Using Machine Learning techniques to determine the impact parameter of collisions in the CBM experiment

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FIAS Frankfurt Institute for Advanced Studies

ErUM-Data IDT

GSI

HGS-HIRe for FAIR
Helmholtz Graduate School for Hadron and Ion Research

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Shriya Soma (PhD Student, funded by funded GSI F&E and Samson AG donation).

Other fields include:

➔ smart power grids, seismology, HR, hydrodynamics etc...

Major collaborations

Applications of AI/DL/ML in fundamental research:

- **ErUM data**
  - DL for CBM experiment
- NA61/SHINE
  - Project “Deep learning for fast TPC data processing”
- Xidian-FIAS International Joint Research Centre
  - Long term center founded in 2019 to research for AI in natural and life sciences
- FIAS-SCNU Guangzhou
  - Planned research center on physics related topics, with focus on High Intensity heavy ion Accelerator Facility (HIAF).
- FIAS Huzhou University
  - Collaboration on physics with focus on HIAF
- More to come...

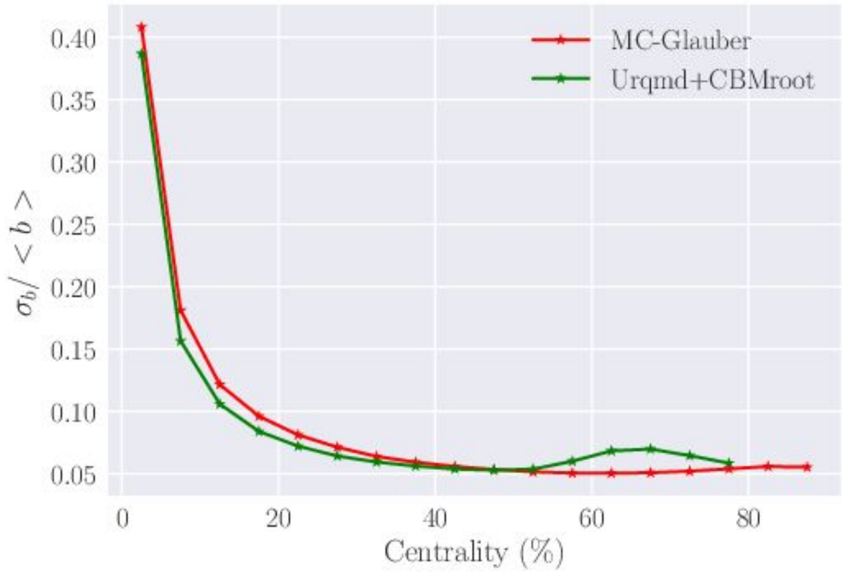
Impact parameter (b) determination in HIC

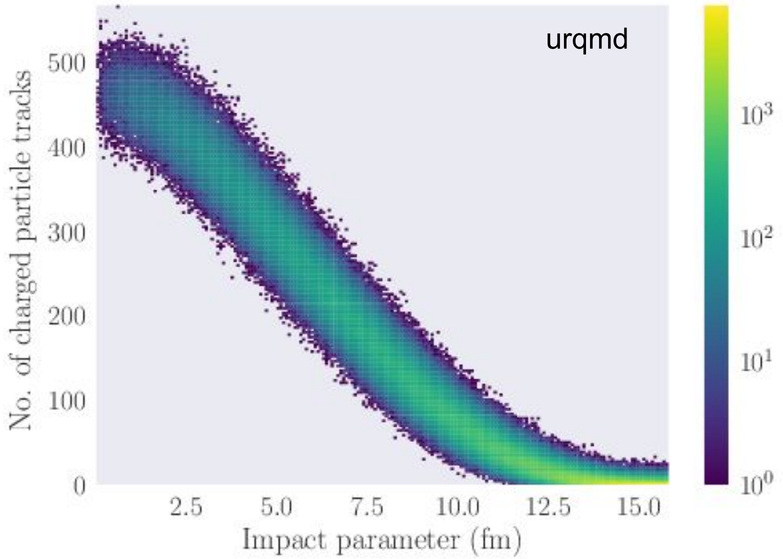
- 'b' is not directly measurable
- Final state observables carry this information
    - eg: charged track multiplicity, spectator energy etc…

