

Particle Physics session of the First MODE workshop

“Differentiable Programming for Experimental Design”

Pietro Vischia¹

¹F.N.R.S. and CP3 — IRMP, Université catholique de Louvain



First MODE Workshop

What is MODE about

- MODE is mostly about these people being right

$$\operatorname{argmax}_{x,y}(\mathcal{L}(x,y)) \neq \left[\operatorname{argmax}_x \left(\int \mathcal{L}(x,y) dy \right), \operatorname{argmax}_y \left(\int \mathcal{L}(x,y) dx \right) \right]$$



Vischia

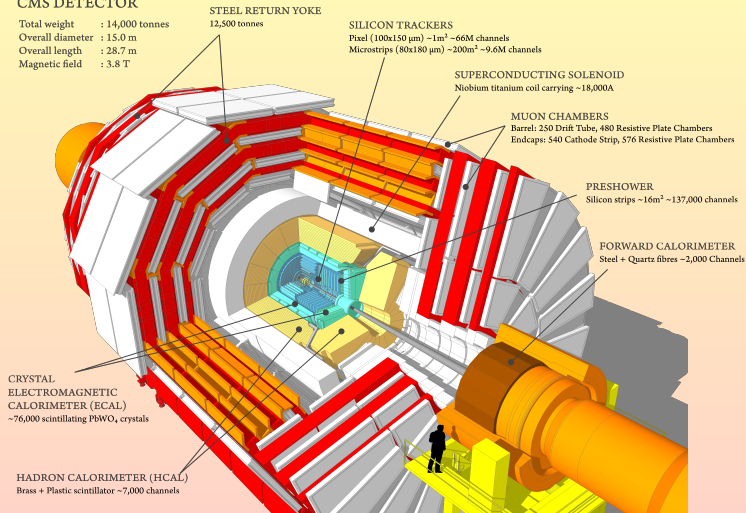


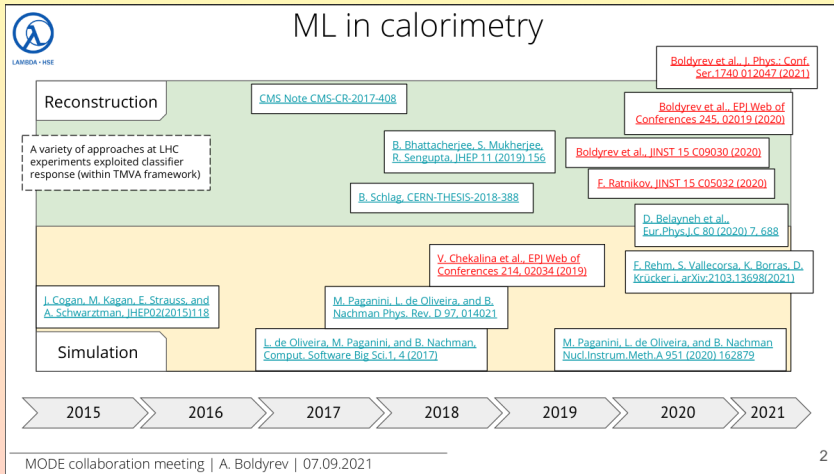
First Workshop of MODE

A typical HEP detector is obscenely complex

CMS DETECTOR

Total weight : 14,000 tonnes
Overall diameter : 15.0 m
Overall length : 28.7 m
Magnetic field : 3.8 T

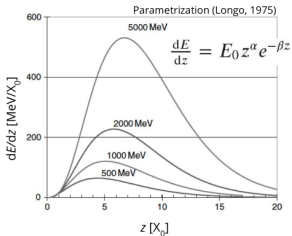






Calorimetry in a nutshell

Longitudinal EM shower profile

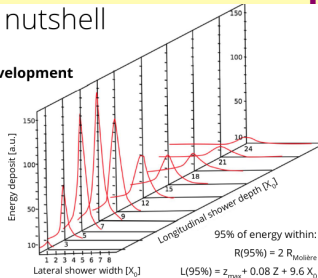


Differences between showers induced by γ & e

$$z_{\max} = \frac{\alpha-1}{\beta} = \ln\left(\frac{E_0}{E_C}\right) + C$$

$$C_\gamma = -0.5, C_e = -1.0$$

EM Shower development



Energy resolution

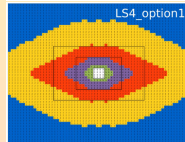
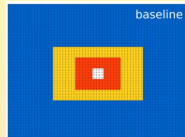
$$\frac{\sigma_{\text{reco}}}{E_{\text{reco}}} = \frac{a}{\sqrt{E_{\text{gen}}}} \oplus b \oplus \frac{c}{E_{\text{gen}}}$$

