Bayesian analysis of risk and uncertainty

ULLRIKA SAHLIN NORDIC CHAPTER SOCIETY FOR RISK ANALYSIS, COPENHAGEN 2019

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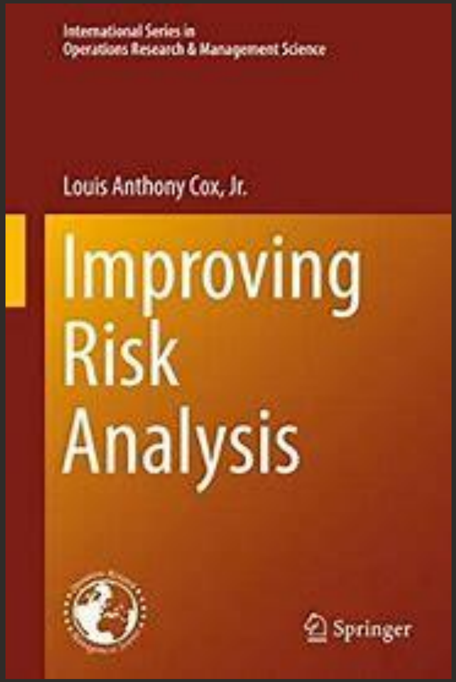
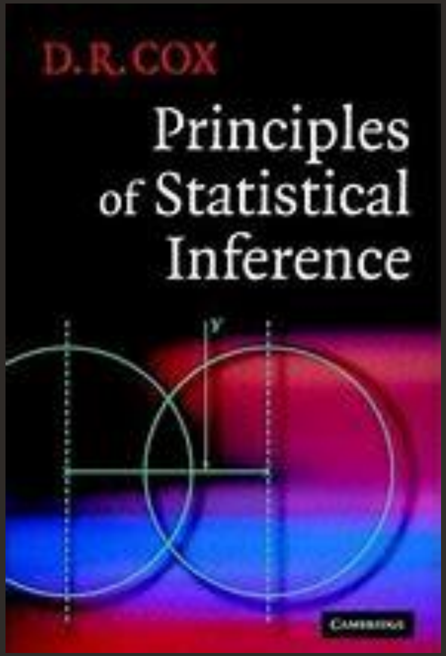


Safety assessments of technological systems, such as nuclear power plants, chemical process facilities, and hazardous waste repositories, require the investigation of the occurrence and consequences of rare events. The subjectivistic (Bayesian) theory of probability is the appropriate framework within which expert opinions, which are essential to the quantification process, can be combined with experimental results and statistical observations to produce quantitative measures of the risks from these systems. A distinction is made between uncertainties in physical models and state-of-knowledge uncertainties about the parameters and assumptions of these models. The proper role of past and future relative frequencies and several issues associated with the elicitation and use of expert opinions are discussed.

Apostolakis 1990



efsa
European Food Safety Authority

A method for uncertainty analysis is ”Bayesian inference quantifying uncertainty about parameters in a statistical model on the bases of data and expert judgement about the values of the parameters. ”

Bayesian analysis:

Framework that quantify epistemic uncertainty by probability

Principle to integrate data and expert knowledge

Principle for parametric and predictive inference

Decision theory - to maximize expected utility

Bayesian analysis of risk and uncertainty

- Risk – likelihood of an event, the magnitude of a concequence, or combinations/versions of these two
- Uncertainty – our uncertainty about the likelihood or magnitude, changeable in light of more knowledge

- What is Bayesian analysis
- Encounters and (mis)conceptions about Bayesian analysis

A Bayesian model is a joint probability distribution of variables and parameters

Hyper parameters

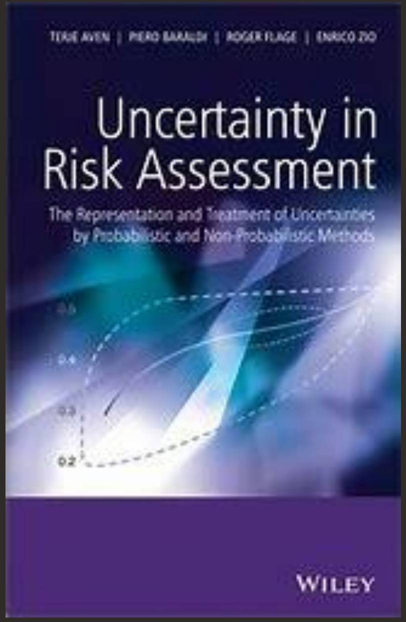
Parameters: $\mu|\sigma \sim N(7,1)$ $\sigma \sim U(0,10)$

Variable: $X \sim N(\mu,\sigma)$ *Data*

”If you don’t have enough data you can use Bayesian methods….”

