



The ML_INFN initiative

L. Anderlini¹, on behalf of the ML_INFN initiative

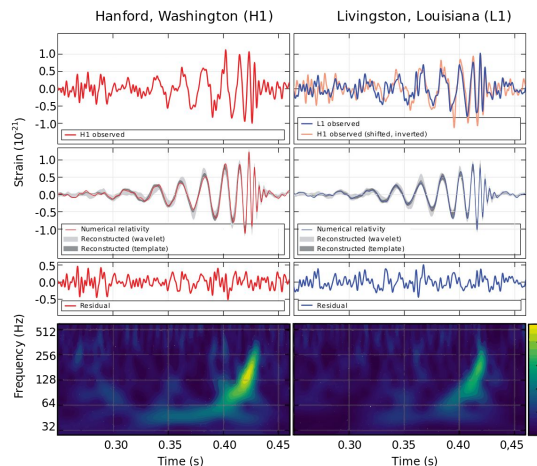


Machine Learning Technologies for INFN

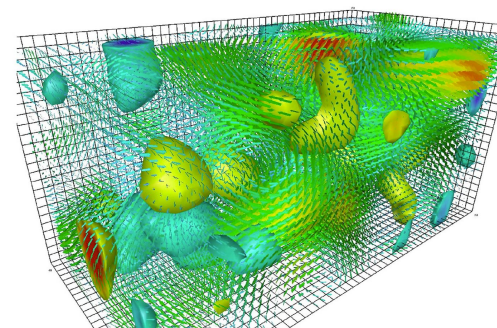
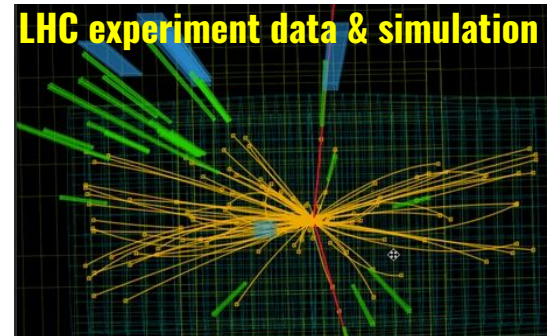
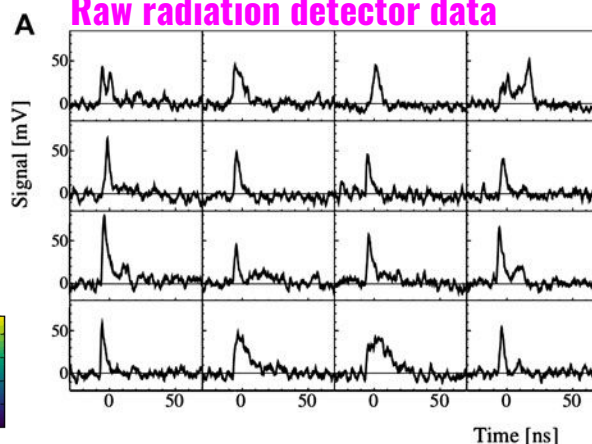
Most of the experiments and initiatives produce, analyse or process digital data.

Enthusiasm on the modern data processing technologies!

Gravitational wave detection



Raw radiation detector data



Theoretical computations on the lattice



Research on innovative imaging technologies

The potential barriers

Employing machine learning techniques often requires:

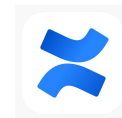
- specialized hardware and software setup



