

Spey

What are we up to these days?

Jack Y. Araz
THOMAS JEFFERSON NATIONAL ACCELERATOR
FACILITY

LPSC Grenoble, FR
June 18th, 2024



U.S. DEPARTMENT OF
ENERGY

Office of
Science



Sales pitch for the talk

- ❖ There is not enough information to construct a reliable likelihood
- ❖ How can we enhance the accuracy of the simplified likelihoods?
- ❖ Full likelihoods can become computationally intensive. Can we simplify them without sacrificing? (Spoiler alert: ML!)
- ❖ There are many different software for hypothesis testing; how can we unify them?

(Re)interpretation of the LHC results for new physics

29 August 2023 to 1 September 2023
Durham University

HS³

High Energy Physics

Statistics Serialization Standard

Carsten Burgard

Tomas Dado, Jonas Eschle, Matthew Feickert, Cornelius Grunwald,
Alexander Held, Robin Pelkner, Jonas Rembser, Oliver Schulz

tu technische universität
dortmund



Outline

- ❖ What on earth is Spey?
- ❖ Plans for world domination
- ❖ Conclusion



What on earth is Spey?

Searches for new physics

Lagrangian

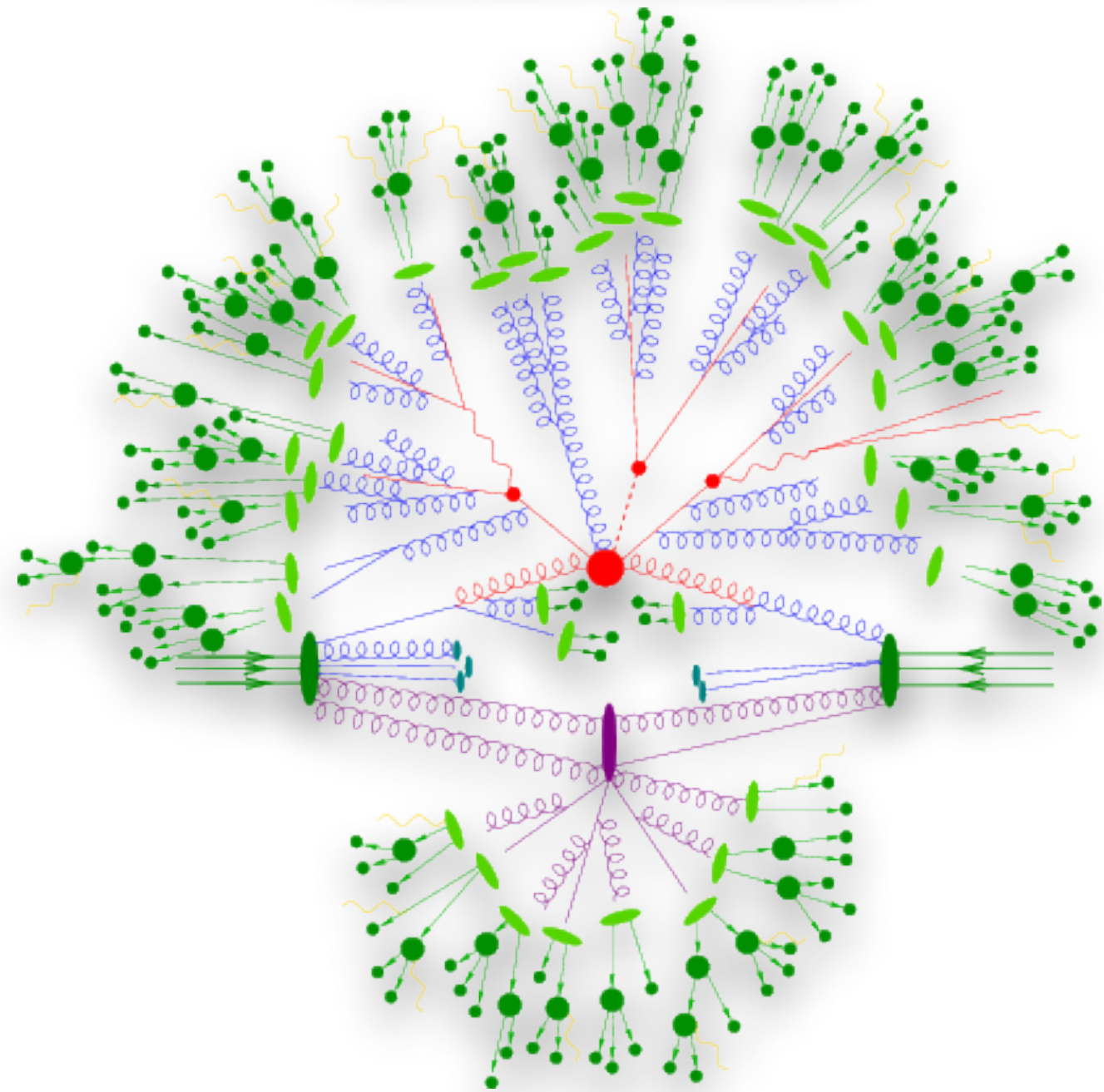


Image credit: Sherpa

Searches for new physics

Lagrangian

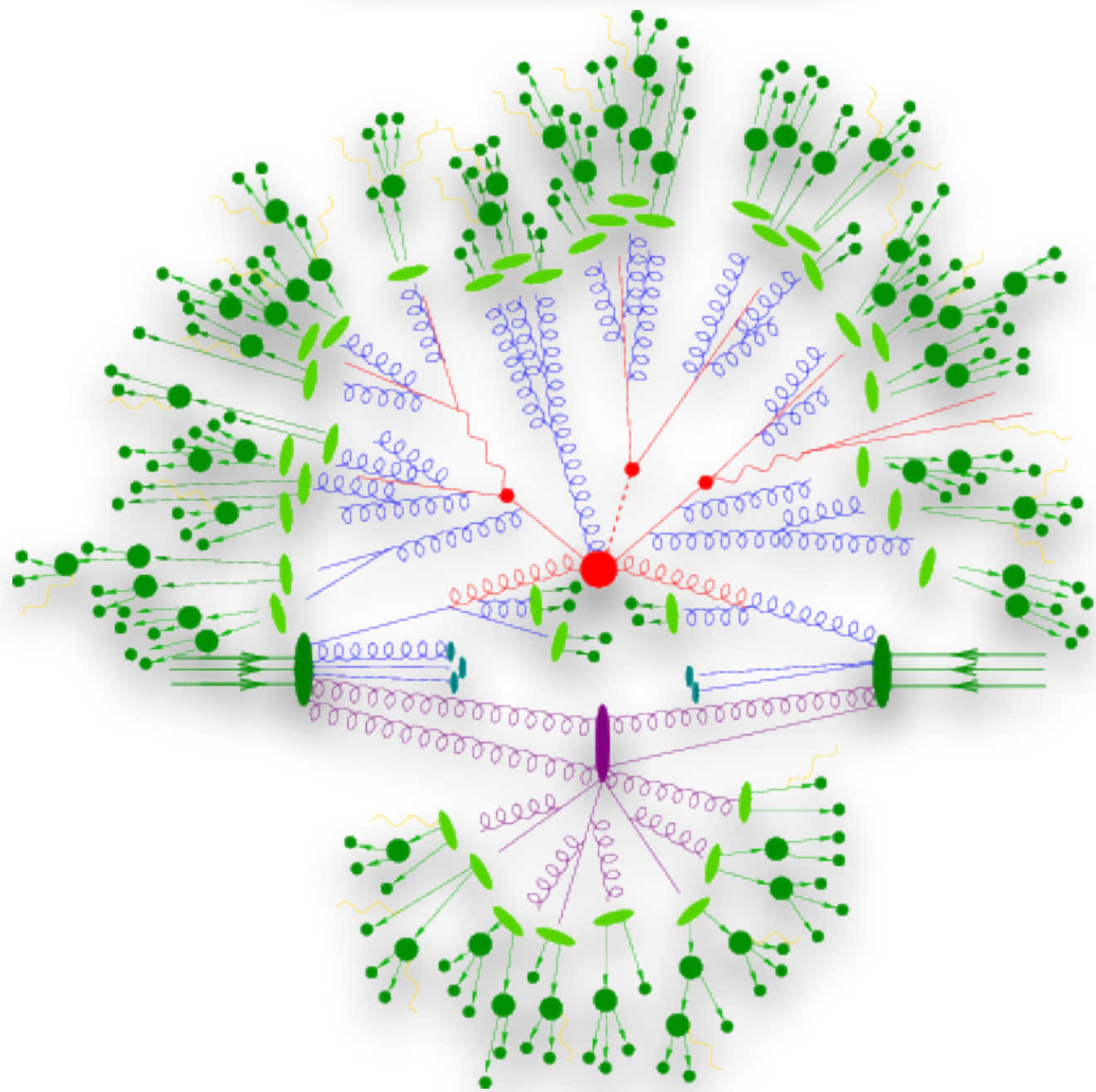
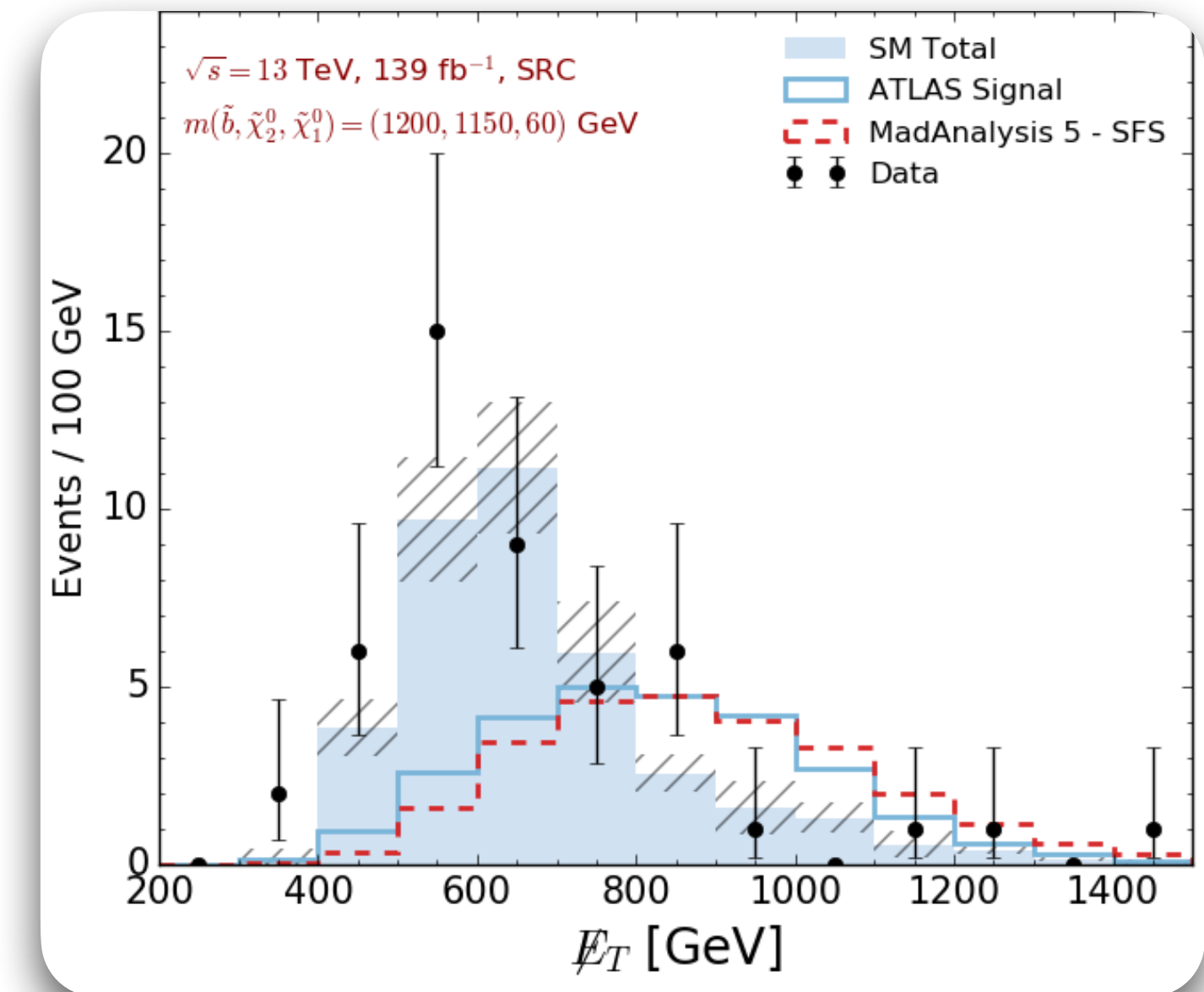
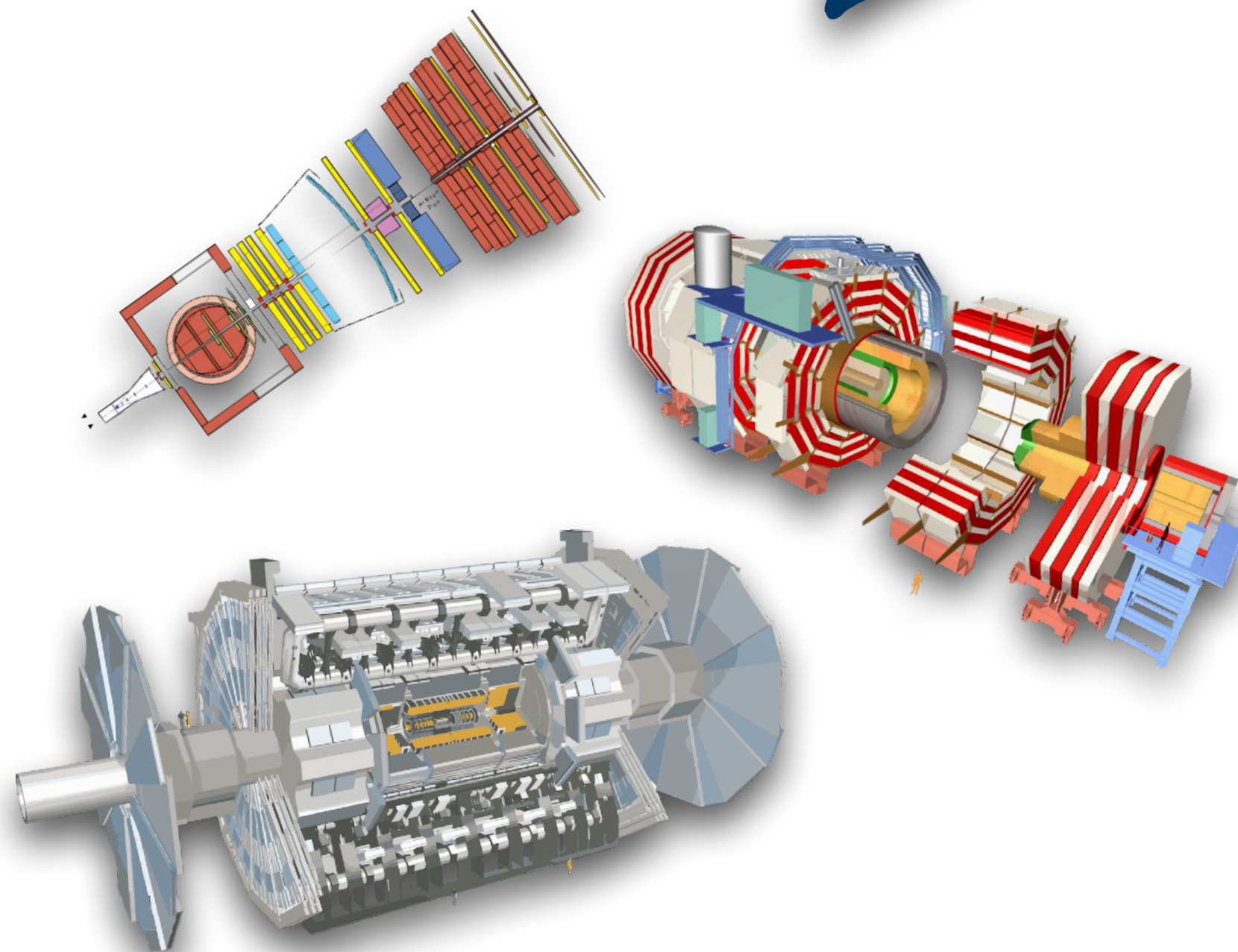


Image credit: Sherpa



Smearred MC \oplus observed data

Searches for new physics

Lagrangian

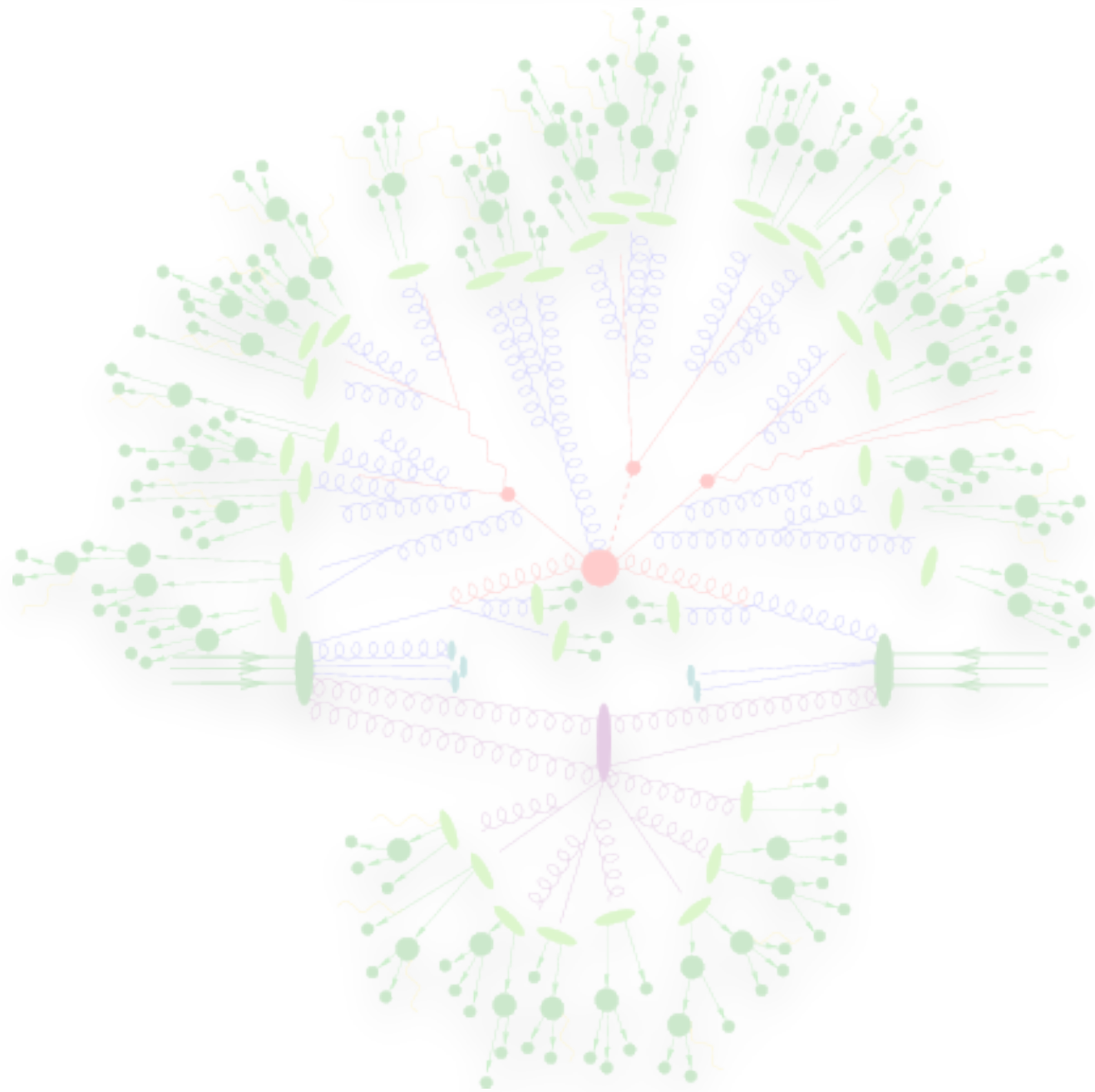
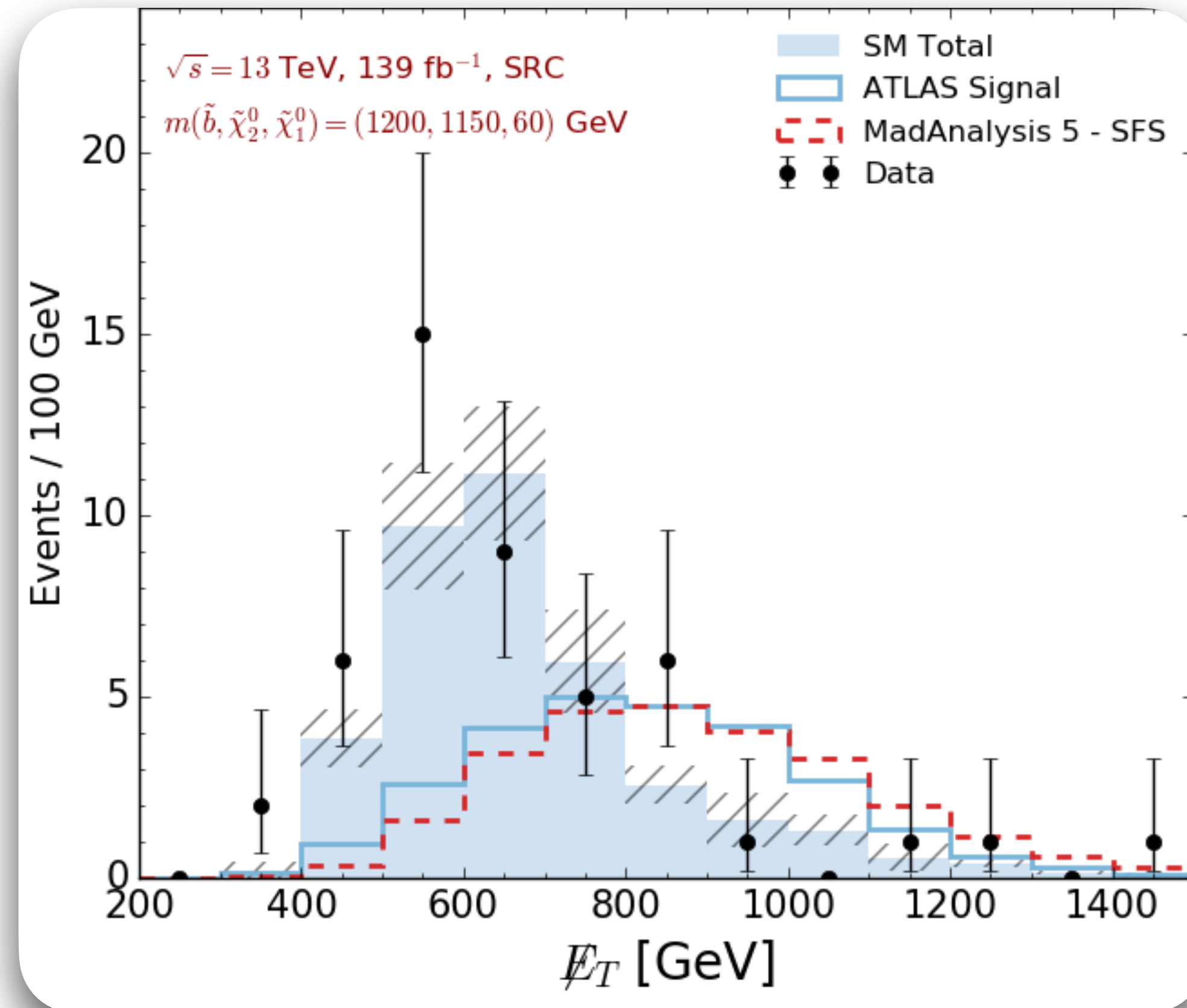


Image credit: Sherpa



I need to construct a statistical model,
 $\mathcal{L}(\mu, \theta) = \dots$,
to test my theory

Smearred MC \oplus observed data

Spey demystified

JYA, SciPost '24

```
$ pip install spey
```

Compute
p-values

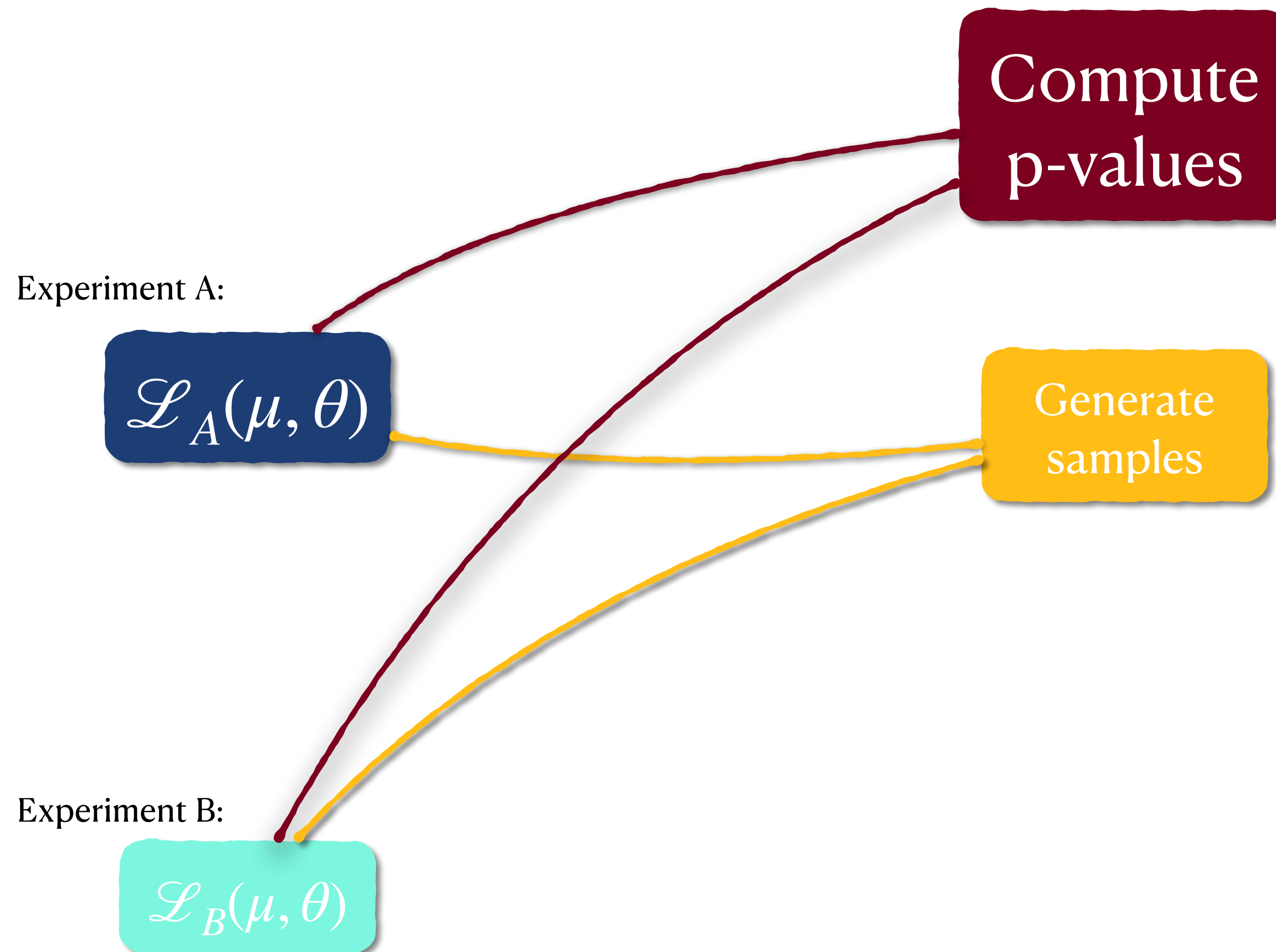
Generate
samples

- ❖ Exclusion limits
 - ❖ χ^2 analysis
 - ❖ POI upper limits
- And more...

