

# Fast Forecasting for Counting Experiments

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[1704.05458](#)

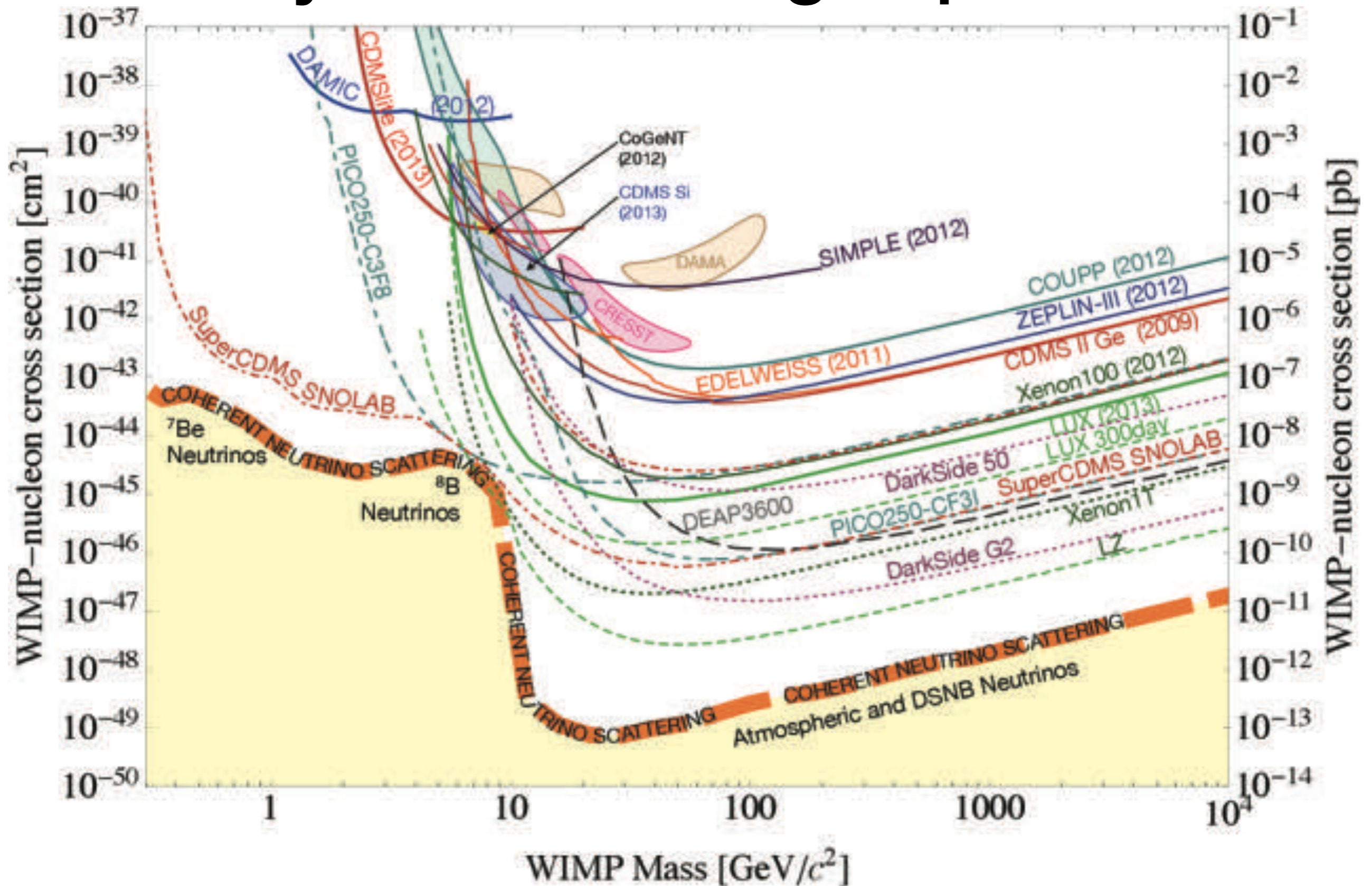
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<https://github.com/cweniger/swordfish>

# What questions am I trying to answer?

- I don't have a strong theoretical prior
- In this case, what is the best way to maximize a discovery?
- If we find something, what is the best set of experiments to build?
- Both questions come down to maximizing the the information gain from multiple experiment for a large variety of models