- 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



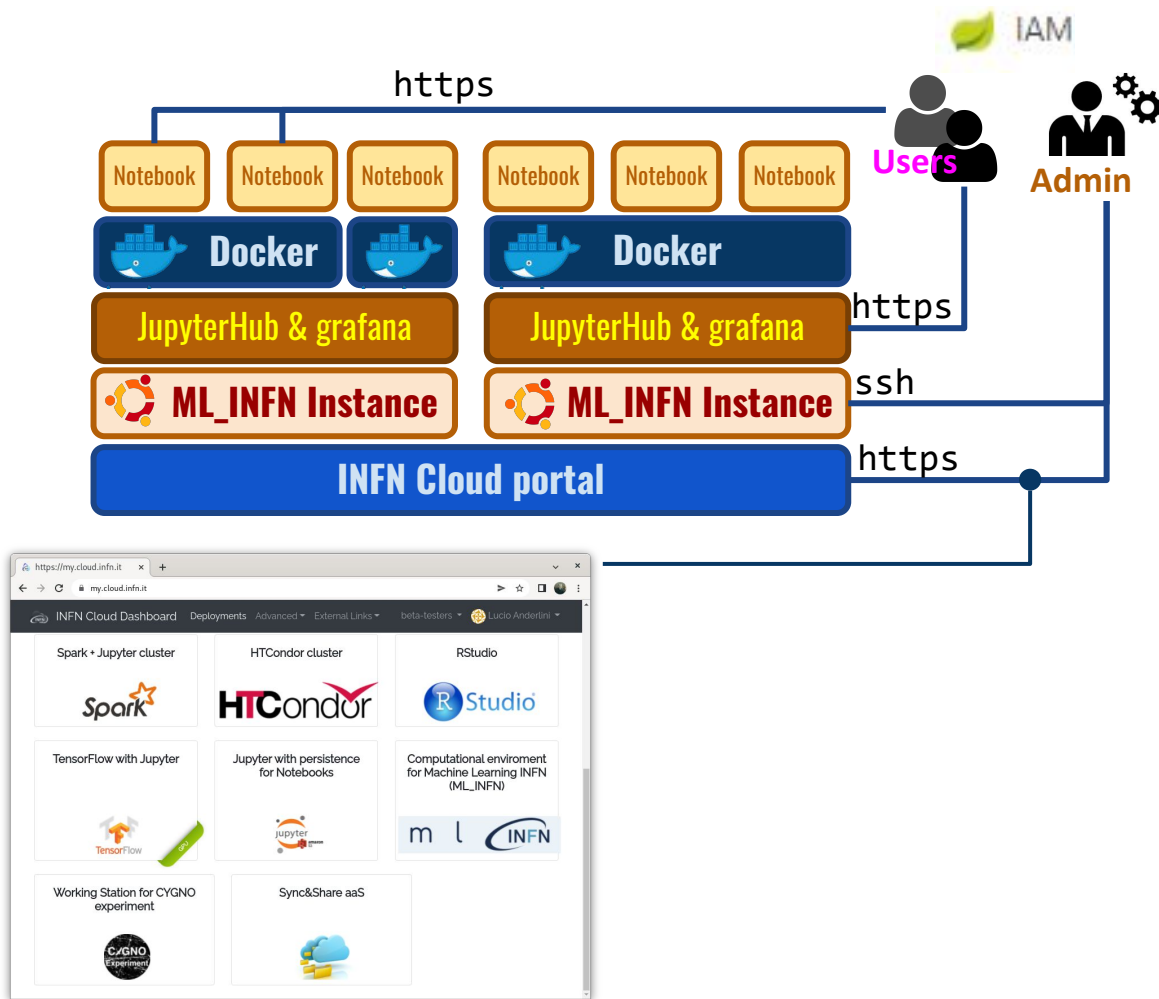
The numbers of ML_INFN

- 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

1x SuperMicro + 1x E4 servers:

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



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

Federated to CNAF OpenStack and INFN Cloud

WP2. Stewardship

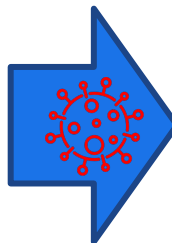
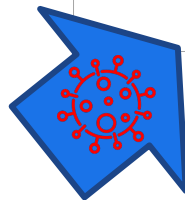
Hackathons in Covid-19 Era

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



First ML-INFN Hackathon (7-9 Oct.)

Welcome to the first edition of the Machine Learning @ INFN (ML-INFN) starting level hackathon, dedicated to INFN Affiliates.

