DRD6 Collaboration Meeting,
CERN - April 10, 2024

Getting More from Hadron Calorimeters

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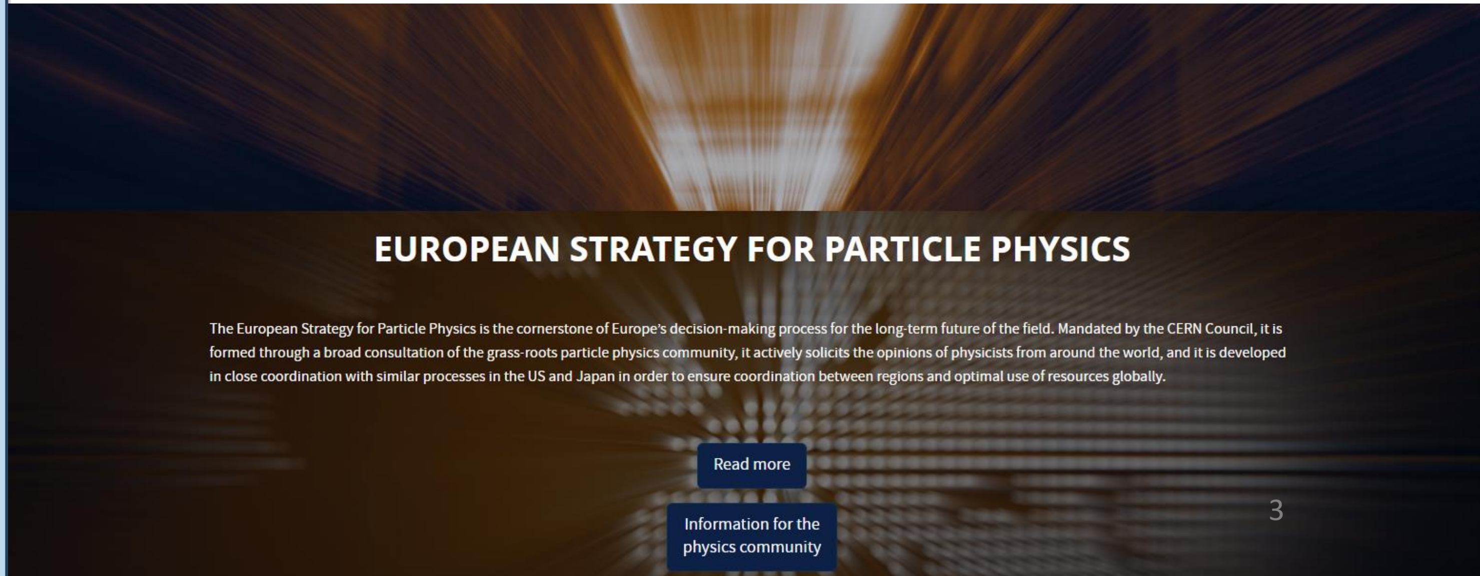
Lulea University of Technology

Universal Scientific Education and Research Network

Contents

1 – A Challenging Future

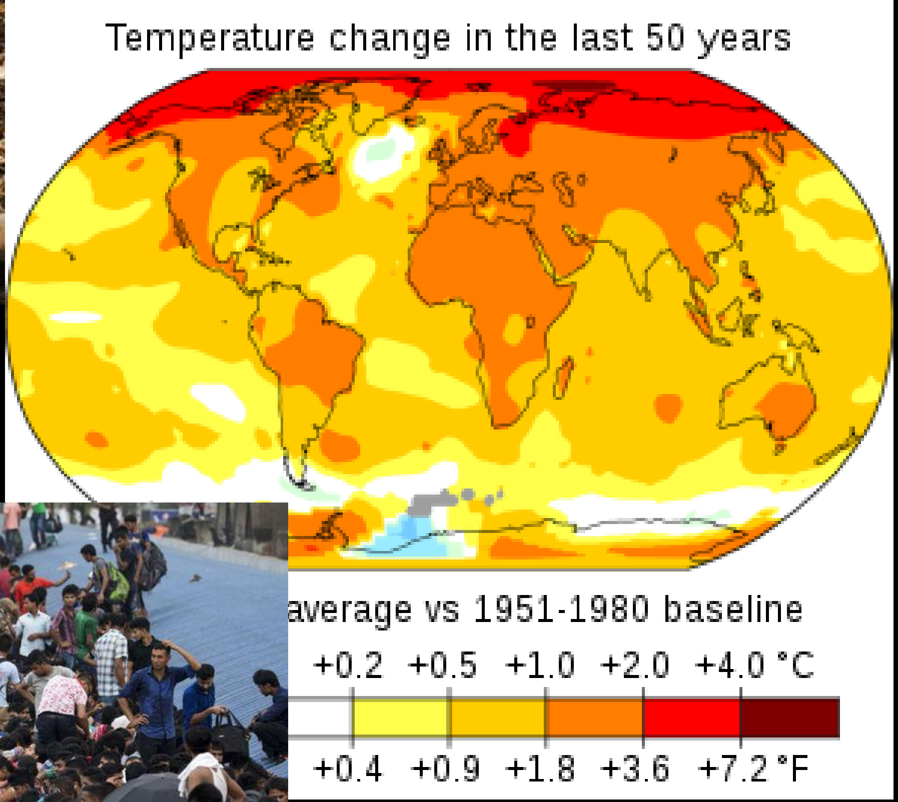
The 2020 update of the European Strategy for Particle Physics (EUSUPP) encourages feasibility studies for new large, long-term projects which will once again push our technological skills to their limits.



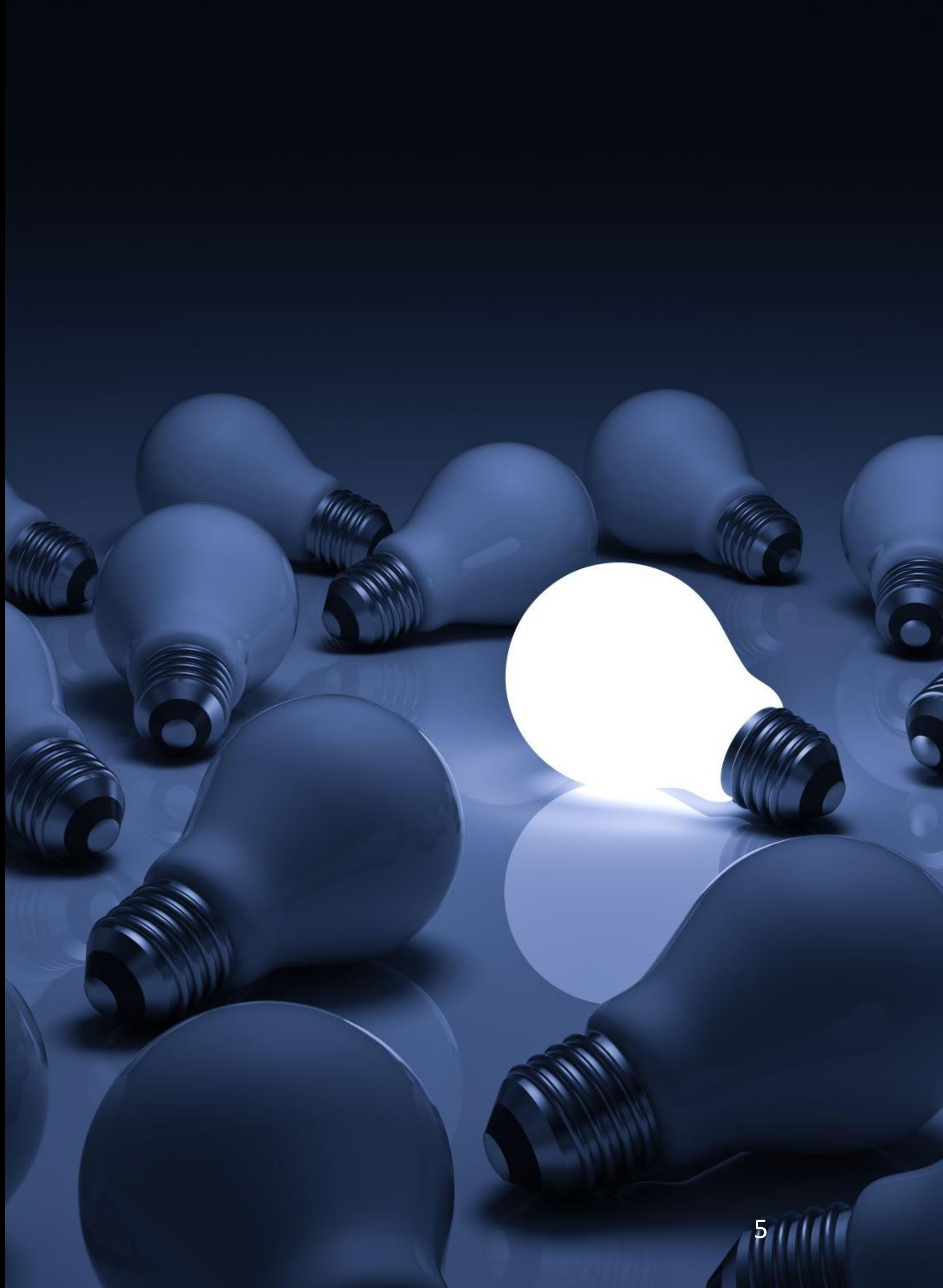
But humanity faces unprecedented global challenges

Resources must be devoted to seek solutions through applied science innovations

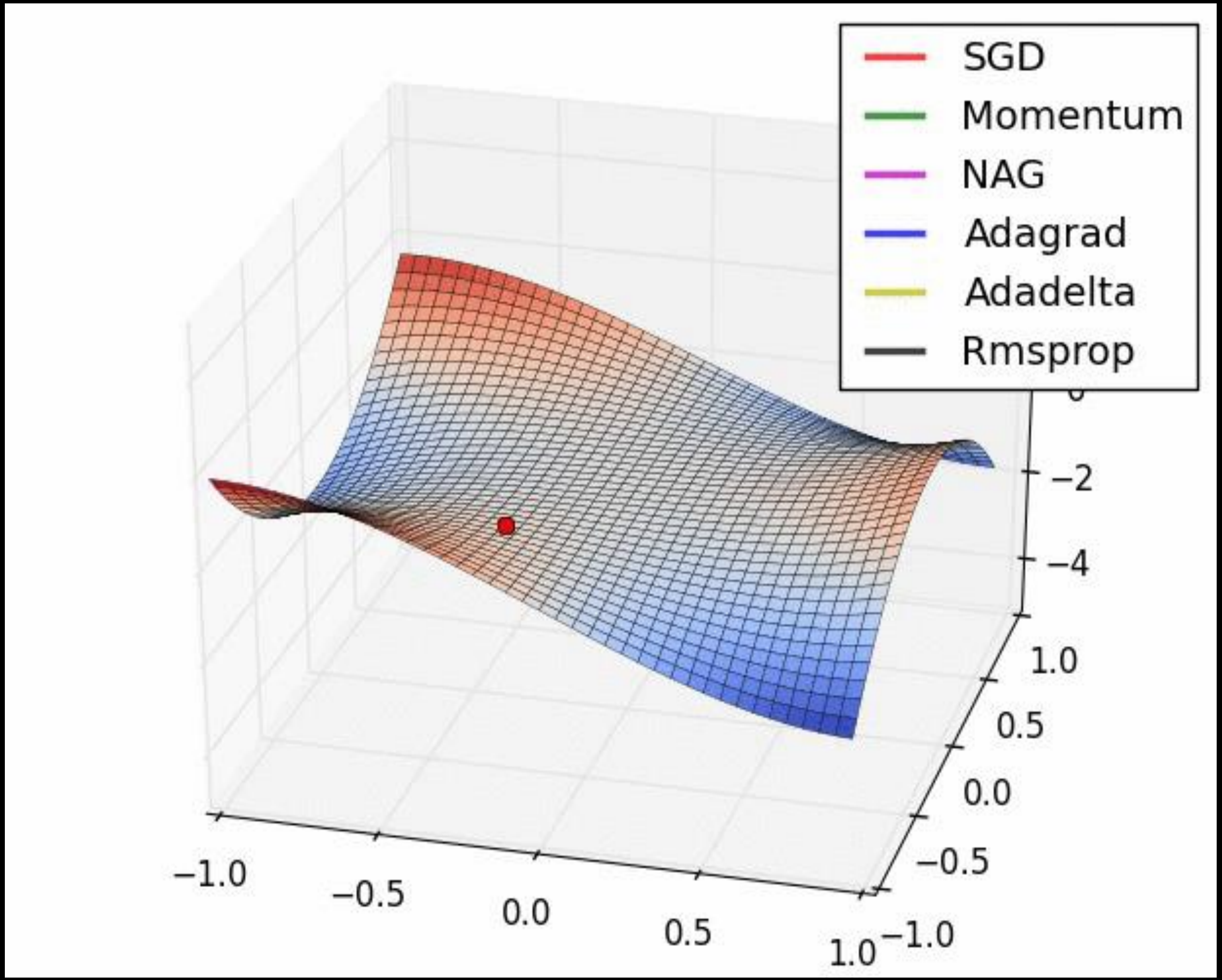
rather than investing in fundamental research.



