

How to Identify the 1.O.P.T QCD Transition by using the Deep Learning Technique

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FIAS Frankfurt Institute
for Advanced Studies



HIC | **FAIR**
for
Helmholtz International Center

JOHANN WOLFGANG  GOETHE
UNIVERSITÄT
FRANKFURT AM MAIN

18 March, Darmstadt

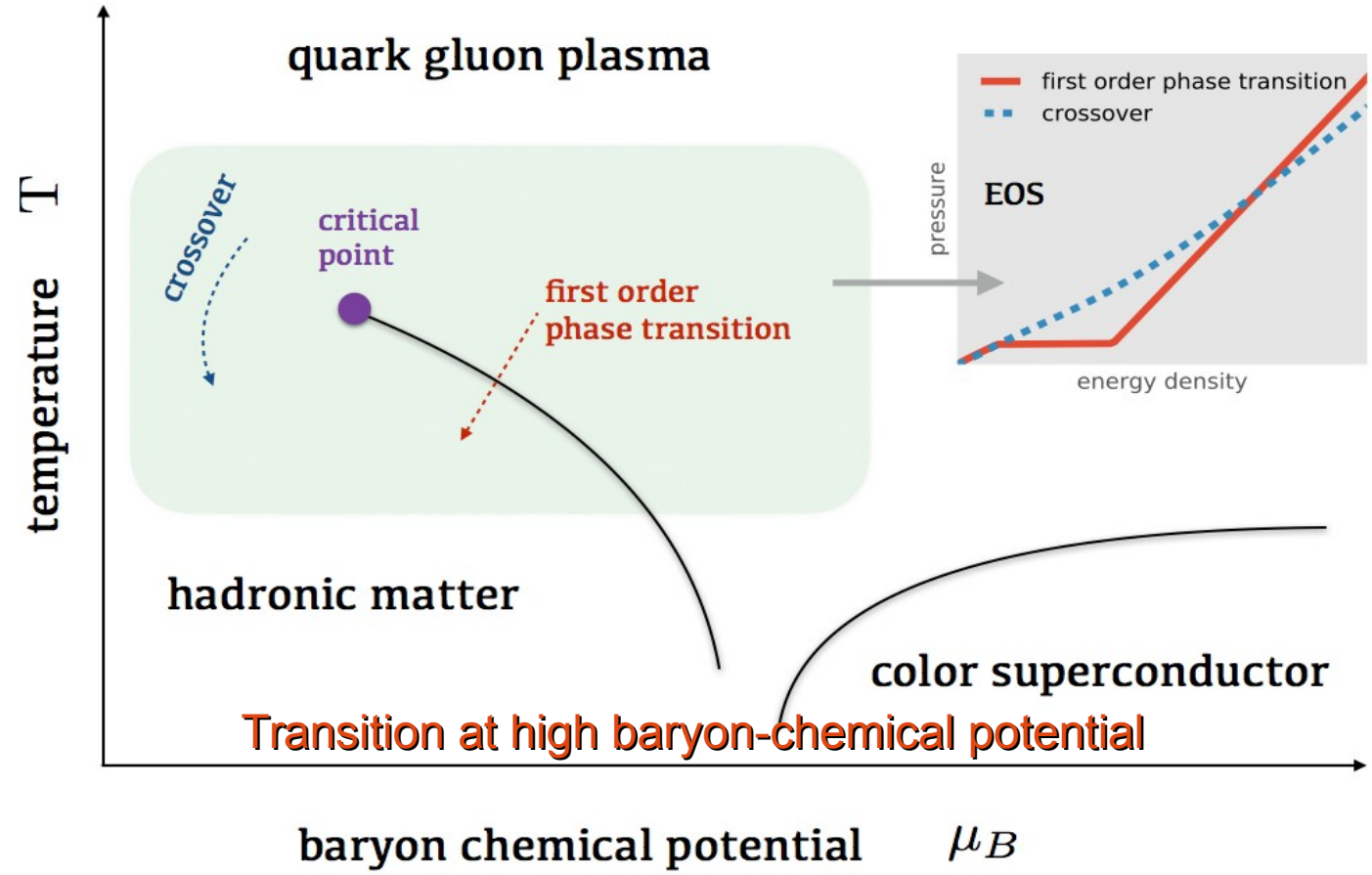
CBM - STAR joint Workshop

Outline

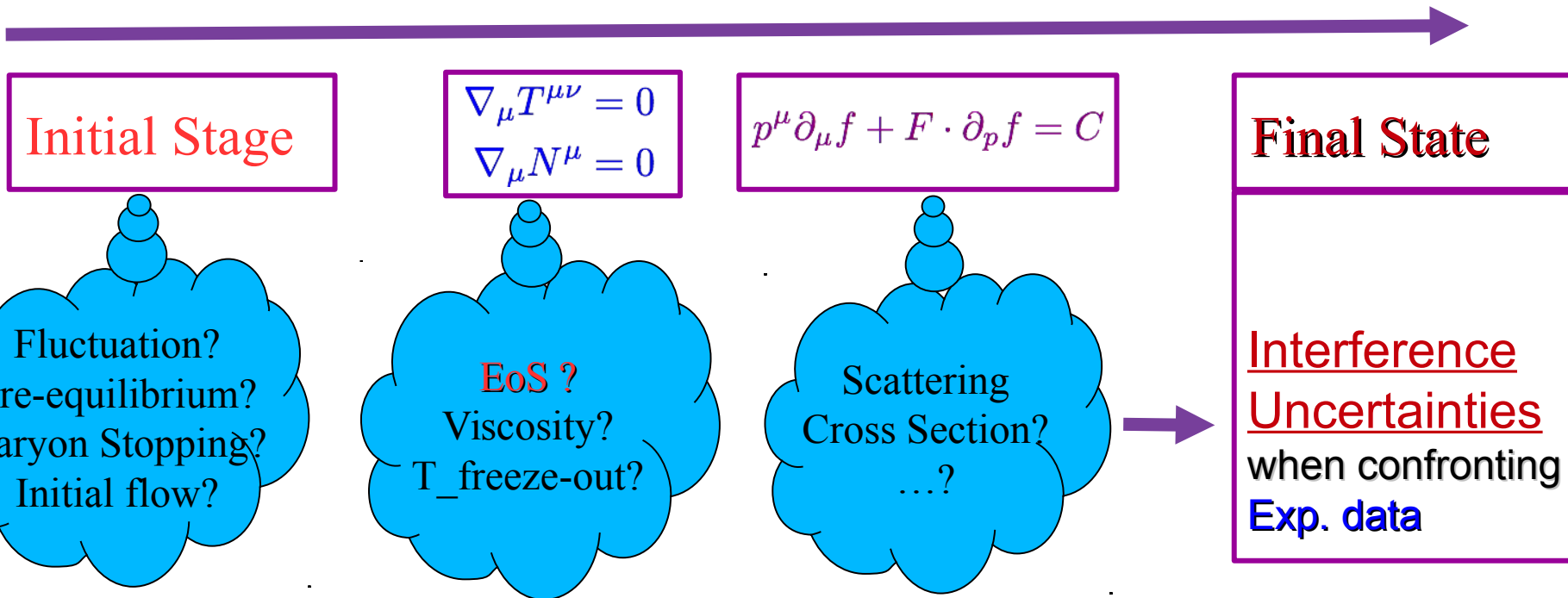
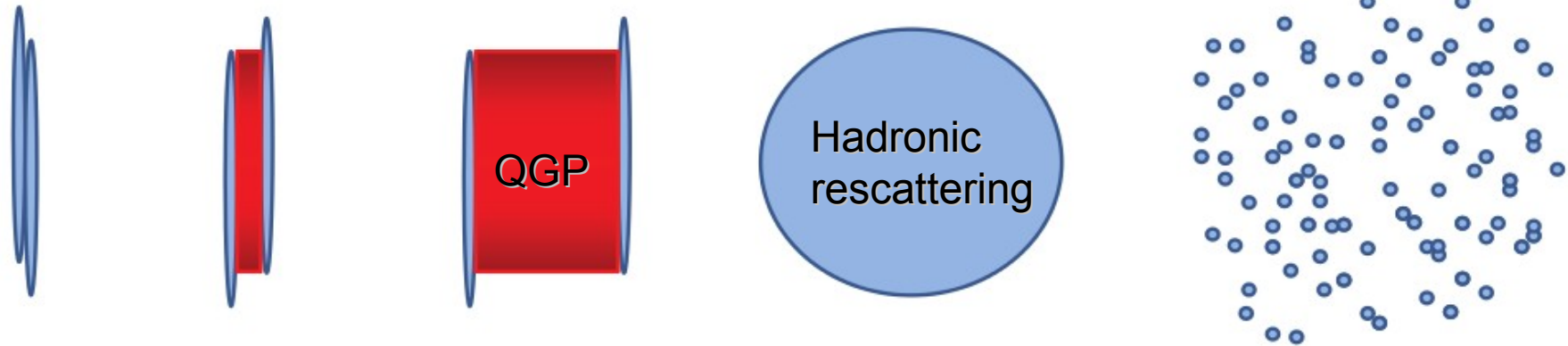
- Introduction: FAIR and RHIC & Deep Learning
- Convolutional Neural network for EoS-Meter
- Novel Perspectives & Outlook

