

# Class 13: stats mini review; the blob, parameters, and analysis dragons

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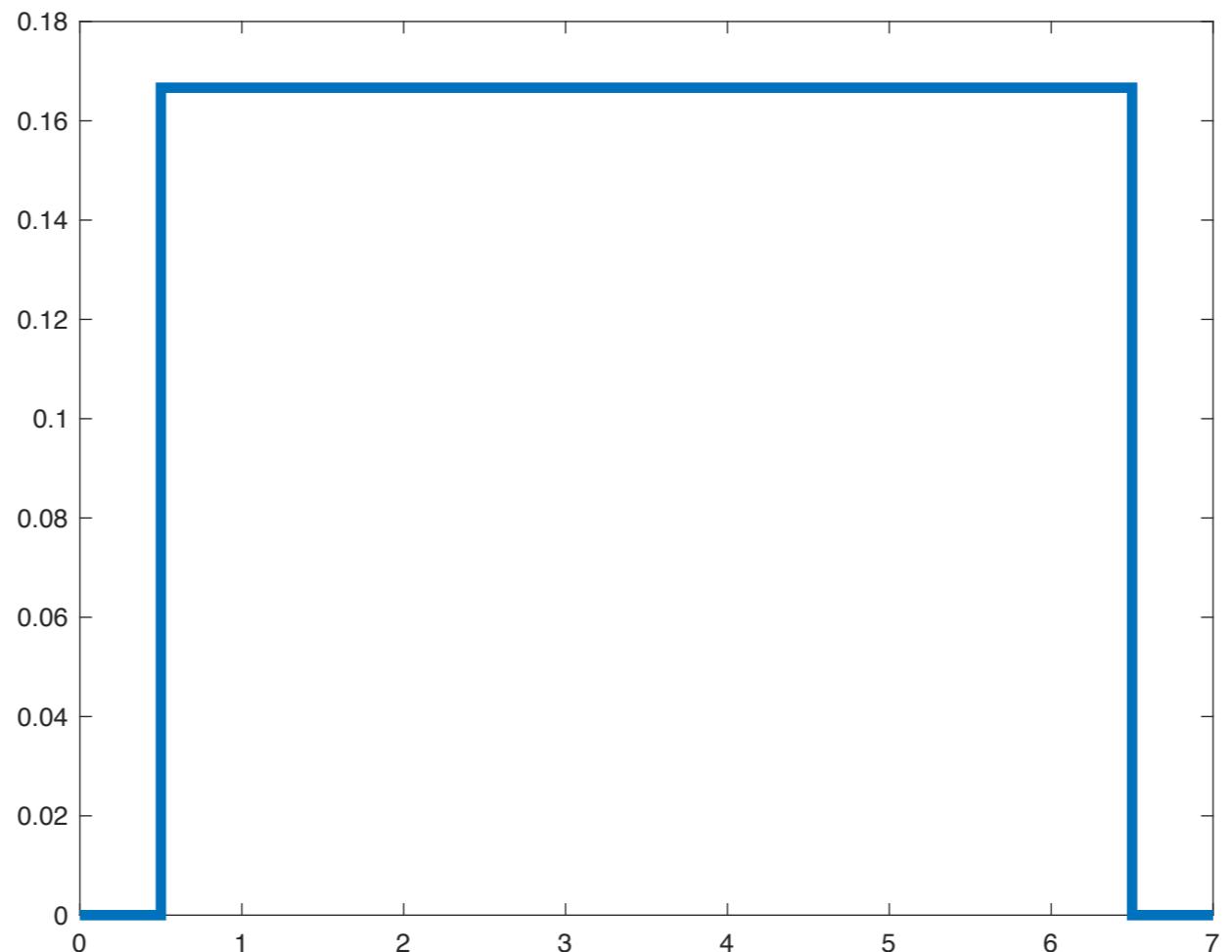
Miguel F. Morales

Bryna Hazelton

# Small stats review

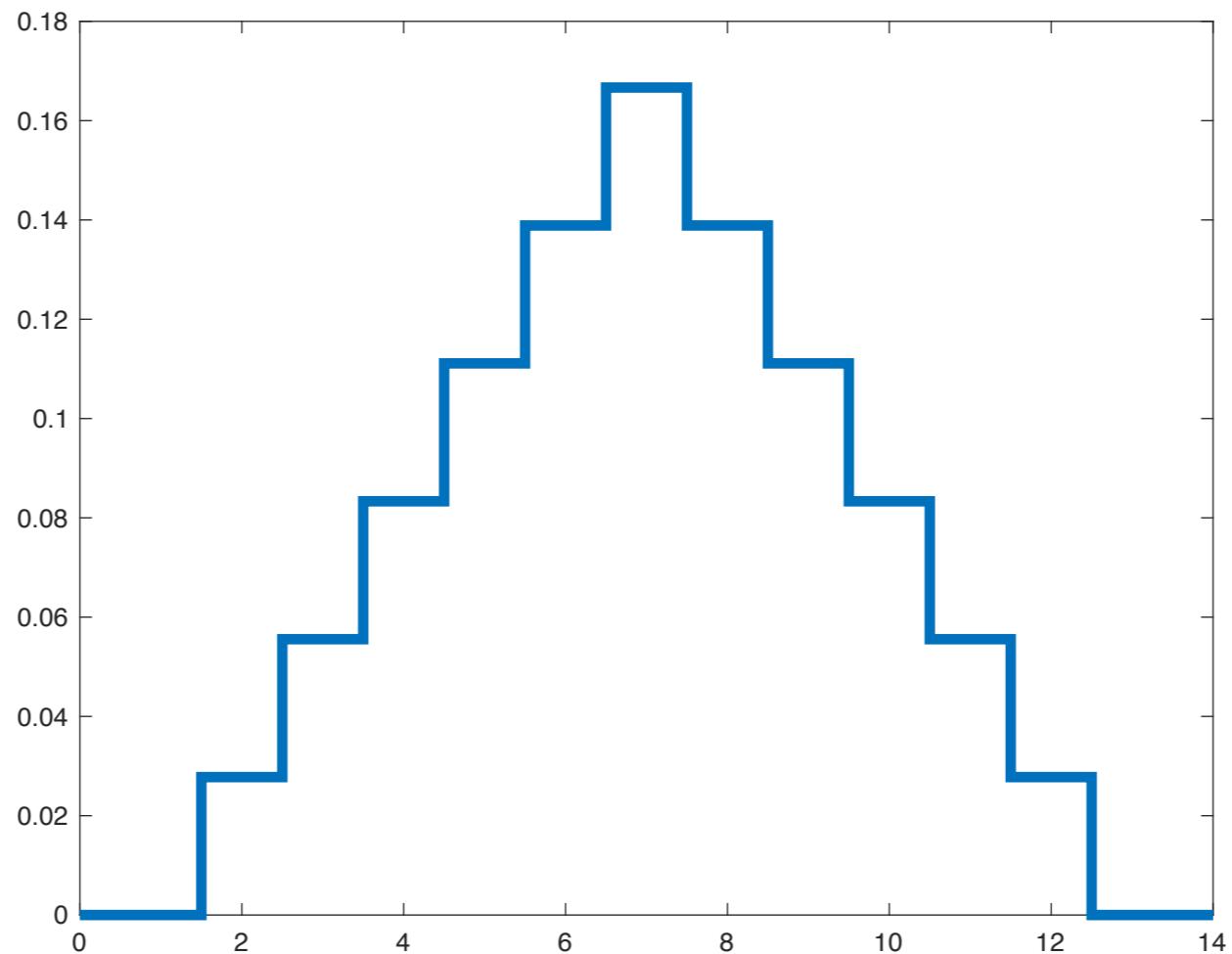
# Convolution, six sided die

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# Convolution, six sided die

