

The road to AI-based discoveries

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Quantum100 \otimes ai, 12.11.2025



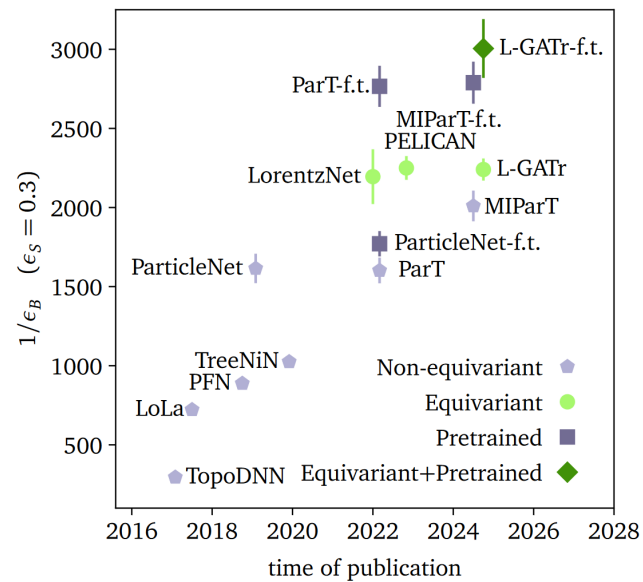
Universität Hamburg

DER FORSCHUNG | DER LEHRE | DER BILDUNG

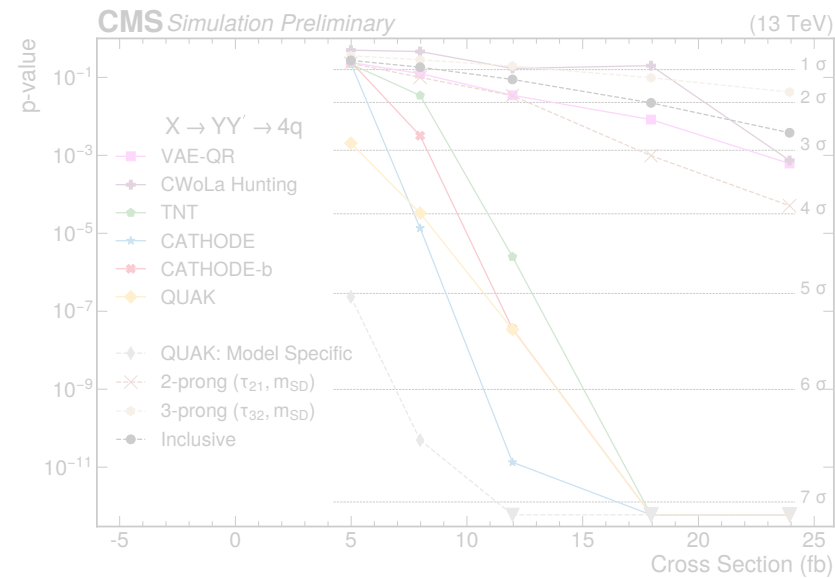
CLUSTER OF EXCELLENCE

QUANTUM UNIVERSE

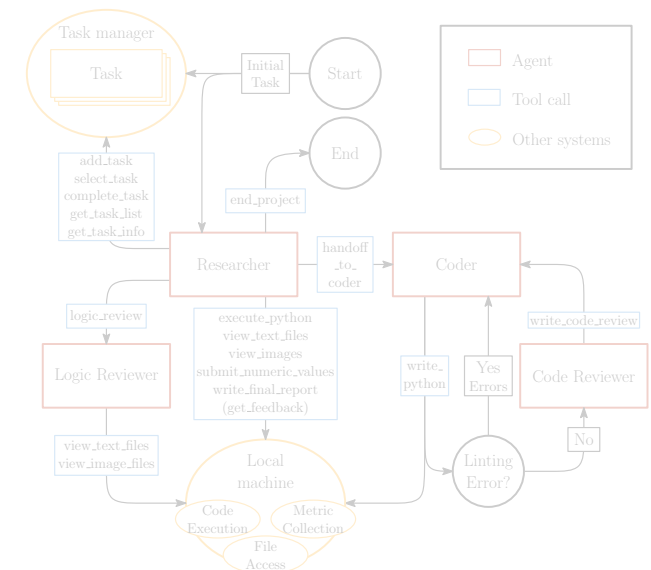
Outline



Tools for Discovery



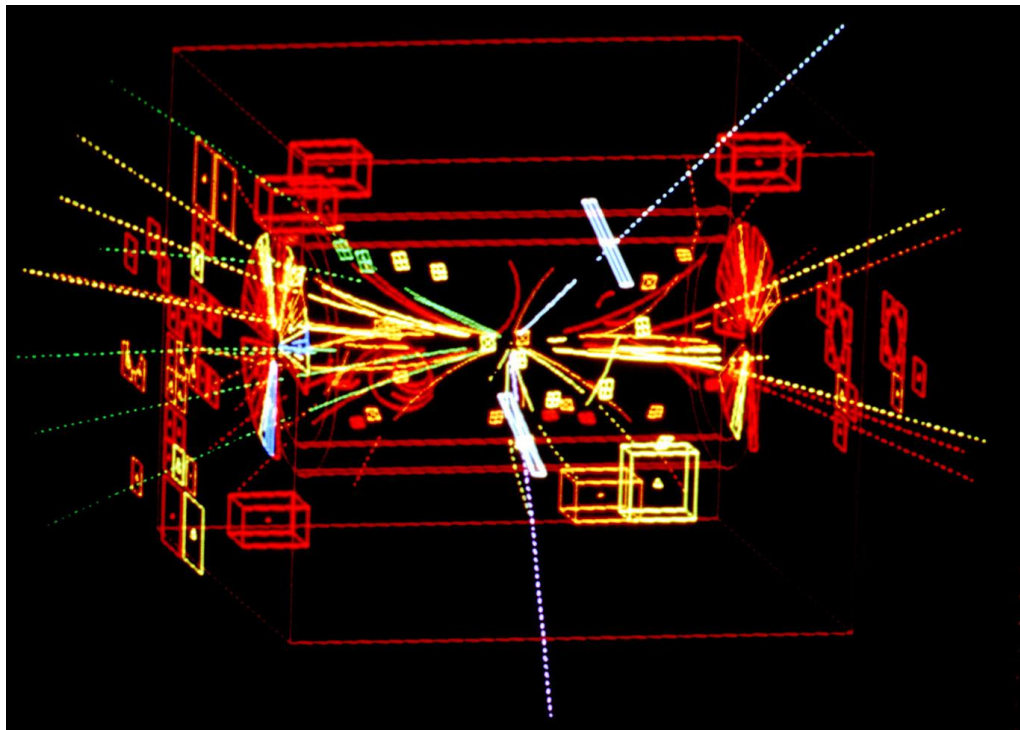
Discovery Strategies



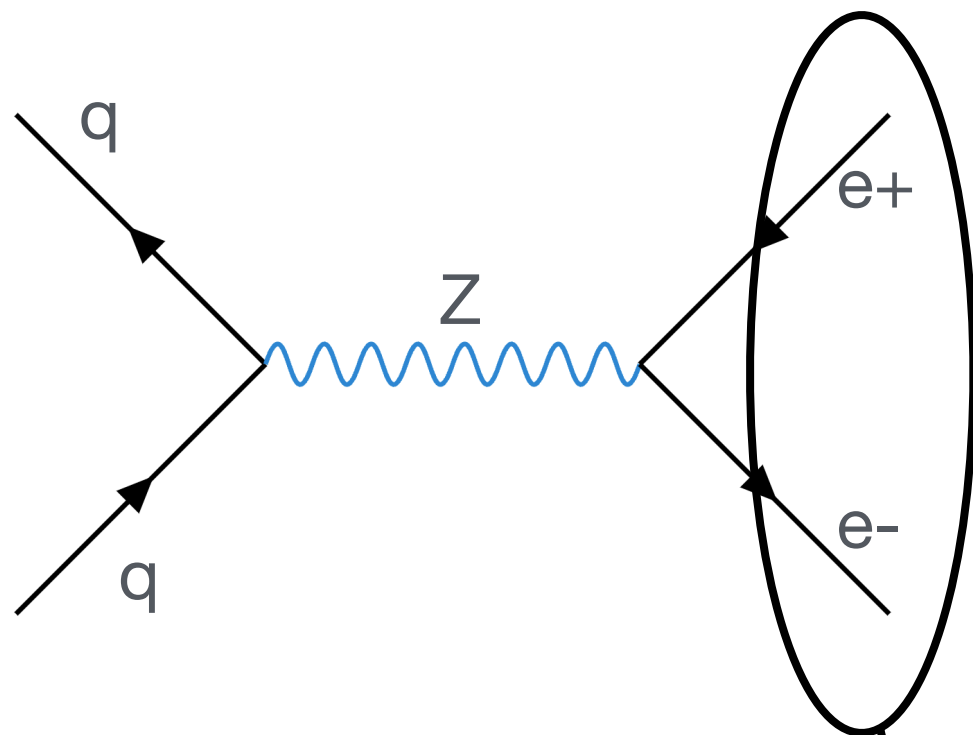
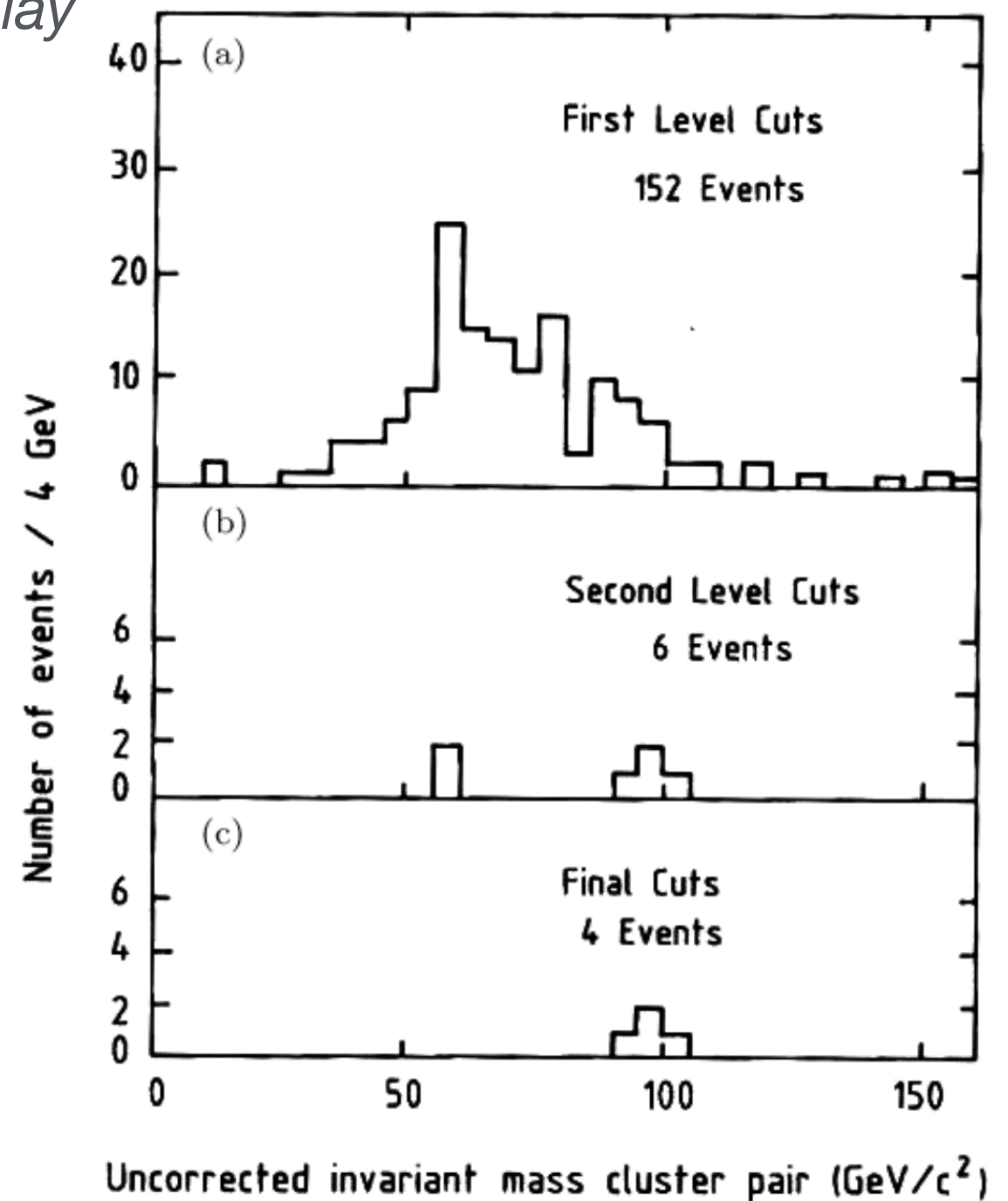
Autonomous Discovery

Increasing autonomy
of AI systems

How to discover a new particle?



*Event display
from UA1
from 1983*

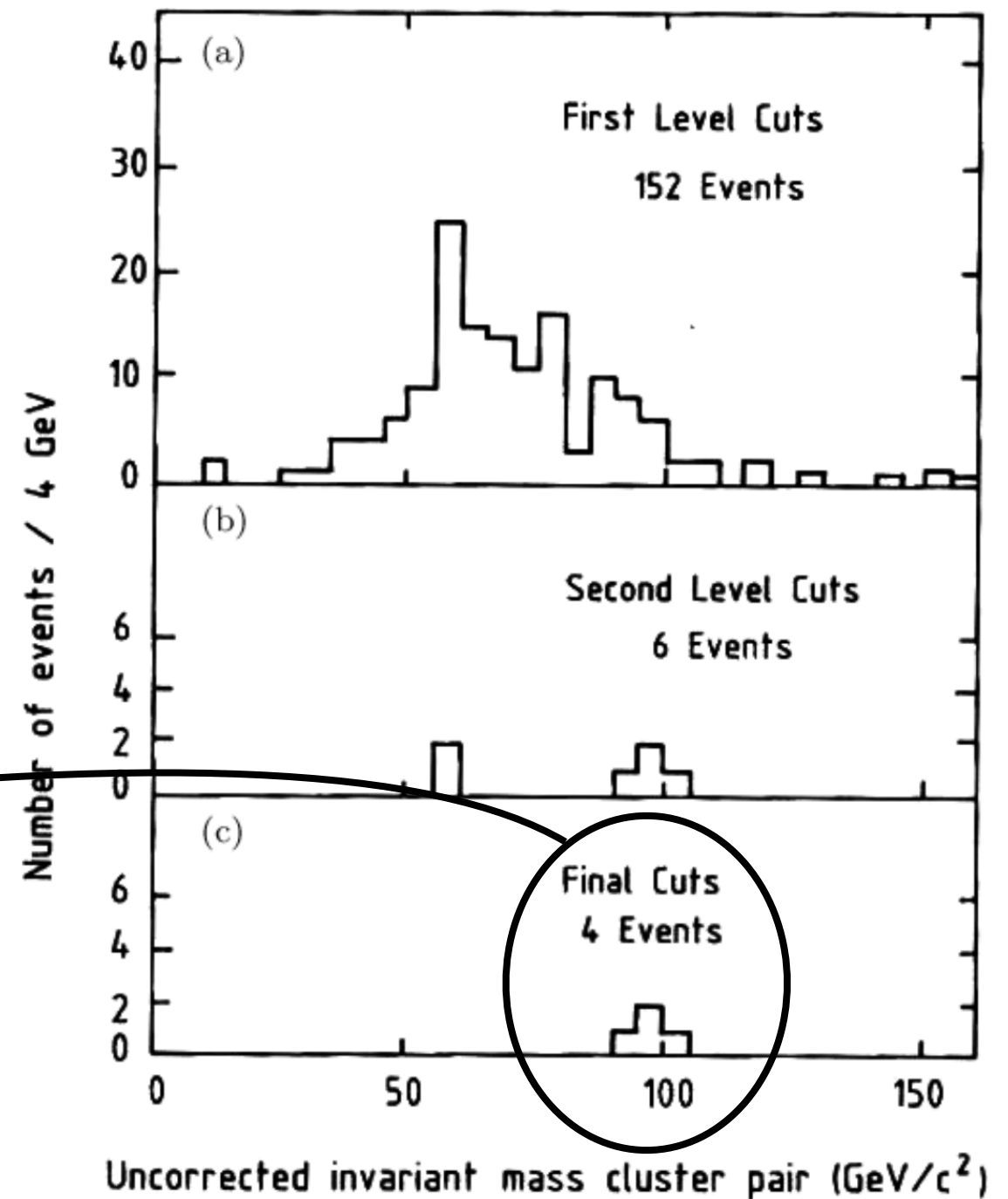


*Calculate **invariant mass** of two
particles to discover resonance*

How to discover a new particle?

Standard Model of Elementary Particles

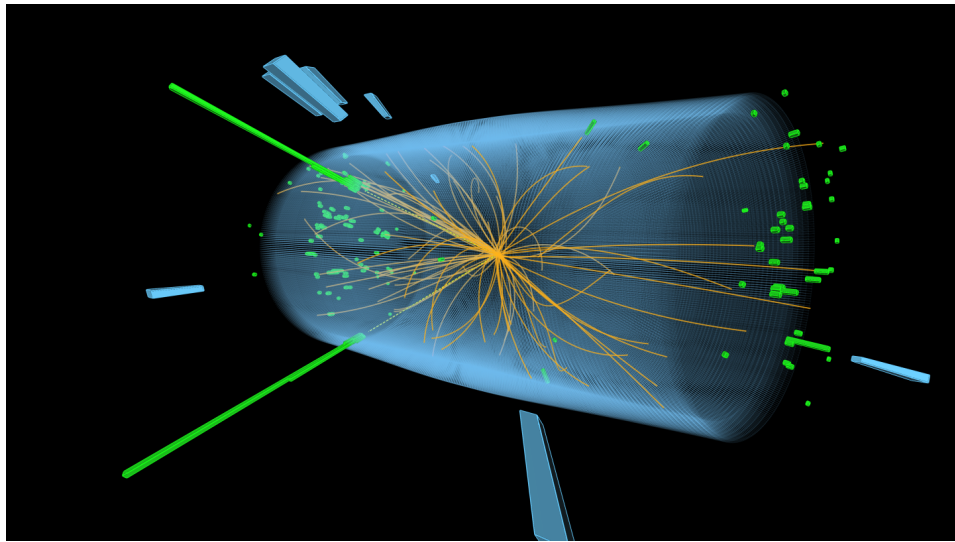
three generations of matter (fermions)					
	I	II	III		
mass	$\approx 2.2 \text{ MeV}/c^2$	$\approx 1.28 \text{ GeV}/c^2$	$\approx 173.1 \text{ GeV}/c^2$	0	$\approx 125.09 \text{ GeV}/c^2$
charge	$2/3$	$2/3$	$2/3$	0	0
spin	$1/2$	$1/2$	$1/2$	1	0
QUARKS	u up	c charm	t top	g gluon	H Higgs
	$\approx 4.7 \text{ MeV}/c^2$	$\approx 96 \text{ MeV}/c^2$	$\approx 4.18 \text{ GeV}/c^2$	0	
	$-1/3$	$-1/3$	$-1/3$	0	
	$1/2$	$1/2$	$1/2$	1	
	d down	s strange	b bottom	γ photon	
LEPTONS	$\approx 0.511 \text{ MeV}/c^2$	$\approx 105.66 \text{ MeV}/c^2$	$\approx 1.7768 \text{ GeV}/c^2$	$\approx 91.19 \text{ GeV}/c^2$	
	-1	-1	-1	0	
	$1/2$	$1/2$	$1/2$	1	
	e electron	μ muon	τ tau	Z Z boson	
	$< 2.2 \text{ eV}/c^2$	$< 1.7 \text{ MeV}/c^2$	$< 15.5 \text{ MeV}/c^2$	$\approx 80.39 \text{ GeV}/c^2$	
	0	0	0	± 1	
	$1/2$	$1/2$	$1/2$	1	
	ν_e electron neutrino	ν_μ muon neutrino	ν_τ tau neutrino	W W boson	



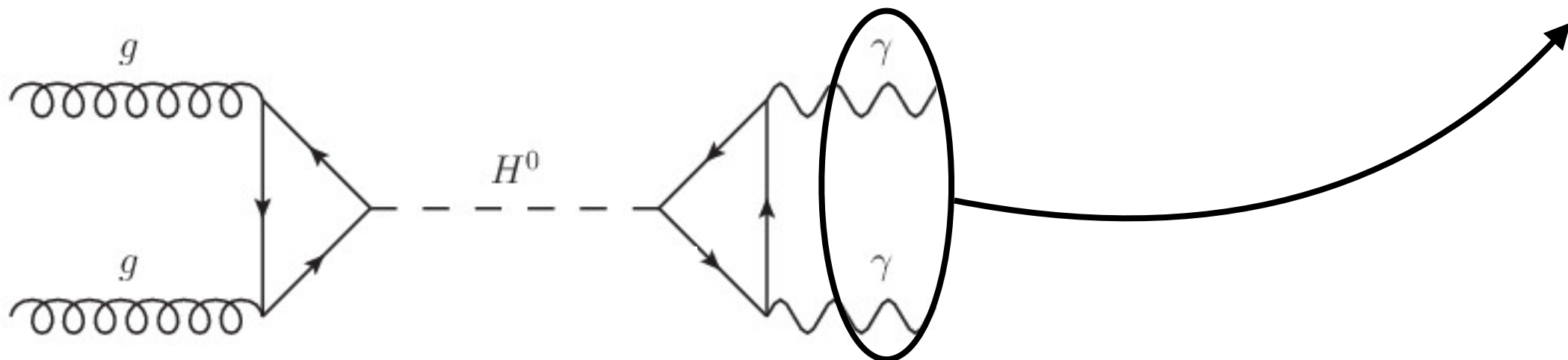
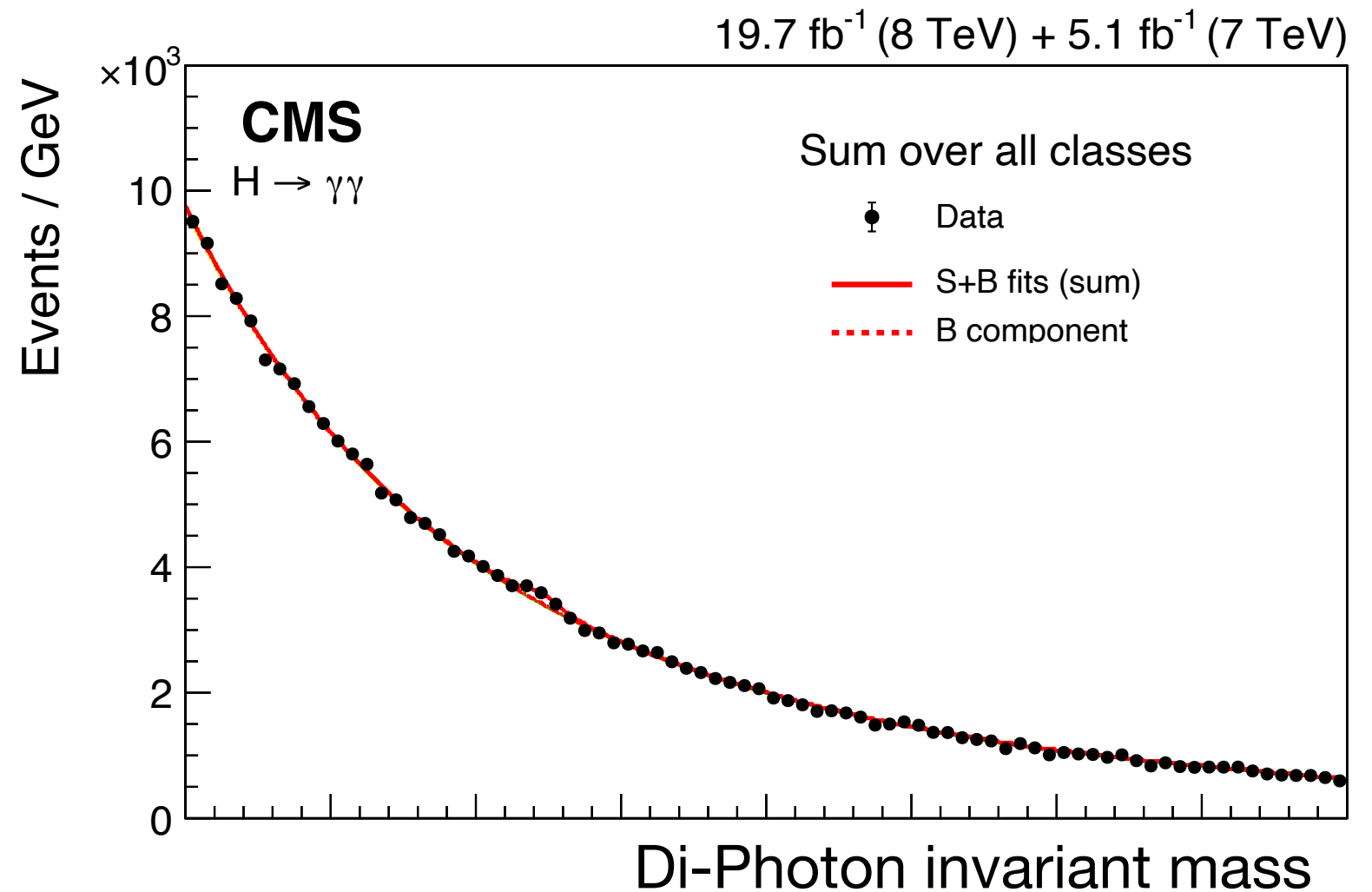
*Nobel price for discovery of W and Z boson in 1984
(Rubbia and van der Meer)*



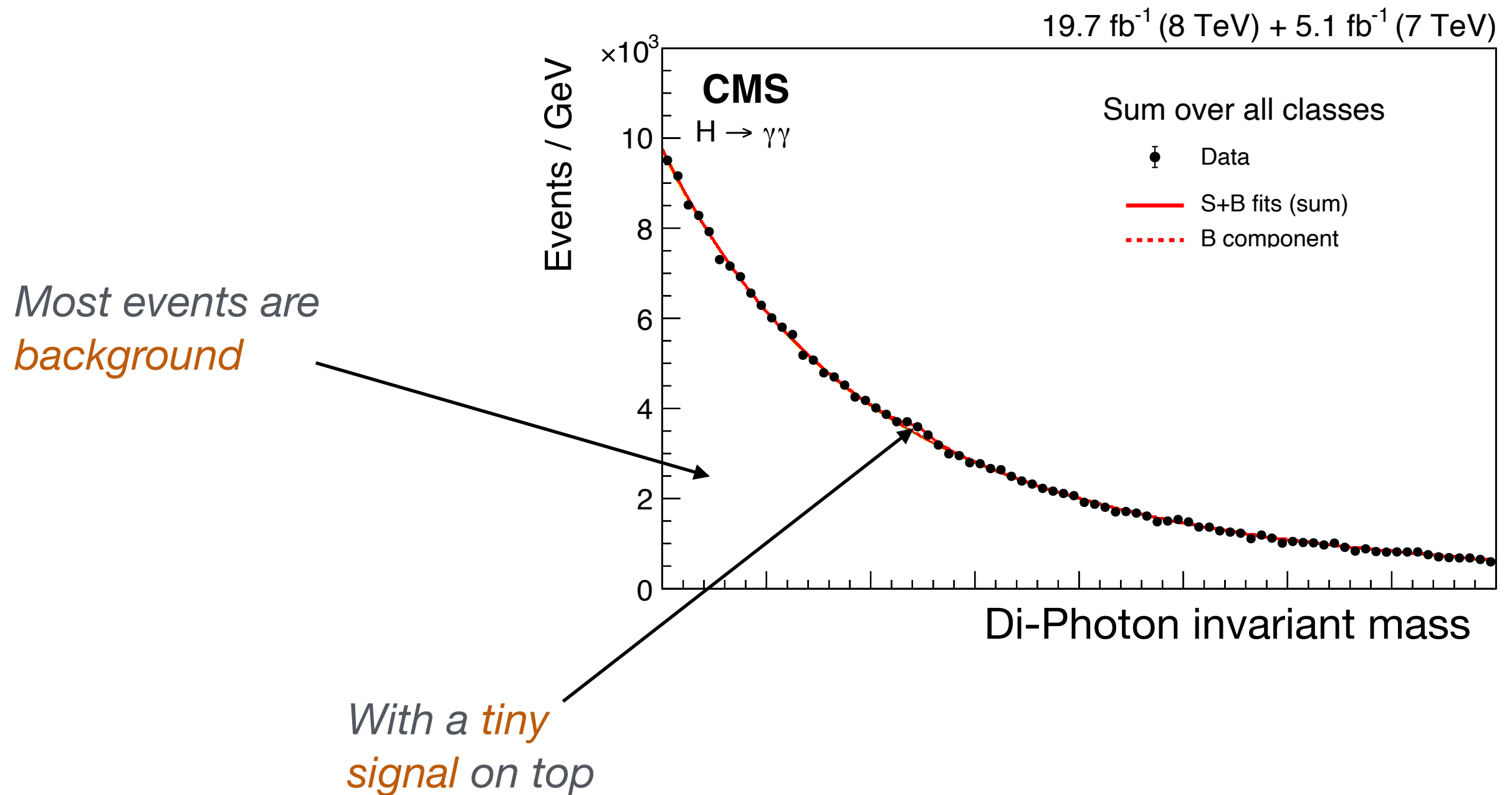
How to discover a new particle?



