HEP.TrkX project

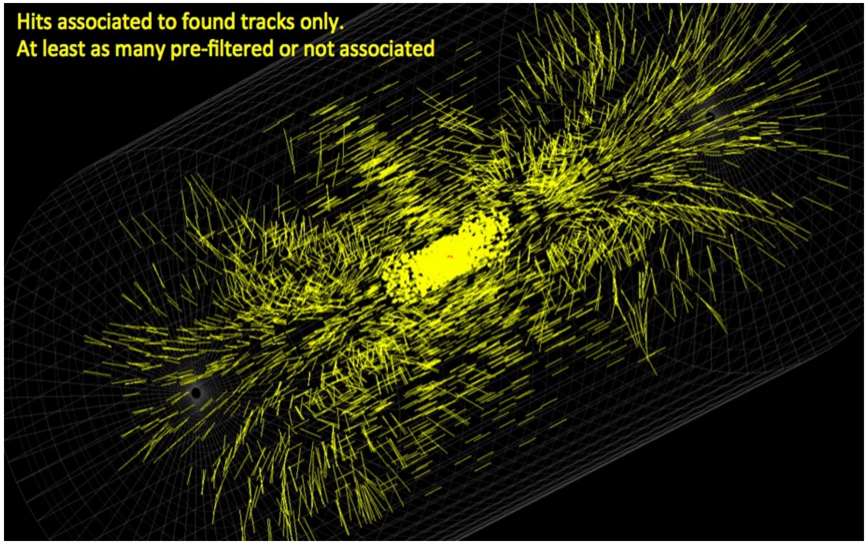
Software and Computing R&D
16 Oct 2017

https://heptrkx.github.io/

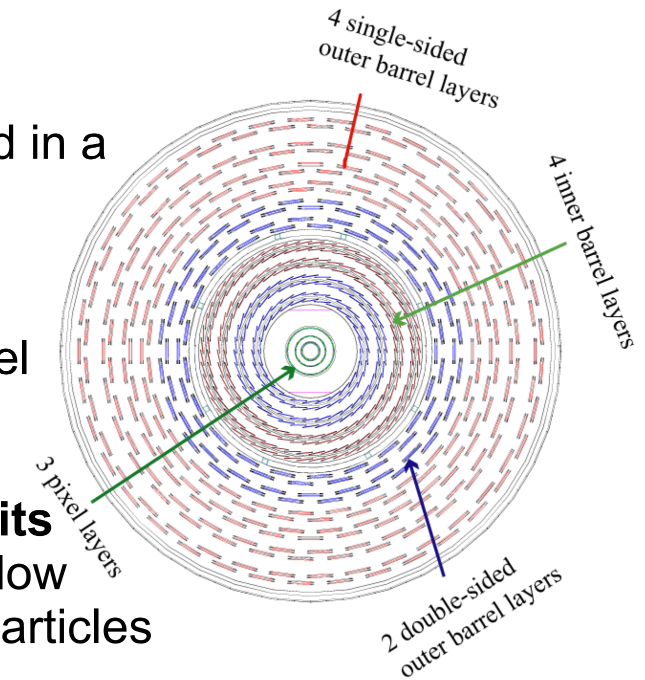
Outline

- Challenge of Charged Particle Tracking
- Pattern Recognition in Data Science
- The HEP.TrkX project
- Several approaches to the problem
- Outlook

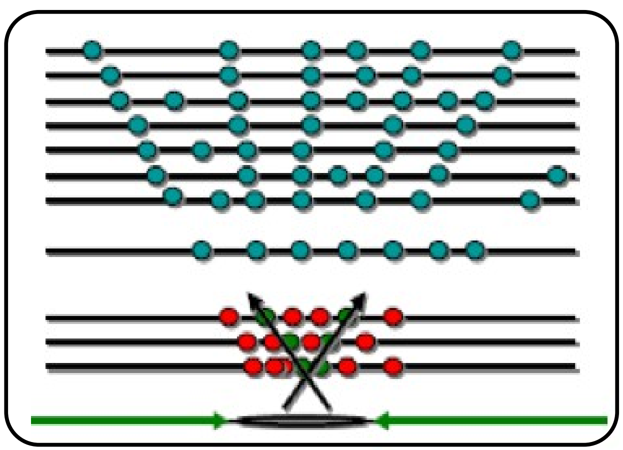
In a Nutshell



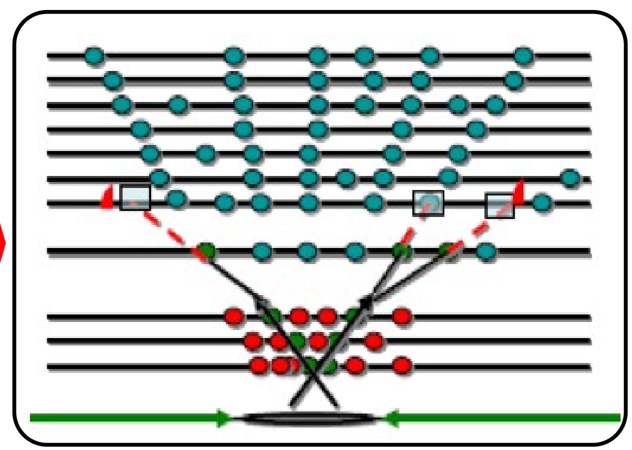
- Particle trajectory bended in a solenoid magnetic field
- Curvature is a proxy to momentum
- Particle ionize silicon pixel and strip throughout several concentric layers
- **Thousands of sparse hits**
- Lots of hit pollution from low momentum, secondary particles

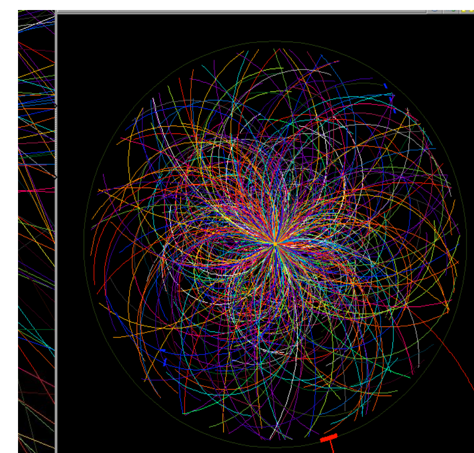


Seeding



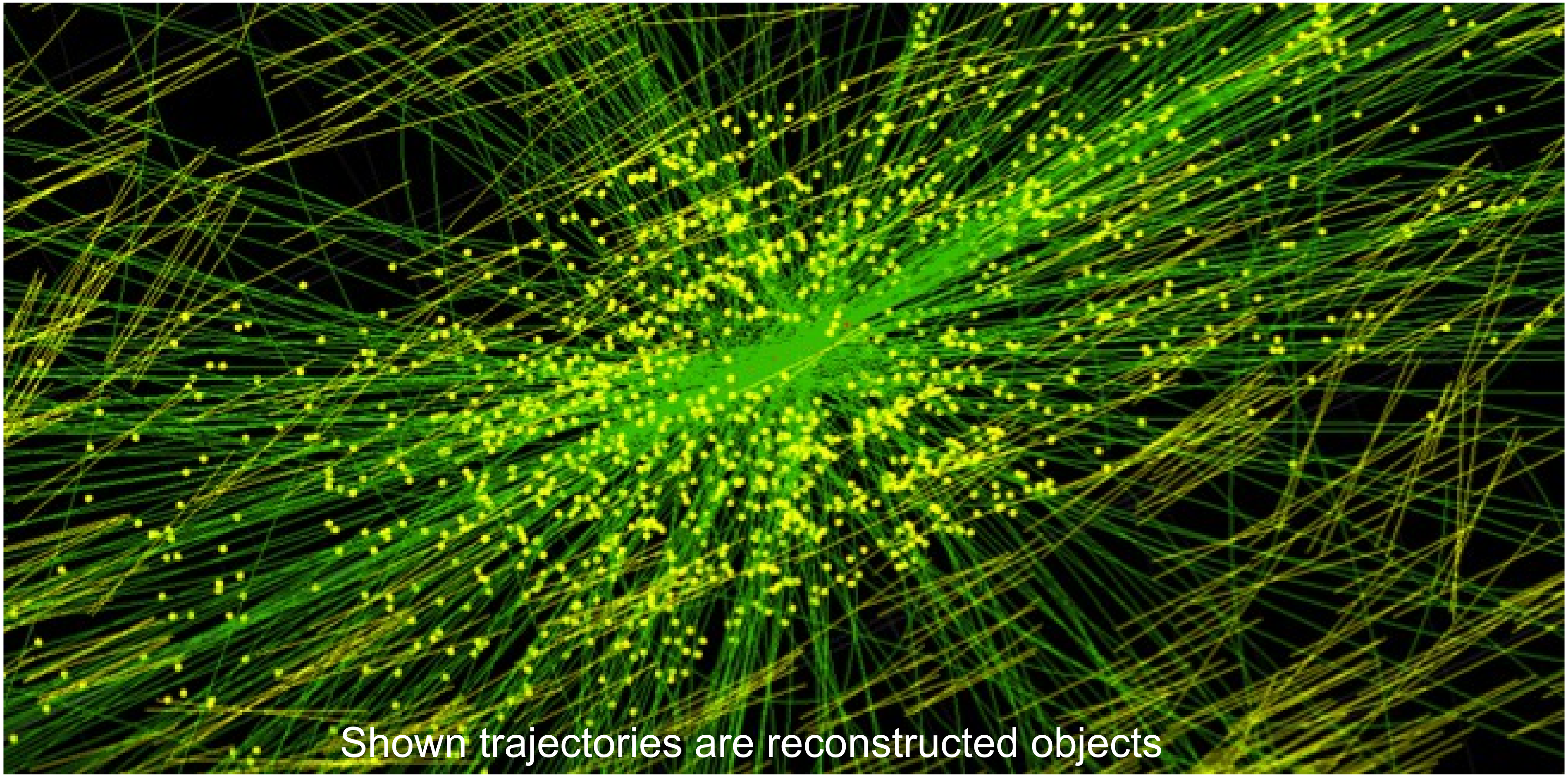
Kalman Filter





- **Explosion in hit combinatorics** in both seeding and stepping pattern recognition
- **Highly time consuming task** in extracting physics content from LHC data