# Why is forecasting important



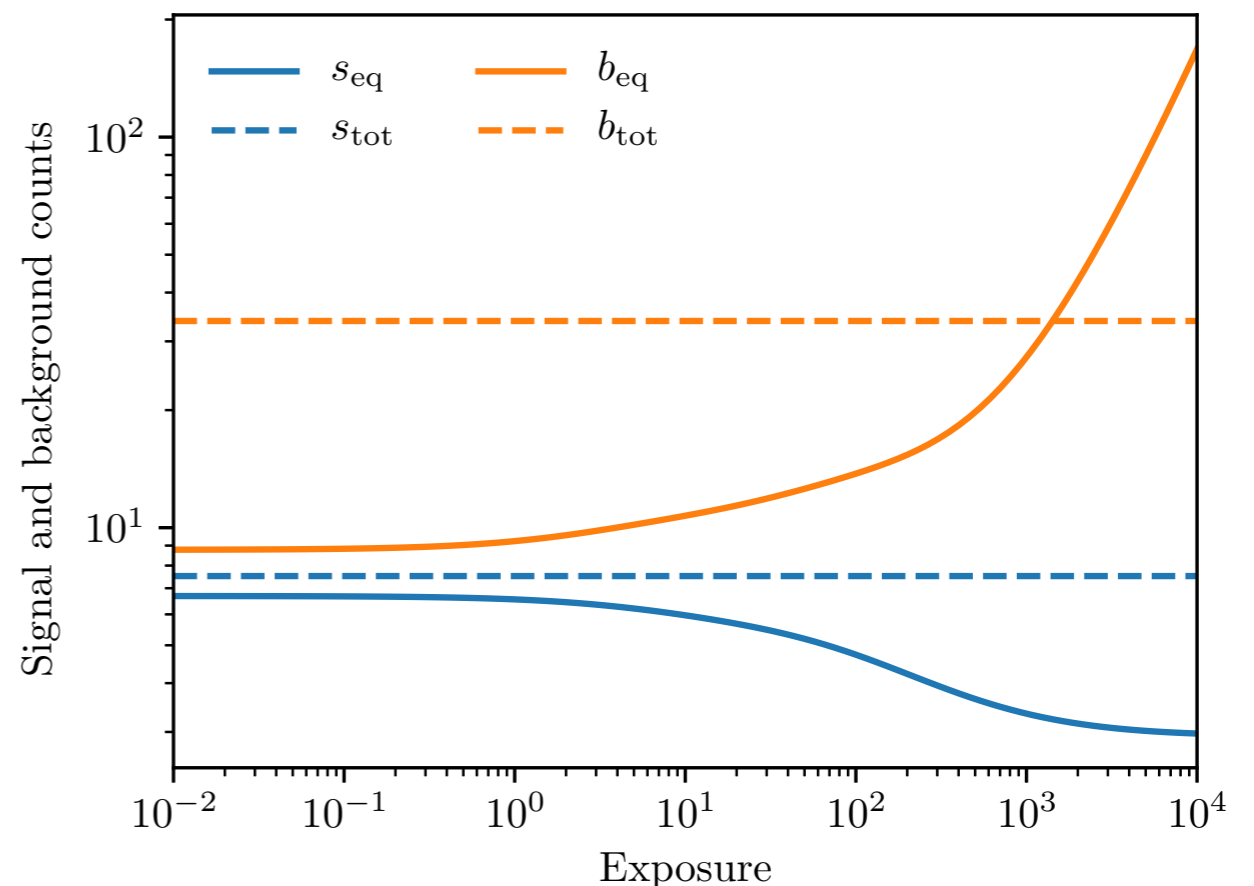
# Equivalent Counts

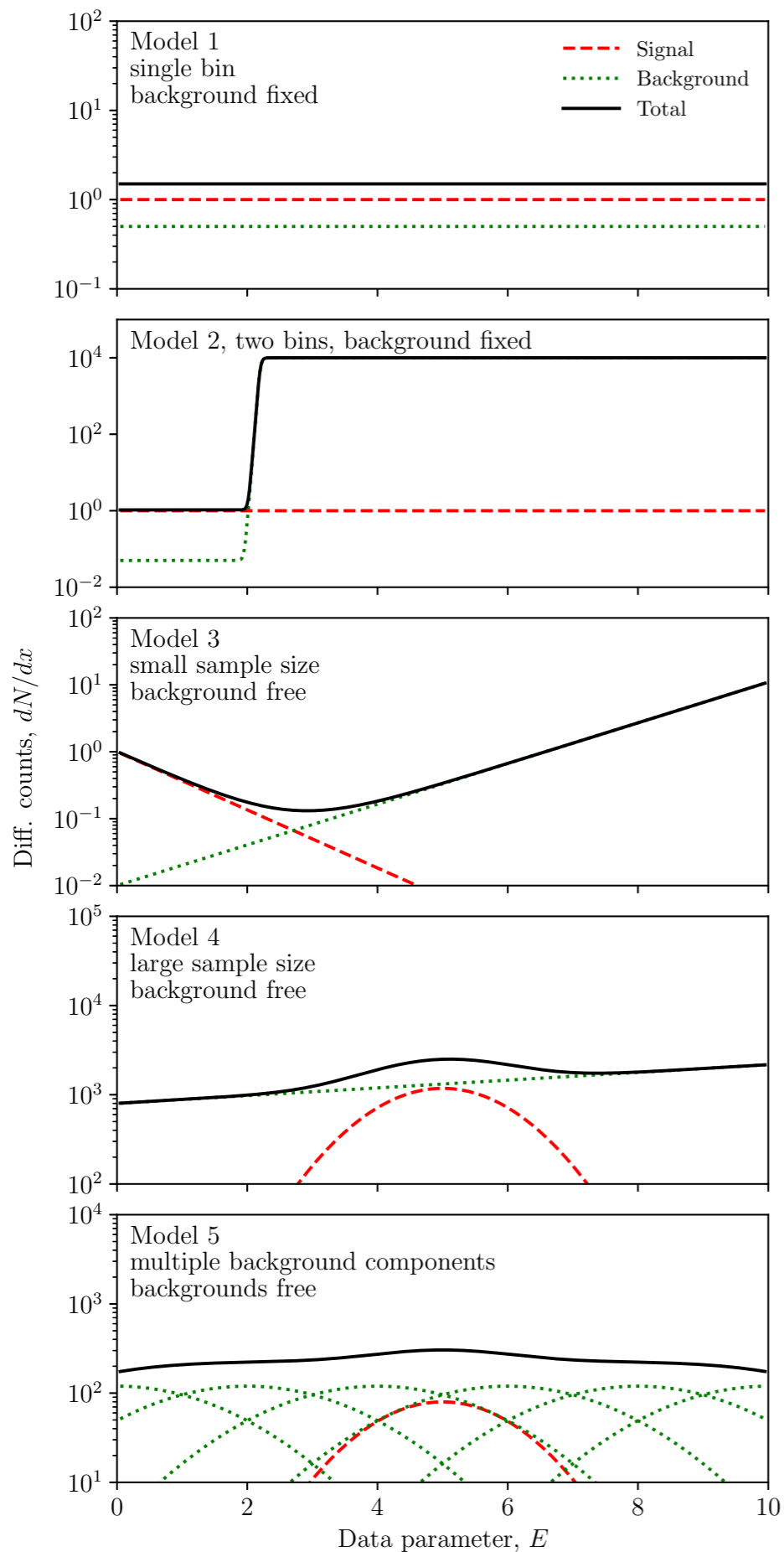
Logic:

- Signal to Noise of events in a single bin example tells us about the significance of the signal
- Extend same technique to multi-bin case
