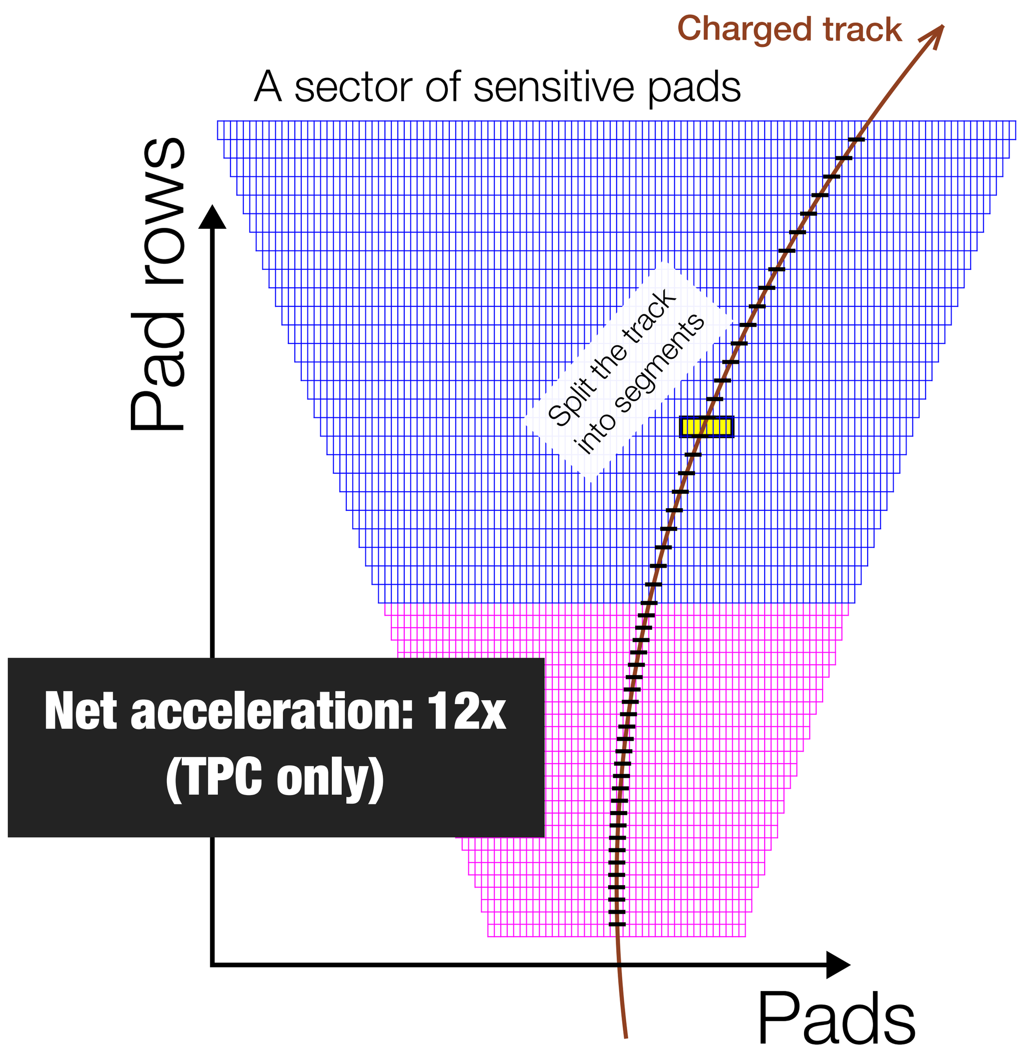
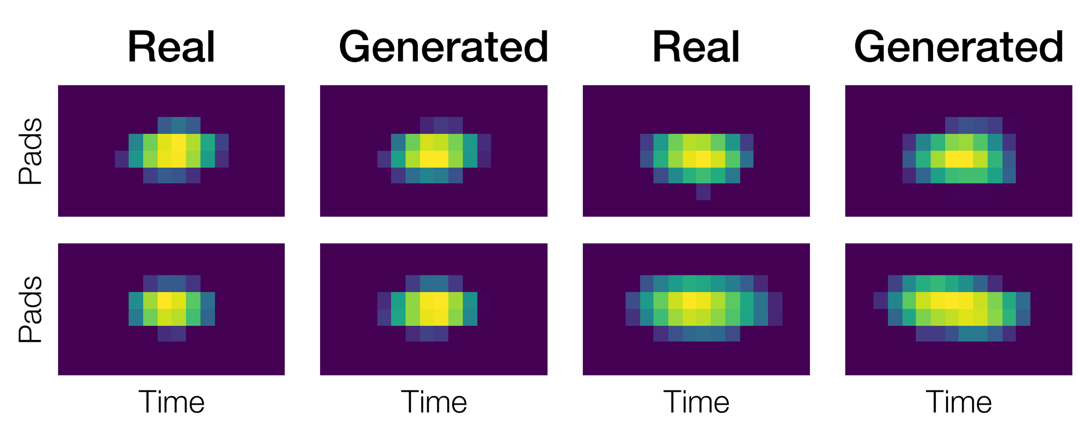
Generative Surrogates for Fast Simulation: TPC Case