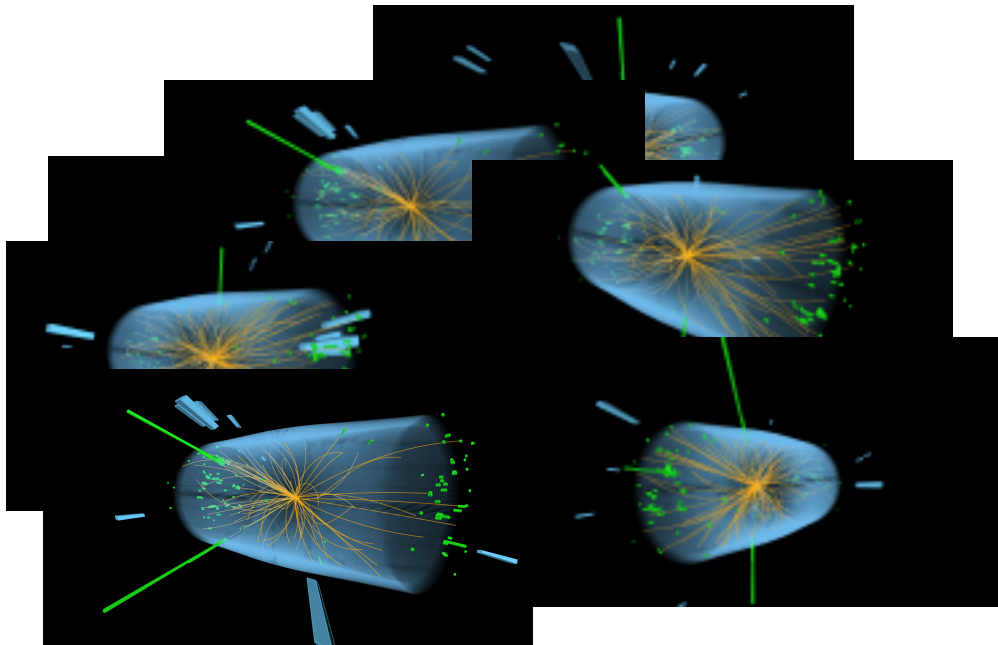
*Event display from
CMS from 2012*



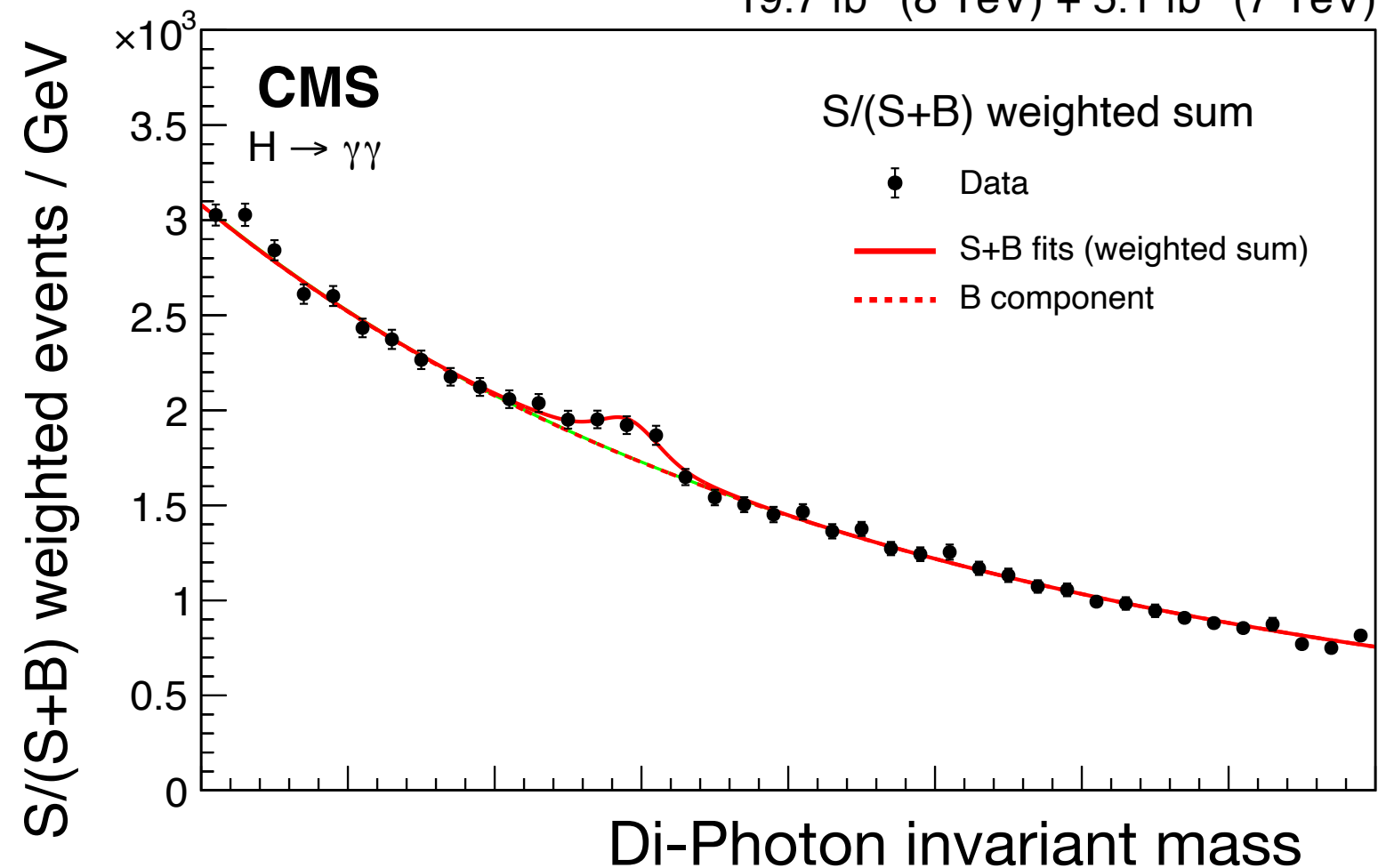
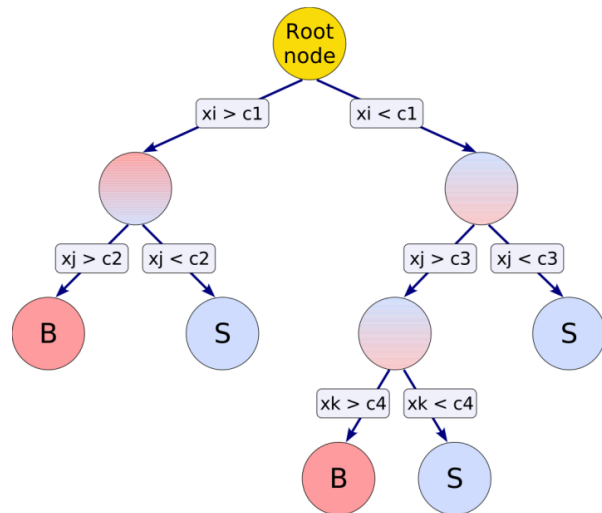
How to discover a new particle?



How to discover a new particle?



Divide into 25 categories according to purity, relative amount of signal using BDTs



Weight events according to expected purity of category

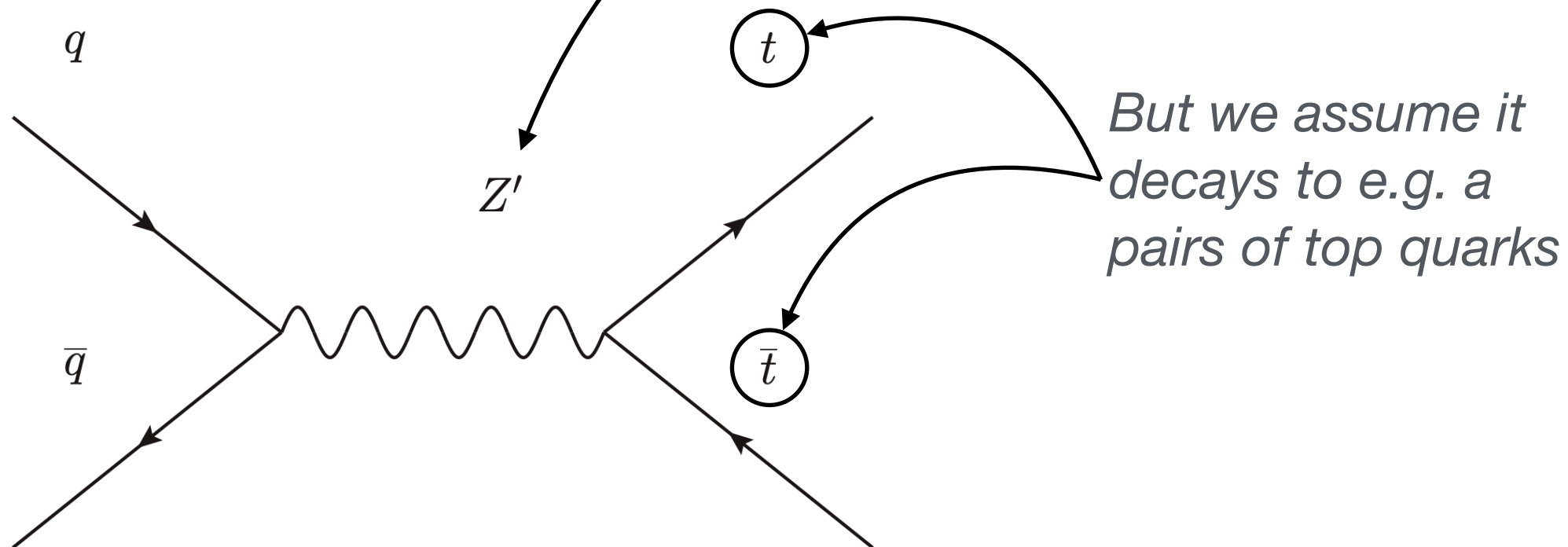
Nobel price for Higgs mechanism 2013 (Higgs and Englert)



How to discover a new particle?

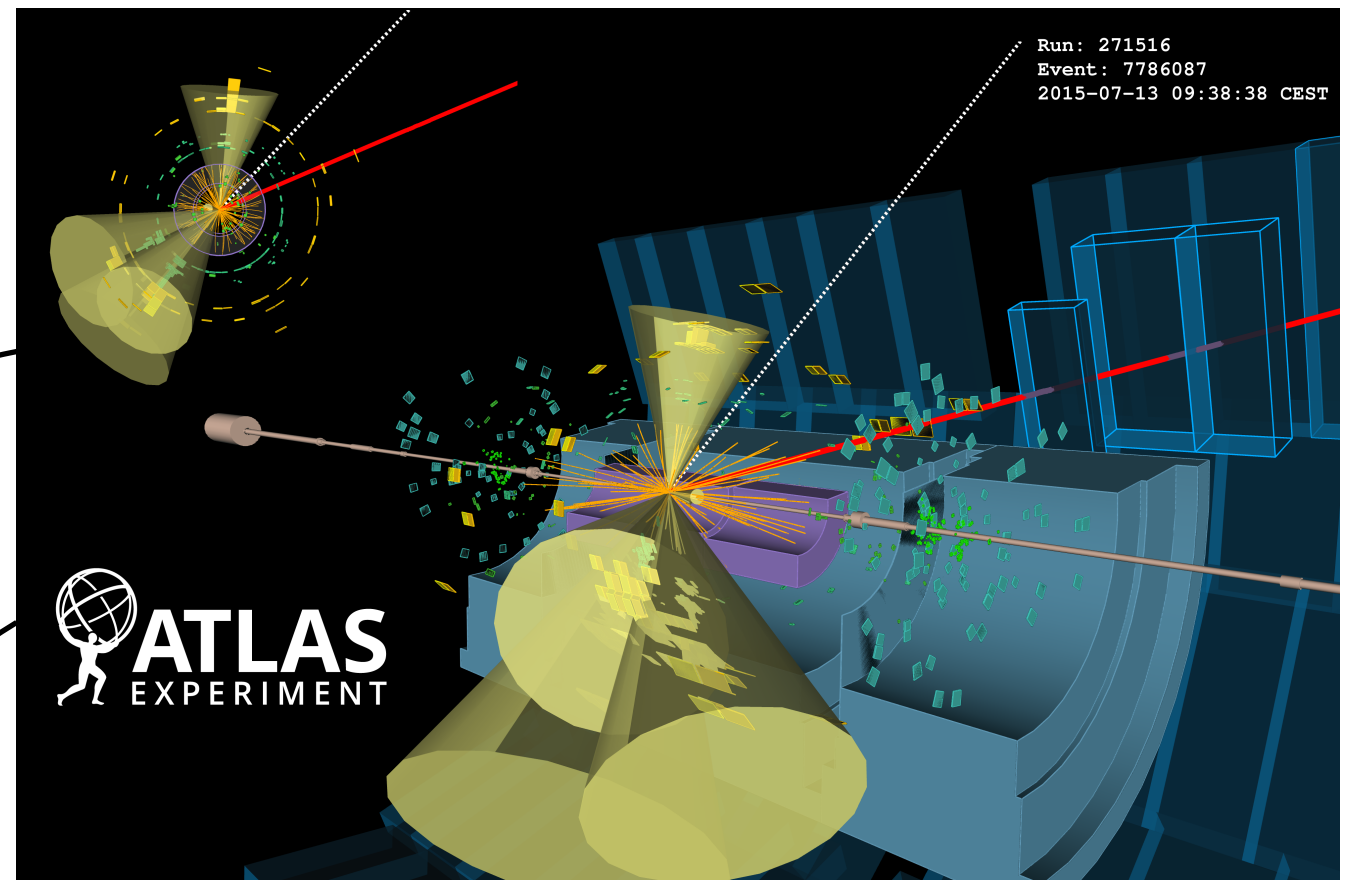
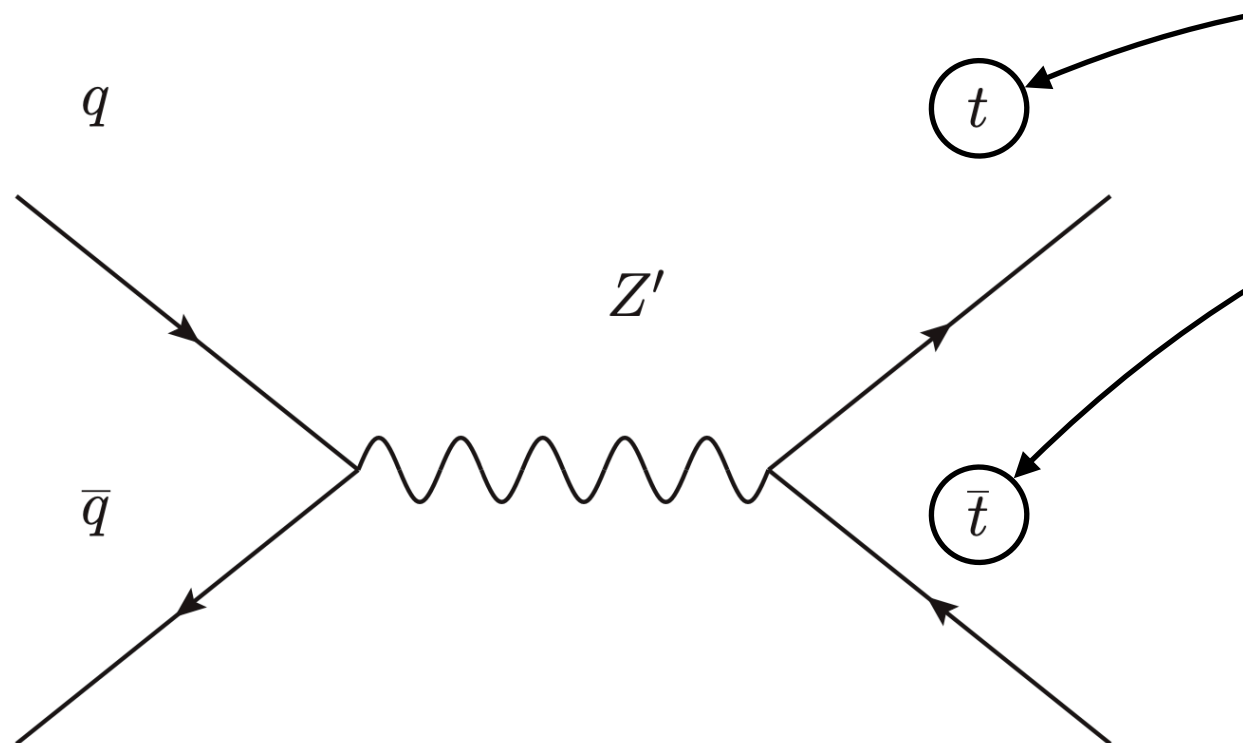
Assume we know what we are looking for: e.g. a heavier version of the Z boson

We don't know the mass of the resonant particle

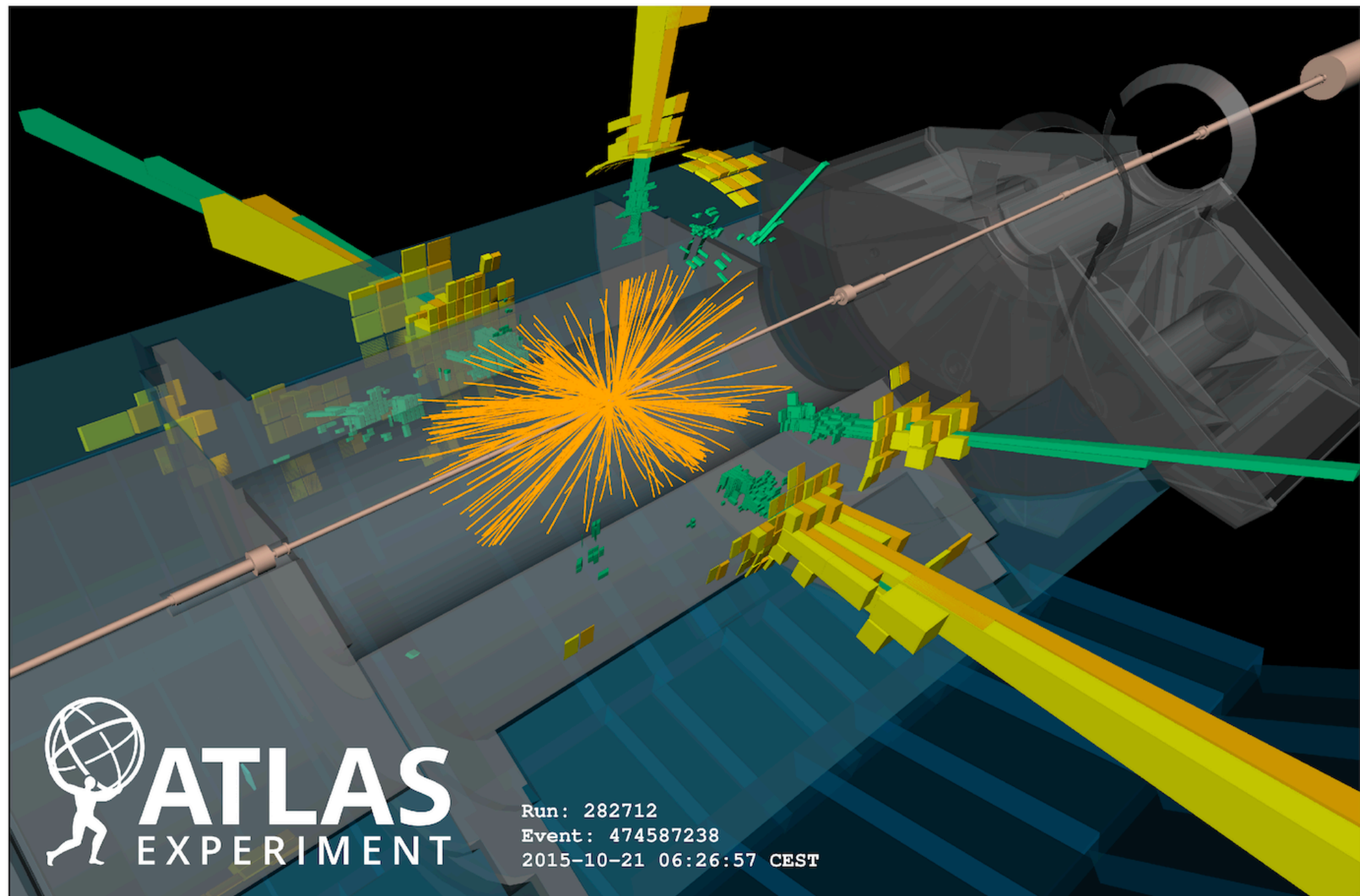


But we assume it decays to e.g. a pairs of top quarks

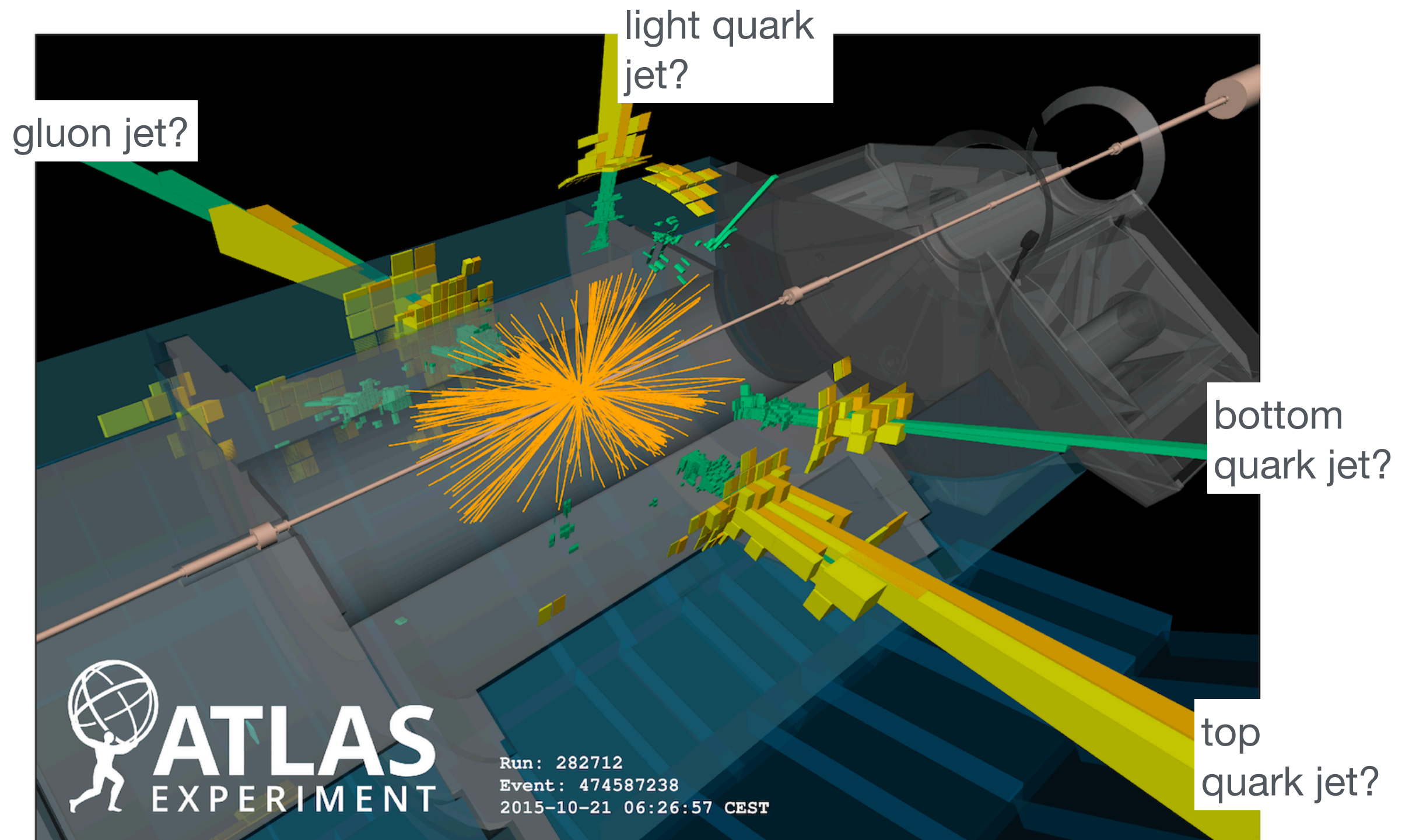
How to discover a new particle?



