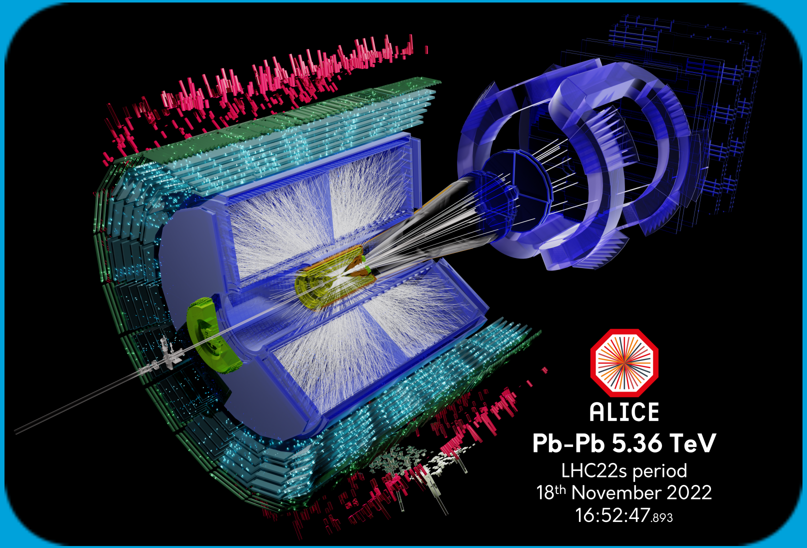
Exploring 4D particle tracking with accelerated computing at the LHC

Panos Christakoglou

Nikhef and UM



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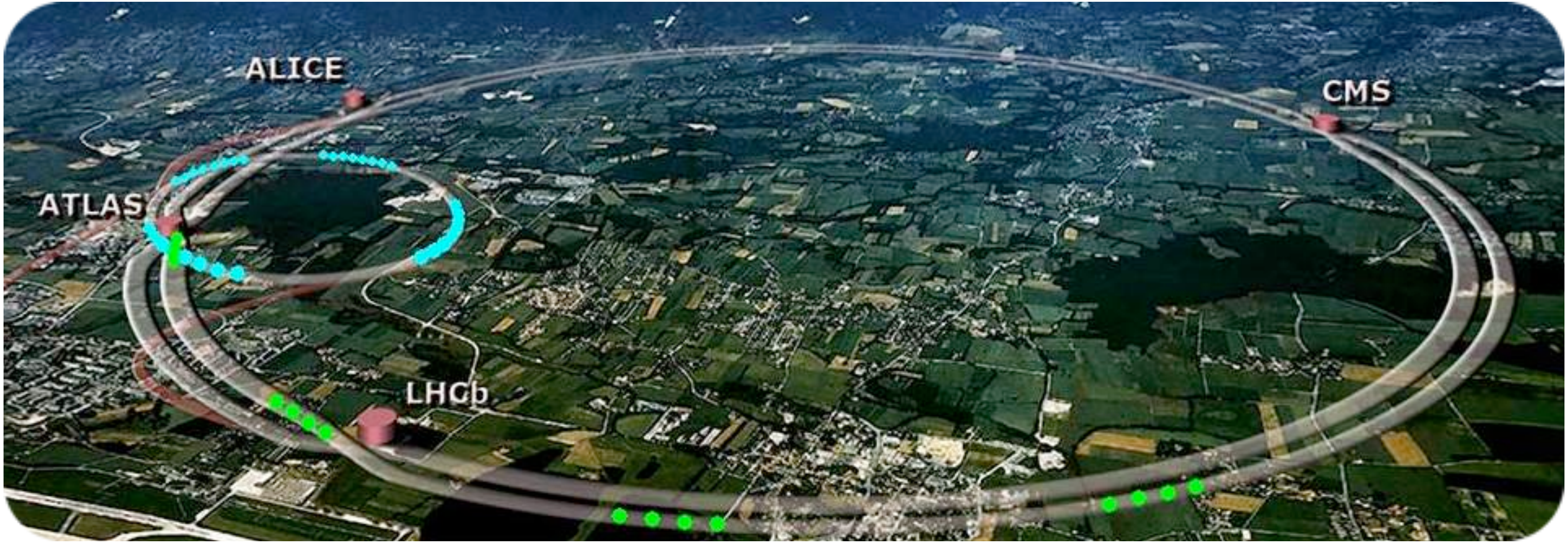
Nikhef

