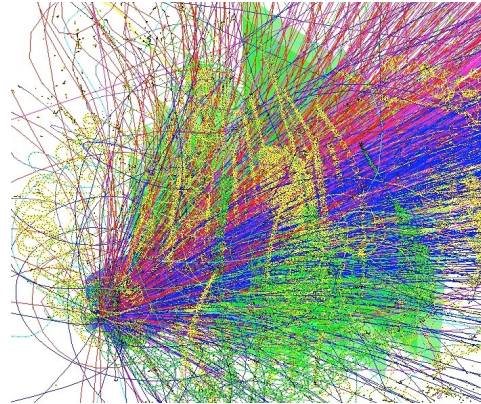


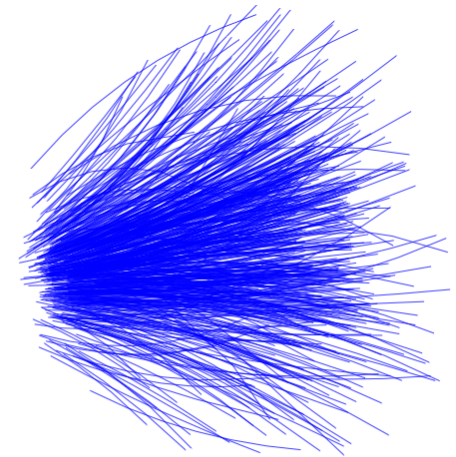
# From particle trajectories to QGP with Artificial Neural Networks

Ivan Kisel

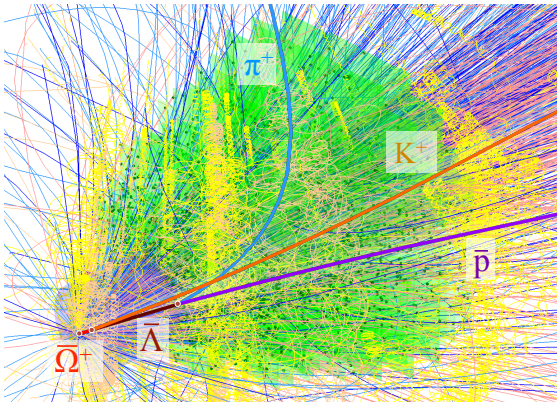
# Outline



(1) Reconstruction



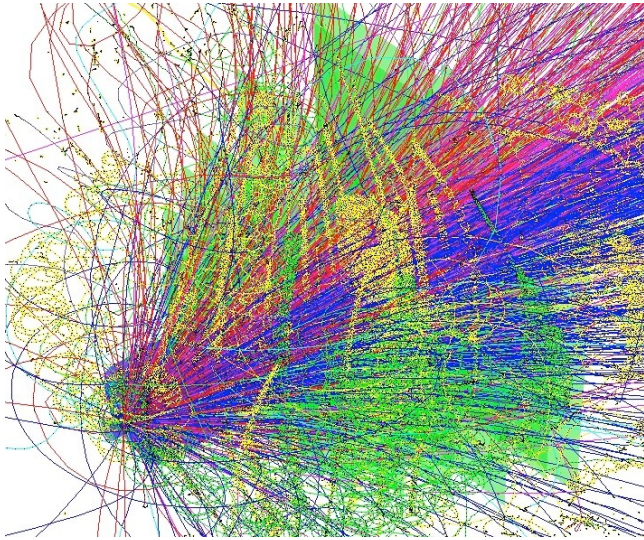
(2) Analysis



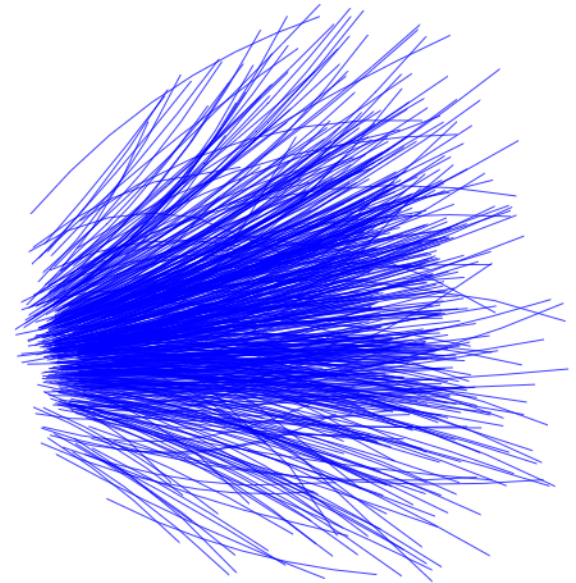
(3) Physics

# (1) Reconstruction

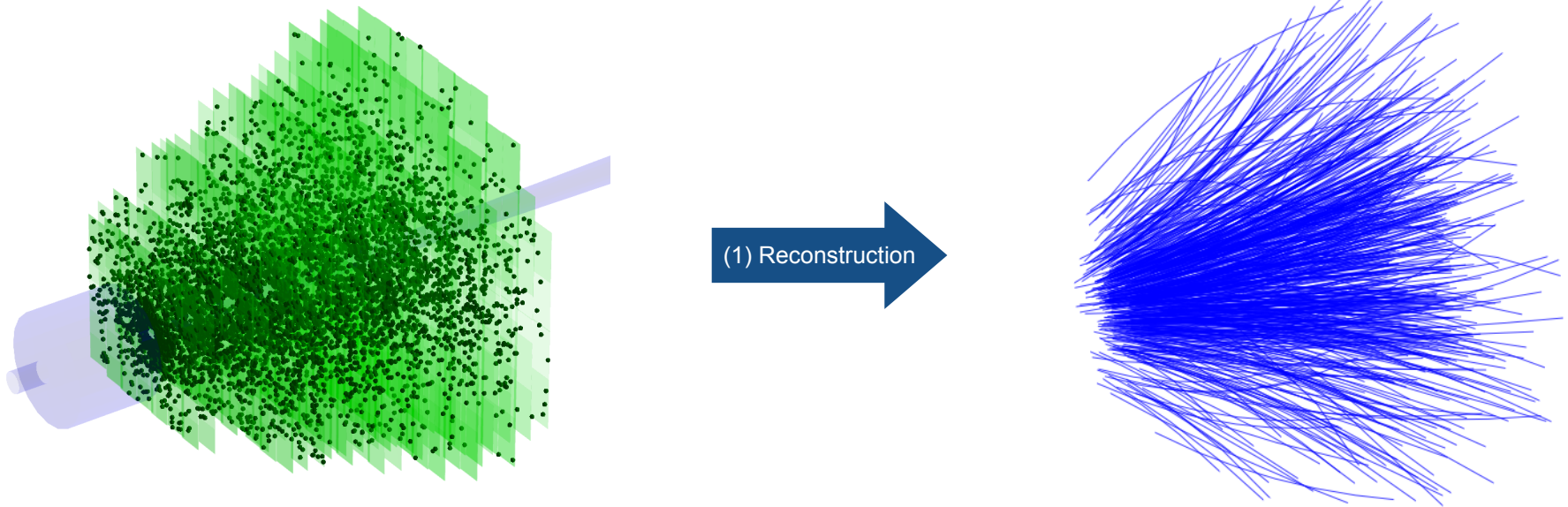
---



(1) Reconstruction

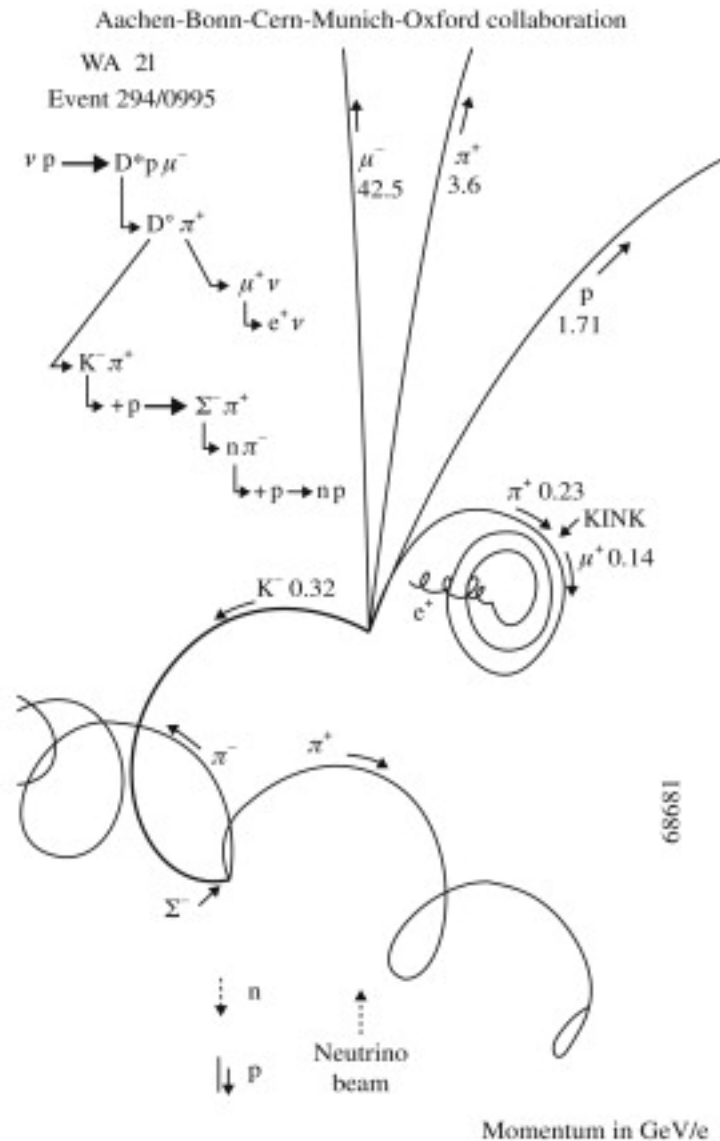
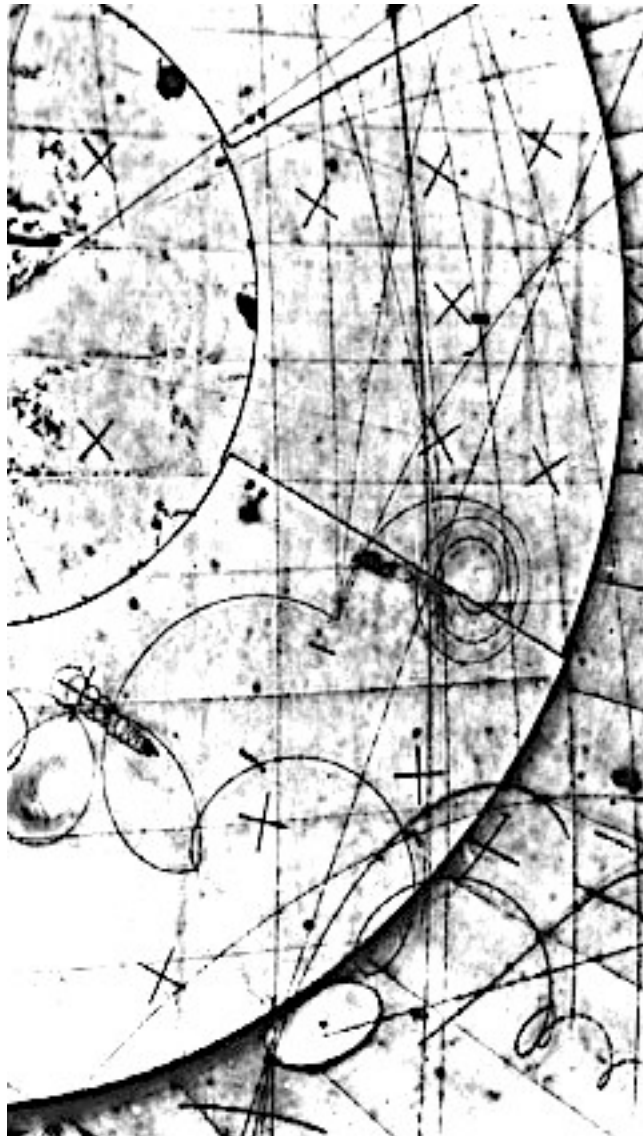


# (1) Reconstruction





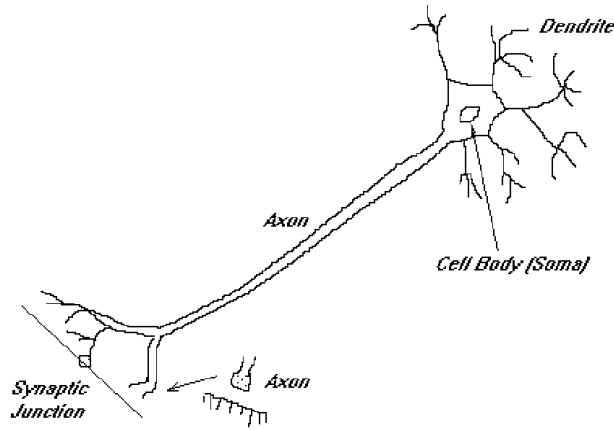
# Reconstruction in Bubble Chambers



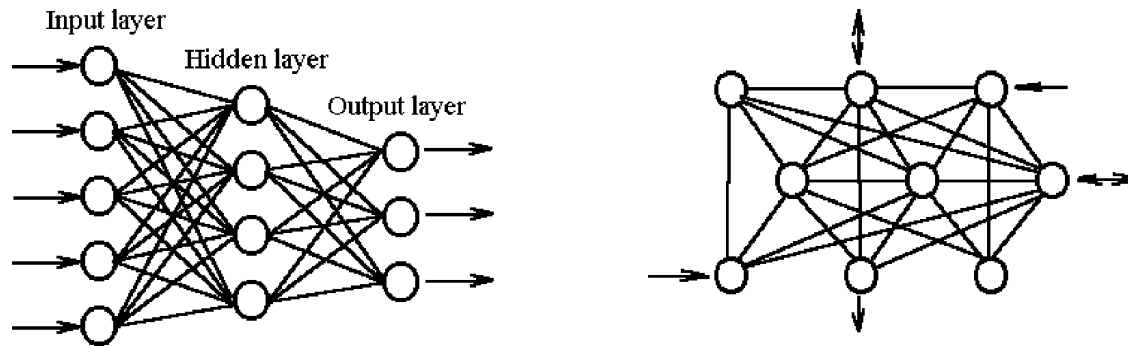
Typical particle tracks seen from a bubble chamber (left) and their interpretations (right). Courtesy of CERN.

# (Oversimplified) Artificial Neural Networks (ANNs)

- Elementary units
- Global communication
- Parallel work
- Reliable system
- Pattern recognition



Schematic structure of a neuron.

