Role of the IA in the industrial applications of muography

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MUON systems

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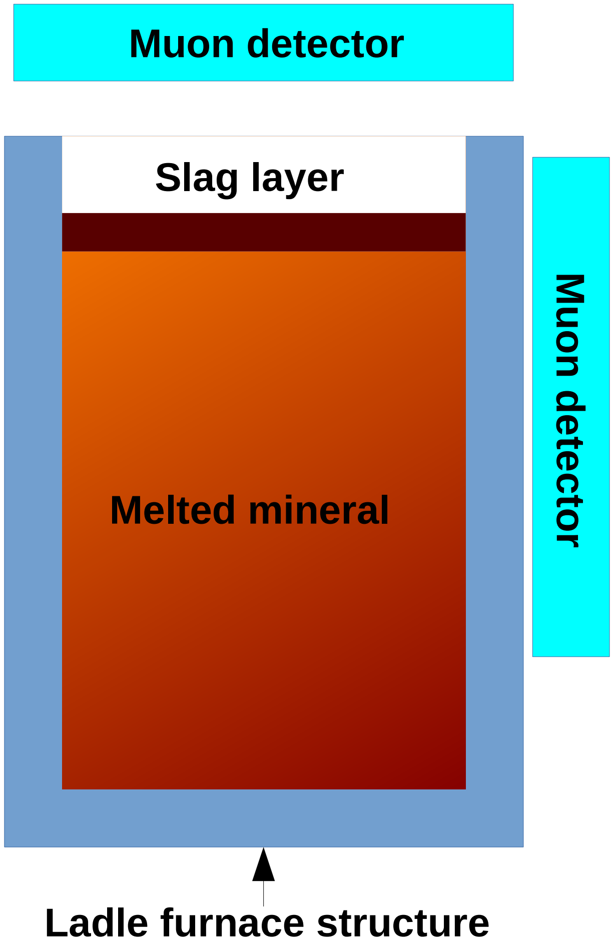
Muography in the industry

- Muography is a new Non-Destructive Testing (NDT) technique that might be exploited in the industry
  - Preventive maintenance of equipment (estimation of the degradation)
  - Quality control of the production process (measurement of liquid interfaces, tolerances, etc)
  - Risk assessment and evaluation (continuous monitoring of structural integrity)
- Large variety of different problems and issues in the industry but some general common points:
  - Relatively large and dense objects (from ~ 50 cm to several meters, iron, steel, etc)
  - In most cases not possible to have any physical access to the object when the factory is in production
  - Relatively harsh environment in terms of dust, temperature and space or time restrictions
- Muography has some unique properties that can be very useful for these applications
  - Large power of penetration (no problem to deal with several meters of steel)
  - No need to physically “touch” the object → it can be applied while the equipment is in production
  - Allows a continuous monitoring of several (typically large structures)
    - Very helpful to detect sudden changes in the production process or anomalies in the equipment

One example: ladle furnace

- To illustrate some of these common features let’s consider the problem of the ladle furnace
- A ladle furnace is a refractary + steel object with 1-2 meters of diameter used to transport melted mixes
- Problem: opaque layer of slag of a few cm appears and doesn’t allow to see the level of mineral
  - Need to estimate the position of the slag-mineral interface to know the amount of mineral in the ladle



Problem specifications:

Surface of the structure very hot → touching not possible

Temperature in the surrounding of about 60 degrees Celsius

Measurement has to be fast → of the order of 5 minutes

Target resolution in the interface position of about 1 cm

Difficulties to place the detectores in the right position

Added value:

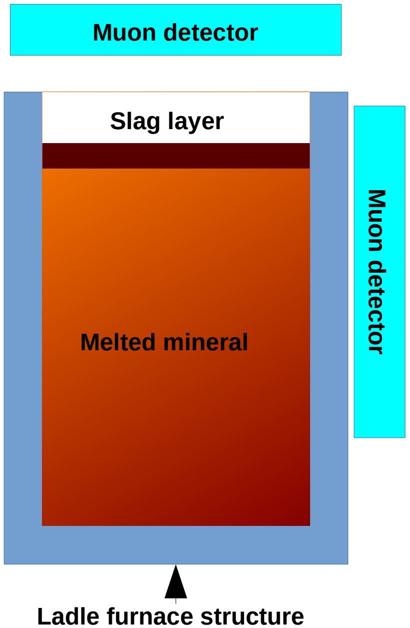
Estimation of the amount of mix in the ladle → savings

Disruptive: this problem is not currently solved

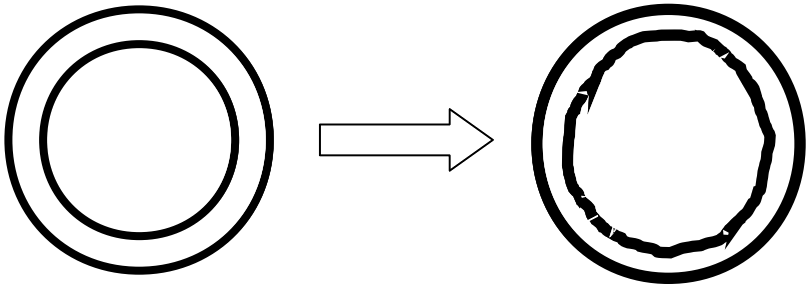
Industrial problems: reduced complexity

- There is one interesting point to be highlighted for most industrial problems
  - The nominal geometry and composition of the equipment/problem is usually very well known
  - Only small variations with respect to the nominal position are targetted
  - This allows to reduce the complexity of the problem to only a (small) set of parameters
- This fact opens the possibility to exploit parameter inference and/or simple IA-based methods
  - No need to “reconstruct” the object, enough to model the possible variations

Ladle furnace: parameter of interest is the position of the slag-mineral interface