Compressed matter in Heavy Ion Collisions FAIR and RHIC

QCD Transition: first order OR crossover



Standard HIC Model facing many Uncertainties



Deep Learning

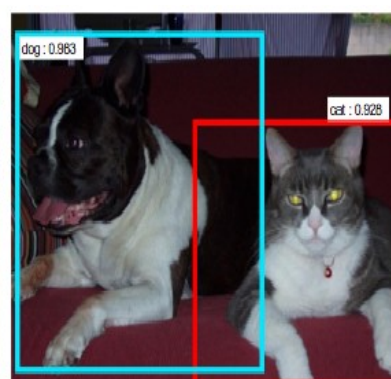
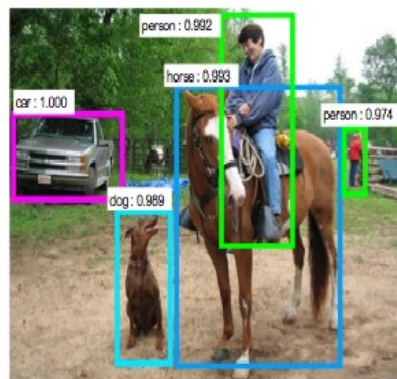
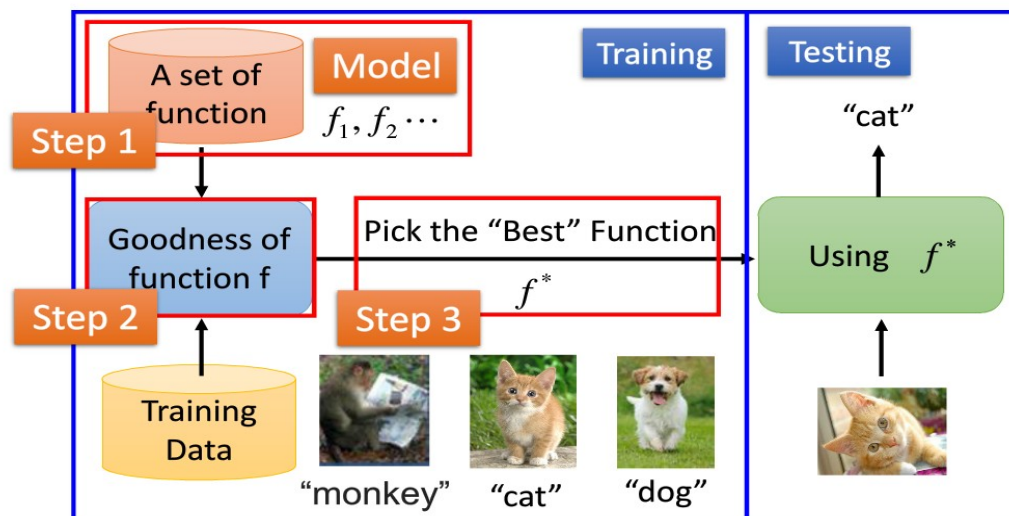


Image Recognition:

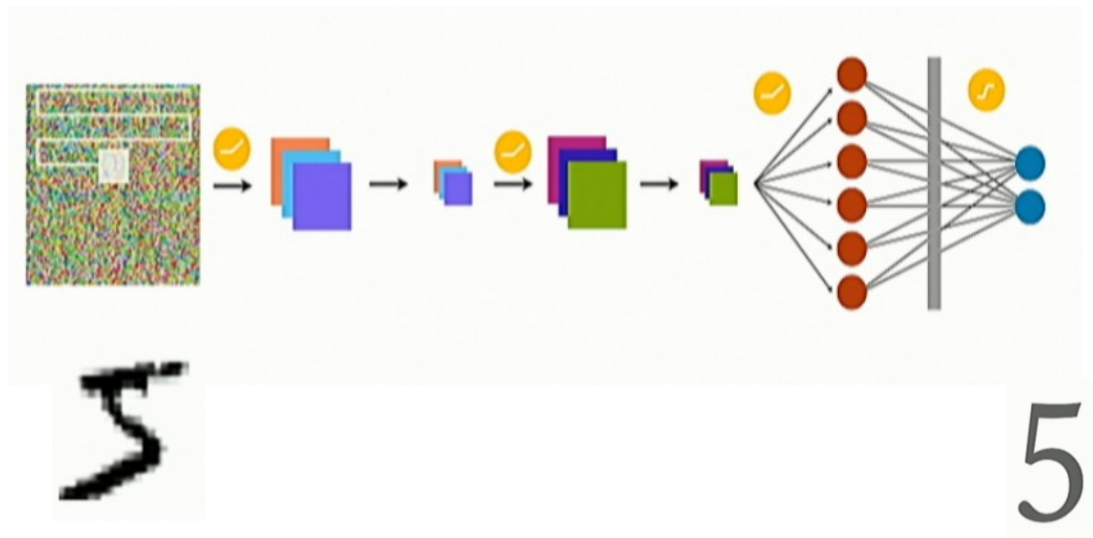
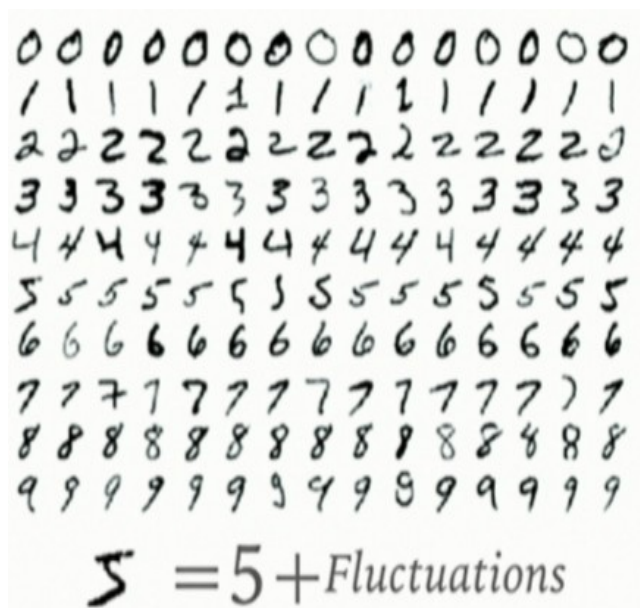
Framework

