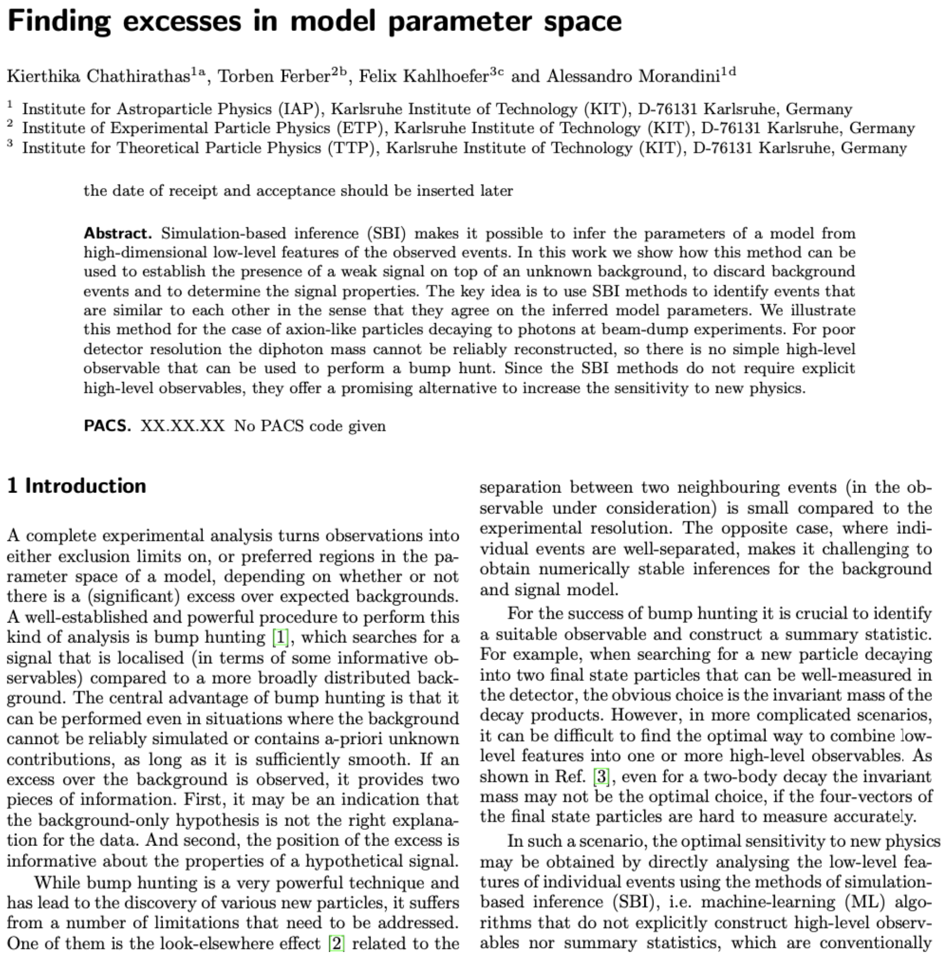
Finding Excesses in Model Parameter Space

Kierthika Chathirathas

Overview

- ML methods for signal detection with unknown rare background, rejection of background, model parameter inference
- central idea: search for compatible events regarding low-level observables allowing common signal hypothesis



Finding excesses in model parameter space

Kierthika Chathirathas[1a], Torben Ferber[2b], Felix Kahlhoefer[3c] and Alessandro Morandini[1d]

[1] Institute for Astroparticle Physics (IAP), Karlsruhe Institute of Technology (KIT), D-76131 Karlsruhe, Germany
[2] Institute of Experimental Particle Physics (ETP), Karlsruhe Institute of Technology (KIT), D-76131 Karlsruhe, Germany
[3] Institute for Theoretical Particle Physics (TTP), Karlsruhe Institute of Technology (KIT), D-76131 Karlsruhe, Germany

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Abstract. Simulation-based inference (SBI) makes it possible to infer the parameters of a model from high-dimensional low-level features of the observed events. In this work we show how this method can be used to establish the presence of a weak signal on top of an unknown background, to discard background events and to determine the signal properties. The key idea is to use SBI methods to identify events that are similar to each other in the sense that they agree on the inferred model parameters. We illustrate this method for the case of axion-like particles decaying to photons at beam-dump experiments. For poor detector resolution the diphoton mass cannot be reliably reconstructed, so there is no simple high-level observable that can be used to perform a bump hunt. Since the SBI methods do not require explicit high-level observables, they offer a promising alternative to increase the sensitivity to new physics.

