

# Class 13: inherited code, parameters & the blob pt 2

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# Presentations

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- Schedule up soon
- (Turn in HW 3 & survey)
- Starting Thursday next week

# Next few days:

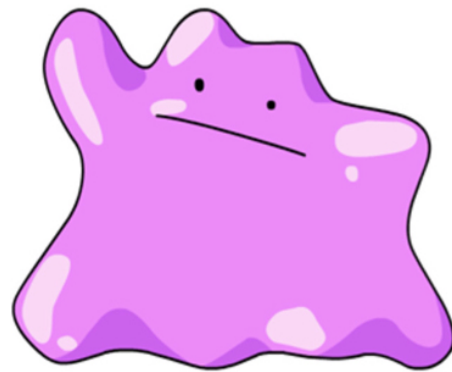
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Th: Blind analyses, with David Hertzog

T: Plots as a language

Th: First batch of presentations

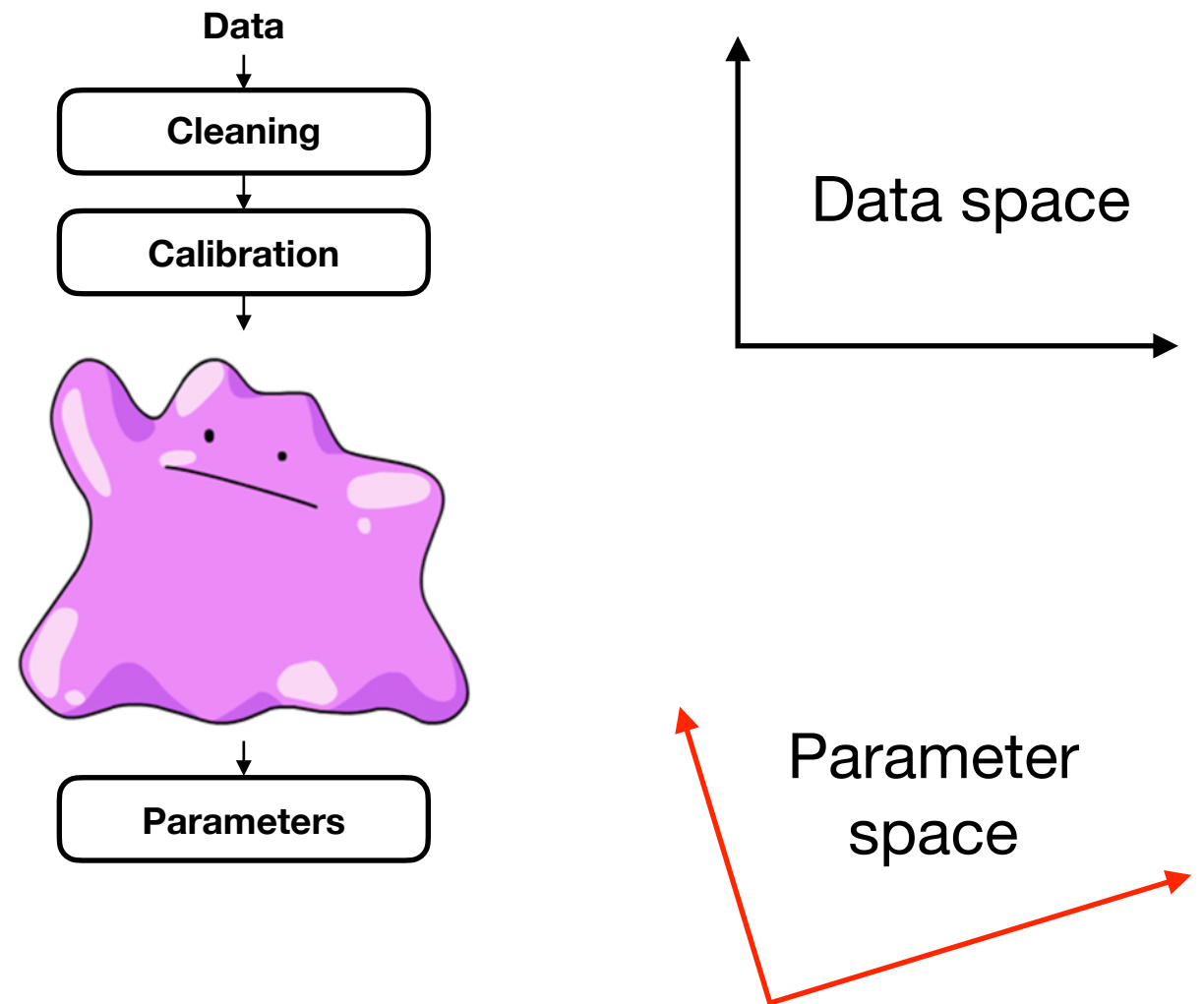
Inherited code & parameters (blob pt 2)



