Identifying QCD transition using a hybrid model and deep learning

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ABSTRACT

In this work, we have pushed forward our previous exploratory study on identifying QCD transition from hydrodynamics simulation data of heavy-ion collisions via state-of-the-art deep learning techniques[1]. By incorporating the hadronic cascade model (UrQMD) after the (2+1)-D relativistic viscous hydrodynamics evolution with a hybrid model (iEBE-VISHNU) [2], we simulate the heavy-ion collisions in a more practically way.

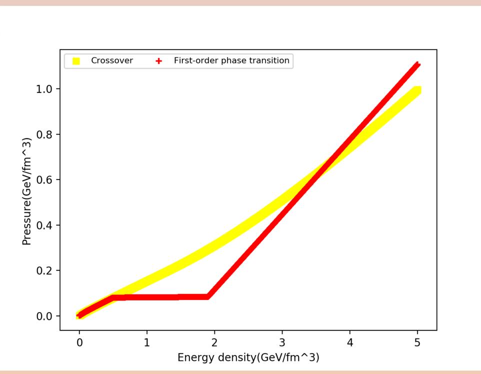
A deep convolutional neural network (CNN) is constructed and trained in supervision to identify the QCD transition from the averaged final-state pion spectra ρ(pT,φ) within the same centrality bin width 1%. Hidden correlations in ρ(pT , φ) are captured by the neural network, which serves as an effective "EoS-meter" in distinguishing the nature of the QCD transition. The EoS-meter is robust against many simulation inputs, such as the collision energy, fluctuating initial conditions, equilibration time, shear viscosity and switching criterion. Thus the EoS-meter provides a powerful tool as the direct connection of heavy-ion collision observables with the bulk properties of QCD.

THE HYBRID MODEL

The iEBE-VISHNU package can perform event-by-event simulations for many different stages of relativistic heavy-ion collisions at different energies:

➢ Fluctuating initial condition generator (MCGlaber or MCKLN).

➢ 2+1 D Viscous H



EoS is necessary as input to close the hydrodynamic equations. In this work, we are trying to classify the EoS of crossover (dubbed as EOSL) and first-order transition (dubbed as EOSQ) from the final-state pion spectra ρ(pT,φ).

➢ UrQMD afterburner

NEURAL NETWORK

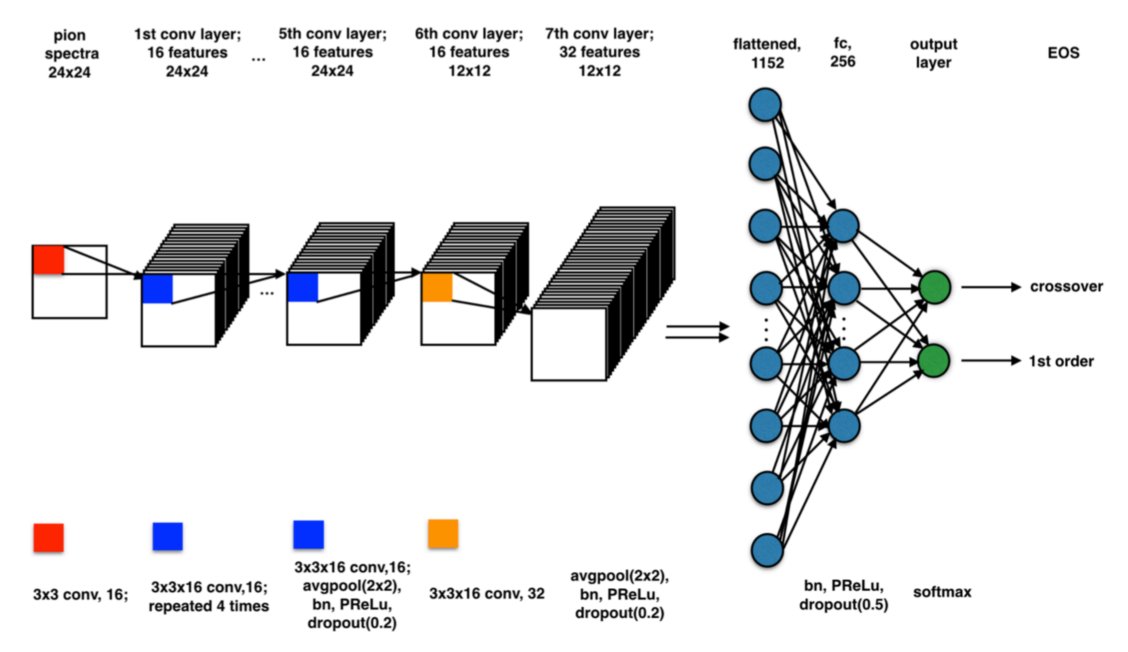


FIG. 1: Our convolution neural network (CNN) architecture for identifying the QCD transition by using pion spectra with 24 transverse momentum p_T bins and 24 azimuthal angle Φ bins.