PACS. XX.XX.XX No PACS code given

1 Introduction

A complete experimental analysis turns observations into either exclusion limits on, or preferred regions in the parameter space of a model, depending on whether or not there is a (significant) excess over expected backgrounds. A well-established and powerful procedure to perform this kind of analysis is bump hunting [1], which searches for a signal that is localised (in terms of some informative observables) compared to a more broadly distributed background. The central advantage of bump hunting is that it can be performed even in situations where the background cannot be reliably simulated or contains a-priori unknown contributions, as long as it is sufficiently smooth. If an excess over the background is observed, it provides two pieces of information. First, it may be an indication that the background-only hypothesis is not the right explanation for the data. And second, the position of the excess is informative about the properties of a hypothetical signal.

While bump hunting is a very powerful technique and has lead to the discovery of various new particles, it suffers from a number of limitations that need to be addressed. One of them is the look-elsewhere effect [2] related to the separation between two neighbouring events (in the observable under consideration) is small compared to the experimental resolution. The opposite case, where individual events are well-separated, makes it challenging to obtain numerically stable inferences for the background and signal model.

For the success of bump hunting it is crucial to identify a suitable observable and construct a summary statistic. For example, when searching for a new particle decaying into two final state particles that can be well-measured in the detector, the obvious choice is the invariant mass of the decay products. However, in more complicated scenarios, it can be difficult to find the optimal way to combine low-level features into one or more high-level observables. As shown in Ref. [3], even for a two-body decay the invariant mass may not be the optimal choice, if the four-vectors of the final state particles are hard to measure accurately.

In such a scenario, the optimal sensitivity to new physics may be obtained by directly analysing the low-level features of individual events using the methods of simulation-based inference (SBI), i.e. machine-learning (ML) algorithms that do not explicitly construct high-level observables nor summary statistics, which are conventionally

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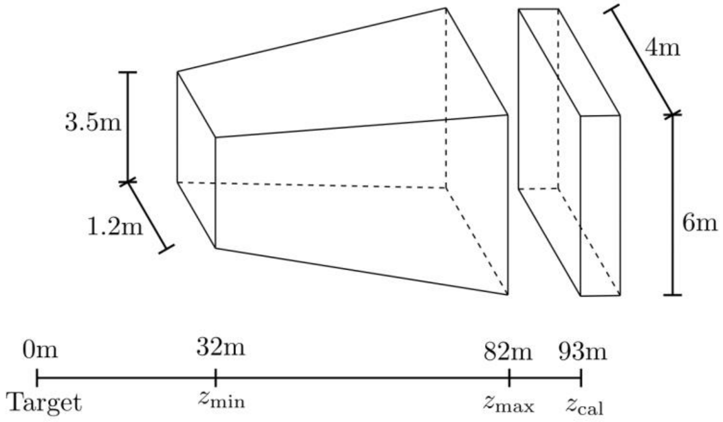
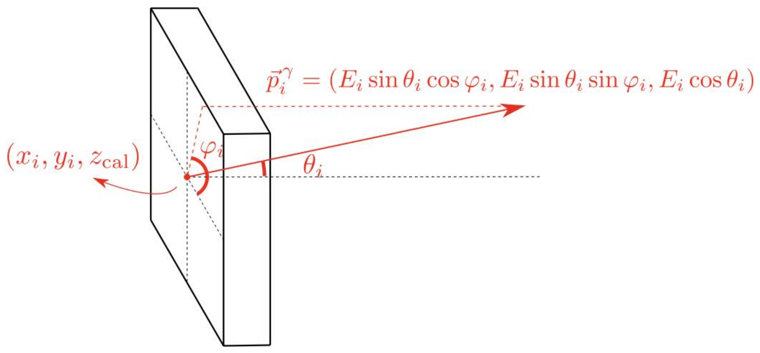
Experimental Setup & Simulation