- Not all signal events statistically contribute if they are drowned out by large backgrounds
- Convenient to define significant signal and background events using the FIM

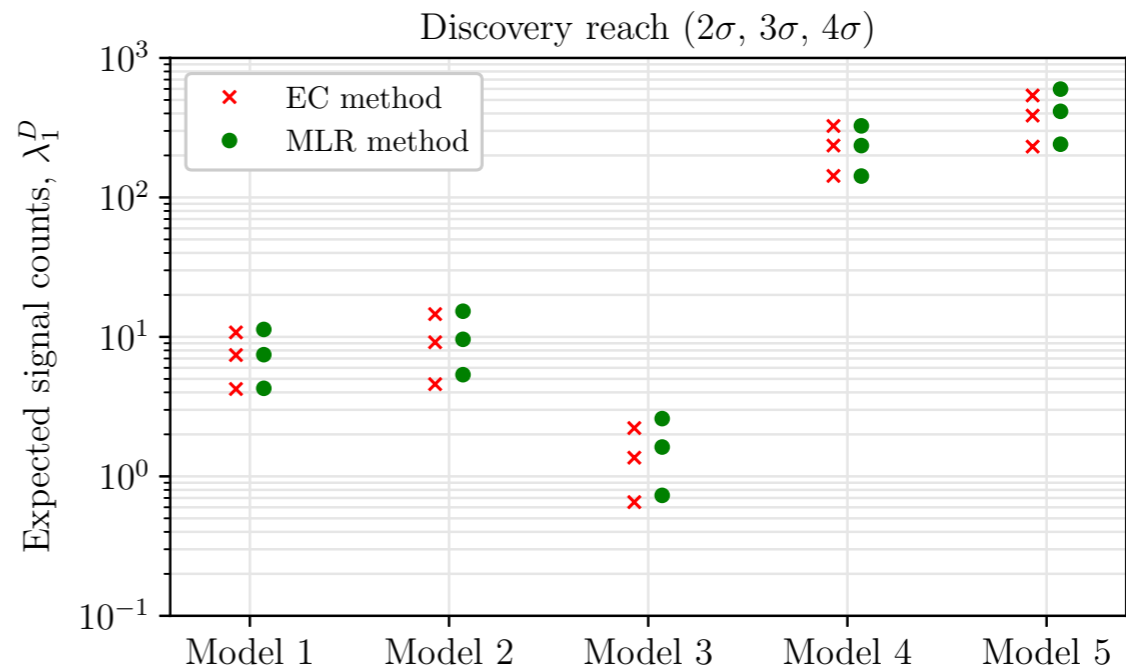
$$s_{\text{eq}}(\theta) \equiv \frac{\theta^2}{\sigma^2(\theta) - \sigma^2(\theta_0)}$$