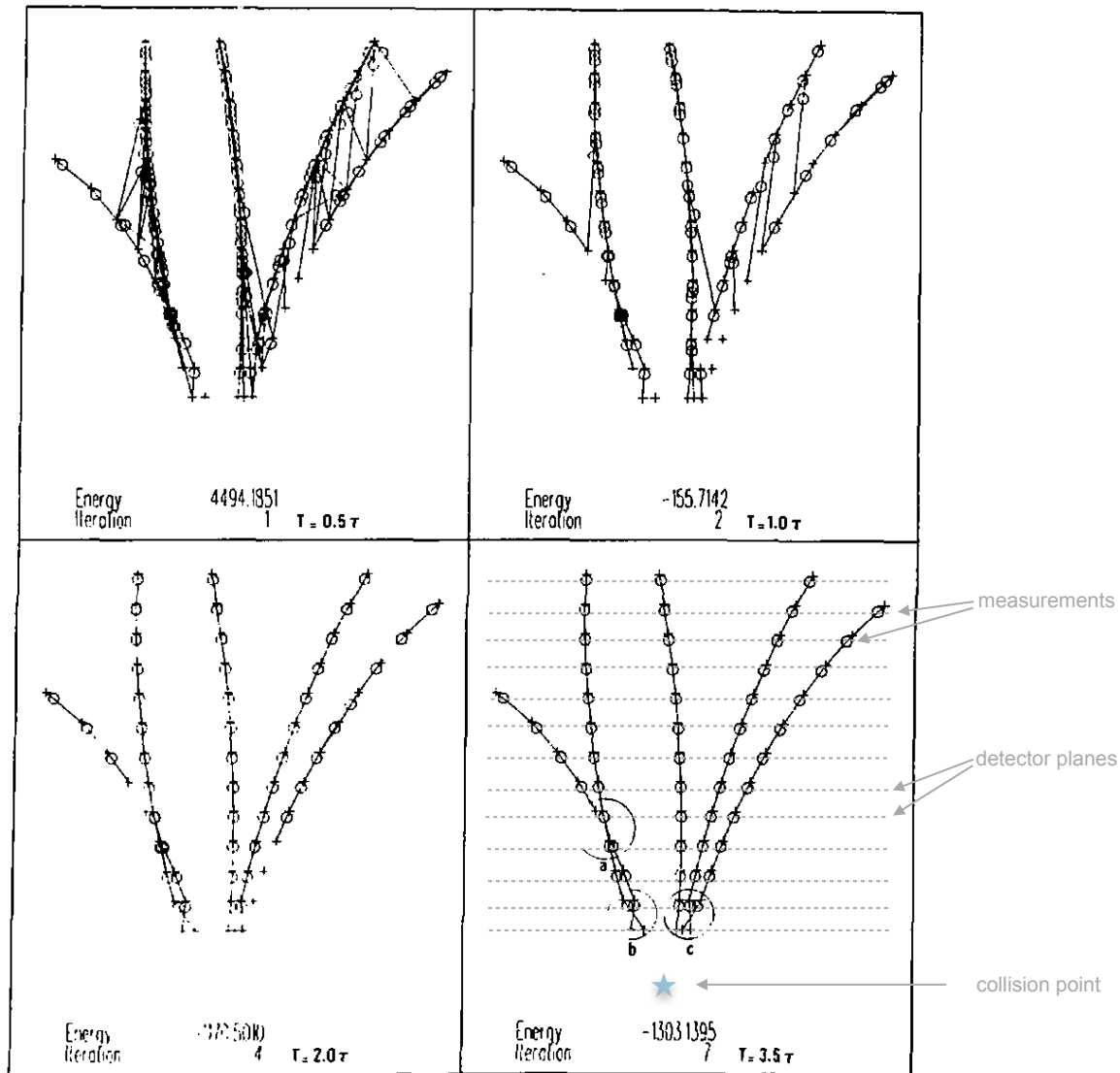


Two models of neural networks: the perceptron model and the recurrent model.

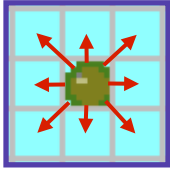
# ANN for Reconstruction of Trajectories

Bruce Denby, Neural Networks and Cellular Automata in Experimental High Energy Physics, 1987

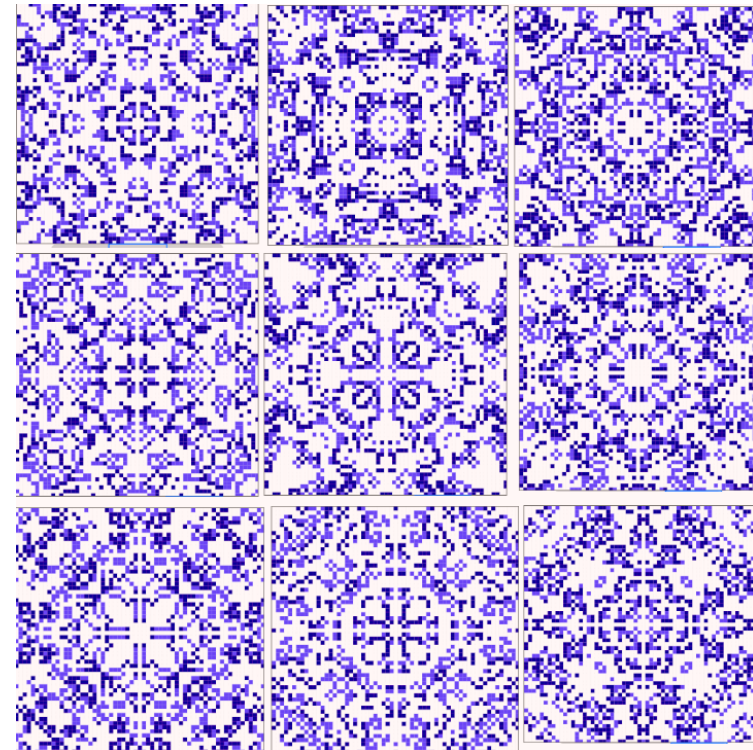
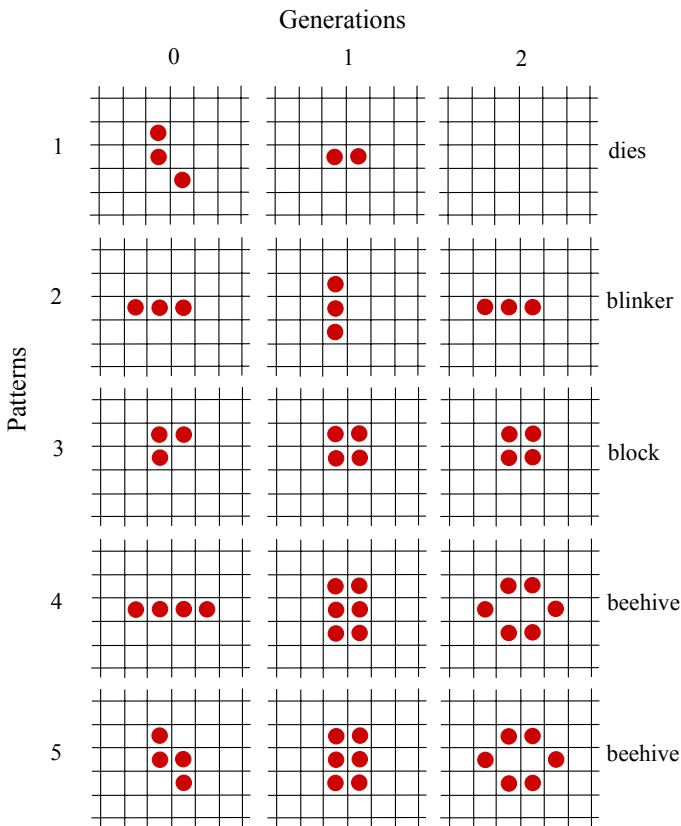
- Energy function
- Global interaction
- Local minima
- Very slow



# Cellular Automaton - Game "Life"

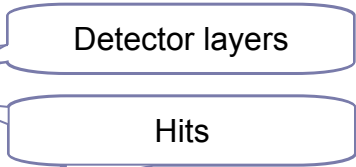
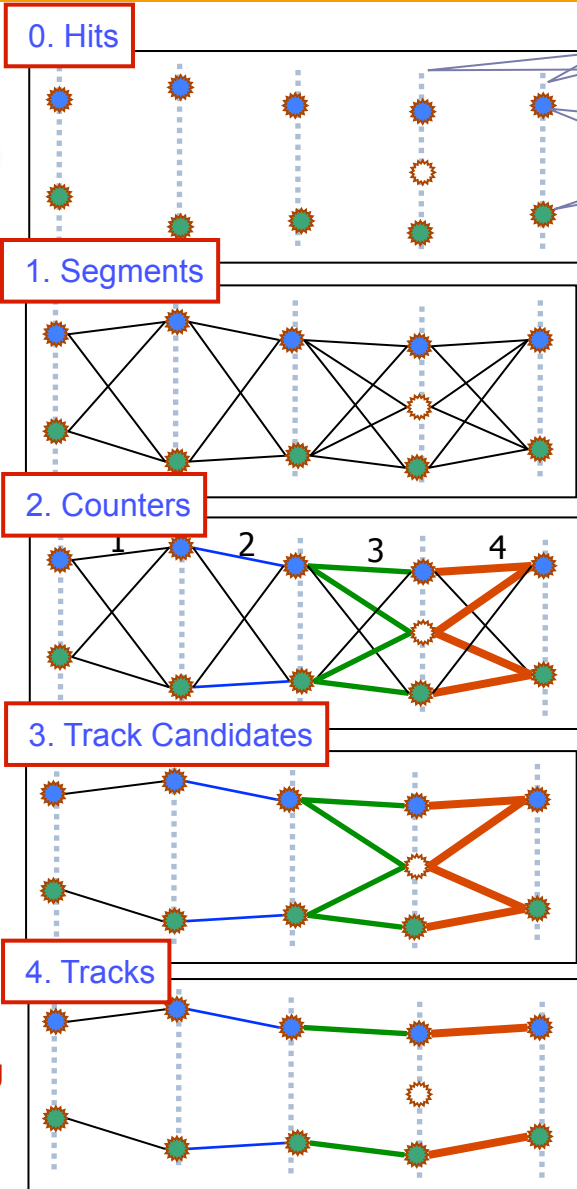
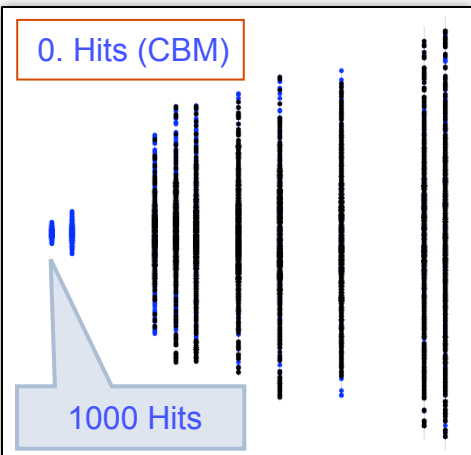


Each **cell** has 8 neighboring cells, 4 adjacent orthogonally, 4 adjacent diagonally. The **rules** are:  
**Survival:** Every counter with 2 or 3 neighboring counters survives for the next generation.  
**Death:** Each counter with 4 or more neighbors dies from overpopulation, with 1 neighbor or none dies from isolation.  
**Birth:** Each empty cell adjacent to exactly 3 neighbors is a birth cell.  
 It is important to understand that all births and deaths occur *simultaneously*.

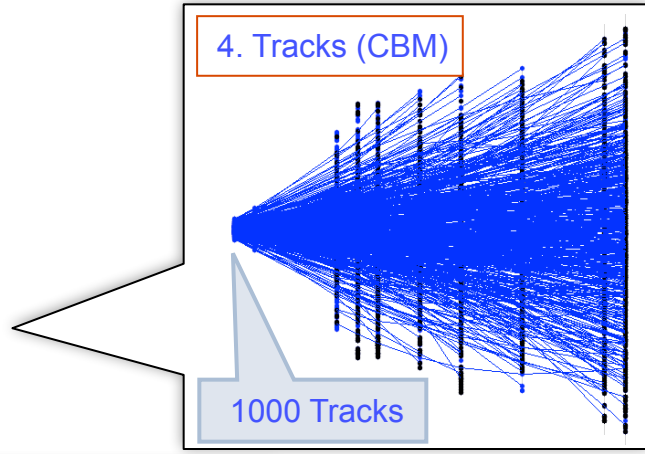




# CBM: Cellular Automaton (CA) Track Finder



- Cellular Automaton:
1. Build short track segments.
  2. Connect according to the track model, estimate a possible position on a track.
  3. Tree structures appear, collect segments into track candidates.
  4. Select the best track candidates.

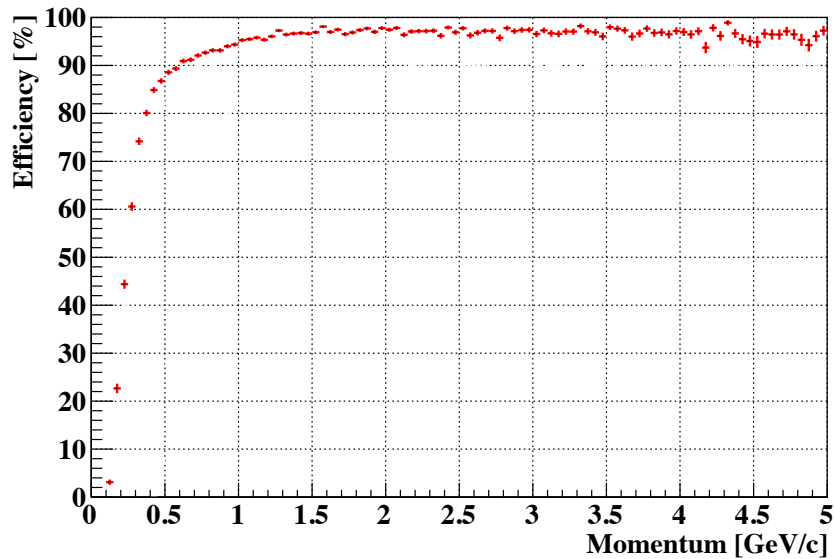
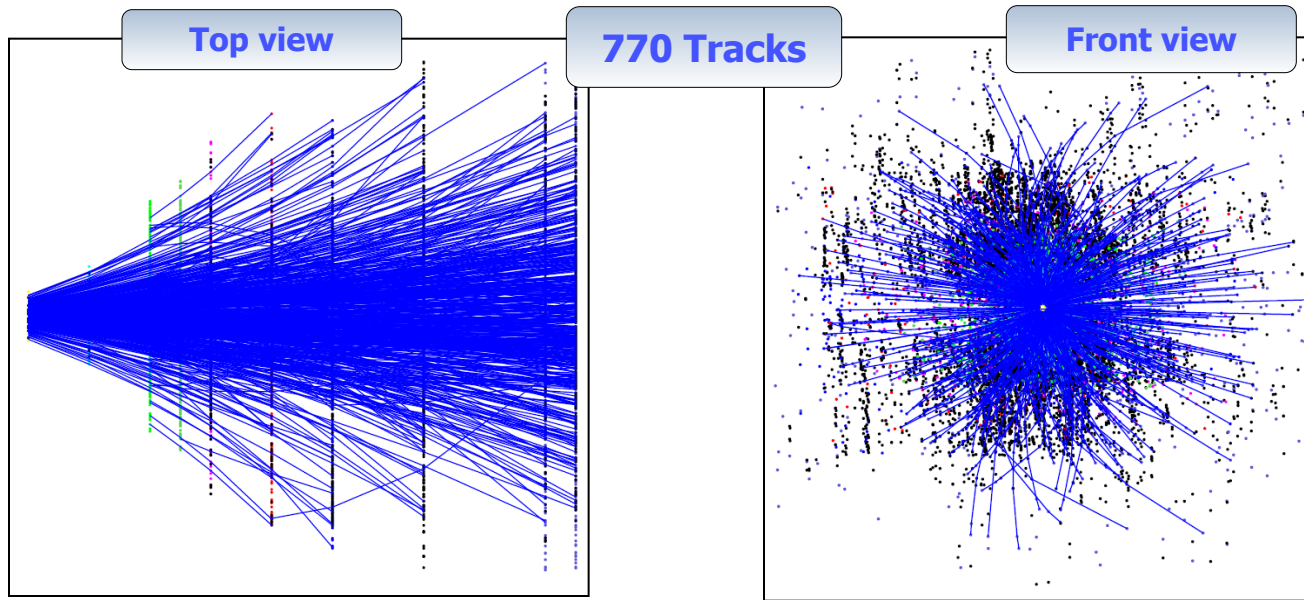


