

HEP in the Cloud Computing and Open Science Era

Lukas Heinrich (CERN), DESY Colloquium

Big Picture Goals

Our job: extract as much information from experimental data

$$p(\text{theory}|\text{data}) = \frac{p(\text{data}|\text{theory})}{p(\text{data})} p(\text{theory})$$



what we want

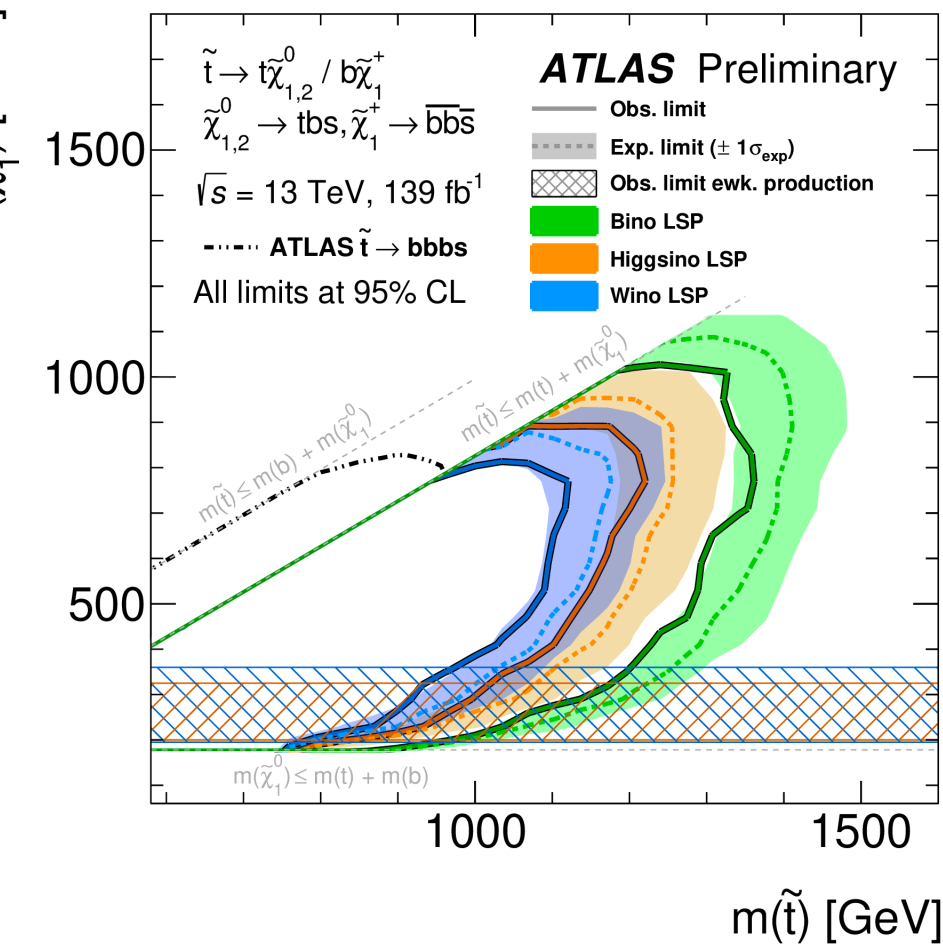
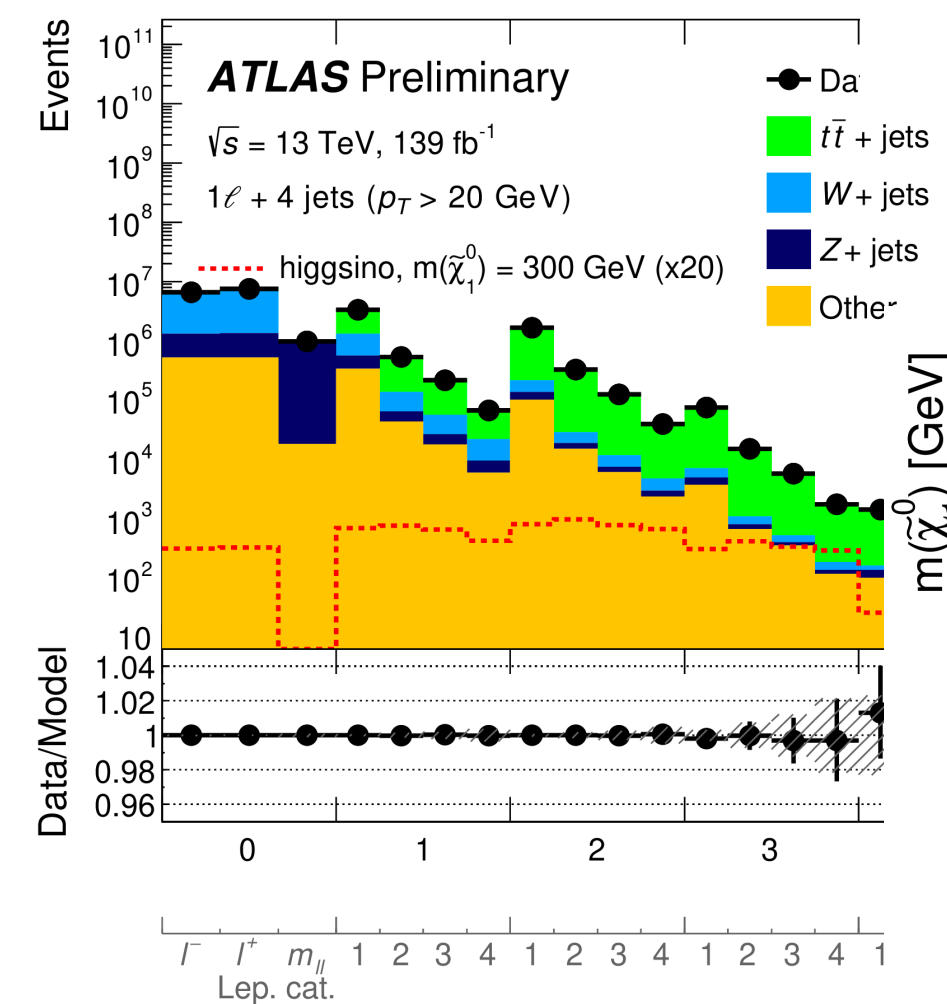
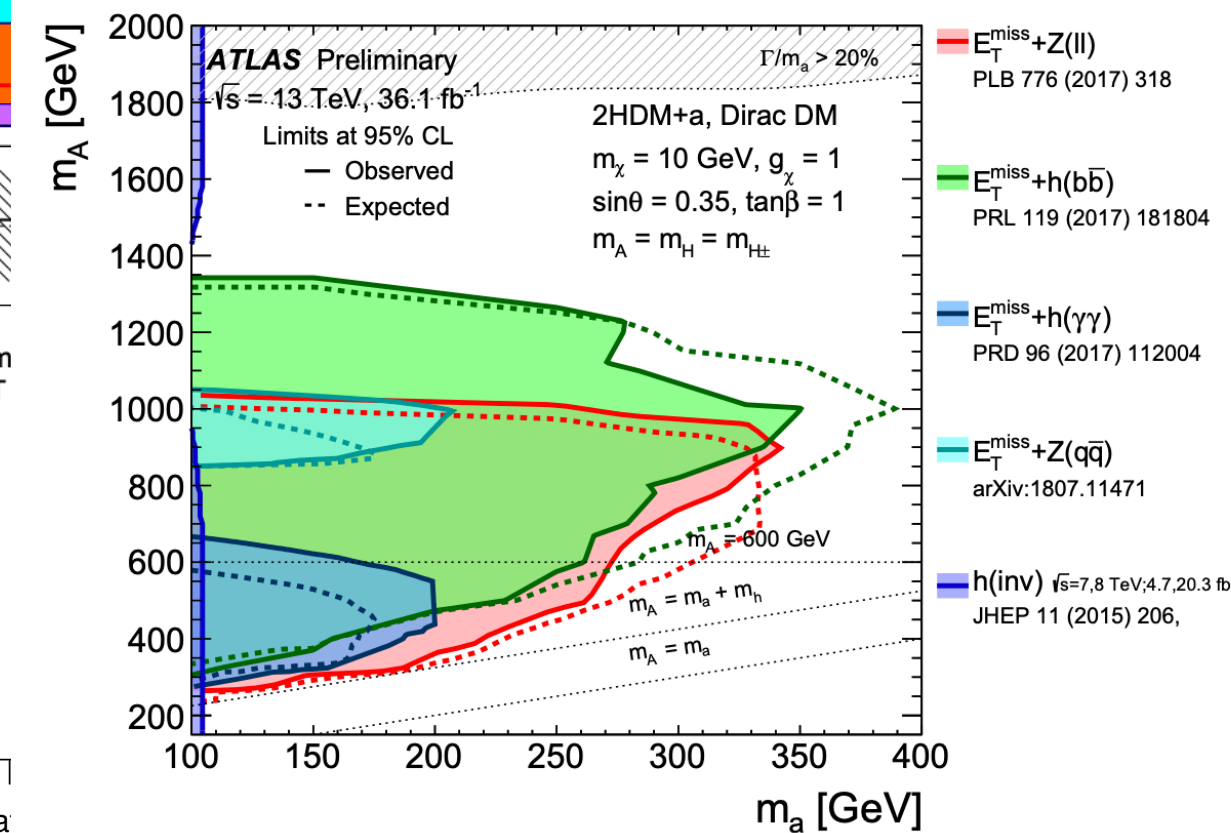
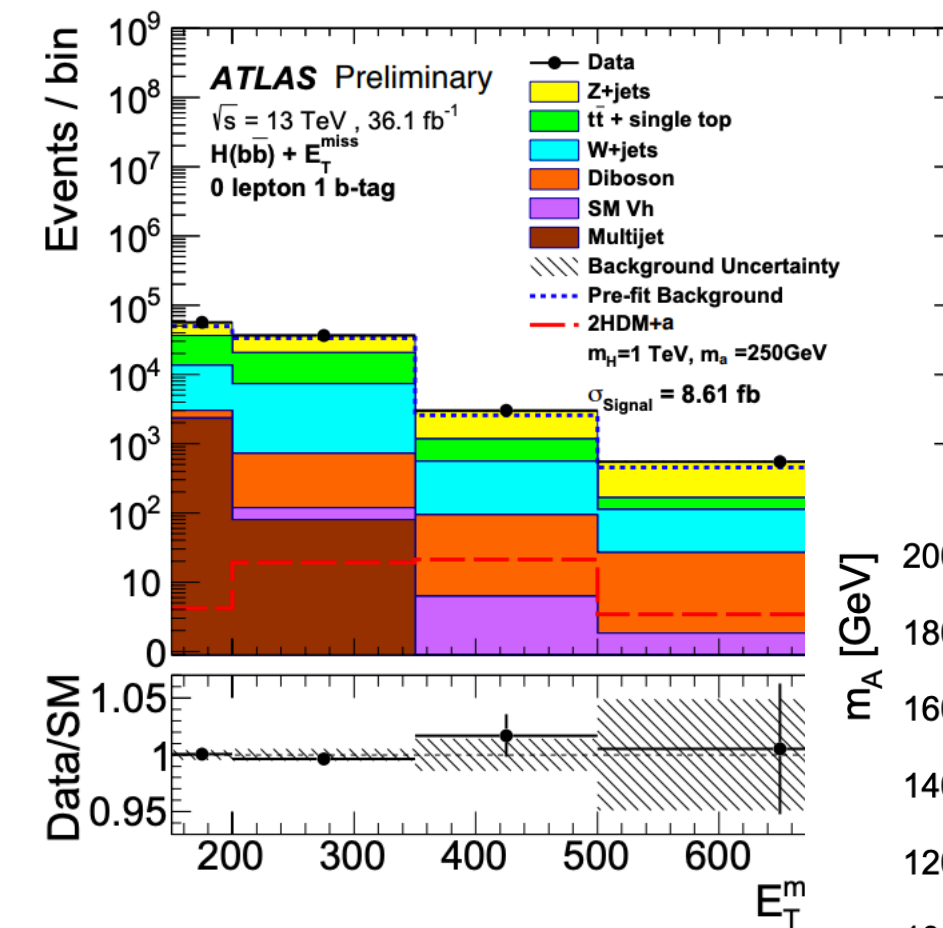
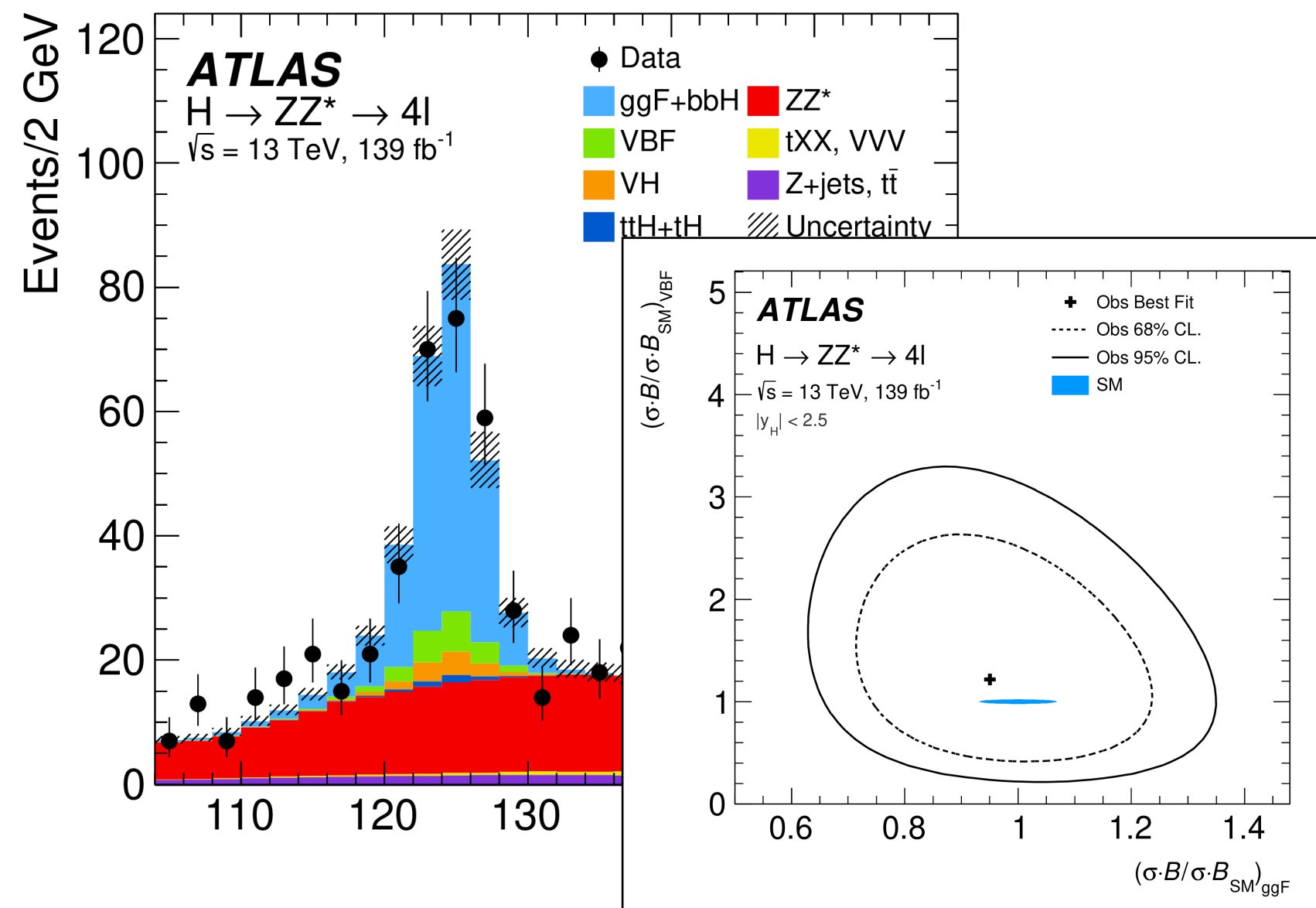
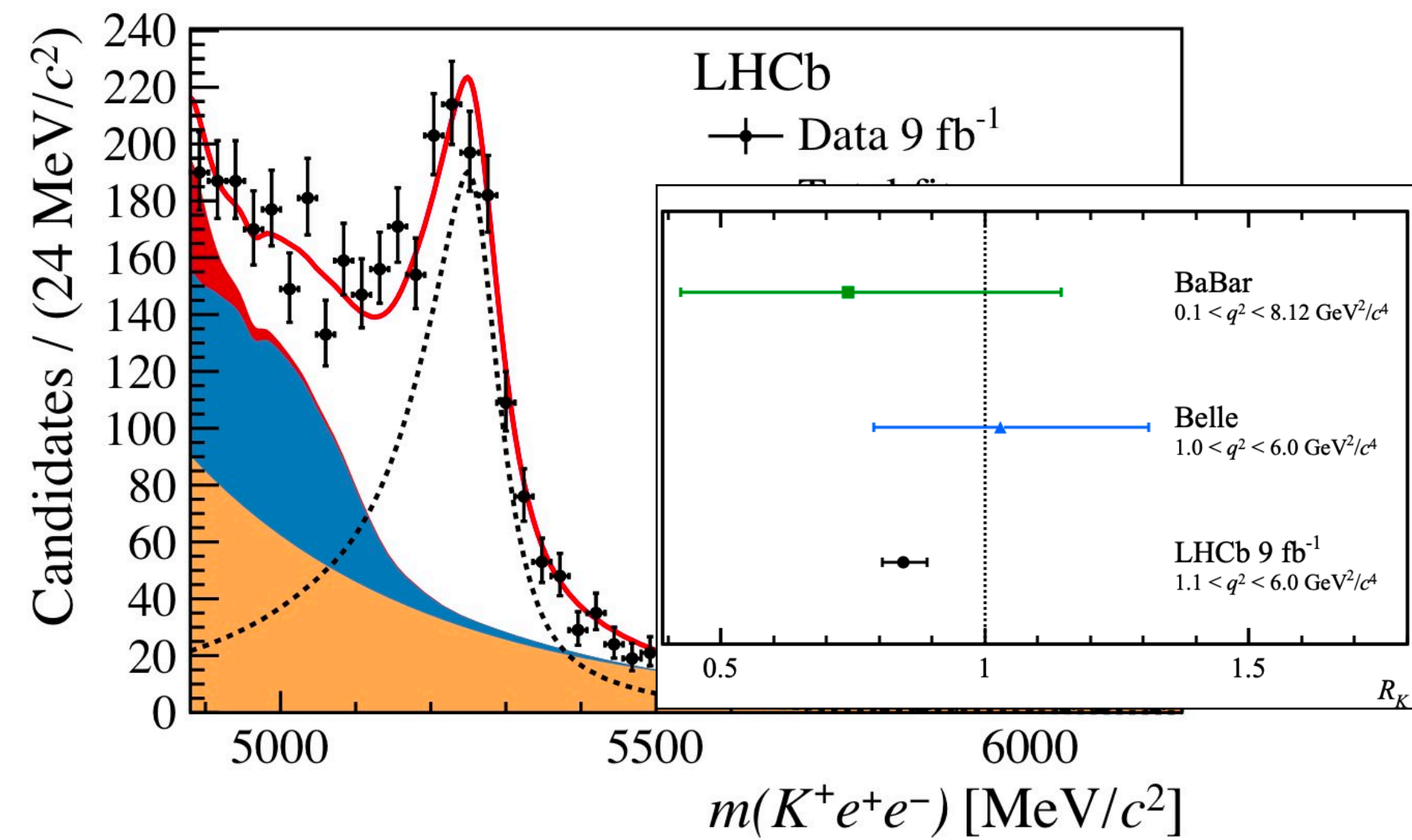


hep-ex



hep-ph/hep-th

Big Picture Goals



Big Picture Goals

Our job: extract as much information from experimental data

$$p(\text{theory}|\text{data}) = \frac{p(\text{data}|\text{theory})}{p(\text{data})} p(\text{theory})$$



what we want



hep-ex



hep-ph/hep-th

- What's the best way to do this in our Big Science setting?
- How can we collaborate best across theory-experiment divide?

Three Challenges of Big Science

1. The data is large:

At a project level:

LHC: 1 EB today, O(30) EB HL-LHC (?)

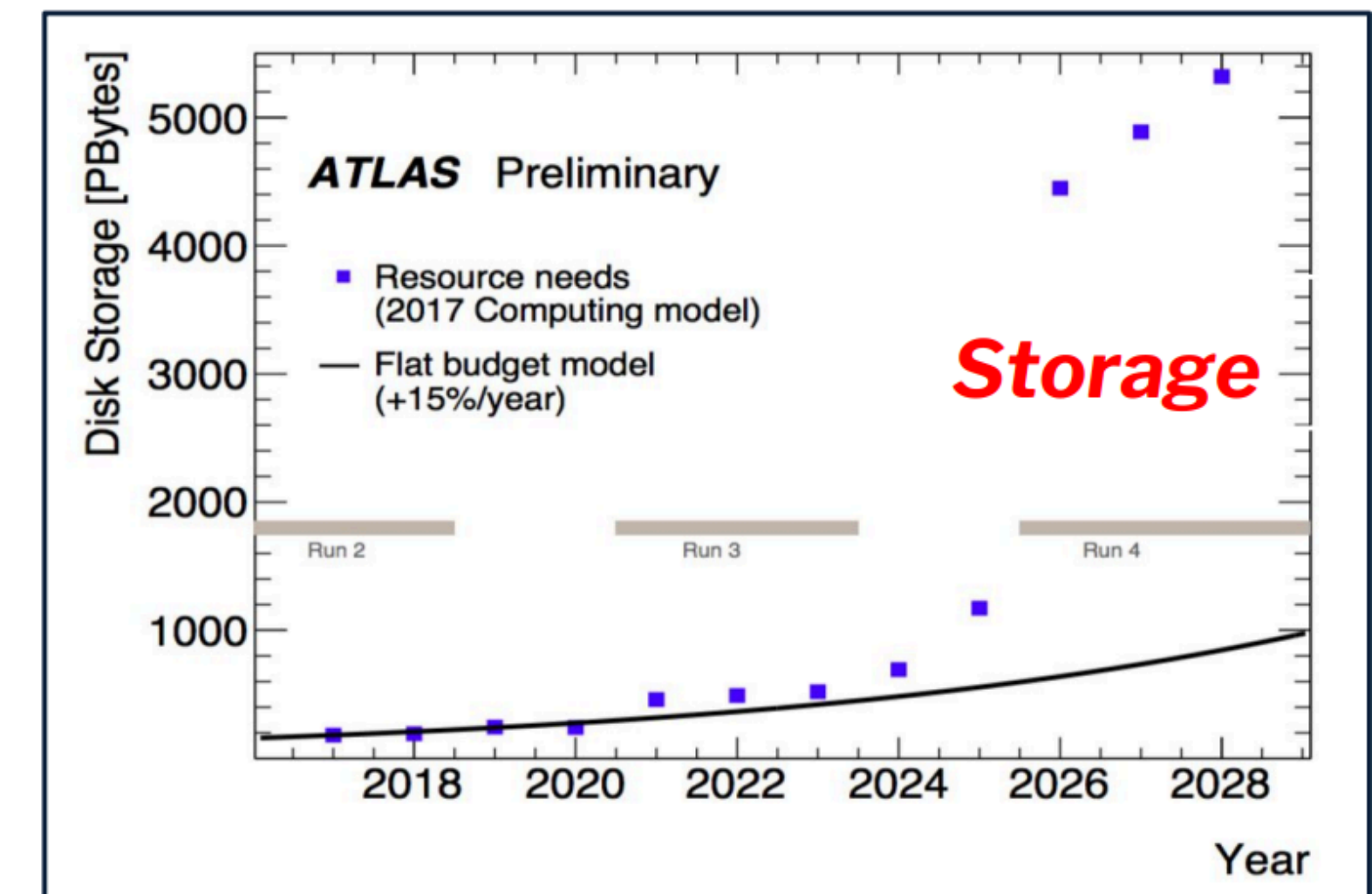
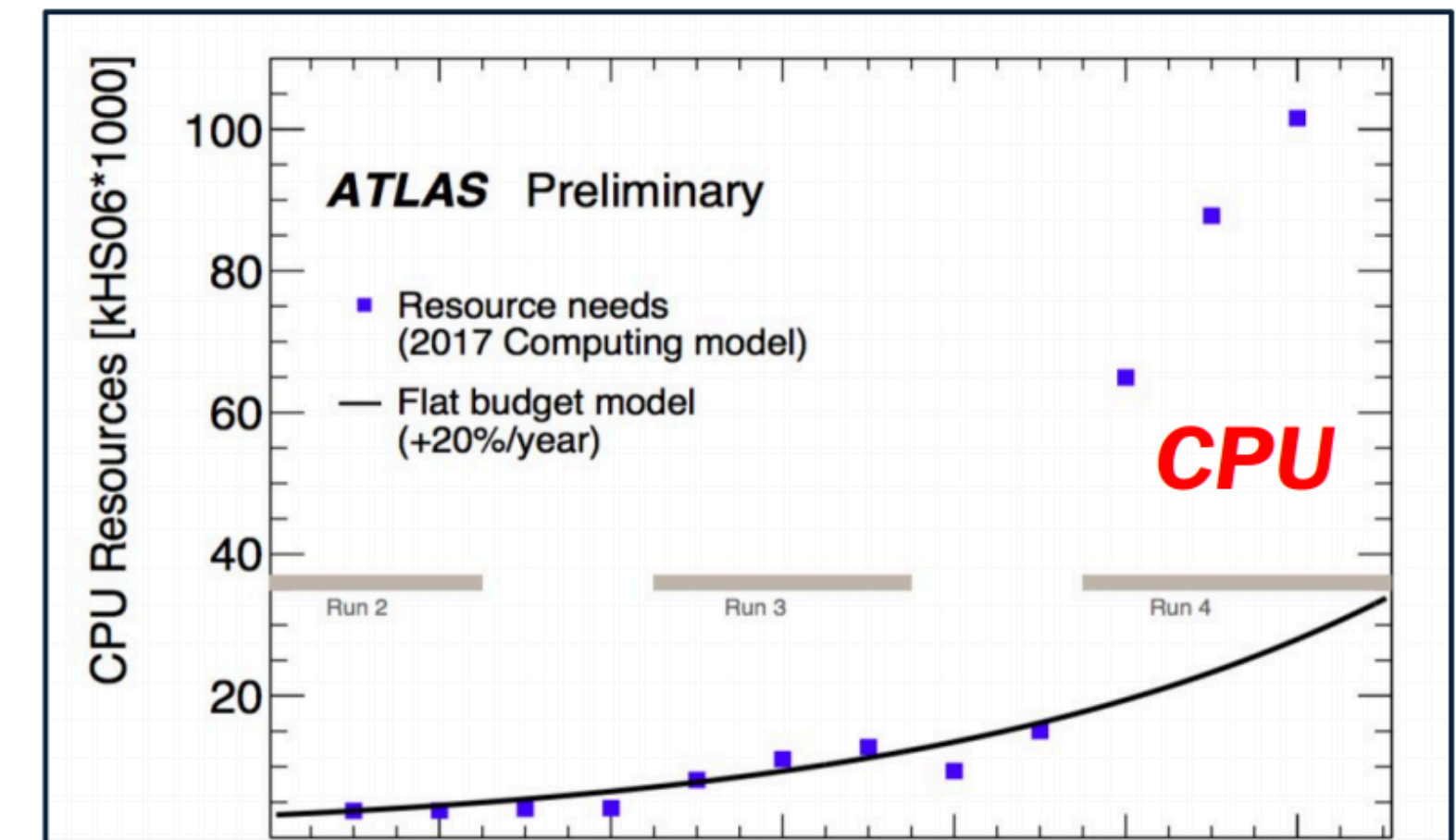
LSST: O(1) EB

SKA: O(0.5) EB/year

At an analysis level:

routinely O(100) TB that analysis teams process as a small group - will be O(PB)

- how do we maintain explorative research?



[LHC Projections]

Three Challenges of Big Science

2. The data is unique:

There is only one LHC / LSST / SKA / ...

