# Particle tracking

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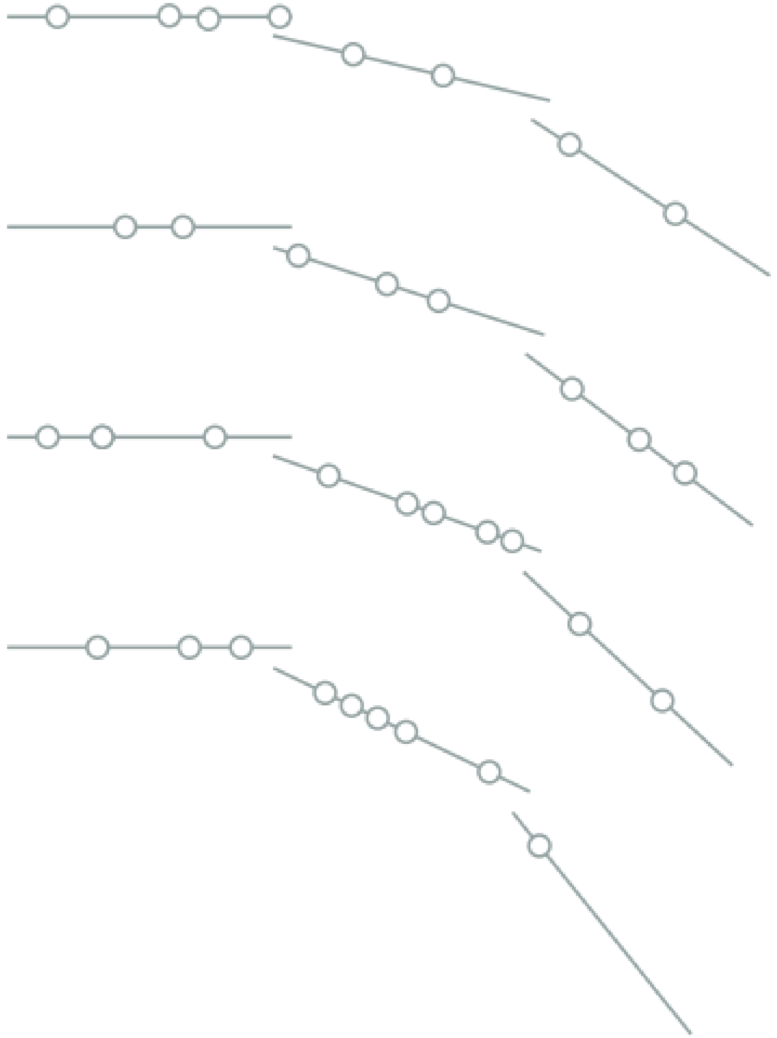
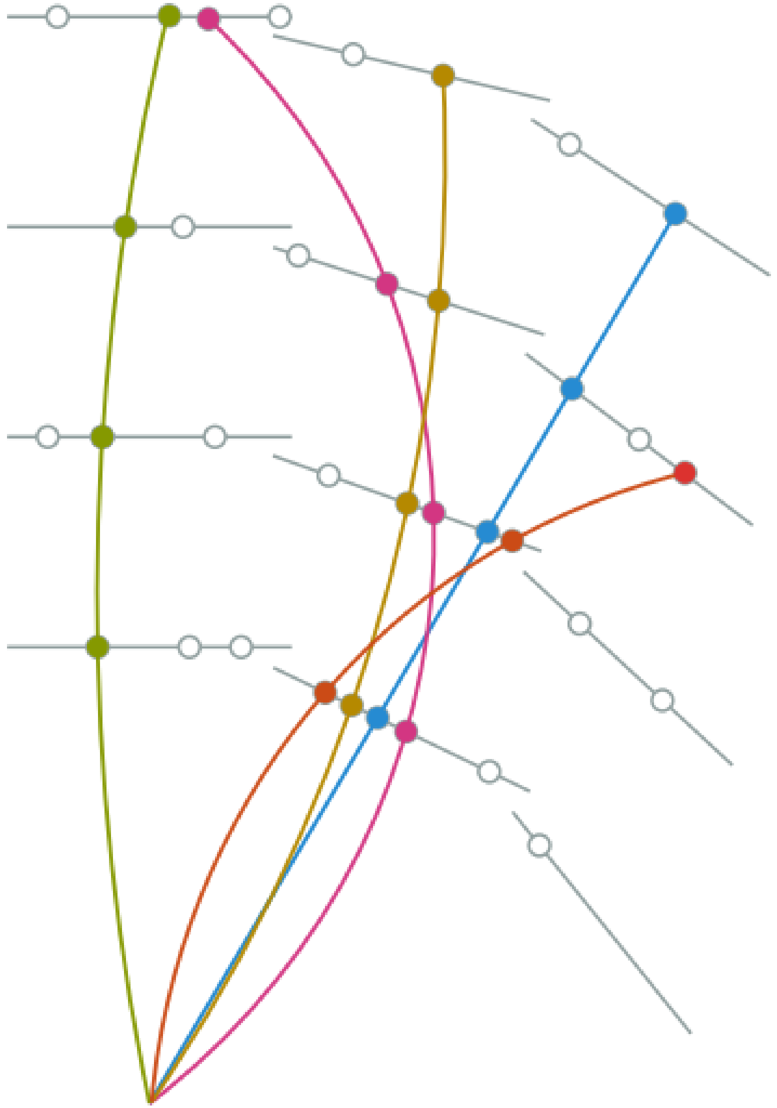




Obviously!

# Overview



Basic ingredients

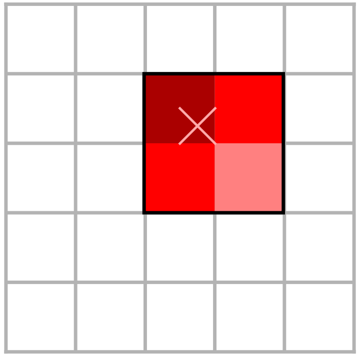
Classical algorithms

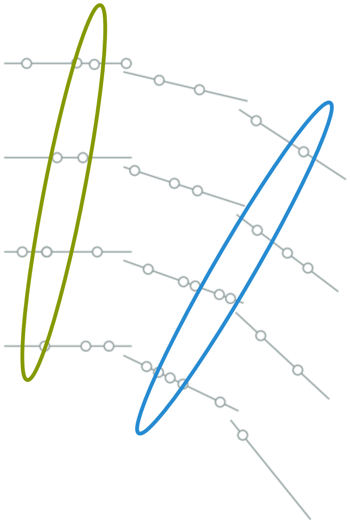
High luminosity and machine learning

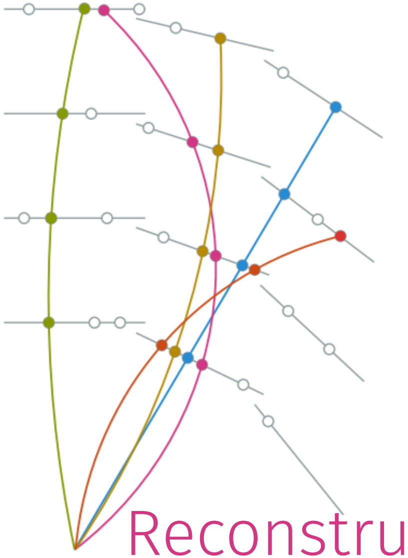
Disclaimer:
This is a personal selection

# Typical reconstruction chain









Reconstruction

## Local Reco

Bits to hits,
clustering

## Track Finding

Group hits to tracks

## Track Fitting

Estimate parameters

## Analysis

# Uncertainty and significance



Significance of marked point?

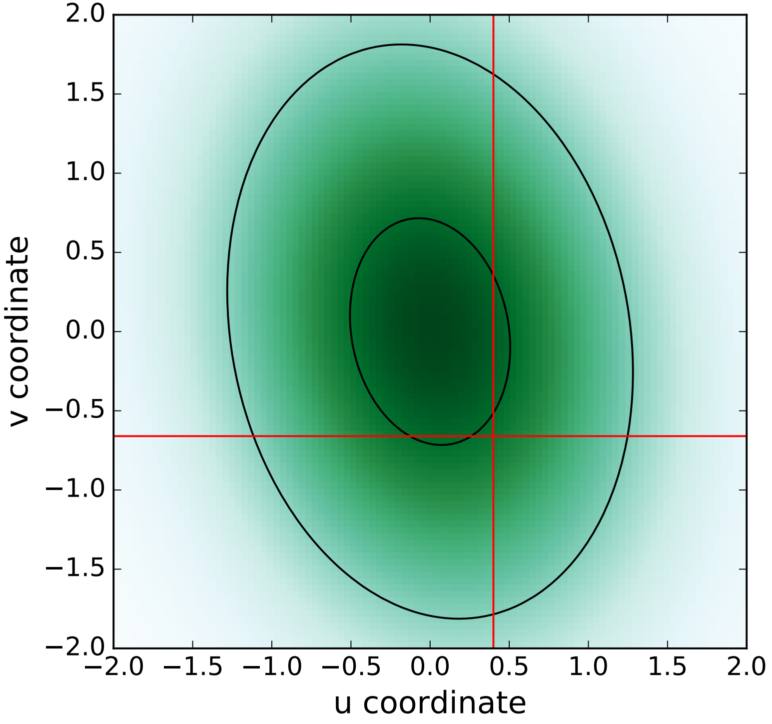
$$s_u = \frac{u}{\sigma_u} < 1 \qquad s_v = \frac{v}{\sigma_v} < 1$$

Ignores correlations

$$\Sigma = \begin{pmatrix} \sigma_u^2 & c_{uv} \\ c_{uv} & \sigma_v^2 \end{pmatrix}$$

Use Nd generalization instead

$$s = \sqrt{\left(\vec{x}^T \Sigma^{-1} \vec{x}\right)}$$



# Track model



Propagated track parameter

Initial track parameter

Propagation length

Stochastic component w/ covariance Q

$$\vec{a} = f(\vec{a}_0, l) + \sigma(Q)$$

Linearize

$$\vec{a} \approx \vec{f}_0 + F\,\overrightarrow{\Delta a_0} + \sigma(Q)$$

Typical parameters w/ reference surface

Forward $(x, y, t, x', y', \beta^{-1})$

Collider $(d_0, z_0, t_0, \phi, \theta, q/p)$

w/o reference surface

$x, y, z, t, p_x, p_y, p_z, q$

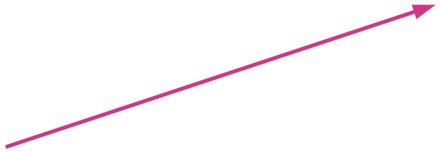
# Deterministic/ stochastic components



## Deterministic trajectory

### No magnetic field

Straight (analytic)

