



Track 3 summary

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Analysis Techniques in Physics Research

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Stony Brook, New York

Charles B Wang Center – Stony Brook University

Abstract Submission by January 20th, 2024

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A universe in two lines

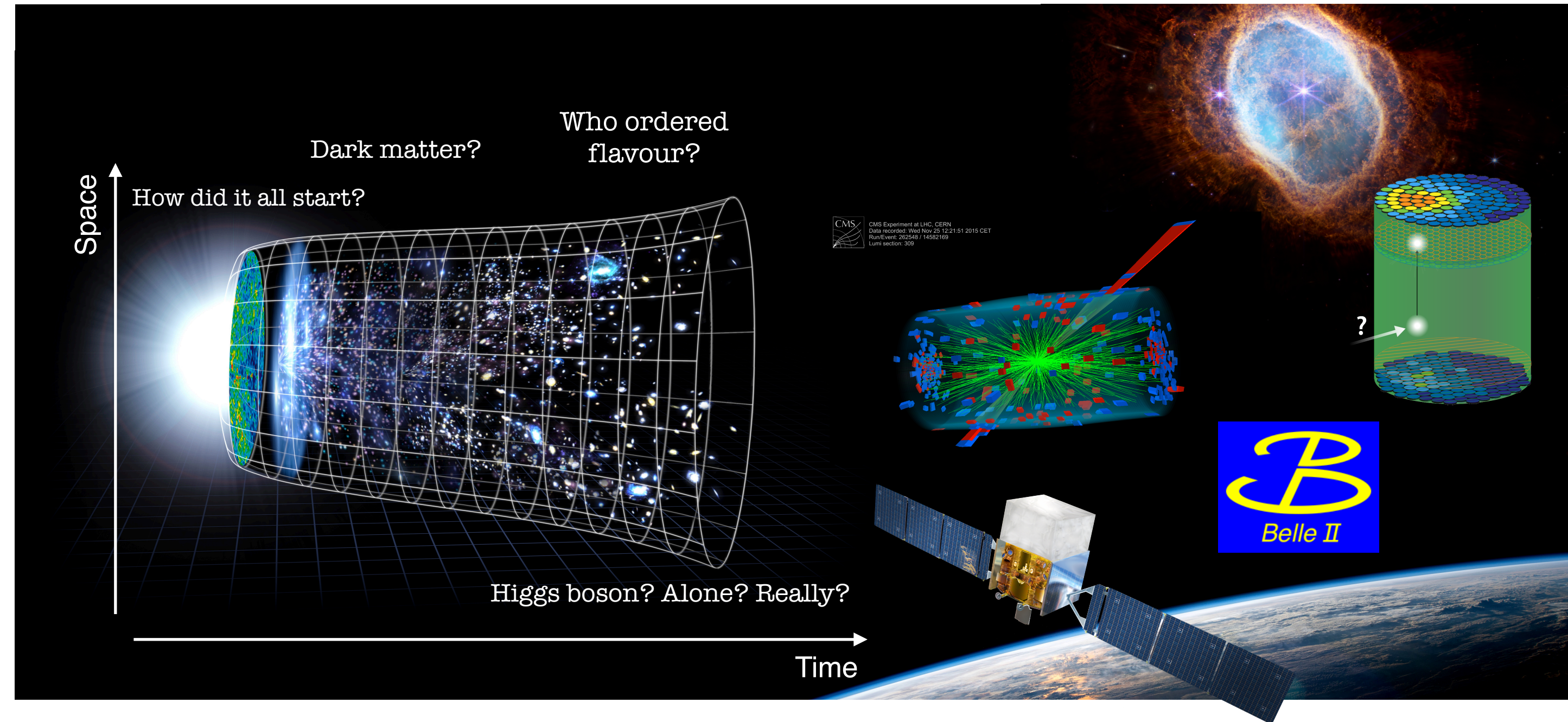
The Standard Model: from colliders to the Universe

- ❖ Standard Model (SM) of particle physics gives us the “code of the Universe” through a compact formula

$$\begin{aligned}
 \mathcal{L}_{SM} = & \underbrace{\frac{1}{4}W_{\mu\nu} \cdot W^{\mu\nu} - \frac{1}{4}B_{\mu\nu} B^{\mu\nu} - \frac{1}{4}G_{\mu\nu}^{\alpha} G_{\mu\nu}^{\alpha}}_{\text{kinetic energies and self-interactions of the gauge bosons}} + \underbrace{\bar{L}\gamma^{\mu} \left(i\partial_{\mu} - \frac{1}{2}g\tau \cdot W_{\mu} - \frac{1}{2}g'YB_{\mu} \right) L + \bar{R}\gamma^{\mu} \left(i\partial_{\mu} - \frac{1}{2}g'YB_{\mu} \right) R}_{\text{kinetic energies and electroweak interactions of fermions}} \\
 & + \underbrace{\frac{1}{2} \left| \left(i\partial_{\mu} - \frac{1}{2}g\tau \cdot W_{\mu} - \frac{1}{2}g'YB_{\mu} \right) \phi \right|^2 - V(\phi)}_{W^{\pm}, Z, \gamma \text{ and Higgs masses and couplings}} + \underbrace{g'' (\bar{q}\gamma^{\mu} T_a q) G_{\mu}^{\alpha}}_{\text{interactions between quarks and gluons}} + \underbrace{(G_1 \bar{L}\phi R + G_2 \bar{L}\phi_c R + h.c.)}_{\text{fermion masses and couplings to Higgs}}
 \end{aligned}$$

[CRC TRR257 poster]

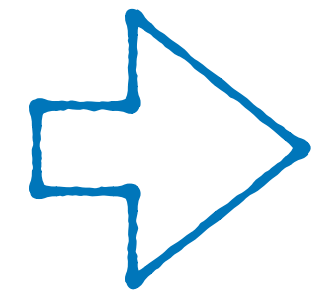
- ❖ The SM explains outcomes of most current terrestrial experiments and many aspects of the evolution of the Universe from the Big Bang through today (add a drop of **General Relativity**).
- ❖ However, many questions remain unresolved.
- ❖ The main goal of the particle physics community is to test the Standard Model as thoroughly as possible and, hopefully, find physics beyond it.



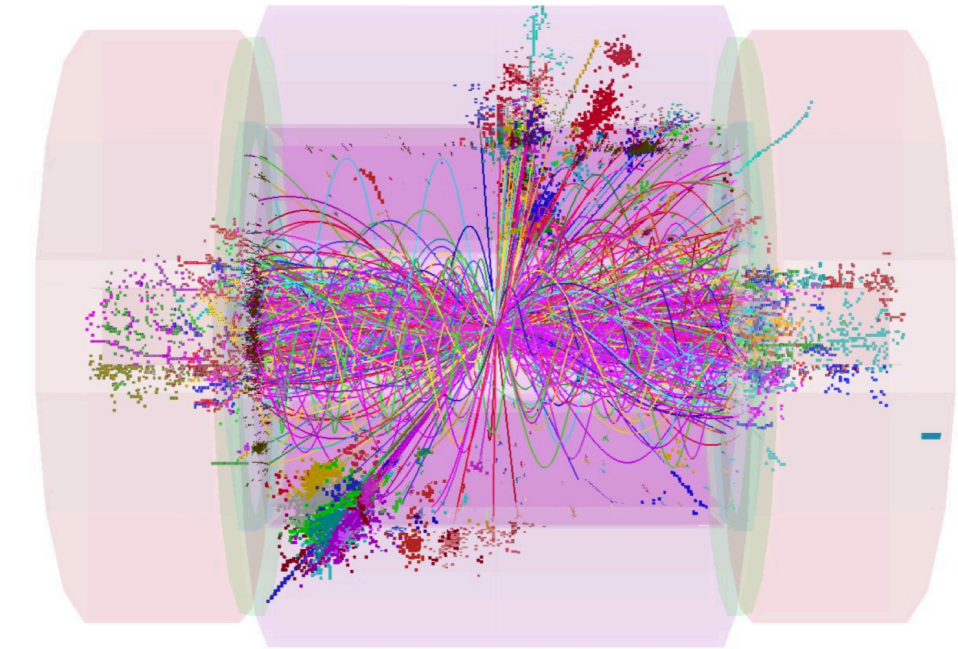
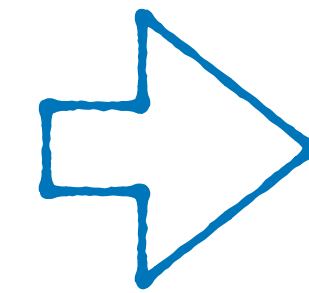
My personal perspective

- ❖ One key aspect of this search is related to collider physics, where **increasing precision requires experimental improvements, but also advances in our understanding of the fundamental underlying theory.**

$$\begin{aligned}\mathcal{L} &= -\frac{1}{4}F_{\mu\nu}F^{\mu\nu} \\ &+ i\bar{\psi}\not{D}\psi + h.c \\ &+ \psi_i y_{ij} \psi_j \phi + h.c \\ &+ |D_\mu\phi|^2 - V(\phi)\end{aligned}$$



Quantitative connections
through a chain of
experimental and theoretical
links

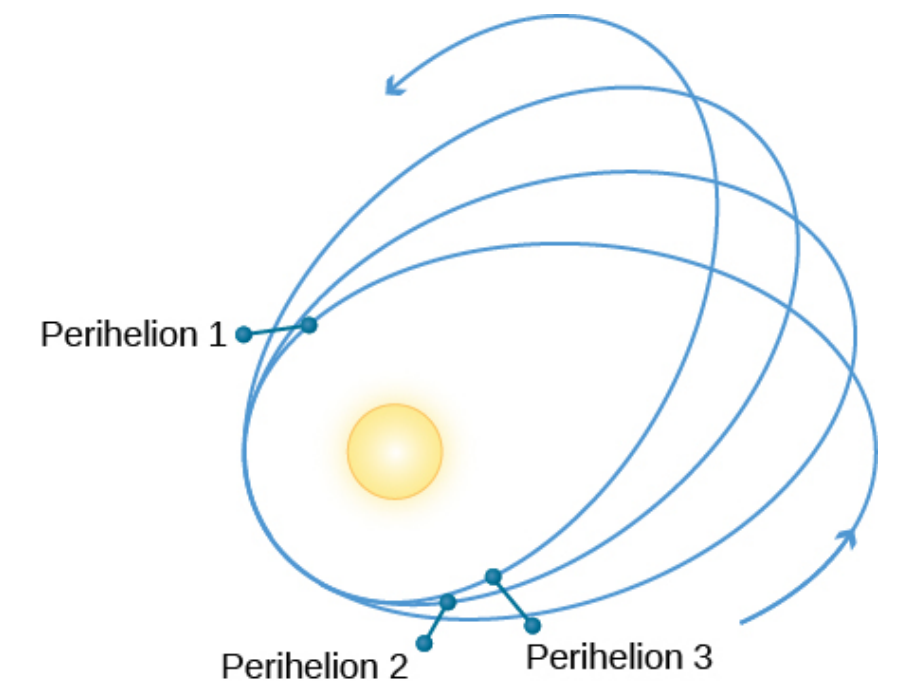


- ❖ **The core idea of theoretical particle research:**

- Develop methods to obtain high **precision** theoretical predictions.
- Exploit these methods for a wide range of **phenomenological studies** to improve our **knowledge of the SM.**

When precision changes the game

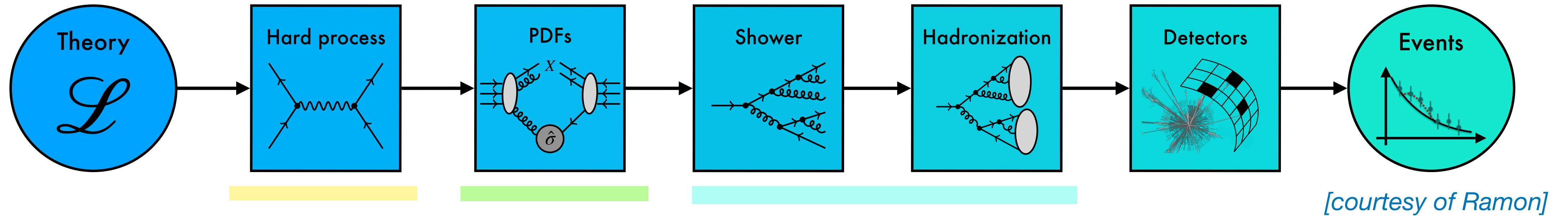
- ❖ Proof of general relativity: **1%** discrepancy with the Newtonian predictions
- ❖ Advent of Quantum Electrodynamics: **0.1%** discrepancy with predictions of QM



Rudiments of particle physics (at colliders)

The success of a percent level phenomenology program relies on our ability to interpret and predict the outcome LHC measurement.