$$b_{\text{eq}}(\theta) \equiv \frac{\theta^2 \sigma^2(\theta_0)}{[\sigma^2(\theta) - \sigma^2(\theta_0)]^2}$$

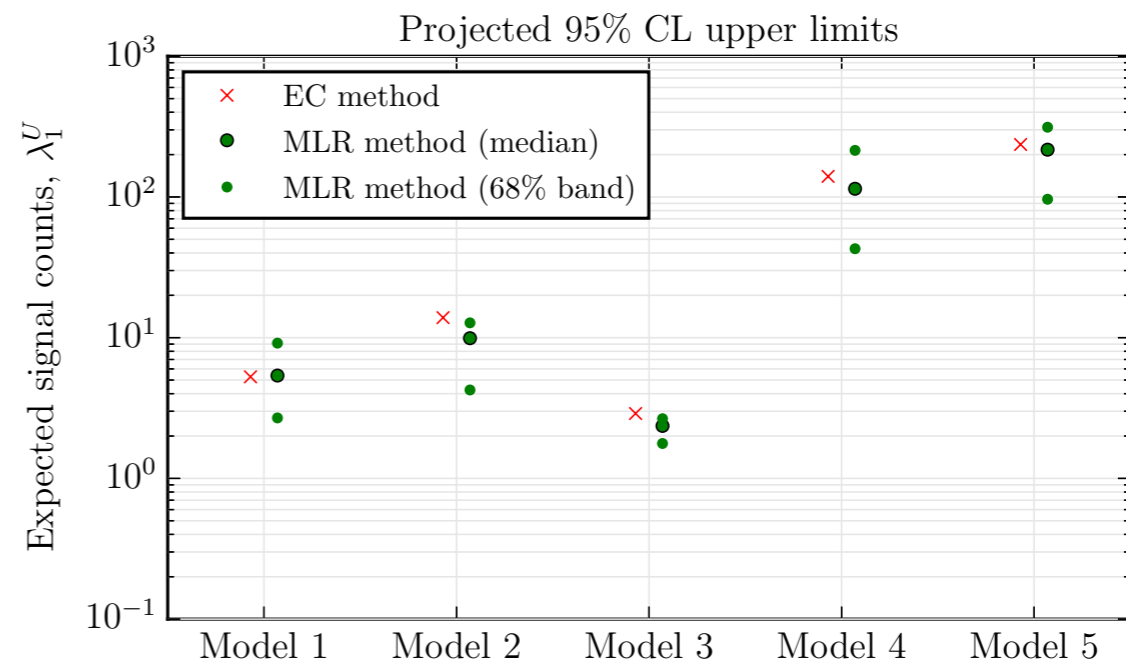




$$-2 \ln \frac{P(s_{\text{eq}} + b_{\text{eq}} | b_{\text{eq}})}{P(s_{\text{eq}} + b_{\text{eq}} | s_{\text{eq}} + b_{\text{eq}})} = Z^2$$