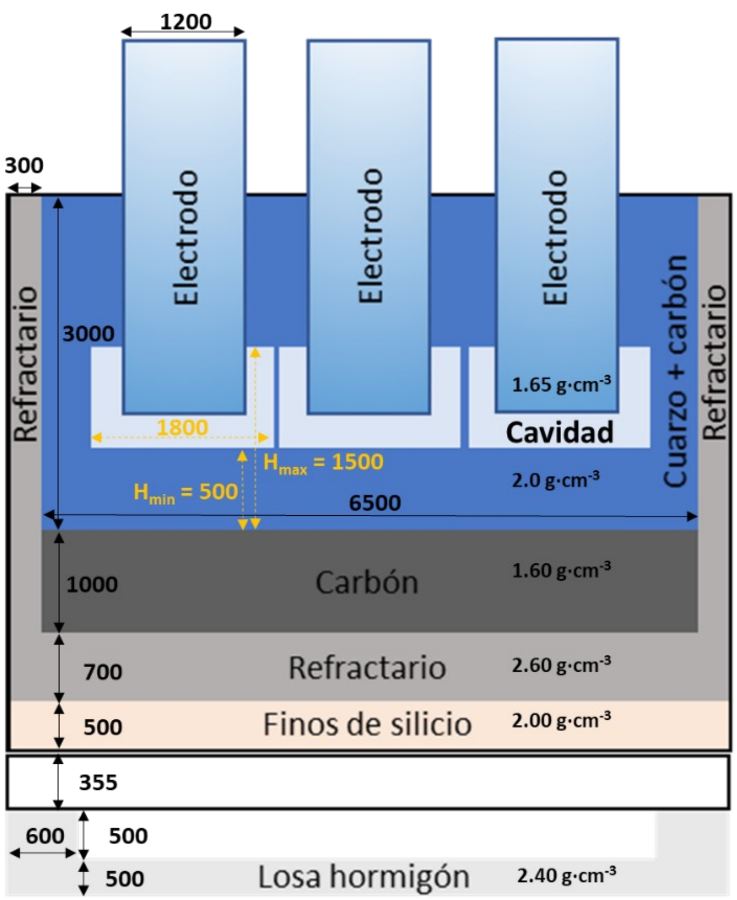
Degradation of pipes: parameter(s) of interest is the thickness of the pipe

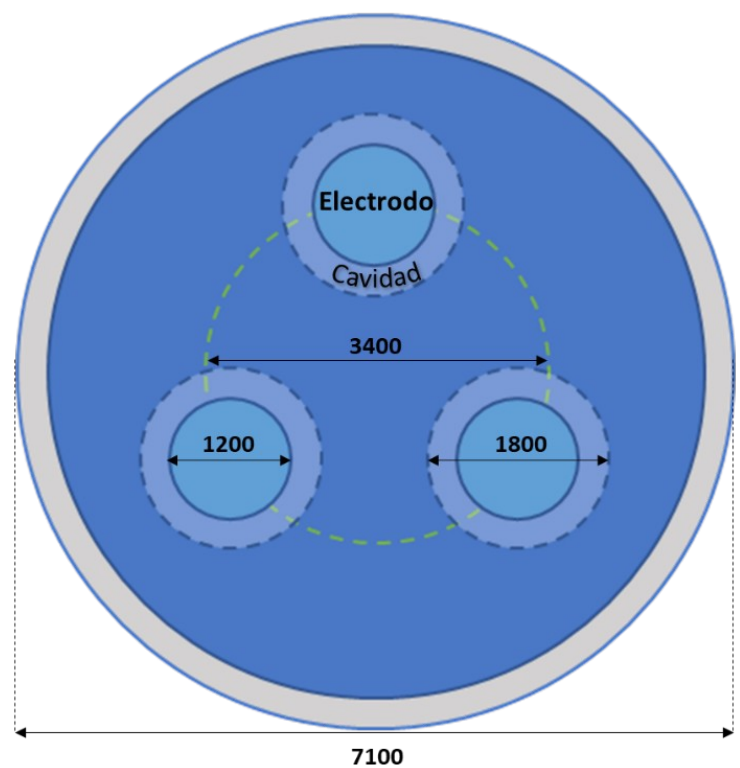


Can use the average thickness of the wall, or the model can be made more complex by using a polygon fitting the inner surface of the pipe

Another example: Electric arc furnaces

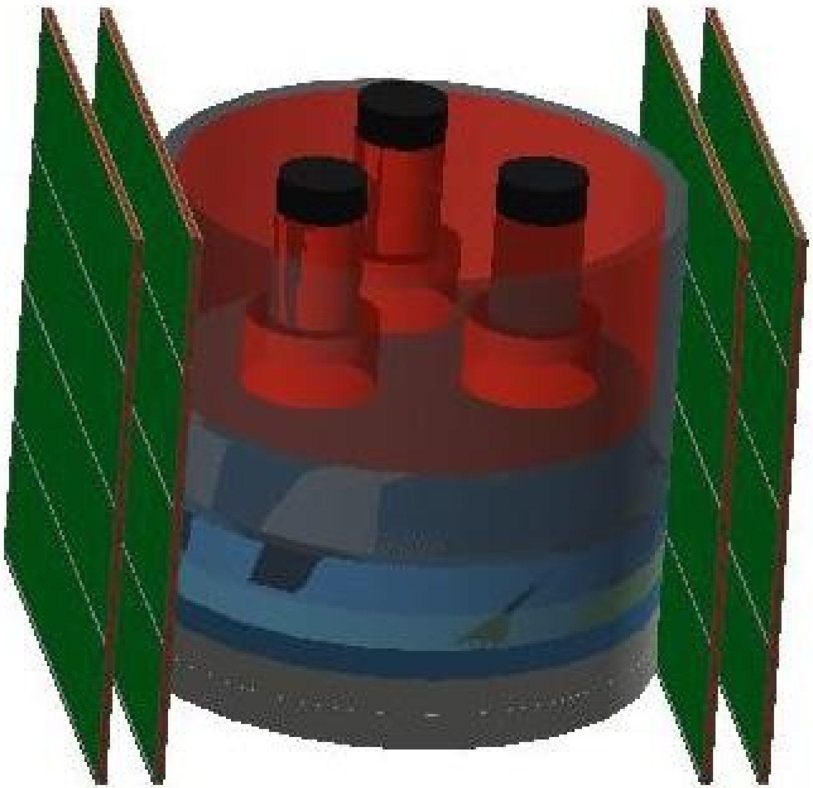
- Consider the example of the stability and efficiency of an electric arc furnace in foundries
- Many factories have issues estimating the exact position of the electrodes in the mixture
  - They suspect that small oscillations of the electrodes are responsible for efficiency losses
  - A precise knowledge (~cm) of this position would allow to correct for the effect