The course is to be considered as “starting level” for Machine Learning topics. The hackathon will be organized over 3 days, distributed as

1. General introduction on ML and on its use in INFN (including Clouds)
2. Tutorials hands-on of specific use cases, attempting to reach fully working products; a review of the ML utilization in specific use cases of INFN interest.
3. The hackathon, with participants working in groups trying to achieve a goal in the form of a realistic analyses. In the latter part, presentation of their work is expected and discussed among all the groups.

The use cases for this hackathon are:

- workshop to satisfy the preference in this topic given
- try to help groups with students with the knowledge of proficiencies, in order to allow for self-tutoring inside the groups

The list of available use cases for the hackathon are currently (there could be additions depending on the registration status and on the status of other opportunities):

1. reconstruction of hadronic jets from light and heavy flavours @ LHC
2. autocoders for VIRGO GW signal analysis
3. classification of lesions in medical physics

Prerequisites

Technical prerequisites

Second ML-INFN Hackathon: Starting Level

13-15 Dec 2021
Zoom
Europe/Rome

Welcome to the second edition of the Machine Learning @ INFN (ML-INFN) starting level hackathon, dedicated to INFN Affiliates.

The course is to be considered as “starting level” for Machine Learning topics. The hackathon will be organized over 3 days, distributed as

1. General introduction on ML and on its use in INFN (including Clouds)
2. Tutorials hands-on of specific use cases, attempting to reach fully working products; a review of the ML utilization in specific use cases of INFN interest.
3. The hackathon, with participants working in groups trying to achieve a goal in the form of a realistic analyses. In the latter part, presentation of their work is expected and discussed among all the groups.

Prerequisites

Technical prerequisites

FIRST INTERNATIONAL WORKSHOP ON MACHINE LEARNING IN PHYSICS

19-21 Oct 2020
Auditorium Folco Portinari
Europe/Rome

Overview

Machine Learning in High Energy Physics

High Energy Physics has been taking advantage of Machine Learning algorithms for more than thirty years to address problems such as pattern recognition for tracking, multivariate classification of collision events, rejection of background events at trigger level.

More recently, representation learning has been explored for a wide range of applications including tracking, jet reconstruction and parameterization of the detector response. Since many modern machine learning algorithms are based on likelihood maximization, applications to data modelling are also investigated.