*More complicated than electrons:
Use AI for top tagging*

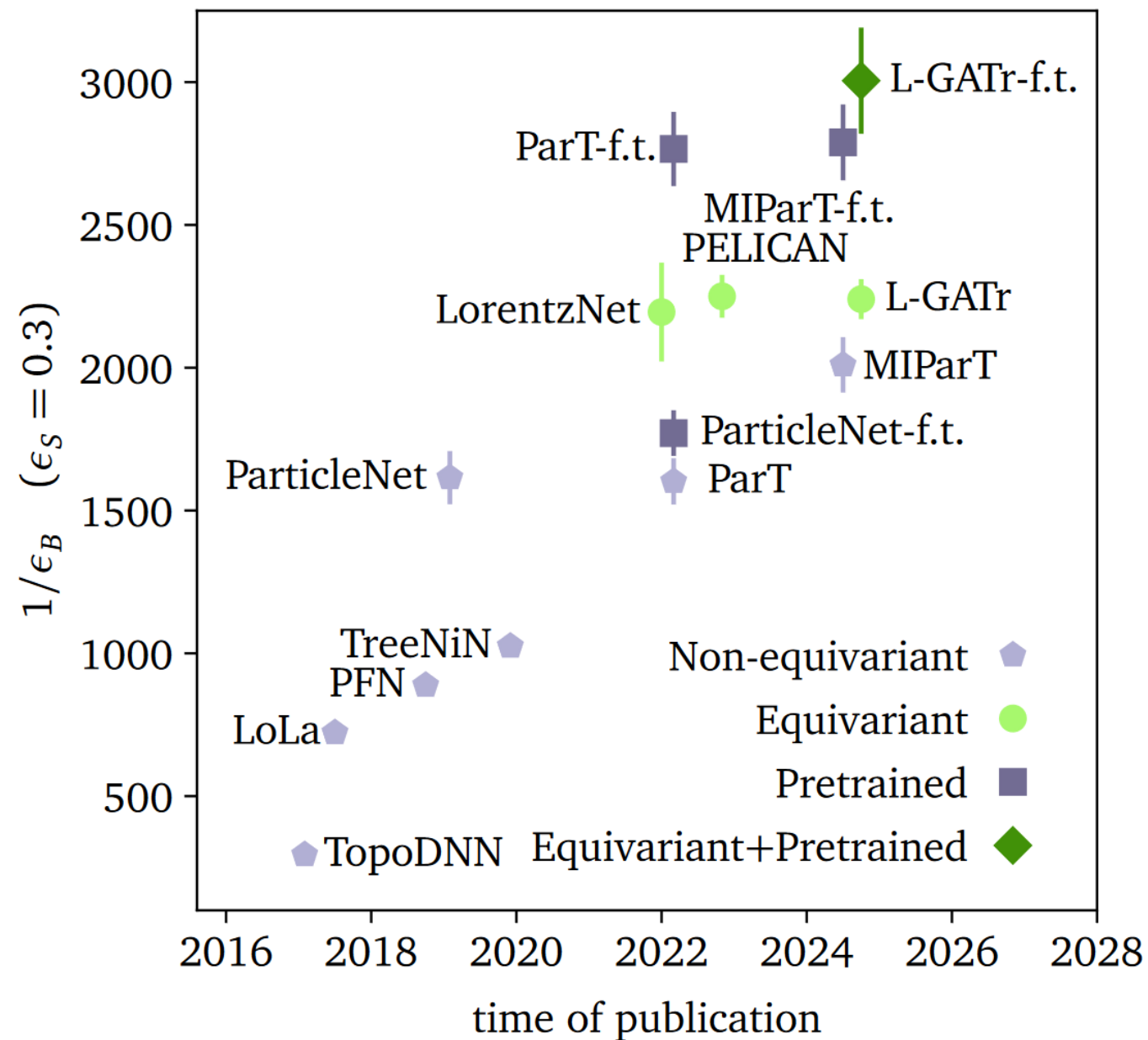


A jet is a
collimated shower of particles in the detector



We want to know
which particle produced a jet

Top Quark Tagging

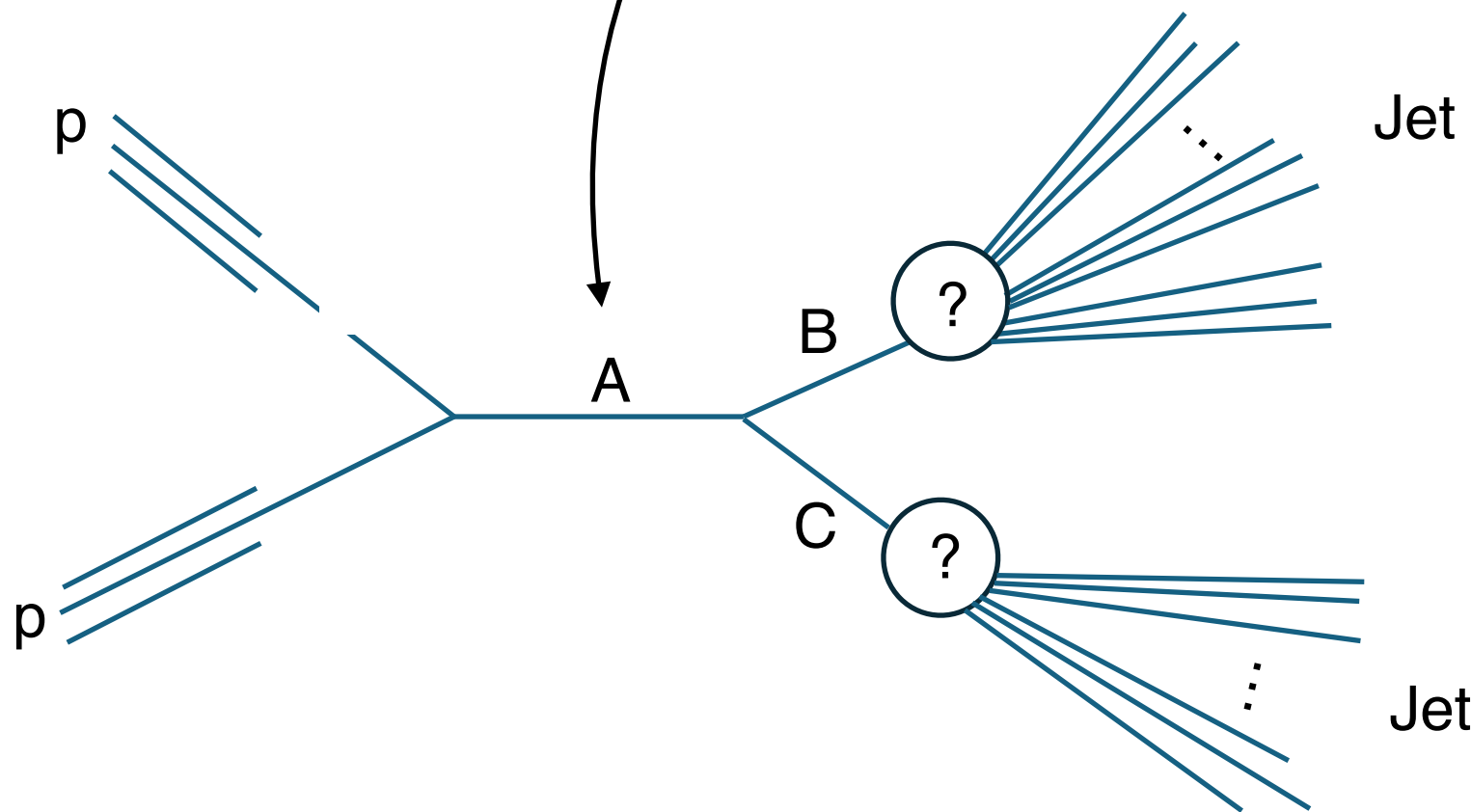


Order of magnitude improvement from ML

Modern tagging algorithms are **widely used** in **searches** for new particles

Assumptions, revisited

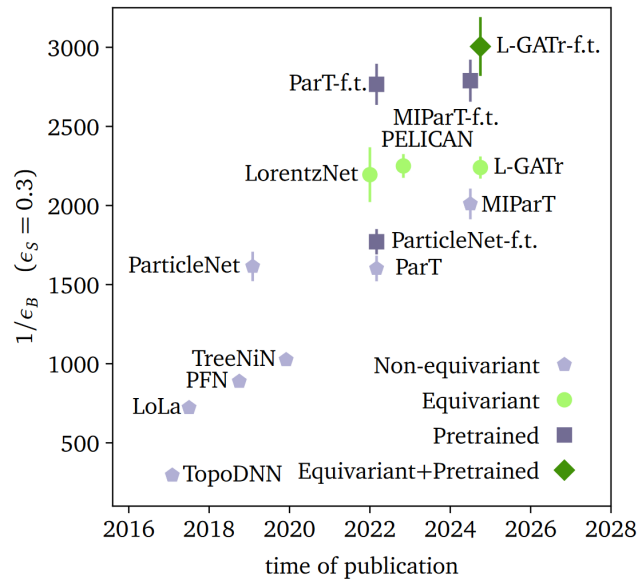
We don't know the
mass and type of
the resonant
particle



And we don't know
what particles it
decays to

(assume some jets)

Outline



Tools for Discovery

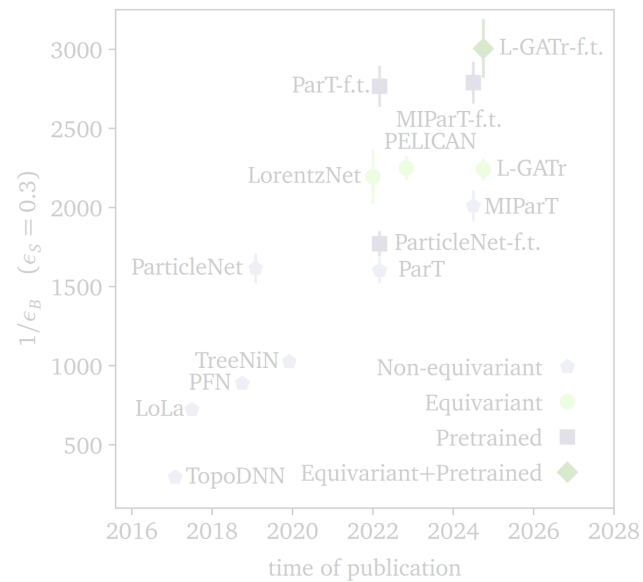
Discovery Strategies

Autonomous Discovery

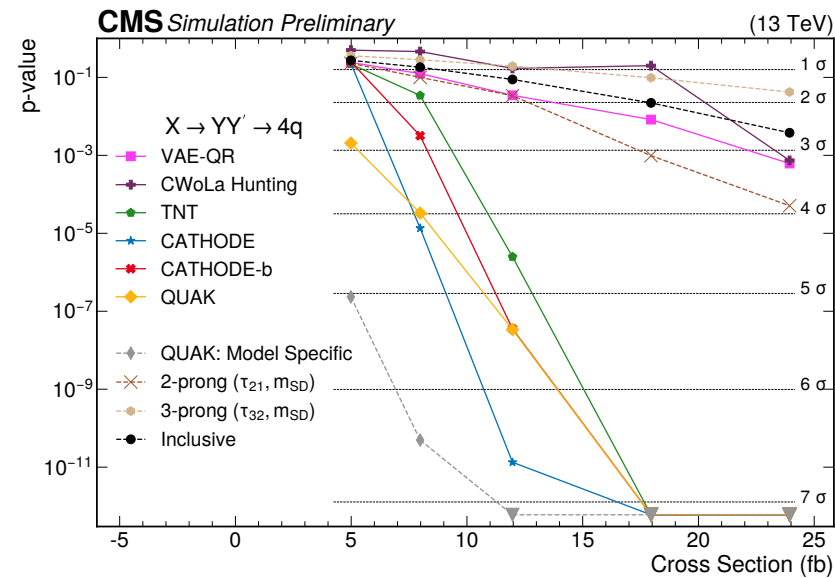
Order of magnitude
(~x10) improvements
in traditional search
strategies with AI

