Higgs physics with neural simulation-based inference at LHC and in ATLAS

Aishik Ghosh

University of Washington

12 November 2024

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ATLAS EXPERIMENT

What's to come

Statistical inference methods developed for Higgs width
Option to follow technical details or intuitive explanations

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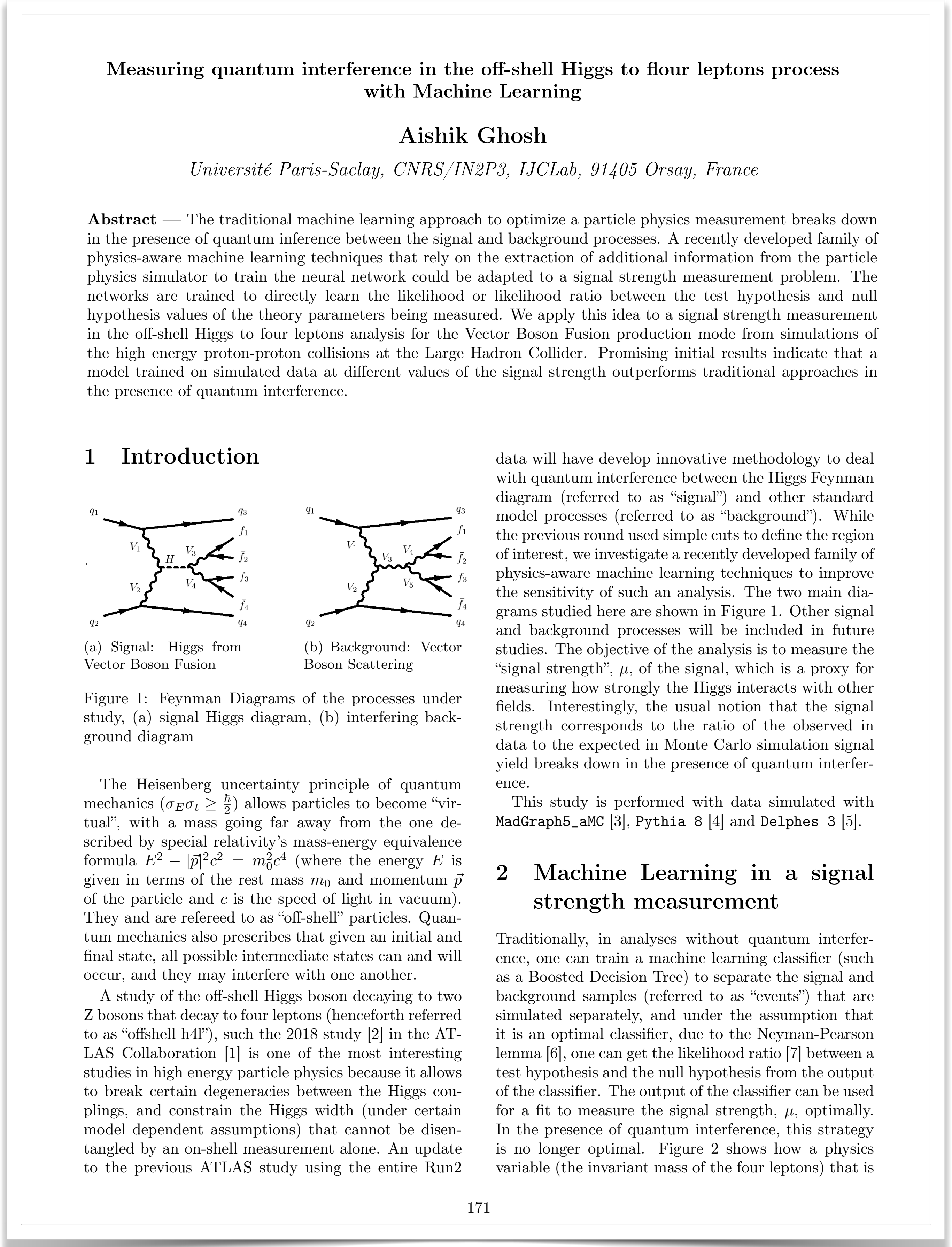

Measuring quantum interference in the off-shell Higgs to flour leptons process with Machine Learning

Aishik Ghosh

Université Paris-Saclay, CNRS/IN2P3, IJCLab, 91405 Orsay, France

Abstract — The traditional machine learning approach to optimize a particle physics measurement breaks down in the presence of quantum inference between the signal and background processes. A recently developed family of physics-aware machine learning techniques that rely on the extraction of additional information from the particle physics simulator to train the neural network could be adapted to a signal strength measurement problem. The networks are trained to directly learn the likelihood or likelihood ratio between the test hypothesis and null hypothesis values of the theory parameters being measured. We apply this idea to a signal strength measurement in the off-shell Higgs to four leptons analysis for the Vector Boson Fusion production mode from simulations of the high energy proton-proton collisions at the Large Hadron Collider. Promising initial results indicate that a model trained on simulated data at different values of the signal strength outperforms traditional approaches in the presence of quantum interference.

1 Introduction

(a) Signal: Higgs from Vector Boson Fusion

(b) Background: Vector Boson Scattering

Figure 1: Feynman Diagrams of the processes under study, (a) signal Higgs diagram, (b) interfering background diagram

The Heisenberg uncertainty principle of quantum mechanics ($\sigma_E \sigma_t \geq \frac{\hbar}{2}$) allows particles to become "virtual", with a mass going far away from the one described by special relativity's mass-energy equivalence formula $E^2 - |\vec{p}|^2 c^2 = m_0^2 c^4$ (where the energy E is given in terms of the rest mass m_0 and momentum $\vec{p}$ of the particle and c is the speed of light in vacuum). They and are refereed to as "off-shell" particles. Quantum mechanics also prescribes that given an initial and final state, all possible intermediate states can and will occur, and they may interfere with one another.

A study of the off-shell Higgs boson decaying to two Z bosons that decay to four leptons (henceforth referred to as "offshell h4l"), such the 2018 study [2] in the ATLAS Collaboration [1] is one of the most interesting studies in high energy particle physics because it allows to break certain degeneracies between the Higgs couplings, and constrain the Higgs width (under certain model dependent assumptions) that cannot be disentangled by an on-shell measurement alone. An update to the previous ATLAS study using the entire Run2 data will have develop innovative methodology to deal with quantum interference between the Higgs Feynman diagram (referred to as "signal") and other standard model processes (referred to as "background"). While the previous round used simple cuts to define the region of interest, we investigate a recently developed family of physics-aware machine learning techniques to improve the sensitivity of such an analysis. The two main diagrams studied here are shown in Figure 1. Other signal and background processes will be included in future studies. The objective of the analysis is to measure the "signal strength", μ, of the signal, which is a proxy for measuring how strongly the Higgs interacts with other fields. Interestingly, the usual notion that the signal strength corresponds to the ratio of the observed in data to the expected in Monte Carlo simulation signal yield breaks down in the presence of quantum interference.

This study is performed with data simulated with `MadGraph5_aMC` [3], `Pythia 8` [4] and `Delphes 3` [5].

2 Machine Learning in a signal strength measurement

Traditionally, in analyses without quantum interference, one can train a machine learning classifier (such as a Boosted Decision Tree) to separate the signal and background samples (referred to as "events") that are simulated separately, and under the assumption that it is an optimal classifier, due to the Neyman-Pearson lemma [6], one can get the likelihood ratio [7] between a test hypothesis and the null hypothesis from the output of the classifier. The output of the classifier can be used for a fit to measure the signal strength, μ, optimally. In the presence of quantum interference, this strategy is no longer optimal. Figure 2 shows how a physics variable (the invariant mass of the four leptons) that is

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Ghosh et al:
hal-02971995(p172)

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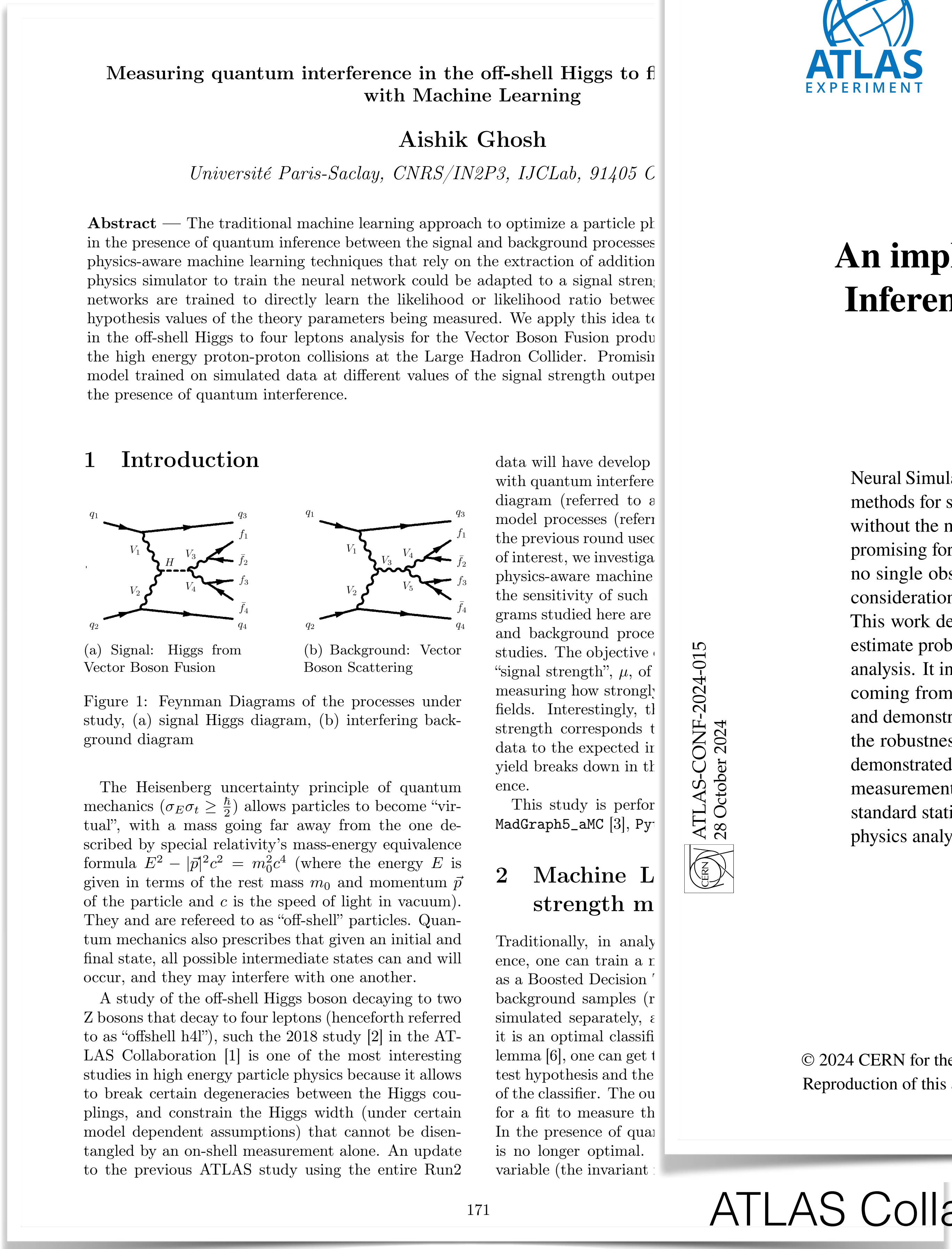

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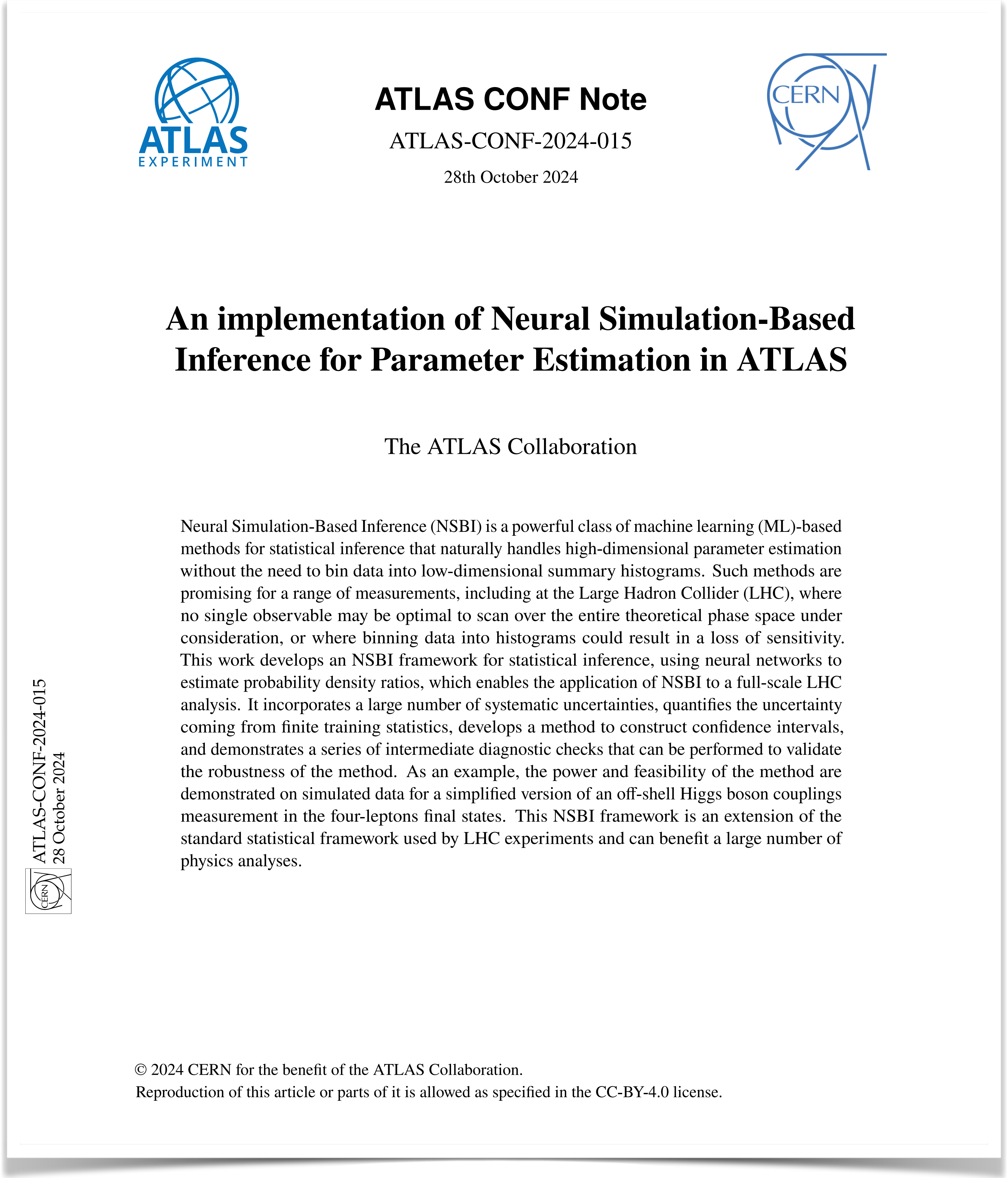

ATLAS CONF Note
ATLAS-CONF-2024-015
28th October 2024

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28 October 2024

An implementation of Neural Simulation-Based Inference for Parameter Estimation in ATLAS

The ATLAS Collaboration

Neural Simulation-Based Inference (NSBI) is a powerful class of machine learning (ML)-based methods for statistical inference that naturally handles high-dimensional parameter estimation without the need to bin data into low-dimensional summary histograms. Such methods are promising for a range of measurements, including at the Large Hadron Collider (LHC), where no single observable may be optimal to scan over the entire theoretical phase space under consideration, or where binning data into histograms could result in a loss of sensitivity. This work develops an NSBI framework for statistical inference, using neural networks to estimate probability density ratios, which enables the application of NSBI to a full-scale LHC analysis. It incorporates a large number of systematic uncertainties, quantifies the uncertainty coming from finite training statistics, develops a method to construct confidence intervals, and demonstrates a series of intermediate diagnostic checks that can be performed to validate the robustness of the method. As an example, the power and feasibility of the method are demonstrated on simulated data for a simplified version of an off-shell Higgs boson couplings measurement in the four-leptons final states. This NSBI framework is an extension of the standard statistical framework used by LHC experiments and can benefit a large number of physics analyses.

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Ghosh et al:
hal-02971995(p172)

ATLAS Collaboration (incl **Ghosh**): CONF Note 1

What’s to come

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ATLAS Collaboration (incl **Ghosh**): [CONF Note 2]

Ghosh et al:
[hal-02971995(p172)]

ATLAS Collaboration (incl **Ghosh**): [CONF Note 1]

What’s to come

Statistical inference methods developed for Higgs width
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Similar story for neutron star astrophysics

Brandes, Modi, **Ghosh**, et all: JCAP 09(2024)009

ATLAS Collaboration (incl **Ghosh**): CONF Note 2

ATLAS Collaboration (incl **Ghosh**): CONF Note 1

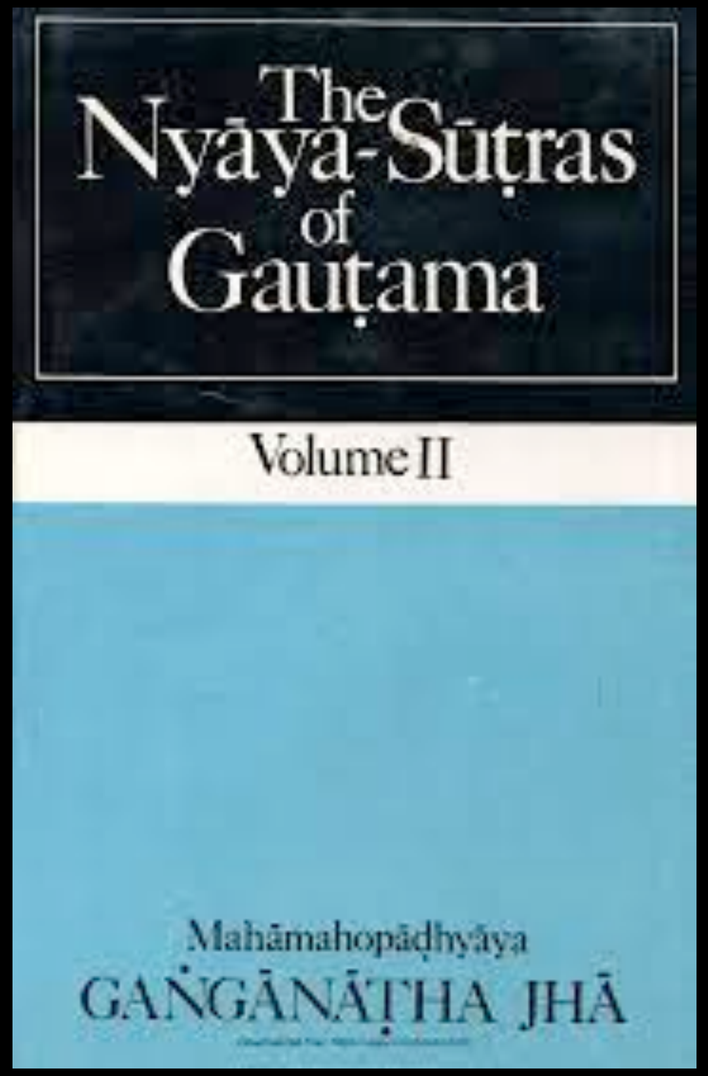
Ghosh et al: hal-02971995(p172)

Some of the oldest questions

Image: Source

What elements make up the universe ?
(5 century BCE)

How sure are we?
Theory of Errors & Empirical Knowledge
(6 century BCE)



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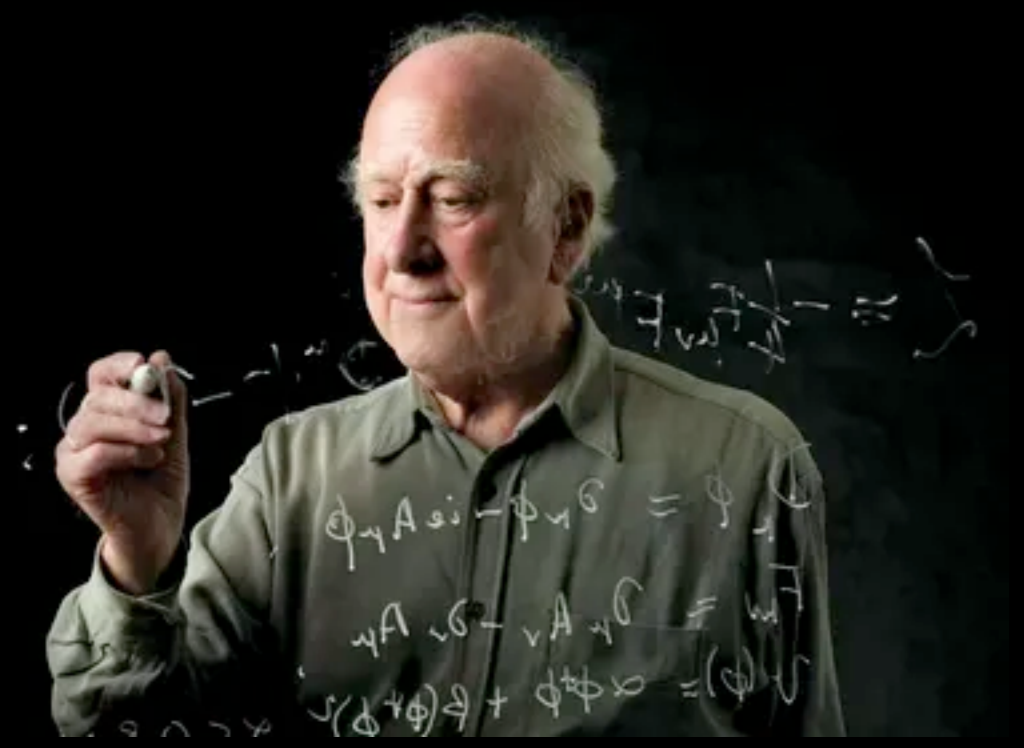

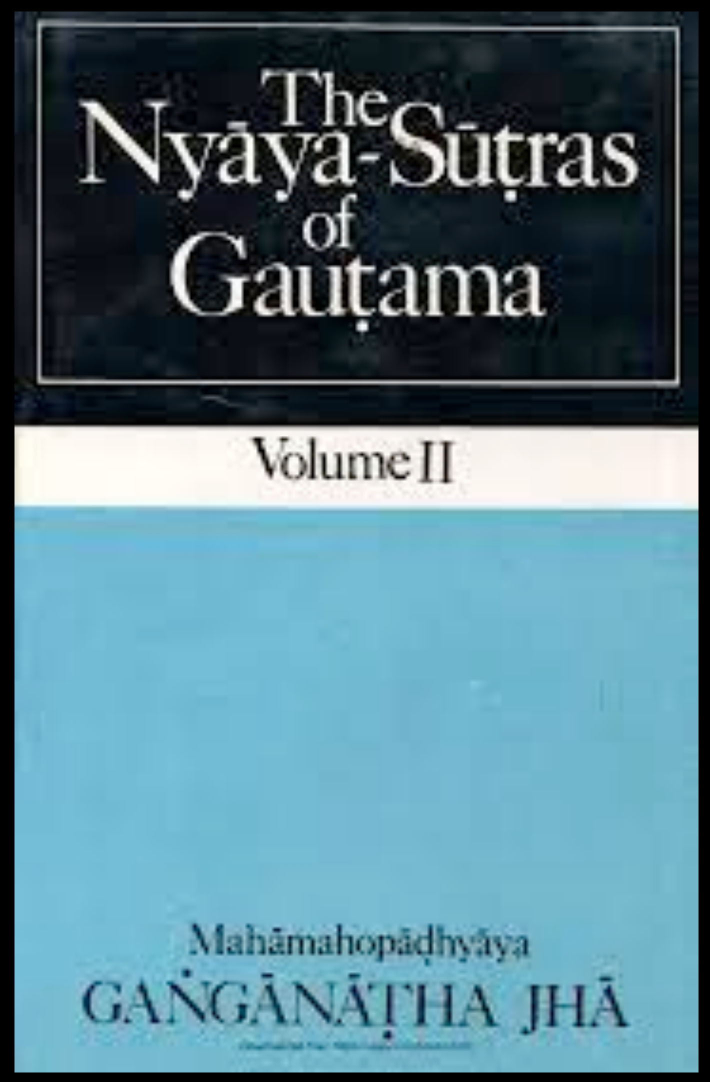

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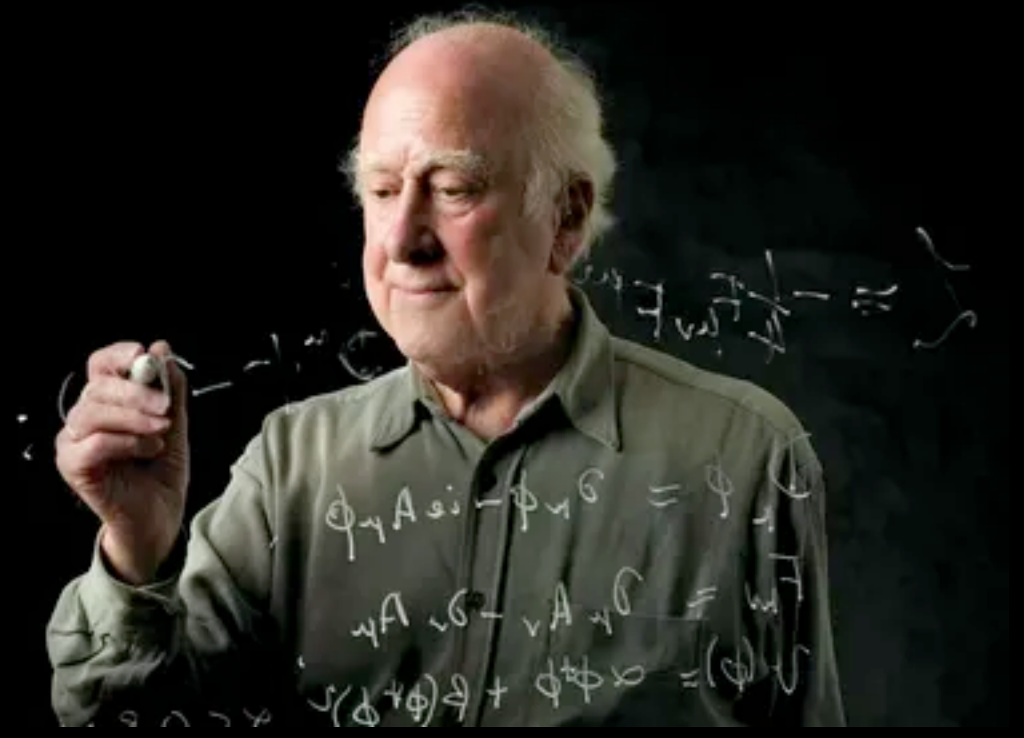

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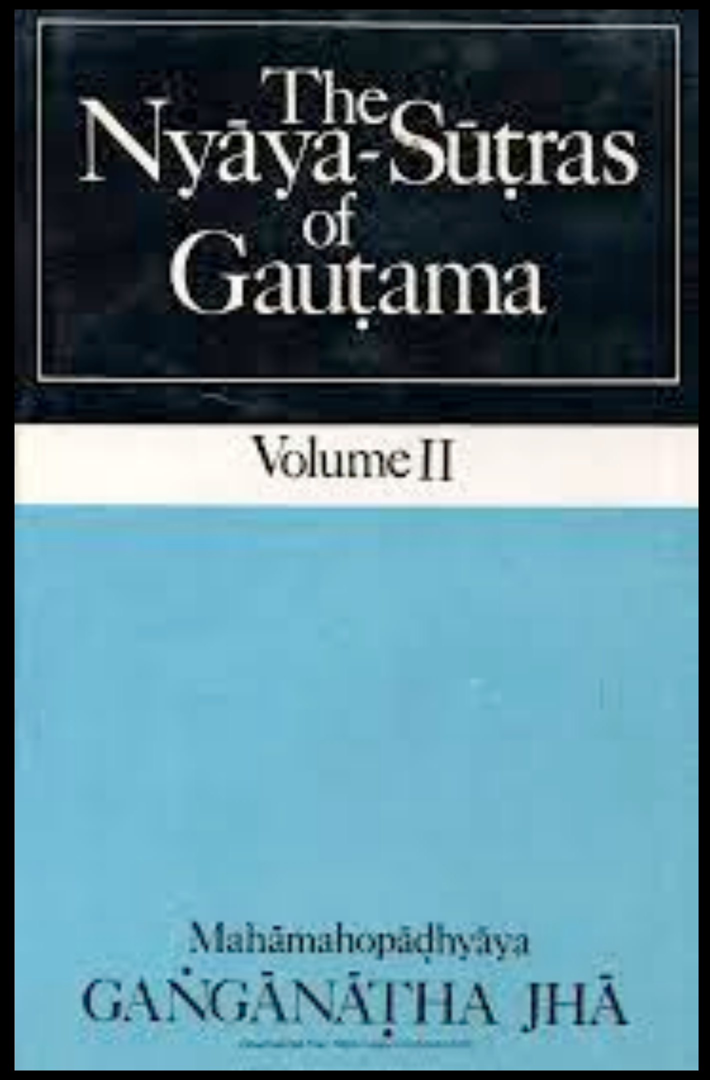

Questions about the universe today…

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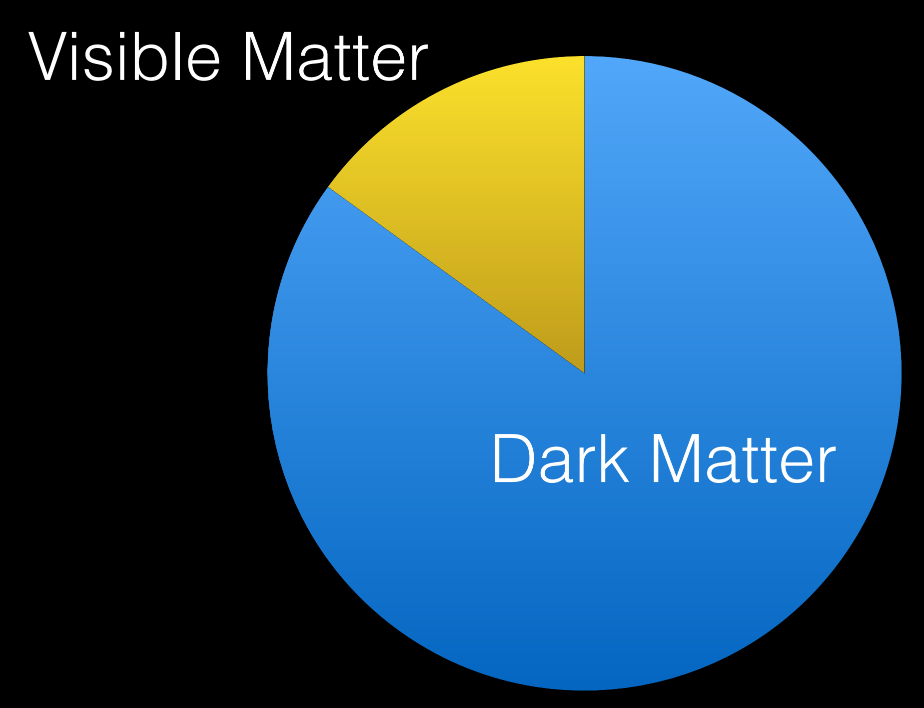
There's so much more dark matter than visible matter in the universe. What is it ?



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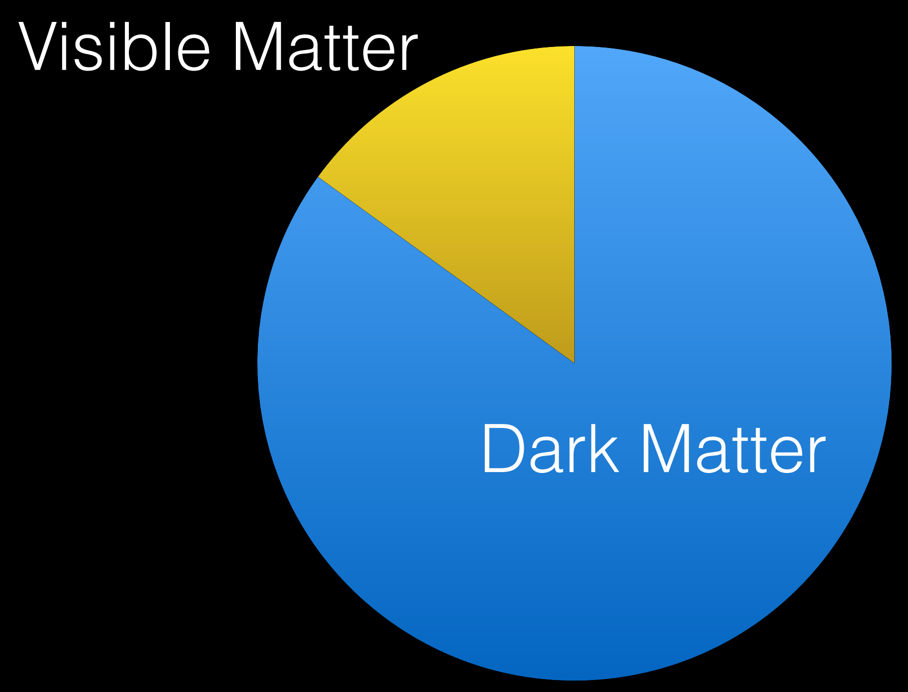

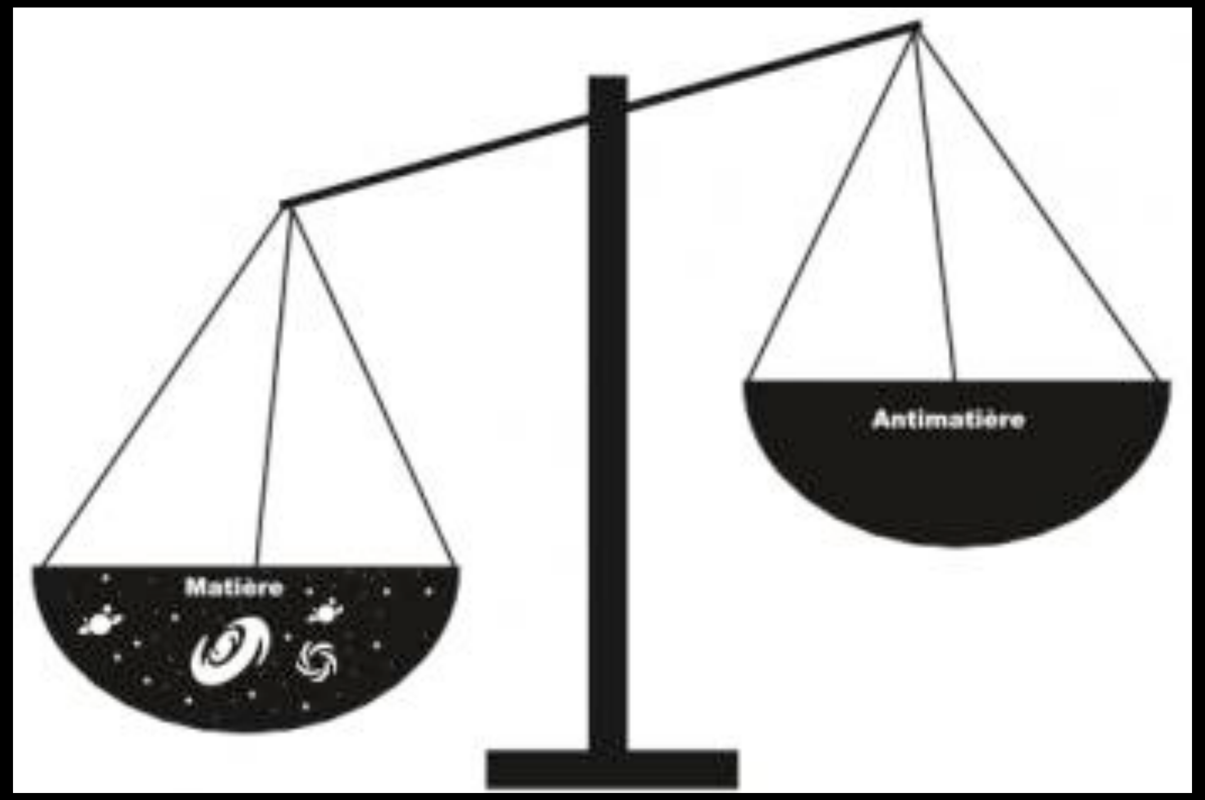

Image: GANIL

Why more matter than anti-matter ?

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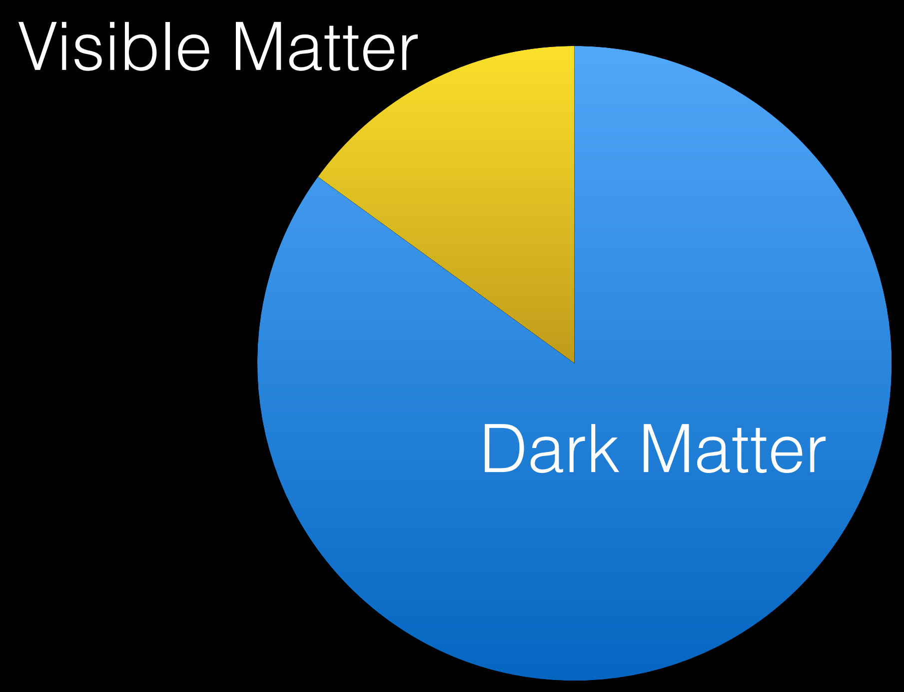

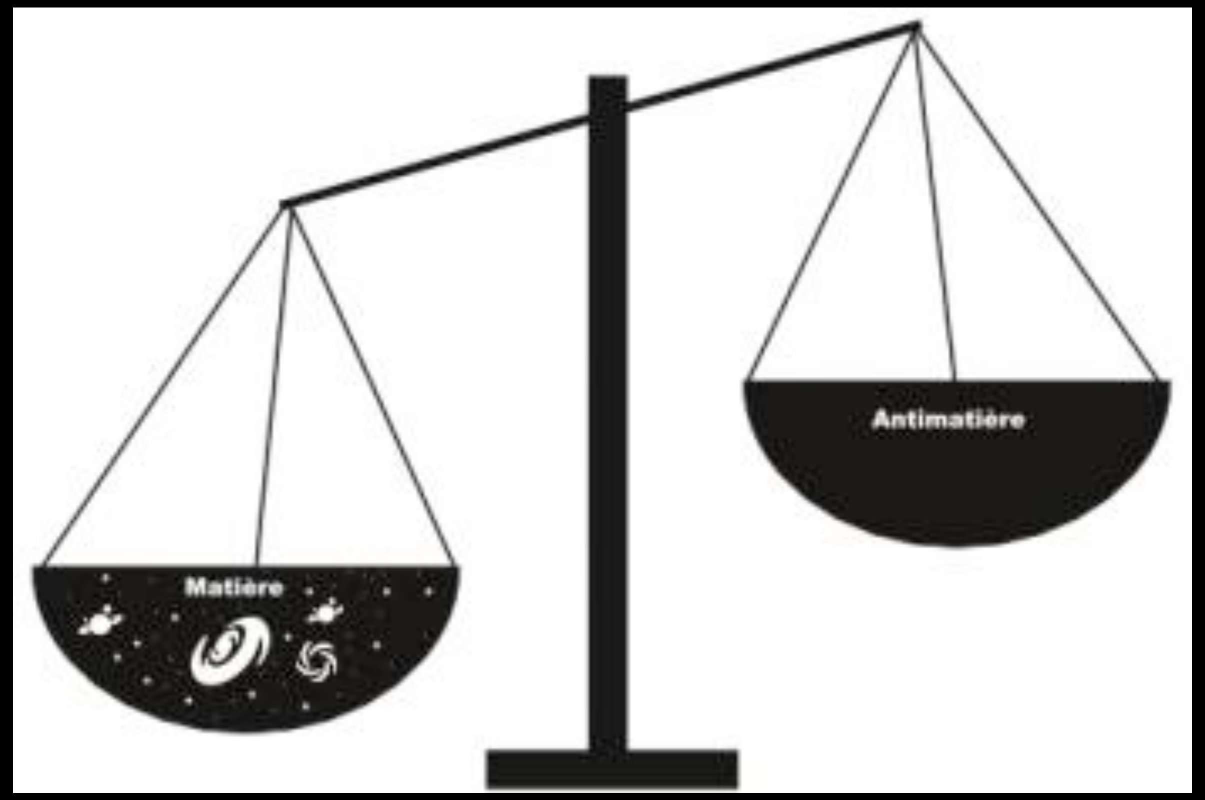

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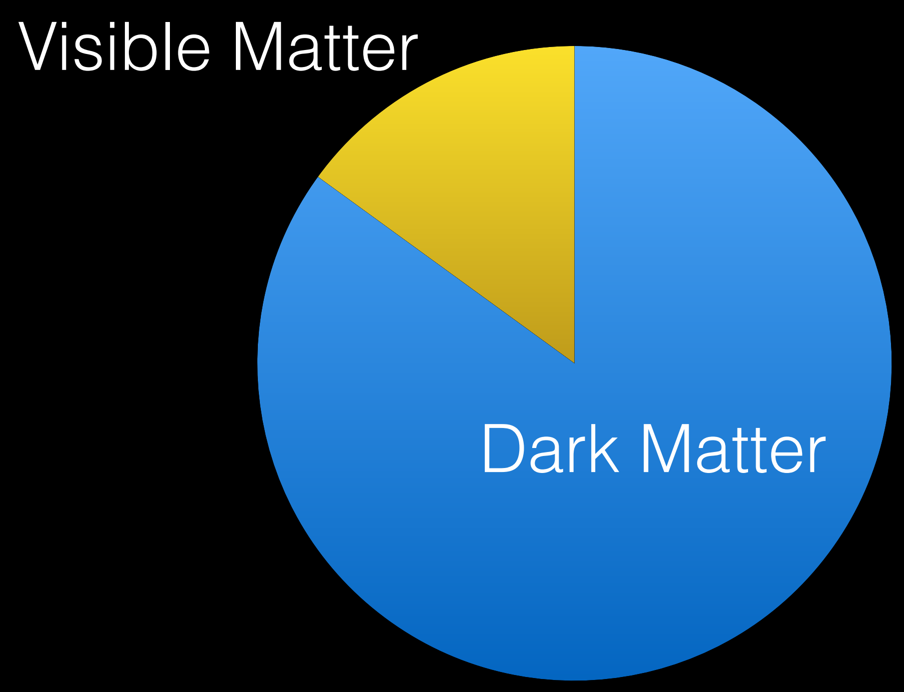

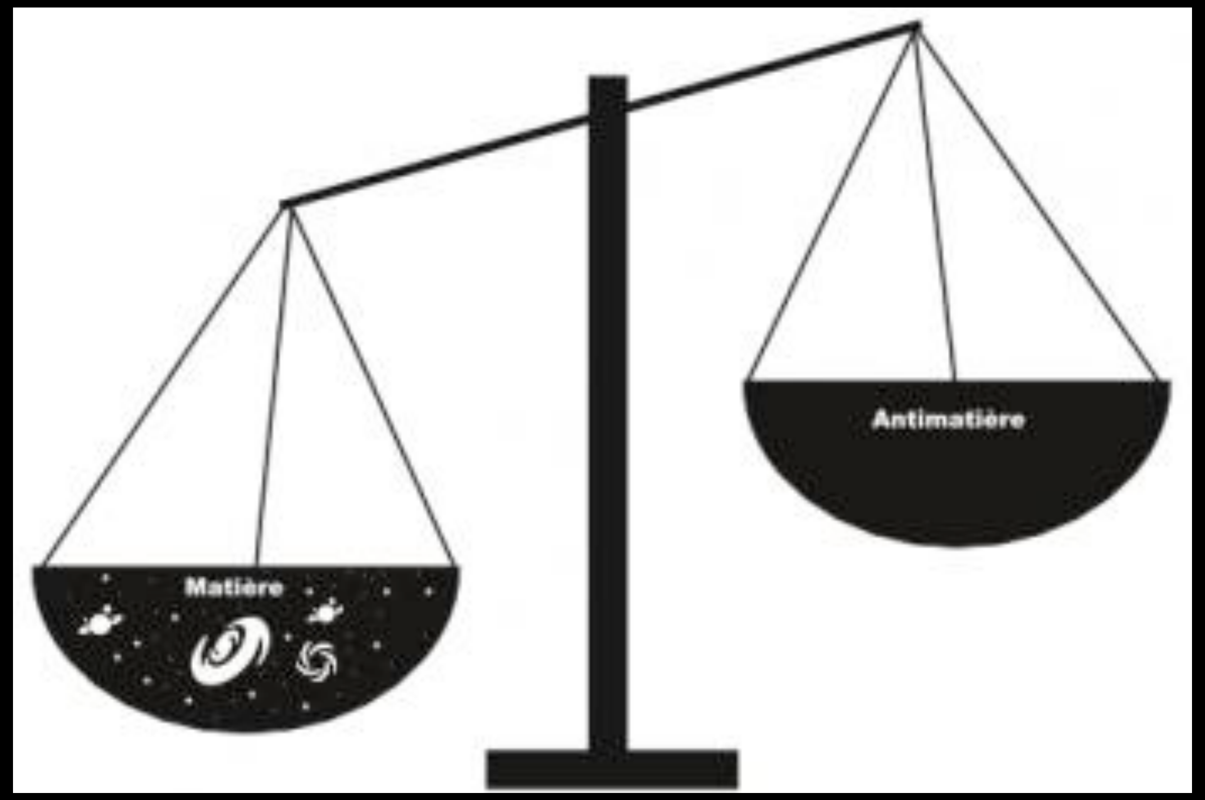

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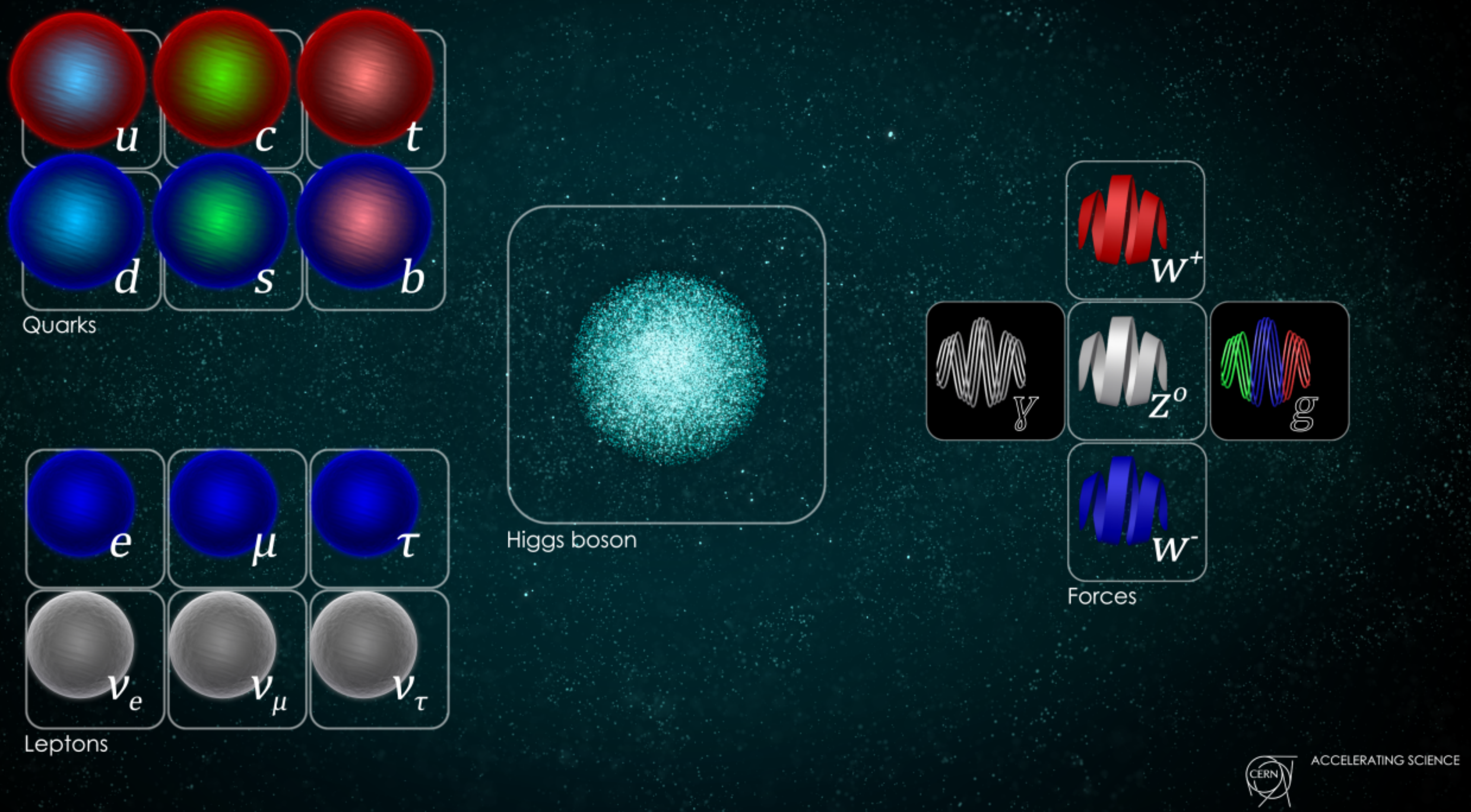
Are there new forces ?

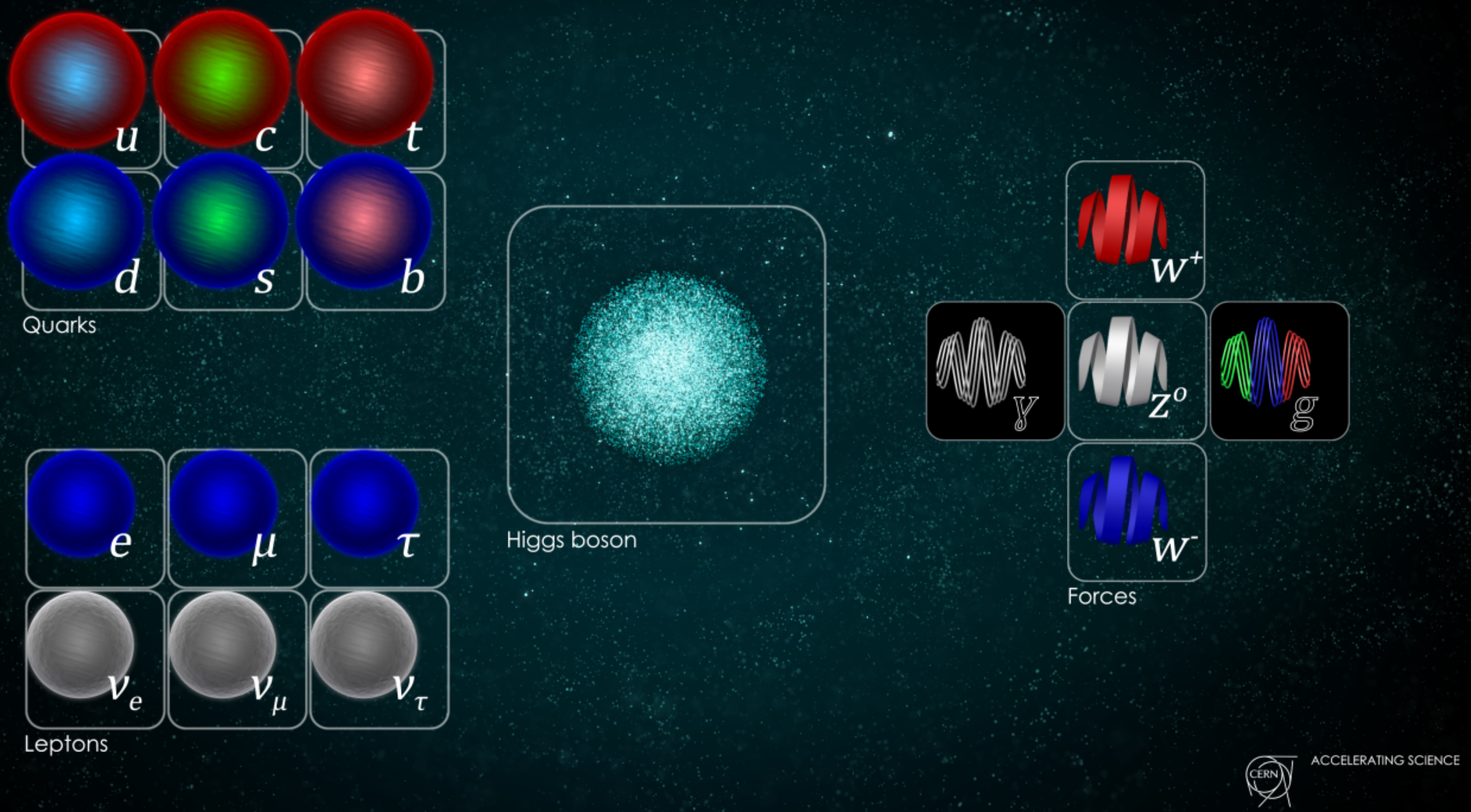
New theories often predict **new particles yet to be discovered**

The most fundamental constituents of matter (that we know of…)



The most fundamental constituents of matter (that we know of…)

Protons are made up of u and d



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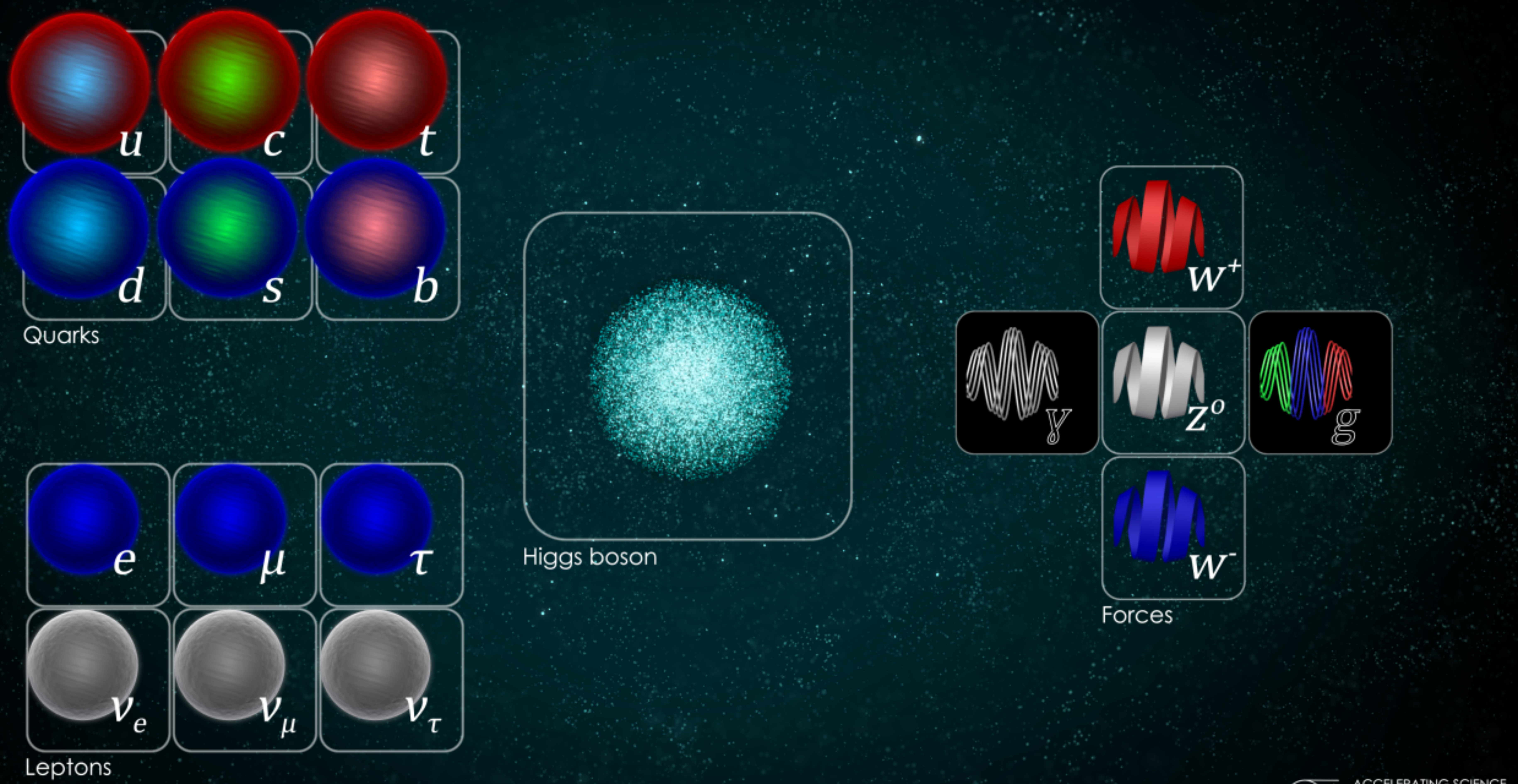

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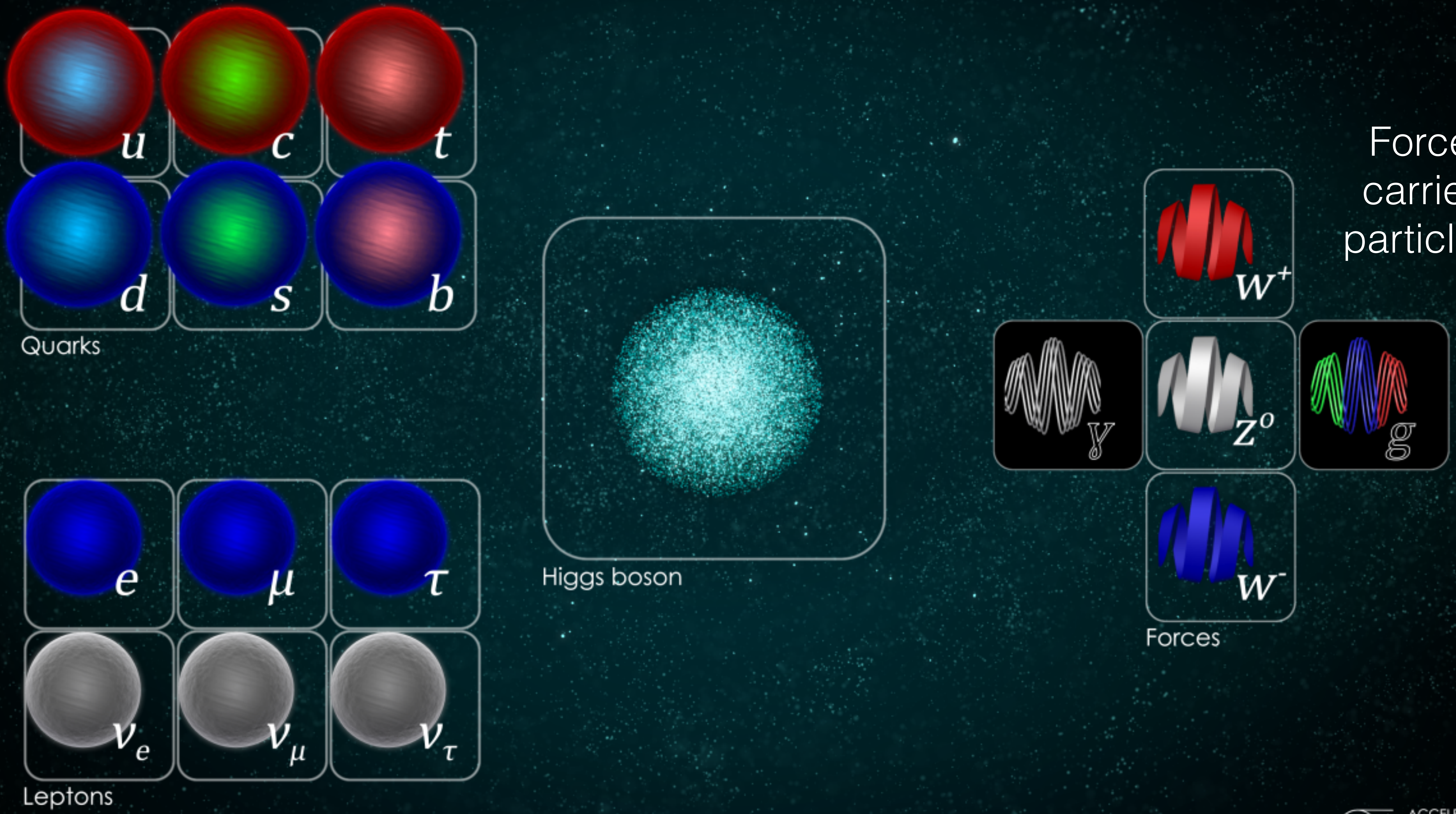

Force carrier particles

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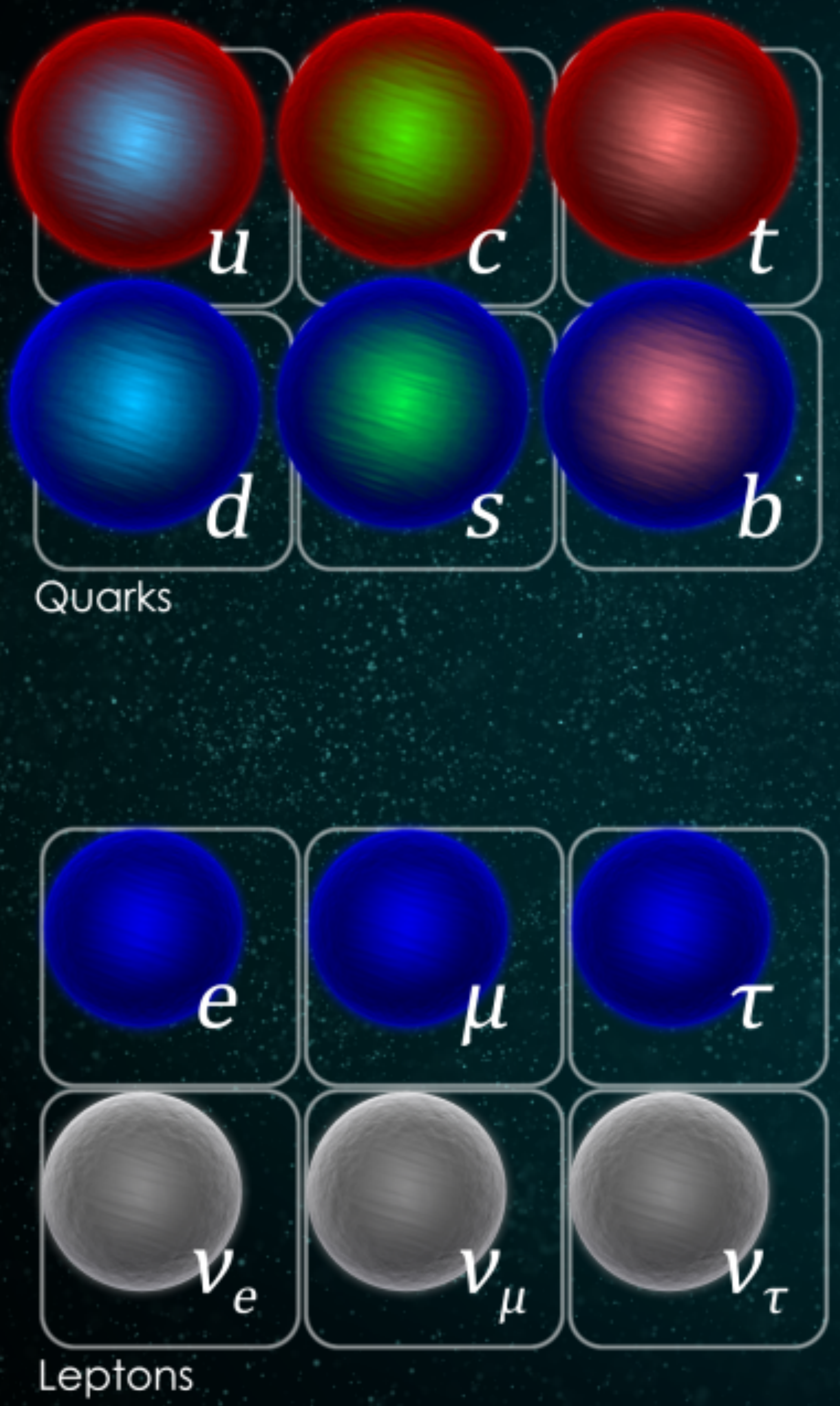


That’s the electron and it’s cousins

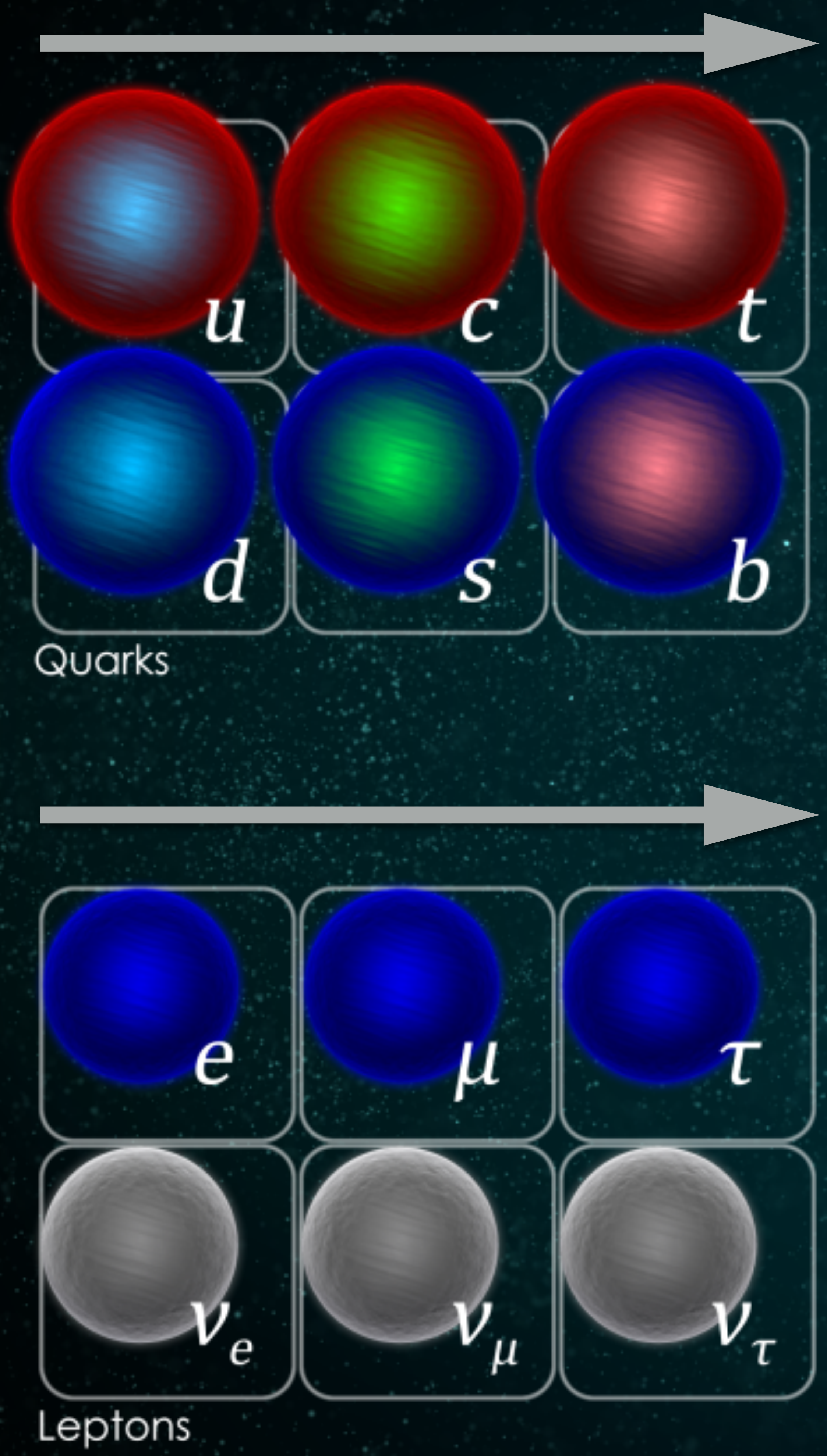
Higgs field gives other particles mass

Force carrier particles

The most fundamental constituents of matter (that we know of…)

Heaver particles, difficult to create

Protons are made up of u and d



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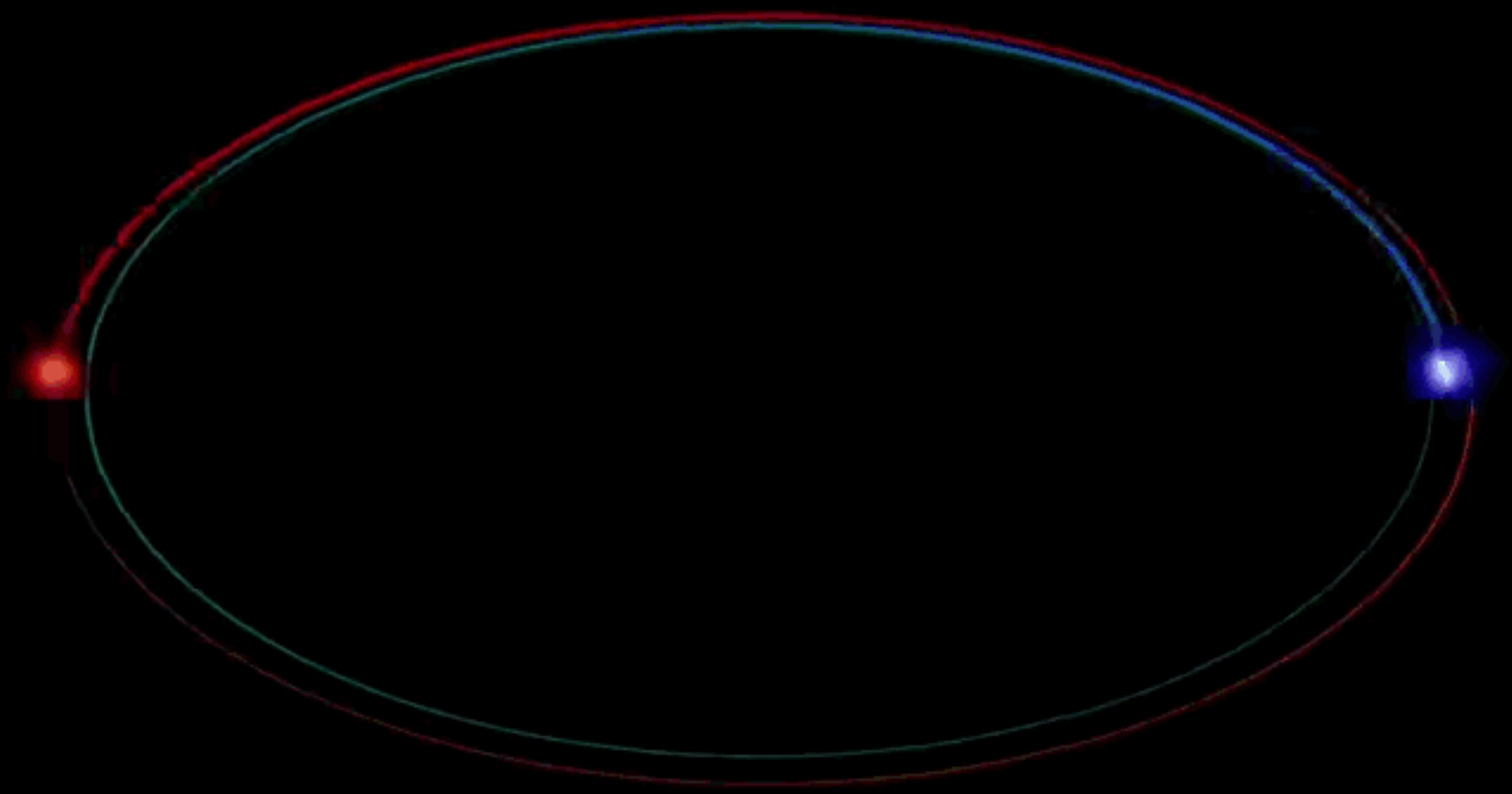
ACCELERATING SCIENCE

Smash particles at Large Hadron Collider



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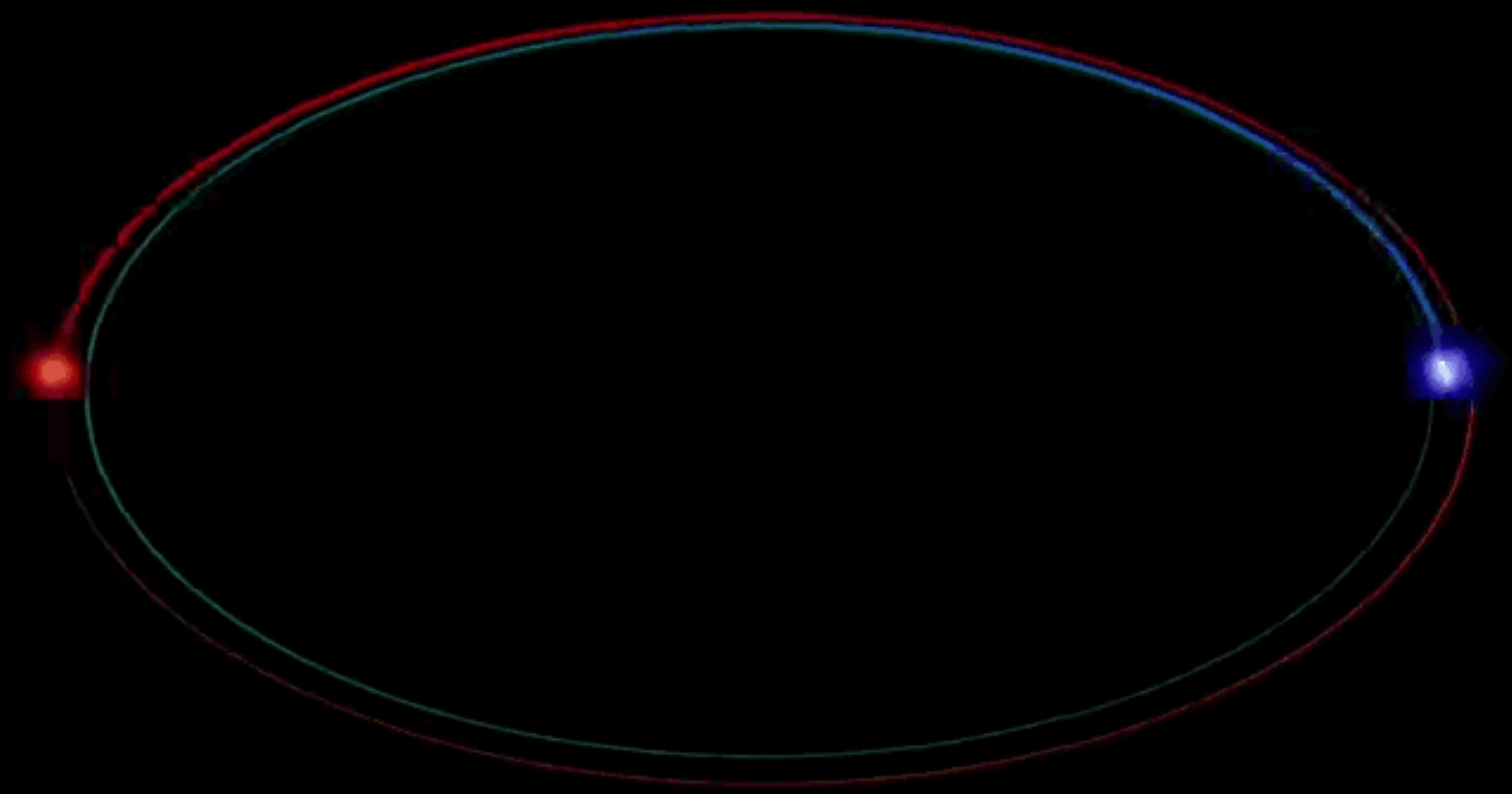