- search for ALPs decaying into 2 photons in SHiP
- produced in rare (mainly *B*) meson decays
- small number of background events produced by muon and neutrino inelastic scatterings

- model parameters: $m_a \in$ [0.1GeV, 4.5GeV] and $c\tau_a / m_a \in$ [0.05 mGeV^{-1}, 500 mGeV^{-1}]
- low-level observables: photon energies, calorimeter hit positions, polar and azimuthal incidence angles
- limited detector resolution: smearing
- background: resemble signals, no fixed mass and lifetime

Conventional Approaches

Traditional Bump Hunt

- construct high-level observable and search for localised signal in more broadly distributed background
- even if background cannot be reliably simulated
- problems:
  - look-elsewhere effect
  - poor detector resolution
  - low number of signal events

Simulation-based Inference

- infer parameters by analysing high-dimensional low-level observables
- do not require construction of explicit high-level observables
- need simulations
- problem:
  - unknown or difficult-to-simulate backgrounds

Combined Approach

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Event Compatibility based on Observables (ECO)

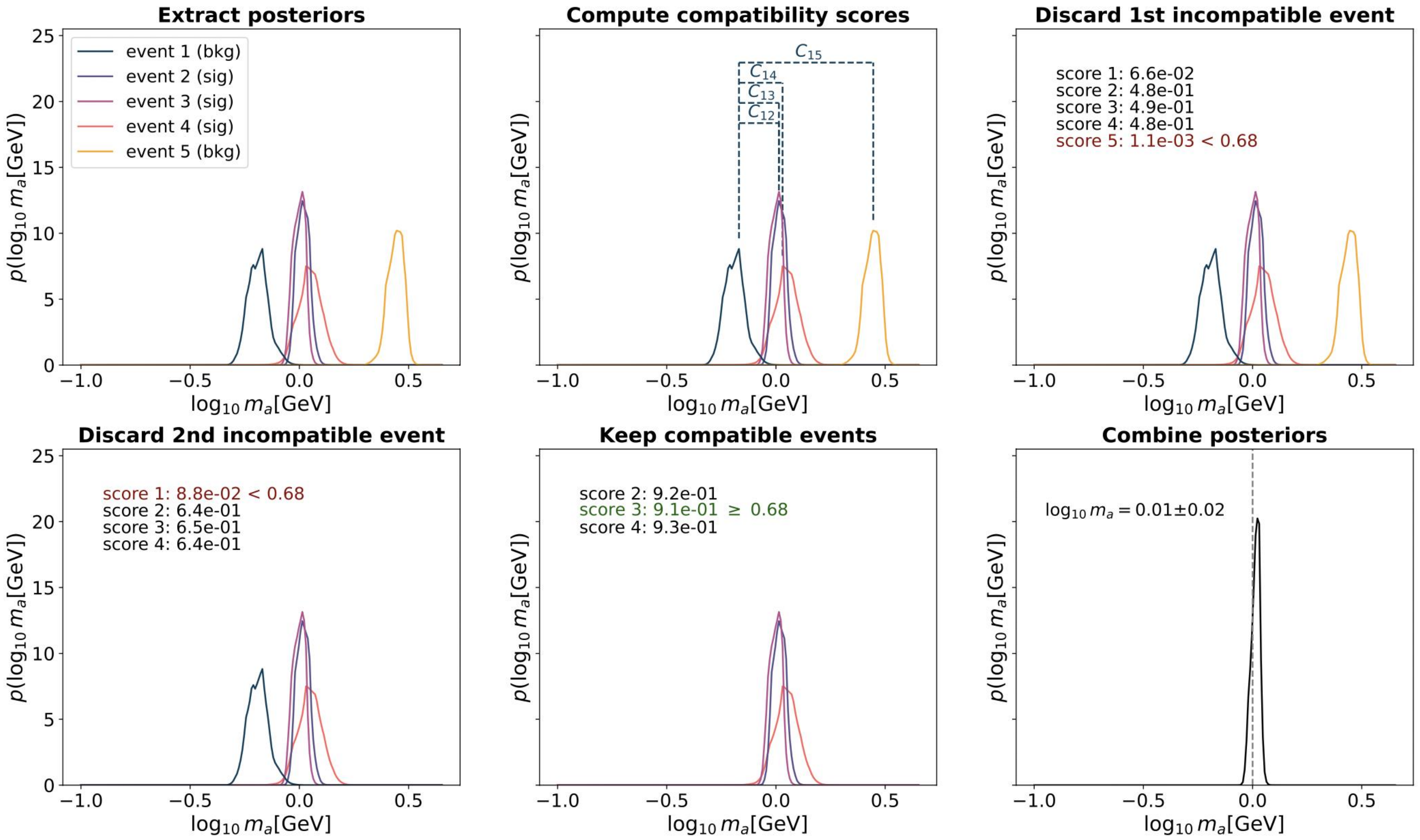
- classifier trained to distinguish pairs of low level observable vectors of signal events from those of background events

