

# Outline of the 2022/2023 Bayesian Statistics Course

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## Grading

The final grade is composed of two parts, the first 50% comes from the homework and the other 50% from an oral exam. We expect there will be around 8 homework assignments. Unless otherwise noted, all homework will be due in two weeks and should be submitted as a short report (from half a page to two pages, depending on the homework) in the pdf format. General feedback to your homework will be provided on the group level via the course's forum. If some of you want more detailed, individual feedback about your work, we will happily provide it on request. Each homework will be graded on a scale from 1 to 5:

- 5 – perfect or nearly perfect submissions,
- 4 – submissions of an above average quality,
- 3 – average submissions,
- 2 – barely acceptable (try to do better in the long run),
- 0 – unacceptable.

To get a positive grade, you need to gather at least 50% of all available points from homework. Your submission that receives the worst grade will be discarded when calculating the final homework grade. Meaning that you can skip one homework without any major repercussions. To finish the course you need to take an oral exam at the end of the semester. Only students that gathered at least 50% of points from the homework are allowed to take the exam. The oral exam will be used to test your knowledge both in the theoretical and in the practical aspects of Bayesian statistics that we covered during lectures.

## Reports

Even though the reports you are submitting are short they should still follow conventions of good scientific and technical writing. A good practice is to follow the IMRAD format (<https://en.wikipedia.org/wiki/IMRAD>, <https://www.youtube.com/watch?v=aO6ipI-d2fw>):

- **Introduction** – In the introductory part of your reports you should establish why you are doing what you

are doing. What is the motivation behind the task you are about to take on? What are we trying to answer with our work? As you will see, all of our homework will be practically oriented and

- **Methods** – Describe the methods, approaches and algorithms you used for tackling the task at hand. Describe them in a transparent and easy to understand way so others can reproduce your work.
- **Results** – Present what you found out in clear and concise fashion. If possible, use graphical visualizations. Good visualizations usually convey your story in a more reader friendly manner than blocks of text or tables. Some libraries (e.g. ggplot in R) are designed in a way so your results will be compliant with modern standards of data visualization, with other libraries some additional work is usually required to get visualizations that look nice.
- **Discussion** – Wrap up your work by summarizing your results and explicitly answering the research questions you tackled. Outline any limitations and possible improvements to your work.

Note that the four sections (Introduction, Methods, Results and Discussion) do not need to be explicitly outlined and denoted, the important thing is that the flow of your reports follows the logic outlined above.

## Lectures

Lectures will span over approximately 14 weeks. Below is a more detailed outline of this year's edition of the course. Note here that what is listed below is only a plan of execution and might change slightly during the course of the year.

### Introduction to Statistical Enquiry [X. 10. 2022]

The main goal of this lecture is to provide an introduction to the process of statistical enquiry. What is statistical enquiry, why is it important, and how do we approach it in a systematic way? We base our introduction on Wild and Pfannkuch's 4 dimensions of statistical enquiry, with special focus on the 1st dimension, the PPDAC investigative cycle (Problem, Plan, Data, Analysis, Conclusions).

**Probabilistic Thinking [X. 10. 2022]**

The main goal of this lecture is to illustrate how uncertainty is part of our everyday lives but in order to deal with it in a systematic way we require the rigor of probability theory. The language of probability theory allows us not only to express uncertainty but also to provide probabilistic interpretations of processes of interest, which then allows us to infer their properties from the data they generate. That is, probability theory is the very foundation of applied statistics.

**Probabilistic Programming [X. 10. 2022]**

Statistical (probabilistic) models are used for describing how certain data we are interested in was generated. Probabilistic programming languages offer both a methodological way for specifying statistical models and tools for performing automated inferences on these models.

Stan is probably the most widespread probabilistic programming language. It couples well with several popular programming languages and offers an intuitive framework for specifying statistical models along with algorithms for full Bayesian inference for continuous variable models through Markov chain Monte Carlo methods such as the No-U-Turn sampler, an adaptive form of Hamiltonian Monte Carlo sampling.

**The Generalized Linear Model [X. 10. 2022]**

The intercept and slope parameters in simple linear regression are easy to interpret and can as such provide key insight into our data generating process. When modeling the relationship between independent and dependent variables, simple linear regression often gives suboptimal results. We need a more powerful tool, especially so in cases where the dependent variable is not metric. Generalized linear model (GLM) is a powerful tool capable of working with dependent variables of various scale types (metric, ordinal, nominal and count) and error distributions other than normal. The simple linear model is actually the simplest of all GLMs. In the GLM, beta coefficients are usually not as easy to interpret as in the case of simple linear regression. Fortunately, we only need some relatively easy math to make them understandable!