# Parameters as measurement

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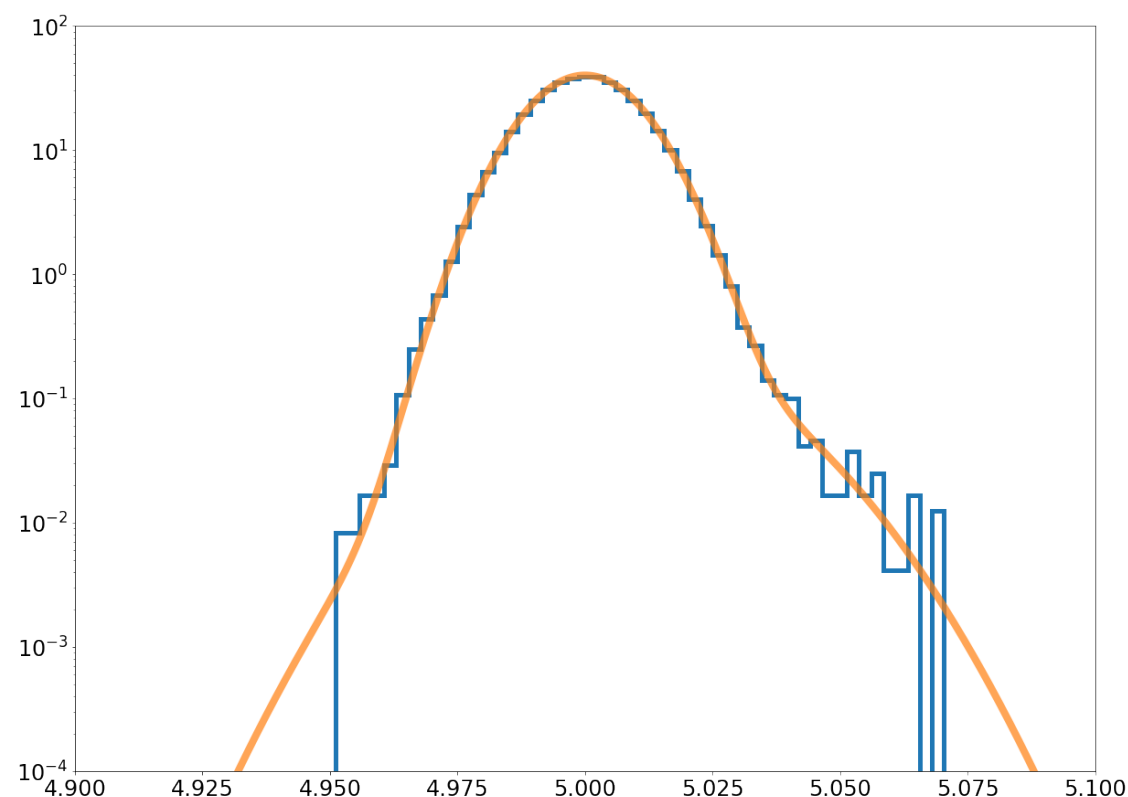
- New measurement 'space'
- Horrible, non-linear, but treat as a new measurement



# Background & parameters

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- Often have 1 ‘signal’ parameter & a few ‘nuisance’ parameters
- Try giving analysis block many data examples with no signal, and histogram signal

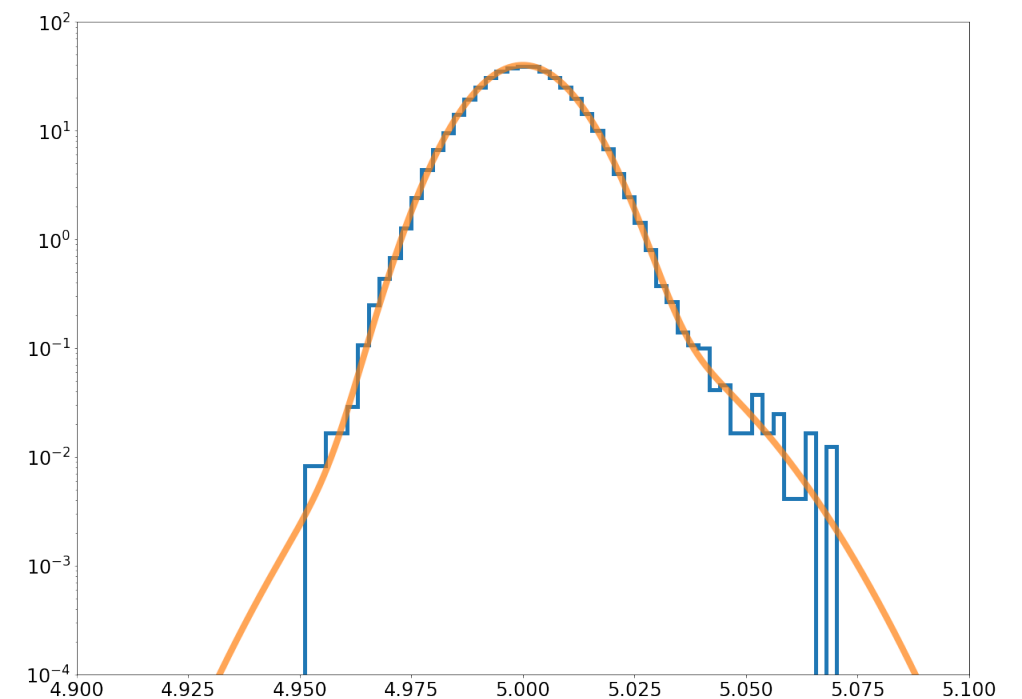


# Background & parameters

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Zero signal examples can be

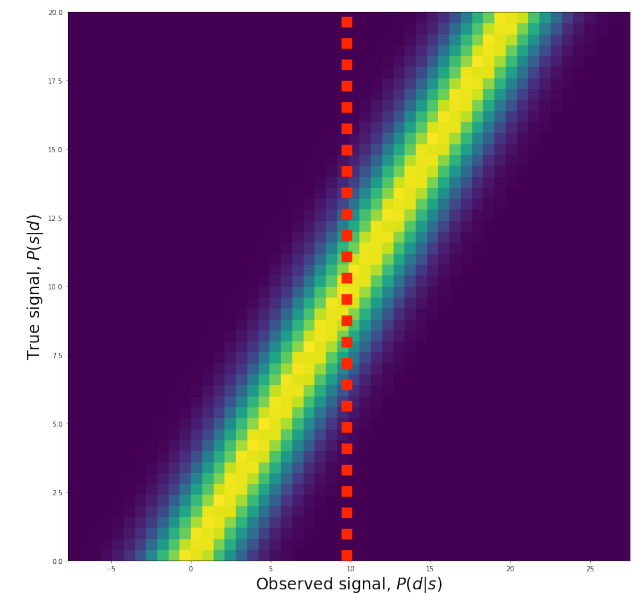
- Signal-free data
- MC simulation (signal turned off)