- In a convolutional layer, each neuron only locally connects to a small chunk of neurons in the previous layer by a convolution operation - this is a key reason for the success of the CNN architecture.
- Average pooling layers reduce the dimension of tensor. PReLU activation layers make non-linear transformation.
- The features in the last convo layer are flattened and then connected to a 128-neuron fully connected layer for the further binary classification.
- Dropout[3], batch normalization[4], PReLU[5] and L2 regularization[6] work together to prevent overfitting that may generate model-dependent features from the training dataset and thus hinder the generalizability of the method.
- There are overall 168118 trainable and 292 non-trainable parameters in our neural network.

DATASETS AND DATA PREPROCESSING

In contrast to the final spectra of particles from hydrodynamics simulation, which are sampled as smooth functions of high statistics from Cooper-Frye formula, the histogram of individual particles' spectra ρ(pT , φ) from hadronic cascade model are sparse matrix of great fluctuations since plenty of probabilistic collisions and decays are involved. In order to accumulate statistics of the inputs fed into the neural network, it is essential and effective to average over the final spectrum of certain numbers of events, say, 30 ones, within the centrality bin width 1% and same parameters setup as the input ρ(pT , φ) with the size of 24×24.

TRAINING DATASET1		
Centrality bin	EOSL	EOSQ
4%-5%	2539	2540
14%-15%	1022	1024
20%-21%	2814	2816
30%-31%	2560	2560
40%-41%	1024	1024
50%-51%	896	1024

TABLE I: Training dataset 1: numbers of $\rho(p_T, \Phi)$ generated by the iEBE-VISHNU package with the Glauber initial conditions in the centrality range 0-60%. Ratio of shear viscosity to entropy density $\eta/s = 0.08$, equilibration time $\tau_0 = 0.5$ fm/c. The freeze-out temperature is set to be 137 MeV. Pb-Pb $\sqrt{S_{NN}} = 2.76$ TeV.

TRAINING DATASET2		
Centrality bin	EOSL	EOSQ
0%-1%	979	1024
10%-11%	2560	2560
20%-21%	1024	1024
30%-31%	1024	1024
40%-41%	2560	2560
50%-51%	2816	2816

TABLE II: Training dataset 2: numbers of $\rho(p_T, \Phi)$ generated by the iEBE-VISHNU package with the Glauber initial conditions in the centrality range 0-60%. Ratio of shear viscosity to entropy density $\eta/s = 0.00$, equilibration time $\tau_0 = 0.4$ fm/c. The freeze-out temperature is set to be 137 MeV. Au-Au $\sqrt{S_{NN}} = 200$ GeV.

As for the standardization of the datasets, we employ the feature standardization rather than the sample standardization.

PREDICTIVE ACCURACY FOR TESTING DATA								
Centrality bin	$\sqrt{S_{NN}}$	Initial Cond	τ_0 (fm/c)	η/s	T_{fo}	EOSL	EOSQ	Accuracy
15%-16%	200 GeV	MCGlb	0.4	0.00	141 MeV	512	512	89.1%
15%-16%	200 GeV	MCGlb	0.4	0.00	140 MeV	2560	2560	95.6%
45%-46%	200 GeV	MCGlb	0.6	0.12	130 MeV	1024	1024	100%
25%-26%	2.76 TeV	MCGlb	0.6	0.16	130 MeV	1024	1024	97.8%
25%-26%	2.76 TeV	MCGlb	0.6	0.12	130 MeV	2560	2560	97.4%
7%-8%	2.76 TeV	MCGlb	0.6	0.12	130 MeV	1280	1279	99.8%
17%-18%	2.76 TeV	MCGlb	0.6	0.12	130 MeV	2560	2560	98.1%

TABLE V: Test datasets with the different $\sqrt{S_{NN}}$, initial conditions, η/s, τ_0, and freeze-out temperature in the centrality range 0-60% and test accuracies

PREDICTIVE ACCURACY FOR TESTING DATA								
Centrality bin	$\sqrt{S_{NN}}$	Initial Cond	τ_0 (fm/c)	η/s	T_{fo}	EOSL	EOSQ	Accuracy
35%-36%	200 GeV	MCKLN	0.6	0.12	142 MeV	896	896	99.4%
15%-16%	200 GeV	MCKLN	0.6	0.12	137 MeV	512	256	98.6%
10%-11%	2.76 TeV	MCKLN	0.6	0.12	142 MeV	150	150	100%
25%-26%	2.76 TeV	MCKLN	0.6	0.12	137 MeV	256	256	84.4%

TABLE VI: Test datasets with the different $\sqrt{S_{NN}}$, initial conditions, η/s, τ_0, and freeze-out temperature in the centrality range 0-60% and test accuracies

CONCLUSION

- The validation and test accuracy can be achieved up to 99.1% and 96.3% on average, respectively, which are robust against different \sqrt{SNN}, fluctuating initial conditions, τ0, η/s, Tfo .
- The final spectrum of samples within centrality bin width 1% in the centrality region 0-50% is additive for extracting the EoS information.
- The existence of an "EoS-encoder" from the transition onto the final pion spectrum ρ(pT , φ) in heavy ion collisions even though hadronic rescatterings and resonance decays are included after the hydrodynamic evolution of the QCD medium.
- The neural network can serve as an effective "EoS-meter" on identifying the nature of QCD transition with well generalization performance.
- One crucial and constructive step towards the final goal of extracting the bulk property of QGP from the experimental raw data realistically.

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