Machine Learning for ATLAS WZ analysis

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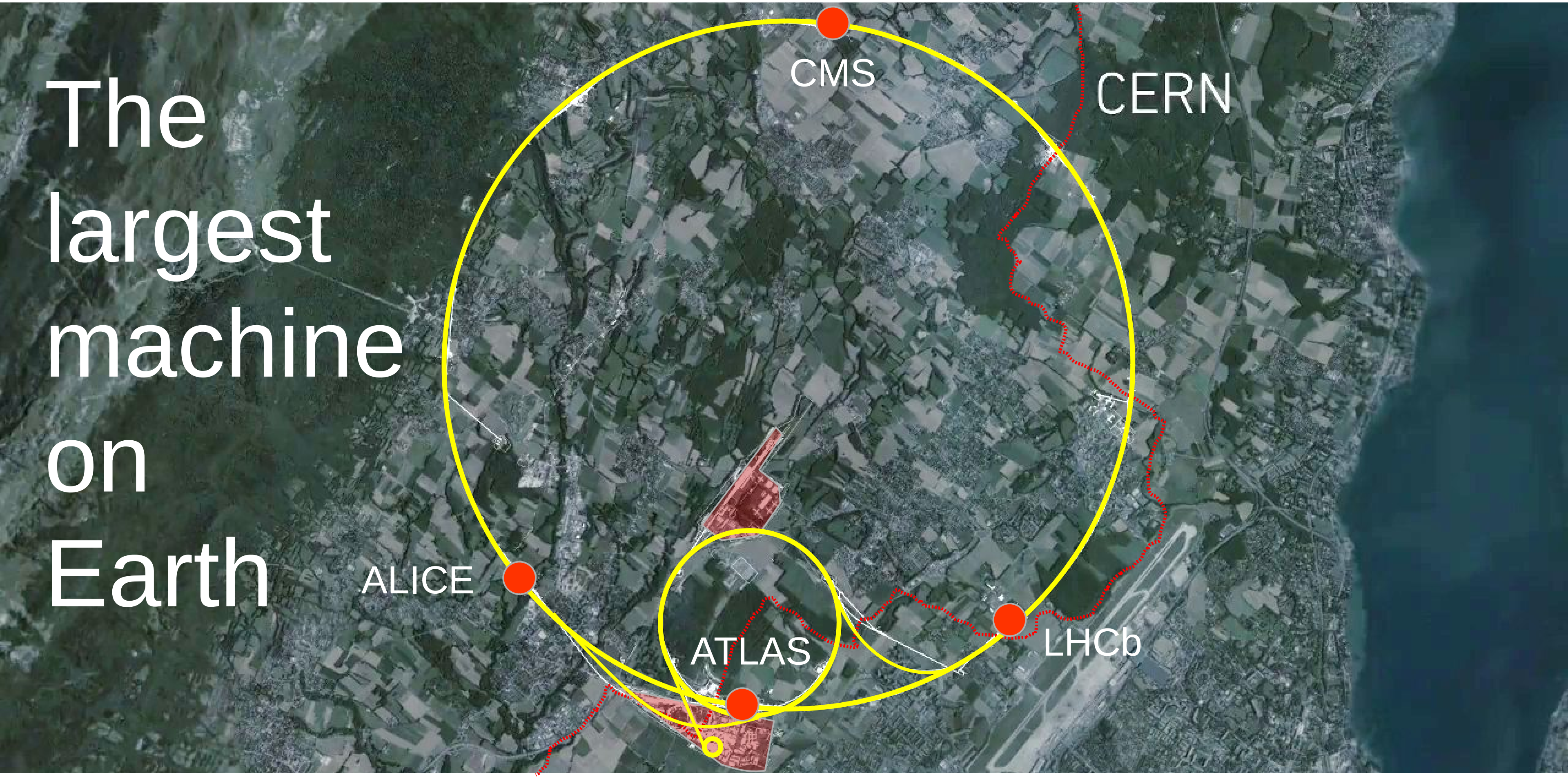
In this talk