Spey demystified

JYA, SciPost '24

```
$ pip install spey
```



- ❖ Exclusion limits
 - ❖ χ^2 analysis
 - ❖ POI upper limits
- And more...

Spey demystified

JYA, SciPost '24

```
$ pip install spey
```

Origin: I don't care!

Experiment A:

$$\mathcal{L}_A(\mu, \theta)$$

Experiment B:

$$\mathcal{L}_B(\mu, \theta)$$

Compute
p-values

Generate
samples

- ❖ Exclusion limits
 - ❖ χ^2 analysis
 - ❖ POI upper limits
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Generate
samples

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 - ❖ POI upper limits
- And more...

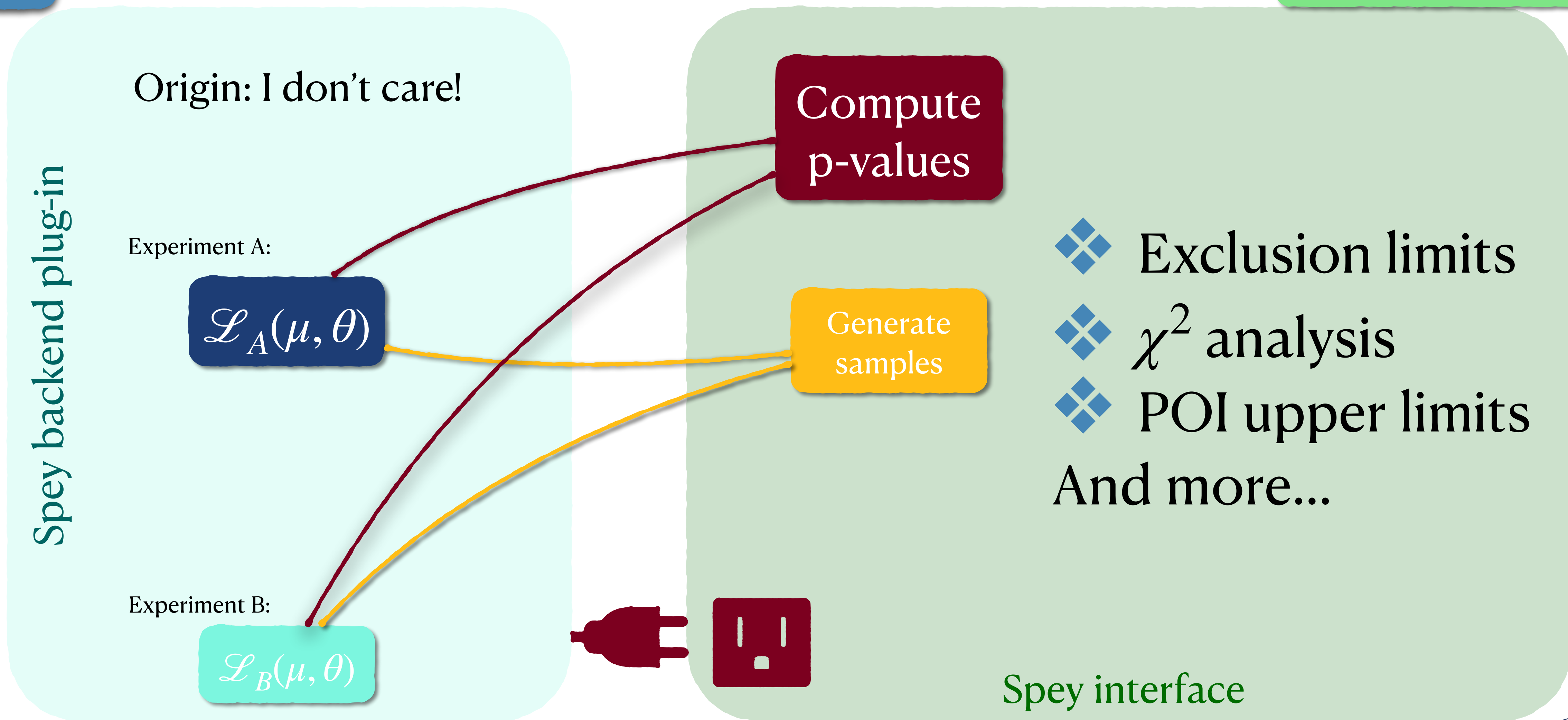


Spey interface

Spey demystified

JYA, SciPost '24

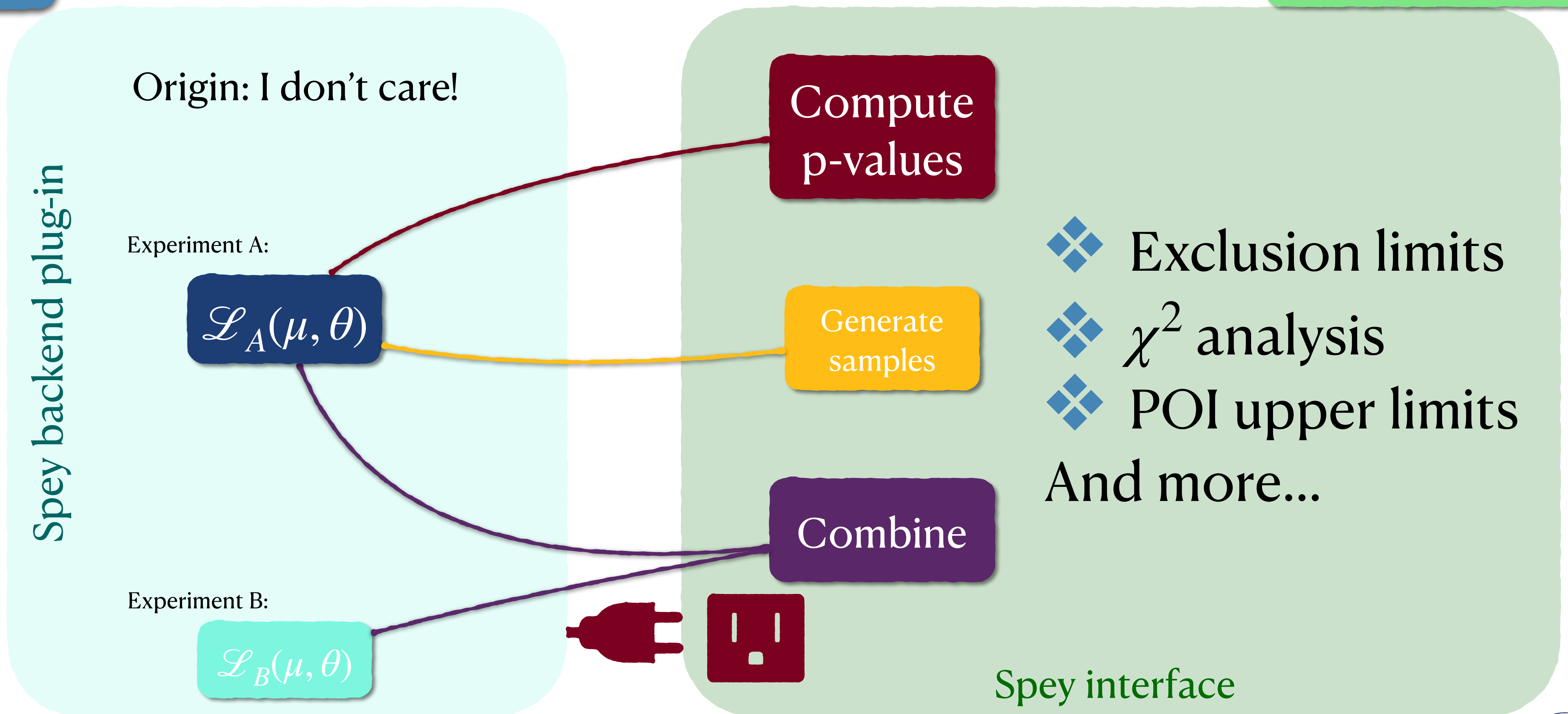
```
$ pip install spey
```



Spey demystified

JYA, SciPost '24

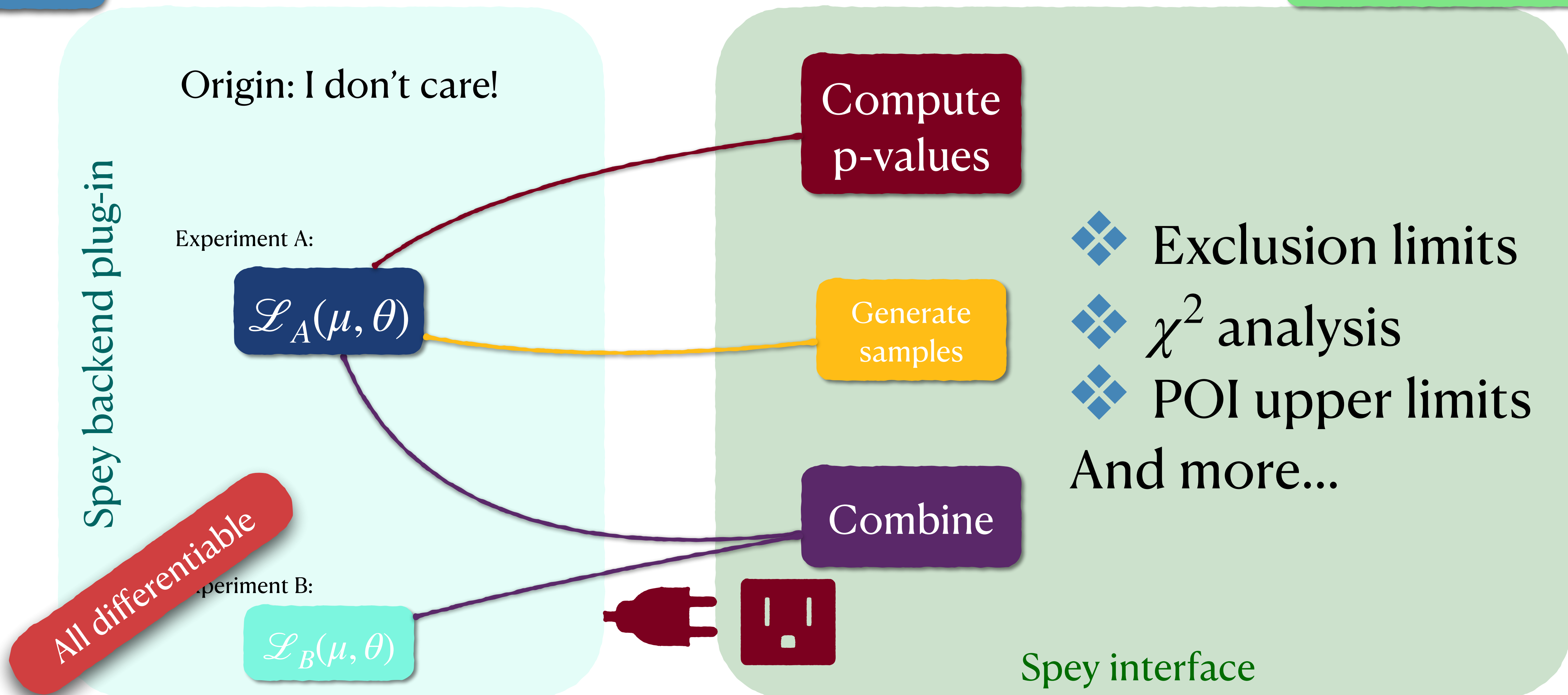
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$ pip install spey
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Spey demystified

