TrackML : a Tracking Machine Learning Challenge

ACAT, Saas-fee, 10-15 March 2019

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Outline

- Forewords on Charged Particle Tracking and Machine Learning
- A Tracking with Machine Learning Challenge
- Accuracy and Throughput Phases
- Lessons Learned and outlook
Charged Particle Tracking
Tracking in a Nutshell

- Particle trajectory bended in a solenoidal magnetic field
- Curvature is a proxy to momentum
- Particle ionize silicon pixel and strip throughout several concentric layers
- **Thousands of sparse hits**
- Lots of hit pollution from low momentum, secondary particles

Seeding

Kalman Filter

- Explosion in hit combinatorics in both seeding and stepping pattern recognition
- Highly computing consuming task in extracting physics content from LHC data
Cost of Tracking

- Charged particle track reconstruction is one of the **most CPU consuming task** in event reconstruction
- Future computing budget flat at best
- Optimizations (to fit in computational budgets) **mostly saturated** and **long way to go** for HL-LHC
- Need factor **10-100 speed-up**
Fast Hardware Tracking

- Track trigger implementation for Trigger upgrades development on-going
- Several approaches investigated
- **Dedicated hardware is the key** to fast computation.
- **Not applicable for offline** processing unless by adopting heterogeneous hardware.

Pattern Recognition With Deep Learning
Scene Labeling

- There exists recent work on applying machine learning and deep learning as we know it to the challenge of particle tracking:
  - Hopfield network: http://inspirehep.net/record/300646/
  - CNN in NOVA: https://arxiv.org/abs/1604.01444
  - HEP.TrkX: https://heptrkx.github.io/
  - TrackML RAMP: https://tinyurl.com/y84yd5hn
  - ... no golden solution yet
Some Early Solutions

\[ E = -\frac{1}{2} \left( \sum_{i,j} w_{ij} s_i s_j - 2 \sum_i \theta s_i \right) \]

Fig. 4. Tracks in the ALEPH TPC reconstructed with a Hopfield net [13].

https://tinyurl.com/y9swquw6

https://arxiv.org/abs/1604.01444

https://tinyurl.com/y87saehf

https://tinyurl.com/yb3v93y9

Hadronic Feature Map

Muon Feature Map

Muon Neutrino
DIS CC

Muon Neutrino
QE CC

https://arxiv.org/abs/1604.01444
Bottom Lines

Current algorithms for tracking are highly performant physics-wise and scale badly computation-wise

Faster implementations are possible with dedicated hardware

Reach out to machine learning community for new methods and possible solution, applicable on commodity hardware
A Tracking with Machine Learning Challenge
Previous Challenges

- 2000 teams. Largest competition at the time
- Winners went to DeepMind and OpenAI
  https://www.kaggle.com/c/higgs-boson

- 700 teams.
- Experienced data exploitation
- Some methods learned and re-applied later
  https://www.kaggle.com/c/flavours-of-physics

The organizing team has participated in the organization of both events
Challenge Datasets

- Accurate simulation engine (ACTS) to produce realistic dataset
  - One file with list 3D points
  - Ground truth: one file with point to particle association
  - Ground truth auxiliary: true particle parameter (origin, direction, curvature)
  - Typical events with ~200 parasitic collisions (~10,000 tracks/event, ~100k hits/event)
- The goal of the challenge is to **assemble hits into tracks**
- Large training sample 100k events, 10 billion tracks ~100 GB
- Run in two phases
  - **Accuracy phase** on Kaggle platform
  - **Throughput phase** on Codalab
The Jury

Markus Elsing, CERN senior staff, group leader of the ATLAS computing and software group.  
**Frank Gaede** senior physicist at DESY (Germany) is software coordinator for ILD.  
**Alison Lowndes** is responsible for NVIDIA's Artificial Intelligence Developer Relations in the Europe, Middle East & Africa region.  
**Maurizio Pierini** is a CERN physicist lead of the machine learning for Particle Physics ERC grant.  
**Danilo Rezende** is Staff Research Scientist at Google DeepMind.  
**Marc Schoenauer** is senior scientist at INRIA-Saclay  
**Svyatoslav Voloshynovskyy** is associate professor at University of Geneva.

Reviewed the documentation made public by contestants of the challenge and decided on the level of innovation.

https://sites.google.com/site/trackmlparticle/international-advisory-committee
# TrackML Particle Tracking Challenge

**High Energy Physics particle tracking in CERN detectors**

**CERN · 653 teams · 7 months ago**

## Overview

### Description

To explore what our universe is made of, scientists at CERN are colliding protons, essentially creating mini-black holes, in their Large Hadron Collider. These highly energetic collisions generate millions of particles that pass through CERN’s silicon detectors.

While interpreting the intricate observations is already a massive scientific accomplishment, analyzing the enormous amounts of data produced from the experiments is becoming an overwhelming challenge.

Event rates have already reached hundreds of millions of collisions per second, meaning physicists must sift through tens of petabytes of data per year. And, as the resolution of detectors improve, ever better software is needed for real-time pre-processing and filtering of the most promising events, producing even more data.