- Intruducion:
  - The Large Hadron Collider and the ATLAS experiment.
- Machine learning application for WZ→$\ell\ell\ell\nu$ analysis:
  - DNN for Vector Boson scattering.
  - Adversarial Neural Network.
- Not in this talk:
  - Classification DNN for WZ polarization measurements.
  - Regression DNN for reconstruction of neutrino longitudinal momentum.



pp collisions at c.o.m. = 13 TeV
PbPb collisions at c.o.m. = 5.02 TeV

The LHC: High energy and high luminosiy

Our aim is to find what happened in LHC collisions, checking the laws of Nature at very high energy and with high precision (rare events).

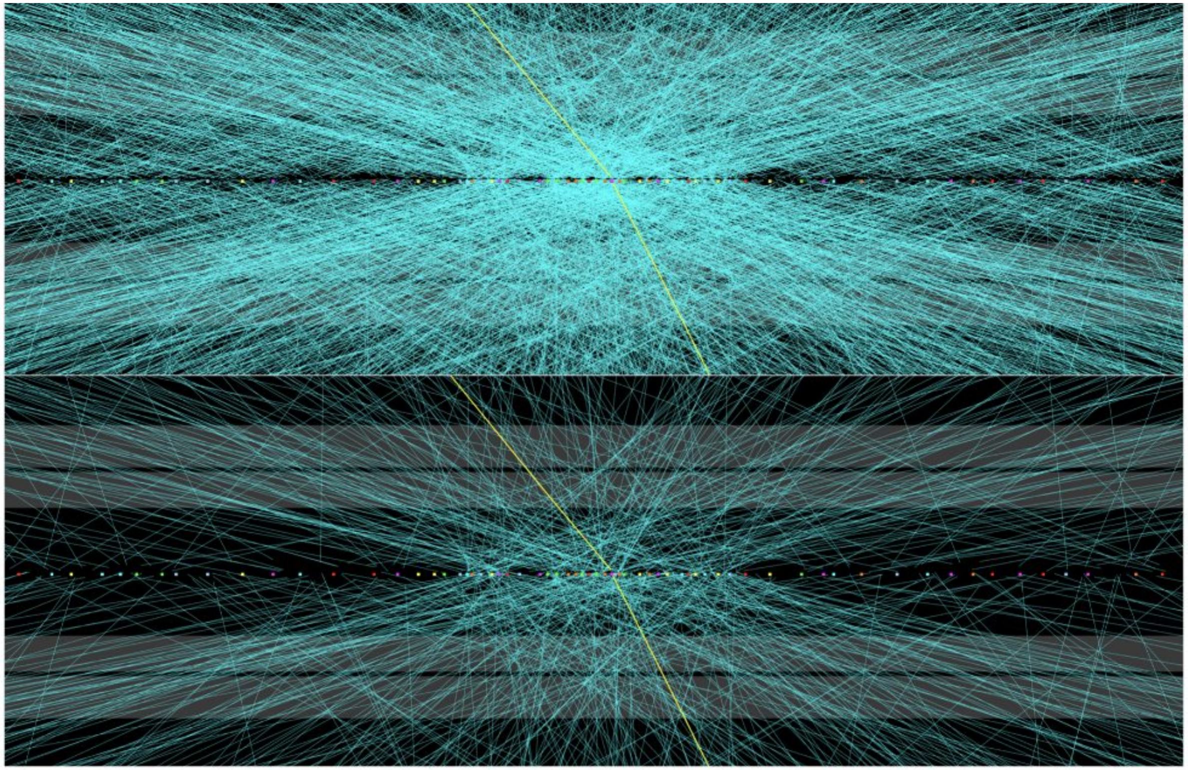
To do so, we can only look at the stable products of the collisions.

During Run 2, the LHC produced 10^{16} collisions.

