AI@INFN - Artificial Intelligence at INFN

2–3 May 2022
Hotel Europa, Bologna

The ML_INFN initiative

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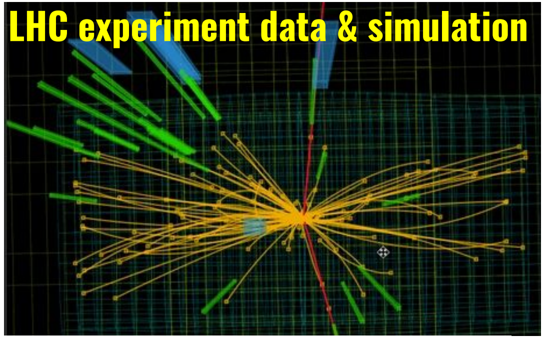
INFN FIRENZE
Istituto Nazionale di Fisica Nucleare

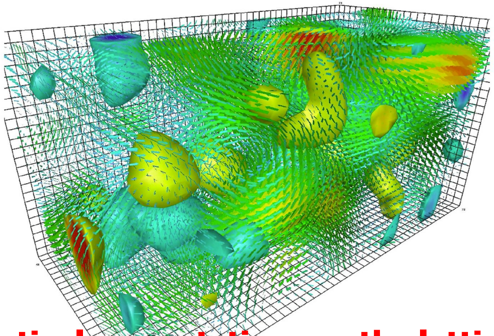
Machine Learning Technologies for INFN

Most of the experiments and initiatives produce, analyse or process digital data.

Enthusiasm on the modern data processing technologies!

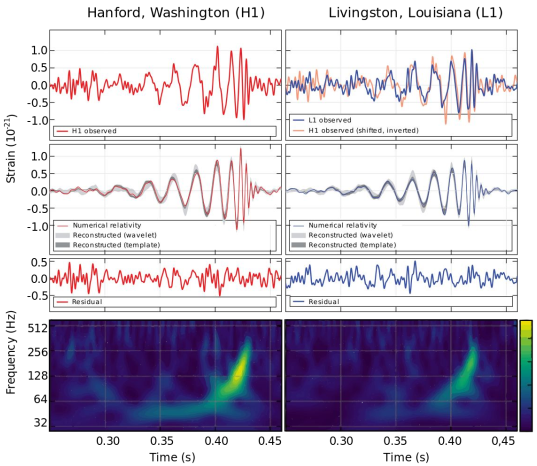


LHC experiment data & simulation

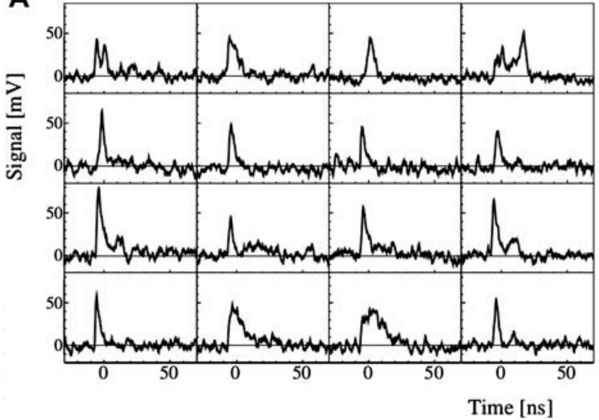


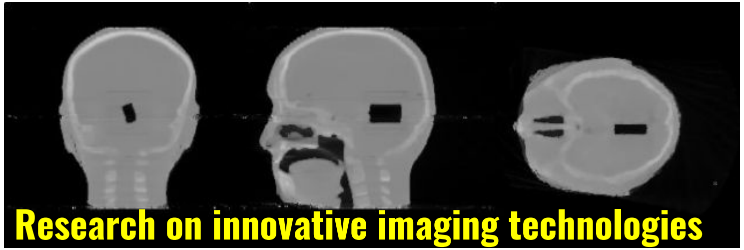
Theoretical computations on the lattice

Gravitational wave detection



Raw radiation detector data





Research on innovative imaging technologies

The potential barriers

Employing machine learning techniques often requires:

- specialized hardware and software setup
- specific training to identify tools and learning resources
- a community of experts providing support to research use cases

Lowering The potential barriers with ML_INFN

Employing machine learning techniques often requires:

- specialized hardware and software setup

WP1: provide a centrally maintained cloud-based infrastructure for interactive and batch ML fast prototyping, with access to modern GPU hardware and systems tuned for ML performance

- specific training to identify tools and learning resources

WP2: organize national training events for INFN users (Machine Learning hackathons)

- a community of experts providing support to research use cases

WP3: provide and organize example applications in a knowledge base

The numbers of ML_INFN

11 INFN **structures** involved in the preparation of the knowledge base

79 **researchers** devoting a fraction of their time to promote ML techniques for research

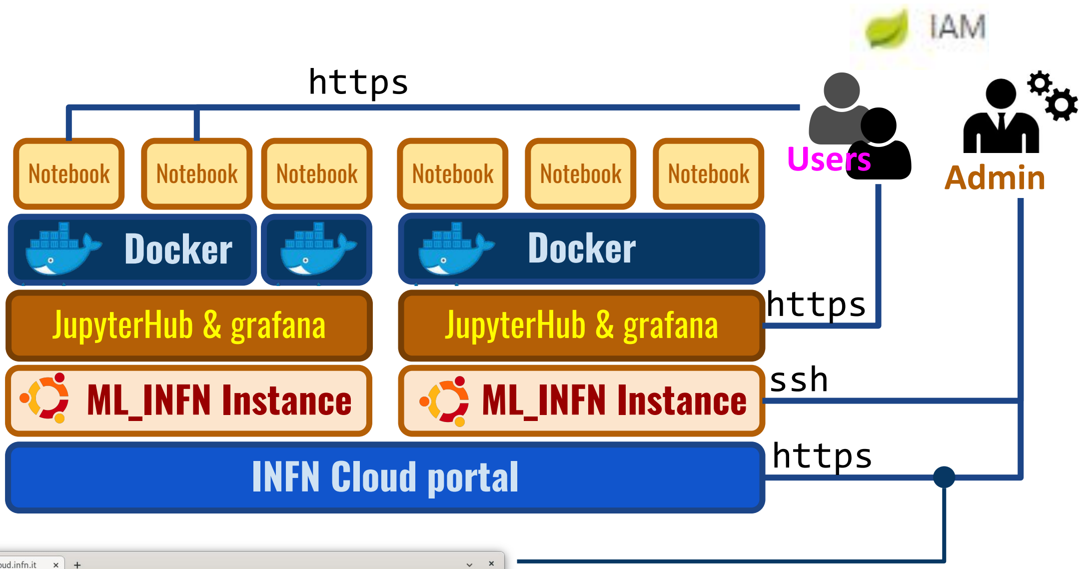
14 professional **GPUs** made available and accessible through the INFN Cloud Interface

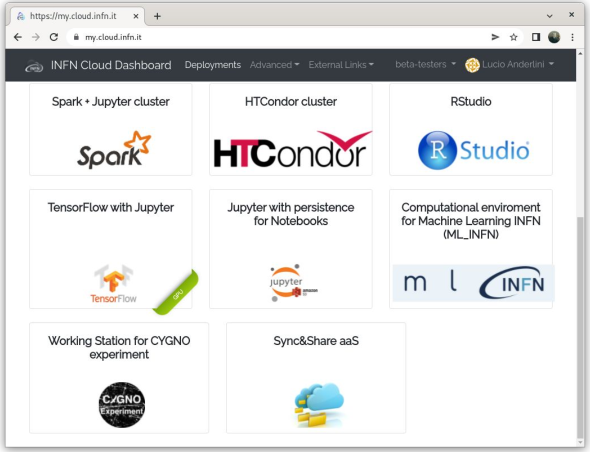
110 **participants** to the **hackathons**, ranging from students to permanent staff members

WP1. The infrastructure

INFN Cloud

ML_INFN is built on top of **INFN Cloud**: a data lake-centric, heterogeneous federated Cloud infrastructure spanning multiple sites across Italy, providing an extensible portfolio of solutions tailored to **multidisciplinary scientific communities**.