$$f(\text{cat image}) = \text{"cat"}$$



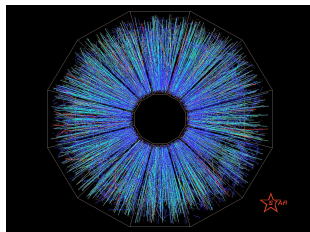
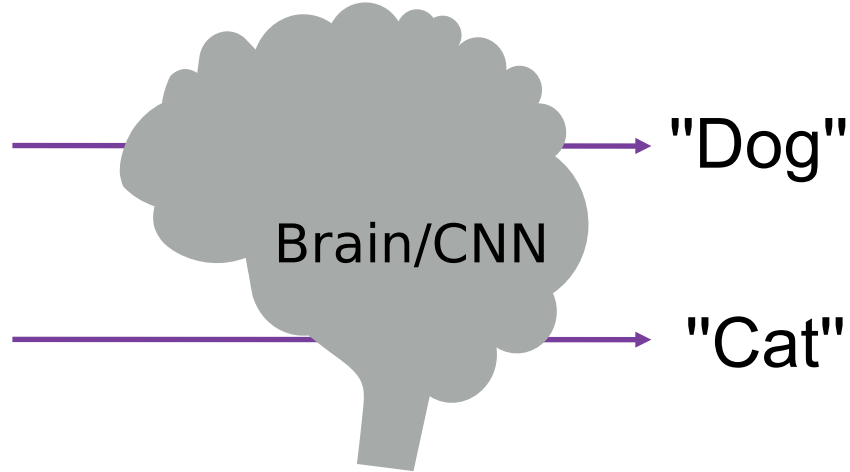
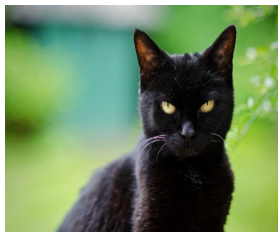
Find and Decode the mapping/representations into Deep Neural Network (----- function).

Convolutional Neural Network

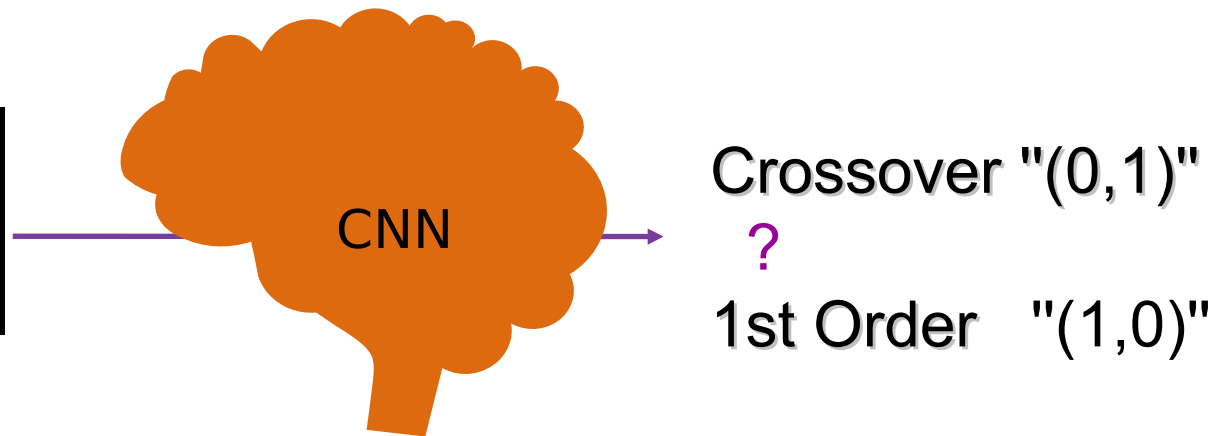


Convolutional Neural Network has proved to be extremely powerful in **Pattern Recognition, Image Classification**

