Introduction to Charged Particle Reconstruction

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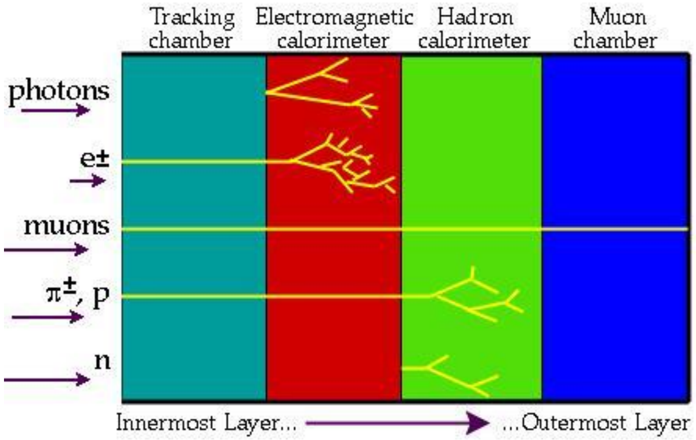
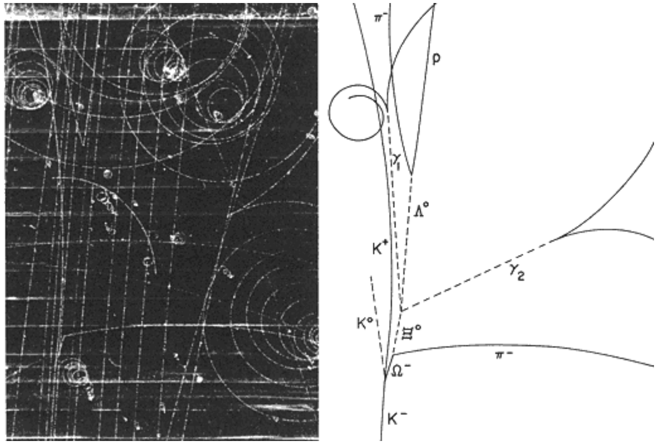
Outline

- Introduction
- Traditional tracking
- Advanced tracking

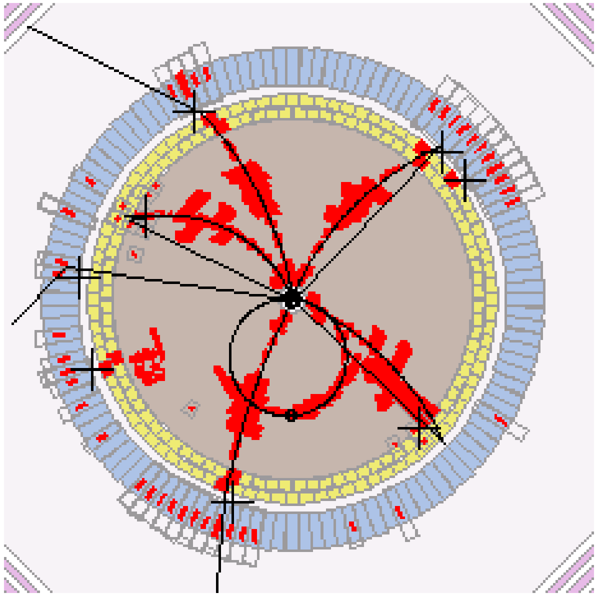
Introduction to tracking

- Discovery of new particles and new physics rely on the knowledge of particles trajectory in detector
- We can only see "final-state" particles
- Our aim is determine the parameters of mother particles precesicesly





Discovery of the **Ω**⁻ in 1964



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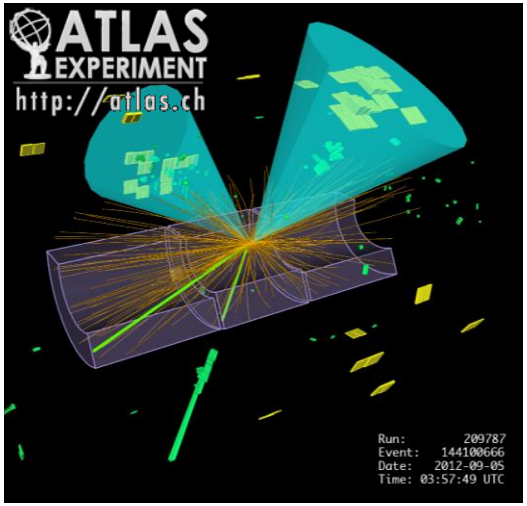
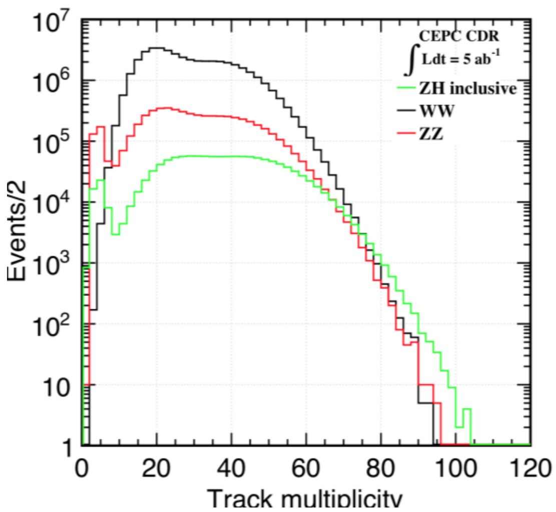


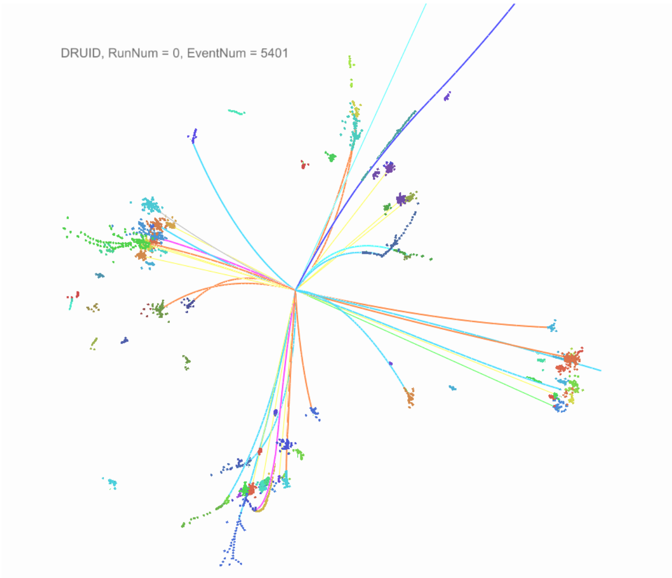
ATLAS:H → ZH → ll bb

Requirements for CEPC Tracking

- **Ultimate goal: trace the whole cascade topology of a physics event, for example, jet substructure!**
- **Requirments:**
  - **Efficient**
  - **Robustness: noisy resistant**
  - **Fast**

Physics process	Measurands	Critical detector	Required performance
$ZH \to l^+l^-X$	m_H, σ_{ZH}	Tracker	$\Delta(1/P_T) = 2\times10^{-5} \oplus \frac{10^{-3}}{P(GeV)\sin^{\frac{3}{2}}\theta}$
$H \to \mu^+\mu^-$	$B(H\to\mu^+\mu^-)$		
$H \to b\bar{b}, c\bar{c}, gg$	$B(H \to b\bar{b}, c\bar{c}, gg)$	Vertex	$\sigma_{r\phi} = 5 \oplus \frac{10}{p(GeV)\sin^{\frac{3}{2}}\theta}(\mu m)$

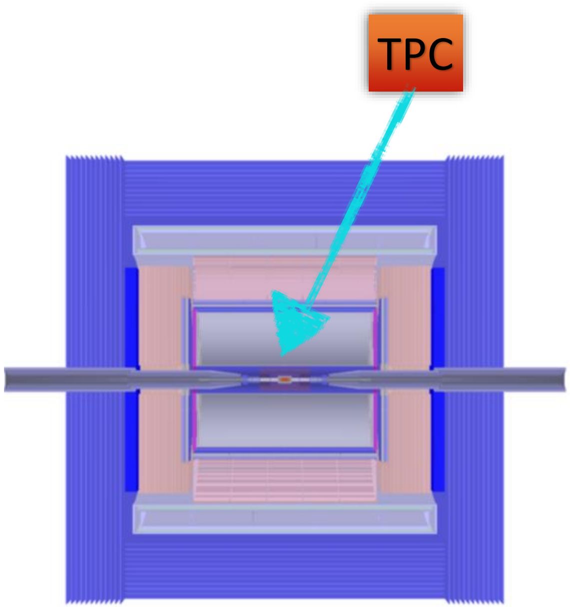


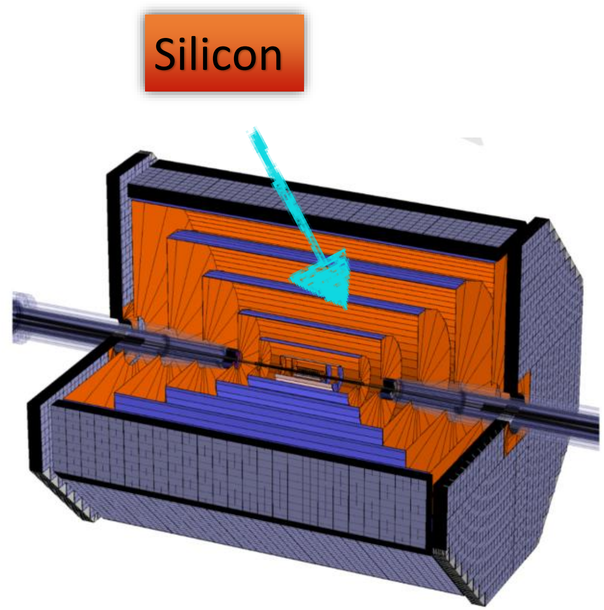


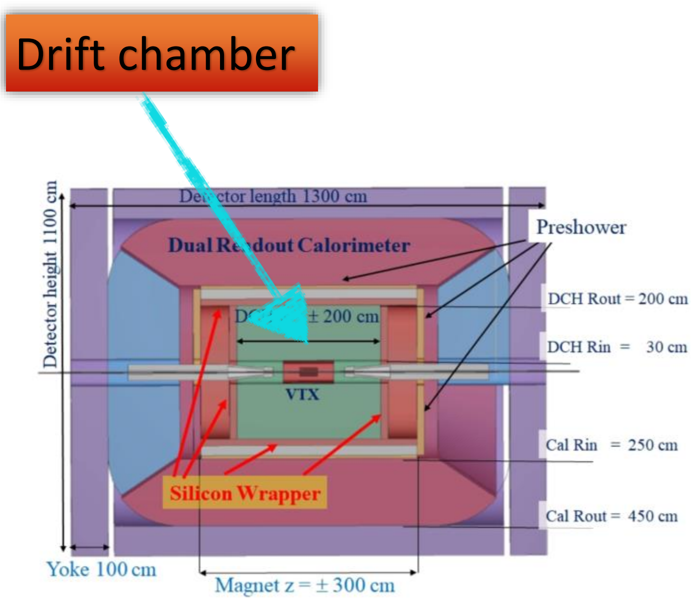
A typical CEPC event

CEPC detector concepts

- Three detector concepts proposed
  - Silicon tracker + TPC + PFA calo - used for full simulation performance study
  - Full silicon tracker + PFA calo
  - Silicon + Drift Chamber + DR calo



