Ensembles of Spiking Neural Networks

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Problem statement

Spiking networks have a higher computational efficiency than their deep learning counterparts. This is due to information being communicated through a small number of spikes, which are generally produced by a subset of the neurons [1], [3].
One reason why these models have not been more widely adopted is due to their incompatibility with popular training methods like BackPropagation. As no equivalently reliable algorithm has been proposed for training spiking networks, such models are generally achieving poorer performances than popular deep learning models [6].
We propose using ensemble learning methods to improve the performance of spiking models and to better understand how they communicate and process information.

Ensemble Learning

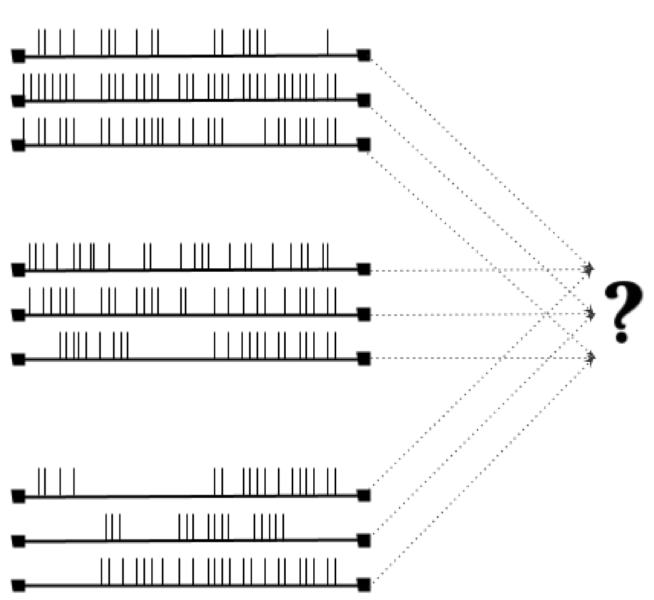
We define a good ensemble as: *a predictor that is on average more accurate than any of the models being combined.* We call such an ensemble the **central model** [2].

$$\bar{q} = \arg\min_{p} \frac{1}{M} \sum_{i=1}^{M} KL(p||q_i) \qquad (1)$$

[2] and [5] show that for an ensemble model to have the property of the central model, it has to minimize the divergence between itself and all other models q_i.

Spiking Neural Networks

A distinguishing characteristic of spiking networks is how information is represented. A spiking neuron communicates information in the form of **spike trains**; a sequence of times at which the neuron has produced a signal (or spike) [4].



Related literature (see [6], [7] to name a few) on this topic does not make enough use of the knowledge acquired by the machine learning community through the study of ensemble systems.

