

# Cautionary examples of statistical errors

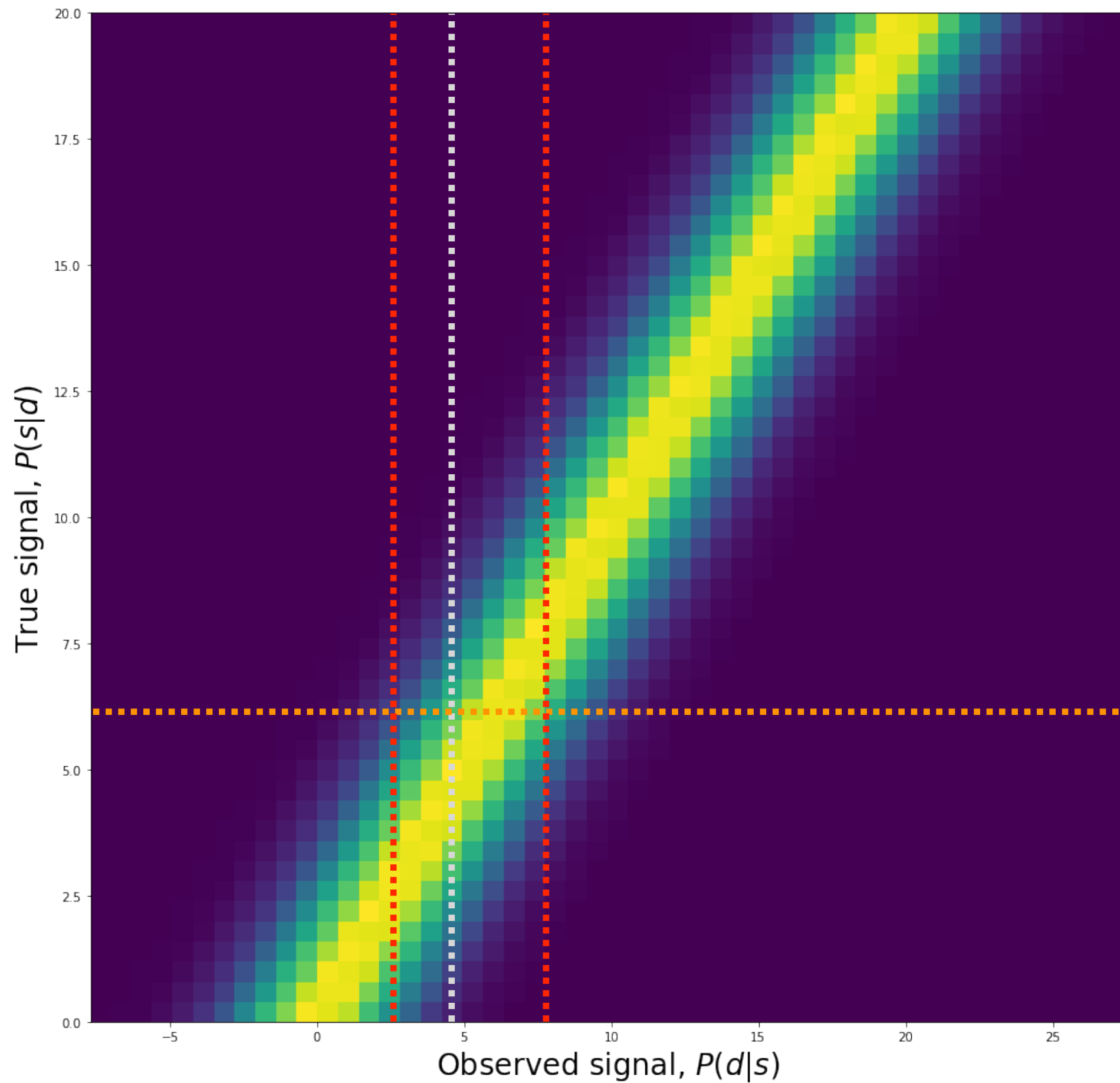
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Review: how to calculate a confidence interval/  
upper limit

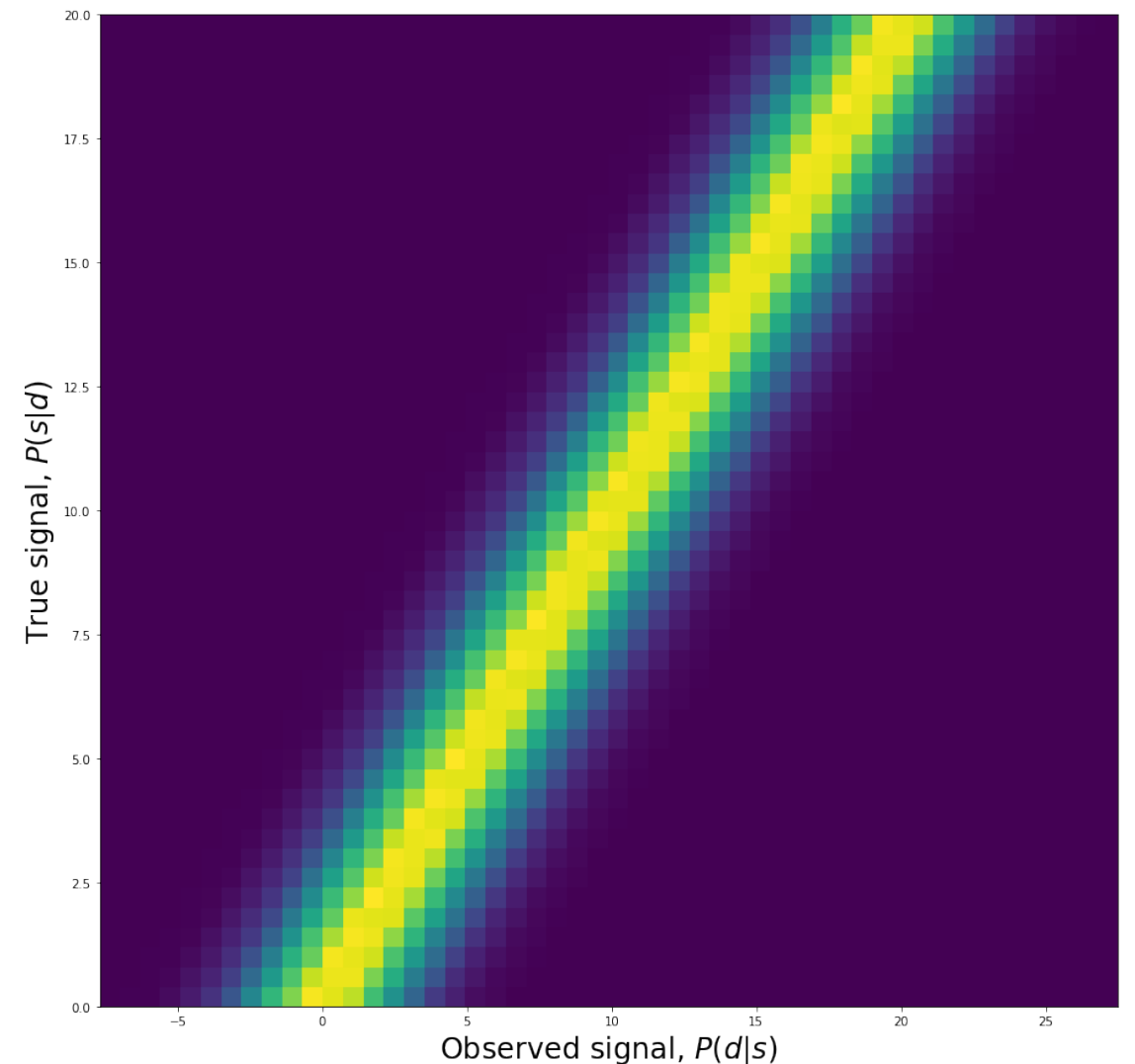
# Simulated observations



# How to calculate

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- Simulate: determine  $P(d | s)$  for every signal value
- Signal injection: take signal free data and inject a face signal to see what it looks like; repeat for every signal value
- Use math: Bayes' theorem