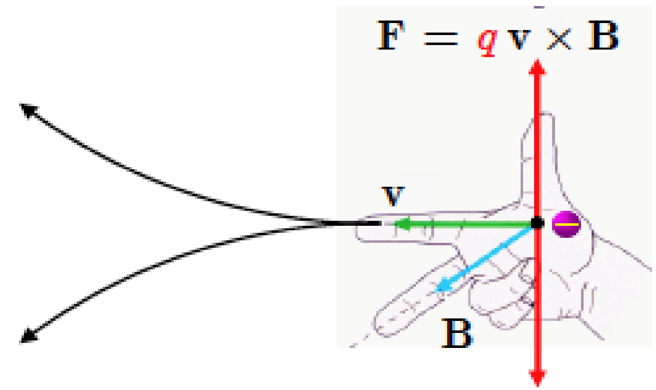




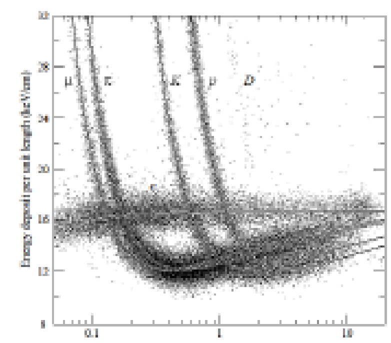
Aim of Charged Particle Tracking

- Provide trigger signal
- Measurement of particles
    1. Sign of the charge
    2. Momentum
    3. Particle ID (mass)
    4. Impact parameter (lifetime tag)

the sign of the charge

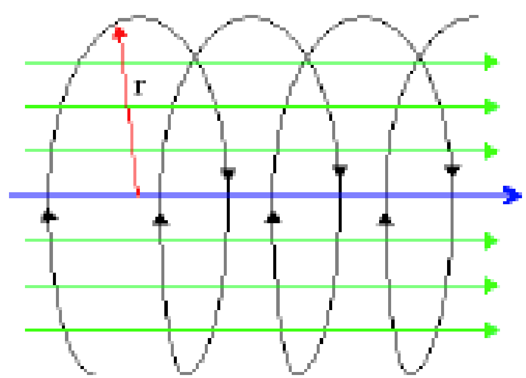


particle ID (mass), not necessarily with the same detector



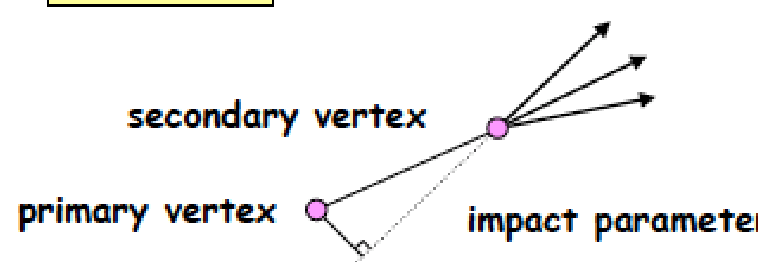
$$p = m_o \gamma \beta$$

momentum (magnetic field)



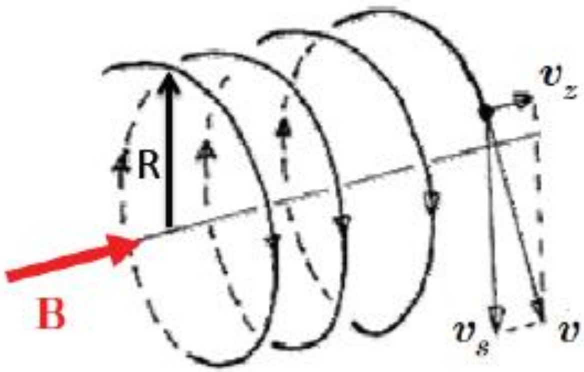
$$p = 0.3 \cdot B \cdot R$$

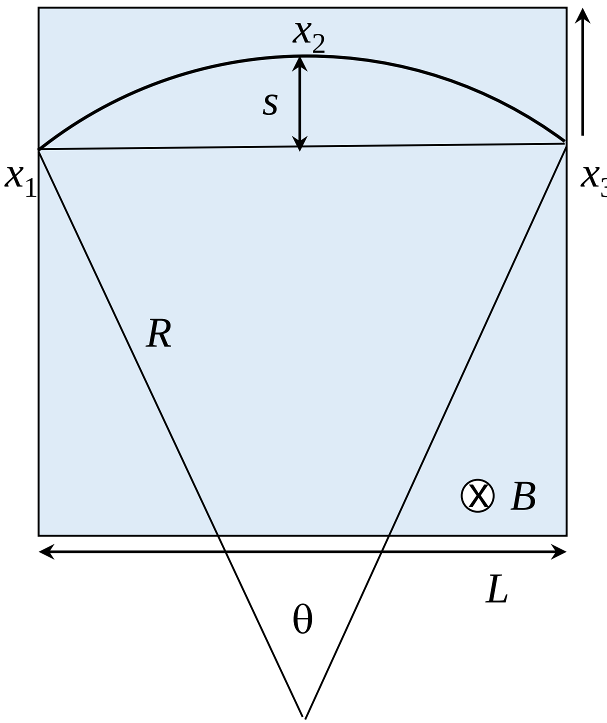
lifetime tag



Momentum measurement

- In case of homogeneous magnetic field the trajectory is given by a helix





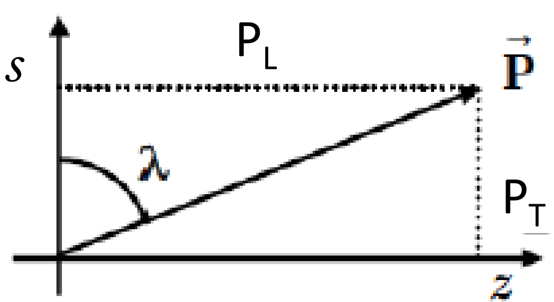
In x-y(or r-ϕ)plane, measure transverse momentum (P_T)

$$R = \frac{P_T}{0.3qB}$$

R: m
P_T: GeV/c
B: Tesla
q: charge of particle

In s-z plane, measure dip angle (λ)

s is path length alone the track in x-y plane



total momentum: $P = P_T/\cos\lambda$

Tracking detectors

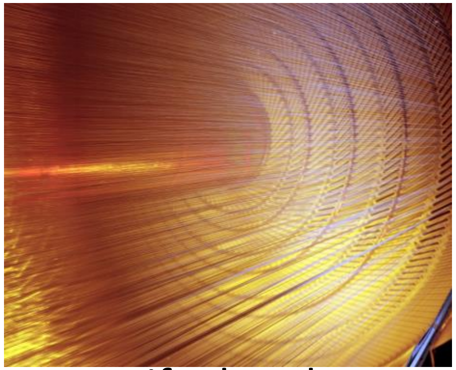
- Gaseous
  - Drift chamber, straw tube, Multi-Wire Proportional Chambers,TPC,(C)GEM
- Solid state
  - Slicon strip,pixcel etc.
- Scintillating

- Each converts the ionization left by the passing of a charged particle into an electrical signal
  - charge collection
  - light collection/conversion with photo-cathode

