Progress on DL applications at FIAS
Part II

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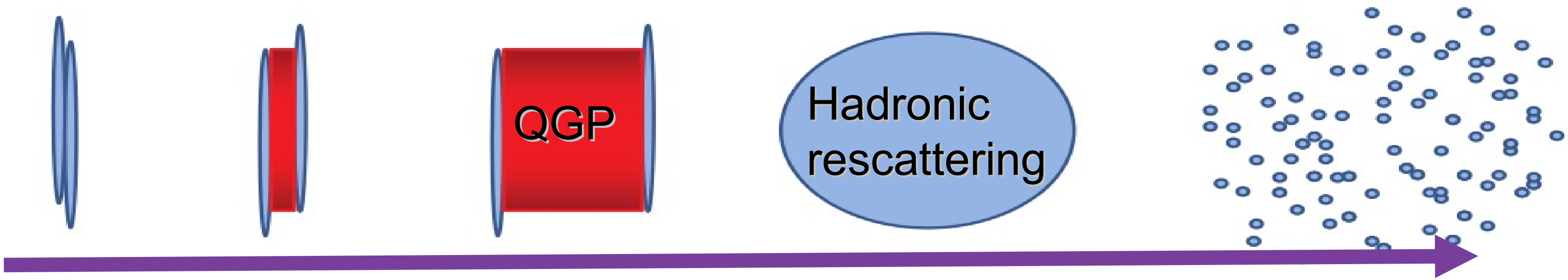
ErUM-Data collaboration Meeting

Projekts 1: Identifying nature of QCD transition in HIC with Deep Learning

(Paper to be online soon)

Standard HIC model - uncertainties



Initial Stage

$$\nabla_\mu T^{\mu\nu} = 0$$
$$\nabla_\mu N^{\mu} = 0$$

$$p^\mu \partial_\mu f + F \cdot \partial_p f = C$$

Final State

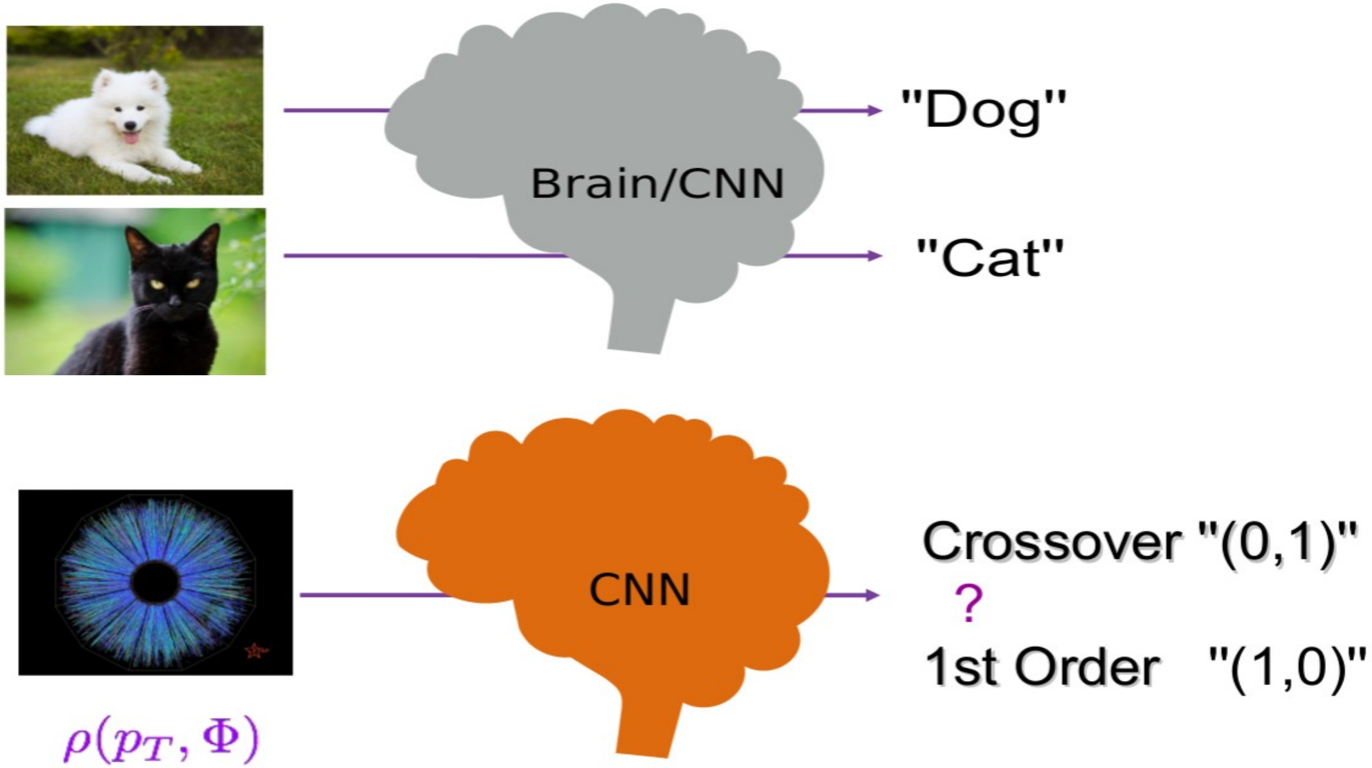
Fluctuation?
Pre-equilibrium?
Baryon Stopping?
Initial flow?