- Cellular Automaton:
- local w.r.t. data
  - intrinsically parallel
  - extremely simple
  - very fast

Deeply appropriate for many-core CPU/GPU

Useful for complicated event topologies with heavy combinatorics

# CBM: Cellular Automaton (CA) Track Finder

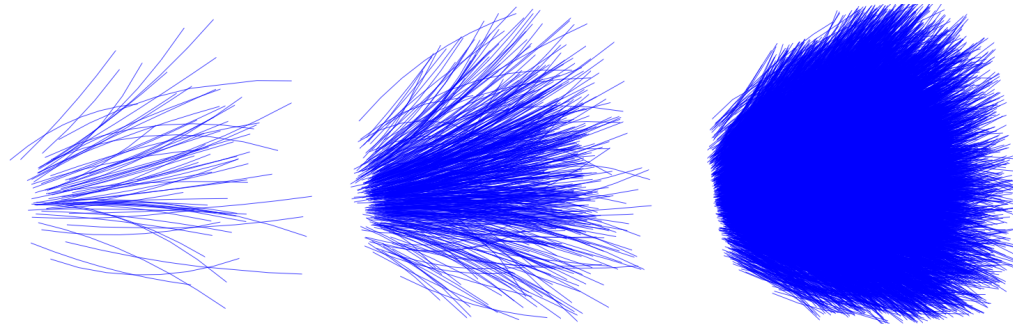


Track category	Eff, %
All tracks	90.9
Primary high- $p$	97.5
Primary low- $p$	92.6
Secondary high- $p$	91.1
Secondary low- $p$	63.8
Clone level	0.4
Ghost level	5.9
MC tracks found	134
Time, ms/ev	10

Fast and efficient track finder

# CBM: CA Track Finder at High Track Multiplicity

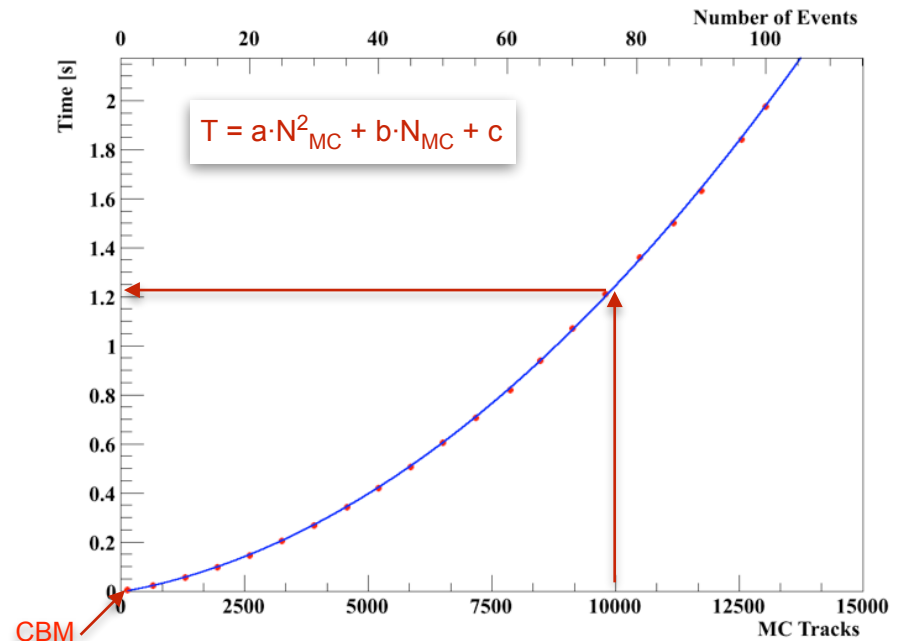
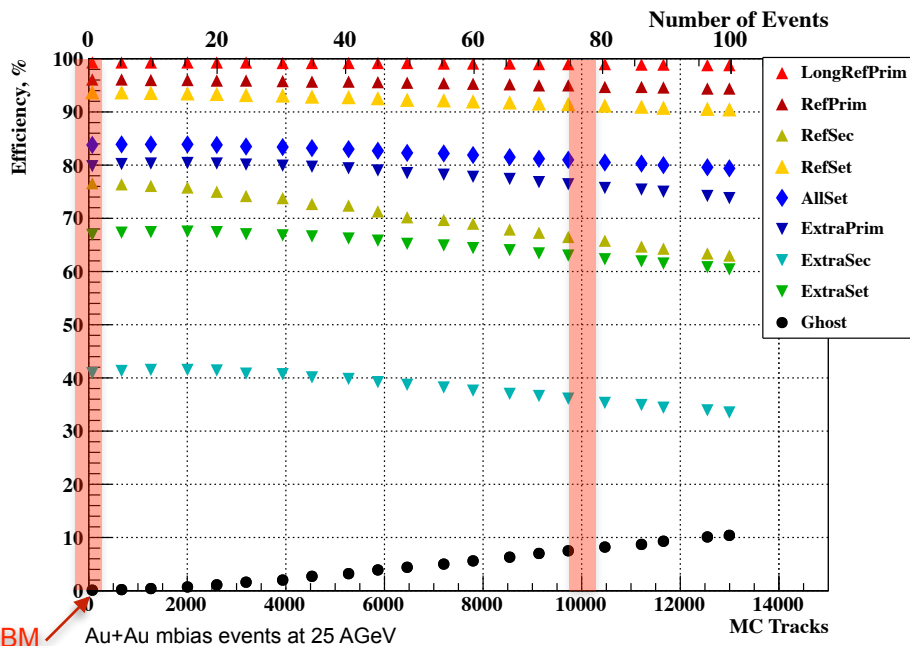
A number of minimum bias events is gathered into a group (super-event), which is then treated by the CA track finder as a single event.



1 mbias event,  $\langle N_{reco} \rangle = 109$

5 mbias events,  $\langle N_{reco} \rangle = 572$

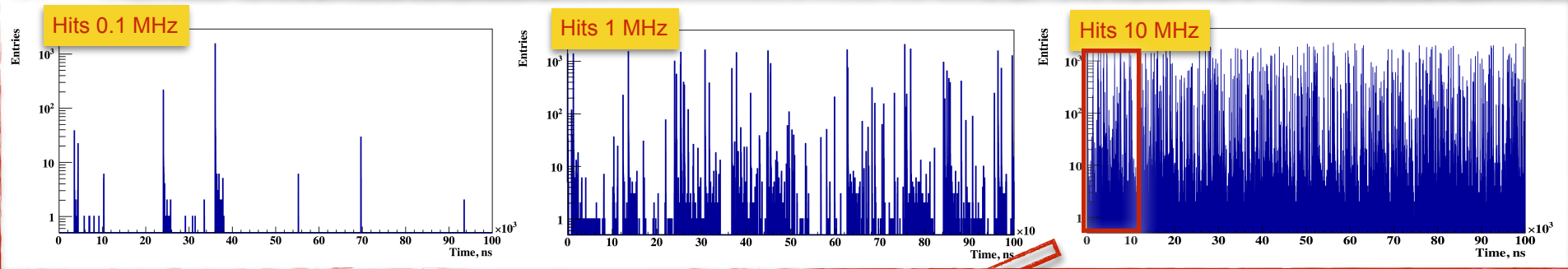
100 mbias events,  $\langle N_{reco} \rangle = 10340$



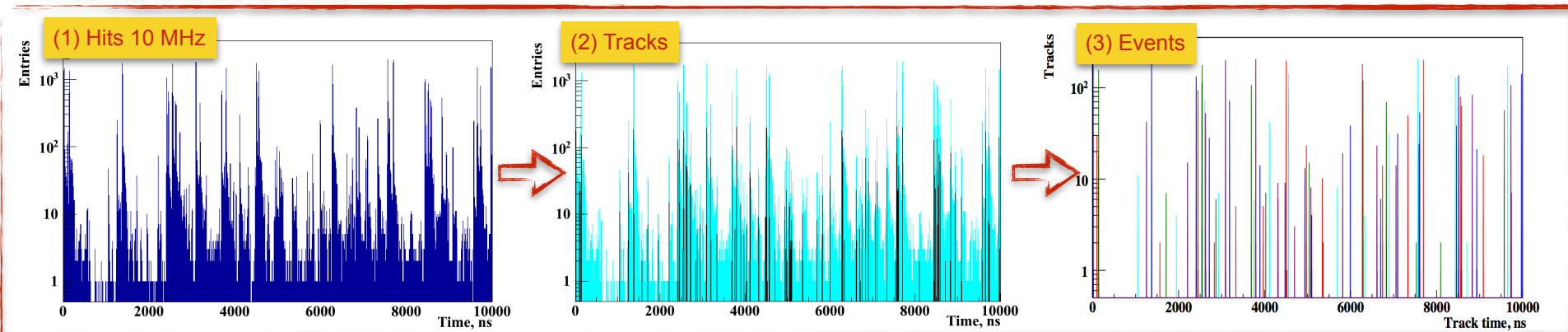
Reliable reconstruction efficiency and time as a second order polynomial w.r.t. to the track multiplicity

# CBM: 4D Event Building at 10 MHz

## Hits at high input rates



## From hits to tracks to events

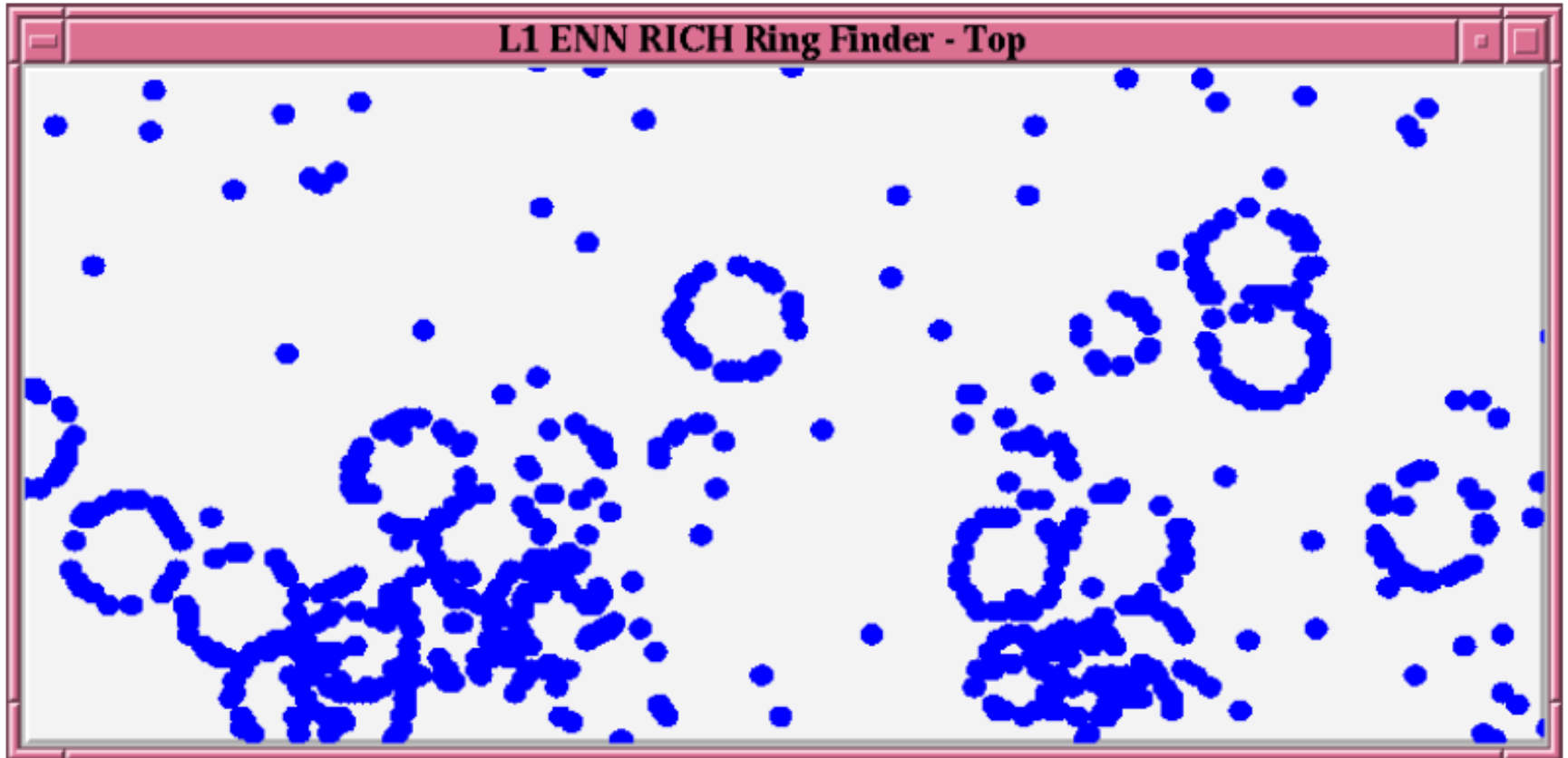


V. Akishina

Reconstructed tracks clearly represent groups, which correspond to the original events