Gaseous Tracking detectors

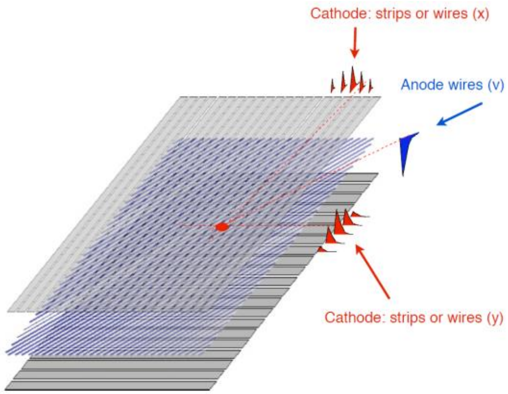
Straw tracker

~ 100 μm



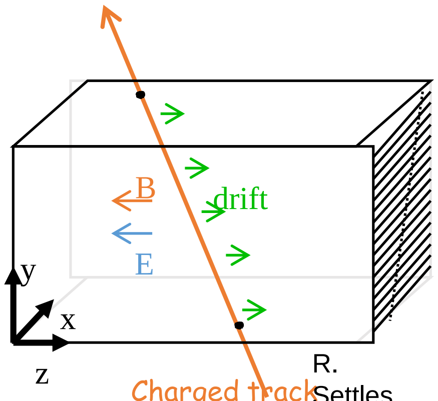
Drift chamber

σ_{xy} ~100μm σ_z~<1mm



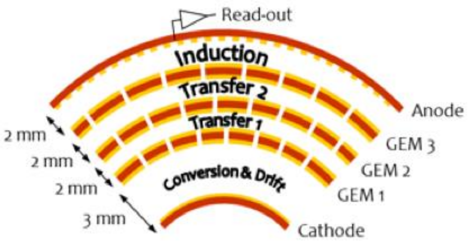
MWPC

~ 300 μm



TPC

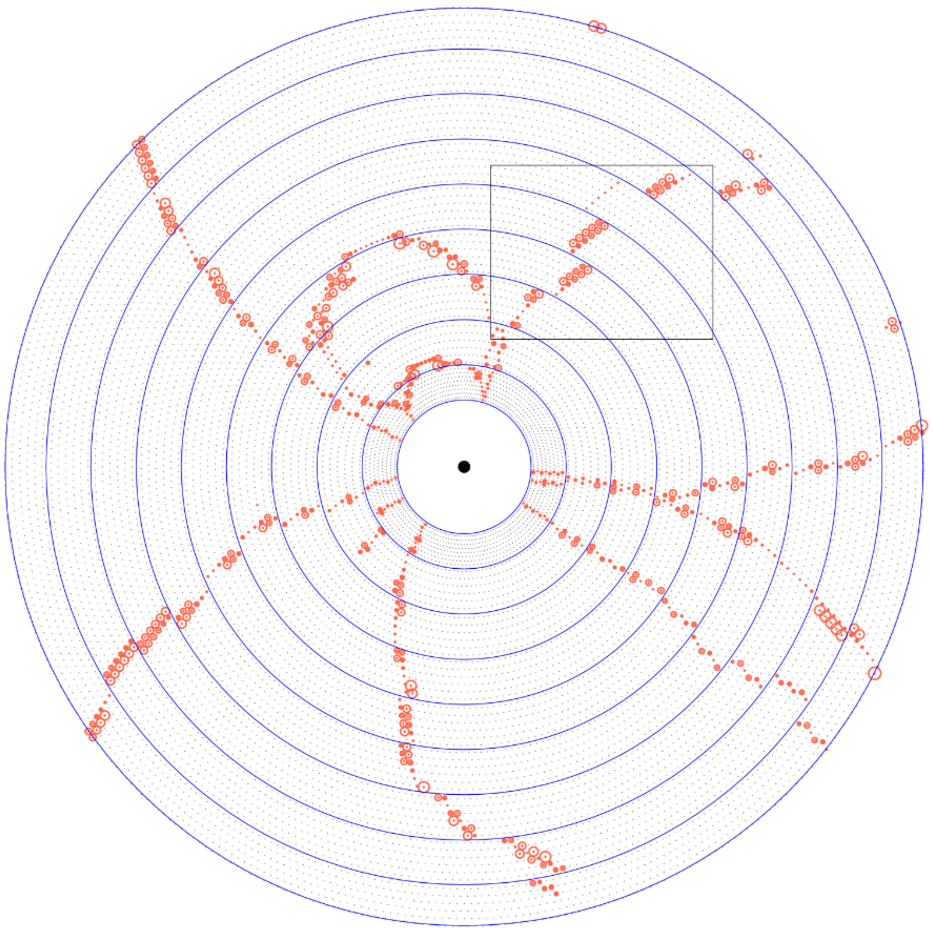
σ_{xy} ~200μm σ_z~<1mm

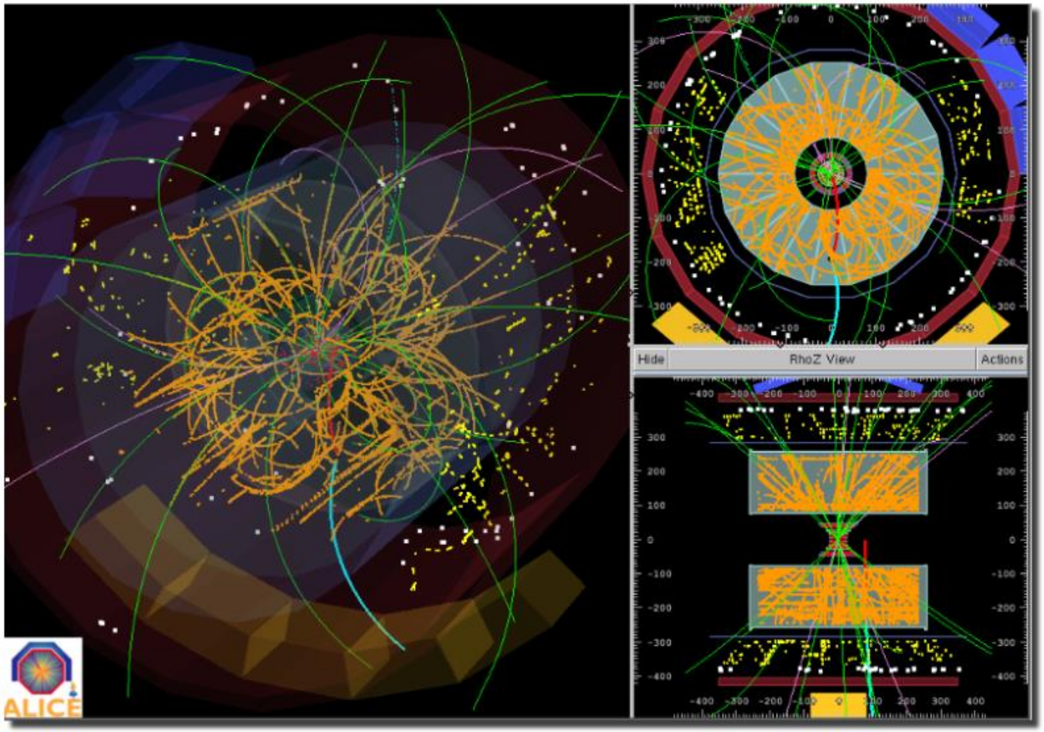


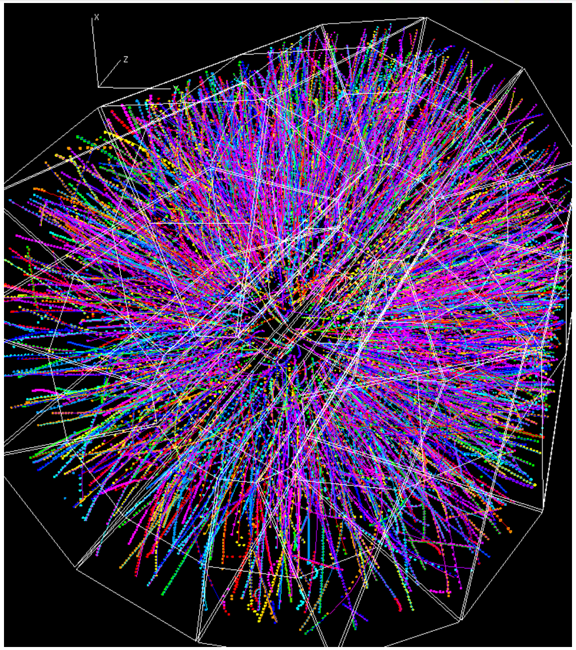
(C)GEM

σ_{xy} ~100μm σ_z~<500um

Event display







BelleII Drift chamber

STAR TPC

Tracking Vocabulary

- "track" : a parametric representation of a charged particle's trajectory
  - usually calculated from the positions of hits in one or more particle detectors assumed to come from a single particle traversing their sensitive areas
- "hit" : a signal or group of adjacent signals in a single layer of a tracking detector that originates from the passage of a single charged particle. Also often called a "cluster"
- "error" : the expected resolution of a hit.
  - can vary with the angle of incidence of the track, the number of hit elements, drift time, etc.
- "pattern recognition" : the process of selecting a group of hits from different layers of a tracking detector that is geometrically consistent with originating from a single charged particle
  - the hardest part of tracking, algorithmically

Tracking Vocabulary

- "fitting" : the process of calculating the parameters of the particle's trajectory using the hit positions and errors
  - can be done iteratively or in a single pass through the hits collected by the pattern recognition algorithm
- "error matrix" : the (usually) 5x5 covariance matrix that gives the uncertainties on the track parameters
- "multiple scattering" : the inevitable deviation of particle paths from a perfect curve caused by coulomb interactions with matter
- "energy loss" : ionization loss caused by interactions of the charged particle with the matter of the detector and ancillary material

Track parameterization and track model

- ## Track parameterization/state vector
  - When tracking in a solenoidal magnetic field, particle trajectories are assumed to be helical, at least locally

  examples:

  1. Charge, momentum, position: **x**= (q,px,py,pz,xb,yb,zb)
  2. track circle parameter : **x**= (d0,ϕ0,q/pt,z0,θ)
     - where

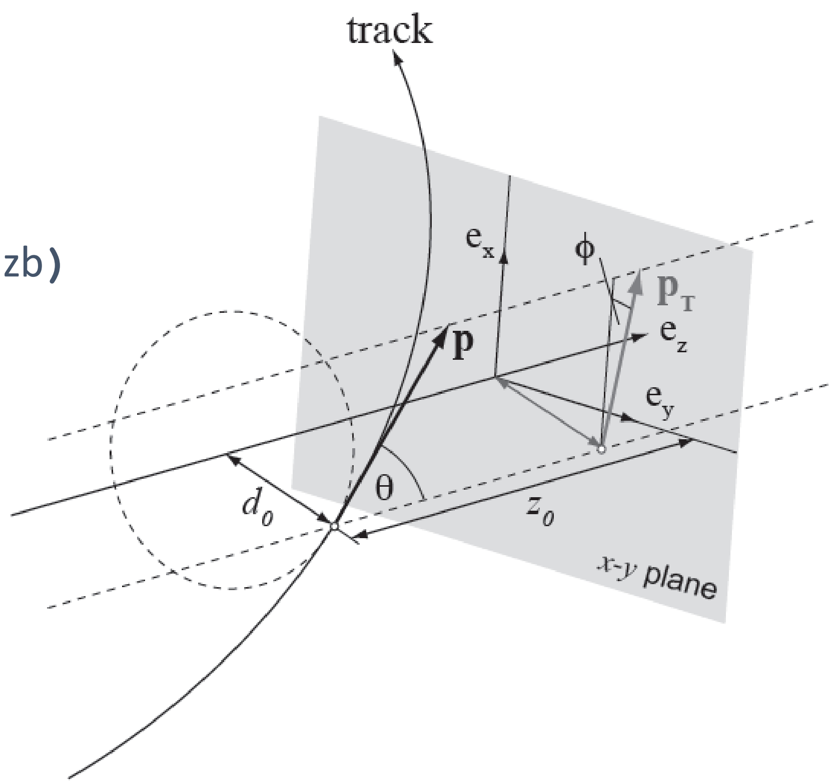
       q is the charge of particle and pt is the transverse momentum

       ϕ_0 is the direction of the track at the closest point to (0,0)

