# Applied Statistics

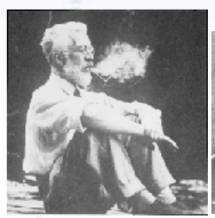
Fitting and Significance





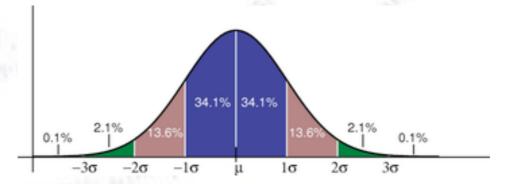








Troels C. Petersen (NBI)



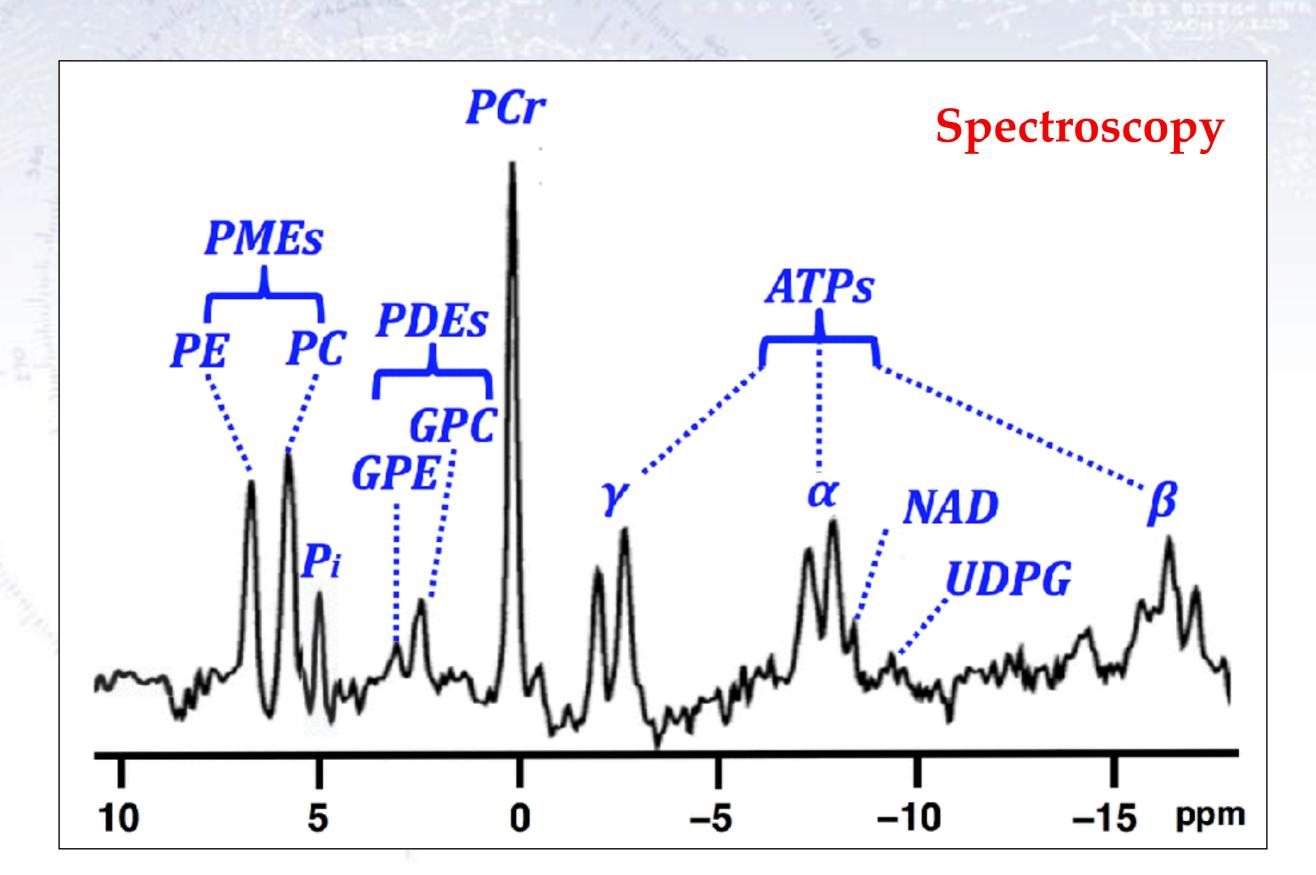
"Statistics is merely a quantisation of common sense"

Often data boils down to a single histogram, from which conclusions are drawn.