JYA, SciPost '24

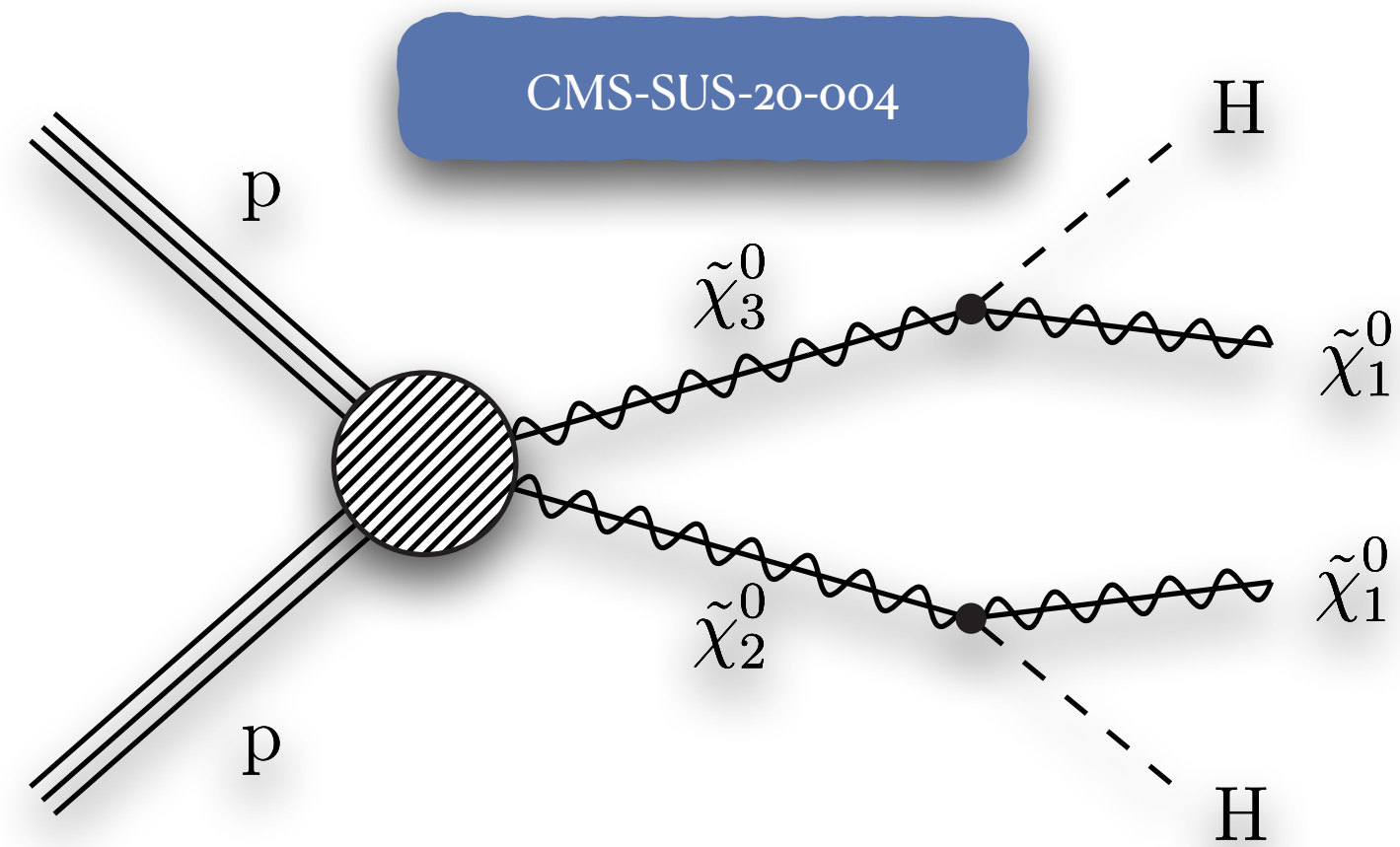
```
$ pip install spey
```



Improving Simplified Likelihoods



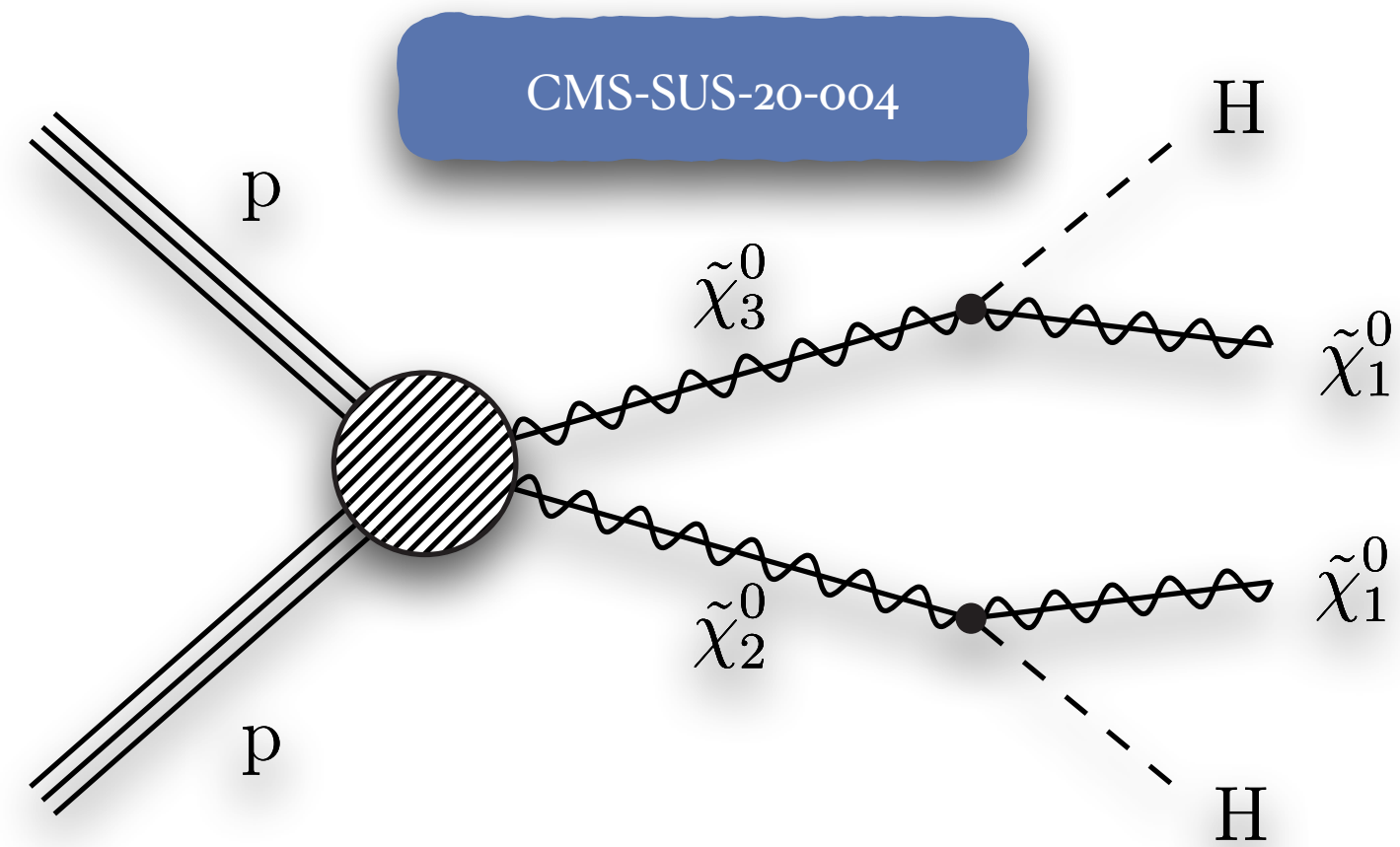
JYA, SciPost '24



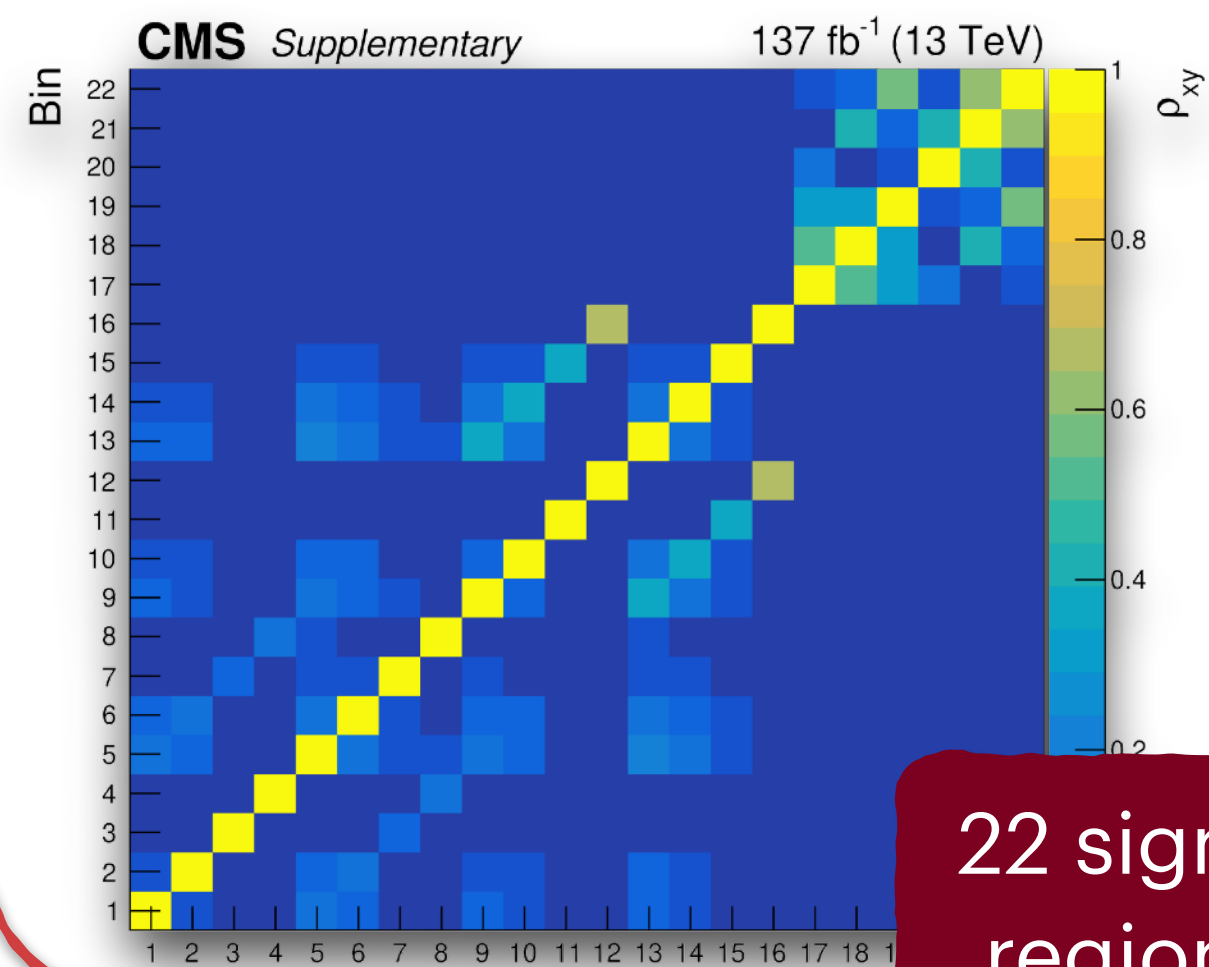
Improving Simplified Likelihoods



JYA, SciPost '24



Correlation Matrix

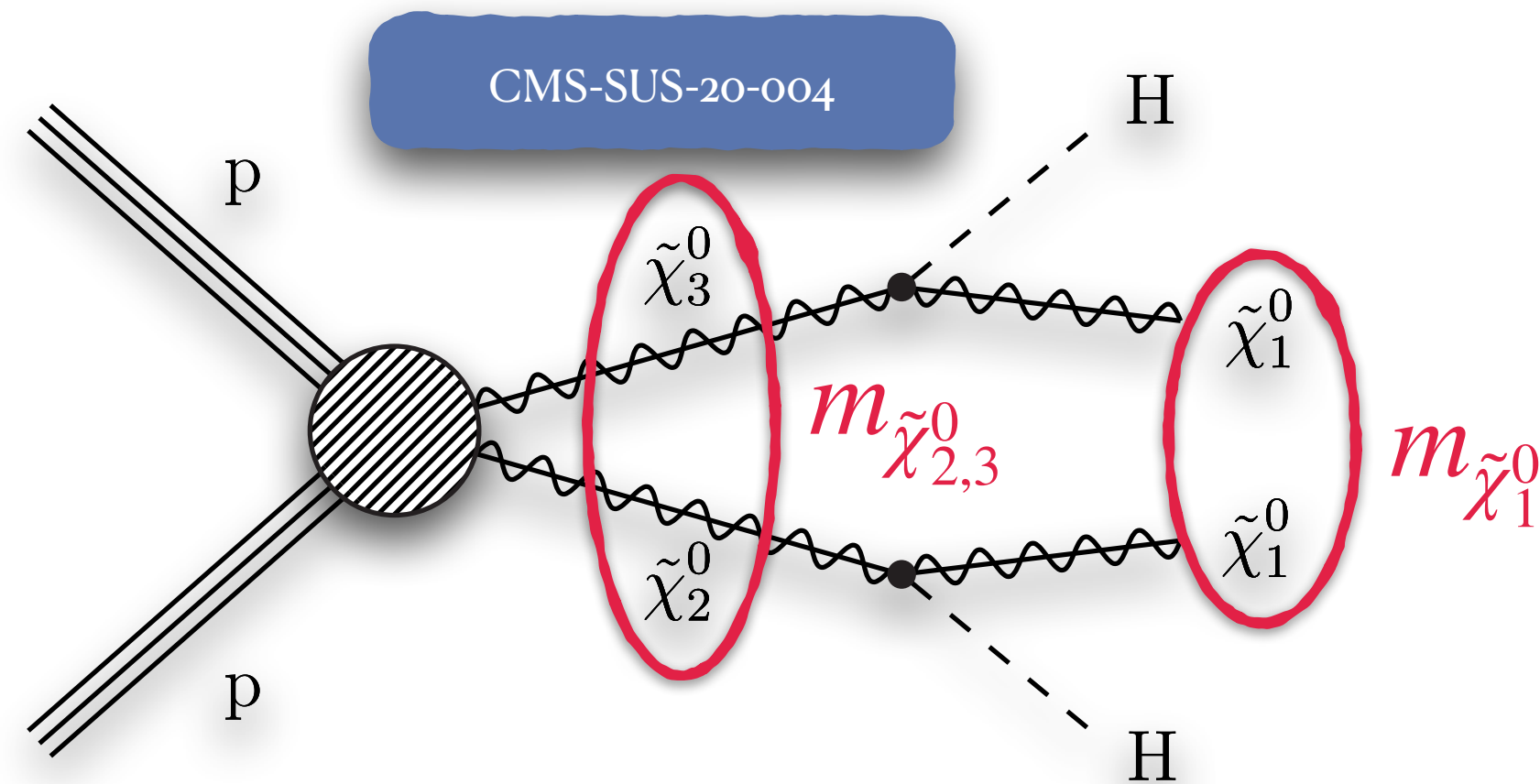


22 signal regions

Improving Simplified Likelihoods

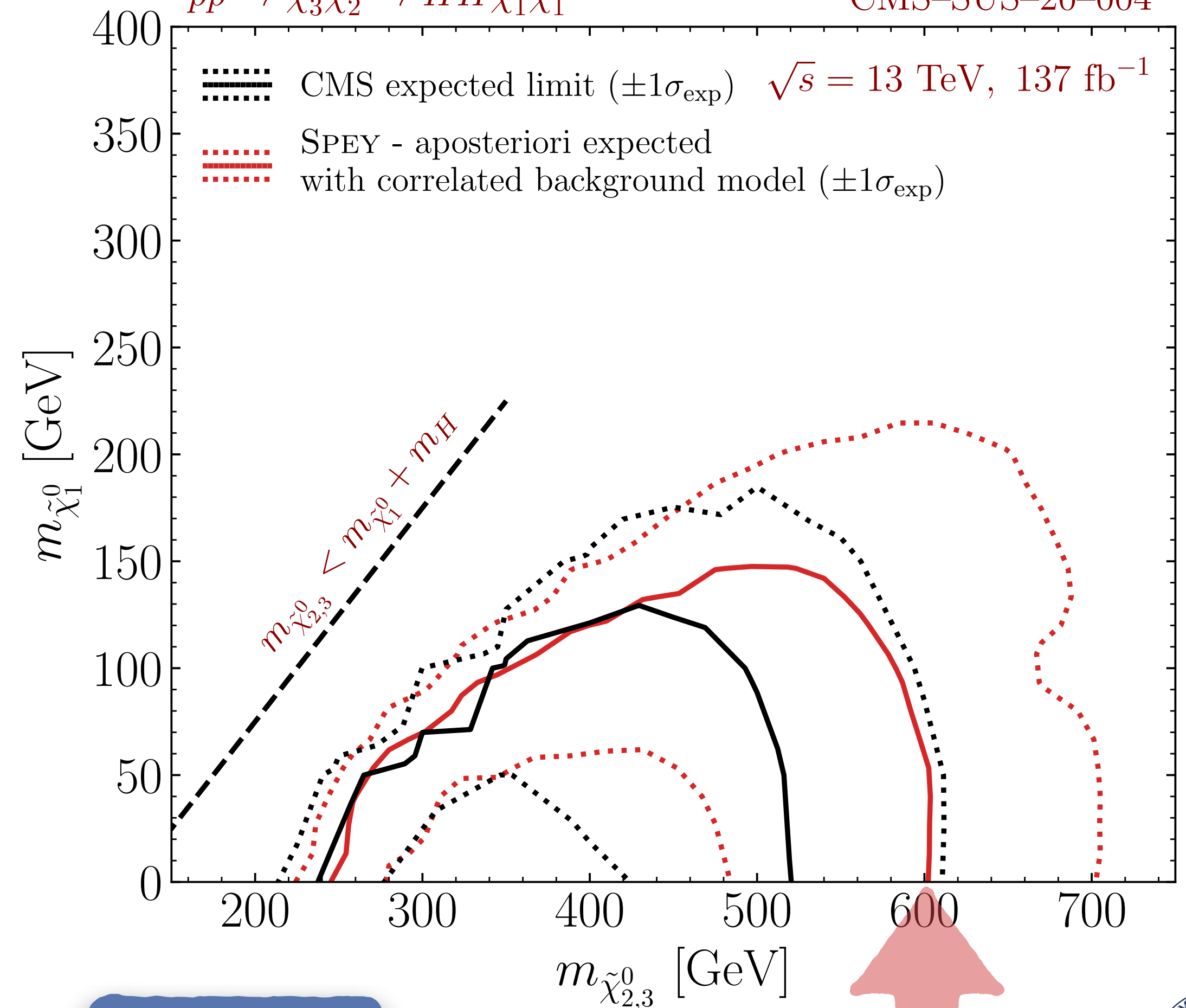


JYA, SciPost '24

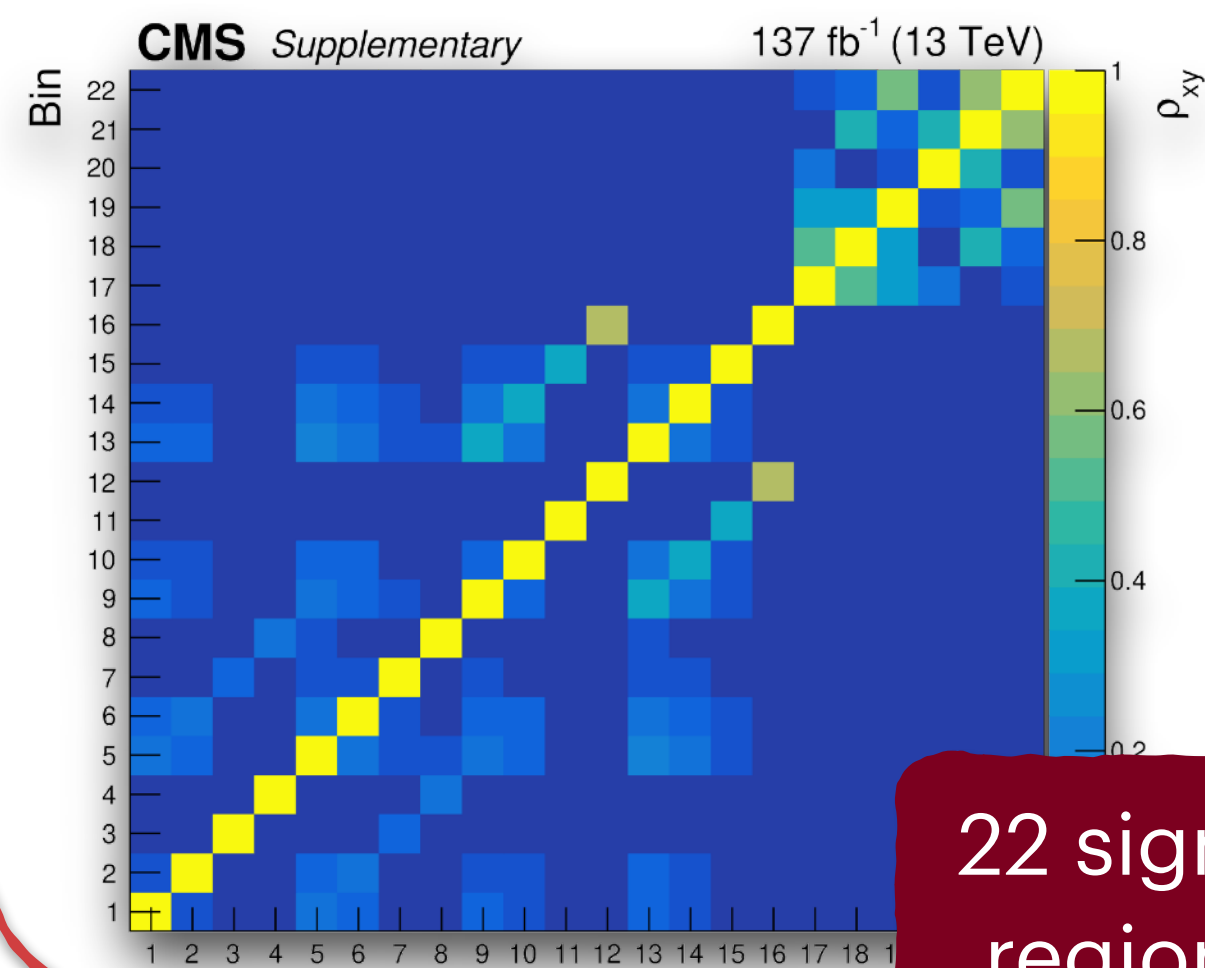


backend="default_pdf.correlated_background"

$pp \rightarrow \tilde{\chi}_3^0 \tilde{\chi}_2^0 \rightarrow HH \tilde{\chi}_1^0 \tilde{\chi}_1^0$ CMS-SUS-20-004



Correlation Matrix



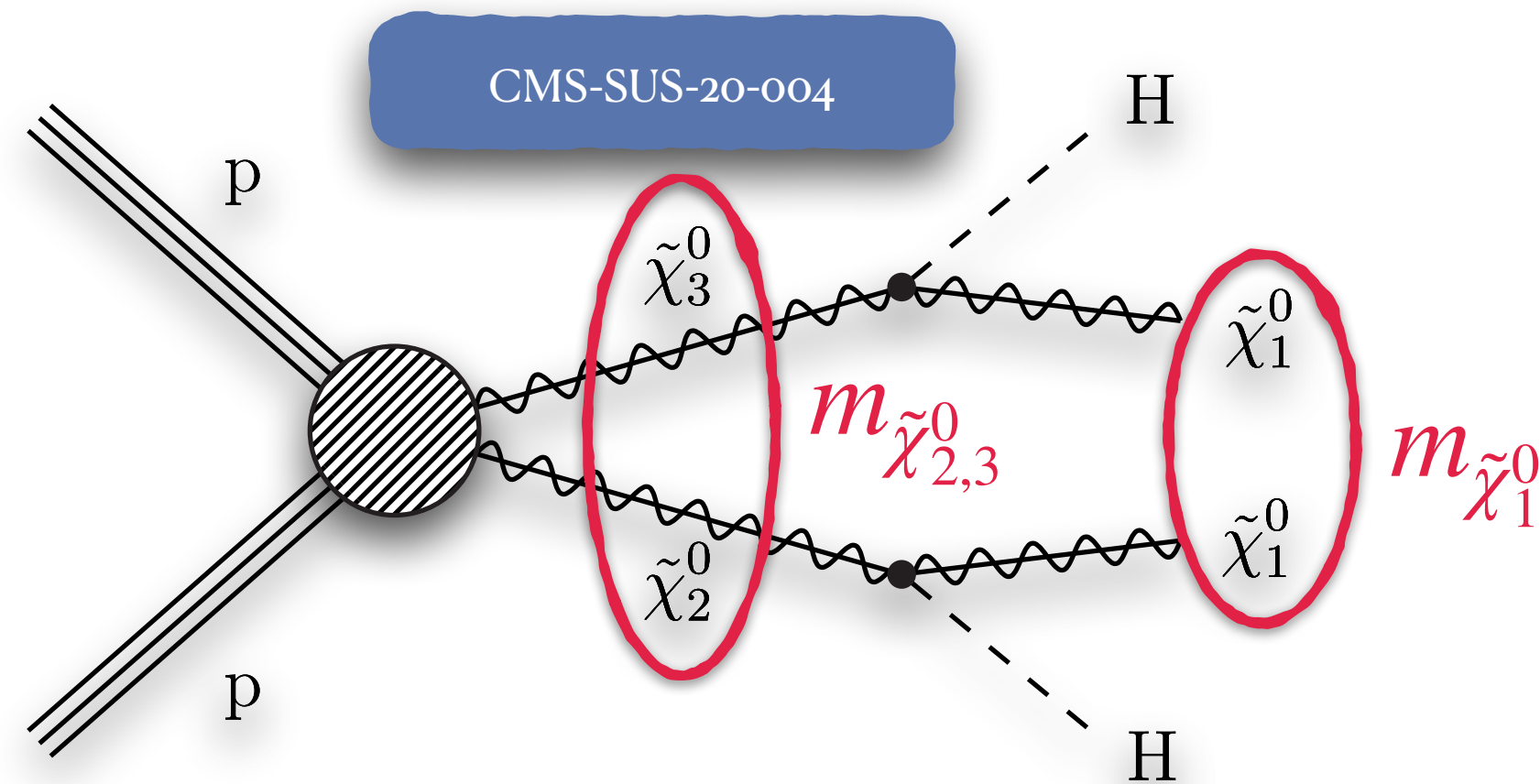
22 signal regions

CMS-NOTE-2017-001

Improving Simplified Likelihoods



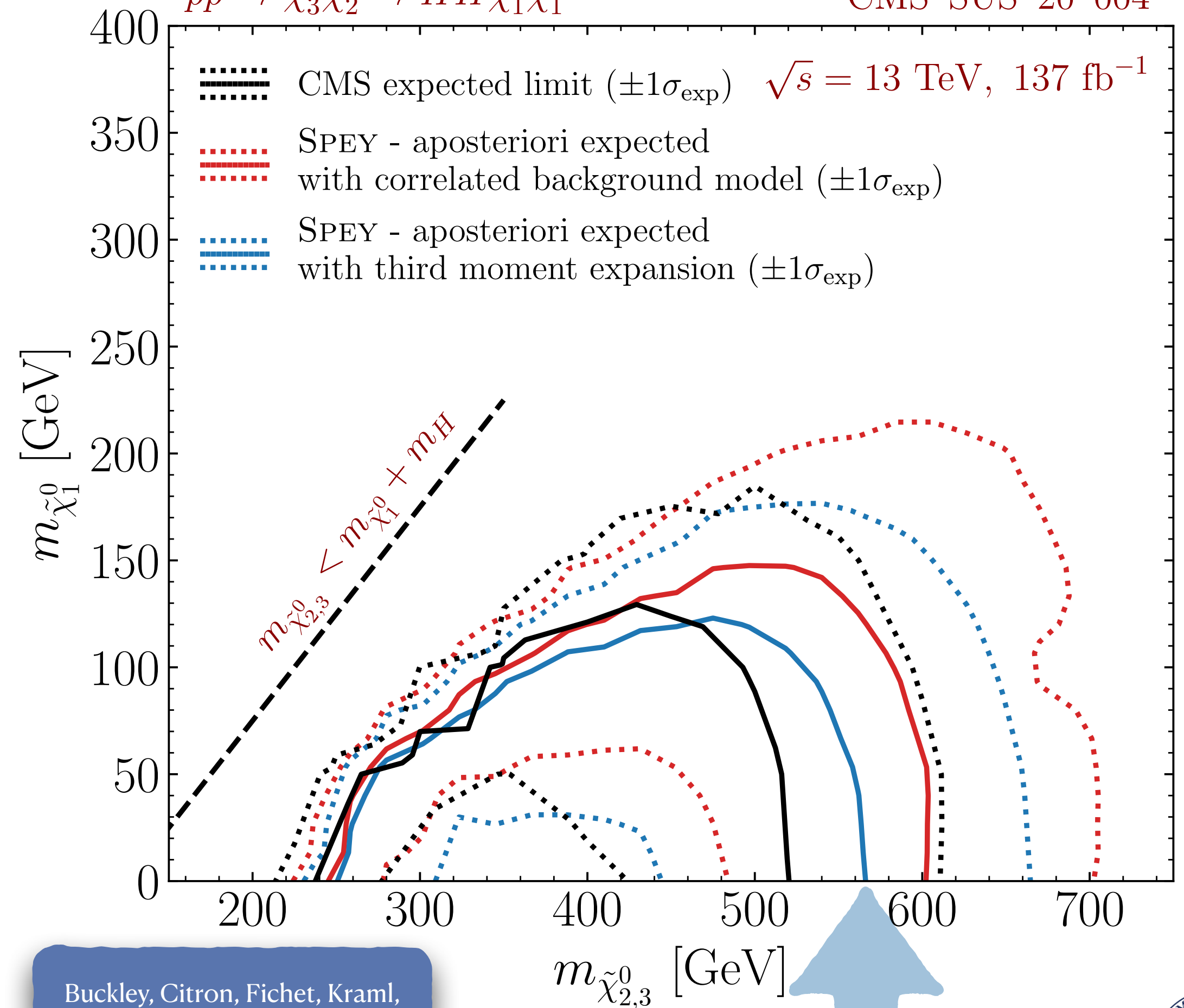
JYA, SciPost '24



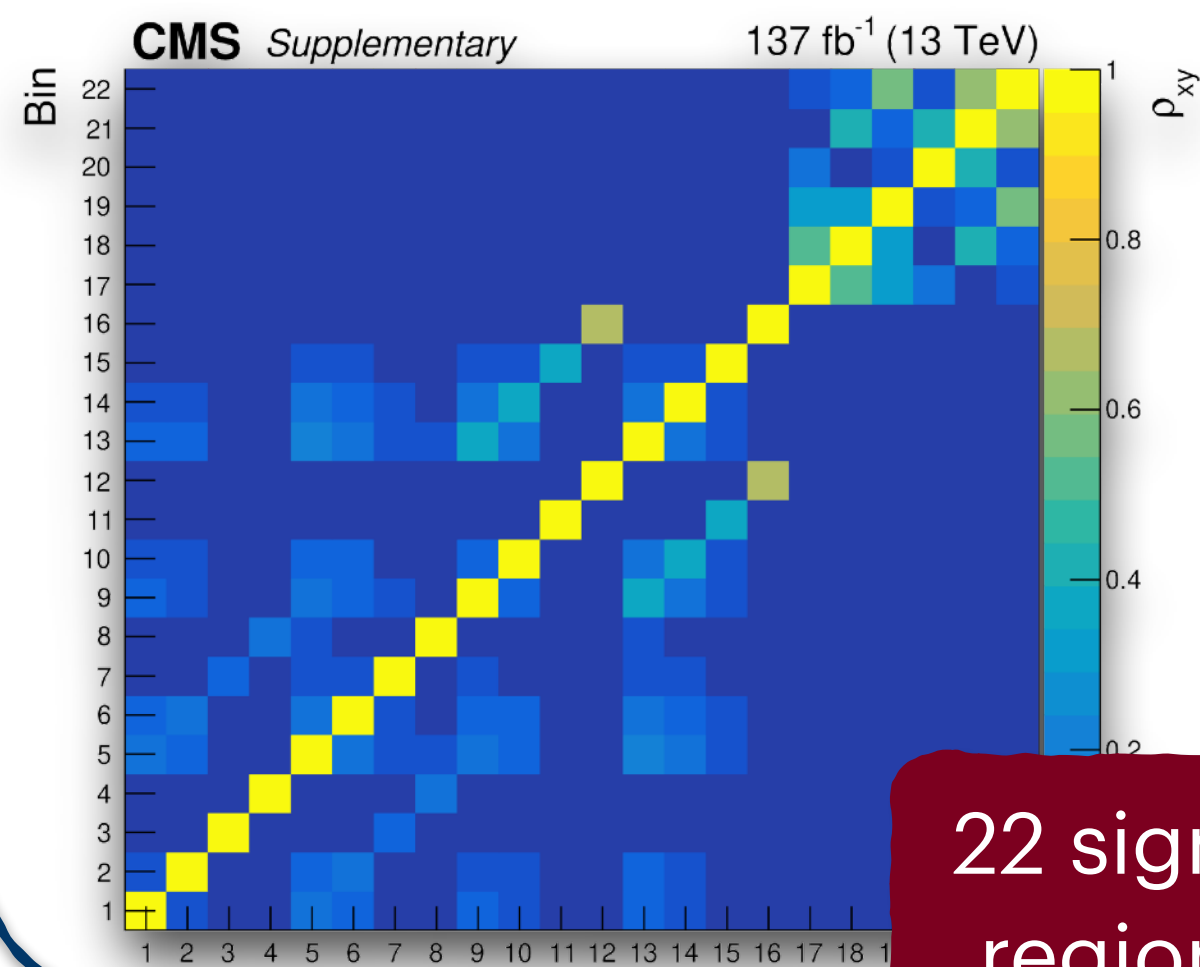
backend="default_pdf.third_moment_expansion"

$pp \rightarrow \tilde{\chi}_3^0 \tilde{\chi}_2^0 \rightarrow HH \tilde{\chi}_1^0 \tilde{\chi}_1^0$

