Deep Learning Stochastic Process with QCD Phase Transition

Speaker: **Lingxiao Wang** (FIAS)

With: **Lijia Jiang** (Northwest Uni. and FIAS) and **Kai Zhou** (FIAS)

Phys. Rev. D 103, 116023 (2021)

15 July, 2021 Transport Meeting

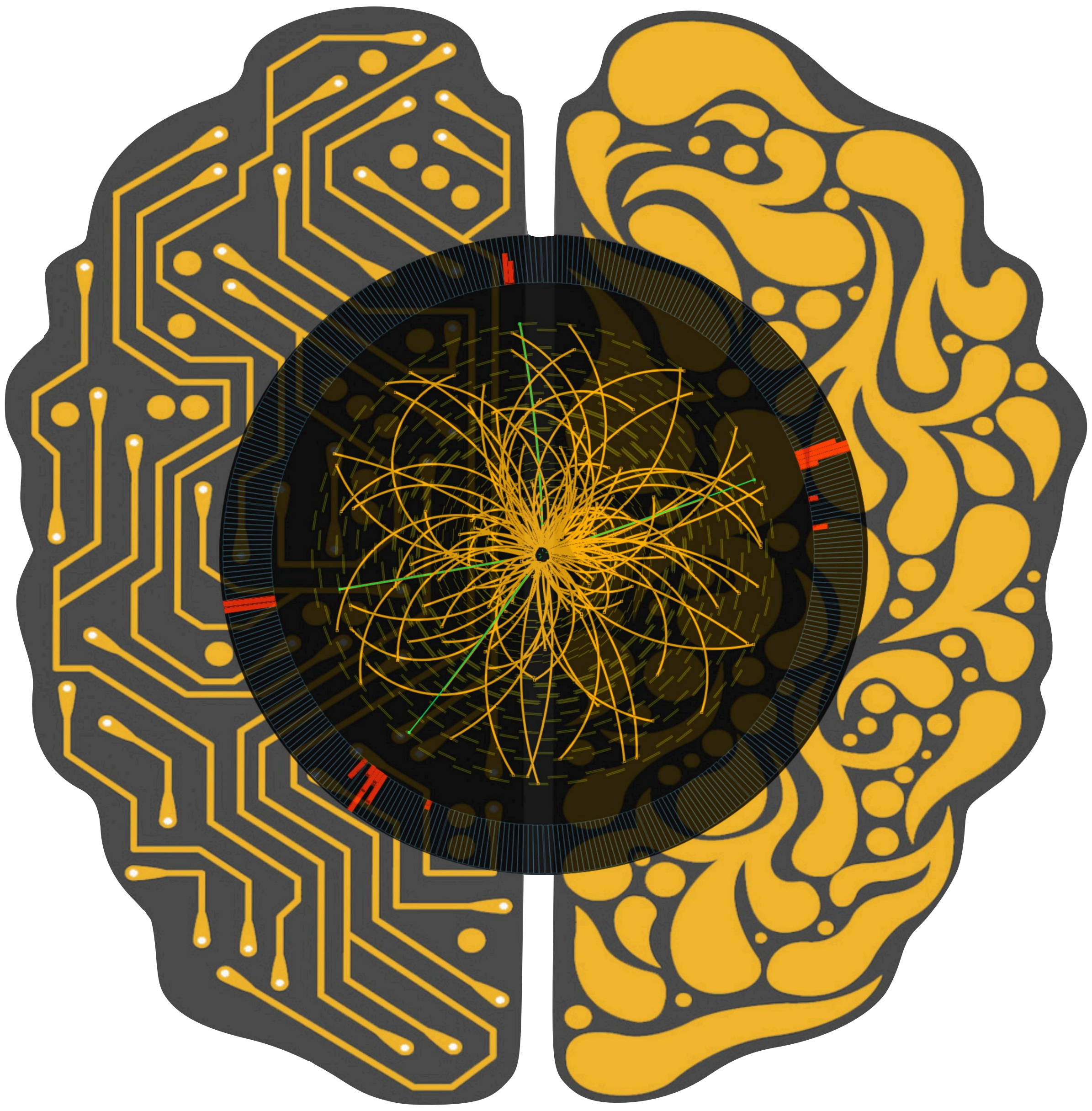
FIAS Frankfurt Institute for Advanced Studies

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Main Content

Deep Learning Meets Physics

- Background
  - QCD phase transition
  - Deep learning in physics
- Deep Learning Dynamics
  - Understanding stochastic processes as images
  - Recognizing phase transition oders
  - Learning dynamical parameters
- Summary



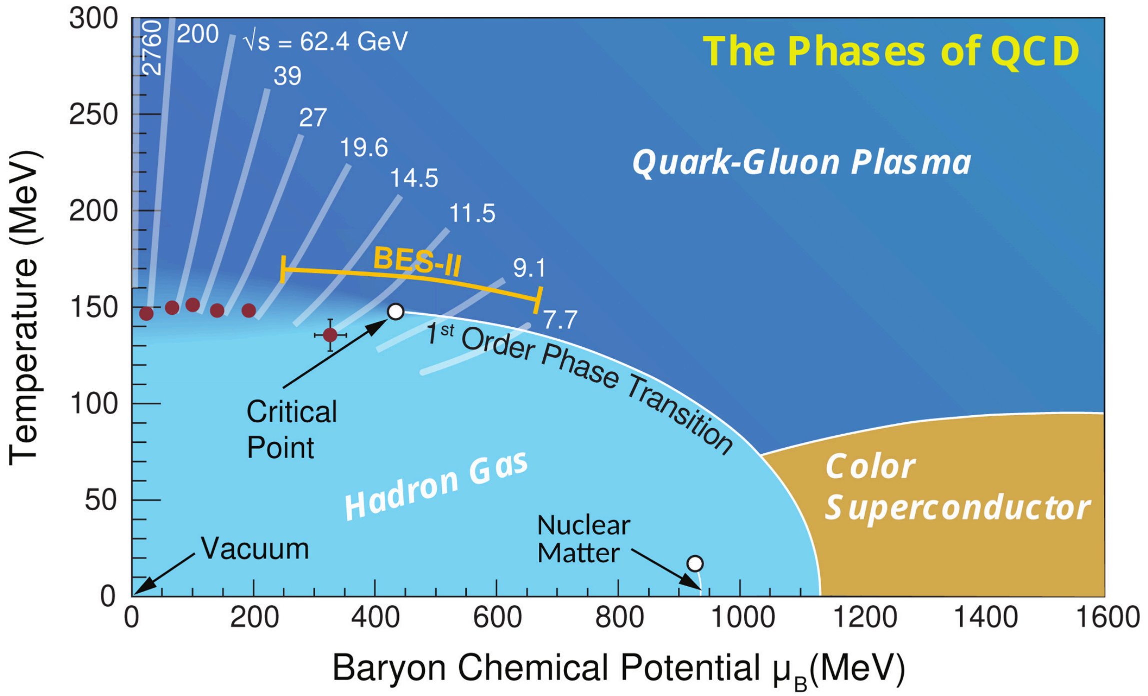
Background

Phase Transition

Critical Point

- **QCD Phase Structures**
  - Chiral symmetry restoration
  - Deconfinement
  - Finite chemical potential $\mu_{\mathrm{B}}, \mu_{\mathrm{I}}, B, \omega$
- **Searching Critical End Point**
  - Theoretical calculations: (P)NJL, QM, FRG, DSE, etc
  - Lattice calculations
  - **Experiments: BES**

A schematic QCD phase diagram



A. Bzdak, S. Esumi, V. Koch, J. Liao, M. Stephanov, and N. Xu, Physics Reports (2020).

Stochastic Process

Criticality

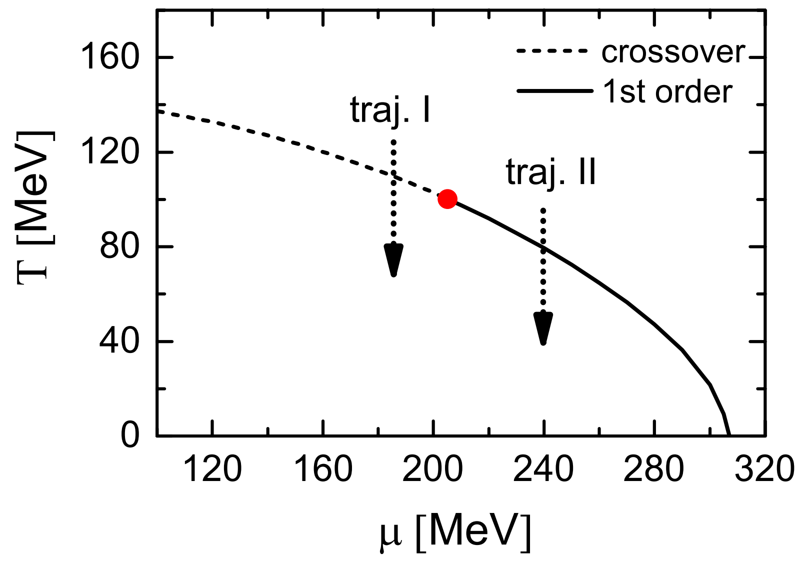
- **Along the freeze-out surface**
  - Critical fluctuations
  - Statistical fluctuations
  - Dynamical critical fluctuations?