EoS ?
Viscosity?
q/h chemistry?
T_freeze-out?

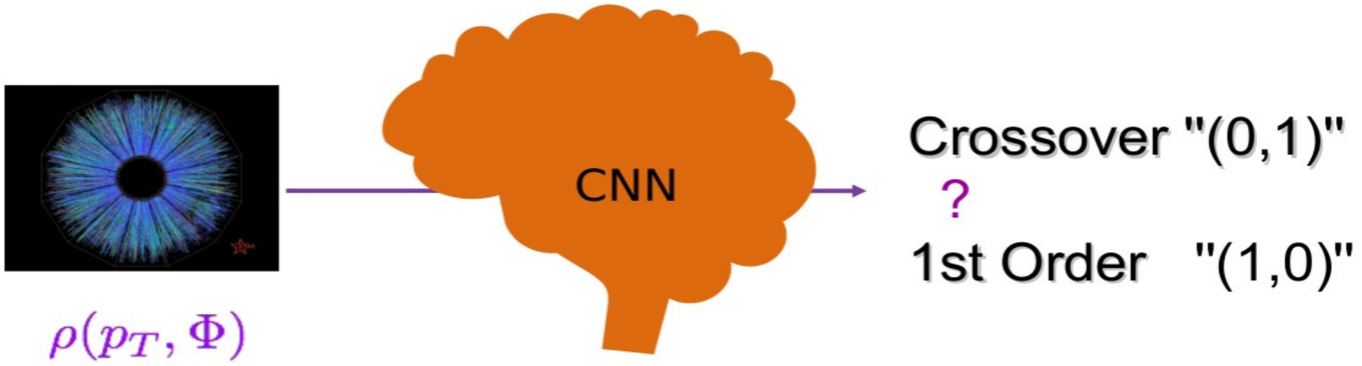
Scattering
Cross Section?
...?

Interference
Uncertainties
when confronting
Exp. data

Inspired from Brain/CNN



Supervised Learning for transition type Binary Classification



Supervised learning using deep CNN with huge amount of labelled training data *(spectra, EoS type)* from **event-by-event** relativistic HIC simulations

Results for pure Hydrodynamic simulation

TESTING DATA	GROUP 0	GROUP 1	GROUP 2
Number of events	4000	7343	8916
Accuracy	$99.88 \pm 0.04\%$	$93.46 \pm 1.35\%$	$95.12 \pm 3.08\%$

- On average ~95% prediction accuracy, the trained CNN model identifies the type of QCD transition solely from the raw spectra

- The performance is robust against : initial conditions, $\eta/s, \tau_0, T_{fo}$
  model independent!