CMS-SUS-20-004



Correlation Matrix



⊕ Third Moments

22 signal regions

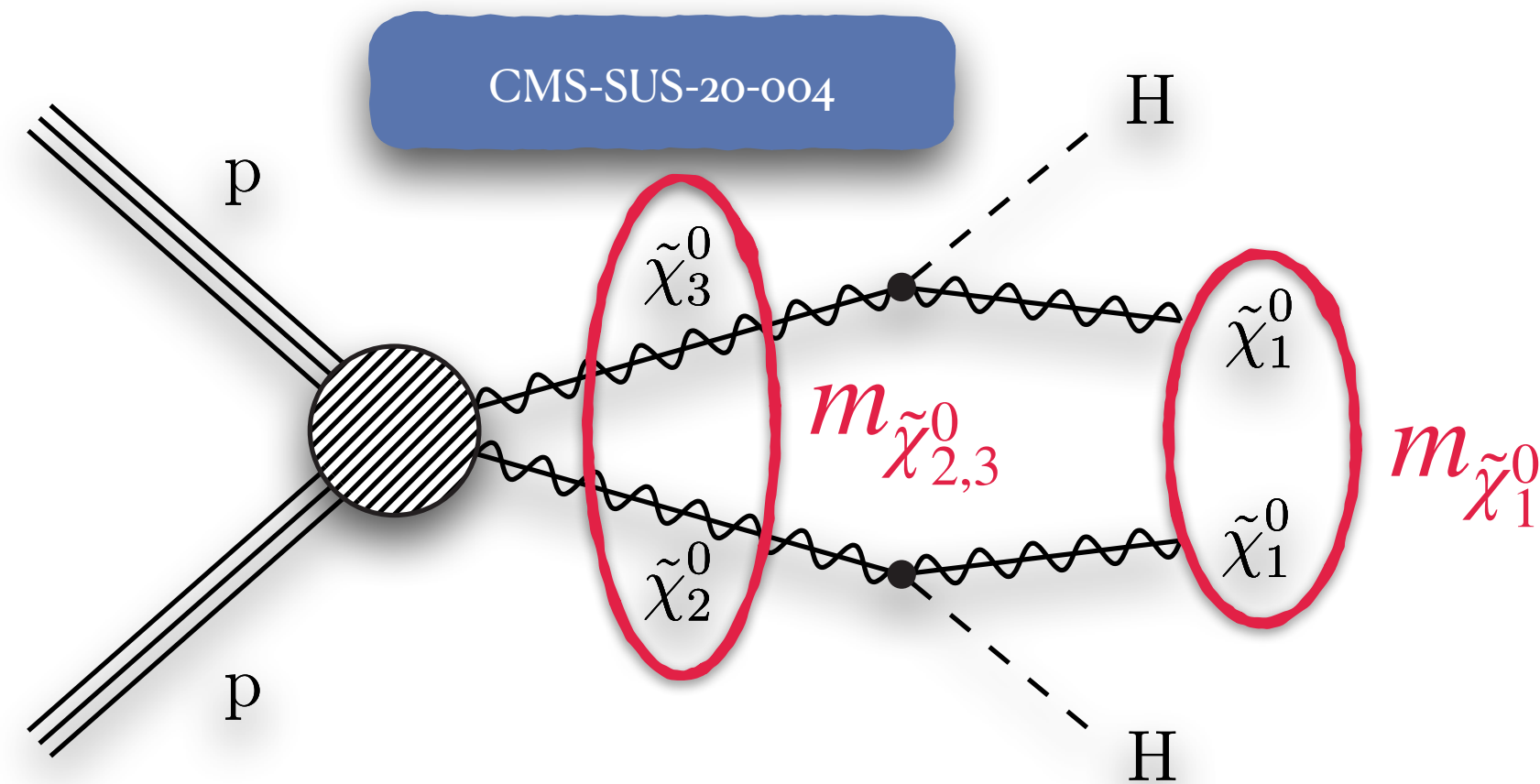
Buckley, Citron, Fichet, Kraml, Waltenberger, Wardle; JHEP '18

-40 GeV

Improving Simplified Likelihoods

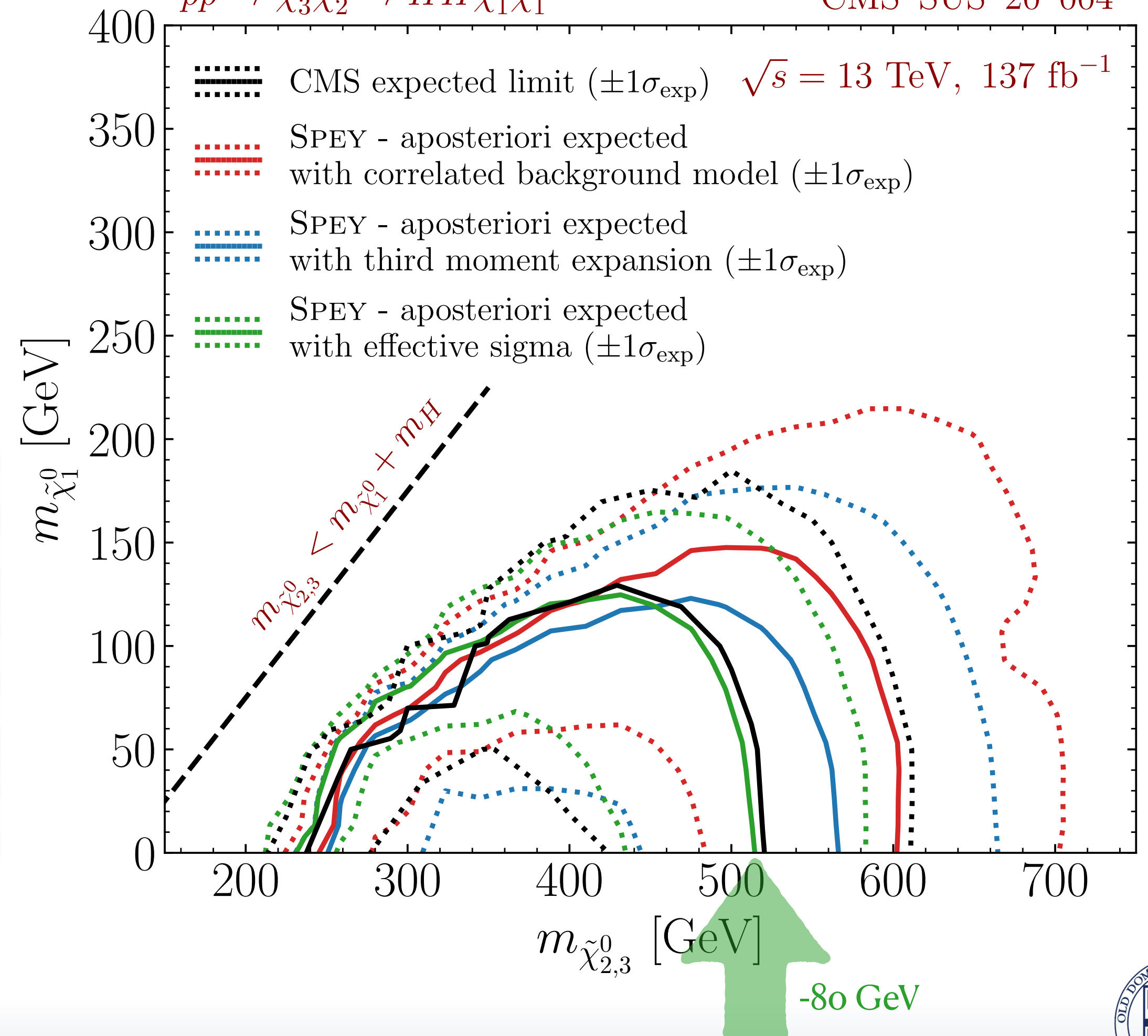


JYA, SciPost '24

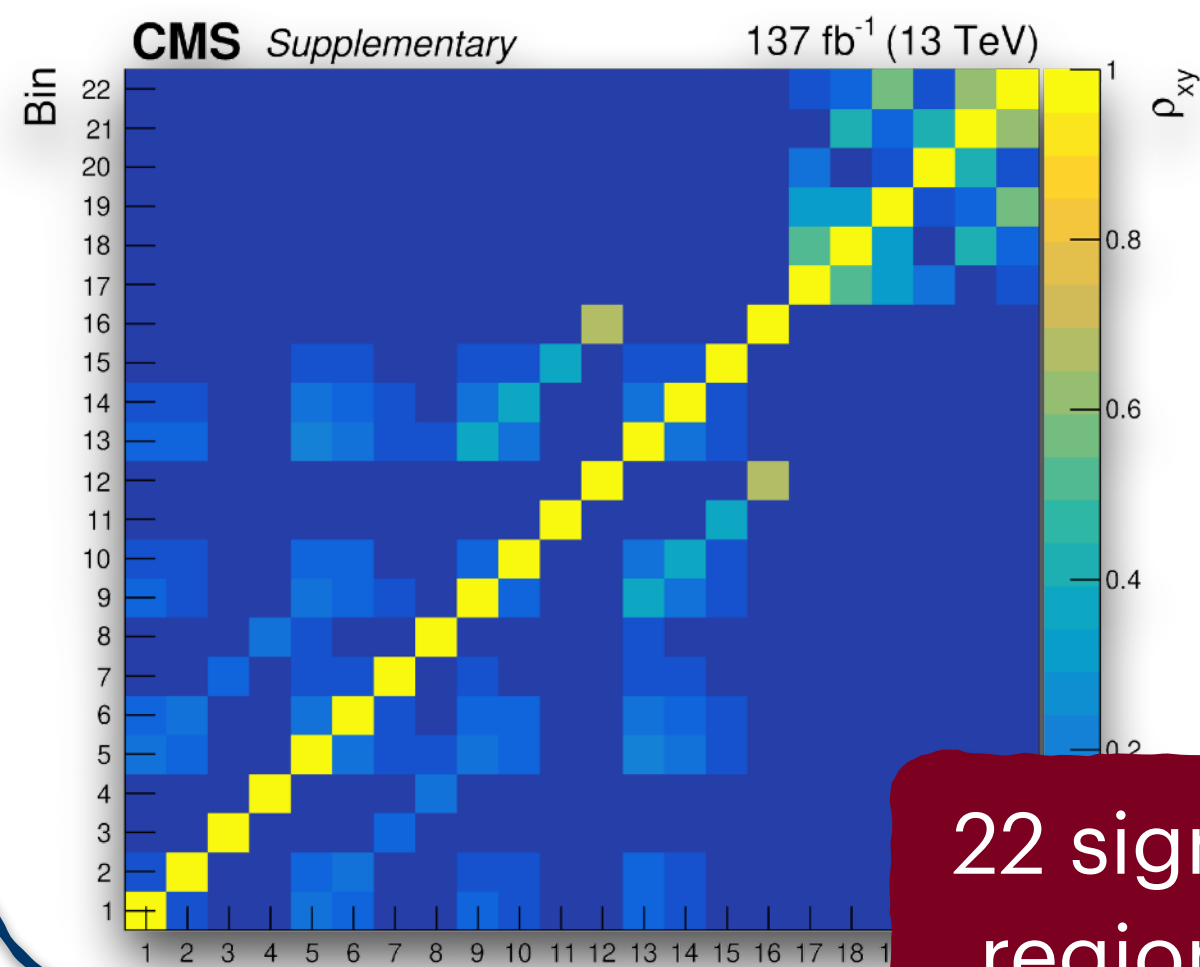


backend="default_pdf.effective_sigma"

$pp \rightarrow \tilde{\chi}_3^0 \tilde{\chi}_2^0 \rightarrow HH \tilde{\chi}_1^0 \tilde{\chi}_1^0$ CMS-SUS-20-004



Correlation Matrix



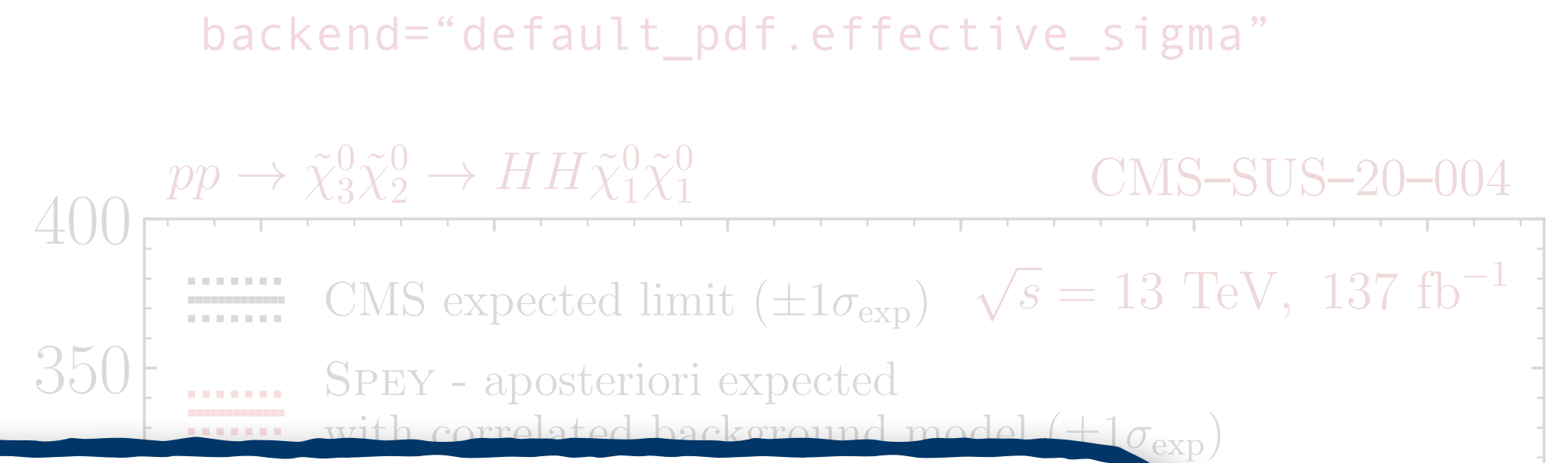
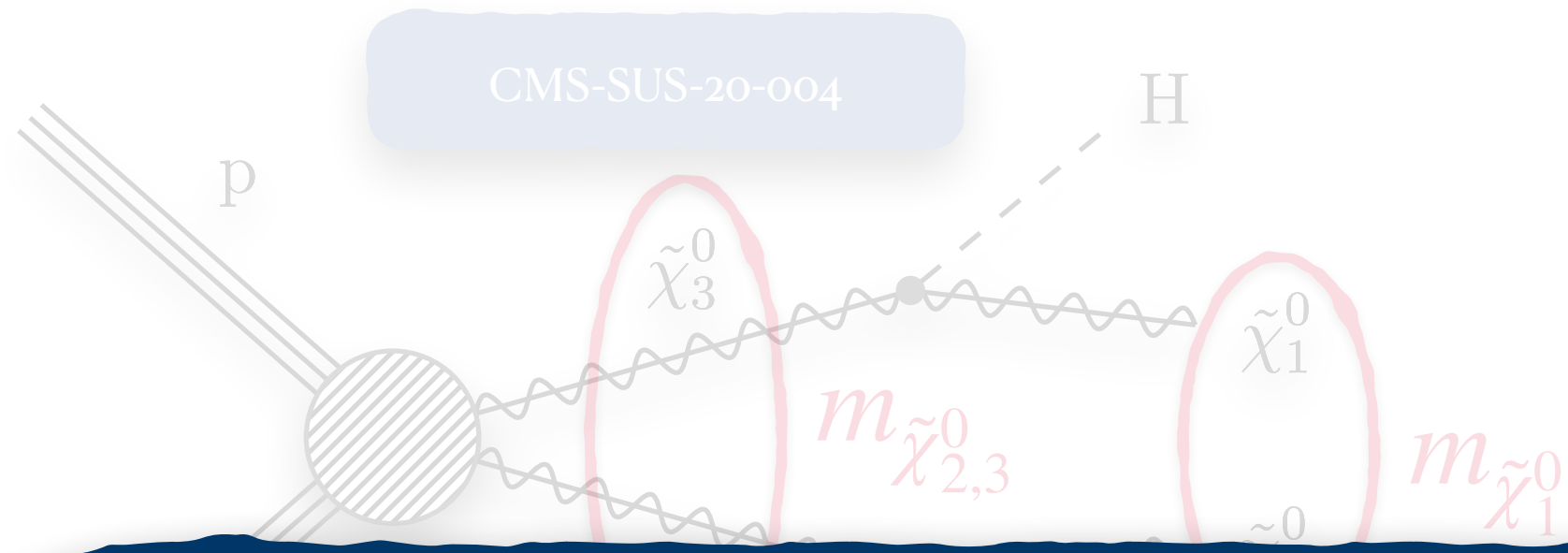
22 signal regions

⊕ Asymmetric uncertainties

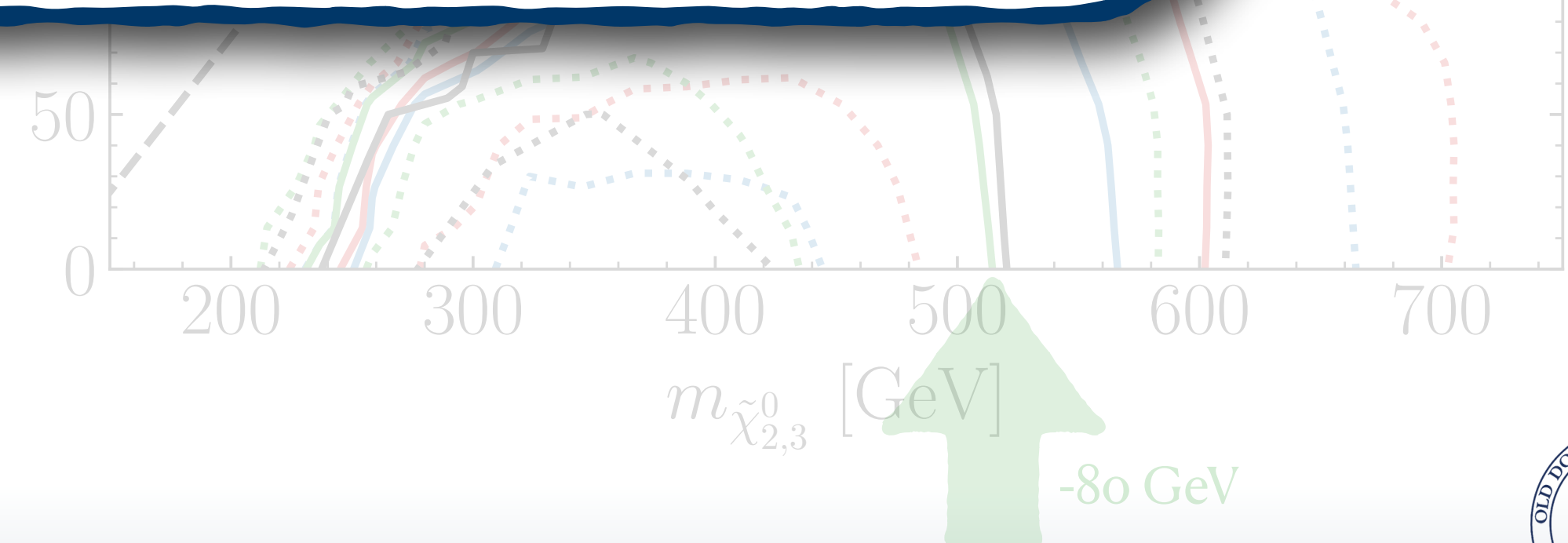
Improving Simplified Likelihoods



JYA, SciPost '24



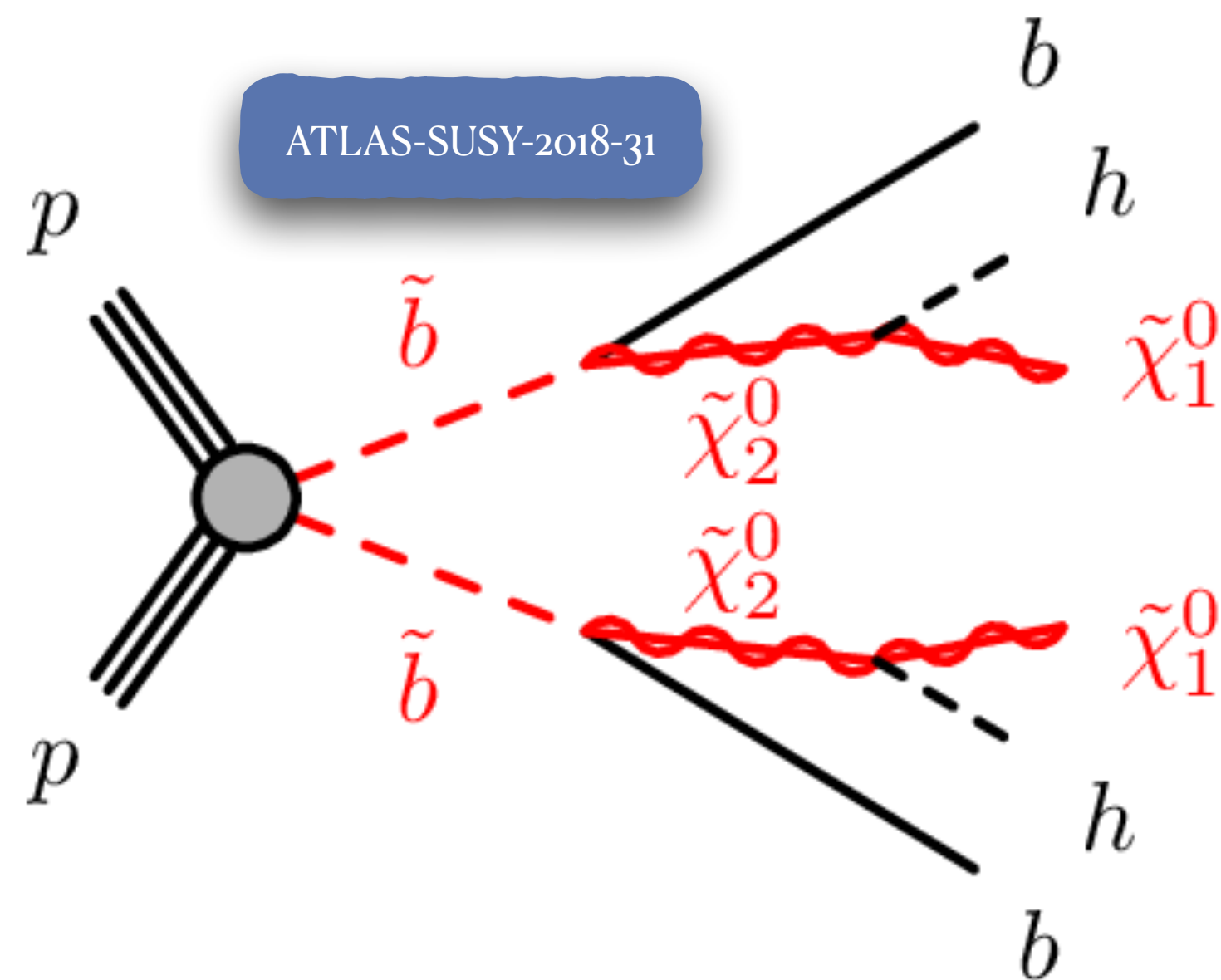
Data and signal are the same!
The only difference is using a better approximation for the likelihood!



