

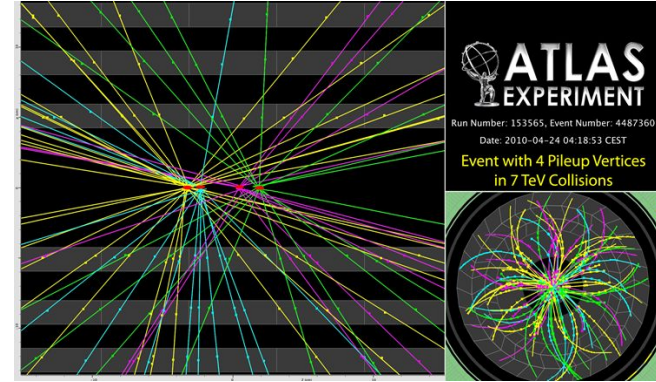
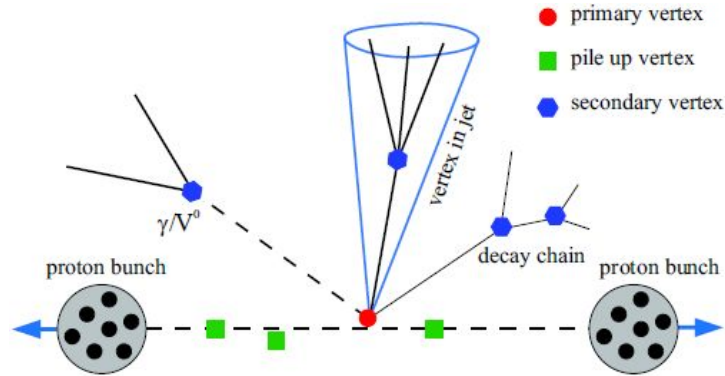
Vertexing using SaltModel: Experiments with ColliderML dataset

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TrackOpt meeting
7th September 2026

Recap: Primary vertexing vs. secondary vertexing



- For our purpose, we call both “**primary vertex**” and “**pileup vertex**” inclusively as the **primary vertices**.
- Each track in an event is associated to one of these **primary vertices**.
 - This includes tracks originating from the **secondary vertices**.

The ColliderML dataset

- Large-scale simulated dataset intended for algorithm research.
- Modelled after a realistic detector for HL-LHC, consists of information from different sub-detectors:
 1. particles (truth-level)
 2. tracker_hits (detector-level)
 3. calo_hits (detector-level)
 4. tracks (reconstruction-level)
- MC events are generated for:
 - Different Physics process (e.g., ttbar, ggf, dihiggs)
 - Different pileup conditions (pu0 = no pileup, pu200 = HL-LHC pileup)

Using ColliderML dataset for vertexing research

Field	Description
<code>event_id</code>	Unique event identifier
<code>track_id</code>	Unique track identifier within event
<code>majority_particle_id</code>	Truth particle with most hits on this track
<code>d0</code>	Transverse impact parameter (mm)
<code>z0</code>	Longitudinal impact parameter (mm)
<code>phi</code>	Azimuthal angle (radians)
<code>theta</code>	Polar angle (radians)
<code>qop</code>	Charge divided by momentum (e/GeV)
<code>hit_ids</code>	List of tracker hit IDs on this track

Field	Description
<code>event_id</code>	Unique event identifier
<code>particle_id</code>	Unique particle ID within event
<code>pdg_id</code>	PDG particle code (11=electron, 13=muon, 211=pion, etc.)
<code>mass</code>	Particle rest mass (GeV/c ²)
<code>energy</code>	Particle total energy (GeV)
<code>charge</code>	Electric charge (units of e)
<code>px, py, pz</code>	Momentum components (GeV/c)
<code>vx, vy, vz</code>	Vertex position (mm)
<code>time</code>	Production time (ns)
<code>perigee_d0, z0</code>	Perigee impact parameters (mm)
<code>primary</code>	Whether particle is primary
<code>vertex_primary</code>	Primary vertex index (1=hard scatter)

Group by (vx,vy,vz)

Using ColliderML dataset for vertexing research

Event number: 0

	vx	vy	vz
640	23.791132	-5.039636	130.088516
643	23.791132	-5.039636	130.088516

	vx	vy	vz
551	28.624298	-22.364754	-344.434326
575	28.624298	-22.364754	-344.434326

Event number: 1

	vx	vy	vz
454	34.311501	-43.547958	-616.7771
472	34.311501	-43.547958	-616.7771

Event number: 2

	vx	vy	vz
1319	-804.349915	-15.901301	-1276.860107
1330	-804.349915	-15.901301	-1276.860107

	vx	vy	vz
882	23.057499	29.151842	33.008316
921	23.057499	29.151842	33.008316

Event number: 3

=====
Event number: 4

	vx	vy	vz
445	-8.490943	-37.420902	154.639587
448	-8.490943	-37.420902	154.639587

	vx	vy	vz
1167	556.873718	594.055725	-748.714478
1168	556.873718	594.055725	-748.714478