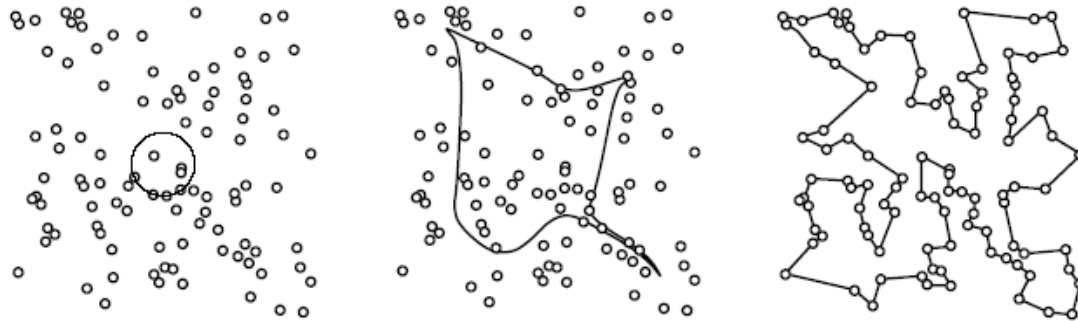


# Ring-Imaging Cherenkov Detector (RICH)

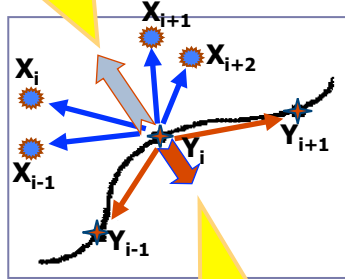


# Elastic Neural Net (EN) for TSP

R. Durbin and D. Willshaw, An analogue approach to the travelling salesman problem, Nature, 326 (1987) 689



Attraction



Elasticity

Attraction

Elasticity

Simple

$$E(s_{ia}, \vec{y}_a) = \sum_{ia} s_{ia} \cdot |\vec{x}_i - \vec{y}_a|^2 + \gamma \cdot \sum_a |\vec{y}_a - \vec{y}_{a+1}|^2$$

$$\Delta \vec{y}_a = \eta \left[ 2 \sum_i v_{ia} \cdot (\vec{x}_i - \vec{y}_a) + \gamma \cdot (\vec{y}_{a+1} - 2\vec{y}_a + \vec{y}_{a-1}) \right]$$

## Discrete EN

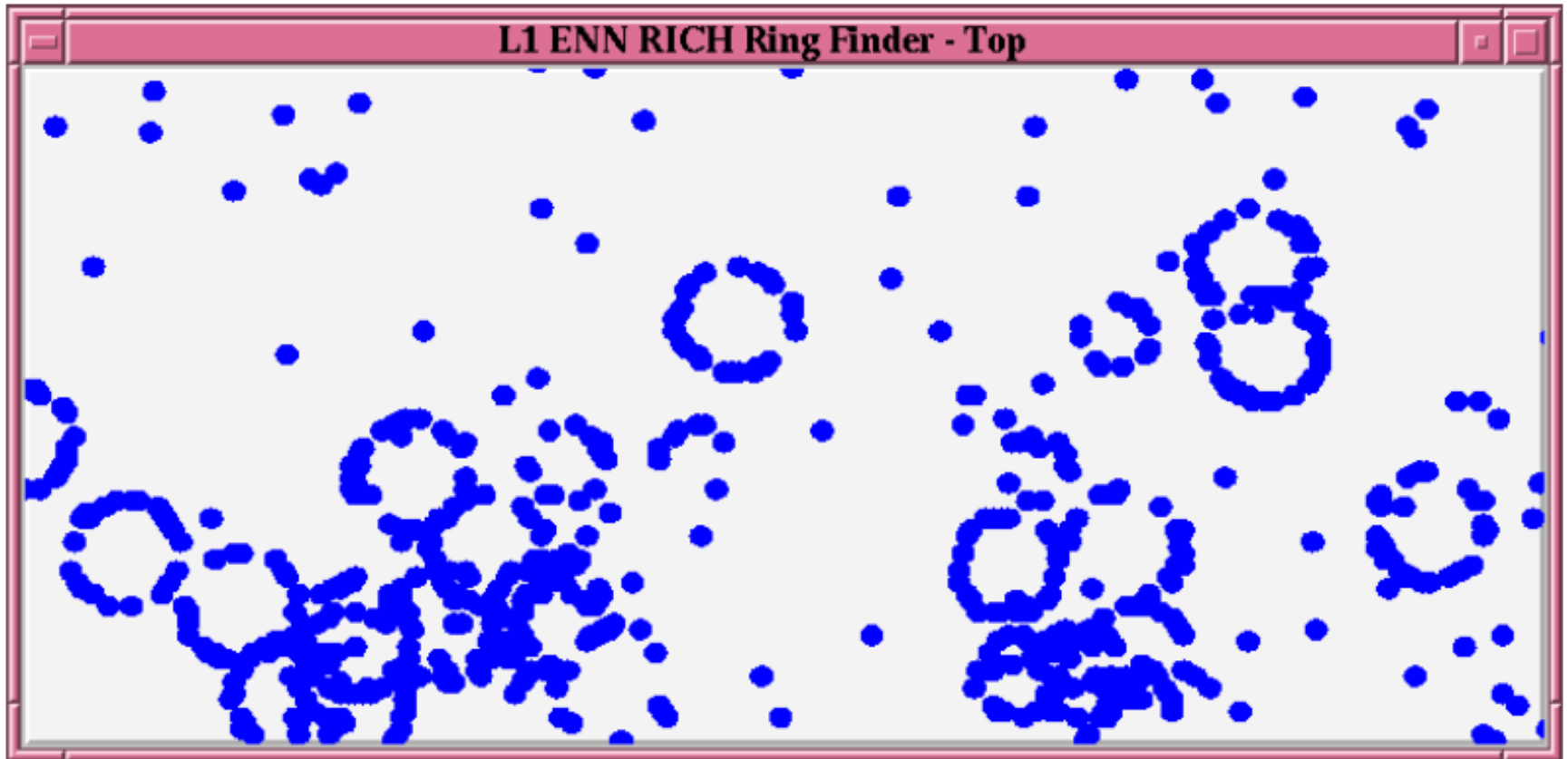
File name	Number of cities	Extra path (%)	Time, ms	Time per city, $\mu$ s
berlin52	52	0.00	0.98	19
st70	70	4.27	1.27	18
kroA100	100	3.03	1.46	15
lin105	105	0.78	1.84	18
ch130	130	5.59	2.56	20
tsp225	225	5.34	4.36	19
pcb442	442	8.37	12.35	28
pr1002	1002	6.12	24.94	25
pr2392	2392	8.42	58.53	24

(\* Pentium IV/2.4 GHz)