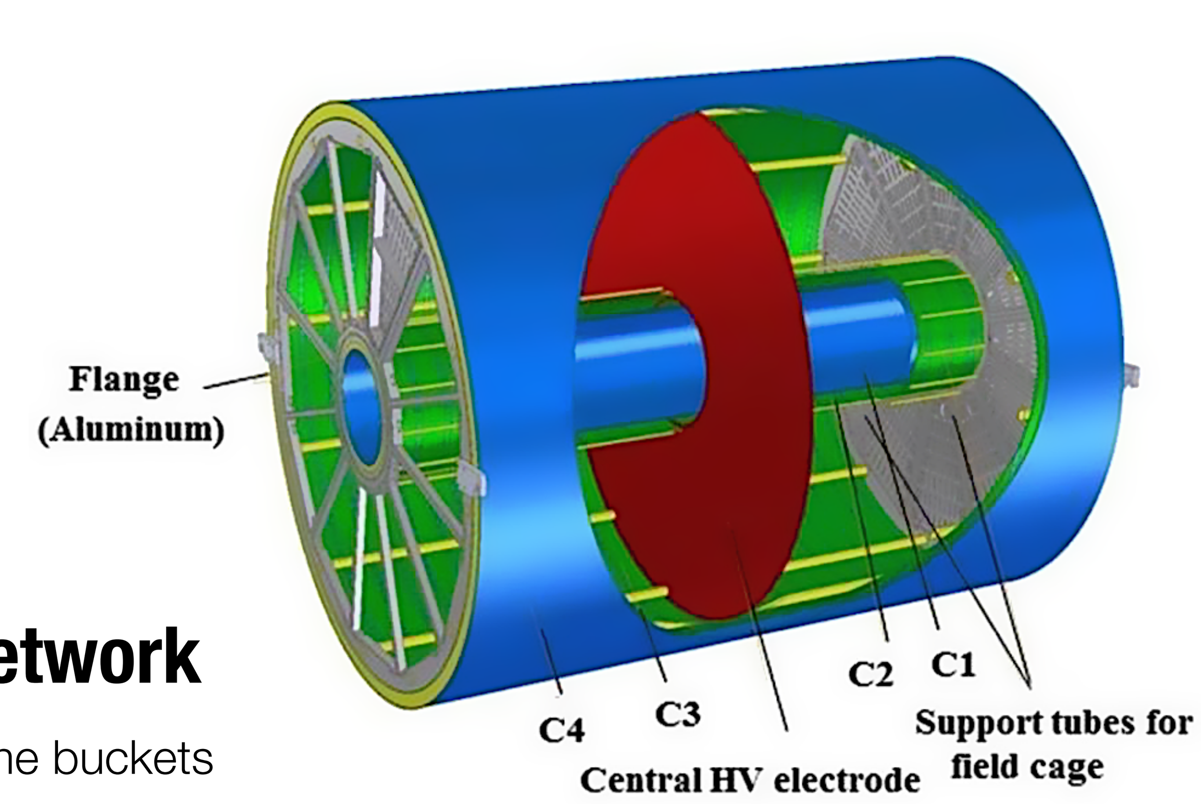


Net acceleration: 12x (TPC only)