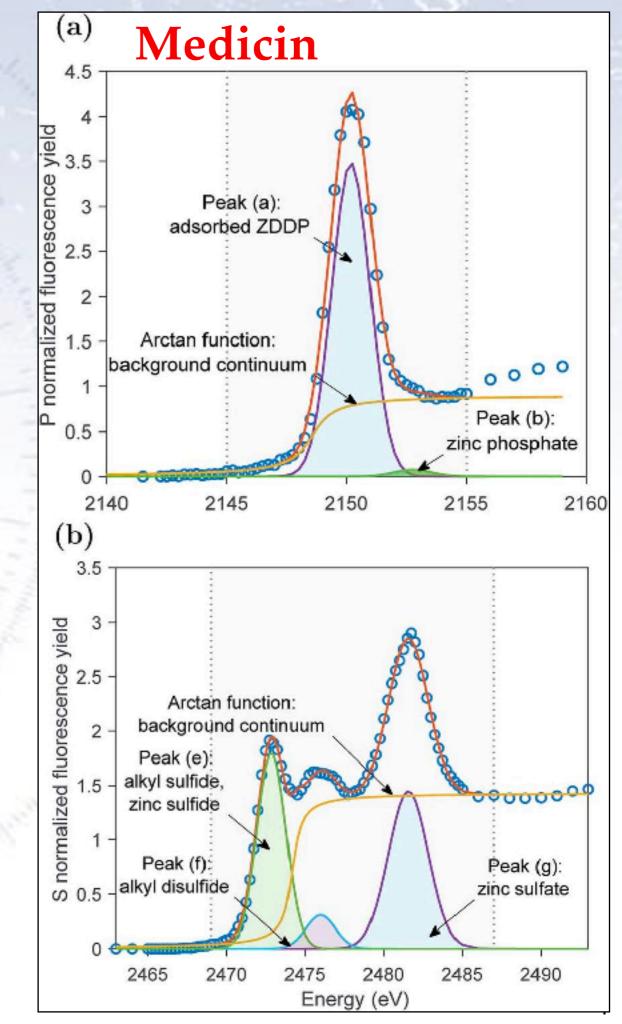
Though more complex representations might display sharper results, one often seeks simplicity, when making conclusions and attempting to convince others.

In such histograms, the most prominent and easily interpretable feature is a peak. Due to finite detector resolution these are mostly Gaussian, and so fitting one or more **Gaussian peaks on a background is a very typical case**.

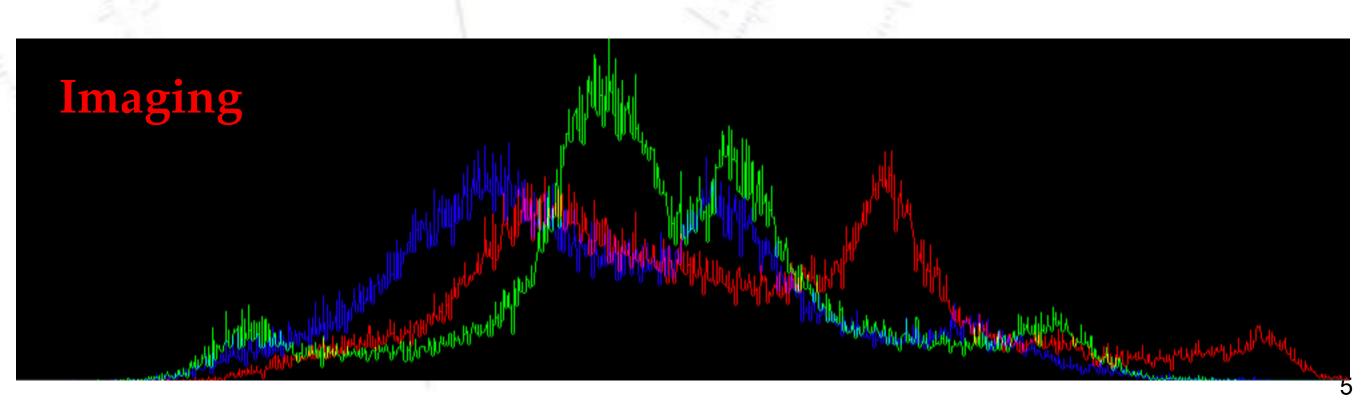
## Fitting peaks - outside physics!