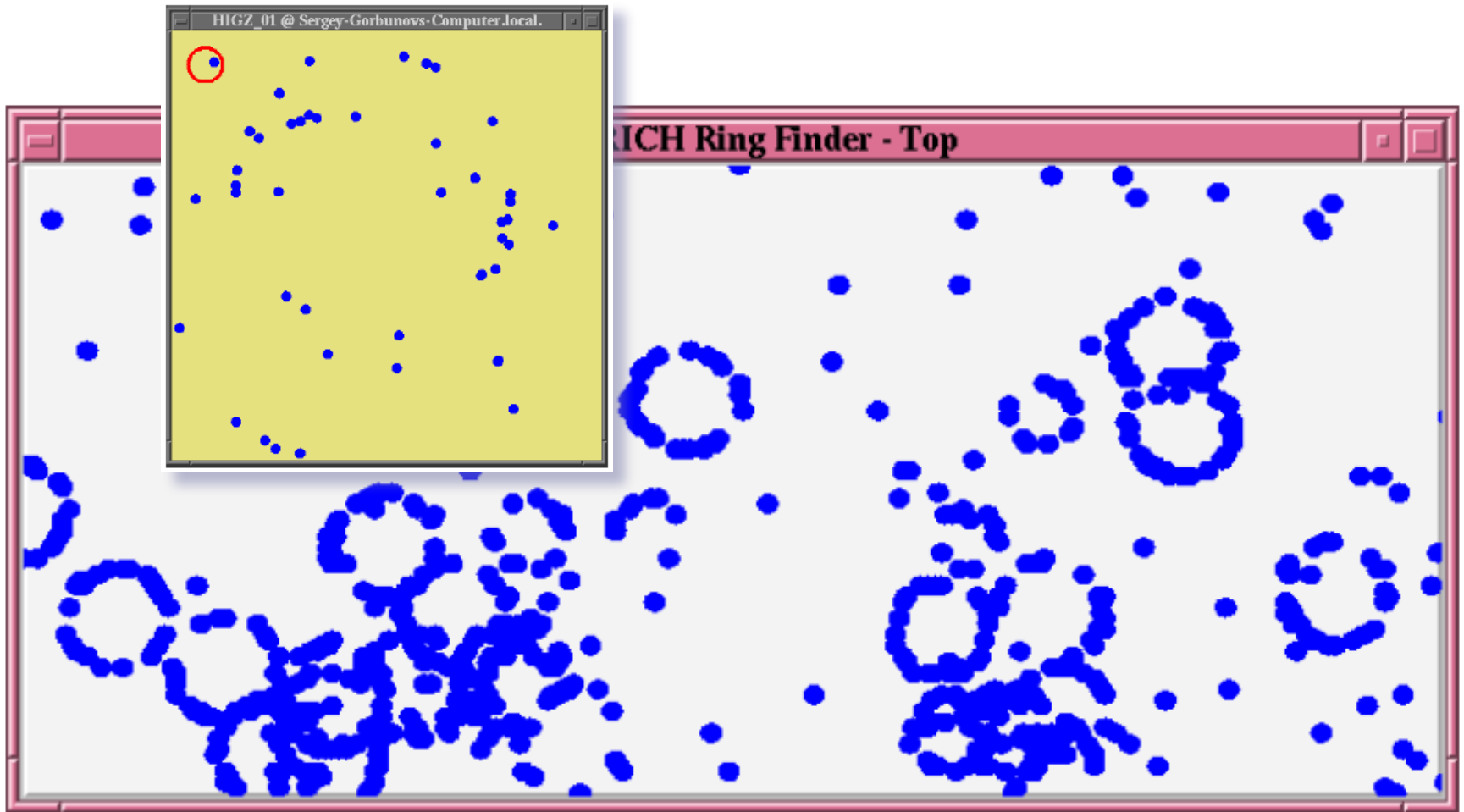
Fast

S. Gorbunov and I. Kisel, Elastic net for standalone RICH ring finding, CBM-SOFT-note-2005-002

# Elastic Neural Net (EN) for RICH

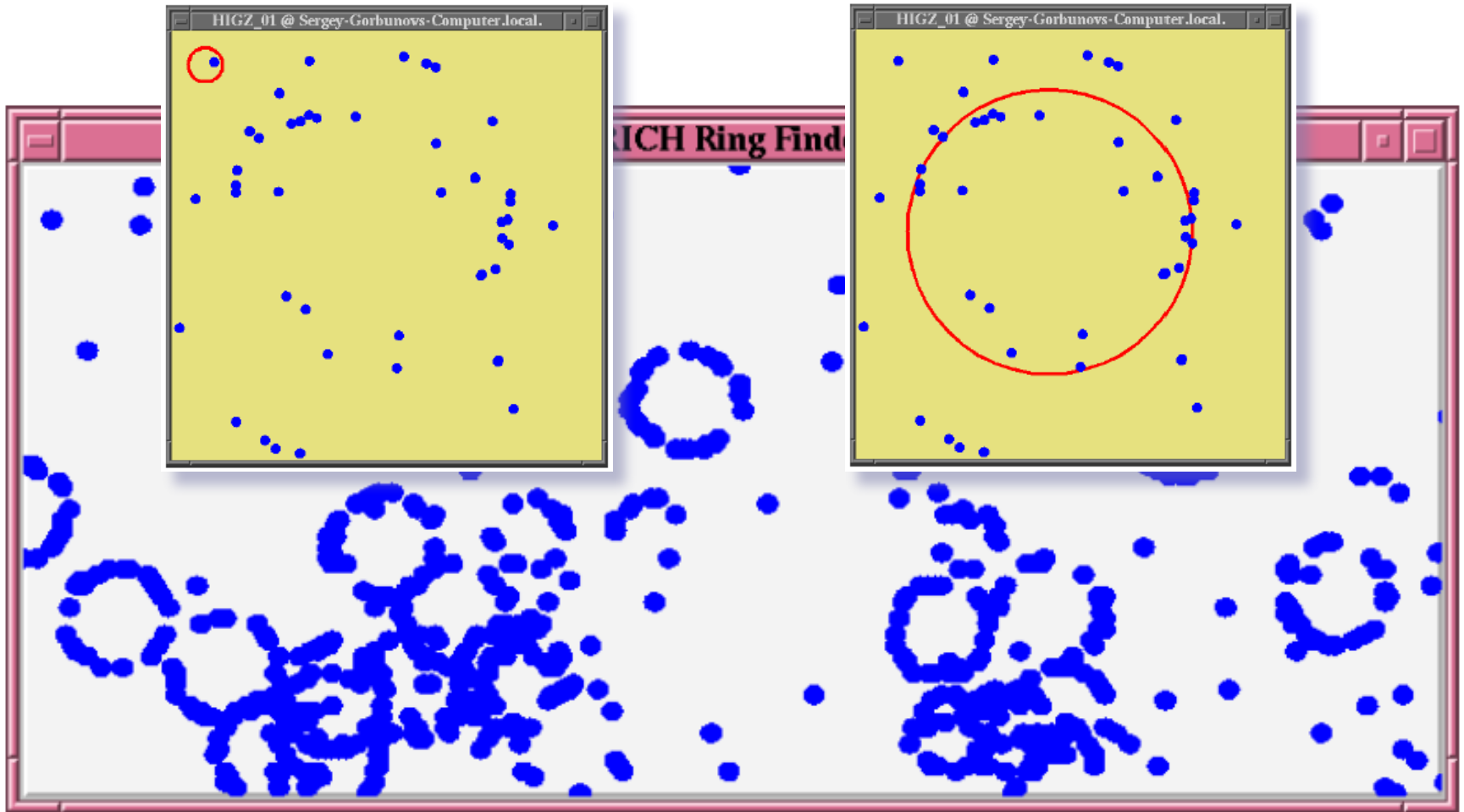


# Elastic Neural Net (EN) for RICH

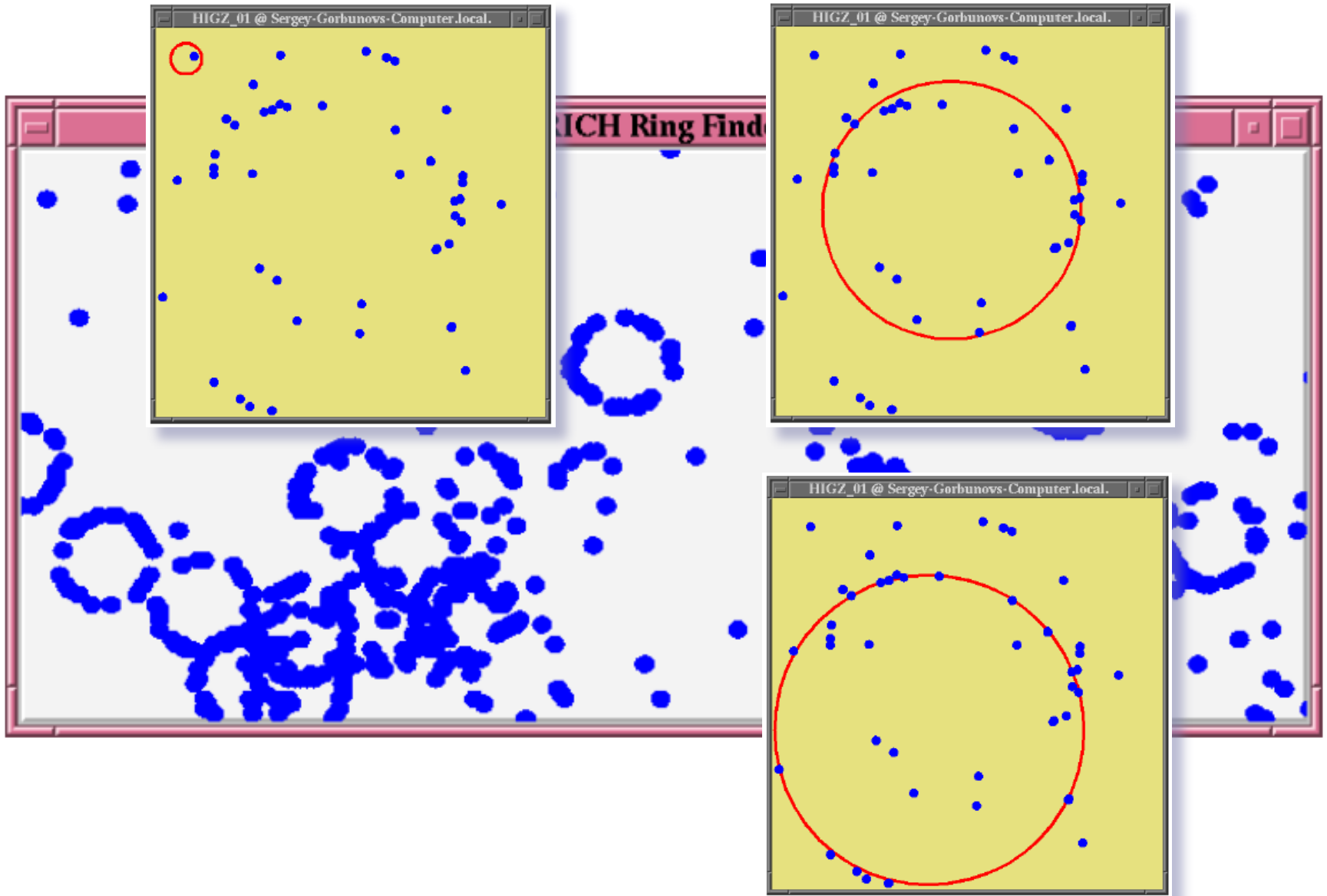




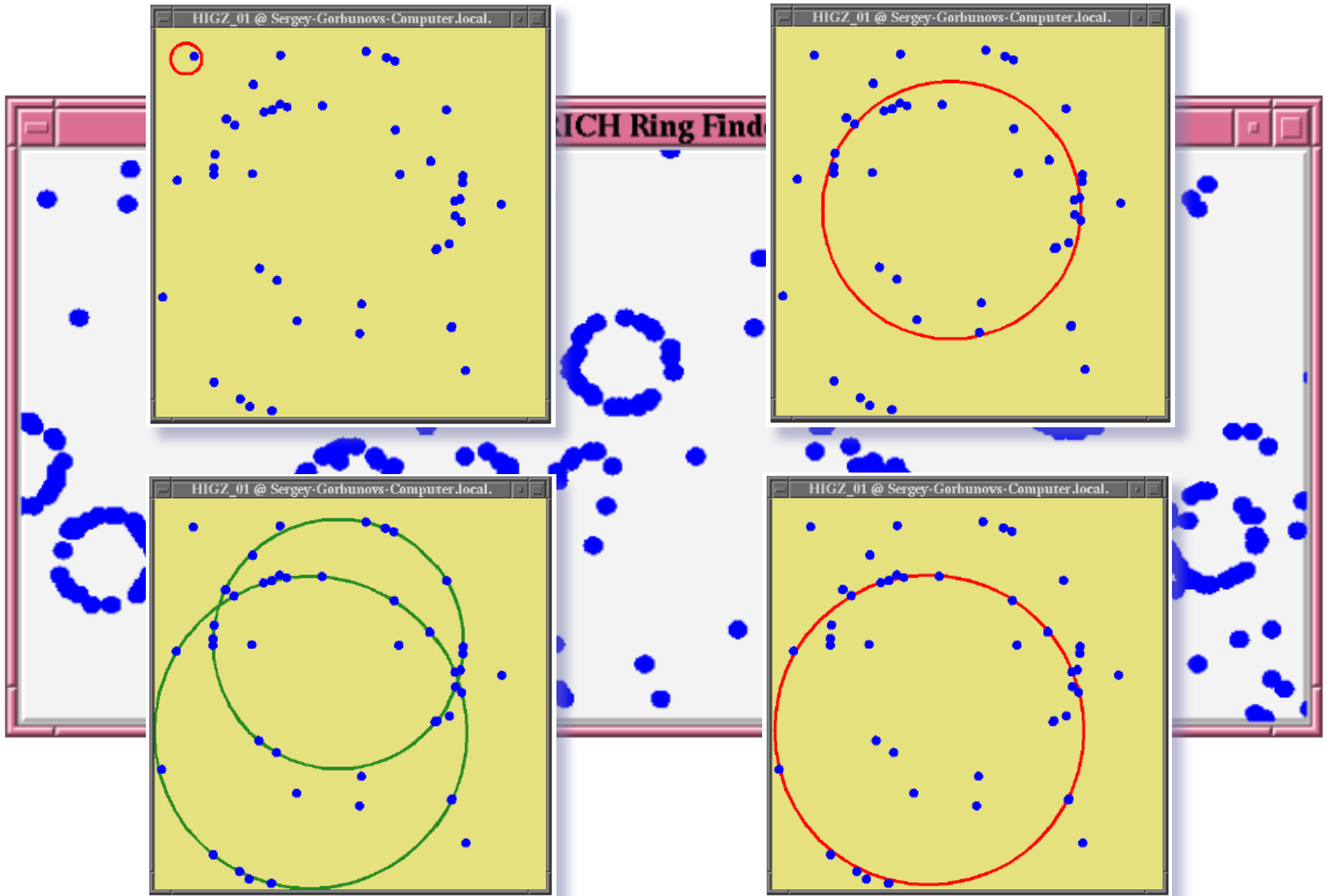
# Elastic Neural Net (EN) for RICH



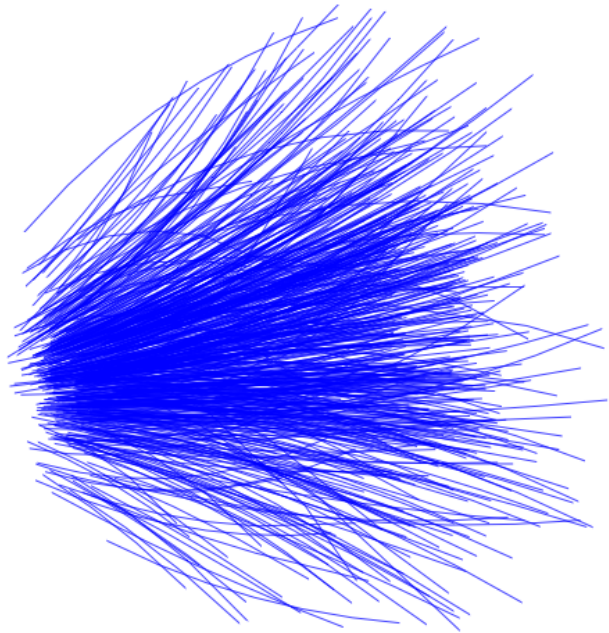
# Elastic Neural Net (EN) for RICH



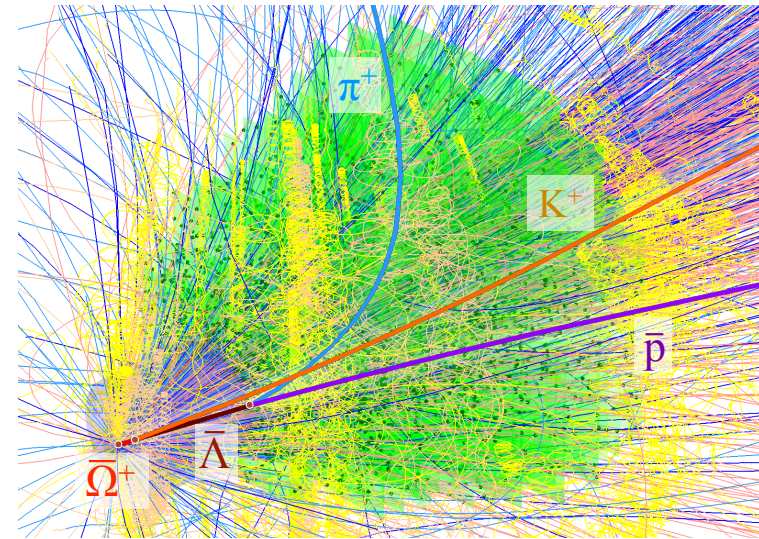
# Elastic Neural Net (EN) for RICH



## (2) Analysis

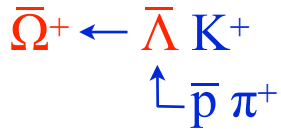
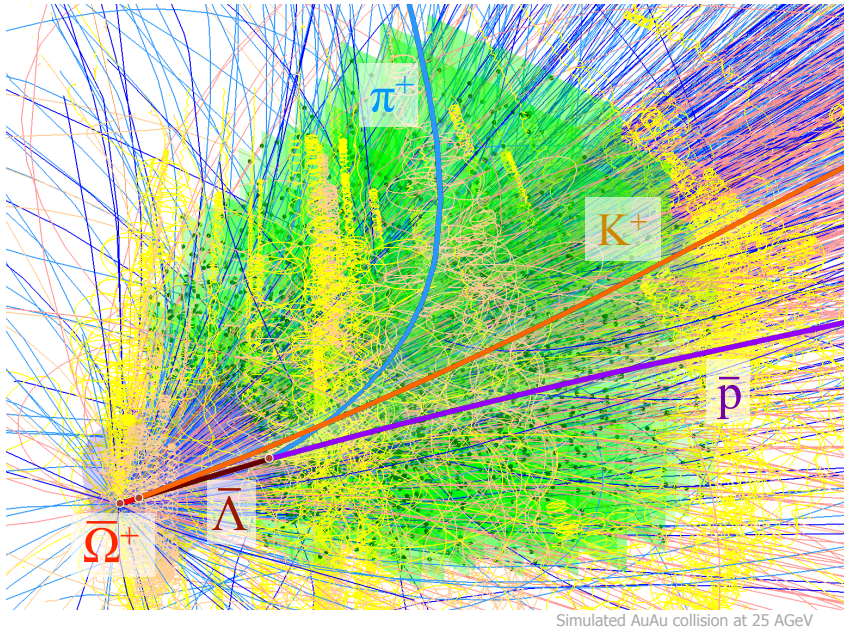


(2) Analysis





# CBM: KF Particle - Reconstruction of short-lived Particles



```

KFParticle Lambda(P, Pi);           // construct anti Lambda
Lambda.SetMassConstraint(1.1157);   // improve momentum and mass
KFParticle Omega(K, Lambda);       // construct anti Omega
PV -= (P; Pi; K);                  // clean the primary vertex
PV += Omega;                        // add Omega to the primary vertex
Omega.SetProductionVertex(PV);      // Omega is fully fitted
(K; Lambda).SetProductionVertex(Omega); // K, Lambda are fully fitted
(P; Pi).SetProductionVertex(Lambda); // p, pi are fully fitted
    
```

$$\mathbf{r} = \{ x, y, z, p_x, p_y, p_z, E \}$$

State vector

$$\mathbf{C} = \langle \mathbf{r} \mathbf{r}^T \rangle =$$

Covariance matrix

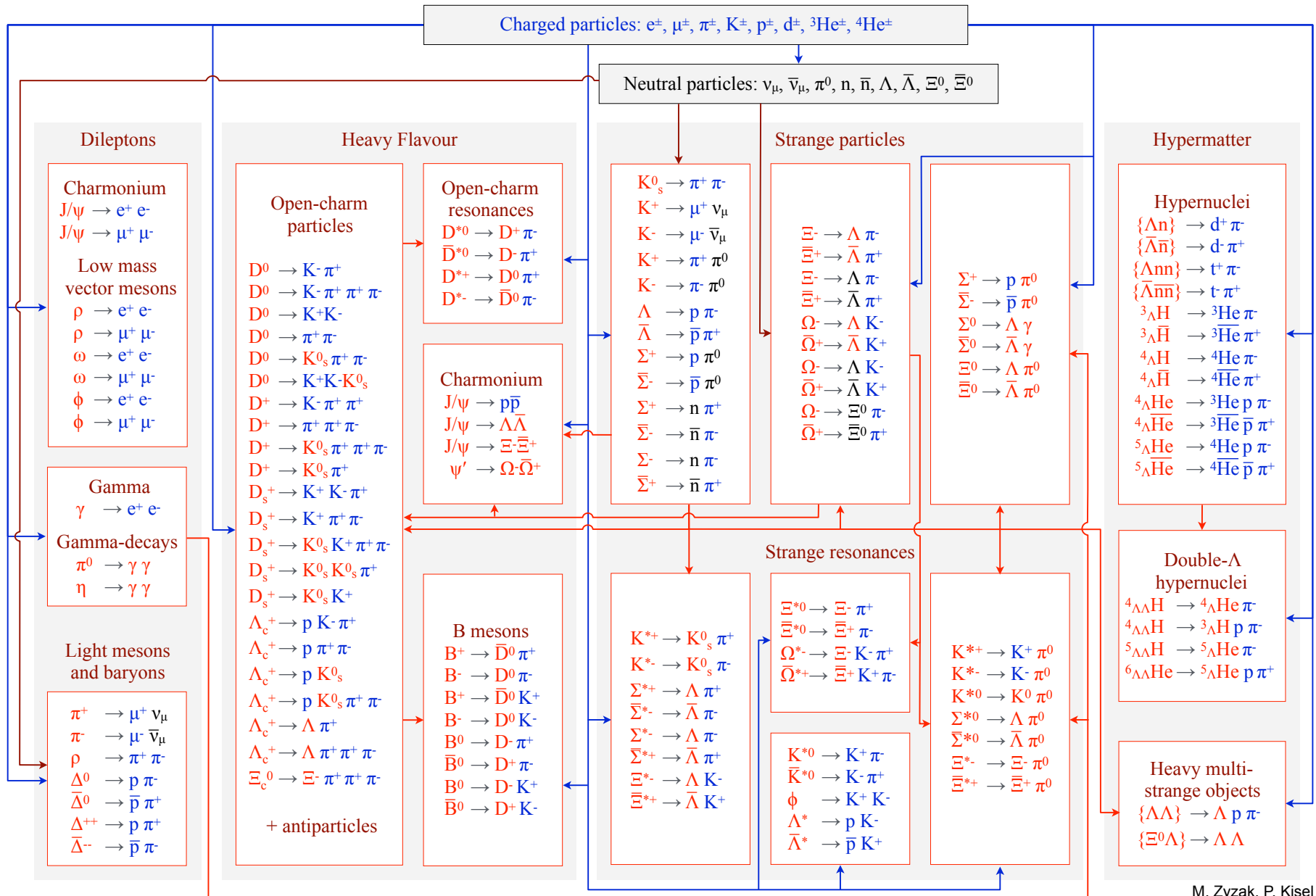
$$\begin{bmatrix} \sigma_x^2 & C_{xy} & C_{xz} & C_{xp_x} & C_{xp_y} & C_{xp_z} & C_{xE} \\ C_{xy} & \sigma_y^2 & C_{yz} & C_{yp_x} & C_{yp_y} & C_{yp_z} & C_{yE} \\ C_{xz} & C_{yz} & \sigma_z^2 & C_{zp_x} & C_{zp_y} & C_{zp_z} & C_{zE} \\ C_{xp_x} & C_{yp_x} & C_{zp_x} & \sigma_{p_x}^2 & C_{p_x p_y} & C_{p_x p_z} & C_{p_x E} \\ C_{xp_y} & C_{yp_y} & C_{zp_y} & C_{p_x p_y} & \sigma_{p_y}^2 & C_{p_y p_z} & C_{p_y E} \\ C_{xp_z} & C_{yp_z} & C_{zp_z} & C_{p_x p_z} & C_{p_y p_z} & \sigma_{p_z}^2 & C_{p_z E} \\ C_{xE} & C_{yE} & C_{zE} & C_{p_x E} & C_{p_y E} & C_{p_z E} & \sigma_E^2 \end{bmatrix}$$