Model an observable	Define centrality classes	Find event centrality from the observable
Track multiplicity ↓ Glauber model	Central events → Large multiplicity Peripheral events → Small Multiplicity	Makes a broad classification of events

- We only extract the 'likely' distribution of b (mean and variance) for all events in a centrality bin

‘b’ spread for Glauber model vs. UrQMD
Au+Au @ 10 AGeV





- The likely ‘b’ distribution depends on the model used!
- The accuracy in ‘b’ determination is limited by the spread of the observable used

DL in High Energy Physics

- DL/ ML models are extensively used in experimental HEP
  - Estimation of observables
  - Track reconstruction
  - Particle identification
  - Identification or rare process
  - And more…
- Several studies have also shown b reconstruction using ML
  - Using event generator output
  - Simplified detector definitions
  - Highly processed data

Can DL methods be used to determine the impact parameter of a collision in CBM experiment from raw experimental output?

Gathering data

1 UrQMD 3.4

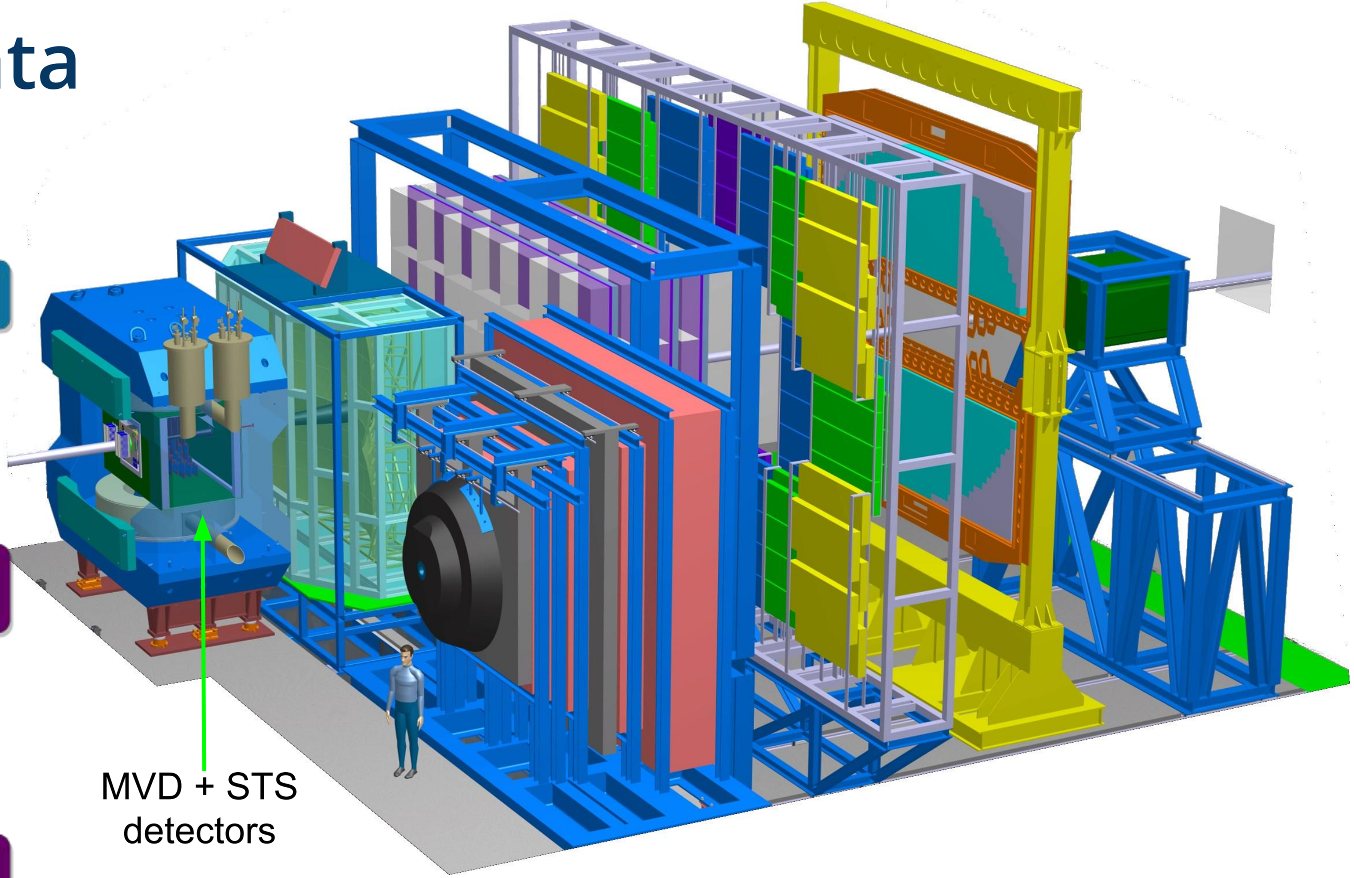
2 Unigen

3 CBMroot : Oct 2019 release

3 Macro: run_transport.C

3 Macro: run_digi.C

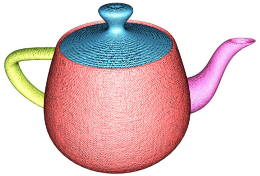
3 Macro: run_reco_event.C

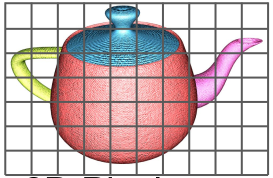


- **Au+Au @ 10 AGeV**

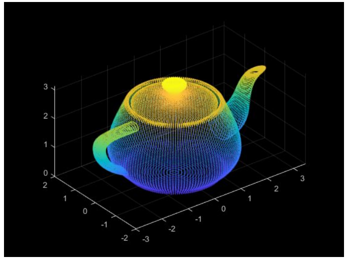
DL model for b reconstruction

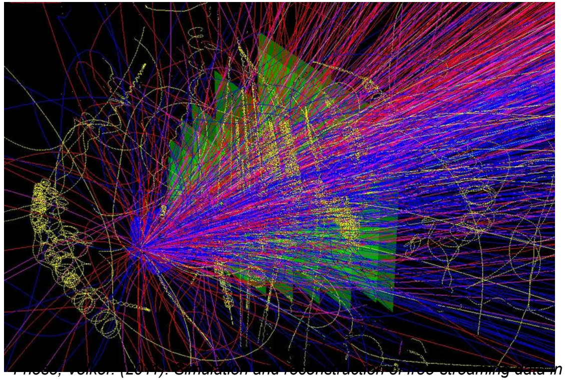
- Experimental data: tracks or hits of particles
    - Each particle is a point in a point cloud
    - The order of input shouldn't affect the output





2D Pixel map





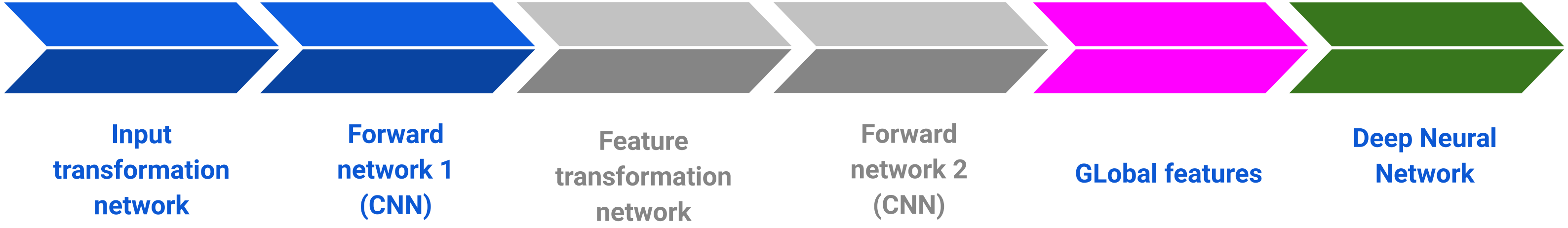
Friese, Volker. (2011). Simulation and reconstruction of free-streaming data in CBM. Journal of Physics: Conference Series. 331. 032008. 10.1088/1742-6596/331/3/032008.

- 3D Voxels map
    - voluminous!
- Pointcloud: Unordered 2D array of (x,y,z) coordinates (or other point attributes) of each point
    - Efficient representation for higher dimensions

X1,y1,z1,.....
X2,y2,z2,.....
X3,y3,z3......
. . .
xn,yn,zn,.....