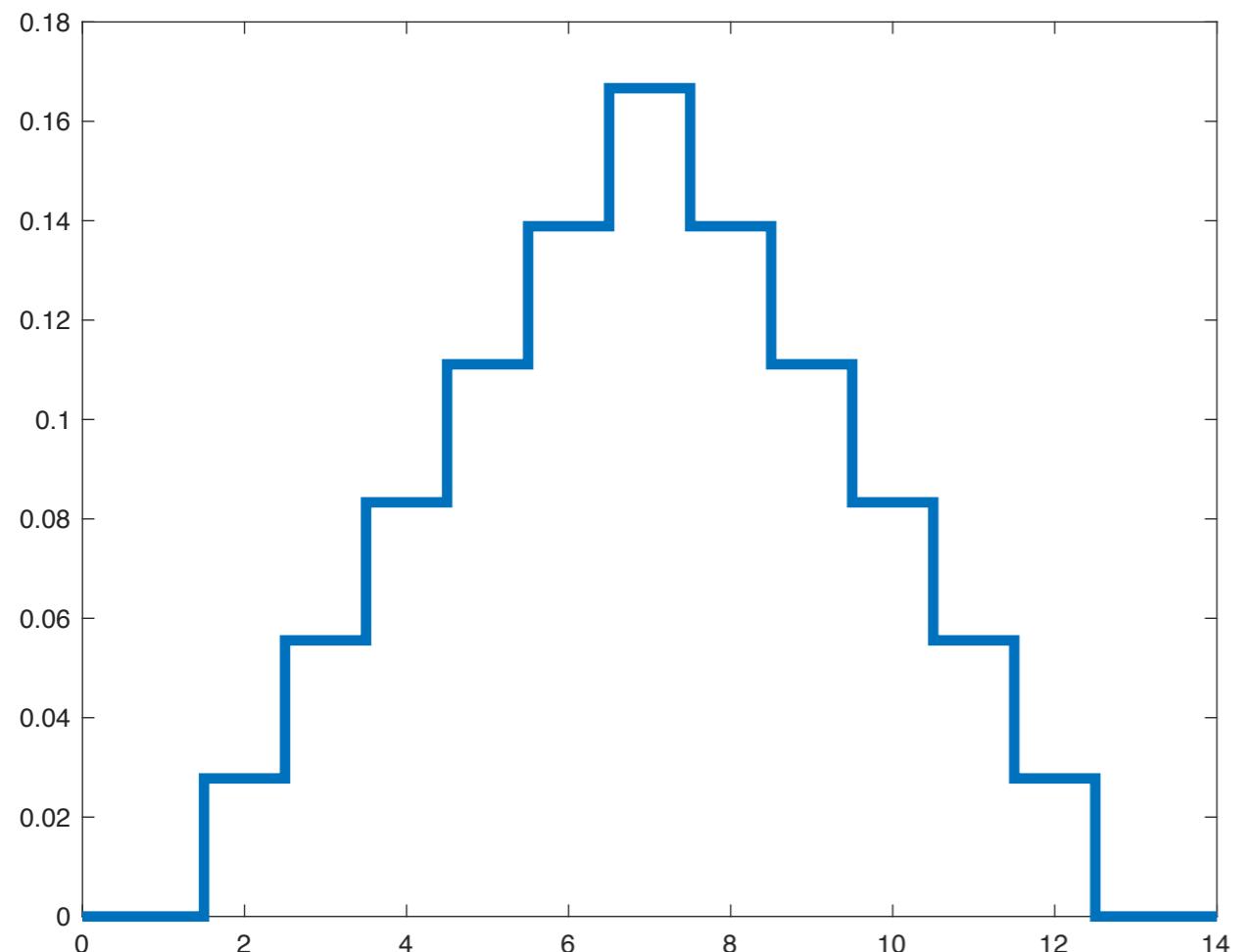
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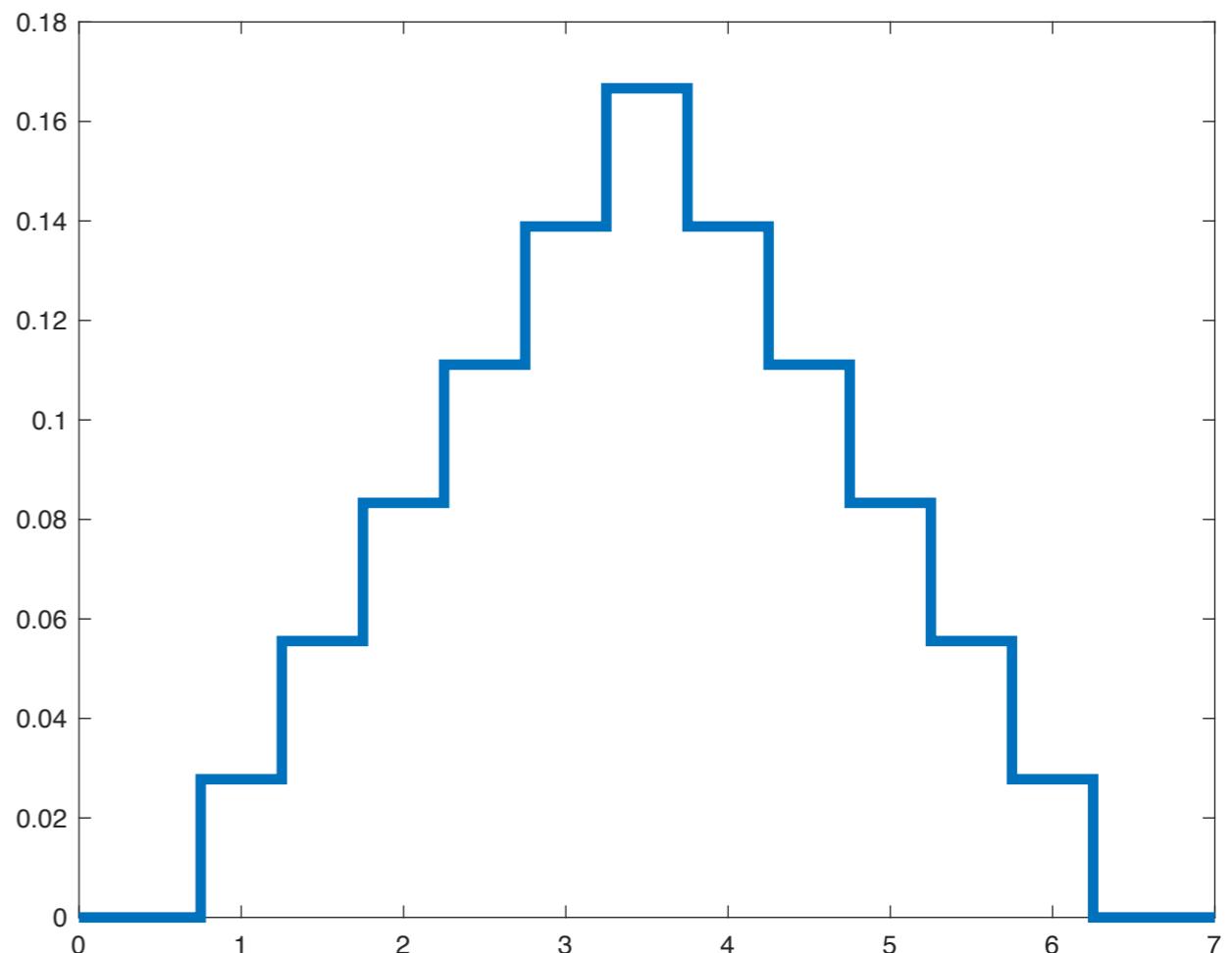
# Convolution, six sided die