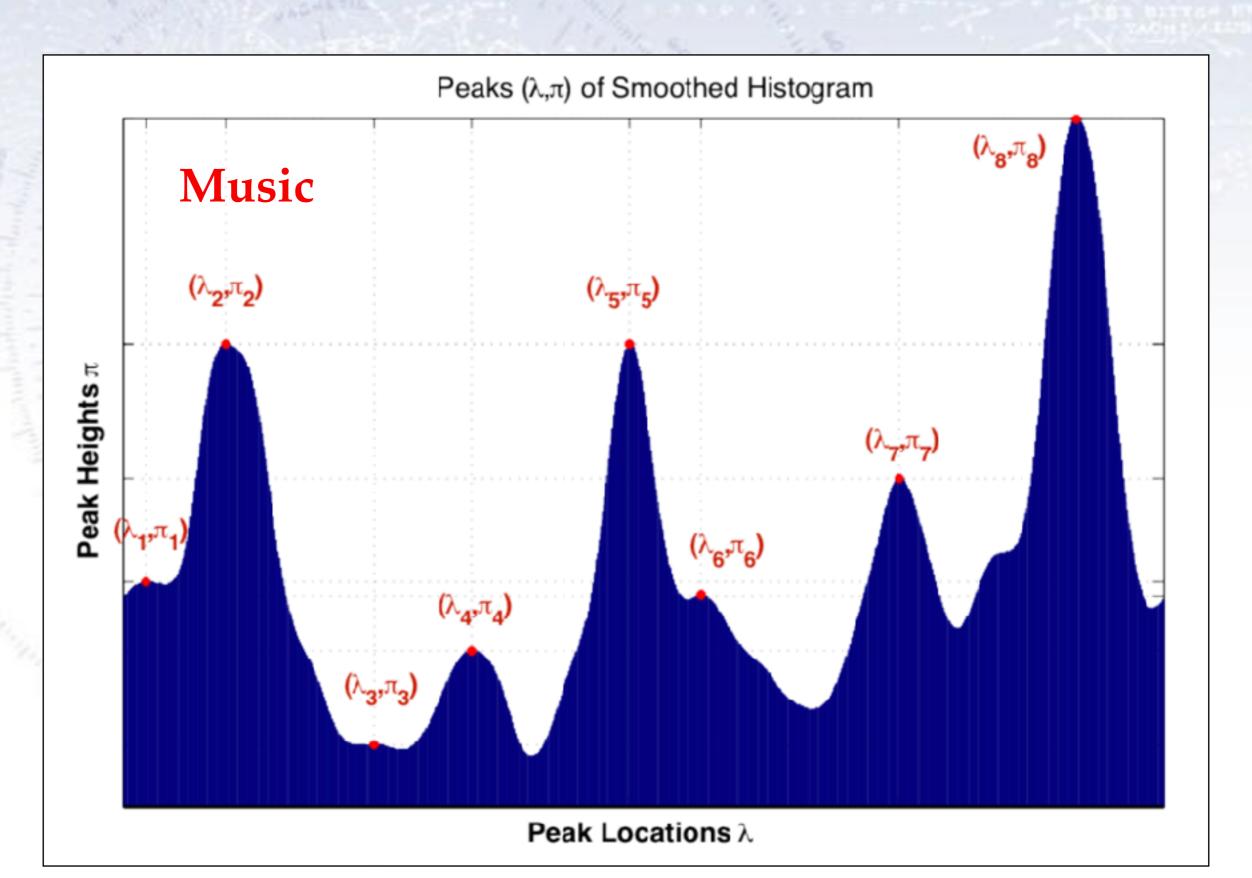
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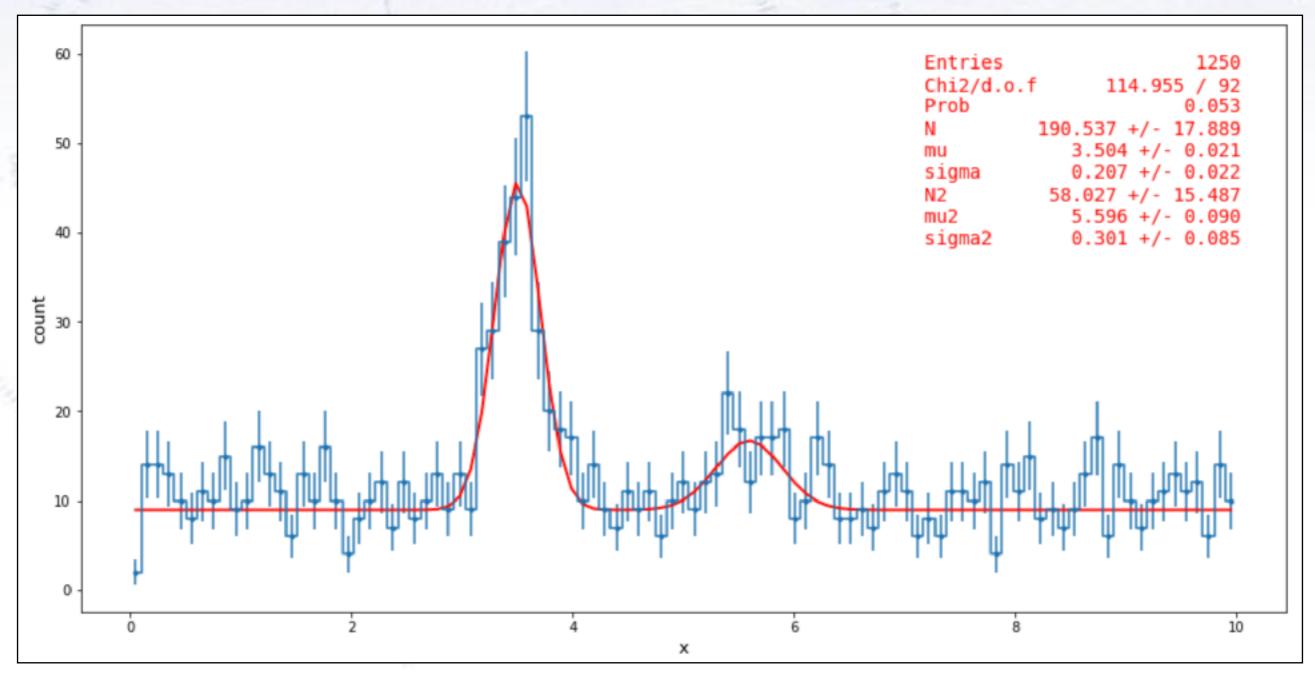
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