=====
Event number: 5

	vx	vy	vz
1990	-22.302839	31.07262	31.330093
2022	-22.302839	31.07262	31.330093

	vx	vy	vz
2115	-1.526555	0.612422	36.911095
2248	-1.526555	0.612422	36.911095

	vx	vy	vz
1119	23.798487	-0.784967	-40.47855
1141	23.798487	-0.784967	-40.47855

=====

Event number: 6

	vx	vy	vz
351	-23.370489	-31.059721	170.855377
355	-23.370489	-31.059721	170.855377

	vx	vy	vz
1440	25.479441	26.947424	112.898849
1444	25.479441	26.947424	112.898849

=====
Event number: 7

	vx	vy	vz
304	-25.171206	-25.622263	-170.397568
311	-25.171206	-25.622263	-170.397568

	vx	vy	vz
1736	24.66535	25.430759	291.385071
1737	24.66535	25.430759	291.385071

	vx	vy	vz
1735	40.272182	42.37019	-529.946106
1738	40.272182	42.37019	-529.946106
1741	40.272182	42.37019	-529.946106

	vx	vy	vz
1497	220.518051	522.27655	1149.442993
1950	220.518051	522.27655	1149.442993

=====
Event number: 8

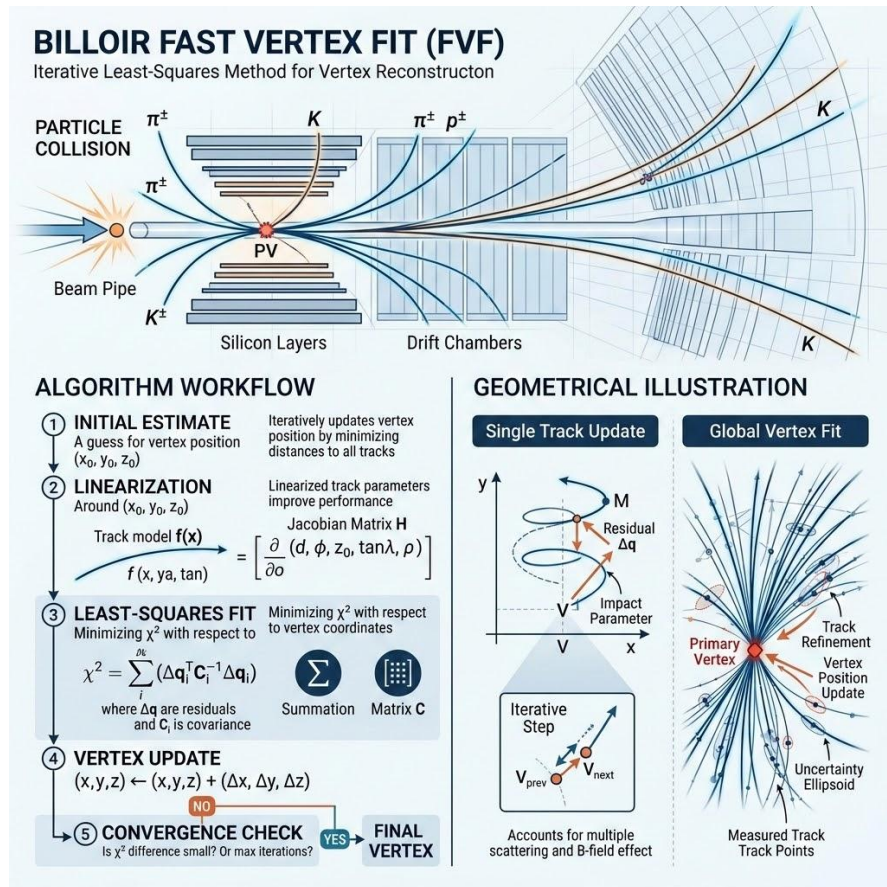
=====
Event number: 9

=====

primary == 0

Billoir fit in Python

- Invented by Pierre Billoir.
- Standard technique for *vertexing*:
 - Whether a set of tracks is originated from the same vertex.
 - Calculate the position of this vertex.
 - Correct the tracks momenta.
- The current implementation (from Vadim) is in ROOT, and not-so-easy to use with the ColliderML dataset.



