Progress on DL applications at FIAS
Part I

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for Advanced Studies

Group Status – FIAS
People working on the project or project related topics

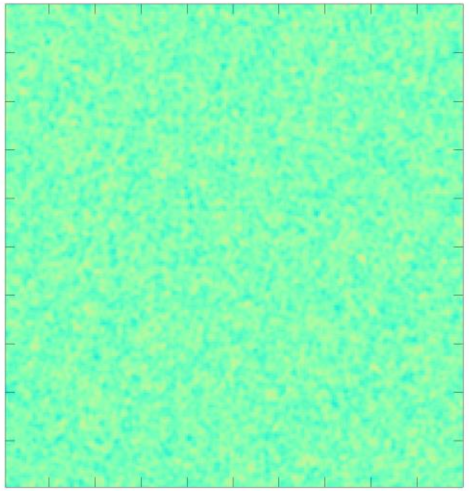
- Dr. Kai Zhou (Funded in part by ErUM-Data and by Samson AG donation)
- Dr. Jan Steinheimer (Funded in part by ErUM-Data and by Samson AG donation)
- Dr. Kyrill Taradyi (Funded by Stiftung Polytechnische Gesellschaft)
- Dr. Olena Linnyk (funded by Samson AG donation)
- Mr. Manjunath Omana Kuttan (PhD Student, funded by Samson AG donation)
- Mrs. Shriya Soma (PhD Student, funded by Samson AG donation)
- Mr. Punnathat Thaprasop (Visiting Master Student from SUT Thailand)

- 1 paper submitted, 1 paper to be submitted, 2 directly related projects running.

Old Project

Identifying Spinodal clumps using deep learning

- An important goal of HIC is the search for the QCD phase transition
- Spinodal decomposition is a unique feature of dynamical phase transitions
- But: How to design observables and what to expect event-by-event wise.



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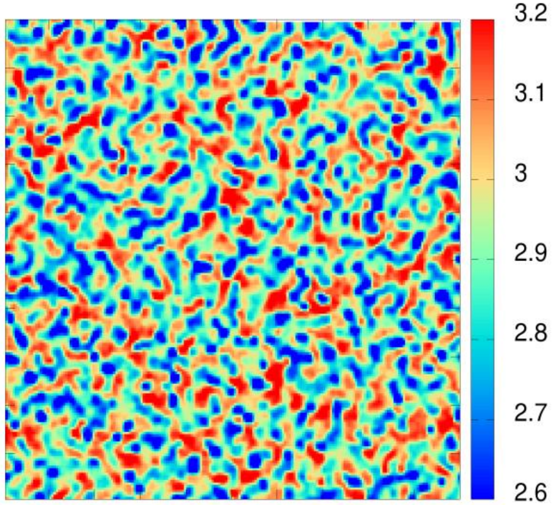