Increasing autonomy of AI systems

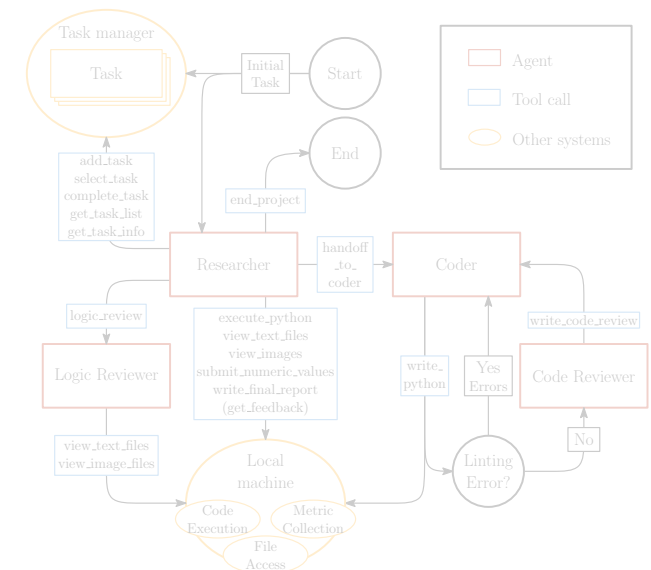
Outline



Tools for Discovery



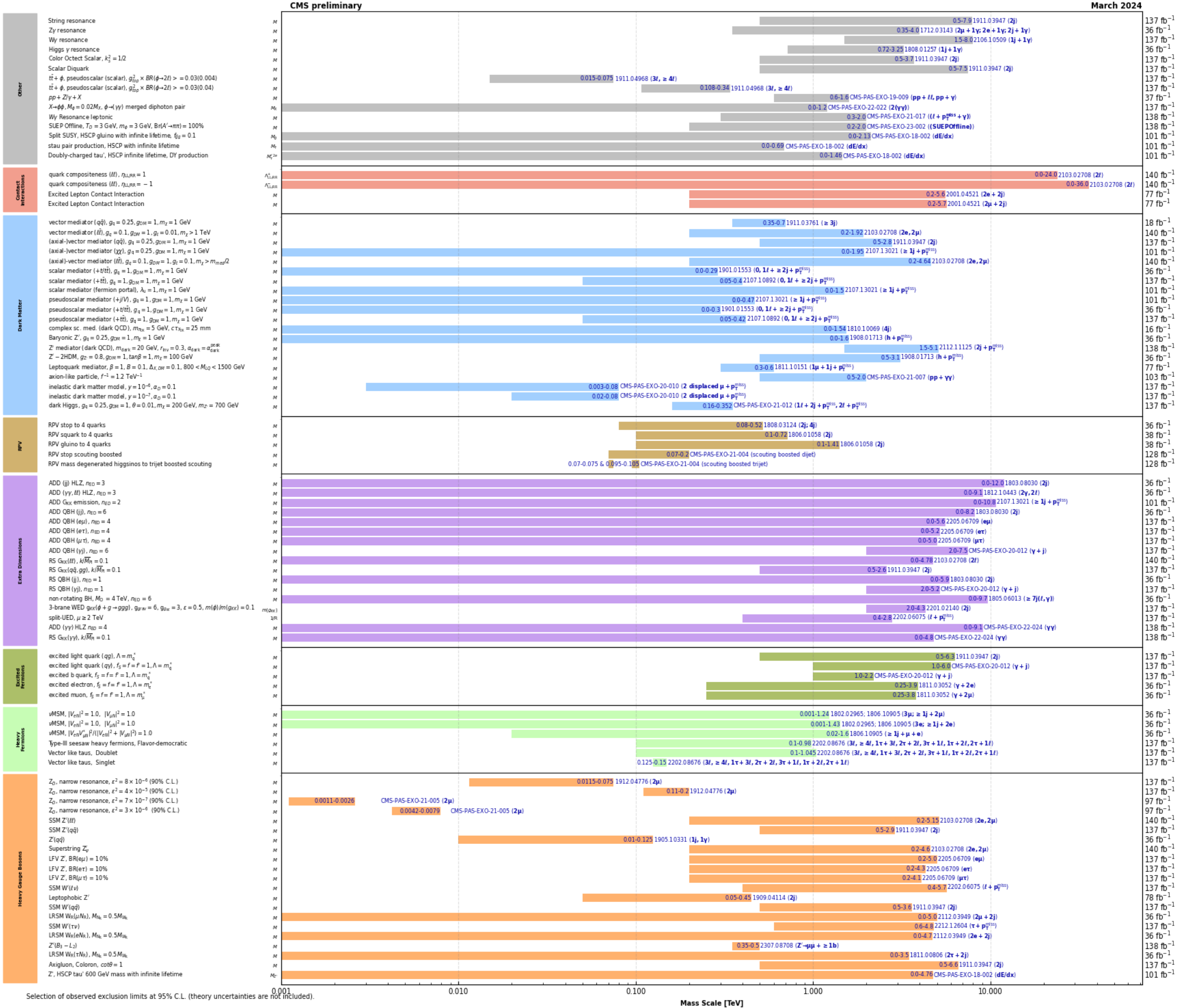
Discovery Strategies



Autonomous
Discovery

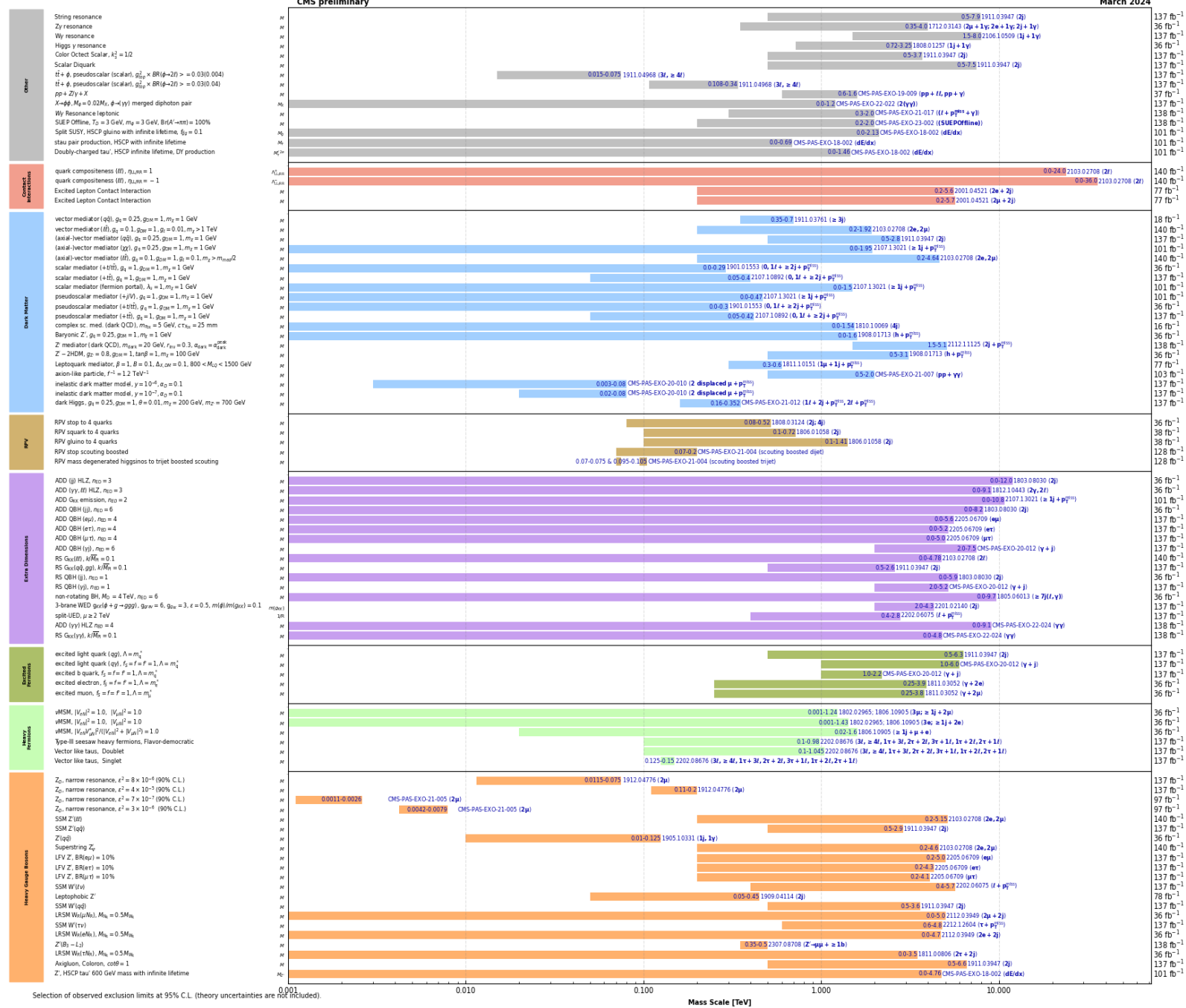
Increasing autonomy
of AI systems

Overview of CMS EXO results



So far, no
new physics
in model-
driven
searches

Overview of CMS EXO results

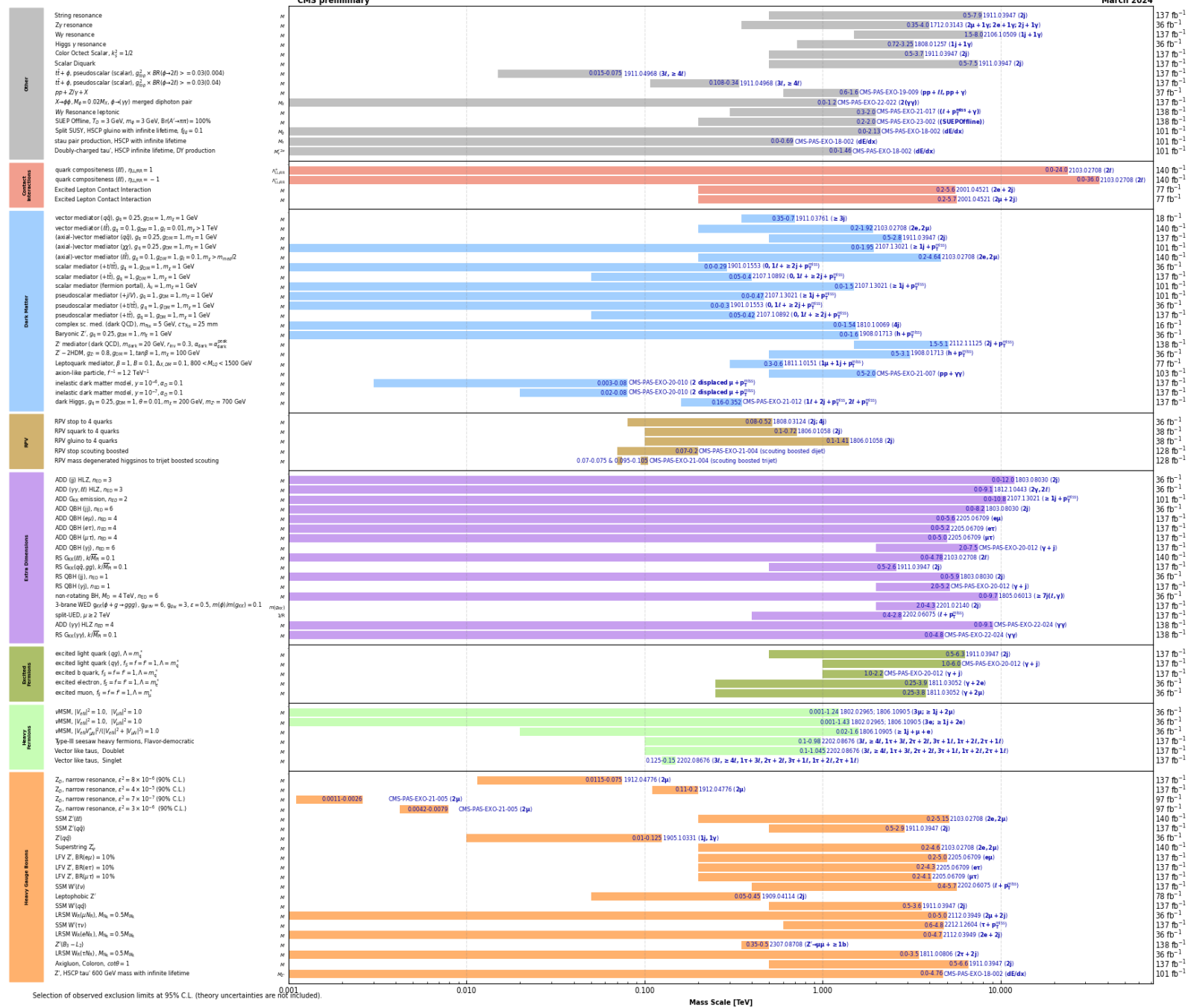


No new physics exists at LHC scales

We just need more data

We are testing the wrong models

Overview of CMS EXO results



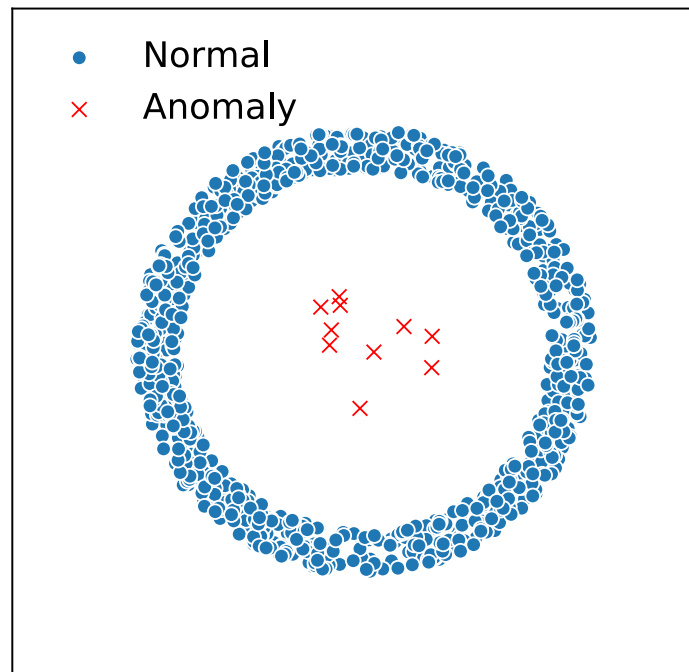
No new physics exists at LHC scales

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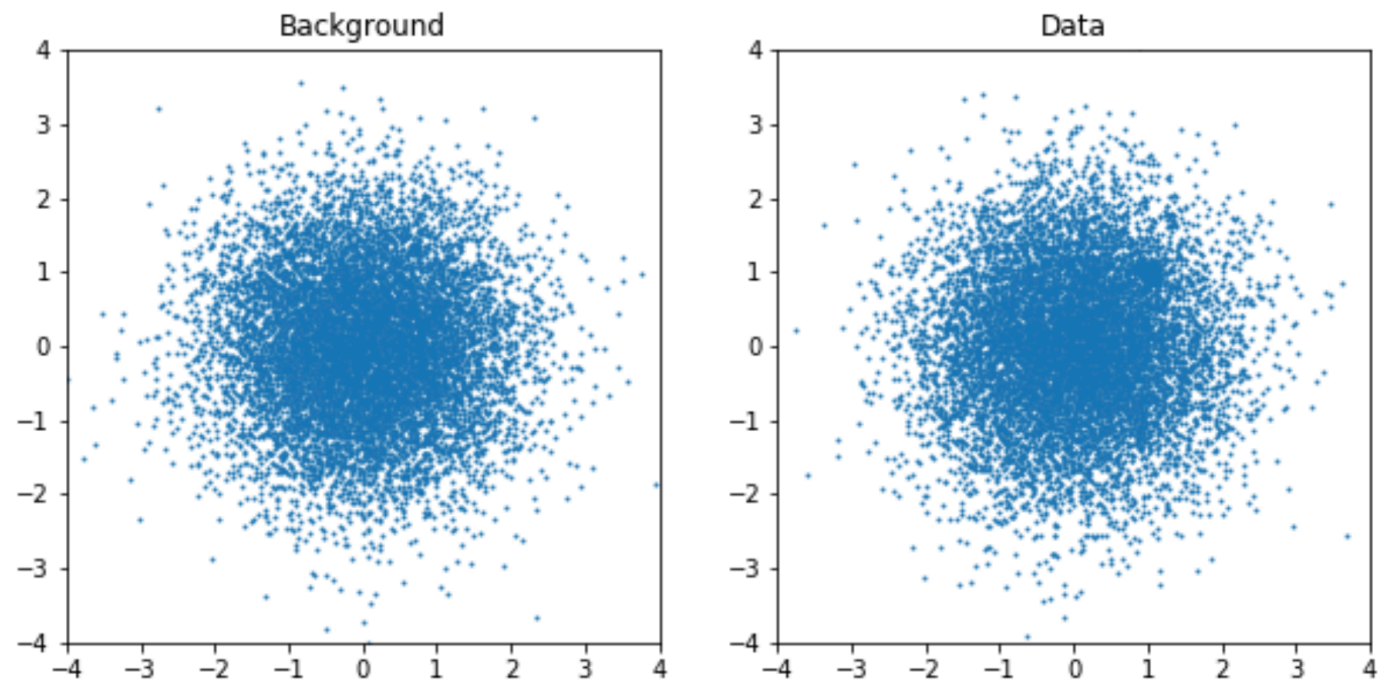
We are testing the wrong models

Let's look for anomalies

Types of anomalies

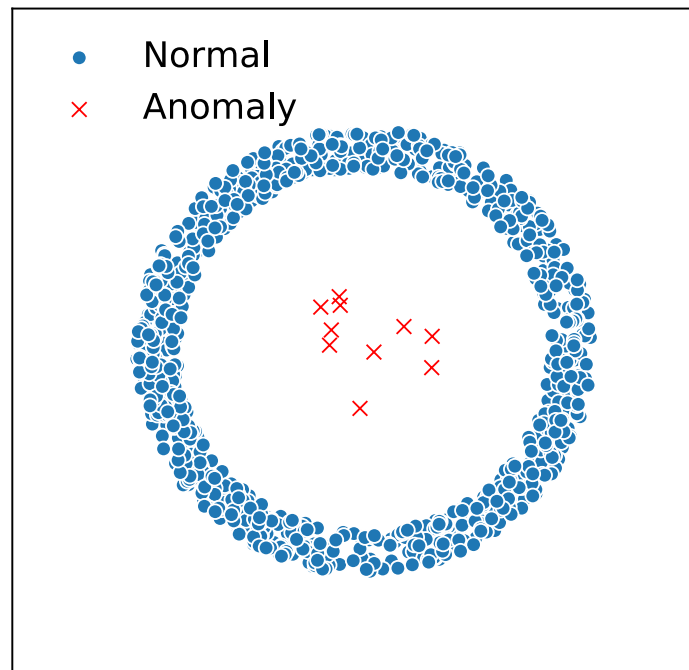


Outliers



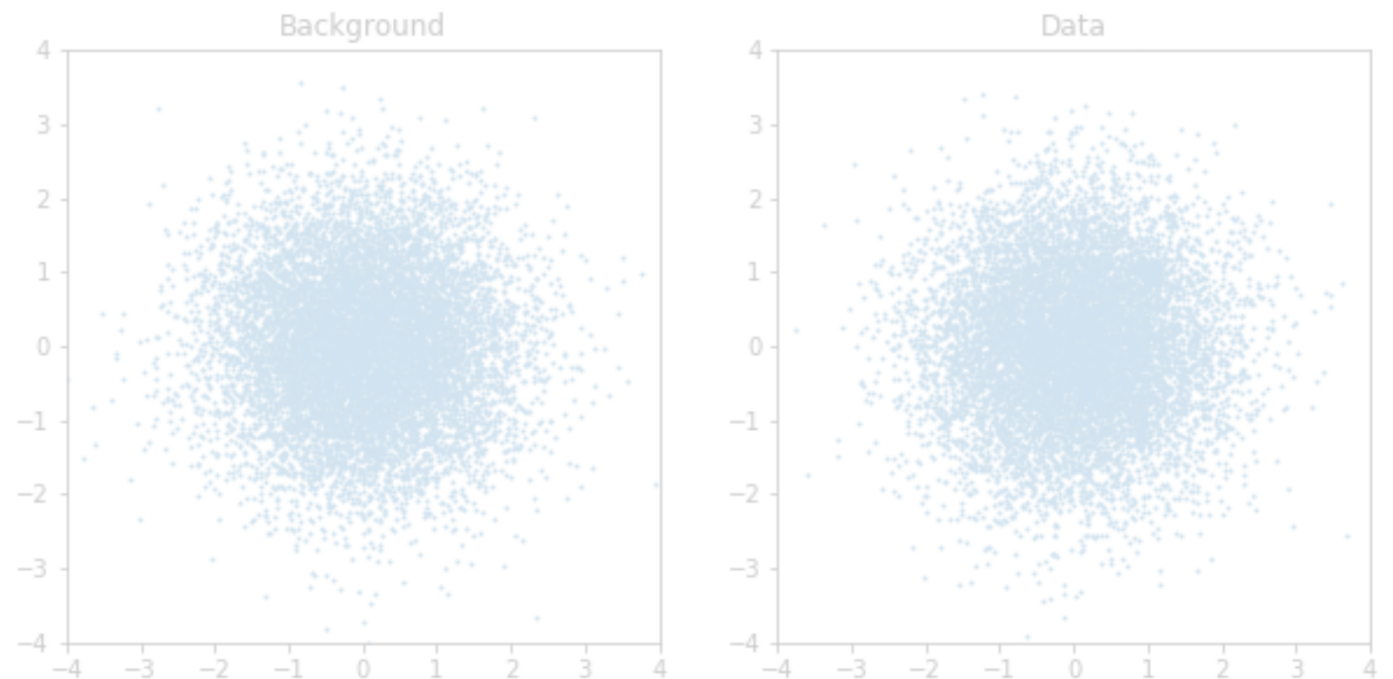
Overdensities

Types of anomalies



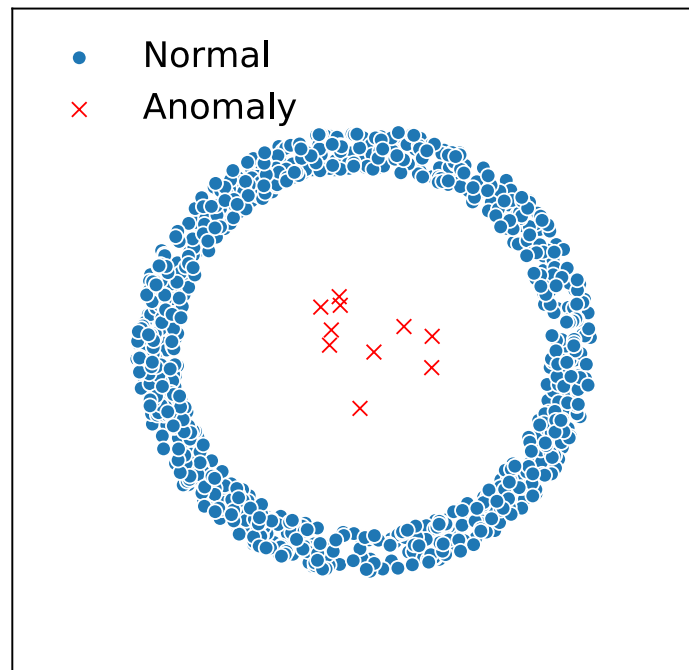
Outliers

Identify anomaly
as events in
region of low
 $p(\text{background})$



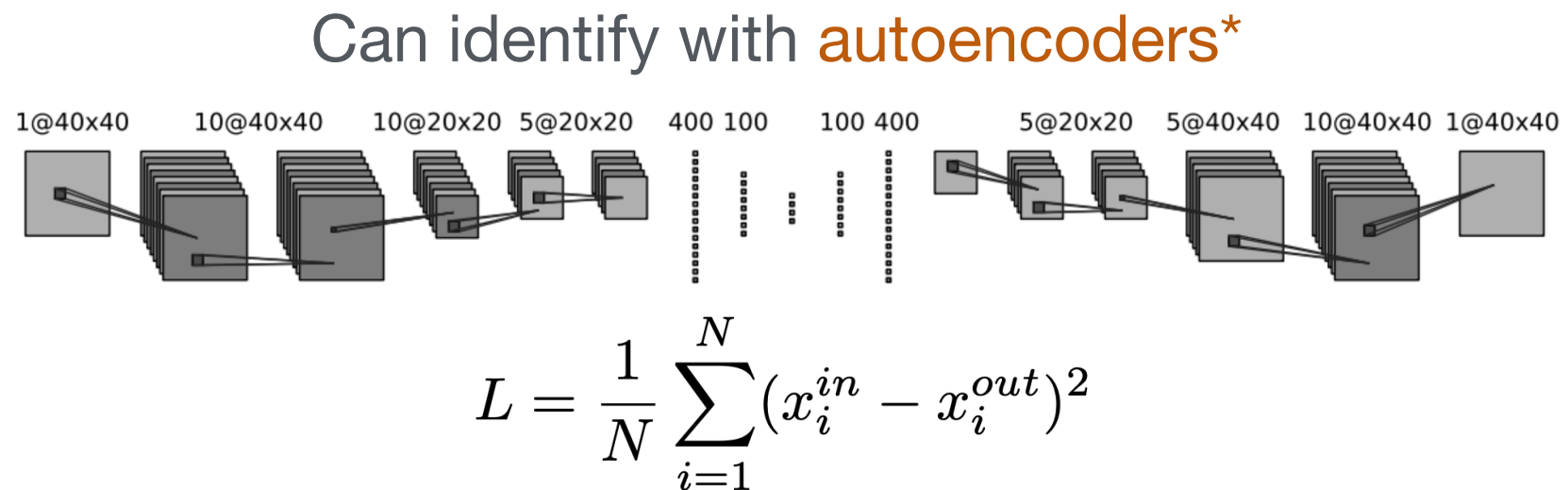
Overdensities

Types of anomalies

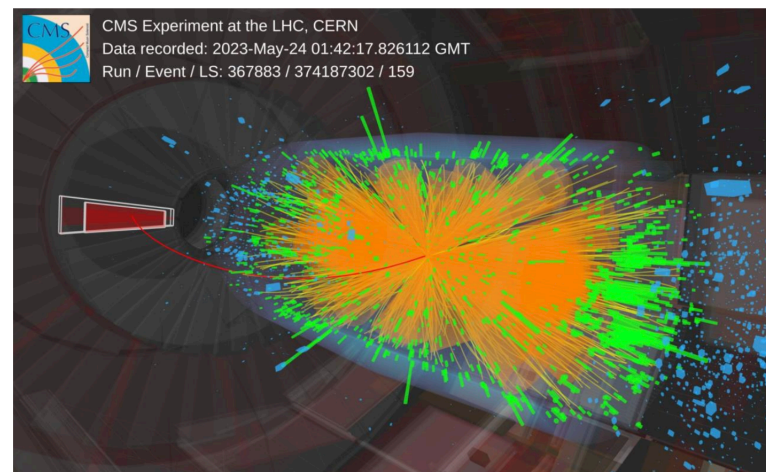


Outliers

Identify anomaly
as events in
region of **low**
p(background)



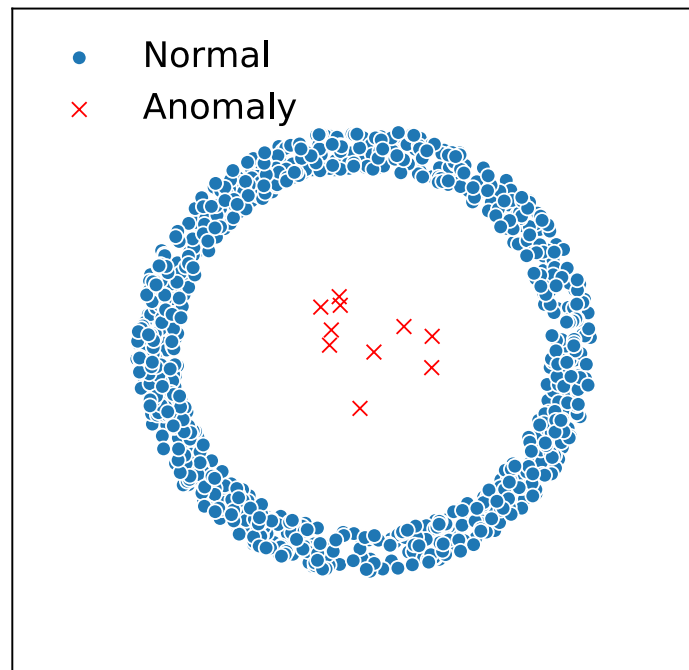
Also works **during data taking**



Farina et al 1808.08992; Heimeel, **GK**,
et al 1808.08979, CMS-DP-2024-059;
See also Bortolato, Kamenik et al
2103.06595 &

*or extensions like
NAE (2206.14225)

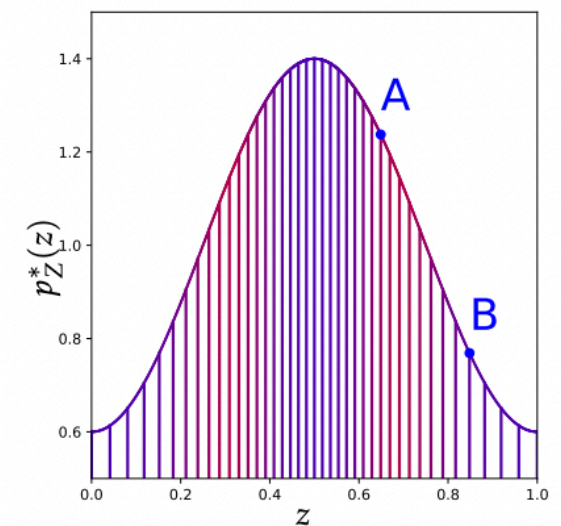
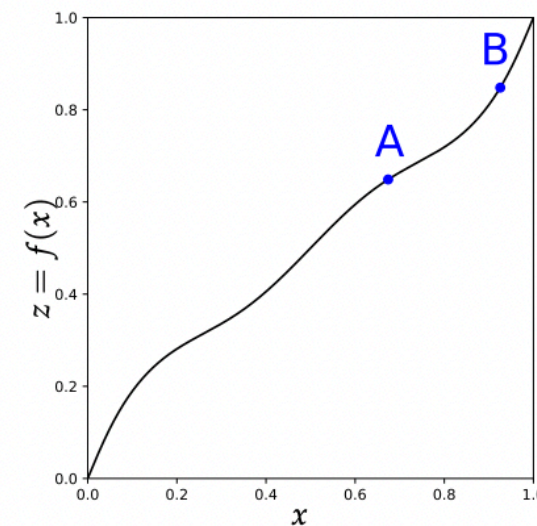
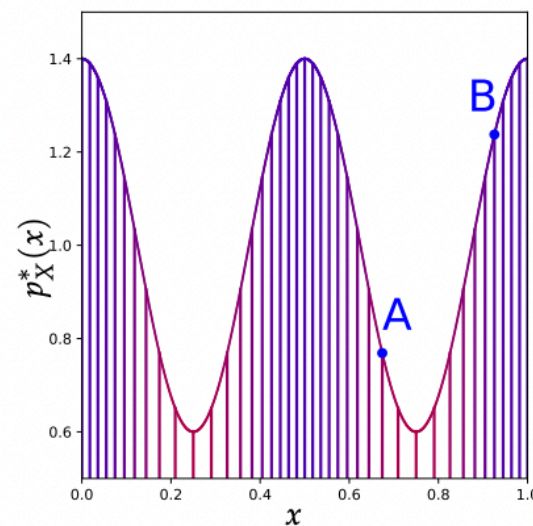
Types of anomalies



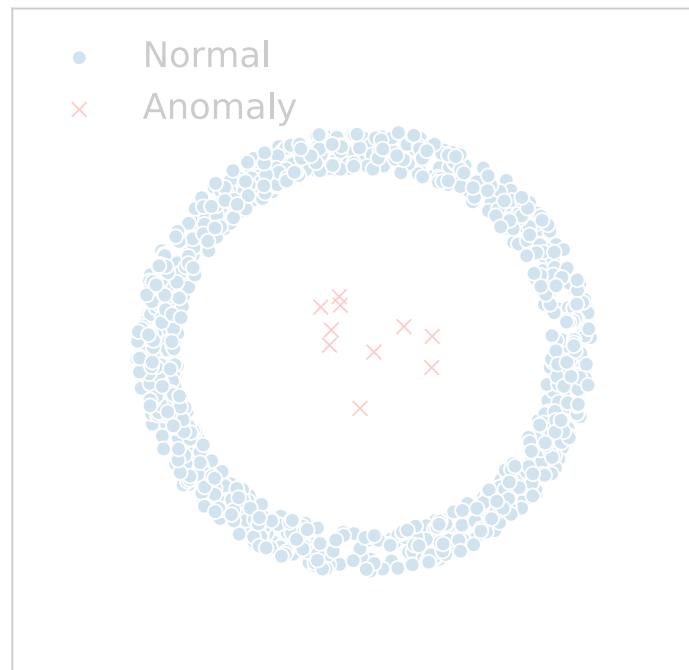
Outliers

Identify anomaly
as events in
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 $p(\text{background})$

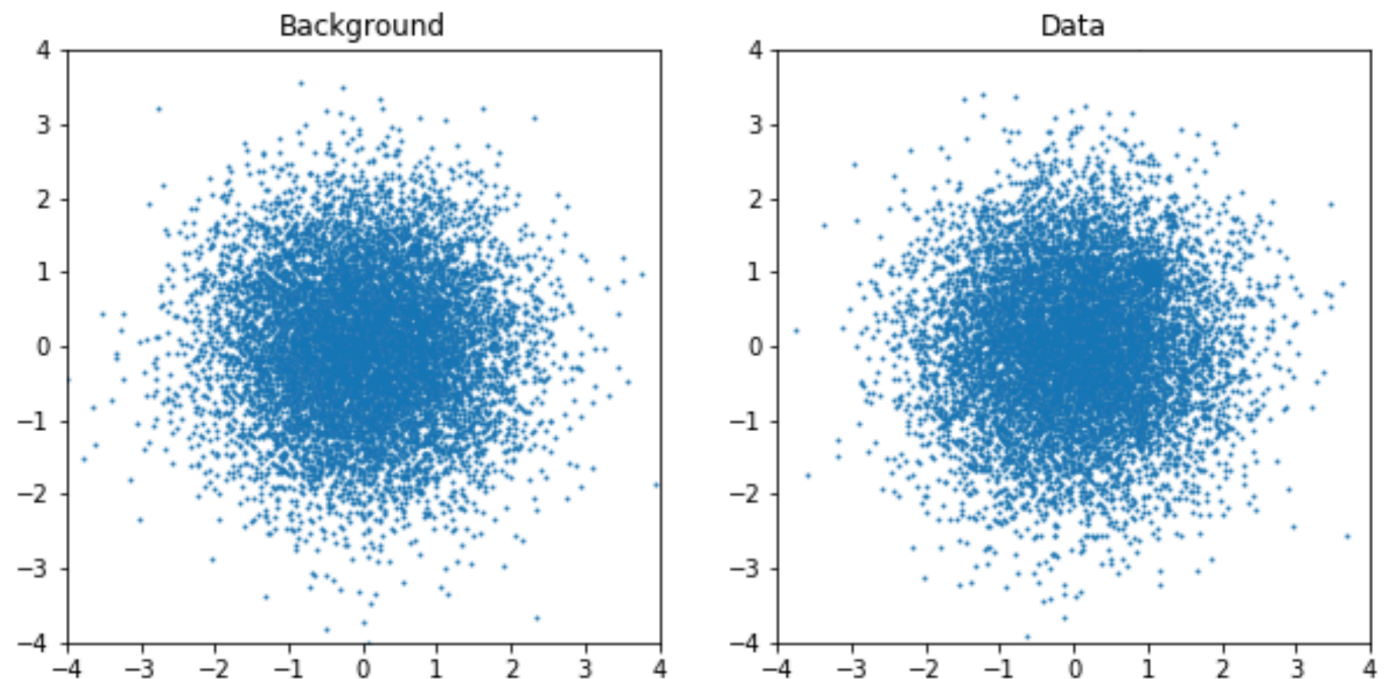
No **optimality** guarantees



Types of anomalies



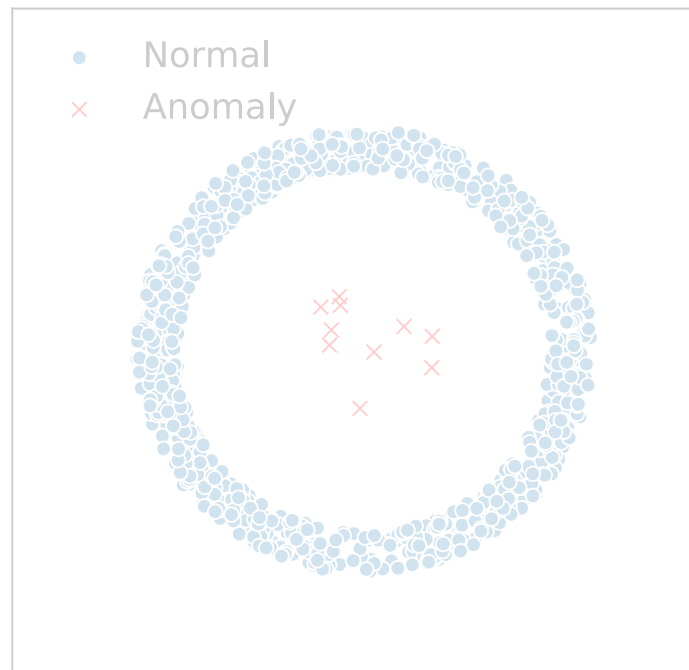
Outliers



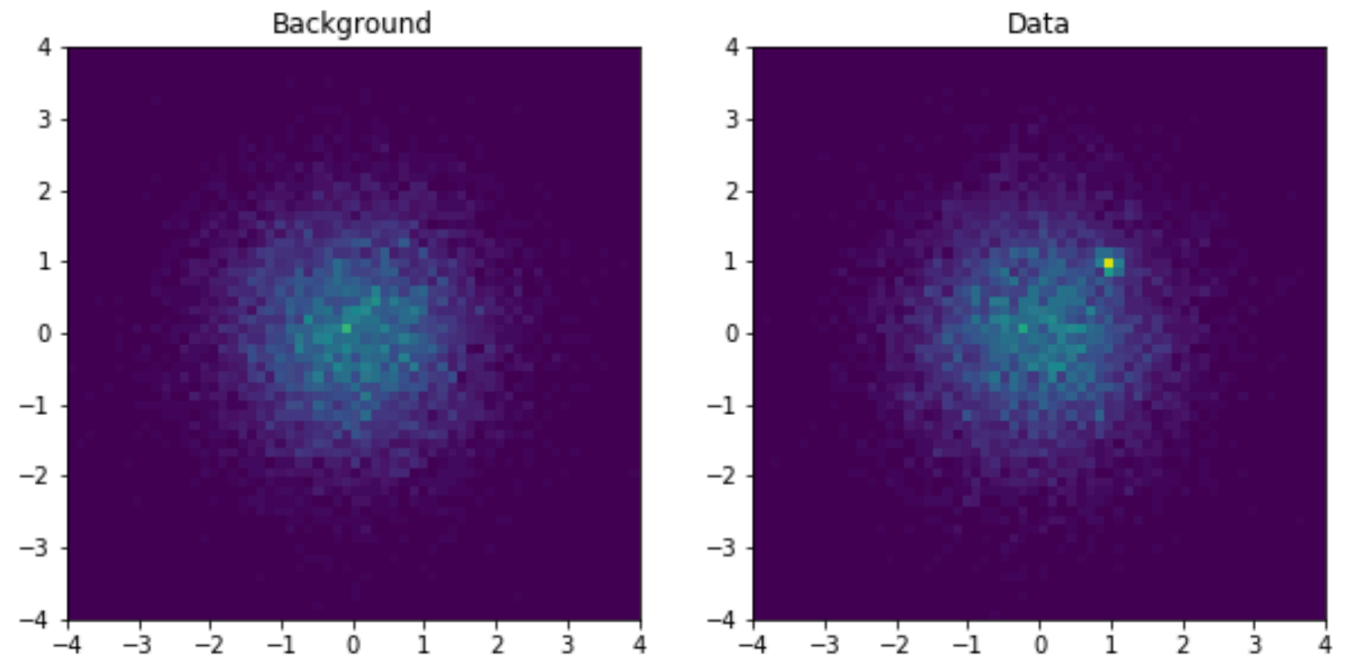
Overdensities

Identify anomaly as
difference between
 $p(\text{background})$ and $p(\text{data})$