Federated baremetal resources

1× SuperMicro + 1× E4 servers:

- 1 TB RAM
- 64-128 CPU cores
- 36 TB local storage (NVMe)
- 8× **Tesla T4** GPUs
- 5× **RTX 5000** GPUs
- 1× **A30** GPU
- 10 GbE connection to CNAF resources

Federated to CNAF OpenStack and INFN Cloud

Storage solutions

Storage from CERN experiments can be mounted with NFS from the Tier-1 storage

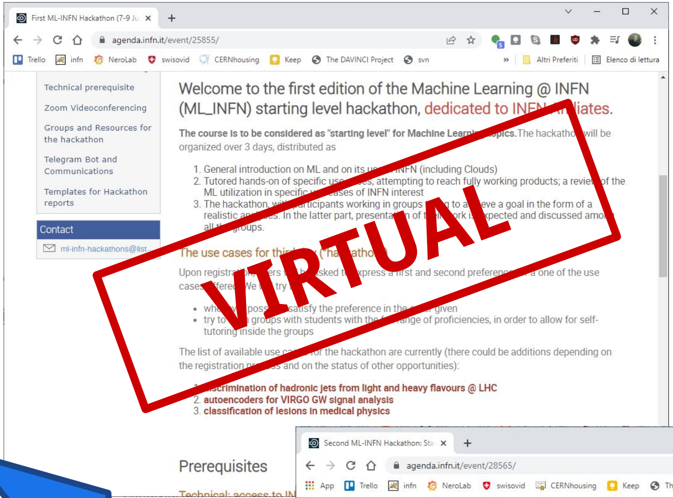
Hypervisors integrated to Ceph to manage persistent virtual volumes accessed from the VM with POSIX

WP2. Stewardship

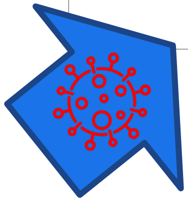
Hackathons in Covid-19 Era

Originally planned as satellite events of scientific workshops, canceled due to pandemic, hackathons have been transformed in virtual events.

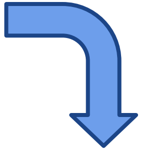
Registrations limited to 60 to guarantee decent tutor-per-student and RAM-per-student ratios.

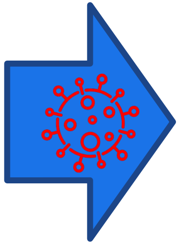


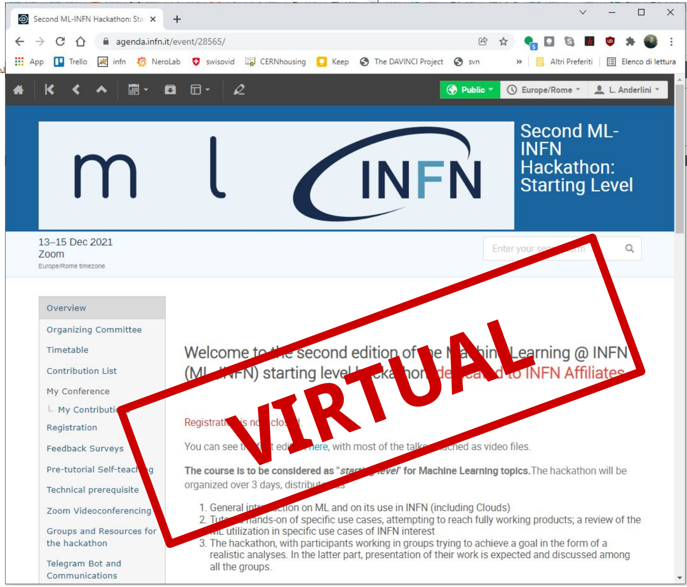
“sold-out” in 72 hours



Repeated







Lecture Program

Day 1	*Day 2*	*Day 3*
Lectures **Theoretical introduction to ML**	Hands-on **Neural Networks**	Hackathon **Exercises with tutors *continuous support***
Lectures **Cloud and Cloud Resources**	Seminars **Deep Neural Network Applications to INFN research**	