Events with Posterior Overlap (EPO)

- classifier extracting mass posteriors from low-level observables with likelihood-trick
- classifier establishing compatibility of events based on posteriors
- signals agree on inferred model parameters

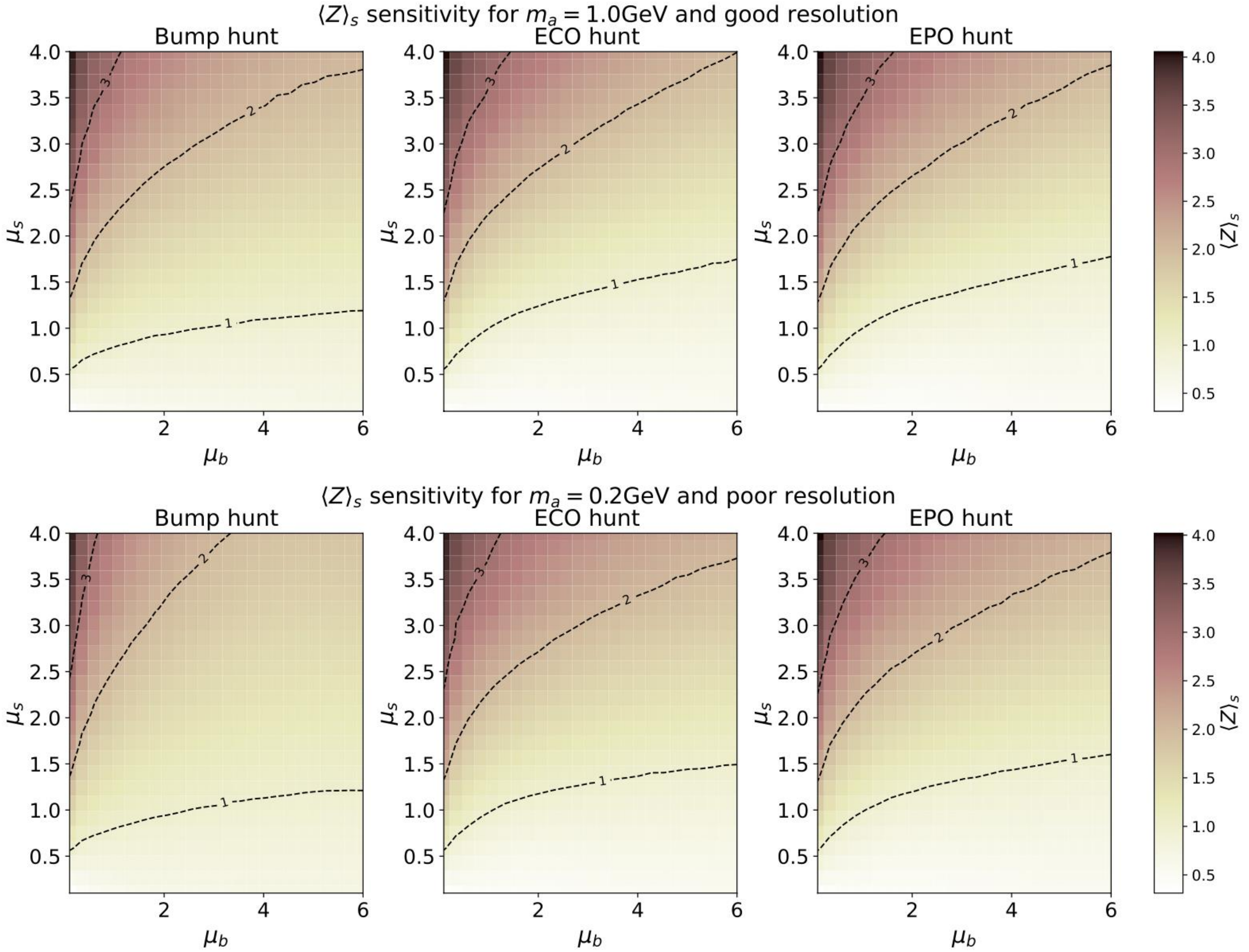
→ signal identified by rarity
→ no look-elsewhere effect
→ adjust threshold to account for different expected background rates

