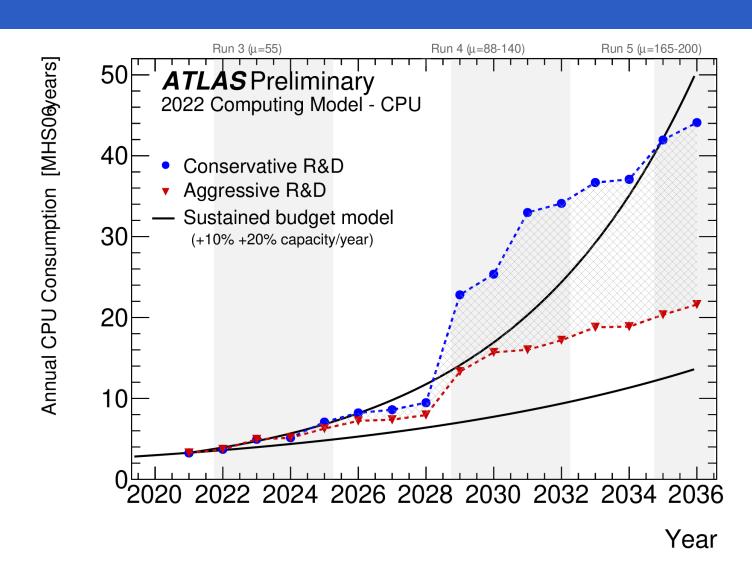
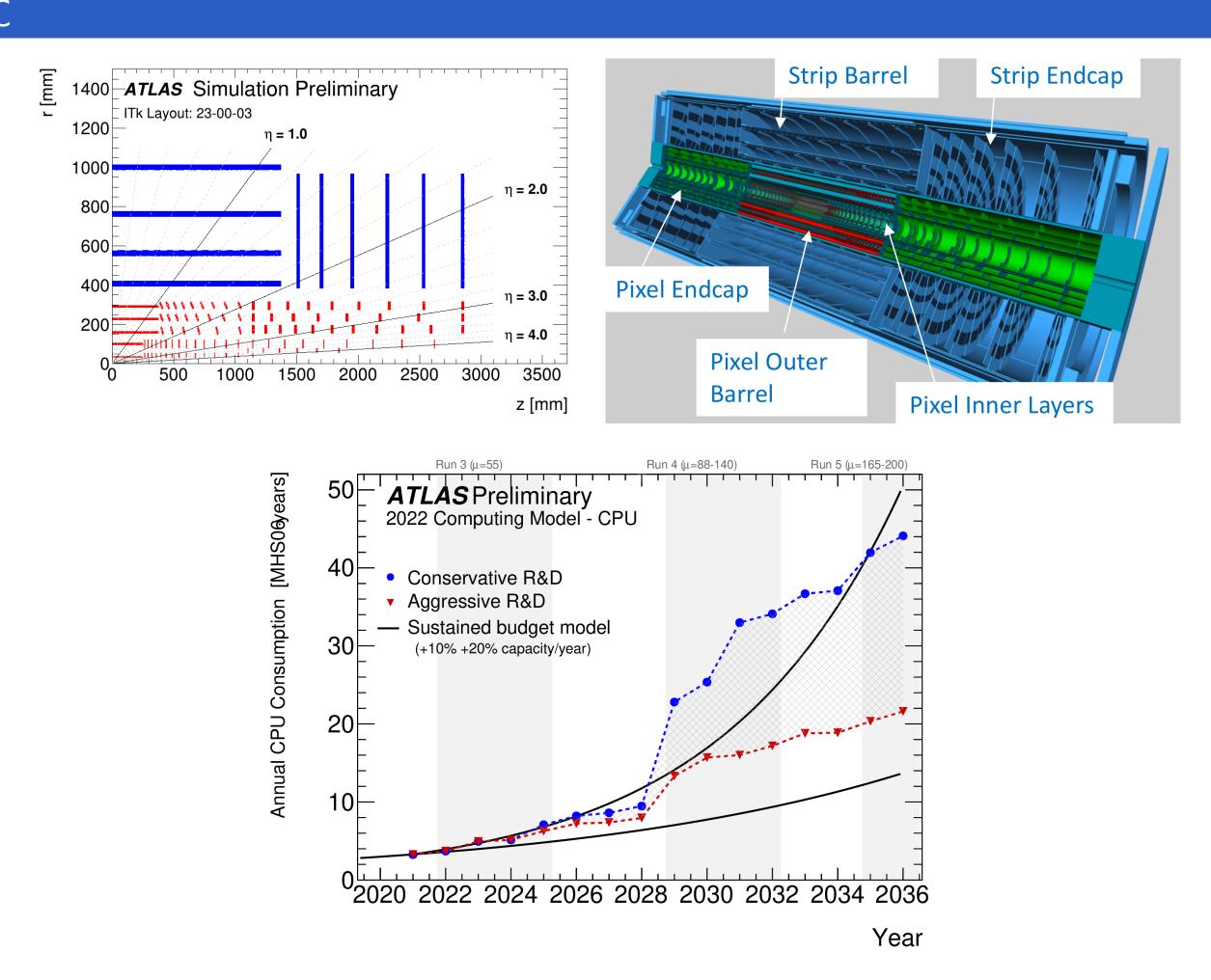
Seeding with ML in ACTS Jeremy Couthures