- Caveats: Hadronic Resattering and Resonance decay lacking

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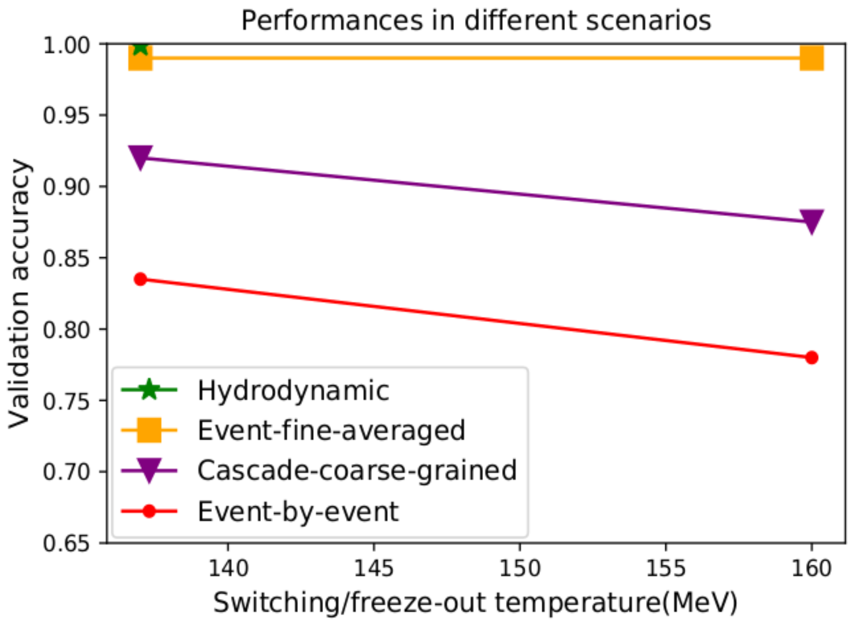
Hybrid Simulation (Hydro + 'afterburner')

1) hadronic cascade "afterburner" is considered:
   finite number of particles, resonance decays

2) Information about EoS in early dynamics is
   not swiped away inside the final-state pion
   spectra – *perspective from deep CNN*

3) more **stochasticity** from resonance decays
   and elongated hadronic cascade **diminish**
   the correlation

4) **enhancement of statistics** and **reduction**
   of fluctuations helps **facilitating** the revealing
   of EoS information via deep CNN



Projekts 2: Anomaly detection for HIC events selection

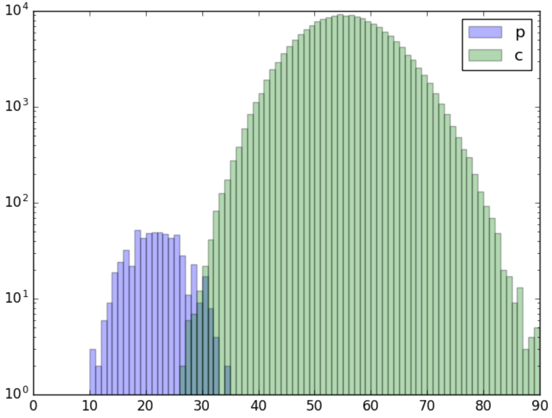
(Paper to be online soon)

Need to find out outliers in HIC events selection

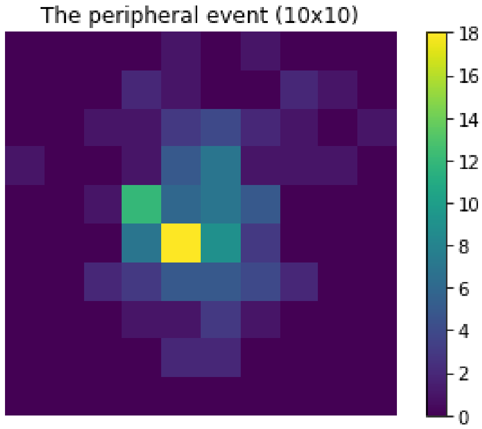
1) In experiments it's crucial to detect new physics more effectively

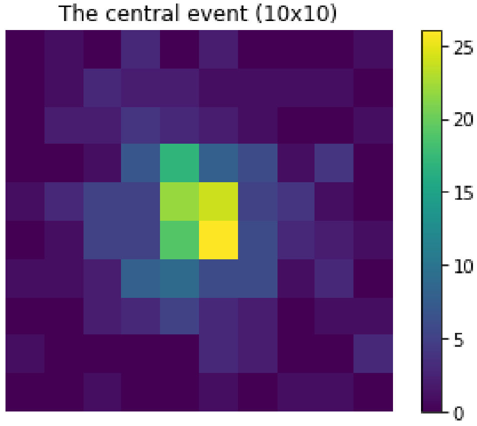
2) Two/multi event classes can explain the cumulants from STAR :
Proton number distribution implies anomaly existence ——
need an Independent way to confirm the events selection.
Also need to identify these outlier events.

3) Number of charged particles are used to select events in centrality classes : centrality selection before phy. analysis might miss some phys.
—— is there alternative way, e.g. using **normalized mom-spectrum**?