# Bayes' theorem

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$$P(s | d) = \frac{\overbrace{P(d | s)}^{\text{Physics Model}} \overbrace{P(s)}^{\text{Prior}}}{\cancel{P(d)}^{\text{Normalization}}}$$

# Bayes' theorem

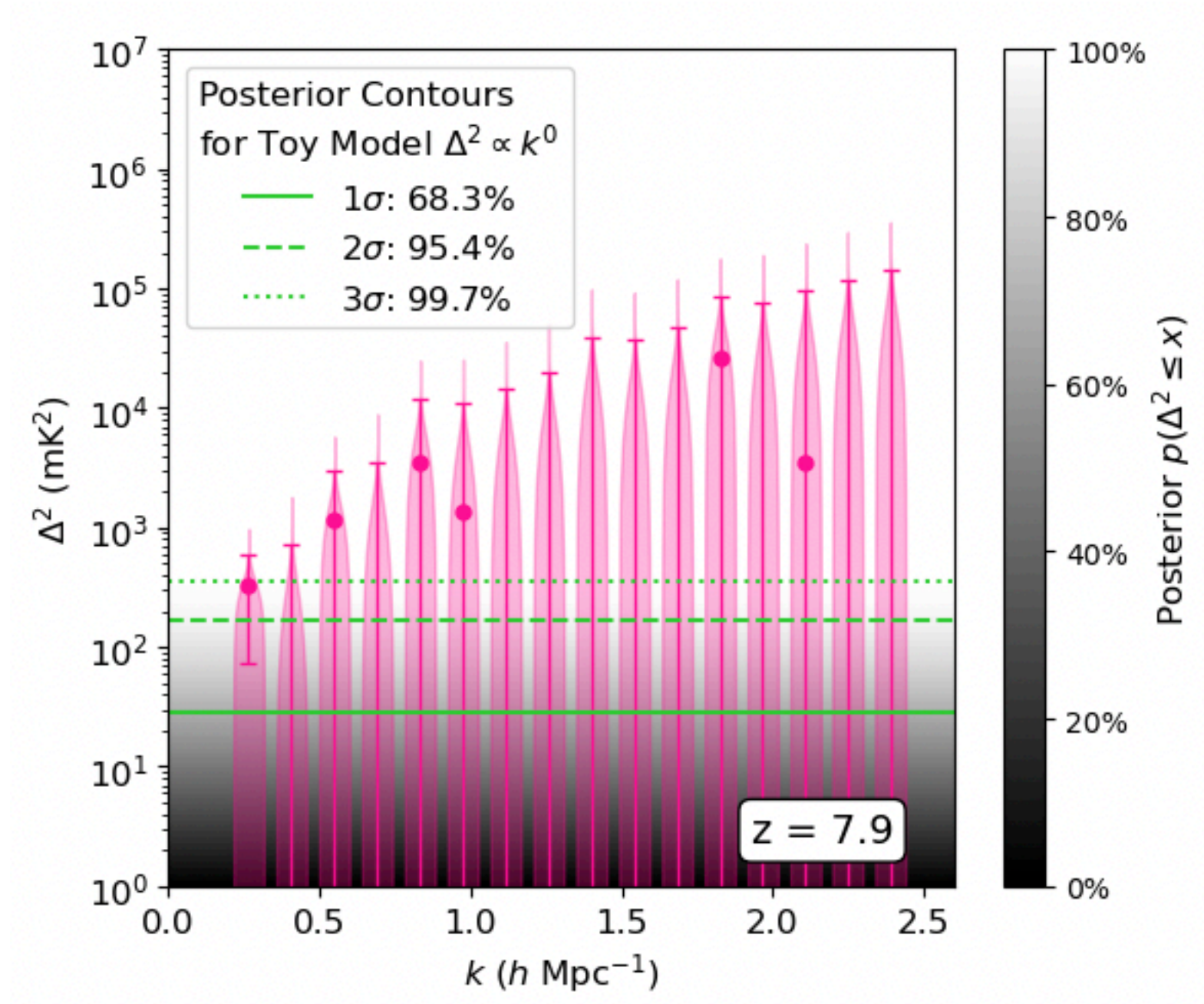
$$P(s | d) = \frac{\overbrace{P(d | s)}^{\text{Physics Model}} \overbrace{P(s)}^{\text{Prior}}}{\cancel{P(d)}}_{\text{Normalization}}$$

- Always interpreting in the framework of a model
  - May be generic/data driven, e.g. a 'top hat pulse'
- Prior necessary to invert
  - Powerful when driven by knowledge
  - ***Dangerous*** when driven by assumptions

