Longitudinal Beam Diagnostics and Phase Space Reconstruction in the LHC Using ML

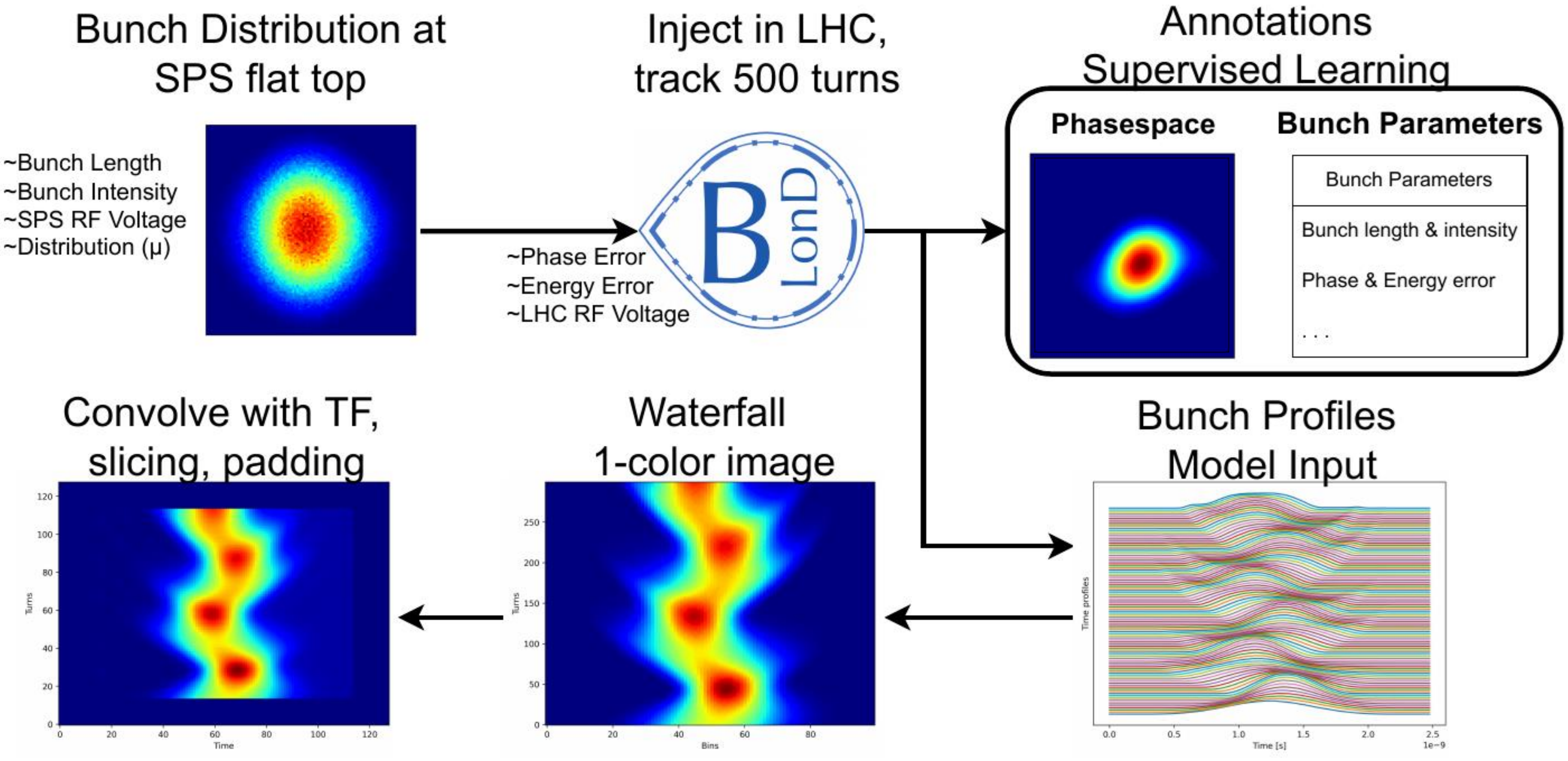
6th Inter-Experiment Machine Learning Workshop,
29Jan-2Feb 2024, CERN, Geneva, Switzerland

Konstantinos Iliakis[1], S. Albright[1], T. Argyropoulos[2], A. Lasheen[1], H. Timko[1], G. Trad[2]
[1]SY-RF, [2]BE-OP
konstantinos.iliakis@cern.ch