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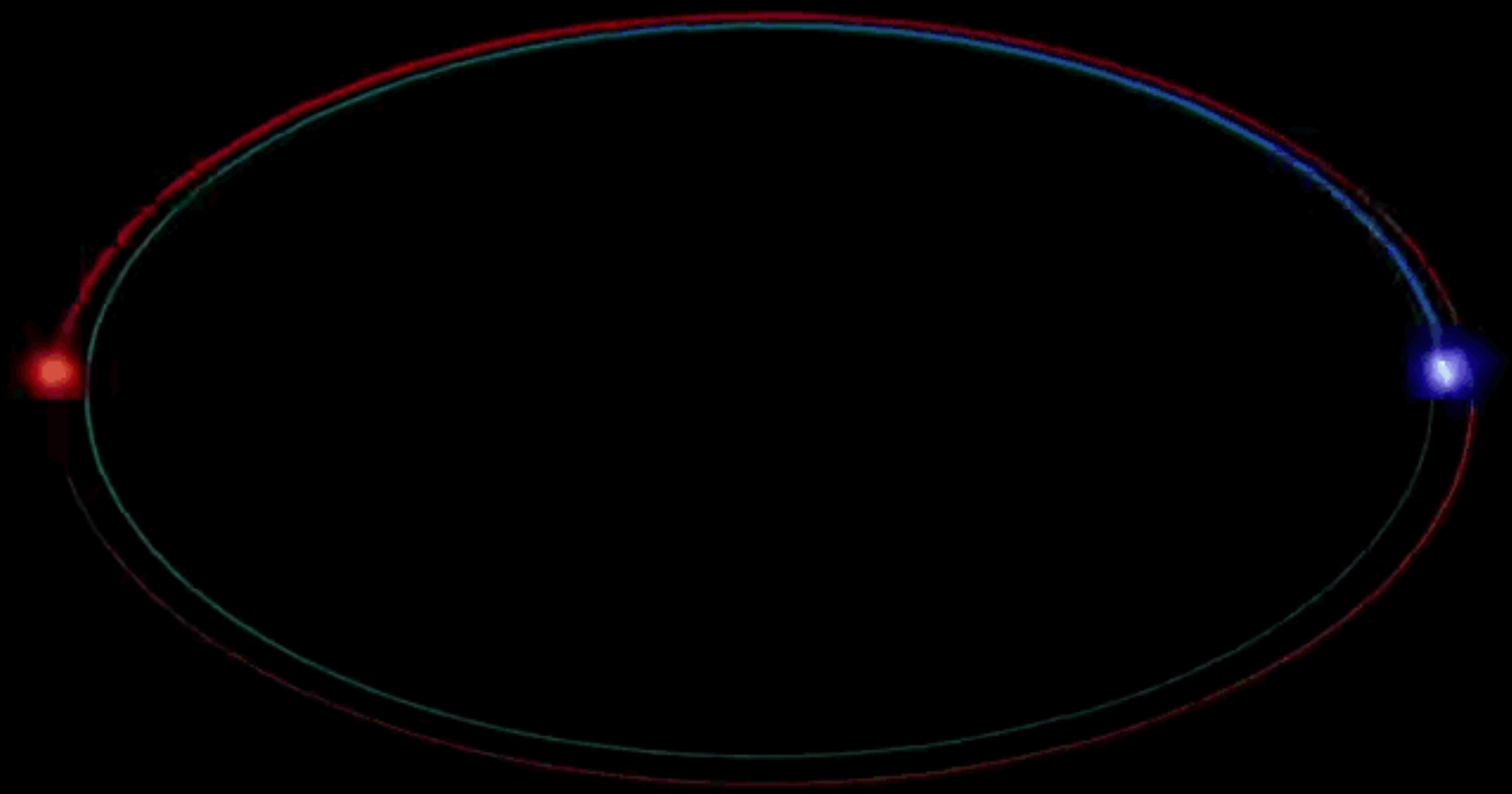

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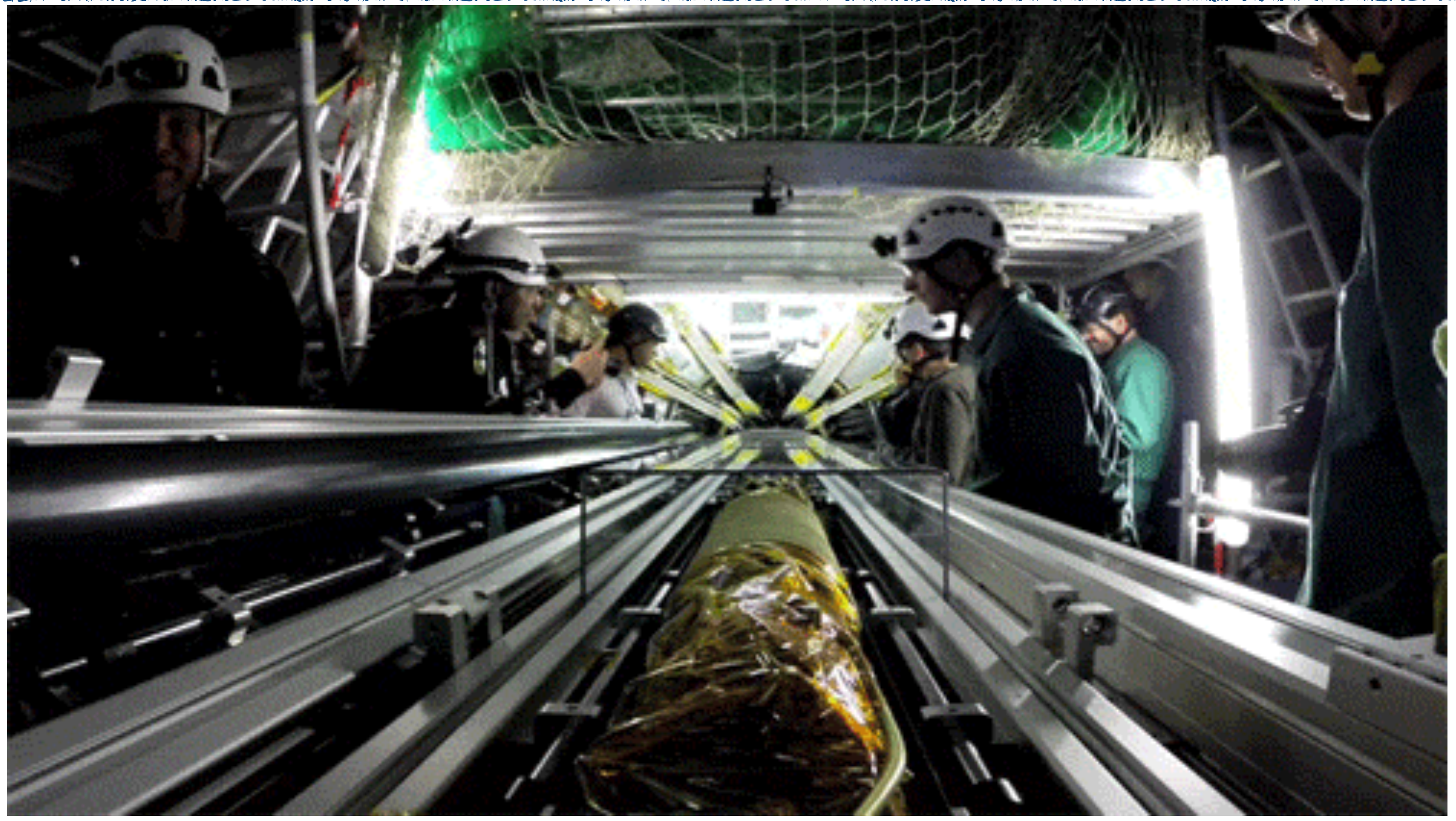
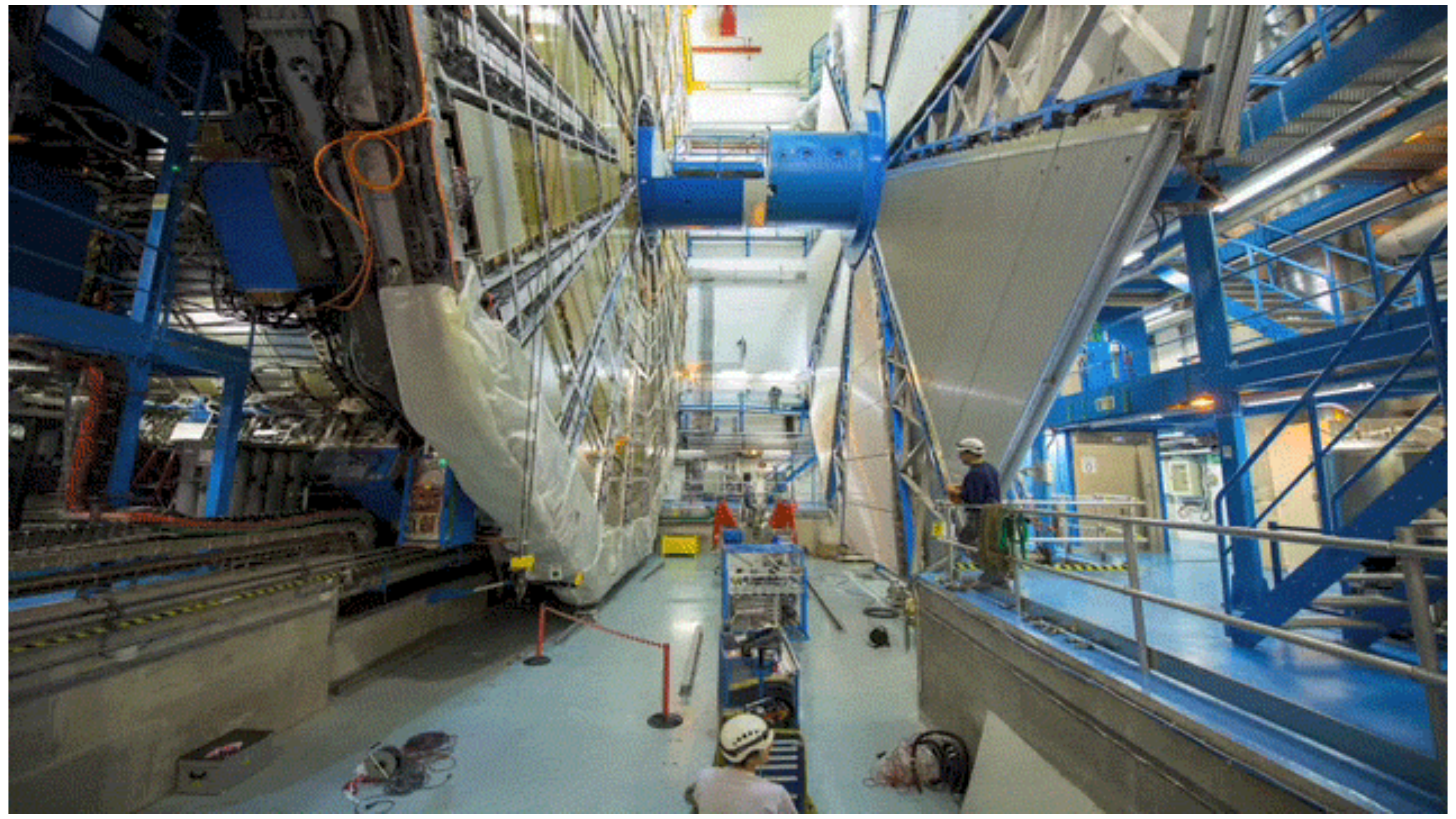
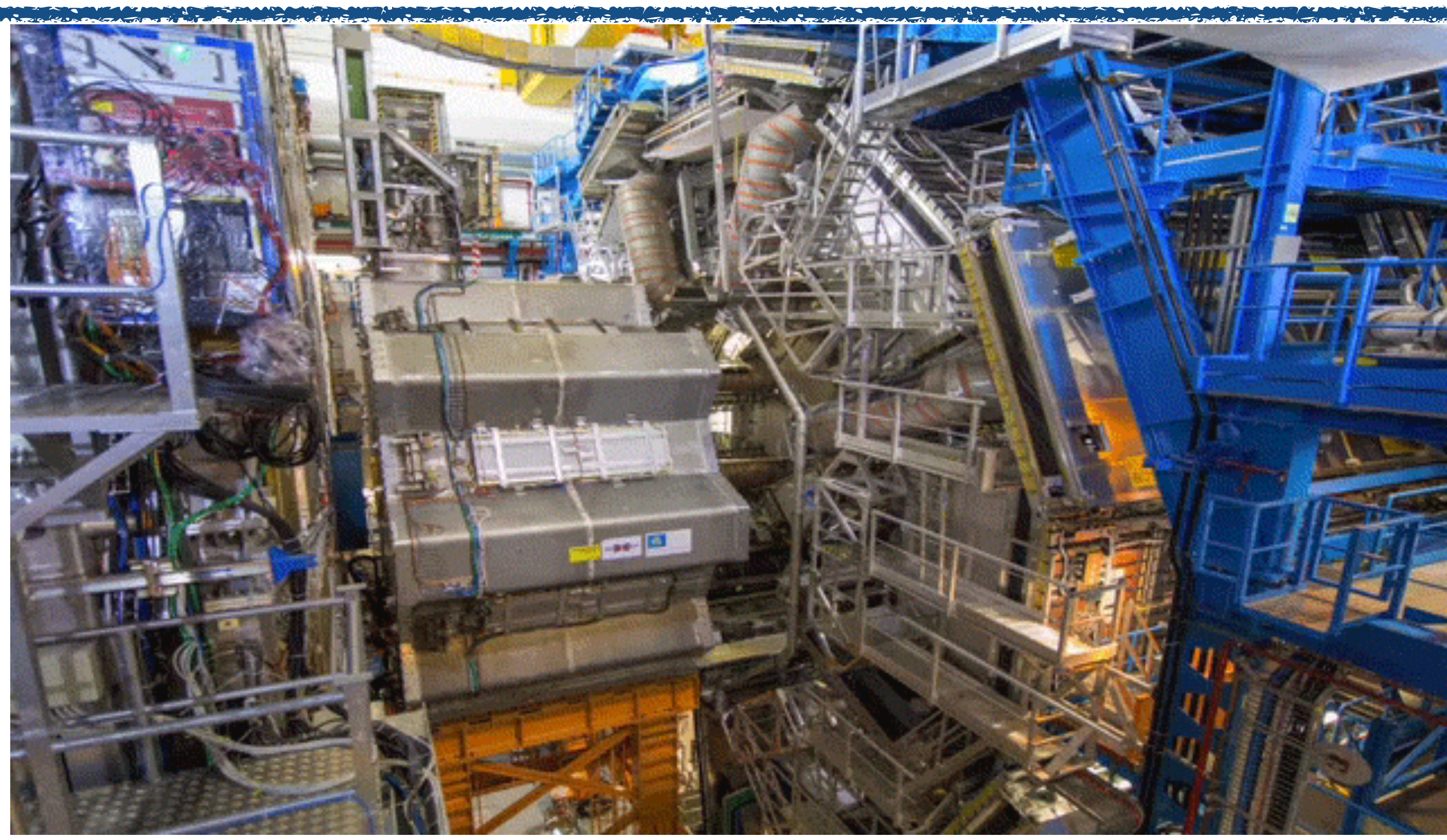
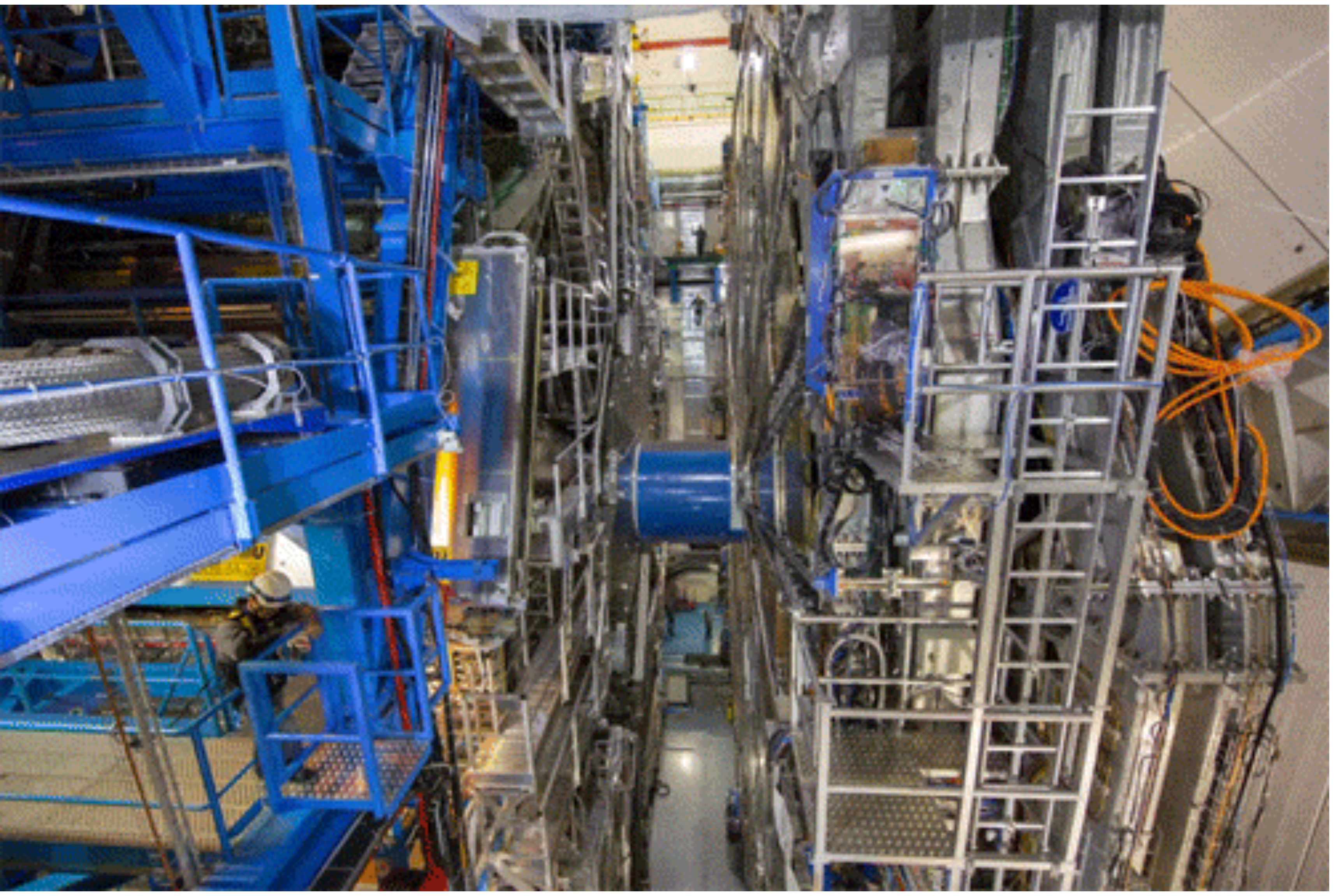
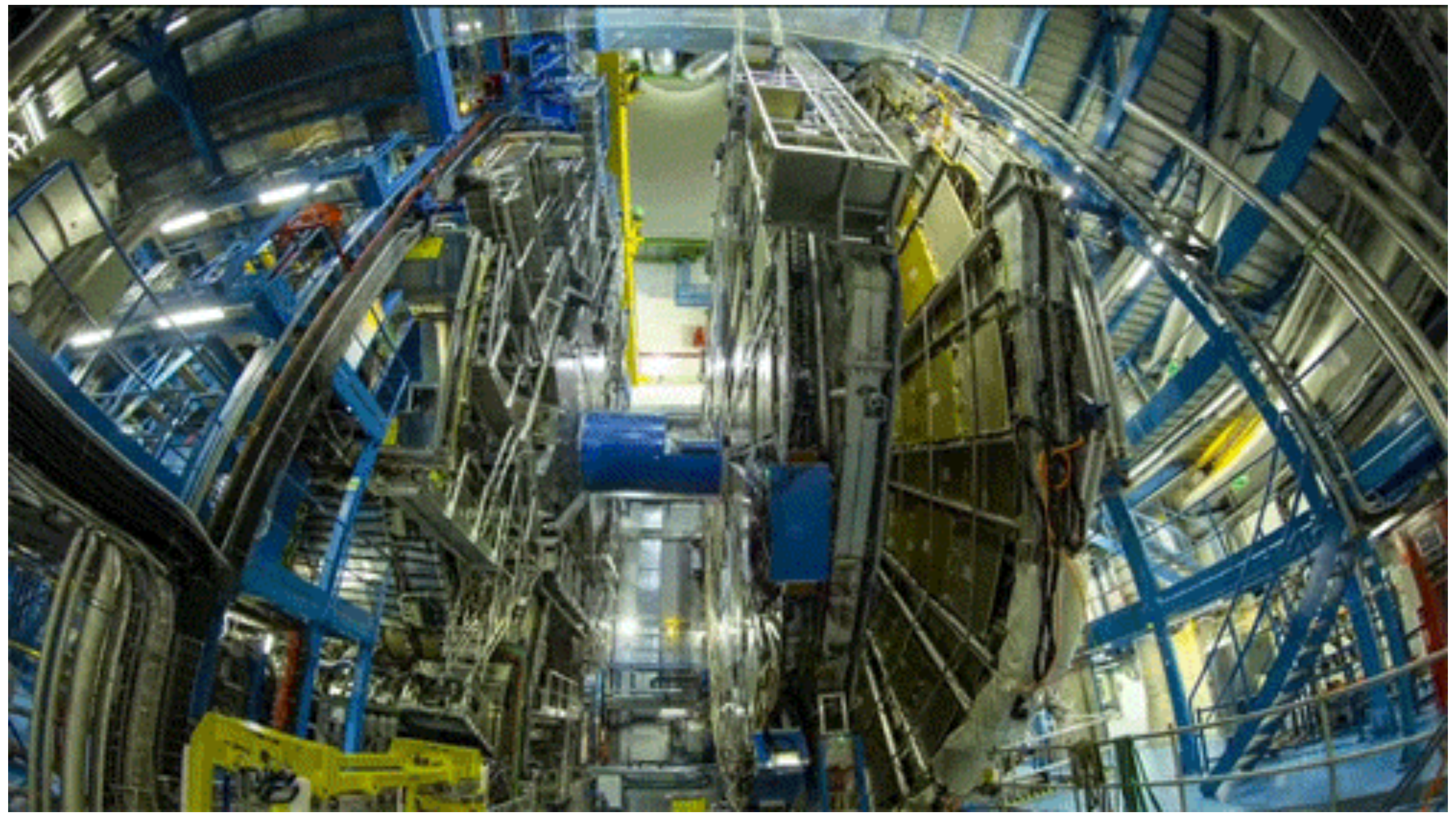
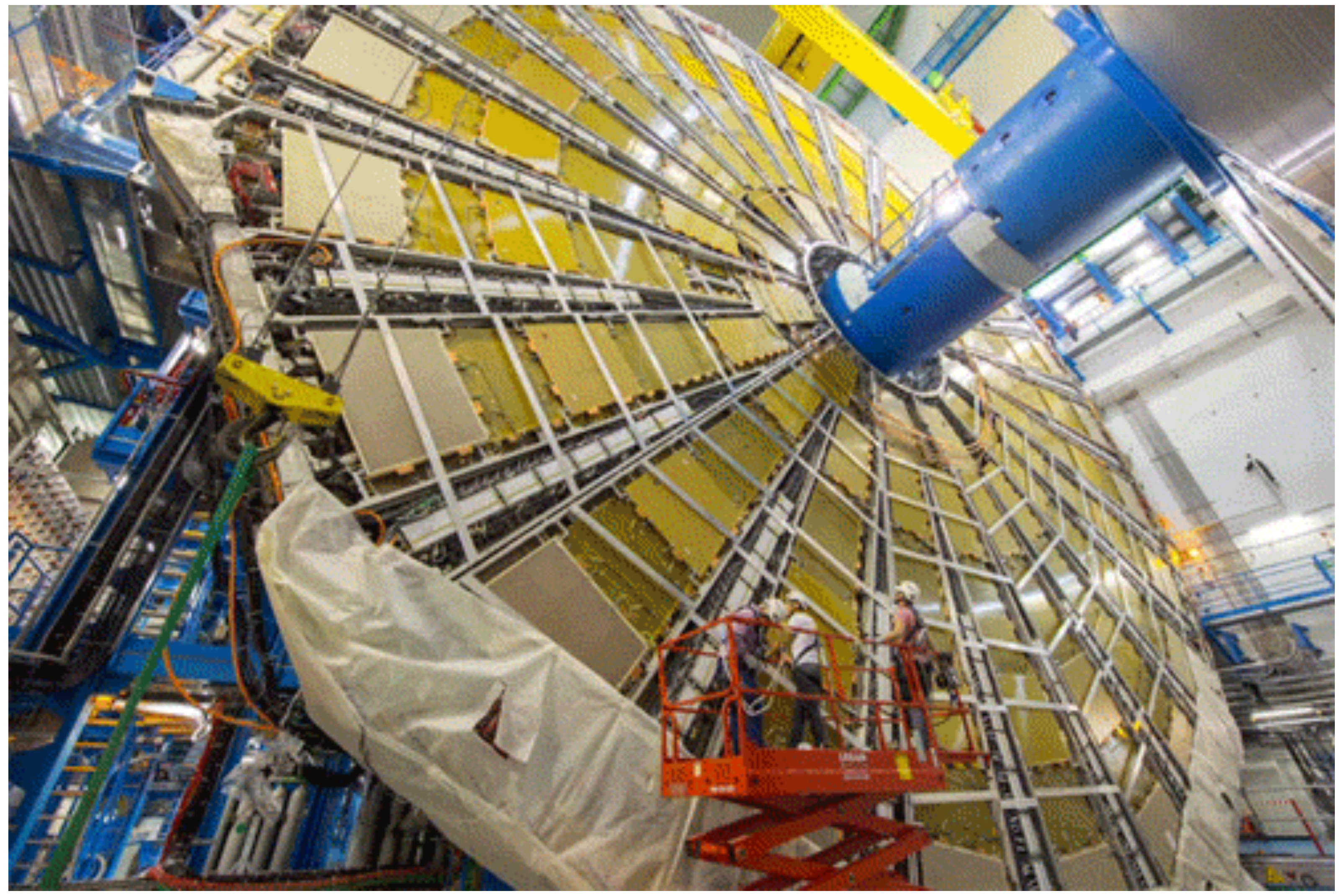
The detectors

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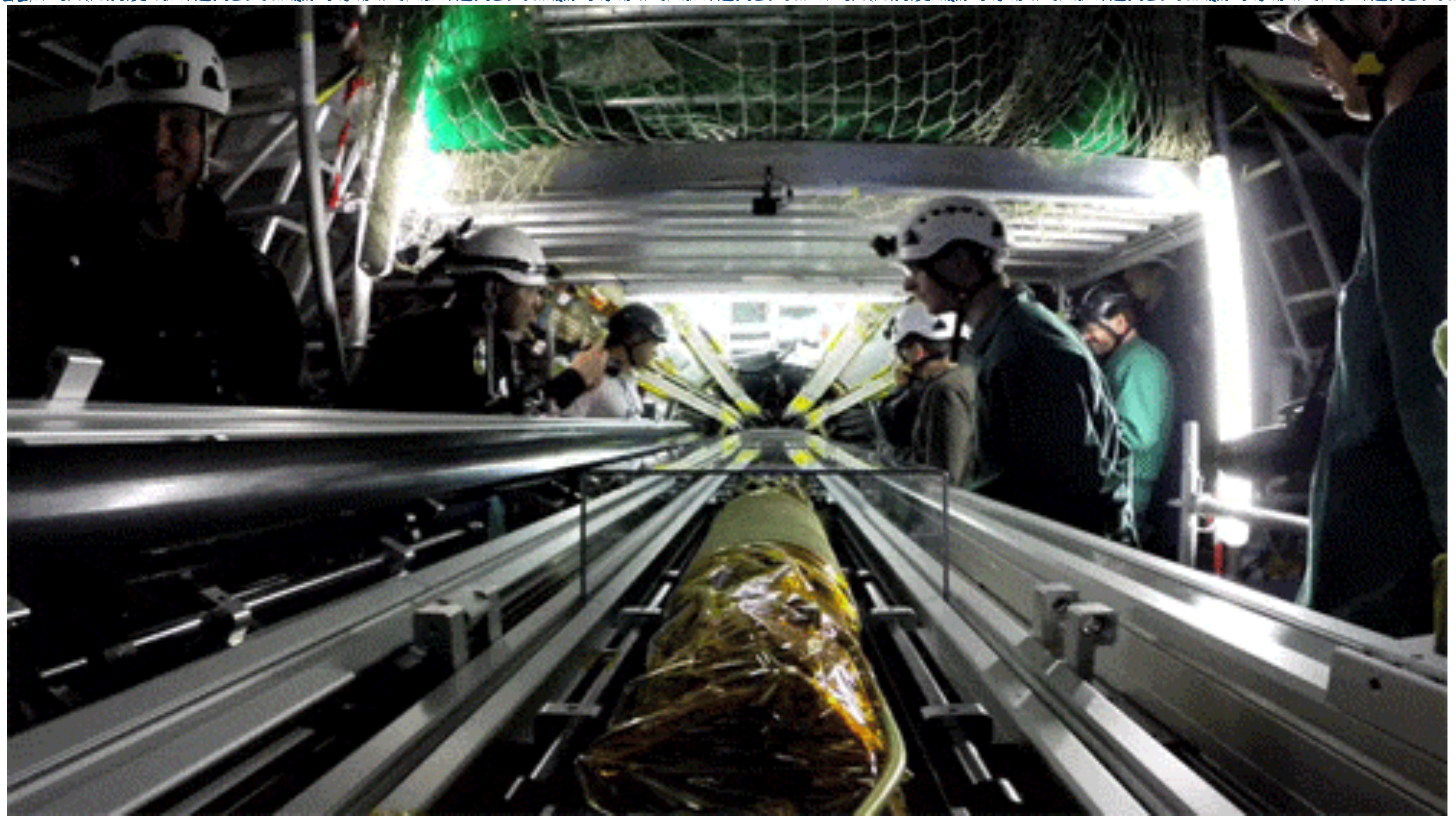
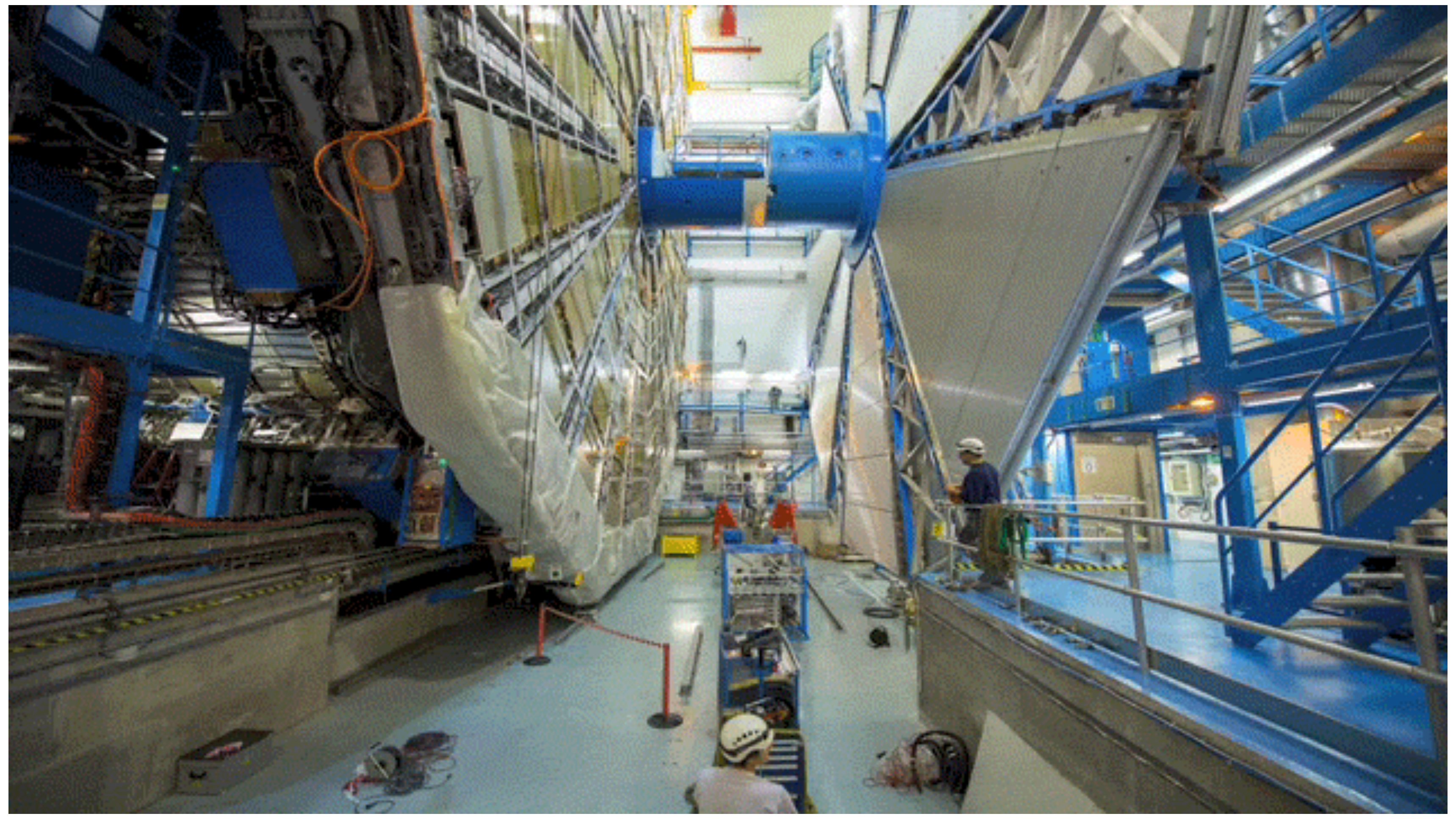
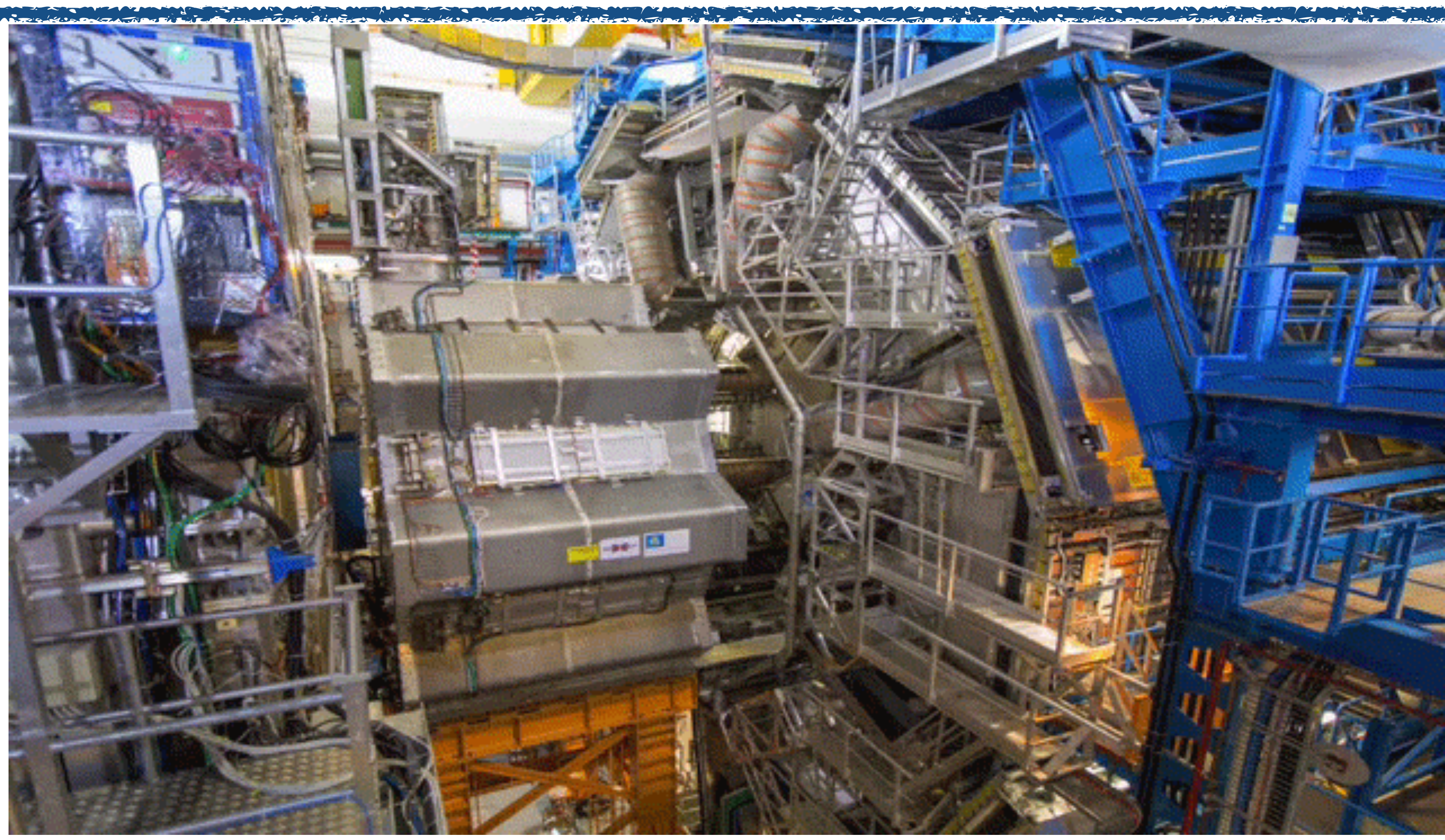
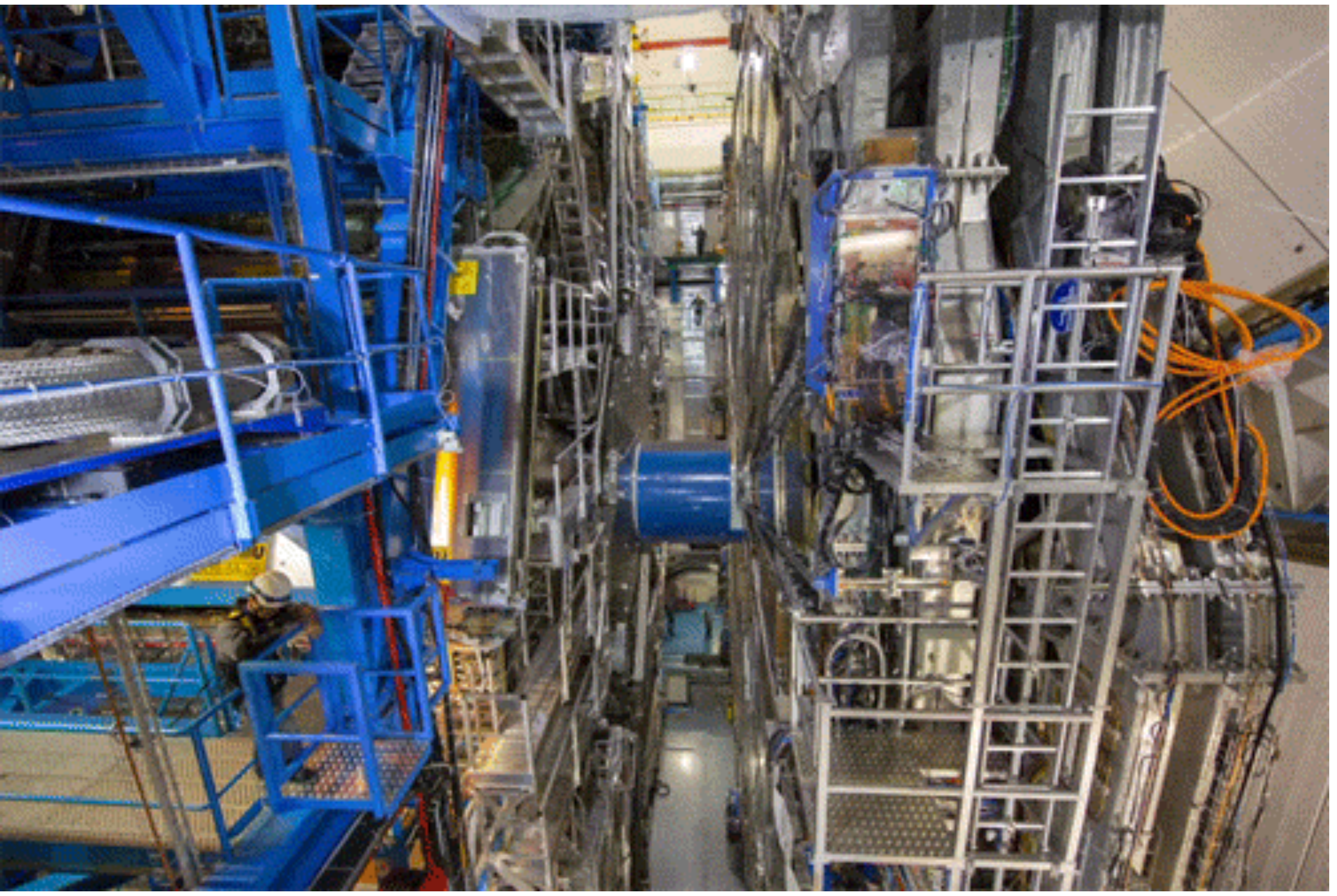
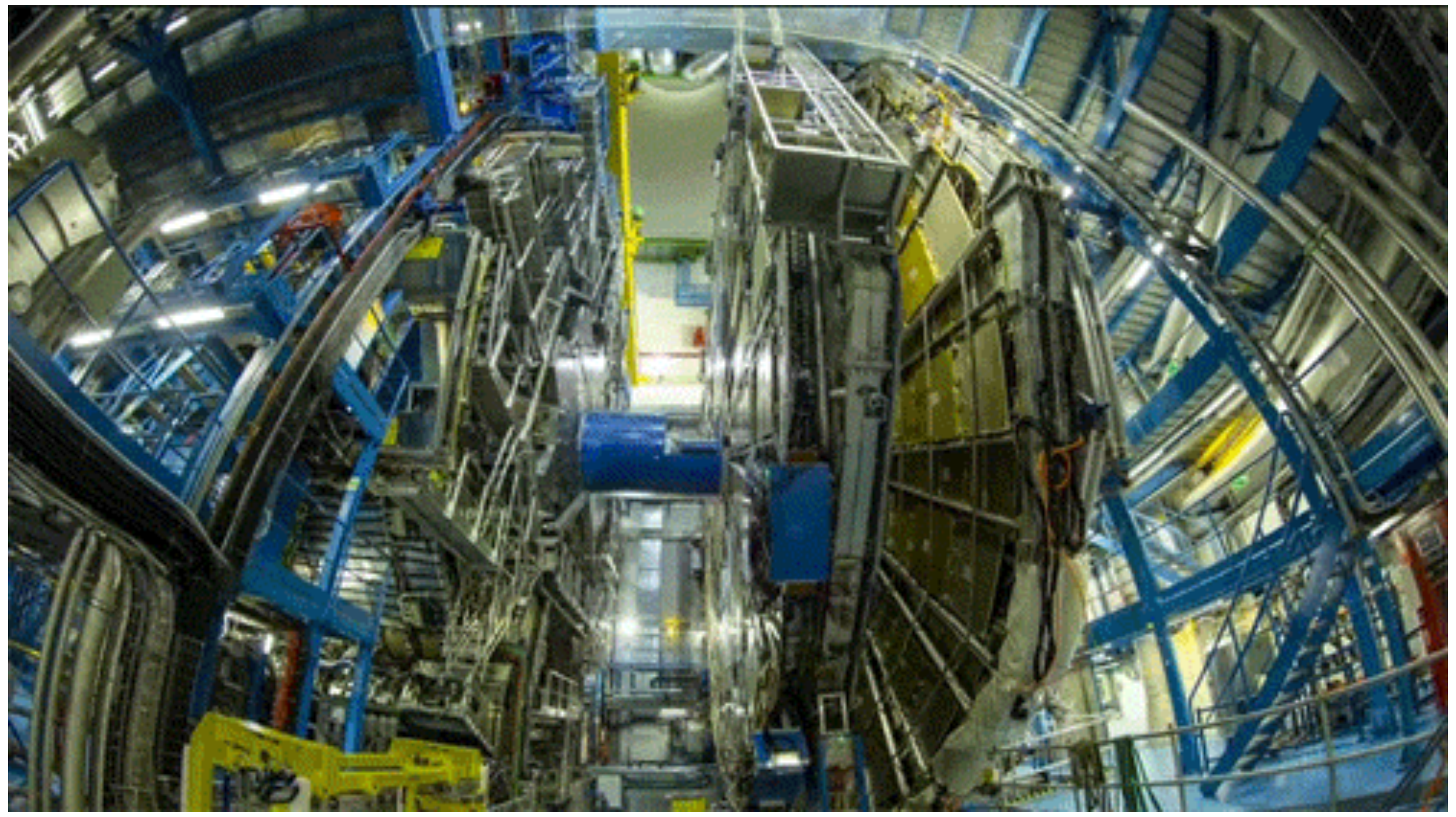
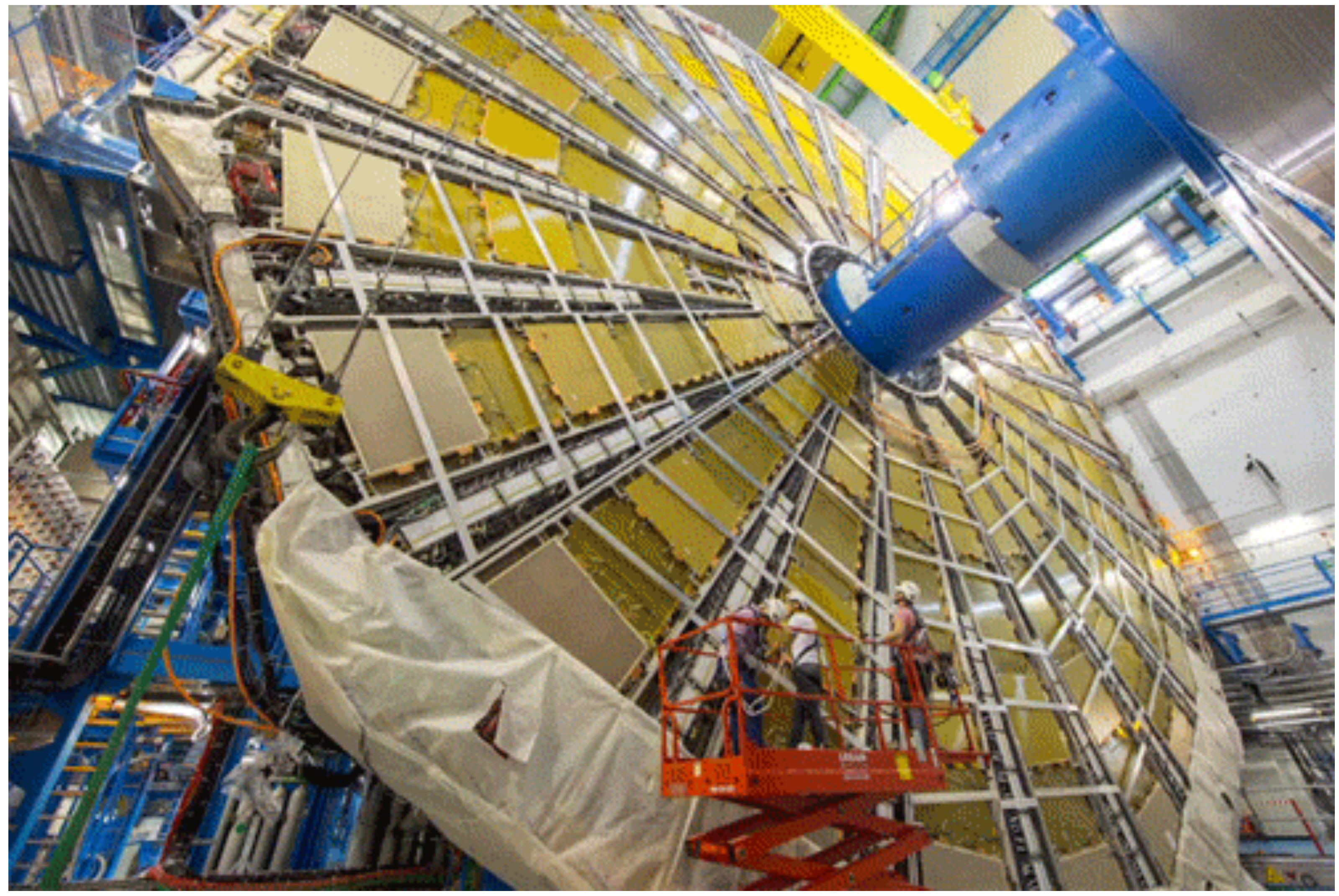
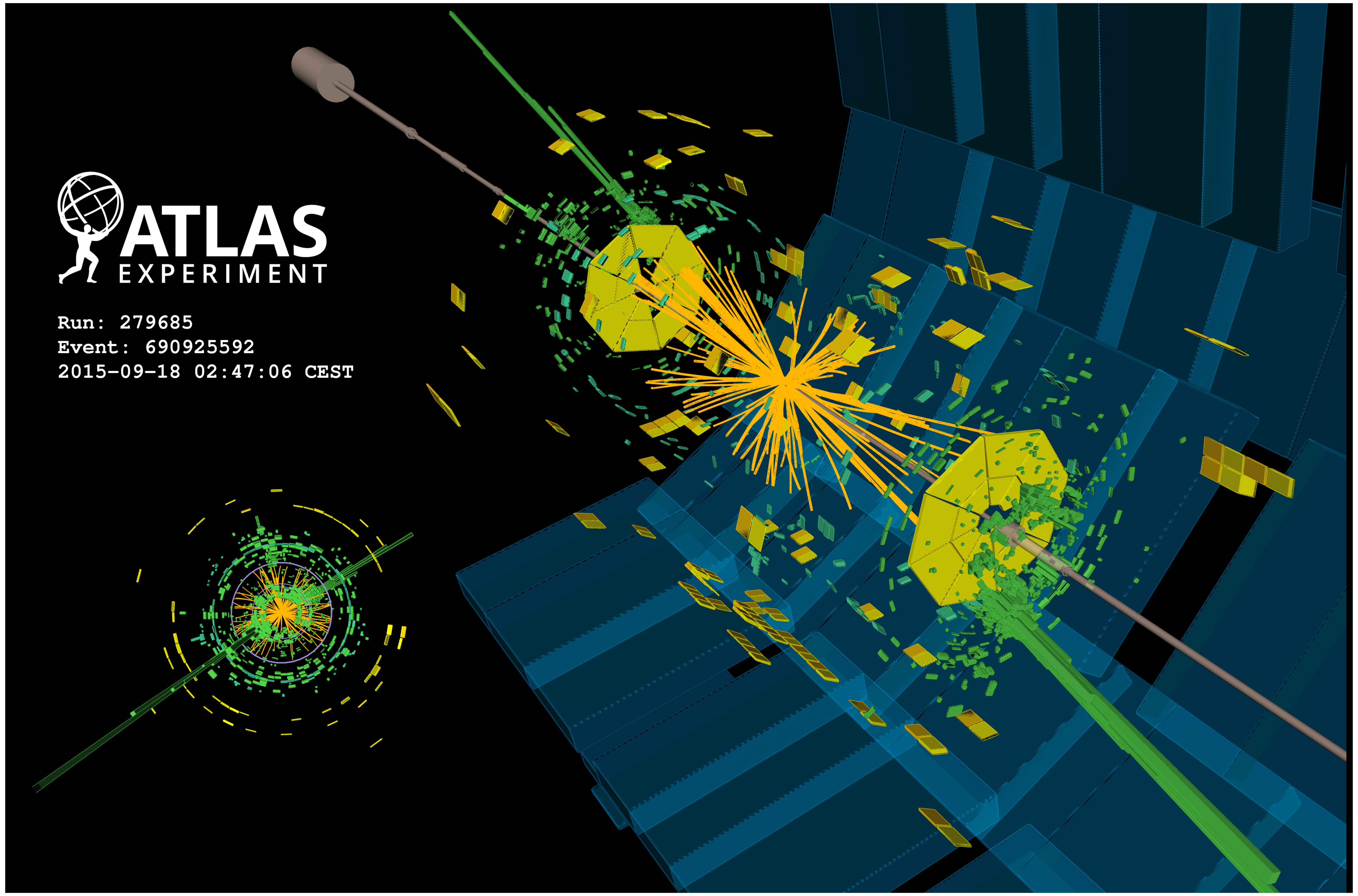







Summarise in low dimensions

- Detector has O(100 million) sensors
- Can't build 100M dimensional histogram

- Reconstruction pipeline, event selection
- Design sensitive one-dimensional observable



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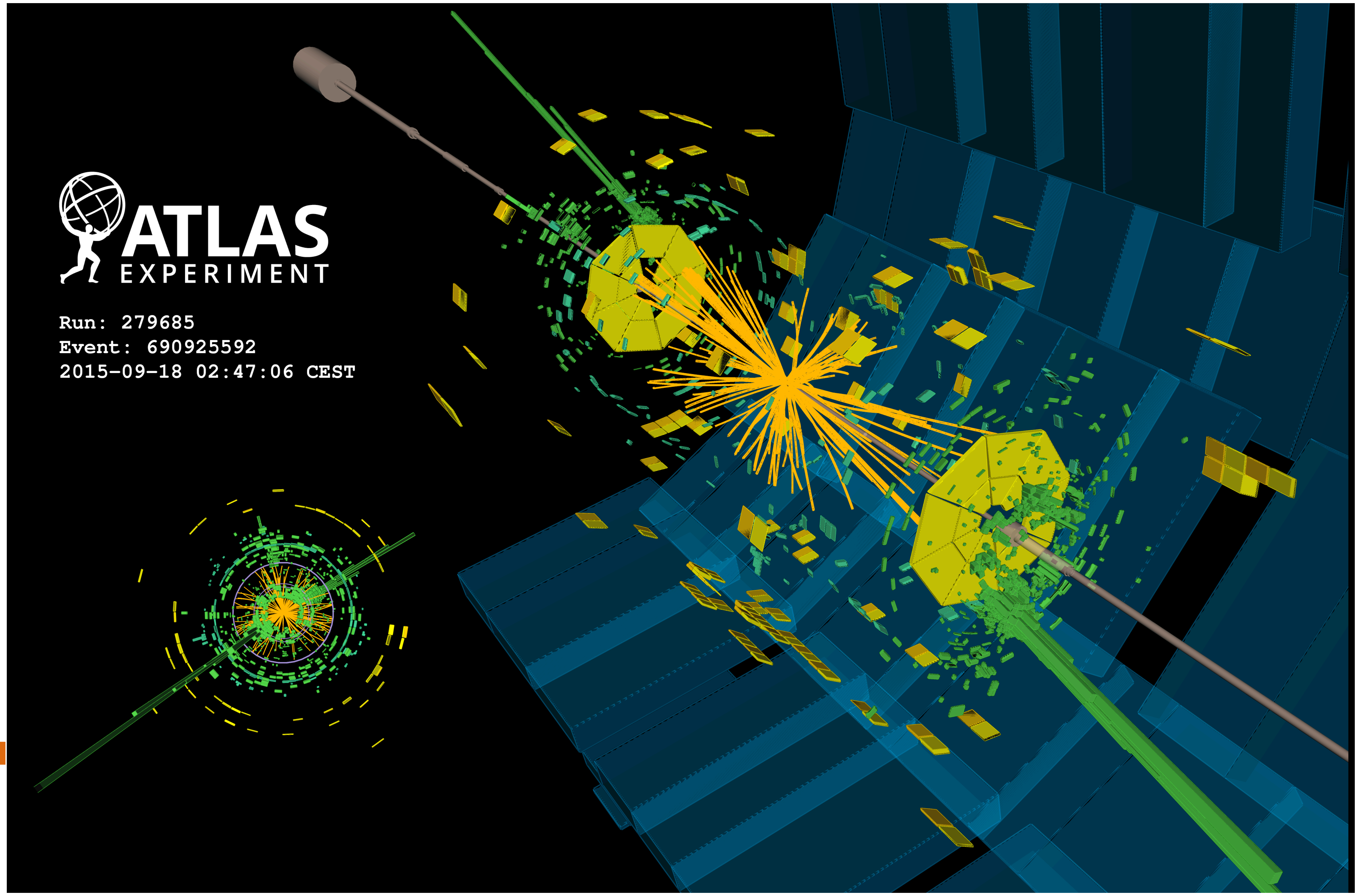
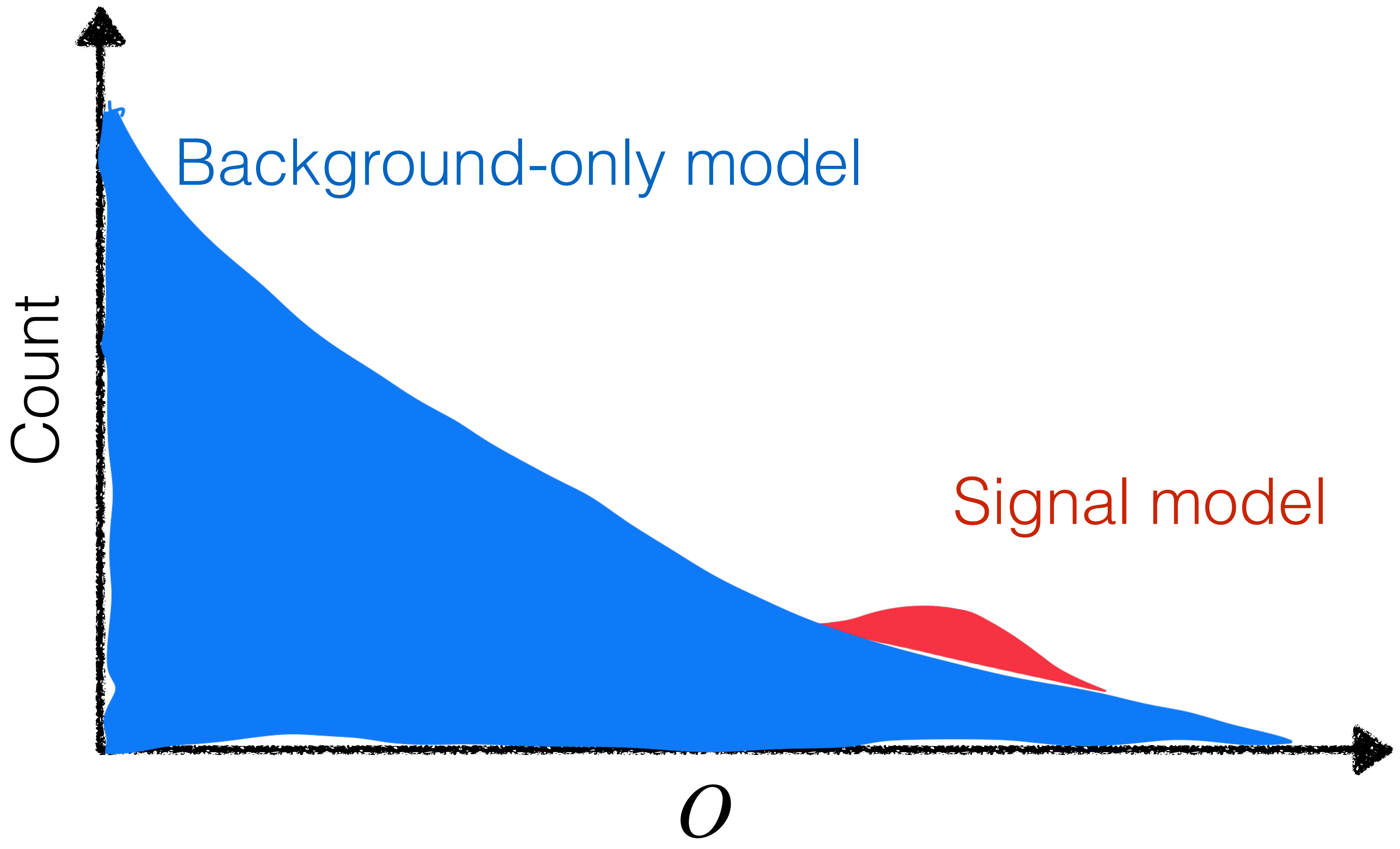
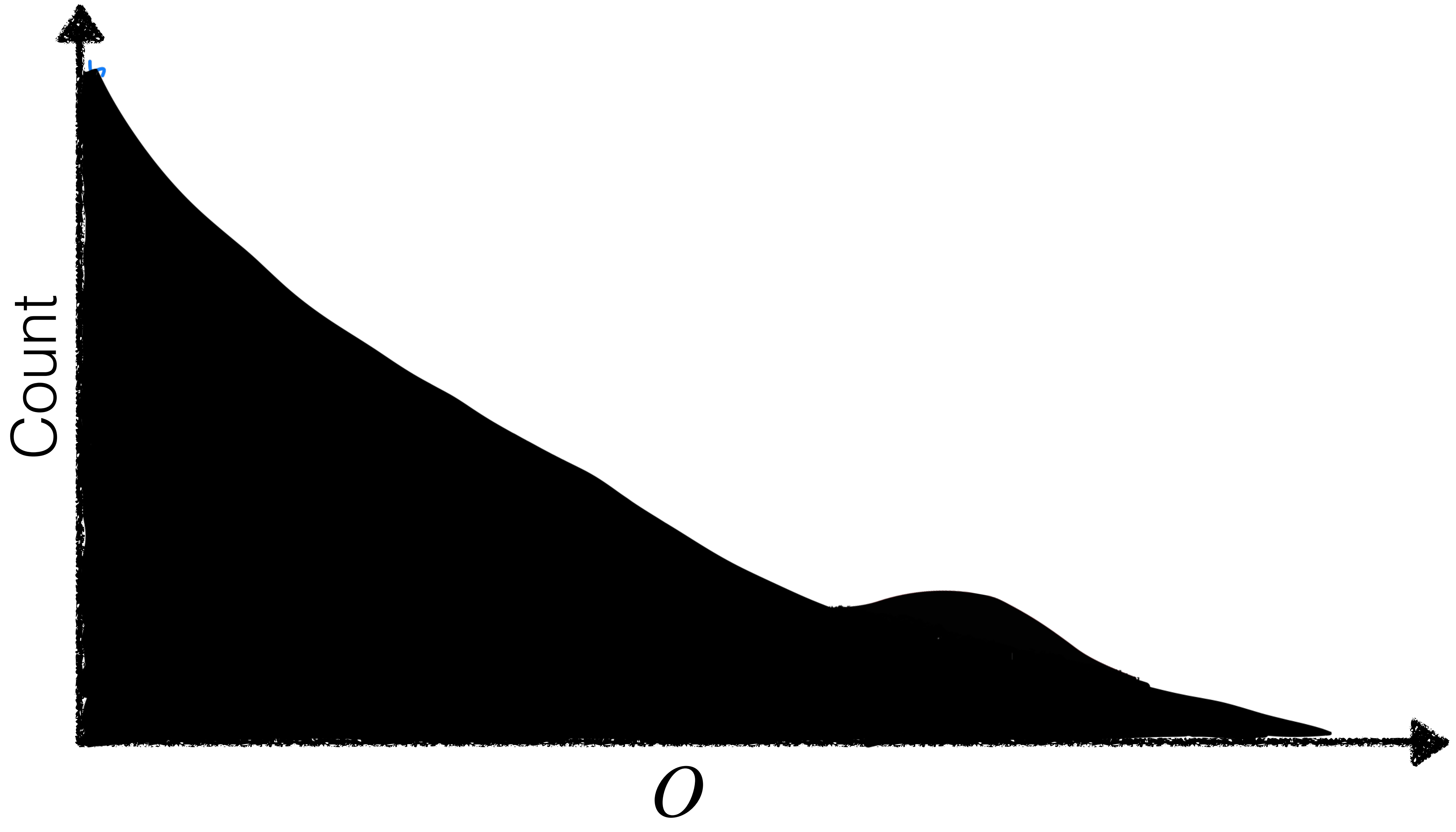


Probability Density Estimation: What we're used to doing..

Theory Predictions



Data



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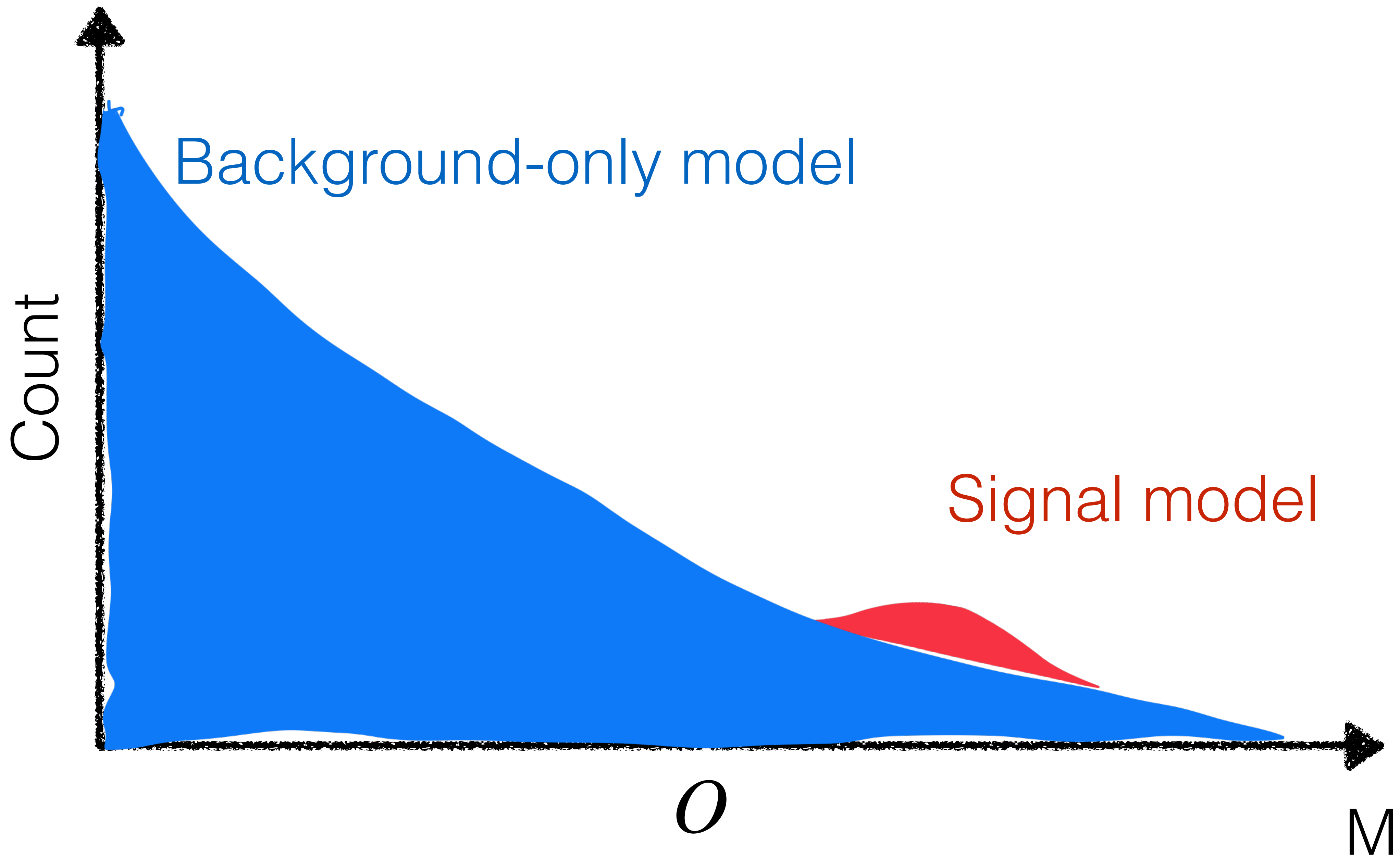

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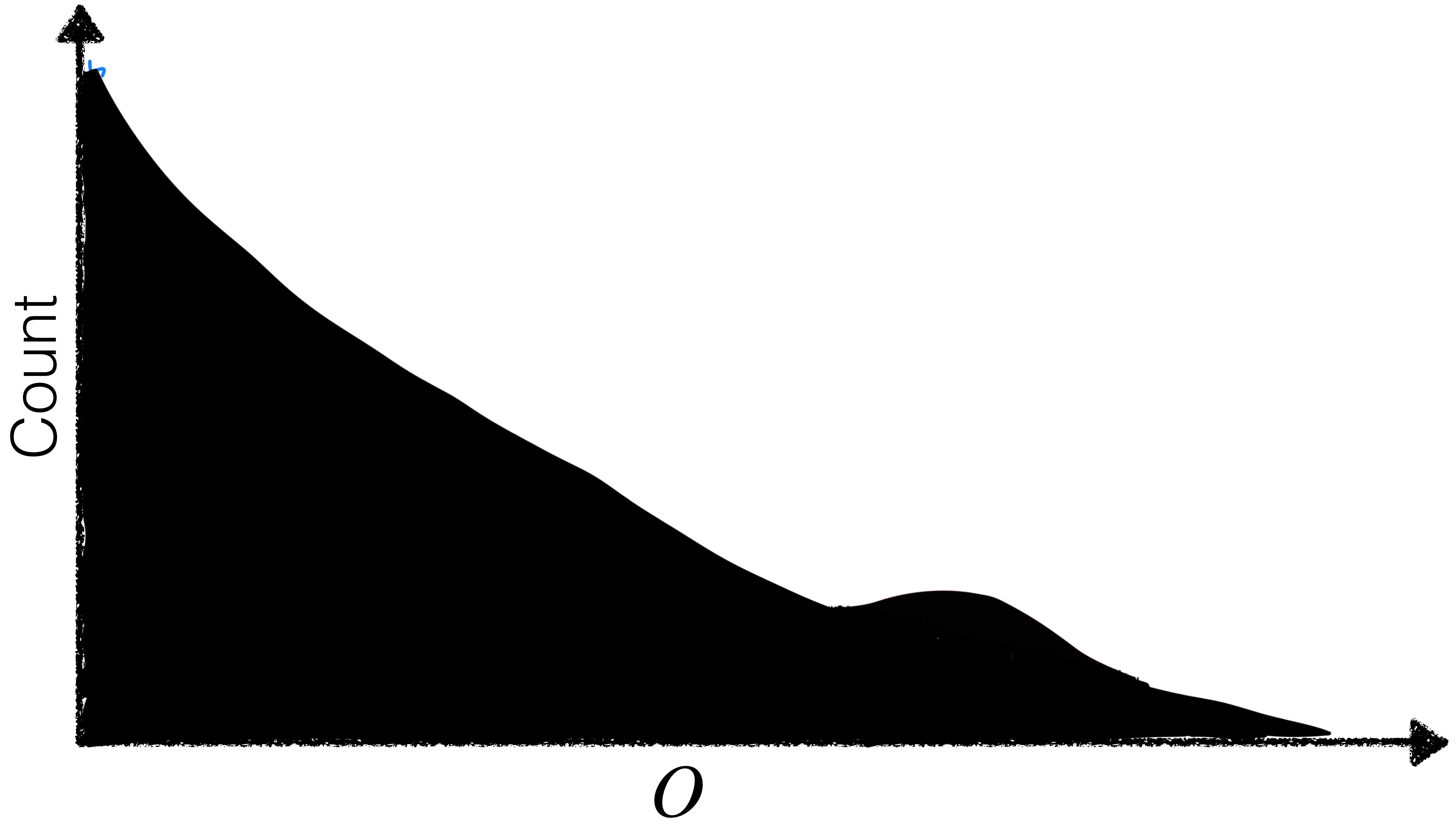

Measure signal strength μ

With histograms we can ask "Given the data, what is the likelihood of $\mu = 1$ hypothesis vs $\mu = 2$ hypothesis?"

