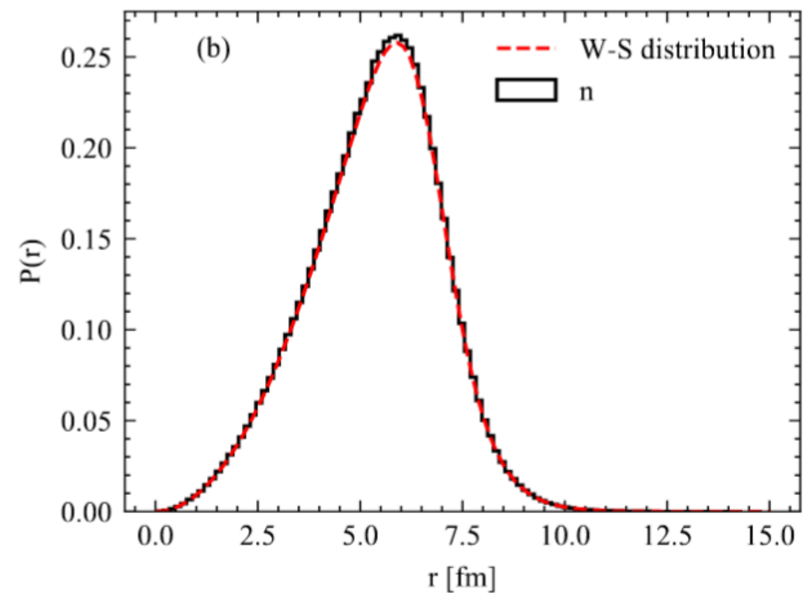
2. Nuclear Science Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

Model

The distribution of sampled neutrons



Sampled distribution .vs. W-S



The sampled protons and neutrons are used to simulate HIC collisions using SMASH in 3 categories: halo-halo, skin-skin, noskin-noskin

Result

1. Failed to identify skin and halo type in binary classification because of large fluctuations at initial state and dynamical evolution

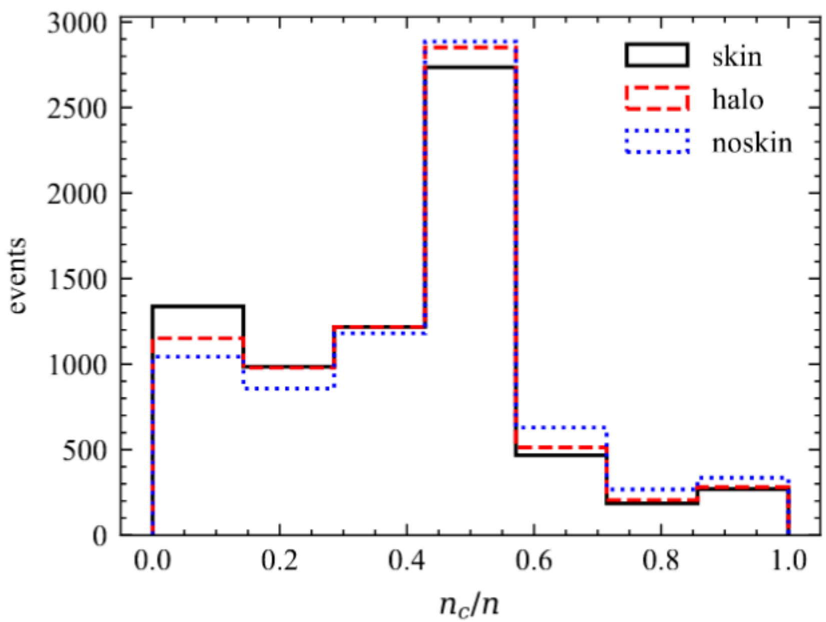
2. Using the coordinates of nucleons inside nucleus, the same network gets prediction accuracy 62% for event-by-event classification

3. The signal (the difference between skin and halo type) is too weak to be identified easily by the neural network after the dynamical evolution

4. On the other hand, the network can distinguish no-skin collisions from skin and halo type, with 4% accuracy above random guess, using ultra central collisions.