Pointnet-based DL models

- Pointnet: Deep learning model for point clouds
  - Unordered
  - Invariant to transformations

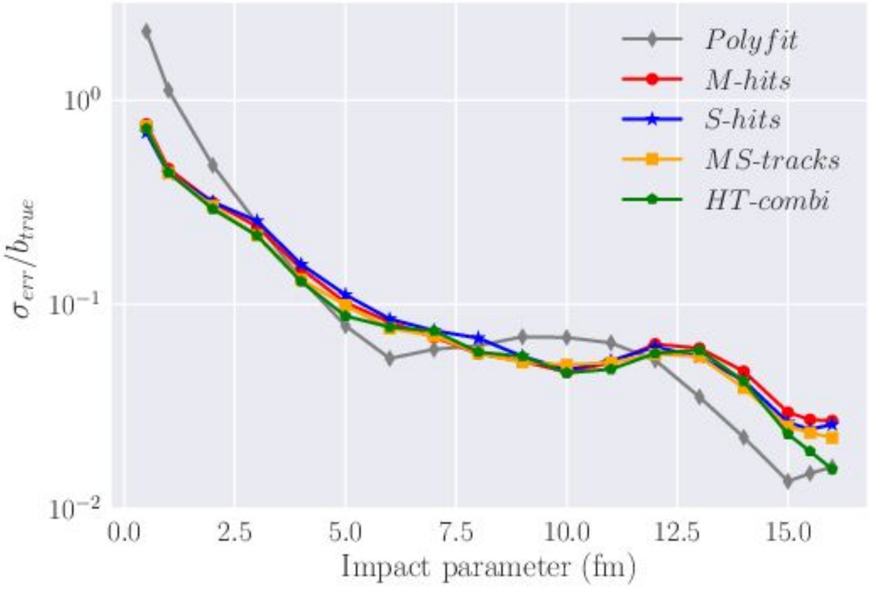


- We have developed pointnet based models which can reconstruct b from 4 different kinds of data

Models

01	**M-hits**	• (x,y,z) of all Hits in MVD
02	**S-hits**	• (x,y,z) of all hits in STS
03	**MS-tracks**	• (x,y,z,dx/dz,dy/dz,q/P) of all tracks in first and last plane from MVD+ STS
04	**HT-combi**	• Hits from MVD and tracks from MVD+STS
05	**Polyfit (non-ML baseline)**	• Third order polynomial fit to multiplicity vs. impact parameter curve

Results: relative precision

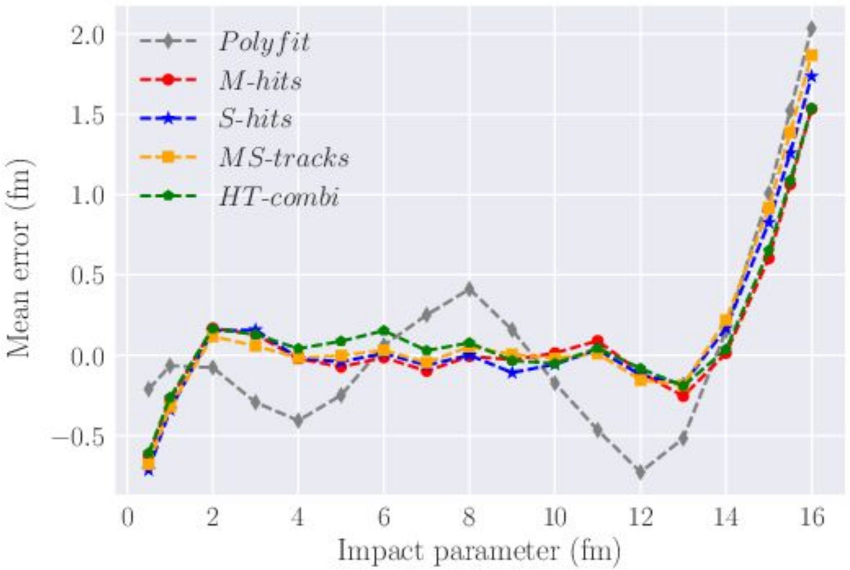


σ_{err} = standard deviation of error in predictions (err= true-predicted)

- Quantifies precision in predictions
- Polyfit fails for central events!
- Similar precision for b>3 fm