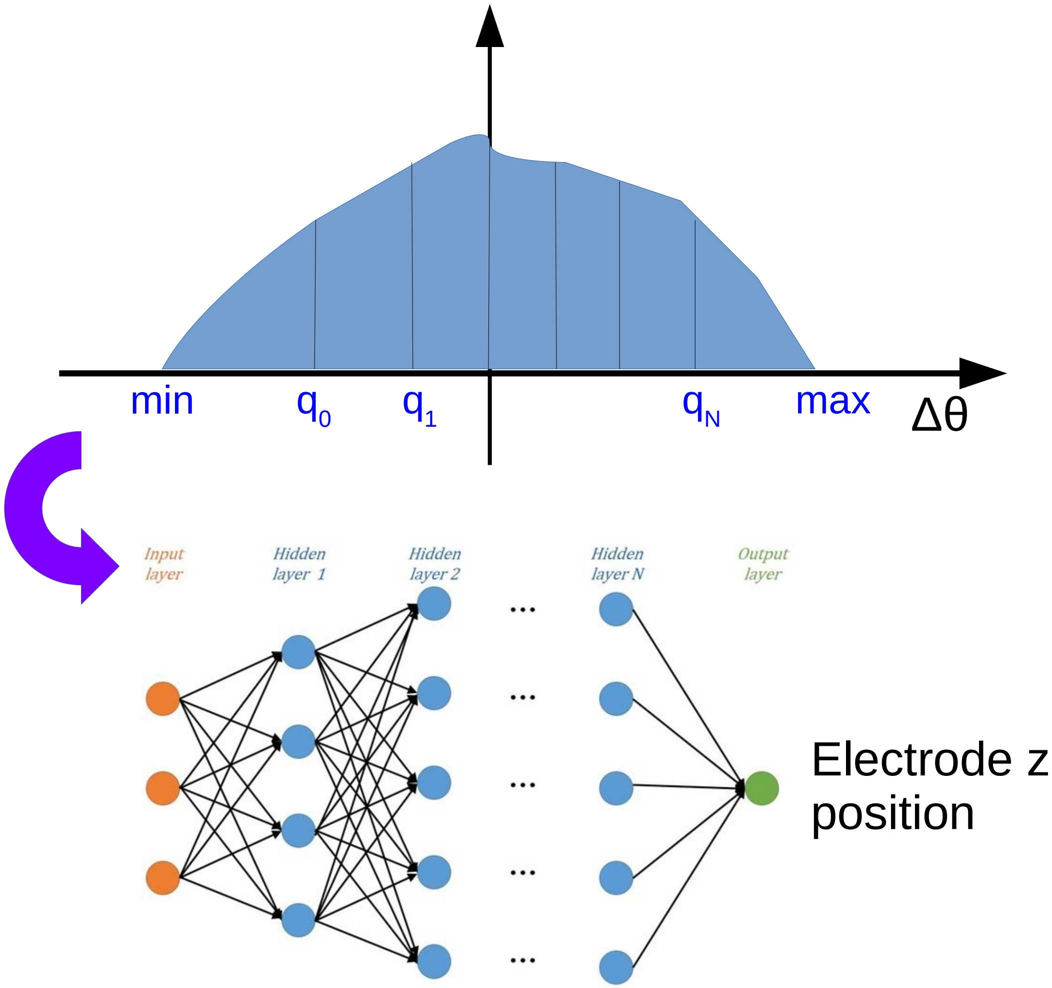




Regression for geometry characterization (I)

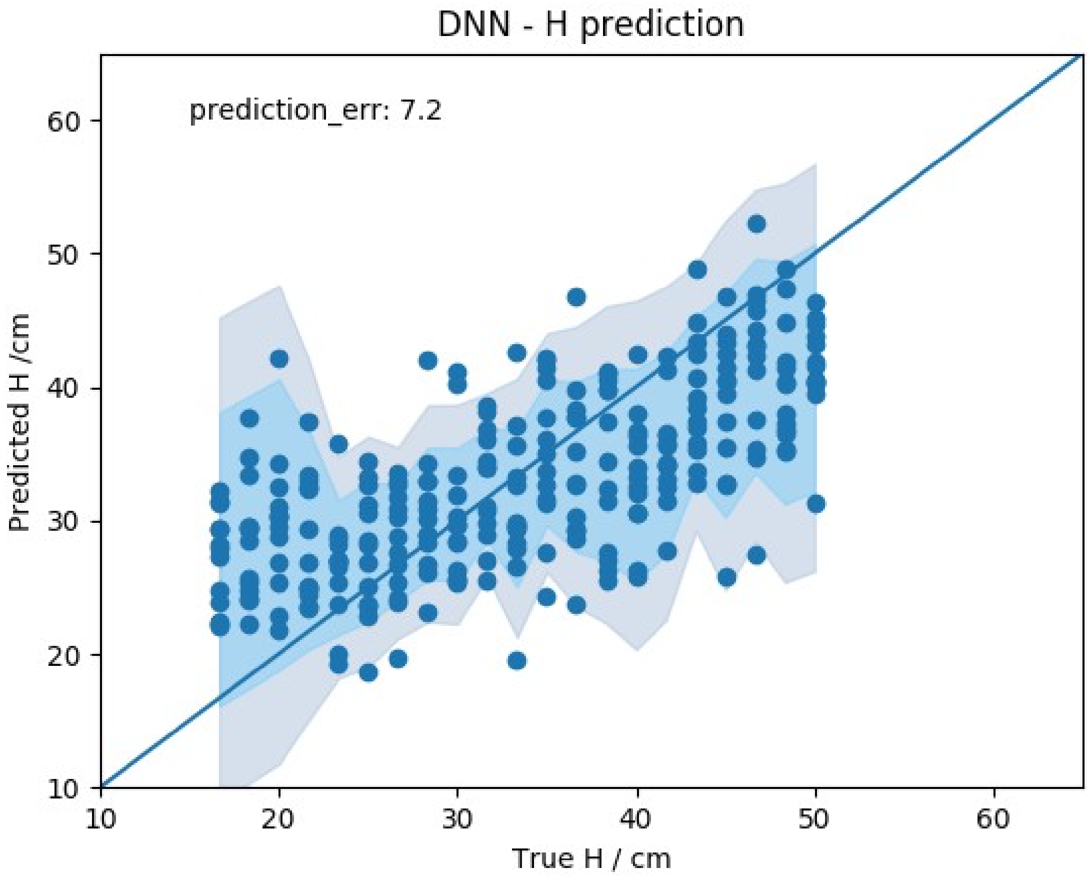
- Built a GEANT4-based model of a furnace with different values for the position of the electrodes
- Artificial Neural Network performing regression on the position of the edge of the electrode in the mix
- ANN using as input data the n-quantiles (+min and max) of the angular scattering distributions