- **What data products are released to the public?**
- **How do we ensure rigorous analysis if public?**



Square Kilometer Array



Rubin Observatory / LSST



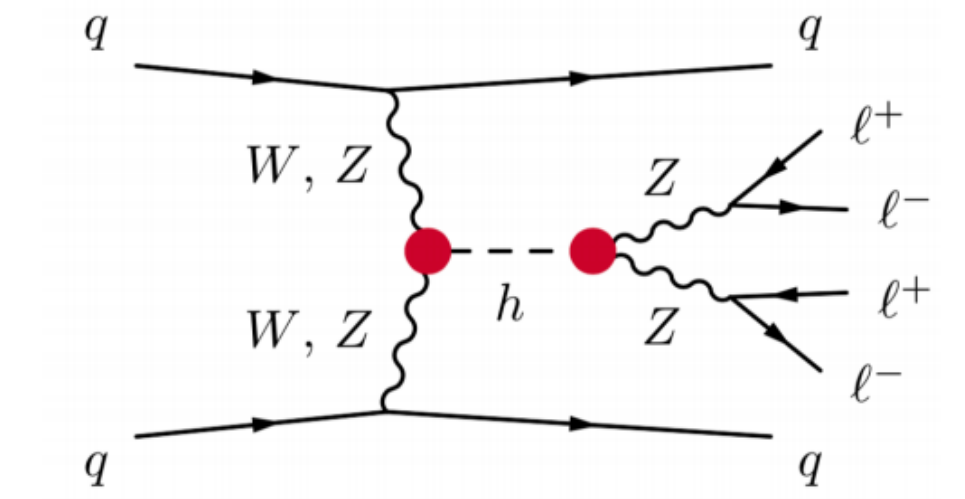
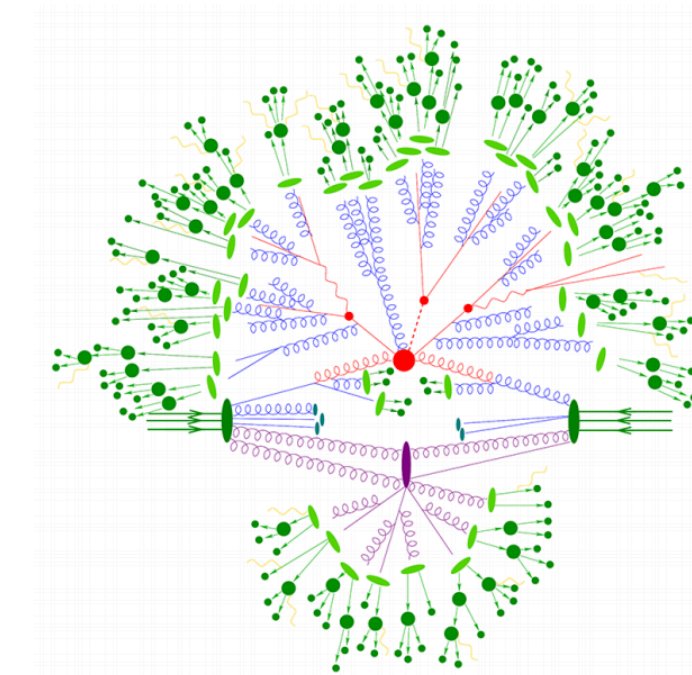
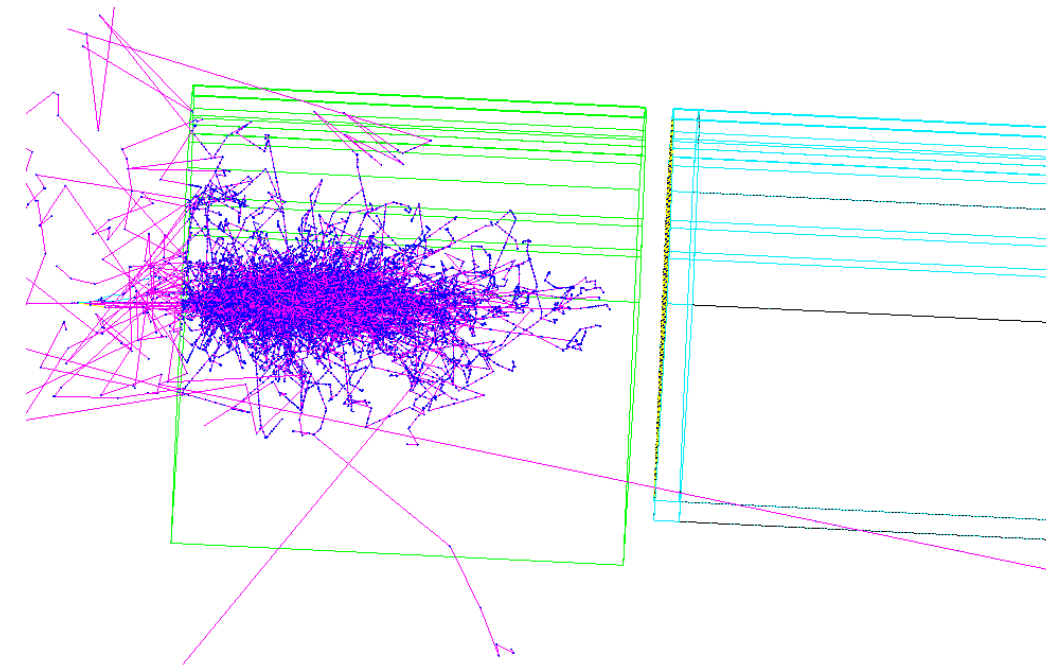
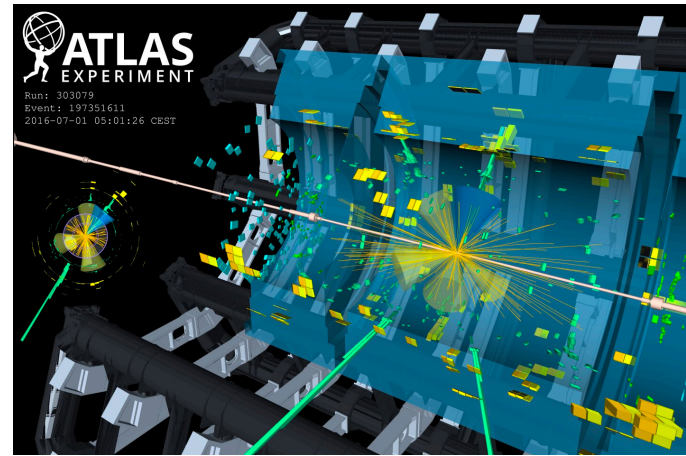
LHC

Three Challenges of Big Science

3. The data is complex:

In HEP:

- complex generative history across many energy scales
- heterogeneous detectors (not a single 100Mpx sensor / image)



$$p(x|\theta, \theta_{\text{nuis}}) = \iiint dz_d dz_h dz_p p(x|z_d, \theta_{\text{sensor}}) p(z_d|z_h, \theta_{\text{geom}}) p(z_h|z_p, \theta_{\text{pQCD}}) p(z_p|\theta)$$

high-dimensional
integrals: needs MC

Three Challenges of Big Science

3. The data is complex:

- analysis heavily simulation-driven
- heavy reconstruction from raw → physics data
- exceeds data volume & resources of actual data
- extremely software-reliant ($O(M)$ LoC)



Analyzing any part of the data is very expensive human resources-wise:

- can we prioritize human time over computing? → interactive analysis
- if we invest so much? → how do we exploit these analyses maximally?

Trends

Technical:

1. Machine Learning

- powerful & creeps into every aspect of scientific workflow
- raises questions of how analysis details are disseminated (th ↔ ex)

2. Cloud Computing & Heterogeneous Future Present

- anybody can get access to vast amounts of compute
- new requirements on hardware / software (GPU, CPU, TPU, Dataflow,...)

**can we use these to create new ways
to push our science forward?**

Trends

Political:

1. Open & FAIR Data

- publicly funded research must be accessible

2. Reproducibility

- Uniqueness of data & analysis → special responsibility

But how does this work at Big Science scale?

- usually not focus of those discussions.
- are there useful ways to interpret these buzzwords?

(Open) Data Analysis at LHC Scale

Open Data

Significant Development in HEP

All LHC Experiments agree to release data publicly.

including software to analyze rigorously

- (e.g. systematic uncertainties)

Intent:

- foster more interdisciplinary collaboration (e.g. ML, Theory, cross-experiment R&D, ...)

CERN announces new open data policy in support of open science

A new open data policy for scientific experiments at the Large Hadron Collider (LHC) will make scientific research more reproducible, accessible, and collaborative

11 DECEMBER, 2020



Data storage solutions at the CERN data centre (Image: CERN)

Geneva, 11 December 2020. The four main LHC collaborations (ALICE, ATLAS, CMS and LHCb) have unanimously endorsed a new open data policy for scientific experiments at the Large Hadron Collider (LHC), which was presented to the CERN Council today. The policy commits to publicly releasing so-called level 3 scientific data, the type required to make scientific studies, collected by the LHC experiments. Data will start to be released approximately five years after collection, and the aim is for the full dataset to be publicly available by the close

Open Data: a growing Ecosystem

New paradigm for HEP, we're learning.



CERN:

- develop supporting cyberinfrastructure (Open Data Portal, Zenodo)


Experiments:

- how to release data to outsiders

Theorists:

- develop data analysis expertise
- own ecosystem of tools

Can you scale to realistic analysis?



EnergyFlow

- Home
- Getting Started
- Installation
- Demos
- Examples
- FAQs

[Docs](#) » [Documentation](#) » [Datasets](#)

CMS Open Data and the MOD HDF5 Format

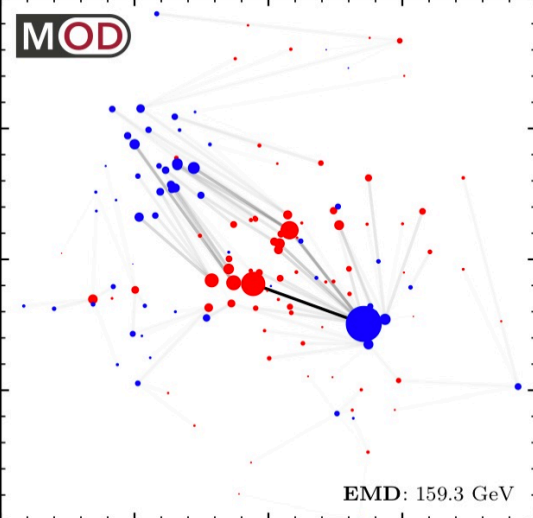
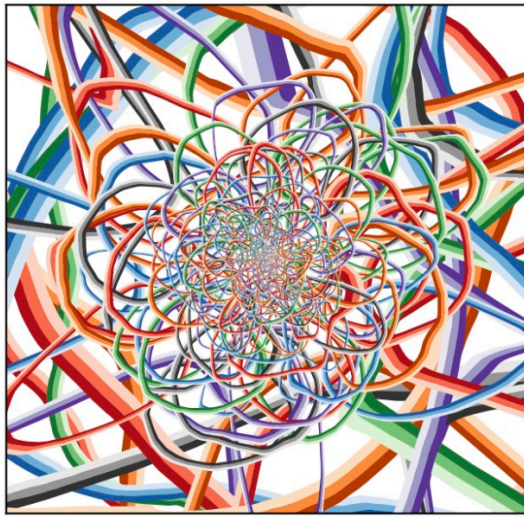
Starting in 2014, the CMS Collaboration began to release research-grade recorded and simulated datasets on the [CERN Open Data Portal](#). These fantastic resources provide a unique opportunity for researchers with diverse connections to experimental particle physics world to engage with cutting edge particle physics by developing tools and testing novel strategies on actual LHC data. Our goal in making portions of the CMS Open Data available in a reprocessed format is to ease as best as possible the technical complications that have thus far been present when attempting to use Open Data (see also [recent efforts by the CMS Collaboration](#) to make the data more accessible).

To facilitate access to Open Data, we have developed a format utilizing the widespread [HDF5 format](#) that stores essential information for some particle physics analyses. This "MOD HDF5 Format" is currently optimized for studies based on jets, but may be updated in the future to support other types of analyses.

To further the goals of Open Data, we have made our reprocessed samples available on the [Zenodo](#).

[Docs](#) » [Home](#)

Welcome to EnergyFlow




EnergyFlow is a Python package containing a suite of particle physics tools:

jupyter

nbviewer

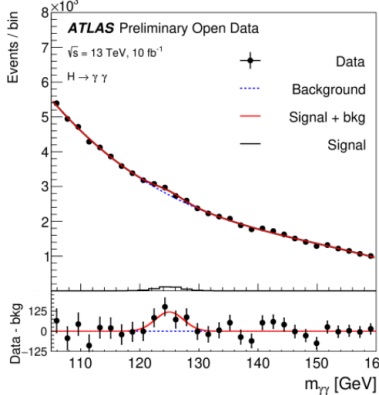
notebooks-collection-opendata / 13-TeV-examples / python



Get running the full H_{yy} analysis using the 13 TeV dataset in 5 minutes!

Introduction The analysis is based on the 13 TeV Open Data. The ATLAS note [ATL-OREACH-PUB-2020-001](#) can be used as a guide on the content, properties, capabilities and limitations of the released datasets.

In the following, in about **5 minutes** we are going to re-produce the H_{yy} analysis plots from the note.



```
In [ ]: import os
import ROOT
from ROOT import TMath
import time

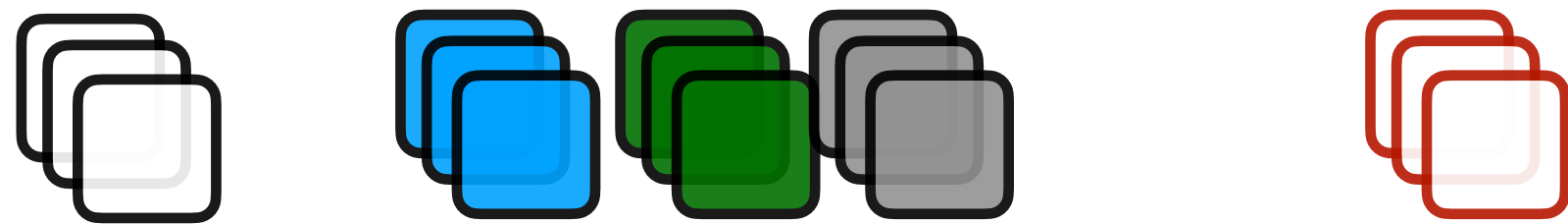
In [ ]: start = time.time()
```

[CMS OD] / [Thaler et al.]

Benchmark Example: CMS Open Data Higgs → 4l Analysis

Anatomy:

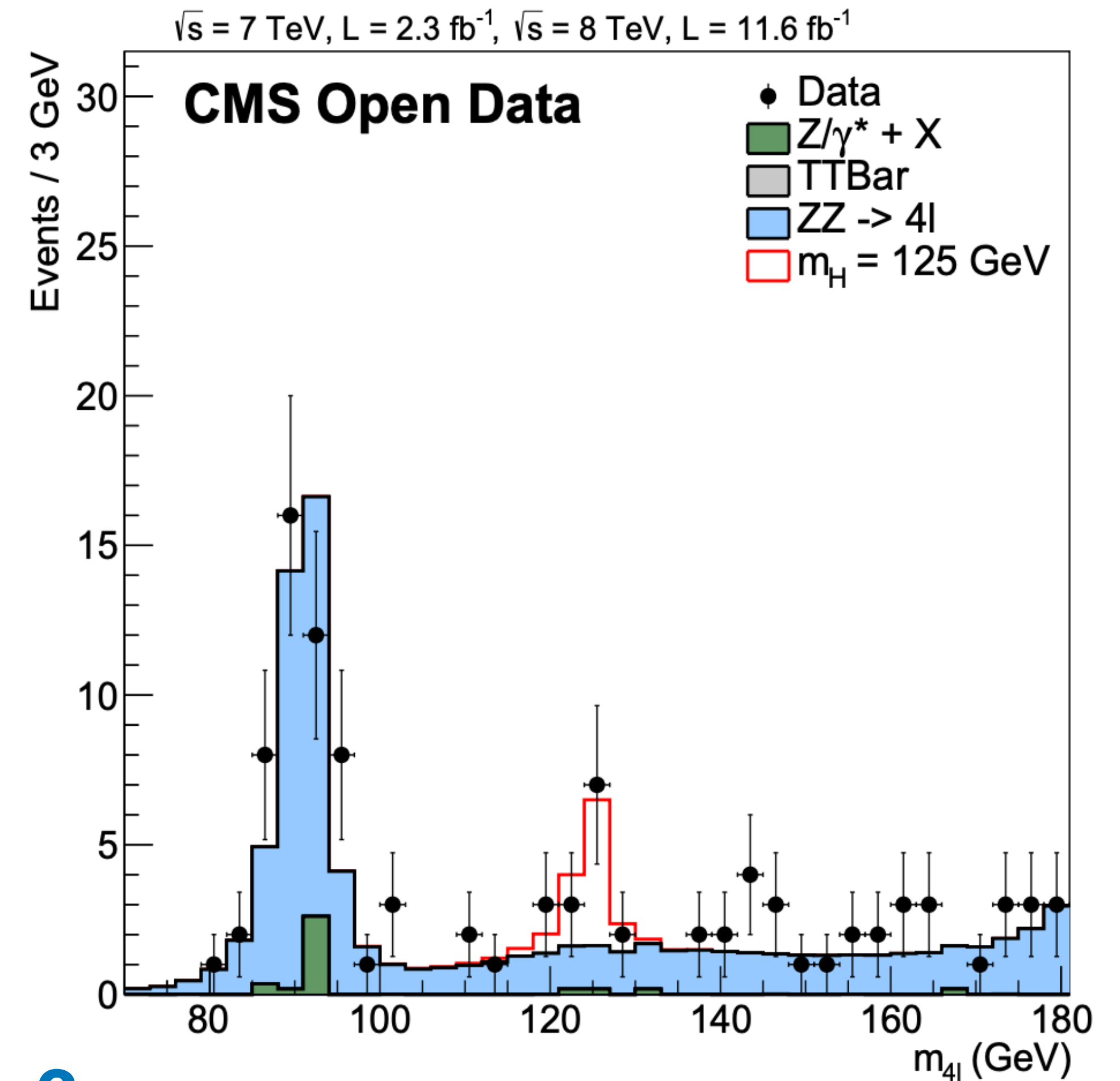
- 70TB / 25k files
- Data, Background + Signal Simulation



- C++ based data analysis (CMSSW)
(event selection + feature comp)

The physics is there:
but requires large-scale compute

Question: How quickly can we analyze the data?

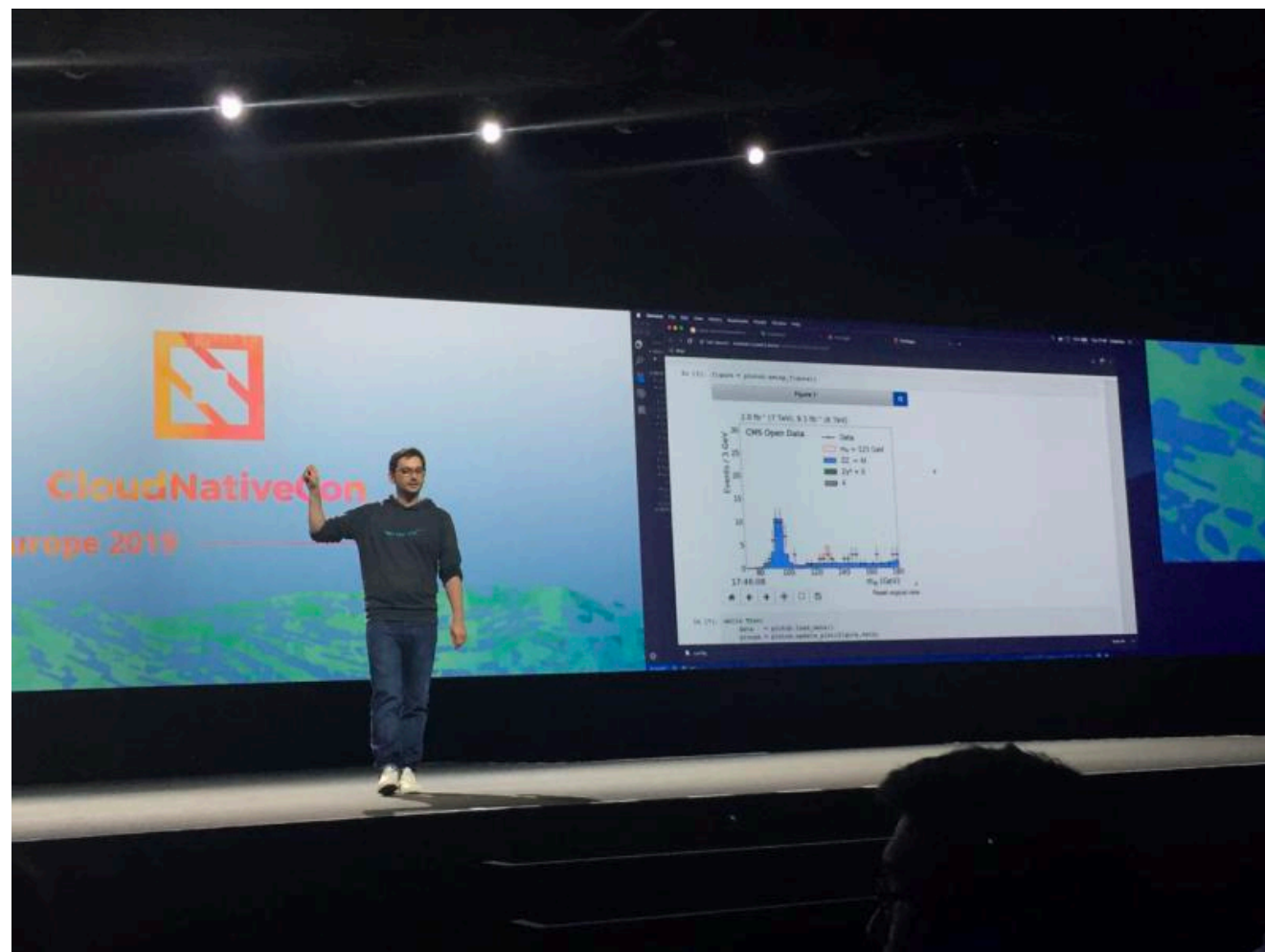


[A. Geiser, N. Jomhari]

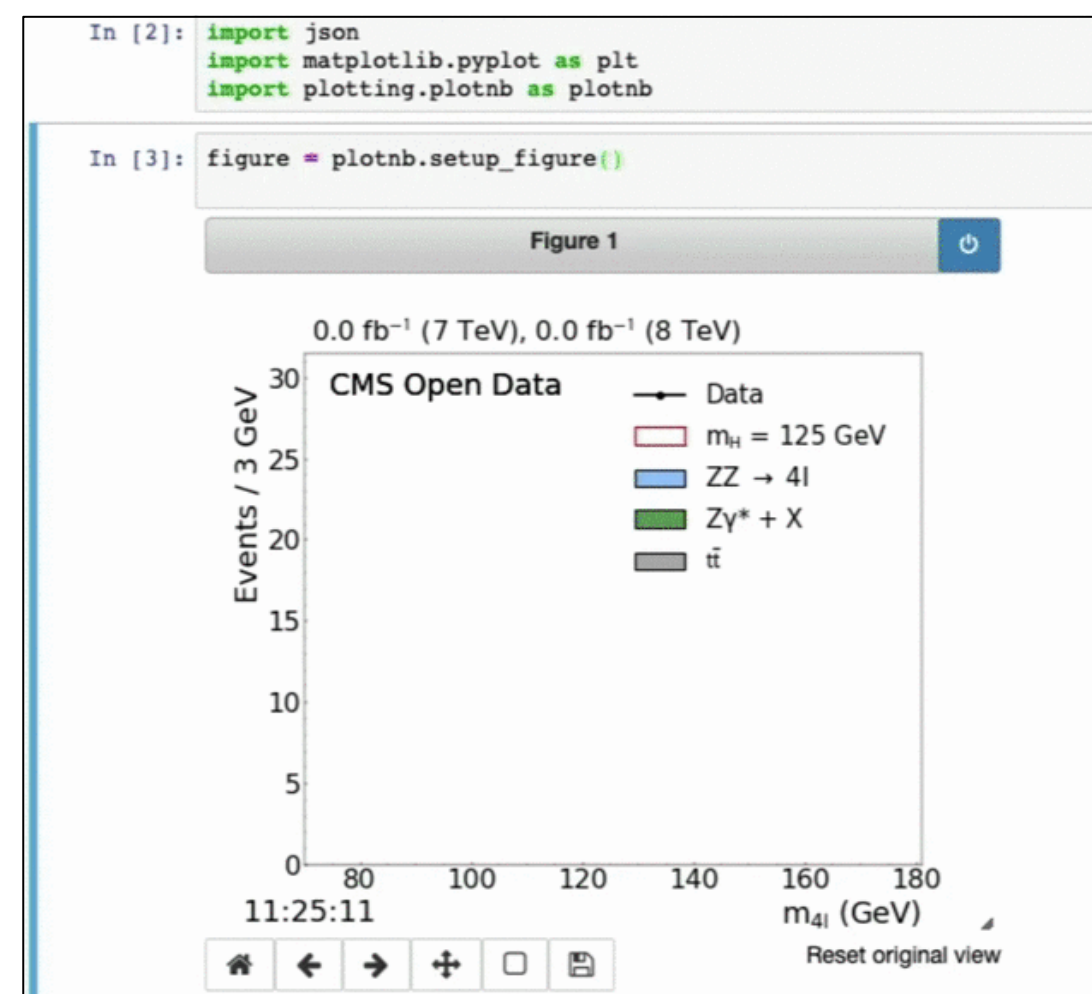
Benchmark Example: CMS Open Data Higgs → 4l Analysis

Answer: 5 minutes with cloud computing techniques → **>1Tbps throughput**
Fast enough to do 70TB analysis in real-time.

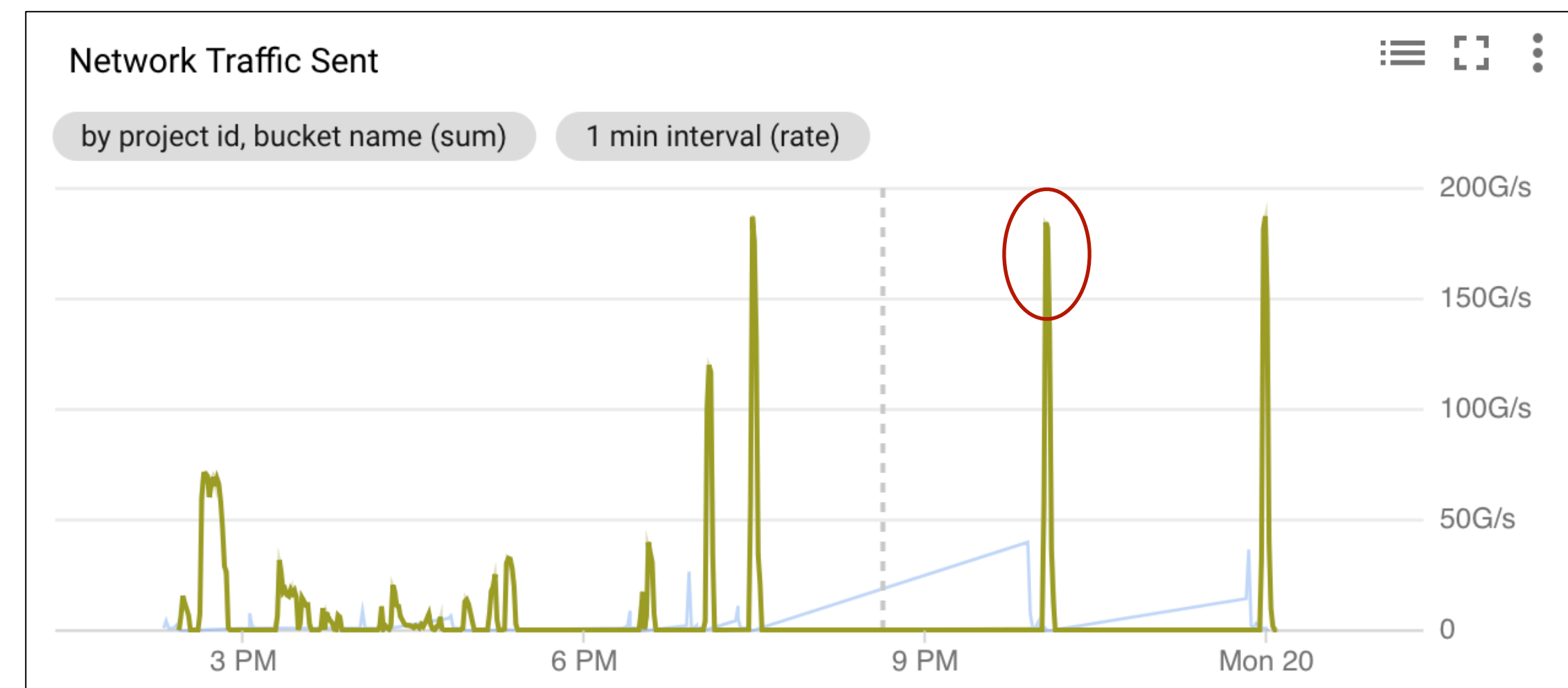
- Open Data as a tool for R&D to develop interactive analysis systems @ HL-LHC



[KubeCon 2019]



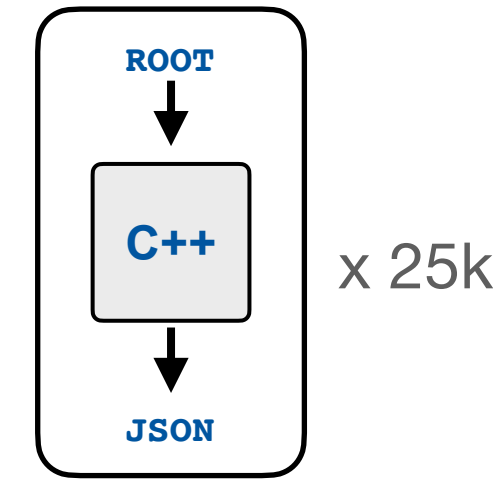
(slightly sped-up version) 15



[R. Rocha (CERN IT), LH (ATLAS), C. Lange (CMS)]

Setup

25k files → 25k cores across 10 clusters



Uses Kubernetes to schedule work

- cluster system originated in Google
- can handle service, batch, interactive work
- containers: easy to deploy HEP s/w

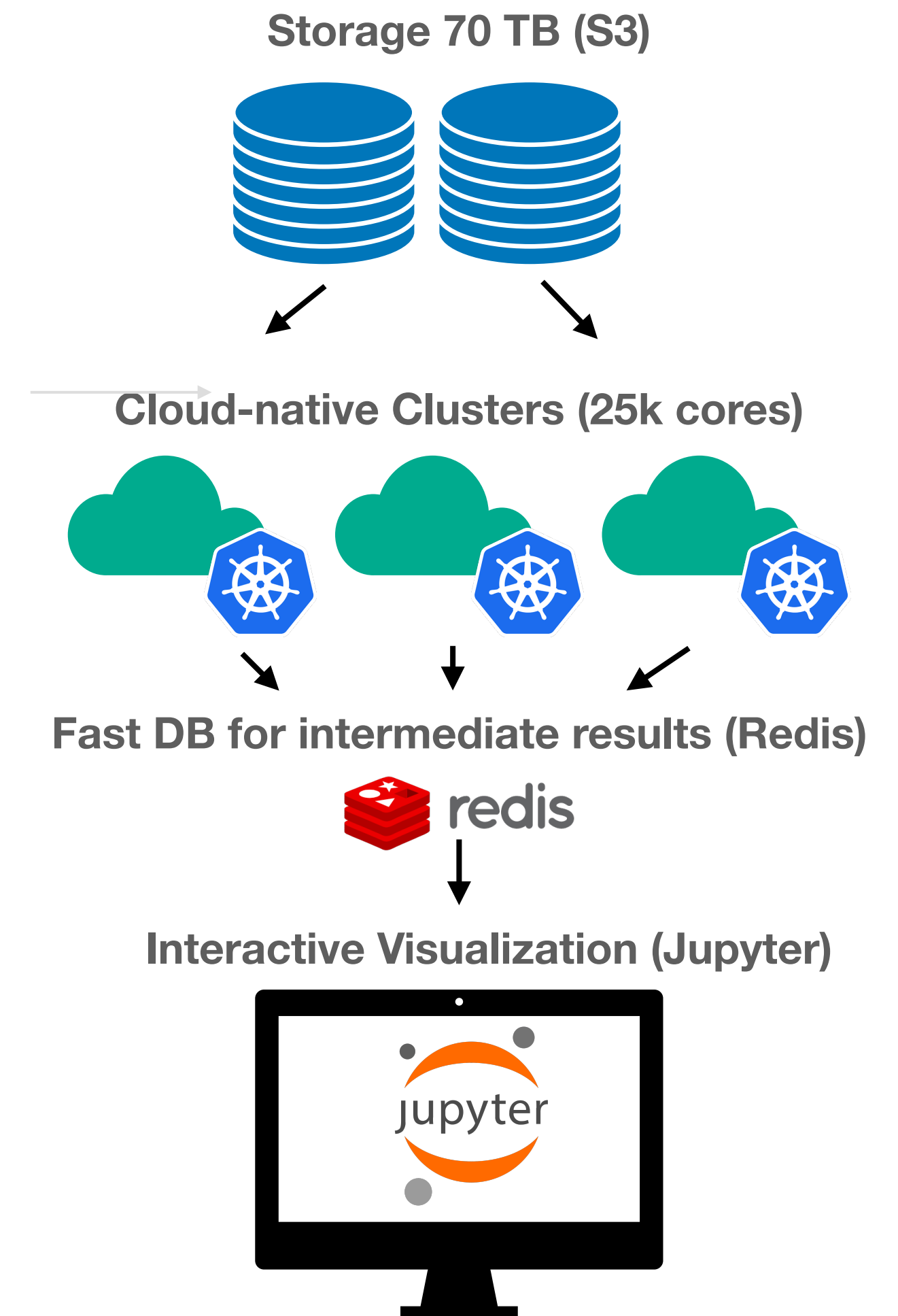
Cloud characteristic: only CPUh matters

- **25k CPU @ 5 minutes = 8 CPU @ 10d**

(not true for physicist-hours, try to minimize time to do physics)

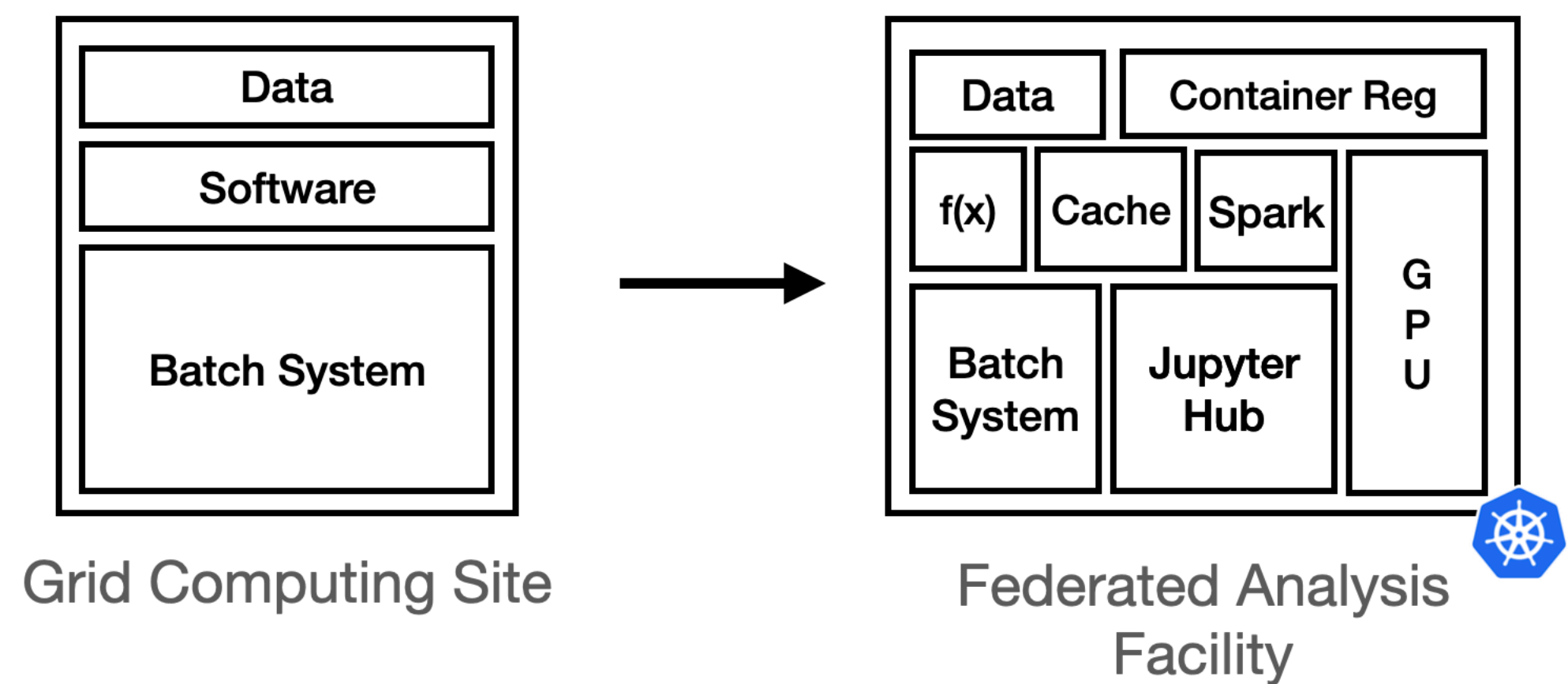
- **individual user can get this on-demand**

(as long as you can pay)



Bringing the technology to HEP

- push to go beyond standard batch/grid picture
→ Analysis Facilities / Science Platforms (cf: PUNCH4NFDI / IRIS-HEP)
- crucial for maintaining physics-driven/explorative data analysis at next phase of physics experiments: **technology choices matter.**



[Adamec et al]

871v1 [cs.DC] 2 Mar 2021

Coffea-casa: an analysis facility prototype

Matous Adamec¹, Garth Jones², and Oksana Shadura¹, and

¹University of Nebraska-Lincoln
²Morgridge Institute for Energy

Abstract. Data analysis loops; users consider data access, resources and interfaces and interactive computing based Coffea. In this paper, we discuss the access and au

[Banek et al]

(I6.1) Why is the LSST Science Platform built on Kubernetes?

