Emergence of Clinical Heterogeneity from Generative Models of Psychiatric Disorders

Niliena Celine Biju

Mentors: Prof. Arjun Ramakrishnan and Dr. Promit Moitra

Introduction

Perceptual models are computational models that simulate or mimic cognitive processes involved in perception. They belong to two broad categories - process models and generative models which focus on different aspects and levels of analysis. Process models focus on describing sequential processes of evidence accumulation required for task execution, such as Drift Diffusion Models, race models, etc. Generative models simulate interactions between higher-level cognitive processes involved in perceptual decision-making, such as learning, memory, attention, and reasoning. Bayesian models, a type of cognitive model, are based on Bayesian inference to represent and update beliefs based on new evidence. They provide a principled approach for reasoning under uncertainty and incorporating prior knowledge into the analysis.

Hierarchical Gaussian Filters

Hierarchical Gaussian Filters (HGF) provide a generalized, nodalized and multi-level structure that utilizes Bayesian Inference to cause belief update in a top down manner through the diffusion of precision-weighted prediction errors under new observations. [3]

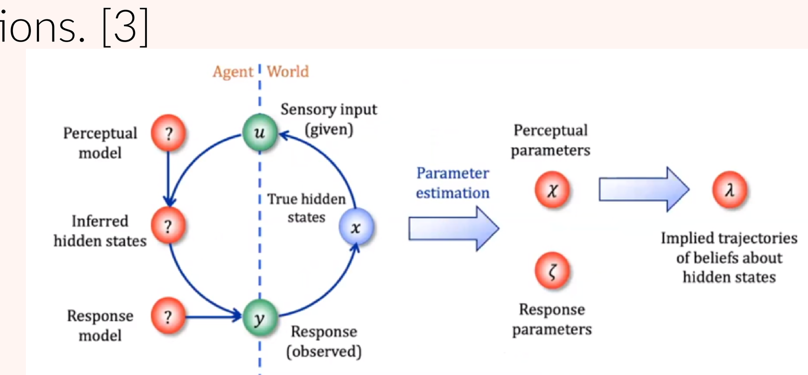

Figure 1. Obtaining Inferred hidden states of the Modelfrom the Sensory Input given and the Response observed. [3]

The generative model that underpins the HGF is a generalisation of the Gaussian Random Walk (GRW). HGFs are able to represent uncertainty about the rate of change of the world, which is important because the world is constantly changing, thereby allowing them to keep up with changes in the environment and adapt their predictions accordingly. They do so by introducing coupling between the hierarchical levels that make up the model. There are two types of coupling between the hierarchical layers :-

- **Volatility Coupling** - The HGF generalize the standard GRW by letting the variance be controlled by a higher-level node.
- **Value Coupling** - Higher-level nodes affect lower-level nodes by affecting their mean.

Volatility coupling and value coupling can occur at the same time, as shown below where x_1 is value coupled with x_2 and volatility coupled with x_3.

$$x_1^{(k)} \sim \mathcal{N}(x_1^{(k)} | x_1^{(k-1)} + \alpha_1 x_2^{(k)}, \exp(\kappa_1 x_3^{(k)} + \omega_1))$$
$$x_2^{(k)} \sim \mathcal{N}(x_2^{(k)} | x_2^{(k-1)}, \exp(\omega_2))$$
$$x_3^{(k)} \sim \mathcal{N}(x_3^{(k)} | x_3^{(k-1)}, \exp(\omega_3))$$

