

Dark Matter Model or Mass: Benchmark-Free Forecasting for Future Detectors

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Questions for a pseudo statistician/physicist

1. What set of experiments we can build to optimise the chance of a discovery if you have no strong theoretical prior?
2. What experiments can we build such that, once a discovery is made, we maximise the information gained about the new particle?

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Statistical method

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graph TD; Q2[2. What experiments can we build such that, once a discovery is made, we maximise the information gained about the new particle?] --> SM[Statistical method]; Q2 --> PR[Physics result];
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Statistical method

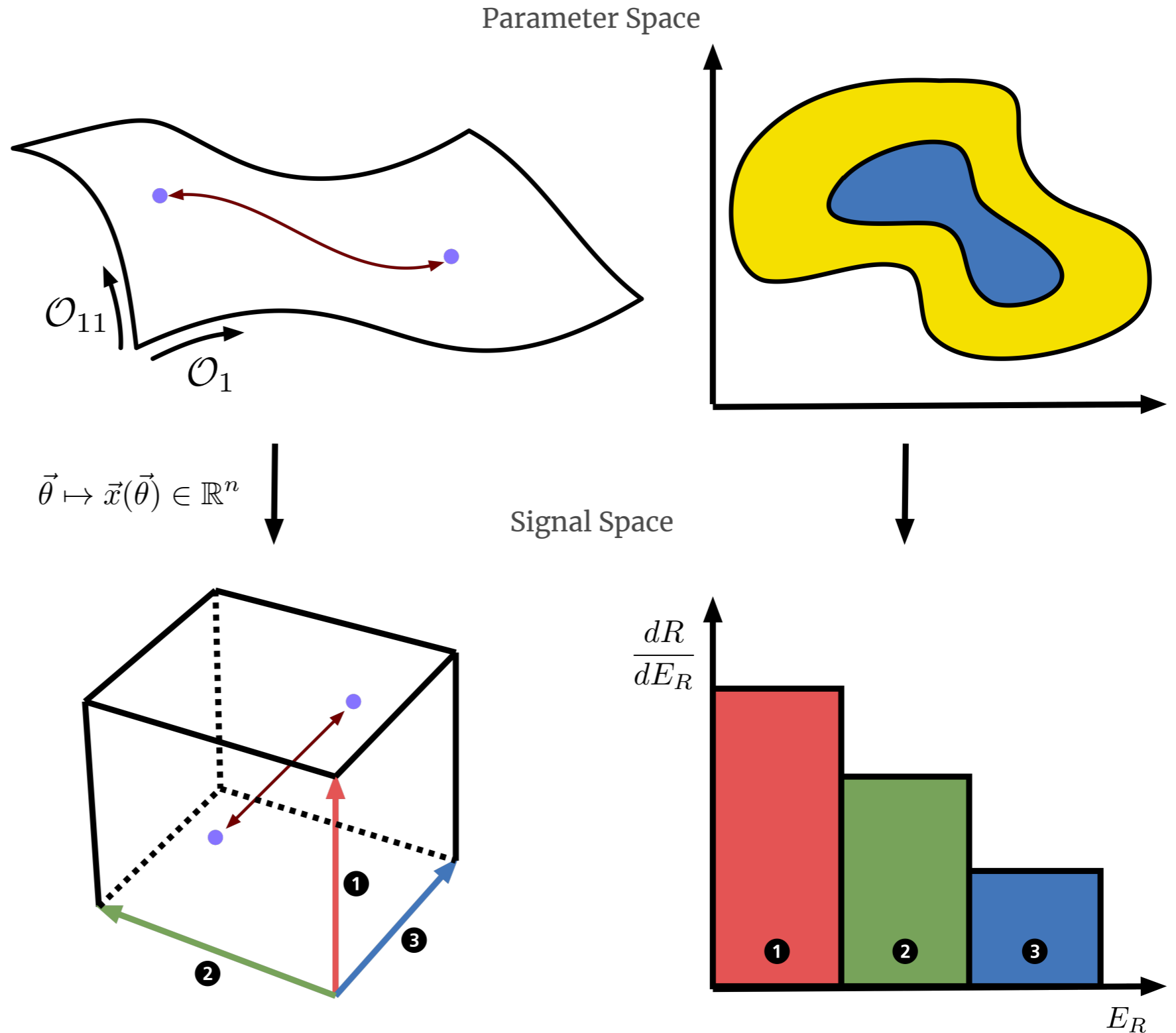
Physics result

Efficient mapping of the maximum likelihood ratio

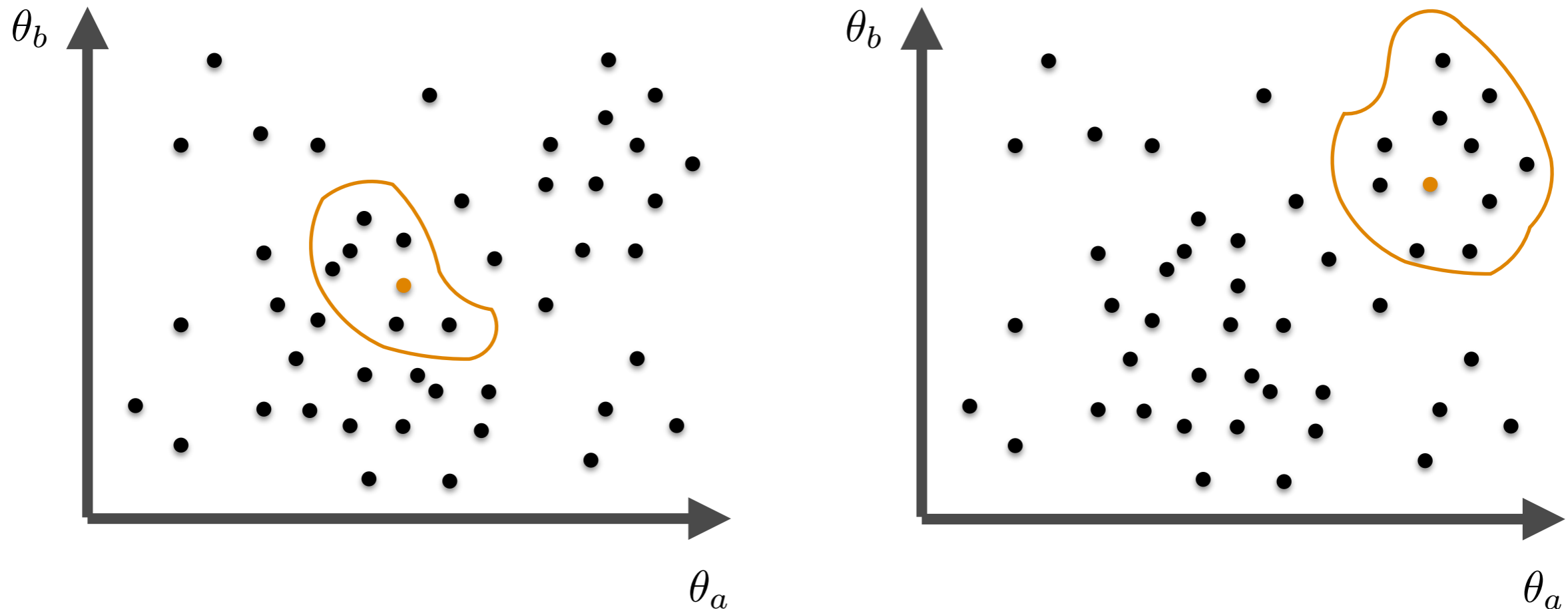
$$\text{TS}(\theta')_{\mathcal{D}(\theta)} \equiv -2 \ln \frac{\mathcal{L}(\mathcal{D}(\theta)|\theta')}{\max_{\theta''} \mathcal{L}(\mathcal{D}(\theta)|\theta'')}$$

- The **statistical distinctness** of points in the parameter space is calculated using the **maximum likelihood ratio (MLR)** test statistic
- This likelihood **surface** has **intrinsic curvature** which is **computationally expensive** to account for
- We define a mapping that approximates the MLR with the **Euclidean distance** between two new, higher dimensional vectors