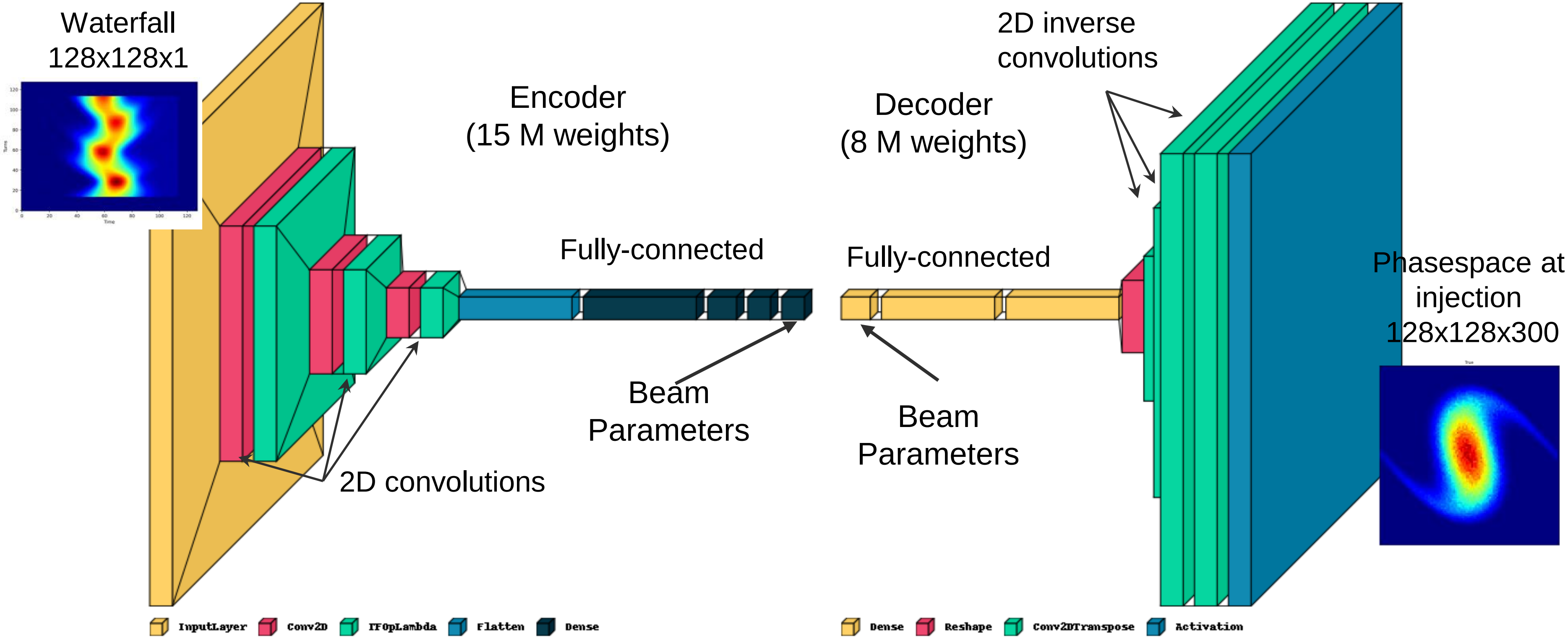
Motivation

- Knowledge of **longitudinal beam parameters** (e. g. energy error, phase error, bunch length and intensity) is **essential for beam performance**
  - Even more so in the HL-LHC era
- Leveraging the **high-resolution measurements of longitudinal bunch profiles**:
  - Using **fitting methods**, bunch length, intensity, injection errors can be calculated
  - Using **longitudinal tomography**, bunch distribution and emittance can be calculated
- Above methods **too time consuming for online use** →limited to single bunch
- **Develop ML model** to:
  - Obtain the desired **beam parameters**,
  - and the 2D **longitudinal beam distribution**
  - **Fast** enough to allow for **online use** with **multi-bunch beams**