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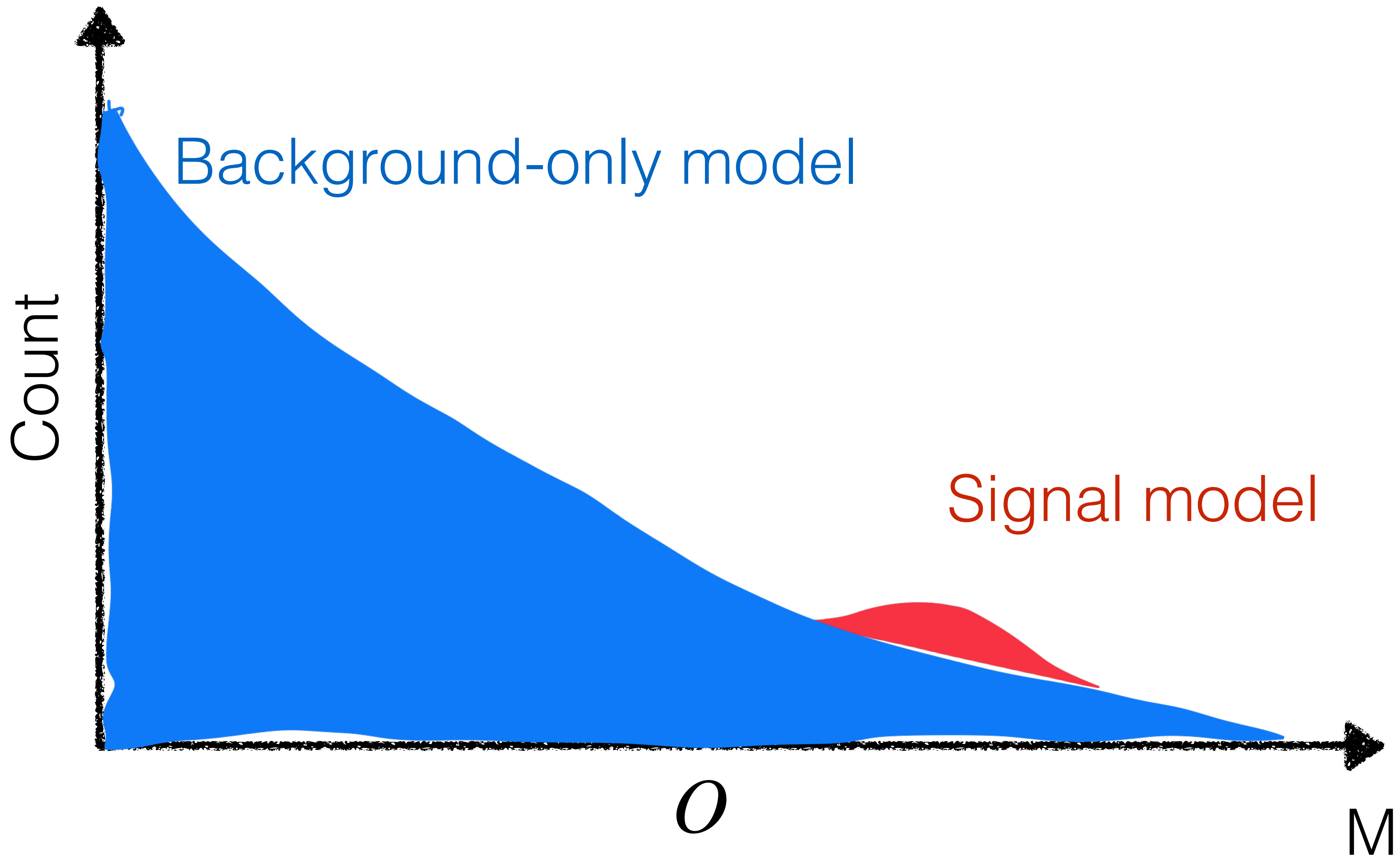

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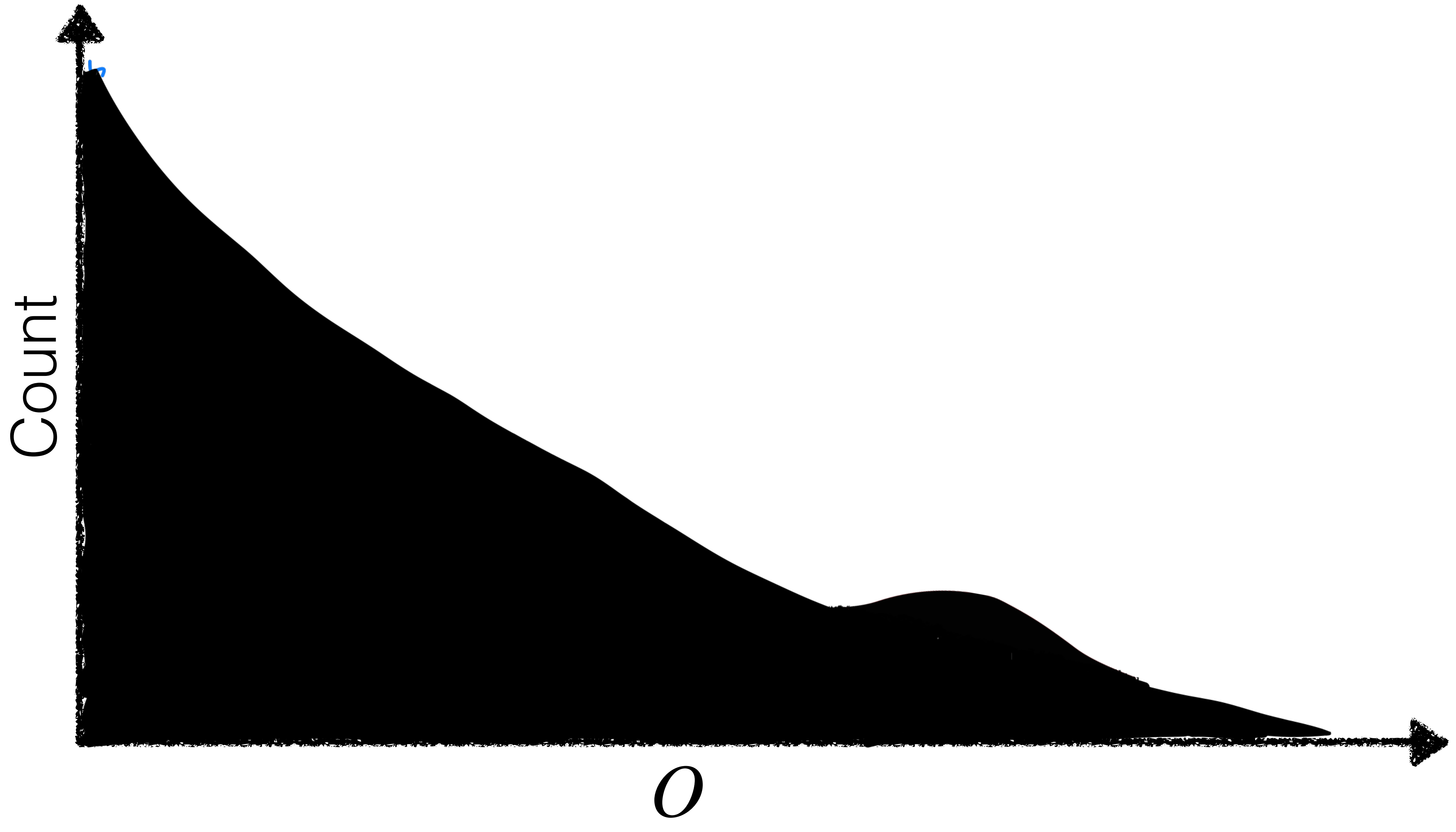

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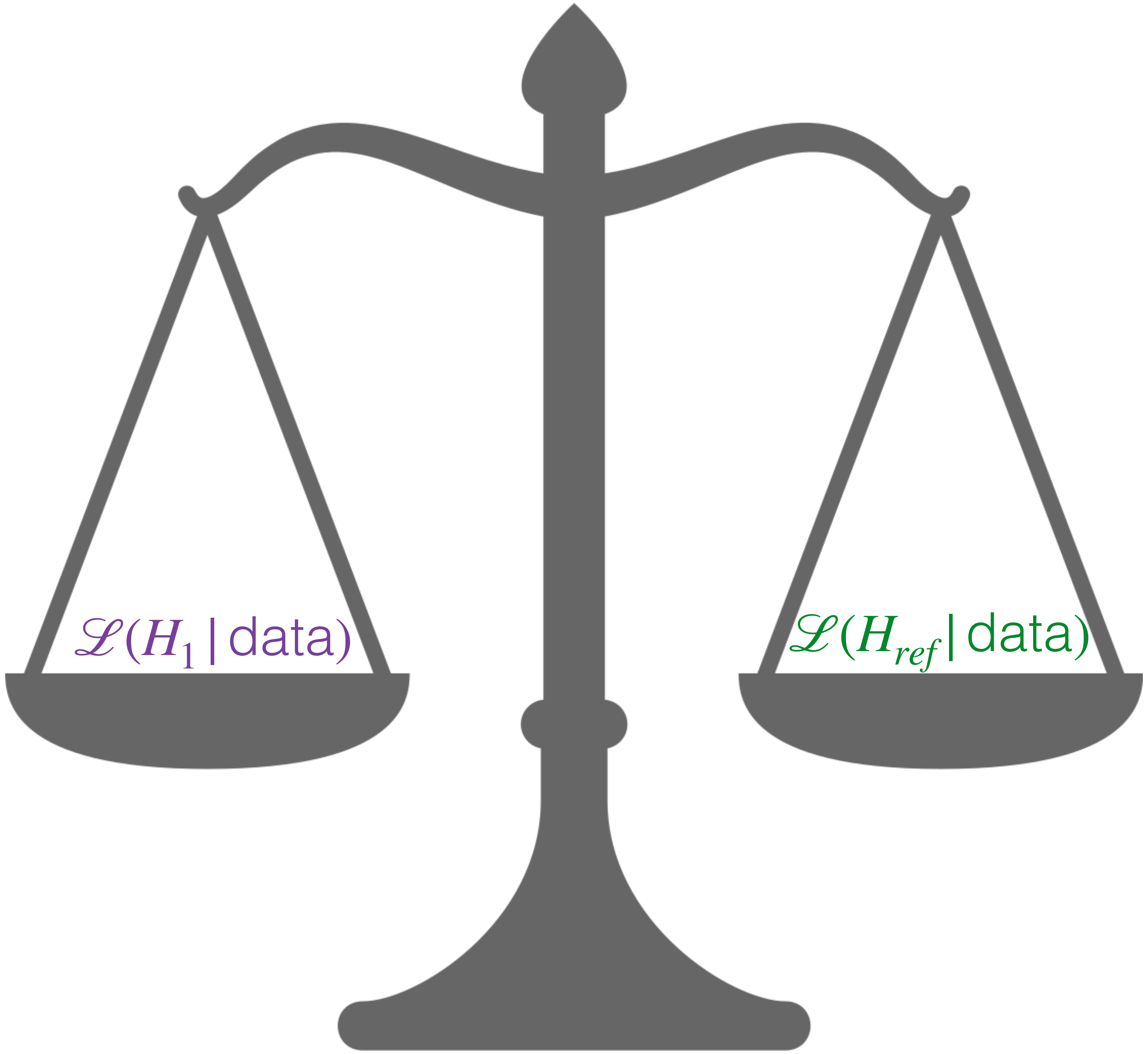
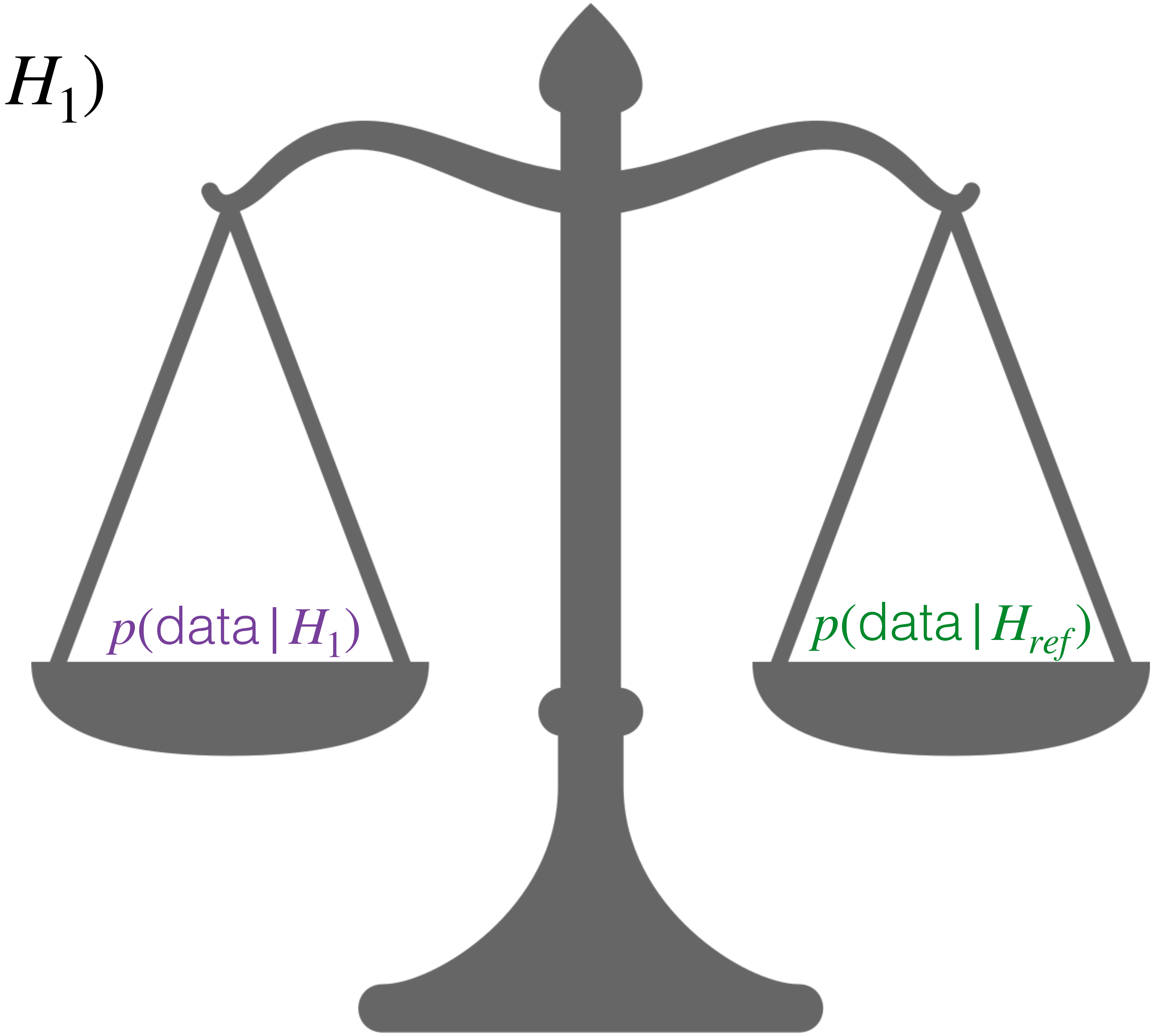
(Frequentist) Hypothesis tests



(Frequentist) Hypothesis tests

$$\mathscr{L}(H_1 \mid \text{data}) = p(\text{data} \mid H_1)$$



Why we can summarise data down to a single observable for typical analysis

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Neyman–Pearson lemma: Likelihood ratio is the most powerful test statistic

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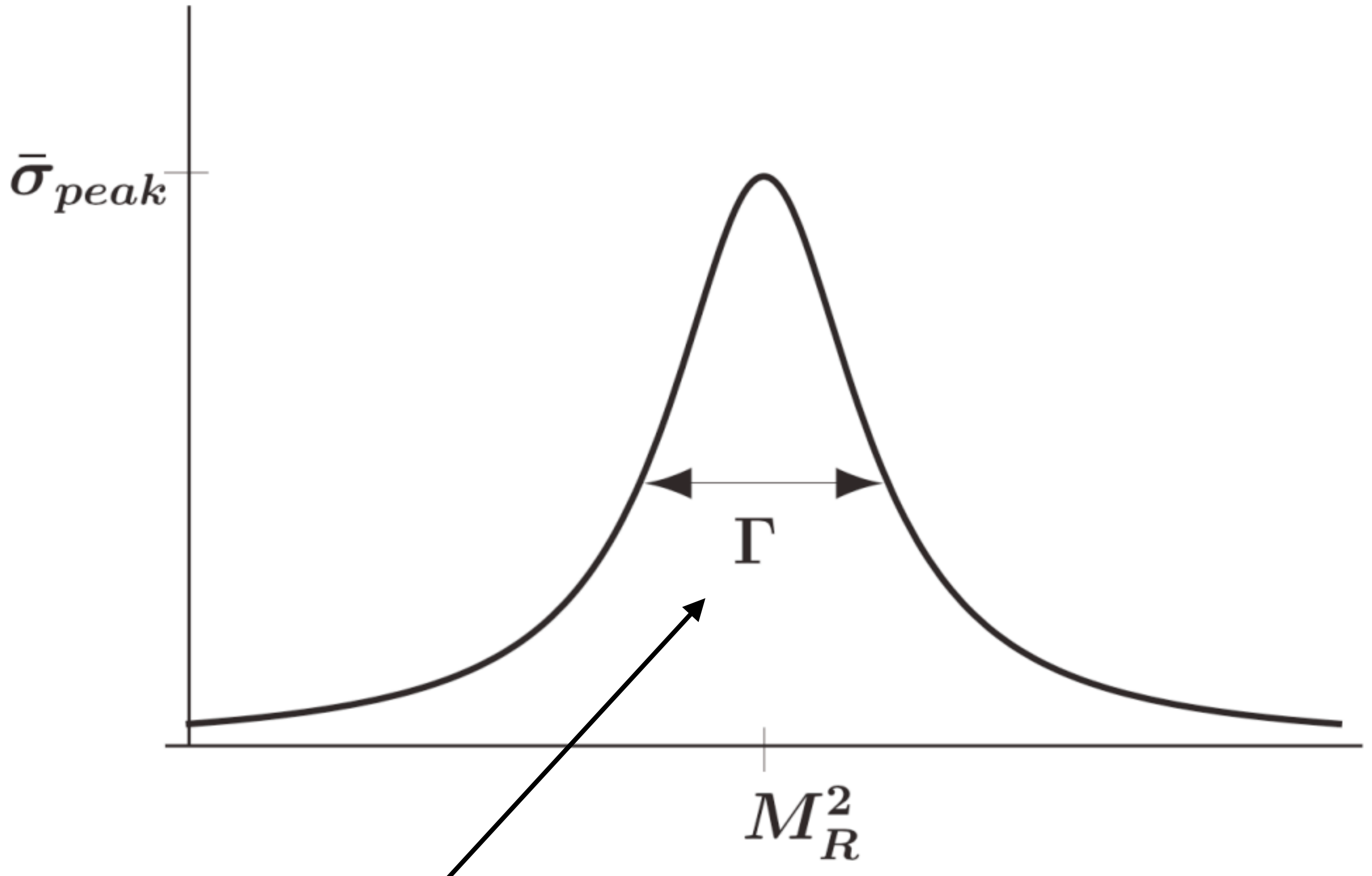
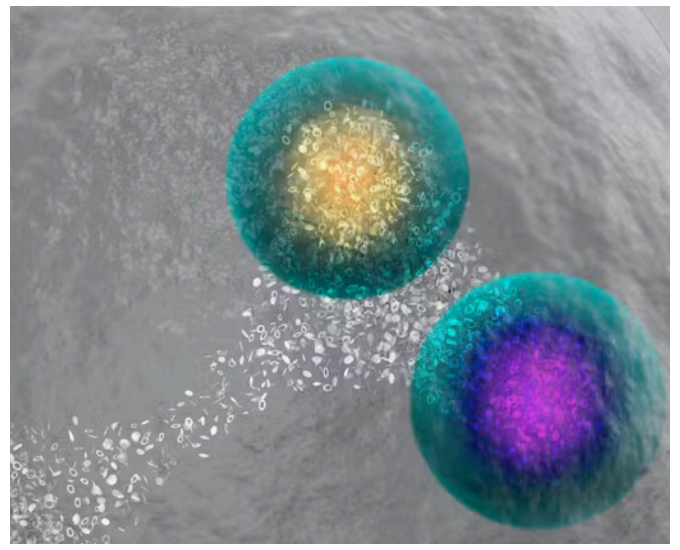
A measurement of the Higgs width



"Width" of the particle

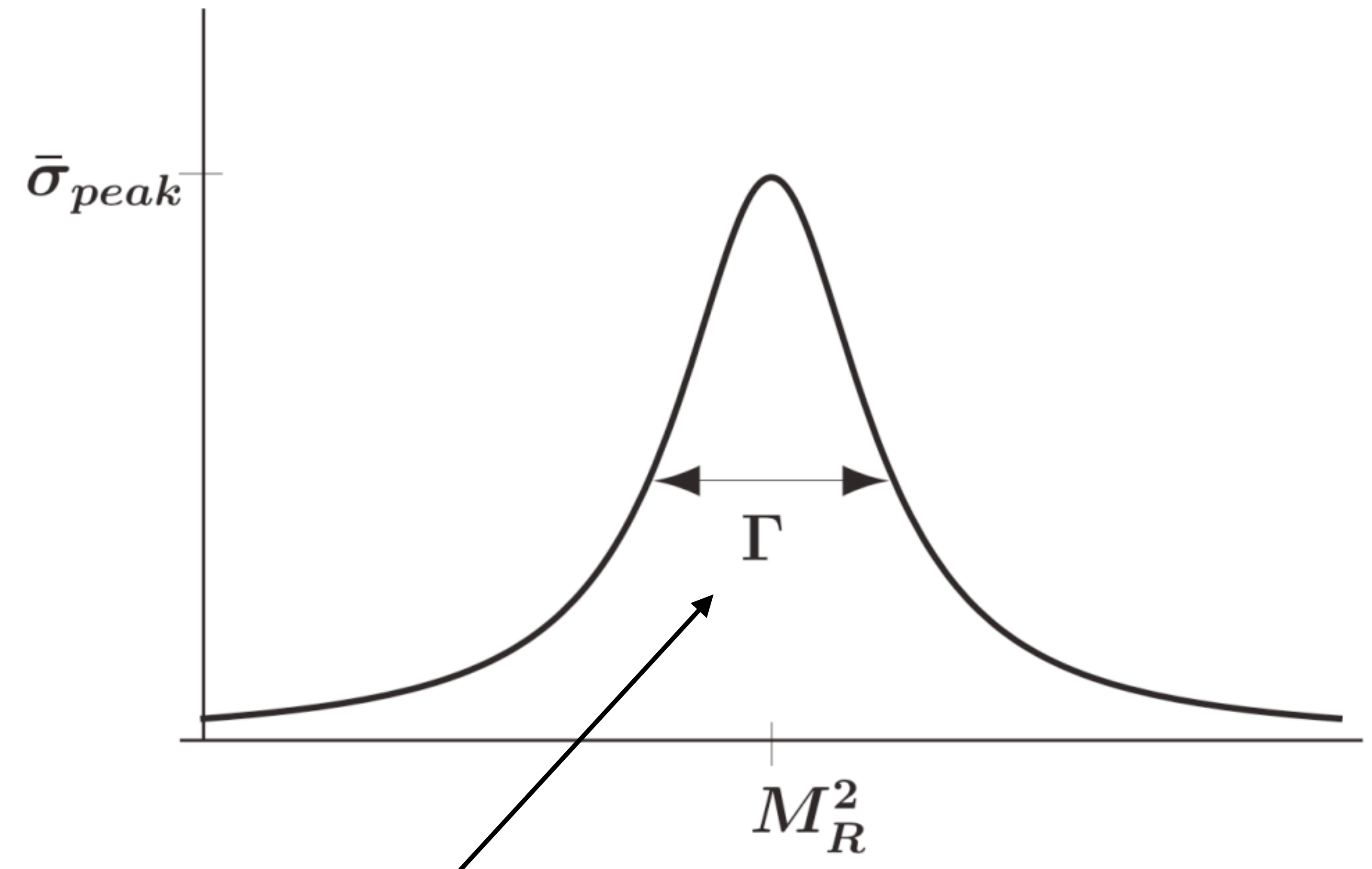


Undiscovered massive particles → H → Γ_H

A measurement of the Higgs width

- Enables the probe of a wide variety of new massive particles, other new physics

- Central topic for future colliders



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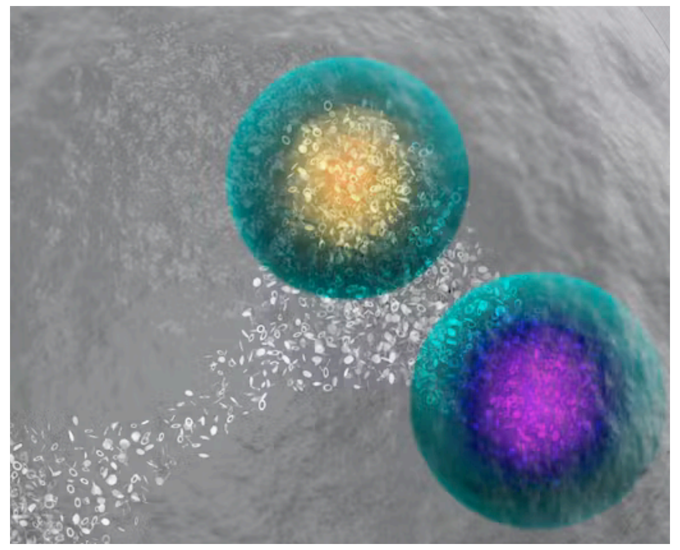
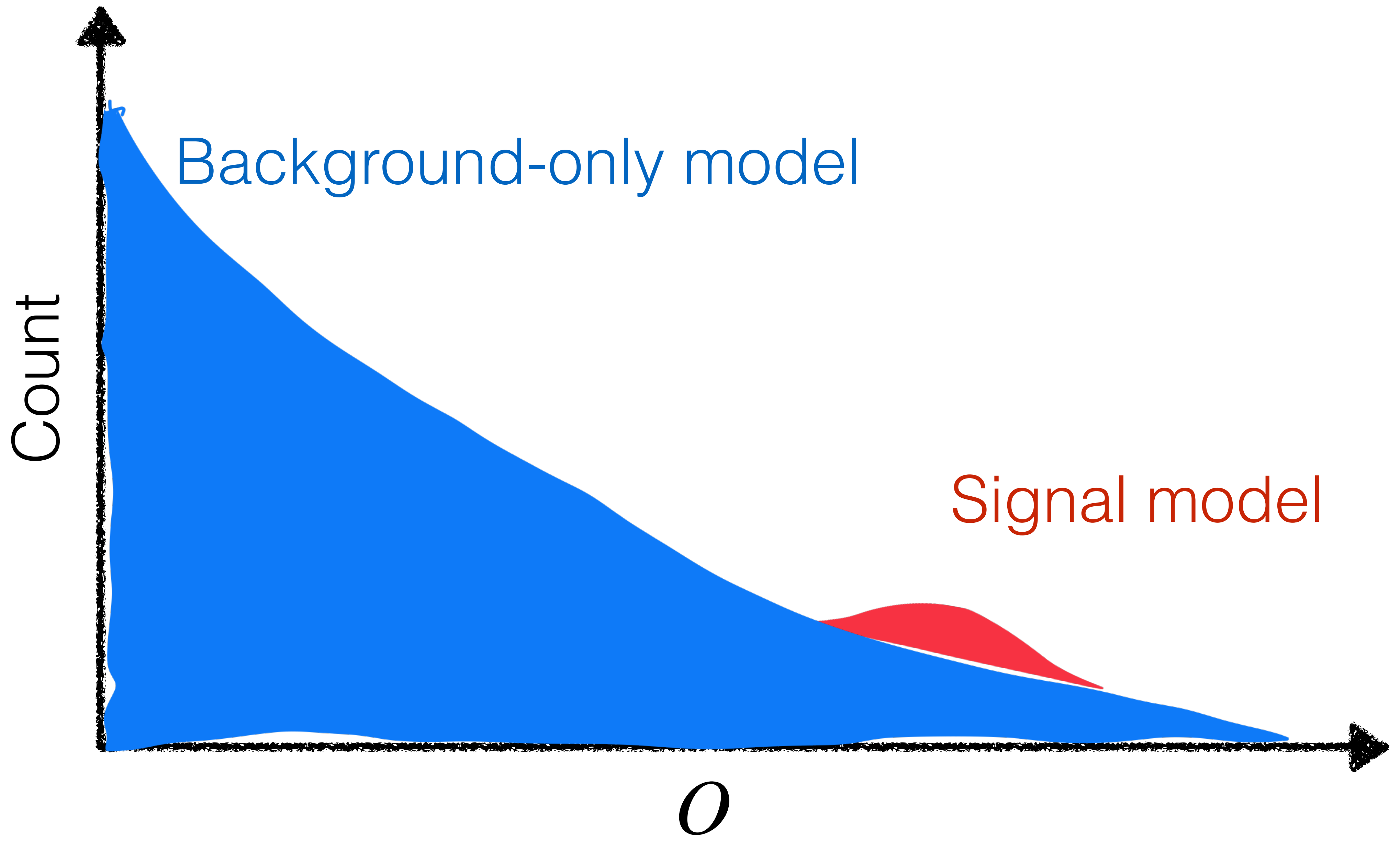


H → Γ_H

Undiscovered massive particles

New challenge: Quantum interference

Non-linear changes in kinematics



Data can no longer be summarised in 1D histogram (see Ghosh et al: hal-02971995(p172)) !

New challenge: Quantum interference
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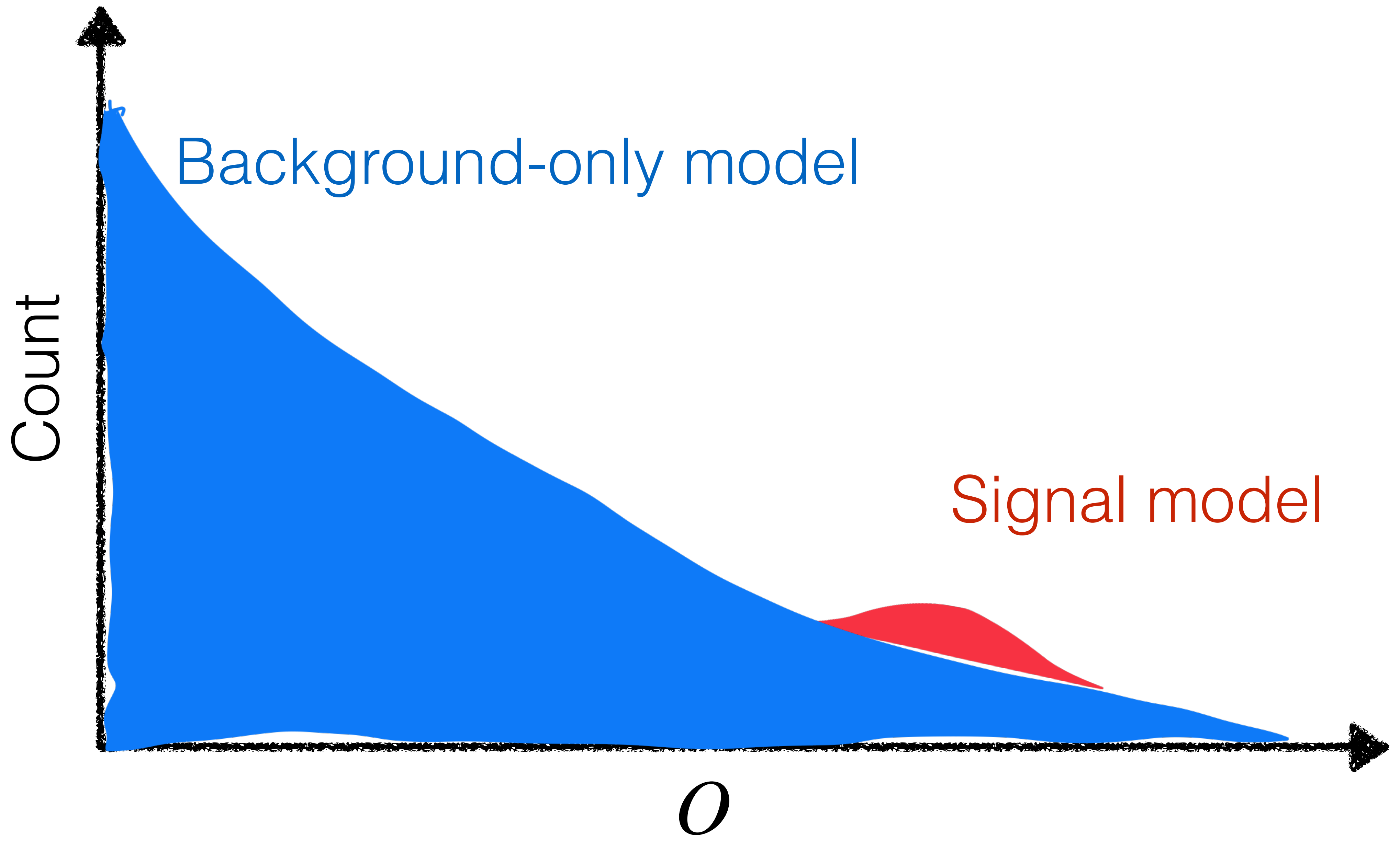
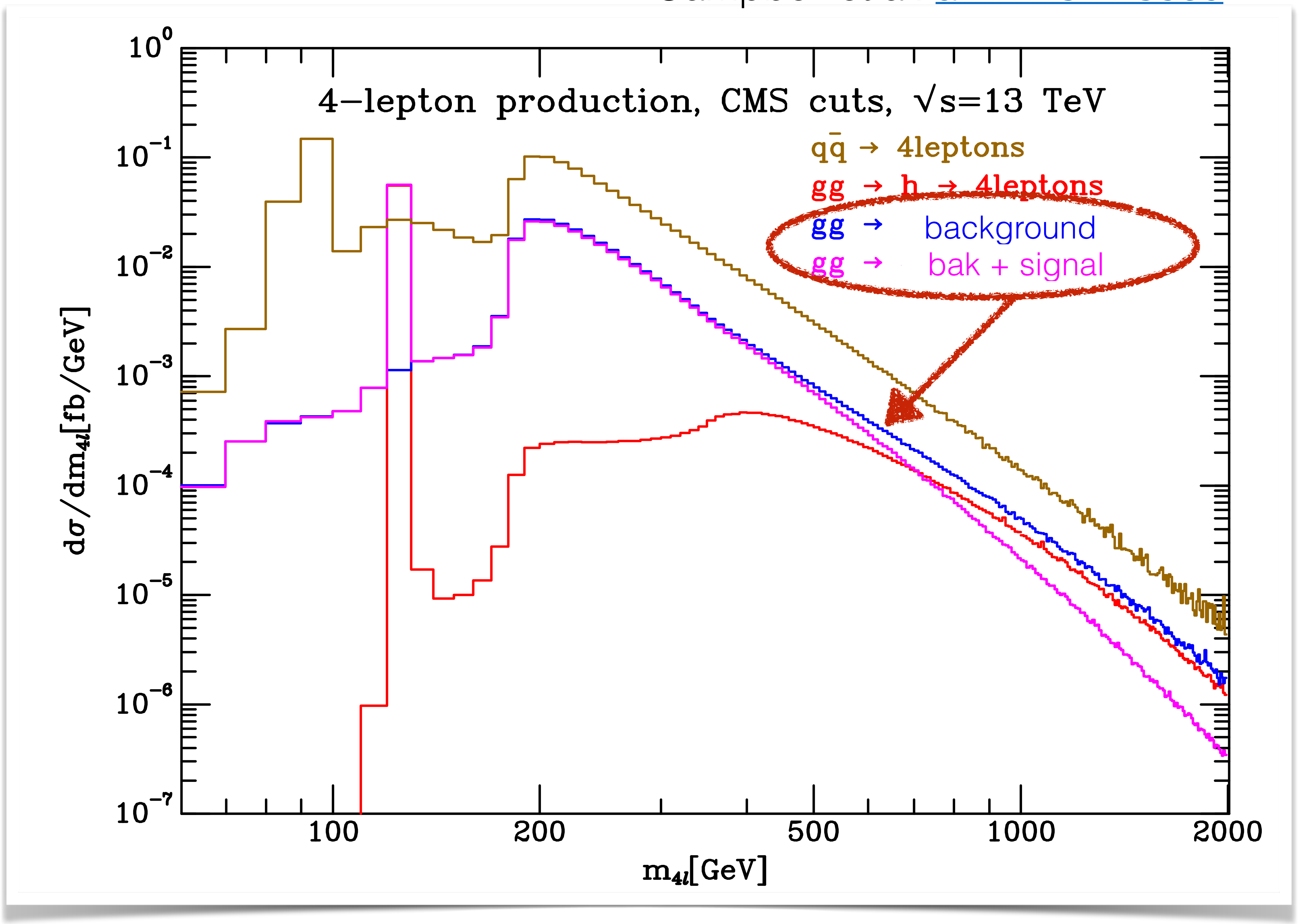
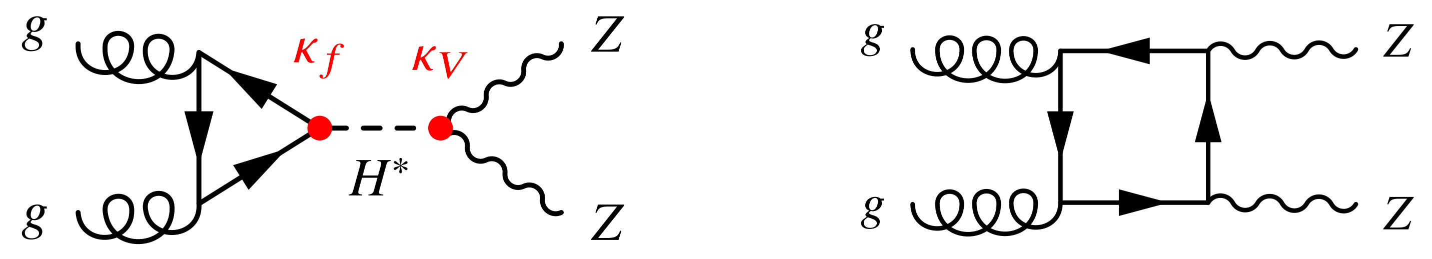


Campbell et al: [arXiv:1311.3589]



Quantum interference:



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The problem with one-dimensional summaries…

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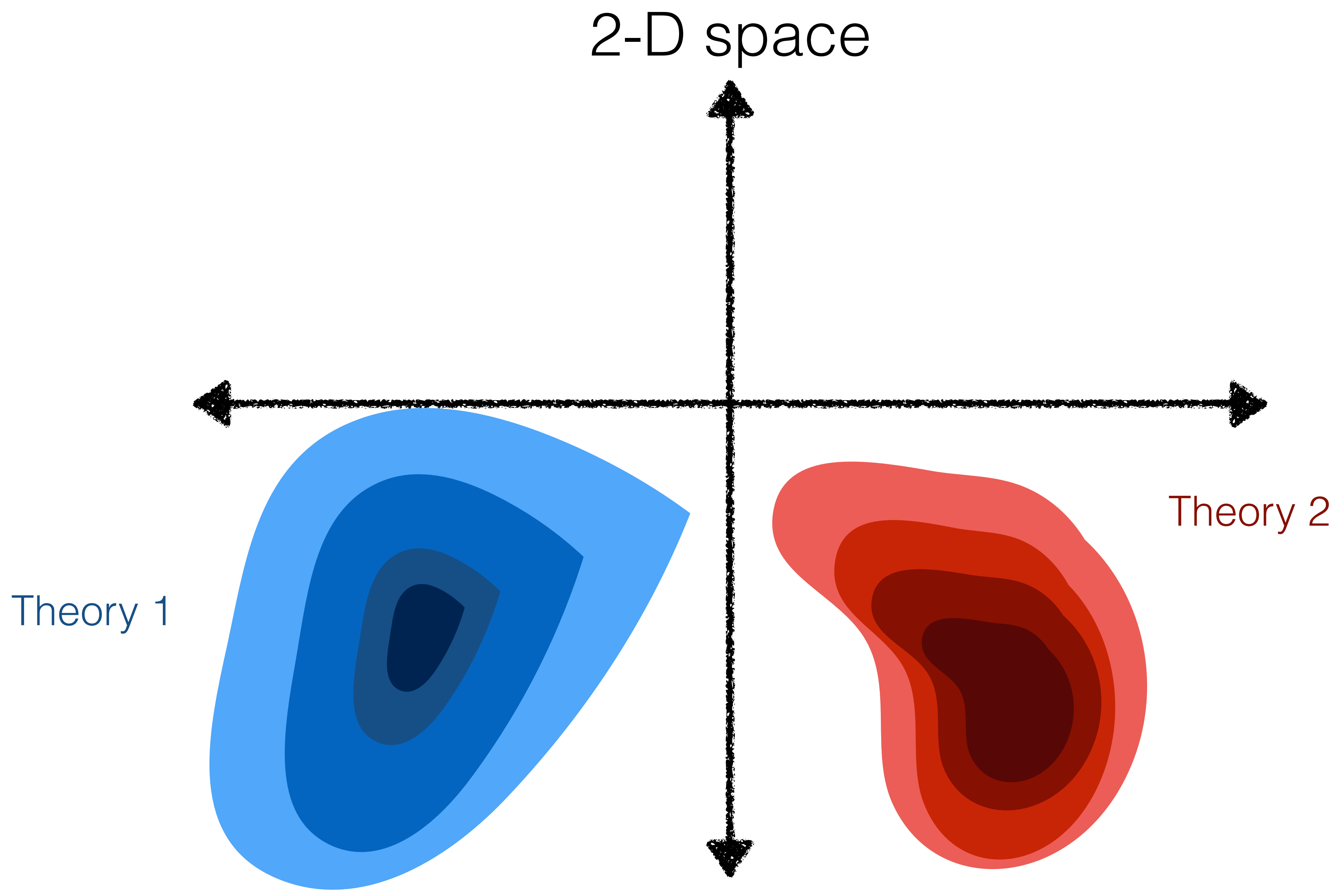

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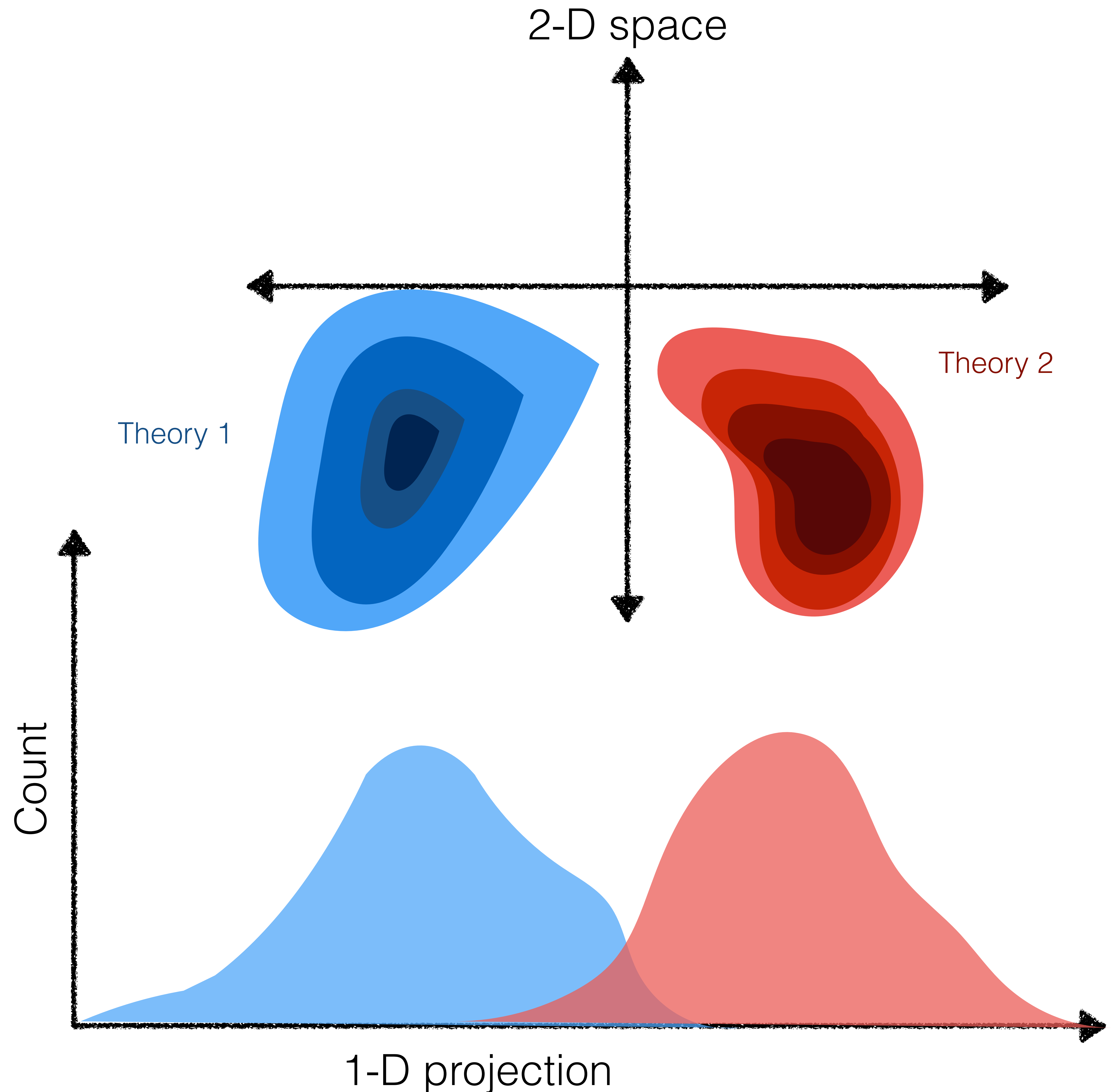

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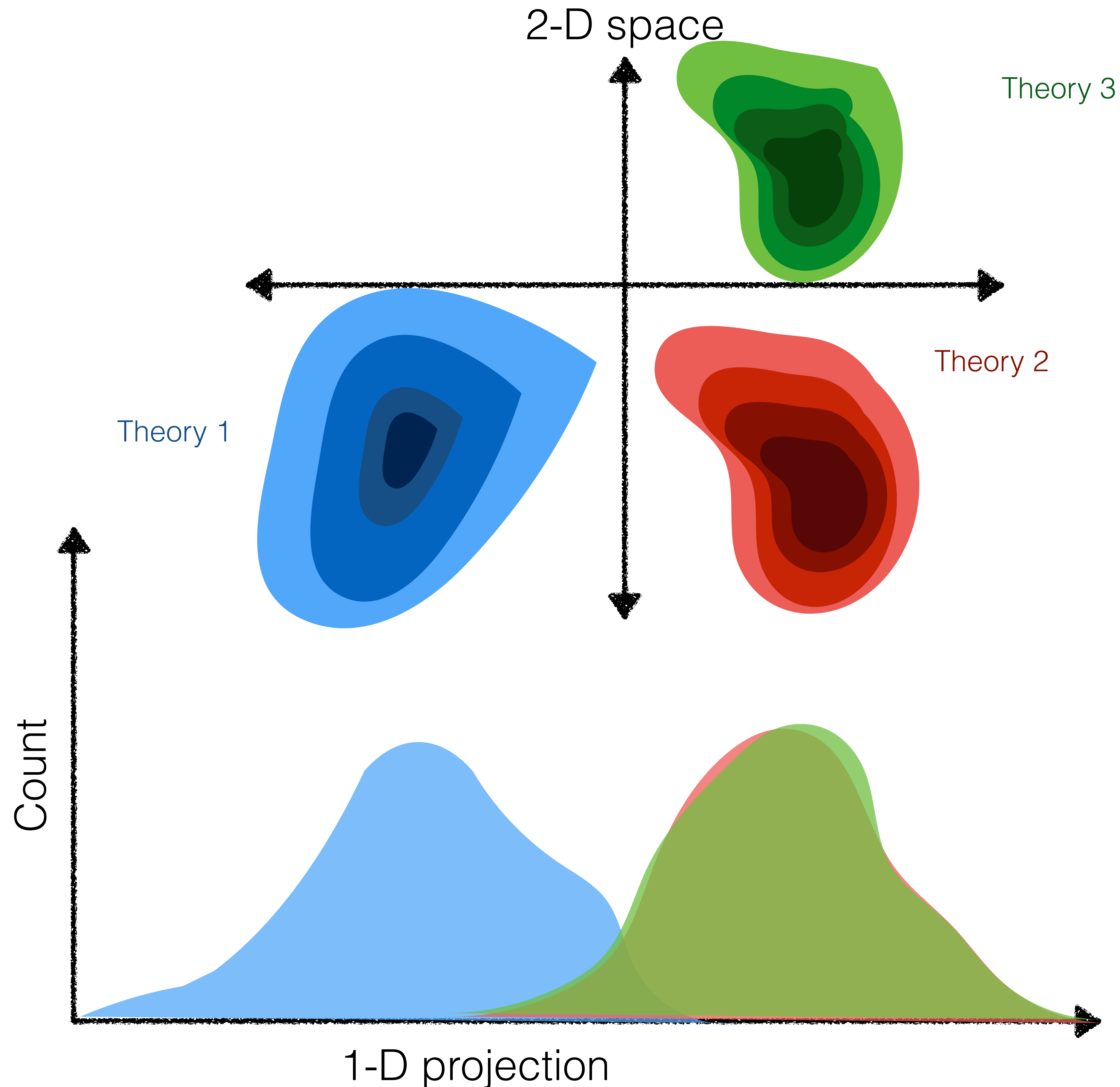

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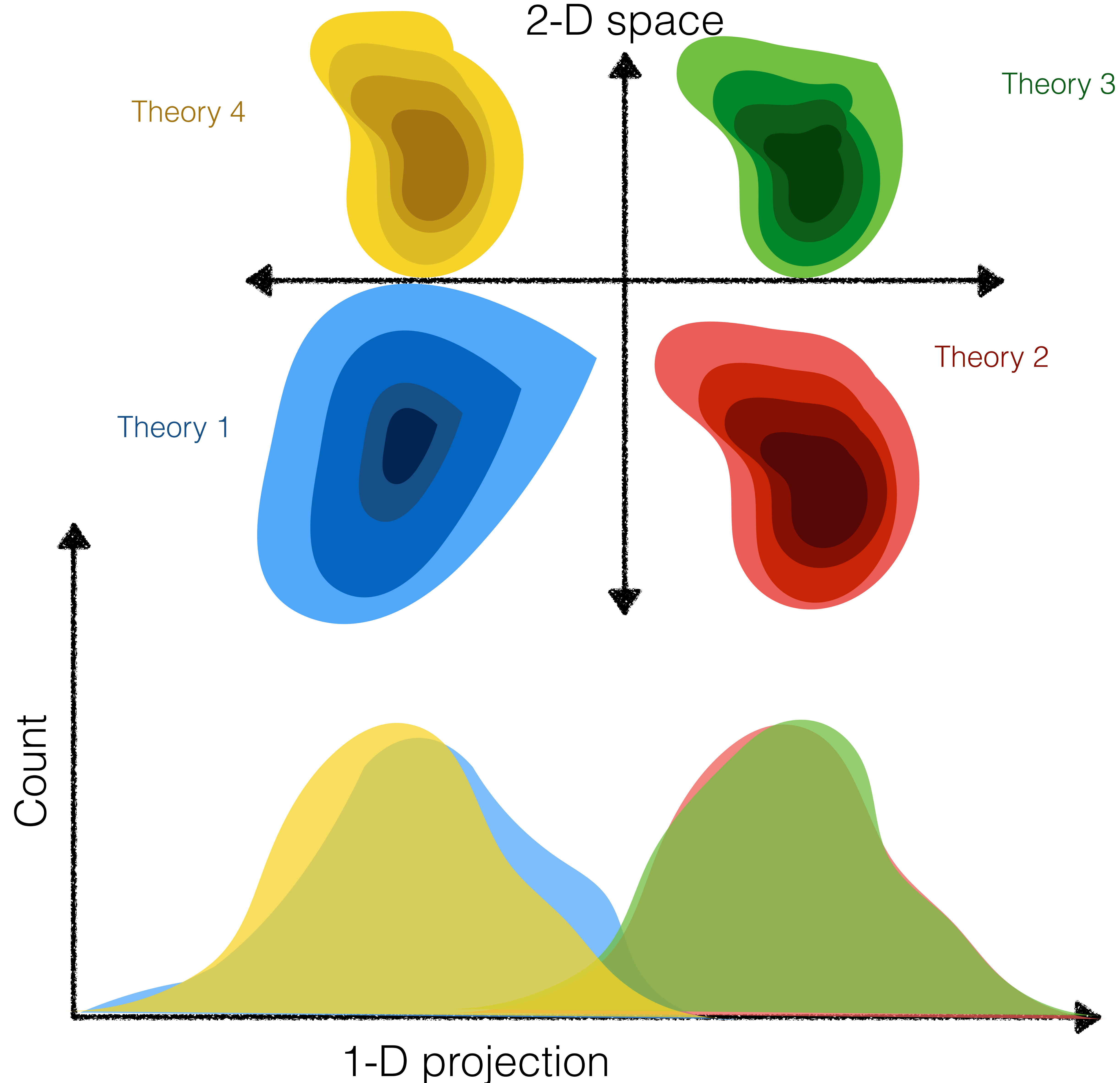

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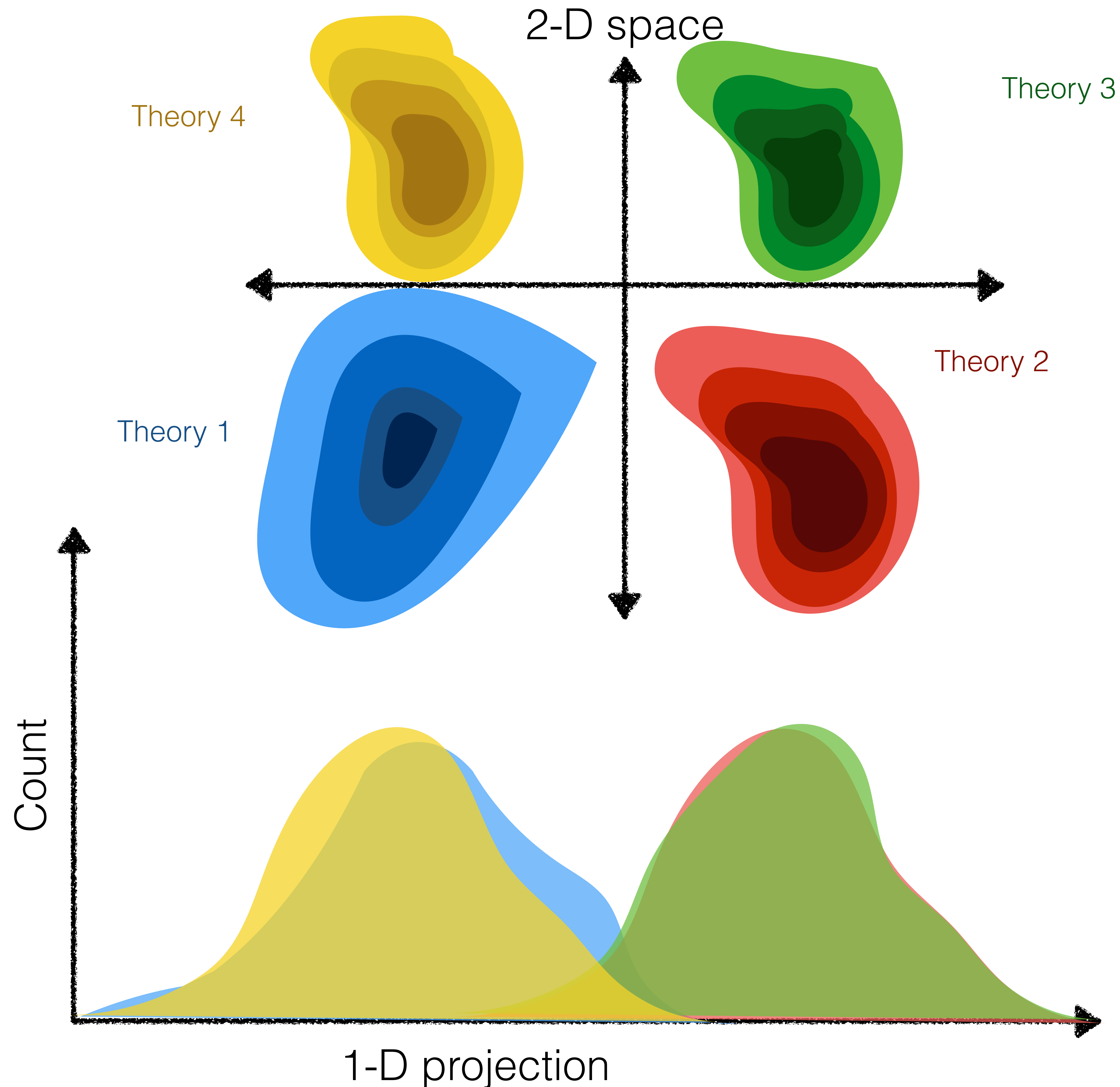


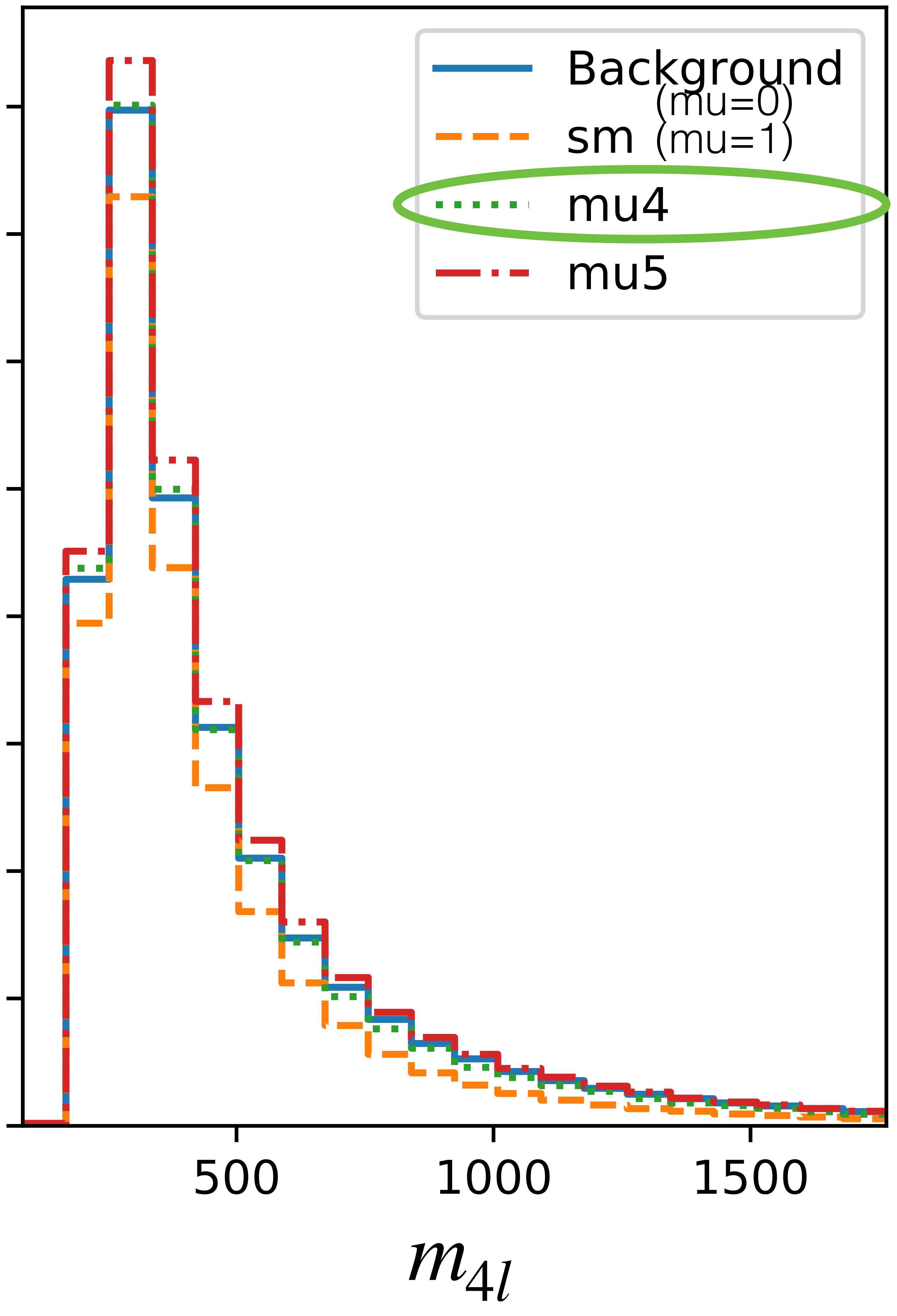
- Clearly separable in 2-D
- No 1-D summary statistic may contain all the information needed to optimally test all theory hypotheses!
- Valuable to have high-dimensional view of data

No single observable captures all information in Higgs width study

Signal-background-inference simulations: MG + Pythia

No single observable captures all information in Higgs width study

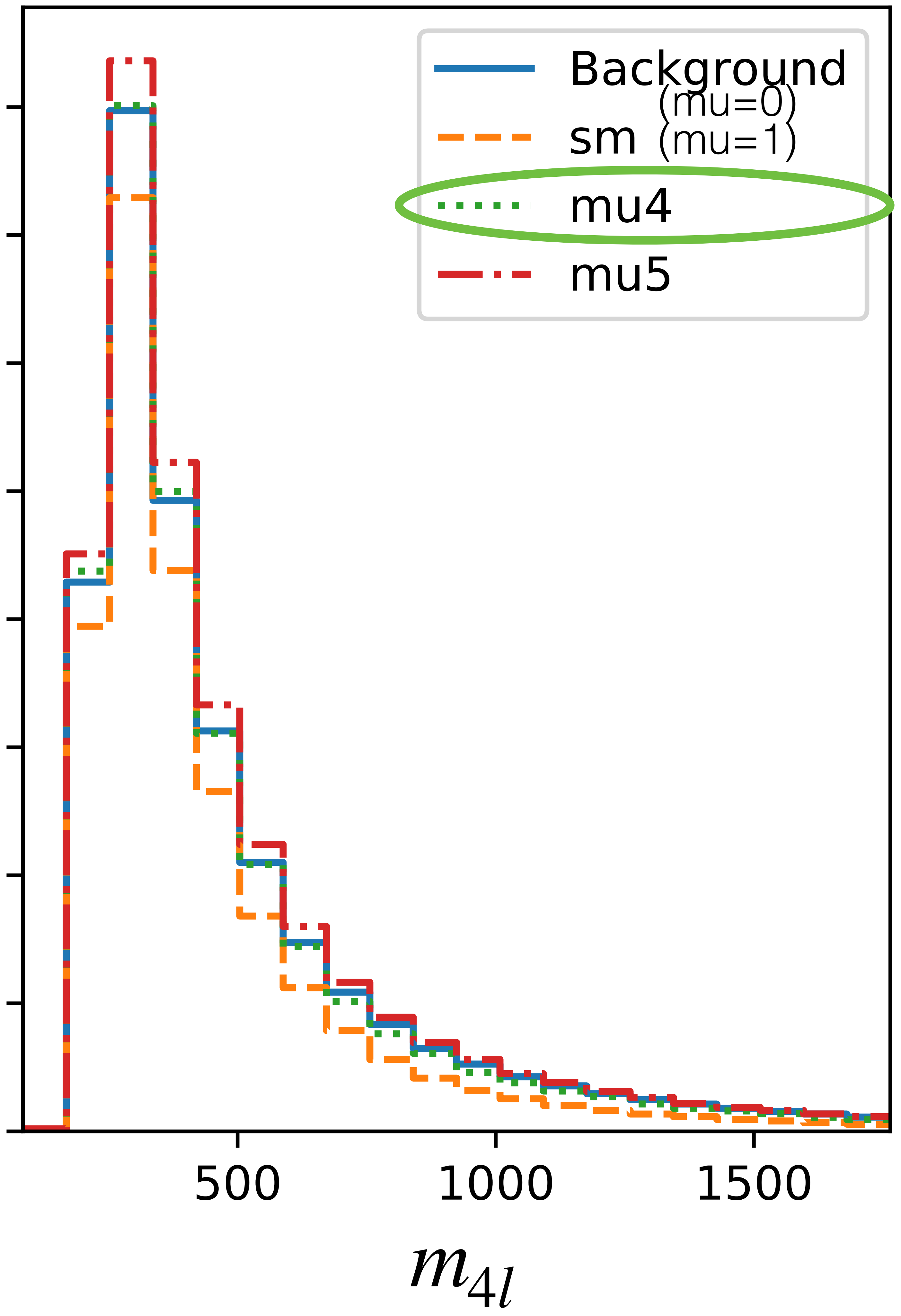
Signal-background-inference simulations: MG + Pythia



Can you spot the green plot?

No single observable captures all information in Higgs width study

Signal-background-inference simulations: MG + Pythia



Can you spot the green plot?

=4 indistinguishable from μ=0
ut other observables can break
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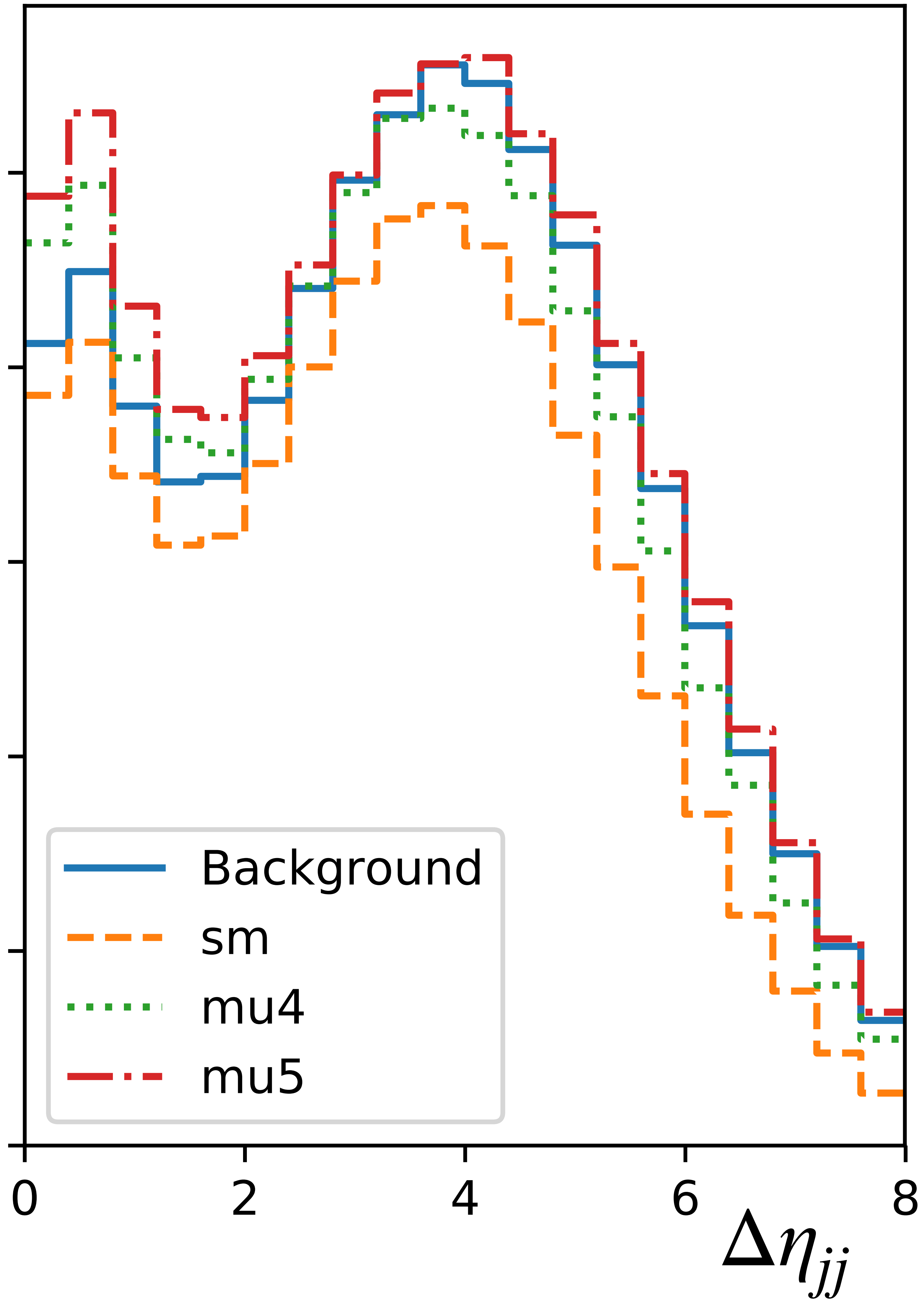


Optimal observable now changes as a function of **μ**: Cannot collapse problem to 1 dimension

What breaks down?

$$P(X) = |M_s(X) + M_b(X)|^2 = \underbrace{|M_s(X)|^2}_{P_s(X)} + \underbrace{|M_b(X)|^2}_{P_b(X)} + \underbrace{2\,\mathtt{Re}(\overline{M_s(X)}M_b(X))}_{P_i(X)}$$

$$N_{exp} = \mu \cdot S + B + \sqrt{\mu} \cdot I$$

A neural network classifier trained on S vs B, estimates the decision function*: $s(x_i) = \dfrac{p(x_i|S)}{p(x_i|S) + p(x_i|B)}$

Which contains all the information required for the likelihood ratio:

$$\frac{p(x_i|\mu)}{p(x_i|\mu=0)} = \frac{1}{\mu \cdot \nu_S + \nu_B} \frac{\mu \cdot \nu_S p(x_i|S) + \nu_B p(x_i|B)}{p(x_i|B)} = \frac{\mu}{\mu \cdot \nu_S + \nu_B} \cdot \left(\frac{s(x_i)}{1 - s(x_i)} + \nu_B \right)$$

Same observable s is optimal to test all μ hypotheses!
No need to develop separate analysis per hypothesis μ

* Equal class weights

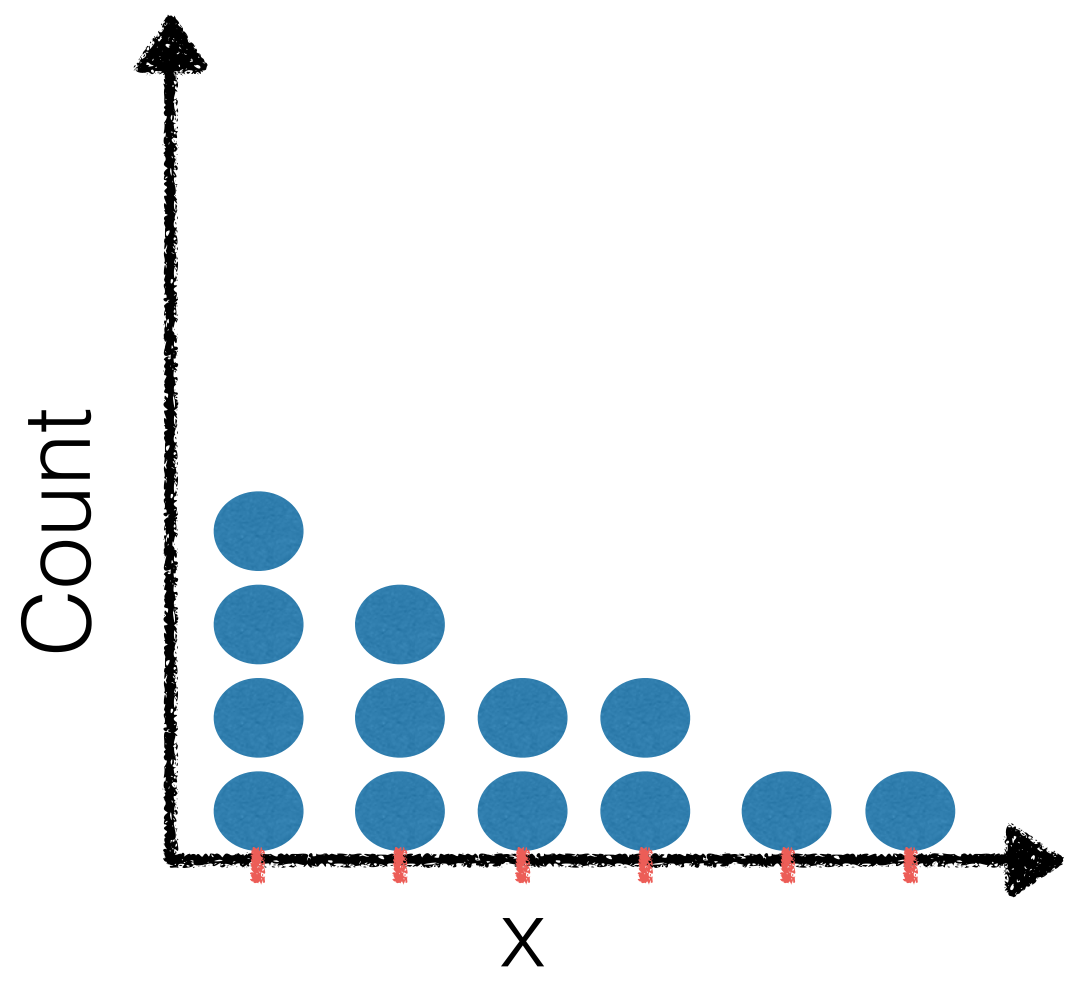
16

No longer in this convenient spacial case: The same observable **no longer optimal due to non-linear effects** coming from quantum interference

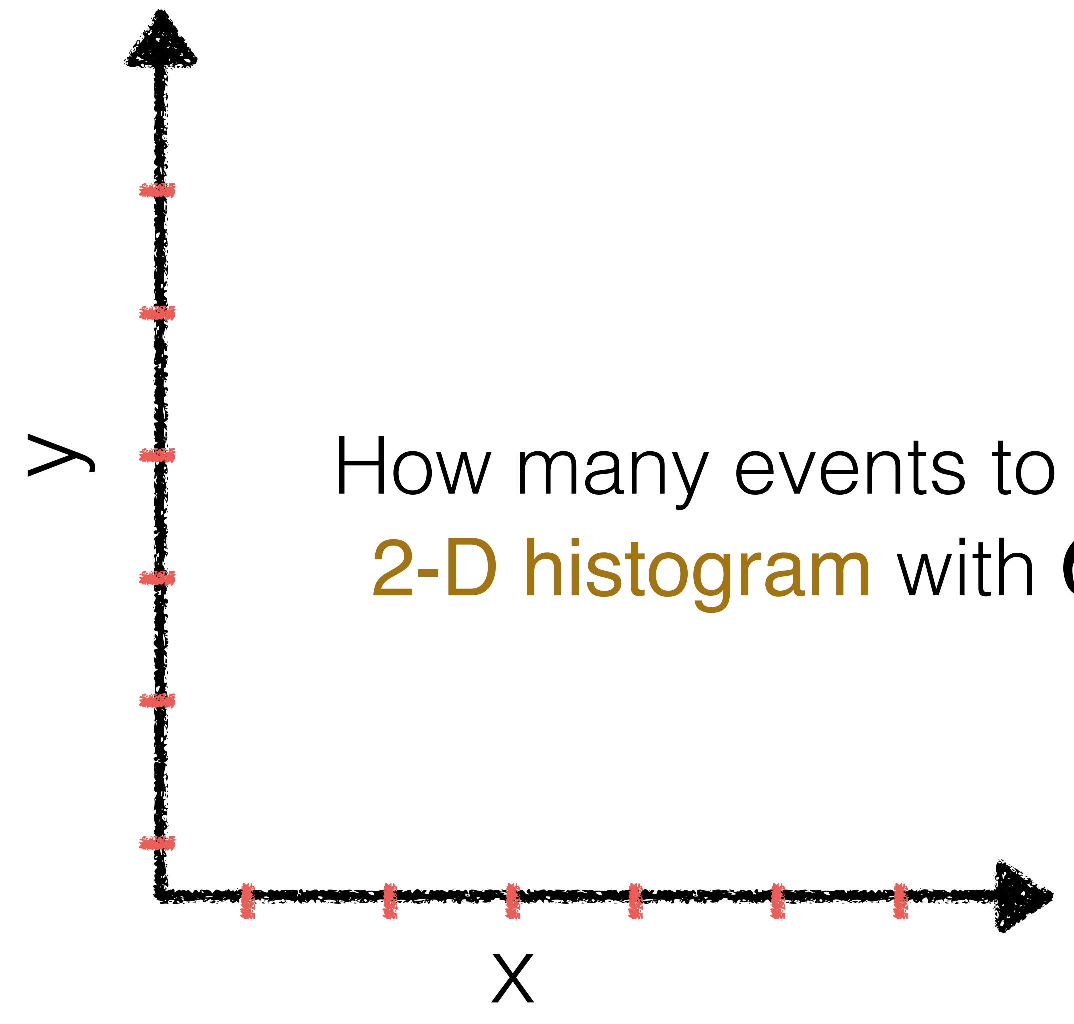
Also **does not generalise to an arbitrary theory parameter θ**, (eg. Effective Field Theory parameters)

Can we modify the LHC analysis methodology to **design near-optimal analyse for the general case?**

But probability density estimation in higher dimensions is hard…



1-D histogram with 6 bins: few events enough to populate it



How many events to populate 2-D histogram with 6^2 bins ?

How many events for 50-D histogram with 6^{50} bins ?

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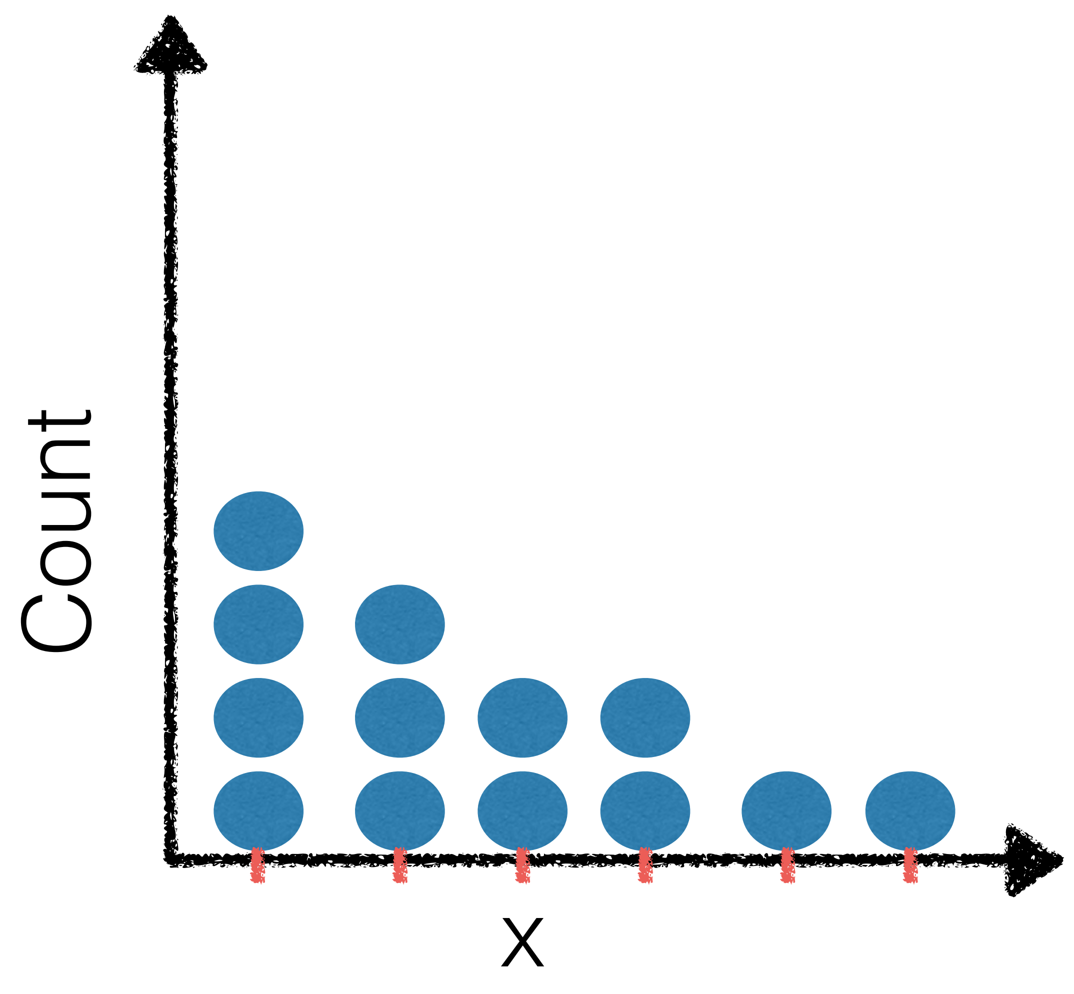

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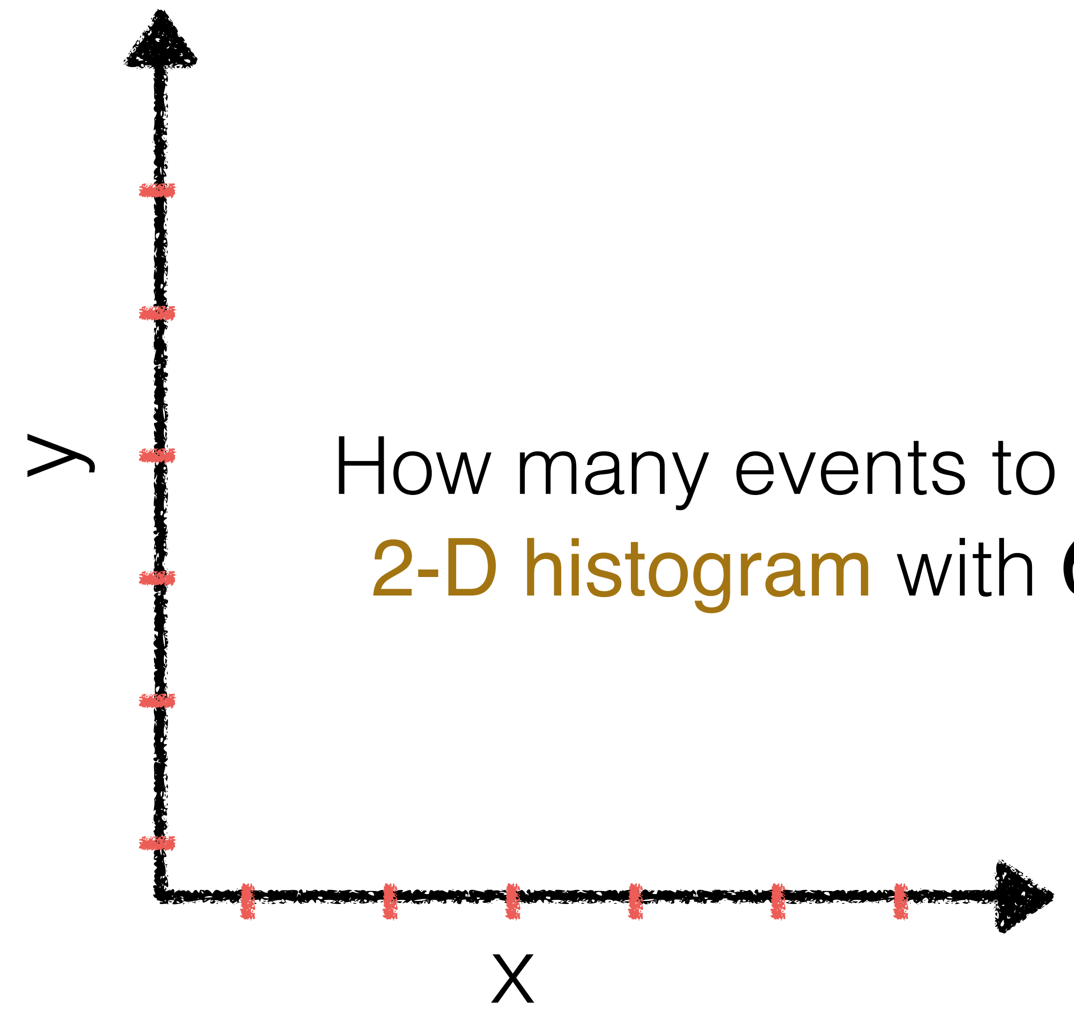


How many events to populate 2-D histogram with 6^2 bins ?