Result: ultra-peripheral event selection

One would expect bigger differences in neutral/charge ratio in ultra-peripheral collisions. But due to large fluctuations, the differences are small



Ratio of charged particles for events whose total multiplicity smaller than 10

Result 2:

In total there are 0.15 million event, selecting ultra-peripheral collisions will reduce the number of events to around 9200.

Using bootstrapping and event-mixing, we get 56% prediction accuracy on skin-halo binary classification.

Conclusion: if events with signal are rare (a tiny fraction in a large amount of events), deep neural network will fail. Event selection based on expert knowledge will help to discard large background.

3. Alpha clusters

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Machine-learning-based identification for initial clustering structure in relativistic heavy-ion collisions

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Initial to final state by AMPT

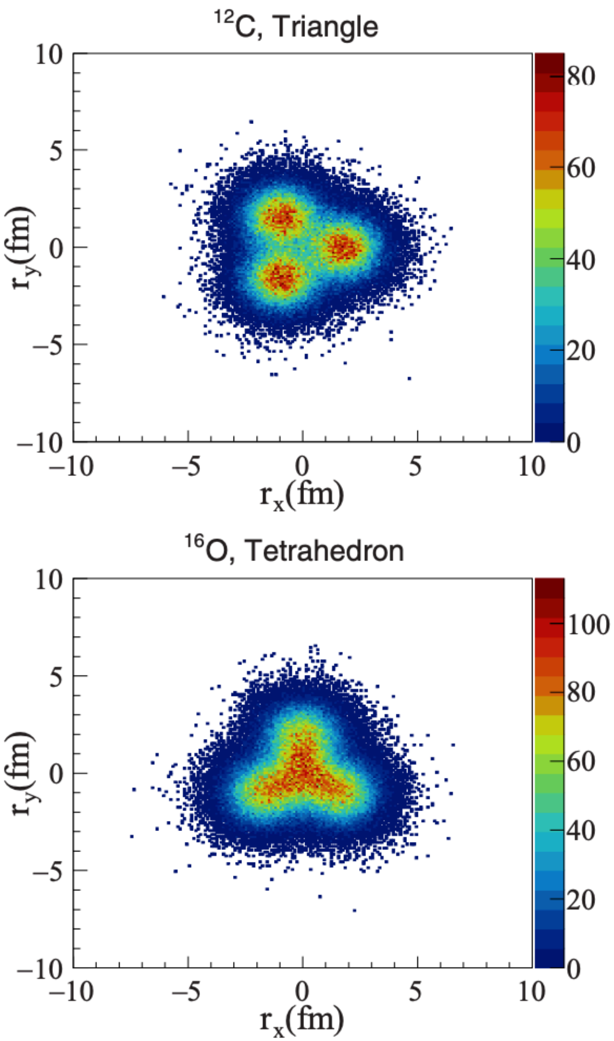
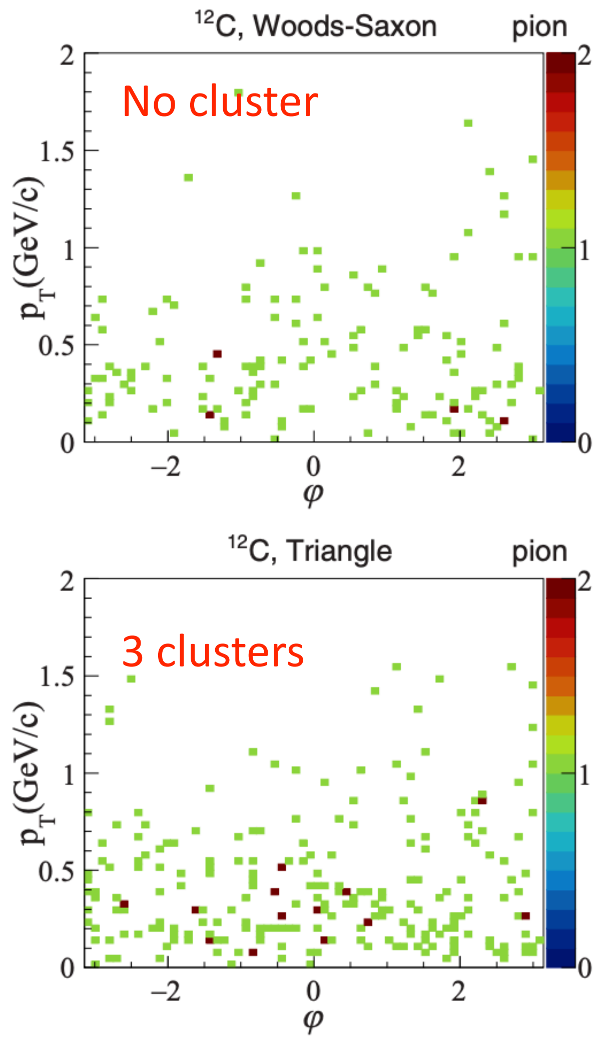
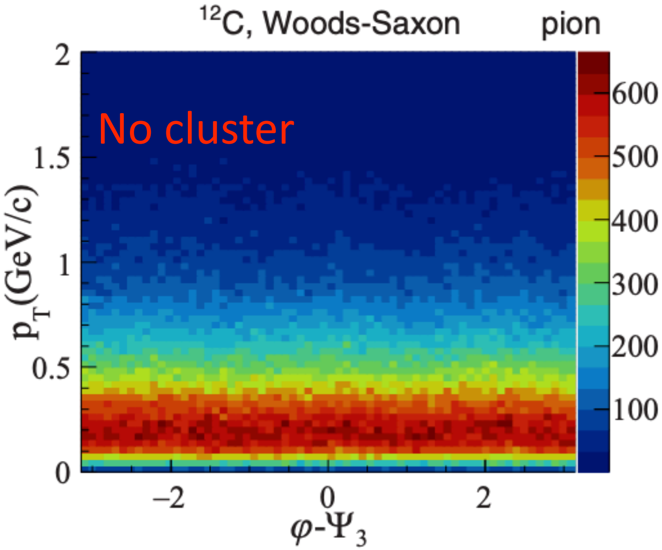
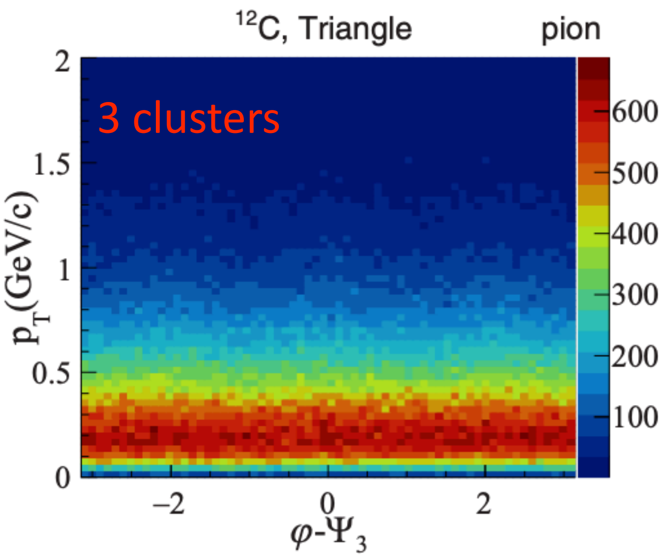


FIG. 1. Nucleon distributions in the transverse plane for clustered ^{12}C and ^{16}O from 10000 events.