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Sum



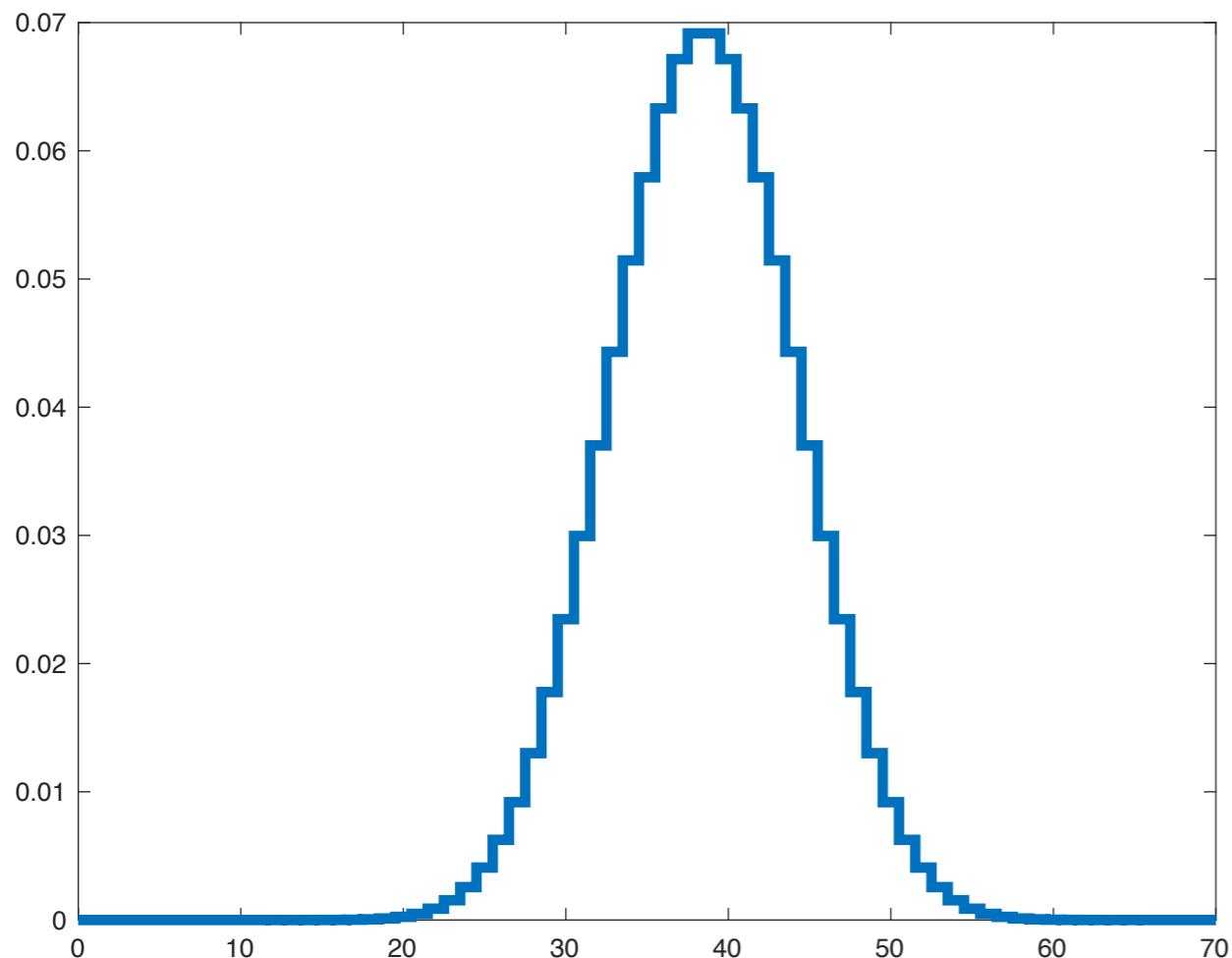
Average



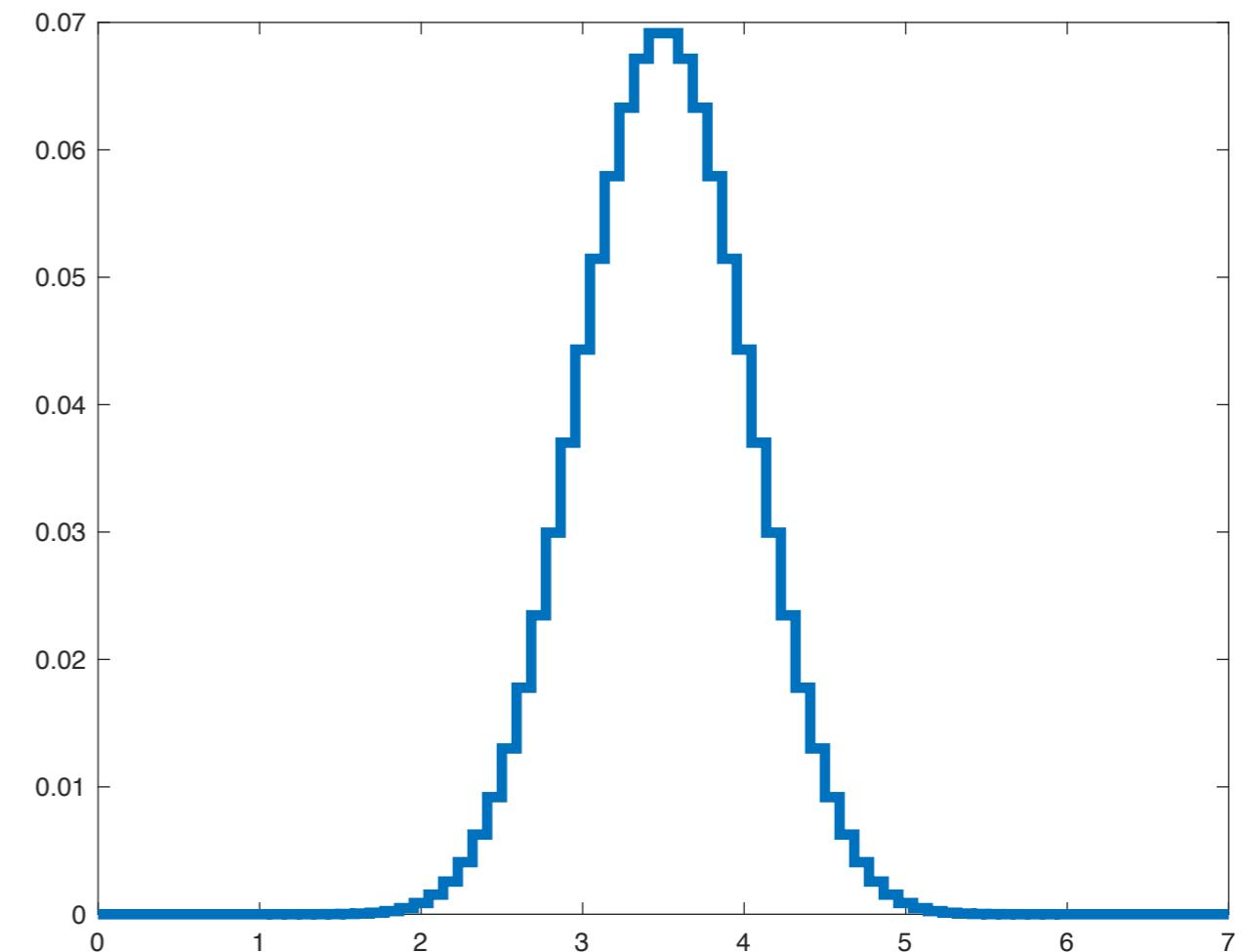
# Convolution, six sided die

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Sum of 11



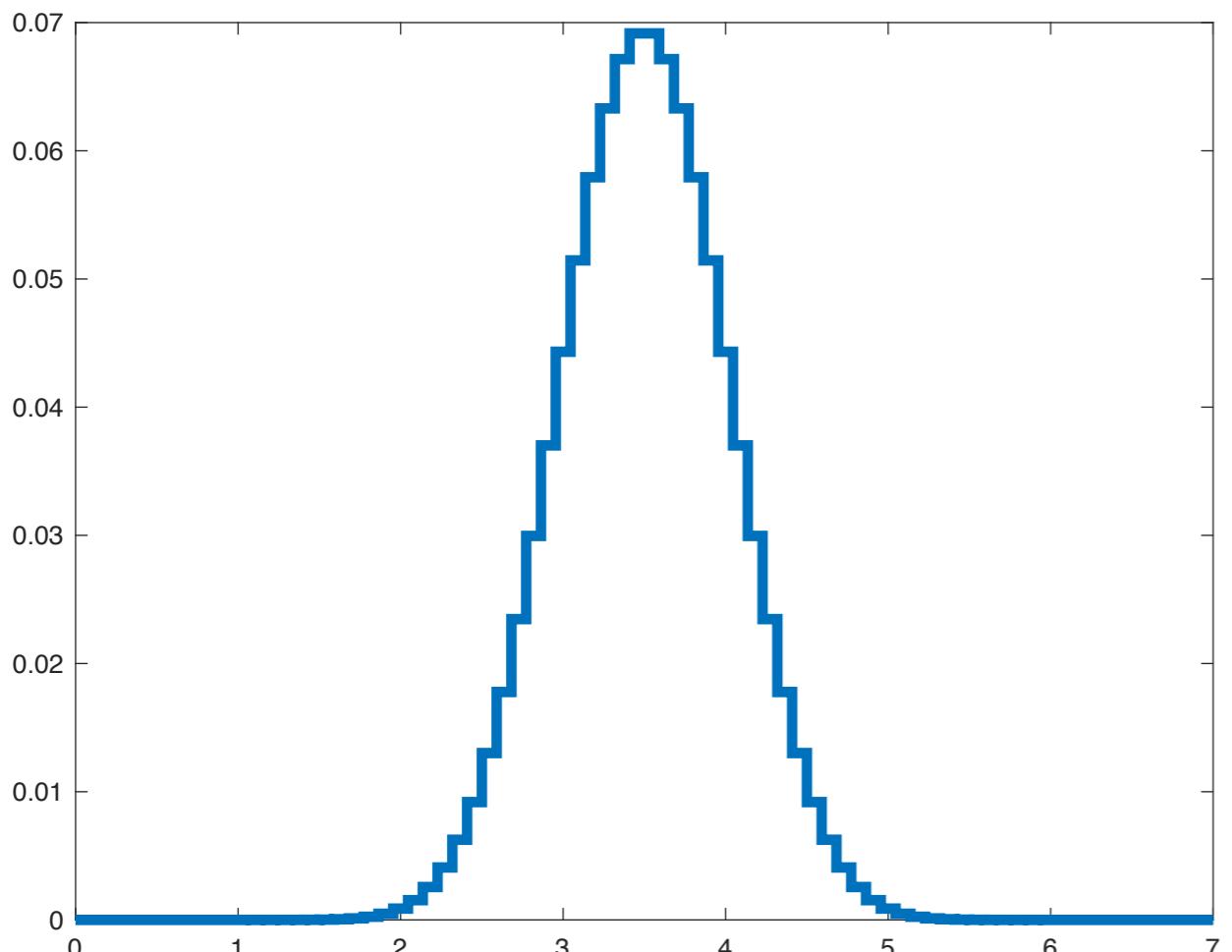
Average of 11



