# A Neural-Network-defined Gaussian Mixture Model for particle identification in LHCb

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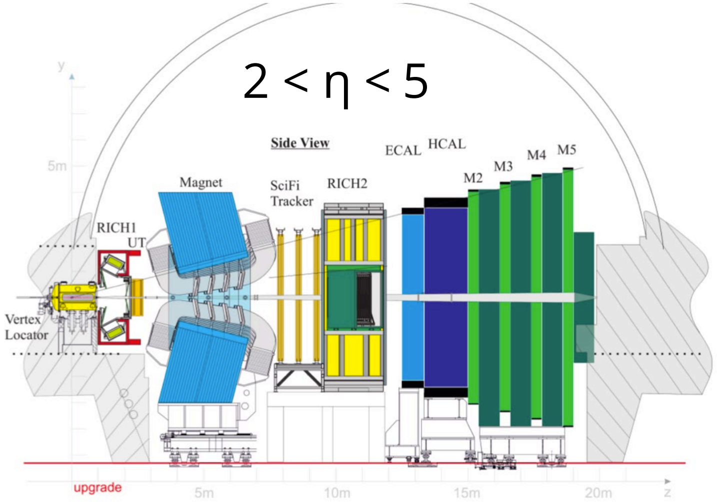
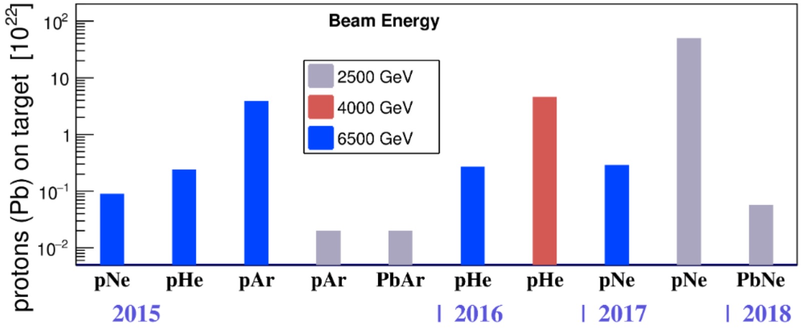
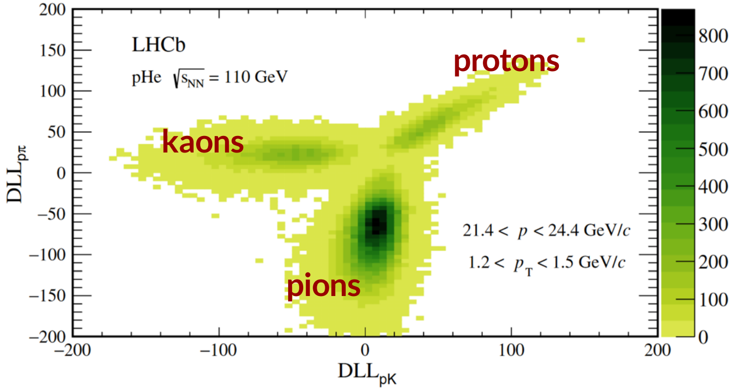
# Motivation and idea

- **LHCb** relies on the Ring Imaging Cherenkov (**RICH**) detector system for the **charged hadron identification** (PID) in a wide momentum range (2 - 100 GeV/c)

- The PID was one of the dominant systematics int the measurement of cross-sections with fixed-target datasets in LHCb:




- This motivated the development of a **novel approach to the modelling of particle identification classifiers** using machine-learning techniques

  - **Explicitly model the marginal probability density function** (pdf) of the PID classifiers → must **depend on the experimental features** $\theta$

  - Extract the marginal pdf using a **Gaussian Mixture Model**, whose parameters are predicted by Multi Layer Perceptrons trained on calibration data

  - **Model each hadron type** $h$ ( $\pi$, $K$ and $p$) PID response independently using the appropriate control modes

# Model and Validation

- In the **bidimensional PID space** the pdf $x$ is defined as: $\underline{x}_h \sim \sum_{j=1}^{N_{g,h}} \alpha_{j,h}(\underline{\theta}) \frac{\exp(-\frac{1}{2}(\underline{x}_h - \underline{\mu}_{j,h}(\underline{\theta}))^T \Sigma_{j,h}^{-1}(\underline{\theta})\,(\underline{x}_h - \underline{\mu}_{j,h}(\underline{\theta})))}{2\pi\sqrt{\det(\Sigma_{j,h}(\underline{\theta}))}}$