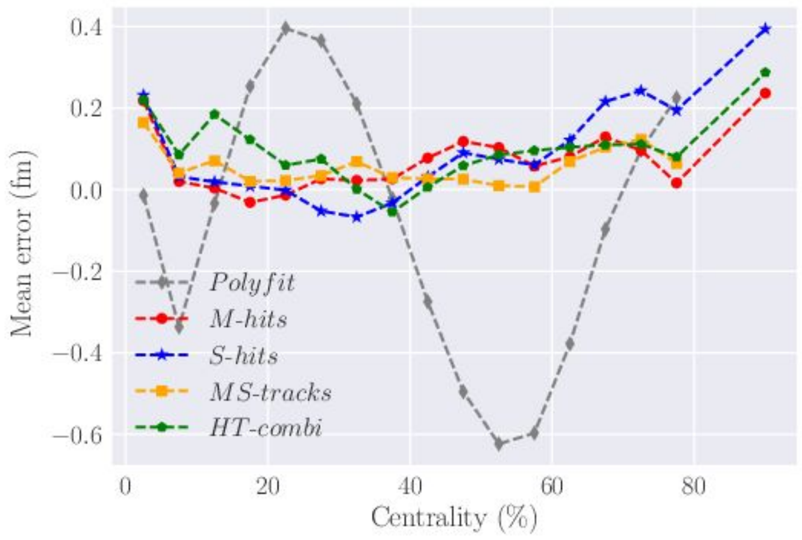
However, the predictions are accurate only if the mean error is close to zero!

Mean error vs. b



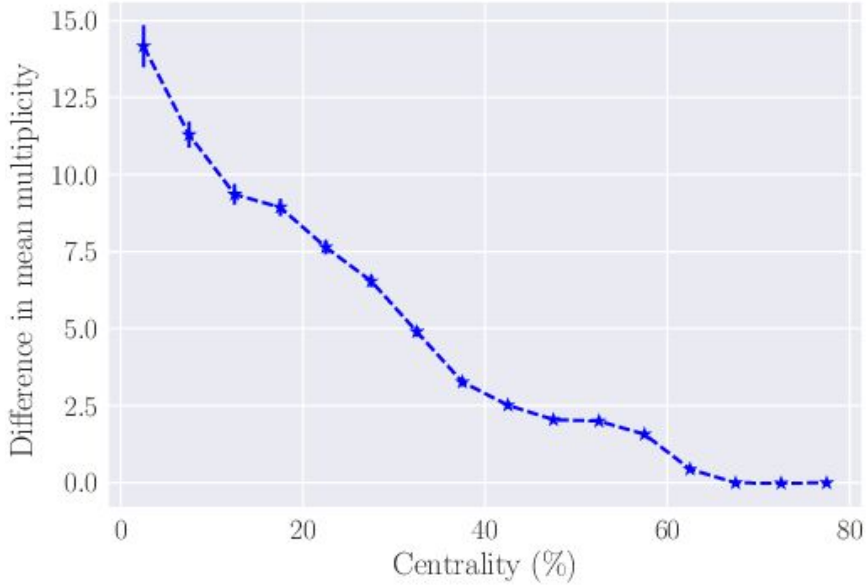
- Quantifies accuracy in predictions
- DL models have mean error between -0.3 and 0.2 fm for b= 2- 14 fm
- Polyfit is highly fluctuating
- All models are less accurate for peripheral events

Mean error vs. centrality



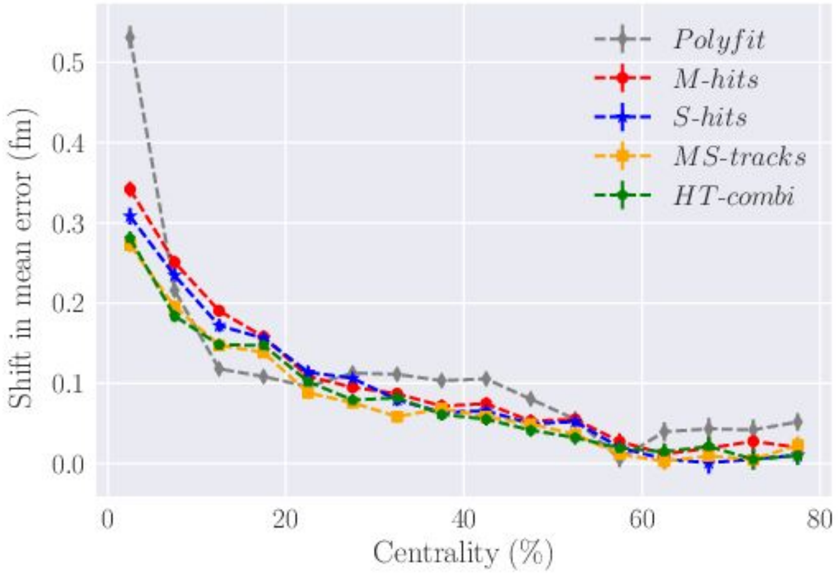
- Data: b=0-16 fm, 1 million events , bdb distribution
- Simulates the realistic b distribution in experiments
- Different from the b distribution of training data
- 5% Centrality bins defined on STS track multiplicity
- DL models have mean error close to zero for most centrality classes