→Ensuring the maximum exploitation of any resources spent on fundamental research is a moral imperative



2 – Differentiable Optimization of Experiment Design and the MODE Project



Outstanding Problems in Fundamental Science

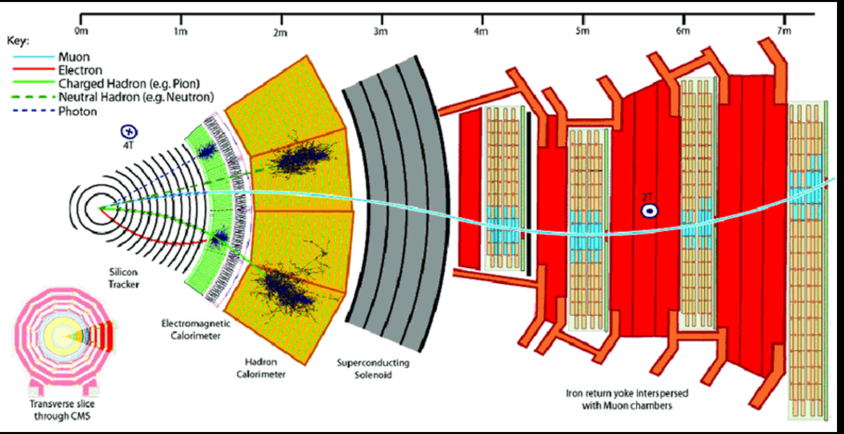
- Formulating new theories of Nature
- Extracting sufficient statistics from high-D data
- Ensuring complete control of our type-1 error rates
- Explore higher energy / higher intensity frontiers, ensuring we do not miss new physics

Nowadays we are doing all of that with deep learning

The above are all data analysis tasks. Looking forward, we must look into our design problems, as time from blueprint to commissioning is O(20) years!

In market-driven human activities, **co-design** of hardware and software is already happening. In HEP we still haven't started doing it systematically

Toward End-to-End Optimization: The *Status Quo* in HEP



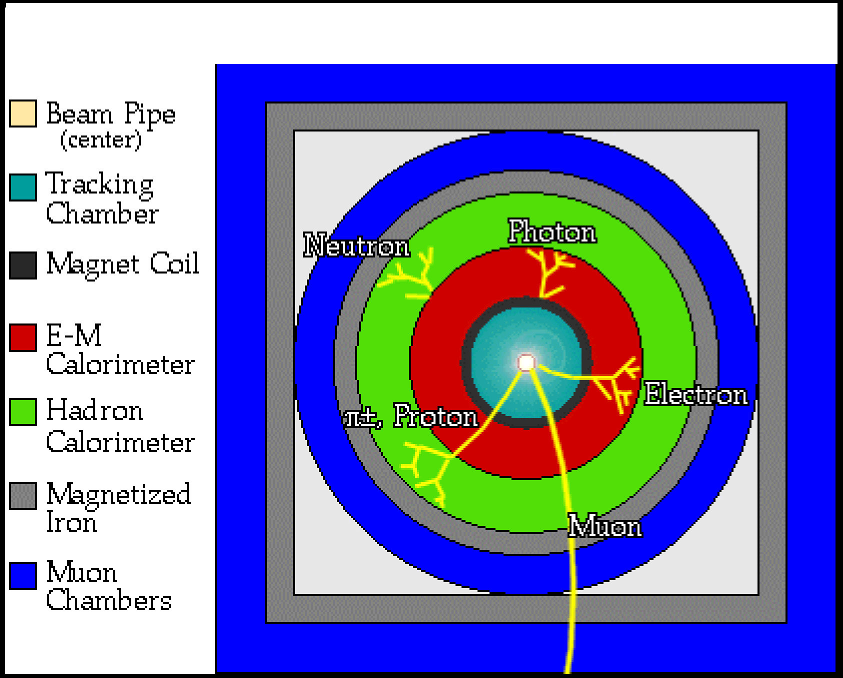
In the past 50+ years the design of new particle detectors leveraged cutting-edge technologies,

yet **a few crucial underlying global paradigms** of experimental design have **remained mostly unchallenged** across decades:

- "Track first, destroy later"
- Redundancy and robustness of detection systems
- Symmetrical layouts

→ No guarantee of optimality!

Above: *a present-day detector (CMS)*
Below: *a 30-years-old detector for LEP*



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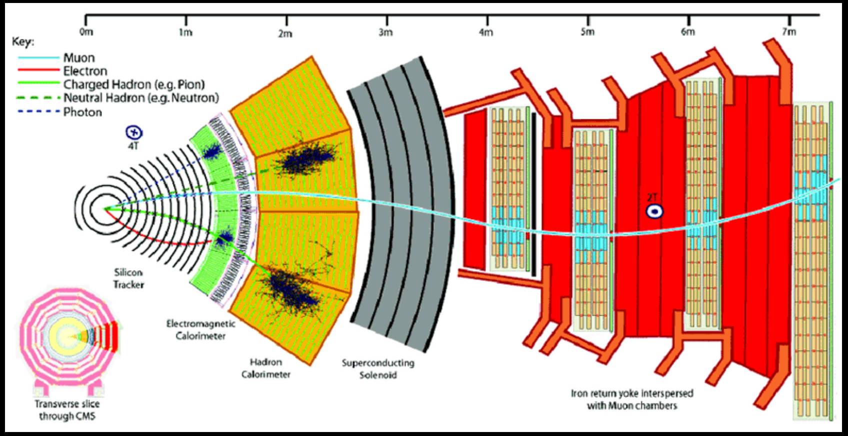

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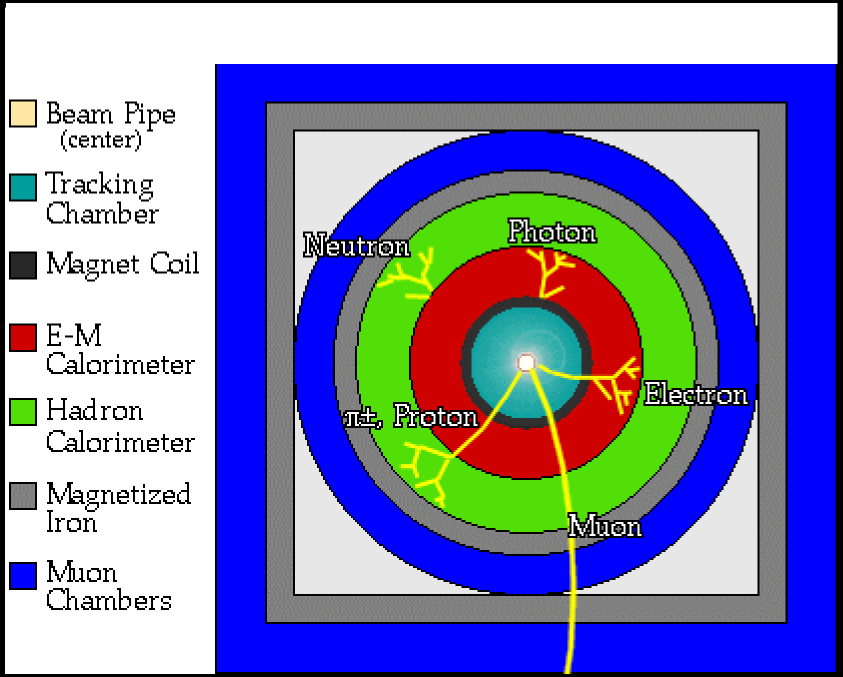

In the past 50+ years the design of new particle detectors leveraged cutting-edge technologies,

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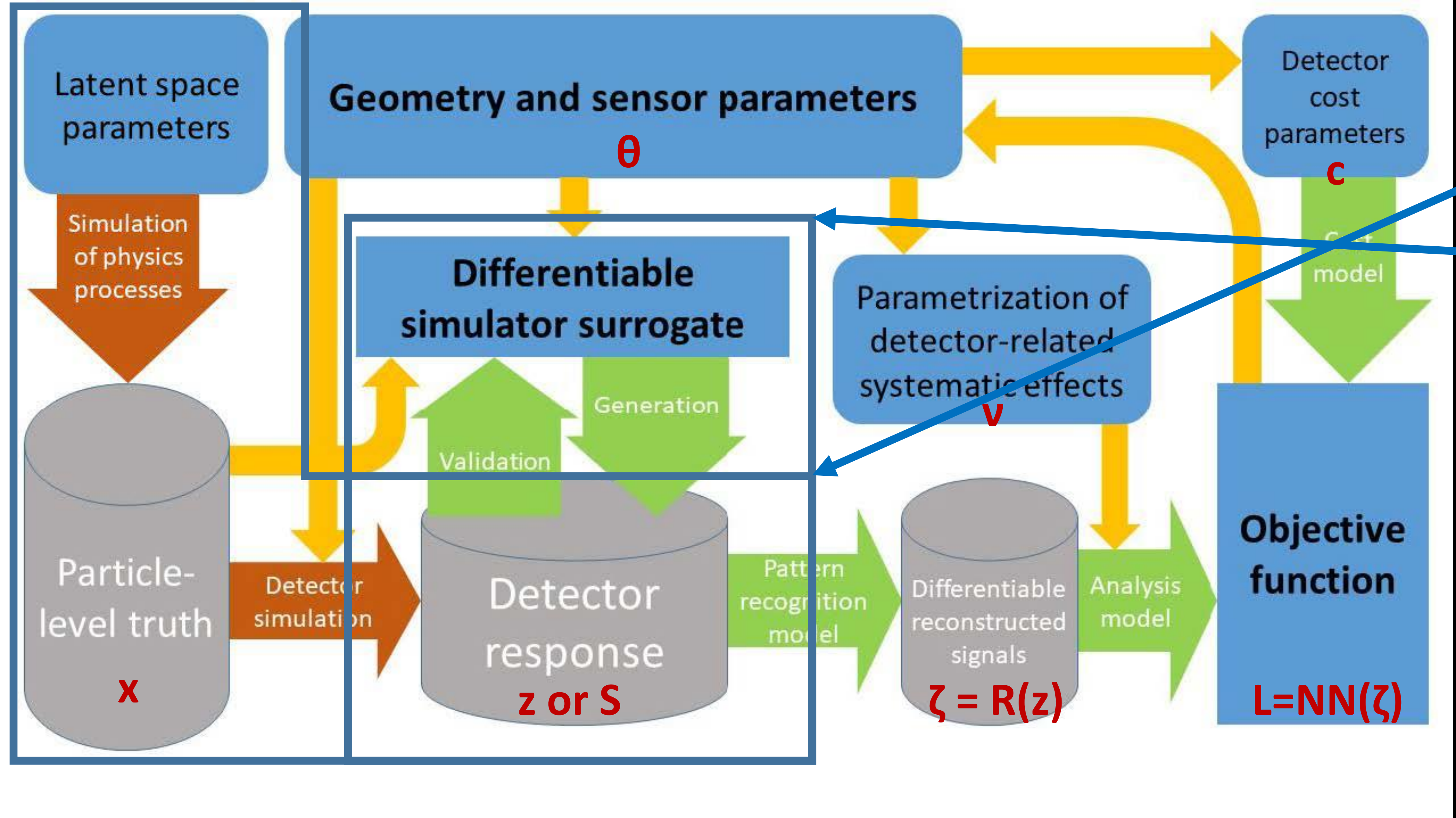
- "Track first, destroy later"
- Redundancy and robustness of detection systems
- Symmetrical layouts

→ No guarantee of optimality!

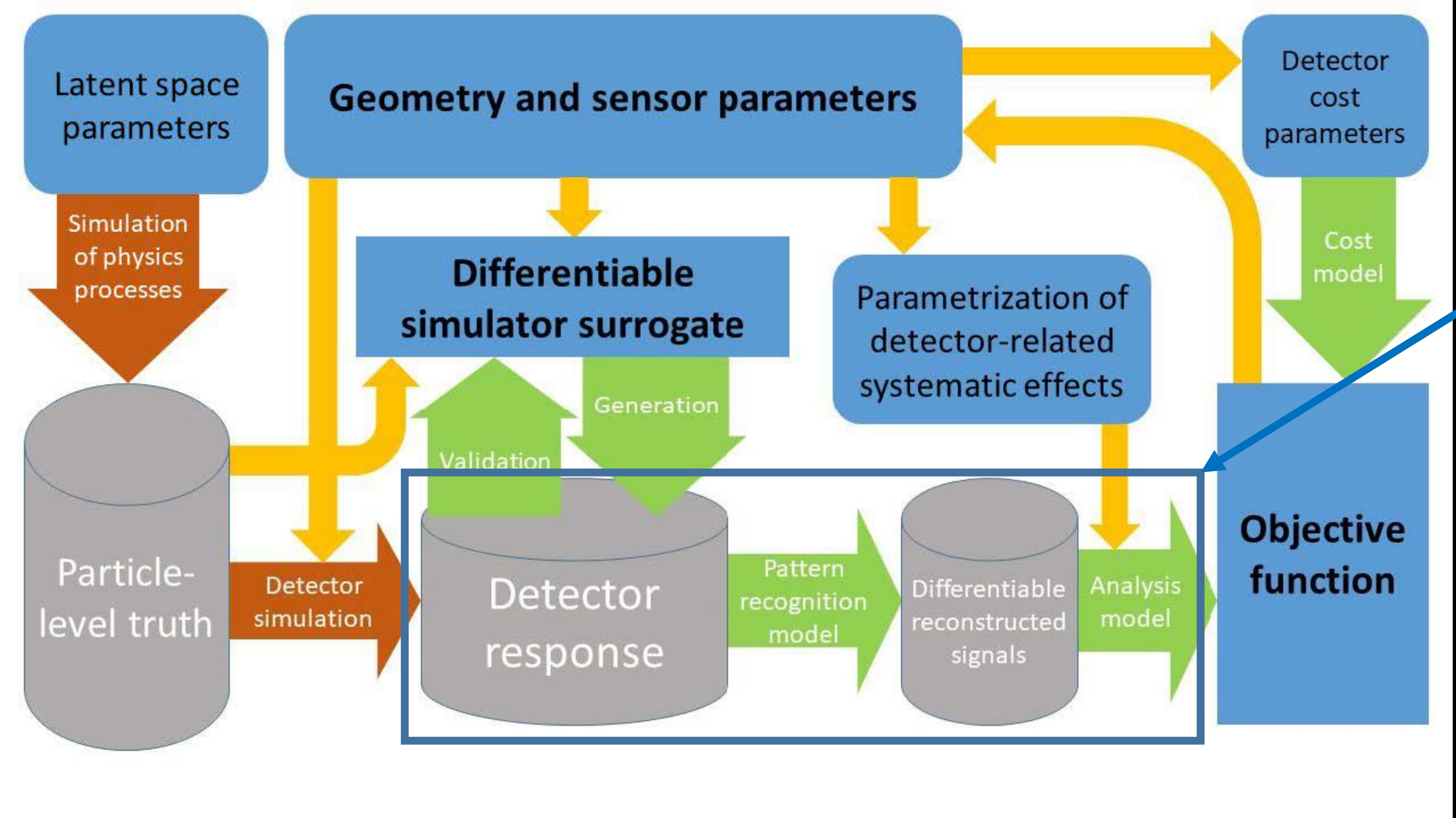
Those choices **do not directly maximize a high-level utility function**, such as the highest discovery reach for a physical process, or measurement precision