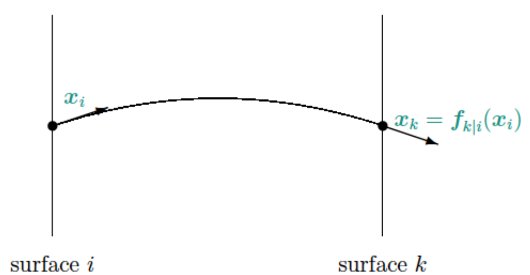
       d_0 is the distance of closest approach to ($x = 0$, $y = 0$)

       θ Is the polar angle measured up from beam axis

       z_0 is the z position of the track when it is at its distance of closest approach to ($x = 0$, $y = 0$)



- ## Track model
  - the solution to the equation of motion
  - describes how the state vector at a given surface depends on the state vector on a different surface
    - example: Runge-Kutta (numerical integration) : treat non-uniformity of magnetic field



$$x_k = f_{k|i}(x_i)$$

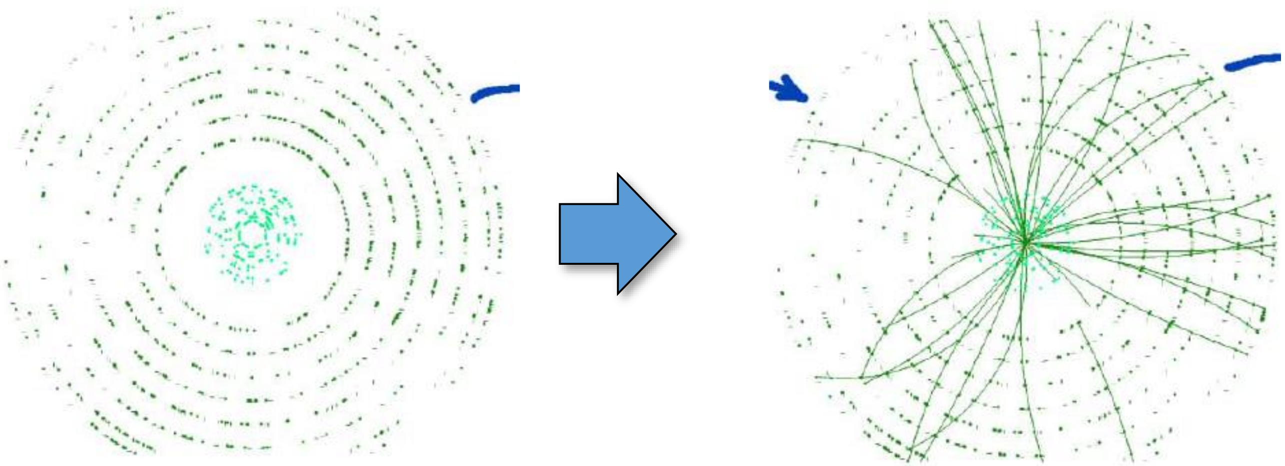
track propagator

Track propagator from surface i to surface k

Tracking tasks

1. Track finding (pattern recognition)
   - classification of hit measurement into subset which original from same track
   - reject the noise hits and background hits
2. Track fitting
   - optimally estimate of track parameters from the set of hit position and give the covariance matrix of the estimate

- Final classification may be deferred to the fitting. The boundary between track finding and track fitting is therefore fuzzy.



Track Finding

- Local track finding
  - seed->compute rode->pick up hits ->confirm track candidate
  - examples:
    - Road method
    - Combinatorial Kalman filter
    - Cellular automaton

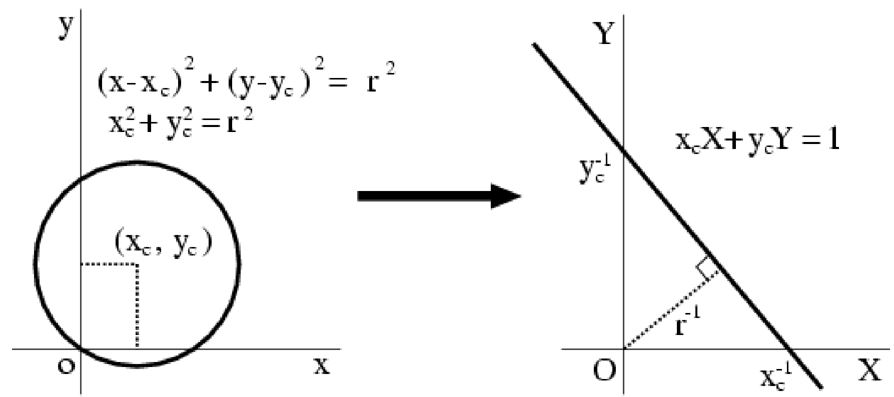
- Global track finding
  - Define a suitable feature space->find clusters in the feature space
  - examples:
    - Histogramming
    - Template matching
    - Hough transform
    - Apollonius circle

- Advanced tracking
  - Machine learning/deep learning

Conformal transform & Histogramming

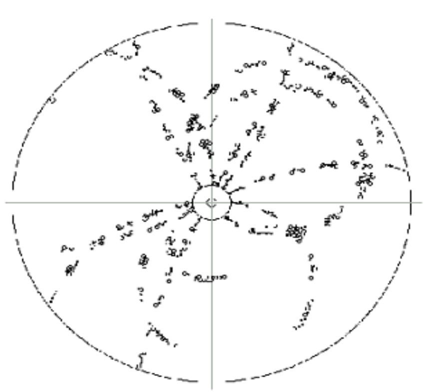
- Convert a circle pass through origin into a line

$$X = \frac{2x}{x^2 + y^2}, \qquad Y = \frac{2y}{x^2 + y^2}.$$

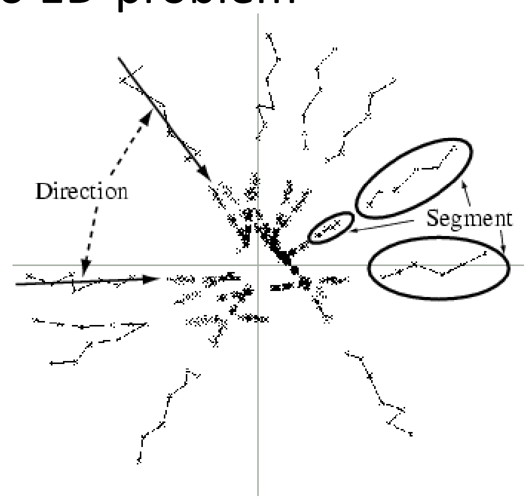


Transforms 2D-problem into 1D-problem

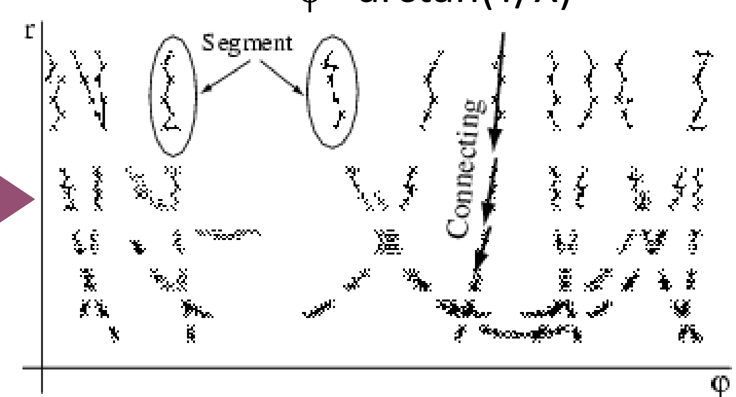
ϕ= arctan(Y/X)



raw hits



After conformal transform



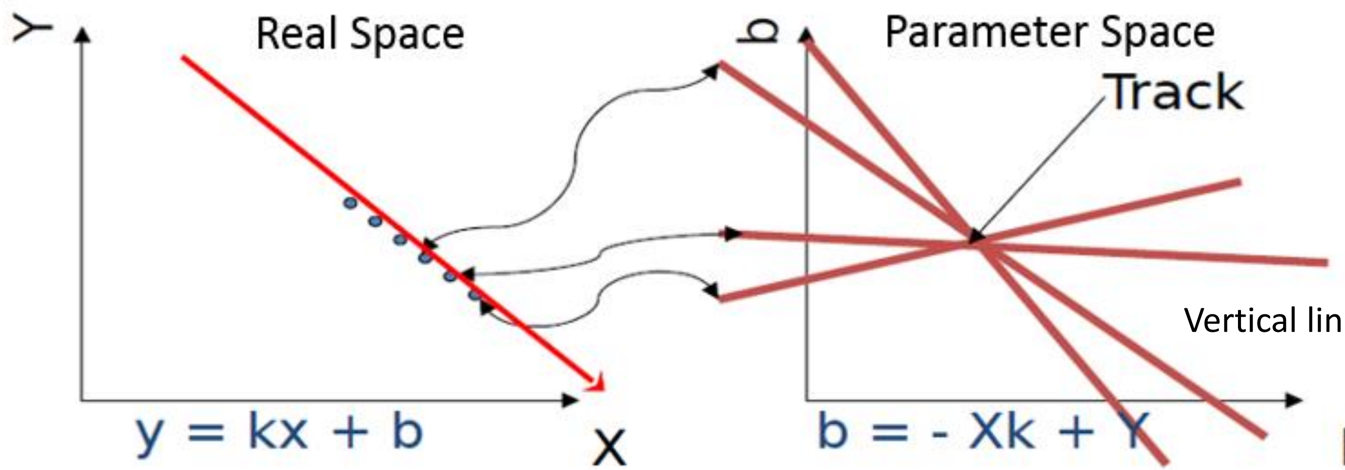
r-phi space

→Fill histogram

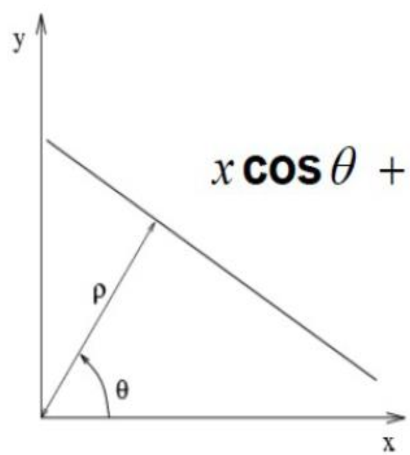
→Find peaks in histogram

Hough transformation

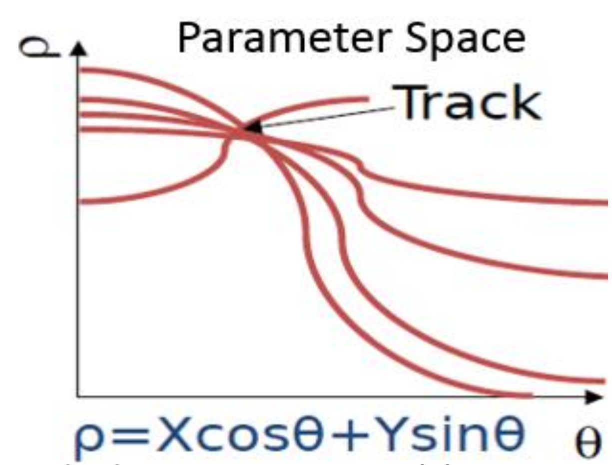
- Points on a line in real space → lines or curves focus in Hough space
- Let each feature vote for all the models that are compatible with it