**Describe the Process [X. 11. 2022]**

When developing statistical models we often fall into the habit of merely fitting some distributions onto our data. In this lecture we will show why this is bad and suboptimal. We should do our best to try and understand the actual data generating process and model it!

**Predictive Checking [X. 11. 2022]**

Bayesian modeling is an iterative process, we start by picking an initial model and settings its priors. To investigate whether our priors have undesirable effects that contradict domain knowledge we start by performing prior predictive checks. Once we are happy with our priors, we fit the model

and diagnose the fitting process (traceplot, convergence, diagnostics ...). If all is good, we then execute posterior predictive checks to evaluate whether our model is suitable for answering the questions we are asking.

**Bayesian Cross-Validation [X. 11. 2022]**

Cross-validation is a widely spread technique for estimating how well our models generalize (how they fare when encountering unknown data). Since in Bayesian statistics we are always working with probability distributions we can use log-score as our go-to model evaluation measure. This allows us to resort to information theory for calculating good cross-validation approximations without actually performing the actual (often very time consuming) cross-validation. An important point to emphasize here is that cross-validation and regularization are not mutually exclusive, they go hand in hand and traditionally we use both at the same time.

**Hierarchical Models [X. 11. 2022]**

In Bayesian modeling hierarchical models (also called multi-level models) are an extremely powerful tool. As already emphasized a couple of times now, when modeling we should try to describe the data generating process (and not fit some distributions to some data). Since data generating processes often have a hierarchical structure (e.g. groups of students, multiple repetitions of an experiment ...), hierarchical models enable us to efficiently describe such data generating processes.

**Questionnaires [X. 11. 2022]**

Measuring things accurately and precisely is difficult to start with, but even more so when we try to measure peoples' psychological characteristics, opinions, preferences, etc. We will discuss the questionnaire as a measuring device. How do we design, test, and validate one. How do we select the type of question and scale. And what are the most common mistakes.

**Sampling [X. 12. 2022]**

This lecture will revolve around the basics of sampling in the context of survey sampling. We will cover three of the most common probability sampling approaches: simple random sampling, stratified sampling, and cluster sampling. We will also briefly discuss non-probability sampling methods: convenience sampling, judgment sampling, quota sampling, and snowball sampling.

**Priors [X. 12. 2022]**

Defining priors is an integral part in Bayesian statistics. The main purpose of priors is to introduce prior expert knowledge about the domain into our models. As we know by now, this is not the only usage of priors, they are also useful for regularization and can be of help during the sampling process which can lead to stabilization of inferences in certain models. Based on the amount of information priors provide they are commonly categorized into three groups: non-

informative priors, weakly informative priors and informative priors. This document briefly explains the differences between these groups and provides some guidance about when to use certain priors. Since one of the main advantages of Bayesian statistics is its ability to facilitate existing knowledge to empower our models the second part of this document talks about approaches for eliciting relevant information from experts.

### **Modelling time-series [X. 12. 2022]**

We are often faced with data that is time sensitive in the form of time-series. Since the time component is usually of paramount importance in such data we have to be extra careful when handling and modelling our data. For this purpose, we will take a look at specialized Bayesian models for modelling time sensitive data.

### **Why skepticism is important in modern science and data analysis [X. 12. 2022]**

We are constantly bombarded with misinformation labeled as facts, be it in our everyday lives or in scientific literature. In this, more lightweight, lecture we will take a look on how to spot such dubious practices and thus keep them from spread-

ing and succeeding.

### **Holiday [X. 12. 2022]**

Happy holidays!

### **COVID case study [X. 1. 2023]**

Our ultimate lecture will be a showcase of Bayesian statistics executed on a nation wide COVID study.

## **Lab practice**

The lab practice slots will be used for a number of activities. Since the work will be dynamic we do not have a clear schedule and will determine the content of the lab practice slots on a week-by-week basis. Some of the activities that could await you are:

- consultations regarding your homework,
- technical tutorials for the tools we will be using,
- communicating with a non-statistics expert,
- practically oriented guest lectures.