Neural Network Poisson Models for Behavioural and Neural Spike Train Data

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Presentation Outline

Introduction

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We propose a novel neural network Poisson process model which:

- Flexibly learns the connections between stimuli and neural as well as neural and behavioural responses;
- Jointly fits both behavioural and neural data;
- Derives spike count statistics disentangled from chosen temporal bin sizes.
- Handles variabilities between response times across different trials by a temporal rescaling mechanism;

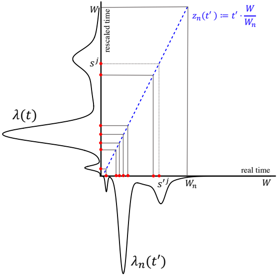

Figure 1: Transformation of the Poisson point process in real time to the rescaled time domain.

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- Output of a hierarchical network model with reciprocally connected sensory and integration circuits (Synthetic dataset [2]).

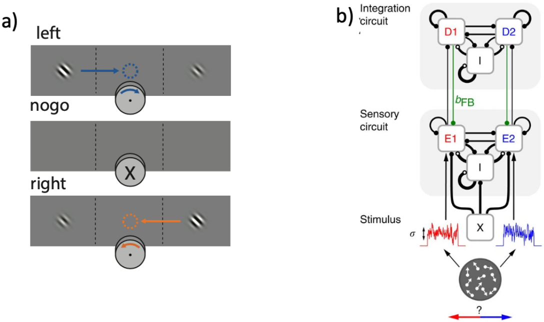

Figure 2: **a.** Steinmetz' visual discrimination task. **b.** Synthetic network model.

Methodology

Theorem

Let $0 < s'^1 < s'^2 <, \ldots, < s'^j \leq W_n \leq W$ *be a realization from an inhomogeneous Poisson point process,* n*, with an intensity function* $\lambda_n(t')$ *satisfying* $0 < \lambda_n(t')$ *for all* $t' \in (0, W_n]$*. Define a one-to-one monotonic transformation function, where:*

$$z_n : [0, W_n] \to [0, W], \textit{and } z_n(0) = 0, z_n(W_n) = W$$

Assume $0 < s^1 < s^2 <, \ldots, < s^j \leq W$ *where* $\forall k \in \{1, \ldots, j\}$*;* $s^k = z_n(s'^k)$*. Then* s^k *are a realization from a second inhomogeneous Poisson point process with* $\lambda(t) = \lambda_n(t')$ *where* $t = z_n(t')$*.*

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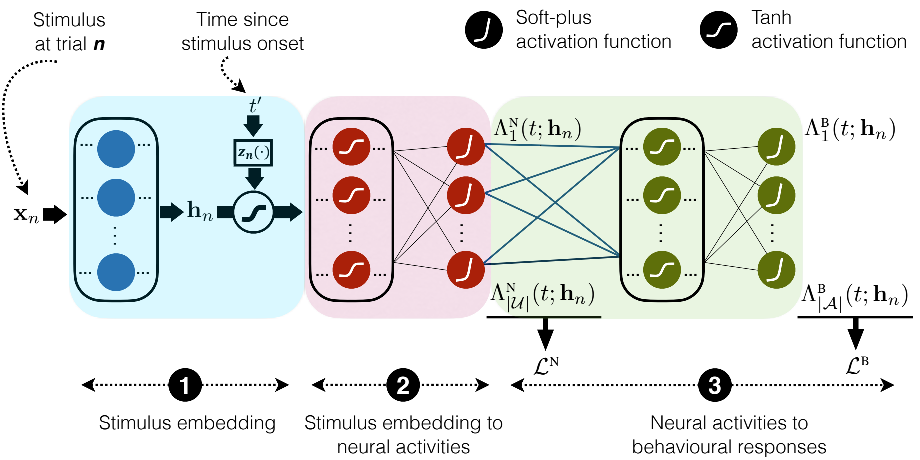
Proposition

For a linear transformation function $z_n(.)$*, as defined in* **Theorem***, the cumulative intensity function of the original and second point process realizations are related as:* $\Lambda(t) = \frac{1}{\partial_t(z_n^{-1})} \cdot \Lambda_n(t')$*.*

