Deep Learning in High Energy Physics: examples from CERN openlab

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IXPUG Conference– September 24th, 2019

CERN openlab

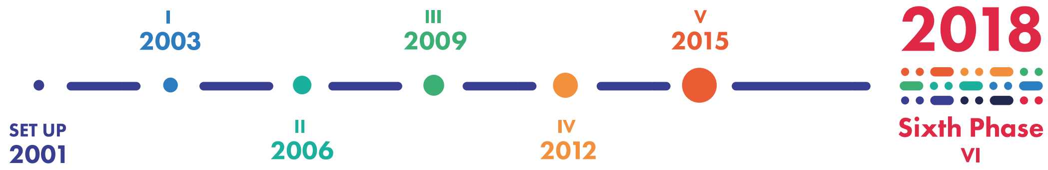
A science – industry partnership to drive R&D and innovation

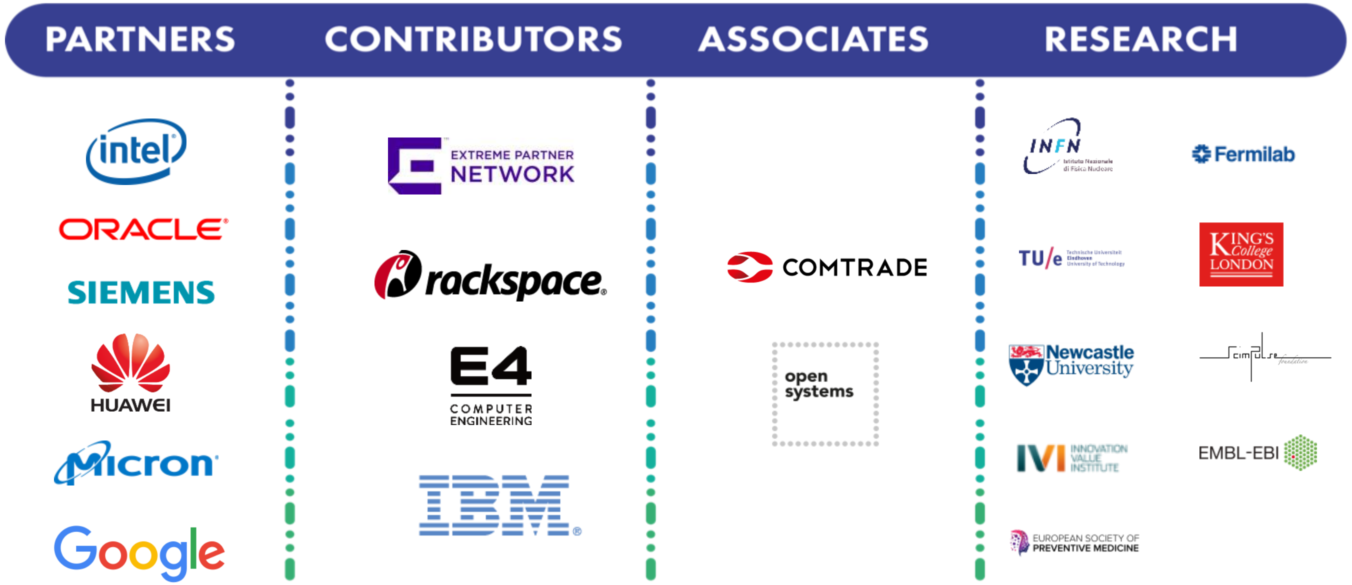
Evaluate **state-of-the-art technologies** in a challenging environment and improve them

Test in a **research environment** today what will be used in many business sectors tomorrow

Training

Dissemination and **outreach**





JOINT R&D PROJECTS

High-bandwidth fabrics, accelerated platforms

Data Acquisition (LHCb, IT-CF)

Code modernization (EP-SFT, IT-CF)

Simulation, HPC on the Cloud, benchmarking

Data Analytics, Machine Learning (many)

Data quality monitoring, anomaly detection, physics data reduction, benchmarking/scalability, systems biology and large-scale multi-disciplinary platforms

Cloud infra (IT-CM)

Cloud federations, containers, scalability

Control Systems (BE-ICS)

Predictive/proactive maintenance and operations

Networks (IT-CS)

Software Defined Networks, Security

Data Storage (IT-ST, IT-DB)

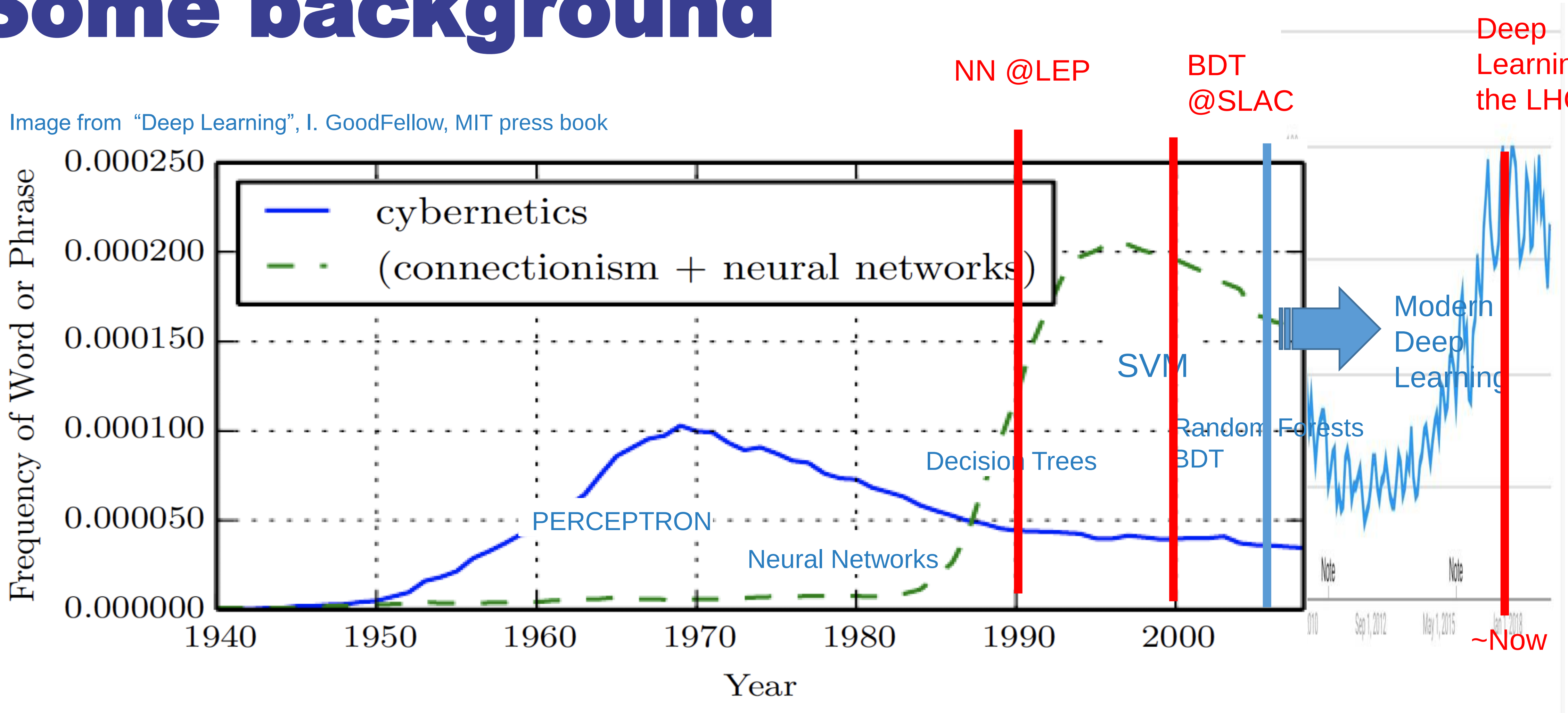
Storage architectures, scalability, monitoring

Outline

- Setting the stage
  - Deep Learning at the LHC
- Addressing physics challenges
  - Examples from Simulation and Reconstruction
- Addressing computing & infrastructure challenges
  - Accelerators
  - Distributed computing
  - Big Data platforms
- Pushing the boundaries
  - Quantum Machine Learning
  - Beyond High Energy Physics

Some background

Image from "Deep Learning", I. GoodFellow, MIT press book



Theories on biological learning
First linear models
Layer-wise pre-training through greedy algorithms

Back-propagation

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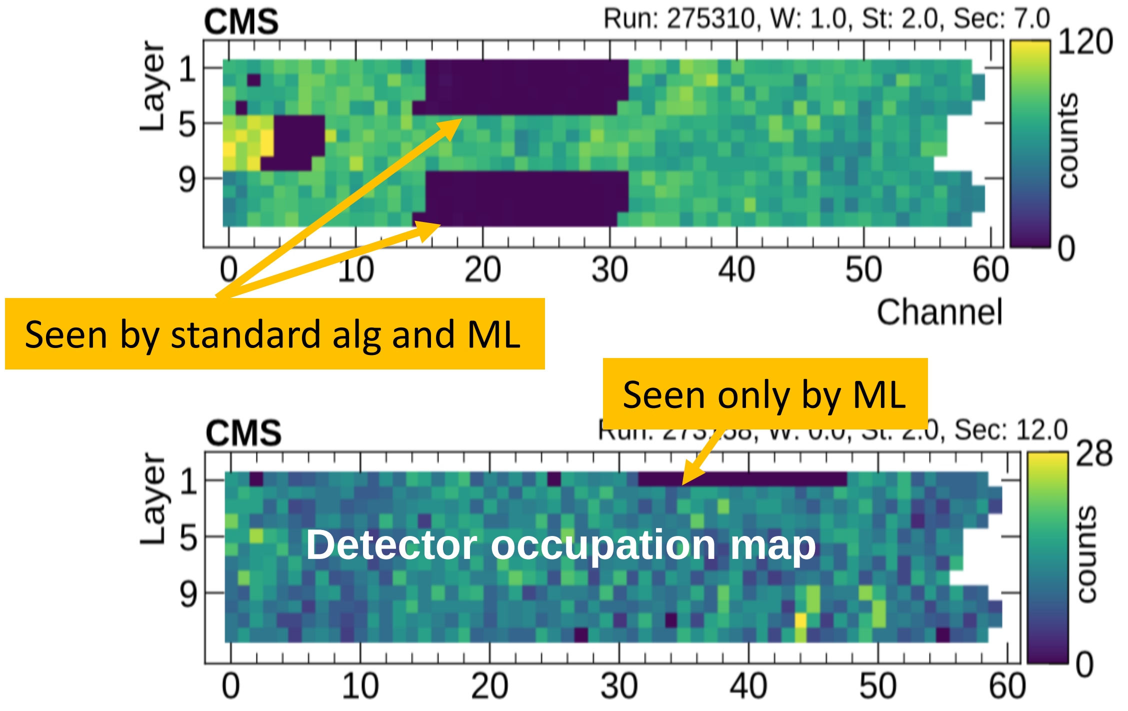
Deep Learning in HEP

Ex. CMS muon chamber monitoring



A. A. Pol, CHEP2018

- Analysis
- New physics searches as anomaly detection
- Reconstruction and particle identification
- Trigger and event filtering
- Data Quality Monitoring and Anomaly Detection in control systems
- Simulation
- Computing resources optimisation (dataset popularity, allocations, …)
- **“Theoretical” studies on model interpretability and systematics**

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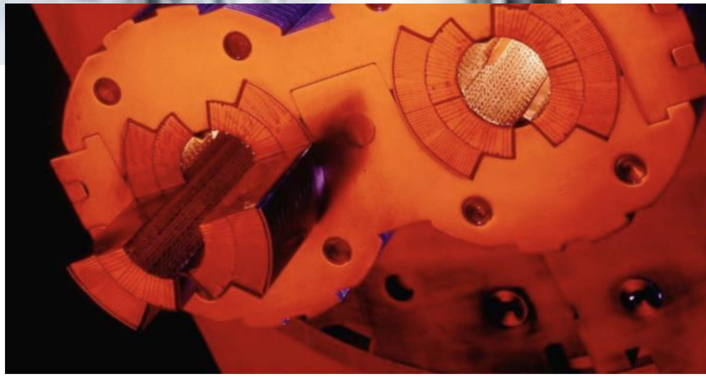
Why? ...Big Data

LHC is entering the Big Data era



Accelerators infrastructure (control systems, monitoring)

9600 magnets for Beam Control

1232 superconducting dipoles for bending

Experiments (detectors & physics data)

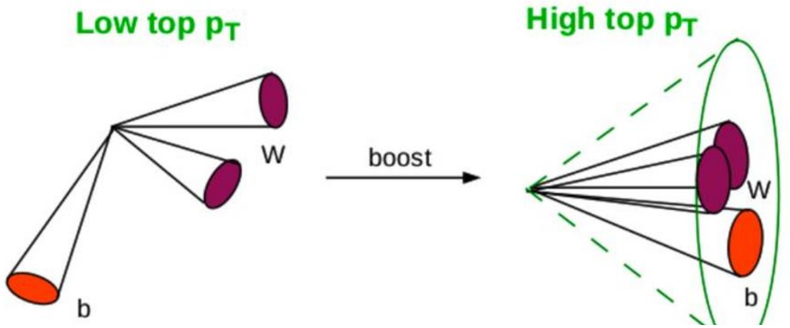
330 PB of collisions data stored by December 2018

The computing infrastructure:

Large sets of metrics collected from system components (CPU and batch, disk and archive storage, network topology and flows, and application throughput)

- LHC data is represent a challenge since it is **multi-structured, hybrid**
  - Metadata
  - Databases Aggregation
  - Evolving Data model

Why? ...New Challenges



Next generation colliders

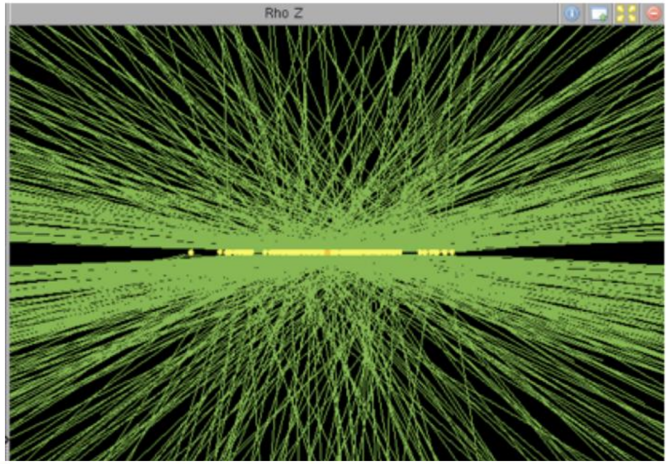
Will require **larger, highly granular detectors** (forward physics, high pT boosted objects)

- Larger, more complex datasets to analyse
- Challenging pattern recognition problems

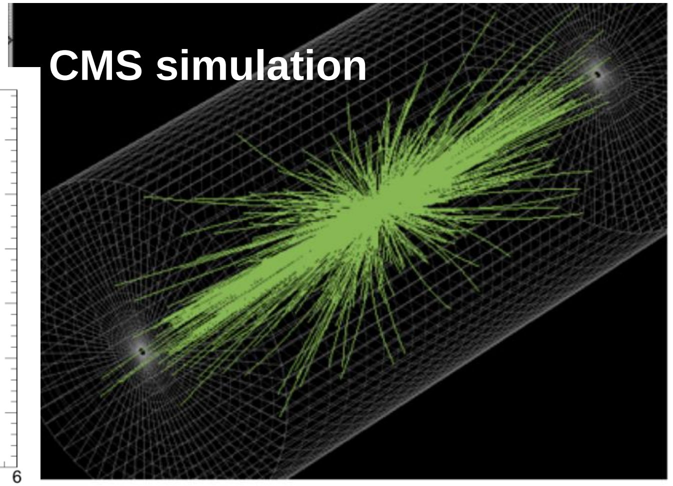
Will generate **huge particle data rates**

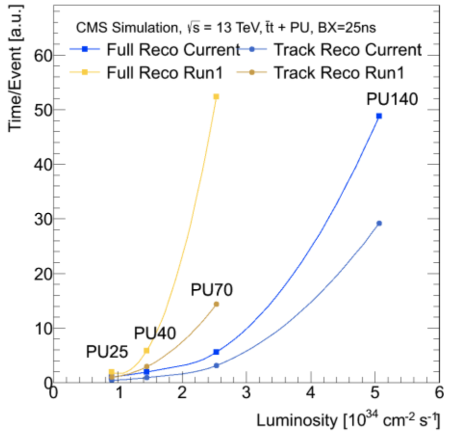
- Efficient, fast real-time selection will be essential
- HL-LHC bunch crossing frequency of 40 MHz and extreme data rates O(100 TB/s)
- L1 trigger latency ~1μs - 100 ms for HLT and offline processing