Putting a Pipeline Together



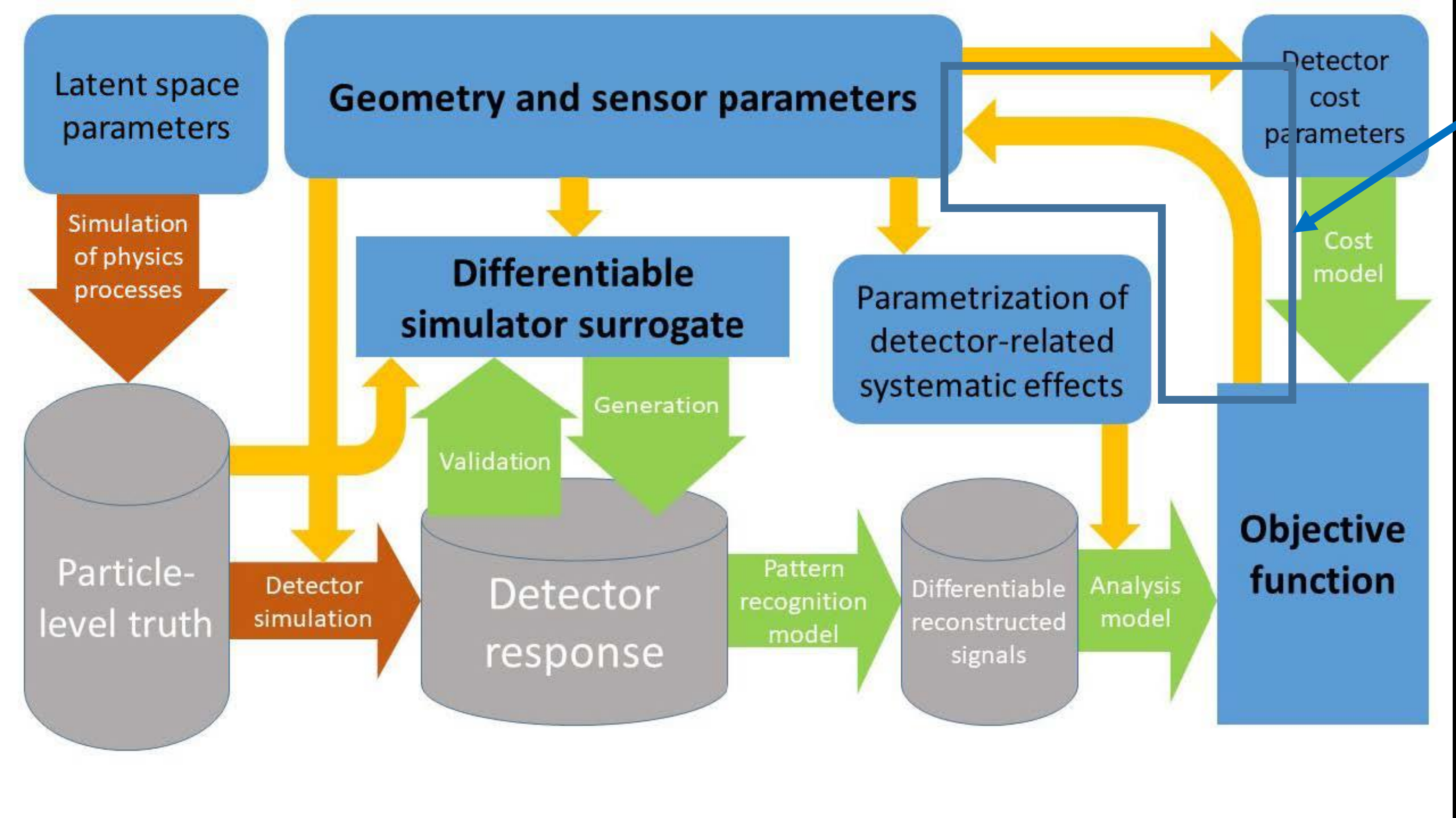
If the **simulation** can be bypassed by a **differentiable surrogate**, we remove the stochasticity of the physics and strongly simplify the problem

Putting a Pipeline Together / 2



The model must include a **model** of the absolute state-of-the-art (or even extrapolated future performance!) of reconstruction and inference to avoid any **misalignment**

Putting a Pipeline Together / 3



Backpropagation of the gradient of the objective function then allows to find optimal parameters **θ** → obtain end-to-end optimality of the instrument

Machine-Learning Optimized Design of Experiments

MODE Collaboration

https://mode-collaboration.github.io

M. Aehle[17], A. G. Baydin[5], A. Belias[10], A. Boldyrev[4], K. Cranmer[8], P. de Castro Manzano[1], Z. Daher[2], T. Dorigo[1,14,21,26], C. Delaere[2], D. Derkach[4], J. Donini[3,26], P. Elmer[18], F. Fanzago[1], S. Gami[27], N.R. Gauger[17], A. Giammanco[2,26], C. Glaser[11], L. Heinrich[12], R. Keidel[17], J. Kieseler[22], C. Krause[28], L. Kusch[17], M. Lagrange[2], M. Lamparth[12], A. Lee[25], M. Liwicki[21], G. Louppe[6], L. Layer[1], L. Masserano[25], F. Nardi[3,14], P. Martinez Ruiz del Arbol[9], F. Ratnikov[4], R. Roussel[20], T. Samui[24], F. Sandin[21], P. Stowell[15], G. Strong[1], M. Tosi[1,14], A. Ustyuzhanin[4], S. Vallecorsa[7], X.C. Vidal[23], P. Vischia[13,26], G. Watts[19], H. Zaraket[16]

1 INFN, Italy
2 Université Catholique de Louvain, Belgium
3 Université Clermont Auvergne, France
4 Laboratory for big data analysis of the HSE, Russia
5 University of Oxford, UK
6 Université de Liege, Belgium
7 CERN, Switzerland
8 New York University, USA
9 IFCA, Spain
10 GSI, Germany
11 Uppsala Universitet, Sweden
12 TU Munchen, Germany
13 Universidad de Oviedo and ICTEA, Spain
14 Università di Padova, Italy
15 Durham University, UK
16 Lebanese University, Lebanon
17 Kaiserslautern-Landau University, Germany
18 Princeton University, USA
19 University of Washington, USA
20 SLAC, USA
21 Lulea University of Technology, Sweden
22 Karlsruhe Institute of Technology, Germany
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27 NISER, India
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Active Projects: a Pot-Pourri

The target of **MODE** is to design a scalable, versatile architecture that can provide end-to-end optimization of particle detectors, proving it on a number of different applications

Idea: if we "solve" a few problems we may construct a library of solutions and exploit the universality of the underlying architecture and its modularity, re-using modeling efforts

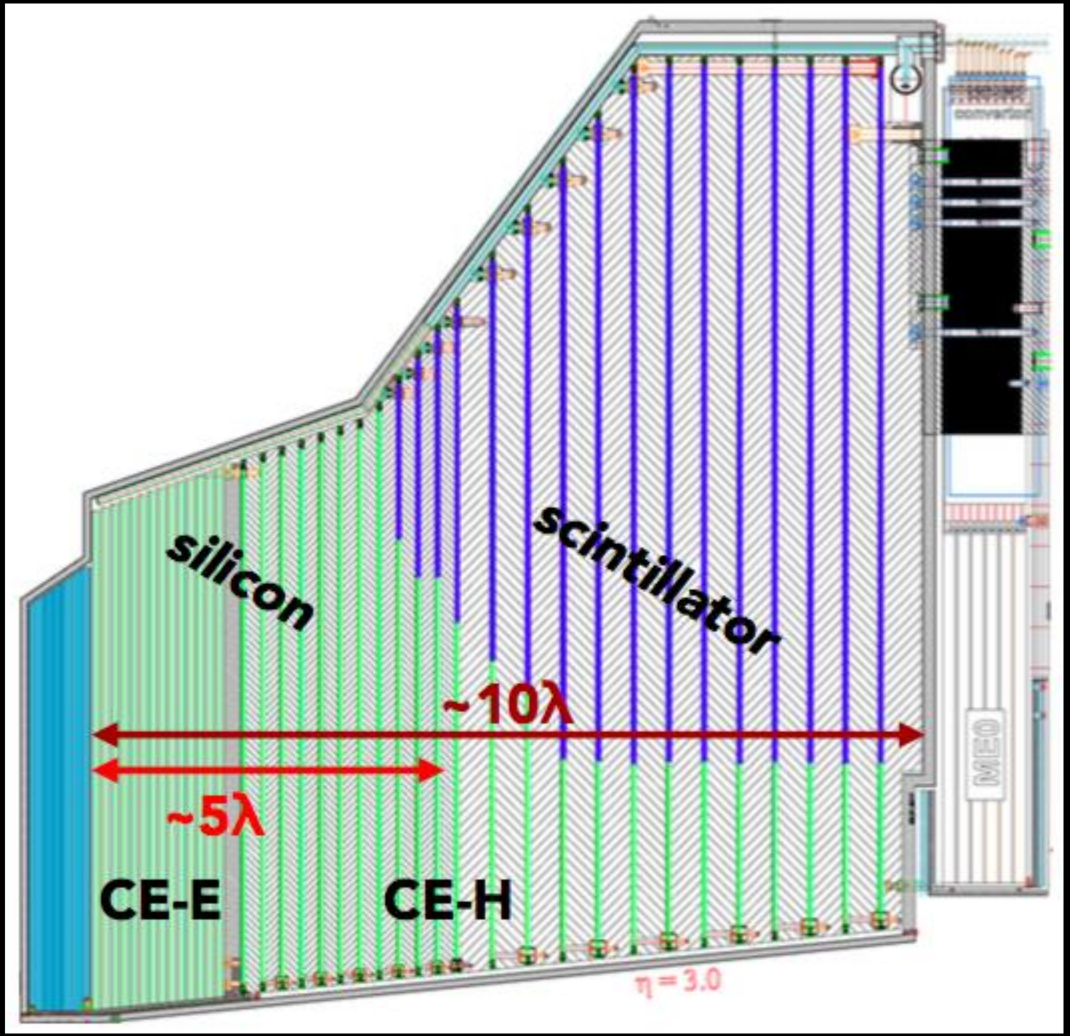
Initial study cases:

- MUonE detector → completed and published
- LHCb EM calorimeter optimization → preliminary results out
- Muon tomography detector optimization → preliminary results out, submitted to journal
- Muon collider EM calorimeter → in progress
- Optimization of detectors for air Cherenkov showers (SWGO) → Preliminary results out, ongoing
- Hybrid calorimeter design integrating tracking layers → started

plus many more envisioned

3 – Optimization of Future Calorimeters

Below: the HGCAL calorimeter for the CMS upgrade



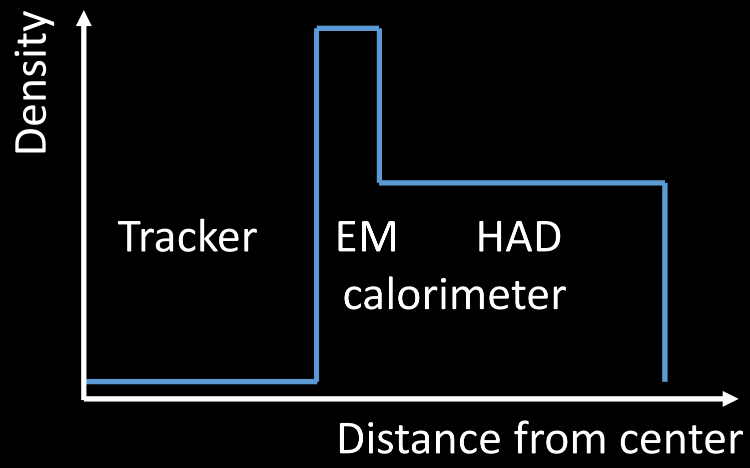
A necessary question: Hybridization

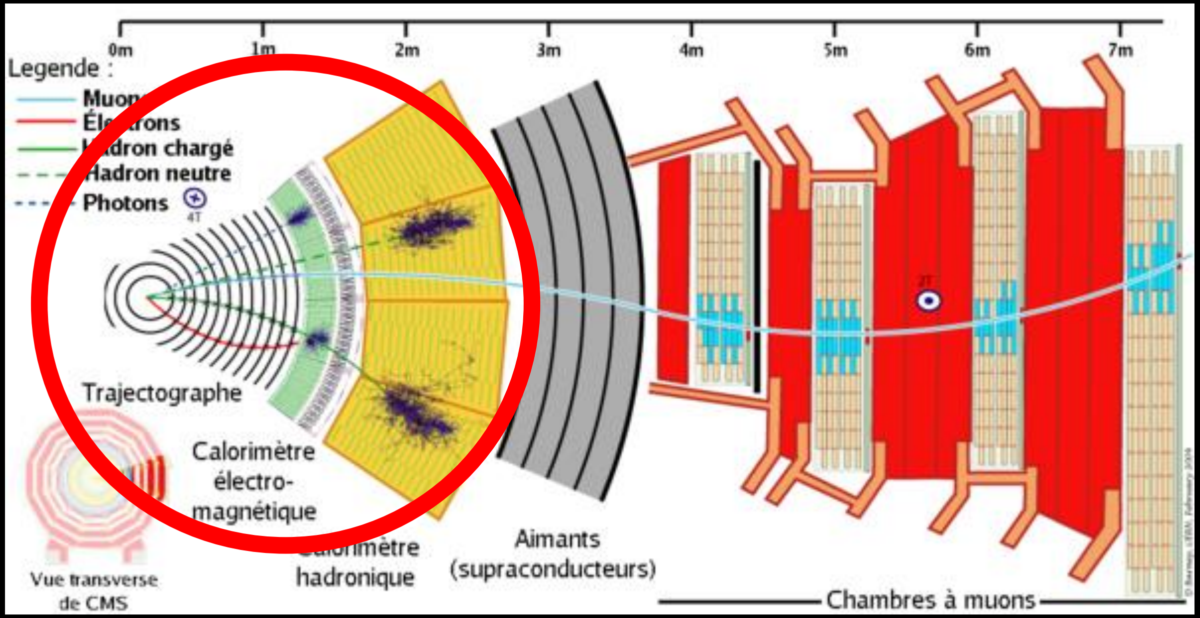
In an impending AI revolution, the design of calorimeters is crying to be rethought.

Standard setup in particle detectors: lightweight tracker → dense calorimeter

Why abrupt change of density?

«Because nuclear interactions…»





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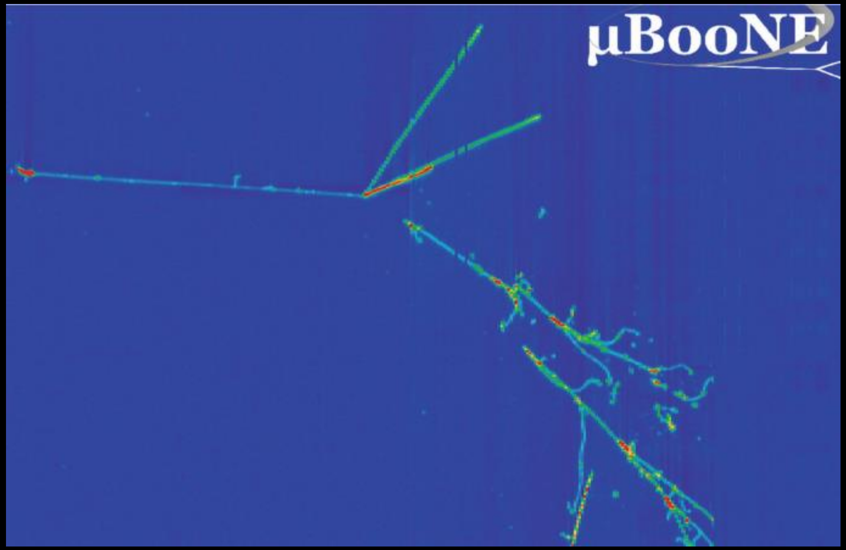


Above: a totally out of context neutrino interaction. Behold the enormous amount of information a single interaction bears!

Why abrupt change of density?

«Because nuclear interactions…»

But today/tomorrow we (will) have AI reconstruction...

Plan: Investigate coupled system of tracker and calorimeter, slowly vary density in z from step function to smoother transition, study effect on extractable information

→Requires high-perf. reconstruction of nuclear interactions in pattern recognition step

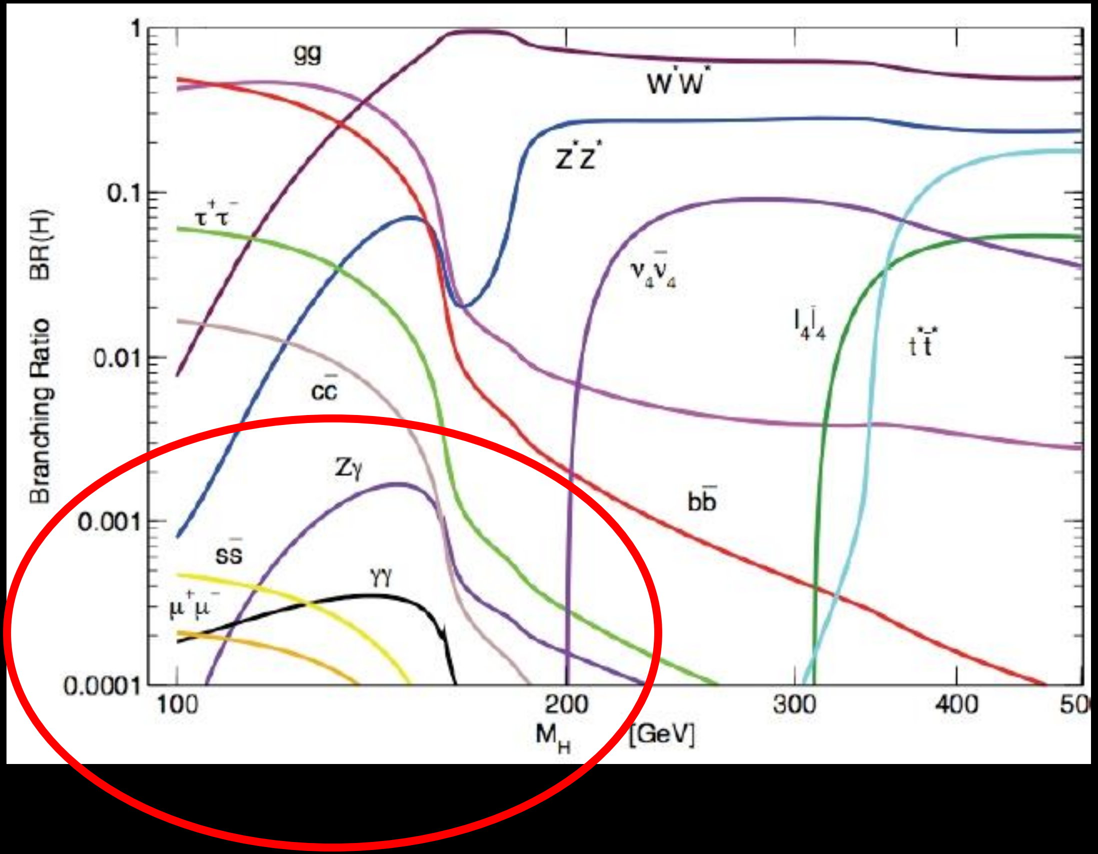
→Likely (almost guaranteed) to discover new ways / overcome standing paradigm

Asking for More to Calorimeters: Particle ID

Charged pions, kaons, and protons constitute the bulk of the hadrons flowing into a hadron calorimeter

Being able to distinguish them would bring in **very large gains**:

- to flavour tagging (killer app: H→ss at a future collider, where you need to tag the fast kaon from s hadronization)
- to energy reconstruction (improved through particle flow techniques)
- to boosted-jet tagging (from improved inner structure reconstruction of jet cores)
- and more



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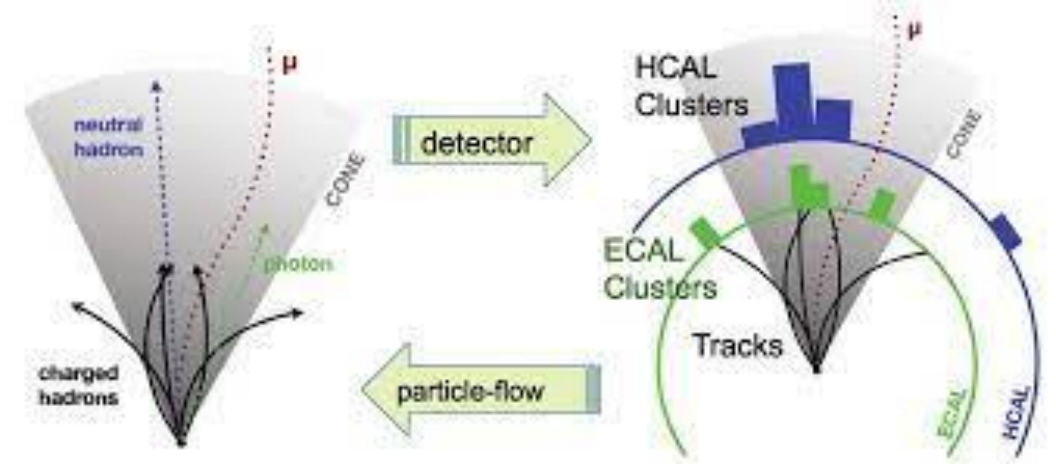

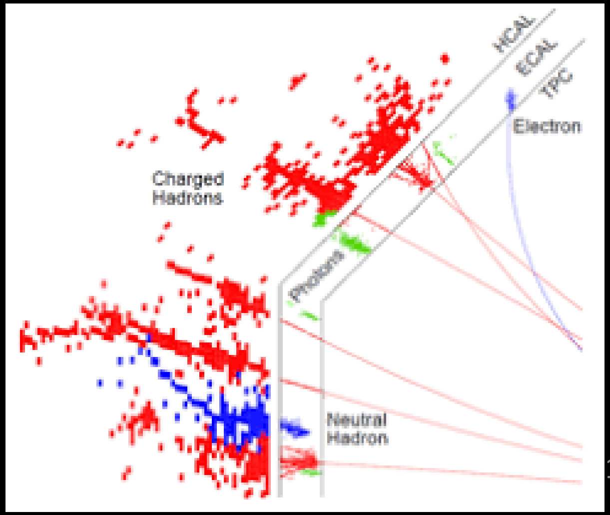

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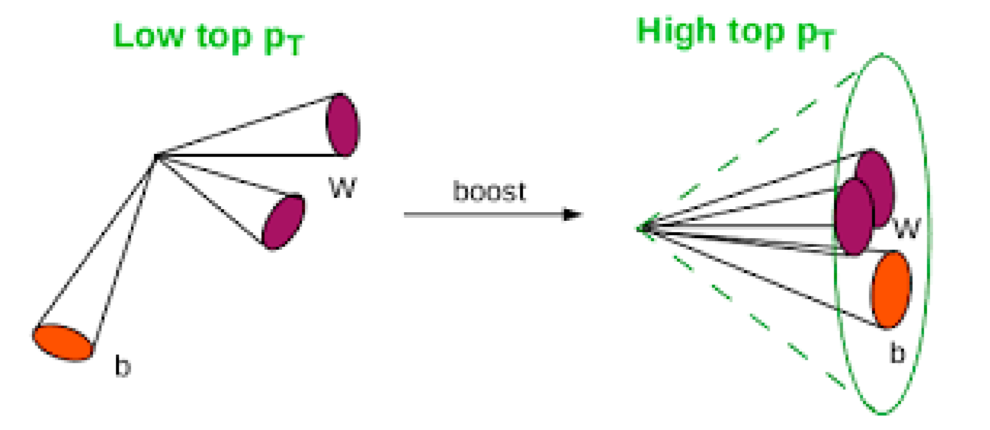