MPD TPC tracker

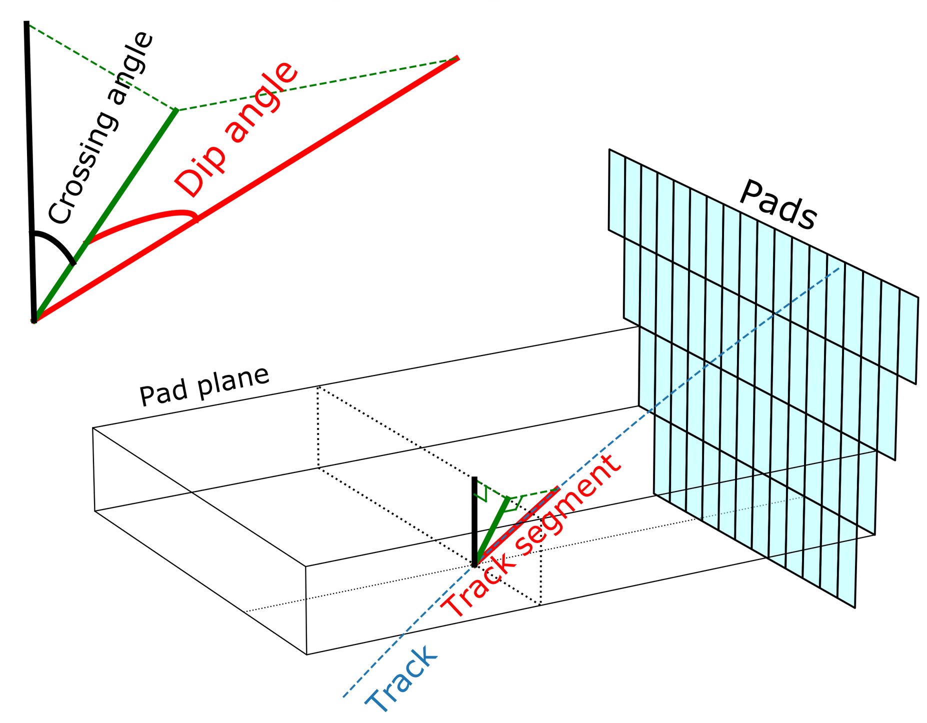
- Main tracker in the central barrel
- PID provided through dE/dx
- Computational bottleneck in the electron drift simulation ⇒ **Fast simulation approach required**



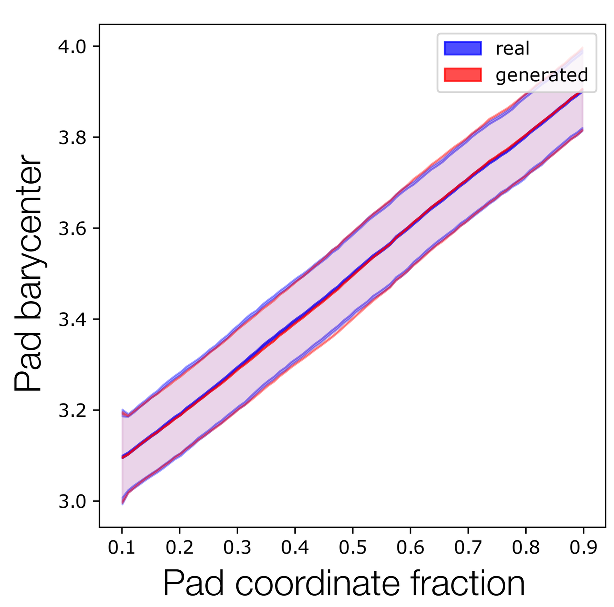
http://mpd.jinr.ru/wp-content/uploads/2019/01/TpcTdr-v07.pdf