Training Data Generation

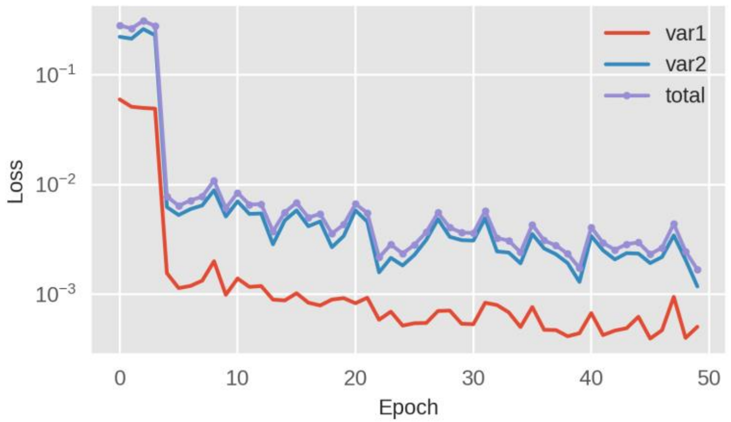


Original Model Architecture: Encoder- Decoder



Original Model Architecture: Limitations

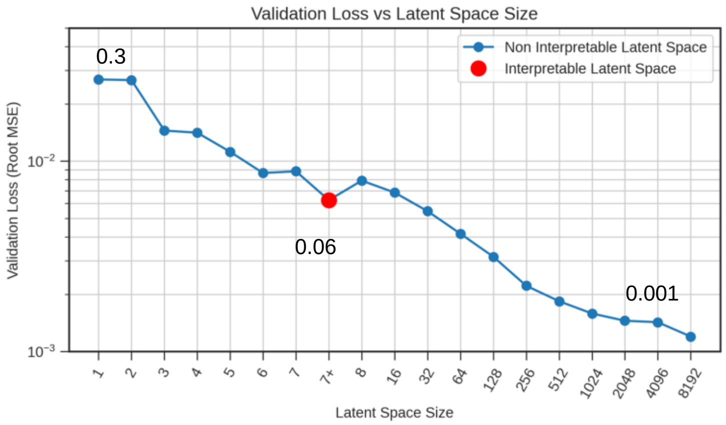
Multi-output Regression: Bottlenecks



Solution: Ensemble of Encoders

- One model per beam parameter
- No bottlenecks
- More weights (total 60M)

Restricted latent space: Sub-optimal



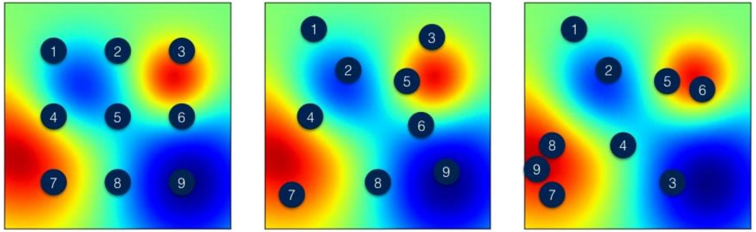
Solution: Unsupervised latent space

- Waterfall to phase-space directly
- Better precision (~25%)
- Does not provide beam parameters
- More weights (151M)

Model Hyperparameter Optimization

- **Huge Parameter Space**
    - 8 Models
    - Convolution layers (number, filters, kernels, activation)
    - Dense layers (number, size, activation function)
    - Regularization (dropout, batch normalization)
    - Learning rate, epochs, batch size
    - Input cropping, etc…
- > 100^100 combinations → **Exhaustive search prohibitive**
- 1000x difference between “good” and “ba
  → **Tuning is essential**
- Grid search optimisation:
    - Intelligent sampling
    - Early-stopping
    - **Faster, near-optimal**
    - **[Optuna library]**

Search algorithms on 2d space



Grid Search | Random Search | Adaptive Selection

Grid space search time comparison

Method	Total Configs	Total Run	Total Pruned	Best solution	Time taken
Optuna	154	26	128	6.78E-06	1.5h
Exhaustive	154	154	0	6.75E-06	6h