Curse of dimensionality

How many events for 50-D histogram with 6^{50} bins ?

Core insight from folks at NYU: Cranmer et al

Neural networks can give us the likelihood ratios

$$\mathcal{L}(\mu \,|\, \mathcal{D}) = p(\mathcal{D} \,|\, \mu)$$

Neyman–Pearson lemma: **Likelihood ratio is the most powerful test statistic**

We want to compare likelihoods:
$$\frac{p(\mathcal{D} \,|\, \mu)}{p(\mathcal{D} \,|\, ref)}$$

A neural network classifier trained on simulated samples from μ_1 vs simulated samples from ref, estimates the decision function:

$$s(x_i) = \frac{p(x_i \,|\, \mu_1)}{p(x_i \,|\, \mu_1) + p(x_i \,|\, ref)}$$

Which contains all the information required for the likelihood ratio:

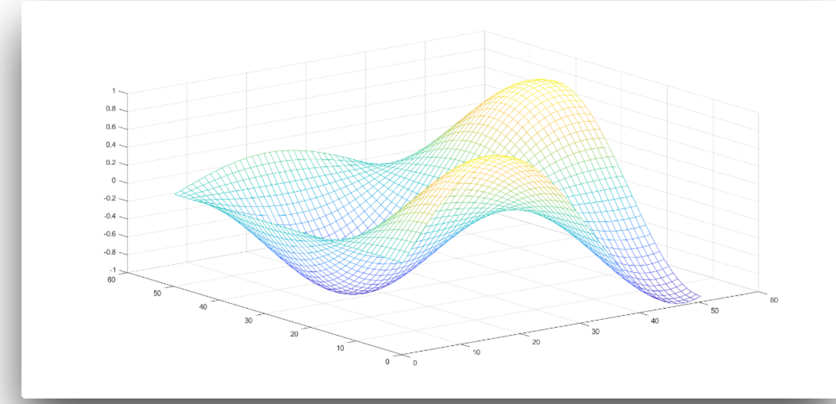
$$\frac{p(x_i \,|\, \mu_1)}{p(x_i \,|\, ref)} = \frac{s(x_i)}{1 - s(x_i)}$$

- Optimal statistic to test each value of μ
- We get the LR *per event* (unbinned)

Cranmer et al: arXiv:1506.02169

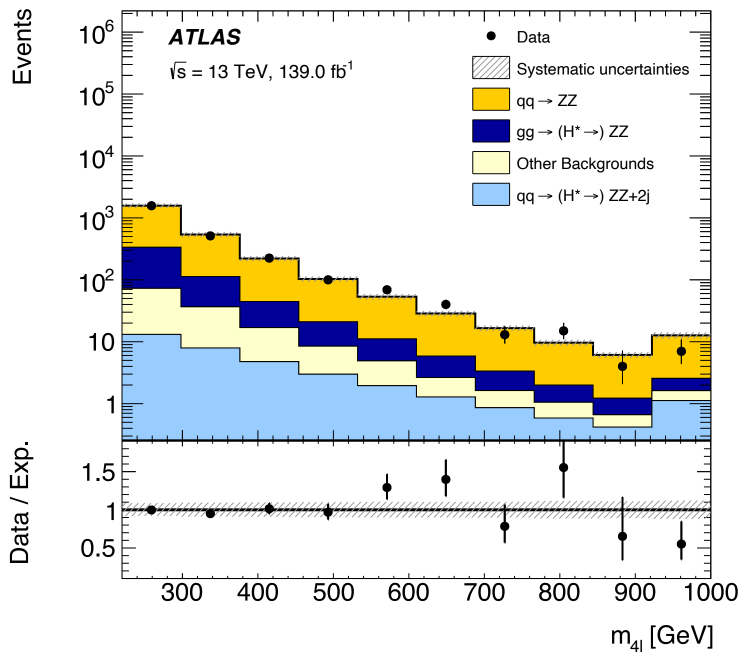
A new paradigm: Neural simulation-based inference

Traditional framework:



High-dim data

Summarisation to histogram

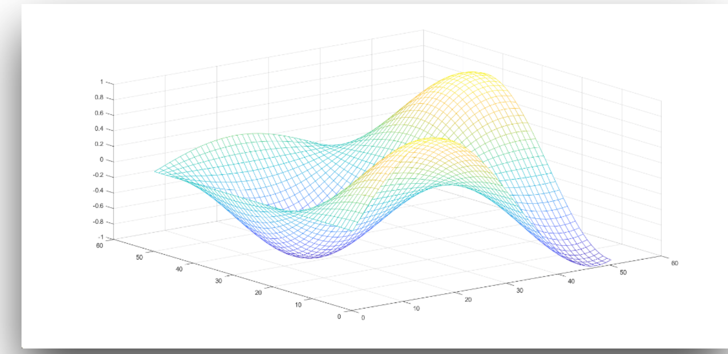


Summary Histogram → Statistical Fit → Likelihood $\mathscr{L}(\mu_1 | \mathscr{D})$

μ_1 → Statistical Fit

μ is now arbitrary parameter of interest(s)

Neural simulation-based inference framework:



High-dim data

Obs Data → Neural Network → Likelihood Ratio $\left(\frac{\mathscr{L}(\mu_1 | \mathscr{D})}{\mathscr{L}(ref | \mathscr{D})}\right)$

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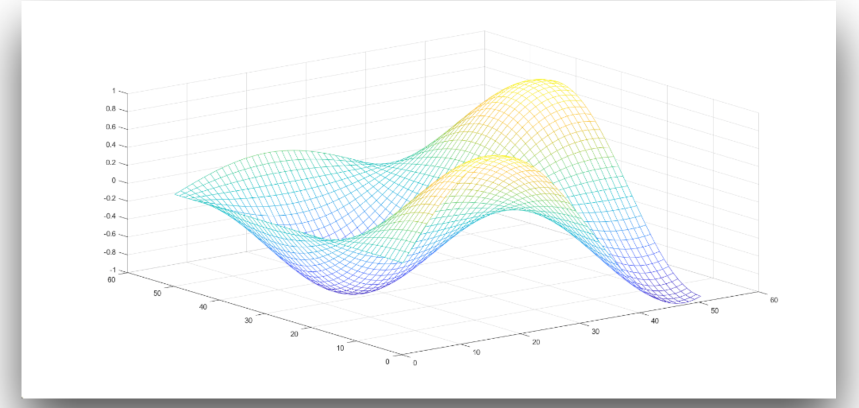

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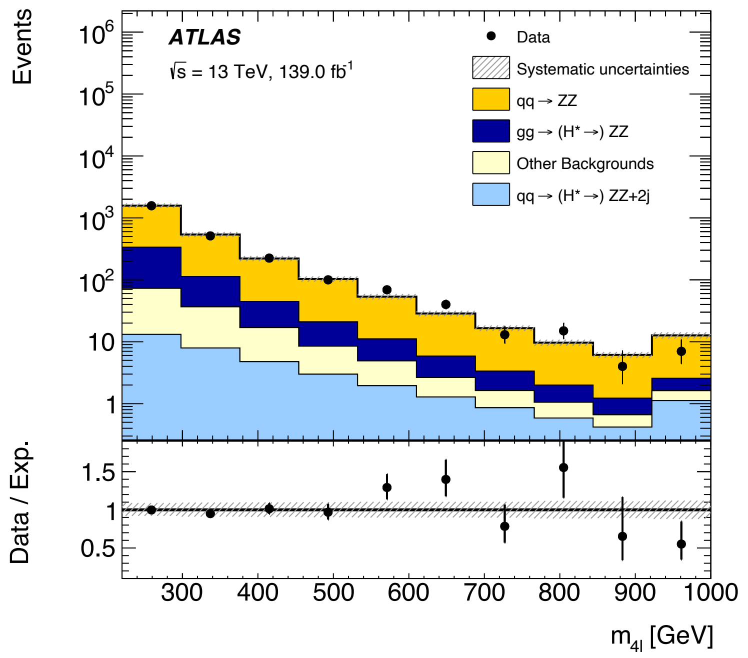

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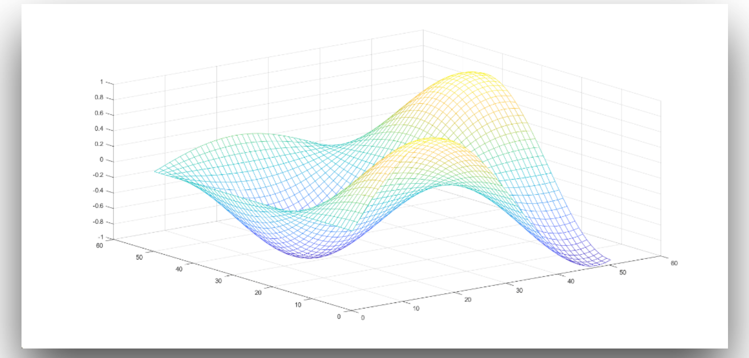

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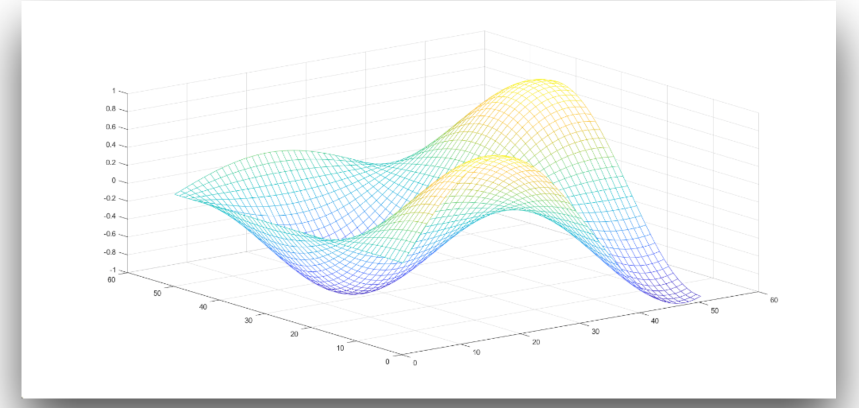

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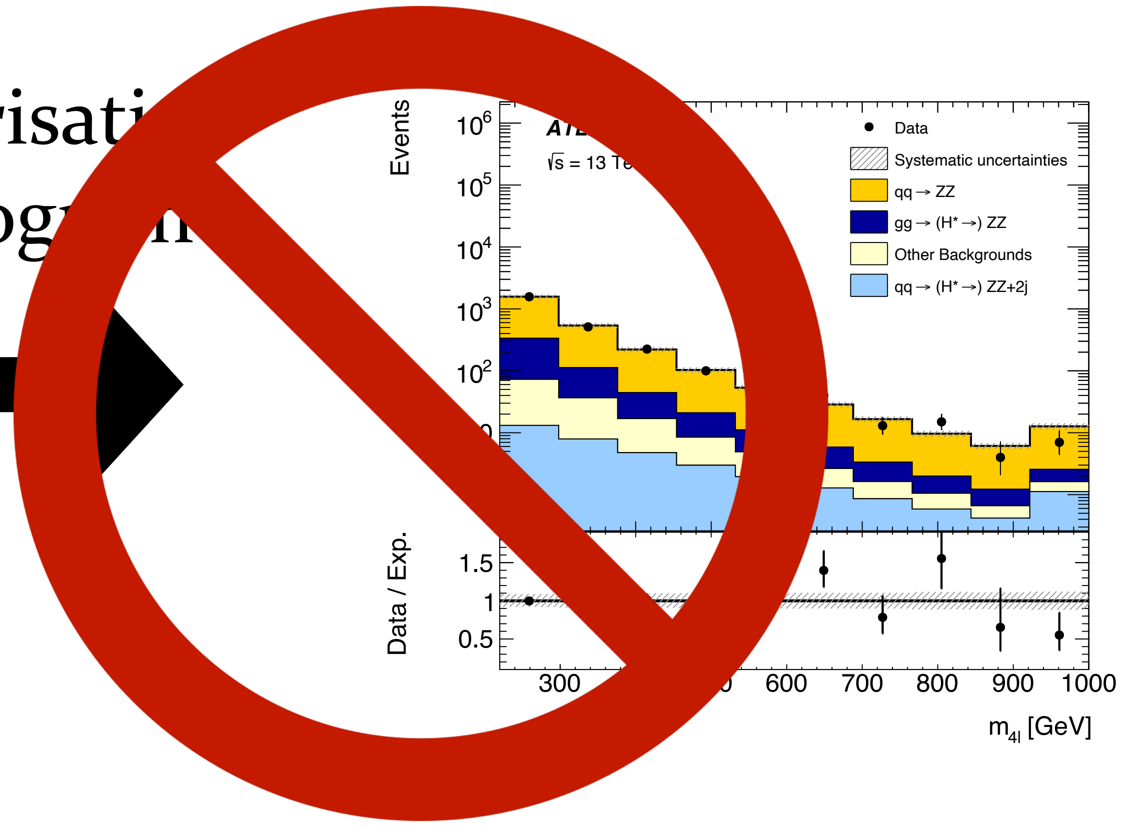

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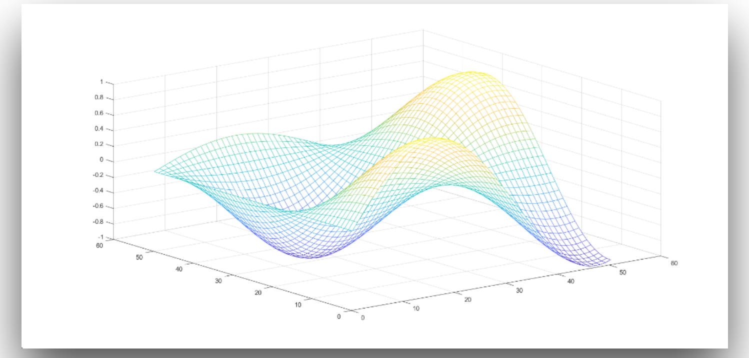

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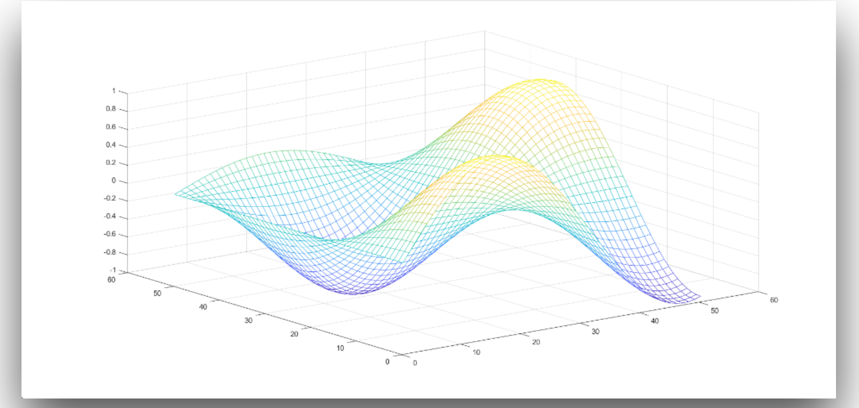

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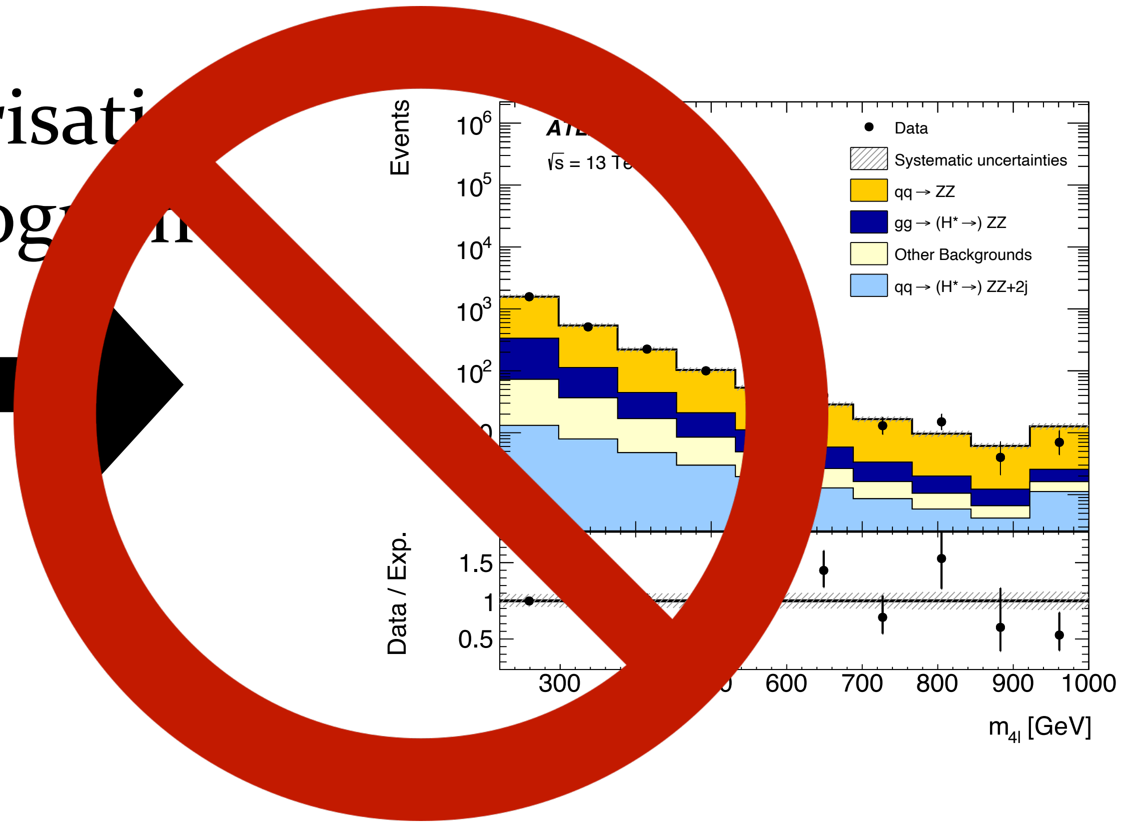
Summarisati
to histog



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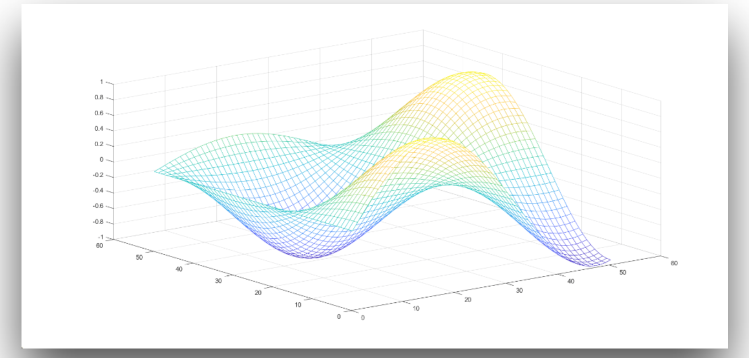

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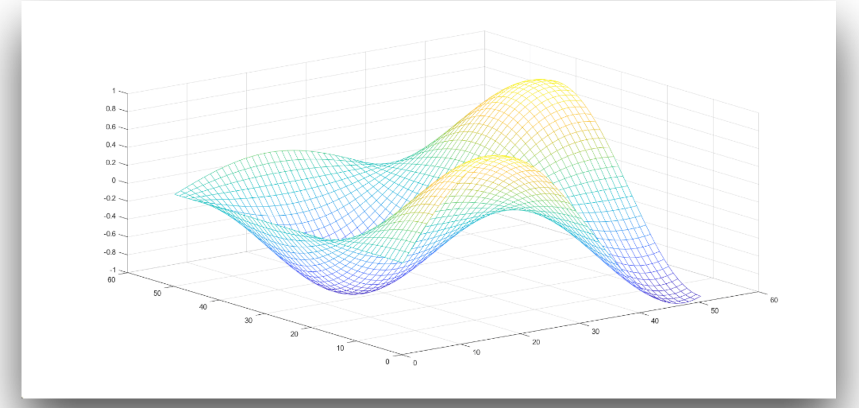

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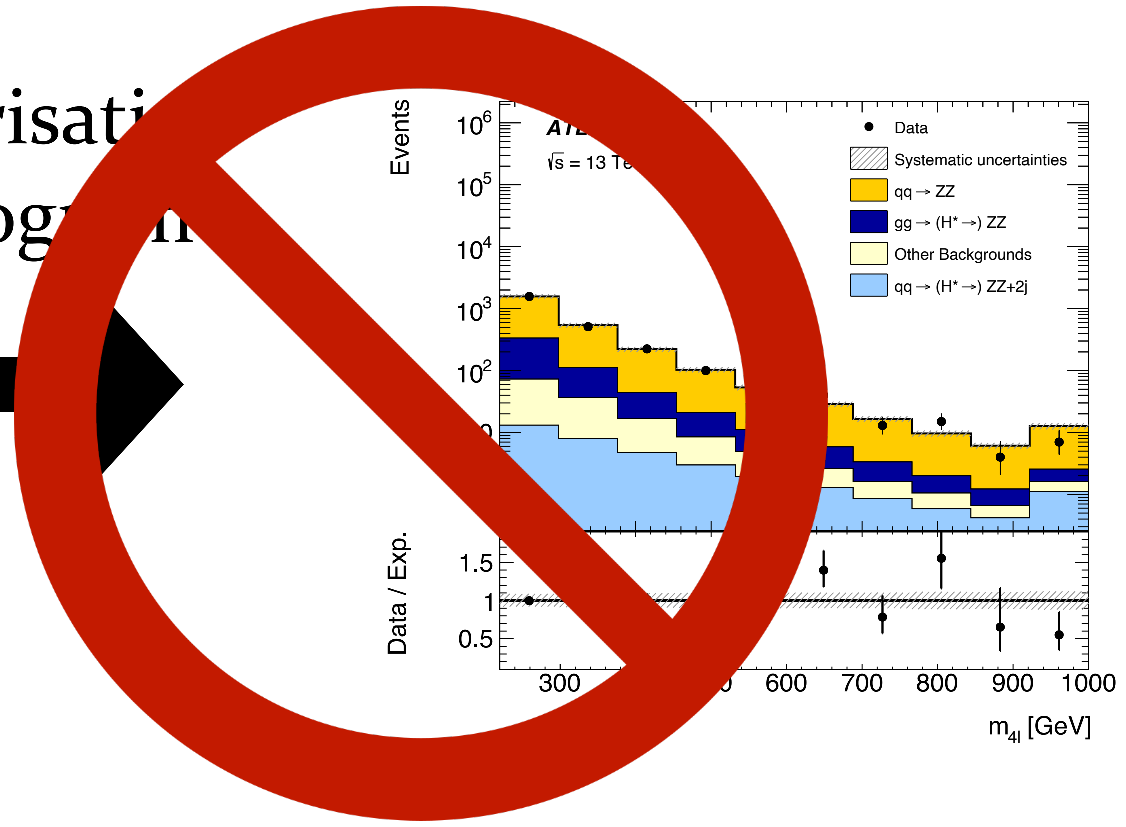

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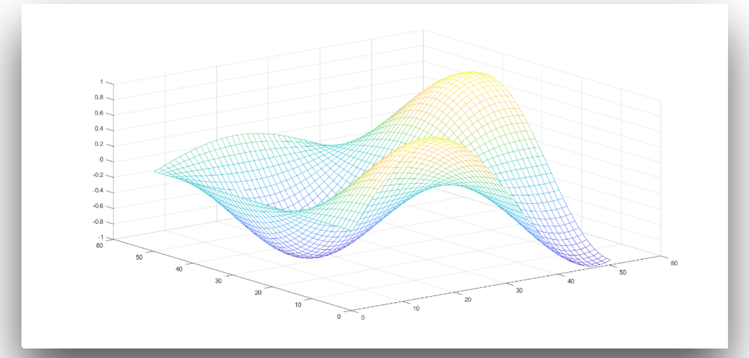

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Hypothesis μ_1

Train on simulations, apply on data

NSBI for Higgs width in proof-of-concept phenomenology study

Expected sensitivity

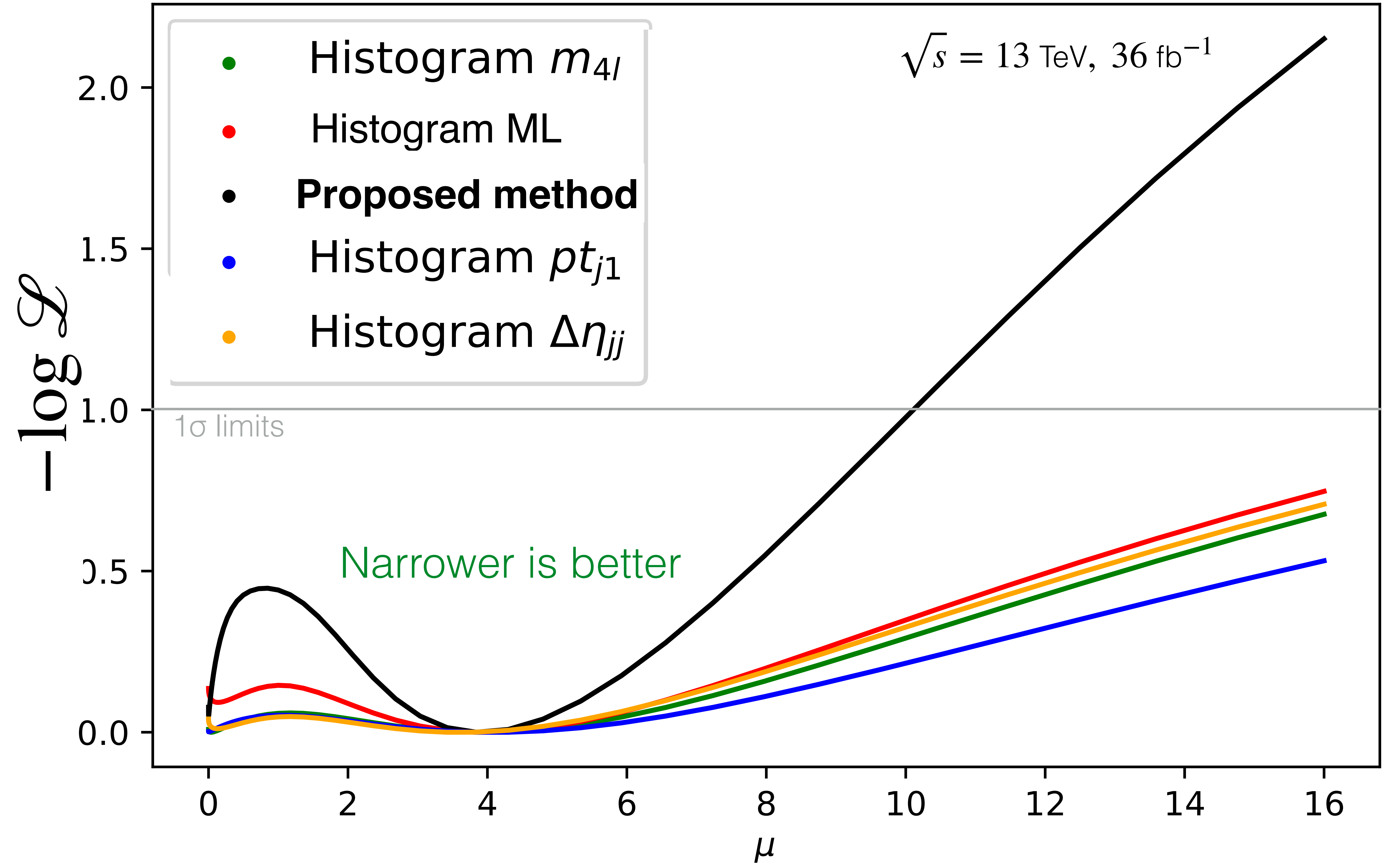
hal-02971995v3 (p172): **Aishik Ghosh**, David Rousseau

(Beyond Standard Model value)

NSBI for Higgs width in proof-of-concept phenomenology study

<u>Expected sensitivity</u>

hal-02971995v3 (p172): **Aishik Ghosh**, David Rousseau



(Beyond Standard Model value) $\mu = 4, \text{ without rate}$

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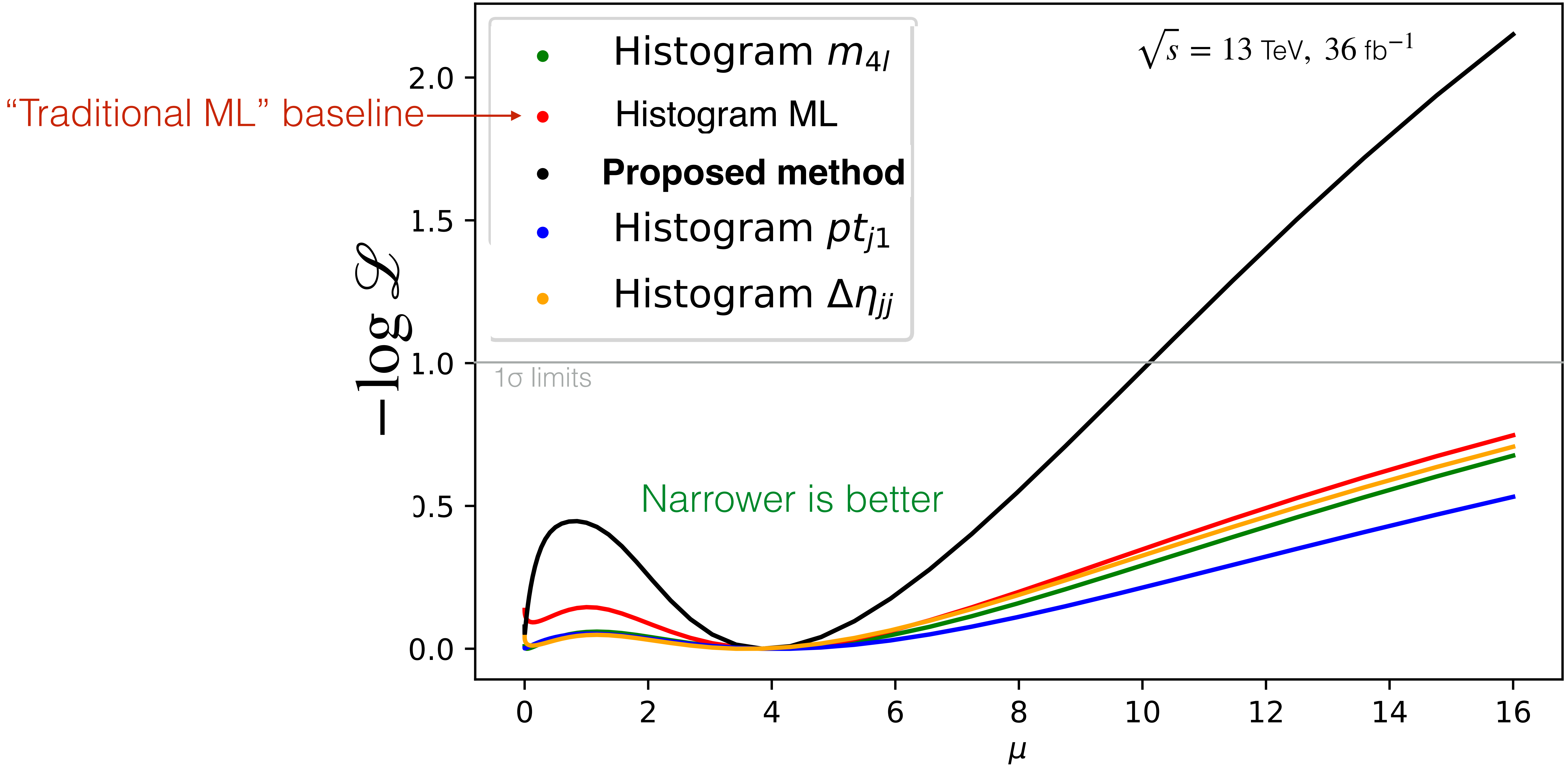
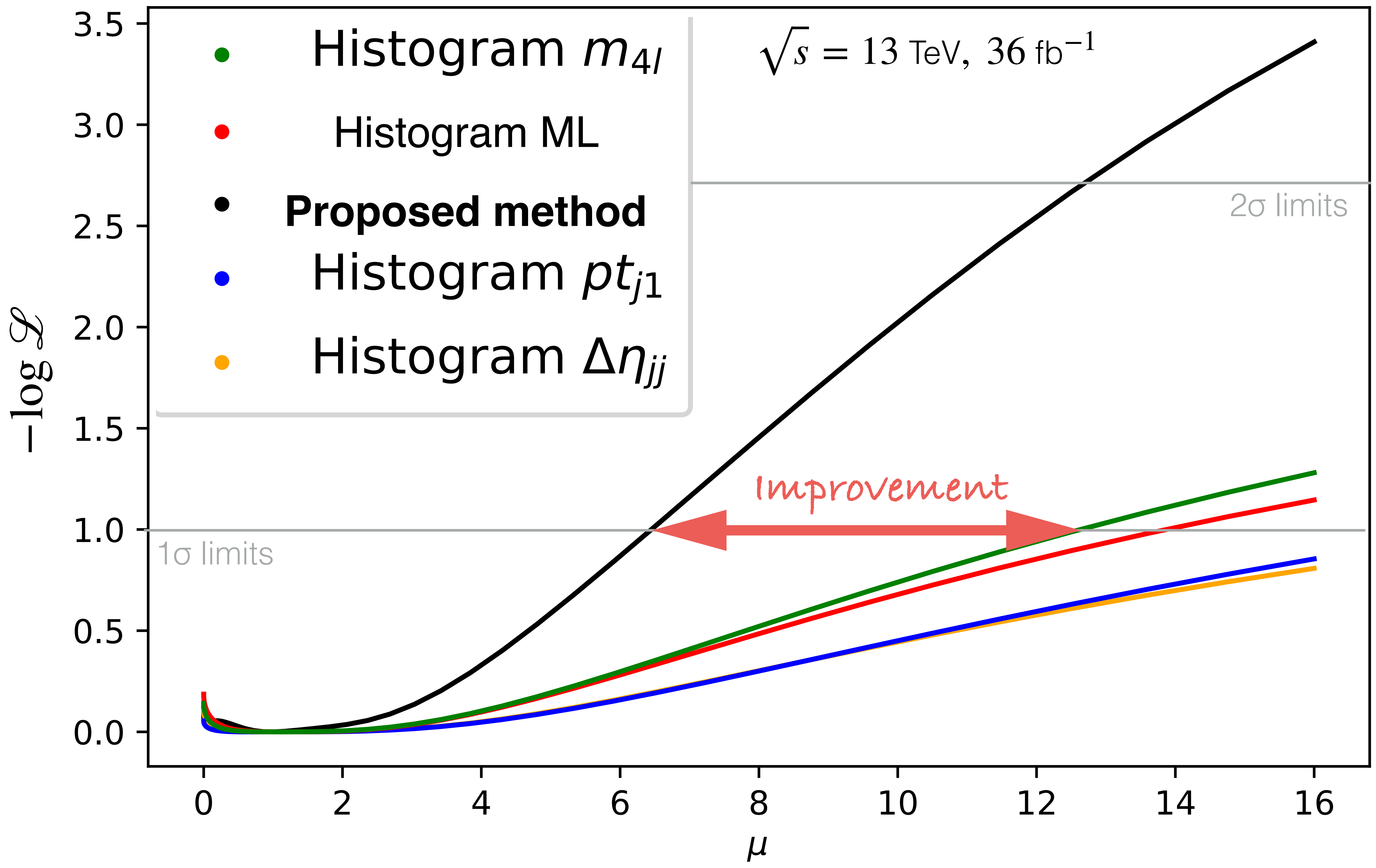


(Beyond Standard Model value) $\mu = 4$, without rate

Expected improvement for Standard Model

hal-02971995v3: **Aishik Ghosh**, David Rousseau



Exciting gains promised!

SM, without rate

Open problems to extend to full ATLAS analysis:

- Robustness: Design and validation
- Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- Neyman Construction: Throwing toys in a per-event analysis

Open problems to extend to full ATLAS analysis:

- Robustness: Design and validation
- Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- Neyman Construction: Throwing toys in a per-event analysis

How frequentists ensure coverage

Solved!

Open problems to extend to full ATLAS analysis:

ATLAS CONF Note

ATLAS-CONF-2024-015

28th October 2024

An implementation of Neural Simulation-Based Inference for Parameter Estimation in ATLAS

The ATLAS Collaboration

Neural Simulation-Based Inference (NSBI) is a powerful class of machine learning (ML)-based methods for statistical inference that naturally handles high-dimensional parameter estimation without the need to bin data into low-dimensional summary histograms. Such methods are promising for a range of measurements, including at the Large Hadron Collider (LHC), where no single observable may be optimal to scan over the entire theoretical phase space under consideration, or where binning data into histograms could result in a loss of sensitivity. This work develops an NSBI framework for statistical inference, using neural networks to estimate probability density ratios, which enables the application of NSBI to a full-scale LHC analysis. It incorporates a large number of systematic uncertainties, quantifies the uncertainty coming from finite training statistics, develops a method to construct confidence intervals, and demonstrates a series of intermediate diagnostic checks that can be performed to validate the robustness of the method. As an example, the power and feasibility of the method are demonstrated on simulated data for a simplified version of an off-shell Higgs boson couplings measurement in the four-leptons final states. This NSBI framework is an extension of the standard statistical framework used by LHC experiments and can benefit a large number of physics analyses.

ATLAS-CONF-2024-015
28 October 2024

Presented at CHEP 2024, Higgs 2024

Solved!

Open problems to extend to full ATLAS analysis:

Applied on Run2 data, superseding previous ATLAS paper on same data !

Presented at CHEP 2024, Higgs 2024

ATLAS CONF Note

ATLAS-CONF-2024-015

28th October 2024

An implementation of Neural Simulation-Based Inference for Parameter Estimation in ATLAS

ATLAS CONF Note

ATLAS-CONF-2024-016

October 31, 2024

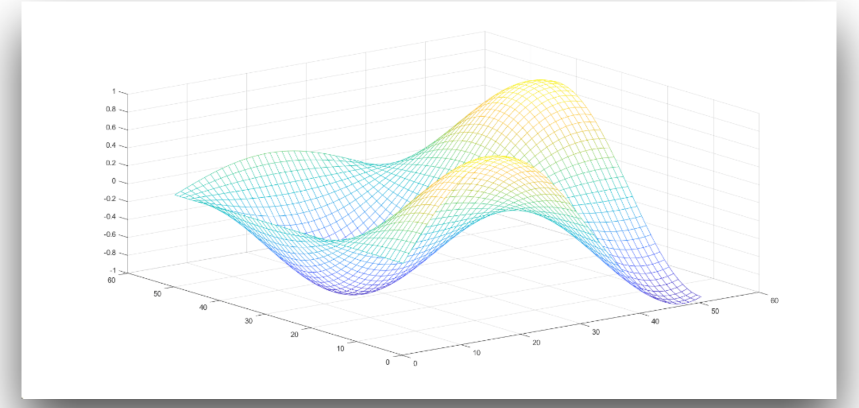
Measurement of off-shell Higgs boson production in the $H^* \to ZZ \to 4\ell$ decay channel using a neural simulation-based inference technique with the ATLAS detector at $\sqrt{s}$ = 13 TeV

The ATLAS Collaboration

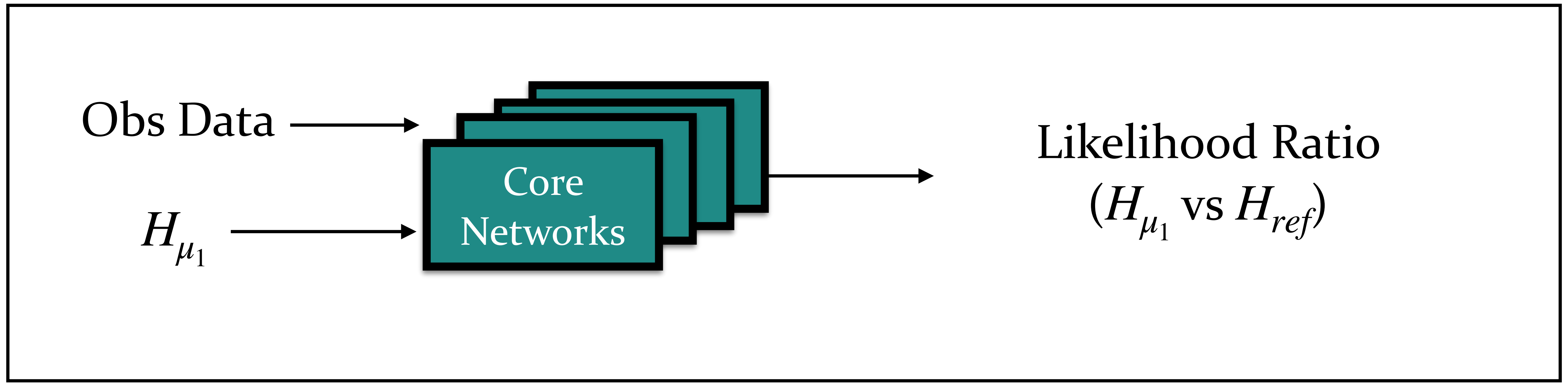
A measurement of off-shell Higgs boson production in the $H^* \to ZZ \to 4\ell$ decay channel is presented. The measurement uses the 140 fb^{-1} of integrated luminosity collected by the ATLAS detector during the Run 2 proton-proton collisions of the Large Hadron Collider at $\sqrt{s}$ = 13 TeV and supersedes our previous result in this decay channel using the same dataset. The data analysis is performed using a neural simulation based-inference method, which builds per-event likelihood ratios using neural networks. The observed (expected) off-shell Higgs boson production signal strength in the $ZZ \to 4\ell$ decay channel is $0.87^{+0.75}_{-0.54}$ ($1.00^{+1.04}_{-0.95}$) at 68% CL. The previous result was not able to achieve expected sensitivity to quote a two-sided interval at this CL. The expected plus-side uncertainty is reduced by 10%. The evidence for off-shell Higgs boson production has an observed (expected) significance of 2.5σ (1.3σ) using the $ZZ \to 4\ell$ decay channel only. The expected significance score is 2.6 times that of our previous result using the same dataset. When combined with our most recent measurement in $ZZ \to 2\ell 2\nu$ decay channel, the evidence for off-shell Higgs boson production has an observed (expected) significance of 3.7σ (2.4σ). The off-shell measurements are combined with the measurement of on-shell Higgs boson production to obtain constraints on the Higgs boson total width. The observed (expected) value of the Higgs boson width is $4.3^{+2.7}_{-1.9}$ ($4.1^{+3.5}_{-3.4}$) MeV at 68% CL.

ATLAS methods note: CDS

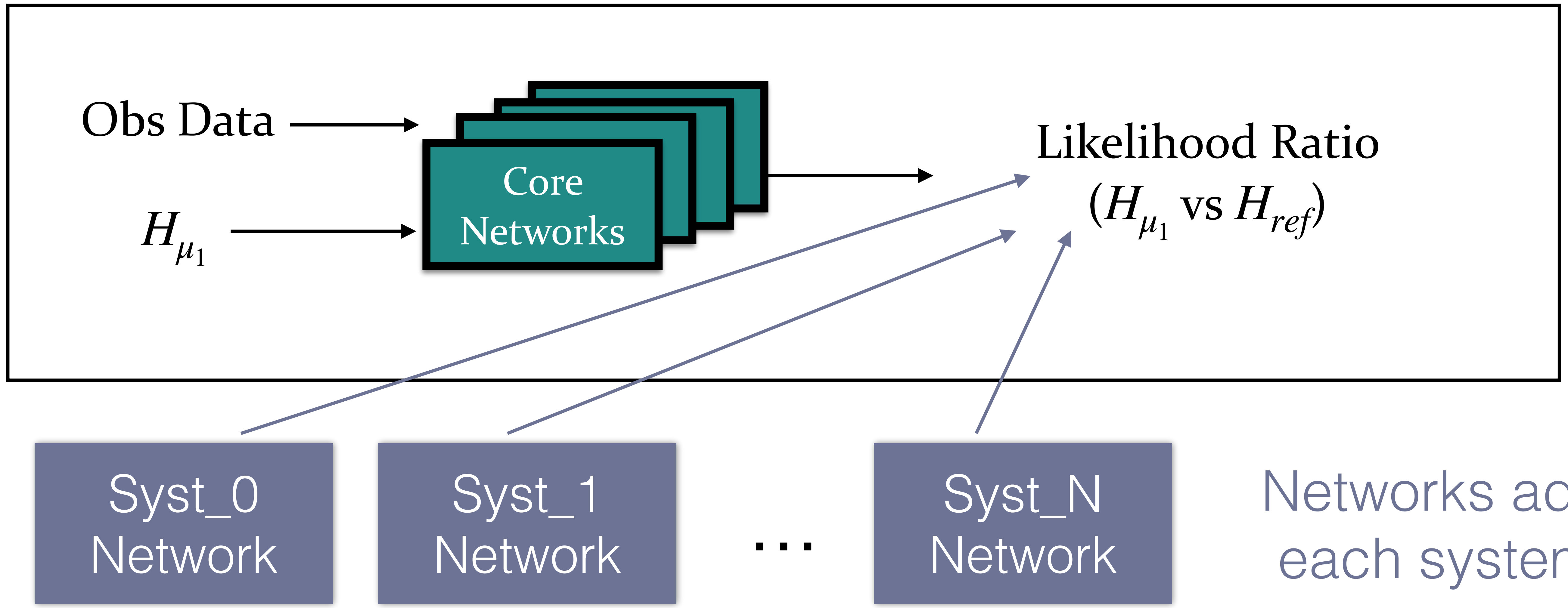
Big picture of full solution developed in ATLAS



$O(16)$ observables

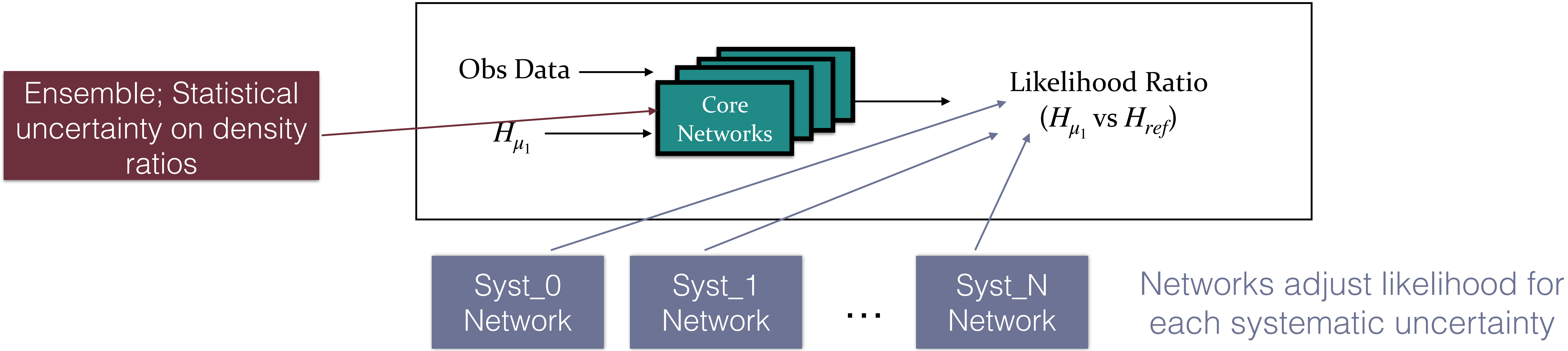


Big picture of full solution developed in ATLAS



Networks adjust likelihood for each systematic uncertainty

Big picture of full solution developed in ATLAS



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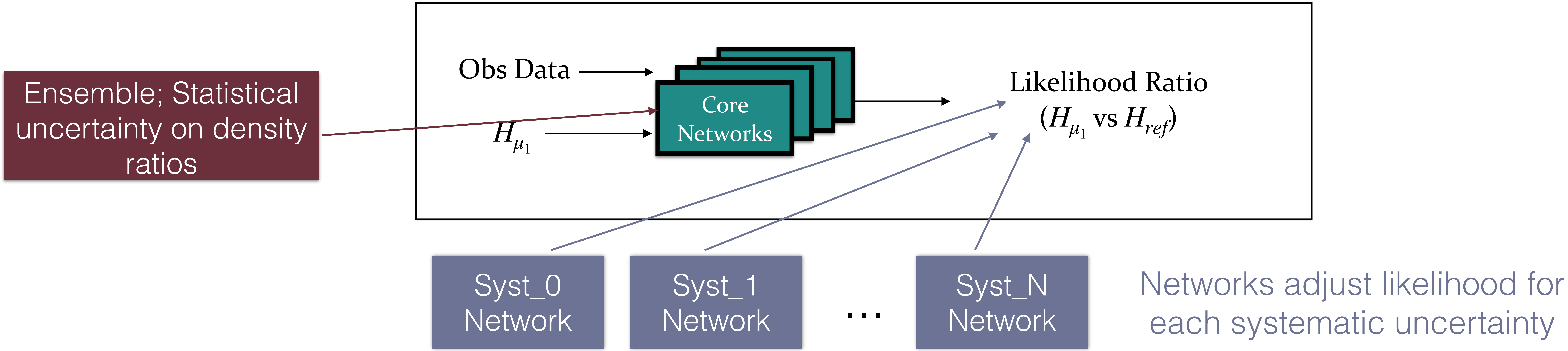

- Train $O(10^4)$ networks on TensorFlow
- Computing resources provided by Google, SMU, other HPC clusters
- Fits with JAX

Open problems to extend to full ATLAS analysis:

- Robustness: Design and validation
- Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- Neyman Construction: Throwing toys in a per-event analysis

Next 2 slides gets a bit technical

Search-Oriented Mixture Model

x_i is one individual event

General Formula

$$p(x_i|\mu) = \frac{1}{\nu(\mu)} \sum_{j}^{C} f_j(\mu) \cdot \nu_j \; p_j(x_i)$$

j runs over different physics process
(Eg. $gg \rightarrow H^* \rightarrow 4l$, $gg \rightarrow ZZ \rightarrow 4l$)

Example use case

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$$p_{\mathrm{ggF}}(x|\mu) = \frac{1}{\nu_{\mathrm{ggF}}(\mu)} \left[(\mu - \sqrt{\mu})\, \nu_S \; p_{\mathrm{S}}(x) + \sqrt{\mu}\, \nu_{\mathrm{SBI}_1} \; p_{\mathrm{SBI}_1}(x) + (1 - \sqrt{\mu})\nu_{\mathrm{B}} \; p_{\mathrm{B}}(x) \right]$$

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Comes from theory model chosen to interpret data

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$$p(x_i|\mu) = \frac{1}{\nu(\mu)} \sum_j^C f_j(\mu) \cdot \nu_j \, p_j(x_i)$$

Event rates estimated from simulations

Comes from theory model chosen to interpret data

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(Eg. $gg \to H^* \to 4l$, $gg \to ZZ \to 4l$)

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Reference hypothesis

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Estimated using an ensemble of networks

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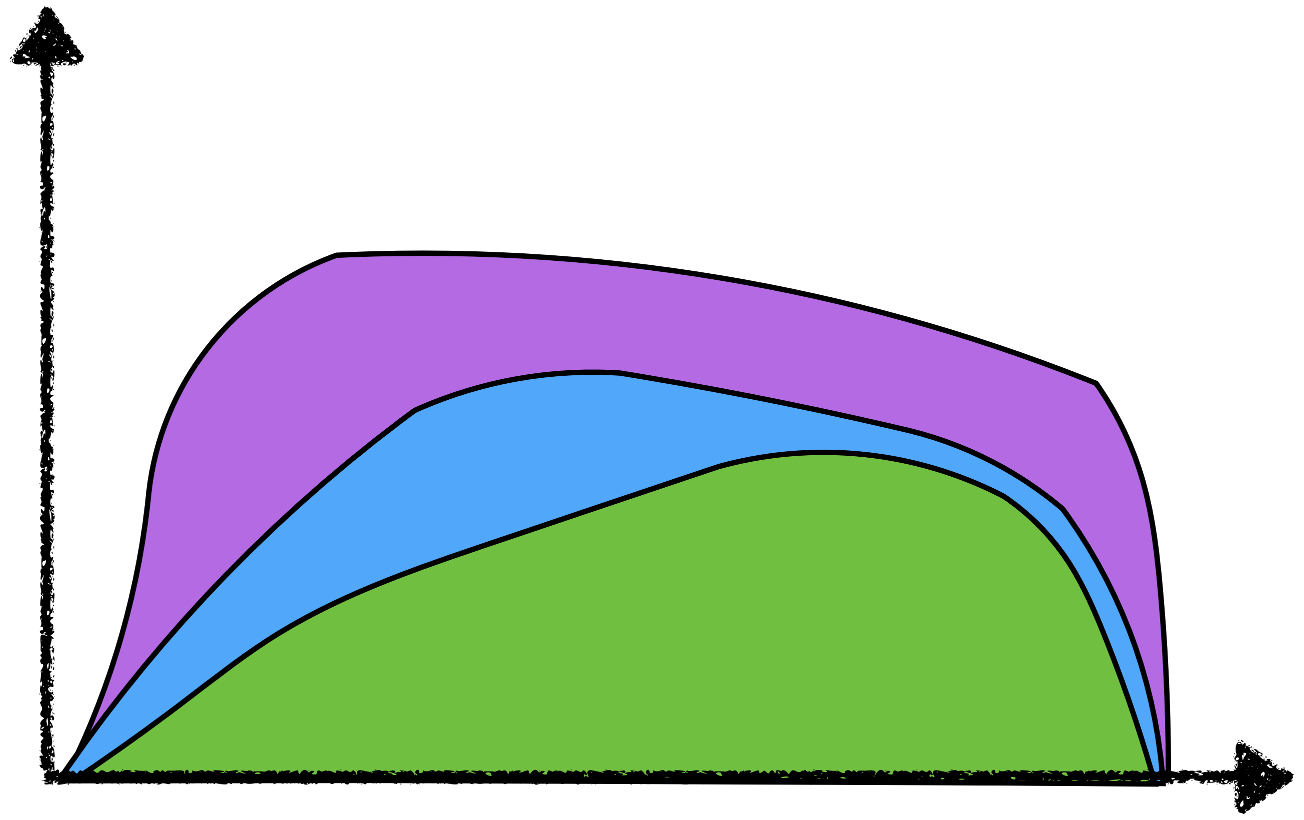
Robust, parameterised classifier without parameterising

H_{ref} : Reference hypothesis

H_μ

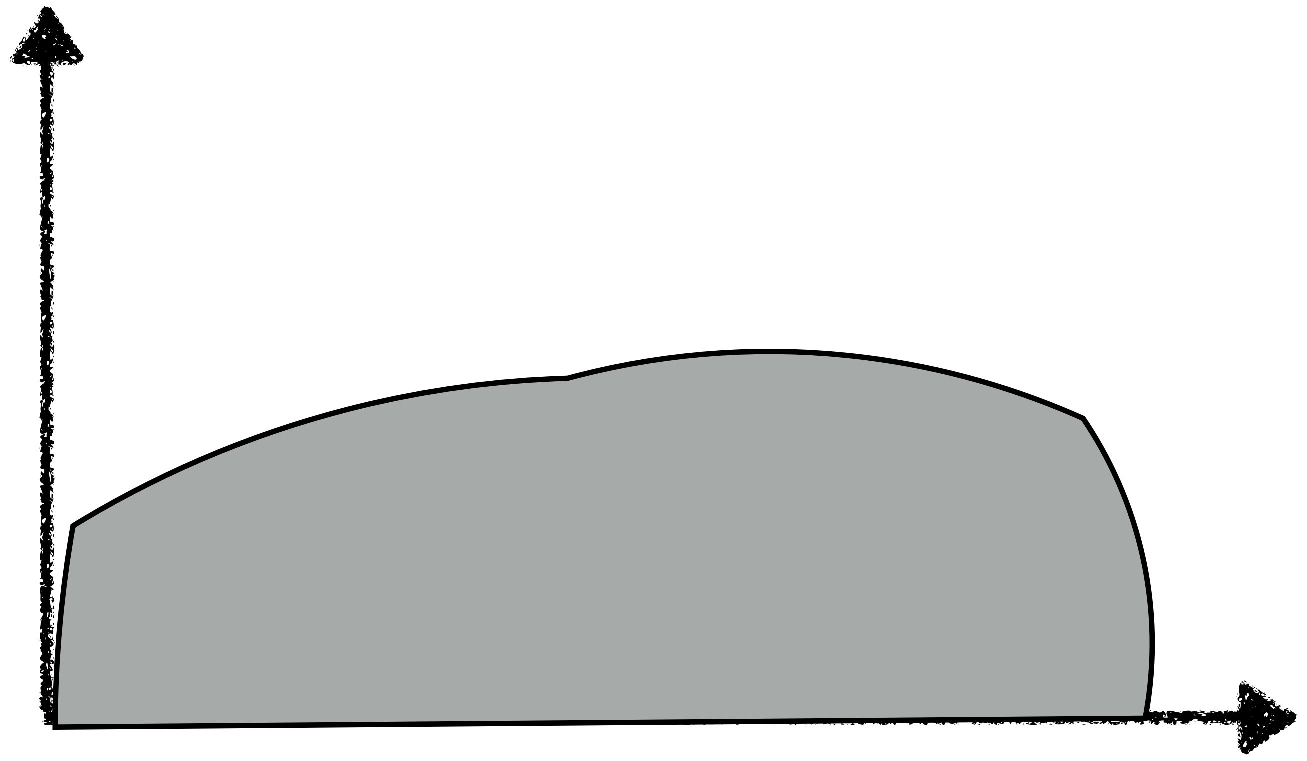
Hypothesis



VS

H_{ref}

Reference hypothesis



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A separate classifier per physics process j

(Eg. $gg \rightarrow H^* \rightarrow 4l$, $gg \rightarrow ZZ \rightarrow 4l$)

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H_μ

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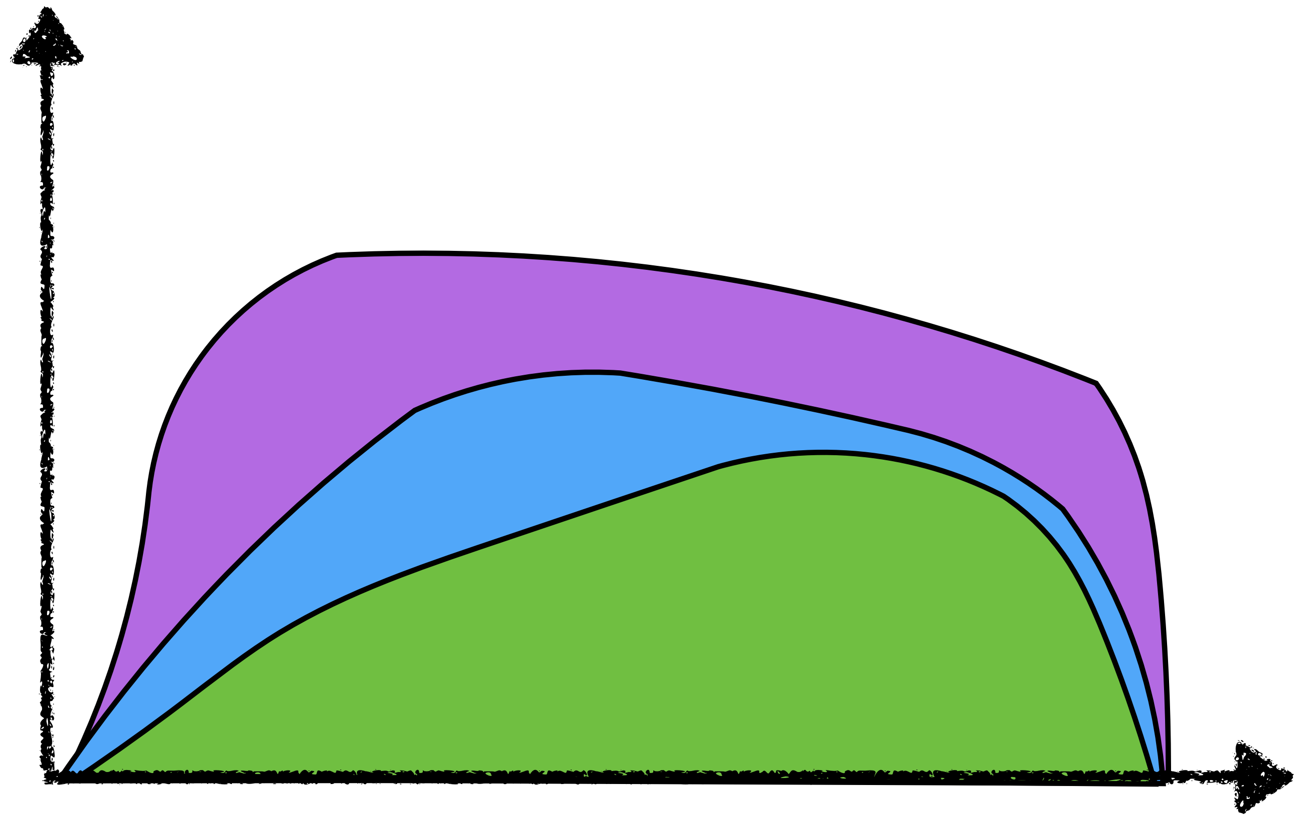

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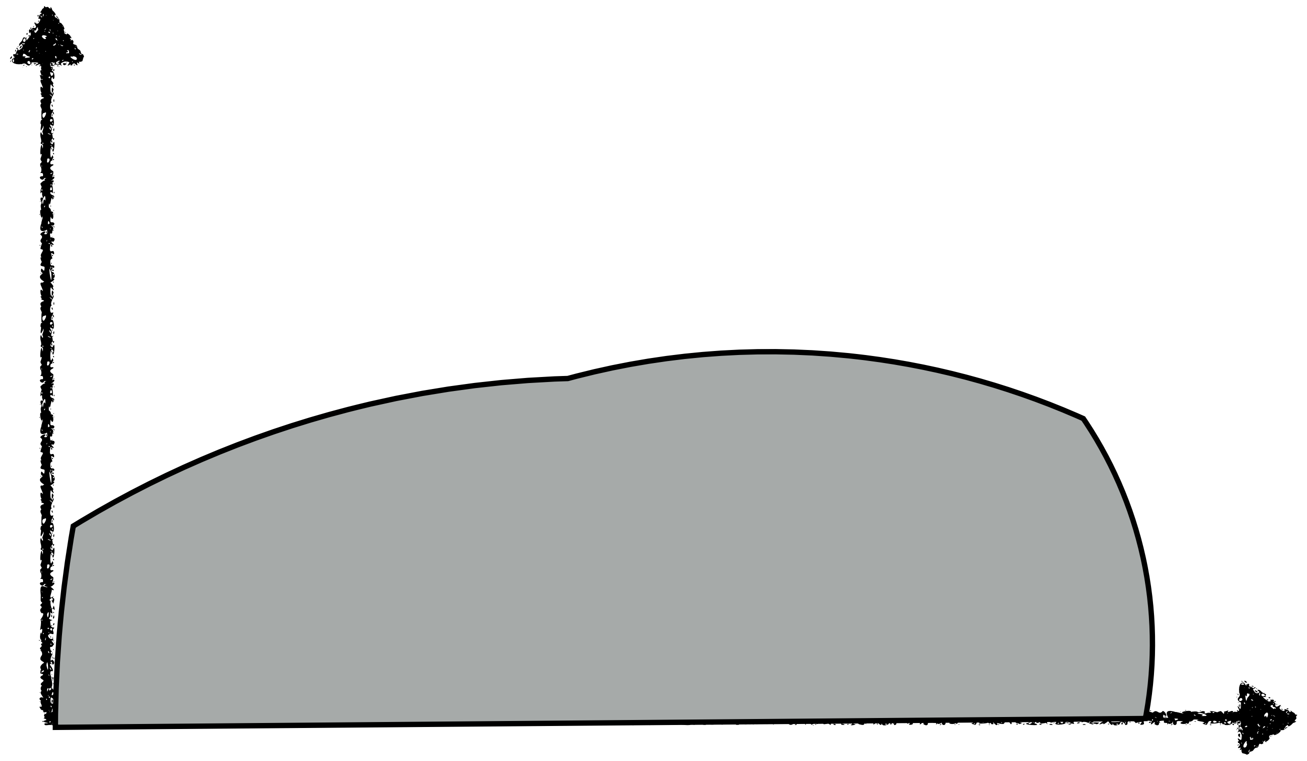

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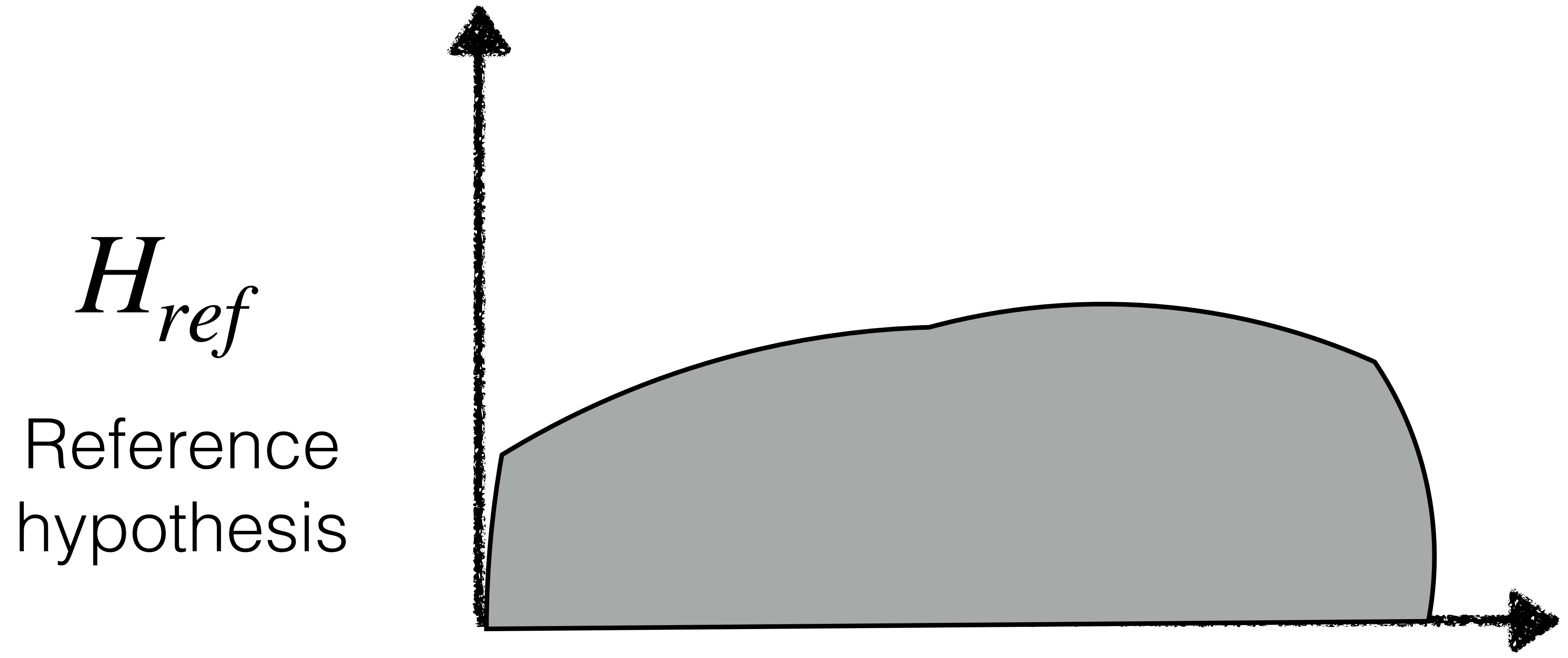

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F
h

Analytically parameterised in μ, allows to get LR for any hypothesis μ without training parameterised networks !

A separate classifier per physics process j
(Eg. $gg \rightarrow H^* \rightarrow 4l$, $gg \rightarrow ZZ \rightarrow 4l$)

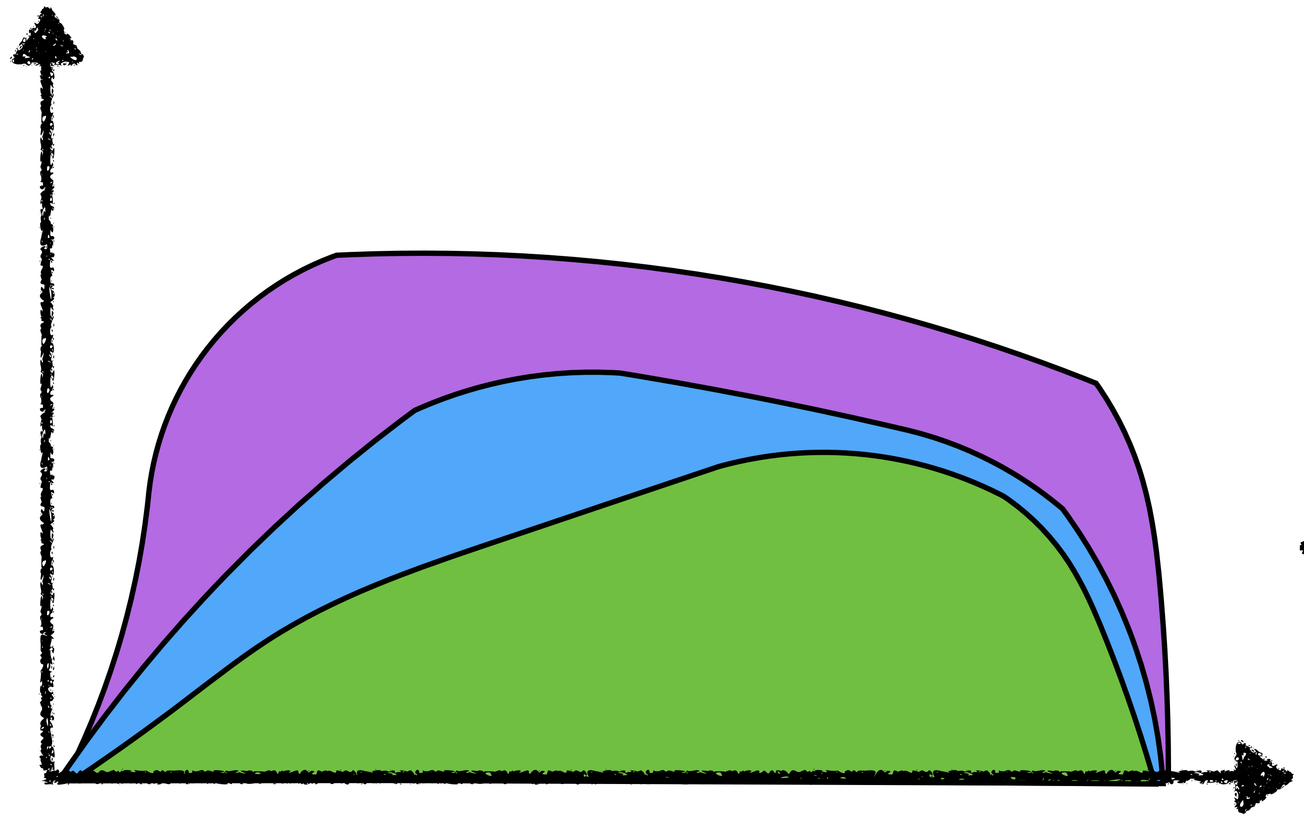
Robust, parameterised classifier without parameterising

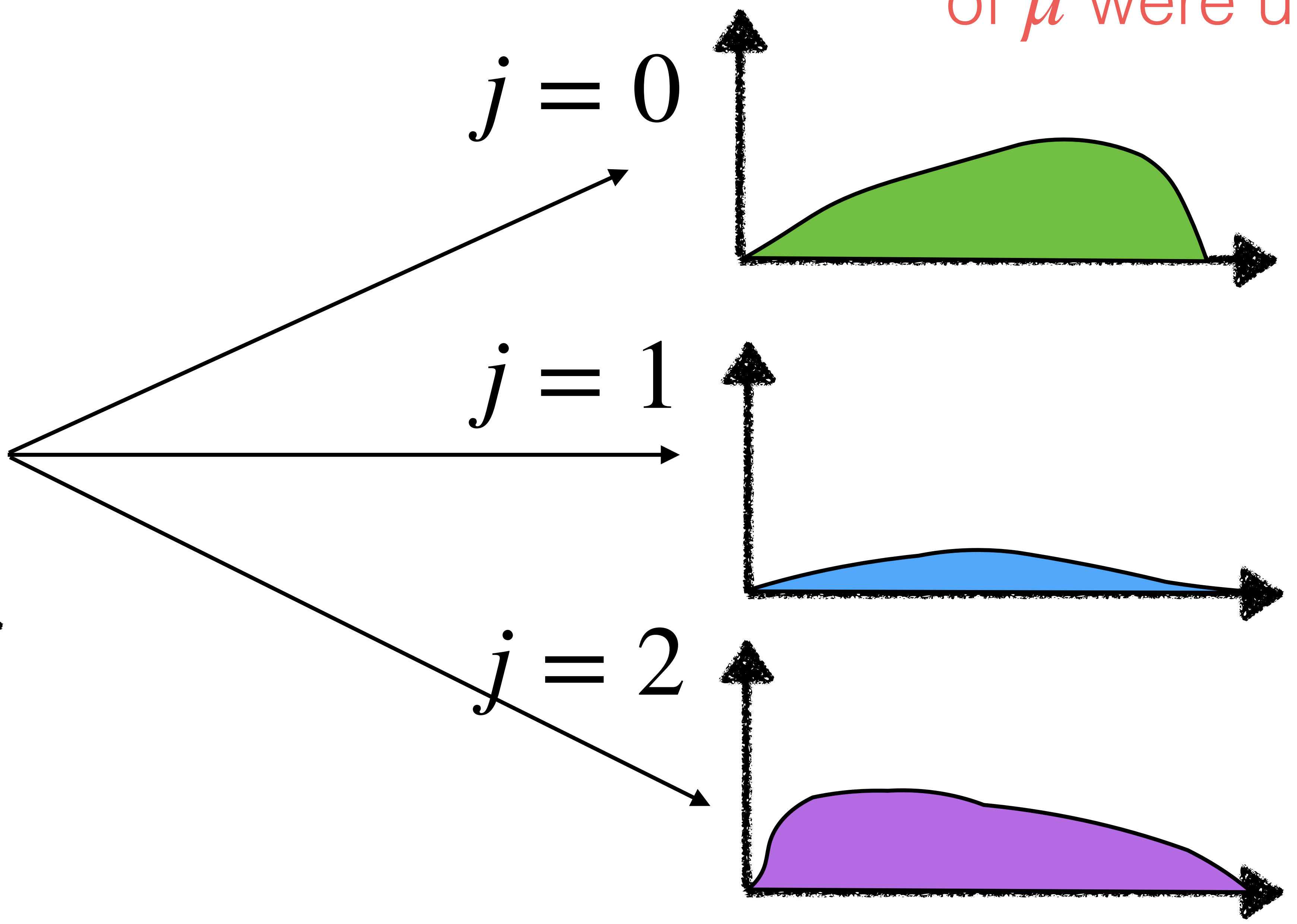
H_{ref} : Reference hypothesis

$f_i(\mu)$ will depend on morphing bases points (which values of μ were used to simulate samples)

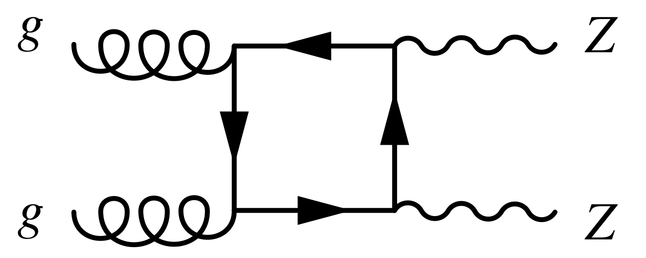
H_μ

Hypothesis

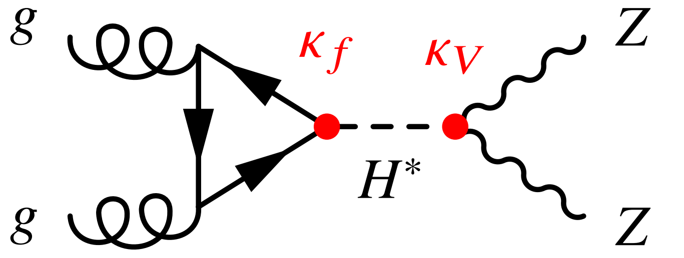




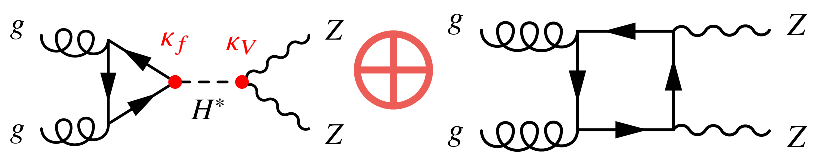
$f_0(\mu) = 1$



$f_1(\mu) = \mu$

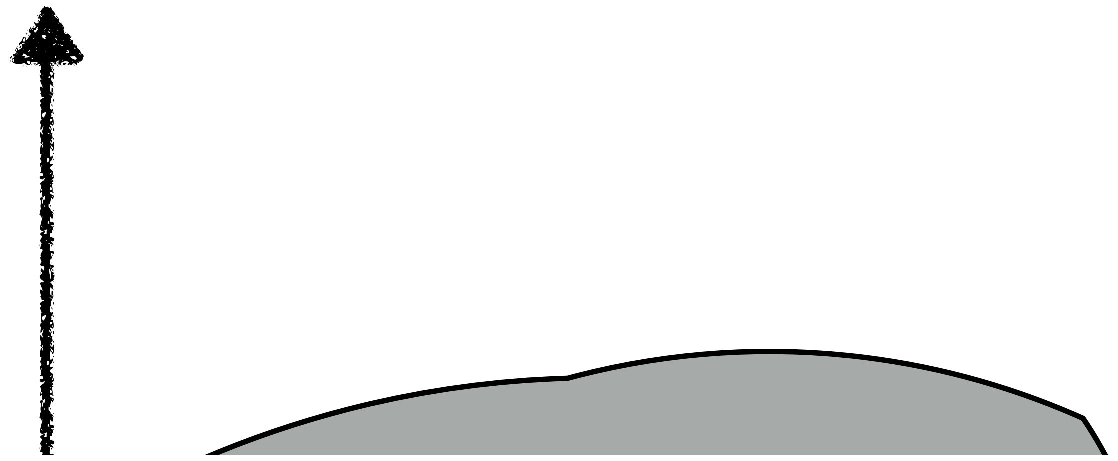


$f_2(\mu) = \sqrt{\mu}$



vs

H_{ref}



F

h

$$\frac{p(x_i|\mu)}{p_{\rm ref}(x_i)} = \frac{1}{\nu(\mu)} \sum_j^C f_j(\mu) \cdot \nu_j \frac{p_j(x_i)}{p_{\rm ref}(x_i)}$$

Analytically parameterised in μ, allows to get LR for any hypothesis μ without training parameterised networks !