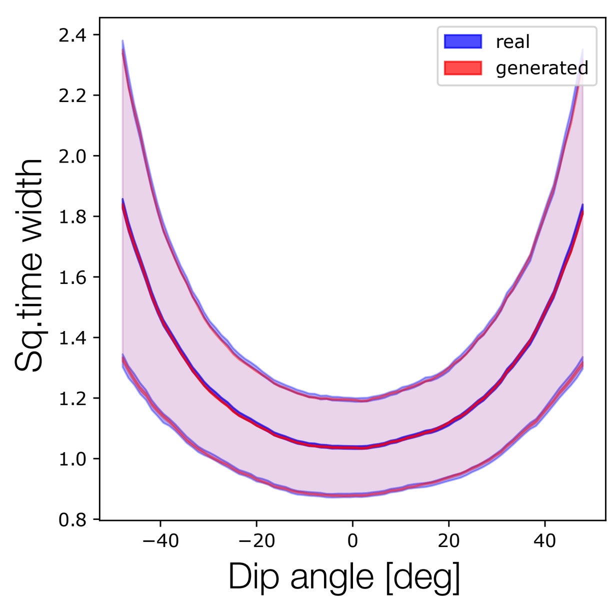
Fast simulation with a neural network

- TPC readout: 95 232 sensitive pads × 310 time buckets per bunch crossing
  - **~30M numbers** to generate
- **Factorize** the problem:
  - Split all tracks into **small segments** contributing to individual pad rows
  - Contributions localized in space and time
    - **8 pads** in a pad row
    - **16 time buckets**
  - Assume additive contributions from the segments
  - Responses conditioned on **segment parameters**
    - location & direction
    - plan to incorporate other characteristics (particle type, momentum, etc.)