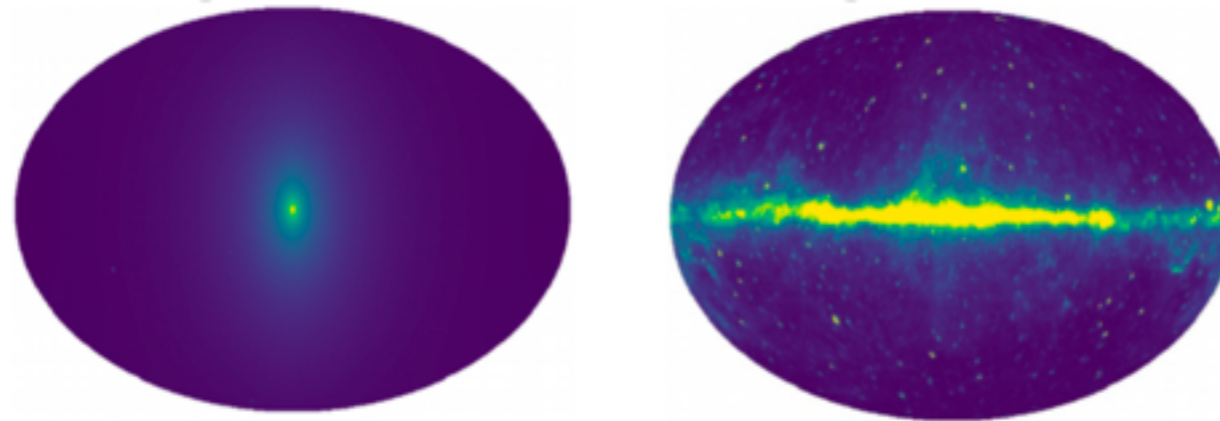
$$s_{\text{eq}} = Z \sqrt{s_{\text{eq}} + b_{\text{eq}}}$$