$$\text{TS}(\theta')_{\mathcal{D}(\theta)} \simeq \|x(\theta) - x(\theta')\|^2$$

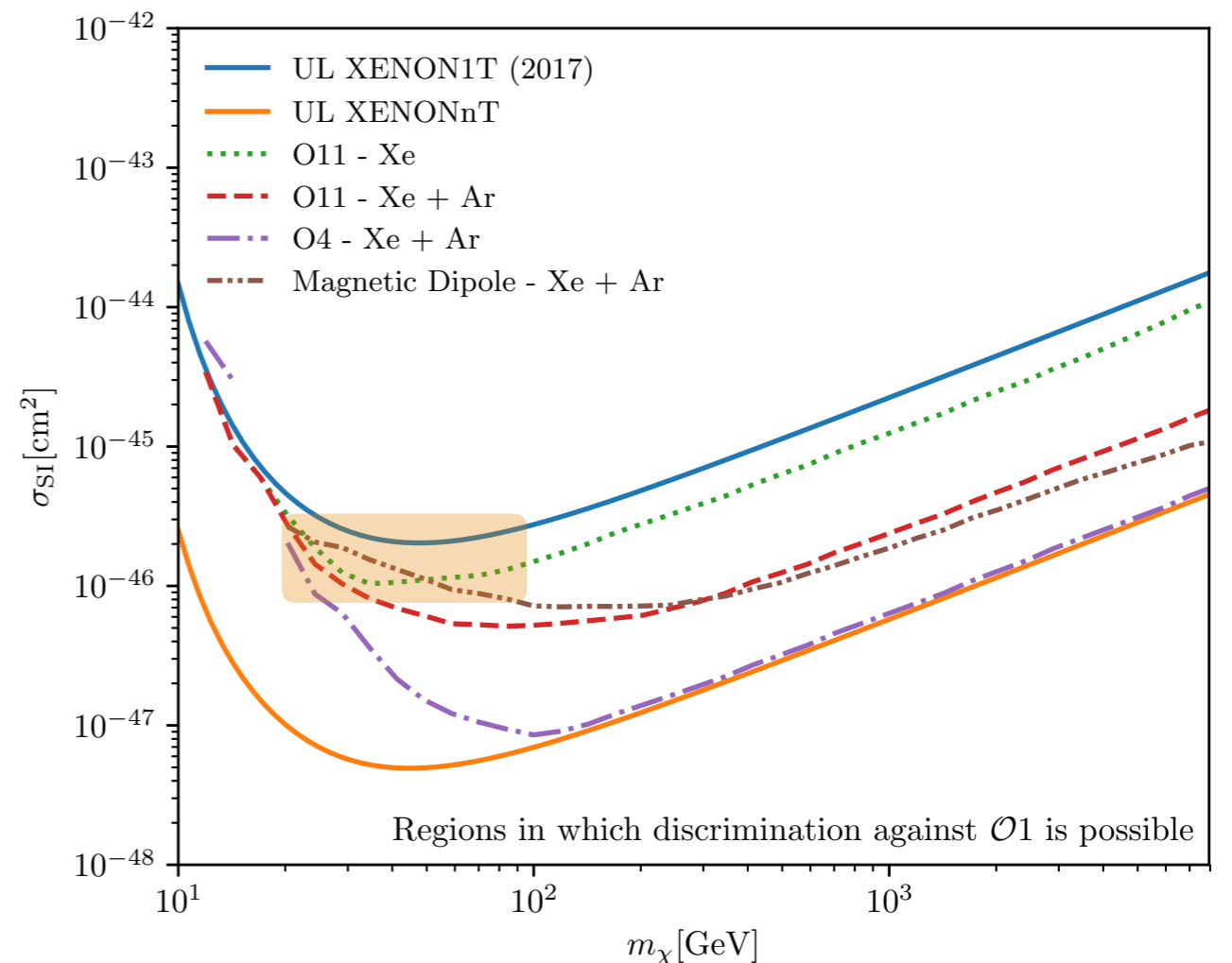
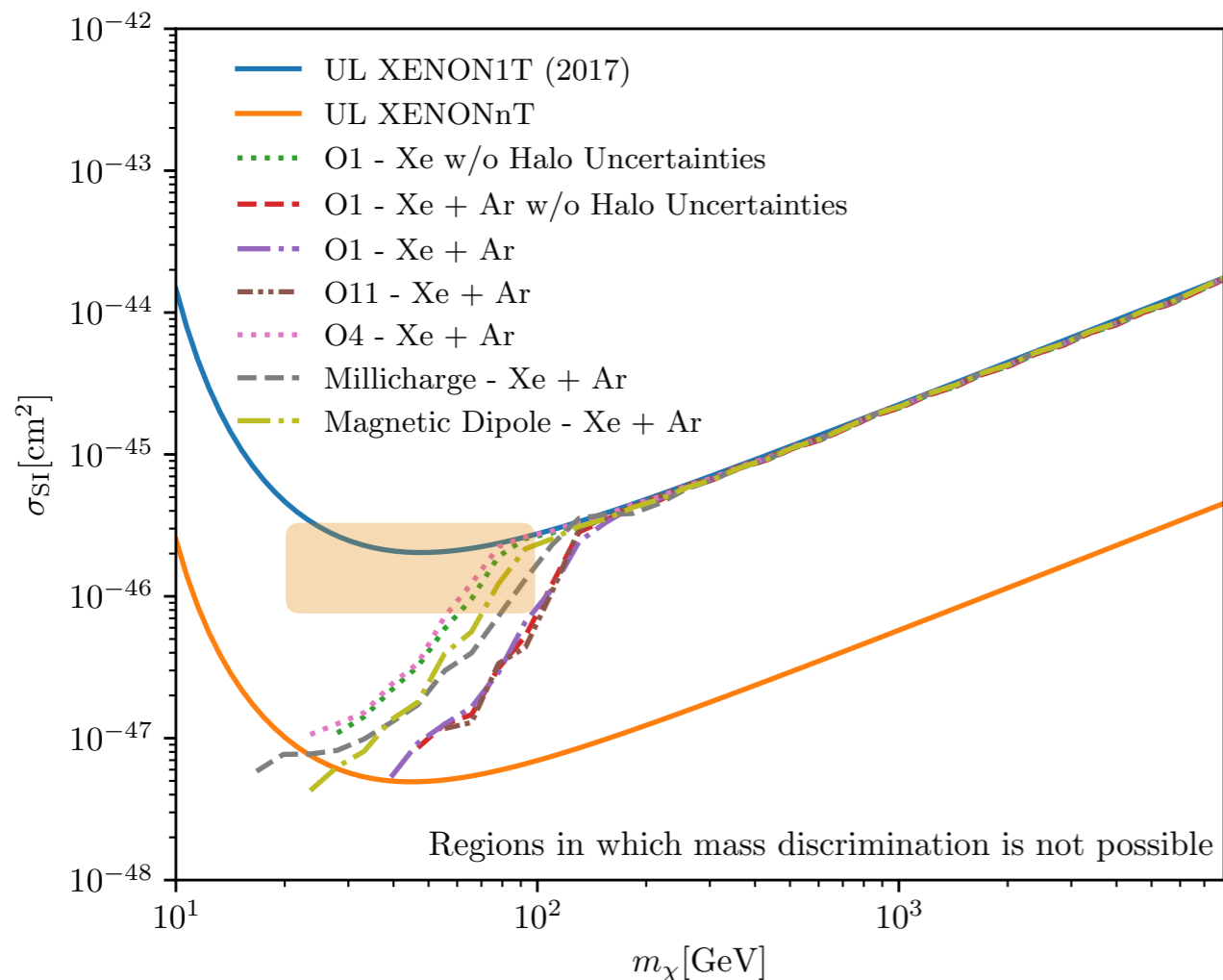