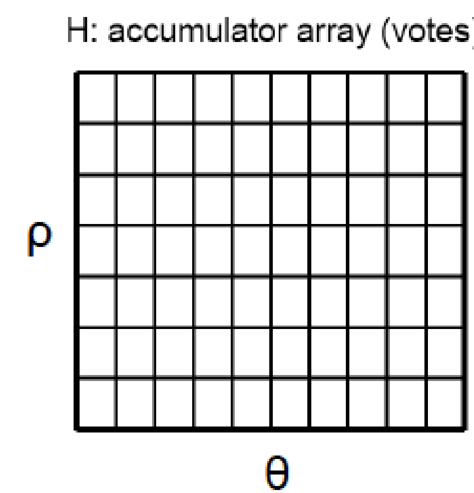


Vertical lines require infinite k



$$x\cos\theta + y\sin\theta = \rho$$

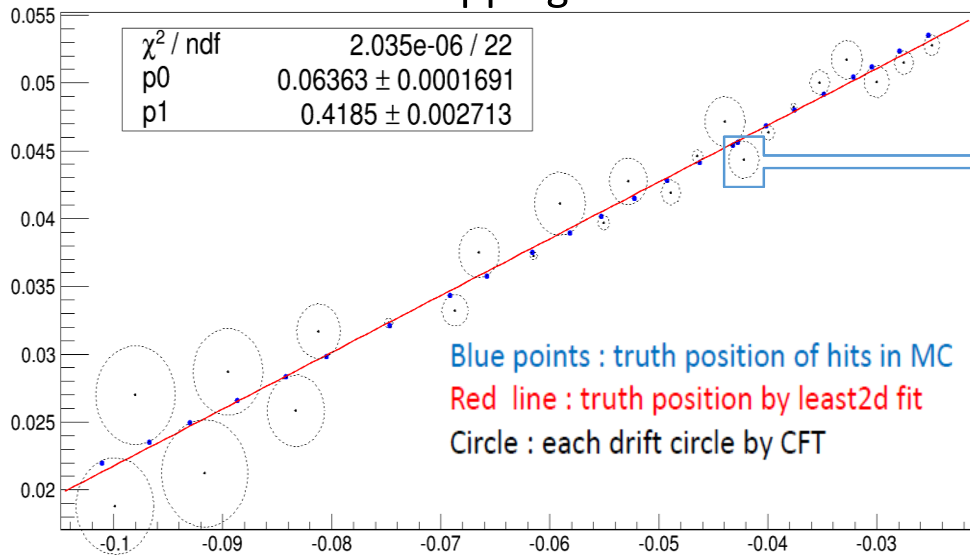




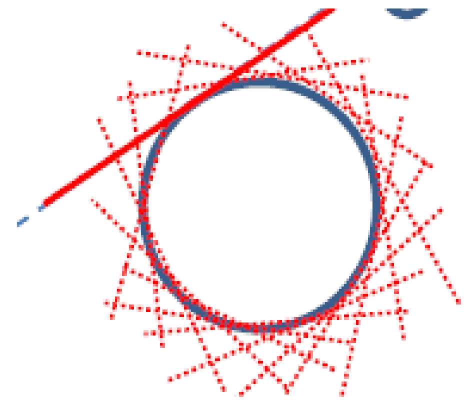
use polar coordinate to avoid unbounded parameter problem

Hough transform example

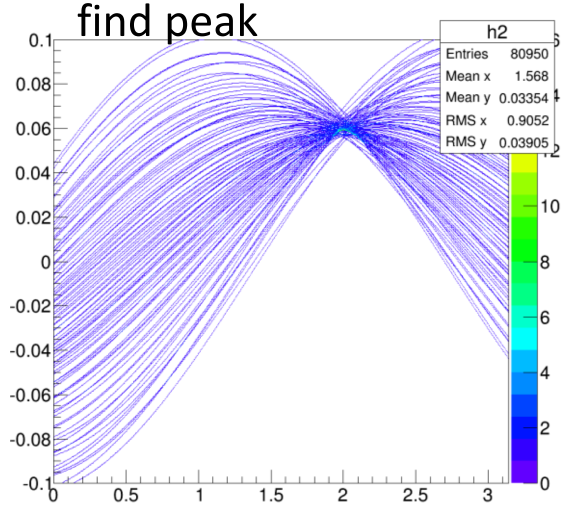
After conformal mapping

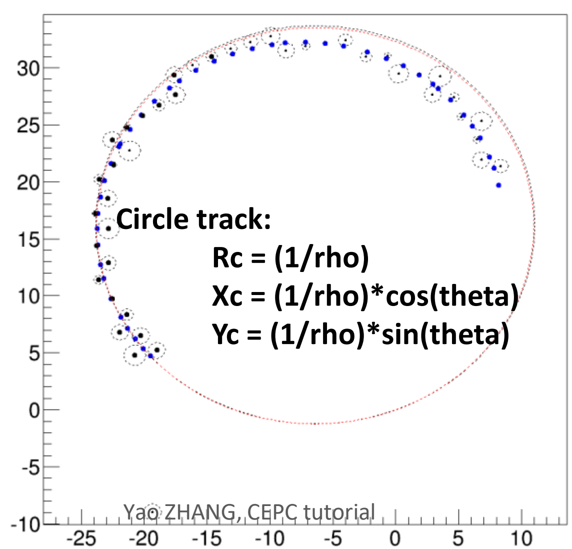


map drift circles on Hough Space



find peak





Apollonius circle (2D/3D)

Apollonius's problem : construct circles that are tangent to three given circles in a plane

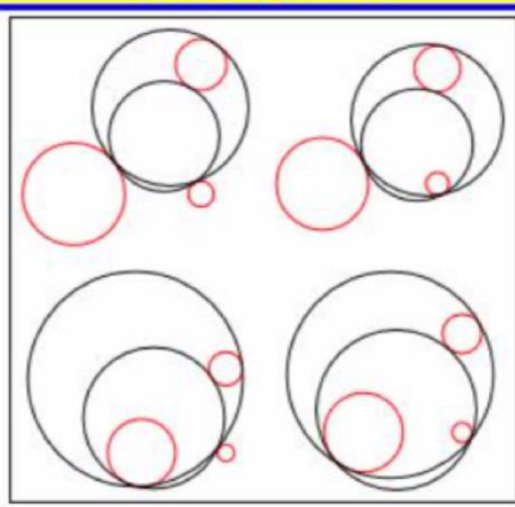
Greek Apollonius of Perga (200 BC)

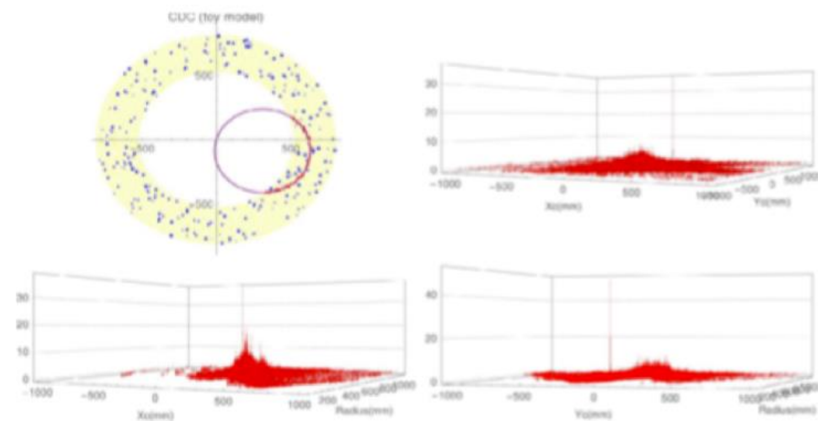
Compass constructions by French François Viète (1600)

Algebraic solution (cyclographic model) :

$$(-x_1+x_s)^2+(-y_1+y_s)^2 = (r_s-r_1\ s_1)^2$$
$$(-x_2+x_s)^2+(-y_2+y_s)^2 = (r_s-r_2\ s_2)^2$$
$$(-x_3+x_s)^2+(-y_3+y_s)^2 = (r_s-r_3\ s_3)^2$$

with $s_{1,2,3} = \pm 1$





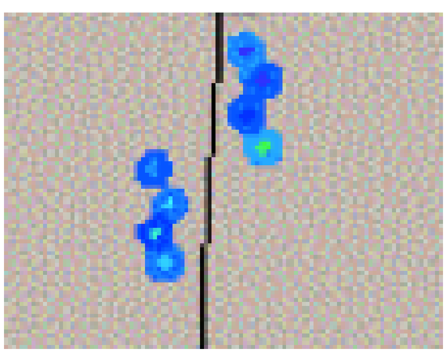
- Triplets fitting on GPUs

Template matching

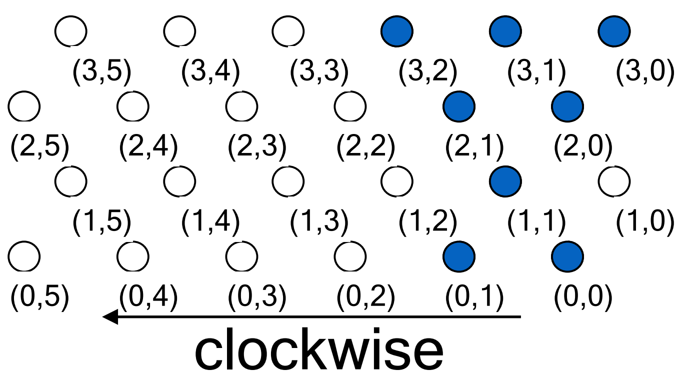
- Prepare template dictionary
  1. Gather the patterns that track leaves in the detector (superlayers)
  2. Make a dictionary of track segment pattern template