Full Likelihoods

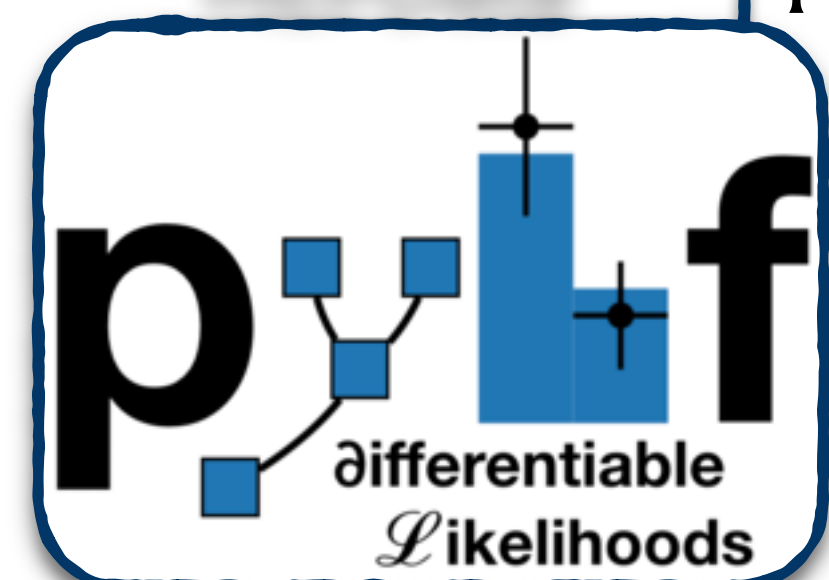
JYA, SciPost '24

```
$ pip install spey-pyhf
```