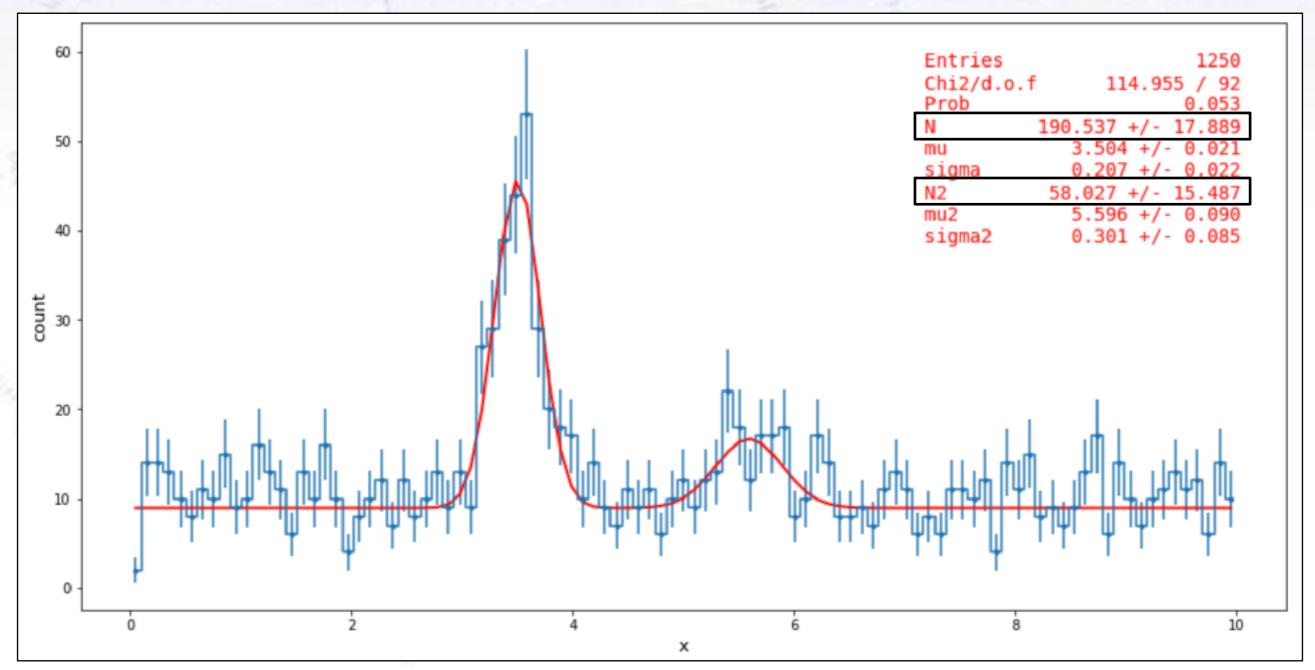
Of course one should make sure to give good starting values, or else the fit won't find the peak(s).