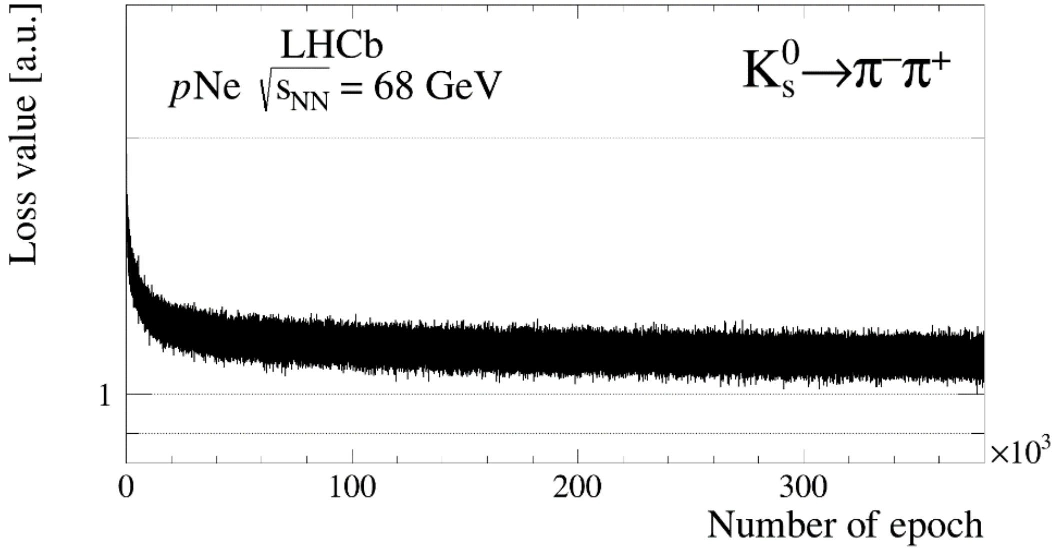
**Training on proton-Neon sample**

- The learning process of the networks relies on the **minimization** of the loss function, defined as the **negative log-likelihood**

$$\mathcal{L} = -\sum_{i=1}^{n_h} w_i \log\left[\sum_{j=1}^{N_{g,h}} \alpha_{j,h}(\underline{\theta}_i)\mathcal{G}(x_i, \mu_{j,h}(\underline{\theta}_i), \sigma_{j,h}(\underline{\theta}_i))\right]$$

- Training performed with **mini-batches gradient descent** with a user-defined number of Gaussians and NN structure

| Input parameter | $K_S^0 \to \pi^- \pi^+$ | $\overline{\Lambda} \to \overline{p}\pi^+$ | $\phi \to K^- K^+$ |
|---|---|---|---|
| Number of Gaussians | 64 | 20 | 64 |
| Number of NN nodes | 128 | 128 | 128 |
| Starting learning rate | $10^{-3}$ | $10^{-4}$ | $5 \cdot 10^{-6}$ |
| Batch size | 10000 events | 10000 events | 20000 events |



