Null Processes for Computational Neuroscience

January 7, 2021

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Recommended competences. Solid understanding of randomized algorithms and discrete probability (especially discrete Markov chains), good background on graph algorithms and programming in Python and a strong desire to work at the interface between computational neuroscience and the theory of algorithms.

Expected duration. The entire project is suitable for a 6-month internship. A mini-projects of 2-months can be carried on by focusing on part of it (see *Acquisition of theoretical background* and *Experimental validation* below), with the intention of assessing the student suitability for carrying on the whole project in a future internship.

The objective of this project is to contribute to the theory of null models in modern computational neuroscience. In the study of statistical properties of graphs, a null model $\mathcal{G}_0$ is a random graph model that satisfies some properties which are characteristic for a family of graphs $\mathcal{G}_1$ (e.g. brain networks derived from DW-MRI data), but which is otherwise an unbiasedly random structure. The null model $\mathcal{G}_0$ is used as a term of comparison, for example to verify whether a given measure f captures some non-trivial features of $\mathcal{G}_1$, by comparing the values of $f(G)$ when G is sampled from $\mathcal{G}_0$ or $\mathcal{G}_1$.

Developing null models in the context of computational neuroscience is a challenging task, since the community is still far from reaching consensus on what kind of typical properties null models should satisfy. As a consequence, in practice only simplistic random graph models are usually considered (Erdős-Rényi model, Chung-Lu model, etc.) The aim of this project is to contribute to such lack of effective null models by introducing a novel approach, based on the idea of considering "null processes", namely stochastic processes which, given a graph G from to the considered family $\mathcal{G}_0$, progressively transform it until its structure reflects that of some basic random graph model $\mathcal{G}_1$. Such null processes thus generate a random graph process G_t which interpolates between real data ($\mathcal{G}_1$) and random graph models ($\mathcal{G}_0$). In the context of the above example of a given candidate measure f, it is then possible to study the evolution of the stochastic process $f(G_t)$, in order to investigate how non-trivial features which seem to be captured by f on $\mathcal{G}_1$ behave while G_t progresses towards $\mathcal{G}_0$.

The project is a unique opportunity for outstanding students with a solid theoretical basis and with a strong desire to work on fundamental problems in theoretical and computational neuroscience. The project is articulated in three main parts:

- **Acquisition of theoretical background.** Reading papers on discrete Markov chains which transform the topology of a graph and on the properties of famous random graph models.
- **Original research.** Identifying theoretical principles which motivate the choice of the null processes to be considered, or possibly the design of new ones.
- **Experimental validation.** Developing an efficient implementation of the null processes under investigation, and validating the behavior of famous graph measures (e.g. centrality measures) when real data is subject to the null processes.

Bibliography. In the following we list some papers which are relevant to the project. The student is not expected to have read their introductory sections, in order to verify his/her interest in the topic and to be confident that (we the help of the supervisor) he/she would be able to understand the main ideas of those papers. We emphasize that for the mathematical papers, the student will not expected to understand the details of the proofs (some of which can be quite advanced even for a mathematician!), but it is obviously expected to be able to clearly understand the statements of the main theorems.

- Cooper, C. et al. (2019) 'The flip Markov chain for connected regular graphs', Discrete Applied Mathematics, 254, pp. 56–79. doi: 10.1016/j.dam.2018.06.019.
- Burt, J. B. et al. (2020) 'Generative modeling of brain maps with spatial autocorrelation', NeuroImage, 220, p. 117038. doi: 10.1016/j.neuroimage.2020.117038.