Large samples of various particles produced:

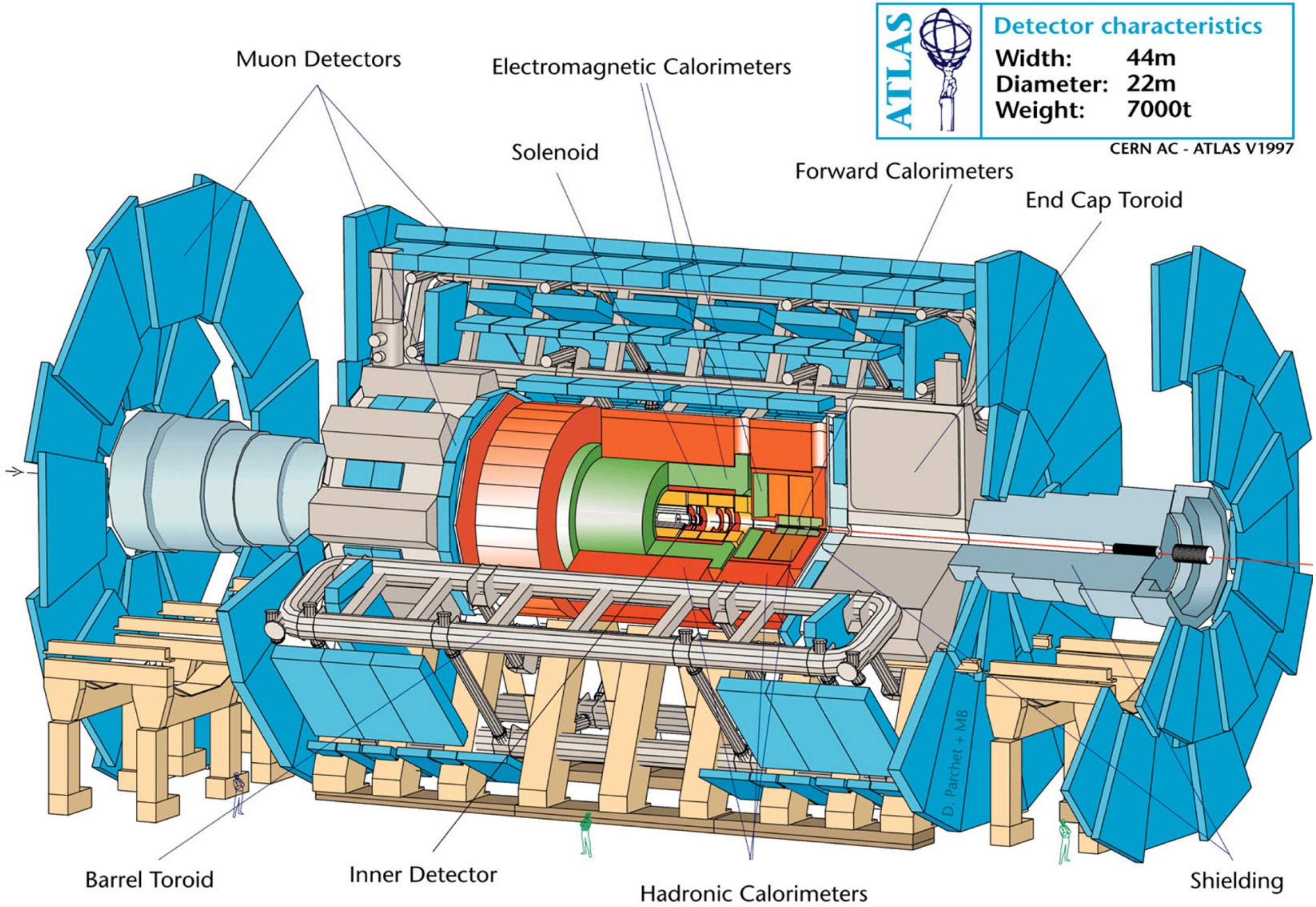
- *W* bosons: 12 billions.
- *Z* bosons: 2.8 billions.
- Higgs bosons: 7.7 millions.

In over 1billion collisions there is only one Higgs boson!