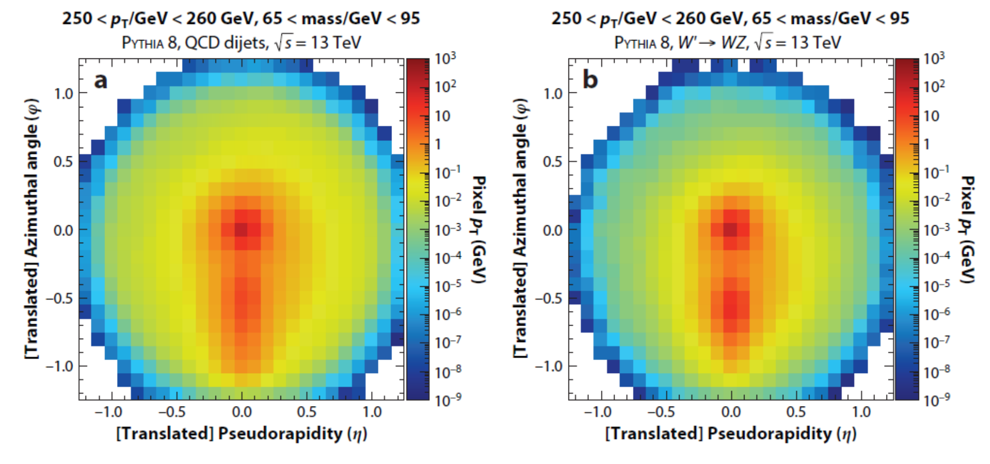

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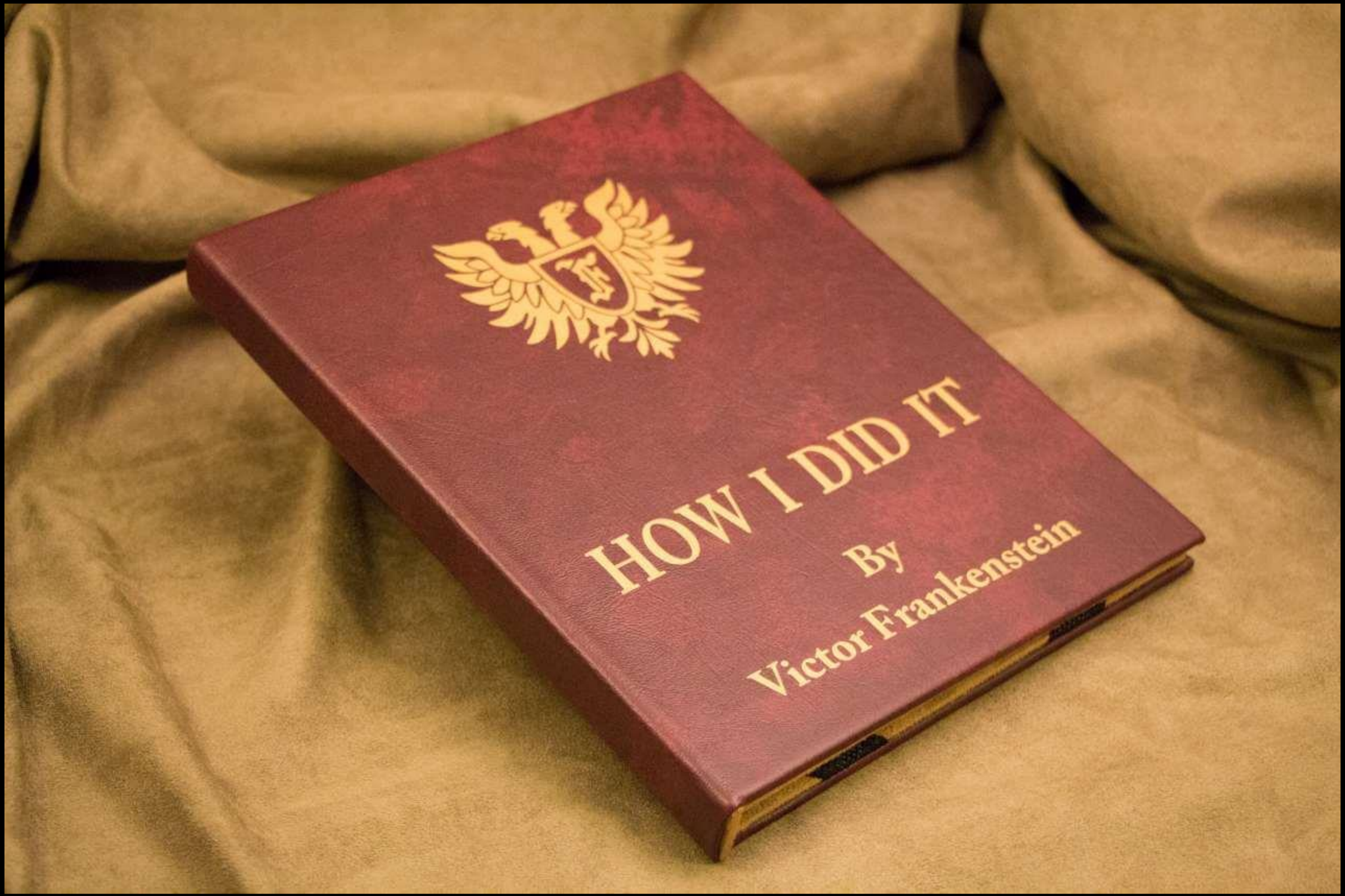
But **can it be done?**

What Information Are We After?

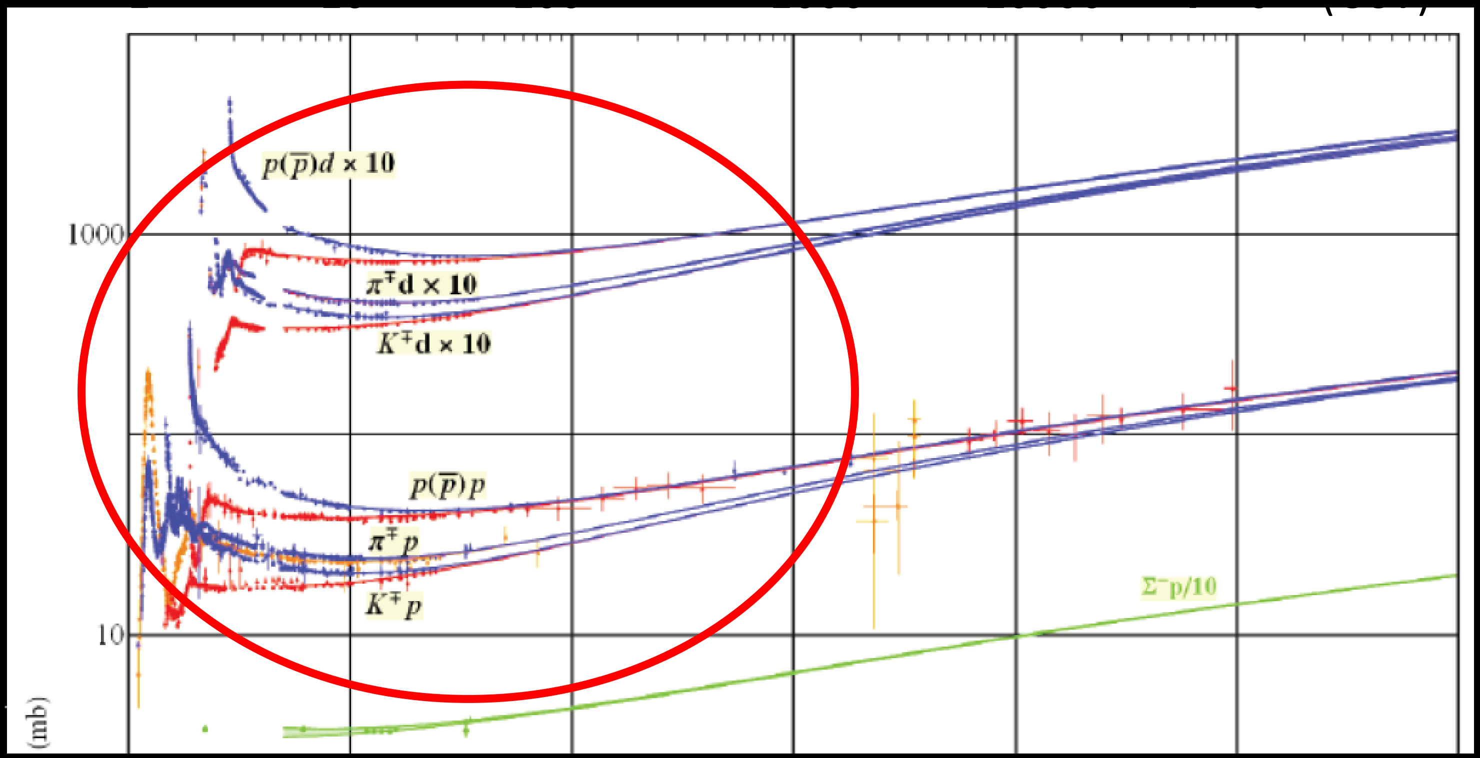


What Information Are We After?

- Protons are larger than pions and kaons, in fact the nuclear interaction cross sections of protons, pions, kaons are significantly different

  →Harder to exploit than it looks,

  but it can be done



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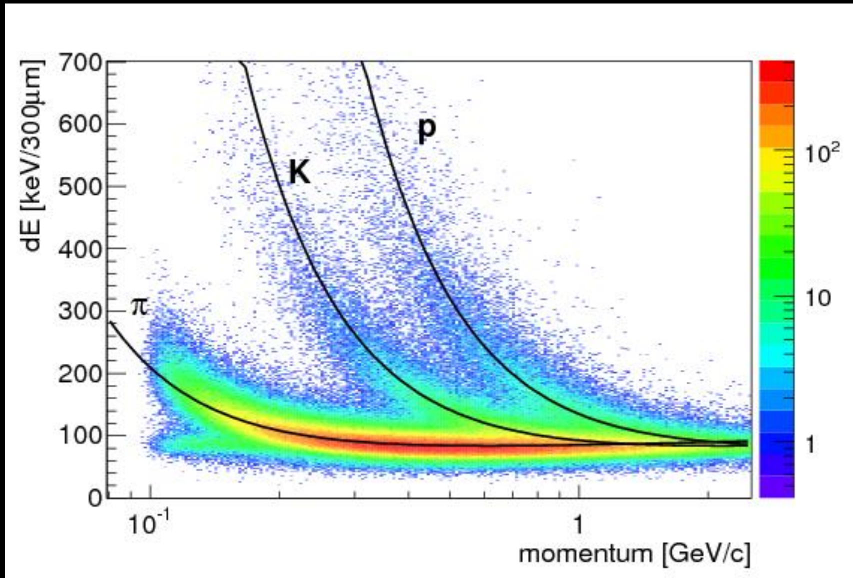
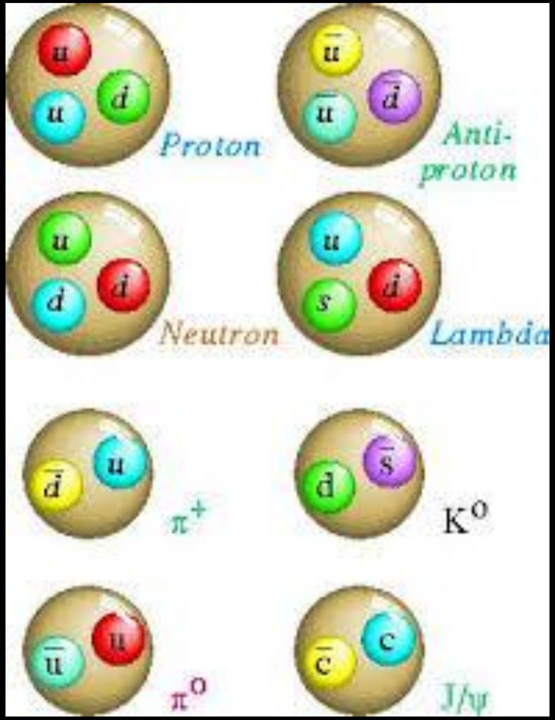
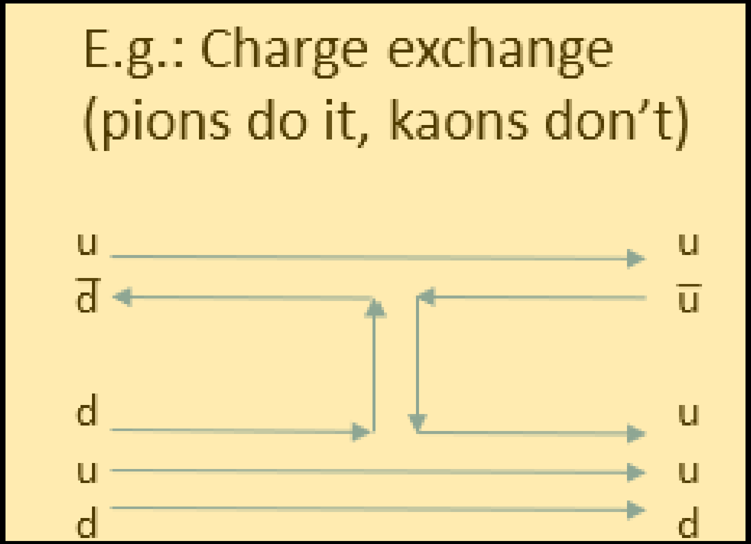


- Ionization power is also different (we only used this in tracking so far)
  →if we have sufficient granularity we can single out the ionization of each particle, at least away from the bulk of the shower
  →This information can then be used by ML tools

$$\left\langle -\frac{dE}{dx} \right\rangle = K z^2 \frac{Z}{A} \frac{1}{\beta^2} \left[\frac{1}{2} \ln \frac{2 m_e c^2 \beta^2 \gamma^2 W_{\max}}{I^2} - \beta^2 - \frac{\delta(\beta\gamma)}{2} \right]$$

What Information Are We After?