Timing resolution

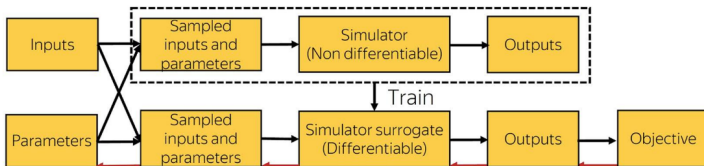
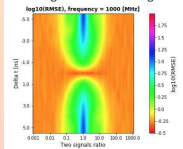
$$\sigma_t = A/\sqrt{E} \oplus B$$

MODE collaboration meeting | A. Boldyrev | 07.09.2021

3



Two signals discriminating

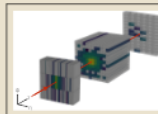


Shirobokov S., Belavin V., Kagan M, AU, Baydin A., NeurIPS'20 paper, [arXiv:2002.04632 \[cs.LG\]](https://arxiv.org/abs/2002.04632)

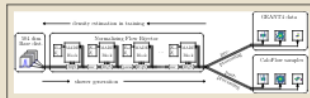
- Fast generation of calorimeter showers by generative models

Generation of Calorimeter Showers with Normalizing Flows: CALOFLOW

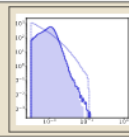
- We use the same calorimeter and GEANT4 setup as the original CaloGAN.
 - Events are 504-dim. showers of e^+ , γ , and π^+
- ⇒ First time application of Normalizing Flows!



- Having $\log p(x)$ allows stable training and straightforward model selection.
- We use a 2-step setup to ensure energy conservation.
- The setup can easily be conditioned on external parameters.

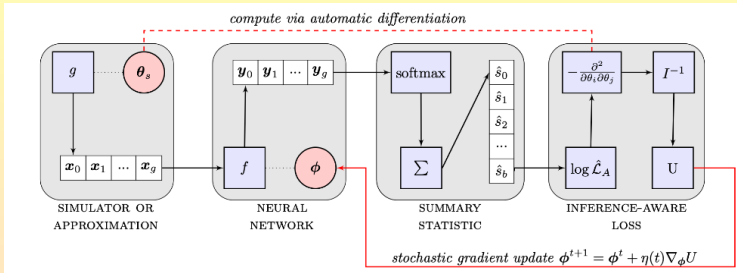


- I argued that a classifier provides the “ultimate test” of a generative model.
- I showed how CALOFLOW passes this stringent test, along with more qualitative comparisons (histograms, images).



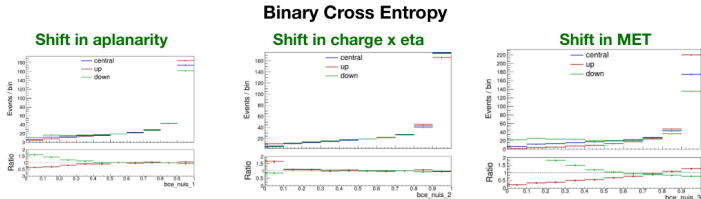
Make your inference aware of uncertainties (L. Layer)

- Extend prototype cases to multiple variables, multiple types of uncertainties



Study II: artificial shift in multiple variables

- Introduce **linear shift** in **up to 3 variables** and train one INFERNO model for each case
- Predict the same **up/down shift** for signal template with BCE model and INFERNO



INFERNO

PIECES OF LQCD COMPUTATION: FROM SIMULATIONS TO THE PROTON MASS

What are the challenges?