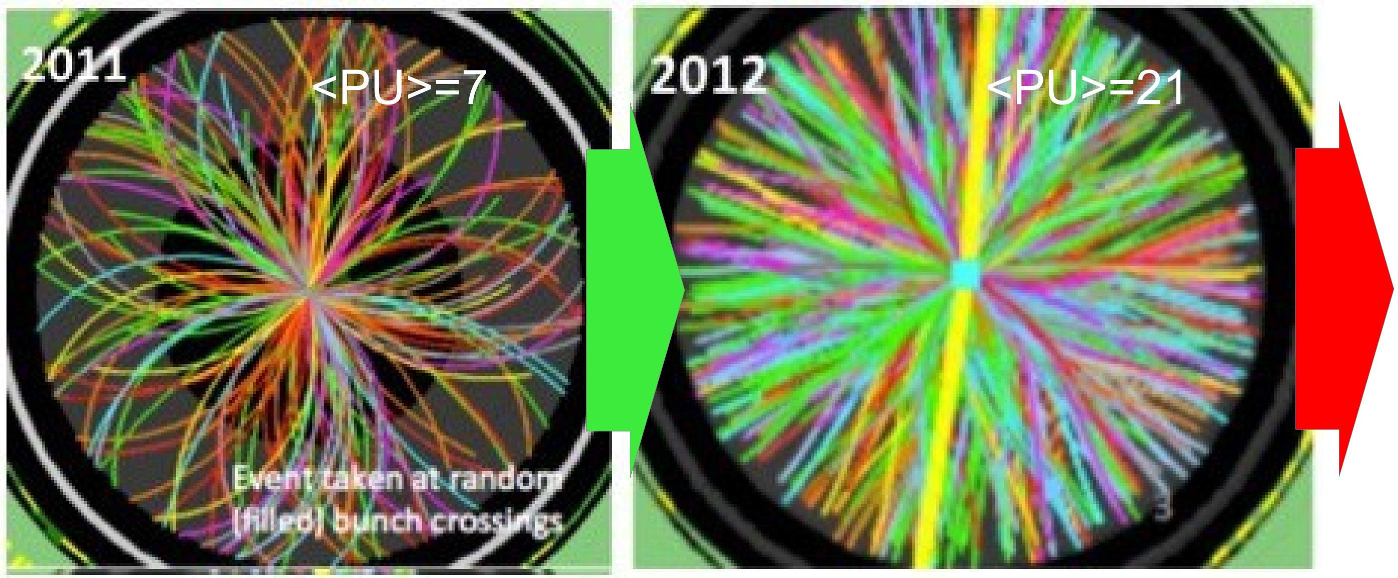
Complexity and Ambiguity



The future is with **x10 more hits**

High Luminosity LHC
The Challenge

HL-LHC Challenge



<PU>=140-200
10x more hits
Circa 2025

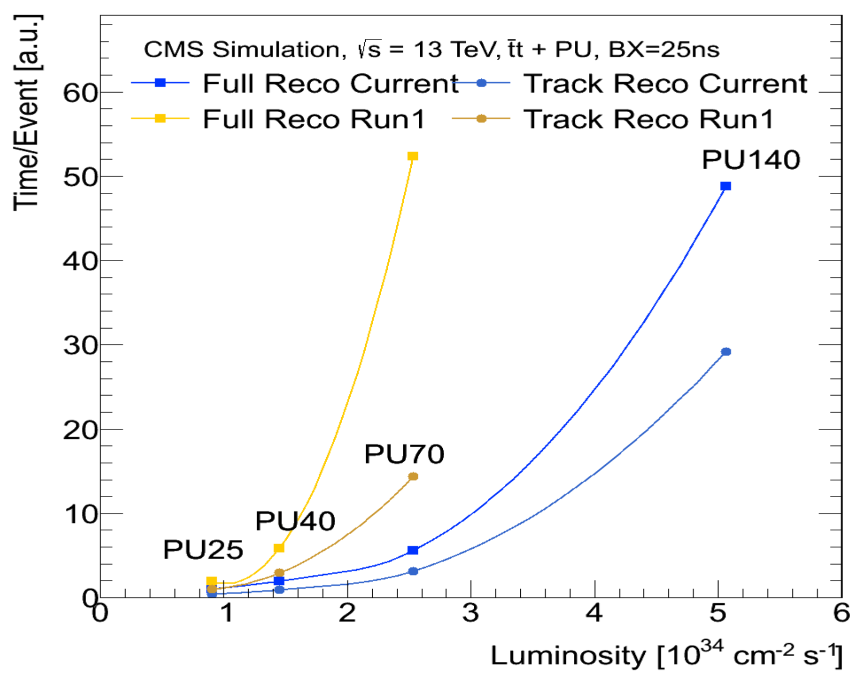
- CPU time extrapolation into HL-LHC era far **surpasses growth in computing budget**
- **Need for faster algorithms**
- Approximation allowed in the trigger

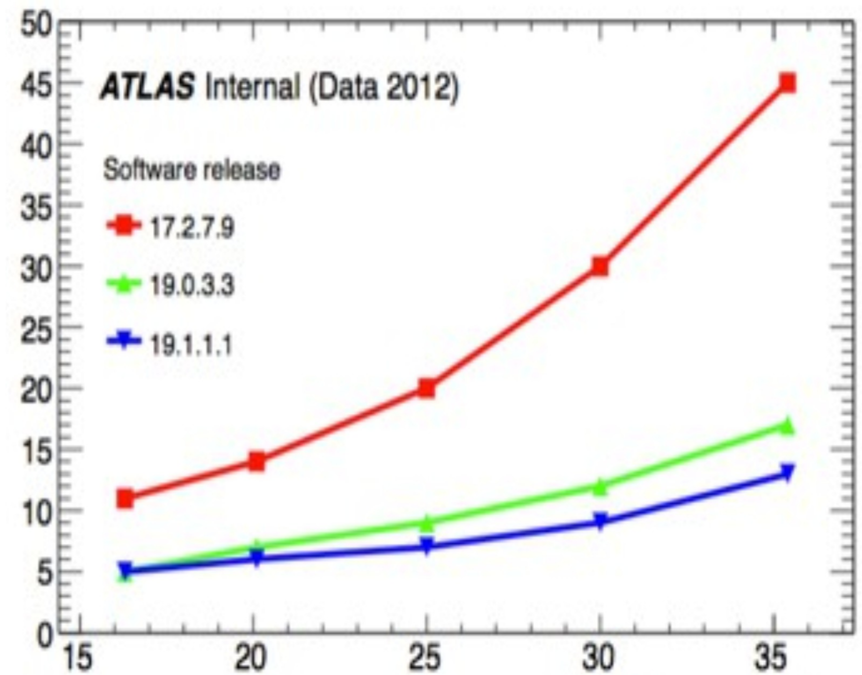
Cost of Tracking

- Charged particle track reconstruction is one of the **most CPU consuming task** in event reconstruction

- **Optimizations (to fit in computational budgets) mostly saturated**

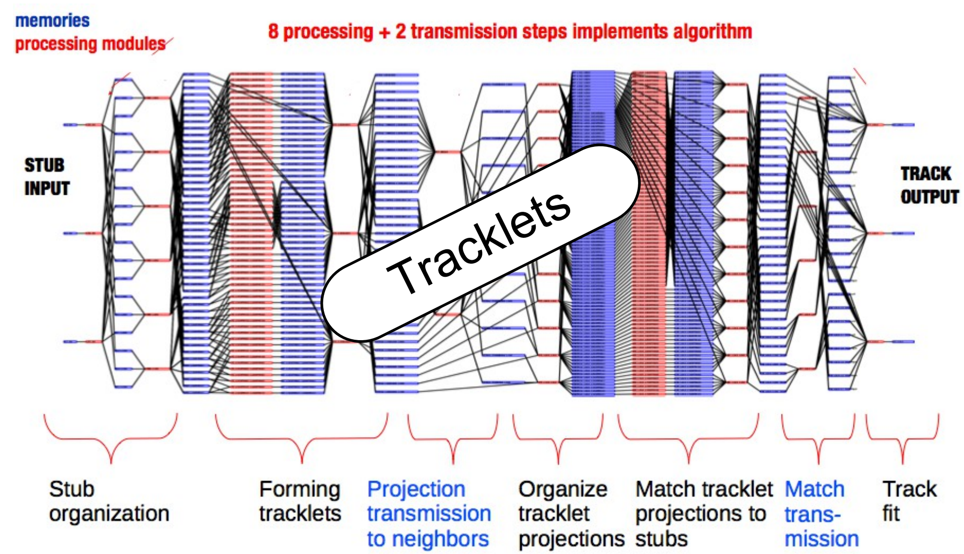
- Large fraction of CPU required in the HLT. **Cannot perform tracking inclusively at CMS and ATLAS.**

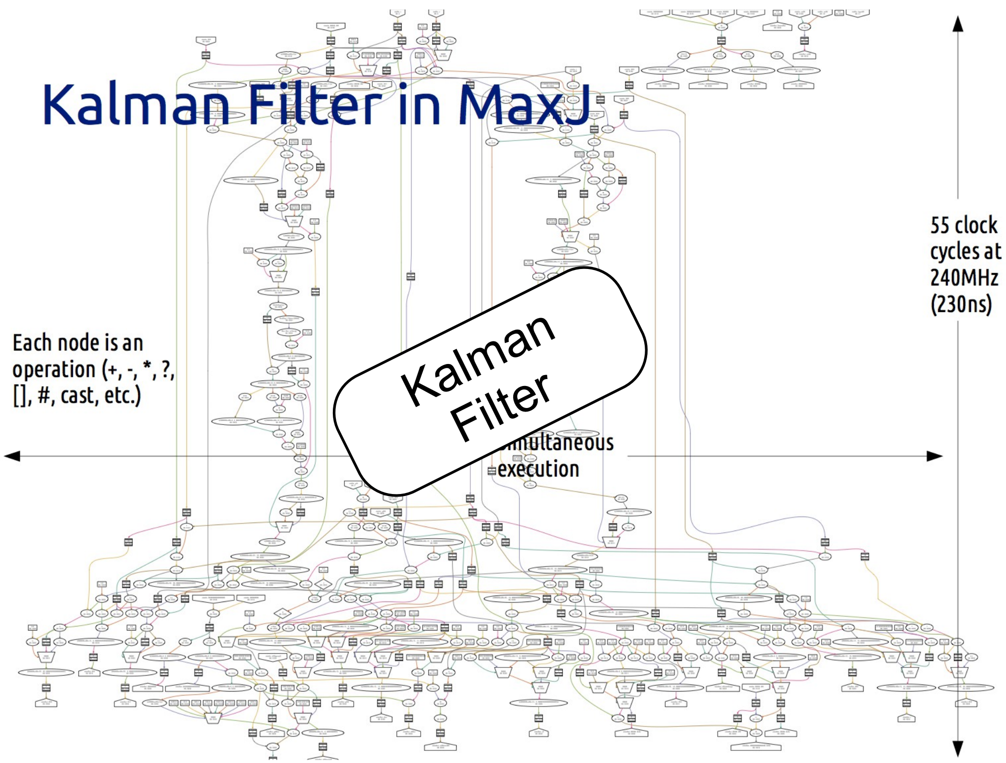


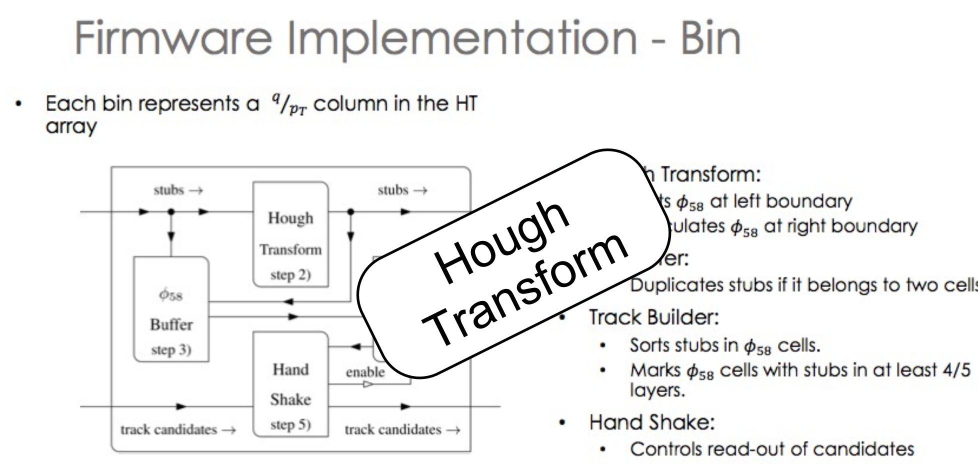


Fast Hardware Tracking

- Track trigger implementation for Trigger upgrades development on-going
- Several approaches investigated
- **Dedicated hardware is the ke**y to fast computation.
- **Not applicable for offline** processing unless by adopting heterogeneous hardware.







See https://ctdwit2017.lal.in2p3.fr/

Bottom Line

Current algorithms for tracking are highly performant physics-wise and scale badly computation-wise