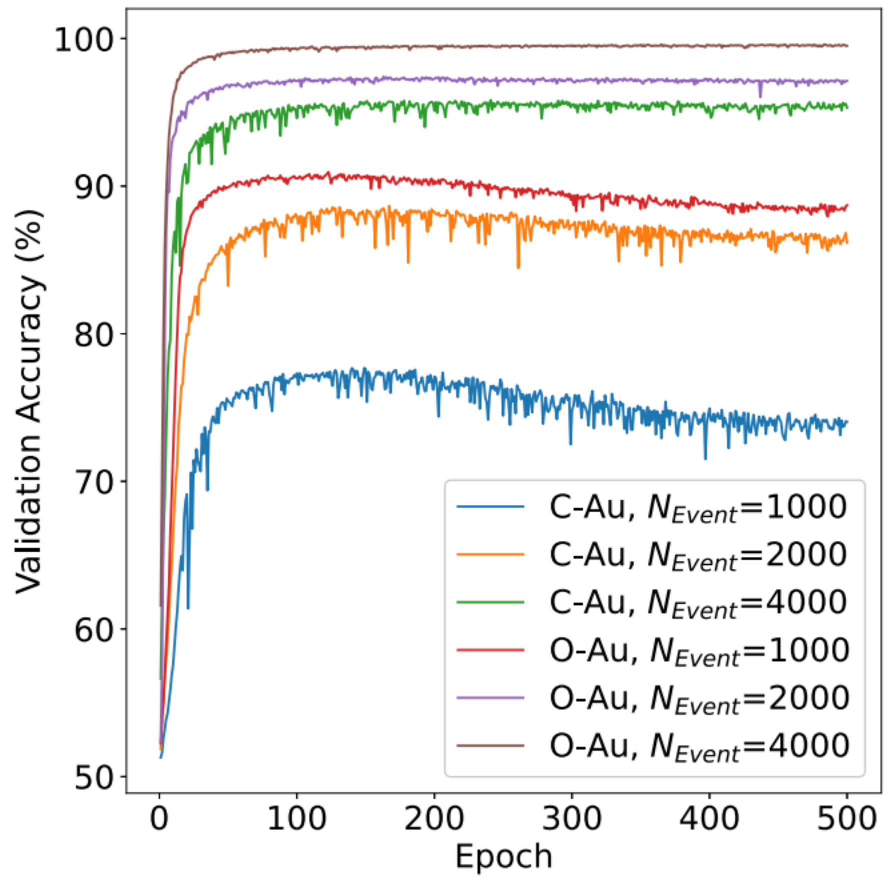


Bootstrapping for deep neural network





Bootstrapping: 4000 events



The deep neural network succeeds on pt-ϕ images with bootstrapping event-averaging, to identify the alpha cluster from data.

Summary

1. Deep learning is used to study the nuclear shape deformation, neutron skin as well as alpha cluster in HIC

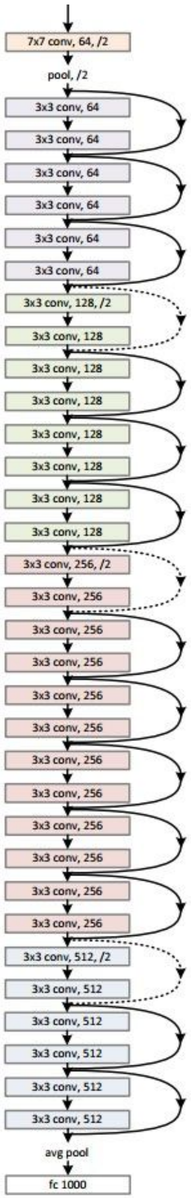
2. Intelligence is robust to non-linear transformation which may provide a powerful tool in extracting nuclear structure

3. In practice, the task is difficult because of large fluctuations at initial state and information loss (entropy production) during the dynamical evolution