Objective/Aim



HL-LHC



The Large Hadron Collider (LHC) is prepping for its future update, the High-Luminosity LHC (HL-LHC). A significant component of this update is the ITk detector of ATLAS.

Baseline

The ATLAS experiment's track reconstruction for the LHC has traditionally incorporated a multi-stage process:

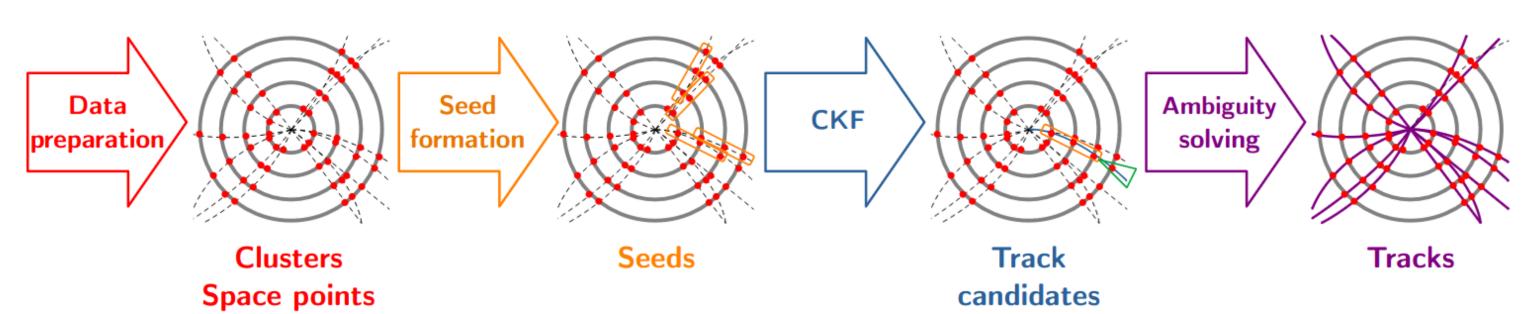
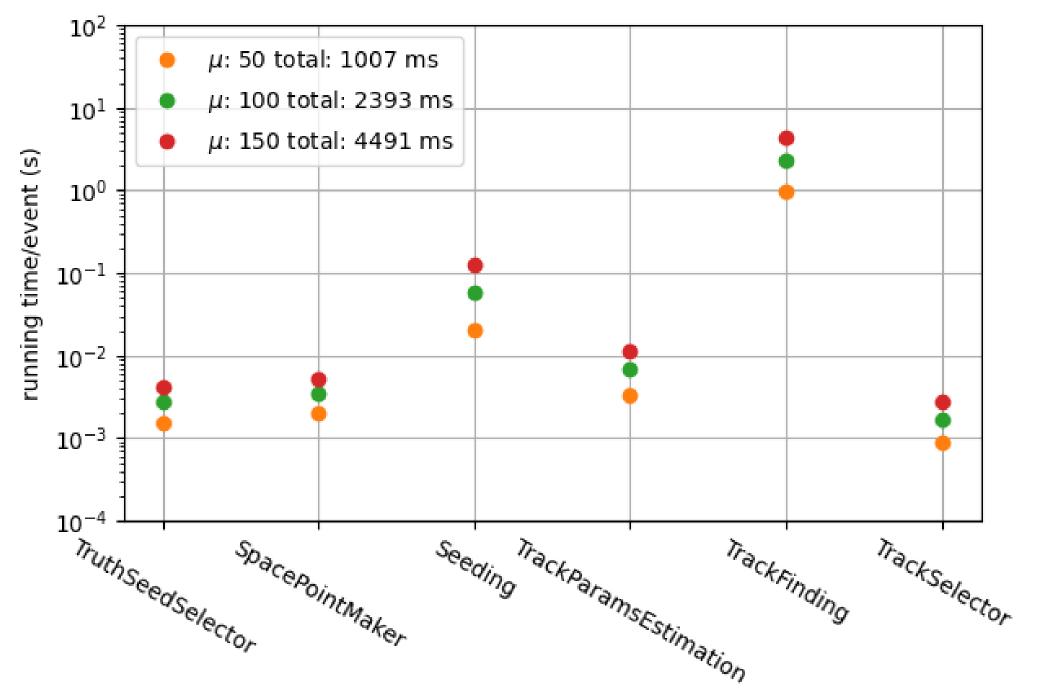