Faster implementations are possible with dedicated hardware

Think outside the box for new methods

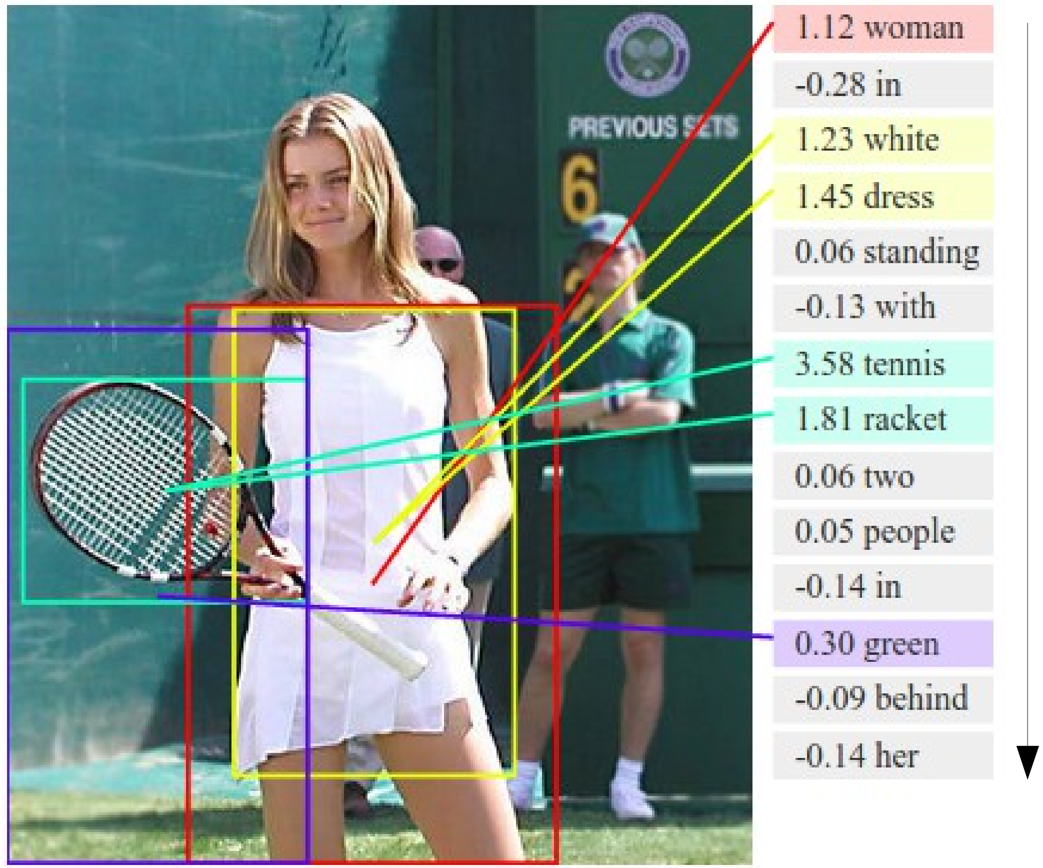
Pattern Recognition With Deep Learning

Scene Labeling

Farabet et al. ICML 2012, PAMI 2013

- Assign hits to track candidates

Scene Captioning

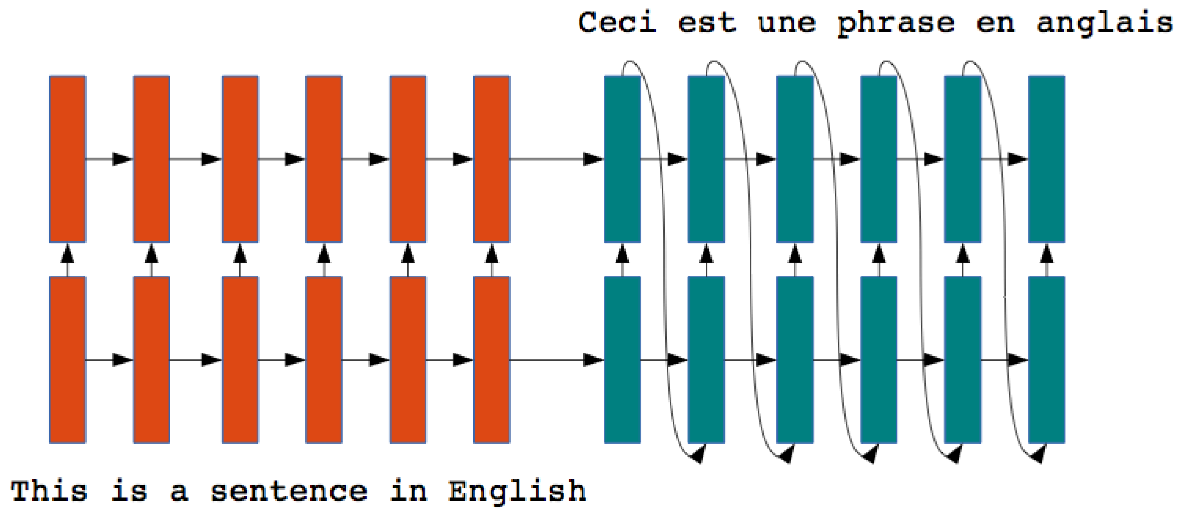


Karpathy, Fei-Fei, CVPR 2015

➔ Compose tracks explanation from image

Text Translation

- [Sutskever et al. NIPS 2014]
  - Multiple layers of very large LSTM recurrent modules
  - English sentence is read in and encoded
  - French sentence is produced after the end of the English sentence
  - Accuracy is very close to state of the art.



➔ From sequence of hits on layer to sequence of hits on track

Similarities and Challenges

- Particle tracking is an active field in data science
  - Different type of particles
  - Not oriented to code performance
- Making a track is a pattern recognition problem
  - Not the usual one in data science
- Tracking data is much sparser than regular images
  - Test and adapt methods
- Tracking device may have up to 10M of channels
  - Scale up deep learning models
  - Perform tracking by sector
- Underlying geometry of sensor more complex
  - More than a simple picture
  - Barrels and end-caps are not the usual pictures
- Not the regular type of sequences
  - Cover new ground of sequence processing
- Defining an adequate cost function
  - Tracking algorithms are optimized by proxy
- A solution must be performant during inference ...

HEP.TrkX Project

https://heptrkx.github.io/

- Pilot project funded by DOE ASCR and COMP HEP
- Part of HEP CCE
- Mission
  - Explore deep learning techniques for track formation

- People
  - **LBL** : Paolo Calafiura, Steve Farrell, Mayur Mudigonda, Prabhat
  - **FNAL** : Giuseppe Cerati, Lindsey Gray, Jim Kowalkowski, Panagiotis Spentzouris, Aristeidis Tsaris
  - **Caltech** : Dustin Anderson, Josh Bendavid, Pietro Perona, Maria Spiropulu, Jean-Roch Vlimant, Stephan Zheng

Possible Application to Tracking

- **Track candidate**
  - Finding the hits that belong to a track
  - Seed + hits → tracks
- **Track parameters**
  - Measuring the physic quantity of tracks
  - Hits → track kinematics
- **Seeding**
  - Putting together hits into tracks
  - Hits → track
- **Vertex Finding**
  - Finding vertex from hits image
  - Hits → vertex

Datasets

A) Highly simplified model* in 2D or 3D

B) More realistic sample from
  2D CtD track RAMP* (https://ctdwit2017.lal.in2p3.fr/)
  3D ACTS* (https://gitlab.cern.ch/acts)

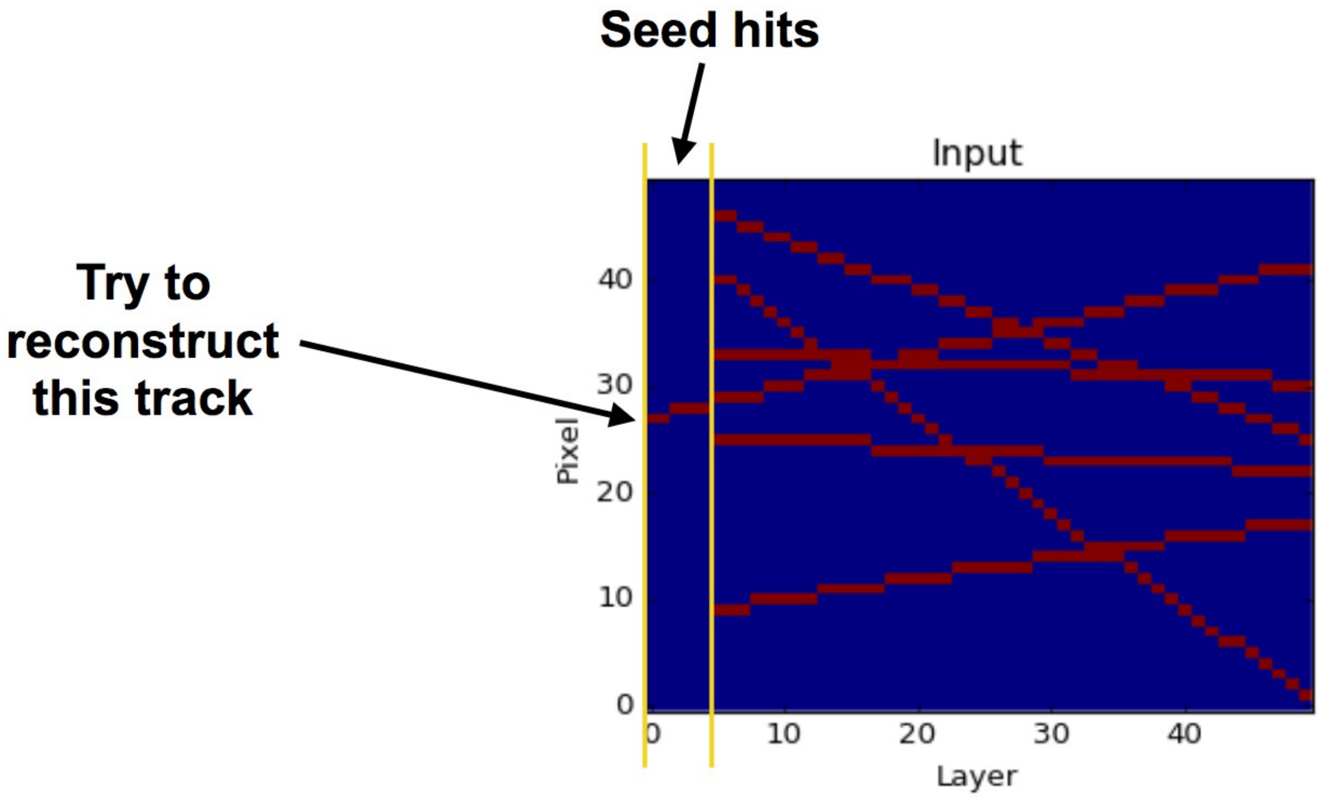
C) Full simulation or real data

*** : this talk**

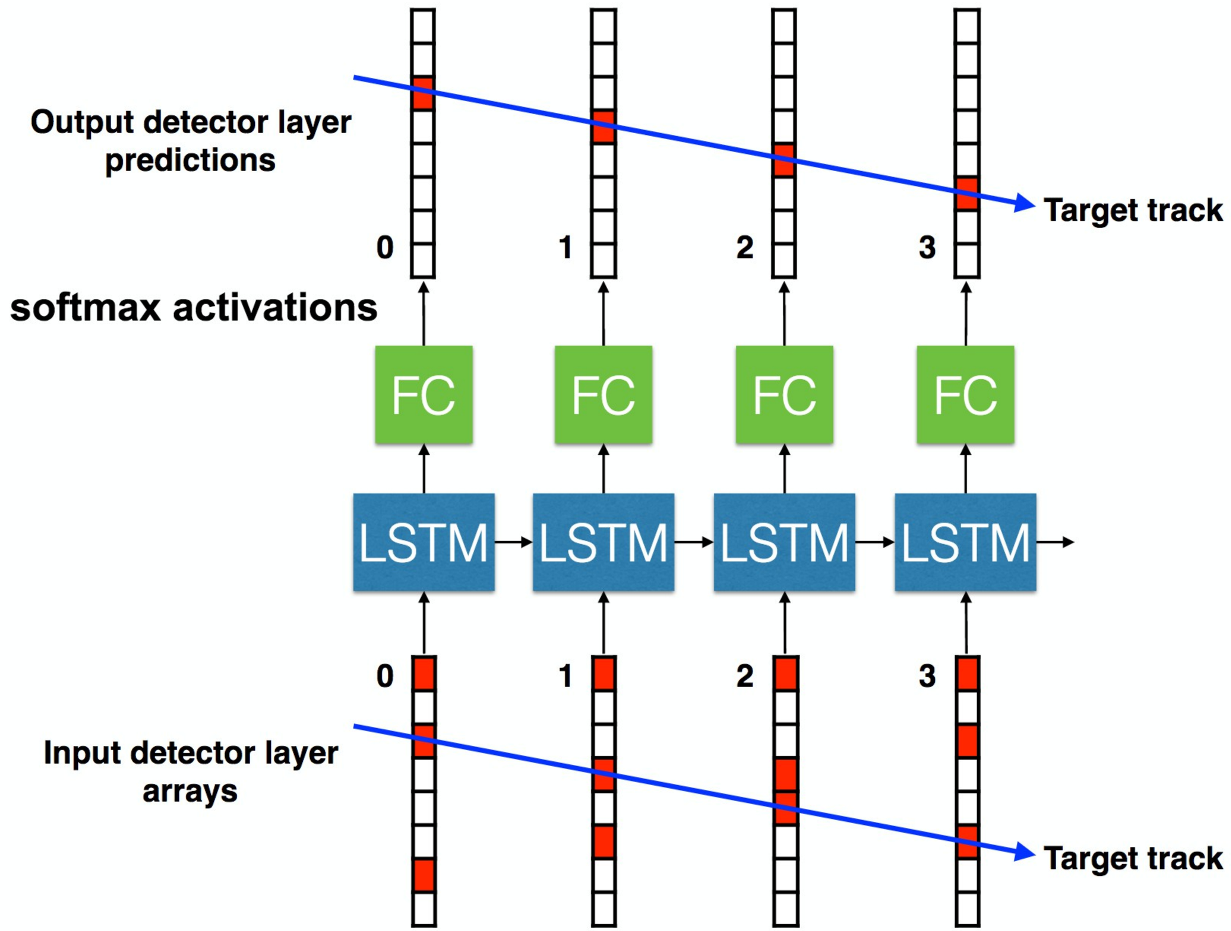
Seeded Track Candidate Making

Seeded Pattern Prediction

- Hits on first 3 layers are used as seed
- Predict the position of the rest of the hits on all layers