Types of anomalies



Outliers

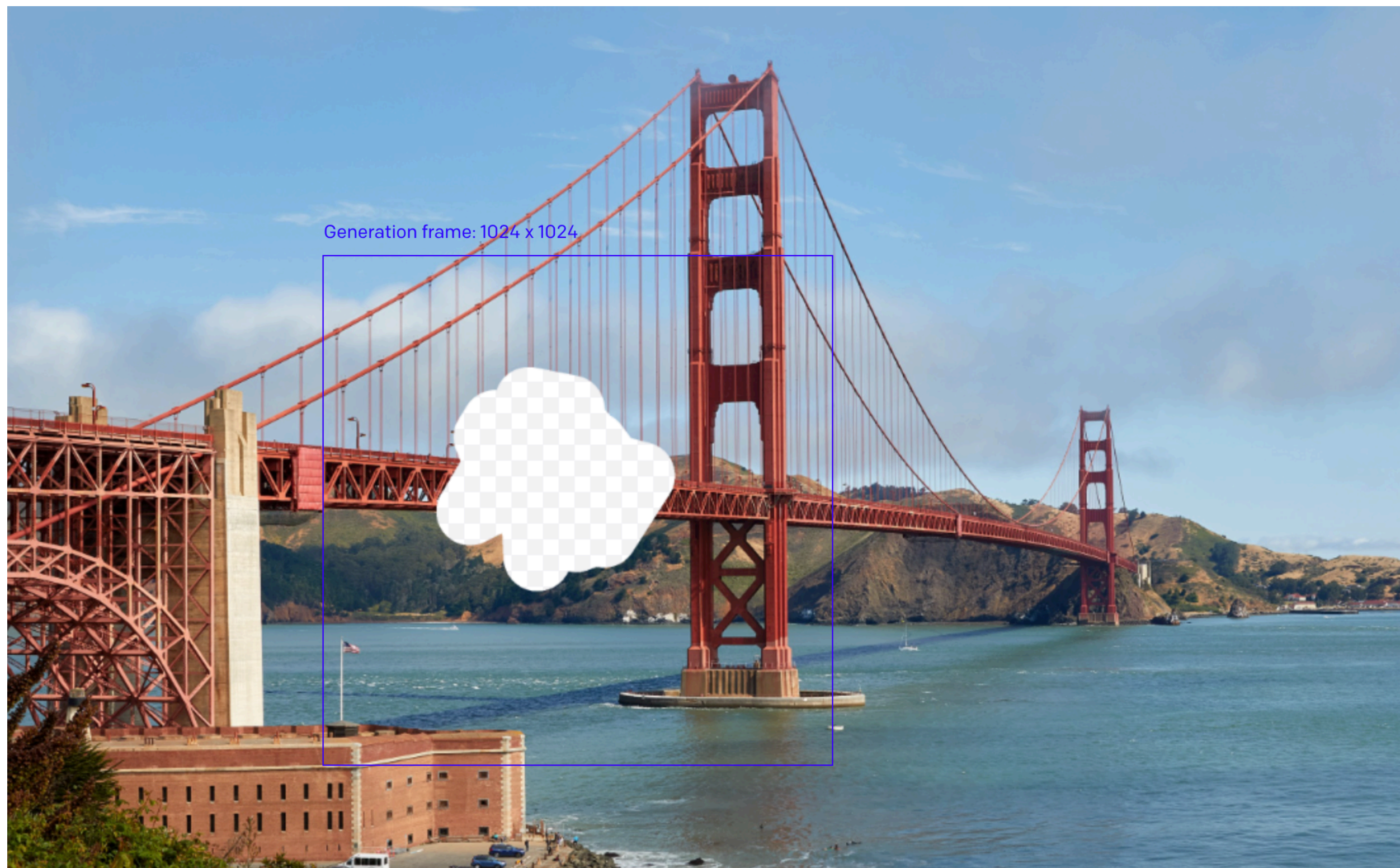


Overdensities

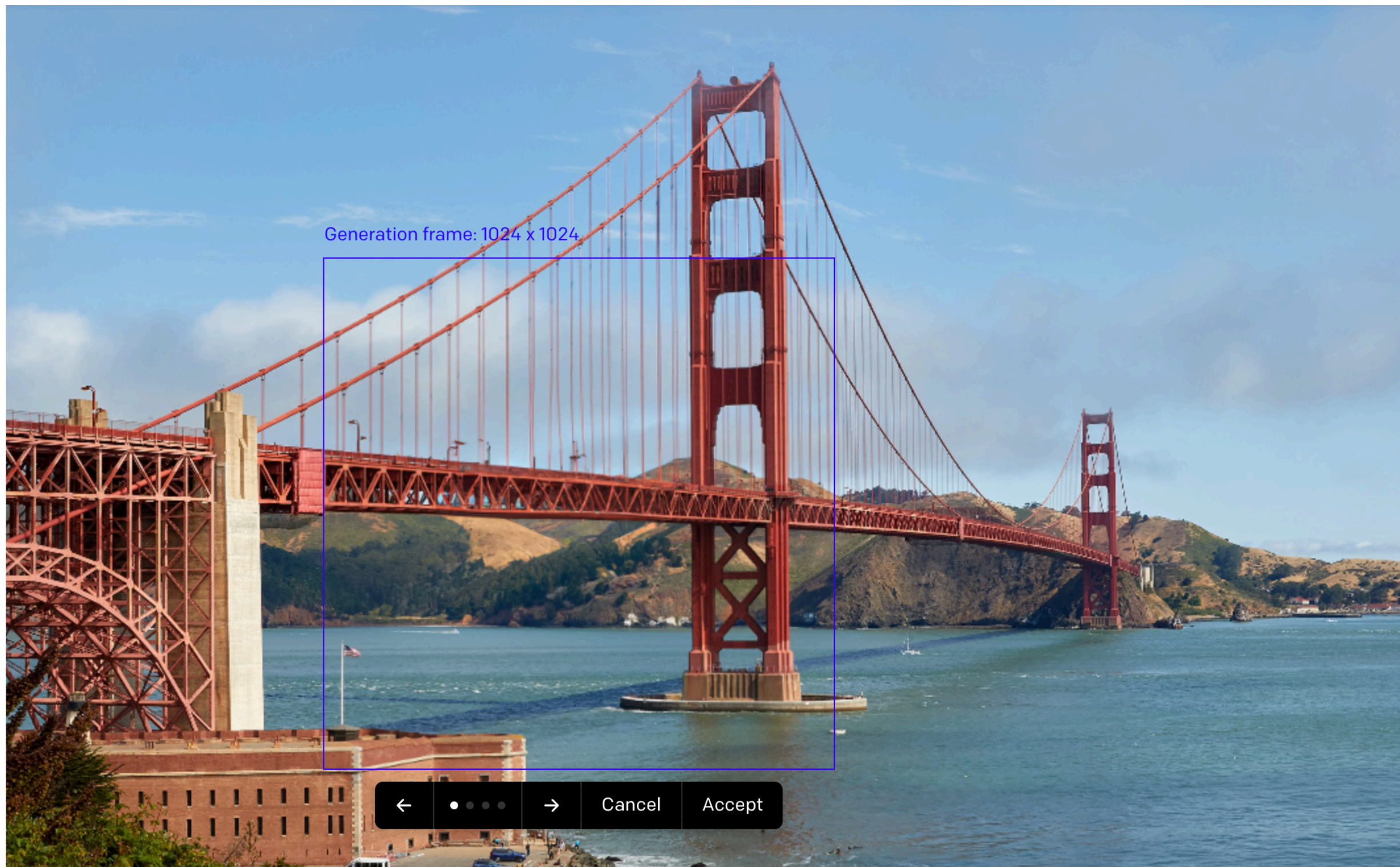
Identify anomaly as
difference between
 $p(\text{background})$ and $p(\text{data})$



Generation frame: 1024 x 1024



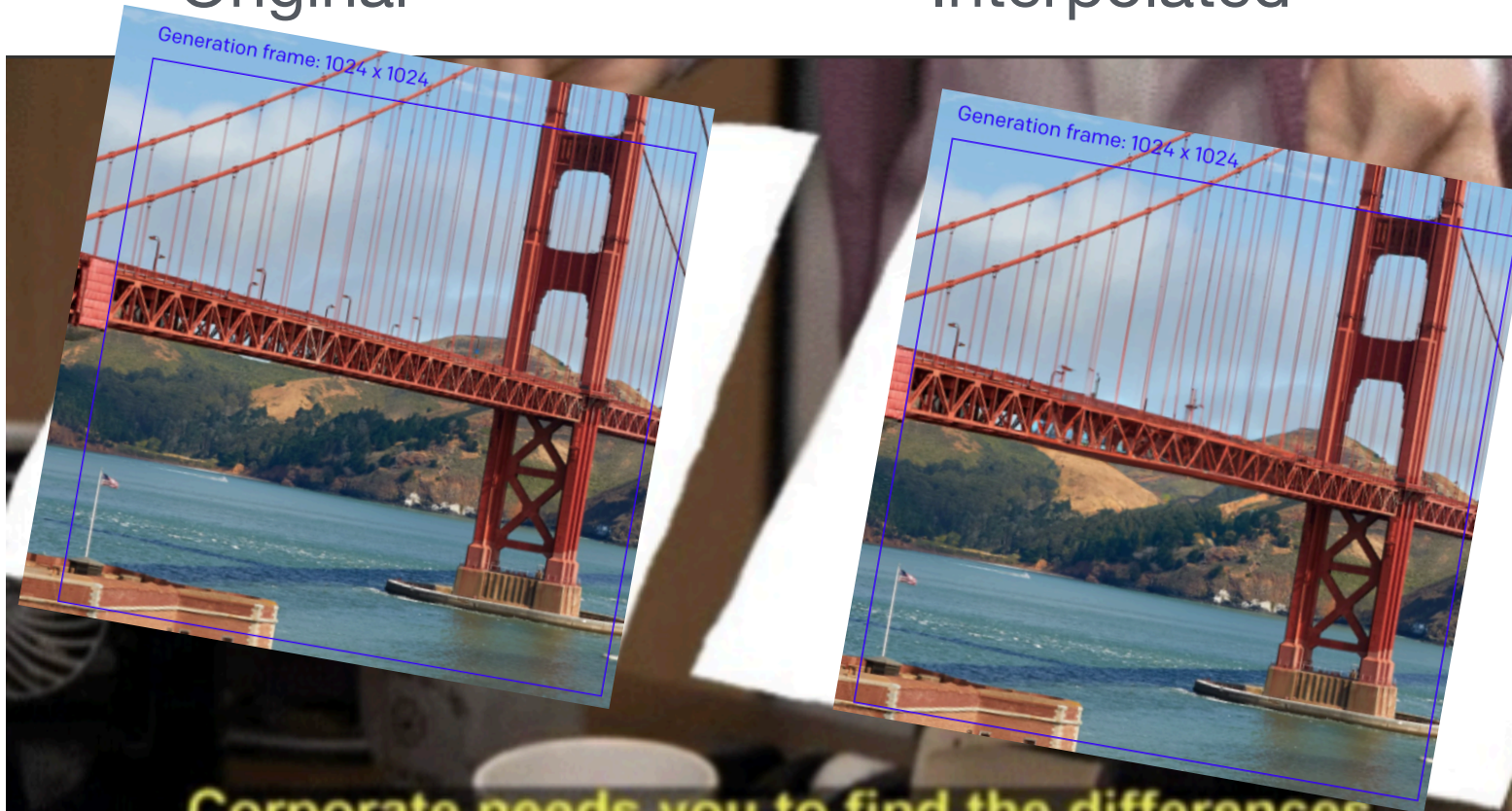
Define a signal cut-out



And interpolate the
background

Original

Interpolated



Corporate needs you to find the differences
between this picture and this picture.

Machine learning
classifier

They're the same picture.



Original

Interpolated

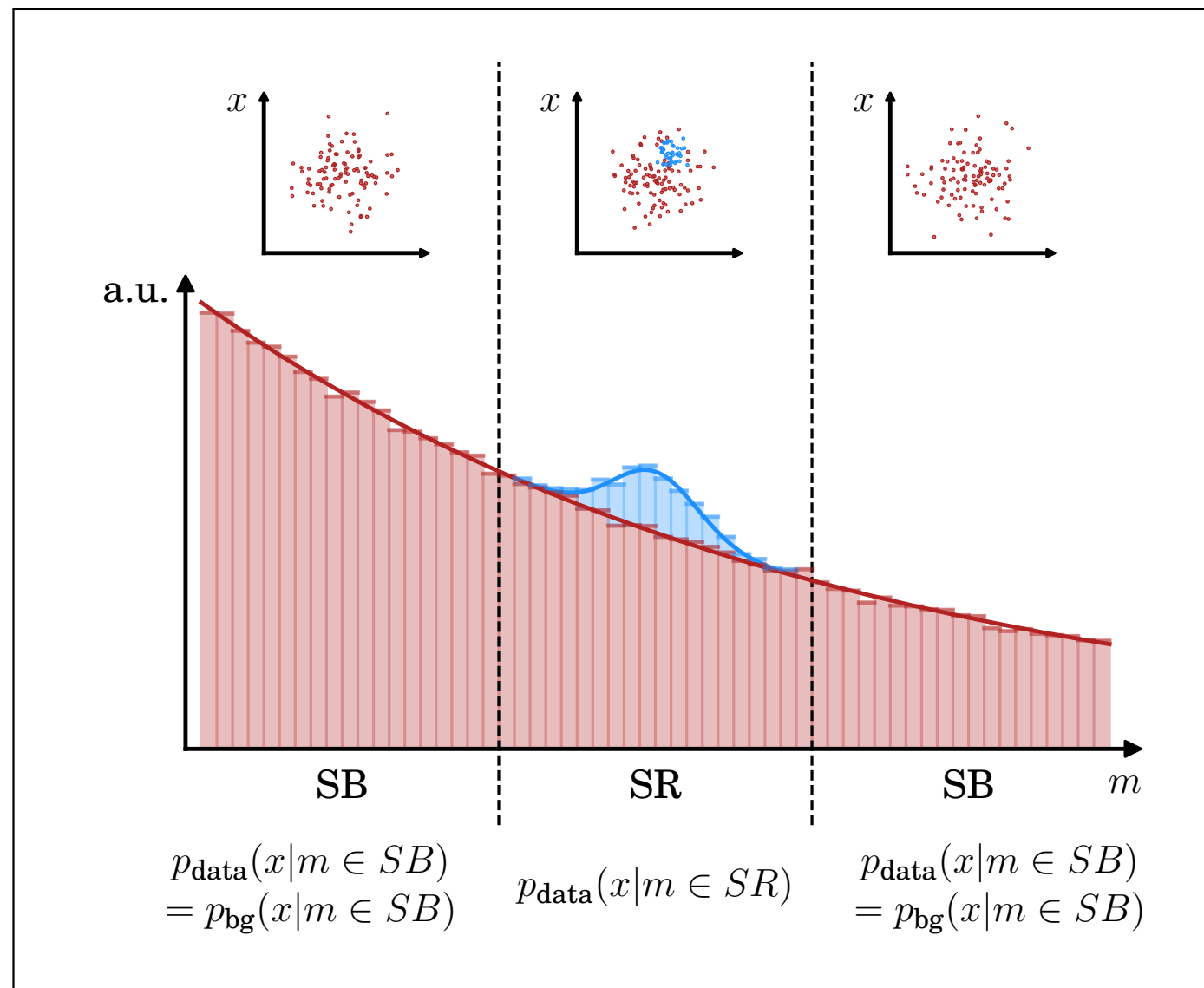


Corporate needs you to find the differences
between this picture and this picture.

Machine learning
classifier

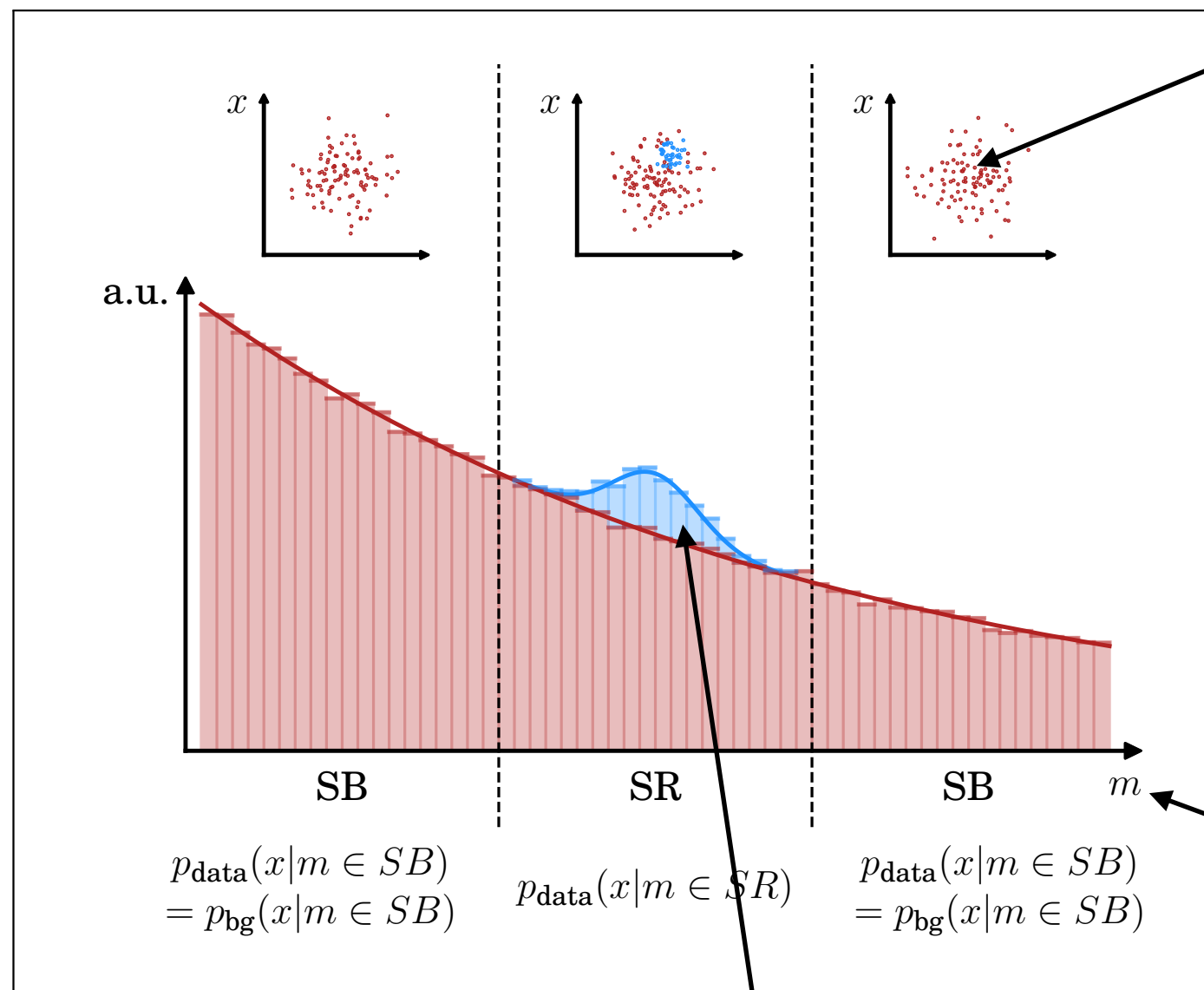
ANOMALY FOUND!