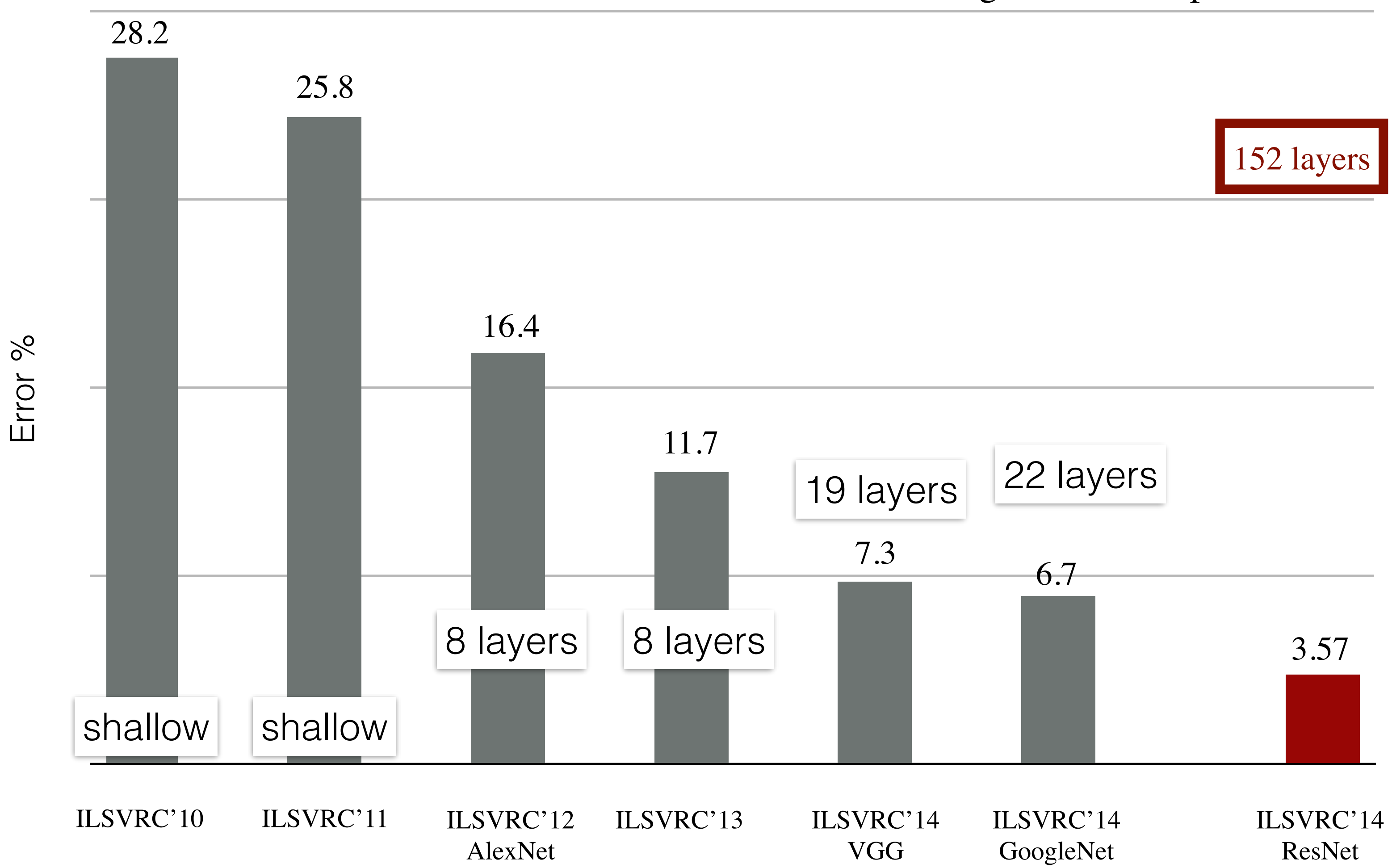
4. Bootstrapping helps to enhance the signal

5. If events with signal are rare, event-selection may help

Revolution of Depth in Deep CNN



Data from KaiMing He's recent presentation



ImageNet classification error top5 %