Related **computing challenges** will touch many aspects



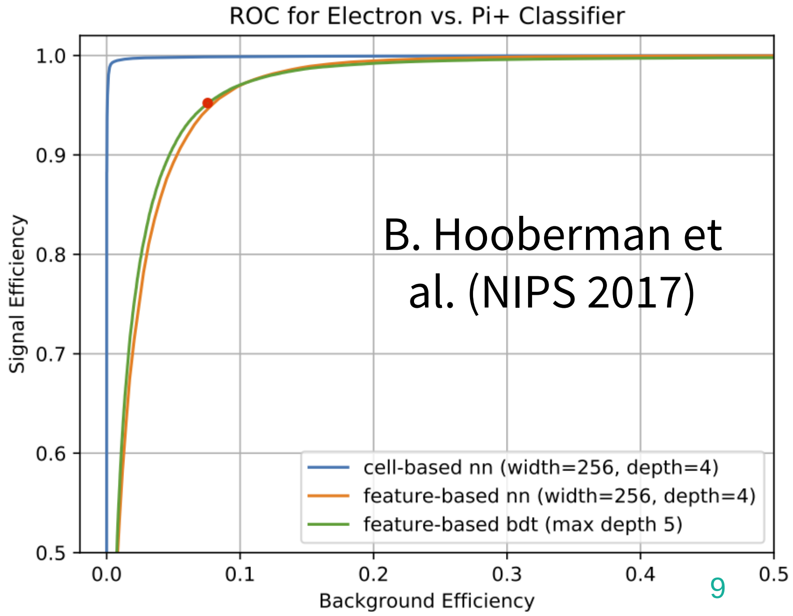
$t\bar{t}$ event at <PU>=140 (94 vertices, 3494 tracks)





How? … Deep Learning

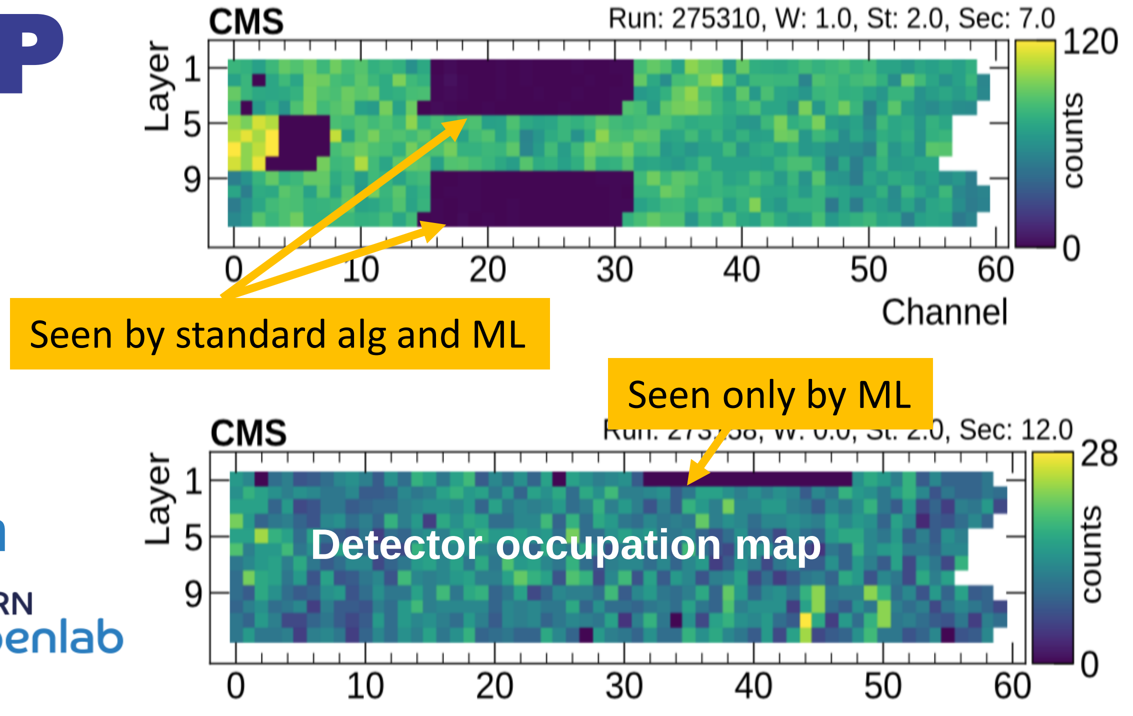
- DL can **recognize patterns** in large complicated data sets
  - DL algorithms can have better performances if applied directly to raw data
- **Re-cast physics problems** as “DL problems”
  - Interpret detector output as **images** and apply techniques borrowed from **computer vision** field
  - Interpret physics events as **sentences** and apply Neuro-Linguistic Prgramming techniques
- Intense R&D activity
- Adapt DL to HEP requirements
  - In terms of model **interpretability**
  - Results **Validation** against classical methods
  - Detailed **Systematics**
- Adopting ”new” computing models
  - **Accelerators** and dedicated hardware
  - **HPC** integration
  - **Cloud** environment
  - **Big Data** platforms



Ex. CMS muon chamber monitoring

Deep Learning in HEP

and CERN openlab



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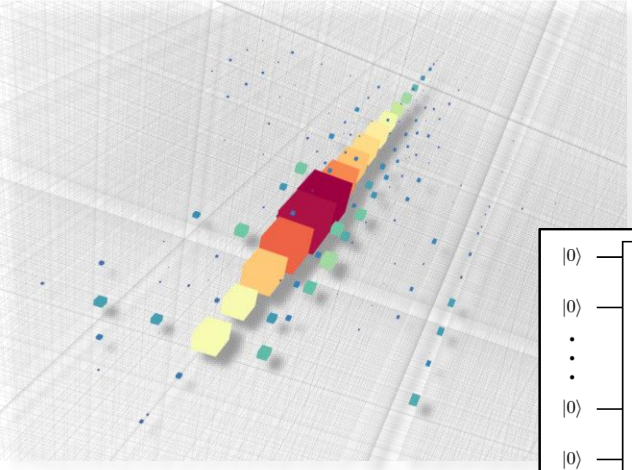
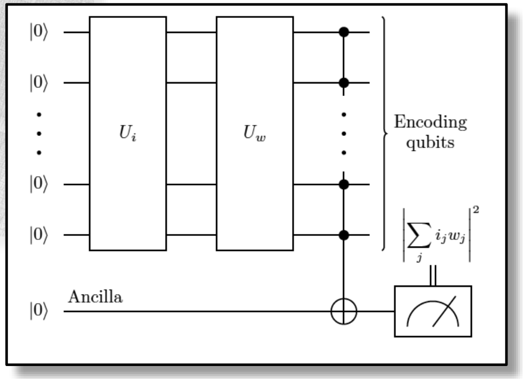
More ML/DL @CERN openlab

- Integration and technologies
  - Big Data technologies
  - Distributed training and optimisation of Deep Learning models
  - Cloud and HPC
  - GPUs, FPGAs
- Applications beyond HEP
  - Medical applications & model interpretability
  - Knowledge discovery and NLP
  - Satellite Image analysis
- Quantum Machine Learning!





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Addressing physics challenges

Examples from simulation and reconstruction

Deep Learning for fast simulation

Simulation is a **major workload** in terms of computing resources.

- With HL-LHC we expect a x100 increase in simulation need

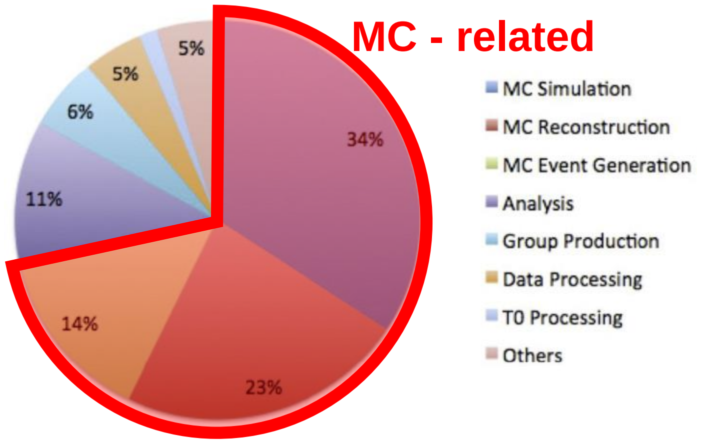
DNN could represent a **generic approach** to replace expensive calculations

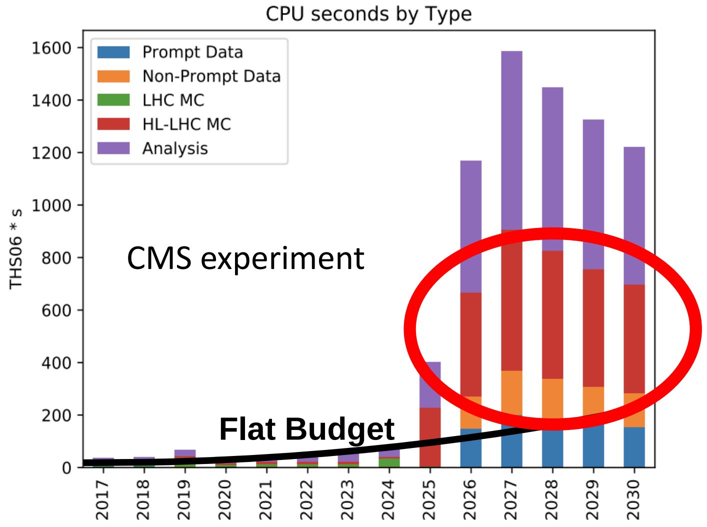
- DNN inference step is faster than Monte Carlo approach

Industry building highly optimized software, hardware, and cloud services.

Numerous R&D activities (LHC and beyond)

WLCG Wall Clock time for the ATLAS experiment





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Deep Generative Models

Internal representations learned by shallow systems are simple (Bengio & LeCun 2007, Bengio 2009)

Incapable of learning complex hidden structures

Require large amounts of labeled data

→ Deep Generative Models

→ Allow higher levels of abstractions

→ Improve generalisation and transfer

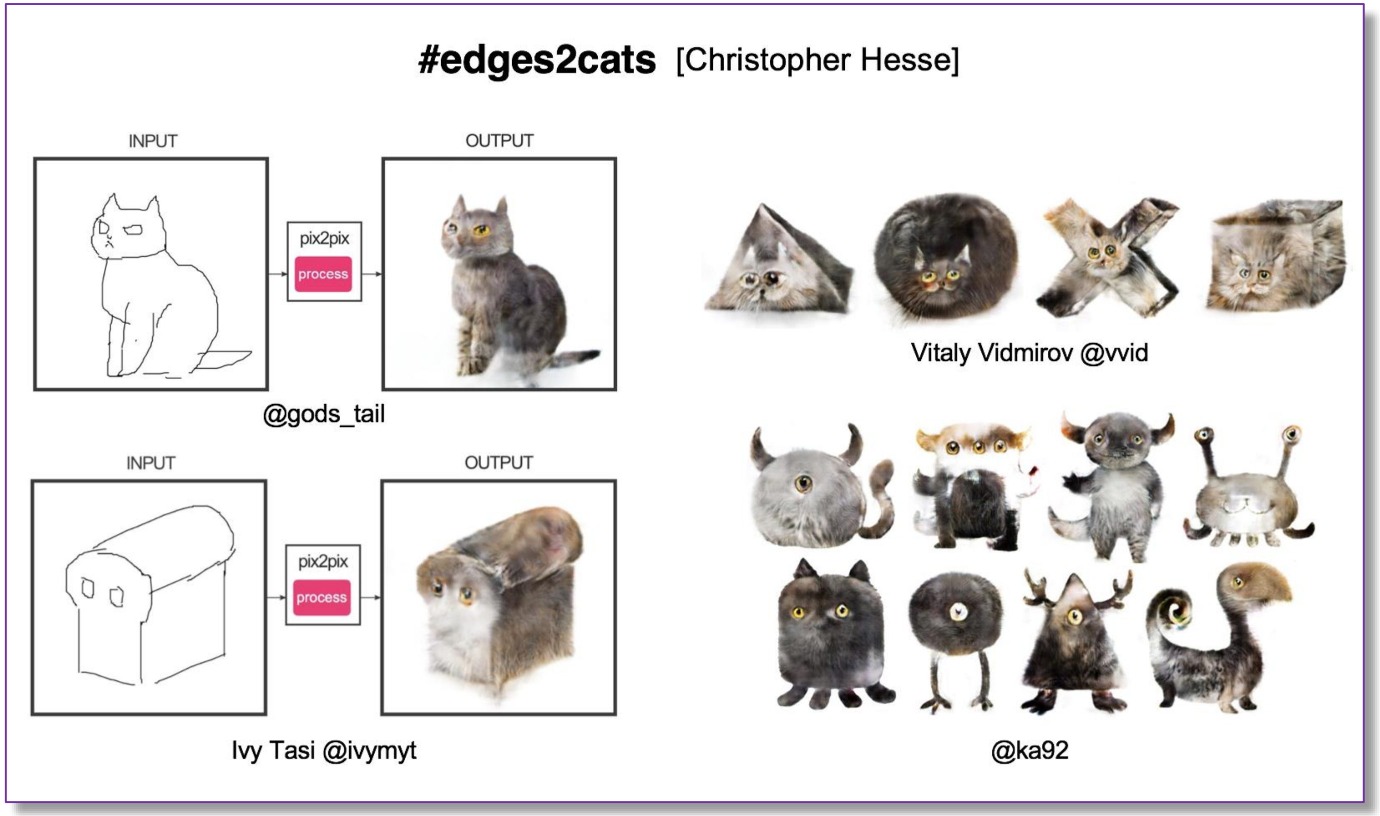
→ Multiple applications

Find Underlying Factors (**Discovery**)

Detect Rare events (**Anomaly Detection**)

Predict future events (**Planning**)

Find Analogies (**Transfer Learning**)



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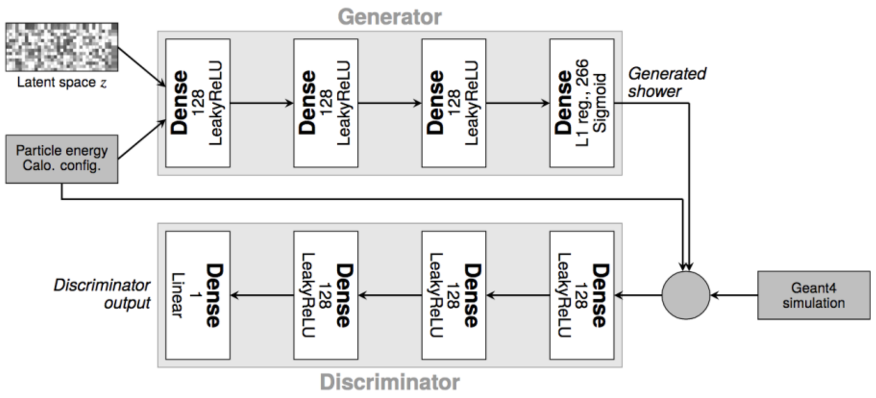
Applications

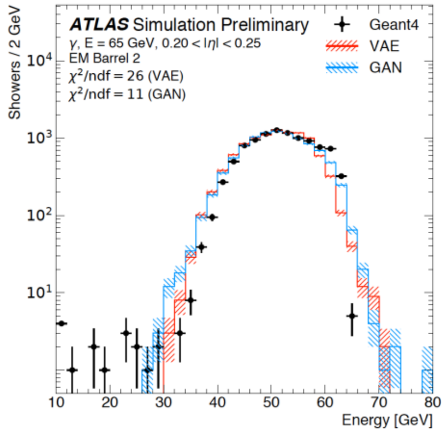
GANs for ATLAS LAr calorimeter

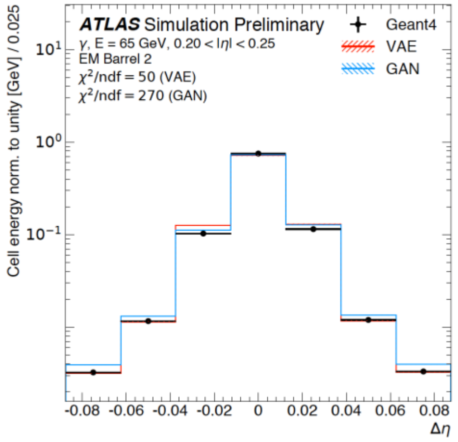
ATL-SOFT-PUB-2018-001

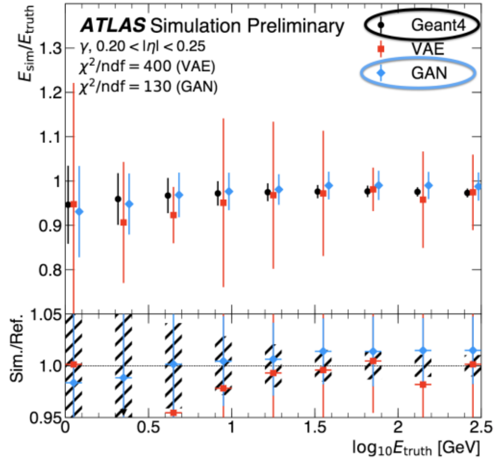
Wasserstein GAN model reproduces the mean energy distribution but not its width

At convergence critic can't see the difference in real and fake images anymore.

