Probabilistic models for neural data
Session 1: Basics of Bayesian inference of neural modeling

To do before this session:
- **Perform refresher/catch-up reading**

Course structure

The course is split into nine sessions. In the first two sessions we cover/refresh the basics of Bayesian inference, and how Bayesian inference can be used to model neural data. In the remaining sessions, we interleave paper discussions, exercise discussions, and the introduction of new statistical concepts that support understanding the papers/exercises of the remaining sessions.

Session 1:
- Seminar on basics of Bayesian inference, and application of Bayesian inference to model neural data

Session 2:
- Short quiz (~5min) that allows you to evaluate the topics you should revisit, and that gives me feedback on everyone's progress
- Discussion (~15-30min) of the first exercise
- Presentation/discussion of Gaussians and linear models, and Bayesian model comparison.

Sessions 3-9 structure:
- Short quiz (~5min) that allows you to evaluate the topics you should revisit, and that gives me feedback on everyone's progress
- Brief discussion (~15min) of the exercise (only some sessions)
- Student-led presentation/discussion (~50min) on a paper using the statistical concepts discussed in the previous session.
- Presentation/discussion of the statistical concepts in preparation for the next session's paper.

The presentation/discussion part will be shorter for sessions in which we discuss exercises. Their purpose is to get a different perspective on statistical concepts and paper, and to act as the basis for discussing them.

Between sessions, all students are expected to
- Read the assigned paper, and prepare the presentation of the figure/paper section assigned to them.
- Read the assigned book chapters/section on particular statistics concepts

- Work through the exercise (only some sessions), prepare a brief write-up, and submit it by 3pm of the day of the next session
- All assigned reading will be on Perusall, an online platform for collective reading (linked from the Canvas page). **You are strongly encouraged to add questions/comments to all assigned reading (at least 3-4 per reading)**, before noon of the date of the next session. These will help identify parts of the reading that are unclear, such that we can discuss them in more detail in class.

Don't worry too much about understanding all the math. The goal of this course is not to become an expert in Bayesian modeling, or to be able to design and implement new models (there isn't enough time). Instead, you should understand the different models' underlying ideas, their structure, how they relate to each other, and (most importantly) what assumptions they make about the data. Having seen the underlying math, even without going through all the details, should help you to achieve this goal.

Between each session, the students will be split into groups. Each group will be assigned one or several paper figures and/or one or several paper sections that they will present in the next session. The individual presentations shouldn't last longer than 5-7min to leave ample time for discussion and questions. The selected papers will use statistical concepts that have been introduced in the preceding session, so make sure to understand them and ask questions if anything is unclear.

The book chapters/sections and papers to read and prepare are listed in the session notes of the sessions in which they will be discussed, and will be available on Perusall. At the end of each session, make sure to consult the session notes for the next session.

Most reading on statistical concepts will be from Bishop (2006), *Pattern Recognition and Machine Learning*, which is available at https://www.microsoft.com/en-us/research/people/cmbishop/ free of charge. In the session notes of this course, PRML *N* refers to Chapter *N*, PRML *N*.0 refers to the introduction of that Chapter, and PRML *X.Y.Z* refers to Section *X.Y.Z* in that book.

Another useful machine learning and information theory reference is MacKay (2003), *Information Theory, Inference, and Learning Algorithms*, available at http://www.inference.org.uk/itila/book.html.

The textbook for computational neuroscience is Dayan & Abbott (2001), *Theoretical Neuroscience*. You can find a copy at http://www.gatsby.ucl.ac.uk/~lmate/biblio/dayanabbott.pdf.

Session 1: Basic of Bayesian inference of neural modeling
Refresher/catch-up reading

The basics of probability and information theory (PRML 1)

Make sure to understand

- Random variables
- Basic rules of probability theory (marginalization, conditionals) (PRML problem 1.3)
- Difference between a probability mass and a probability density and their relationship
- Expectation, variance, and their relationship (PRML problem 1.5, 1.6)
- Components of Bayes' rule: prior, likelihood, posterior, marginal likelihood, and why the proportionality notation works (https://arbital.com/p/bayes_rule/?l=1zq)
- Assumption of independent and identically distributed (i.i.d.) data
- The univariate Gaussian distribution (PRML problem 1.9 (univariate only), 1.12 (challenging))
- Maximum likelihood (PRML problem 1.11) and maximum a-posterior estimates
- Model selection through cross-validation (posterior predictive checks) and information criteria
- Bayesian decision theory, and the role/impact of different loss functions
- Entropy, relative entropy, the Kullback-Leibler divergence, and mutual information (PRML problem 1.37, 1.41, 1.39, 1.35, 1.30 (challenging))

If you are unsure if you understand these concepts, try some of the exercises at the end of PRML 1. Some of the ones you might want to try are included in the list above. The solutions to those are provided in Canvas. I will revisit most of these concepts in the first session, but it would be good if you have heard about them before I do so.

Exercise

This week's exercise focuses on trying out some of the above concepts to fit simple stimulus-response models. It assumes binning the stimulus into a set of bins, and modeling the neural response as i.i.d. within each bin. That is, you will fit a different (set of) parameter(s) of the response likelihood for each stimulus bin. Subsequently, you will determine the best set of parameters, and/or number of bins by model comparison, using either cross-validation or Bayesian model comparison. The same exercise will be repeated with different prior parameters.

To get started with the exercise, open the Colab notebook at https://colab.research.google.com/drive/1osnJ1JEuAbT7mwnXvLwYk-KPgKiaYpDG?usp=sharing

This notebook contains all the required instructions for completing the exercise, as well as some questions that you should address in your writeup.

Once you have completed the exercise, please describe the results of your exercise, and your interpretation of the results (suggested length: 450-650 words). The exercise notebook provides more specific information on what to describe. Use figures to help describe your results; please embed the figures in your text description. Please be as specific as possible, and submit the write-up before noon on the day of the next session.