OPTUNA

Synthetic Data Evaluation: Ground truth available

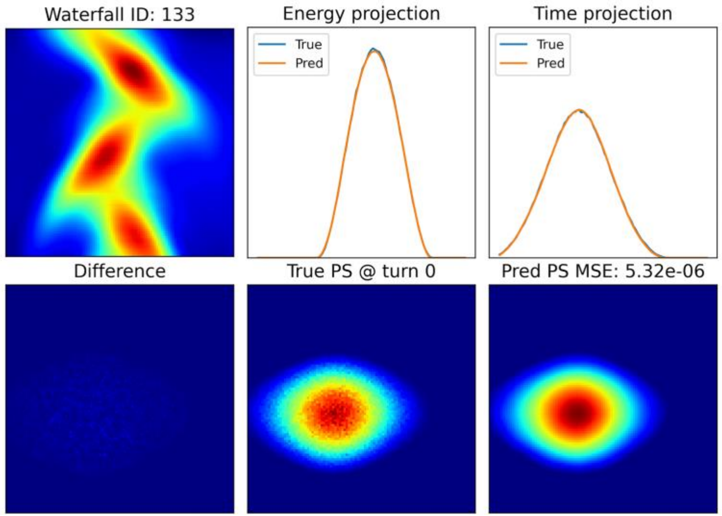
Encoder Ensemble Evaluation

- Matches or surpasses precision of classical methods
- Not all parameters equally “interesting”
- Independent set of parameters
  - Easily modifiable

	95-percentile
Phase Error	0.3 deg
Energy Error	1.56 MeV
LHC V_RF	0.05 MV
Bunch Length	13.2 ps
Intensity	1.2e9 p
SPS V_RF	0.16 MV
Distribution μ	0.14 a.u.

