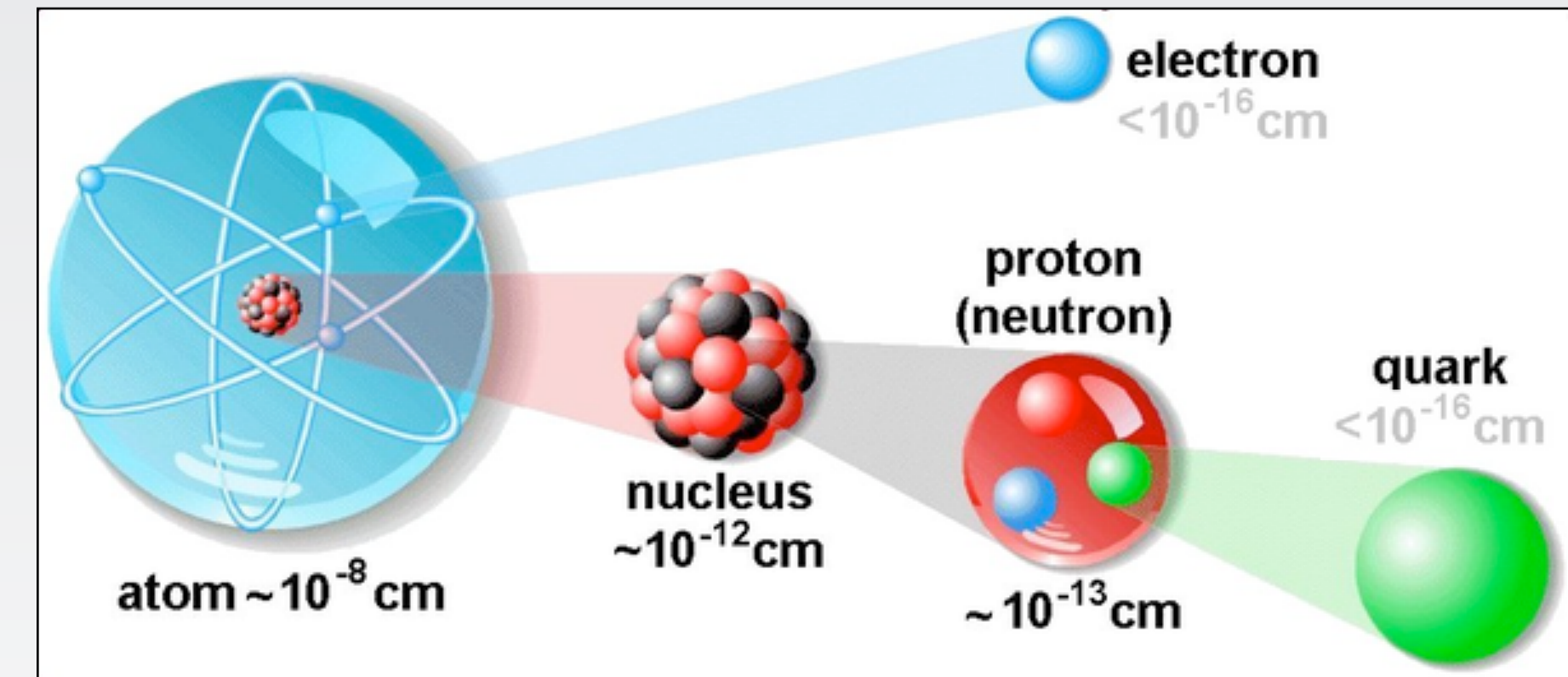


AI-Designed Detectors

Jan Kieseler

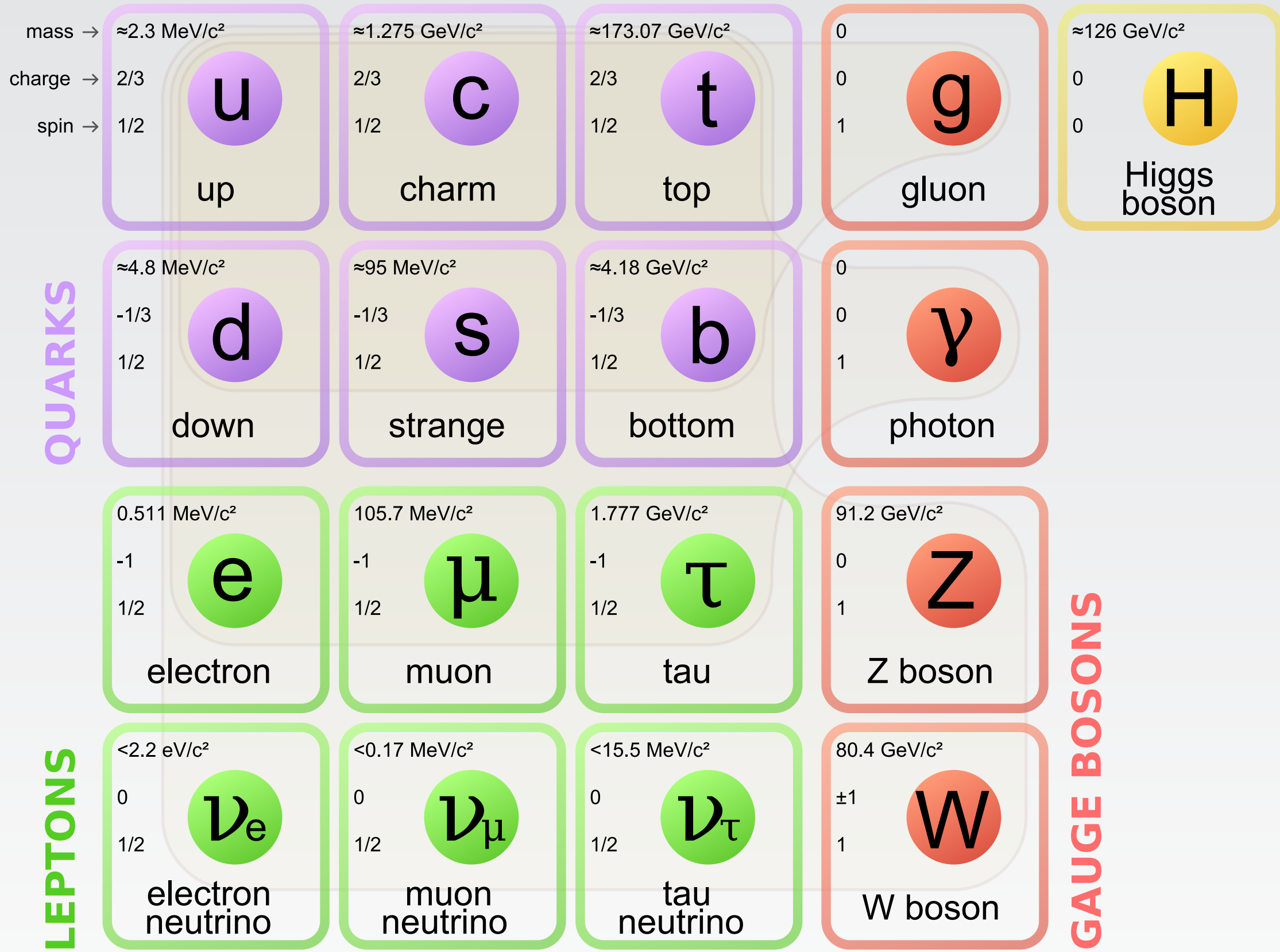
23.10.2025

What are we looking for



The Standard Model: Very Successful yet Incomplete

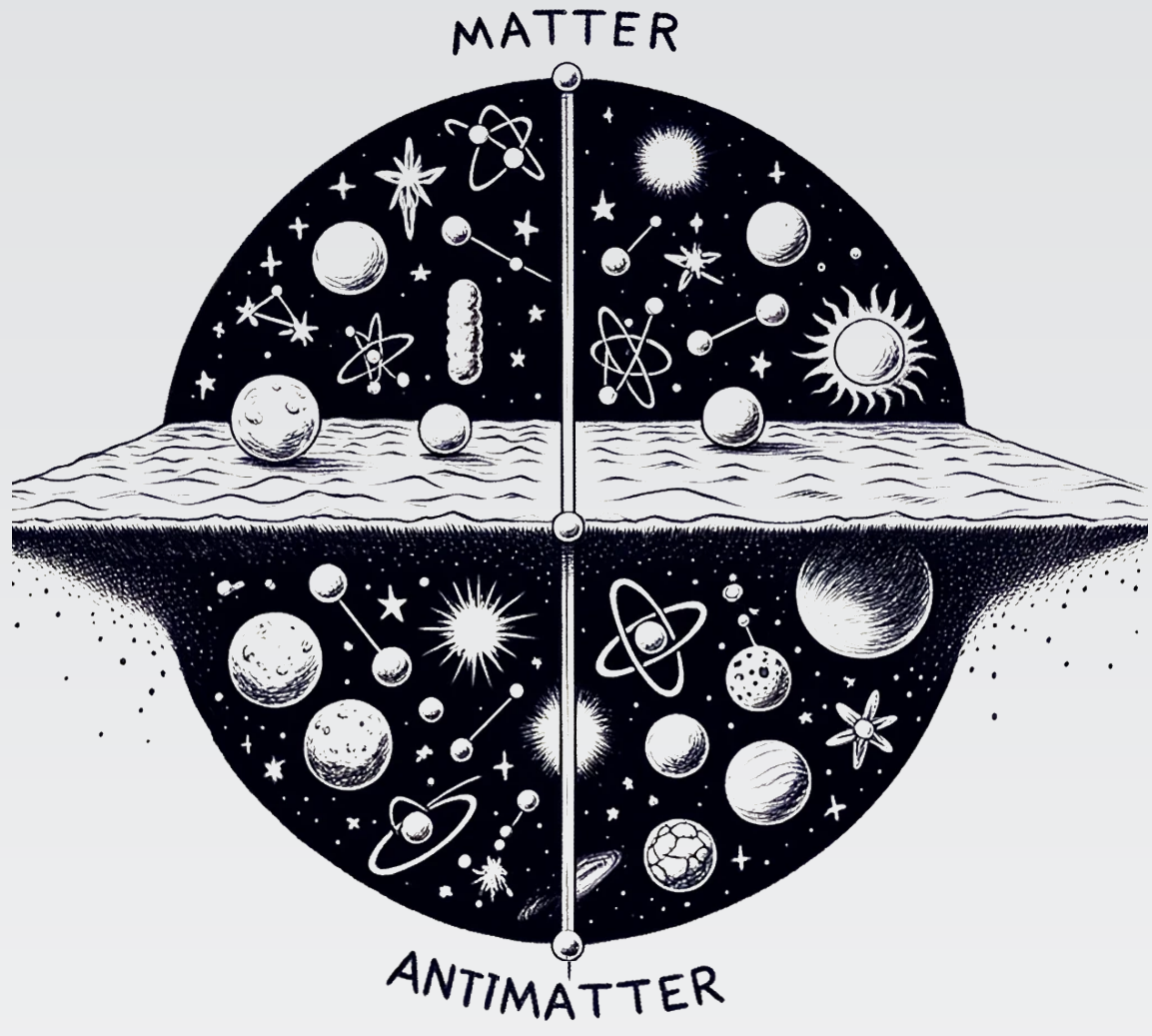
Particles of the Standard Model



The Standard Model: Very Successful yet Incomplete

Particles of the Standard Model

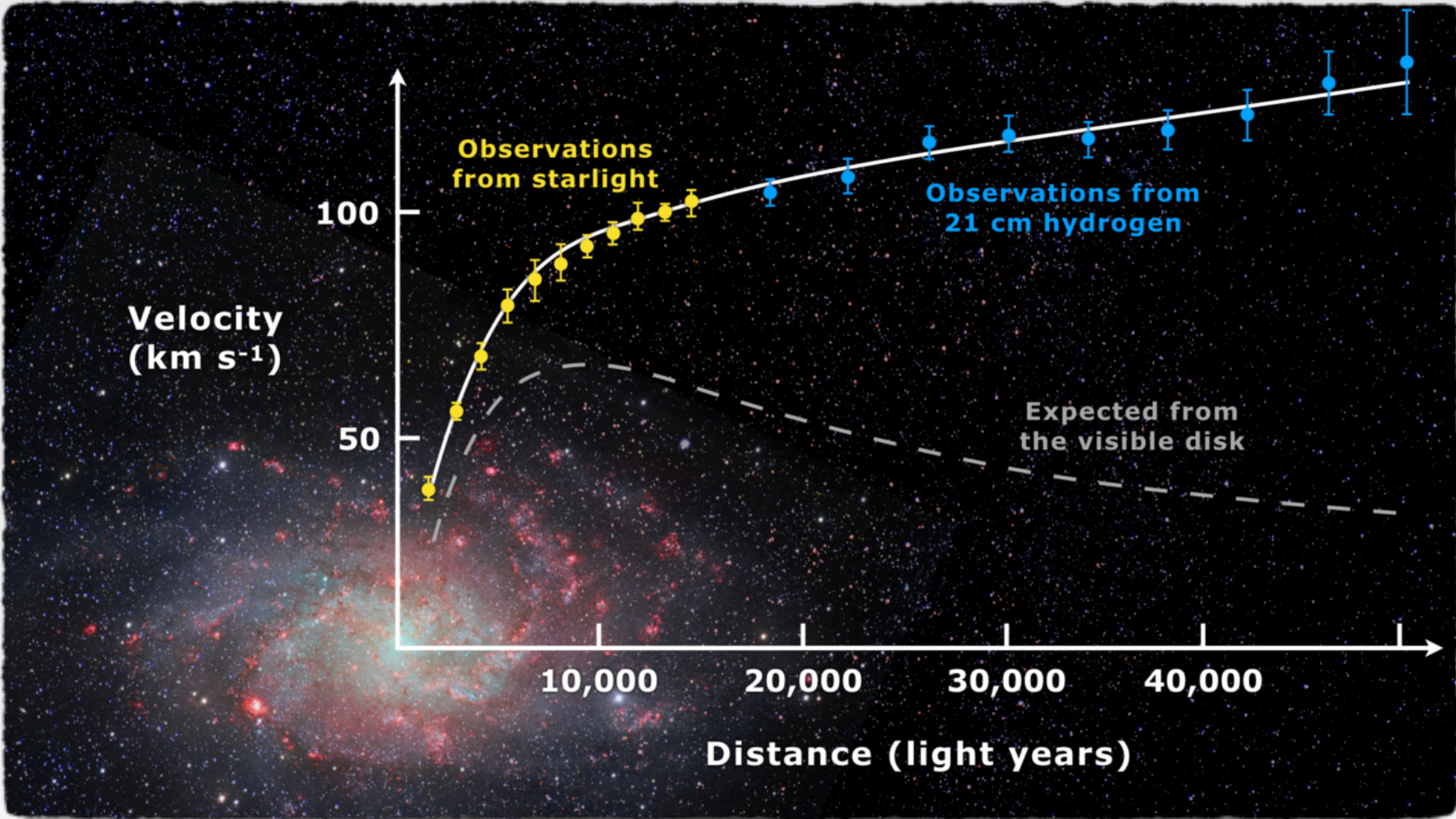
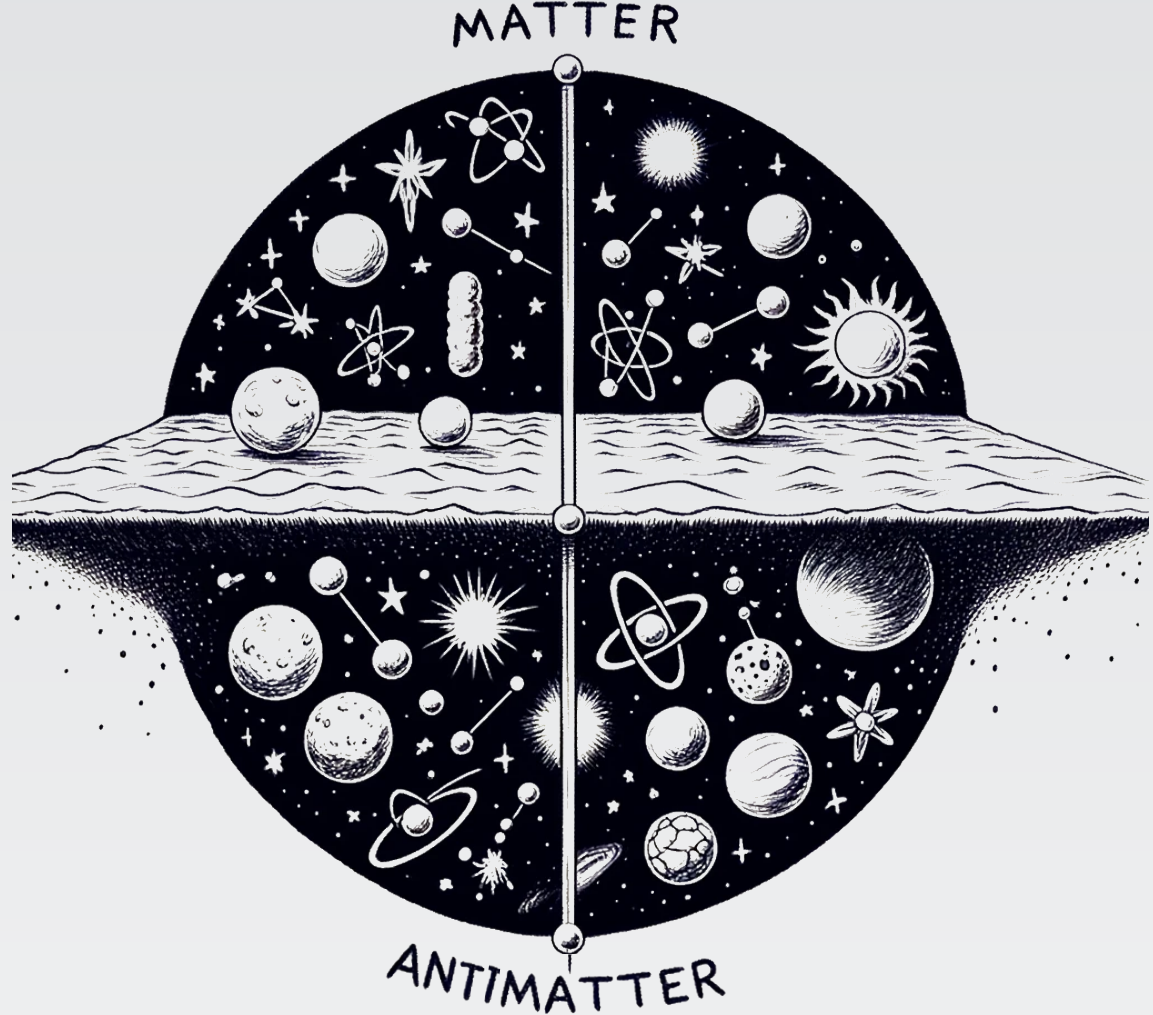
mass →	$\approx 2.3 \text{ MeV}/c^2$	$\approx 1.275 \text{ GeV}/c^2$	$\approx 173.07 \text{ GeV}/c^2$	0	$\approx 126 \text{ GeV}/c^2$
	charge → $2/3$	$2/3$	$2/3$	0	0
	spin → $1/2$	$1/2$	$1/2$	1	0
QUARKS	u up	c charm	t top	g gluon	H Higgs boson
	$\approx 4.8 \text{ MeV}/c^2$	$\approx 95 \text{ MeV}/c^2$	$\approx 4.18 \text{ GeV}/c^2$	0	
	charge → $-1/3$	$-1/3$	$-1/3$	0	
	spin → $1/2$	$1/2$	$1/2$	1	
	d down	s strange	b bottom	γ photon	
LEPTONS	$0.511 \text{ MeV}/c^2$	$105.7 \text{ MeV}/c^2$	$1.777 \text{ GeV}/c^2$	$91.2 \text{ GeV}/c^2$	
	charge → -1	-1	-1	0	
	spin → $1/2$	$1/2$	$1/2$	1	
	e electron	μ muon	τ tau	Z Z boson	
	$< 2.2 \text{ eV}/c^2$	$< 0.17 \text{ MeV}/c^2$	$< 15.5 \text{ MeV}/c^2$	$80.4 \text{ GeV}/c^2$	
	charge → 0	0	0	± 1	
	spin → $1/2$	$1/2$	$1/2$	1	
	ν_e electron neutrino	ν_μ muon neutrino	ν_τ tau neutrino	W W boson	
				GAUGE BOSONS	

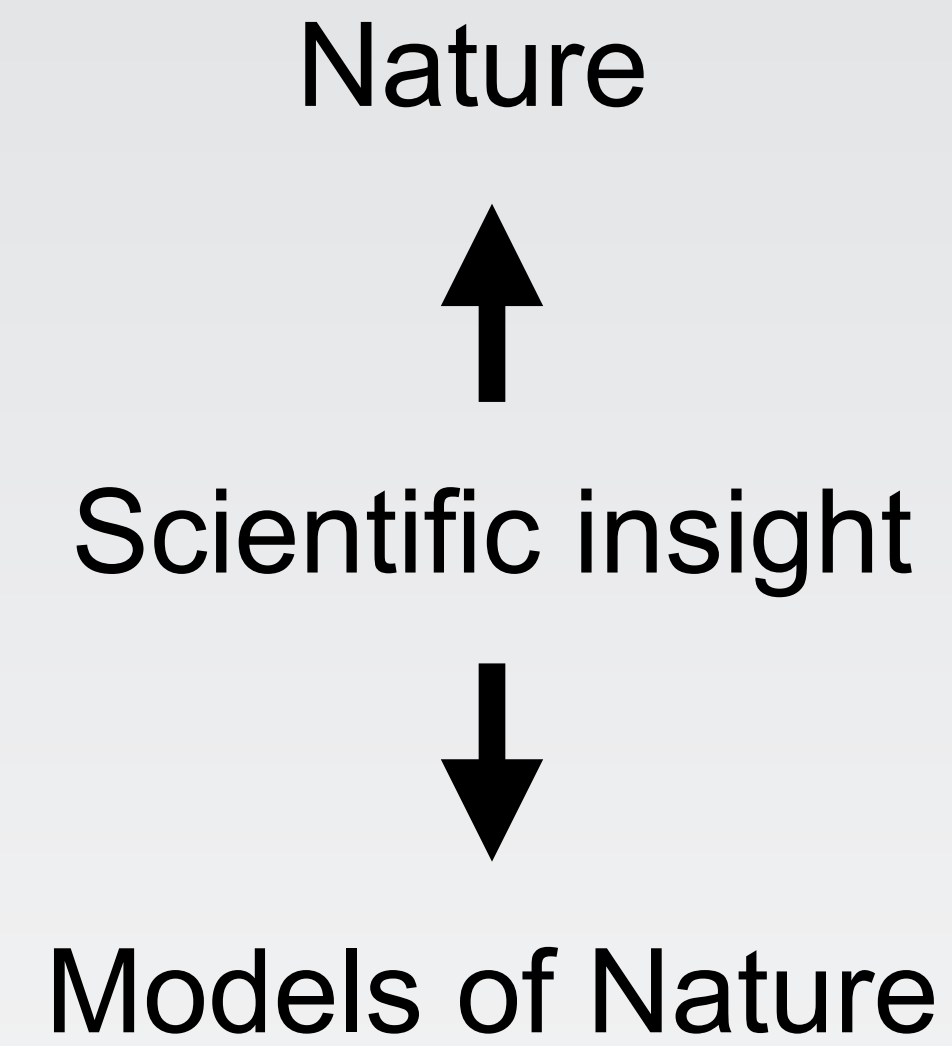


The Standard Model: Very Successful yet Incomplete

Particles of the Standard Model

mass → charge → spin →	$\approx 2.3 \text{ MeV}/c^2$ $2/3$ $1/2$	$\approx 1.275 \text{ GeV}/c^2$ $2/3$ $1/2$	$\approx 173.07 \text{ GeV}/c^2$ $2/3$ $1/2$	0 0 1	$\approx 126 \text{ GeV}/c^2$ 0 0
	u	c	t	g	H
	up	charm	top	gluon	Higgs boson
QUARKS	$\approx 4.8 \text{ MeV}/c^2$ $-1/3$ $1/2$	$\approx 95 \text{ MeV}/c^2$ $-1/3$ $1/2$	$\approx 4.18 \text{ GeV}/c^2$ $-1/3$ $1/2$	0 0 1	
	d	s	b	γ	
	down	strange	bottom	photon	
LEPTONS	$0.511 \text{ MeV}/c^2$ -1 $1/2$	$105.7 \text{ MeV}/c^2$ -1 $1/2$	$1.777 \text{ GeV}/c^2$ -1 $1/2$	$91.2 \text{ GeV}/c^2$ 0 1	
	e	μ	τ	Z	
	electron	muon	tau	Z boson	
GAUGE BOSONS	$< 2.2 \text{ eV}/c^2$ 0 $1/2$	$< 0.17 \text{ MeV}/c^2$ 0 $1/2$	$< 15.5 \text{ MeV}/c^2$ 0 $1/2$	$80.4 \text{ GeV}/c^2$ ± 1 1	
	ν_e	ν_μ	ν_τ	W	
	electron neutrino	muon neutrino	tau neutrino	W boson	





Gaining Scientific Insight

$$\text{Nature}' = D^{-1}R^{-1}A^{-1} \text{ Measurement}$$



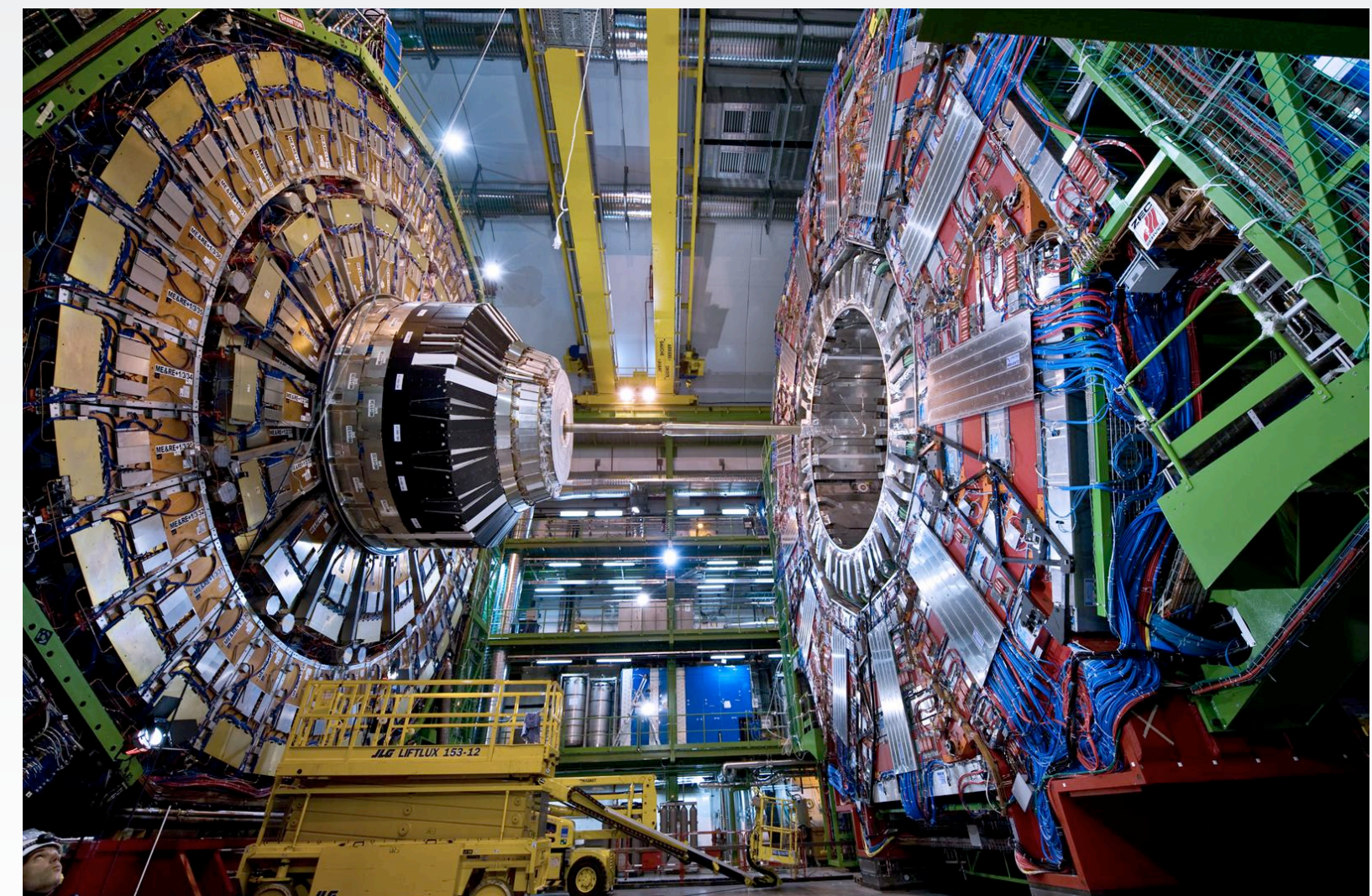
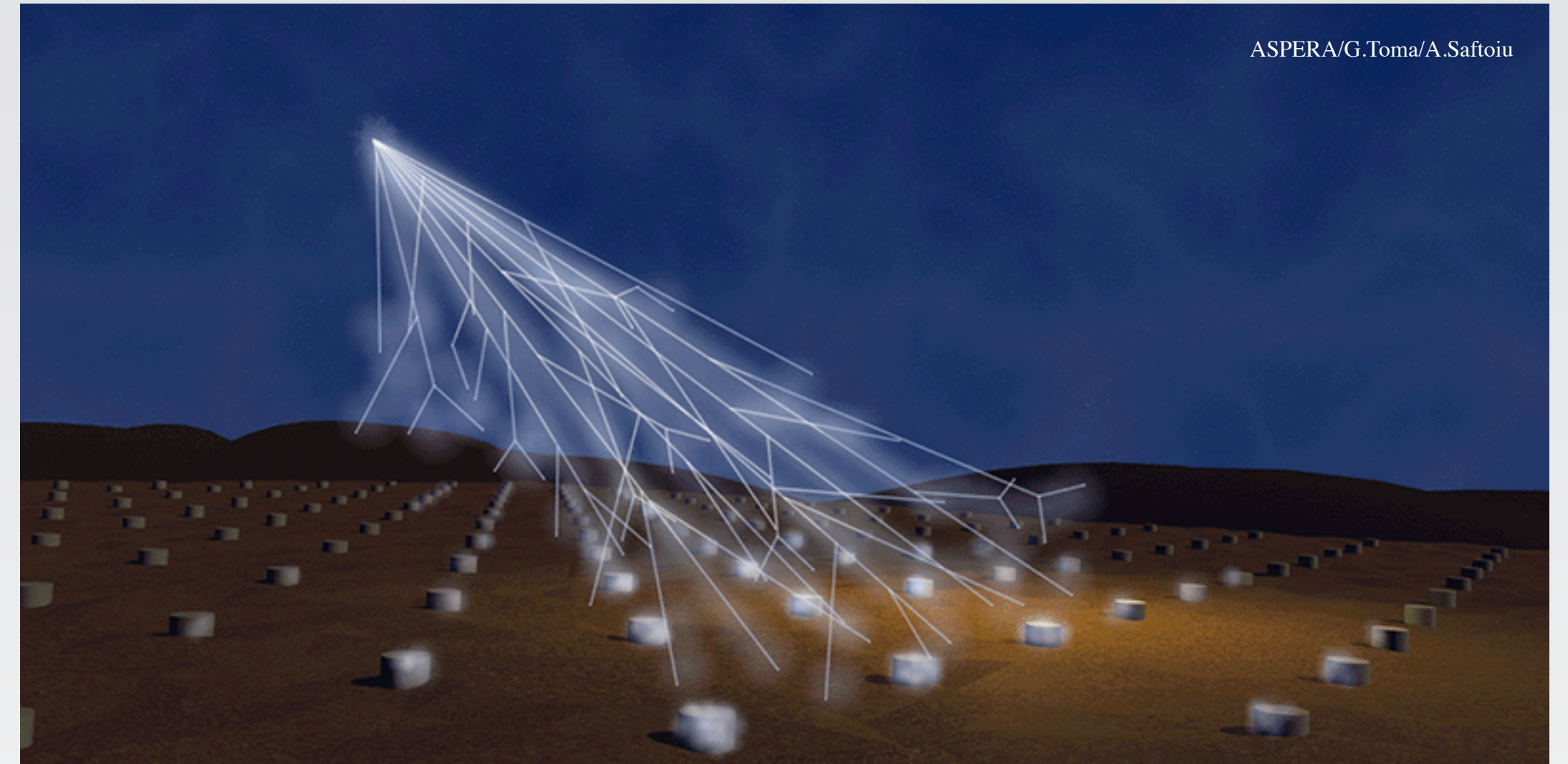
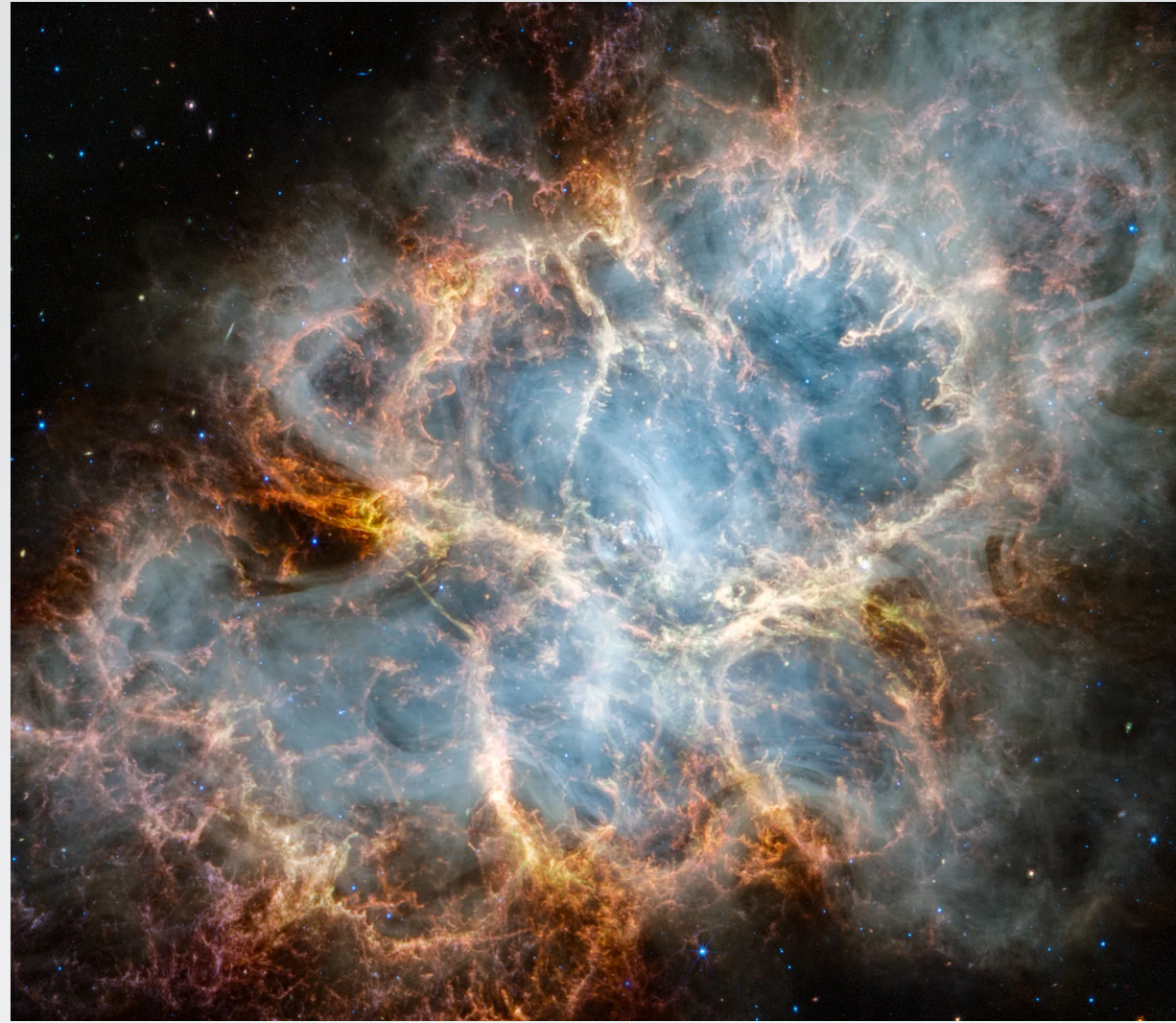
Scientific insight



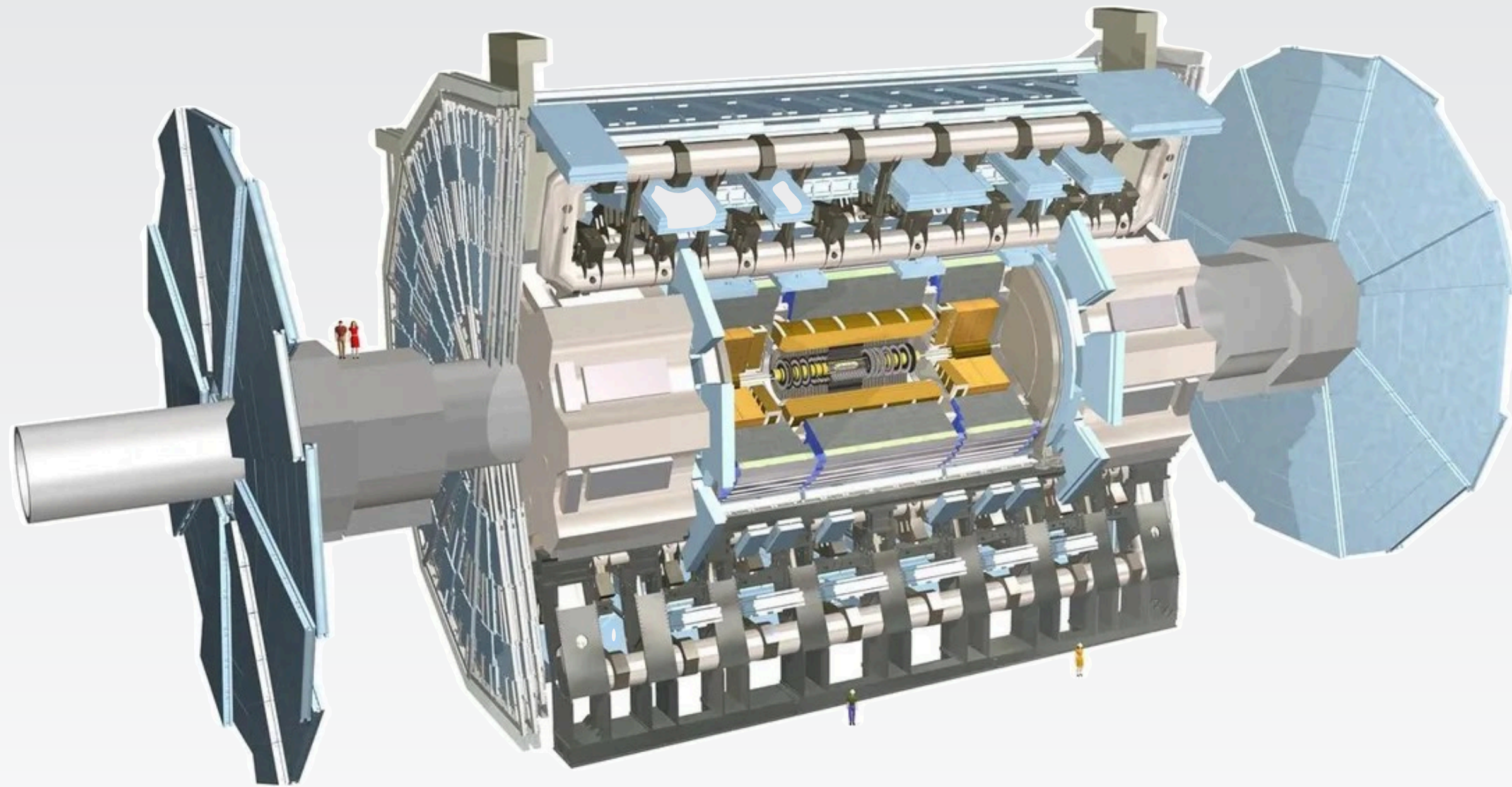
Models of Nature



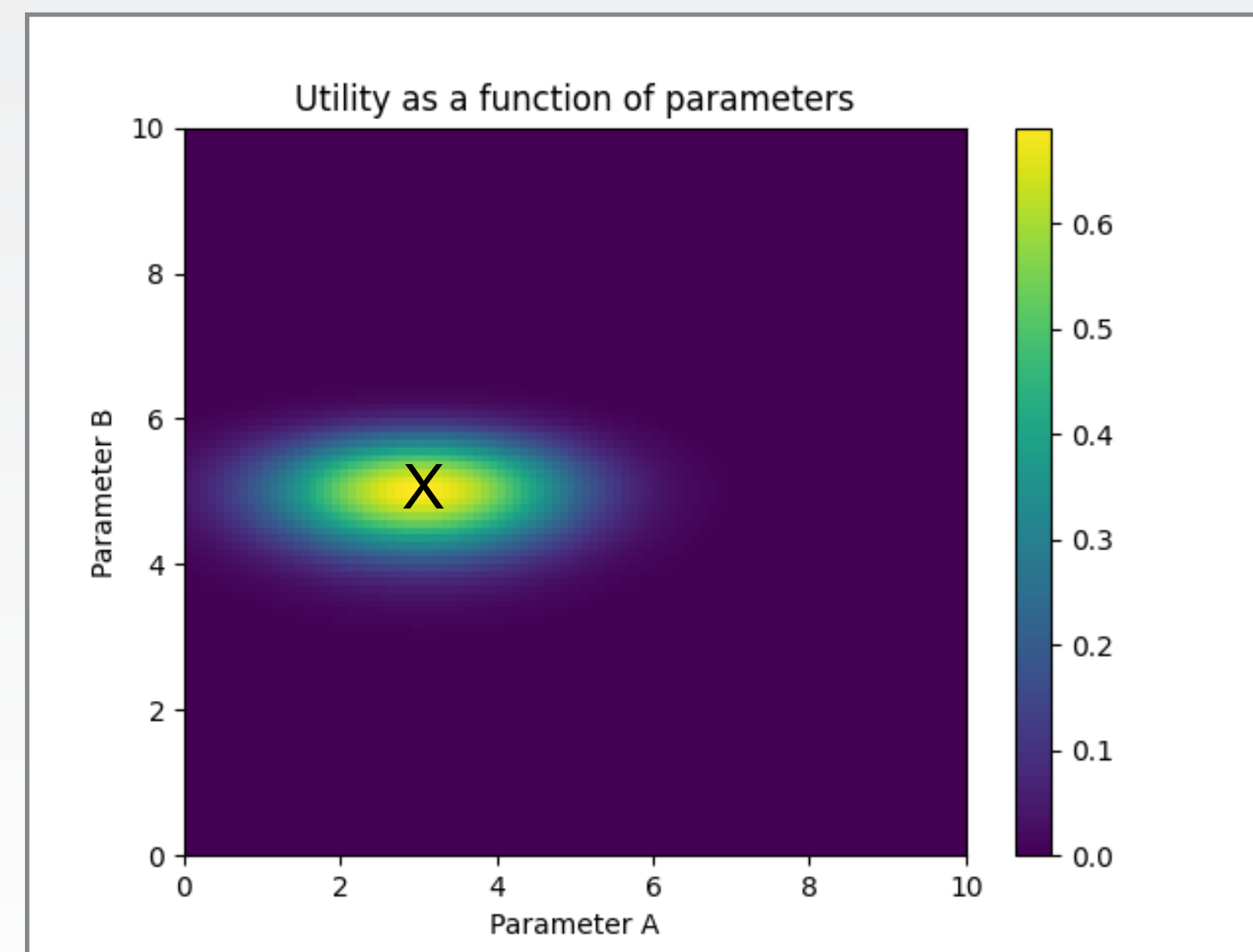
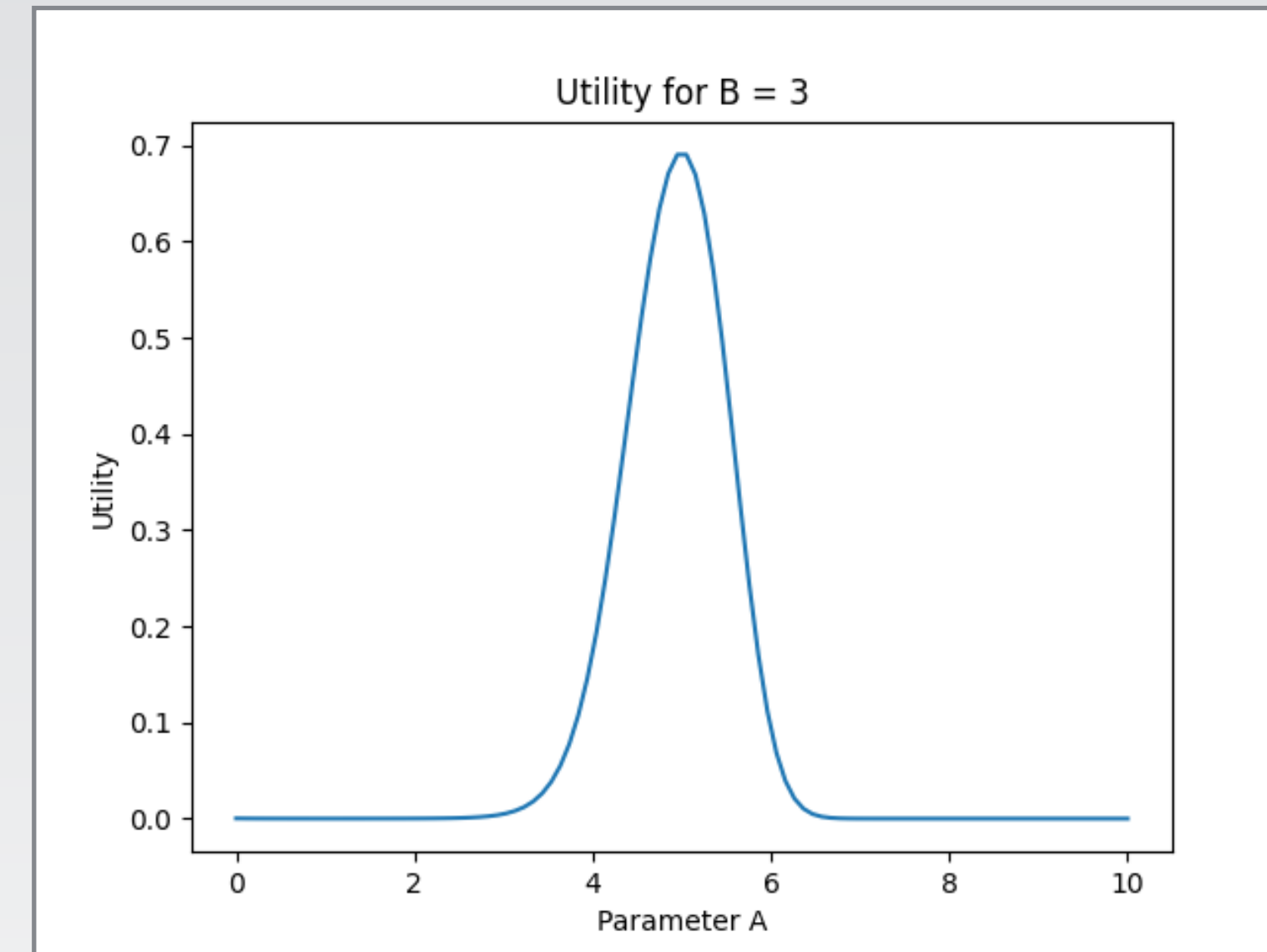
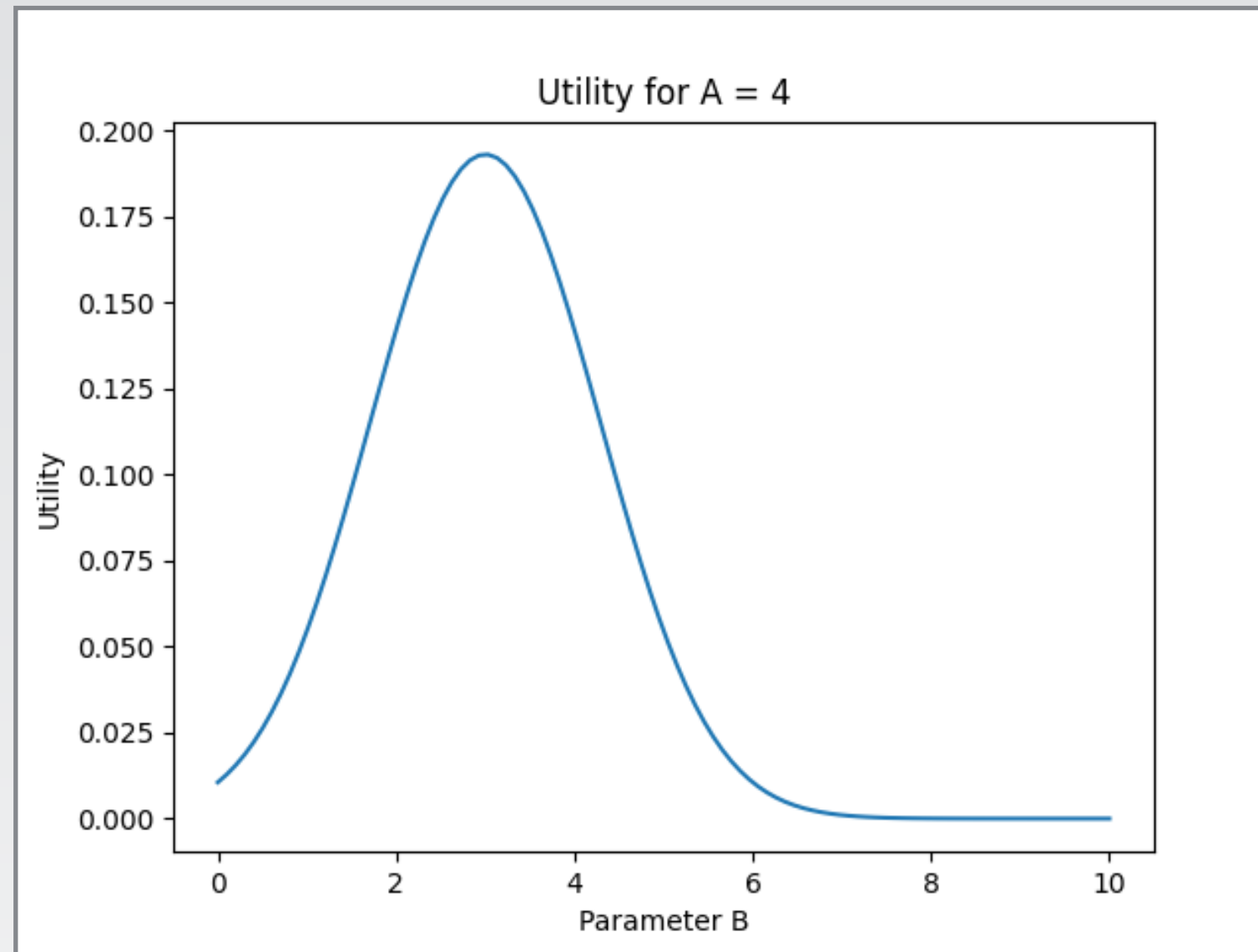
We measure Indirectly

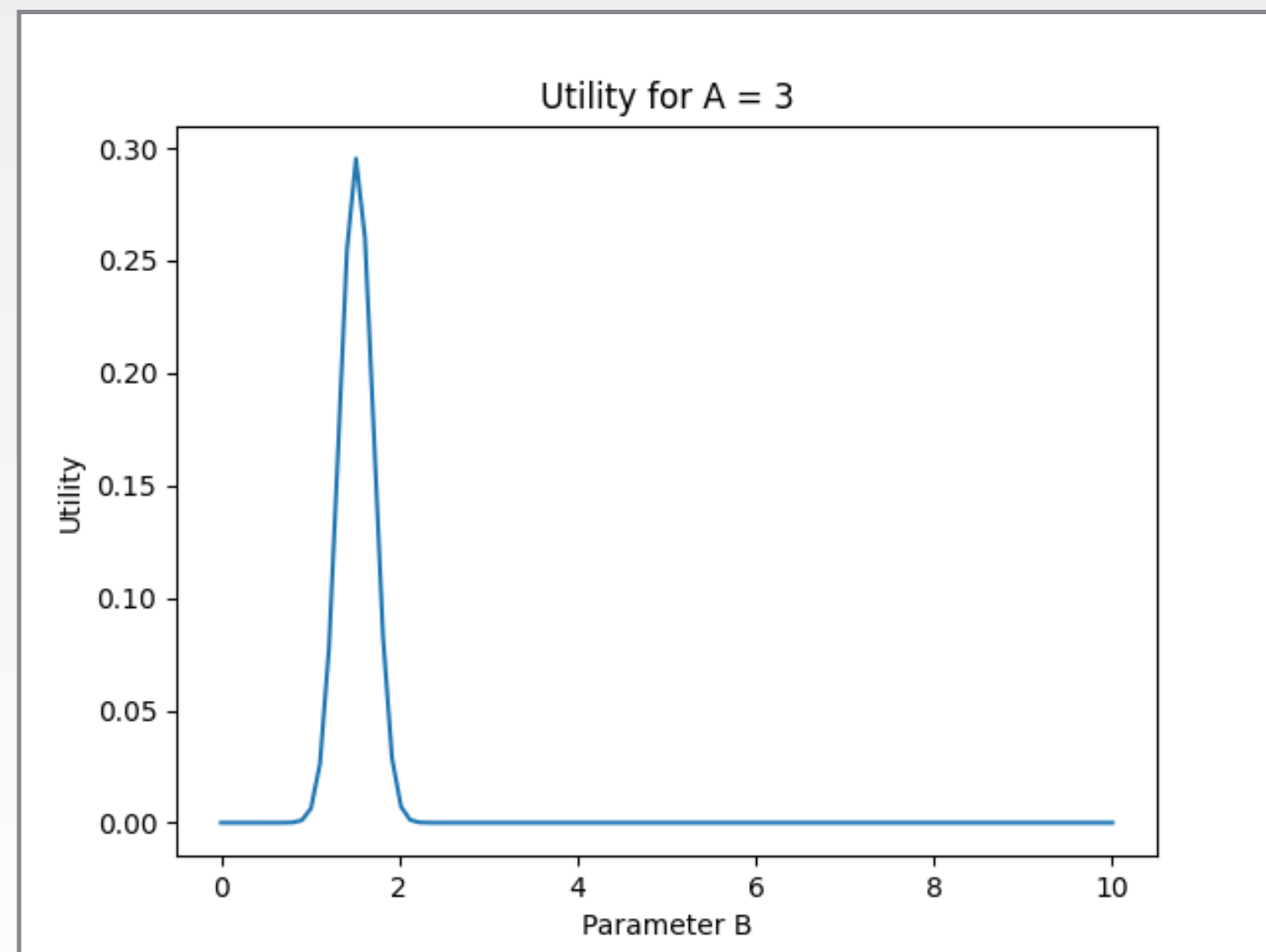
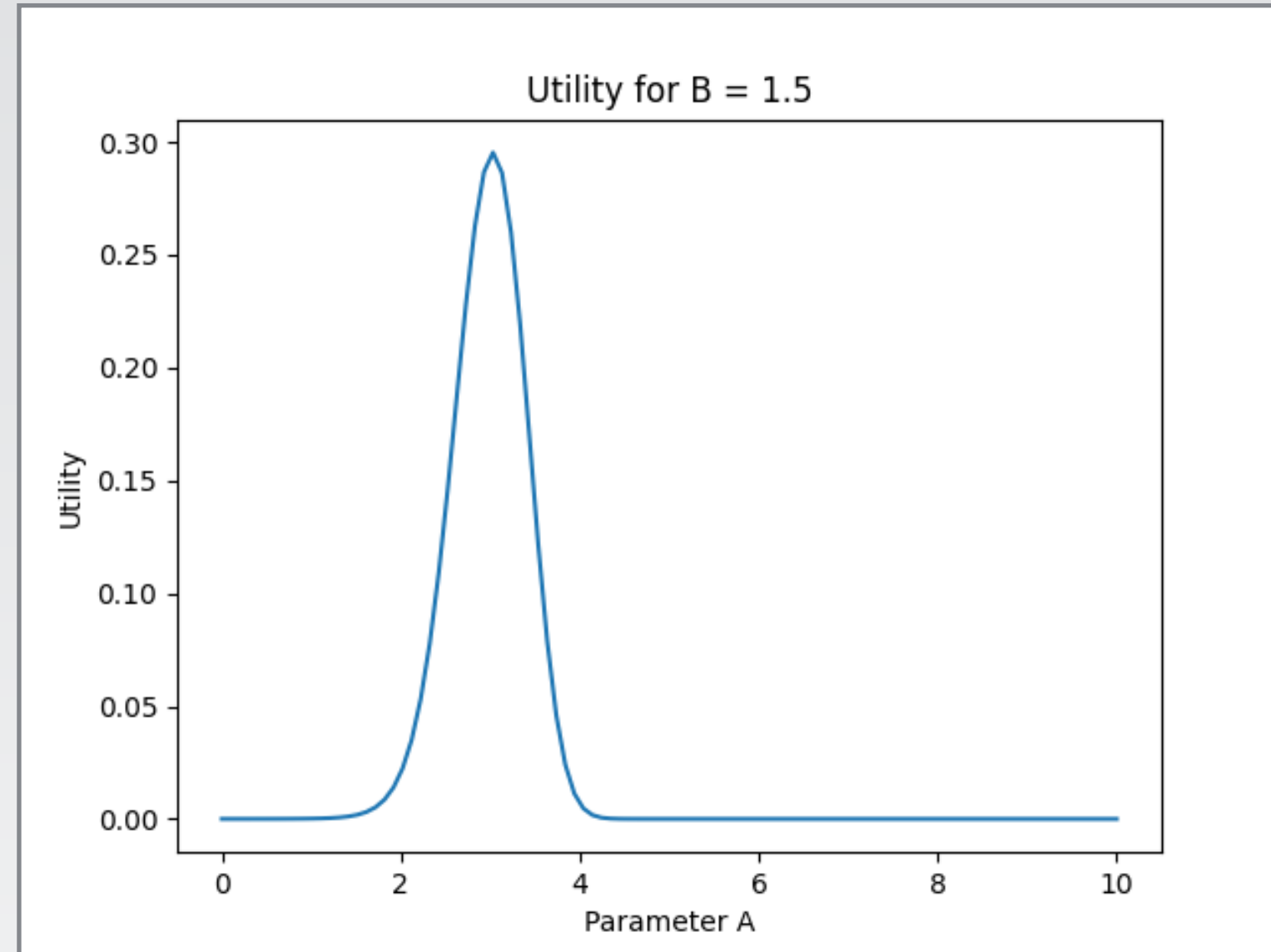


