中山大學 物理与天文学院
SUN YAT-SEN UNIVERSITY SCHOOL OF PHYSICS AND ASTRONOMY

Nuclear liquid-gas phase transition with machine learning

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6.28.2022 Journal club

Outline

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

Nuclear liquid-gas phase transition with machine learning

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1. **Preliminaries**
2. **Experimental data processing**
3. **Machine learning results**
4. **Highlights of this work**

Preliminaries

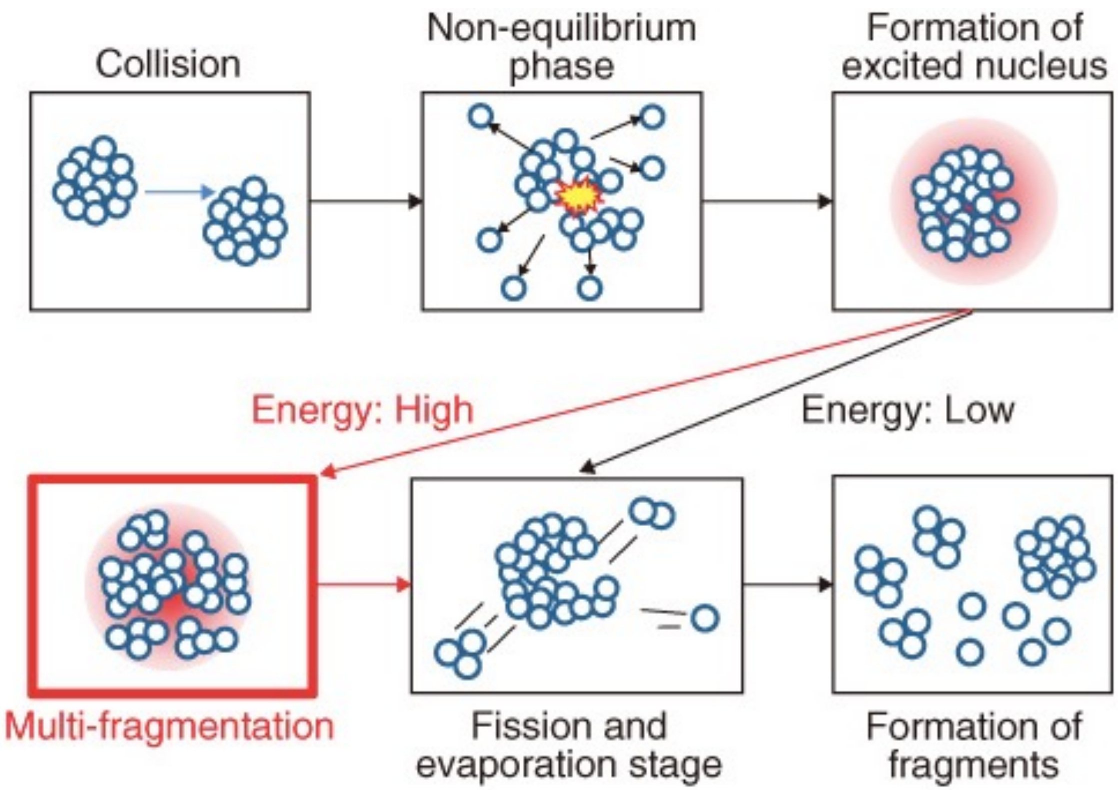
Heavy-ion reaction

Nuclear multifragmentation

^{40}Ar on ^{27}Al & ^{48}Ti at 47 MeV/nucleon

@TAMU K500 superconducting cyclotron
with detector NIMROD

TEXAS A&M UNIVERSITY