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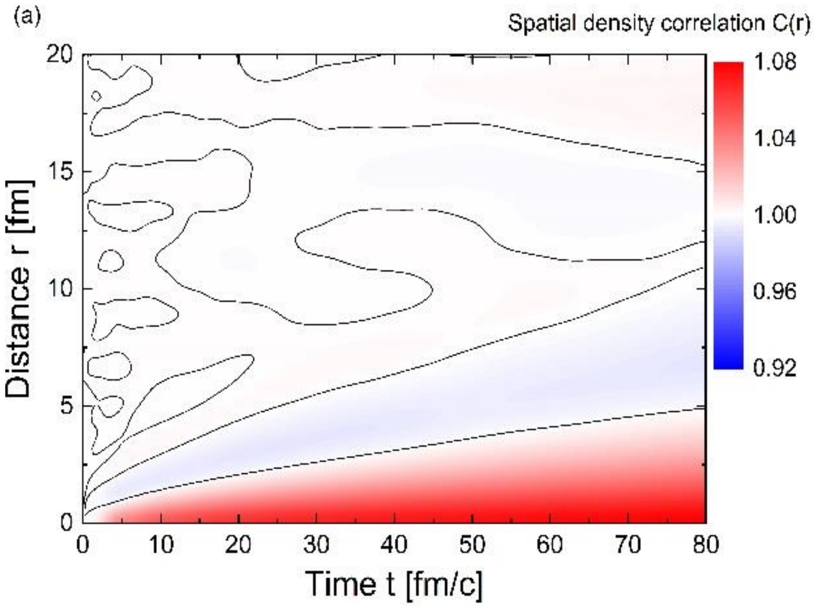
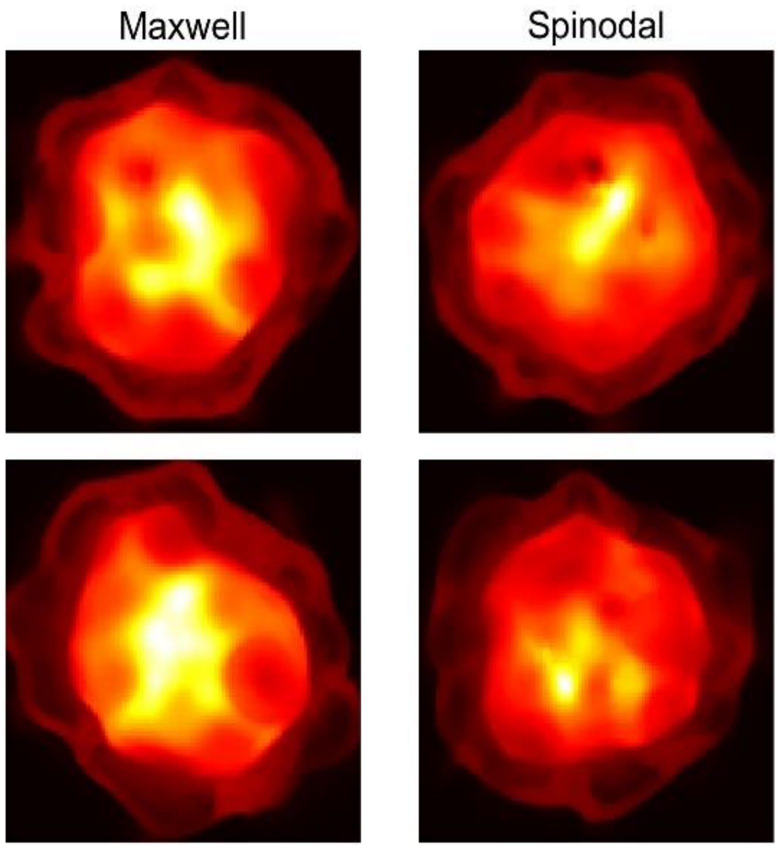
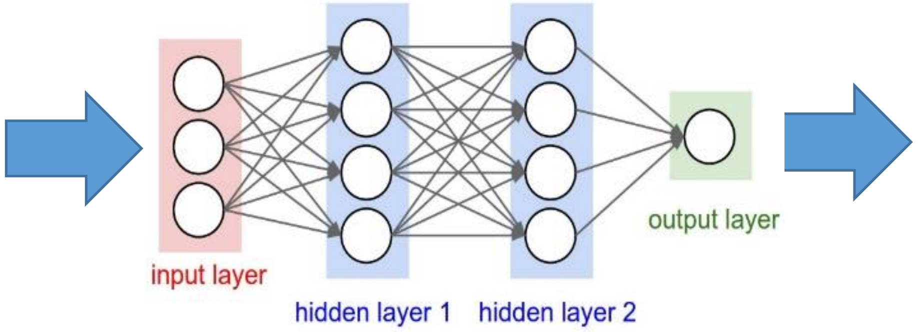
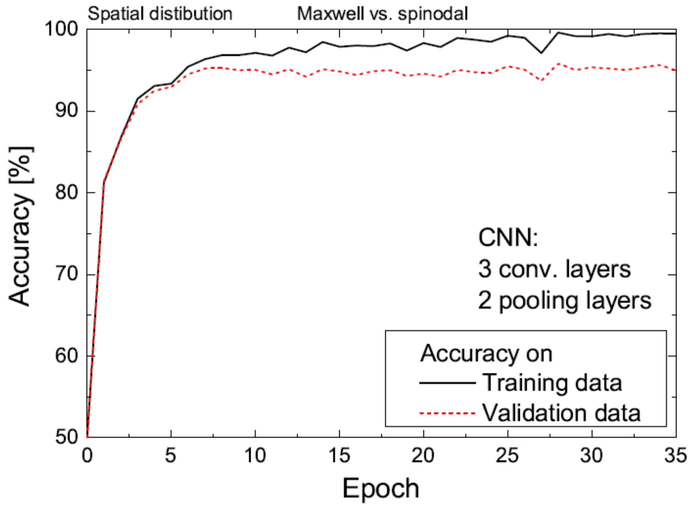