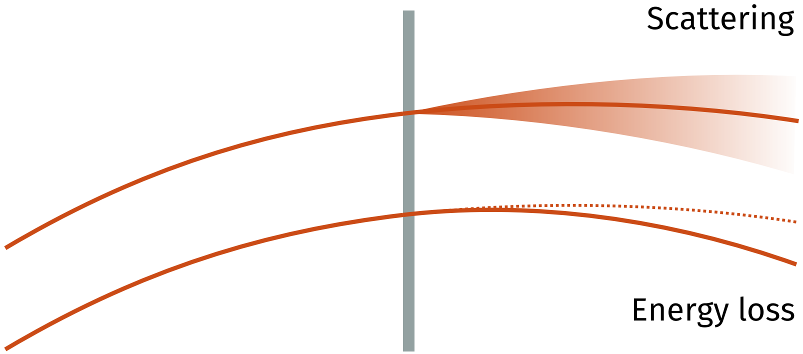


### With magnetic field

Helix for const (analytic)

Helical for non-const (numeric)

## Stochastic material interactions

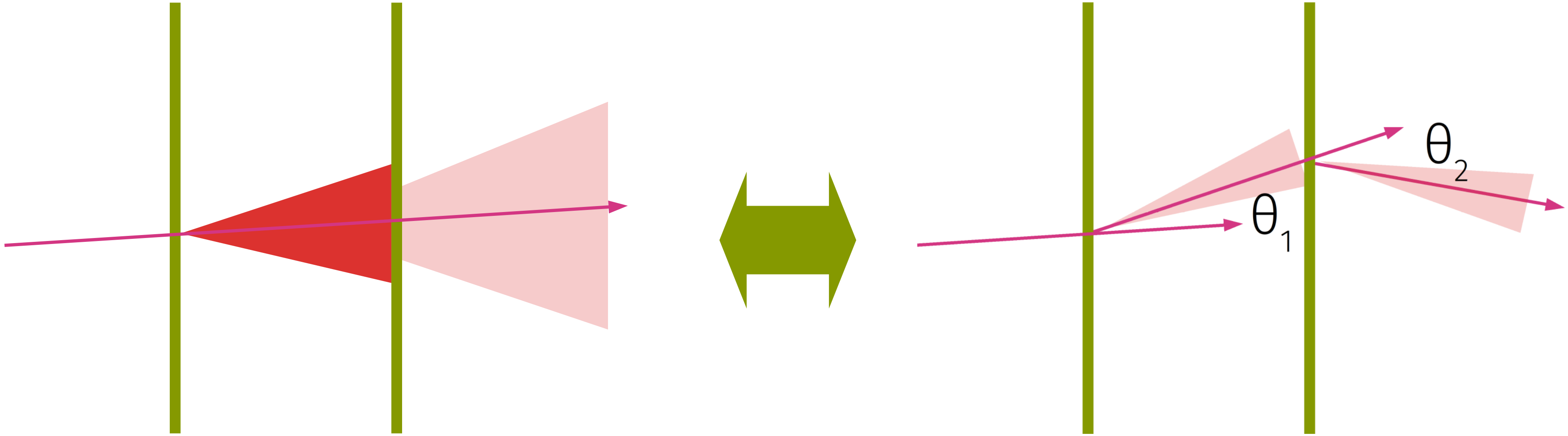



Particle and material dependent

# Possible trade-offs



## Example: multiple scattering




Simple trajectory,
Correlated covariance

Explicit parameters
Simplified covariance

# Measurement model



Position in measurement frame

Track parameters at intersection

Stochastic measurement uncertainty w/ covariance V

$$\vec{m} = h(\vec{a}) + \sigma(V)$$

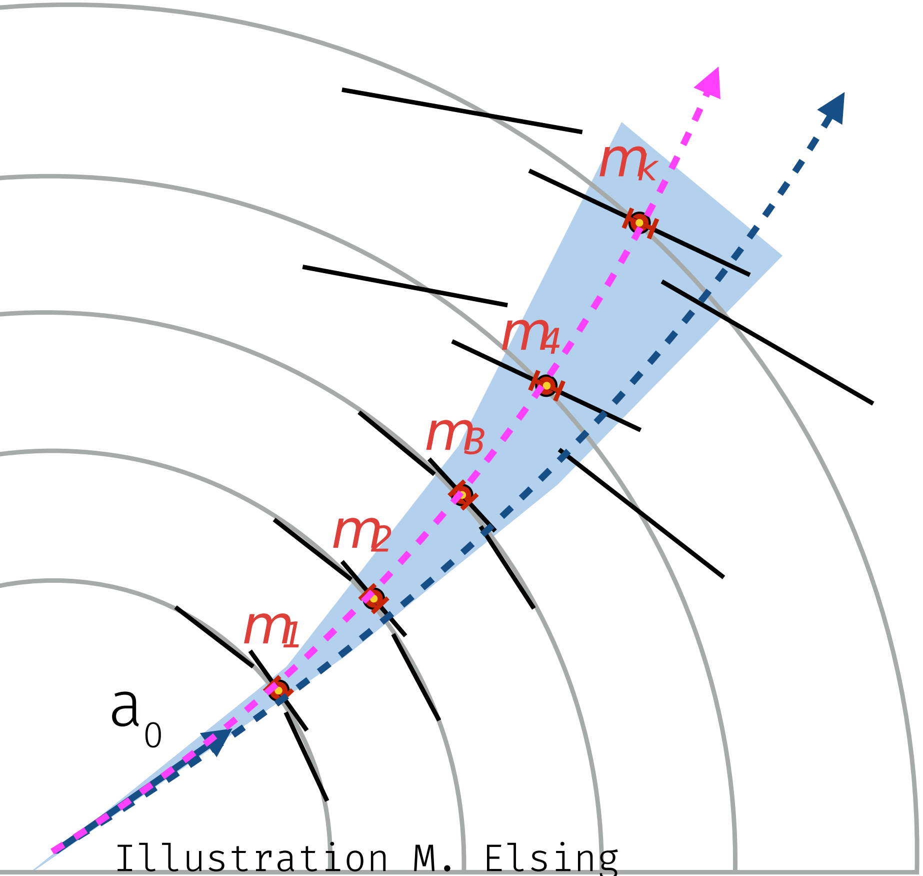
Linearize

$$\vec{m} \approx \vec{h_0} + H\,\overrightarrow{\Delta a} + \sigma(V)$$

Typically:
$h_0$ vanishes, H rotation/projection

# Least squares fitting






Define residuals

$$\vec{r}_i = \vec{y}_i - h_i(f_i(\vec{a}_0))$$

Combine components

$$\vec{r} = \begin{pmatrix} \vec{r}_0 \\ \vec{r}_1 \\ \vdots \end{pmatrix} \qquad \Sigma = \begin{pmatrix} \Sigma_{00} & \Sigma_{01} & \cdots \\ \Sigma_{01} & \Sigma_{11} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

Minimize

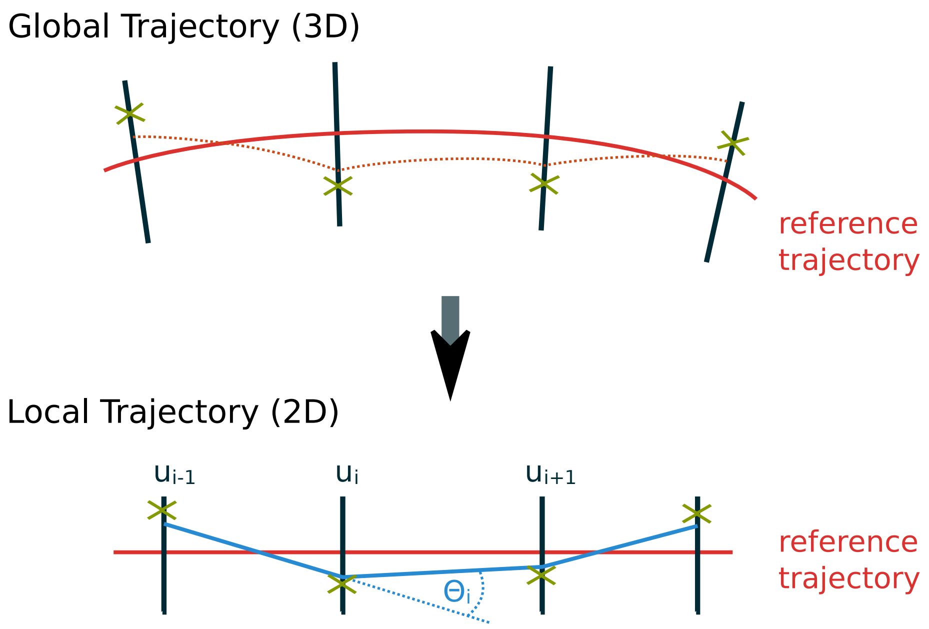
$$S = \vec{r}^T \Sigma^{-1} \vec{r}$$

Solve linearized

$$\overrightarrow{\Delta a_0} = (F^T H^T \Sigma^{-1} H F)^{-1} F^T H^T \vec{r}$$

# General Broken Lines






Specific track model with explicit scattering angles

$$S = \sum \vec{u}_i^T \Sigma_u^{-1} \vec{u}_i + \sum \vec{\beta}(\vec{u})_i^T \Sigma_\beta^{-1} \vec{\beta}(\vec{u})_i$$

No global measurement covariance

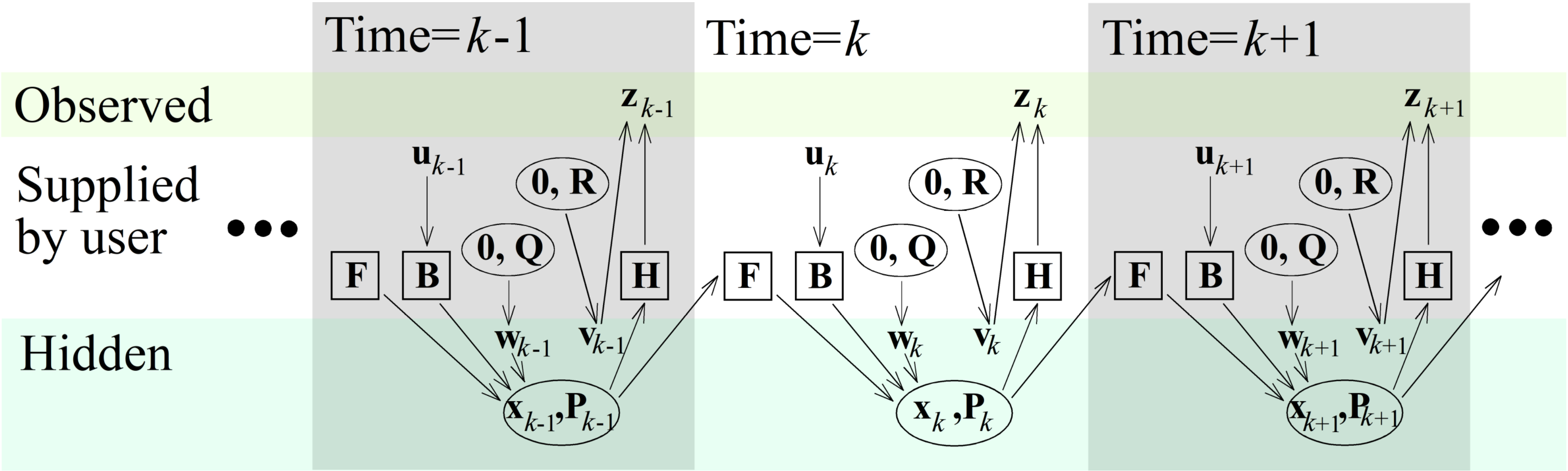
Global parameter covariance

O(N) solution

GBL Website

# Kalman filter a.k.a rocket science






First used in the Apollo space program:
Continously estimate/control hidden state from noisy measurements