A complex problem



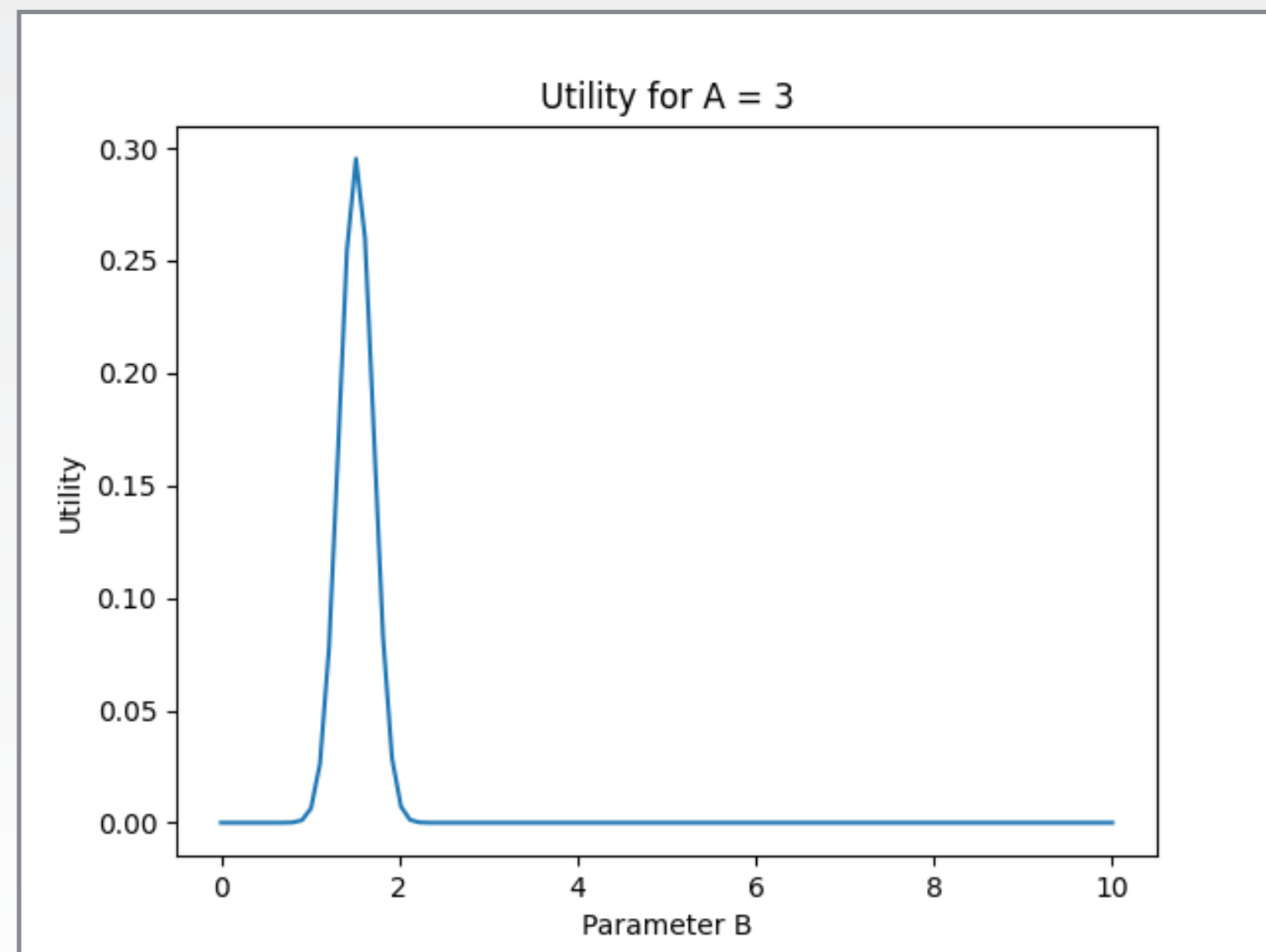
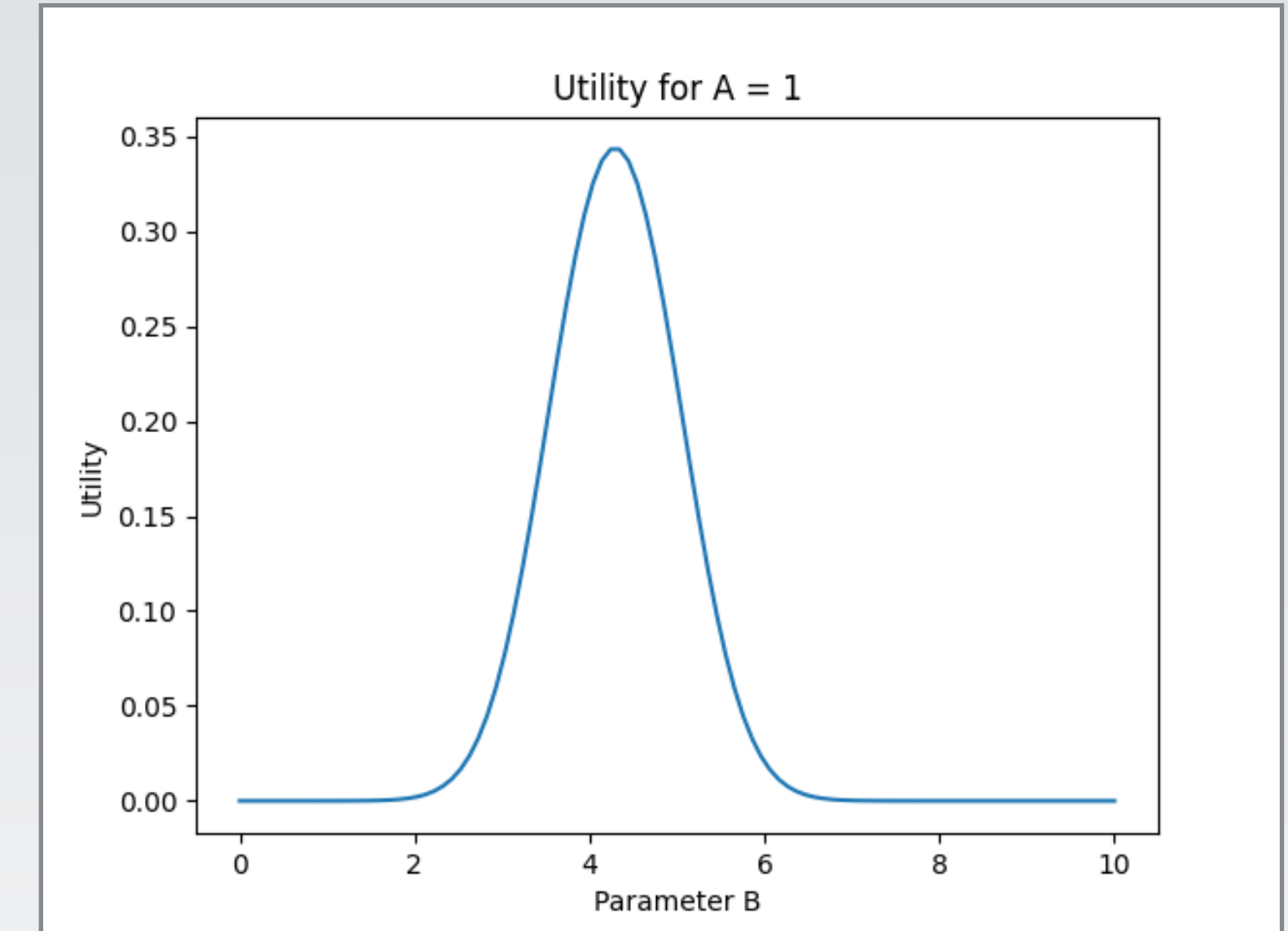
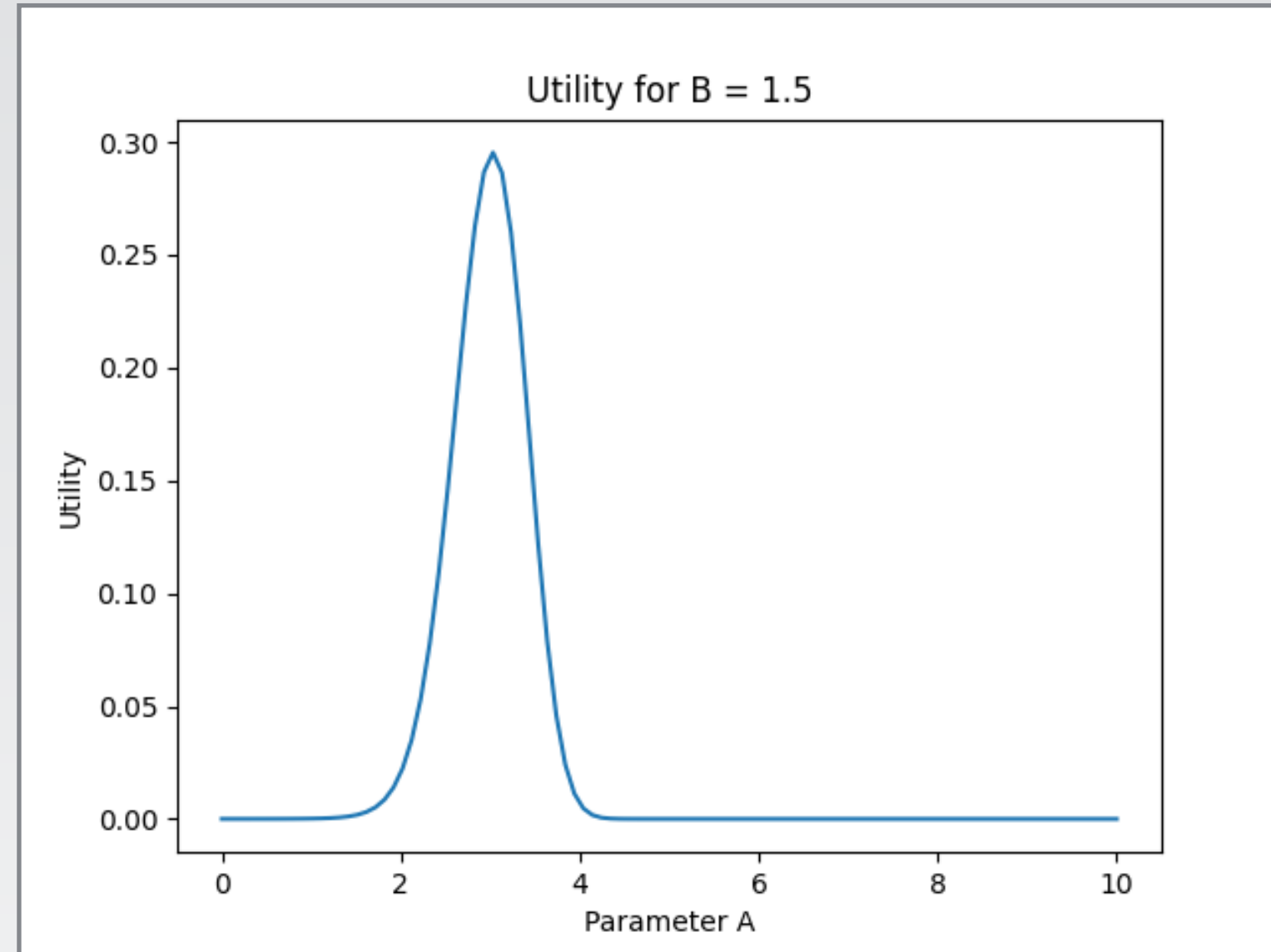
2 Parameter Optimisation





x

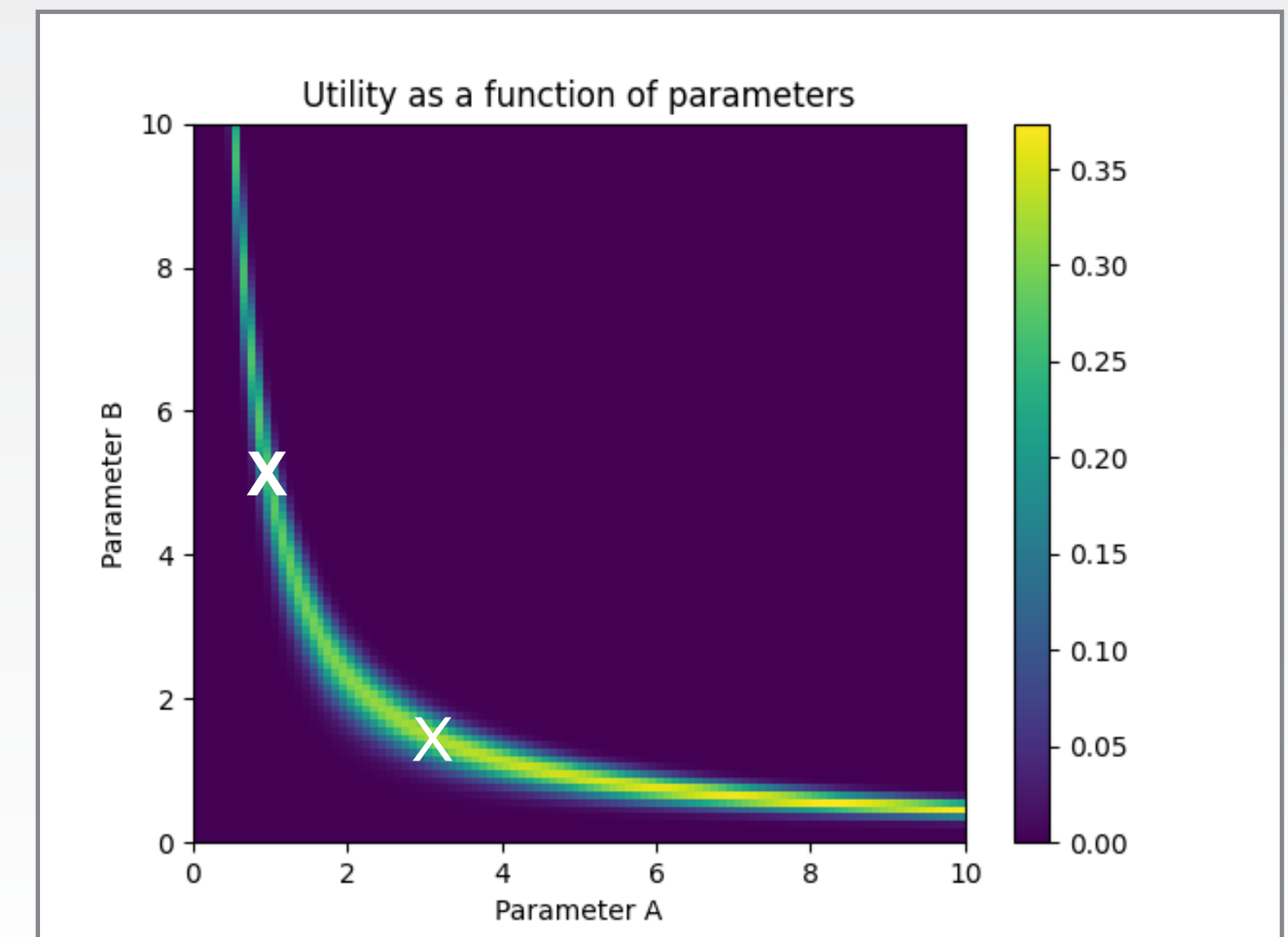
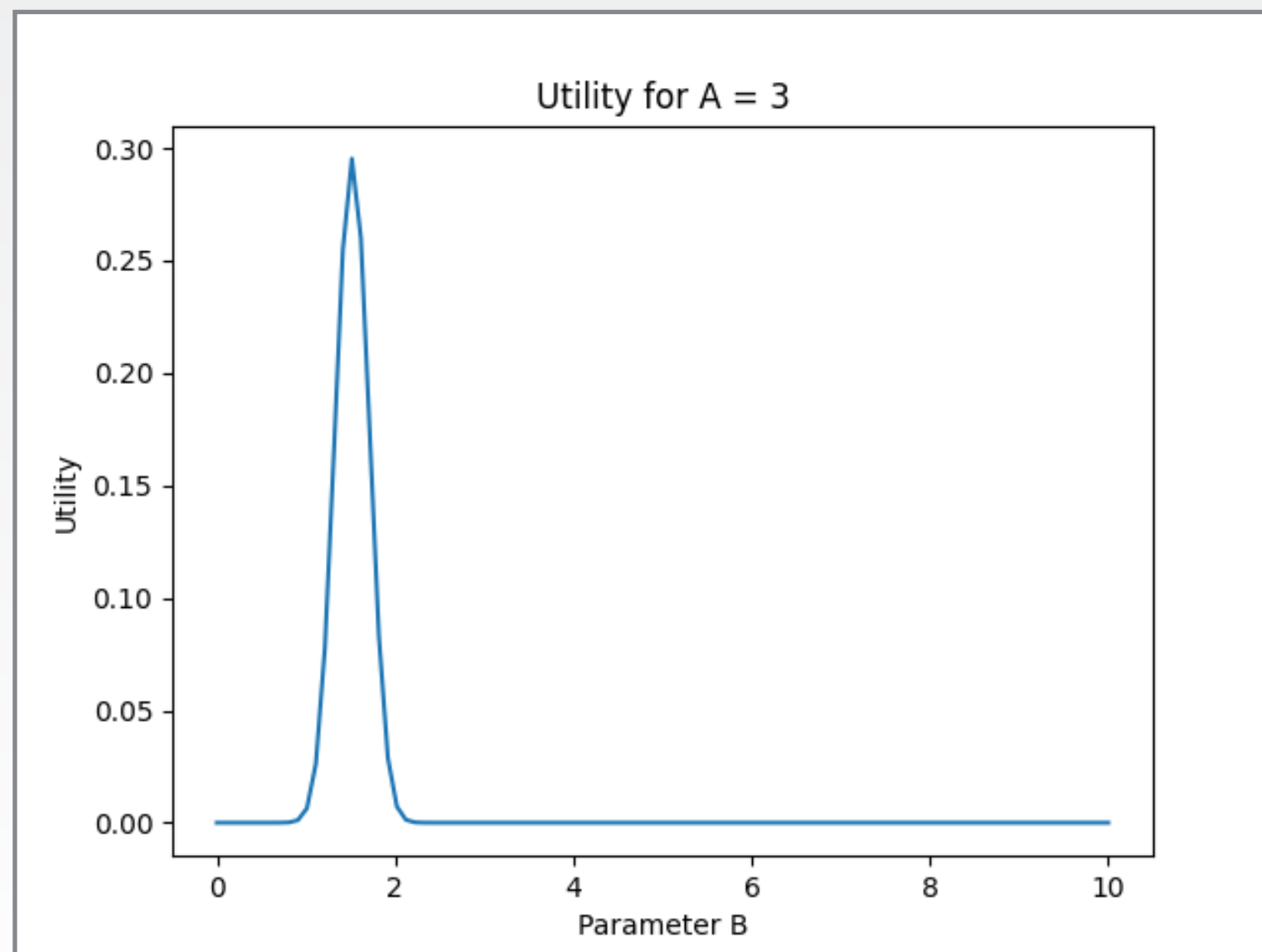
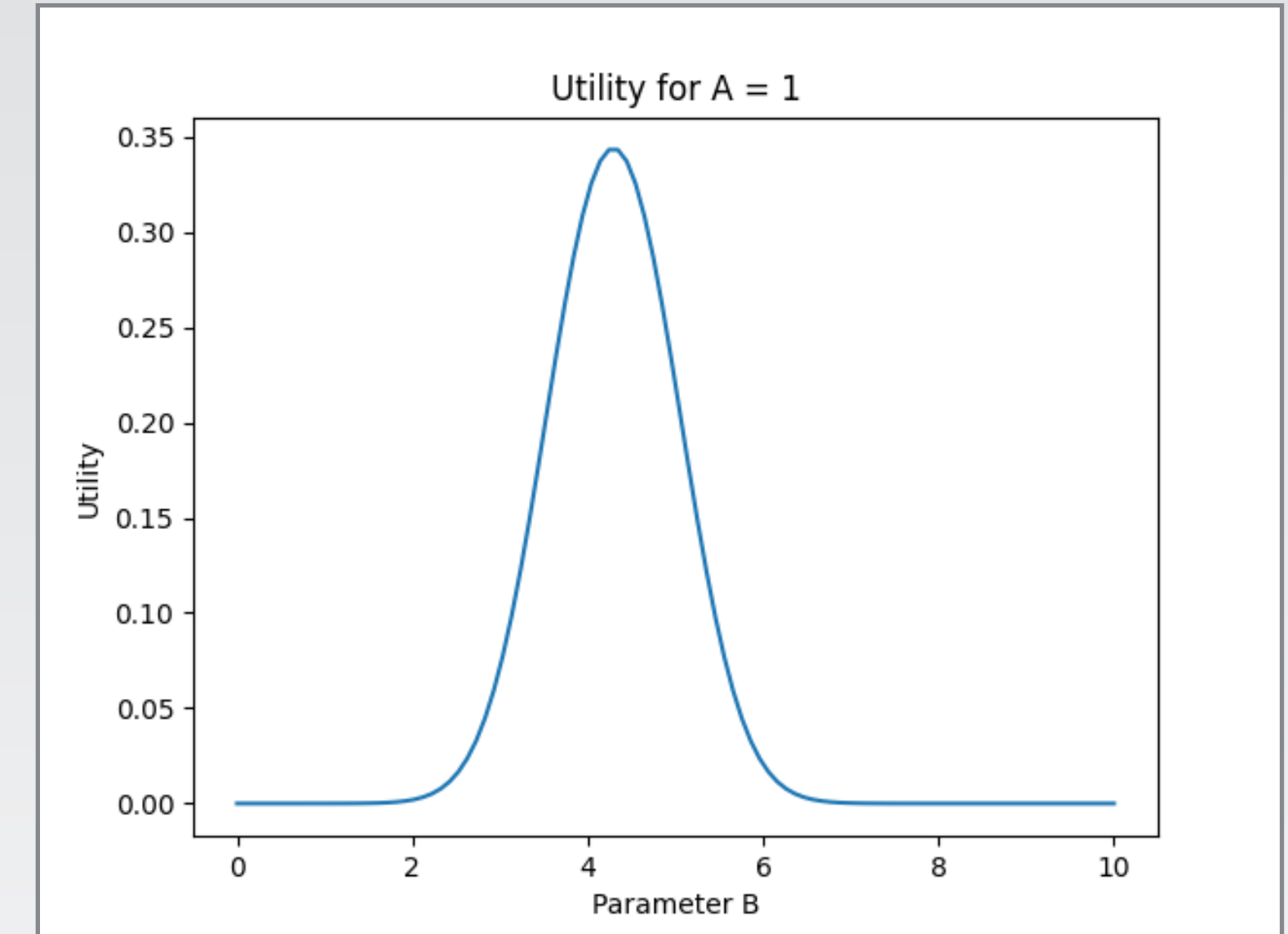
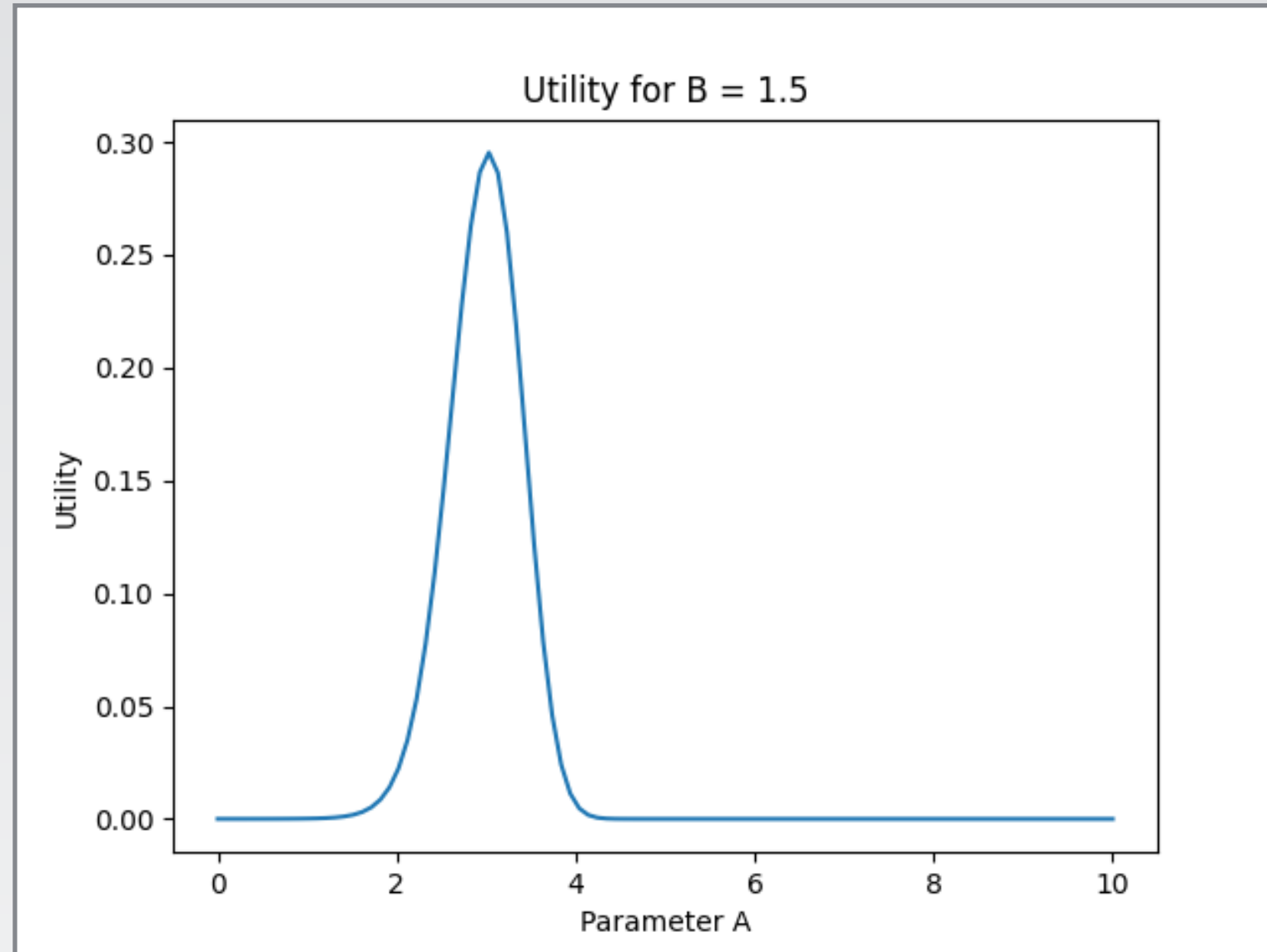
x

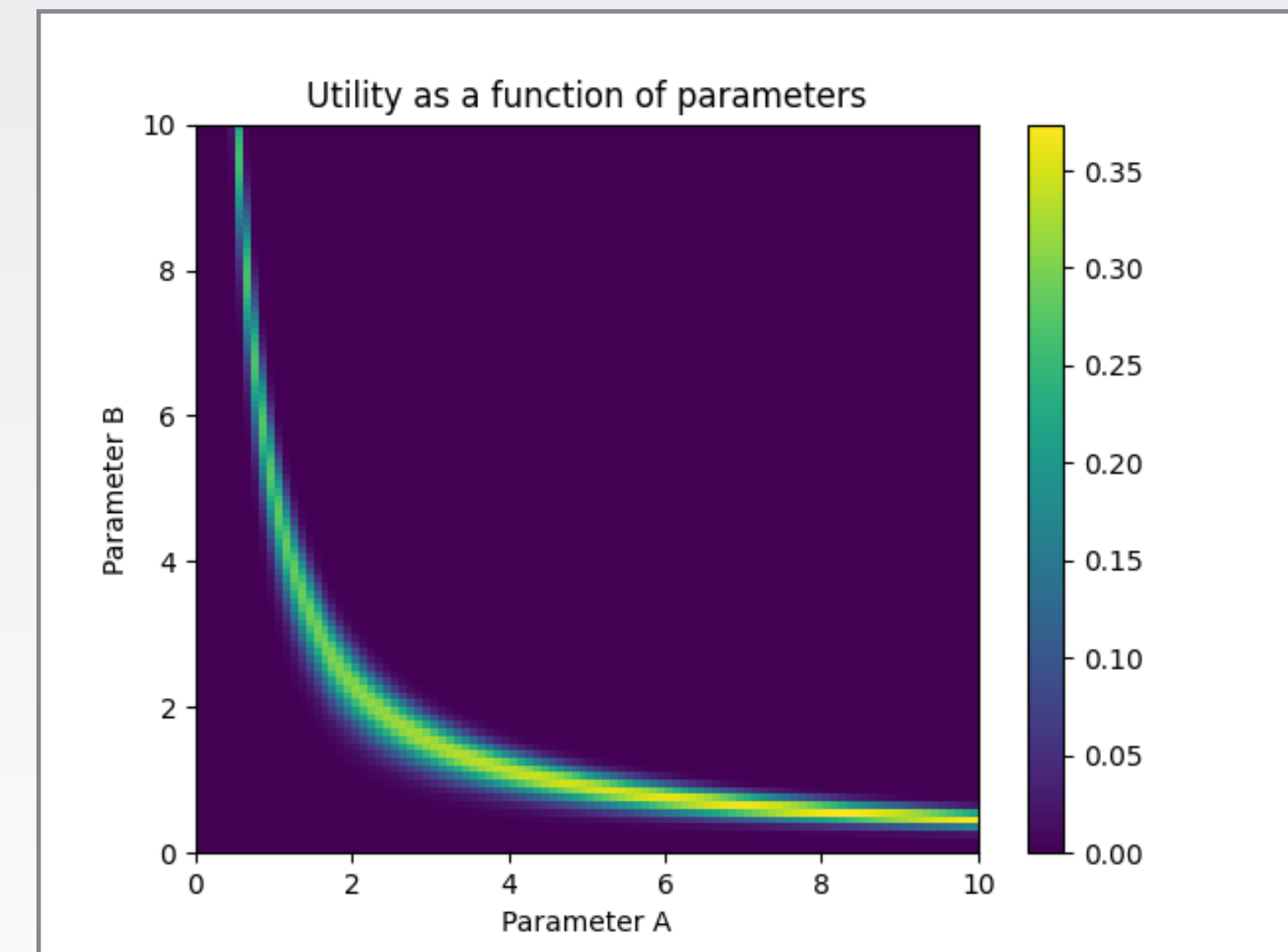
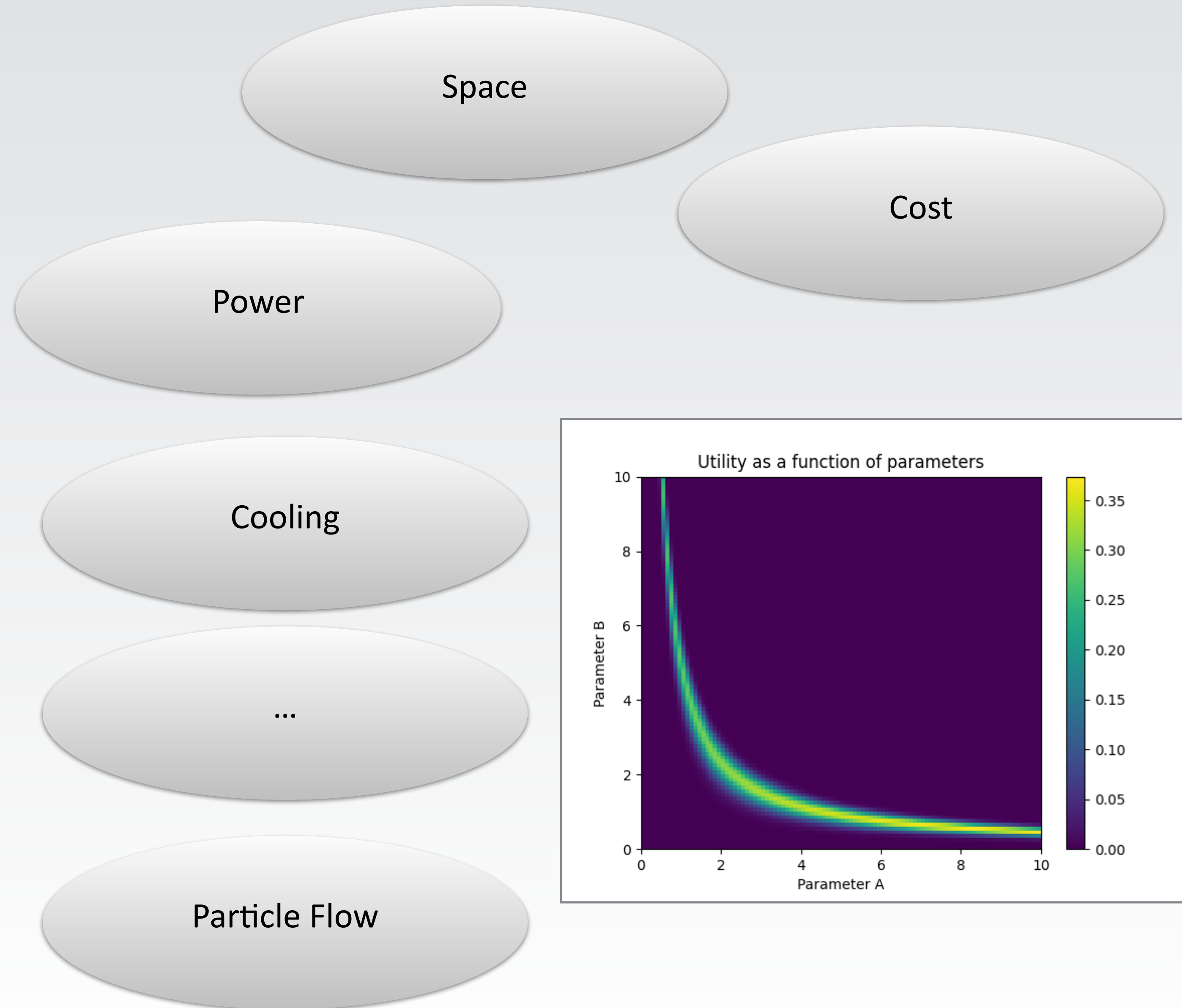


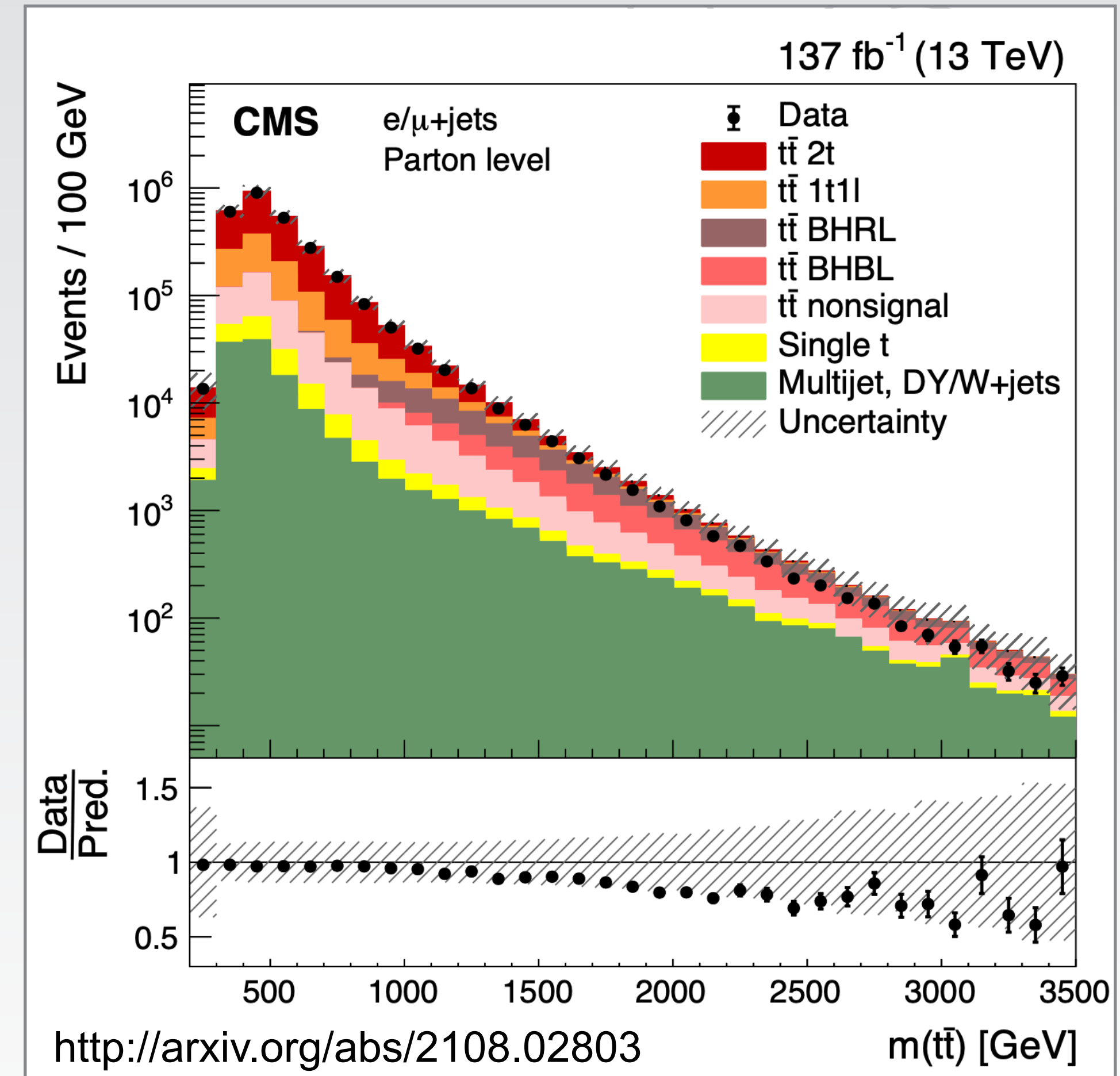
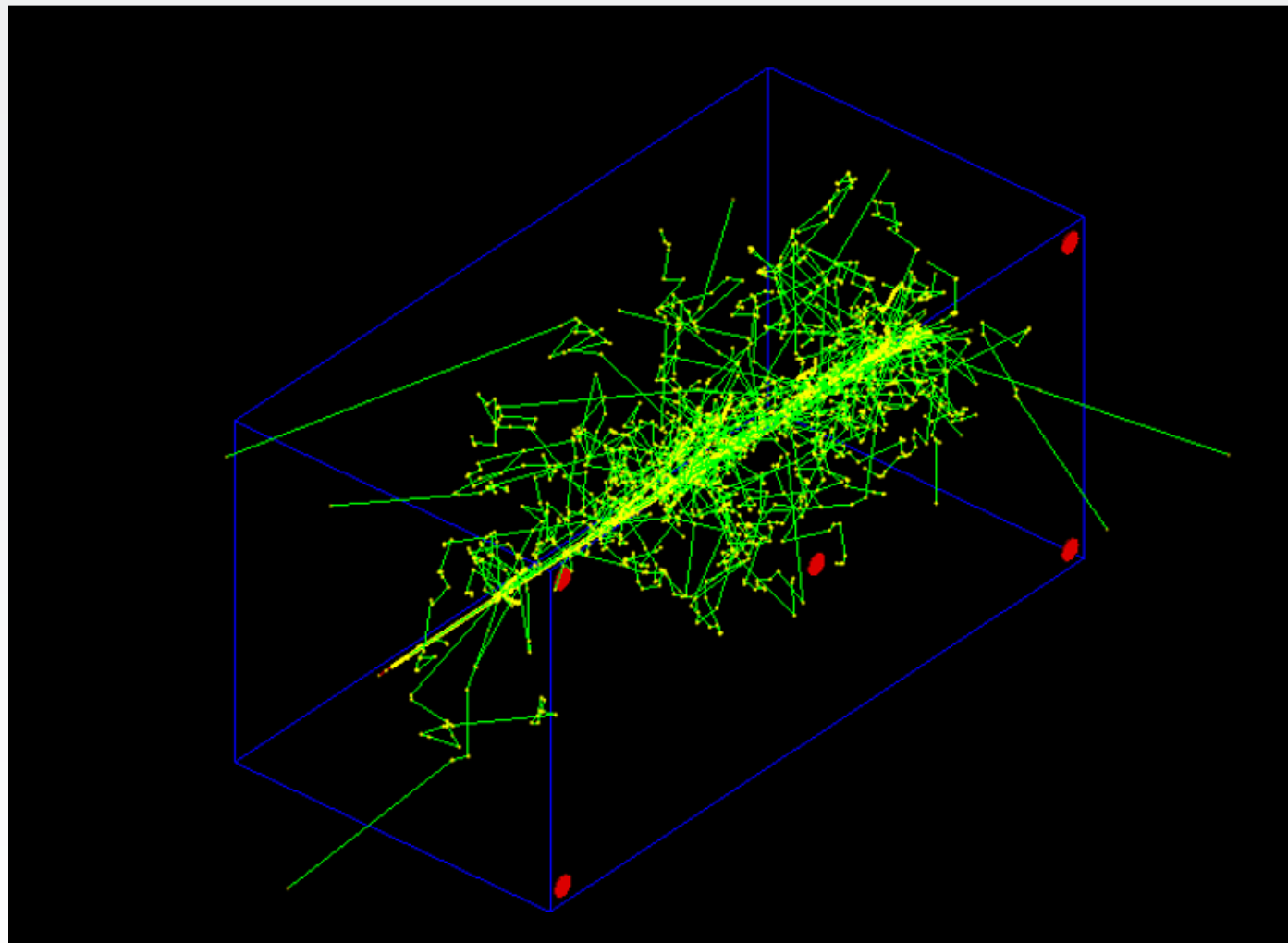
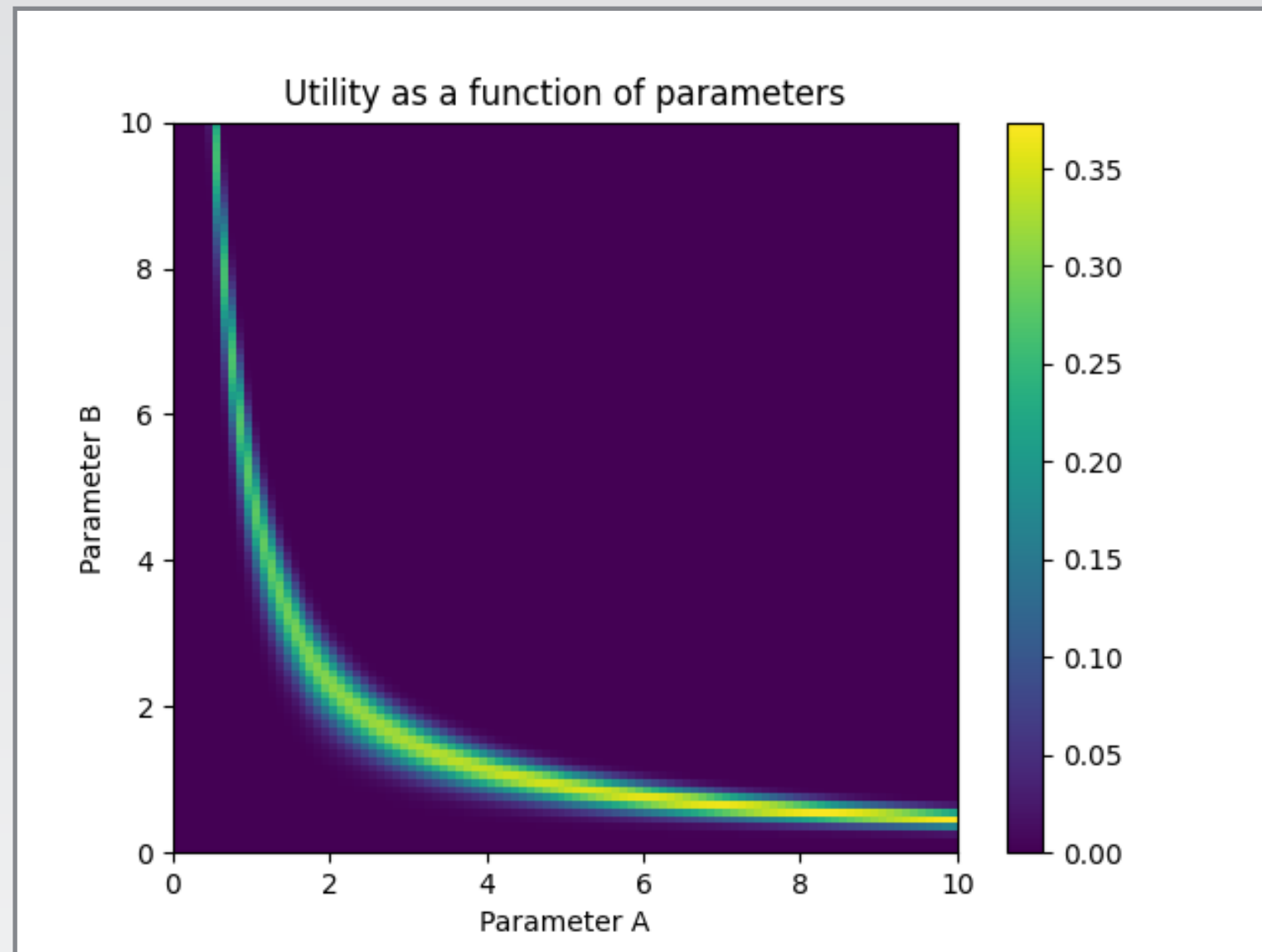
x

x

Another example







- ... but (too) slow: a grid scan is not feasible for a medium dimensional parameter space
- ... and impossible for a high dimensional parameter space

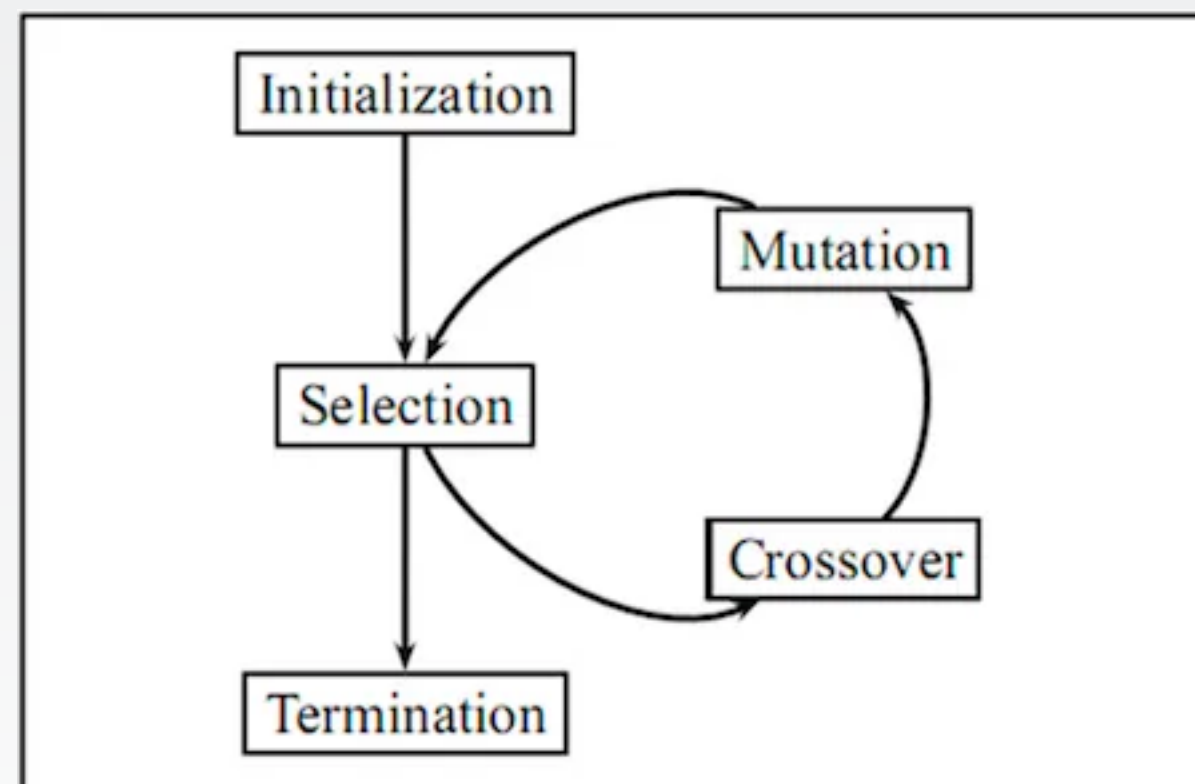
The Evolved Antenna

≡ Evolved antenna

Article [Talk](#)

From Wikipedia, the free encyclopedia

In [radio communications](#), an **evolved antenna** is an [antenna](#) designed fully or substantially by an automatic computer design program that uses an [evolutionary algorithm](#) that mimics [Darwinian evolution](#). This



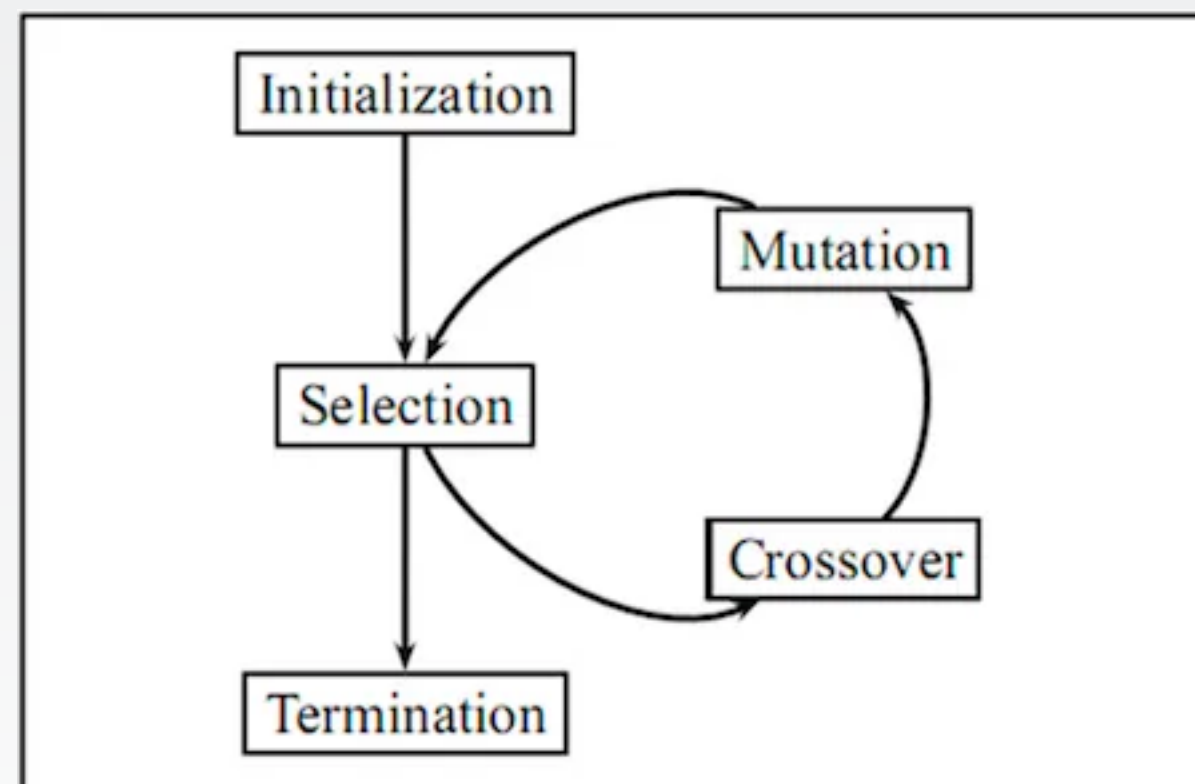
The Evolved Antenna

≡ Evolved antenna

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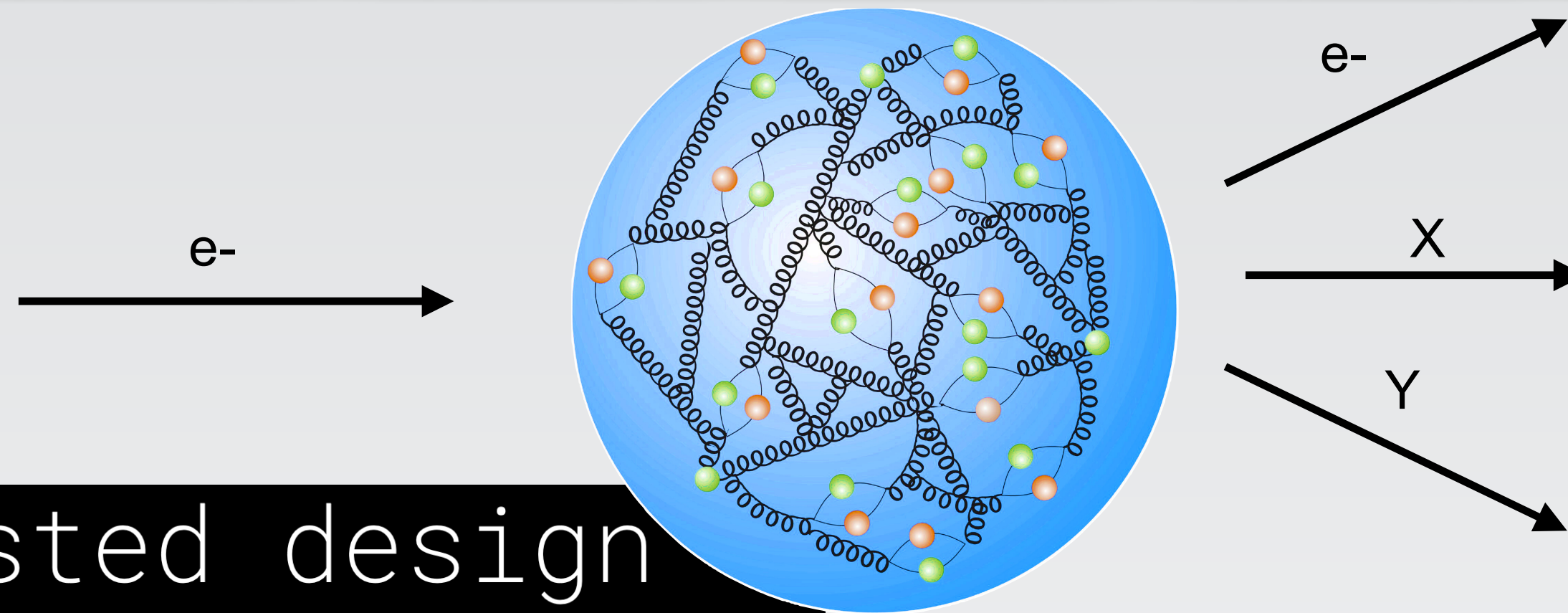
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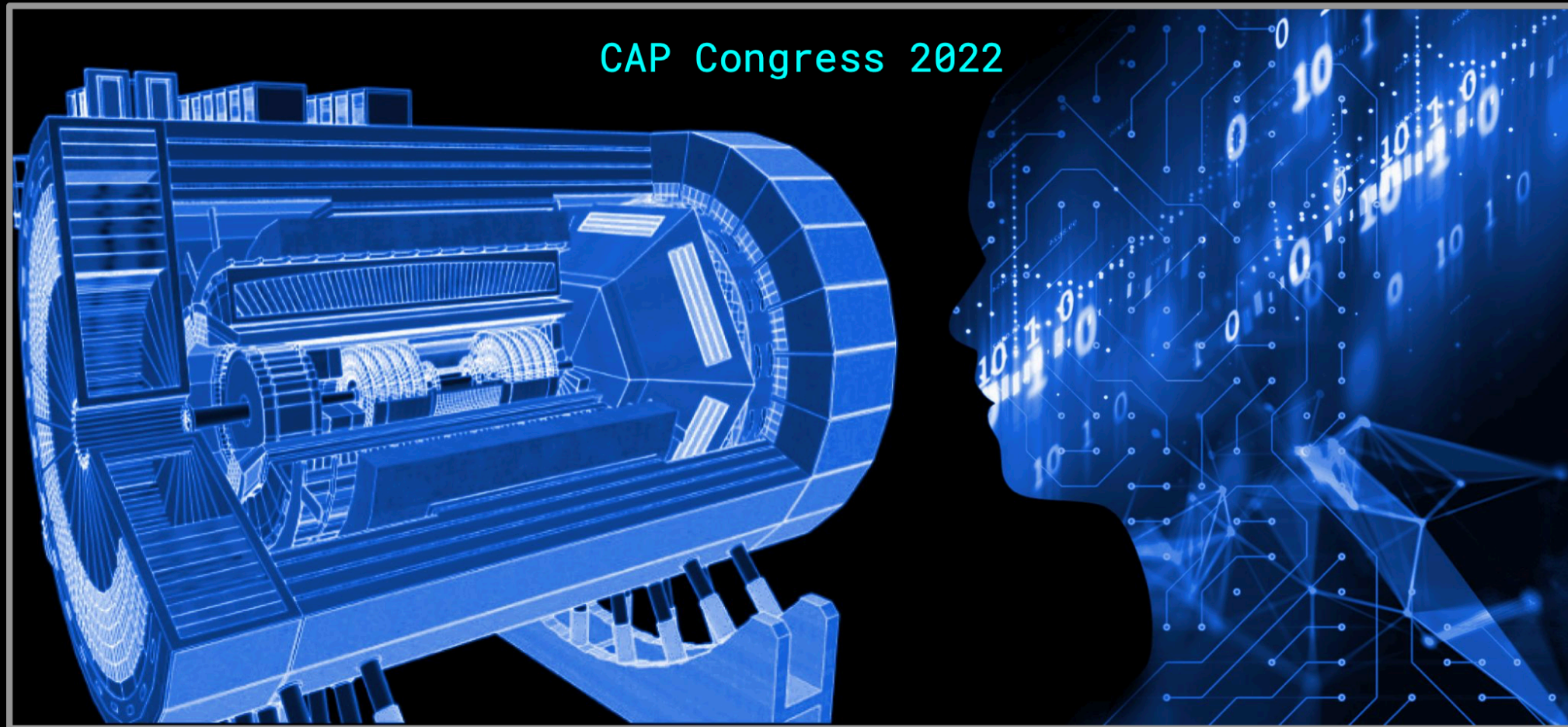
The optimal design may be unexpected

The ECCE tracker (EIC)



AI-assisted design of the EIC Detector

CAP Congress 2022



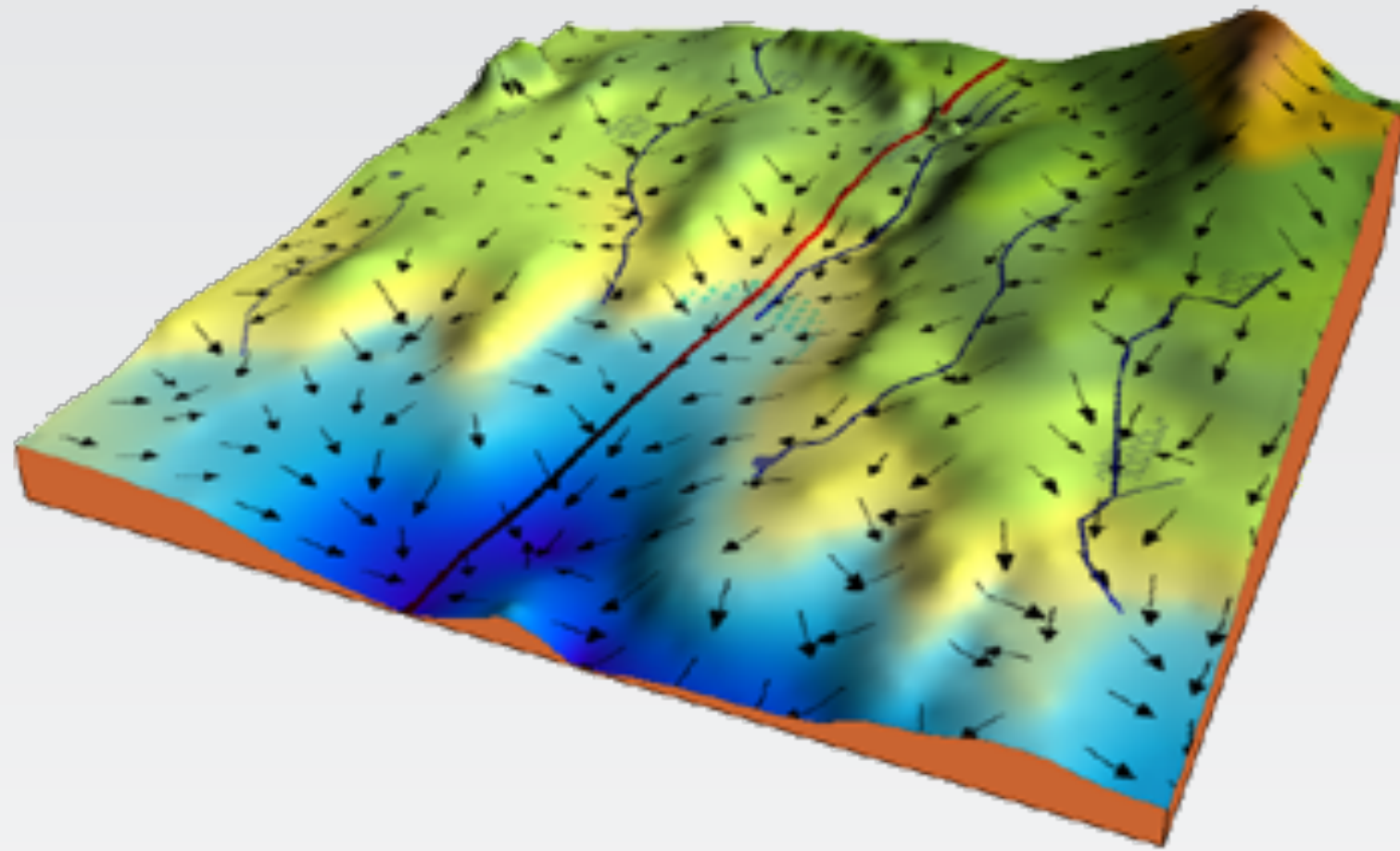
Cristiano Fanelli

- Optimise positions of tracker layers: 11 (9) parameters
- Multi-objective optimisation for charged pion tracks
 - Momentum resolution
 - Angular resolution
 - Efficiency
- About 10% better mass momentum resolution for meson decays to pions w.r.t. baseline design
- Fixed reconstruction
- Objective reduced to representative but specific goal

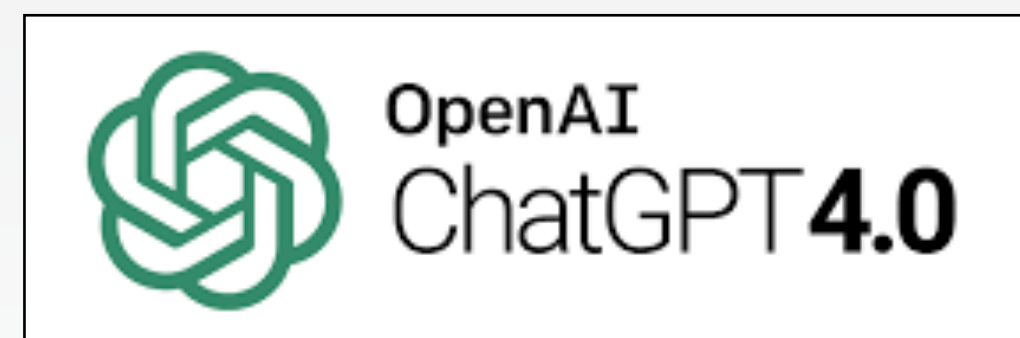
C. Fanelli, et al., arXiv:2205.09185, NIMA 2022

Beyond a Handful of Parameters: Gradients

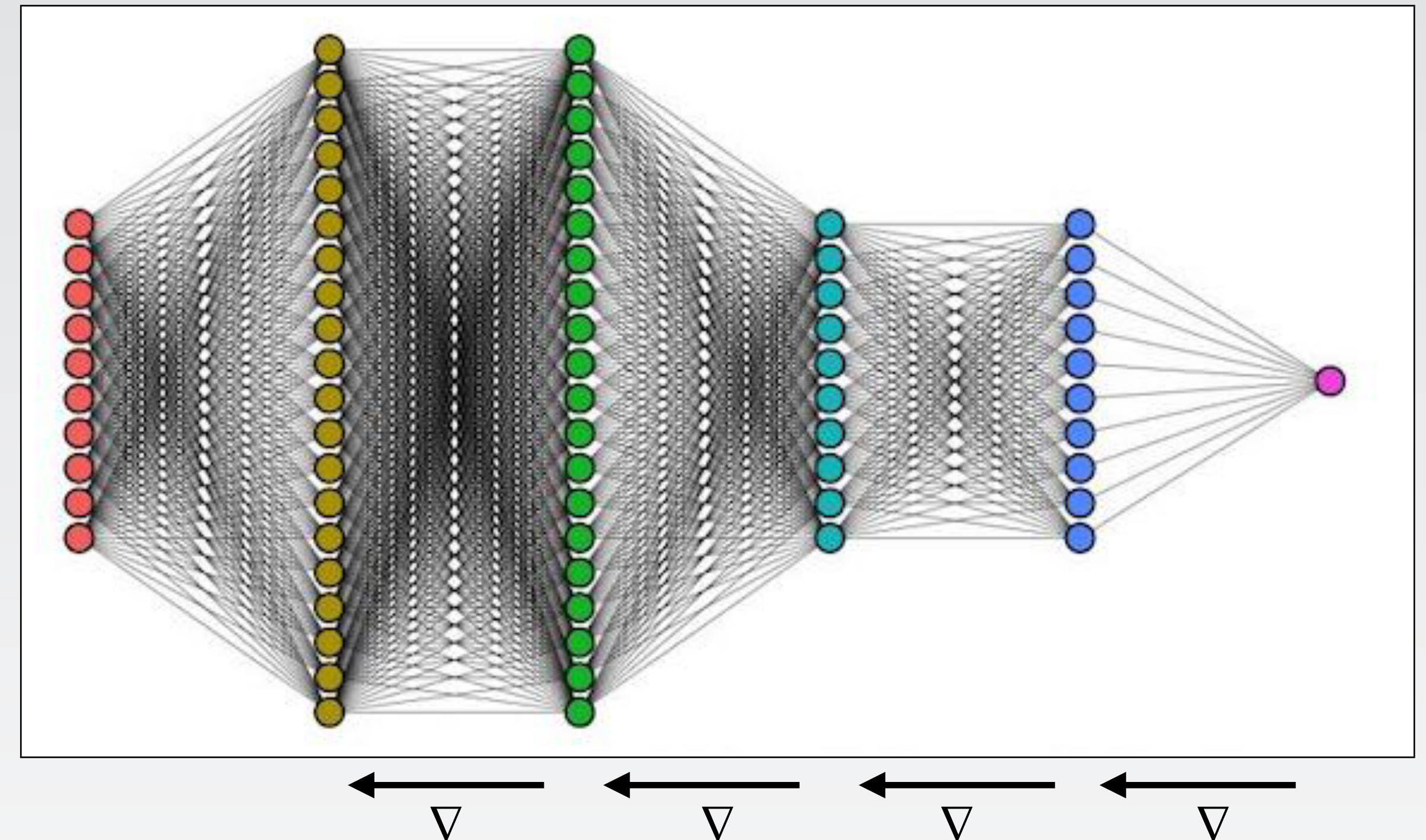
$$\theta^{(s+1)} = \theta^{(s)} - \eta \nabla_{\theta^{(s)}} L(C(\theta^{(s)}, x(P)), P)$$



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html



Rumours: 1.7 Trillion parameters

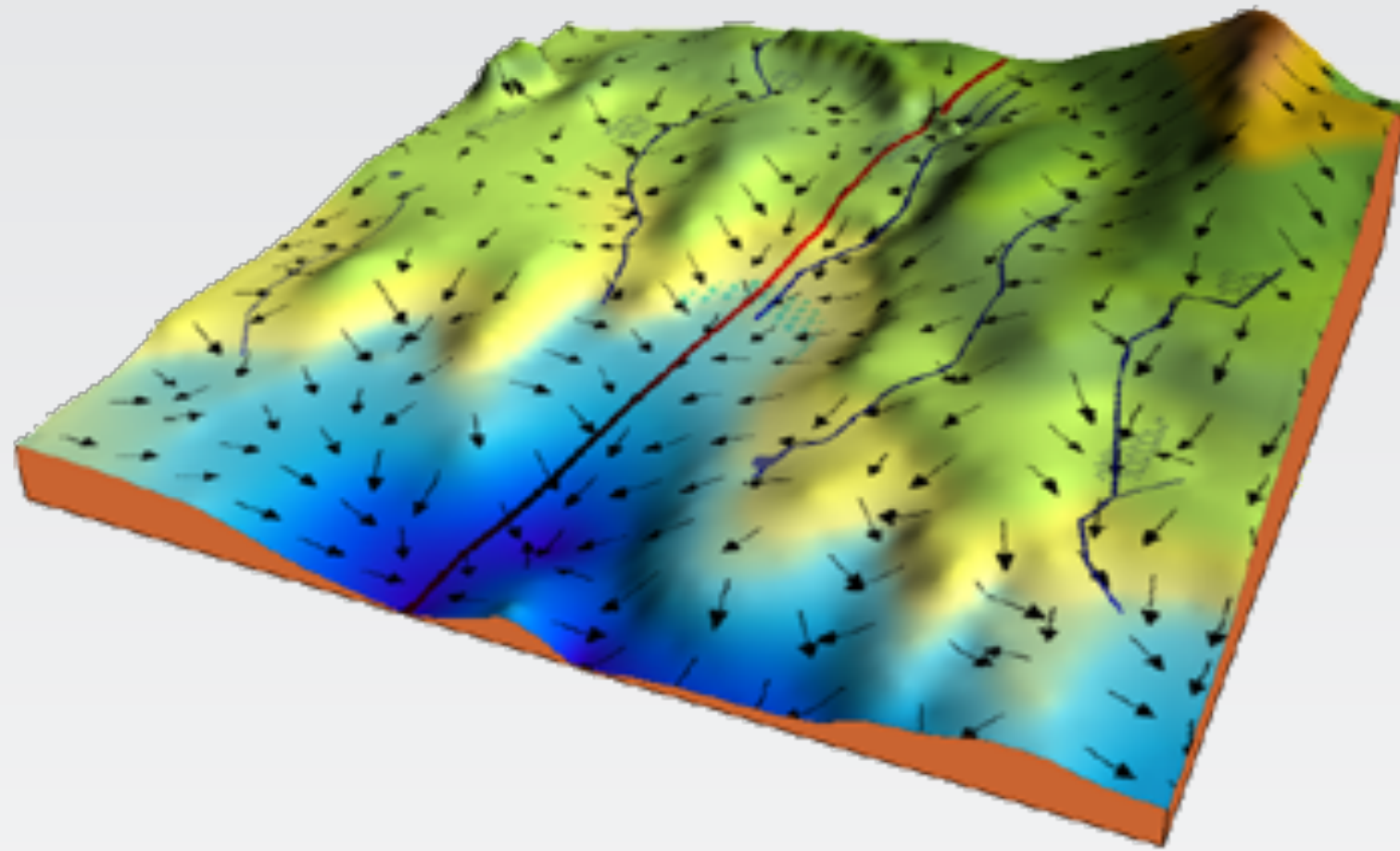


Answer to: I want to improve the physics precision - how much do I need to change the tracking layer position?

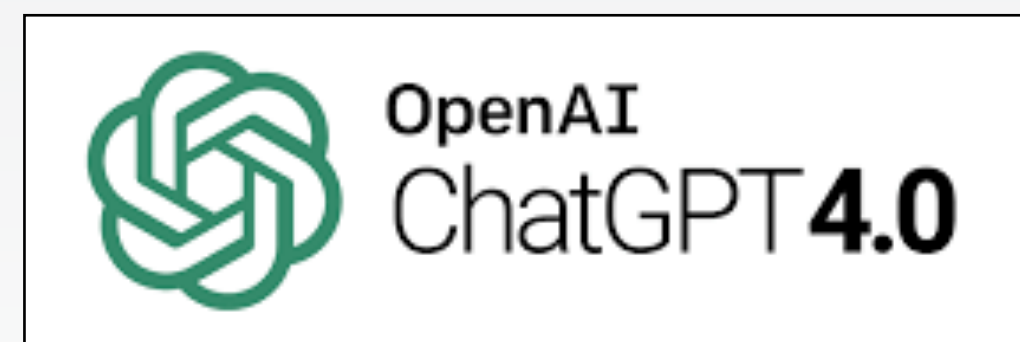
Implemented through *back-propagation*

Beyond a Handful of Parameters: Gradients

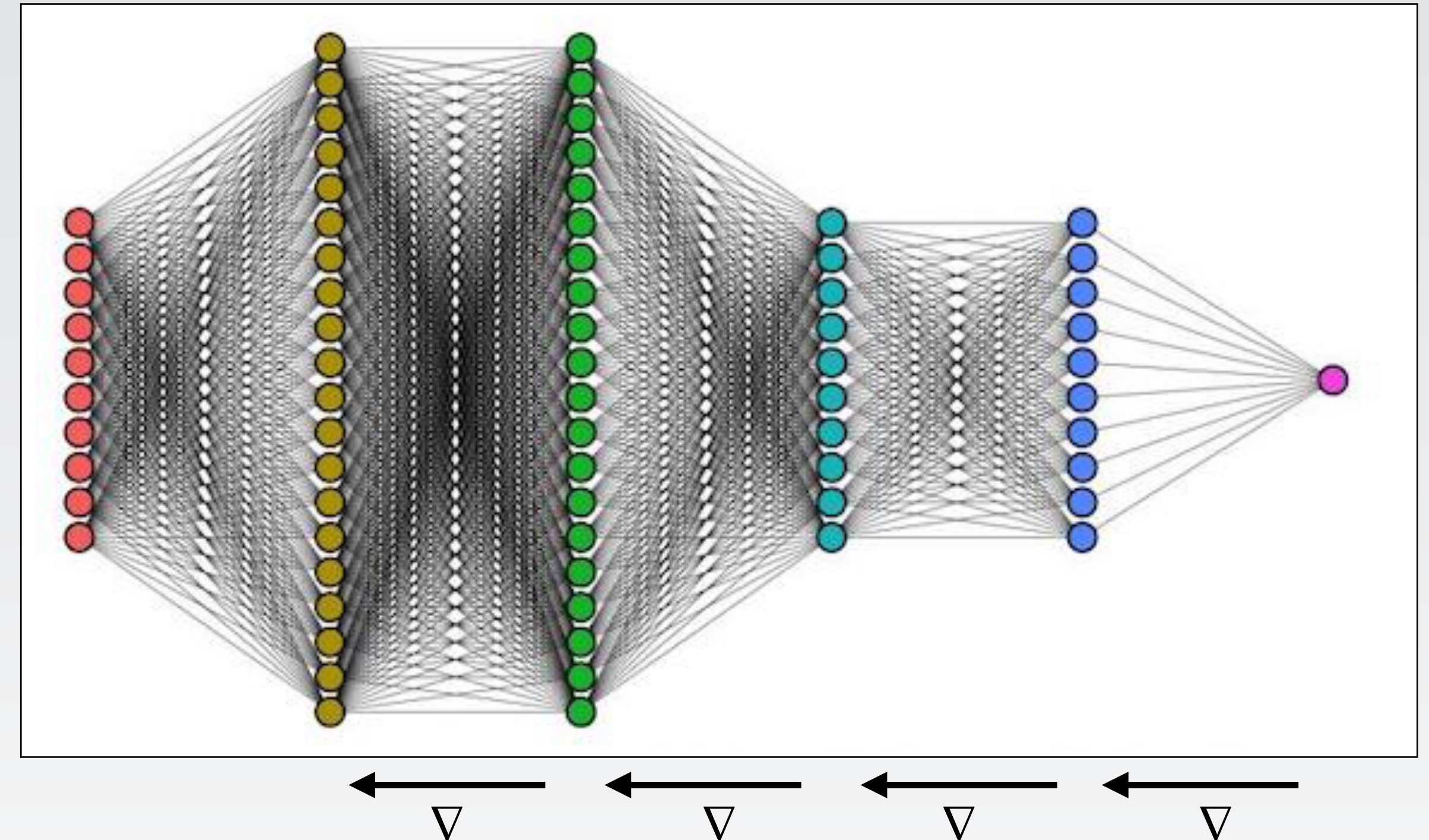
$$\theta^{(s+1)} = \theta^{(s)} - \eta \nabla_{\theta^{(s)}} L(C(\theta^{(s)}, x(P)), P)$$



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html



Rumours: 1.7 Trillion parameters

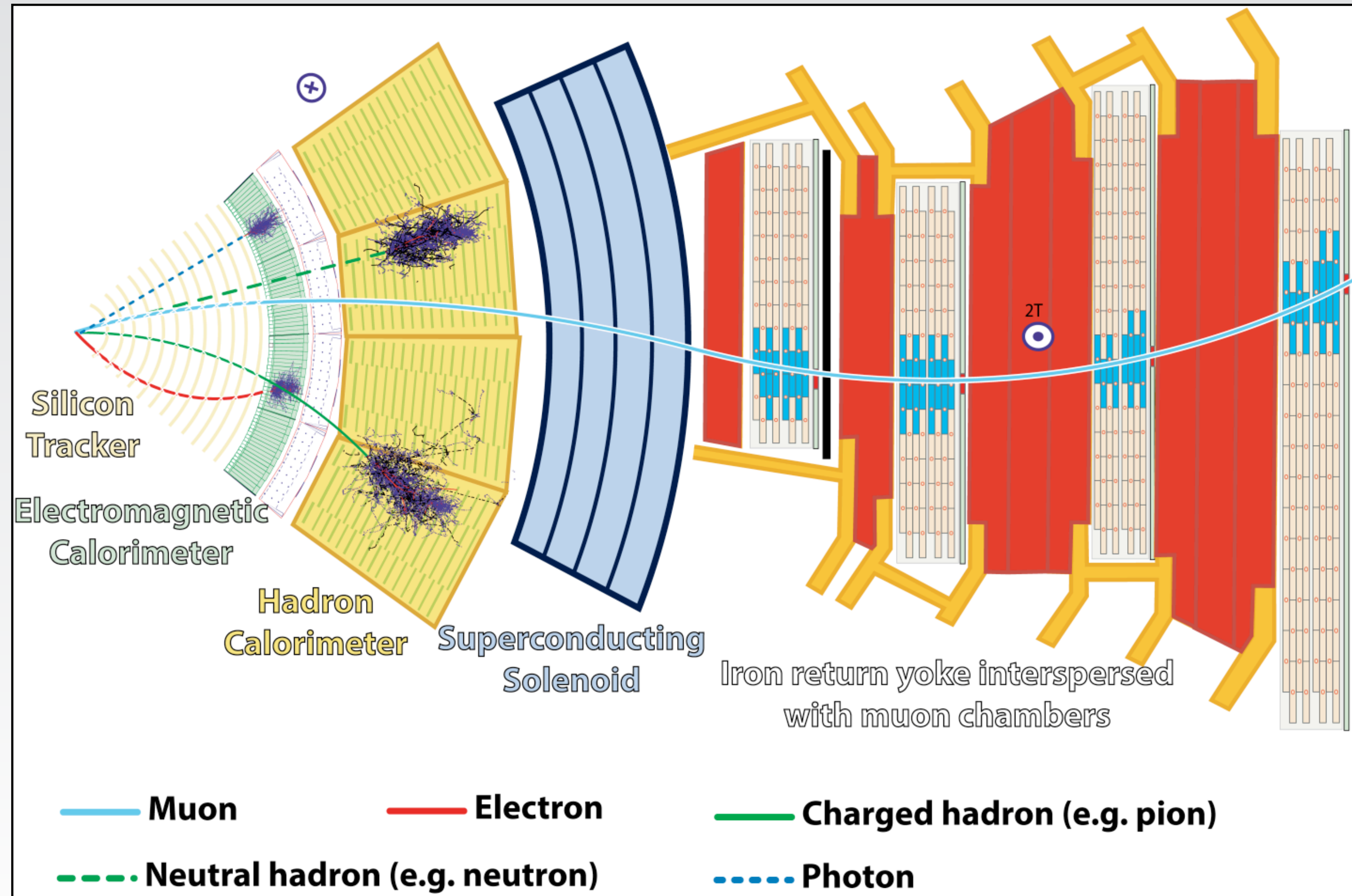


Answer to: I want to improve the physics precision - how much do I need to change the tracking layer position?