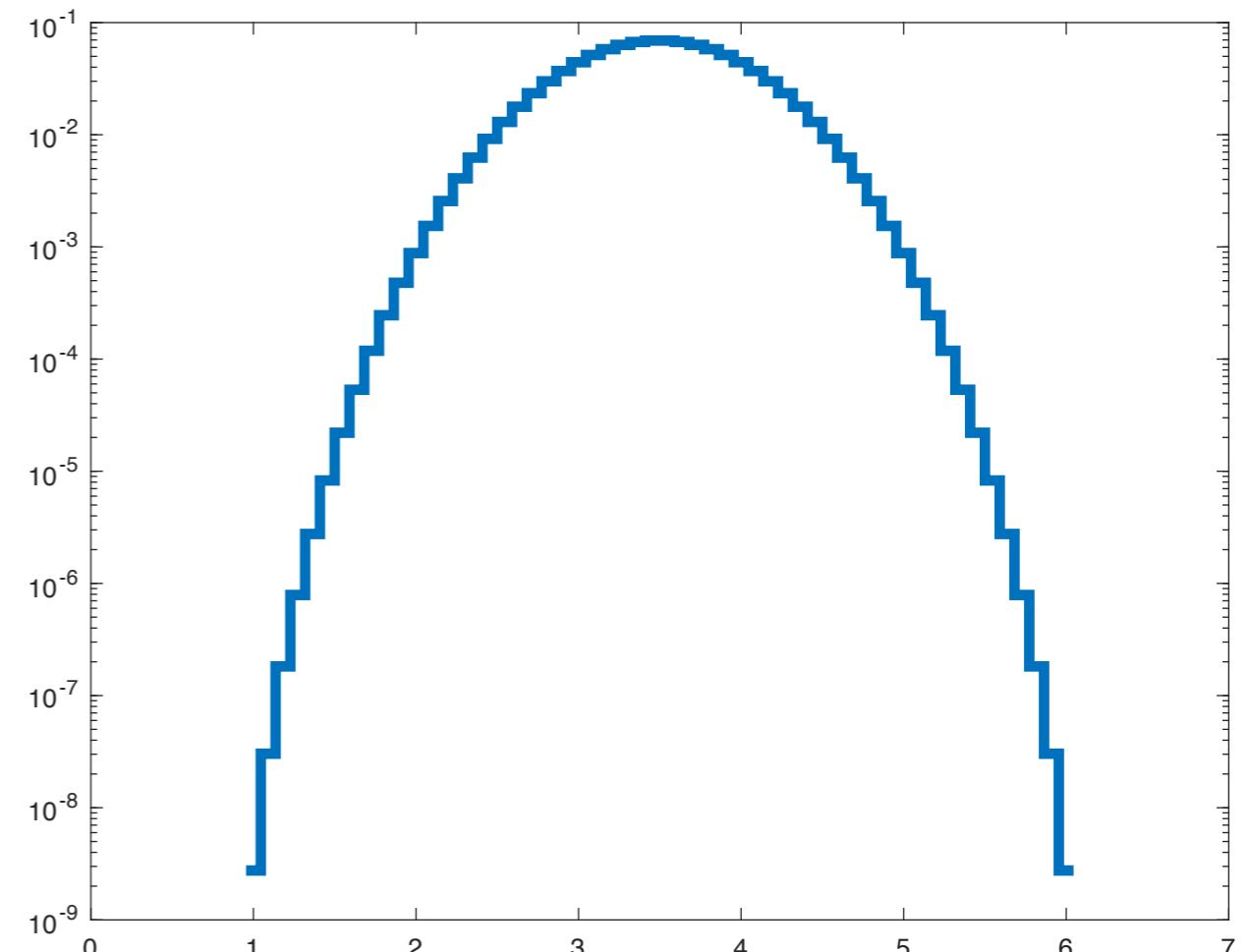
# Convolution, six sided die

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Average of 11

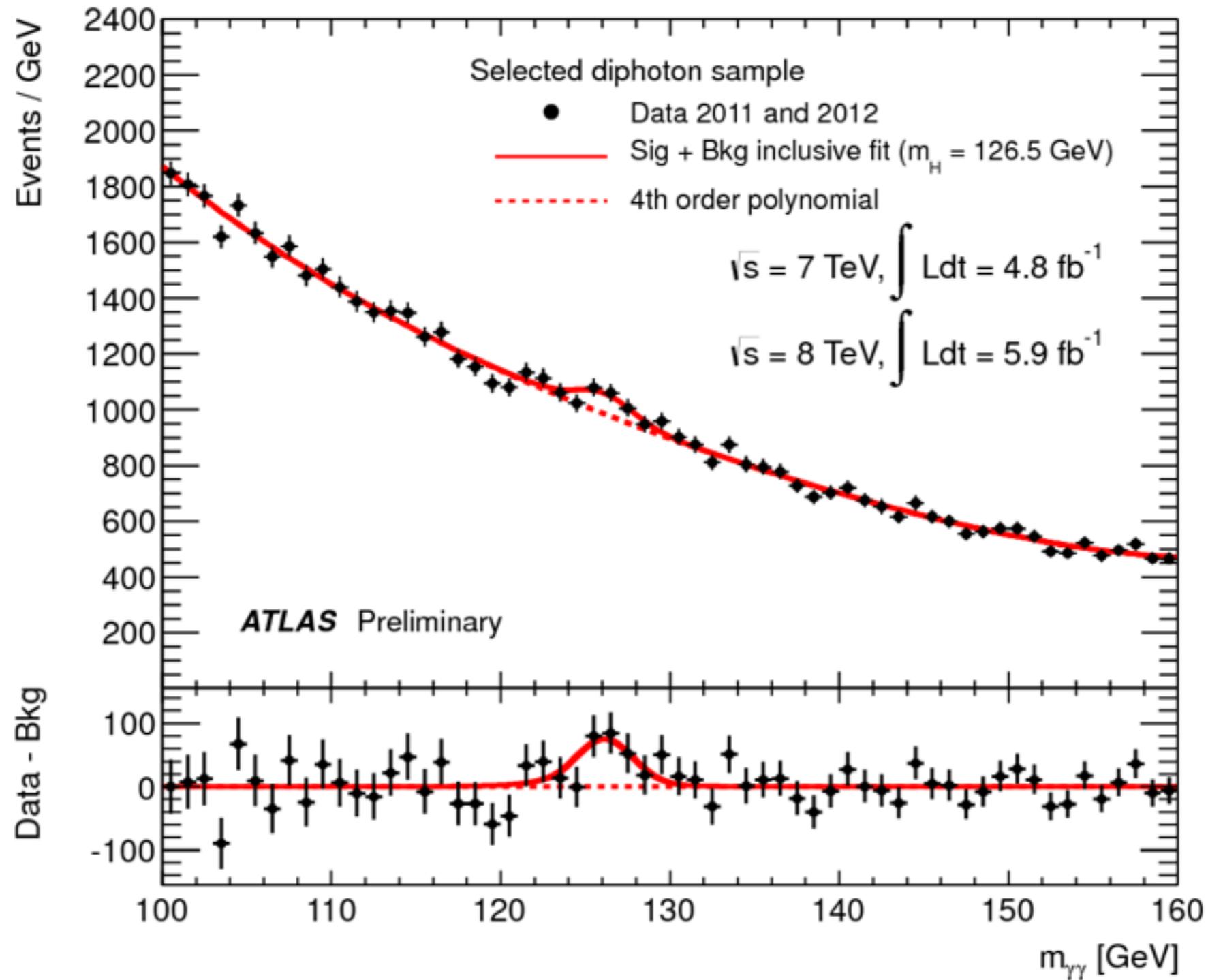


Average of 11

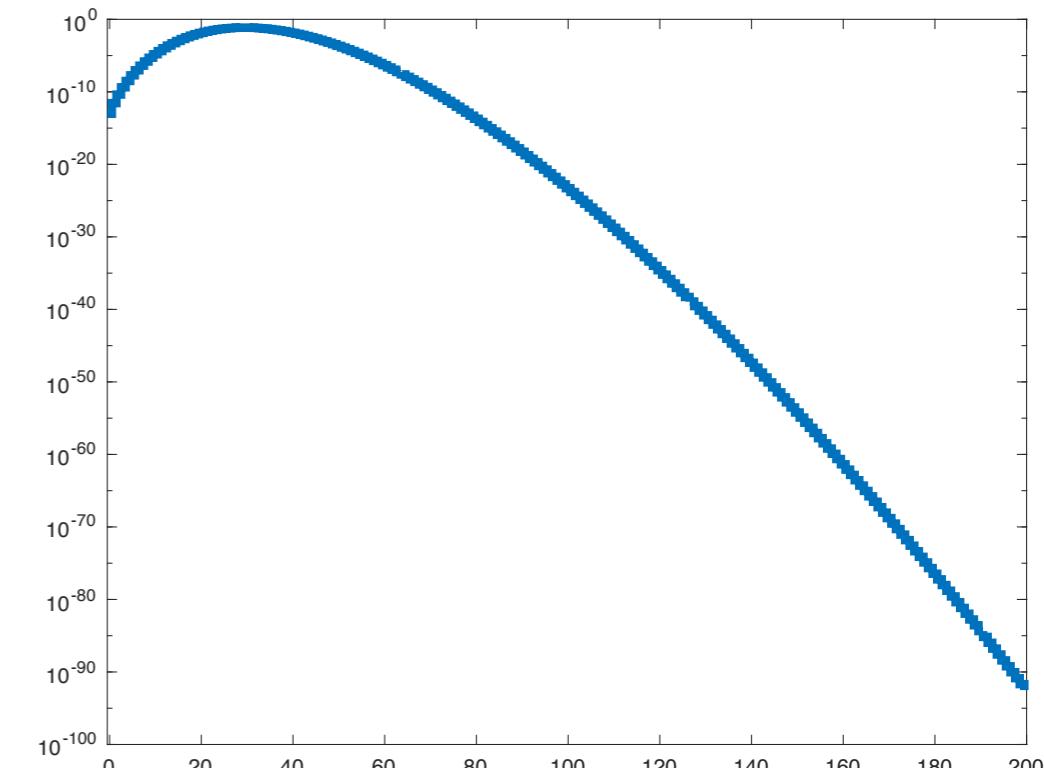
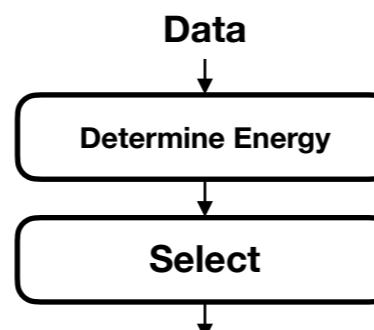
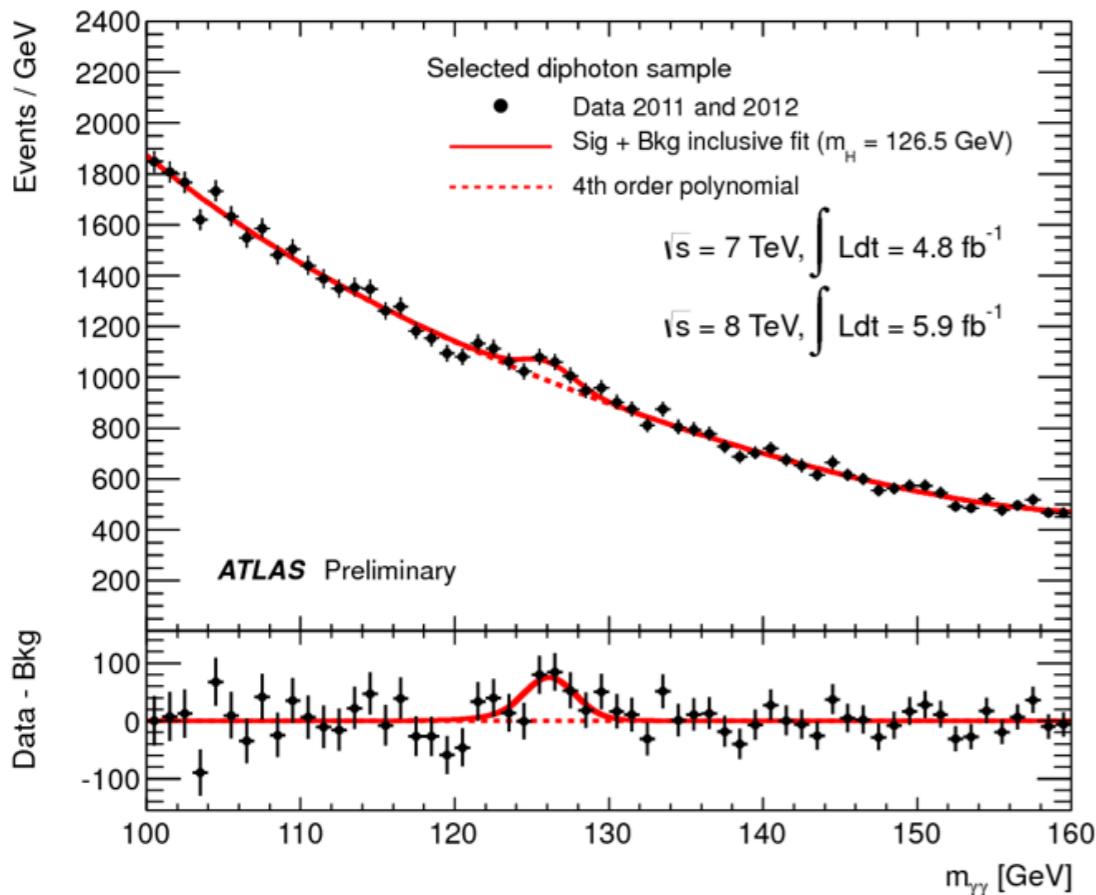


Background?