Source, Public domain

# Kalman forward filter



Predict

$$\vec{a}_{k,k-1} = F_{k-1,k}\vec{a}_{k-1}$$
$$C_{k,k-1} = F_{k-1,k}^{T} C_{k-1,k-1} F_{k-1,k} + Q_k$$

Residuals

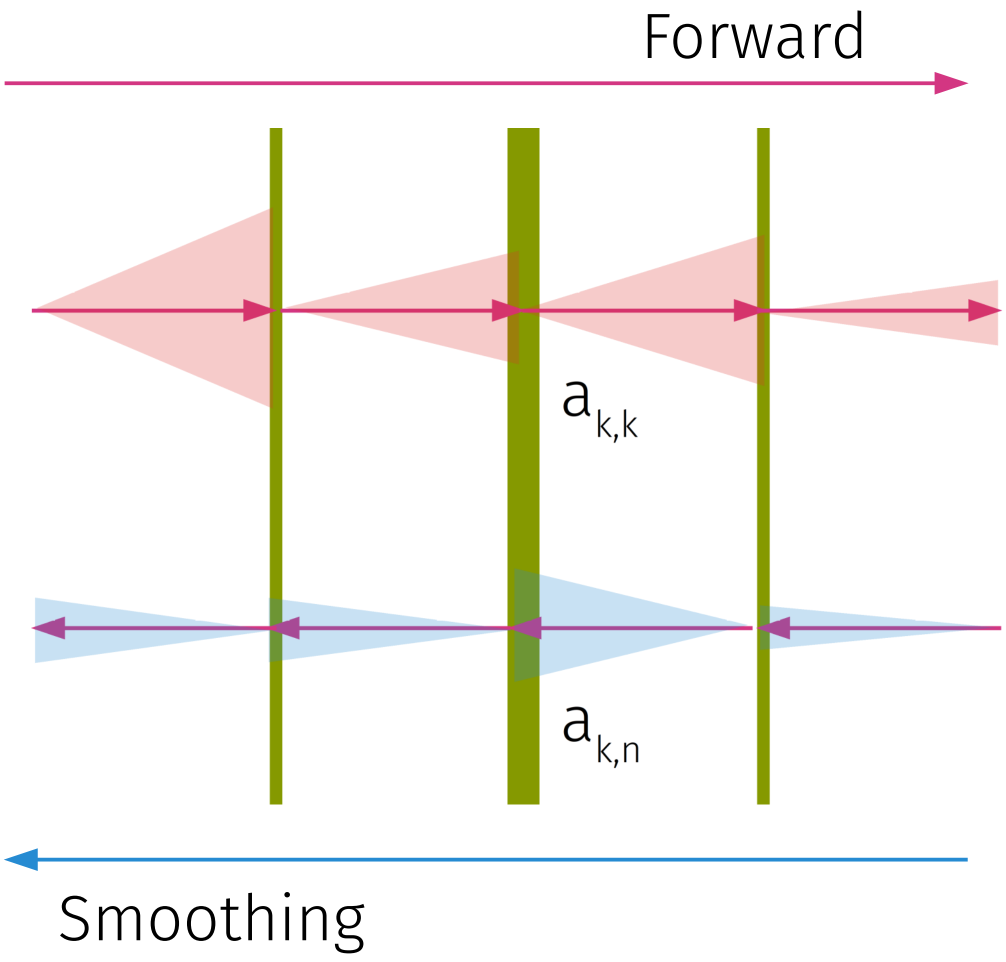
$$\vec{r}_{k,k-1} = \vec{y}_k - H_k \vec{a}_{k,k-1}$$
$$R_{k,k-1} = H_k C_{k-1,k-1} H_k^T + V_k$$

Kalman gain matrix

$$K_k = C_{k,k-1} H_k^T R_{k,k-1}^{-1}$$

Update

$$\vec{a}_{k,k} = \vec{a}_{k,k-1} + K_k \vec{r}_{k,k-1}$$
$$C_{k,k} = \left(I - K_k H_k\right) C_{k,k-1}$$



# Kalman smoothing



Smoother gain matrix

$$K_k = C_{k,k} F^T_{k+1,k} C^{-1}_{k+1,k}$$

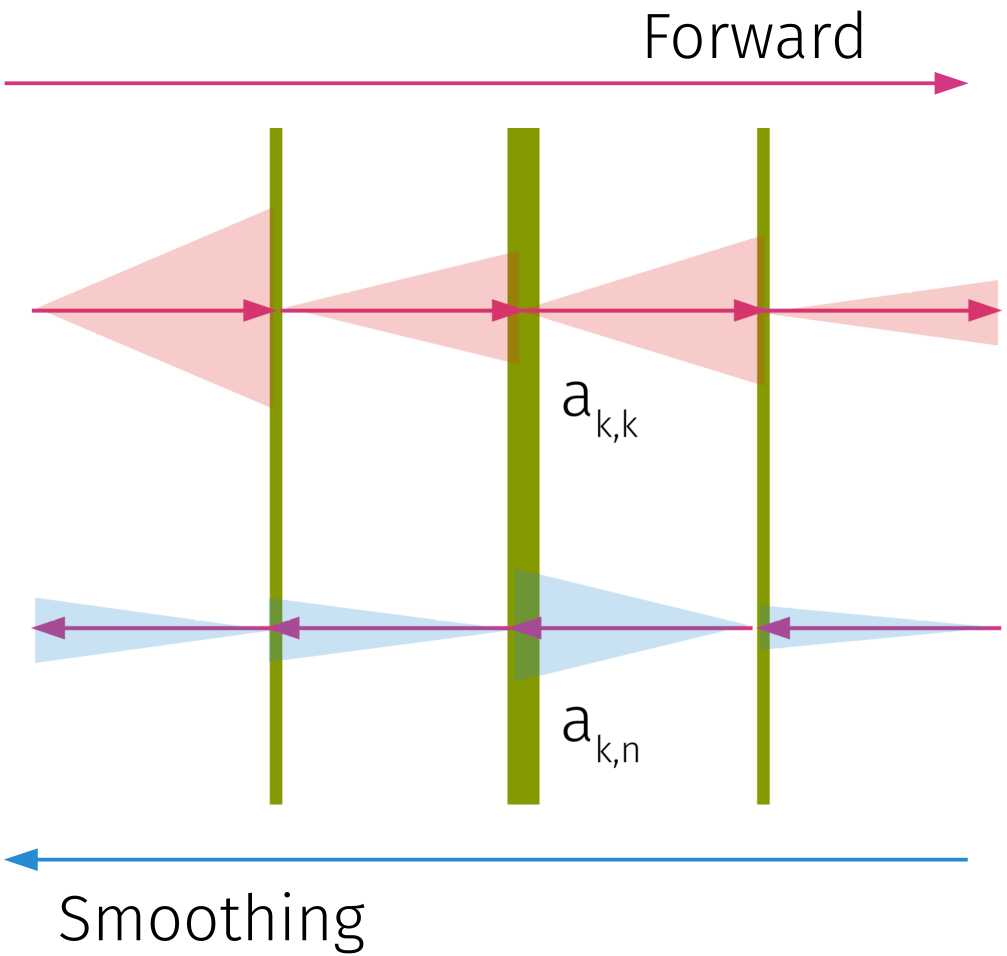
Back smoothing

$$\vec{a}_{k,n} = \vec{a}_{k,k} + A_k \left( \vec{a}_{k+1,n} - \vec{a}_{k+1,k} \right)$$