[Snowmass'2021 whitepaper]



→ Theoretical predictions in hep-ph require description of physics across many different energy scales

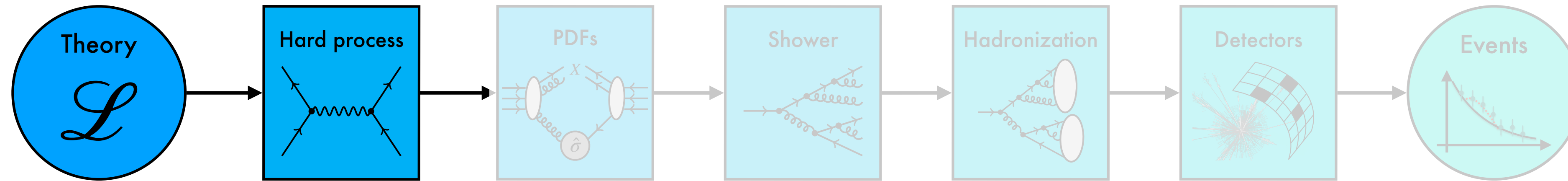
$$d\sigma = \sum_{ij} \int dx_1 dx_2 f_{i/p}(x_1) f_{j/p}(x_2) d\hat{\sigma}_{ij}(x_1 x_2 s) \left(1 + \mathcal{O}\left(\frac{\Lambda_{\text{QCD}}^n}{Q^n}\right) \right), \quad n \geq 1$$

Parton distribution functions
 $\pm(3 - 5) \%$

Hard scattering
 (perturbative quantum field theory)
 aim for few % level!

Non perturbative effects
 (fragmentation, hadronisation)
 $\sim \% (?)$

Higher-order corrections to hard processes: main difficulties



$$d\sigma = d\sigma_{\text{LO}} + \alpha_s d\sigma_{\text{NLO}} + \alpha_s^2 d\sigma_{\text{N}^2\text{LO}} + \alpha_s^3 d\sigma_{\text{N}^3\text{LO}} + \dots$$

Strong couplings:

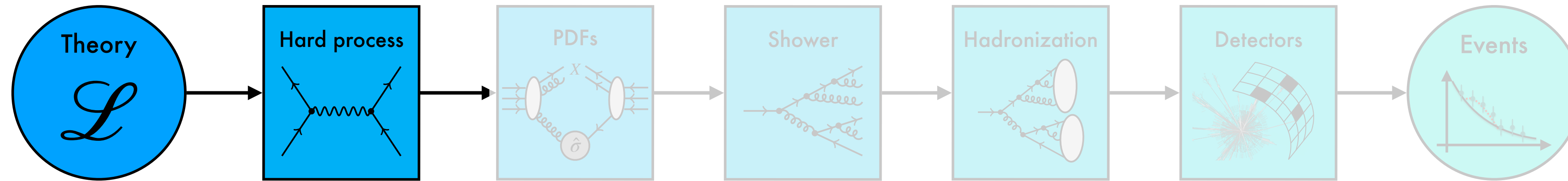
$$\alpha_s \sim 0.1$$

$$\mathcal{O}(\alpha_s) \sim 10\%$$

$$\mathcal{O}(\alpha_s^2) \sim 1\%$$

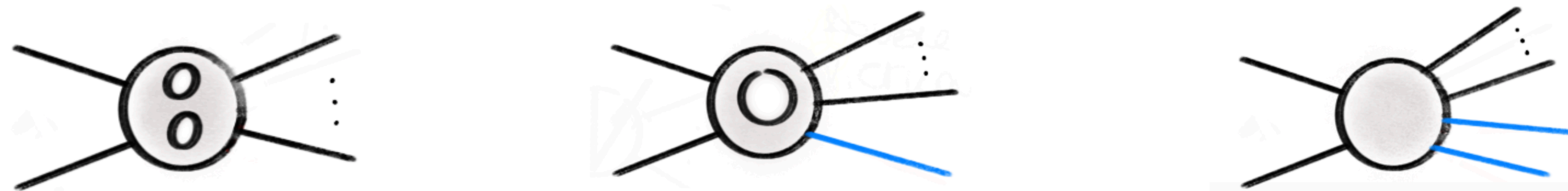
$$\mathcal{O}(\alpha_s^3) \sim 0.1\%$$

Higher-order corrections to hard processes: main difficulties



$$d\sigma = d\sigma_{\text{LO}} + \alpha_s d\sigma_{\text{NLO}} + \boxed{\alpha_s^2 d\sigma_{\text{N}^2\text{LO}}} + \alpha_s^3 d\sigma_{\text{N}^3\text{LO}} + \dots$$

$$d\sigma_{\text{N}^2\text{LO}} = \int d\Phi_n VV_n + \int d\Phi_{n+1} RV_{n+1} + \int d\Phi_{n+2} RR_{n+2}$$



Each ingredient presents significant **technical challenges**.

Virtual amplitudes:

- Multi-loop integrals involving multiple scales, arising from different masses and many legs

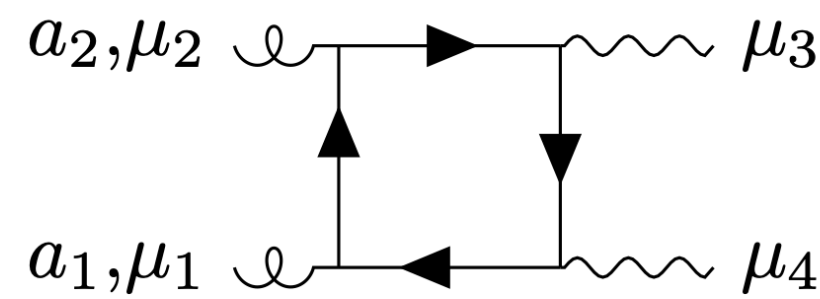
Real radiation singularities

- Extraction of soft and collinear singularities

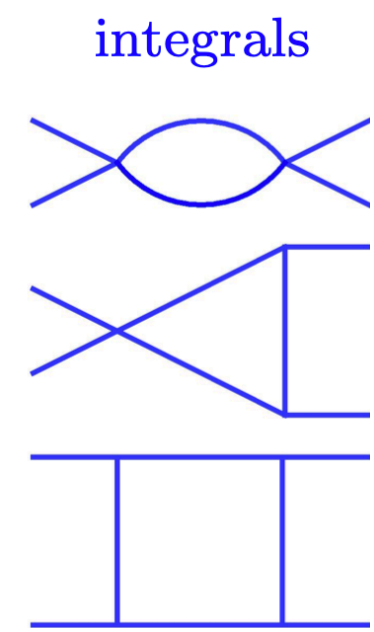
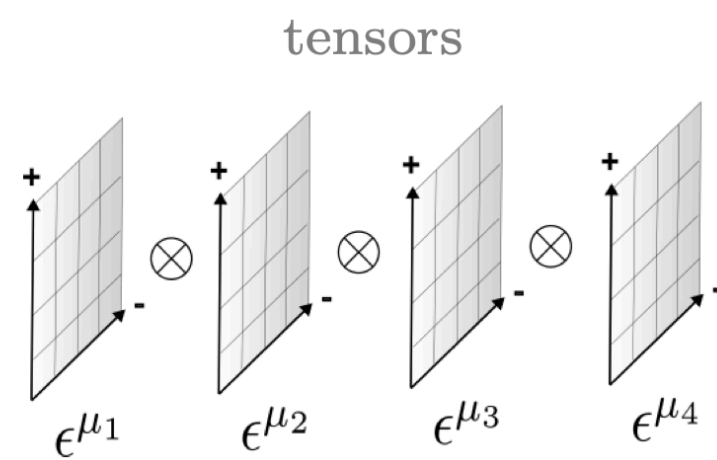
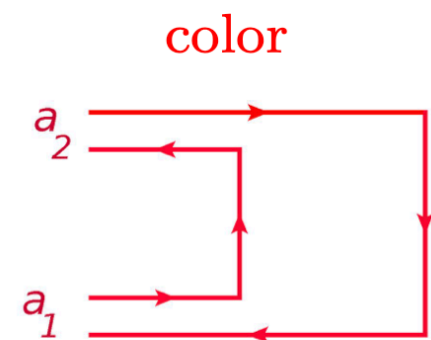
Loop amplitudes

- Increasing complexity: more legs, more loops, more masses.
- Need for a representation of the amplitudes that can be evaluated efficiently and yields numerically reliable results.