Implemented through *back-propagation*

Gradient-based optimisation requires the full pipeline to be differentiable

Detect Particles and Processes

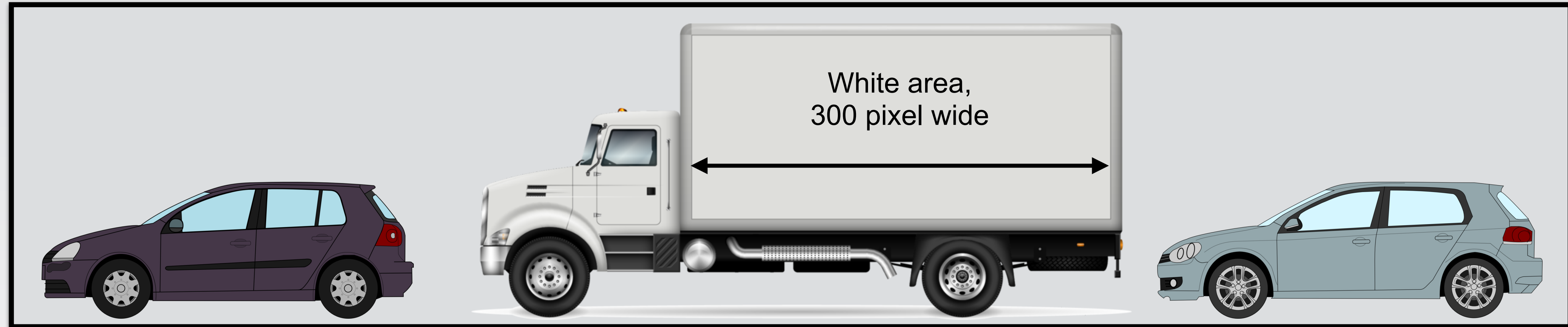


Determine the Fraction of Trucks on the Road



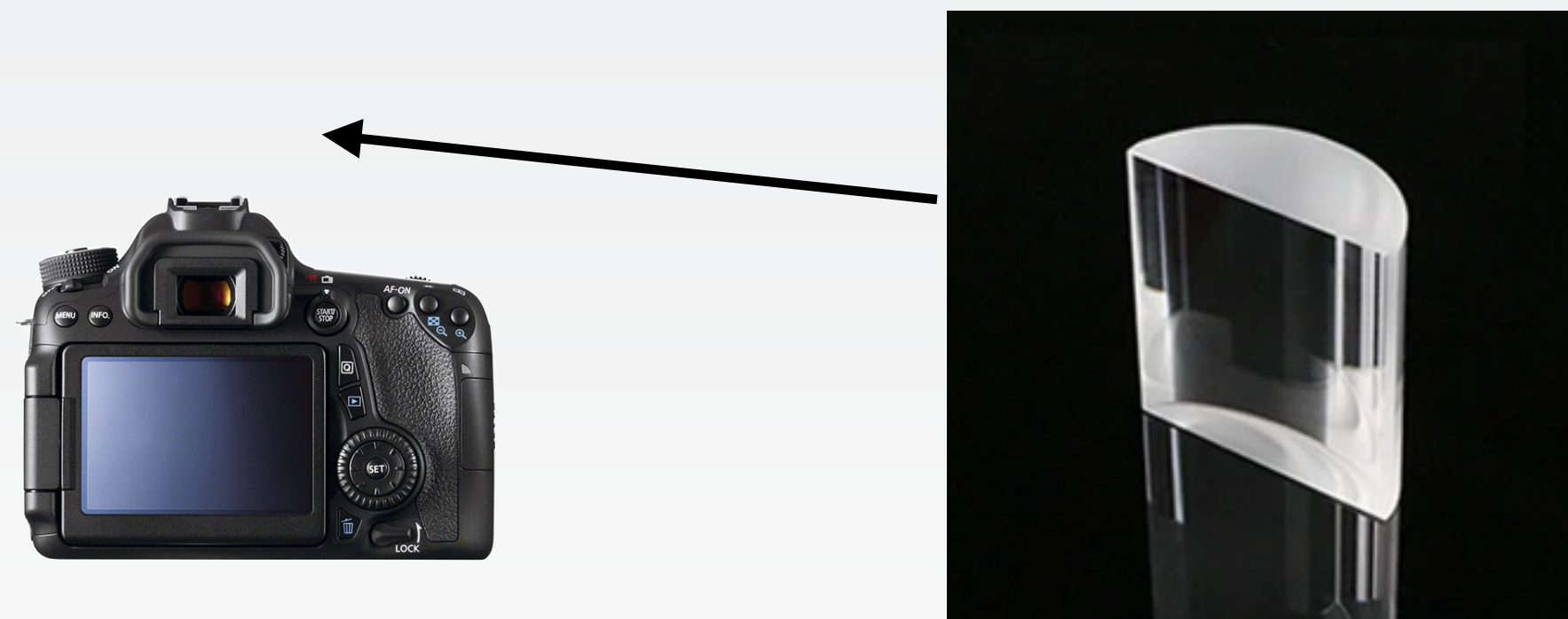
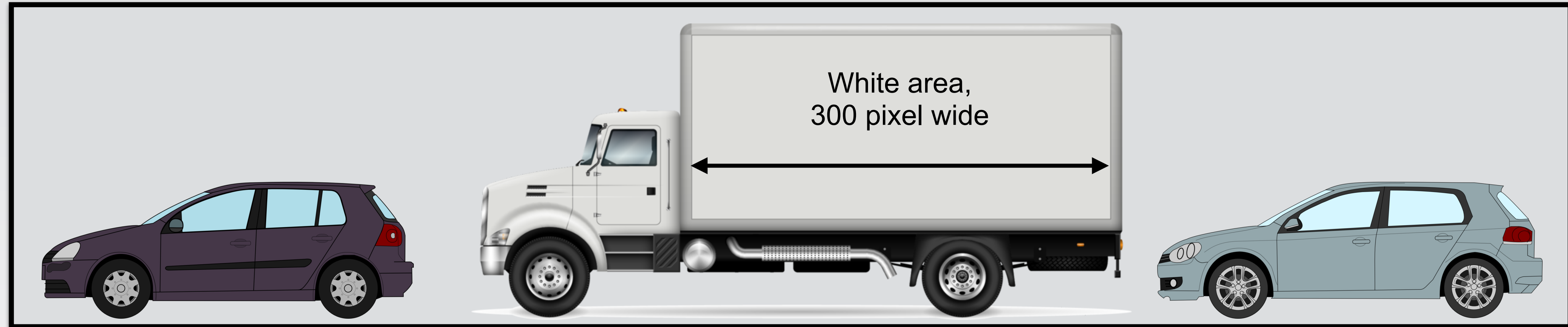
- Take a picture every hour
- Count trucks

Determine the Fraction of Trucks on the Road



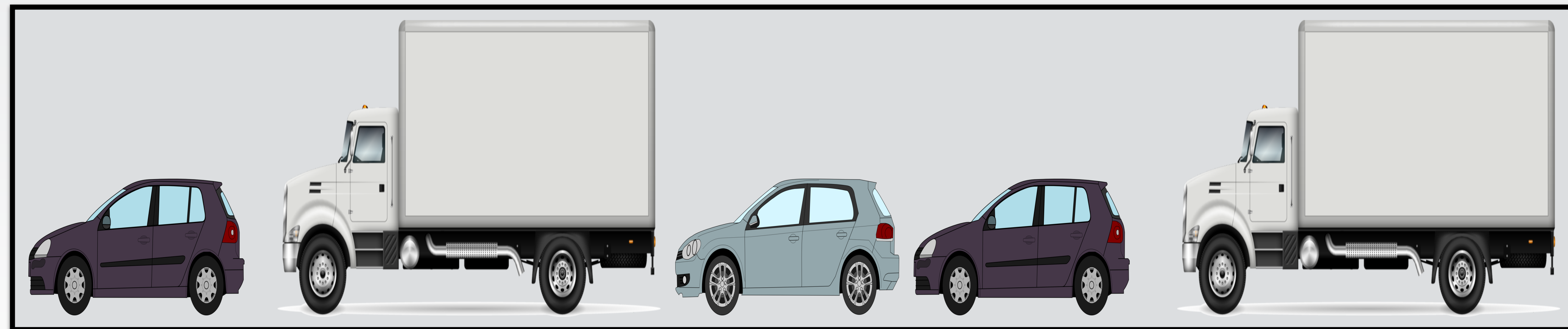
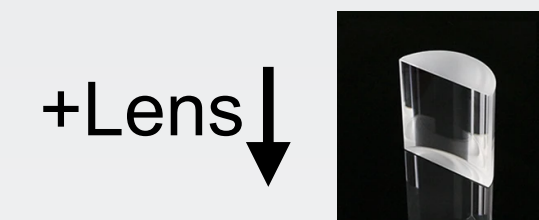
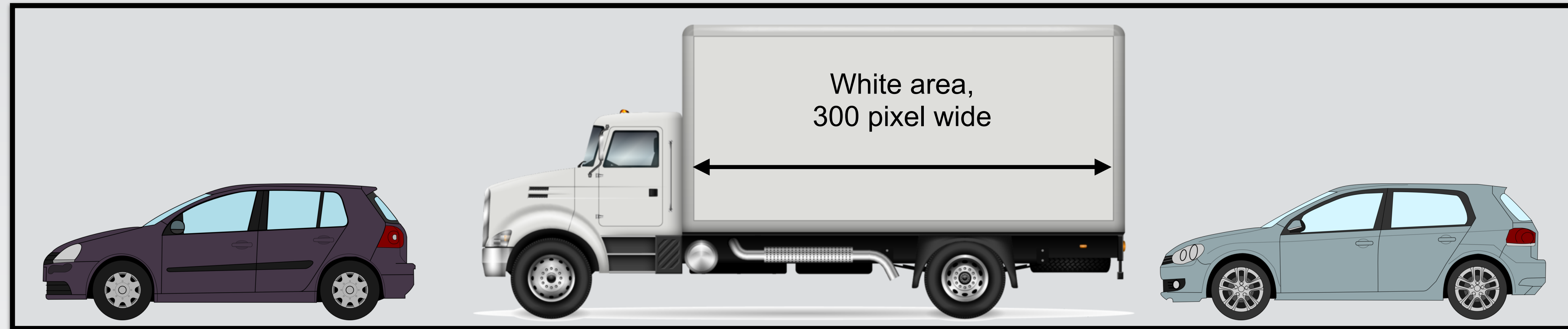
- Take a picture every hour
- Count trucks

Determine the Fraction of Trucks on the Road



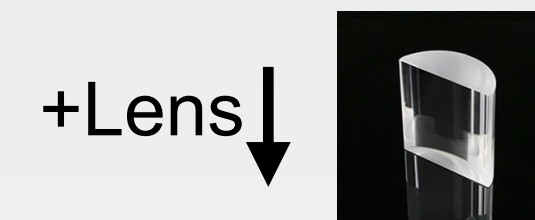
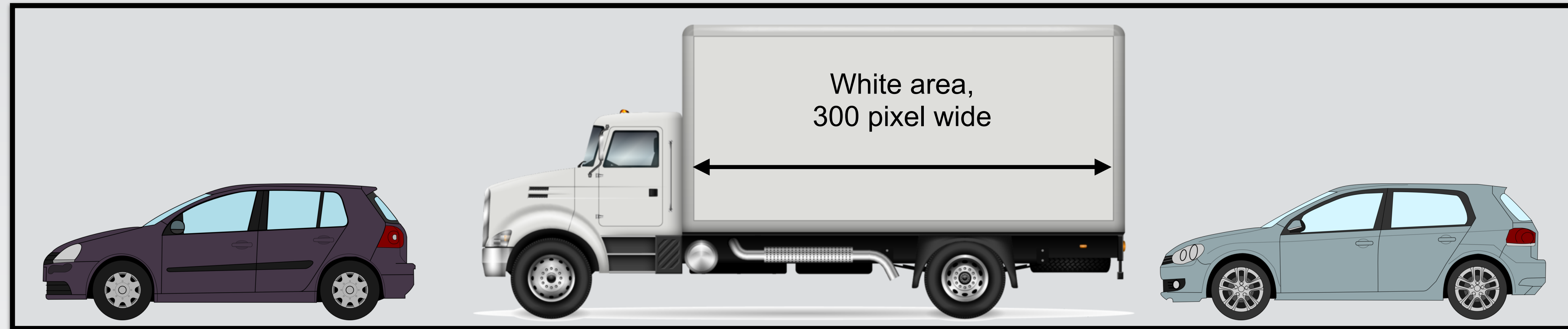
- Take a picture every hour
- Count trucks

The Algorithm is Crucial



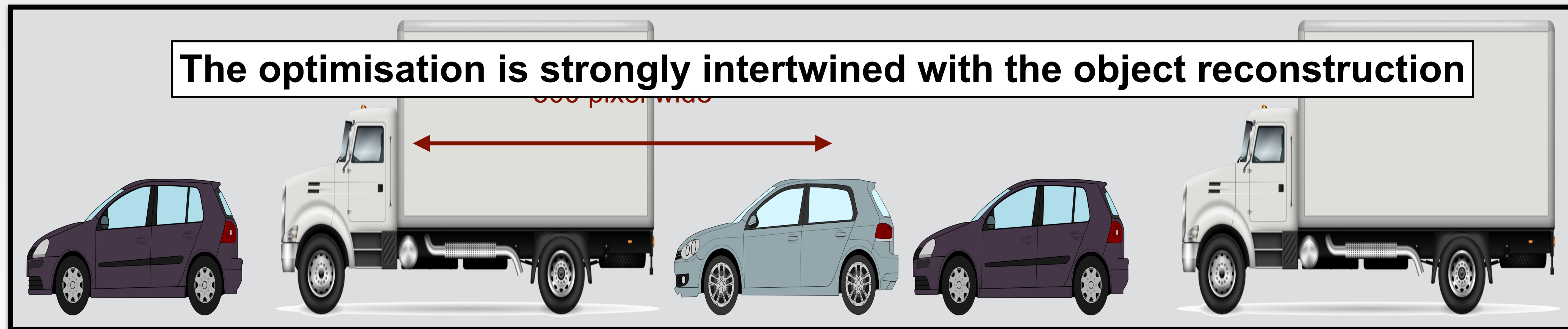
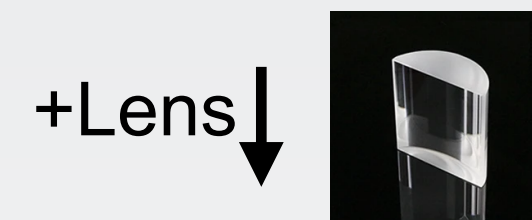
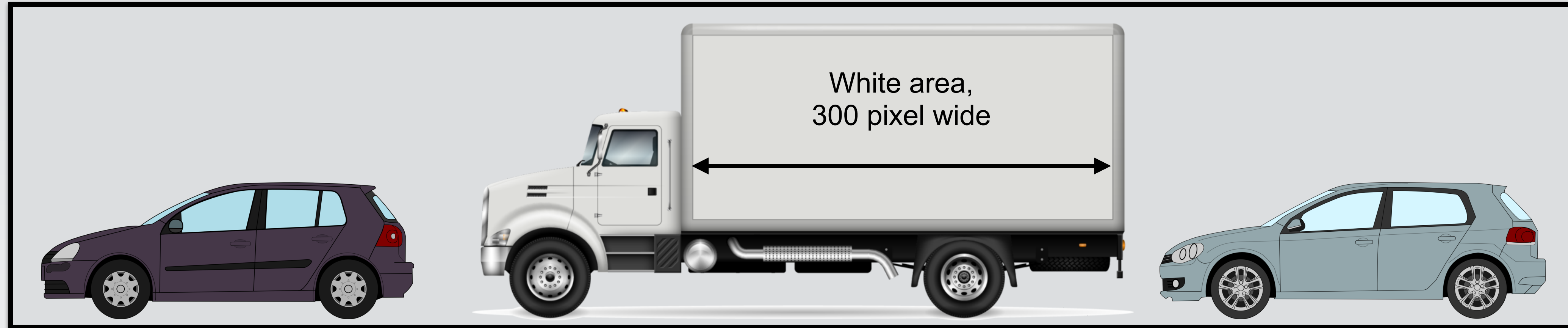
- Do we see more trucks?

The Algorithm is Crucial



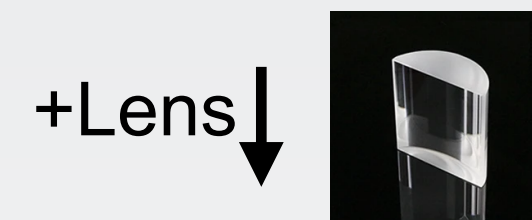
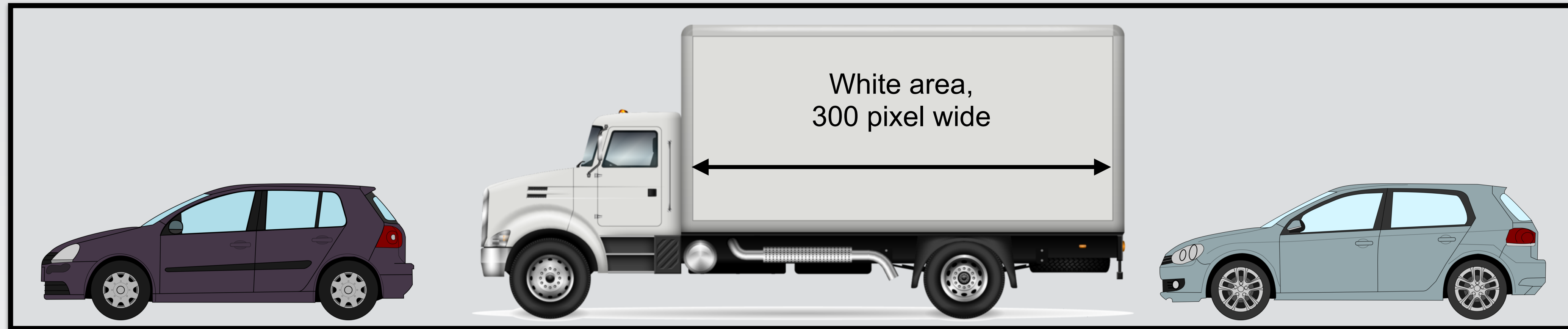
- Do we see more trucks? ➡ We see zero trucks!

The Algorithm is Crucial



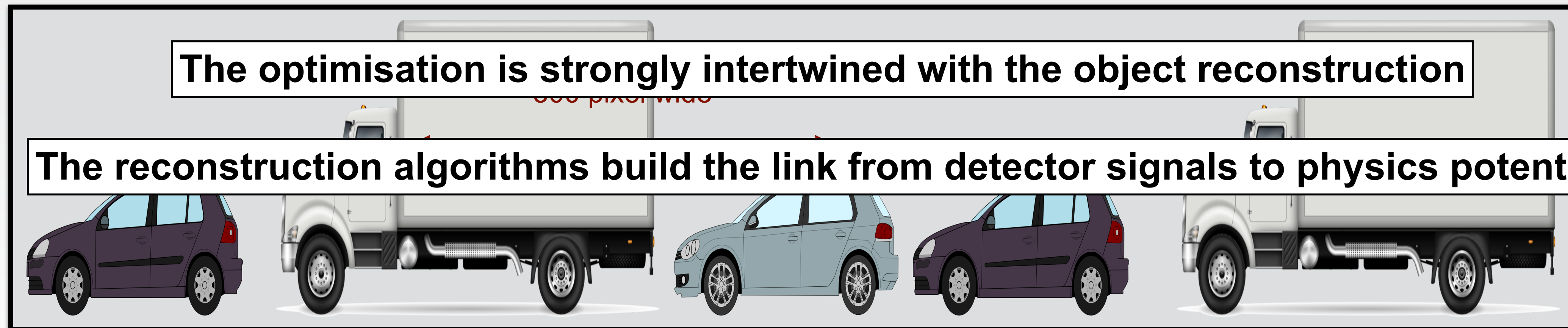
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The Algorithm is Crucial



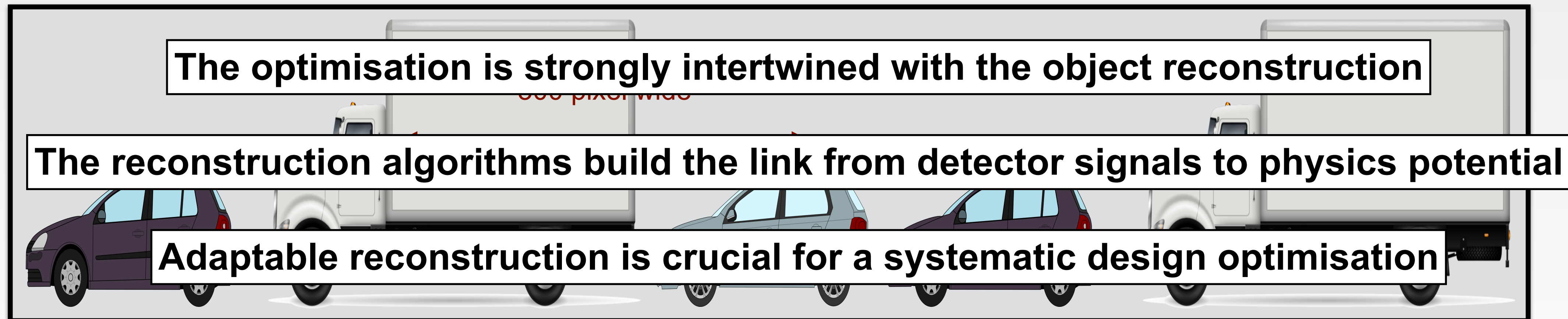
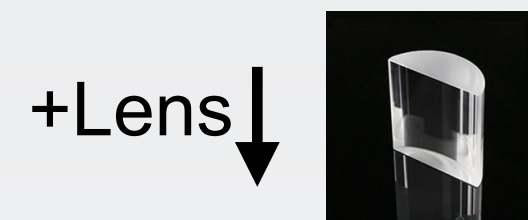
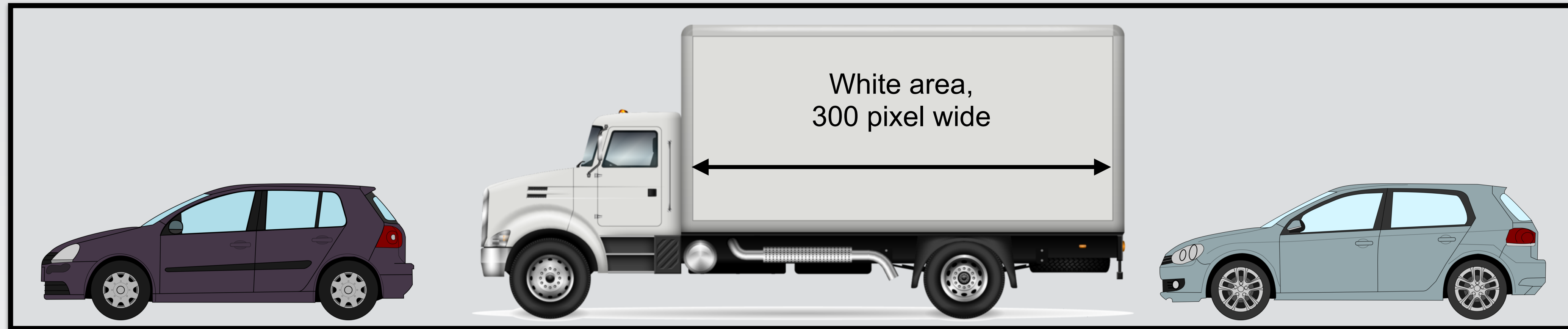
The optimisation is strongly intertwined with the object reconstruction

The reconstruction algorithms build the link from detector signals to physics potential



- Do we see more trucks? ➡ We see zero trucks!

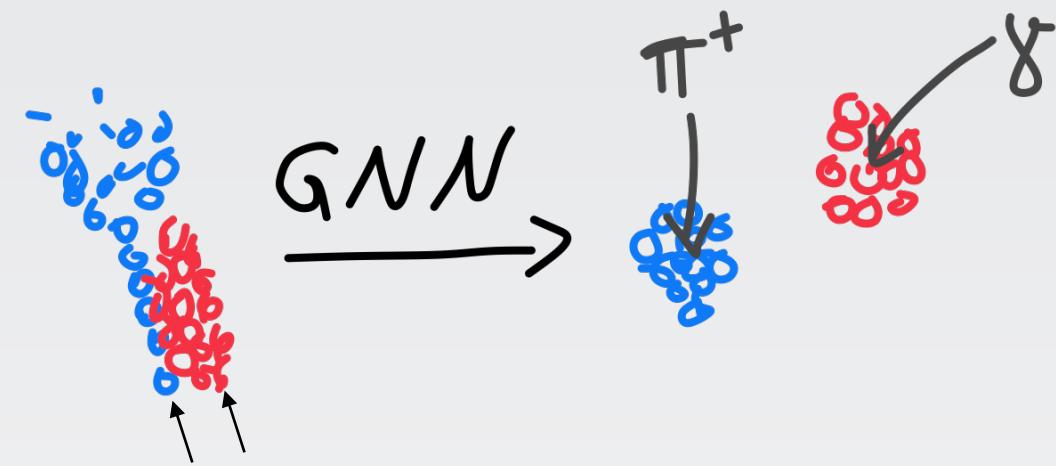
The Algorithm is Crucial



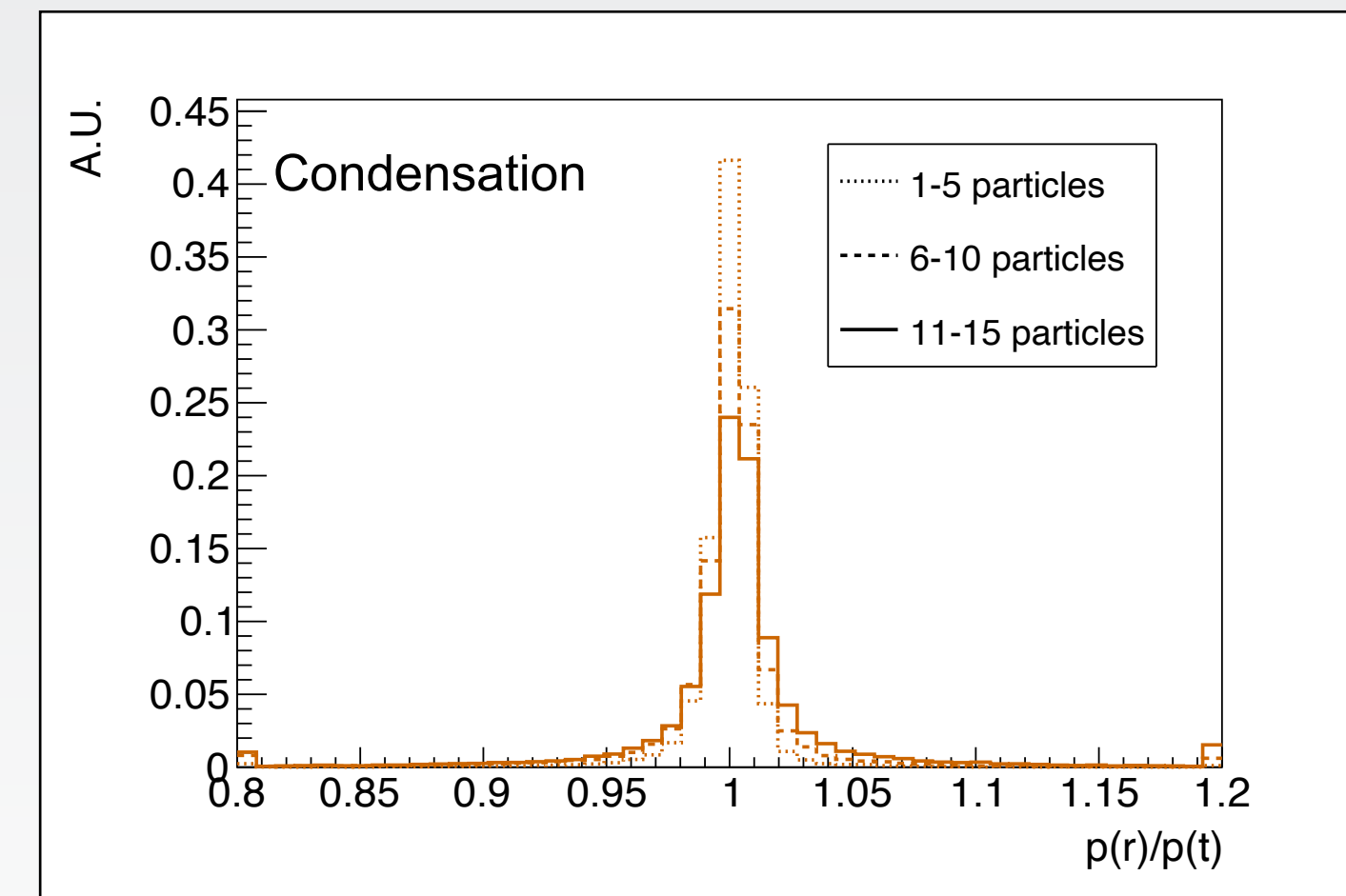
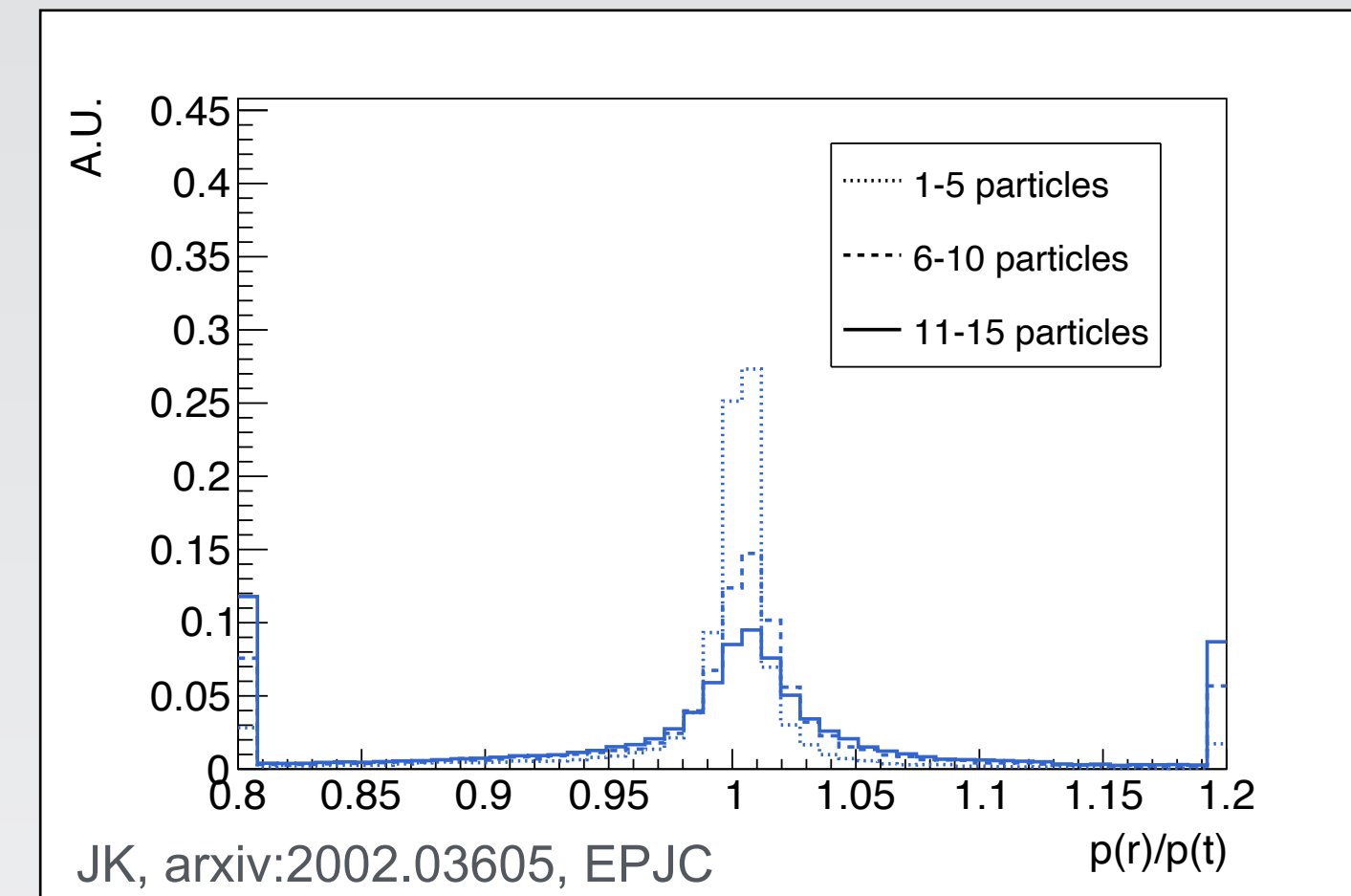
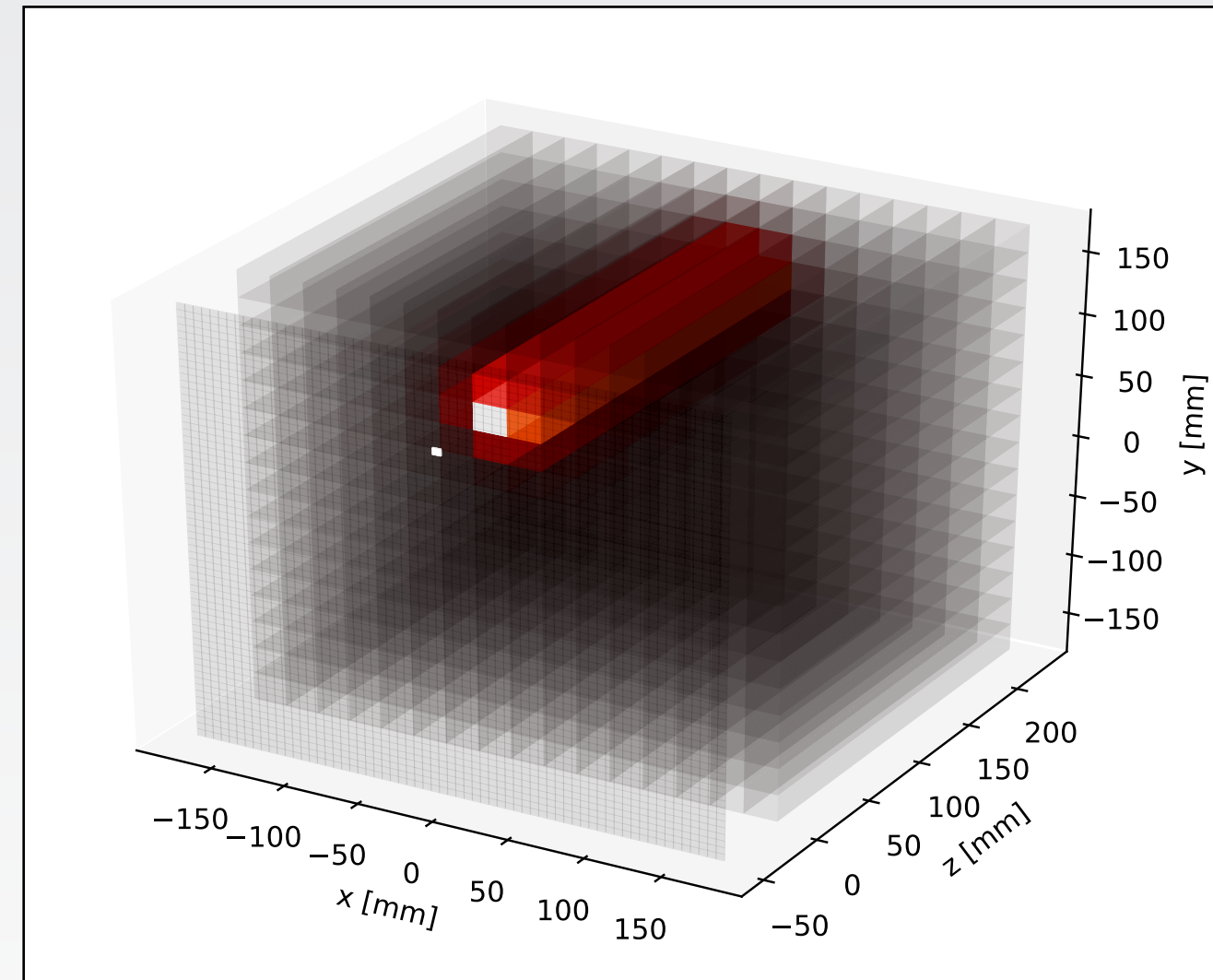
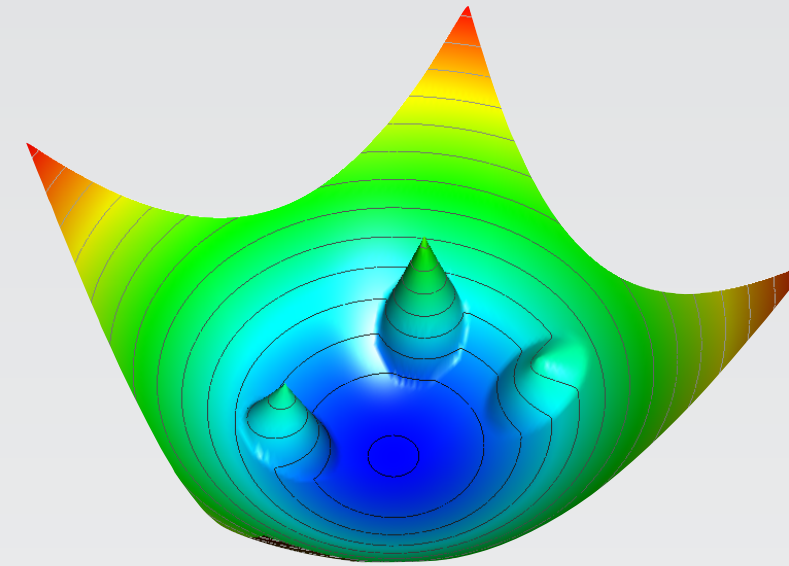
- Do we see more trucks? ➡ We see zero trucks!

Differentiable Hit-to-Particle Reconstruction

- GravNet and Object Condensation: hit-to-particle reconstruction

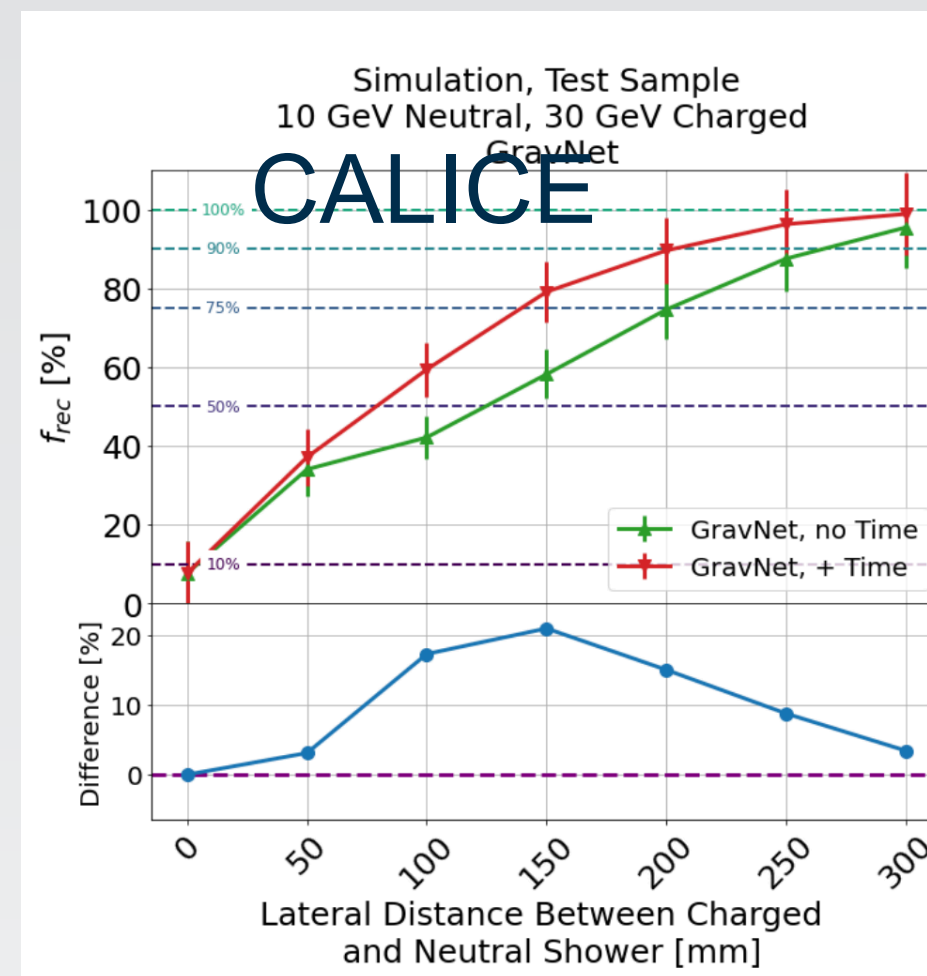
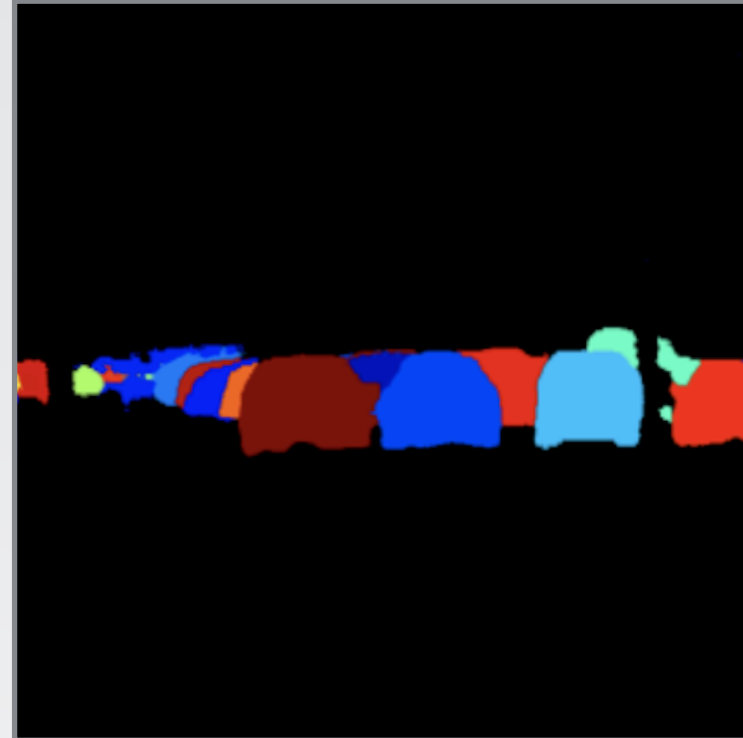


- Combine information from multiple detectors
- Proven to have good physics and computing performance
- Adapts to different detectors and geometries

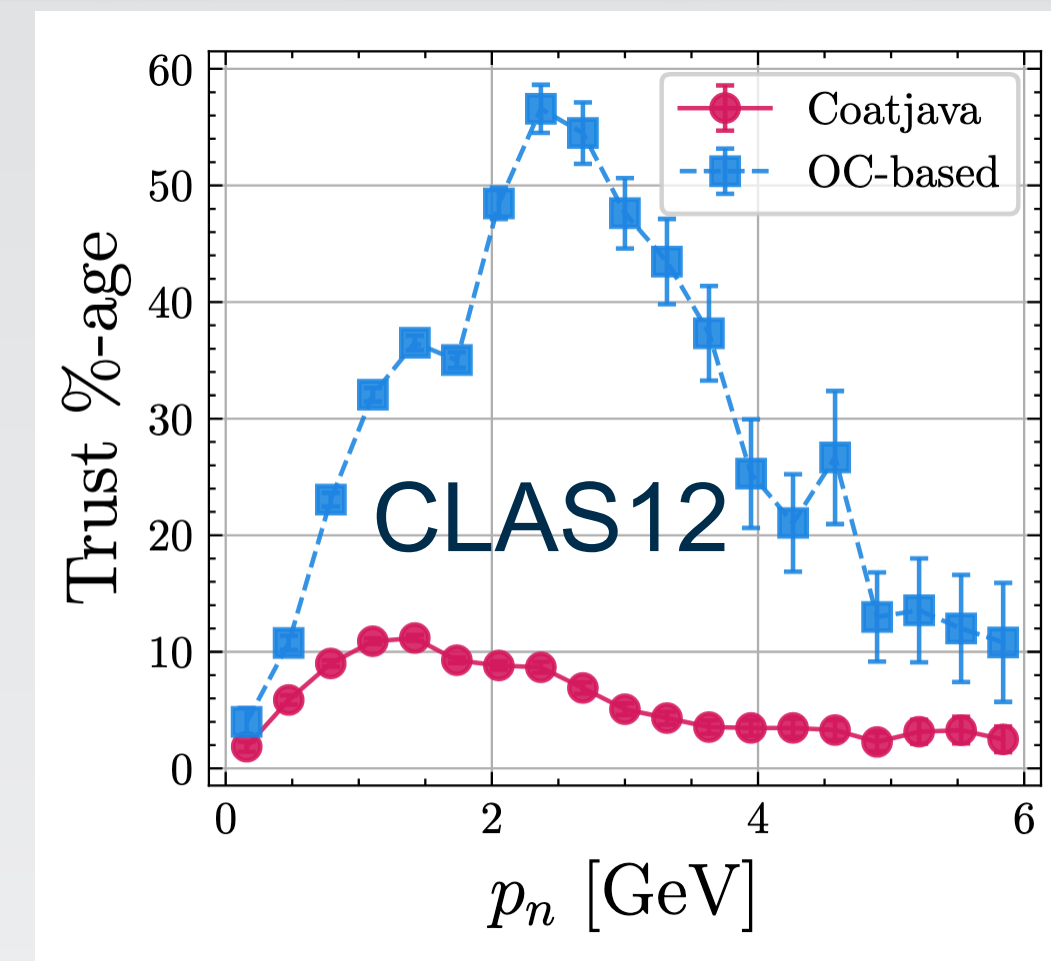


S.R. Qasim, J. K., Y. Iiyama, M Pierini, arXiv:1902.07987
JK, arxiv:2002.03605, EPJC
S.R. Qasim, N. Chern. J.K., arXiv:2204.01681,
S. Battarchaya, .., J.K., et al., arXiv:2203.01189,
S. Qasim, K. Long, J.K., et al., arXiv:2106.01832
I. Iiyama, .. J.K., et al, arXiv:2008.03601

https://pytorch-geometric.readthedocs.io/en/latest/modules/nn.html#torch_geometric.nn.conv.GravNetConv
https://github.com/cms-pepr/pytorch_cmspepr

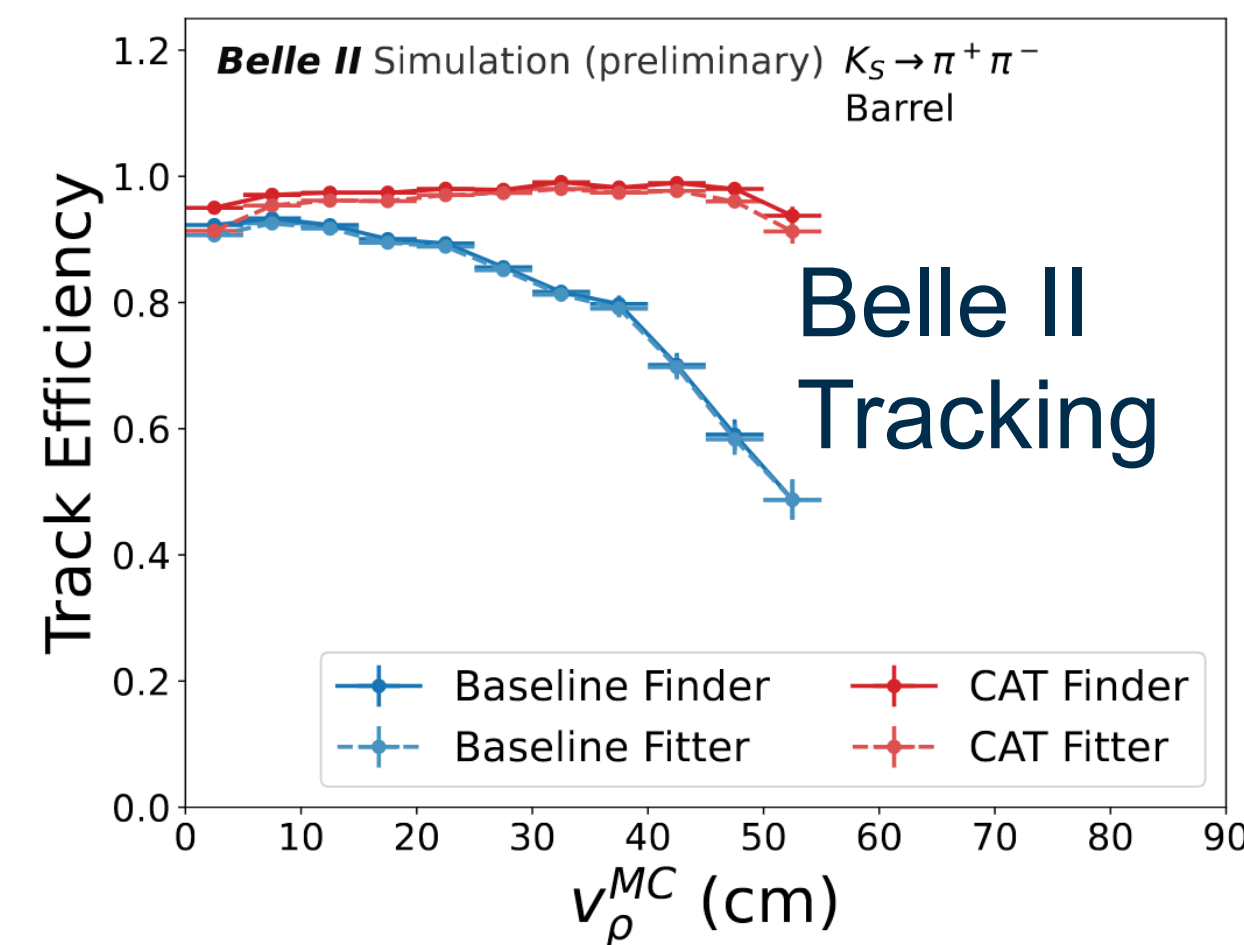
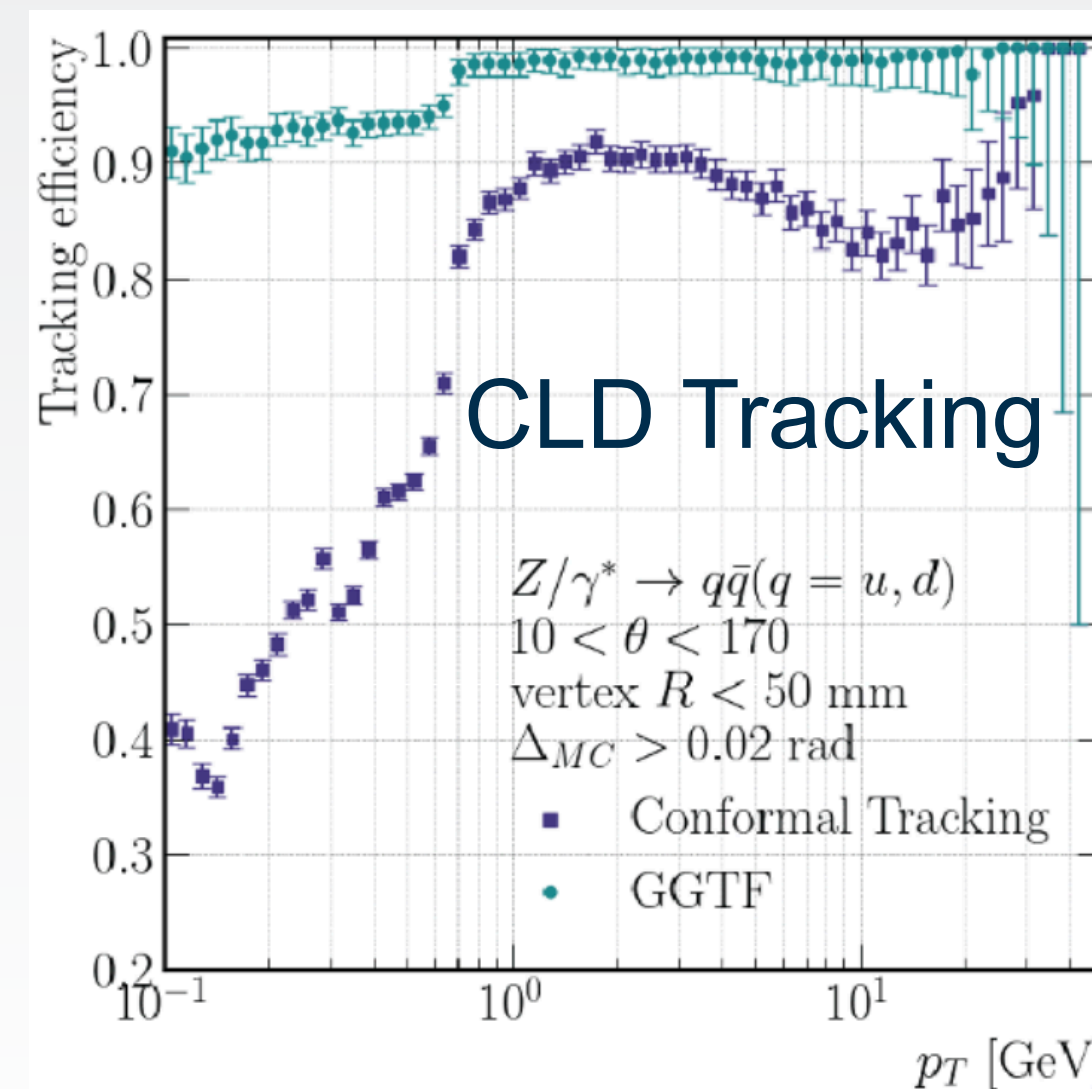
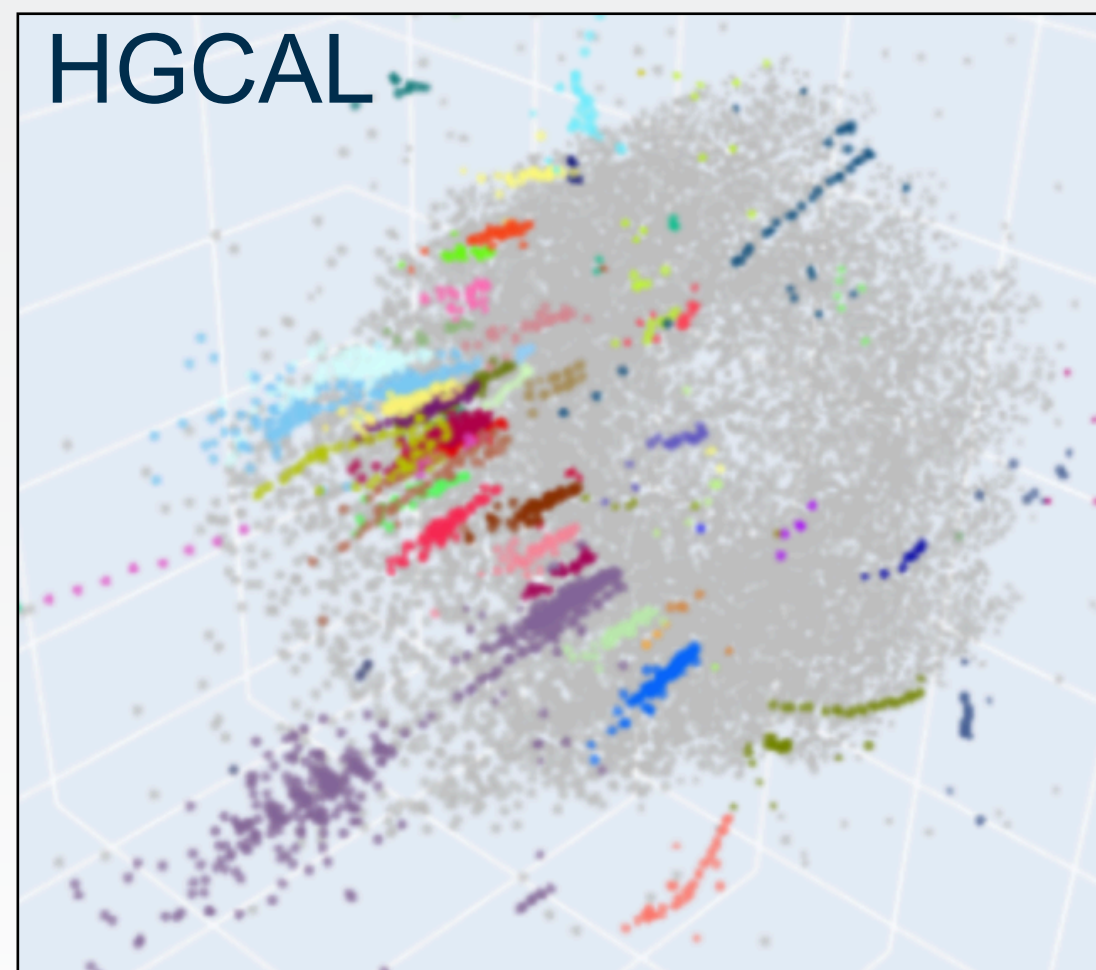


S. Lai, et al, arXiv:2407.00178



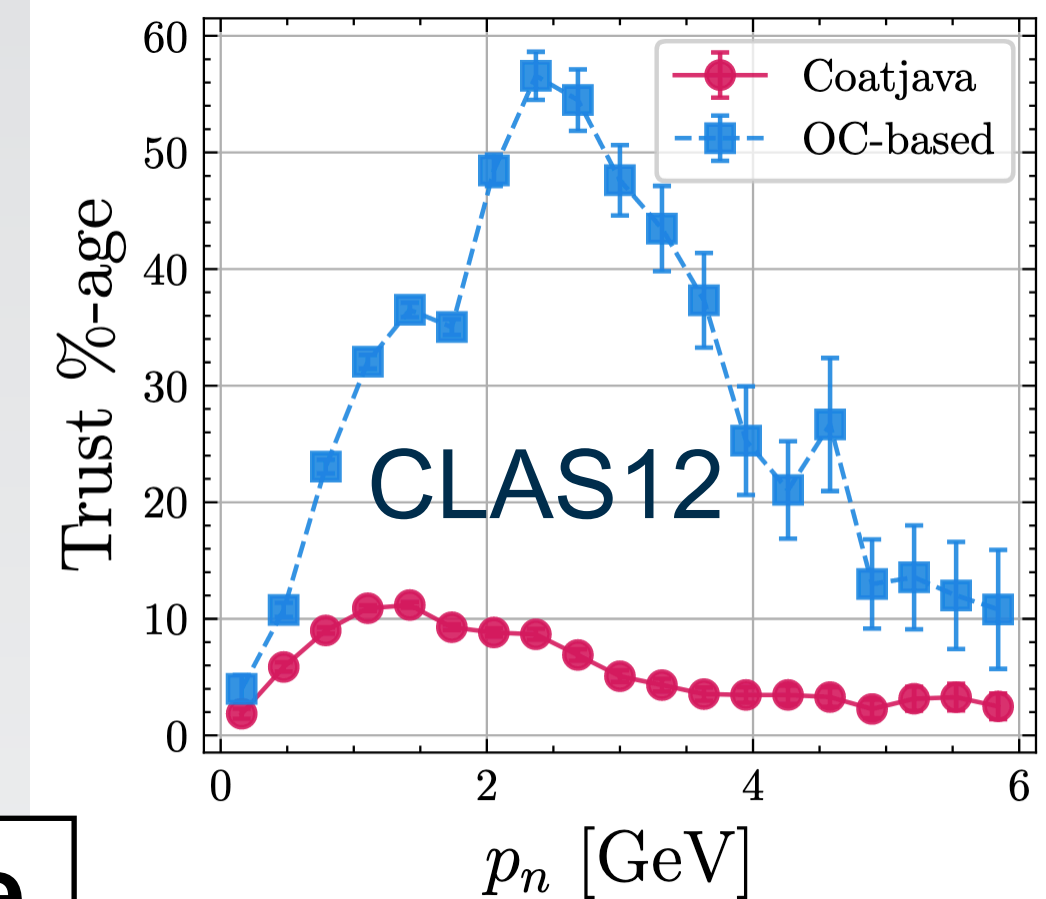
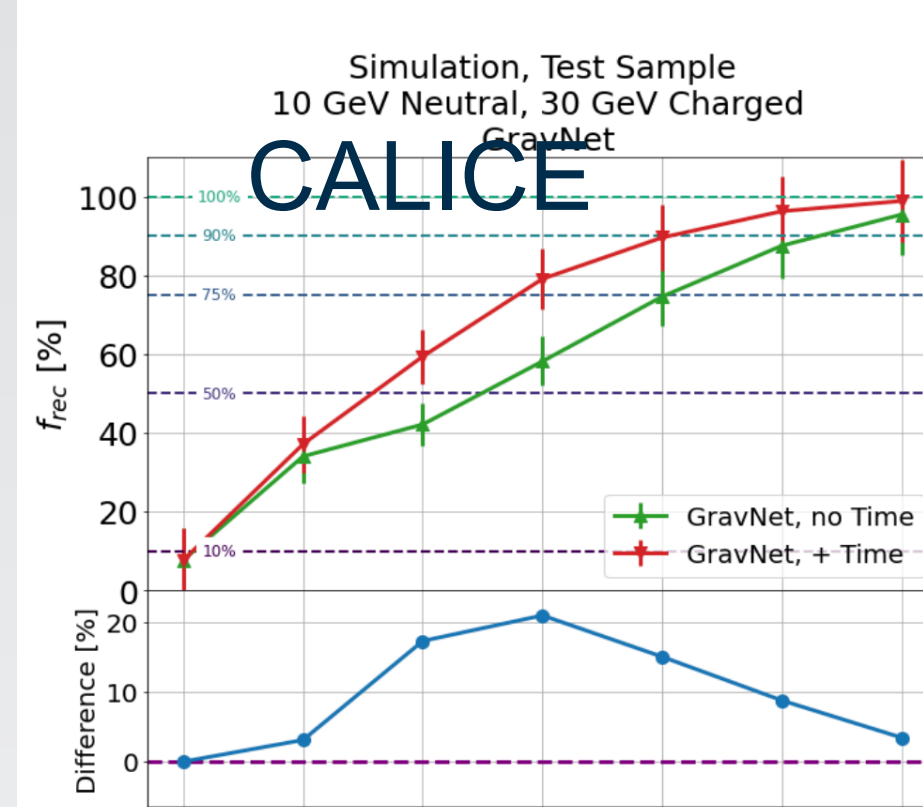
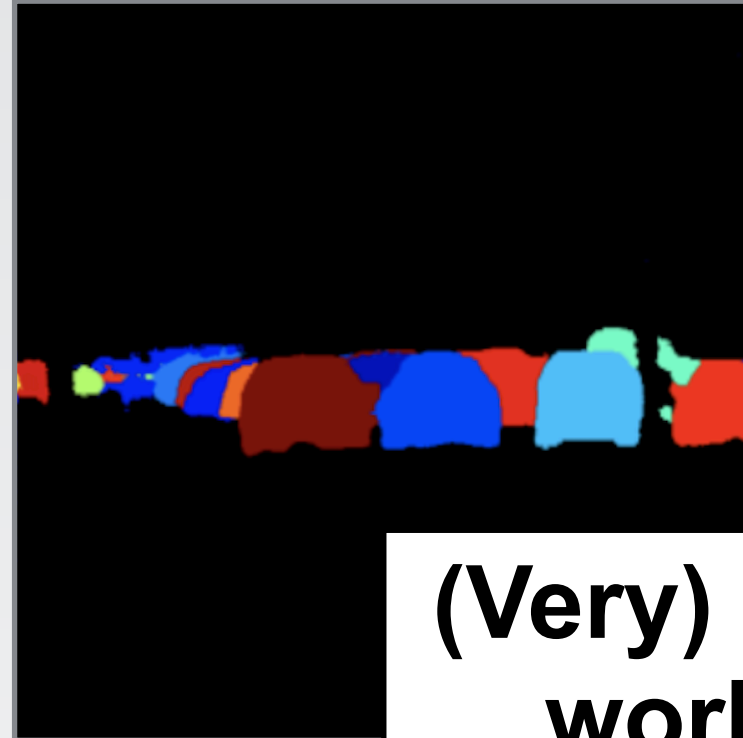
G. Matousek, V. Anselm, arxiv:2503.11277

CERN-CMS-DP-2022-004



(d) $K_S^0 \rightarrow \pi^+ \pi^-$, v_ρ^{MC} .