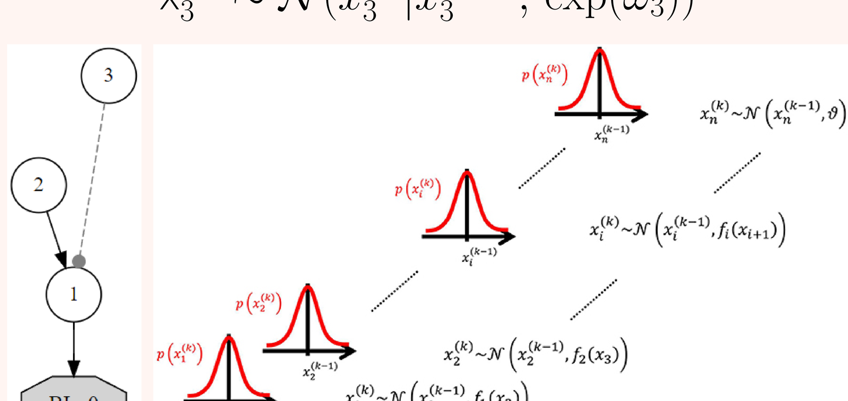

Figure 2. (A) shows the example network structure as described before. (B) represents the a linear HGF node structure with only volatility coupling [3].

Interpreting HGF Levels

HGF levels can be interpreted as belief states regarding environmental features, which are updated sequentially based on sensory input. We explore this in two case studies.

- The player has to choose one from three decks and the top card is flipped as shown in Figure 3. Each deck has winning cards (+100 pts) and losing cards (-50 pts) with different probabilities [4]. The player must choose decks in order to maximize total points. The probability of winning and losing cards associated with each deck changes across blocks. The HGF levels account for the environment such that x1 represents trial-by-trial win or loss feedback, x2 is the stimulus-outcome association and x3 is the perception of the overall reward contingency context (volatility). The task studies the deck switch (stay) rate after getting a winning (losing) card.

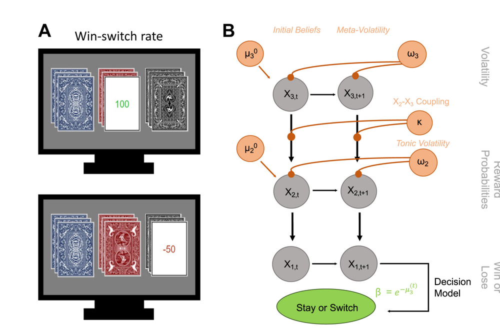

Figure 3.

- The task has a cue followed by a fixation cross and finally, the outcome (as shown in Figure 4), about which the player has to make a prediction [2].The task includes the concept of prior information (cue), which can be used to make the prediction. The cue varies in shape and color, of which one of the attributes correlates to the outcome and the other is irrelevant. The relevant attribute changes across blocks, checking for the player's ability to determine salience. The responses can be studied using the HGF framework, such that x1 correlates to the outcome, x2 to the cue variation, and x3 to the block volatility.

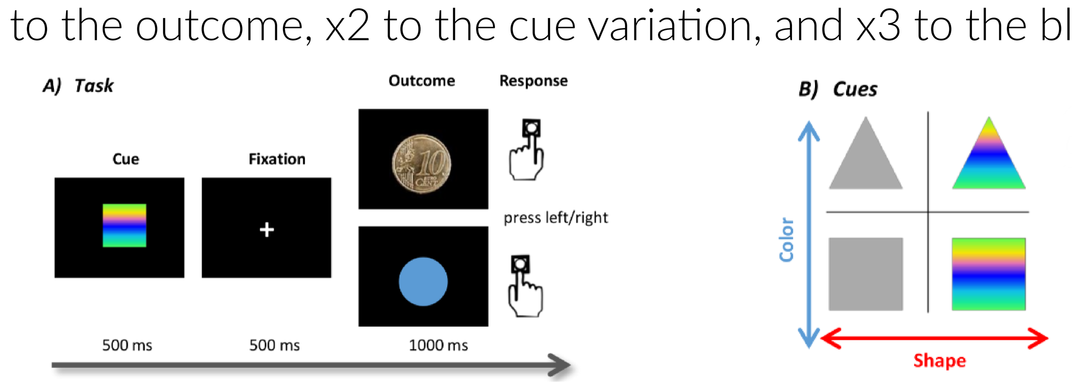

Figure 4.

Circular Inference Model

The relationships between different nodes in HGF are exclusively top-down, with parent levels affecting child levels and no relation the other way around. In contrast, the Circular Inference model suggests not only top down, but also bottom up interactions resulting in final perception.

