

ACTS Developers Workshop 2022

Exa.TrkX & ACTS tutorial session

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Overview

- Introduction to Exa.TrkX pipeline
- Tutorial
 - Generate training data
 - Configure & run training
 - Monitor & tune training performance
 - Convert models
 - Run inference in ACTS

Spacepoints (+ cluster information)



Embedding-Stage (= graph building)



Filter-Stage (= graph size reduction)



GNN-Stage (= edge scoring)



Track building

- Multi-stage machine-learning pipeline for track finding
 - Event as a graph (nodes = hits, edges = potential track segments)
 - Use GNNs to find edges that correspond to track segments
- See <u>talk</u> by Xiangyang yesterday

Prerequisites

- Build acts with torchscript backend
- Docker images for training & inference under <u>github.com/acts-project/machines</u>
- ACTS_BUILD_EXAMPLES_EXATRKX:BOOL=ON
 ACTS_BUILD_PLUGIN_EXATRKX:BOOL=ON
 ACTS_EXATRKX_ENABLE_ONNX:BOOL=OFF
 ACTS_EXATRKX_ENABLE_TORCH:BOOL=ON
- Take a look at the Dockerfile to for precise install instructions
- Training:
 - CUDA, torch + family, pytorch-lightning, traintrack*, faiss, frnn (install from github)
 - GPU with lots of memory (~30 GB for ODD event with 200 pileup)
- ACTS inference:
 - CUDA, libtorch, torch-scatter (needs to be compiled locally)
 - Not so much GPU memory (~14 GB for ODD event with 200 pileup)

Training data generation

- Slightly modified Exa.TrkX code works with ACTS CSV output
- Required writers:
 - CsvTrackingGeometryWriter
 - CsvParticleWriter
 - CsvSimHitWriter
 - CsvMeasurementWriter (optional)
- Fixed directory structure
- Can be trained using truth hits or measurement data
 - Switch in the processing.yaml

```
detectors.csv
train_all
— event000000000-cells.csv
— event000000000-measurements.csv
— event000000000-measurement-simhit-map.csv
— event000000000-particles.csv
— event000000001-cells.csv
— event000000001-measurements.csv
— event000000001-measurement-simhit-map.csv
— event000000001-particles.csv
— event000000001-truth.csv
```

Configure the training

- Training steered by traintrack (by Daniel Murnane)
 - Project configuration at ./configs/project_config.yaml
 - Some other options possible (for schedulers etc.)

```
# Location of libraries
libraries:
    model_library: LightningModules
    artifact_library: tmp

# Which logger to use - options are Weights & Biases [wandb], TensorBoard [tb], or [None]
logger: wandb
```

Configure the training

```
stage_list:
    - {set: Processing, name: TrackMLFeatureStore, config: processing.yaml}
    - {set: Embedding, name: LayerlessEmbedding, config: embedding.yaml}
    - {set: Filter, name: VanillaFilter, config: filter.yaml, resume_id: 1suumxob}
# - {set: GNN, name: InteractionGNN, config: gnn.yaml}
```

- State list defines
 - "set" (basically subfolder)
 - Python class (in <Set>/Models/)
 - Configuration file (in <Set>)
 - resume_id
 - Allows to overwrite hyperparameters

```
iahtninaModules
  Embeddina
      Models
          inference.py

    layerless embedding.pv

      embedding_base.py
      embedding.yaml
  Filter
      Models
        inference.py
        vanilla_filter.py
      filter_base.py
      filter.yaml
      Models
        inference.py
          interaction_gnn.py
      gnn_base.py
      qnn.yaml
  Processing
      Models 

       feature construction.pv
      utils
      feature_store_base.py
      processing.yaml
```

```
Input/output configuration
# Dataset parameters
  signal cut: 0.0
# Model parameters
     channels: 0
  train: 0.2
   al: 0.2
  test: 0.2
  rain: 0.1
 : 0.0003
# Postprocessing
```

Configure the training

- Lots of parameters
 - Does evaluate environment variables
 - project used e.g., by wandb
 - callbacks generate output
 - [[...]] necessary for list

Run the training

- Set environment variables like \$EXATRKX DATA
- Run: \$ traintrack <pipeline-config-file>
- Can take very long dependent on data/event size
- If embedding/filter stages do not perform well enough,
 GNN stage can fail due to memory requirements
- **Note:** Training example of workshop does NOT aime for good performance, should just run in a few minutes

Resume from checkpoint

- Runs aborted due to connection errors etc. can be resumed:
 - Find out run id:

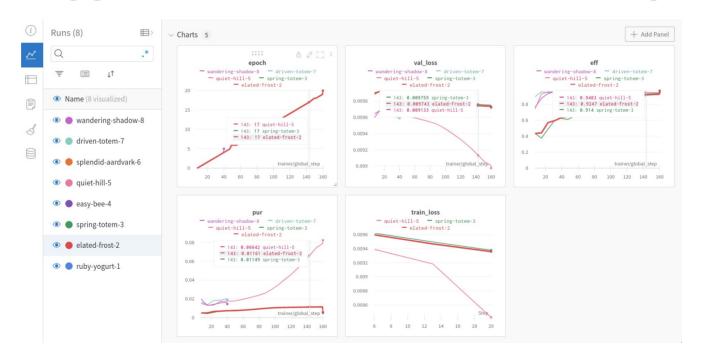
tmp/workshop-demo-embedding/us5xg97y/checkpoints