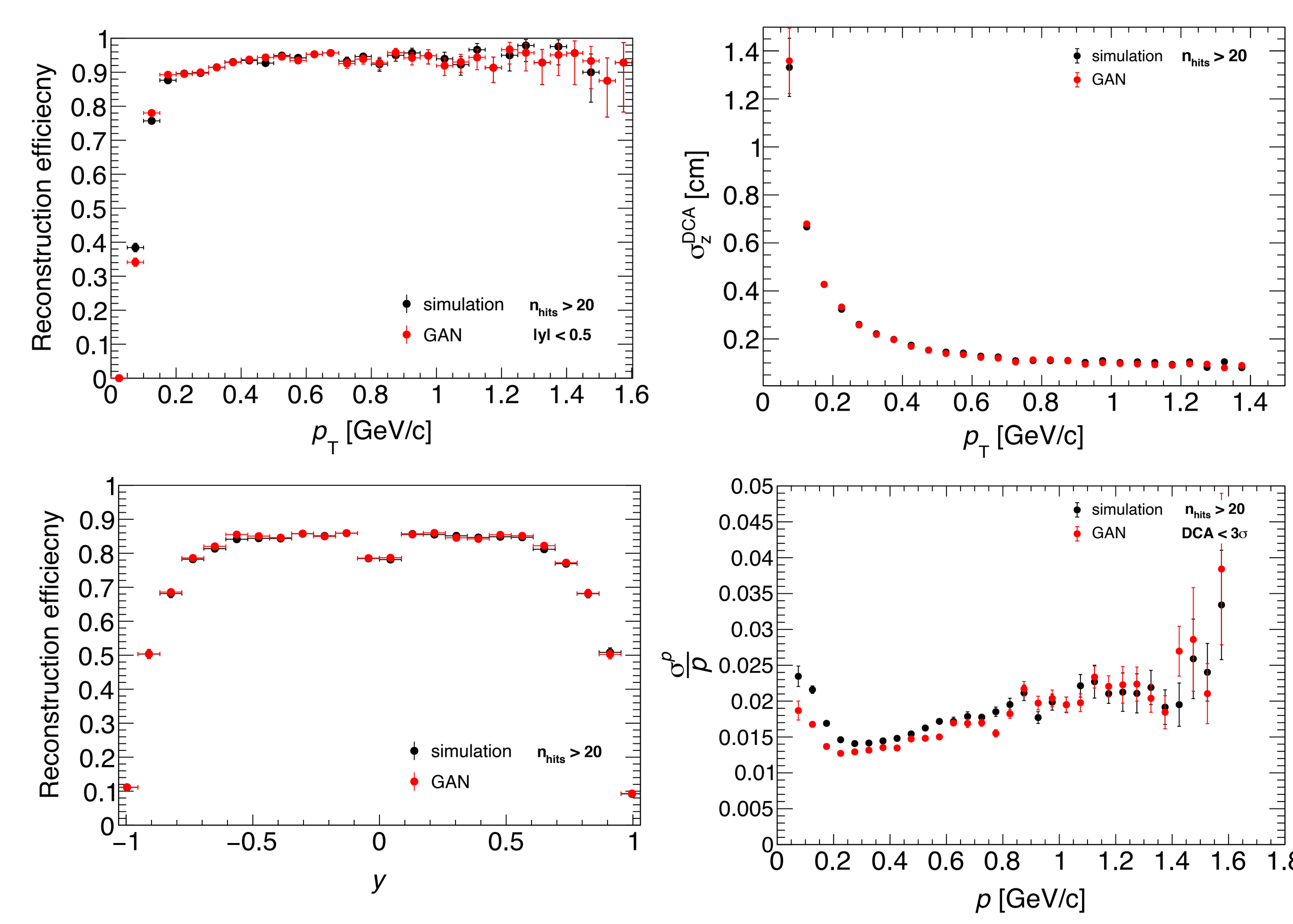
Track segment parameters



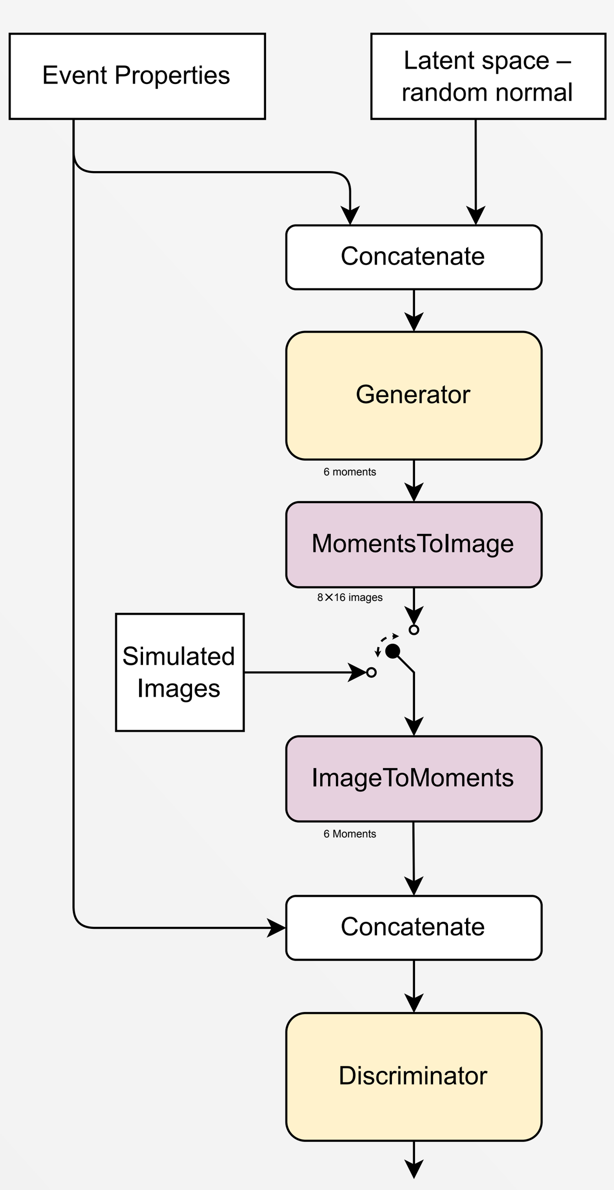


Validating the model

- At raw response level:
  - Describe responses with **6 parameters**:
    - pad/time barycenters (2), widths (2) and covariance (1), integrated amplitude (1)
  - Compare distributions for each of these parameters between GAN and detailed simulation
    - comparison **as a function of track segment characteristics**
- At reconstruction level:
  - Coordinate resolution, reconstruction efficiencies, and other (see the paper)
  - **Very good agreement**
  - Few inconsistencies well understood and will be improved in the next iteration of model development