Algebraic complexity + analytic complexity



$$= g_s^4 \text{Tr}\{T^{a_1} T^{a_2}\} \int \frac{d^d k}{(2\pi)^d} \frac{\text{tr} \left[(\not{k}) \not{\epsilon}_1 (\not{k} + \not{p}_1) \not{\epsilon}_2 (\not{k} + \not{p}_{12}) \not{\epsilon}_3 (\not{k} + \not{p}_{123}) \not{\epsilon}_4 \right]}{(k)^2 (k + p_1)^2 (k + p_{12})^2 (k + p_{123})^2}$$



[Bargiela@ICHEP22]

Astonishing improvements using different approaches:

- **Analytic**
 - Fast, precise evaluation
 - Wider applications (e.g. changing parameters)
- **Approximate**
 - Not universal
 - Non-trivial to find a good small parameter
- **Numerical**
 - Flexible
 - The challenge is to have fast and stable implementations

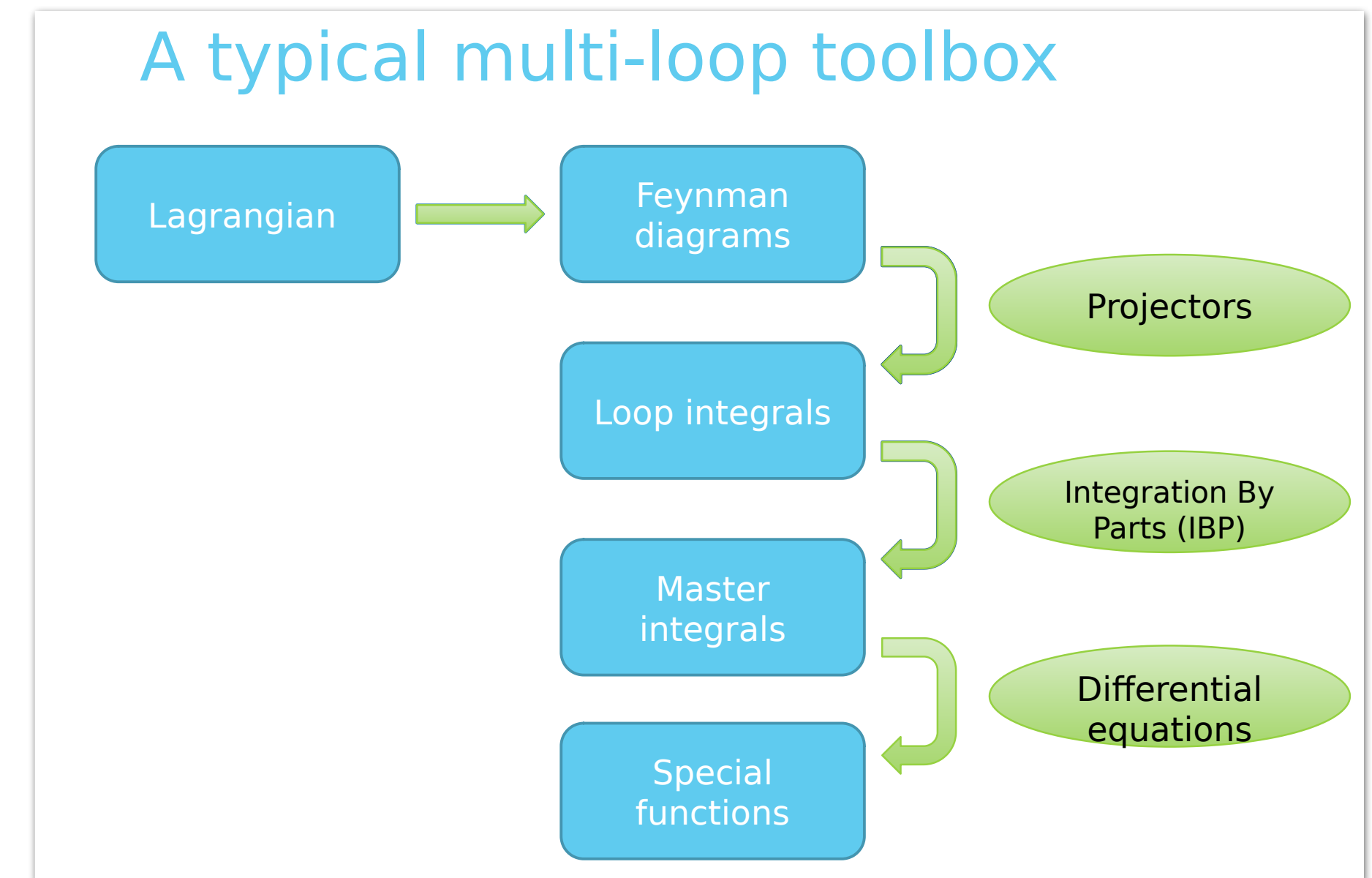
Loop amplitudes

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Algebraic complexity + analytic complexity

Analytic → standard workflow, but crucial “tricks” in different steps

[courtesy of Herschel]



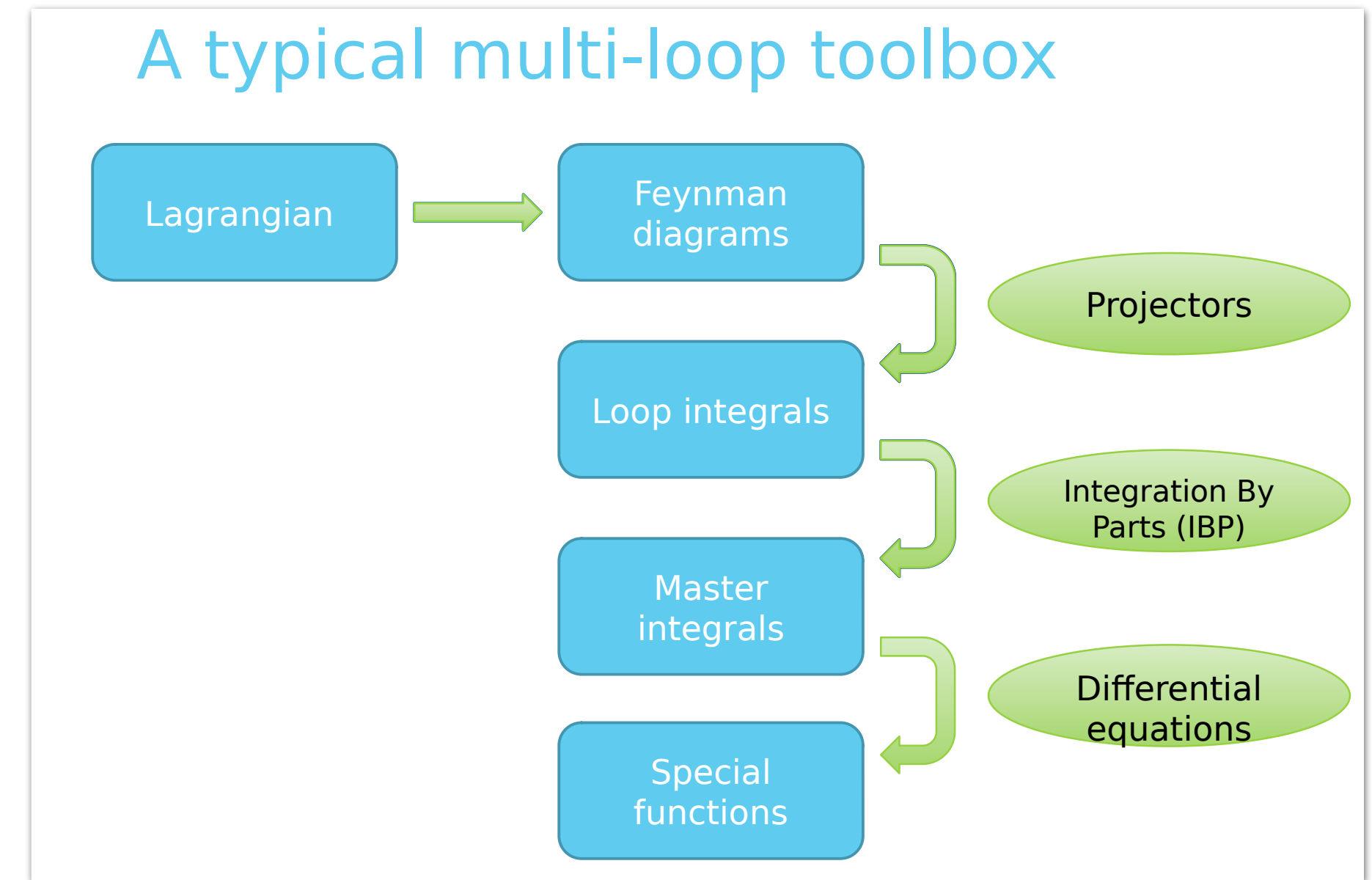
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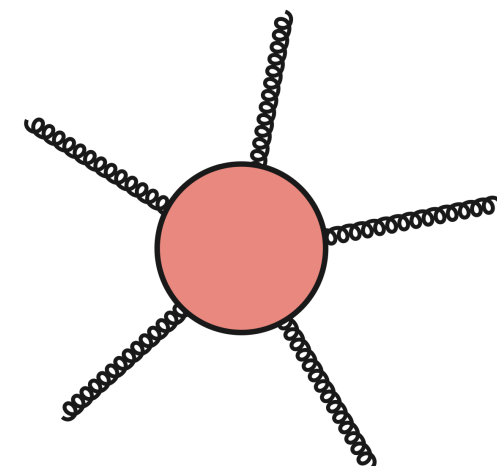
Algebraic complexity + analytic complexity

Analytic → standard workflow, but crucial “tricks” in different steps



- Simplify large rational functions arising from IBP by means of partial fractioning:

- Singular+MultivariateApart



5-point 2-loop full-color

GCD 3GB $\xrightarrow[\text{MultivariateApart}]{\text{Singular}}$ **Partial Fractioned** 24MB

See F. Devoto's talk

- p-adic numbers

5-point 2-loop $\gamma\gamma$ production

Expression	Size	Parameters to fit
Original	605 MB	1,369,559
Reconstructed	4.5 MB	52,527 (of which 15,403 non-zero)

See H. Chawdhry's talk

Loop amplitudes

- Increasing complexity: more legs, more loops, more masses.
- Need for a representation of the amplitudes that can be evaluated efficiently and yields numerically reliable results.

Algebraic complexity + analytic complexity

Numeric

- Automatic adaptive integration of loop integrals
- Efficiency based on GPUs, iterated integration and double extrapolation

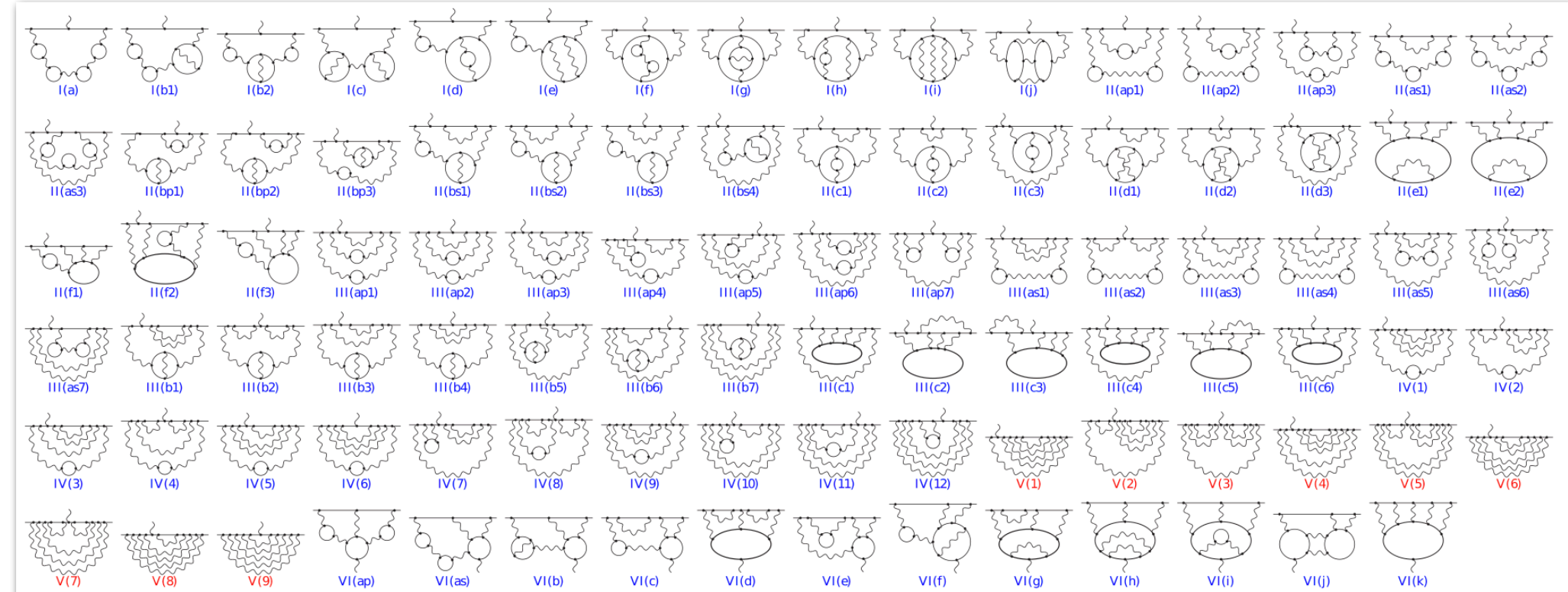
- Reduction to finite integrals (no MI)
- MC integration (non-adaptive)
- Parallel realisation