# Statistics & Parameters

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- Just treat like a measurement
- Background distribution for null hypothesis ( $\sigma$  significance)
- Confidence intervals
- All just like ‘measurement’ was the parameter\*





\*Common problems with parameters

# Problems with parameters

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- Implicit priors
- Local minima
- Degeneracy, catastrophic errors, chaos

# Implicit priors

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- Nuisance parameters ( $n_i$ )

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

$$P(\{s, n_1, n_2, \dots\} | d) = \frac{P(d | \{s, n_1, n_2, \dots\}) P(s) P(n_1) P(n_2) \dots}{P(d)}$$

# Implicit priors

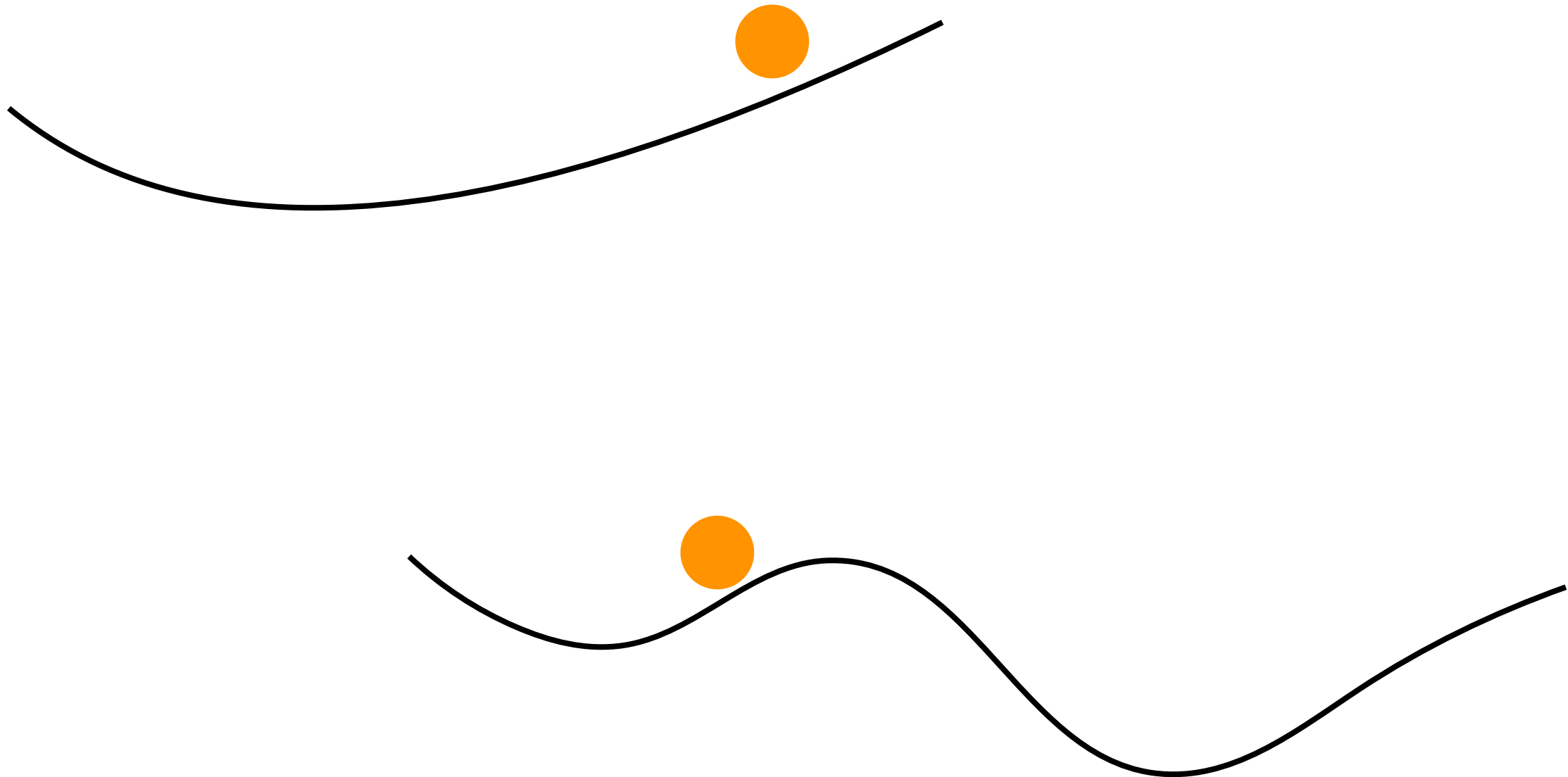
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- Does the real data have the same occurrence distribution  $P(n_i)$  as your signal-free data or MC?
- Data example(s)
- MC example(s)

$$P(\{s, n_1, n_2, \dots\} | d) = \frac{P(d | \{s, n_1, n_2, \dots\}) P(s) P(n_1) P(n_2) \dots}{P(d)}$$