$$C_{k,n} = C_{k,k} - A_k \left( C_{k+1,k} - C_{k+1,n} \right) A^T_k$$

Final residuals and X²

$$\Delta \chi^2_{k,n} = \vec{r}^{\,T}_{k,n} R^{-1}_{k,n} \vec{r}_{k,n}$$



# Track fitting summary

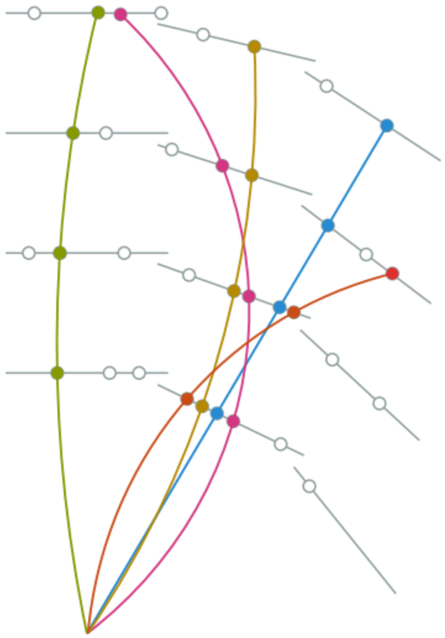


Alll methods require lineariz(ed,able) track models

Model = trajectory + noise

You always need initial parameters

No single algorithm fits for everything



# Track finding



Global methods

Example: Hough transform

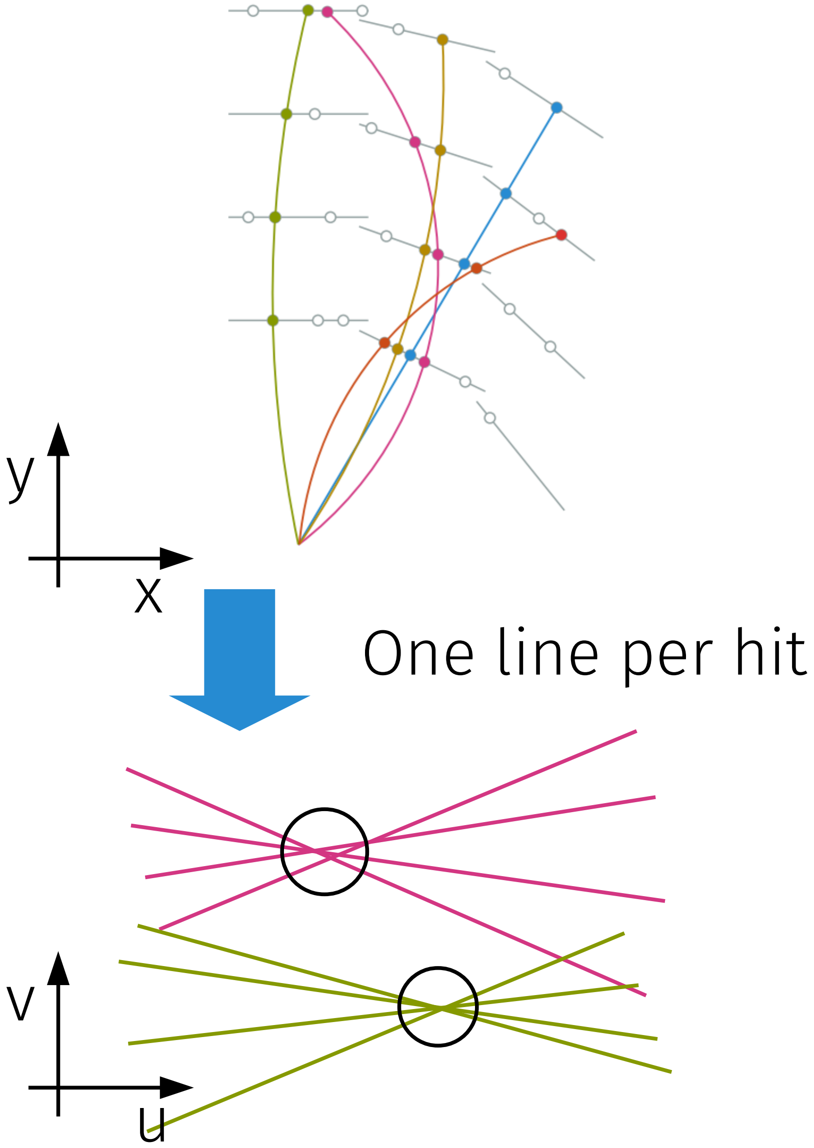
Transform hit

$$u=\frac{x}{x^2+y^2} \qquad v=\frac{y}{x^2+y^2}$$

Draw line for u/v that satisfy

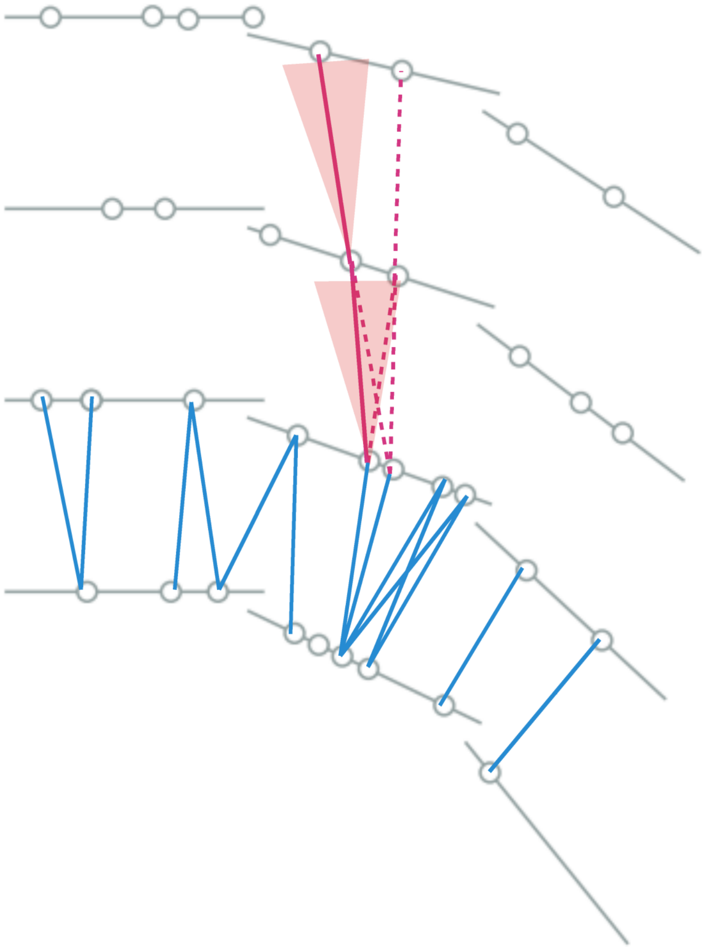
$$v=-\frac{x}{y}u+\frac{x^2+y^2}{2y}$$

Fast, but assumes perfect circles
Sensitive to density



# Combinatorial Kalman Filter





Build track seeds w/ 2-4 hits

Estimate initial track parameters

Propagate through detector and pick up matching hits

- SKF: only the best match
- CKF: bifurcate matches

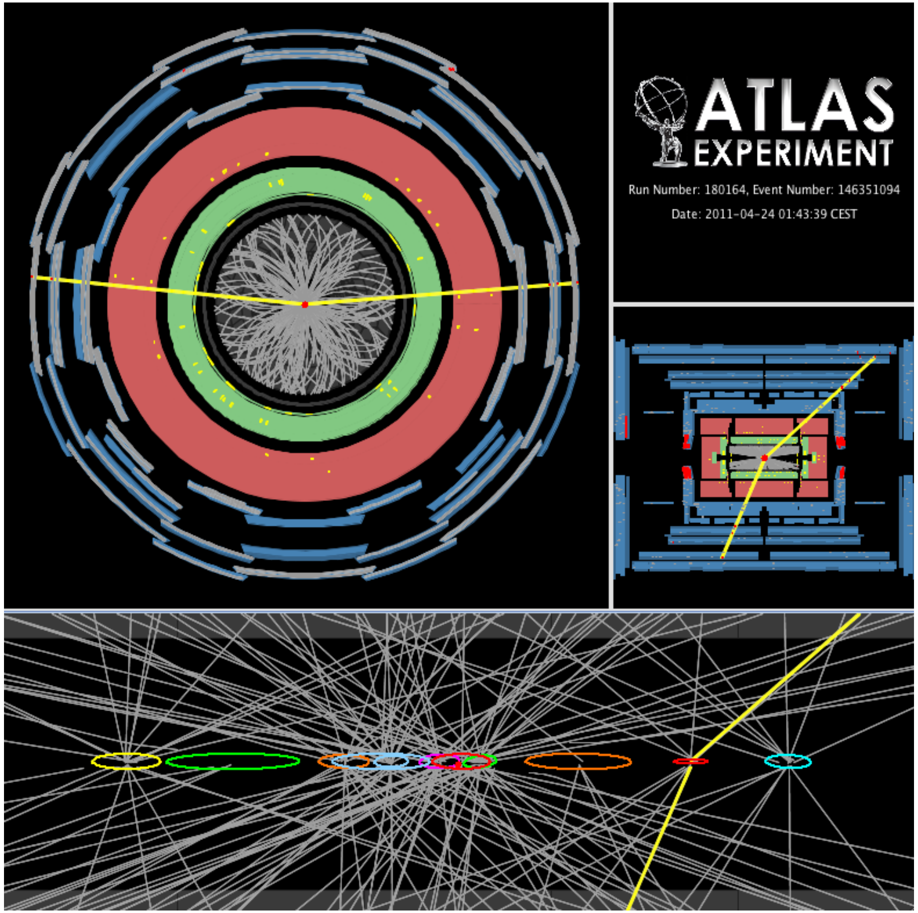
KF already provides matching criterium / significance