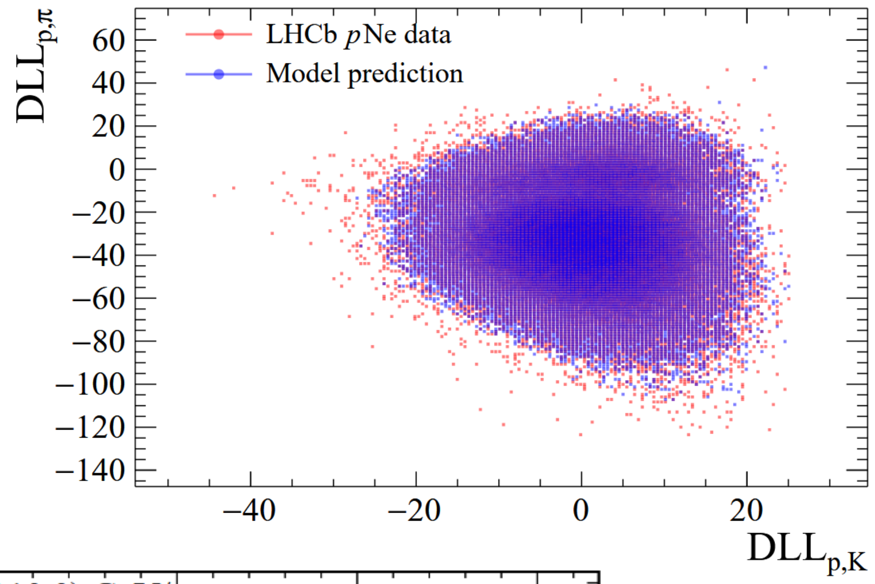


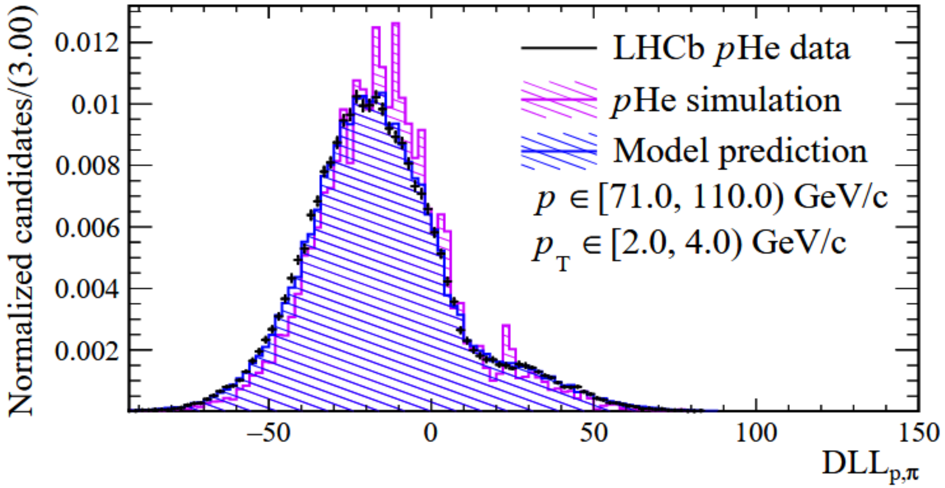

Paper : https://iopscience.iop.org/article/10.1088/1748-0221/17/02/P02018/meta

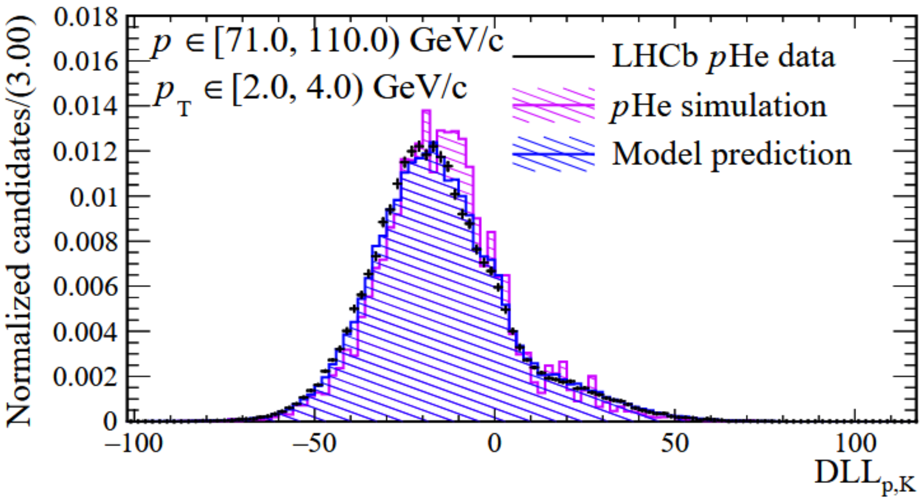
# Model and Validation

**Validation on <u>fixed-target</u> datasets**

- Marginal-pdf prediction validated for the same training dataset and then **applied to two independent lower-statistics samples** of proton-Helium and proton-Argon collisions
  - **significant modifications of the kinematic distributions** of the produced particles
  - **different events multiplicity** and the detector occupancy
  - **identical detector and data-taking conditions** can be assumed
- **Data description quality improved by the model** compared to simulation
- The method is generic, not relying on a specific set of experimental feature variable



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