# Local minima

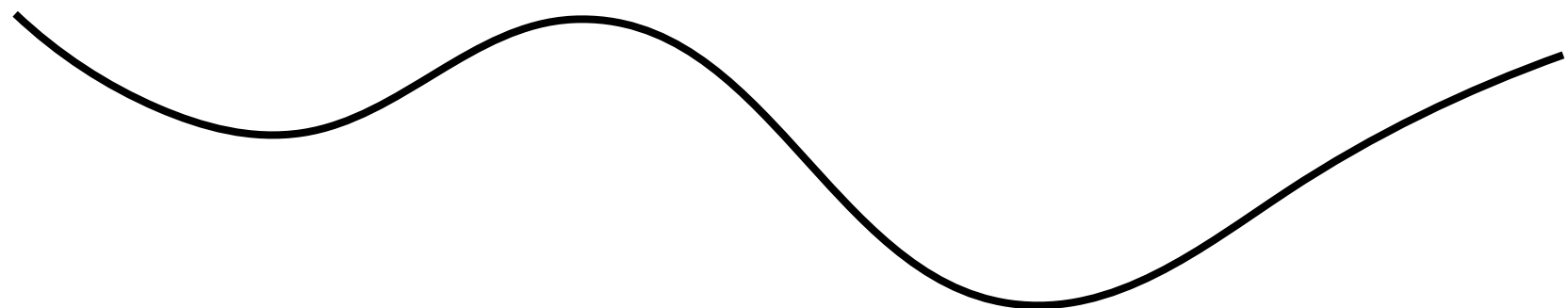
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# Local minima

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- Simulated annealing
- Genetic algorithms
- Markov Chain Monte Carlo sampling



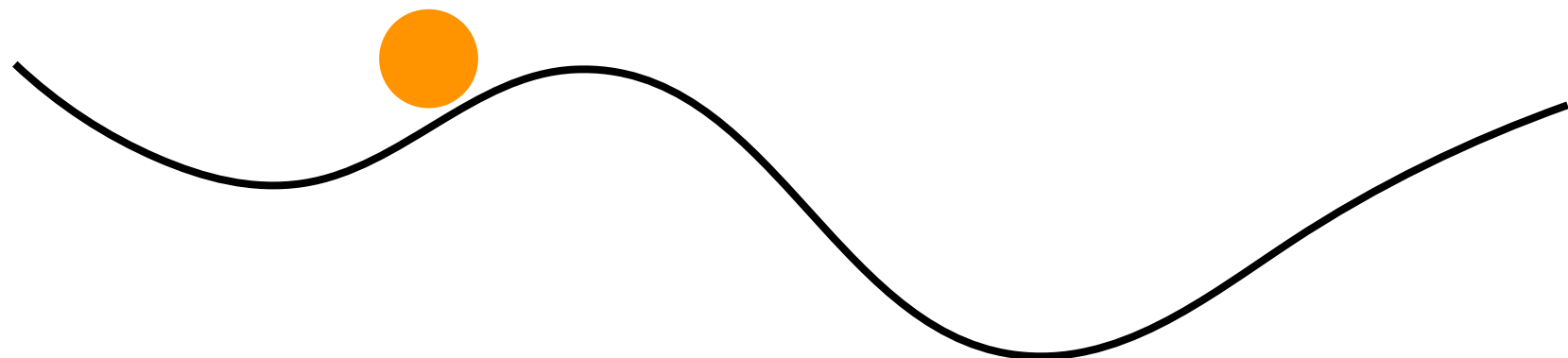
# Local minima

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Lots of options

Make sure you actually need them...

- Related to degeneracies (telling you something)
- Adding more (or different) information can sometimes remove local minima