True, but shouldn’t you already be using it if you want to quantify uncertainty by probability?

What are the alternative ways to quantifying uncertainty? Are they that good, so we only use Bayes when we dont have enough data? Or don’t we have uncertainty when we have lots of data?



”Bayesian analysis always quantifies uncertainty”

Not always
Distinguish between Bayesian learning and Bayesian reasoning/forecasting!

Are your parameters expressed with uncertainty? What is a parameter in your model?

Bayesian learning

Bayesian updating using Bayes rule

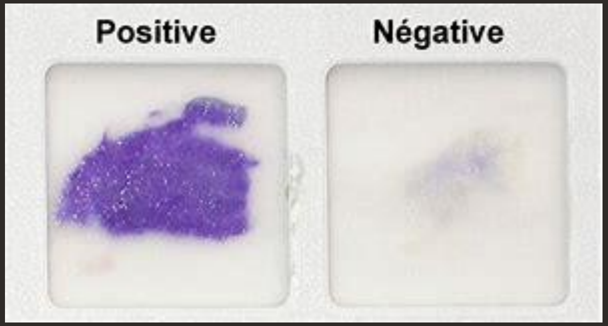
Prior	Likelihood	Posterior
Our uncertainty about parameters	How likely are data we have given certain values on parameters	Our uncertainty about parameters after learning from data

Bayesian learning

Bayesian updating using Bayes rule

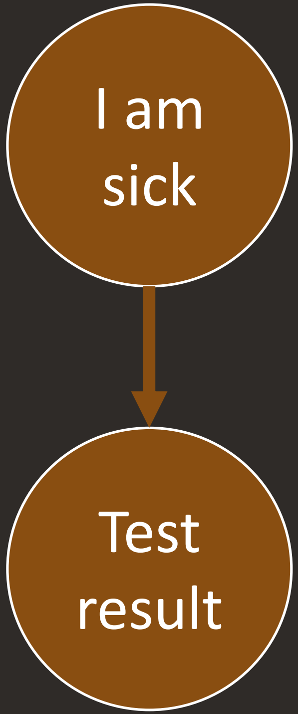
Prior	Likelihood	Posterior
Our uncertainty about parameters	How likely are data we have given certain values on parameters	Our uncertainty about parameters after learning from data
Expert judgement on parameters, data or quantities Posterior from previous analysis	A probabilistic model for P(data|parameters)	P(parameters|data) A probabilistic model for P(variables|parameters)

Bayesian reasoning



P(TRUE) & P(+ |TRUE)
P(- |FALSE) *gives* P(TRUE| +)

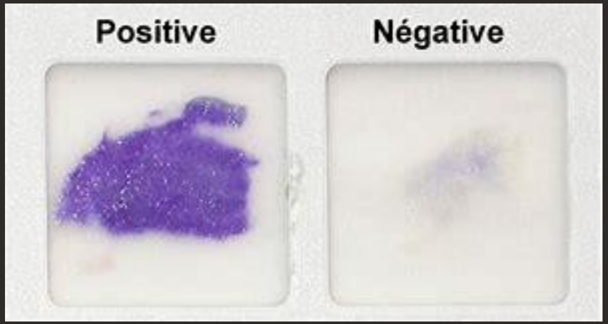
Bayes rule



TRUE	FALSE

Sick	+	-
TRUE		
FALSE		

Bayesian reasoning



P(TRUE) & P(+ |TRUE)
P(- |FALSE) *gives* P(TRUE| +)

Bayes rule

I am sick

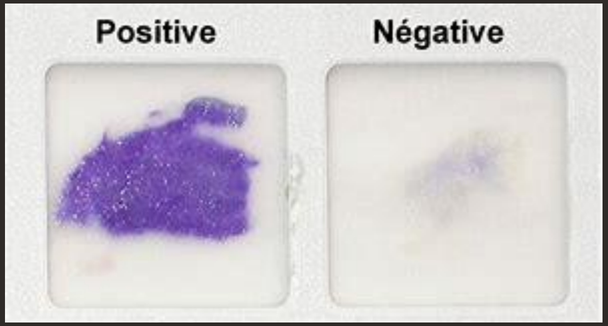
TRUE	FALSE

Forward calculation

Test result

Sick	+	-
TRUE		
FALSE		

Bayesian reasoning



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https://www.countbayesie.com/blog/2015/2/18/bayes-theorem-with-lego

This paper is concerned about how to define and describe risk in an engineering context. There exist many definitions of risk in such a setting, but most of them include the following three components:

A: what can go wrong (the initiating events).
C: the consequences of these events if they should occur.
P: the probabilities of *A* and *C*.