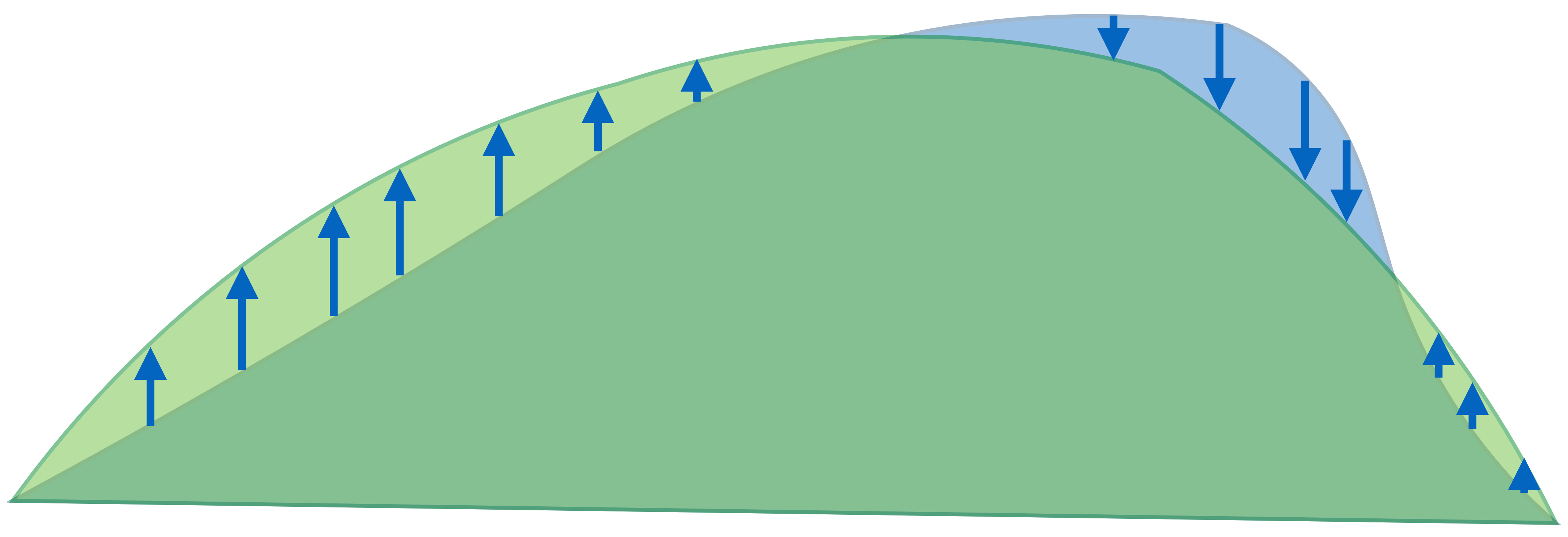
A separate classifier per physics process j (Eg. $gg \to H^* \to 4l$, $gg \to ZZ \to 4l$)

Open problems to extend to full ATLAS analysis:

- Robustness: Design and validation
- Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- Neyman Construction: Throwing toys in a per-event analysis

Validate quality of LR estimation with re-weighting task

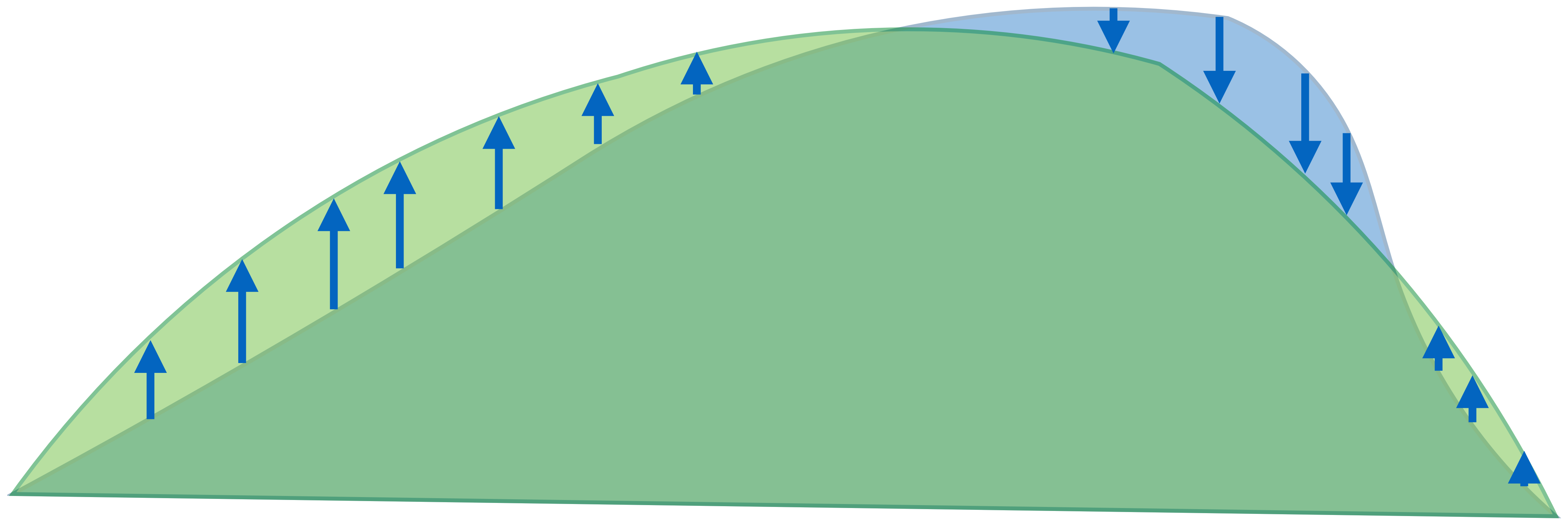
Reweighting: Calculate weights w_i for events x_i in blue sample to match green sample



Validate quality of LR estimation with re-weighting task

Reweighting: Calculate weights w_i for events x_i in blue sample to match green sample

$$w_i = r(x_i, \mu_0, \mu_1) = \frac{p(x_i | \mu_0)}{p(x_i | \mu_1)}$$



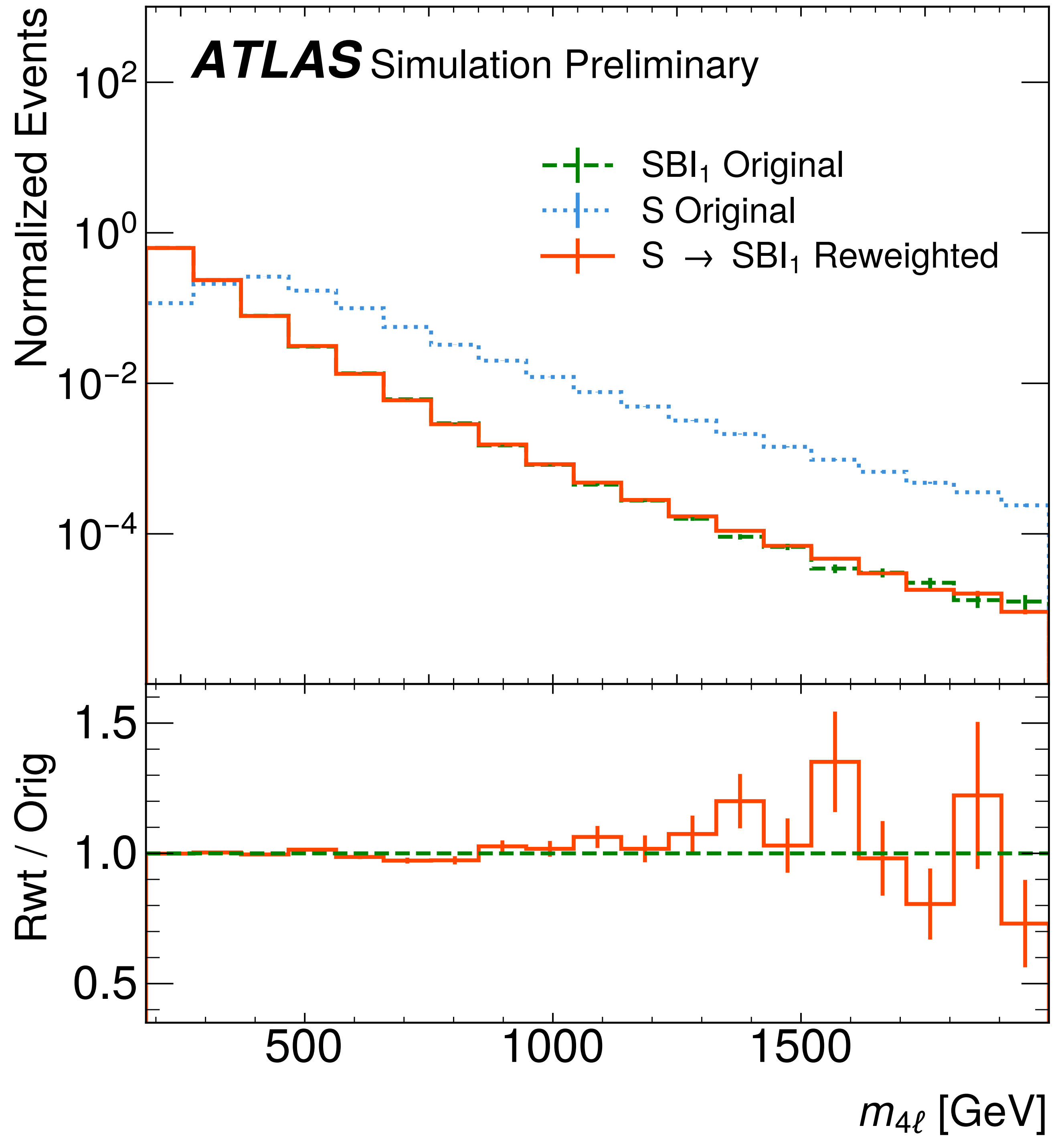
Already estimated using an ensemble of networks

ATLAS methods note: CDS

Re-weight closures

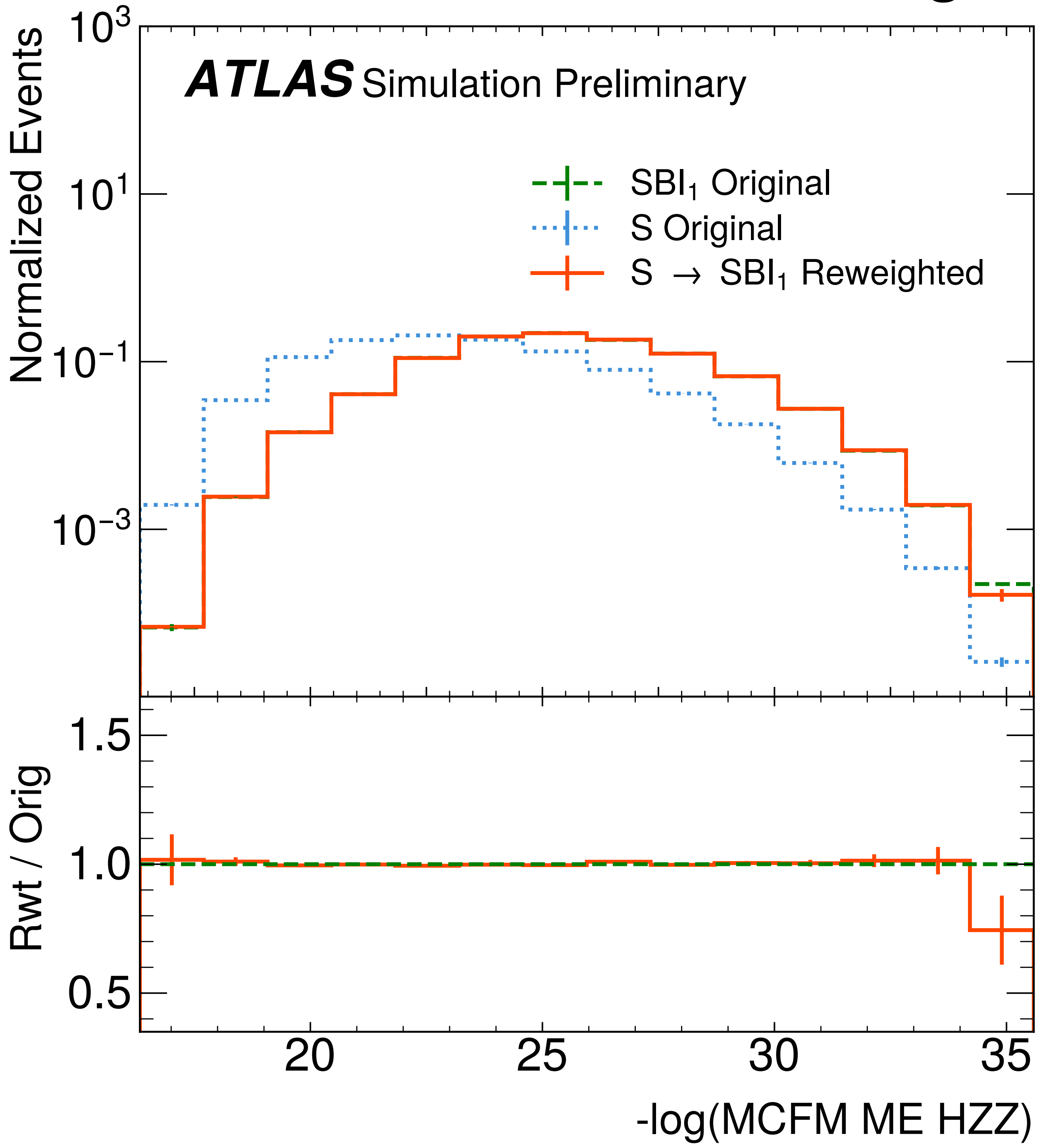
Source
Target
RW

Variable used in training



m_{4l}

High-level variable never used in training



Matrix-Element-based Observable (ggF from MCFM)

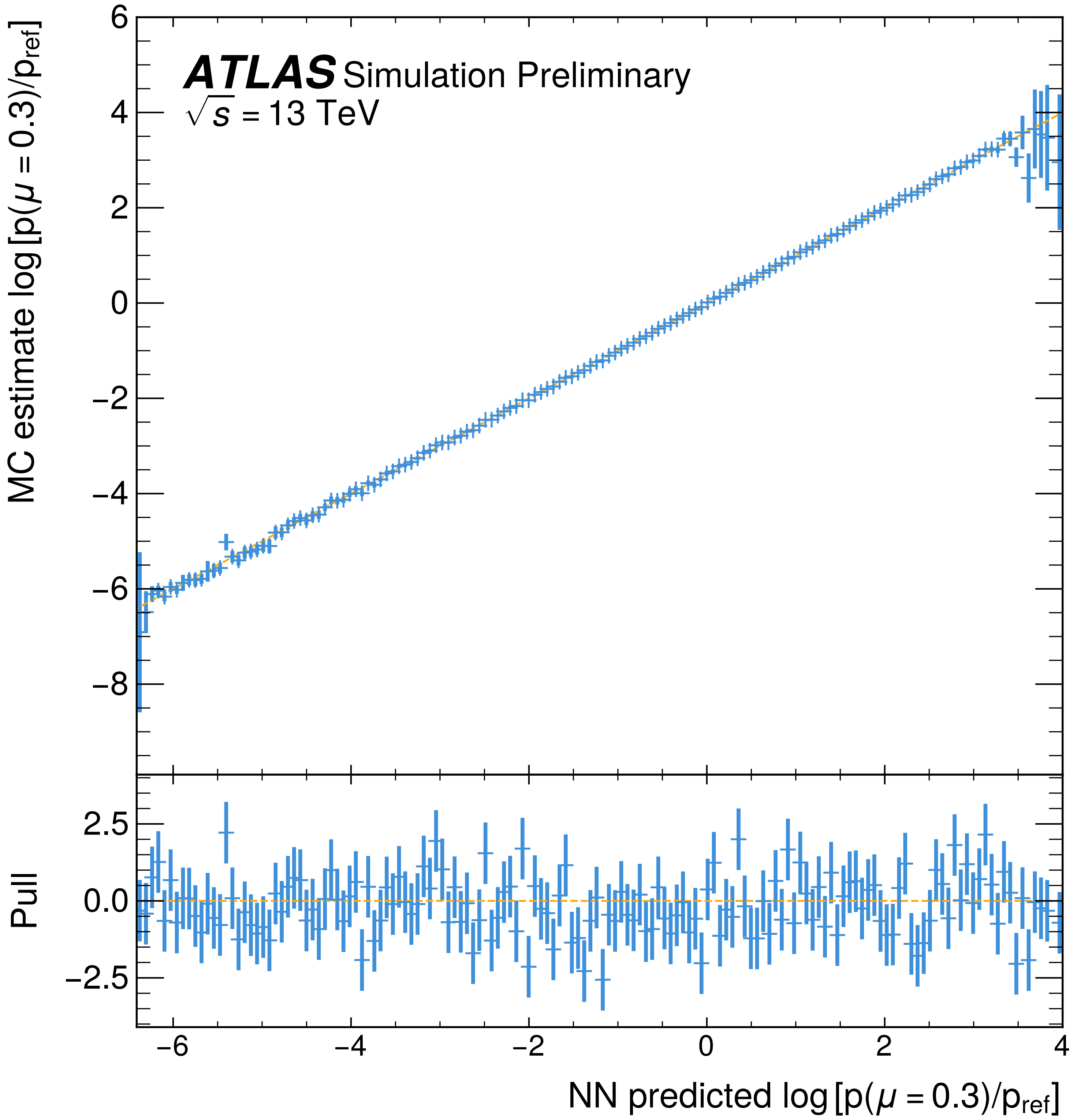
High-Dim Classifier Test:
Train independent classifier on RW vs Target, AUC=0.5 ⇒ LRs well estimated

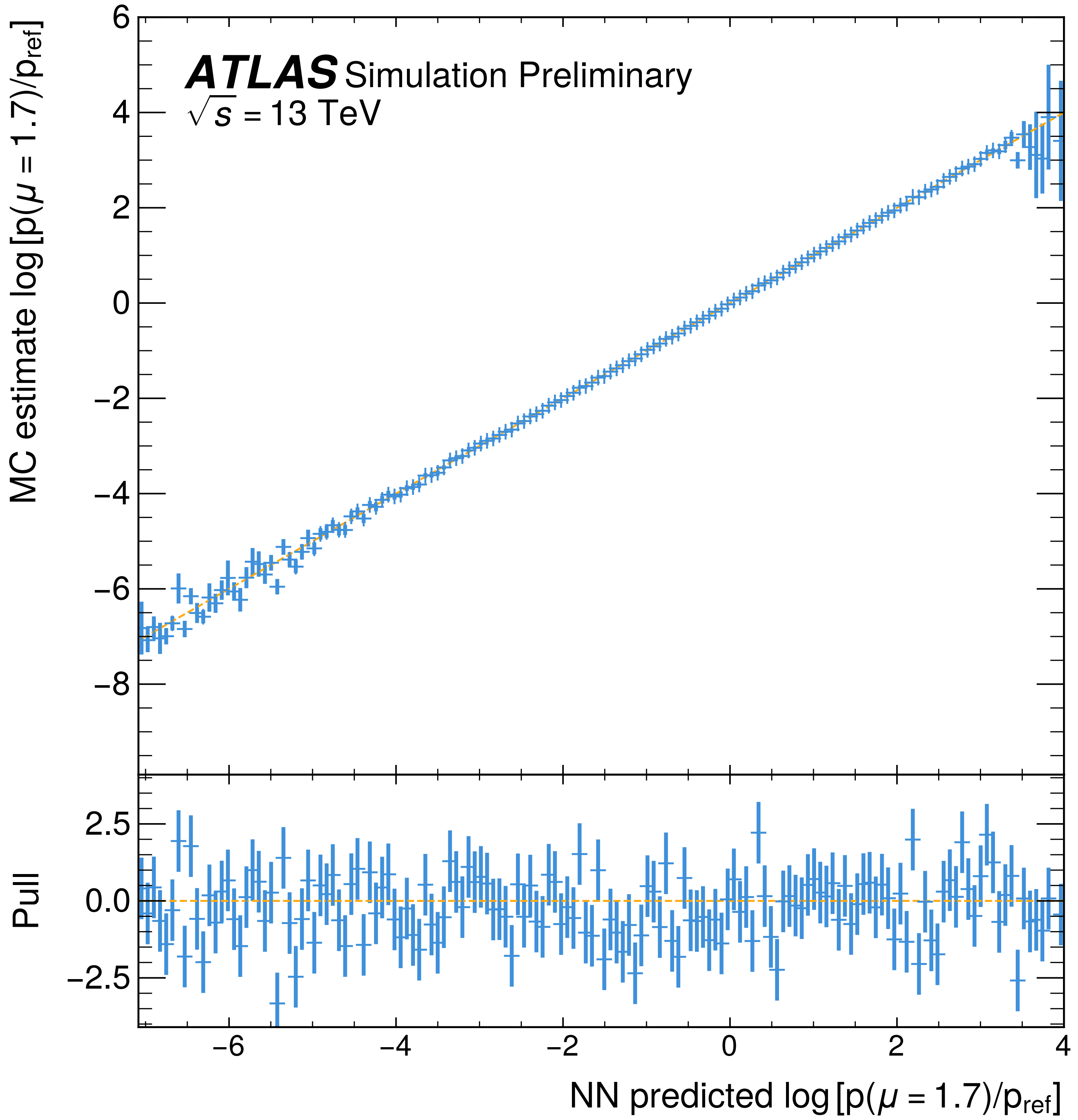
Calibration curves of probability density ratios

$$\frac{p_{\mu=0.3}(x_i)}{p_{ref}(x_i)}$$

$$\frac{p_{\mu=1.7}(x_i)}{p_{ref}(x_i)}$$

Binned estimate

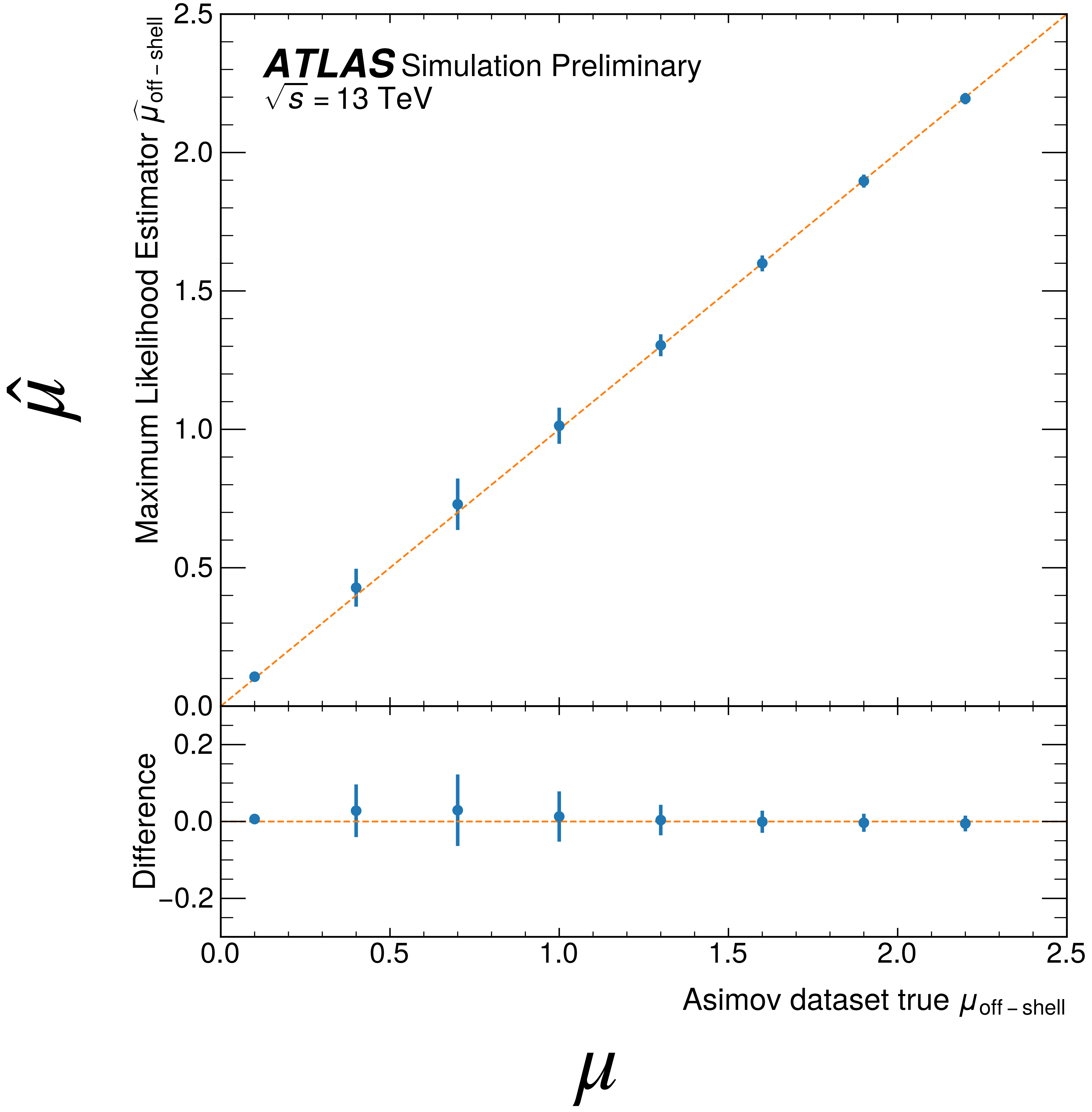




Ensemble prediction

Ensemble prediction

Testing full analysis on samples from different values of μ



No bias: Method recovers correct value of μ on average

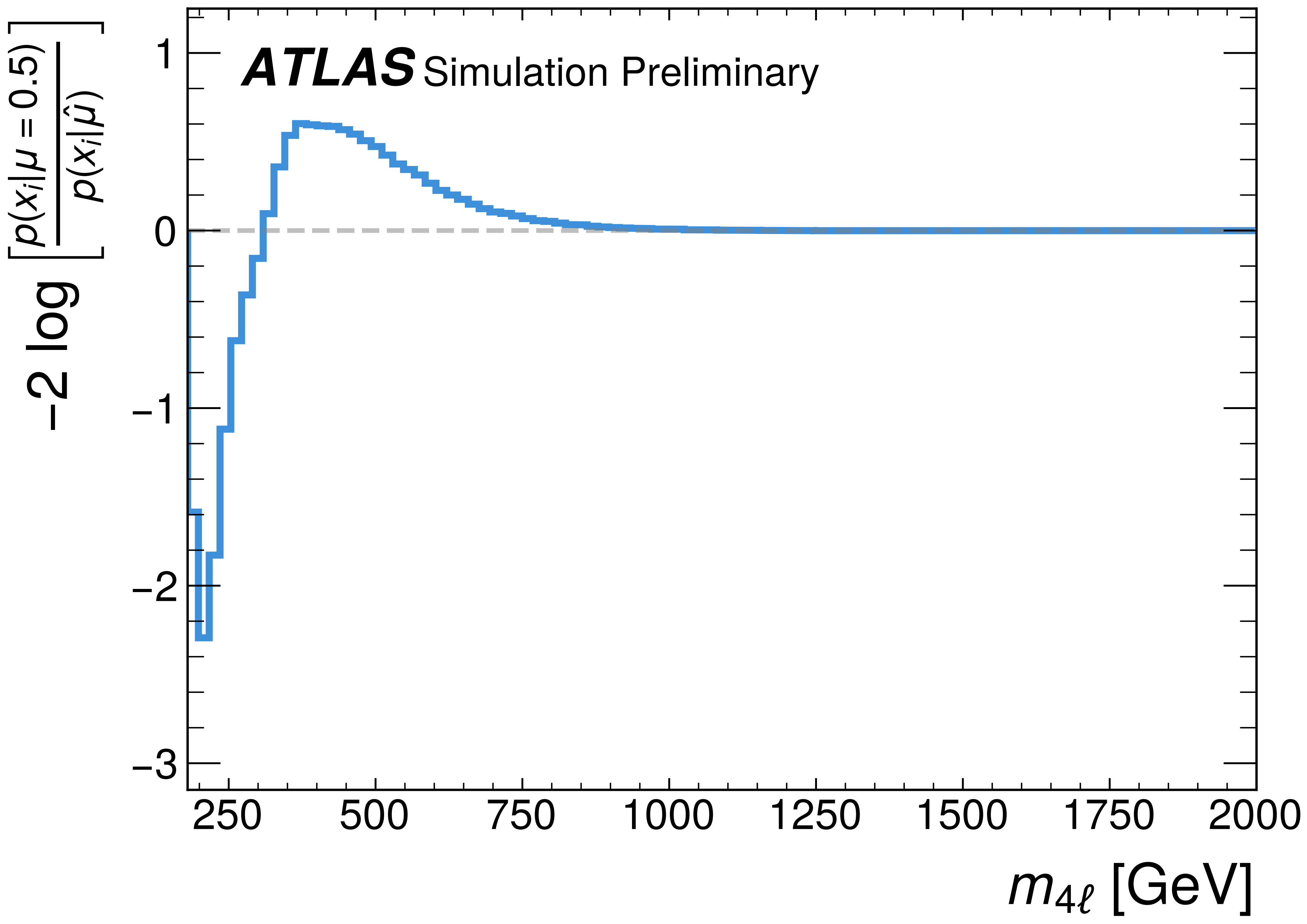
(Correct value when tested on the median 'Asimov dataset')

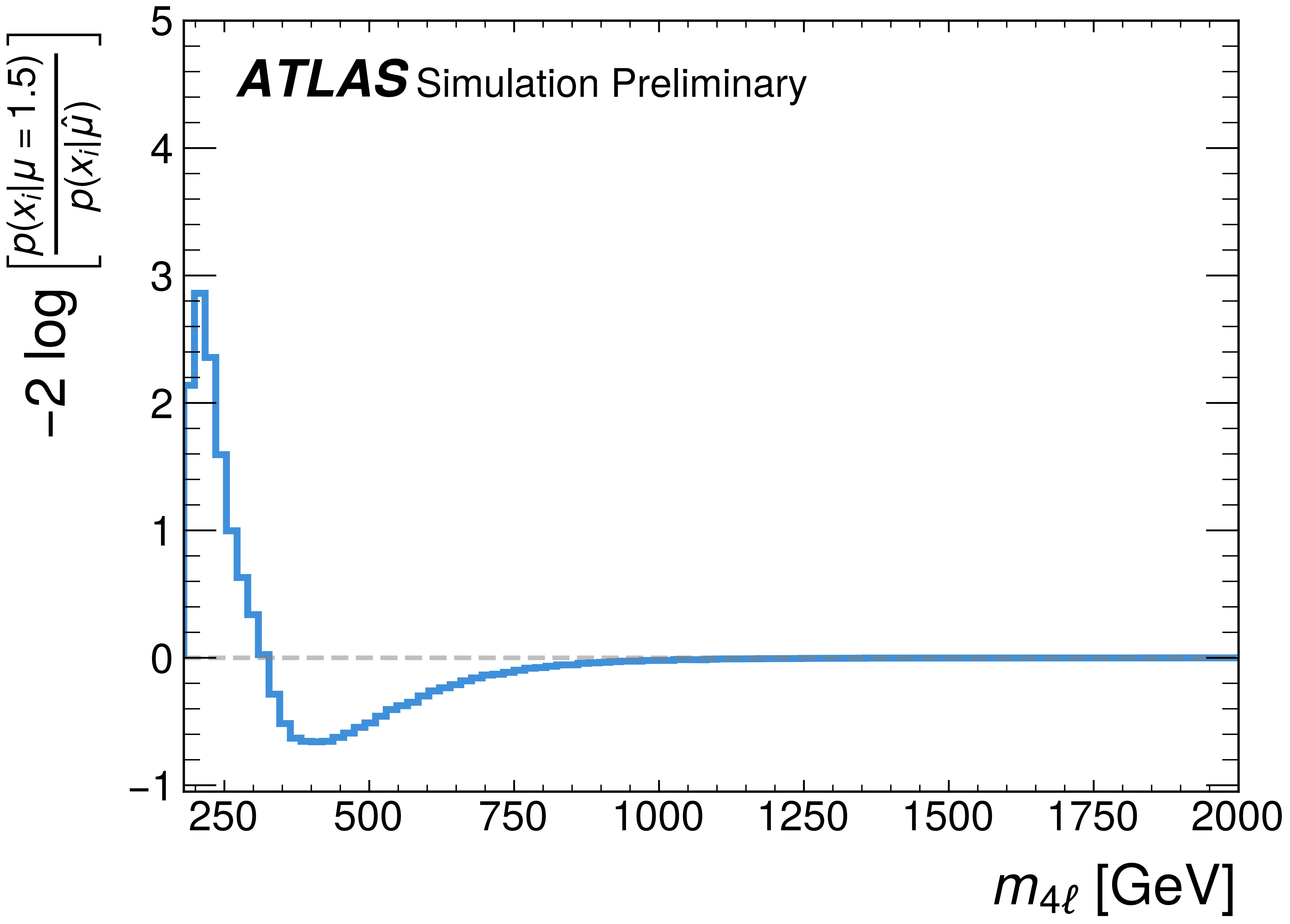
And many more diagnostics (see backup)

Interpretability:
Which phase space favours one hypothesis over another?

$$-2 \cdot log \frac{P(x_i | \mu = 0.5)}{P(x_i | \mu = 1)}$$

$$-2 \cdot log \frac{P(x_i | \mu = 1.5)}{P(x_i | \mu = 1)}$$





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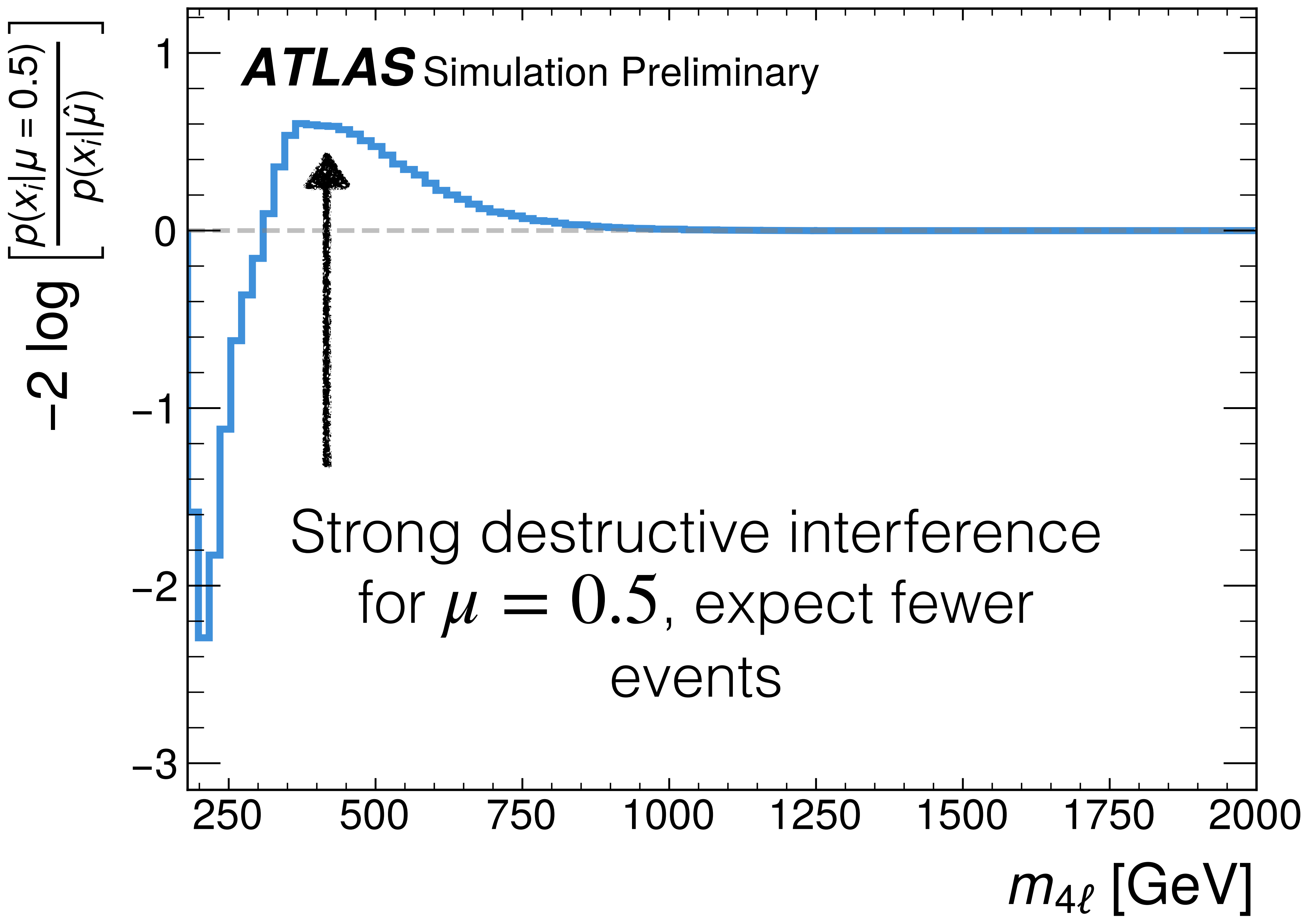

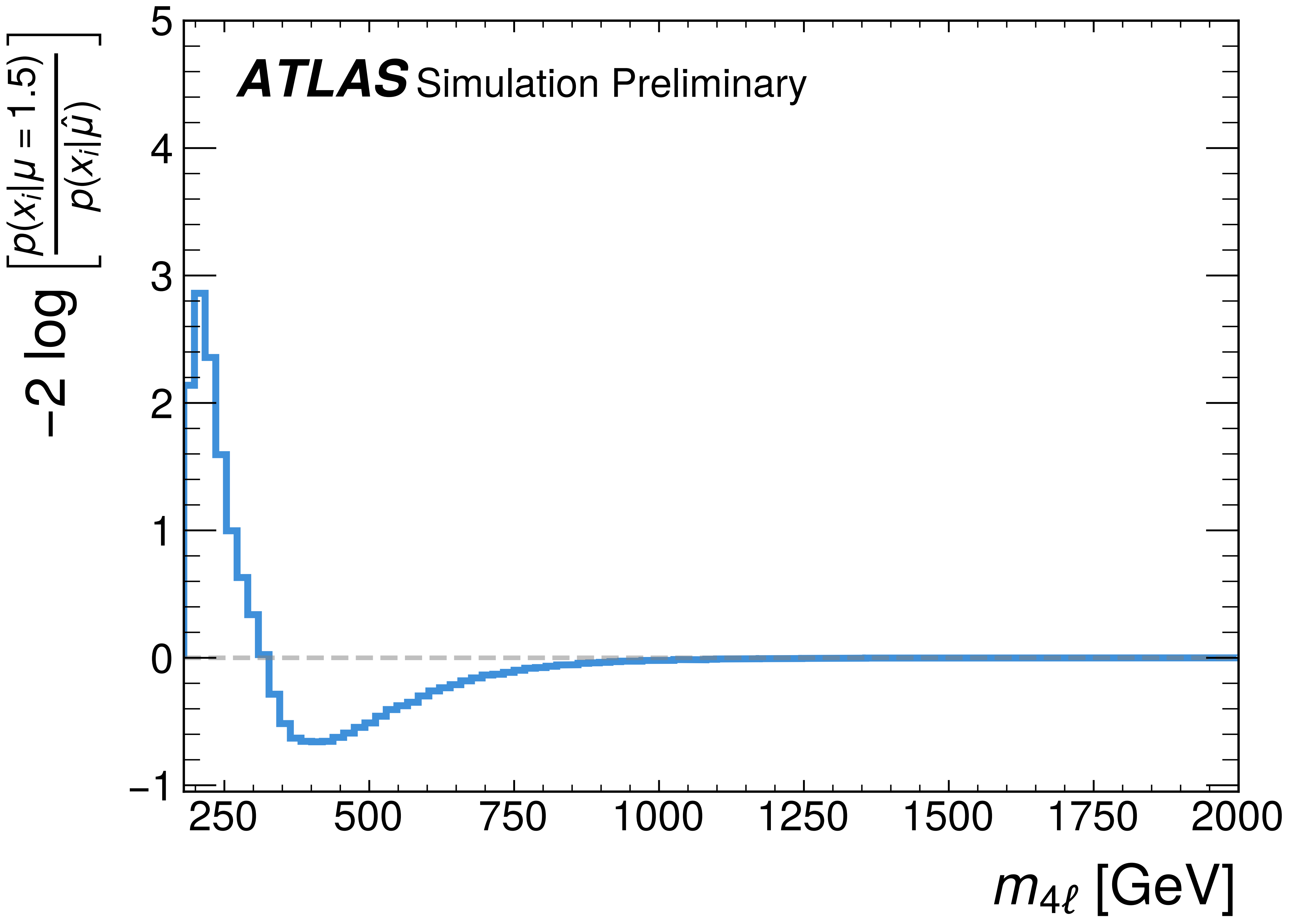

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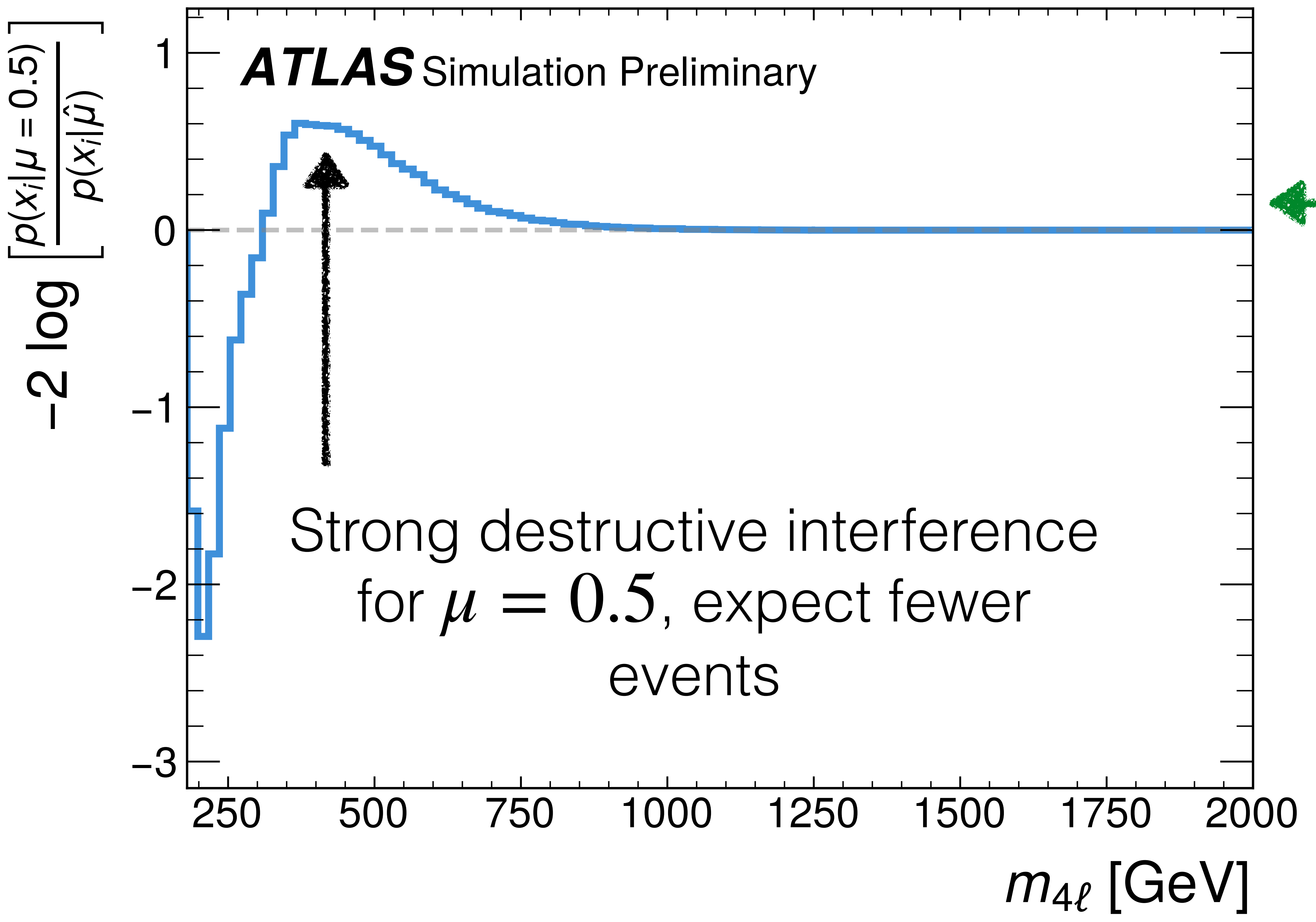

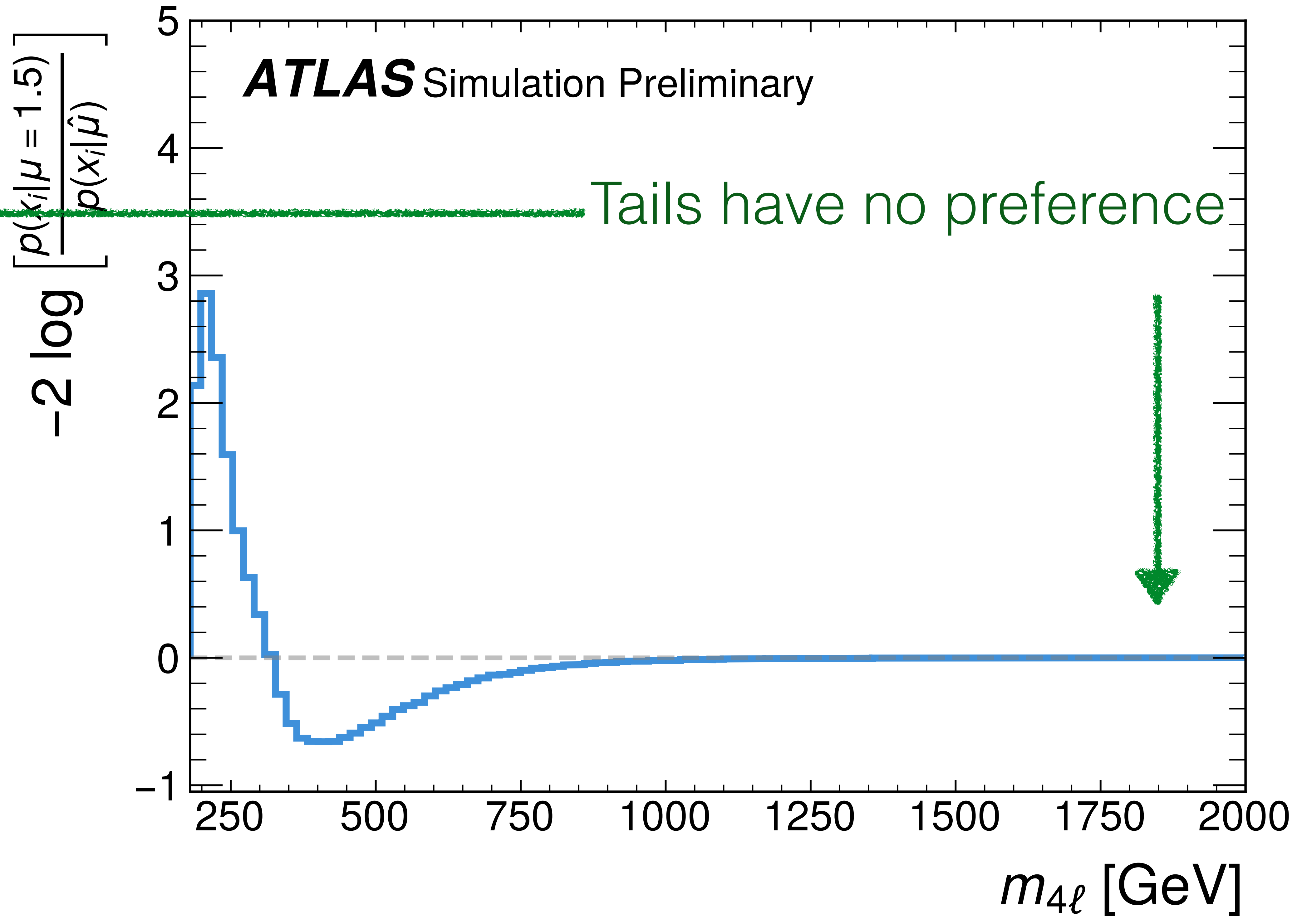

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- ✓ Robustness: Design and validation
- ‣ Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- • Neyman Construction: Throwing toys in a per-event analysis

Systematic uncertainties

Experimental uncertainties:

Eg. Inaccuracies in the calibration of our detector

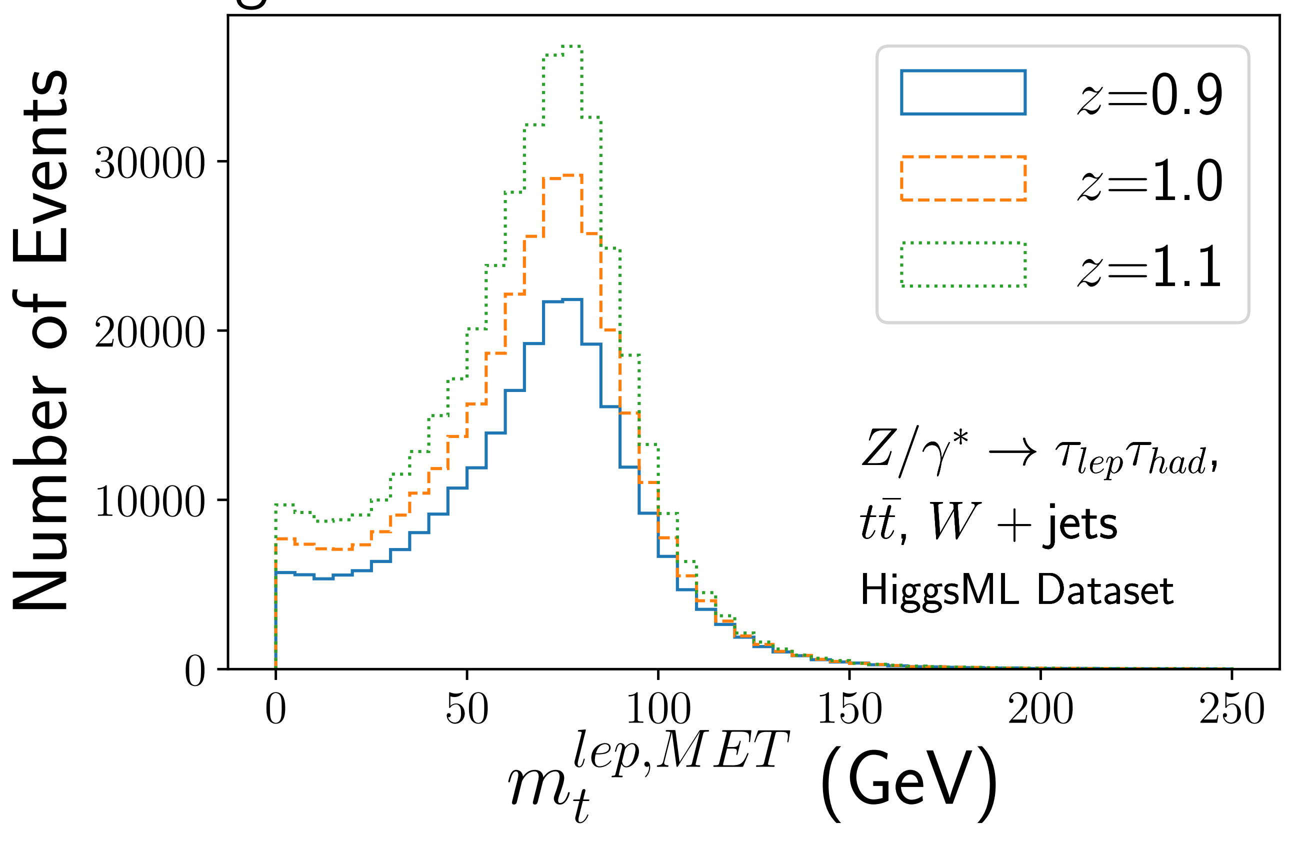


Image: arXiv:2105.08742

Theory uncertainties:

Eg. Inability to compute QFT to infinite order

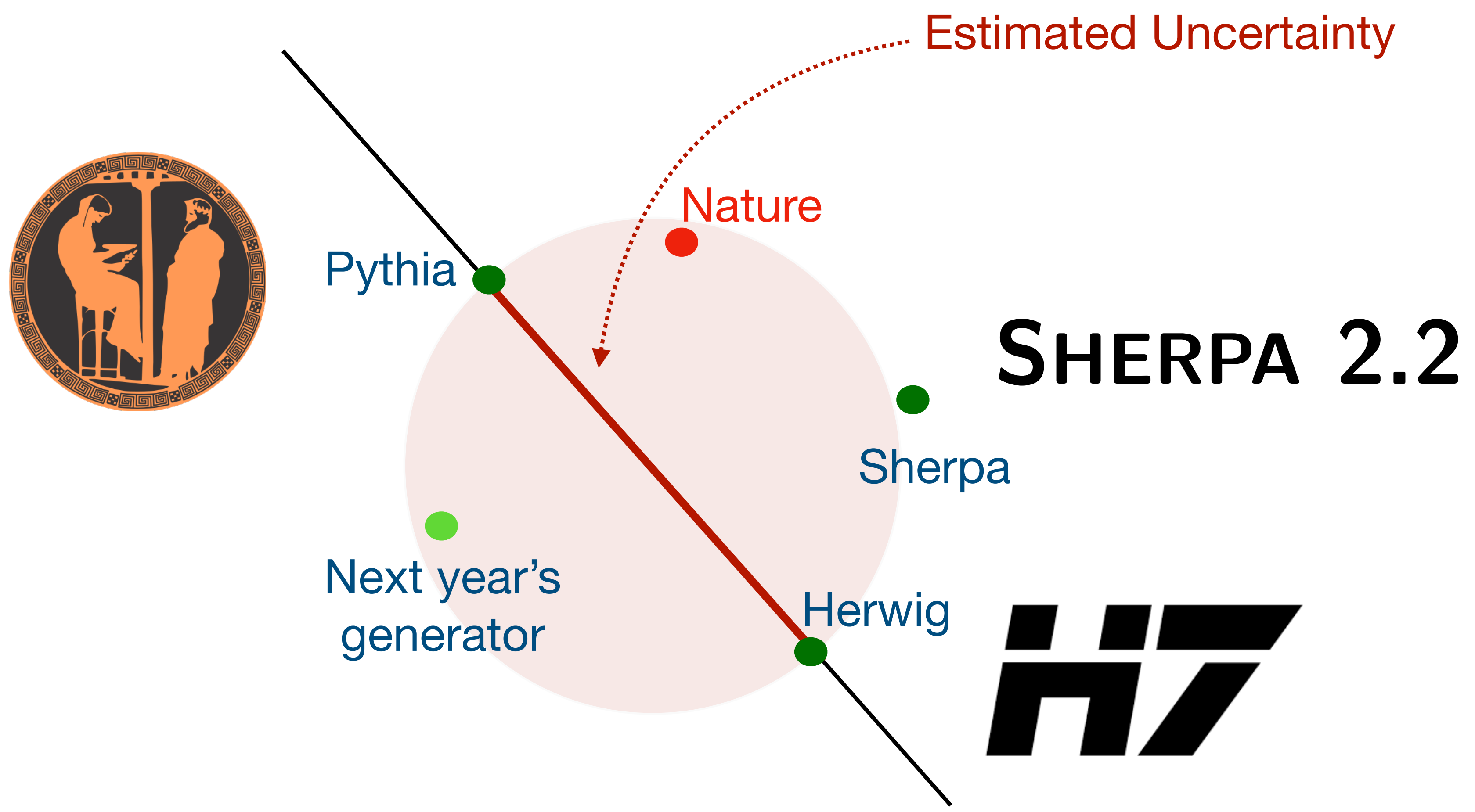


Image: arXiv:2109.08159

Systematic uncertainties

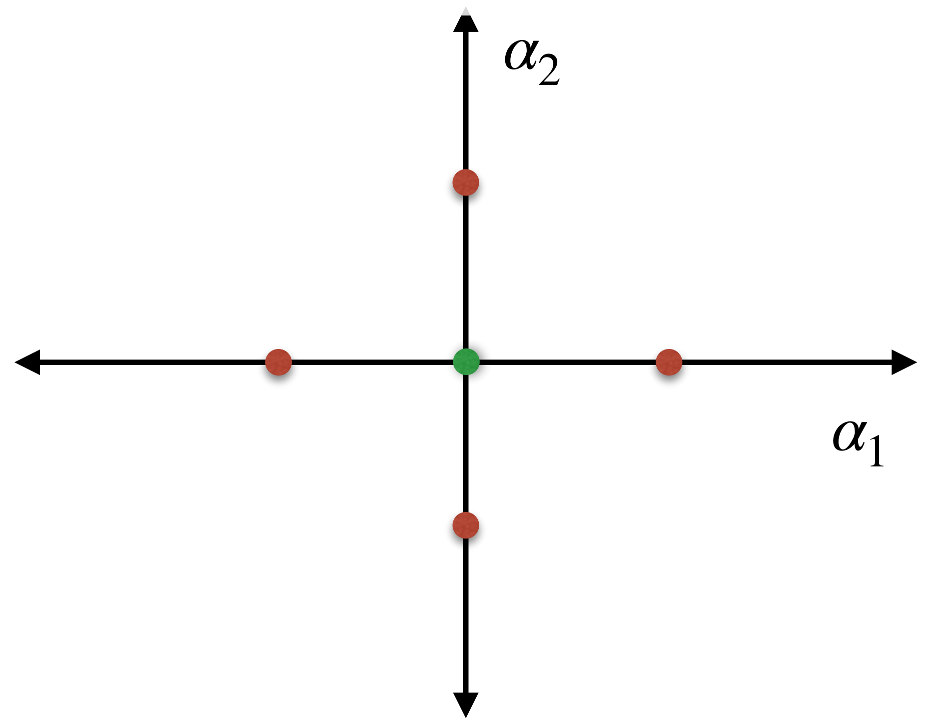
Experimental uncertainties:
Eg. Inaccuracies in the calibration of our detector

Image: arXiv:2105.08742

Theory uncertainties:
Eg. Inability to compute QFT to infinite order

Image: arXiv:2109.08159

- We only have simulations at 3 variations of each nuisance parameter α_k



Known interpolation strategies

See formula used in backup

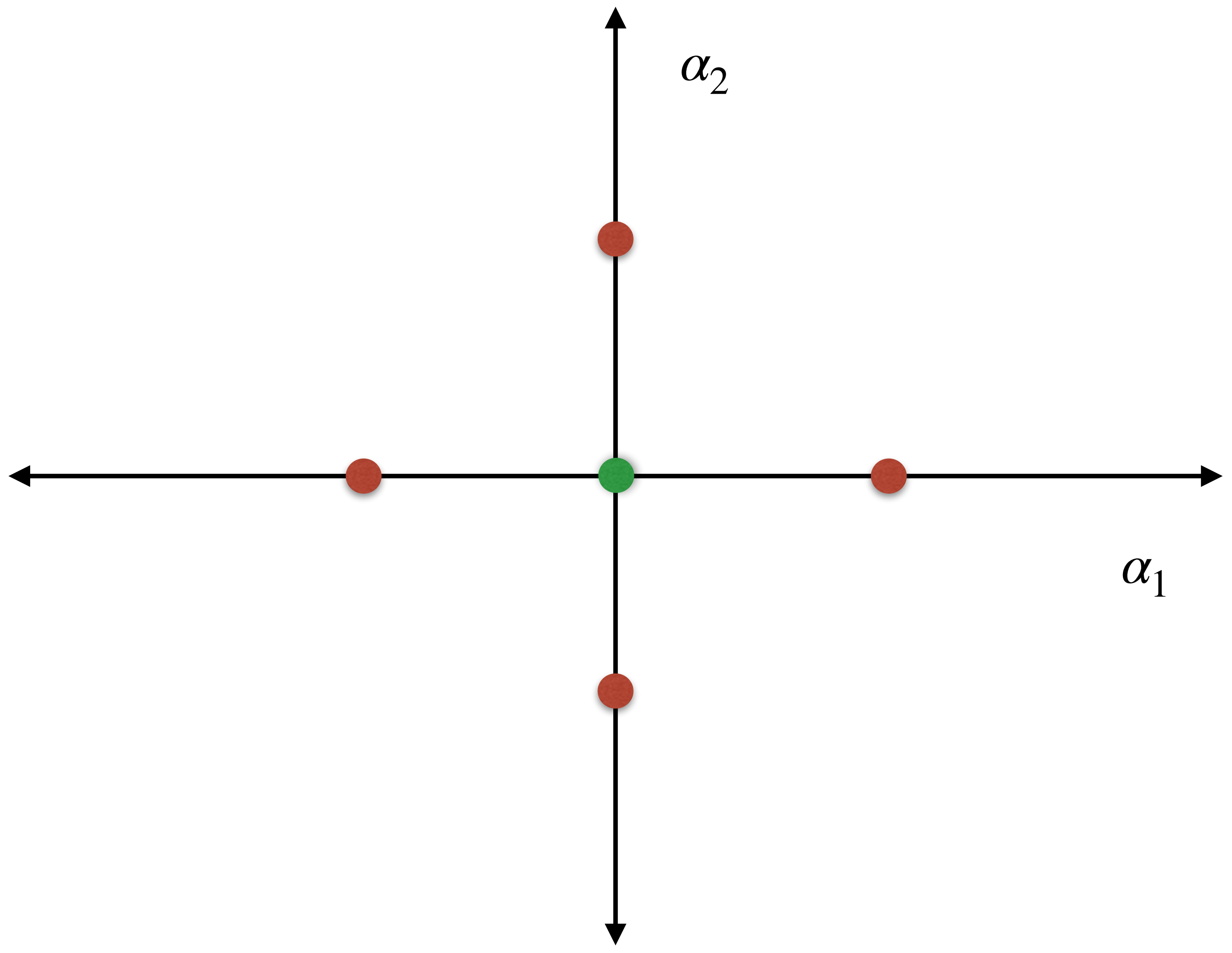
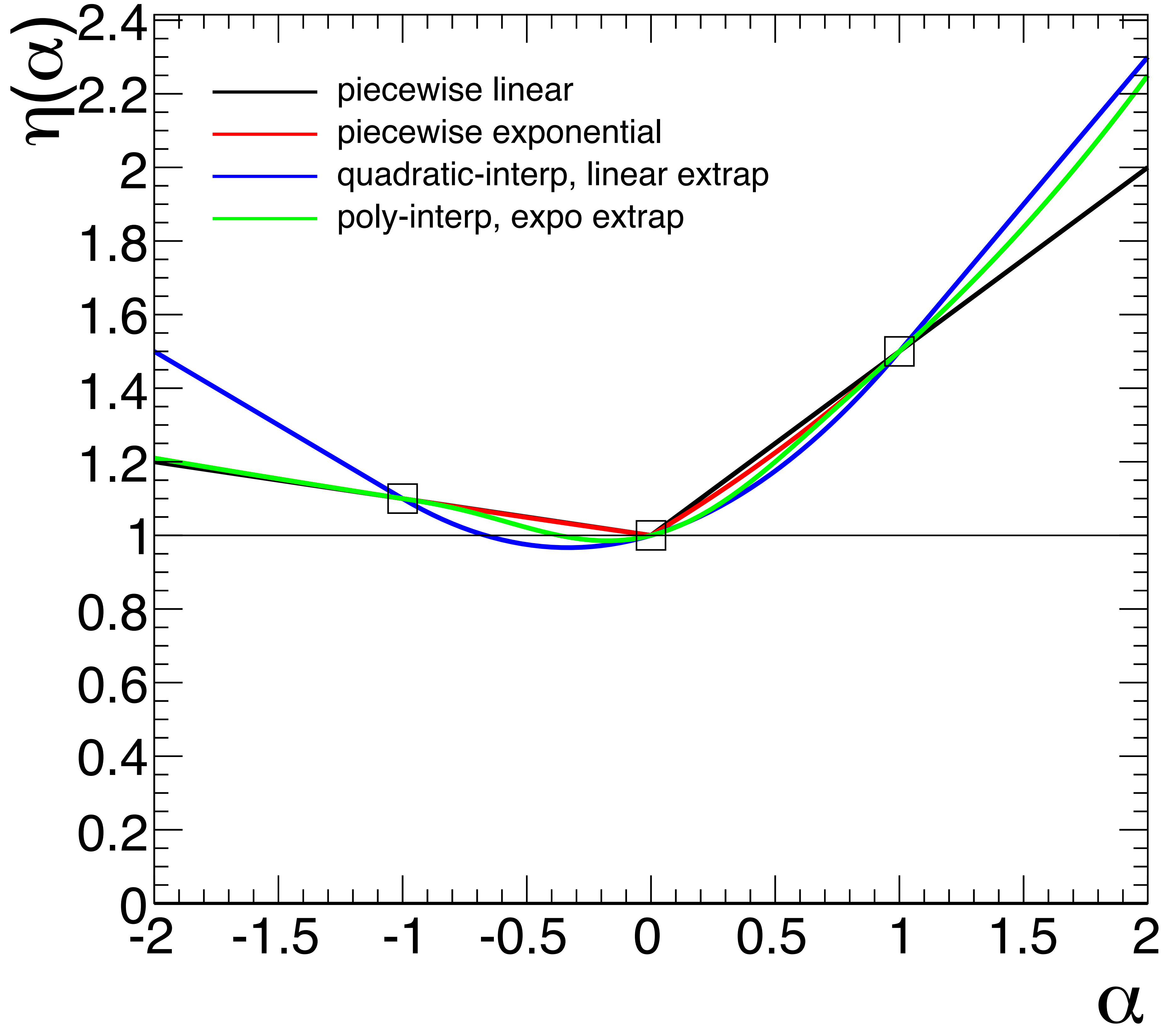


Image: arXiv:1503.07622

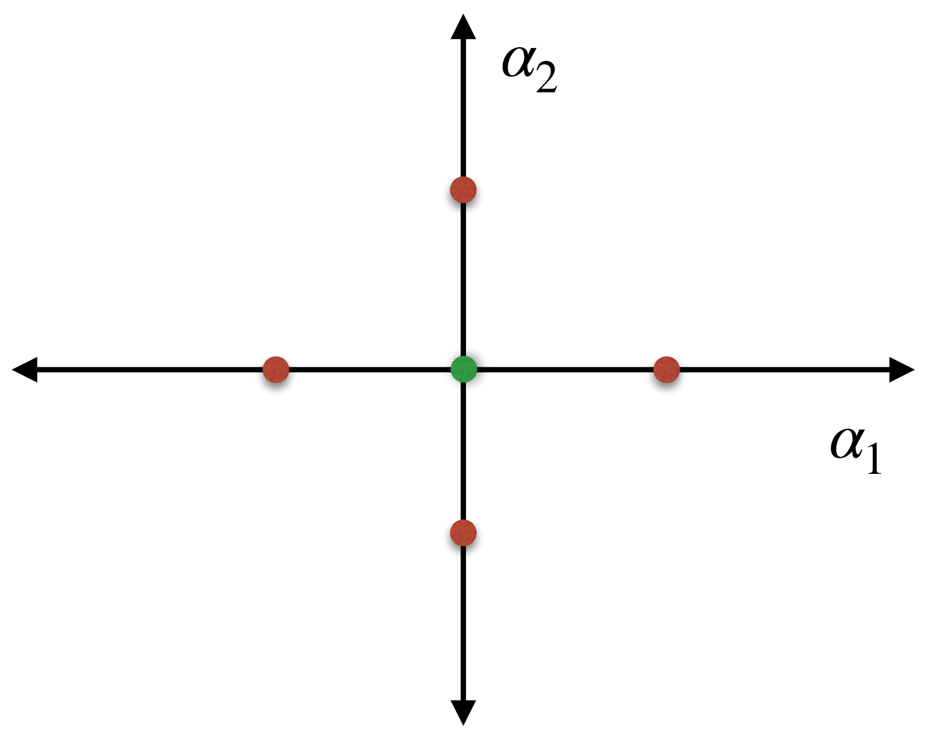


⇒ Combine these traditional interpolation with neural network estimation of per-event likelihood ratios

Probability density ratio including nuisance parameters (α)

x_i is one individual event

$$\frac{p(x_i \mid \mu, \alpha)}{p_{ref}(x_i)} =$$

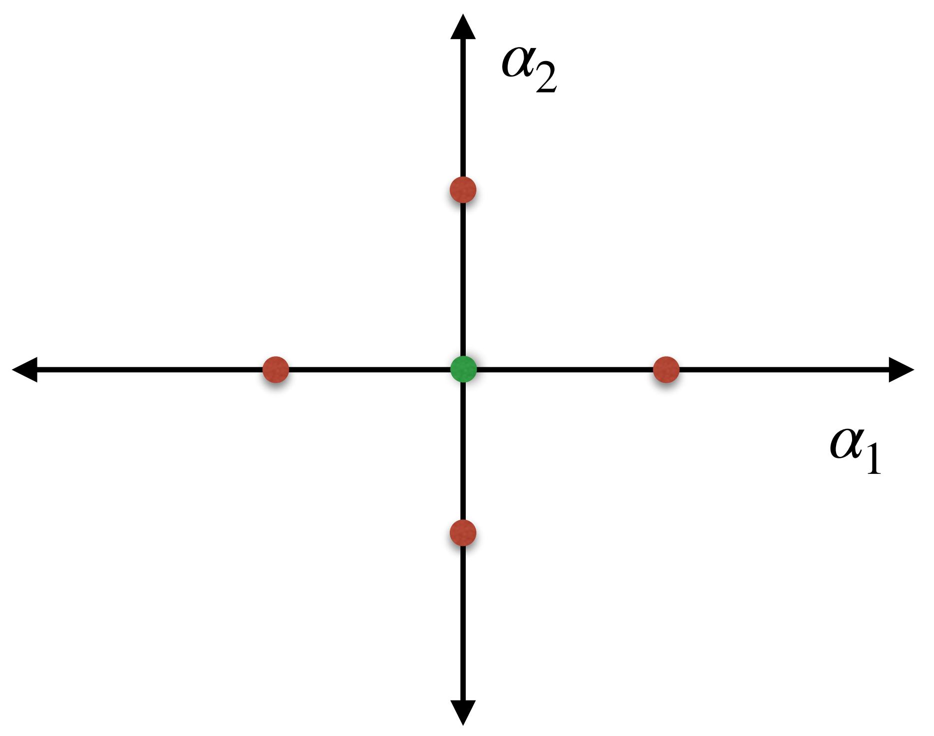


See details of vertical interpolation for $G_j(\alpha_k), g_j(x_i, \alpha_k)$

Probability density ratio including nuisance parameters (α)

x_i is one individual event

$$\frac{p(x_i \,|\, \mu, \alpha)}{p_{ref}(x_i)} = \frac{1}{\nu(\mu, \alpha)} \sum_{j}^{C} f_j(\mu) \cdot \nu_j \cdot \frac{p_j(x_i)}{p_{ref}(x_i)} \cdot \prod_{k}^{N_{syst}} G_j(\alpha_k) \cdot g_j(x_i, \alpha_k)$$



$$g_j(x_i, \alpha_k) = \frac{p_j(x_i, \alpha_k)}{p_j(x_i)}$$

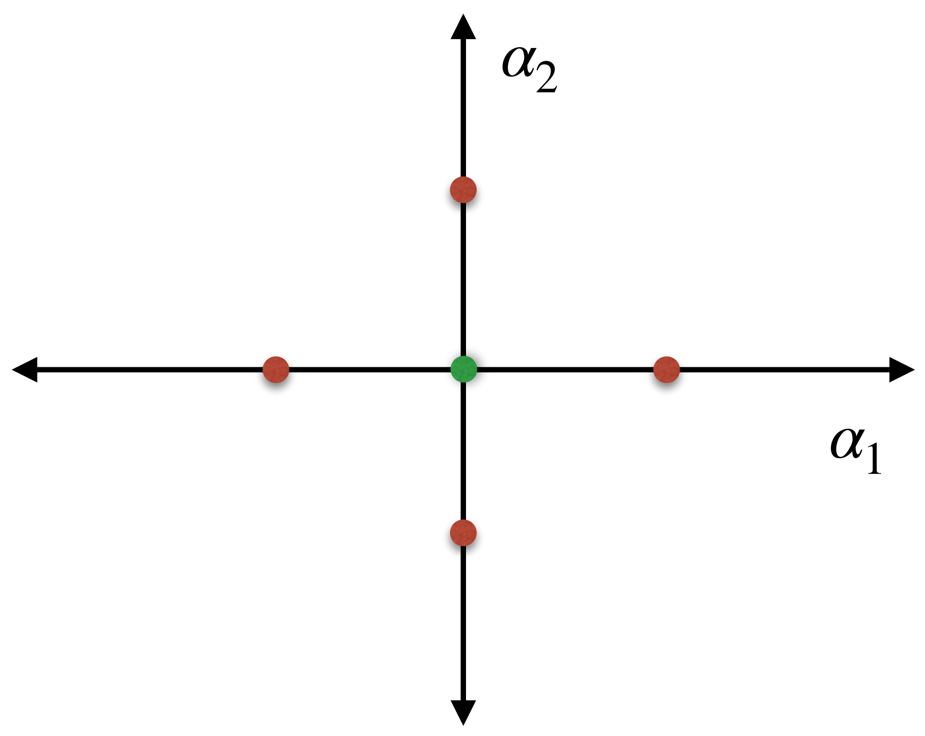
See details of vertical interpolation for $G_j(\alpha_k)$, $g_j(x_i, \alpha_k)$

