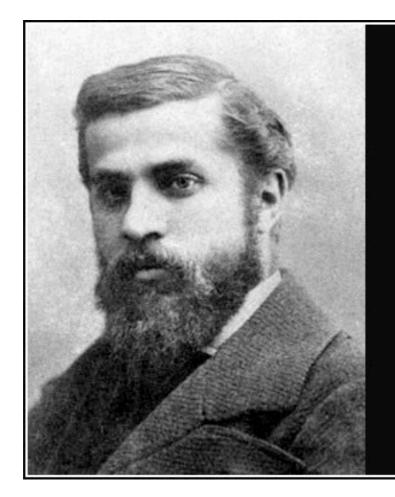


A brief overview of e/y Reconstruction in ATLAS

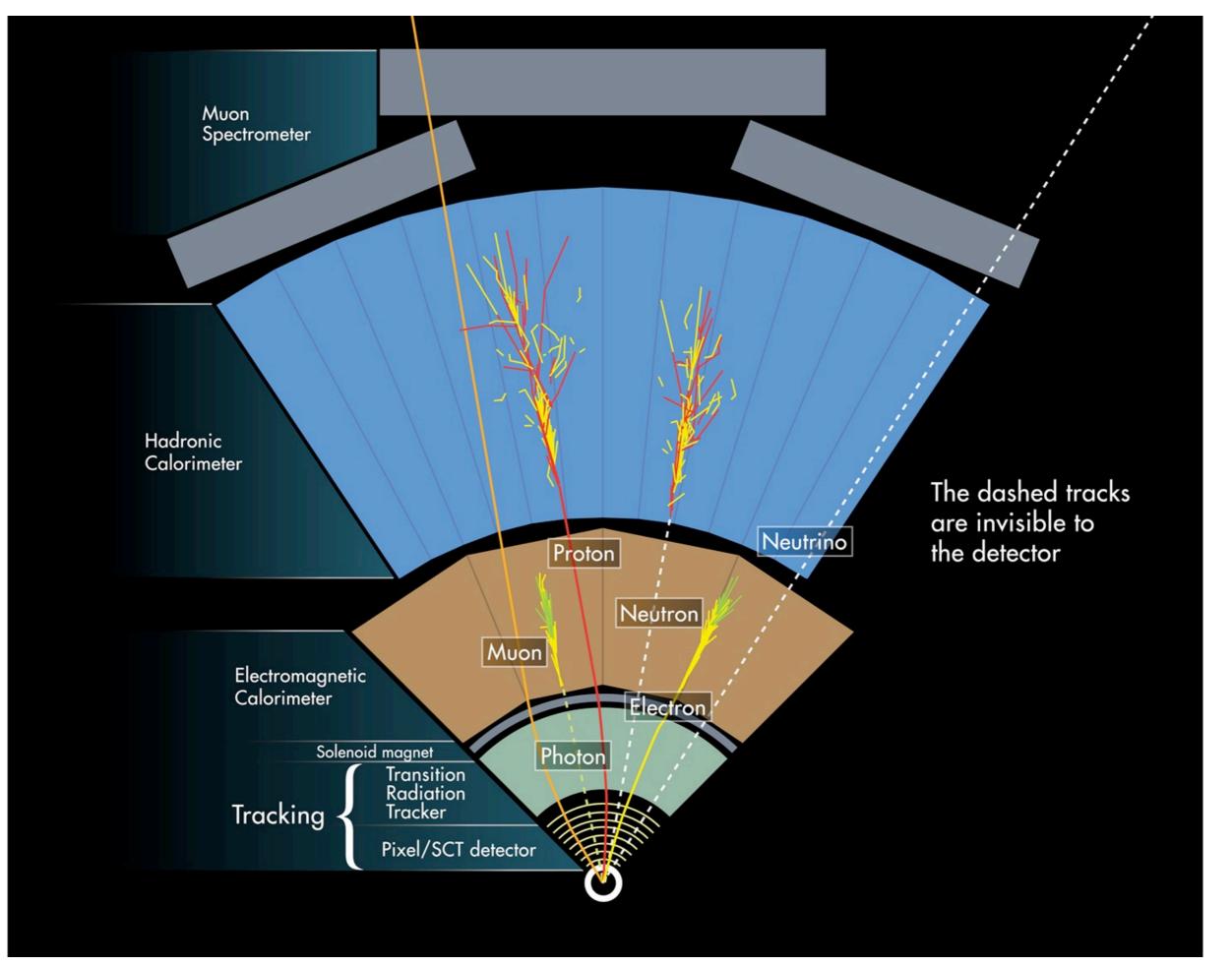


Originality implies a return to the origins, original is returning to the simplicity of the first solutions.

— Antonio Gaudi —

AZQUOTES

Christos Anastopoulos



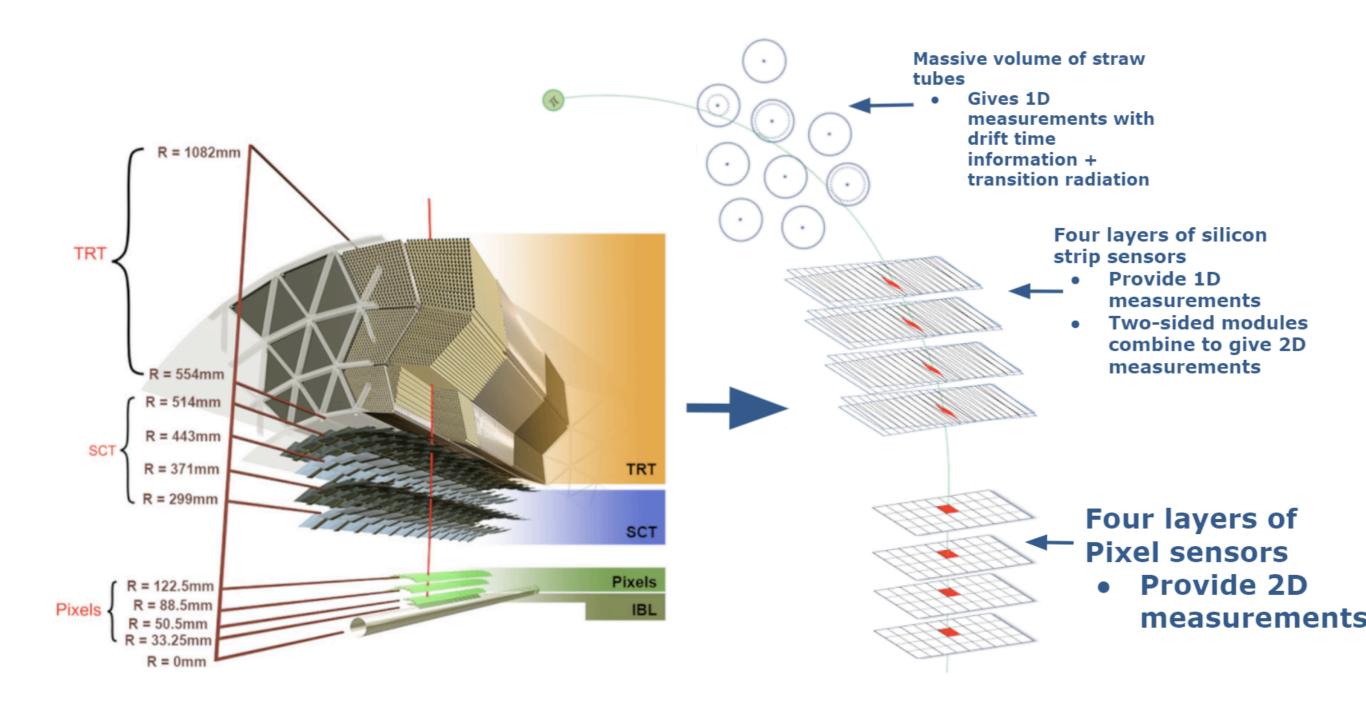
Tracking

A good reference "Pattern Recognition, Tracking and Vertex Reconstruction in Particle Detectors" <u>link</u>. <u>Rudolf Frühwirth</u>,<u>Are Strandlie</u>

Home > Book



Measurements



Equation of Motion

In what follows tracking will refer to the reconstruction of charged particle trajectories starting from measurements in the tracking detectors.

Equation of motion :

$$\frac{\mathrm{d}\boldsymbol{p}}{\mathrm{d}t} = kq\,\boldsymbol{v}(t) \times \boldsymbol{B}(\boldsymbol{r}(t)) \quad \boldsymbol{p} = \gamma \, \boldsymbol{m}\,\boldsymbol{v}$$

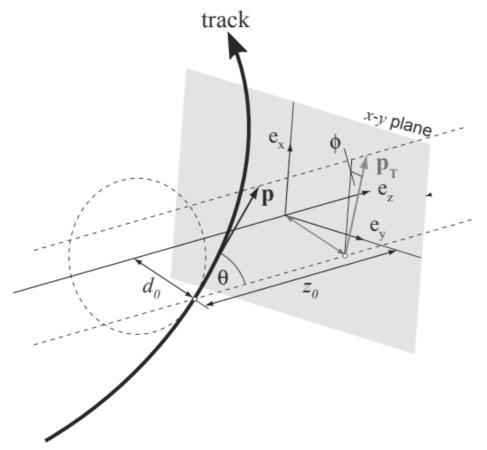
GeV/c for \boldsymbol{p} , meter for \boldsymbol{r} , and Tesla for \boldsymbol{B}
 $k = 0.29979 \,\mathrm{GeV}/c \,\mathrm{T}^{-1} \,\mathrm{m}^{-1}$

<u>Six degrees</u> of freedom e.g the initial position (x,y,z) and the initial momentum (p_x,p_y,p_z) .

Wrt to a reference surface, five degrees of freedom are sufficient.

Track Parametrisation

Wrt to a reference surface, five degrees of freedom are sufficient.



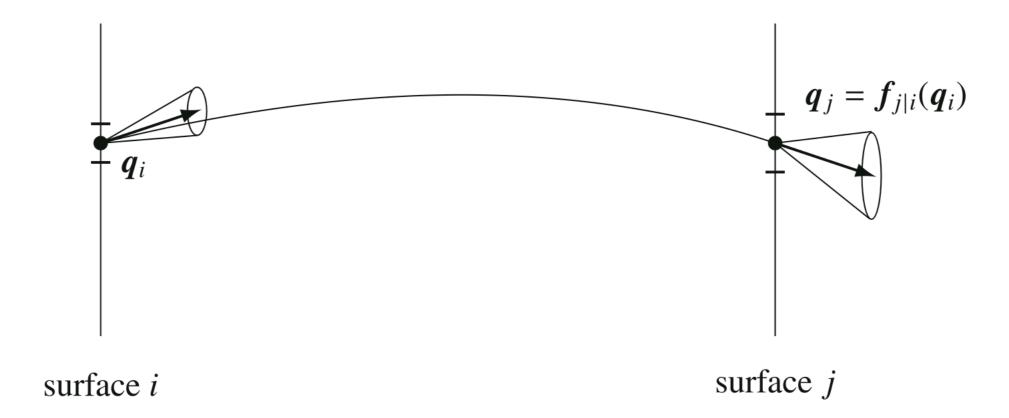
At the end we want to be able to estimate these parameters for each Charged particle.