    S. Mukherjee, R. Venugopalan, and Y. Yin, Phys. Rev. C **92**, 034912 (2015).
    L. Jiang, S. Wu, and H. Song, EPJ Web Conf. **171**, 16003 (2018).

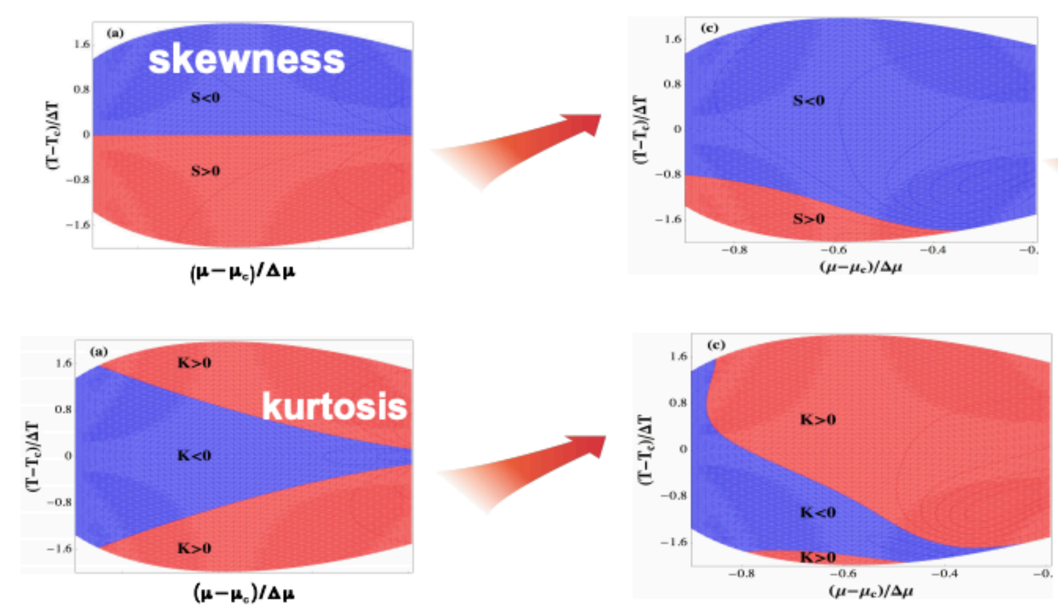
    - Memory effects from dynamical evolution
    - The Skewness and Kurtosis of the high order cumulants could be different from the equilibrated
- **With Deep Learning**
  - Detecting phase transition
  - Extracting dynamical information

  … in stochastic processes

QCD phase diagram from the linear signa model with constituent quarks



L. Jiang, S. Wu, and H. Song, Nuclear Physics A **967**, 441 (2017).



from Swagato's talk @201509,Kobe

Deep Learning

AI in Physics

- **Classify phases**

  Phys. Rev. B 94, 195105 (2016), Phys. Rev. X 7, 031038 (2017), Nat. Phys. 13, 431 (2017).

- **Predict properties/signals**

  Phys. Rev. Lett. 120, 241602 (2018), Phys. Rev. Materials 3, 104405 (2019).

- **Innovate computation**

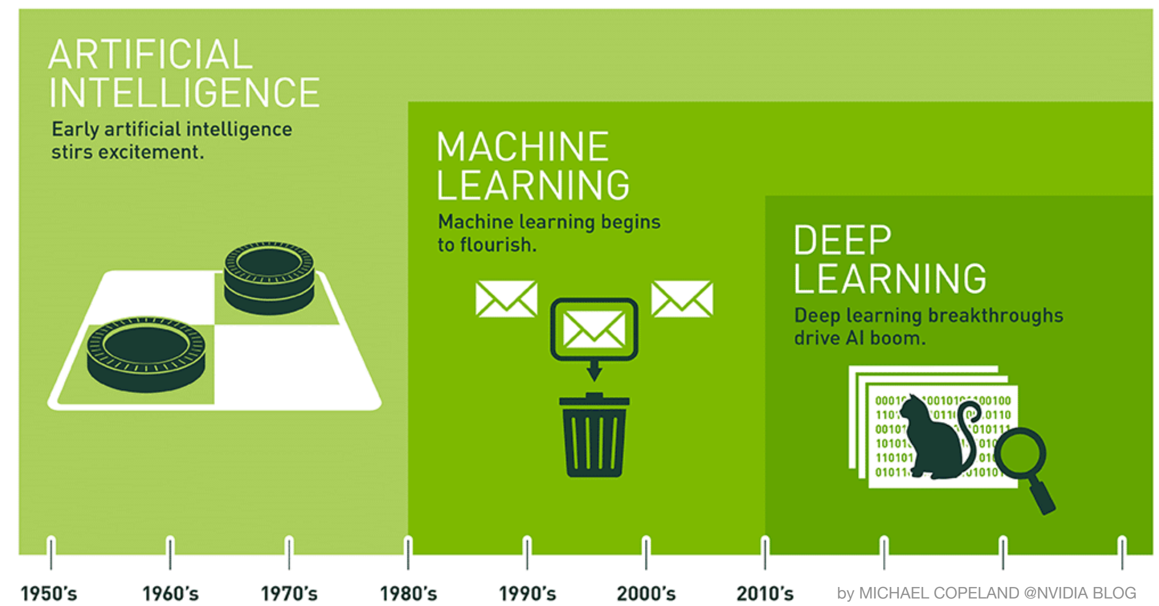
  Science 355, 602 (2017), Phys. Rev. B 97, 205140 (2018), Phys. Rev. Lett. 122, 080602 (2019).

- **New developments**

  arXiv:1410.3831, Nat. Phys. 14, 578 (2018), Science Bulletin 64, 1228 (2019), Phys. Rev. Lett. 124, 010508 (2020).

Machine Learning and the Physical Sciences, Rev. Mod. Phys. **91**, 045002 (2019).
Machine Learning Meets Quantum Physics, Physics Today **72**, 48 (2019).

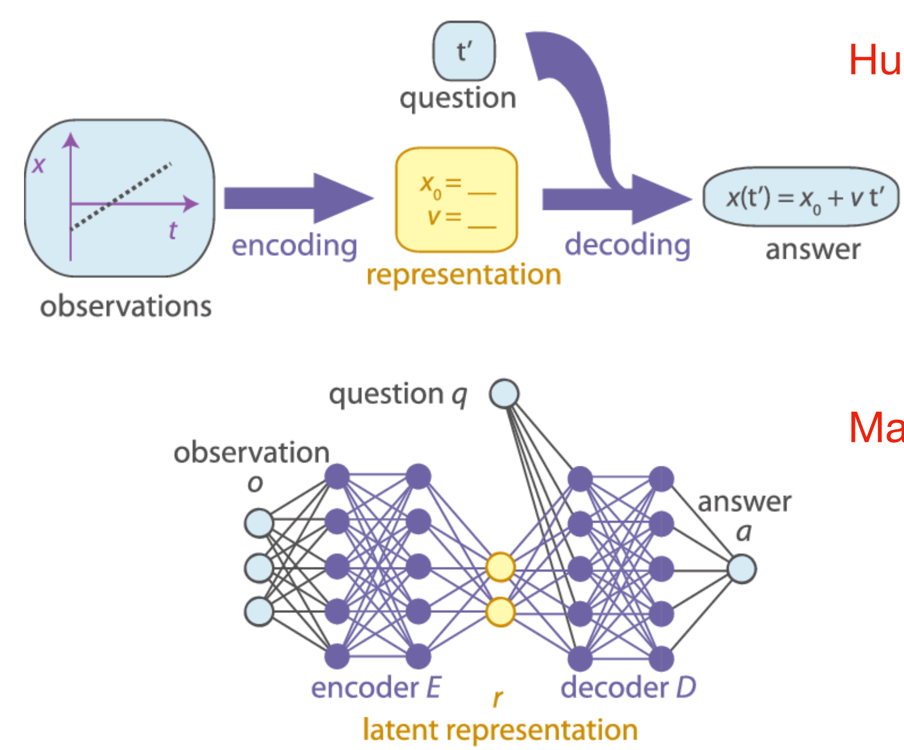
AI, Machine Learning and Deep Learning



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Learning physical representations

Human Learning



Machine Learning

Phys. Rev. Lett. 124, 010508 (2020).