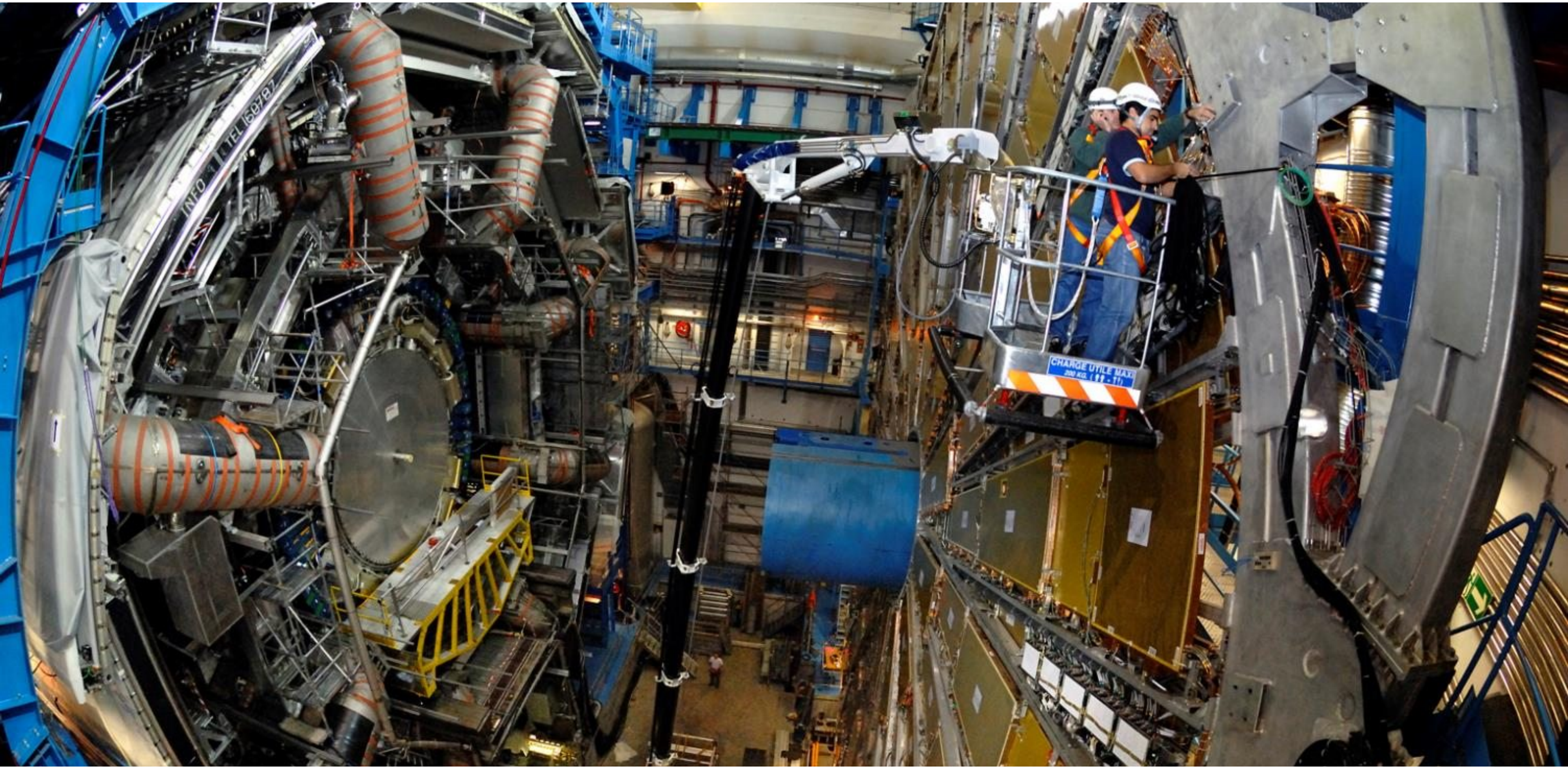


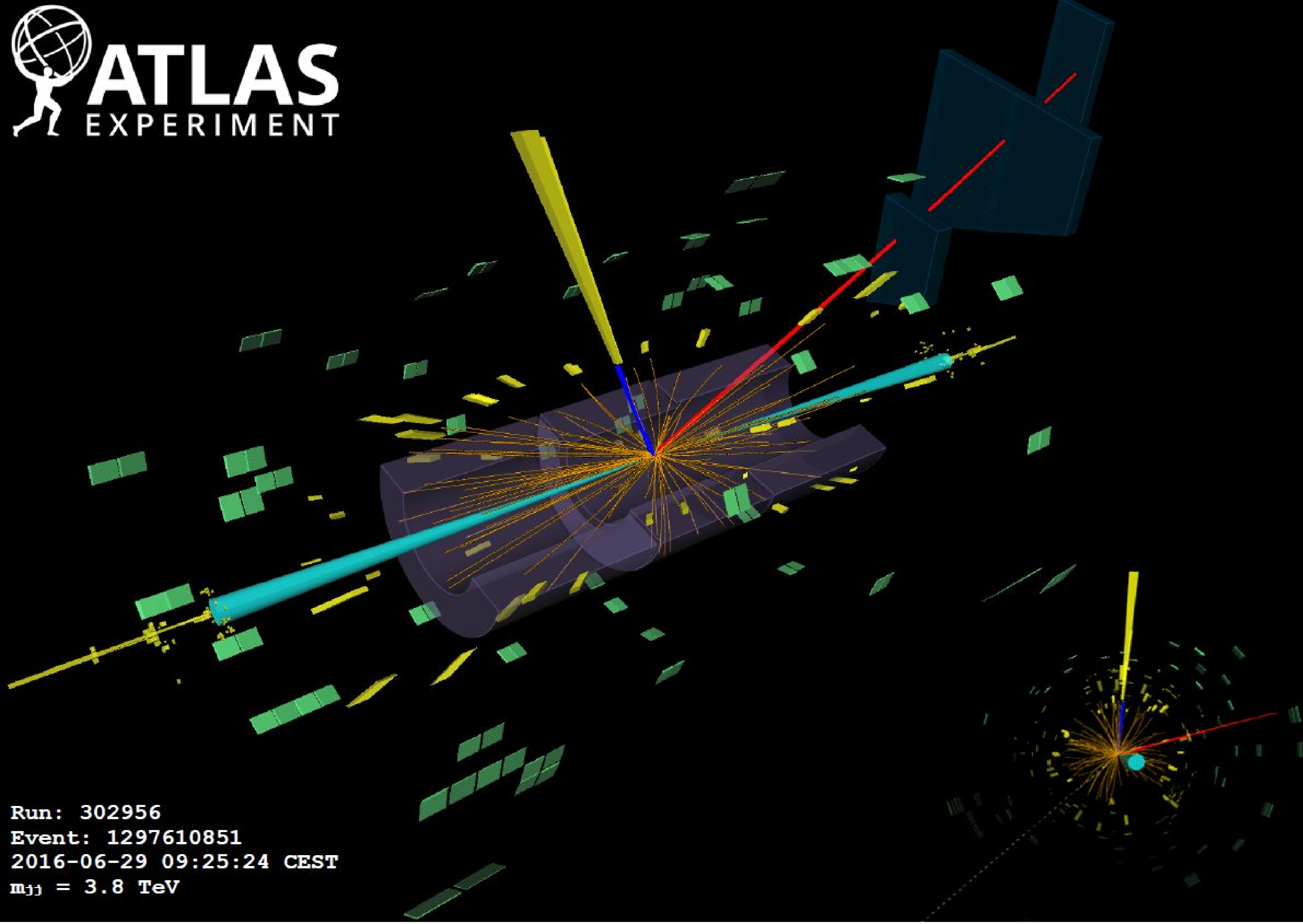
Event displays showing a Z→ll candidate produced with 65 reconstructed proton-proton collisions (top: 100 MeV tracks, bottom 1 GeV tracks)