- Match hit pattern in the dictionary
  1. Map wire neighbors into the hits combine group
  2. Looks for patterns of hits group and calls the valid ones segments
  3. Link segments into tracks according to their parameter

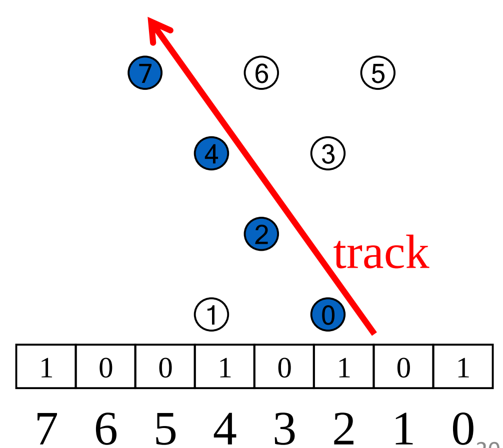
hits in detector



hit neighbors in superlayer

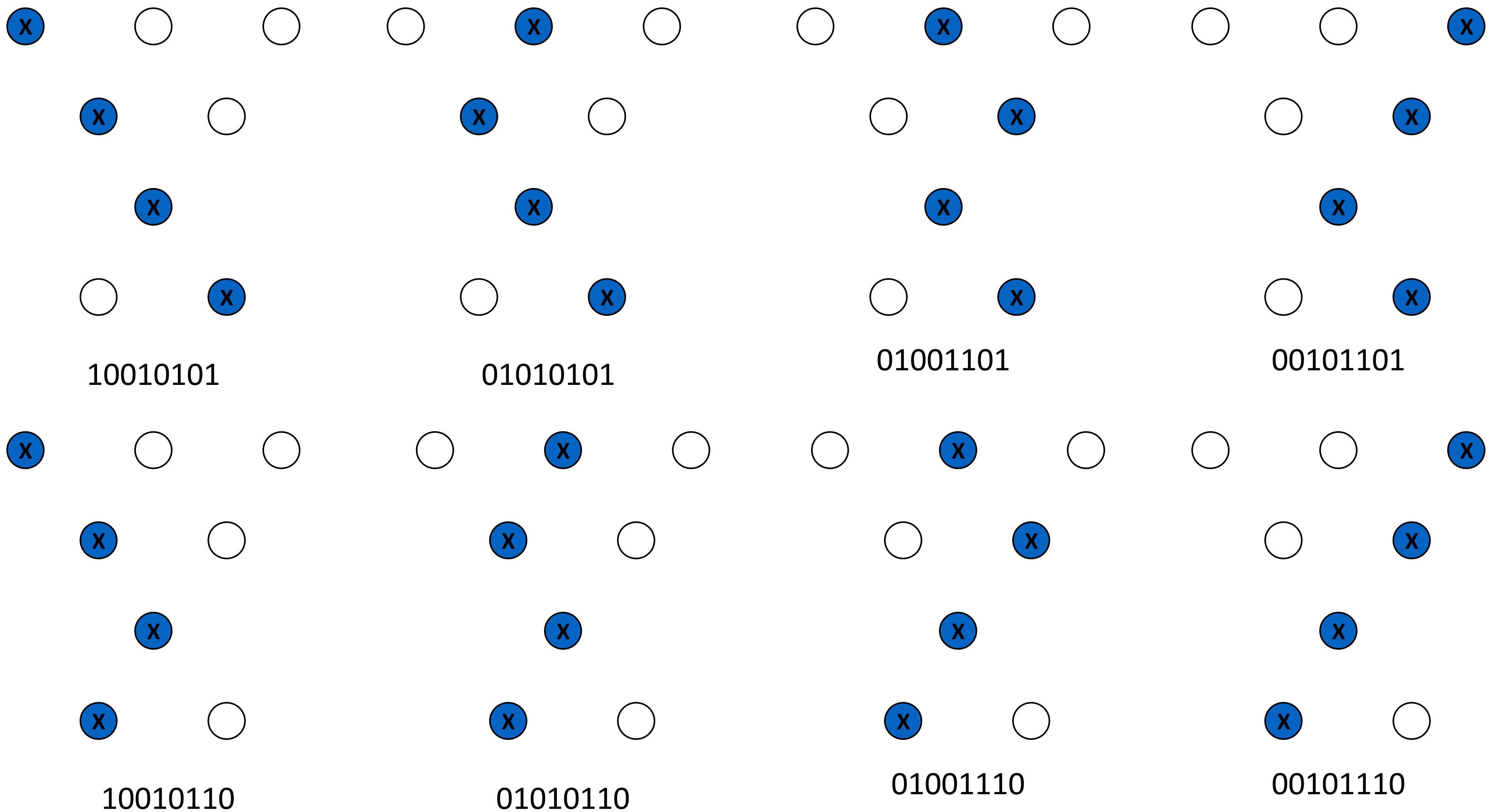


One segment pattern



4-hits pattern dictionary

each 8-binary digit indicate a track segment pattern



Cellular automaton

- The cellular automaton is faster and more robust algorithm which employs a sequential approach for the optimization effectively taking the discrete and parallel nature of the optimization problem into account.

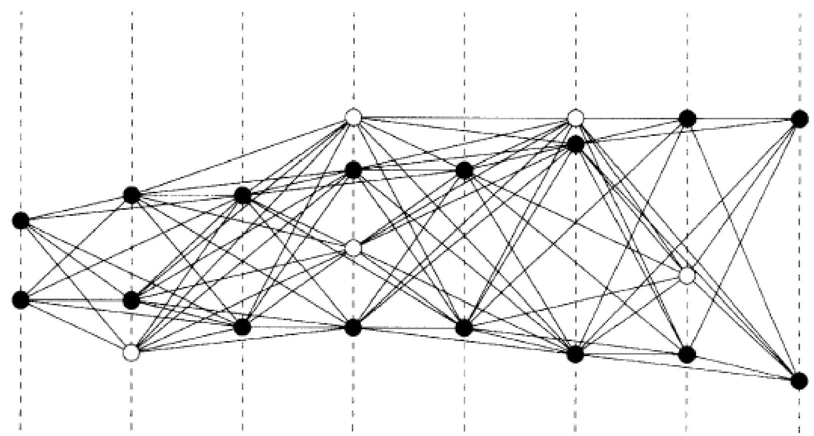


Fig. 3. A simple illustration of the segment model: segments connect hits across one or two layers.

Let the performance index of such an optimization problem be

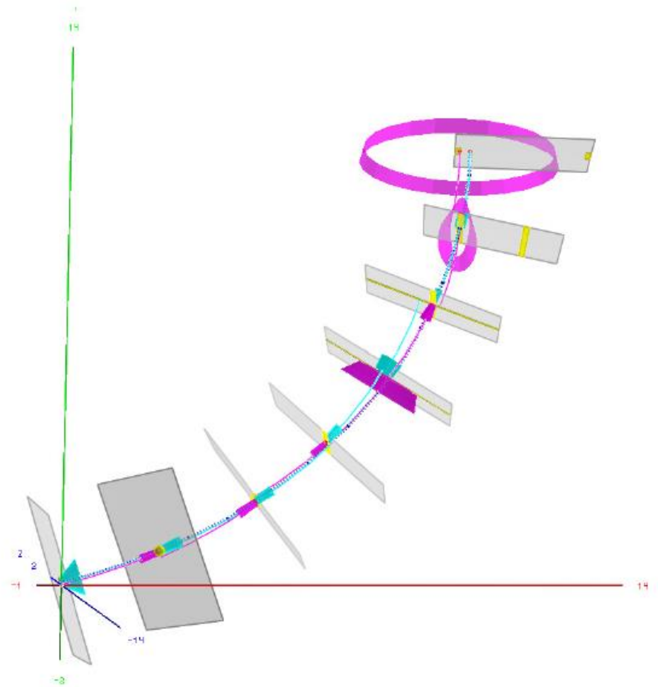
$$J(U) = N - \gamma \sum_{i=1}^{N-1} \frac{\varphi(s_{i+1}, s_i)}{z_{i+1,r} - z_{i,l}} \to \max_{U} \qquad (1)$$

I. Abt et al. / Nuclear Instruments and Methods in Physics Research A 489 (2002) 389–405

Track fitting

- Global least square fit
  - use helix as track model
  - neglecting the inhomogeneous magnetic field and material effects
  - Fits parameters on a single predefined surface
- Minimize χ^2
  - $\chi^2 = \sum_{i=1}^{n}(\frac{m-f(a)}{\sigma^2})^2$, where *m* is the measurement and *f(a)* is the fitted value
- Kalman filter fitting
  - Iterative Least Square estimation of the state vectors in all measurement layers (or even material layers).
  - Two steps are repeated:
    - Prediction: extrapolate the state to the next layer, add up multiple scattering, subtract energy loss
    - Update: combine the predicted state with the current measurement
  - Need a good initial state (seed)

Kalman filter fitting



(c) Forward (cyan) and backward (magenta) fit with covariances of the state updates.