Billoir fit in Python: ROOT vs numpy

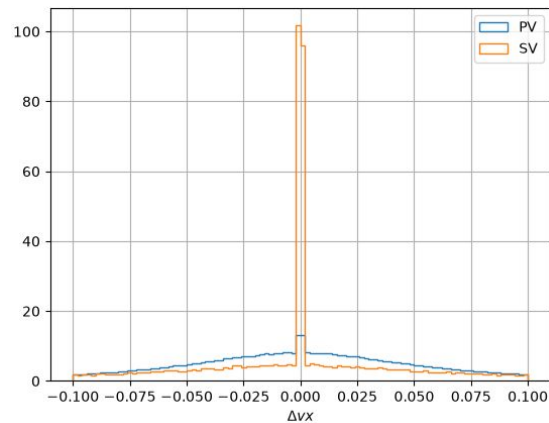
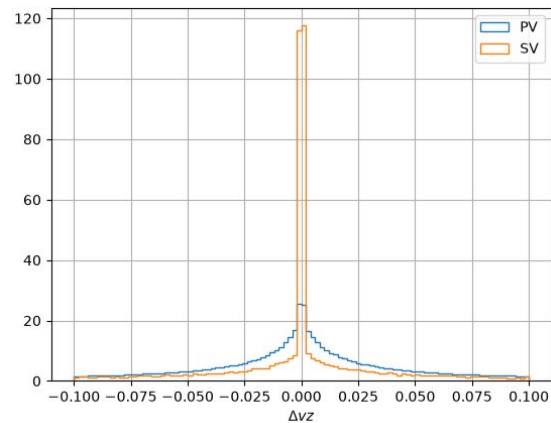
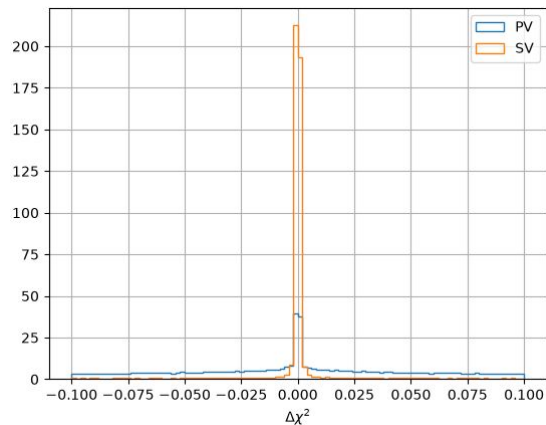
Implemented in ~150 lines of numpy code. The implementation is slow, but I could readily translate it to numba and pytorch using LLMs, which are significantly faster.

t_vx	vadim_vx	dipta_vx
-0.335286	-0.502742	-0.502699
-13.725449	-13.852321	-13.851948
11.359540	11.833704	11.833023
1.530382	1.521566	1.521566
-32.385628	-32.434696	-32.434685
-1.512289	-1.701477	-1.701271
-3.292901	-3.282216	-3.282206
-3.292901	-3.471185	-3.471200
-3.292901	-3.489085	-3.489002
-3.304003	-3.350973	-3.350984

t_vy	vadim_vy	dipta_vy
-0.153082	-0.304685	-0.304674
-29.455383	-29.655619	-29.654898
3.374577	3.507995	3.507789
0.813375	0.852308	0.852308
17.882717	17.917532	17.917527
-2.867919	-3.218182	-3.217758
7.530176	7.467003	7.466973
7.530176	8.032998	8.033029
7.530176	7.981745	7.981614
7.553091	7.653723	7.653755

t_vz	vadim_vz	dipta_vz
-7.037555	-7.451469	-7.451402
-118.613693	-119.481049	-119.478010
-19.370573	-20.469828	-20.468259
40.106155	40.079216	40.079215
-347.082581	-347.721069	-347.721056
-11.381413	-11.699656	-11.699209
-101.123314	-100.693695	-100.693542
-101.123314	-104.247940	-104.248151
-101.123314	-104.191864	-104.191009
-101.282906	-102.079597	-102.079826

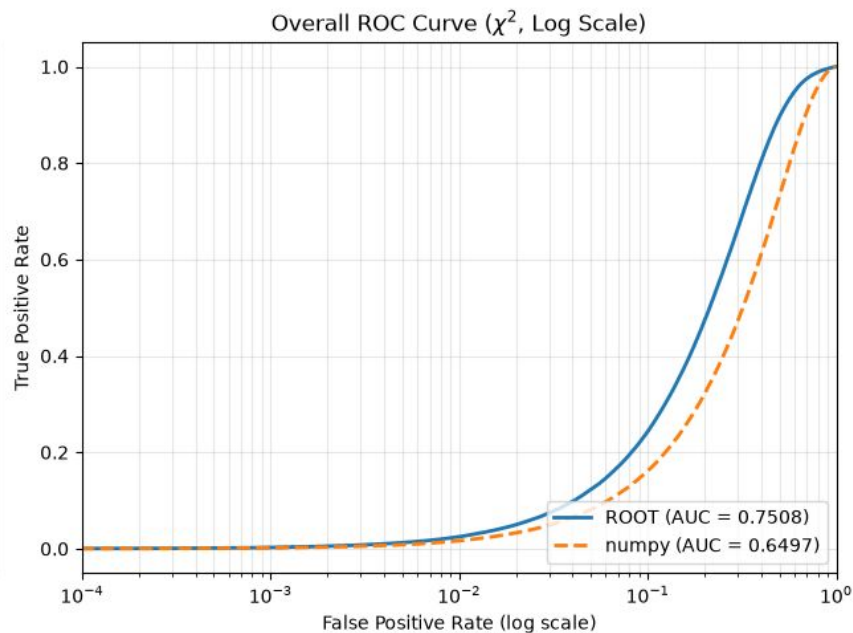
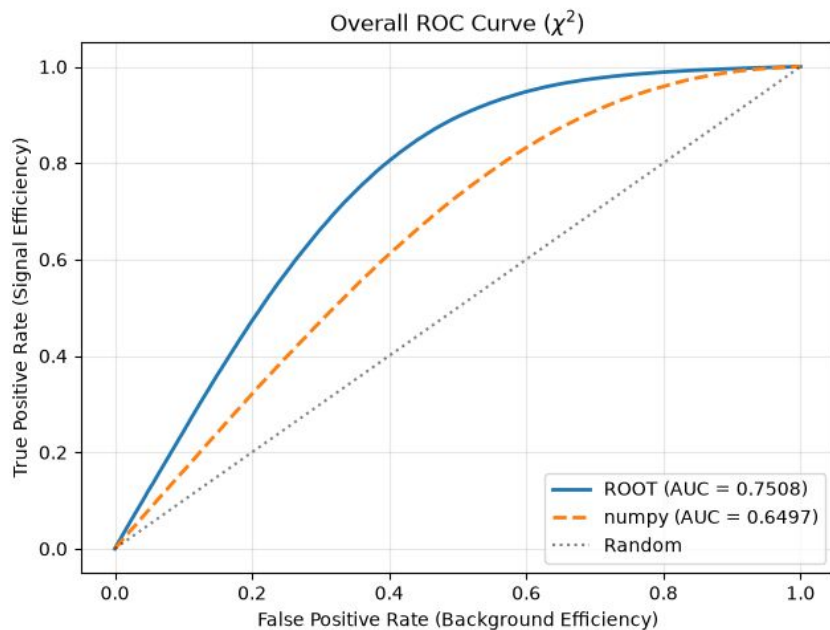
Billoir fit in Python: ROOT vs numpy