Number of proton number



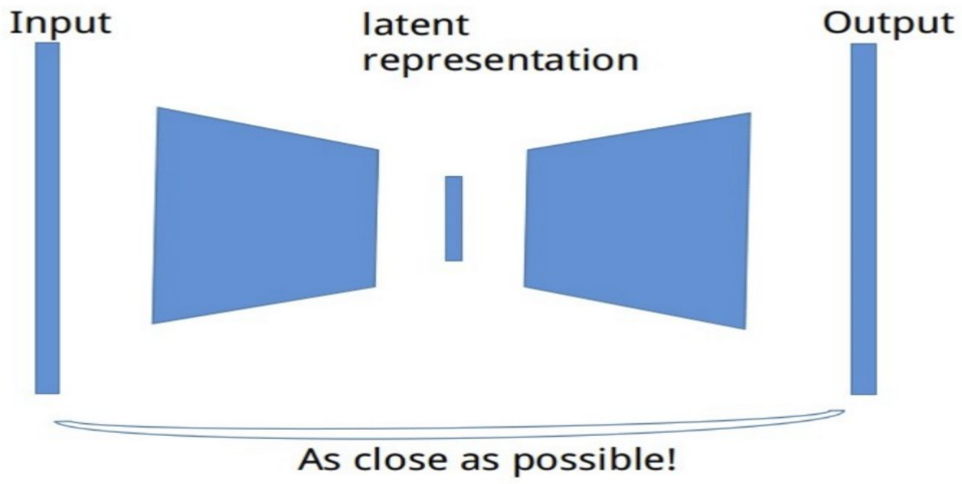


Anomaly detection using unsupervised learning

1) **Principle Components Analysis** and **Autoencoder** help selecting anomaly events

2) **Principle Components** from PCA or **Latent Space** from AE encode compact information about the data structure

3) **Reconstruction Error** (RE) can help identifying the outliers/anomalous



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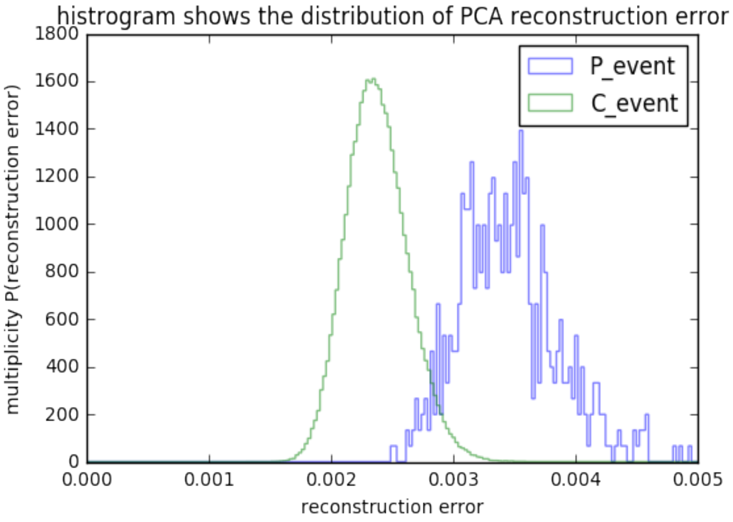

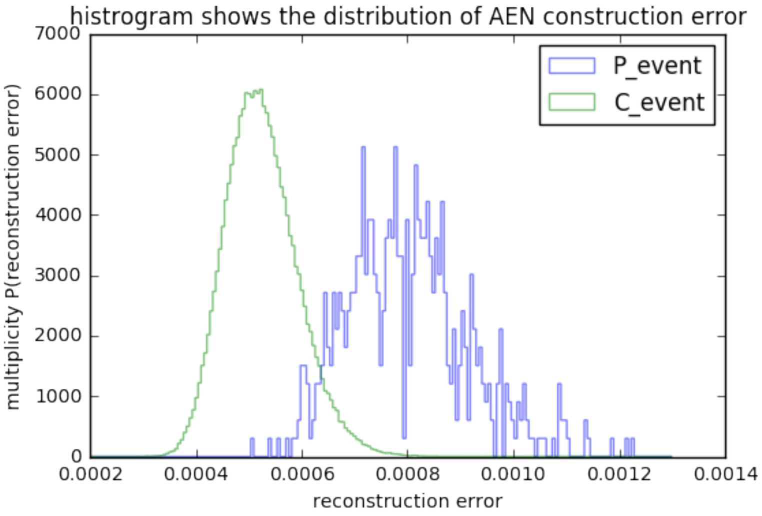

Anomaly detection using unsupervised learning

2) **ROC** curve shows that PCA outperforms AutEnc for 10x10 with 5-d or 10-d latent space

3) for PCA, here lower dimensional latent space does better job in finding outliers.

4) from a preliminary try, the CNN doen't do better here.