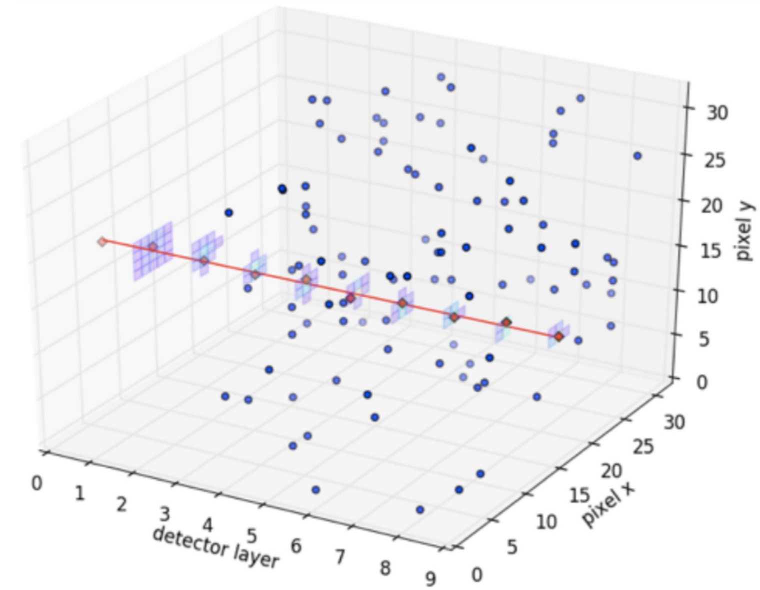
LSTM ≡ Kalman Filter

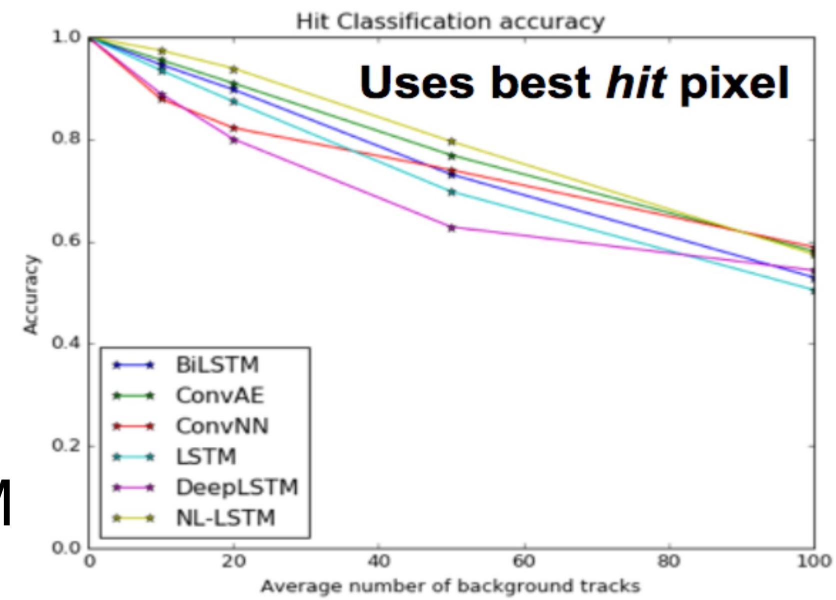


Seeded Pattern Recognition Insights

- For a simplified track models, predicting the track pattern from the seed works
  - In 2D and 3D
  - With some level of noise
  - With other tracks present
  - On layers with increasing number of pixels

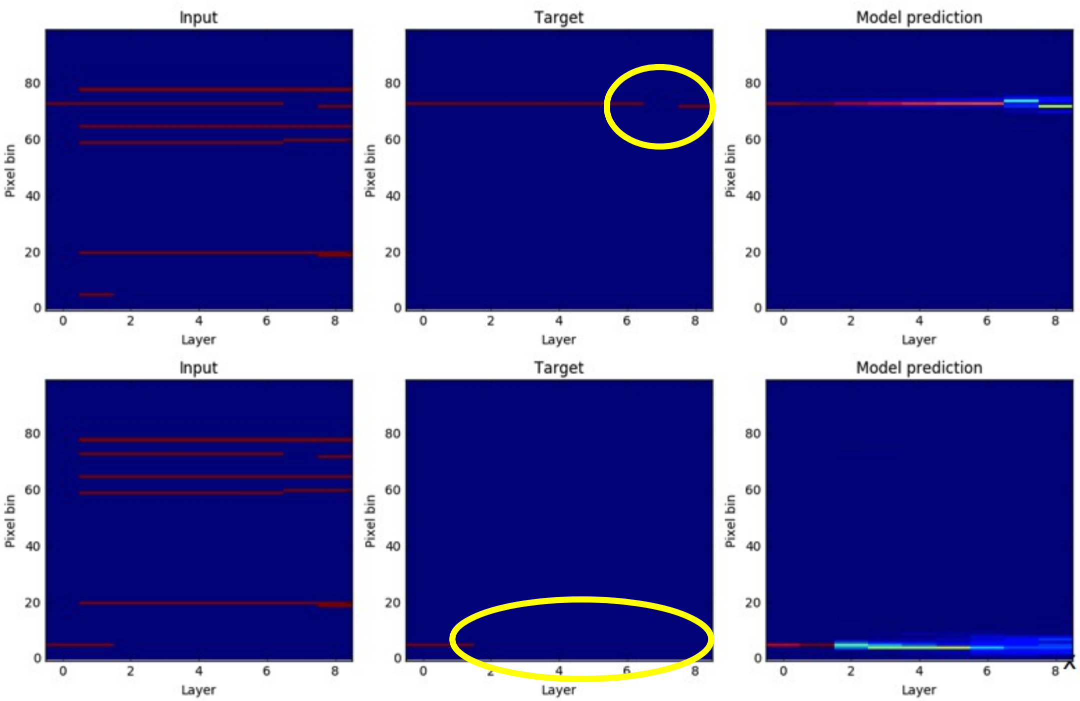
- Several other architectures tried
  - Convolutional neural nets (no LSTM)
  - Convolutional auto-encoder
  - Bi-directional LSTM
  - Prediction on next layer with LSTM





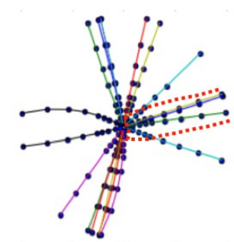
Tracking RAMP at CtD

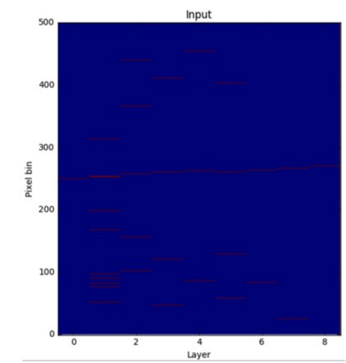
S. Farrell : Best solution in the Machine Learning category
https://indico.cern.ch/event/577003/contributions/2509988/

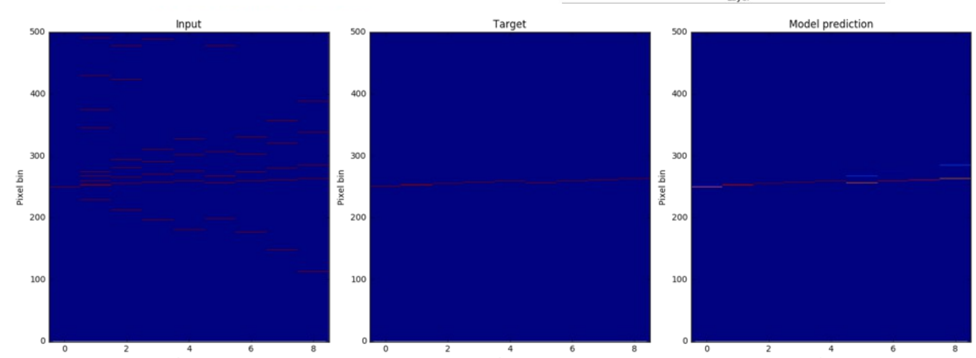


- Down-sampling layer to 100 bins
- LSTM for hit assignment
- 92% efficiency
- Robust to holes and missing hits

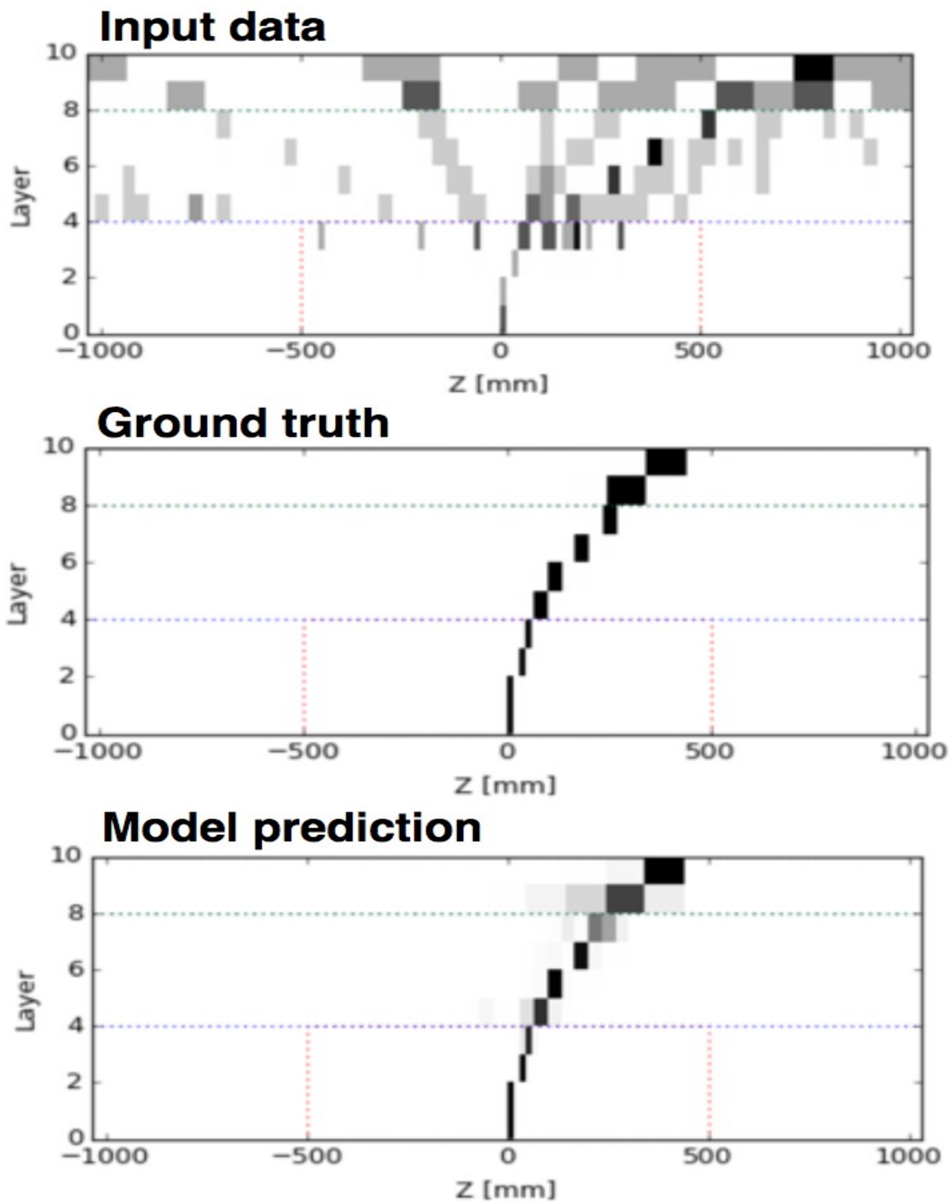
- Increased granularity in “road”
- LSTM for hit assignment
- 95% efficiency







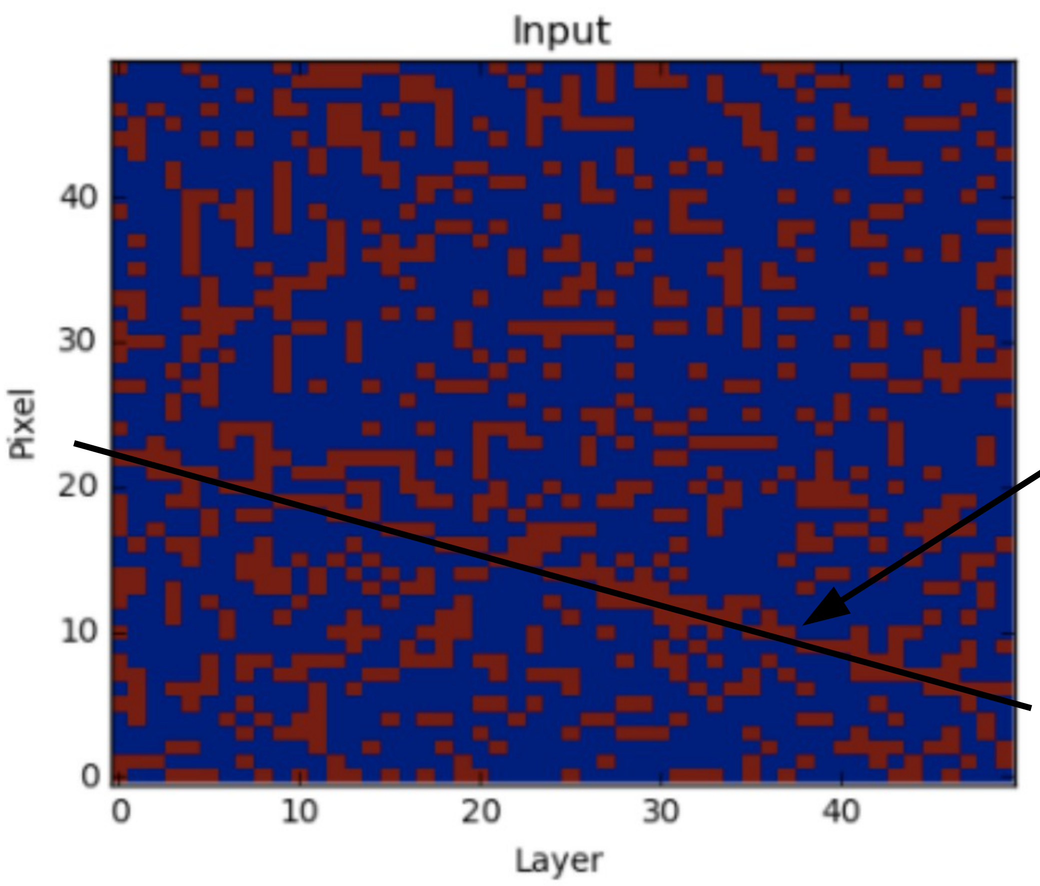
Tracking on ACTS



- Down-sampling layers per ACTS volume
- LSTM for hit assignment
- Promising results of applying a simplistic model to more realistic dataset
- Further work on-going