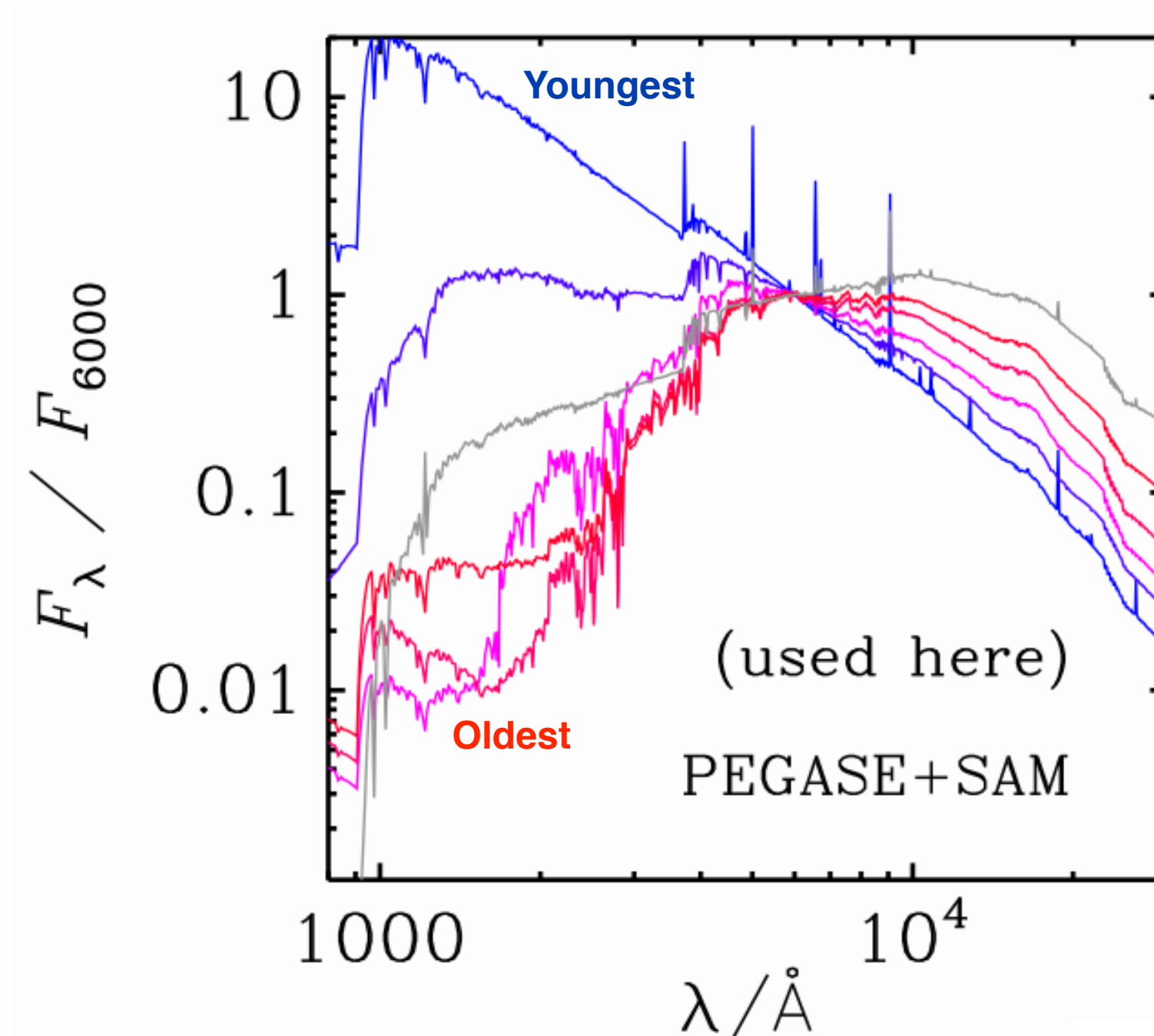


Degeneracy, catastrophic errors, chaos



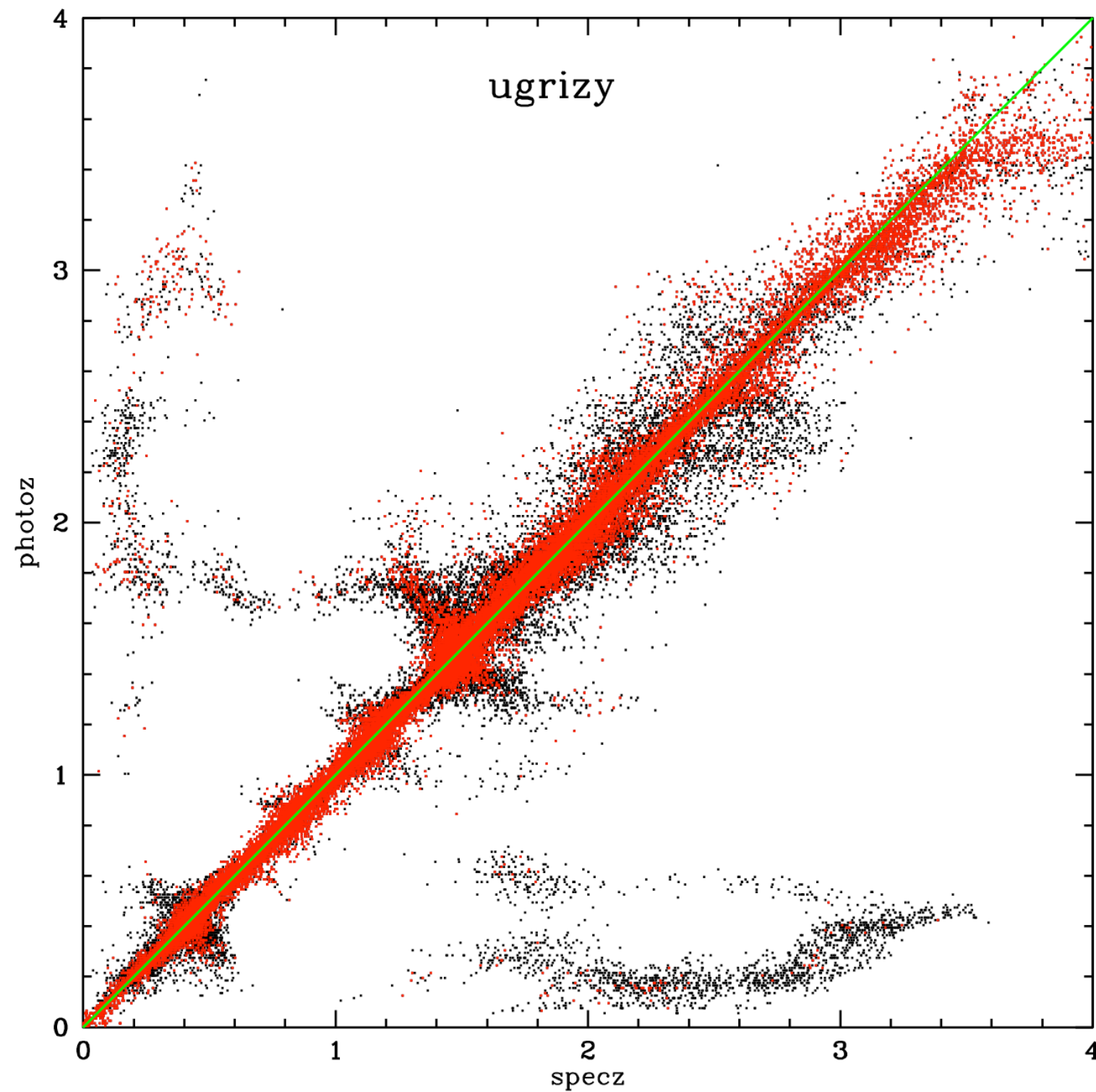


# Catastrophic photo-z

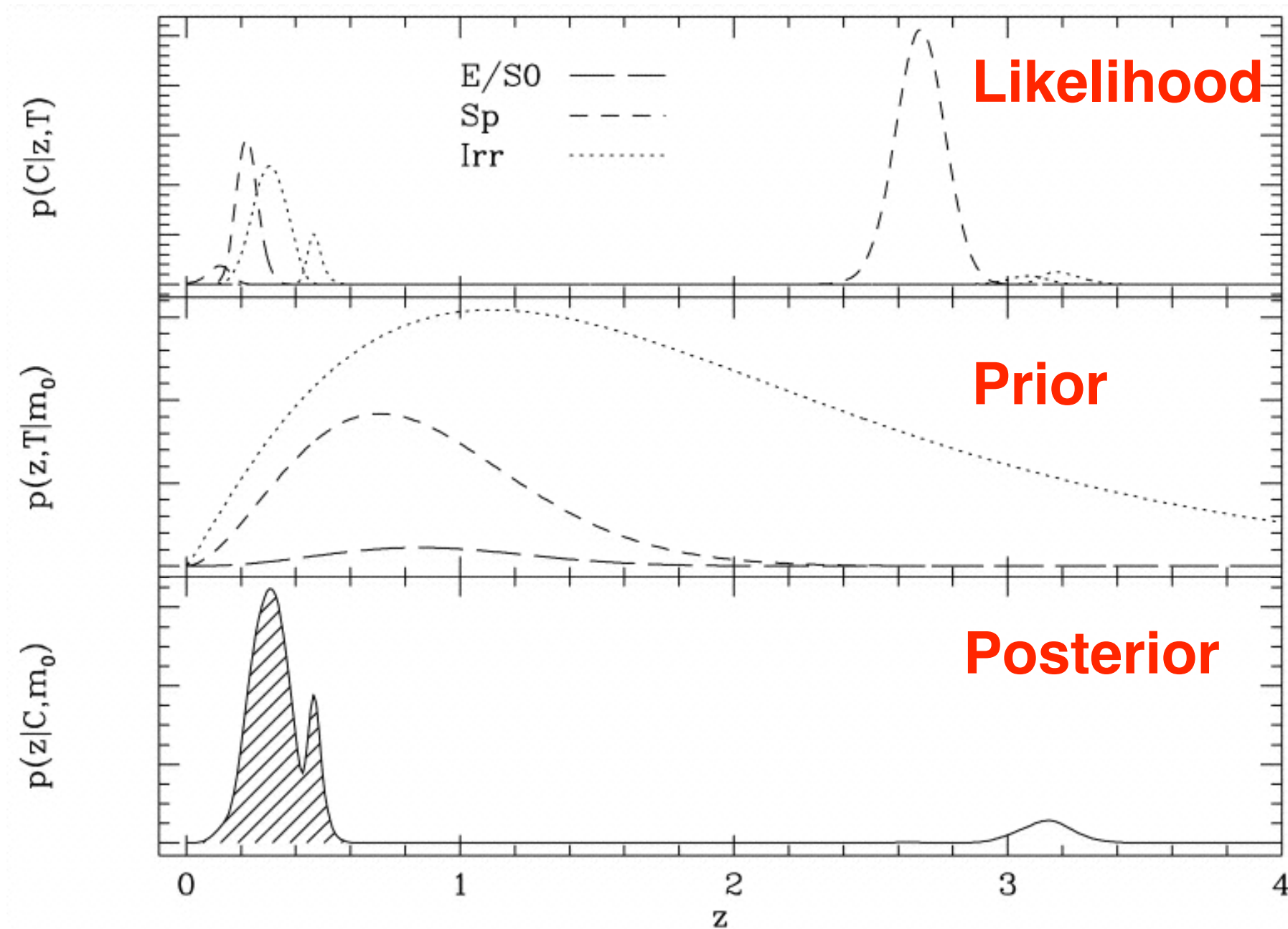


# Catastrophic photo-z