In short we write Risk = (A, C, P). There are basically two ways of interpreting the probability *P*:

(a) as a relative frequency, i.e. the relative fraction of times the event occurs if the situation analyzed were hypothetically "repeated" an infinite number of times.
(b) as a subjective measure of uncertainty, conditional on the background knowledge (the Bayesian perspective).

The former interpretation means that probability is used to reflect variation (i.e. what is commonly referred to as stochastic or aleatory uncertainty, Apostolakis, 1990), where

Aven 2015

”I don’t like ”subjective” as in subjective probability”

Subjective probability is a measure of epistemic uncertainty.

Second order probability e.g. uncertainty about a frequency.

Someone is uncertain.

The assessment of a subjective probabilty can be done in an objective way.

”What if my prior matter?”

Priors matters more when data is sparse or absent.

When so, priors informed by expert judgement are to be used.

Why shouldn’t priors matter? It is like saying that expert judgement shouldn’t matter.

”The decision maker is not comfortable with a Bayesian analysis”

Decision makers often think as if a Bayesian analysis has been done

Experts are often not comfortable due to lack of experience

Confidence Interval (CI)

Uncertainty Interval

Probability Interval

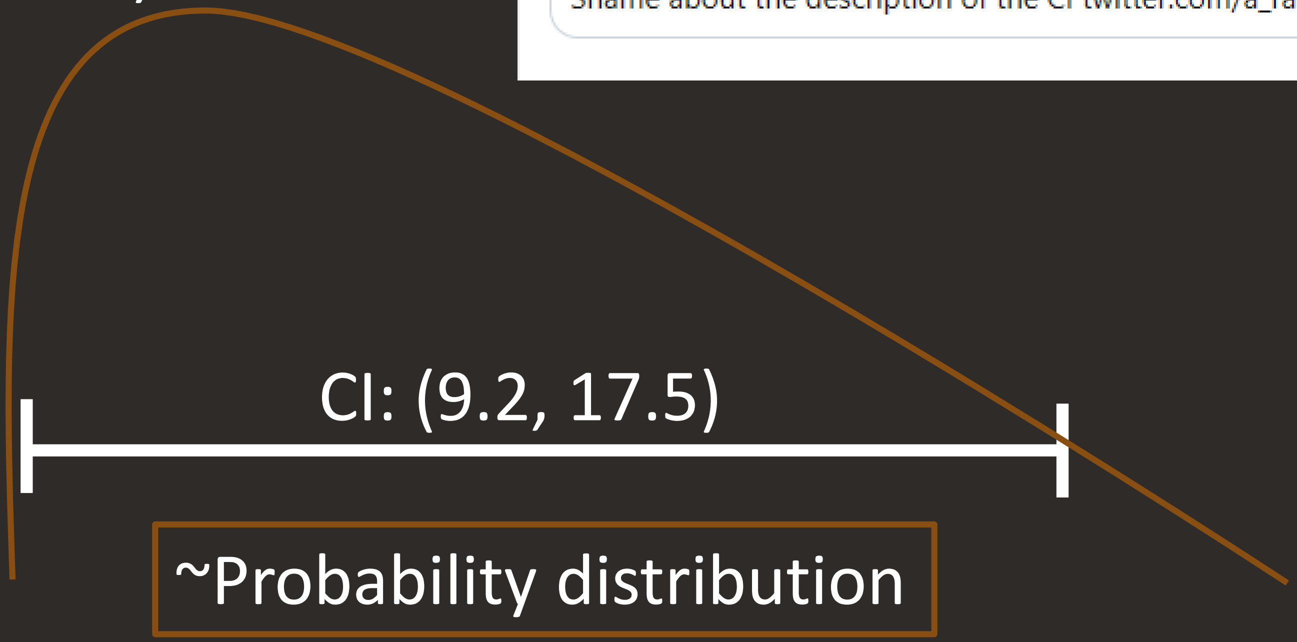
Credible Interval (CI or CrI)


David Spiegelhalter
@d_spiegel

maybe better to call them uncertainty intervals, and then the Bayesian interpretation would be fine

Översätt tweeten

Giusi Moffa @a_randomwalker · 2 nov.
Svarar @d_spiegel
Shame about the description of the CI twitter.com/a_randomwalker...



”Bayesian analysis is too difficult”

No, a problem is that we learn frequentist statistics first
Yes, it requires some knowledge of probability theory

Yes, many lack training or experience
No, it has never been more easy

```r
bmod <- brm(y ~ x + (1|g), data = df, family = poisson())
```

```r
mod <- glmer(y ~ x + (1|g), data = df, family = poisson)
```

Bayesian analysis

Principal strengths:
output is a subjetive probability distribution representing uncertainty and which may incorporate information from both data and expert judgement

Principal weakness:
limited familiarity with Bayesian inference amongst EFSA assessors – likely to need specialist support

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