Figure: a nice plot

Within the ACTS framework, seeding is the foundation for subsequent tracking stages. Seeds are constructed with triplets of space points compatibles with a track. The seeds are then filtered based on manually-defined scores, focusing on computational efficiency. Each of these seeds is then expanded, resulting in as many tracks as seeds.

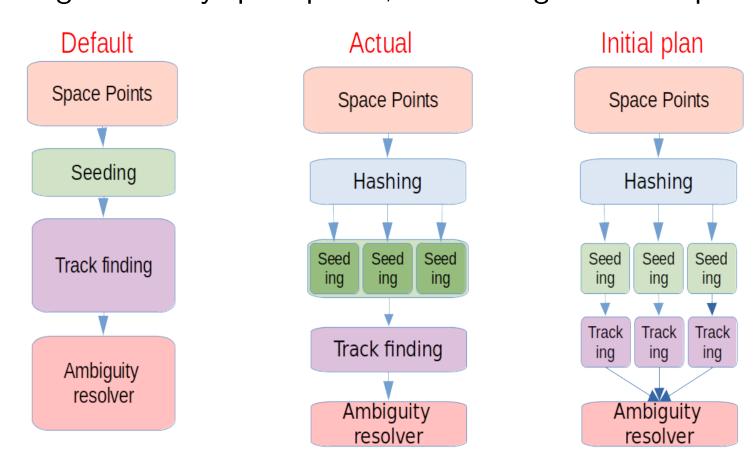
Time per event Default



Methodology

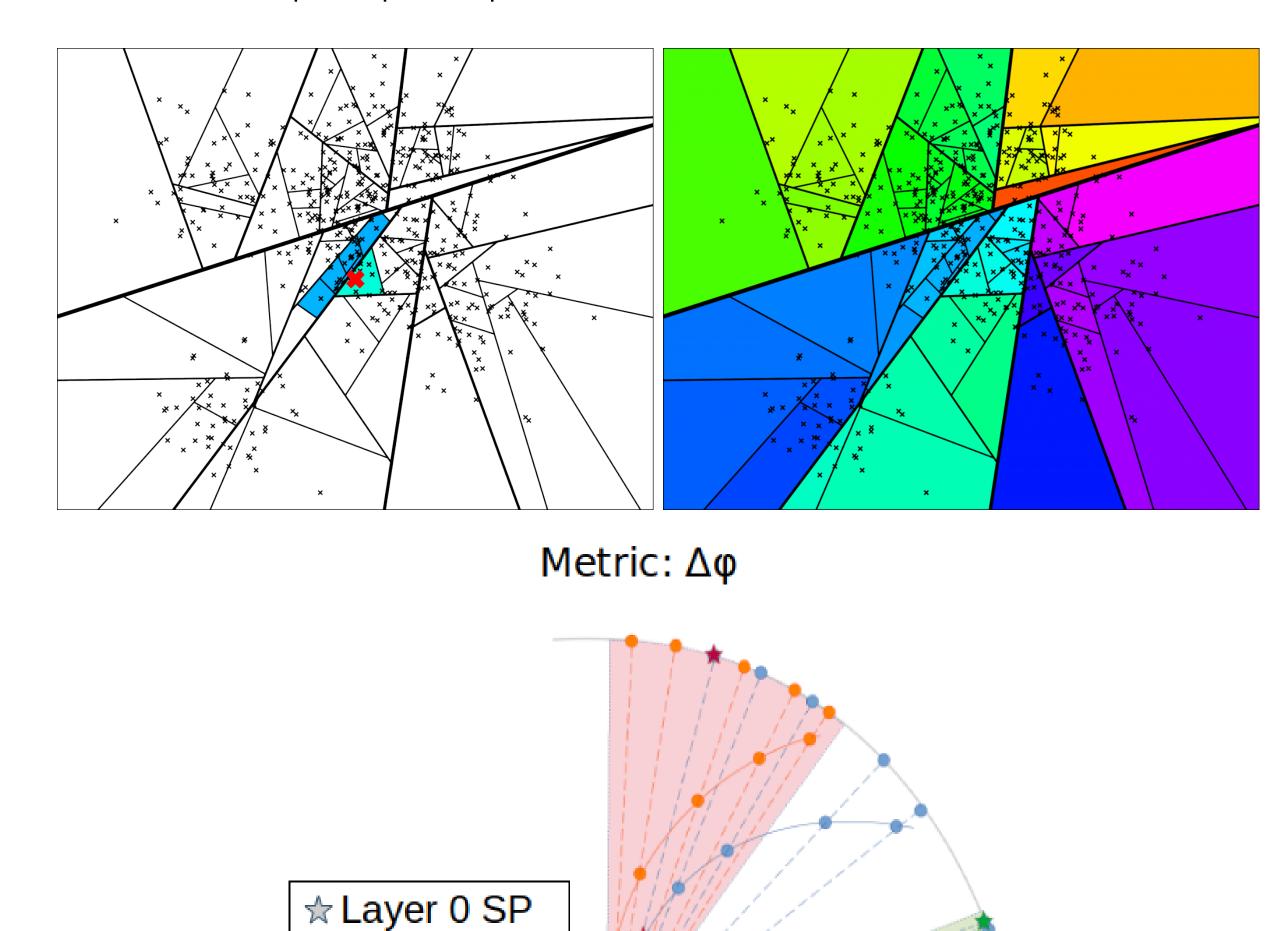
The method employed in this study is based on grouping space points into buckets using a k Nearest Neighbours algorithm, this process is also called Hashing.

Instead of the traditional seeding with every space points, the seeding is done in parallel on the buckets.



The actual implementation is only parallelizing the seeding, doing one seeding per bucket. The seeds found in the different buckets are then merged together and used in the tracking. In a following work, the seeding and the tracking could be both done per bucket reducing the combinatorics of the tracking.

The software used for the k Nearest Neighbours algorithm is called Annoy. It splits the space by selecting two randoms points and creating an hyperplan between them. In each newly created subspace, the process is repeted until a maximum number of points per subspace is reached.