The LHC

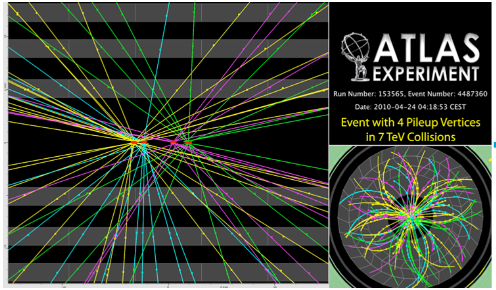


Delivers pp collisions for ~11 months per year and PbPb (or pPb) for one month

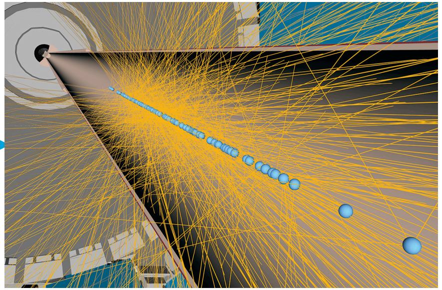
Some of the challenges at the LHC

- Extreme event rates of 40MHz
- Extreme pile-up in pp collisions:
  - Up to 200 overlapping proton-proton interactions per bunch crossing at HL-LHC
  - ~**10,000 detector hits** per event in tracking systems
  - Makes it extremely hard to tell which hit belongs to which particle/interaction
- Extreme track densities in heavy ion collisions
- Low momentum tracking is essential → unique focus of ALICE