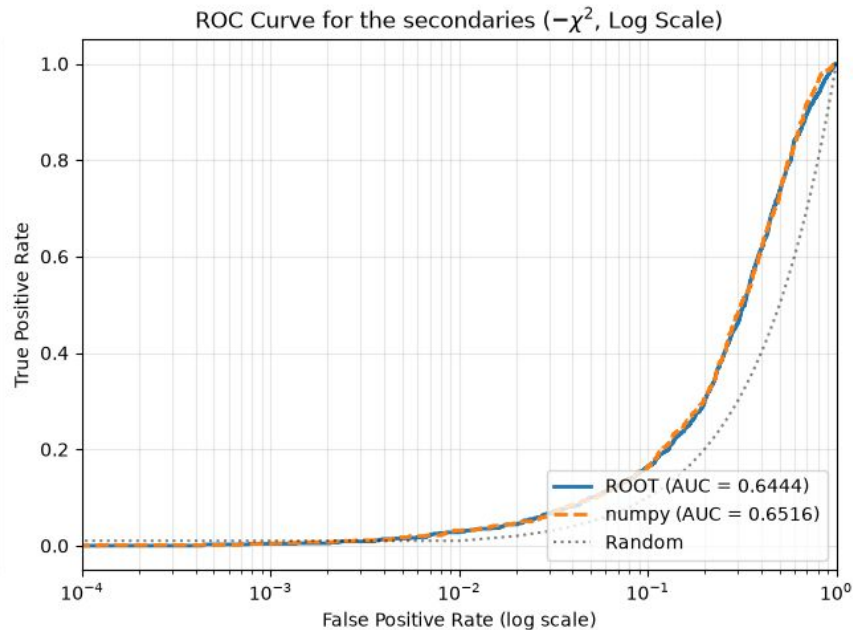
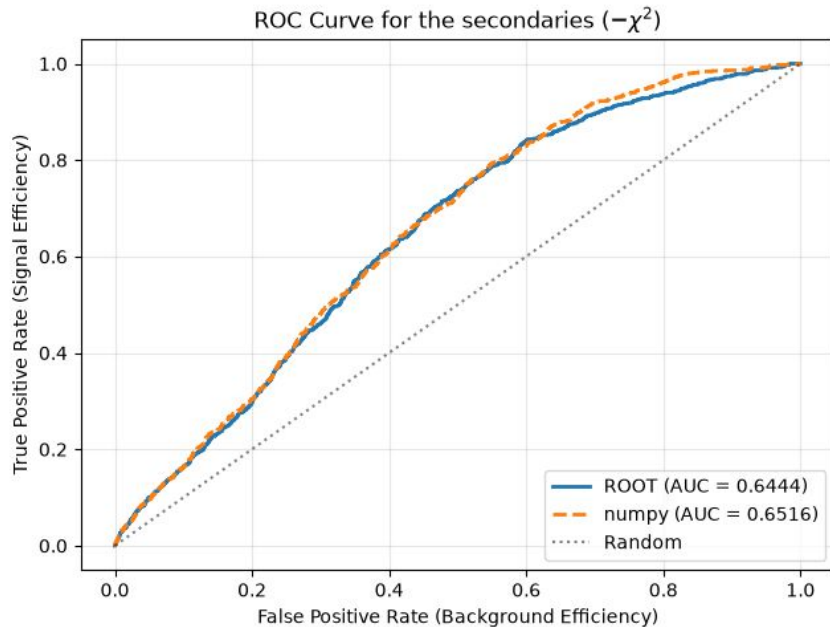
PV: $t_{vx}^2 + t_{vy}^2 < 0.01$