Probability density ratio including nuisance parameters (α)

x_i is one individual event

$$\frac{p(x_i \,|\, \mu, \alpha)}{p_{ref}(x_i)} = \frac{1}{\nu(\mu, \alpha)} \sum_j^C f_j(\mu) \cdot \nu_j \cdot \frac{p_j(x_i)}{p_{ref}(x_i)} \cdot \prod_k^{N_{syst}} G_j(\alpha_k) \cdot g_j(x_i, \alpha_k)$$

We have this already



$$g_j(x_i, \alpha_k) = \frac{p_j(x_i, \alpha_k)}{p_j(x_i)}$$

See details of vertical interpolation for $G_j(\alpha_k)$, $g_j(x_i, \alpha_k)$

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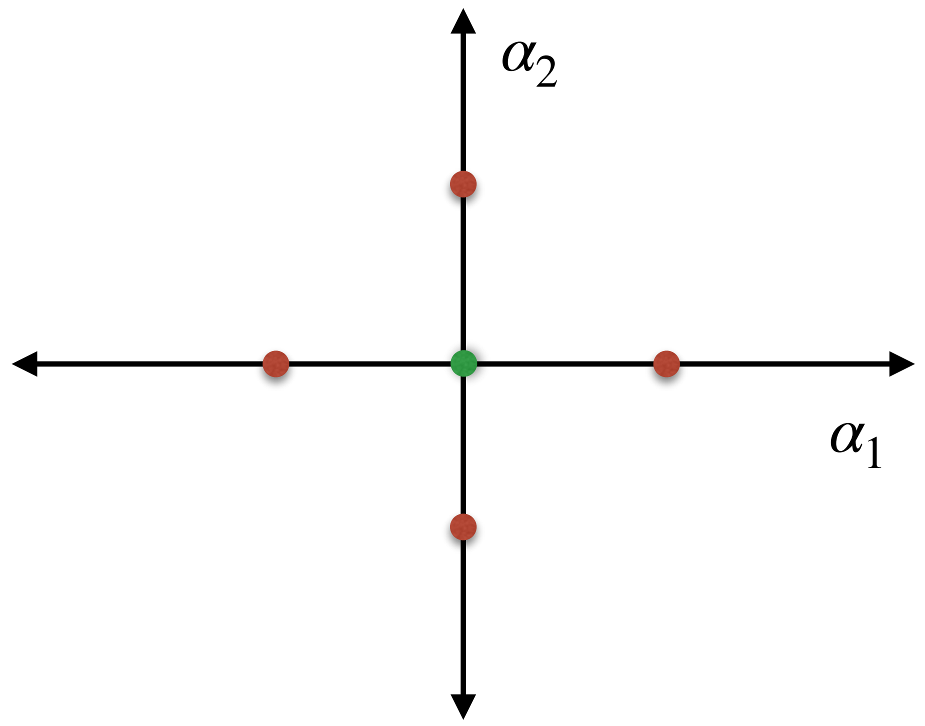
Estimate from simulations and existing interpolation methods



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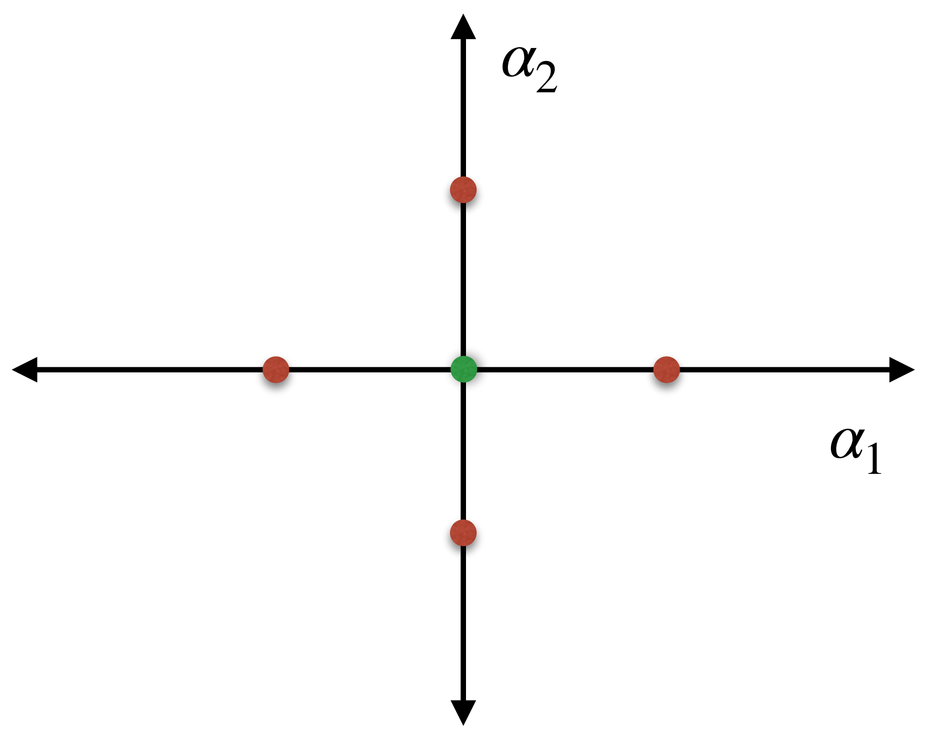
We have this already

Per-event terms estimated using another ensemble of networks and interpolation methods

$$g_j(x_i, \alpha_k) = \frac{p_j(x_i, \alpha_k)}{p_j(x_i)}$$



Estimate from simulations and existing interpolation methods

See details of vertical interpolation for $G_j(\alpha_k)$, $g_j(x_i, \alpha_k)$

Final test statistic

x_i is one individual event

$$\frac{L_{\text{full}}(\mu, \alpha|\mathcal{D})}{L_{\text{ref}}(\mathcal{D})} = \text{Pois}(N_{\text{data}}|\nu(\mu, \alpha)) \prod_{i}^{N_{\text{data}}} \frac{p(x_i|\mu, \alpha)}{p_{\text{ref}}(x_i)} \prod_{k} \text{Gaus}(a_k|\alpha_k, \delta_k)$$

Final test statistic

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From previous slide

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From previous slide

Prod over events

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From previous slide

Rate term

Prod over events

Final test statistic

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From previous slide

Rate term

Prod over events

Constrain term

Final test statistic

x_i is one individual event

$$\frac{L_{\text{full}}(\mu, \alpha|\mathcal{D})}{L_{\text{ref}}(\mathcal{D})} = \text{Pois}(N_{\text{data}}|\nu(\mu,\alpha)) \prod_i^{N_{\text{data}}} \frac{p(x_i|\mu,\alpha)}{p_{\text{ref}}(x_i)} \prod_k \text{Gaus}(a_k|\alpha_k,\delta_k)$$

From previous slide

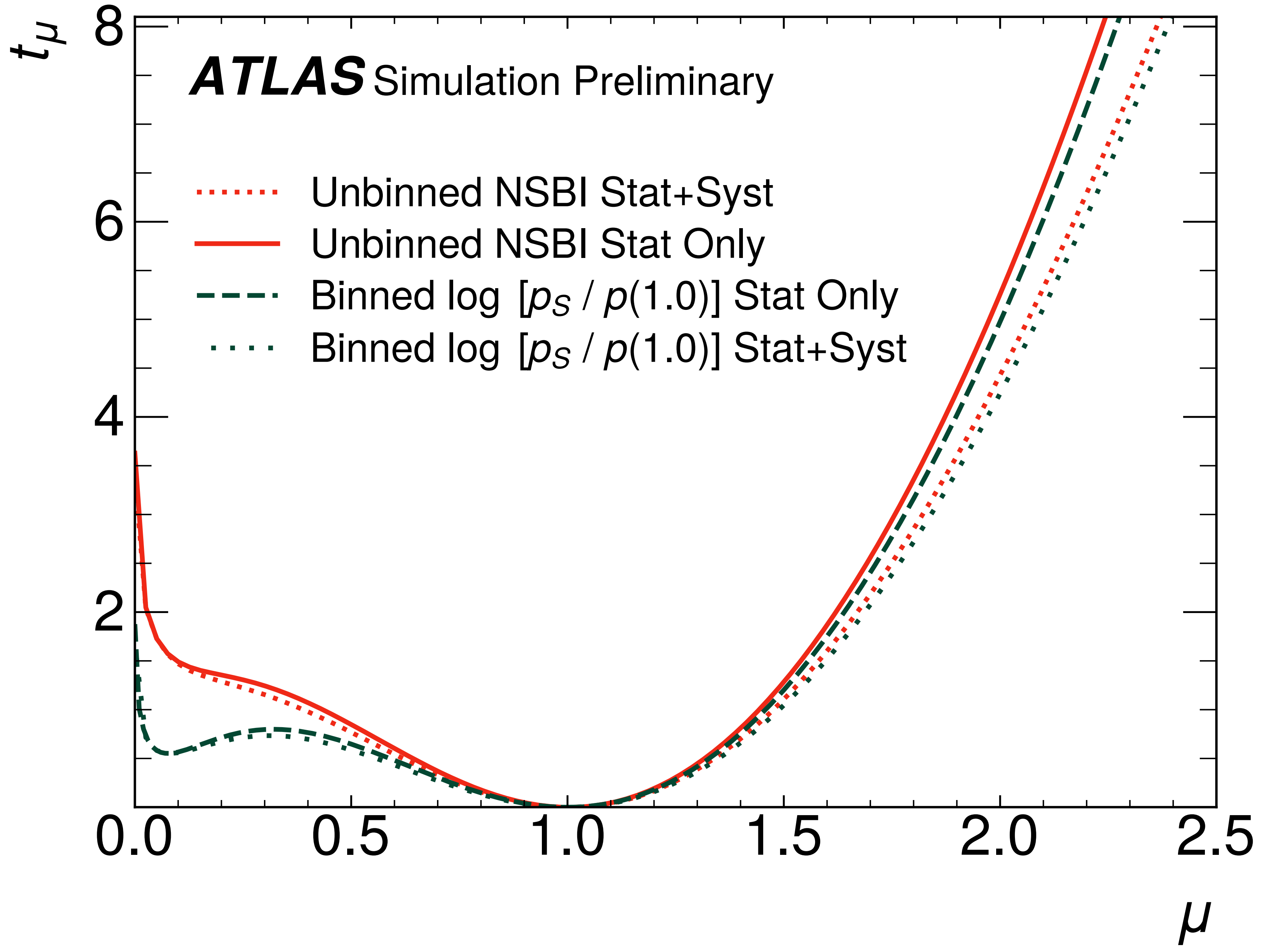
Rate term

Prod over events

Constrain term

Profiling: $$t_\mu = -2\ln\left(\frac{L_{\text{full}}(\mu,\hat{\hat{\alpha}})/L_{\text{ref}}}{L_{\text{full}}(\hat{\mu},\hat{\alpha})/L_{\text{ref}}}\right)$$

This is why we define p_{ref} to be independent of μ



Final test statistic

x_i is one individual event

From previous slide

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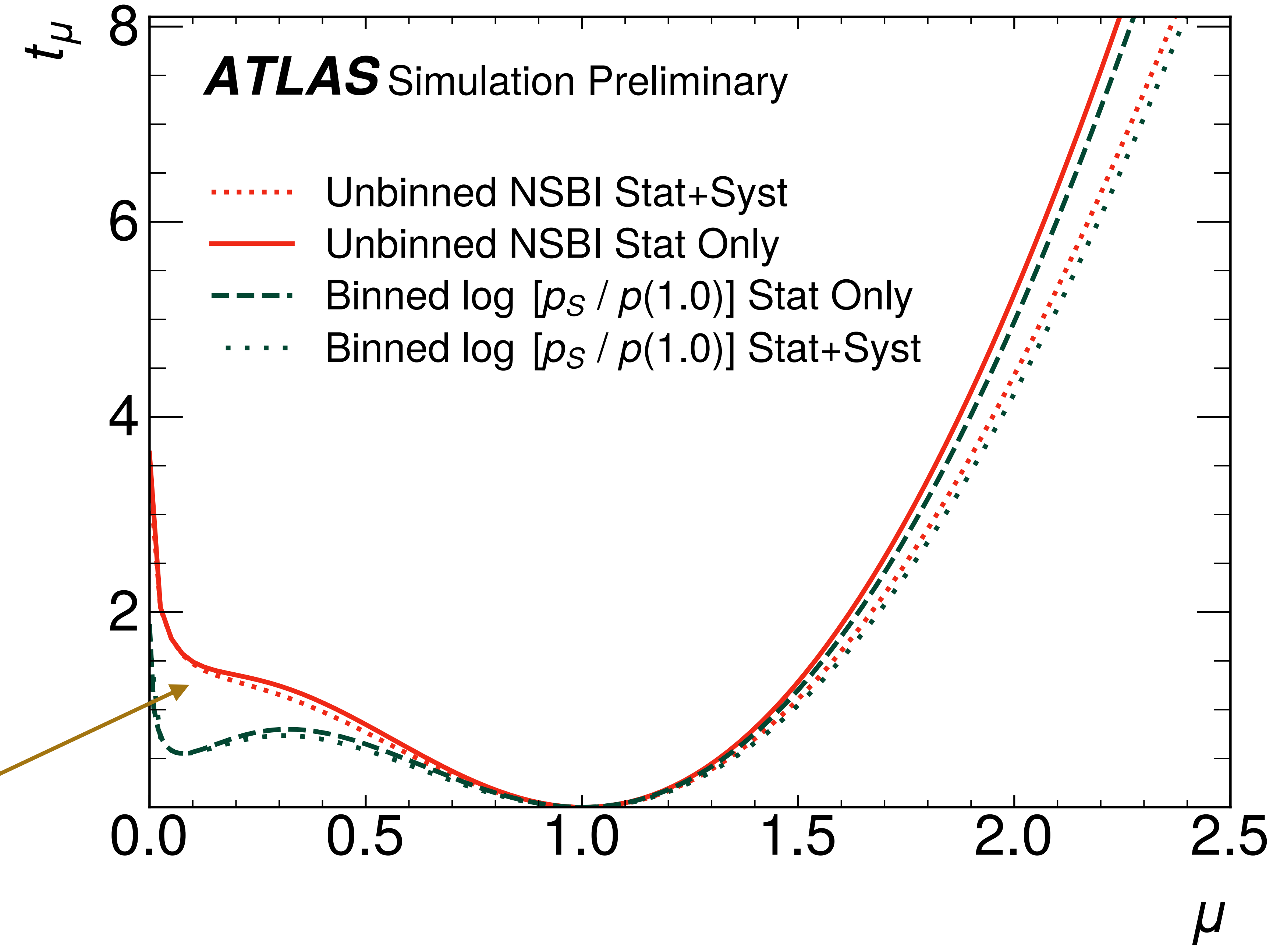

Non-parabolic shape due to non-linear effects from quantum interference

Reference Sample

A combination of signal samples, to ensure there's non-vanishing support entire region of analysis
Does not have to be physical!

$$p_{\mathrm{ref}}(x_i) = \frac{1}{\sum_k \nu_k} \sum_k^{C_{\mathrm{signals}}} \nu_k \cdot p_k(x_i)$$

⇒ In our dataset, $p_{ref}(\,\cdot\,) = p_S(\,\cdot\,)$

Choice of $p_{ref}(\,\cdot\,)$ can be made purely on numerical stability of training, as it drops out in profile step

$$t_\mu = -2\ln\left(\frac{L_{\mathrm{full}}(\mu,\hat{\hat{\alpha}})/\cancel{L_{\mathrm{ref}}}}{L_{\mathrm{full}}(\hat{\mu},\hat{\alpha})/\cancel{L_{\mathrm{ref}}}}\right)$$

Uncertainty from finite training samples

Estimating the variance on mean: Bootstrapping

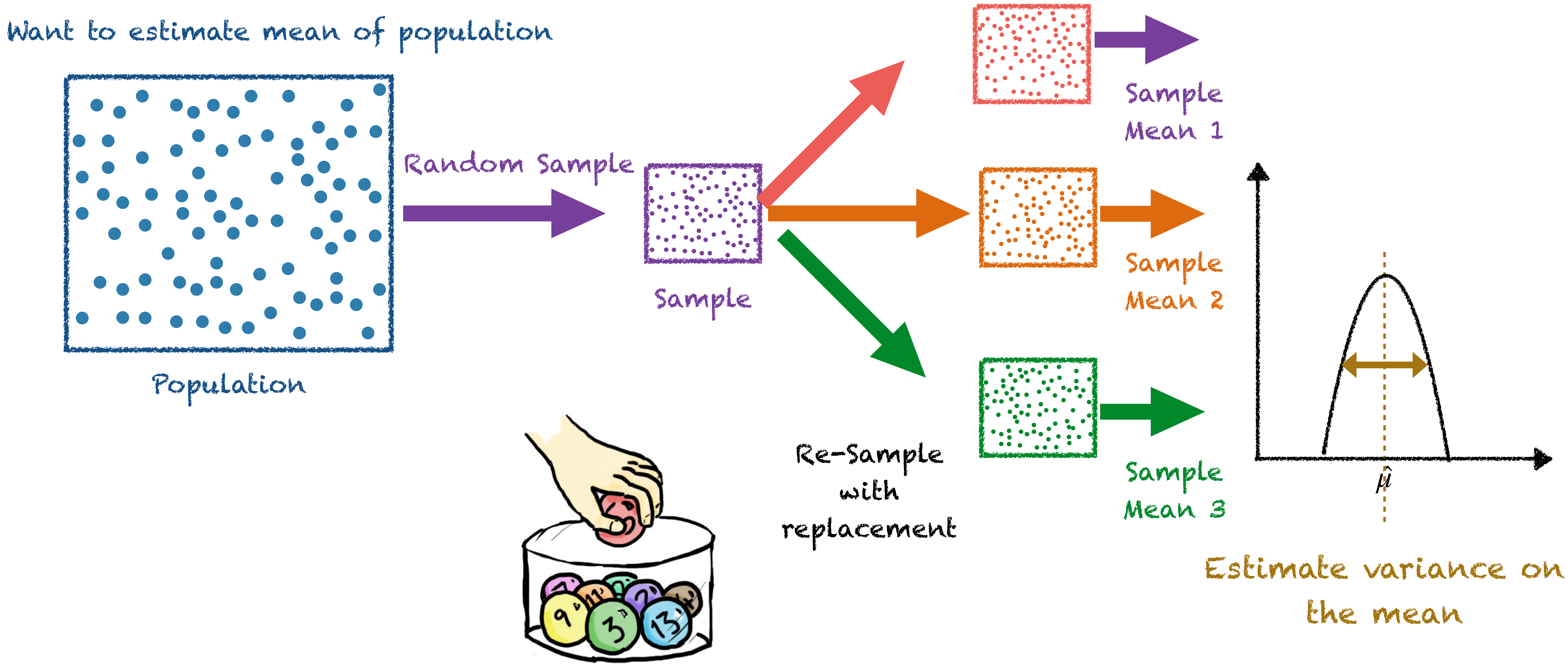

Image: Source

Quantifying uncertainty on estimated density ratio

$$w_i \rightarrow w_i \cdot Pois(1)$$

- Train an ensemble of networks, each on a Poisson fluctuated version of the training dataset
- Ensemble average used as final prediction, estimate the variance on mean from bootstrapped ensembles

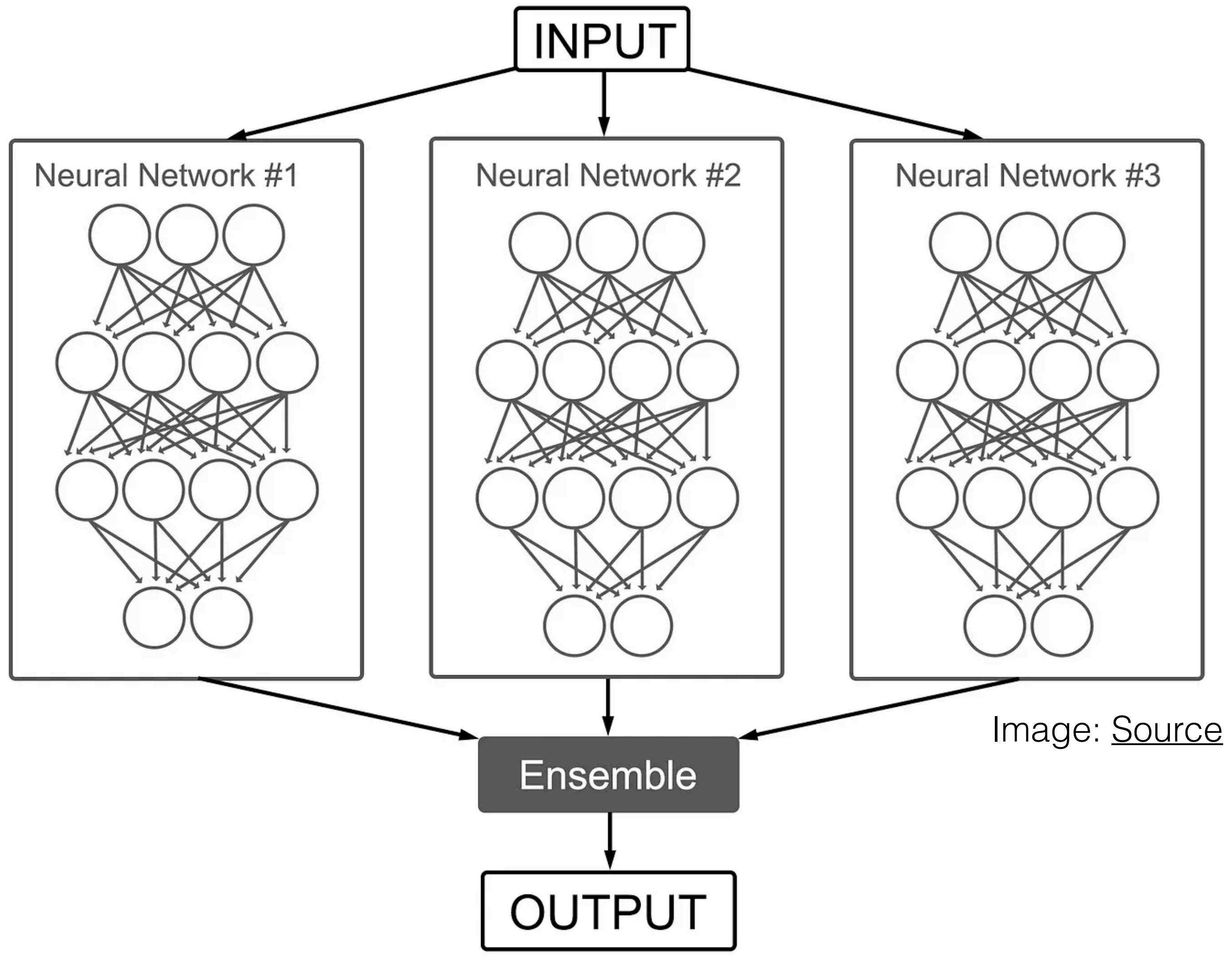

Image: Source

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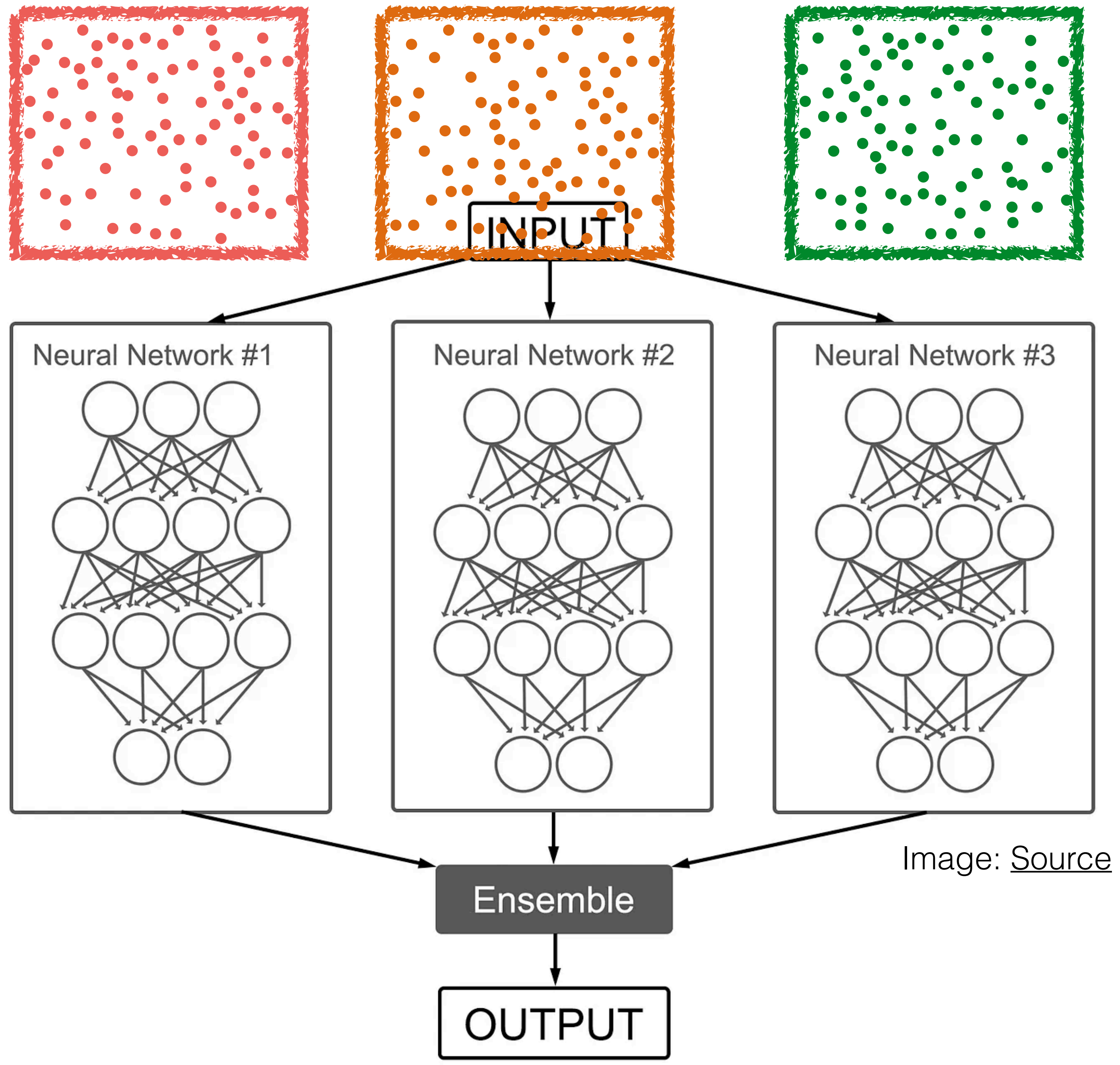

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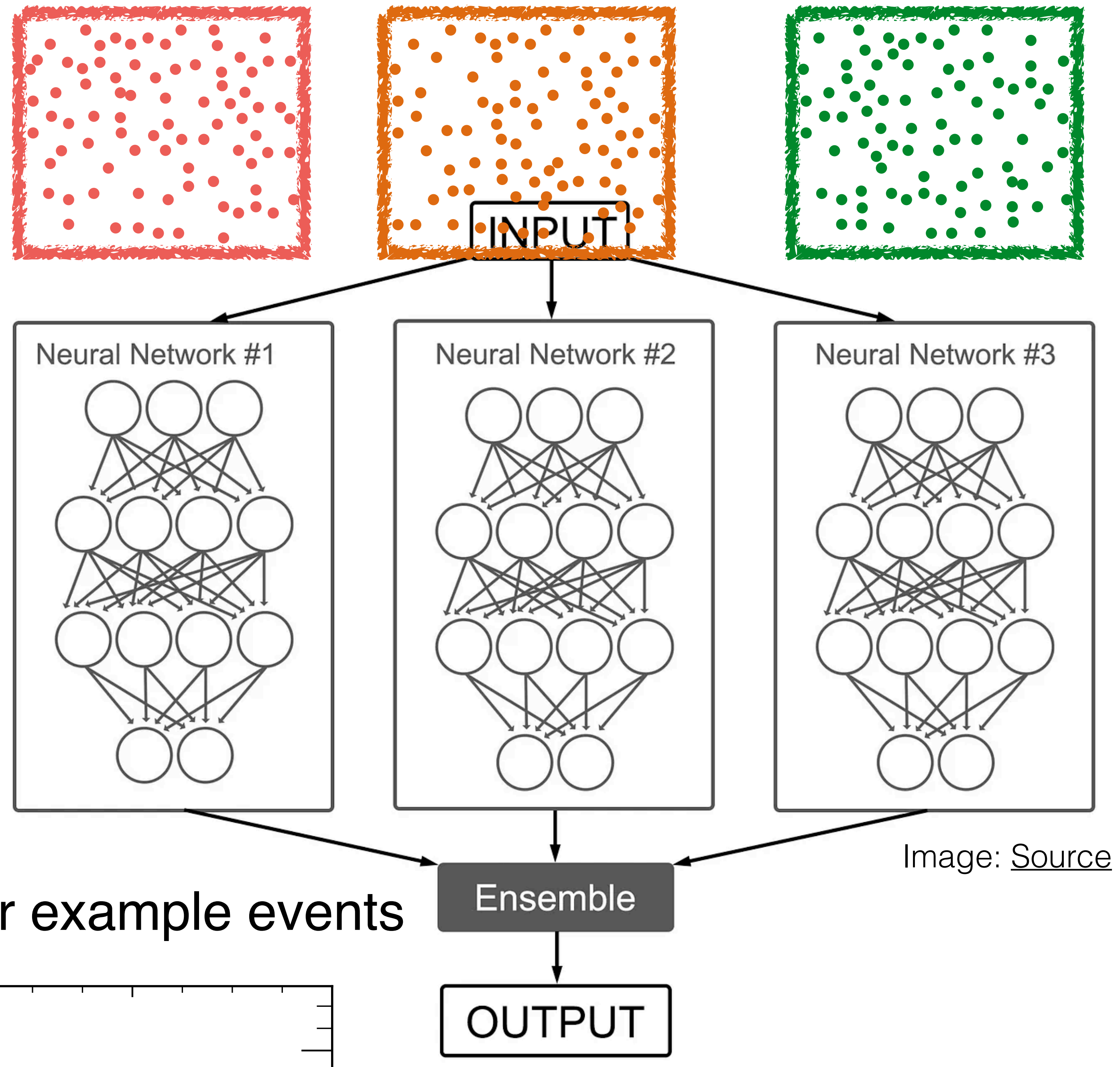

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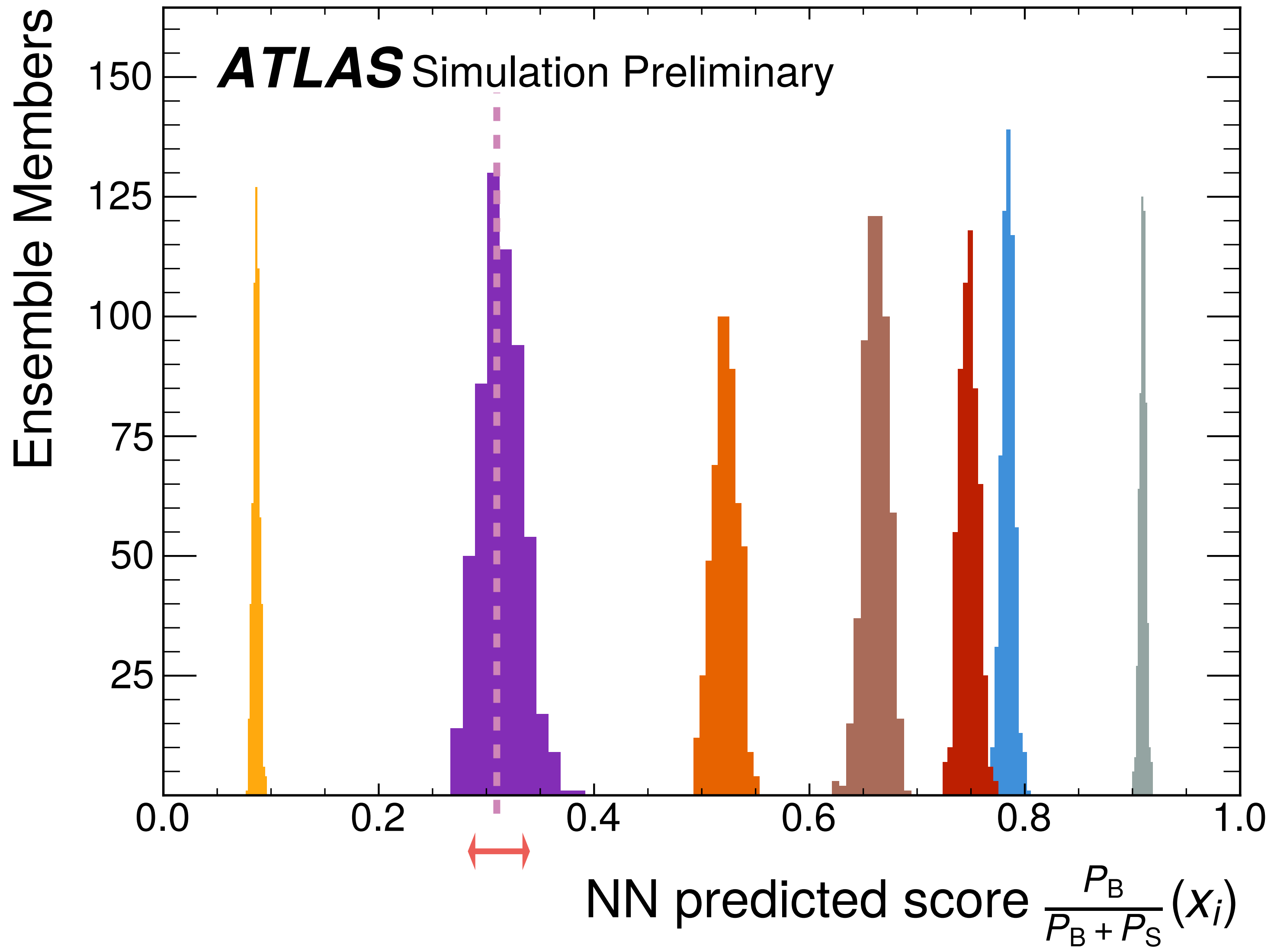
Distribution of NN predictions for example events



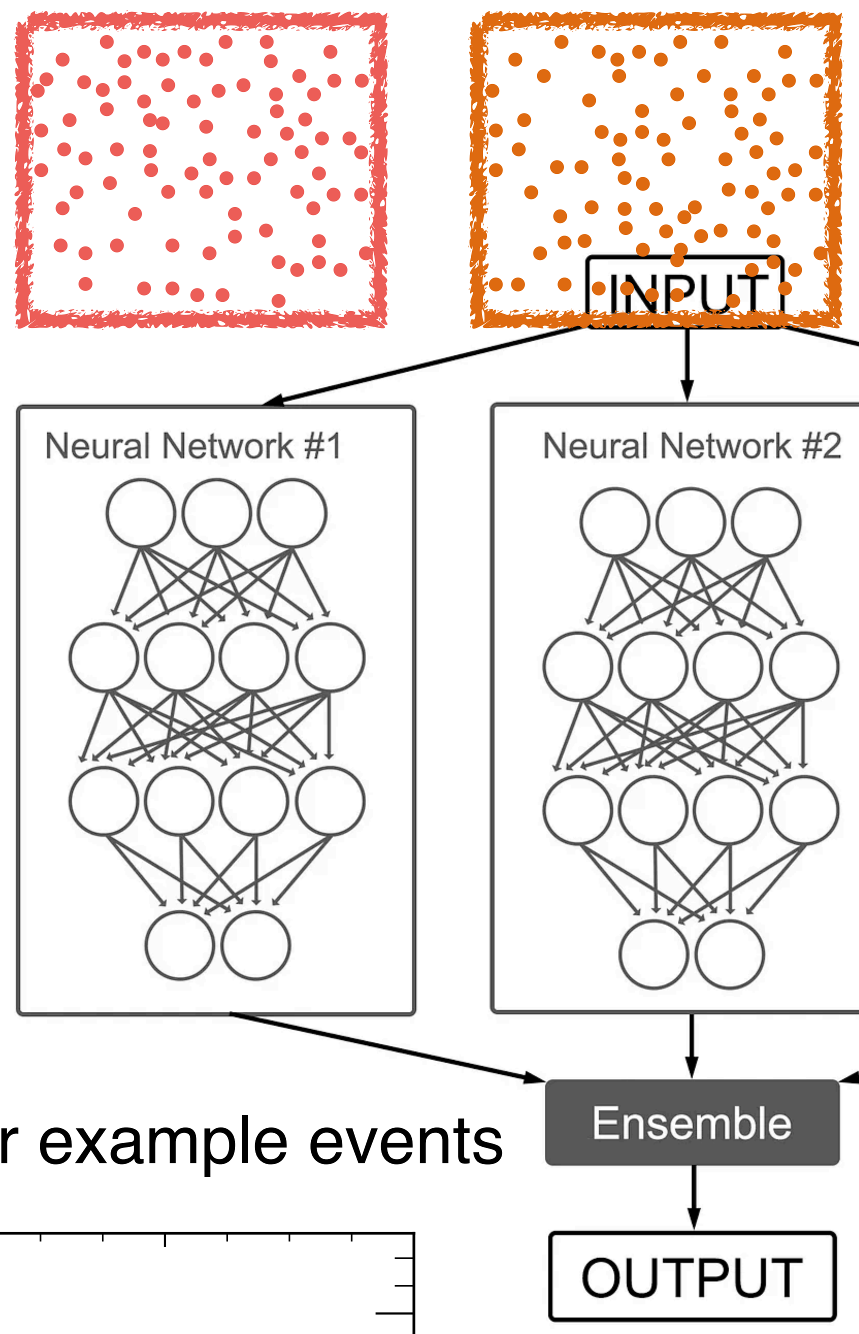
Quantifying uncertainty on estimated density ratio

$$w_i \to w_i \cdot Pois(1)$$

- Train an ensemble of networks, **each on a Poisson fluctuated version of the training dataset**
- Ensemble average used as final prediction, **estimate the variance on mean from bootstrapped ensembles**
- Propagate with spurious signal method

$$f_j(\mu) \to f_j(\mu + \alpha \cdot \Delta\hat{\mu}(\mu))$$

Constraint term: $Gauss(0,1)$



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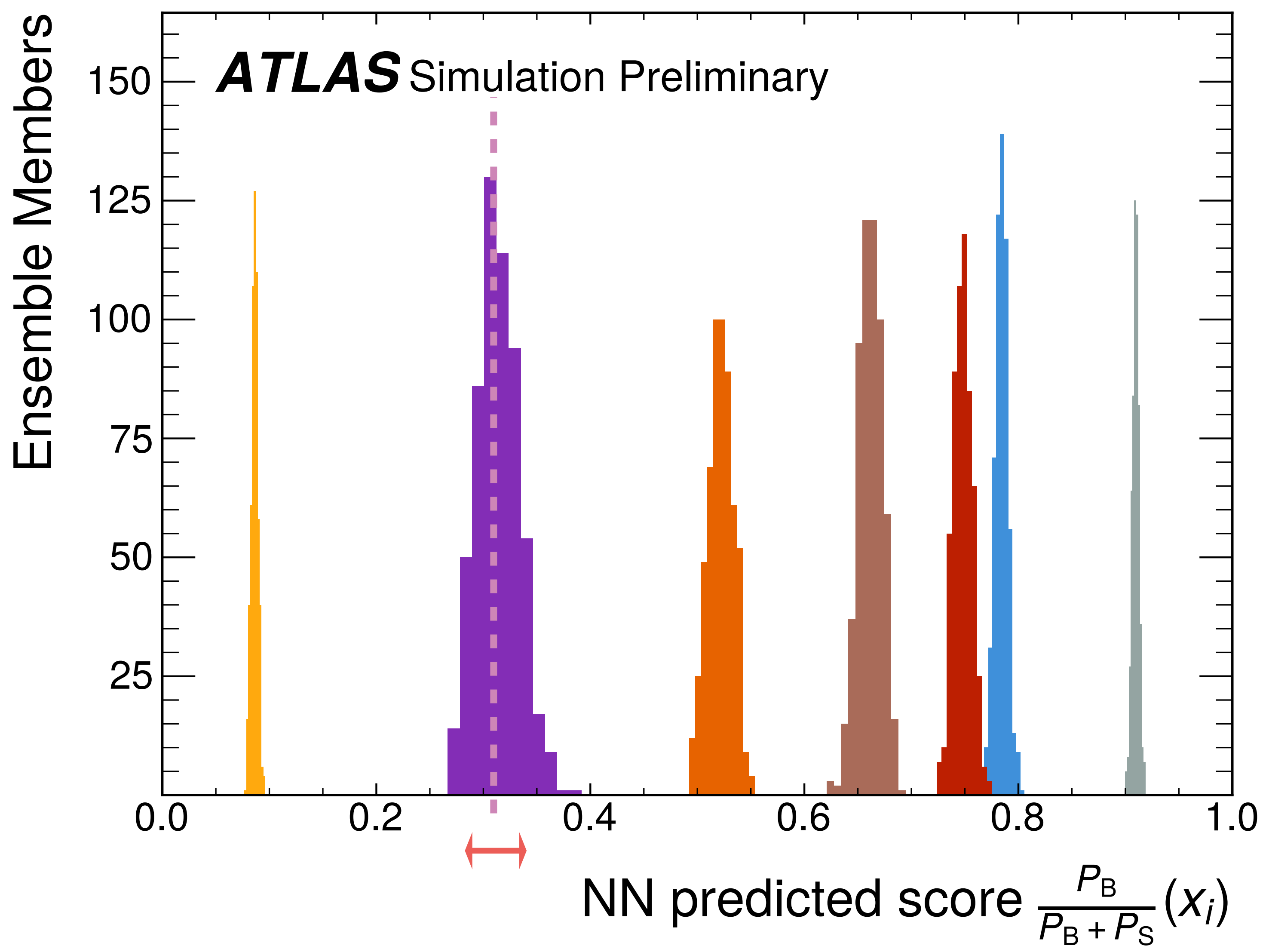


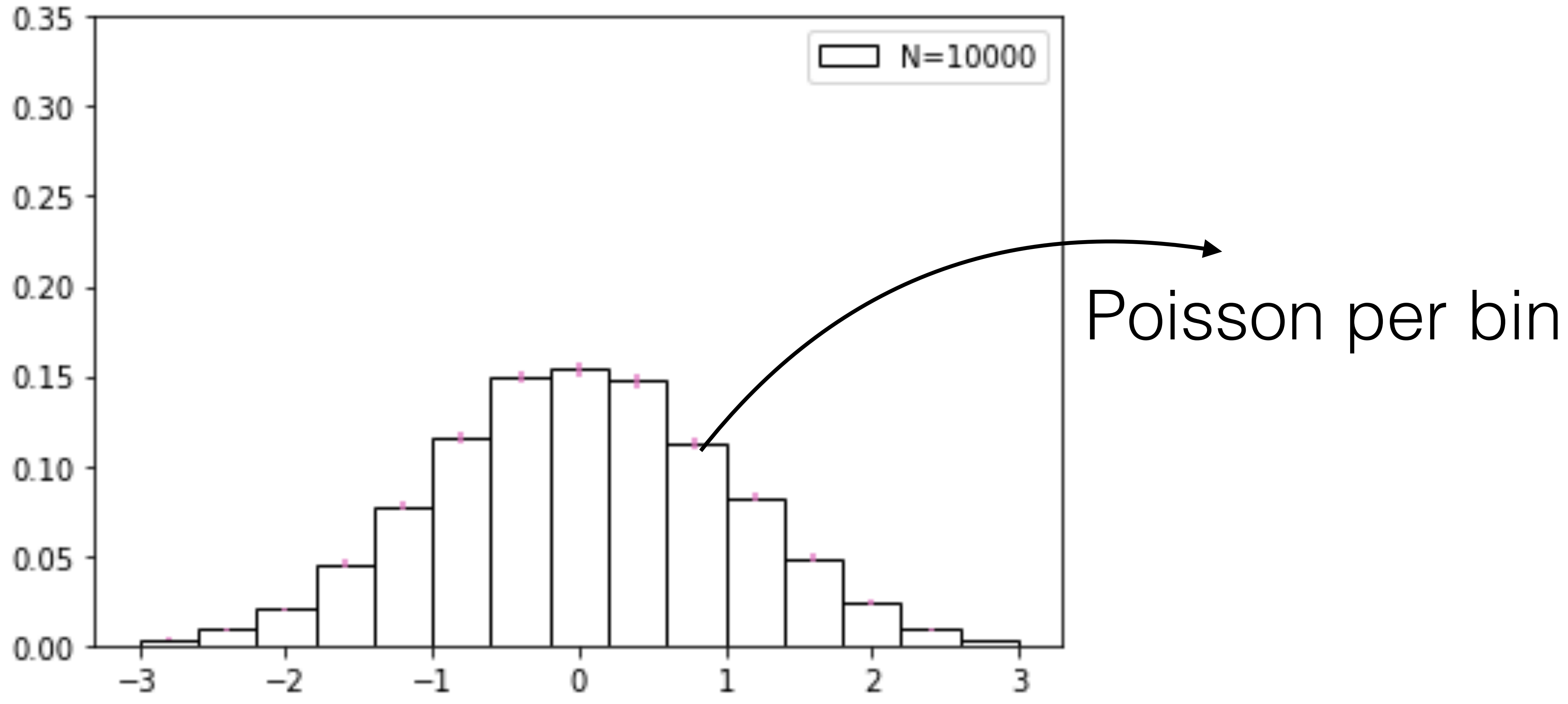
Open problems to extend to full ATLAS analysis:

- ✓ Robustness: Design and validation
- ✓ Systematic Uncertainties: Incorporate them in likelihood (ratio) model
- ‣ Neyman Construction: Throwing toys in a per-event analysis

Generating event-level pseudo-experiments

Need to generate random possible datasets we could collect at the LHC

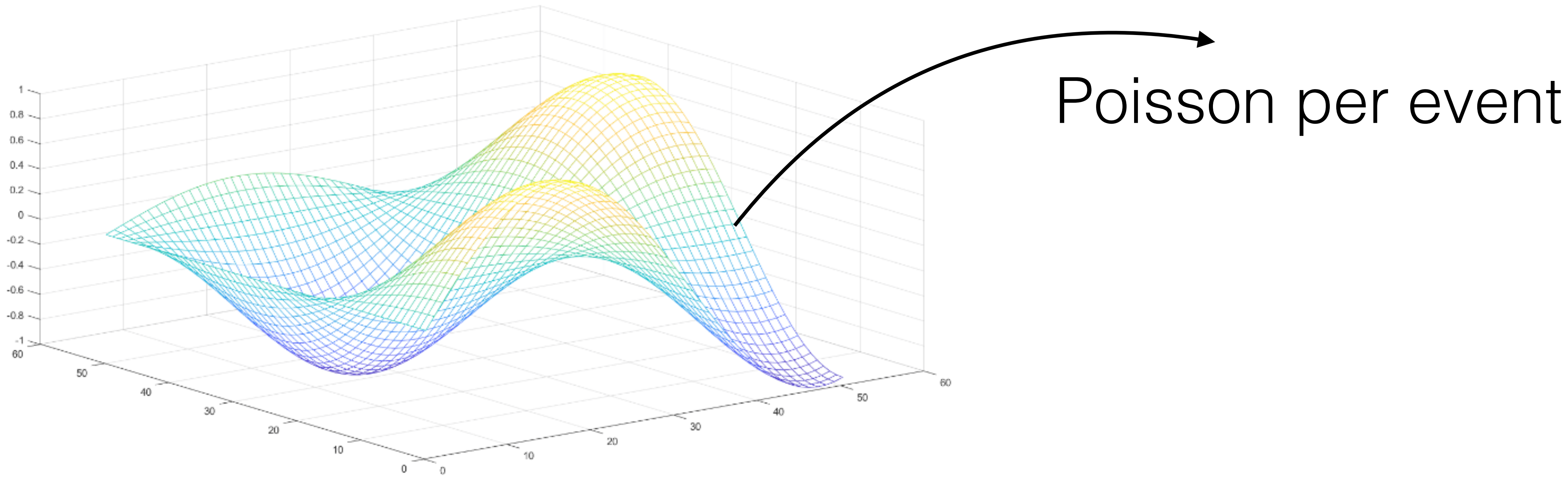
Traditionally:



Asimov Histogram

$$N_i^{toy} = Poisson(N_i^{Asimov})$$

NSBI:



$$w_i^{toy} = Poisson(w_i^{Asimov})$$

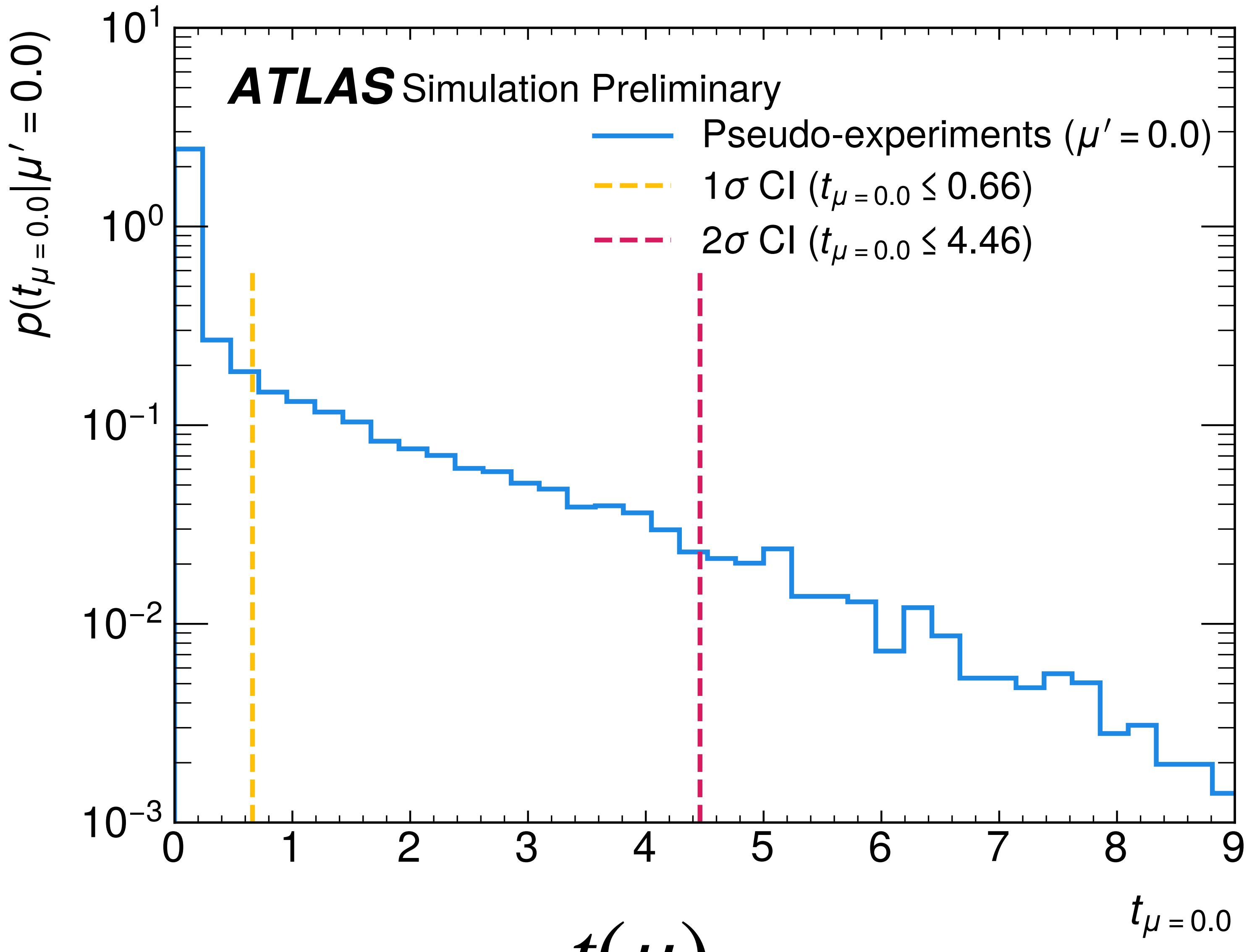
('Unweighted' events, i.e. integer weights)

What if we have negative weighted events? See backup

Neyman Construction

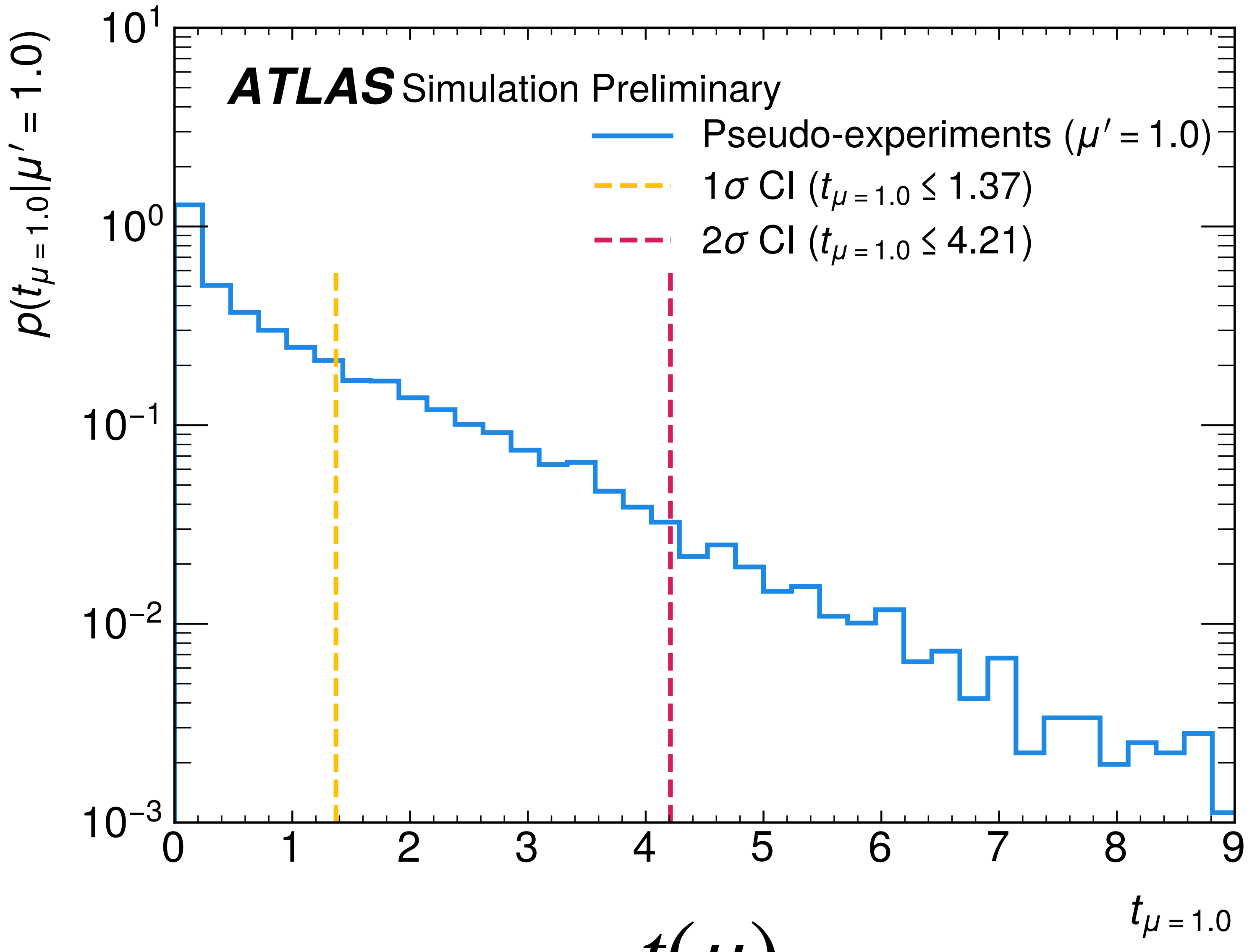
- To build confidence intervals, we need to 'invert the hypothesis test'
- Generate pseudo-experiments ('toys') and determine 1σ & 2σ CI as a function of parameter of interest

True $\mu = 0$



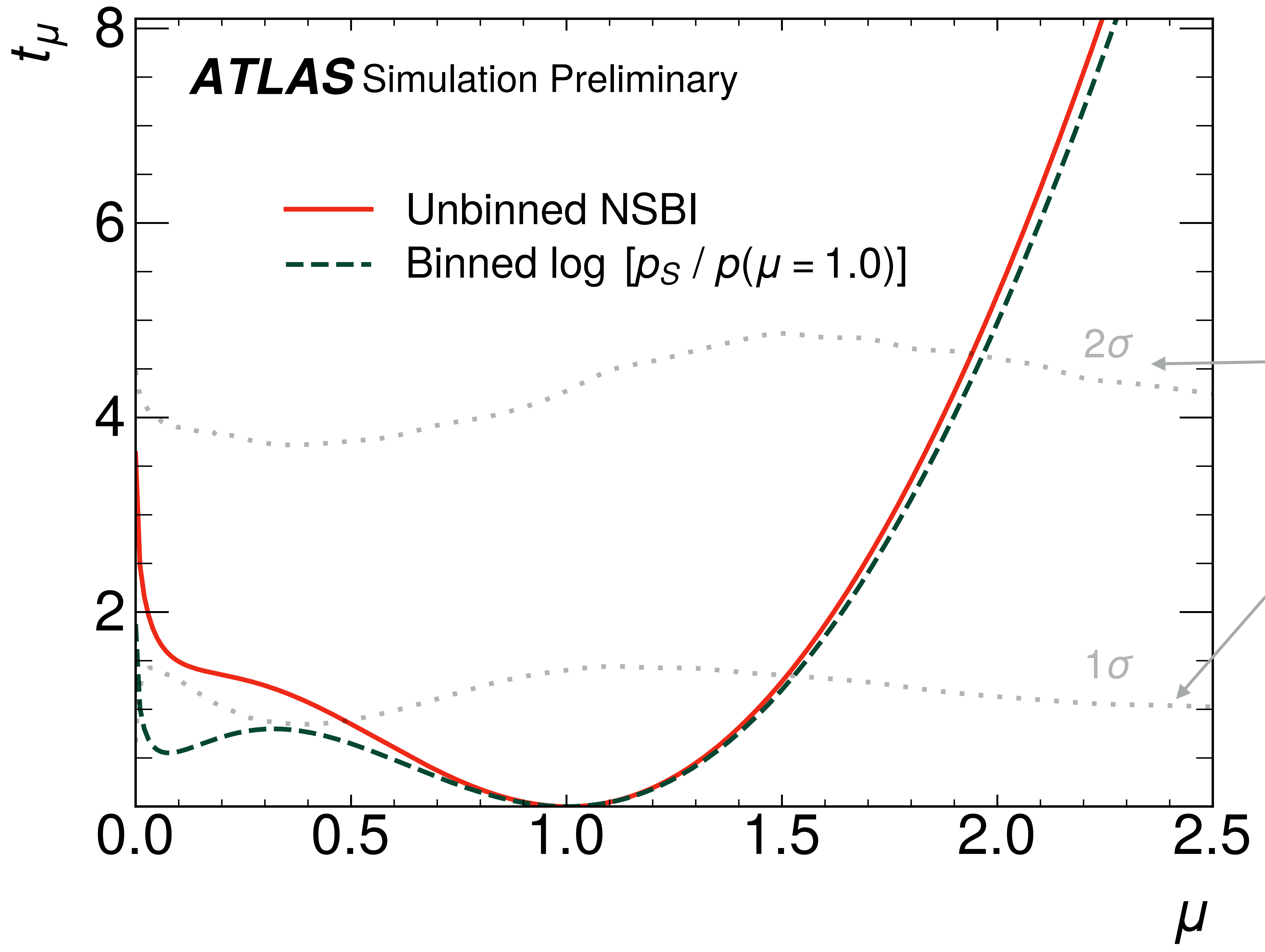
$t(\mu)$

True $\mu = 1$



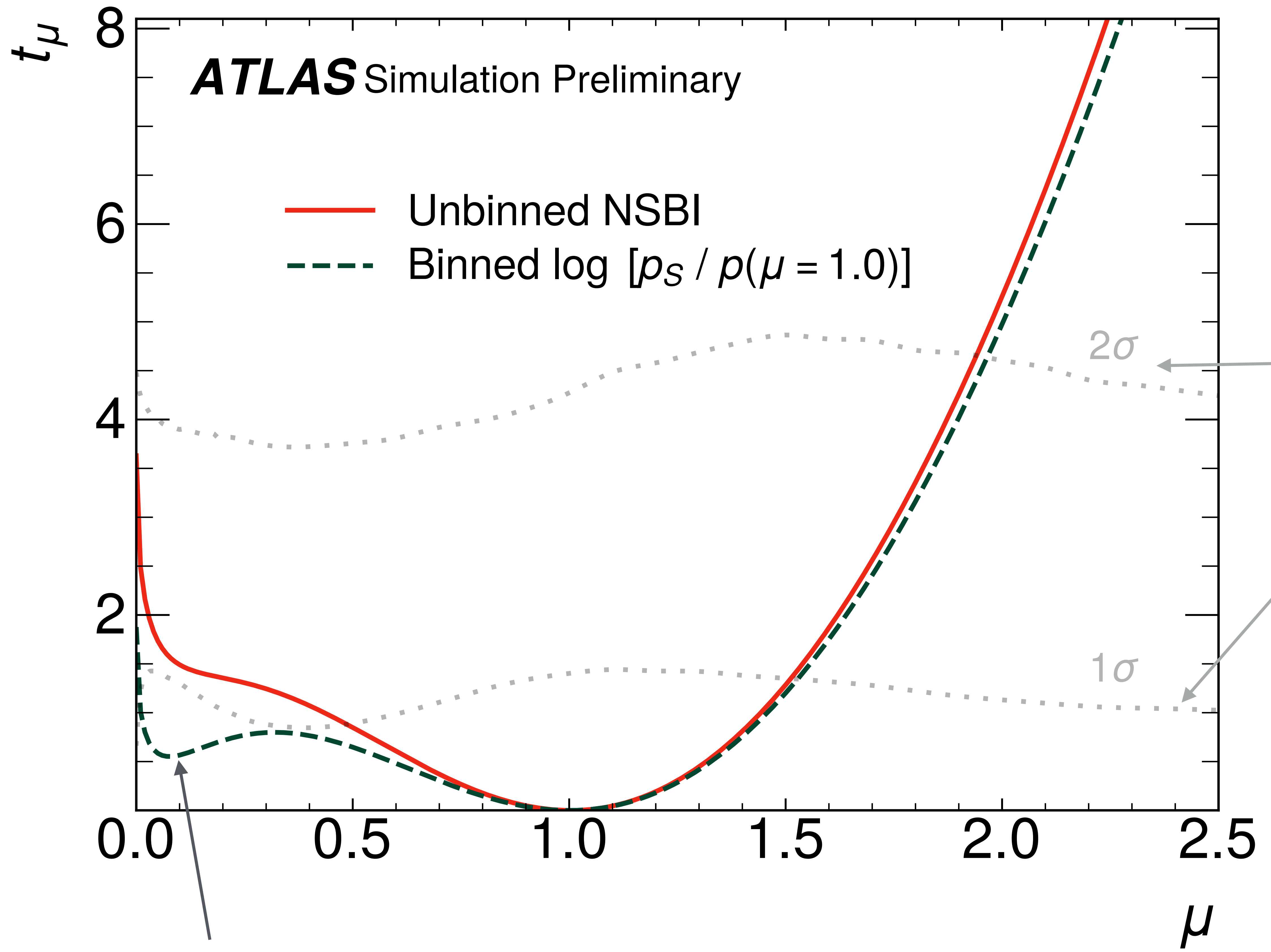
$t(\mu)$

Confidence belts



Similar to structure seen in histogram analysis

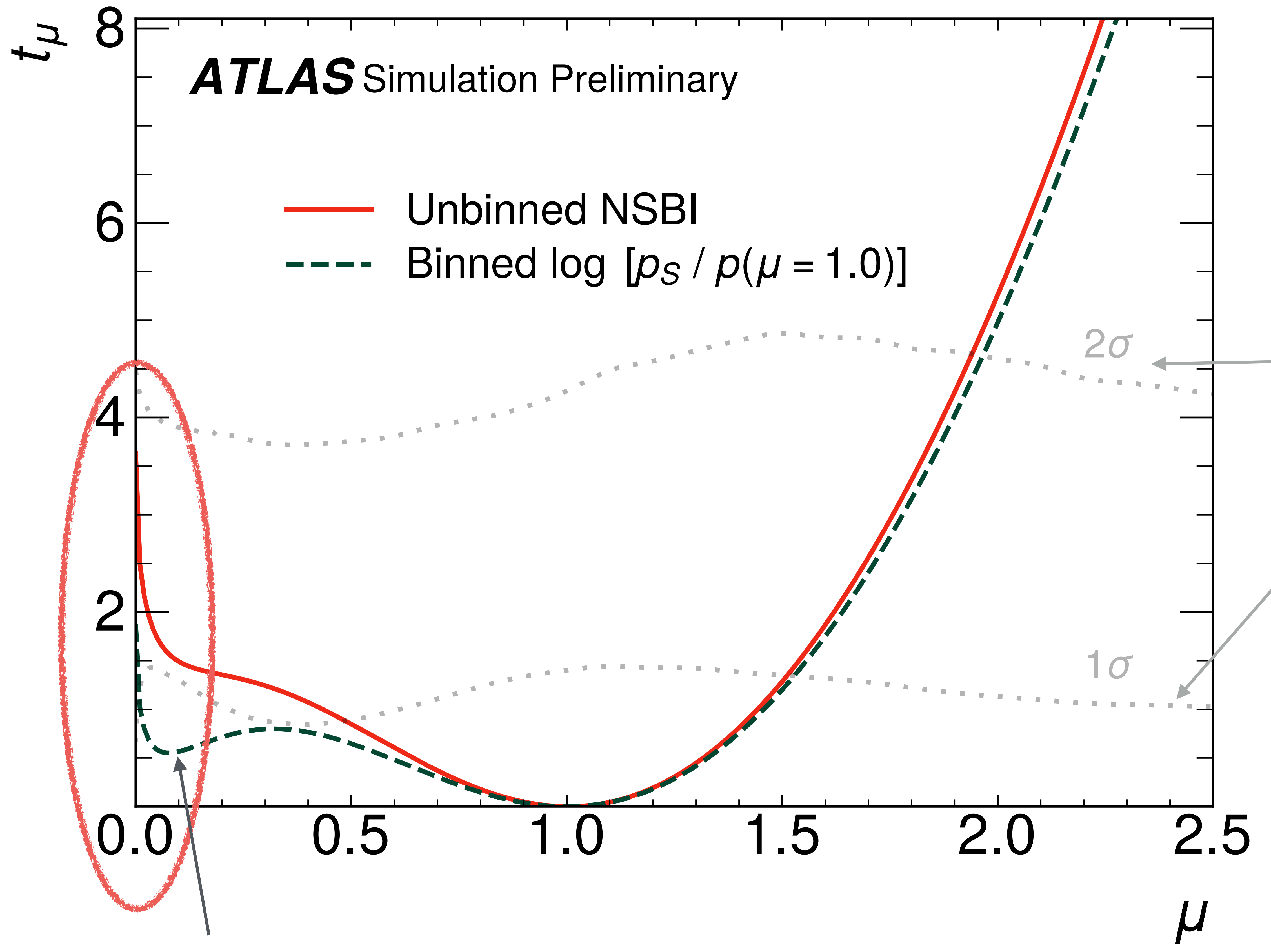
Confidence belts



Similar to structure seen in histogram analysis

Significant improvement in QI impacted region

Confidence belts



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Significant improvement in QI impacted region

Expect a dramatic improvement in ability to reject null hypothesis

Why does NSBI work better than traditional analyses?

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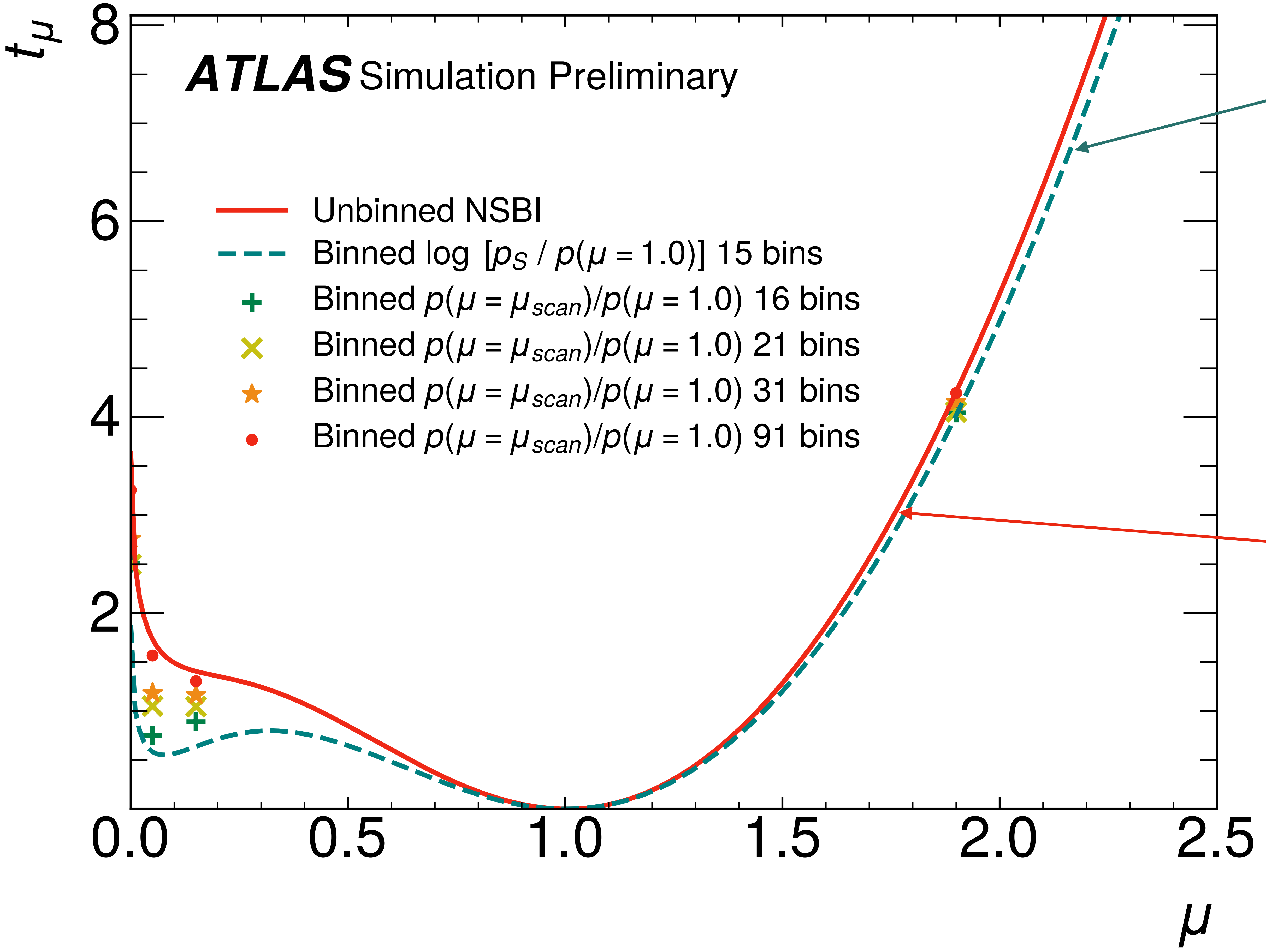

$O_{\text{fixed}} = \log \frac{p_S(x_i)}{p_{SBI}(x_i)}$: Similar to histogram analysis

NSBI: Parameterised, unbinned

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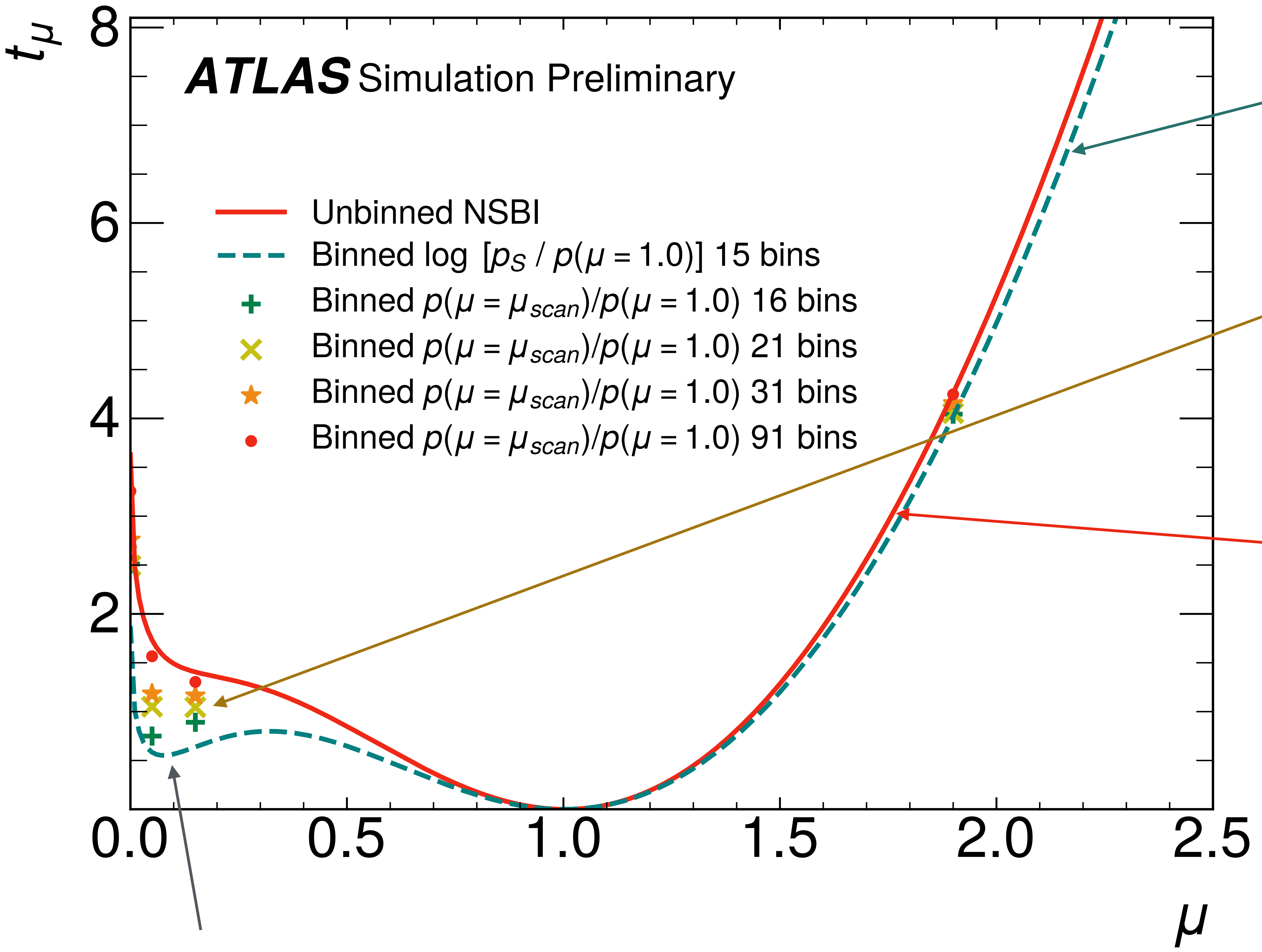

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$O_\mu = \dfrac{p(x_i \mid \mu)}{p(x_i \mid \mu = 1)}$: Parameterised observable, histogram fit

NSBI: Parameterised, unbinned

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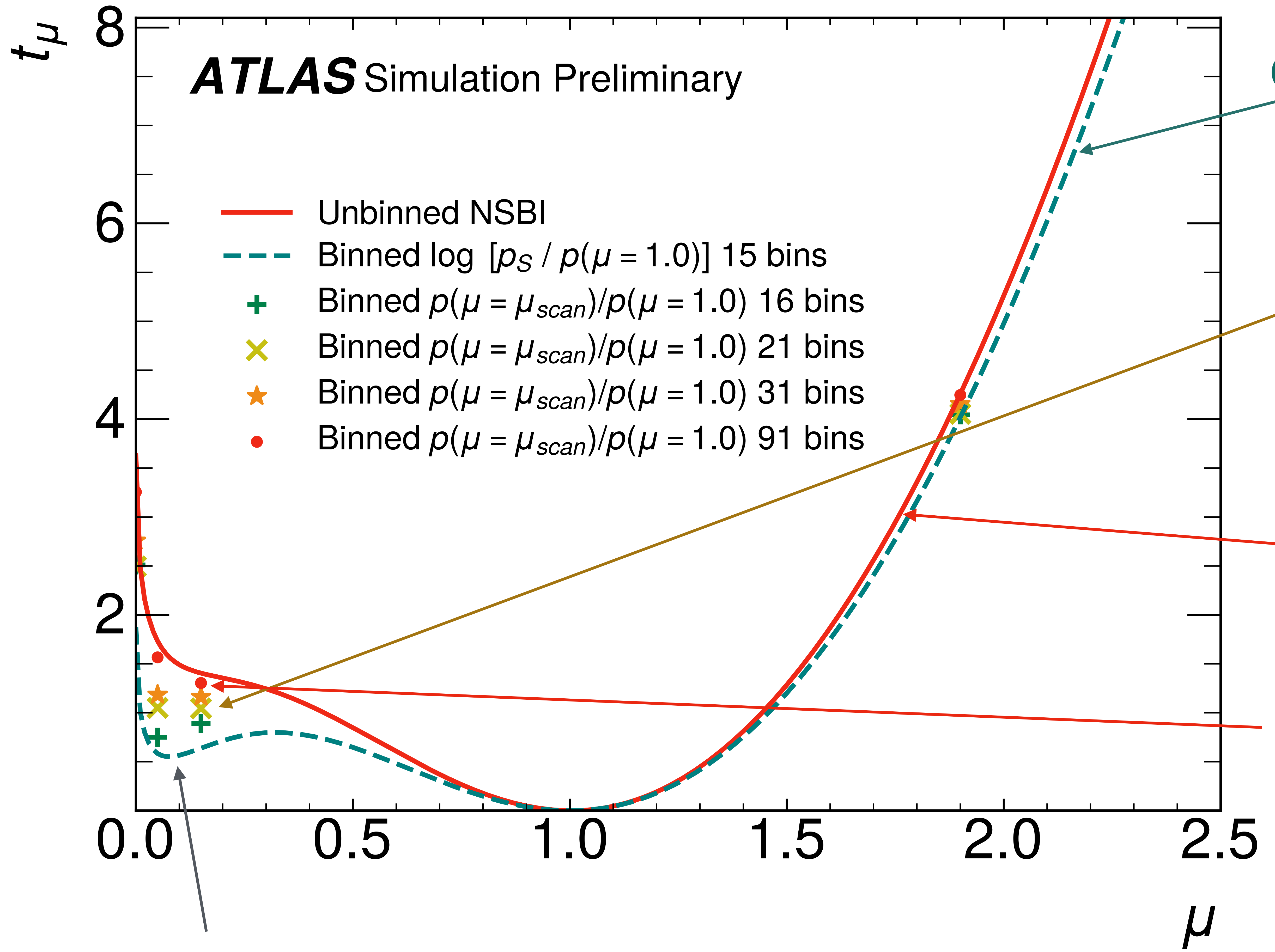

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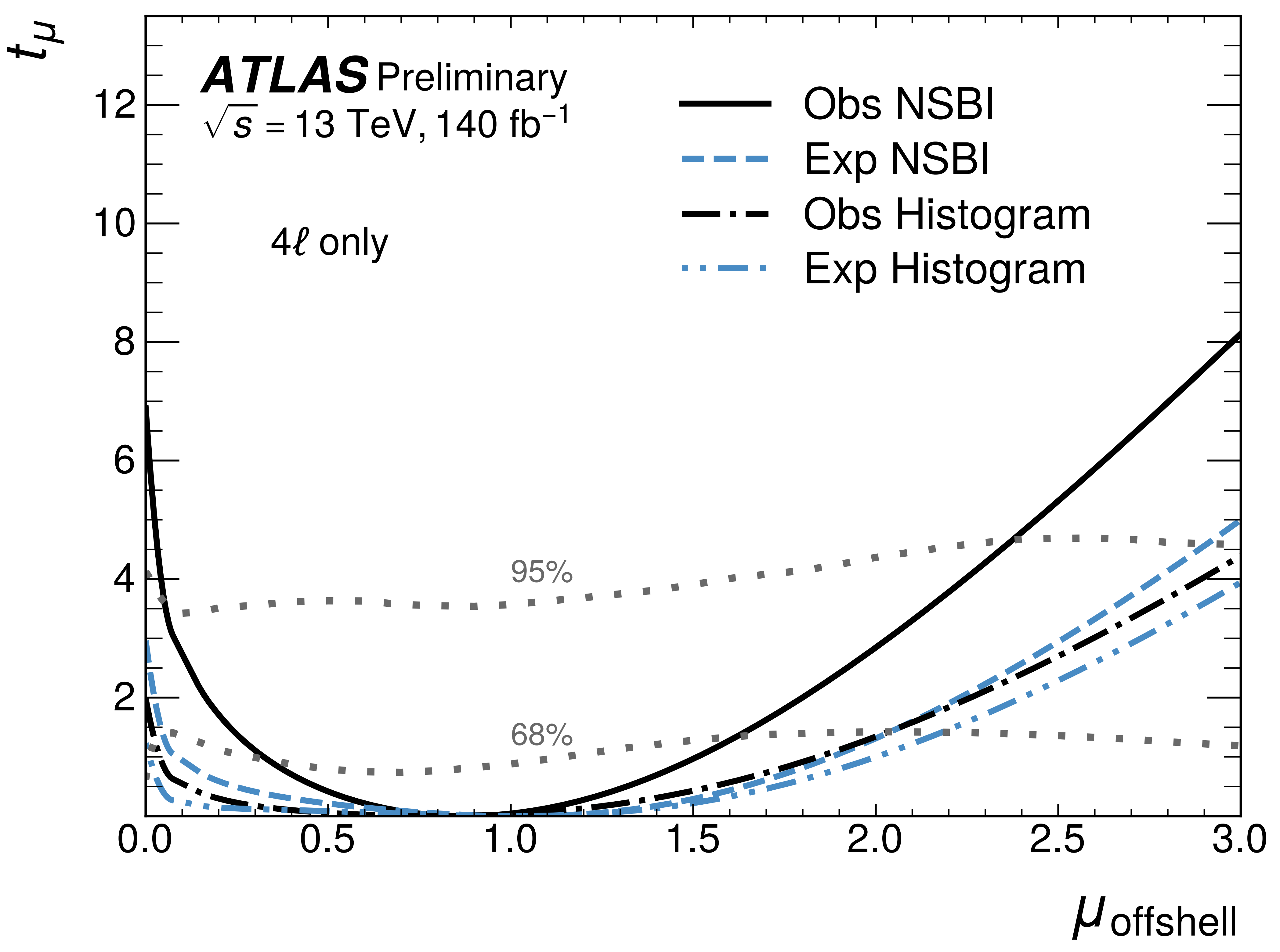
NSBI: Parameterised, unbinned

O_μ approaches NSBI as nBins $\rightarrow \infty$

Significant improvement in QI impacted region

Final results: Apply on real data and supersede previous Run2 paper!