Results

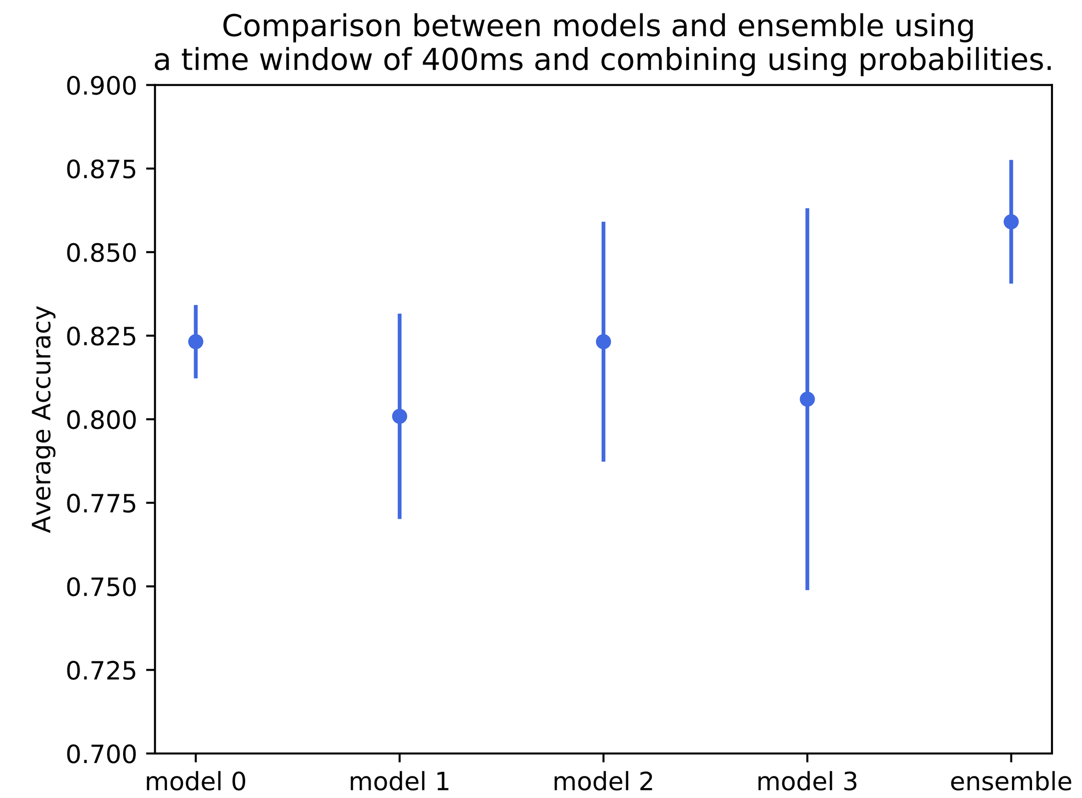
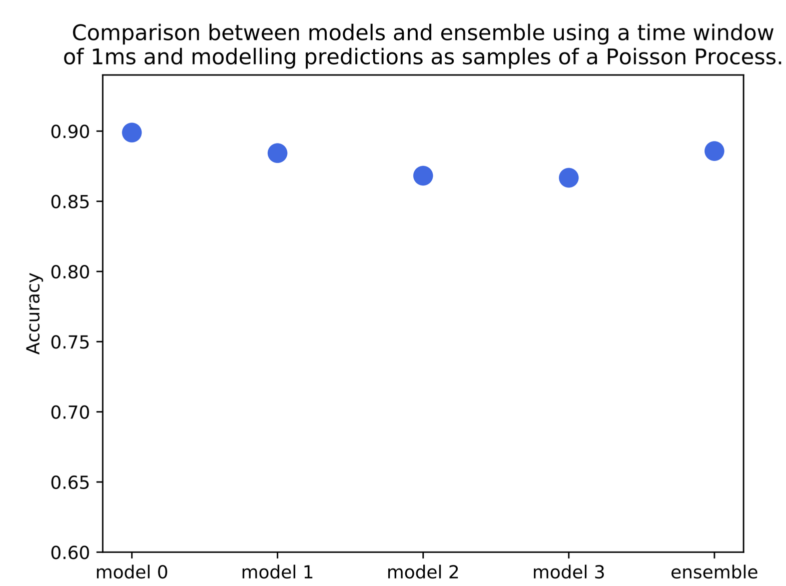
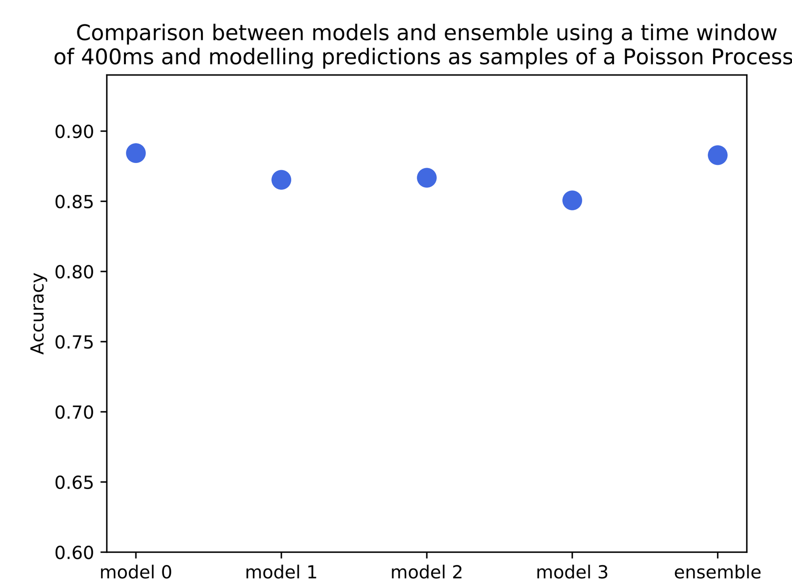