SV: $t_{vx}^2 + t_{vy}^2 > 0.01$

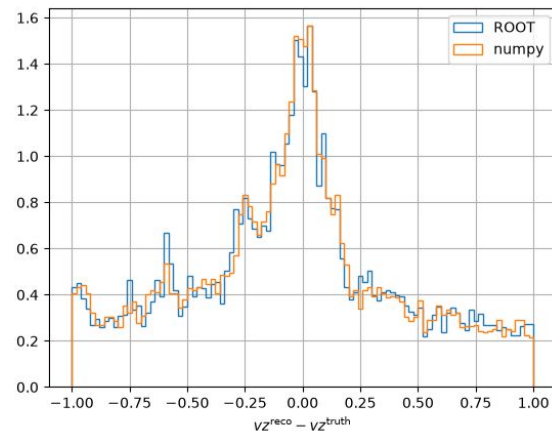
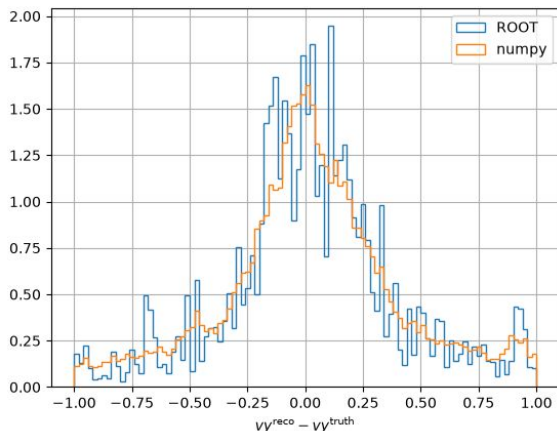
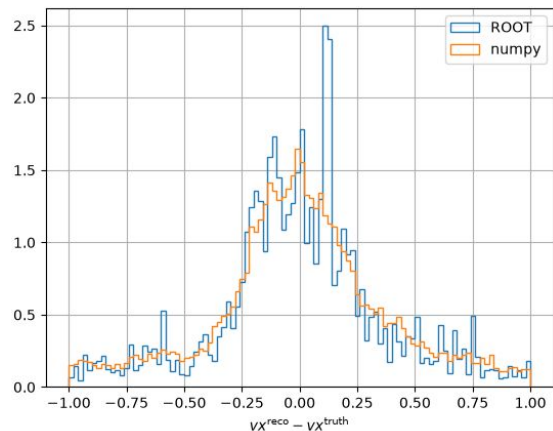
Billoir fit in python: ROOT vs numpy