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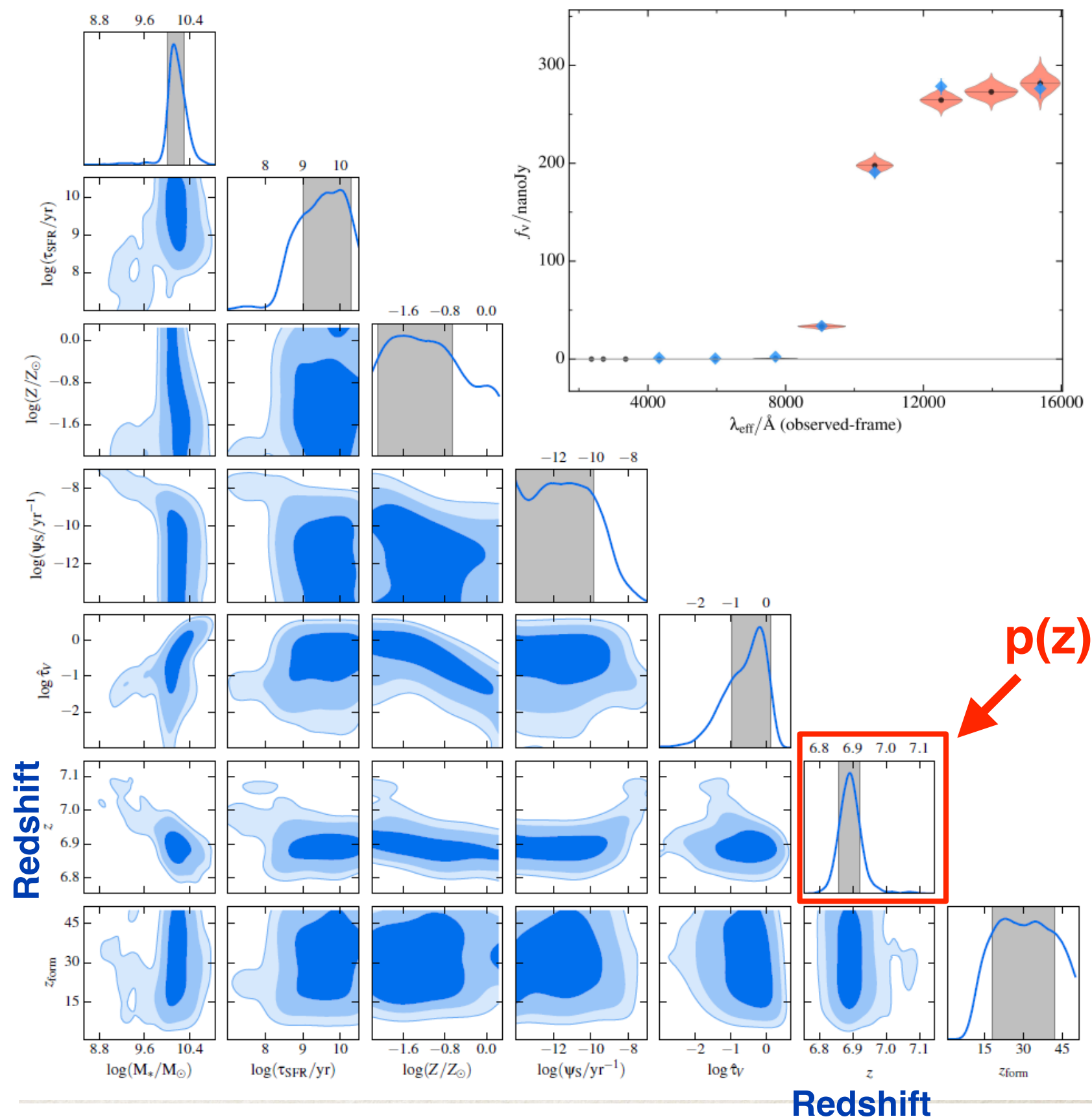
# Catastrophic photo-z



$$P(\{s, n_1, n_2, \dots\} | d) = \frac{P(d | \{s, n_1, n_2, \dots\}) P(s) P(n_1) P(n_2) \dots}{P(d)}$$