Lecture Program

Day 1

Lectures

Theoretical introduction to ML

Lectures

Cloud and Cloud Resources

Day 2

Hands-on

Neural Networks

Seminars

Deep Neural Network
Applications to INFN research

Day 3

Hackathon

Exercises
with tutors *continuous support*

Lunch break

Hands-on

Numpy, Pandas and Keras

Hands-on

Exercises
with tutors *on demand*

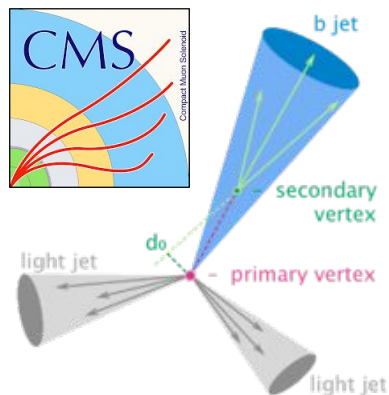
Closure

Reports from the students

Hackathon use cases: 10 groups, one tutor per group

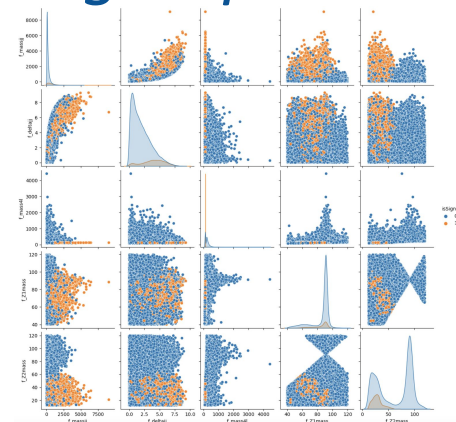
Jet b-tagging at CMS

Recurrent Neural Networks with LSTM



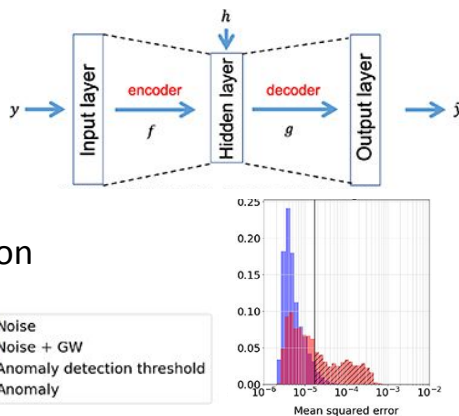
Higgs searches at CMS

Deep Neural Networks and Advanced Keras



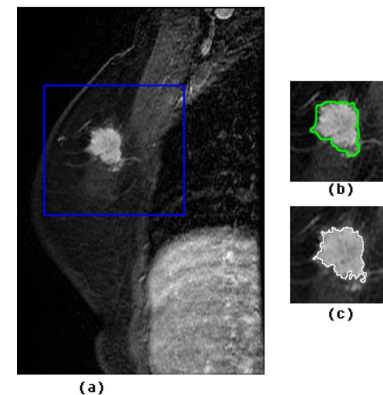
Gravitational Waves with Virgo

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

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

The Cloud / Jupyter setup

Did you find the technical setup using Cloud + Jupyter reasonable for ML oriented analyses?

A. Yes, worked for me: 19 (95.00%)

B. Yes, it generally worked for me (please add comment below): 1 (5.00%)

C. No (please explain below why): 0 (0.00%)



On the difficulty level:

Too easy

Too difficult



Appropriate

On the choice of topic:



expected more

Interesting

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

Machine Learning Knowledge Base

This section of the ML-INFN Confluence Space contains the Knowledge Base of fully implemented use cases. This has been created in order to provide new users getting close to Machine learning with concrete examples, with step by step guides for reproducibility.

The division into categories is multidimensional

- Dimension 1: per Machine Learning technology (CNN, Auto encoders, LSTM, GraphNet, ...)
- Dimension 2: per scientific field (High Energy Physics, Gravitational Waves, Medical Physics, ...)
- Dimension 3: per type of used tool

and is implemented via Confluence labels.

Table of Use cases

Name and Link	ML Technologies	Scientific Field	ML Tools	Comments
Tagging in CMS (templated version)	CNN, LSTM	High Energy Physics	Keras + Tensorflow	Realistic application
LHCb Masterclass, with Keras	DE, MLP	High Energy Physics	ROOT + Keras + TF	Introductory tutorial
MNIST in a C header	MLP		Keras	Free-styling tutorial
LUMIN: Lumin Unifies Many Improvements for Networks	CNN, RNN, GNN	High Energy Physics	PyTorch	Package use examples
INFERNO: Inference-Aware Neural Optimisation	NN	High Energy Physics	Keras + Tensorflow	Technique application example
An introduction to classification with CMS data	Fisher, BDT, MLP	High Energy Physics	Scikit-learn, TE2	Tutorials for Master