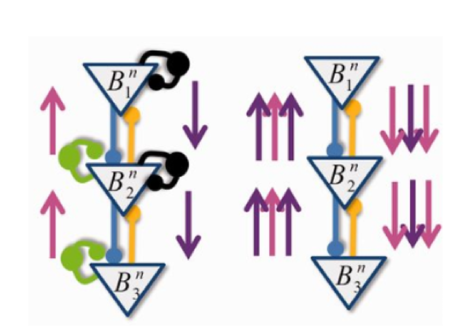

Figure 5. Circular Inference Model: The model accounts for both top down and bottom up relationships between layers. Two way interaction (blue and yellow connections) results in signals getting reverberated and falsely amplified (arrows) leading to inaccurate perception. This is rectified by the feedback loops (green - upward inhibitory (ascending) and black - downward inhibitory (descending)). [1]

Modelling Circular inference using HGF framework

The currently available Circular Inference model framework is very specific and applicable to only specific task paradigms and cannot be extended to more general cases. On the other hand, there are multiple frameworks available for HGF modeling. In the project, we attempted to model Circular Inference using the available HGF framework. We have been able to create a generative model of Circular Inference using an HGF framework, namely pyhgf, as shown in Figure 6.

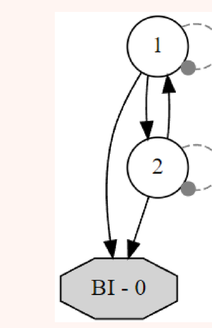

Figure 6. Potential Circular Inference model created using an HGF framework (pyhgf). The two nodes account for prior and sensory information, which are coupled to result in perception which is the input, BI (Binary Input). The nodes have been coupled with each other causing the reverberatory effect in Circular Inference. The nodes have been value coupled on their own which accounts for the inhibitory feedback loops.

Summary and Future Plans

pyhgf allows for the creation of complex networks with probabilistic belief update nodes as shown above, and generation of simulated data. However, parameter estimation is restricted to linear hierarchical belief updates only. Circular Inference provides a viable alternative, which shares the probabilistic belief update structure. It incorporates bidirectional feedback between nodes as well as inhibitory self loops.
While attempting to obtain the update sequence of the HGF model mimicking Circular Inference, the model is unable to estimate parameters due to the presence of self loops and bidirectional coupling causing a recursion error. To solve this issue, we intend to design an asynchronous belief propagation algorithm and integrate it with the larger model.
We intend to implement the Circular Inference model to investigate the mechanism of susceptibility to Visual illusions and understand the role of aberrant salience in the same. [5]

References

[1] R. Jardri and S. Denève.
Circular inferences in schizophrenia.
Brain, 136(11):3227–3241, 09 2013.

[2] T. Katthagen, C. Mathys, L. Deserno, H. Walter, N. Kathmann, A. Heinz, and F. Schlagenhauf.
Modeling subjective relevance in schizophrenia and its relation to aberrant salience.
PLOS Computational Biology, 14(8):1–23, 08 2018.

[3] C. D. Mathys, E. I. Lomakina, J. Daunizeau, S. Iglesias, K. H. Brodersen, K. J. Friston, and K. E. Stephan.
Uncertainty in perception and the hierarchical gaussian filter.
Frontiers in Human Neuroscience, 8, 2014.

[4] J. M. Sheffield, P. Suthaharan, P. Leptourgos, and P. R. Corlett.
Belief updating and paranoia in individuals with schizophrenia.
Biological Psychiatry: Cognitive Neuroscience and Neuroimaging, 7(11):1149–1157, 2022.

[5] V. Weilnhammer, L. Röd, A.-L. Eckert, H. Stuke, A. Heinz, and P. Sterzer.
Psychotic Experiences in Schizophrenia and Sensitivity to Sensory Evidence.
Schizophrenia Bulletin, 46(4):927–936, 02 2020.

Application no. : 2330352
Name : Niliena Celine Biju
Mentor Name : Prof. Arjun Ramakrishnan and Dr. Promit Moitra
Mentor Department : Biological Sciences and Bioengineering