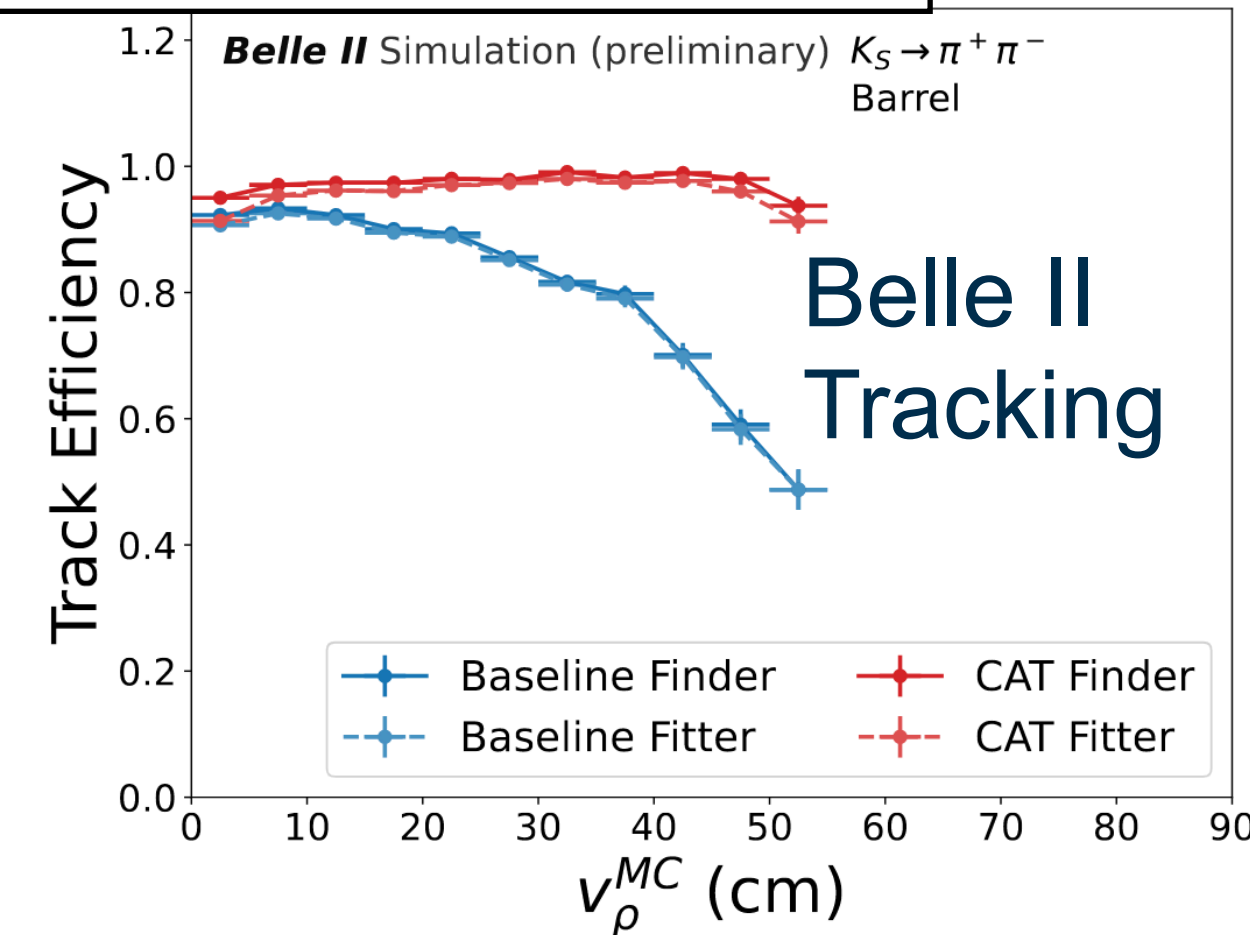
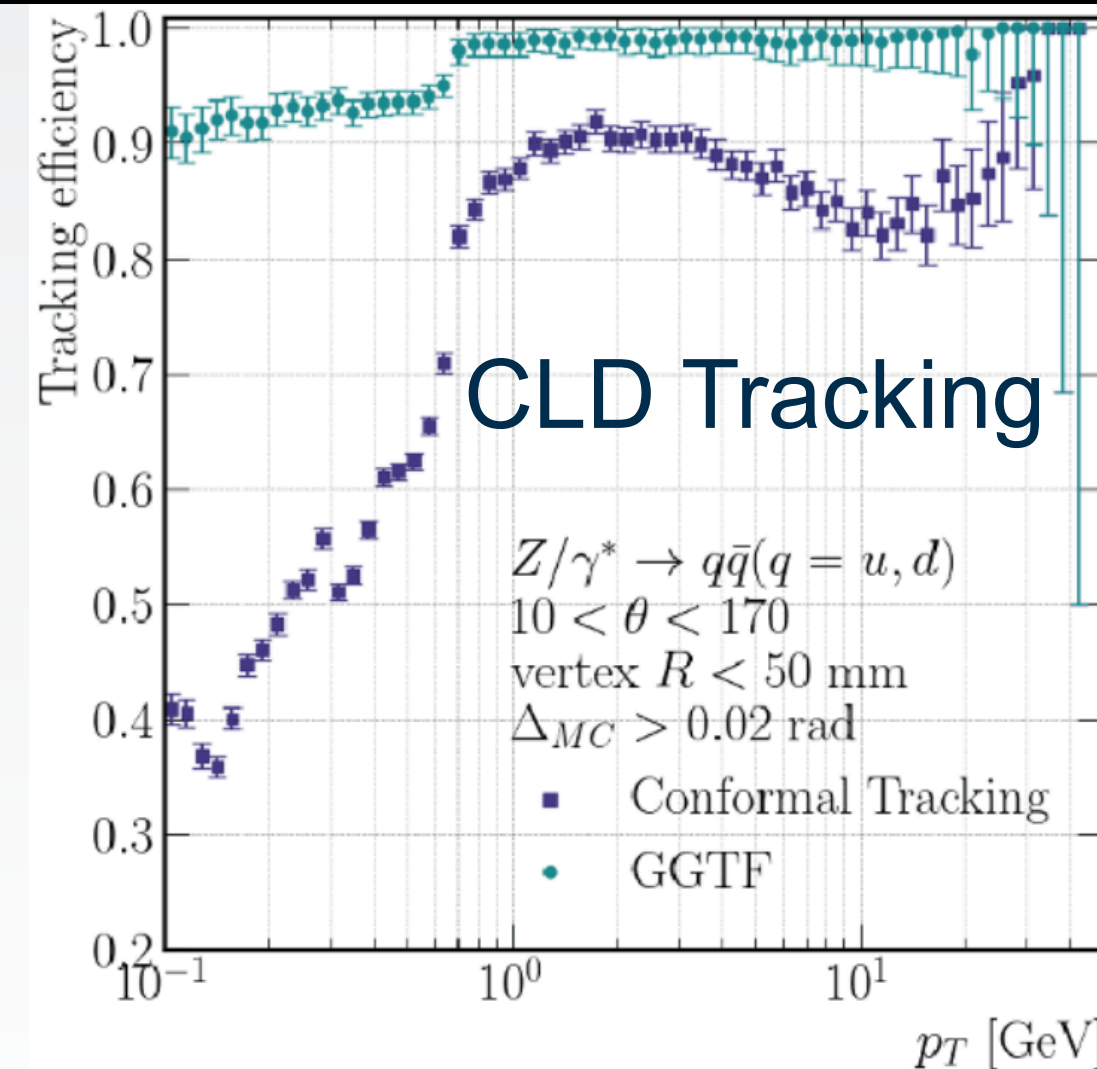
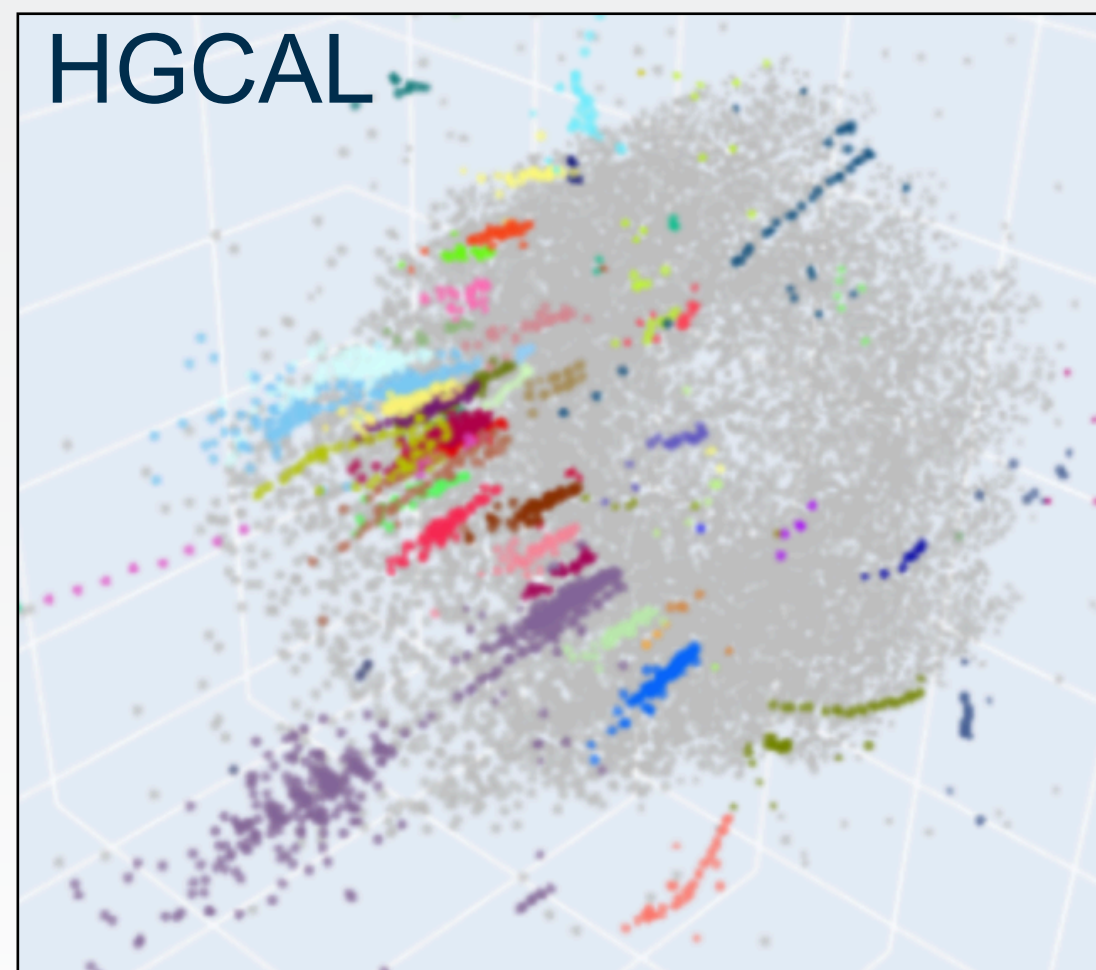
S.R. Qasim, J. K., Y. Iiyama, M. Pierini, arXiv:1902.07987
JK, arxiv:2002.03605, EPJC
S.R. Qasim, N. Chern. J.K., arXiv:2204.01681,
S. Battarchaya, .., J.K., et al., arXiv:2203.01189,
S. Qasim, K. Long, J.K., et al., arXiv:2106.01832
I. Iiyama, .. J.K., et al, arXiv:2008.03601



(Very) adaptive reconstruction algorithms are working and are actively being improved (and generalised)

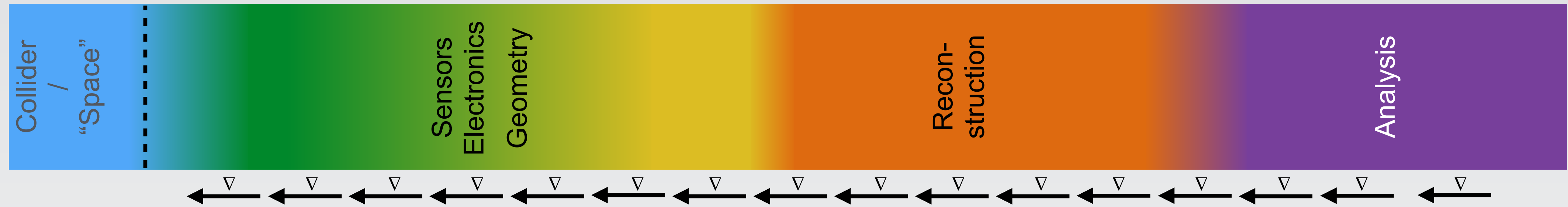
atousek, V. Anselm, arxiv:2503.11277
11.13596, PRD

CERN-CMS-DP-2022-004



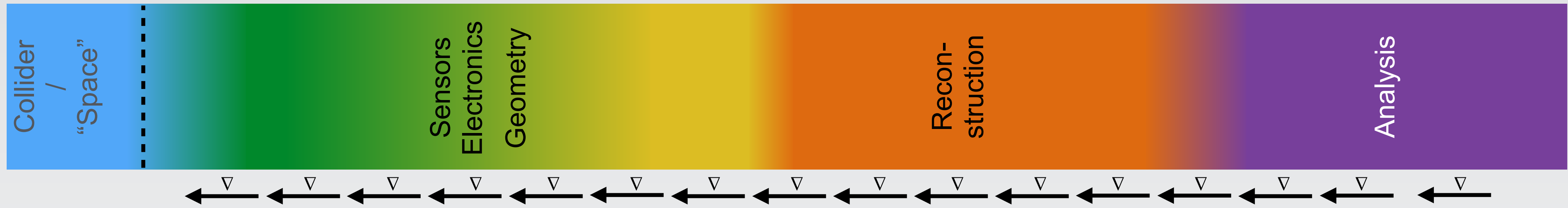
(d) $K_S^0 \rightarrow \pi^+ \pi^-$, v_ρ^{MC} .

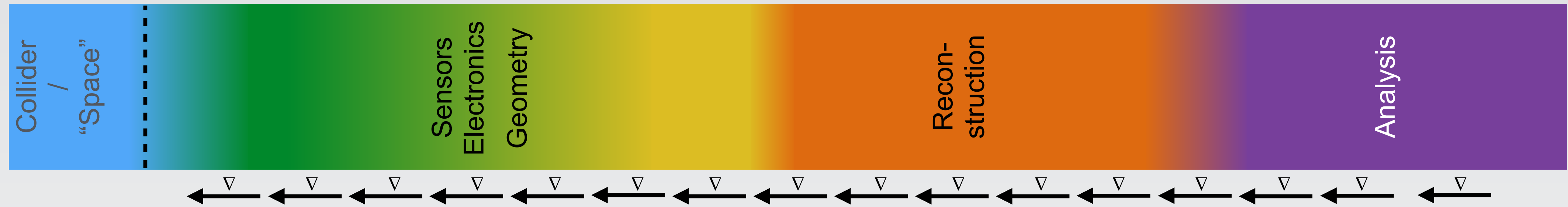
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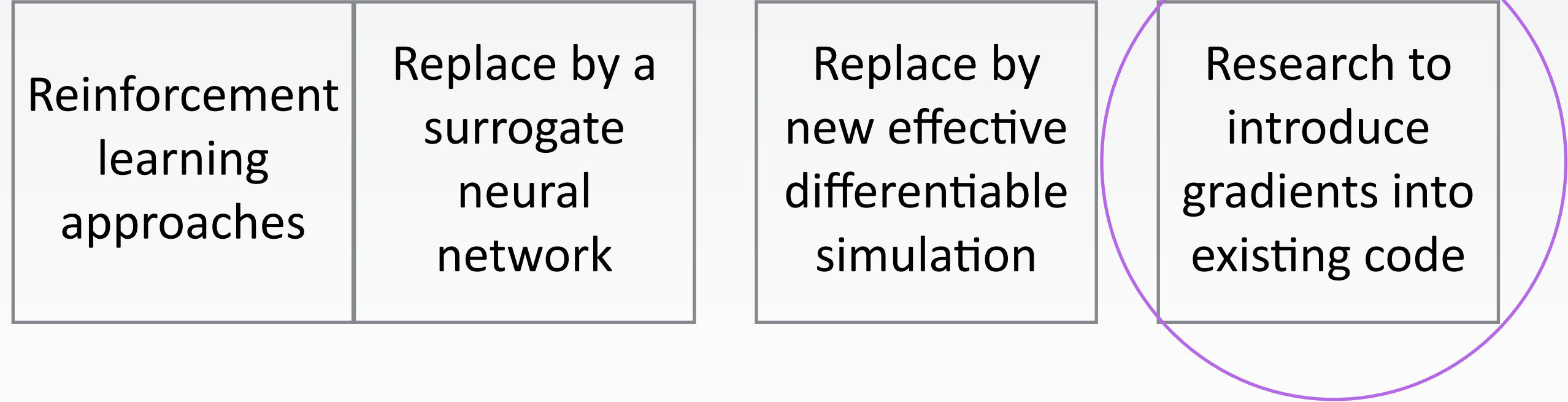
works

- [1] P. Castro, T. Dorigo, arxiv:1806.04743v2
- [2] S. Wunsch, et al., arXiv:2003.07186
- [3] N. Simpson, L. Heinrich, arXiv:2203.05570
- [4] CMS-PAS-MLG-23-005
- general: K. Cranmer, et el., arXiv:1911.01429





Simulation is not differentiable



ML ✓



ML ✓

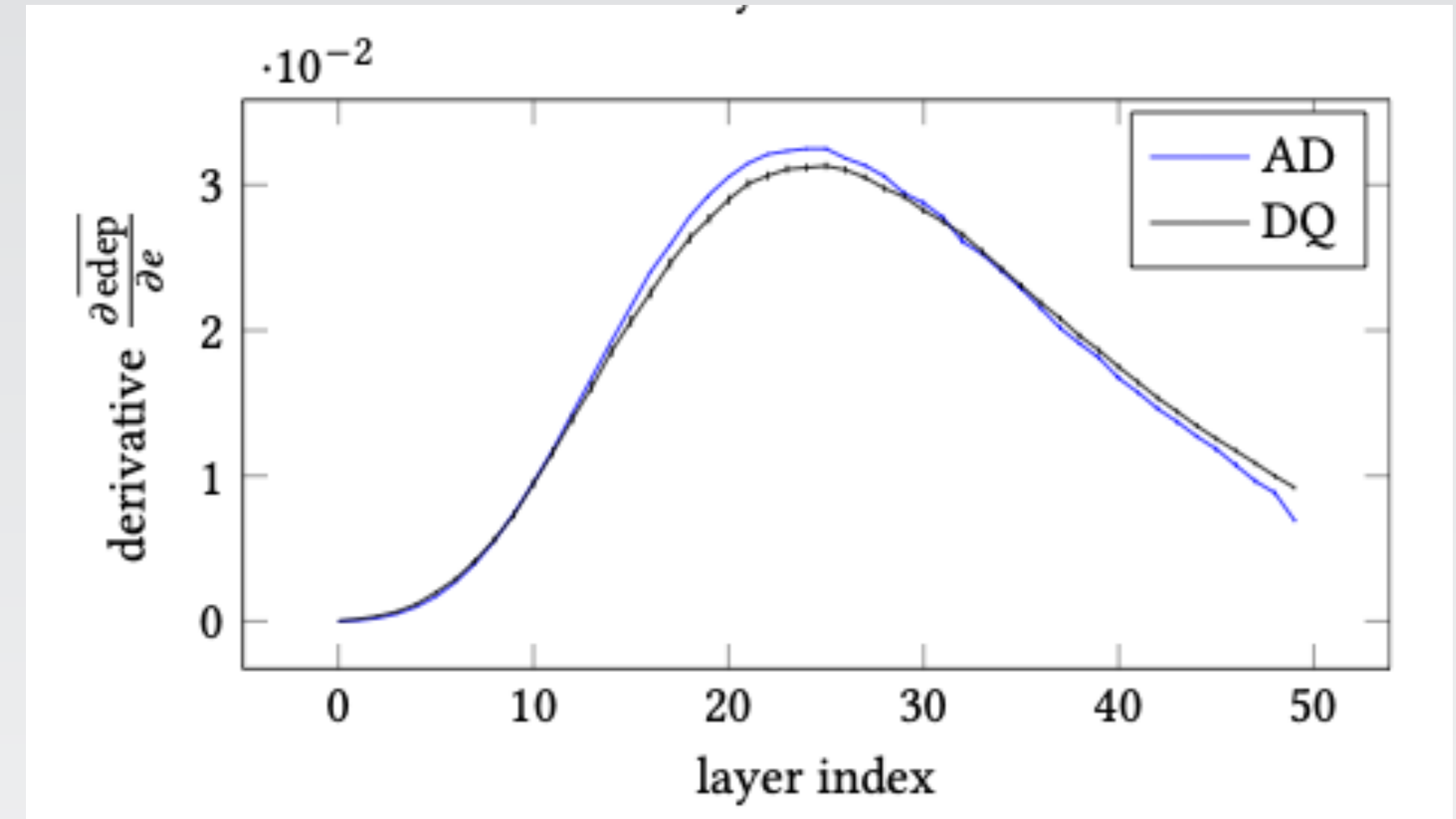
Gradients in Geant4



$$c = a + b$$

$$g = \boxed{c \cdot w}$$

$$\frac{dg}{da} = \frac{dg}{dc} \cdot \frac{dc}{da}$$



- Yet, on average gradients can be calculated using operator overloading tools without rewriting 1M lines of code [1]
- Sometimes additional tweaks are needed
- Even MCS tackled now [2]
- Cannot differentiate step functions by construction

```
if(p > 0.5):  
    ... do_something()
```

[1] arXiv:2405.07944

[2] <https://indico.cern.ch/event/1481852/timetable/?view=standard#105-differentiable-geant4-inco>

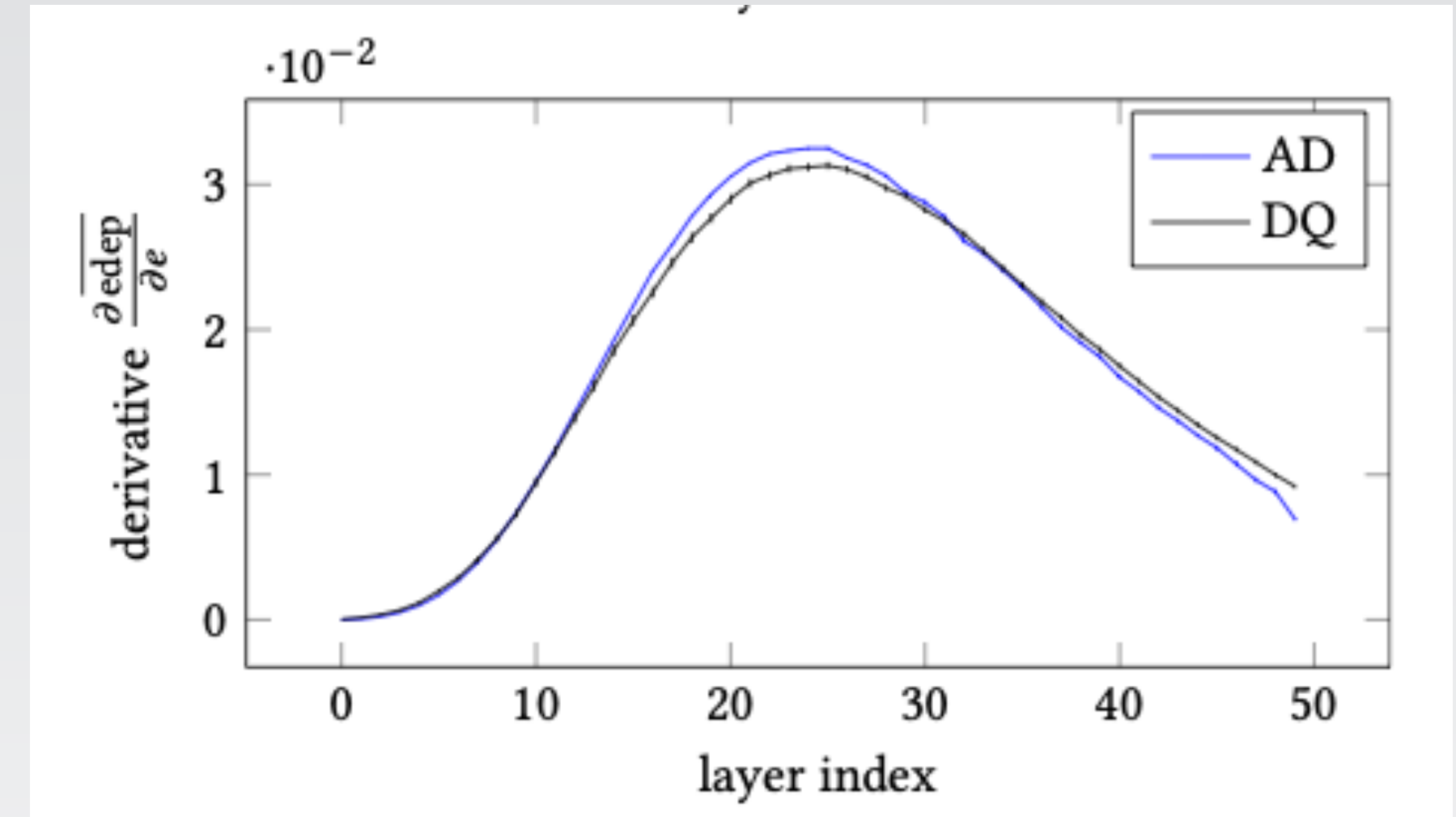
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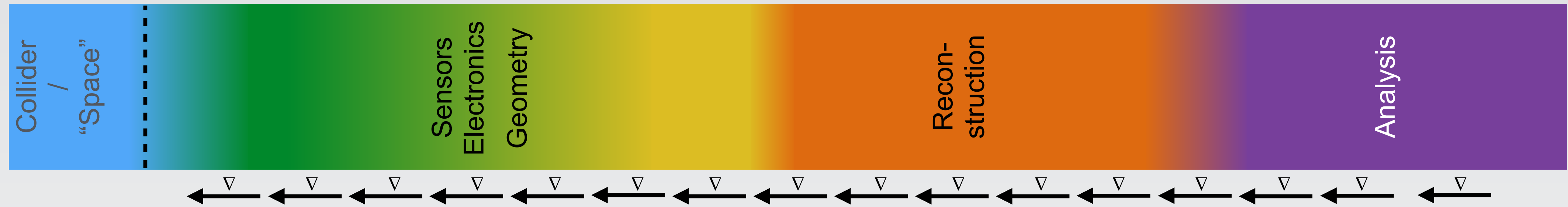


- Yet, on average gradients can be calculated using operator overloading tools without rewriting 1M lines of code [1]
- Sometimes additional tweaks are needed
- Even MCS tackled now [2]
- Cannot differentiate step functions by construction

Even programs that are not differentiable can be made differentiable without rewriting their code

[1] arXiv:2405.07944

[2] <https://indico.cern.ch/event/1481852/timetable/?view=standard#105-differentiable-geant4-inco>



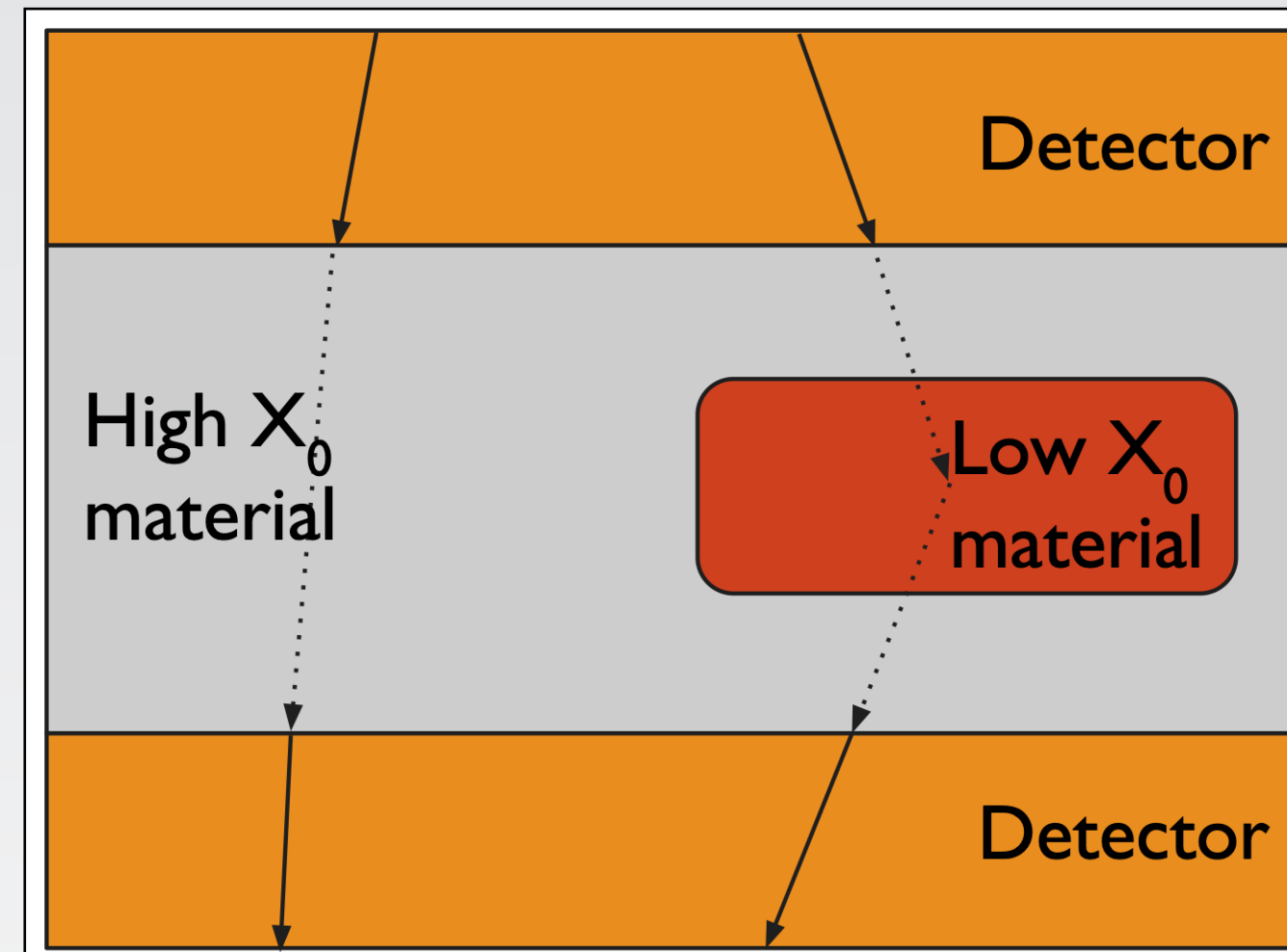
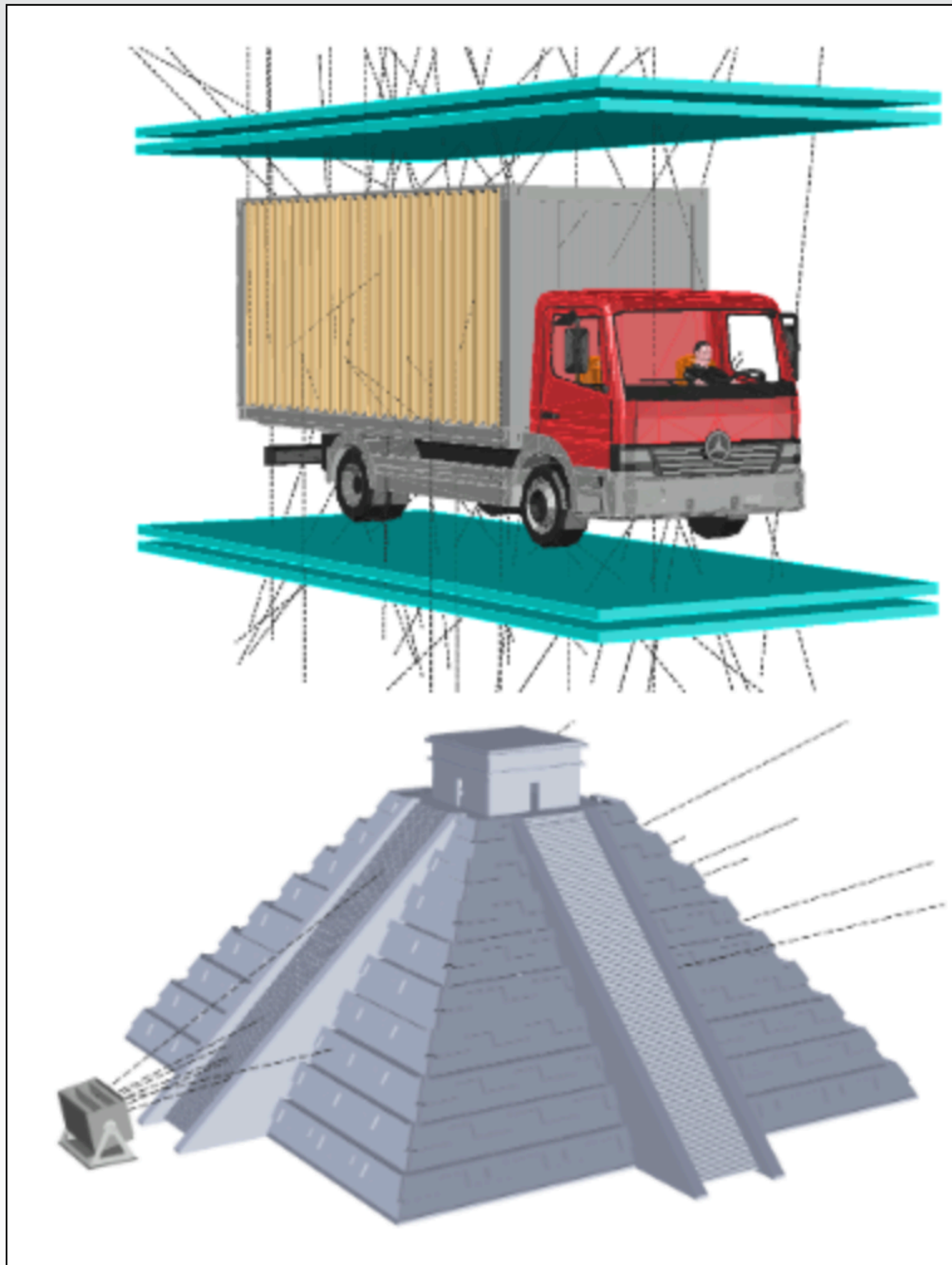
Simulation is not differentiable

- Reinforcement learning approaches
- Replace by a surrogate neural network
- Replace by new effective differentiable simulation
- Research to introduce gradients into existing code



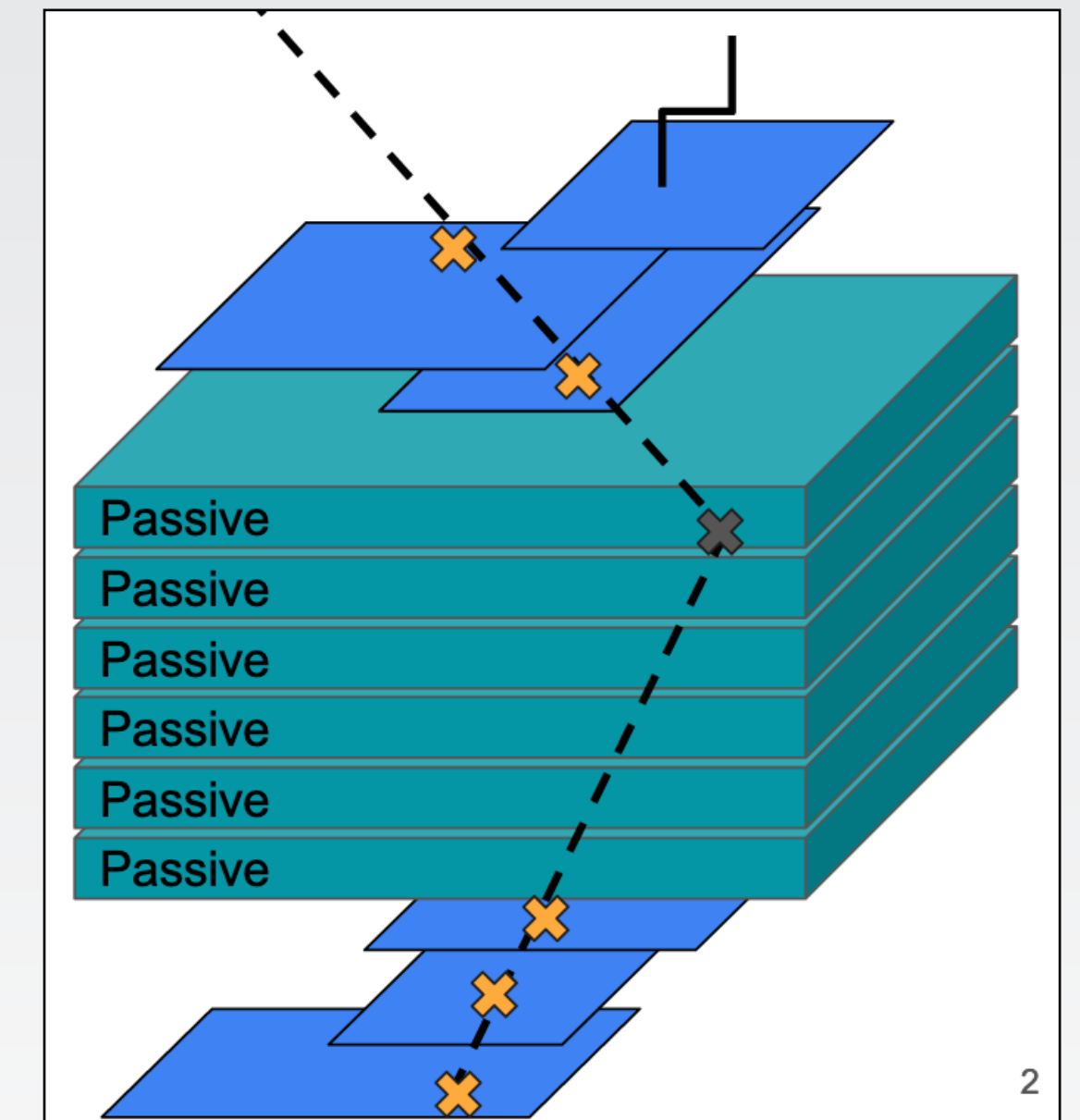
Writing a Differentiable Simulator: TOMOPT

L. Bonechi, R. D'Alessandro, A. Giammanco
arXiv:1906.03934



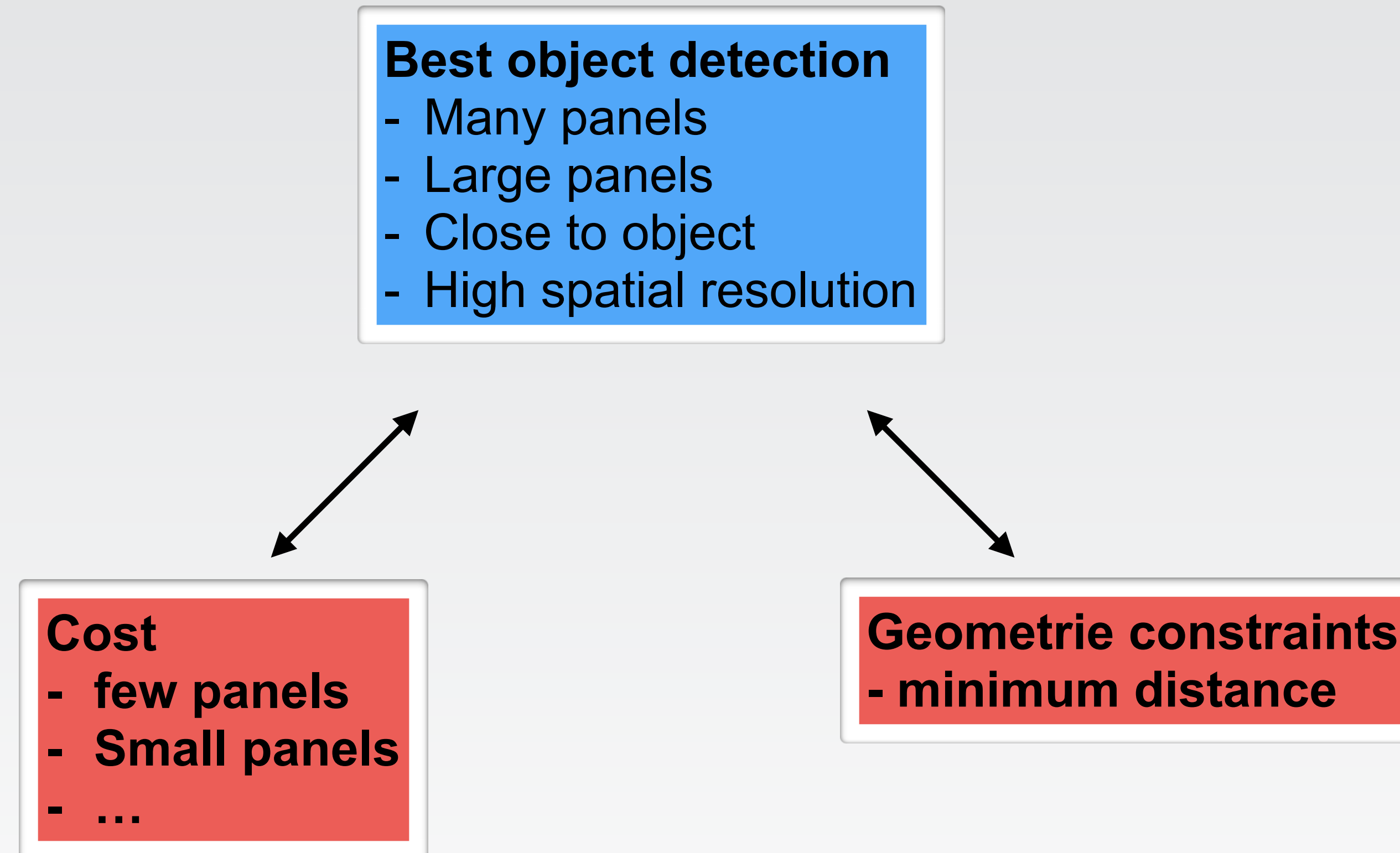
$$X_0 = \frac{A}{4\pi N_A Z^2 r_e^2 \ln \frac{183}{Z^{1/3}}}$$

- Problem can be simplified enough for a dedicated simulator
- Lessons learned can serve as a starting point for more complex detectors



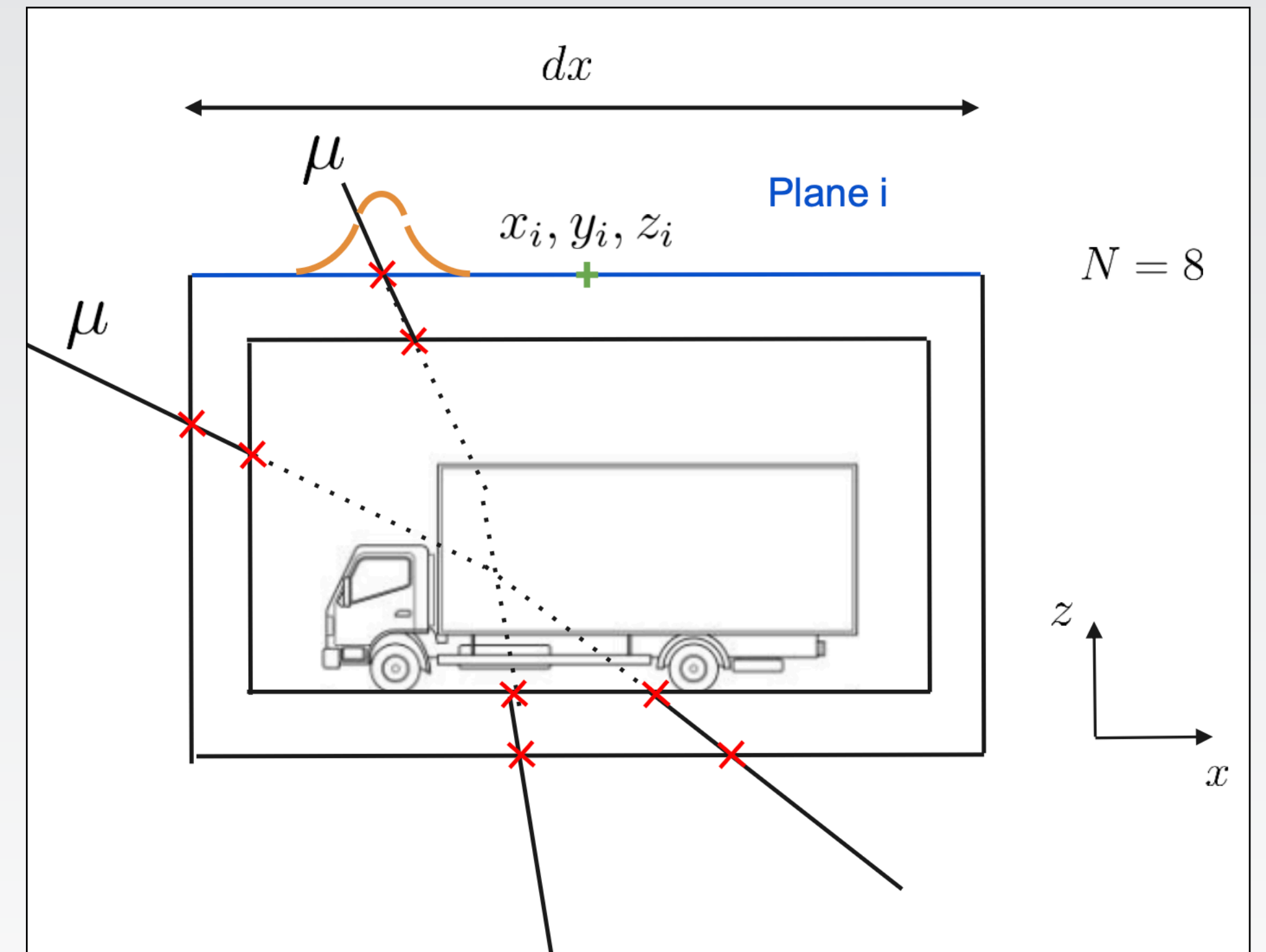
G. Strong, et al., arxiv:2309.14027

The Main Competitors



How to write a Differentiable Simulator

- Define detector parameters
 - Number of detection planes
 - Placements
 - Dimensions
 - Effective spatial resolution
 - Effective efficiency
 - Cost
- Implement the physics
- Provide differentiable reconstruction



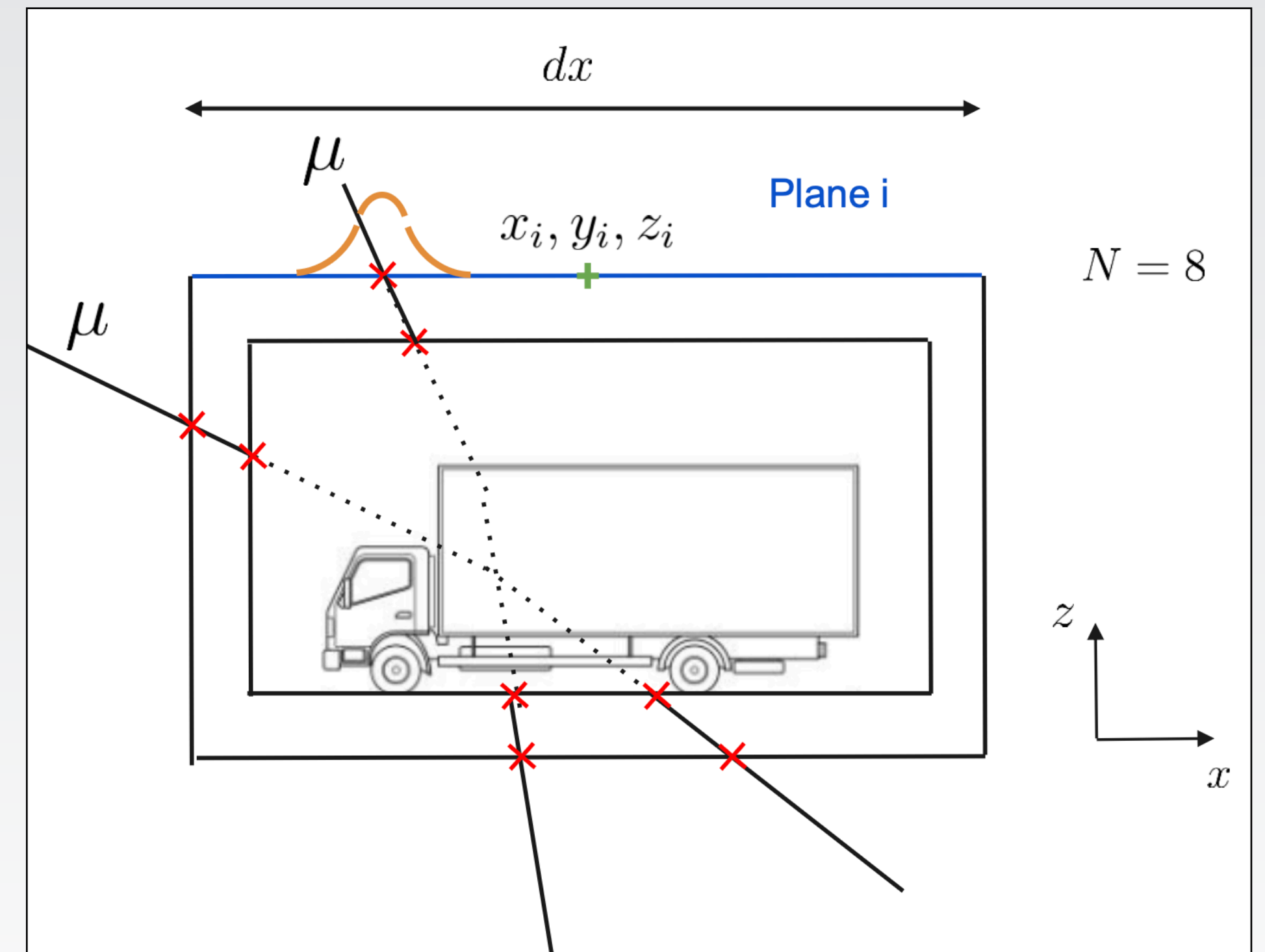
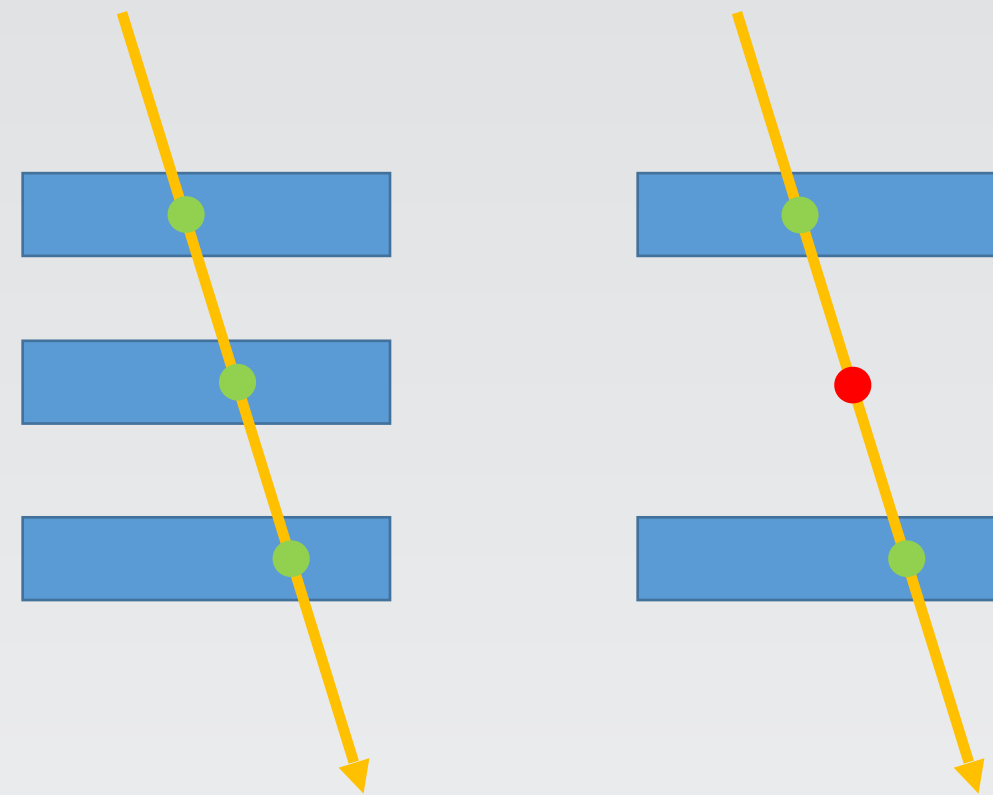
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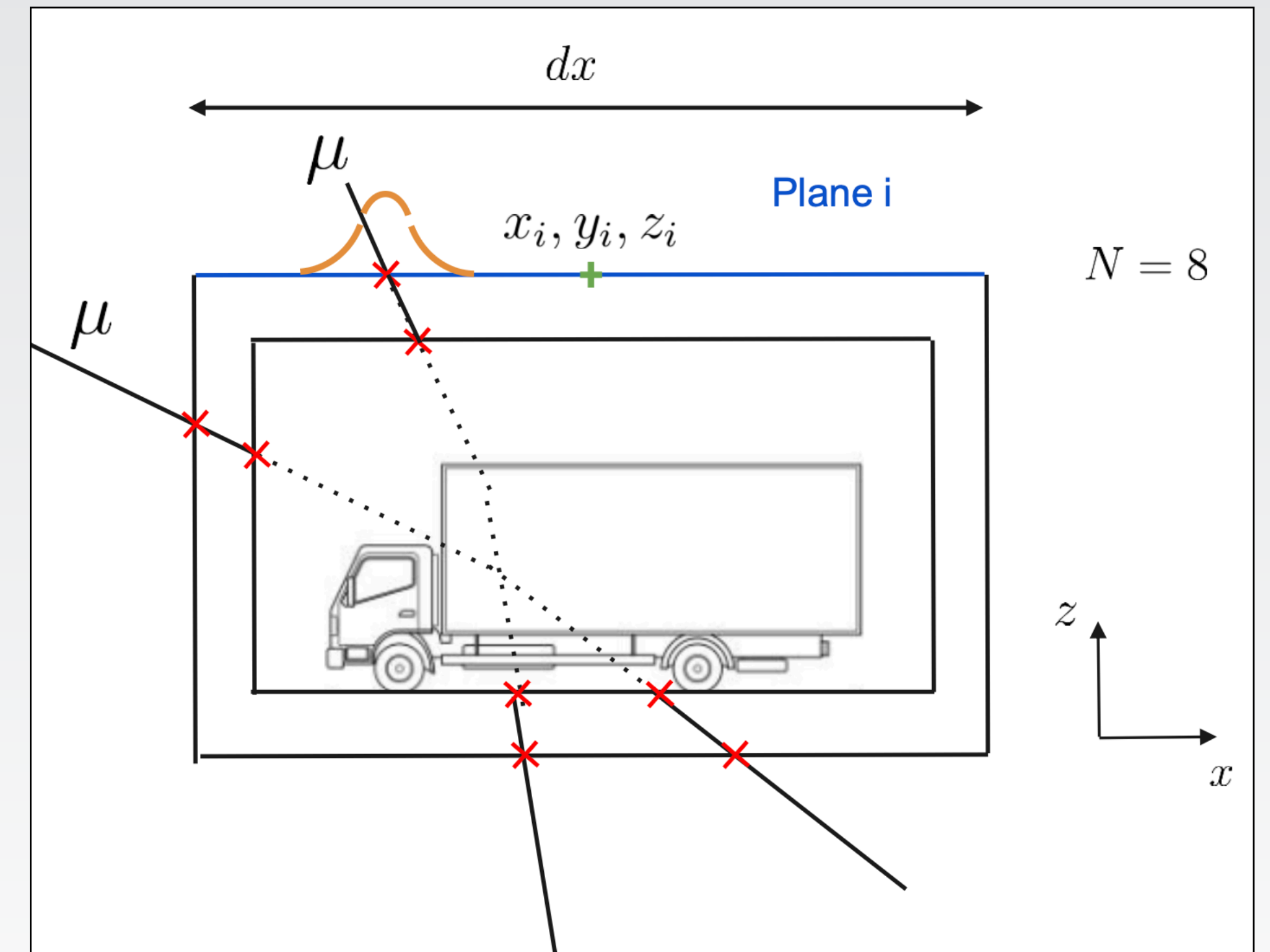
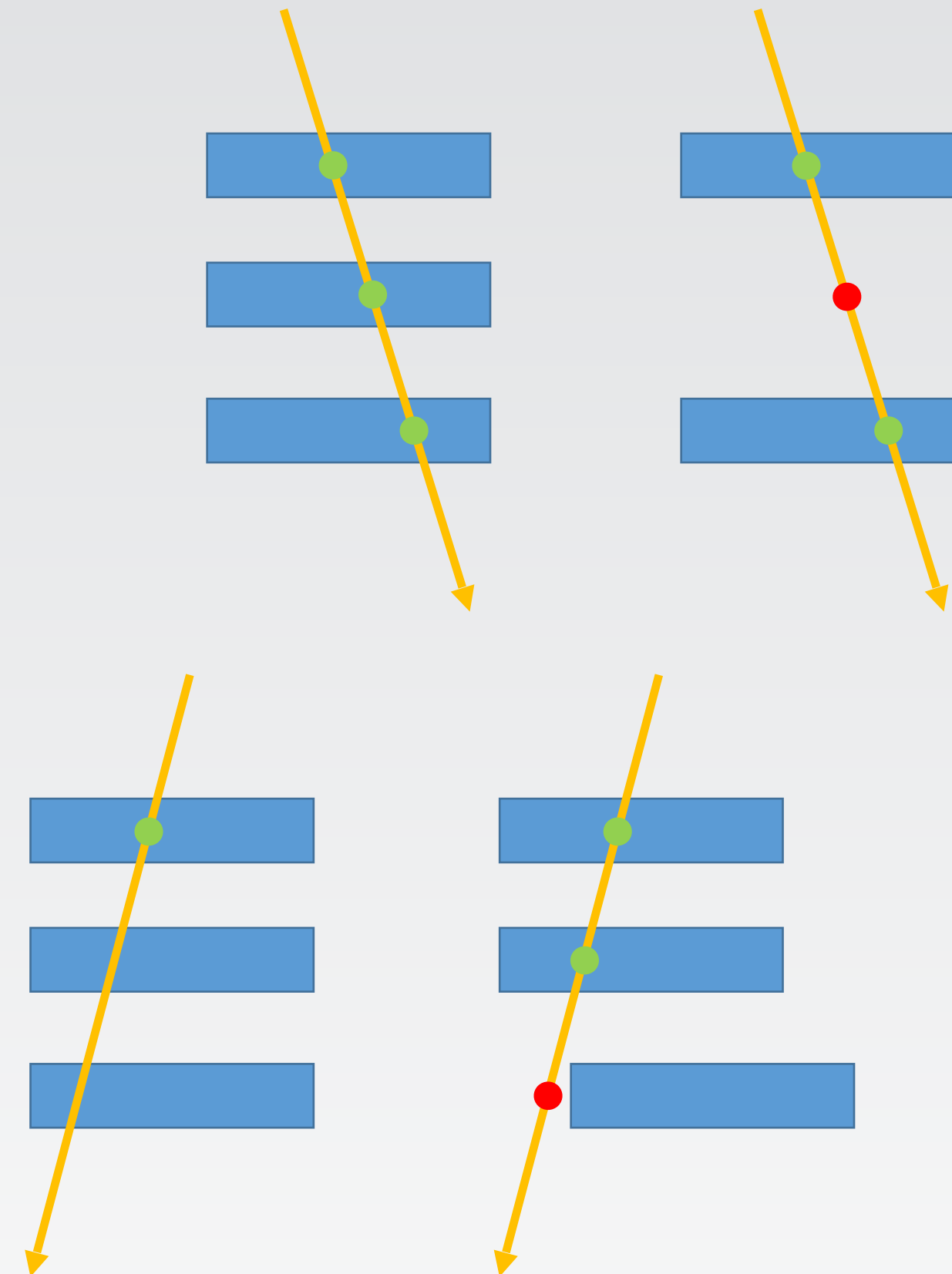
How to write a Differentiable Simulator

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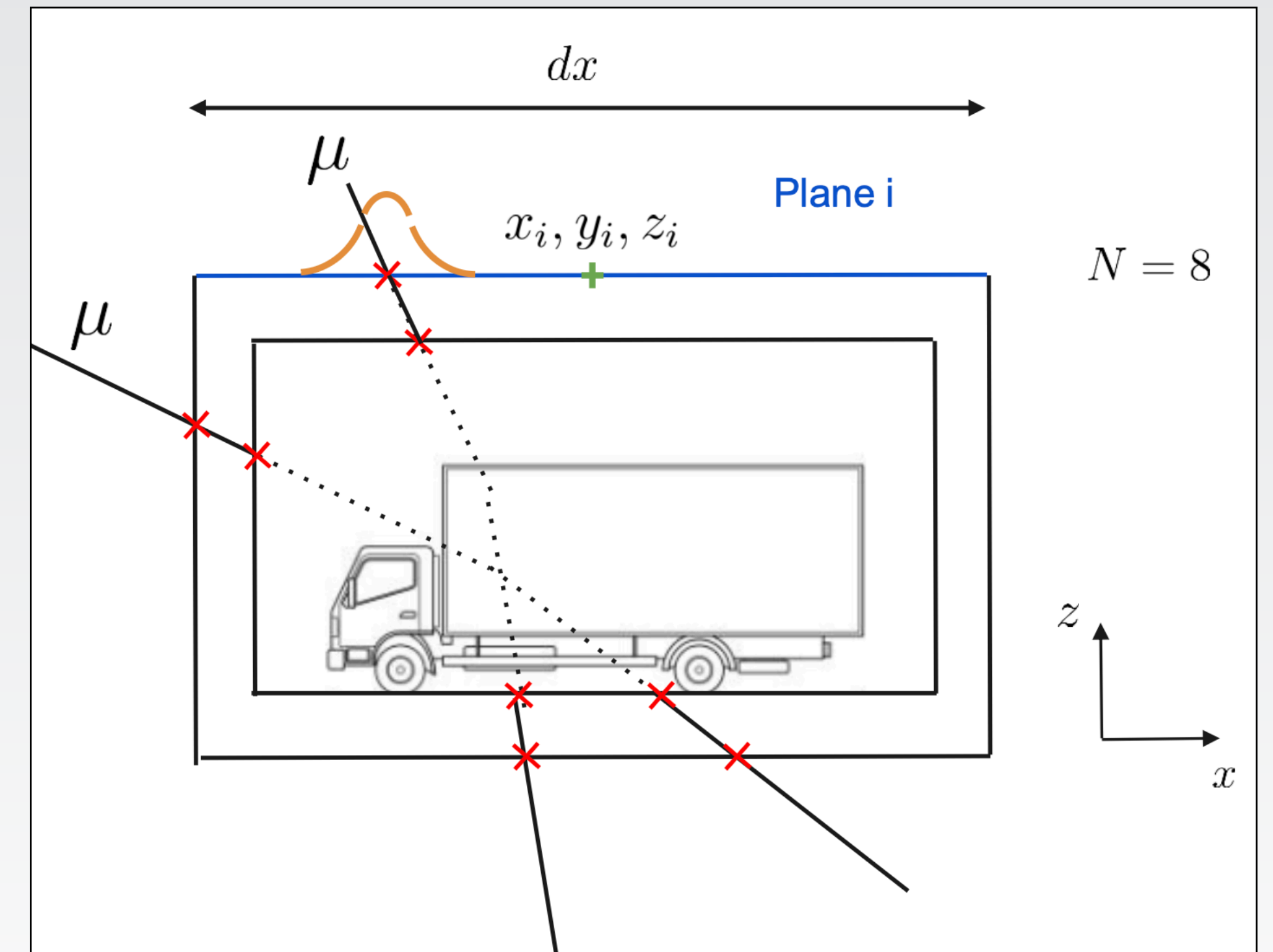
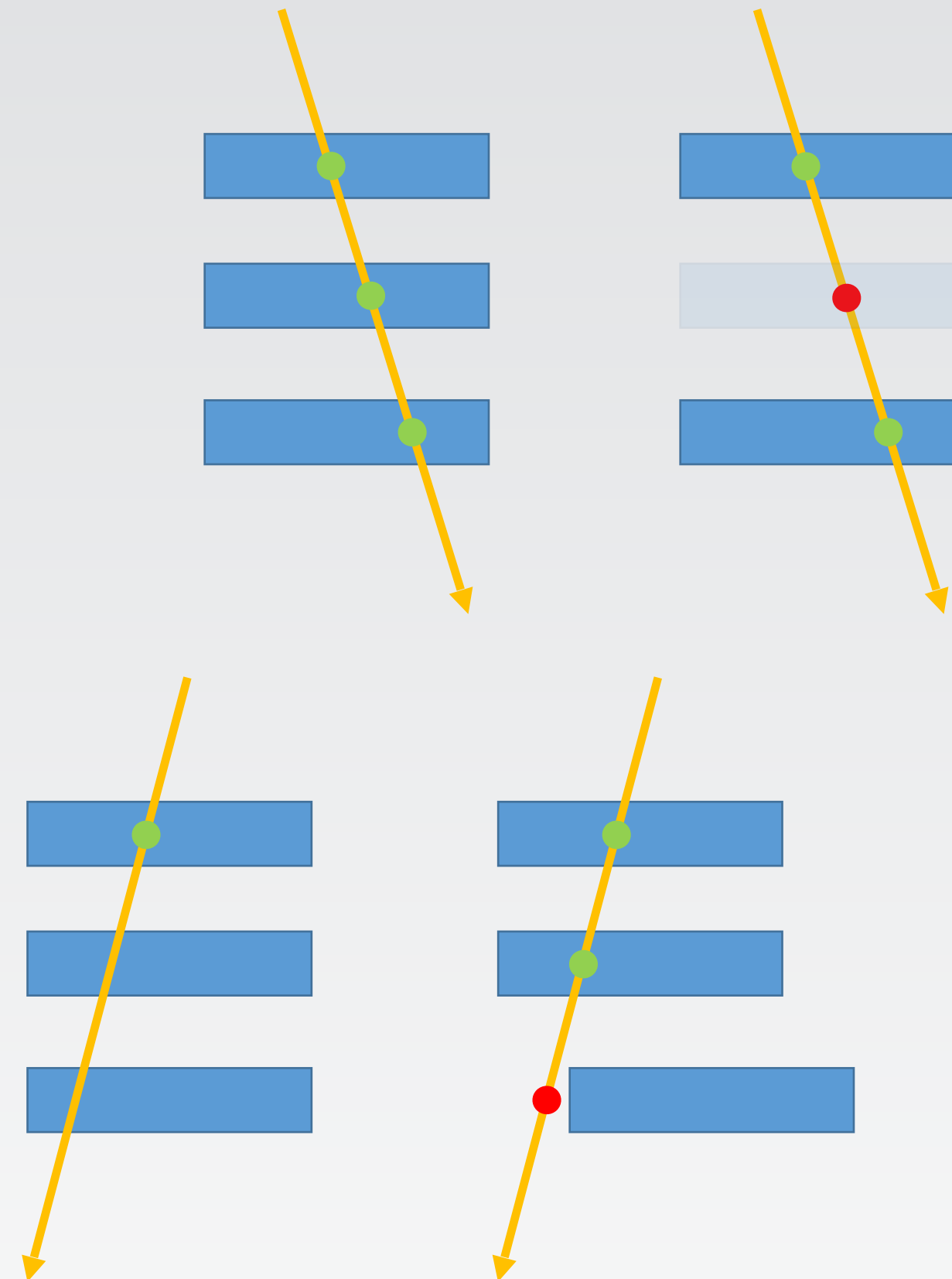
How to write a Differentiable Simulator