Cyclotron Institute

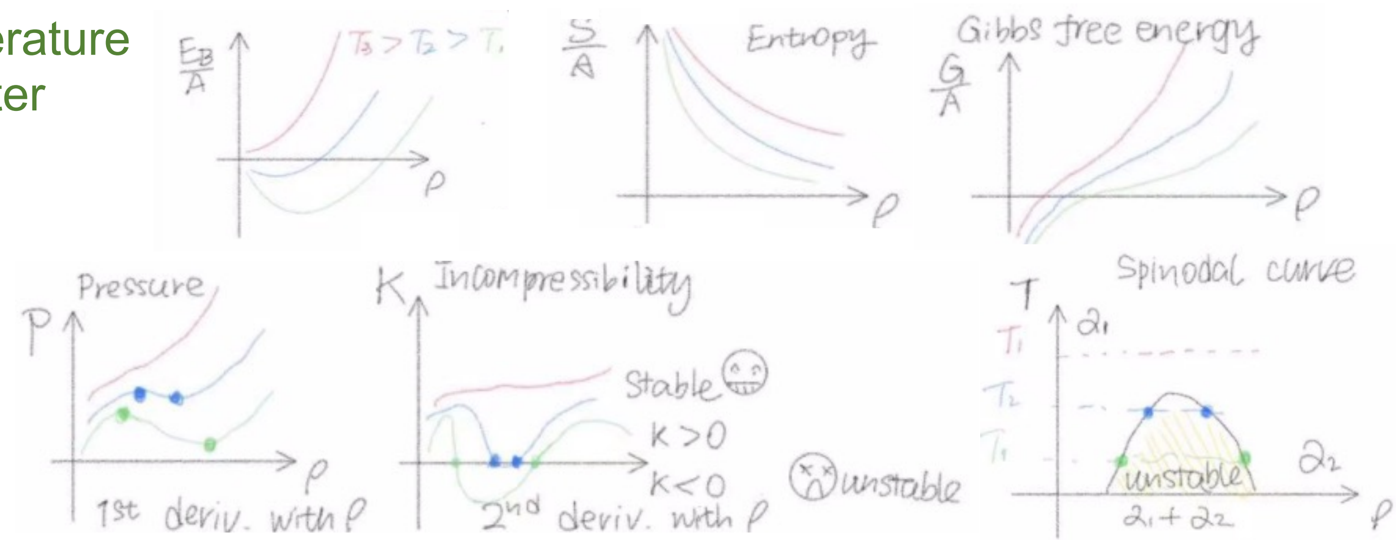


Hot, *deformed* projectile nucleus

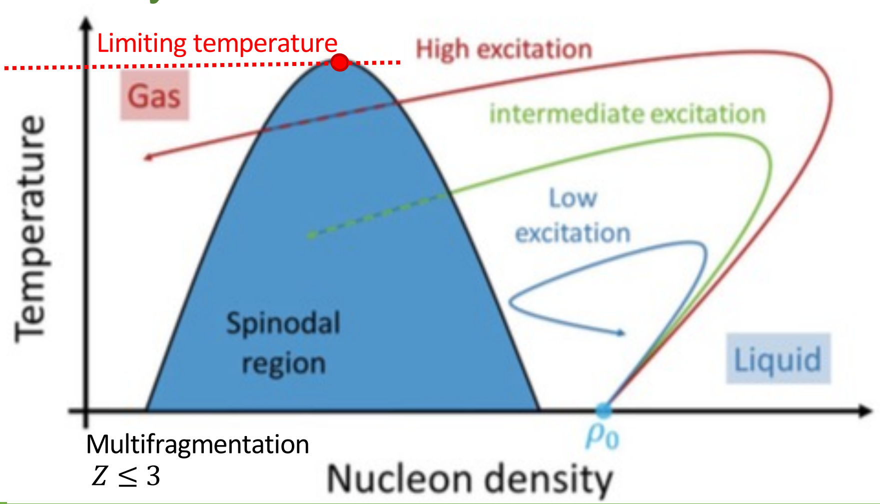
See more on https://rdreview.jaea.go.jp/review_en/2013/e2013_8_2.html

Spinodal decomposition

Finite-temperature nuclear matter

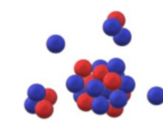


Heavy-ion reaction



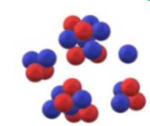
Liquid like

low excitation (0.9–2.8 MeV)



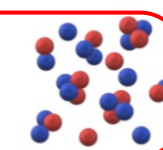
Coexistence

intermediate excitation (5.3 –5.4 MeV)



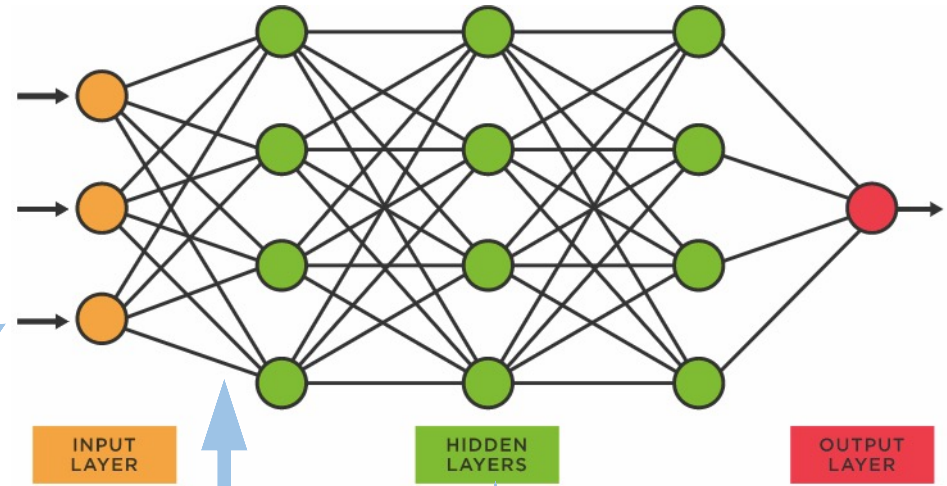
Gas like

high excitation (8.1–13.0 MeV)



Machine learning: neural network (NN)

A vedio nicely introduces NN: https://www.youtube.com/watch?v=aircAruvnKk



<u>Raw data</u>
(preprocessing)