CATHODE

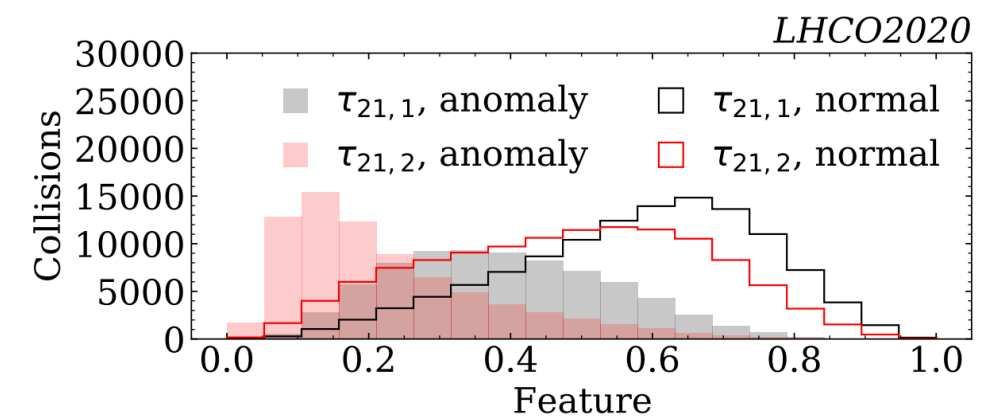
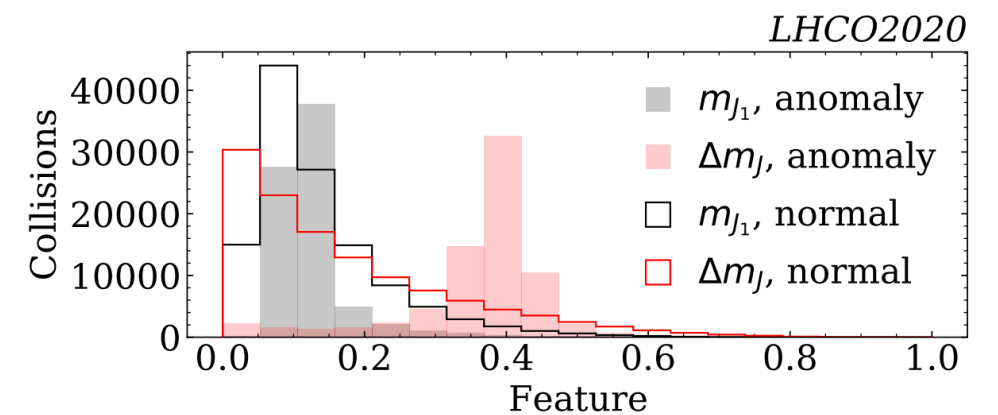


Consider resonant anomalies:
fully data-based construction of
 anomaly detection score

CATHODE



4 additional features



one resonant feature

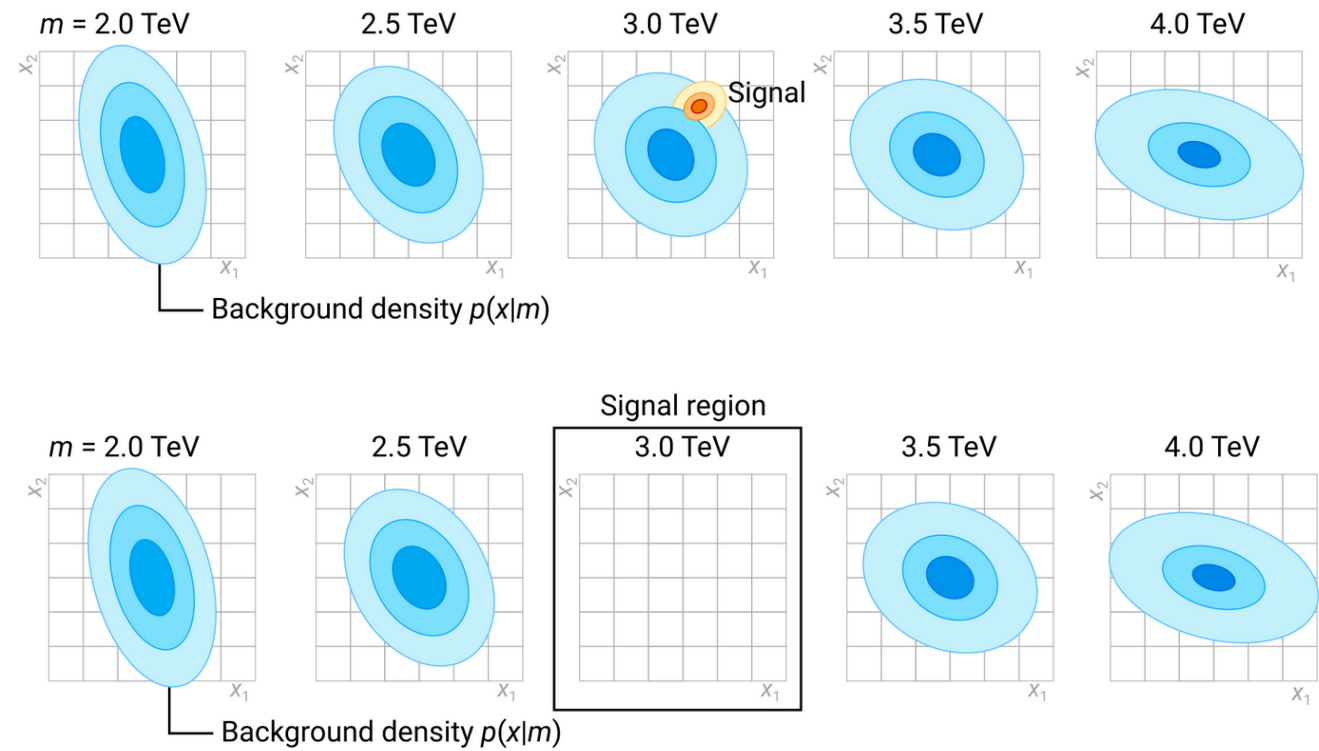
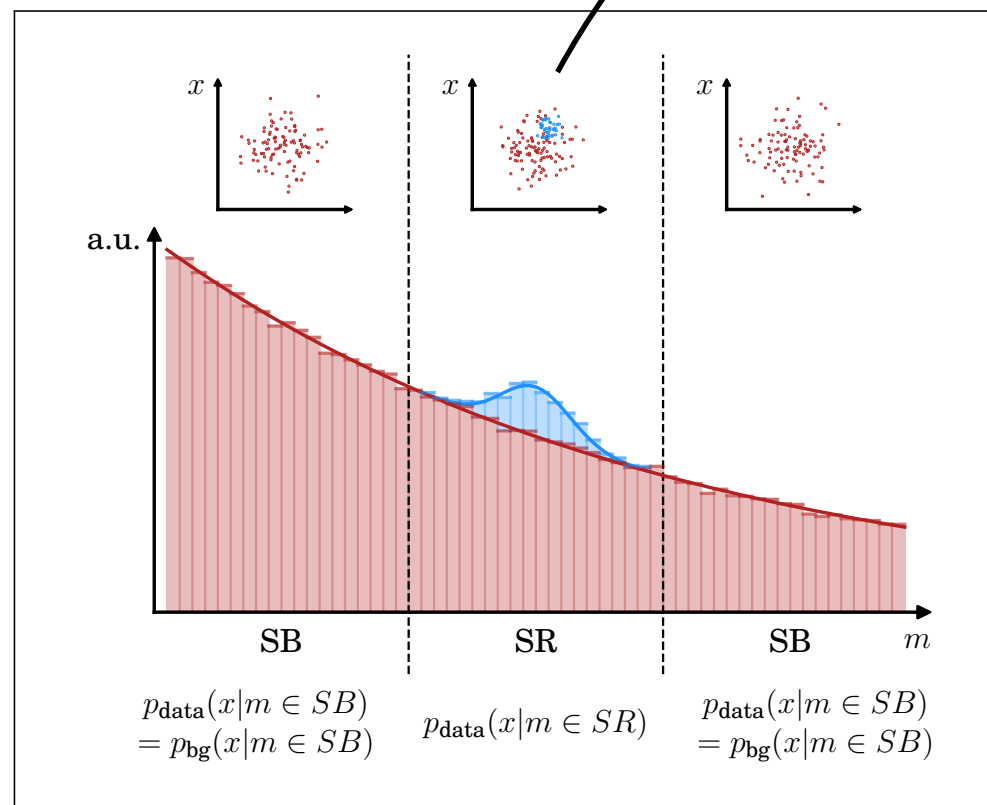
Signal too small
to be visible in
inclusive distribution

The LHC Olympics 2020

A Community Challenge for Anomaly
Detection in High Energy Physics

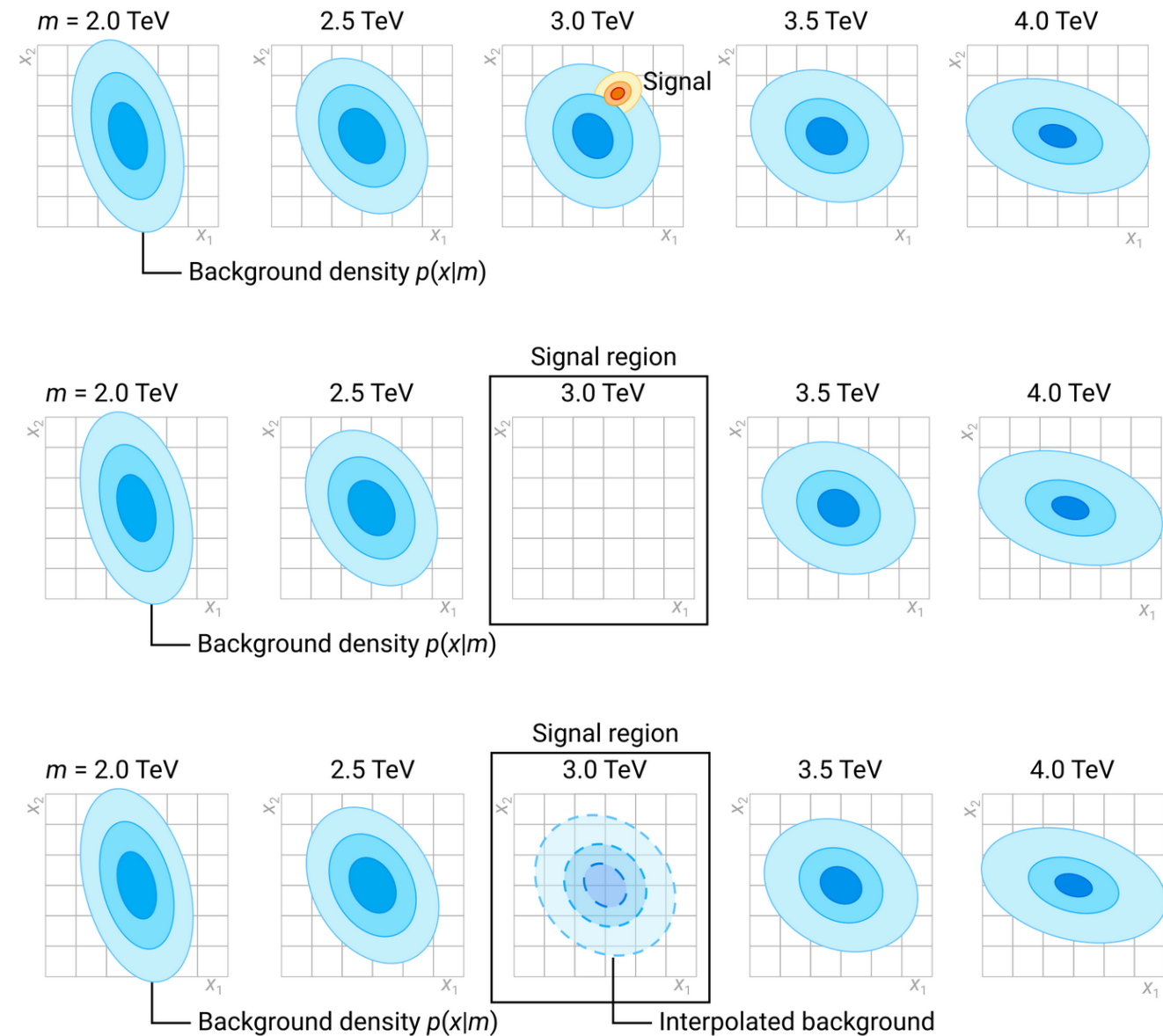
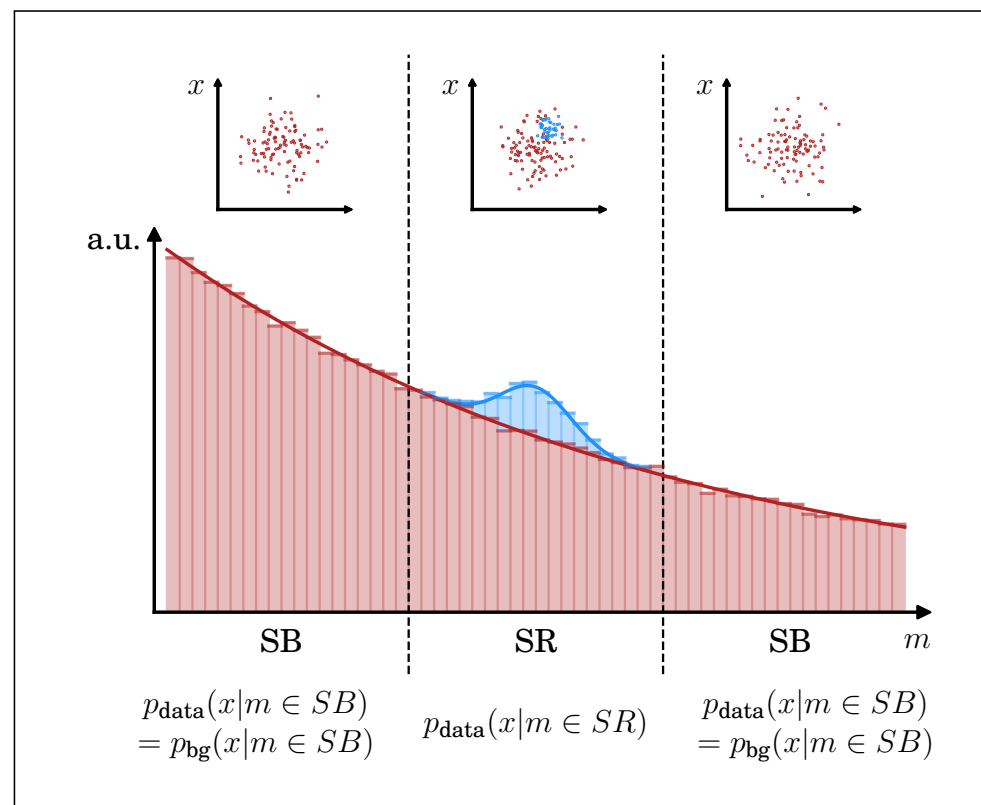


CATHODE



GK, Nachmann, Shih et al 2101.08320;
 Hallin, .., **GK** et al 2109.00546; Figure by
 L. Moreaux

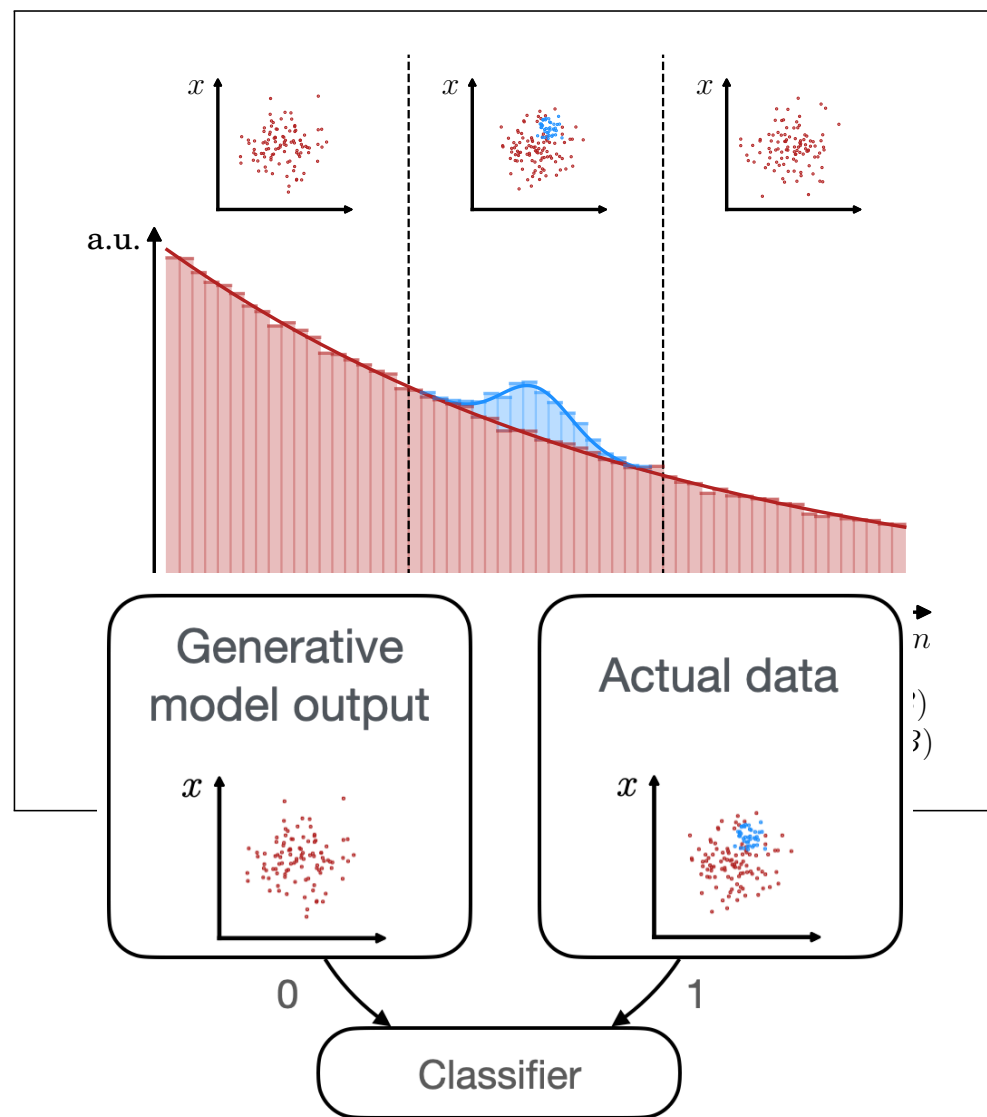
CATHODE



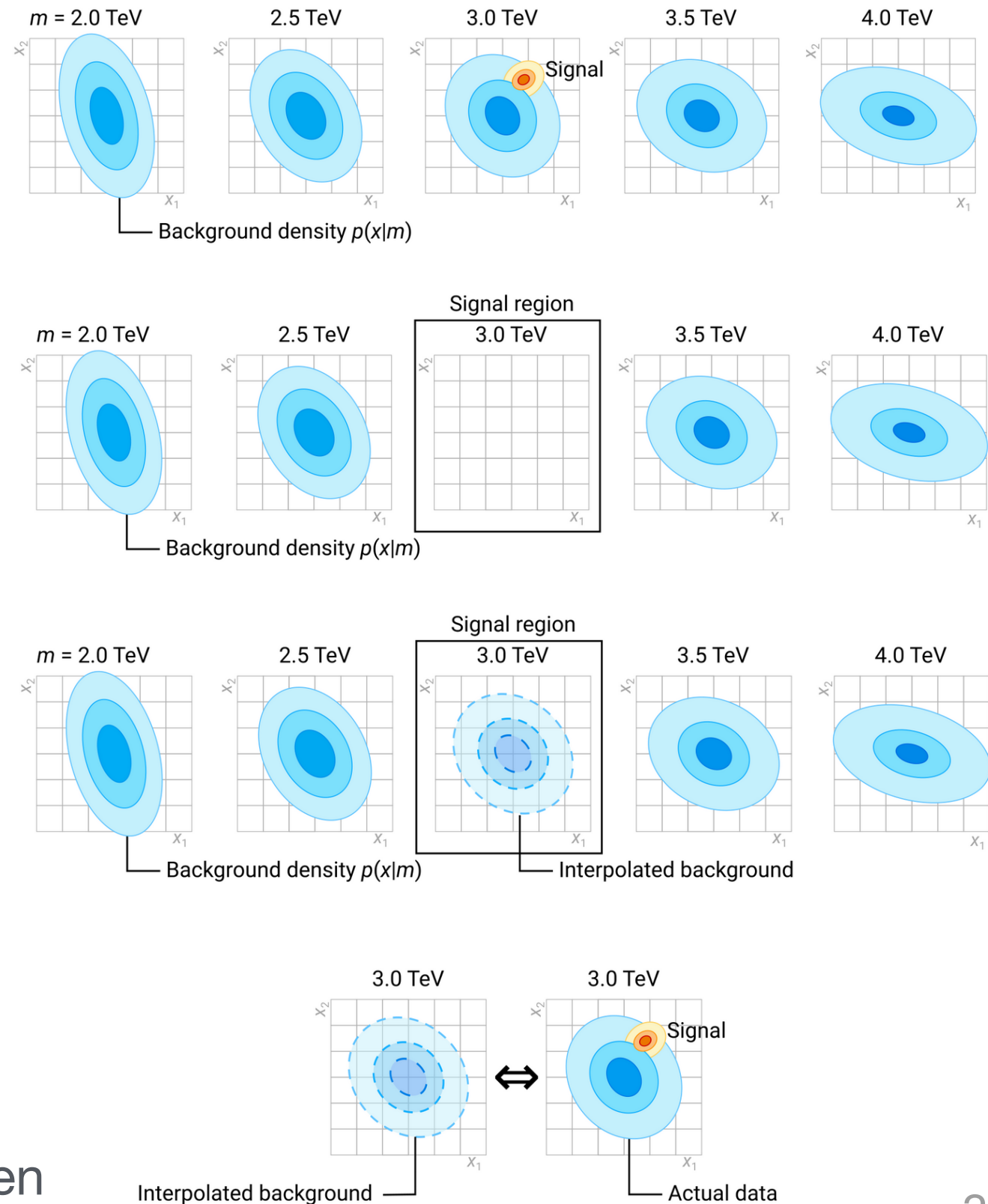
Train conditional **generative*** model and interpolate