See S. Volkov's talk

3-loop Feynman integrals in the Euclidean or physical kinematical region

See E. De Doncker's talk

Total 10-th order QED electron anomalous magnetic moment calculation

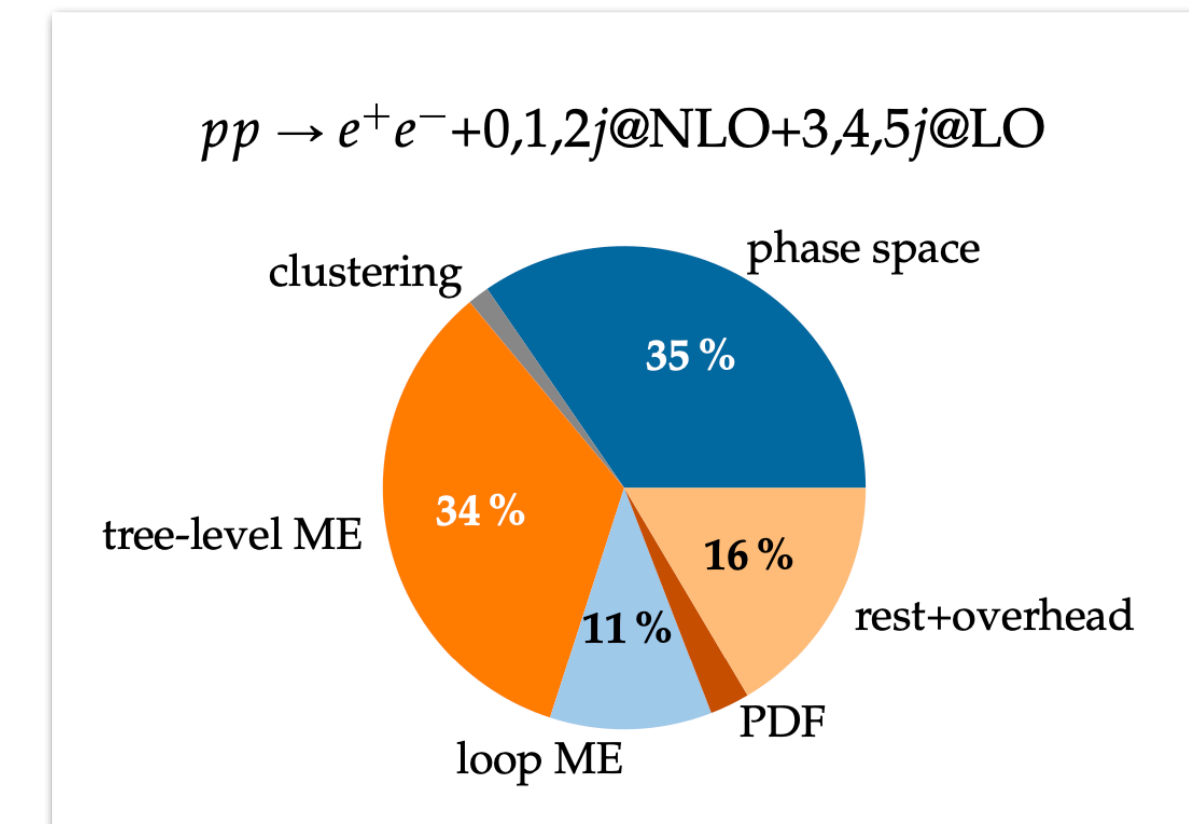


Computing amplitudes/matrix elements with Machine Learning techniques

❖ Largest portion of MC time spent on MEs (by far)

See E. Bothmann's talk

Can ML step in and help?

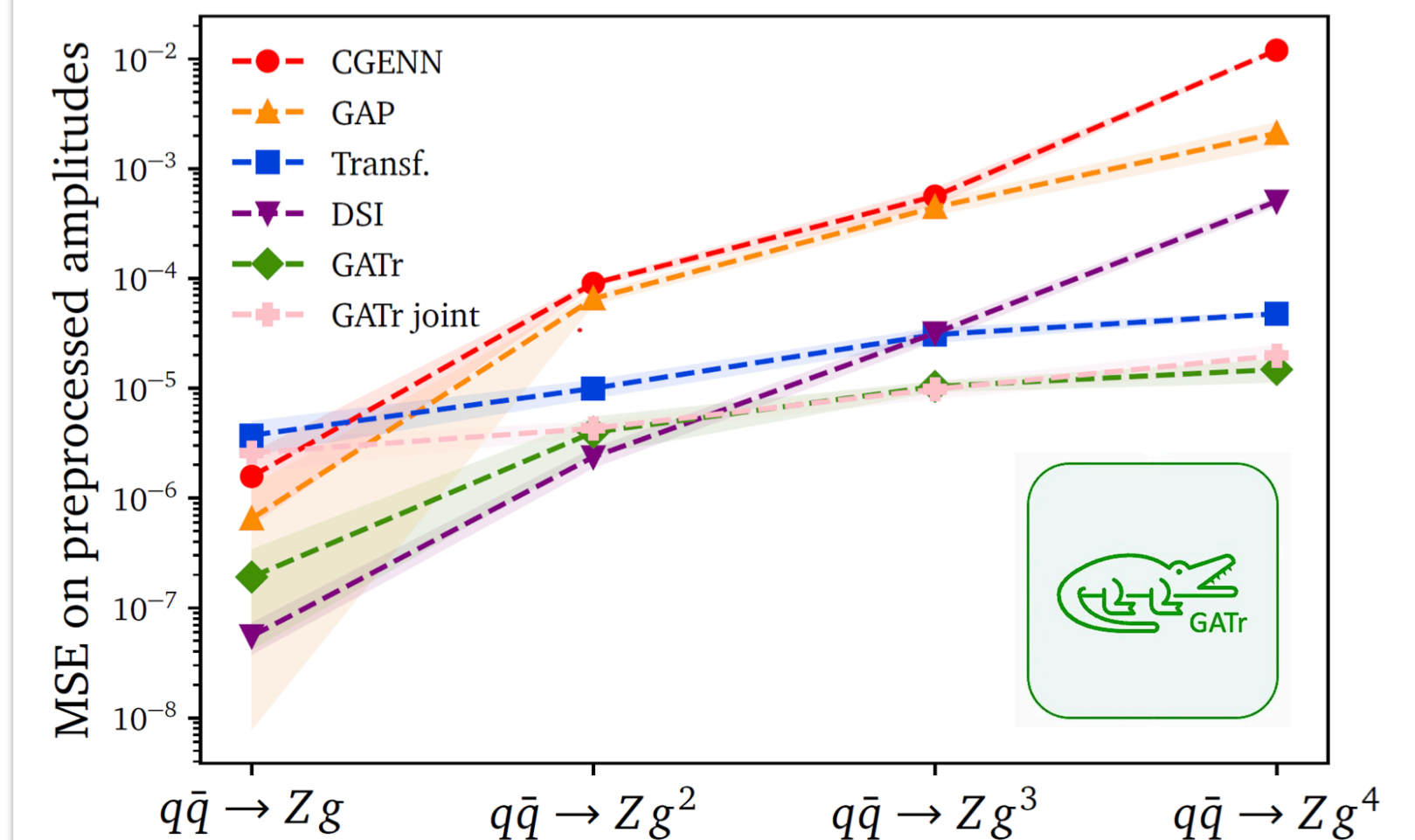


- ▶ **Problem:** Build an algorithm that can predict interaction amplitudes from phase space points for multiple processes
- ▶ Machine learning approaches struggle for 2 reasons:
 1. The output range covers a **very large interval**
 2. There exists a **scaling problem**. The more particles, the more complicated it is to estimate the amplitude

Bayesian and Symmetry Preserving Networks

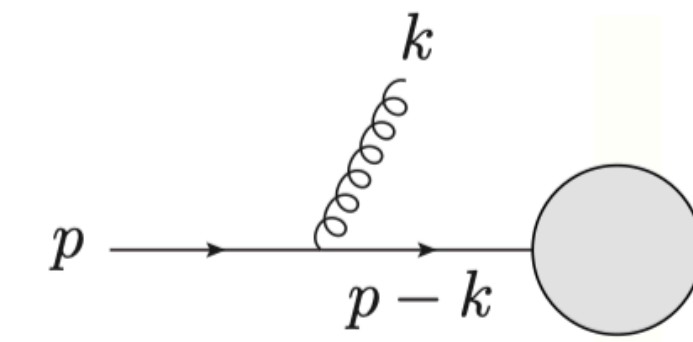
See V. Bresó Pla's talk

AMPLITUDE SURROGATE APPLICATION

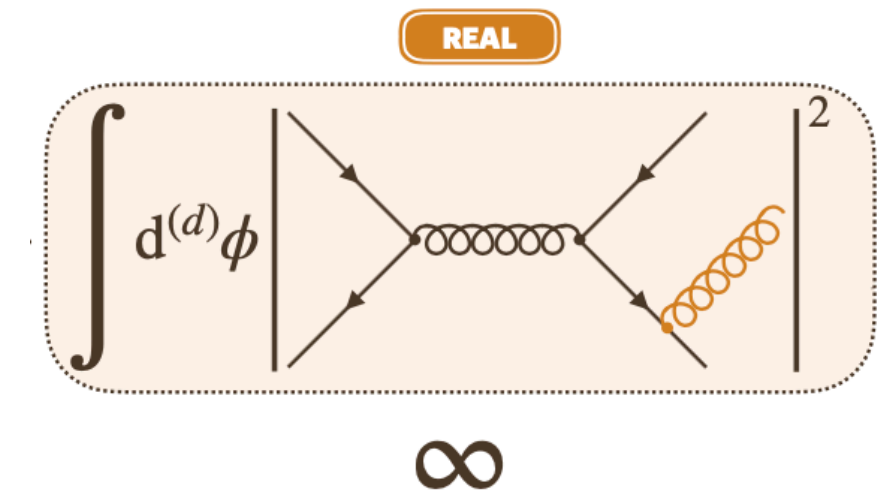


Real corrections

- Affected by singularities that arise after integrating over the phase space



$$\sim \frac{1}{(p-k)^2} = \frac{1}{2E_p E_k (1 - \cos \theta)} \xrightarrow{E_k \rightarrow 0 \text{ or } \theta \rightarrow 0} \infty.$$