NIM A(262)1987 444-450

Material effects treated in fitting

- For minimum ionizing particles, two principal material effects:
  - Multiple Coulomb scattering (MS) (in thin material)
    - scattering angle that treated in Gaussian approximation which rms is:

$$\theta_0 = \frac{13.6\ \mathrm{MeV}}{\beta c p}\, z\, \sqrt{x/X_0}\Big[1 + 0.038\ln(x/X_0)\Big]$$

  - Energy Loss (dE/dx)
    - tr $\left\langle -\frac{dE}{dx}\right\rangle = Kz^2\frac{Z}{A}\frac{1}{\beta^2}\left[\frac{1}{2}\ln\frac{2m_ec^2\beta^2\gamma^2W_{\max}}{I^2} - \beta^2 - \frac{\delta(\beta\gamma)}{2}\right]$ he-Bloch formula

- For electrons (or very high energy muons), an additional effect:
  - Bremsstrahlung(emission of photons in the electric field of the nucleus)

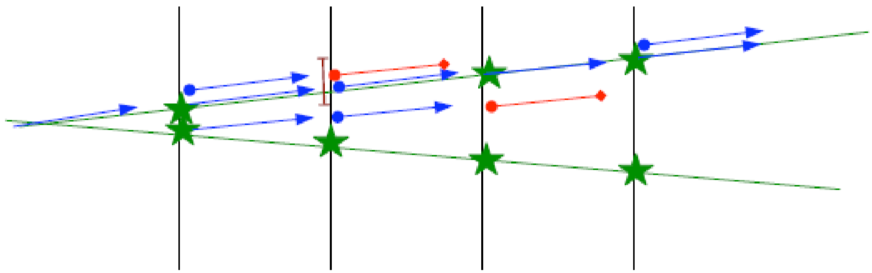
$$-\left\langle\frac{dE}{dx}\right\rangle_{Brems} = \frac{E}{X_0}$$

X_0 is the radiation length in [g/cm^2]: After passage of one X_0 electron has lost all but (1/e) th of its energy

Combinatorial Kalman Filter(CKF)

- Start from a track seed
- Extrapolated trajectory from layer to next layer by Kalman filter procedure, add hits while fitting
- Turns Kalman filter to a pattern recognition procedure

- Shortcoming
  - Combinatorial explosion and time consuming
  - Large number of duplicated and overlapping tracks
  - Leads to ambiguities (mutually exclusive track candidates that have too many hits in common)



Machine learning on HEP

- Cover many topics
  - Physics Analysis, DQM, Fast simulation, Trigger/Reconstruction, Event and particle ID, Flavor Tagging, Physics analysis, Computing/Data Management, etc.
  - Become new track or section in HEP software conference
  - Growing contributions
- Parallel
- Deep learning library
  - TMVA since 2016, development ongoing
  - Tensorflow, Keras,Pytorch
  - …

CHEP 2018 Sofia, Bulgaria

- Machine Learning
- Physics Analysis
- Data Preservation

- 47 presentations
- 14 posters

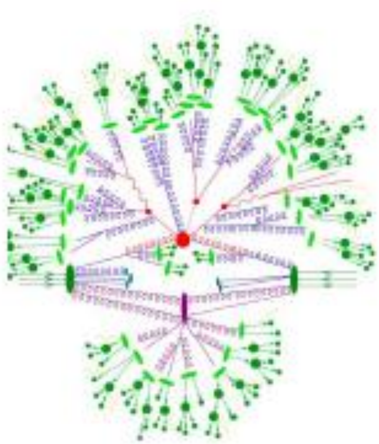
70% of contributions related to machine learning

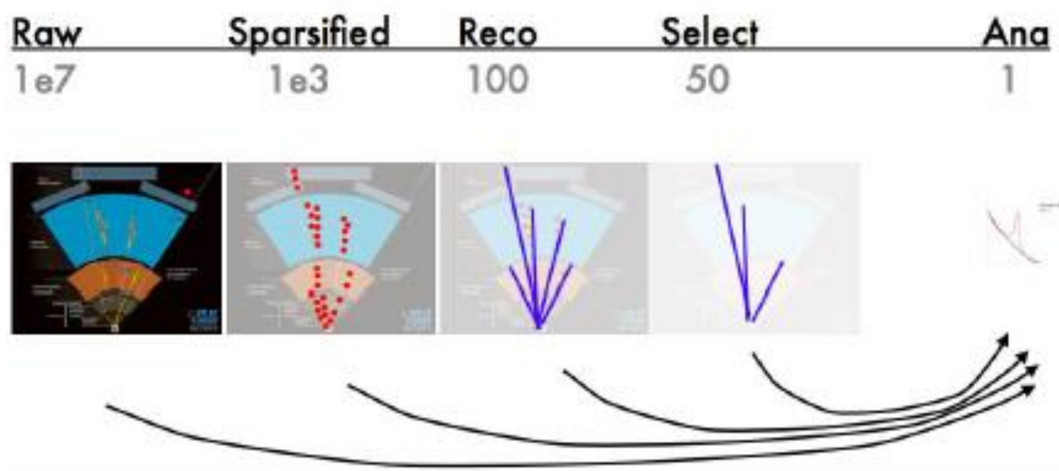
+ Theory/Phenomenology

End-to-End Learning

Can we fully exploit the detectors:

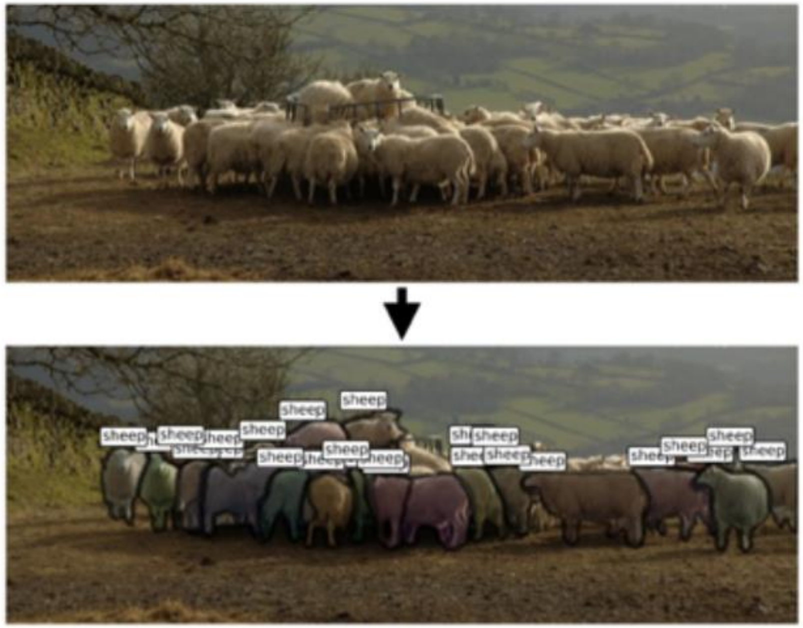
- Raw data, low-level variables





Some Deep Learning Inspirations

Image Segmentation using R-CNN



Zagoruyko et al, https://arxiv.org/pdf/1604.02135.pdf

Our goal (more or less…):

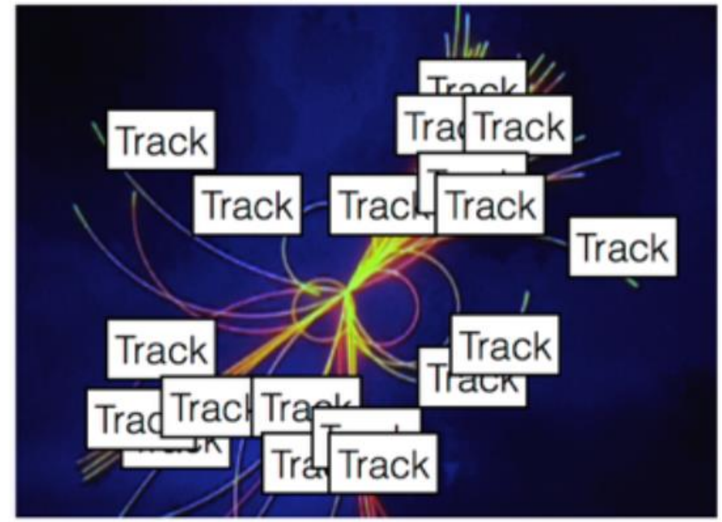
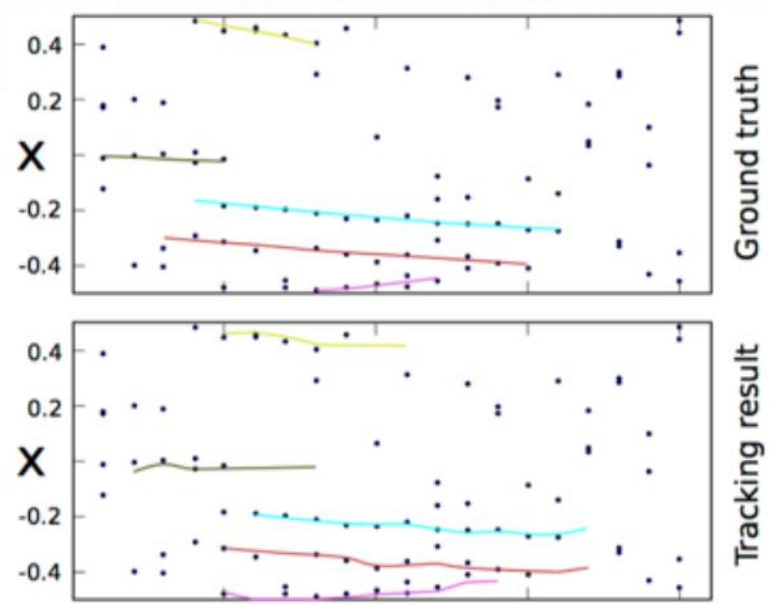


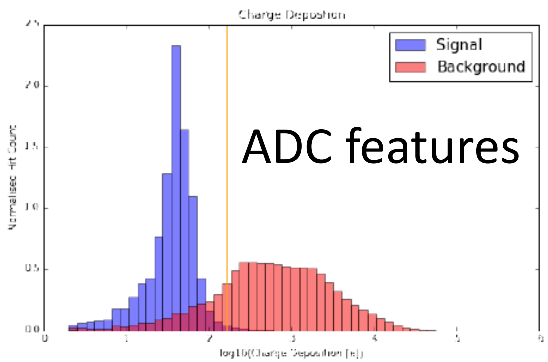
Photo by Pier Marco Tacca/Getty Images

Online object tracking using RNN

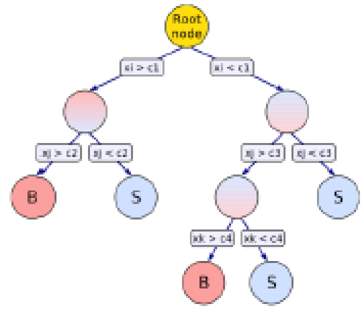
Anton Milan et al, https://arxiv.org/pdf/1604.03635.pdf