Christine Banek,¹ A. K. Simon Krughoff

¹AURA/LSST, Tucson

Abstract. LSST has the LSST Science Platform decision, including the We then discuss the as the deployment ba example of how an e to deploy their own needs. Finally, we di gain similar benefits.

1. Introduction

The Large Synoptic Survey easily stored, copied, or analyzed, due to

[Megino et al]

ATLAS EXPERIMENT

Using Kubernetes as an ATLAS computing site

Fernando Barreiro Megino, Jeffrey Ryan Albert, Frank Berghaus, Danika MacDonell, Tadashi

The diagram shows the ATLAS computing site architecture. A 'PanDA job' is submitted to a 'Harvester' which contains a 'Core' and 'K8s Submitter'. The 'K8s Submitter' creates 'K8s jobs' which are sent to a 'K8s master'. The 'K8s master' manages a 'K8s cluster' consisting of multiple 'Nodes'. Each 'Node' contains 'Pods' (labeled 'Pilot') and a 'K8s Sweeper'. The 'K8s Sweeper' cleans up 'K8s jobs' and polls 'K8s job states'. The 'K8s cluster' is connected to an 'RSE' (Remote Storage Element) via 'I/O'.

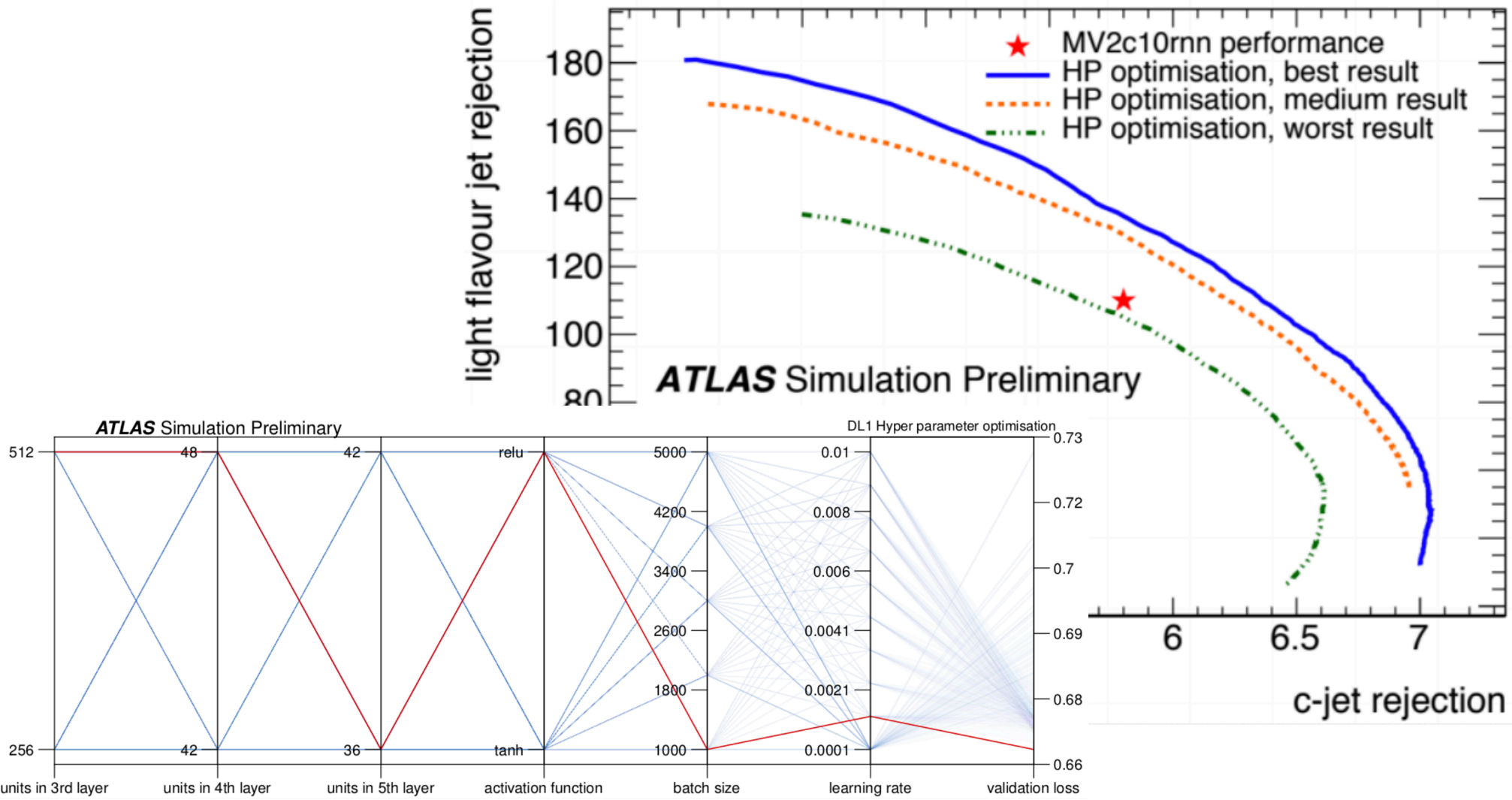
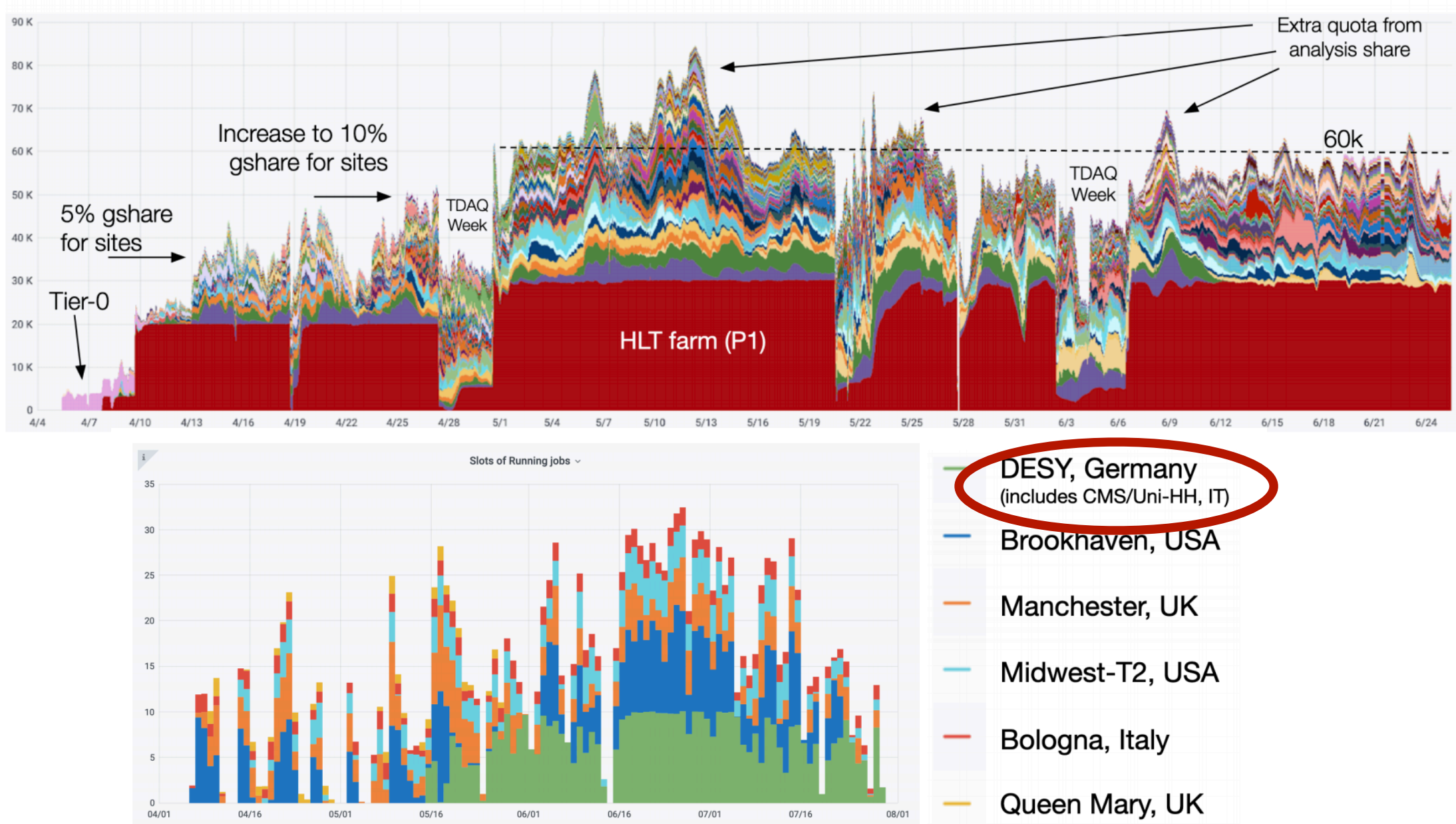
Bringing the technology to HEP

In production:

- Grid-scale ML on GPUs (ATLAS)
- WLCG for volunteer computing (folding@home, 50k cores)

Key: Containers allowing user-defined s/w environment

A Forti, M Guth, D Guest, C Pollard, LH



Folding@Home Teams Overall Rankings										
Teams are color coded based on 24 hour average production. Color codes are as follows: 0 / 1+ / 100k+ / 250k+ / 500k+ / 1M+ / 2.5M+ / 5M+ / 10M+										
Rank Overall	Team Name	Users Active	Users Total	Change 24hr	Change 7days	Points 24hr Avg	Points Update	Points Today	Points Week	P...
1	Default (Team 0)	1,200	2,000			14,868,491,388	1,629,724,245	4,966,192,700	33,501,103,756	732,3
2	LinusTechTips Team	26,910	105,550			5,072,271,918	595,799,121	1,704,651,305	11,430,427,220	378,6
3	Curecoin	3,887	23,837			1,209,843,224	154,586,434	445,858,938	2,809,558,226	1,164,5
4	DC Master Race - DCMB	7,746	48,847			1,056,141,646	114,336,343	330,371,240	2,302,740,356	83,5
5	CERN & LHC Computing	145	214	+1 ▲	+7 ▲	794,993,726	103,003,621	301,591,243	1,862,010,985	20,4
6	NVIDIA Corp	46	74		+6 ▲	943,008,120	83,172,296	236,982,978	1,861,543,403	26,3
7	folding@evga	1,003	19,610			644,096,447	78,377,970	230,860,571	1,477,464,856	379,0
8	VMware	769	1,696		+2 ▲	450,549,575	56,778,849	172,933,812	1,081,783,018	18,9

Is dumping PB of data open enough?

Beyond Open Data

Open Data: with great freedom comes great responsibility

- allows looking at uncovered corners of the dataset (comp. feasible)
- but: cost of developing an analysis *in full rigour* is enormous

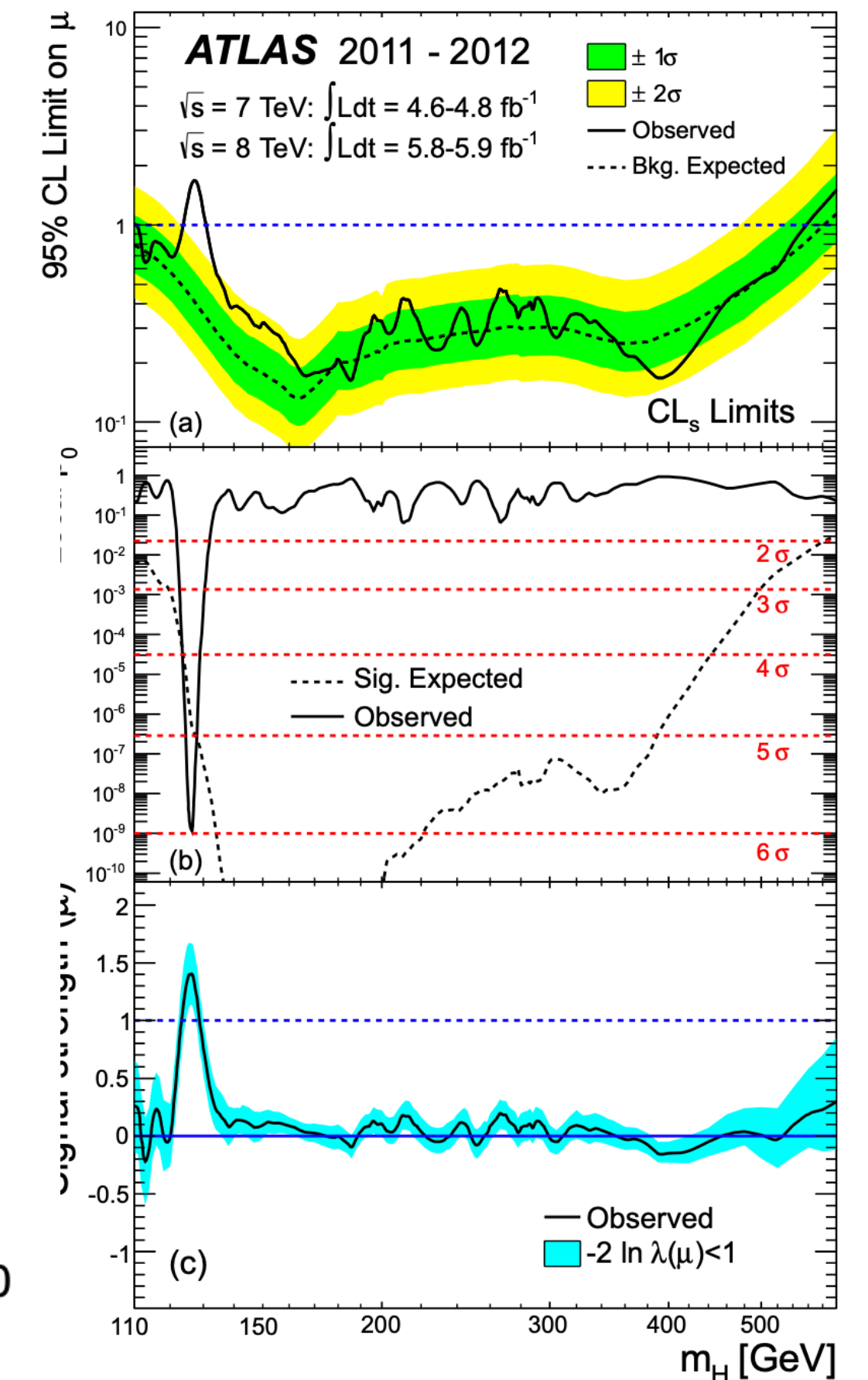
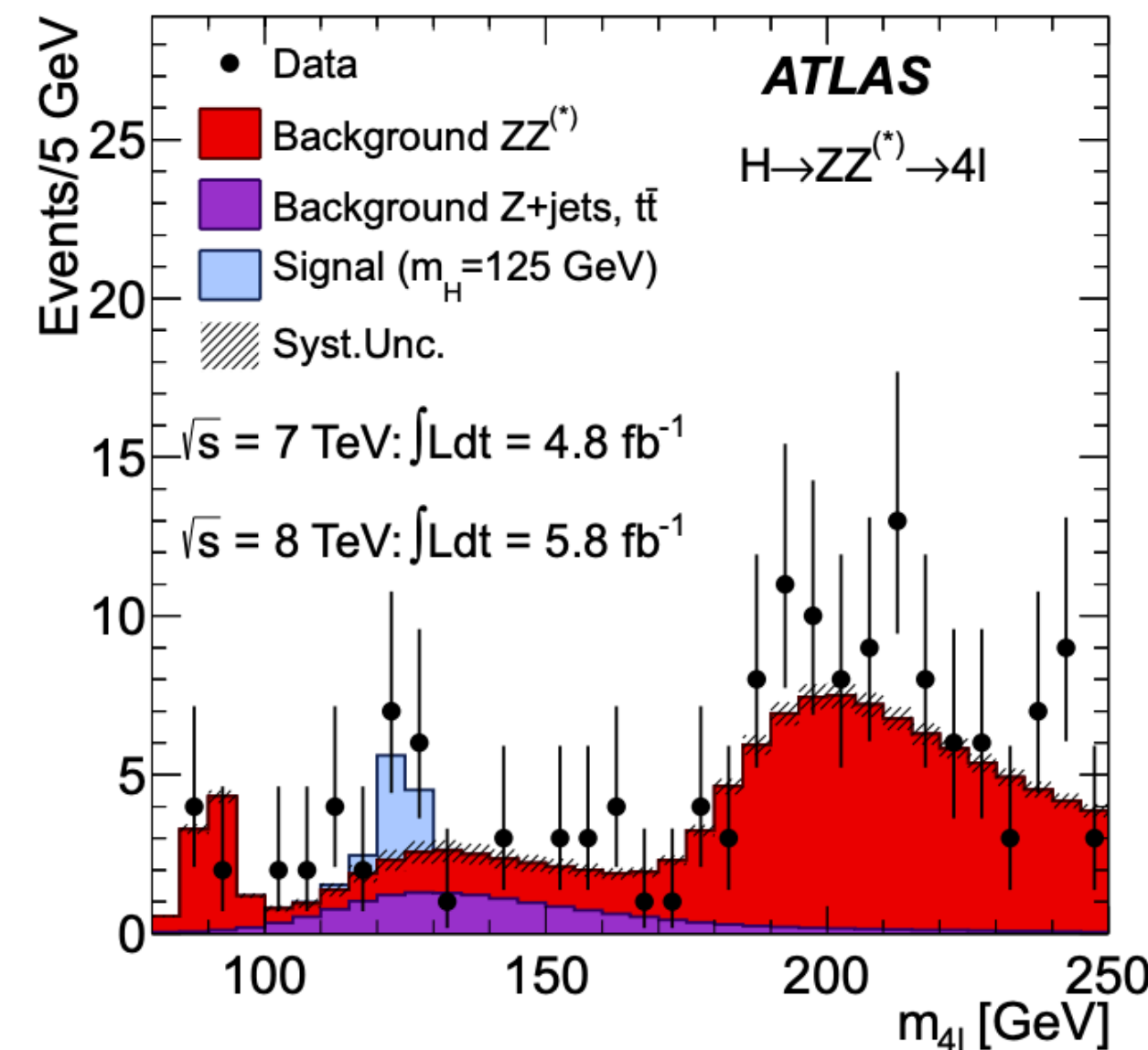
Are there other ways data can be "open"?

→ instead of the source data, release the result data

What should we release?

- many types of results

Event Counts, post-fit parameters
p-value scans,



Remember:

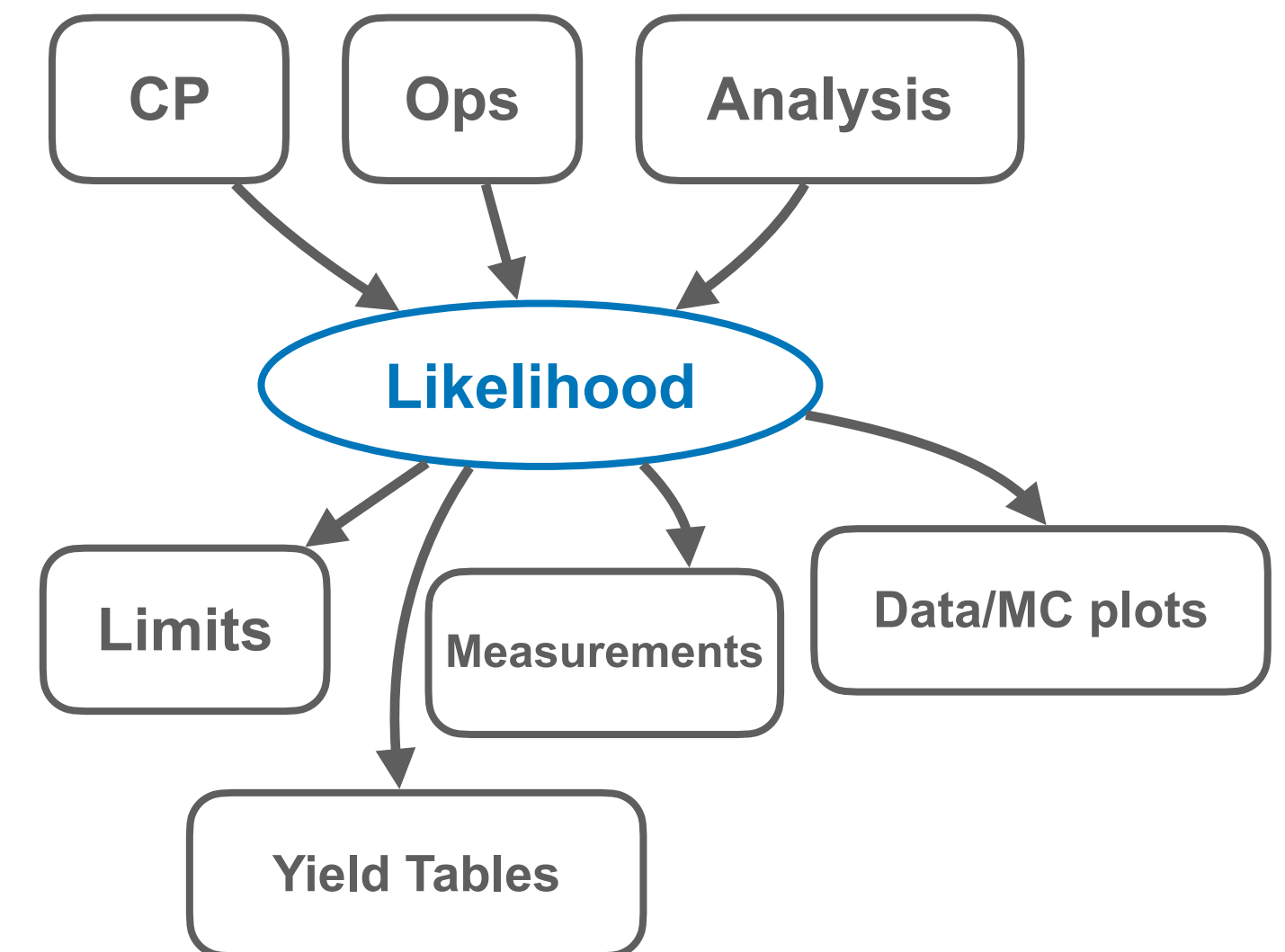
$$p(\text{theory}|\text{data}) = \frac{p(\text{data}|\text{theory})}{p(\text{data})}p(\text{theory})$$

Likelihood Principle:

Full experimental information captured in the likelihood $p(x | \theta)$!

- all analysis details are reflected in it
- most other types of results are derived from it.

Best, almost lossless summary of the measurements performed by a data analysis



1st PHYSTAT workshop:

- preserve the likelihood!
- universal concept applicable to a broad set of experiments (also beyond HEP)

CERN 2000-005
30 May 2000

516200026

ORGANISATION EUROPÉENNE POUR LA RECHERCHE NUCLÉAIRE
CERN EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH

WORKSHOP ON CONFIDENCE LIMITS

CERN, Geneva, Switzerland
17-18 January 2000

CERN LIBRARIES, GENEVA



P00037096

PROCEEDINGS

Editors: F. James, L. Lyons

GENEVA
2000

Massimo Corradi

It seems to me that there is a general consensus that what is really meaningful for an experiment is *likelihood*, and almost everybody would agree on the prescription that experiments should give their likelihood function for these kinds of results. Does everybody agree on this statement, to publish likelihoods?

Louis Lyons

Any disagreement ? Carried unanimously. That's actually quite an achievement for this Workshop.

Likelihoods

How do we archive likelihoods?