Global track parameters e.g. wrt. perigee

$$\left(d_0, z_0, \phi, \theta, \frac{q}{p} \right)$$

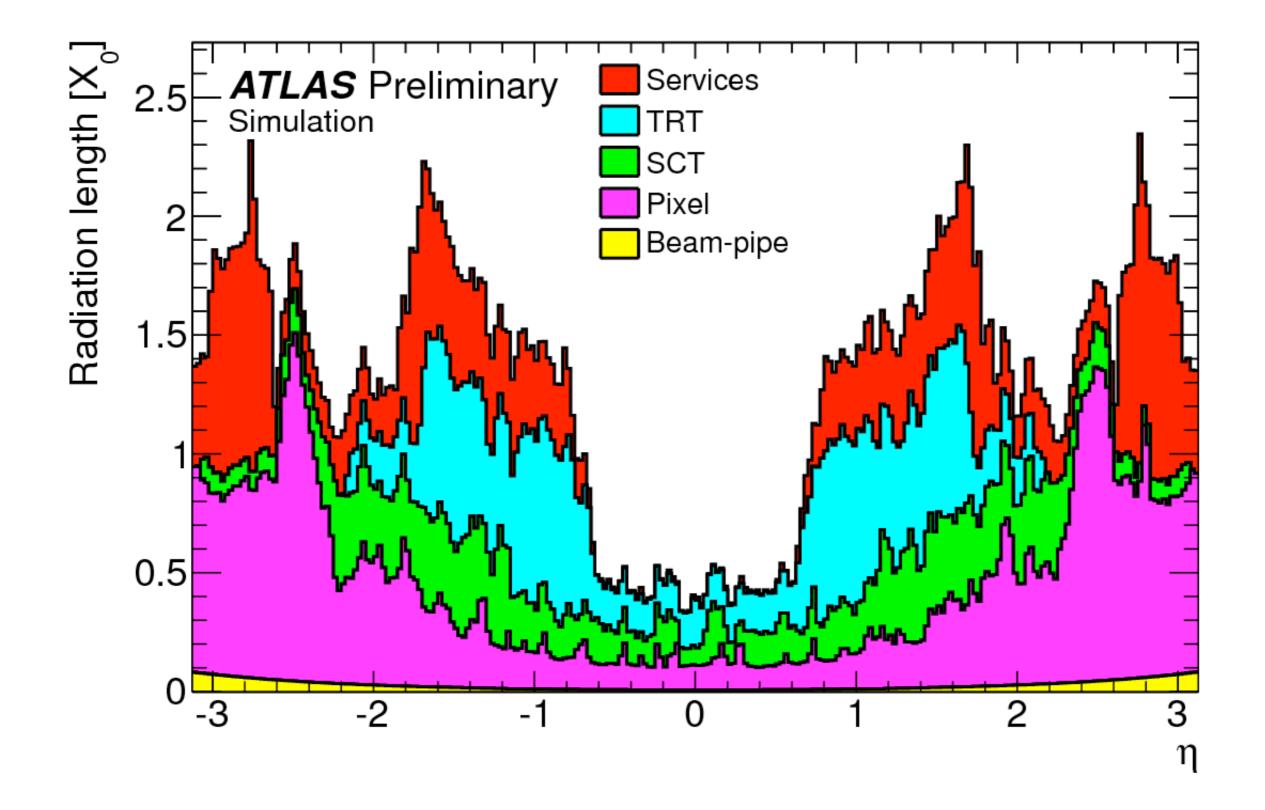
Propagation

Knowing the Magnetic Field, Geometry, material "being able to go from surface to surface" accounting for uncertainties and material effects



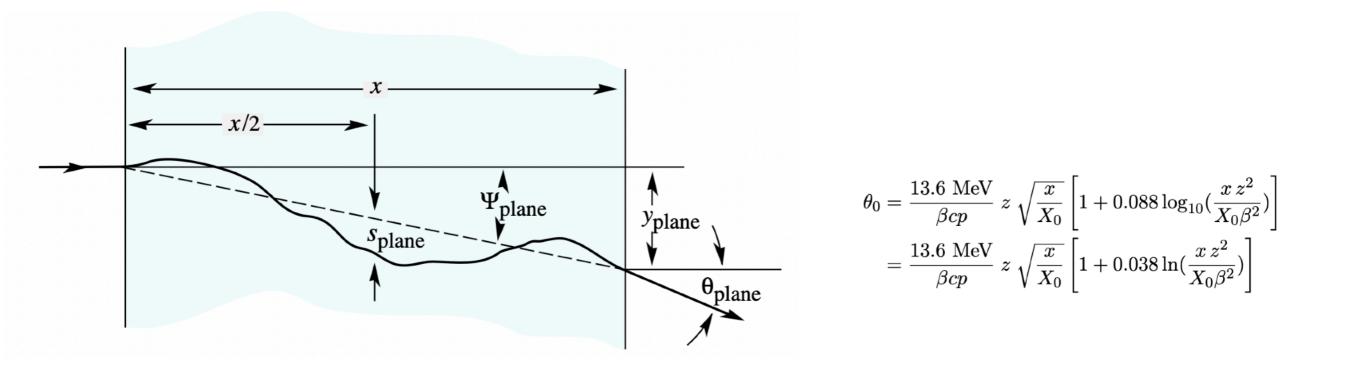
In ATLAS this is done using numerical integrations see : <u>ATLAS RungeKuttaPropagator</u>, <u>ATLAS STEP_Propagator</u> <u>ACTS Propagator</u>

Material effects



Material effects

Multiple Scattering —> augment the covariance matrix by the additional uncertainty on direction (and possibly position) caused by multiple scattering.



Ionisation energy loss : The "Bethe-Bloch" formula is used to modify the momentum part of the track parameter vector.

Fluctuations in the ionisation energy loss are often considered so small/neglected.

Material effects

Energy Loss by Bremsstrahlung—> "Interesting" problems that we will return to in various places in this talk. "Electrons" are special.

h·f=E₁-E₂ **Bethe - Heitler** 20 $t = 0.20 \ \mu = 0.819 \ \sigma = 0.241$ $t = 0.10 \ \mu = 0.905 \ \sigma = 0.186$ $t=0.05~\mu=0.951~\sigma=0.138$ 15 $t = 0.02 \ \mu = 0.980 \ \sigma = 0.089$ (z) f $f(z) = \frac{(-\ln z)^{t/\ln 2 - 1}}{\Gamma(t/\ln 2)}.$ 5Brem point $z = E/E_0$ **Conversion** point $t = s/X_0$ 0 **Electron tracks** 0.20.40.60.8 0 1 **Electron track**

Distribution can not be described just from mean and variance.

Typically described by a <u>GaussianMixture</u>.

SCT

Kalman Filter Interlude

Discovery of the Kalman Filter as a Practical Tool for Aerospace and Industry

Leonard A. McGee and Stanley F. Schmidt (NASA-TM-86847) DISCOVERY OF THE KALMAN N86-13311 FILTER AS A PHACTICAL TCCL FCR ALBOSPACE AND INDUSTRY (NASA) 24 p HC A02/MF A01 CSCL 17G ULCLAS G3/04 04905 CO 1985 RECEIVED NASA STI FACILITY

SUMMARY

The Kalman filter in its various forms has become a fundamental tool for analyzing and solving a broad class of estimation problems. The first publicly known application was made at NASA Ames Research Center in the early 1960s during feasibility studies for circumlinear navigation and control of the Apollo space capsule. This paper recounts the fortunate sequence of events which led the researchers at Ames Research Center to the early discovery of the Kalman filter shortly after its introduction into the literature. The scientific breakthroughs and reformulations that were necessary to transform Kalman's work into a useful tool for a specific aerospace application are described. The resulting extended Kalman filter, as it is now known, is often still referred to simply as the Kalman filter. As the filter's use gained in popularity in the scientific community, the problems of

link

Kalman Filter Interlude

Optimal Filtering B. Anderson, and J. Moore. Prentice-Hall, (1979). Offers a quite detailed treatment.

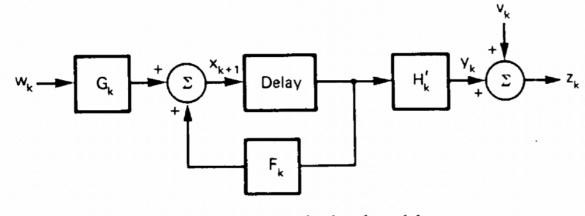


Fig. 3.1-1 Basic signal model.

 \mathbf{F}_k is the state transition model which is applied to the previous state \mathbf{x}_k

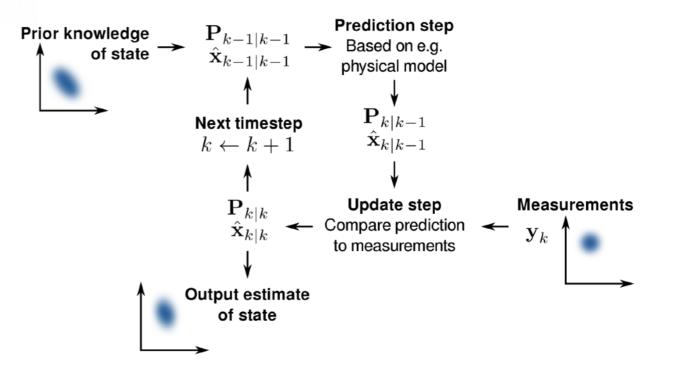
 \mathbf{w}_k is the process noise, which is assumed to be a (multivariate) normal distribution

At time k an observation (or measurement) \mathbf{z}_k of the true state \mathbf{x}_k is made

 \mathbf{H}_{k} is the observation model, which maps the true state space into the observed space

 \mathbf{v}_k is the observation noise, which is assumed to be also normal

$$\begin{aligned} x_{k+1} &= F_k x_k + G_k w_k \\ z_k &= H'_k x_k + v_k \end{aligned}$$

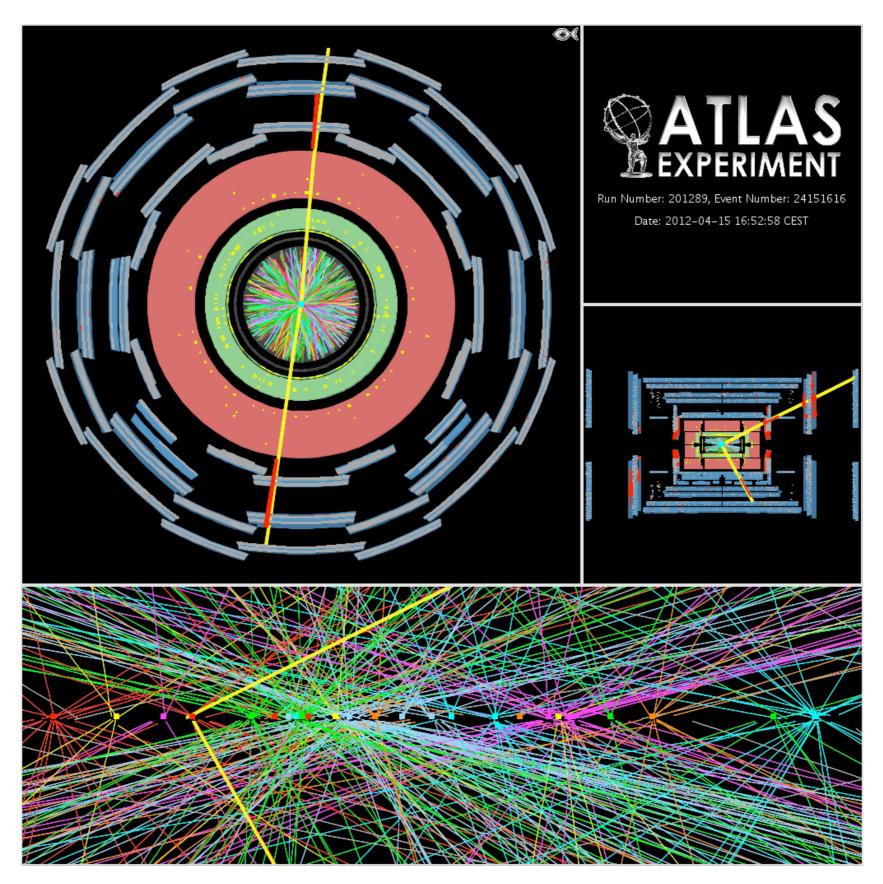


Kalman Filter Interlude

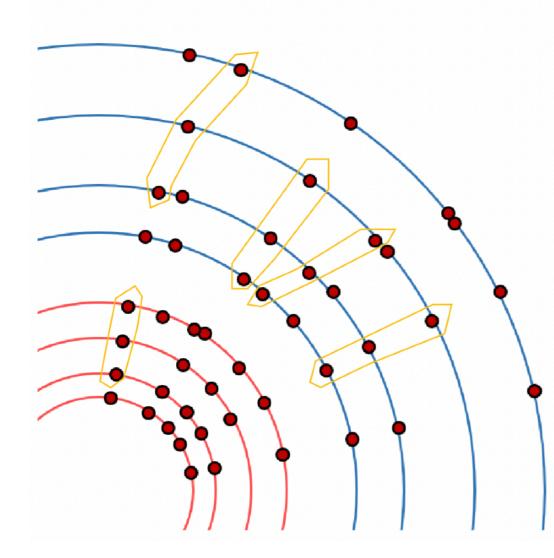
"A "progressive" or recursive version of the LS regression for track fitting was first proposed in [2]. Soon, it was realized that this was the same as an (extended) Kalman filter [3]

The Kalman filter has the advantage that only small matrices have to be inverted, that the track fit follows the track as closely as possible, and that material effects such as multiple scattering and energy loss can be treated locally in each measurement or material layer."