Analysis Strategy



Results

- performance comparison:
  - TS: number of remaining events
  - p-value: $p(l) = \sum_{m \geq l}^{N_{max}} p_b(m)$
  - expectation value of significance $Z(l) = \sqrt{2}\mathrm{erf}^{-1}\left(1 - p(l)\right)$
- EPO and ECO hunt outperform traditional bump hunt for poor detector resolution



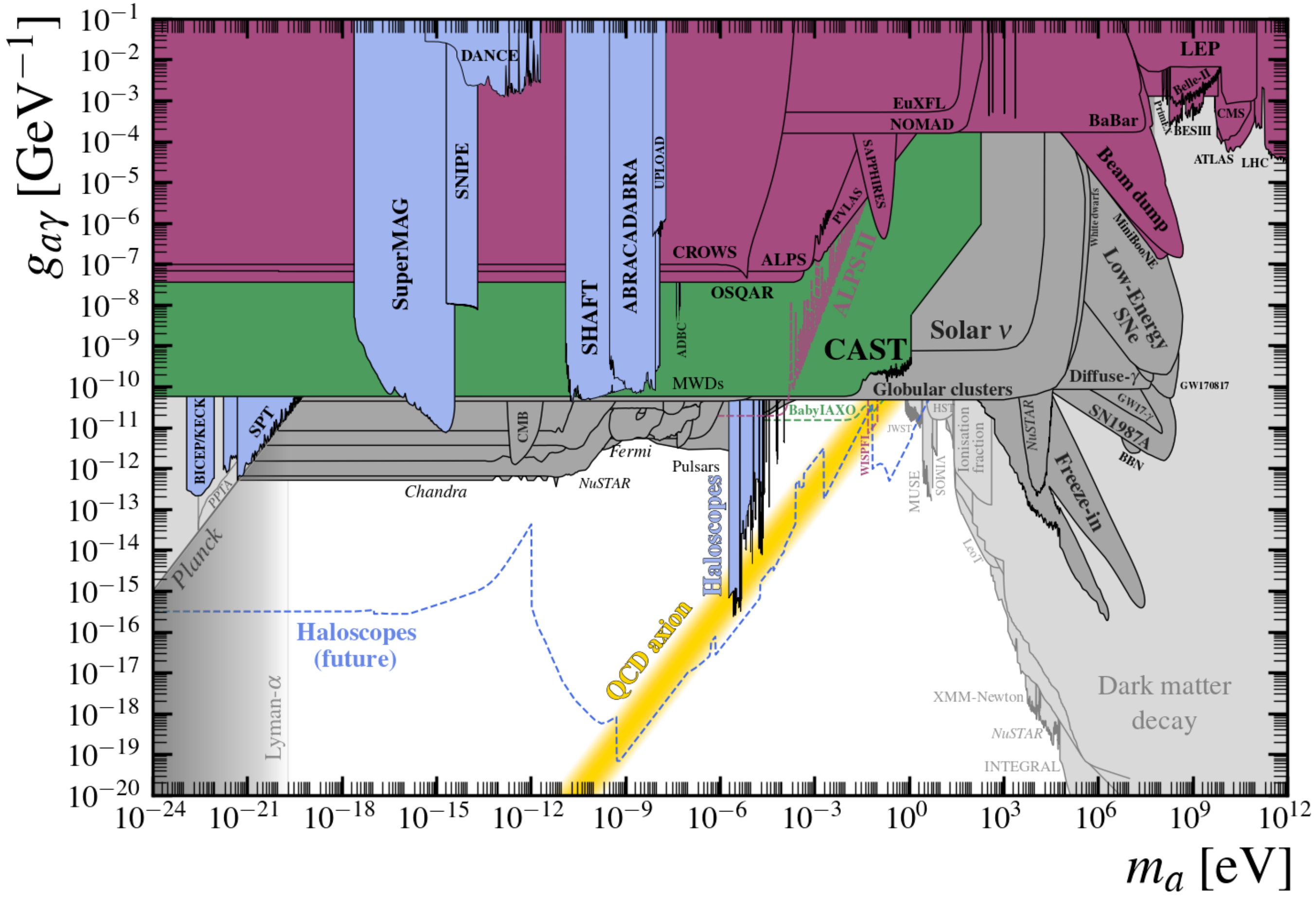
Sensitivity parameter as function of background normalisation and signal strength