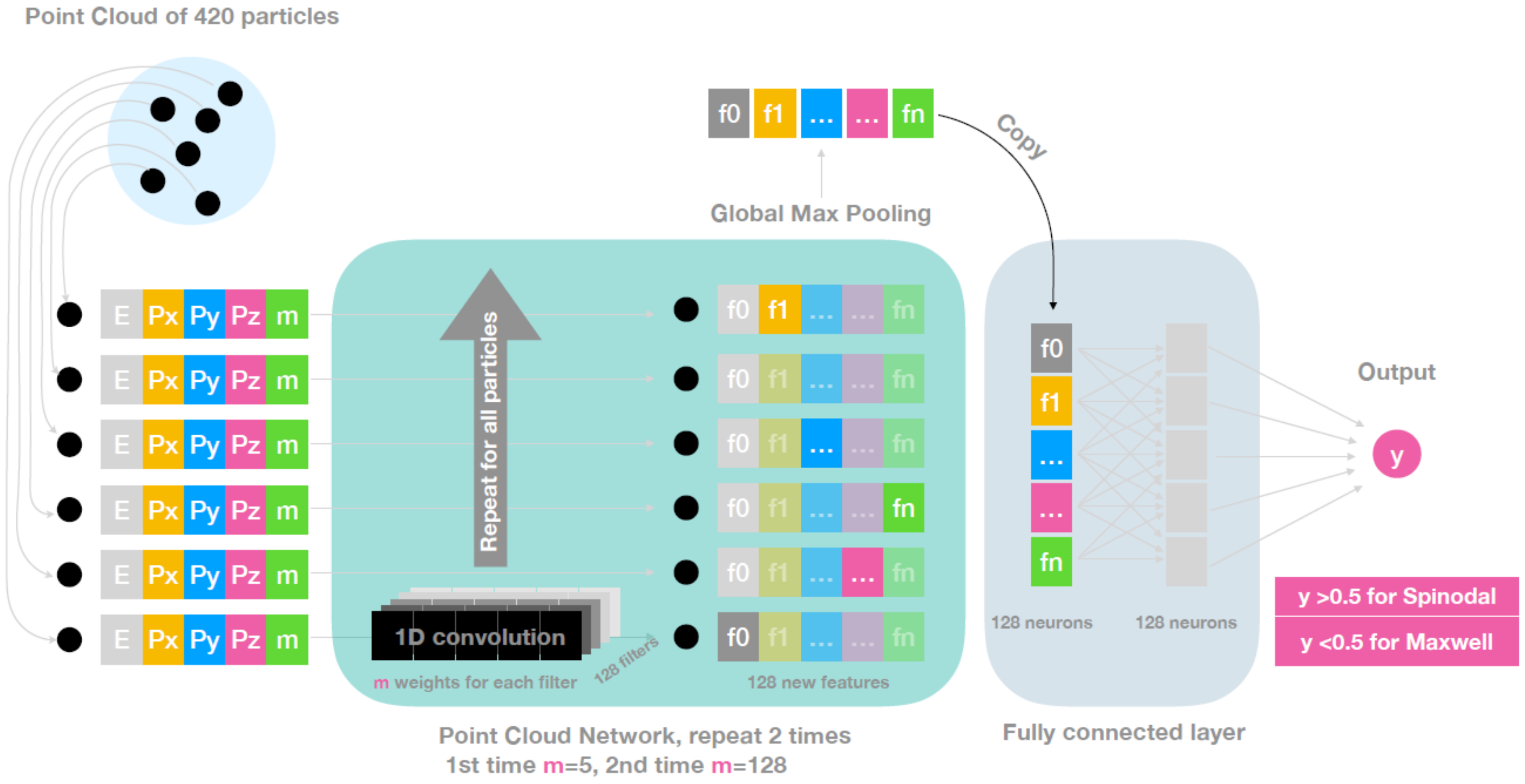


Results (Paper is with journal, should be published soon)**:**

- A CNN works well to identify the clumps in coordinate space event-by-event > 94% accuracy

How to got to momentum space correlations?