**Benitez 2000**

# Catastrophic photo-z



# Degeneracy & catastrophic errors

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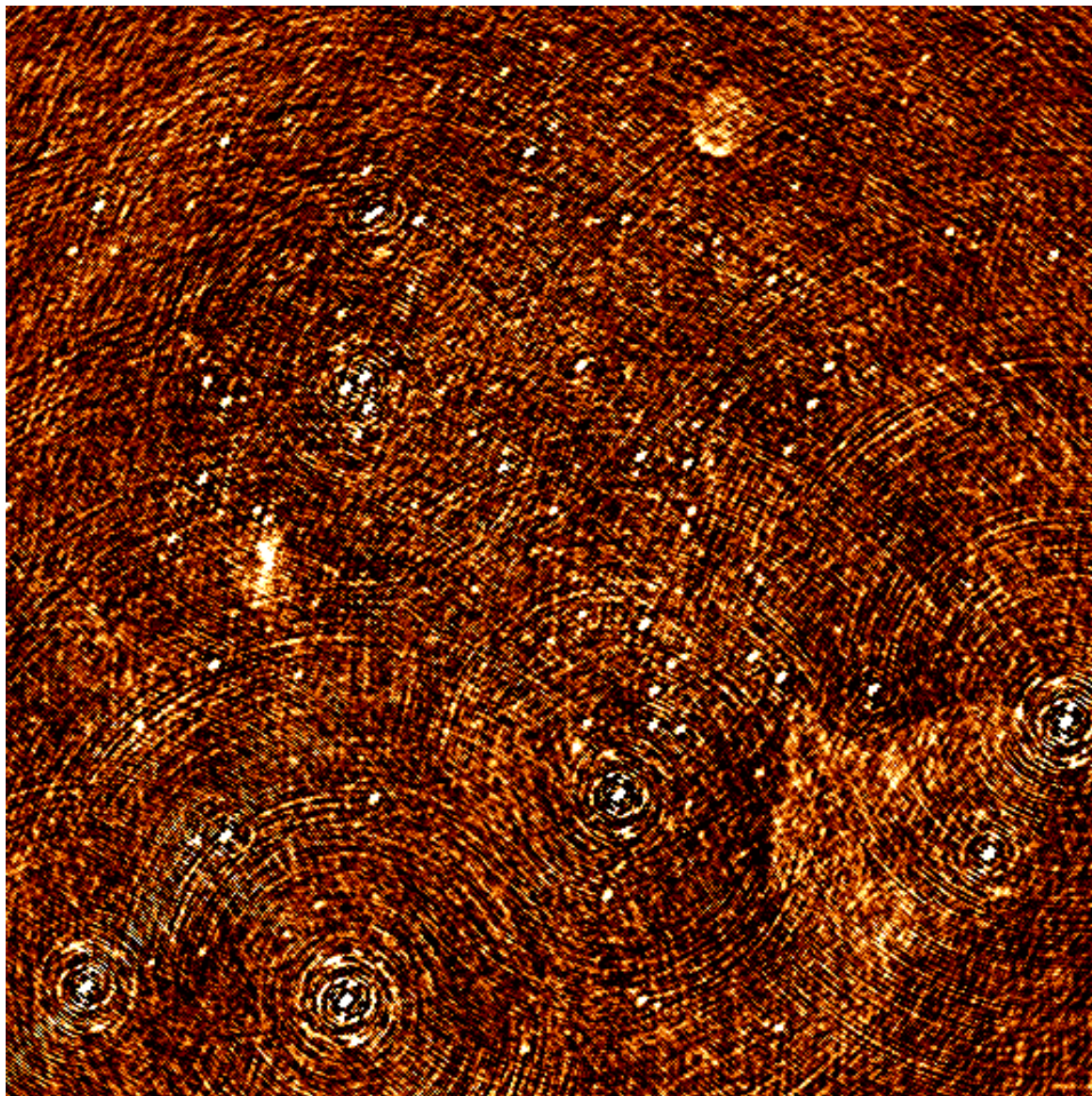
- Does it impact science?
- Can you get more information?
- Are priors your friend?