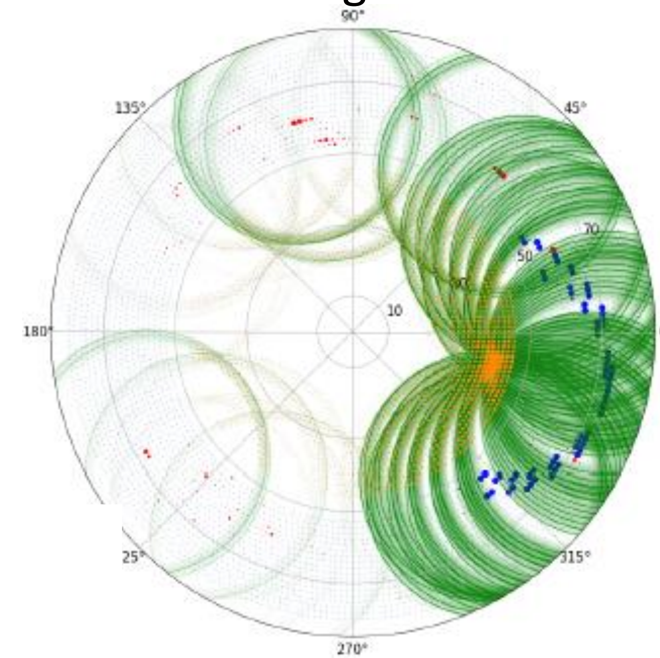
Identify background from signal hits
---Machine learning with Boosted Decision Tree

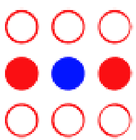


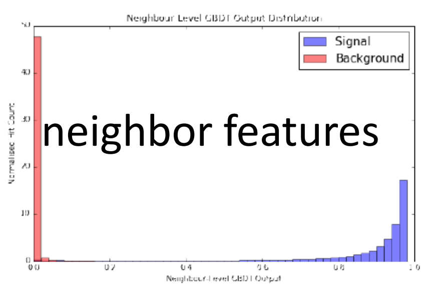
decision tree



Reversed Hough transform





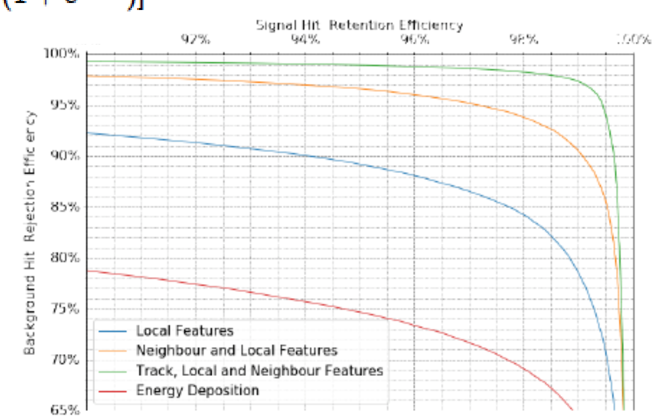


Gradient boost decision tree

Decision Tree i: $h_i(\mathbf{f}) = +1 \text{ or } -1$

GBDT: $y_{\text{Grad}}(\mathbf{f}, \mathbf{b}) = \sum_{i=0}^{N_{\text{trees}}} b_i h_i(\mathbf{f})$

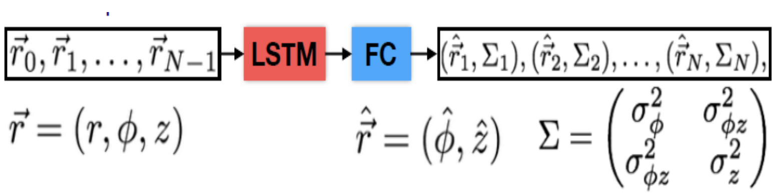
Loss Function: $F(y_{\text{Grad}}, y) = -2\left[y \cdot y_{\text{Grad}} + \ln\left(1 + e^{y_{\text{Grad}}}\right)\right]$



- Machine learning to train the boosted decision tree

Track (pre)-fitting with RNN+LSTMs

- Expected to do track building(substitution of track finding) and track parameter estimation(substitution of Kalman Filter)
  - use LSTM and RNN to estimate track position $r(t), \phi(t), z(t)$



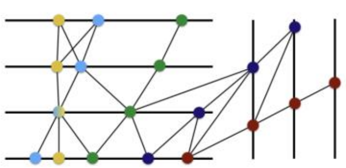


Figure 8. Illustration of a graph representation of track hit data. Hits are connected on adjacent layers if they are compatible according to some criteria.

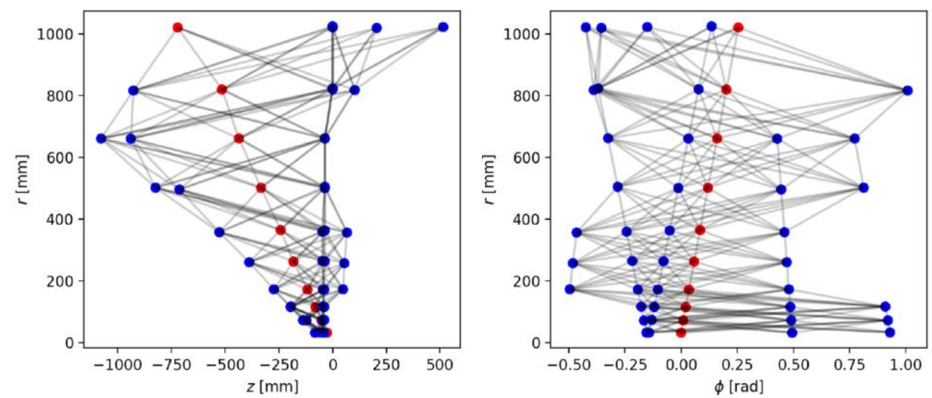


Figure 11. Example hit classification graph for a track. The colors indicate the model score, with red indicating 1 (correct hit) and blue indicating 0.

https://doi.org/10.1051/epjconf/201715000003

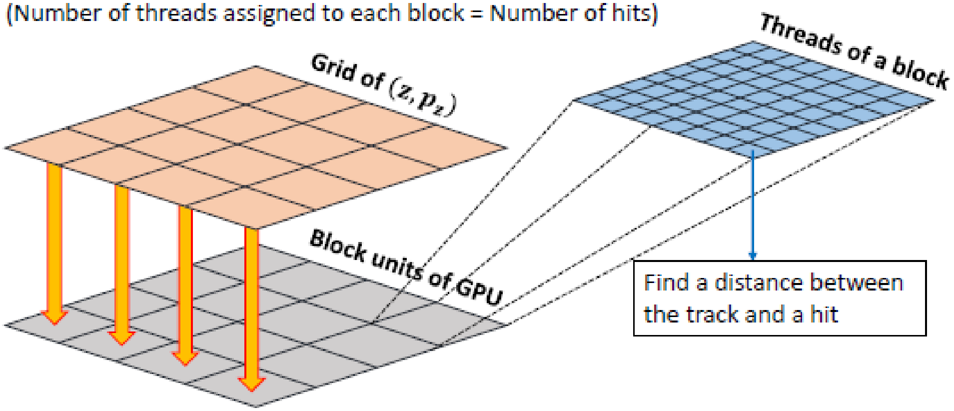
GPU tracking to scan track parameter

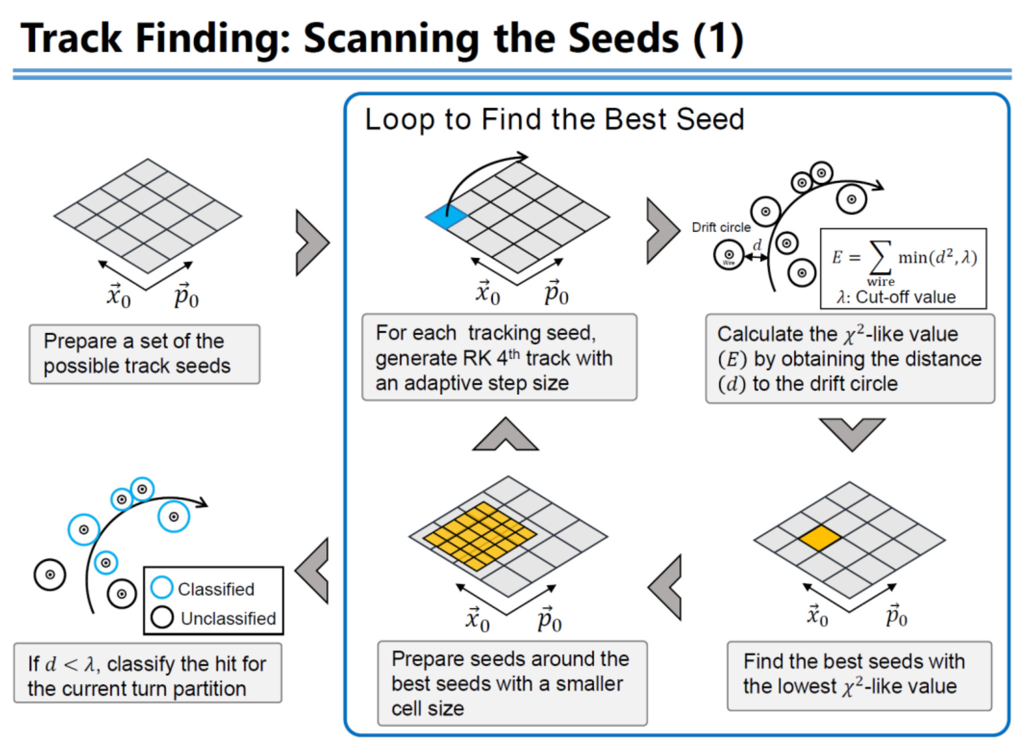
Track parameter seed is used for each core to calc. distance between track and hits

Parallel calculation using GPU programming (C API called CUDA)

1. (z, p_z) for each cell are delivered to the block unit of GPU, made of many threads (Number of blocks = Number of cells in grid)

2. Threads in a block calculate the distance between an Runge-Kutta track and a hit (Number of threads assigned to each block = Number of hits)





Summary

- Traditional track reconstruction method have been introduced
- Machine learning may be a promising method to deal with complicate classification problems for high energy particle reconstruction

References

- Mike Hildreth – Charged Particle Tracking
- Pattern recognition and event reconstruction in particle physics experiments, R Mankel, 2004
- R. Fruhwirth, NIM A262(1987)
- R. Fruhwirth, Comp.Phys.Comm. 120, 197
- R. Mankel, Kalman Filter Techniques