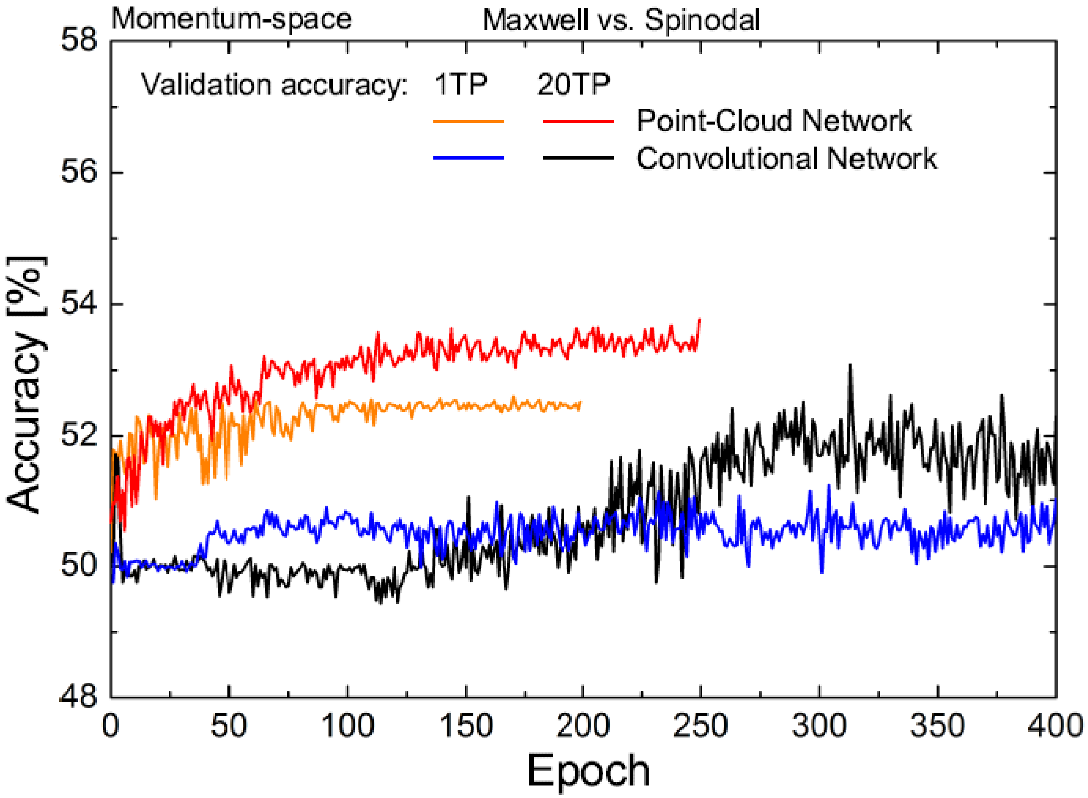
- First issue: discrete particles/tracks are measured.
- Translating this into a 2D image for a CNN may loose information.