## Features:

- KF Particle class describes particles by the **state vector** and the **covariance matrix**.
- Covariance matrix contains essential information about tracking and **detector** performance.
- The method for **mathematically correct** usage of covariance matrices is provided by the KF Particle package based on the **Kalman filter** (KF).
- Heavy mathematics of KF requires **fast** and **vectorised** algorithms.
- **Mother** and **daughter** particles are treated in the same way.
- The **natural** and **simple interface** allows two reconstruct easily complicated decay chains.
- The package is geometrically independent and can be adapted to **different experiments** (CBM, ALICE, STAR).

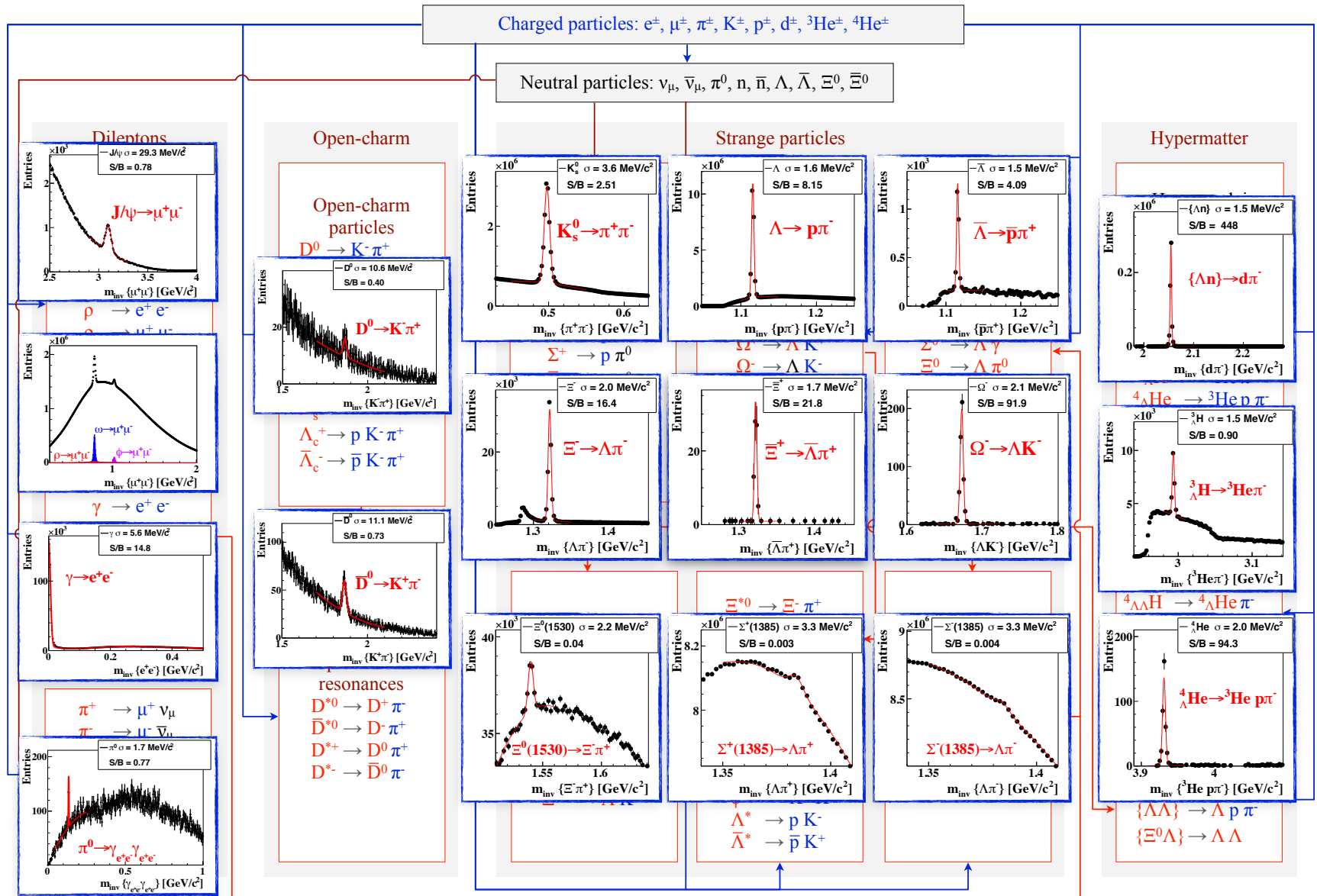
KF Particle provides a simple and very efficient approach to physics analysis