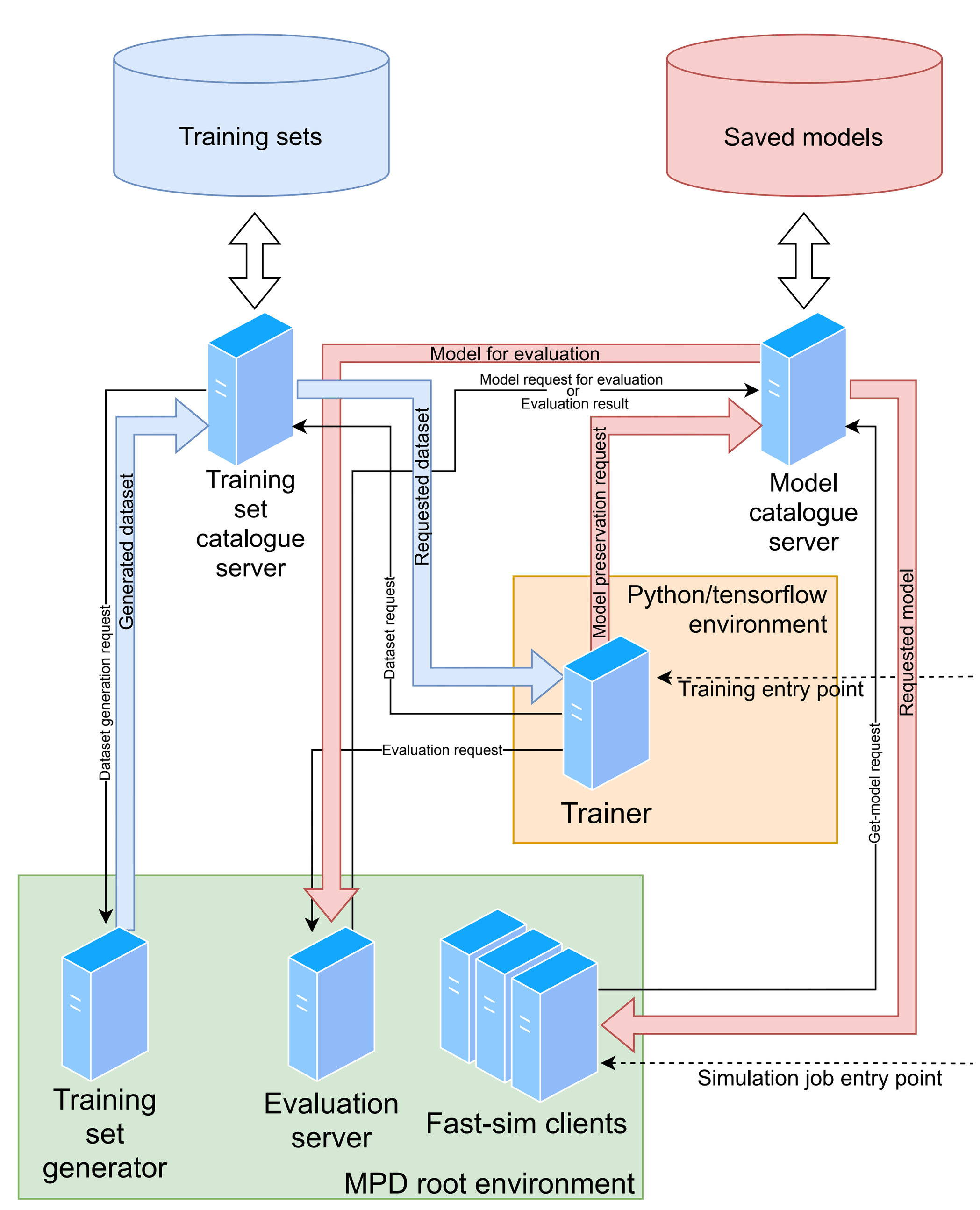


Alternative: generating the 6 parameters directly



- The 6 low-level parameters contain **most of the information** important for reconstruction:
  - Barycenters ⇔ cluster coordinates
  - Widths and covariance ⇔ two-track resolution
  - Amplitude ⇔ dE/dx
- Idea: generate just the 6 parameters, then build a 8x16 response matrix deterministically (discretized gaussian)
  - Gaussian discretization introduces bias
    - Can **correct for it automatically** by plugging biased generator responses to the discriminator

- Motivation: generating in lower-dimensional space may be simpler (quicker and/or lead to better quality)
- However, experiments show that it requires a lot of hyper-parameter tuning to get to a reasonable quality
  - **Do GANs "prefer" higher-dimensional representations?..**



Production pipeline

- Goal: make an **automated solution**
- Various simulation configurations may arise
- Requirements:
  - **Automated training**
    - Training data generation
    - Model training, evaluation and selection
  - **Model library**
    - Database for storage and prompt model retrieval
- Design choices (preliminary):
  - Store models in **ONNX format**, **ONNXruntime** for inference
  - **Airflow** to manage the workflow
    - Pipelines described as Directed Acyclic Graphs (DAGs)
    - Tasks and dependencies defined in Python
    - Then scheduled and executed by Airflow
- **MLflow** for model library
  - We use the **"Model Registry"** component
    - Model versioning and tagging
    - Web interface
    - REST API to download a model for inference
  - Customizable model description in the web interface
    - Can be modified through API (e.g., automatically attach validation results to the model description)

See our EPJC paper for more details

Eur. Phys. J. C 81, 599 (2021)