Machine learning based Ambiguity Solver in ACTS

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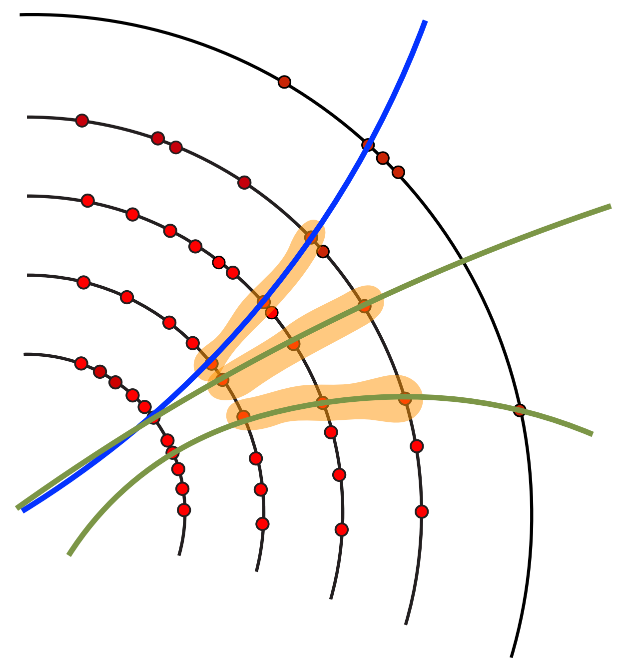
Ambiguity Solving

- After the track reconstruction, many tracks are **duplicate** of one another (default ODD config 10 tracks per truth particles)
- **Fake** tracks (combination of arbitrary hits not belonging to the same particle) also present
- The ambiguity solver is implemented after the track fitting to **remove both** and handle **hits shared** by multiple tracks
- A naive algorithm has already been in Acts, performs decently but is quite slow
- Since in comes down to a classification problem, it is a great opportunity to try an **ML based solution** in Acts



Machine learning based Ambiguity Solving

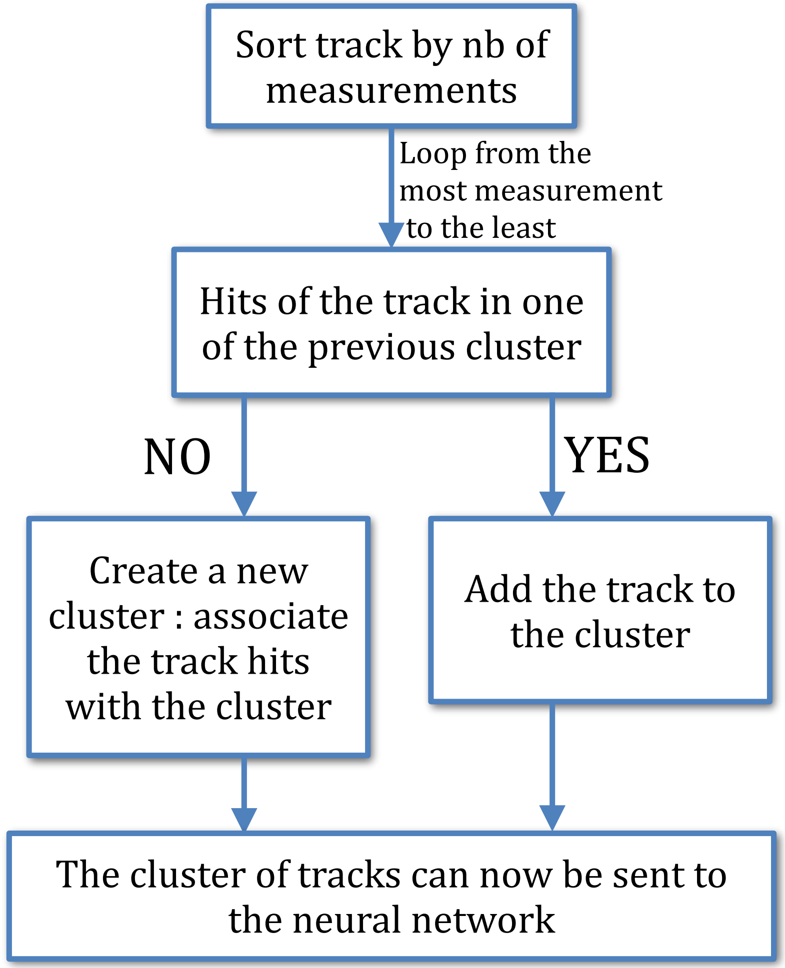
Cluster Tracks together → Network to determine the best track per cluster → Network to Clean the remaining tracks