- Maximum deviations from coverage corrected Monte Carlos up to 40%

**1704.05458**

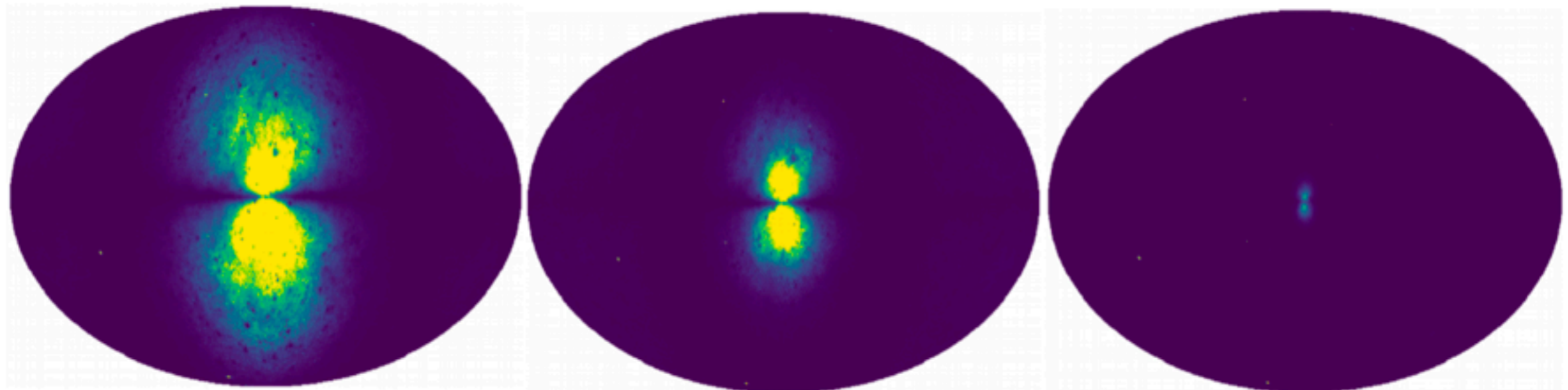
**Dark Matter  
Halo**



**Background -  
assumed 10%  
error with a 10  
degree  
correlation  
length**

$$\mathcal{F}_i \equiv \frac{\partial(1/\sigma^2)}{\partial E_i}$$

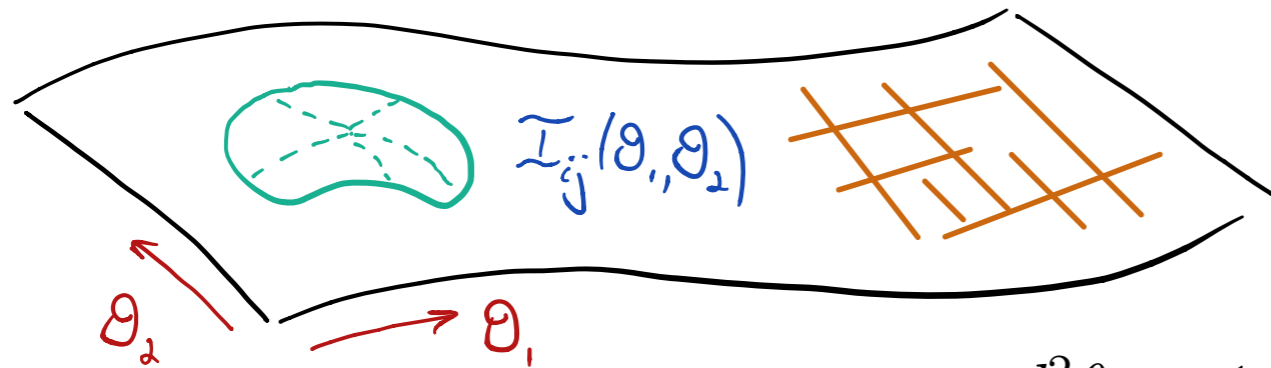
**Increasing Exposure** →



 = High Information

 = Low Information

# Visualisation



**Treat the Fisher Information Matrix as a local metric on the space of parameters**

$$\frac{d^2\theta_i}{ds^2} + \frac{1}{2}\mathcal{I}_{ij}^{-1} \left( \frac{\partial\mathcal{I}_{lj}}{\partial\theta_k} + \frac{\partial\mathcal{I}_{kj}}{\partial\theta_l} - \frac{\partial\mathcal{I}_{kl}}{\partial\theta_j} \right) \frac{d\theta_k}{ds} \frac{d\theta_l}{ds} = 0$$