Regression for geometry characterization (II)

- Simulations performed for 21 different positions of the electrode H in the range [16cm, 50cm]
- A total of 10 simulations is performed per point with a total of 1 hour exposition each

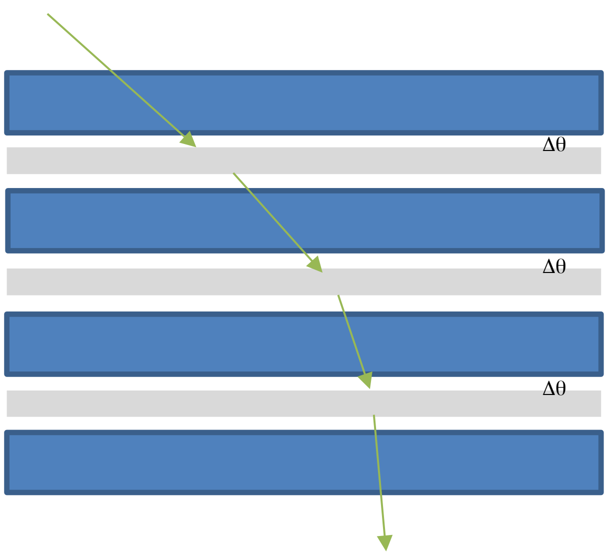


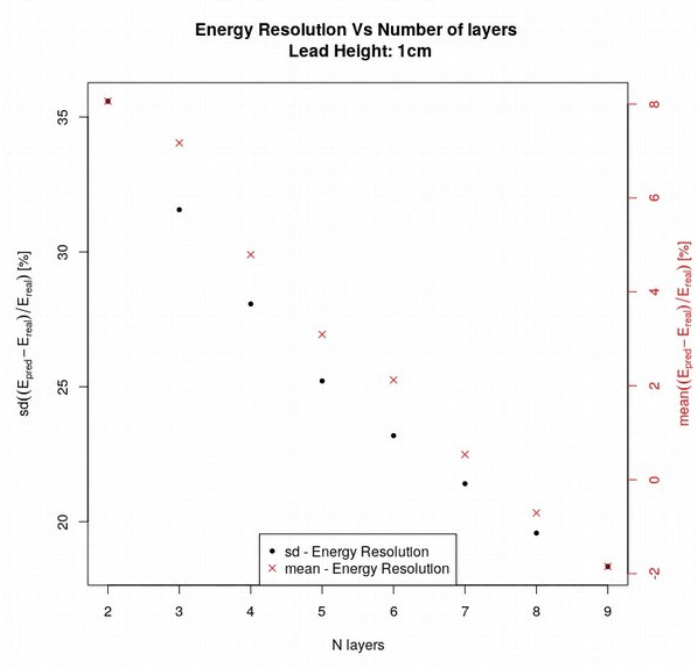
- Very poor discrimination achieved using this method → looking for alternatives

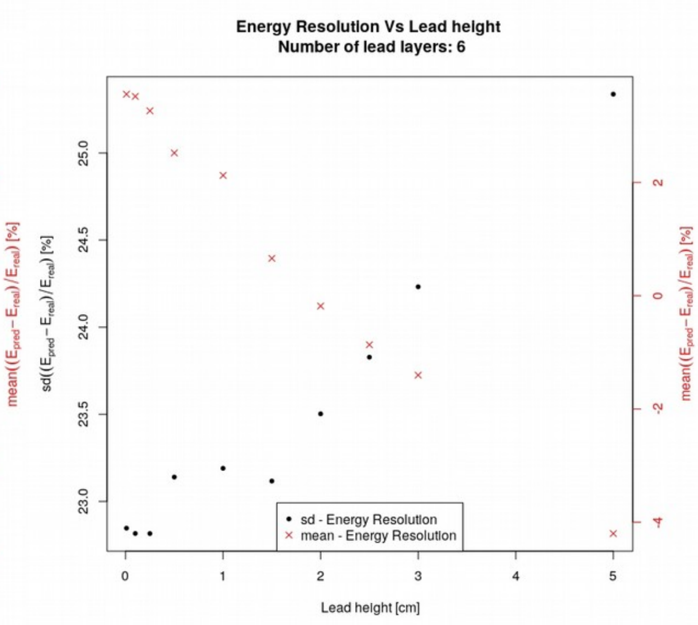
What about the energy?

- Results in the previous study not encouraging → need to find new information for the system
- One obvious possibility is to provide the energy of the muons although this quantity is hard to measure
- A DNN in regression mode can be used one more time to extrapolate the energy with a proper setup
- The idea is to extend the second muon detector with additional layers with known-width lead layers
- A DNN is trained using the angular distributions as input and regressing to the energy of the muon