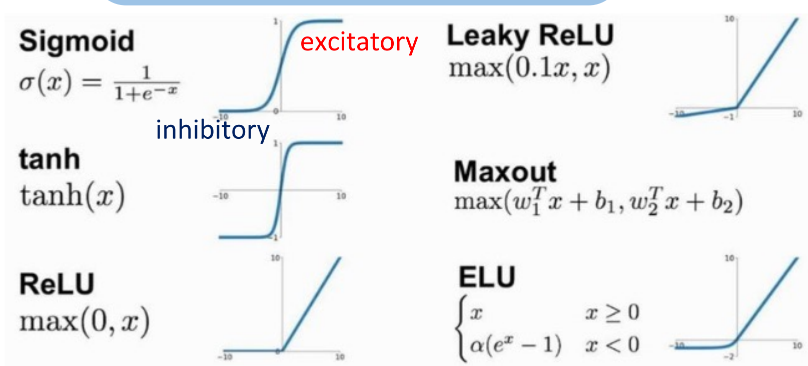
training set

$\mathbf{X} = \{\mathbf{x}_1 \ldots \mathbf{x}_N\}$

testing set

<u>Activation functions</u>

$f(\mathbf{w}_i \mathbf{x}_i + b_i)$



<u>Hidden layers</u>

$$y_i = g(\mathbf{x}_i)$$
$$\approx f_\ell(\ldots f_1(\mathbf{W}_1 \mathbf{x}_i + \mathbf{b}_1))$$

<u>Training (supervised)</u>

finding $\{\mathbf{W}_\ell, \mathbf{b}_\ell\}$ to minimize object function

Experimental data pre-processing

Reconstructing quasiprojectile (QP)

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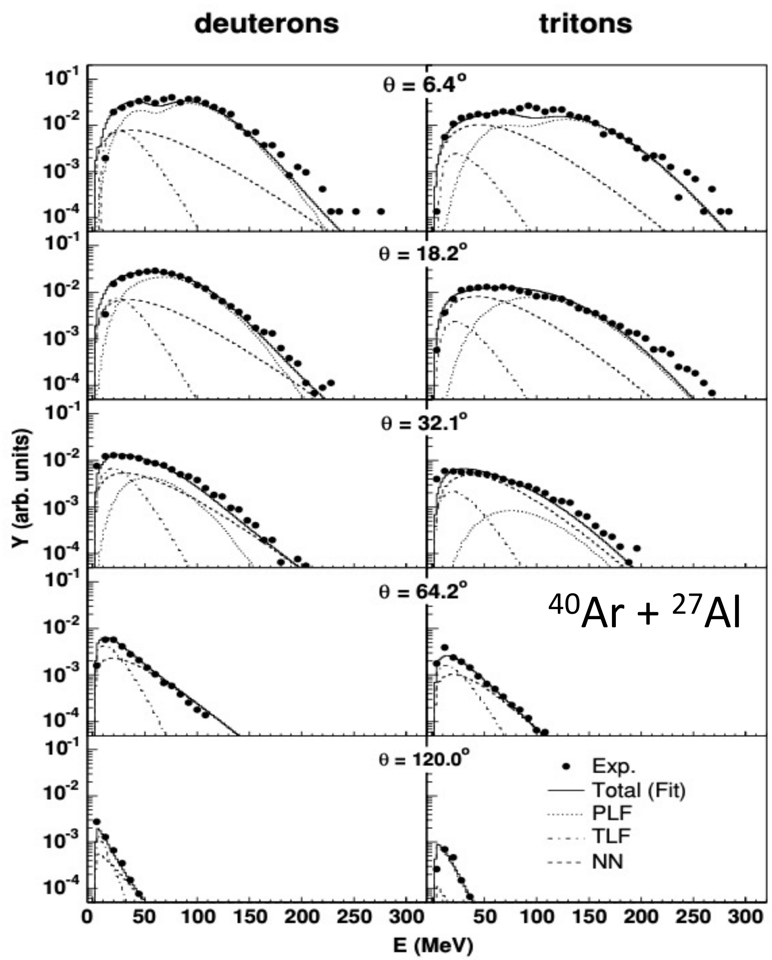
Y. G. Ma, et al., PhysRevC71, 054606 (2005)

It is well known that the laboratory frame kinetic energy spectra of most light ejectiles can be reproduced with the assumption of emission from three different sources: (i) a quasiprojectile (QP) source, (ii) an intermediate velocity or nucleon-nucleon (*NN*) source, and (iii) a quasitarget (QT) source. To better understand origins of the emitted particles the ideal situation would be to have the ability to attribute each particle to its source on an event-by-event basis. However the spectral distributions from the different sources overlap significantly, making such an attribution not possible. Previous techniques to reconstruct QP have included identifying high-velocity components of the QP [54,55] or treating only particles emitted in the forward hemisphere in the projectile frame and then assuming identical properties for particles emitted in the backward hemisphere to recreate the QP source [33,34]. Such a technique is limited in its application and not suited to situations in which fluctuations are to be investigated.