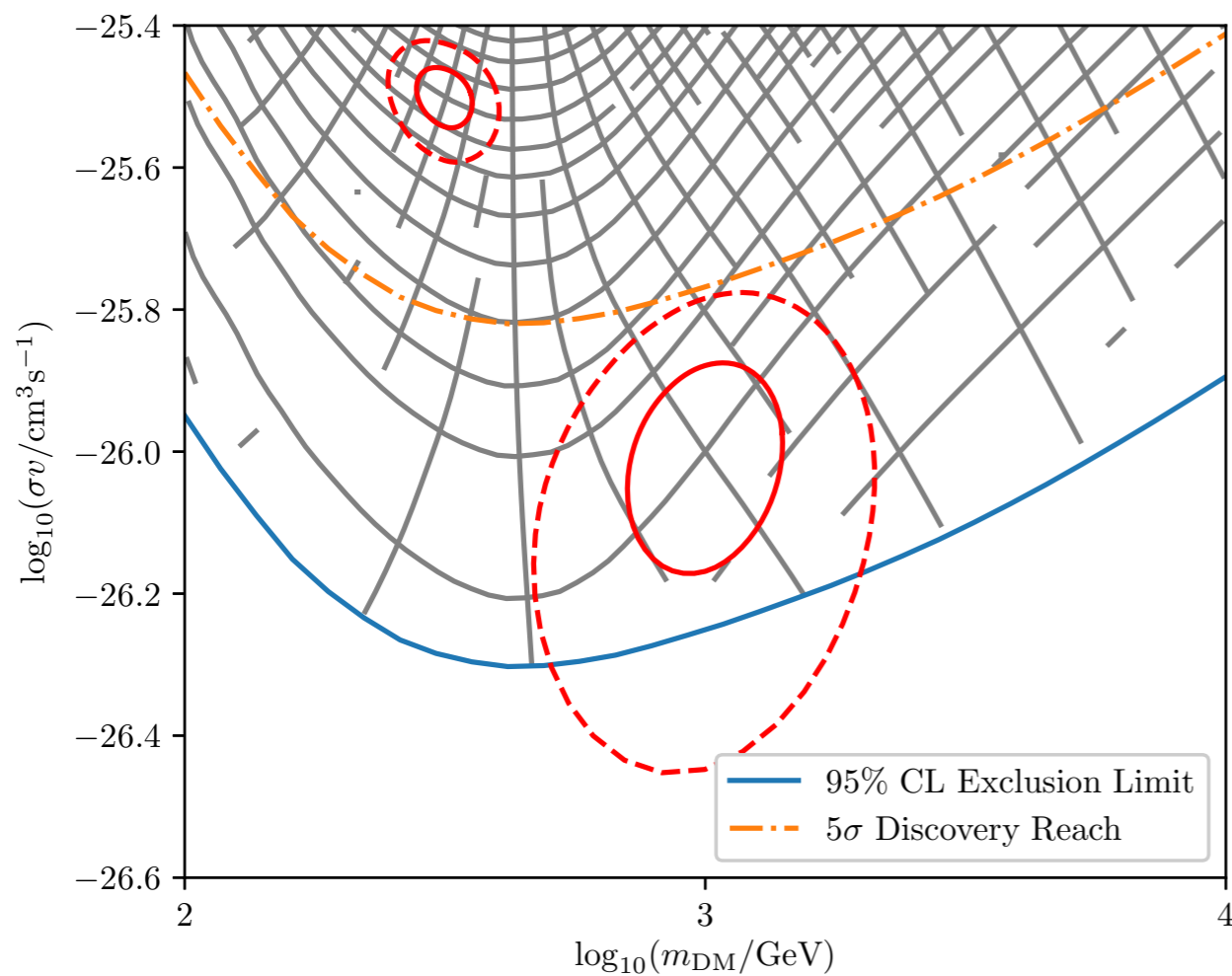
## Equal Geodesic Confidence Contours

- Trace geodesics in different directions and connect the curves
- Matches very accurately with traditional confidence contours

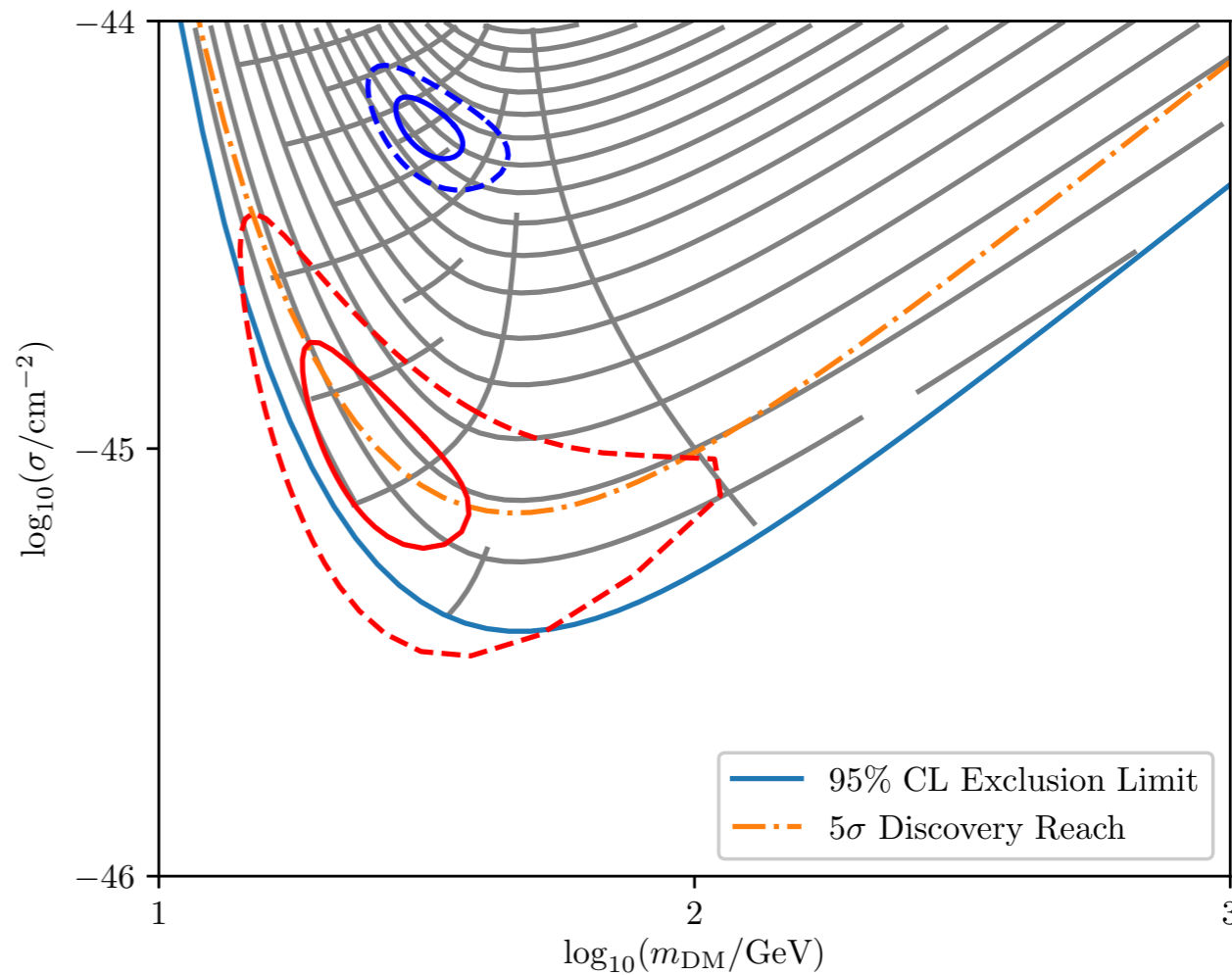
## Streamline Density

- The distance between two parallel streamlines corresponds approximately to  $1\sigma$  in the direction perpendicular to the streamlines.
- The latter condition is realized by adding or removing lines as necessary.