- Define detector parameters

- ▶ Number of detection planes
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- ▶ Dimensions
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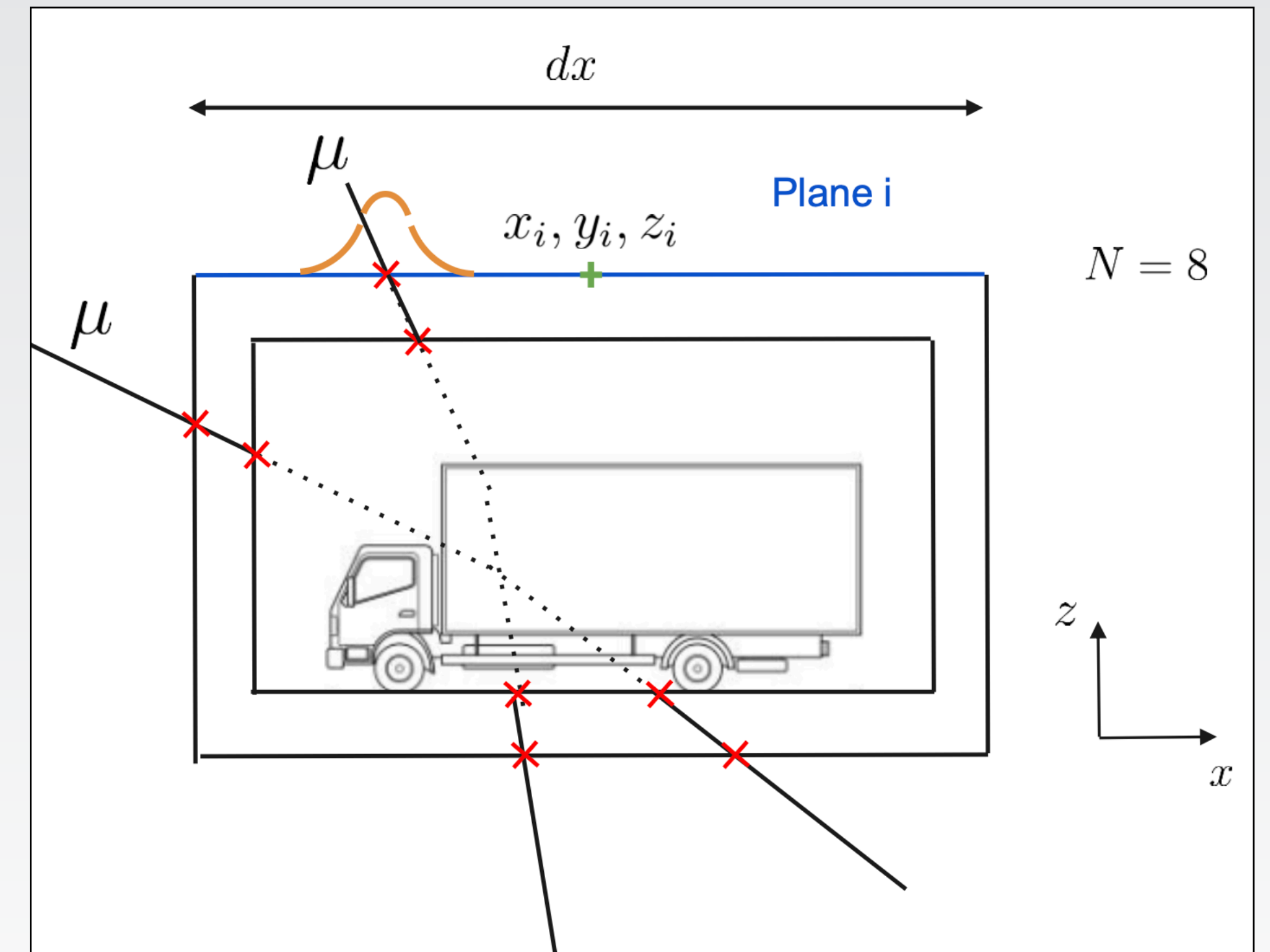
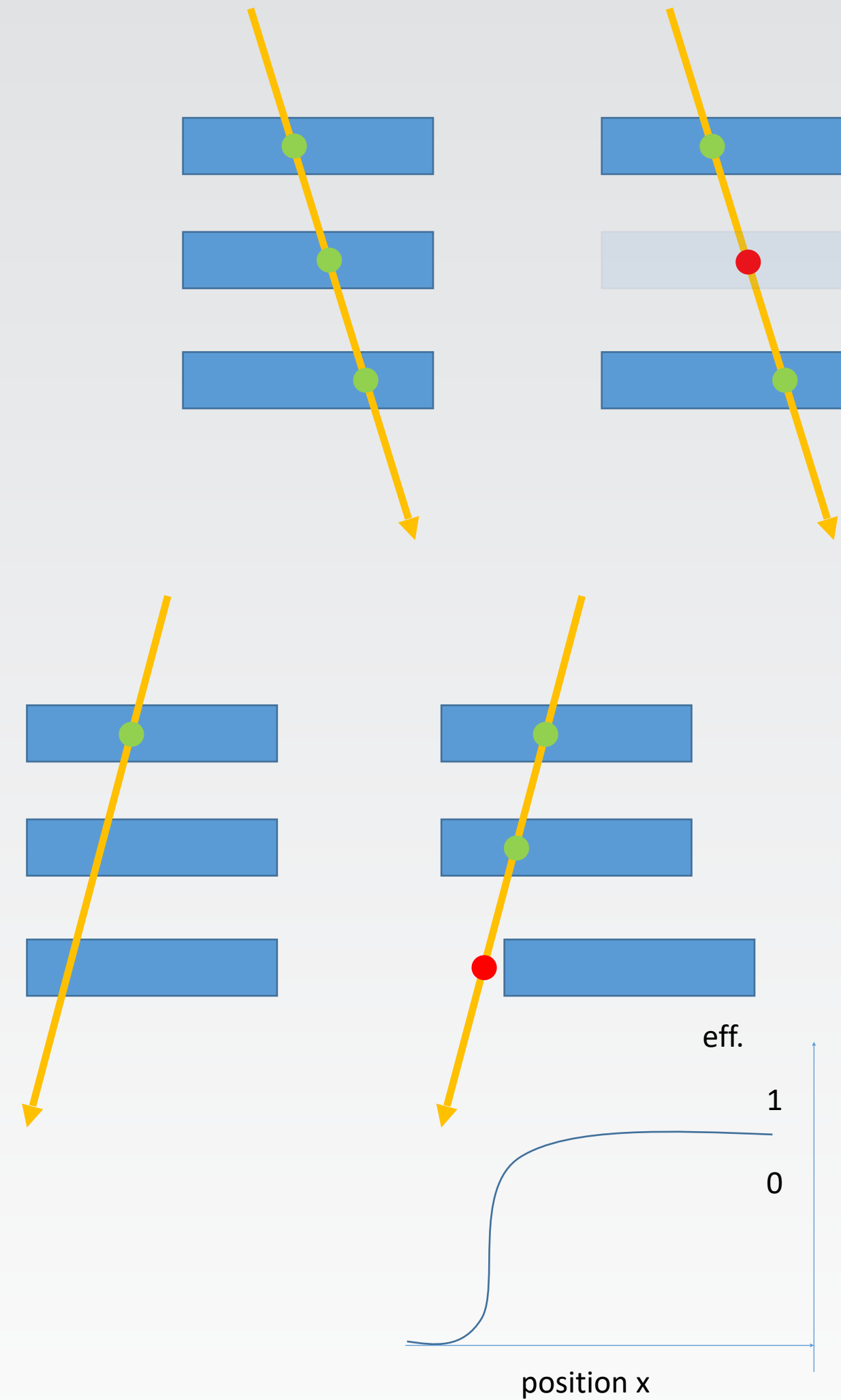
How to write a Differentiable Simulator

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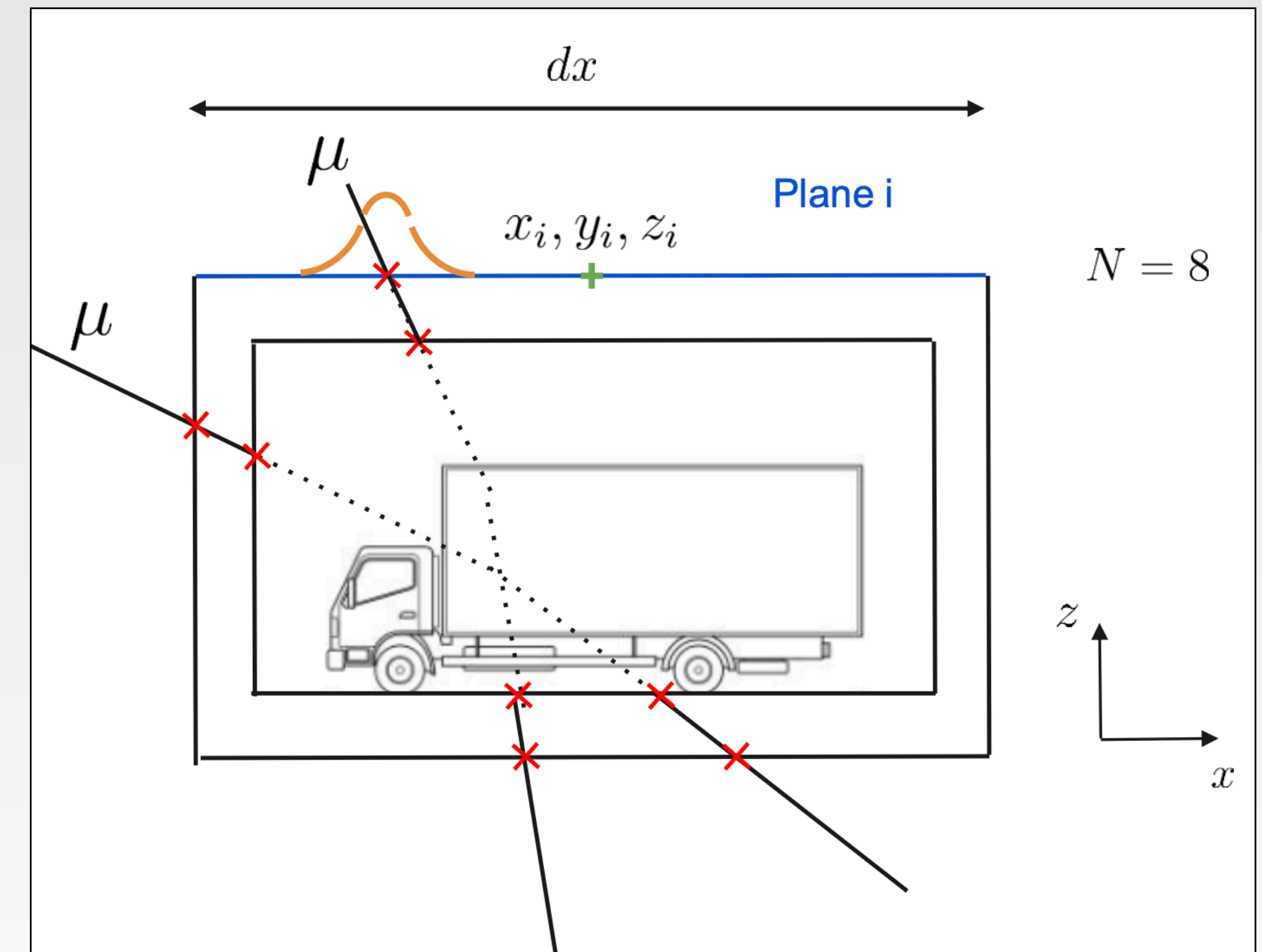
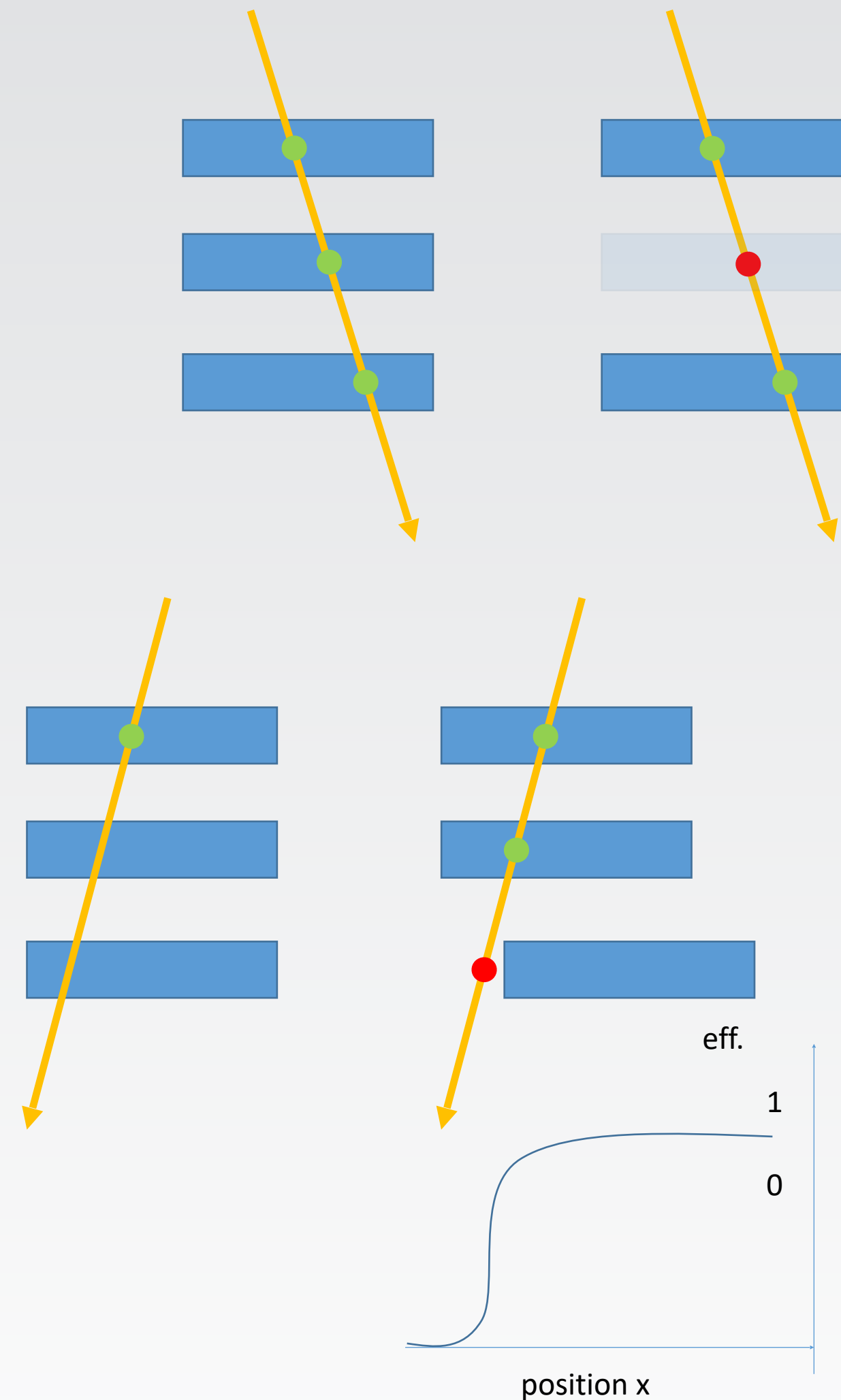
How to write a Differentiable Simulator

- Define detector parameters

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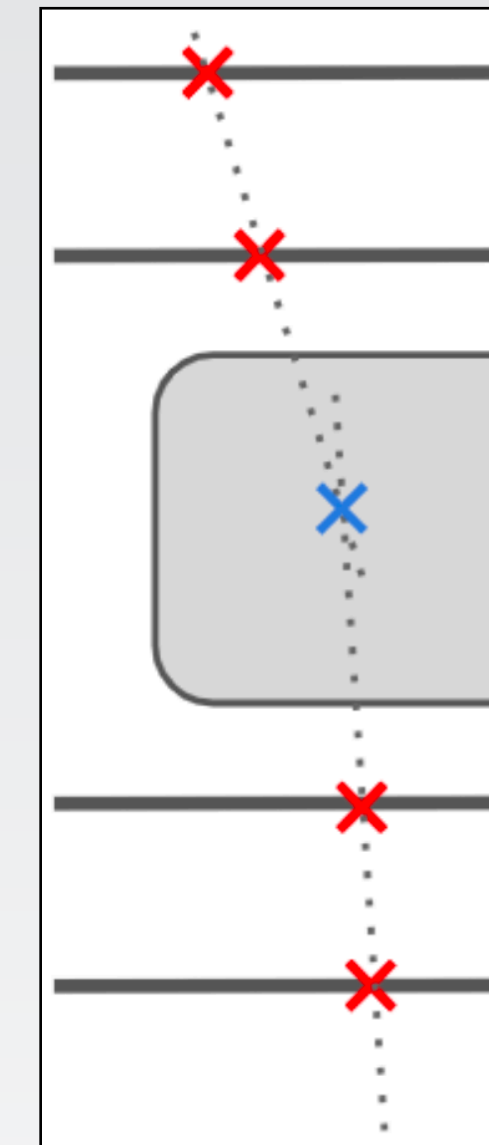
Also here, we can approximate non-differentiable operations with differentiable ones

Implement the While Chain

- Input a batch of muons
- Use “PDG” ad-hoc scattering model

$$\theta_0 = \frac{0.0136 \text{ GeV}}{p} \sqrt{d/X_0} \cdot (1 + 0.038 \ln(d/X_0))$$

- No radiative losses
- *Sample* from a Gaussian with width θ_0
- Reconstruct muons
- Identify different objects by looking at point of closest approach

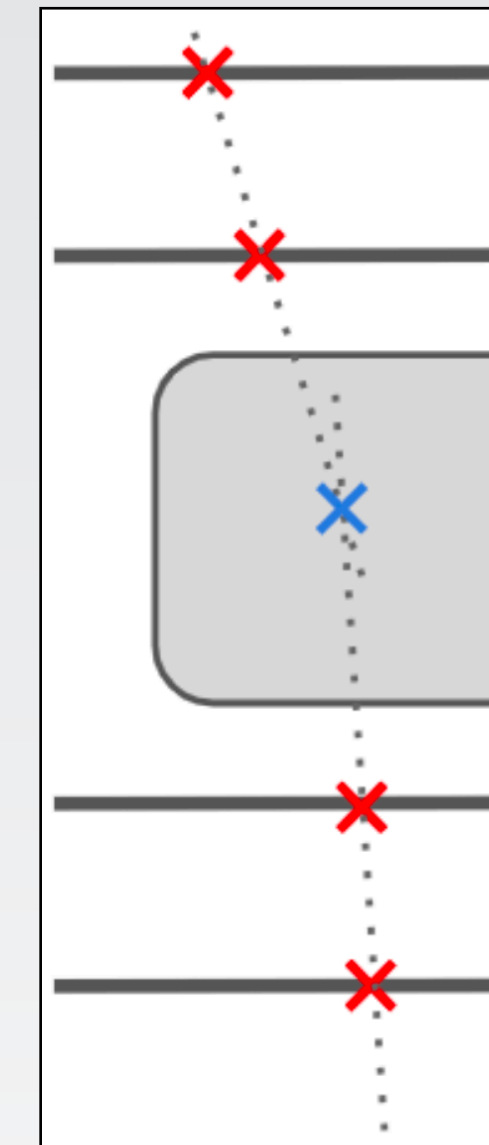


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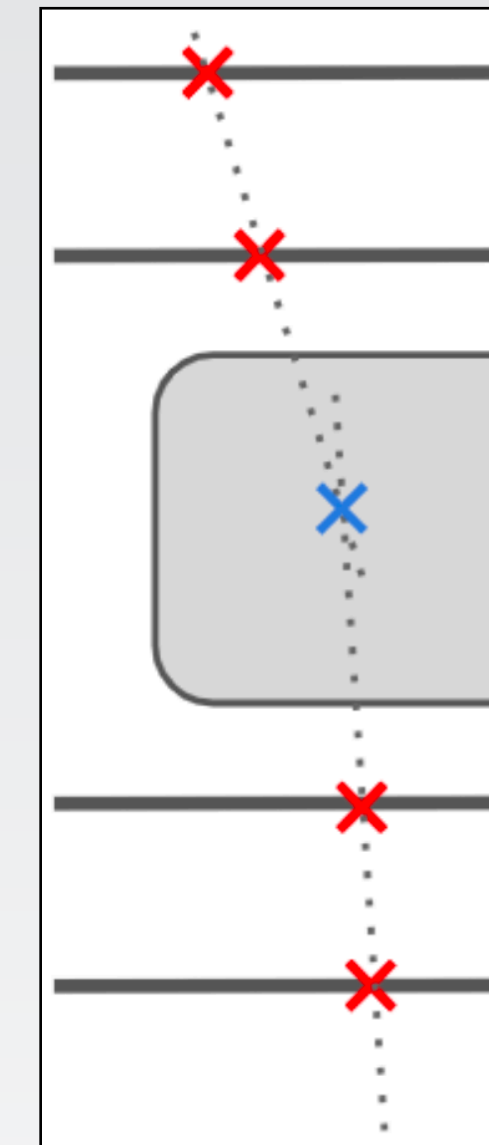
Inherently probability-based parts can be sampled

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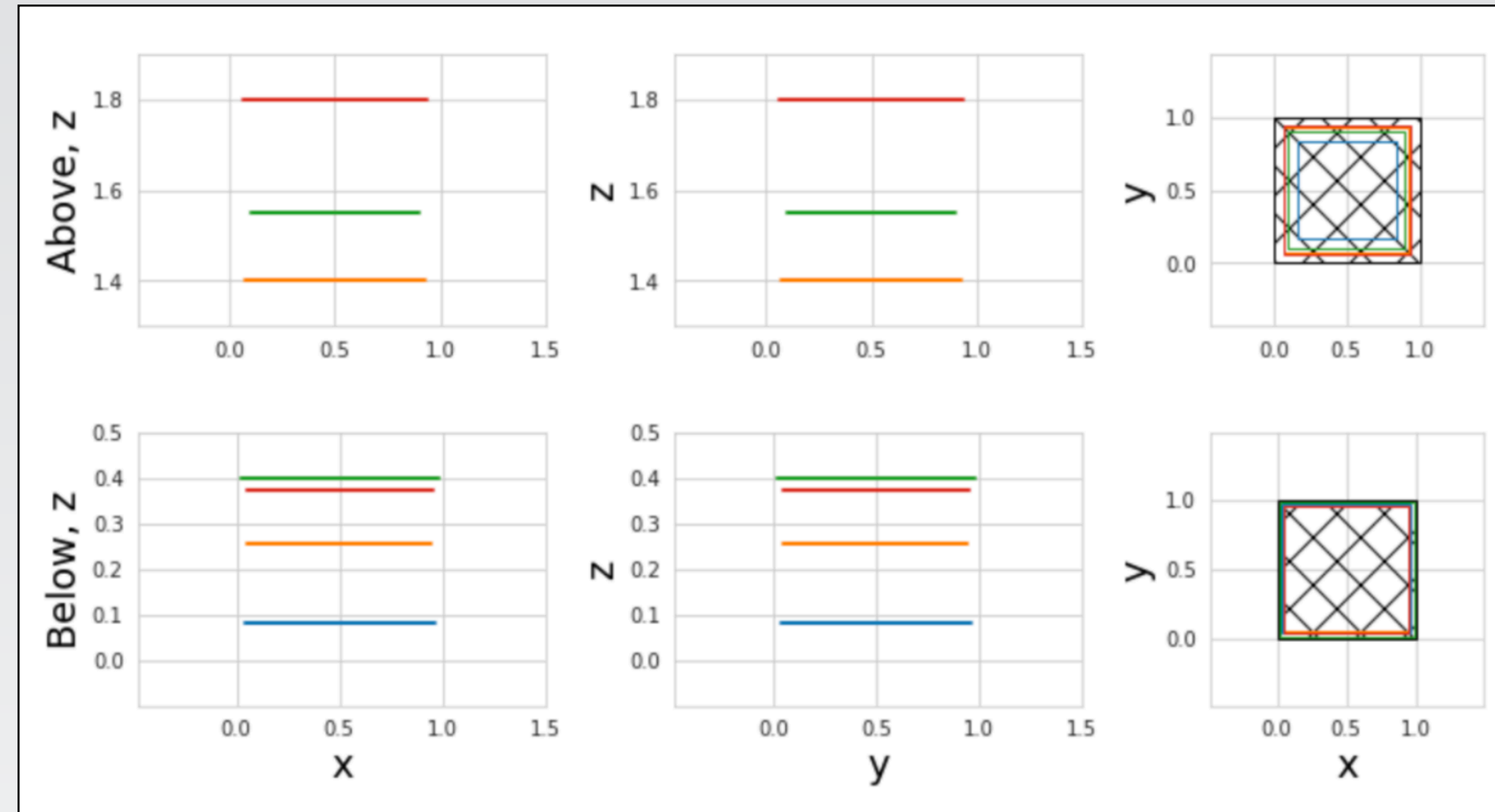
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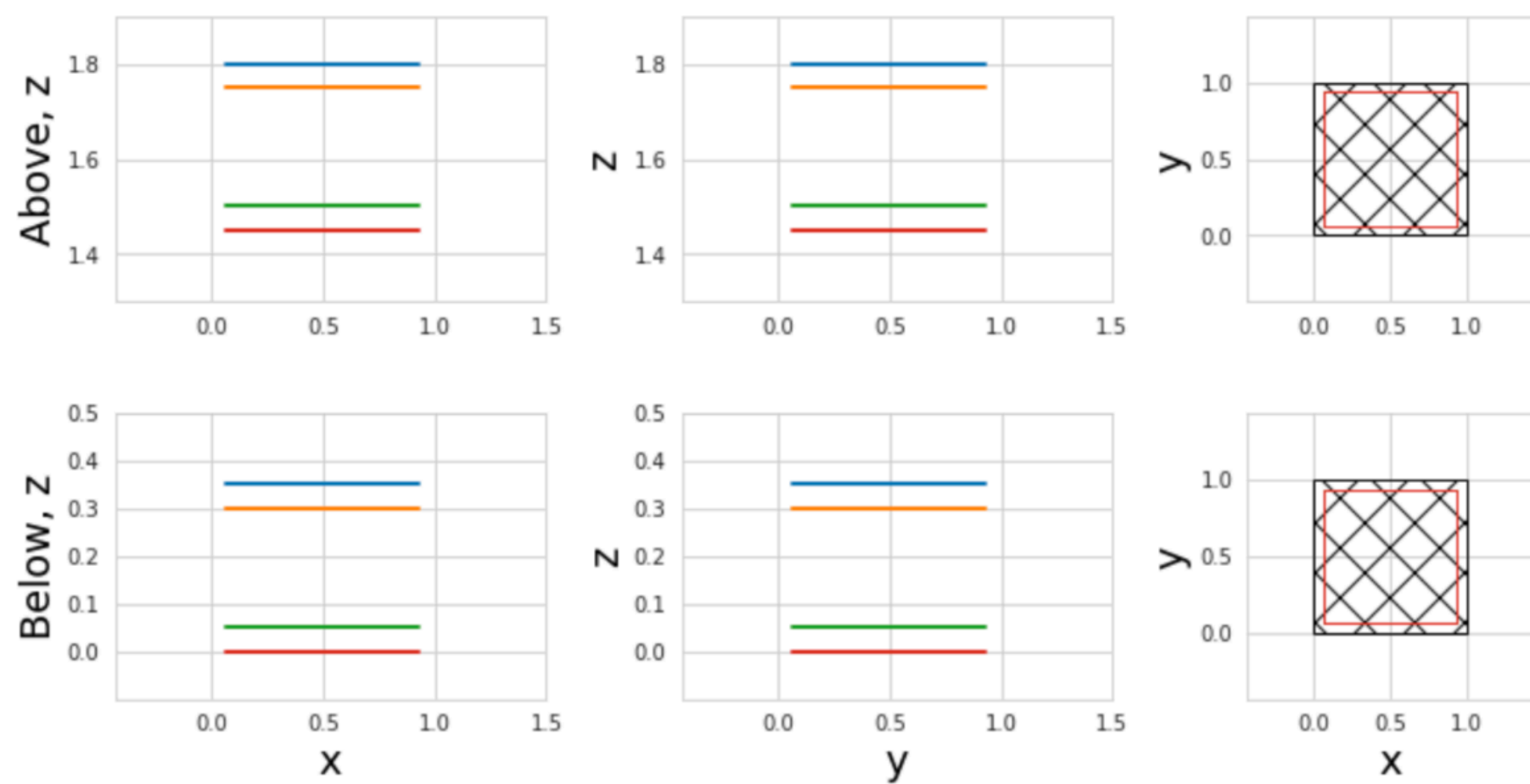
Inherently probability-based parts can be sampled

End-to-end: the performance is evaluated on the final objective: the object reconstruction

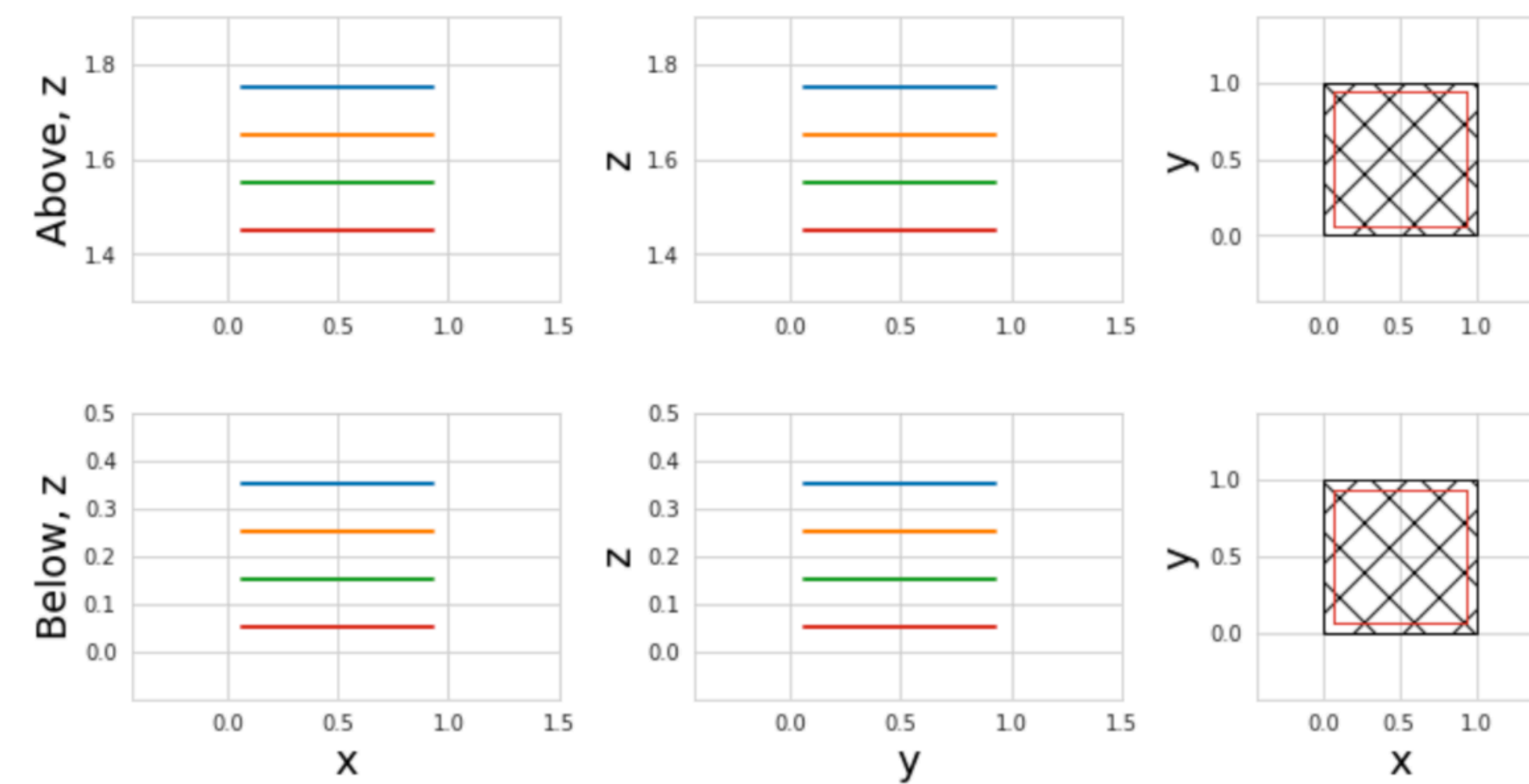
An Industry Application



TOMOPT detector:
Slightly better performance
than both baselines

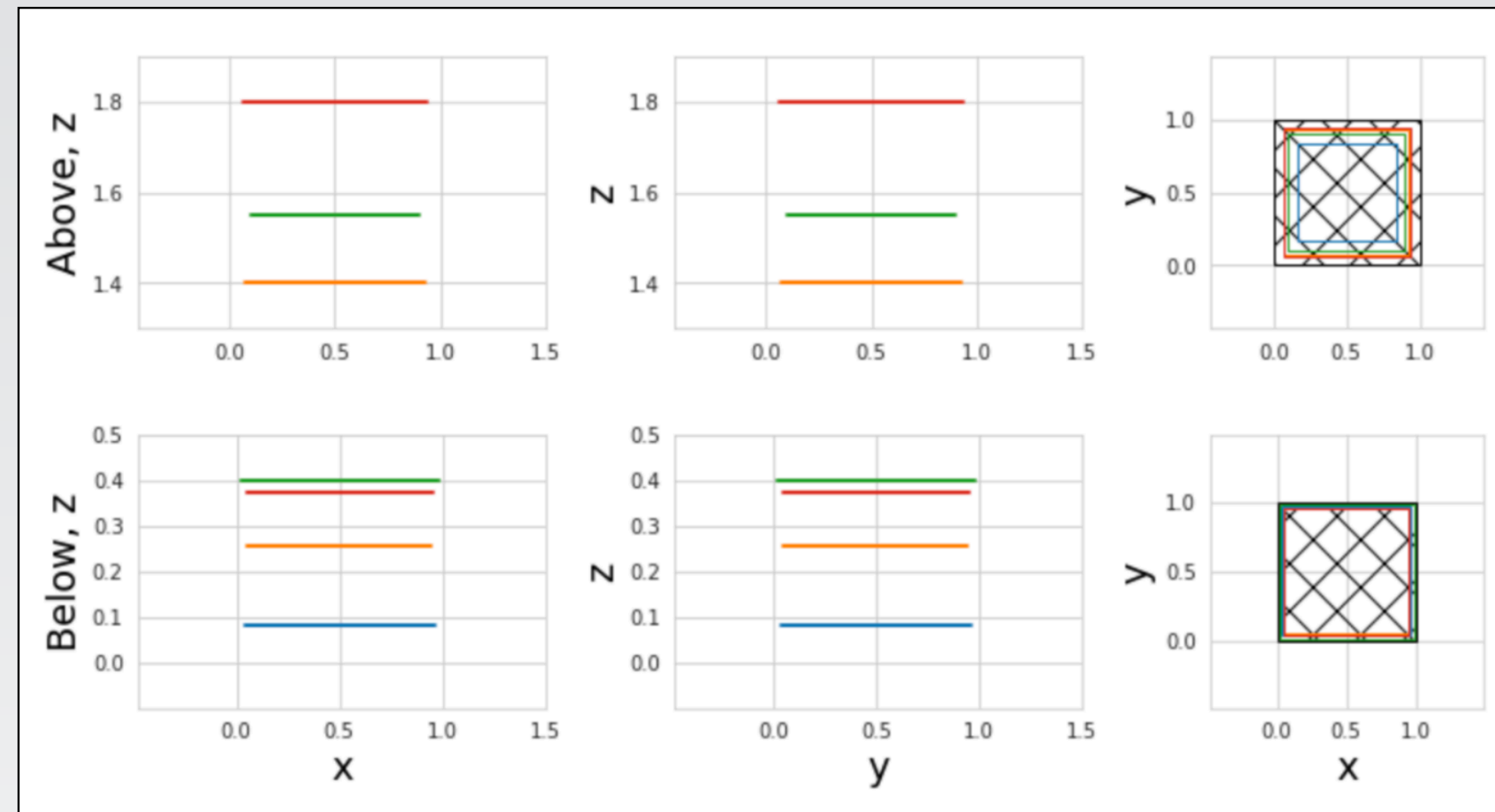


(a) Baseline detector 1.

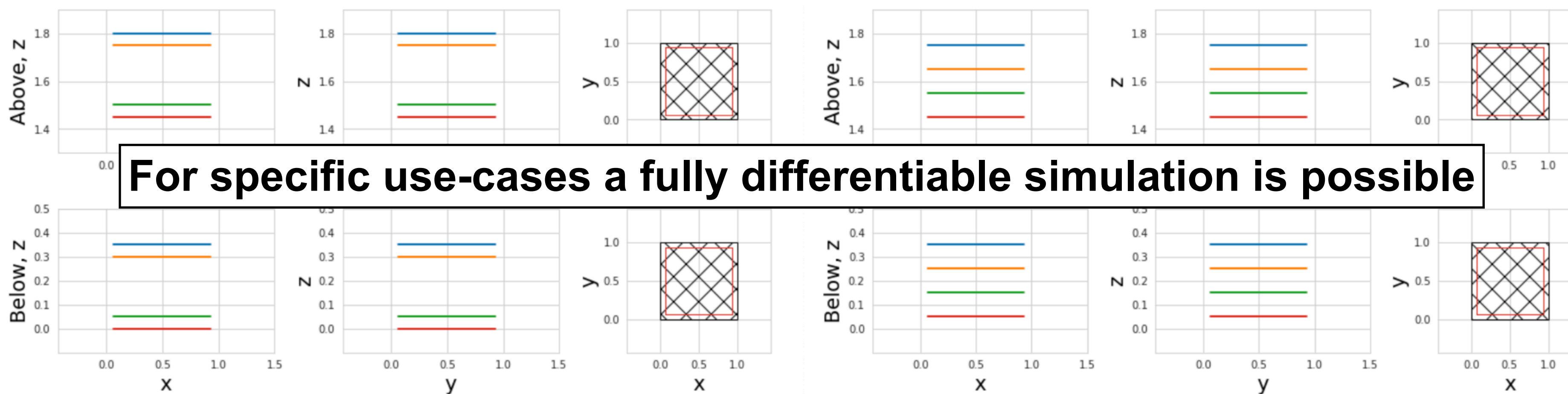


(b) Baseline detector 2.

An Industry Application



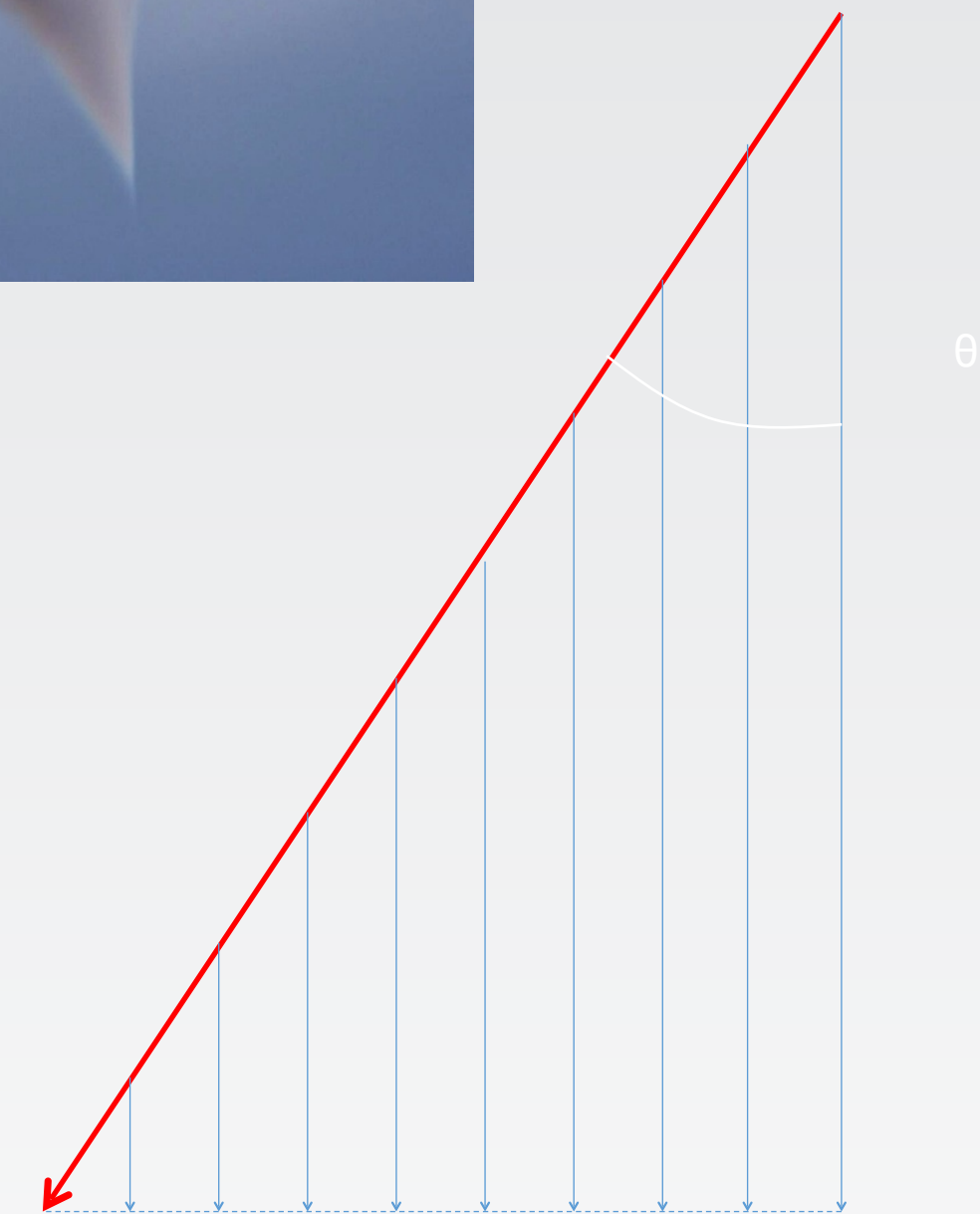
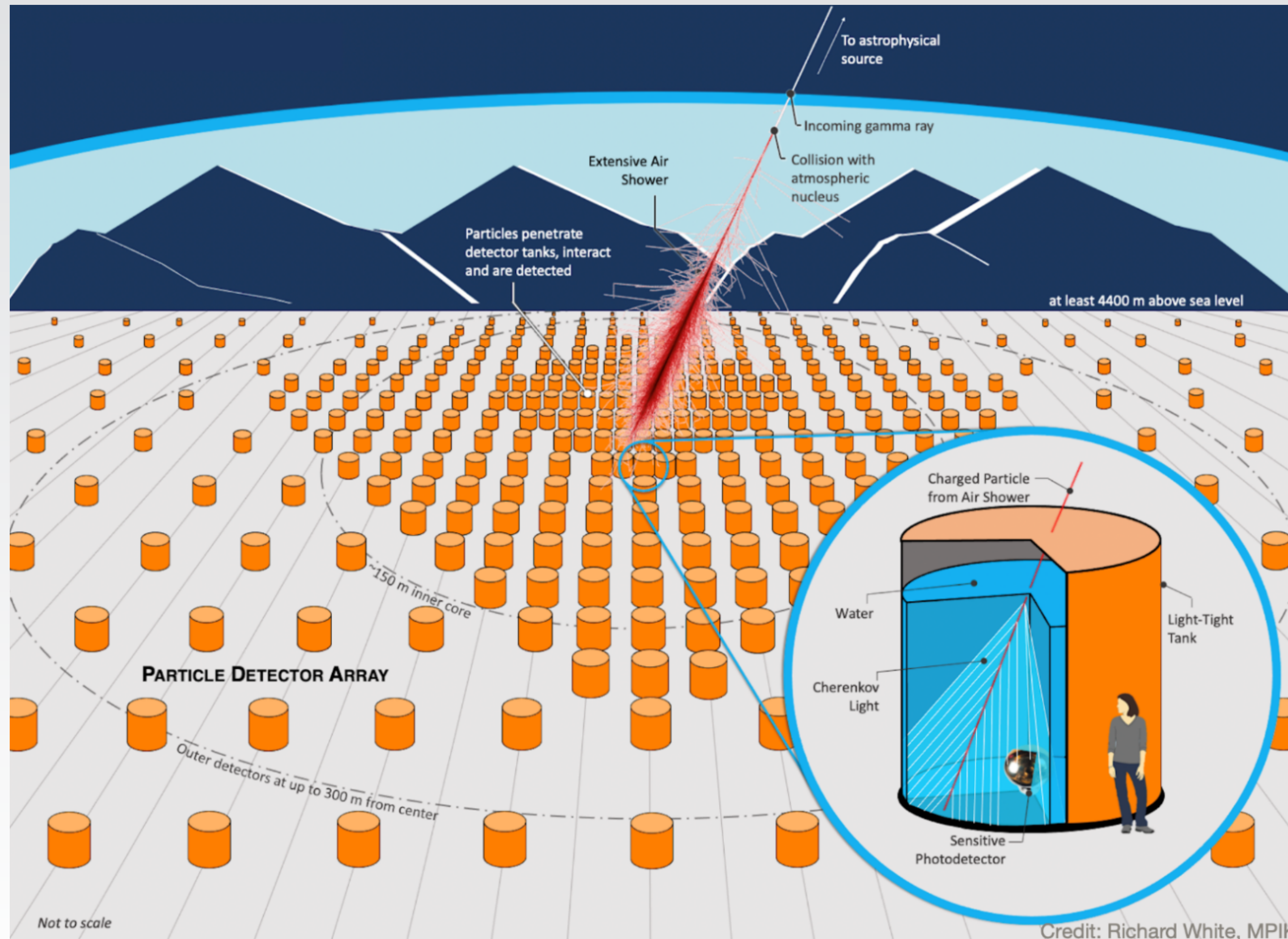
TOMOPT detector:
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(a) Baseline detector 1.

(b) Baseline detector 2.

Southern Wide-field Gamma-ray Observatory

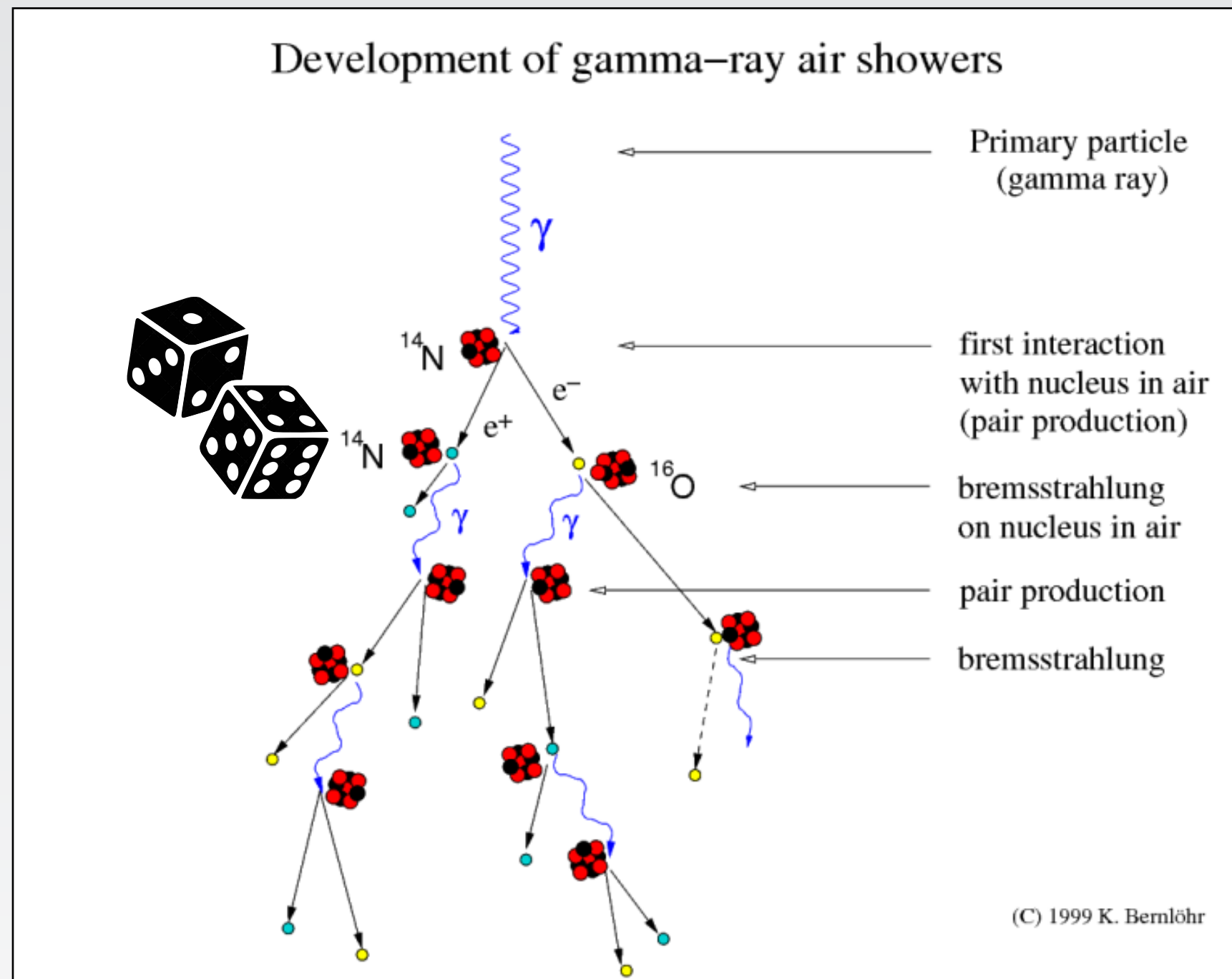


- Approx. 6000 water tanks: endless possibilities for their placement (Solution space: R^{2N-3})

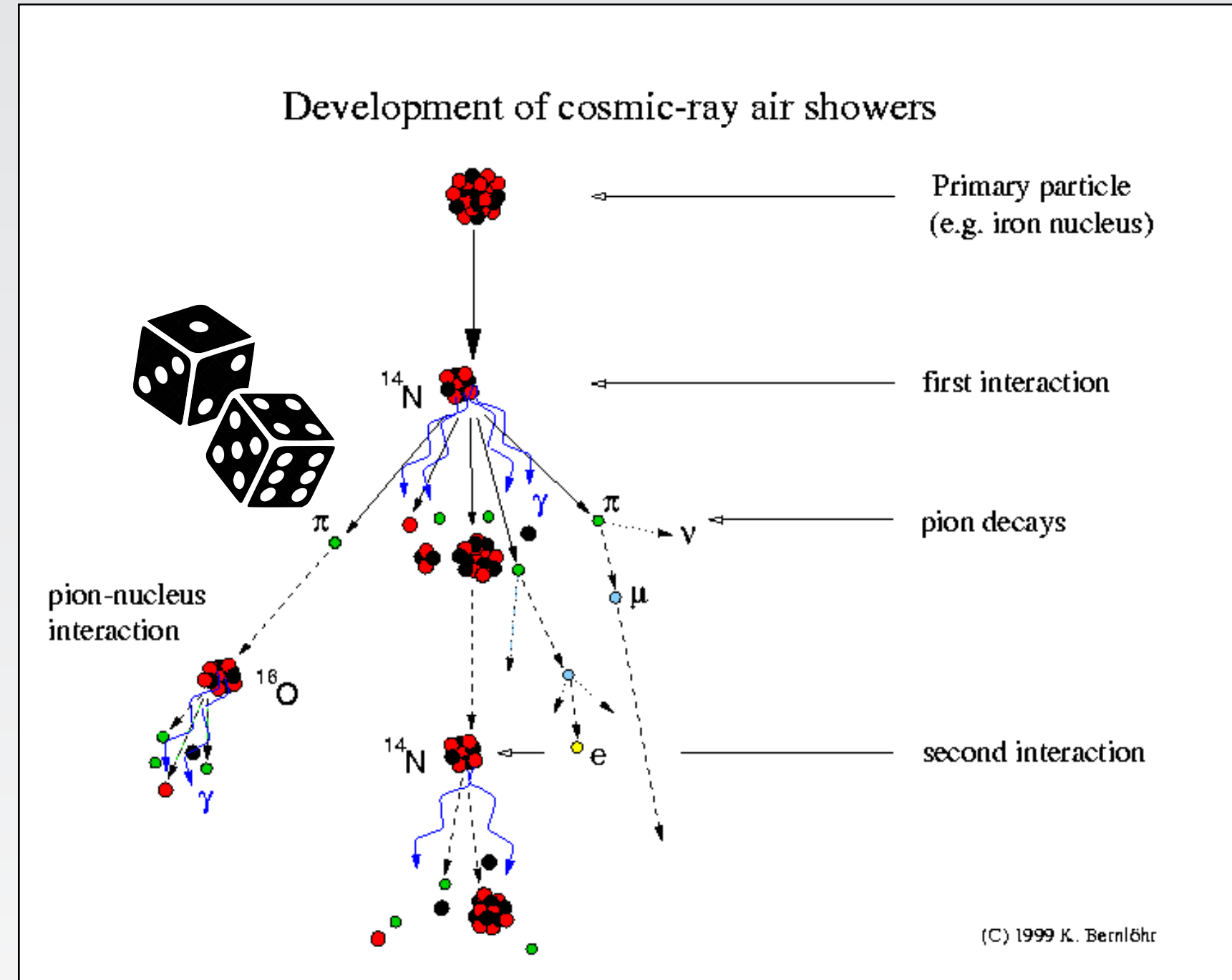
A Simplified Differentiable Simulation (WIP)

Low rate

Direction
reveals source



Development of cosmic-ray air showers



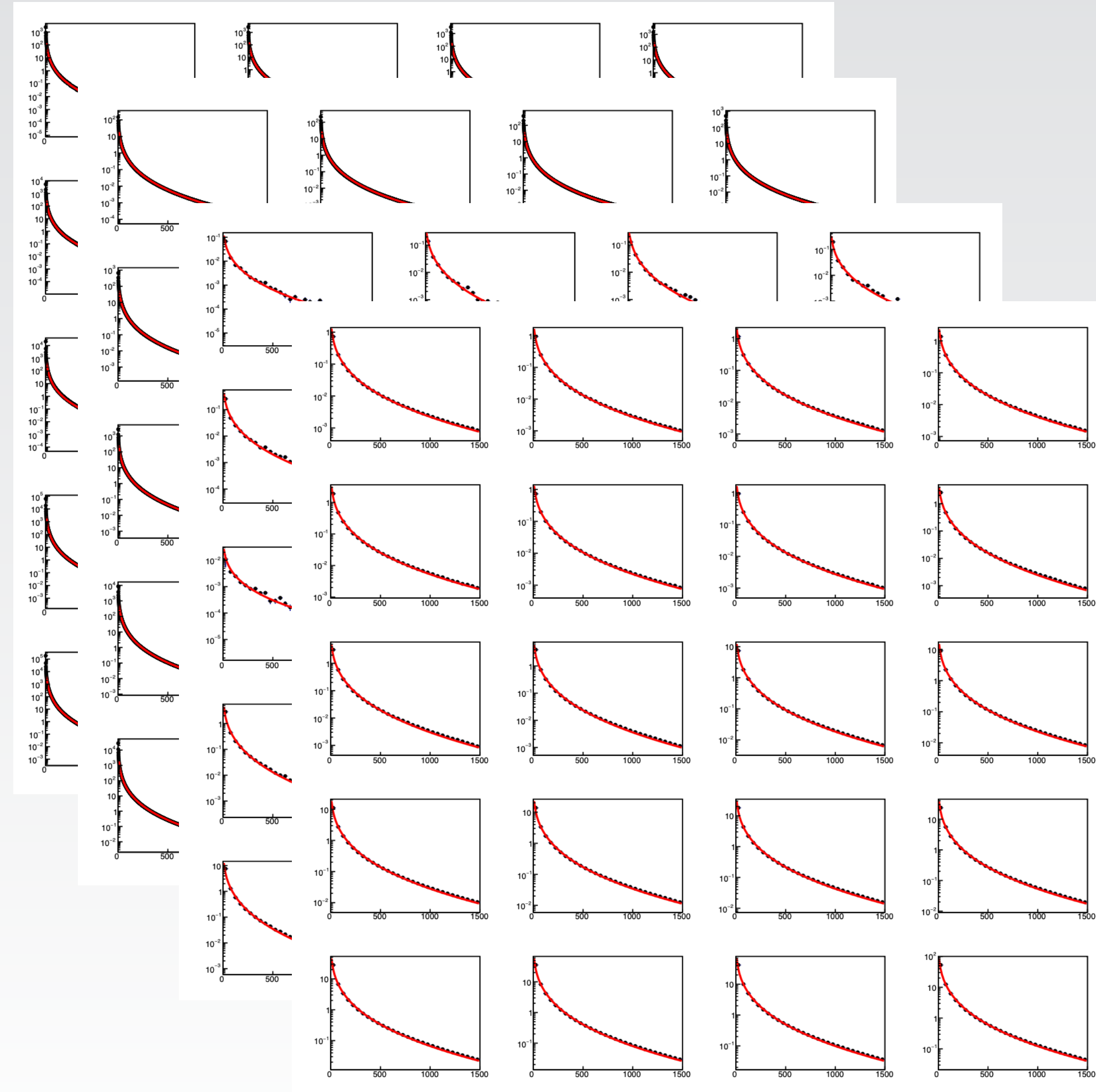
Large rate

Source not
easily
reconstructable

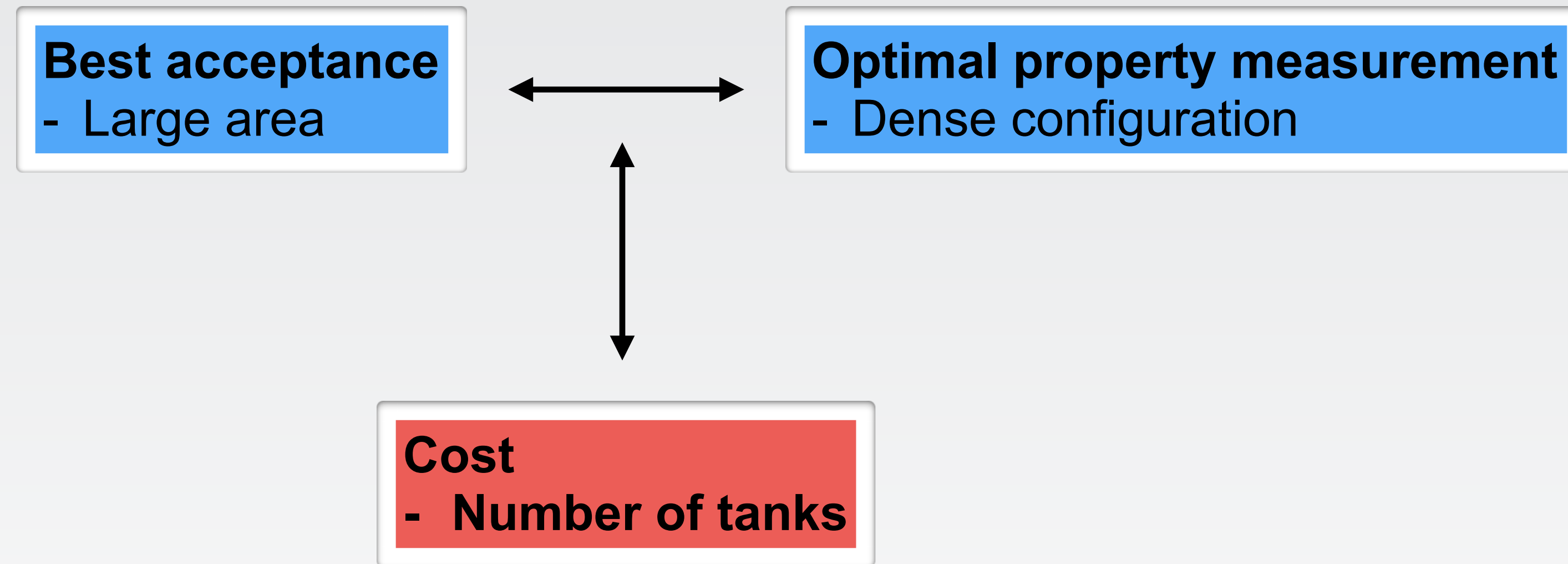
- Showers effectively parametrised (fit to CORSIKA) as a ellipsoids of particles that reach the ground: **0.1 - 10 PeV**
- Sample from parametrisation
- Subject to expected efficiencies and positions of detectors
- Hypothesis test on sampled data → **shower properties and flux**
- **Can be optimised end-to-end**

T. Dorigo, et al., arXiv.2310.01857, Nuclear. Physics. B (2025)

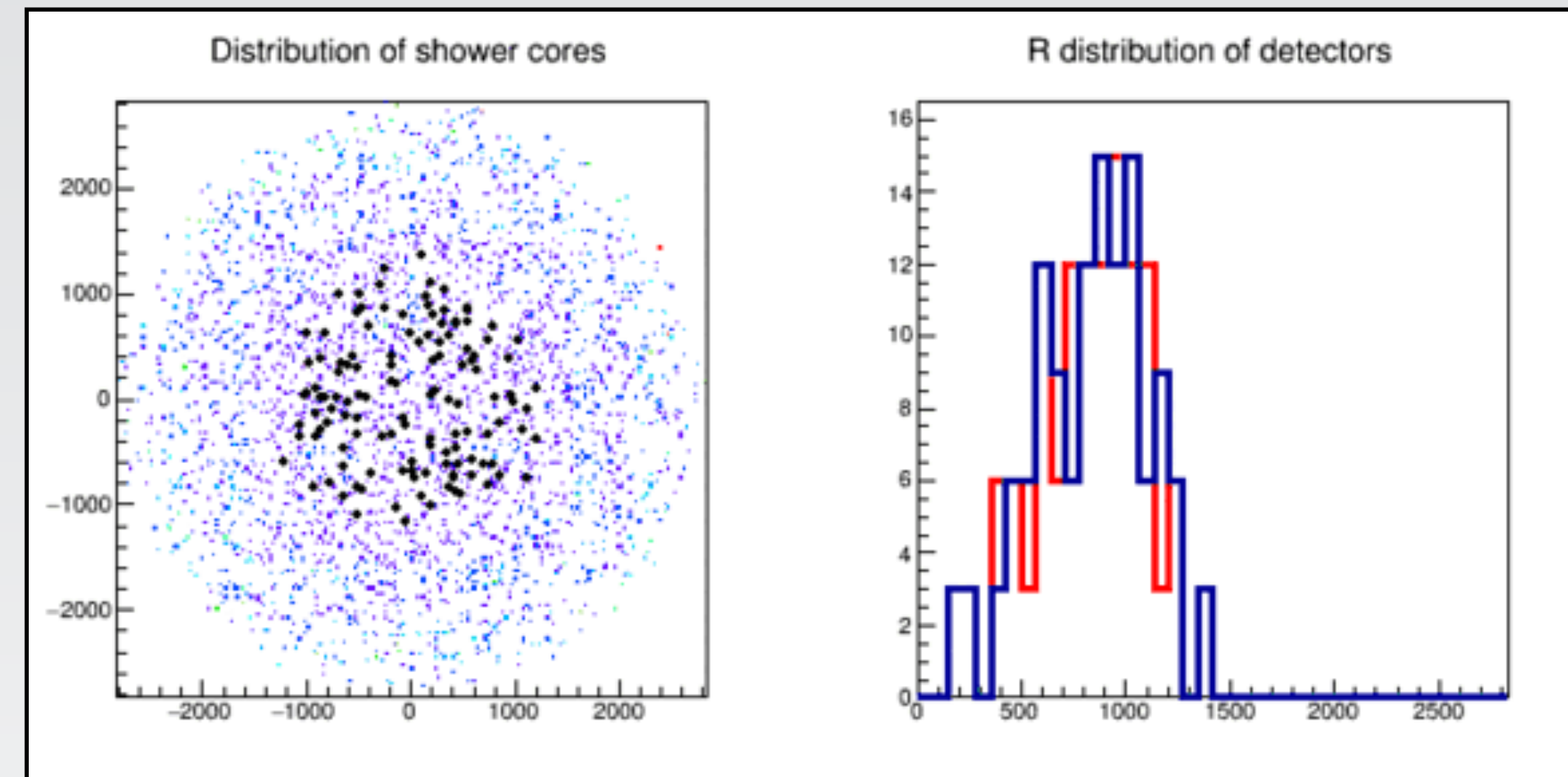
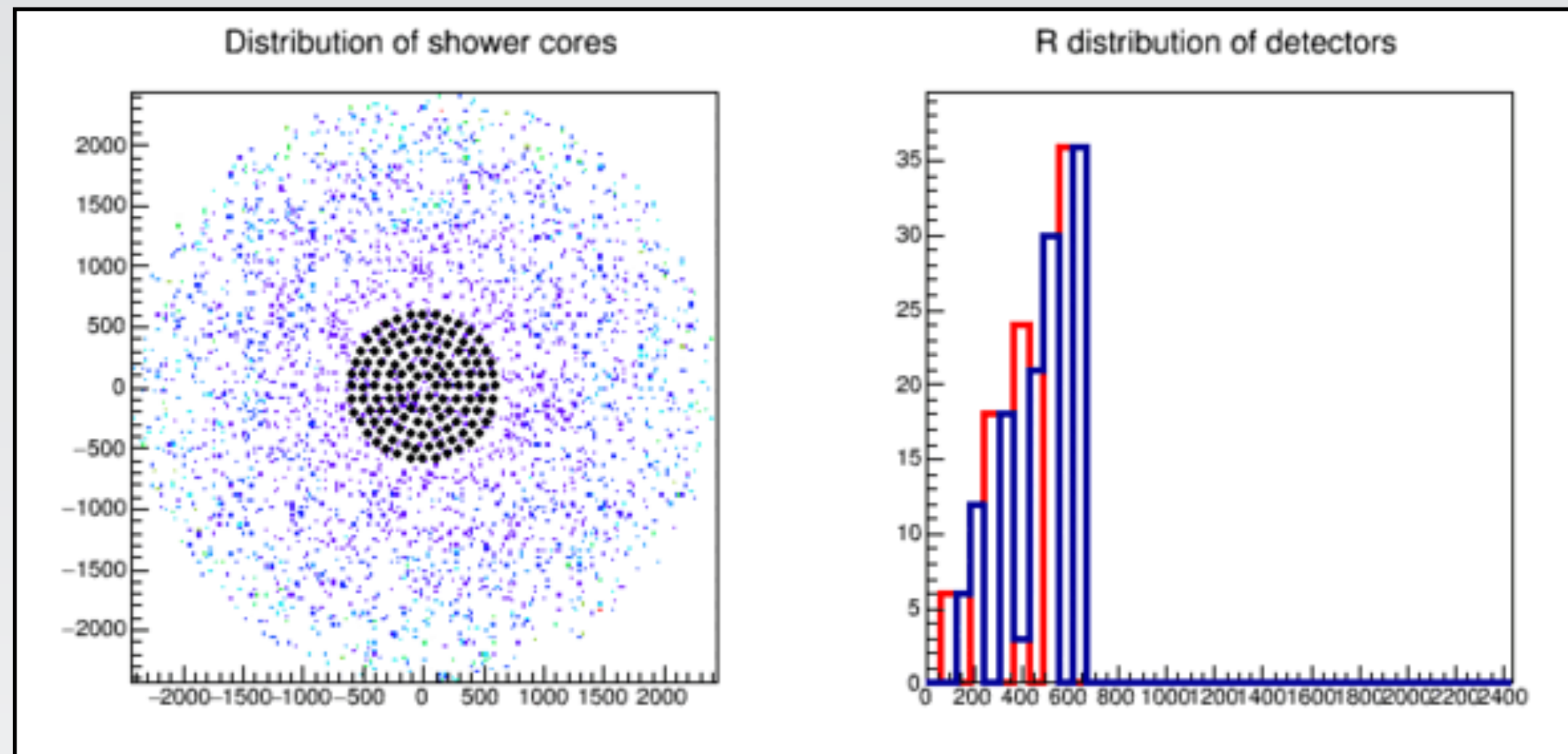
A parametrised diff.-able simulation



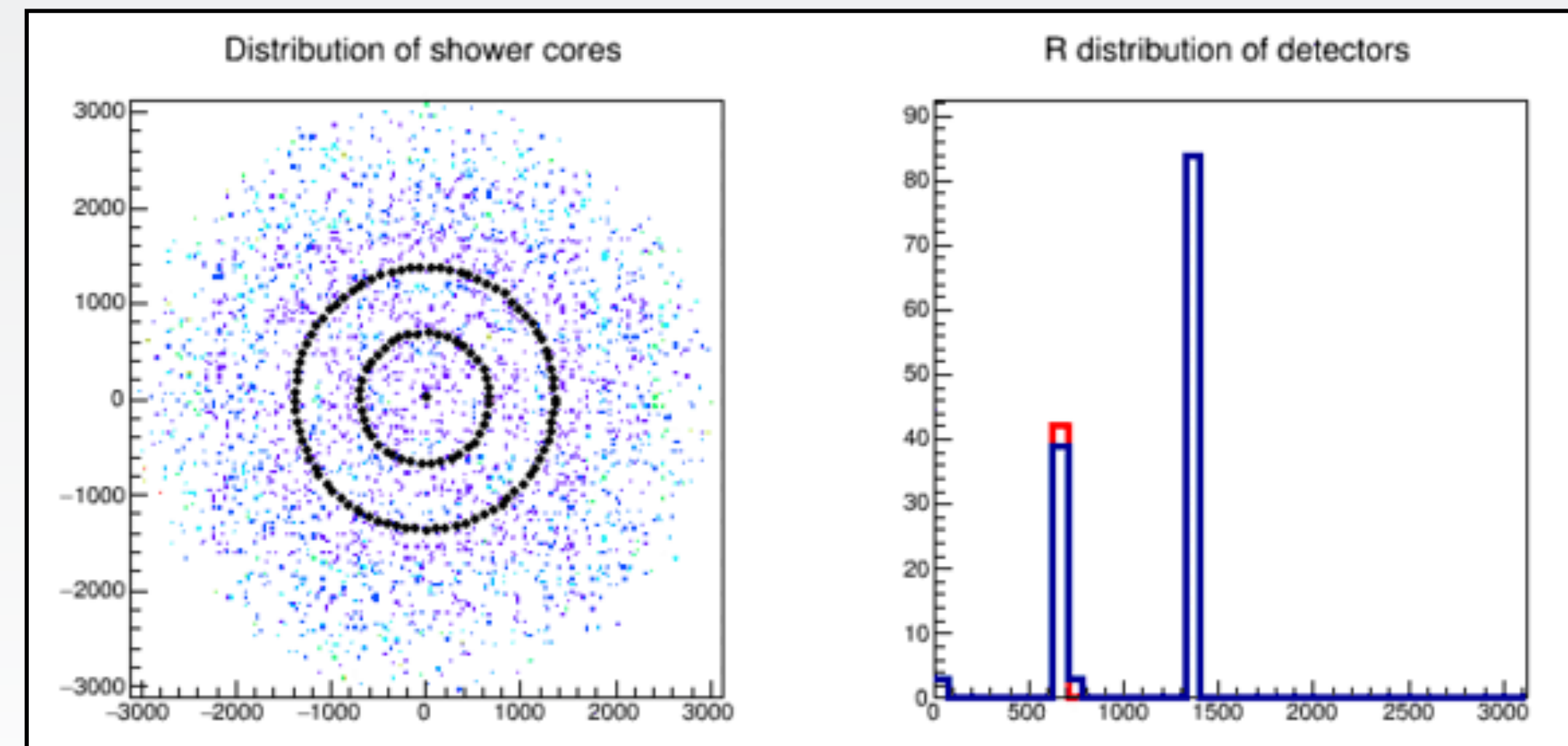
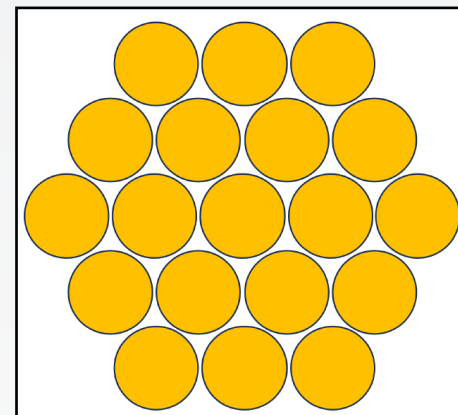
The Main Competitors