But what to do if one is searching for peaks?
How can one evaluate, if the peaks are real or just fluctuations of noise?
And can a combined/simultaneous fit to several peaks improve the result?

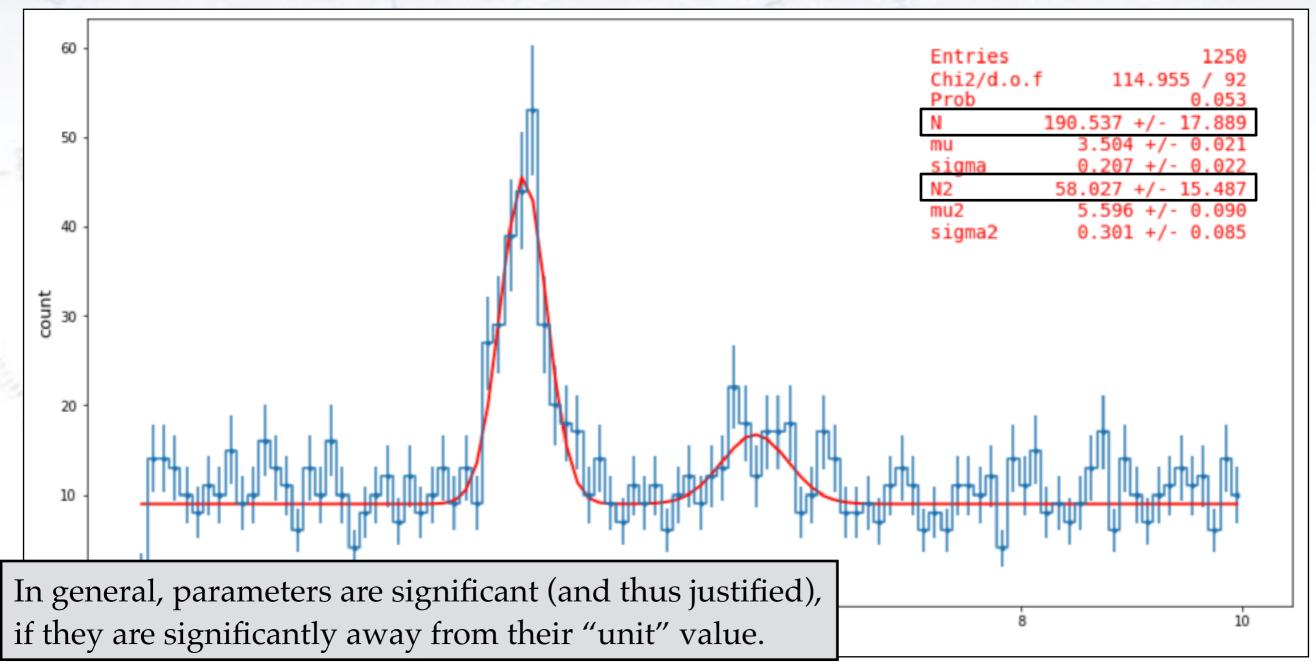
The (local) significance of a peak can be determined by considering how far away from zero the normalisation is. In the below case, the two peaks have significance?