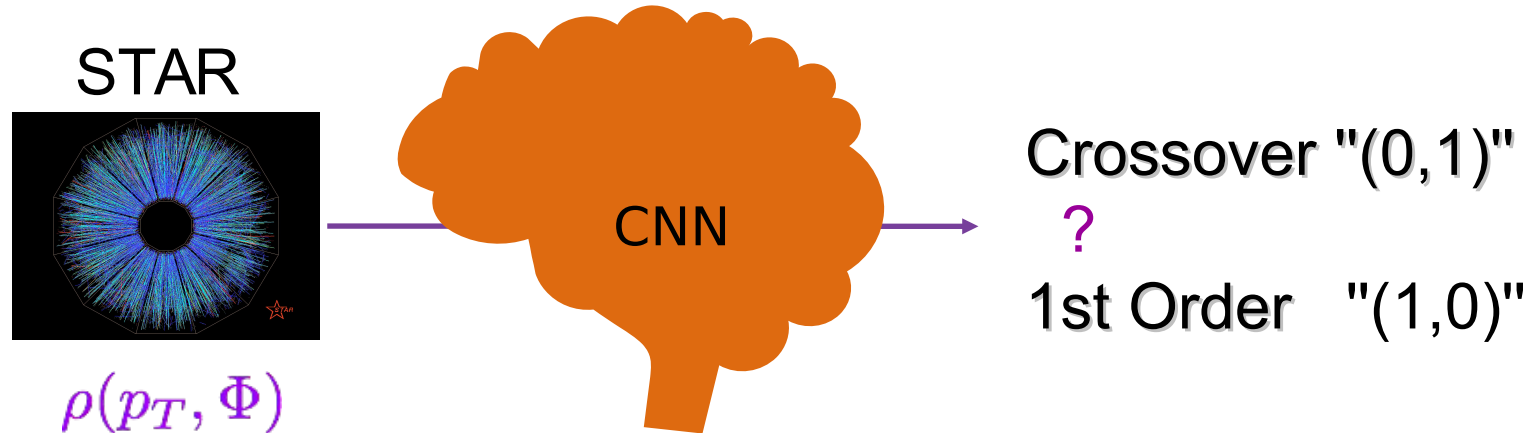
Inspired from Brain/CNN



$$\rho(p_T, \Phi)$$



Inspired from Brain/CNN



Supervised learning using deep Convolution Neural Network

with huge amount of labelled training data (spectra, EoS type) from

event-by-event relativistic Hydrodynamic simulations.

Training Dataset

Final Spectra for charged pions at mid-rapidity : $\rho(p_T, \Phi) \equiv \frac{dN_i}{dY p_T dp_T d\Phi} = g_i \int_{\sigma} p^{\mu} d\sigma_{\mu} f_i$

TRAINING DATASET		$\eta/s = 0$		$\eta/s = 0.08$	
		EOSL	EOSQ	EOSL	EOSQ
RHIC	Au-Au $\sqrt{s_{NN}} = 200$ GeV	7435	5328	500	500
LHC	Pb-Pb $\sqrt{s_{NN}} = 2.76$ TeV	4967	2828	500	500

➤ CLVisc 3+1 D viscous hydrodynamics with AMPT initial conditions

➤ τ_0 is 0.4 fm for Au-Au STAR and 0.2 fm for Pb-Pb

➤ $T_{\text{freeze-out}}$ is 137 MeV

~22000 events, doubled by left-right flipping along ϕ ,
10% for validation during the training