Implicit or explicit logarithmic priors

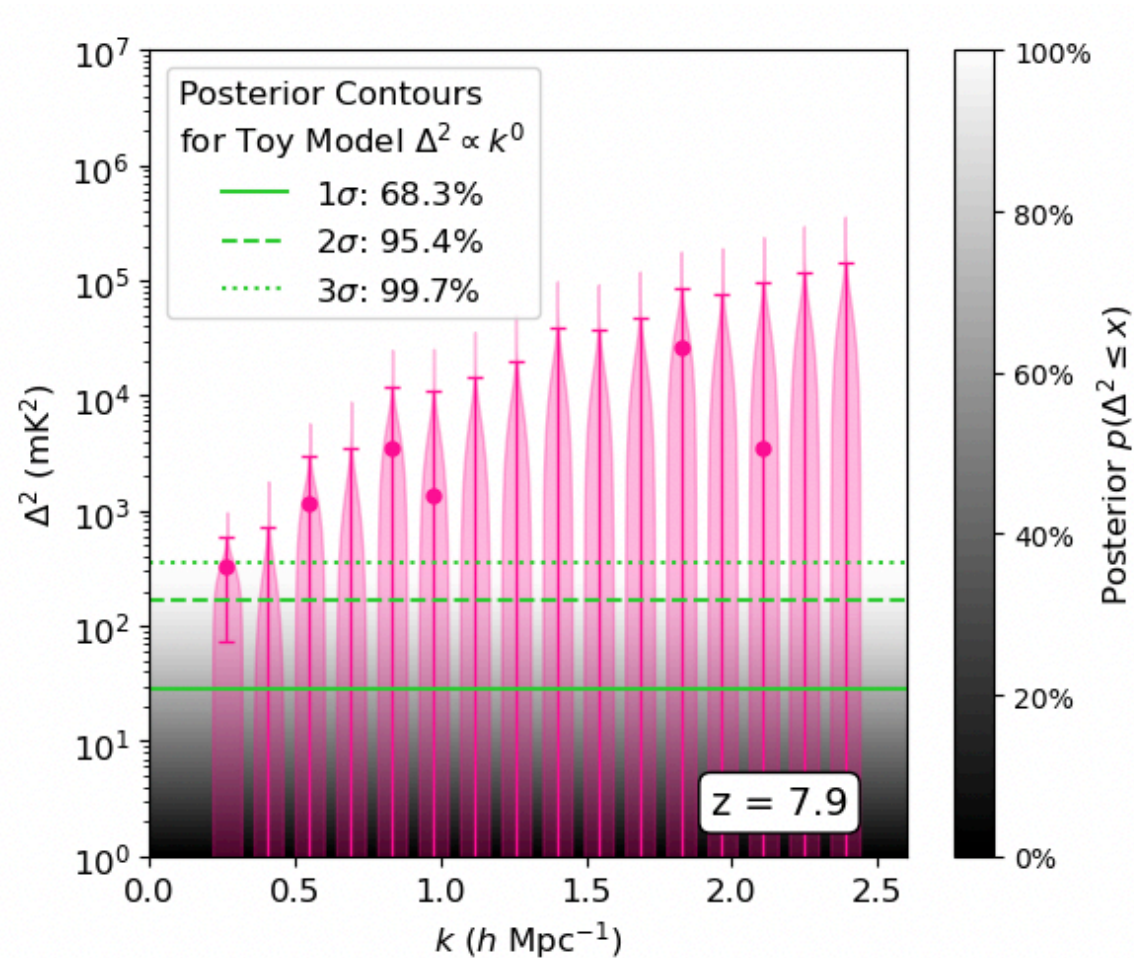
# Case study

- Combined upper limit combining many limits
- Use Bayes' theorem to invert
- Logarithmic prior