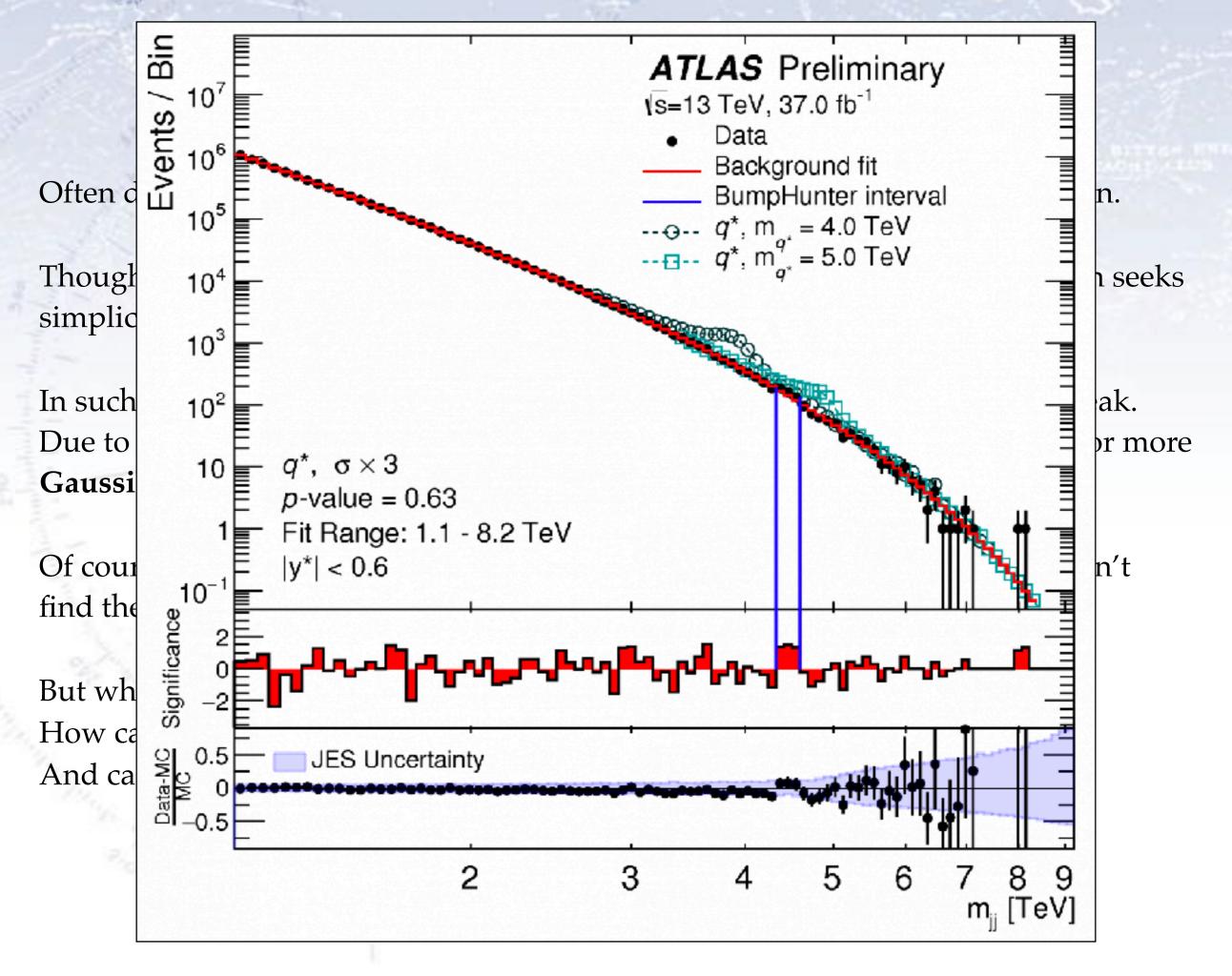


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#### Three attempts at answers

- a) What to do if one is searching for peaks?
  - First of all, establish a good (non-peaking) background model (crucial!). Secondly, determine the expected signal resolution.

    Only then, start fitting the background with a potential peak with **fixed width**.
- b) How can one evaluate, if the peaks are real or just fluctuations of noise? The significance of the (floating) amplitude tells you the <u>local</u> significance. As you might be searching in many places, this reduces your certainty to the <u>global</u> significance:

$$p_{global} = 1 - (1 - p_{local})^N \approx N p_{local}$$

c) And can a combined/simultaneous fit to several peaks improve the result? Yes! If you are fitting several peaks, which you expect to have overlapping parameters (e.g. same width), then fitting with a reduced number of parameters makes the fit more constrained, accurate, and convergent.

Note, that in the last case, this is why a "calibration channel" is great to have.

### How many parameters to use?

Numquam ponenda est pluralitas sine necessitate.

Plurality must never be posited without necessity.

[William of Ockham, 1330ies]

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Do not put in more parameters than necessary and explainable! What does this mean?

With too few, you might have a poor model, where some parameters try to "make up for" the missing degrees of freedom.

With too many, you might "dilute" your model strength, and render the crucial parameters insignificant despite being so.