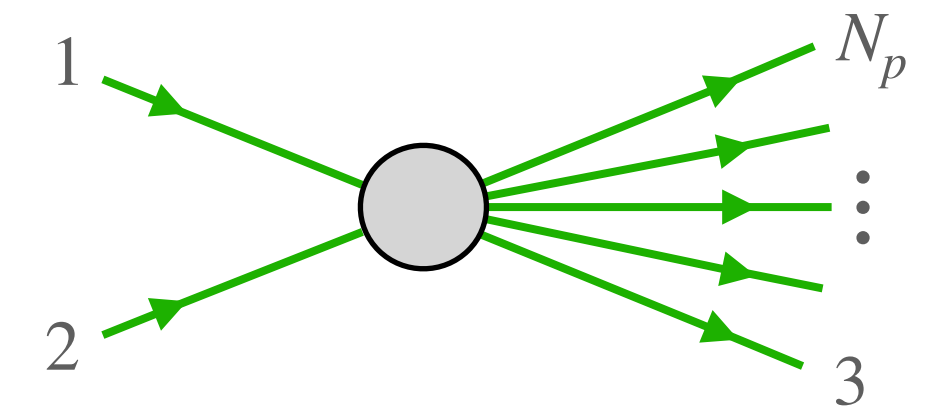


- Goal: **extract IR singularities** preserving fully differential prediction

The frontier: NNLO for arbitrary partonic process [local and analytic]

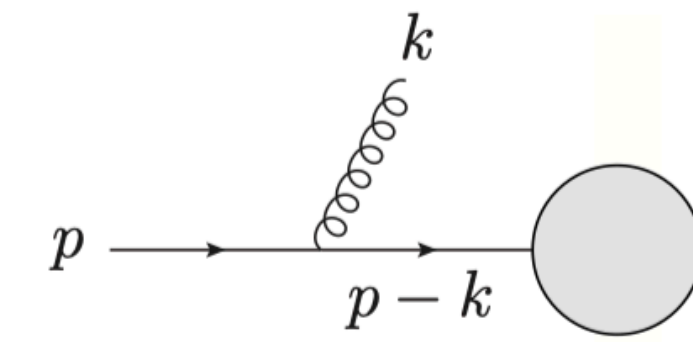
Conceptual + technical complexity

- Overlapping singularities,
- Integration of intricate functions analytically** in d-dimensions.
- Bookkeeping** becomes immediately **cumbersome** → large number of subtraction terms.
- Standard approaches may **hide a number of simplifications** that can occur **before explicit evaluation**.

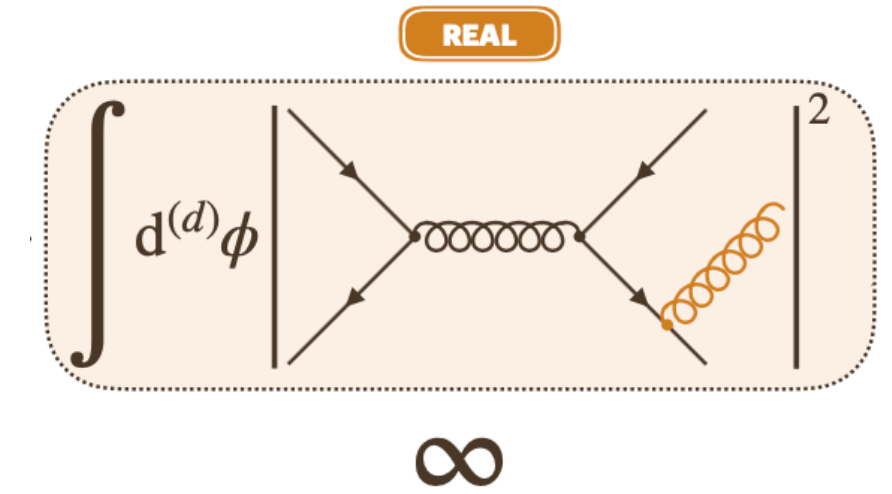


Real corrections

- Affected by singularities that arise after integrating over the phase space



$$\sim \frac{1}{(p-k)^2} = \frac{1}{2E_p E_k (1 - \cos \theta)} \xrightarrow[\theta \rightarrow 0]{E_k \rightarrow 0} \infty.$$



- Goal: extract IR singularities preserving fully differential prediction

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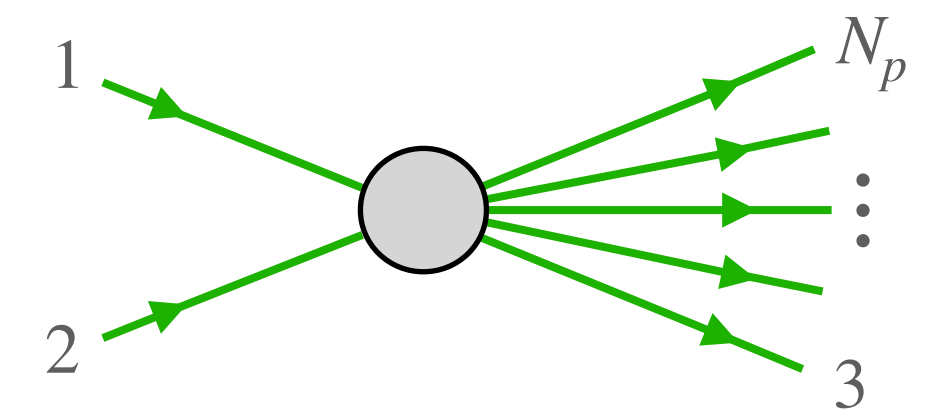
Conceptual + technical complexity

Searching for recurring structure seems to be the key...

See D. M. Tagliabue's talk

Virtual component Soft component Collinear component

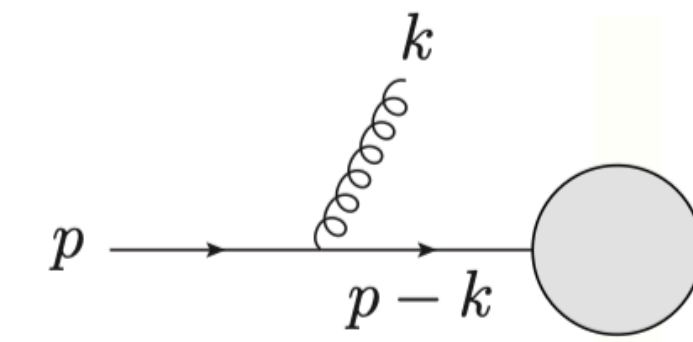
$$I_T(\epsilon) = I_V(\epsilon) + I_S(\epsilon) + I_C(\epsilon)$$



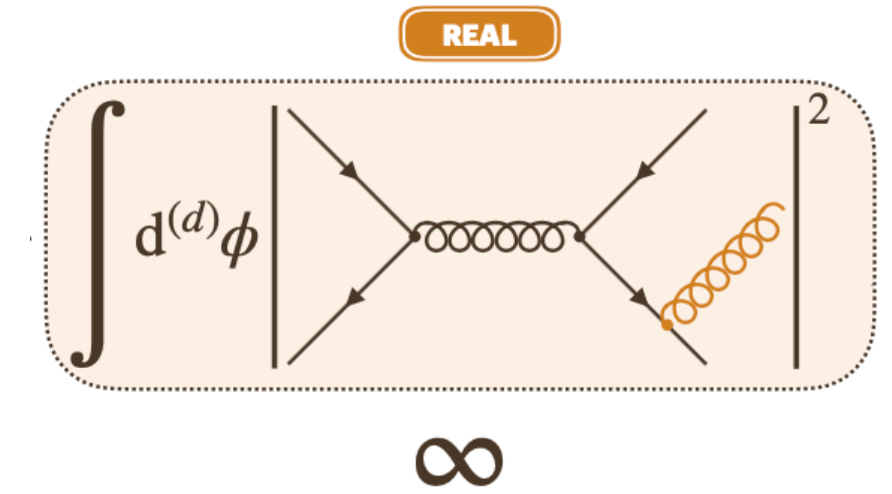
Free of poles
Fully general in the number of partons

Real corrections

- Affected by singularities that arise after integrating over the phase space



$$\sim \frac{1}{(p-k)^2} = \frac{1}{2E_p E_k (1 - \cos \theta)} \xrightarrow{E_k \rightarrow 0 \text{ or } \theta \rightarrow 0} \infty.$$

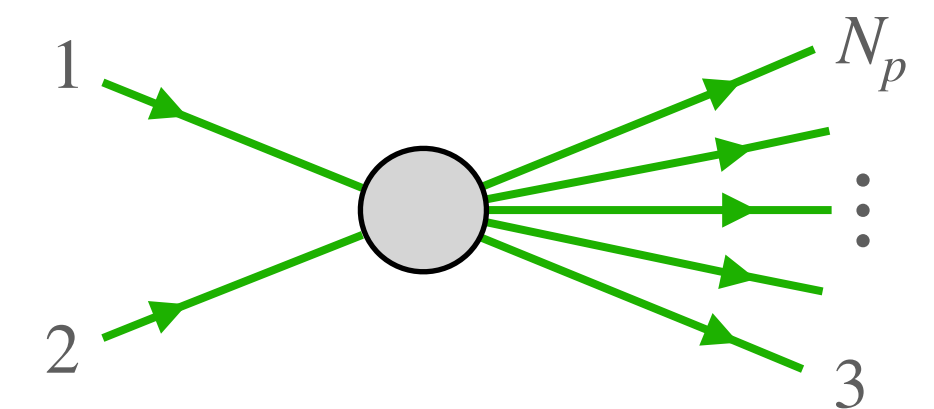


- Goal: extract IR singularities preserving fully differential prediction

The frontier: NNLO for arbitrary partonic process [local and analytic]

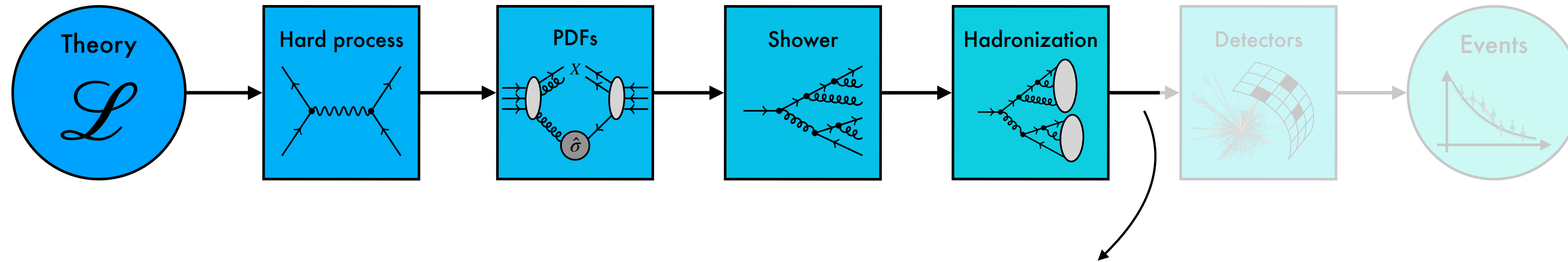
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Searching for recurring structure seems to be the key...