For this work we have developed a new method for the assignment of each light-charged particle (LCP) to an emission source. This is done with a combination of three source fits and Monte Carlo sampling techniques. We first obtain the laboratory energy spectra for different LCP at different laboratory angles and reproduce them using the three source fits. In the laboratory frame, the energy spectra of LCP can be modeled as the overlap of emission from three independent moving equilibrated sources (i.e., the QP, *NN*, and QT sources). For

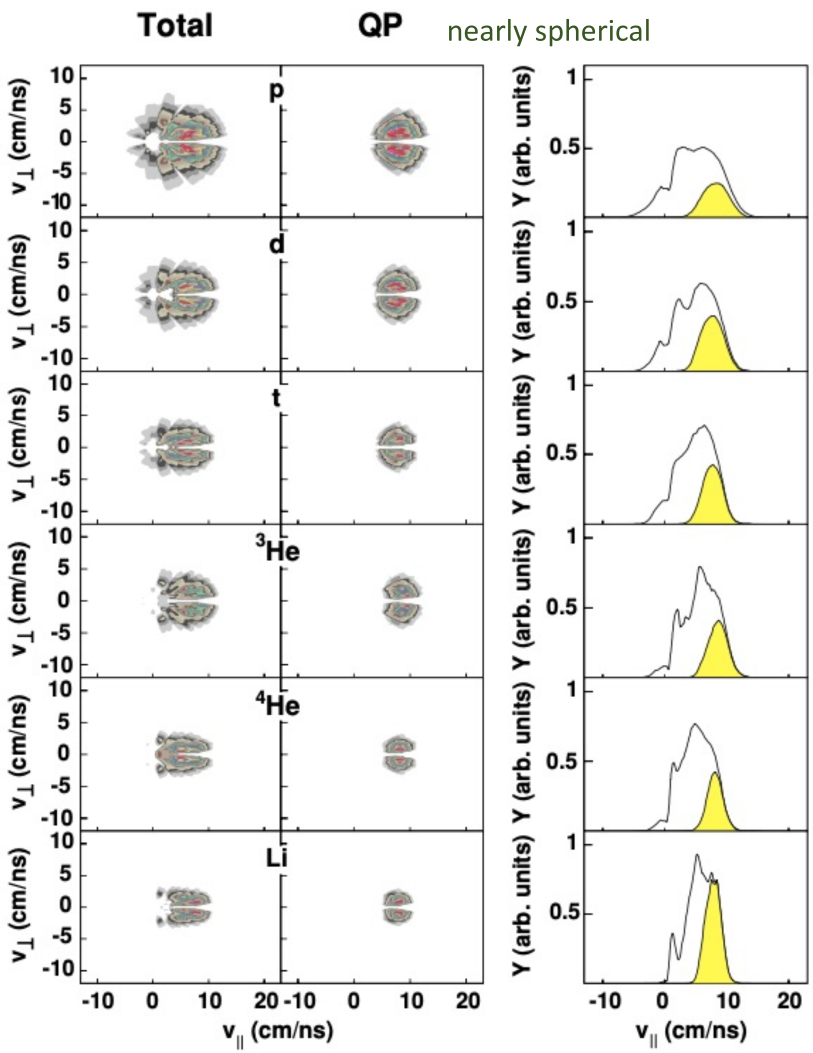
Reconstructed differential cross section through **three-source fitting**