# CBM: KF Particle Finder for short-lived Particles



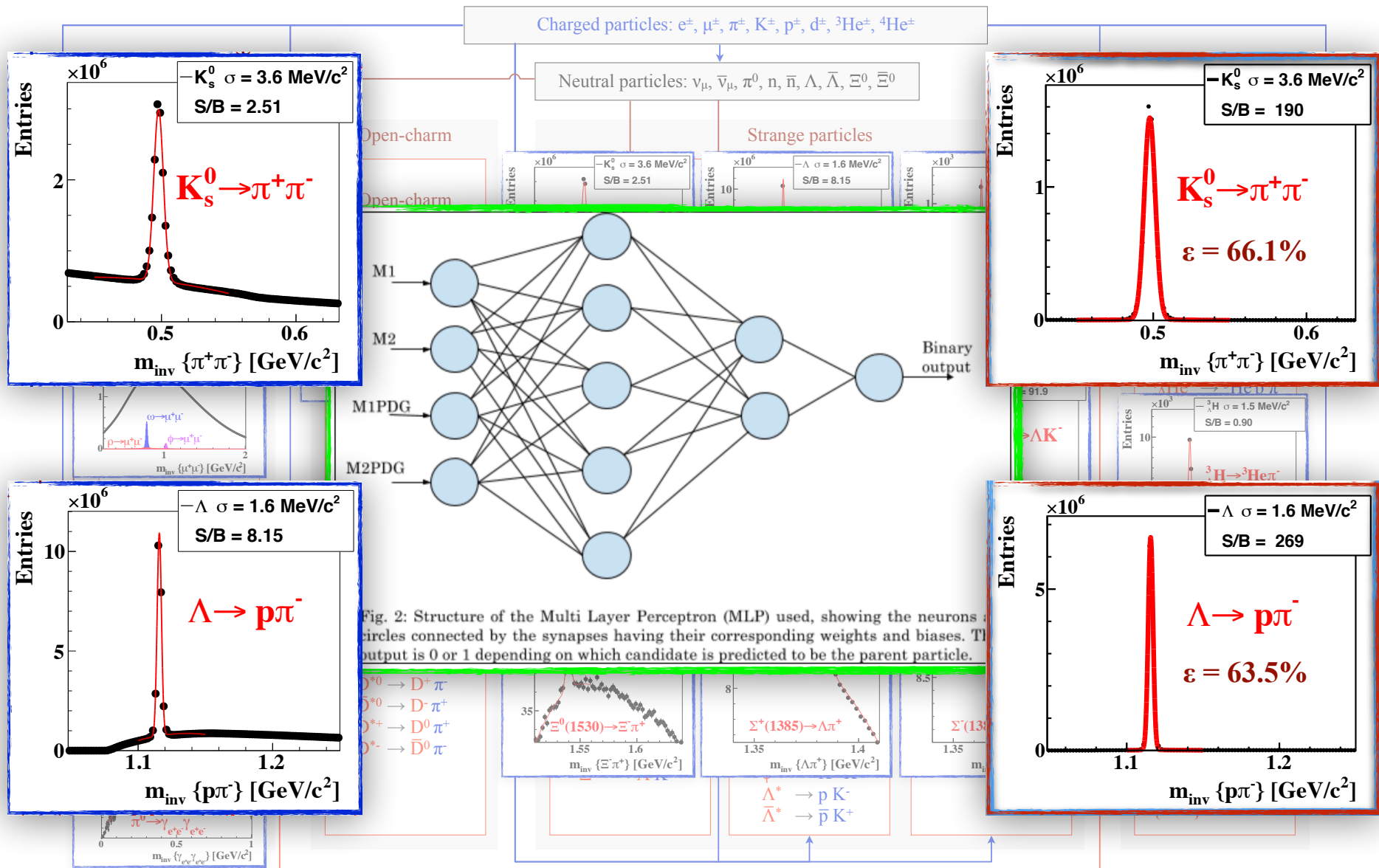
M. Zyzak, P. Kisel

# CBM: KF Particle Finder for short-lived Particles

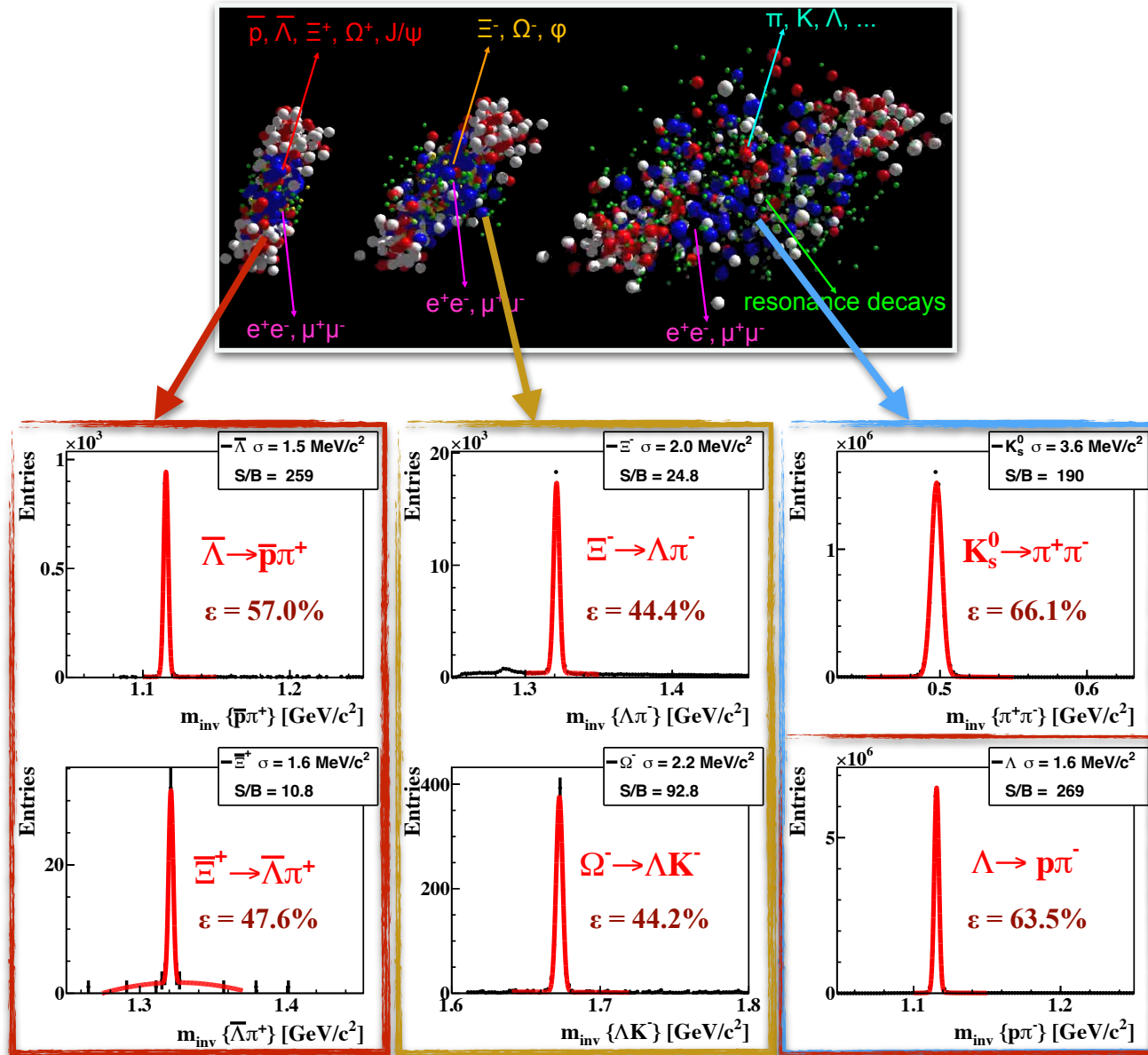


1.4 ms/event/core

# ANN for Identification of short-lived Particles



# CBM: Very Clean Probes of Collision Stages

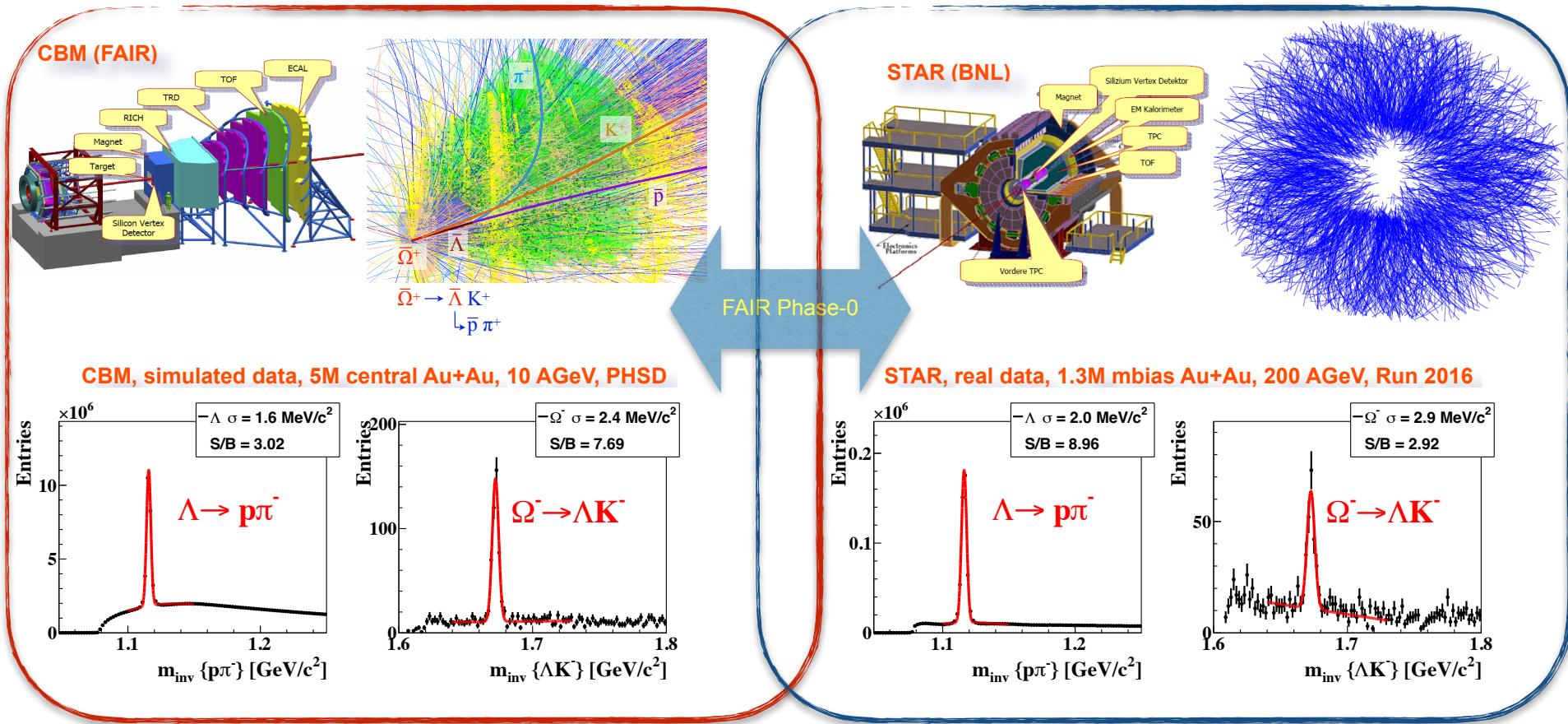


AuAu, 10 AGeV, 3.5M central UrQMD events, MC PID



# CBM → STAR: Reconstruction and Analysis Software

Within the FAIR Phase-0 program the CBM KF Particle Finder has been adapted to STAR and applied to Au+Au collisions recorded during 2014, 2016 and BES-I.

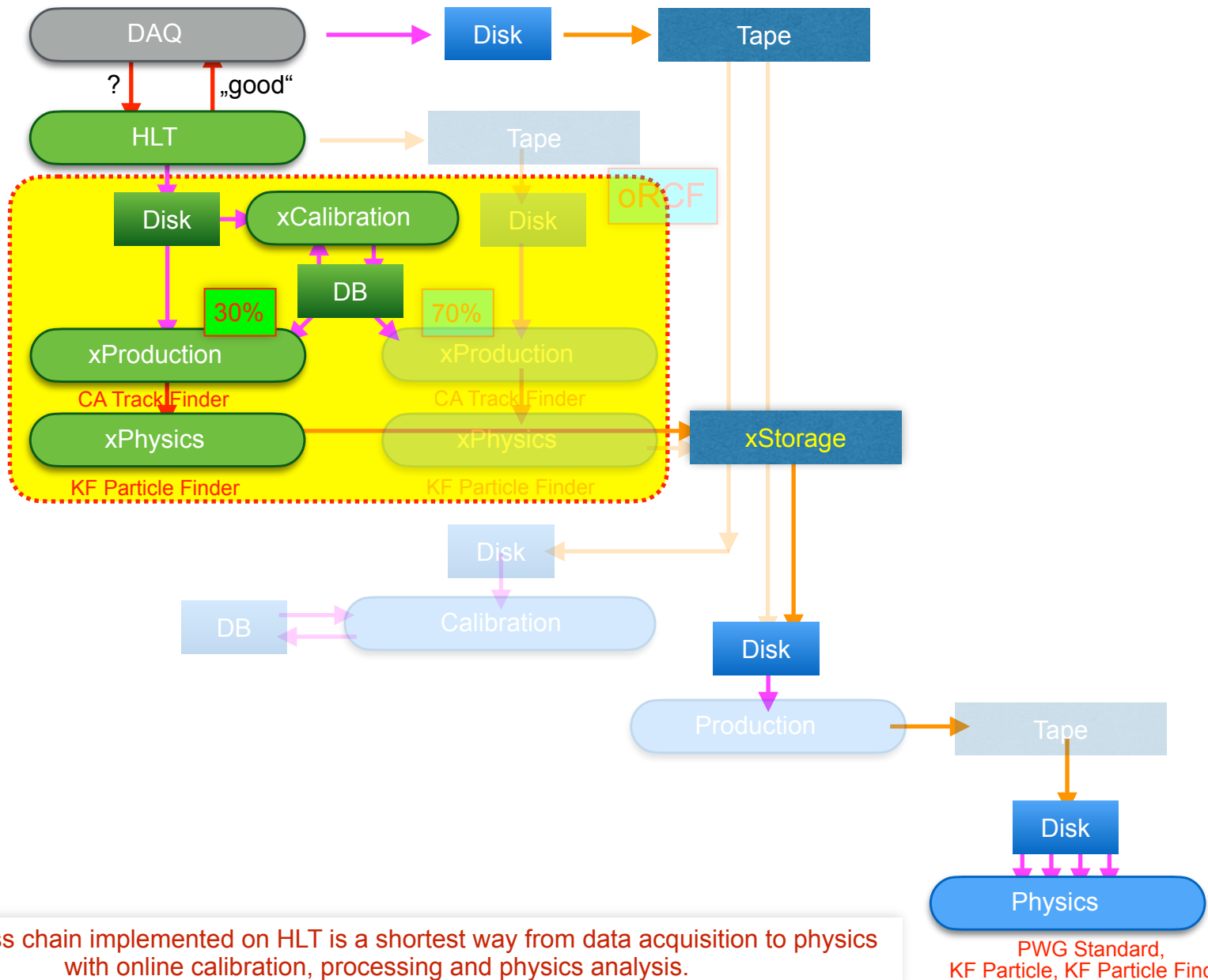


- ✓ Since 2016 the Cellular Automaton (CA) Track Finder is the default STAR track finder for data production. Use of CA provides 25% more  $D^0$  and 20% more  $W$  by reprocessing 2013 pp 510 GeV data sample.
- ✓ The KF Particle Finder provides a factor 2 more signal particles than the standard approach in STAR. The integration of the KF Particle Finder into the official STAR repository for use in physics analysis is currently in progress.

Used for the real-time express physics analysis during the BES-II runs (2018-2021)

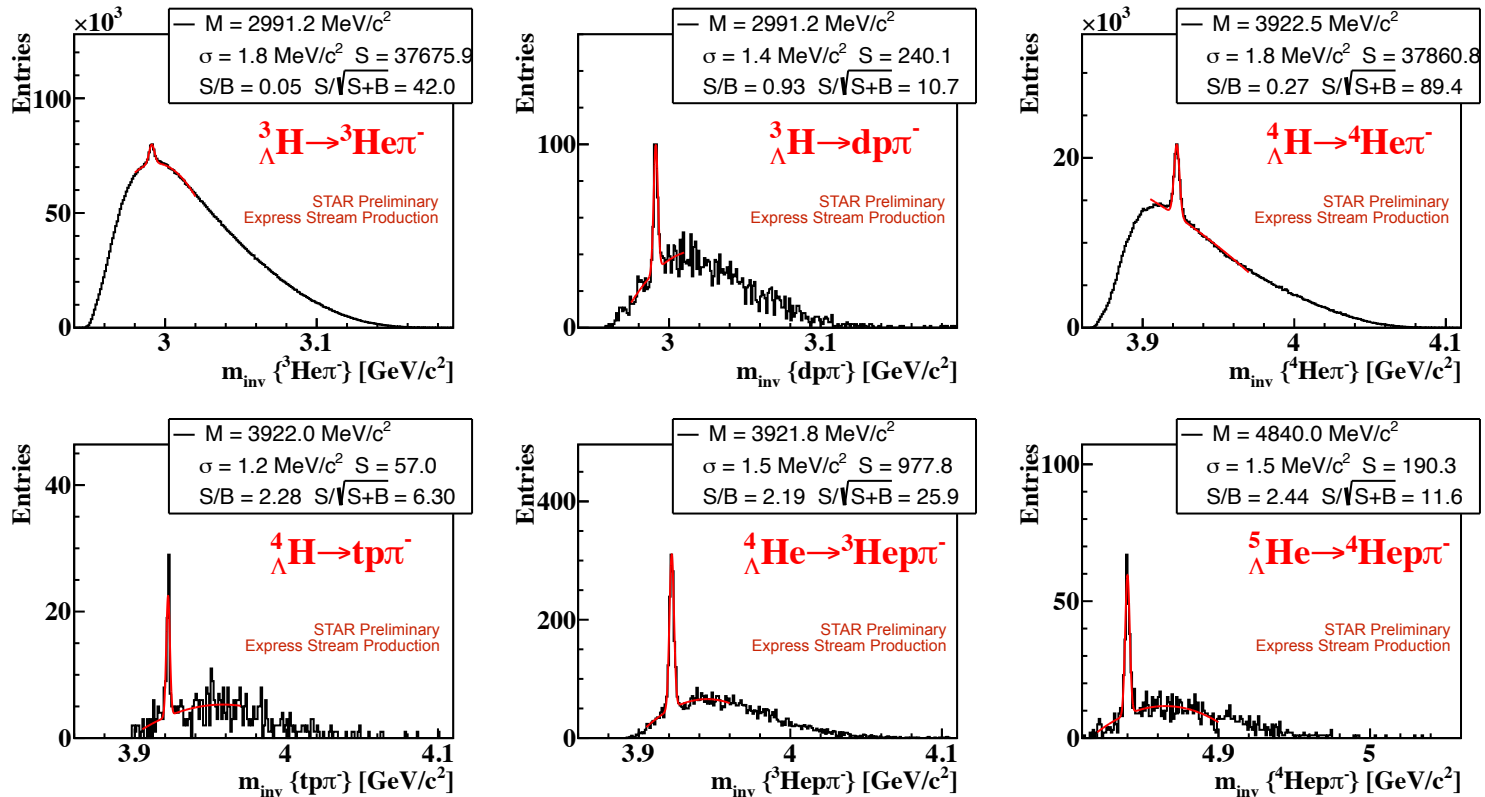


# STAR BES-II: Express Production Data Stream



# STAR BES-II: Hypernuclei

2018, 2019, 2020, 2021x FXT and 2021x collider at 7.7 GeV



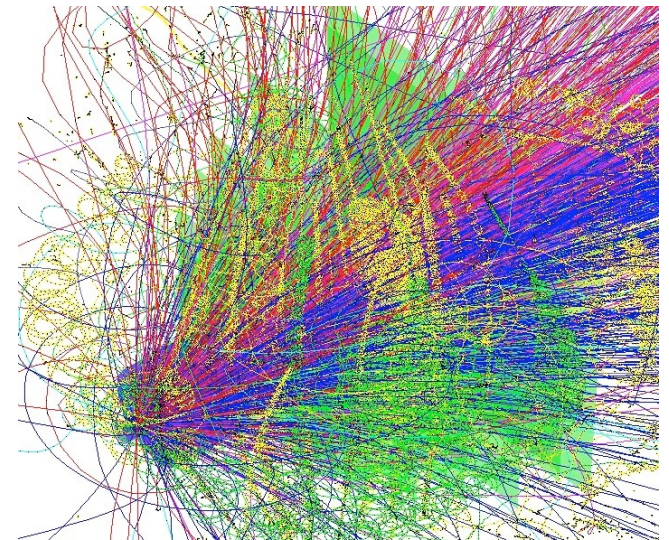
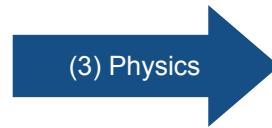
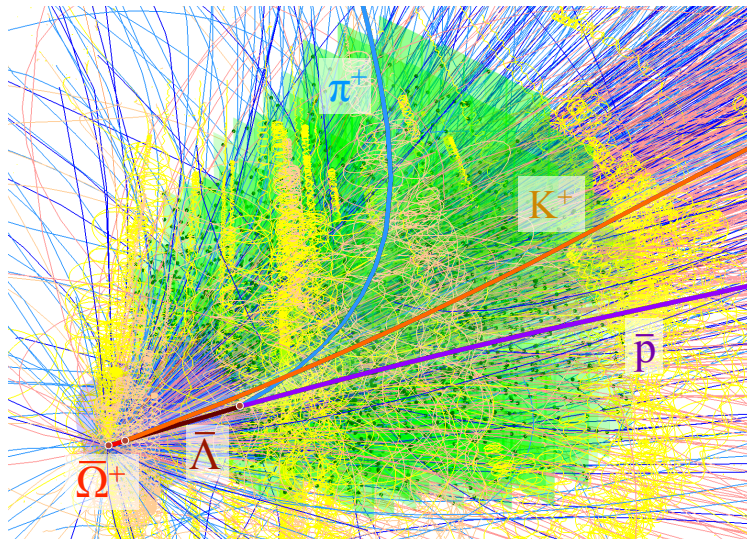
I. Kisel (for the STAR Collaboration), EPJ Web of Conferences 271, 08001 (2022)

- With the same procedure all FXT data from 2018, 2019 and 2020 were analyzed.
- In all (standard and express) production data  ${}^5_{\Lambda}\text{He}$  is visible with significance **11.6  $\sigma$** .