Not straightforward:

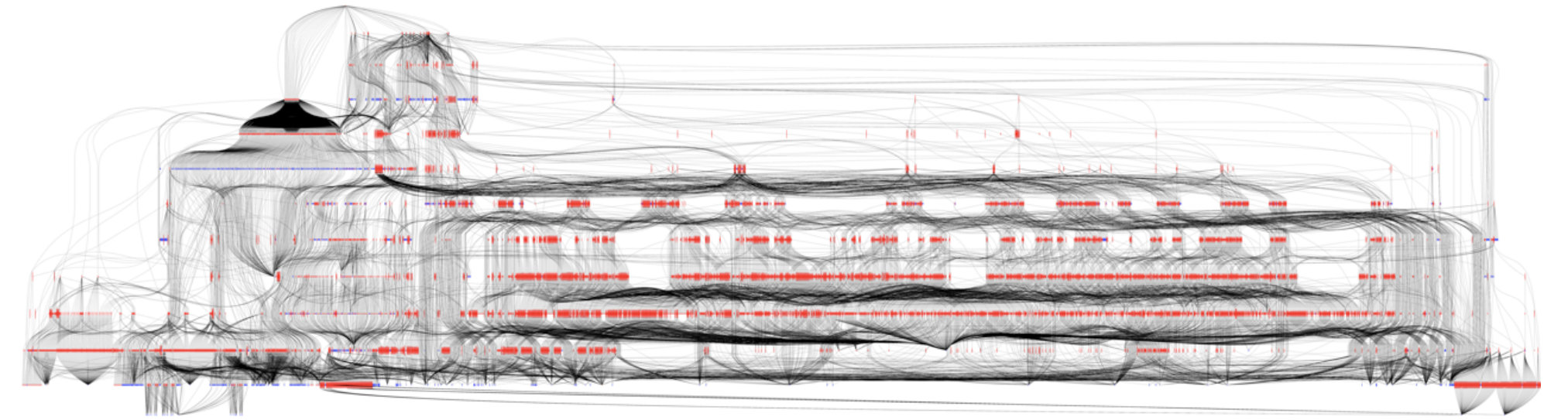
$p(x | \theta)$ could be anything! (Open World)

Obvious Candidate: RooFit workspaces

- Key development in early LHC stats
- designed as "sharable data product"

But:

- opaque, binary format
- tied to specific data analysis tool



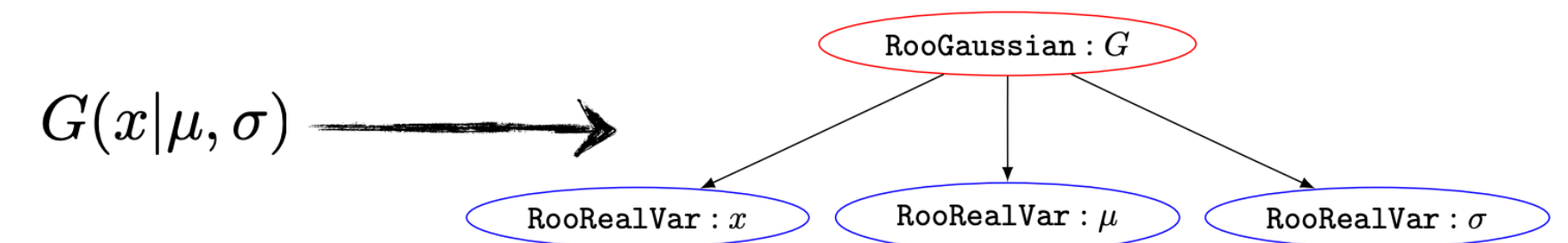
What goes in a Workspace



The workspace stores the full probability model and any data necessary to evaluate the likelihood function

- it is the code necessary to evaluate the likelihood function at an arbitrary point in the parameter space. It is not a big table of likelihood values!
- we are using the same ROOT technology that the LHC experiments are using to save their data
 - well supported, and supports "schema evolution" / backwards compatibility
- the probability model also allows you to generate toy data for any given parameter point
 - necessary for frequentist methods, goodness of fit, coverage)
- PDFs and functions can be extended by the user (source stored in workspace)

I will show some visualization of real-life LHC probability models. Let's start with a simple example:



Likelihoods

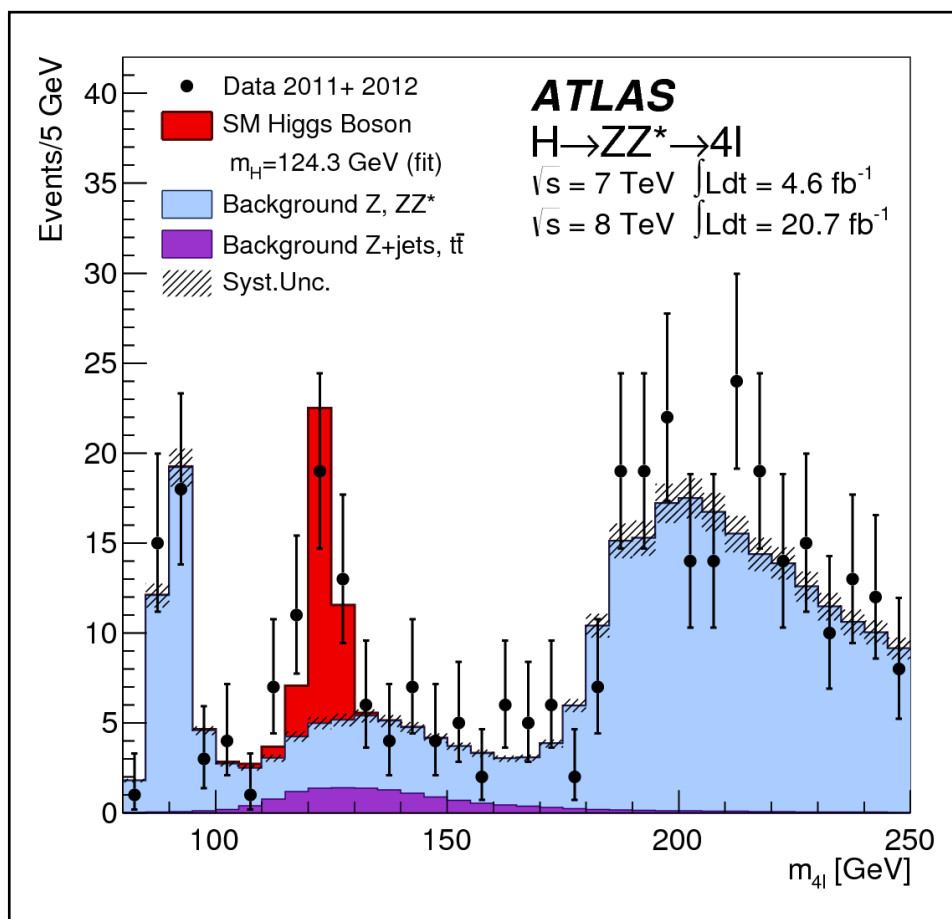
$p(x | \theta)$ could be anything... but in reality they're not!

For LHC a very large fraction of analyses use standardized binned likelihood functions built from **data counts + simulation-derived templates**

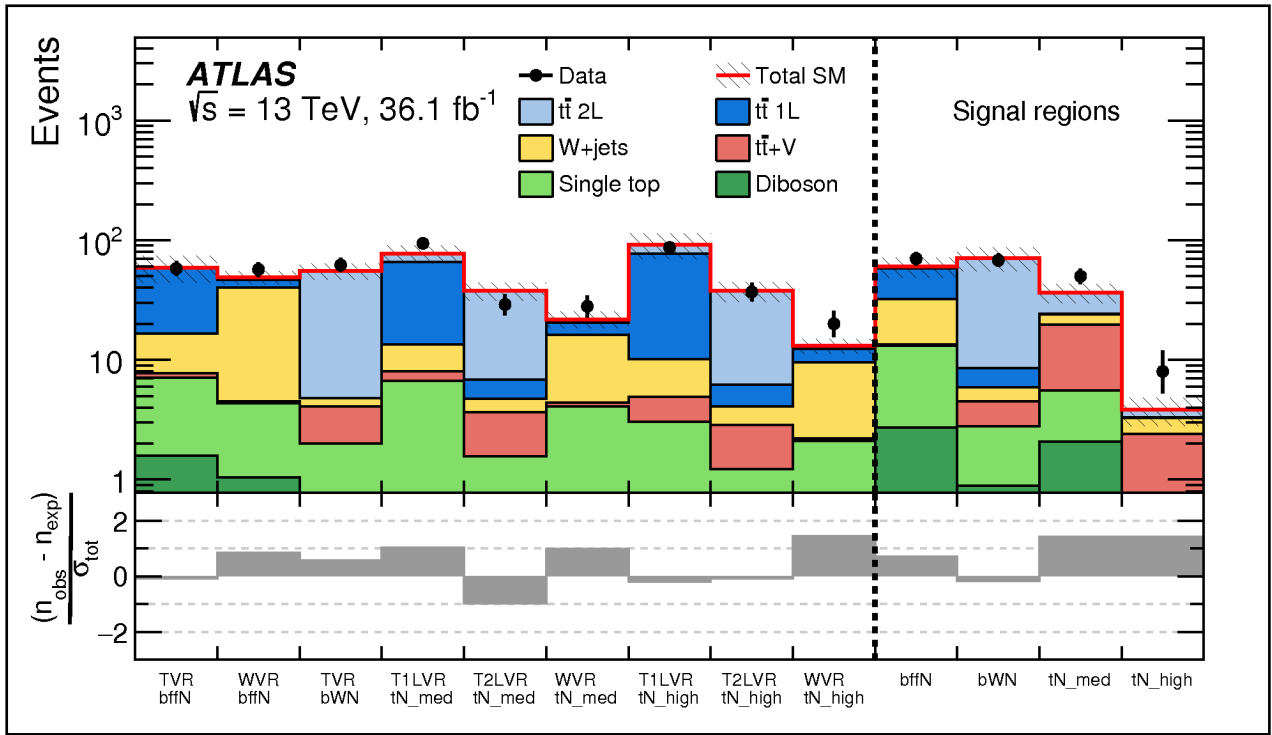
ATLAS: HistFactory
CMS: HiggsCombine

→

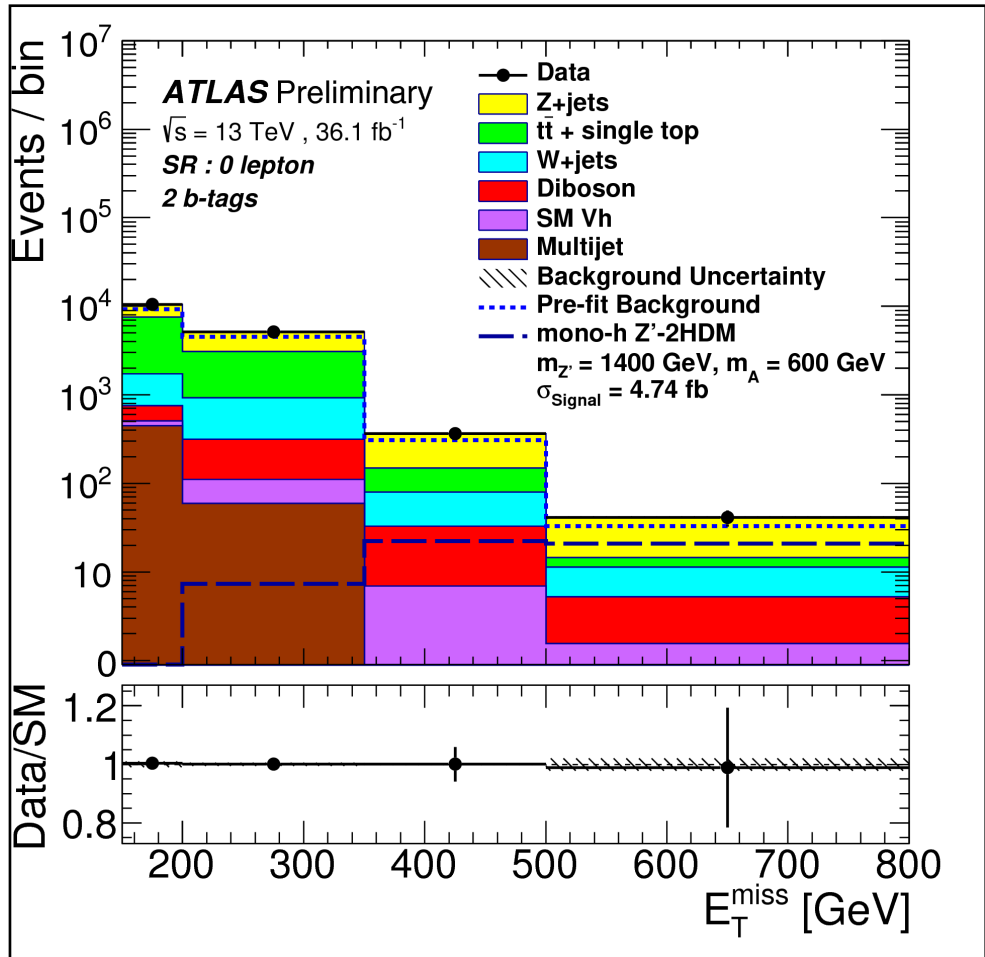
$$f(n, a | \eta, \chi) = \underbrace{\prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb} | \nu_{cb}(\eta, \chi))}_{\text{Simultaneous measurement of multiple channels}} \underbrace{\prod_{\chi \in \chi} c_{\chi}(a_{\chi} | \chi)}_{\text{constraint terms for "auxiliary measurements"}},$$



SM



SUSY



Exotics

HistFactory

Fixed Template (Closed World) simplifies likelihood problem:

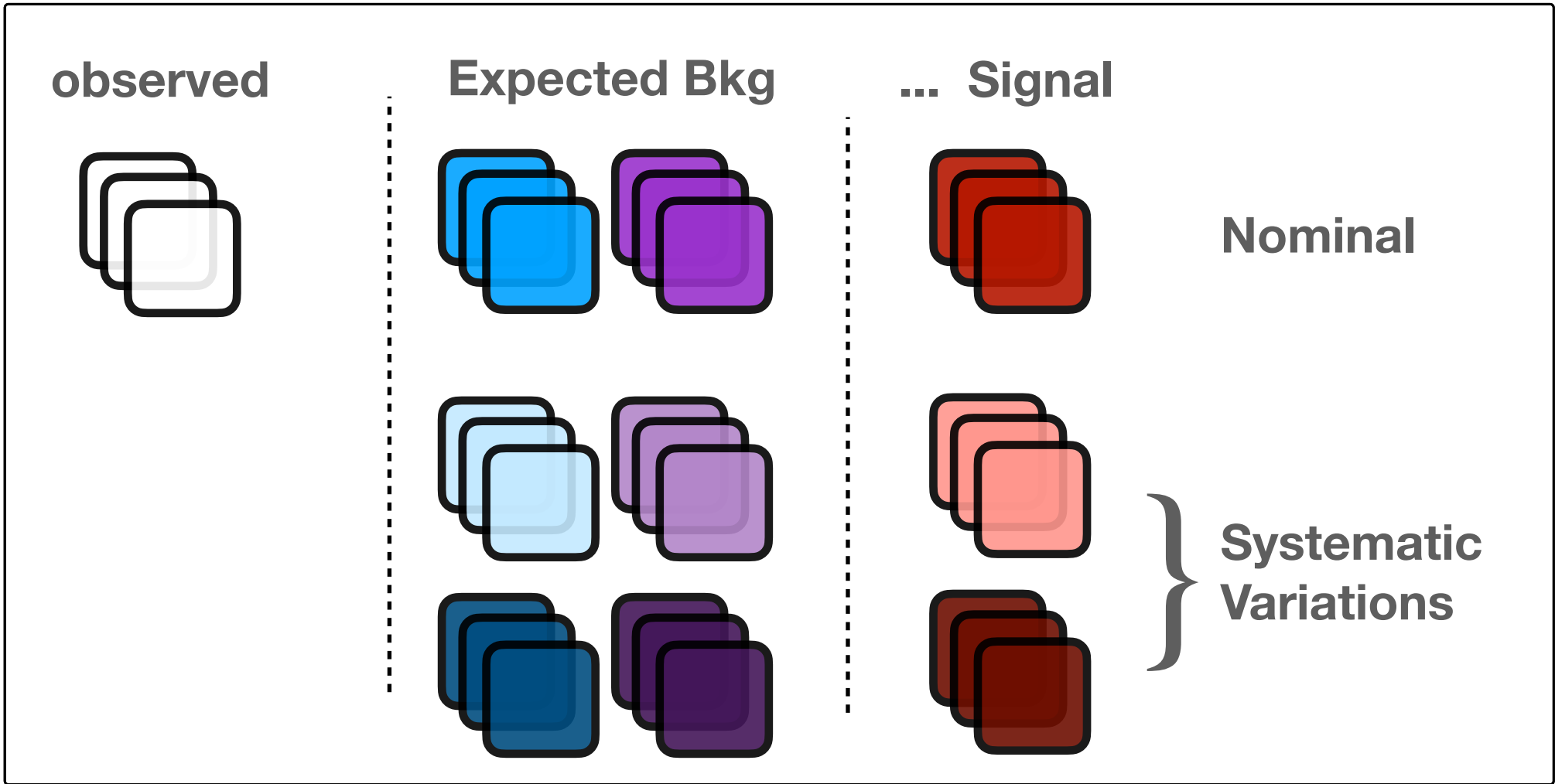
- archive template ingredients
(pure tabular data)
- template math defined independent
of implementation - not tied to s/w

Fixed Likelihood template

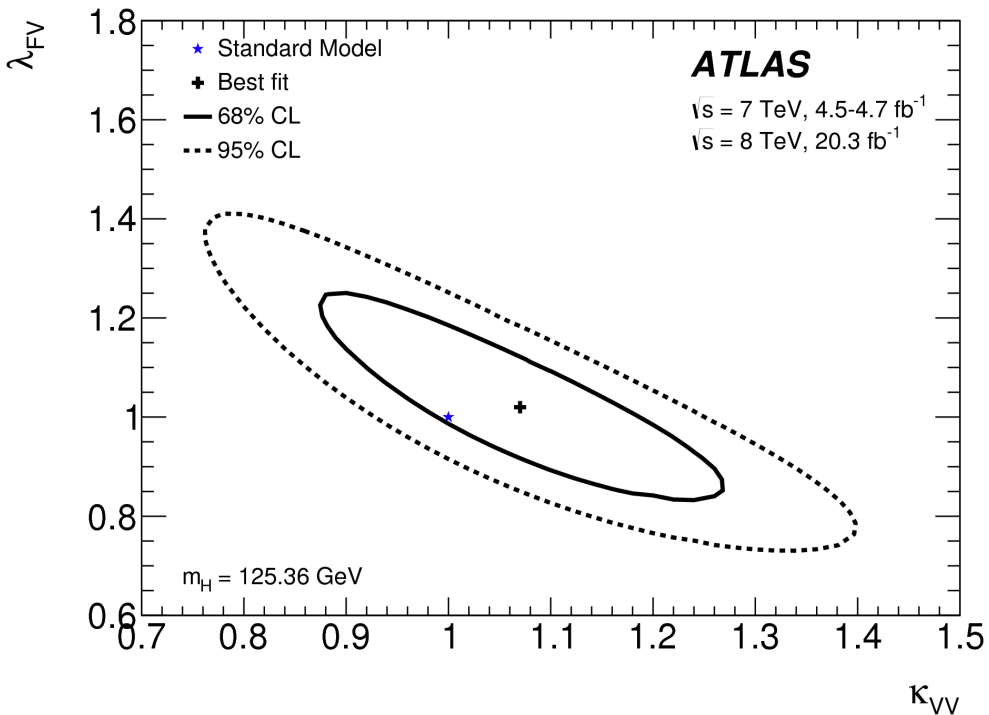
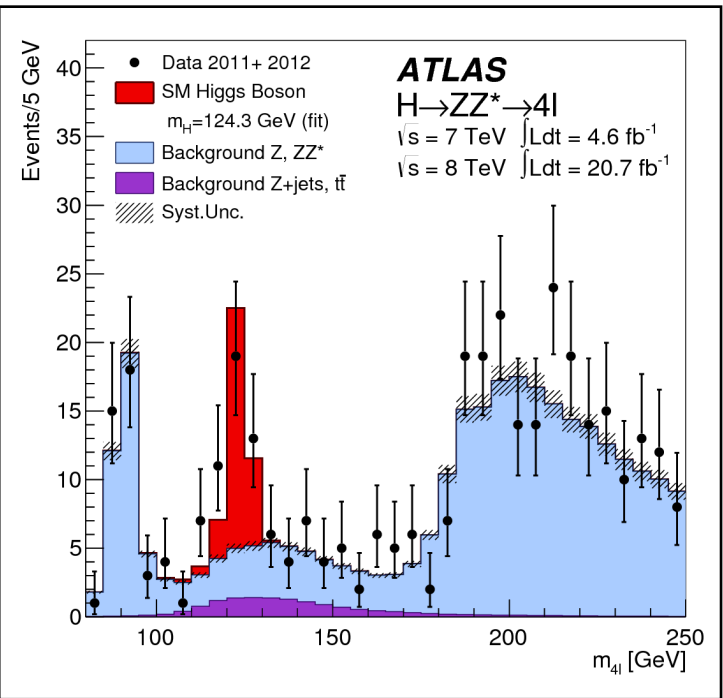
$$f(n, a | \eta, \chi) = \underbrace{\prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb} | \nu_{cb}(\eta, \chi))}_{\text{Simultaneous measurement of multiple channels}} \underbrace{\prod_{\chi \in \chi} c_{\chi}(a_{\chi} | \chi)}_{\text{constraint terms for "auxiliary measurements"}},$$

+

Likelihood ingredients



=



pyhf byproduct: JSON serialization

Plain-text format for HEP Workspaces

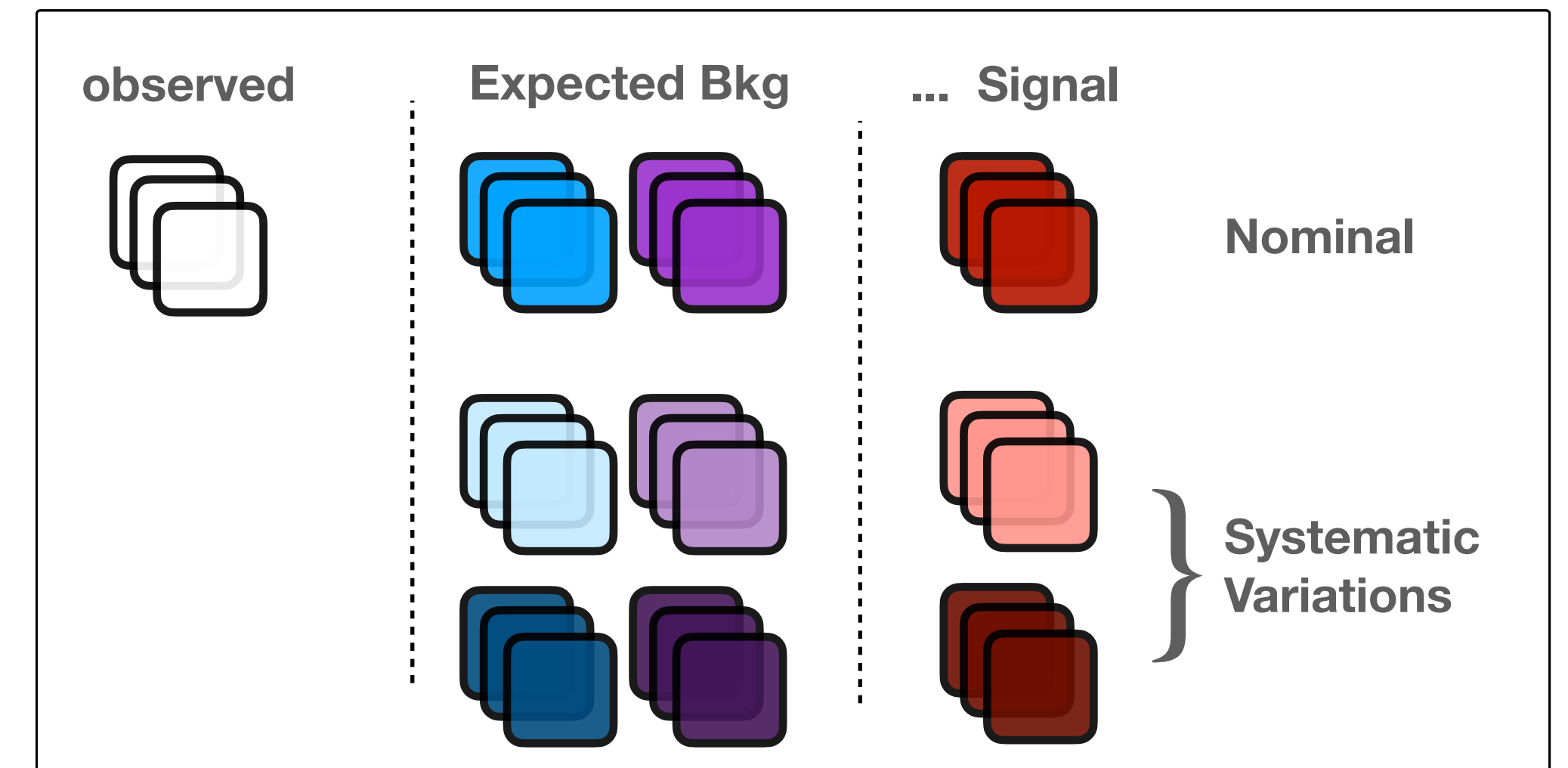
(for those using HistFactory template)

Ubiquitous format: JSON

- readable in any language
- independent of s/w implementation

Ideal for long-term archival of likelihoods

→ as promised in 2000

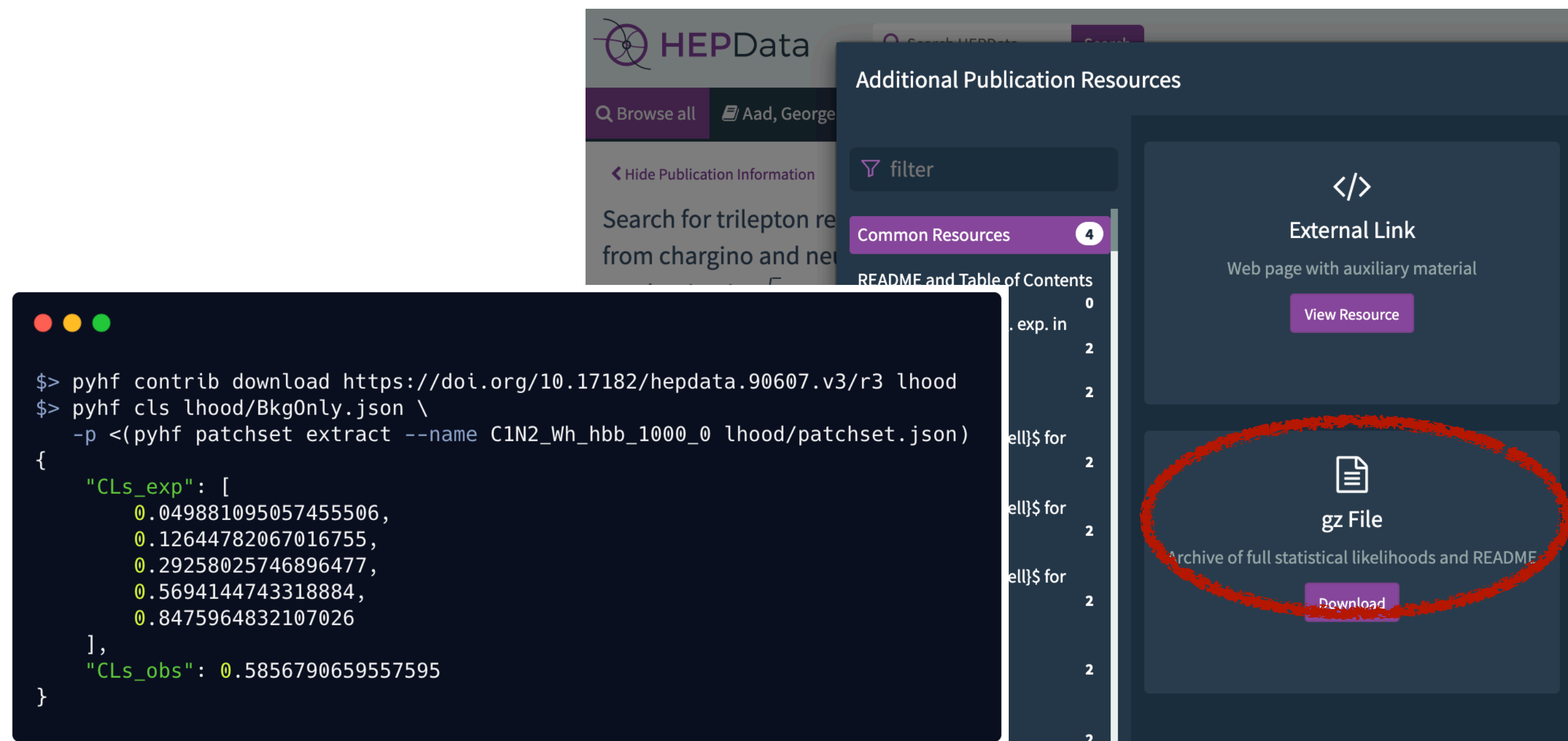


```
{
  "channels": [
    {
      "name": "singlechannel",
      "samples": [
        {
          "name": "signal",
          "data": [7.0, 2.0],
          "modifiers": [ { "name": "mu", "type": "normfactor", "data": null } ]
        },
        {
          "name": "background",
          "data": [50.0, 60.0],
          "modifiers": [ { "name": "uncorr_bkguncrt", "type": "shapesys", "data": [5.0, 12.0] } ]
        }
      ]
    }
  ],
  "data": {
    "singlechannel": [50, 60]
  },
  "measurements": [
    {
      "name": "Measurement",
      "config": { "poi": "mu", "parameters": [] }
    }
  ]
}
```


Likelihood Preservation in ATLAS

ATLAS first experiment to publish full likelihood

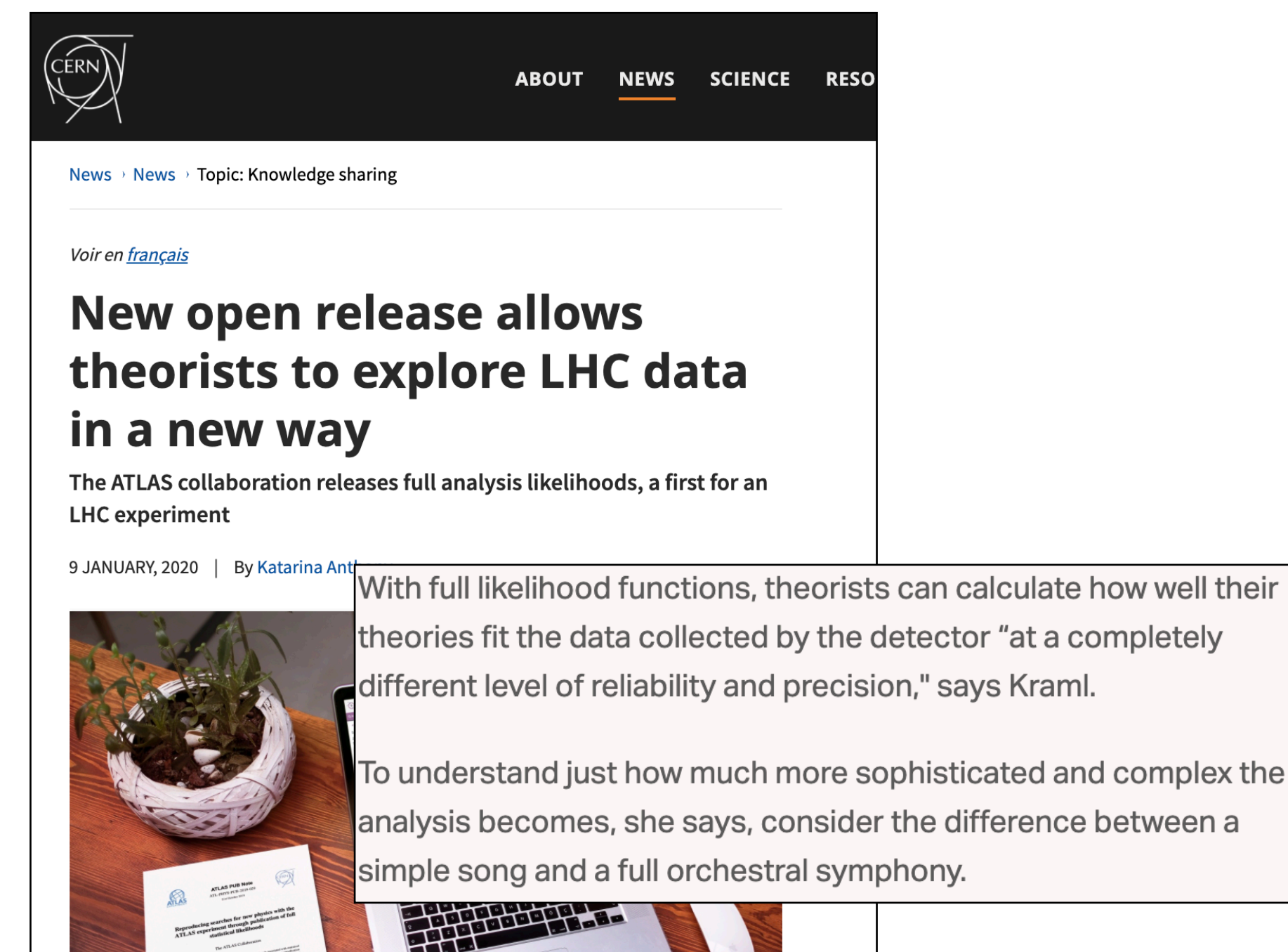
- stored on public archive as citable data product: HepData DOI
- continuation of long-term effort (cf. simplified l'hoods in CMS) [N. Wardle et al]
- best information we have **even within experiment**
full set of systematics → global fits / combinations / ...



The image shows a terminal window on the left and a HepData web interface on the right. The terminal displays the following commands and output:

```
$> pyhf contrib download https://doi.org/10.17182/hepdata.90607.v3/r3 lhood
$> pyhf cls lhood/BkgOnly.json \
-p <(pyhf patchset extract --name C1N2_Wh_hbb_1000_0 lhood/patchset.json)
{
  "CLs_exp": [
    0.049881095057455506,
    0.12644782067016755,
    0.29258025746896477,
    0.5694144743318884,
    0.8475964832107026
  ],
  "CLs_obs": 0.5856790659557595
}
```

The HepData interface on the right shows a search for 'trilepton re' and a list of 'Additional Publication Resources'. A red circle highlights the 'gz File' section, which contains the text 'Archive of full statistical likelihoods and README' and a 'Download' button.