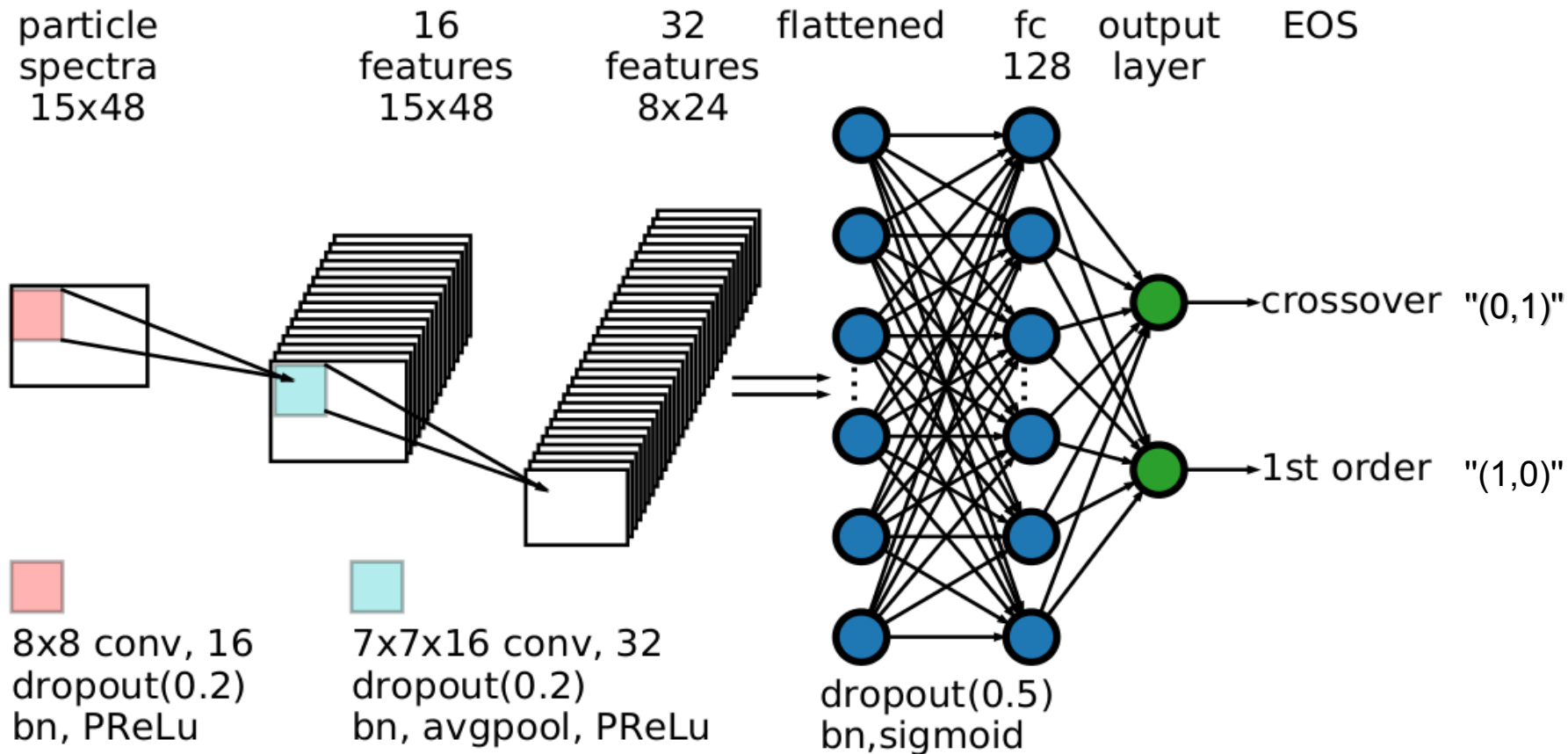
Testing Dataset

TESTING DATASET GROUP 1 : iEBE-VISHNU + MC-Glauber						
Centrality:	$\eta/s \in [0, 0.05]$		$\eta/s \in (0.05, 0.10]$		$\eta/s = (0.10, 0.16]$	
10-60%	EOSL	EOSQ	EOSL	EOSQ	EOSL	EOSQ
Au-Au $\sqrt{s_{NN}} = 200$ GeV	650	850	900	750	200	950
Pb-Pb $\sqrt{s_{NN}} = 2.76$ TeV	500	650	600	644	499	150
TESTING DATASET GROUP 2 : CLVisc + IP-Glasma						
Au-Au $\sqrt{s_{NN}} = 200$ GeV	EOSL			EOSQ		
$b \lesssim 8$ fm & $\eta/s = 0$	4165			4752		

- **iEBE-VISHNU** a hydro packag with a different numerical solver and with different initial condition (**MC-Glauber**)
- τ_0 is 0.6 fm , eta/s within [0, 0.16]
- **T_freeze-out** in [115, 142] MeV for iEBE-VIS, 137 MeV for CLVisc

Convolutional Neural Network architecture

STAR,CBM...

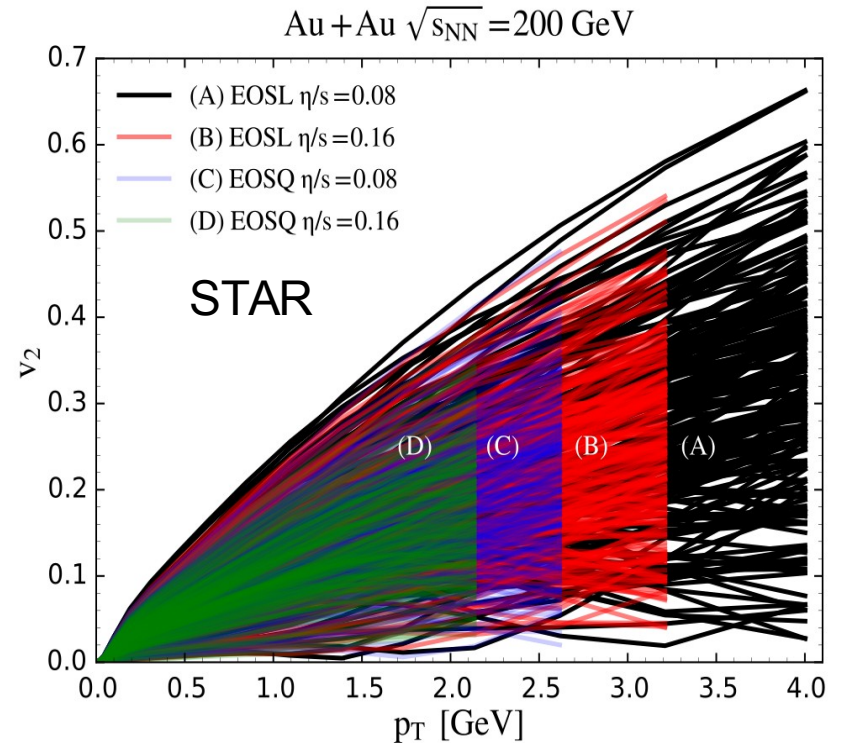
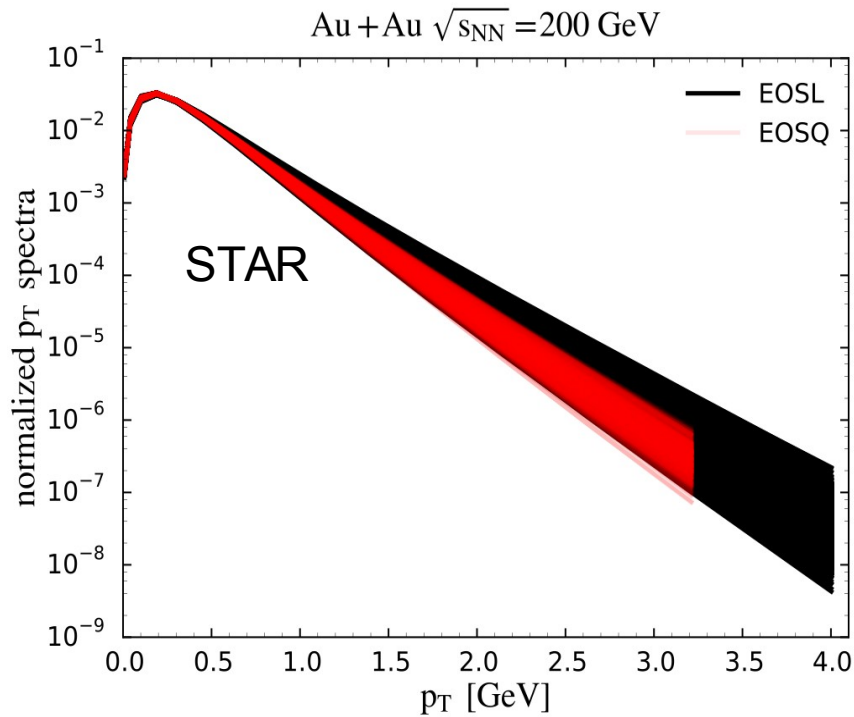