FIAS, GSI, BNL

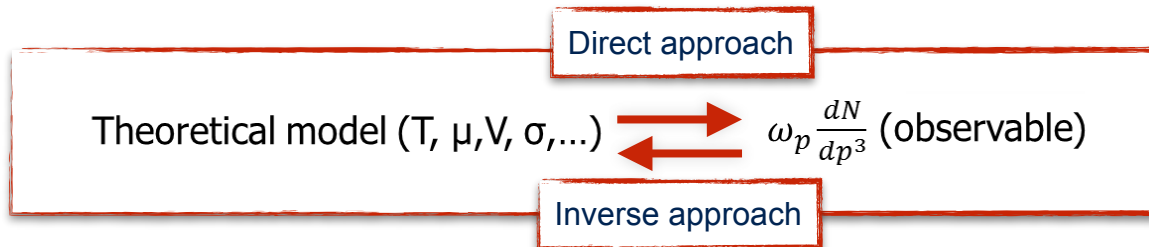
The collected statistics is enough to measure yields, lifetimes and spectra of these hypernuclei

# (3) Physics



# CBM: Online Physics Analysis?

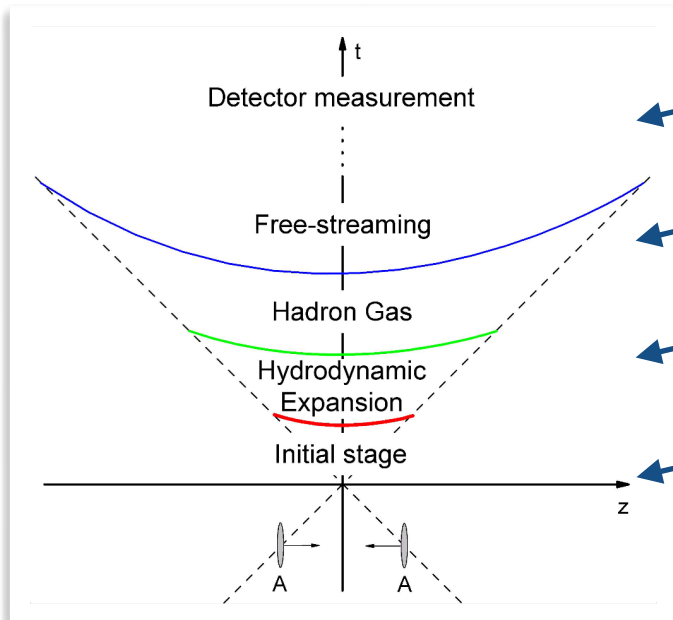
Online physics analysis = online extraction of medium properties in heavy-ion collisions



## Motivation:

- determination of physical properties of QCD matter created in HIC (temperature, flow, phase transitions, ...),

## Stages of collision

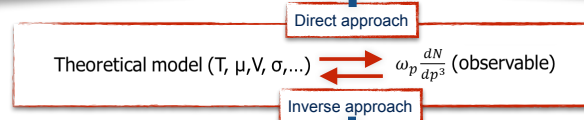
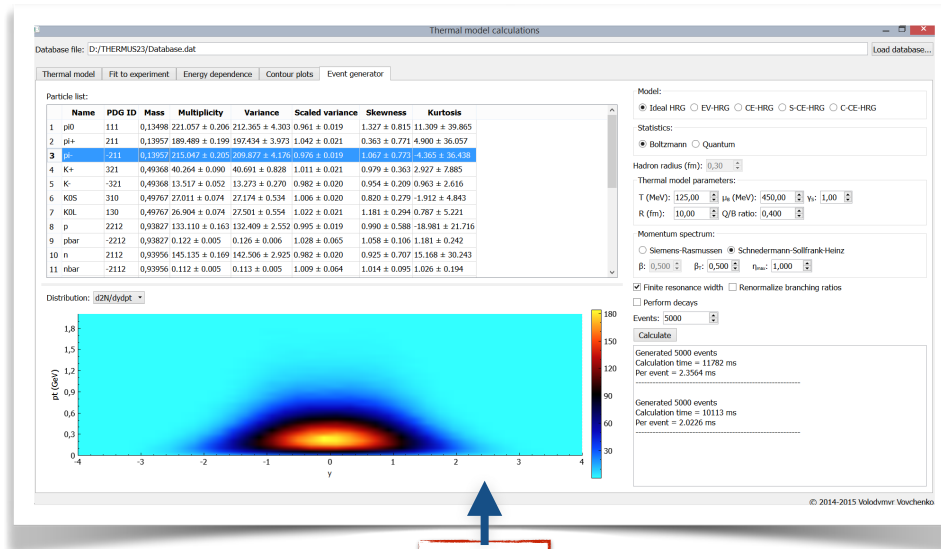


## Models for different stages

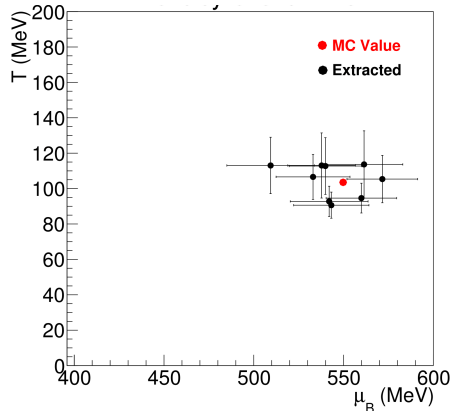
- Final momentum spectrum (**Blast-Wave**, Tsallis, ...)
- Statistical-thermal models for chemical freeze-out (**ideal hadron gas**, **Van der Waals hadron gas**, Hagedorn states, ...)
- Relativistic hydrodynamics (**ideal**, viscous; **(0+1)D**, **(1+1)D**, **(3+1)D**, ...)
- Initial stage (**Glauber**, CGC, ...)

How to extract the parameters of theoretical models?

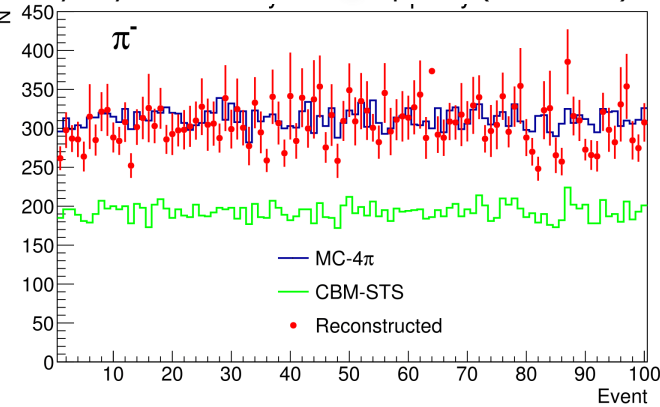
# CBM: Online Physics Analysis (macroscopic)



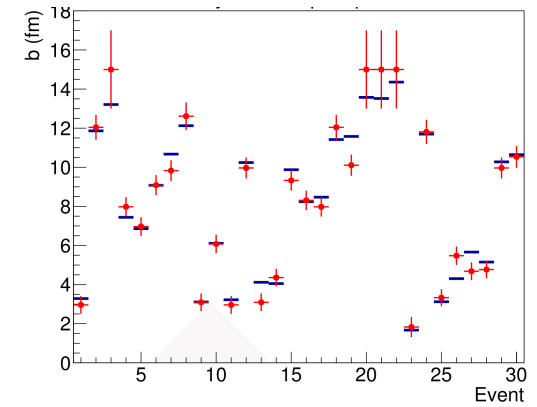
E.-by-E. extraction of  $T$  and  $\mu_B$  (HRG)



E.-by-E. yield estimate incl. acceptance (Blast-Wave)



E.-by-E. impact parameter (Glauber)

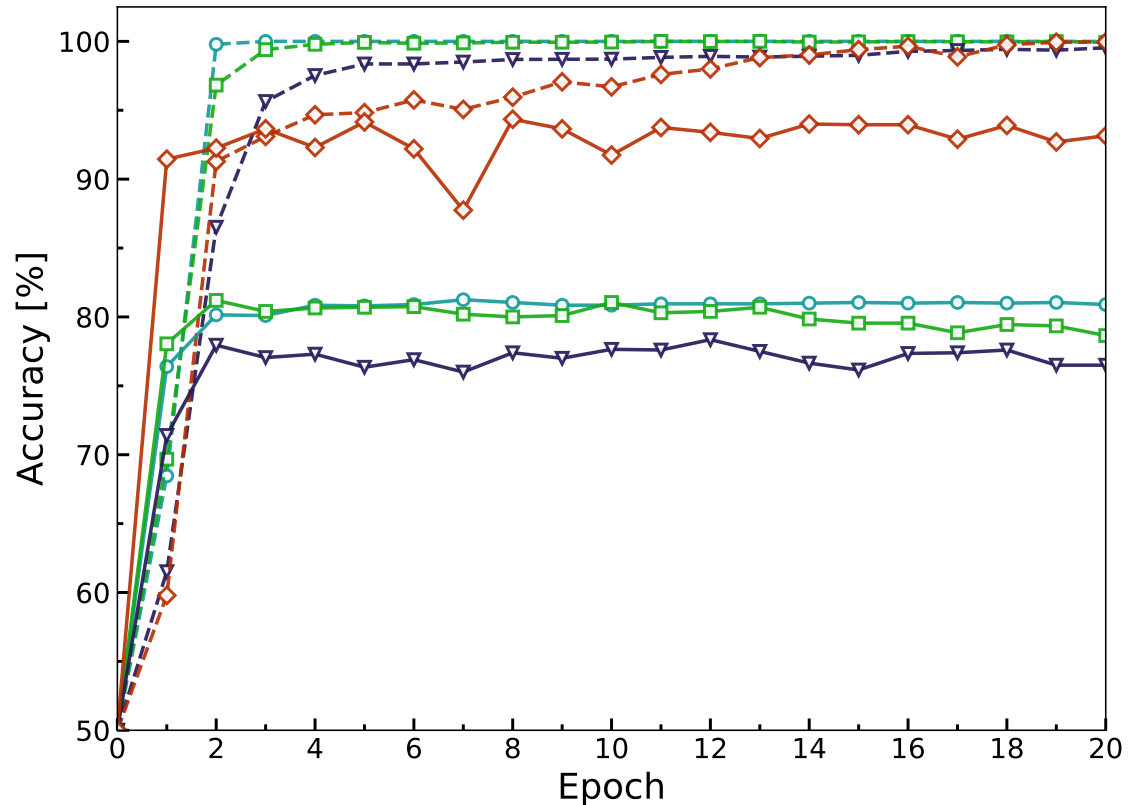
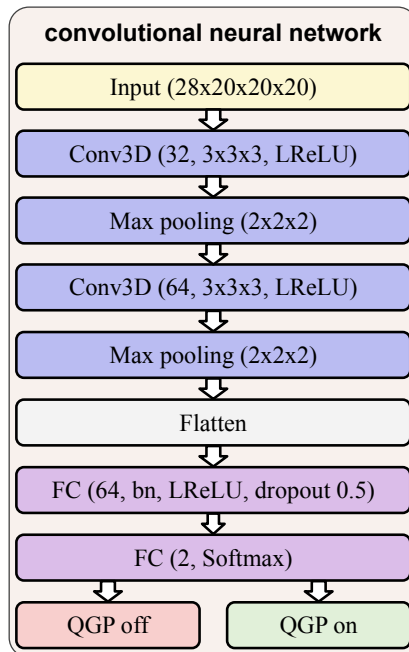
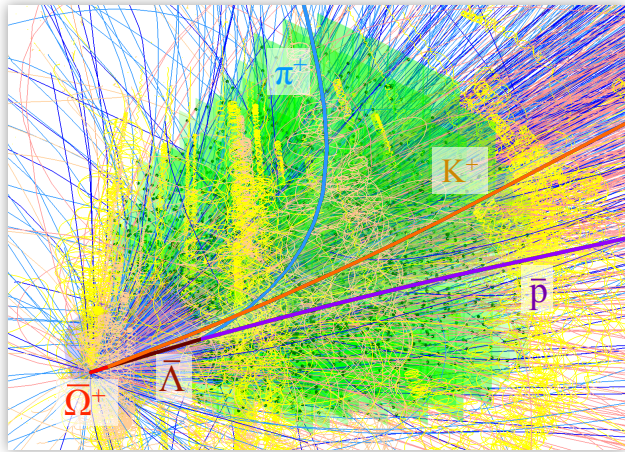


I. Kisel, V. Vovchenko

A package to extract the parameters of macroscopic theoretical models in CBM experiment is implemented



# CBM: Online Physics Analysis (microscopic)

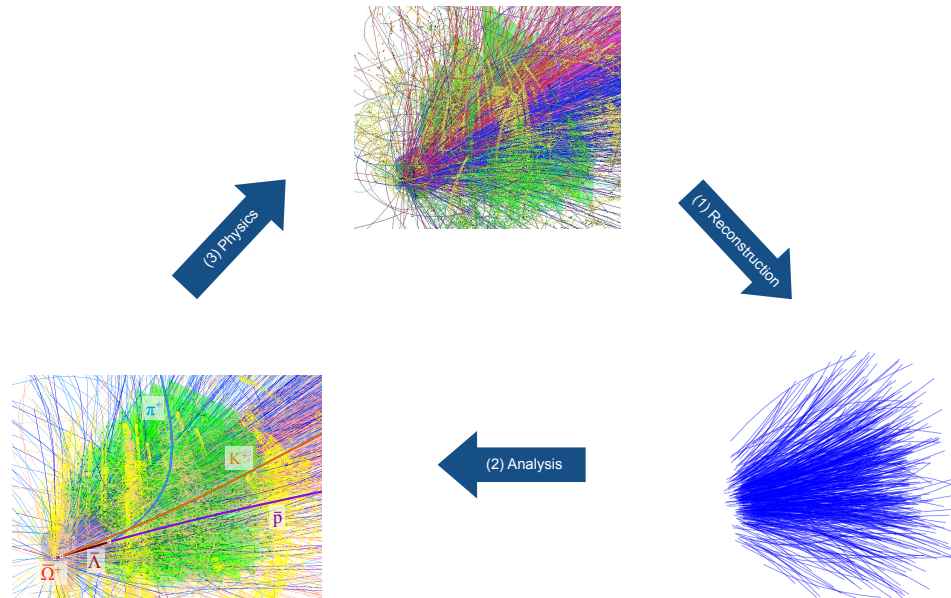


F. Sergeev, E. Bratkovskaya, I. Kisel and I. Vassiliev, Int. Mod. Phys. A, Vol. 35, No. 33, 2043002 (2020)

An ANN package to extract the parameters of microscopic theoretical models in CBM experiment is under development



# Summary



- Our reconstruction and analysis algorithms have shown high efficiency and reliability on both **simulated** data of the **CBM** experiment and **real** data of the **STAR** experiment in **online** mode.
- Our **Frankfurt** group of 3 PhD students and 6 master and bachelor students, together with the group of Dr. Gligorov (**LPNHE**, Paris), is currently working on developing a **package of neural network algorithms** for the tasks of reconstruction and analysis of experimental data.
- With the artificial neural network approach, we expect to make further progress both quantitatively and qualitatively in investigating the **properties of matter** in heavy ion collisions.