Track Finding in ATLAS

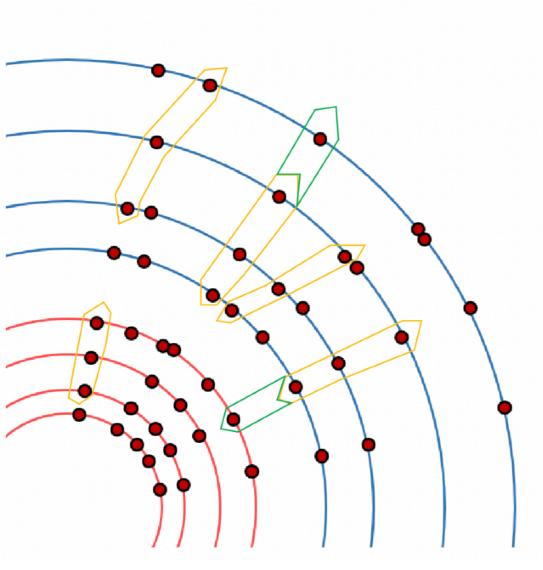


Inside-Out: Track Seeding



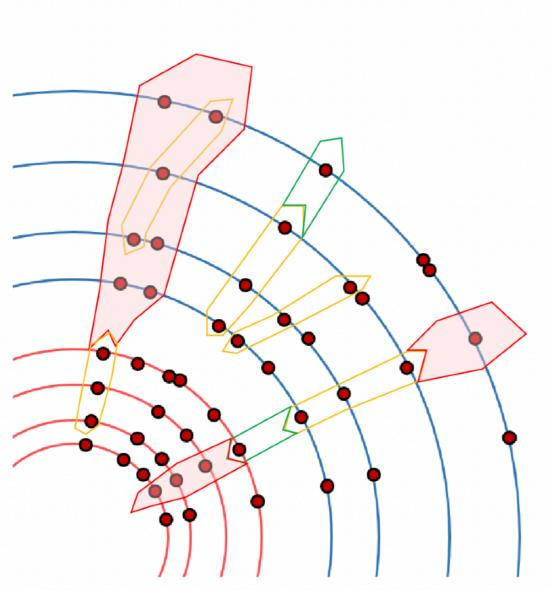
- Track seeds are produced from combinations of 3 Space-Points (SP)
 - Global positions in [x y z]
 - Made up of 3 pixel SPs (PPP)
 - ... or 3 SCT SPs (SSS)
- Compatibility with a helix model
 - Apply some criteria on the candidate seeds
 - For example: cuts on impact parameters
 - Apply slightly looser criteria than further down the chain to account for less precision

Inside-Out: Track Seeding



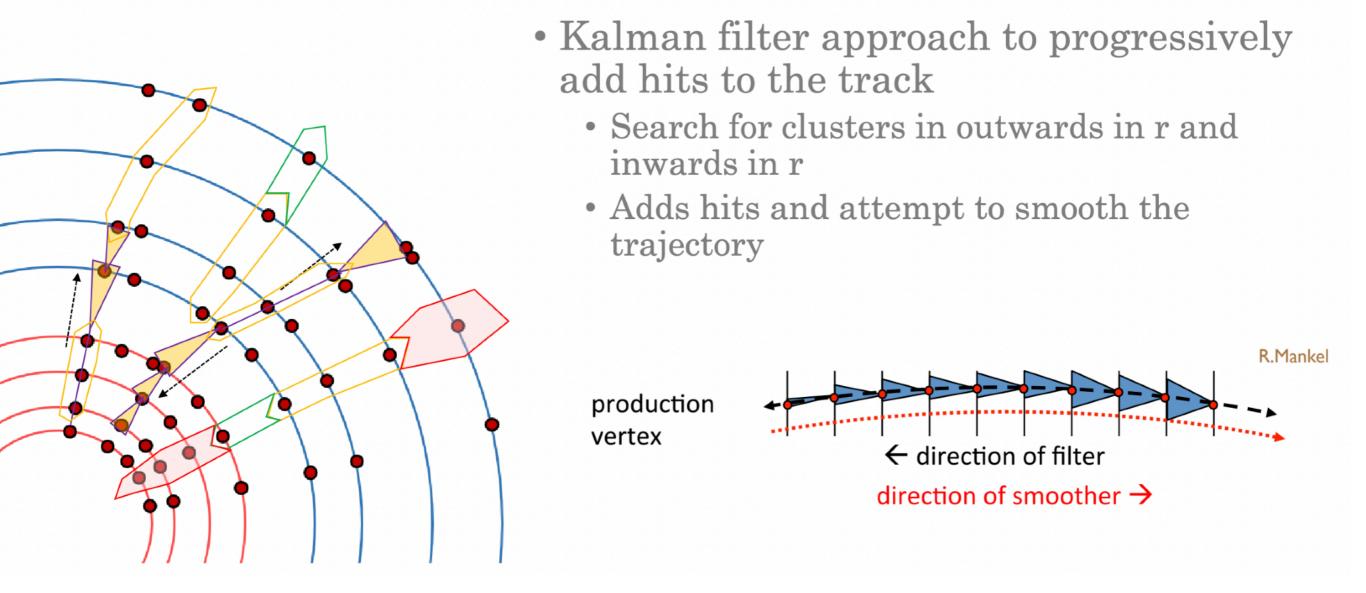
- Attempt to extend the seeds to a nearby layer inwards or outwards
 - Call this seed-confirmation
 - This is done to assess seed quality and potential to extend the seed into a full track

Inside-Out: Track Finding

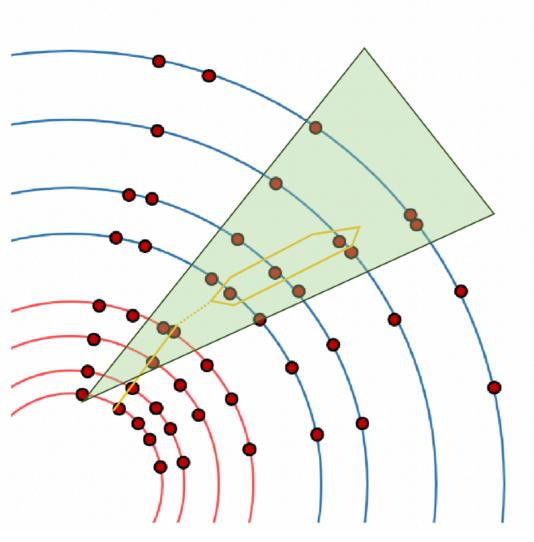


- Perform a road-search along the direction of the track seeds
 - "Collect" the detector elements in the path
 - Only consider clusters on the modules
 →Reduces the combinatorics!

Inside-Out: Track Finding

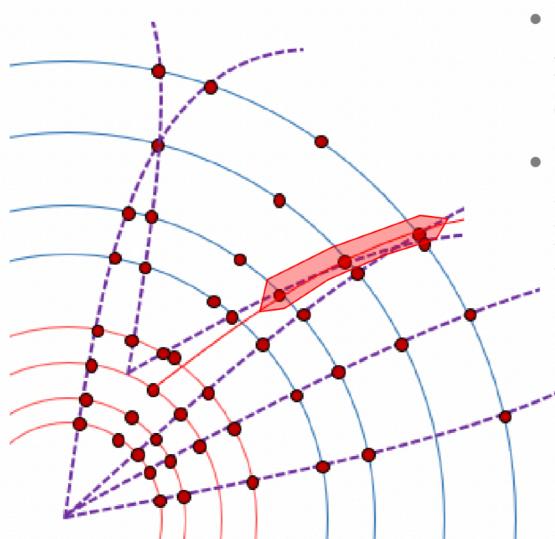


Inside-Out: Brem Recovery



- Potential seeds that fail the track finding are checked for calorimeter compatibility
 - If the seed are within a region of interest (ROI) the track finding is re-done allowing for an extra kink on the track
 - Brem(sstrahlung) Recovery
- This helps recover efficiency for electron reconstruction!

Inside-Out: Track Finding



- End result of the track finding / pattern recognition is a set of potential track candidates
- Kalman filter does a simple/fast fit for the pattern recognition to improve the CPU performance
 - Less precise determined track parameters
 - Doesn't handle ambiguities
 - Shared hits amongst candidates

Track Finding

Track finding is semi-empirical. There is no "systematic" theory. At the end of this step not all candidates will be valid candidates and no final/best parameters have been obtained

The method described before is referred to as "Combinatorial Kaman Filter" (CKF).

Possible to use cellular-automaton (CA), or Graph Neural Network or combination of the two. In my best knowledge these idea are actively pursued in LHC experiments.

CA:

Cells —> short track segments connecting hits in adjacent detector layers; A cell has an inner hit and an outer hit.

Create chains of segments that correspond to actual tracks.

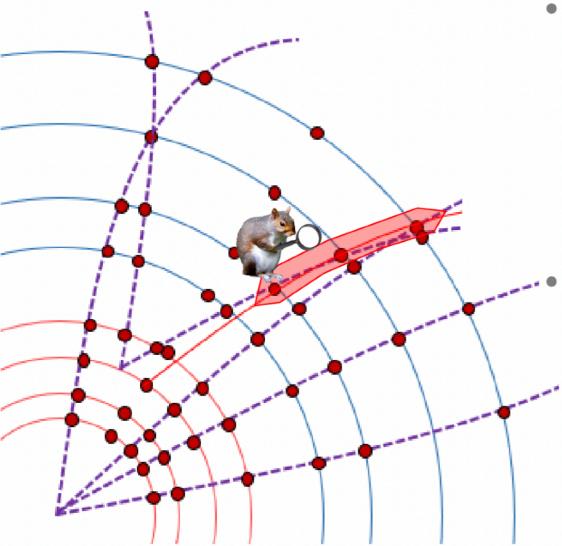
GNN:

Nodes (Vertices) —> detector hits

Nodes are connected if they are compatible based on some criterion GNN used to classify if nodes/hits or edges that belong to a track (or not)

Track Finding

Inside-Out: Ambiguity Processing

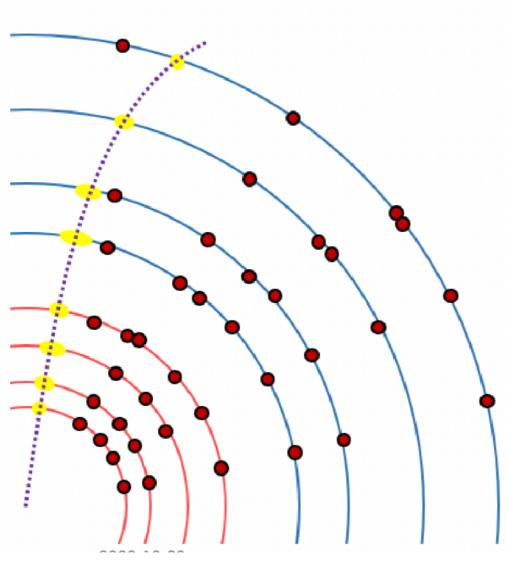


- The ambiguity processor involves three main steps
 - Score tracks and reject low quality candidates
 - Handle ambiguities
 - High precision fit
- Ambiguities ...
 - Shared are often an indicator of fakes or low quality tracks
 - Decides which track gets to keep the hit and whether the other track is kept or rejected sans hit

Track Fitting

This does not work well for electrons

Inside-Out: Global χ^2 fitter

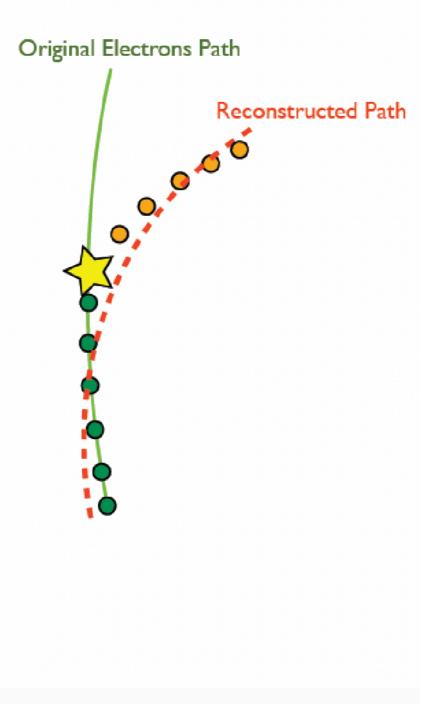


- Remaining candidates are fit with the global χ^2 fitter
 - Minimise χ^2 the track-hit residuals of the track candidates
 - Include and fit all measurements at the same time
 - Account for errors on the measurements and the expected uncertainties for e.g. multiple scattering
 - Out-weight hits as outliers

Electron track Fitting The problem

- Currently all tracks are fitted under the hypothesis they are pions.
- For electrons this leads to the track parameters being poorly reconstructed. Especially in the bending plane.
 - No energy loss due to brem is allowed.
 - As a result the momentum is underestimated.
 - Not optimal track parameters in the bending plane (e.g d₀).
 - This also affects the Δφ matching with the cluster and the E/P.