# CTA and Xenon1T



**Replicated analysis from  
Silverwood et al.**

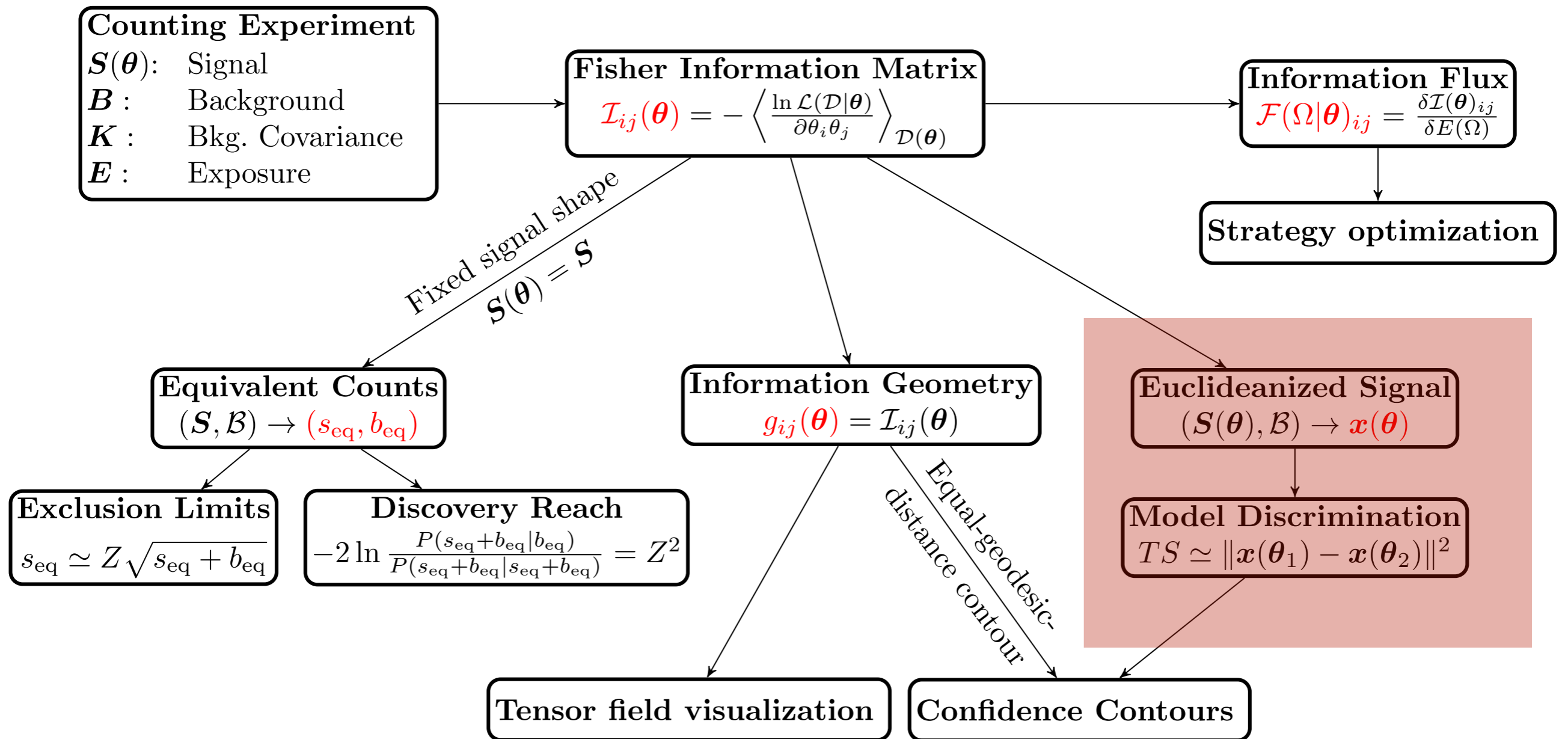


**Simplified 1-D Xenon1T projection**



# Swordfish

Physics that you need to worry about



= C. Weniger's talk (later today)

## Questions? - for you

- **In what other ways can we develop the tool such that it's useful?**
- **Any other quantities we can compute from the fisher matrix which would be useful for forecasting**

## Questions? - for us

- **Are there other nice ways to visualize the parameter space?**
- **Is there any additional information we can derive from the likelihood surface... manifold learning, clustering?**

# Backup