Network Architecture



Results on Synthetic Dataset

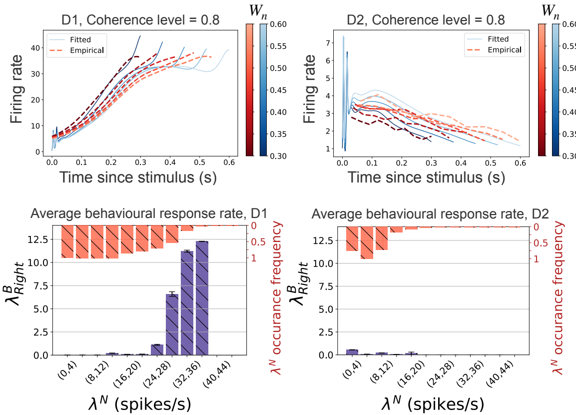


Figure 3: **Upper panels.** The empirically derived firing rates (dashed lines) compared to the neural activity estimated using the proposed model (solid lines).
Lower panels. The average response rate (purple bars) and the proportion of trials (orange bars) with the neural response in each interval.

Results on Steinmetz Dataset

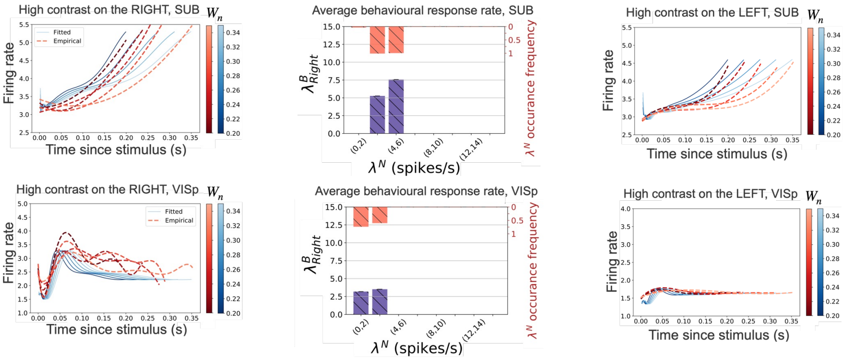


Figure 4: **Left panels.** The empirically derived firing rates (dashed lines) compared to the neural activity estimated using the proposed model (solid lines).
Middle panels. The average response rate (purple bars) and the proportion of trials (orange bars) with the neural response in each interval.
Right panels. Neural activities for contralateral and ipsilateral stimuli.

Behavioural Predictions of the Model

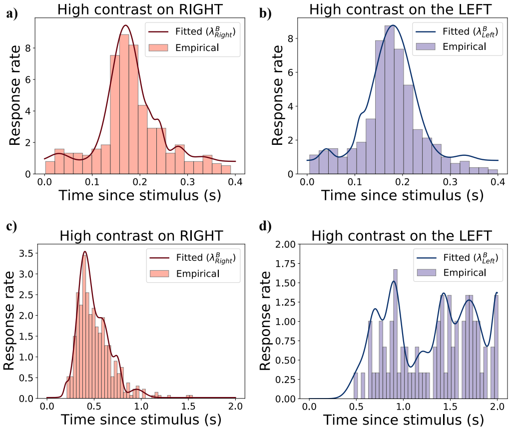


Figure 5: Fitted behavioral intensities (solid lines) match the empirical response rate densities (colored bars) for high contrast on RIGHT and LEFT.
Upper panels: Steinmetz dataset, **Lower panels: Synthetic dataset.**

Comparison with Baselines

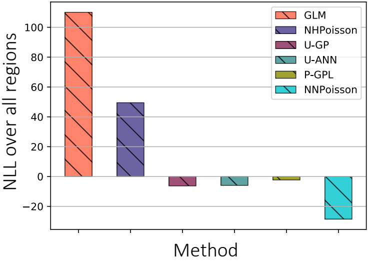


Figure 6: Total NLL of the estimated neural intensity function on Steinmetz test set over all the 37 test regions in the test set.

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- Capturing richer aspects of behaviour that are known to couple to neural activity.
- Integrating and/or substituting spiking activity with calcium imaging.
- Implementing novel approaches such as the auto-regressive linear-nonlinear-Poisson (LNP) models.
- Differentiating more finely the activity in different regions.

List of References

[1] Nicholas A Steinmetz et al. "Distributed coding of choice, action and engagement across the mouse brain". In: *Nature* 576.7786 (2019), pp. 266–273.

[2] Klaus Wimmer et al. "Sensory integration dynamics in a hierarchical network explains choice probabilities in cortical area MT". In: *Nature communications* 6.1 (2015), pp. 1–13.

Thank You So Much!

For more details, please refer to our paper:

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