# LHC Higgs discovery

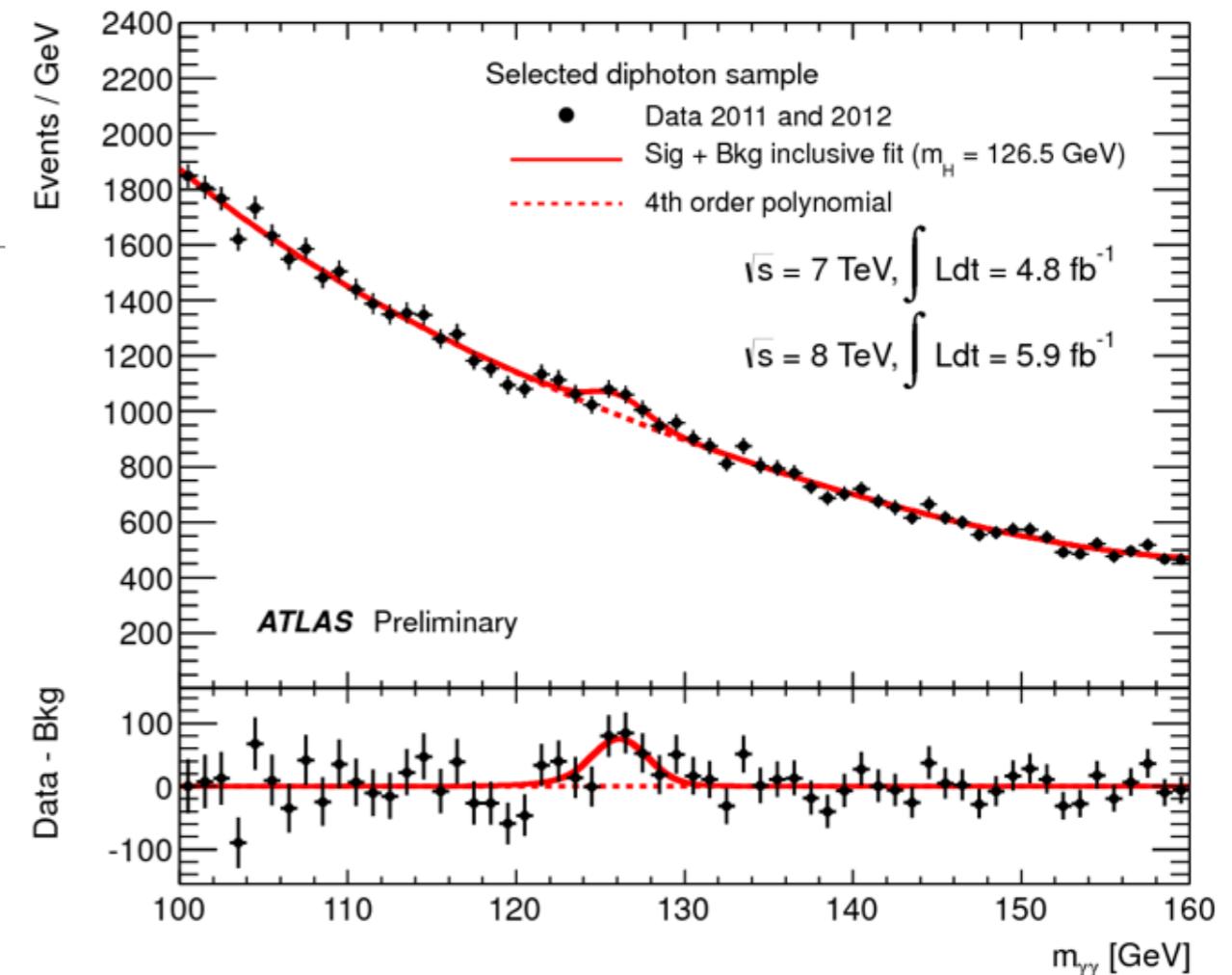


# LHC Higgs discovery, binned analysis

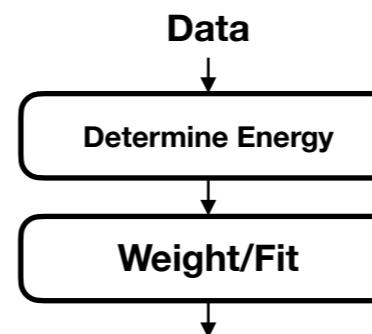
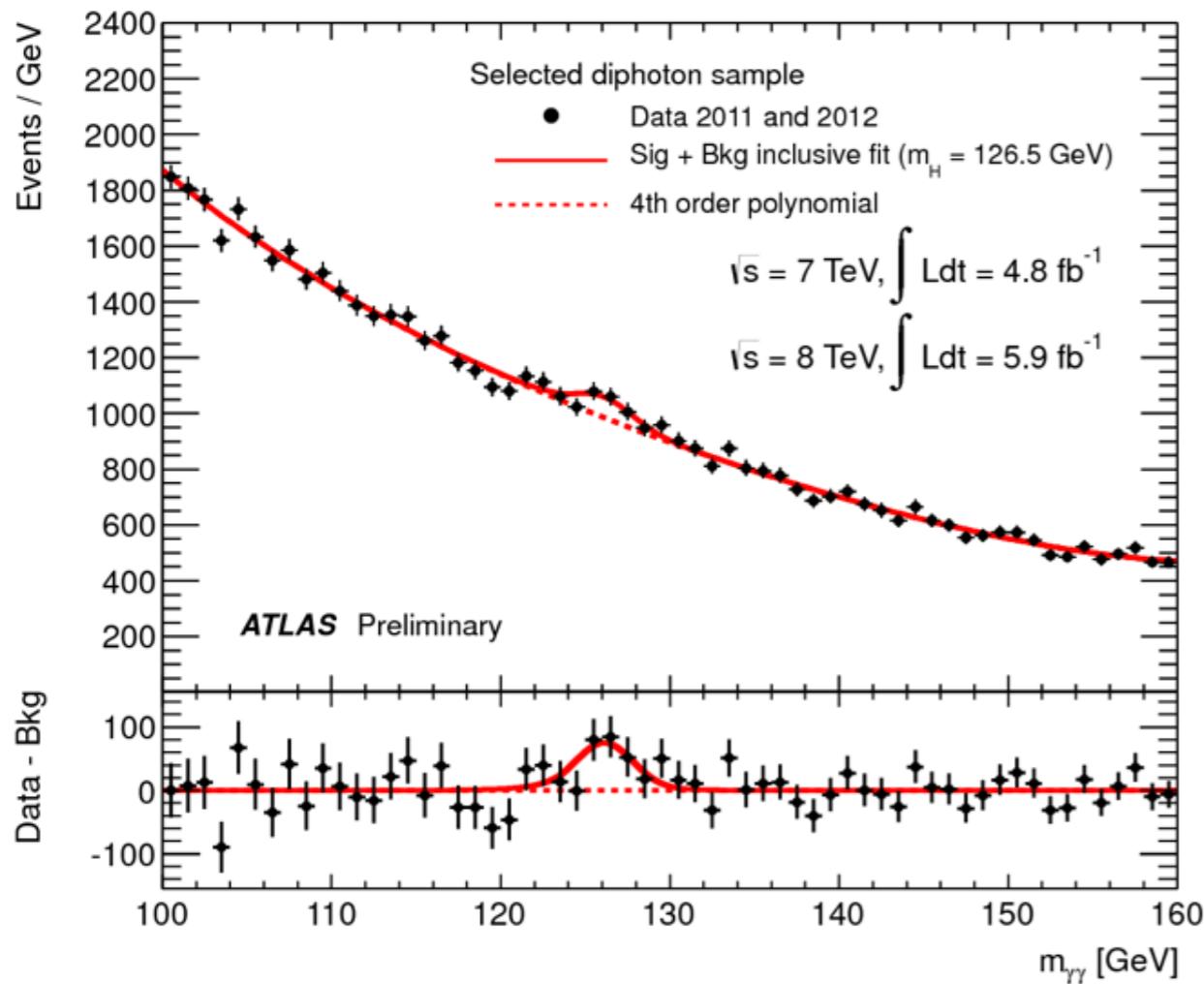


# Poisson background

- Mean expected background is integral over spectrum in selection
- Signal strength also depends on selection



# LHC Higgs discovery, weighted or Maximum Likelihood analyses



# Why is ML (a little) better?

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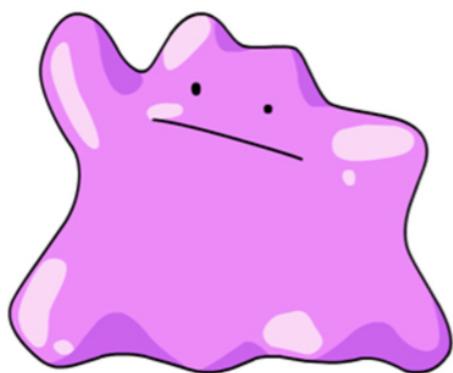
# Review

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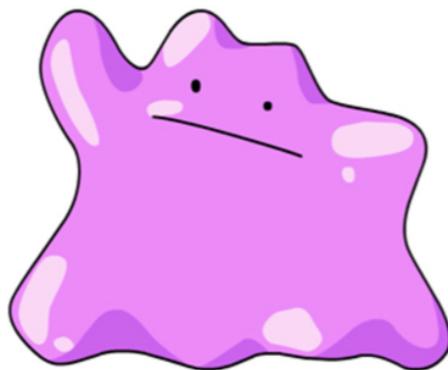
- Multiple dimensions
- Key is what is probability of distribution of background after analysis steps
- Distribution depends on analysis choices



Common analysis problems (part 1 of  $\infty$ )



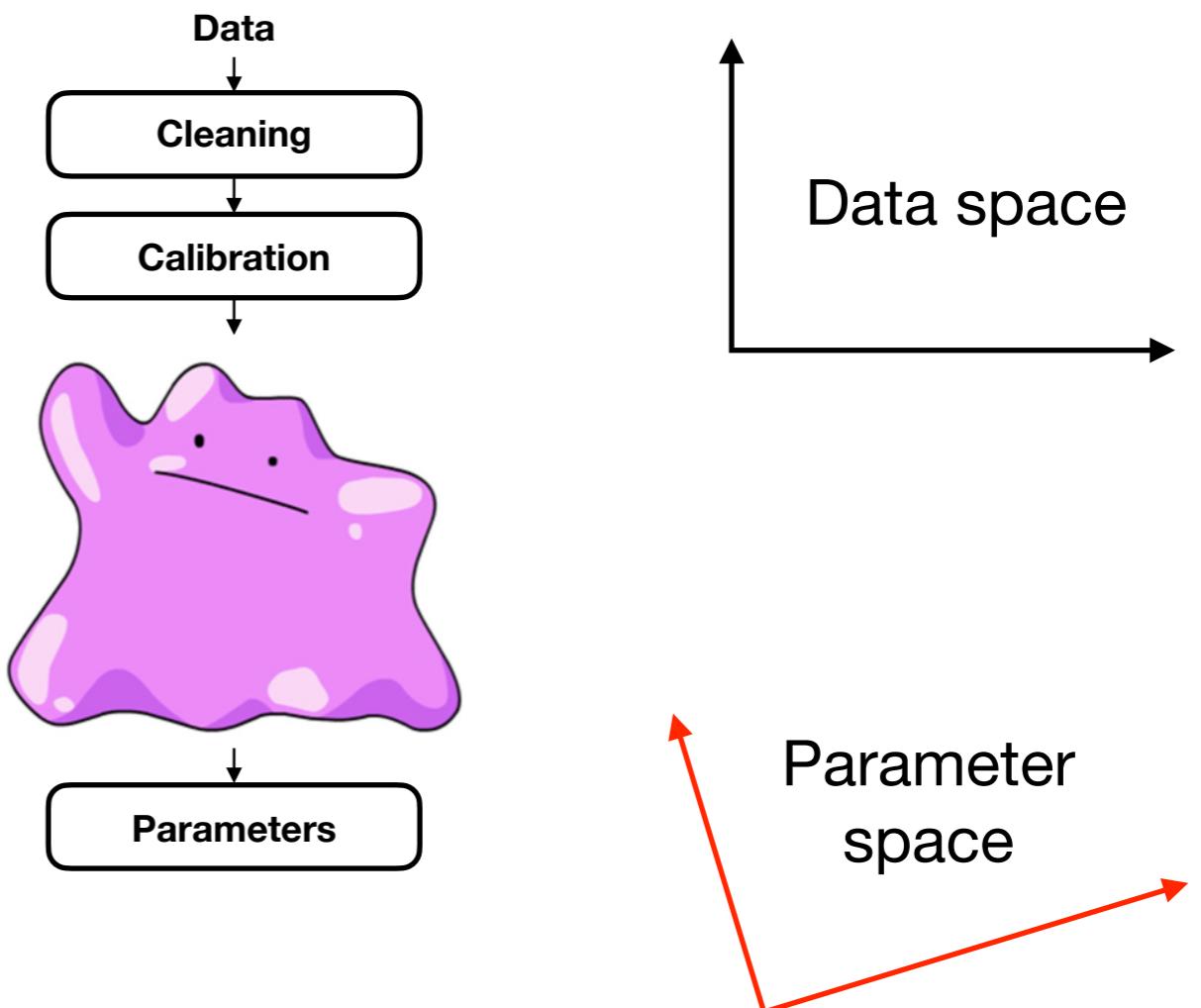
Inherited code, ML, and the analysis blob