NSBI vs histogram analysis



Observed data happens to provide stronger than expected constrains for both hist and NSBI (consistent)

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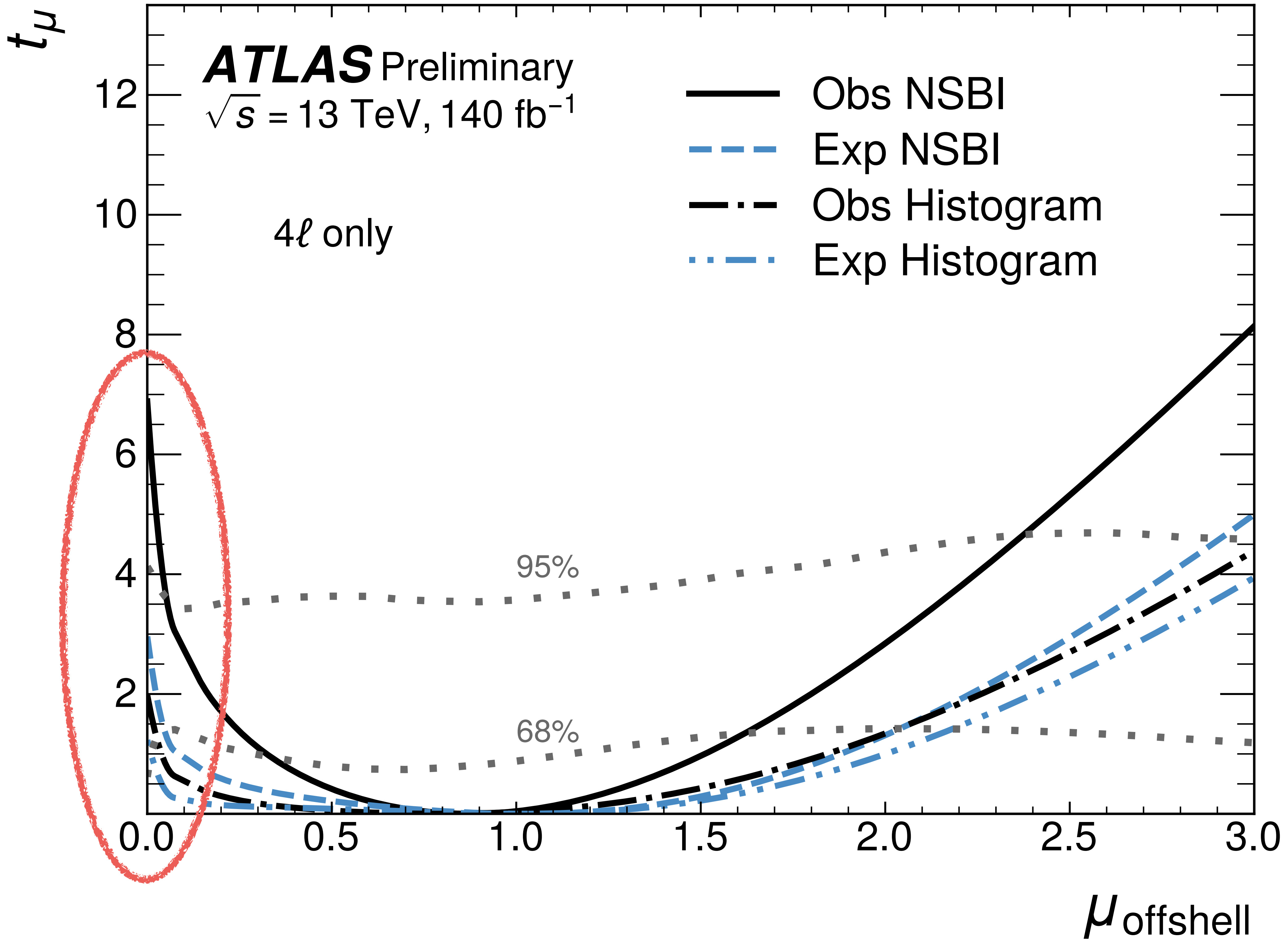

Unprecedented improvement in ability to reject null hypothesis! (2.6x gain over previous method)

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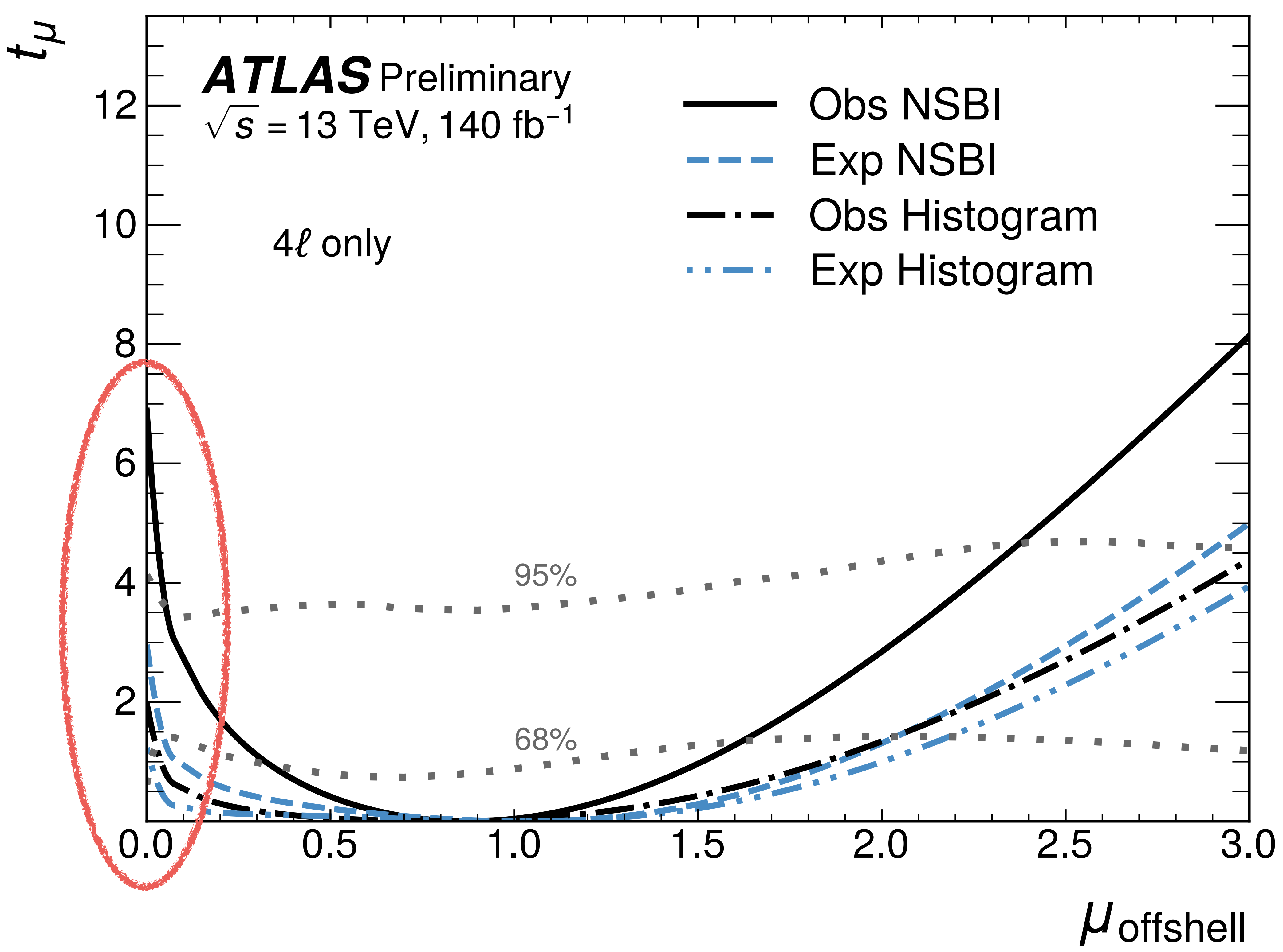

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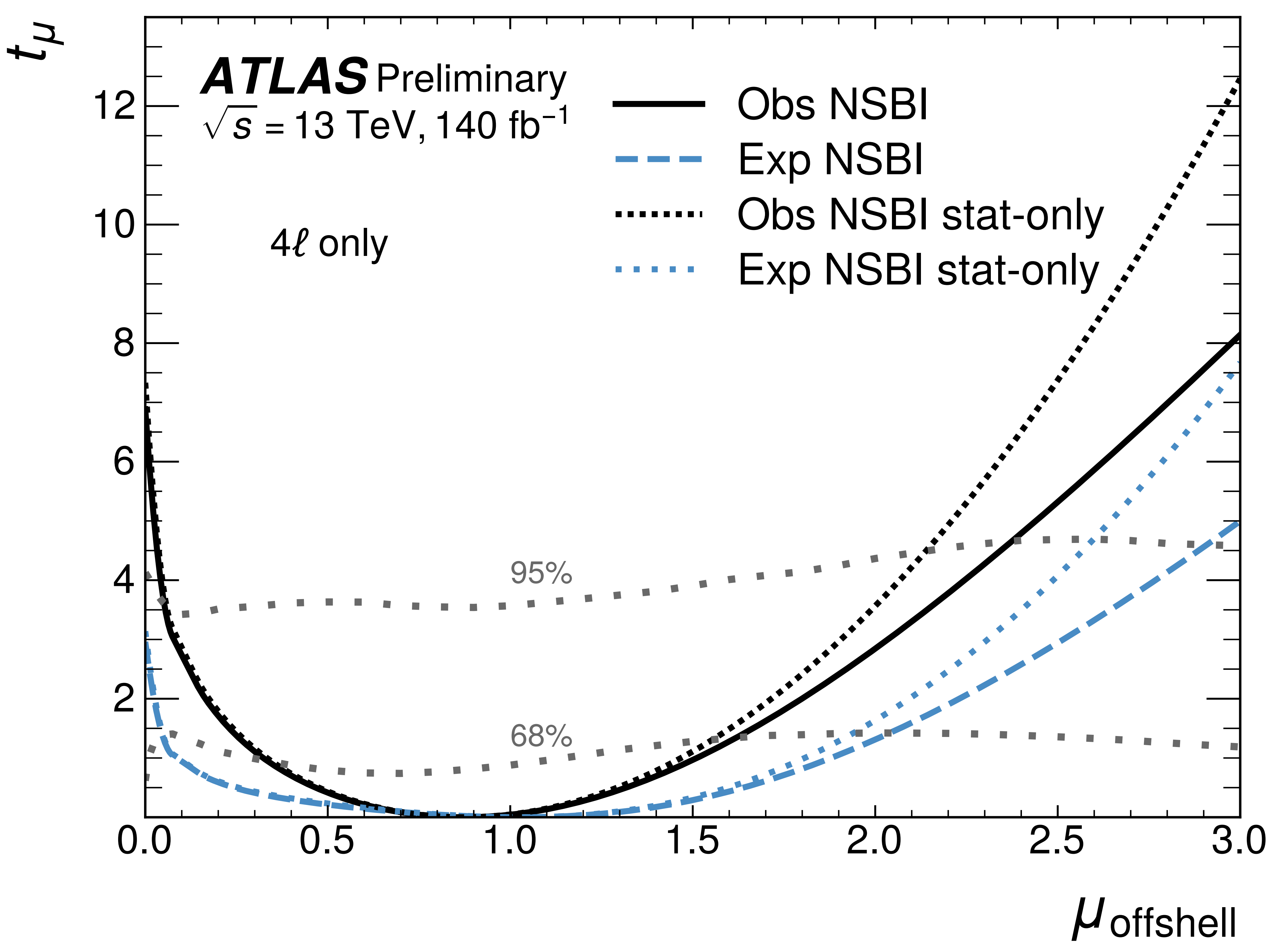
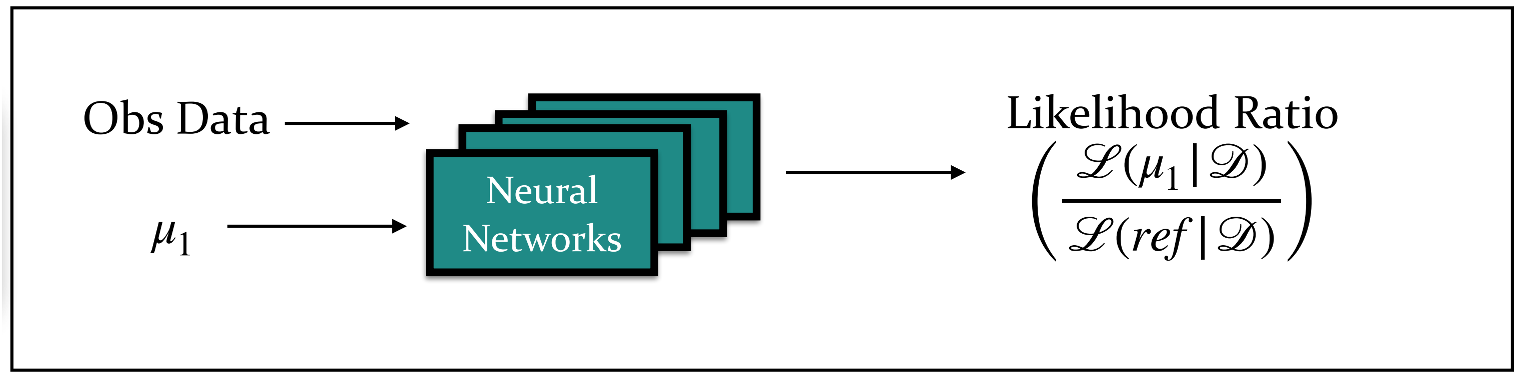
Stat-only vs Stat+Syst uncertainties



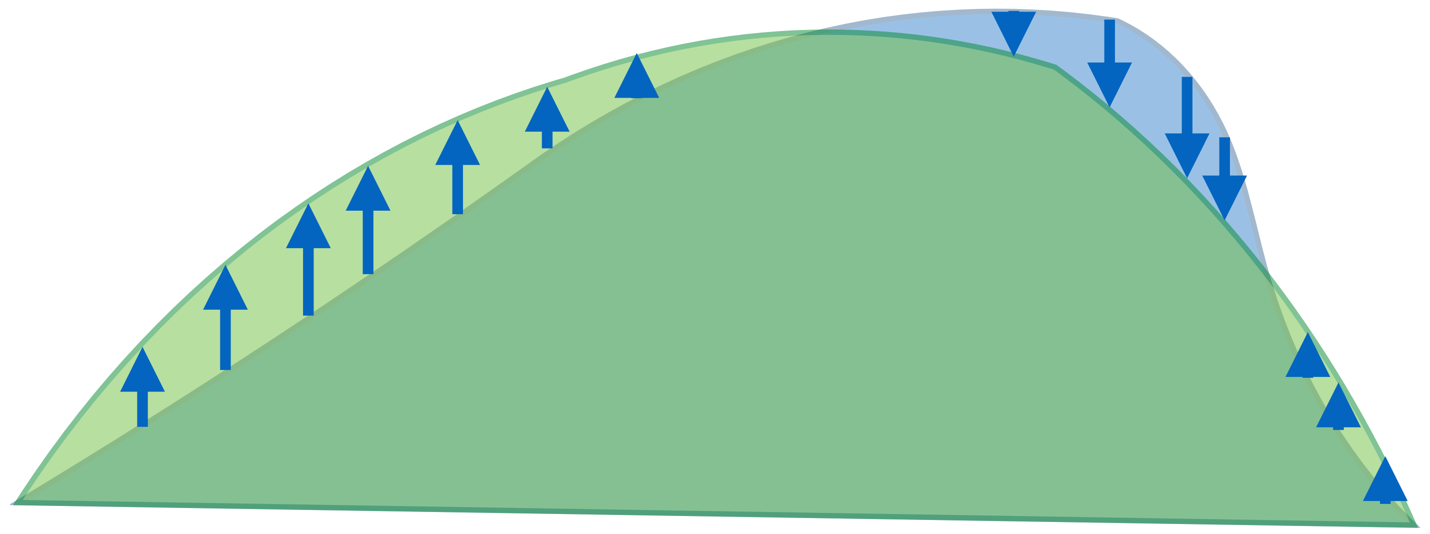
Nuisance parameters decrease sensitivity, as expected

Conclusion

- Quantum interference breaks assumptions in traditional statistical methods at LHC
- Neural inference can optimally handle these challenges for Higgs width:
    - Shown in phenomenology study
    - Developed method for deployment in ATLAS
    - Re-analysed Run 2 data and achieved a dramatic improvement in sensitivity ($H \rightarrow 4l$)



- NSBI has wide-ranging applications, in particle physics, astrophysics and beyond!
- Weaknesses: Same as traditional analyses (systematics, training statistics). Developed diagnostic tools to help
- Uncertainty quantification tools let you use more powerful data analysis techniques [1, 2, 3, 4, 5]



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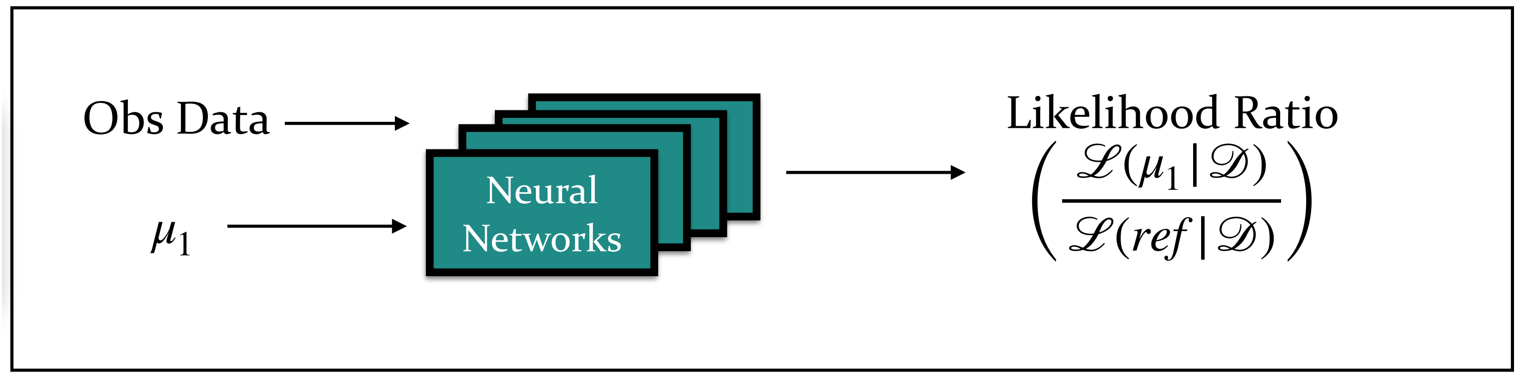

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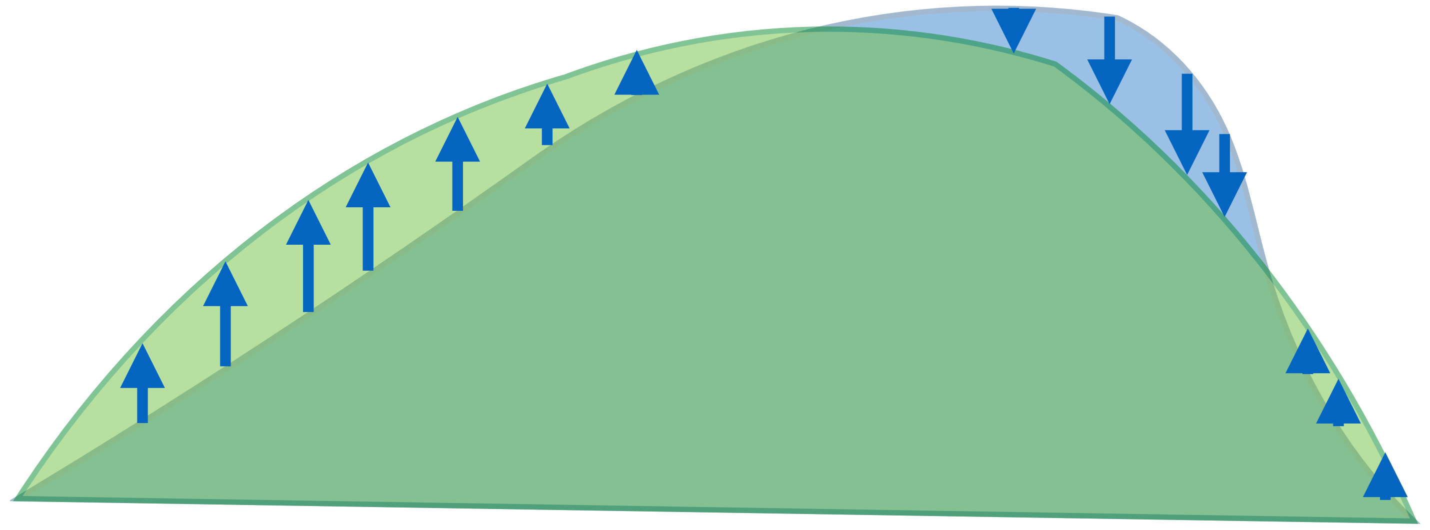


Thanks !

Dealing with negative weighted events

$$w_i^{toy} = Poisson(w_i^{Asimov})$$

Simulated samples include events with negative weights due to the way we calculate QFT higher order effects

Use a positive weighted sample instead:

1. Start from a positive weighted reference sample

2. Re-weight it to intended parameter point in μ, α

3. Throw toys from this sample

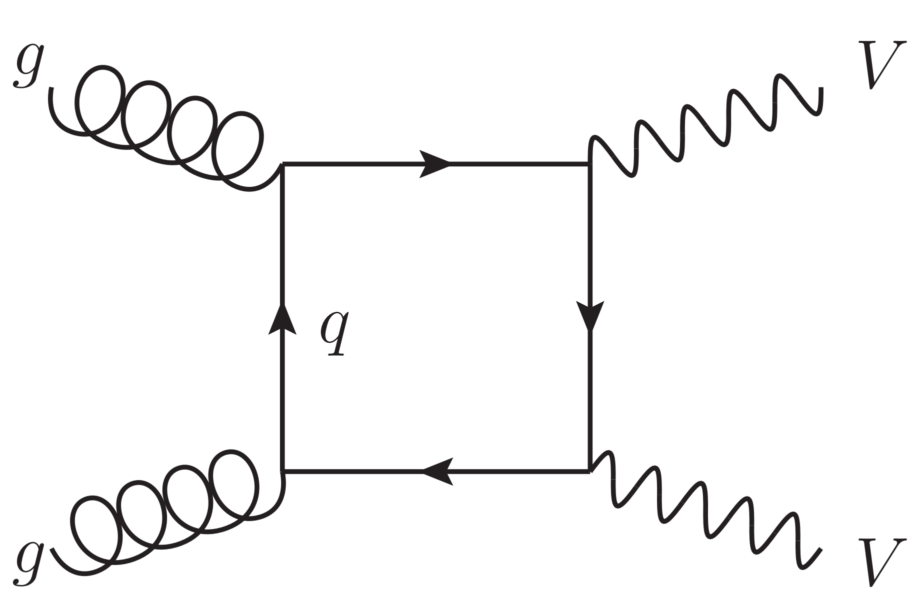
$$w_i^{\text{rwt-ref}} \rightarrow w_i^{\text{Asimov}}(\mu, \alpha) = \frac{\nu(\mu, \alpha)}{\nu_{\text{rwt-ref}}} \cdot \frac{p(x_i | \mu, \alpha)}{p_{\text{rwt-ref}}(x_i)} \cdot w_i^{\text{rwt-ref}}$$

Non-linear problem

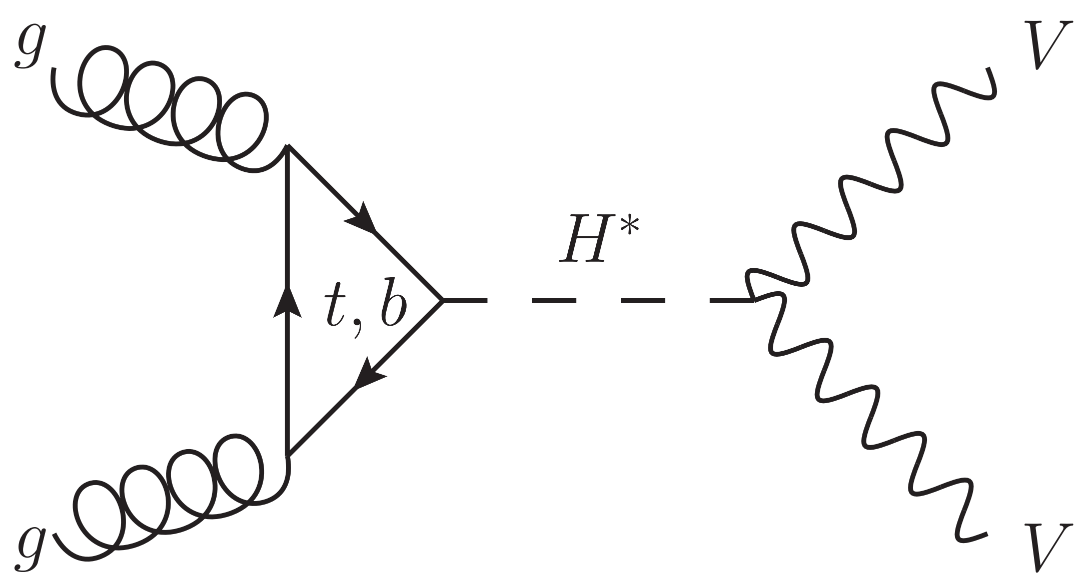
hal-02971995v3: Ghosh et al.

$$P(X) = |M_s(X) + M_b(X)|^2 = \underbrace{|M_s(X)|^2}_{P_s(X)} + \underbrace{|M_b(X)|^2}_{P_b(X)} + 2\,\underbrace{\mathtt{Re}(\overline{M_s(X)}M_b(X))}_{P_i(X)}$$

This term is negative



gg Background



ggF Signal

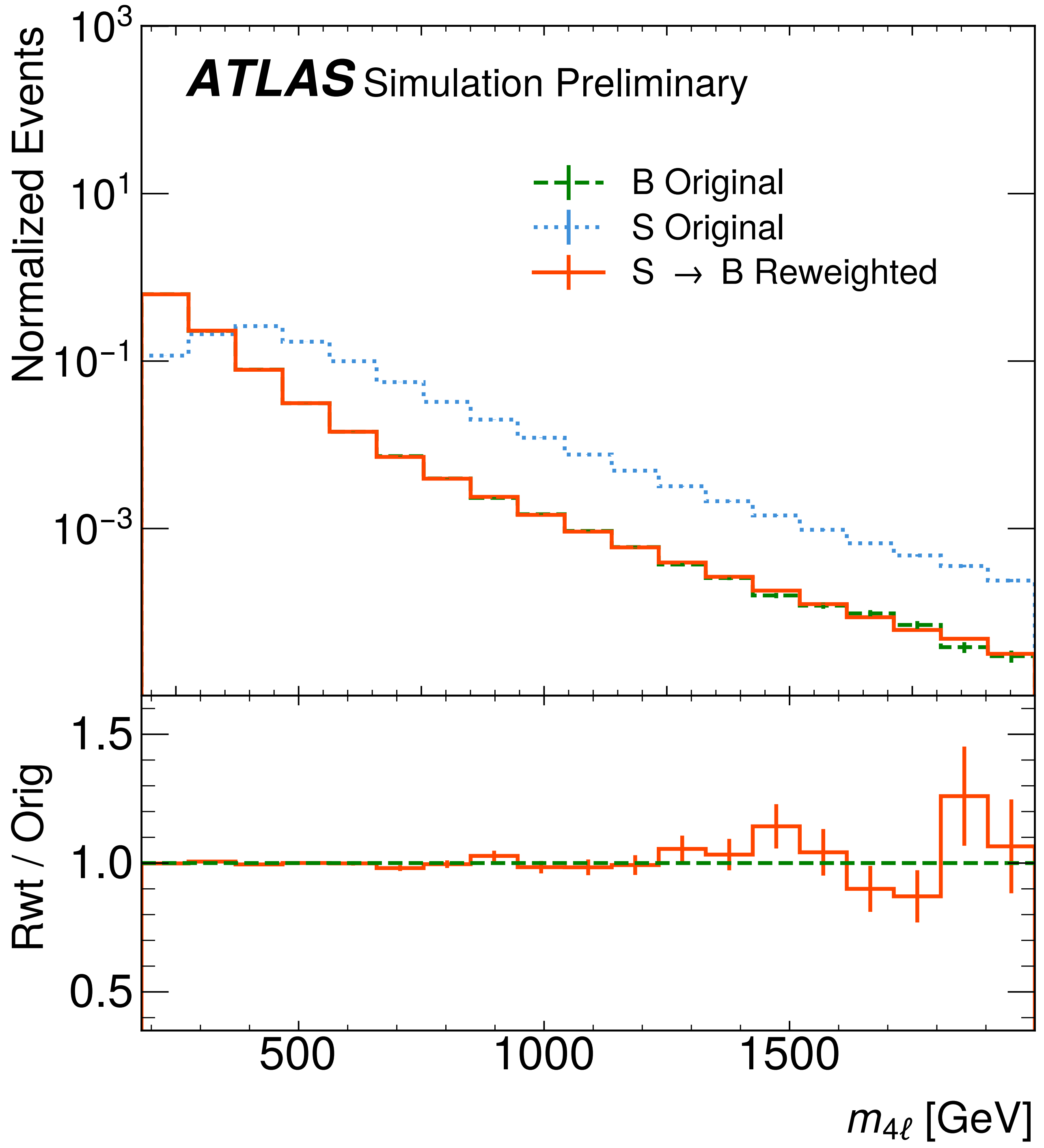
Scale by signal strength μ:

$$|M_s(X)|^2 \to |\sqrt{\mu} \cdot M_s(X)|^2,$$

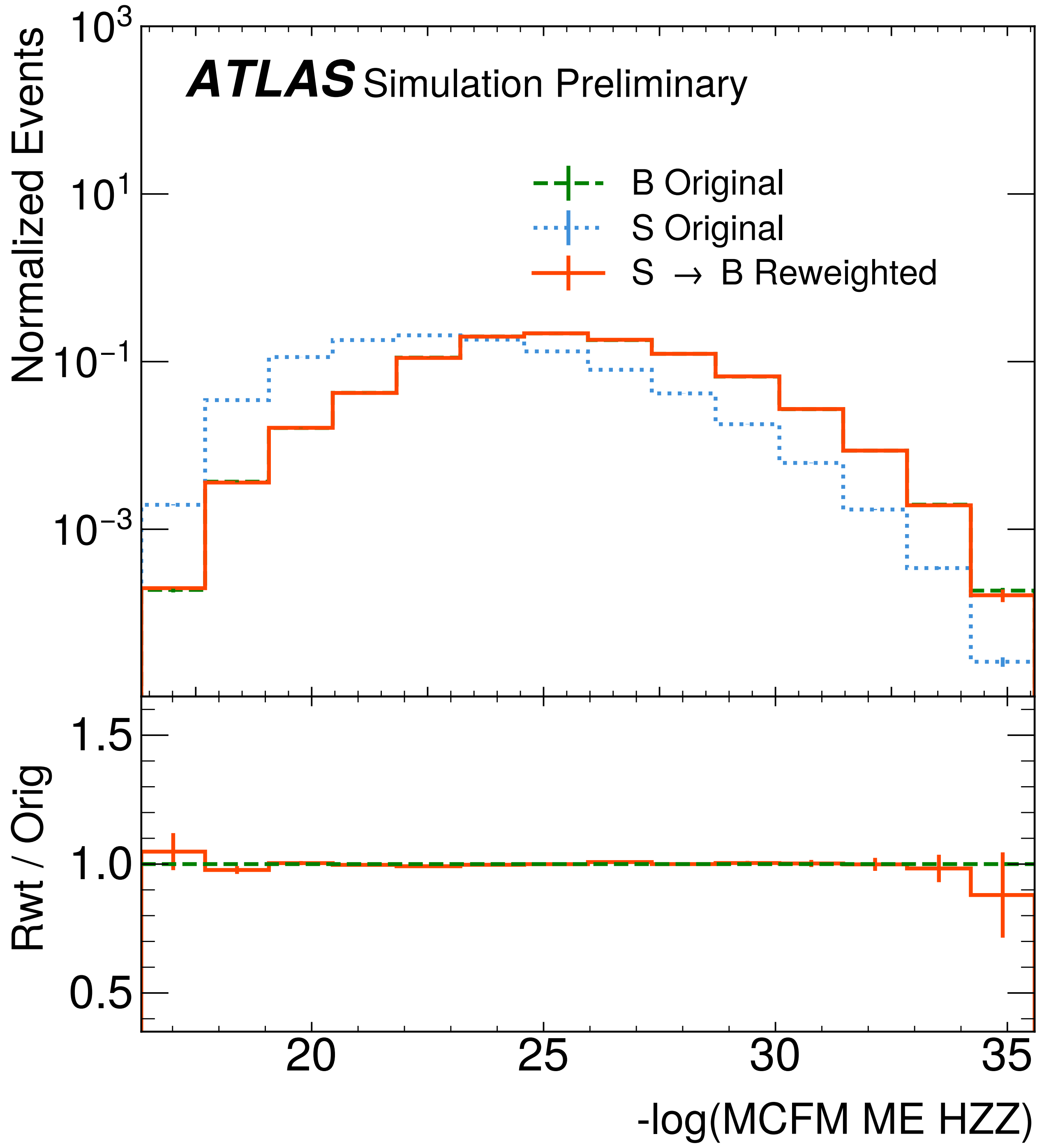
$$P_{\text{scaled}}(X) = \mu \cdot P_s(X) + P_b(X) + \sqrt{\mu} \cdot P_i(X).$$

More diagnostics

Re-weight closures for B



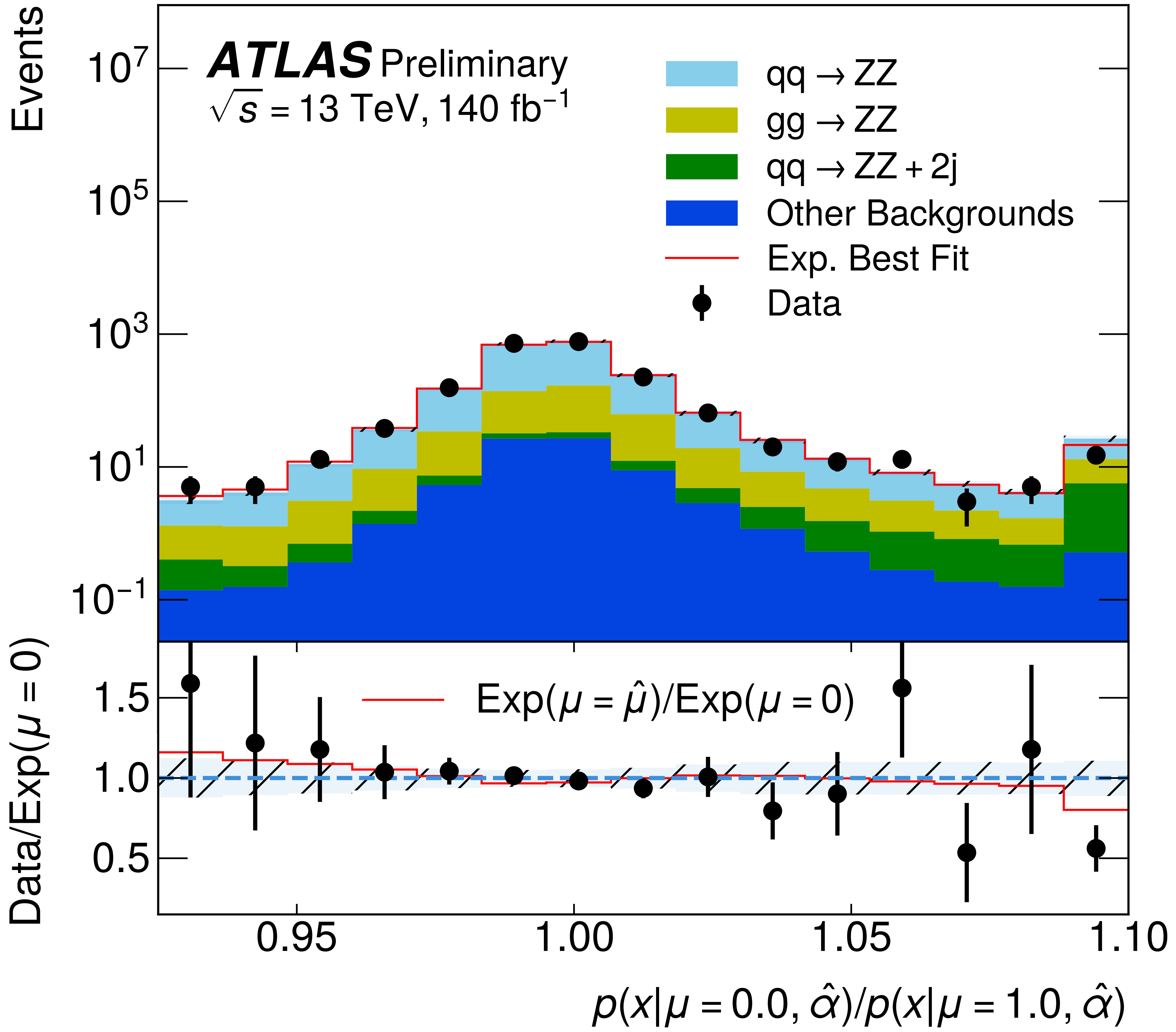
m_{4l}



Matrix-Element-based Observable
(ggF from MCFM)

Data-MC validation

NN observable



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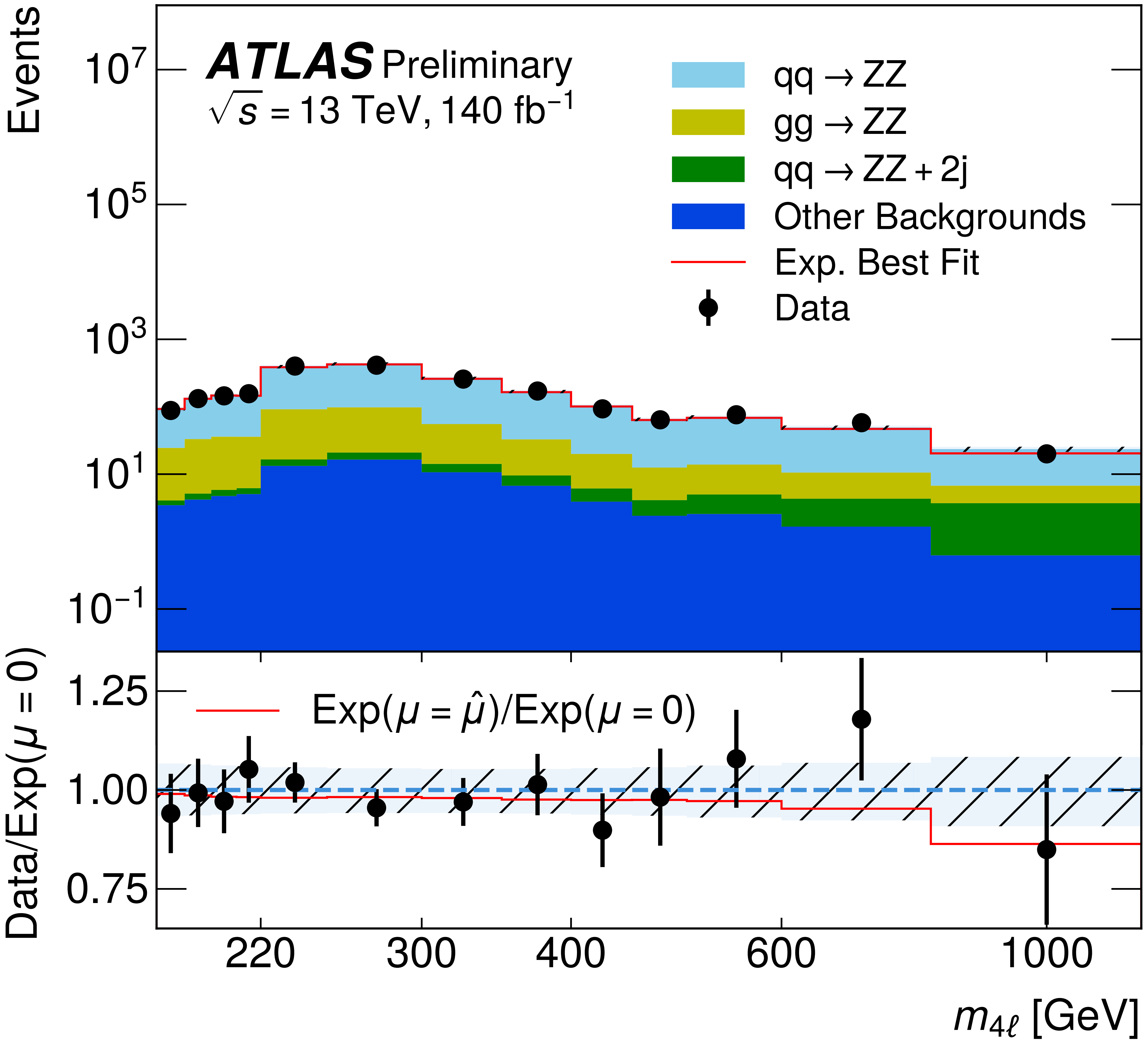
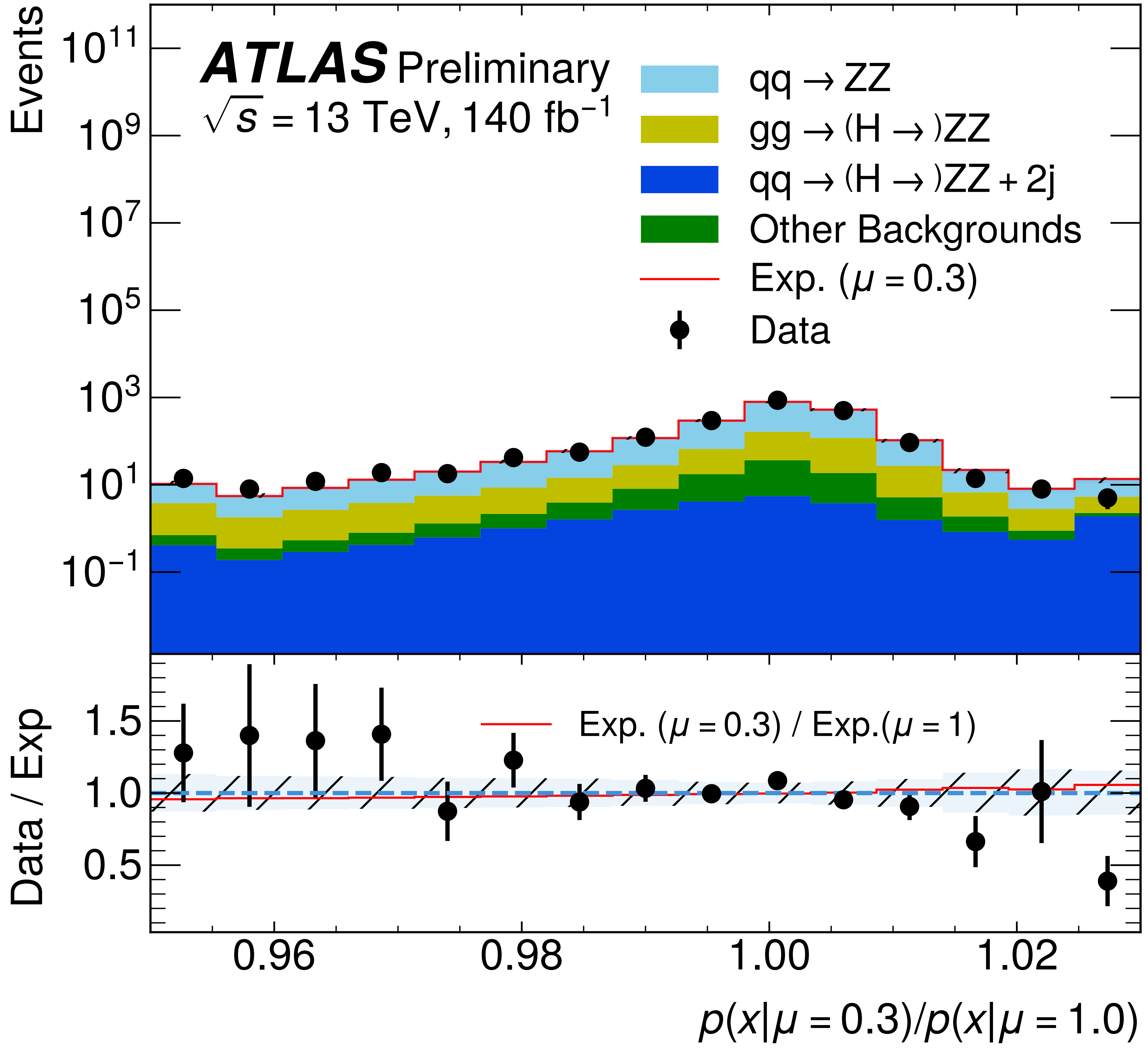
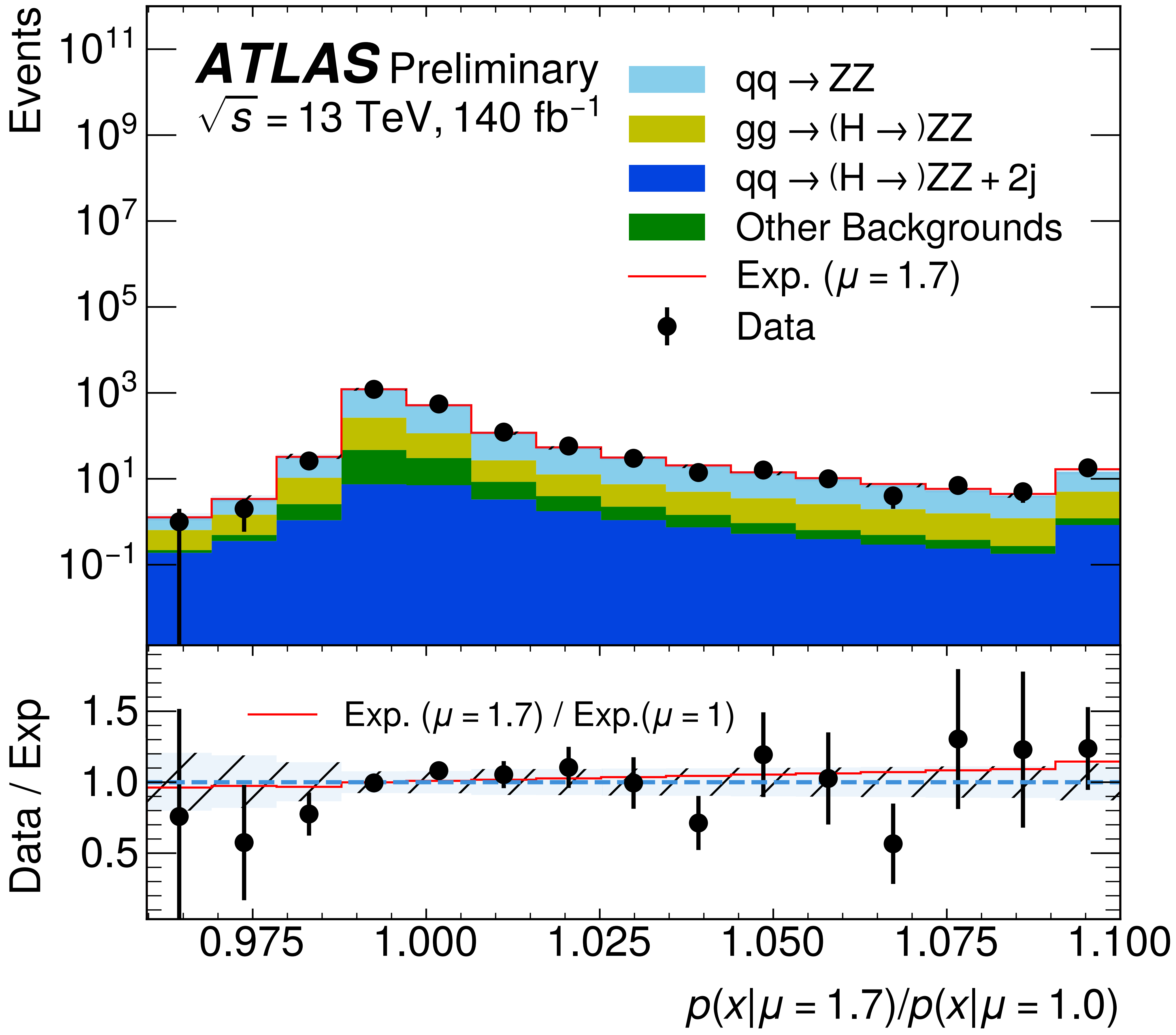


Data-MC validation

Different NN observables





Combination with histogram analyses

$$\frac{L_{\text{comb}}(\mu,\alpha)}{L_{\text{ref}}} = \frac{L_{\text{full}}(\mu,\alpha)}{L_{\text{ref}}} \; L_{\text{hist}}(\mu,\alpha)$$

Calculating pulls and impacts in JAX

$$\lambda(\mu, \alpha) = -2\ln(L_{full}(\mu, \alpha)/L_{ref})$$

Hessian:

$$C_{nm} = \left[\frac{1}{2}\frac{\partial^2 \lambda}{\partial \alpha_n \partial \alpha_m}(\hat{\mu}, \hat{\alpha})\right]^{-1}$$

Pulls:

$$\frac{\hat{\alpha}_k - \alpha_k^0}{\sqrt{C_{kk}}}.$$

Post-fit Impact:

$$\Gamma_k = \frac{\partial \hat{\mu}}{\partial \alpha_k} \times \sqrt{C_{kk}}$$
$$= -\left[\frac{\partial^2 \lambda}{\partial^2 \mu}(\hat{\mu}, \hat{\alpha})\right]^{-1} \frac{\partial^2 \lambda}{\partial \mu \partial \alpha_k}(\hat{\mu}, \hat{\alpha}) \times \sqrt{C_{kk}},$$

Vertical interpolation

$$G_j(\alpha_k) = \begin{cases} \left(\frac{\nu_j(\alpha_k^+)}{\nu_j(\alpha_k^0)}\right)^{\alpha_k} & \alpha_k > 1 \\ 1 + \sum_{n=1}^{6} c_n \alpha_k^n & -1 \leq \alpha_k \leq 1 \\ \left(\frac{\nu_j(\alpha_k^-)}{\nu_j(\alpha_k^0)}\right)^{-\alpha_k} & \alpha_k < -1 \end{cases}$$

$$g_j(x_i, \alpha_k) = \begin{cases} \left(g_j(x_i, \alpha_k^+)\right)^{\alpha_k} & \alpha_k > 1 \\ 1 + \sum_{n=1}^{6} c_n \alpha_k^n & -1 \leq \alpha_k \leq 1 \\ \left(g_j(x_i, \alpha_k^-)\right)^{-\alpha_k} & \alpha_k < -1 \end{cases}$$

With some continuity requirements

Physics analysis results

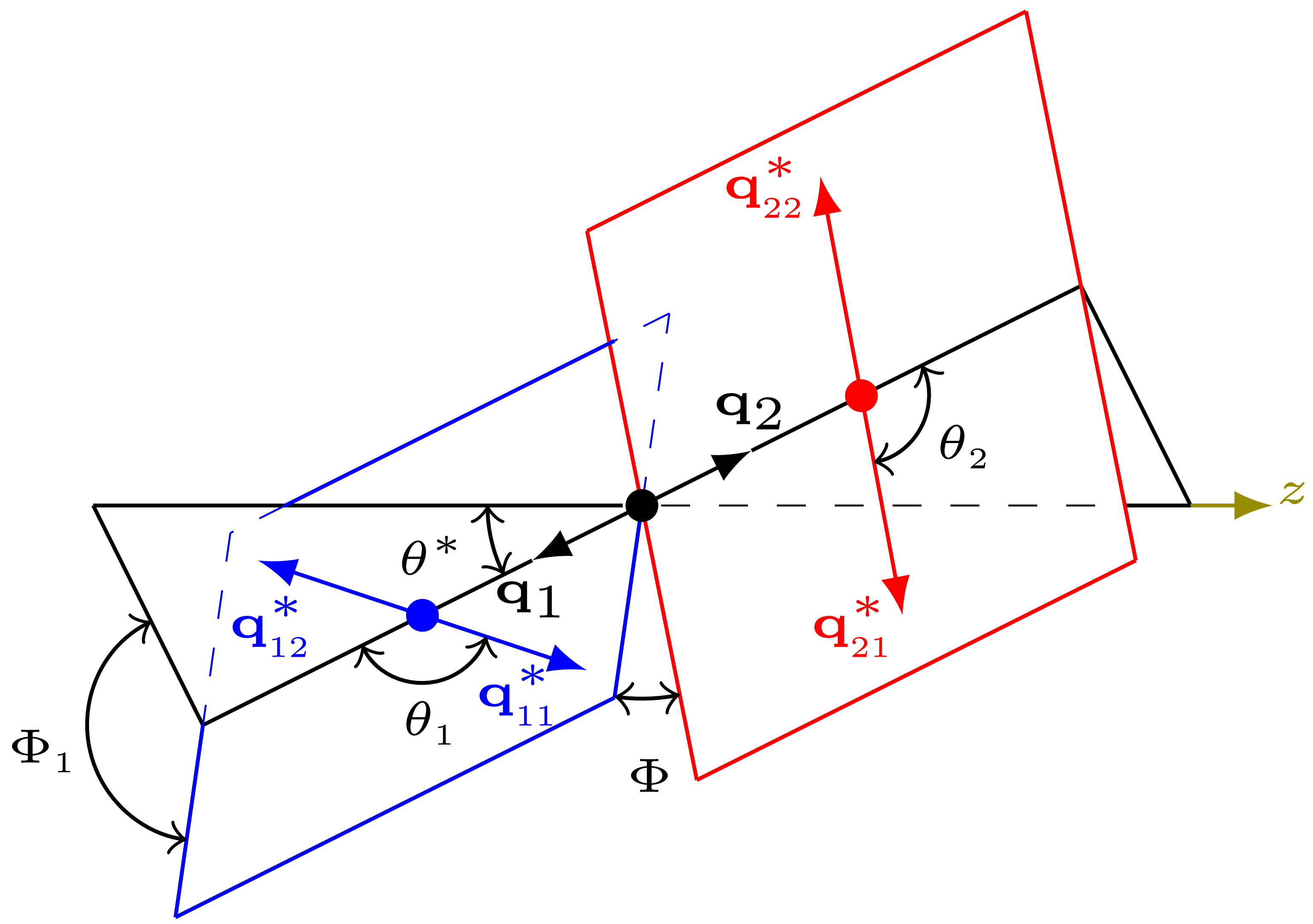
Impact of nuisance parameters

Systematic Uncertainty Fixed	$\mu_{\text{off-shell}}$ **Value at which** $t_{\mu_{\text{off-shell}}} = 4$	
	NSBI analysis	**Histogram-based**
All (stat-only)	1.96	2.13
Parton shower uncertainty for $gg \to ZZ$ (normalization)	2.07	2.26
Parton shower uncertainty for $gg \to ZZ$ (shape)	2.12	2.29
NLO EW uncertainty for $q\bar{q} \to ZZ$	2.10	2.27
NLO QCD uncertainty for $gg \to ZZ$	2.09	2.29
Parton shower uncertainty for $q\bar{q} \to ZZ$ (shape)	2.12	2.29
Jet energy scale and resolution uncertainty	2.11	2.26
None (full result)	2.12	2.30

Full probability model, input variables

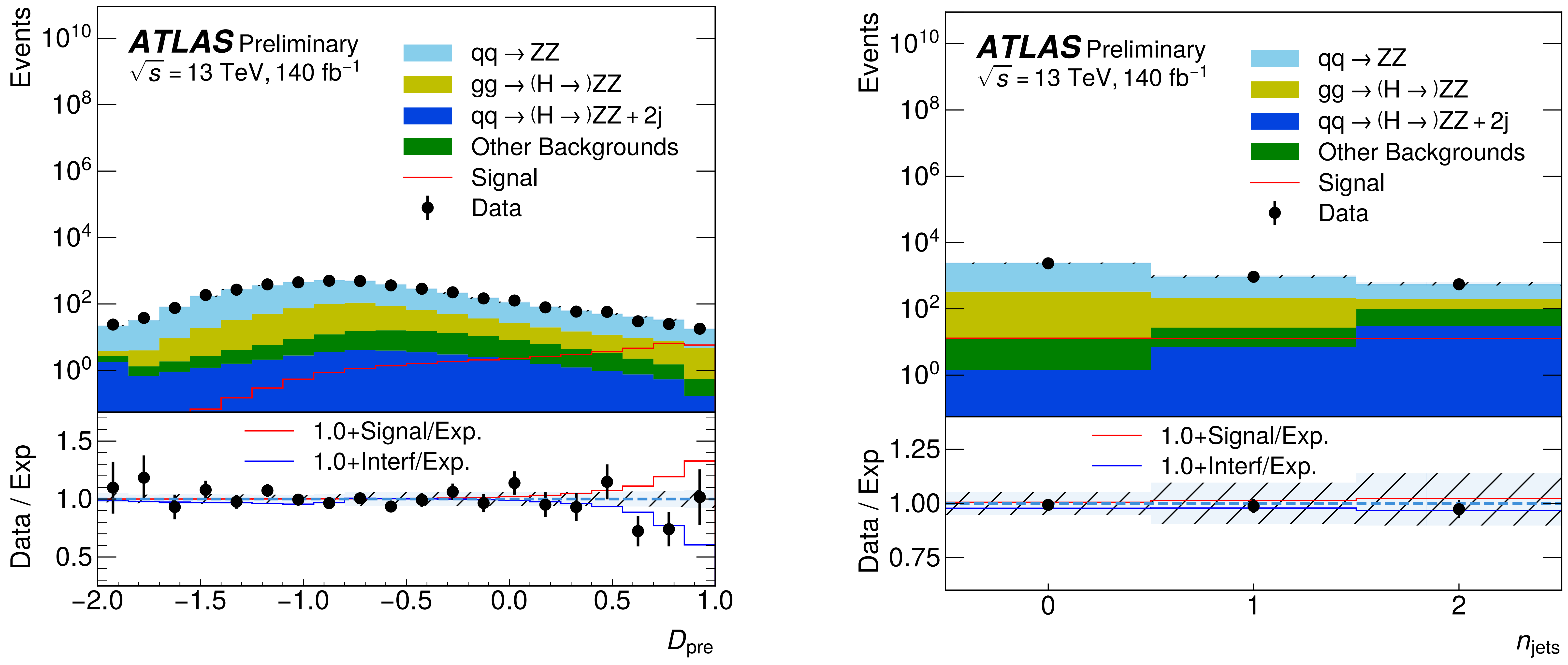
$$p(x|\mu^{\text{ggF}}_{\text{off-shell}}, \mu^{\text{EW}}_{\text{off-shell}}) = \frac{1}{\nu(\mu^{\text{ggF}}_{\text{off-shell}}, \mu^{\text{EW}}_{\text{off-shell}})} \times \Bigg[\mu^{\text{ggF}}_{\text{off-shell}} \nu^{\text{ggF}}_{\text{S}} p^{\text{ggF}}_{\text{S}}(x) + \sqrt{\mu^{\text{ggF}}_{\text{off-shell}}} \nu^{\text{ggF}}_{\text{I}} p^{\text{ggF}}_{\text{I}}(x) + \nu^{\text{ggF}}_{\text{B}} p^{\text{ggF}}_{\text{B}}(x) + \mu^{\text{EW}}_{\text{off-shell}} \nu^{\text{EW}}_{\text{S}} p^{\text{EW}}_{\text{S}}(x) + \sqrt{\mu^{\text{EW}}_{\text{off-shell}}} \nu^{\text{EW}}_{\text{I}} p^{\text{EW}}_{\text{I}}(x) + \nu^{\text{EW}}_{\text{B}} p^{\text{EW}}_{\text{B}}(x) + \nu_{\text{NI}} p_{\text{NI}}(x) \Bigg],$$

Variable	Definition
$m_{4\ell}$	quadruplet mass
m_{Z1}	Z_1 mass
m_{Z2}	Z_2 mass
$\cos\theta^*$	cosine of the Higgs boson decay angle $[\mathbf{q}_1 \cdot \mathbf{n}_z / \lvert\mathbf{q}_1\rvert]$
$\cos\theta_1$	cosine of the Z_1 decay angle $[-(\mathbf{q}_2) \cdot \mathbf{q}_{11} / (\lvert\mathbf{q}_2\rvert \cdot \lvert\mathbf{q}_{11}\rvert)]$
$\cos\theta_2$	cosine of the Z_2 decay angle $[-(\mathbf{q}_1) \cdot \mathbf{q}_{21} / (\lvert\mathbf{q}_1\rvert \cdot \lvert\mathbf{q}_{21}\rvert)]$
Φ_1	Z_1 decay plane angle $[\cos^{-1}(\mathbf{n}_1 \cdot \mathbf{n}_{\text{sc}})\,(\mathbf{q}_1 \cdot (\mathbf{n}_1 \times \mathbf{n}_{\text{sc}})/(\lvert\mathbf{q}_1\rvert \cdot \lvert\mathbf{n}_1 \times \mathbf{n}_{\text{sc}}\rvert)]$
Φ	angle between Z_1, Z_2 decay planes $[\cos^{-1}(\mathbf{n}_1 \cdot \mathbf{n}_2)\,(\mathbf{q}_1 \cdot (\mathbf{n}_1 \times \mathbf{n}_2)/(\lvert\mathbf{q}_1\rvert \cdot \lvert\mathbf{n}_1 \times \mathbf{n}_2\rvert)]$
$p_T^{4\ell}$	quadruplet transverse momentum
$y^{4\ell}$	quadruplet rapidity
n_{jets}	number of jets in the event
m_{jj}	leading dijet system mass
$\Delta\eta_{jj}$	leading dijet system pseudorapidity
$\Delta\phi_{jj}$	leading dijet system azimuthal angle difference

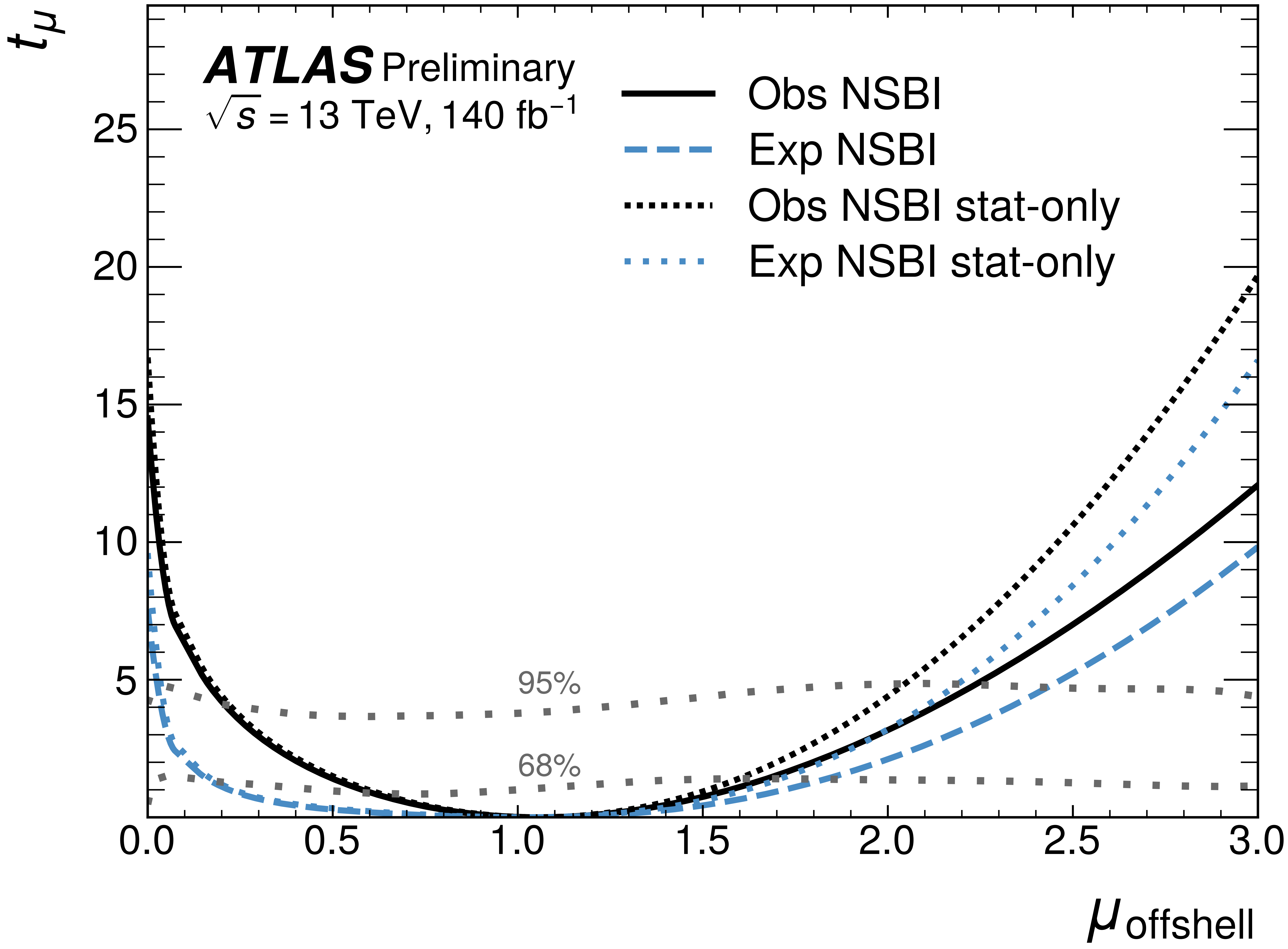


Pre-selection region definition

$$D_{\text{pre}}(x) = \log \frac{s^{\text{ggF}}_{\text{pre, S}}(x) + s^{\text{EW}}_{\text{pre, S}}(x)}{s^{\text{ggF}}_{\text{pre, B}}(x) + s^{\text{EW}}_{\text{pre, B}}(x) + s_{\text{pre}, q\bar{q}ZZ}(x)},$$



Result after combination with $ll\nu\nu$



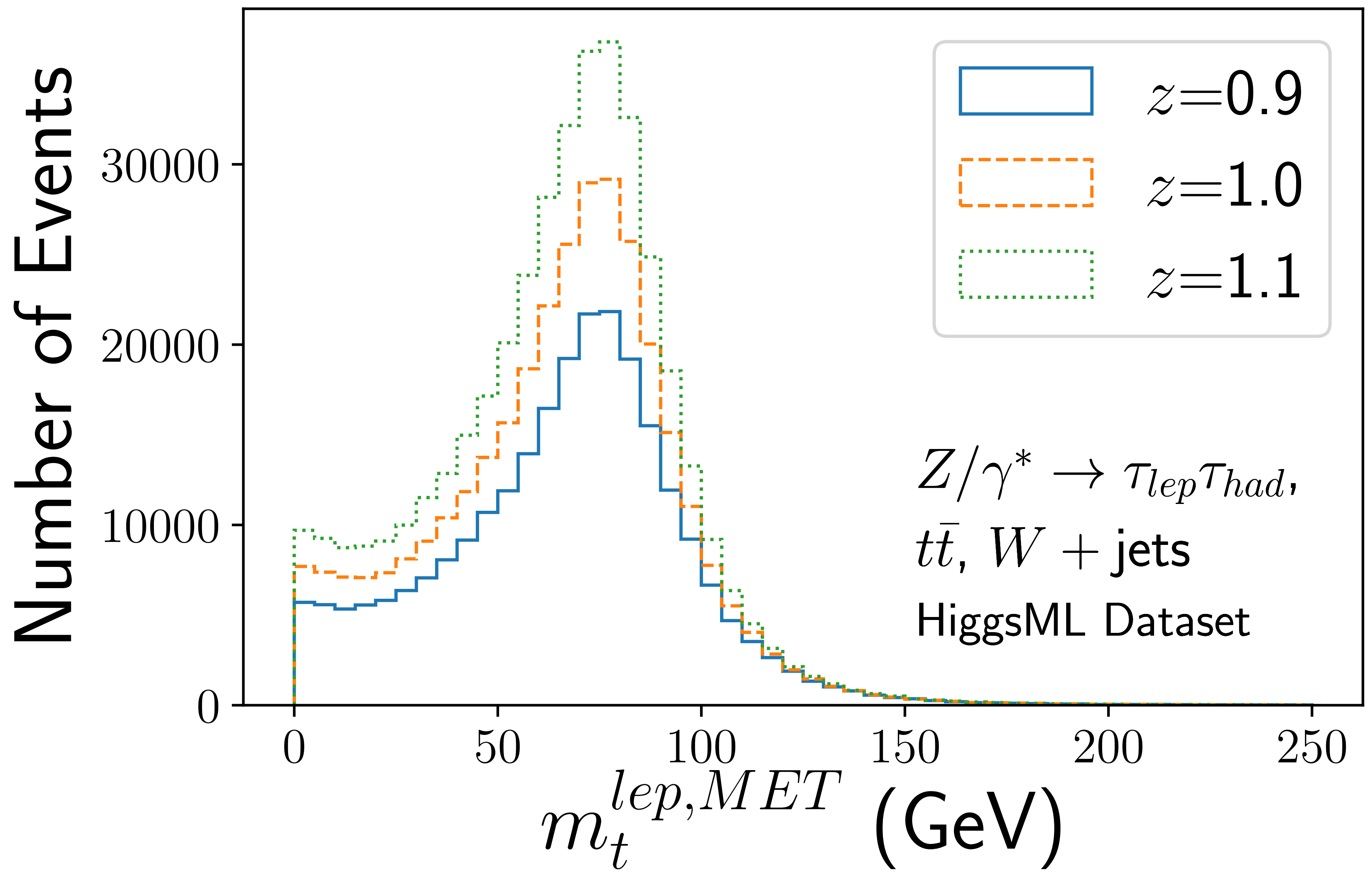
Able to set two-sided limit at 68% CL now

Traditionally ignoring systematic uncertainties during analysis optimisation

PRD.104.056026: **Aishik Ghosh**, Benjamin Nachman, and Daniel Whiteson

Experimental uncertainties:

Eg. Inaccuracies in the calibration of our detector



- Current analyses strategies **optimised while ignoring systematic uncertainties**
- Added in post-facto
- Leads to loss in sensitivity compared to uncertainty-aware optimisation (see details)