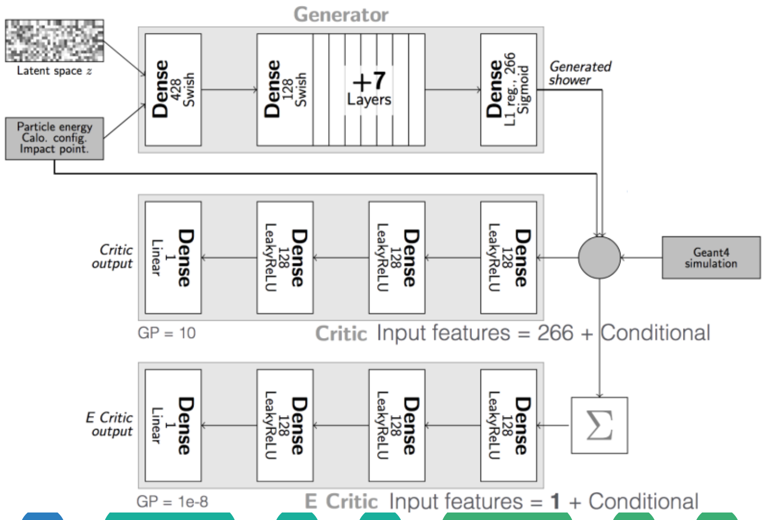


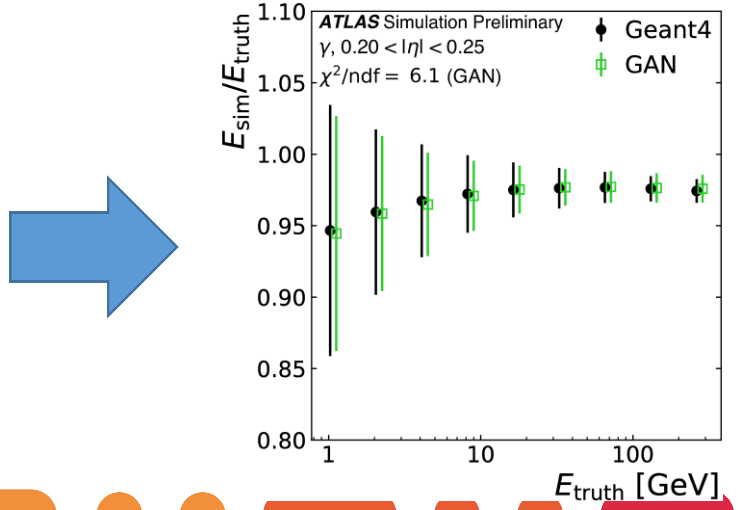






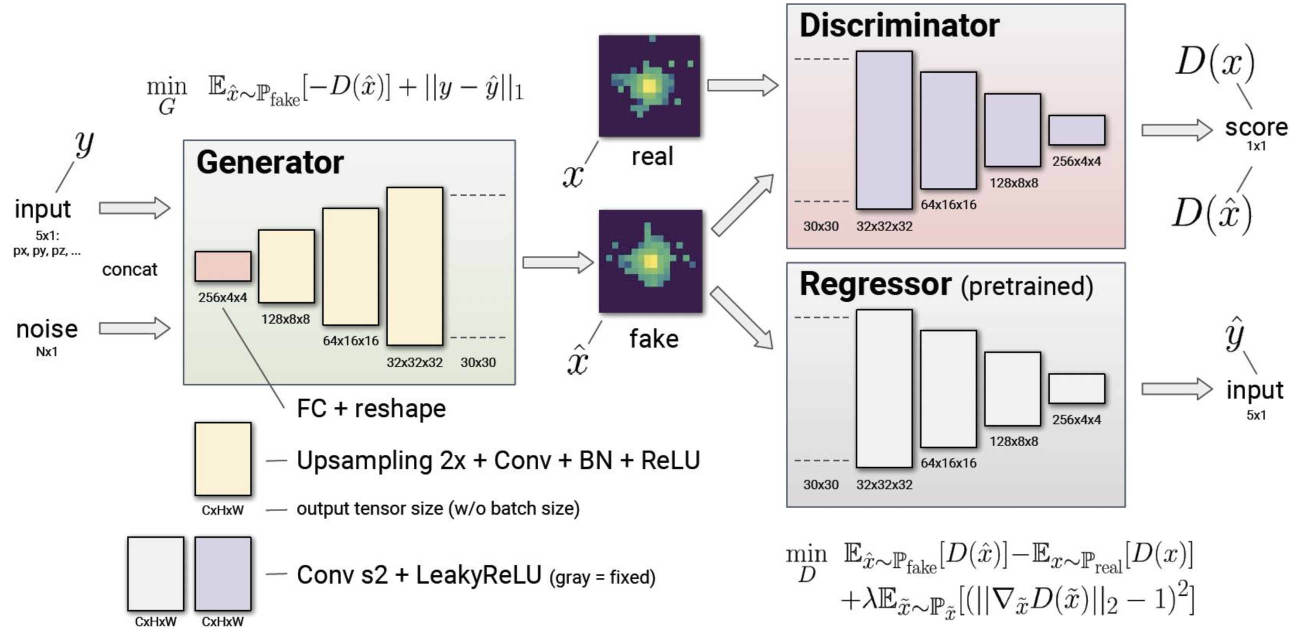
Train the generator against two critics

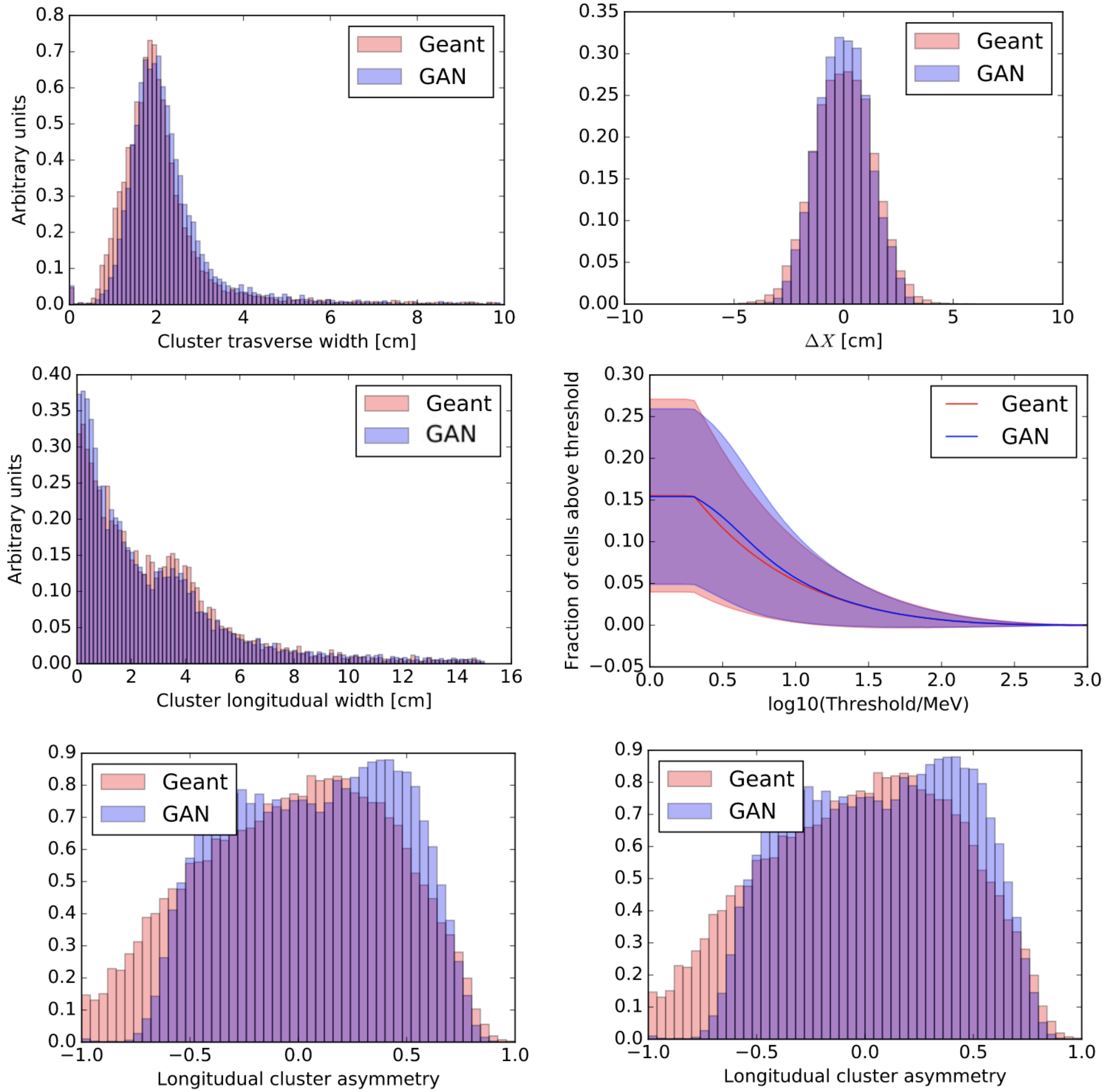




LHCb Calorimeter fast simulation

Wasserstein Convolutional GAN



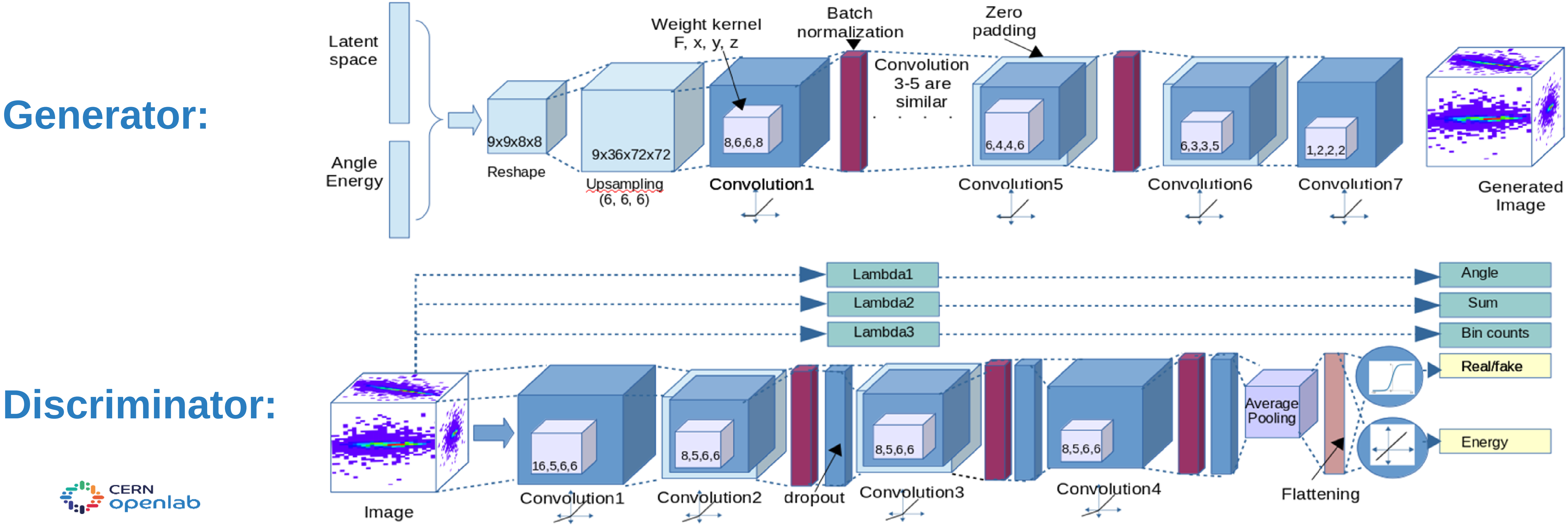


3D convolutional GAN

Openlab.cern

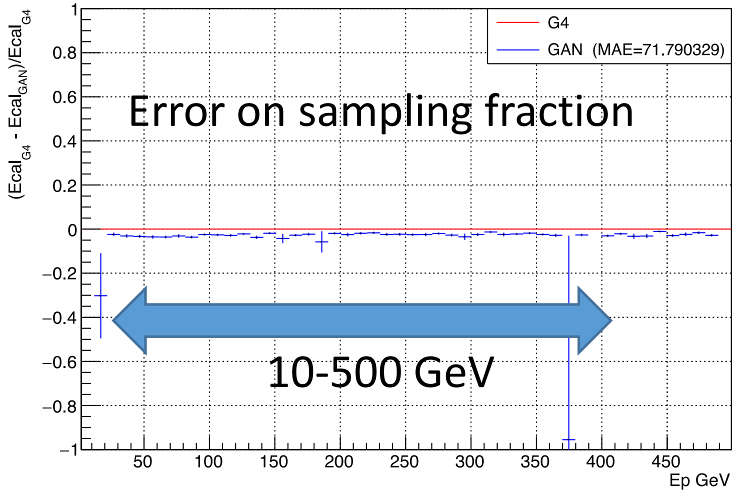
Condition training on input **particle energy** and **incident angle**, **Custom losses**

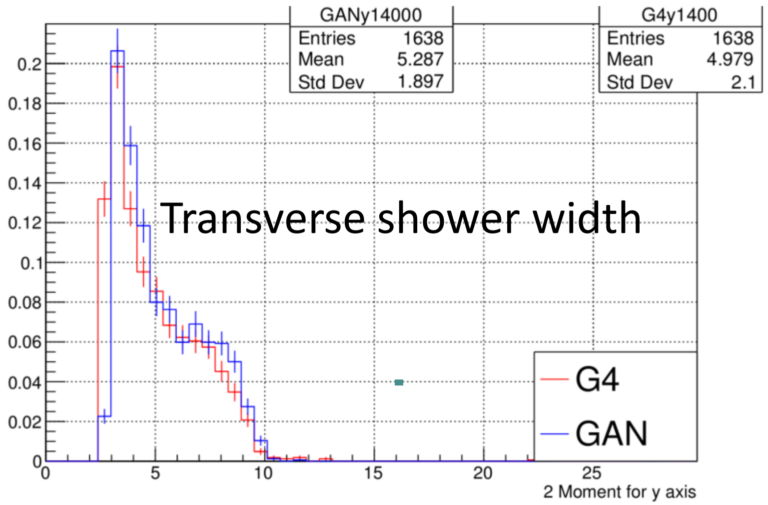
Auxiliary regression tasks assigned to the discriminator

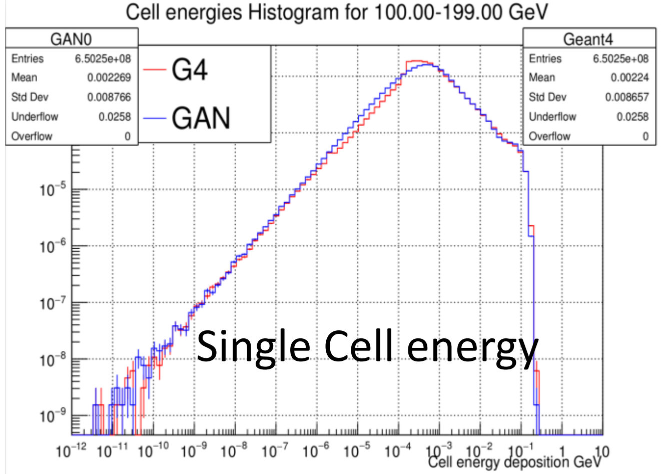


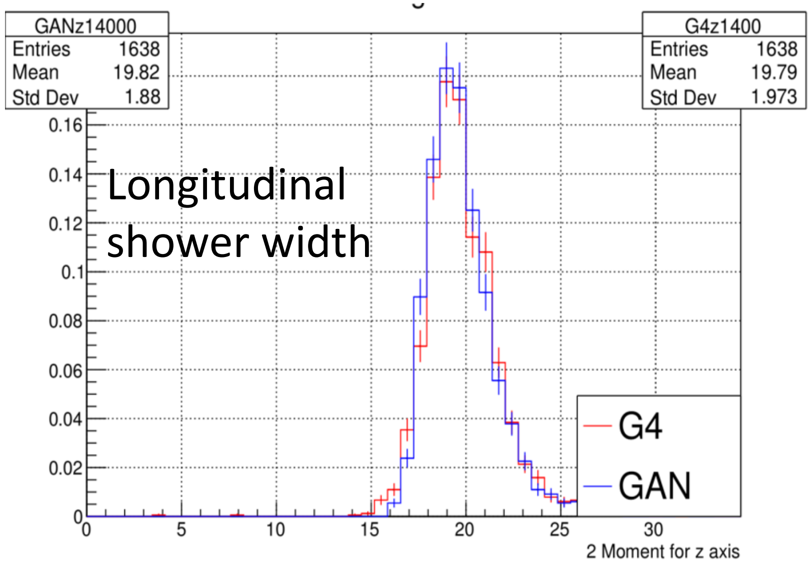
Two steps training

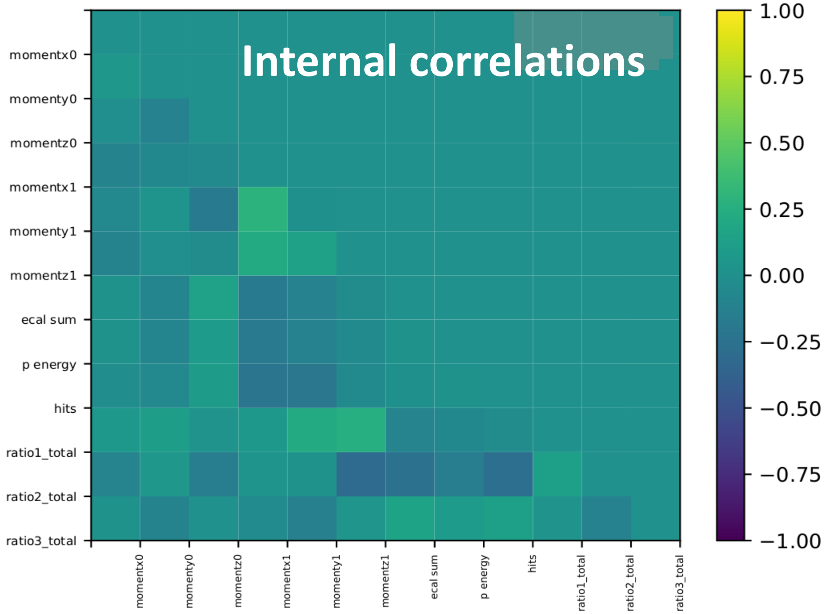
- Train on 100-200 GeV energy range
- Transfer learning to full spectrum