# Parameters as measurement

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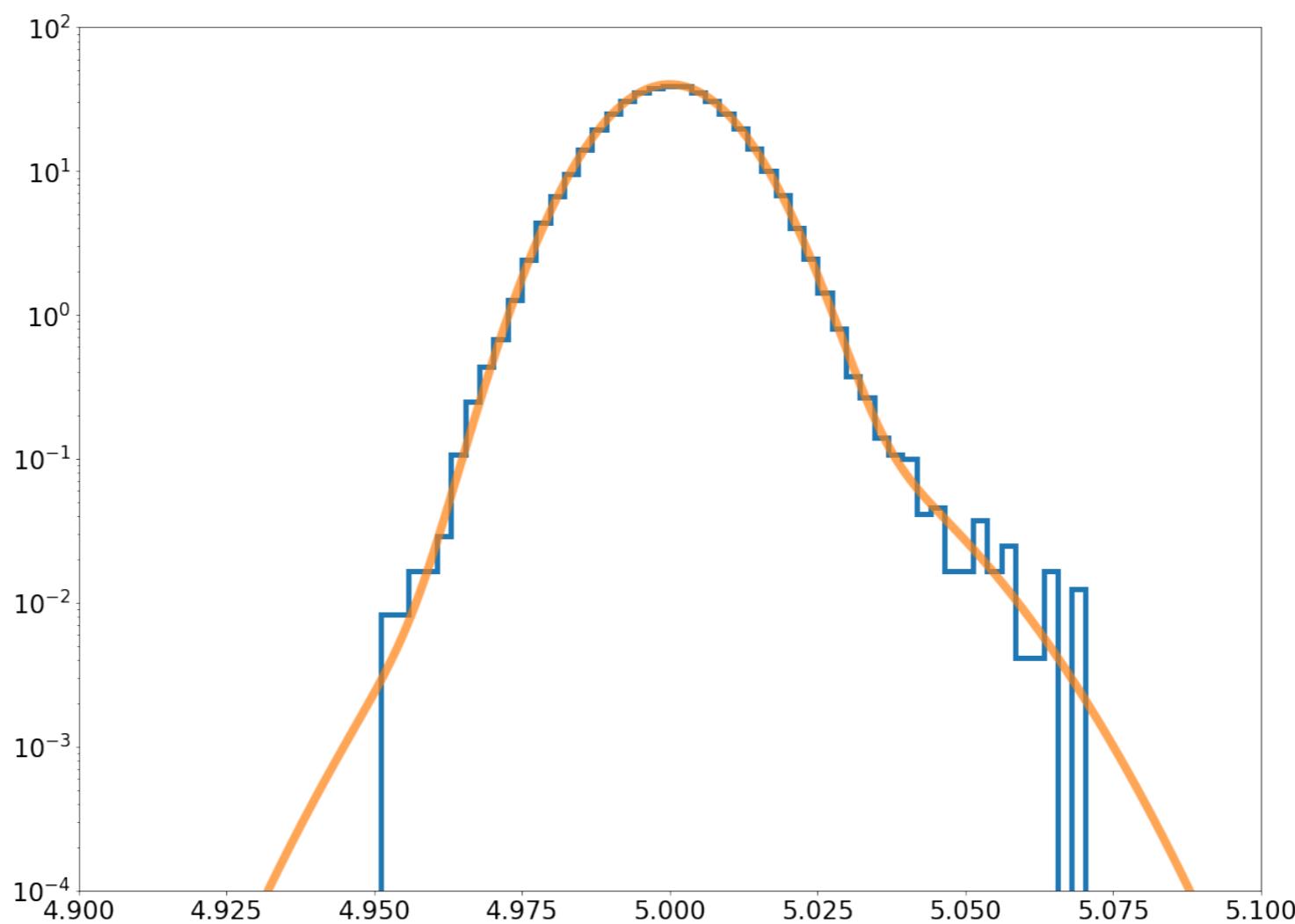
- New measurement ‘space’
- Horrible, non-linear, but treat as a new measurement



# Treat data after blob as new measurement

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- Histogram background to determine the background `pdf()` in this new abstract space

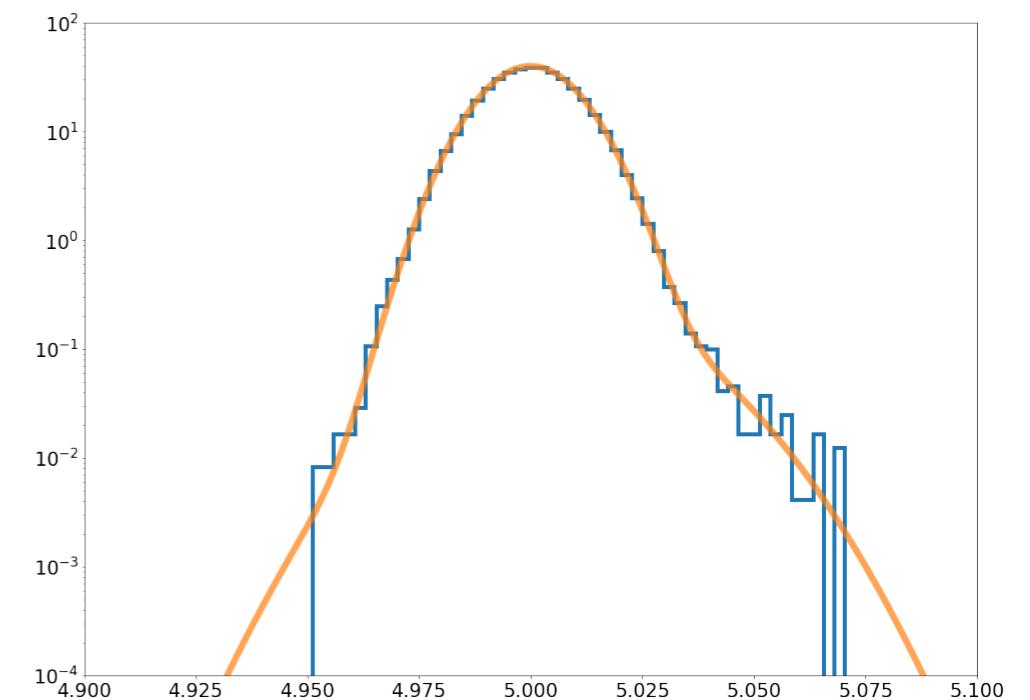


# Background & parameters

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Zero signal examples can be

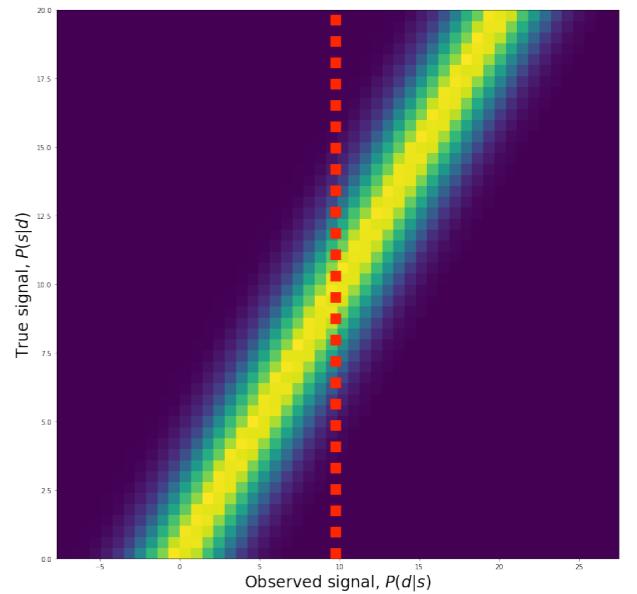
- Signal-free data
- MC simulation (signal turned off)



# 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 output of the blob
- Cost is no analytic errors



# Parameter fitting

# Problems with parameters

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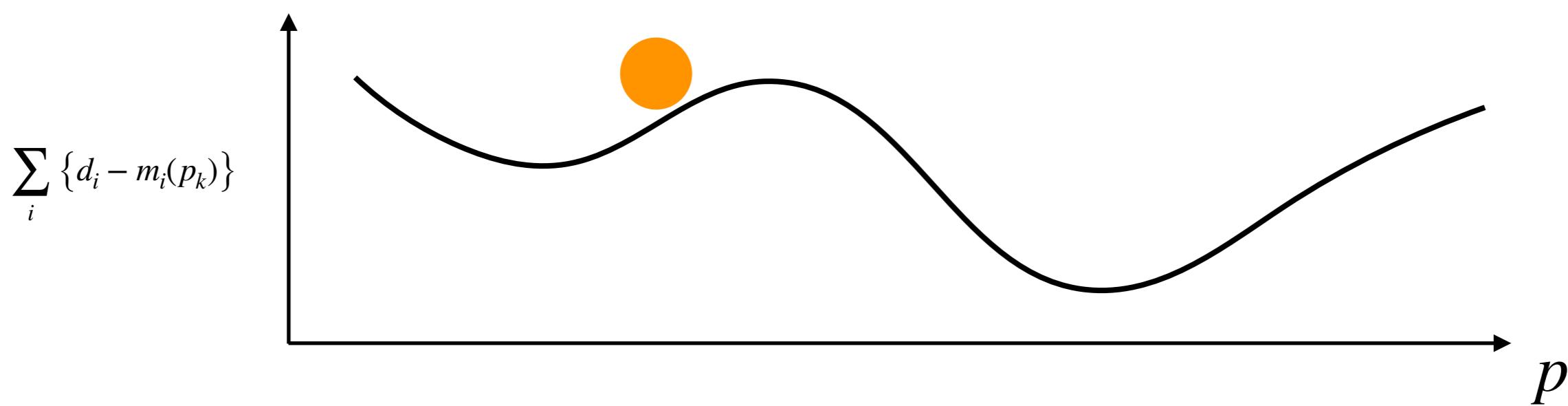
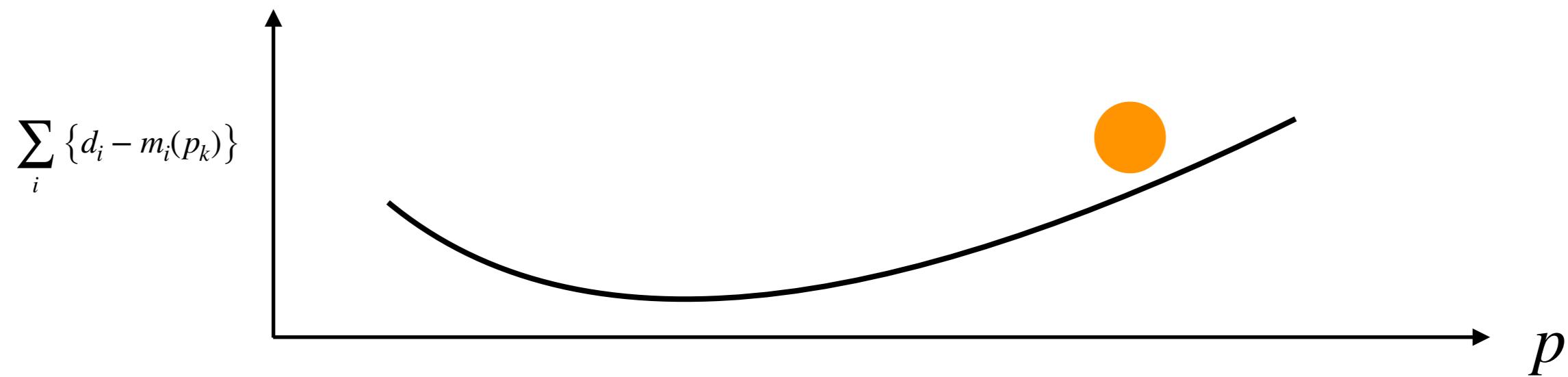
- Local minima
- Degeneracy, catastrophic errors, chaos