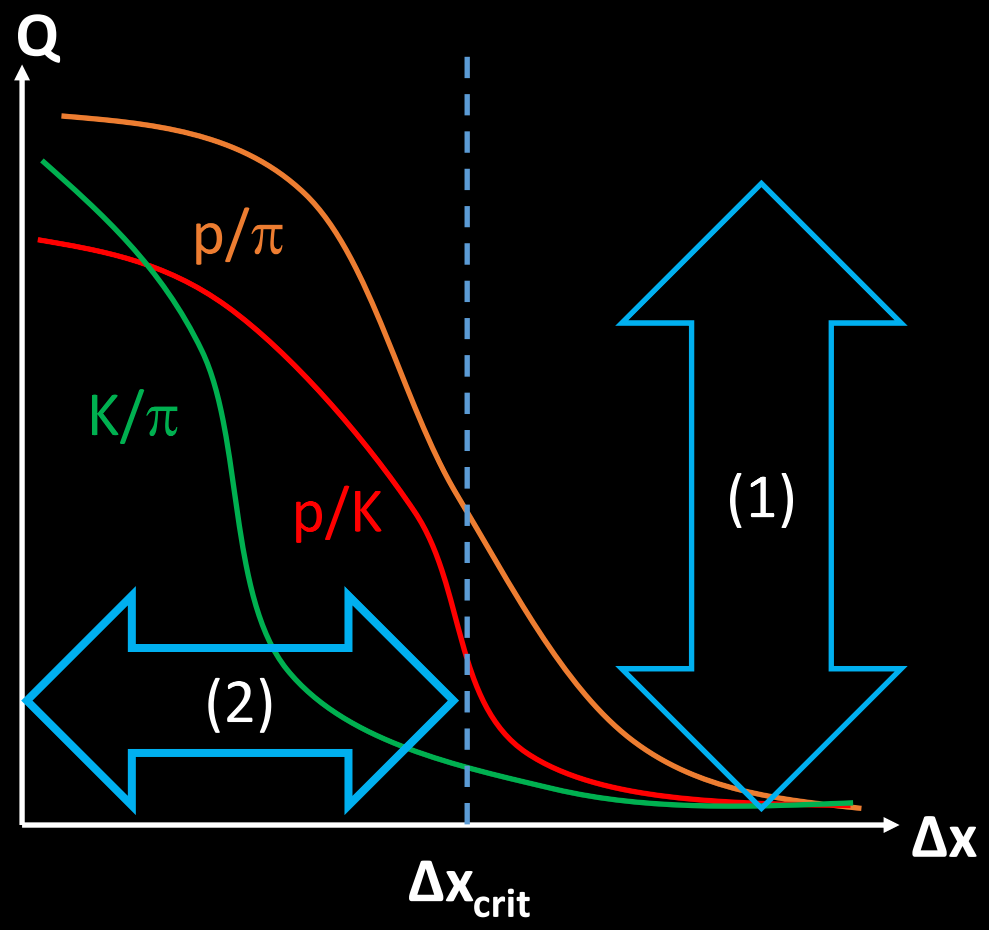


- Kaons contain one unit of strangeness, pions (and protons) do not
  → the daughters in nuclear collisions are different

Research Questions and a Money Plot

(1) What are the ultimate particle ID capabilities of a granular hadron calorimeter, assuming no limit on size Δx of readout cells?

(2) How does particle ID capability degrade as Δx is increased, and for what value Δx_{crit} does it get lost in conceivable setups?



Research Questions / 2

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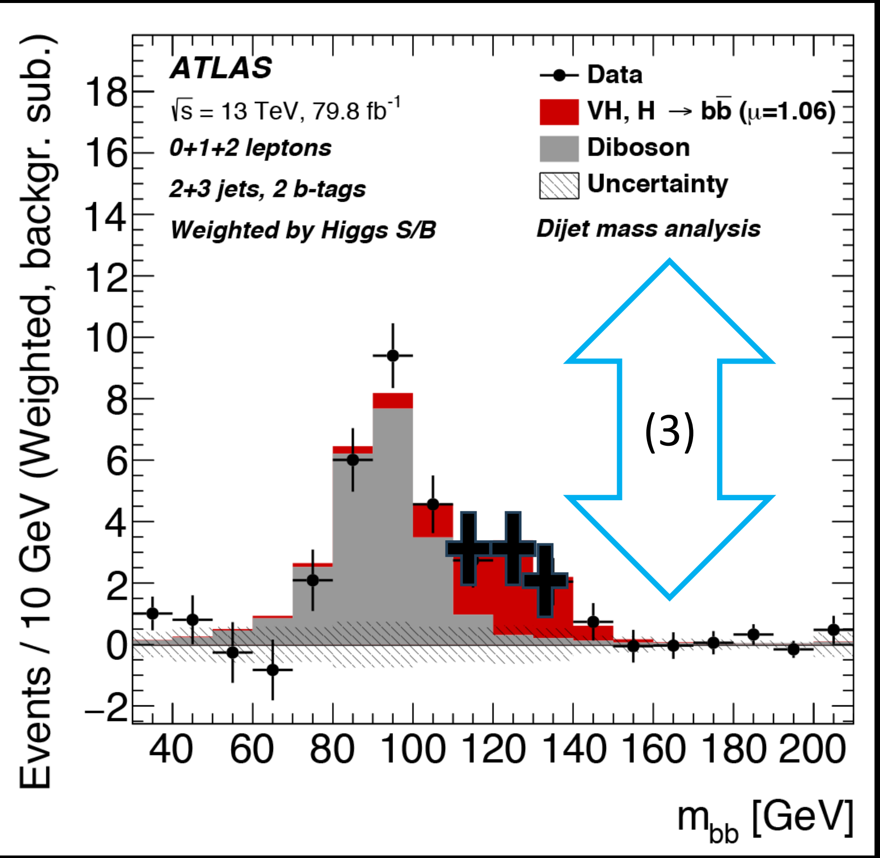
(3) By how much would that information improve the performance of hadronic jet reconstruction in specific benchmarks of interest (e.g., H->bb, H→ss)?



Research Questions: timing

(1) What are the ultimate particle ID capabilities of a granular hadron calorimeter, assuming no limit on size Δx of readout cells?

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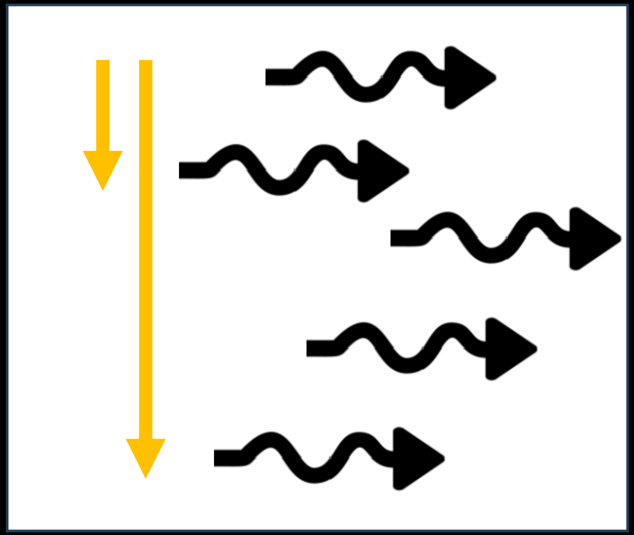
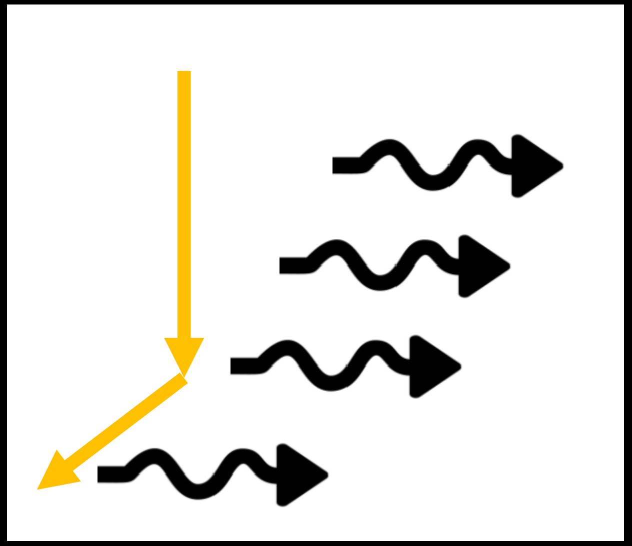
(3) By how much would that information improve the performance of hadronic jet reconstruction in specific benchmarks of interest (e.g., H->bb, H→ss)?

(4) How much further gain is possible by exploiting timing information?





But can we afford mm-size cells?

Costly/unfeasible to have multi-million cell calorimeters. But is it also overkill, or are we limiting ourselves?

Also, in hadron colliders we strive for highest possible collision rate, which has three implications:

1 - Cannot afford to save all data

- Not a real issue, most collisions are un-interesting… but still a limitation

2 - Pileup complicates pattern recognition

- LHC challenged to retain performance as luminosity increases

3 - Have trouble using highest-granularity subdetectors for online selection

- Using pixel detectors inside ATLAS/CMS for triggering purposes is problematic

A new, far-fetched idea

Introduce fast online preprocessing of light signals by nanophotonic devices embedded in the detector

→ exploit timing structure

→ transmit to back end higher-level primitives

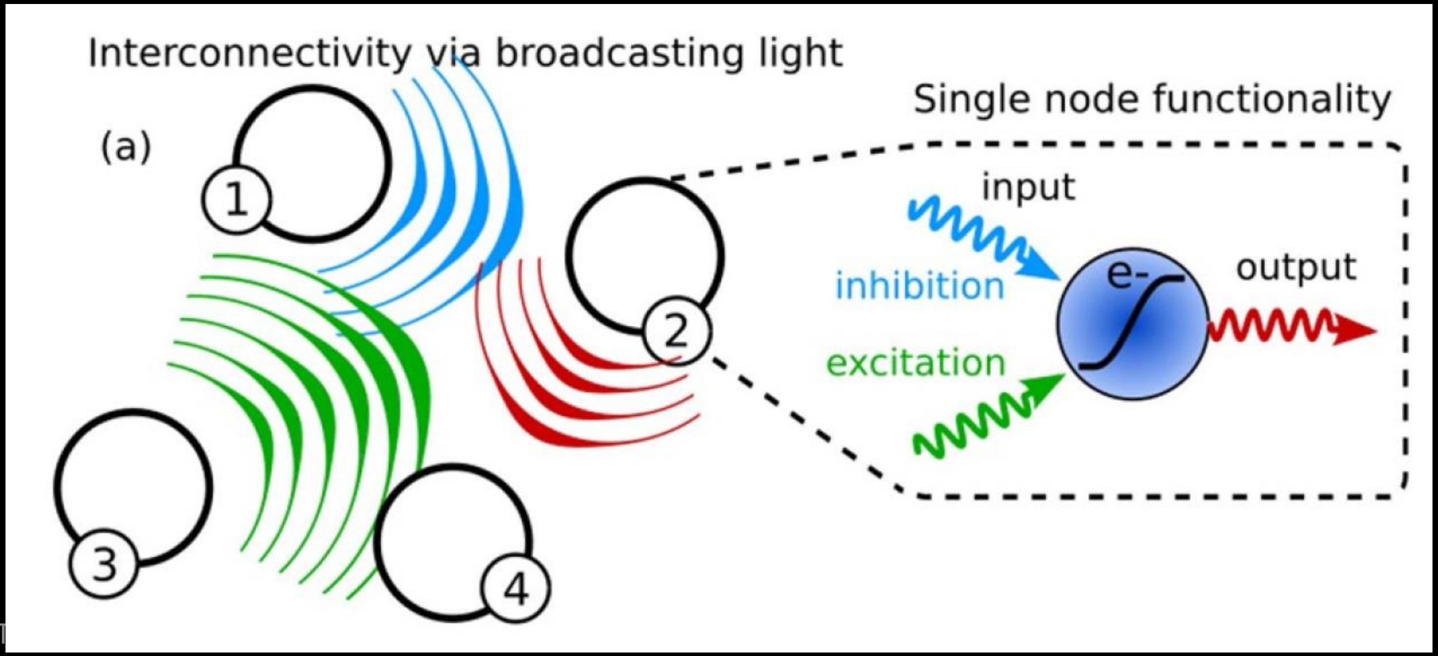
→ enable smarter triggering

→ improve information extraction

Timing with Neuromorphic Computing

Recent developments in nanophotonics: can use arrays of nanowires (light receivers/emitters) in micrometric substrates

→ create neuromorphic network encoding and exploiting time structure of photon signals from scintillation/Cherenkov



Timing with Neuromorphic Computing

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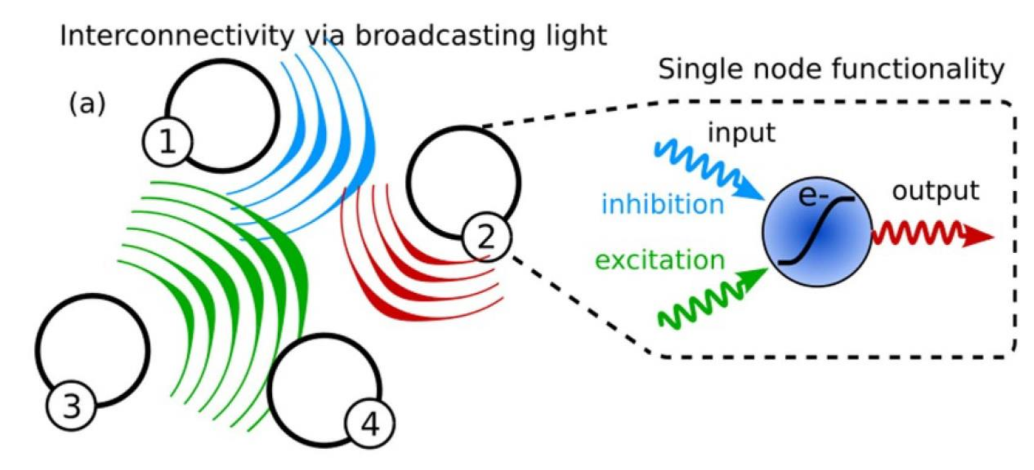
→ may create neuromorphic network encoding and exploiting time structure of photon signals from scintillation/Cherenkov