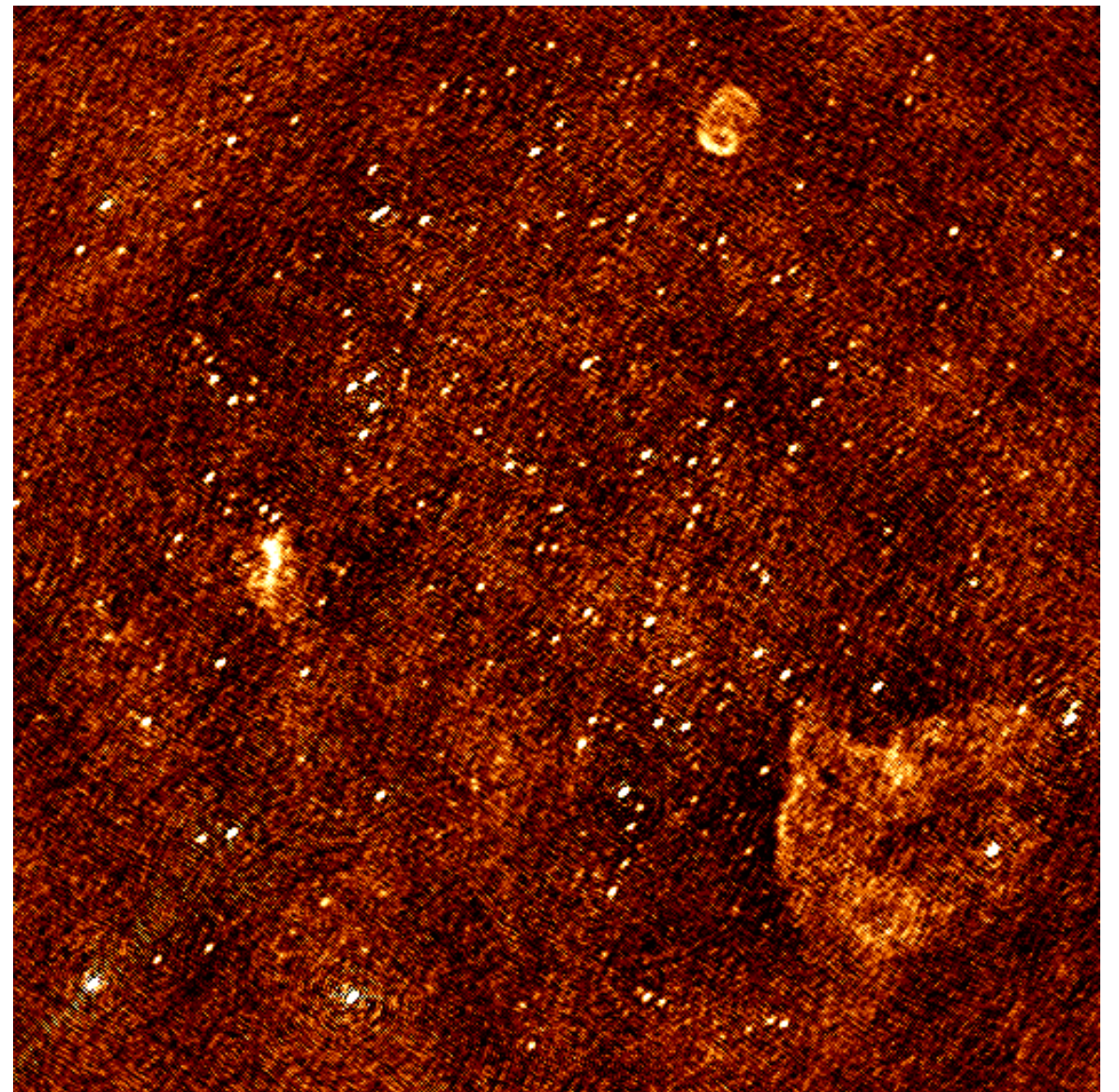
# Chaotic algorithms (deconvolution)

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clean-dirty.fits



clean-image.fits





# Formally chaotic algorithms

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- ‘Decision points’ in algorithm
- Gain or step control to help convergence
- Tend to have algorithm settings, which depend on implicit priors

# Degeneracy, catastrophic errors, chaos

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So what do you do?

- Be careful
- Test (implicit) assumptions
- Beware of walking out of applicability