Conclusion

- Challenge: rare and hard-to-model backgrounds, unknown optimal high-level observables
- ECO and EPO hunt leveraging classifiers
- EPO enables inference of model parameters

Backup Slides

ALP Parameter Space



https://cajohare.github.io/AxionLimits/

Detector Resolution

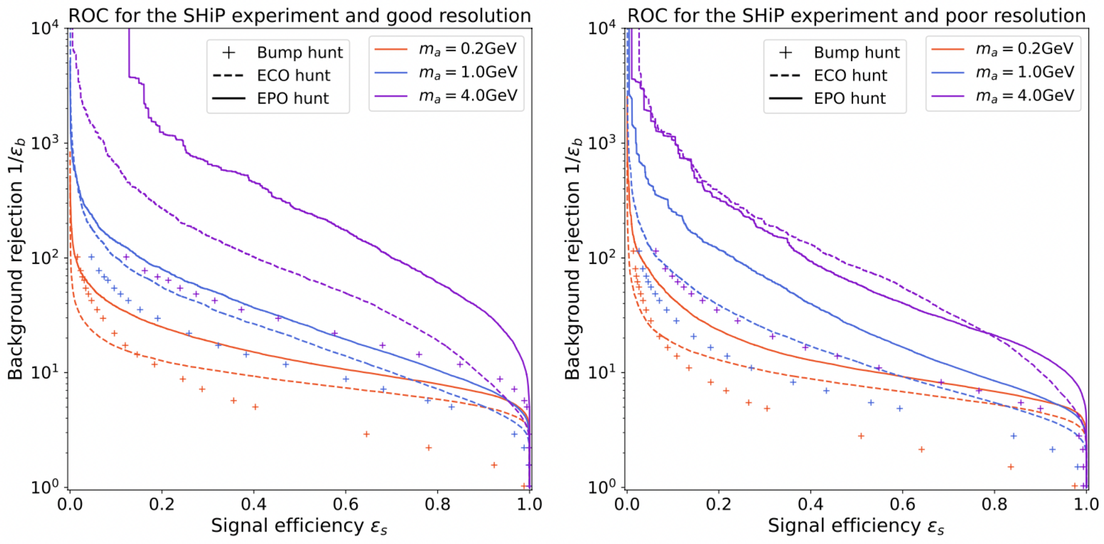
- limited detector resolution:
  - smearing of truth-level observables
  - good resolution: $\frac{\sigma(E)}{E} = 0.05,\ \sigma(\theta) = \sigma(\phi) =$ 5mrad
  - poor resolution: $\frac{\sigma(E)}{E} = 0.1,\ \sigma(\theta) = \sigma(\phi) =$ 10mrad
  - calorimeter hit position resolution of 1 mm