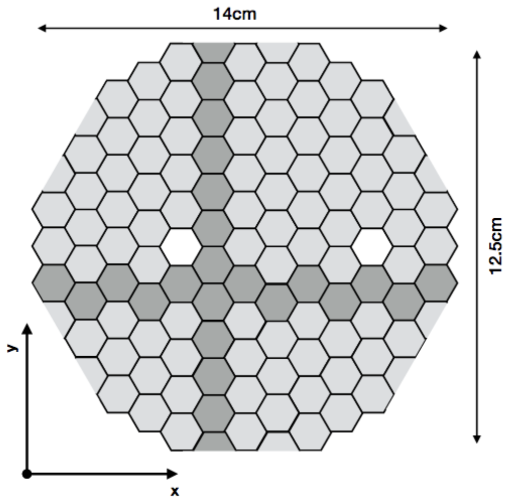






CMS HGCAL prototype

High Granularity and Hexagonal cells prototype for CMS upgrade



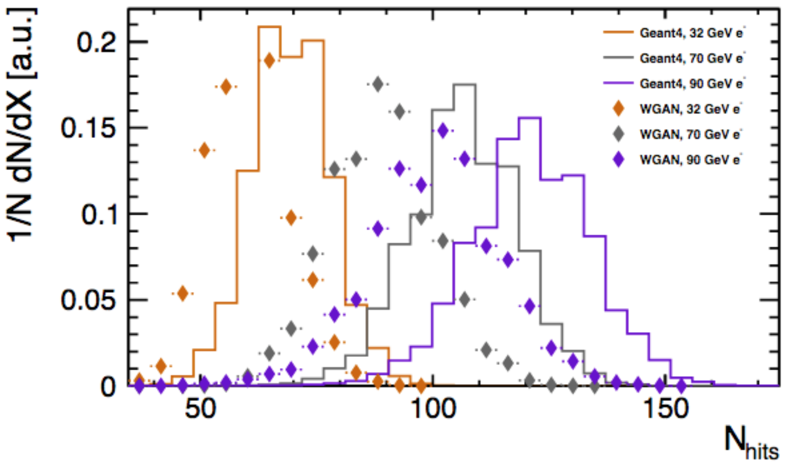
Wasserstein conditional GAN (convolutions)

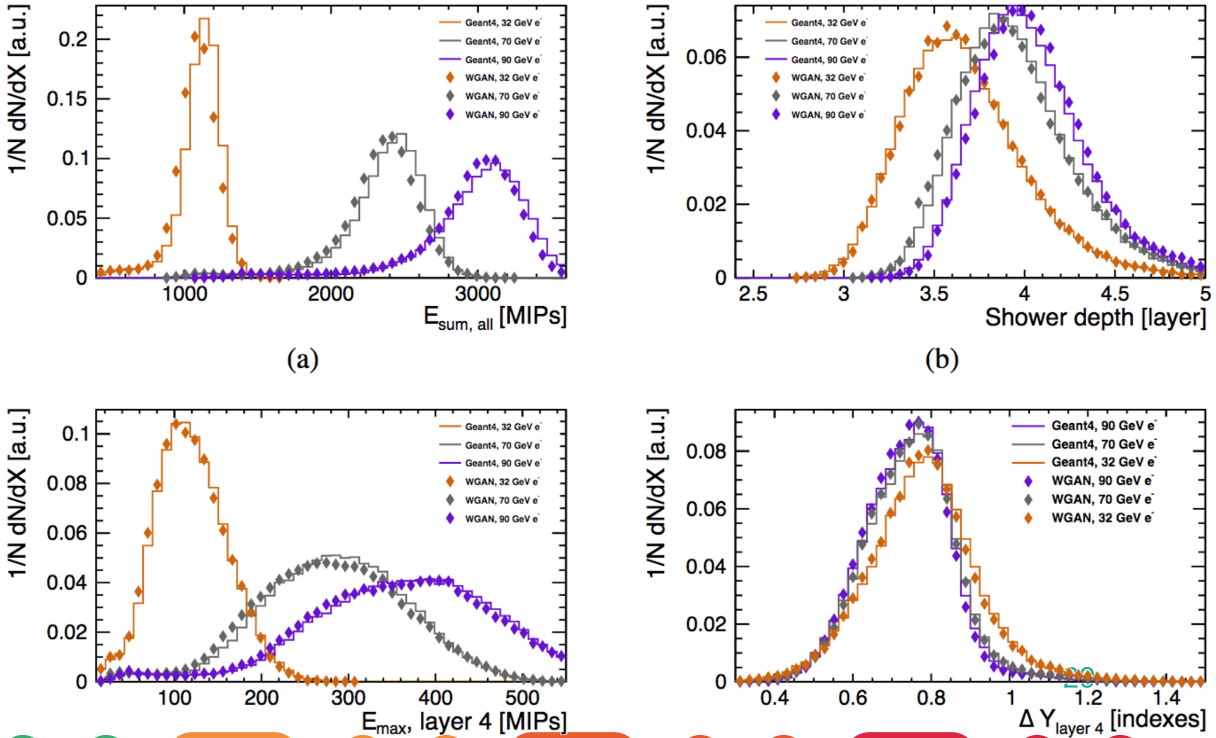
Train a generator against a critics and 2 constrainer networks reconstructing energy and impact point coordinates

Good agreement with Geant4

Some problems at low energy

arxiv.org: 1807.01954





(a)

(b)

Other applications in HEP

Generative models for ALICE TPC simulation (ACAT2019)

Conditional Wasserstein GANs for fast simulation of electromagnetic showers in a CMS HGCAL prototype (IML WG 04/18)

Variational AutoEncoders to simulate ATLAS LAr calorimeter (PASC18)

Wasserstein GANs to generate high-level physics variables based on Monte Carlo ttH (superfast-simulation) (IML WG 04/18)

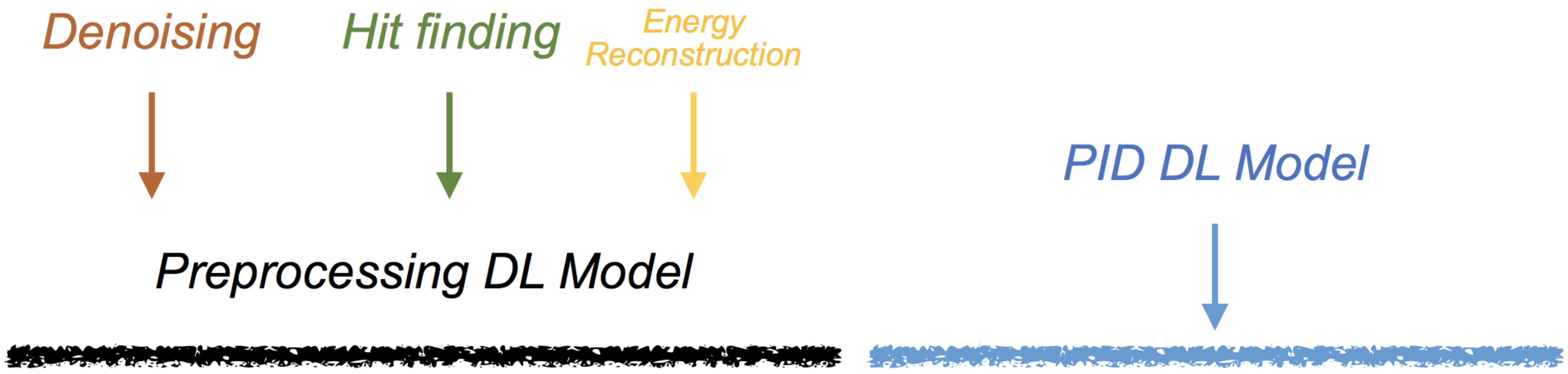
Particle-GAN for Full Event Simulation at the LHC (ACAT2019)

Refining Detector Simulation using Adversarial Networks (IML WG 04/18)

Model-Assisted GANs for the optimisation of simulation parameters (IML WG 04/19)

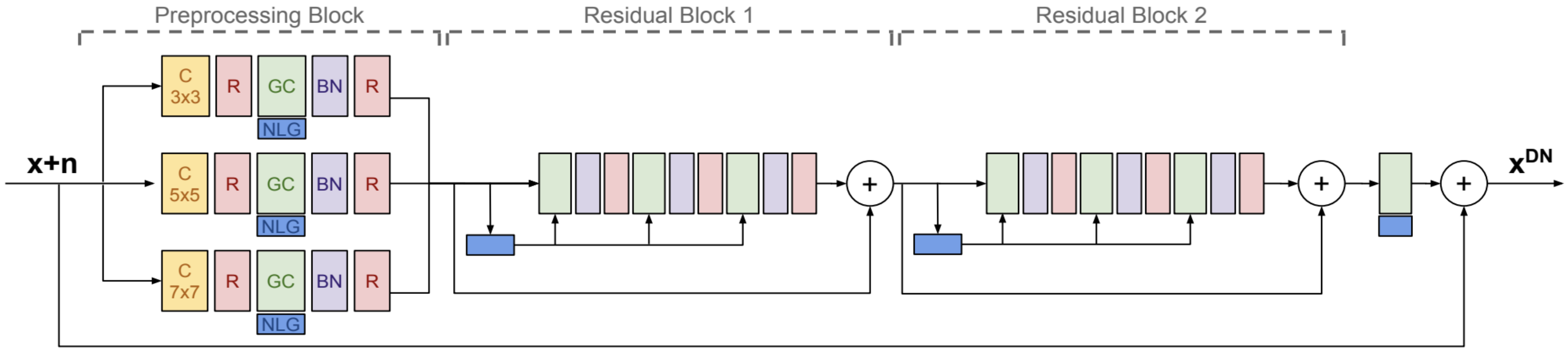
Neutrino Event Reconstruction in Dune

- Neutrino event **reconstruction** is a **multi-step, time consuming** problem
  - Several R&D activities exist to replace different stages
- Combine **different approaches** (CNN + GNN) for a **end-to-end solution**
  - start from raw detector output
  - Interpret it as “images” but also time-series data



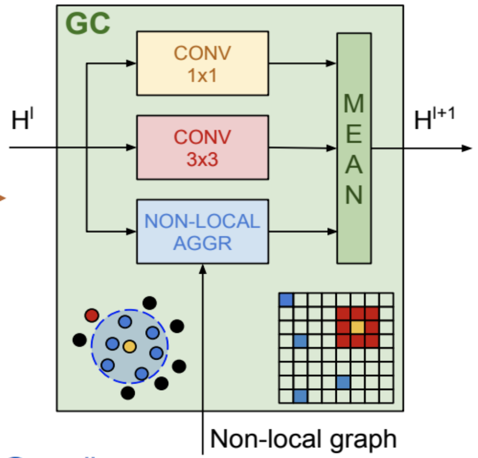
Test 1: Denoising Dune data

Combined CNN (Fast, Reliable, Easy-to-use) to GNN (Non-local features, Increased receptive field, Dynamically updates the image)



C 3x3 → *Convolutional Layer 3x3*

GC → *Graph-Convolutional Layer* →



Model defined in arxiv:1905.12281

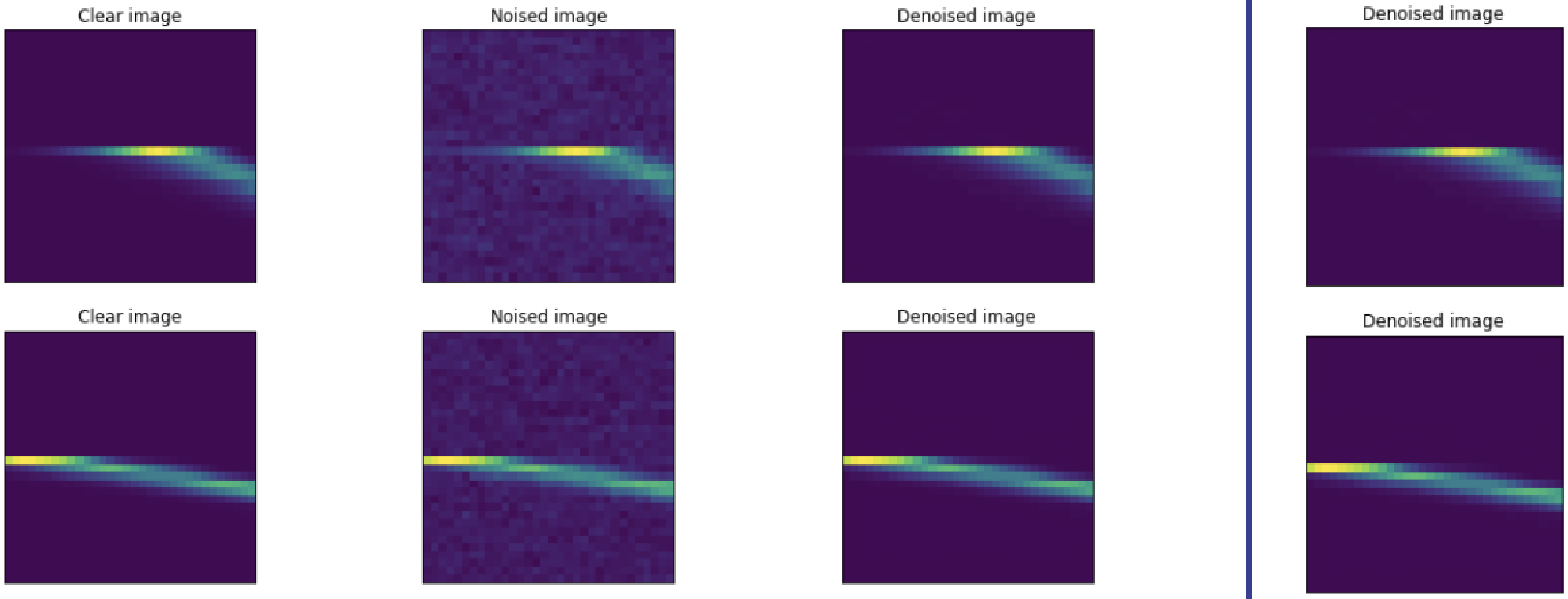
$$H_i = \sigma\left(\underbrace{\sum_{j\in N_i} \frac{F_{w_i}(H_j - H_i)}{|N_j|}}_{\text{neighborhood}} + \underbrace{W_i H_j}_{\text{node}} + \underbrace{b}_{\text{bias}}\right)$$

Preliminary Results

Initial tests are run on Monte Carlo data

Gaussian Filter

CNN+GNN



Further examples

Prototyping of a DL-based Particle Identification System for the Dune Neutrino Detector (Dune, P. Sala, M. Pierini)

Fast Detector Simulation with Deep Learning (CMS HGCAL, M. Pierini, F. Pantaleo)

Particle Reconstruction as Image Detection with Deep Learning (Calorimeter reconstruction, CMS, V. Innocente, M. Rovere)

LHCb RICH reconstruction using Convolutional Neural Networks (LHCb)