The ATLAS Experiment



The ATLAS Experiment

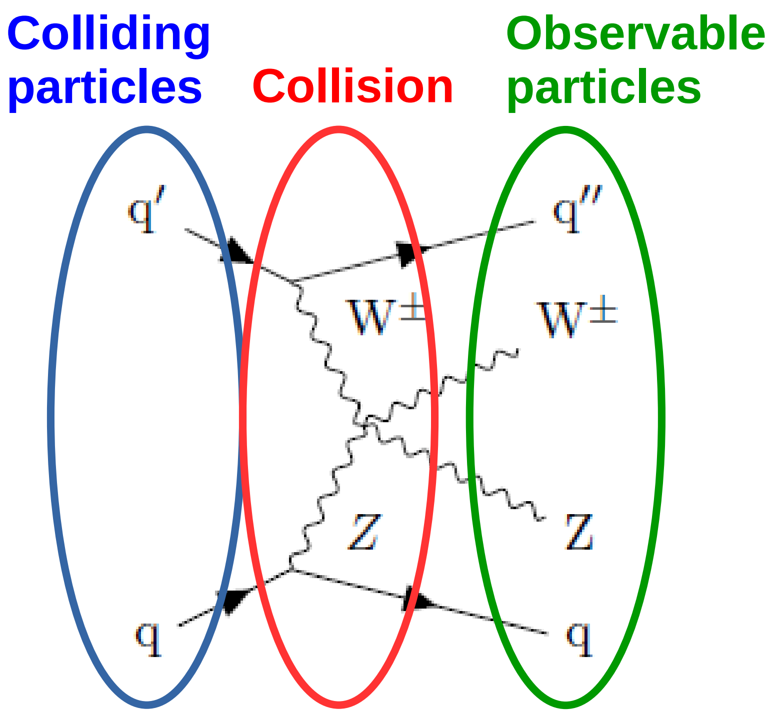




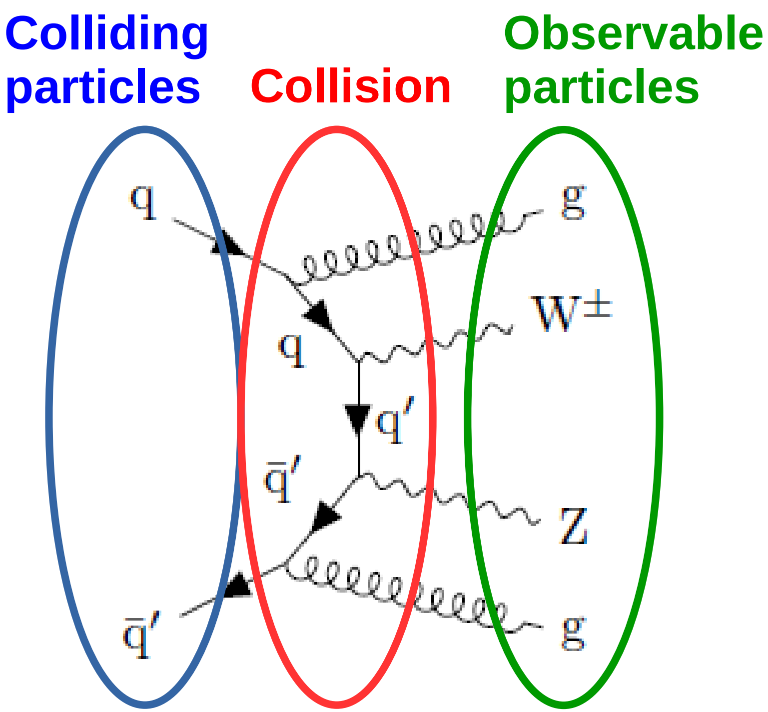
An electroweak $W^{\pm}W^{\pm}jj$ candidate event. The jets have $p_{\mathrm{T}}=118$ GeV and $p_{\mathrm{T}}=104$ GeV, with $m_{jj}=3.8$ TeV and $\Delta y_{jj}=7.1$.