Deep Learning

AI in High Energy Nuclear Physics

- **White Paper**

  P. Bedaque, A. Boehnlein, M. Cromaz, M. Diefenthaler, L. Elouadrhiri, T. Horn, M. Kuchera, D. Lawrence, D. Lee, S. Lidia, R. McKeown, W. Melnitchouk, W. Nazarewicz, K. Orginos, Y. Roblin, M. S. Smith, M. Schram, and X.-N. Wang, *Report from the A.I. For Nuclear Physics Workshop*, (2020).

- **Experiments**

  Phys. Rev. Lett. 120, 241602 (2018), SciPost Physics 7, 014 (2019), Nat. Phys. 15,1113-1117 (2019), …

- **Lattice calculations**

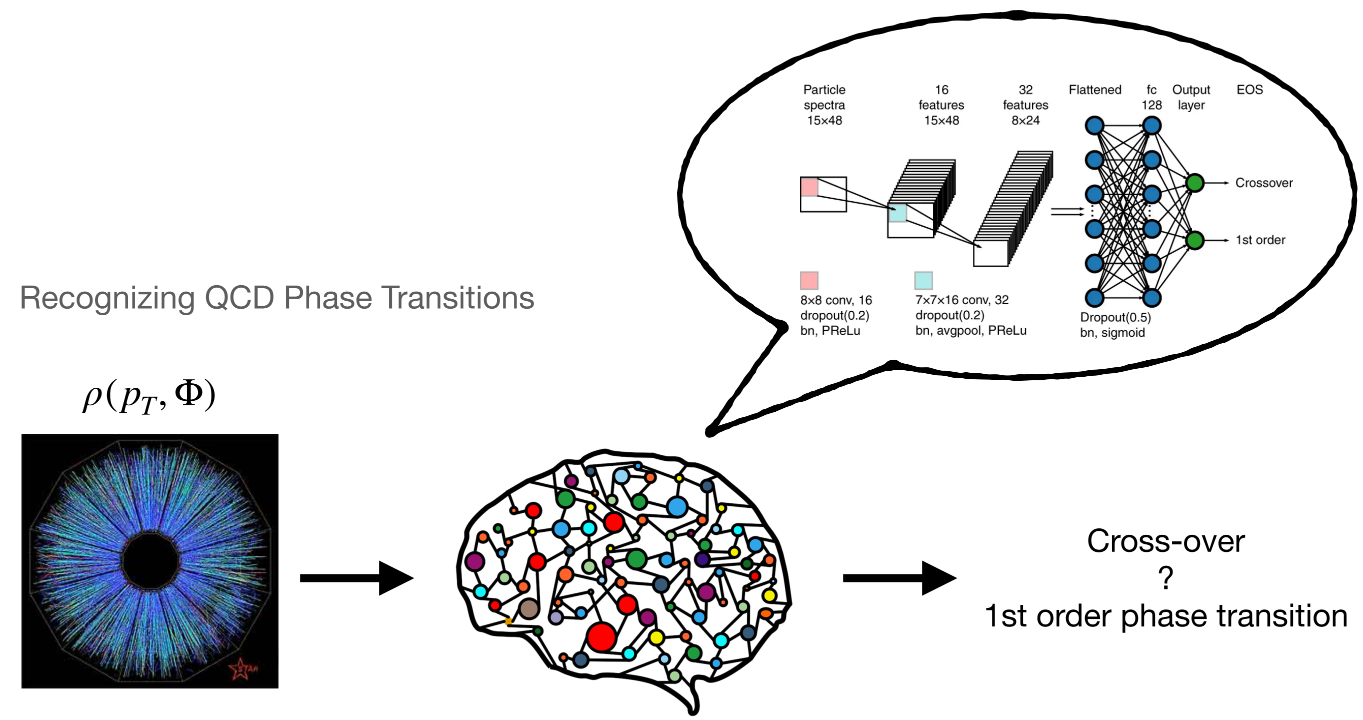
  Phys. Rev. D **100**, 011501 (2019), Phys. Rev. D **101**, 094507 (2020), Phys. Rev. Lett. **125**, 121601 (2020), Phys. Rev. D **102**, 096001 (2020), …

  - From lattice QCD to in-medium heavy-quark interactions via deep learning
    Kai Zhou *24 June, Transport Meeting 2021*

- **New Developments**

  Phys. Rev. D **98**, 023019 (2018), A&A **642**, A78 (2020), Eur. Phys. J. C **79**, 870 (2019), JHEP, **2019,** 122 (2019), …

  - **Compact stars**
  - **Phase structures**
  - **Dynamical processes**



L.-G. Pang, **K. Zhou**, N. Su, H. Petersen, H. Stöcker, and X.-N. Wang, Nature Commun. **9**, 210 (2018).

Deep Learning
Critical Dynamics

Problem Set-Up

Stochastics Process

- **QCD phase transition in Langevin equation**

$$\partial^\mu \partial_\mu \sigma(t,x) + \eta \partial_t \sigma(t,x) + \frac{\delta V_{eff}(\sigma)}{\delta \sigma} = \xi(t,x)$$

η: damping coefficient

- **Flucuations**

$$\langle \xi(t) \xi(t') \rangle = \frac{1}{V} m_\sigma \eta \coth\left(\frac{m_\sigma}{2T}\right) \delta(t-t')$$

$$\xi(x) = B \sqrt{\frac{1}{V} m_\sigma \eta \coth\left(\frac{m_\sigma}{2T}\right) \frac{1}{dt}} G(x)$$

$$\mathscr{L} = \bar{q}\left[i\gamma^\mu \partial_\mu - g\left(\sigma + i\gamma_5 \vec{\tau}\cdot\vec{\pi}\right) + \gamma_0 \mu\right] q + \frac{1}{2}\left(\partial_\mu \sigma \partial^\mu \sigma + \partial_\mu \vec{\pi} \partial^\mu \vec{\pi}\right) - U(\sigma, \pi)$$

Linear Sigma Model

$$V_{eff}(\sigma) = U(\sigma) + \Omega_{q\bar{q}}(\sigma; T, \mu)$$

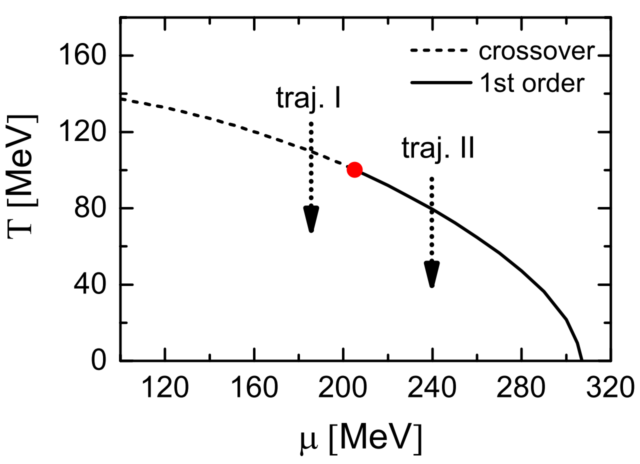
Effective potential

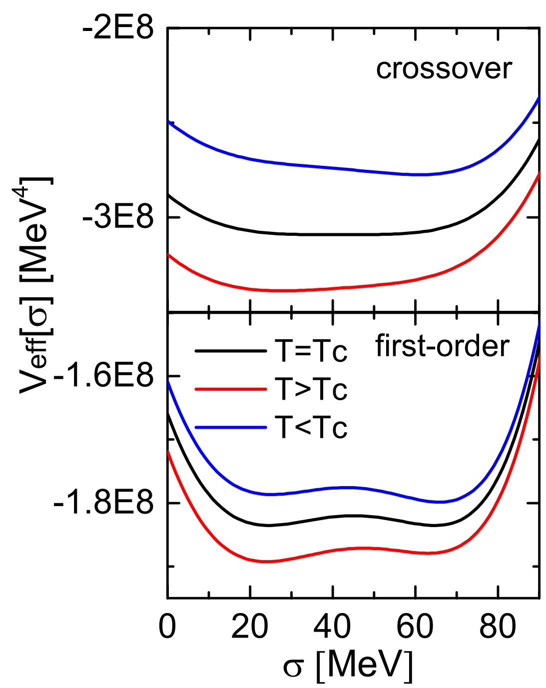
$$U(\sigma) = \frac{1}{4}\lambda^2\left(\sigma^2 - v^2\right)^2 - h\sigma - U_0$$