# Fitting parameters

$$\sum_i \{d_i - m_i(p_k)\}$$

$$\sum_i \frac{|d_i - m_i(p_k)|^2}{\sigma_i^2}$$

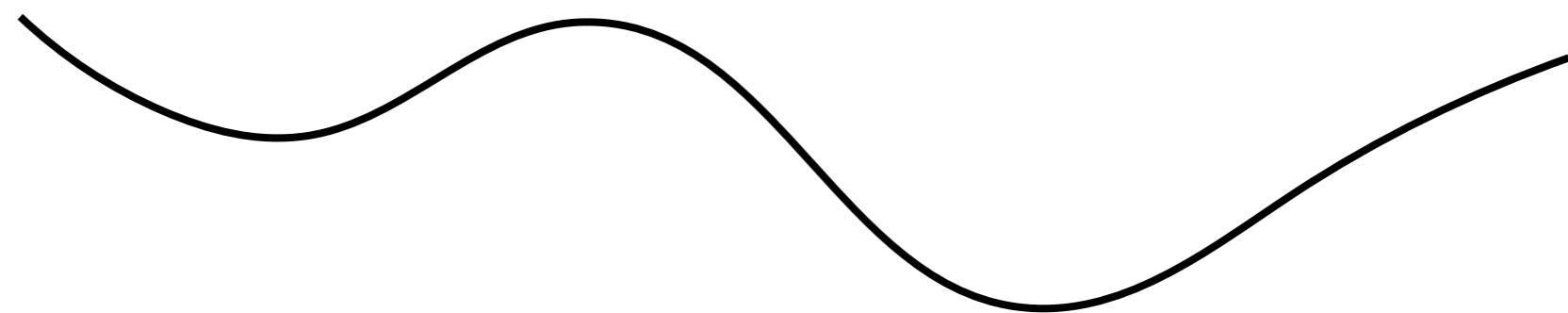
# Local minima



# Local minima

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



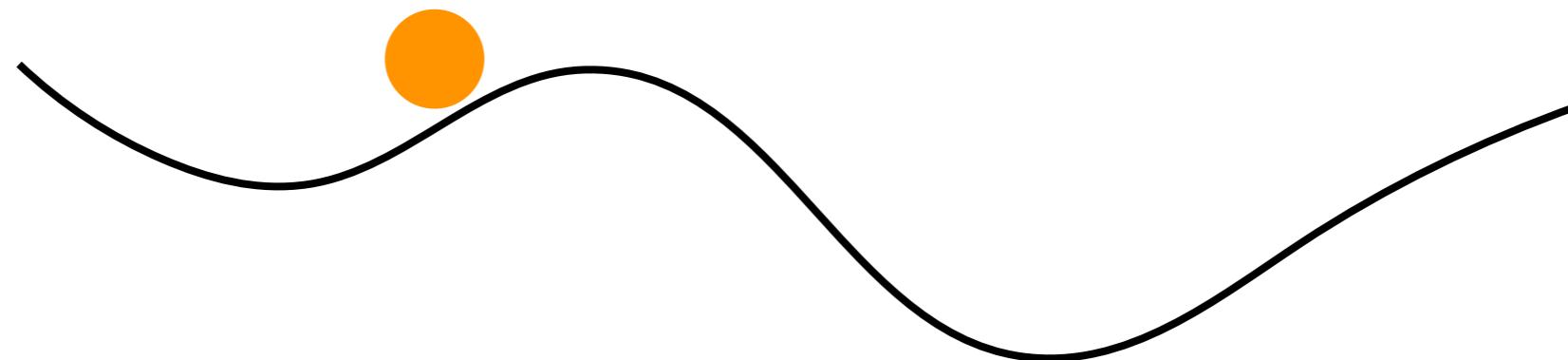
# Local minima

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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