To help address this problem, a team of Machine Learning experts and physics scientists working at **CERN** (the world largest high energy physics laboratory), has partnered with Kaggle and prestigious sponsors to answer the question: can machine learning assist high energy physics in discovering and characterizing new particles?

### Evaluation

### Timeline

**Accuracy Phase**

April 30 – August 13, 2018

### Prizes

### About The Sponsors

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Scoring

- At least 50% hits from the same ground truth particle
- At least 50% hits of the ground truth particle in the track
- Sum of weights \( (w_{\text{order}} \times w_{pT}) \) of truth matched hits

- Score normalized to sum of weights: ideal score is 1
- 100 events used for scoring: precision \(~0.1\%\)
Final Leaderboard

https://www.kaggle.com/c/trackml-particle-identification/leaderboard
The “Physics Score”

Weighted distribution of track parameters in the dataset
Physics Performance

Highest score correlates well with the tracking efficiency
• **Good** track and particle purities above 50% (goes into the score)
• **Split** particle purity below 50%, track purity above 50%
• **Multiple** Particle purity above 50%, but track purity below 50%
• **Bad** Both below 50%
Insight on Algorithms 1/2

• **First : Top Quarks**
  ▶ Johan Sokrates is an industrial Mathematics master student
  ▶ Pair seeding, triplet extension, **trajectory following**, track cleaning,
    all with **machine learning** for quality selection

• **Second :**
  ▶ Pei-Lien Chou is a software engineer in image-based deep learning in Taïwan
  ▶ **Machine learning** to predict the adjacency matrix

• **Third :**
  ▶ Sergey Gorbunov is a physicist, expert in tracking
  ▶ Triplet seeding, **trajectory following**
Insight on Algorithms 2/2

- **Jury Innovative prize**
  - Yuval Reina is an electronic engineer and Trian Xylouris is an entrepreneur
  - Marginalized Hough transform with **machine learning classifier**

- **Jury Clustering prize**
  - Jean-François Puget CPMP is a software engineer at IBM. He is both competition and discussion Kaggle grandmaster
  - **DBSCAN clustering** with iterative Hough transform

- **Jury Deep Learning prize**
  - Nicole and Liam Finnie are software engineers
  - DBSCAN seeding, **trajectory following with LSTM**

- **Organization pick**
  - Diogo R. Ferreira is a professor/researcher, focusing on data science and nuclear fusion
  - **Pattern matching**
Lesson Learned

• Preparing a challenge is a hard process
• Not too surprising to find trajectory following in winning solutions. Great to have machine learning added
• Noise-driven control of the combinatorial explosion
• Controlling efficiency along the algorithm
• Data driven estimation of the magnetic field
• Computational cost of deep learning
• Tuning of algorithm parameters
Throughput Phase

Oct 12 – March 12, 2019

Modifications to the dataset
- Same detector geometry with half thinner modules
- Beamspot corrected from 5.5 mm to 5.5 cm
- Loopers are not simulated
- Bug on electron multiple scattering fixed

https://competitions.codalab.org/competitions/20112
Scoring

Zero score if time > 600s and accuracy < 0.5

\[
\sqrt{\log \left(1 + \frac{600}{\text{time}}\right)} \times (\text{accuracy} - 0.5)^2
\]
## Leaderboard

<table>
<thead>
<tr>
<th>#</th>
<th>User</th>
<th>Entries</th>
<th>Date of Last Entry</th>
<th>score ▲</th>
<th>accuracy_mean ▲</th>
<th>accuracy_std ▲</th>
<th>computation time (sec) ▲</th>
<th>computation speed (sec/event) ▲</th>
<th>Duration ▲</th>
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<td>0.944 (2)</td>
<td>0.00 (14)</td>
<td>28.06 (1)</td>
<td>0.56 (1)</td>
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<td>0.944 (1)</td>
<td>0.00 (15)</td>
<td>55.51 (16)</td>
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<td>0.928 (3)</td>
<td>0.00 (13)</td>
<td>364.00 (18)</td>
<td>7.28 (18)</td>
<td>407.00 (8)</td>
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<td>0.895 (4)</td>
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<td>10.00 (19)</td>
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<td>48.63 (4)</td>
<td>0.97 (4)</td>
<td>86.00 (3)</td>
</tr>
</tbody>
</table>

**HEP people**

**PH+CS**

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Final leaderboard to be determined from more precise time measurement.
Incidentally, best solutions are also best accuracy and best timing. Software will be submitted and analyzed in the coming weeks.
Summary & Outlook

• Active challenge on both platforms.

• Some lesson learned so far. Chapter in NeurIPS 2019 competition book.

• Traditional trajectory following was used. Some machine learning technique presented.

• Further work required to extract the novel ideas proposed during the challenge. Ongoing work to port it in ACTS.

• Final version of the dataset will be on the cern open data portal. Already used in several benchmarking.

• Stay tune for the aftermath of the throughput phase.
Extra Material
Complexity and Ambiguity

Shown trajectories are reconstructed objects

The future is with x10 more hits
Scene Labeling

Farabet et al. ICML 2012, PAMI 2013