$$\Omega_{q\bar{q}}(\sigma; T, \mu) = -d_q \int \frac{d^3p}{(2\pi)^3}\left\{E + T\ln\left[1 + e^{-(E-\mu)/T}\right] + T\ln\left(1 + e^{-(E+\mu)/T}\right)\right\}$$

$$\frac{T(t)}{T_0} = \left(\frac{t}{t_0}\right)^{-0.45}$$

Hubble-like





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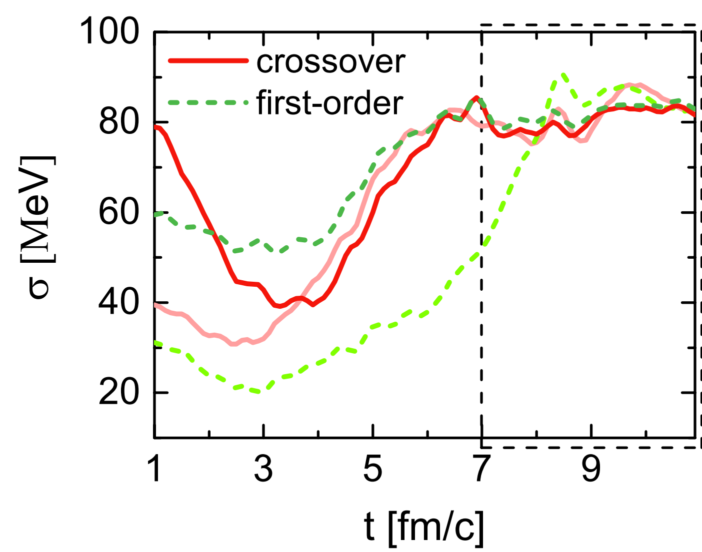
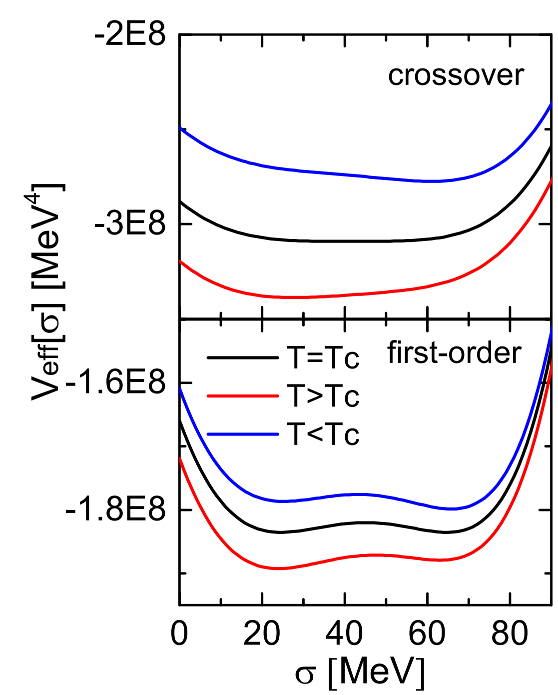
Hubble-like

Sigma configurations





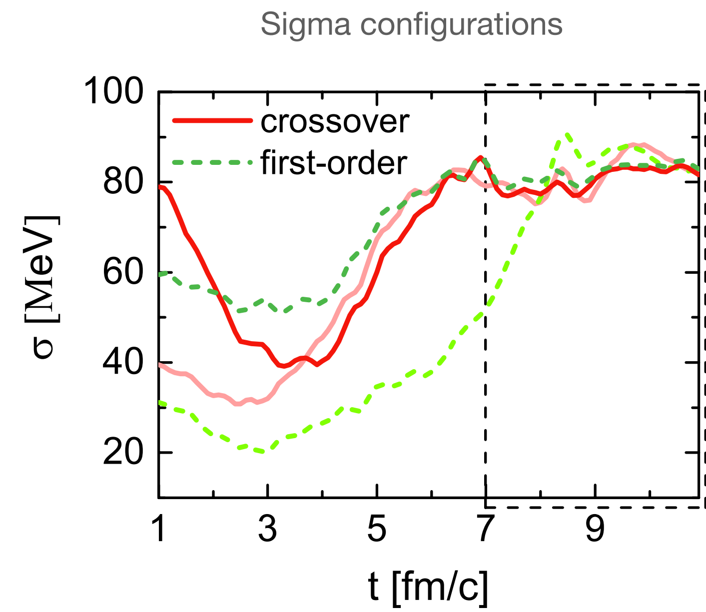
Problem Set-Up

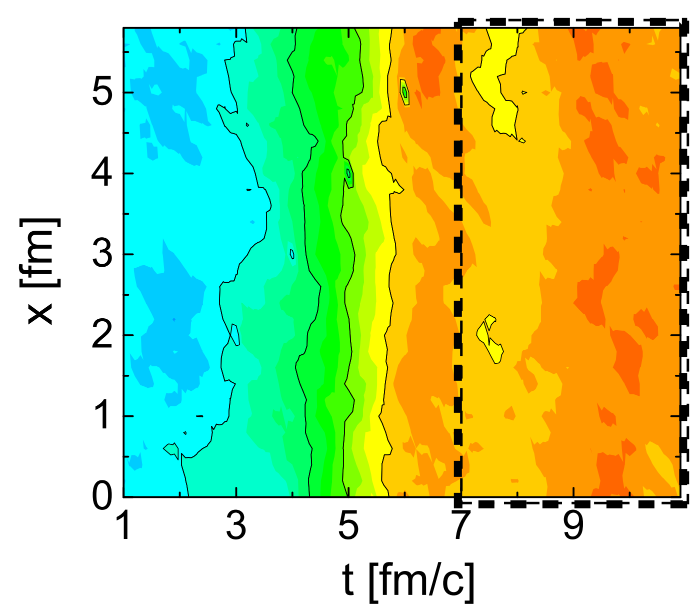
Stochastics Processes as Images

- **Preparing configurations**
  - Initial profiles sample with

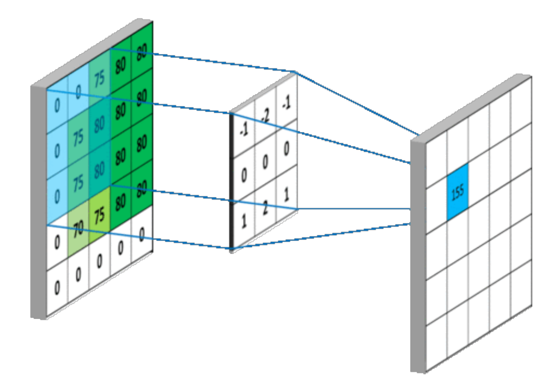
    $$P[\sigma(\mathbf{x})] \sim \exp(-\varepsilon(\sigma)/T) \qquad \varepsilon(\sigma) = \int dx \left[\frac{1}{2}(\nabla\sigma(x))^2 + V_{eff}(\sigma(x))\right]$$

  - Simulated 10,000 events at each parameter
    - μ = 180 MeV as “cross-over”
    - μ = 240 MeV as “1st order”
    - B = 0.5, 1
- **Compressing $\sigma(x, t)$ as images**
  - dx = 0.2 fm, dt = 0.1 fm/c
  - L = 6.0 fm, t in [7, 11] fm/c
  - $N_t \times N_x$ = 40 × 30 = 1200 pixels





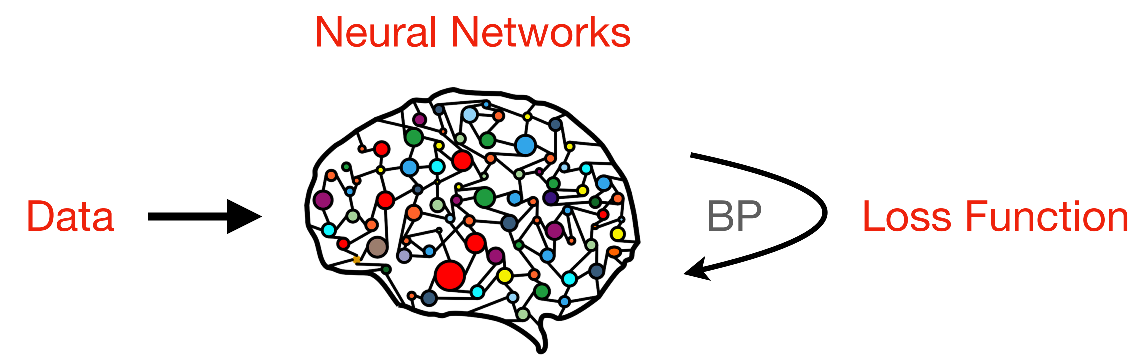
Convolutional Operation



Spatial-Temporal Correlation!