$$\Delta\chi^2_{k,k} = \vec{r}^{\,T}_{k,k} R^{-1}_{k,k} \vec{r}_{k,k}$$

# Tracking at High Luminosity

# Track density at low luminosity



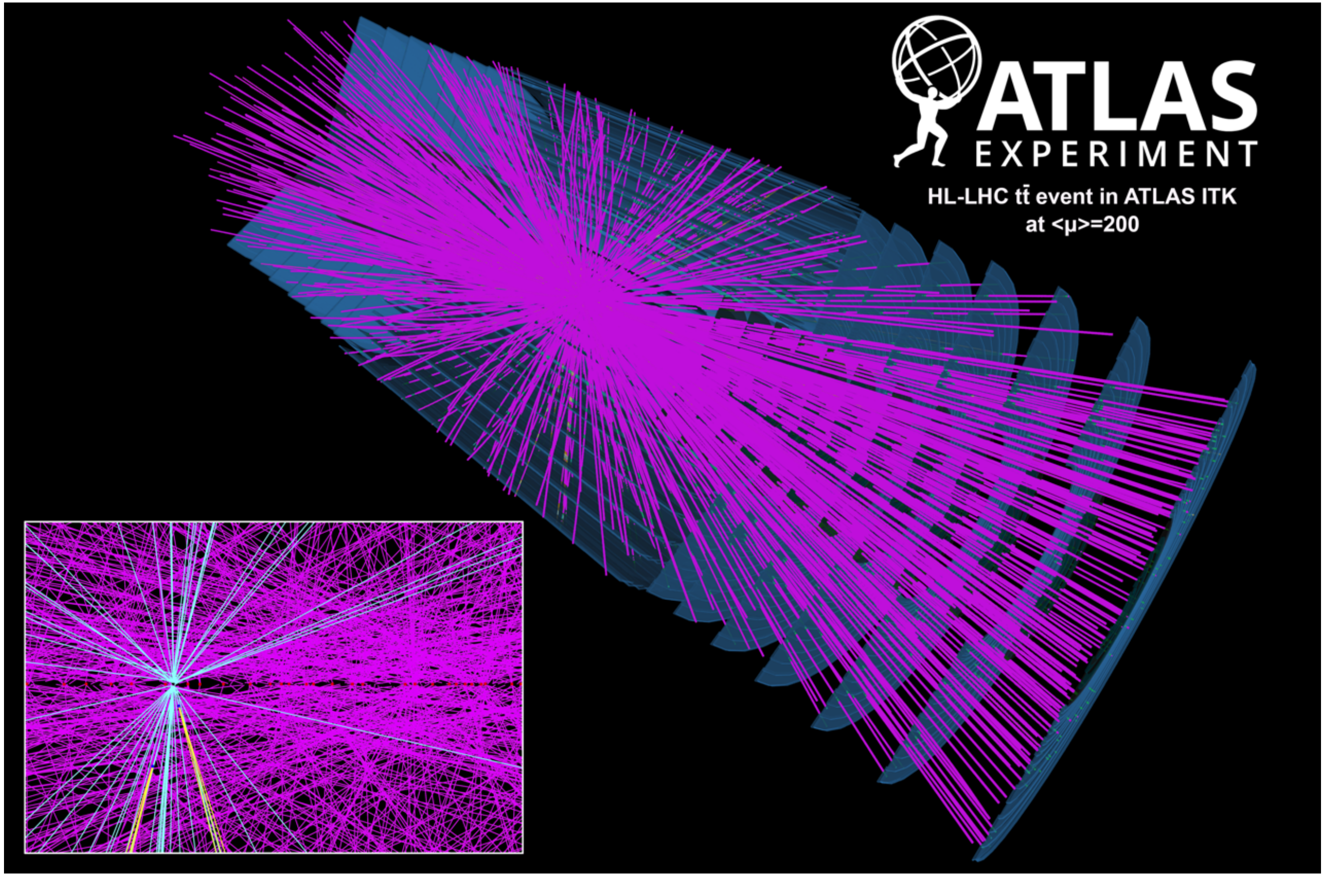



Run 1 conditions

11 reconstructed vertices

# Track density at high luminosity

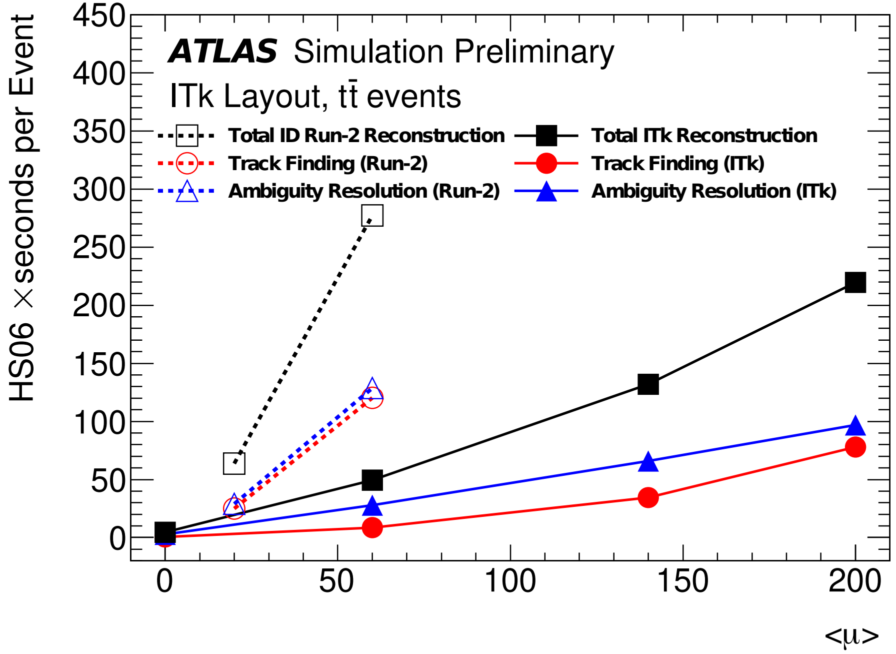


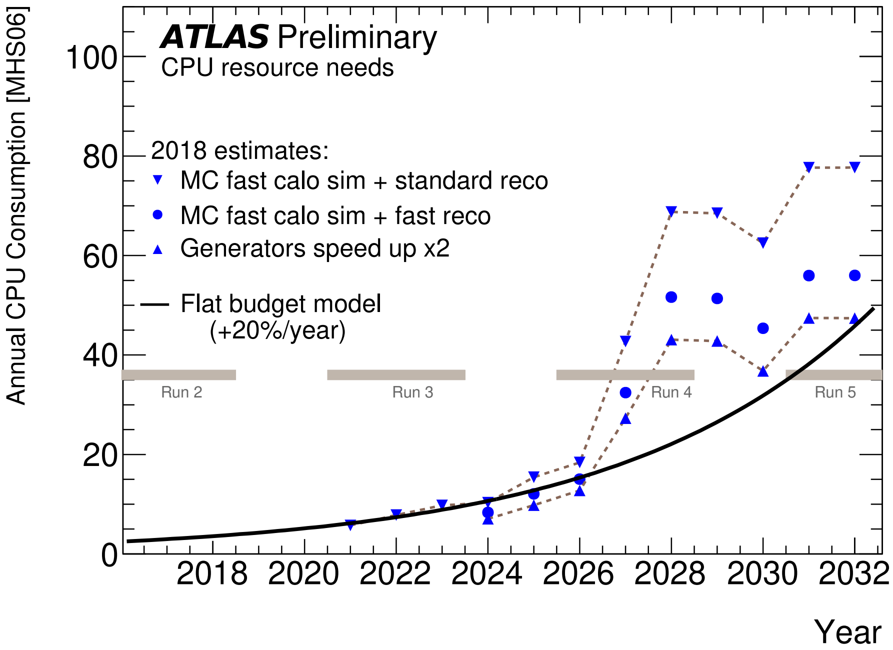



Run 4 conditions (expected)

~200 interactions

# Runtime scaling combinatorial approach 




What can we do?

- Improve implementation
- Improve algorithms

See ATL-PHYS-PUB-2019-041

# ACTS – A Common Tracking Software



- Experiment-independent, platform for tracking tools:
  - Geometry, navigation, track finding and fitting, …
- Open-source (MPLv2)
- Modern code for modern architectures
- Hackable

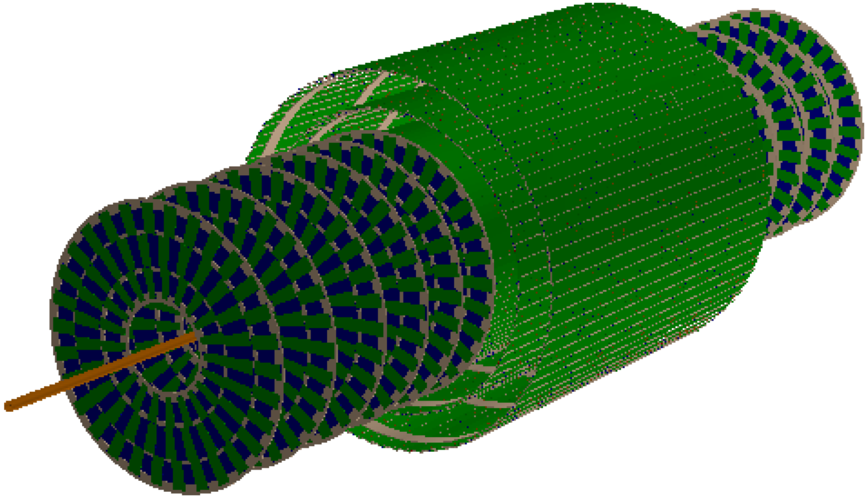
cern.ch/acts

# Example detector geometries

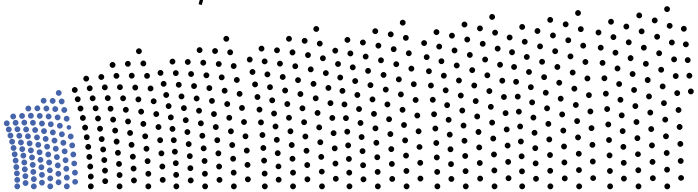


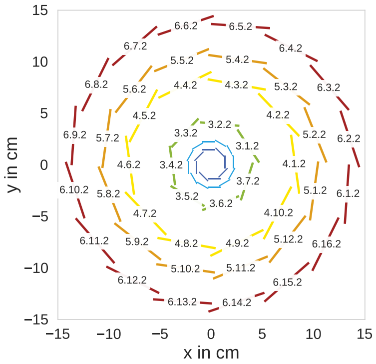
## OpenDataDetector

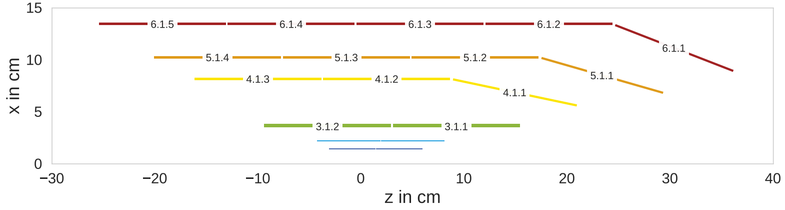
Virtual, test detector



## Belle 2 CDC/ VXD






Both are Work-in-Progress

# The TrackML challenge



Modern algorithms
Non-obvious approaches

For charged particles in (high energy) colliders

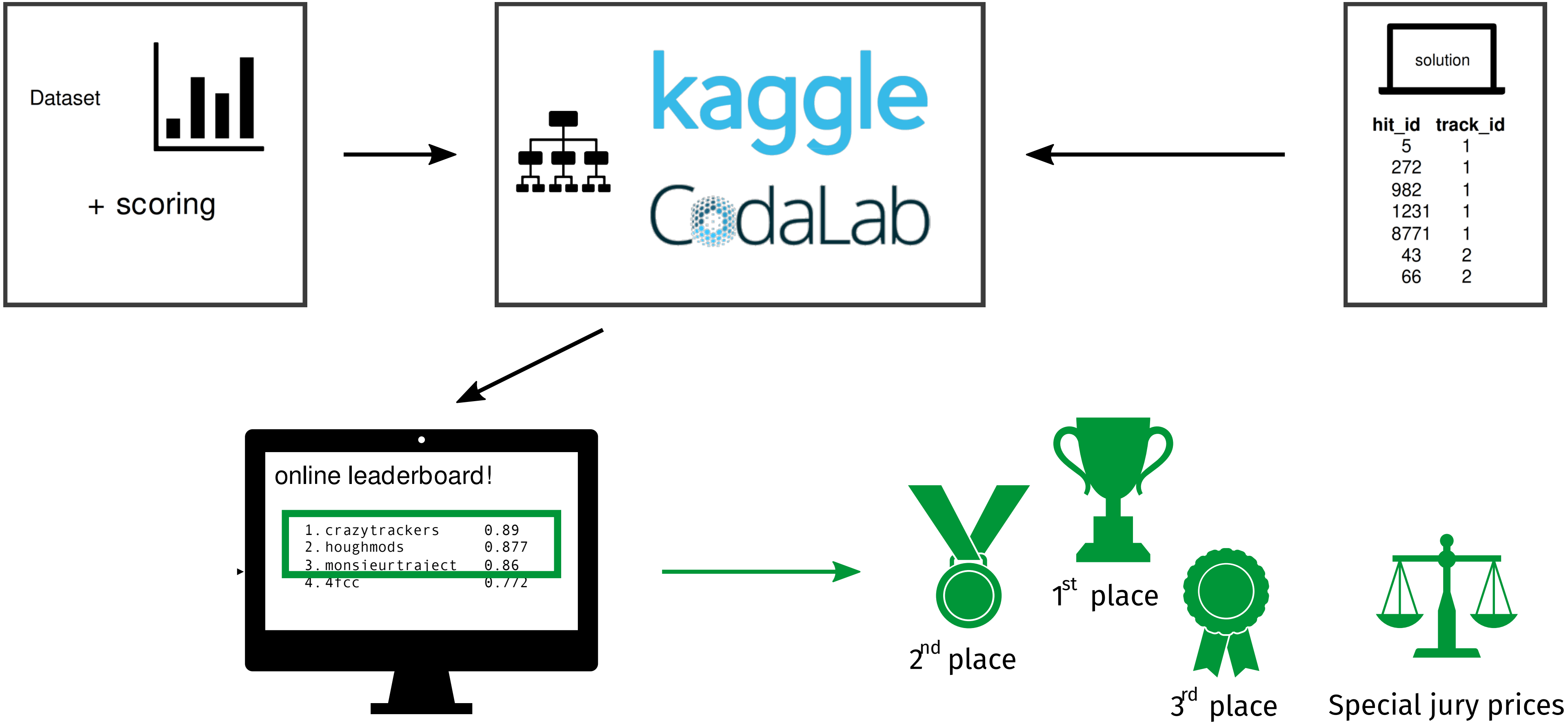
A public machine learning challenge for tracking algorithms

Fresh eyes not just physicists

Cash prizes for motivated participants

On Kaggle and on Codalab and the final workshop

Task/problem Platform Participants 

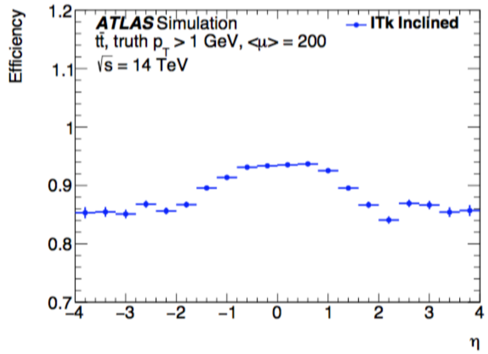


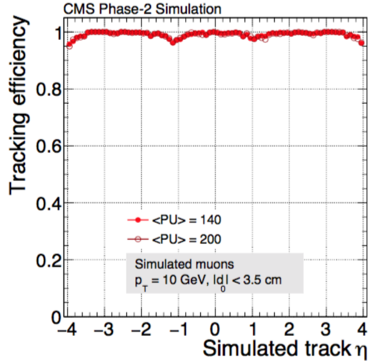
# What is the main problem?