An avalanche of disruptive advancements:

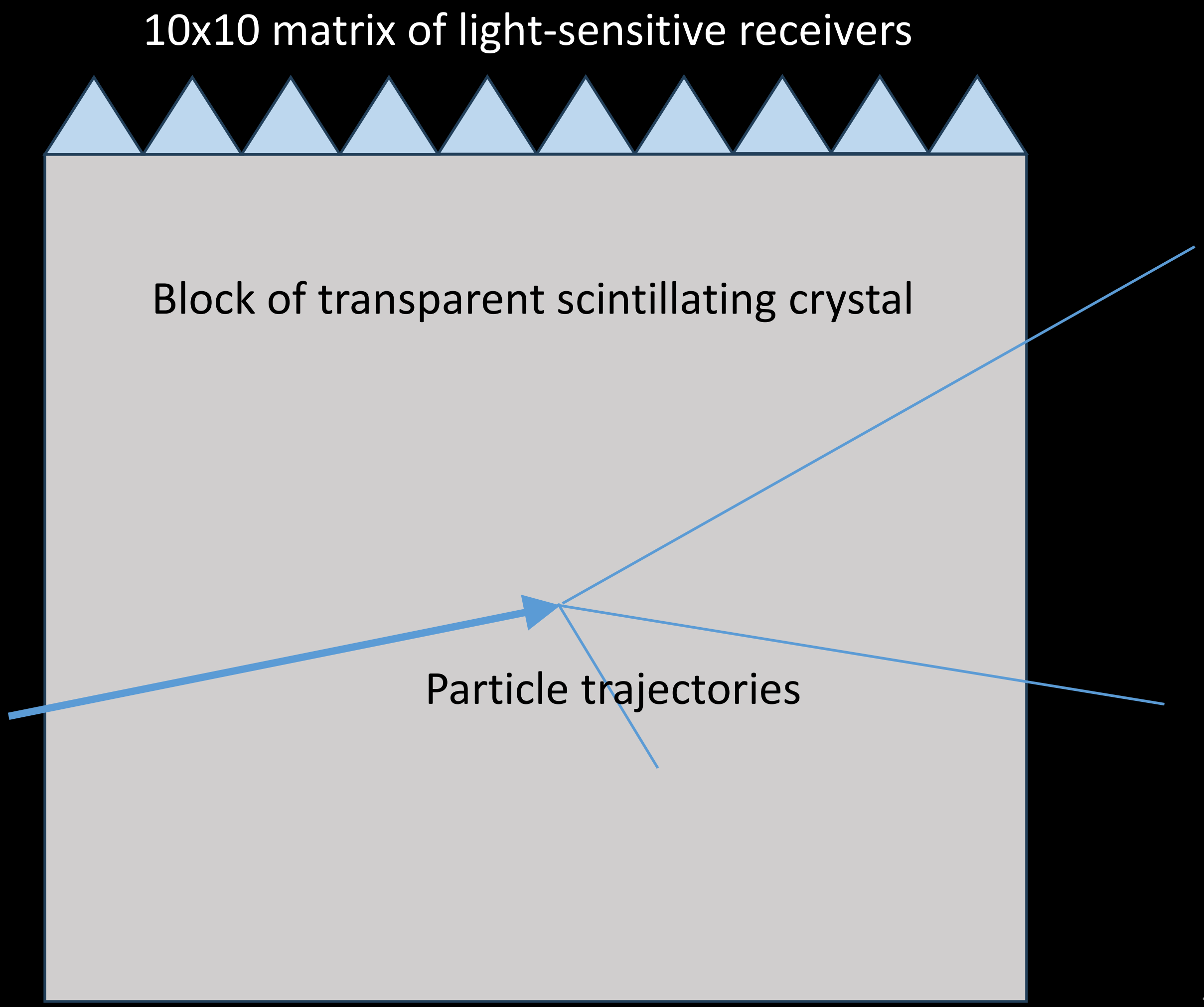
- No transduction (PMT gone) – photons are the signal AND the computation tokens
- On-site fast computing
- Ultra-high energy efficiency
- Natural exploitation of time structure



An AI problem to solve (if the rest works)

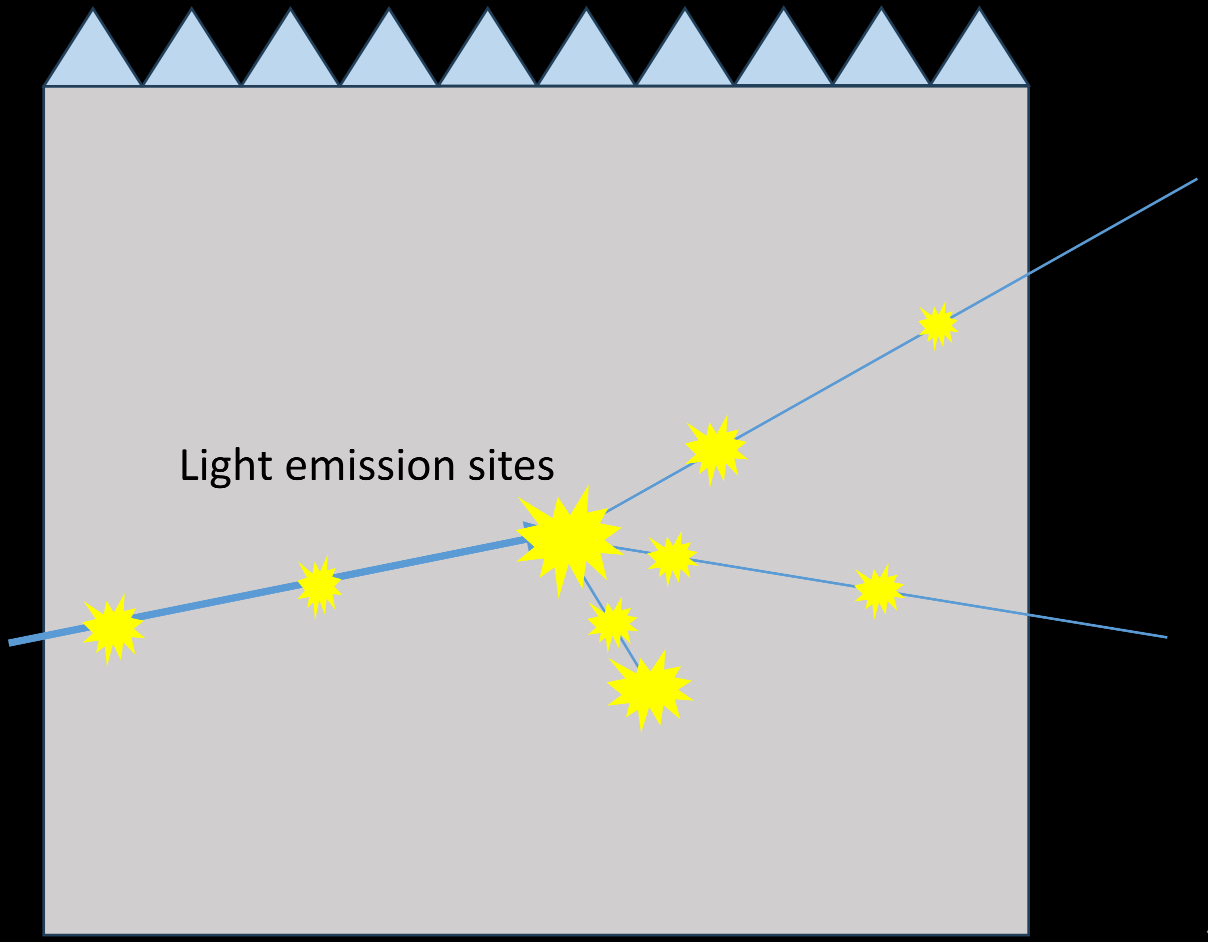
Consider a small element of scintillating material in a calorimeter

(e.g., few cm^3)



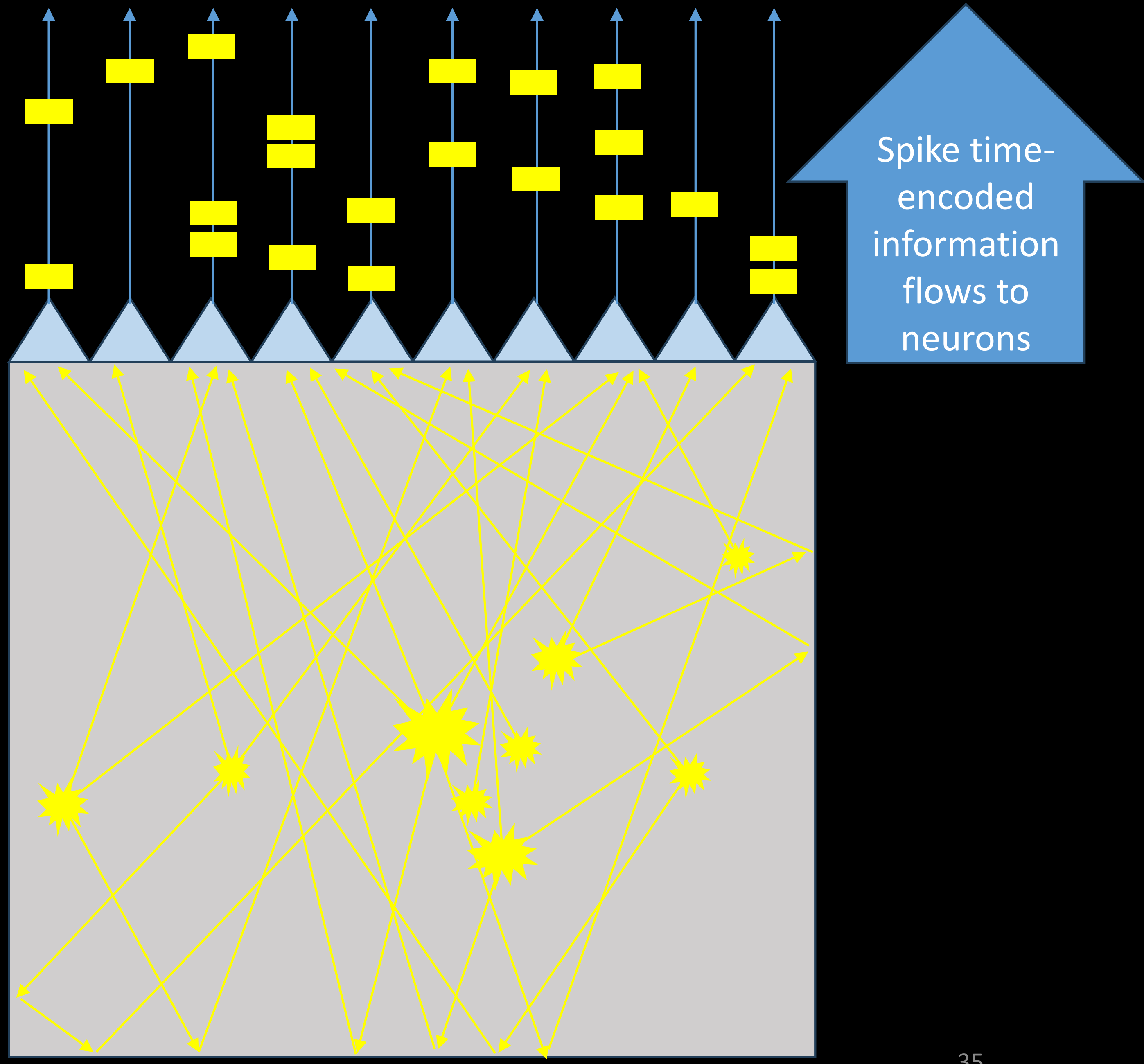
An AI problem to solve (if the rest works)

The space-time structure of photon emission contains information on the processes locally taking place in the cubelet



Photon arrival front at interface provide for automatic (but not trivial) encoding

→ May try using a neuromorphic network to reconstruct the topology of interactions– or simply compress information into useful summaries, given detected photons emitted along the path and their arrival times



Reflective side (increase yield of detectable photons)

An invitation

Within MODE we created a group that is looking into these matters:
- Particle ID information extraction from high-granularity data
- End-to-end modeling via differentiable programming, for optimization
- Exploitation of neuromorphic computing to reconstruct space-time patterns
- Readout and processing with nanowires

Institutions involved:
- INFN, Padova (Dorigo), RPTU (Gauger), LTU (Sandin), Lund (Mikkelsen), CMU (Lee)
- Projects seeking funding: several

- If you would like to participate, you are more than welcome!

