Bayesian data analysis with TensorFlow Probability

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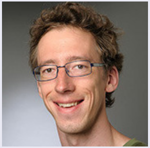
DataScienceConference Europe 2020

Your hosts

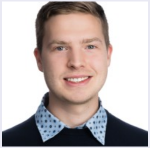
Simeon



...will give the presentation

- background in computational structural biology
- Data Scientist at Tweag I/O since May 2019

Dorran



... will happily answers your questions in the chat

- background and previous positions in geophysics
- Data Scientist at Tweag I/O since August 2019

Tweag I/O

TODO

Tweag I/O is a software innovation lab and consultancy based in Paris, but with employees all around the world.

We specialize in

- software engineering, with a focus on functional programming
- DevOps, with a focus on reproducible software systems and builds
- data science

What you're in for

This tutorial consists of alternating blocks of

- theory / example slides
- practical examples on either external websites or Google Colab notebooks. Links are provided at `https://github.com/tweag/tutorial-dsc-2020/`

Requirements:

- a Google account (for the practical exercises)
- elementary knowledge in probability theory and statistics

Bayesian vs frequentist probabilities

Example: fair coin flip with $p(\text{head}) = p(\text{tail}) = \frac{1}{2}$

Frequentist probability

$p(\text{"flip results in head"} | b = \frac{1}{2}) = \frac{1}{2}$:

$\frac{\#\text{ of heads}}{\#\text{ total flips}}$ for ∞ many fair coin flips

Bayesian probability

$p(\text{"flip results in head"} | b = \frac{1}{2}) = \frac{1}{2}$:

measure of *belief* in the statement "flip results in head" given single fair coin flip

TODO: this slide looks complicated and is aesthetically offputting

Prior beliefs

Assume: unknown bias b

Prior probability

Encodes prior belief in b *before* flipping the coin

What is known about b?

- b is a probability: $0 \leq b \leq 1$
- most coins are fair

→ choose prior distribution defined between 0 and 1, with maximum at and symmetric around $b = \frac{1}{2}$

Example:

$$b \sim \mathrm{Beta}(\alpha = 2, \beta = 2)$$

with

$$\mathrm{Beta}(x|\alpha, \beta) \propto x^{\alpha-1}(1-x)^{\beta-1}$$

Posterior belief

Now: flip coin one time, result: head

Posterior belief

$p(b|\text{head})$: updated prior belief after obtaining new data

TODO: some illustration of shifting distribution

Update rule

Bayes' theorem

$$p(A|B) = \frac{p(B|A) \times p(A)}{p(B)}$$

(easily derived from rules for conditional probabilities)

In data analysis:

$$\underbrace{p(x|D, I)}_{\text{posterior}} = \underbrace{p(D|x, I)}_{\text{likelihood}} \times \underbrace{p(x|I)}_{\text{prior}} \,/\, \underbrace{p(D|I)}_{\text{evidence}}$$

x: model parameter

D: data

I: prior information (often not made explicit)

Update rule

In our coin flip example:

prior: $p(b) \propto b^{\frac{1}{2}}(1-b)^{\frac{1}{2}}$

likelihood : $D \sim \mathrm{Bernoulli}(b)$, thus:

$$bla$$