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ASTROPHYSICS WITH GRAVITATIONAL WAVE DETECTIONS: DATA ANALYSIS

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ABSTRACT

This series of three lectures is intended to give you an introduction to the data analysis techniques used in gravitational wave astrophysics and astrostatistics more generally.

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1. SYLLABUS

The goal of this course is to introduce you to some of the techniques used in gravitational wave astrophysics and also to give you some practice with the *implementation* of statistical analyses. To that end, the "lectures" will hopefully be very interactive, with opportunities to ask questions, work with your peers to develop code, and see in real-time the results of your analyses. Of course you do not have to participate to this degree if you do not want; nevertheless, I think you will get the most out of the school if you do.

Before Monday afternoon, please install a working `Stan` implemtation (Carpenter et al. 2017). I personally favour `PyStan` (Stan Development Team 2017) on top of the Anaconda `Python` distribution, but if you are more familiar with `R`or the command line, go ahead. If you are using `PyStan`, you will know your installation is working when you can run the "eight schools" example from the `PyStan` manual[1].

Each lecture will come with reading material; some I will ask you to familariase yourself with in advance, and some is just in case you are interested to go further than I do in the lecture. Please have a look (it doesn't have to be extensive—just get familiar with the content, or have questions about wherever you get stuck) at the material before the lecture so we can discuss it straight away.

The material for the course, including this document, can be found on GitHub.

1.1. *Lecture 1: Monday Afternoon. The Bayesics*

It may seem simple, but this entire lecture will be concerned with the material in Hogg et al. (2010). Please familarise yourself with it before the lecture; we will be writing code to solve some of the associated problems during the lecture.

We will spend a bit of time talking about statistical notation and the notion of conditional versus joint distributions, and then we will dive in to fitting a line to data! If you internalise all the discussion from Hogg et al. (2010) you will be ready to build models that are better than 90% of the "state-of-the-art" papers on the arXiv. To explore the ideas in Hogg et al. (2010), we will use the modelling language `Stan`(Carpenter et al. 2017), so I will give a brief tutorial on the structure of the language (the syntax should be familiar to those who have programmed in `C` or similar languages before) and how it is optimised for describing and solving the sorts of statistical problems we are going to be talking about in this course.

Further reading (for those interested) includes this blog post by Daniel Foreman-Mackey, Kelly (2007), Lieu et al. (2017), ...

1.2. *Lecture 2: Thursday Morning. Extracting Astrophysical Information from Gravitational Waves.*

[1] For an interesting, intuitive description of hierarchical modelling—which will feature in Lecture 3—see here.

This lecture will discuss the physics from Abbott et al. (2017) and the techniques described in Veitch et al. (2015) for extracting information about gravitational wave sources. Please familarise yourself with these references before the lecture.

We will explore how the various parameters of a merging compact object system are encoded in the gravitational waveform (Abbott et al. 2017). We will talk about the noise sources in interferometric gravitational wave detectors and justify the likelihood function given in Veitch et al. (2015). We will implement this likelihood function in `Stan`, and use it to estimate the parameters of GW150914 (Abbott et al. 2016a) from actual LIGO data.

For further reading, consider Abbott et al. (2016b), Abbott et al. (2016c), ...

1.3. *Lecture 3: Friday Afternoon. Population Modelling.*

This lecture will deal with three different topics in population modelling. First, we will derive the "fundamental likelihood" of population modelling, following this blog post by Dan Foreman-Mackey. Then we will show how this likelihood generalises to a *mixture* model used to infer rates of black hole mergers in Abbott et al. (2016d); we will write some `Stan` code to infer rates of binary black hole mergers and apply it to real data from that paper. Finally, we will discuss *model selection* in a gravitational waves context, following Farr et al. (2017). Please familiarise yourself with these references before the lecture.

For further reading, consider Abbott et al. (2016e), Foreman-Mackey et al. (2014), Farr et al. (2015), Loredo & Wasserman (1995), Farr et al. (2011), ...

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