Addressing Computing challenges

Millions of operations

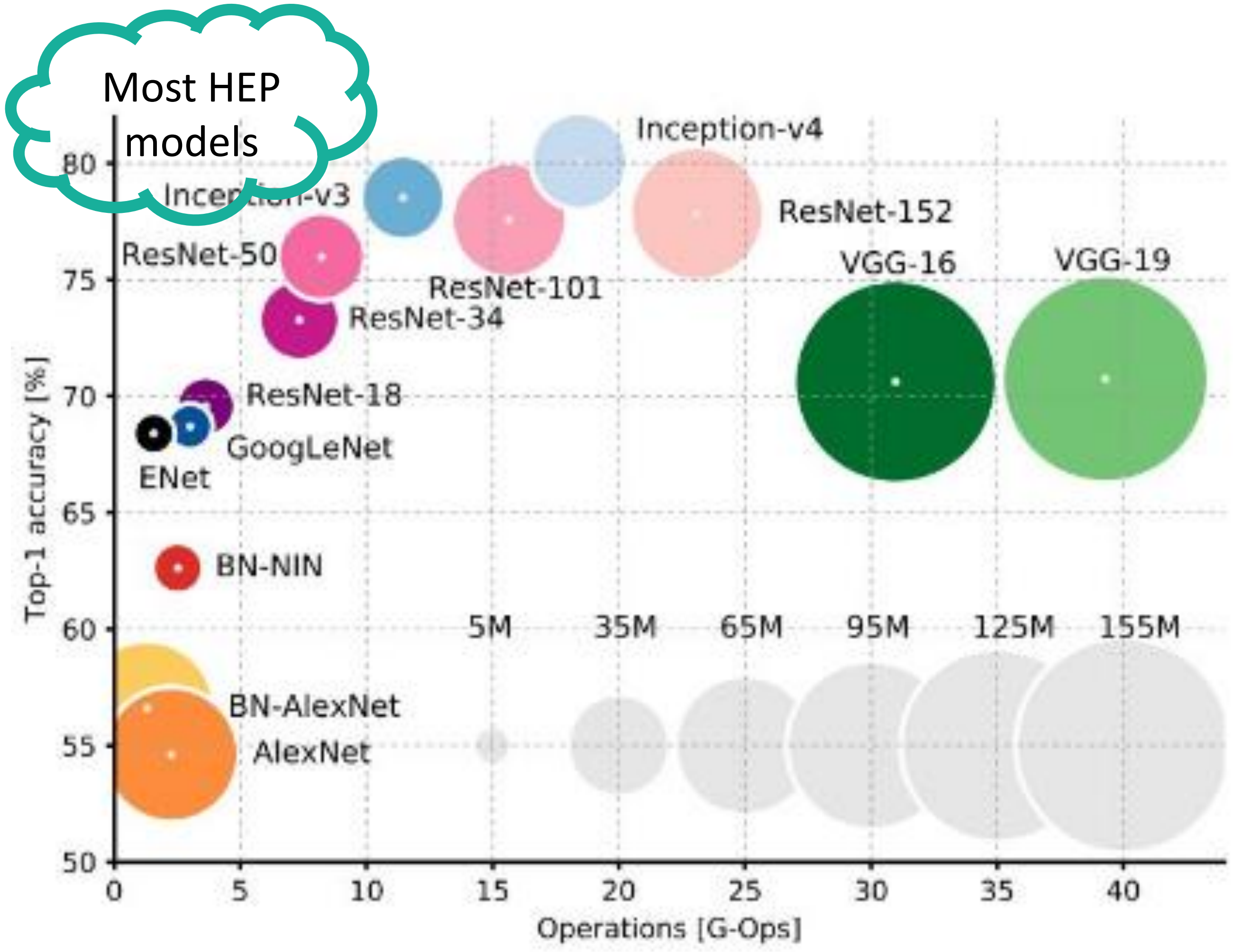
- Mostly matrix-multiplications

HEP models are designed and **optimised for specific tasks**

- Generally custom models
- ~Fewer weights and operations than out-of-the-box tools
- Higher accuracy

Depending on the task, we might need:

- Fast inference
- Online training capability
- Fast training for large optimisations

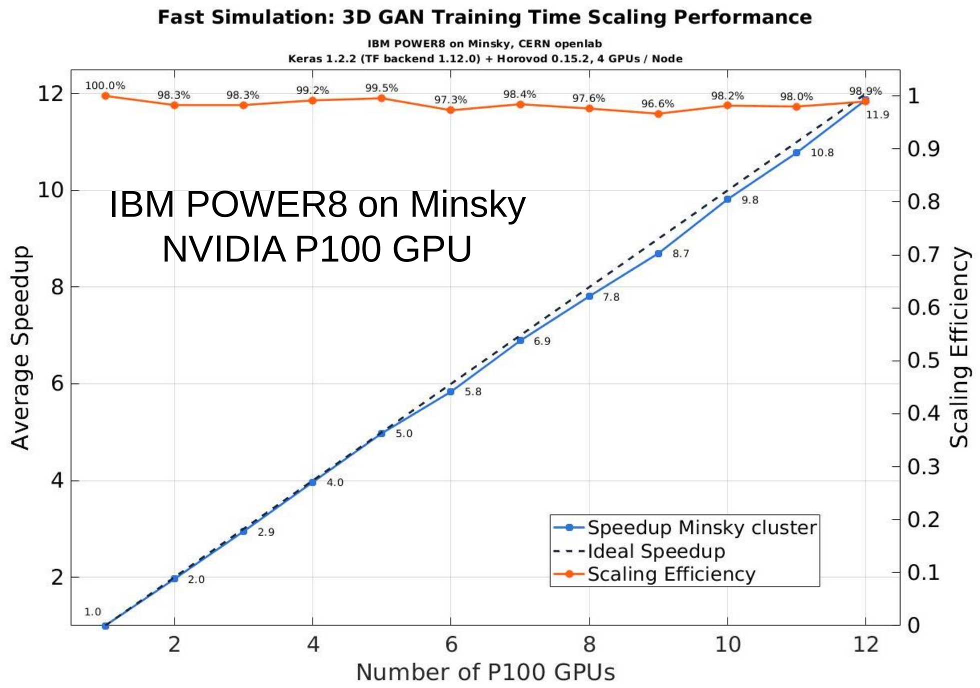


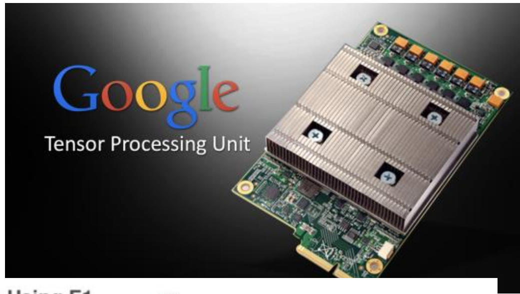
Low precision operations

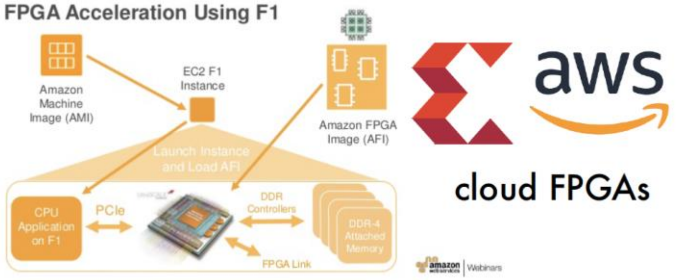
- Most DL applications use 32-bit FP for inference and training
- Both steps could be performed with **lower precision** with no accuracy loss
  - **Better cache usage** and the reduction of memory bottlenecks
  - Lower-precision multipliers require less silicon area and power to execute a **greater number of operations per second.**
- Most vendors are implementing lower precision ops in their hardware
- Use 3DGAN to test new **Intel DL Boost AVX512-VNNI** (Vector Neural Network Instruction) for next generation Intel Xeon Scalable Processor (Cascade Lake)
  - Simulation use case is particularly interesting (classical Monte Carlo simulation is run in double precision)

Accelerators

- Deep Learning workloads are naturally **accelerator friendly**
  - Large number of frameworks and ecosystems to simplify deployments
  - Can work with half precision arithmetic (16FP, …)
- GPUs are de-facto **standard** to run DL
  - R&D on reducing bottlenecks (memory size, I/O. …)
- FPGAs can provide **low latency** inference
  - Network compression/quantization/parallelisation
  - Different programming approaches Hardware Description Language vs High Level Synthesis
- Frameworks exist that “compile” ML code for different hardware
  - Customisation
- Available in cloud environments for **on-demand access**
  - Initial tests to time inference on cloud vs local







FPGAs

Prototyping of a DL-based Particle Identification System for the Dune Neutrino Detector (Dune, P. Sala, M. Pierini)

Fast Deep Learning Inference on FPGA (**hls4ml project**, CMS, J. Ngadiuba, M. Pierini)

- Extend hls4ml support to Intel FPGAs architectures

Data Streaming and Machine Learning for trigger Filtering (CMS, M. Zanetti)

FPGA-based Inference for Fast Simulation (prof. Herman Lam, University of Florida, SHREC*)

- Design for a **Heterogeneous Computing** (CPUs, GPUs and FPGAs) system to accelerate DNN workflows.
- A collaborative effort between SHREC and NERSC (Berkeley National Lab), openlab, Dell EMC, Intel.

TALK ON THURSDAY

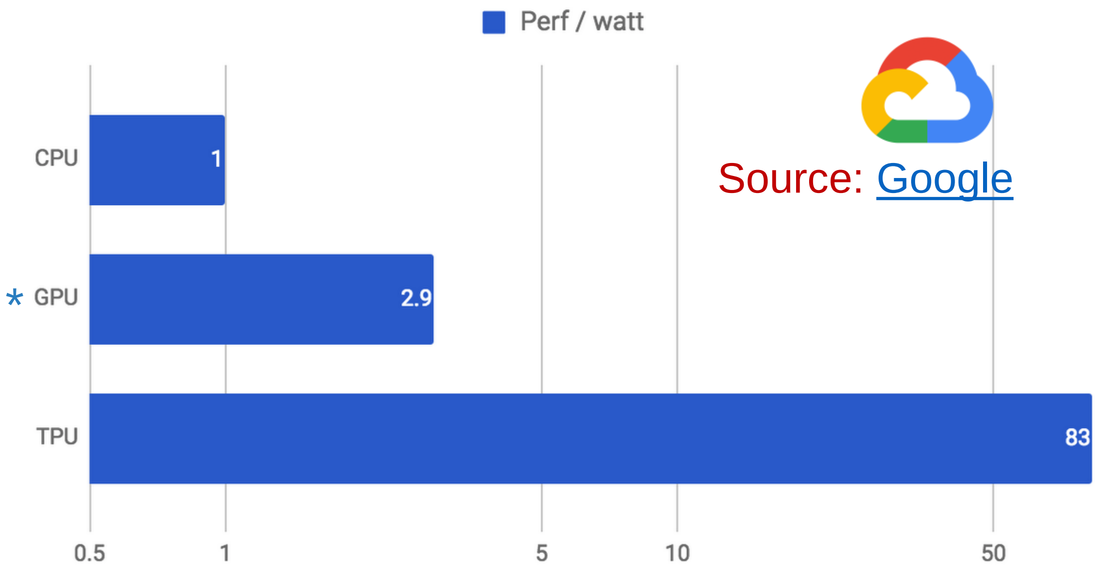
*NSF Center for Space, High-Performance, and Resilient Computing: www.nsf-shrec.org

TPUs

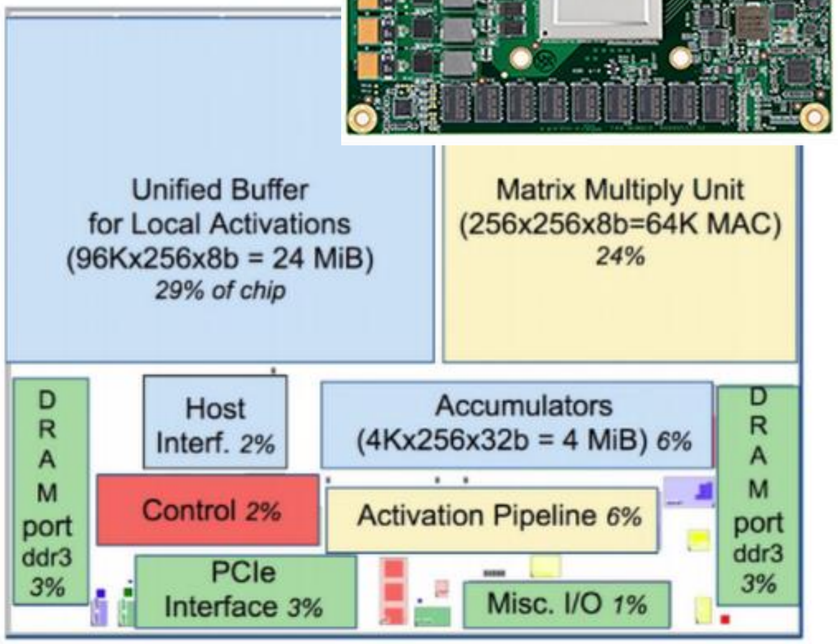
Custom ASIC optimized for high volume of **low precision matrix manipulation**

- matrix processor for $O(10^5)$ operations per clock cycle
- int & float support for both training and inference

Google has been using TPUs for years in their search engines



Source: [Google]



TPUs promise incredible speed-ups for both inference and training

Several R&D projects (openlab/Google collaboration)

- Run tests on Google Cloud and on-prem

*but GPUs have tensor cores too

Addressing Computing challenges

Distributed computing and Big Data technologies

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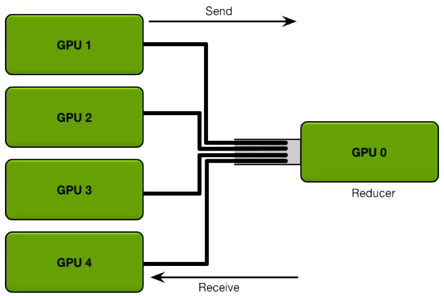
Distributing the training process

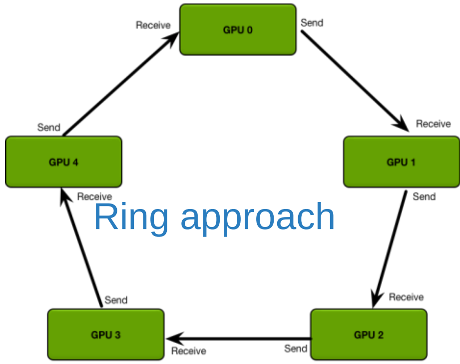
Training complex models over large datasets can take days

- **Data parallelism** is the most common approach
  - Compute gradients on several batches independently
  - Update the model synchronously or asynchronously
- Many frameworks available, mostly **MPI based**
  - Horovod, Distributed TF , PyTorch Distributed, ..
- Alternative approach via **Big Data** technologies
  - BigDL/Spark

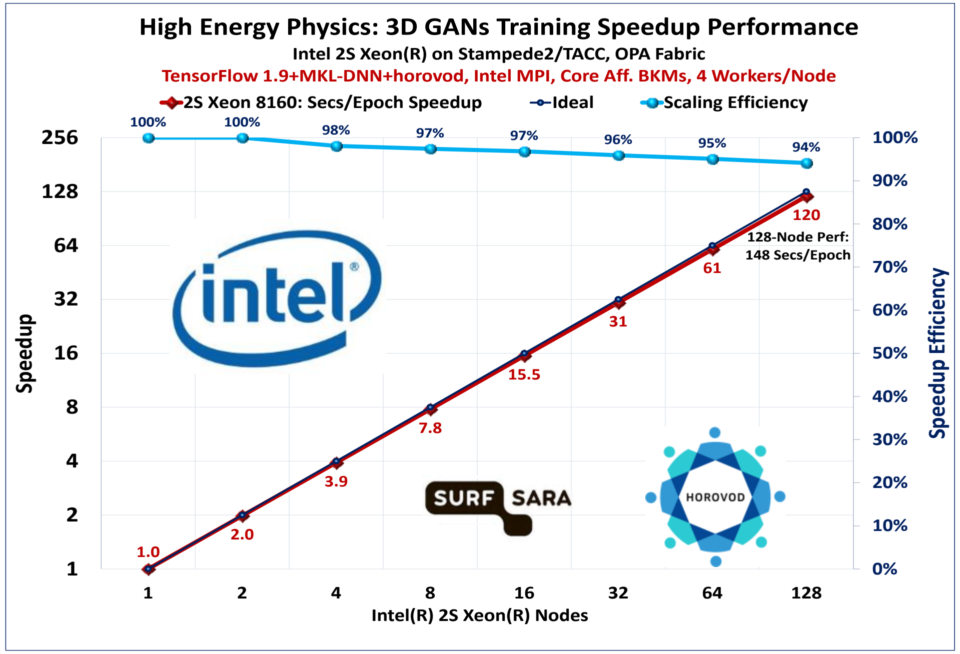
Several projects are on-going (collaboration with CMS, SURFSARA, …)

Server approach





Ring approach



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Ex. openlab, Intel SURFSARA on data parallel 3DGAN training

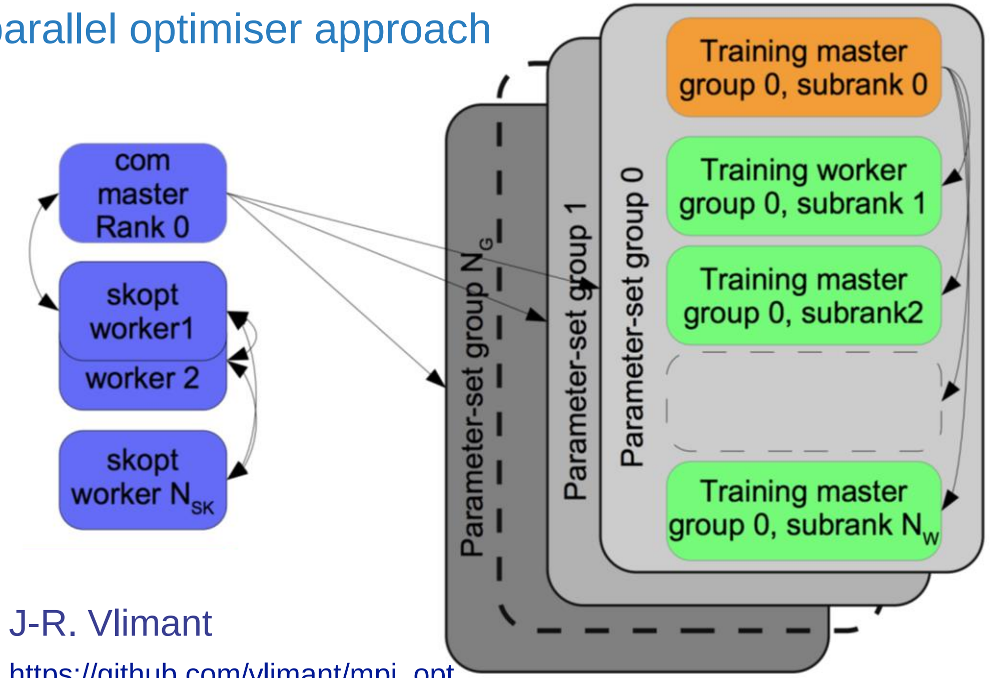
Neural Network optimisation

Architecture hyper-parameters optimisation

Various parameters of the model cannot be learned by gradient descent

- Tuning the right architecture cannot be done by hand
- Full parameter scan is resource/time consuming.