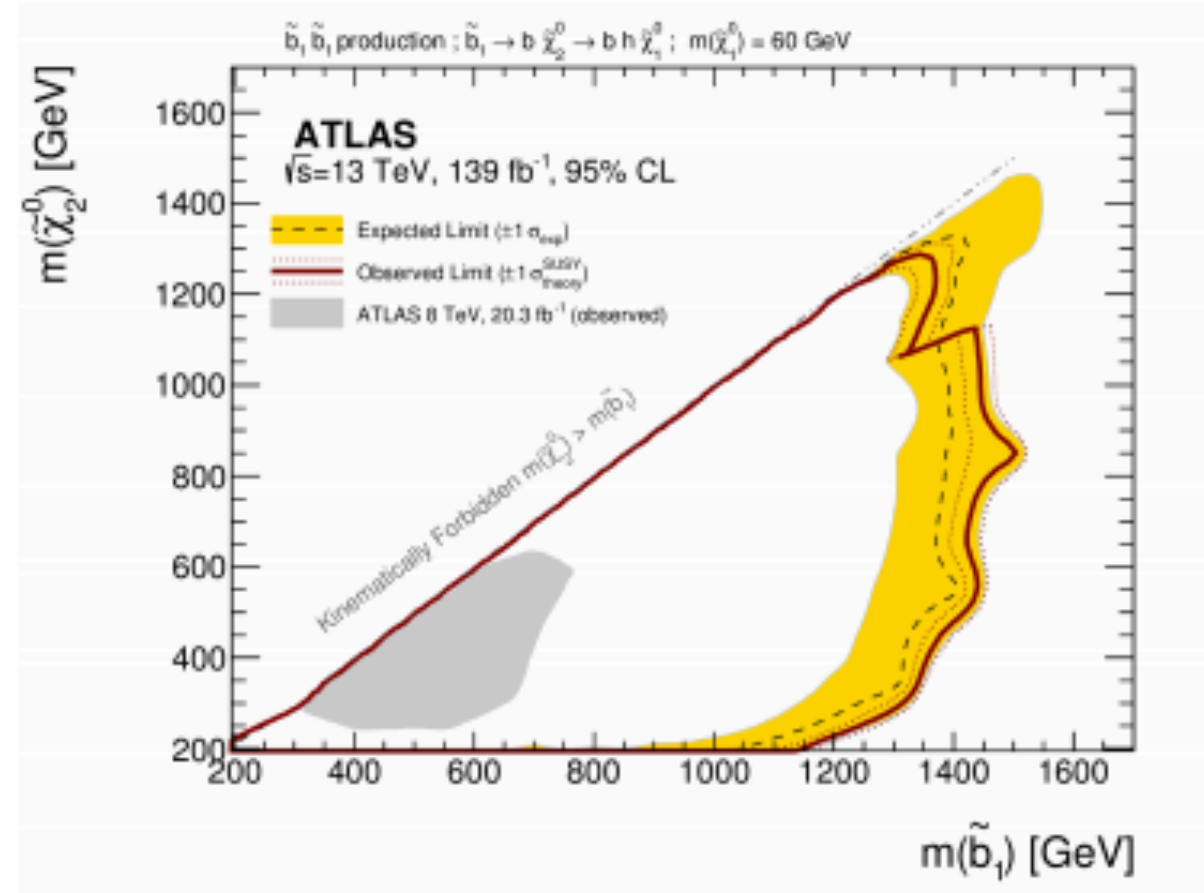


The image shows a CERN news article titled "New open release allows theorists to explore LHC data in a new way". The article is dated 9 JANUARY, 2020 and is by Katarina Ant. The text of the article is as follows:

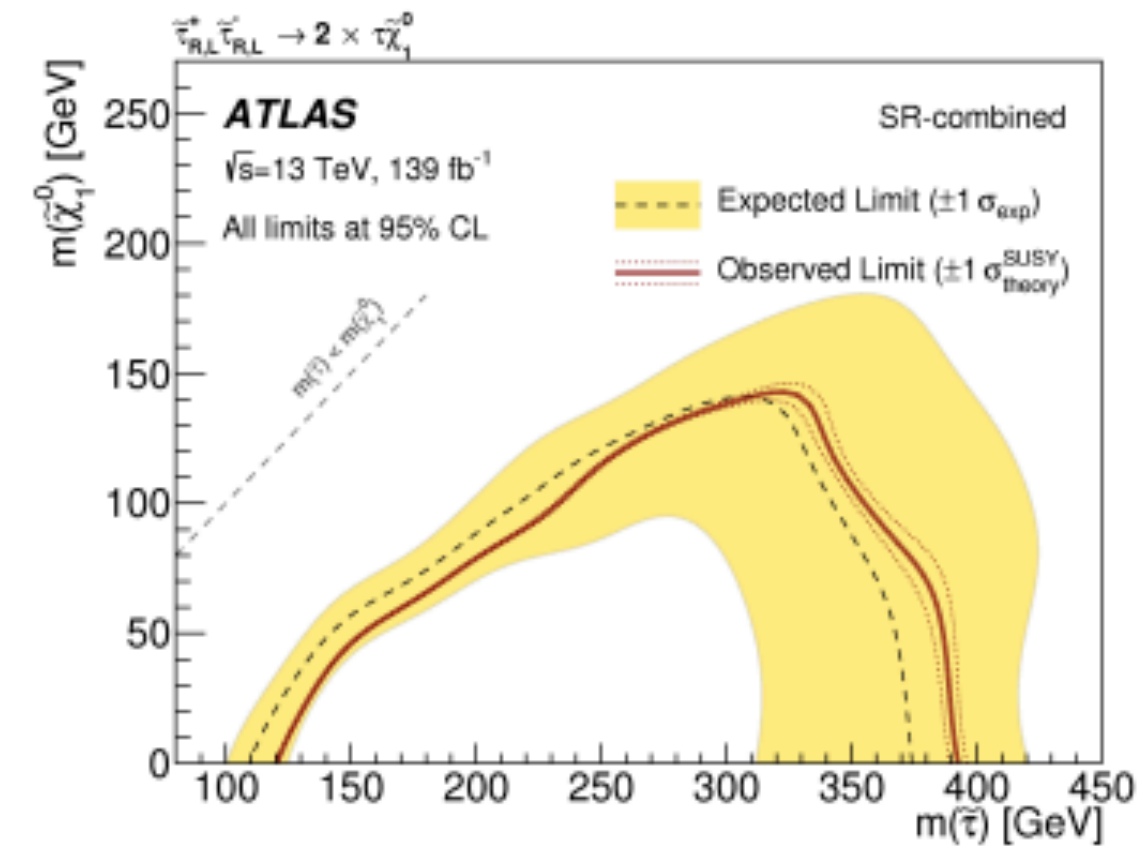
With full likelihood functions, theorists can calculate how well their theories fit the data collected by the detector "at a completely different level of reliability and precision," says Kraml.

To understand just how much more sophisticated and complex the analysis becomes, she says, consider the difference between a simple song and a full orchestral symphony.

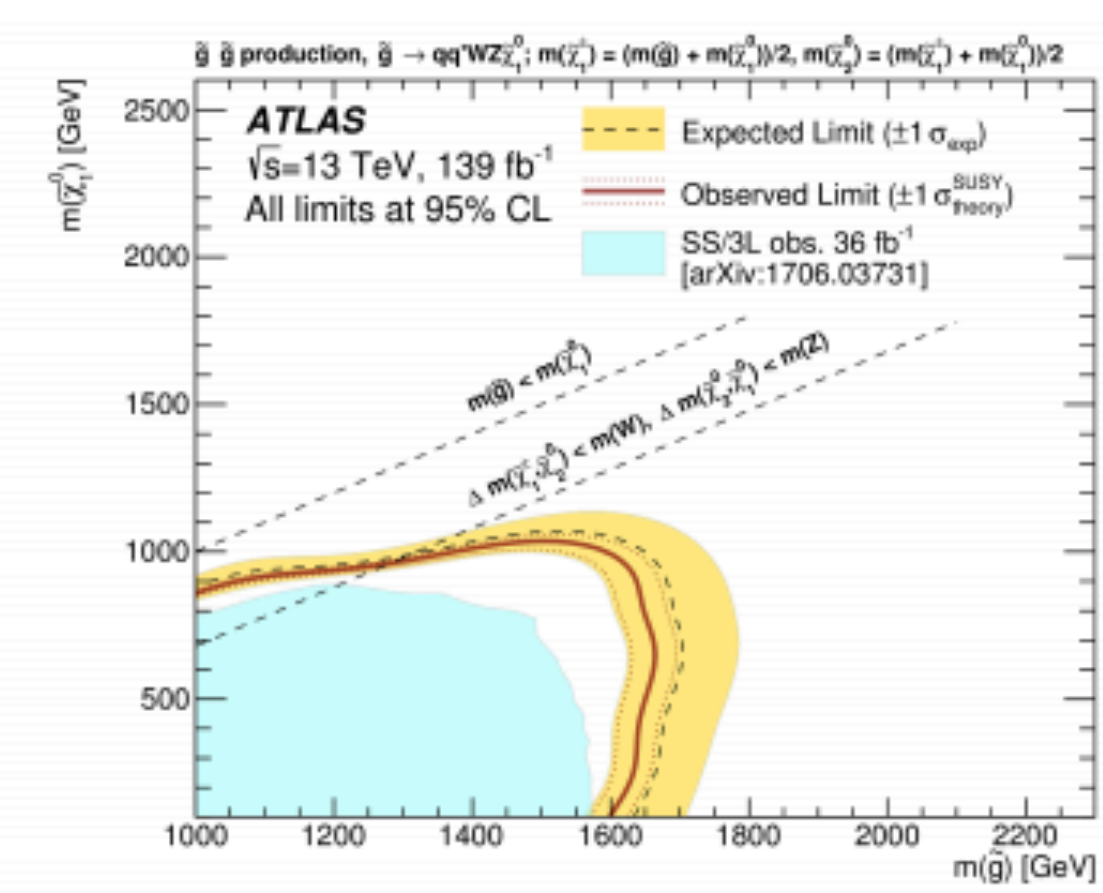
DOI 10.17182/hepdata.89408.v2



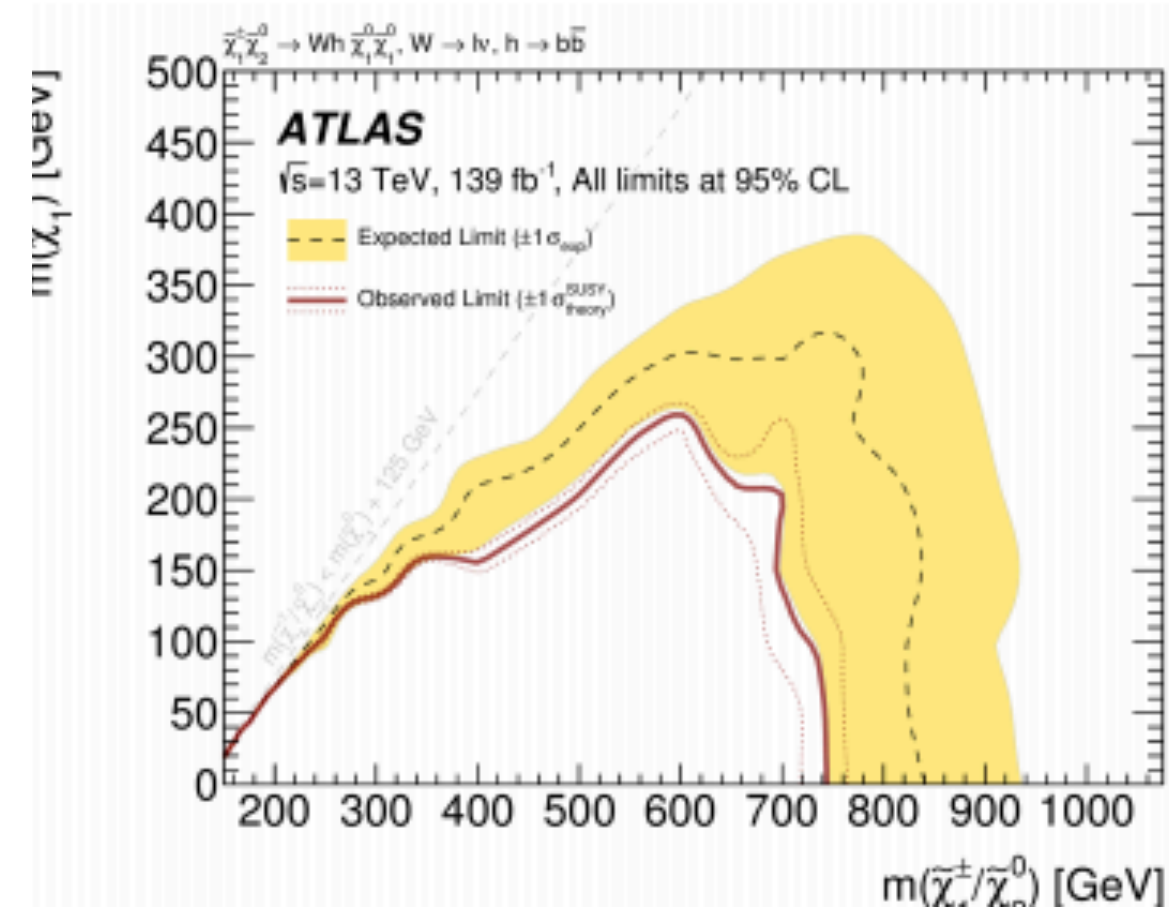
DOI 10.17182/hepdata.92006.v2



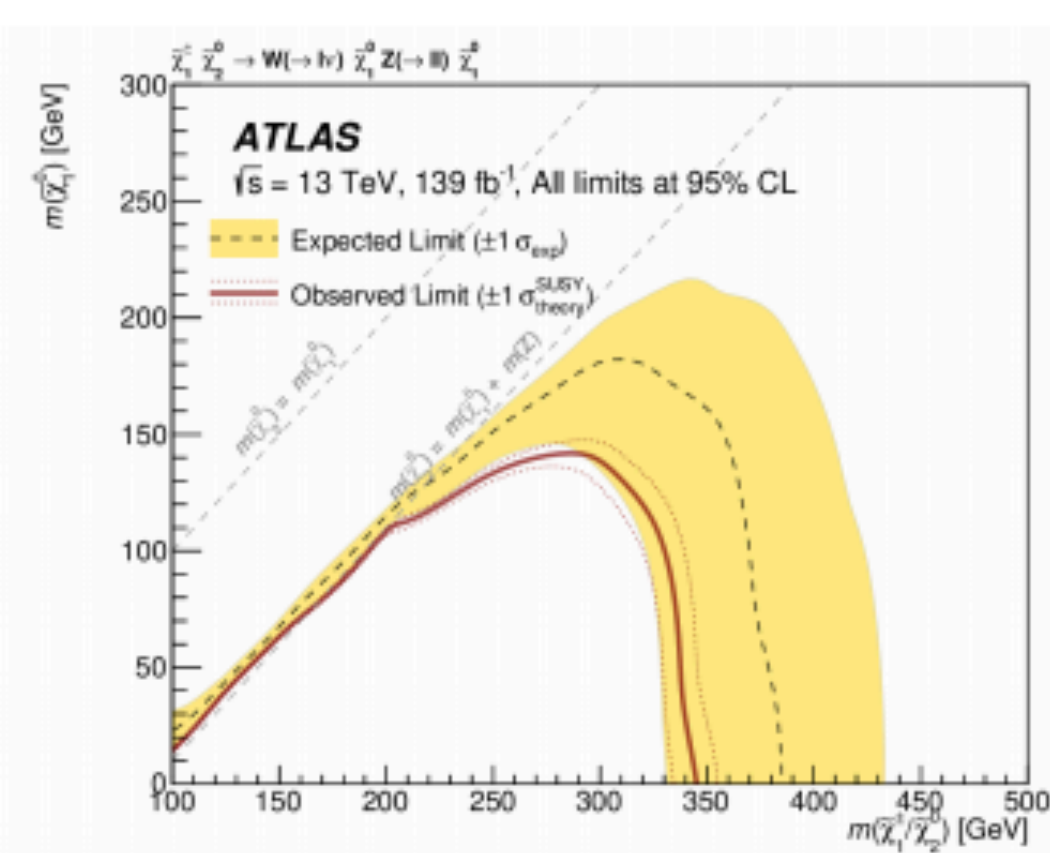
DOI 10.17182/hepdata.91214.v3



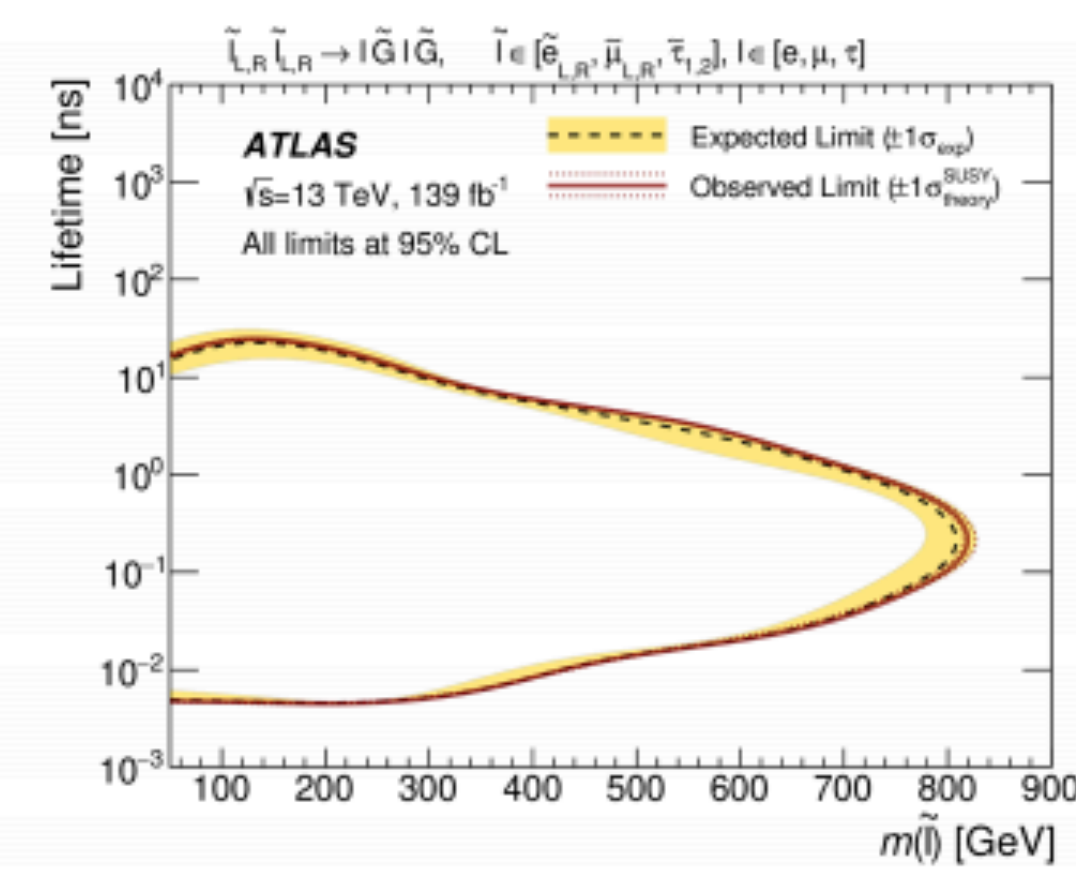
DOI 10.17182/hepdata.90607.v3



DOI 10.17182/hepdata.91127.v2

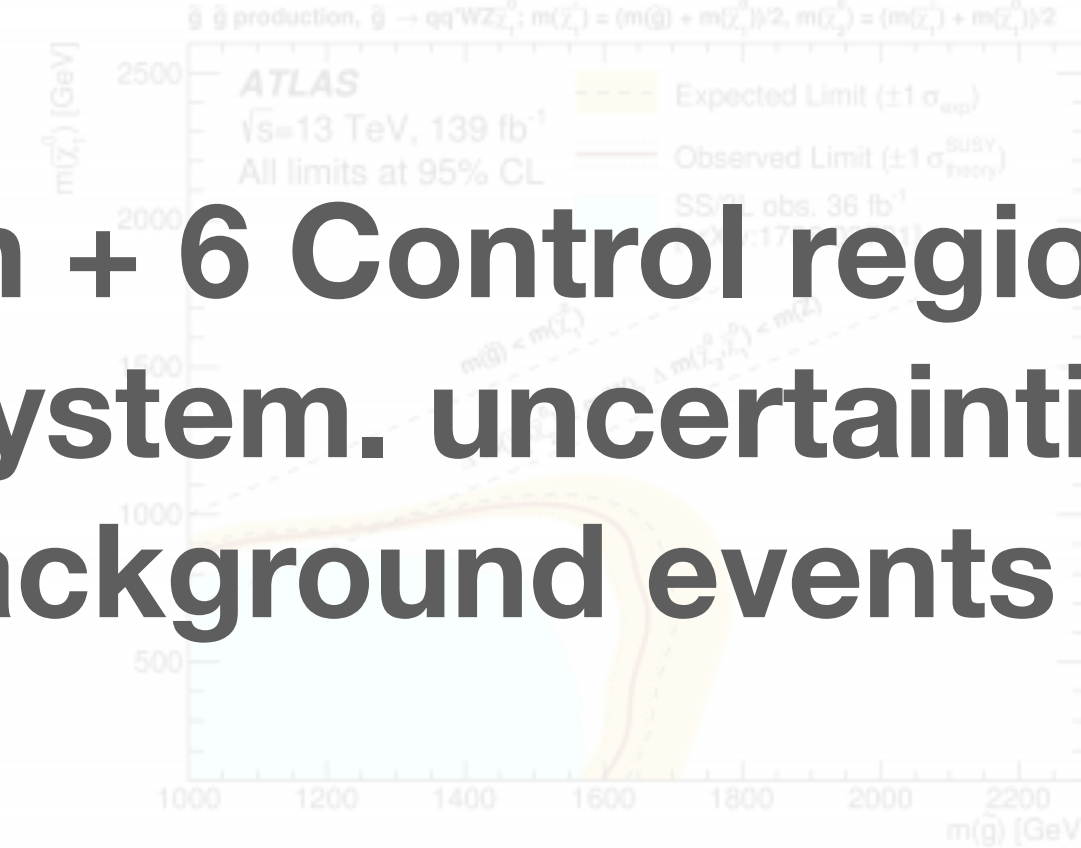
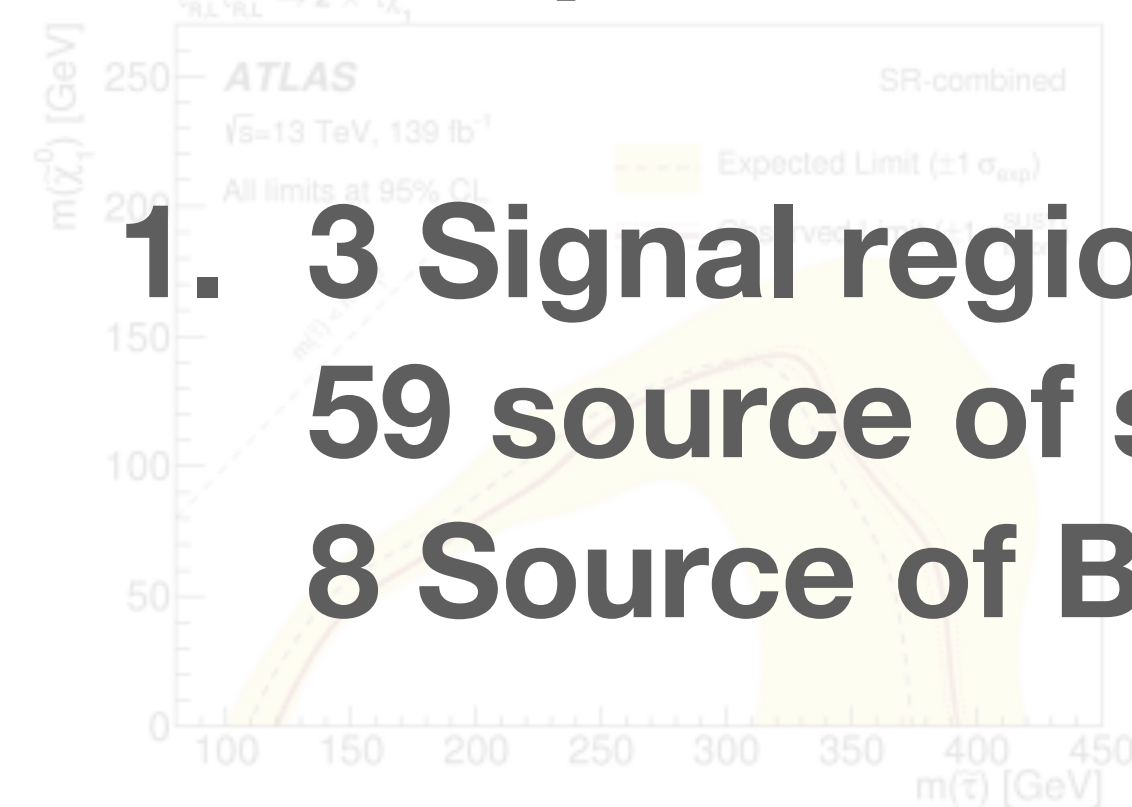
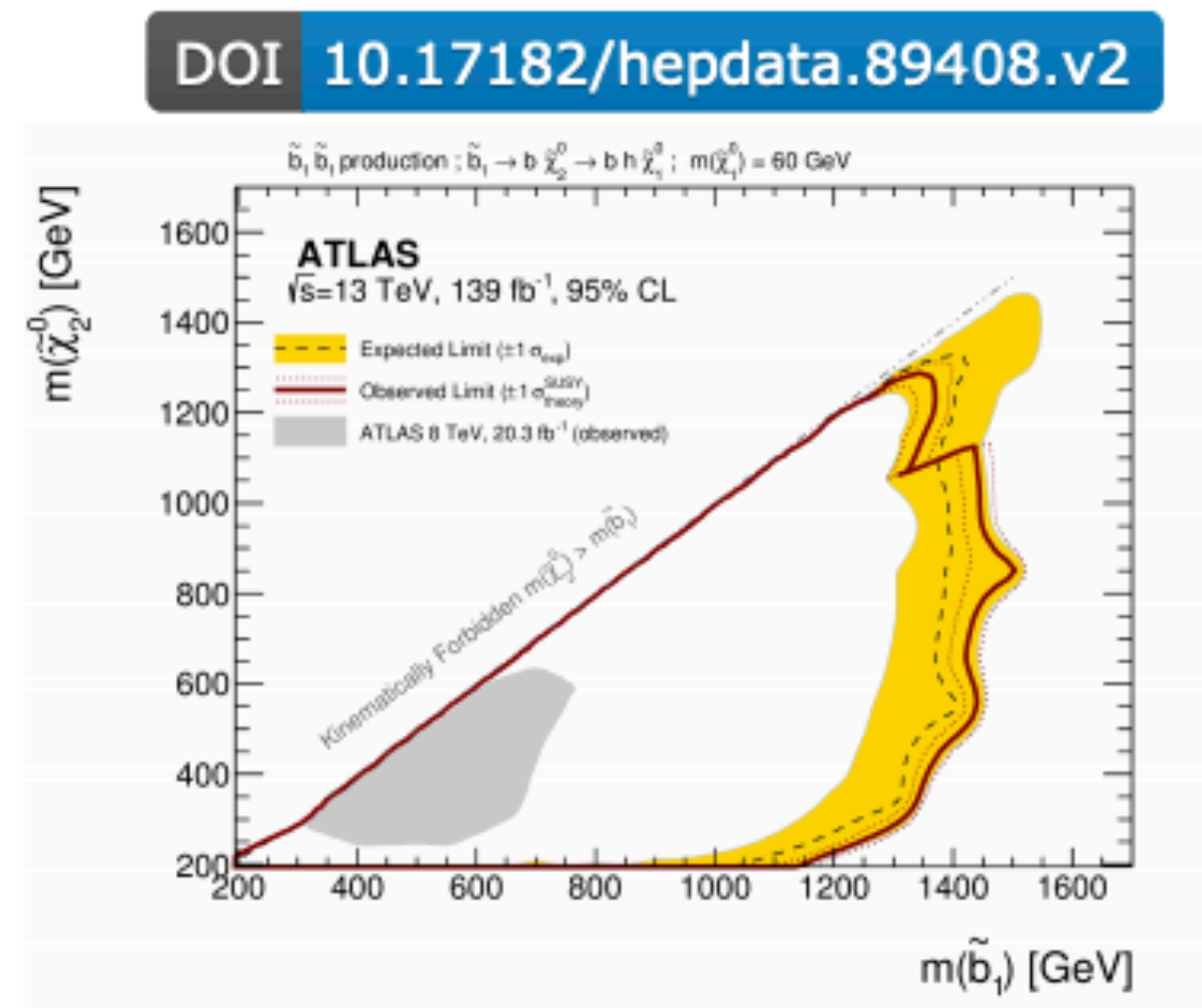


DOI 10.17182/hepdata.98796.v2

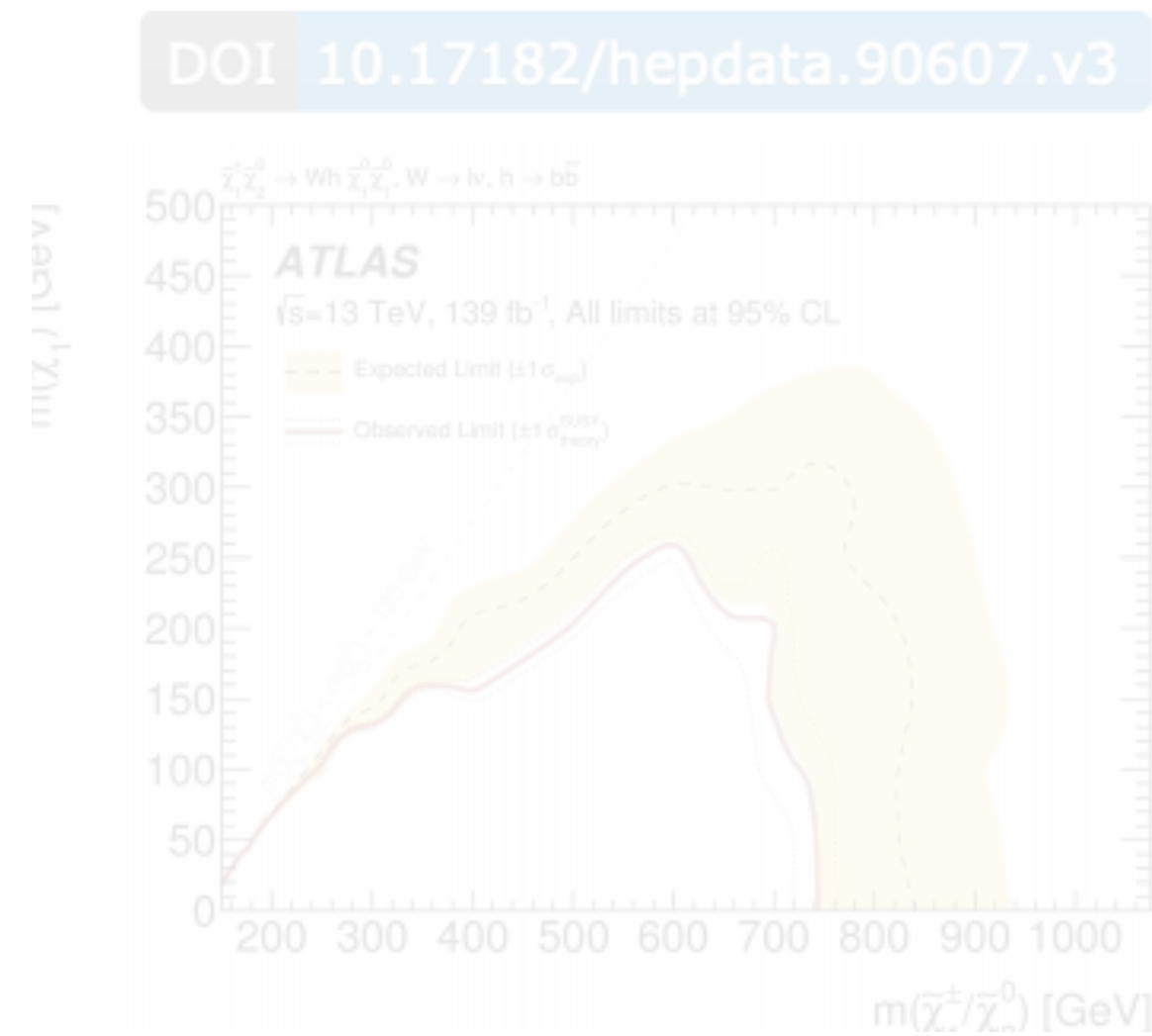


Let's reproduce this result!