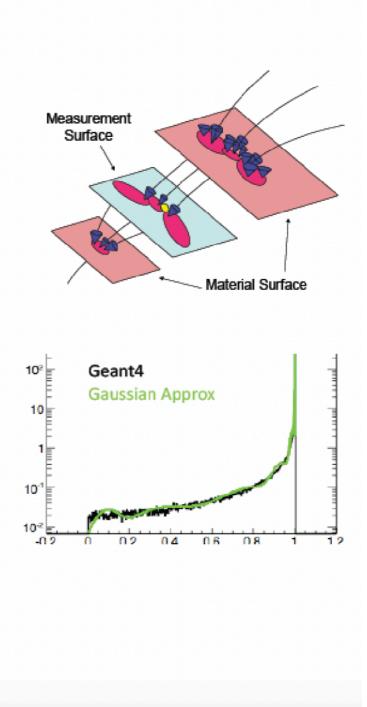
Electron track Fitting Brem Fitters

Two Brem fitters available in ATLAS:

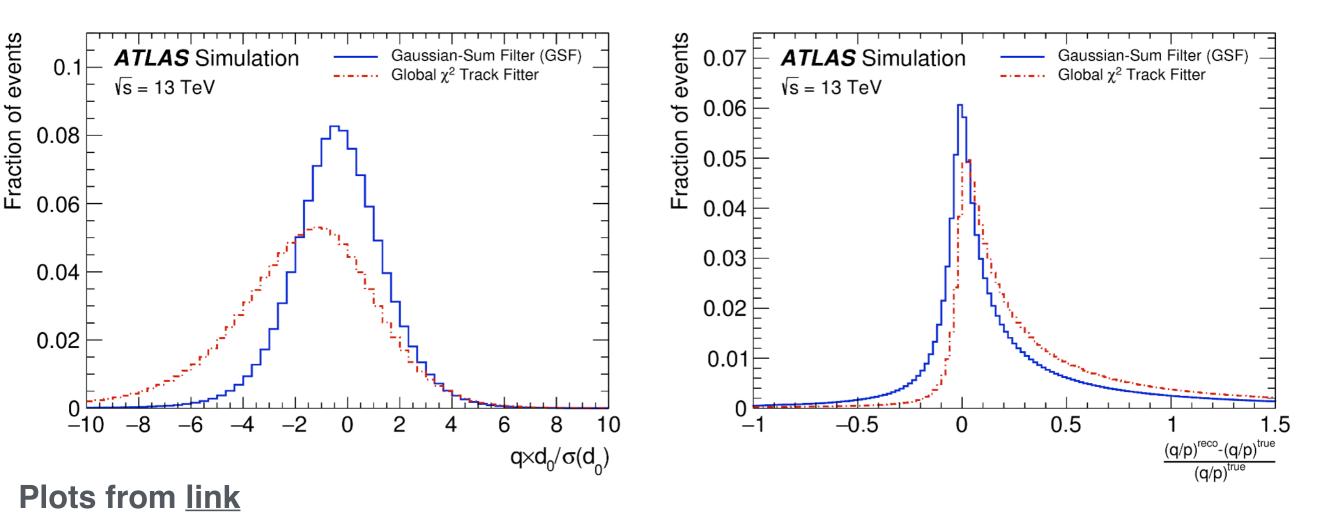
GSF (Gaussian Sum Filter)
 DNA (Dynamic Noise Adjustment)

- GSF is a non-linear expansion of the Kalman Filter:
 - Energy loss is modelled by a sum of Gaussians.
 - At each surface the track state is convolved with material effects.
 - GSF produces a PDF (a weighted sum of Gaussians) describing the track parameters.





Electron track Fitting



Track of electron candidates need to be (re) fitted accounting for Bremsstrahlung.

Proper hypothesis Properly accounting for material effects.

GSF now fast enough for HLT

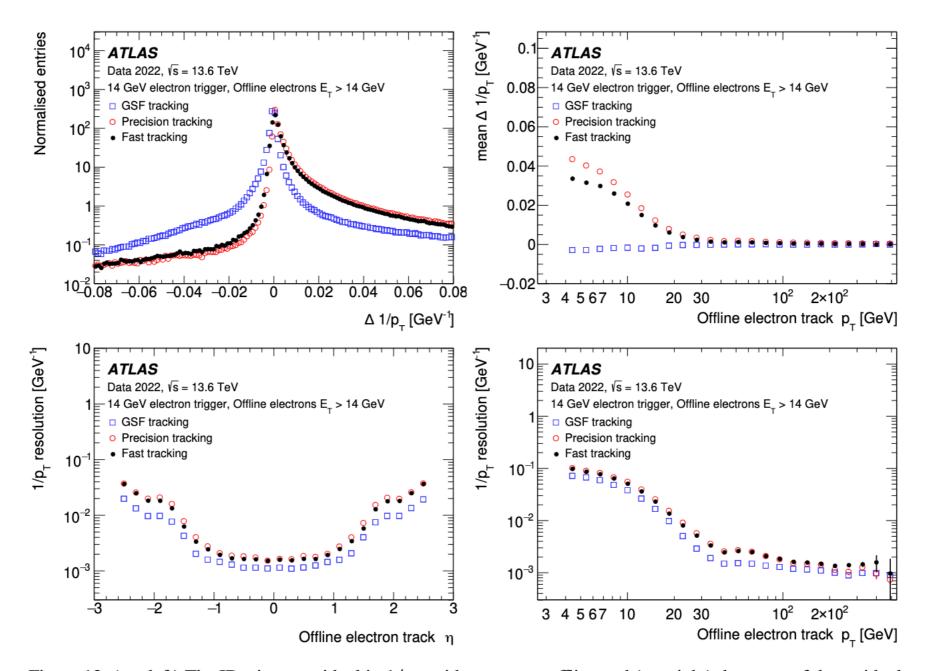


Figure 12: (top left) The ID trigger residual in $1/p_T$ with respect to offline and (top right) the mean of the residual as a function of the offline track p_T . The resolution in the inverse transverse momentum as a function of offline track (bottom left) η and (bottom right) p_T . Distributions are shown for the fast, precision and GSF tracking algorithms for electron candidates selected with electron performance trigger with $E_T > 14$ GeV and passing the offline electron $E_T/p_T > 0.8$ requirement. Only statistical uncertainties are shown.

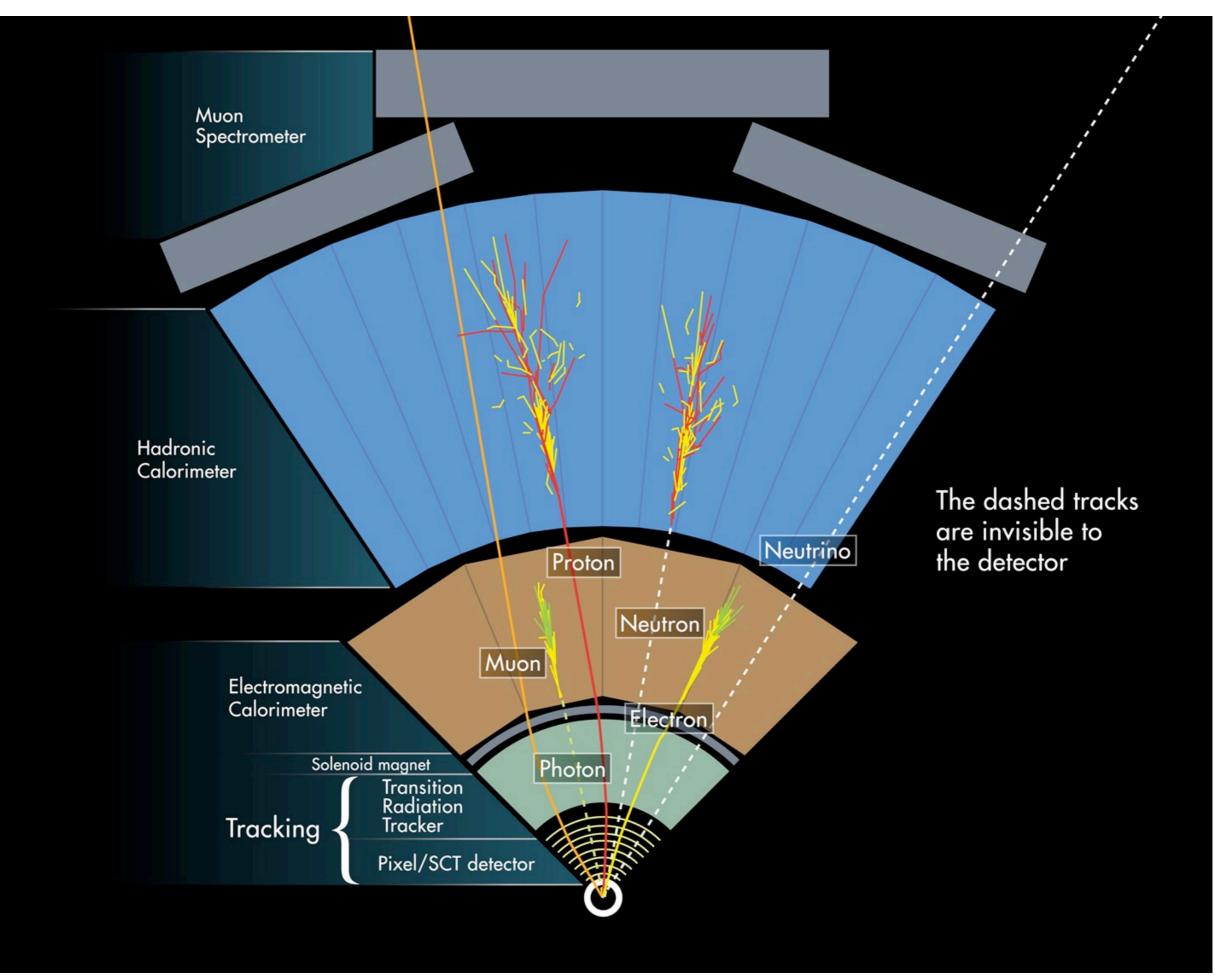
Electron track Fitting

At each surface the track state is convolved with material effects.

Hmmm, how things do not explode ? Let's say 6 Gaussians for the material effects.

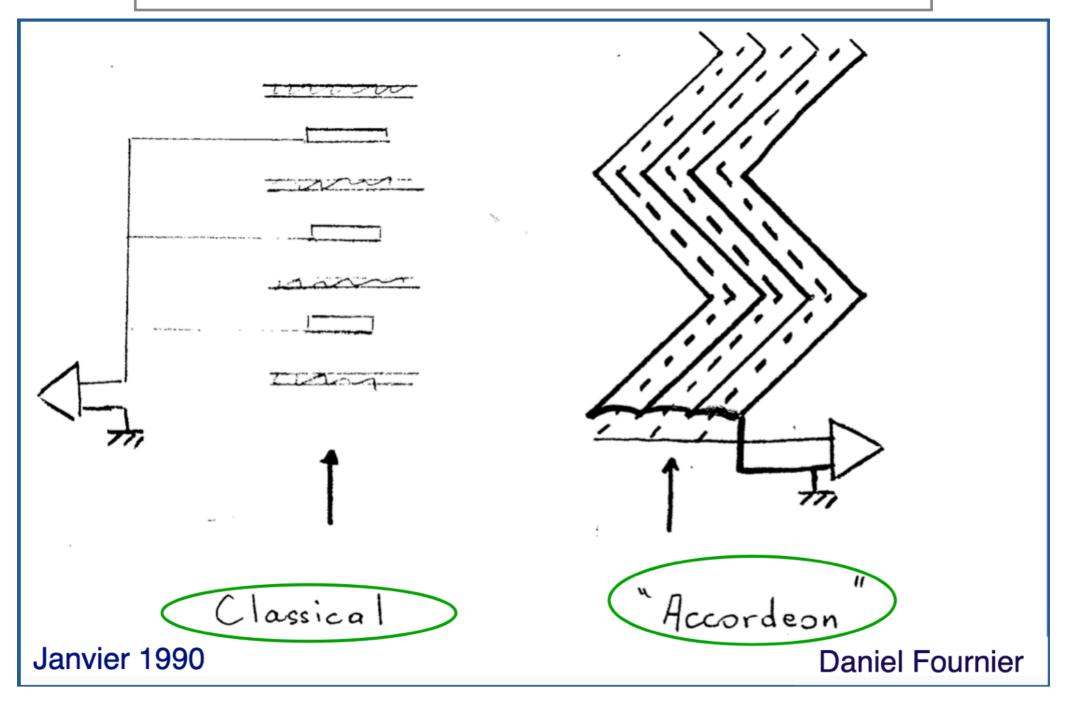
The state becomes 6 Gaussian , next step becomes 36 , the next 216