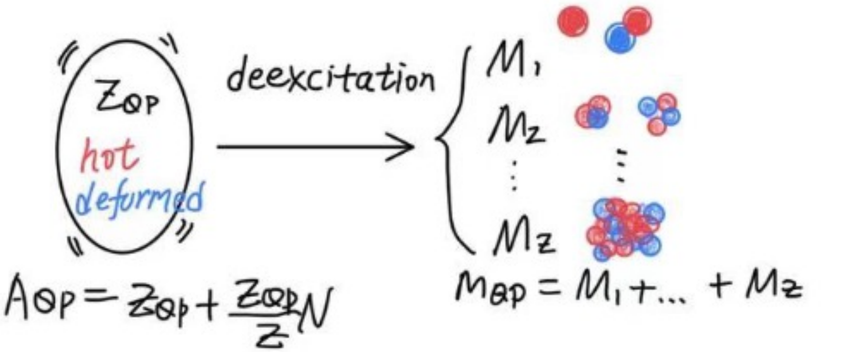
Reconstructing QP, cont'd

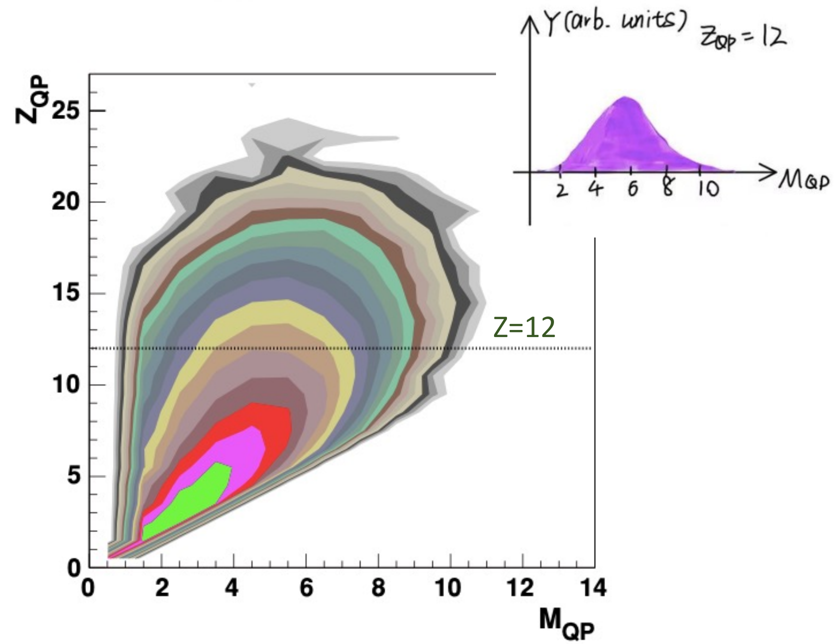
Velocity distributions

nearly spherical



QP deexcitation





Reconstructing QP, cont'd

Event-by-event reconstructed QP

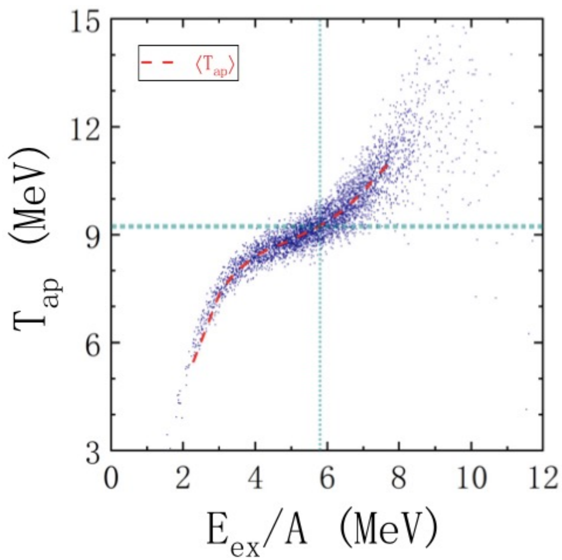
$$\mathbf{x}_i = \{M_1, \dots \dots, M_{12}, E_{\text{ex}}/A, \langle T_{\text{ap}} \rangle\}$$

The caloric curve

$$E_{\text{ex}} = \sum_{i=1}^{M_{\text{QP}}} E_i^{\text{kin}} + \frac{3}{2} M_n T - Q$$

$$\langle T_{\text{ap}} \rangle = \sqrt{\frac{\langle Q_{xy}^2 \rangle - \langle Q_{xy} \rangle^2}{4m^2}}$$