Track Parameters Measurement

Track Parameter Estimation

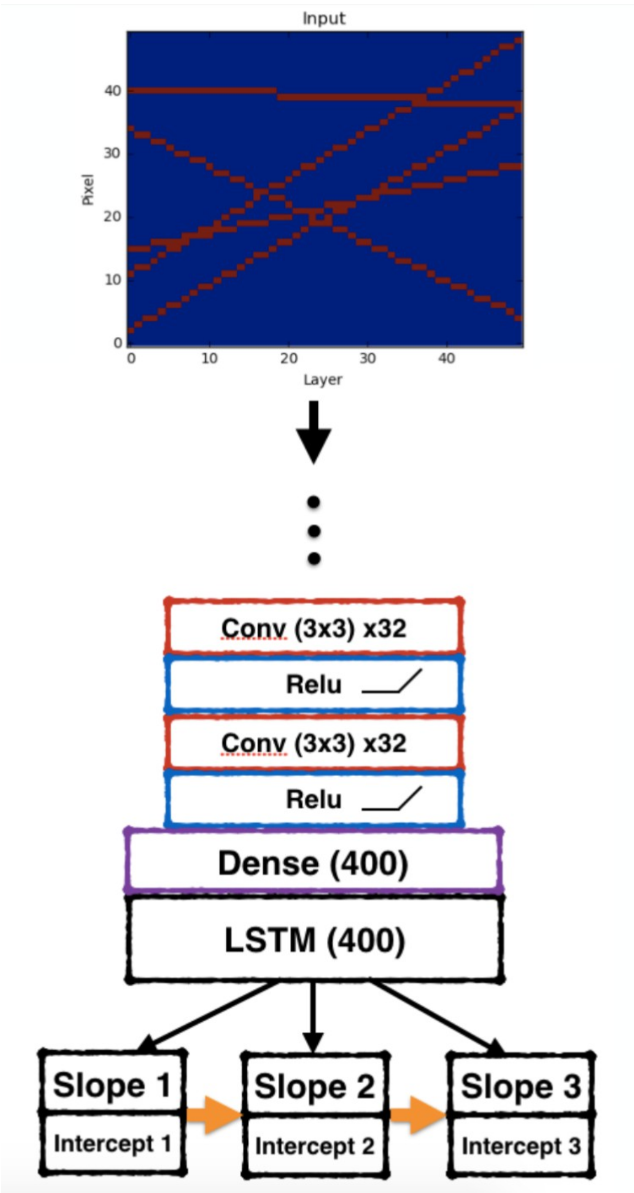


Try to predict the slope and intersect of this track

Multi-Track Prediction with LSTM

- Hit pattern from multiple track processed through convolutional layers

- LSTM Cell runs for as many tracks the model can predict.

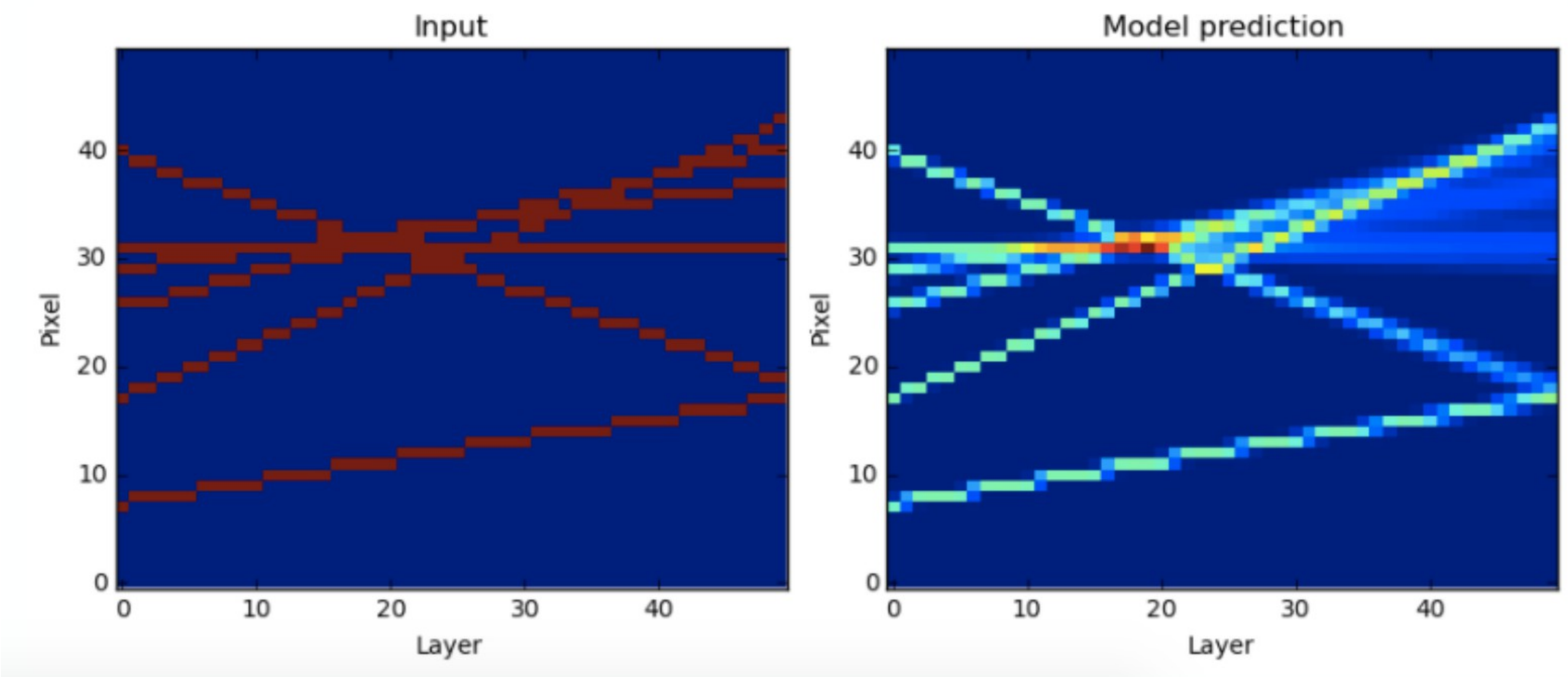


Prediction Track Covariance

Model is modified to predict a covariance matrix for which there is no ground truth, but is used with the modified loss function

$$L(\boldsymbol{x}, \boldsymbol{y}) = \log|\boldsymbol{\Sigma}| + (\boldsymbol{y} - \boldsymbol{f}(\boldsymbol{x}))^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{y} - \boldsymbol{f}(\boldsymbol{x}))$$

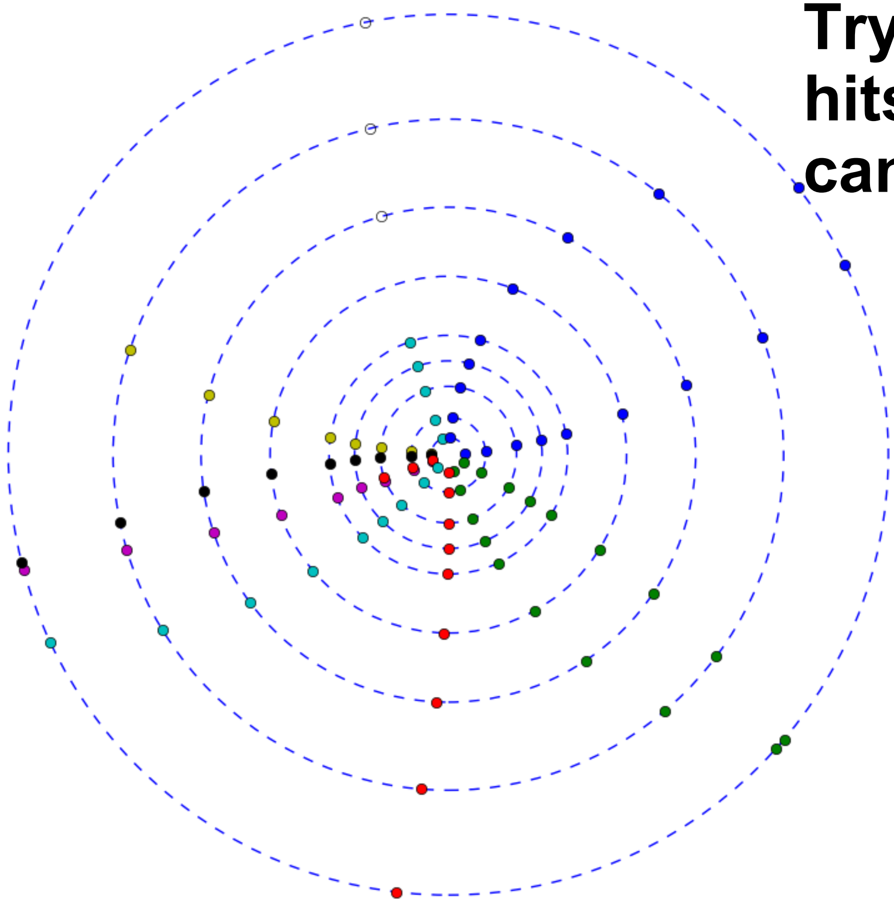
Track Parameters Uncertainty



Representation of track slope, intersect and respective uncertainties

Pattern Recognition / Seeding

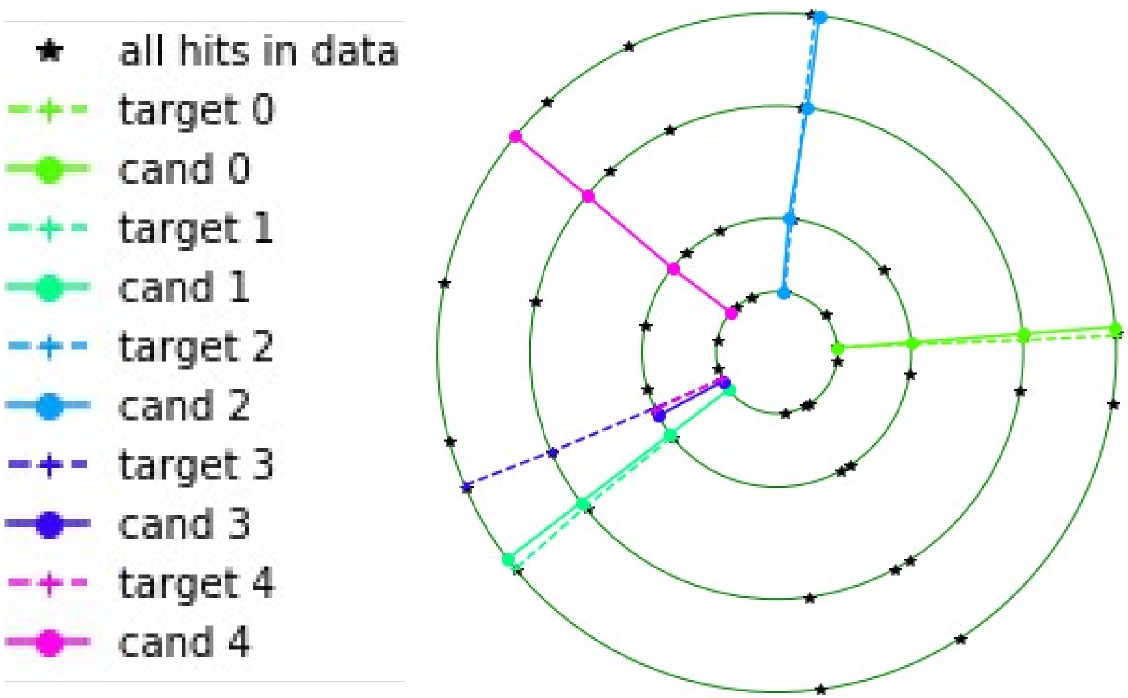
Pattern Recognition



Try to assemble hits into track candidates.