Neural Networks

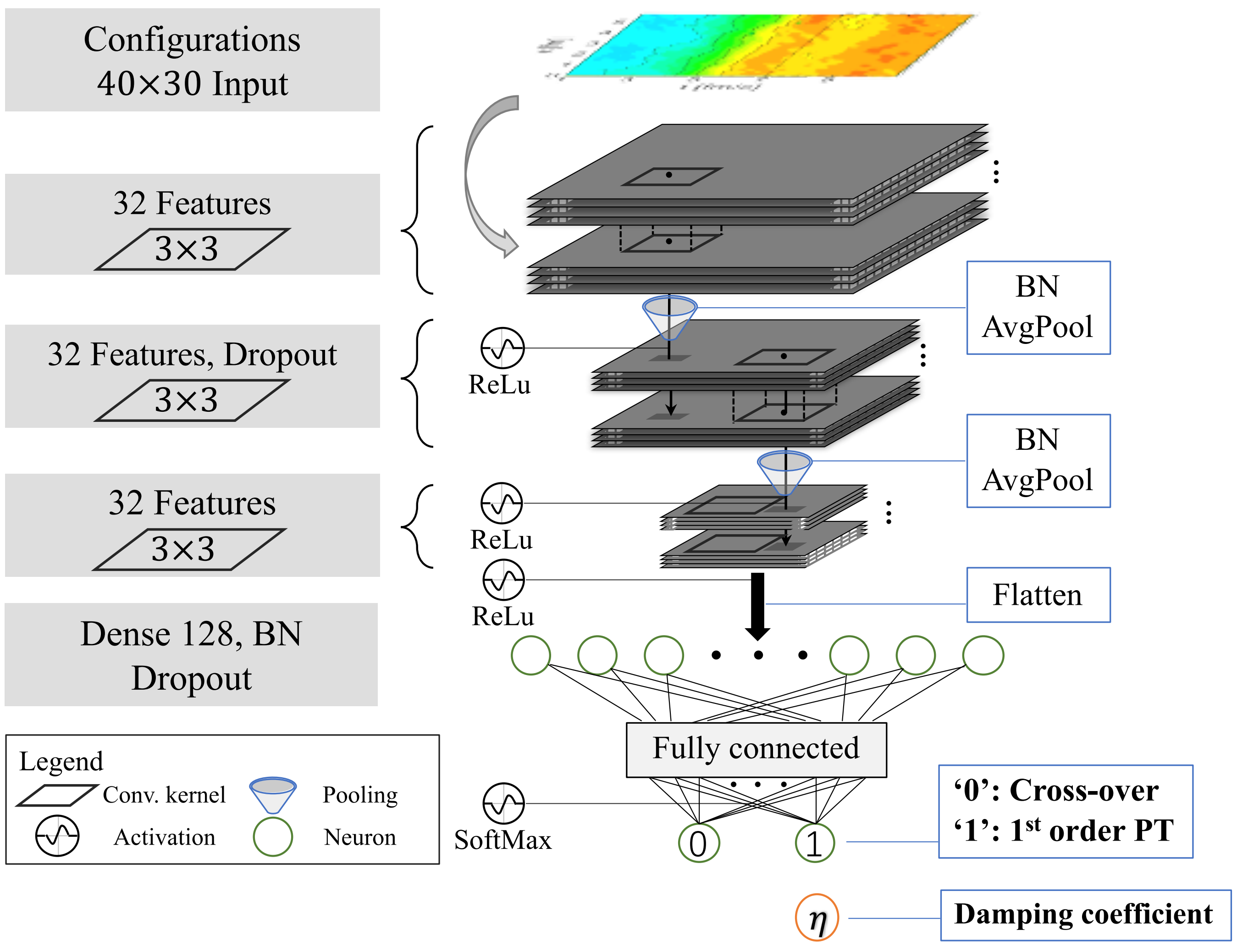
Deep CNNs



- **Compressing $\sigma(x, t)$ as images**
  - $N_t \times N_x$ = 40 × 30 = 1200 pixels
  - Data-sets: 8:2 = training: validation
- **Architecture**
  - Inputs : $\sigma(x, t)$ configurations
  - 3 CNNs
  - 1 Fully-Connected layer
  - Outputs: 0,1 / damping coefficient η
- **Loss function**
  - Categorical cross entropy

$$\text{loss} = -\sum_{i=1}^{C} y_i \log f_i(x)$$

  - Mean Square Error



Recognition

Phase Transition Oders

- **Flucutations**

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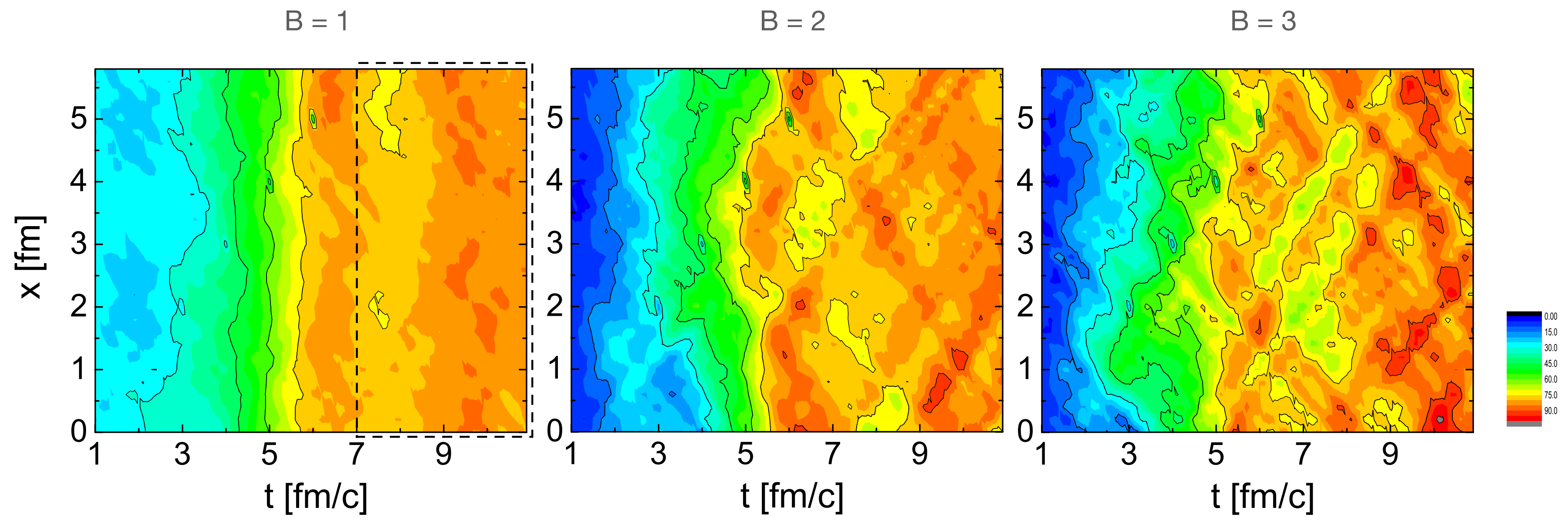
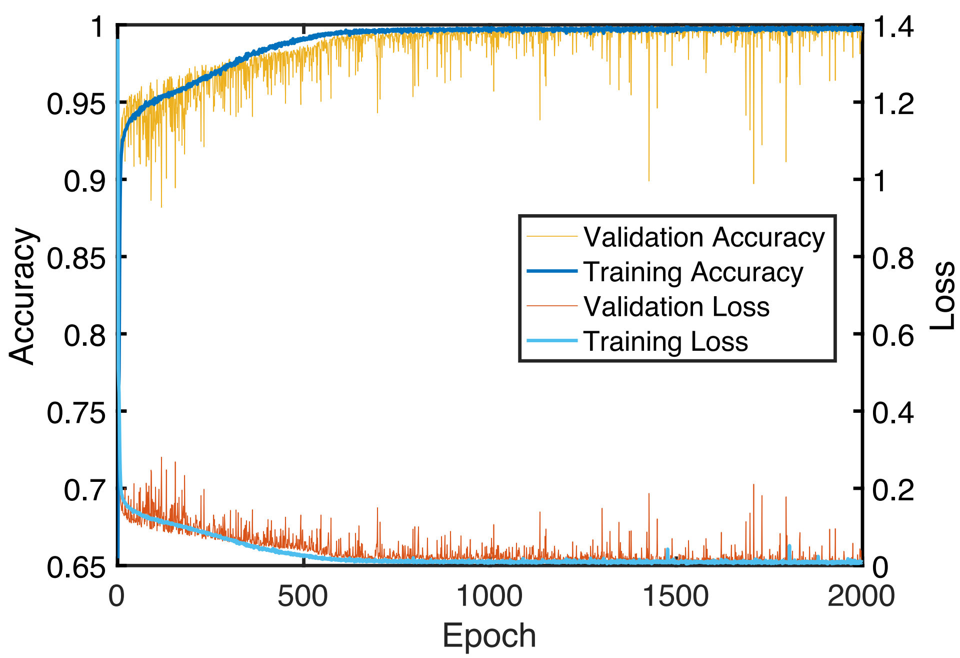