$$Q_{xy} = p_x^2 - p_y^2$$

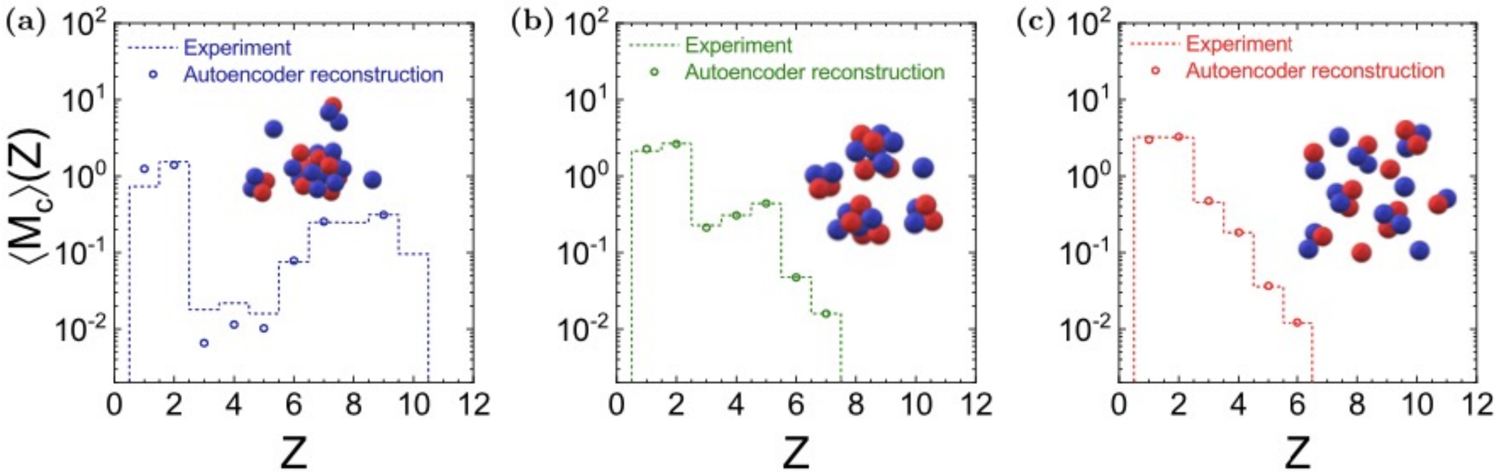


$$\tilde{c} \equiv \frac{d(E_{\text{ex}}/A)}{dT_{\text{ap}}}$$

$E_{\text{ex}}/A = 5.6 \pm 0.5$ MeV

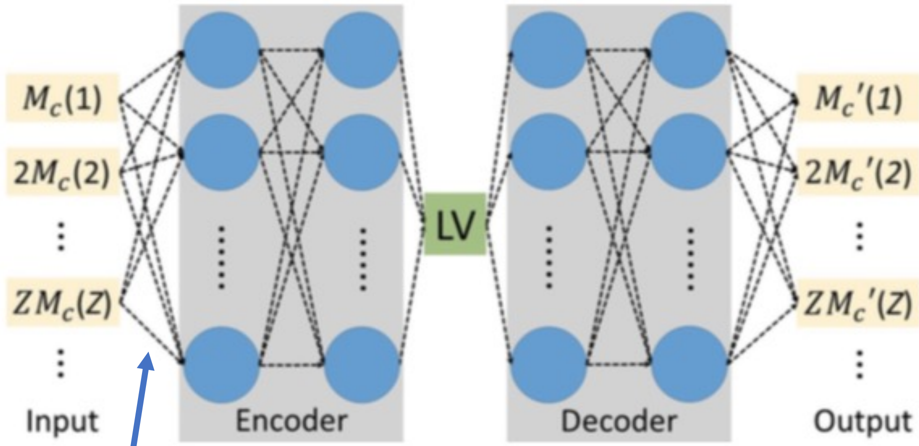
$T_{\text{ap}} = 8.3 \pm 0.5$ MeV

The averaged charge multiplicity distribution $\langle M_c \rangle(Z)$ of the QP fragments



Machine learning results

Construction of autoencoder



Activation function $ReLU(\mathbf{Wx} + \mathbf{b})$

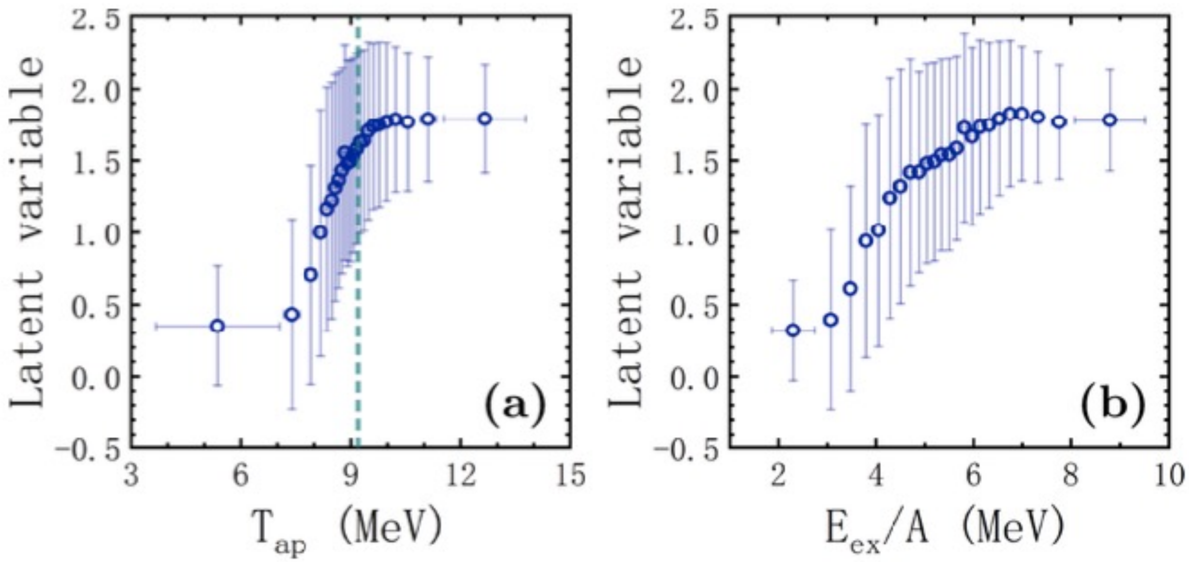
Layer	Neuron number	Activation
Input	12	*tanh*
Encoder first layer	8–64	*tanh*
Encoder second layer	4–32	*tanh* or *ReLU*
Latent variable	1	*tanh*
Decoder first layer	4–32	*tanh*
Decoder second layer	8–64	*ReLU*
Output	12	–

Loss function with regulator to be minimized

$$\tilde{C}(\tilde{\mathbf{y}}, \mathbf{y}) = (\tilde{\mathbf{y}} - \mathbf{y})^2 + l_2(\|\mathbf{W}\|^2/2 + \|\mathbf{b}\|^2/2)$$