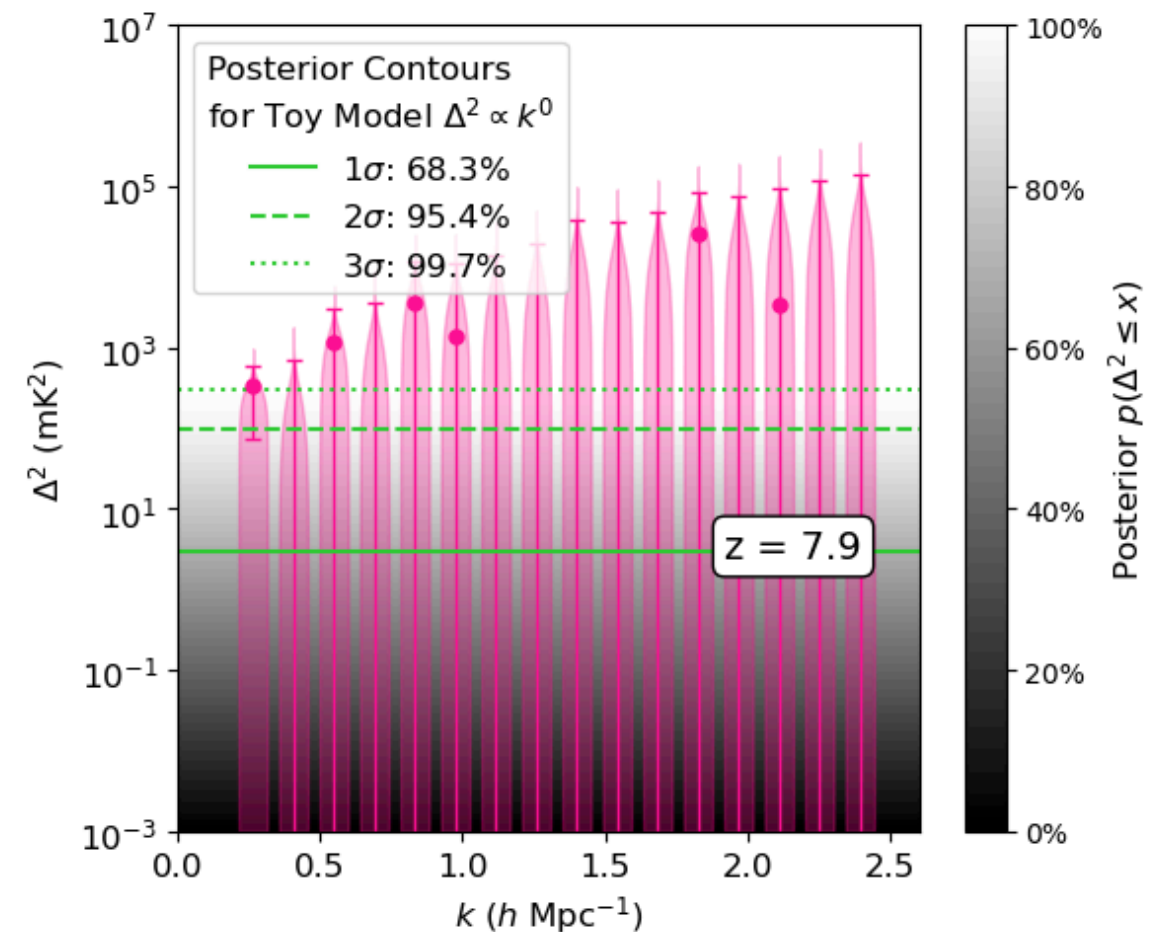




I asked to change lower bound from 1 to 1e-3

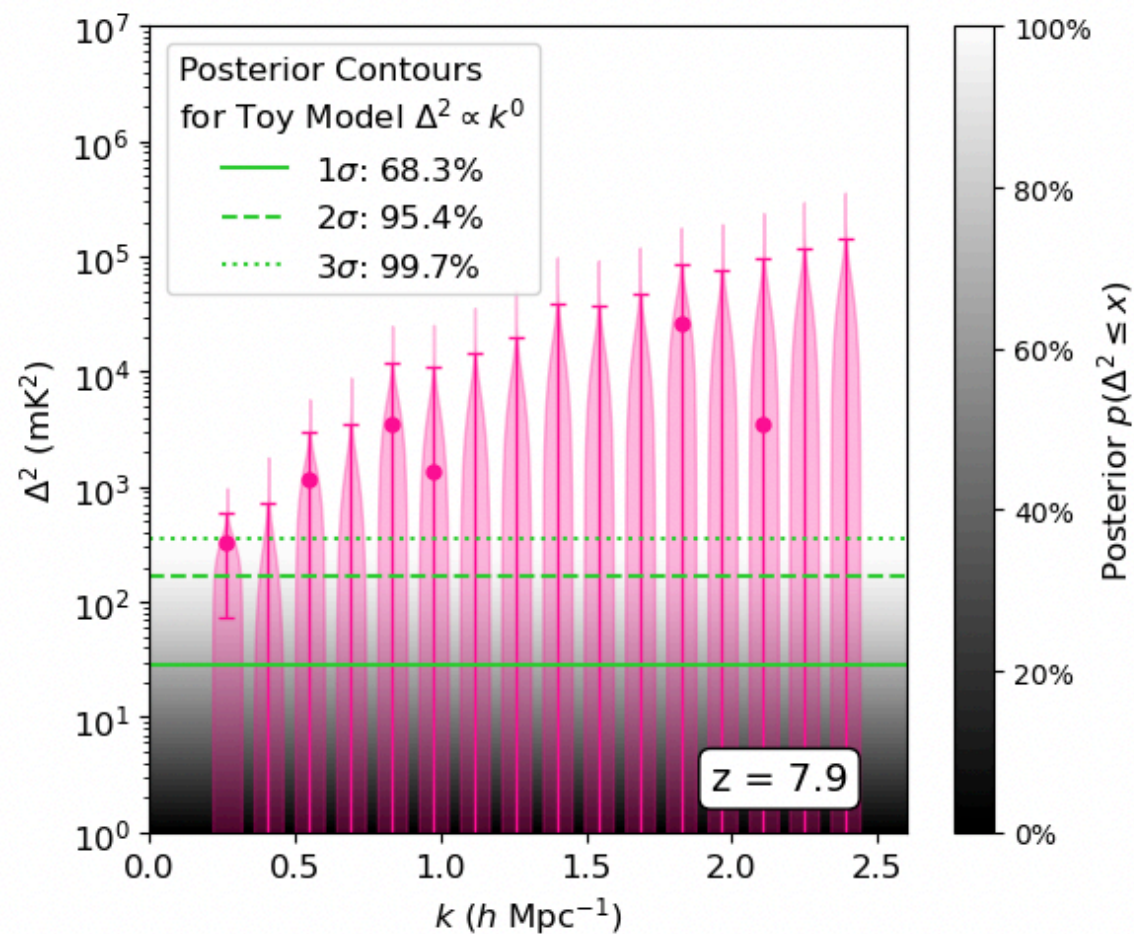


2 $\sigma$  upper limit: 16.7 mK<sup>2</sup>

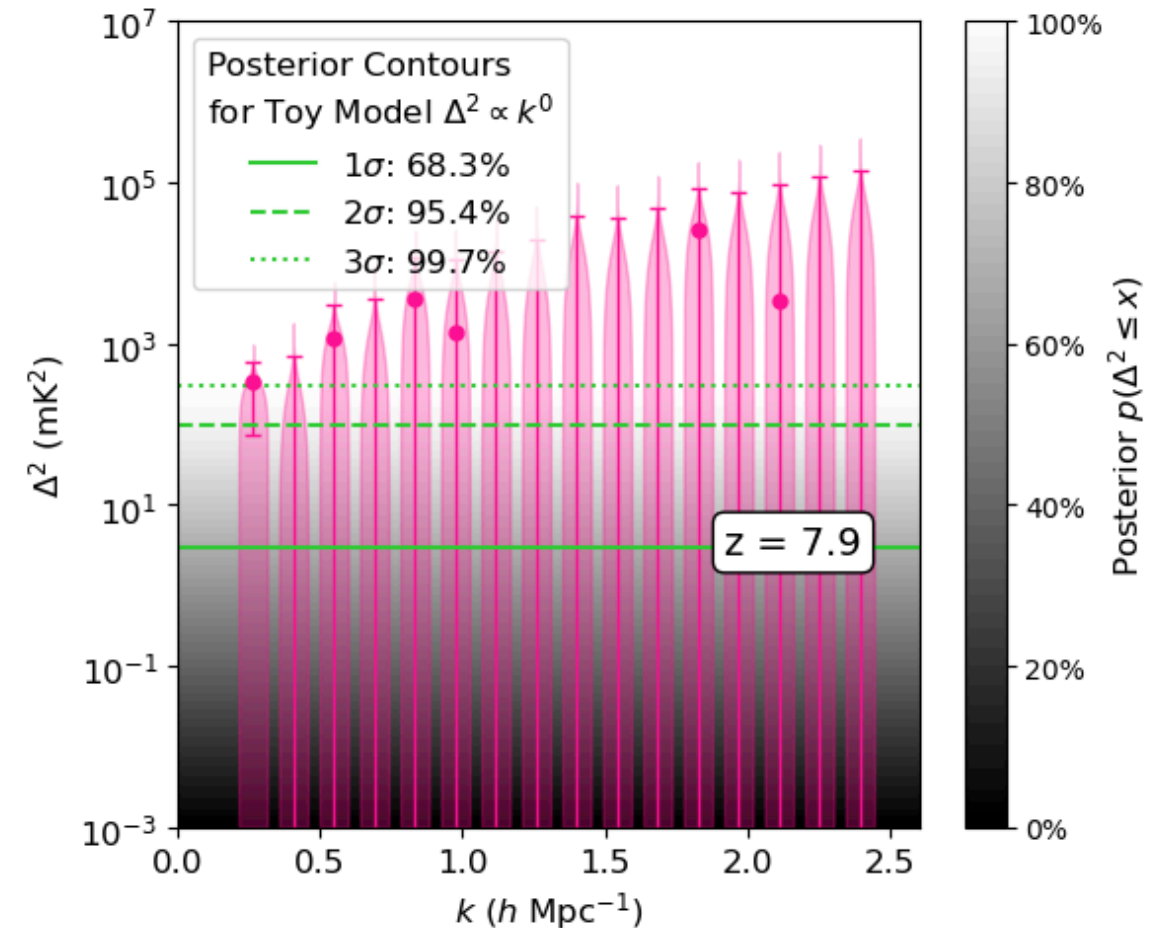


2 $\sigma$  upper limit: 9.7 mK<sup>2</sup>

Moving **lower** prior bound by  $<1 \text{ mK}^2$  changed **upper** limit by  $7 \text{ mK}^2$ !