Energy resolutions of about 25% for 5 detection layers

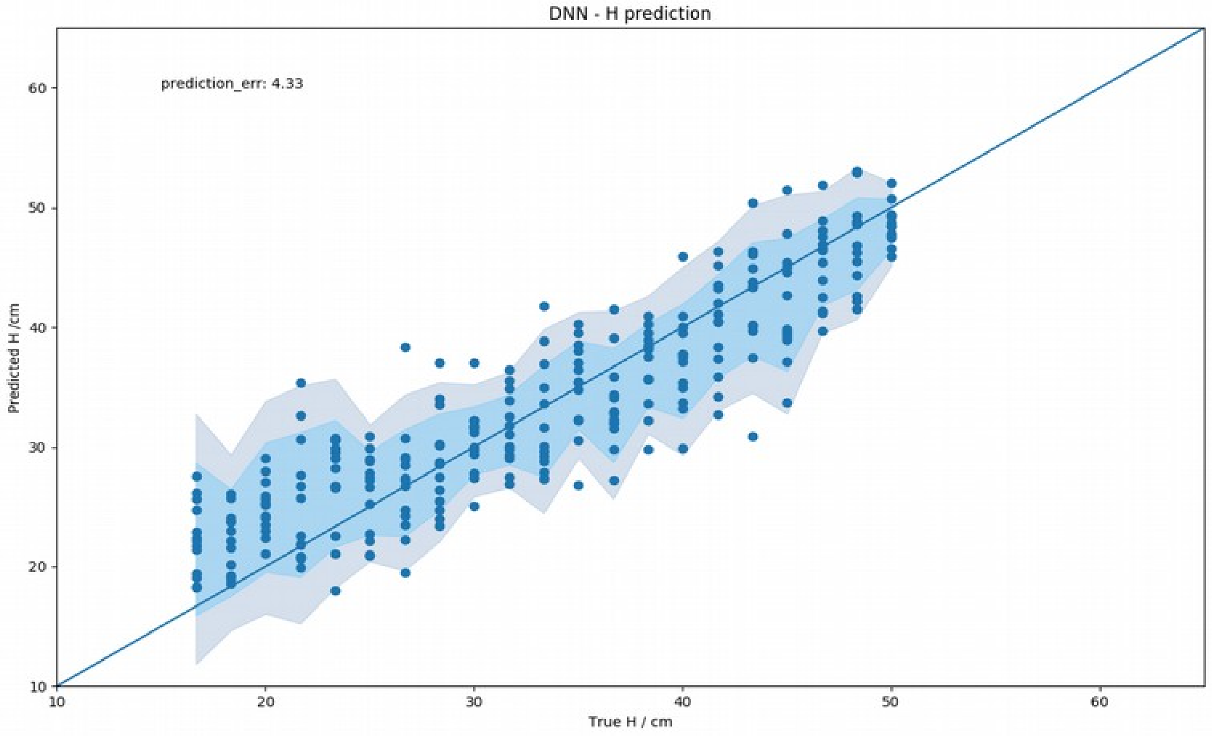






Additional variables + data augmentation

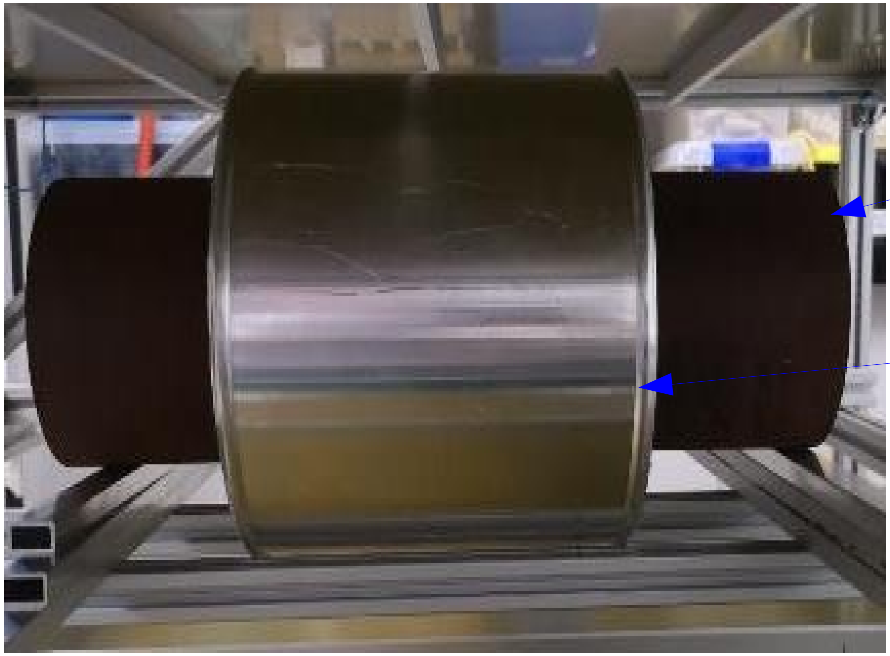
- Aim to to add the information of other variables: position and energy*
- Data augmentation performed defining cross product variables: angle x energy, angle x position, etc
- Quantiles of all distributions are computed and given as input to the DNN



- Encouraging results, a resolution of about 4 cm is achieved (more than acceptable for the problem)

Another example: insulated pipe thickness

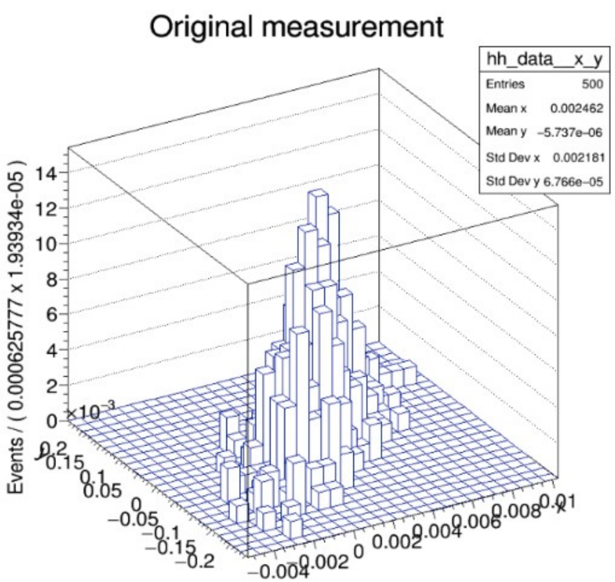
- Oil and gas pipes in petrol refinement plants suffer from wear and degradation due to the flow
- The radius of the pipes can range from ~ 10 cm to more than 1 metre.
- All pipes have to be inspected with a certain periodicity to assess the thickness of the walls
- Factories usually have several kilometres of pipes so the inspection has to be quick (~minutes)
- In many occasions pipes are themally insulated to prevent from heat loses during transportation
  - The insulation covers make the application of acustical or electric NDT a hard task
  - They are usually made of rock wool a very low density material