Three steps plan for the ML based Ambiguity Solving :

- **Clustering** : cluster together nearby track, ideal 1 cluster = 1 truth particle
  - Tested with **DBScan** (a classic clustering algorithm) ➡ perform well in python (imported from scikit-learn)
  - How to use in cpp ? ➡ mlpack C++ implementation of many ML algorithm, really old (16+ years) still maintained to this day !
  - Not implemented in Acts yet
  - Right now : fast **shared hit based clustering** with unordered_map ➡ probably almost as fast but a bit less efficient in the end

Shared hits based clustering

- Idea : 1 cluster = 1 truth particle
- Still needed in the DBScan case to create sub-cluster with hits sharing tracks
- Base purely on unordered_map, the speed shouldn't decrease with the number of tracks
- 1 Cluster ~ 1 track with large number of measurements (More measurements ➡ better track)
- Add track to cluster if they share a hit with the primary track



Machine learning based Ambiguity Solving

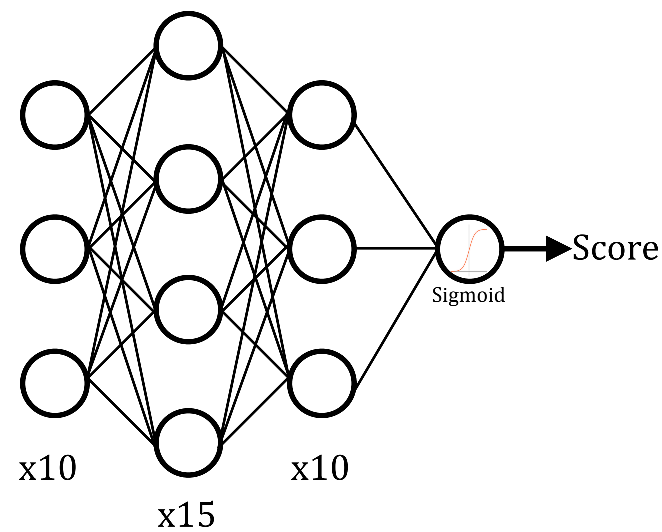
Cluster Tracks together → Network to determine the best track per cluster → Network to Clean the remaining tracks

Three steps plan for the ML based Ambiguity Solving :

- **Neural Network** : Score the track in each cluster, keep the highest score per cluster
  - This is not a classification problem but a **ranking** one
  - Not an extremely complex problem : a small MLP is enough (3 layers)
  - No parameter tuning needed for a new detector, just need to retrain the network (use 100 ttbar events, takes ~ 1h)
  - Use **Onnxruntime** to perform the inference in C++ inside Acts (all the result I will show today are from Acts)

Ranking Neural Network

- Simple 3 layers MLP with 10, 15, 10 nodes
- Use 8 parameters as input :
  - Number of states
  - Number of measurements
  - Number of Outliers
  - Number of Holes
  - NDF
  - Chi2/NDF
  - Eta
  - Phi
- Return **one score per track**
- Training performed per truth particles :
  - 1 loss function per truth
  - Implemented a margin ranking loss that try to separate the good track from the duplicate and fakes
  - Can then be use on cluster tracks