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

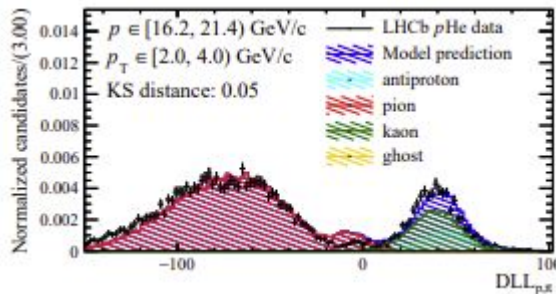
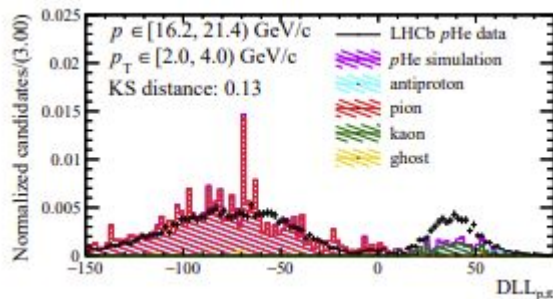
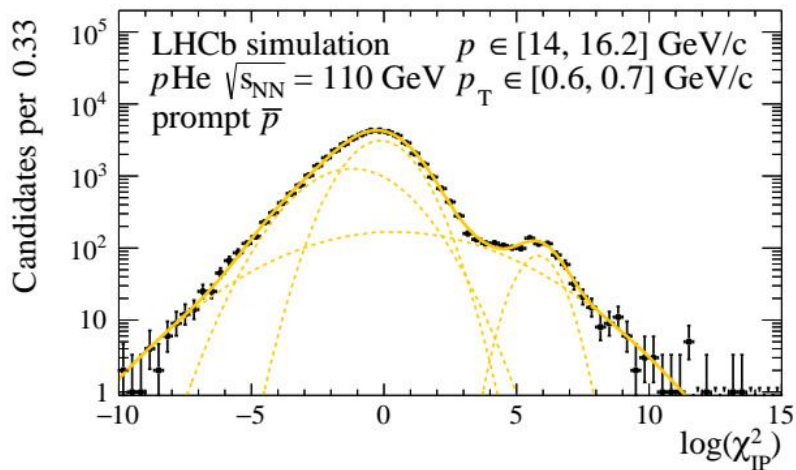
A. Palermo et al. “Machine learning approaches to the QCD transition”, *LATTICE 2021*, *arXiv:2111.05216*



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

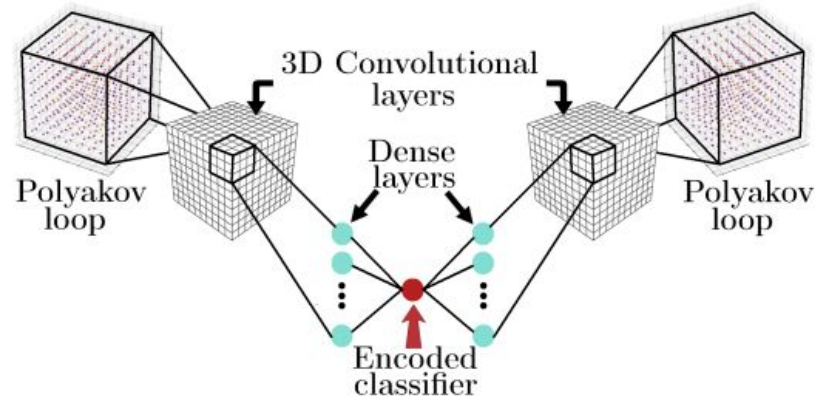
S. Mariani *et al*,
 “A Neural-Network-defined Gaussian Mixture Model for particle identification applied to the LHCb fixed-target programme”, JINST 17 (2022) P02018



Public repository
PID4SMOG

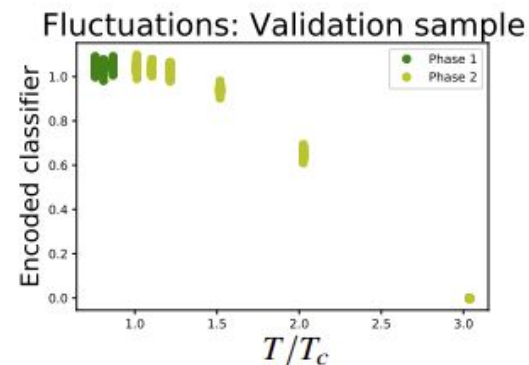
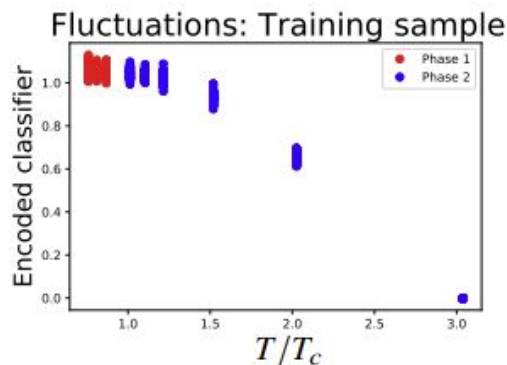
Stories of success [2]: *studying LQCD with CNNs*

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.