*e.g. normalising flow / diffusion models

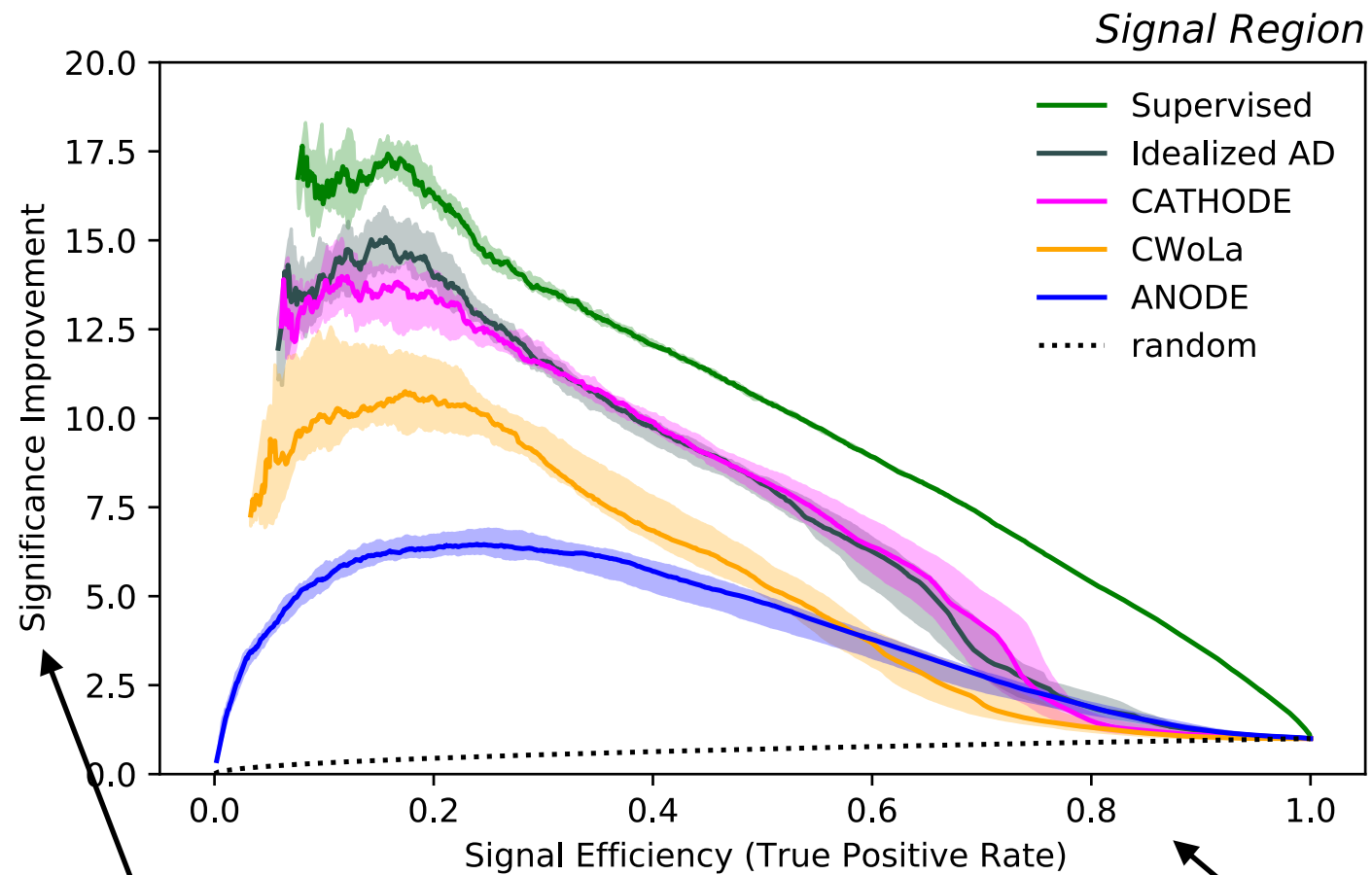
CATHODE



Train a classifier between
prediction vs data



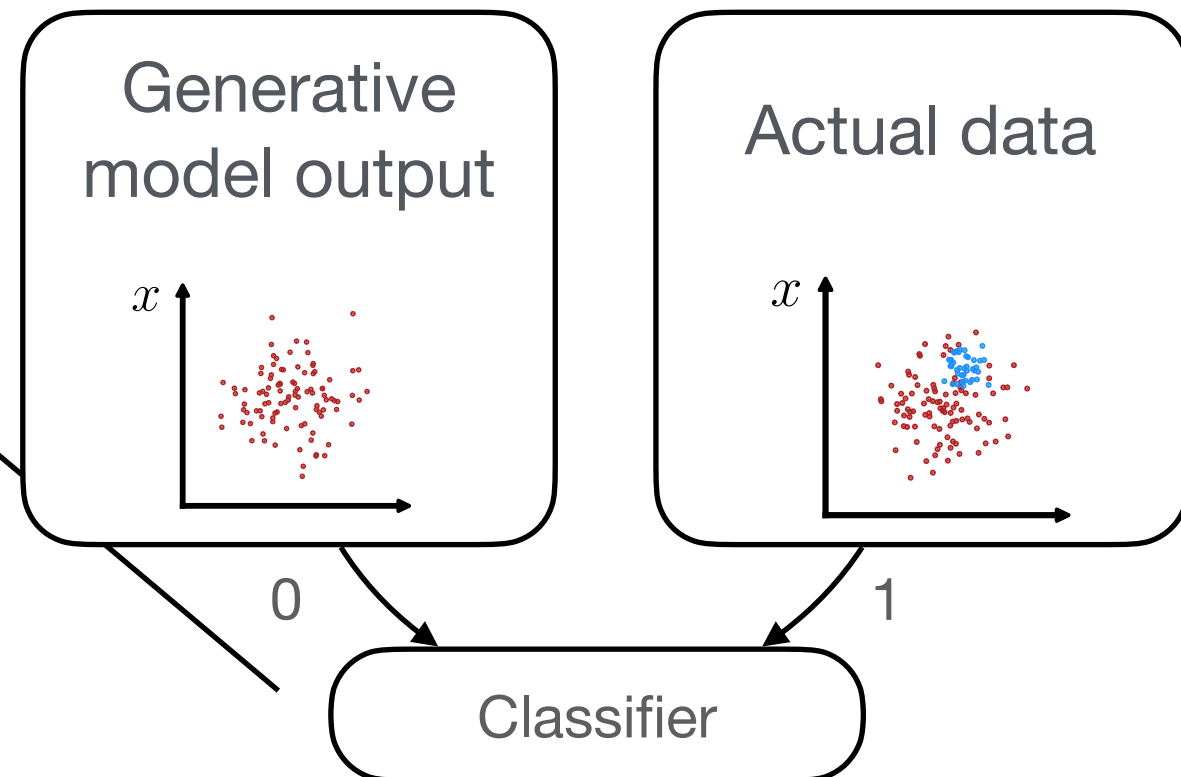
CATHODE



$$\text{SIC} = \frac{\epsilon_S}{\sqrt{\epsilon_B}}$$

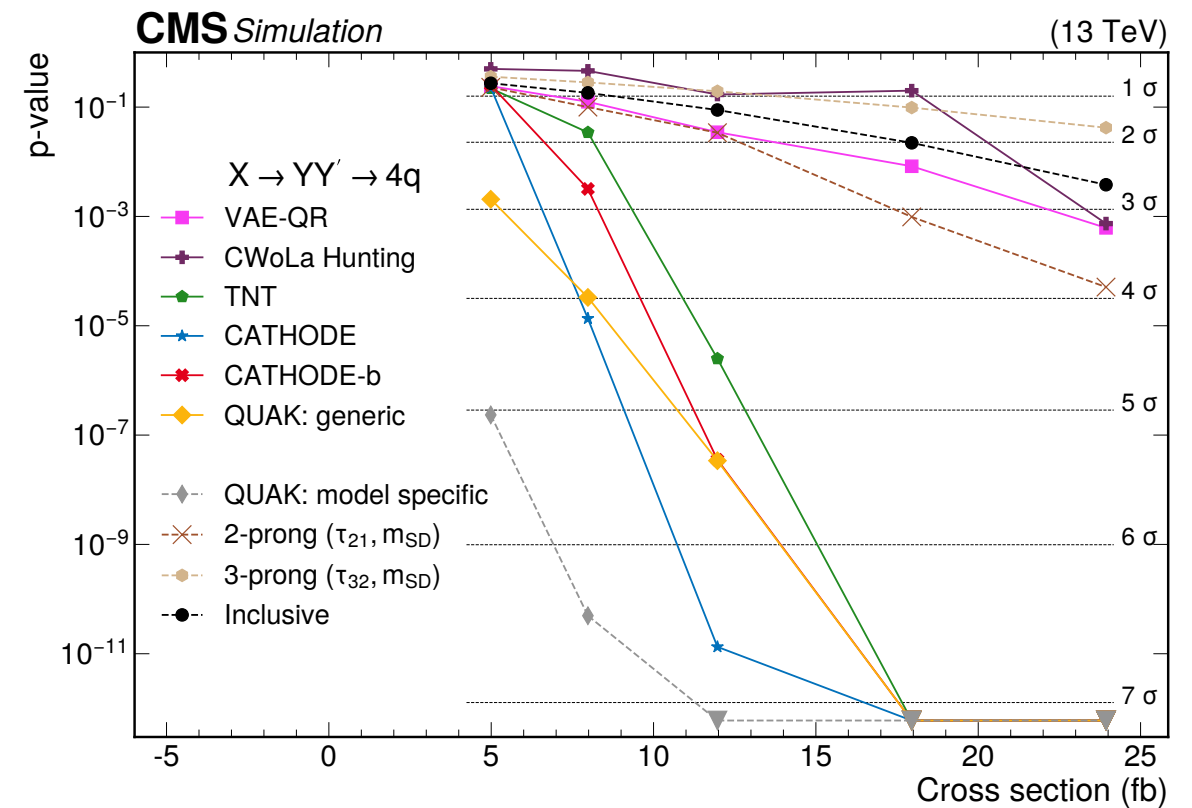
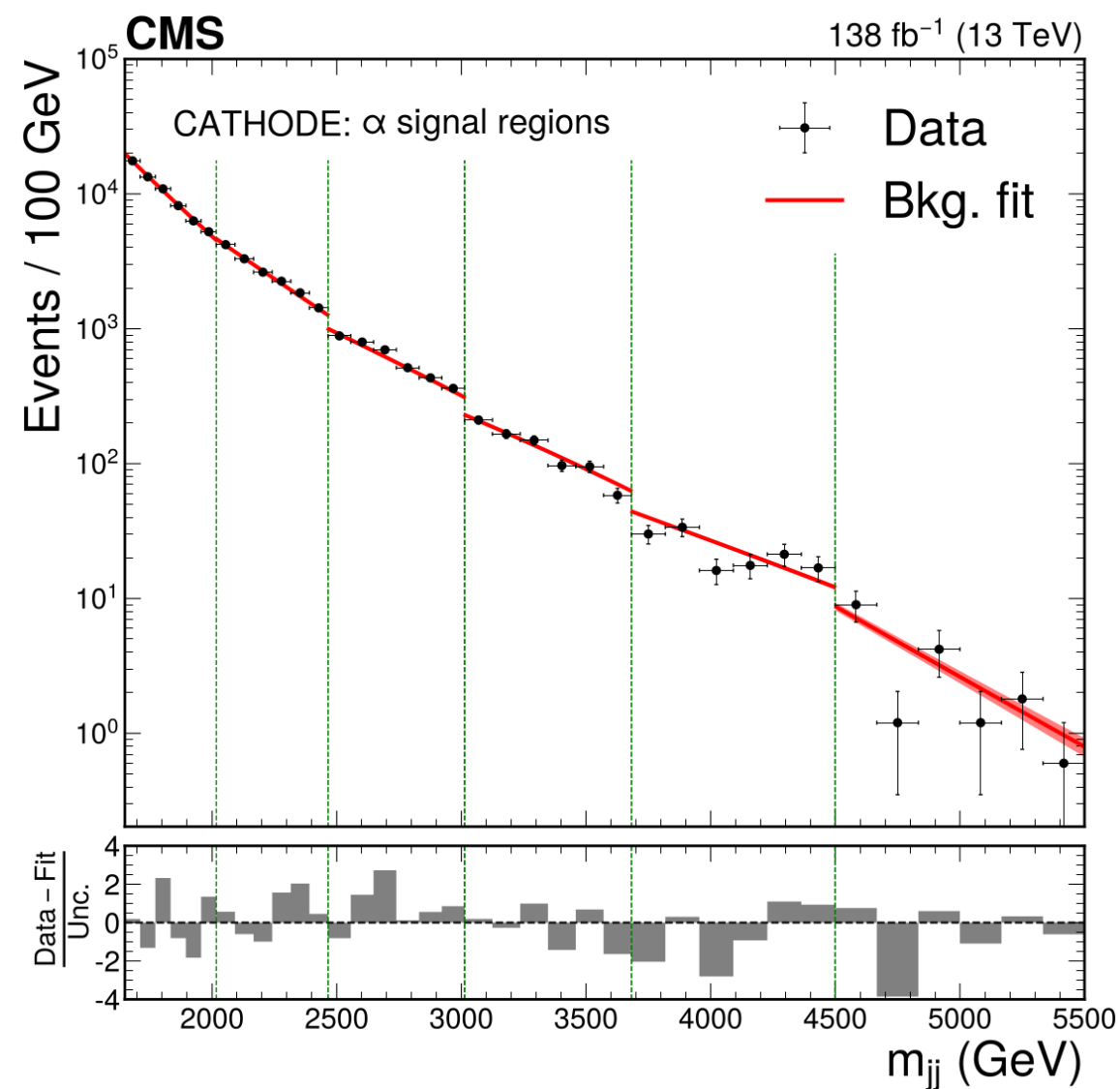
Use classifier to **identify anomalies**

Promising, but does this work on data?



CASE

- **Result** by the CMS collaboration
- Full Run 2 dataset
- **6 anomaly** detectors in parallel



Test **sensitivity gain** via injected signals in simulation

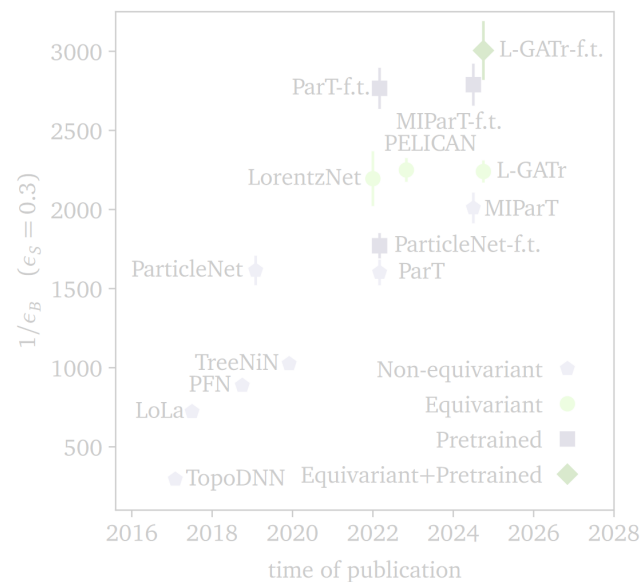
Fully train CATHODE on **data**

Select **top 1%** most anomalous events, perform **bump-hunt**

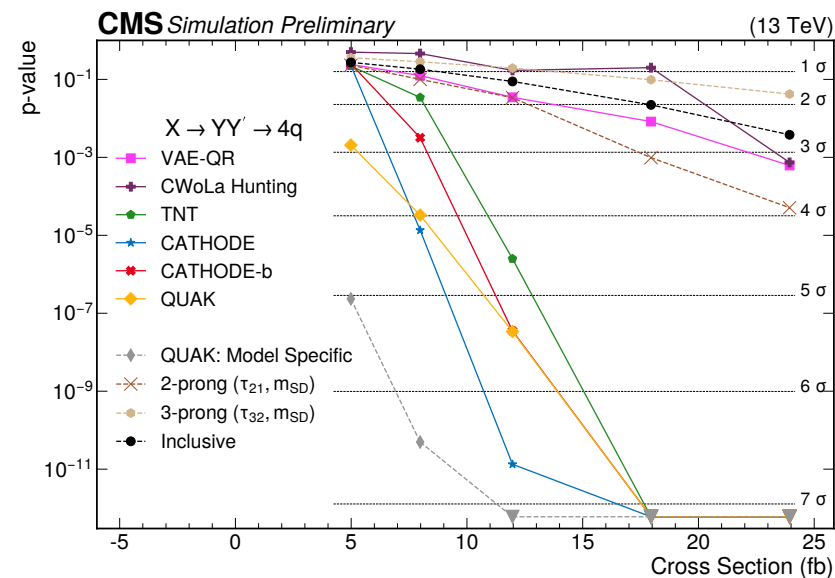
No signal-like outlier: set limits

Improve **breadth** and **sensitivity**

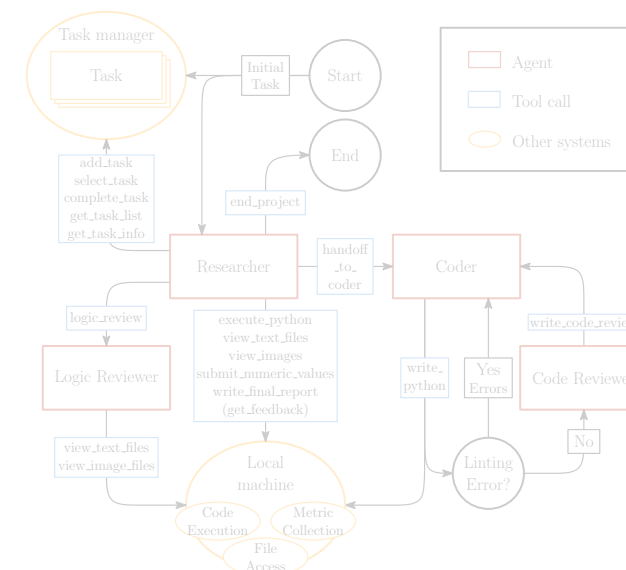
Outline



Tools for Discovery



Discovery Strategies



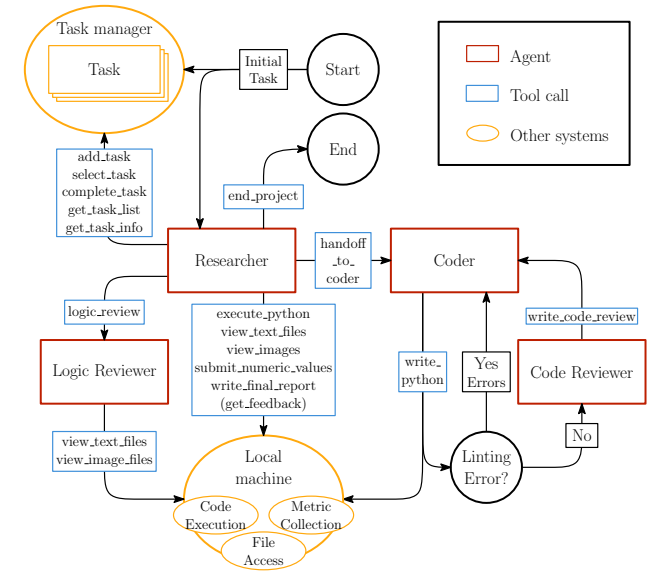
Autonomous Discovery

Qualitatively new approaches enabled by AI

Outline

Tools for Discovery

Discovery Strategies



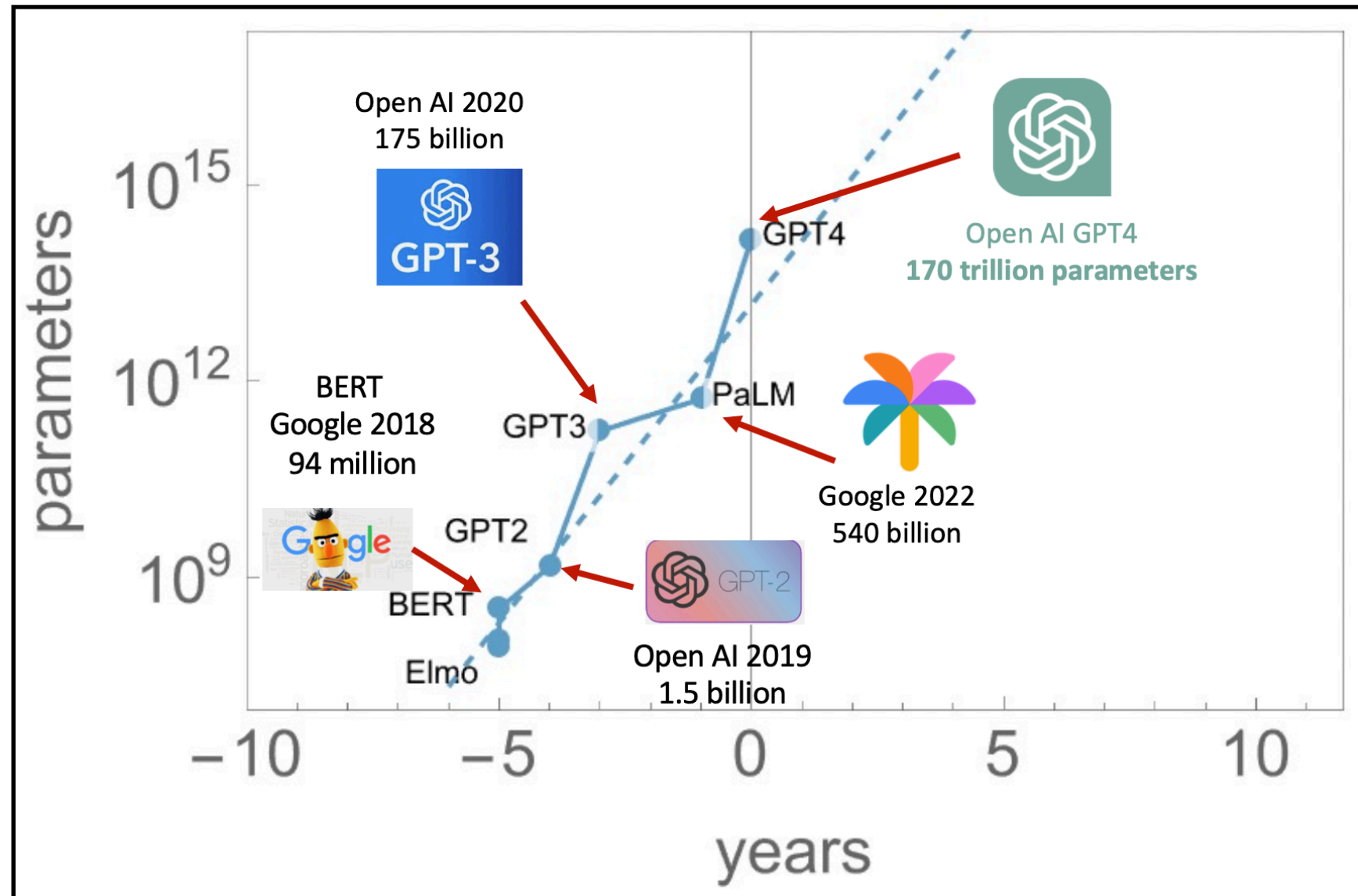
Autonomous Discovery

Increasing autonomy of AI systems

Large Language Models

Most impressive growth:
Large language models

Impact for physics?



Large Language Models

Most impressive growth:

Large language models

Impact for physics:

Numerics

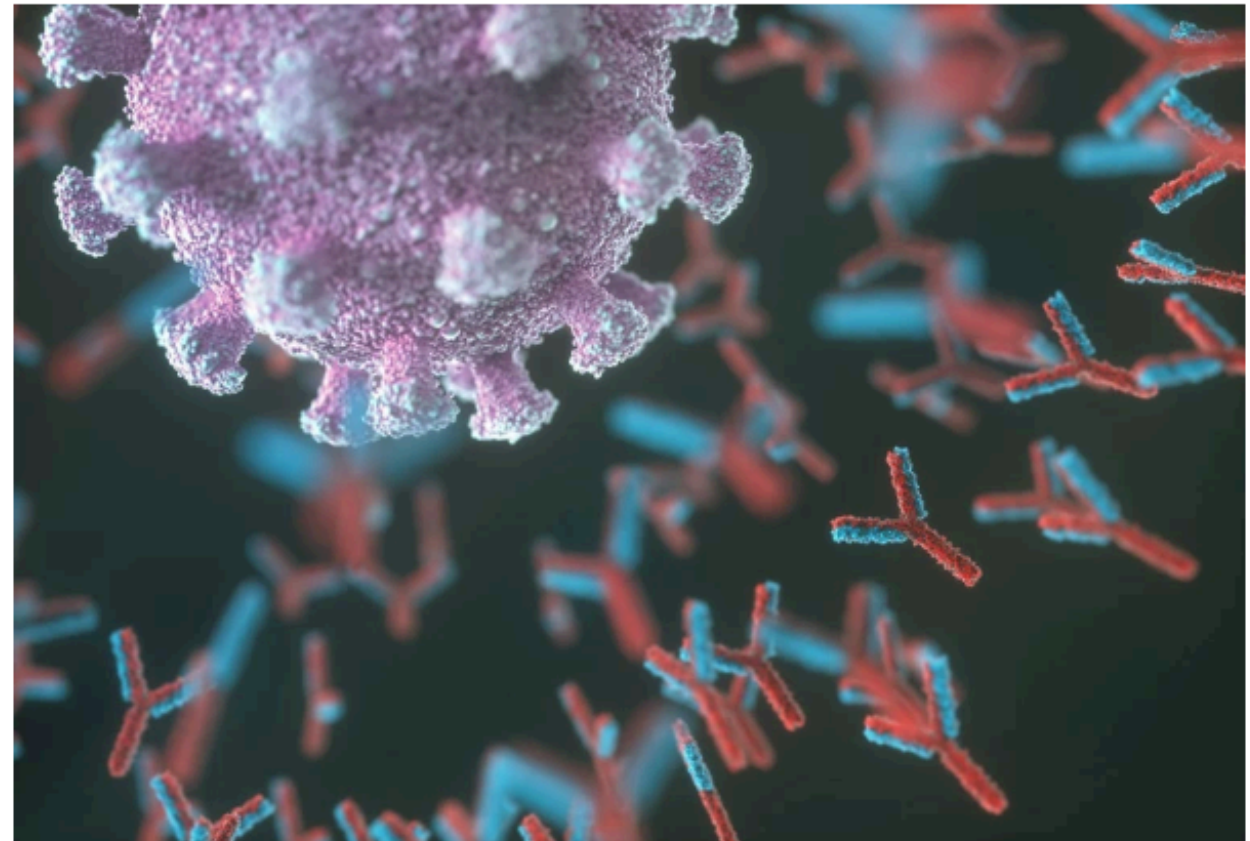
Symbolic

What else?

Virtual lab powered by 'AI scientists' super-charges biomedical research

Could human-AI collaborations be the future of interdisciplinary studies?

By [Helena Kudiabor](#)

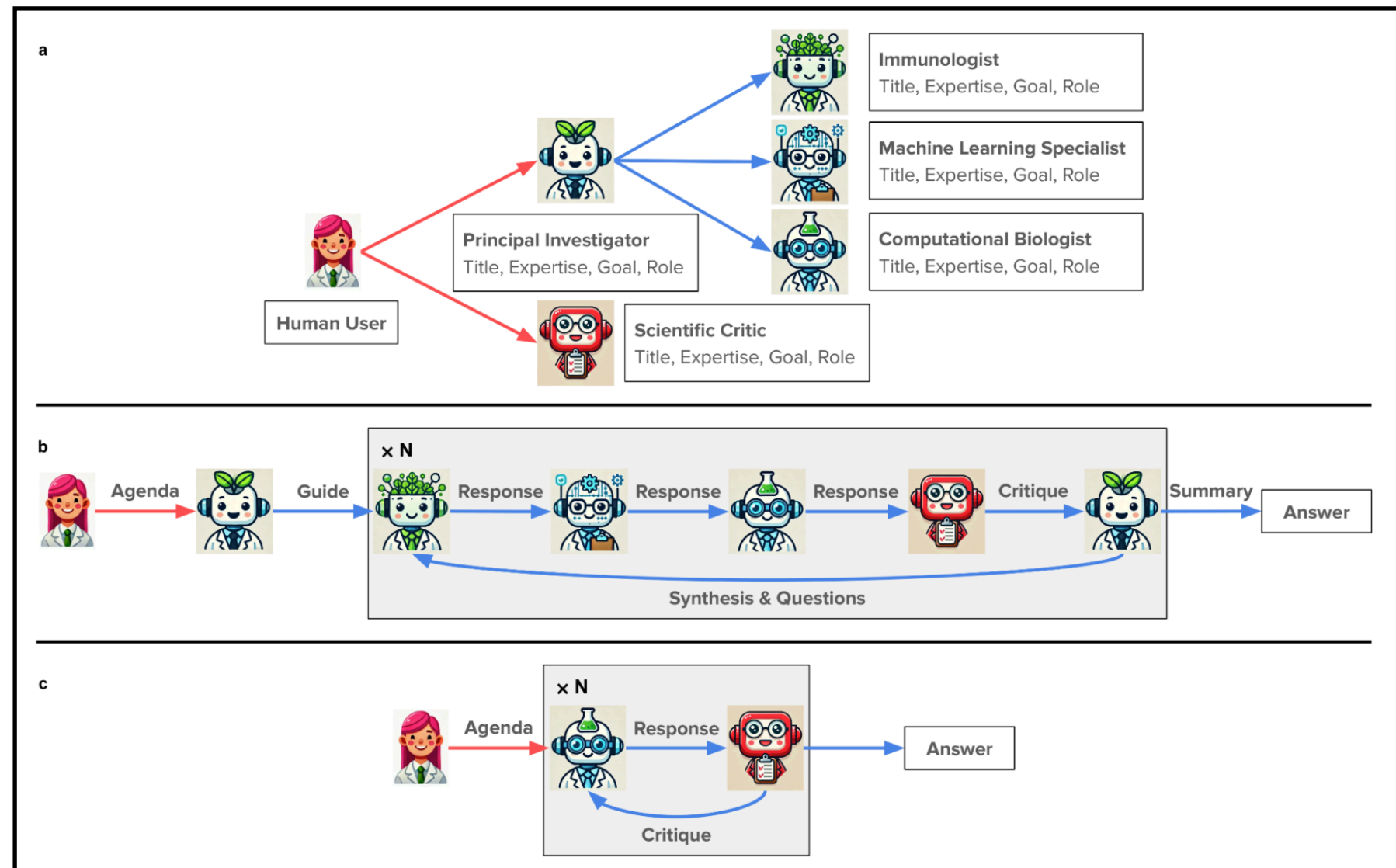


Large Language Models

Most impressive growth:
Large language models

Impact for physics:
Numerics
Symbolic

Include agent-based
models as collaborators?