Pattern Recognition with LSTM

- Input sequence of hits per layers (one sequence per layer)
  - One LSTM cell per layer
- Output sequence of hits per candidates
  - Final LSTM runs for as many candidates the model can predict

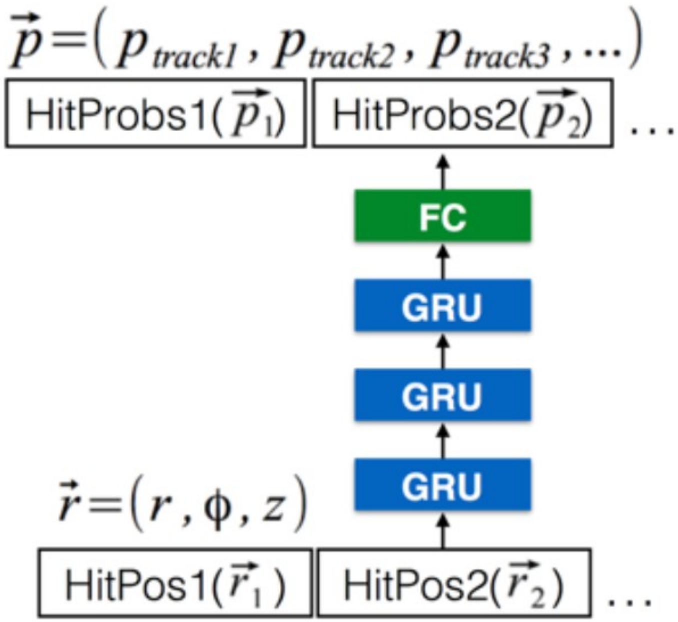


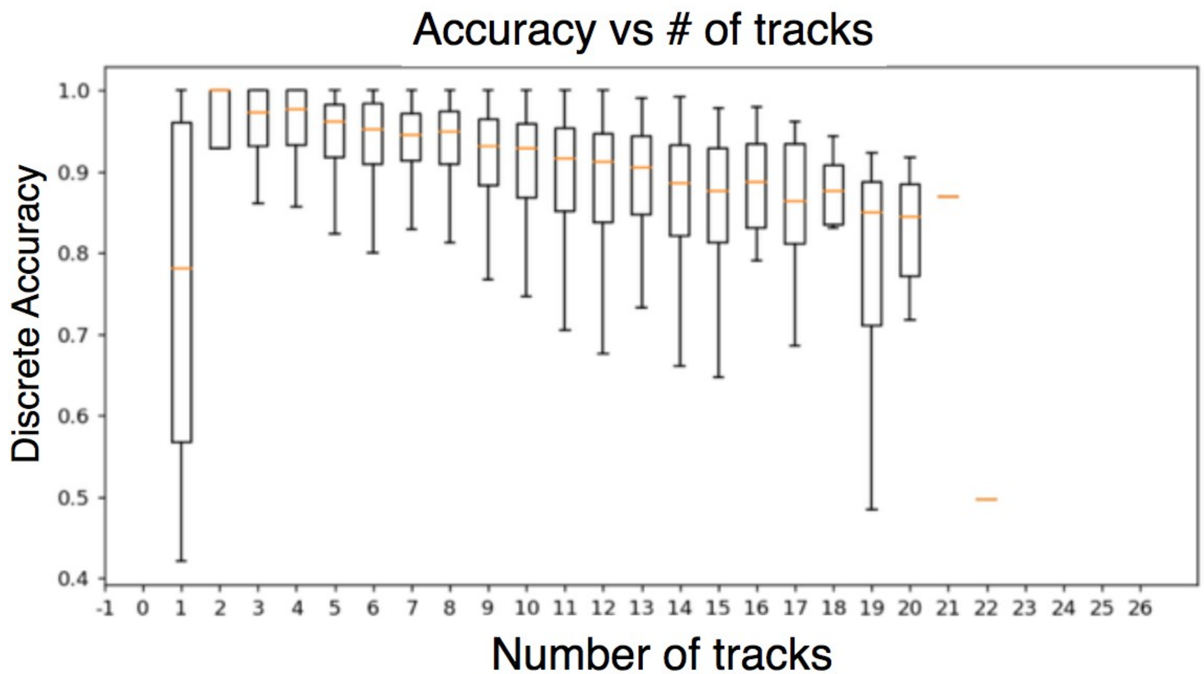
- Still work in progress
- Restricted to 4 layers (with seeding in mind)
- Work to some extend

Hit Assignment with GRU

- Input a sequence of points r,z,ϕ coordinate
- Output the probability to below to track N

- Tracking efficiency is not a exact metric. Does depend on where you cut on probability when dealing with multiple hit-track association. On-going work.

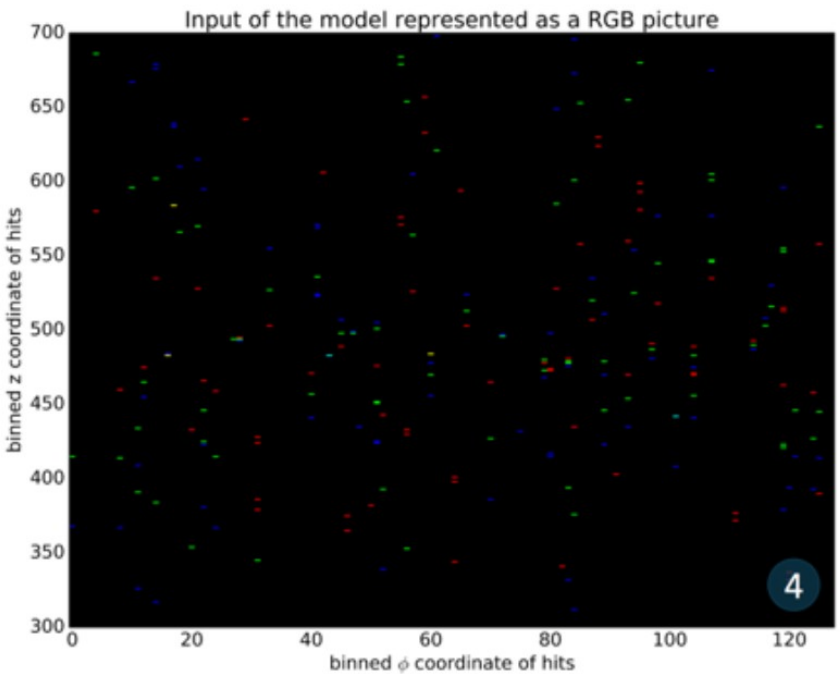


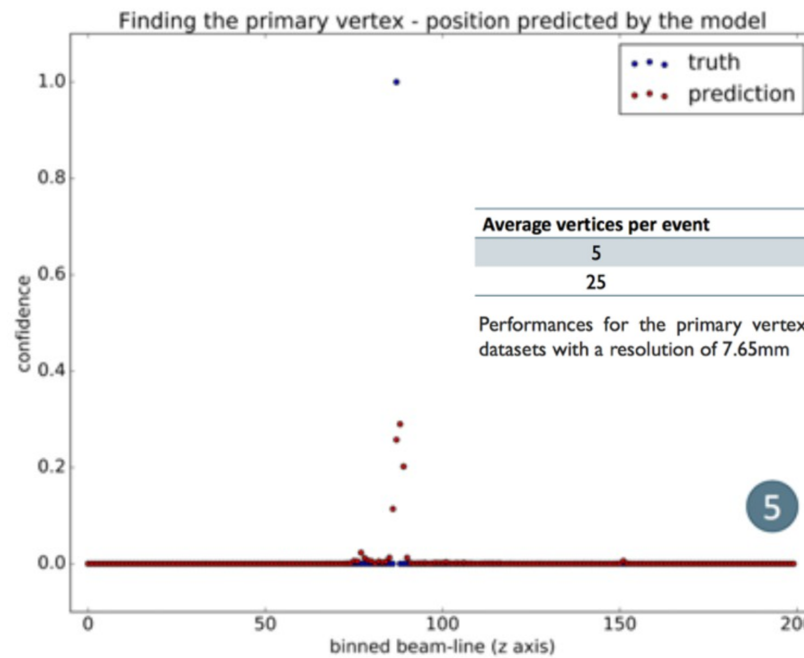


Vertex Finding

LeNet Vertex Finding

- Look at the hit-map on the first 3 layers of the pixel detector, using convolutional model similar to LeNet
- Output a binned distribution of the primary vertex “z”
- Needs more work to converge





Average vertices per event	Accuracy
5	0.46
25	0.15

Performances for the primary vertex finding on two different datasets with a resolution of 7.65mm

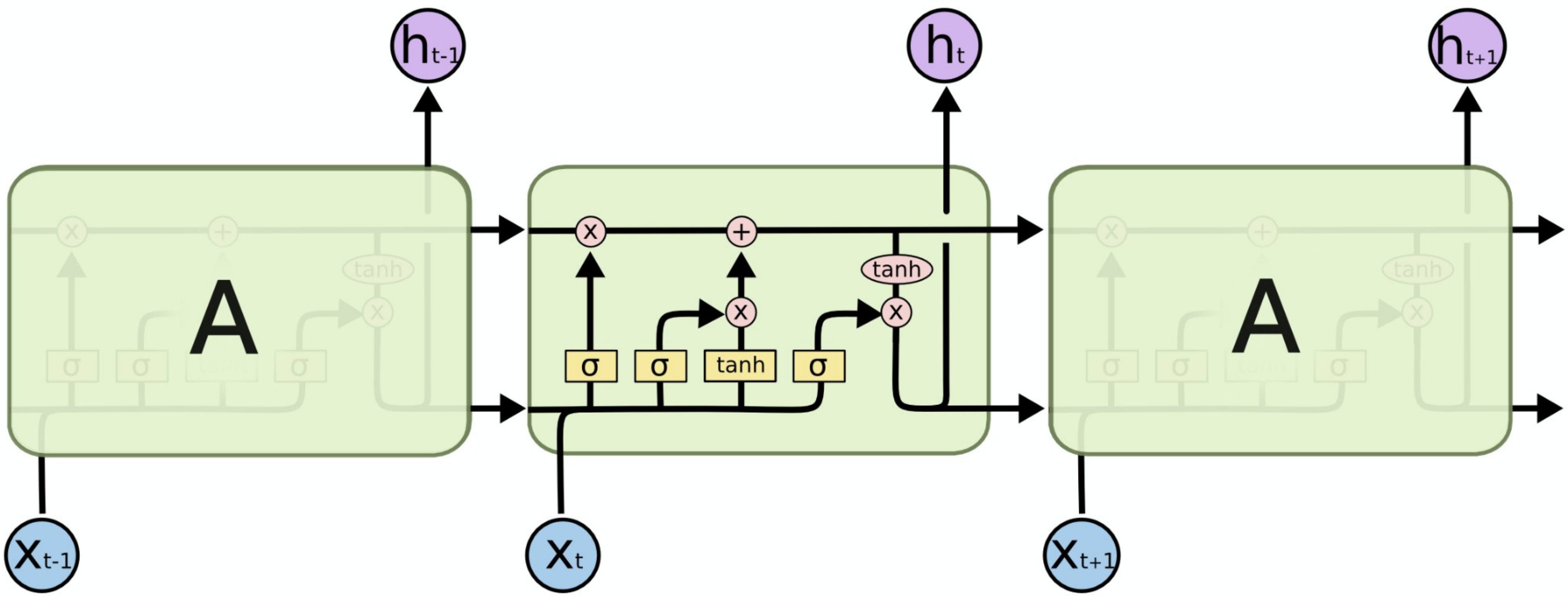
Conclusions

- Pilot project to explore new ideas for track reconstruction
- Promising insights from simplistic and more realistic ACTS datasets
- Keep an open mind to new approaches
- Further on with more realistic datasets

Backup

Long Short Term Memory - LSTM

Breakthrough in sequence processing by carrying over an internal state, “memory” of the previous items in the sequence, allowing for long range correlation



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

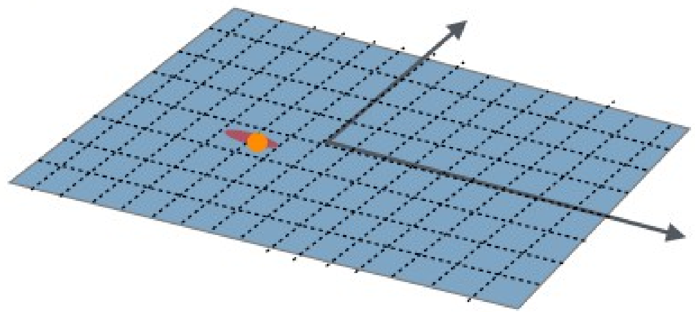
Tracking **Not** In a Nutshell

Several Times

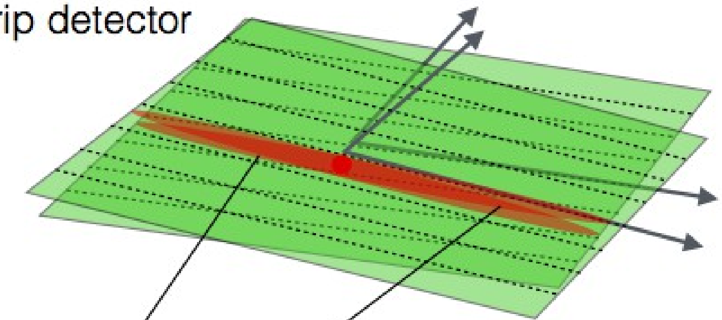
- **Hits preparation**
- **Seeding**
- **Pattern recognition**
- **Track fitting**
- **Track cleaning**