| Kullback-Leibler Approach to Gaussian Mixture Reduction Publisher: IEEE Cite This PDF | | | |
|---|--------|-----------------------------------|--|
| A.R. Runnalls All Authors | | | |
| 240 Cite Pap | es in | 1824 Full Text Views | R < © 📂 🌲 |
| Abstract | | | Abstract: |
| Document Sections | | Sections | A common problem in multi-target tracking is to approximate a Gaussian mixture by one containing fewer components; similar problems can arise in integrated navigation. A common approach is |
| I. Introduction | | n | successively to merge pairs of components, replacing the pair with a single Gaussian component |
| II. General Background | | ackground | whose moments up to second order match those of the merged pair. Salmond [1] and Williams [2, 3] have each proposed algorithms along these lines, but using different criteria for selecting the pair to |
| III. Kullback-Leibler Discrimination | | | be merged at each stage. The paper shows how under certain circumstances each of these pair- selection criteria can give rise to anomalous behaviour, and proposes that a key consideration should the the Kullback-Leibler (KL) discrimination of the reduced mixture with respect to the original mixture. |
| IV. | SALMON | D'S | Although computing this directly would normally be impractical, the paper shows how an easily |
| CRITERION | | ON | computed upper bound can be used as a pair-selection criterion which avoids the anomalies of the earlier approaches. The behaviour of the three algorithms is compared using a high-dimensional |



Energy reconstruction

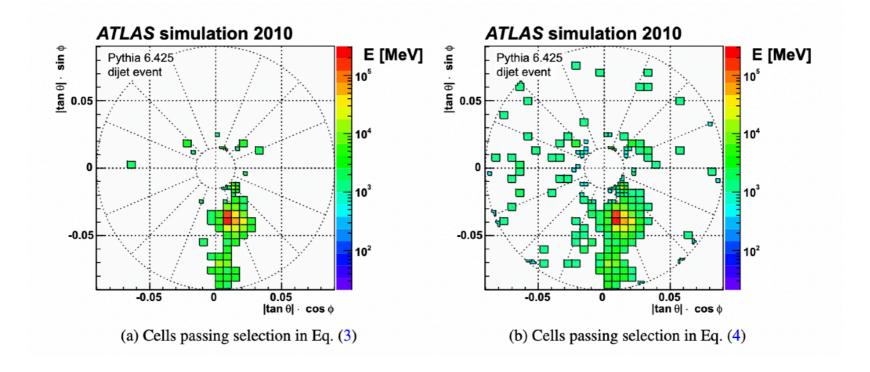
Wigman's book "Calorimetry: Energy Measurement in Particle Physics"



Energy reconstruction

The main algorithm for clustering calorimeter cells in ATLAS is the so-called topological clustering (see http://arxiv.org/pdf/1603.02934)

$$\begin{split} \varsigma_{\text{cell}}^{\text{EM}} &= \frac{E_{\text{cell}}^{\text{EM}}}{\sigma_{\text{noise,cell}}^{\text{EM}}}. \\ & \left| E_{\text{cell}}^{\text{EM}} \right| > S \sigma_{\text{noise,cell}}^{\text{EM}} \Rightarrow \left| \varsigma_{\text{cell}}^{\text{EM}} \right| > S \qquad (\text{primary seed threshold, default } S = 4); \\ & \left| E_{\text{cell}}^{\text{EM}} \right| > N \sigma_{\text{noise,cell}}^{\text{EM}} \Rightarrow \left| \varsigma_{\text{cell}}^{\text{EM}} \right| > N \qquad (\text{threshold for growth control, default } N = 2); \\ & \left| E_{\text{cell}}^{\text{EM}} \right| > P \sigma_{\text{noise,cell}}^{\text{EM}} \Rightarrow \left| \varsigma_{\text{cell}}^{\text{EM}} \right| > P \qquad (\text{principal cell filter, default } P = 0). \end{split}$$



Energy reconstruction

The main algorithm for clustering calorimeter cells in ATLAS is the so-called topological clustering (see <u>http://arxiv.org/pdf/1603.02934</u>)

Topological clusters on average correspond to a single particle: Electron, Photon, charged Pion, neutral Pion etc

They are the starting point / main ingredient point for Particle Flow, Jet clustering (either via PFO or directly) and e/γ reconstruction.

The fact of that all domain start from the same inputs is central to the Global Pflow Effort in ATLAS.

Here we will focus on e/γ specifics.

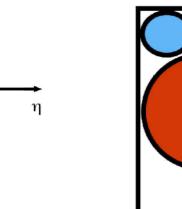
Dynamic Clusters

<u>link</u>

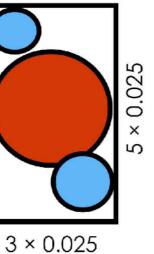
All e[±], γ:

Electrons only:

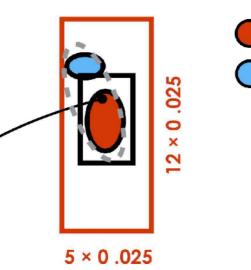
Add all clusters within 3 × 5 window Seed, around seed cluster. **match**



φ



Seed, secondary cluster match the same track.

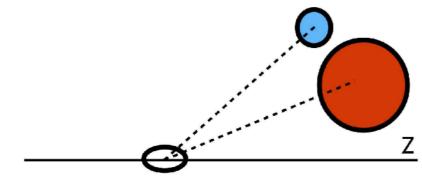


Seed cluster

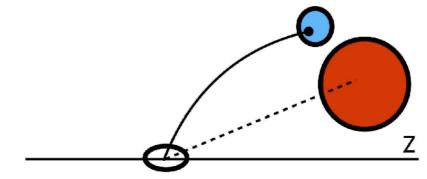
Satellite

Converted photons only:

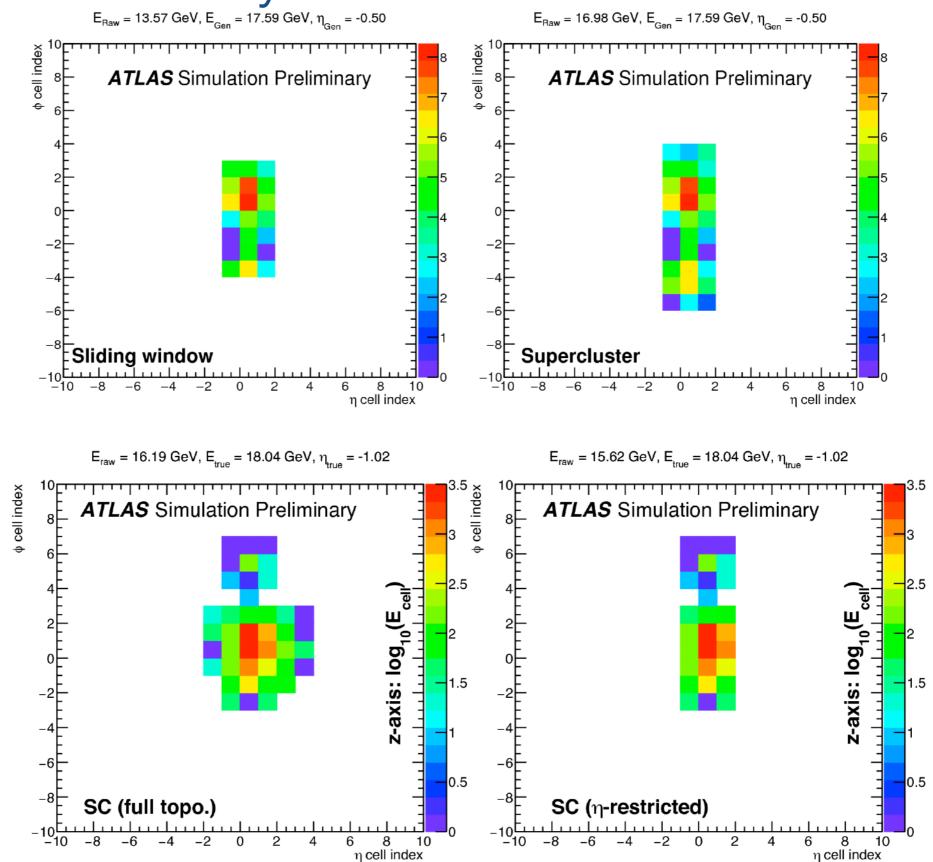
Add topo-clusters that have the **same conversion vertex** matched as the seed cluster.



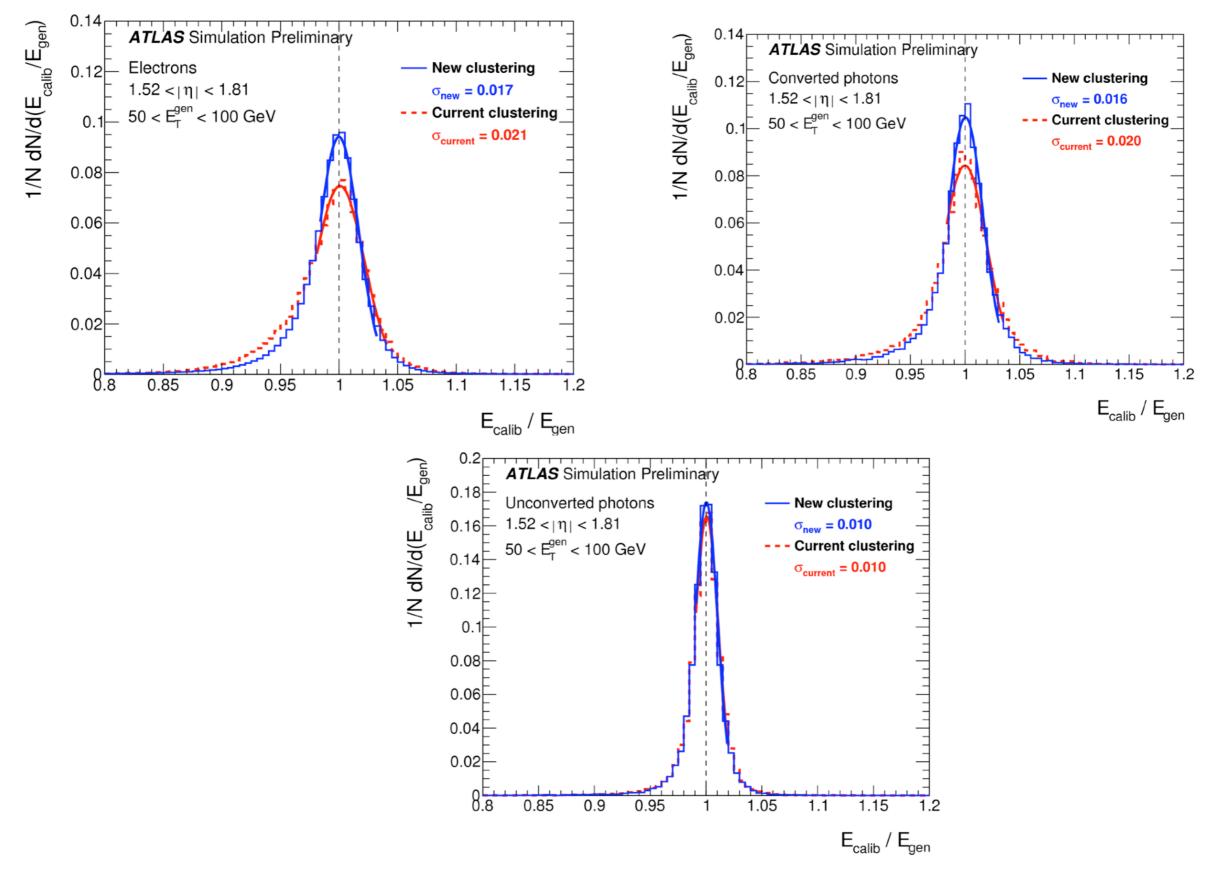
Add topo-clusters with a track match that is part of the conversion vertex matched to the seed cluster.