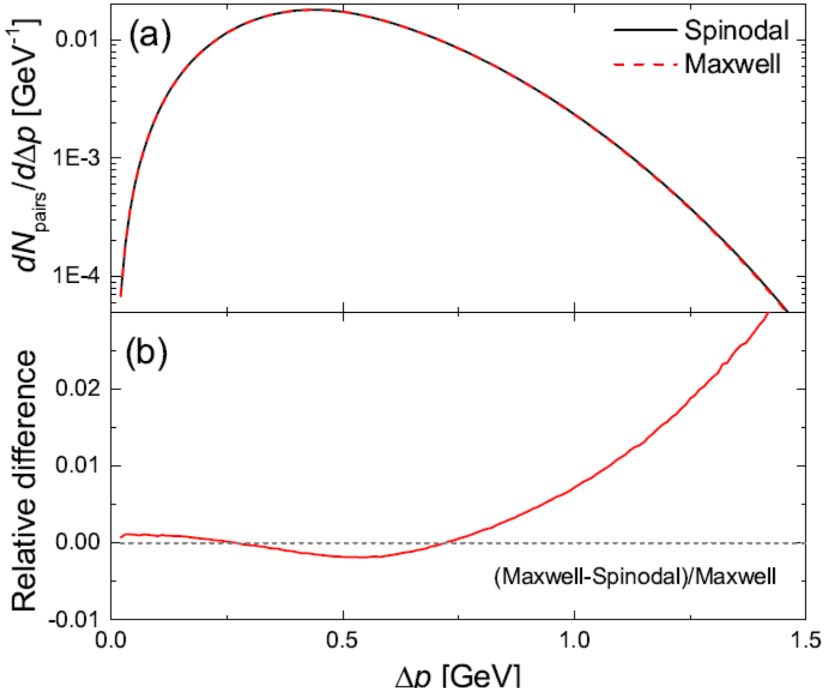
A point cloud network

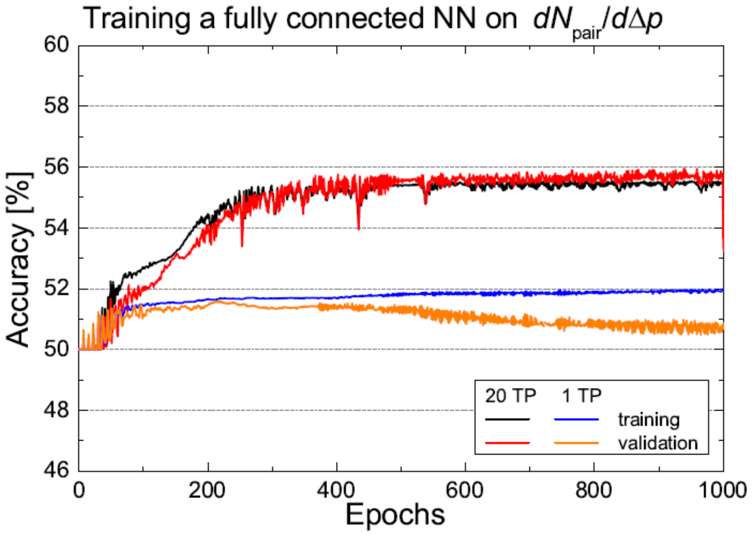
- Each particle has 5 features
- For events with less than the maximum particles, pad with zeros.
- Can deal with discrete particles and varying list length.

- Momentum space it is much worse: correlations are more hidden.
- Can the network stand up to a handcrafted feature?