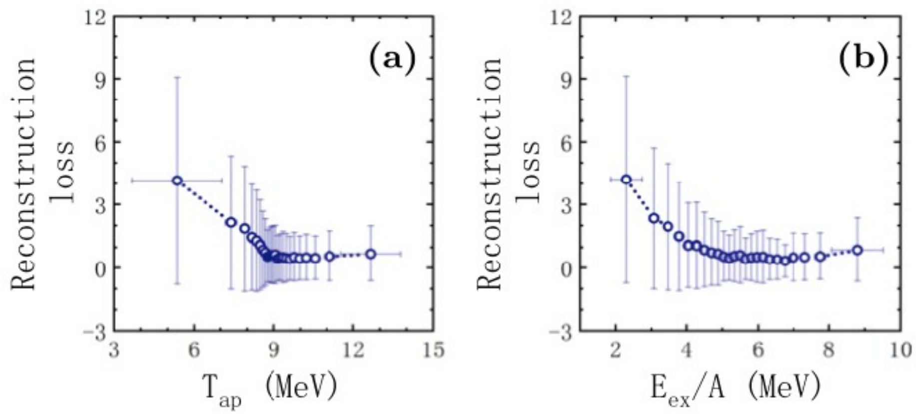
A latent variable

The mean and standard deviation of the latent variable in different T_{ap} and E_{ex}/A bins



The mean and standard deviation of the event-by-event reconstruction loss of the autoencoder network

$$\sum_{Z=1}^{12} |ZM_c(Z) - ZM_c'(Z)|$$

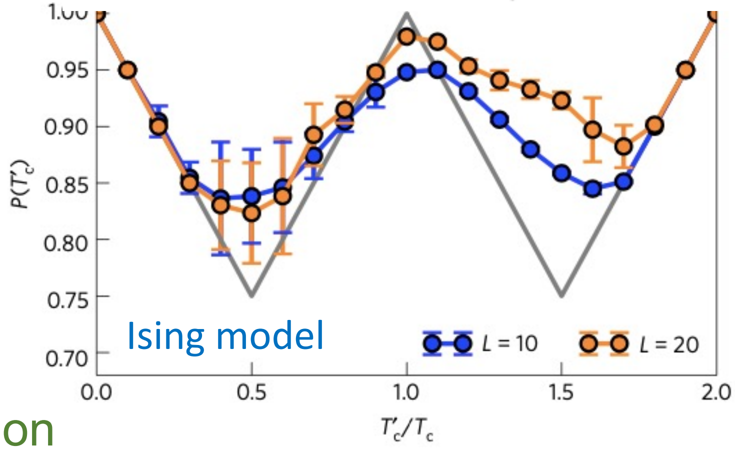


Confusion scheme

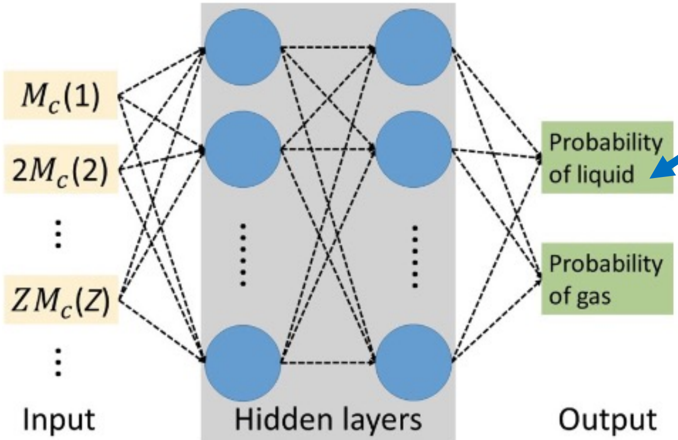
E P L van Nieuwenburg, et al. , NatPhys13, 435-439 (2017)

In this Letter we demonstrate that it is possible to find the correct labels, by *purposefully mislabelling the data* and evaluating the performance of the machine learner.

$$H = J\sum_{i=1}^{L} S_i \cdot S_{i+1} + \sum_{\alpha=x,y,z}\sum_{i=1}^{L} h_i^\alpha S_i^\alpha$$