The Optimal Layout: A Test

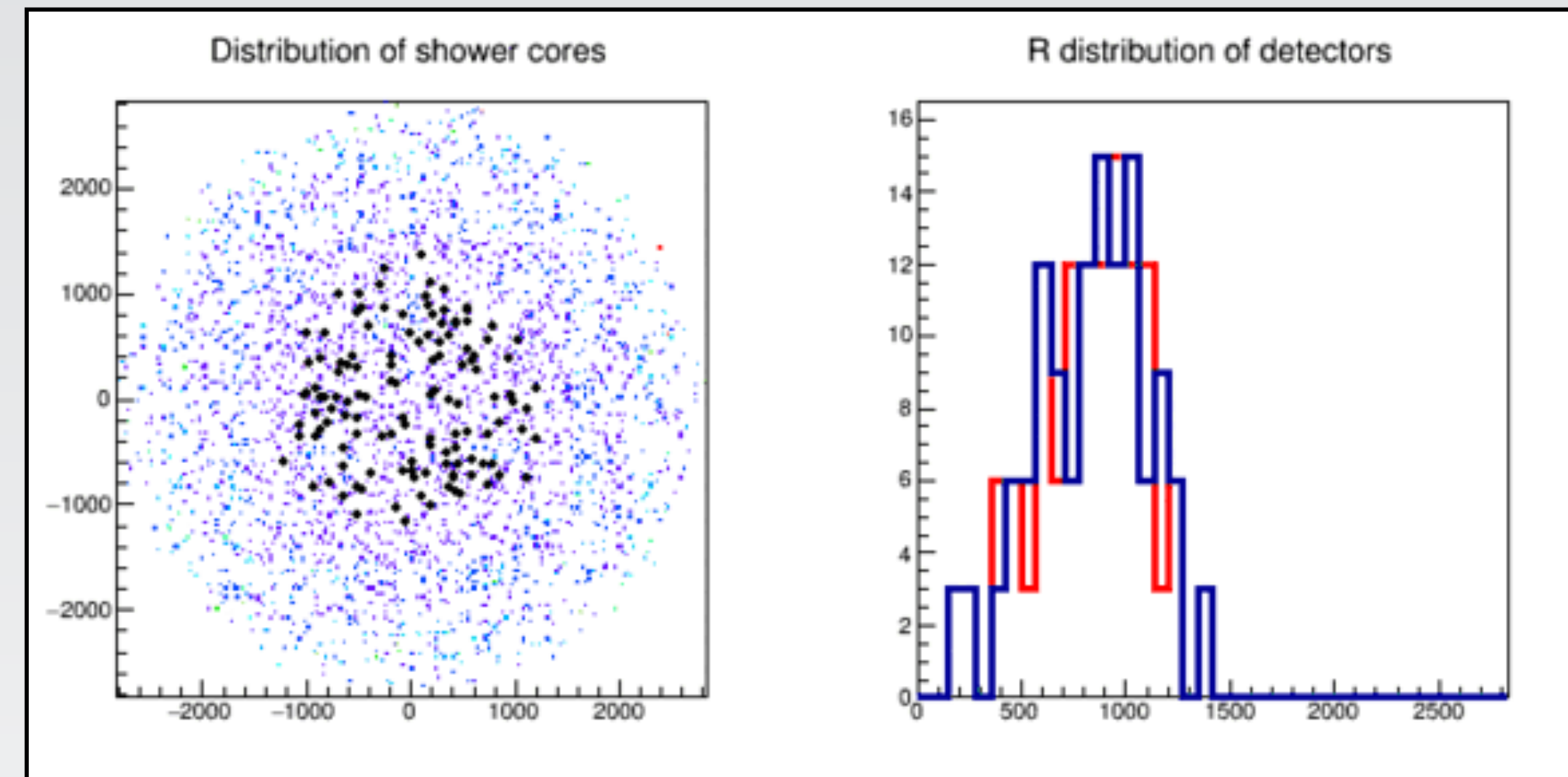
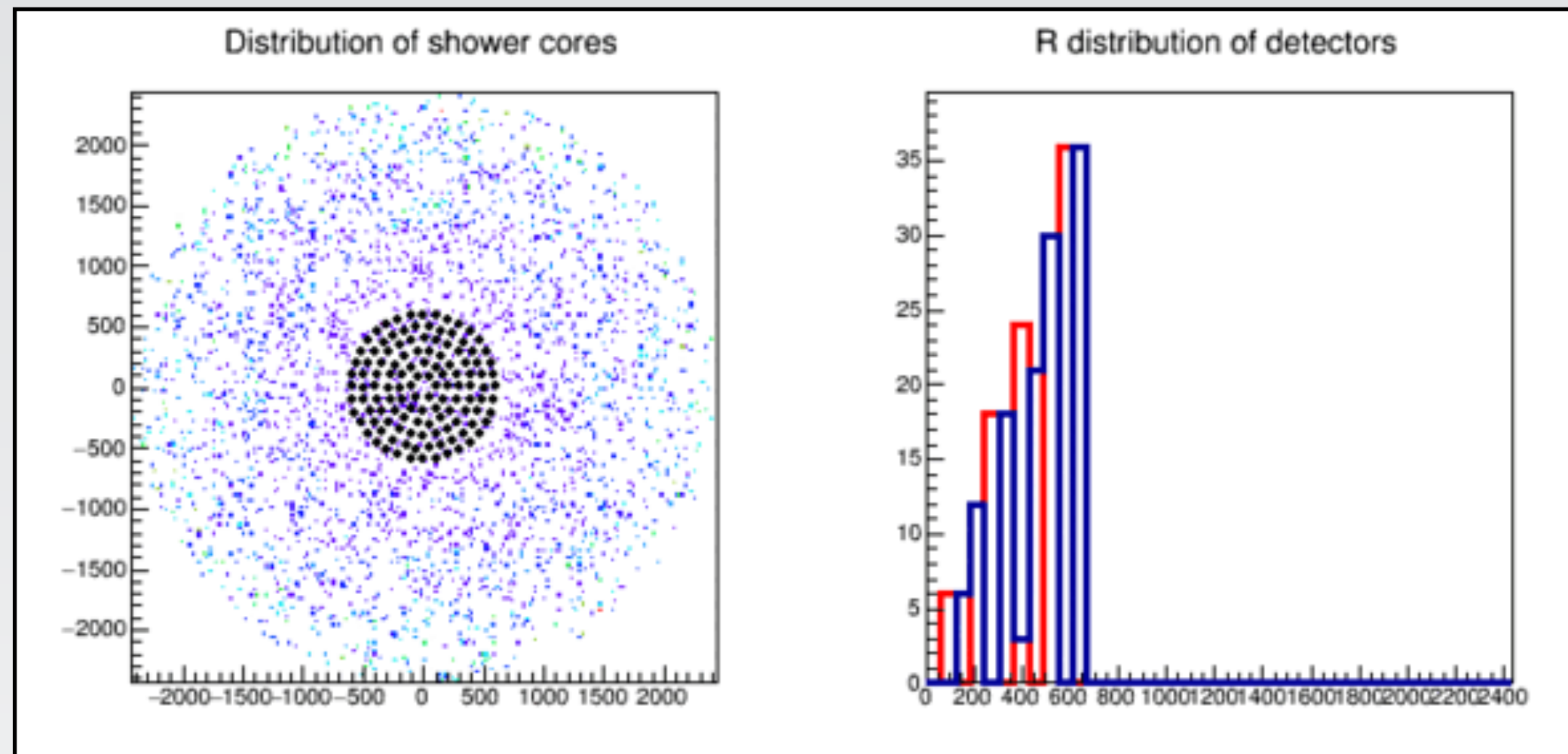


- Optimise photon flux
 - Layouts converge to the same optimum
-
- Final run with 300 aggregates (5700 tanks)
 - Optimise photon flux **and** energy measurement

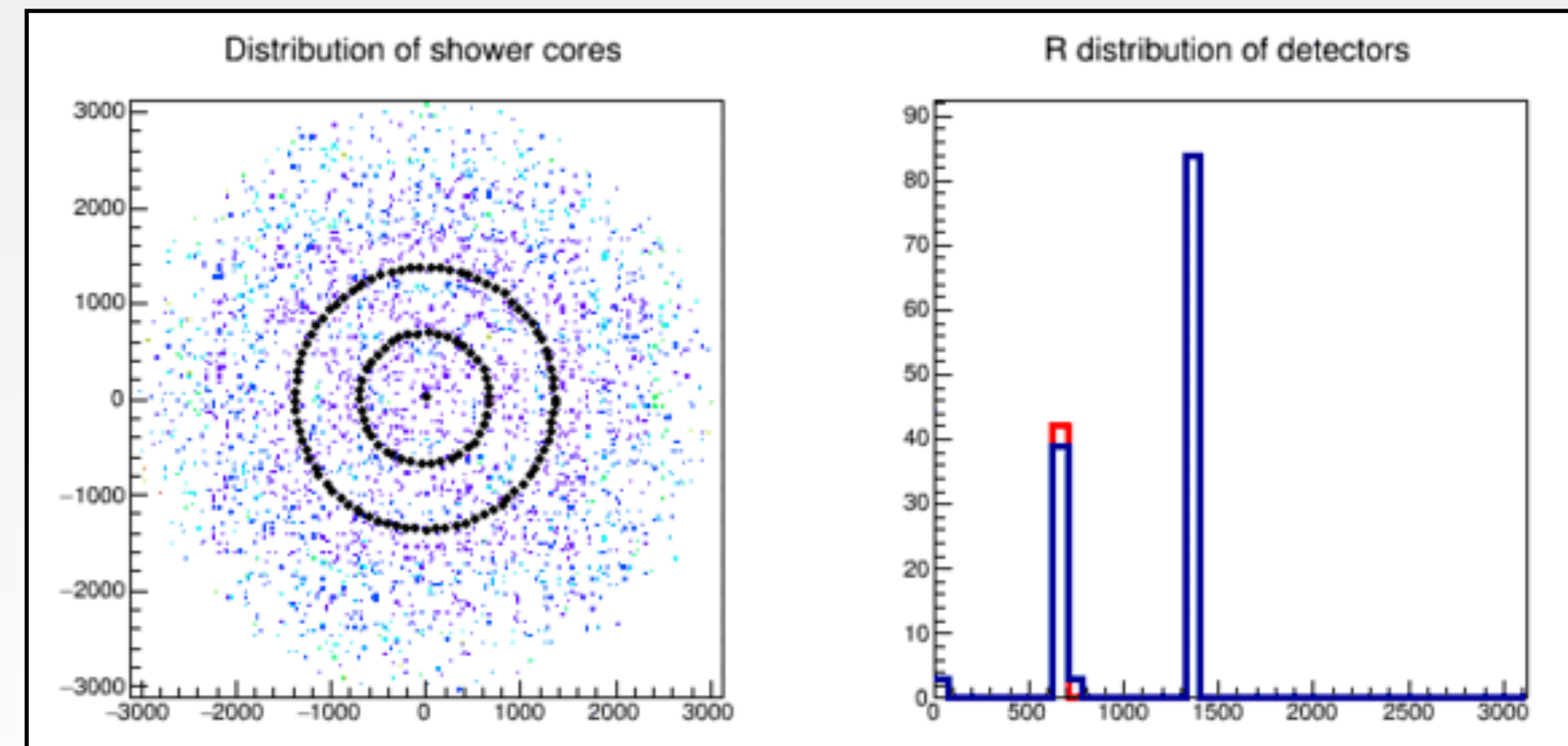
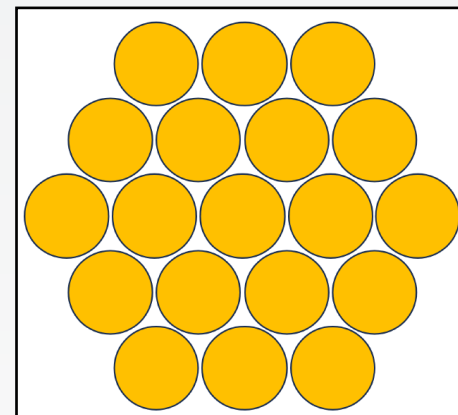


T. Dorigo, et al., arXiv.2310.01857

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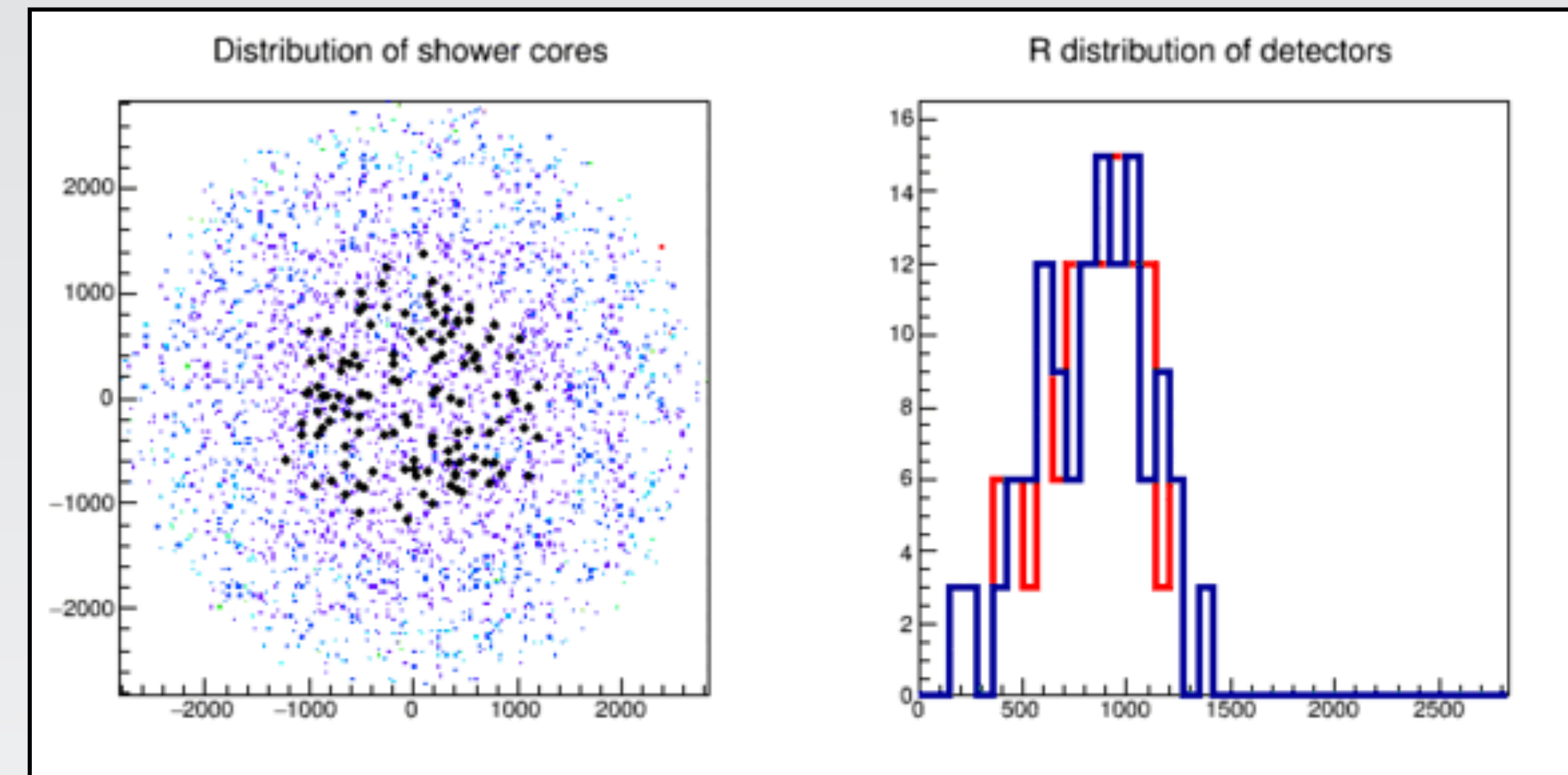
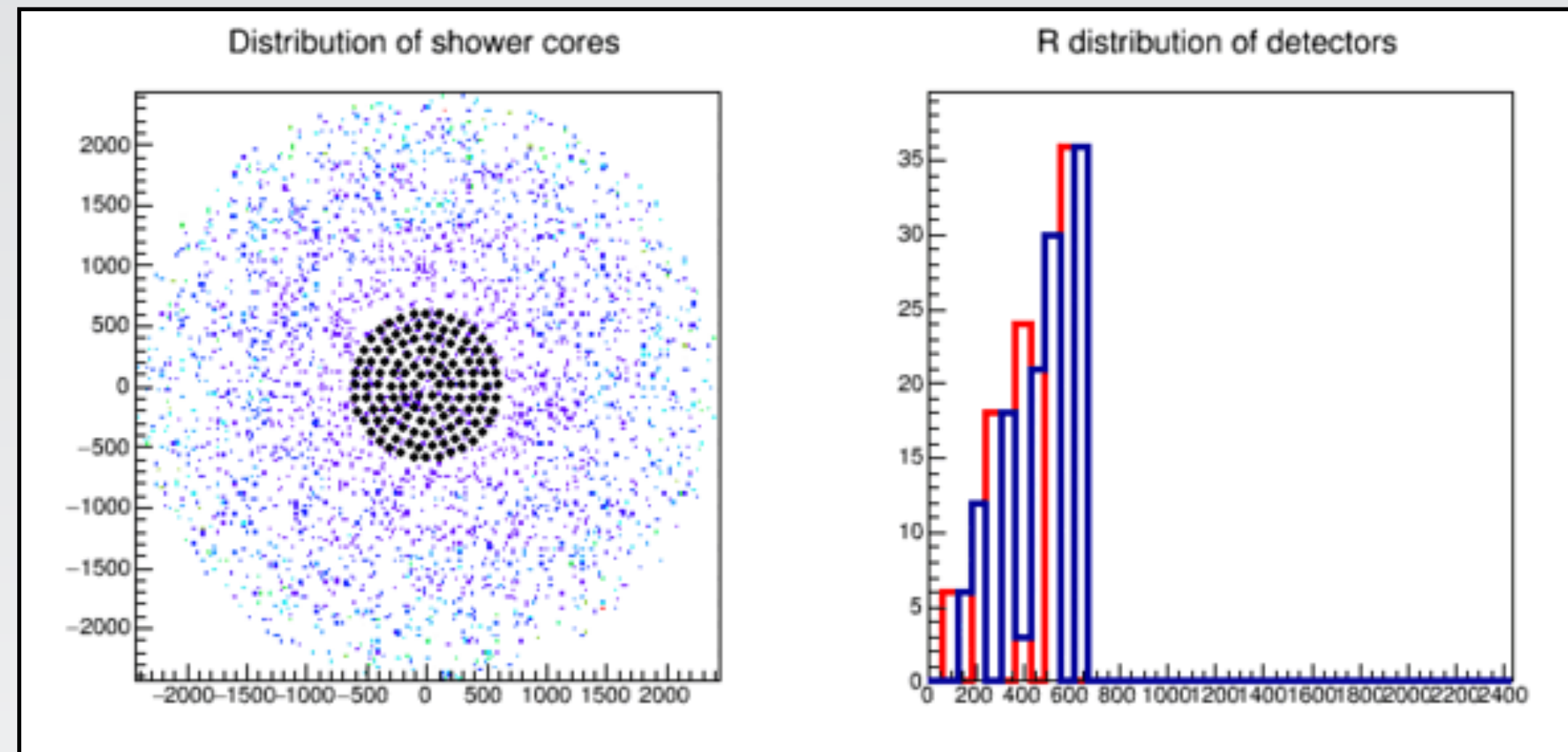


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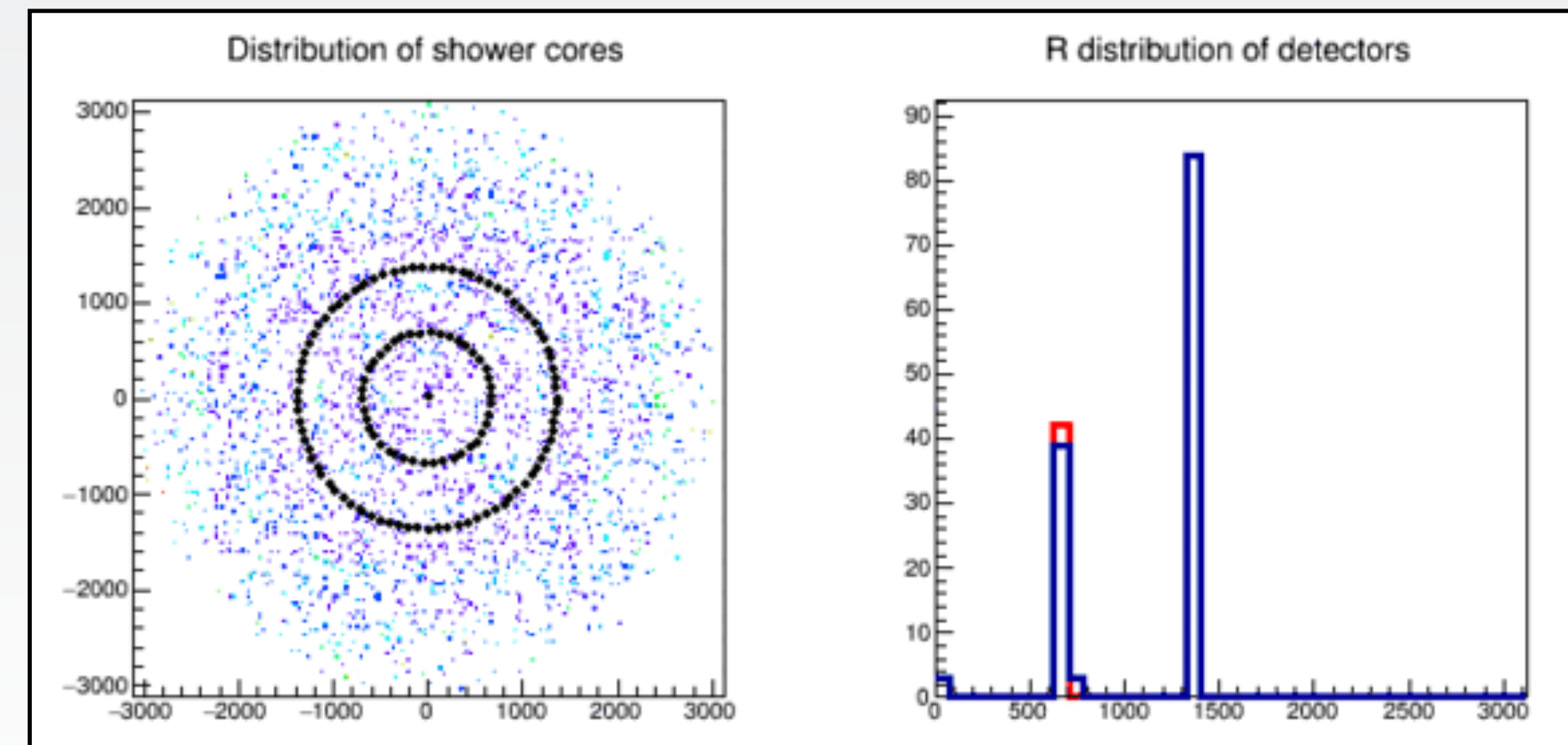
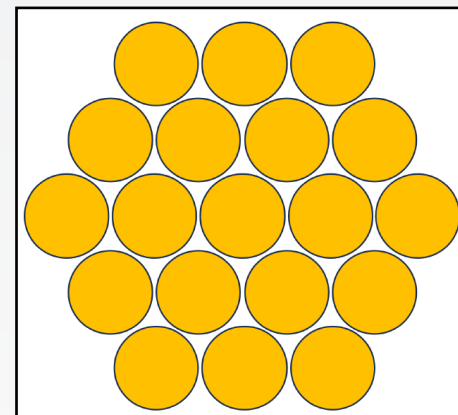
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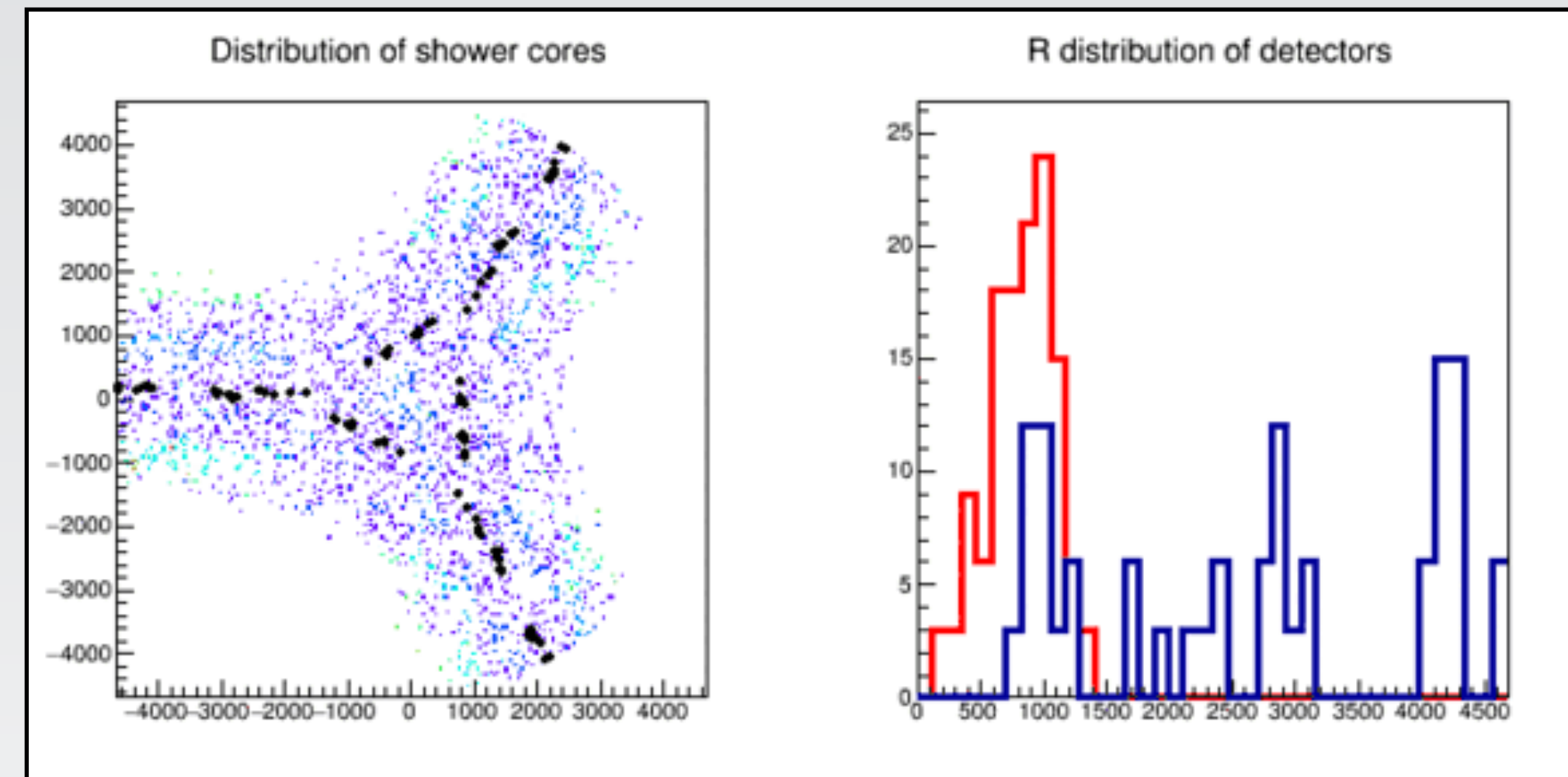
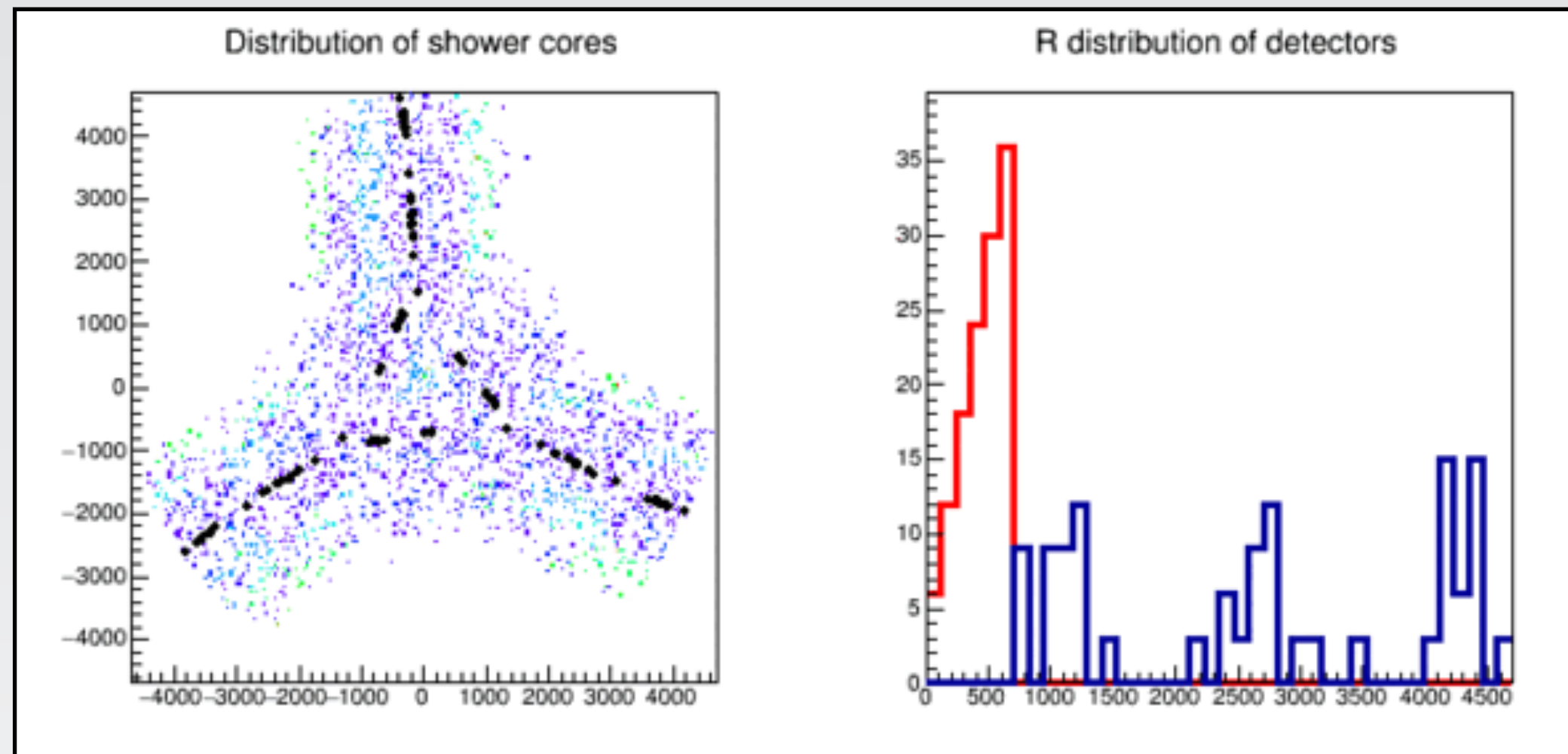
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Non trivial in $O(100)$ D parameter space

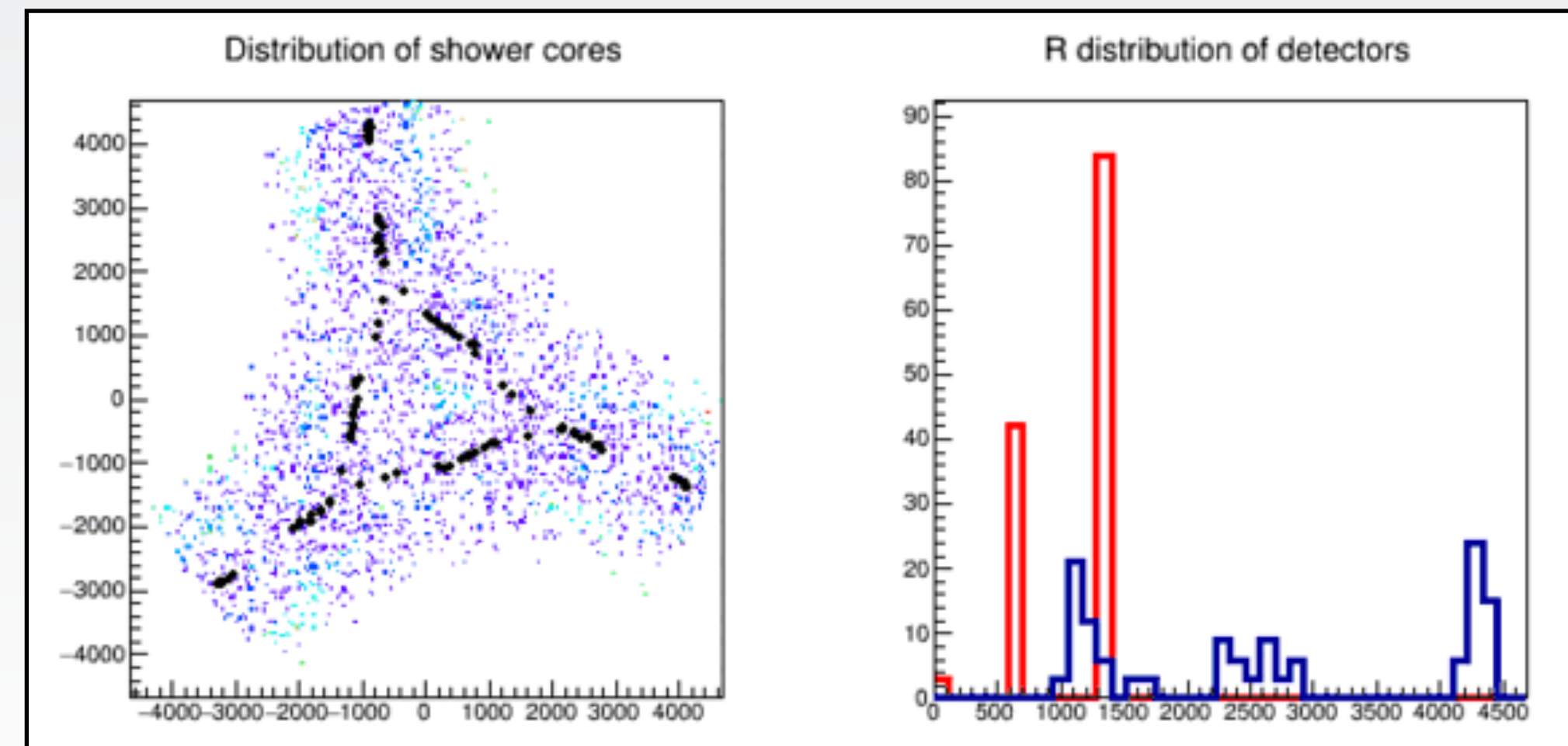
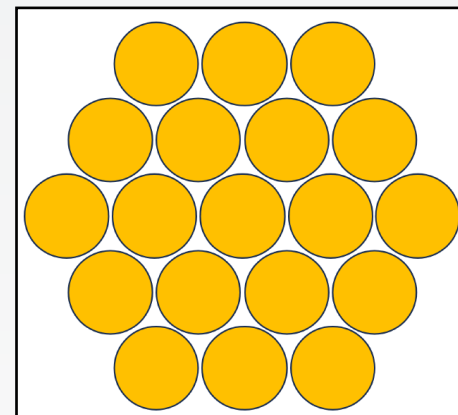


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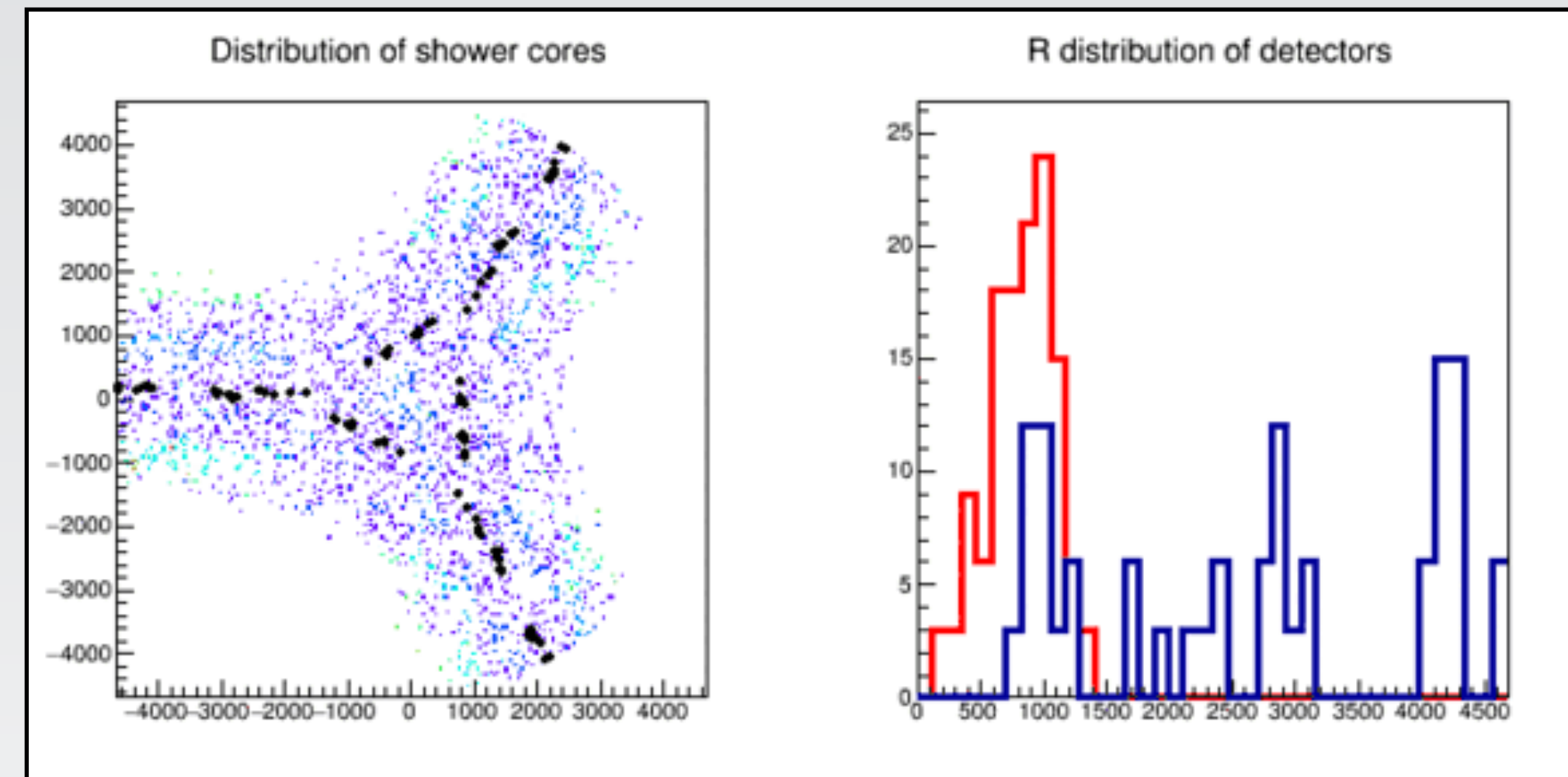
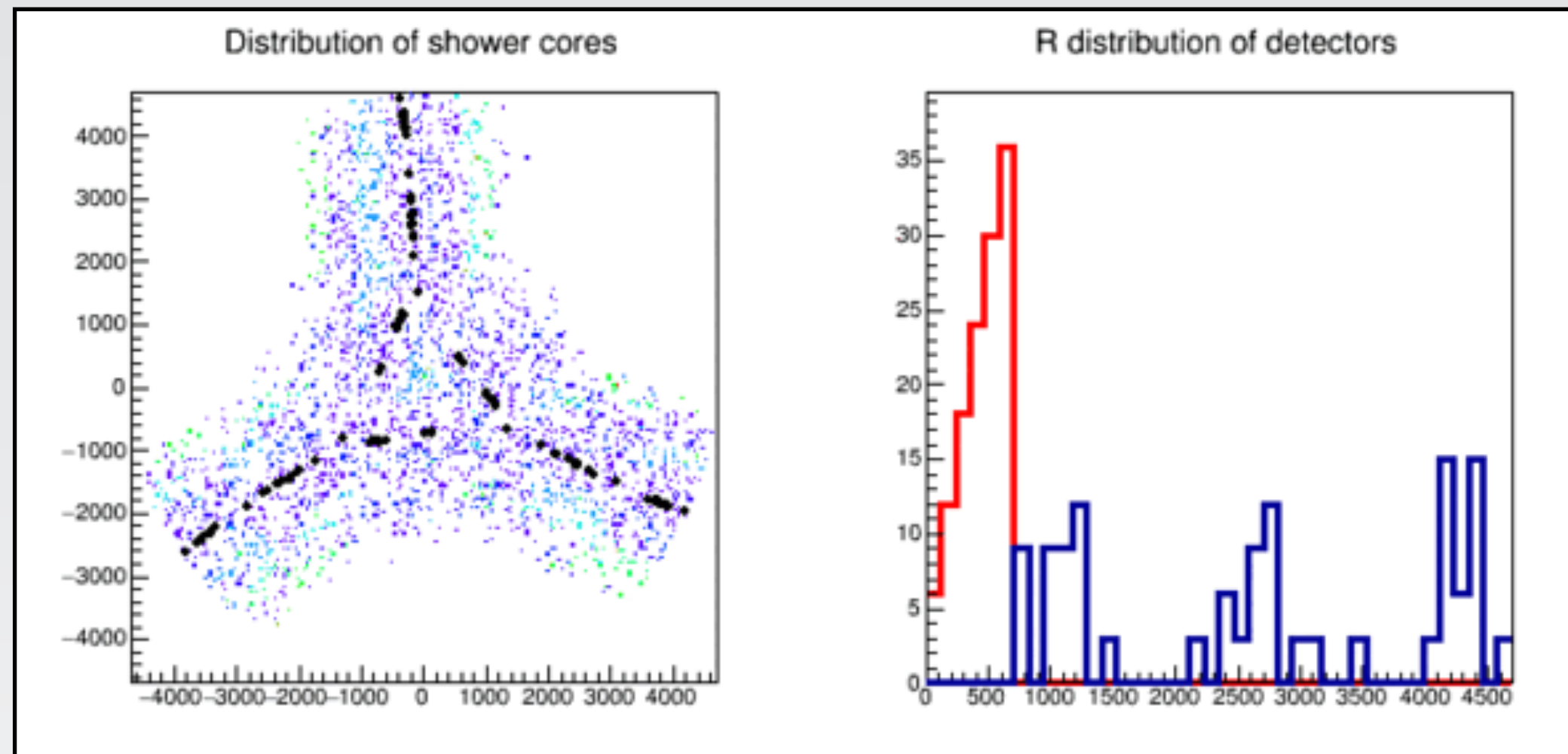
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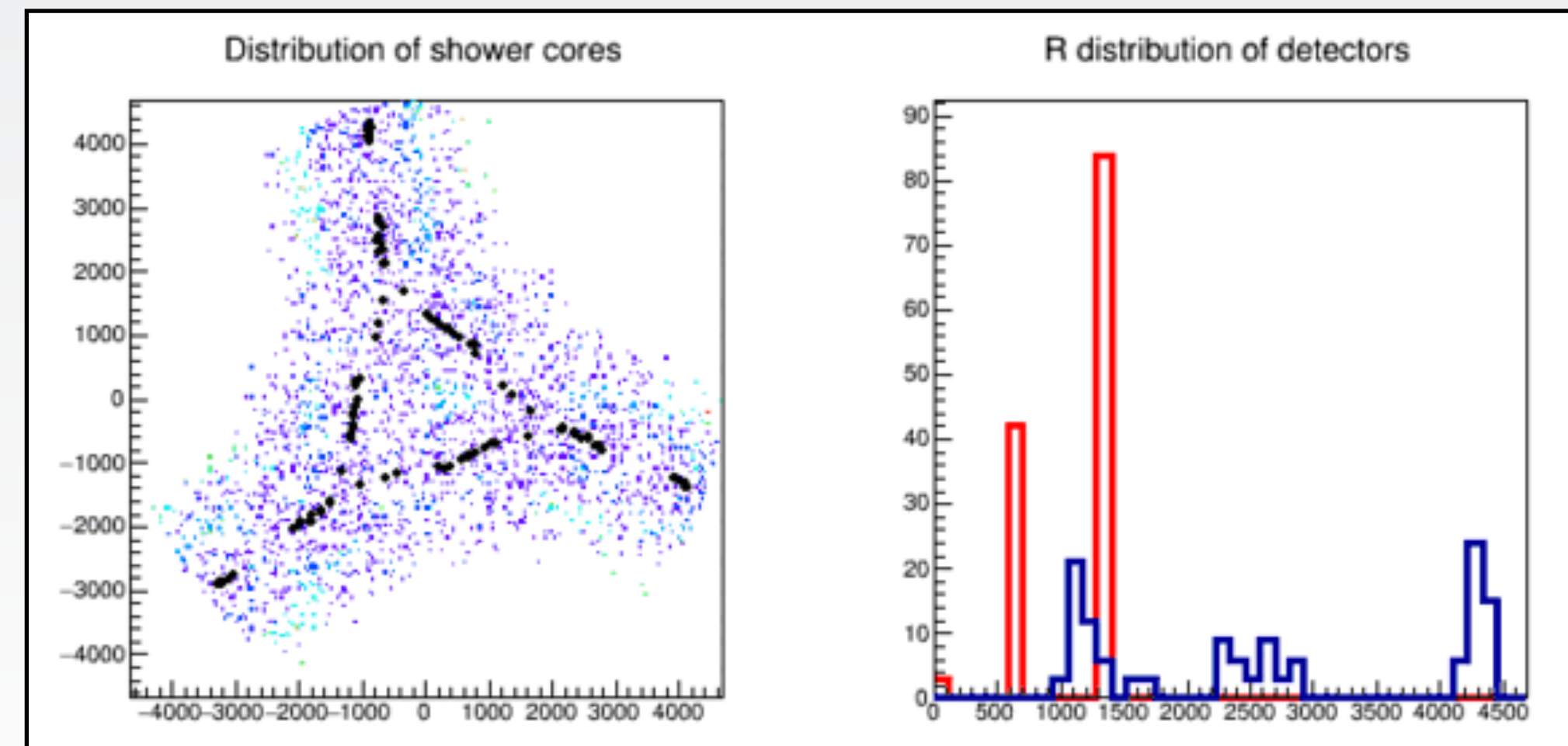
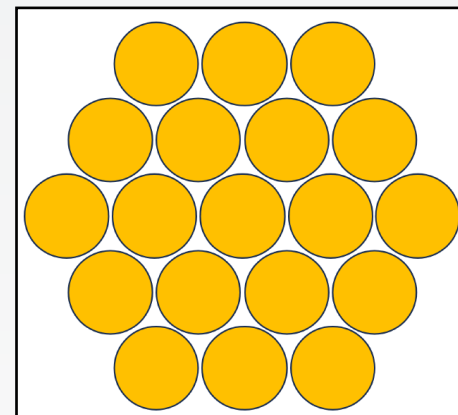
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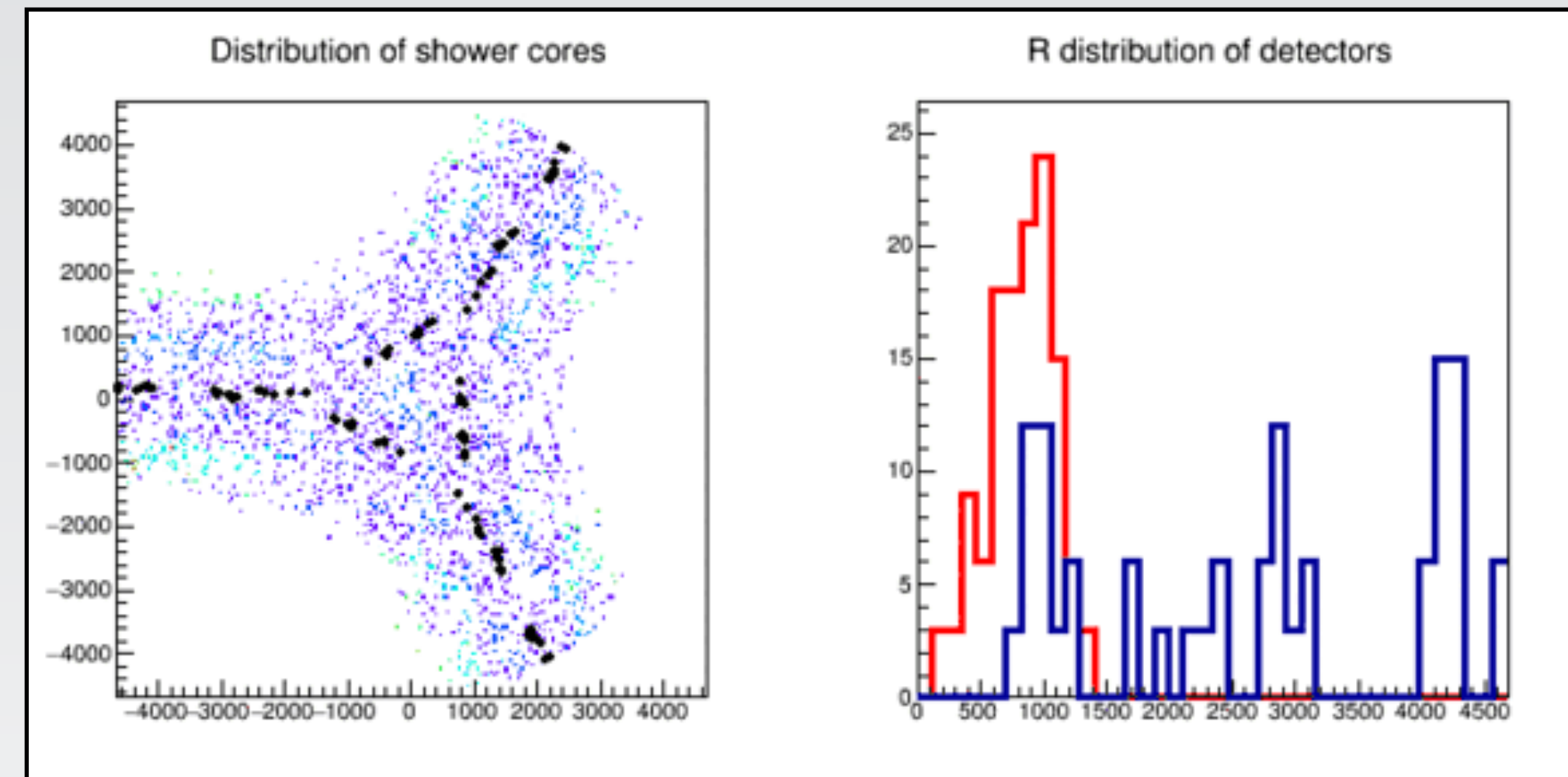
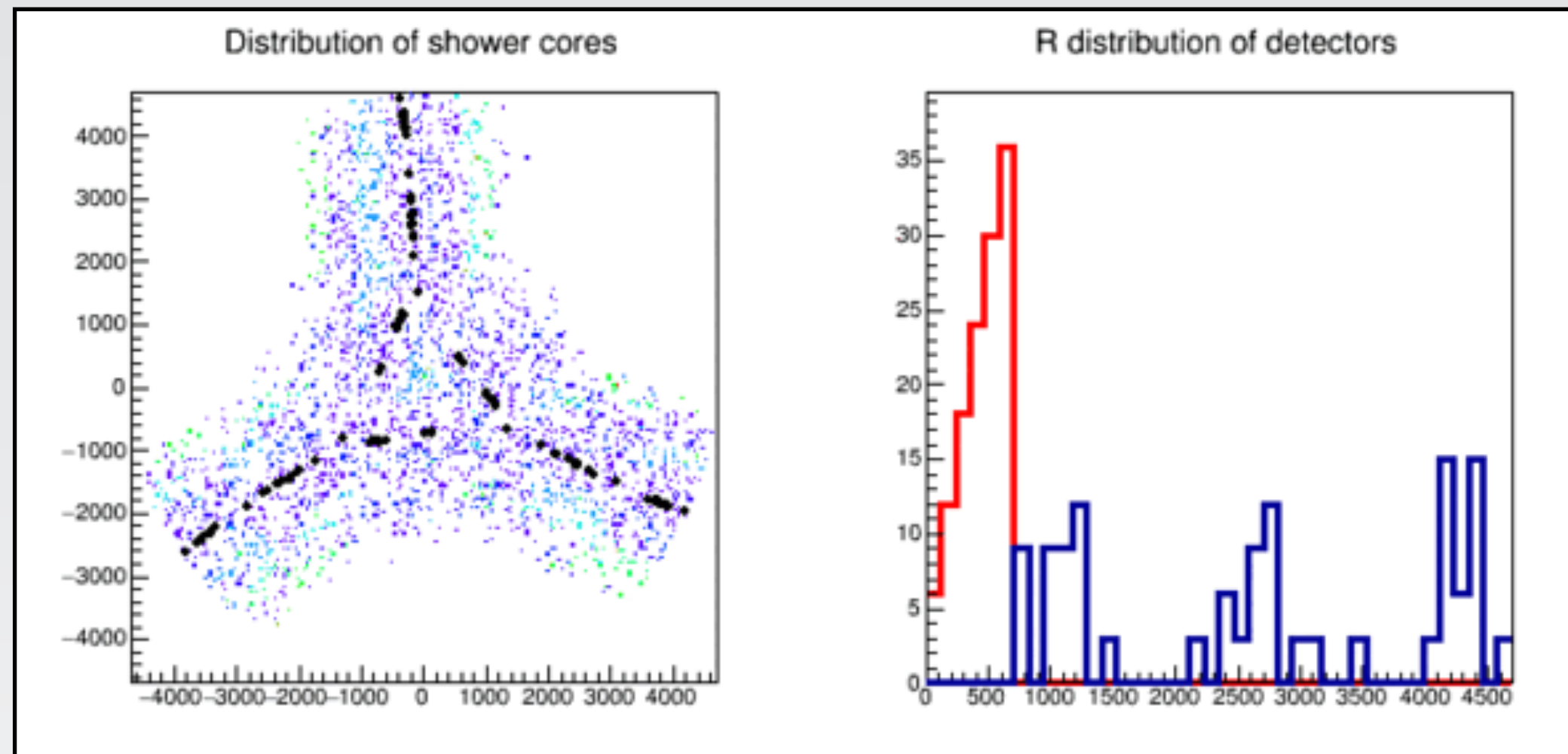
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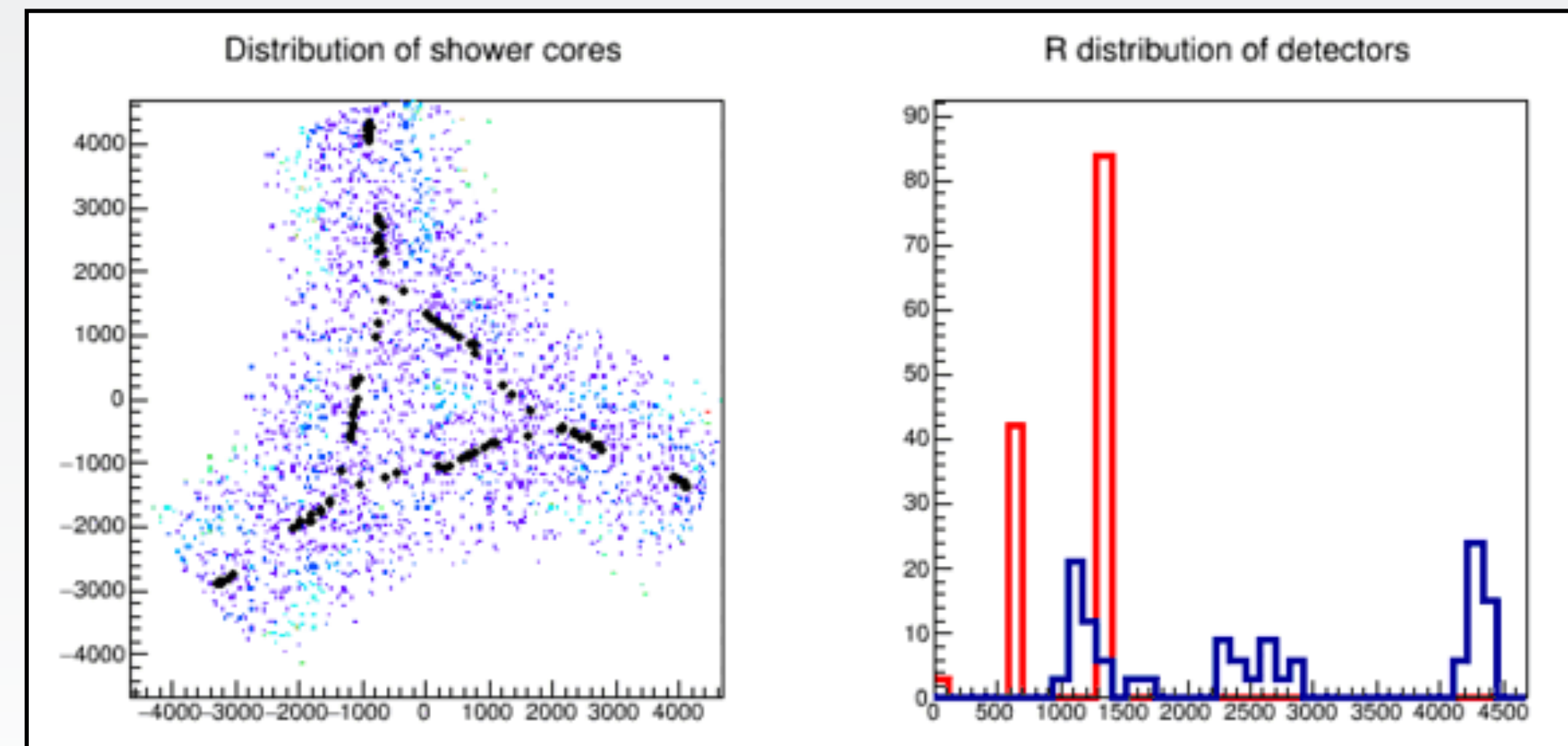
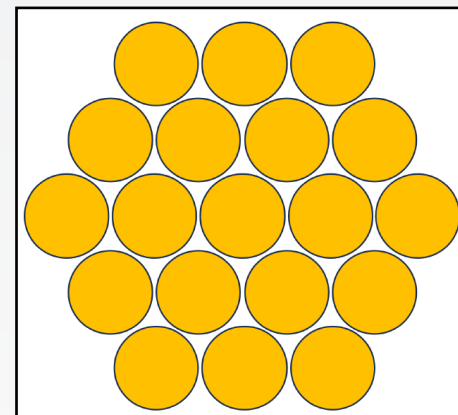


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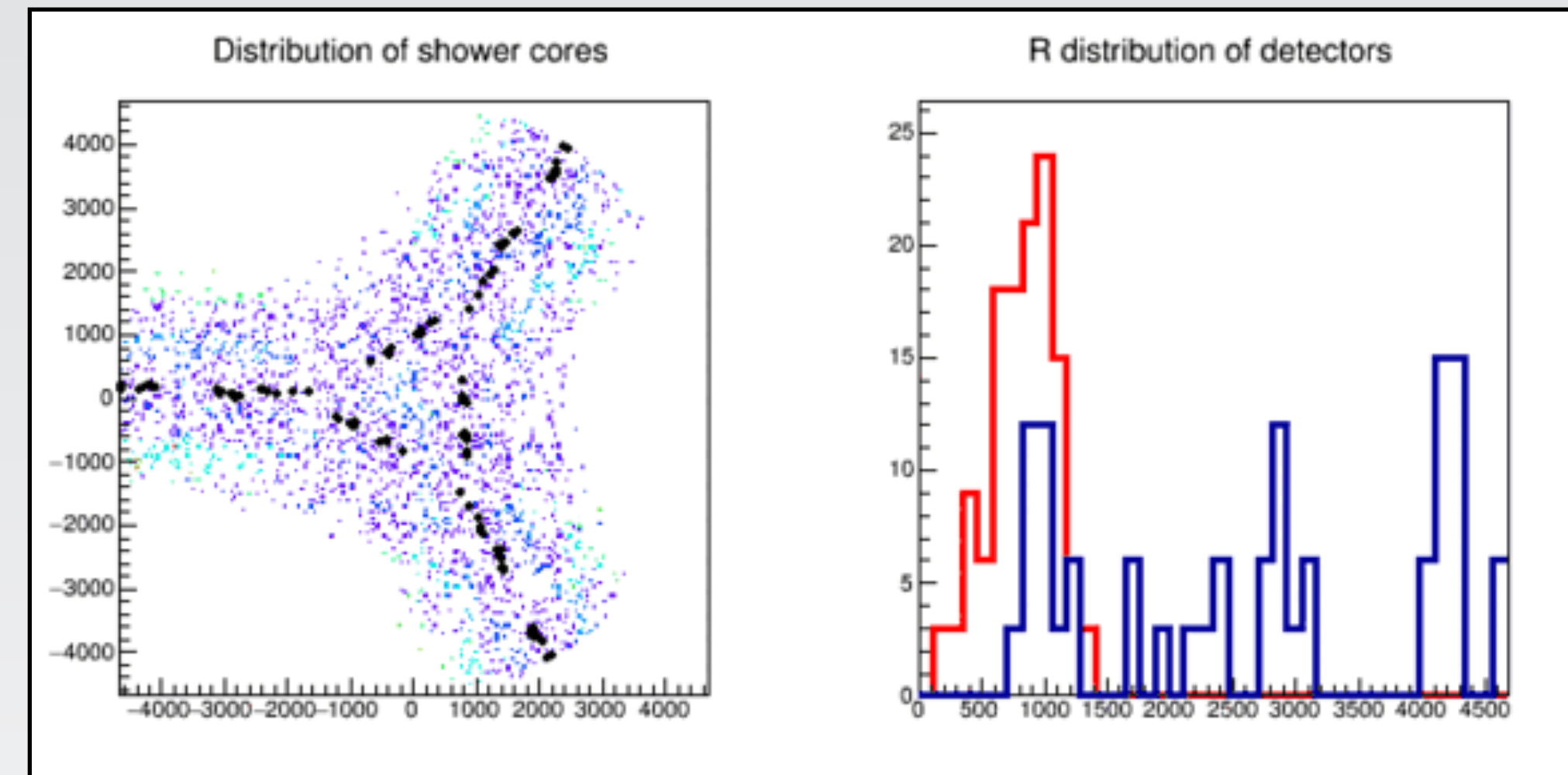
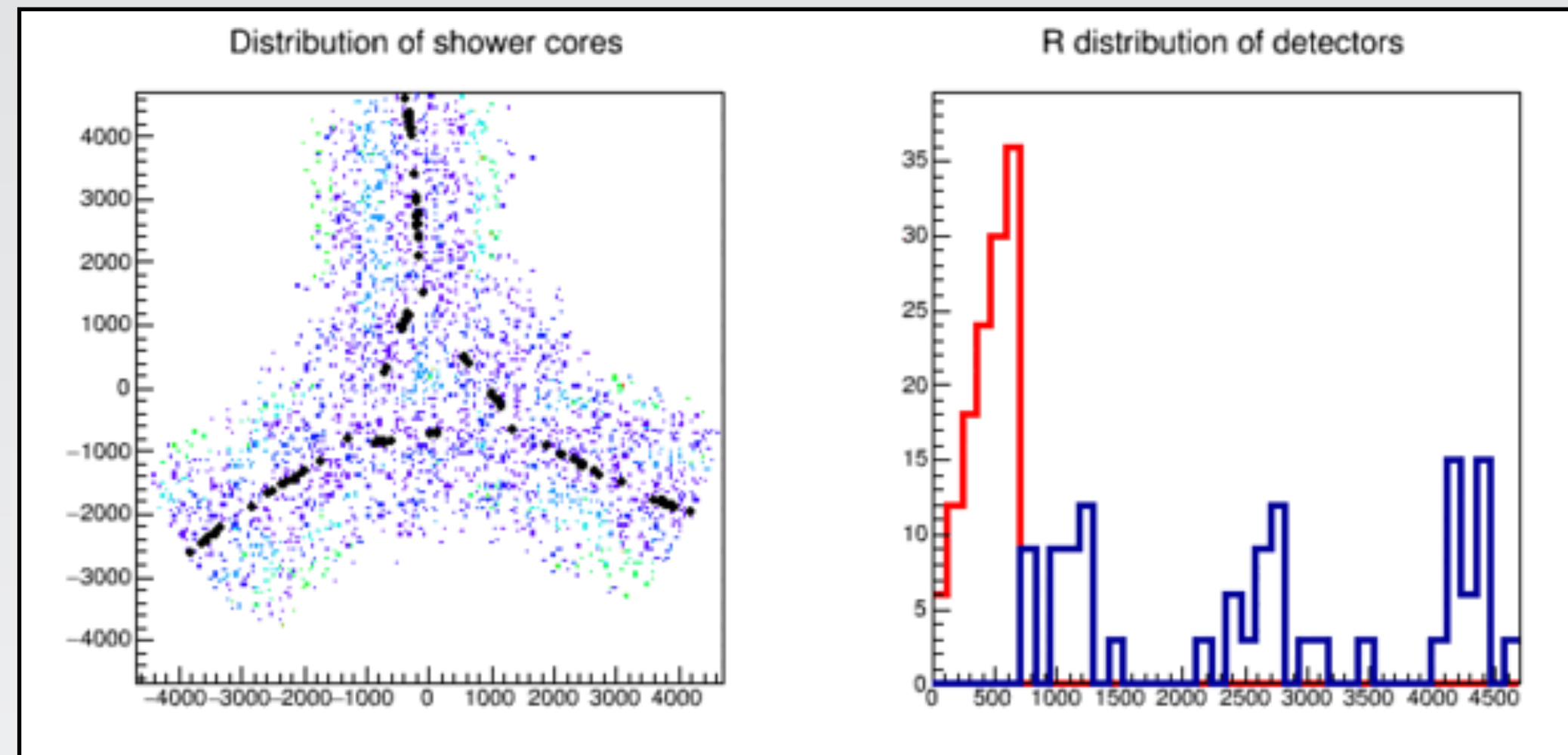


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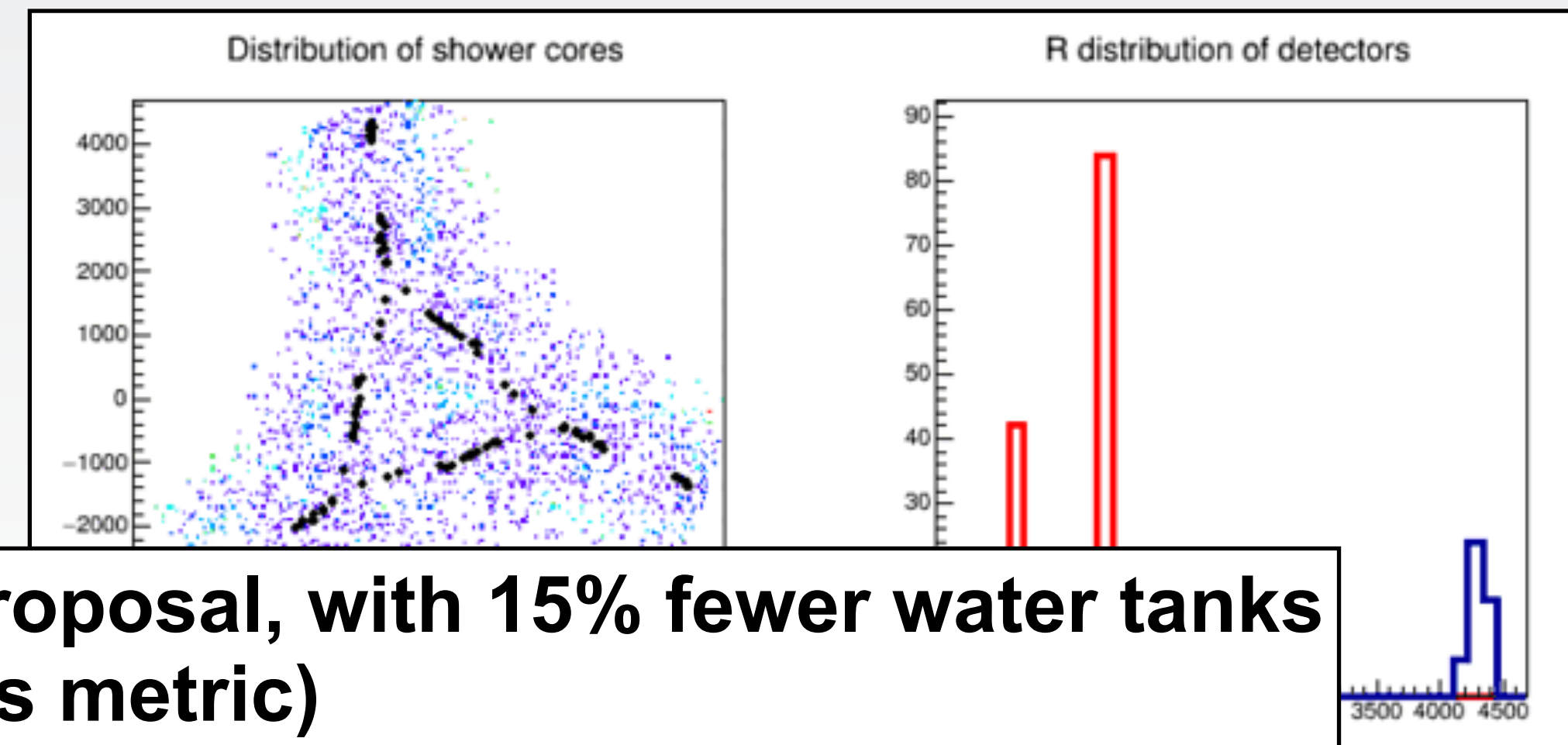
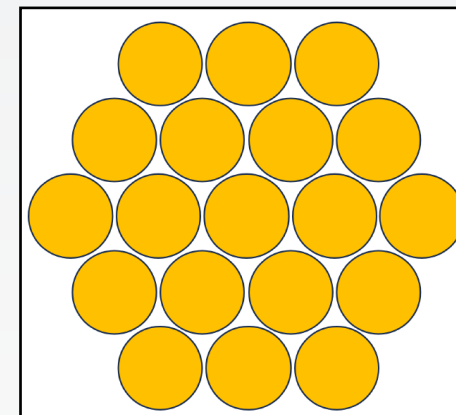