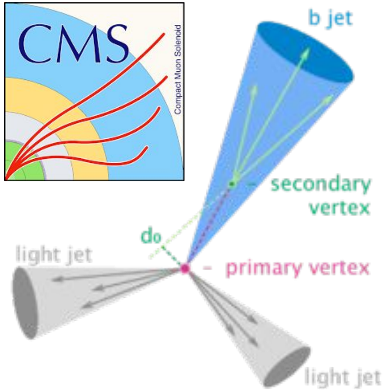
Lunch break

Hands-on **Numpy, Pandas and Keras**	Hands-on **Exercises with tutors *on demand***	Closure **Reports from the students**

Hackathon use cases: *10 groups, one tutor per group*

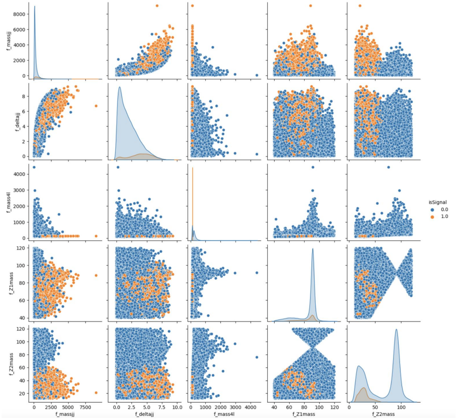
Jet b-tagging at CMS

Recurrent Neural Networks with LSTM



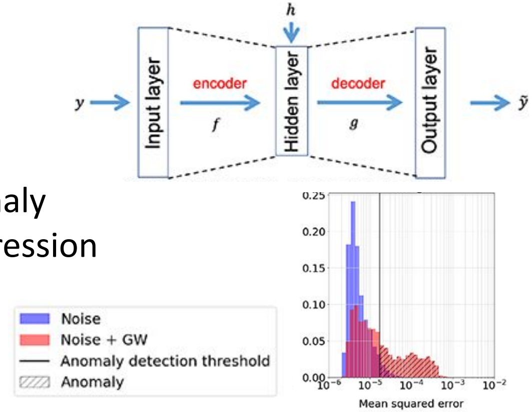
Higgs searches at CMS

Deep Neural Networks and Advanced Keras



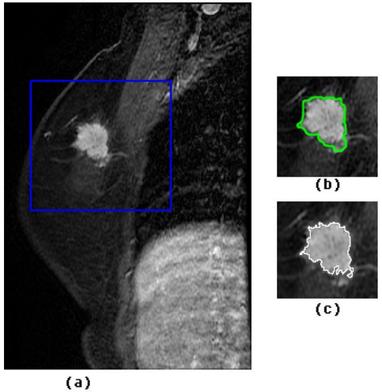
Gravitational Waves with Virgo

Autoencoders, anomaly detection and compression



Segmentation of CT scans

Convolutional Neural Networks Handling 2D and 3D datasets

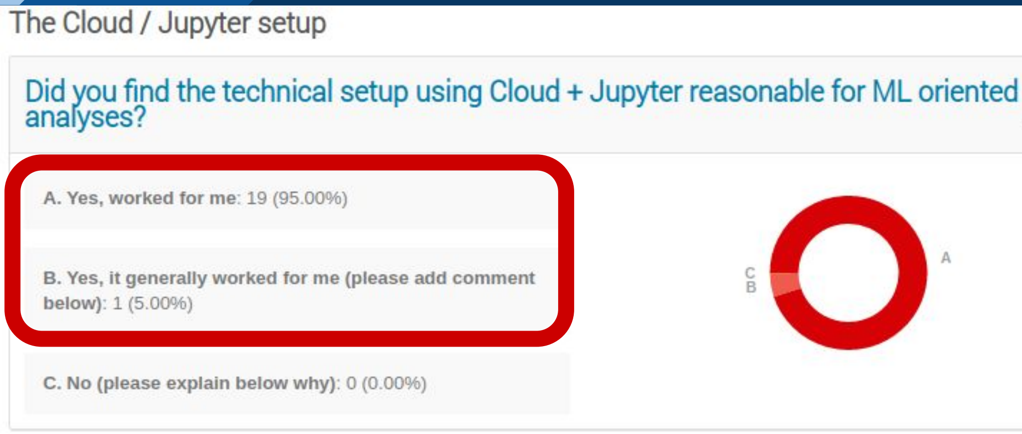


Final survey

A satisfaction questionnaire was submitted to the participant at the end of each event.