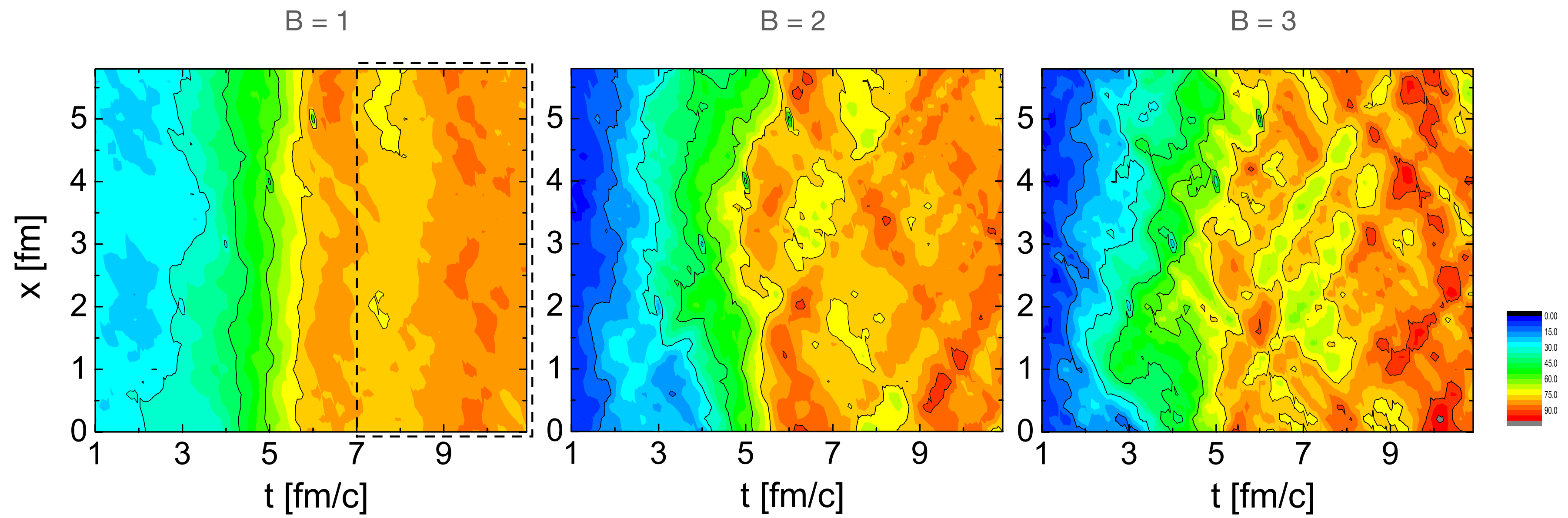
- **Training**
  - B = 0.5, 1
  - Reaching saturation without over-fitting
- **Testing**
  - B = **0.5, 1**, 1.5, 2, 2.5
  - Accurate on low-noise configurations
  - Robust to the noises

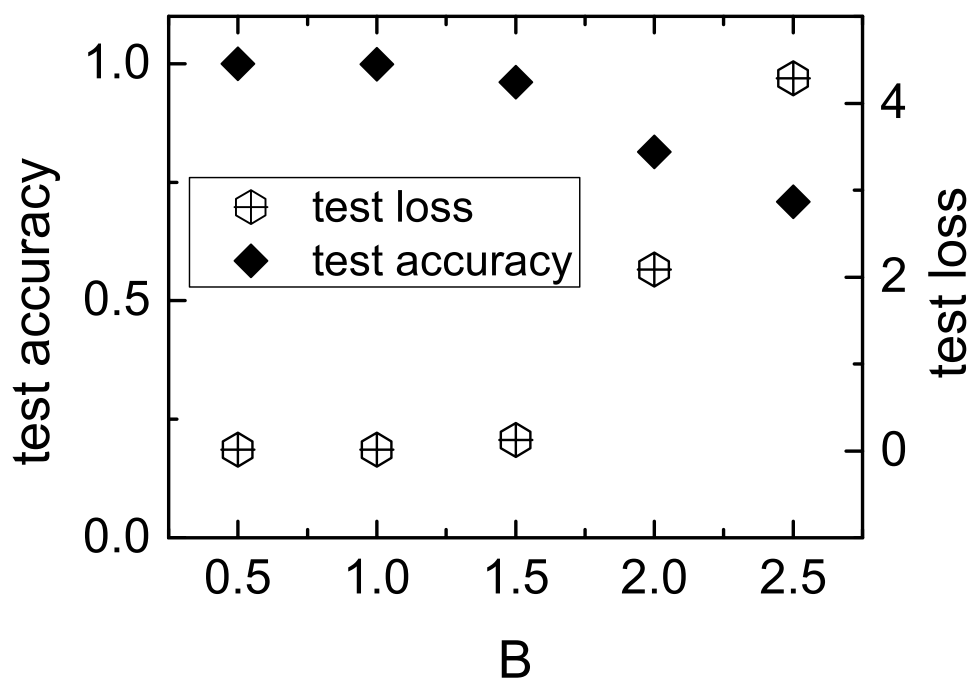


Recognition

Phase Transition Oders

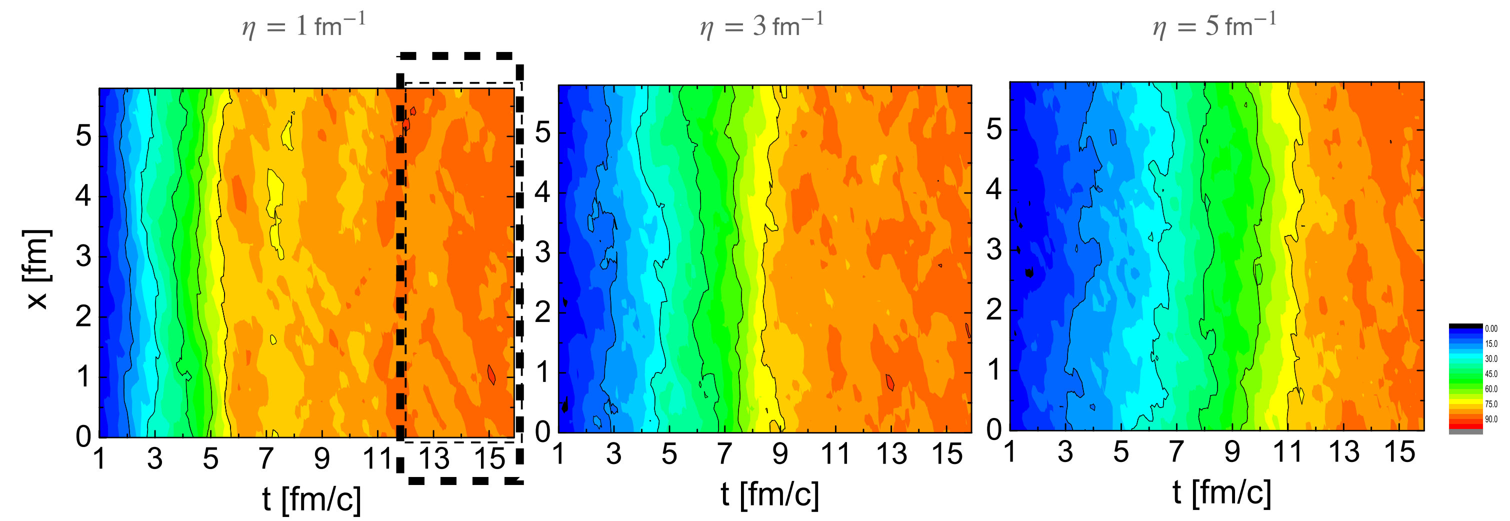
- **Training**
  - B = 0.5, 1
- **Testing**
  - B = 0.5, 1, **1.5, 2, 2.5**
  - Accurate on low-noise configurations
  - Robust to the noises
- Recognizing the phase transition orders on the spatial-temporal configurations
  - with spatial and initial fluctuations