Testing on different physics



- Increased Urqmd pion production cross section
  - Delta baryon absorption decreased by factor of 2
  - Notable for central collisions
- The increased pion production is reflected in mean multiplicity change
  - Difference= New data - Old data

Shift in mean error



- Testing models on modified urqmd data
- Correlation with multiplicity change is visible
- DL models are less dependent than Polyfit especially at central collisions

Testing speed

Model	Speed (events/ s)
M-hits	660
S-hits	159
MS-tracks	1092
HT-combi	435

- Tested on a **Nvidia Geforce RTX 2080 Ti** card with a graphics processing memory of 12 GB
- More room for optimization

Summary

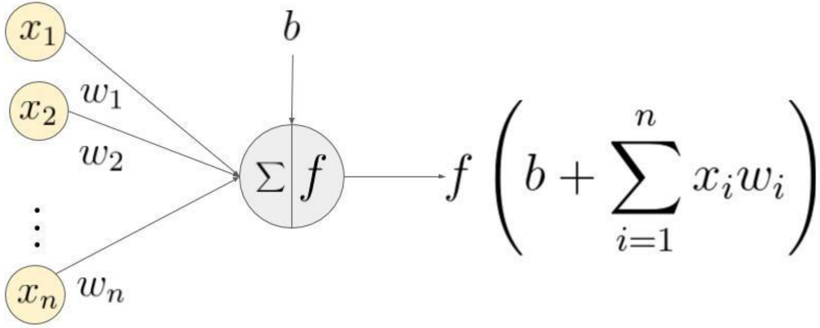
The deep learning models outperforms conventional methods for impact parameter determination

- ❖ Reconstruct the impact parameter on an **event by event** basis
- ❖ Prediction speed upto 1000 events/ s on single GPU
    - ➢ Real time analysis of collected data
- ❖ Reconstruct the impact parameter using the **hit information alone**
    - ➢ Run time AI event selector
    - ➢ Detect faults in detector during data taking
- ❖ Robust to small changes in physics model in comparison to conventional models
- ❖ General framework which can be used for other tasks (e.g. flow extraction)

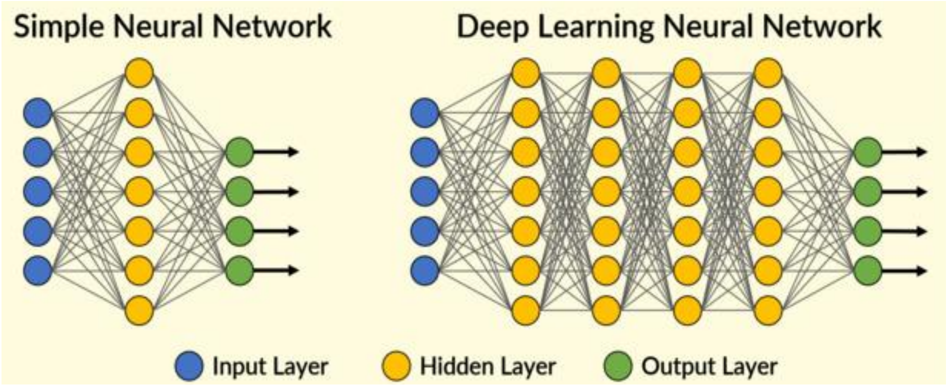
A paper based on this work is available at arXiv:2009.01584