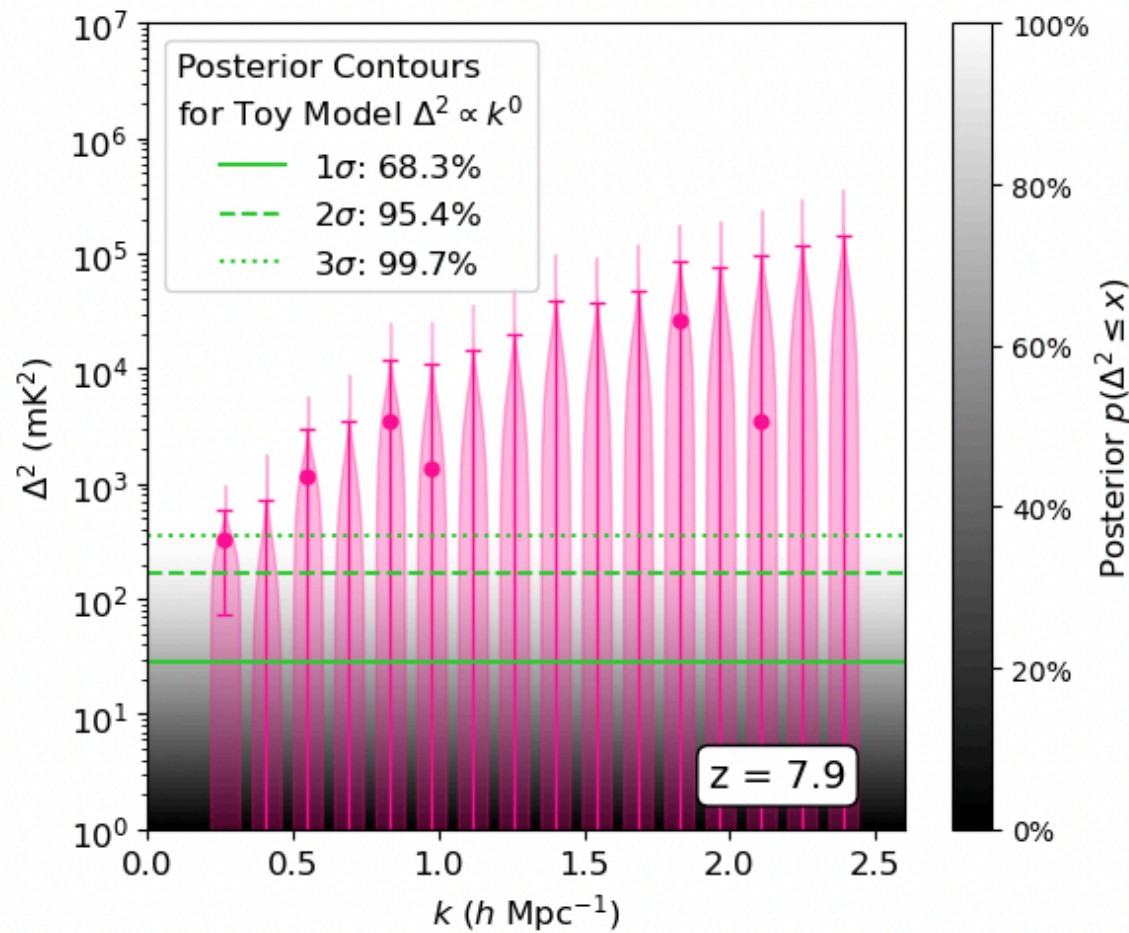


2 $\sigma$  upper limit:  $16.7 \text{ mK}^2$

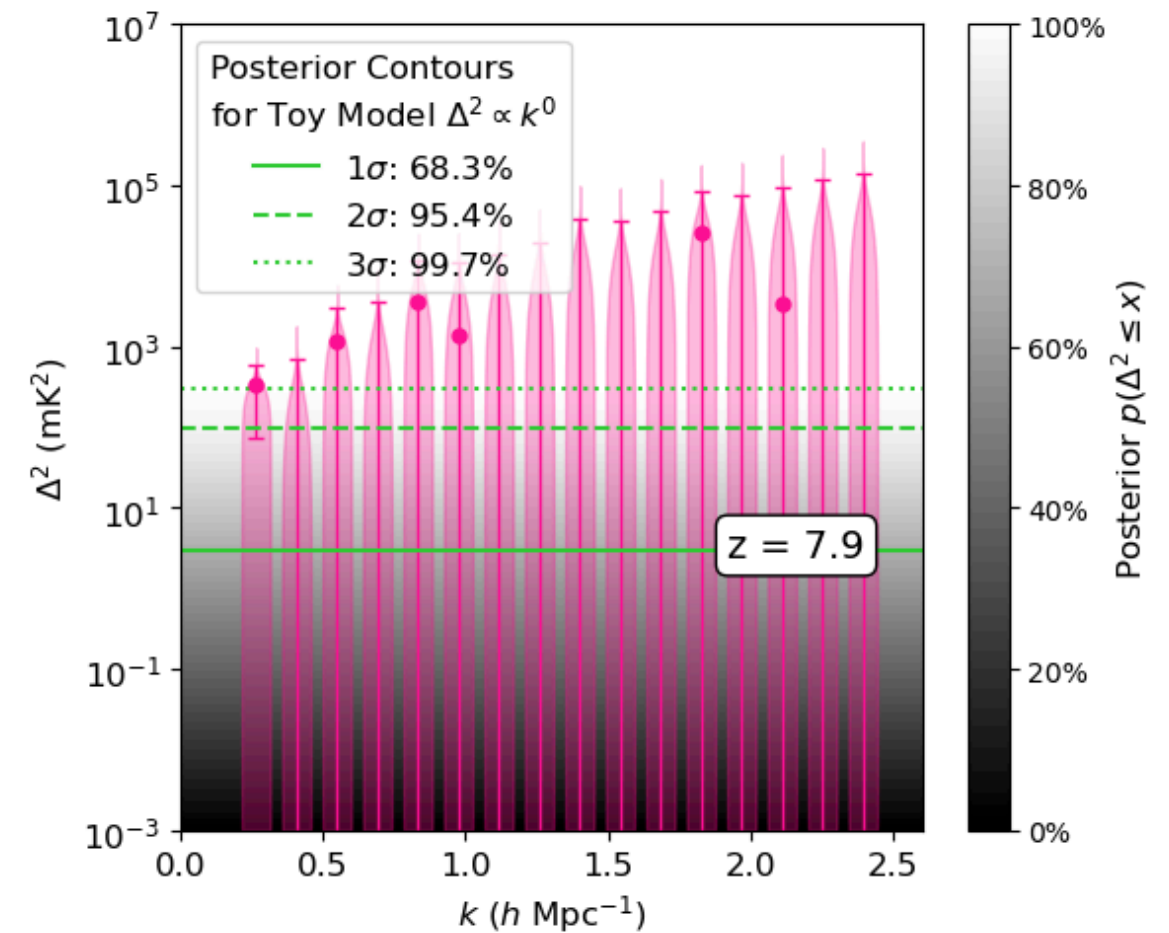


2 $\sigma$  upper limit:  $9.7 \text{ mK}^2$

# Which was right?



2 $\sigma$  upper limit: 16.7 mK<sup>2</sup>

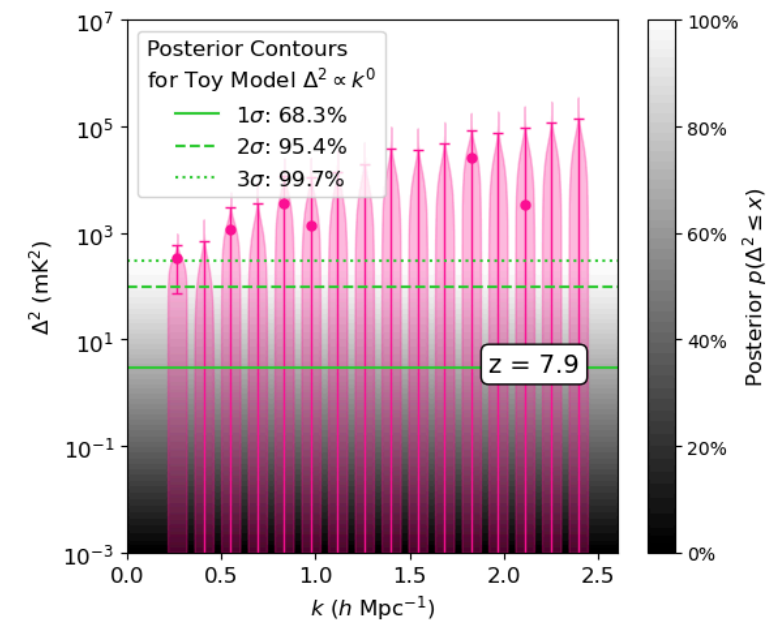


2 $\sigma$  upper limit: 9.7 mK<sup>2</sup>

Neither!