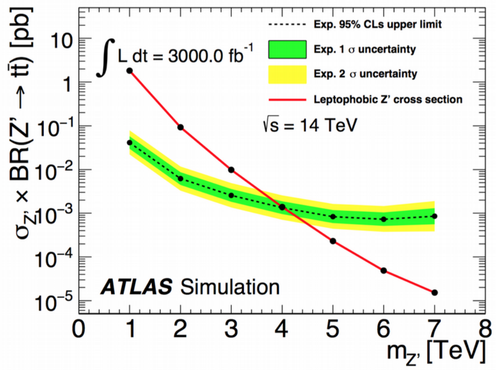


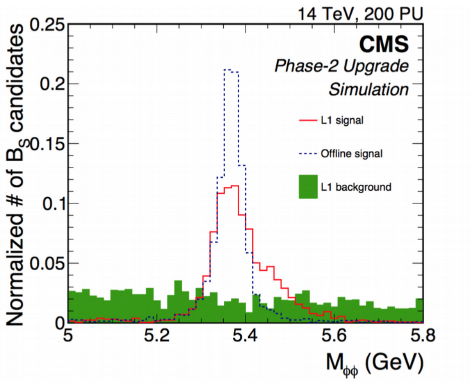
Tracking has many metrics

- Global efficiency
- Efficiency for certain classes
- Fake rate vs. purity
- Momentum resolution
- Impact resolution
- Physics impact
- …



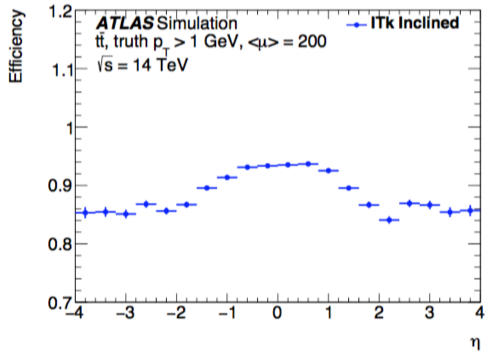



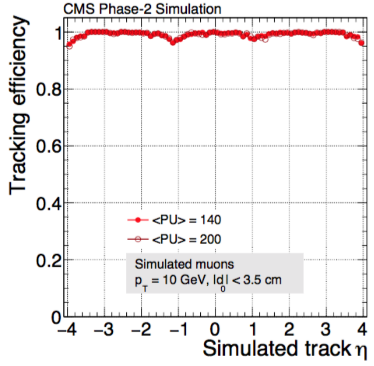
# What is the main problem?

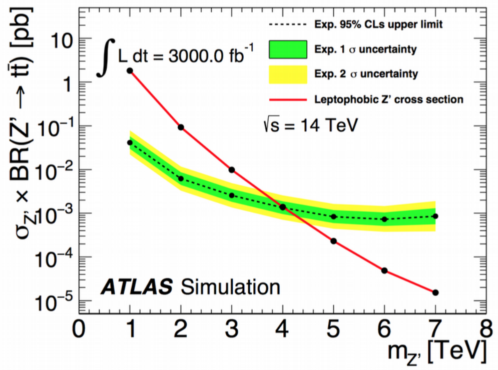


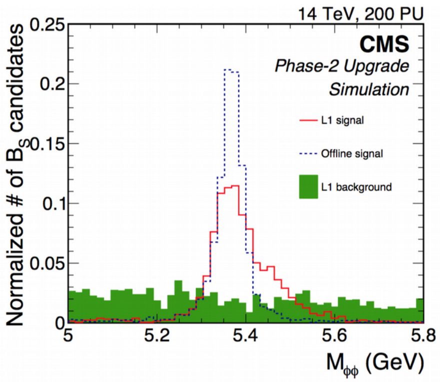
Tracking is multitudes

- Track seeding
- Track finding (extension)
- Track fitting
- Primary/secondary vertex finding
- …



# The problem is connecting the dots

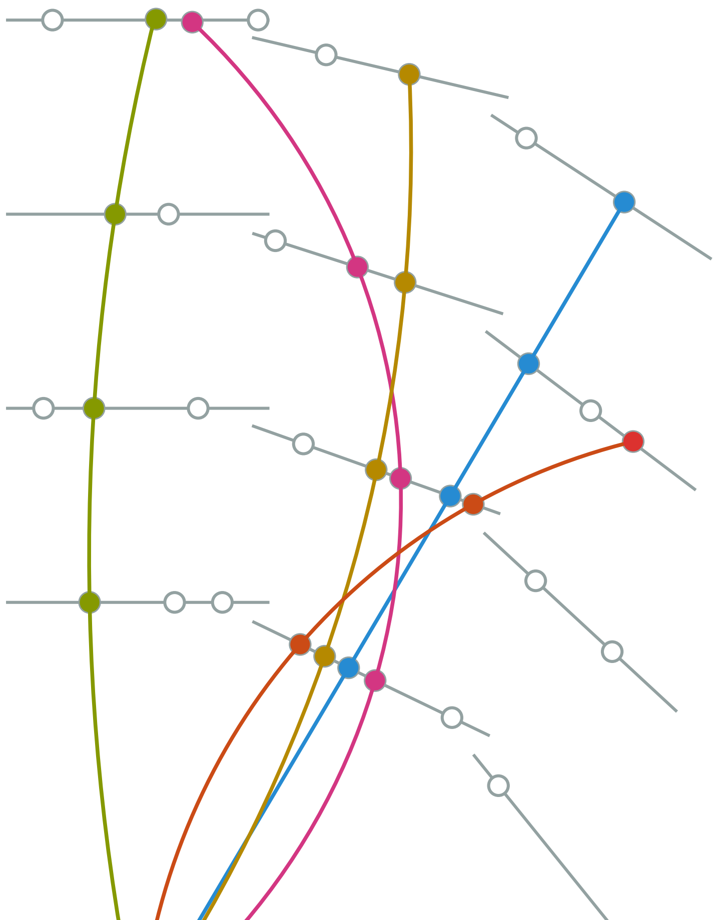


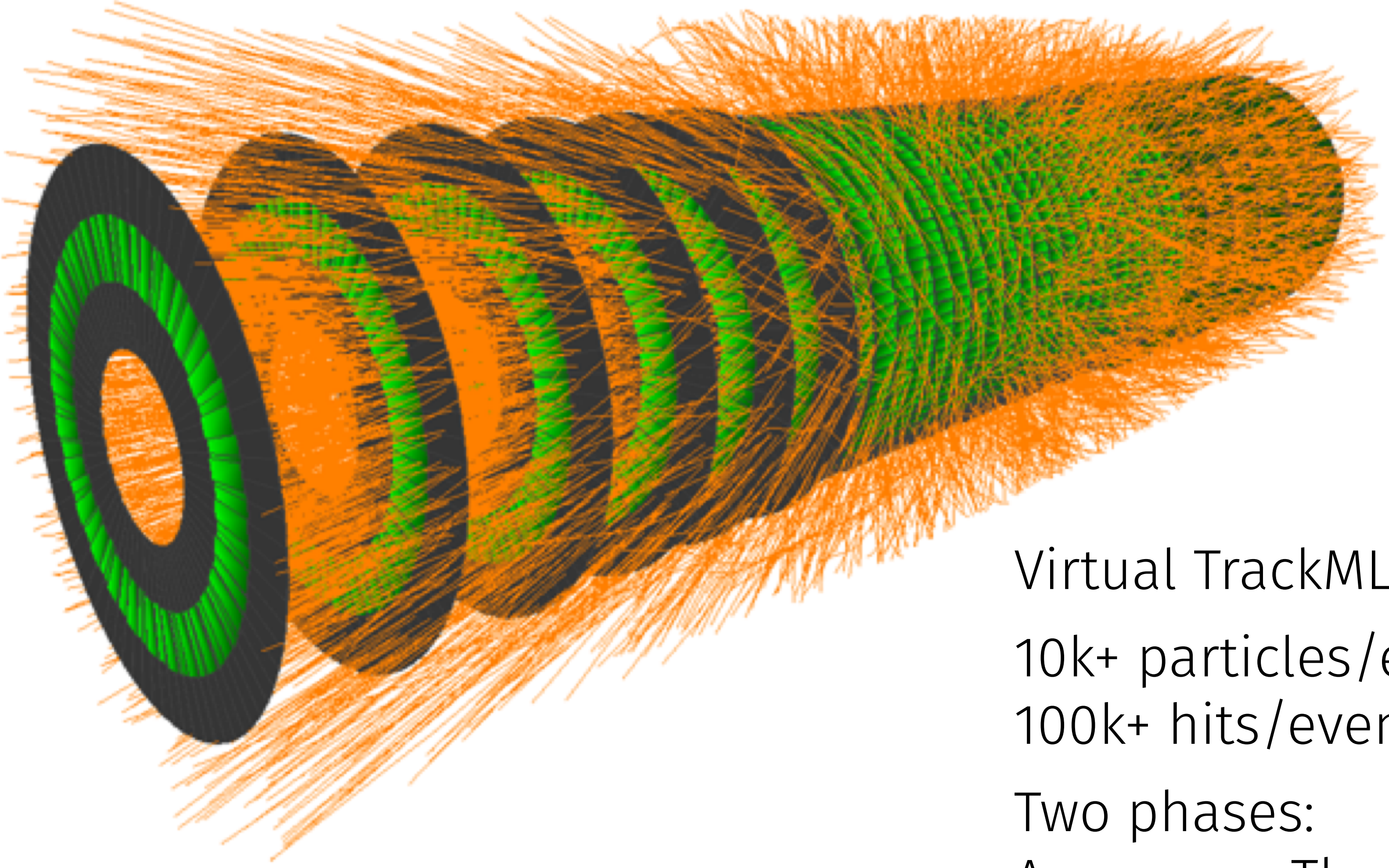
No parameter estimation

(Kalman filter works)

No hit merging/splitting

(NN mostly work)





Virtual TrackML Detector

10k+ particles/event
100k+ hits/event

Two phases:
Accuracy + Throughput

# Accuracy phase on kaggle



Ran until August 2018

600+ participants

Submit results only

Only measure accuracy

12k€, 8k€, 5k€ prizes
+ NVIDIA V100 GPU

| | | | | | |
|---|---|---|---|---|---|
| 1 | — | Top Quarks | | 0.92182 | 10 |
| 2 | — | outrunner | | 0.90302 | 9 |
| 3 | — | Sergey Gorbunov | HEP | 0.89353 | 6 |
| 4 | — | demelian | HEP | 0.87079 | 35 |
| 5 | — | Edwin Steiner | | 0.86395 | 5 |
| 6 | — | Komaki | | 0.83127 | 22 |
| 7 | — | Yuval & Trian | | 0.80414 | 56 |
| 8 | — | bestfitting | | 0.80341 | 6 |
| 9 | — | DBSCAN forever | | 0.80114 | 23 |
| 10 | — | Zidmie & KhaVo | | 0.76320 | 26 |
| 11 | — | Andrea Lonza | | 0.75845 | 15 |
| 12 | — | Finnies | | 0.74827 | 56 |
| 13 | — | Rei Matsuzaki | | 0.74035 | 12 |
| 14 | — | Mickey | | 0.73217 | 10 |
| 15 | — | Vicens Gaitan | | 0.70429 | 19 |
| 16 | — | Robert | | 0.69955 | 3 |
| 17 | — | Yuval-CPMP tribute band | | 0.69364 | 20 |
| 18 | — | N. Hi. Bouzu | | 0.67573 | 9 |
| 19 | — | Steins;Gate | | 0.66763 | 12 |
| 20 | ▲1 | Victor Nedel'ko | | 0.66723 | 4 |