What does this allow you to do?



- Euclidean distance estimators are **computationally efficient**. Clustering algorithms (such as BallTree algorithms) allow for the efficient **pairwise comparison** of a large numbers of points.
- Once the BallTree is constructed, simply select a point and call for all other points within the required distance. This allows for the efficient computation of **confidence intervals across the entire space**.

Physics Result: Model or Mass, but not both



- We consider the non-relativistic effective field theory for Dark Matter Direct Detection with two future liquid noble gas experiments - **XENONnT** and **Darkside20k**
- At high DM masses the mass and interaction cross section become **degenerate**. This is the same region in which it is possible to constrain the DM-nucleon interaction. Only a small part of the parameter space remains in which **both** can be constrained

Summary

- We have defined a **new statistical procedure** to **avoid** the need to use **benchmark points** in the parameter space.
- The method is **general and applies to all counting experiments** since its foundation is a Poisson likelihood.
- Direct detection experiments can (unfortunately) only simultaneously constrain the **DM-nucleon interaction and mass** for a **small part of the parameter space**. There are some ways to get around this i.e. higher recoil energies and inelastic signals.

Edwards, Kavanagh & Weniger [1805.04117](#)

Edwards & Weniger [1712.05401](#)

github.com/cweniger/swordfish

github.com/bradkav/WIMpy_NREFT

github.com/tedwards2412/benchmark_free_forecasting

Euclideanized signals approximately match the standard log-likelihood ratio test statistic

- Approximation tested by considering a large number of **random** models (illustrated with 3 bins)
- Background kept constant whilst covariance function and signal randomly generated
- Flat exposure used:
 - *Signal limited*: No covariance and high signal to noise
 - *Systematics limited*: Low signal to noise with high covariance
 - *Poisson limited*: Low signal to noise with no covariance