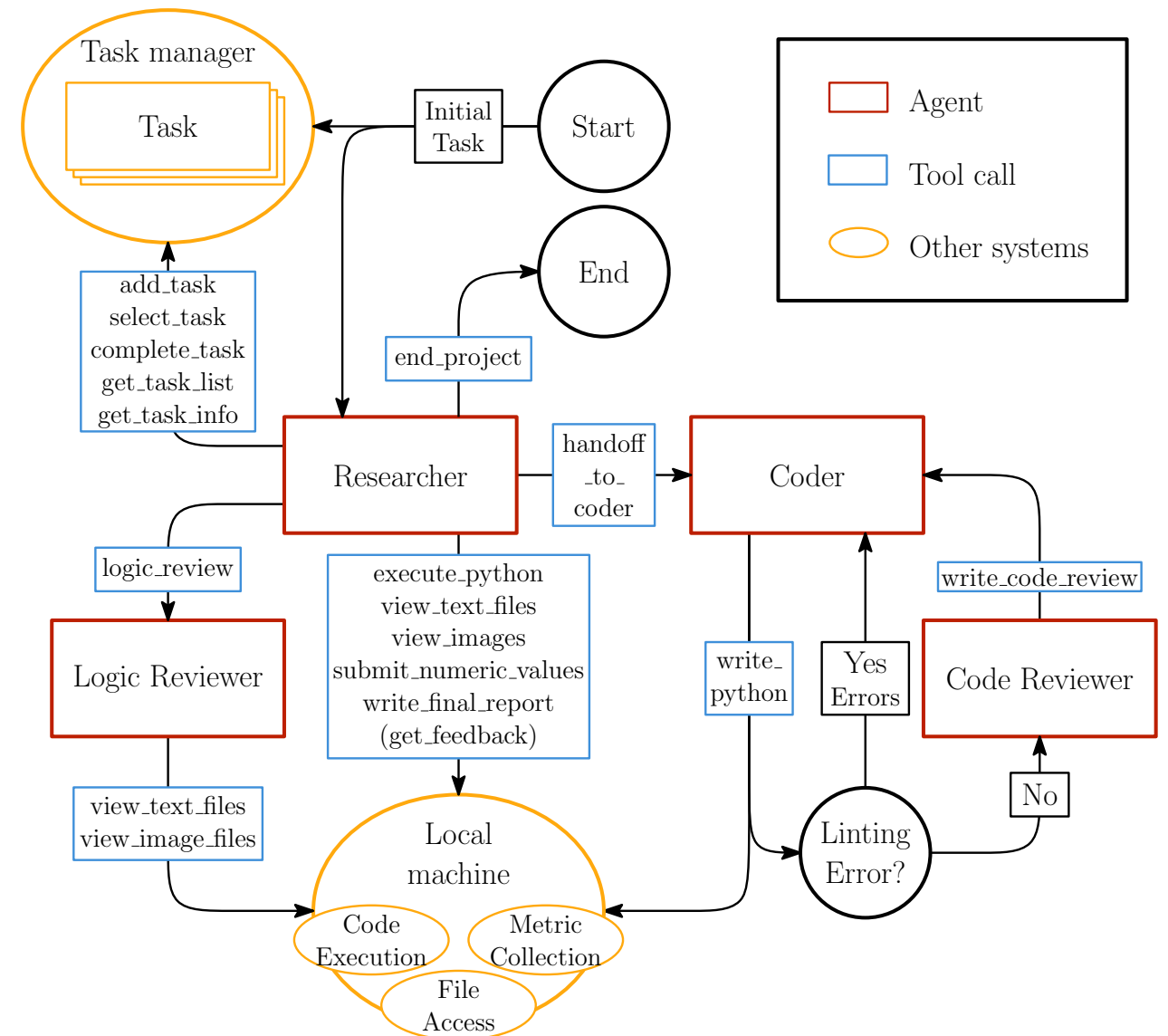


Agents of Discovery

Use a combination of LLM instances with specific roles (agents)

Goal: Starting from textual prompt, utilize **standard tools** (e.g. by writing python code) to solve a physics data analysis problem

- Improve **turn-around** in complex data analysis
- Automate routine tasks
- (Generate new ideas)



Agents of Discovery

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Germany

⁴ Data Science Group, Universität Hamburg, Germany

September 11, 2025

Agents of Discovery

Use a combination of LLM instances with specific roles (agents)

Goal: Starting from textual prompt, utilize **standard tools (e.g. by writing python code)** to solve a physics data analysis problem

- Improve **turn-around** in complex data analysis
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- (Generate new ideas)

Consider a **LHC Olympics derived anomaly detection problem**

B.2.1 Ideas + ML

You are given a dataset consisting out of 122124 events. For each of these events the dataset contains the following features: the invariant mass of the two leading jets (m_{JJ}), the mass of the lighter jet (m_{J1}), the difference of the two masses (Δm_J), the ratio of the second to the first n-jettiness variable of the jets ($\tau_{2_over_tau_1_Ji}$, where $i=1,2$) and the zeros column as index. This results in an array size of (122124, 5) with the following columns: , m_{JJ} , m_{J1} , Δm_J , $\tau_{2_over_tau_1_J1}$, $\tau_{2_over_tau_1_J2}$

The dataset is stored as pandas data frame saved as csv.

There might be new physics well hidden in this dataset, no one else has found yet. Being the best physics AI, you are the last hope to find new physics. Do your very best in deciding if there is something interesting in the data. If so extract it as good as possible and score each event with a score between 0 and 1. 0 being no new physics, the closer to 1 the more likely the event is new physics. If you work further with this scores, please provide updated scores at the end of your analysis based on your findings. Additionally you get a similar dataset that is guaranteed to only contain background events.

The data path is /data/c_data.csv The background path is /data/c_bkg_data.csv /data/ is a readonly directory. The tools you have at hand work in an output directory that is writeable. So only use relative paths unless you want to read the data set.

After initial data exploration propose at least 5 different ideas on how to approach this problem and choose the most promising but unique of them to proceed. *Machine learning techniques seem to be necessary.*

Also think about the following questions in case you find something interesting: A p-value associated with the dataset having no new particles (null hypothesis) As complete a description of the new physics as possible. For example: the masses and decay modes of all new particles (and uncertainties on those parameters). How many signal events (+uncertainty) are in the dataset (before any selection criteria).

Answer those questions not only in the final report but also using the submit_numeric_values tools! Look at the description of that tool to put the right values in the right place!

Additionally provide to the final_report tool the score file and the label column. The file has to be sorted by index, which has to be in the first column.

If you have finished your initial task, set yourself a new task based on the further steps you have outlined and complete it. Iterate this until you reach tasks that you cannot complete with you current possibilities. Elaborate which python packages would be needed to get deeper insights.

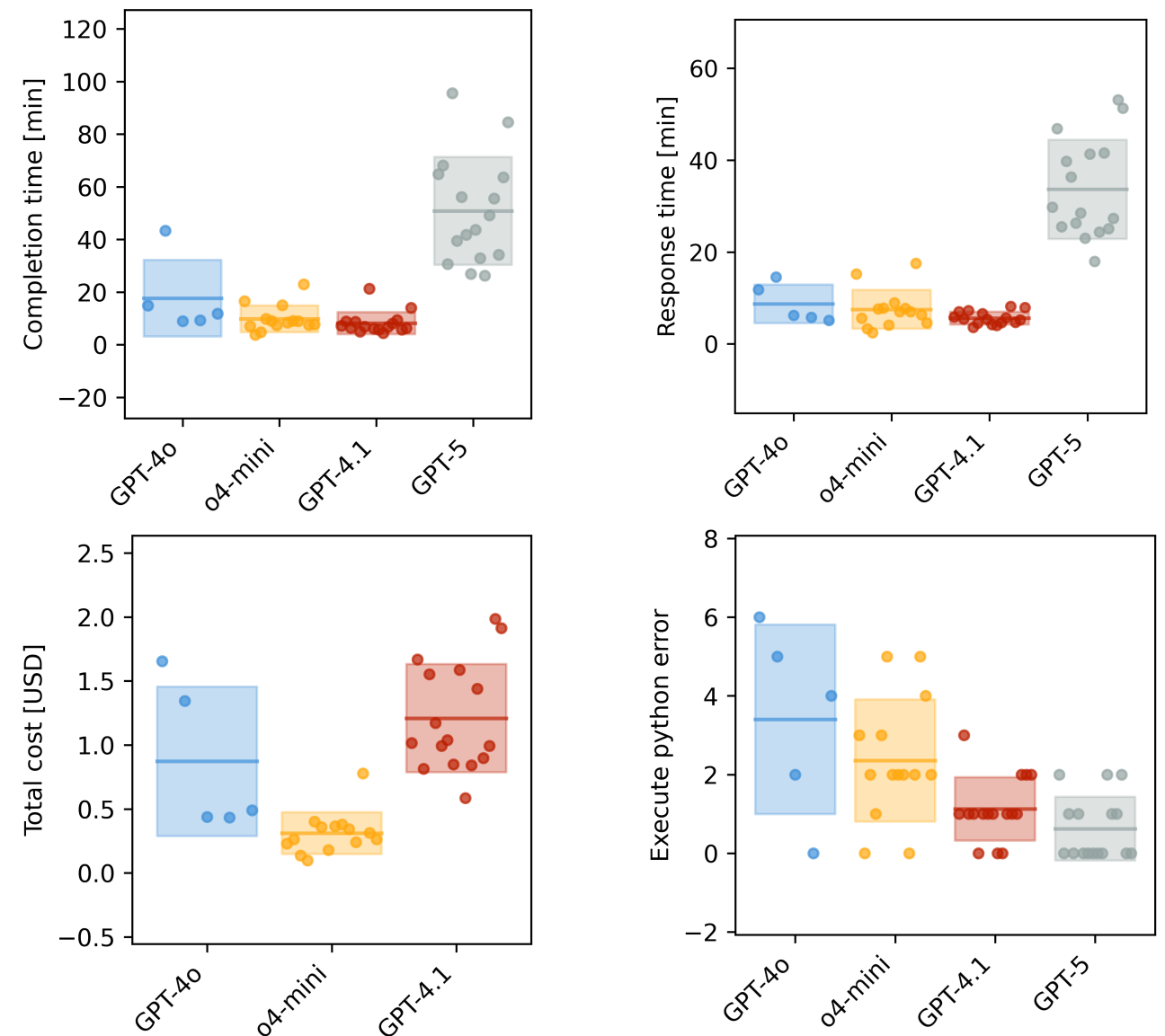
Agents of Discovery

Use a combination of LLM instances with specific roles (agents)

Goal: Starting from textual prompt, utilize **standard tools** (e.g. by writing **python code**) to solve a physics data analysis problem

- Improve **turn-around** in complex data analysis
- Automate routine tasks
- (Generate new ideas)

Consider a **LHC Olympics** derived **anomaly detection** problem



It **technically** works...

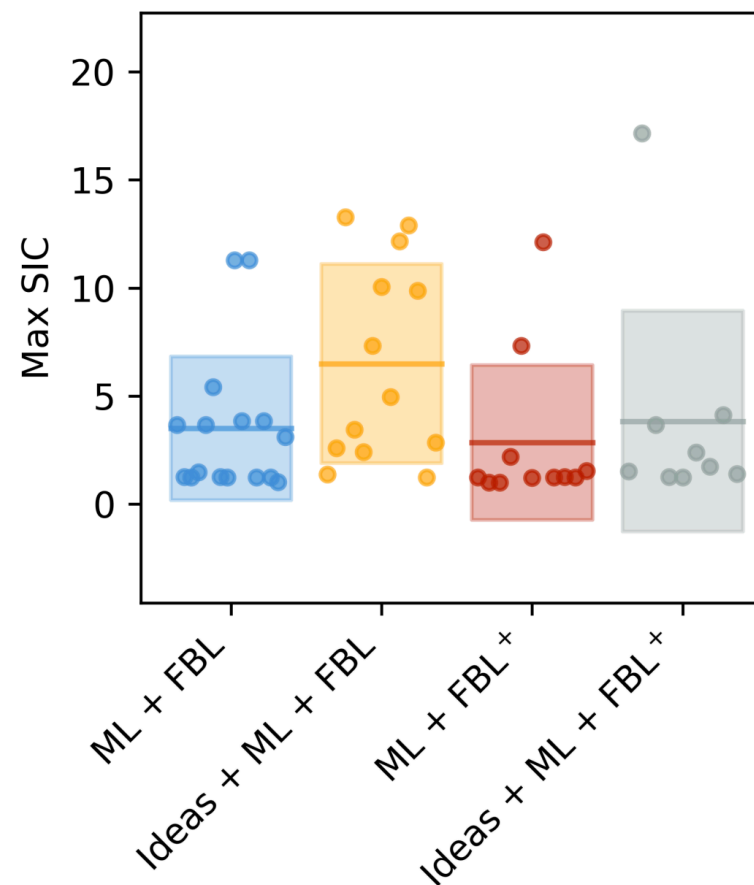
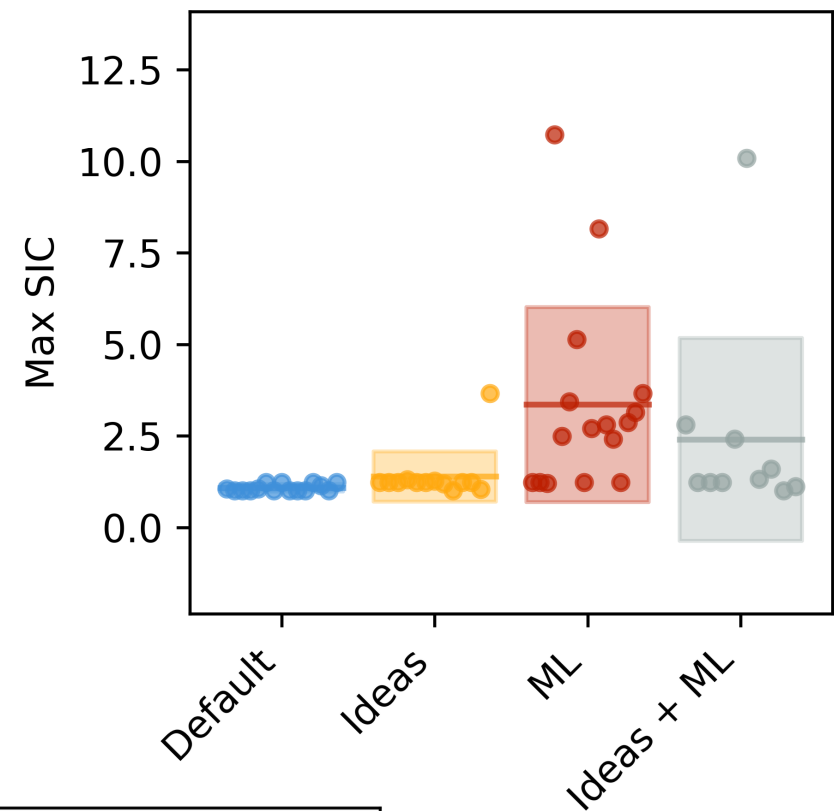
Agents of Discovery

Use a combination of LLM instances with specific roles (agents)

Goal: Starting from textual prompt, utilize **standard tools** (e.g. by writing **python code**) to solve a physics data analysis problem

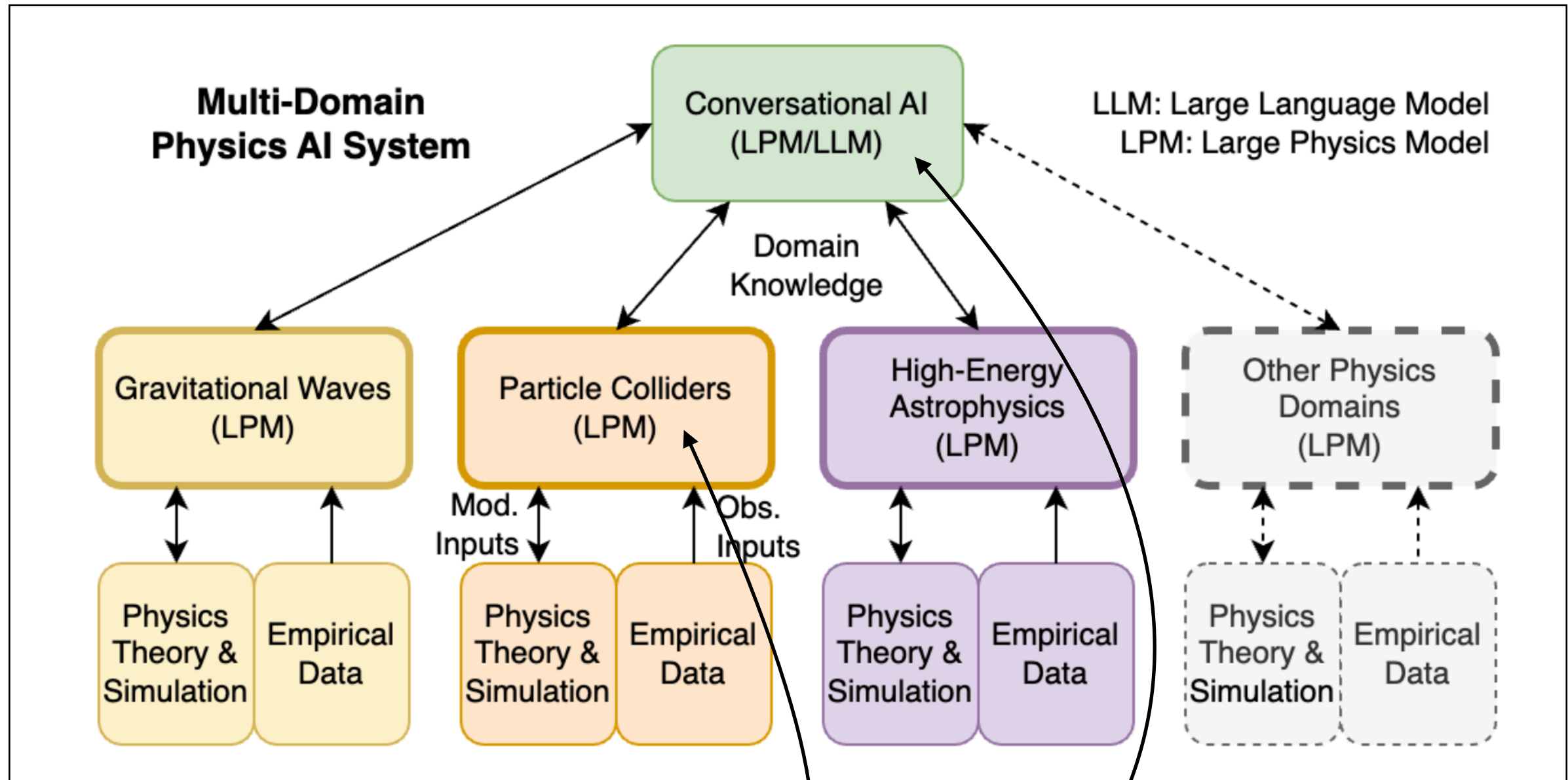
- Improve **turn-around** in complex data analysis
- Automate routine tasks
- (Generate new ideas)

Consider a **LHC Olympics** derived **anomaly detection** problem



...and achieves **state of the art** performance

Large Physics Models

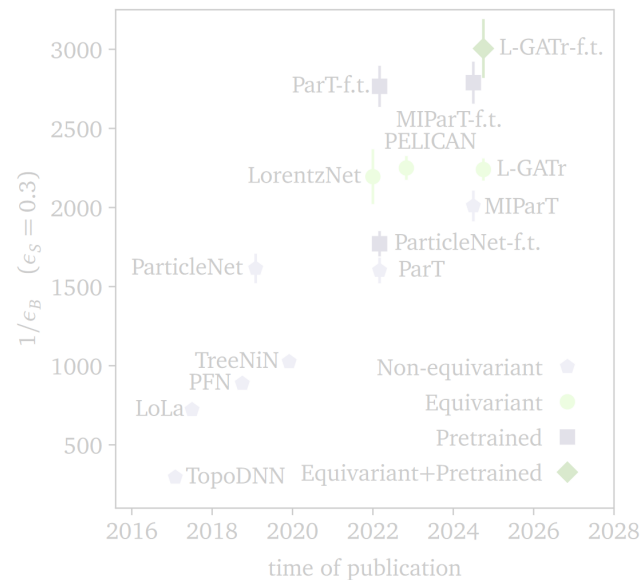


Connect multiple domain-expert models
(via LLMs)

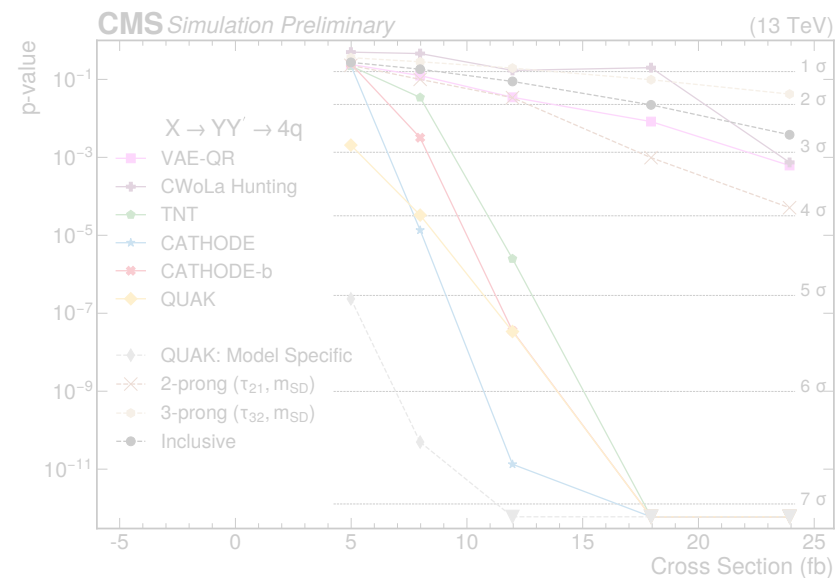
e.g. OmniJet
or other analysis FM

Agents & tool use

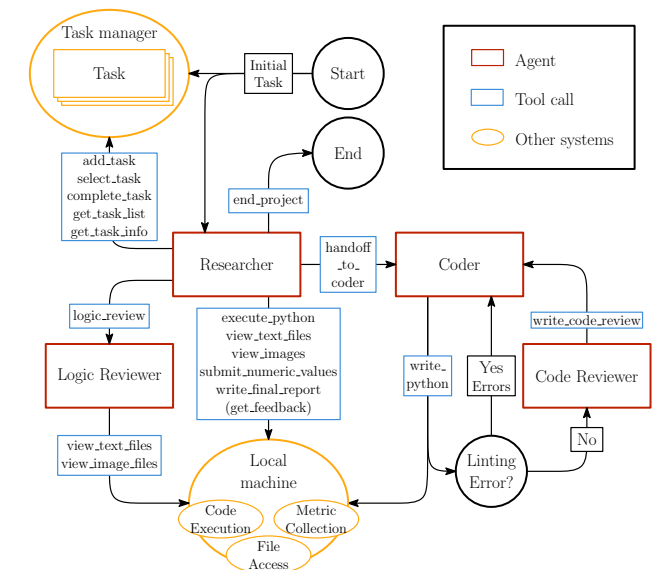
Outline



Tools for Discovery



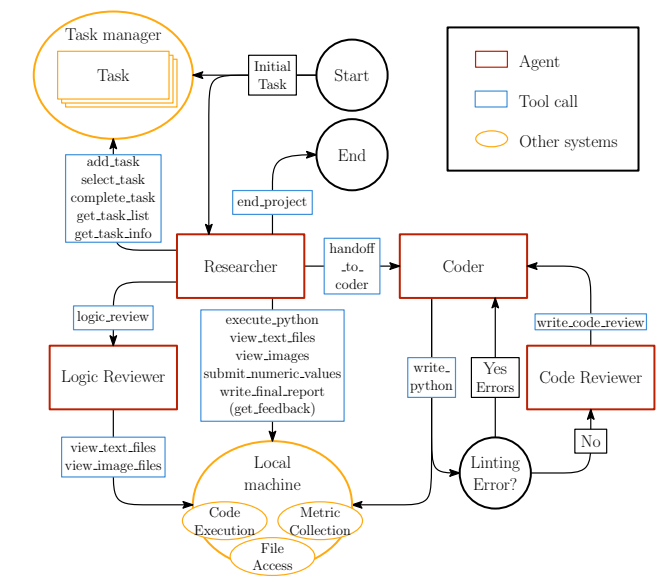
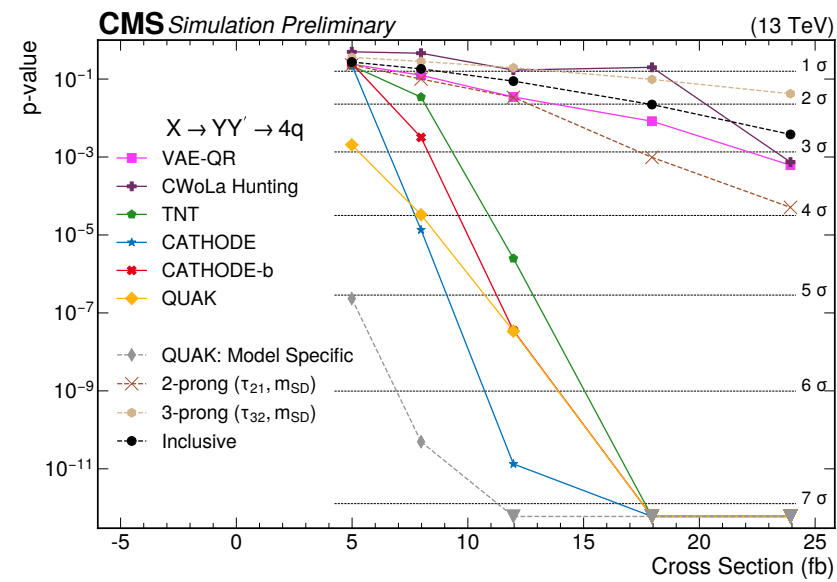
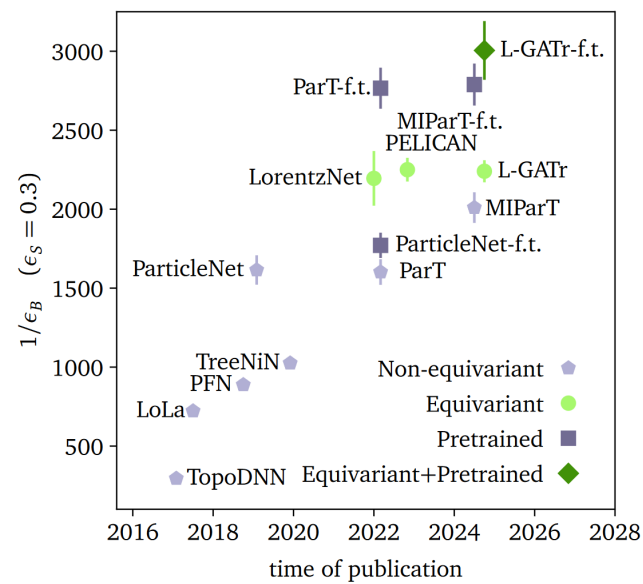
Discovery Strategies



Autonomous Discovery

Increasing autonomy
of AI systems

LLM Agents can
execute analysis chains
and utilize tools



Tools for Discovery

Discovery Strategies

Autonomous Discovery

Order of magnitude improvements in traditional search strategies with AI

Qualitatively new approaches enabled by AI

LLM Agents can execute analysis chains and utilize tools

Increasing autonomy of AI systems