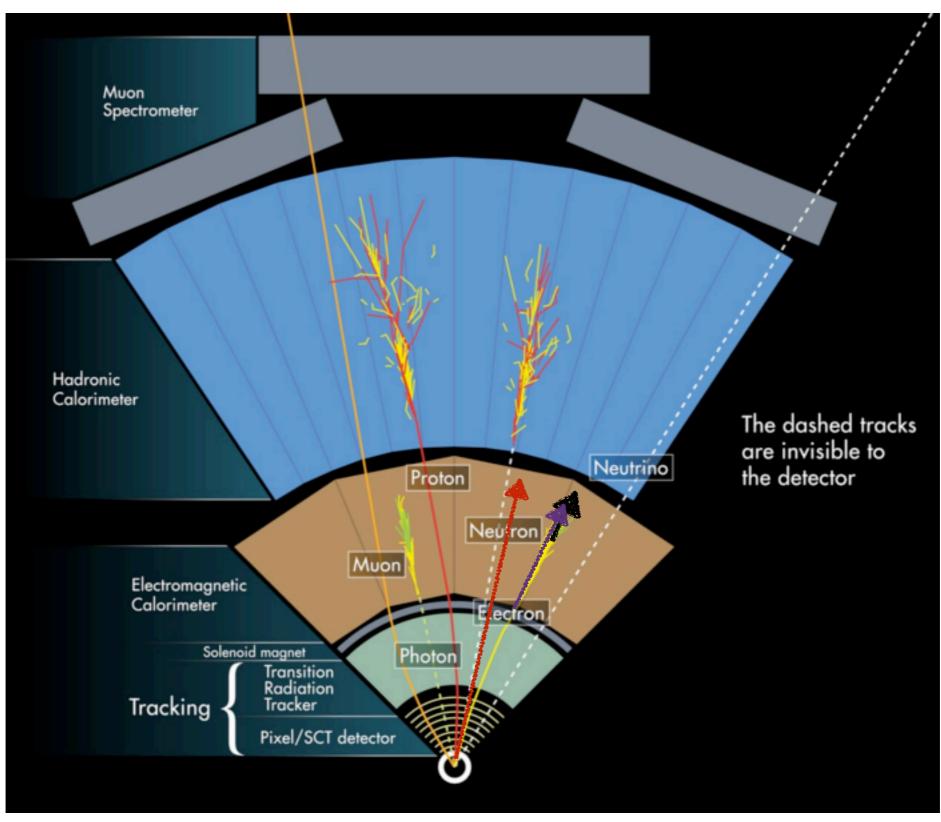
Dynamic Clusters



Dynamic Clusters



Track cluster matching



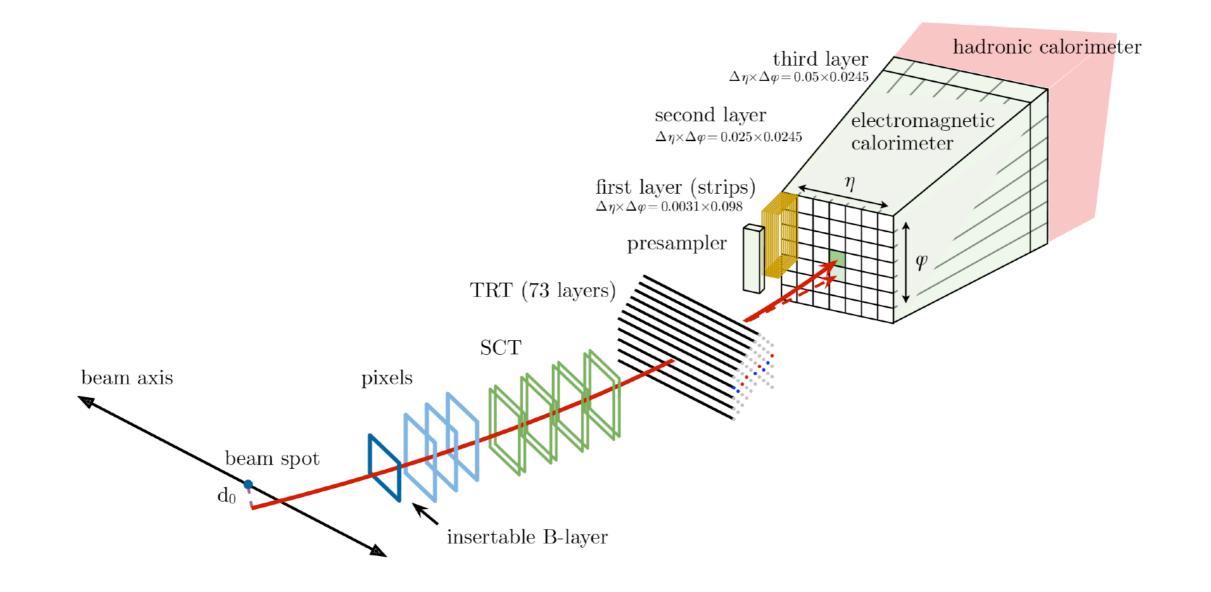
Where do we do the "matching"

Electron Identification

At the end of the "reconstruction" chain,

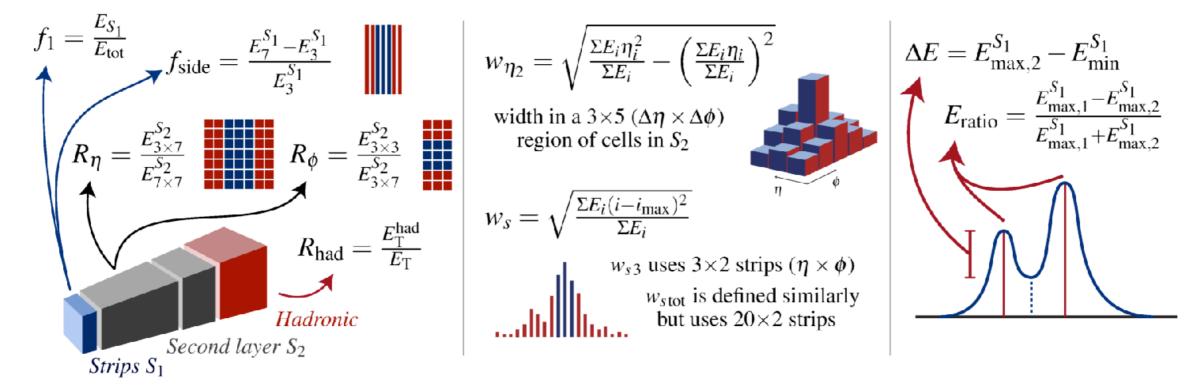
quite a few (actually majority...) of the electron/photons are "fakes".

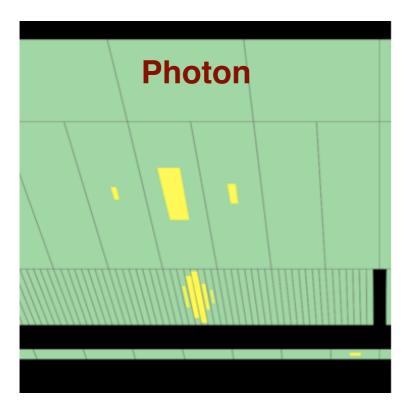
We employ so called shower shape variables, tracking and track matching information to identify the real e/γ objects / reject fakes.

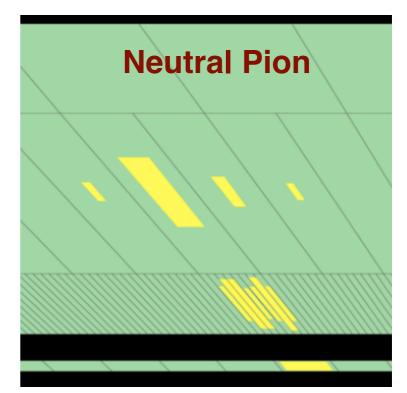


Electron Identification

We employ so called shower shape variables, tracking and track matching information to identify the real e/γ objects / reject fakes. See (link and link)



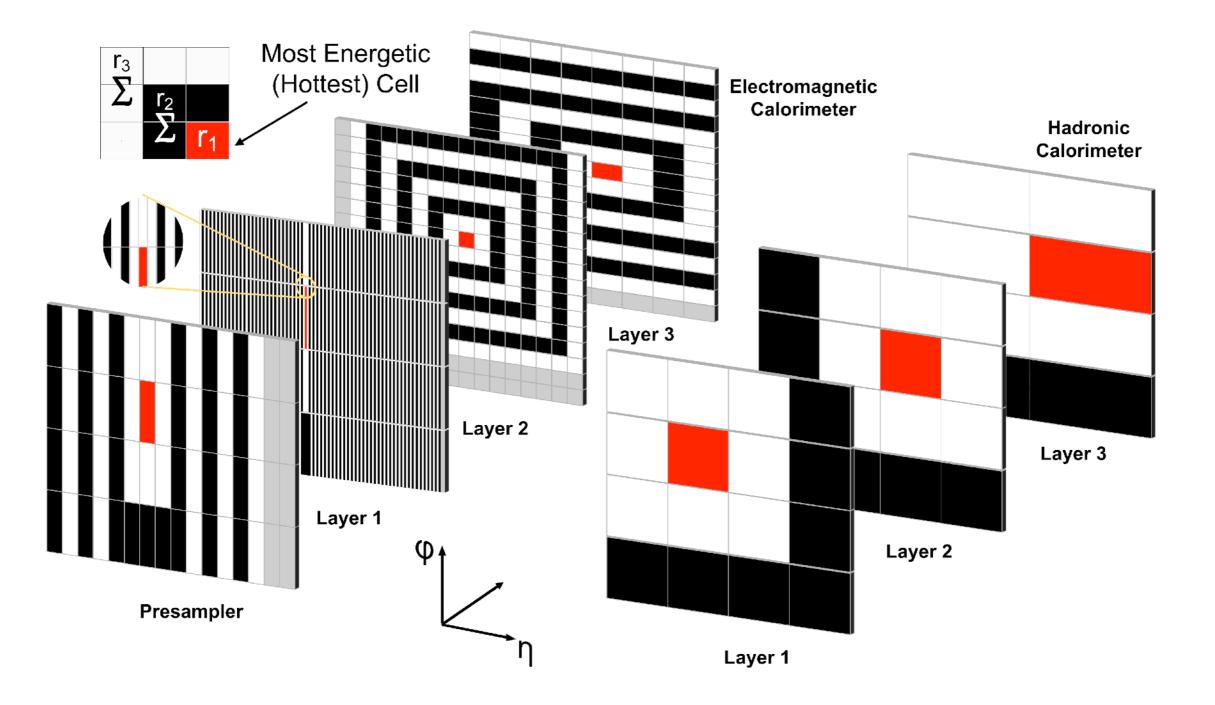




Electron Identification

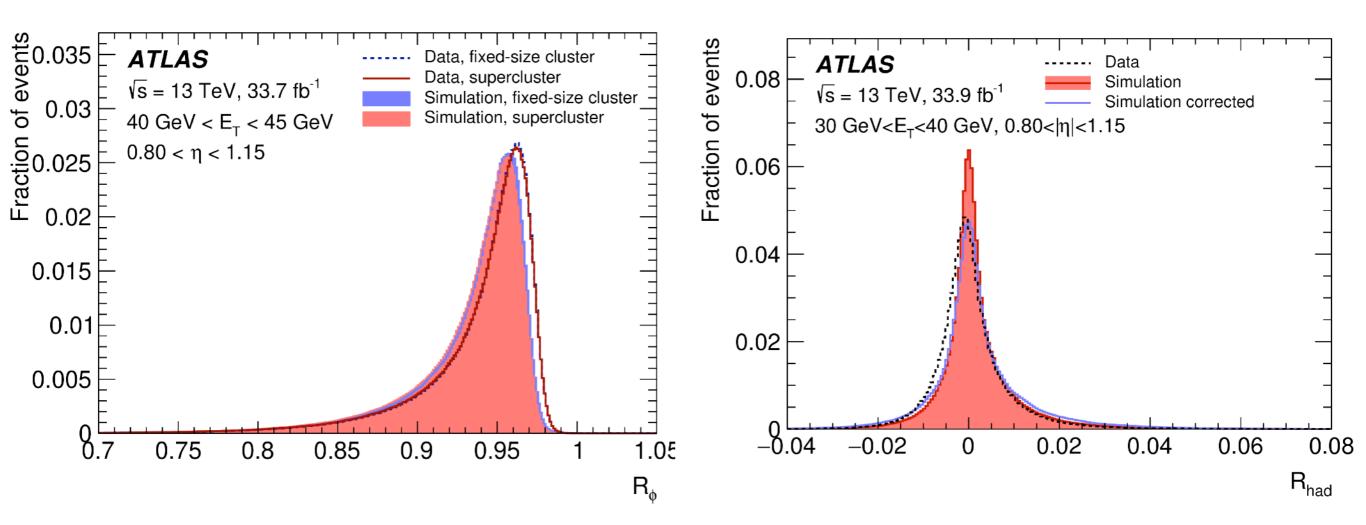
In HLT so called Ringer NN algorithm is used. EM showers approximately conical around the initial particle (see <u>link</u>).