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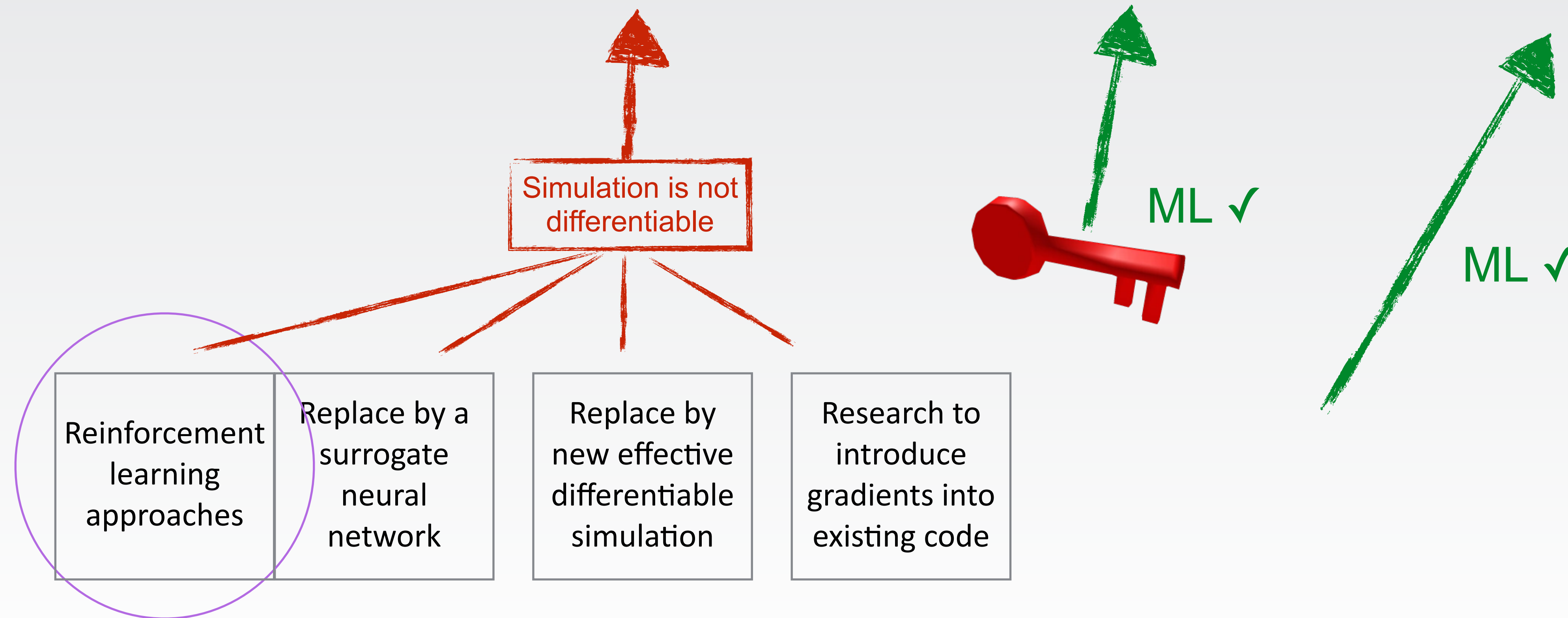
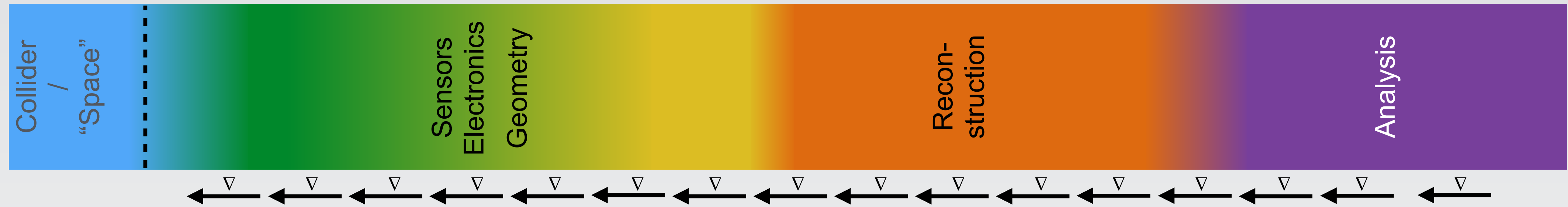


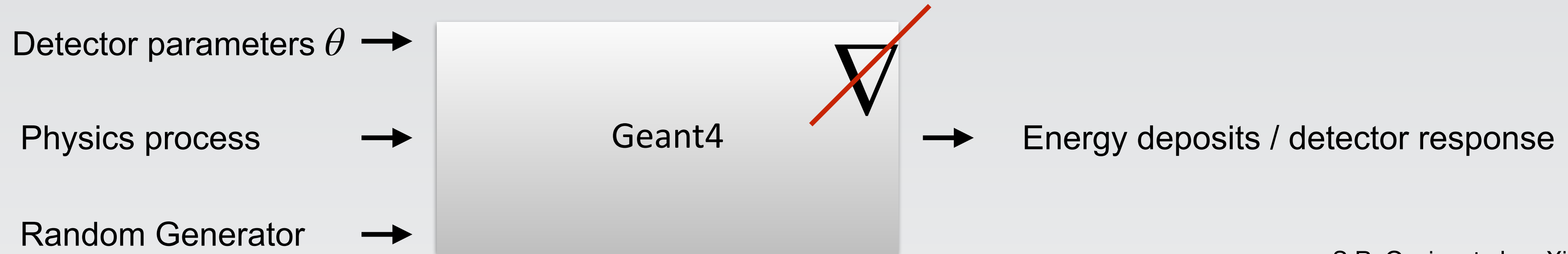
- Optimise photon flux
- Layouts converge to the same optimum
- Final run with 300 aggregates (5700 tanks)
 - Optimise photon flux **and** energy measurement

Non trivial in $O(100)$ D parameter space



About 17% improvement over best proposal, with 15% fewer water tanks (within this metric)





S.R. Qasim et al , arXiv:2412.10237, MLST

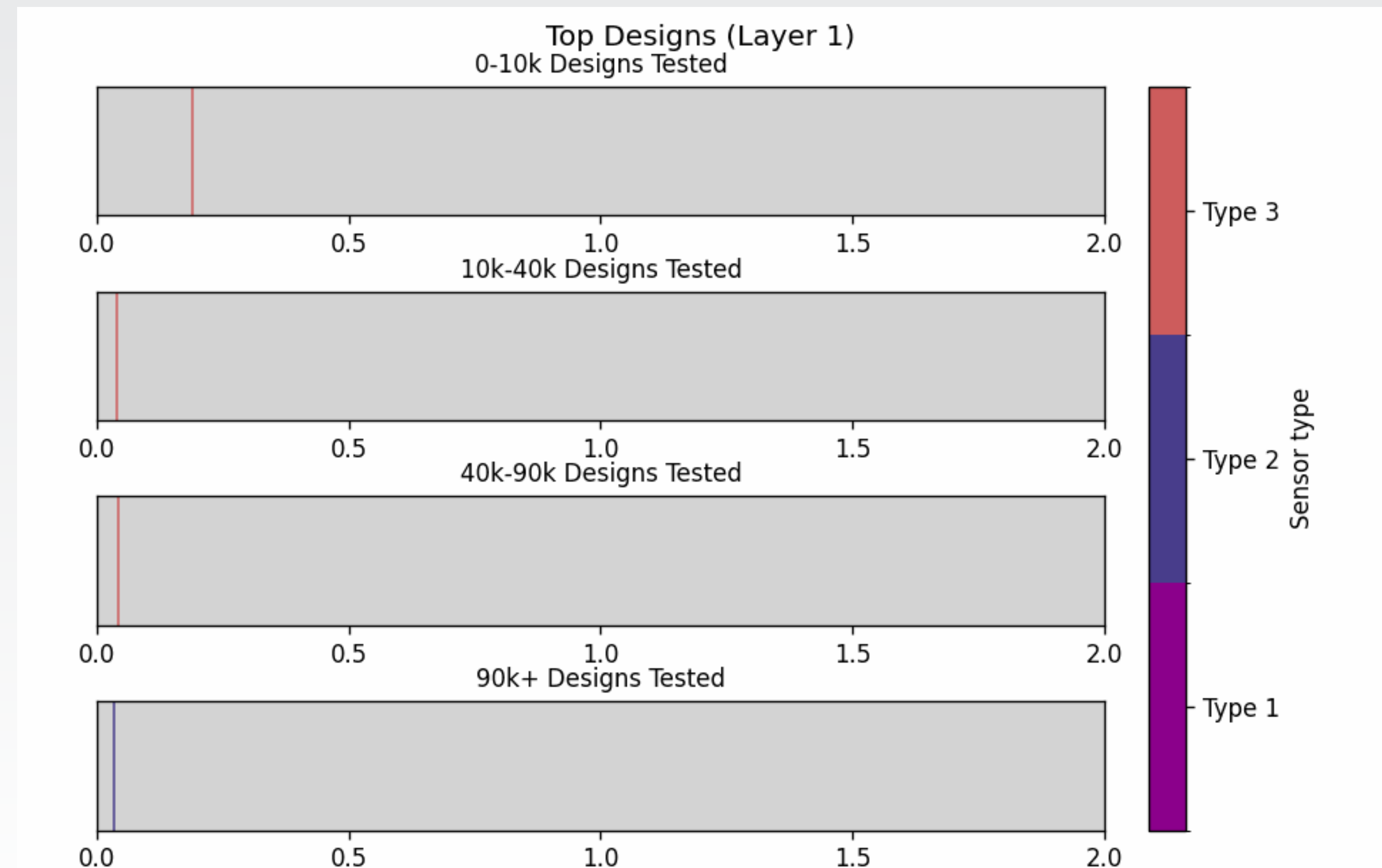
RL in a nutshell

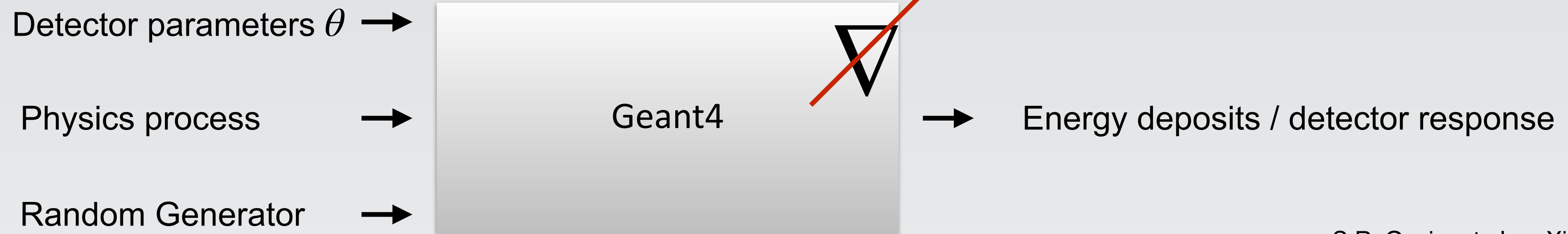
- Sample an **actions/detector parameters** from $\pi(a | s, \xi)$,
e.g. $a = \{\theta\}$, $\theta = \mathcal{N}(\mu, \sigma)$
- Evaluate the **environment/detector response**
(**does not need a gradient**)
- Calculate an **advantage/physics reach** for each set variation: A
- Maximise to find better $\xi \approx$ *weighted ML fit*

$$\sum_i A_i \log \pi(a_i | s, \xi)$$

Provides gradients

Constant weights without gradients





S.R. Qasim et al , arXiv:2412.10237, MLST

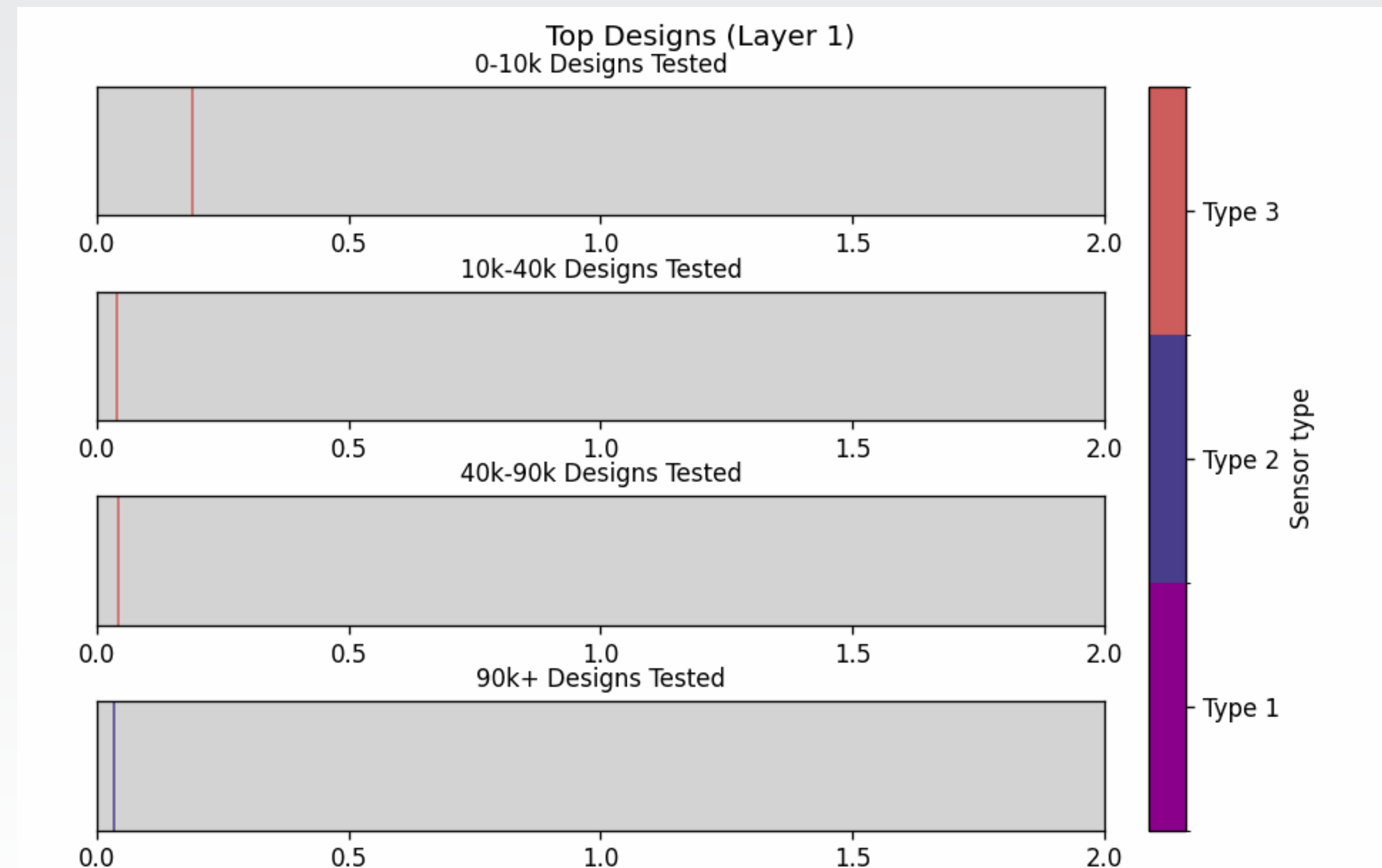
RL in a nutshell

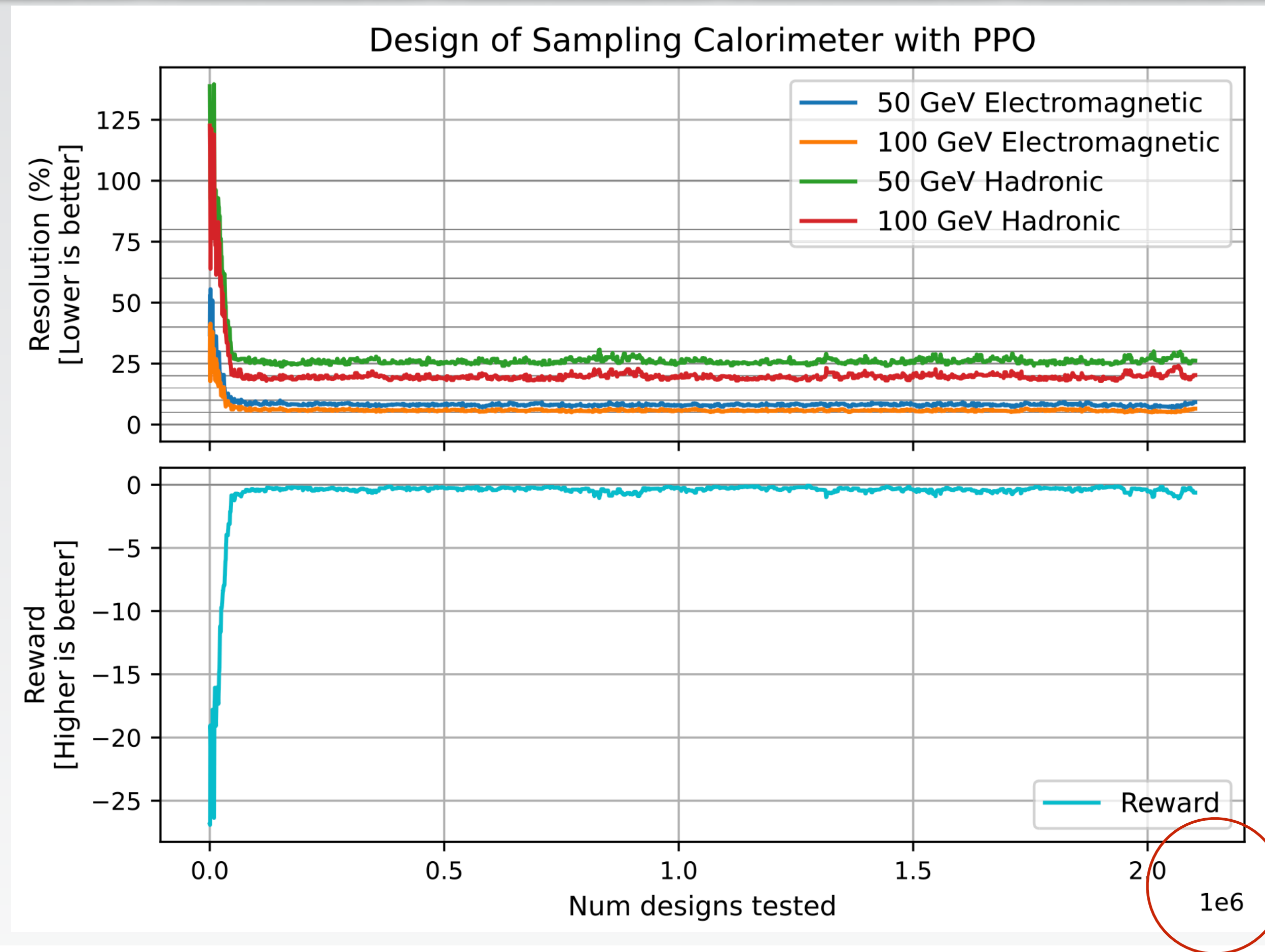
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Provides gradients

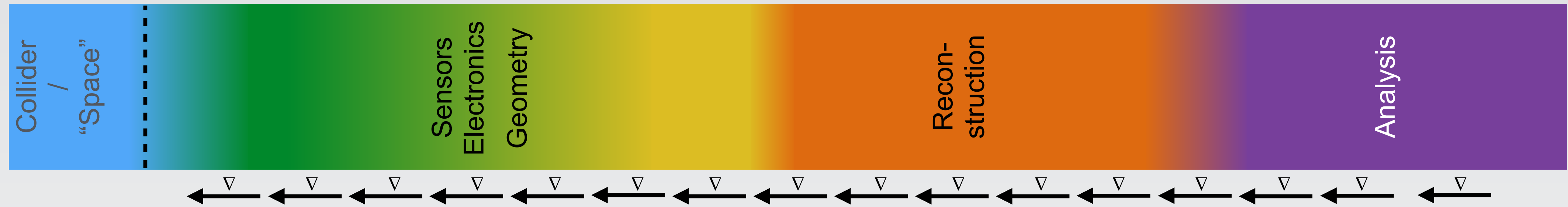
Constant weights without gradients





S.R. Qasim et al , arXiv:2412.10237, MLST

	50 GeV EM	100 GeV EM	50 GeV Had	100 GeV Had
Baseline design	8.15 ± 0.16	5.96 ± 0.12	32.13 ± 0.64	25.19 ± 0.50
RL design	7.91 ± 0.16	5.65 ± 0.11	24.29 ± 0.49	18.07 ± 0.36



Simulation is not differentiable

- Reinforcement learning approaches
- Replace by a surrogate neural network
- Replace by new effective differentiable simulation
- Research to introduce gradients into existing code

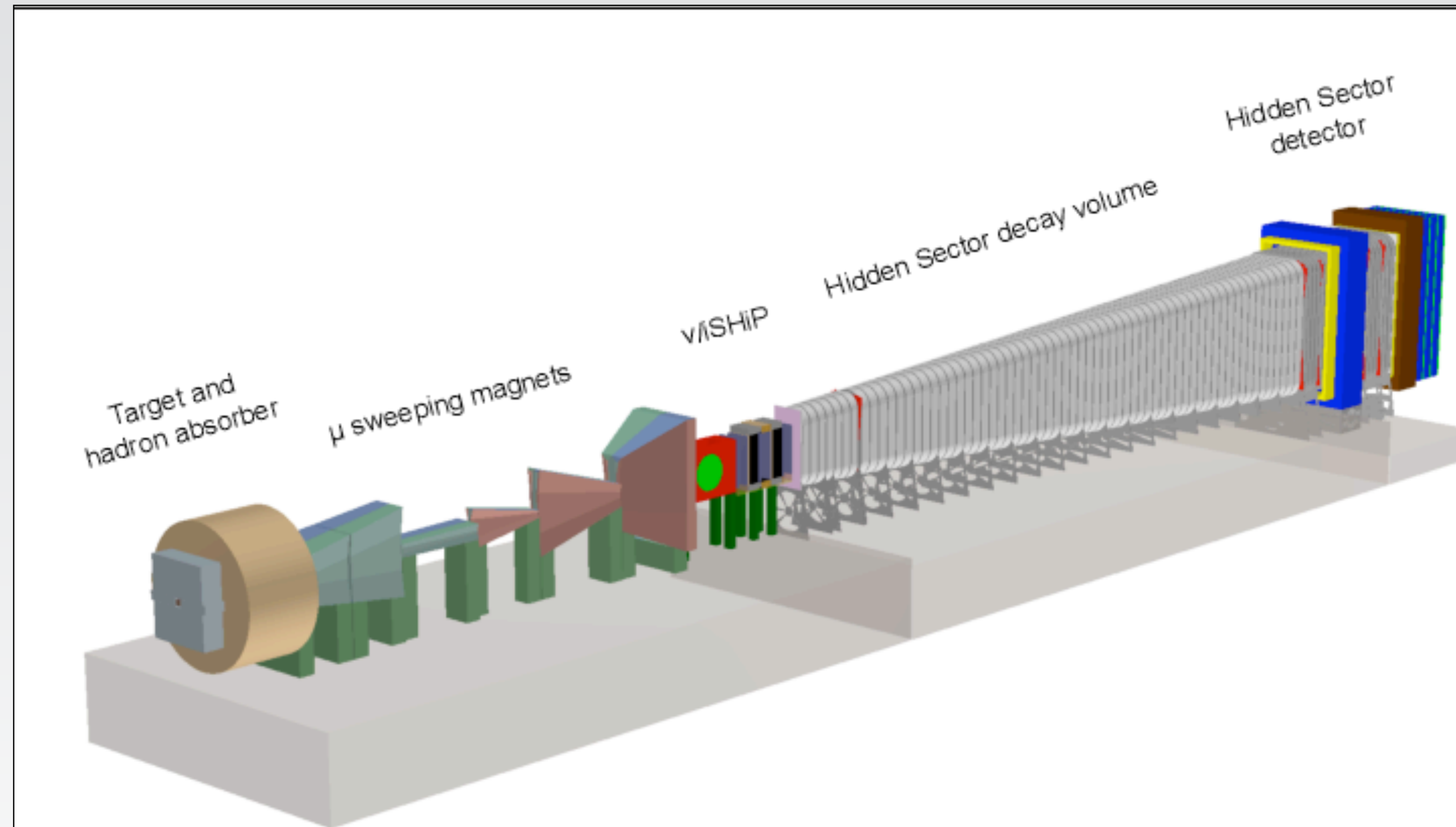


ML ✓



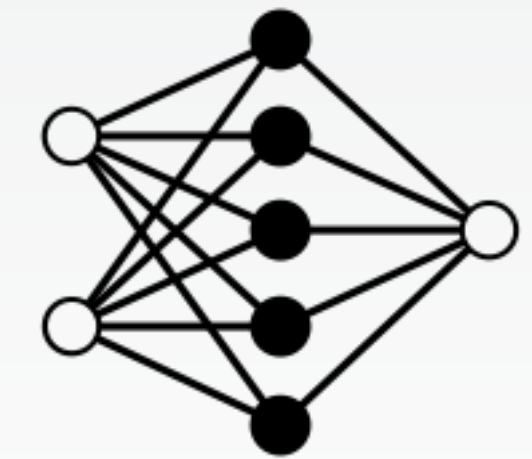
ML ✓

Local Surrogates: SHiP (Search for Hidden Particles)



- Objective: As few muons as possible reach the detector.
- Example: learn **local ML surrogates of the gradient** for optimising the SHiP muon shielding

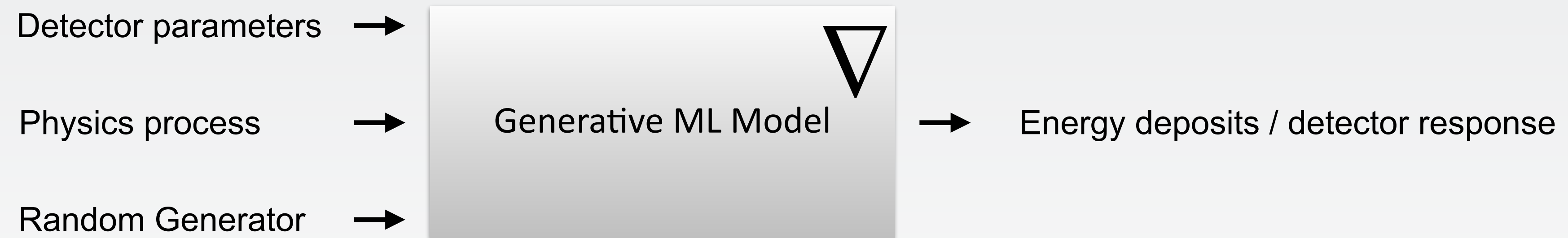
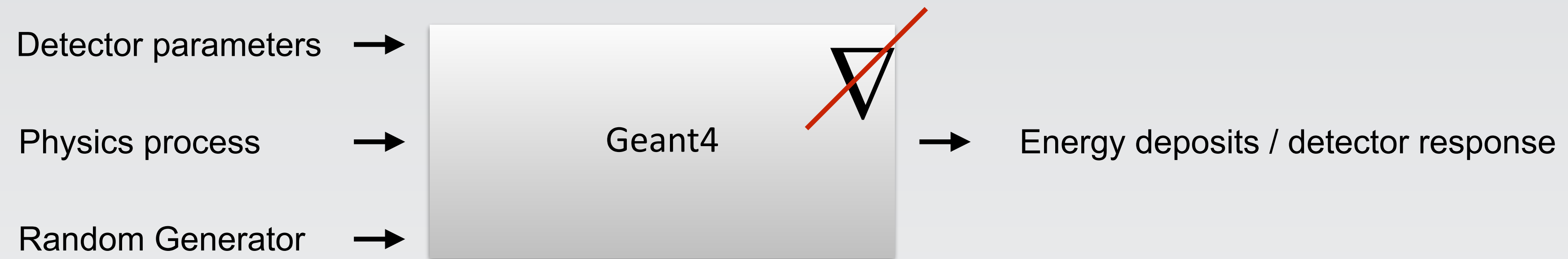
Not differentiable
simulator



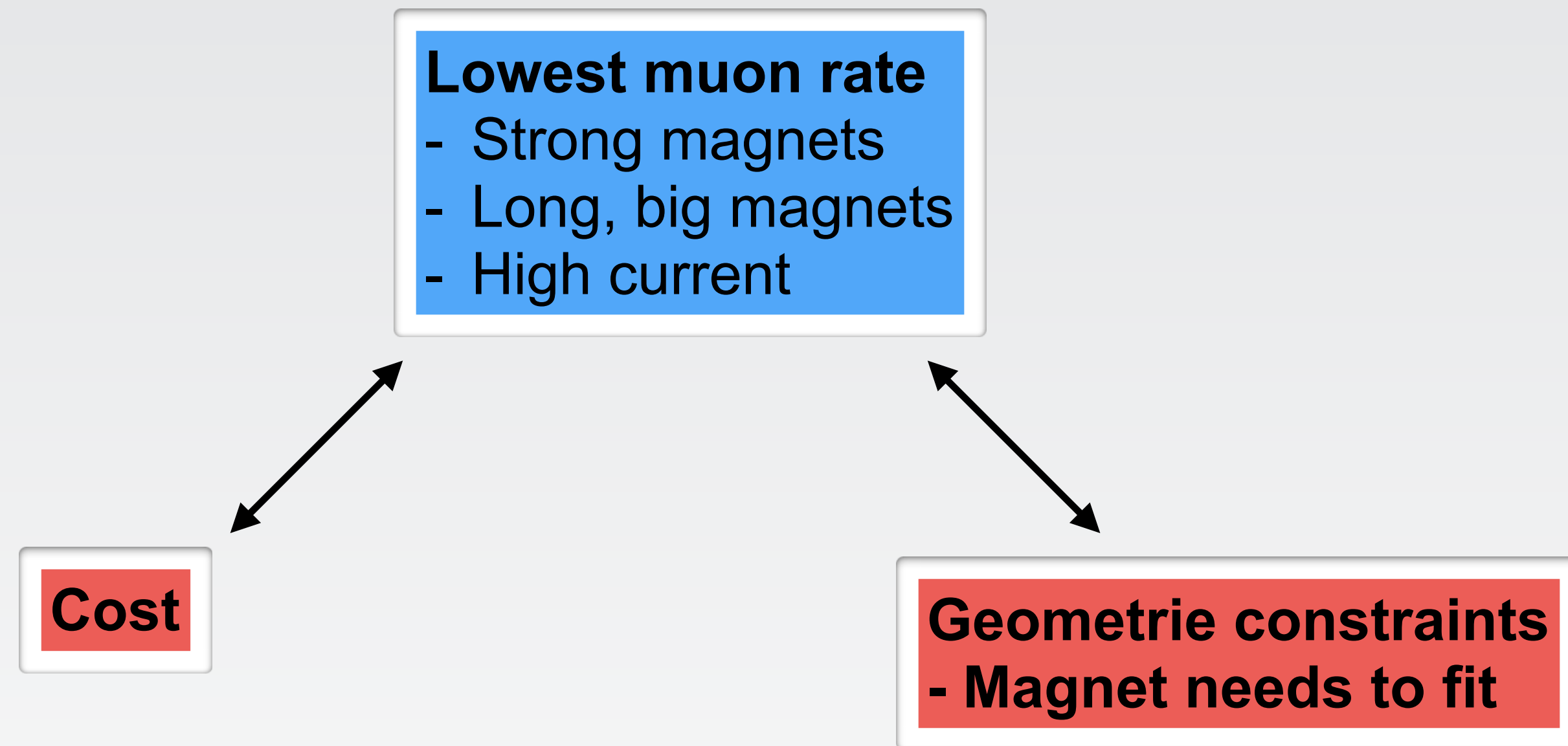
Differentiable ML surrogate

S. Shirobokov, et al., arXiv:2002.04632

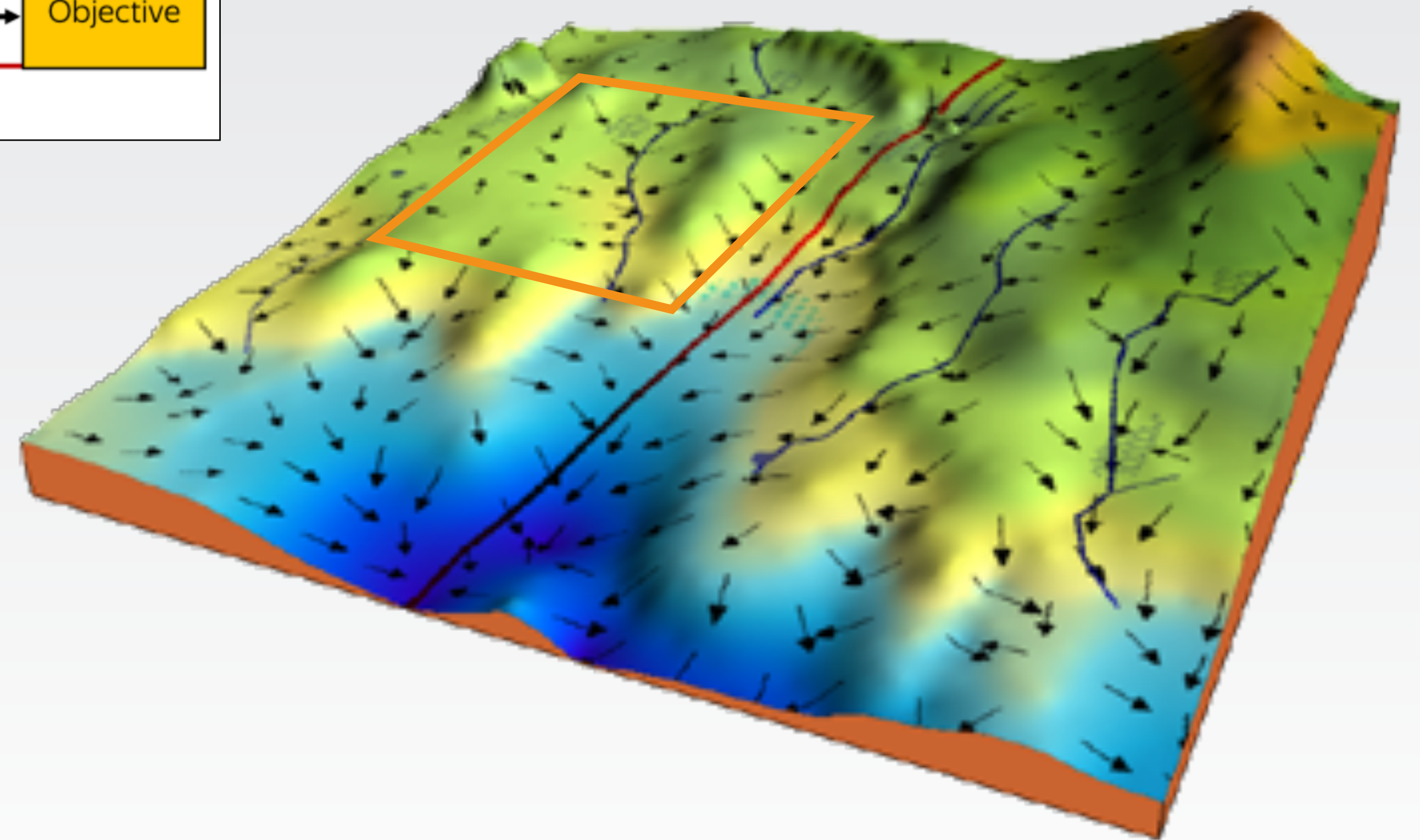
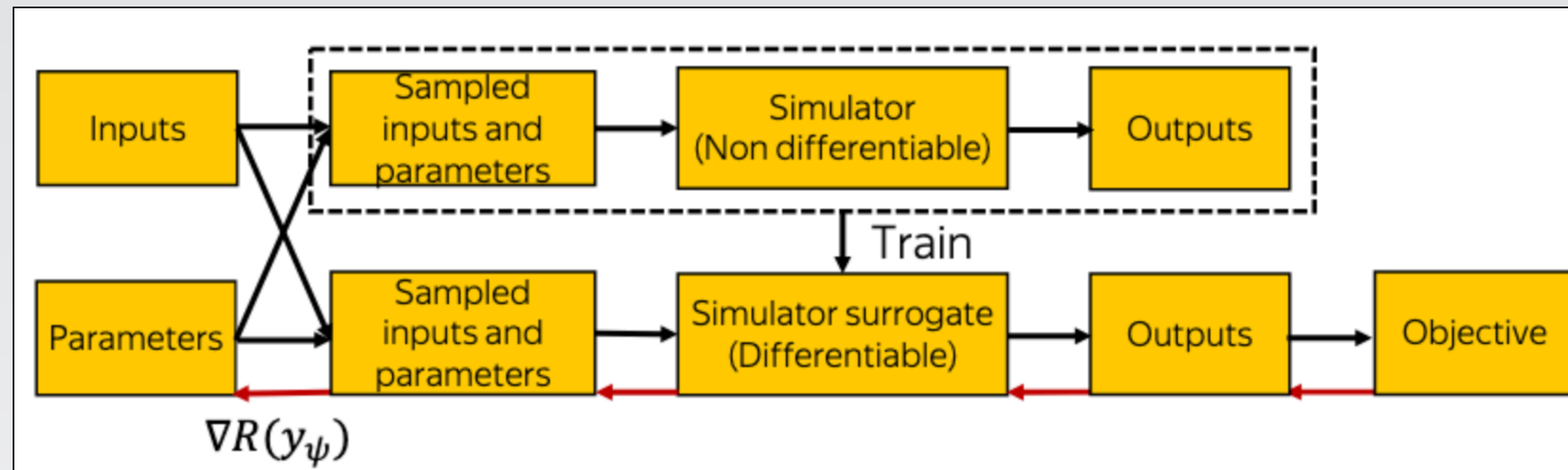
A generative surrogate model



The Main Competitors



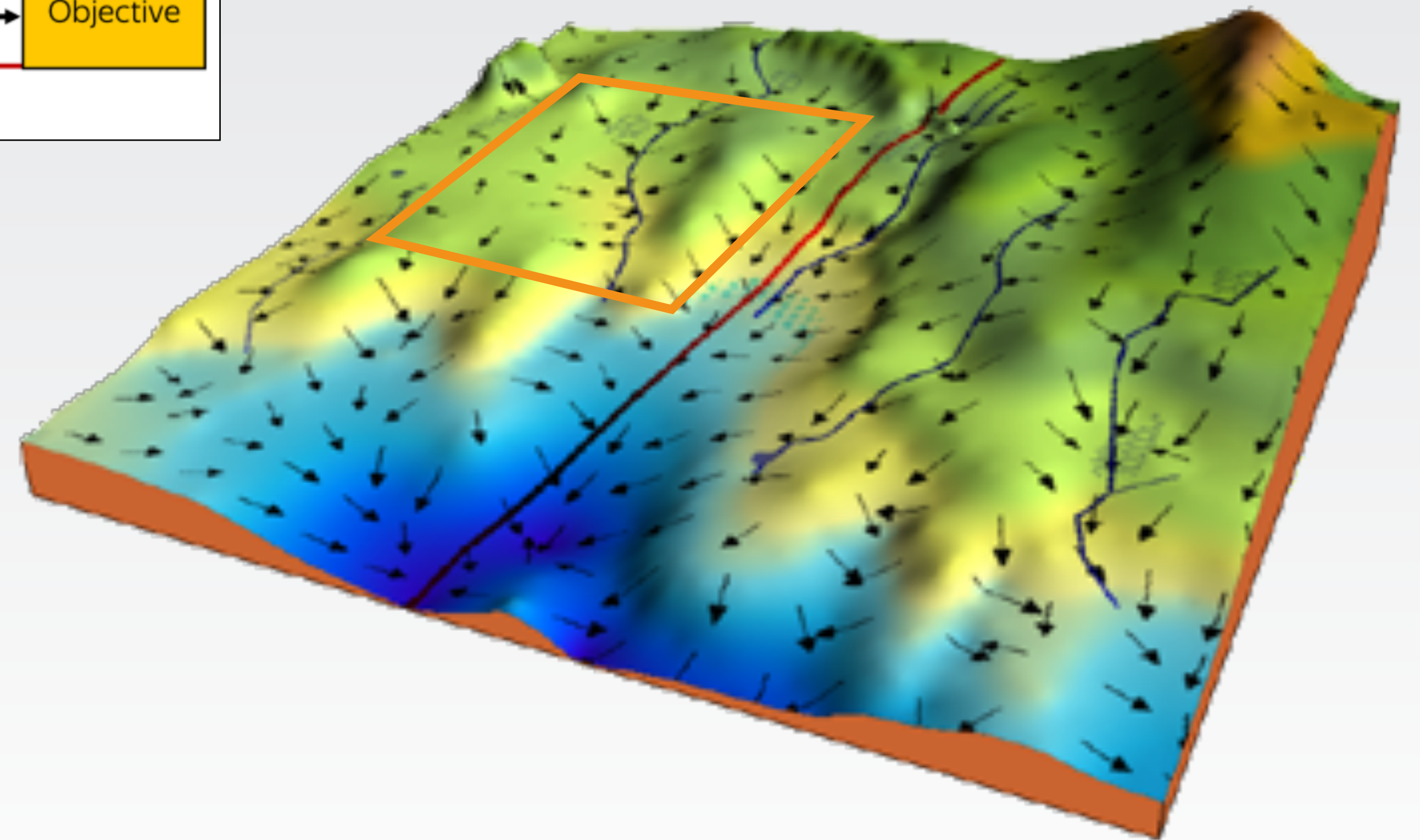
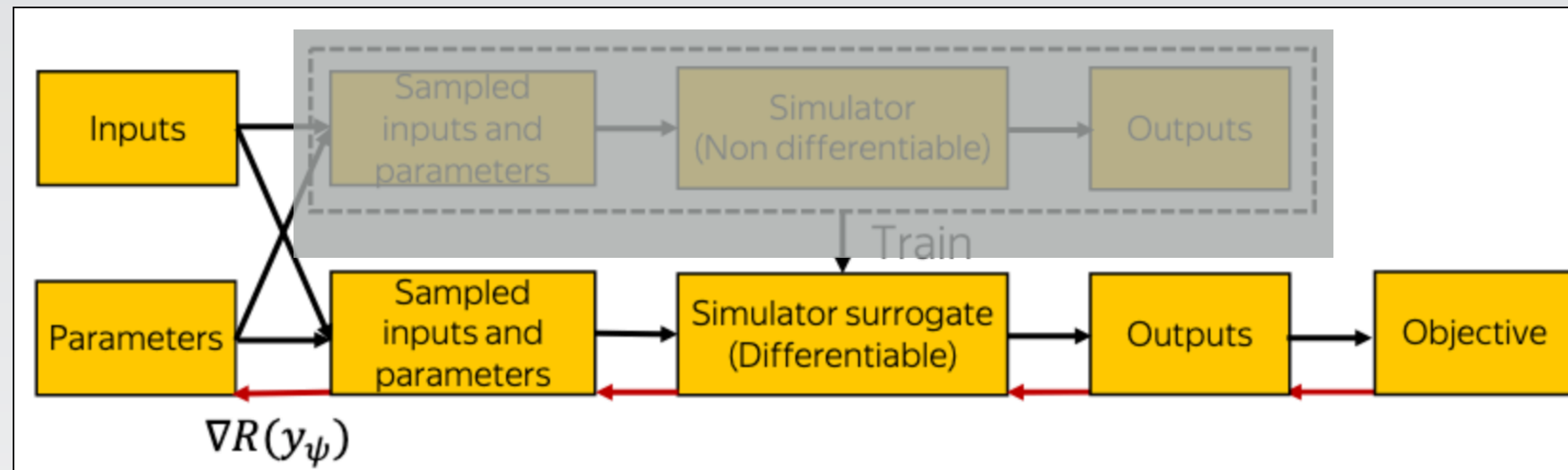
A Local Surrogate



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

S. Shirobokov, et al., arXiv:2002.04632

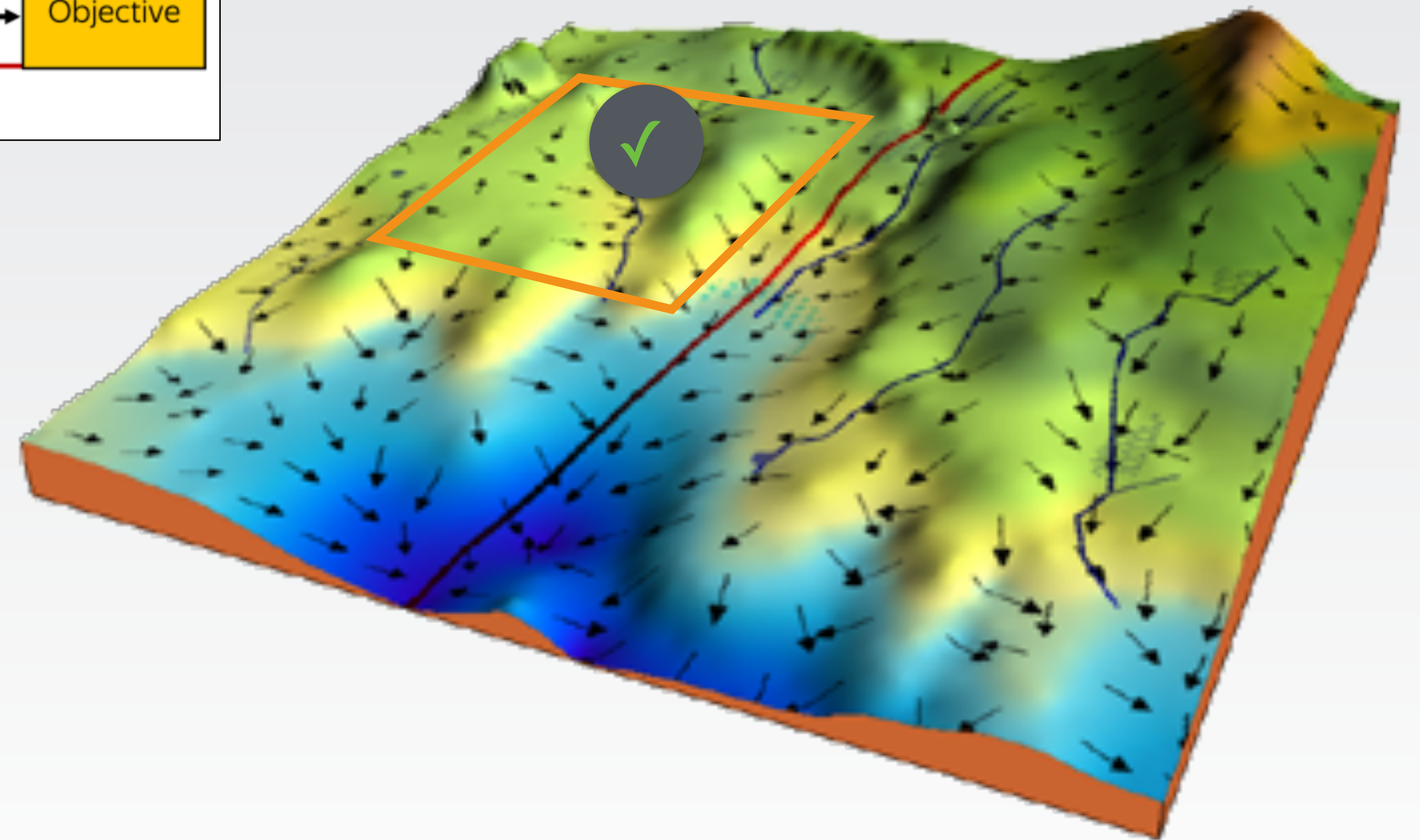
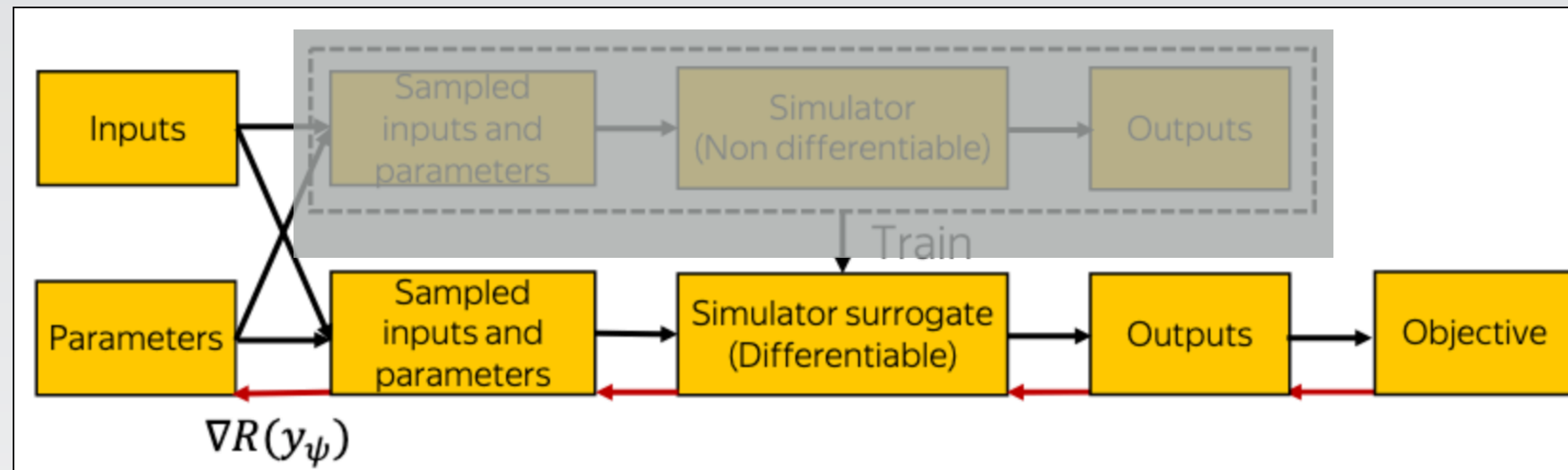
A Local Surrogate



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

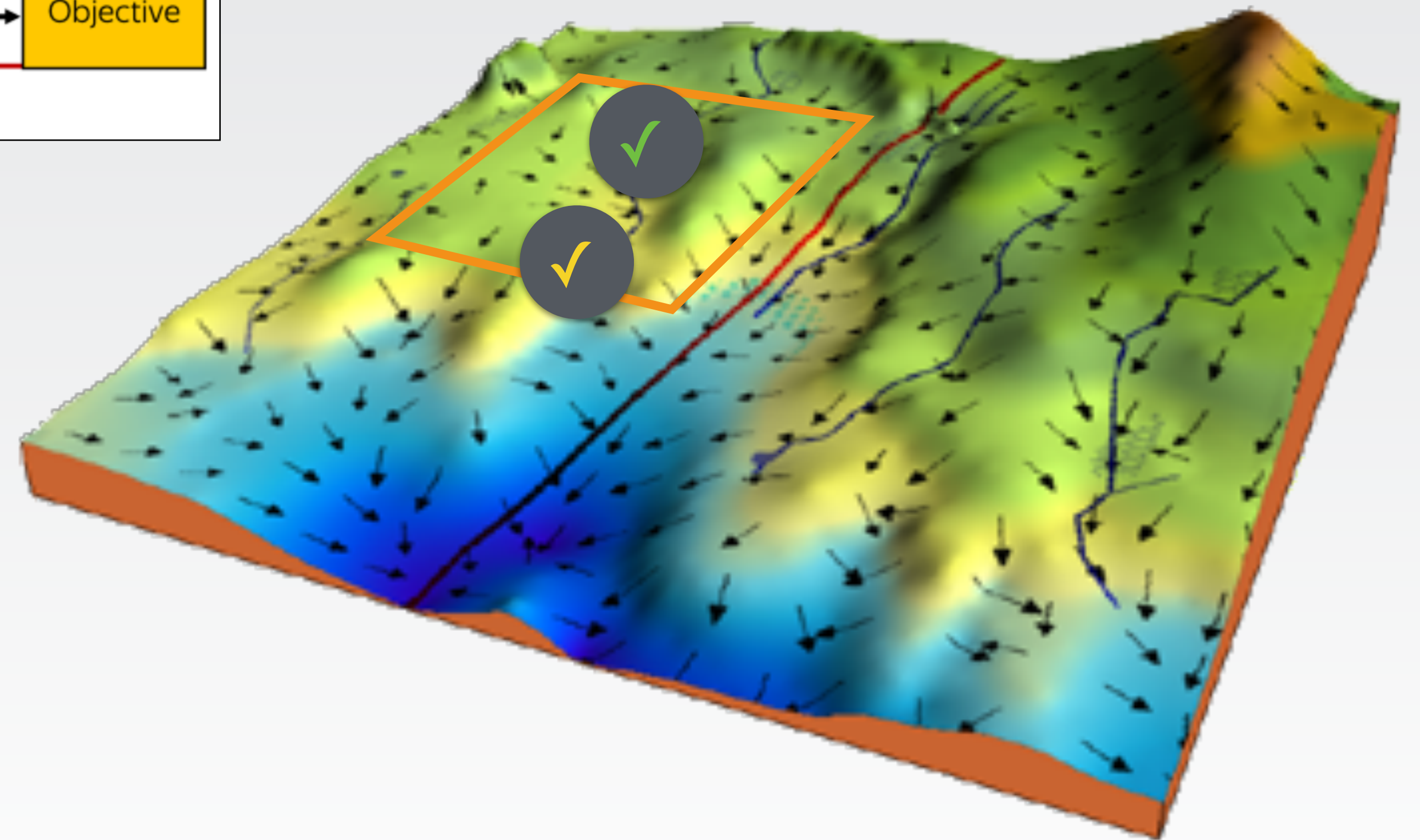
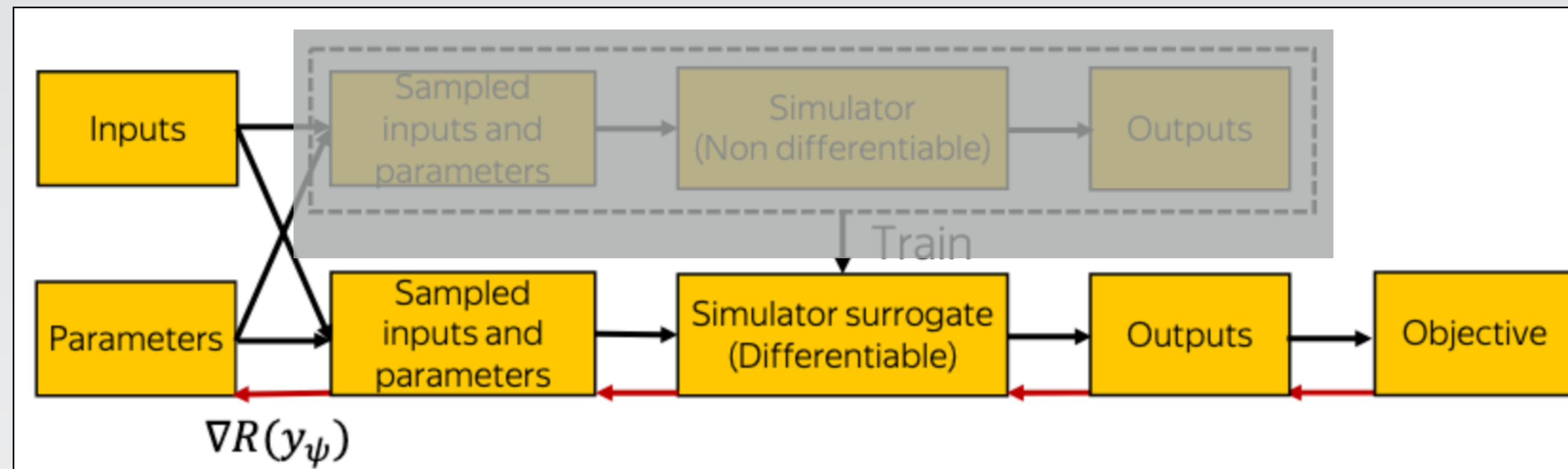
S. Shirobokov, et al., arXiv:2002.04632

A Local Surrogate



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

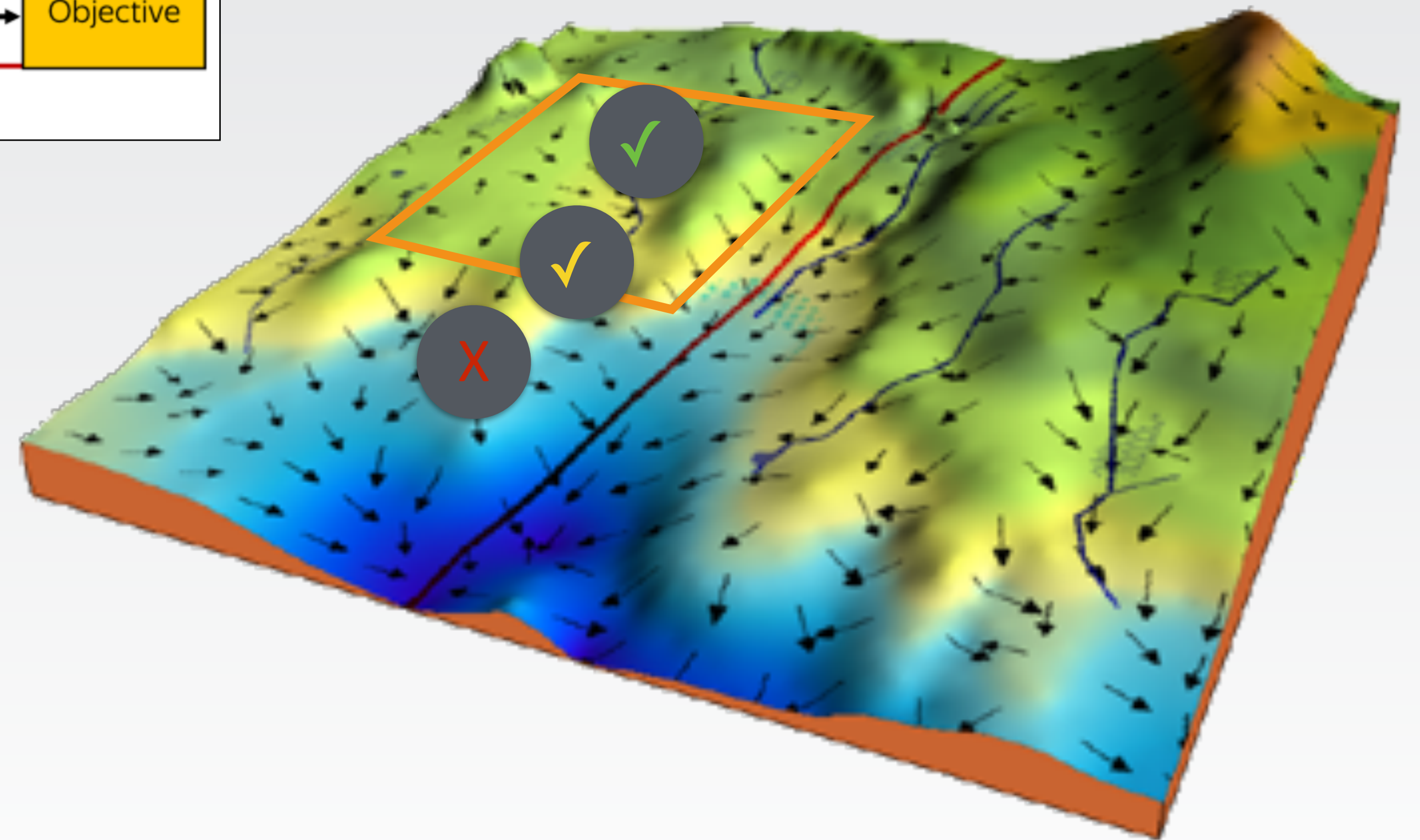
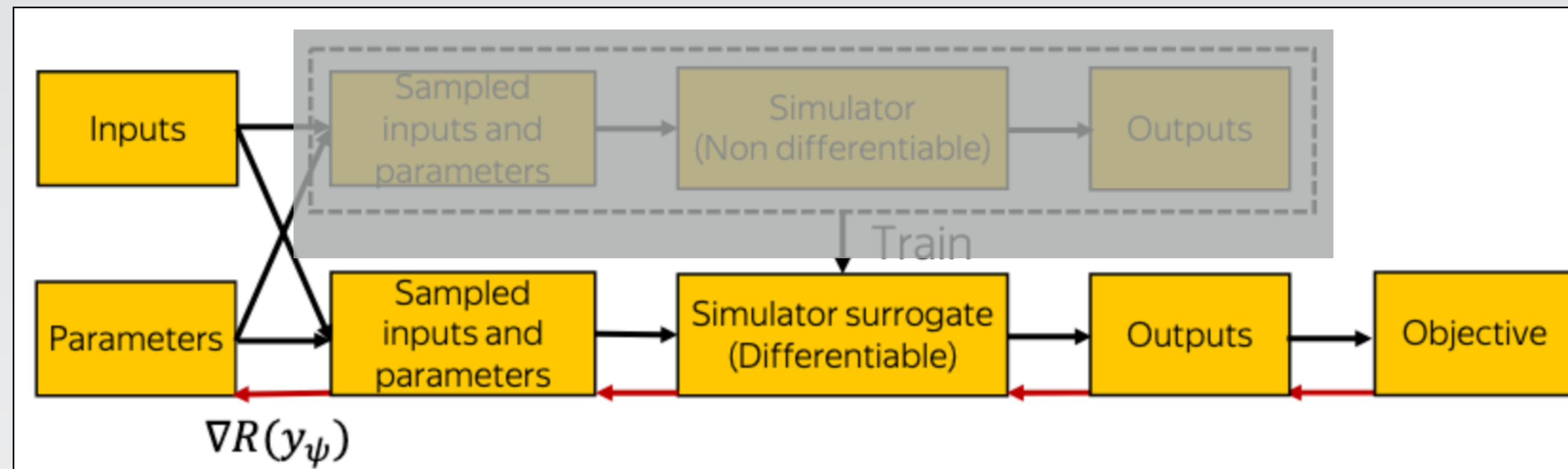
A Local Surrogate



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S. Shirobokov, et al., arXiv:2002.04632