Two separate measurements:



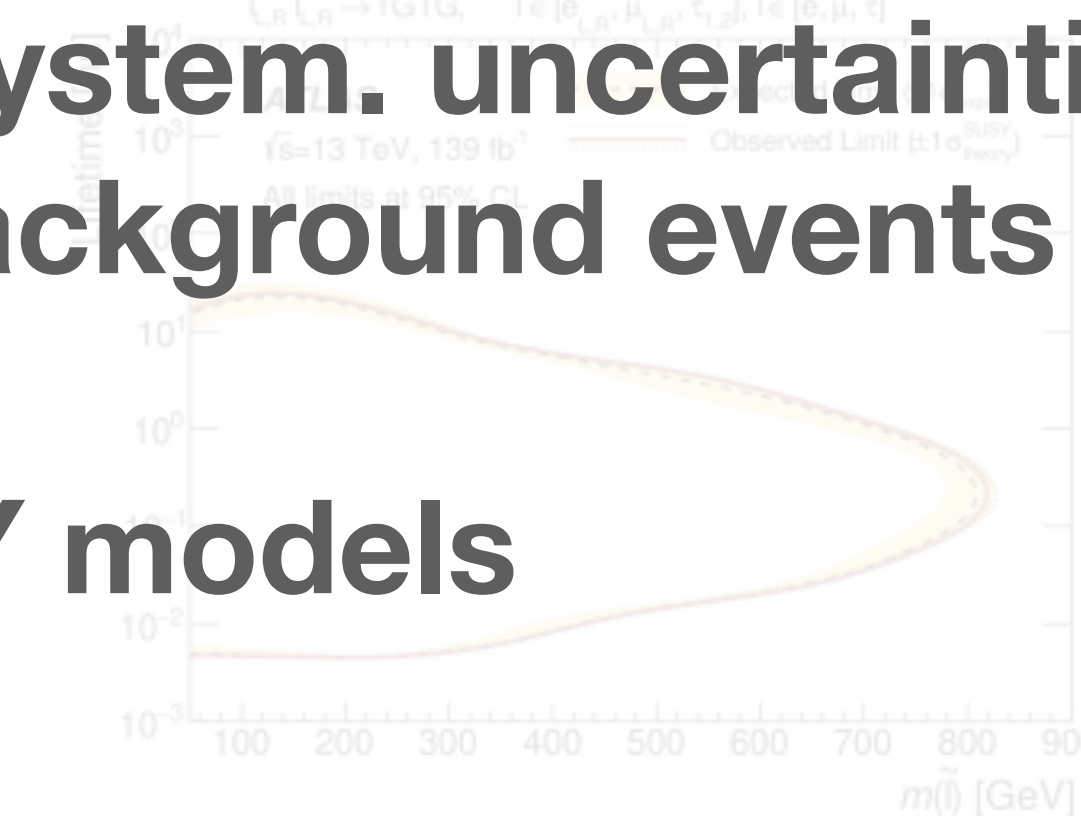
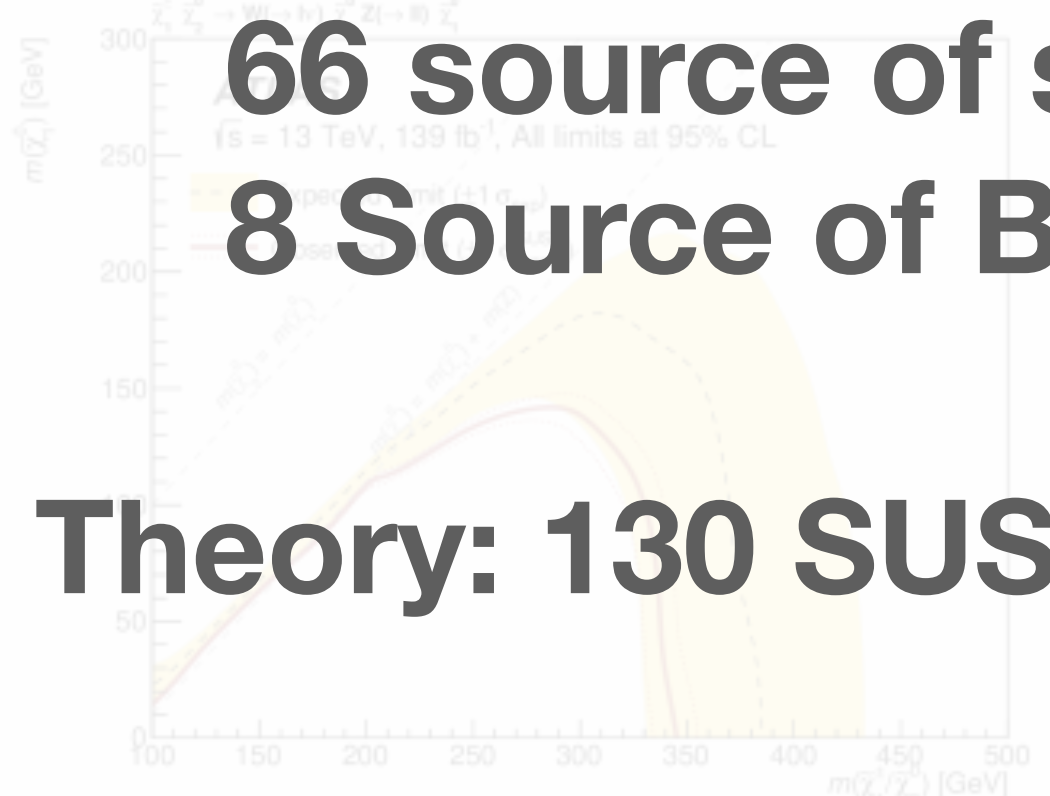
- 3 Signal region + 6 Control regions
 59 source of system. uncertainties
 8 Source of Background events



- 4 Signal region + 5 Control regions
 66 source of system. uncertainties
 8 Source of Background events

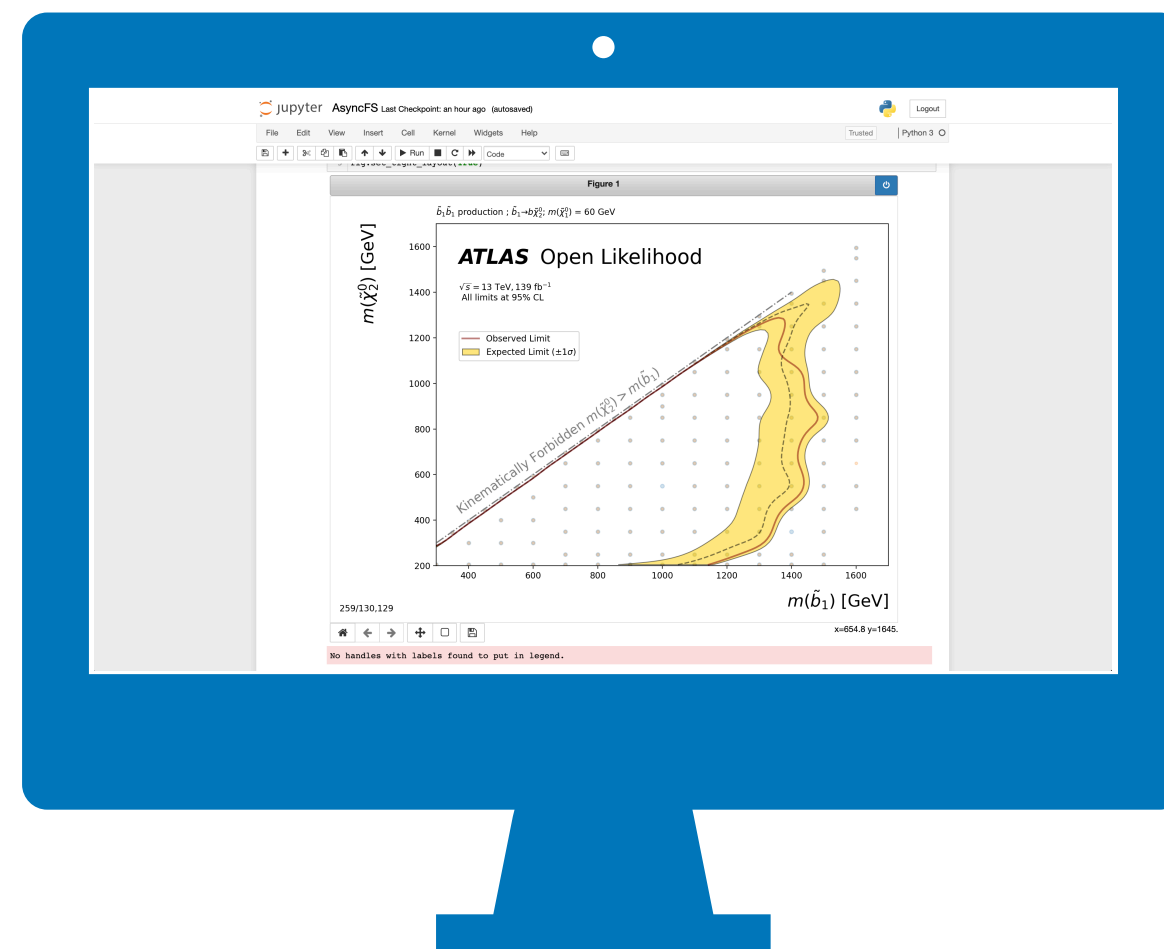
Theory: 130 SUSY models

Measurements overlap:
 take most sensitive result



Demo: reproduce full contour (260 CLs) for simplified SUSY model using cloud APIs

- auto-scaling, distributed statistics



User Session

$$L(\theta, \theta_{\text{nuis}}) = p(x_{\text{obs}} | \mu s(\theta) + b(\theta_{\text{nuis}}))$$

send likelihood



get results



$$CL_s(\theta)$$

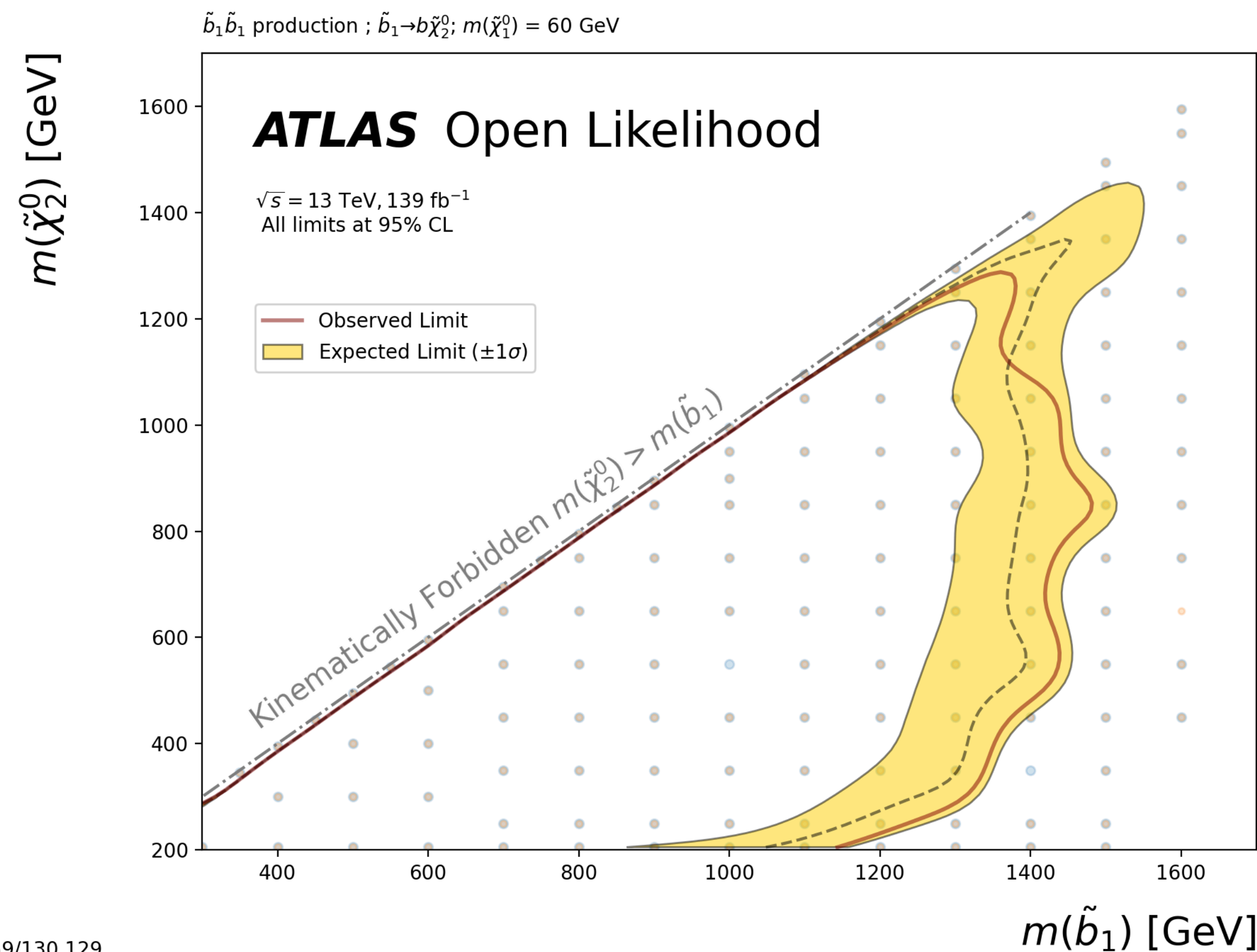


Cloud Fitting Service

Demo

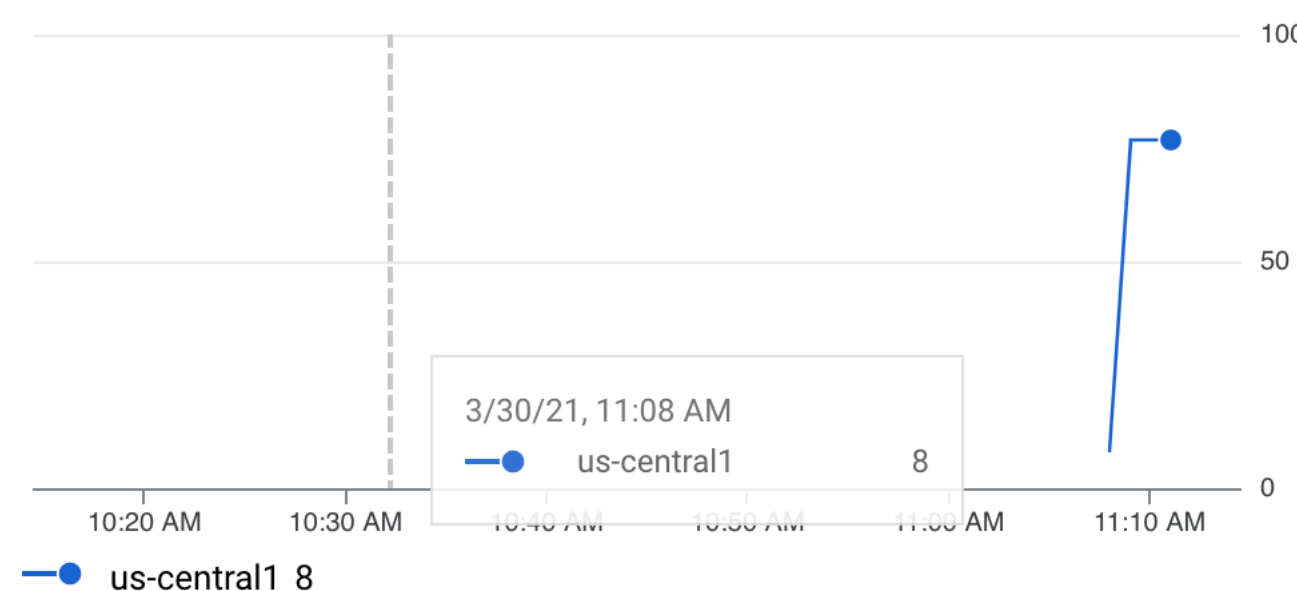
```
3 fig.set_size_inches(9.33,7)
4 apply_decorations(ax,label = 'Open Likelihood (in progress)')
5 fig.set_tight_layout(True)
```

Figure 1



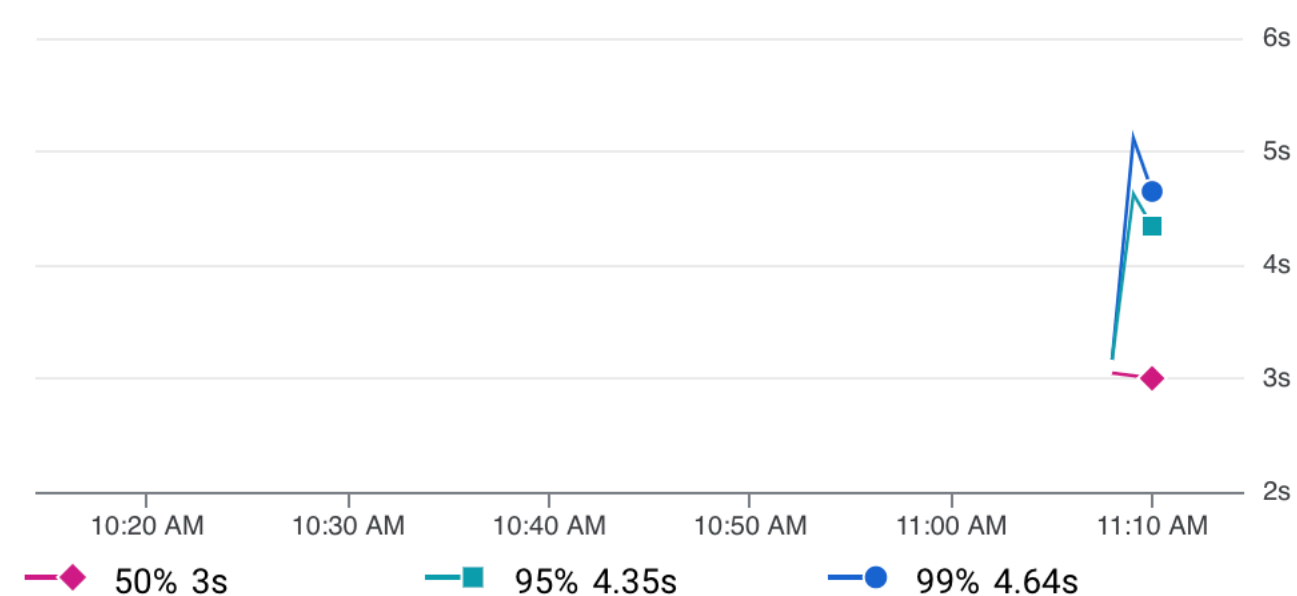
259/130,129

Active instances



Execution time

Milliseconds/call



(Cost: 0.05\$)

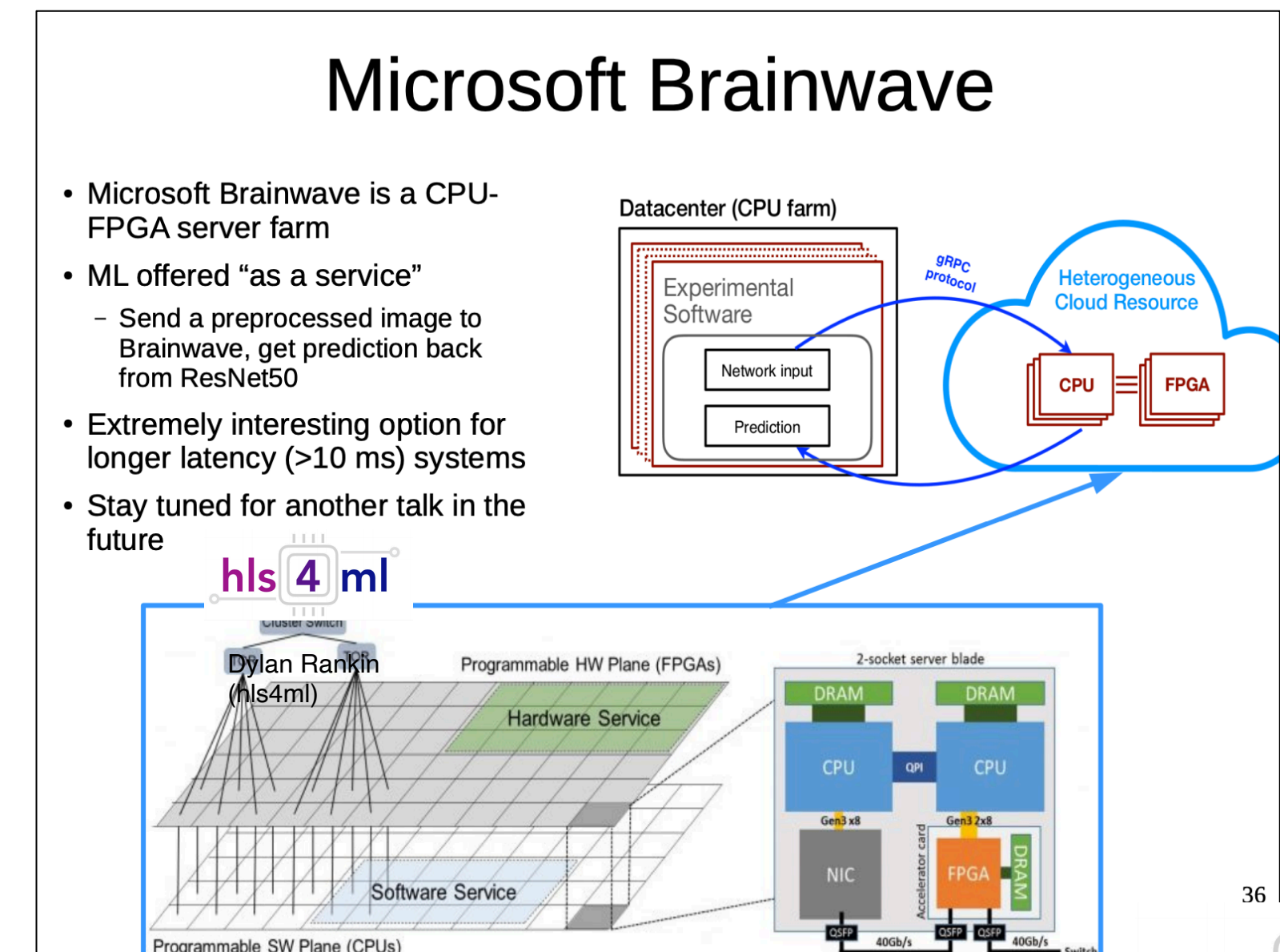
pyhf - with functions as a service

As with Higgs example:

- Open Data provides access to LHC data: **but now a more refined product.**
- can offload heavy computation to cloud - cost only per CPUh
scale to hundreds of (private) cores within seconds
- Here: "Fitting-as-a-service": user only needs a URL
can optimize hardware for stat. analysis.

Related: ML-as-service

- Investigated for fast FPGA-based inference (Trigger, Reco, ...)



Hold on, why so restrictive?
(just reproducing things is boring)

Reinterpretation

Did we over-correct from Open Data? Open Likelihood is great for

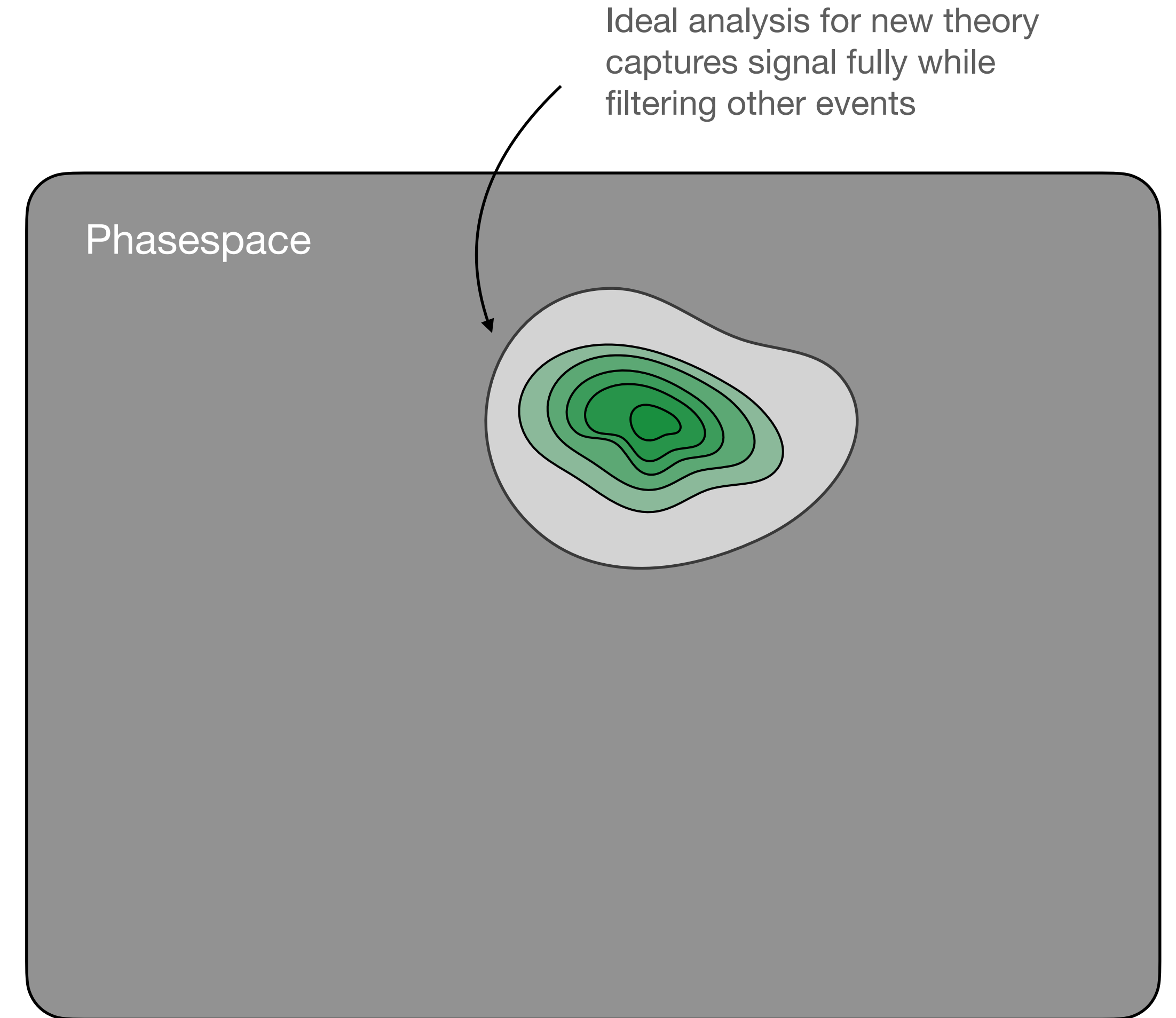
- reproducing results
 - combination with other measurements wrt. to **same theory** ("global fits")
- but not enough to study **new theories**

Reinterpretation

Main Concern creating new analyses internally & externally (w/ Open Data)

Human resources for

- analysis design
- background estimation
- systematic analysis



Can we maybe reuse the analysis we already have?

Reinterpretation

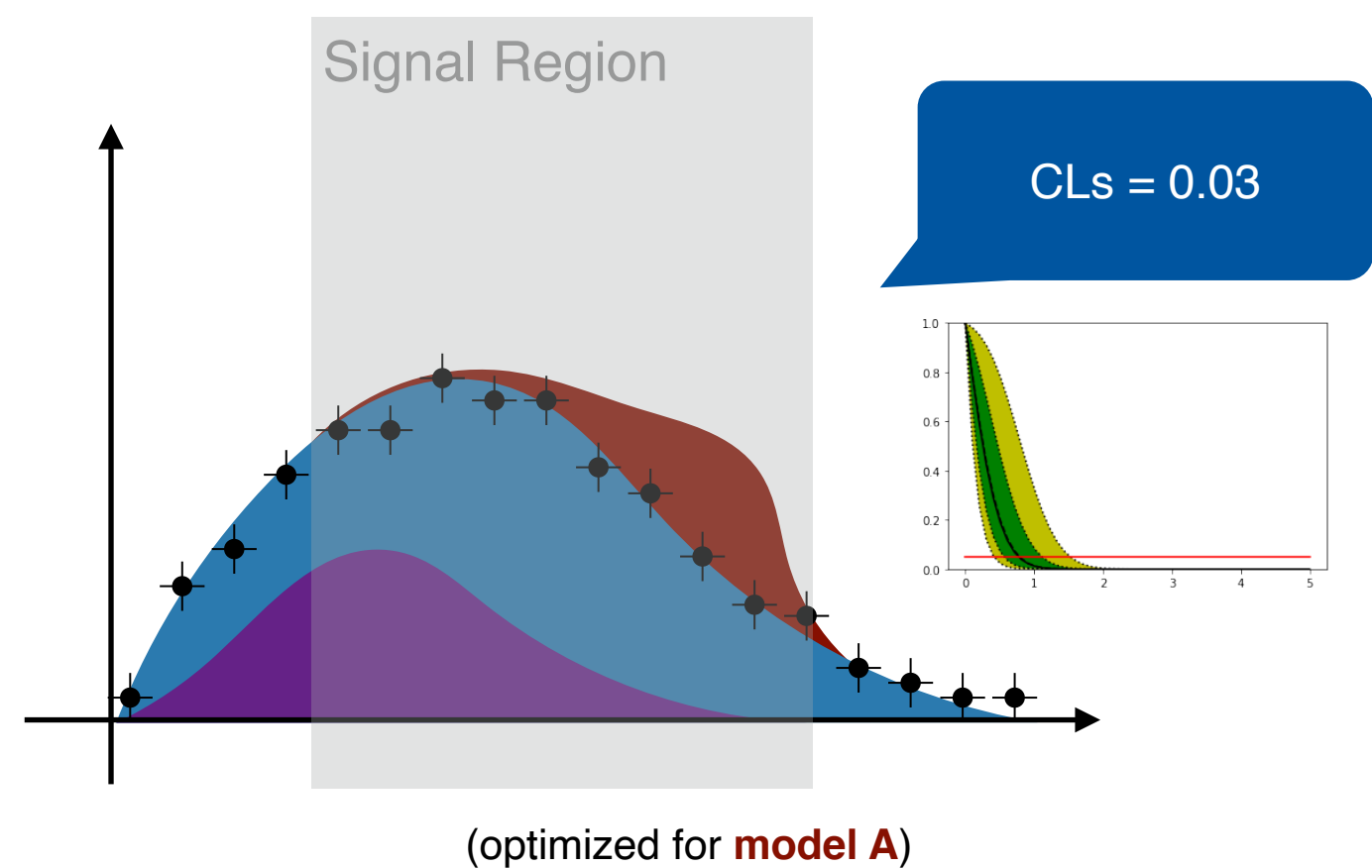
Increasing coverage of data space as LHC progresses.