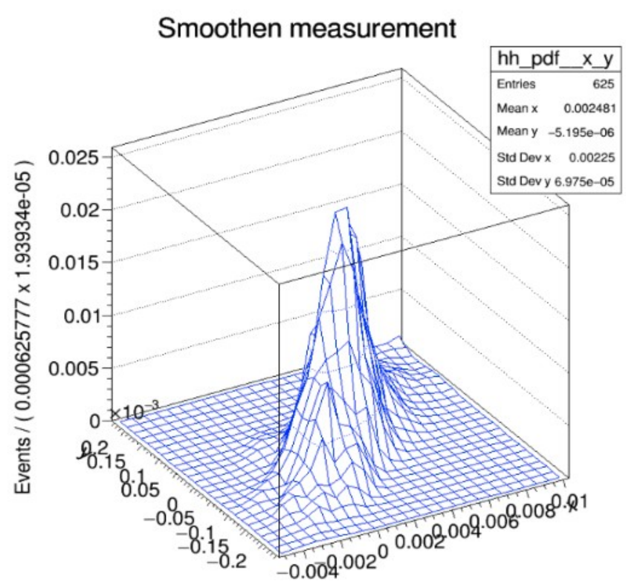


Likelihood-based thickness measurement (I)

- Since the number of parameters is relatively small a likelihood-based parameter estimation can be tried
- Even if very time consuming the observable distributions can be simulated and used in a likelihood

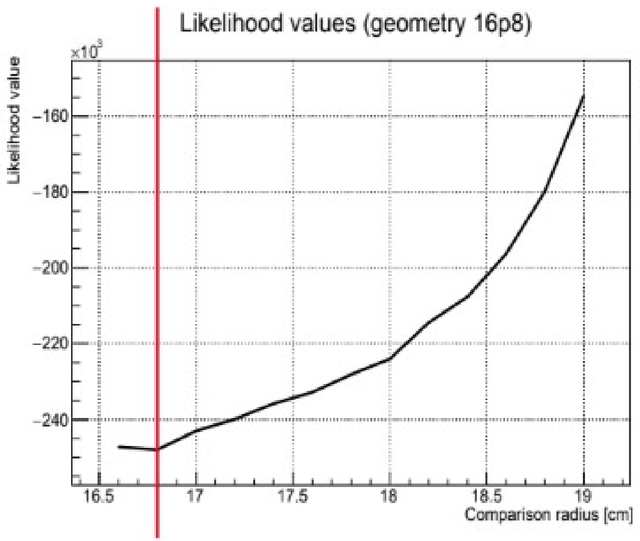
Muon data → Event (x_1, y_1, vx_1, vy_1) (x_2, y_2, vx_2, vy_2) → N propagations to detector 2 under test geometry → Observable distribution + kernel fit → Evaluate track2 in kernel fit as a probability → Repeat for all events + make likelihood → Minimize likelihood

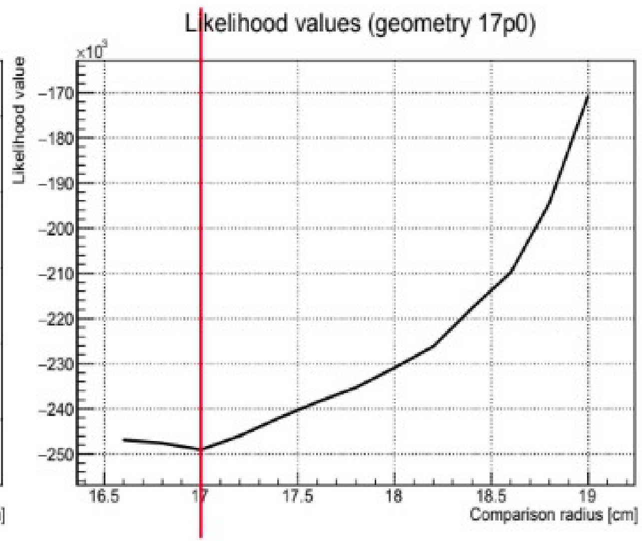


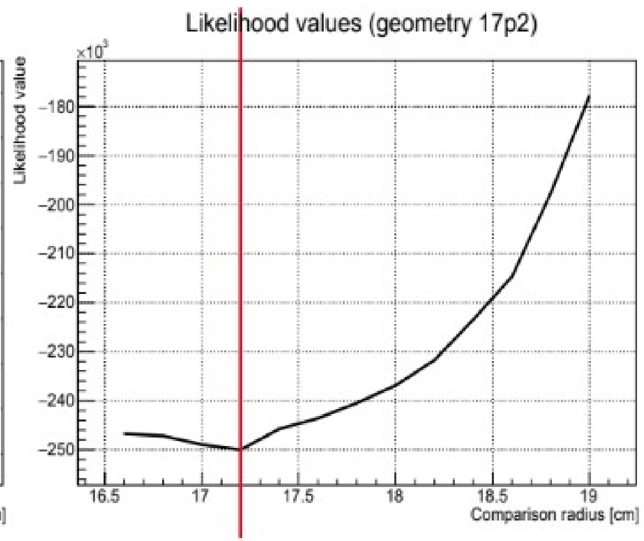


Likelihood-based thickness measurement (II)

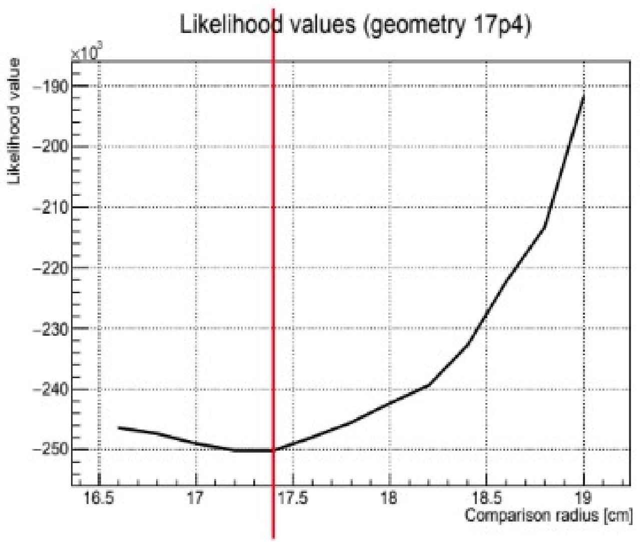
$r = 16.8\text{cm}$ | $r = 17.0\text{cm}$ | $r = 17.2\text{cm}$