Log prior in linear space

$$P(s | d) = \frac{\overbrace{P(d | s)}^{\text{Physics Model}} \overbrace{P(s)}^{\text{Prior}}}{\cancel{P(d)}} \quad \text{Normalization}$$



# Logarithmic priors are shockingly dangerous

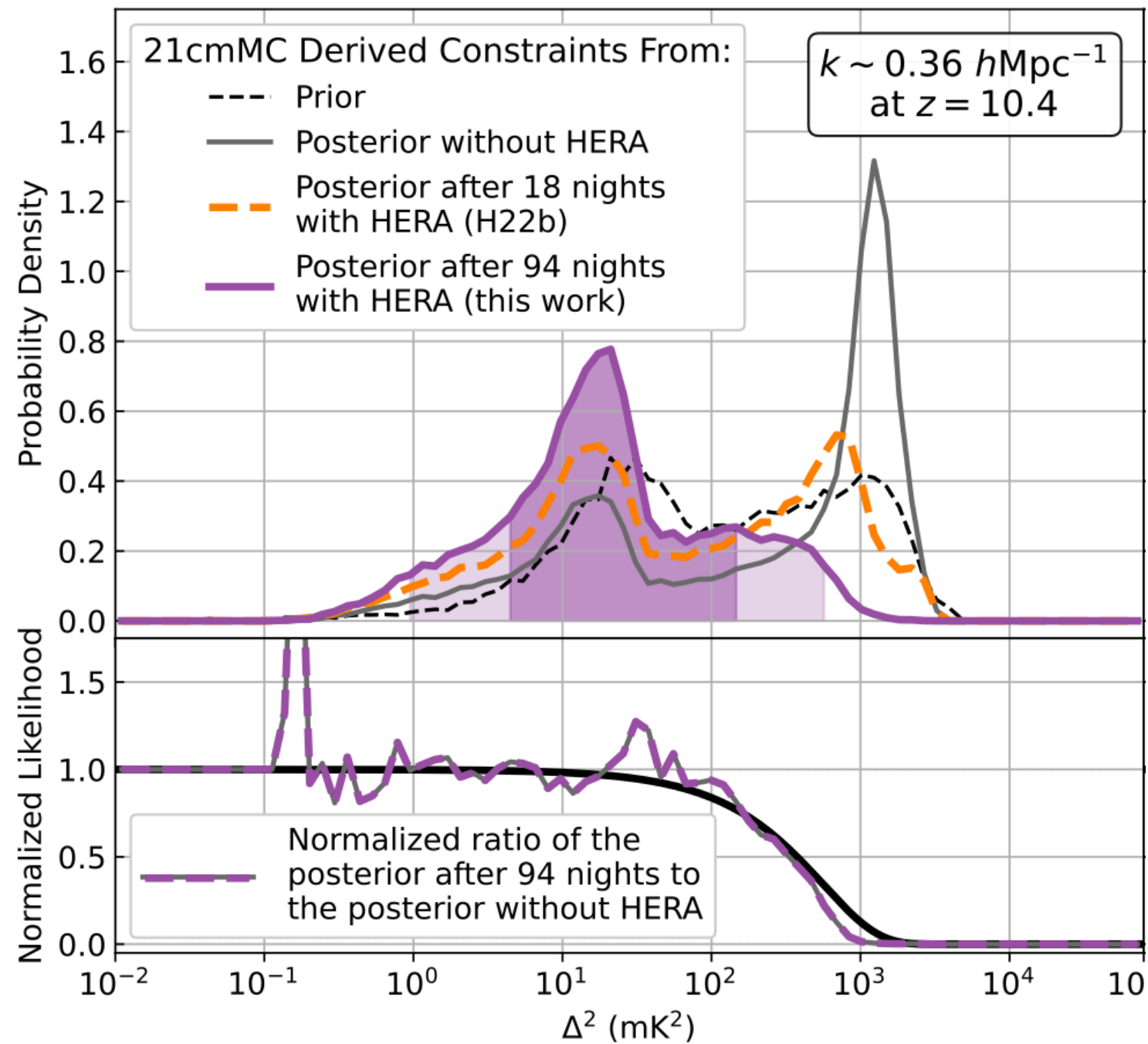
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- A lower value must be chosen so  $\int P(s) = 1$
- Upper and lower values tightly linked by normalization requirement
- Most common bad statistical mistake I see
- Rule of thumb: never use logarithmic priors

Asking the wrong question



# Misusing Bayes' theorem



# 3 questions

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- In what region does the brightest 5% of the models live?

- $\int_{\gamma}^{\infty} P(d | s) P(s) ds$



Theory landscape question

- Given only our physics model, what are the brightest 5% of the models consistent with our data?

- $\int_{\gamma}^{\infty} P(d | s) (\text{uniform prior}) ds$



Observer's question v1

- If we repeated our experiment, at what signal level would we have detection 95% of the time?