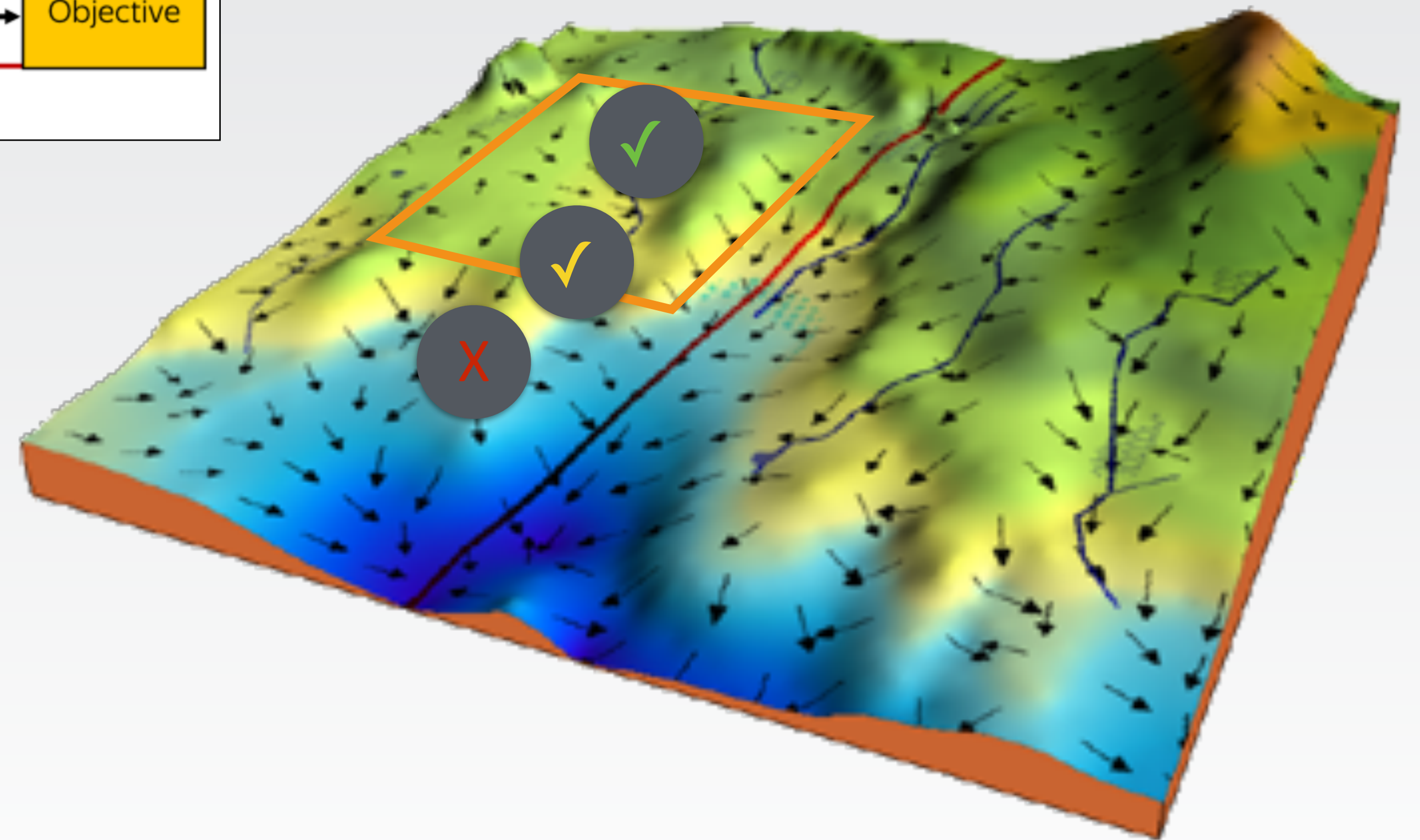
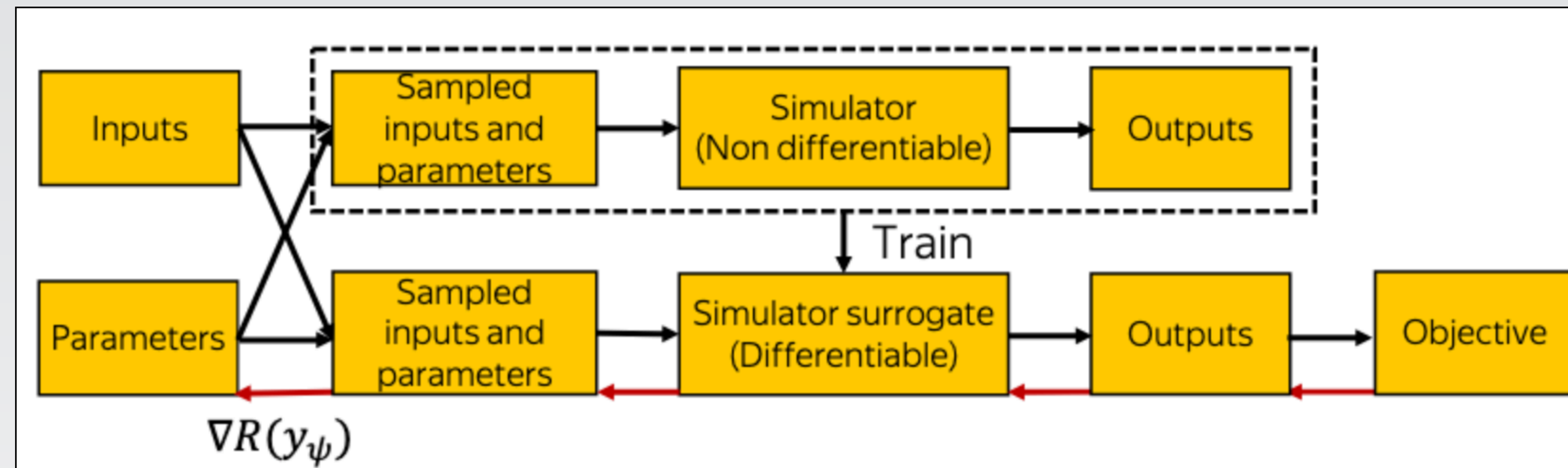
A Local Surrogate



https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

S. Shirobokov, et al., arXiv:2002.04632

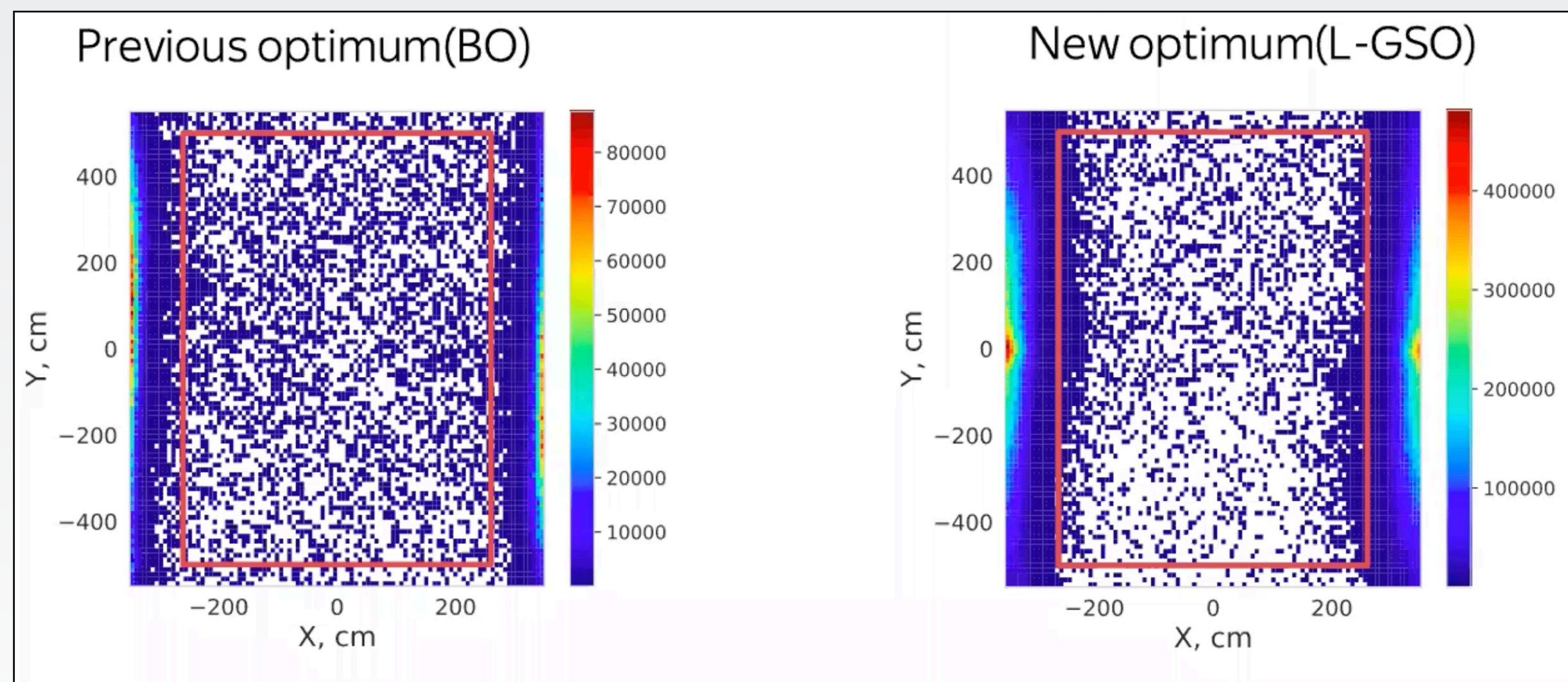
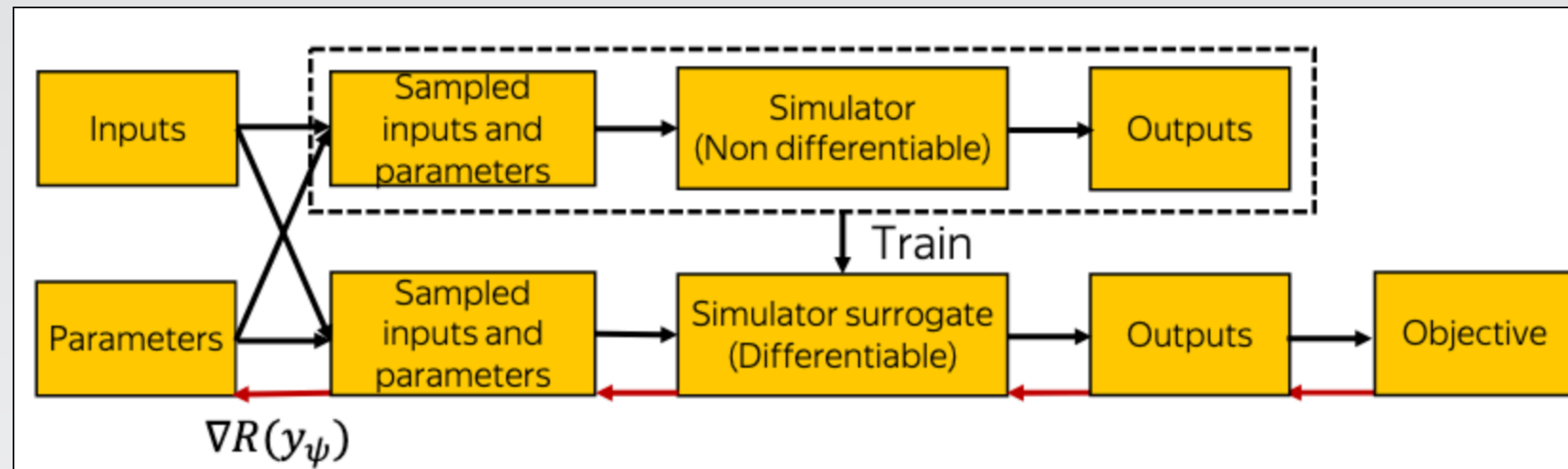
A Local Surrogate



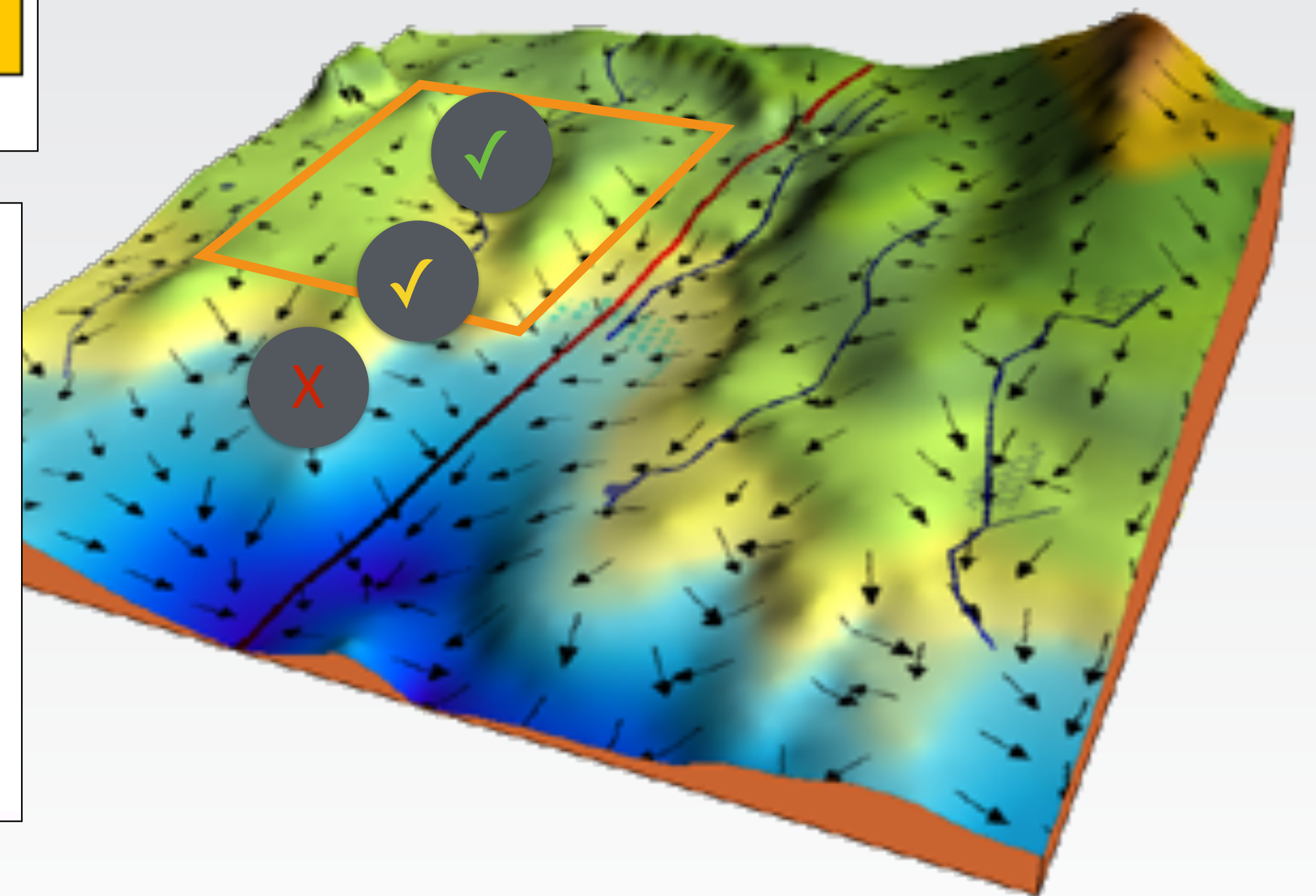
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S. Shirobokov, et al., arXiv:2002.04632

A Local Surrogate



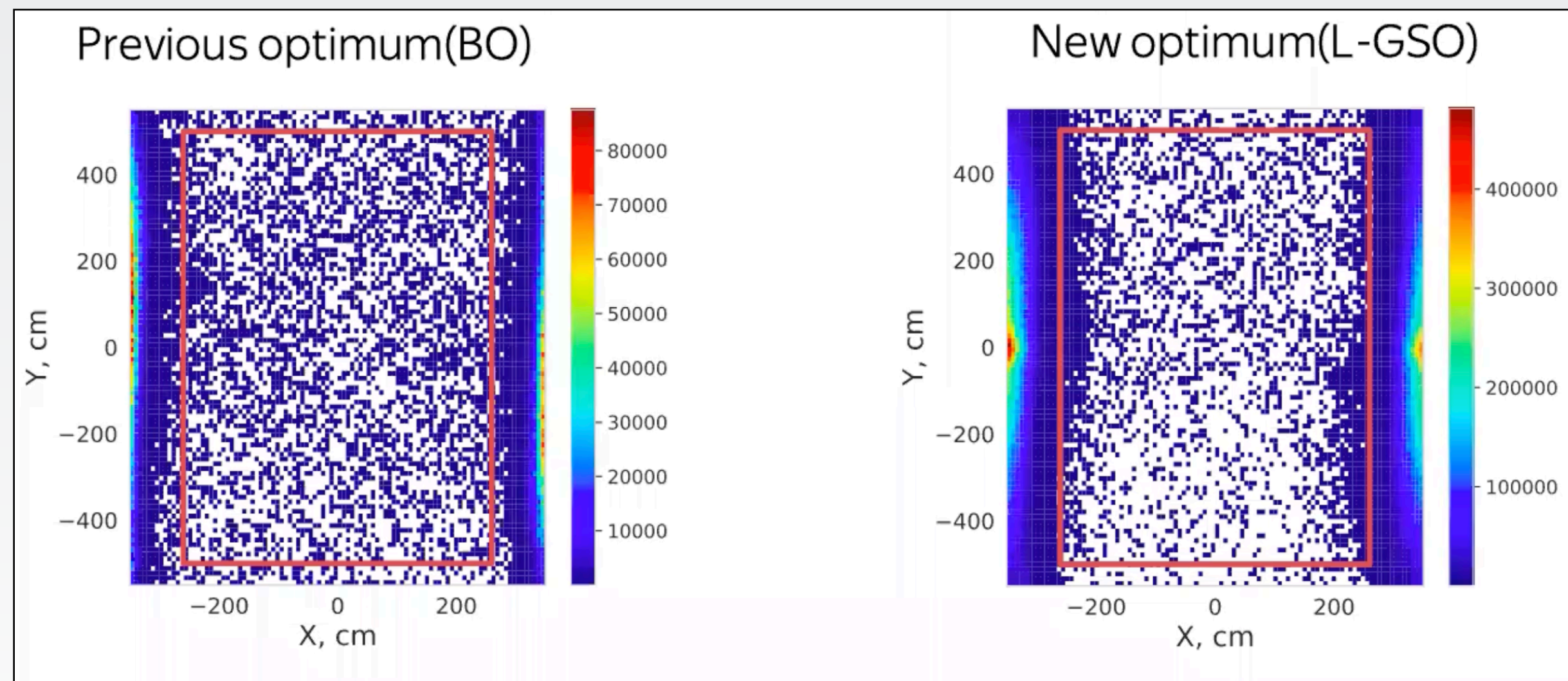
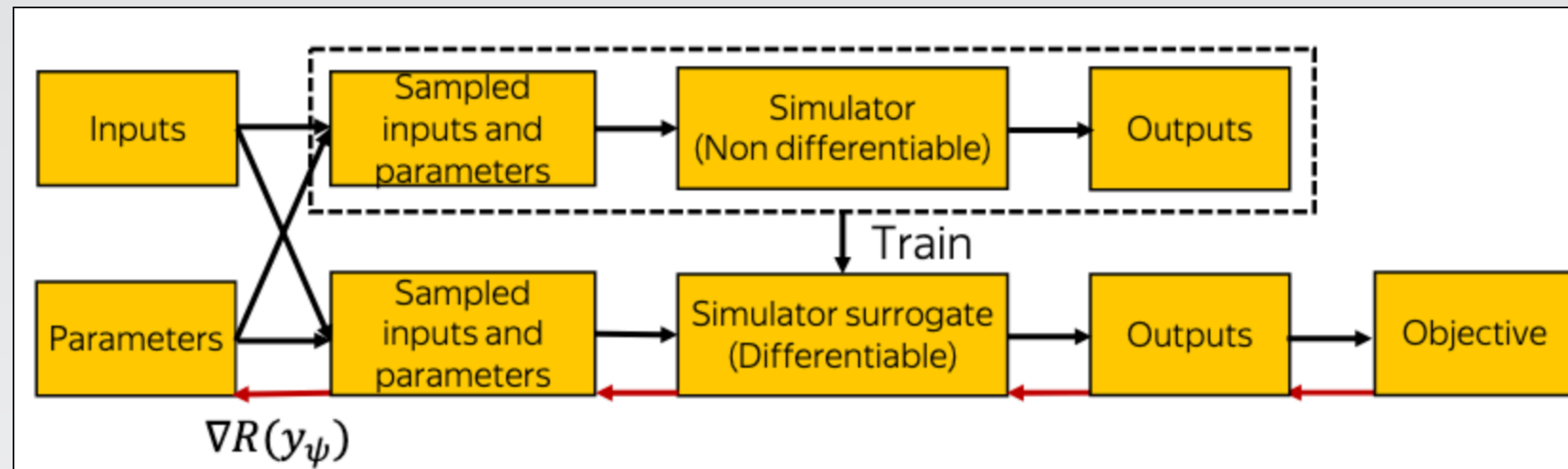
Approx. 30% improvement with a 30% lighter magnet



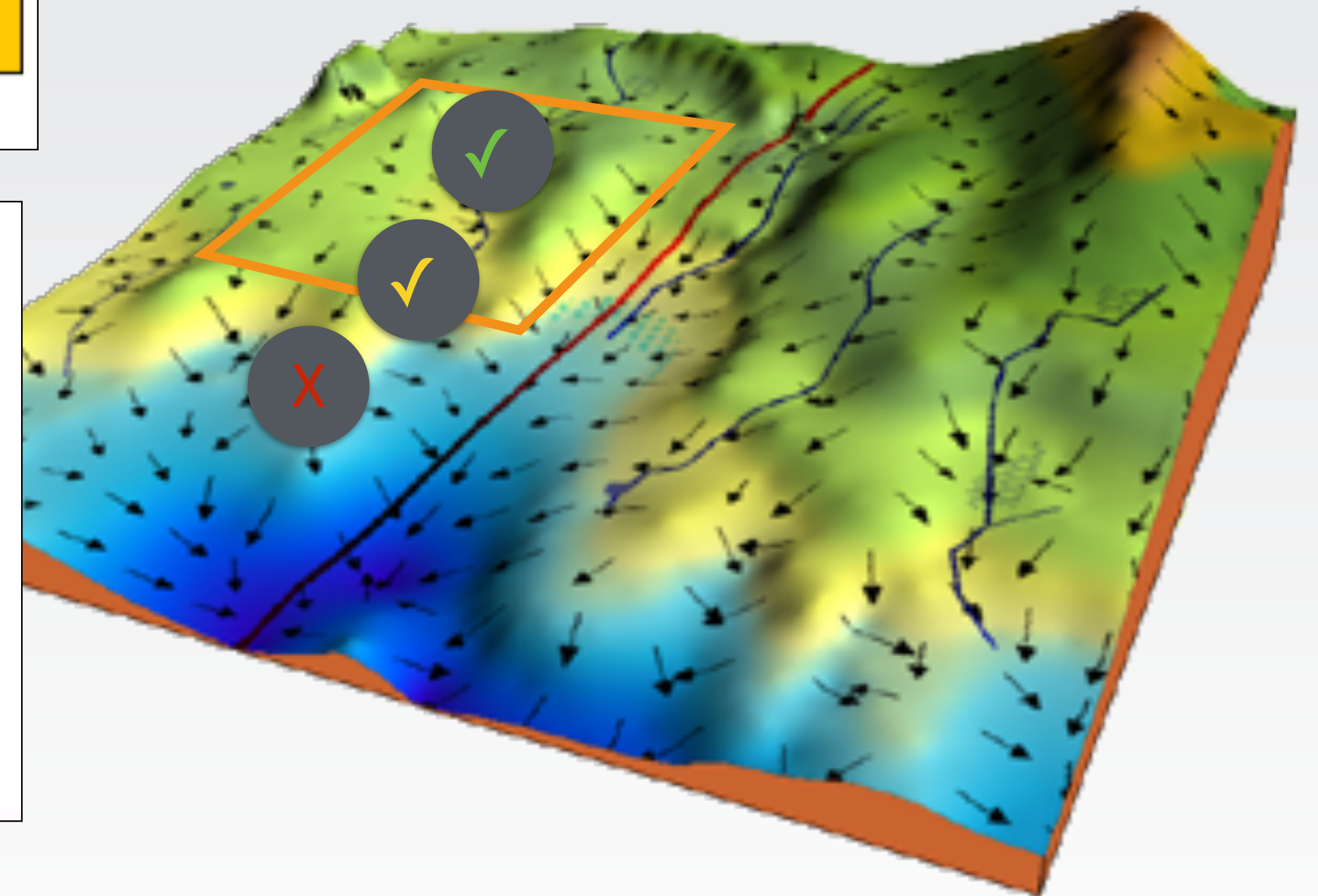
https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

S. Shirobokov, et al., arXiv:2002.04632

A Local Surrogate



Approx. 30% improvement with a 30% lighter magnet



Local surrogates are a powerful tool to work around non-differentiable parts of the chain arxiv.org/abs/2002.04652

S. Shirobokov, et al., arXiv.2002.04652

Make Wider Steps?

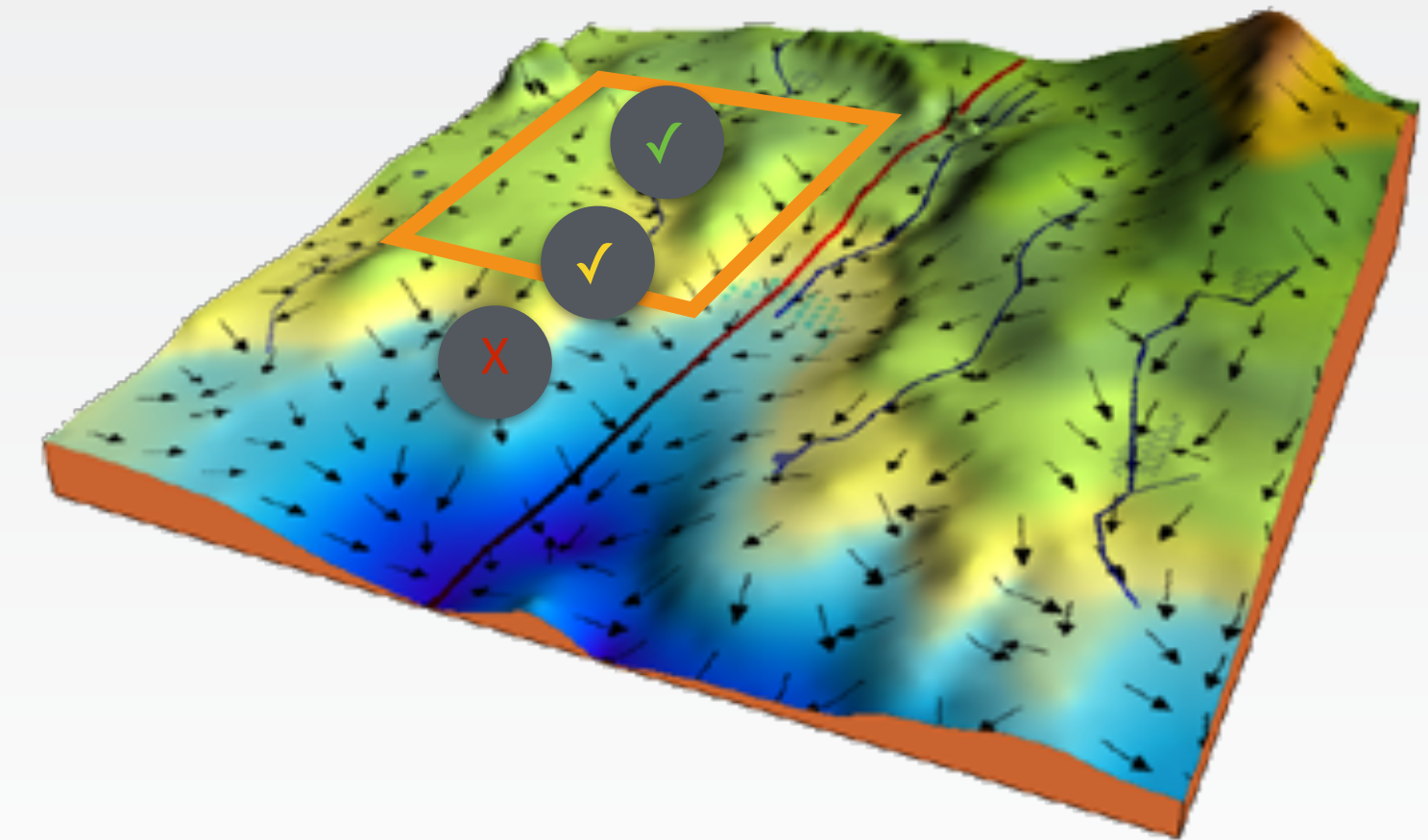


A few quantities

Many pixels, detector elements, hits

A few quantities

Very complex surrogate model



Make Wider Steps?



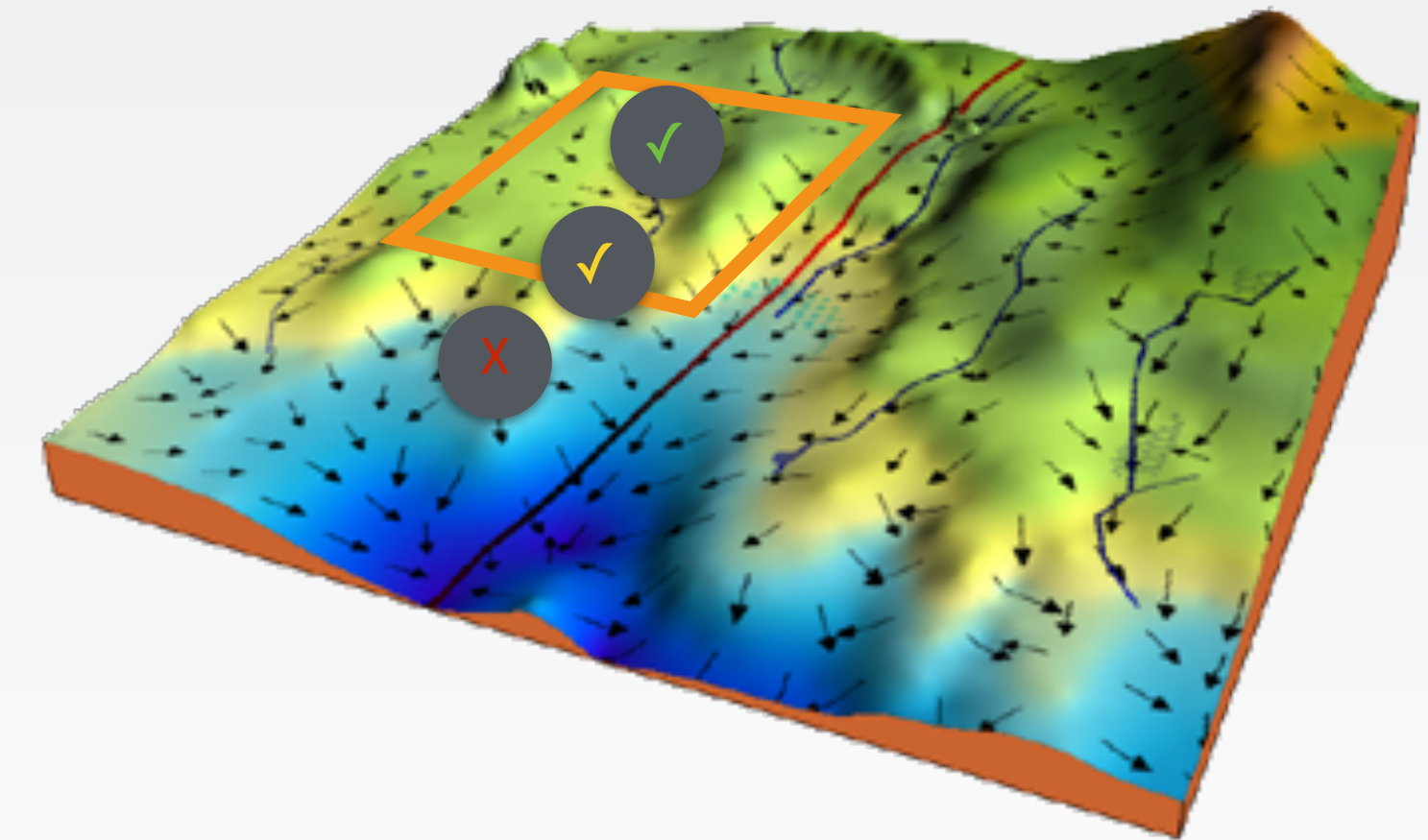
A few quantities

Many pixels, detector elements, hits

A few quantities

Very complex surrogate model

✓ Much simpler surrogate model



Make Wider Steps?



A few quantities

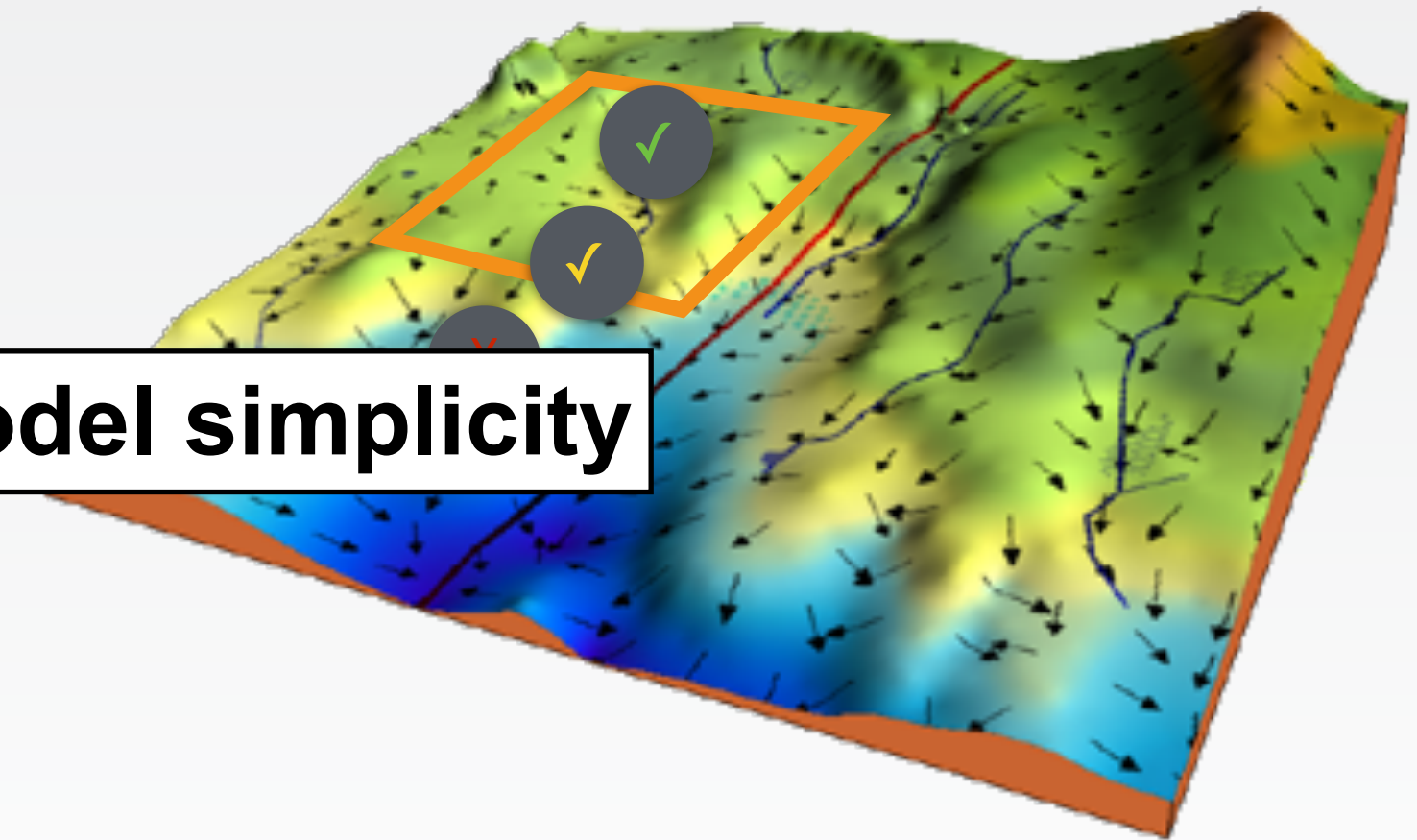
Many pixels, detector elements, hits

A few quantities

Very complex surrogate model

✓ Much simpler surrogate model

Trade off between computing resources and surrogate model simplicity



Make Wider Steps?



A few quantities

Many pixels, detector elements, hits

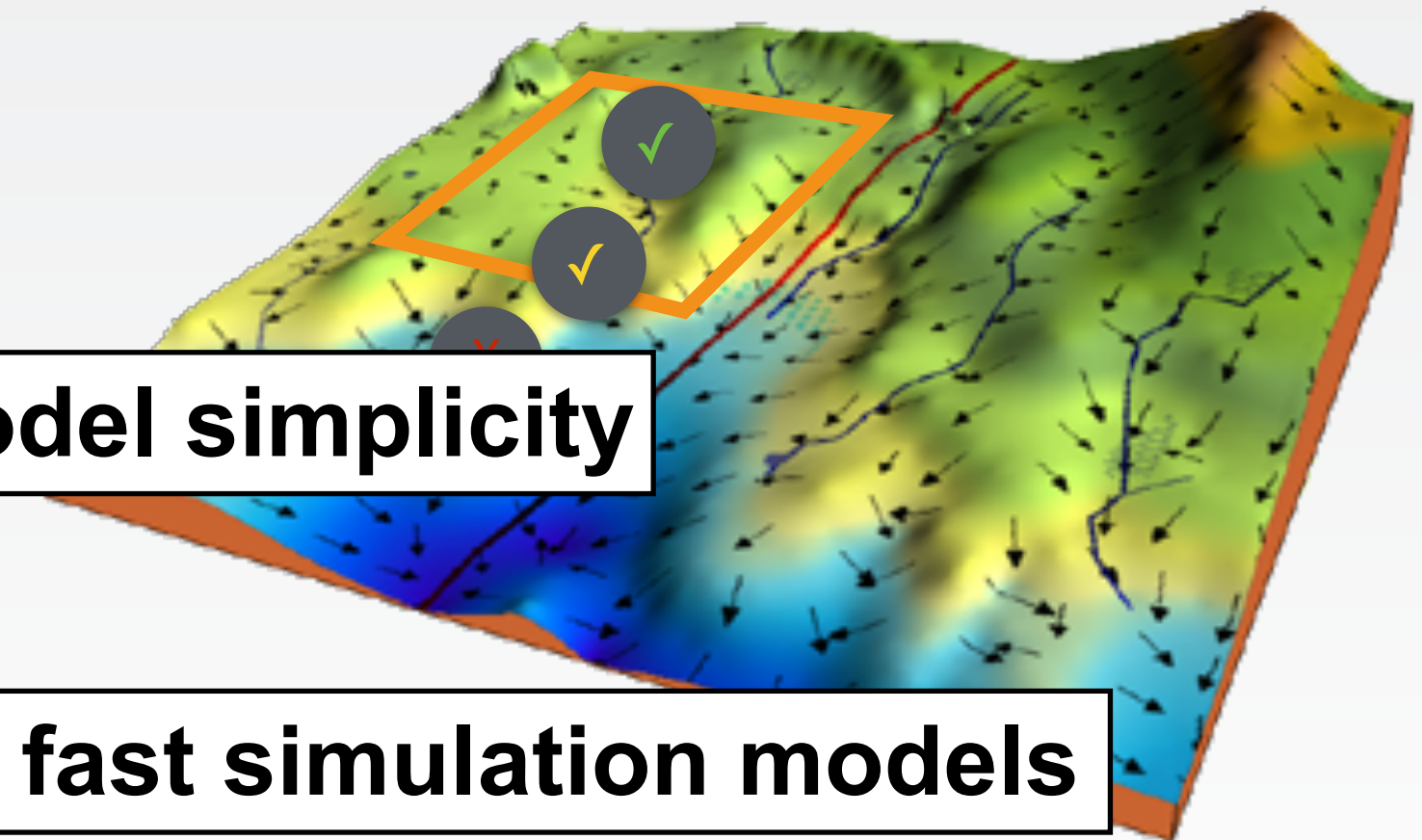
A few quantities

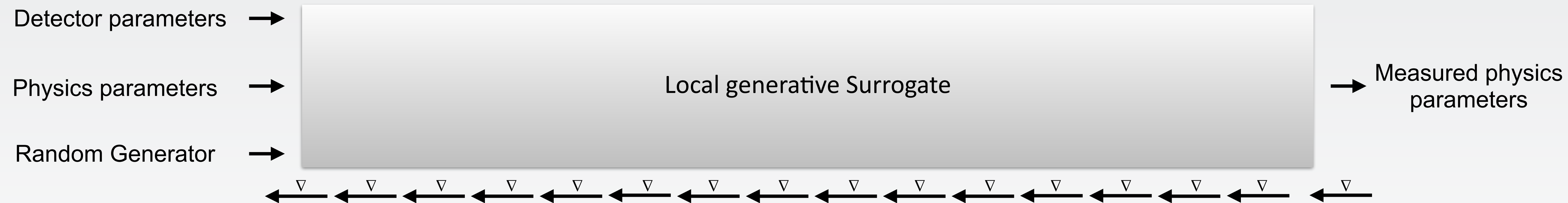
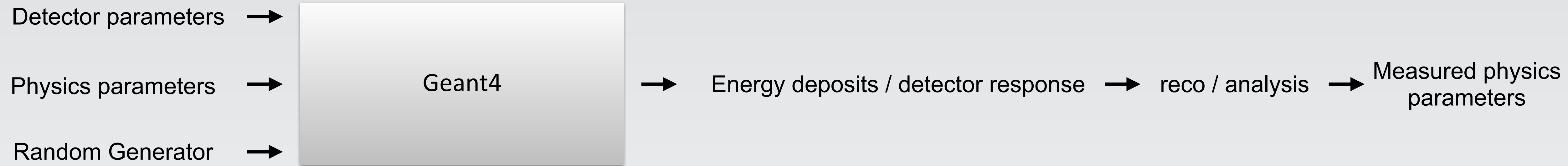
Very complex surrogate model

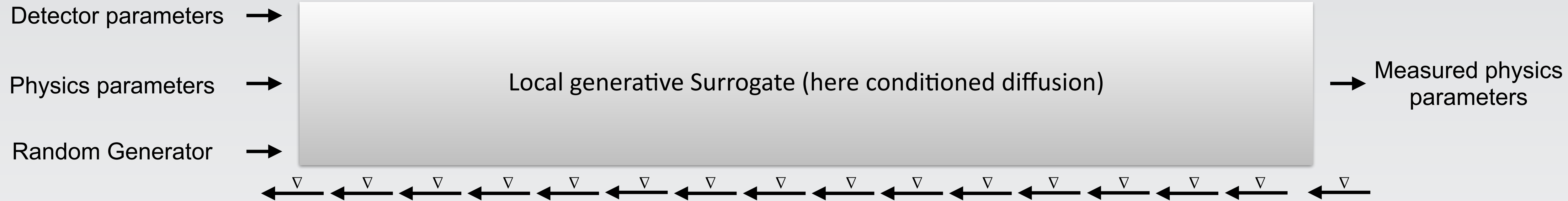
✓ Much simpler surrogate model

Trade off between computing resources and surrogate model simplicity

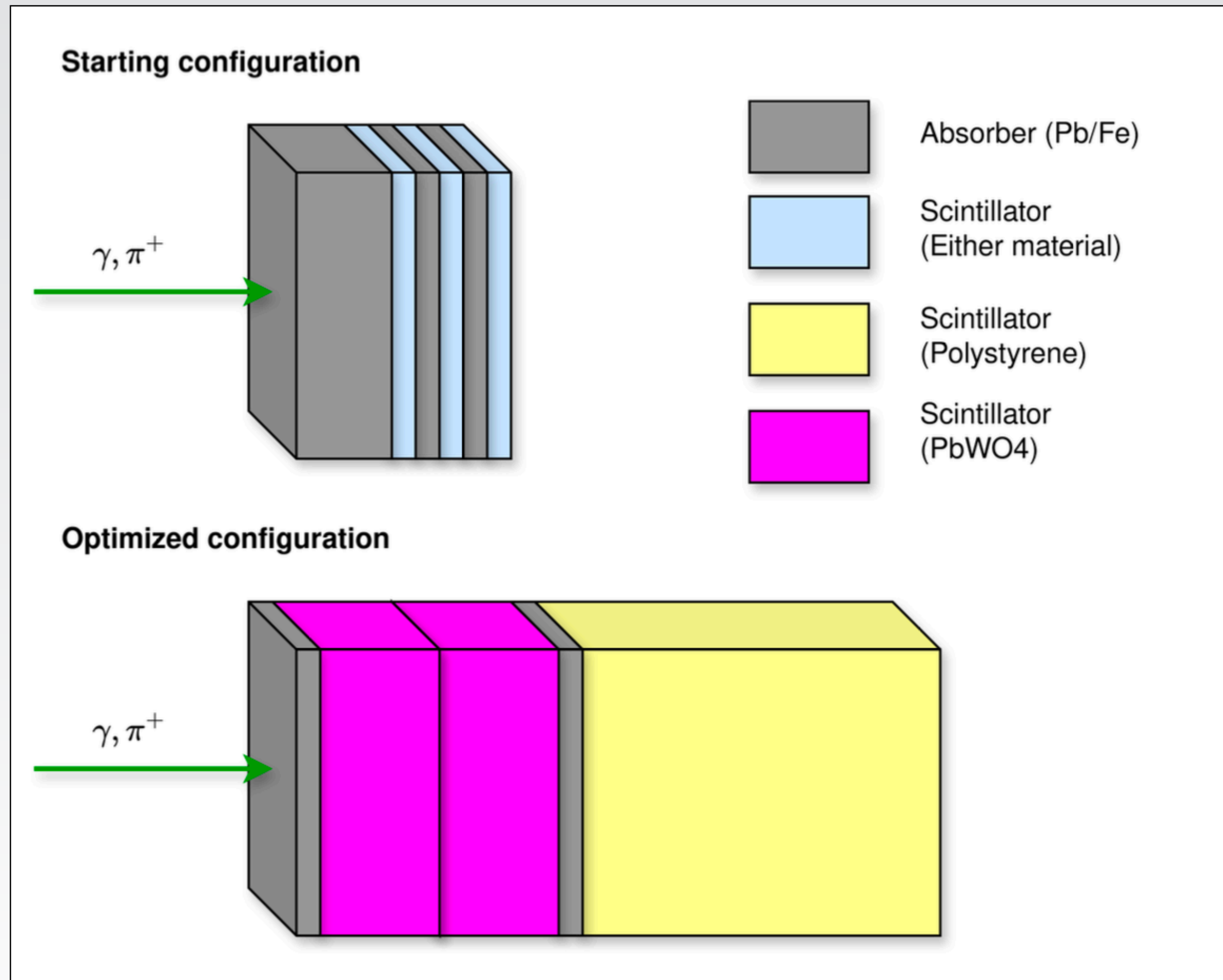
These models, applied to existing detectors, are generative (ultra) fast simulation models



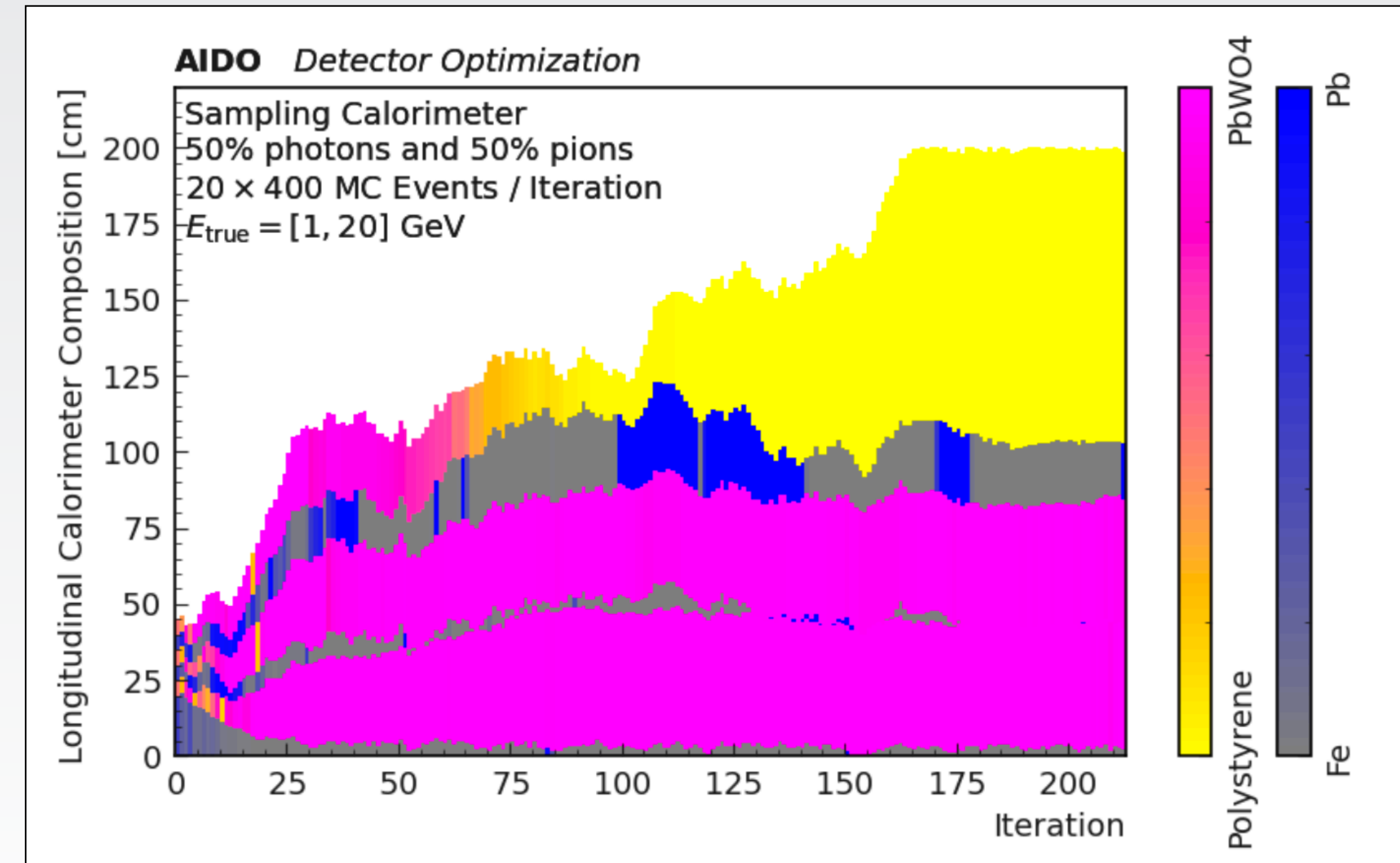




- Detector parameters can be **discrete**
- **This works - out-of-the-box** for reinforcement learning
- **But also in genreal:** ML models are “surprisingly” good at interpolating → can be exploited to also tackle discrete parameters such as material



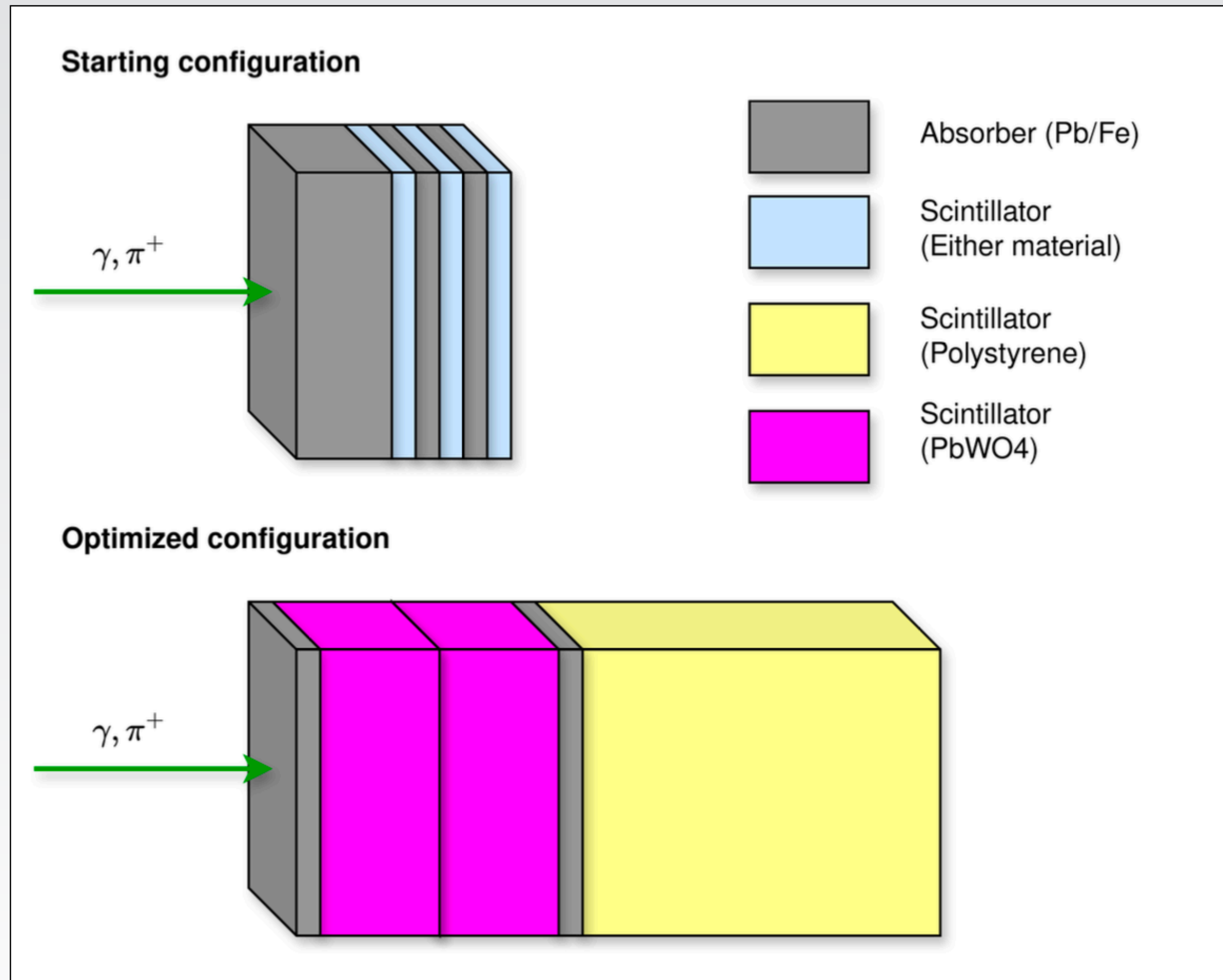
- Add cost and space constraints
- Model cost of materials carefully



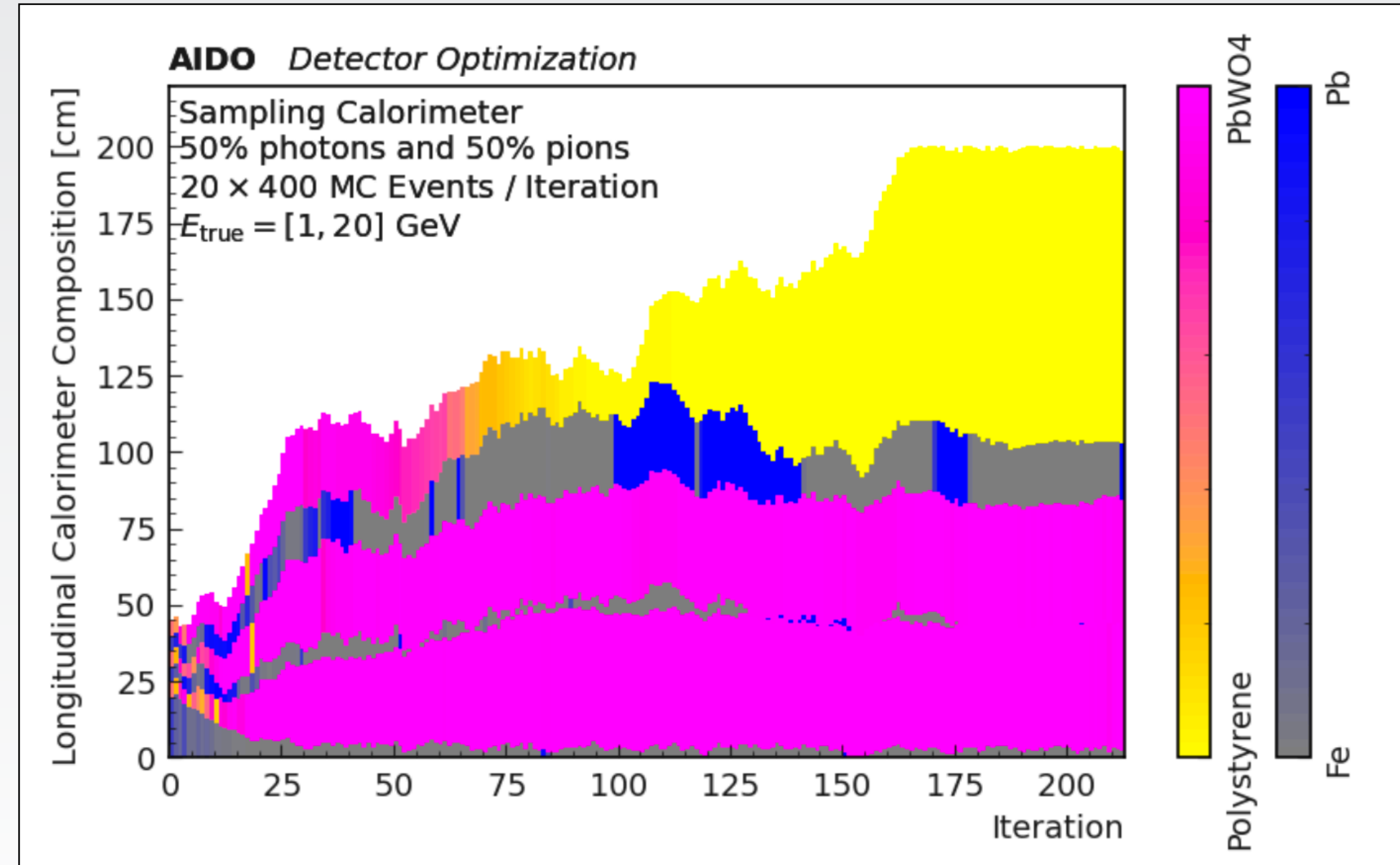
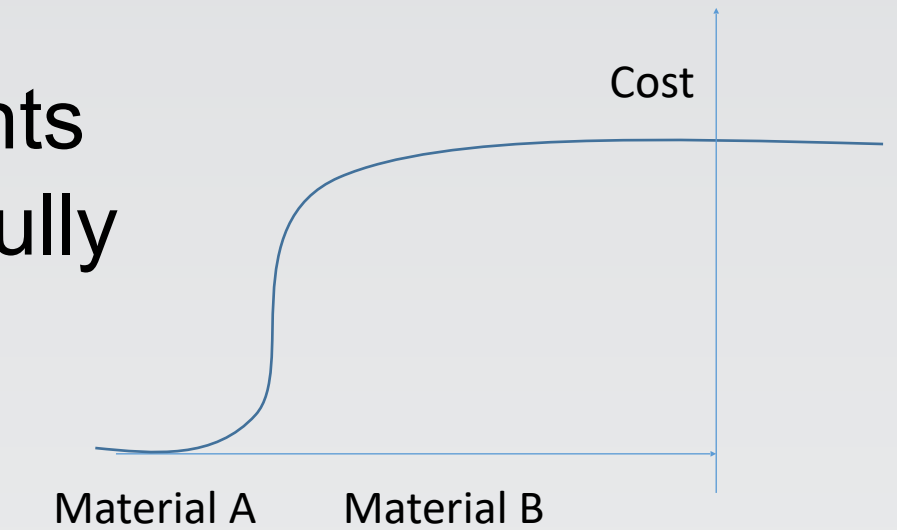
- Best mean resolution of all configurations

About 4k designs, 1.6M events

K.Schmidt, et al., arXiv:2502.02152



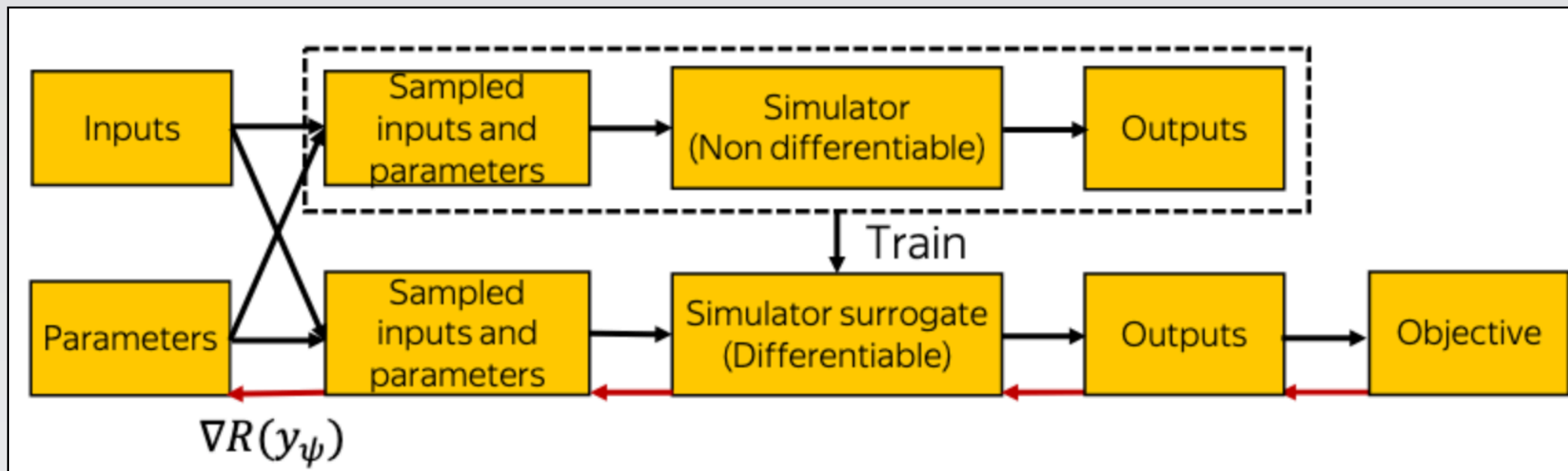
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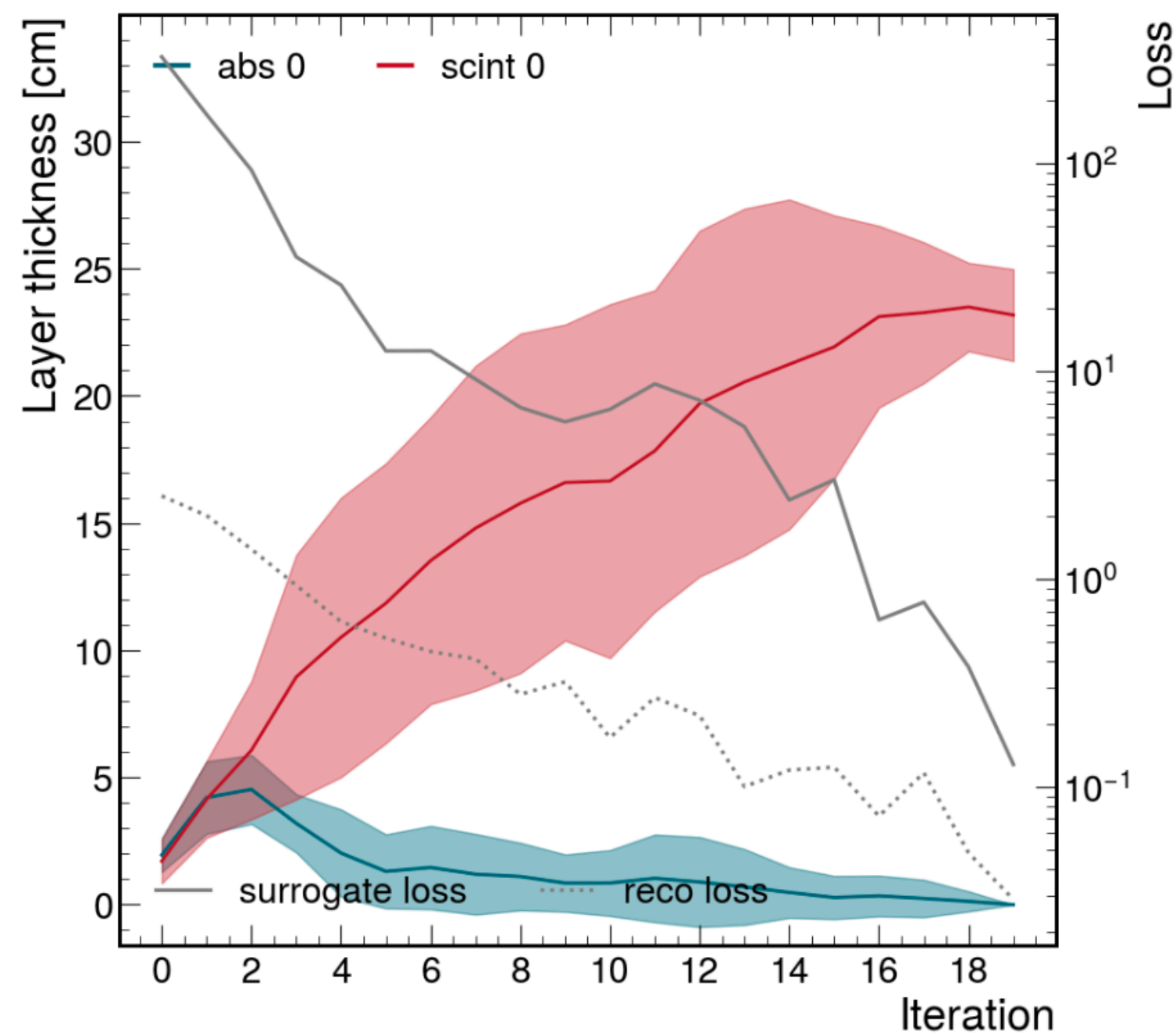
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About 4k designs, 1.6M events

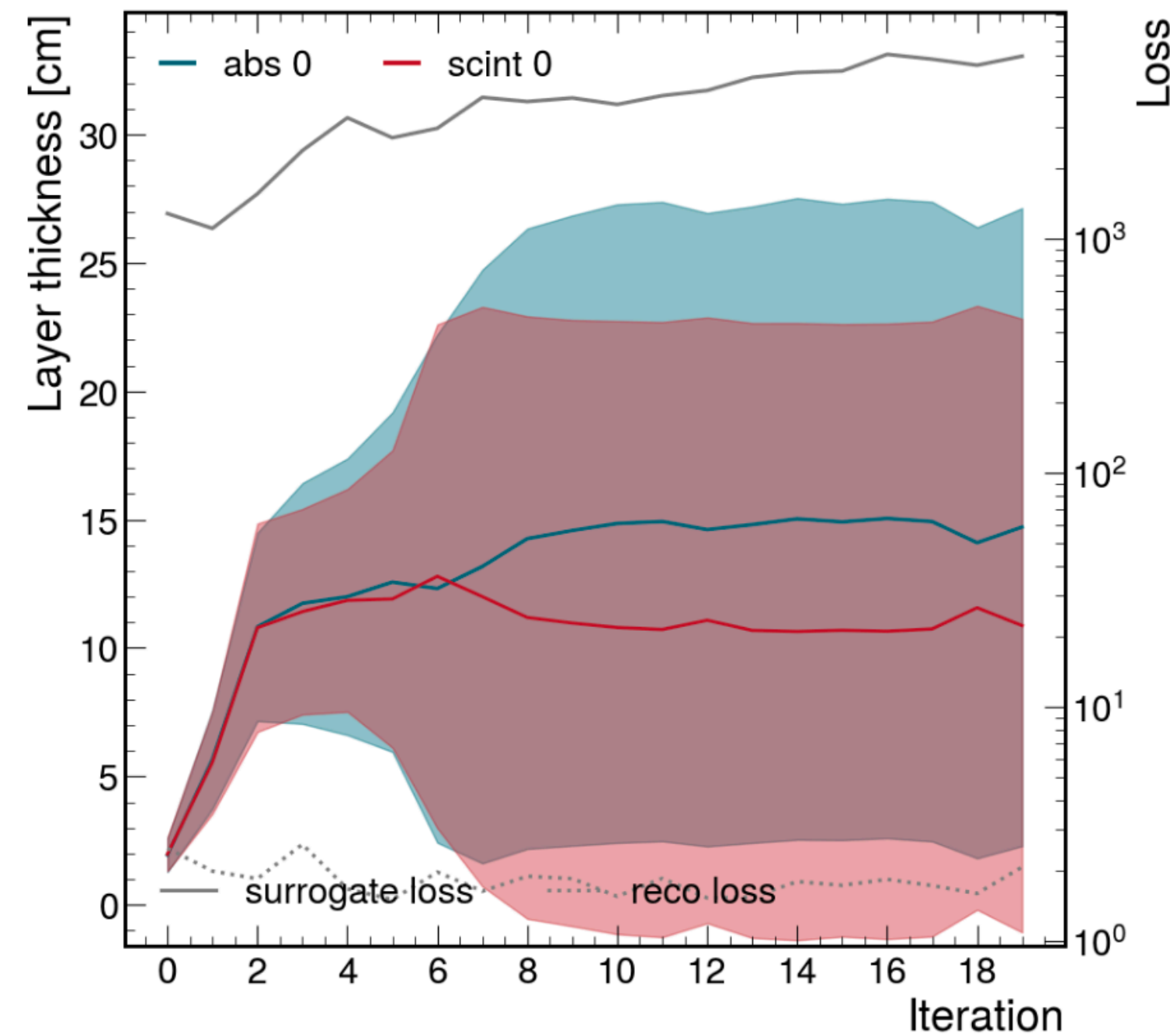
K.Schmidt, et al., arXiv:2502.02152



- Transfer learning: only adjust the reconstruction model and surrogate model at each step, do not re-initialise
- Only 5 events per parameter set (30) and step are sufficient for optimisation thanks to transfer learning



(a) RECO-OPT with TL, 5 events



(b) RECO-OPT without TL, 5 events

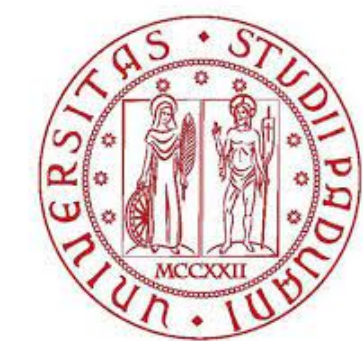
- A total of about 600 tested designs is sufficient here
- Only 3000 events are needed to optimise a simple calorimeter
- Very generator-efficient!

K. Wozniak, et al., arXiv:2503.14342

Summary

- Aiding Detector Designers is a promising frontier for ML in HEP
- It is a young topic, but tools start to become available
- It is the time to tackle it
 - Paradigm shifts in reconstruction are strong enablers
 - Many small experiments on short time scales
 - Large future detector proposals within the next decade
- We have a chance to enhance our physics reach for the next generation of experiments significantly and very systematically





Lebanese University



Machine-Learning Optimized Design of Experiments

MODE Collaboration

<https://mode-collaboration.github.io>

At INFN and Università di Padova Dr. Tommaso Dorigo, Dr. Pablo De Castro Manzano, Dr. Federica Fanzago, Dr. Giles Strong, and Dr. Mia Tosi
At Université catholique de Louvain Dr. Andrea Giammanco, Ms. Zahraa Daher, and Mr. Maxime Lagrange
At Universidad de Oviedo and ICTEA Dr. Pietro Vischia
At Université Clermont Auvergne, Prof. Julien Donini, and Mr. Federico Nardi (joint with Università di Padova)
At the Higher School of Economics of Moscow, Prof. Andrey Ustyuzhanin, Dr. Alexey Boldyrev, Dr. Denis Derkach, and Dr. Fedor Ratnikov
At the Instituto de Física de Cantabria, Dr. Pablo Martínez Ruíz del Árbol
At Karlsruhe Institut für Technologie, Dr. Jan Kieseler
At University of Oxford Dr. Atilim Gunes Baydin
At New York University Prof. Kyle Cranmer
At Université de Liège Prof. Gilles Louppe
At GSI/FAIR Dr. Anastasios Belias
At HEPHY Vienna (OeAW) Dr. Claudius Krause
At Uppsala Universitet Prof. Christian Glaser
At TU-München, Prof. Lukas Heinrich
At Sheffield University Dr. Patrick Stowell
At Lebanese University Prof. Haitham Zaraket
At University of Kaiserslautern-Landau Prof. Nicolas Gauger, Mr. Max Aehle, Dr. Long Chen, Prof. Ralf Keidel
At Eindhoven University of Technology, Prof. Lisa Kusch
At Princeton University Prof. Peter Elmer
At University of Washington Prof. Gordon Watts
At SLAC Dr. Ryan Roussel
At Lulea University of Technology Prof. Fredrik Sandin and Prof. Marcus Liwicki
At IGFAE and Universidad de Santiago de Compostela Prof. Xabier Cid Vidal and Ms. María Pereira Martínez
At ISER Ms. Sarjeeta Gami
At Carnegie Mellon University Prof. Ann Lee and Mr. Luca Masserano
At IISER Kolkata Dr. Tousik Samoui
At Sofia University, Kalina Dimitrova, Prof. Venelin Kozhuharov, Prof. Peicho Petkov
At ECAP - FAU Erlangen-Nürnberg, Dr. Christian Haack
At NASA, Dr. Stephen M. Casey