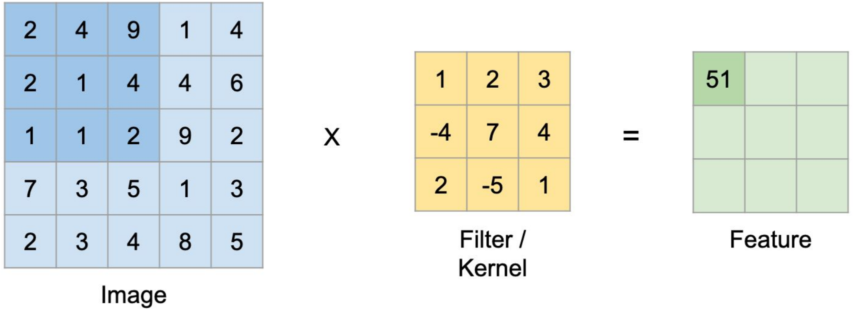
Backup slides

Neural Networks & Convolution Neural Networks

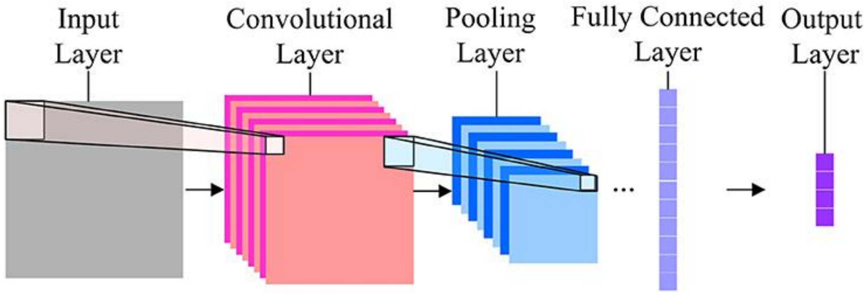


A neuron

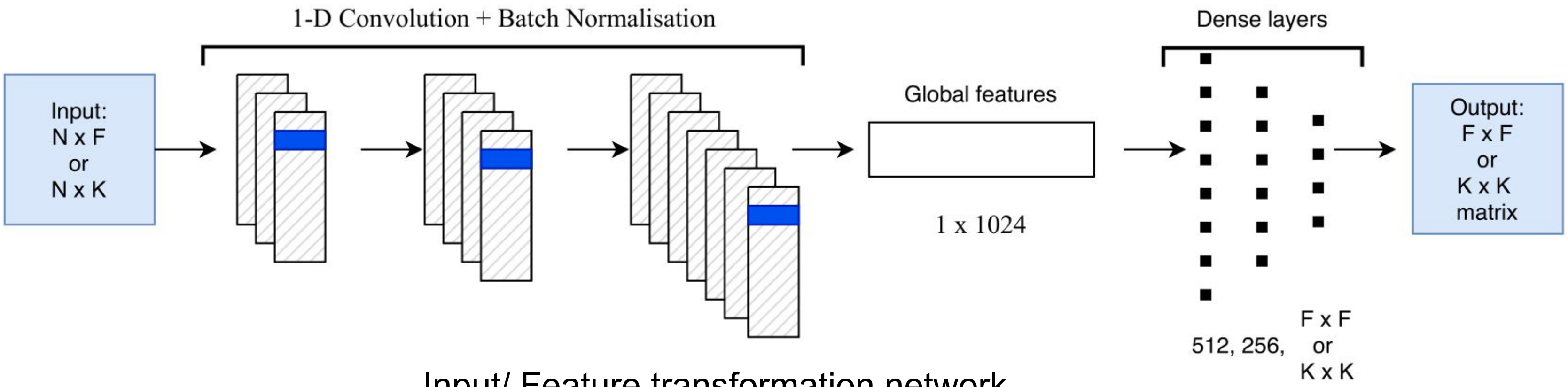




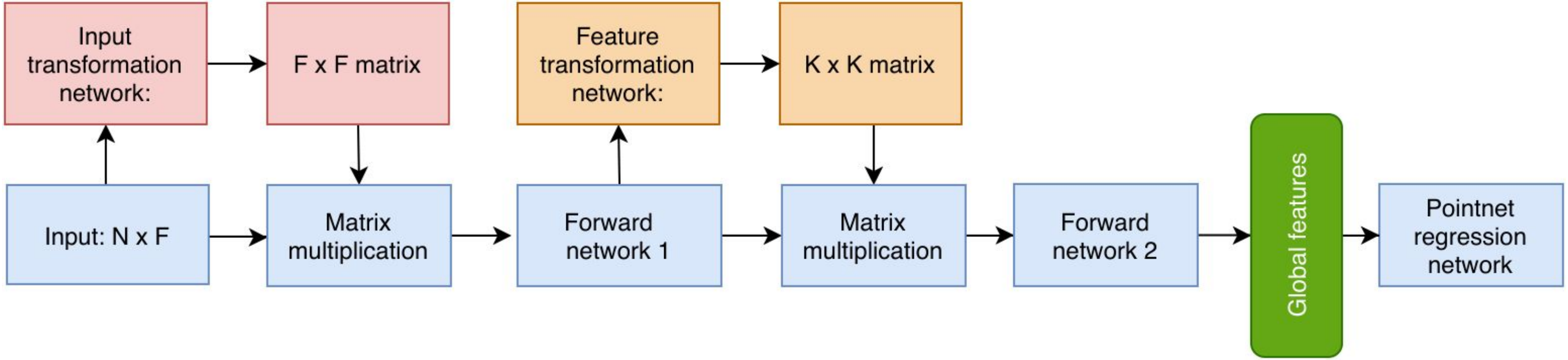