Handcrafted feature: Two particle correlation function

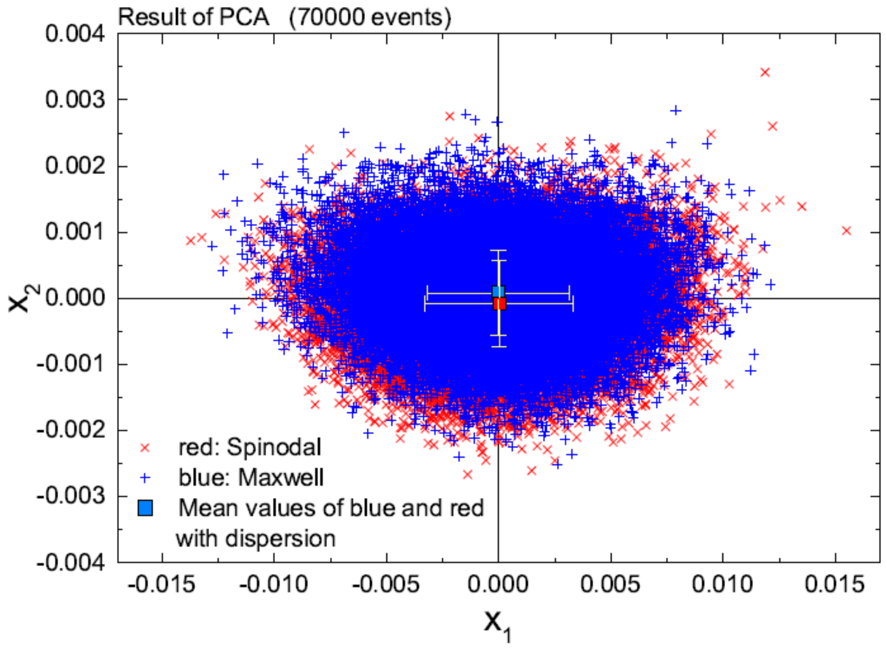


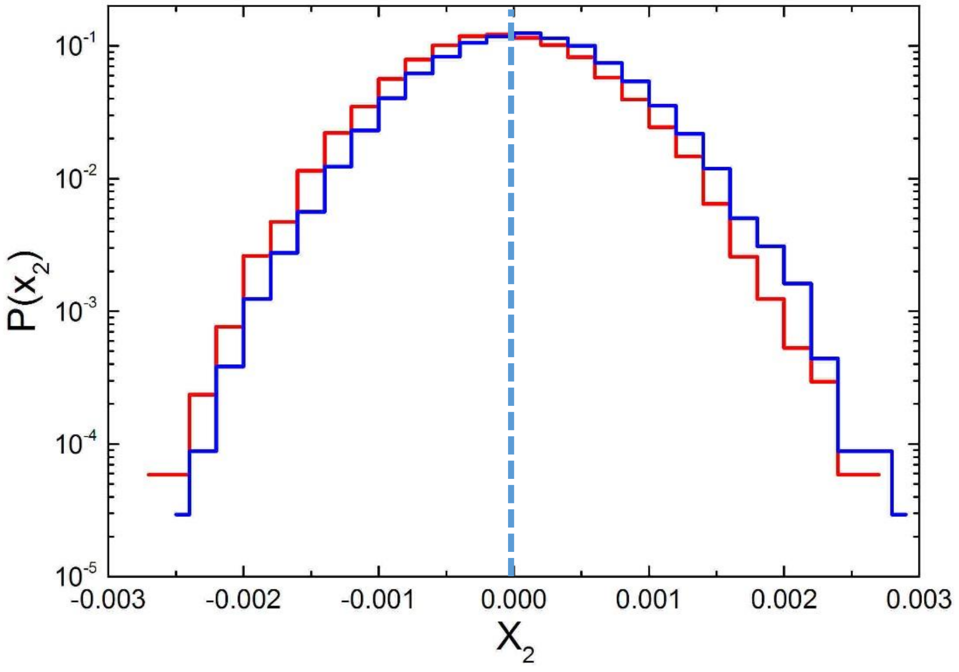


The handcrafted feature fares no better.

What did we learn?

- Even though the accuracy was not very good, we used unsupervised learning to understand the 'decision making' of the network.
- Distribution of principal components appear very much overlapping





- Decision made according to small shift in mean.

New Project

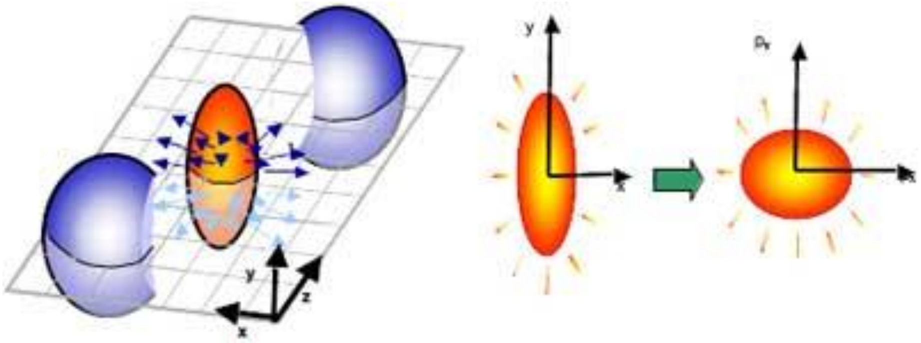
Data analysis and physical observables, using DL
(Just started)