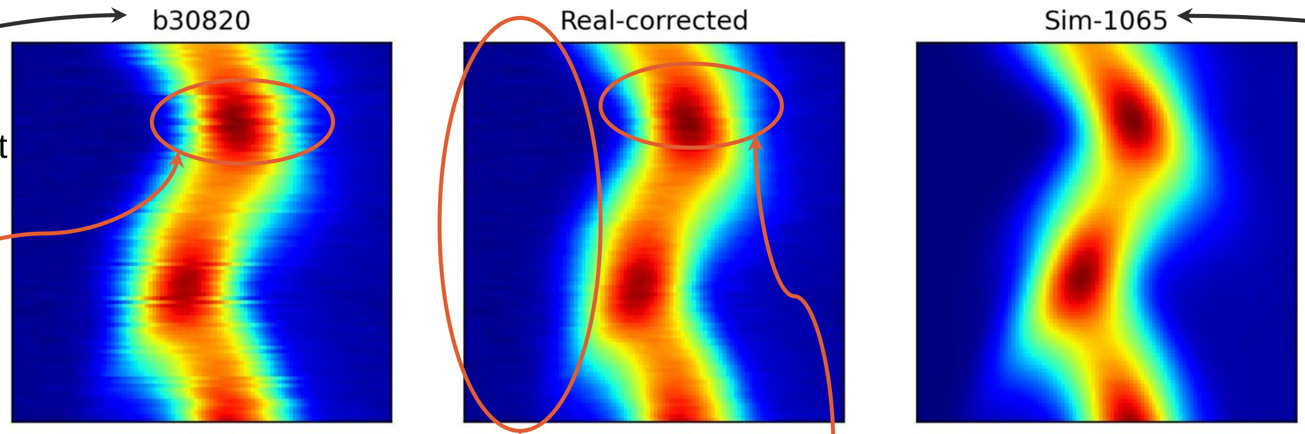
Tomoscope Evaluation

- MAE: 0.001 (1‰)
- Visually indistinguishable



Evaluation on Measurements: Reality Gap

Raw measurement data



Most similar to measurement b30820

Jitter due to trigger

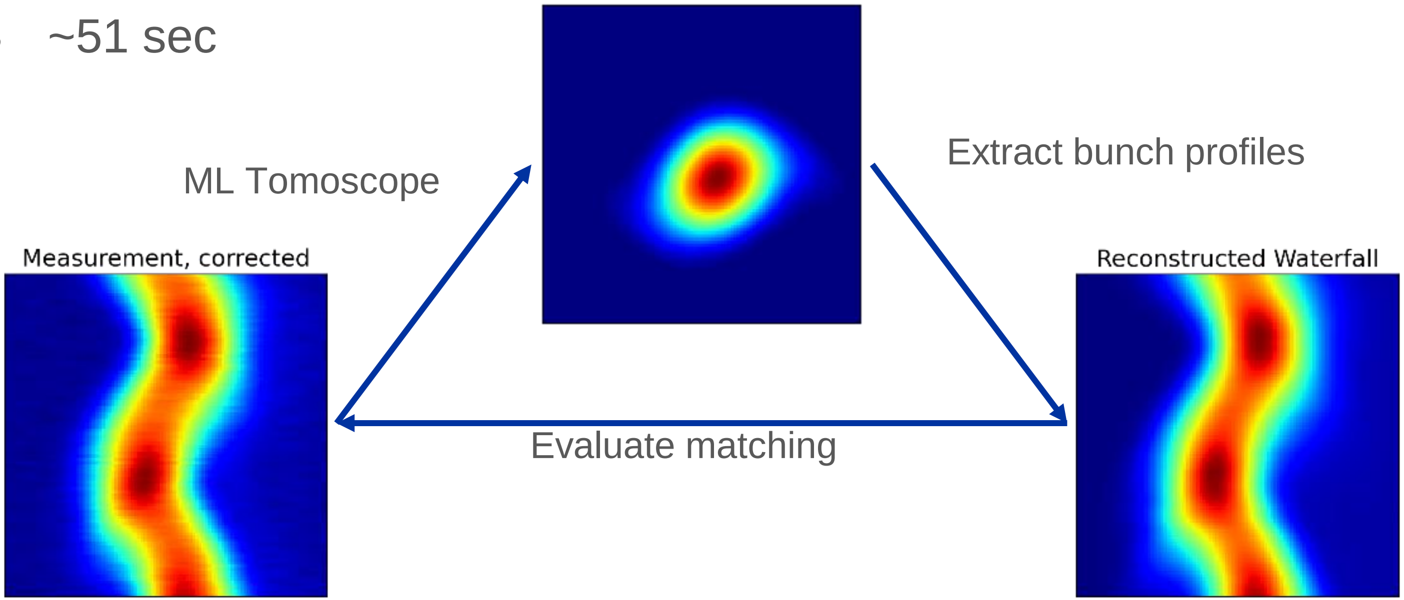
Not zero, random noise

Still some jitter, despite removal

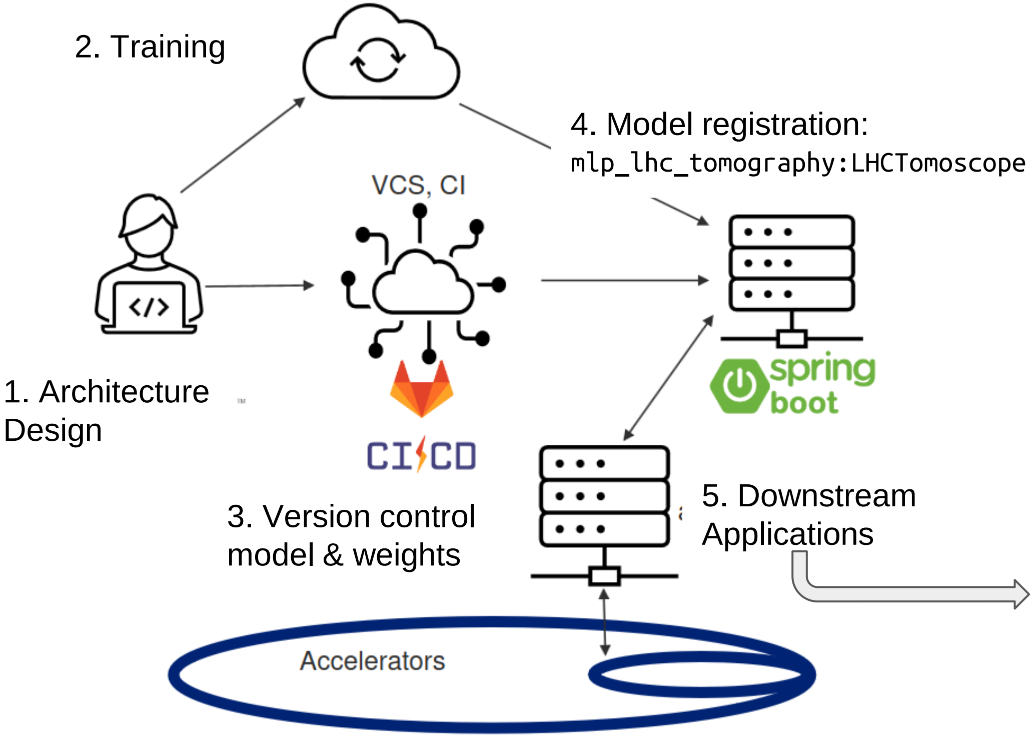
- **Ground truth not fully available**
  - Some measurements, fitting or alternative methods
- Multi-bunch measurements, single-bunch simulations

Evaluation on Real Data: End-to-End

- **Visually indistinguishable**
  - Pixel-to-pixel, MAE: **0.03**
- **Full reconstruction (48 bunches, 300 turns)**
  - ~51 sec