# Throughput phase on CodaLab



Ran until March 2019

Only 10+ active participants

Submit results only

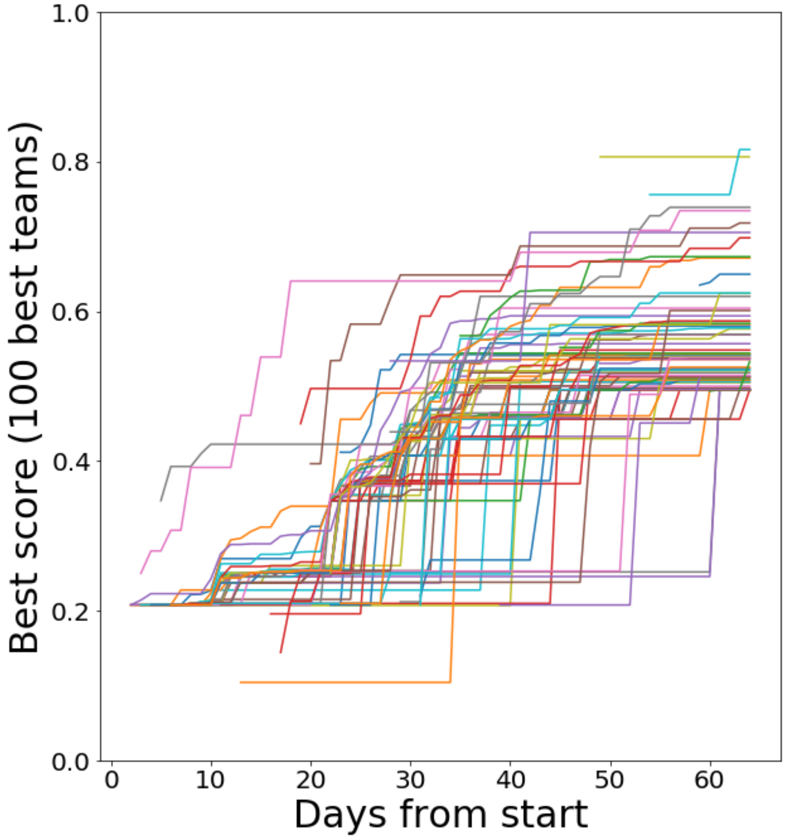
Measure accuracy and speed

7k€, 5k€, 3k€ prizes
+ NVIDIA V100 GPU

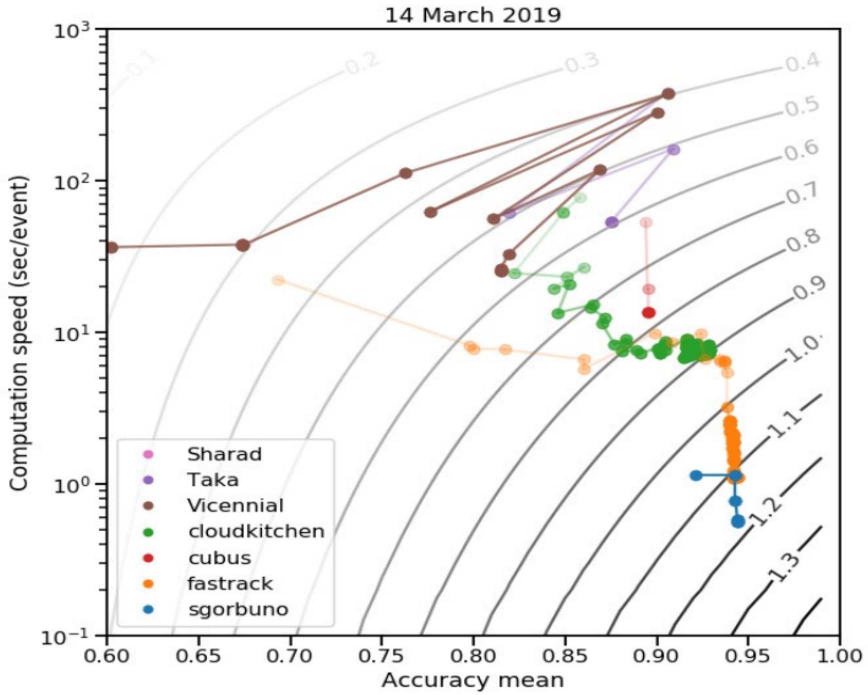
| RESULTS | | | | | | | |
|---|---|---|---|---|---|---|---|
| # | User | Entries | Date of Last Entry | score ▲ | accuracy_mean ▲ | accuracy_std ▲ | com (sec |
| 1 | sgorbuno HEP | 9 | 03/12/19 | 1.1727 (1) | 0.944 (2) | 0.00 (14) | 28. |
| 2 | fastrack HEP | 53 | 03/12/19 | 1.1145 (2) | 0.944 (1) | 0.00 (15) | 55. |
| 3 | cloudkitchen (HEP) | 73 | 03/12/19 | 0.9007 (3) | 0.928 (3) | 0.00 (13) | 364 |
| 4 | cubus | 8 | 09/13/18 | 0.7719 (4) | 0.895 (4) | 0.01 (9) | 675 |
| 5 | Taka | 11 | 01/13/19 | 0.5930 (5) | 0.875 (5) | 0.01 (12) | 266 |
| 6 | Vicennial | 27 | 02/24/19 | 0.5634 (6) | 0.815 (6) | 0.01 (10) | 127 |
| 7 | Sharad | 57 | 03/10/19 | 0.2918 (7) | 0.674 (7) | 0.02 (4) | 190 |
| 8 | WeizmannAI | 5 | 03/12/19 | 0.0000 (8) | 0.133 (11) | 0.01 (11) | 88. |
| 9 | harshakoundinya | 2 | 03/12/19 | 0.0000 (8) | 0.085 (13) | 0.01 (6) | 49. |
| 10 | iWit | 6 | 03/10/19 | 0.0000 (8) | 0.082 (15) | 0.01 (8) | 48. |

# Score progression

## Accuracy




## Throughput



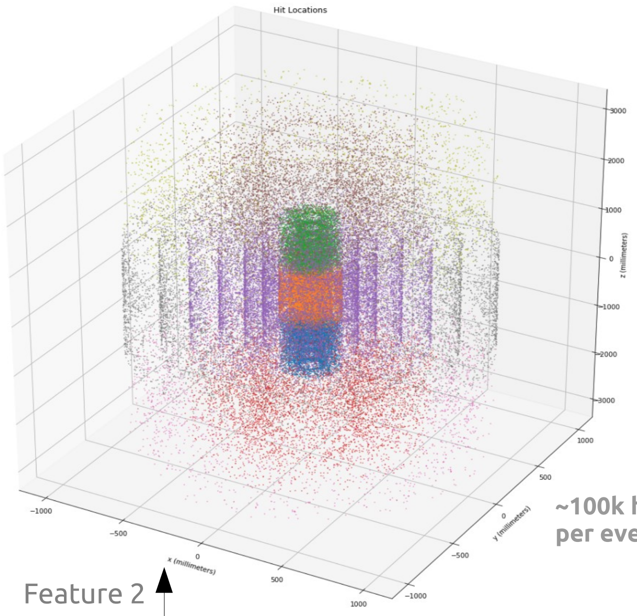

Plots from Laurent Basara

# Accuracy #12: Finnies (Jury Deep Learning Prize)

Liam Finnie & Nicole Finnie
IBM Germany R&D
Bosch Centre for AI

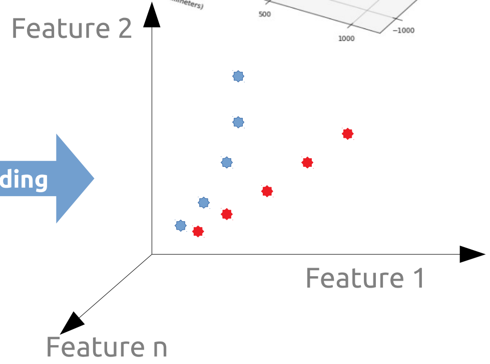
https://github.com/jliamfinnie/kaggle-trackml

# Solution Pipeline




~100k hits (~10k tracks) per event

seeding




inference

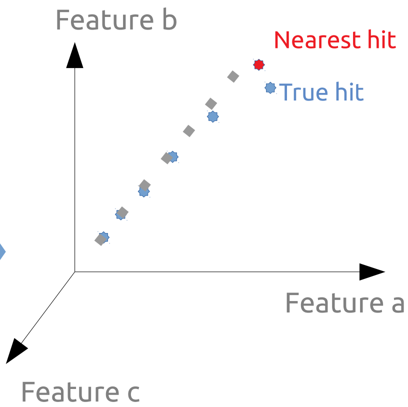
Bi-LSTM

LSTM

LSTM

LSTM

fitting

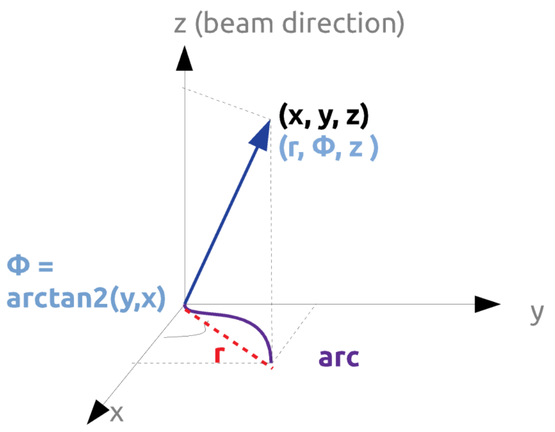



**Track seeding**
(clustering)

**Inference & Ensembling**

**Track fitting**
(k-nearest neighbour)

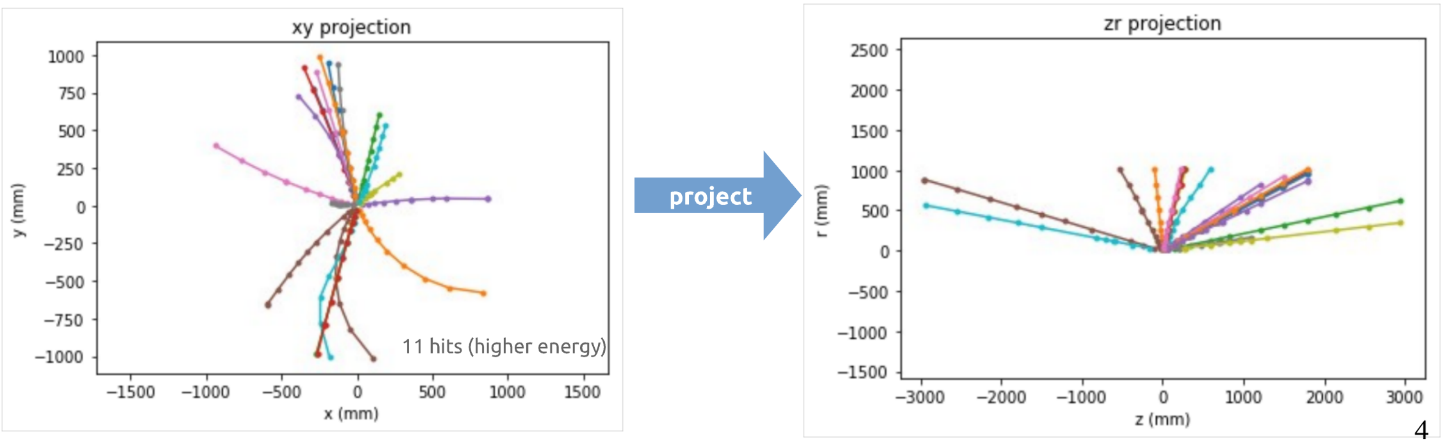
# Feature Engineering… for people who don't know physics :D