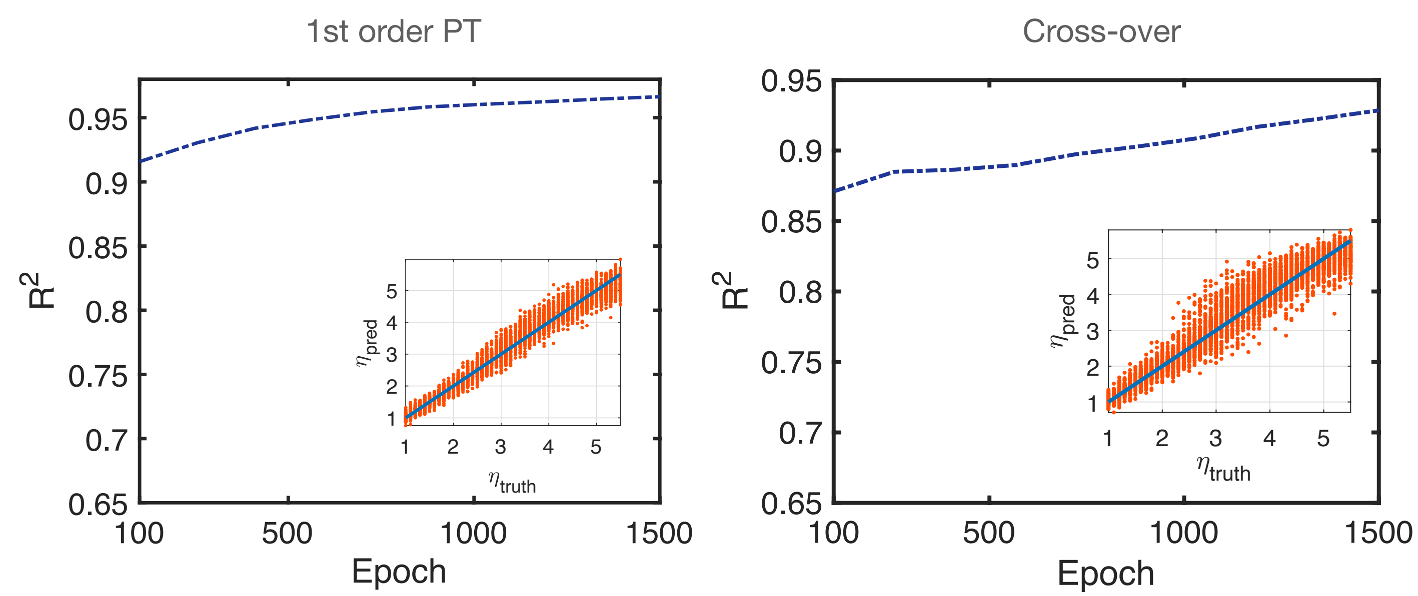
Learning Dynamics

Damping Coefficients



- **Training**
  - L = 6.0 fm, *t* in [12, 16] fm/c
  - $N_t \times N_x$ = 50 × 30 = 1500 pixels
  - $\eta = (1.0 - 2.5), (4.6 - 5.5)\ \mathrm{fm}^{-1}$
    - $d\eta = 0.1\ \mathrm{fm}^{-1}$
    - 1000 events in each bin

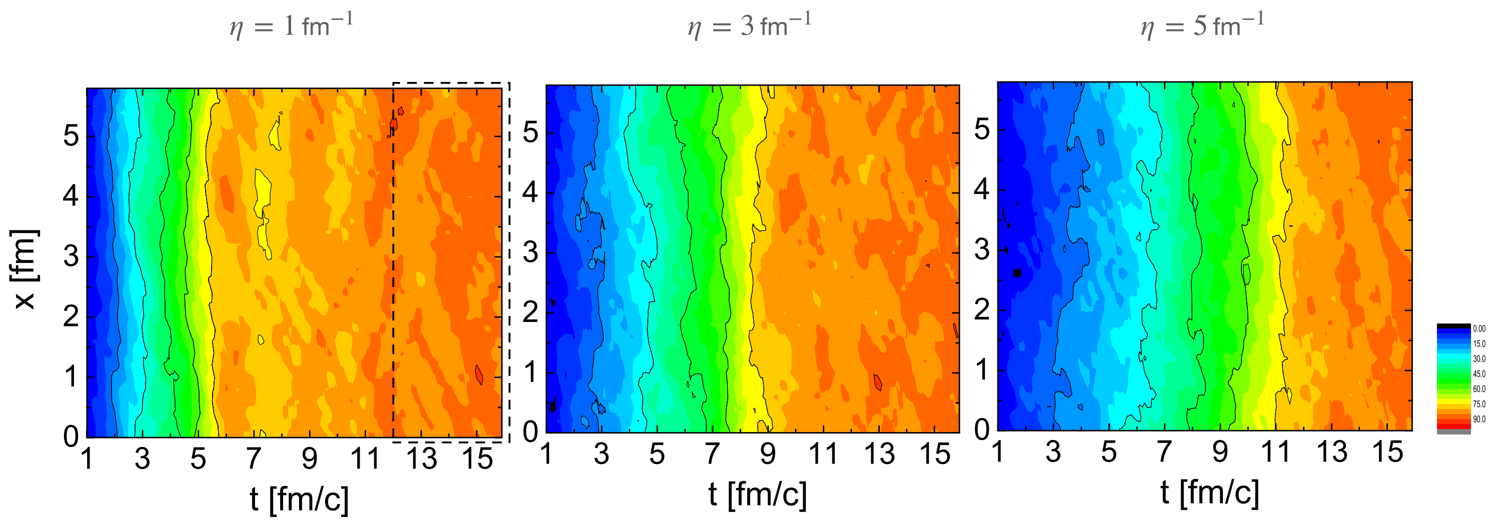
$$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}} \qquad SS_{\mathrm{res}} = \sum_i \left(\eta_{i,\ \mathrm{truth}} - \bar{\eta}_{\mathrm{truth}}\right) \qquad SS_{\mathrm{tot}} = \sum_i \left(\eta_{i,\ \mathrm{truth}} - \eta_{i,\ \mathrm{pred}}\right)$$



- **Testing**
  - Ground truth vs Predictions
  - $\eta = (2.6 - 4.5)\ \mathrm{fm}^{-1}$