mpi_opt parallel optimiser approach



$$N_{nodes} = 1 + N_G \times N_F \times (N_M \times N_W \times N_{GPU})$$

N_G : # of concurrent hyper-parameter set tested
N_F : # of folds
N_M : # of masters
N_W : # of workers per master
N_{GPU} : # of nodes per worker (1node=1gpu)

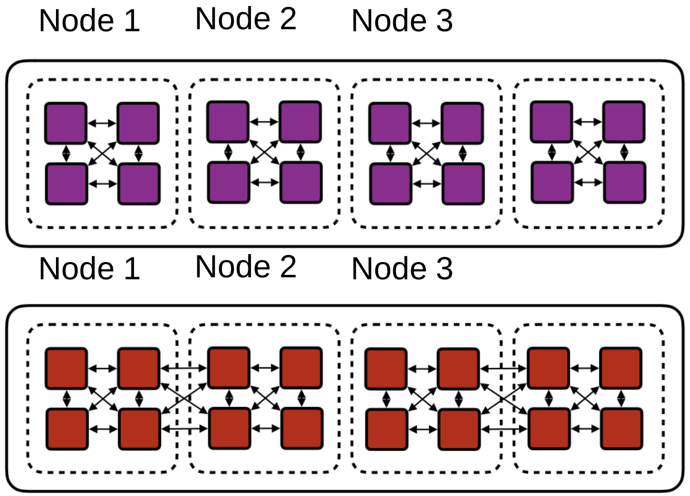
Need HPC to “create” new DL models

J-R. Vlimant

https://github.com/vlimant/mpi_opt

HPC resources

HTC



Efficient intra/inter-node communication is key

- Most powerful systems are hybrid
  - Ease access to the resources
  - Good integration in HEP infrastructure
- Software stack deployment ?
  - Containers
  - Most DL framework provide containerised versions
- Workflow management ?
  - Native DL platforms are natural choice (i.e. Kubeflow)
  - Adapt HTC job schedulers ?
- Data access/management ?
  - S3 works very well
  - Supported widely in commercial clouds
  - Not all HPC centers allow access to it

Kubeflow docker kubernetes

CERN openlab

Cloud resources

On-site accelerators are an interesting solution for real-time selection

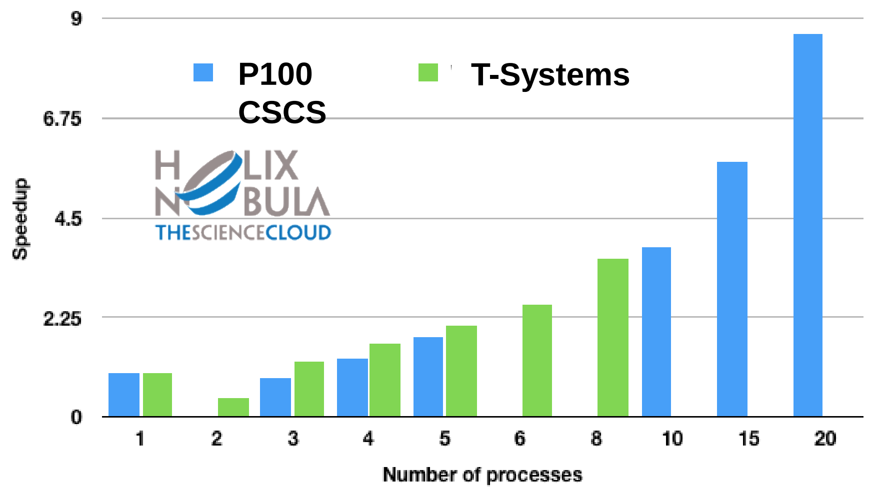
For offline, the best solution is probably the cloud environment

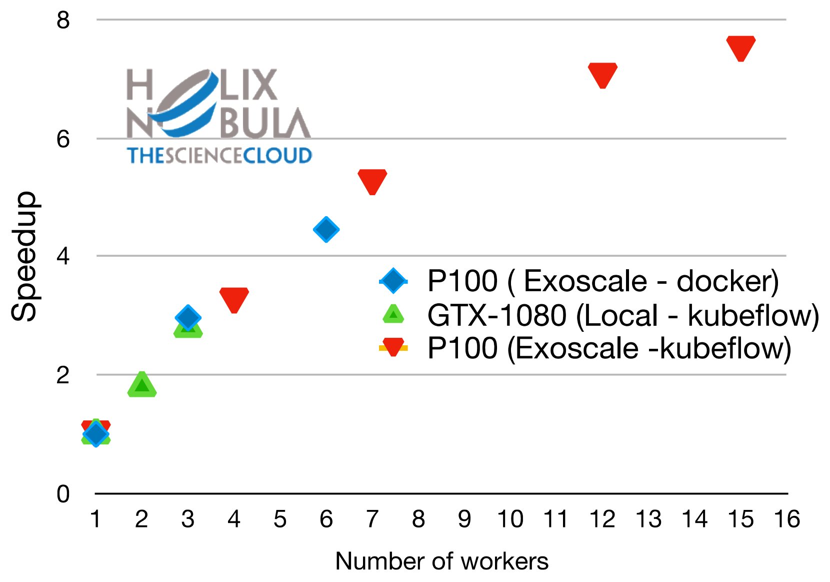
- Not always feasible/effective to buy specialized hardware

But most MLaaS solutions are not customizable enough for scientific use cases

- Great opportunities for R&D with industry

New initiatives to increase access to commercial clouds and deploy hybrid models (OCRE in the context of the EOSC)

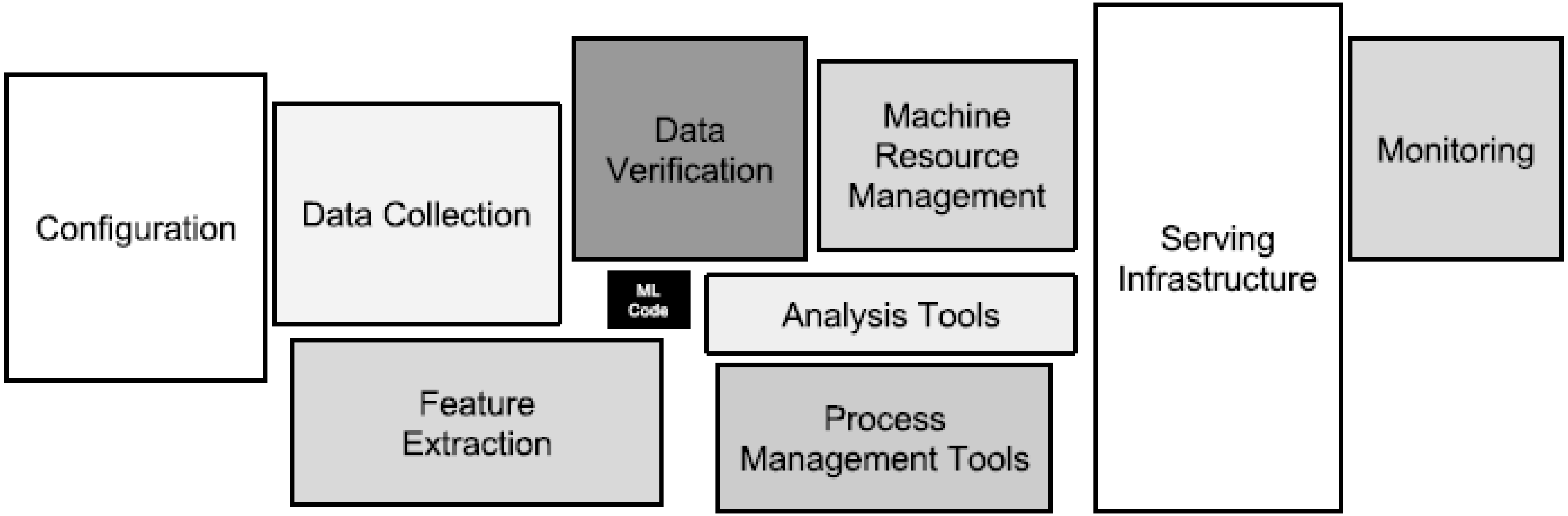




OCRE
Open Clouds for Research Environments

Ex: 3DGAN training via mpi-learn (J-R. Vlimant, Caltech)
Cloud deployment via docker + Kubernetes/Kubeflow (R. Rocha, IT-CM)

Engineering Efforts to Enable Effective ML

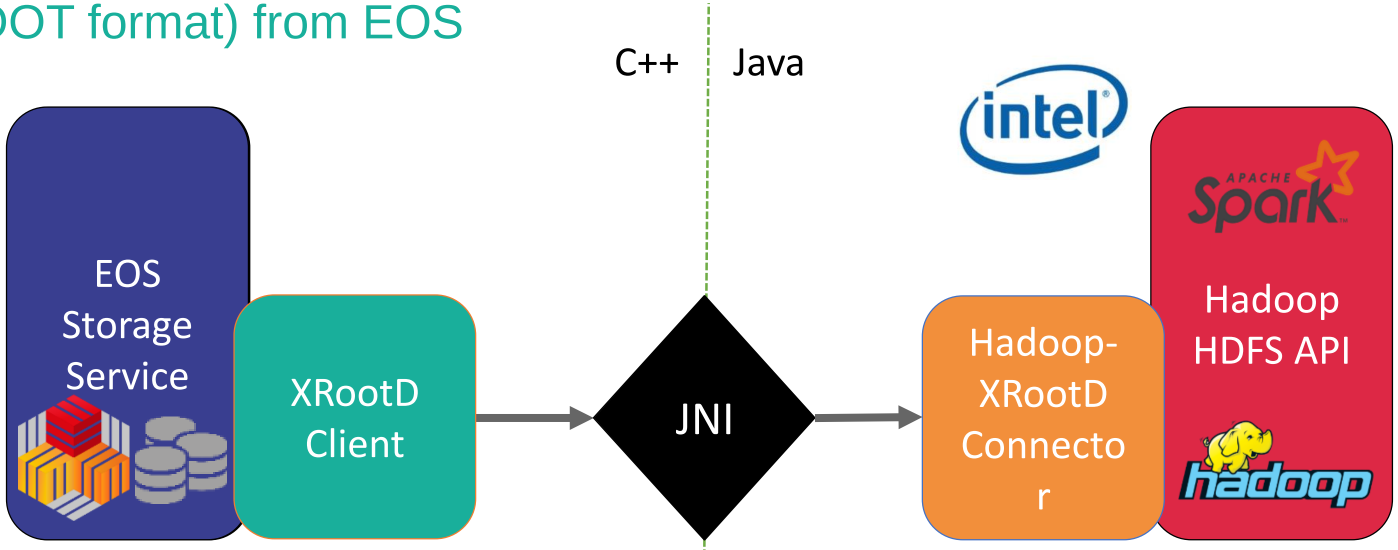


From “Hidden Technical Debt in Machine Learning Systems”, D. Sculley at al. (Google), paper at NIPS 2015

R. Castellotti, M. Migliorini, L. Canali, M. Girone

Big Data Analytics Platforms

- Not only analytics
  - Scalable workloads and parallel computing
  - Integration with DL/AI
- YARN/Hadoop and Spark on Kubernetes clusters @CERN
- openlab, Intel, IT-DB collaboration on several projects
  - Extending Spark to read physics data (ROOT format) from EOS
  - ML/DL with Spark & BigDL



https://github.com/cerndb/hadoop-xrootd
https://github.com/diana-hep/spark-root

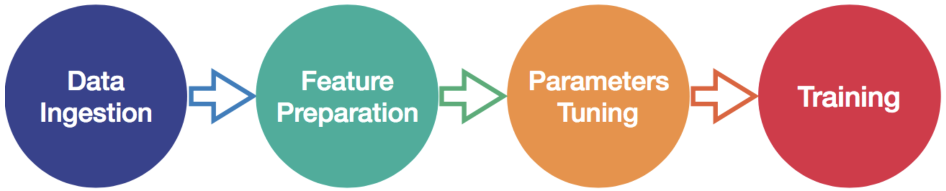
R. Castellotti, M. Migliorini, L. Canali, M. Girone

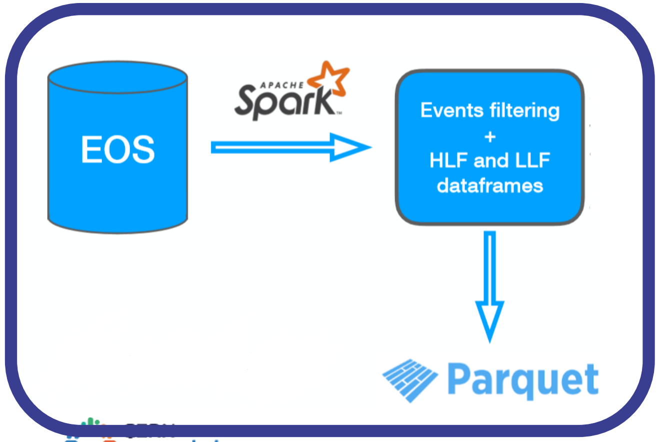
Big Data Analytics and Deep Learning

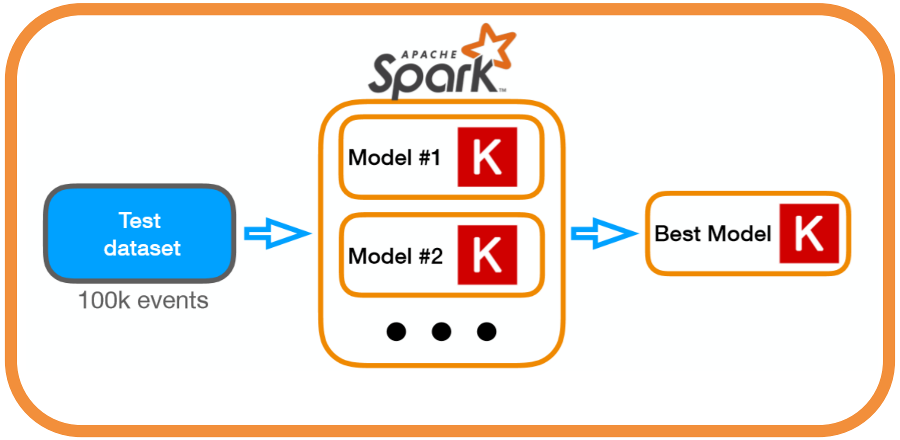
More info at IT-DB technical forum
https://indico.cern.ch/event/759118/

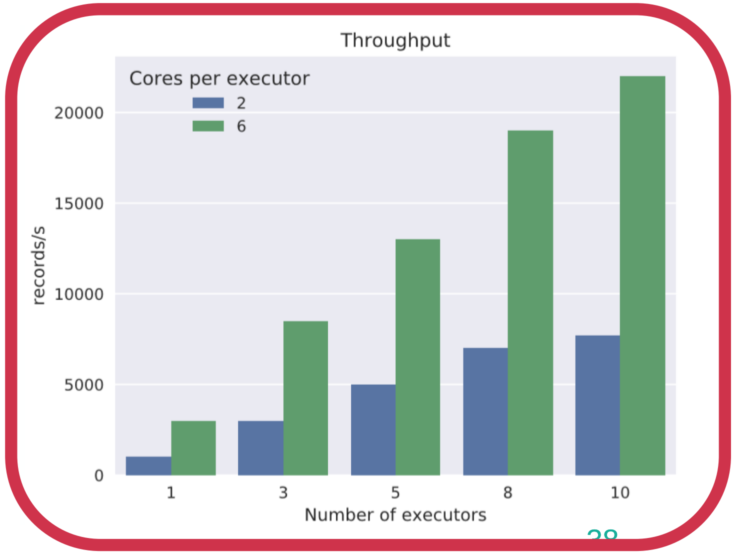
An end-to-end demonstrator to run ML pipelines on Spark using BigDL and Intel Analytics Zoo*

Tested on a real use case: topology classifier for real-time event selection at the LHC (arxiv:1807.00083)









*New Intel platform for **unified** analytics and AI on Apache Spark leveraging BigDL / Tensorflow

Summary & Conclusions

CERN openlab has an **exciting, diversified research program** on Deep Learning

- From pure application R&D to the understanding of DL software and hardware integration in HEP workflows

A **collaborative approach is essential** to the success of this program

- We directly (or indirectly) participate in numerous activities together with HEP experiments, other sciences and different fields of society

Tech companies consider ML/DL top spending priority

- **Collaboration with industry is essential to bring large benefits for our community**

New technologies (and Deep Learning) are developed and **evolve very rapidly**

- A continuous research approach is need
- New paradigms emerge and should be tested

Most of those projects received **substantial contributions** from **openlab Summer Students**

Pushing the boundaries

Quantum Computing

Why Quantum Machine Learning?