Results

Note:

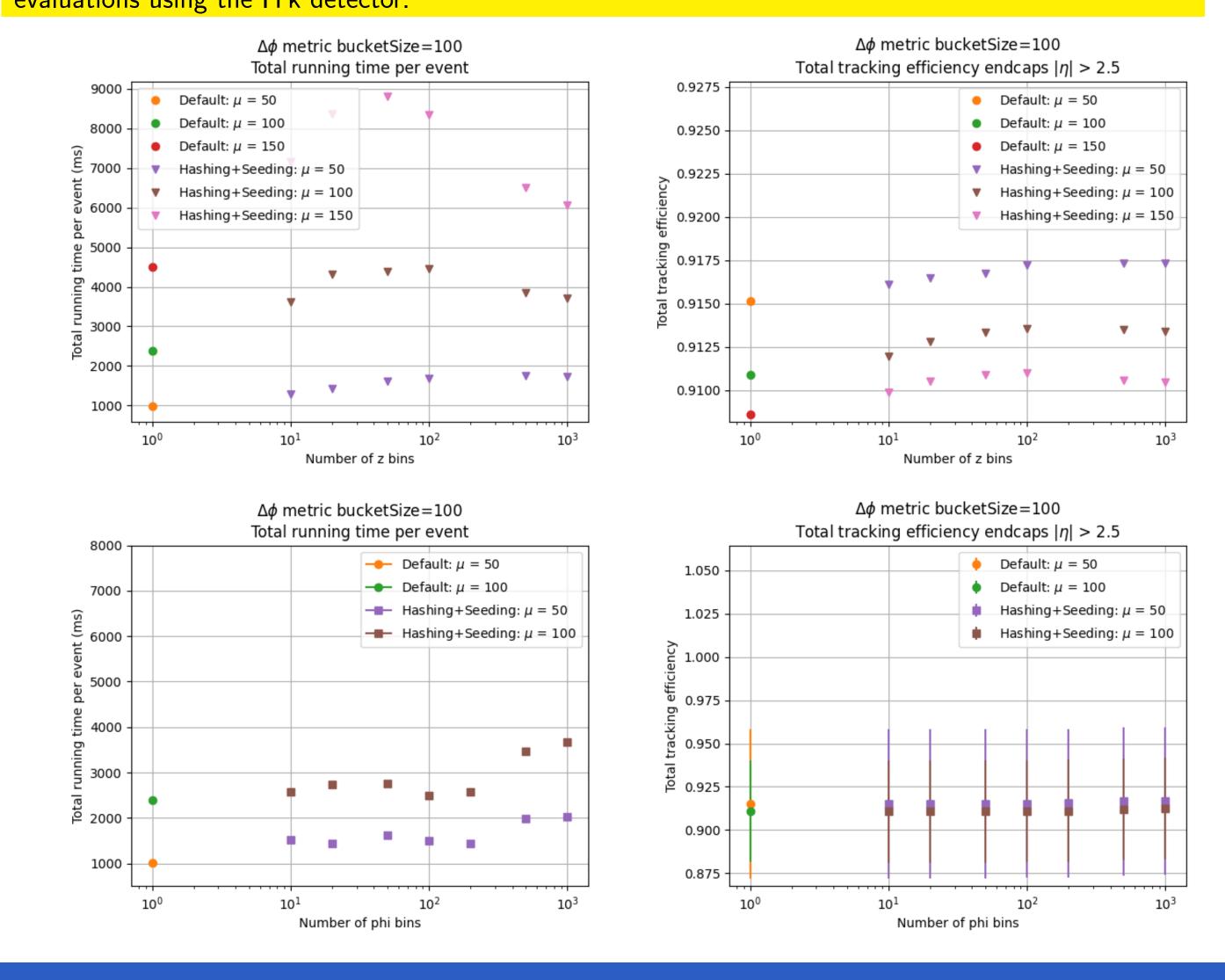
The results presented in this poster are based on simulations for the TrackML detector, referred to as the generic detector within the ACTS framework. They serve as initial study and foundation for future evaluations using the ITk detector.

SP

Bucket

_Track

- Projection



Discussion/Conclusion

Future Work

The next steps involve transitioning towards metric learning for a more dynamic and efficient tracking algorithm.













