data don't speak for themselves

a quick introduction to Bayesian statistics

João P. Faria

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Bayesian Stats

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Welcome everyone! Thank you for coming.

We had a few courses about Bayesian statistics in the past given by Michael Bazot and Alex and by Pascal Bordé.

I decided to do this course because that was already 2 years ago, and because those courses did not focus on learning statistics from intuition.

I think that's important, and whether or not I'll be able to do it myself I'll leave for you to judge.

Just to mention that the title is only in part a joke,

as we will see by the end.

Disclaimer

I'm not a statistician.

I never gave this course before.

I borrowed (heavily) from material presented in the references.

But, unless otherwise noted, all opinions are my own.

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Outline

- main differences between frequentist and Bayesian statistics
  - problems with p-values, confidence intervals and null hypothesis testing
- the basic rules of probability theory
- how to assign probability distributions
  - the role of priors
  - the likelihood
- the simplest models in Bayesian statistics
  - linear regression
  - beta-binomial model
  - hierarchical models

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This is the outline that I sent to Carlos and that he sent to you when announcing the course.

I hadn't prepared the course yet when I wrote this
so there's a few things that I won't have time to cover.

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I will only speak very briefly about frequentist statistics
I'll speak about p-values and confidence intervals only if someone asks.

These simple models in red I will only discuss in the practical classes, but not the beta-binomial model

And I will speak about MCMC today.

Q/A

Bayesian Stats

Of course you can ask whatever questions you want,
but I will put up these Q/A slides at every section
and I would ask you to save your questions until one of these shows up.

So... questions already?

Introduction

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brief historical sketch

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Let's start with a bit of history.

I think it's fair to say that statistics started with people trying to solve astronomy problems.

the initial concerns were about observational errors and how to combine observations by different people

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this was formalised (maybe most famously) by Gauss

but many great names worked on predicting the position of astronomical objects, for example

they were using essentially Bayesian methods.

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in the 20th century, statistics turned its attention to biological and social sciences

and it kept developing but

new statistical concepts such as maximum likelihood emerged only slowly in astronomy

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in the late 1990s some collaborations between astronomers and statisticians started emerging

mainly problems in cosmology and image reconstruction

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and today we're at this stage where

most research in statistics is Bayesian

and I think it's still fair to say that many astronomers have this inherent, *a priori* scepticism for statistical analyses

which is because of many different reasons, one of which is certainly lack of training

frequentist and Bayesian

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Calculate their mean $\bar{x}$ and standard deviation σ

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- Bayesians assign a probability to what is *unknown*

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Blocks

Three different block environments are pre-defined and may be styled with an optional background color.

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Example
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Math

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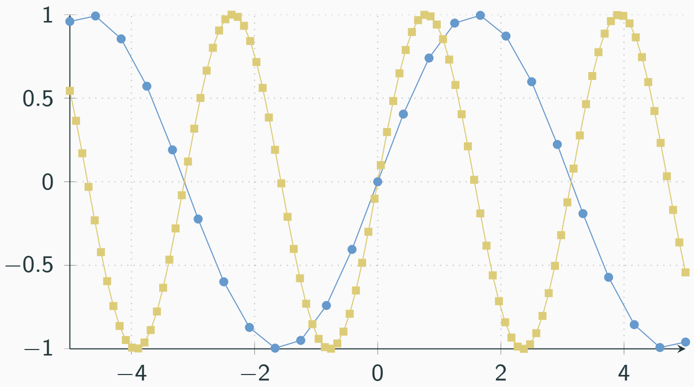
Line plots



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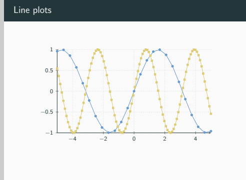
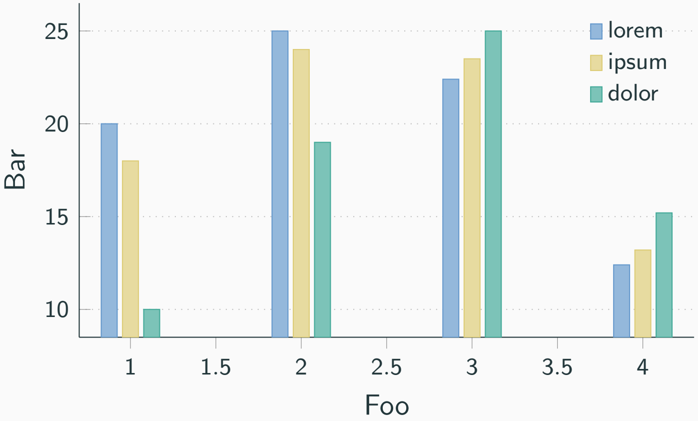
└Introduction

└Line plots



Bar charts



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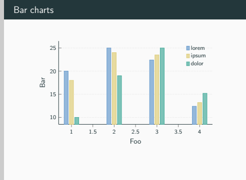
Bayesian Stats

└─Introduction

└─Bar charts



Quotes

Veni, Vidi, Vici

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References

Some references to showcase [allowframebreaks] [4, 3, 1, 2]

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Conclusion

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Summary

Get the source of this theme and the demo presentation from

`github.com/matze/mtheme`

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Q/A

everything

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  Astronomy and Astrophysics, 570:A21, Oct. 2014.
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