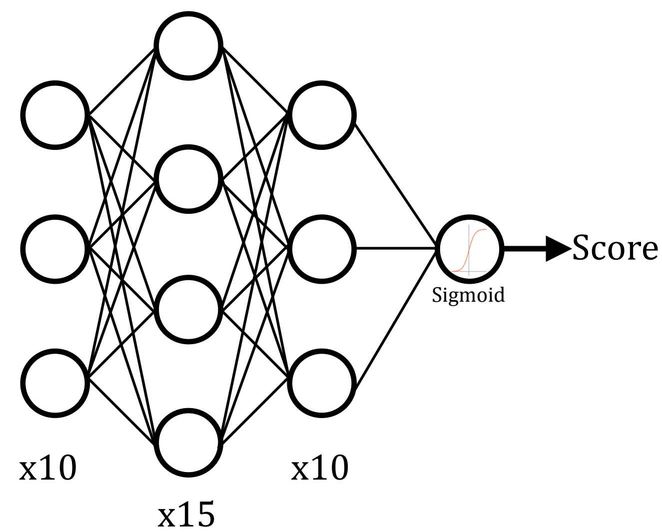


Ranking Neural Network

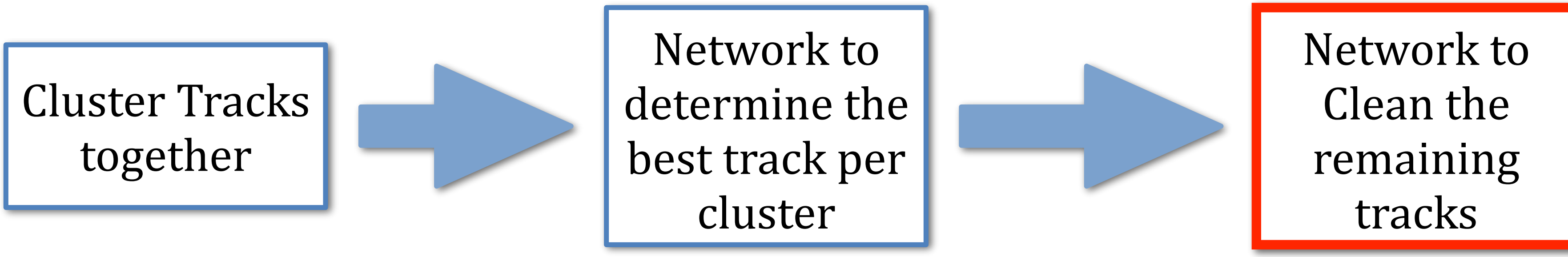
Margin Ranking Loss :

$$loss(x, y) = max(0, -1 \times (x - y) + margin)$$

- x : track score y : score good track
- Return 0 if $score_{duplicate} > (score_{good} - marging)$ else return the difference minus the margin
- Try to **separate the good and bad scores** by at least *margin*
- Here *margin*=0.05
- The effect of the merging value hasn't been fully tested but *margin*=0 doesn't converge



Machine learning based Ambiguity Solving



Three steps plan for the ML based Ambiguity Solving :

- **Cleaning** : remove the remaining fake and duplicate
  - Almost trivial, just a basic classifier
  - **Not implemented** right now, the performances are more than good enough without
  - Would be important if we start having fakes further away from the good track which would not be picked by the clustering

Performances : definition

- Used the **ODD full chain** to study the performance of the algorithm in Acts and compare it with the current Algorithms.
- Geant4 + Pythia simulation of 20 ttbar event (for the perf, 100 for training)
- Save as CSV files the tracks after the CKF, MLAmbiguity Solver and classic Ambiguity Solver ➡ compare with a python script
- Timing measured roughly on my machine
- In this study I only consider tracks with ≥7 measurements
- Definition :
  - **Good track** : for a given truth particle, track with the most truth match measurements, then the fewer outliers, then the smallest chi2
  - **Duplicate** : > 50% truth matched measurements
  - **Fake** : < 50 % truth matched measurements

Performances : Efficiency

- We run the **ODD full chain** with the default parameters 20 ttbar events
- The Efficiency (good tracks) : Fraction of the original good track still present
- Efficiency (truth tracks) : Fraction of the original truth particle still present
- The rates are with respect to the number of track after the solver
- More work needed in timing evaluation
- In my python version I can increase both efficiency by 1% using DBScan

	Number of tracks	Number of truth particles	Efficiency (good tracks)	Efficiency (truth tracks)	Duplicate Rate	Fake Rate	Solver speed [s/event]
CKF	6566.2	761.05	100 %	100 %	88.4 %	0.027 %	0
CKF + Solver	763.1	760.8	18.7 %	99.97 %	0.19 %	0.11 %	23.38
CKF + ML Solver	750.8	749.65	93.6 %	98.5 %	0.10 %	0.05 %	0.5

Performances : What is missing ?

- The algorithm show great performances, but the simulation might be too simple :
  - The parameters of the full chain are **not optimised** so the improvement is with respect to that configuration
  - Not so many fakes exist (and most of them are just poorly reconstructed tracks), should we **simulate the noise** in the detector ?
  - The **definitions** of truth particle and good particle are pretty basic right now (only at the hits level), better (track level) definition ?
- Clustering and inference implemented in Acts, I am in the process of opening a few PR for them
- The DBScan clustering seem to improve the performances of the MLSolver, I will need to see what is needed to use mlpack in ACTS

Next steps

- For now the training is based on truth particles, I want to try using the cluster in the training
- Do some proper timing measurement, identify possible inefficiency sources (what is the impact of the network size ?)
- All the test so far have been performed with the ODD, how well does this translate to other detector (ITk ?)
- A talk will be given at CHEP this year on this subject

BACKUP