Likelihood-Trick

- Neyman-Pearson lemma: likelihood ratio test is strongest measure between two groups A ($score(x)$ = 0) and B ($score(x)$ = 1) with probability distributions μ_A and μ_B, respectively
- Optimal decision function: $score(x) = \frac{L(x|\mu_A)}{L(x|\mu_A)+L(x|\mu_B)}$
- Train classifier to distinguish between two groups, such that $score(x) = \frac{p(x,\mu)}{p(x,\mu)+\Pi(\mu)p(x)}$
- Apply on observed data: $\frac{score(x_{obs})}{1-score(x_{obs})} = \frac{p(x_{obs},\mu)}{\Pi(\mu)p(x_{obs})} = \frac{L(x_{obs}|\mu)\Pi(\mu)}{\Pi(\mu)p(x_{obs})} = \frac{L(x_{obs}|\mu)}{p(x_{obs})} = LER(x_{obs}|\mu)$
- Posterior from Bayes‘ Theorem: $p(\mu|x_{obs}) = LER(x_{obs}|\mu)\Pi(\mu)$

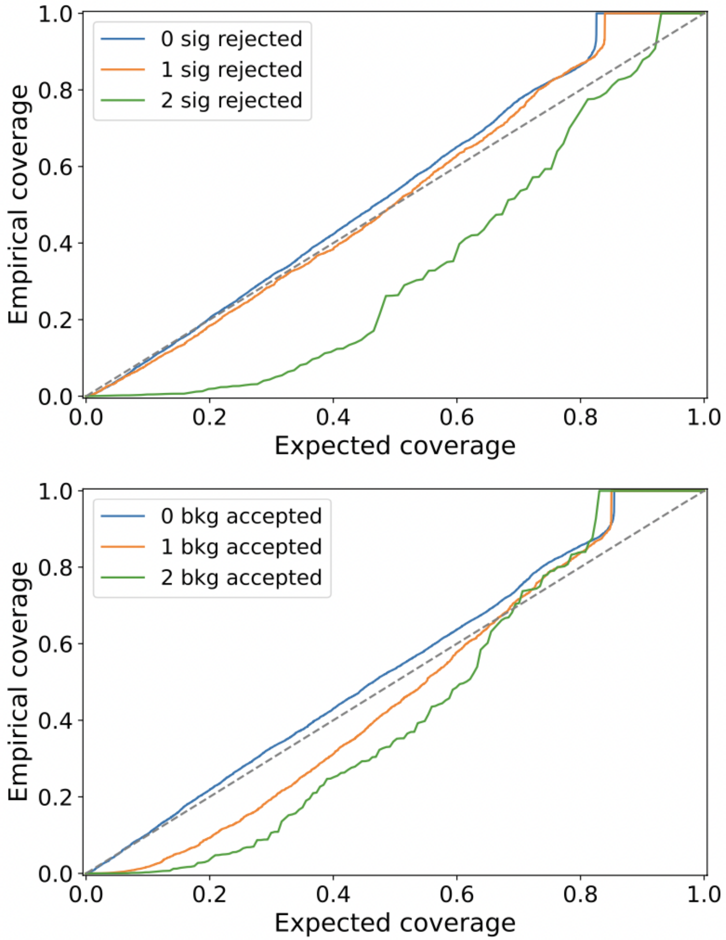
Background Rejection

- compromise between falsely accepted background events and falsely rejected signal events when fixing threshold
- performance comparison: Receiver Operator Characteristic (ROC) curve
- focus on large signal acceptance



Parameter Inference

- combine single-event posteriors to extract posterior from multiple observed events
- multiply ratios together and with prior, normalization
- signal events are incorrectly rejected or background events are incorrectly accepted: empirical coverages smaller than expected



four signal events plus one background event (top) and three signal events plus two background events (bottom)