Quantum approach to ML could solve more complicated problems… faster

- ML based tool can recognize complicated (hidden) patterns in data
- Quantum processors can produce statistical patterns that are computationally difficult to produce with classical approaches

→ Could quantum processors recognize more complicated patterns in data?

A quantum advantage for ML?

- Defining what quantum speed-up means is a complicated task
  - I/O, data transfer and query complexity
    - Quantum states preparation, output retrieval and memory access
  - Computational
    - How many computing steps are needed to solve a problem
- Need to compare to the “best available” classical algorithm
  - For ML/DL the “best” classical algorithm is often not known

Biamonte et al. arxiv: 1611.09347

A quantum advantage for ML?

- Quantum linear algebra is generally faster than classical counterpart
  - Quantum Basic Linear Algebra subroutines (qBLAS) exhibit exponential speedup
    - Fourier transforms, eigenvectors and eigenvalues calculation, matrix multiplication and inversion
- Some standard ML techniques estimate the ground state of Hamiltonians
  - Quantum approach may have an advantage
    - Quantum Boltzman Machines
- ML algorithms have some tolerance to errors
  - Less affected by quantum instability of results
- Specific quantum techniques can be exploited to bring further improvement
  - Amplitude amplification and quantum annealing
    - Advantage from special purpose processors, such as quantum annealers

Biamonte et al. arxiv: 1611.09347

Quantum ML

... and ML for Quantum Computing

QML introduces quantum algorithms as part of a larger implementation

- Fully quantum or hybrid classical/quantum approaches
- Input data could be quantistic → ML for QC

How do we construct Quantum Neural Networks (QNN) ?

- Direct association between neurons and qubits
- Encode information into amplitudes of a quantum state

How do we represent learning rules?

- Need association rule between NN activation patterns and pure quantum states

How do we address data loading?

- Quantum state preparation
- Direct access through qRAM ?
    - Possible to train on large datasets by only loading a small number of samples!

Some Examples

Quantum Nearest Neighbors Clustering **[Zhan]**

Quantum Principal Component Analysis **[Lloyd]**

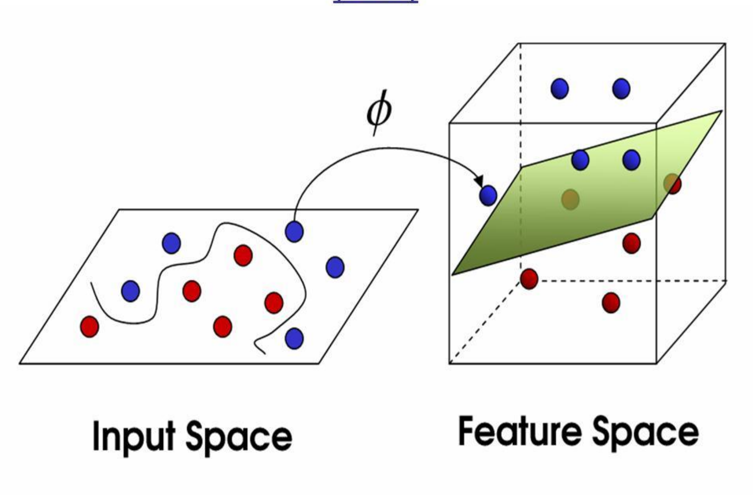
Quantum Support Vector Machines **[Rebentrost]**

Quantum Boltzmann Machines **[Amin]**

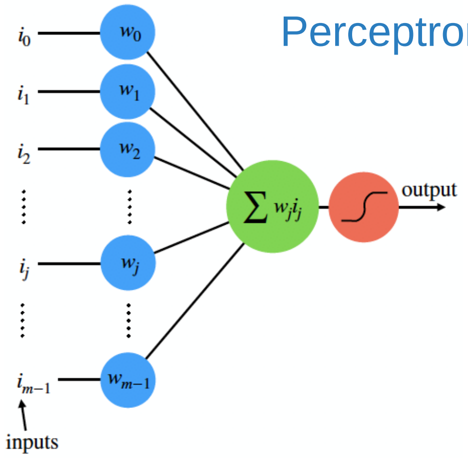
Quantum Generative Models **[Khoshaman]**

Quantum implementation of a single Perceptron **[Tacchino]**

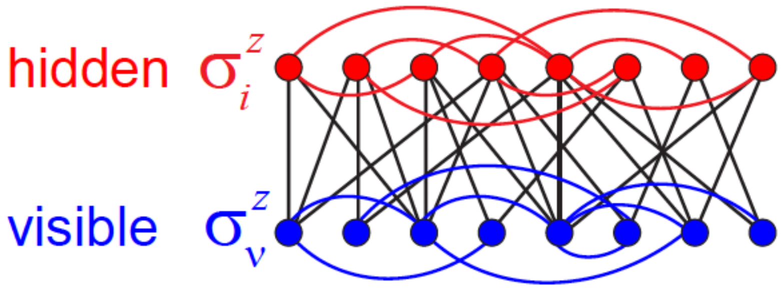
Principle of Support Vector Machines (SVM)



Perceptron



Boltzman Machine



Quantum Boltzmann Machines

Classical Boltzmann Machine consists of visible and hidden binary units $\mathbf{z_a}$.

- Trained by adjusting weights so that the thermal statistics of the units $\mathbf{P_z}$ reproduces the statistics of the data

QBM replaces units with quantum spins and rewrite the Hamiltonian according to QFT formalism

- Classical Ising Hamiltonian is augmented with a transverse field.
- Training process is inspired to Gradient descent approach but it is not trivial

Trained QBM performed better on simple examples (~10 units) than classical counterpart

$$z_a \in \{-1, +1\}$$

$$E_{\mathbf{z}} = -\sum_a b_a z_a - \sum_{a,b} w_{ab} z_a z_b.$$

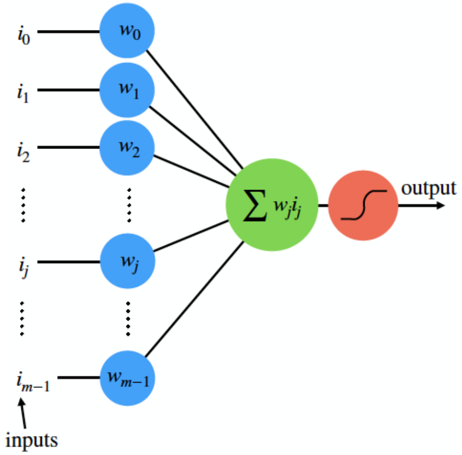
$$P_{\mathbf{v}} = Z^{-1} \sum_{\mathbf{h}} e^{-E_{\mathbf{z}}}, \qquad Z = \sum_{\mathbf{z}} e^{-E_{\mathbf{z}}},$$

$$\boxed{H = -\sum_a \Gamma_a \sigma_a^x - \sum_a b_a \sigma_a^z - \sum_{a,b} w_{ab} \sigma_a^z \sigma_b^z}$$

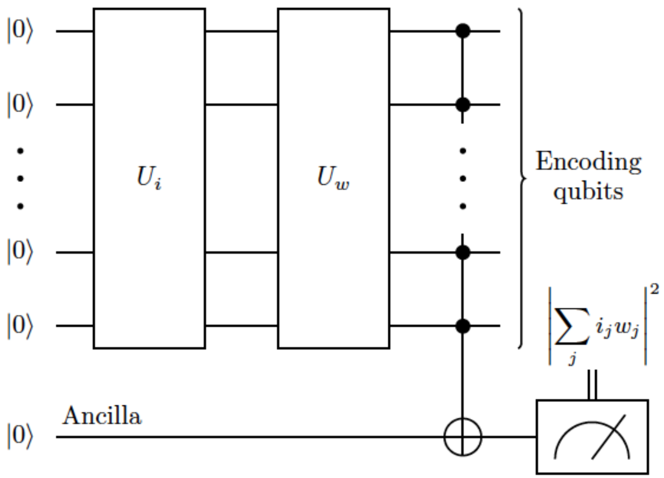
[Tacchino]

Quantum implementation of a binary perceptron

- Represent **m** classical inputs and weights with **N** qubit: $\mathbf{m=2^N}$
- Quantum system is initialized in his idle state
- Apply two unitary transformations as a series of gates:
  - Prepare the quantum state
  - Apply weights
- Store output in ancilla qubit
  - Apply activation function by measuring ancilla
  - An additional ancilla allows coherent propagation of output to second perceptron
- N=2 perceptron tested on IBM Q-5



$$\vec{i} = \begin{pmatrix} i_0 \\ i_1 \\ \vdots \\ i_{m-1} \end{pmatrix} \qquad \vec{w} = \begin{pmatrix} w_0 \\ w_1 \\ \vdots \\ w_{m-1} \end{pmatrix}$$



$$|\psi_i\rangle = \frac{1}{\sqrt{m}} \sum_{j=0}^{m-1} i_j |j\rangle;$$

$$|\psi_w\rangle = \frac{1}{\sqrt{m}} \sum_{j=0}^{m-1} w_j |j\rangle$$

Some HEP related applications

Classification with Quantum Annealing on the D-Wave System (J-R. Vlimant)

https://indico.cern.ch/event/719844/contributions/3047935

Quantum Support Vector Machines (W. Guan)

https://indico.cern.ch/event/719844/contributions/3197680

Quantum Variational AutoEncoder (Vinci, D-Wave)

https://indico.cern.ch/event/719844/contributions/3101600

Applications in Astrophysics (ORNL, FNAL)

https://indico.cern.ch/event/719844/contributions/3105972

Machine Learning for Quantum Computing

- Deep reinforcement learning approach for fast qubit control (A. Ustyuzhanin)
  - https://indico.cern.ch/event/719844/contributions/3167608

Quantum Support Vector Machine

Quantum SVM for ttH ($H \rightarrow \gamma\gamma$) classification

QSVM is simulated on IBM Qiskit simulator

- different numbers of qubits and events

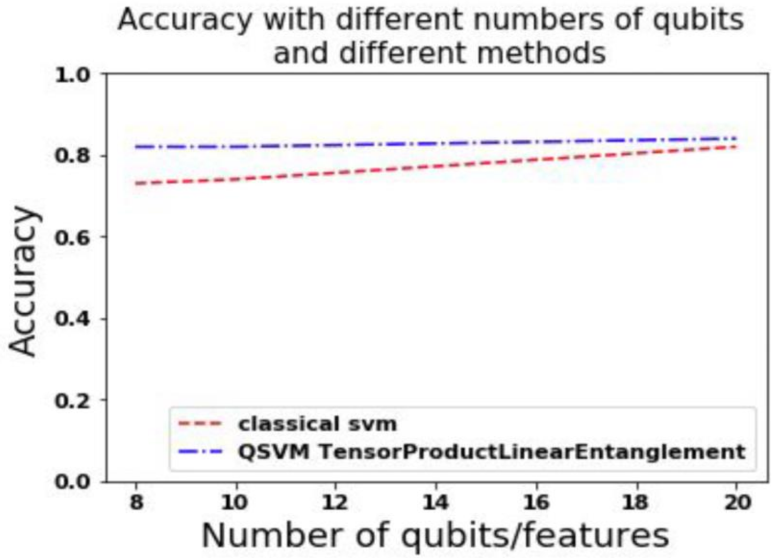
Entanglement is used to encode relationships between features

Apply PCA to input data features

- Reduced from 45 to 8,10 or 20 (limited by number of qubits)

Running full training with quantum simulators requires large computing resources

- Memory increases with qubit, training events and complexity



$$Accuracy = \frac{\text{Number of correct prediction}}{\text{Total number of predictions}}$$

Bridging out to different communities

T. Aliyev
openlab-KCL collaboration

CNNs for medical application

Interpretability of CNN

The "Black-box" CNN

- Understanding learned abstract features could lead to new insights

Case Study:

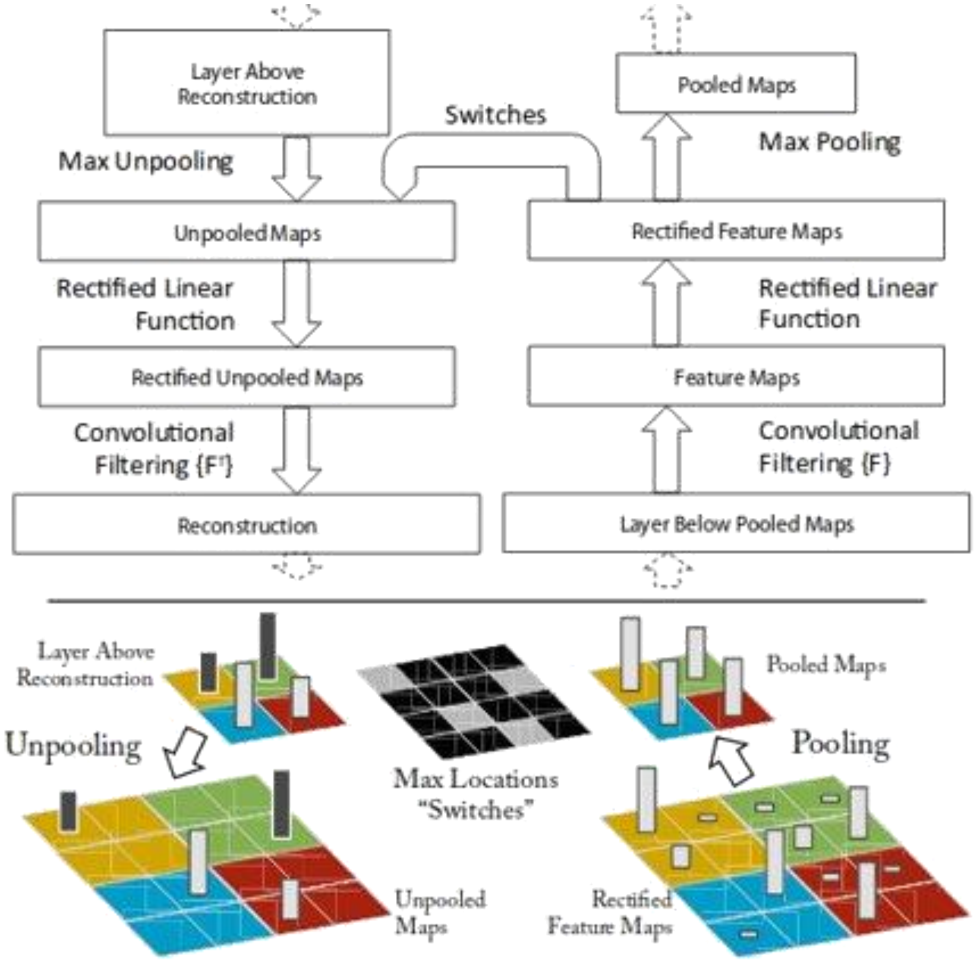
- Understanding which facial features correlate to heritable traits in UK Twins study

Pipeline of the project:

- Run images through CNN, extract hidden layers, find interesting neurons, map back to input space

Two approaches:

- Empirical – Black-out parts of the input
- Analytical – Reversing operations layer-by-layer



Interpretability of CNN

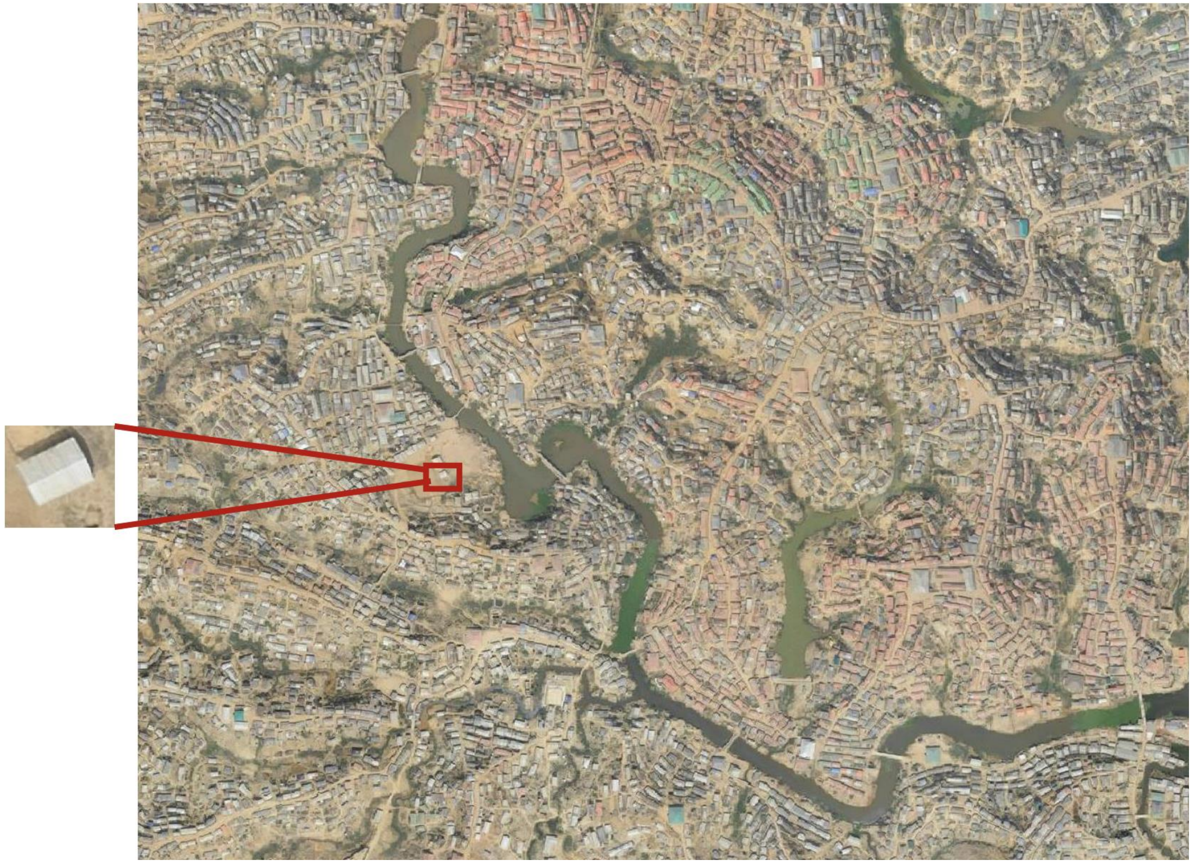
Initial Results

Blacking out inputs gave us significant and important results correlated to the types of twins