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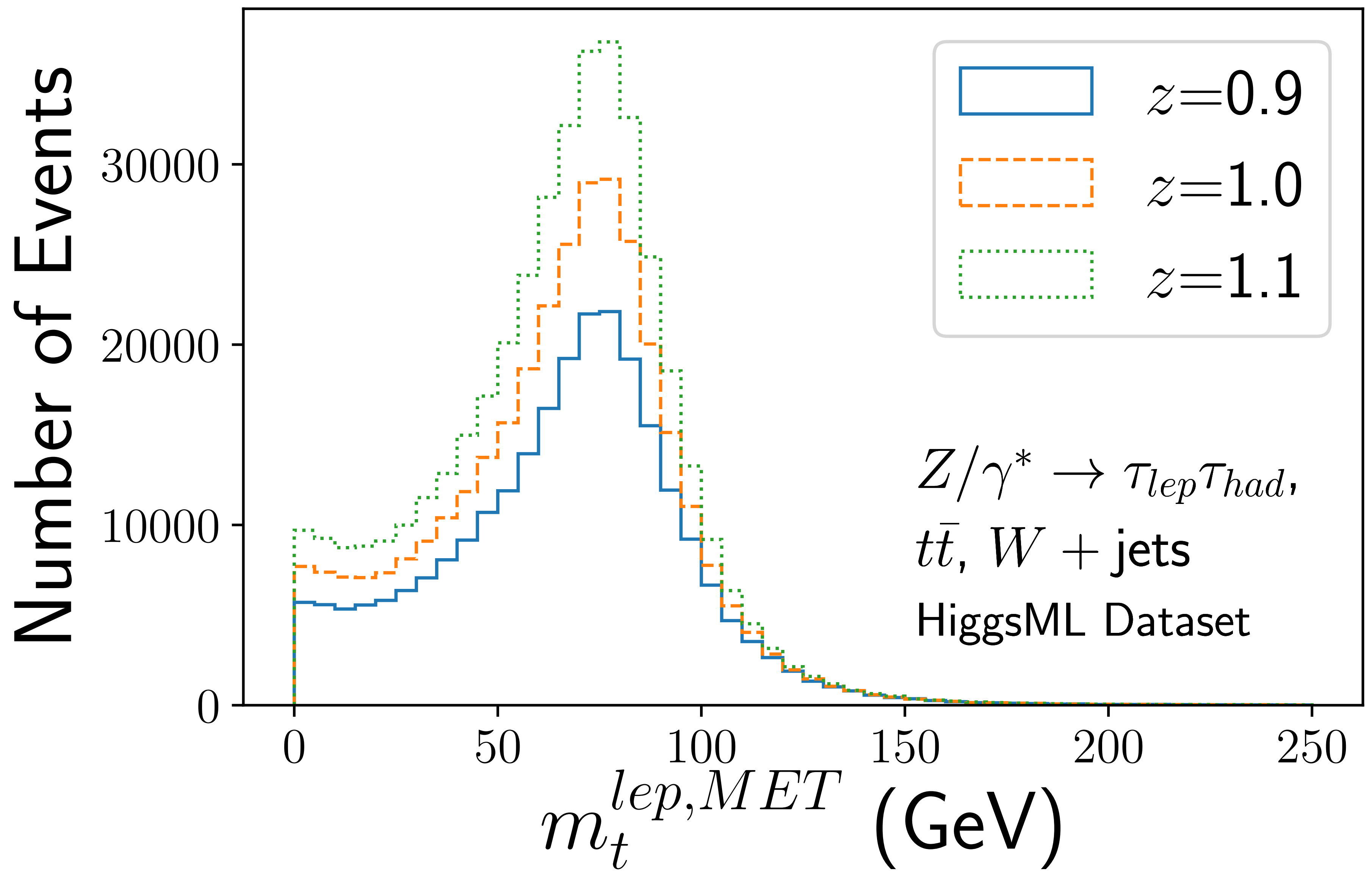

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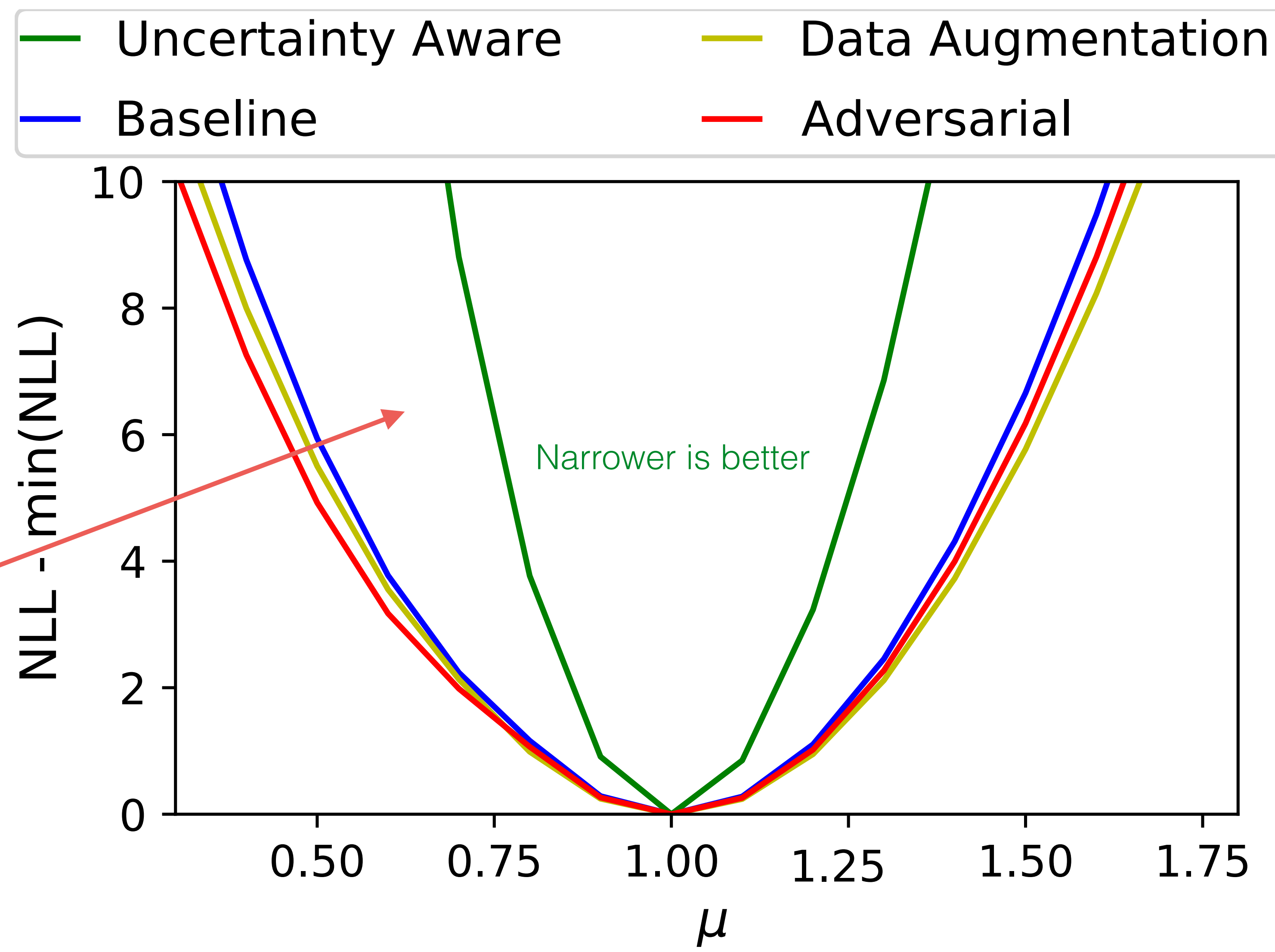
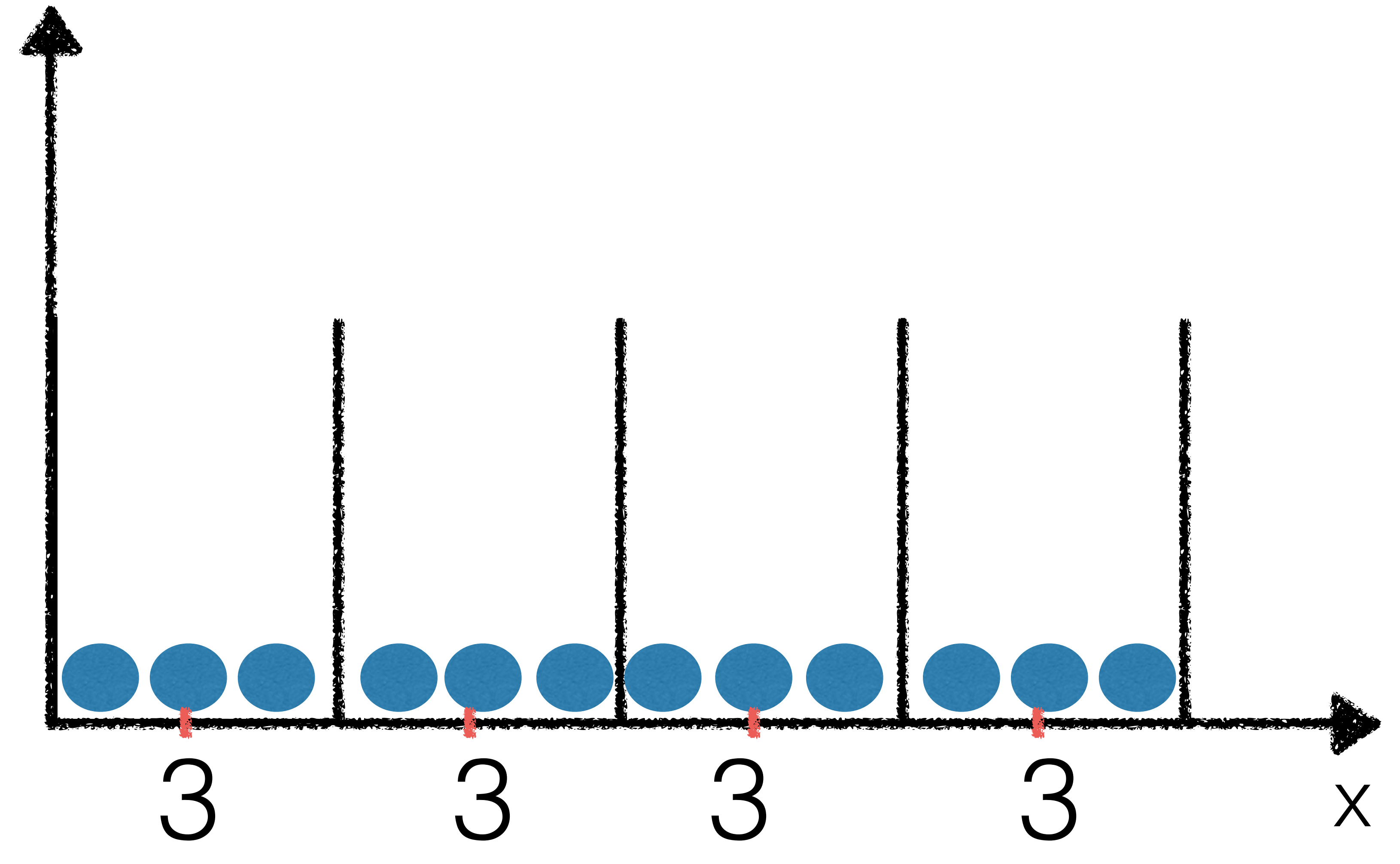
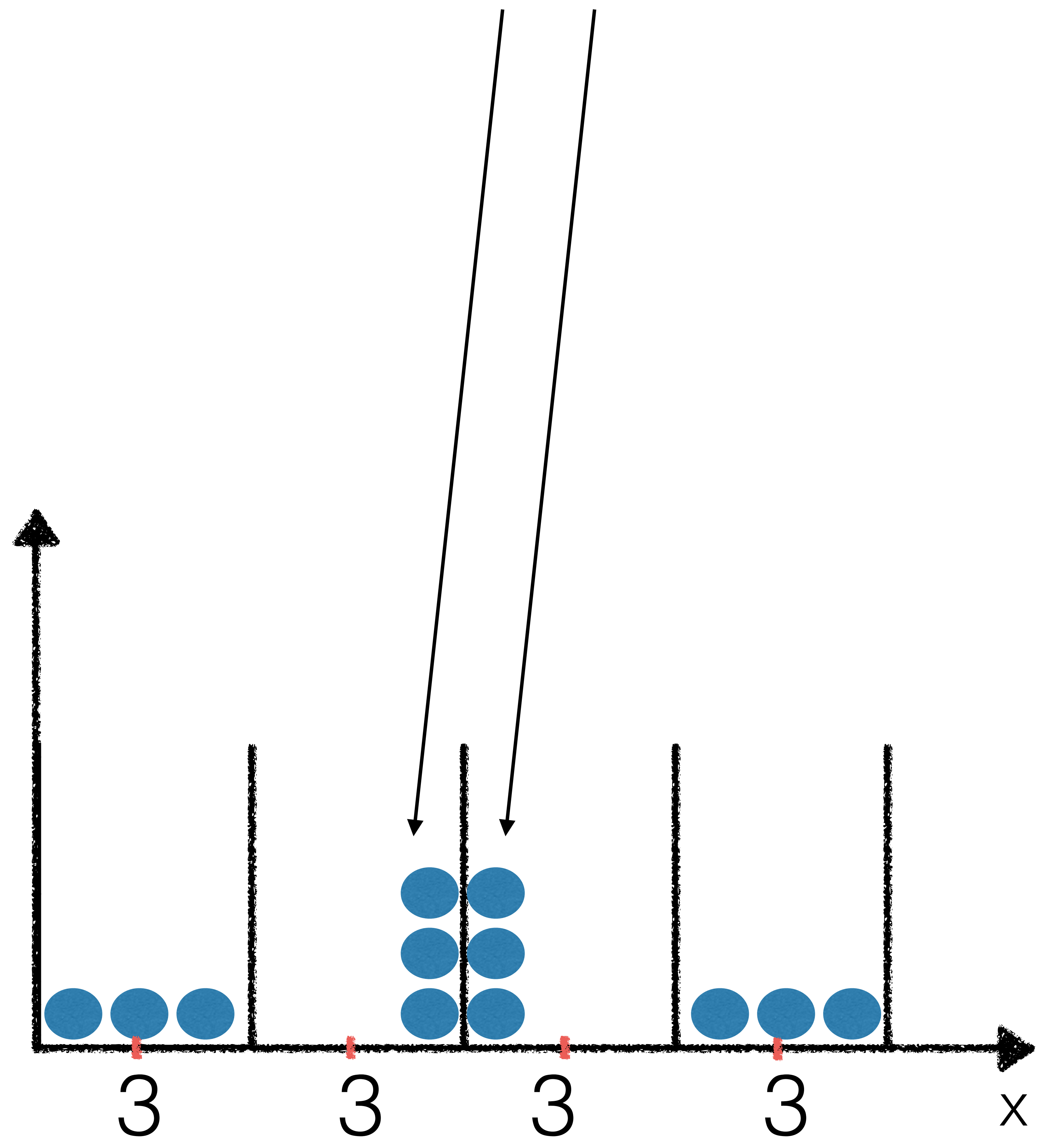


Difference b/w post-facto and uncertainty-aware

Avoids binning data into histograms, which is another lossy compression



Information on individual events lost!



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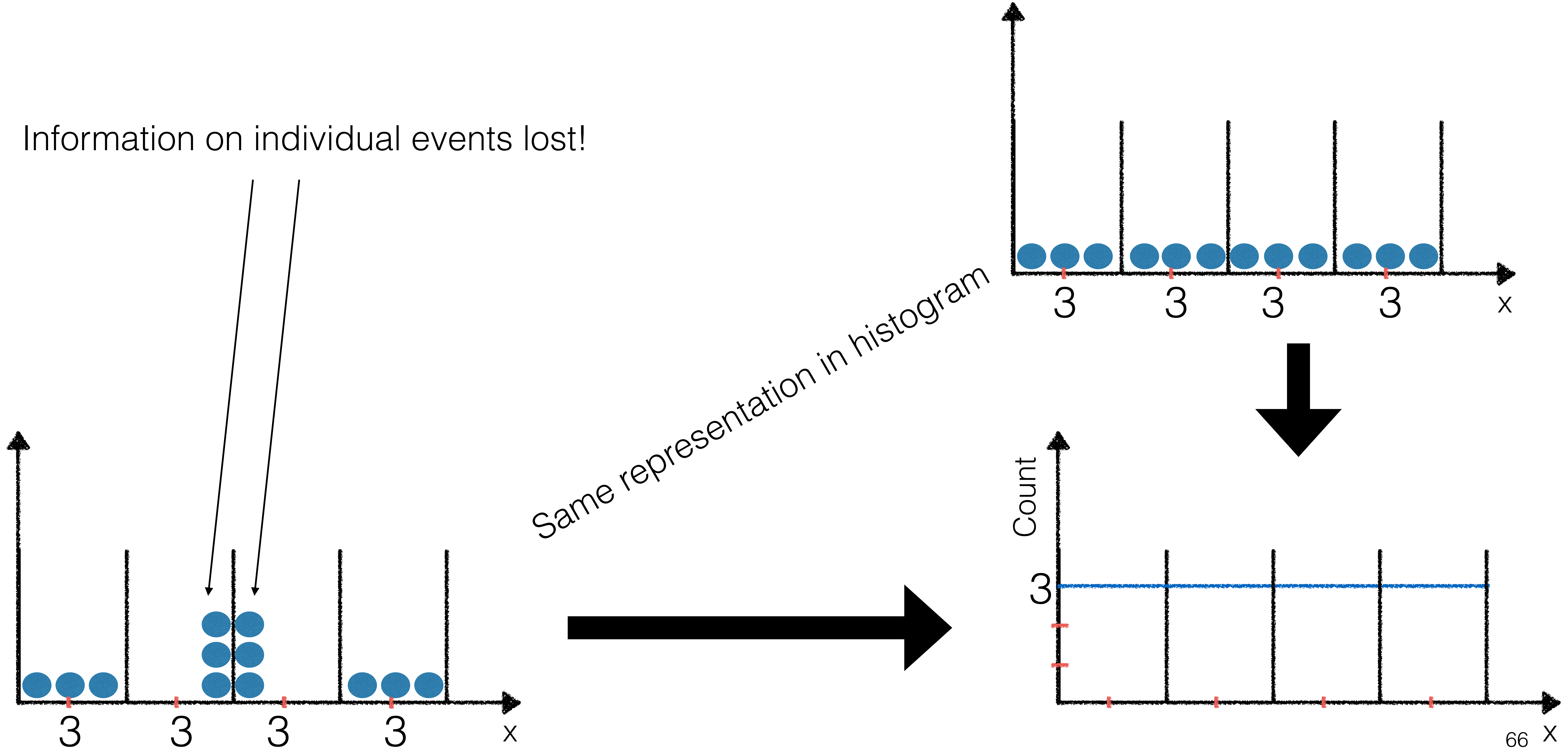


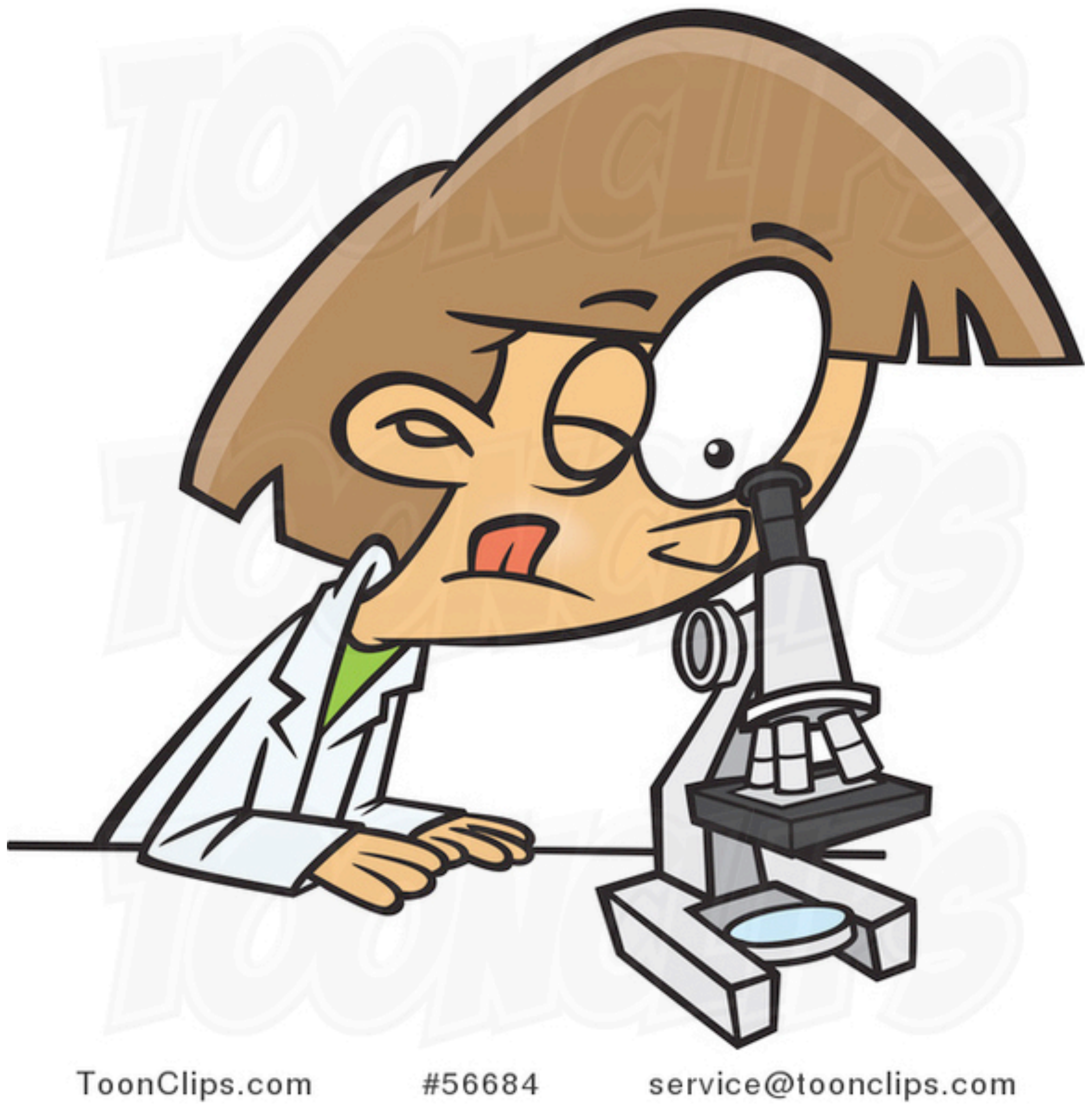
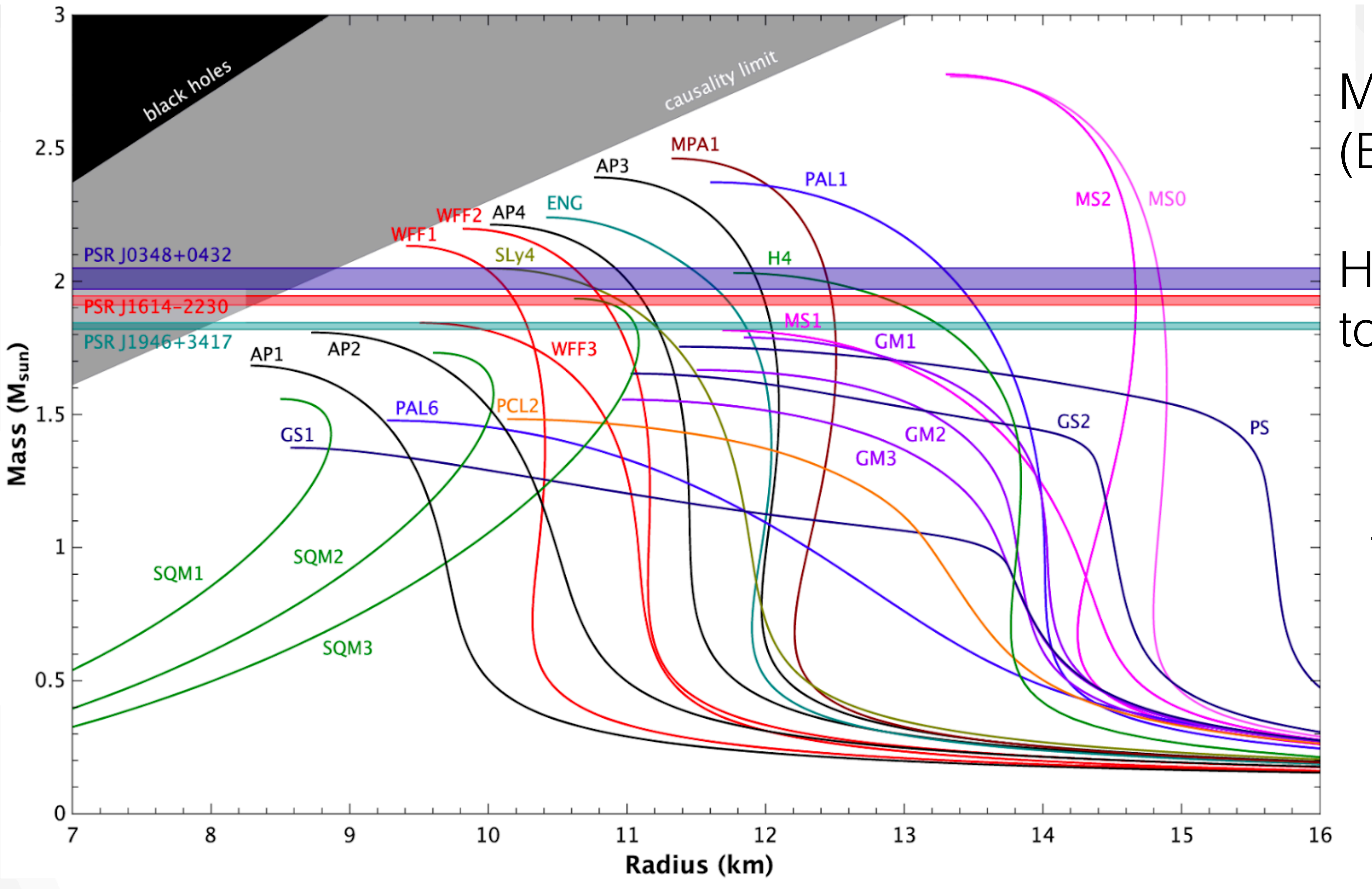

ToonClips.com #56684 service@toonclips.com

Image: Source


VAUGHAN

Telescope measurements of energy spectra of neutron stars



Mass-radius curves created by different equation of state (EoS) models

Horizontal bars show massive neutron star observations used to “rule out” EoS models.

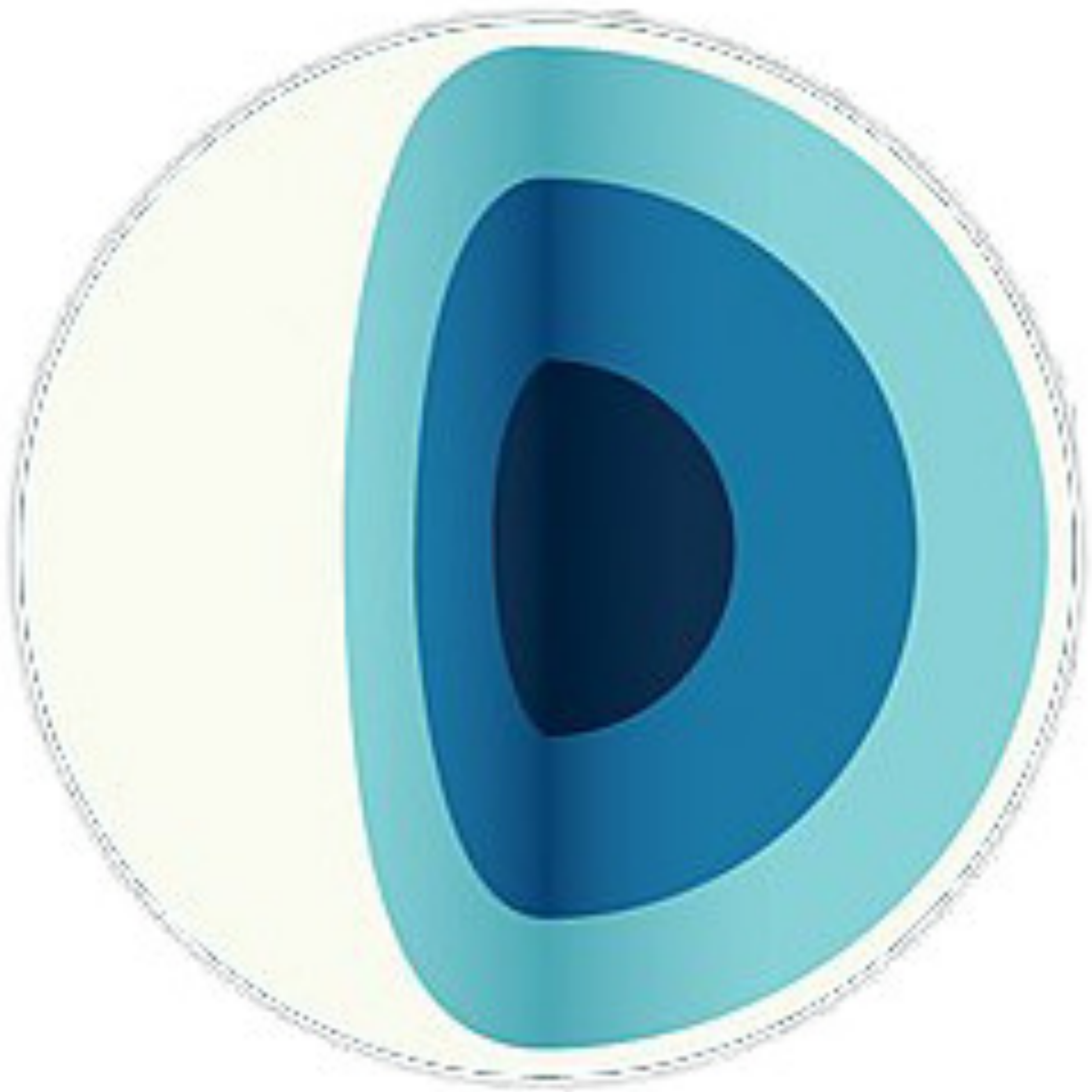
Two communities:

- Astrophysicists measure mass/radius from telescope
- Nuclear theorists measure EoS from mass/radius

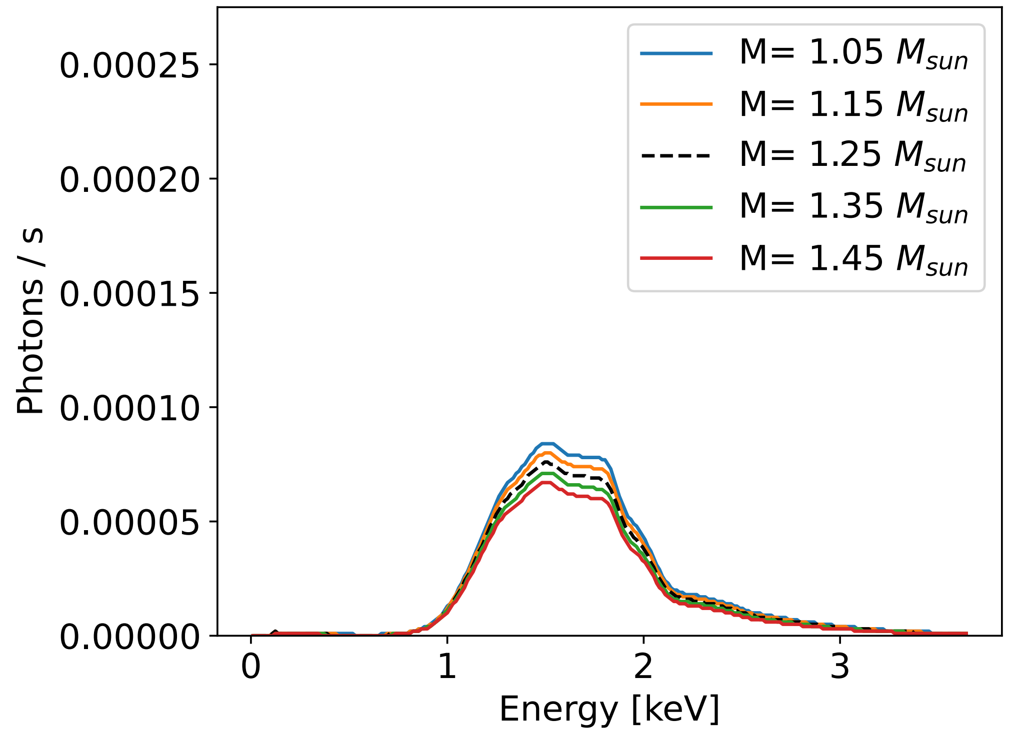
Figure from Lattimer J. M., Prakash M., 2001, The Astrophysical Journal, 550, 426–442

Telescope measurements of energy spectra

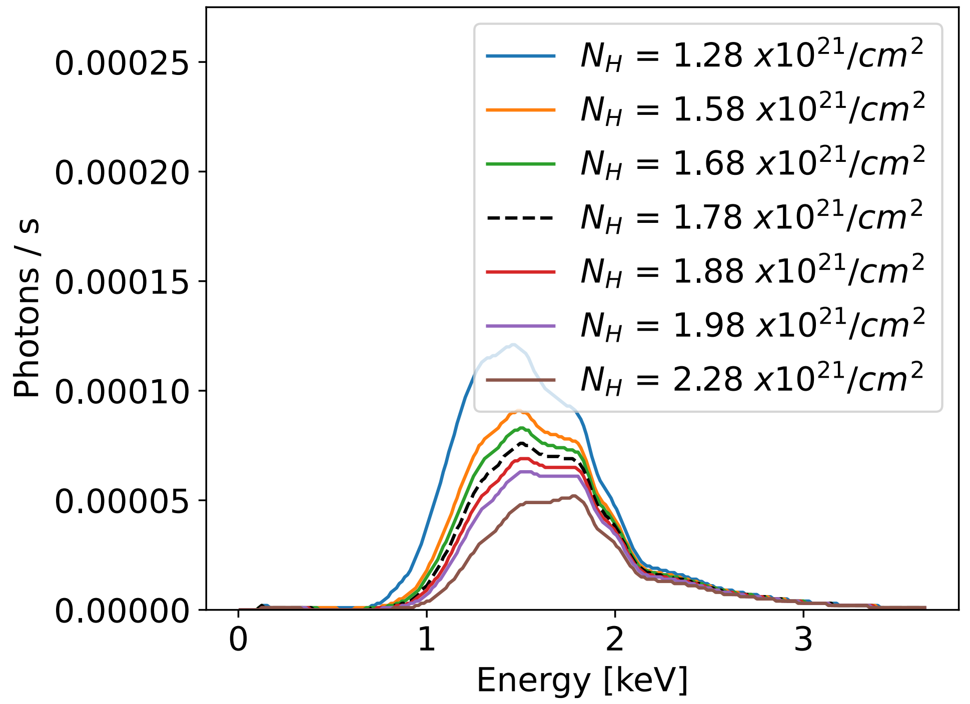
Probe the interior:
Equation of State parameters
λ_1, λ_2



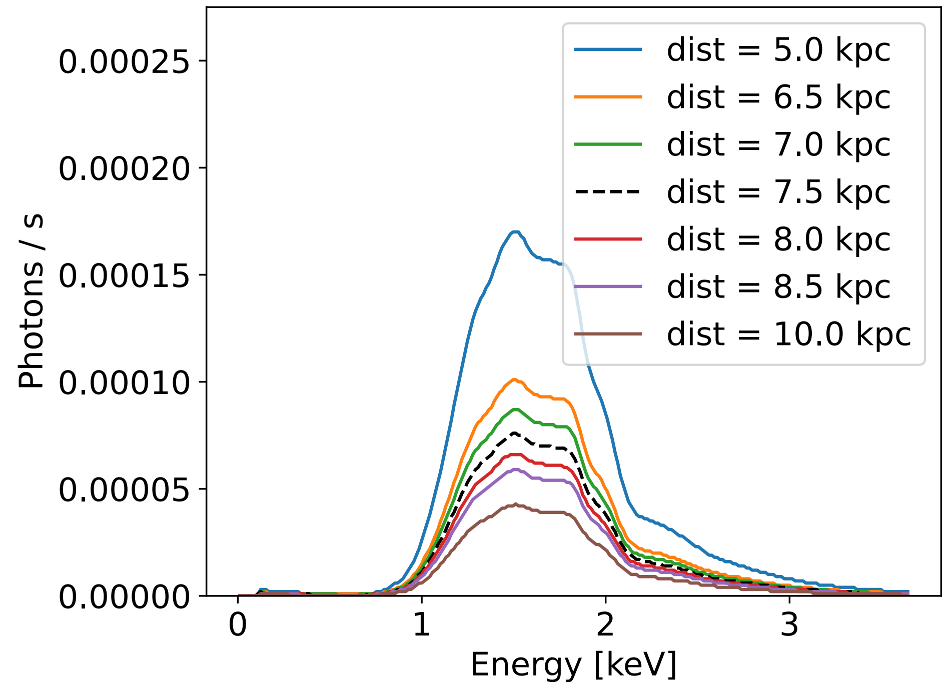
Mass

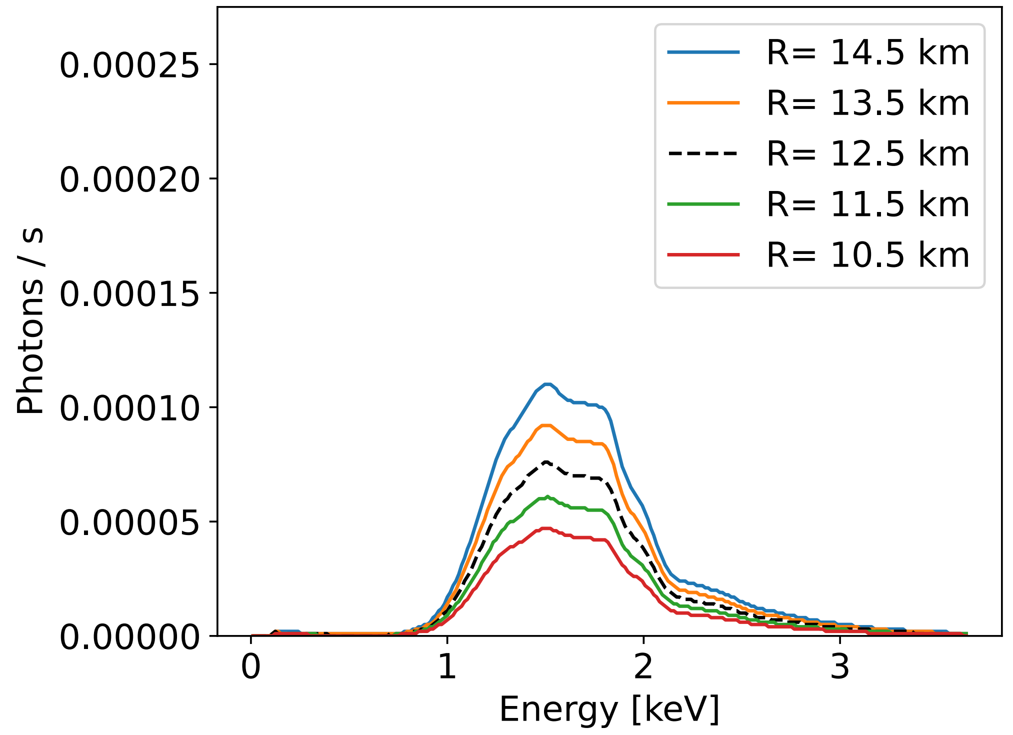


Hydrogen Column

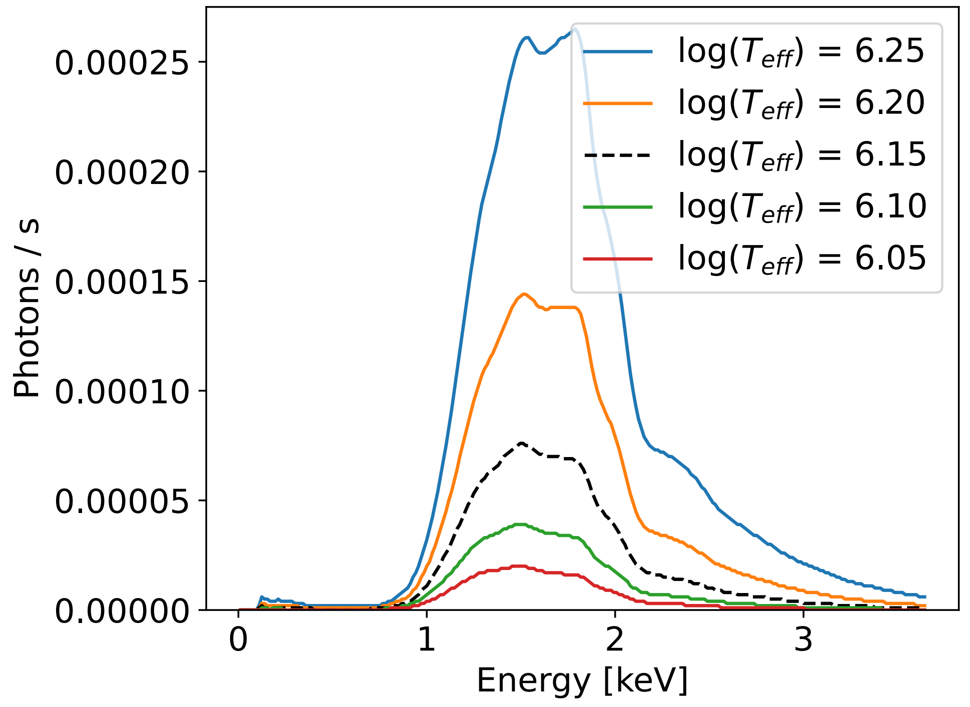


Distance





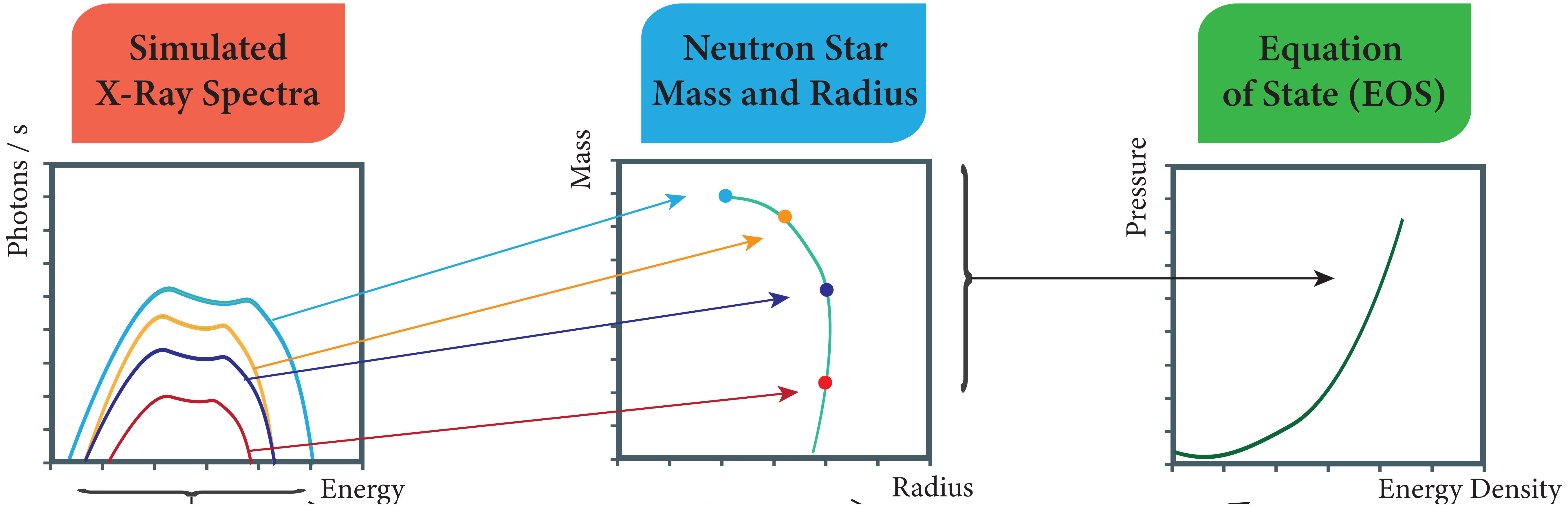
Radius



Effective Temperature

Traditional method: Two-step inference

Neutron star in sky



Astrophysicists

Nuclear theorists

JCAP.020P.0922: Delaney Farrell, Pierre Baldi, Jordan Ott, **Aishik Ghosh**, Andrew W. Steiner, Atharva Kavitkar, Lee Lindblom, Daniel Whiteson, Fridolin Weber

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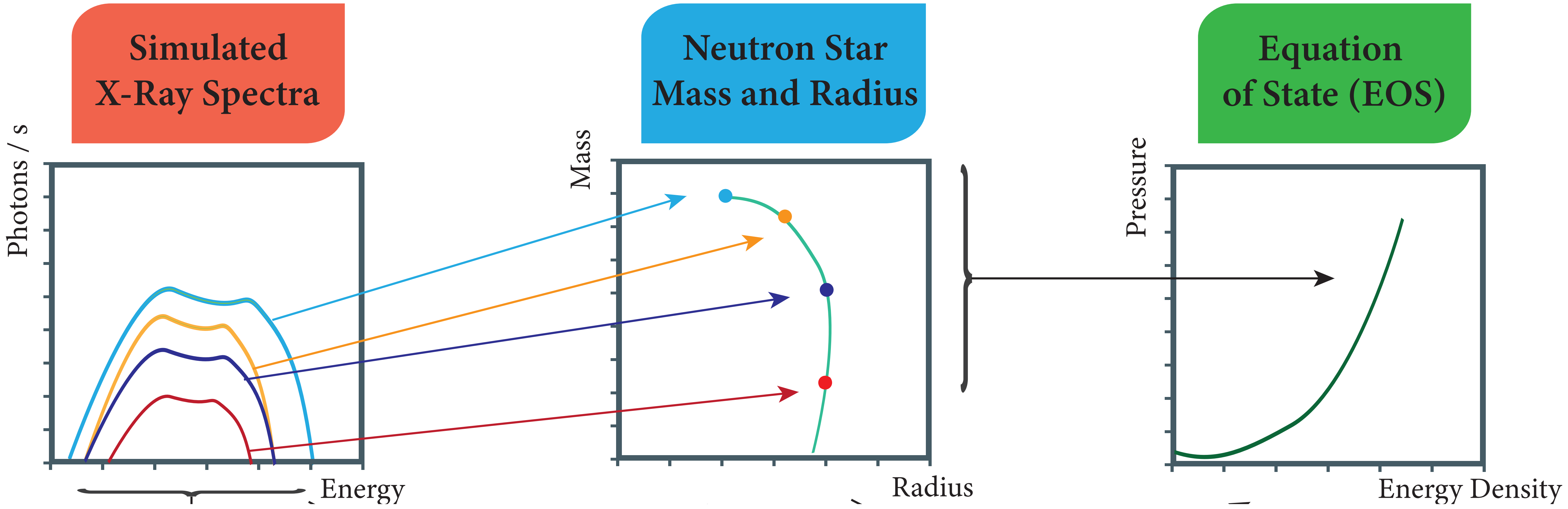

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Leak some information on uncertainties in the handover

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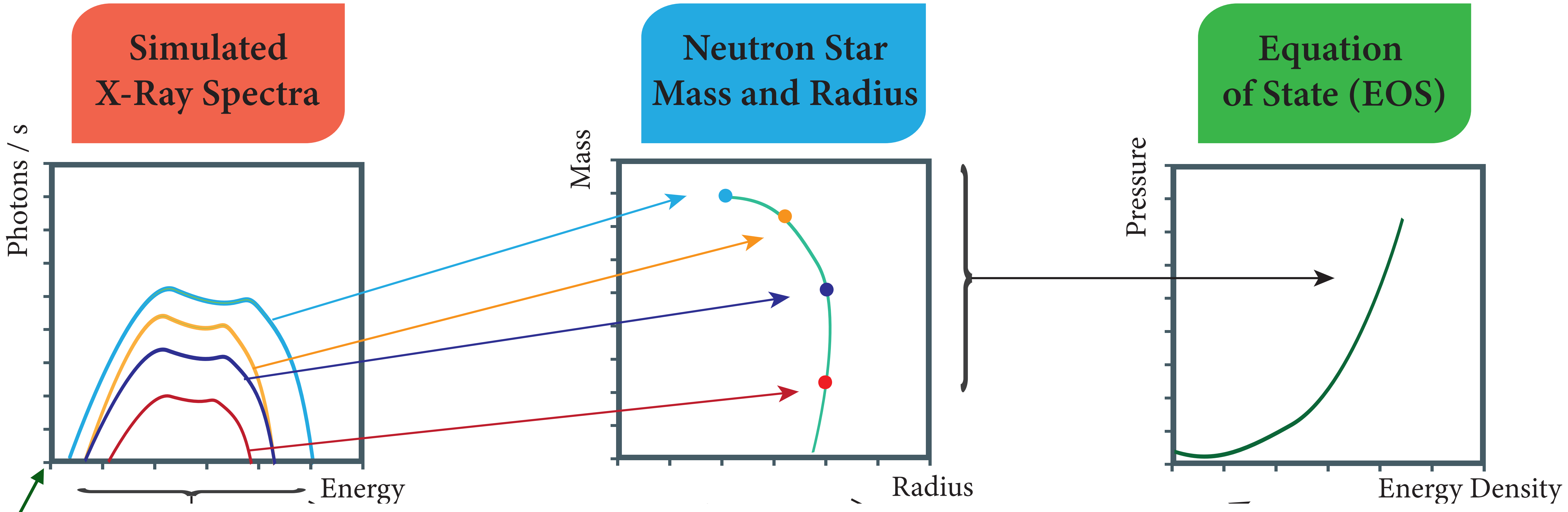


Astrophysicists

Nuclear theorists

NPs

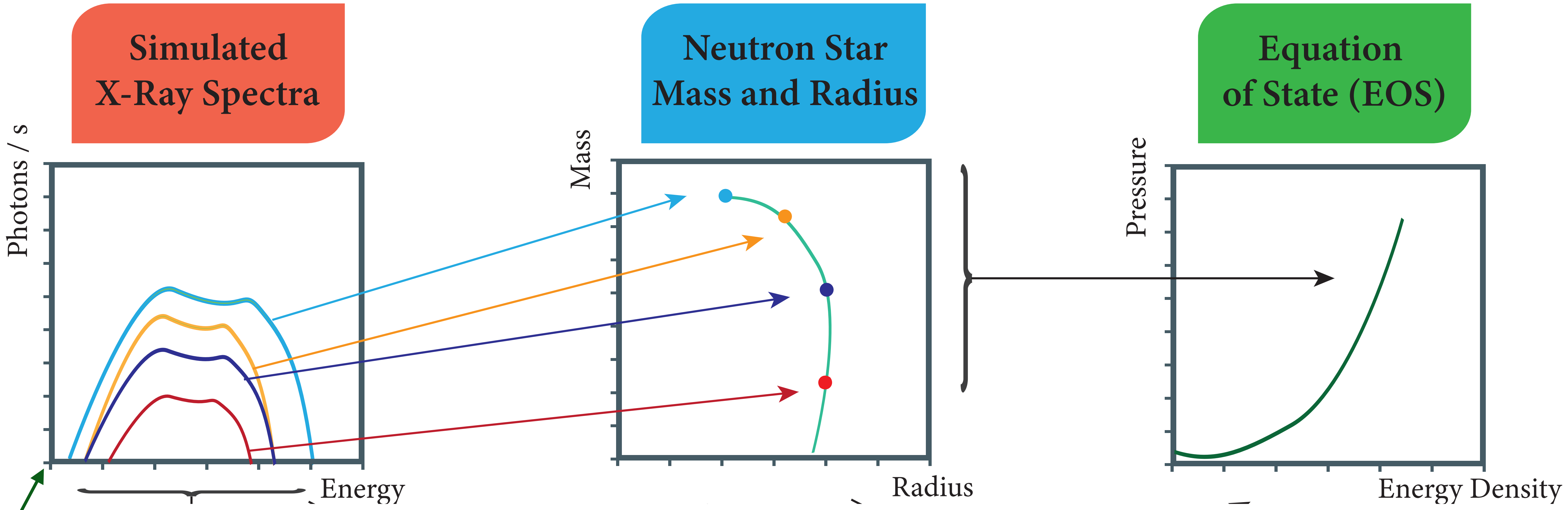
Leak some information on uncertainties in the handover

Traditional method: Two-step inference

SOTA collapsed information into 2 numbers + assumed uncorrelated Gaussian uncertainties

Real uncertainties look quite different

Neutron star in sky



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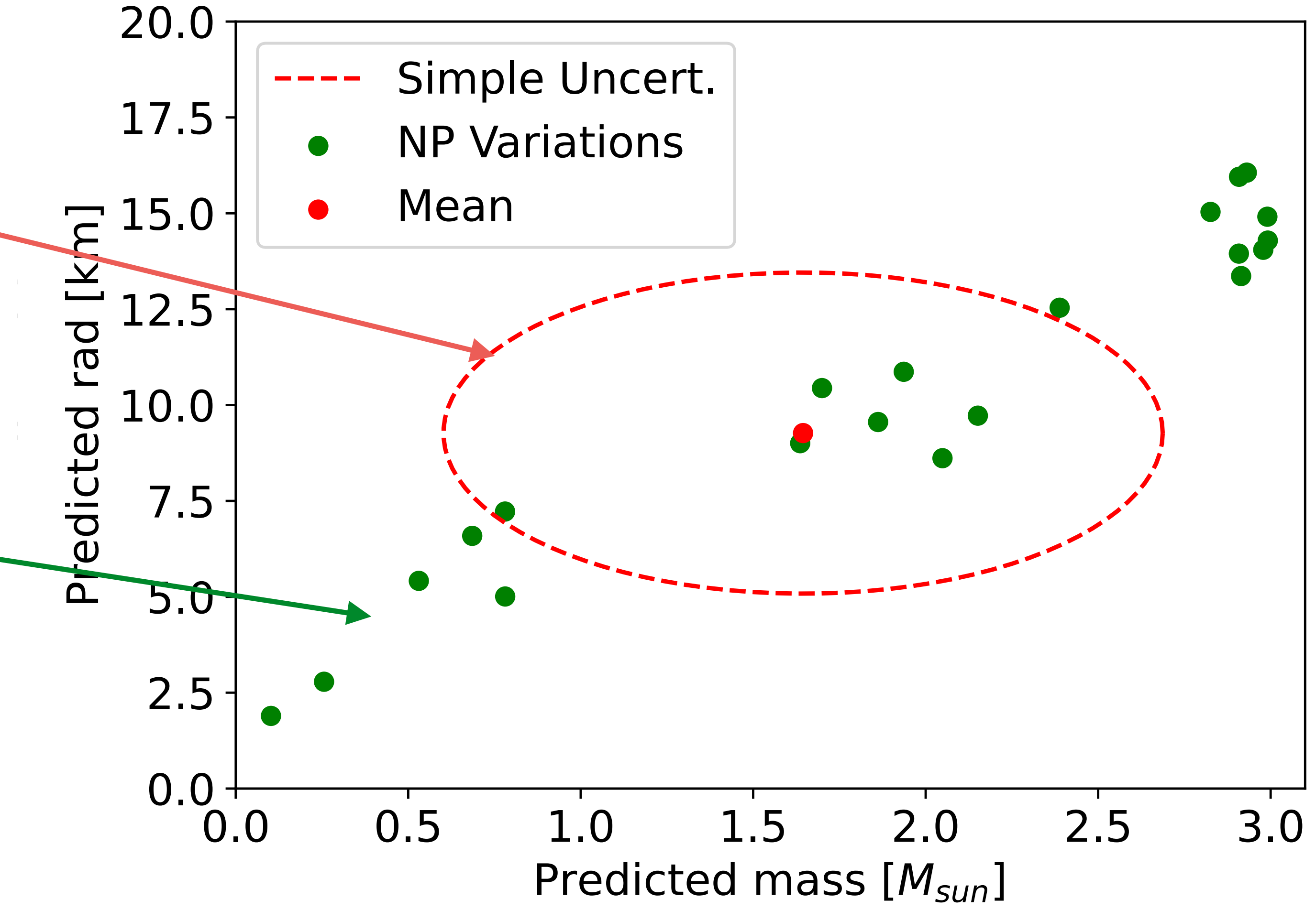
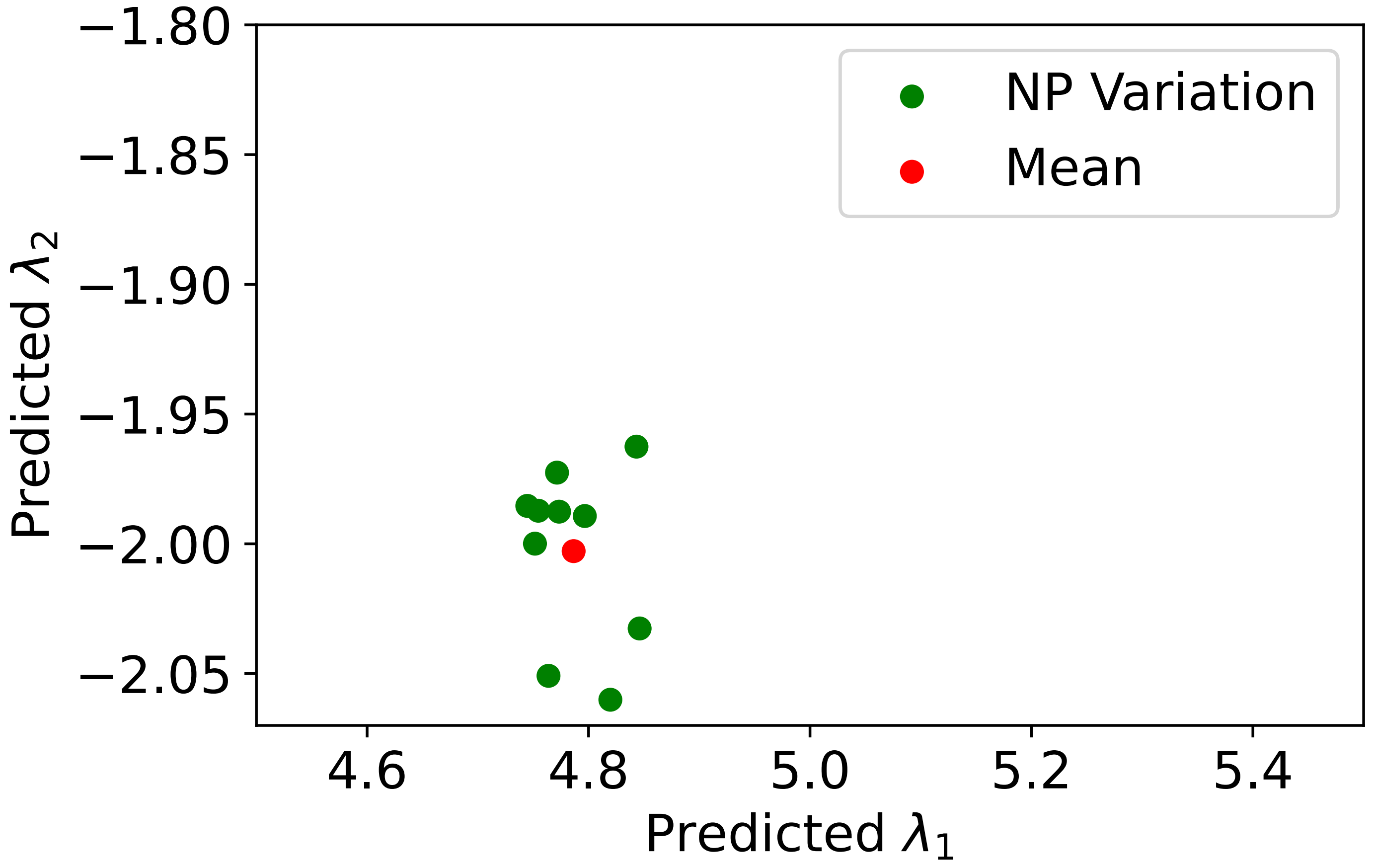
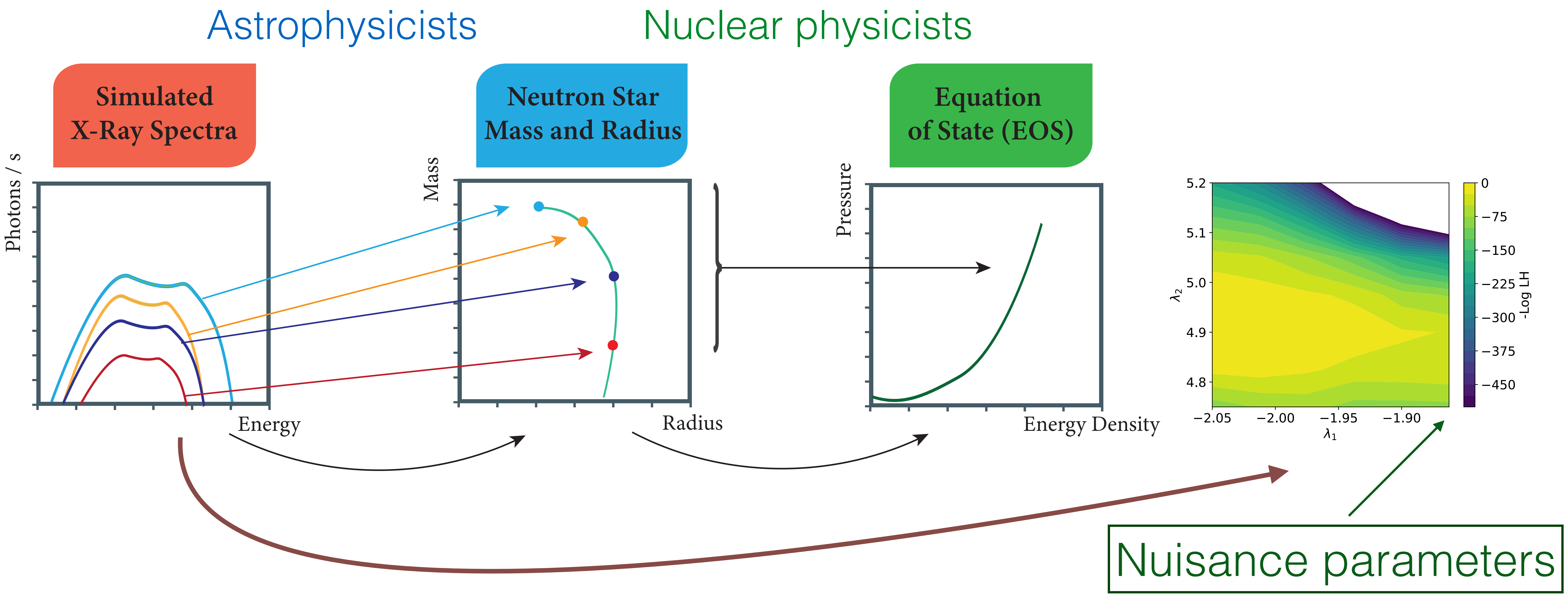




Inferring neutron star EoS parameters with NSBI

Recover the likelihood of EoS + NPs **directly from the raw high-dimensional telescope spectra!**

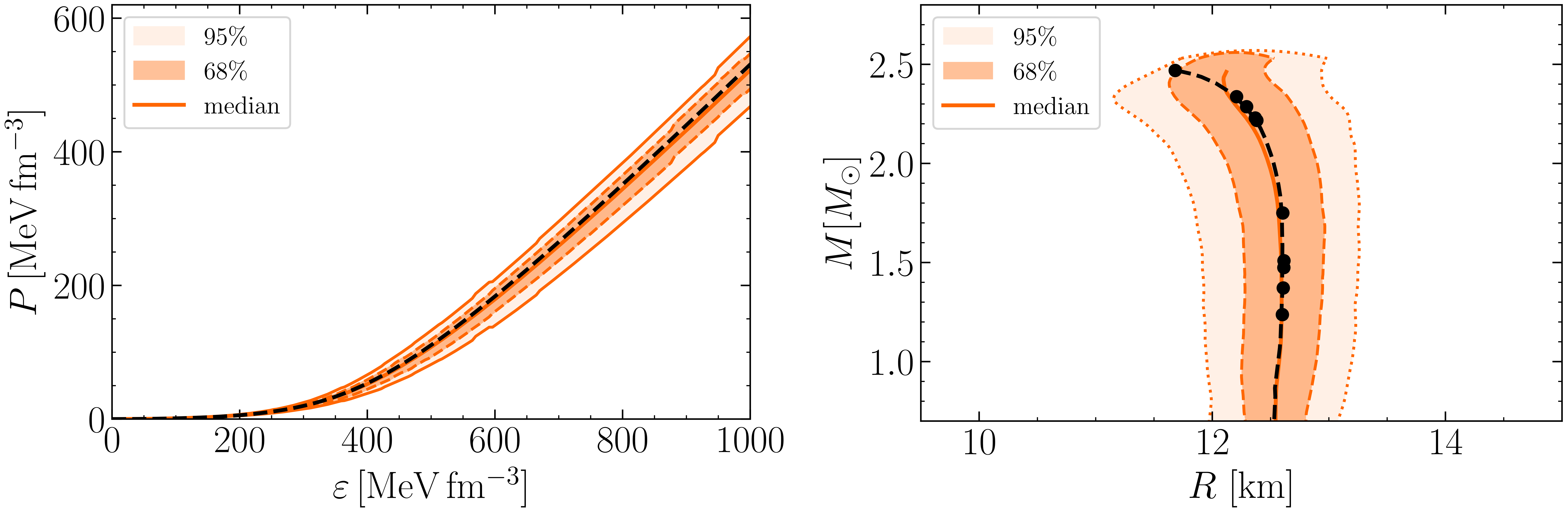
Neutron star in sky



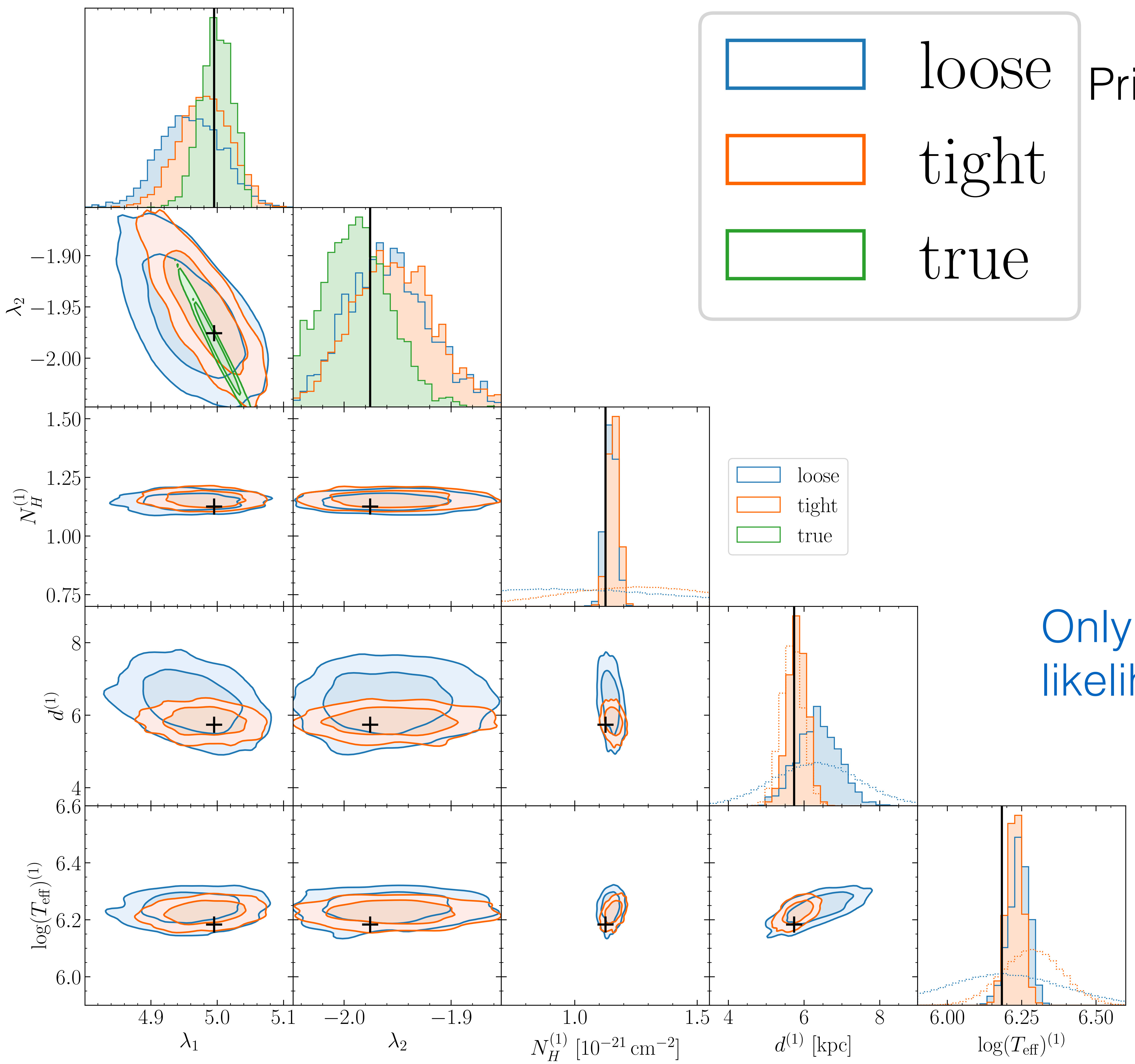
Direct estimation of likelihood from high-dimensional raw data allows more reliable uncertainty propagation and better measurements!

Meaningful posteriors, most sensitive method !

Bayesian Posteriors and credible intervals



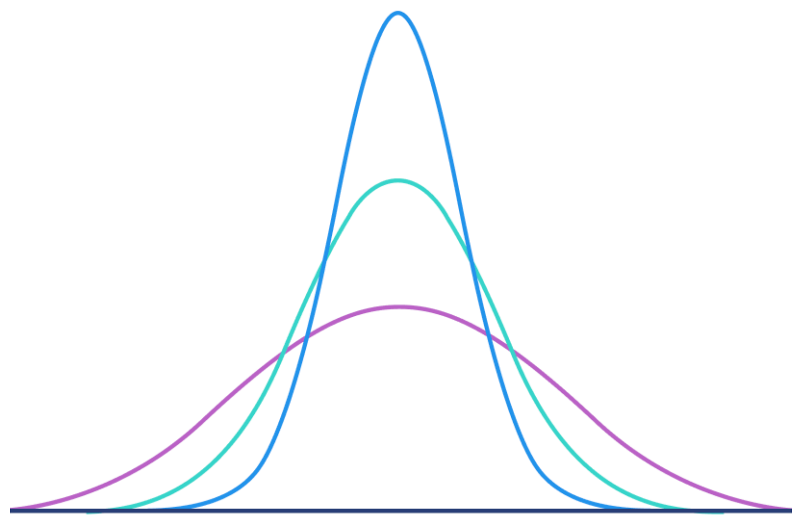
Enhanced Interpretability: Effect of nuisance parameters



Prior knowledge on nuisance parameters

Only possible to visualise these due to the fast and differentiable likelihood from networks

Most sensitive method for EoS inference to date!



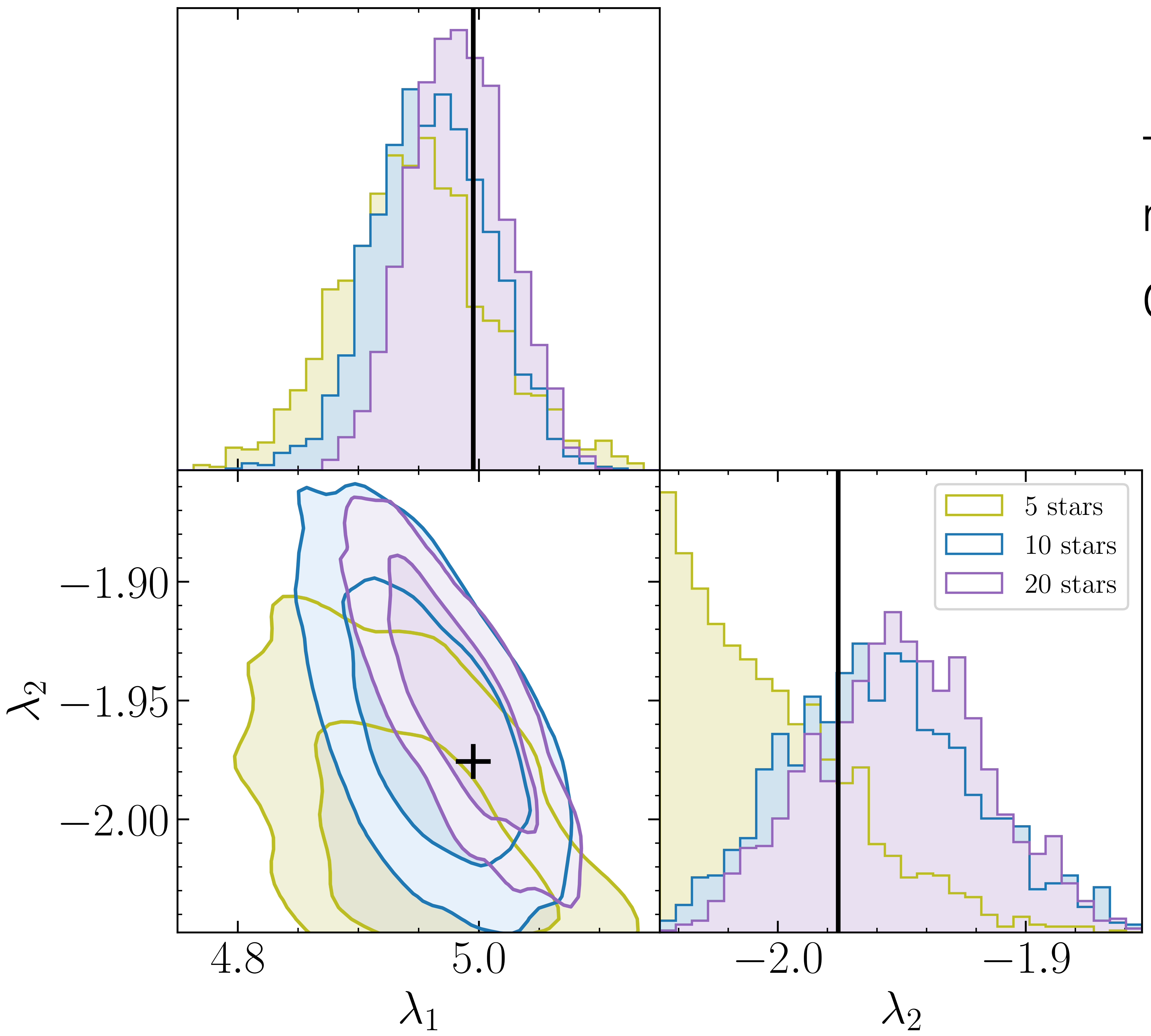
NP priors

Pretend that nuisance parameters known exactly →

Realistic scenarios:

$p(\nu)$	Method	$\lambda_{1,\mathrm{pred}} - \lambda_{1,\mathrm{truth}}$ μ	σ	$\lambda_{2,\mathrm{pred}} - \lambda_{2,\mathrm{truth}}$ μ	σ	Combined σ_{tot}
true	ML-Likelihood$_{\mathrm{EOS}}$	-0.02	0.066	**0.01**	0.070	0.096
	NN(Spectra)	-0.02	0.066	**0.01**	0.075	0.099
	NN(M, R via XSPEC)	-0.03	0.065	**0.01**	**0.055**	**0.085**
	NLE	**0.00**	**0.056**	**-0.01**	0.070	0.090
tight	ML-Likelihood$_{\mathrm{EOS}}$	-0.02	0.078	0.03	0.081	0.112
	NN(Spectra)	0.02	0.085	-0.02	0.077	0.115
	NN(M, R via XSPEC)	-0.03	0.081	**0.01**	**0.056**	0.098
	NLE	**0.00**	**0.066**	-0.02	0.071	**0.097**
loose	ML-Likelihood$_{\mathrm{EOS}}$	-0.04	0.089	0.03	0.081	0.120
	NN(Spectra)	-0.03	0.131	**-0.01**	0.078	0.152
	NN(M, R via XSPEC)	-0.03	0.123	**0.01**	**0.058**	0.136
	NLE	**0.00**	**0.085**	**-0.01**	0.074	**0.113**

Which neutron stars should we measure next ?



Test potential improvement in sensitivity coming from new measurements

Could inform decisions on which stars to measure next!

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

What we all want (Posterior)

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

What we all want (Posterior)

Likelihood

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

What we all want (Posterior)

Likelihood

Prior

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

Evidence