Billoir fit in python: ROOT vs numpy



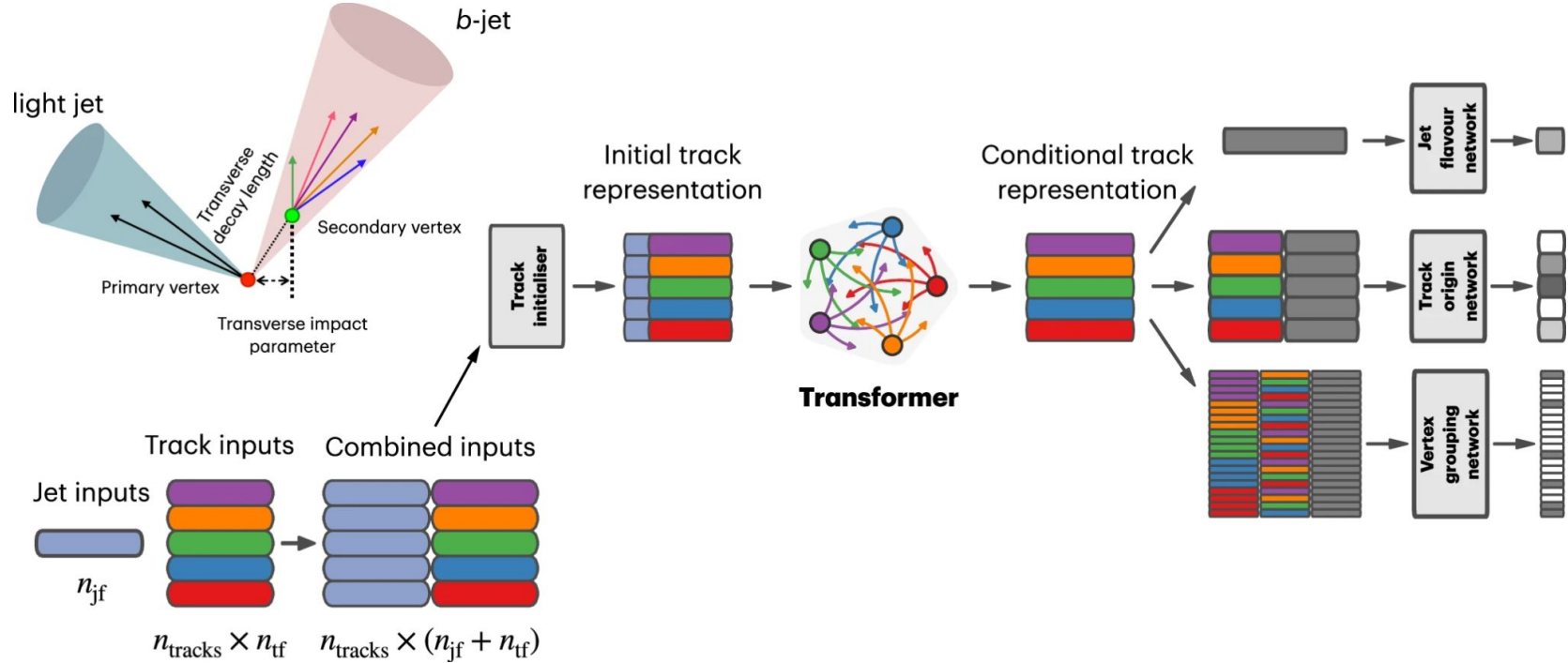
Billoir fit in python: ROOT vs numpy



Using SVs only

SV: $t_{vx}^{**2} + t_{vy}^{**2} > 0.01$

Vertexing using SaltModel



The GN2 flavour tagger implemented as a SaltModel

What is *salt* and SaltModel?

Salt is the state-of-the-art ML framework maintained by *ATLAS Jet Flavour Tagging* group, intended for building *end-to-end* unified *transformer-based* models.

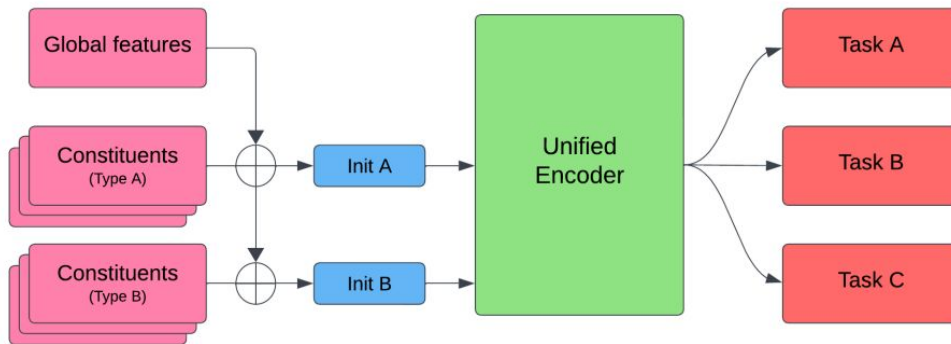


Figure 1: This diagram illustrates the flow of information within a generic model trained using Salt. In this example, global object features are provided alongside two types of constituents, “Type A” and “Type B”, which represent different input modalities such as charged particle trajectories or calorimeter energy depositions. The model is configured with three training objectives, each of which may relate to the global object or one of the constituent modalities. Concatenation is denoted by $\oplus$.

Reference: Salt: Multimodal Multitask Machine Learning for High Energy Physics

Jackson Barr¹, Diptaparna Biswas², Maxence Dragnet³, Philipp Gadow⁴, Emil Haines¹, Osama Karkout⁵, Dmitrii Kobylanskiy⁶, Wei Sheng Lai¹, Matthew Leigh⁷, Nicholas Luongo¹⁰, Ivan Oleksiyuk⁷, Nikita Pond¹, Sébastien Rettie⁴, Sébastien Vaitkus¹, Samuel Van Stroud¹, and Johannes Wagner⁹

Vertexing using SaltModel

variables:

```
events:
  - ntracks
tracks:
  - d0
  - z0
  - qop
  - phi
  - theta
```

encoder:

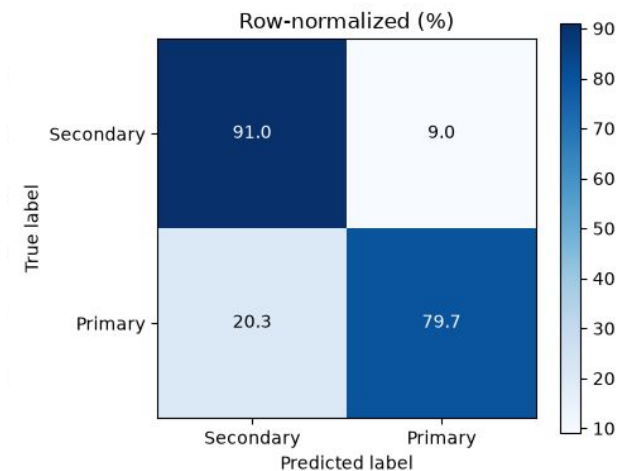
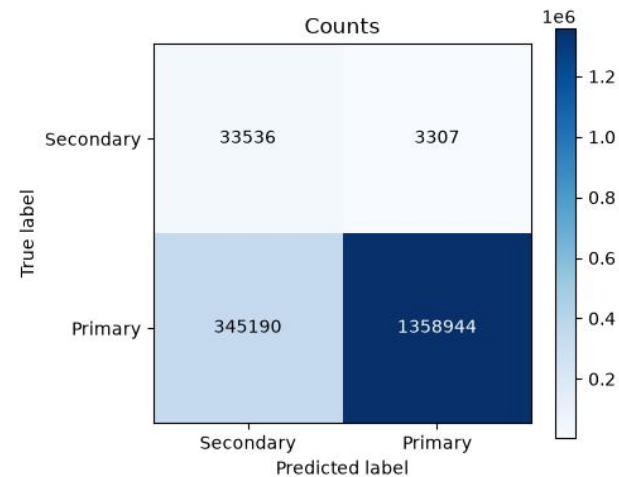
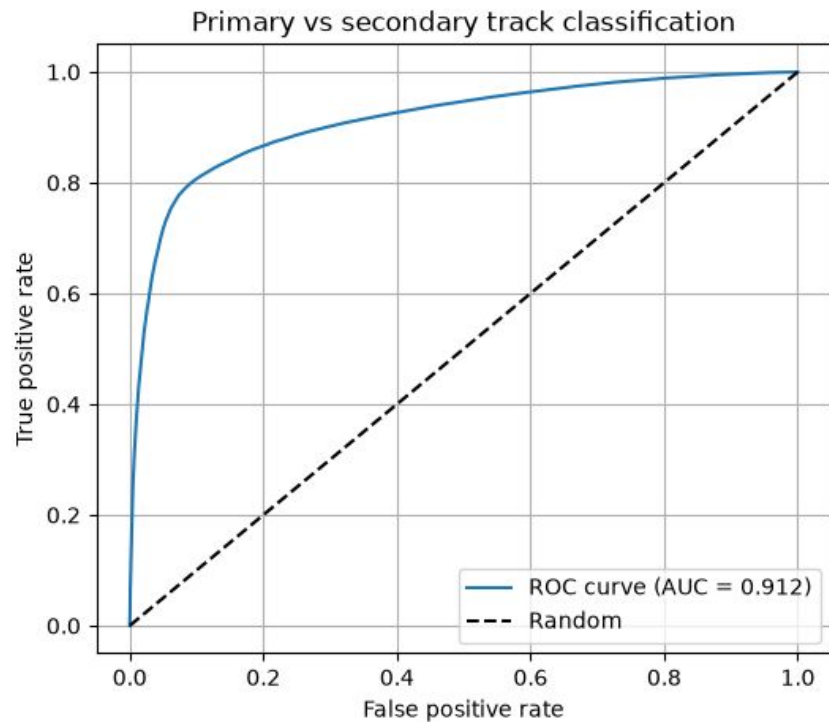
```
class_path: salt.models.Transformer
init_args:
  num_layers: 4
  embed_dim: 32
  out_dim: 32
  attn_type: flash-varlen
  norm: RMSNorm
  norm_type: hybrid
  dense_kwargs:
    activation: SiLU
  gated: True
  attn_kwargs:
    num_heads: 4
  num_registers: 4
```

tasks:

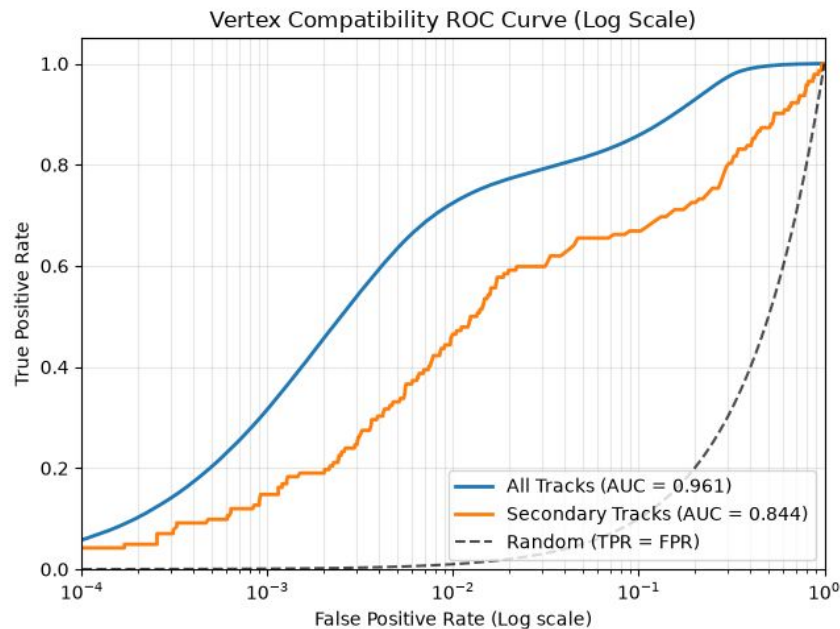
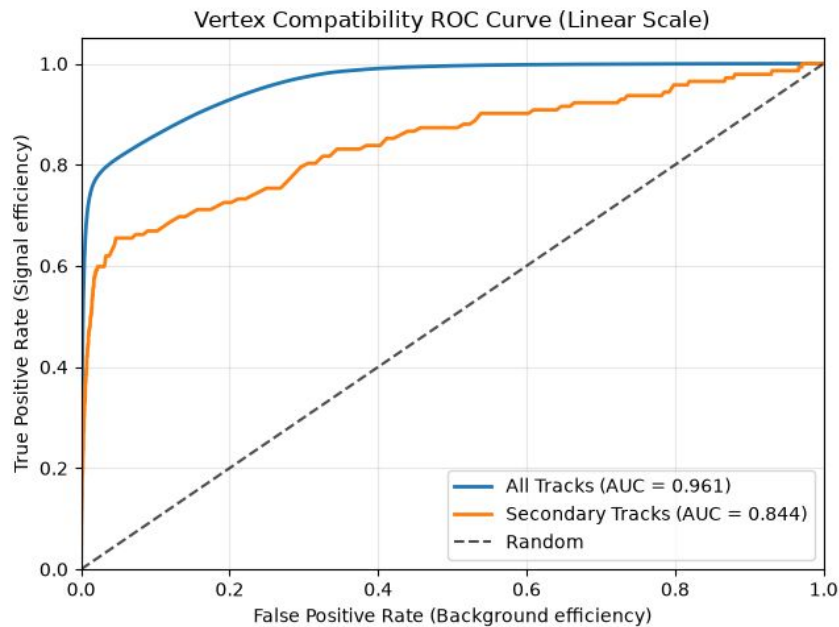
```
- class_path: salt.models.ClassificationTask
  init_args:
    name: track_origin
    input_name: tracks
    label: primary
    use_class_dict: True
    class_names: [secondary, primary]
    loss: torch.nn.CrossEntropyLoss
    dense_config:
      output_size: 2
      hidden_layers: [64, 32]

- class_path: salt.models.VertexingTask
  init_args:
    name: track_vertexing
    input_name: tracks
    label: vertex_id
  loss:
    class_path: torch.nn.BCEWithLogitsLoss
    init_args: { reduction: none }
  dense_config:
    input_size: 64
    output_size: 1
    hidden_layers: [64, 32]
```