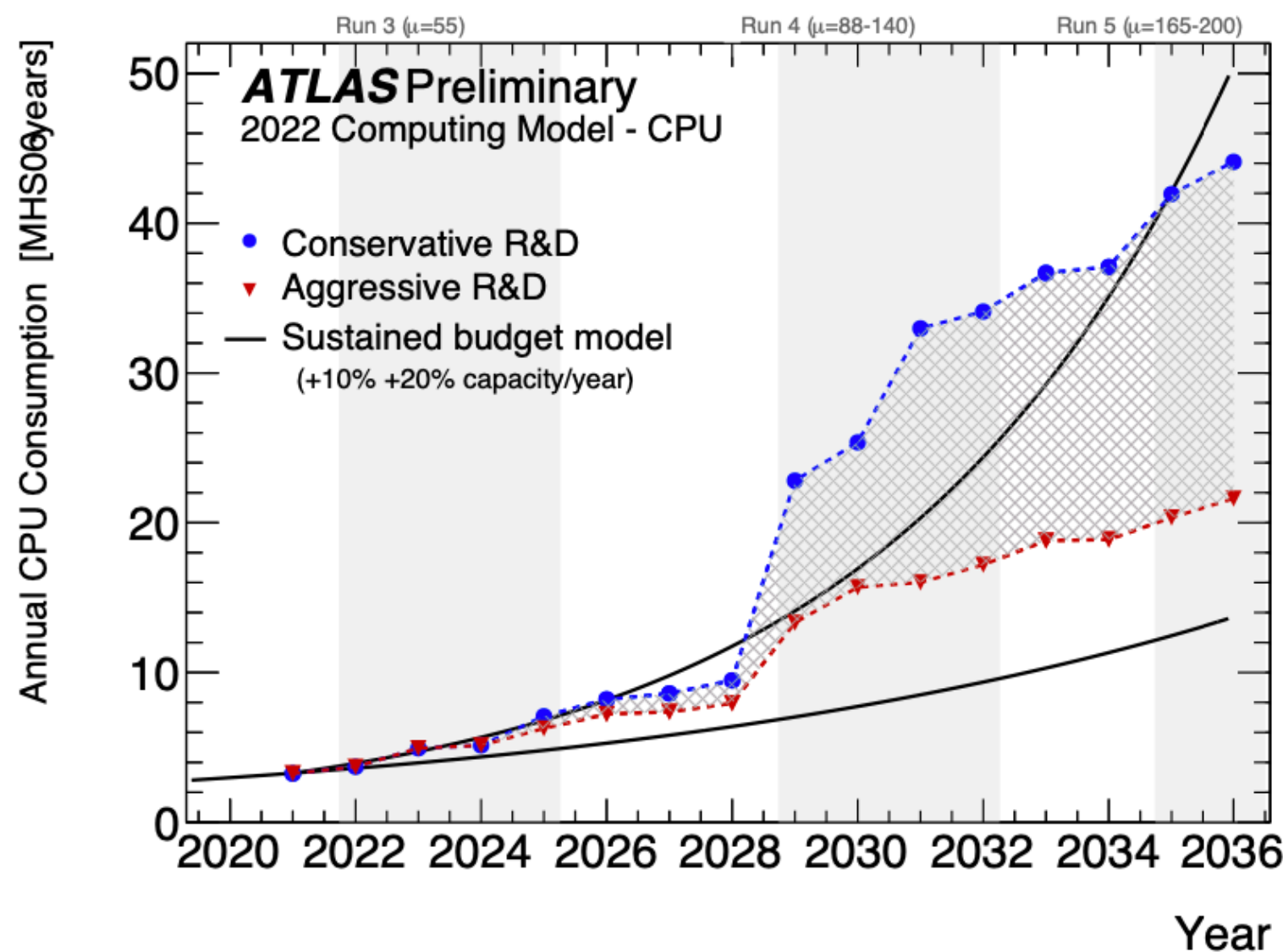
Can AI help us recognise such recurring structures?

From paper to nature: Monte Carlo event generator



MC event generator's desirable features:
speed + portability + scalability

See C. Gütschow and E. Bothmann's talk



Components we need to consider:

- Tree-level Matrix elements
- Phase space generation
- PDF's

$pp \rightarrow e^+e^- + 0,1,2j@NLO + 3,4,5j@LO$

phase space 35%

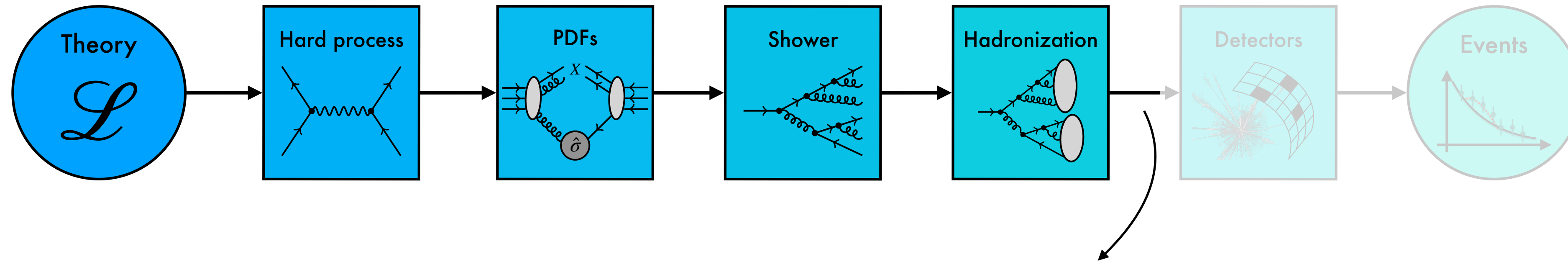
tree-level ME 34%

loop ME 11%

PDF 16%

rest+overhead 16%

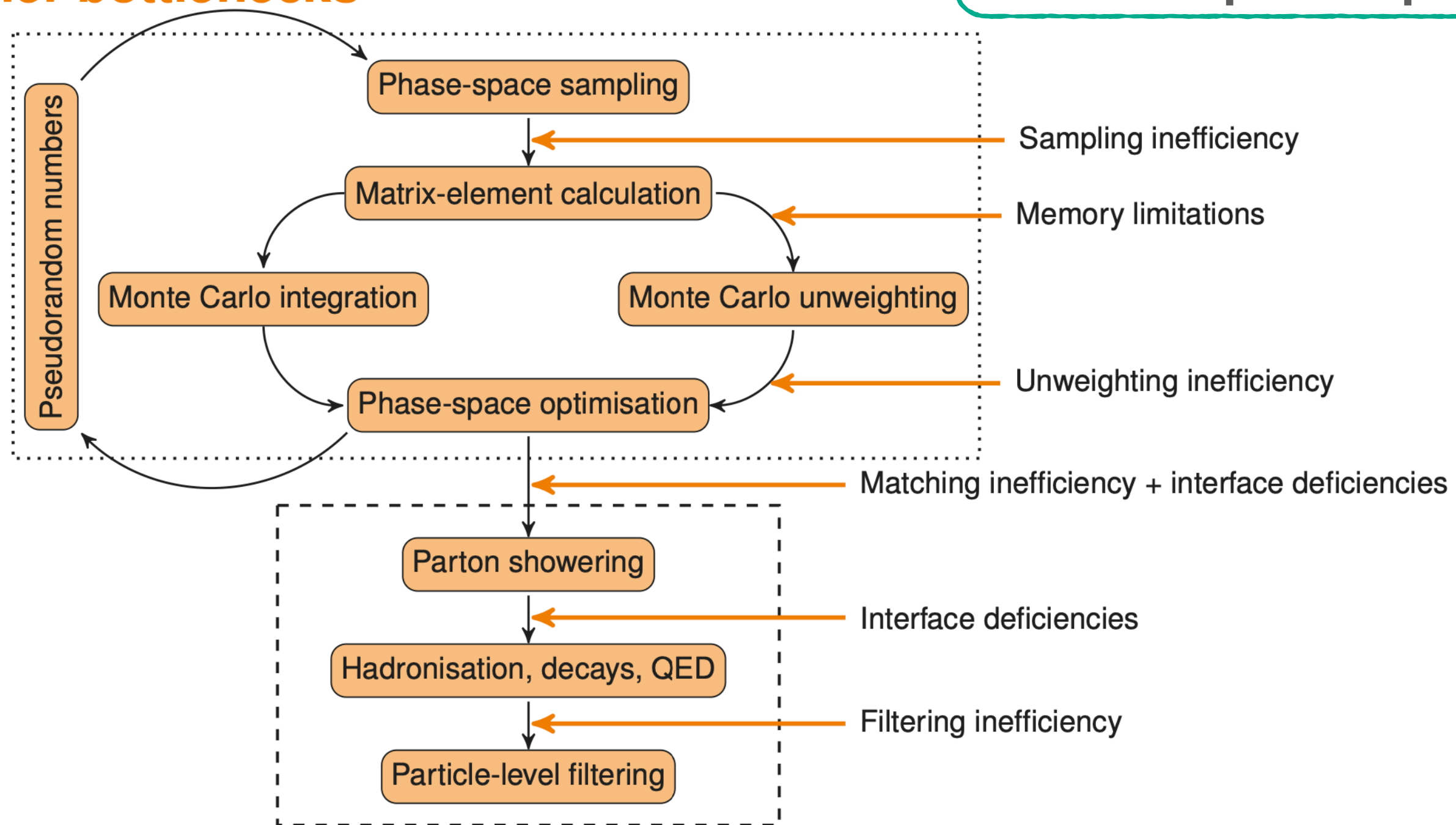
From paper to nature: Monte Carlo event generator



See C. Gütschow's talk

MC event generator's desirable features:
speed + portability + scalability

Other bottlenecks

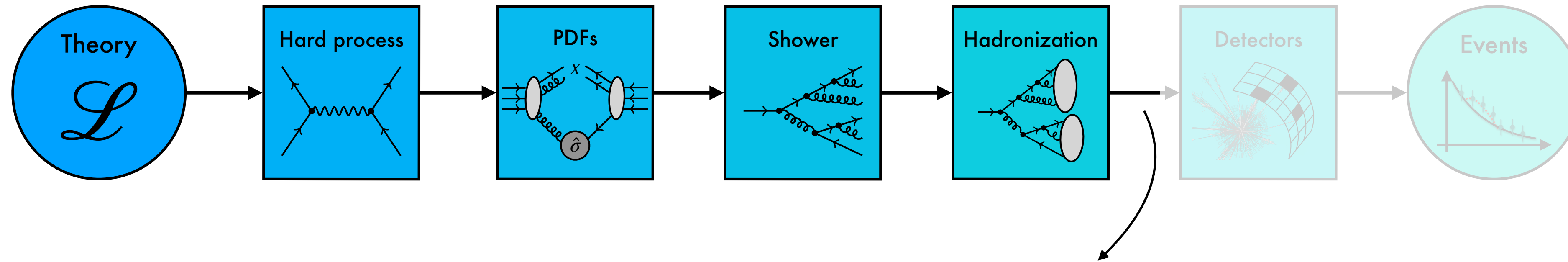


Very diverse and composite layers of complexity...

...the problem seems hopeless.

However...