DNN for WZ VBS

- Target: EW production of $W^{\pm}Z \rightarrow \ell\ell\ell\nu$.
- We are looking for one of the rarest process LHC can probe with a very similar background (events producing a similar signature but coming from a different production).



Electroweak-induced



QCD-induced production

We have: Monte Carlo simulation of signal and background events.
We need: cutting-edge ML tools for classification.

DNN for WZ VBS

- Previous analysis, *PLB 793 (2019) 469*, employed a BDT with gradient boost as implemented in the TMVA package of ROOT[*]
- Difficult to estimate the improvement brought by the BDT over standard classification techiniques, but for sure previous analysis would not have been able to observe the WZ VBS process without BDT (fist time ever done).
- Several attemps to improve by using feed-forward DNN:
  - Multiclass classification to tackle non-dominant bkgs.
  - Add all information from reconstructed physics objects.
  - Fine tuning of DNN hyper-parameters.
- For this kind of problem, no improvement of FF DNN over BDT.
  - Due to: very powerful kinematic variables motivated by Physics reasoning which are very well exploited by the BDT.

[*] https://root.cern/manual/tmva

- In order to improve the estimation of the background and reduce its uncertainty we need to decorrelate the classifier output from mJJ, a discriminating but not well modelled variable/feature.
- **Adversarial NN**: two NNs in competition with each other.

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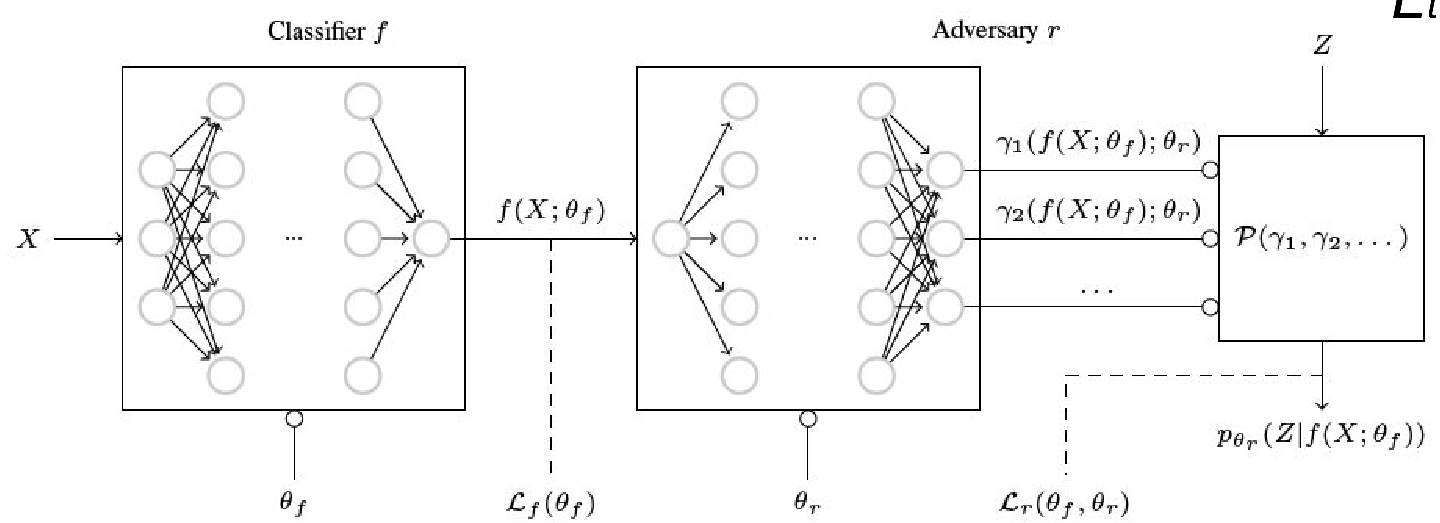
- The first NN can be used to maximize the classification perf.
- The second NN is trained to reconstruct mJJ from the output of the first NN (hence finding correlation).
- The minimization of the global loss function guarantees optimal classification performance with reduced mJJ correlation.