It's likely that a analysis already did all the hard work for us

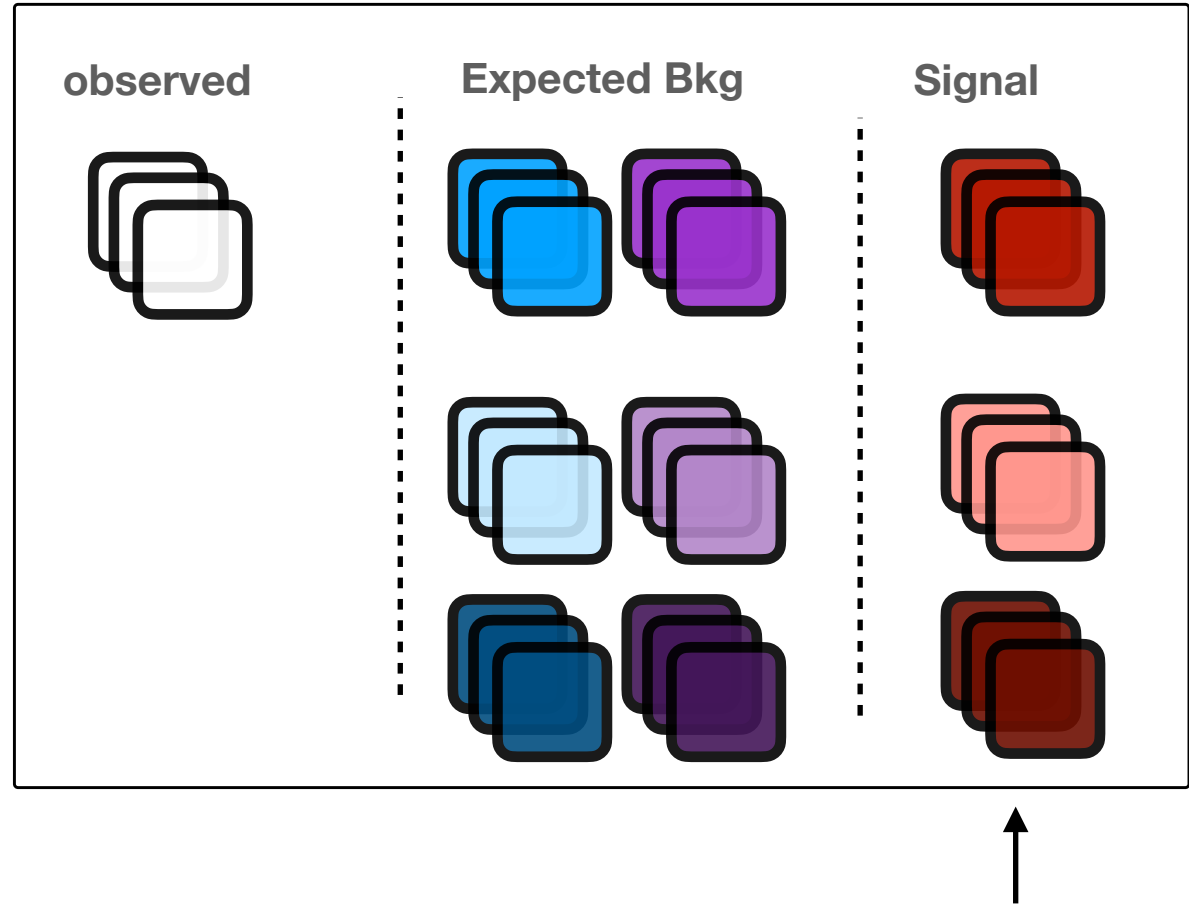
Not optimized for new theory but can be quite sensitive



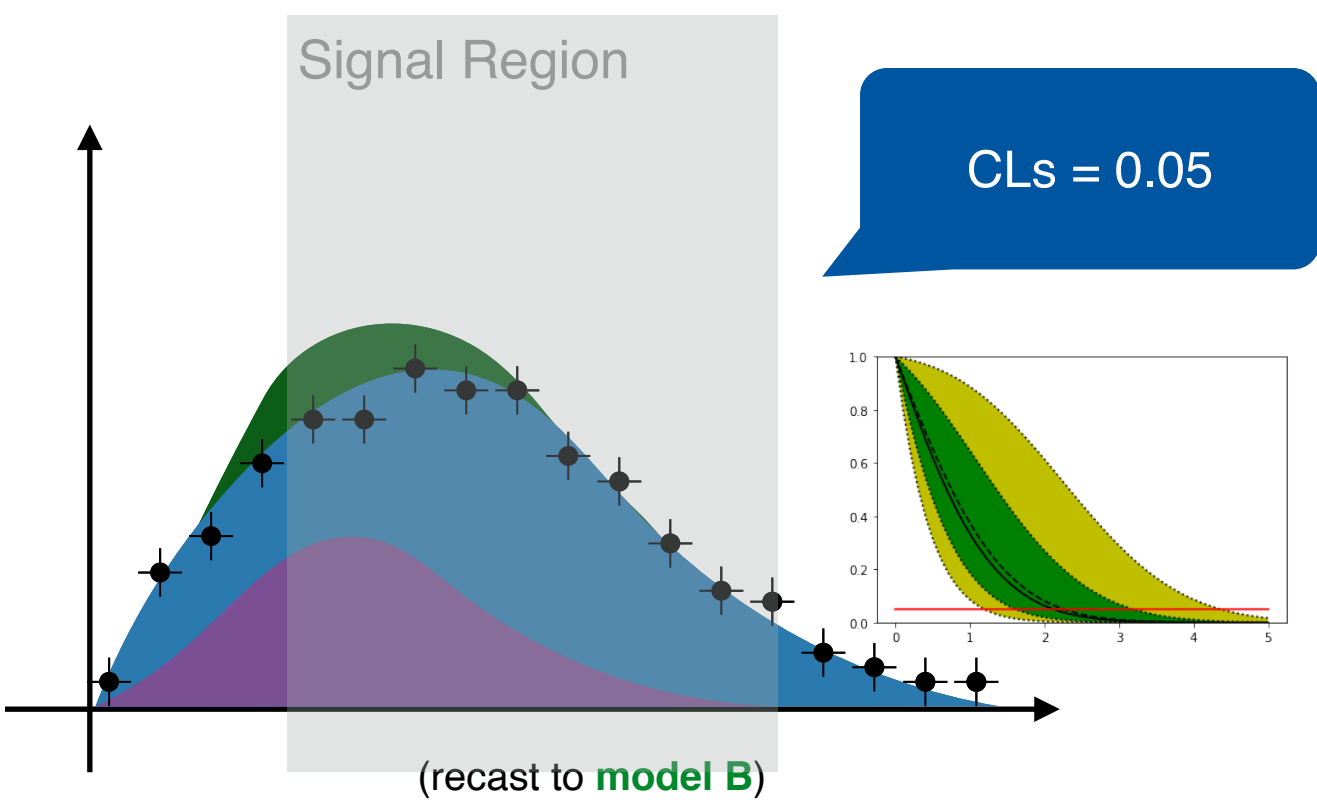
Reinterpretation



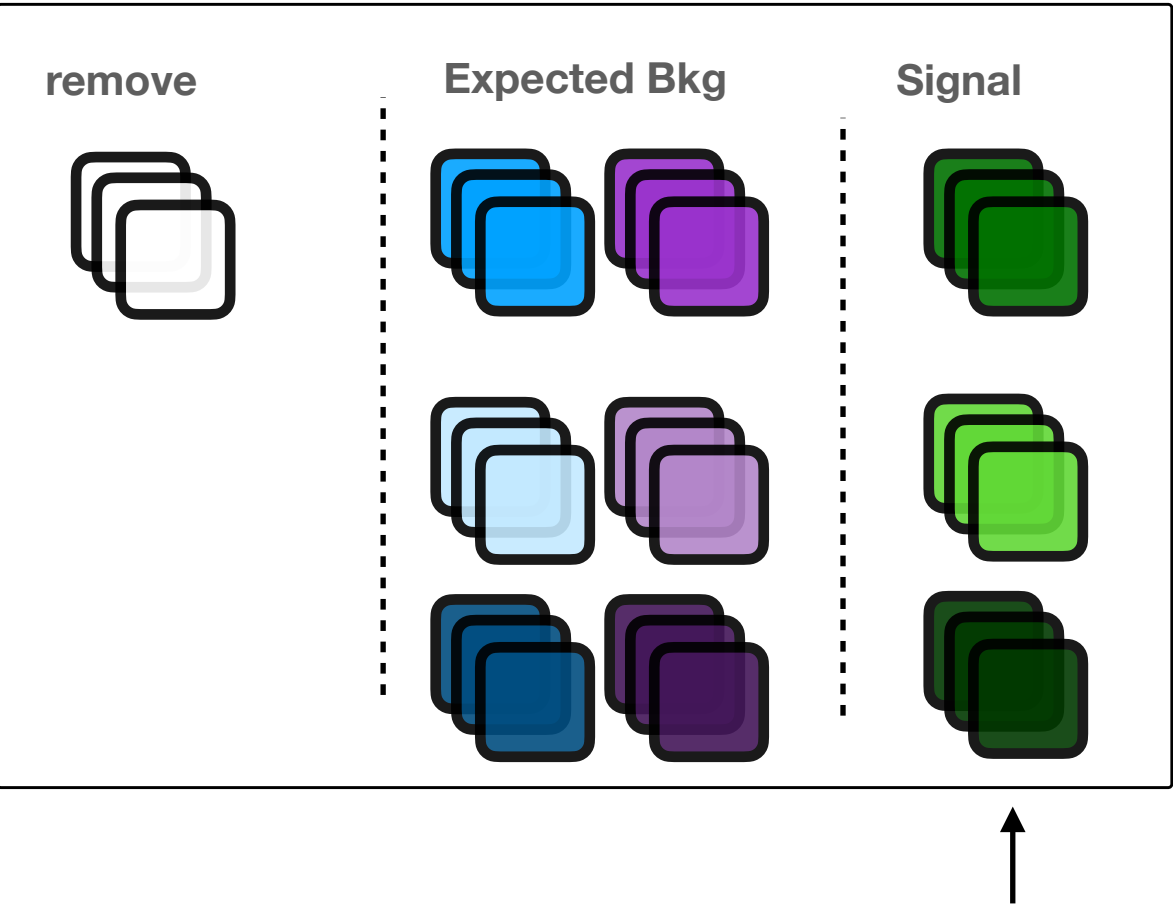
"Original Likelihood"



- RECAST:
- remove old signal
 - compute new signal
 - inject into likelihood
 - run stat. analysis



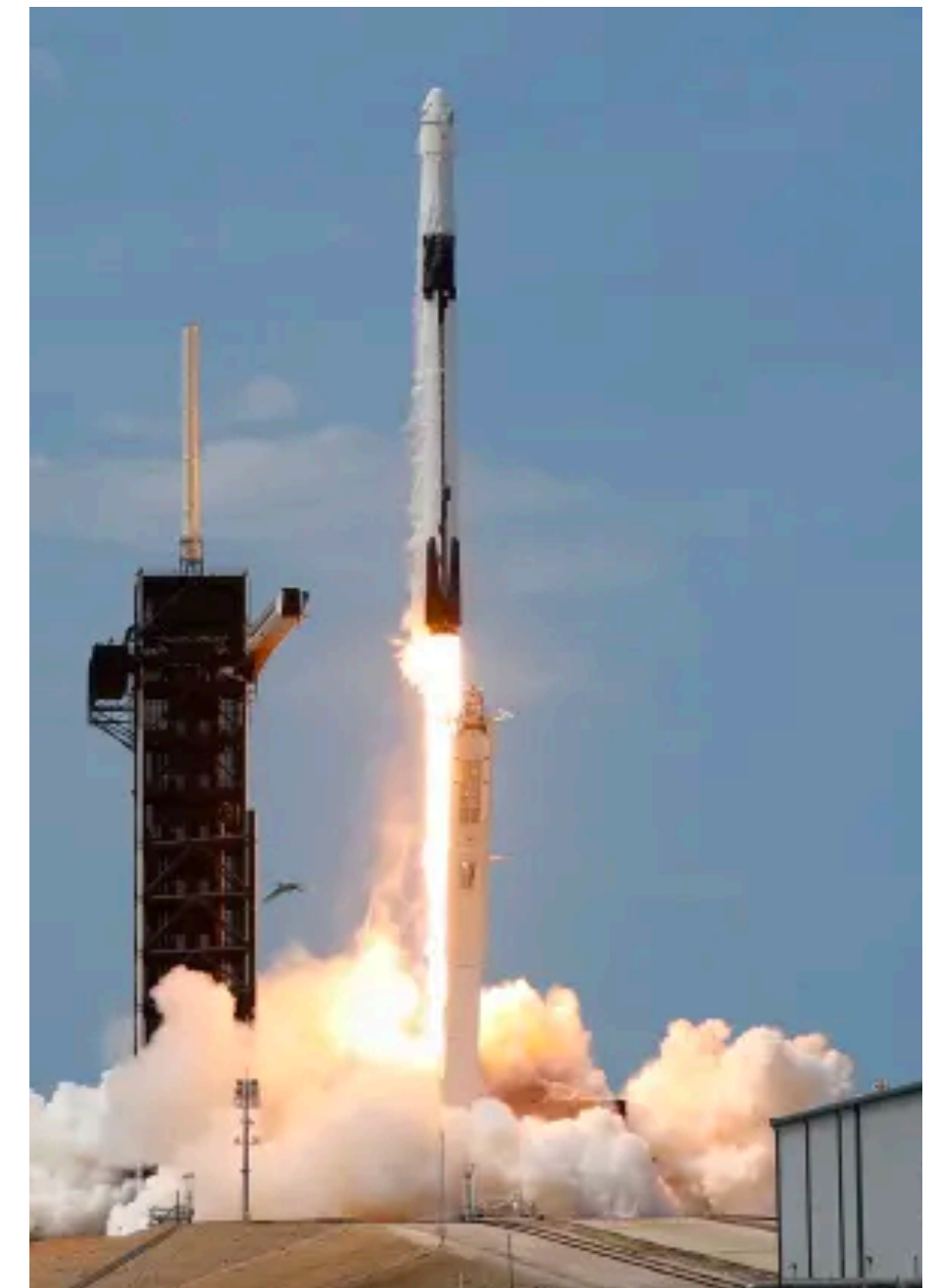
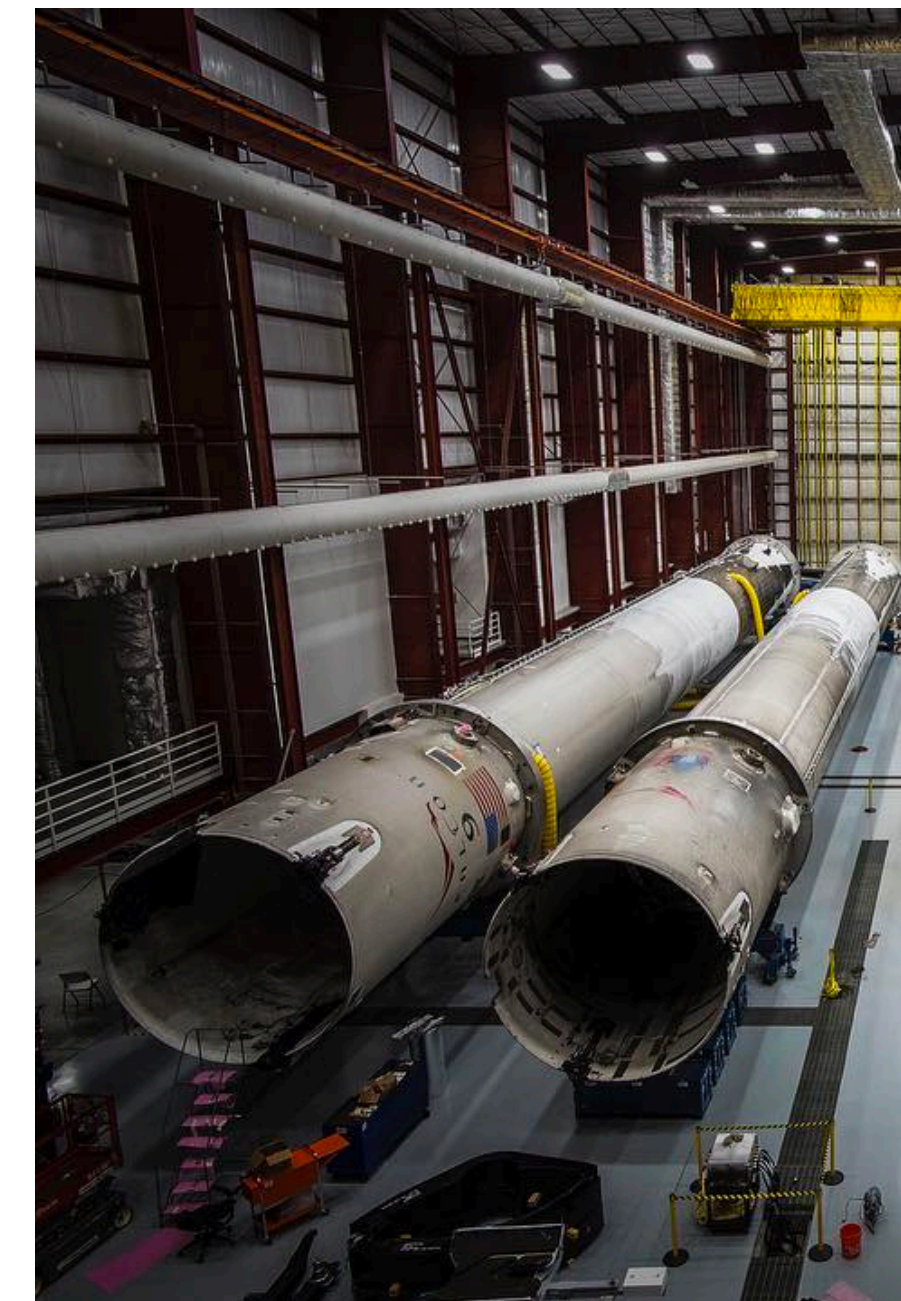
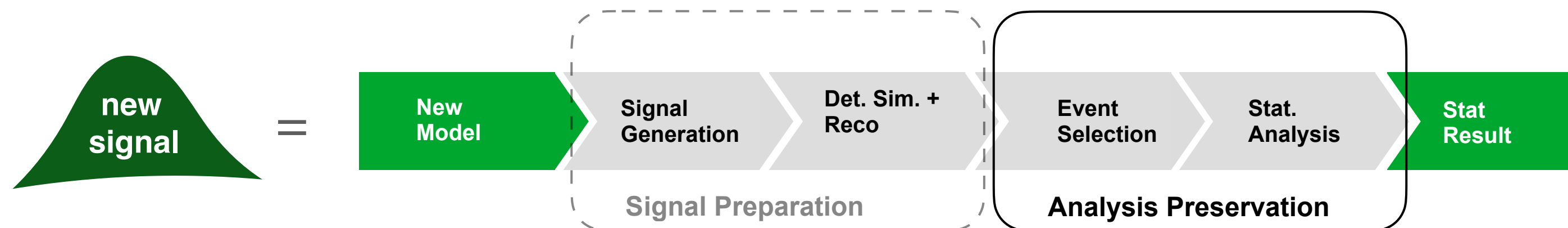
"Recasted Likelihood"



More Physics through Analysis Preservation

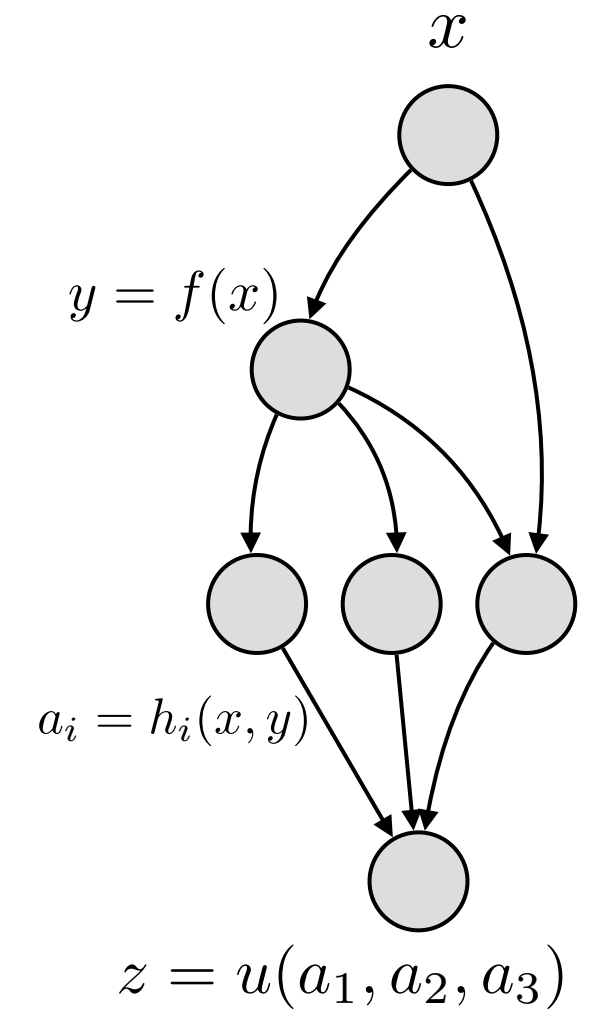
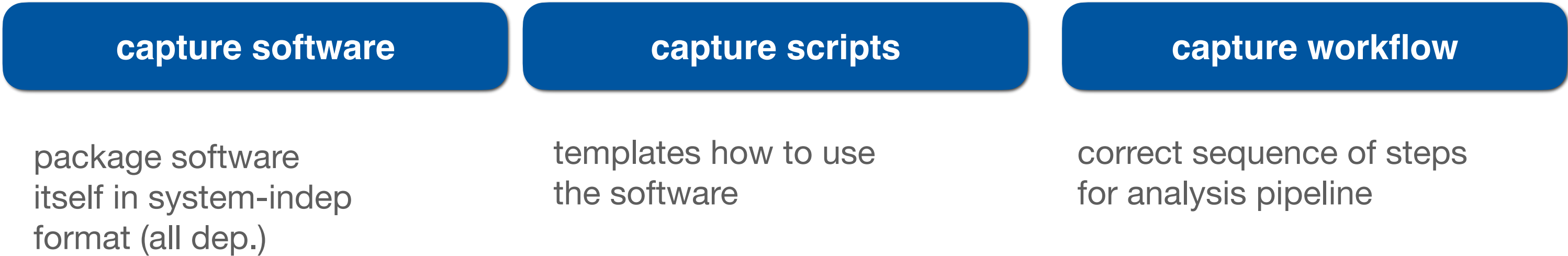
Simple/Obvious Idea: whats the problem?

- Need to be able to compute new signal component
- Need an archived, **but operational** version of the analysis
 - ready to be re-run if needed
- **"reuse" much more powerful than "reproducibility"**



More Physics through Analysis Preservation

Analysis Preservation



In ATLAS, we provide common infrastructure to make this easy

- automation for software archiving via containers
- workflow language to capture physics logic
- requirement now for across BSM program

Similar efforts across many data-intensive sciences:

Nextflow

Data-driven computational pipelines

Nextflow enables scalable and reproducible scientific workflows using software containers. It allows the adaptation of pipelines written in the most common scripting languages.

Workflows & Pipelines

Container native workflow engine for Kubernetes supporting both DAG and step based workflows.

[DOCS](#)

Snakemake


Gitpod ready-to-code Bioconda 286k python 3.5 pypi v6.0.5 docker container passing CI passing

stack overflow Follow 2.1k discord chat 24 online Stars 911

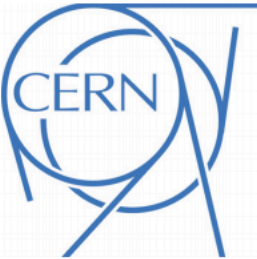
The Snakemake workflow management system is a tool to create **reproducible and scalable** data analyses. Workflows are described via a human readable, Python based language. They can be seamlessly scaled to server, cluster, grid and cloud environments, without the need to modify the workflow definition. Finally, Snakemake workflows can entail a description of required software, which will be automatically deployed to any execution environment.

More Physics through Analysis Preservation

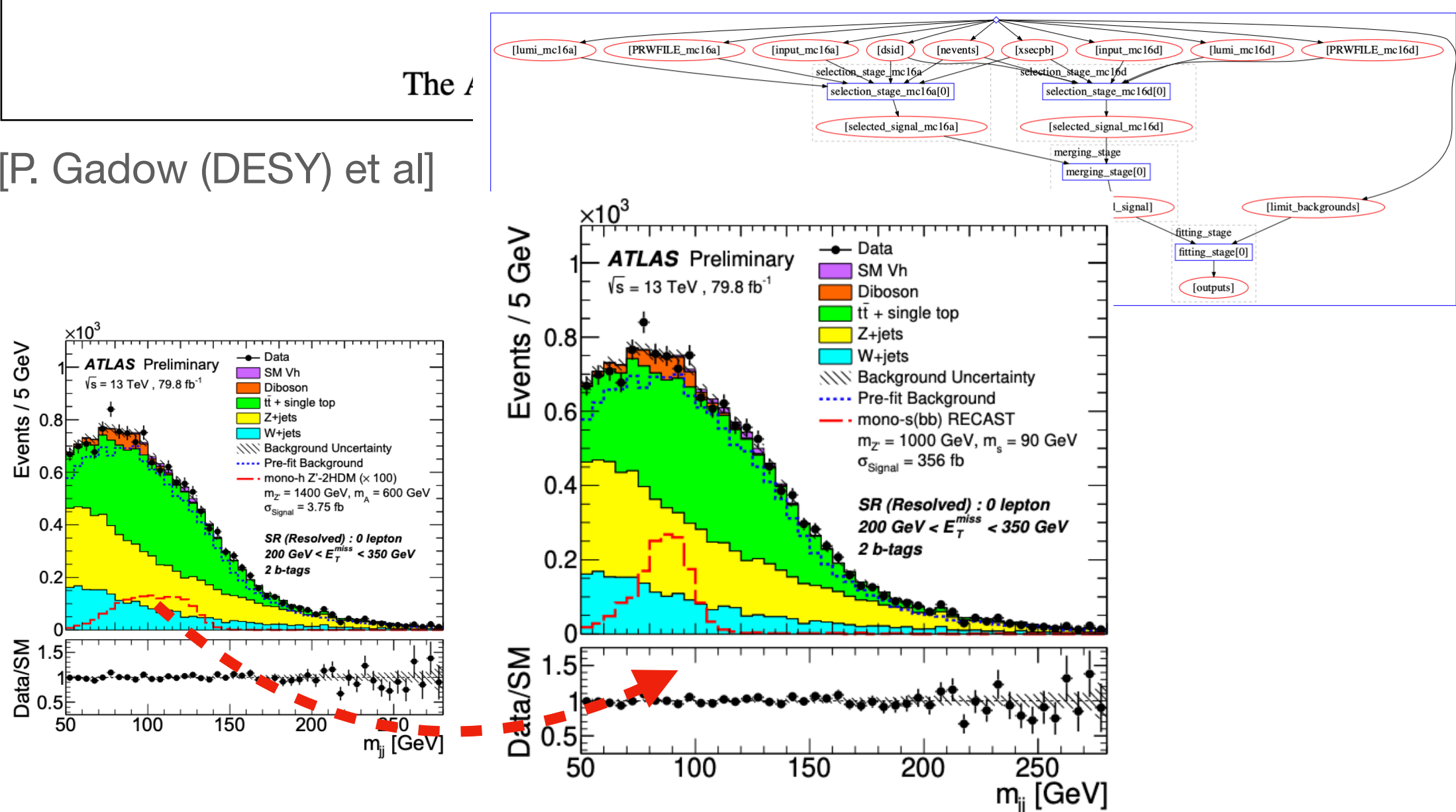
From Cartoon to reality:




ATLAS PUB Note
ATL-PHYS-PUB-2019-032
11th August 2019




RECAST framework reinterpretation of an ATLAS Dark Matter Search constraining a model of a dark Higgs boson decaying to two *b*-quarks