Convolution operation



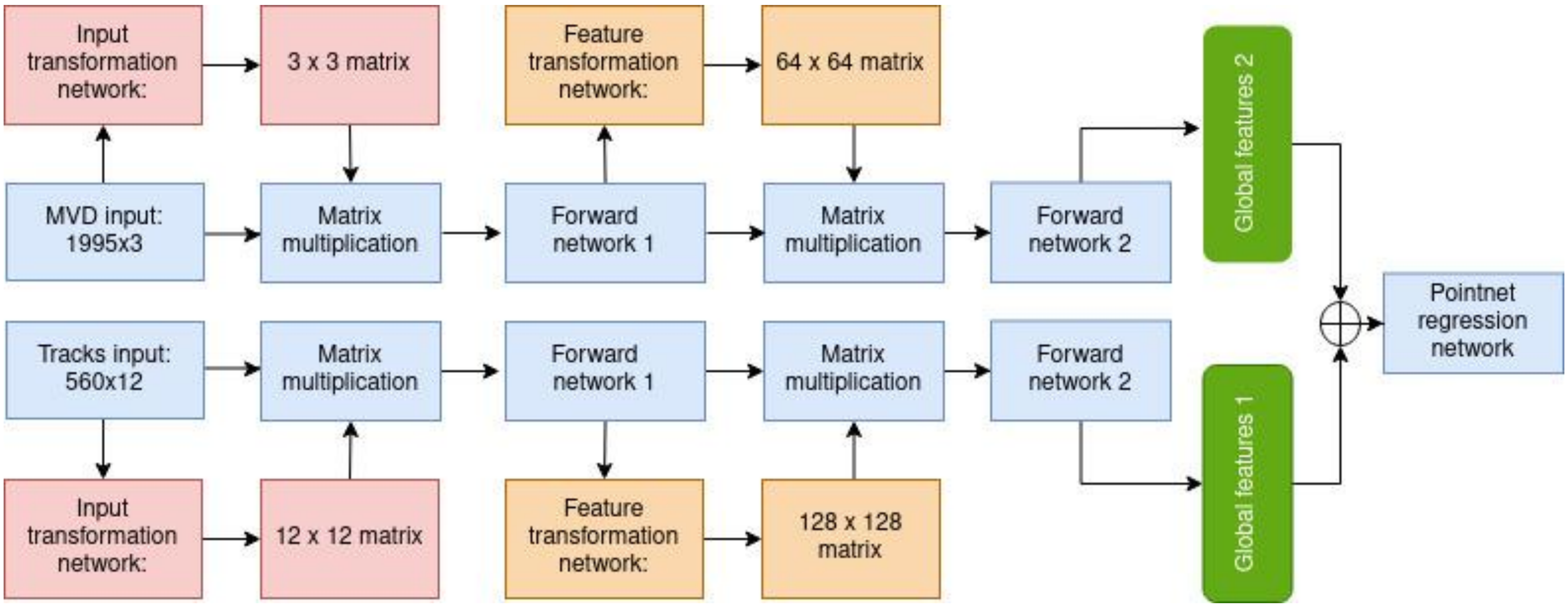
Convolution Neural Network



Input/ Feature transformation network



General structure of Mhits, Shits and MStracks models



Structure of HT-combi model