HEPData

Full likelihoods
from ATLAS



ATL-PHYS-PUB-2019-029

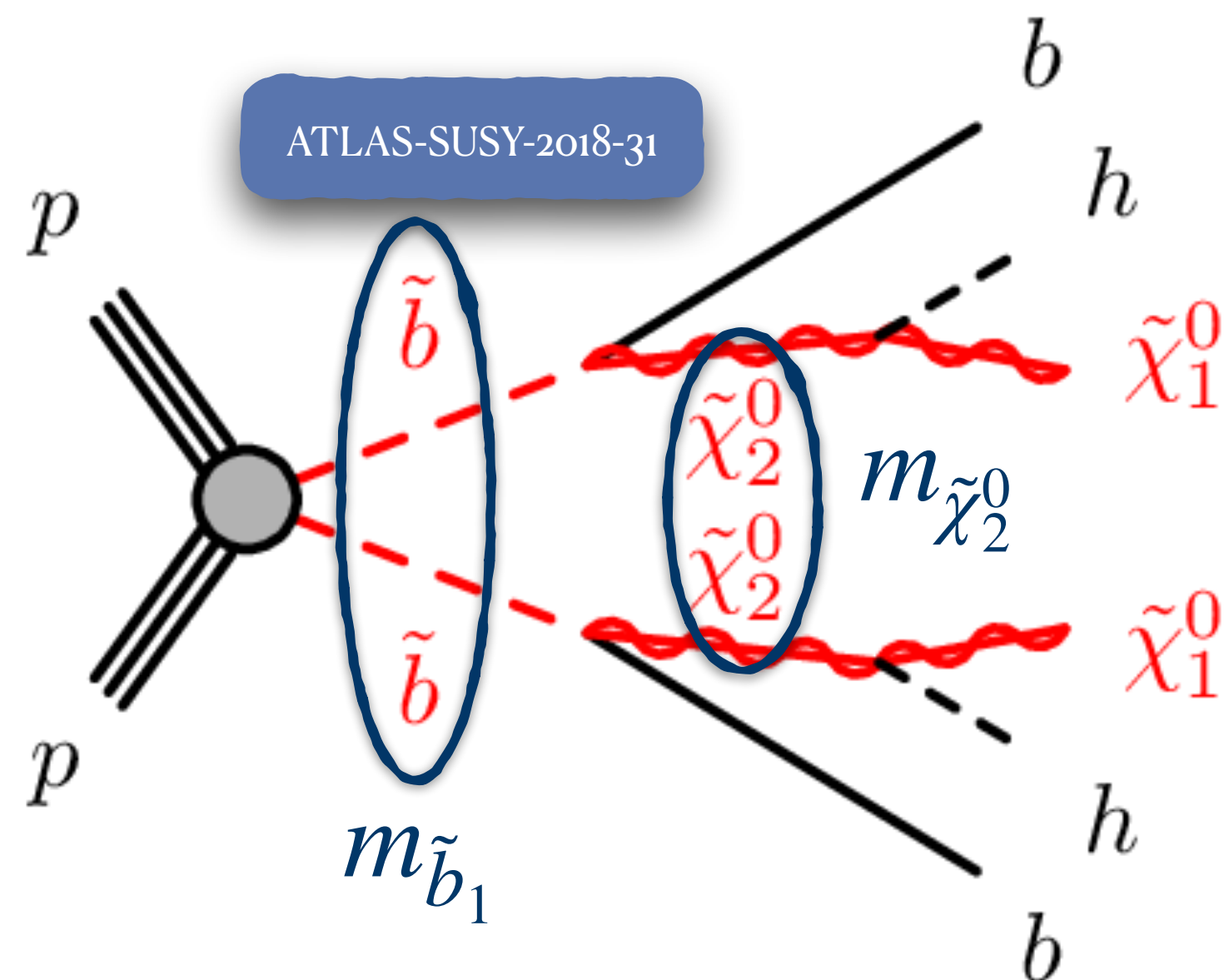
Full Likelihoods

JYA, SciPost '24

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$ pip install spey-pyhf
```

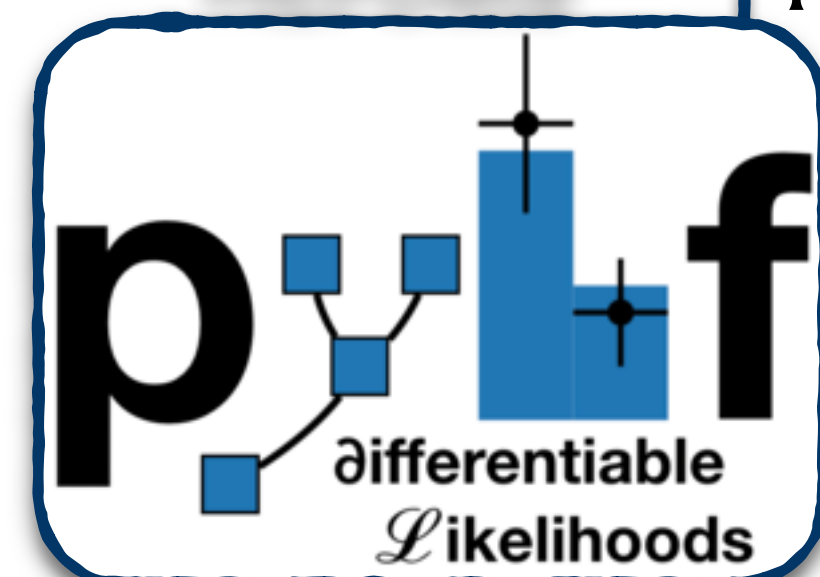


This analysis includes three distinct super regions!

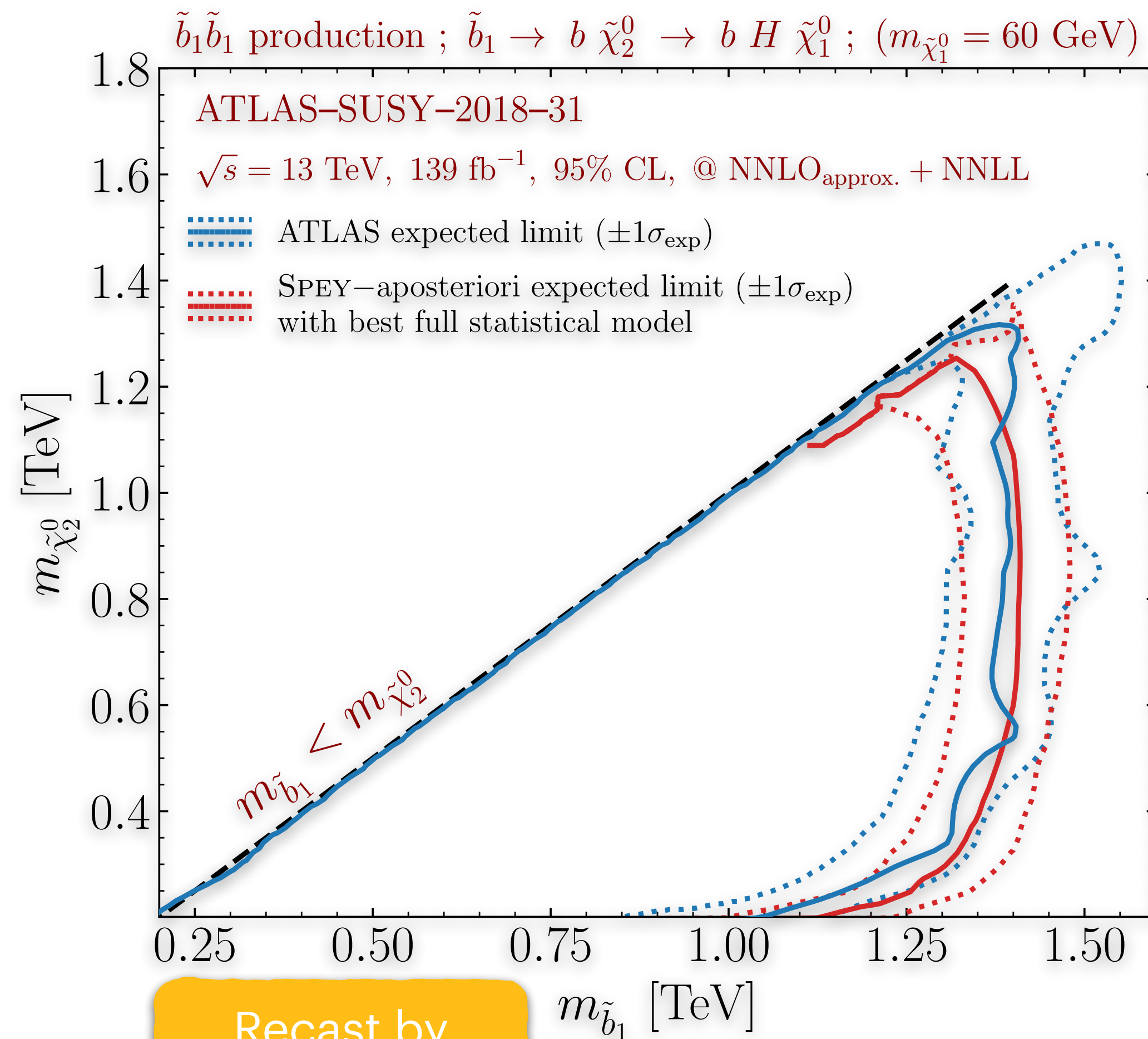


HEPData

Full likelihoods from ATLAS



ATL-PHYS-PUB-2019-029



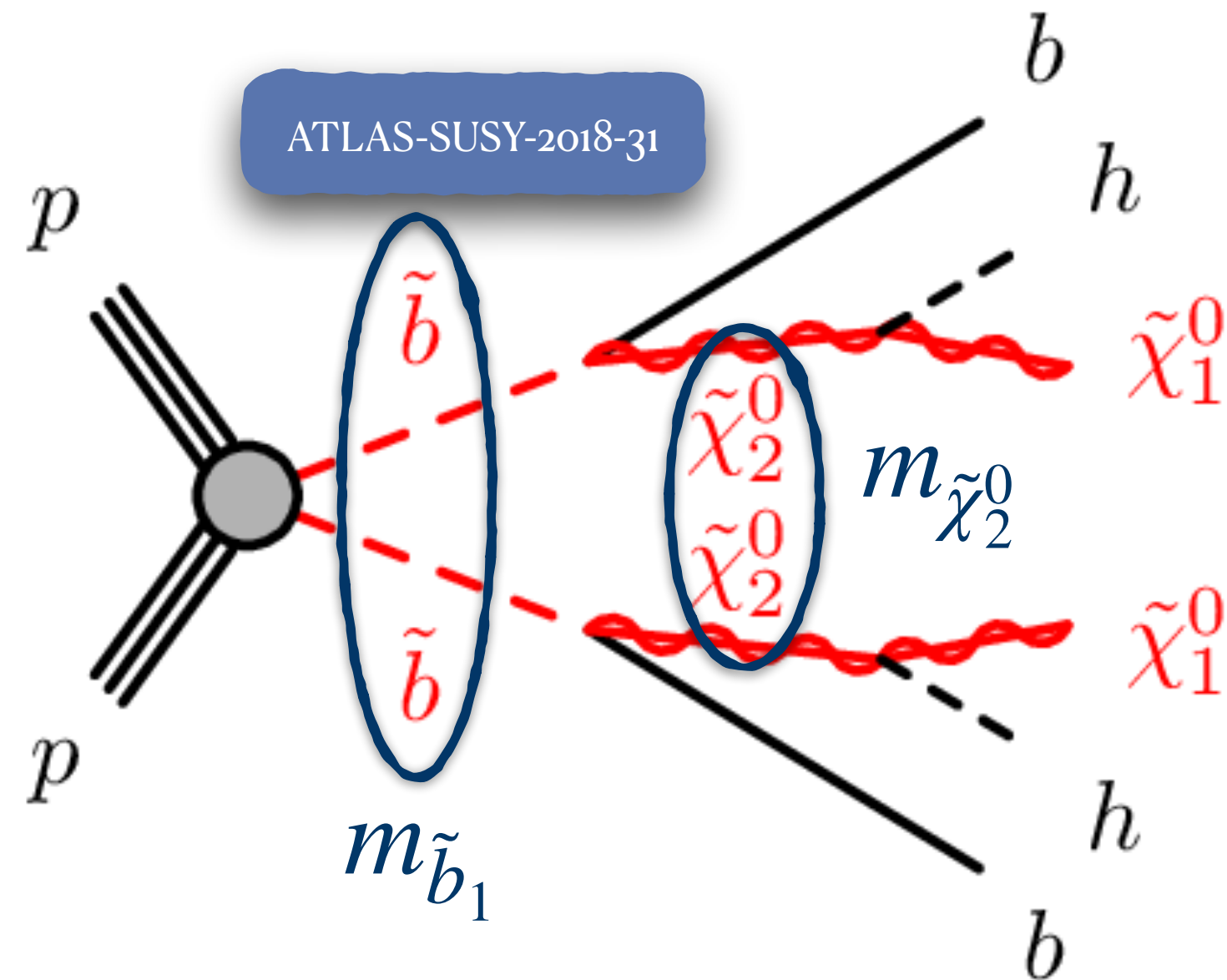
Full Likelihoods

JYA, SciPost '24

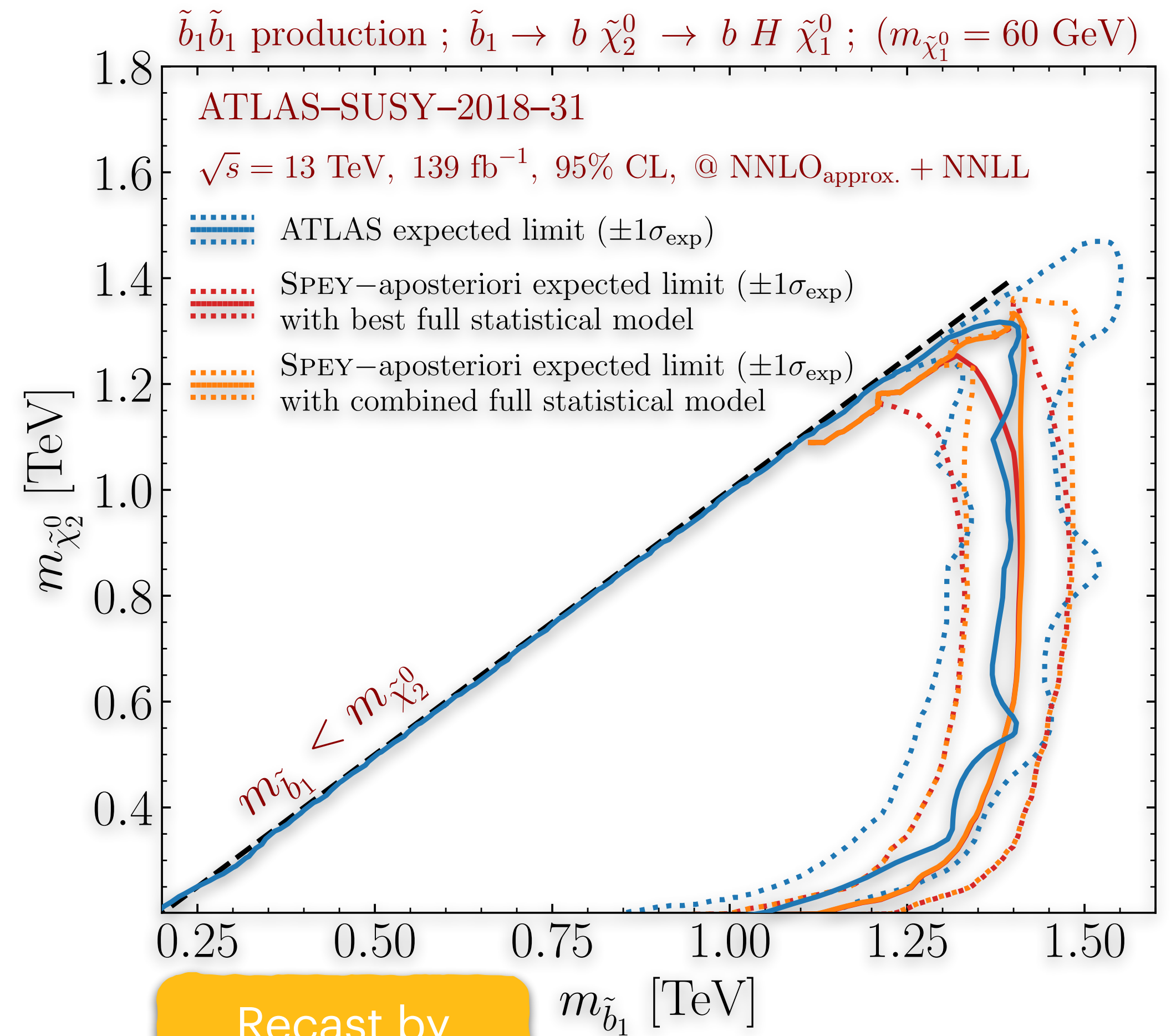
```
$ pip install spey-pyhf
```



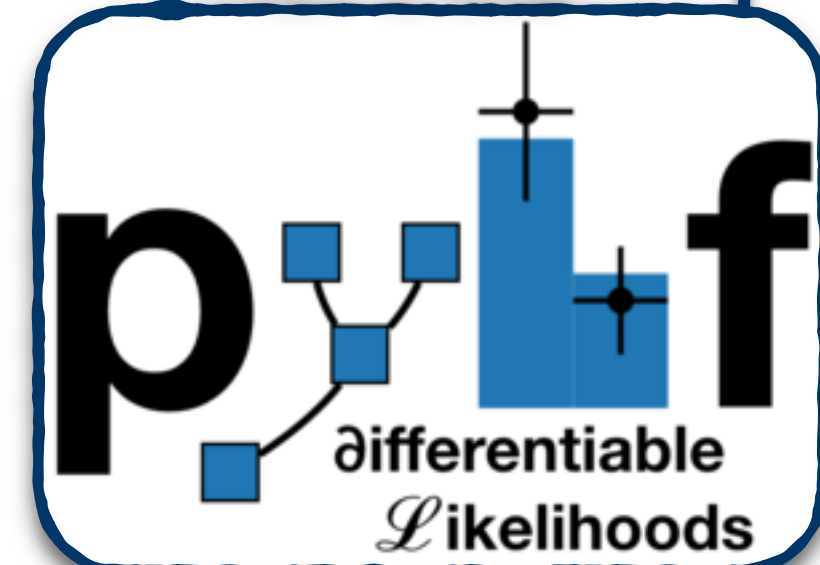
This analysis includes three distinct super regions!



Full likelihoods include all the necessary information to mix and match nuisance parameters to combine them!



Full likelihoods from ATLAS



ATL-PHYS-PUB-2019-029

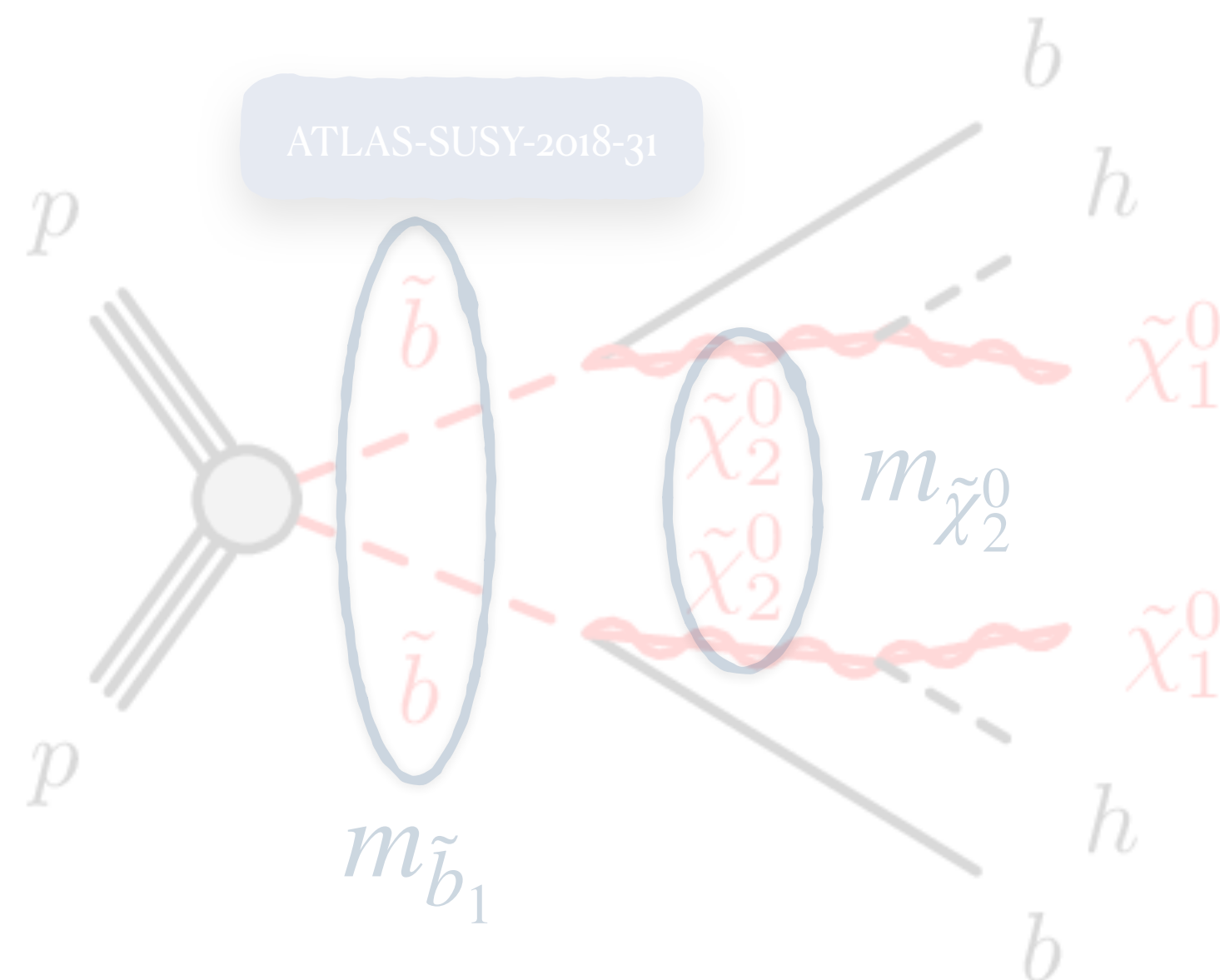
Full Likelihoods

JYA, SciPost '24

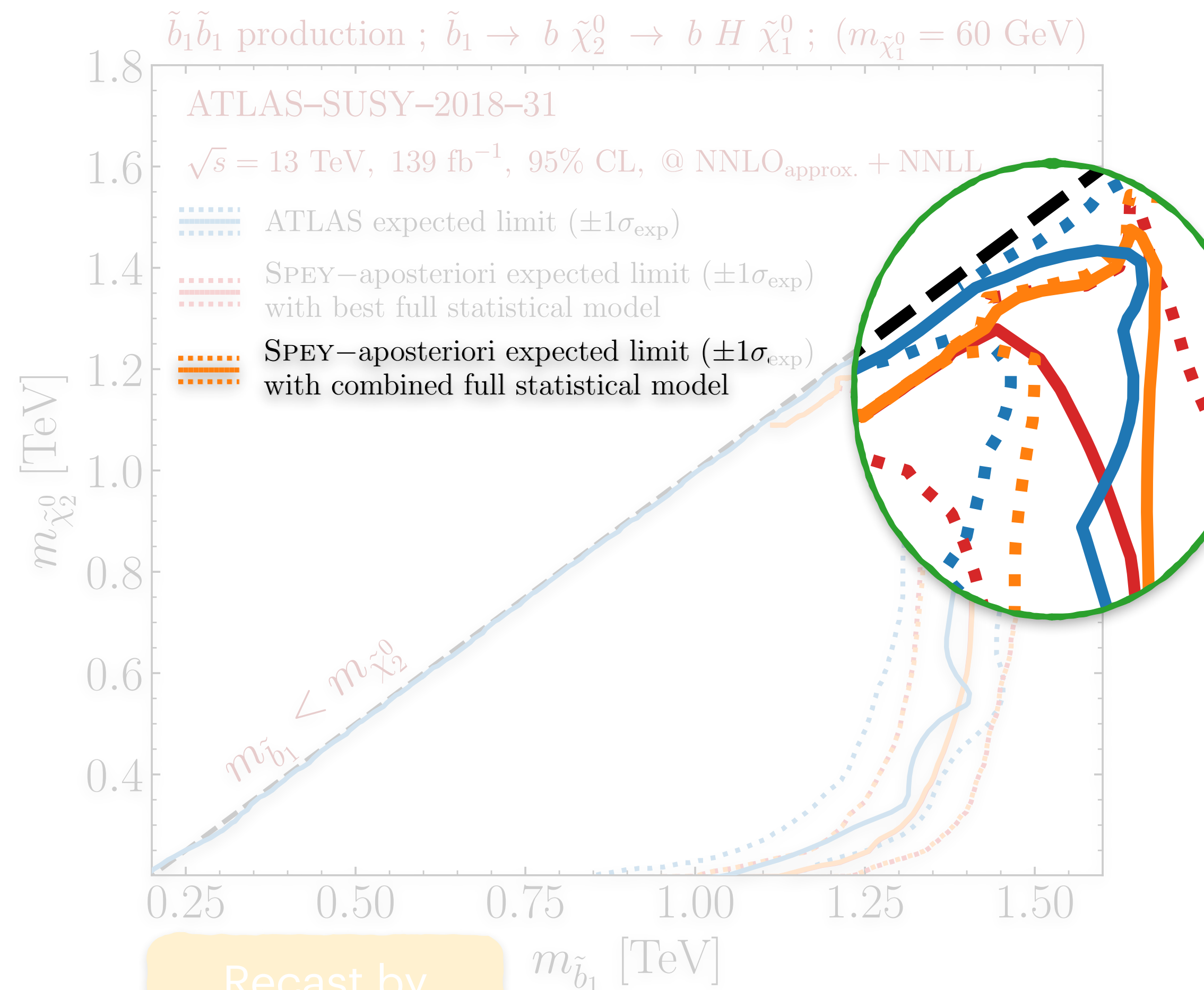
```
$ pip install spey-pyhf
```



This analysis includes three distinct super regions!



Full likelihoods include all the necessary information to mix and match nuisance parameters to combine them!



Recast by MadAnalysis 5



HEPData

Full likelihoods from ATLAS

ATL-PHYS-PUB-2019-029



Towards global sensitivity



JYA, SciPost '24

\mathcal{L}  ATLAS

\mathcal{L}  CMS

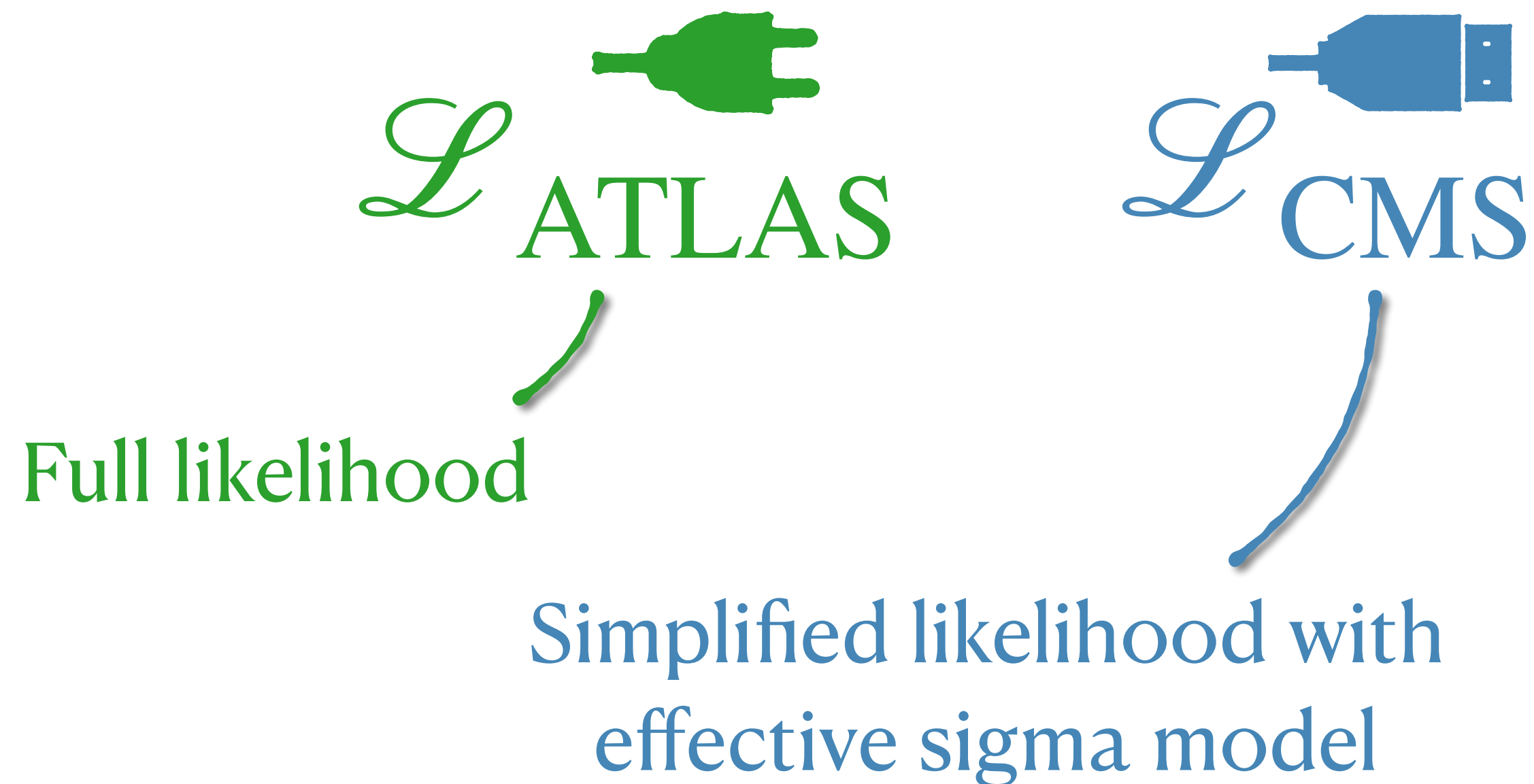
Full likelihood

Simplified likelihood with
effective sigma model

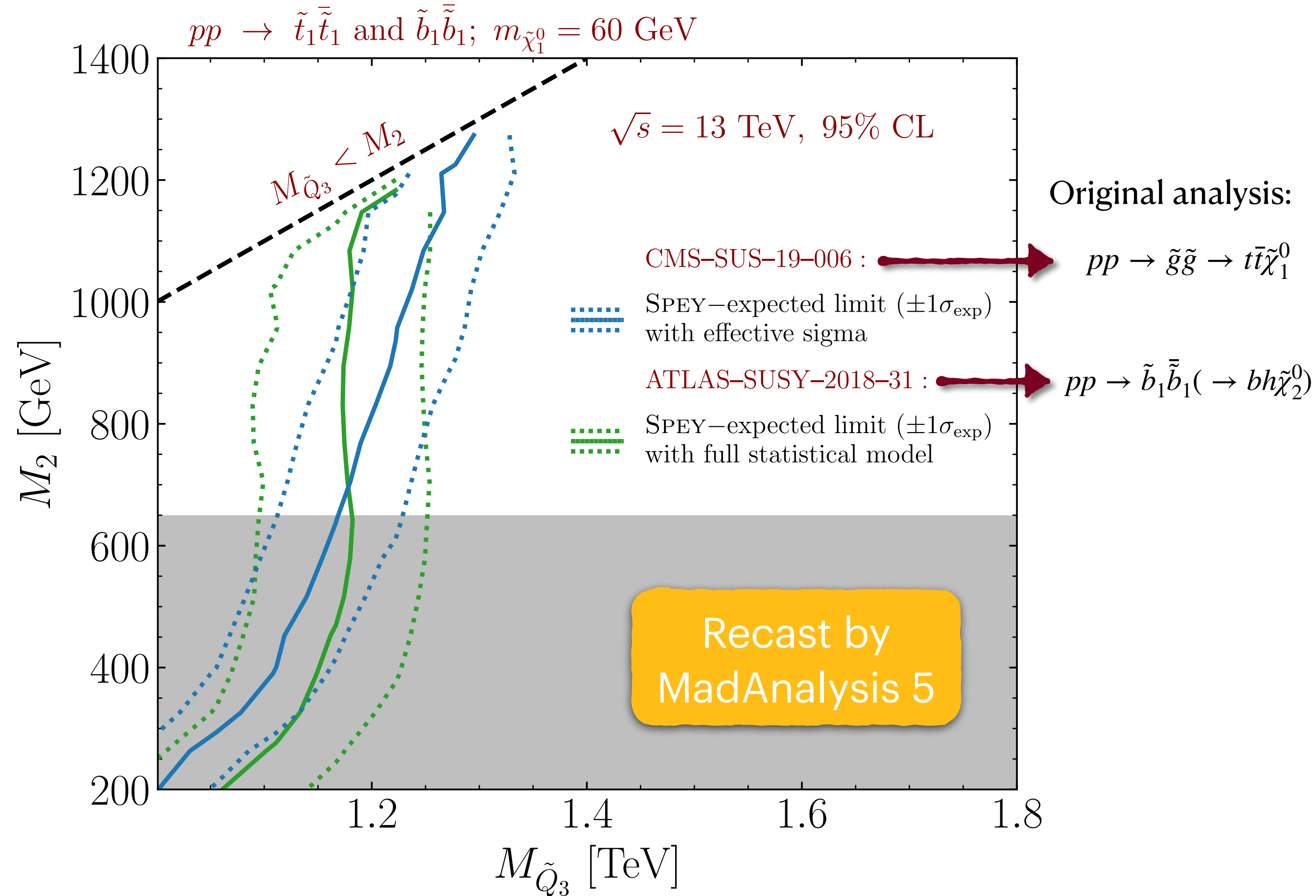
Towards global sensitivity



JYA, SciPost '24



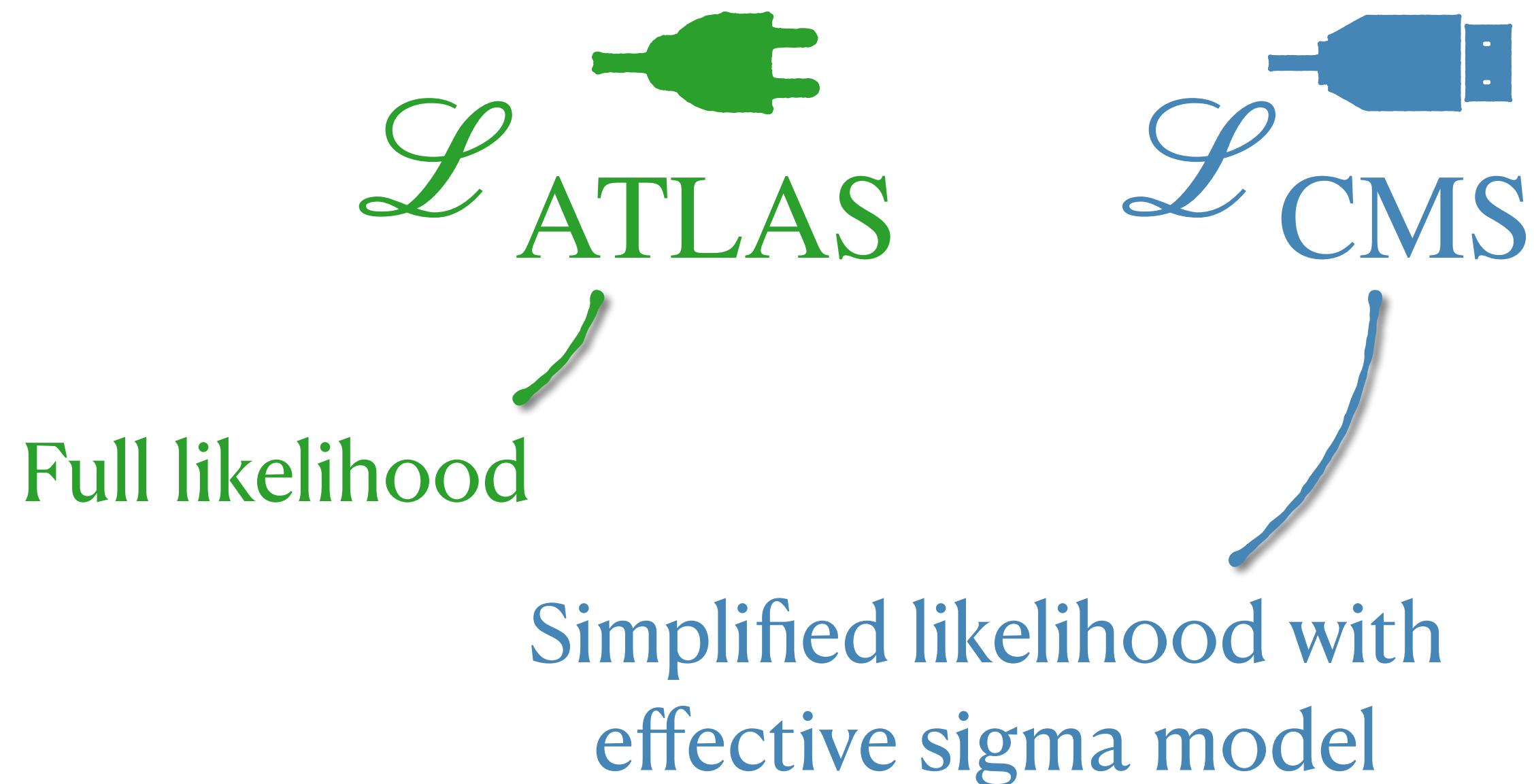
MSSM: $M_1 = M_2 = M_3 = M_{\tilde{Q}}$ at GUT scale



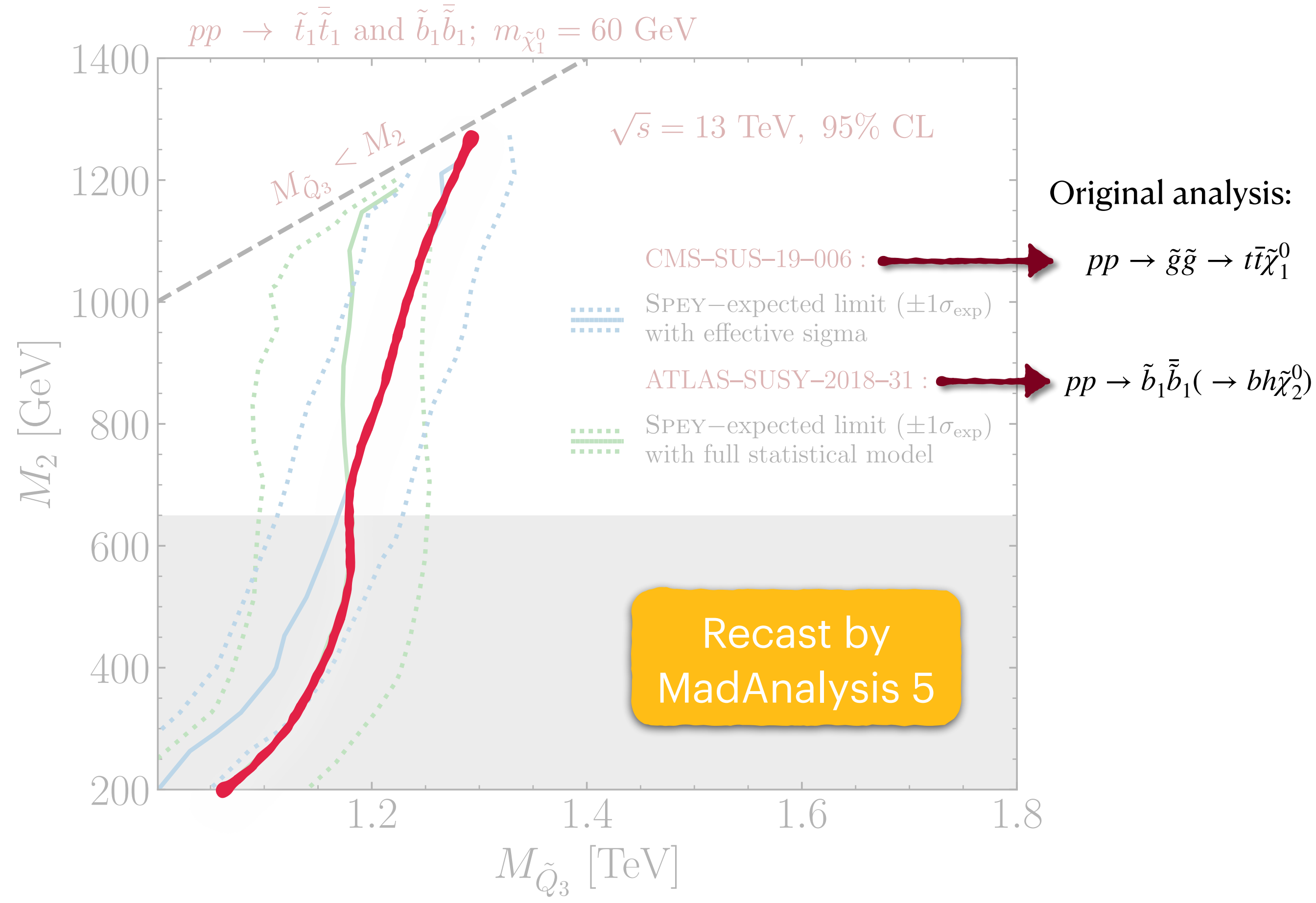
Towards global sensitivity



JYA, SciPost '24



MSSM: $M_1 = M_2 = M_3 = M_{\tilde{Q}}$ at GUT scale



Towards global sensitivity



JYA, SciPost '24

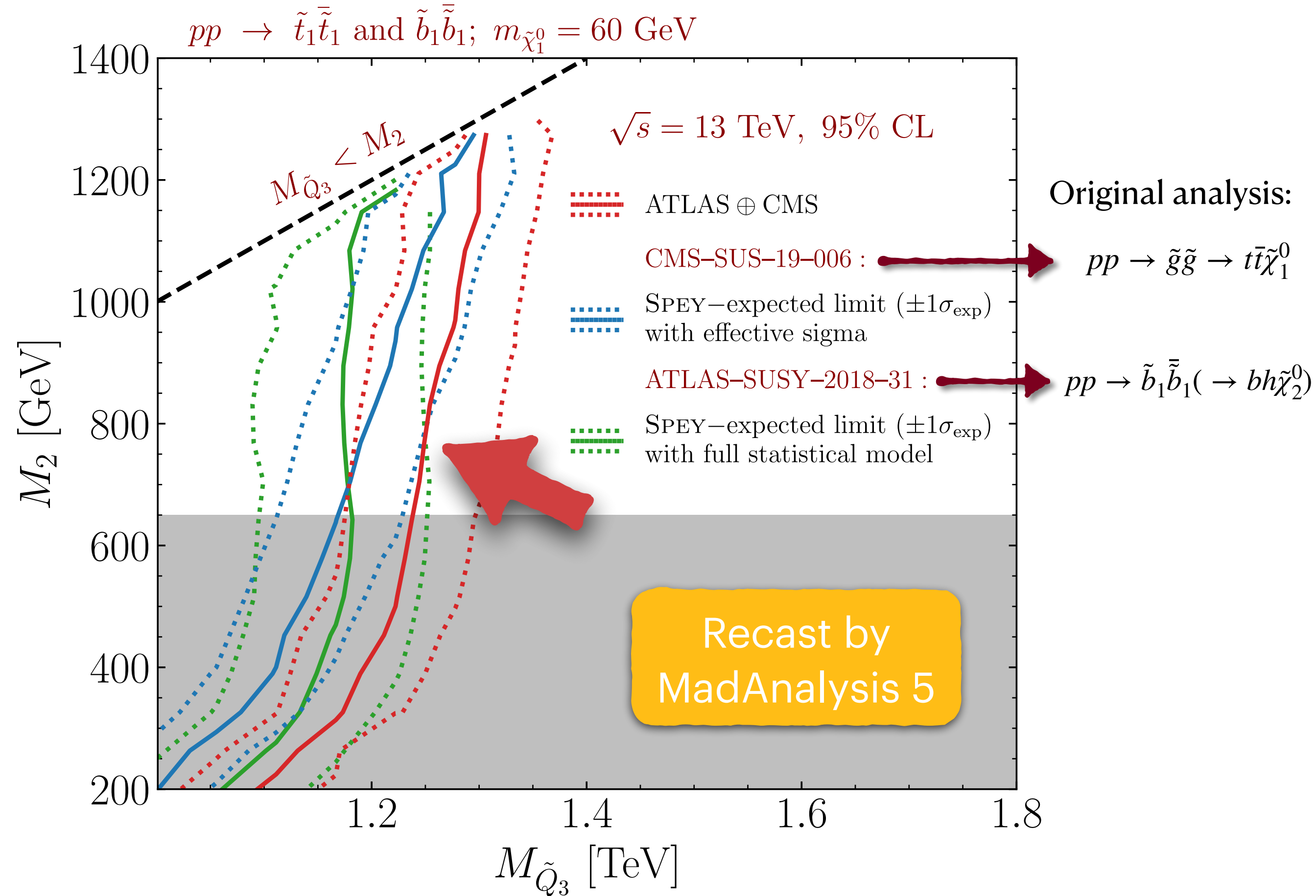
$$\mathcal{L}' = \mathcal{L}_{\text{ATLAS}} \oplus \mathcal{L}_{\text{CMS}}$$

Full likelihood

Simplified likelihood with effective sigma model

A combination of analyses, rather than regions, contains much more information!

MSSM: $M_1 = M_2 = M_3 = M_{\tilde{Q}}$ at GUT scale



Towards global sensitivity



JYA, SciPost '24

MSSM: $M_1 = M_2 = M_3 = M_{\tilde{Q}}$ at GUT scale

$$\mathcal{L}' = \mathcal{L}$$

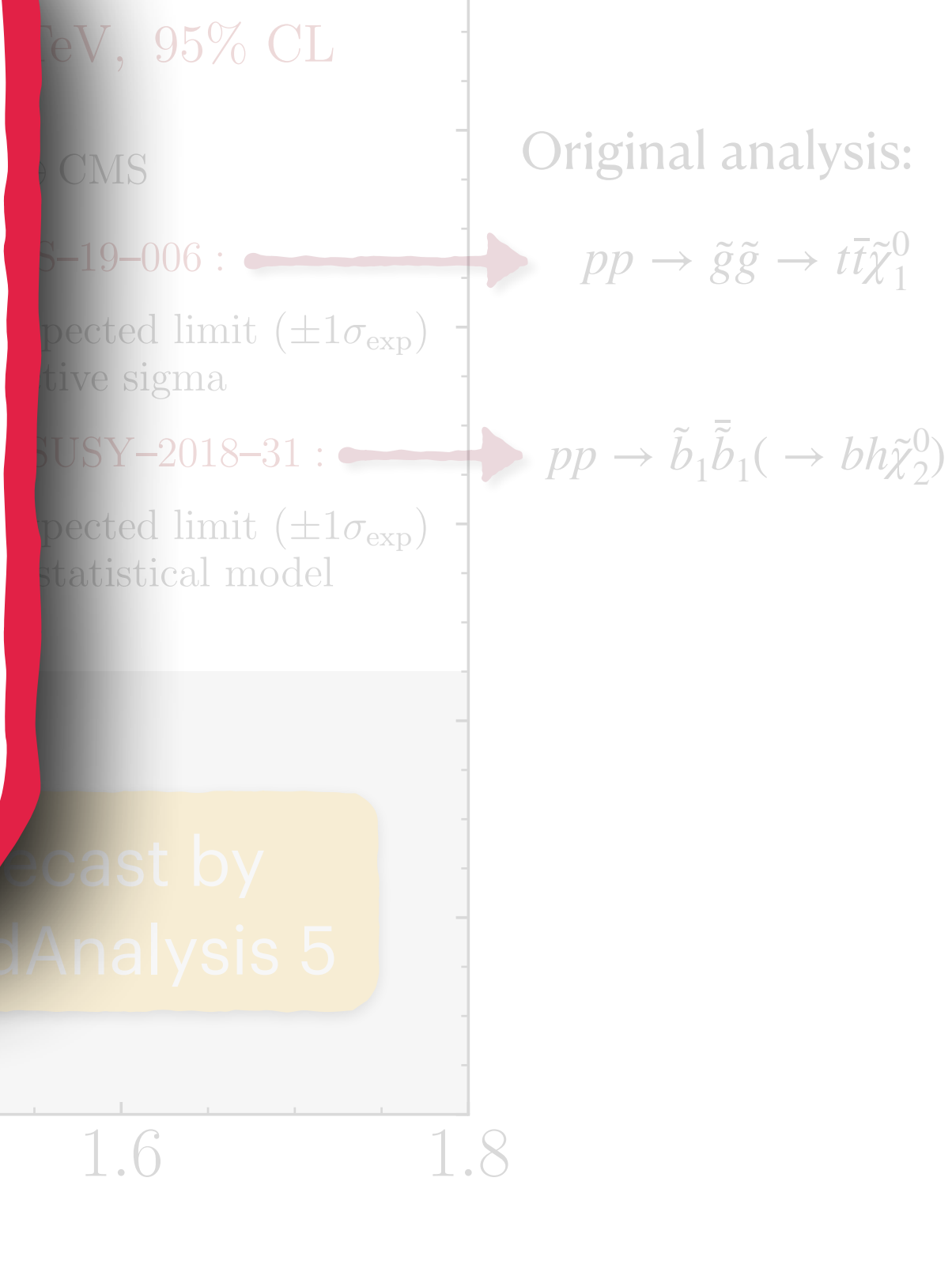
ATTN

Do **NOT** Drink
and Combine!

Full likelihood

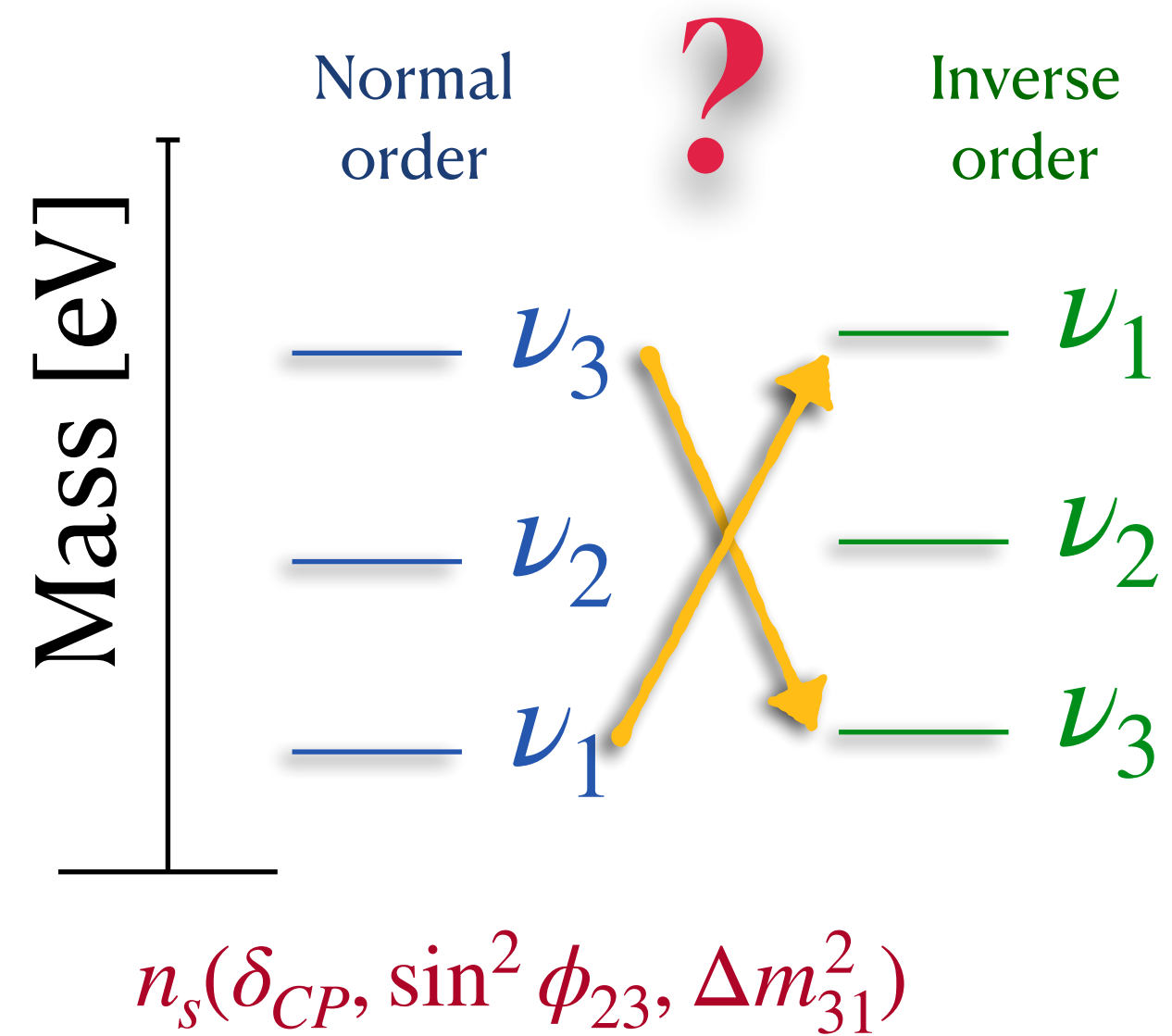
Simpl
eff

A combination of analyses, rather than regions, contains much more information!



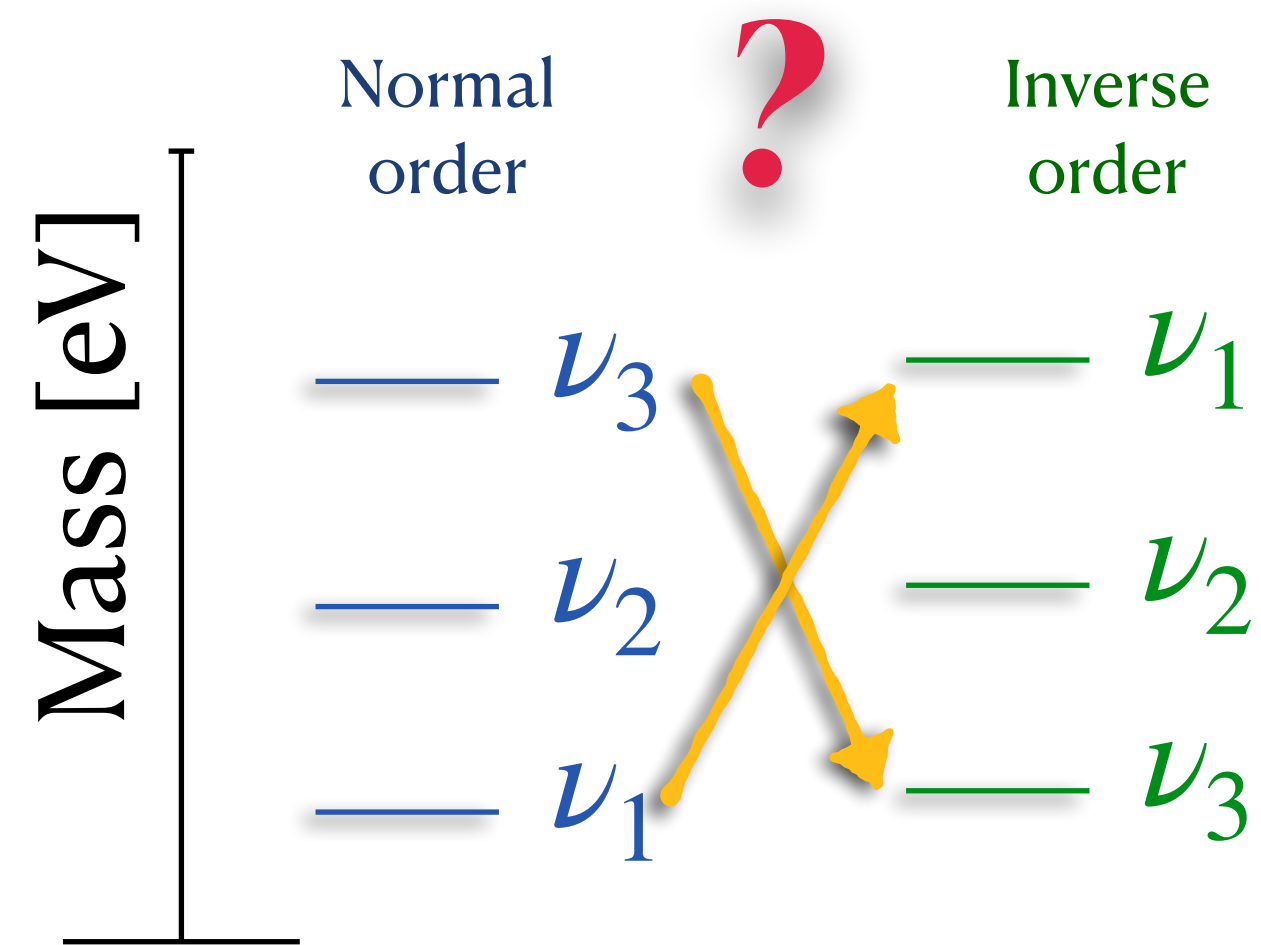
Beyond LHC: Neutrino mass ordering problem

JYA, SciPost '24



Beyond LHC: Neutrino mass ordering problem

JYA, SciPost '24



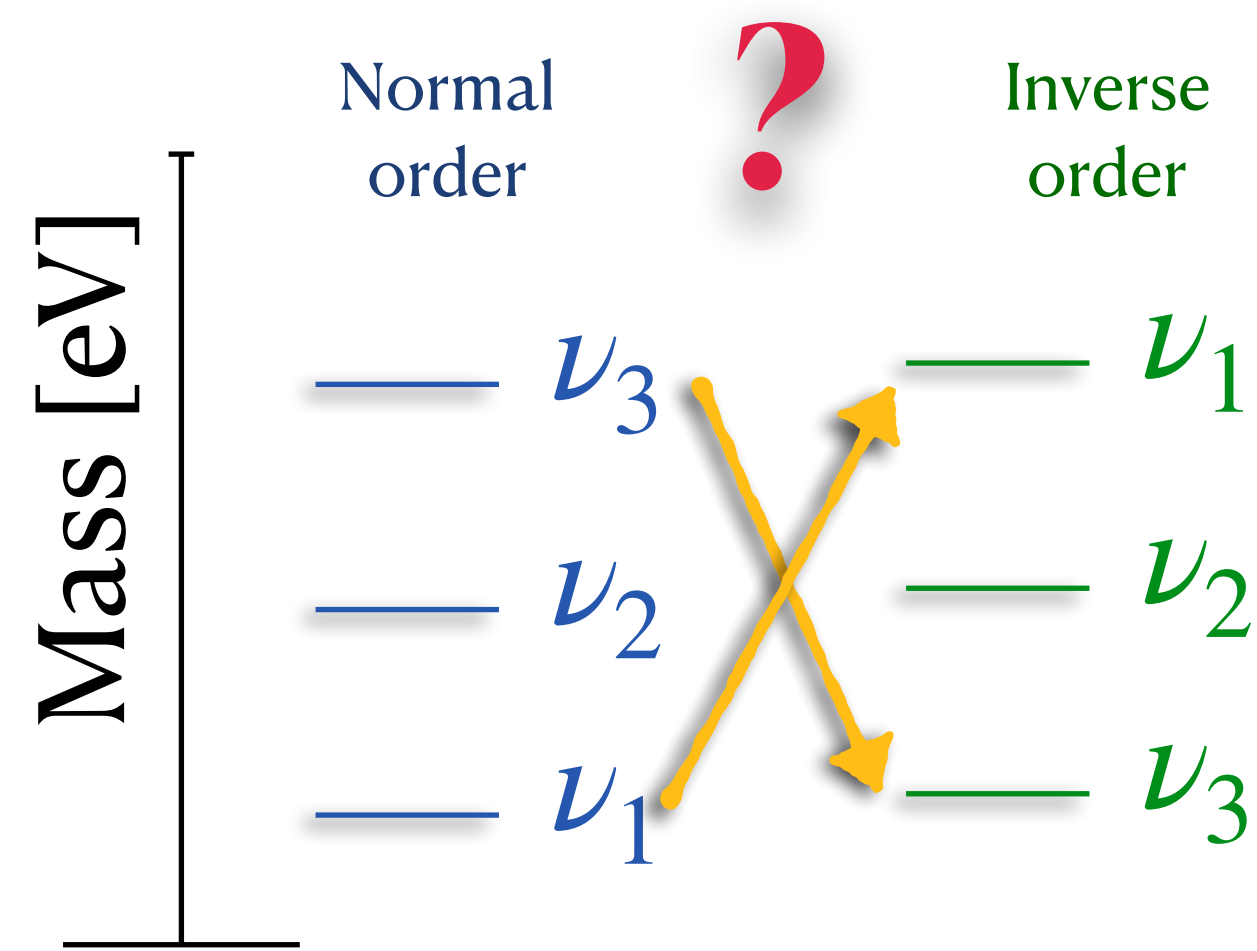
$n_s(\delta_{CP}, \sin^2 \phi_{23}, \Delta m_{31}^2)$

T2K Experiment
5 channels, 40 bins each

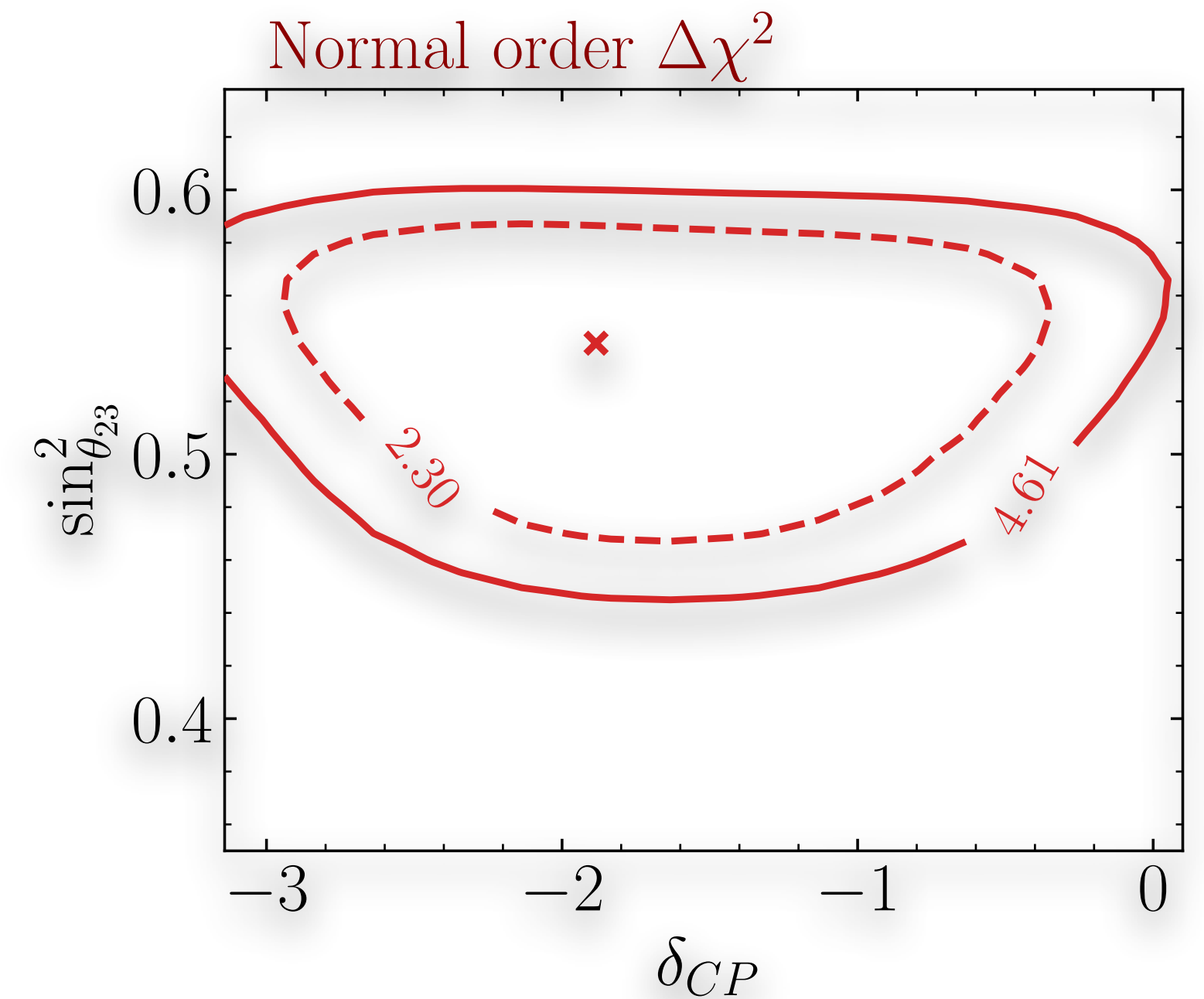
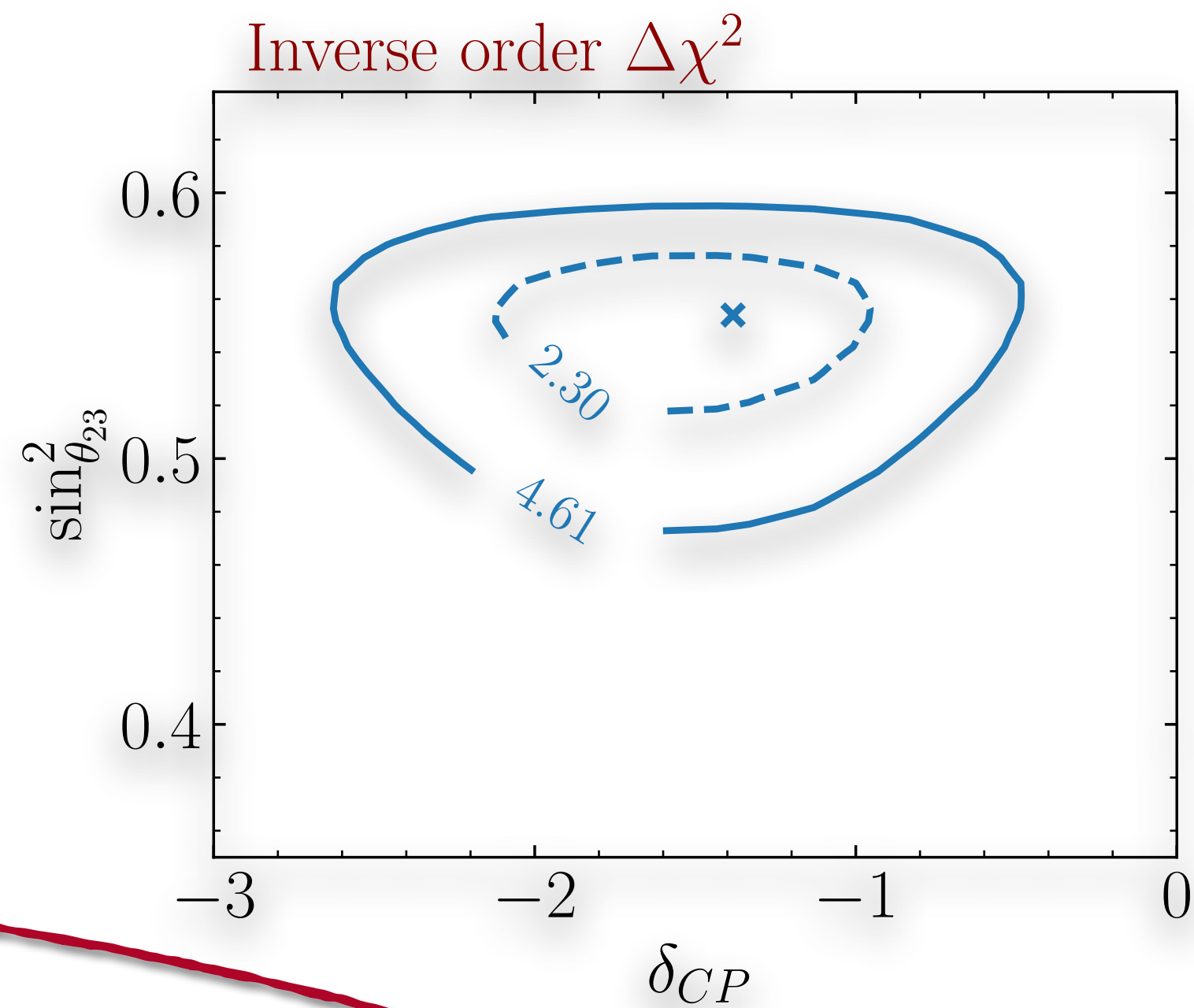
$$\mathcal{L}(\mu, \theta) = \left[\prod_{i \in \text{channels}} \prod_{j \in \text{bins}} \text{Pois} \left(\underbrace{n^j}_{\text{Observed}} \mid \underbrace{(\mu n_s^j + n_b^j)(1 + \theta^j \sigma_b^j)}_{\text{Expected}} \right) \right] \cdot \prod_{k \in \text{nuis}} \mathcal{N}(\theta^k \mid 0, 1)$$

Beyond LHC: Neutrino mass ordering problem

JYA, SciPost '24



$n_s(\delta_{CP}, \sin^2 \phi_{23}, \Delta m_{31}^2)$



T2K Experiment
5 channels, 40 bins each

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Future Plans & Conclusion

Spey in Reinterpretation tools



Contur (→Rivet):



Jon Butterworth & Joe Egan

Spey in Reinterpretation tools



Contur (\rightarrow Rivet):



Jon Butterworth & Joe Egan



Wolfgang Waltenberger

CHECKMATE



Krzysztof Rolbiecki

Spey in Reinterpretation tools



Contur (\rightarrow Rivet):



Jon Butterworth & Joe Egan



Wolfgang Waltenberger

CHECKMATE



Krzysztof Rolbiecki



Any analysis,
regardless of their
origin, can be
combined for
statistical
inference

CMS Full Likelihoods



Plug-in



NEW

See Aliya's talk just after this one!

Citing the proper source