A Workshop

On September 23-25 we will hold the fourth MODE workshop in Valencia (Spain)

Please consider coming / presenting plans for detector design optimization there! https://indico.cern.ch/event/1380163/overview

Summary

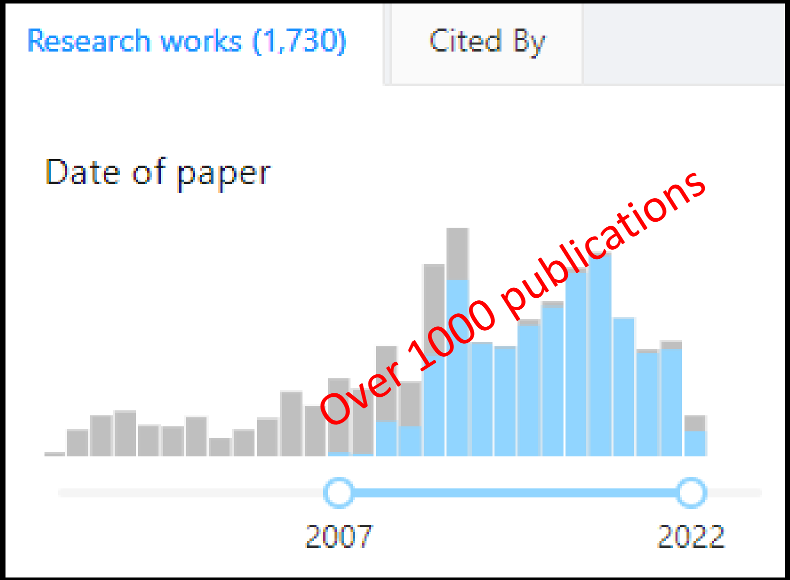
- After the paradigm shift of 2012 (AlexNet, Higgs discovery) it is not reasonable any longer to do complex multidimensional inference without machine learning tools
- The next paradigm shift enabled by AI is the assistance of properly interfaced tools in design of complex systems
- We can do more with calorimeters tomorrow, provided that we ensure that extractable information is suitably generated
- Some bold new ideas need to be investigated by considering the issue as an end-to-end optimization problem

Thank you for your time!

Optimal for What?

The reason why detectors are complex is not only that the studied physics is complex: Science is a demanding job. Physicists want to study *everything* and do it *better* than their predecessors

CMS has over 4000 members, who use the data for a LARGE number of *different* measurements and searches...



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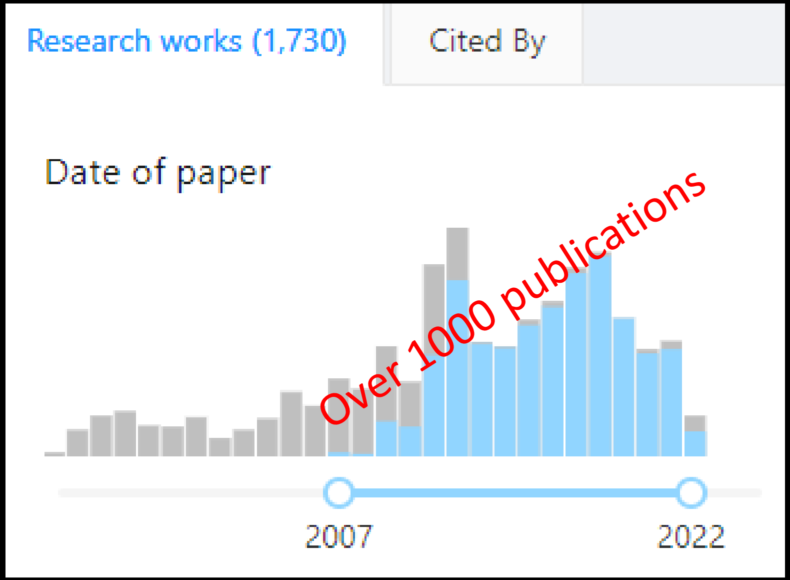
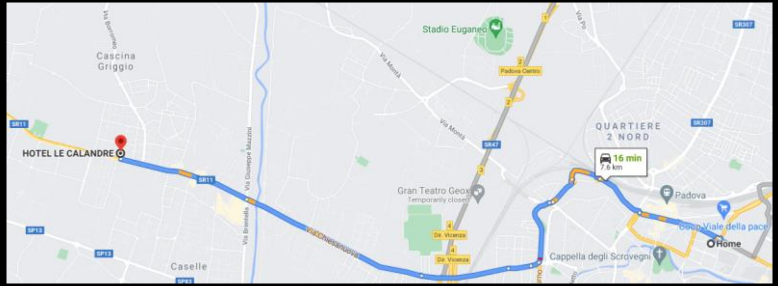


So, what does it mean for a detector to be *optimal*?

What loss function do we aim to minimize?

Does it make sense to speak of an experiment-wide utility function?

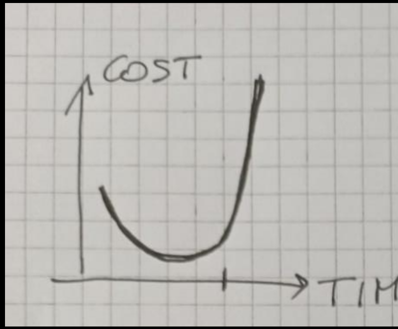
Recipe for a Perfect Dinner



We are not alien to confidently taking complex decisions in a **multi-objective space**. We actually do it routinely...

Of course, we are not deterred by knowing that the exact form of our optimization target is arbitrary

Recipe for a Perfect Detector



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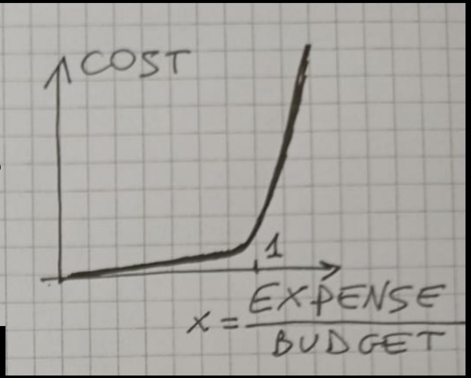
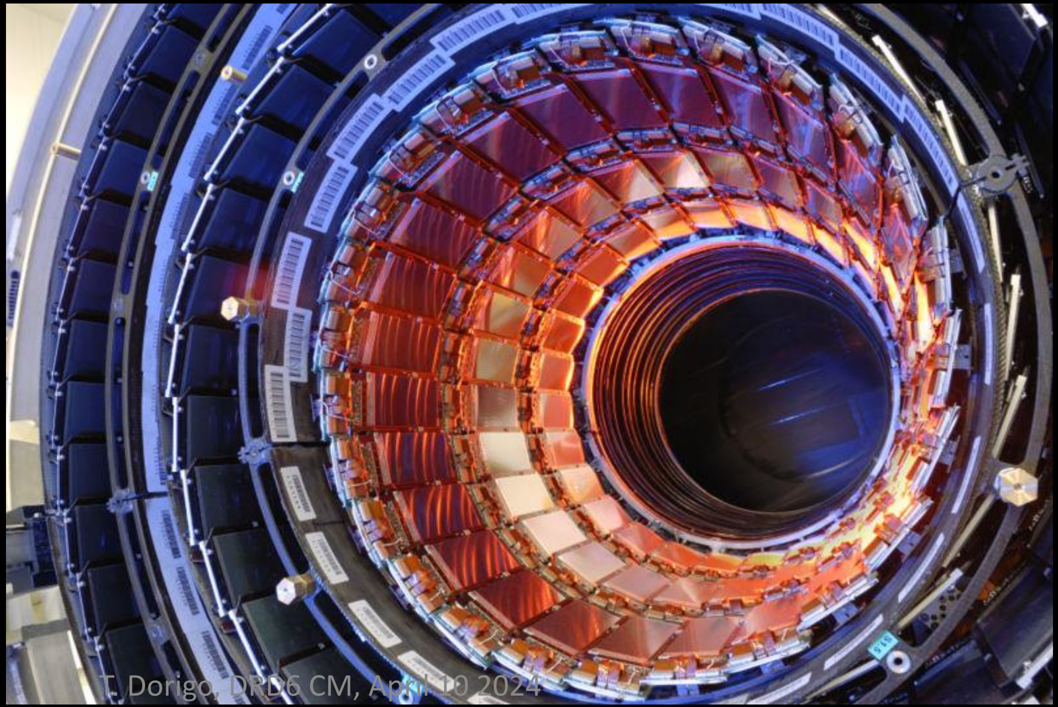
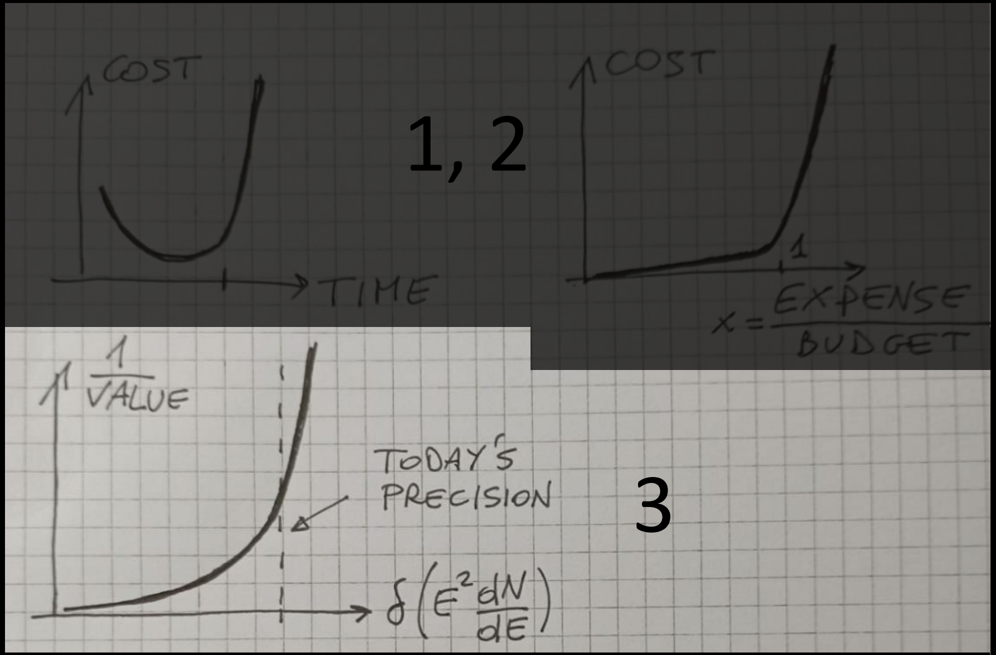


1. Assess your total **budget** and **time**-to-completion
2. Model as a steep function the **cost** of overriding budget or time



Recipe for a Perfect Detector

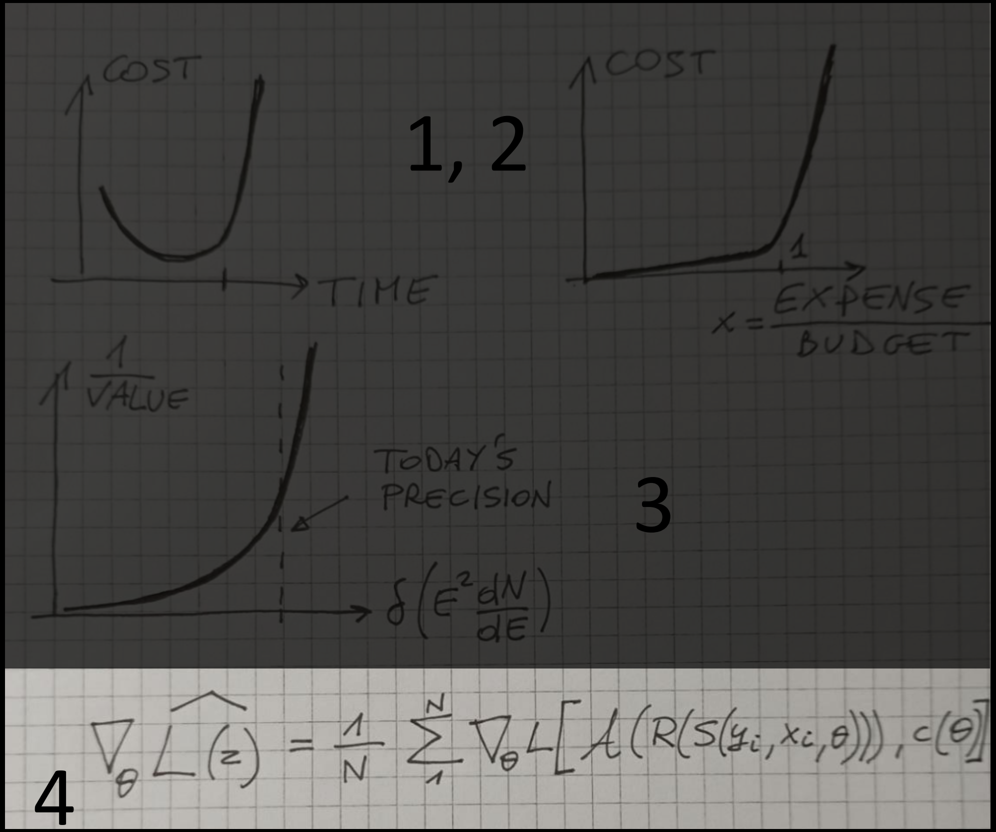
1. Assess your total **budget** and **time**-to-completion
2. Model as a steep function the **cost** of overriding budget or time
3. Assess the **scientific impact** of each achievable scientific results



Recipe for a Perfect Detector

1. Assess your total **budget** and **time**-to-completion
2. Model as a steep function the **cost** of overriding budget or time
3. Assess the **scientific impact** of each achievable scientific results
4. **Create a differentiable model** of the geometry, the components, the information-extraction procedures, and the utility function

$$\frac{\partial}{\partial x}$$



Recipe for a Perfect Detector

1. Assess your total **budget** and **time**-to-completion
2. Model as a steep function the **cost** of overriding budget or time
3. Assess the **scientific impact** of each achievable scientific results
4. **Create a differentiable model** of the geometry, the components, the information-extraction procedures, and the utility function
5. Construct a pipeline with those modules, enabling backpropagation and gradient descent
6. Let the chain rule of differential calculus do the hard work for you