$L_t = L_f - c\ L_r$



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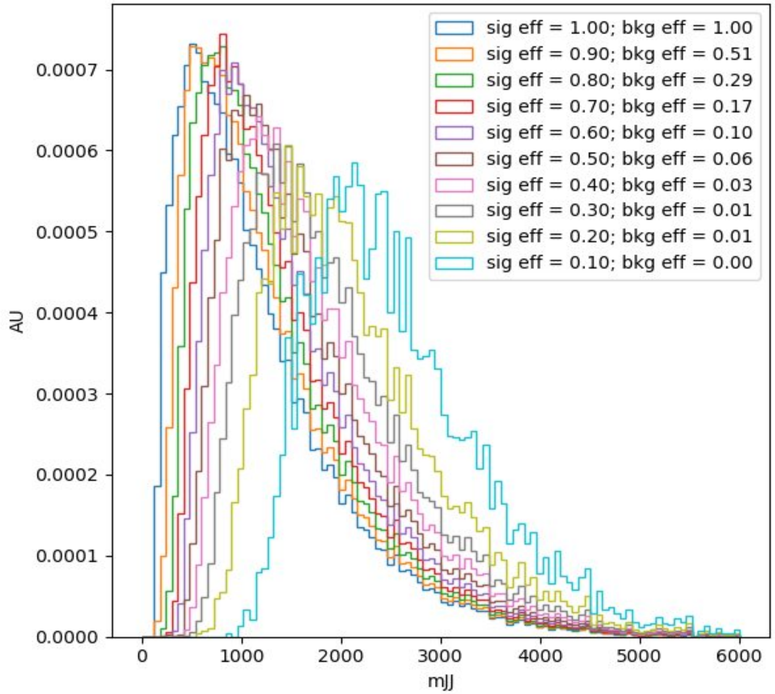
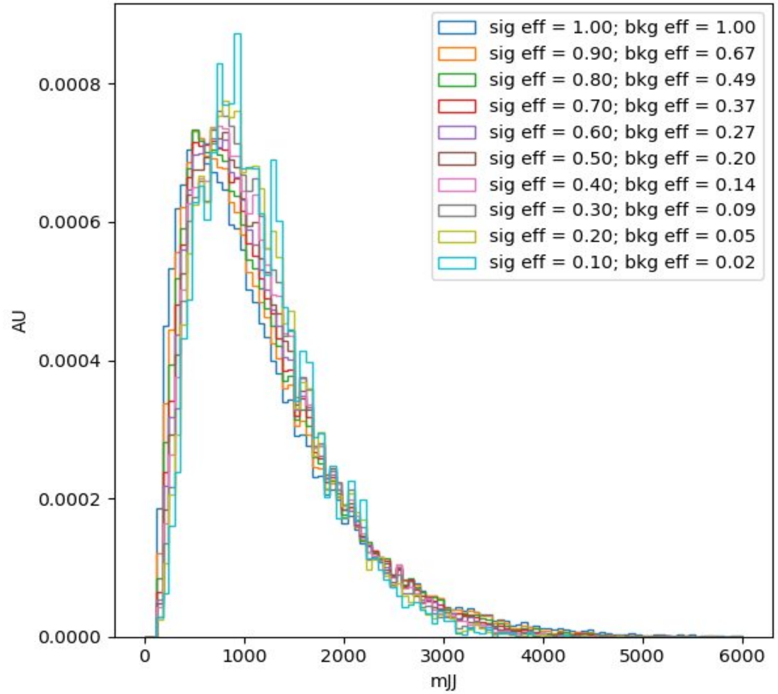
mJJ distribution as a funciton of DNN/ANN score.

FF DNN



ANN



Perfect superposition in the case of ANN means no visible correlation!

- The WZ analysis team in the LAPP ATLAS group has been using ML tools since many years.
- The main use is the classification of signal from background events, but some effort involving regression techniques is also ongoing (reconstruciton of the longitudinal momentum of the neutrino).
- We are interested in novel ML techniques with:
  - Increased classification performance.
  - Better control of systematic uncertainties.