Efforts to move to DNN or CNN for both "offline" and "online".

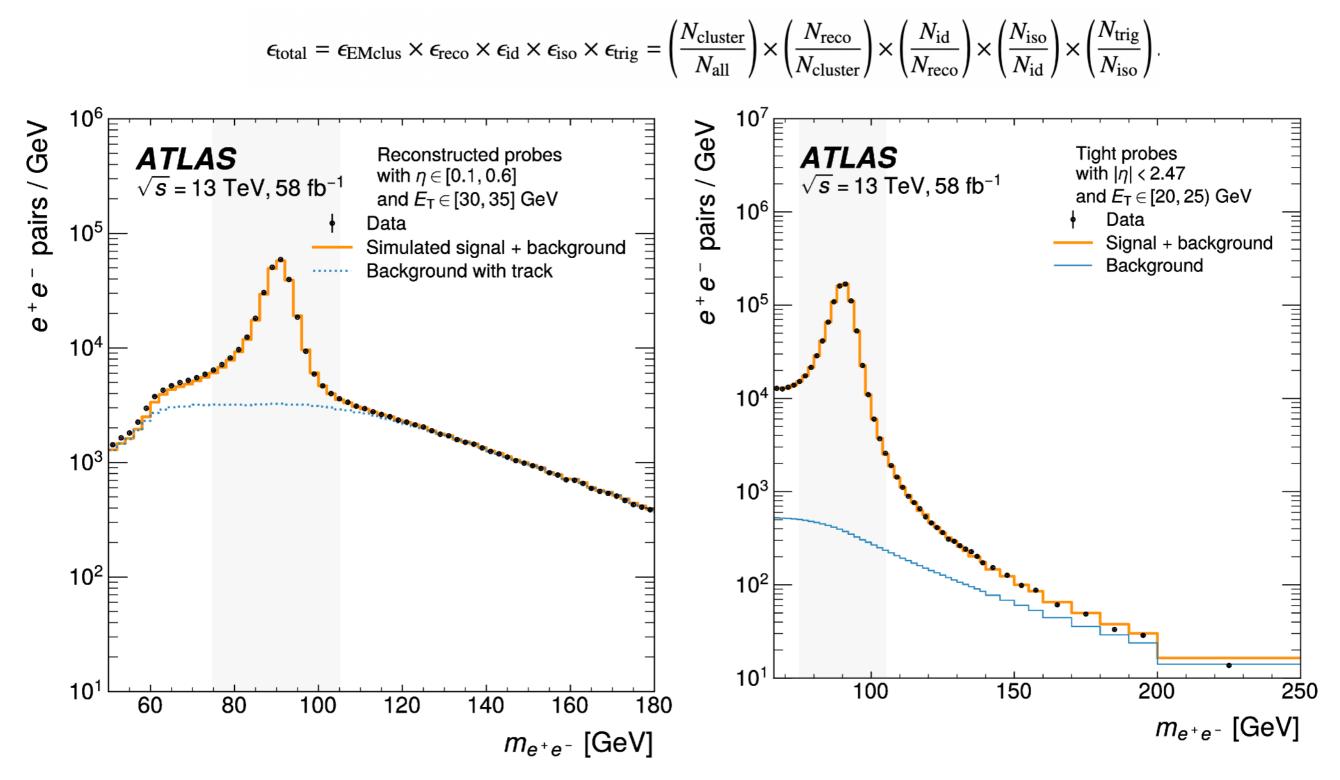


We know that our simulation (Geant4 based) does not accurately describe the EM shower. Also uncertainties from the knowledge of upstream material, alignment etc... This causes some challenges on how to move to more deep learning methods.

We derive correction factors typically employing the Z peak and also use/check the J/ ψ peak.

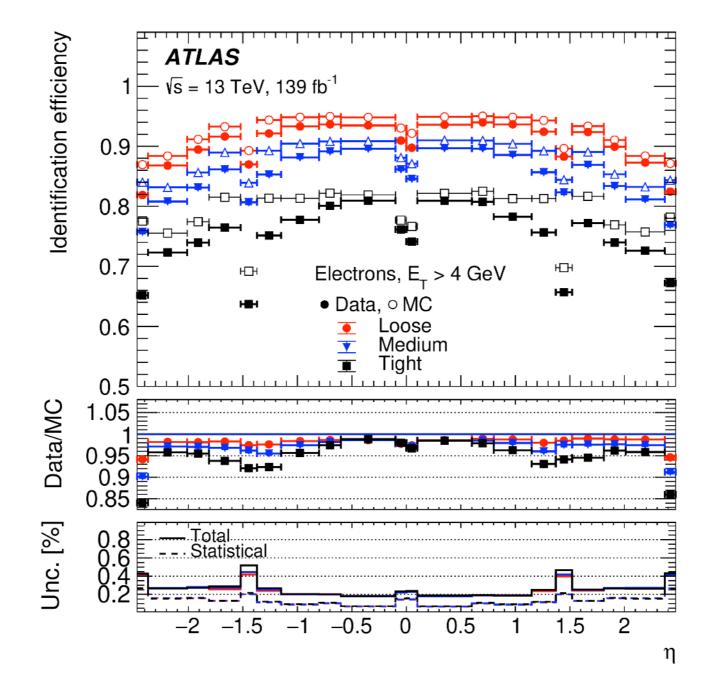


We derive correction factors typically employing the Z peak and also use/check the J/ ψ peak.



We derive correction factors typically employing the Z peak and also use/check the J/ ψ peak.

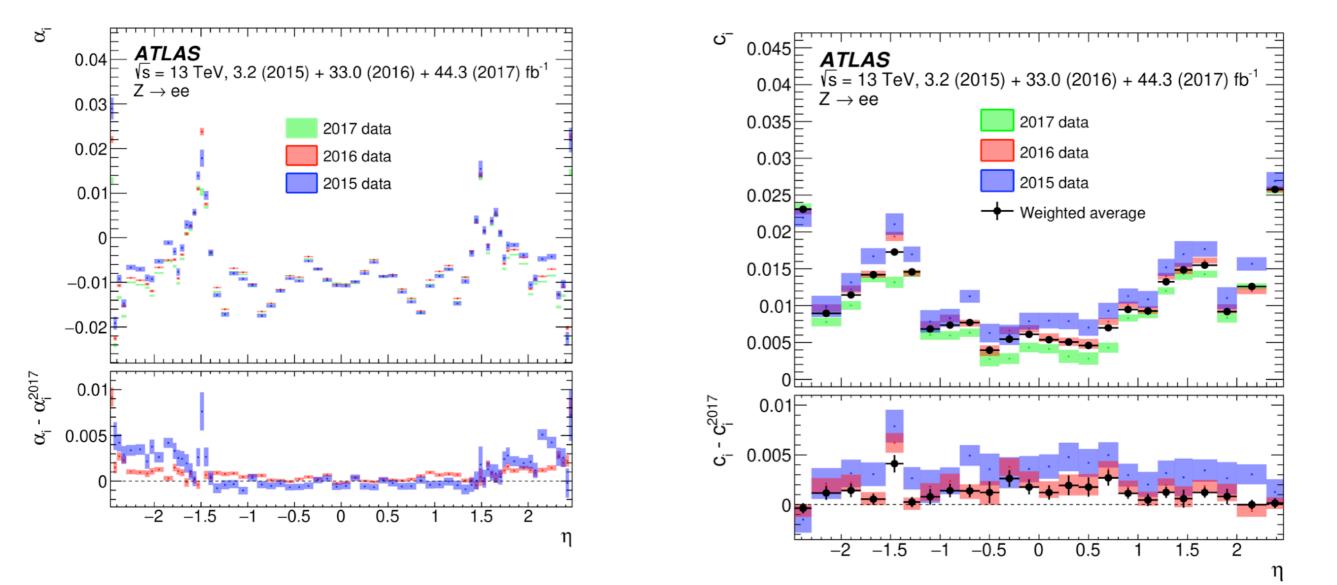
$$\epsilon_{\text{total}} = \epsilon_{\text{EMclus}} \times \epsilon_{\text{reco}} \times \epsilon_{\text{id}} \times \epsilon_{\text{iso}} \times \epsilon_{\text{trig}} = \left(\frac{N_{\text{cluster}}}{N_{\text{all}}}\right) \times \left(\frac{N_{\text{reco}}}{N_{\text{cluster}}}\right) \times \left(\frac{N_{\text{id}}}{N_{\text{reco}}}\right) \times \left(\frac{N_{\text{iso}}}{N_{\text{id}}}\right) \times \left(\frac{N_{\text{trig}}}{N_{\text{iso}}}\right)$$



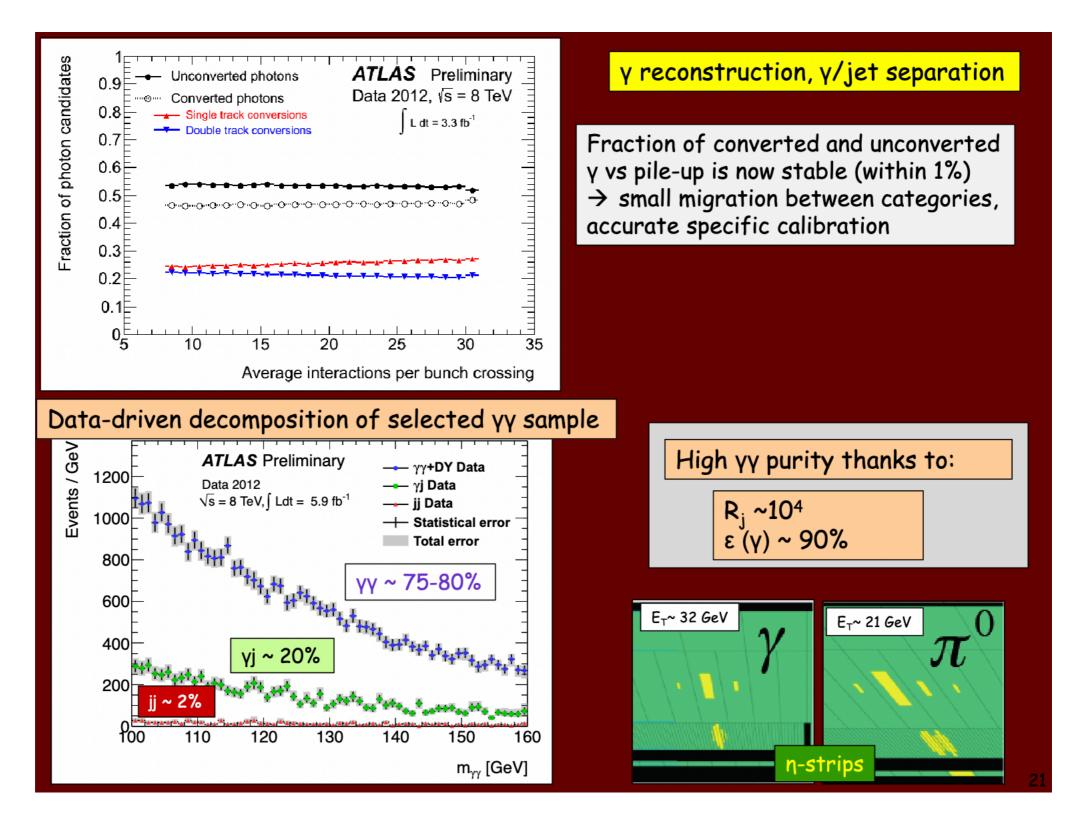
Similar for the energy calibration

$$E^{\text{data}} = E^{\text{MC}} \left(1 + \alpha_i\right), \qquad \left(\frac{\sigma_E}{E}\right)^{\text{data}} = \left(\frac{\sigma_E}{E}\right)^{\text{MC}} \oplus$$