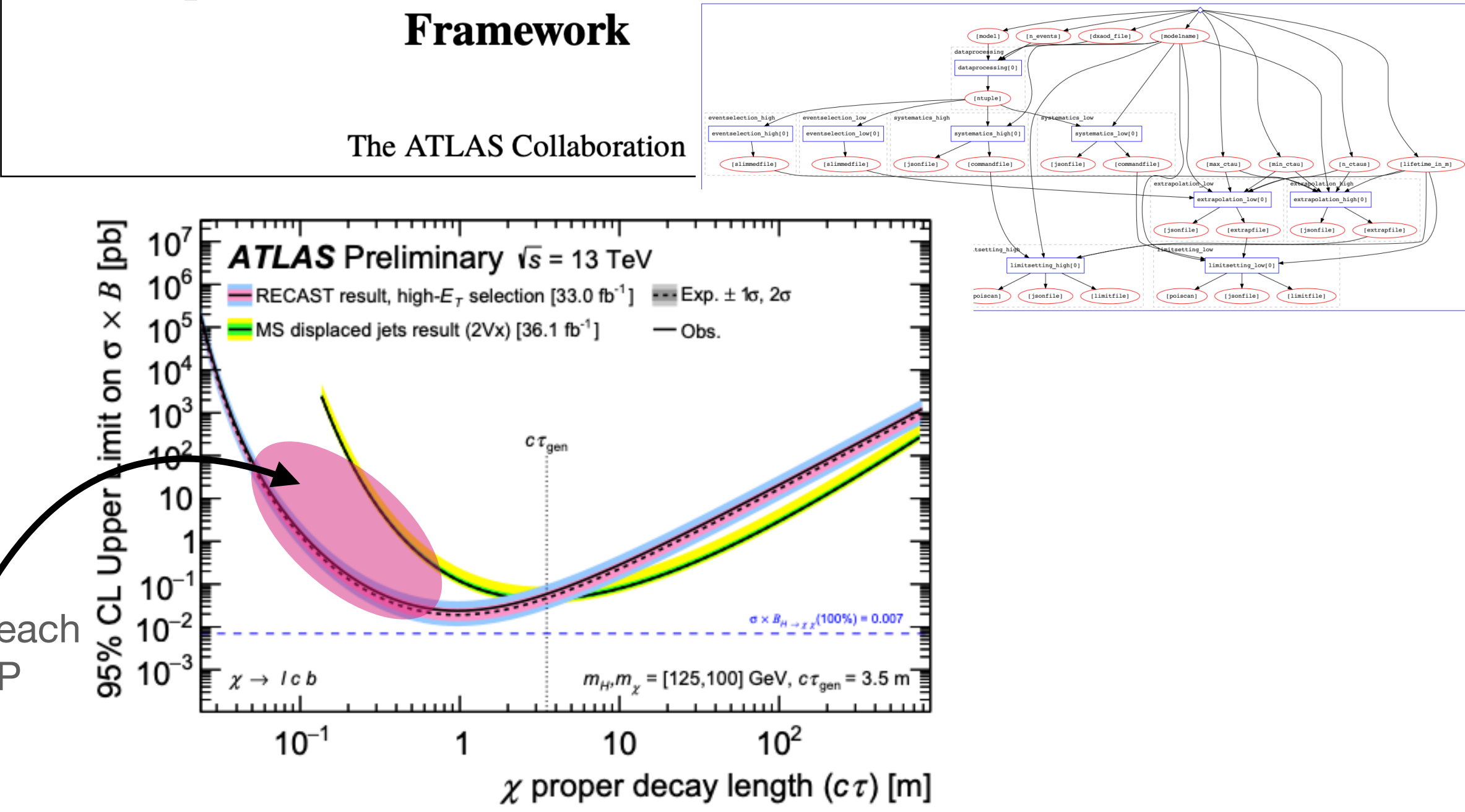


ATLAS PUB Note
ATL-PHYS-PUB-2020-007
27th March 2020



Reinterpretation of the ATLAS Search for Displaced Hadronic Jets with the RECAST Framework

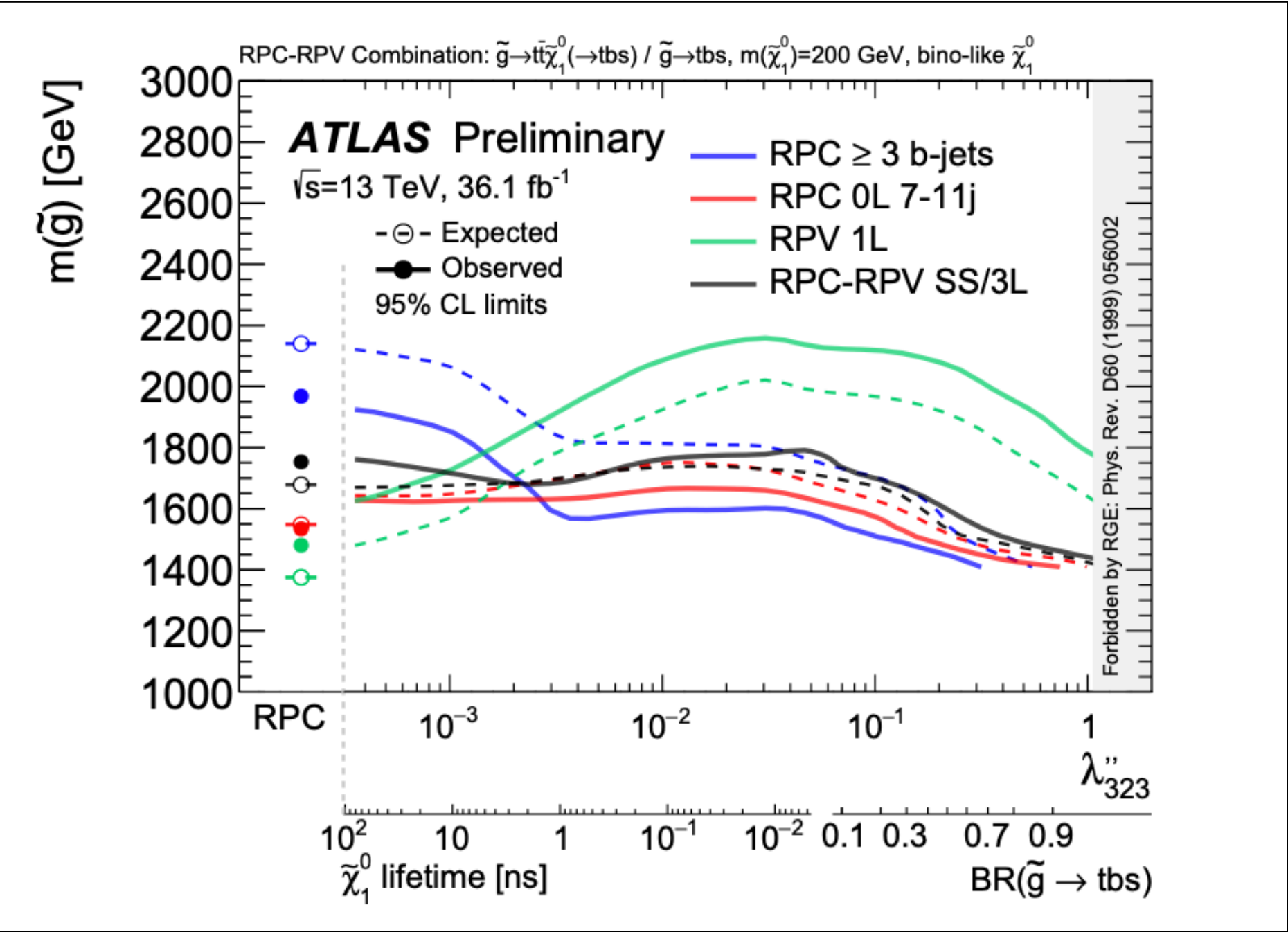
The ATLAS Collaboration



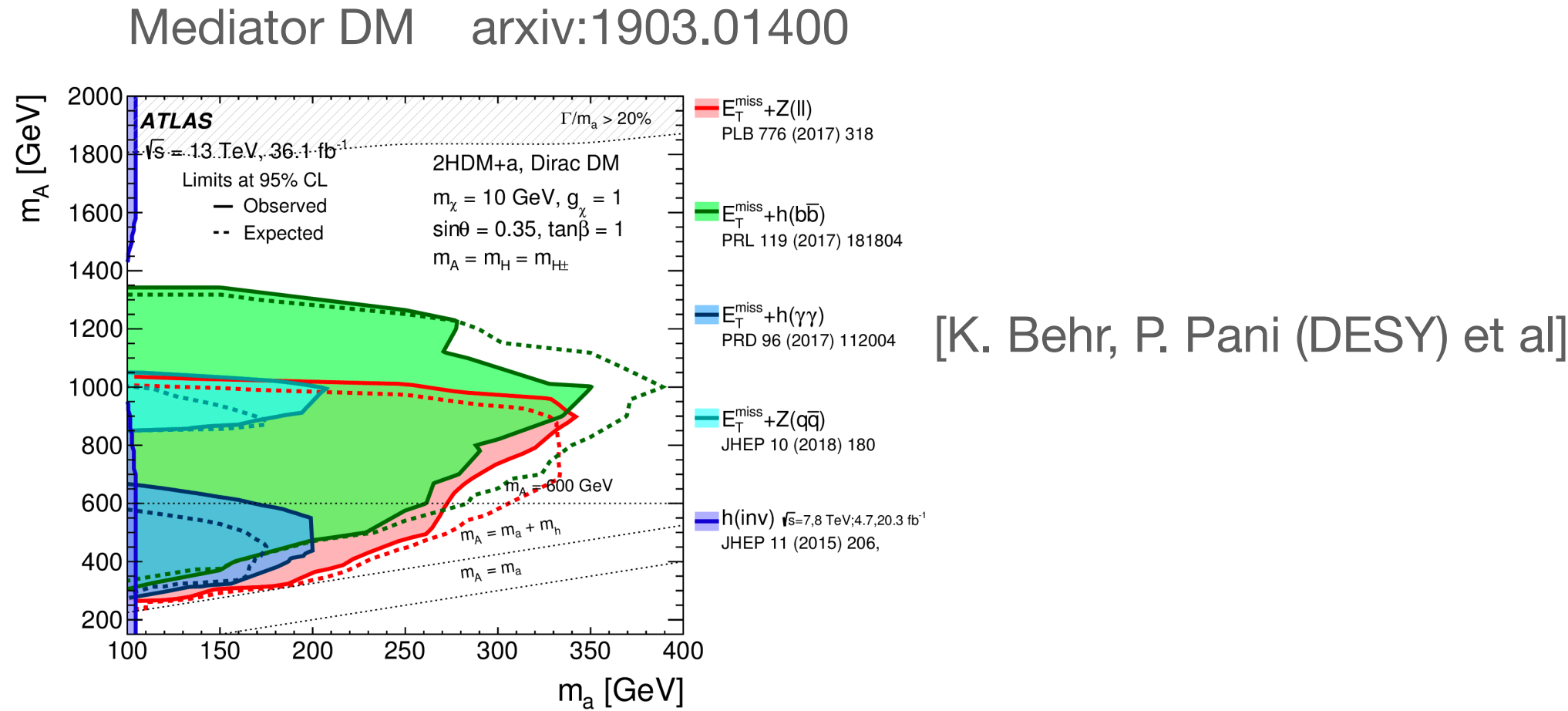
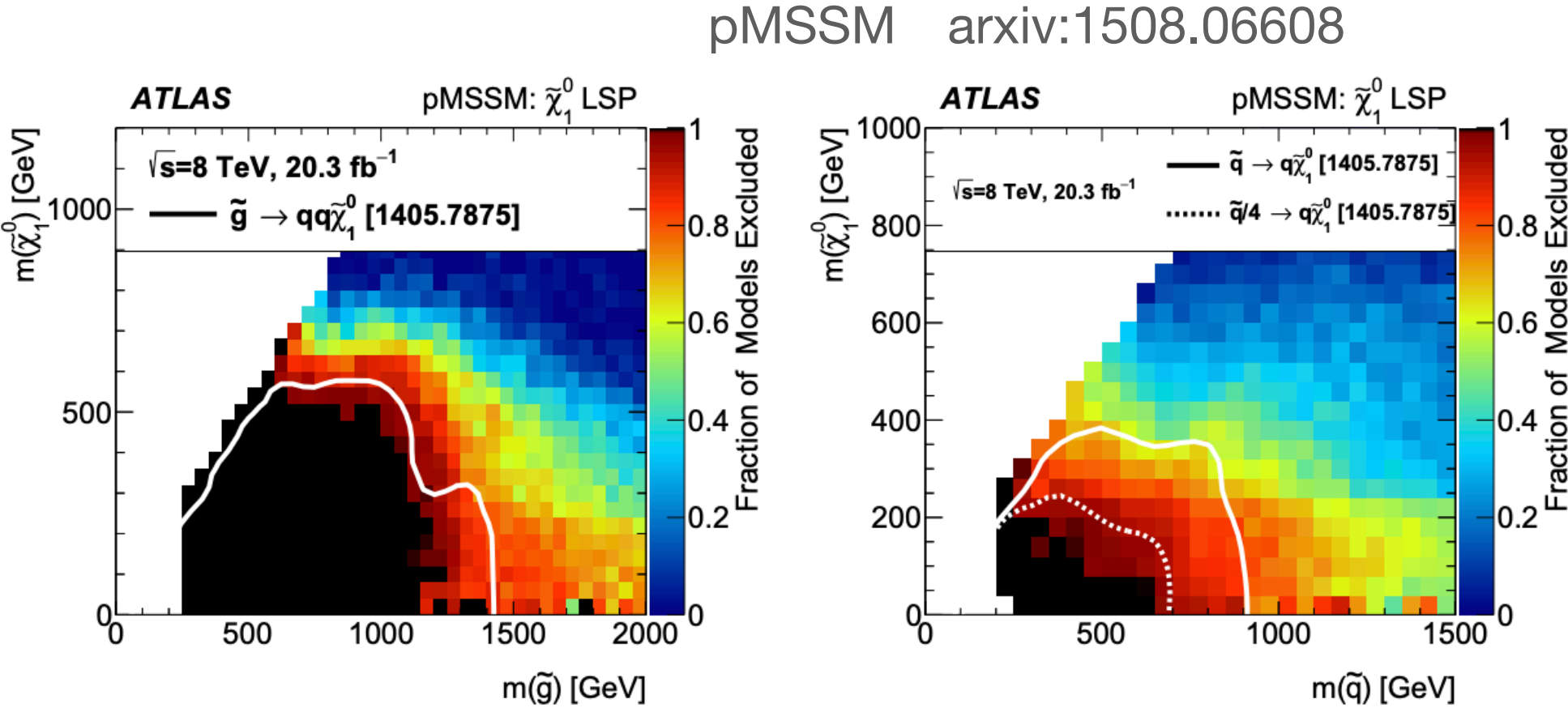
More Physics through Analysis Preservation

Used in cross-cutting summary analyses w/ multiple analyses

- Dark Matter models at the LHC
- SUSY reinterpretations

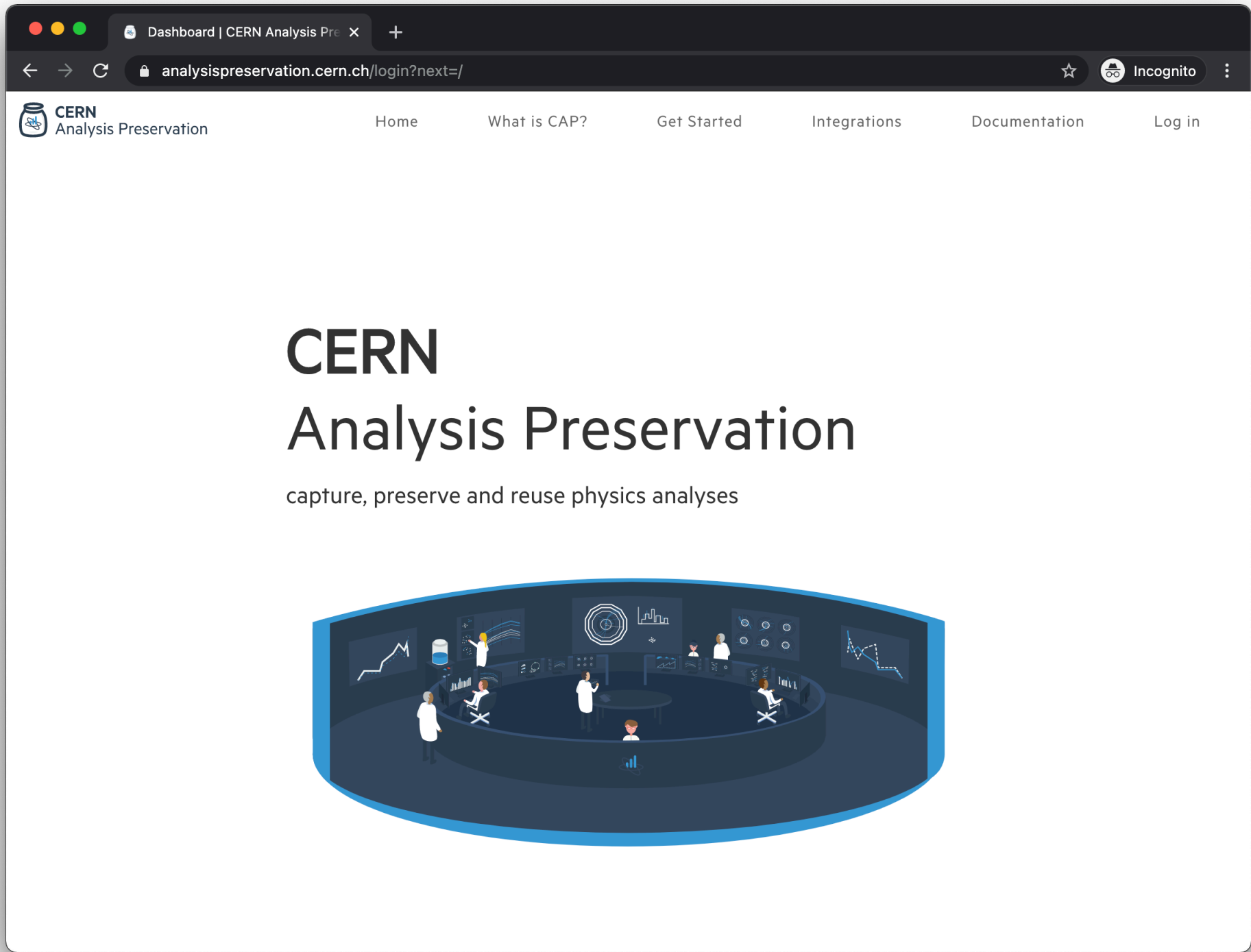


RPV SUSY

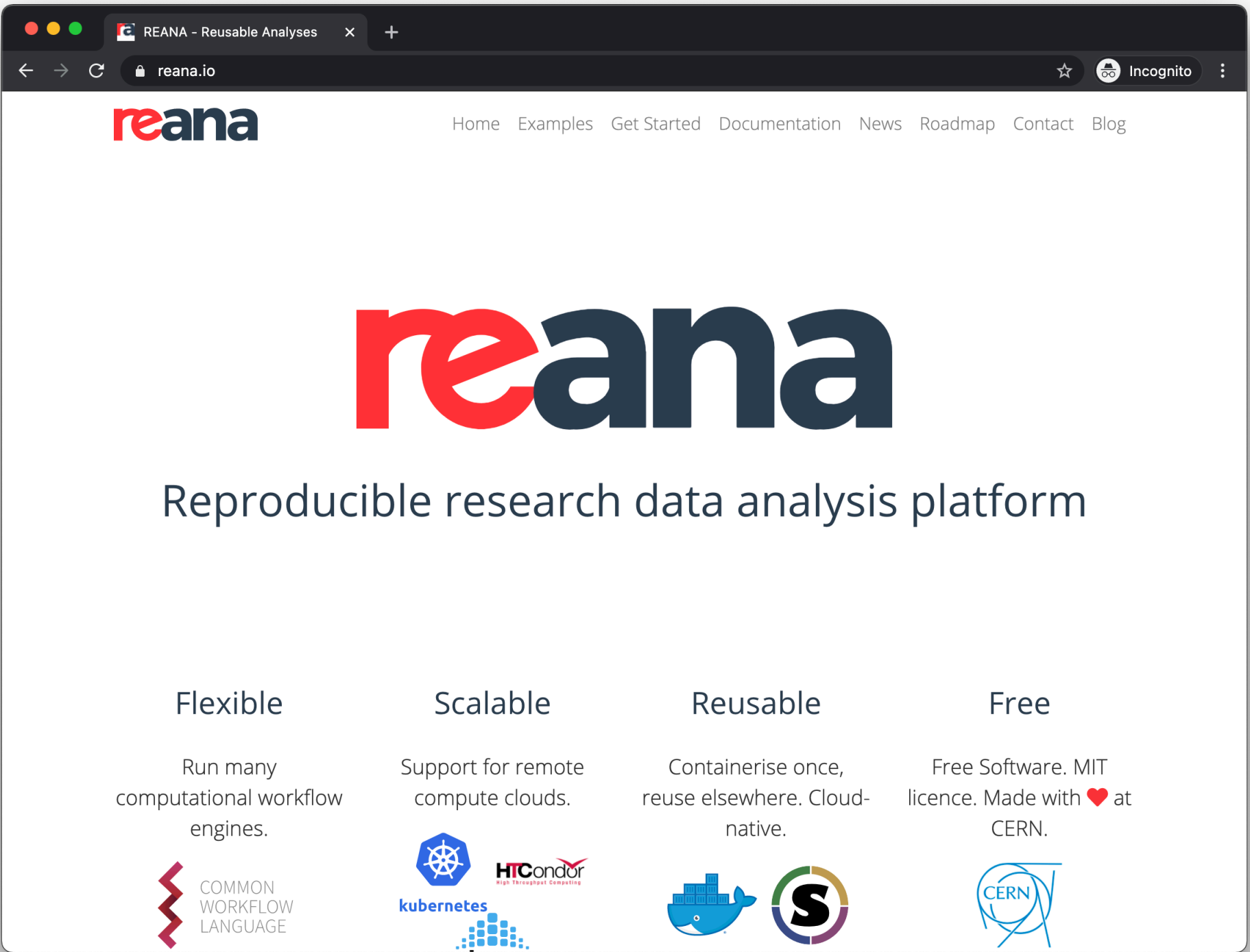


Institutional Support

CERN investing in infrastructure to systematically archive and re-run analyses on using cloud technologies



Archive



Re-run

Future

Once we gain experience: **Open Data at a higher abstraction level**

- allow external researches to query LHC wrt. to new theories

Theorist



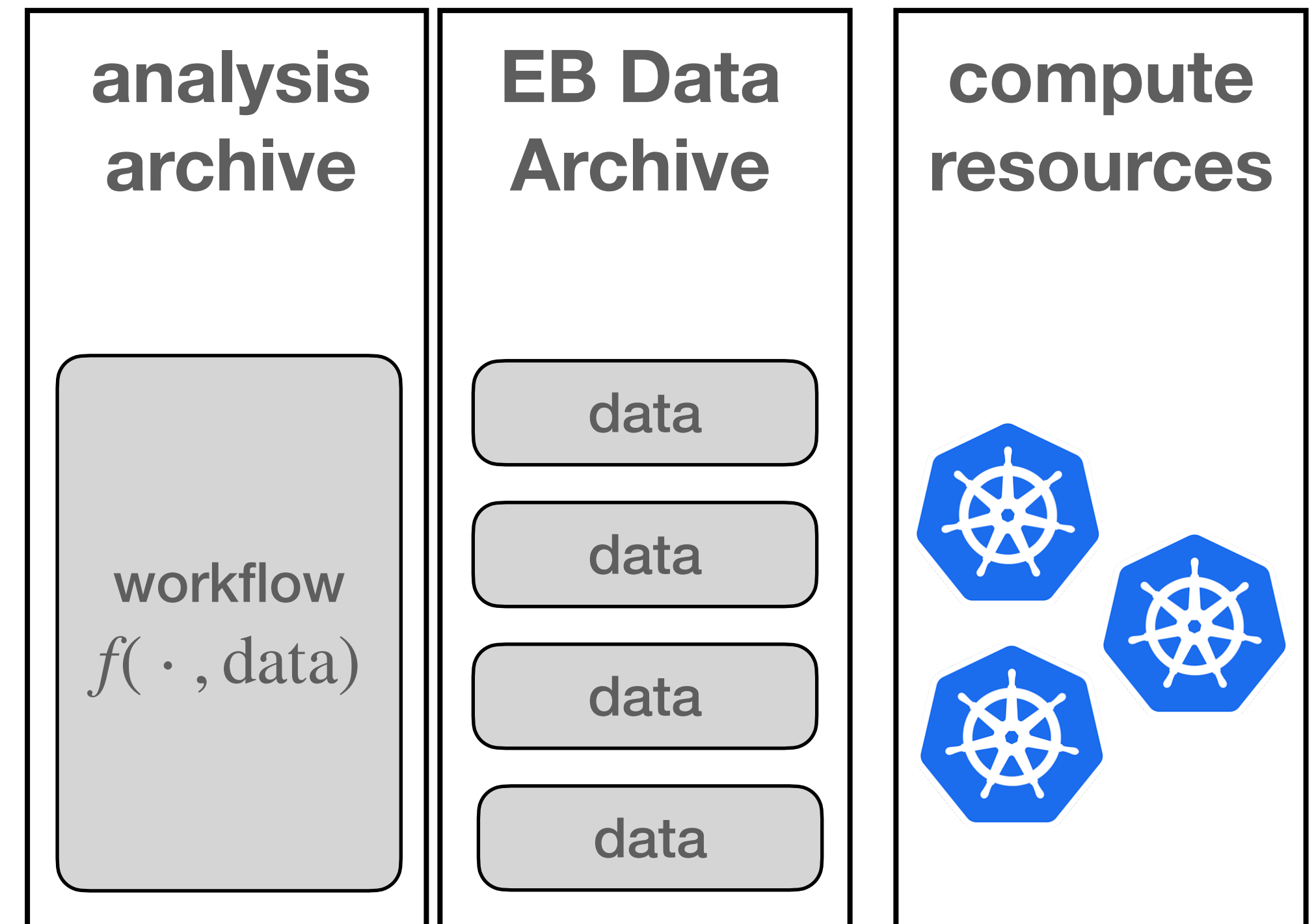
BSM model
→



$CLs(model) = f(model, data)$
←



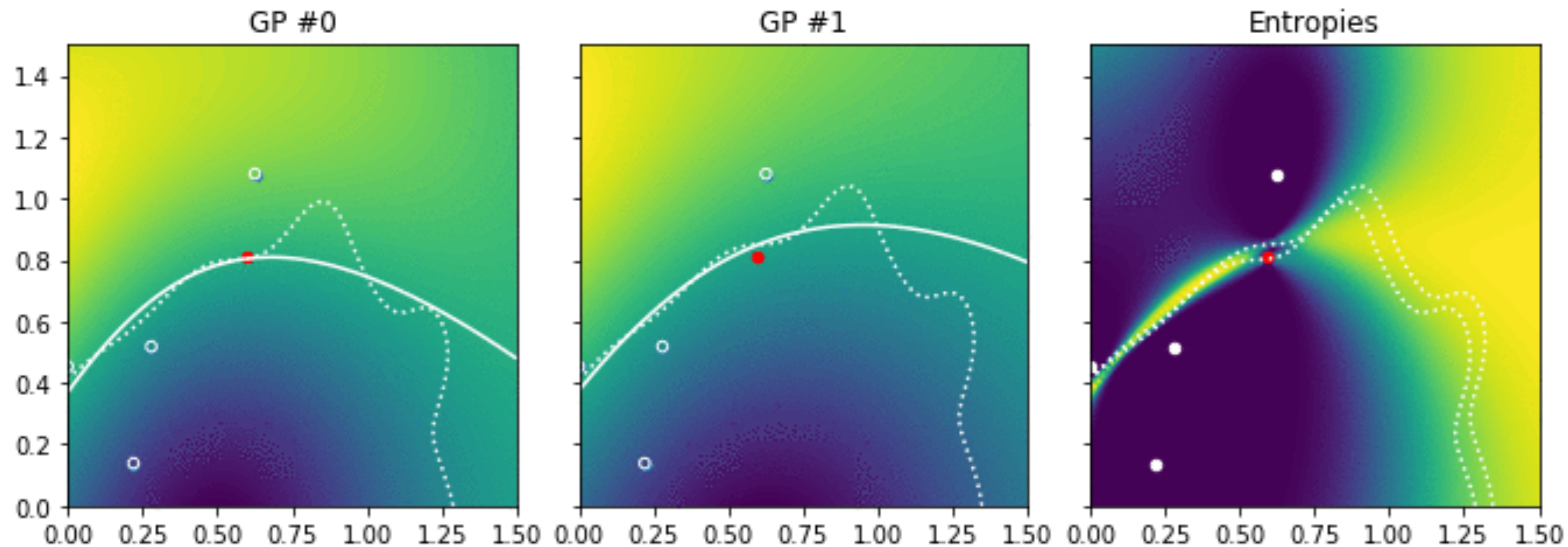
CERN/DESY/...



Future

Theory space is large, LHC is not sensitive everywhere.

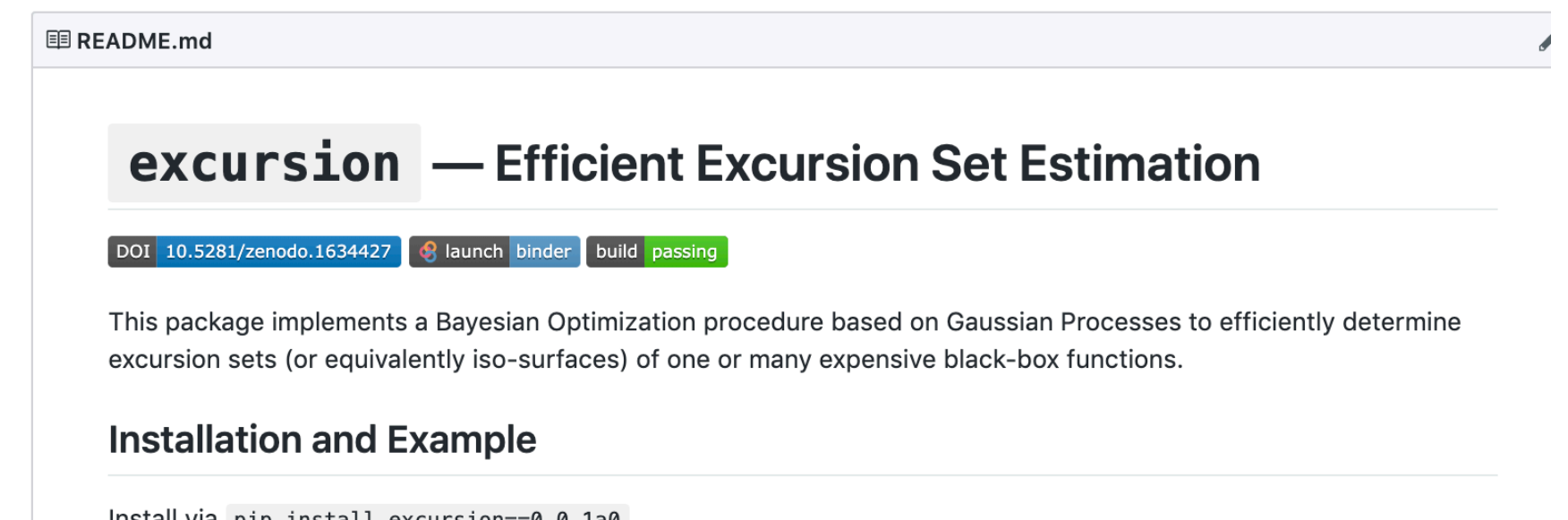
With streamlined reinterpretation, use ML to identify interesting models



[LH, G. Louppe]

Now being tested in ATLAS - stay tuned!

[P. Rieck, P. Gadow, J. v. Ahnen, I. Espejo +]



Outlook

HEP & other big science have unique challenges due to scale

Recent trends in IT, Data Science, ML bring us new tools

- **possibility to fundamentally rethink how we approach analysis**
- **foundation of HL-LHC analysis & computing is defined now (join!)
→ PB-scale interactive analysis?**
- **Technology can drive physics reach**

Open Data, Reproducibility: How can we fill the buzzwords with life?

- **LHC-wide policy: growing community & ecosystem of external tools**
- **Open Likelihoods: release the best info we have**
- **RECAST: reuse vs just reproduce**