```
bibtex = spey.get_backend_bibtex("default_pdf.third_moment_expansion")
print(bibtex["inspire"][0])
```

```
@article{Buckley:2018vdr,
  author = "Buckley, Andy and Citron, Matthew and Fichet, Sylvain and Kraml, Sabine and Waltenberger, Wolfgang and Wardle, Nicholas",
  title = "{The Simplified Likelihood Framework}",
  eprint = "1809.05548",
  archivePrefix = "arXiv",
  primaryClass = "hep-ph",
  doi = "10.1007/JHEP04(2019)064",
  journal = "JHEP",
  volume = "04",
  pages = "064",
  year = "2019"
}
```

Possible queries:

- ❖ Inspire HEP
- ❖ doi.org
- ❖ Zenodo

```
bibtex = spey.get_backend_bibtex("default_pdf.effective_sigma")
print(bibtex["inspire"][0])
```

```
@inproceedings{Barlow:2004wg,
  author = "Barlow, Roger",
  title = "{Asymmetric statistical errors}",
  booktitle = "{PHYSTAT (2005): Statistical Problems in Particle",
  eprint = "physics/0406120",
  archivePrefix = "arXiv",
  reportNumber = "MAN-HEP-04-02",
  pages = "56--59",
  month = "6",
  year = "2004"
}
```

```
bibtex = spey.get_backend_bibtex("pyhf")
print(bibtex["inspire"][0])
print(bibtex["doi.org"][0])
```

```
@article{Heinrich:2021gyp,
  author = "Heinrich, Lukas and Feickert, Matthew and Stark, Giordon and Cranmer, Kyle",
  title = "{pyhf: pure-Python implementation of HistFactory statistical models}",
  doi = "10.21105/joss.02823",
  journal = "J. Open Source Softw.",
  volume = "6",
  number = "58",
  pages = "2823",
  year = "2021"
}
```

```
@misc{https://doi.org/10.5281/zenodo.1169739,
  doi = {10.5281/ZENODO.1169739},
  url = {https://zenodo.org/doi/10.5281/zenodo.1169739},
  author = {Lukas Heinrich, and Matthew Feickert, and Giordon Stark, },
  keywords = {physics, statistics, fitting, scipy, numpy, tensorflow, pytorch, jax, auto-differentiation},
  title = {scikit-hep/pyhf: v0.7.6},
  publisher = {Zenodo},
  year = {2024},
  copyright = {Apache License 2.0}
}
```


ML integration in Spey



Differentiable programming

```
spey.math.value_and_grad( $\mathcal{L}(\theta)$ )  
spey.math.hessian( $\mathcal{L}(\theta)$ )
```

$$\frac{\partial \log \mathcal{L}(\theta)}{\partial \theta}$$

$$\frac{\partial^2 \log \mathcal{L}(\theta)}{\partial \theta_i \partial \theta_j}$$

- ❖ Custom optimiser implementation
- ❖ Using likelihoods in AI workflows
- ❖ Developing new techniques

ML integration in Spey



Differentiable programming

```
spey.math.value_and_grad(L(theta))  
spey.math.hessian(L(theta))
```

$$\frac{\partial \log \mathcal{L}(\theta)}{\partial \theta}$$

$$\frac{\partial^2 \log \mathcal{L}(\theta)}{\partial \theta_i \partial \theta_j}$$

- ❖ Custom optimiser implementation
- ❖ Using likelihoods in AI workflows
- ❖ Developing new techniques

(Re)interpretation of the LHC results for new physics

29 August 2023 to 1 September 2023
Durham University



Converting full statistical models to the simplified likelihood framework

Although full statistical models contain all the necessary information to reconstruct the original analysis, it might be computationally costly. Thus, we implement methodologies to convert full likelihoods into simplified likelihood frameworks using `"default_pdf.correlated_background"` or `"default_pdf.third_moment_expansion"` models. Details on the [simplified models can be found in this link](#).

This particular example requires the installation of three packages, which can be achieved by using the line below