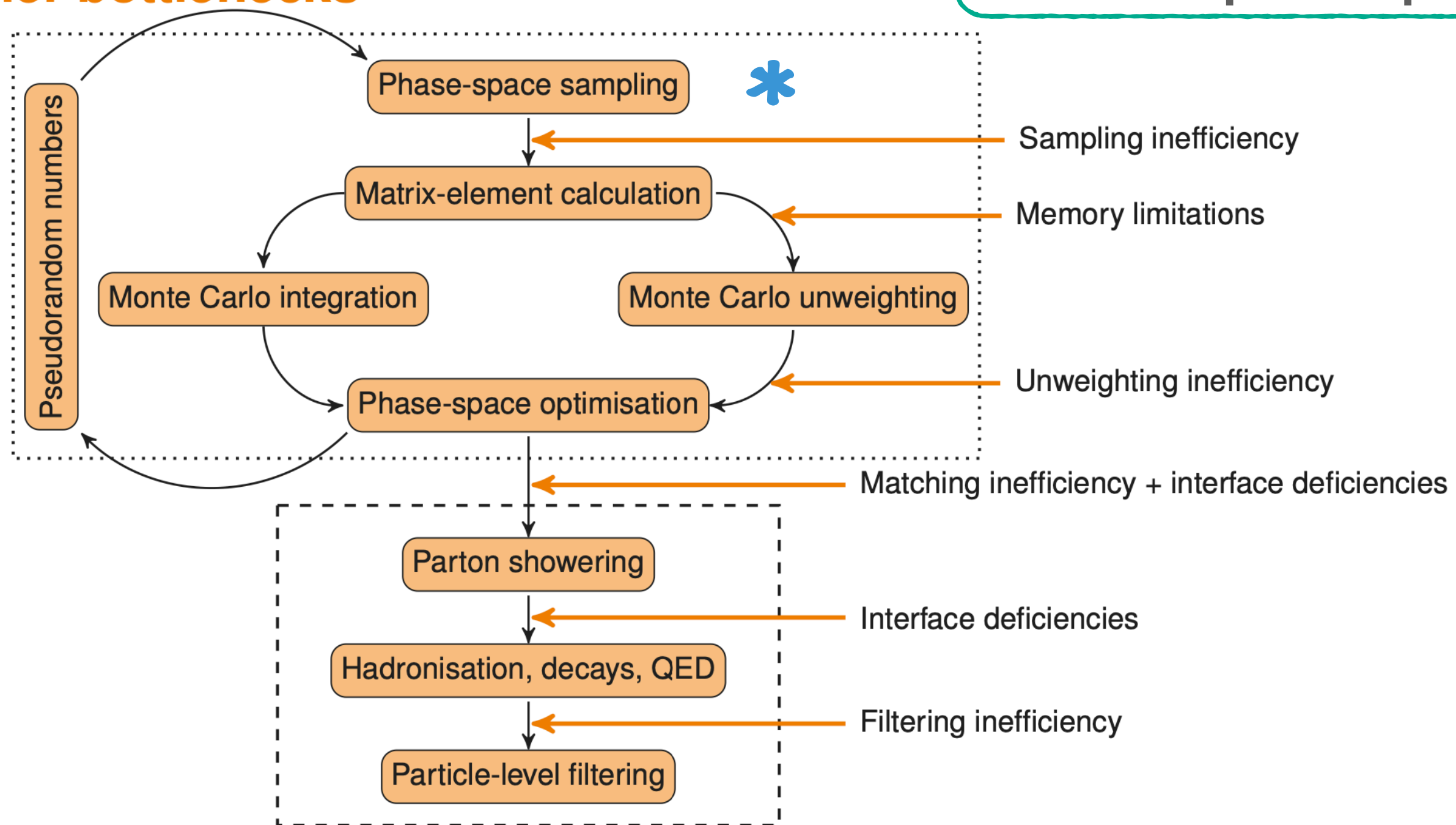
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* Neural Importance Sampling



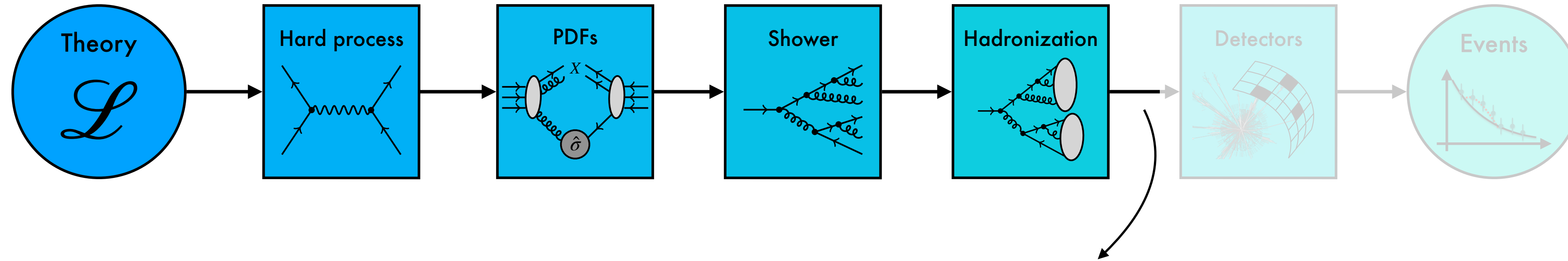
See T. Heimel's talk

The MadNIS Reloaded

Large improvements, even for high multiplicities and complicated processes!

[2311.01548]

From paper to nature: Monte Carlo event generator



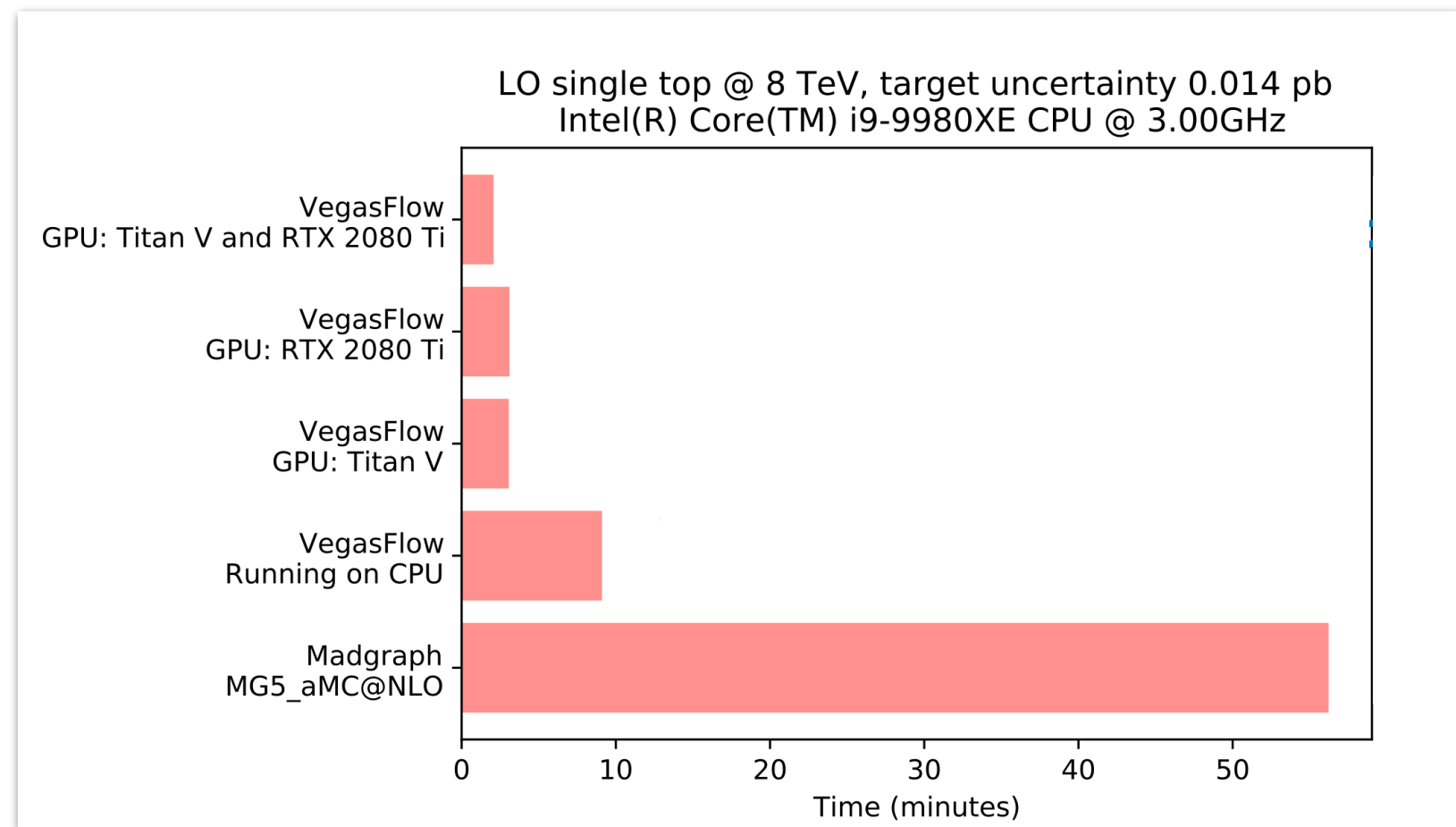
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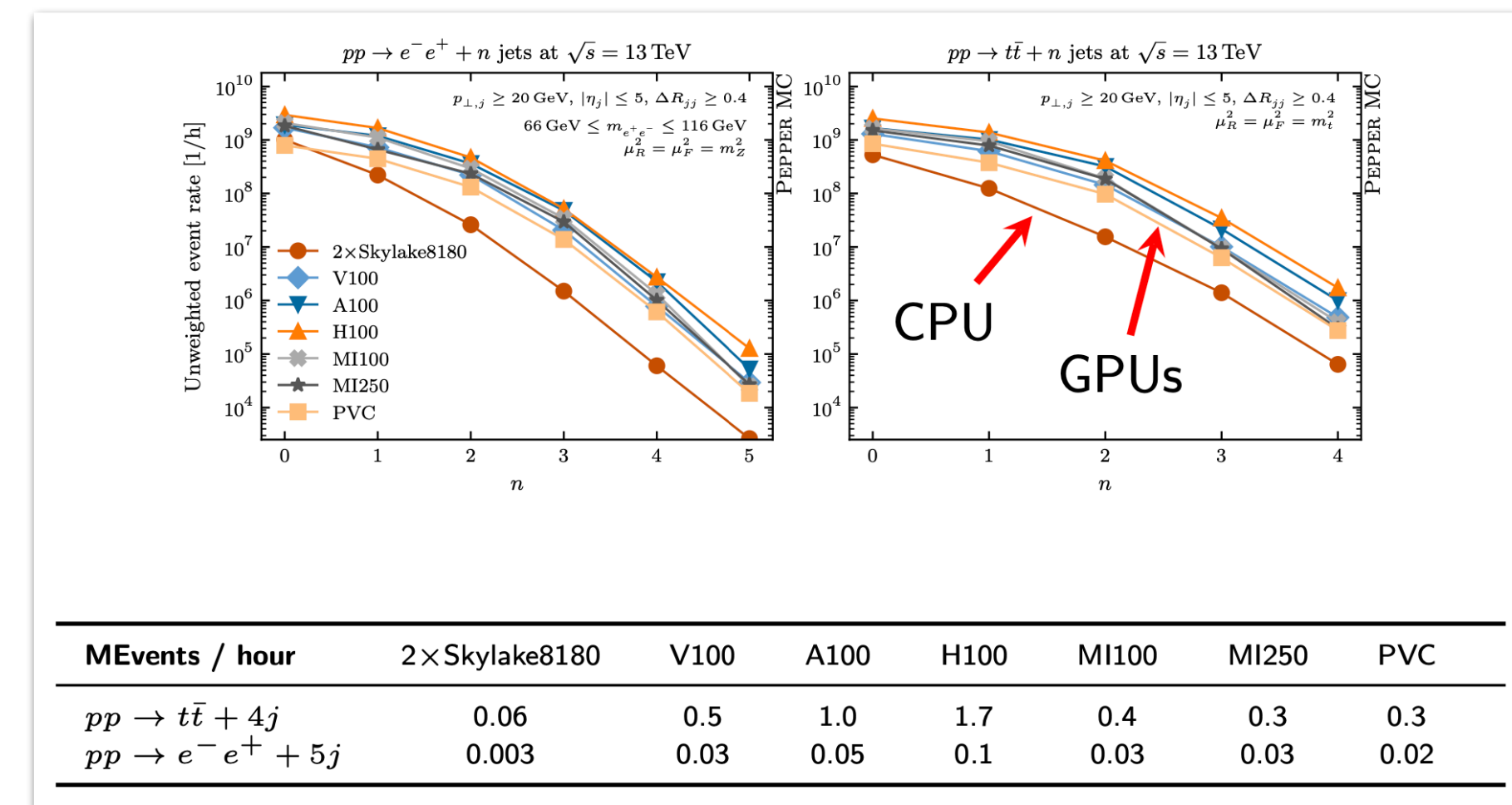
See S. Carrazza's talk