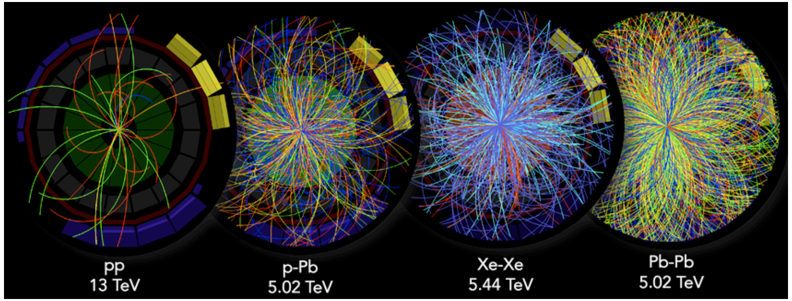
Run 1@LHC



HL-LHC

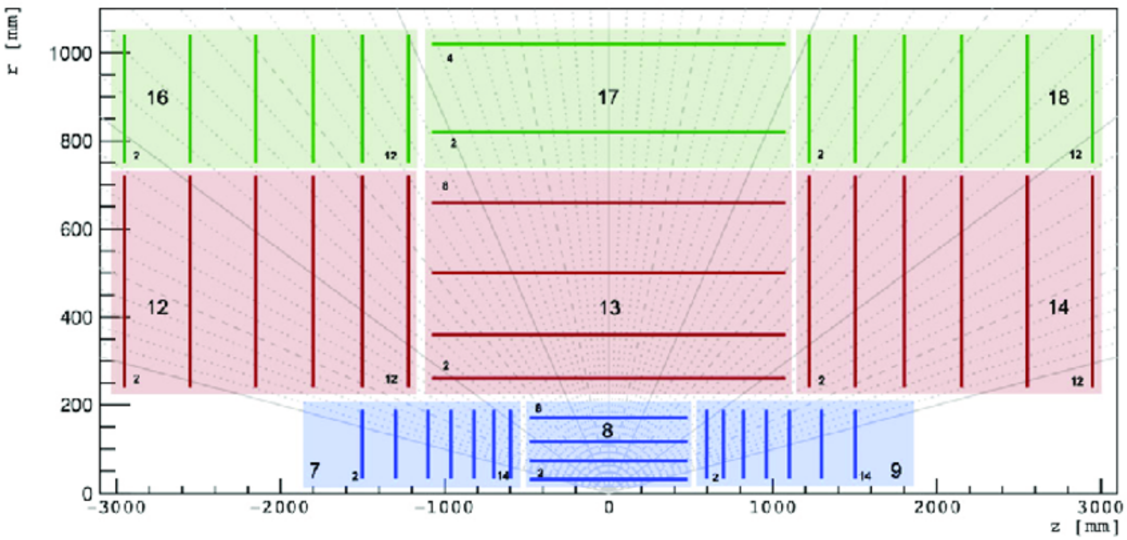


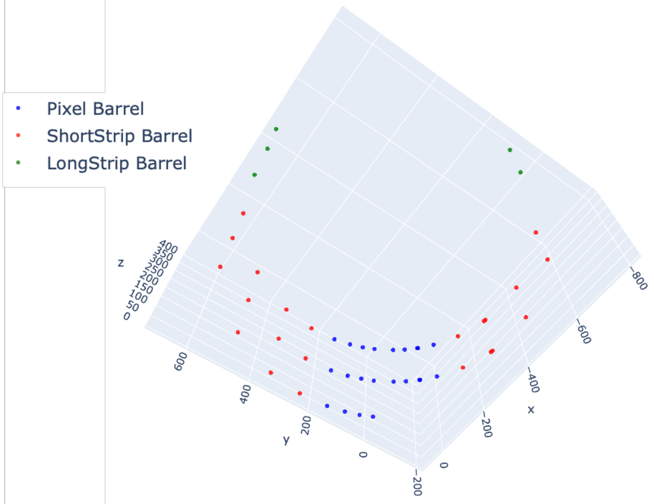
Heavy-ions@LHC



First look at looping particles…

ACTS framework



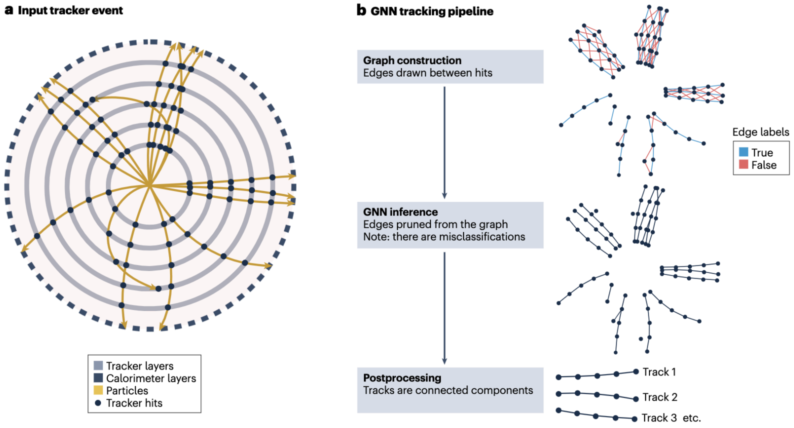


Bart Kuipers (UvA MSc student)

New paradigm

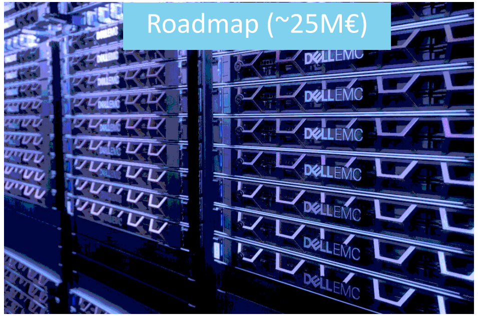
- AI/ML Models (GNNs, CNNs, Transformers)
  - Capable of learning **global event structure**,
  - Robust, in principle, to missing hits, pile-up, and non-ideal detector conditions
- Usage of GPUs or/and **FPGAs**:
  - excellent for **parallelizable** workloads like clustering, track seeding, real-time pattern recognition (e.g., trigger applications).
- Quantum computing
  - Collaboration with DACS or/and GWFP

G. DeZoort et al., Nature Rev. Phys. (2023)



An expanding team

Funded



Roadmap (~25M€)

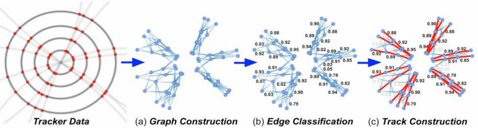
4D-tracking

1st generation (NWO-XL ~3M)

Justus Rudolph (PhD@Nikhef)

Being drafted now

2nd generation (NWO-XL ~3M)



PhD@Nikhef PhD@Nikhef

ML (NN)

Staff@Nikhef

Starting in February

MSc@UvA BTR/HRP@MSP

HPC

Charis Kouzinopoulos (DACS)

BSc@DACS

QC

?