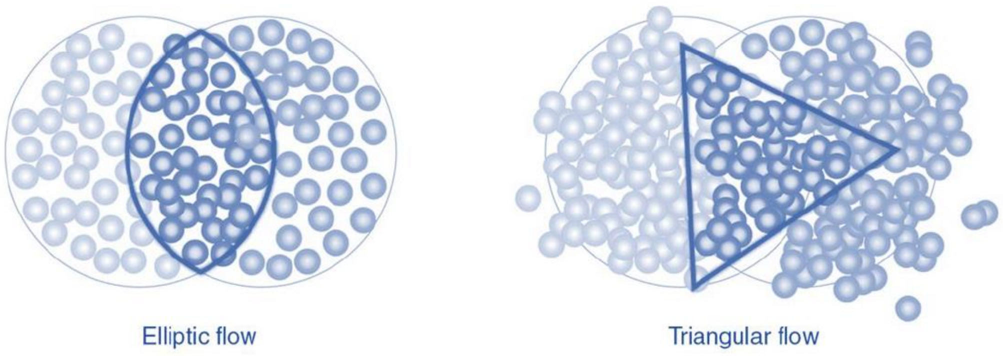
New PhD Student: Manjunath Omana Kuttan

- Data analysis (for HIC) involves many steps.
- Even after track reconstruction
- Observables need to be corrected for acceptance, efficiency etc.
- Often the results depend on the applied cuts during analysis.

- Can we implement some DL-tool for fast extraction of certain observables for a quick event classification?
- How well does this method compare with the ‘by-hand’ analysis method?
- How generalizable is this method w.r.t. system size and beam energy variations?

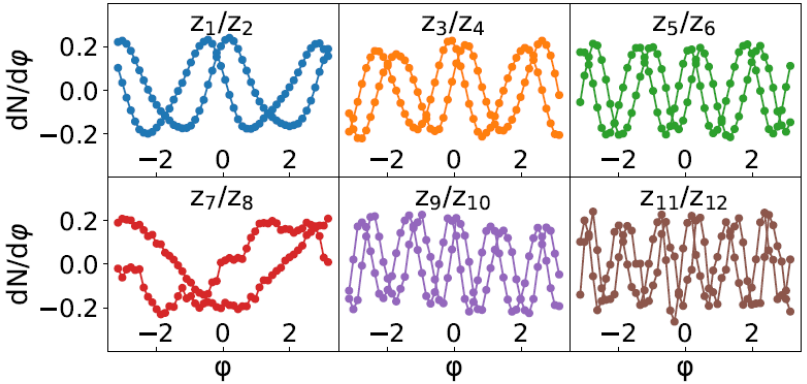
Example: flow coefficients using ML/DL

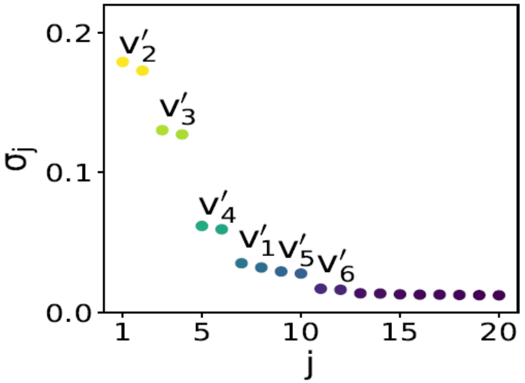


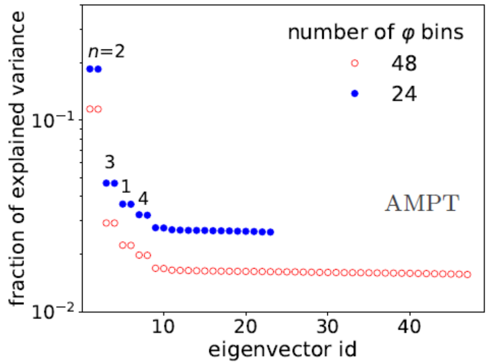


Elliptic flow

Any-order flow coefficients







A PCA gives principal components equivalent to the flow coefficients

Ziming Liu[a], Wenbin Zhao[a,b], Huichao Song[a,b,c]

I. Altsybeev [a,1]

Data analysisa and physical observables, using DL
(Just started)

- The above example works for model simulations at LHC energies and event-by-event

CBM:
- Smaller number of particles per event.
- Detector acceptance and efficiency not taken into account.

The project:
- Teach a DNN to extract observables, like the flow coefficients, on an event-by-event basis.
- Use uncorrected data as input
- Creates a quick and dirty event observable.
- How well does the event average compare to the extended human analysis?
- Different observables can be extracted to make quick event classifications.