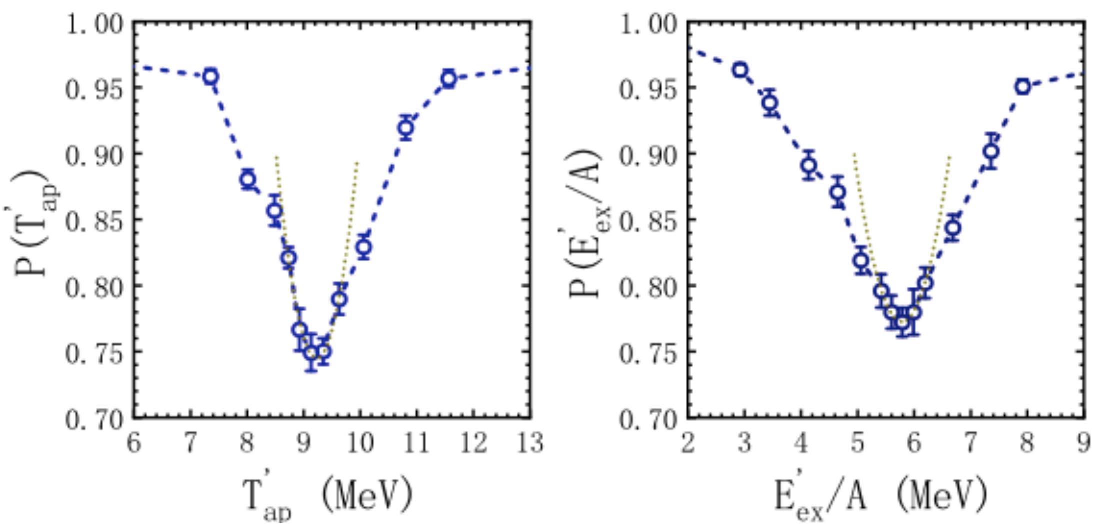


Confusion scheme for T'_{ap} in heavy-ion reaction



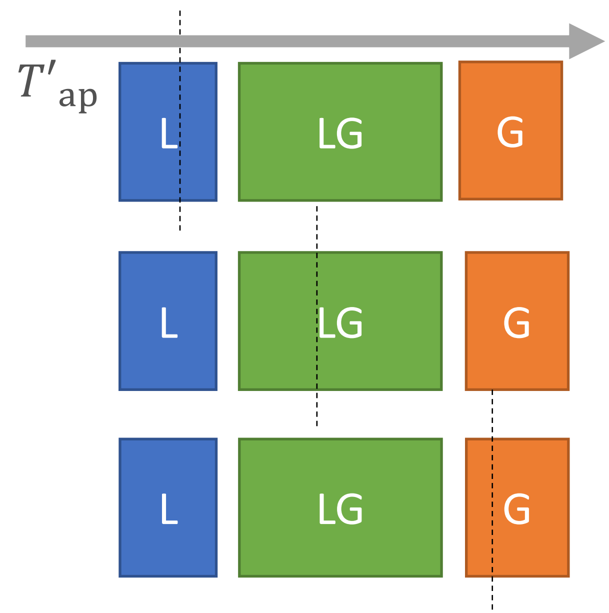
Give a wrong T'_{ap} for classification & train the network

The performance in the test data set



$$E_{\mathrm{ex}}/A = 5.79 \pm 0.02\ \mathrm{MeV}$$

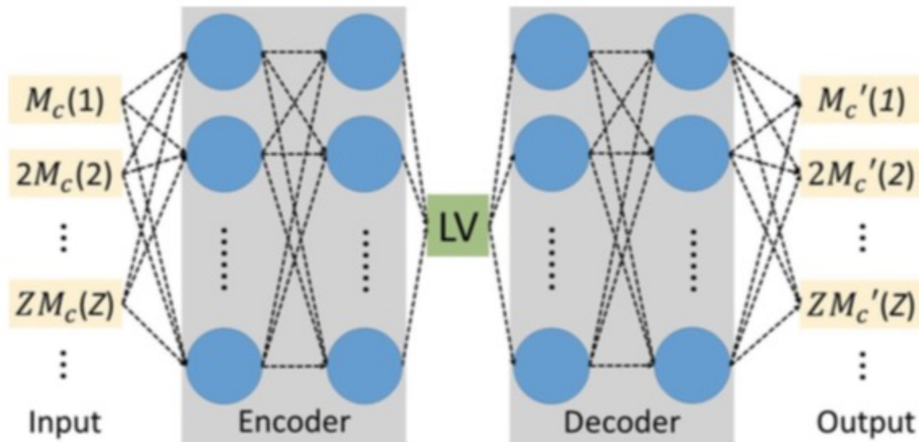
$$T_{\mathrm{ap}} = 9.24 \pm 0.04\ \mathrm{MeV}$$



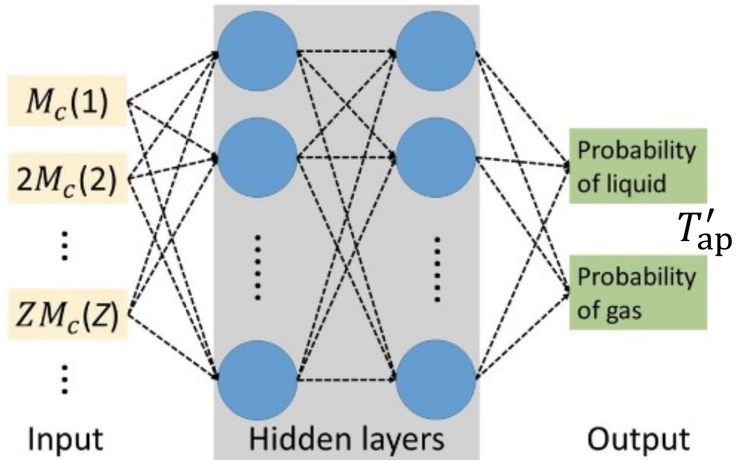
Highlights of this work

Autoencoder & latent variable

LV as kind of order parameter



Confusion scheme



Thank you for your attention