Testing Results

TESTING	1OPT		1OPT	
	GROUP 1		GROUP 2	
ACCURACIES	EOSL	EOSQ	EOSL	EOSQ
Number of events	3349	3994	4164	4752
Accuracy	98.5%	91.6%	99.2%	99.2%

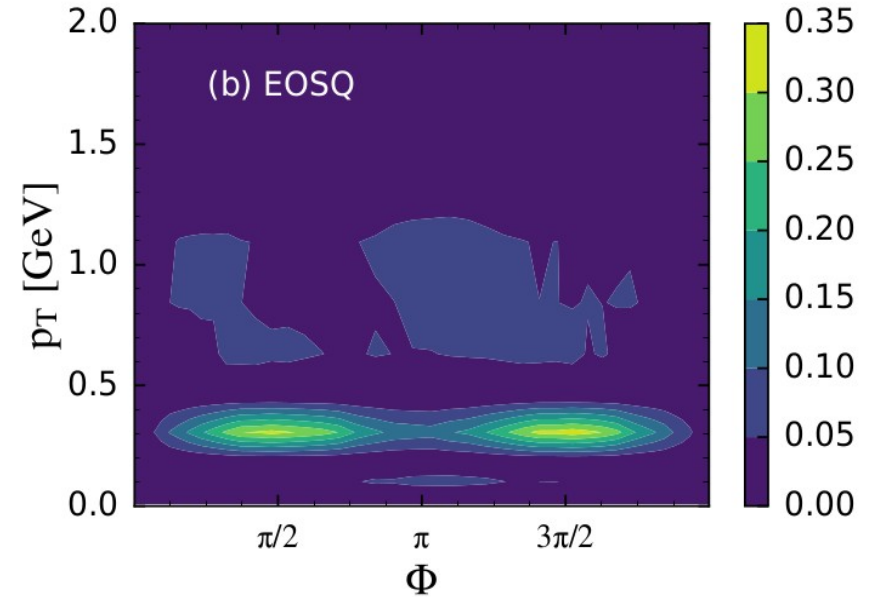
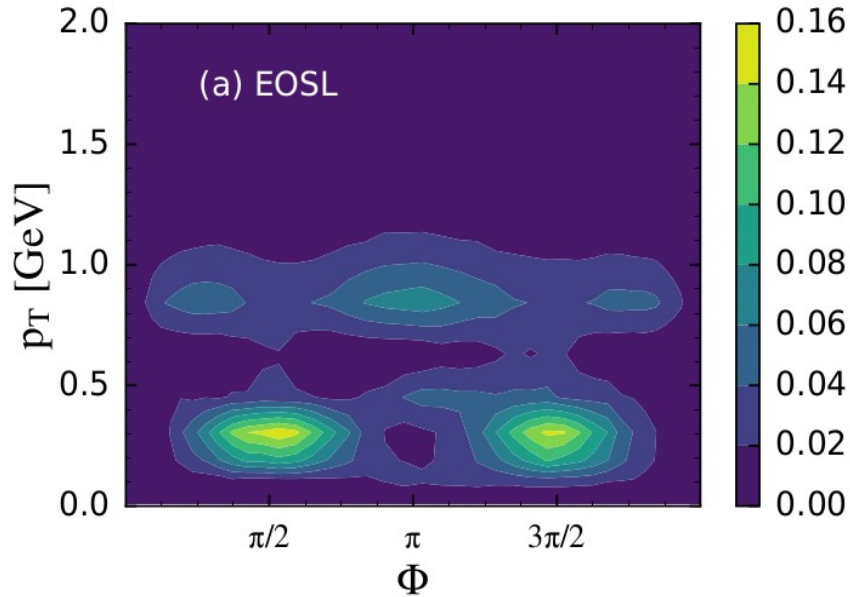
- On average **~97% prediction accuracy**, the trained CNN model identifies the type of QCD transition **solely from the raw spectra**
- The performance is **robust against** : initial conditions, η/s , τ_0 , T_{fo}
model independent!