Learning Dynamics

Damping Coefficients



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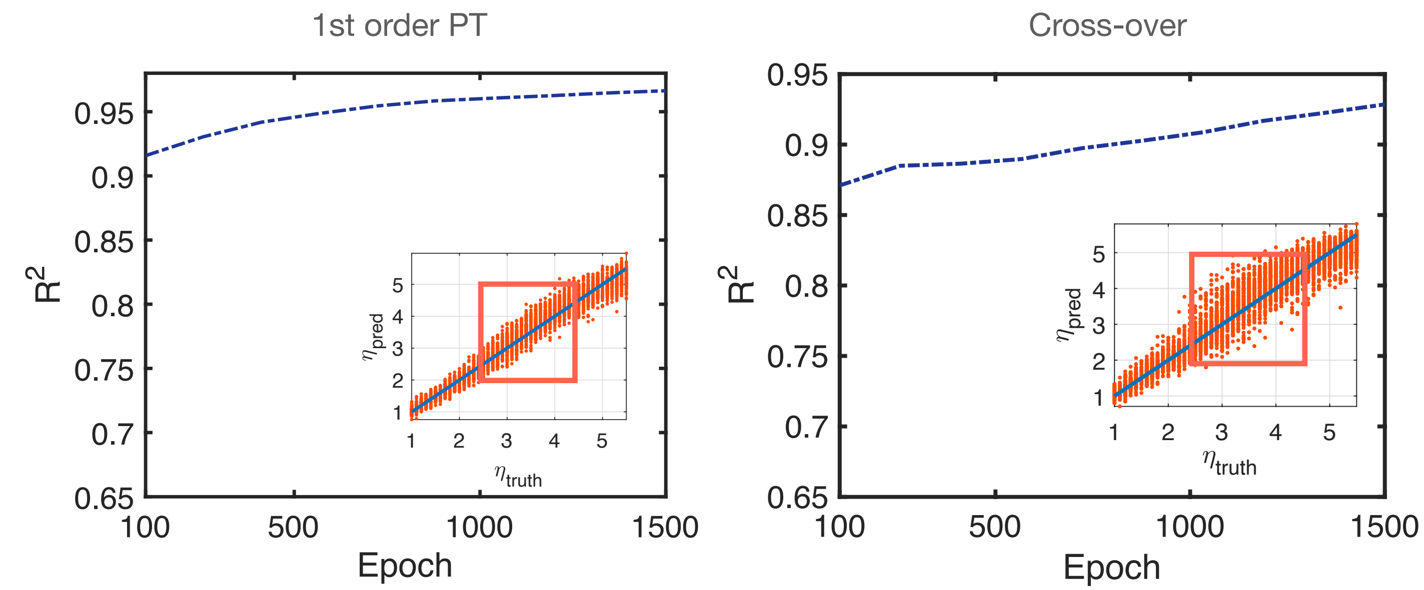
$$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}}$$

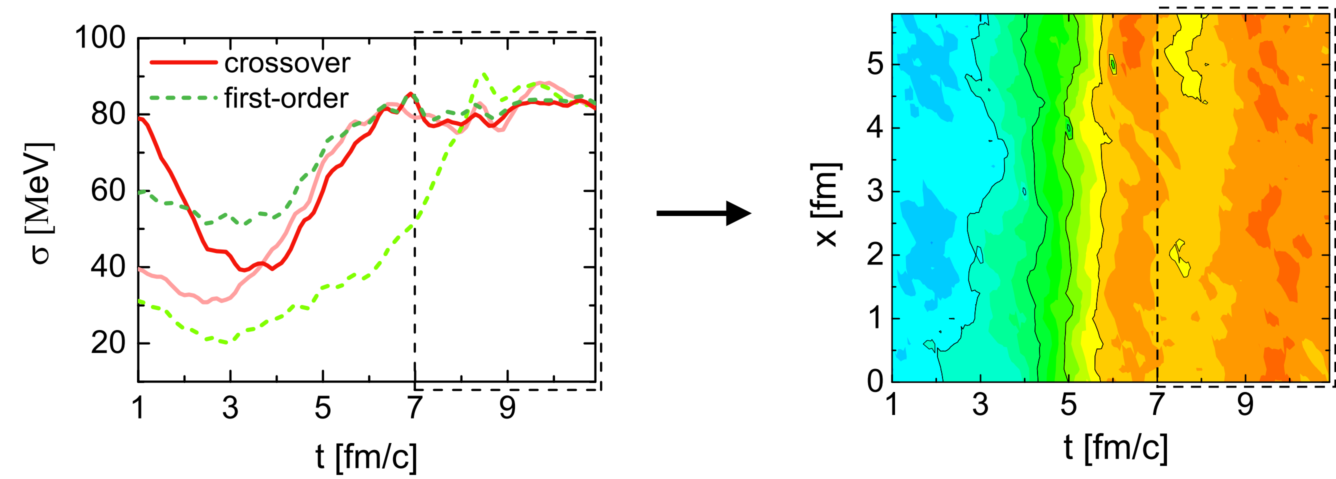
- **Testing**
  - Ground truth vs Predictions
  - $\eta = (2.6 - 4.5)\ \mathrm{fm}^{-1}$
- Learning dynamics of stochastic processes from configurations driven by the damping coefficient

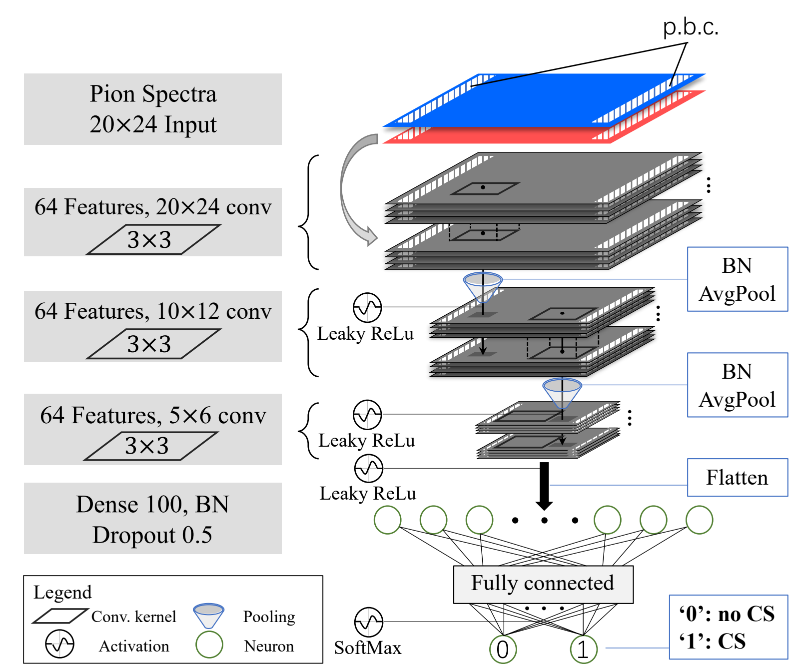


Summary

Summary
and Outlooks

- **Take-home messages**
  - Treat time-series as images
  - Learn dynamics from a stochastic process
  - The phase transition informations are encoded in the latent stage
- **Related works**
  - Detecting CME
    - from Pion Spectra
    - as a CME-meter
    - validated in AuAu and ZrZr, RuRu collision systems



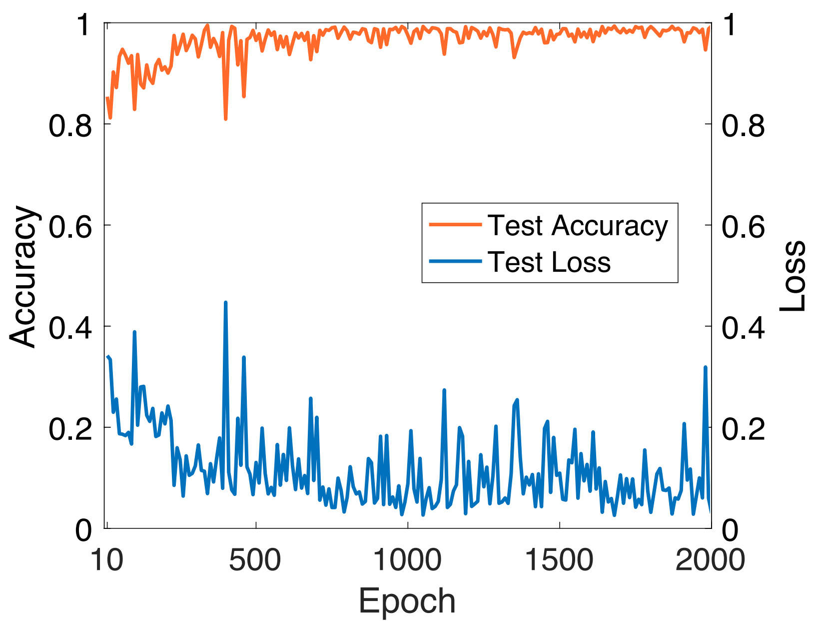


Yuan-Sheng Zhao, Lingxiao Wang, Kai Zhou, Xu-Guang Huang, ***ArXiv:2105.13761***

Summary
and Outlooks

- **Take-home messages**
  - Treat time-series as images
  - Learn dynamics from a stochastic process
  - The phase transition informations are encoded in the latent stage
- **Future works**
  - 2+1D Langevin equation
    - Preparing $\sigma(x, y, t)$
    - Conv3D layers
  - Track dynamics with Generative Models

Testing performance on 2+1D evolutions



Faces generated by Generative Adversarial Networks(GANs)

Future

AI in Physics, opportunities and challenges