- $\int_d^{\infty} P(d | s_{\gamma}) \partial d$

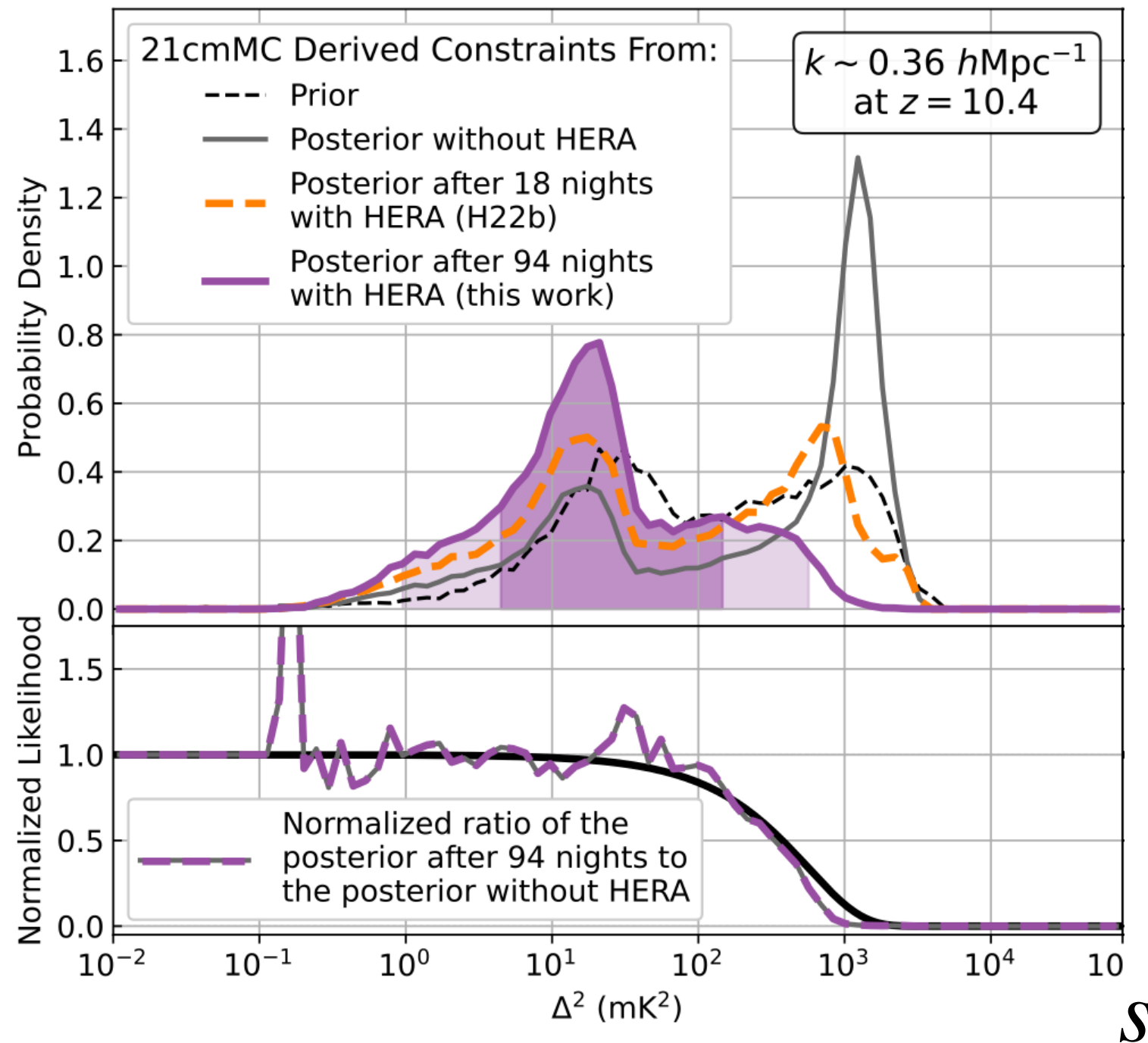


Observer's question v2



# Using Bayes' theorem

$$P(s | d) = P(d | s)P(s)$$



$$P(s | d) = P(d | s)P(s)$$

## 3 questions

- In what region does the brightest 5% of the models live?

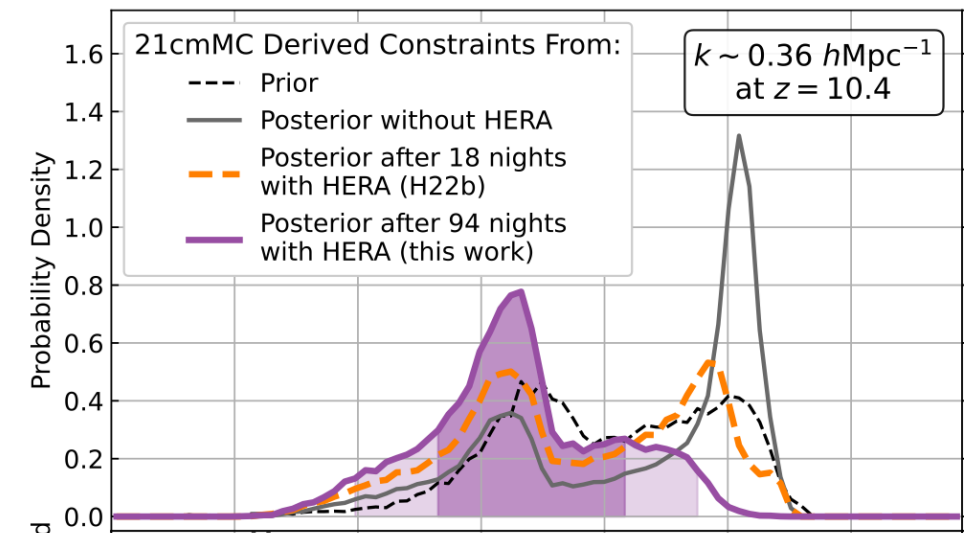
$$\cdot \int_{\gamma}^{\infty} P(d | s)P(s) ds$$

- Given only our physics model, what are the brightest 5% of the models consistent with our data?

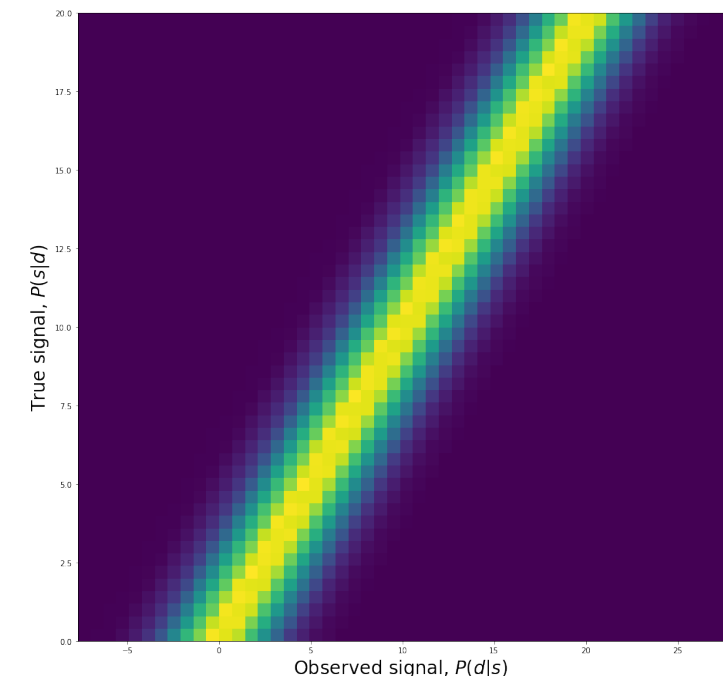
$$\cdot \int_{\gamma}^{\infty} P(d | s)(\text{uniform prior}) ds$$

- If we repeated our experiment, at what signal level would we have detection 95% of the time?