Generous feedback on:

- Level of difficulty
- Relevance and interest
- Technical setup



On the difficulty level:

Too easy

Too difficult

Appropriate

On the choice of topic:

expected more

Interesting

About a half of the participant responded they would have been willing to spend **more time** on the hands on and/or the hackathon.

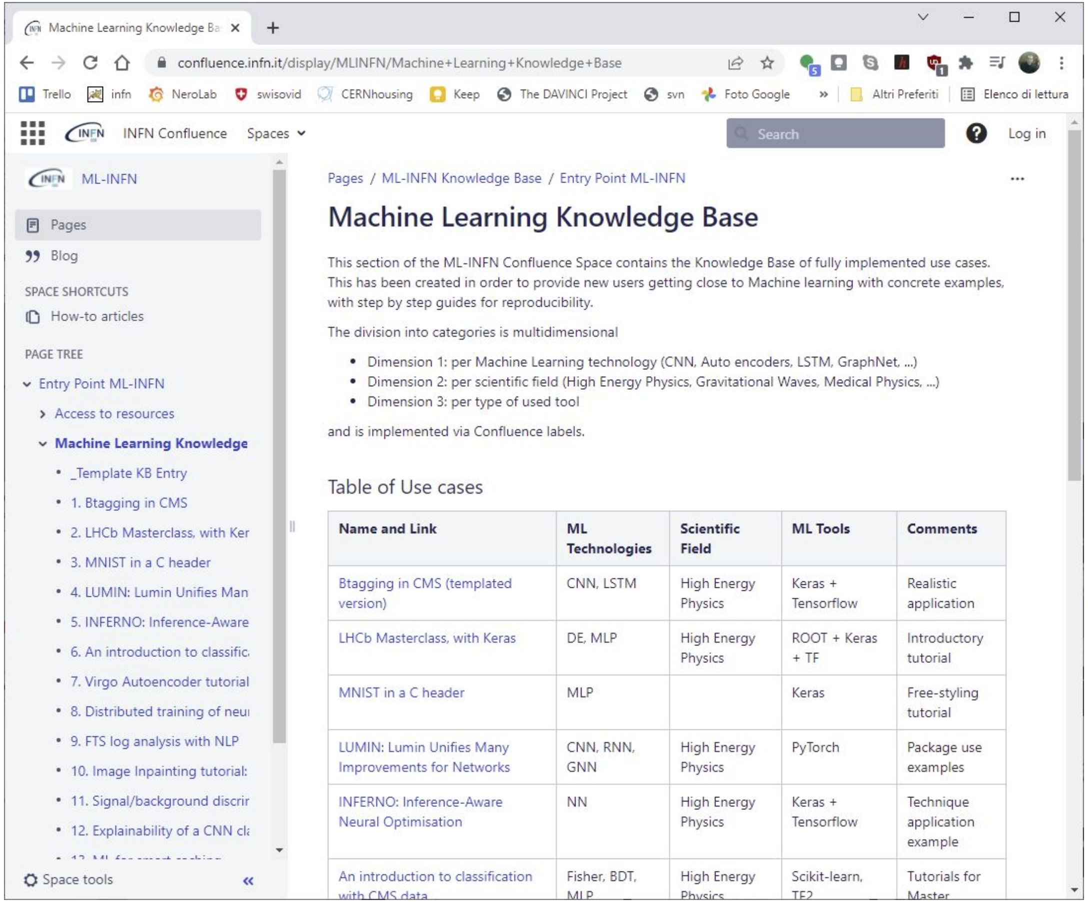
WP3. Network and Knowledge Base

Confluence Knowledge Base

Atlassian Confluence was used to build a **Knowledge Base** reporting several machine-learning use cases, including those discussed at the hackathon.