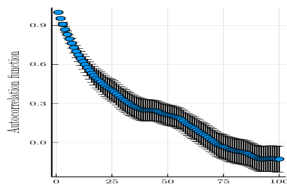
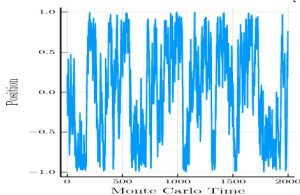
- ▶ Observables measured on the **same** configurations are correlated
- ▶ Measurements show autocorrelations

Error analysis in lattice QCD code should be aware of:

- ▶ Derived observables: **Complicated functions** of Monte Carlo measurements
- ▶ Autocorrelation of observables (affect error estimates)
- ▶ Correlation of observables measured on the same ensemble

HANDLING MONTE CARLO DATA

- ▶ Generate a random walk in the interval $[-1, 1]$

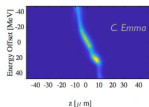


- ▶ Input a Monte Carlo history as uwreal. Correlations handled automatically

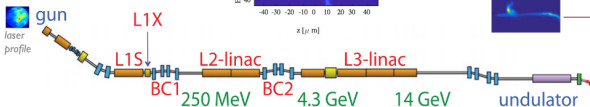
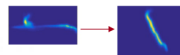
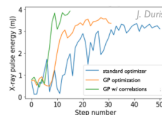
Several major areas for ML to play a role

anomaly detection
failure prediction

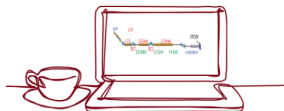
diagnostics
(reconstruct / analyze beam)



automated control
+ optimization



incorporate
physics
information



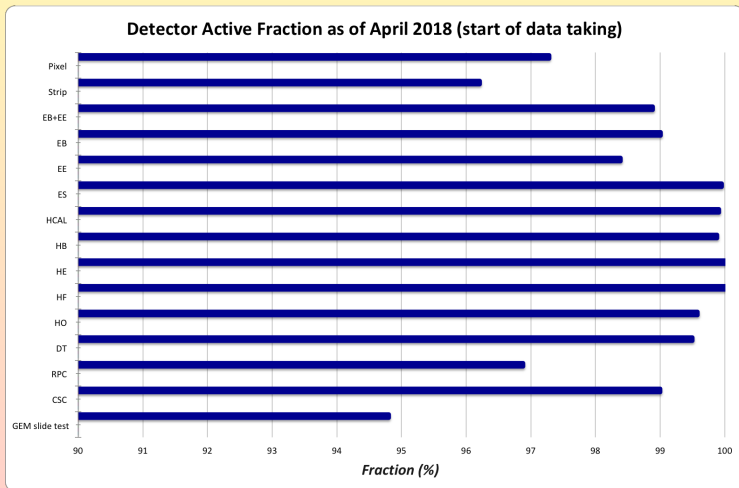
digital twins + online modeling
(planning, model-based control, finding differences between sim/machine)

extract unexpected
relationships
(feed into control / design)

+ need uncertainty
quantification for all

A personal note on detectors: can we push this further?

- Not all detector channels are active at any given time. Can we account for this?
- Worst-case scenarios, or identification of areas at risk as a function of DC fraction
- Realtime reconfiguration of the detector (shutting down channels?)



Maybe premature, but if interested then let's talk!

- Hardcore detector developers may resist the introduction of these methods
 - Can all the elements necessary for the AI training be quantified in a way applicable to the AI?
 - There may be the perception that we aim at substituting “many very experienced people working many years” in a naïve and simplistic way
 - There may be feelings that factorization is still the best approach, even if this is easily mathematically disproven
- We must convey our objectives with clarity
- We must make clear that domain knowledge will still be crucial in setting up these pipelines
- We must explain the way we model domain knowledge into our pipelines in a way that is digestible to resisting people

- HEP detectors are ultracomplex
- Calorimetry is an obvious first candidate to MODE methods
 - Some work already done by MODE members
 - Interested people face similar optimization problems, e.g. in future muon colliders (see L. Sestini slides after this summary)
 - Synergies and collaborations can and should be built
- We are physicists, uncertainties are our daily bread (an uncertain bread, until tenure 😊)
 - Make machine learning aware of systematic uncertainties
 - Deal with tricky correlations and autocorrelations
- Push this further! Can we optimize a detector geometry in real time?
 - Maybe premature, but if interested then let's talk!
- We must not forget sociology
 - The way we present our results may be as crucial as the methods themselves if we want to pioneer these concepts and methods