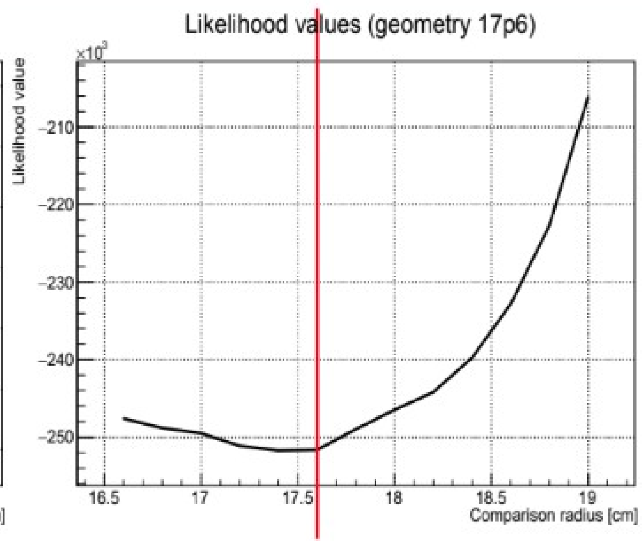


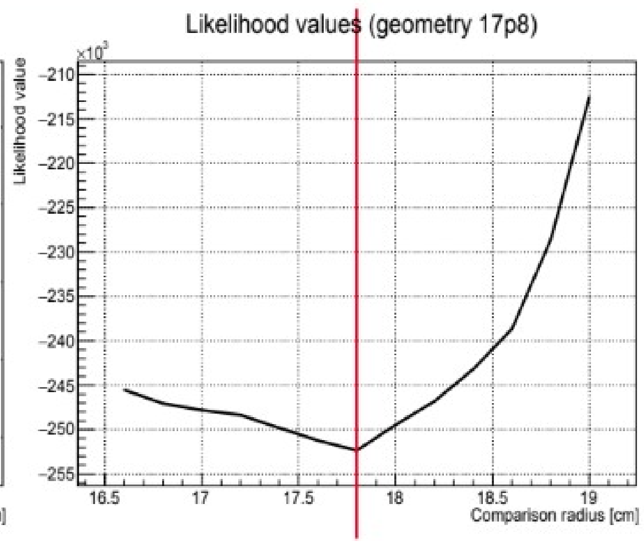




$r = 17.4\text{cm}$ | $r = 17.6\text{cm}$ | $r = 17.8\text{cm}$

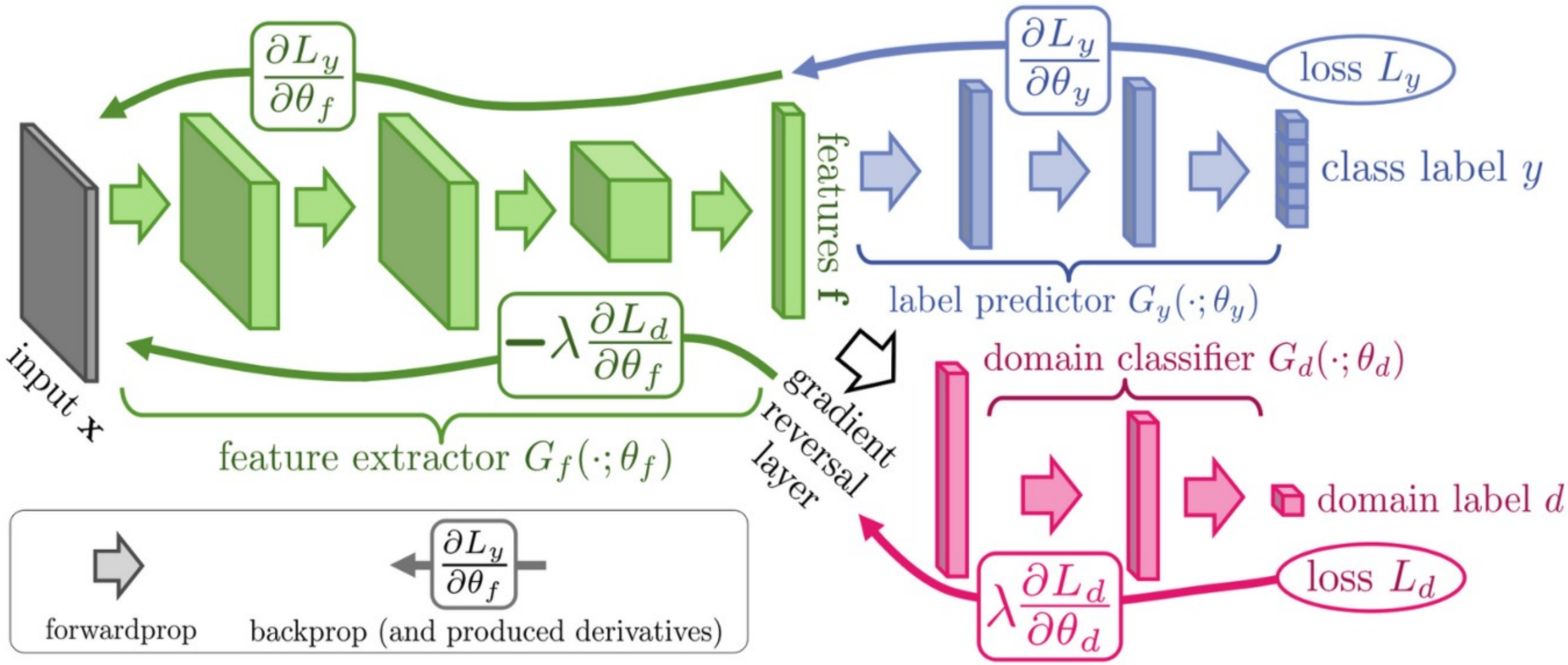






The problem of simulation (and how IA helps)

- The previous method heavily relies on simulation to generate the distributions
- This is a problem (as usual) because of two reasons:
  - Need to quickly produce all this simulation
  - The simulation must be reliable, including also the detector-measurement process
- Generative adversarial neural networks can be used in order to achieve this goal