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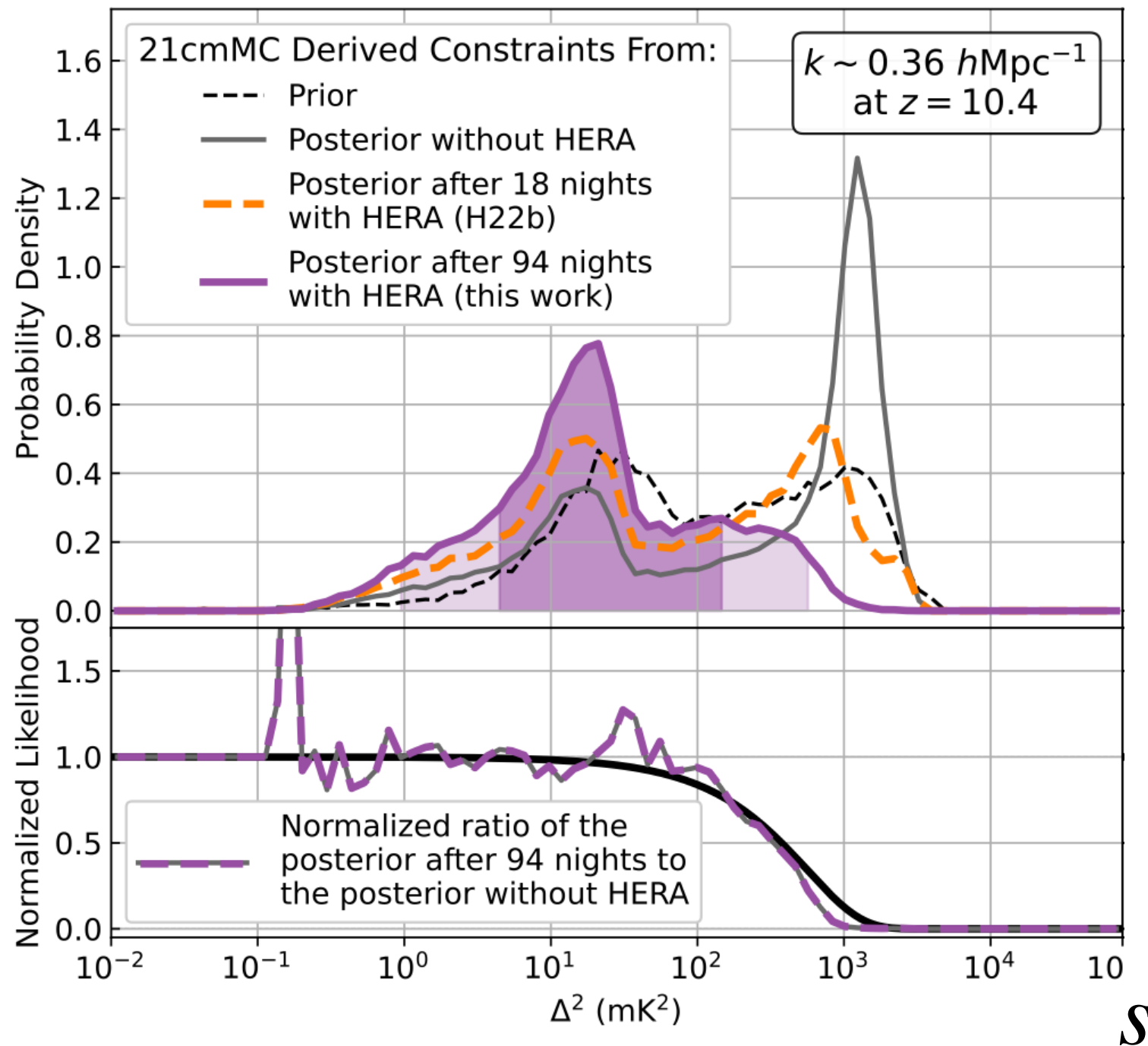


Same as above, but flat  $P(s)$



# Using Bayes' theorem

$$P(s | d) = P(d | s)P(s)$$

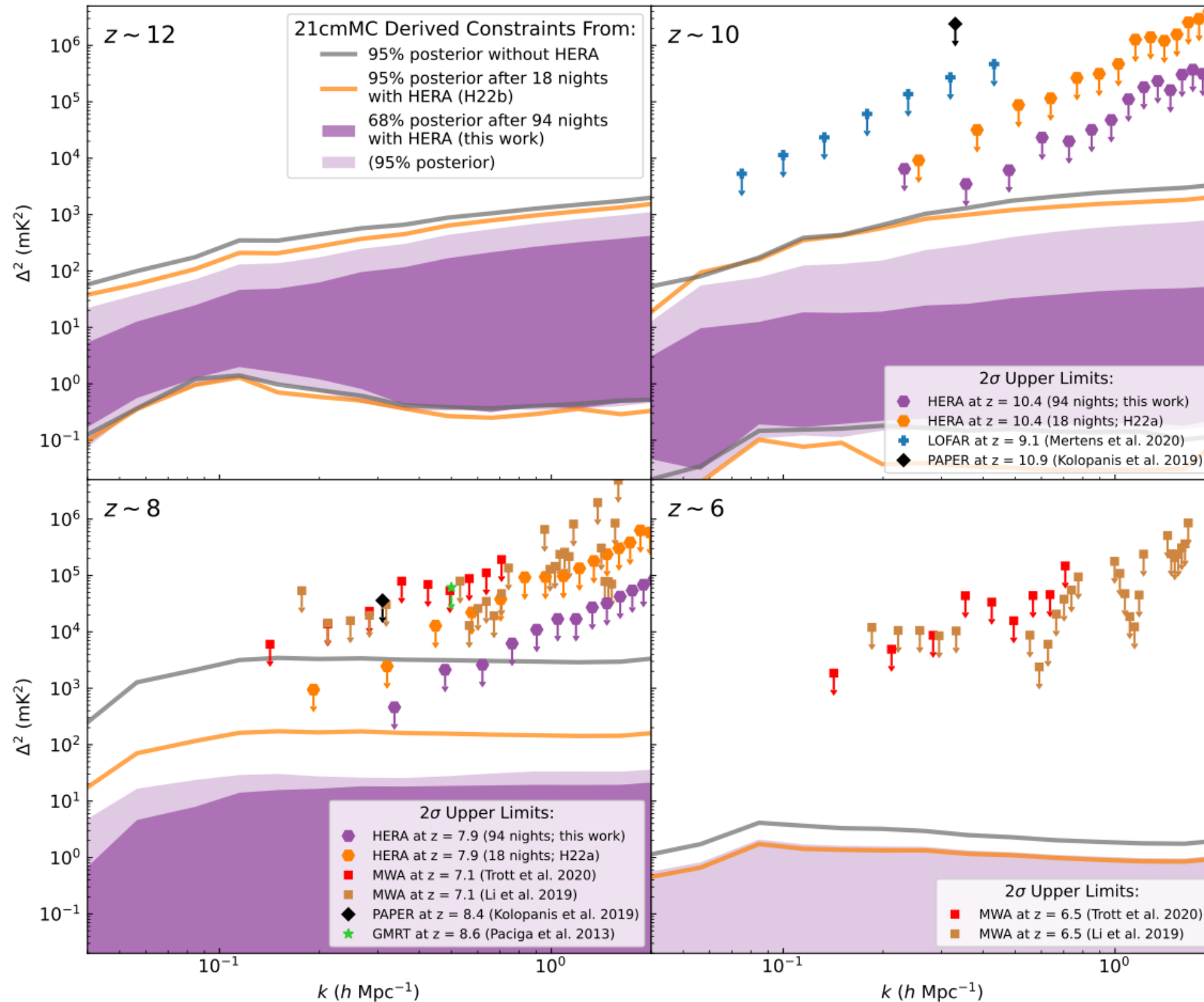


# Mistake is not in the math

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- Theory landscape is a fine question, ***for a theorist***
- Saying we have an observational upper limit (we'd see this signal 95% of the time) when what you calculated was fraction of theory landscape is ***wrong***.
- Math answered a different question

# Signature of ‘shy’ limits

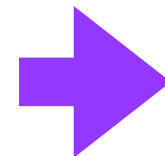


Priors

$$P(s | d) = \frac{P(d | s)P(s)}{P(d)}$$

To invert you need a prior  $P(s)$ ,  
key questions:

- Is your prior based on things you know? e.g. measurements, or strong theory constraints
- Is your prior based on assumptions, guesses, or convenience?



**Use prior**



**Flat prior or  
no prior**

# Rules of thumb

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- Data driven priors are fine
- You want your science conclusion to depend on your data, not on your prior → uninformative or flat priors
  - Flat priors
  - Priors that are flat over region of interest
- ‘Frequentist’ methods don’t usually run into these problems (clearer question)