Model Deployment



Machine Learning Platform (MLP):

- Standardizes the storage, versioning and distribution of ML models.
- Exposes uniform API (load, save, fit, predict)
- Model updates transparent to downstream applications
- Standalone deployment: Inference in remote server, no local installation.
- Available at: acc-py-repo.cern.ch/browse/project/mlp-lhc-tomography

UCAP Node

- Live Subscriptions
- Storage for off-line processing

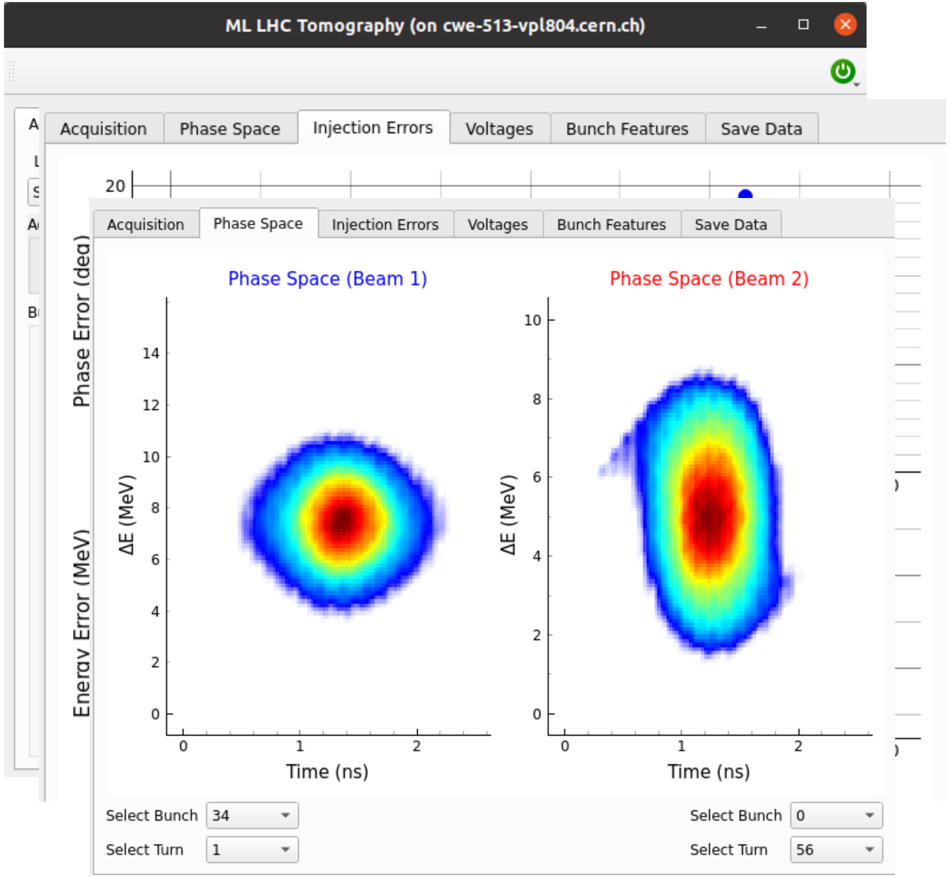
MLP Workflow, source: https://indico.cern.ch/event/1175862/

GUI Application

Target: Minimal user interaction
- Reads input from UCAP node
- Updates with every new injection

Capabilities:
- Subscribe to UCAP
- Inspect Bunch Profiles
- Bunch-by-bunch beam diagnostics
- Longitudinal tomography
- Edit settings, save to file

Extensions:
- Unify with classical tomography
- Allow for direct comparison



Conclusions

- **ML a powerful and promising solution to both:**
  - Extraction of essential beam parameters in real-time
  - Multi-bunch tomography in real-time
  - Less than 1 min for 300 turns phasespace reconstruction of 48 bunches
- **Tool is in operational state**
  - To be tested on next run
  - GUI for real time display
  - Output data stored post-processing

Thank you for your attention!

Future Work

- **Hybrid, Tracking+ML approach**
  - Predict initial bunch distribution, then track with BLonD
- **Domain Adaptations/ Adjustments:**
  - Multi-bunch beams
  - Ions
  - Phases of the acceleration
  - Machines (PS, SPS)
- **Transfer learning**
  - Re-use core model architecture
  - Combine with smaller, simpler model per task