```
>>> pip install spey spey-pyhf jax
```

Methodology

The Simplified likelihood framework contracts all the nuisance parameters into a single bin and represents the background uncertainty as a single source. To capture the correlations between nuisance parameters, one needs to construct a statistical model only from **control and validation** regions, which is ideally purely dominated by the background, henceforth called the control model \mathcal{L}^c . Once nuisance parameters are fitted for the control model without the signal, one can compute the covariance matrix between the nuisance parameters using the Hessian of the negative log probability distribution,

$$\mathbf{V}_{ij}^{-1} = -\frac{\partial^2}{\partial \theta_i \partial \theta_j} \log \mathcal{L}^c(0, \theta_0^c) \quad (1)$$

Thanks to Nick Wardle, Sabine Kraml & Wolfgang Waltenberger

ML integration in Spey



Differentiable programming

```
spey.math.value_and_grad(L(theta))  
spey.math.hessian(L(theta))
```

$$\frac{\partial \log \mathcal{L}(\theta)}{\partial \theta}$$

$$\frac{\partial^2 \log \mathcal{L}(\theta)}{\partial \theta_i \partial \theta_j}$$

- ❖ Custom optimiser implementation
- ❖ Using likelihoods in AI workflows
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Although full statistical models contain all the necessary information to reconstruct the original analysis, it might be computationally expensive to implement methodologies to convert full likelihoods into simplified likelihood frameworks using `"simplified_background"` or `"default_pdf.third"`. The simplified models can be found in this link.

This particular example can be achieved by using the line below

```
>>> pip
```

Contents:

Spey Documentation

Quick Start

[Converting full statistical models to the simplified likelihood framework](#)

Tutorials

Description of all functions and classes

Citation

Release Notes

Methodology

The Simplified likelihood framework treats the background uncertainty as a single parameter. In this case, one needs to construct a statistical model dominated by the background, henceforth called the control model. For the control model without the signal, one can compute the parameters using the Hessian of the negative log probability

$$\mathbf{V}_{ij}^{-1} = -\frac{\partial^2}{\partial \theta_i \partial \theta_j} \log \mathcal{L}^c(0, \theta_0^c)$$

Thanks to Nick Wardle, Sabine Kraml & Wolfgang Waltenberger

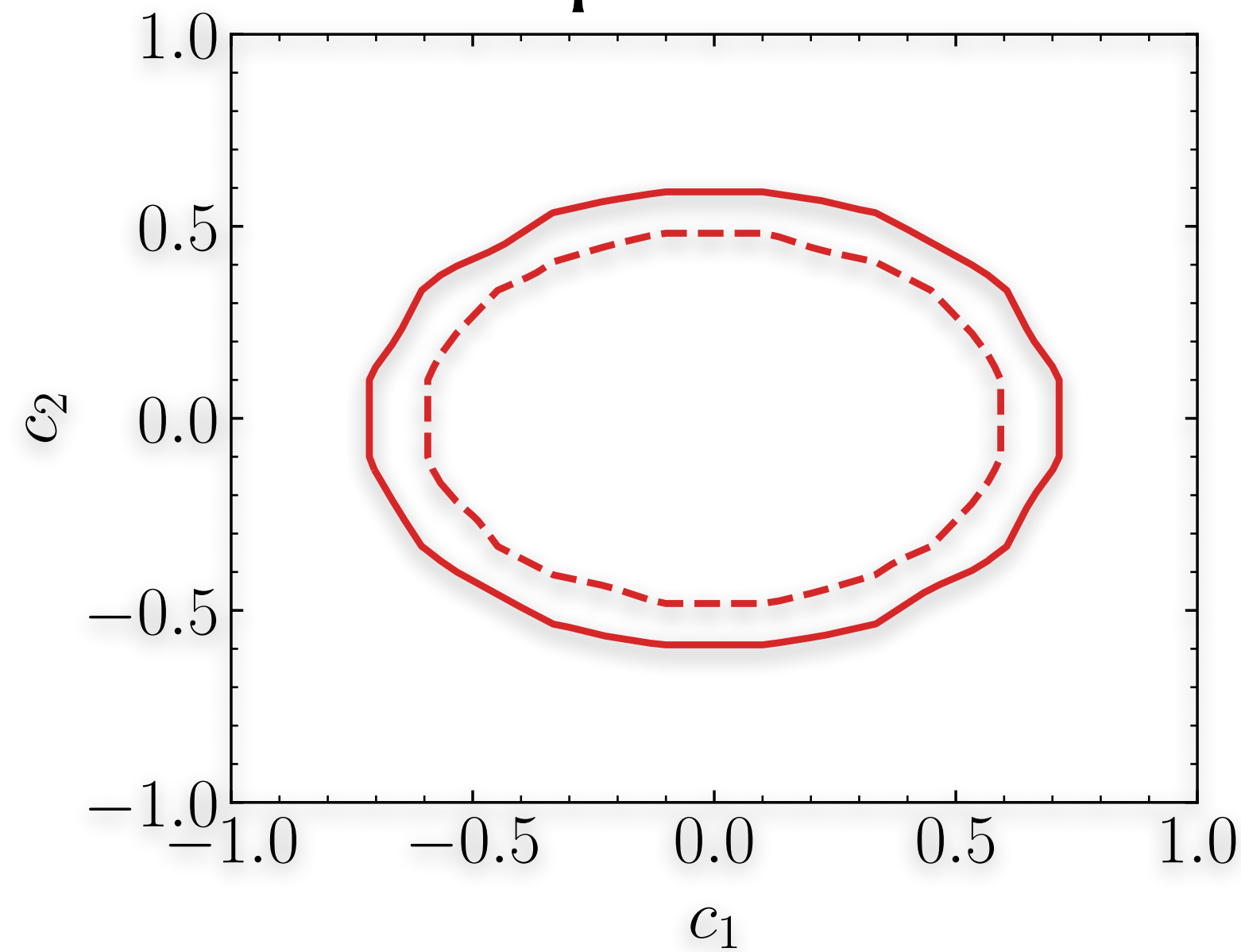
See Rafal's talk on Machine-learning full likelihoods!

Coming Soon: functional signal-based likelihoods

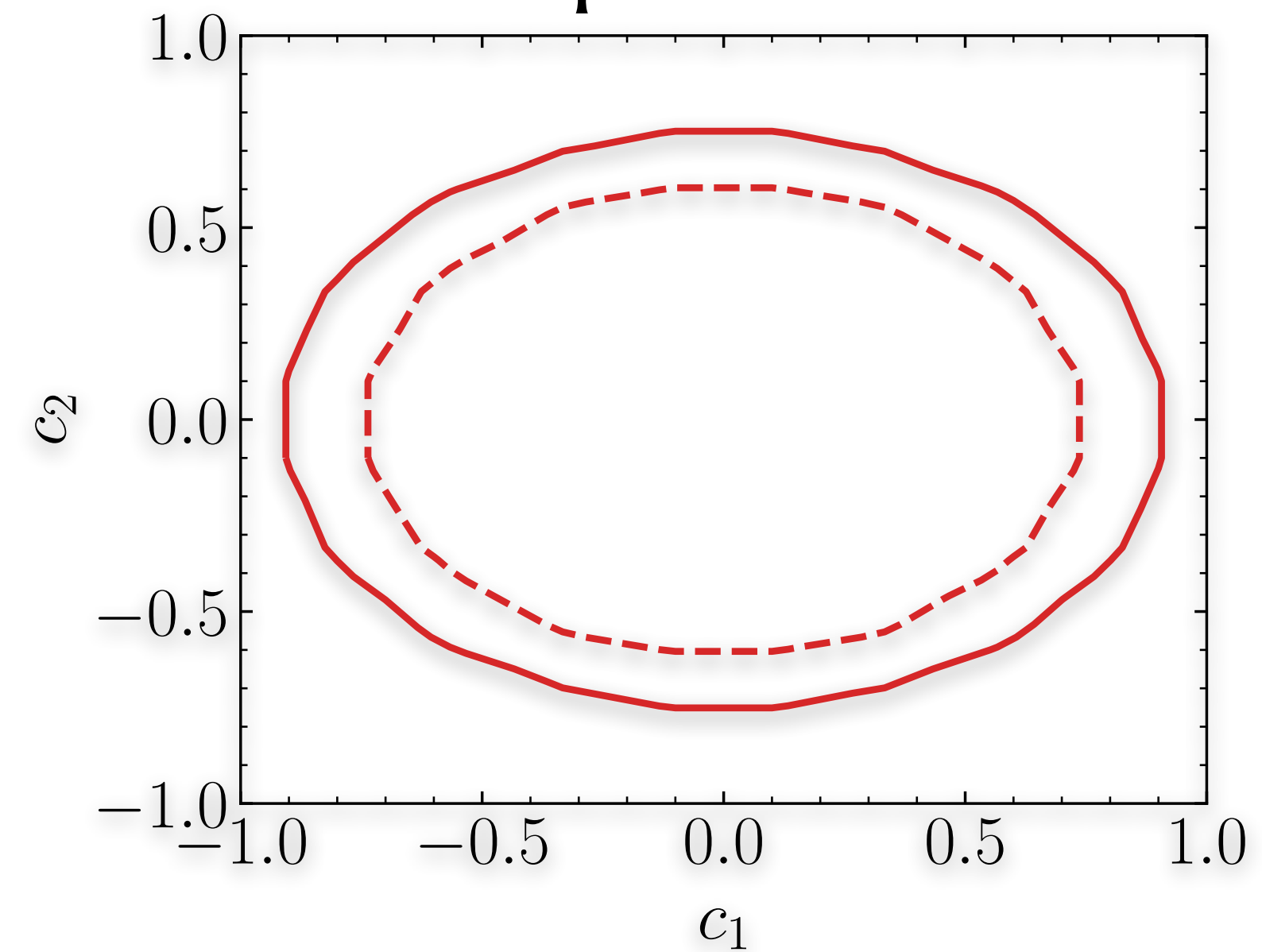
$$n_s \equiv \alpha c_1^2 + \beta c_2^2$$



Experiment A



Experiment B

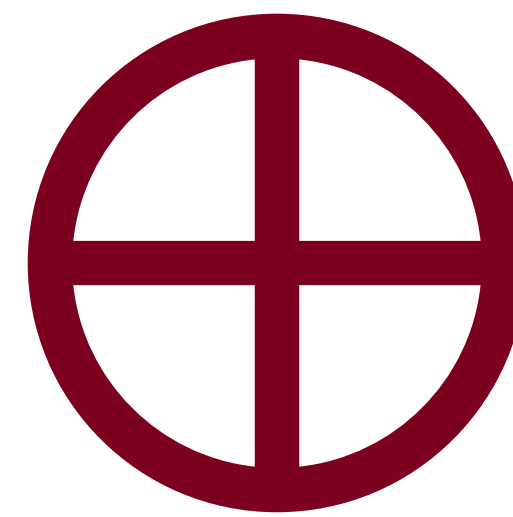
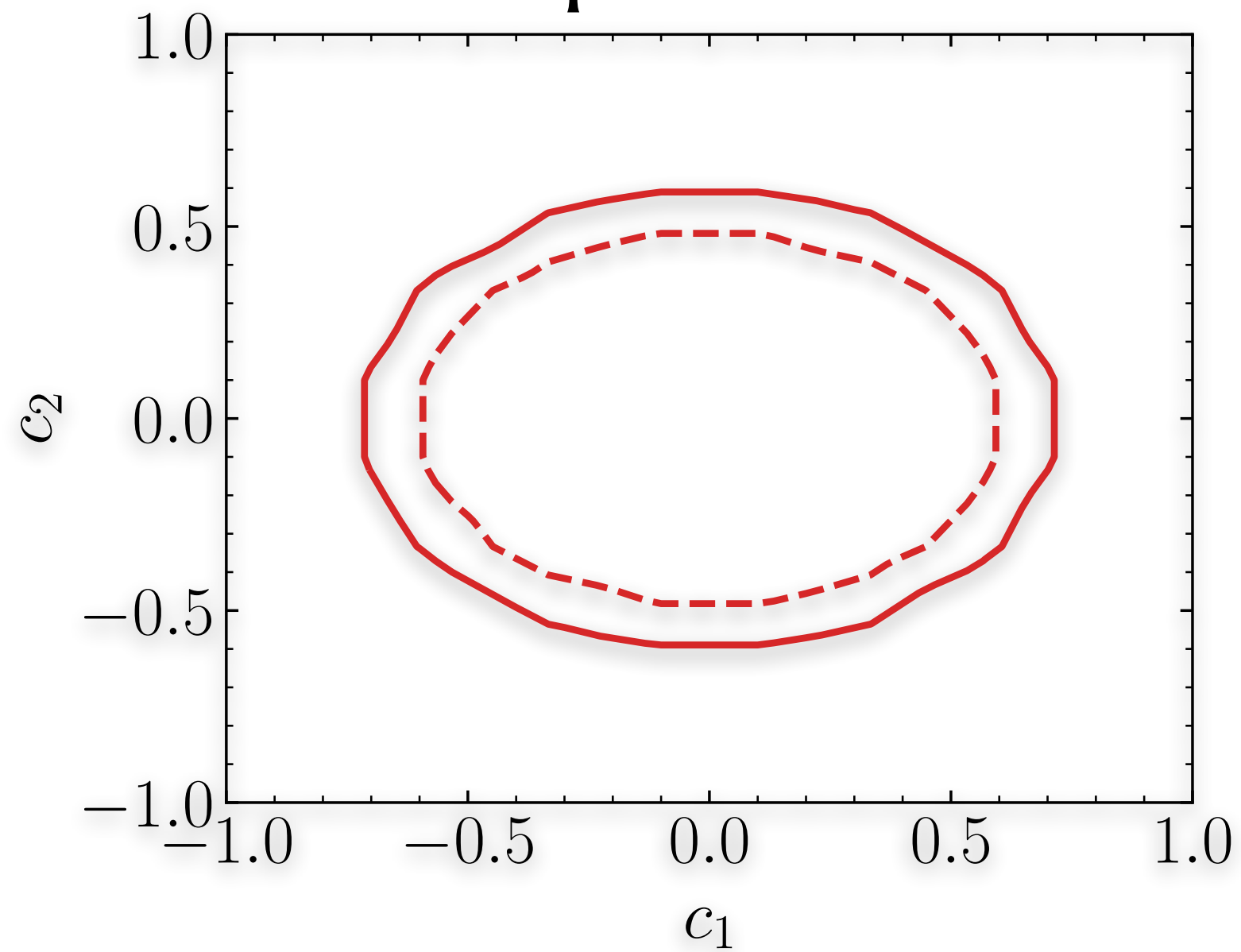


Coming Soon: functional signal-based likelihoods

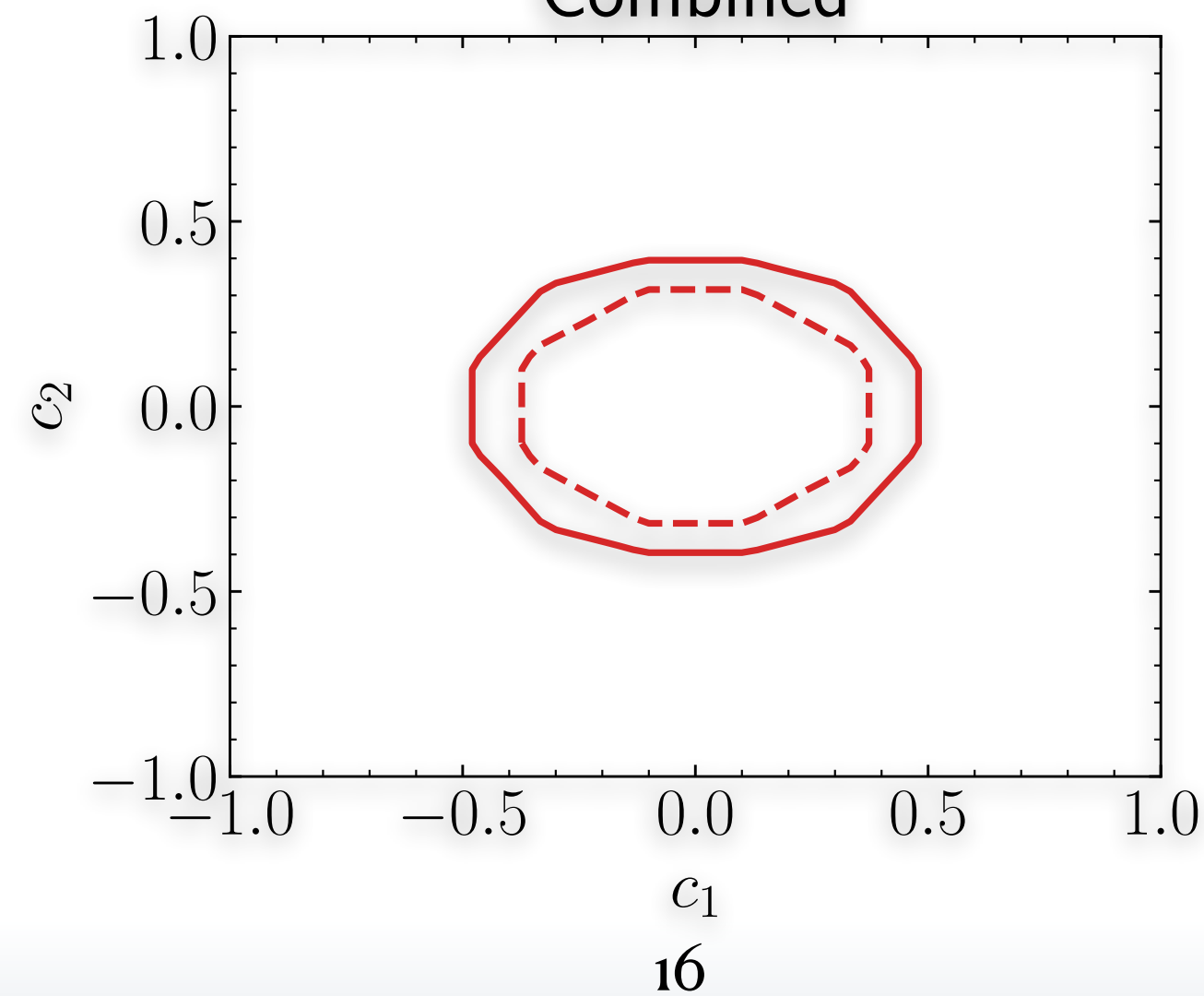
$$n_s \equiv \alpha c_1^2 + \beta c_2^2$$



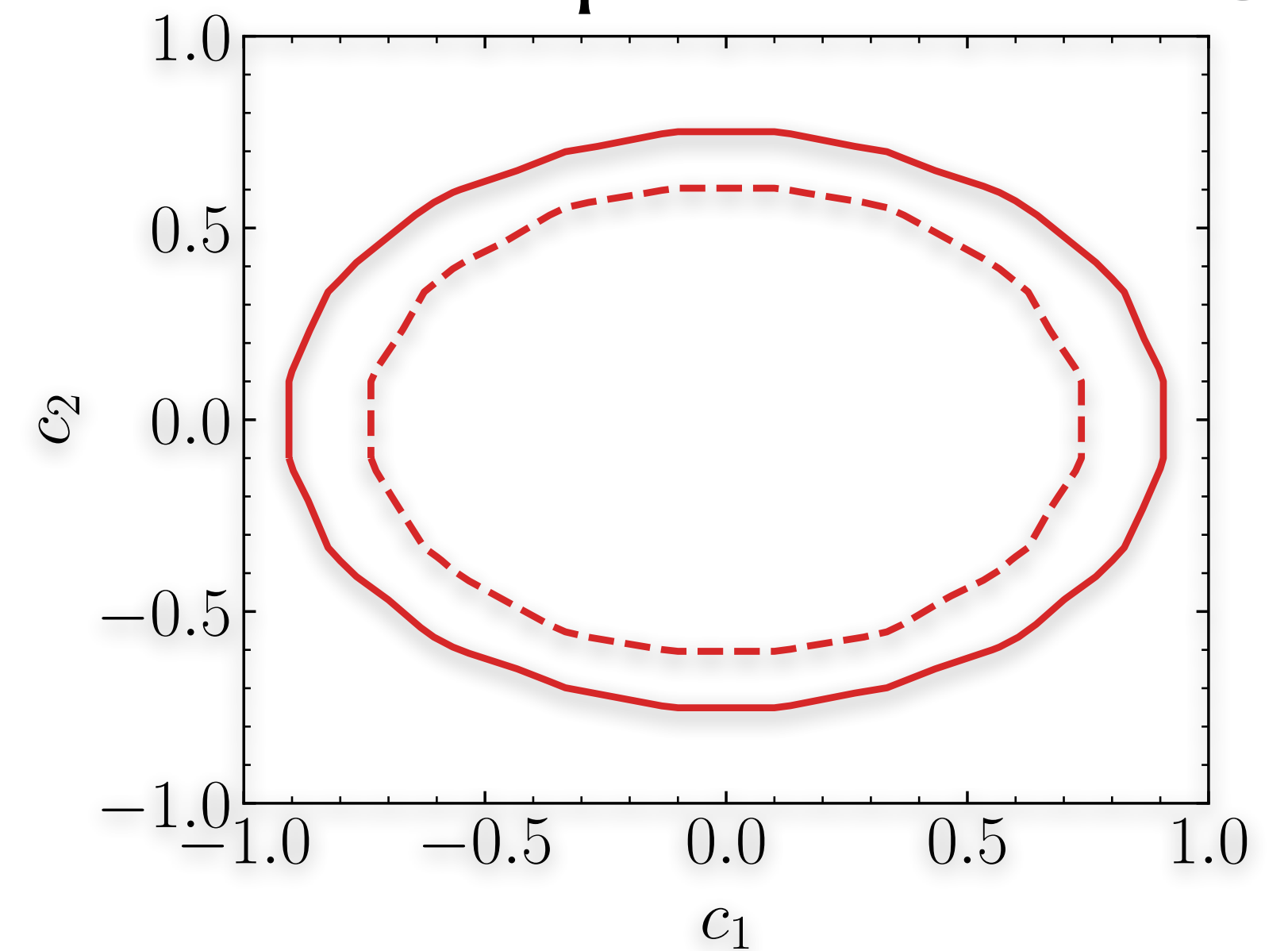
Experiment A



Combined



Experiment B



Jack Y. Araz

Tell me more!



arXiv 2307.06996 pypi v0.1.8

Search [] + K

- Contents:**
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 - Kitchen Sink
 - Description of all functions and classes
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Welcome to the documentation of Spey

issues 1 open DOI 10.21468/SciPostPhys.16.1.032 DOI 10.5281/zenodo.10671596

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- [Gradient of a Statistical Model](#)
- [Signal Uncertainties](#)
- [Building a Plug-in](#)
- [Introduction to Spey \(PyHEP 2023\)](#)

Description of all functions and classes

spey.readthedocs.io

Tell me more!

Tool description

How to build your own custom likelihood

Tutorials



The screenshot shows the Spey documentation website. At the top, it says "Welcome to the documentation of Spey" and provides links for issues (1 open) and DOIs (10.21468/SciPostPhys.16.1.032 and 10.5281/zenodo.10671596). The "Contents:" section is highlighted in green and includes: Quick Start, Installation, What is Spey?, First Steps, Exclusion limits, Plug-ins, Default Plug-ins, External Plug-ins, and Combining Statistical Models. The "Building a plugin" section is highlighted in yellow and includes: What a plugin provides, Creating your Statistical Model Prescription, Identifying and installing your statistical model, and Citing Plug-ins. The "Kitchen Sink" section is highlighted in pink and includes: Using Spey with experimental data, Inference with parameter dependent signal yields, Statistical inference on Histogram, Gradient of a Statistical Model, Signal Uncertainties, Building a Plug-in, and Introduction to Spey (PyHEP 2023). A search bar and a table of contents are also visible. The URL "spey.readthedocs.io" is overlaid in blue text.

spey.readthedocs.io

Tell me



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Contributing to Spey

We welcome contributions to `spey` via [Pull Requests to our GitHub repository](#). To get started, fork the `main` repository.

For anything beyond minimal fixes that do not require discussion, please first [open an issue](#) to discuss your request with the development team.

If your proposed changes are more extensive than a few lines of code, please create a draft pull request. This draft should include the context of the change, a description, and the benefits of the implementation.

- For changes within the Python interface of the program, please run standard tests and write additional tests if necessary.
- Ensure you add examples demonstrating the new implementation.
- Specify any drawbacks of your implementation and offer possible solutions if available.

Pull request procedure

Follow these steps to submit a pull request:

1. Fork the `spey` repository.
2. Open an issue and discuss the implementation with the developers.
3. Commit your changes to a feature branch on your fork and push all your changes.
4. Start a draft pull request and inform the developers about your progress.
5. Pull the `main` branch to ensure there are no conflicts with the current code developments.
6. Modify the appropriate section of `docs/releases/change-log-dev.md`.
7. Once complete, request a review from one of the maintainers.

Come join!
Statistics is fun!
Really!