PEPPER

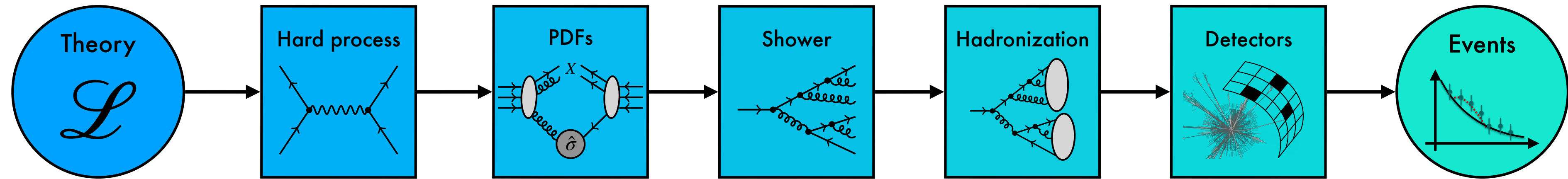
See E. Bothmann's talk



- ❖ portable event generator that incorporates GPU resources into high-precision simulations
- ❖ Parallelisation desired
- ❖ Scalability from a laptop to a Computing Facility.



Going for the likelihood



$$\int dx_{hard} p(x_{hard} | \alpha) \underbrace{p(x_{reco} | x_{hard}, \alpha) \epsilon(x_{hard}, \alpha)} = p(x_{reco} | \alpha)$$

Three network setup makes the **MEM tractable**

- 1) **Transfer-Network** encoding the transfer probability $p(x_{reco} | x_{hard})$
- 2) **Acceptance-Network** encoding the efficiency $\epsilon(x_{hard})$
- 3) **Sampling-Network** encoding the proposal distribution $q(x_{hard})$

See N. Huetsch's talk

* if you are not interested in the full likelihood you can also just do **unfolding from detector to particle level**

See J. Mariño Villadamigo's talk

- ▶ Unfolding to parton-level is not only inverting detector effects, but **rather inverting the entire forward simulation chain**
- ▶ **Faithful modeling of complex correlations** at parton-level, i.e., W boson and top mass resonances
- ▶ **Non-trivial combinatorics** between physics objects at both levels

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A Living Review of Machine Learning for Particle Physics

Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

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Expand all sections

Collapse all sections

Reviews

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- Specialized reviews
- Classical papers
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- Datasets
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Matrix elements

Parameter estimation

Parton Distribution Functions
(and related)

Lattice Gauge Theory

Function Approximation

Symbolic Regression

Equivariant networks.

Equivariant networks:

Symbolic Regression

Function Approximation

Lattice Gauge Theory

Parton Distribution Functions

- ❖ Do you have an idea that relies on ML techniques?
- ❖ Do you want to apply ML to your favorite problem?

❖ **Take a look at the literature first!**

Stay tuned for many other **ML4HEP** applications



The world is not only LHC...

Low-energy QED scattering

See Y. Ulrich's talk

Multiscale Lattice Gauge Theory algorithms

See P. Boyle's talk

fixed-order NNLO QED framework

- provided: matrix elements by us or others
- output: **physical cross section** for any physical observable
- McMULE: phase space generation, subtraction, stabilisation, integration, etc.
- all leptonic $2 \rightarrow 2$ processes in QED at NNLO (+ a few others)
- integrator & generator
- user defines cuts through arbitrary function that is loaded at run time

Get the code here: <https://mule-tools.gitlab.io>
Read the docs here: <https://mcmule.readthedocs.io>



McMULE

Software: <https://www.github.com/paboyle/Grid>

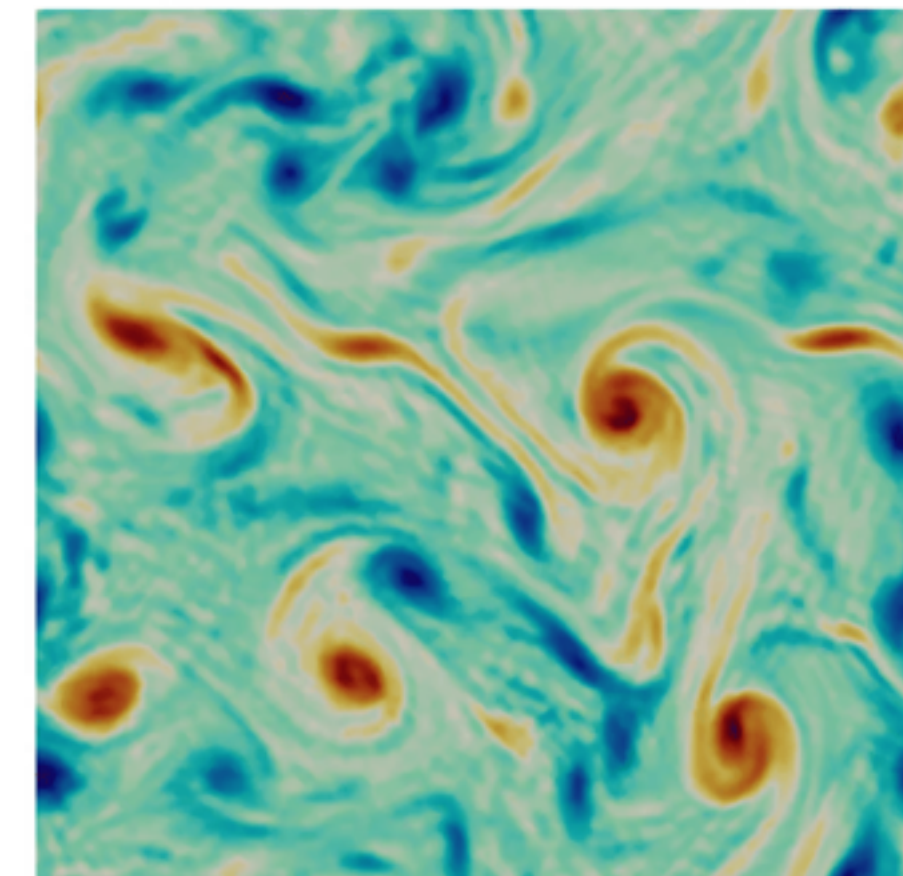
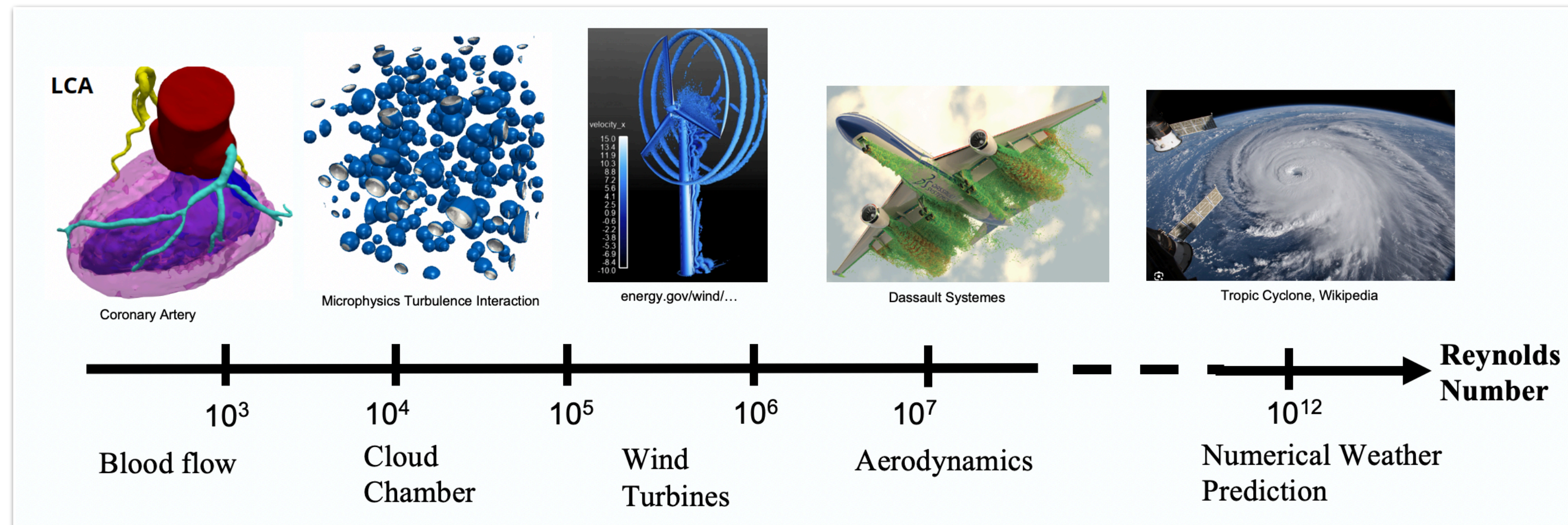
- Lattice QCD and muon g-2
- Grid code for structured Lattice Gauge theory calculations, developed under ECP
 - Parallelization & portability: *covariant programming*
 - Performance
- Exascale algorithms and SciDAC-5
 - Multiple right-hand-side multigrid and GPU tensor units



The world is not only LHC...

...and it is not only colliders...

Study of **turbulence**: computational challenge with a variety of declinations:



See M. Atif's talk

Fourier Neural Operator as a surrogate for Navier-Stokes solver

**Interconnection between different field and complementary expertise
can unlock the doors of an exciting wonderland...**

Thank you for your attention!



E. Golzio