Conventional Observables



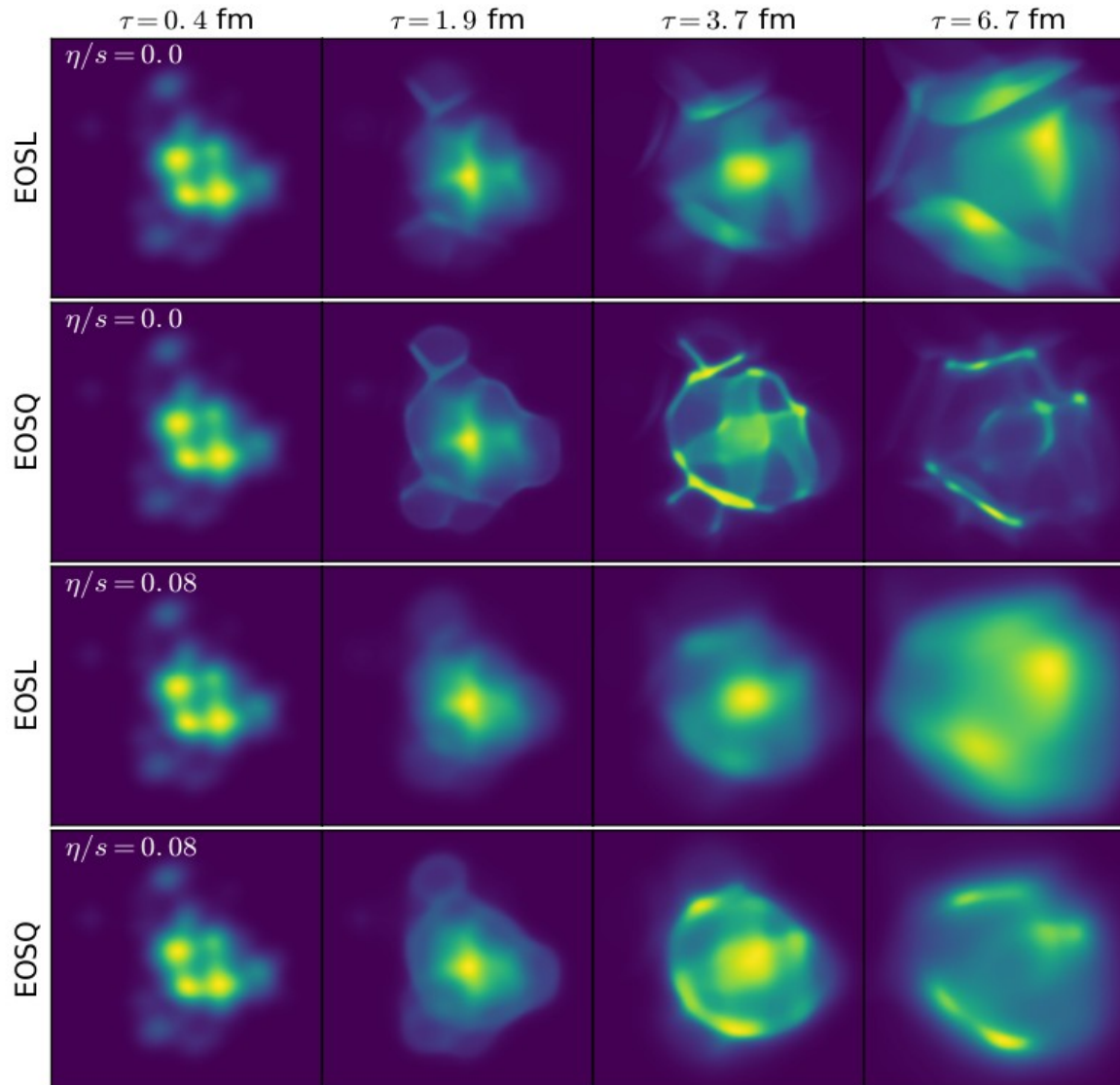
- Strongly depends on initial fluctuations and other uncertainties !

Importance Maps



- Distinct structure of relevant feature space for each class
- Low p_T relevance can be taken care of at FAIR/CBM & STAR/BES

Evolution history of QGP energy density in x-y plane



➤ Hot-spots in initial stage

➤ Hot ridges ~ 1.9 fm

➤ **Skeletons for EOSQ**
diffusion out for **EOSL**

➤ Cooper-Frye to spectra
?

Novel Perspectives

- We found the "**Encoder**" (mapping / projection) of the QCD Transition onto final state Raw Spectra (pT, phi)
Although it is NOT intuitive for traditional observables

This Encoder is **CLEAN** - robust to uncertainties and other parameters

- Deep CNNs provide powerful and efficient "**Decoder**" for this "Encoder"
which can act as "**EoS-Meter**"
- Deep CNNs help to directly connect CBM & STAR with QCD properties
help searching for critical end point.

Outlook

- Extend to CBM & STAR data
- Other dynamical properties : η/s , bulk visc, freeze-out
- Use lattice configurations to correlate to CBM and STAR data
and study phase structure of QCD

Thank you !