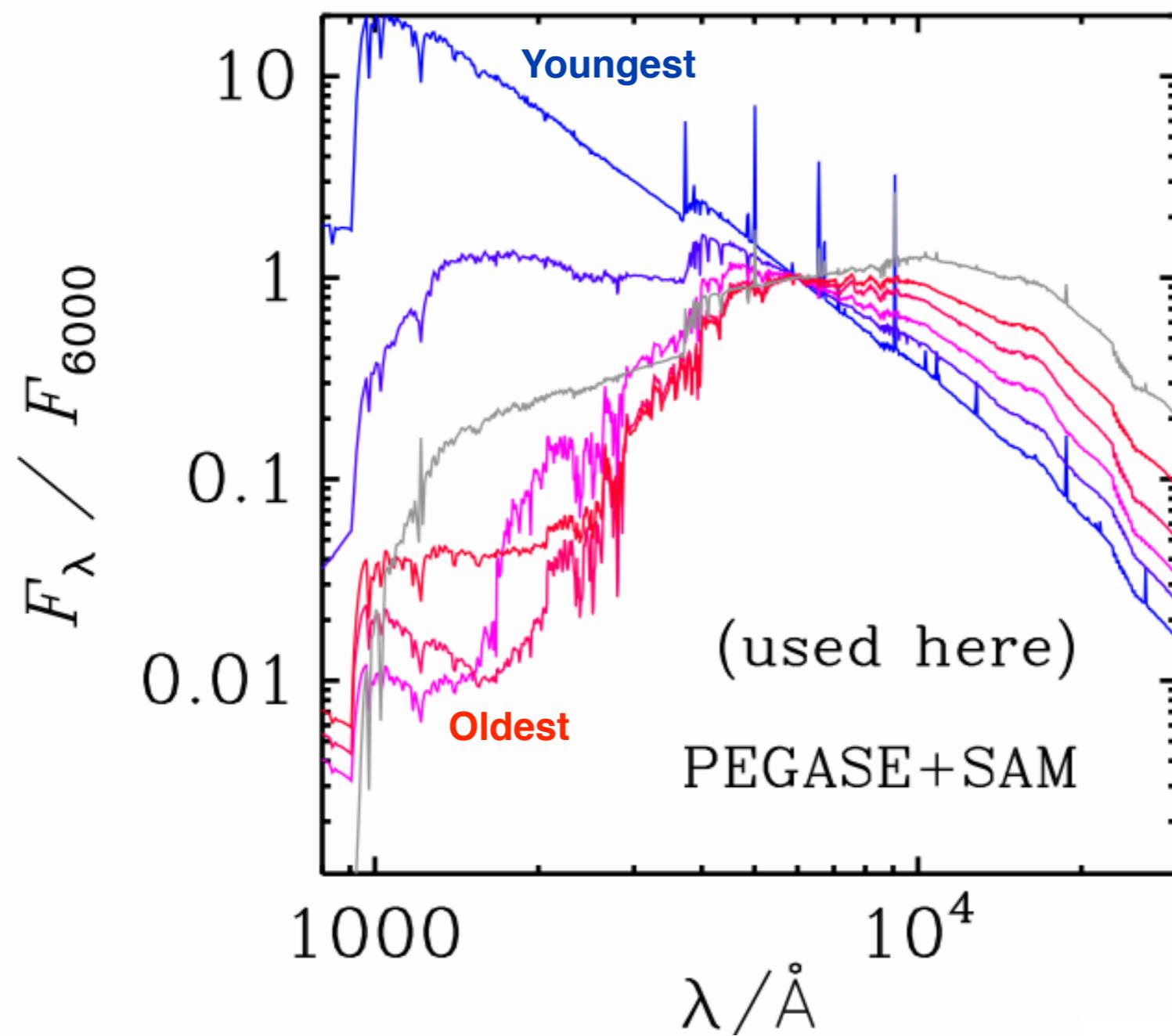


Degeneracy, catastrophic errors, chaos



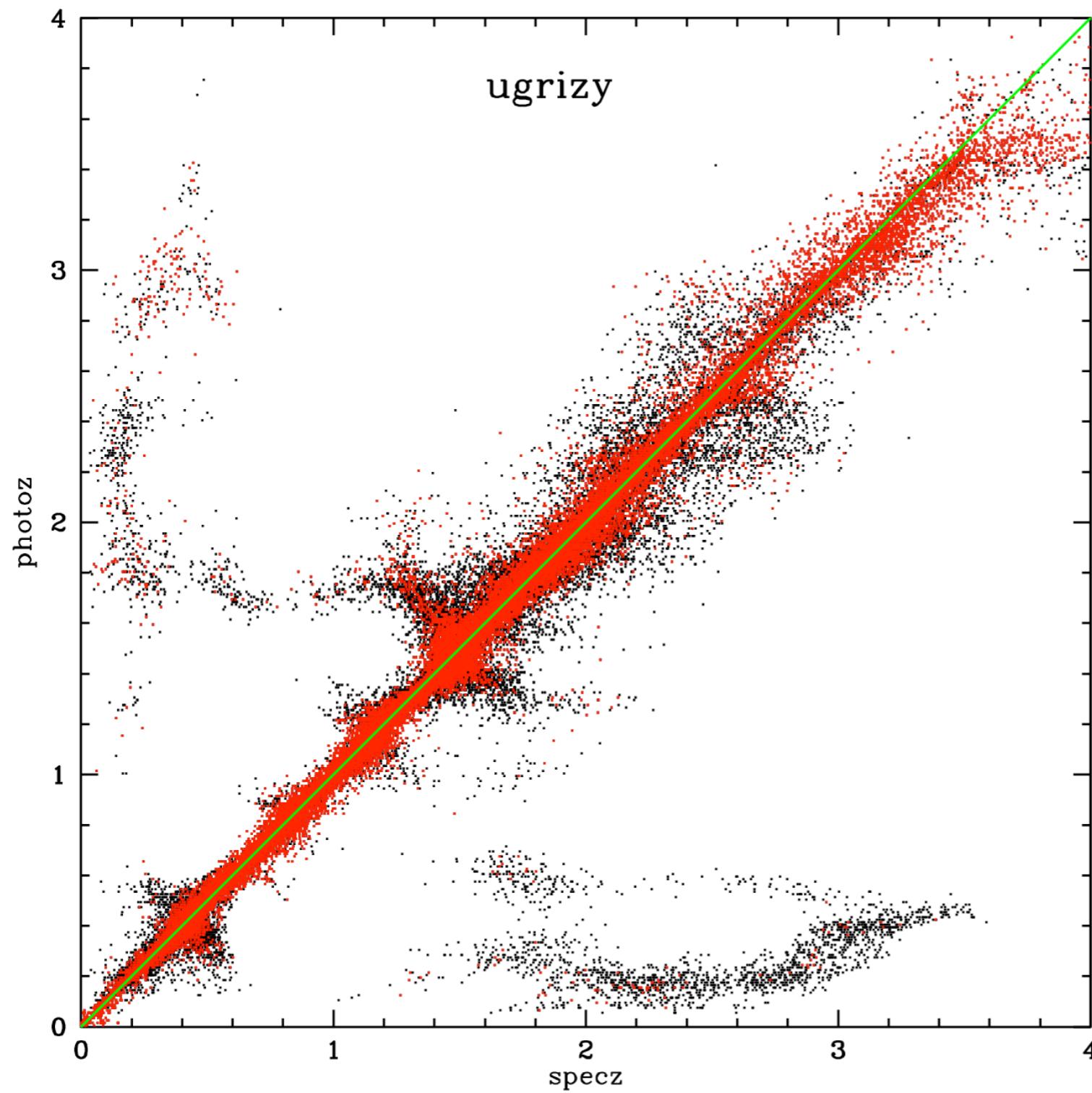
# Catastrophic photo-z

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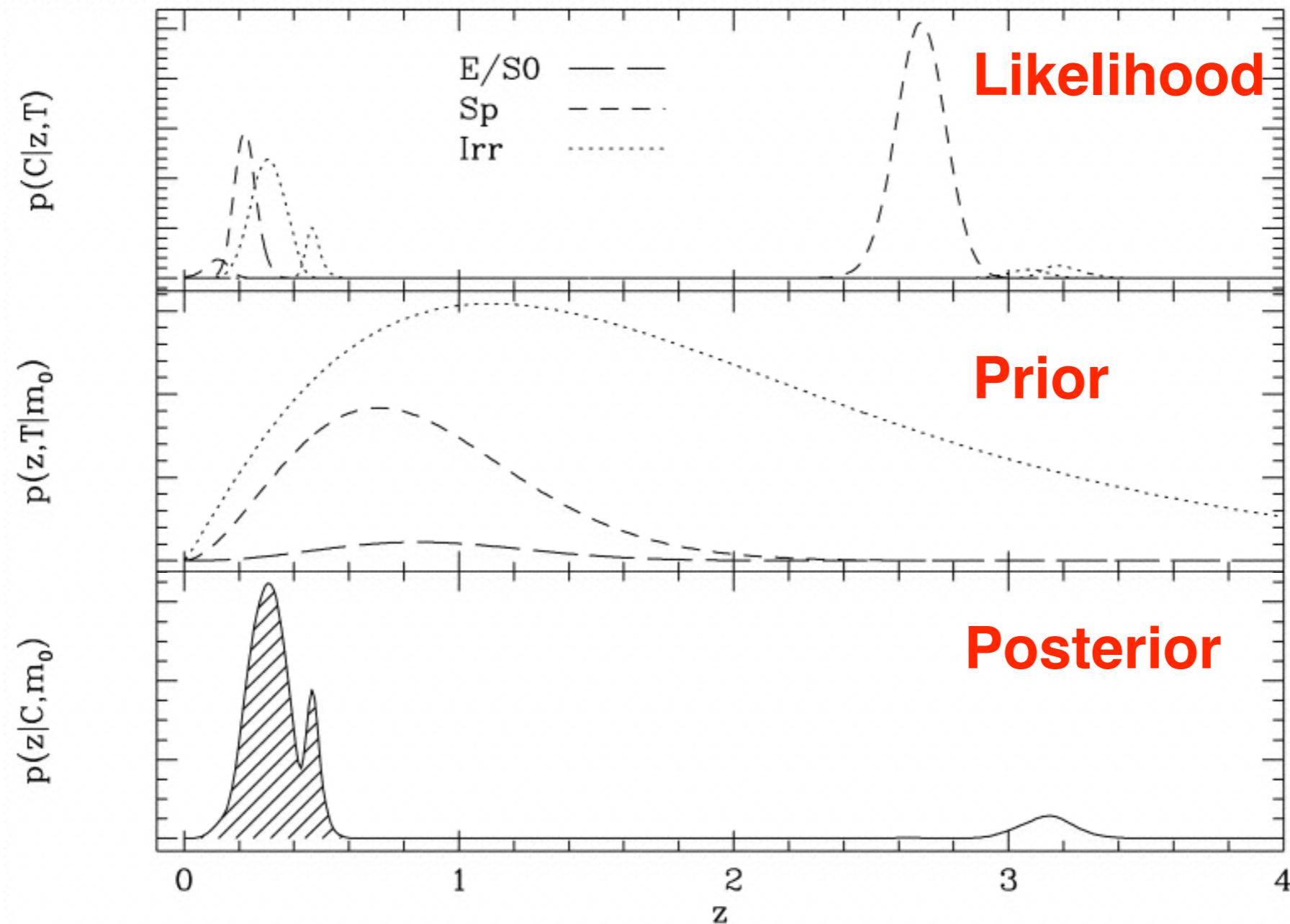


# Catastrophic photo-z

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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**

# Degeneracy & catastrophic errors

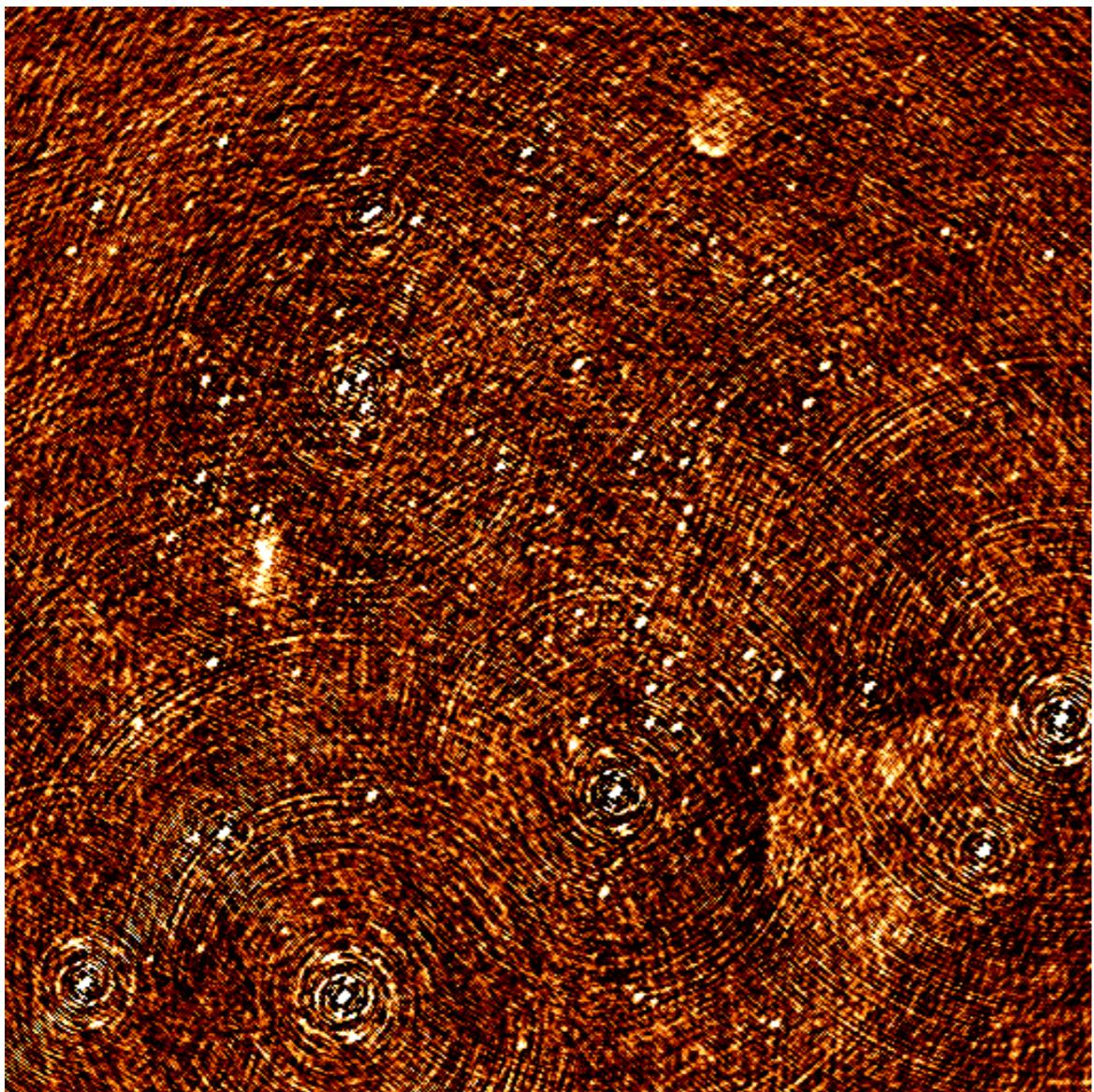
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- Does it impact science?
- Can you get more information?
- Are priors your friend?

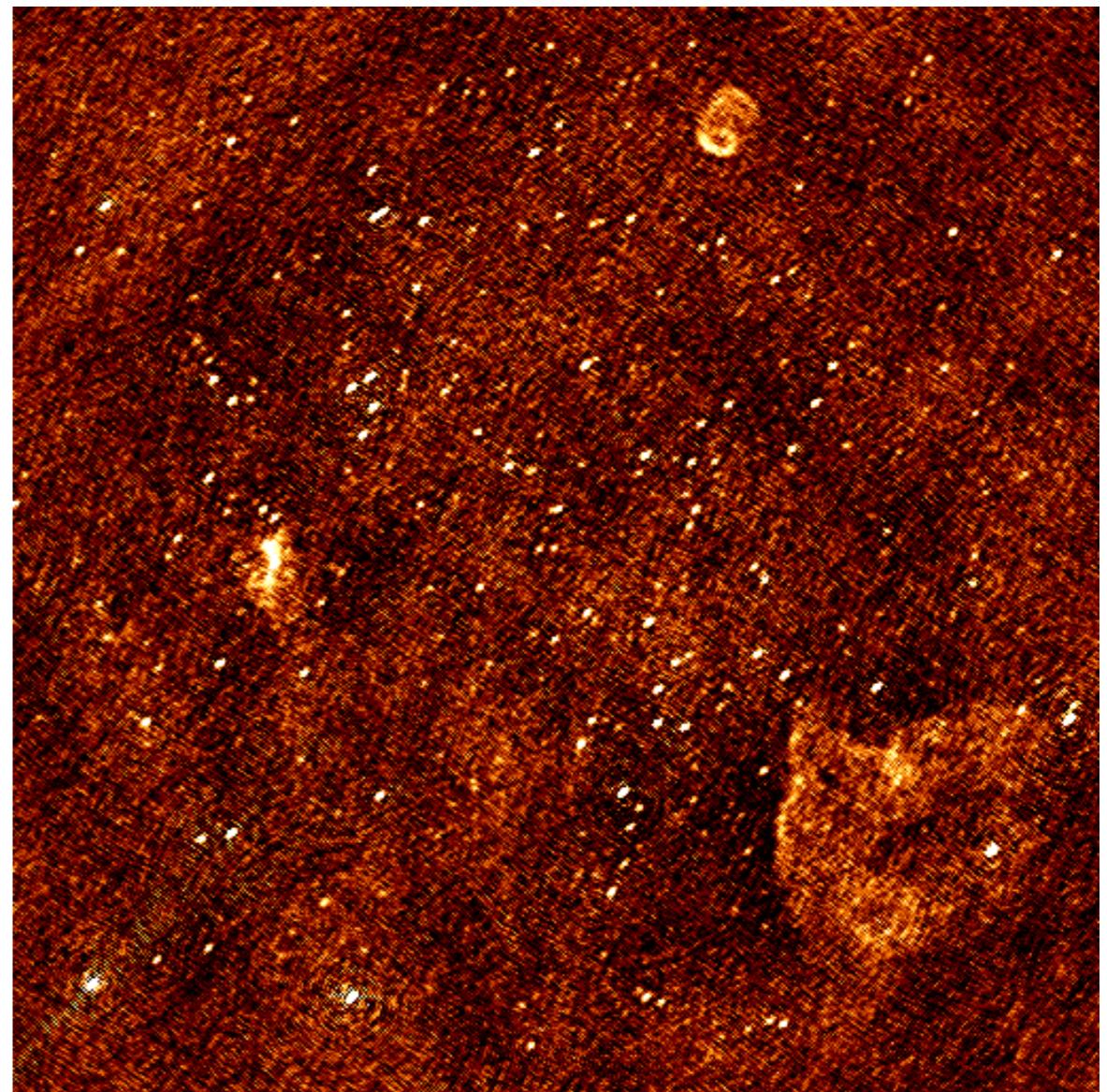
# Chaotic algorithms (deconvolution; CLEAN)

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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