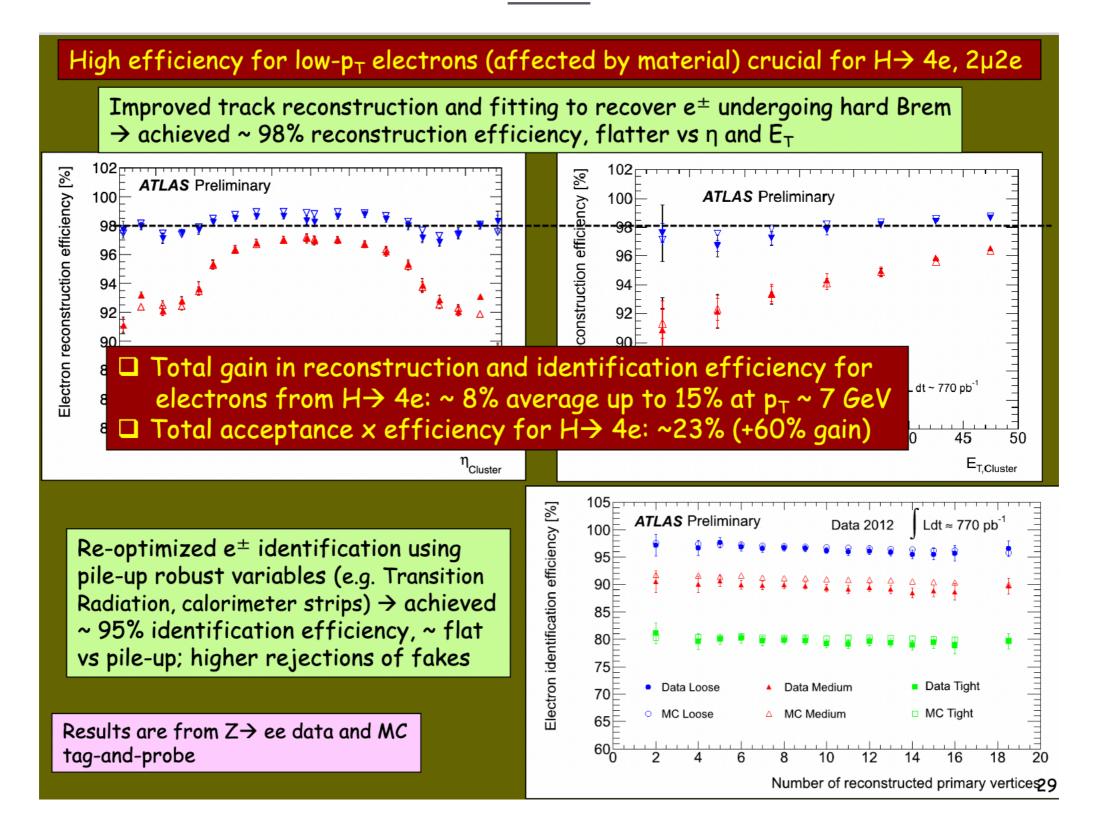
 c_i ,



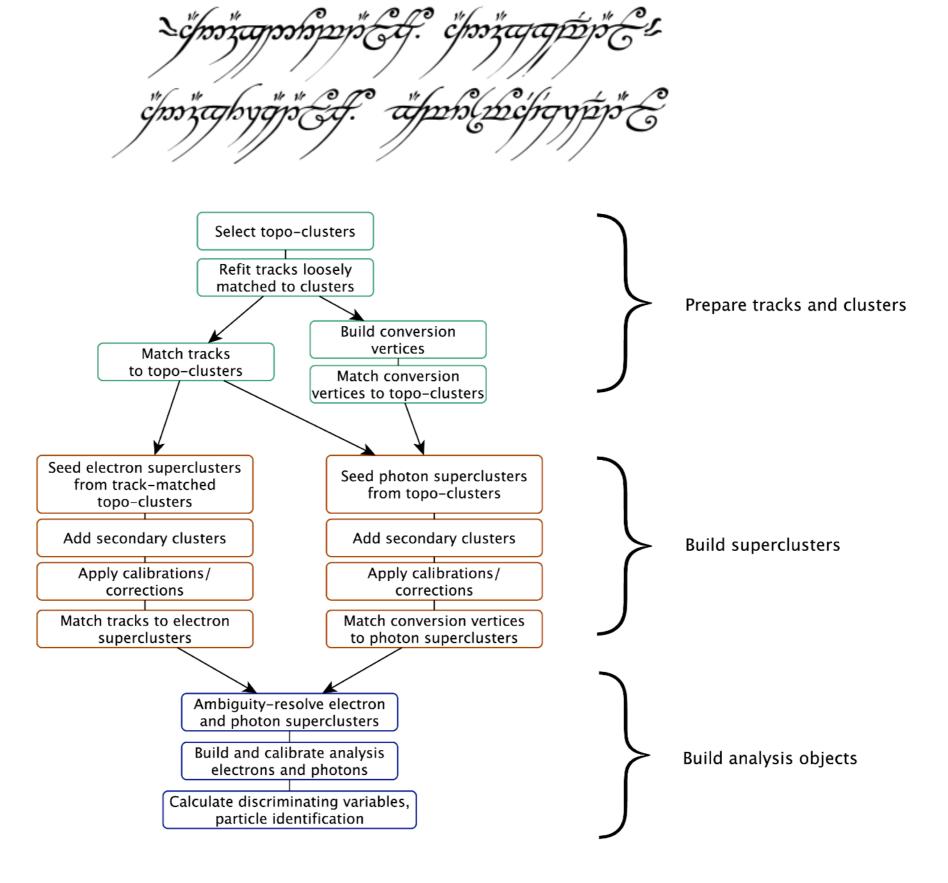
In place of conclusions <u>link</u>



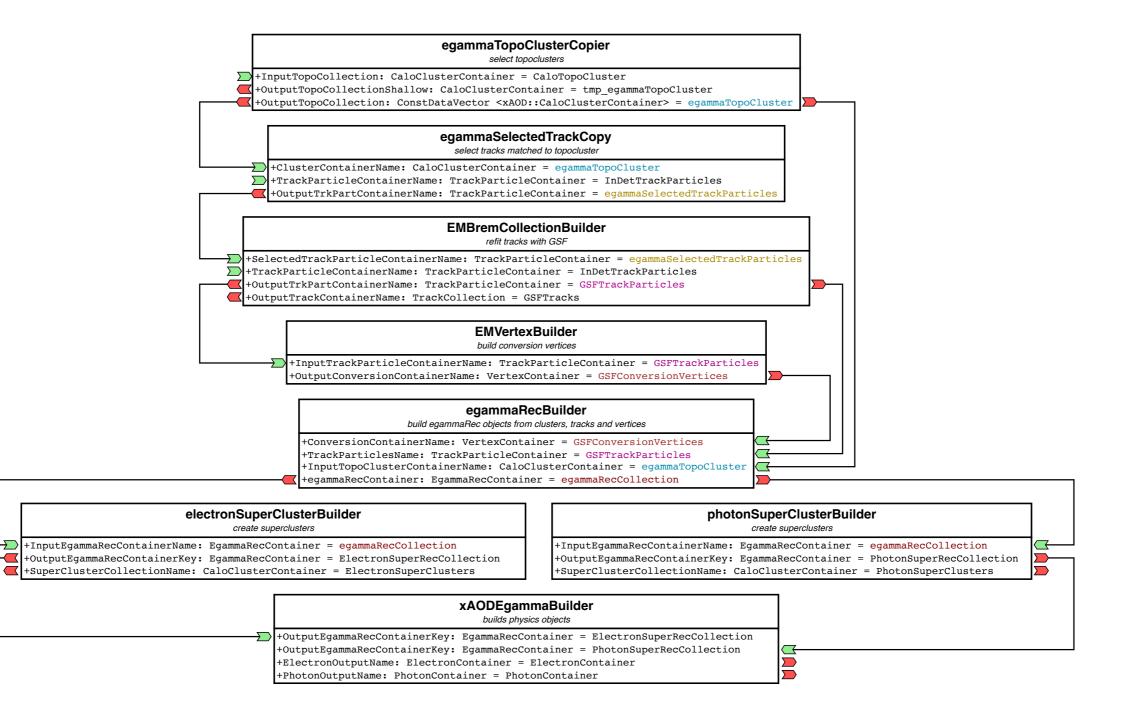
In place of conclusions link



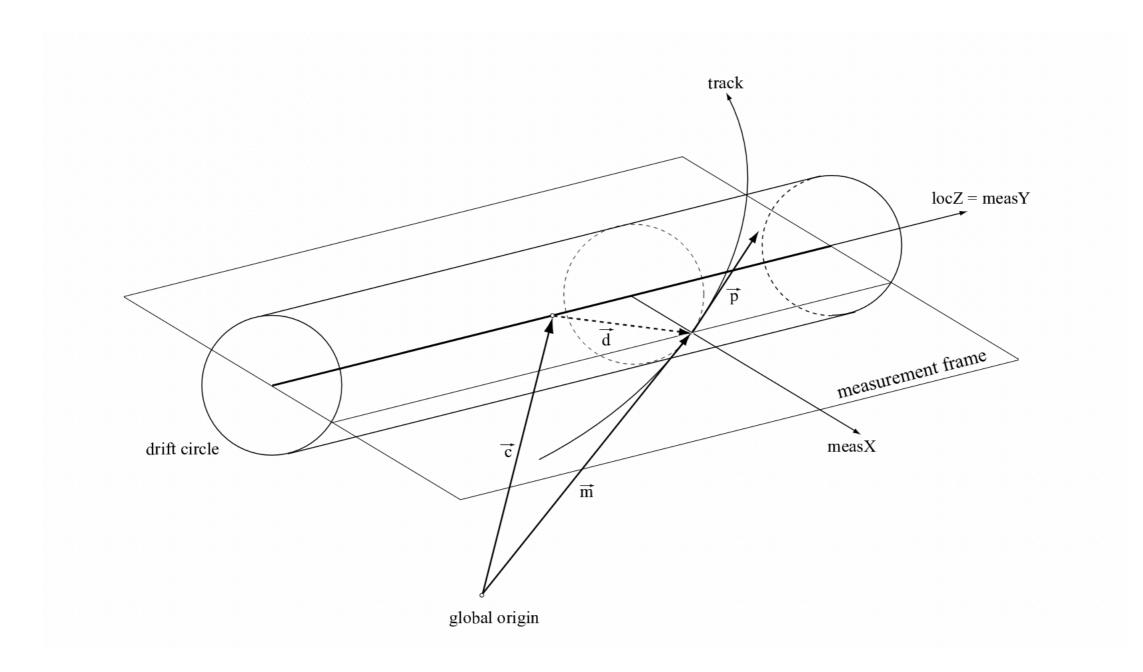
Backup



https://gitlab.cern.ch/atlas/athena/-/blob/main/docs/images/egammaAlgs_algos.svg



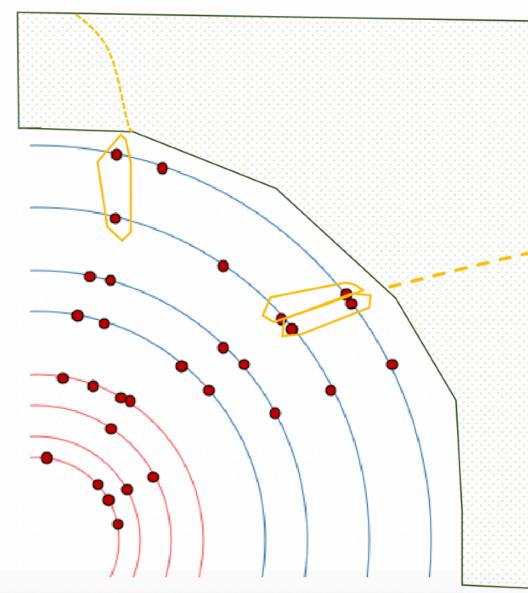
https://cds.cern.ch/record/973401/files/soft-pub-2006-004.pdf



$$sign(d) = sign\left((\vec{p} \times \vec{l}_z) \cdot \vec{d} \right)$$

Outside-in: Si-Backward Extension

- The TRT segments are used as a starting point to search for backwards extension into the silicon volume
 - SCT SP are used to form two SP seeds
 - Only use hits that were not assigned to tracks from the first pass
- Check the seeds for compatibility with the TRT Segments



Outside-in: Si-Backward Extension

- Similar strategy as for Inside-out...
- Preform the road-search and kalman filter along the road to pick-up hits
- The track candidates then passes through the ambigutity processor and are finally fit with the global χ^2 fitter
 - Selection criteria on the number of hits and impact parameters are adjusted to accommodate secondaries
- Lastly the final tracks are again extended to the TRT