**Data we use:** (x, y, z) coordinates of hits

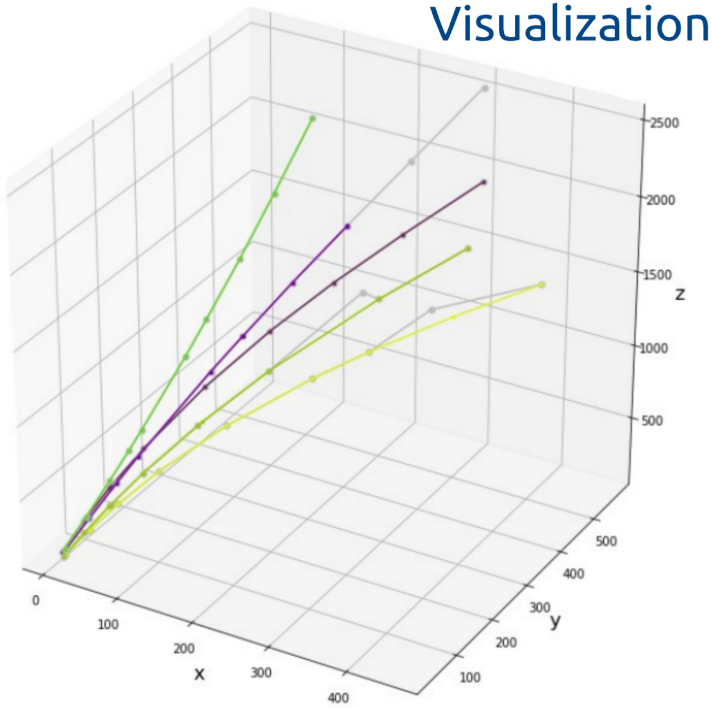
**For clustering**: sin(Φ), cos(Φ), z/arc
(new feature: generate possible arcs using train data)

**For LSTM**: Φ, r, z, z/r



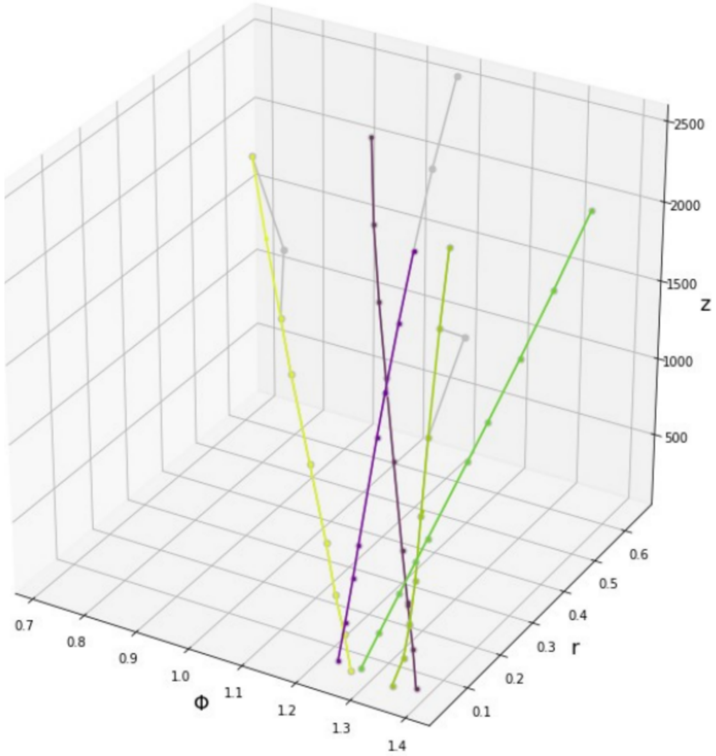

Cartesian -> Polar coordinates: **easier for LSTM to learn**

# Visualization after fitting




Cartesian coordinates

--- predicted (grey)
--- ground truth (colour)




Polar coordinates

# Accuracy #2: outrunner

Pei-Lien Chou

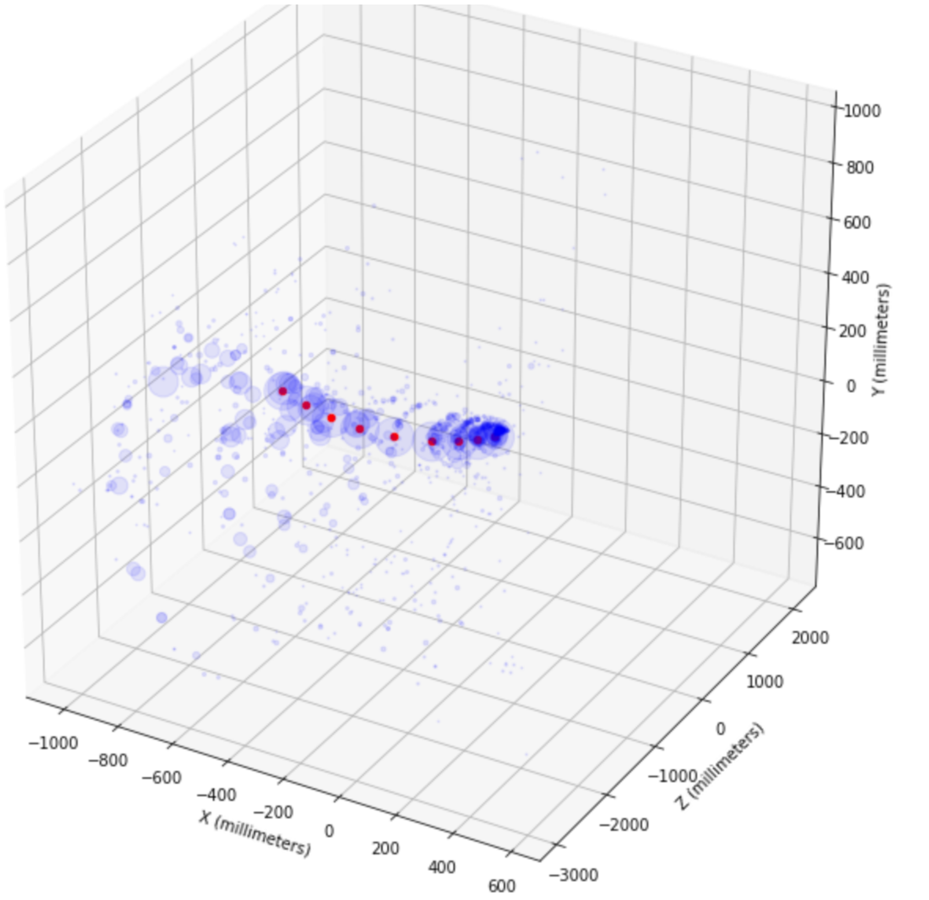
Software engineer image-based deep learning in Taiwan.

Kaggle Notebook

# outrunner – Setup



- Train DNN on hit pairs
  - 27 inputs (x,y,z,cells,…)
  - 4k-2k-2k-2k-1k hidden layers
- Compute full hit adjacency matrix: probability P(i,j) that 2 hits match
- Pick high probability comb.
- Helix-like fit for cleaning




Graphics from outrunner

# ML vs classical reconstruction



Classical reconstruction

Local Reco

Bits to hits, clustering

Track Finding

Track Fitting

Parameter estimation

Analysis

Simulation (Reality)

Digitized hits

Material interactions

Propagation

Particles

ML (supervised): try to learn inverse solution directly

# Summary



Tracking is core reconstruction for many particle physics experiment

Rich set of classical algorithms

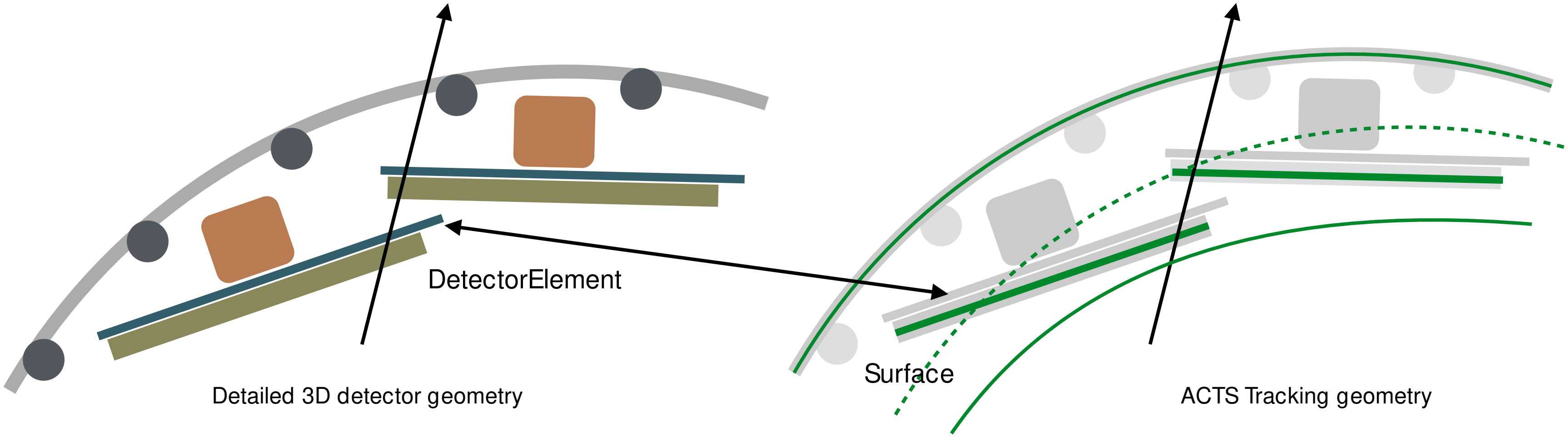
Interesting machine-learning based solutions

Things I did not talk about:

- Tracking on accelerators
- Triggering with tracks
- Local reconstruction
- Outliers and robustness
- Alignment
- …

# Appendix

# (Tracking) Geometry




Simplified geometry based on tracking surfaces

# TrackML Organizers



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