Each entry includes:

- Runnable **example** as a jupyter notebook or a git repository
- **Contact information** of one or more experts



Publications

A. Abba et al., “The novel Mechanical Ventilator Milano for the COVID-19 pandemic featured”, Physics of Fluids 33, 037122 (2021)

L. Banchi *et al., “*Measuring Analytic Gradients of General Quantum Evolution with the Stochastic Parameter Shift Rule”, Quantum 5, 386 (2021).

L. Banchi *et al.* “Generalization in Quantum Machine Learning: A Quantum Information Standpoint” , PRX Quantum 2, 040321

P. Braccia *et al.,* “How to enhance quantum generative adversarial learning of noisy information”, New J. Phys. 23 053024 (2021)

D. Carlotti *et al.,* “Deep learning method for TomoTherapy Hi-Art: prediction three-dimensional dose distribution”, RADIOTHER ONCOL 161 (2021)

S. Francescato *et al.* “Model compression and simplification pipelines for fast deep neural network inference in FPGAs in HEP”, Eur. Phys. J. C 81, 969 (2021).

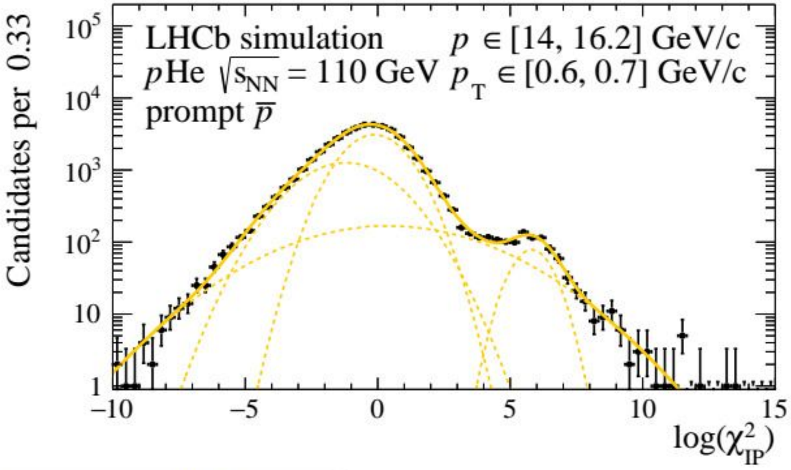
G. Graziani et al., “A Neural-Network-defined Gaussian Mixture Model for particle identification applied to the LHCb fixed-target programme”, JINST 17 (2022) P02018

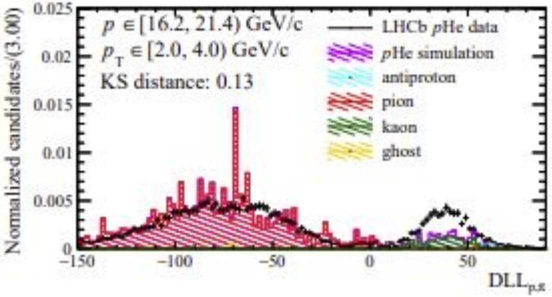
A. Palermo *et al. “Machine learning approaches to the QCD transition”, LATTICE 2021, arXiv:2111.05216*

Stories of success [1]: *building template models for LHCb*

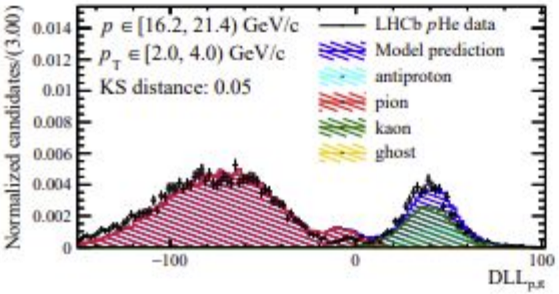
ML_INFN infrastructure was used to develop a model for the Particle Identification response of the LHCb detector as a Gaussian-Mixture model.

With Gaussian parameters inferred with a Deep Neural Network.