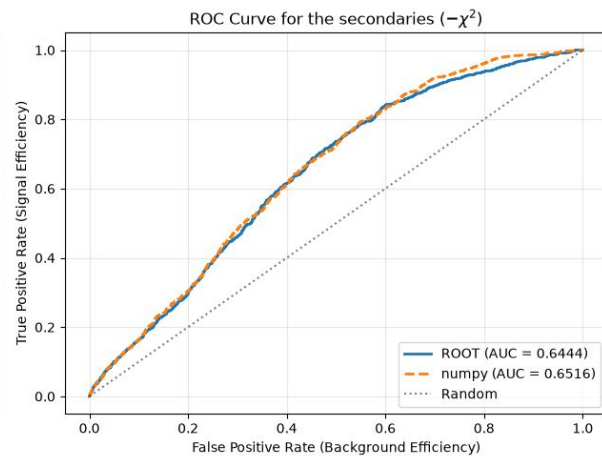
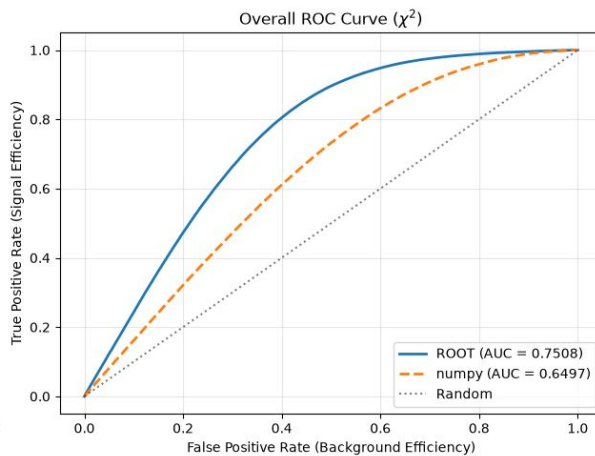
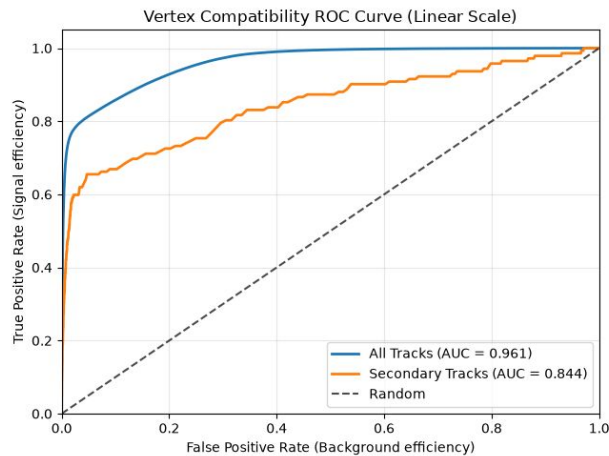
Track-origin classification



Track-pair compatibility



Track-pair compatibility



Method	AUC for all tracks	AUC for secondaries
Billoir fit (ROOT)	0.751	0.644
Billoir fit (numpy)	0.650	0.652
SaltModel	0.961	0.844

Summary and outlook

- Implemented Billoir fit in numpy, closely following Vadim's original implementation in ROOT.
 - Streamlined 1000+ lines of C++ code across 10+ files into ~150 lines of python code.
- The numpy implementation is then translated into pytorch using antigravity.
 - The implementation is ~ 800 lines long, and produces identical numbers.
 - Can be easily integrated into *salt* data-loader to calculate EDGE features.
- `SaltModel` predicts the track-pair compatibility matrix with a much better accuracy than the standalone Billoir fit.
 - This can be used with graph-partitioning, providing an alternate approach to MaskFormer.
 - Next step: integrate Billoir fit into *salt* data-loader and use EDGE features.