Generative Adversarial Neural Networks

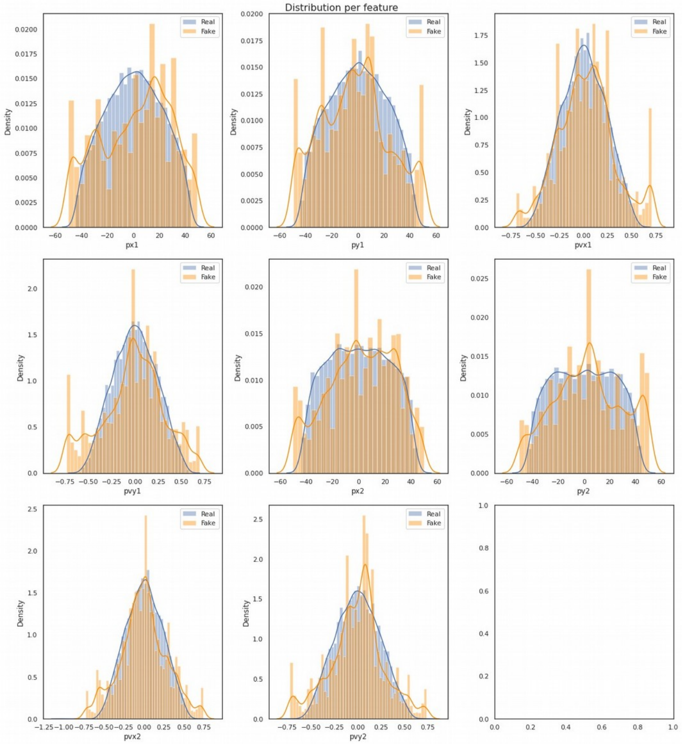
- Technical coordinates: Tensorflow running on GPU RTX Ge-force 3090
- Feature space: the x, y, v_x, v_y of the first detector + the difference with respect to second detector
  - The initial distribution of the tracks should be the one associated to cosmic muons
  - However it also contains information about the detection process (so the variables are kept)
- Two approaches being studied: classic one and Wasserstein (no large difference observed)
- So far not achieving a full equilibrium of generator and discriminator

Training with 200 Kevents of full GEANT4 simulation

Best convergence found at epoch ~ 100

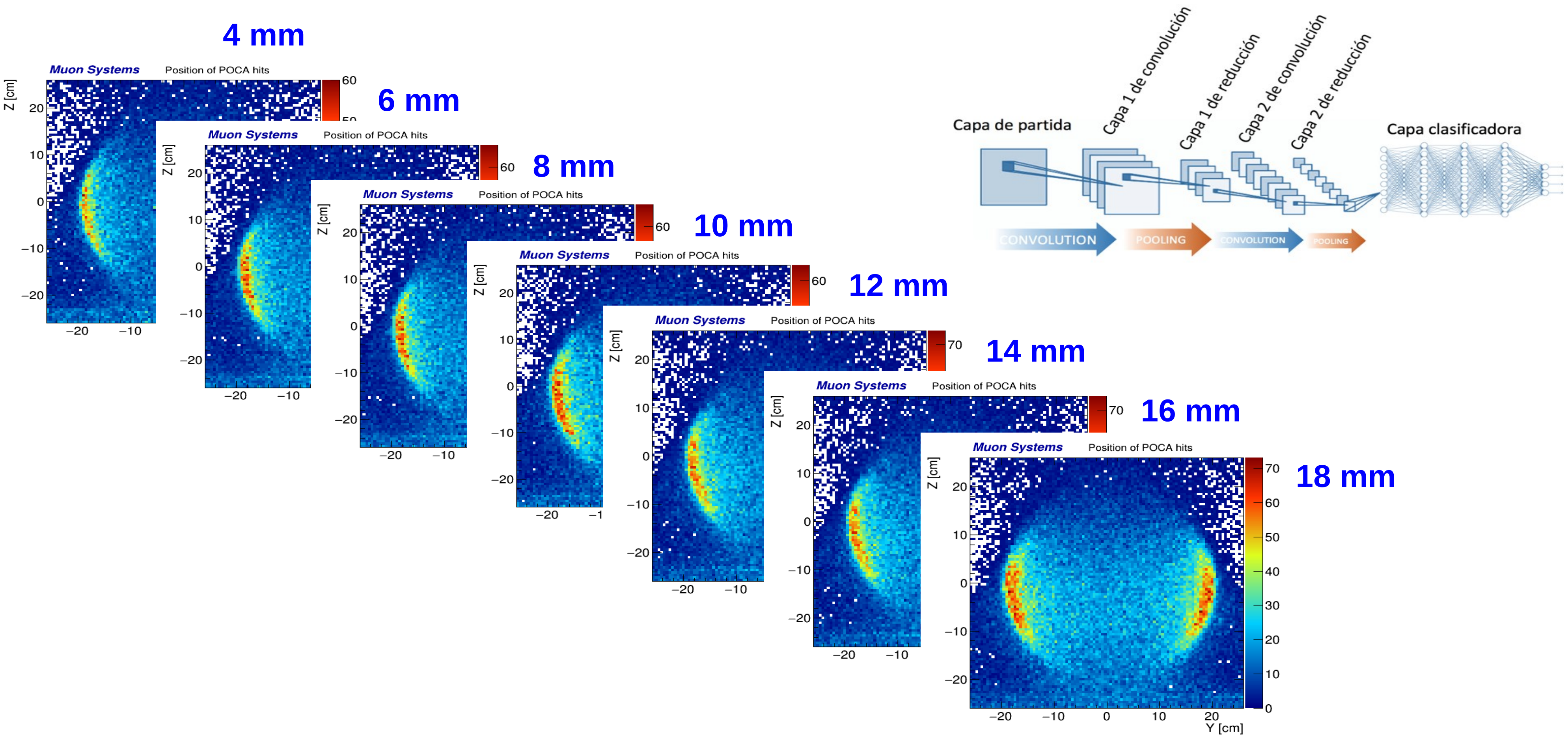
Relative capacities of generator and discriminator models being explored

Work is ongoing...



Switch to images: traditional methods + CNN

- The output of traditional methods like POCA can also be used with Convolution Neural Networks
- The ideas is one more time the same: have the CNN working in regression mode
- In this example: 10 30-minute-exposure-time images for several thicknesses of the wall are used
- The CNN achieves a resolution of about 2 mm on the thickness of the pipes



Conclusions

- Industry is a great consumer of NDT techniques where Muography could have a significant place
  - It allows to perform inspection of large and dense structures
  - It allows to perform the inspection while the facility is in production (online monitoring as well)
- The nature of industrial problems differs from other Muography applications
  - Geometries are almost known → large reduction of parameters
- Modern Deep Learning techniques can be exploited in this context of which I highlight:
  - ANNs in regression mode for several cases and applications
  - GANs in order to produce fast and reliable simulation to be used with parameter inference models
  - Combination of traditional reconstruction methods with Convolutional neural networks
- Lots of work ahead!

Thanks

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