Traditional method based on reweighted MC



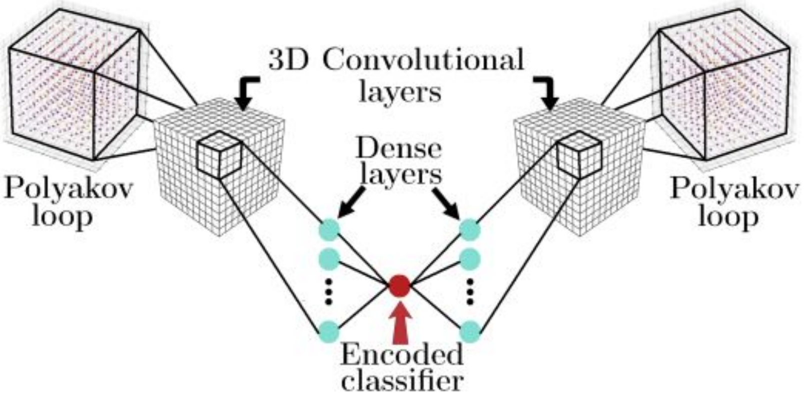
Deep Learning model

S. Mariani *et al*, *"A Neural-Network-defined Gaussian Mixture Model for particle identification applied to the LHCb fixed-target programme"*, JINST 17 (2022) P02018

Public repository **PID4SMOG**

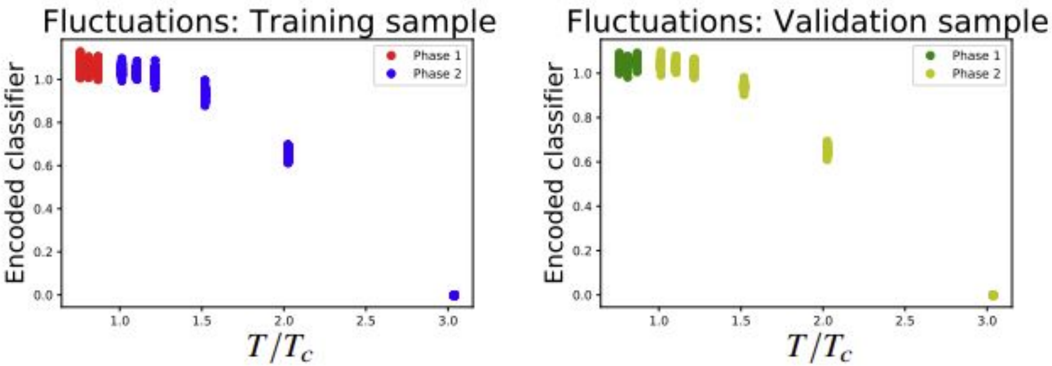
Stories of success [2]: *studying LQCD with CNNs*

A Deep Neural Network is trained in a semi-supervised manner to define an effective order-parameter for Gauge theory where a real order-parameter is not defined.



The study was made possible thanks to the GPUs provided by the ML_INFN initiative.

A. Palermo, M.P. Lombardo *et al.*
"Machine learning approaches to the QCD transition", Proceeding of LATTICE21



Summary and conclusions

Summary

The ML_INFN initiative has been providing many INFN experiments with the hardware and the knowledge base to assess the potential **benefit of machine learning to their research** for three years.

The **ML_INFN** project relies on **INFN Cloud** solutions and it federates resources optimized for ML performance in interactive and batch-like usage patterns (high-end professional GPUs, NVMe disks, many-core high-RAM systems)

A series of national training events (***machine learning hackathons***) and a collection of tutorials and real applications within the INFN community (***knowledge base***) contribute to building **a network of experienced and enthusiast machine learning practitioners**, lowering the skill gap to benefit from machine learning developments.

Outlook

Machine Learning is here to stay. In the next future:

- We will organize ***Advanced Training Course(s)*** on Deep Learning
- We will provide Cloud-based access to **FPGAs** as **Machine Learning accelerators**
    - Two U50 and a U250 Xilinx FPGAs recently federated to the cloud
- We will keep supporting students and researchers employing **Machine Learning technologies** in their daily activities.