Hit Preparation

pixel detector



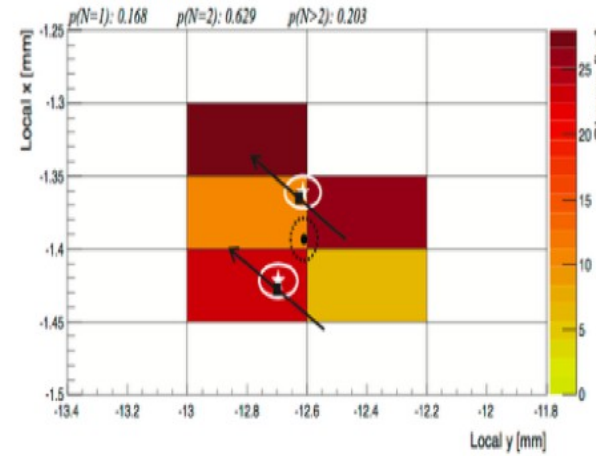
strip detector



using beam spot assumption

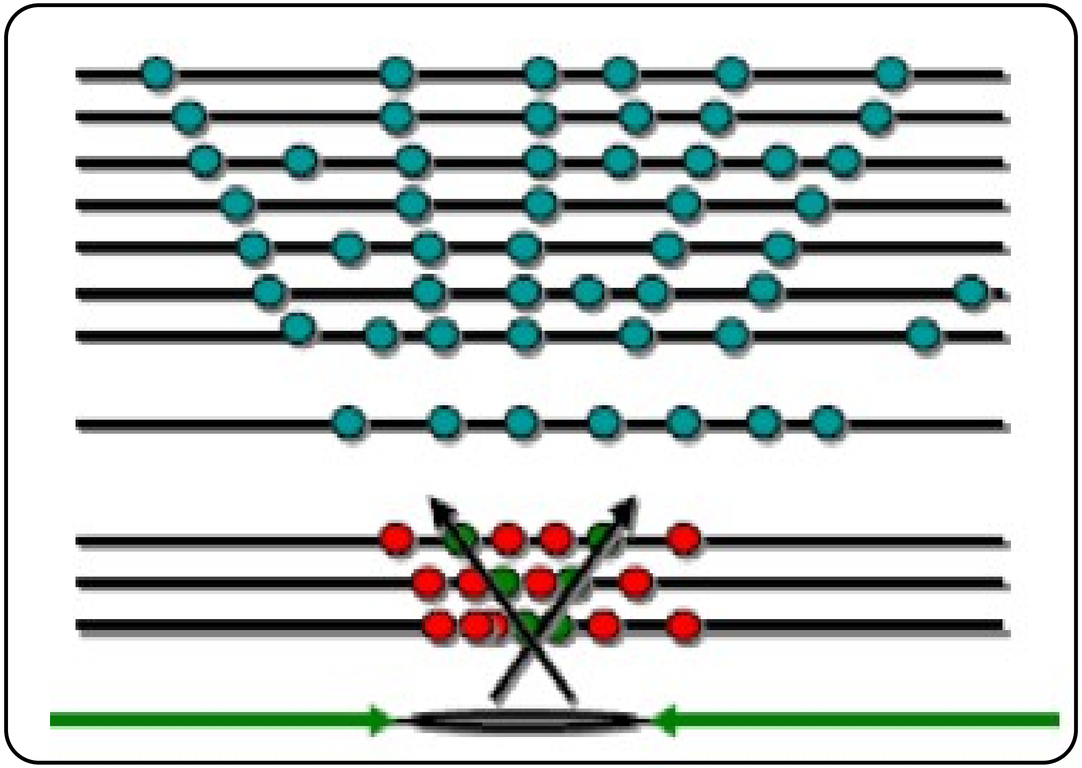
- Calculate the hit position from barycenter of charge deposits
- Use of neural net classifier to split cluster in ATLAS
- Access to trajectory local parameter from cluster shape
- Remove hits from previous tracking iterations
- HL-LHC design include double layers giving more constraints on the local trajectory parameters

first NN output



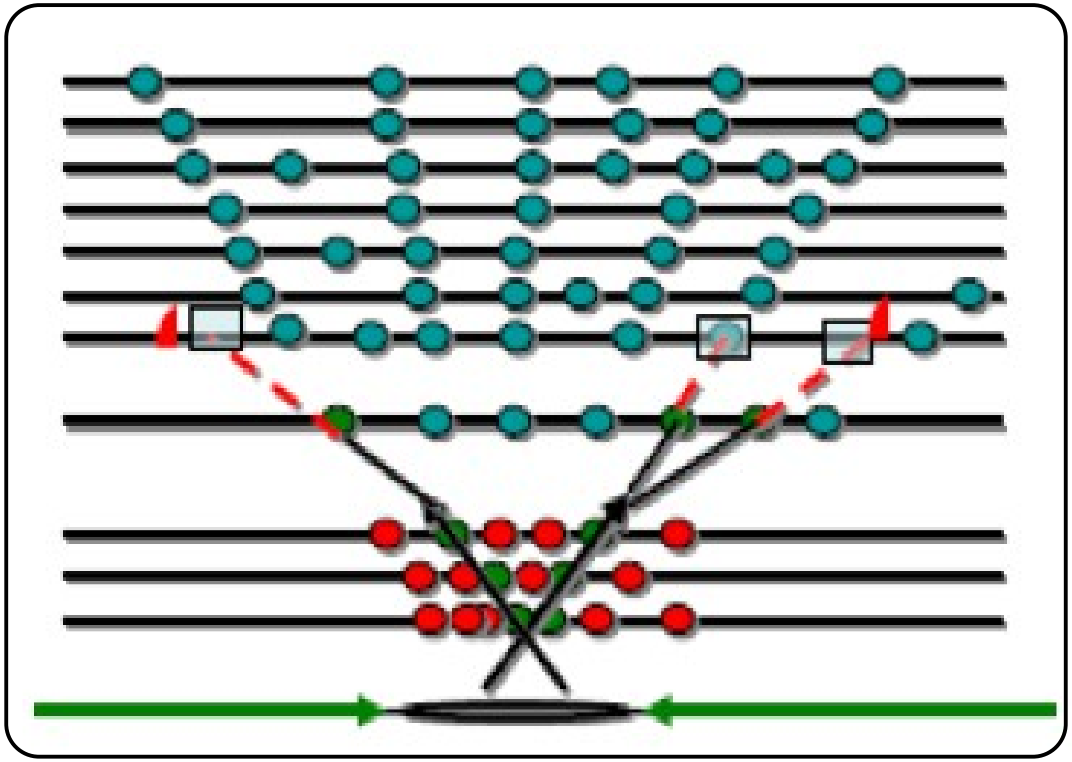
Example of cluster split

Seeding



- Combinatorics of 2 or 3 hits with tight/loose constraints to the beam spot or vertex
- Seed cleaning/purity plays in an important in reducing the CPU requirements of sub-sequent steps
  - ➔ Consider pixel cluster shape and charge to remove incompatible seeds
- Initial track parameters from helix fit

Pattern Recognition



- Use of the Kalman filter formalism with weight matrix
- Identify possible next layers from geometrical considerations
- Combinatorics with compatibles hits, retain N best candidates
- No smoothing procedure
- Resilient to missing modules
- Hits are mostly belonging to one track and one track only
- Hit sharing can happen in dense events, in the innermost part
- Lots of hits from low momentum particles

Kalman Filter

$$K_k = C_{k|k-1} H_k^{\top} (V_k + H_k C_{k|k-1} H_k^{\top})^{-1}$$
$$p_{k|k} = p_{k|k-1} + K_k (m_k - H_k p_{k|k-1})$$
$$C_{k|k-1} = (I - K_k H_k) C_{k|k-1}$$

H_k is the projection matrix

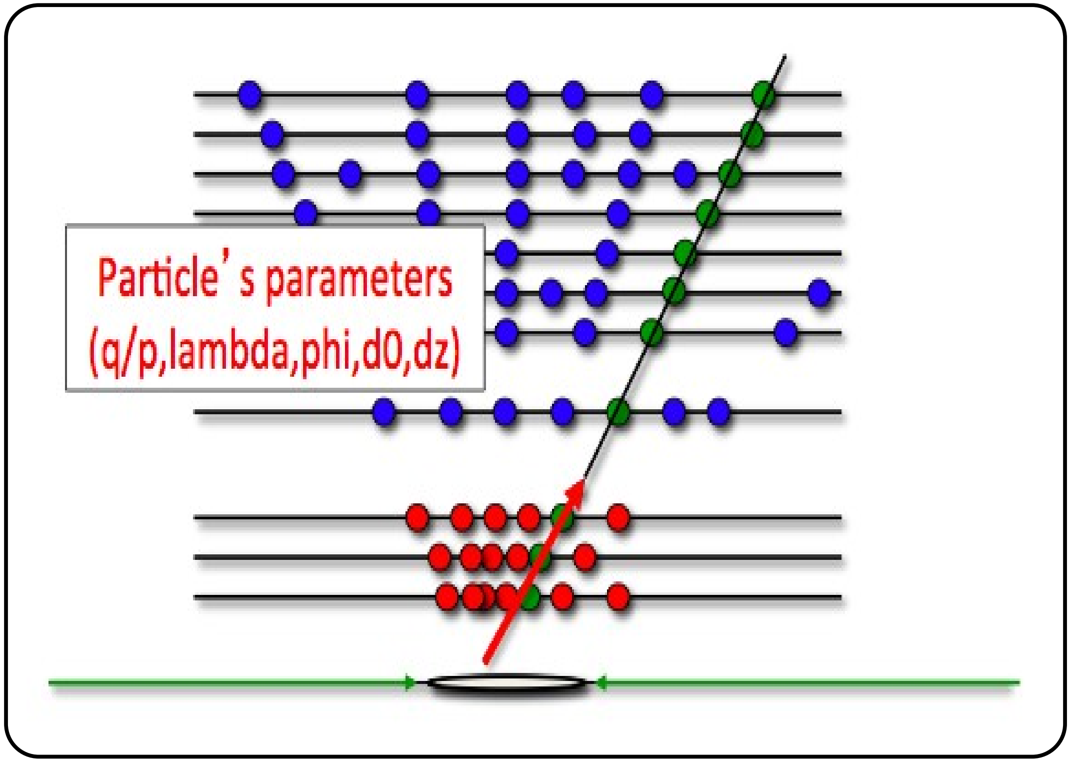
V_k is the hit covariance matrix

$p_{i|j}$ is the trajectory state at i given j

$C_{i|j}$ is the trajectory state covariance matrix at i given j

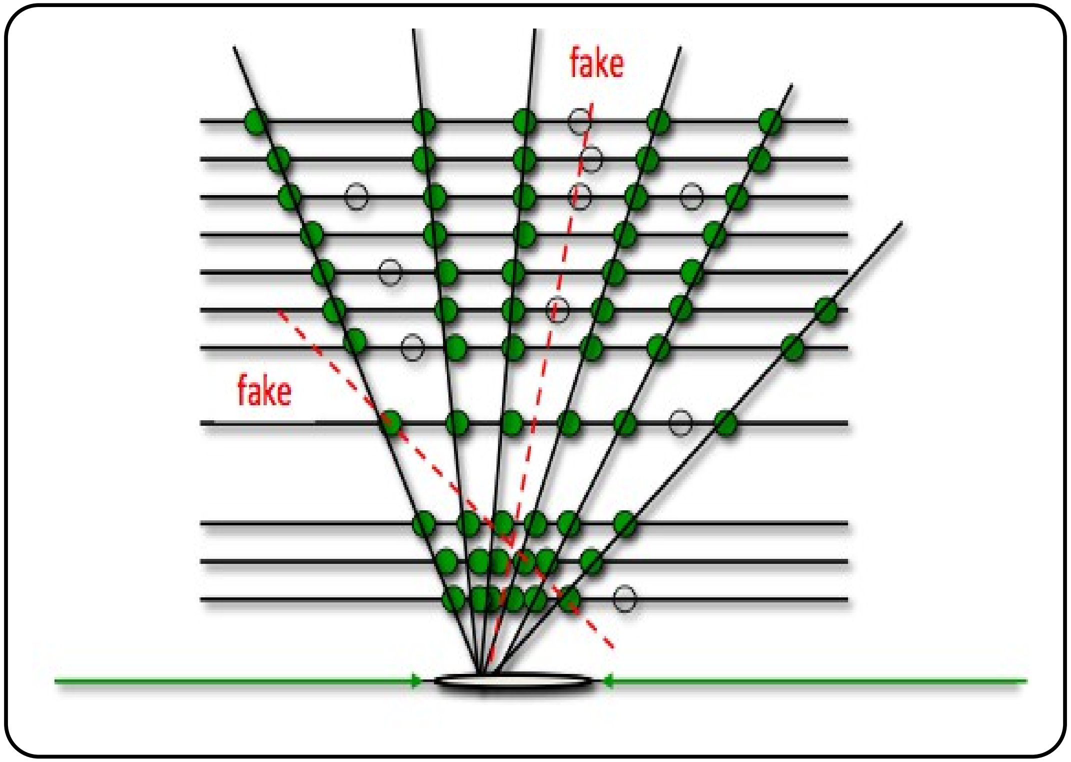
- Trajectory state propagation done either
  - ✓ Analytical (helix, fastest)
  - ✓ Stepping helix (fast)
  - ✓ Runge-Kutta (slow)
- Material effect added to trajectory state covariance
- Projection matrix of local helix parameters onto module surface
  - → Trivial expression due to local helix parametrisation
- Hits covariance matrix for pixel and stereo hits properly formed
  - ✗ Issue with strip hits and longitudinal error being non gaussian (square)