- Change pipeline.yaml accordingly

```
# - {set: Processing, name: TrackMLFeatureStore, config: processing.yaml}
    - {set: Embedding, name: LayerlessEmbedding, config: embedding.yaml, resume_id: us5xg97y}
    - {set: Filter, name: VanillaFilter, config: filter.yaml}
    - {set: GNN, name: InteractionGNN, config: gnn.yaml}
```

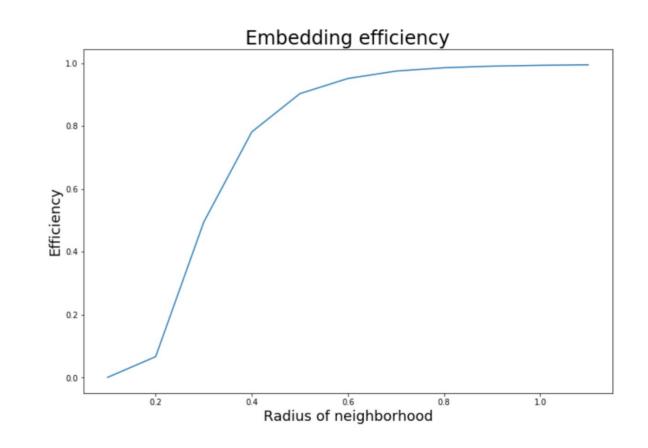
Monitor metrics

wandb logger allows real-time monitoring, etc.



Tune training

- Important HPs to controll efficiency/purity:
 - Embedding: radius
 - Filter: filter cut
 - GNN: edge cut
- Callbacks produce analysis graphs as *.pdf
 - Can also be done e.g. in a jupyter notebook (see <u>here</u>)
- General HP tuning possible with wandb



Convert to torchscript

- Straight forward:
 - load model from checkpoint (see <u>here</u>)
 - Look for last.ckpt in the tmp/<project>/<run-id> directory
 - Call model.eval() to leave training mode
 - Convert to torchscript (see <u>here</u>)
 - Prepare example input if use tracing mode:

```
n_nodes = 10
x = torch.rand(n_nodes,3)
edge_index = torch.randint(0,n_nodes,(2,10))
```

Run inference

- Setup Trackfinding algorithm:
 - Make spacepoints for whole detector
 - Needs geometry selection of whole detector
 - Add ExaTrkX algorithm
 - See also here
 - Ensure hyperparameter match the trained model
- CPU only not really possible now with the ACTS implementation

```
exaTrkXConfig =
    "modelDir": str(modelDir),
    "spacepointFeatures": 3,
    "embeddingDim": 8,
    "rVal" 0.05
    "knnVal": 500,
    "n_chunks": 12,
    "filterCut": 0.01
    "edgeCut": 0.5
```

Evaluate performance

- Use TrackFinderPerformanceWriter
- Two TTrees
 - track finder particles: particle based metrics

event	_id	particle_id	particle_type	vx	vy	vz	vt	рх	ру	pz	m	q	nhits	ntracks	ntracks_majority
	0	4503599677702144	-211	0.00e+00	0.00e+00	0.00e+00	0.00e+00	1.32	0.07	-24.55	1.40e-01	-1.0	5	1	1
	0	4503599694479360	211	0.00e+00	0.00e+00	0.00e+00	0.00e+00	-0.49	0.21	3.87	1.40e-01	1.0	11	1	1
	0	4503599711256576	-211	0.00e+00	0.00e+00	0.00e+00	0 00e+00	0.56	0.37	2 79	1 40e-01	-1 0	13	1	1

- track finder tracks: track based metrics

event_id	track_id	size	nparticles	particle_id	particle_nhits_total	particle_nhits_on_track
0	40	8	2	[680104020496351232, 76599679290179584]	[5, 3]	[5, 3]
0	43	8	2	[689050744396972032, 855683929217171456]	[4, 4]	[4, 4]
0	134	10	2	[833182425969328128 770149623439294464]	[10 1]	[9 1]

Evaluate performance

- Then do the analysis like you want
 - I have a jupyter notebook (see provided files)

```
fig. ax = plt.subplots(1,3, figsize=(18,5))
fig.suptitle("Efficiency")

ax[0].hist(particles_df.efficiencies)
ax[0].set_xlabel("efficiency")

#ax[0].scatter(particles_df.eta, particles_df.reconstructed, alpha=0.01)
ax[1].scatter(particles_df.eta, particles_df.efficiencies, alpha=0.005)
ax[1].set_ylabel("efficiency")
ax[1].set_ylabel("efficiency")
ax[2].scatter(particles_df.efficiencies, alpha=0.005)
ax[2].set_xlabel("efficiency")

= ax[1].set_ylabel("efficiency")

Efficiency

Efficiency

0.8
```

How can I do this at home?

- There is some code attached to the indico session
 - Some modifications compared to <u>upstream training code</u> of Exa.TrkX to support
 - mainly in the Preprocessing to support latest Writers
- I will add a "How to" soon to the ACTS documentation
- As well as a proper repository/fork with analysis scripts
- There will be soon a training CI in ACTS that could also be used as reference
- There are also tutorial-notebooks by Exa.TrkX (see here)
- If you encounter any problems:
 - E-mail: <u>benjamin.huth@ur.de</u>
 - Contact me on ACTS Mattermost channel

Developement Outlook

- Cluster information cannot be used yet
 - Should come soon
- More fine-grained interfaces for graph-building and edge-labeling (see talk by Xiangyang yesterday)
 - To allow for composable algorithms