Analytical approach (below) produces preliminary results that are meaningful and logical at this stage:

eyes, noses being the expected heritable features

Counting shelters in refugee camps



UNOSAT consists of a team of highly trained analysts

Scan million pixels satellite photos for disaster relief

- Time-costly operation and only 5% of requests are answered

The information is needed to determine the amount of aid

- In conflict zones: Damage assessment, pre-mission information for rescue teams
- High level of precision required (> 95%)

The project

Make more data usable

UNITAR's standard approach uses **single points** to count tents

- fast but not representative enough

Polygons drawn around tents perimeter would represent more information

- time consuming, only couple camps have been "polygonised"

Make more data usable by training a Region-based CNN[1] (RCNN) to draw polygons from point data

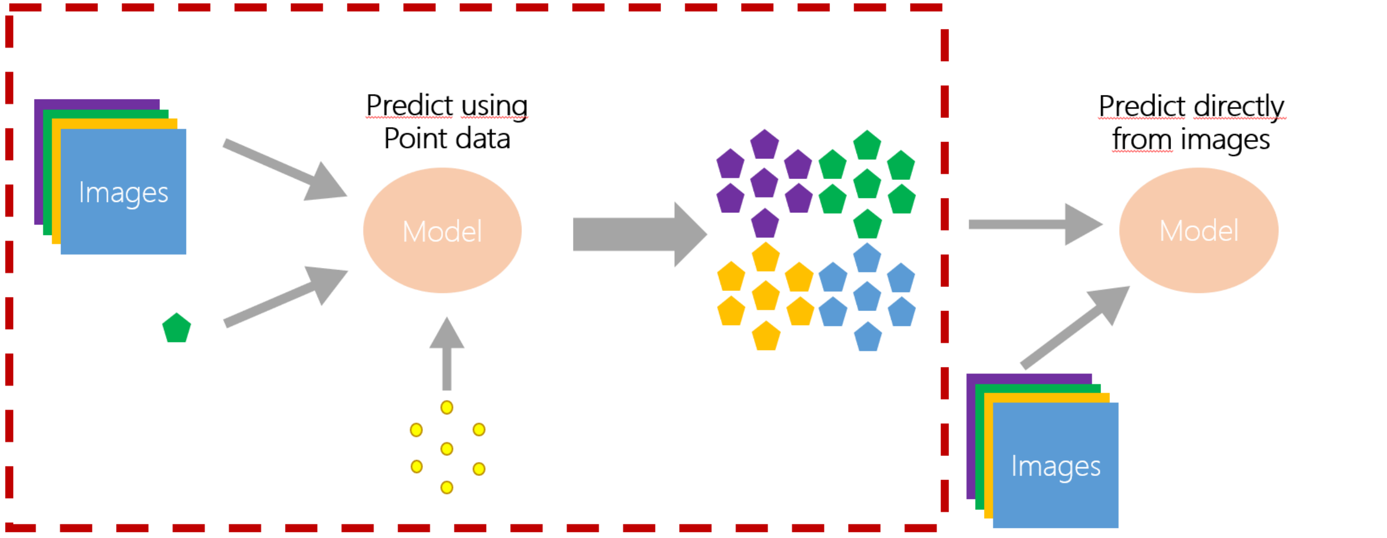
Large variatey of image quality, environment and shelter size/shapes is challange

Our Approach

Translation of point data generated by UNOSAT Analyst to entire tents

1. Already implemented

2. Next step :



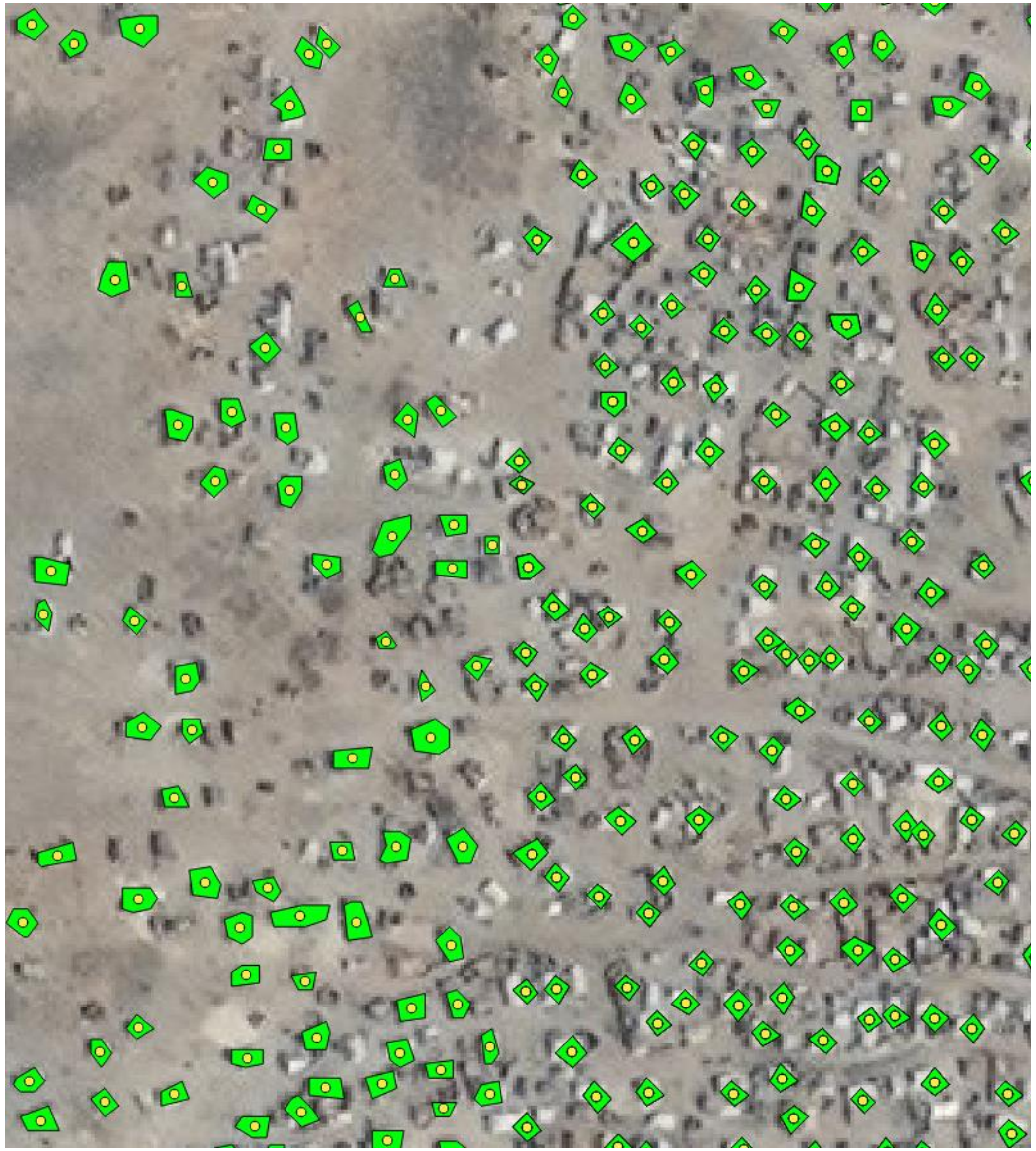
Transfer learning from RCNN model

Detectron Framework (FacebookAI) Unosat Adapted model

Results

Point Data

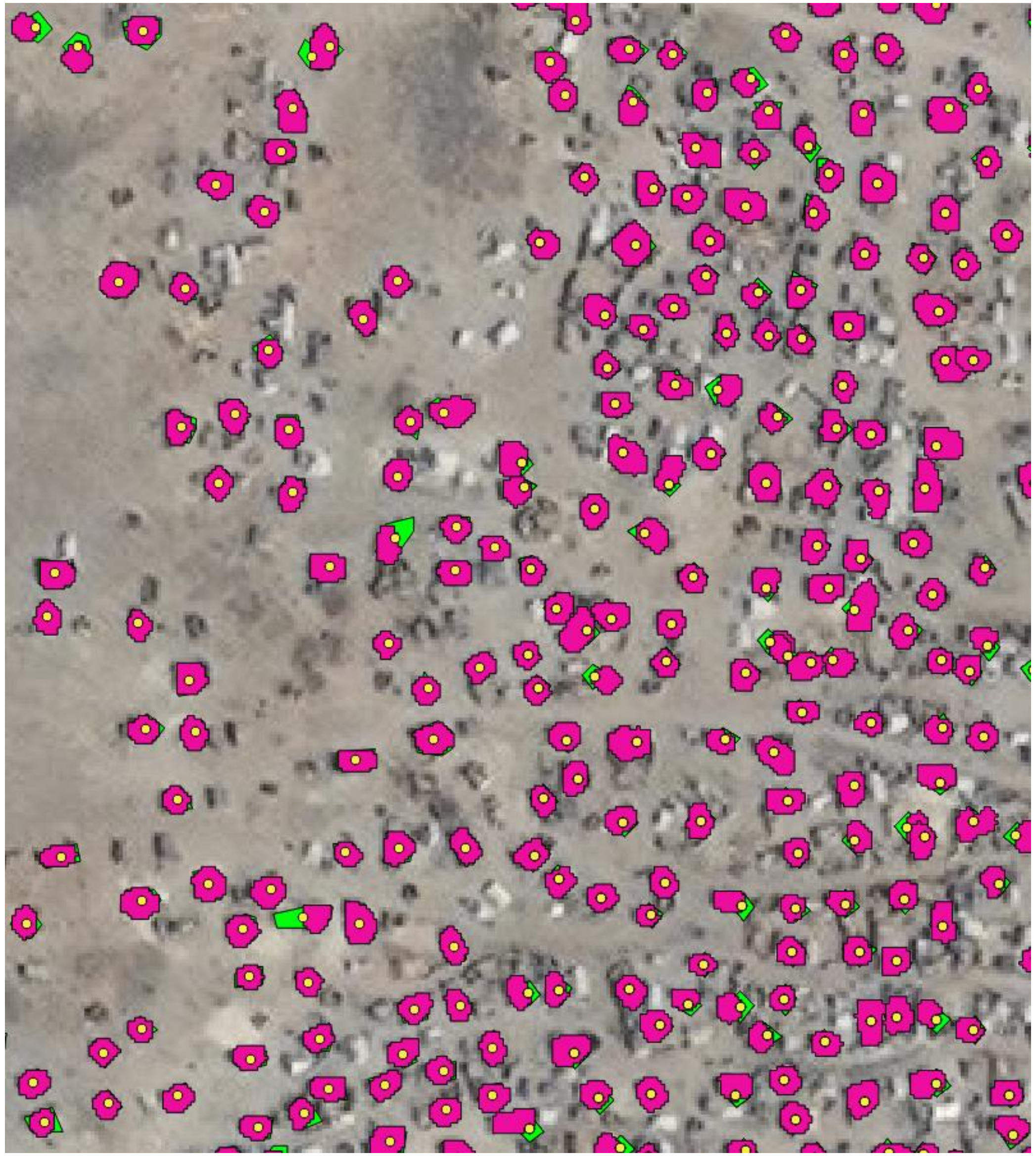
Results



Point Data

Human Ground Truth

Results



Point Data

Human Ground Truth

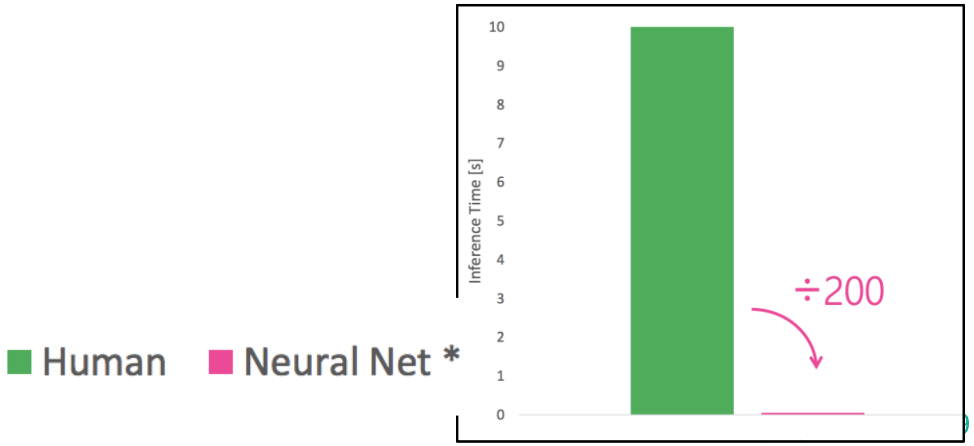
Neural Network Prediction

CERN openlab

Results

Average precision is 82%
Speedup is x200

Results to be directly used by the UN Global Pulse office to enrich and refine their prediction tools by providing them with larger training and validation data sets
New projects are starting on cultural heritage and flood detection



GANs for earth observation

Training data availability is a problem

- Interesting events are often “rare” events

To develop and improve DL based models we need to increase dataset size

Use progressive growing GANs to generate synthetic satellite imagery to train DNN

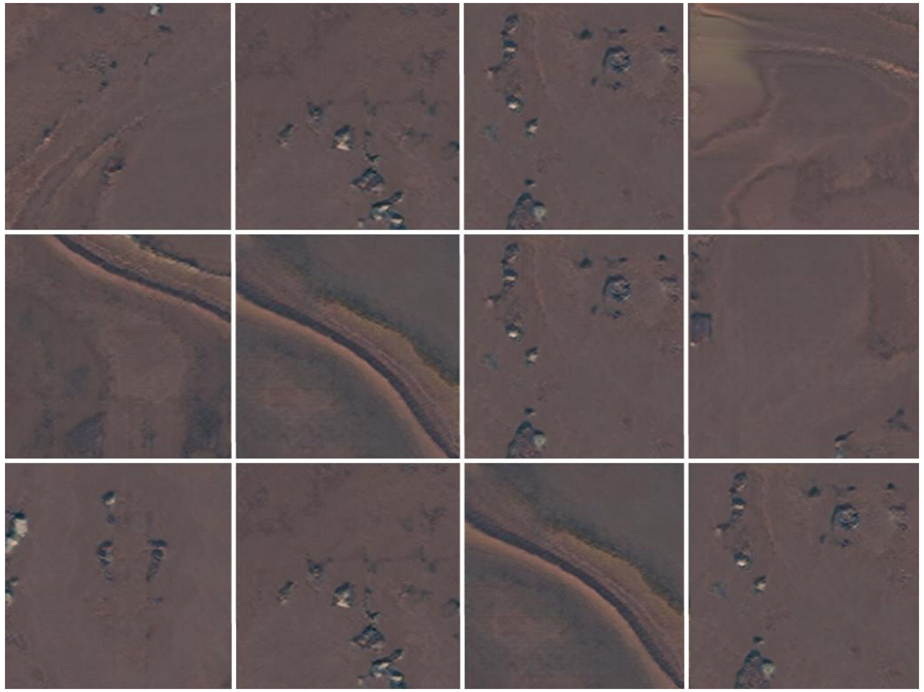
RGB image of the Rukban Camp (Jordan) is segmented in 44060 tiles

Progressive growing: model size grows through-out the training.

- The model first learns large scale properties in the dataset
- Then shifts to progressively finer data.

Start with generating 4x4 pixels imagery, then 16x16 pixels, then double the size at each phase until reaching **256x256 pixels.**

1 week training on 2 NVIDIA Titan GPUs



Smart Knowledge Platforms

- **Common challenge**: harness the amounts of information being produced every second of our lives, focus on reproducibility, ease-of-use, relevance
- **Our focus:** narrative interfaces and NLP (chatbots), several NLP models, QANet, DSSM (Deep Semantic Similarity Models), BERT (Bidirectional Encoder Representations from Transformers)



Education	Research	Industrial/Social
Adaptative, personalized education environments, guiding the students to achieve their learning objectives	Data Analysis, Preservation, Reproducibility, Knowledge Discovery platforms, tasks automation, suggesting non-obvious links across disciplines and people	Smart personal assistants informing you about your environment, the use of your personal information, smart expert systems

Unfortunately there are many interesting topics I couldn’t cover

Please find more information on our website

https://openlab.cern

2019 openlab Technical Workshop

https://indico.cern.ch/event/755842/overview

Thanks!

Questions?