Track Fitting



- Use of the Kalman filter formalism with weight matrix
- Use of smoothing procedure to identify outliers
- Field non uniformity are taken into account
- Detector alignment taken into account

Cleaning, Selection



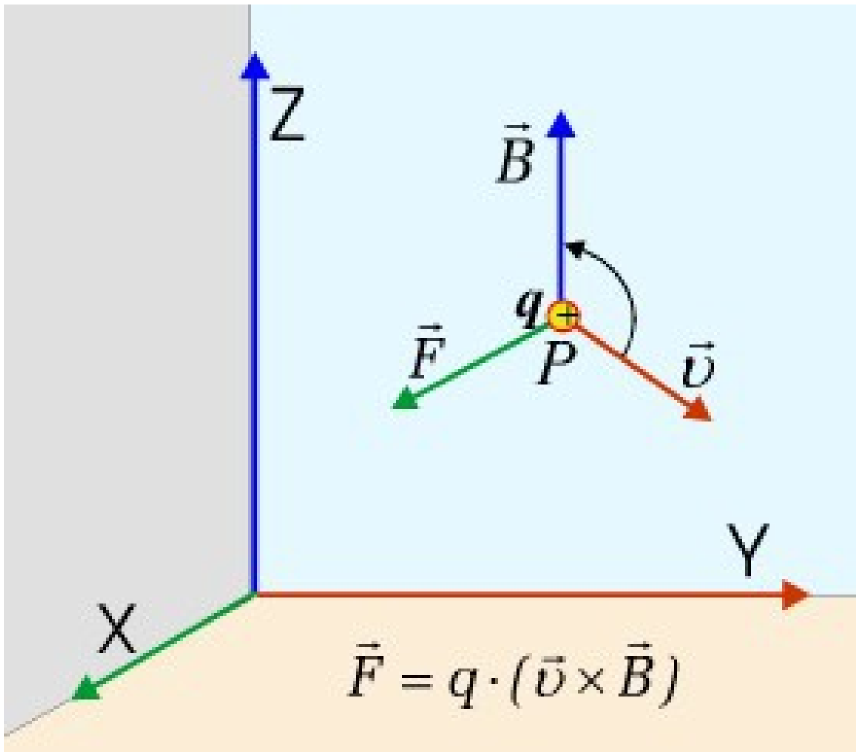
- Track quality estimated using ranking or classification method
  ➔Use of MVA
- Hits from high quality tracks are remove for the next iterations where applicable

A Charged Particle Journey

First order effect : electromagnetic elastic interaction of the charge particle with nuclei (heavy and multiply charged) and electrons (light and single charged)

Second order effect : inelastic interaction with nuclei.

Magnetic Field

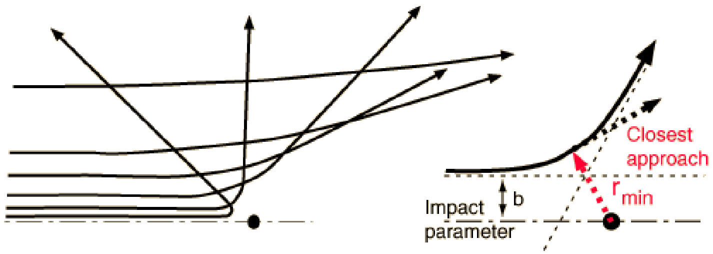


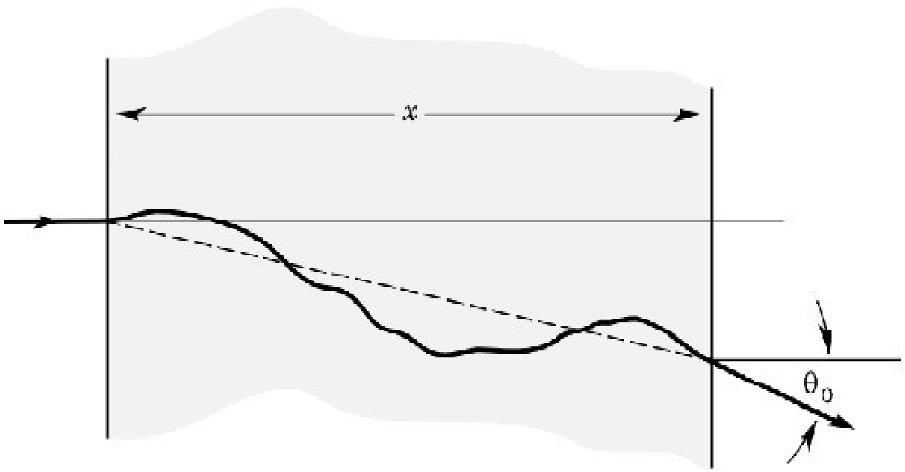
- Magnetic fieldB acts on charged particles in motion : Lorentz Force
- The solution in uniform magnetic field is an helix along the field : 5 parameters
- Helix radius proportional to the component of momentum perpendicular to B
- Separate particles in dense environment

→ Bending induces radiation : bremsstrahlung

→ The magnetic field has to be known to a good precision for accurate tracking of particle

Multiple Scattering





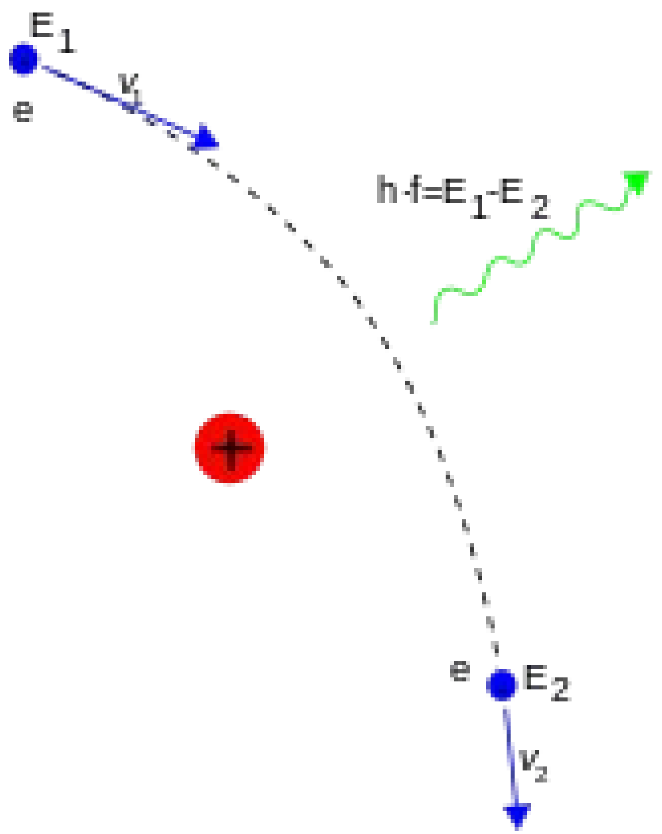
- **Deflection on nuclei** (effect from electron are negligible)
- Addition of scattering processes
- Gaussian approximation valid for substantial material traversed

Gaussian Approximation

$$\theta^2 = \left(\frac{13.6MeV}{\beta c p}\right)^2 * \frac{x}{X_0}$$

β -particle velocity
ρ – material density
P - particle momenta

Bremsstrahlung



- Electromagnetic radiation of charged particles under acceleration due to nuclei charge
- Significant at low mass or high energy
- Discontinuity in energy loss spectrum due to photon emission and track curvature

→ Can be observed as kink in the trajectory or presence of collinear energetic photons

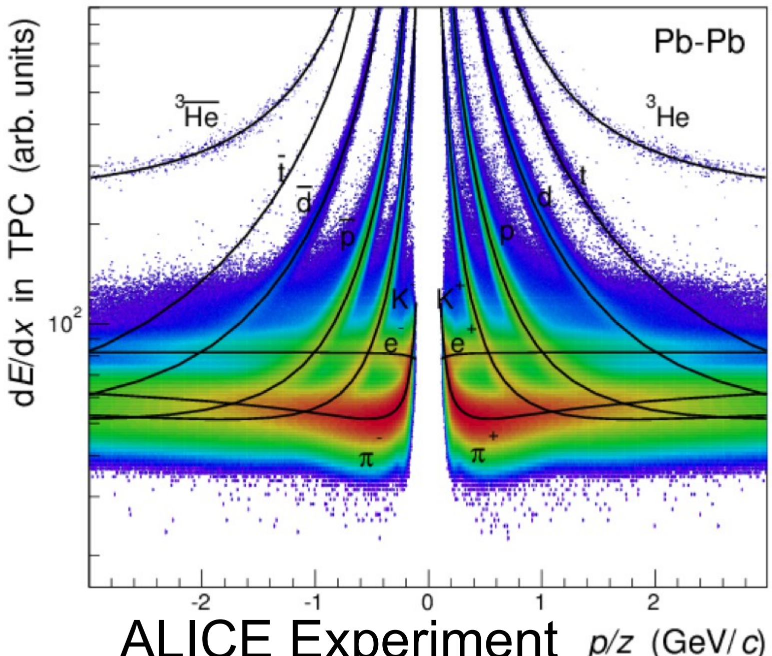
Energy Loss

- Momentum transfer to electrons when traversing material (effect of nuclei is negligible

- Energy loss at low momentum depends on mass : can be used as mass spectrometer

$$dE/dx = k_1 \frac{Z}{A}\frac{1}{\beta^2}\rho\left(\ln\left(\frac{2m_e c^2\beta^2}{I(1-\beta^2)}\right) - \beta^2 - \frac{\delta}{2}\right)$$

β -particle velocity
ρ – material density
Z - atomic number of absorber
A – mass number of absorber
I – mean excitation energy
δ – density effect correction factor – material dependent and β dependent



ALICE Experiment

Summary on Material Effects

- Collective effects can be estimated statistically and taken into account in how they modify the trajectory

- Bremstrahlung and nuclear interactions significantly distort trajectories

Scene Labeling

From talk of LeCunn at CERN

Scene Labeling

LeCunn Seminar at CERN

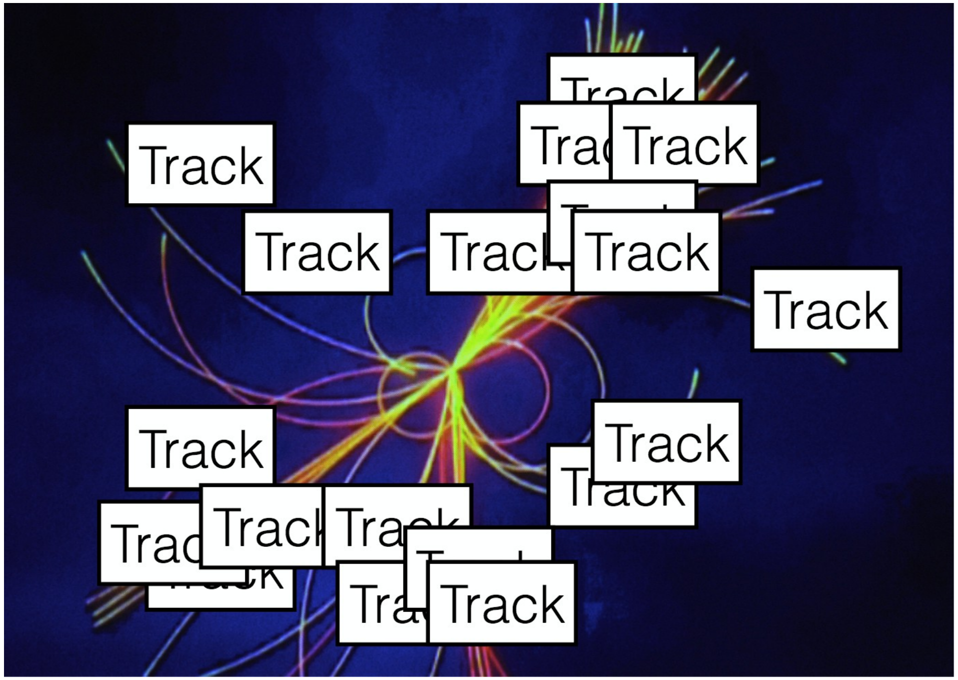


Photo by Pier Marco Tacca/Getty Images