Thank you for your attention!

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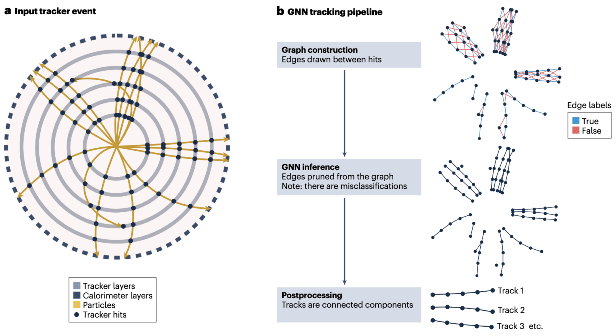
Possible directions for ALICE Computing

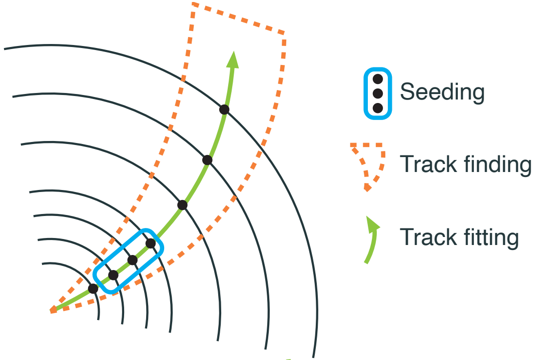
- Collision data
  - Online reconstruction using GPUs
  - 4D tracking accelerated algorithms
    - ML applied to track finding e.g. GNN
- Simulation (>50% of CPU consumption)
  - Data vs MC matching w/ ML algorithms
    - Expected significant effect (i.e. reduction) on systematic uncertainties
  - porting (parts of the simulation) code to GPUs
  - porting of generators to GPUs

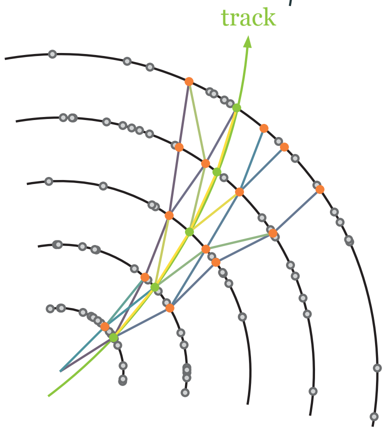
G. DeZoort *et al.*, Nature Rev. Phys. (2023)



Particle tracking

- Charged particle detection
  - Interaction of charged particles with material
- From raw data to clustering
- Spacepoint formation
- Seeding
- Track finding/fitting
- Taking into account material effects
  - Geometry and material modelling





Based on Kalman filter

Traditional tracking challenges

- High track density
  - In high-pileup (pp) or heavy-ion events, the detector sees **hundreds to tens of thousands of overlapping tracks**.
  - The **combinatorics explode**, making it hard to associate hits correctly.
- Complex detector topologies
  - Detectors like ATLAS, CMS, and ALICE have **non-uniform geometry** and **inhomogeneous magnetic fields** while KF assume more regular geometry.
- Sequential processing
  - KF track **one particle at a time**, which limits **parallelism** and **hardware acceleration**.
  - This doesn't scale well with modern many-core or GPU architectures.
- Inefficient with missing or ambiguous hits
  - Real detectors have **inefficiencies** and **noisy hits**. That KF-based seeding and propagation find it challenging
- Computational bottleneck
  - With increased pile-up or multiplicity, tracking can consume **over 50% of total CPU time** in HLT systems.
  - Real-time reconstruction at full LHC rates becomes **infeasible** without acceleration or smarter algorithms.
- Difficult to incorporate timing (4D): KF is traditionally spatial (3D), and adapting it to include **per-hit timing** in the track model is **non-trivial** and computationally expensive.

New paradigm

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