Fig. 2: Spikes as class probabilities





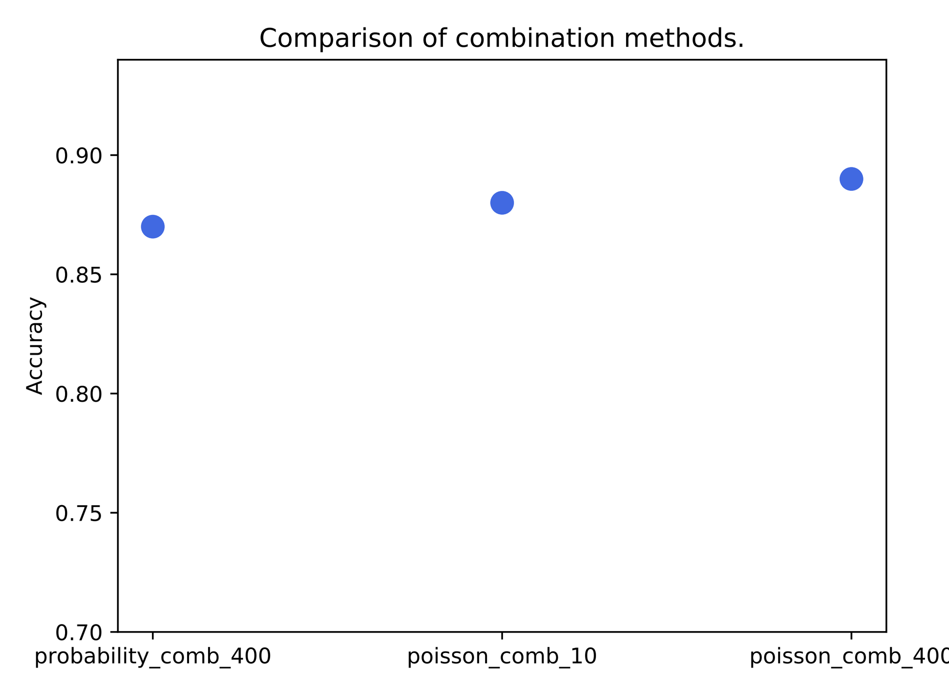
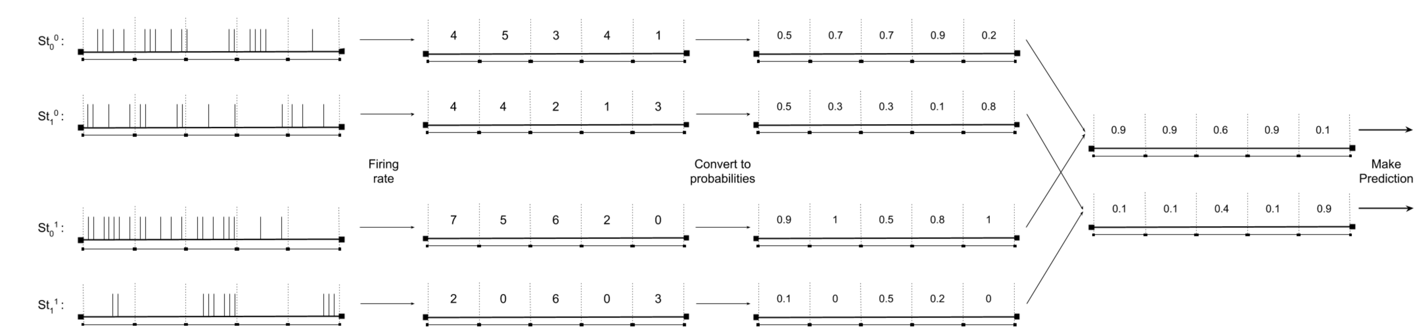


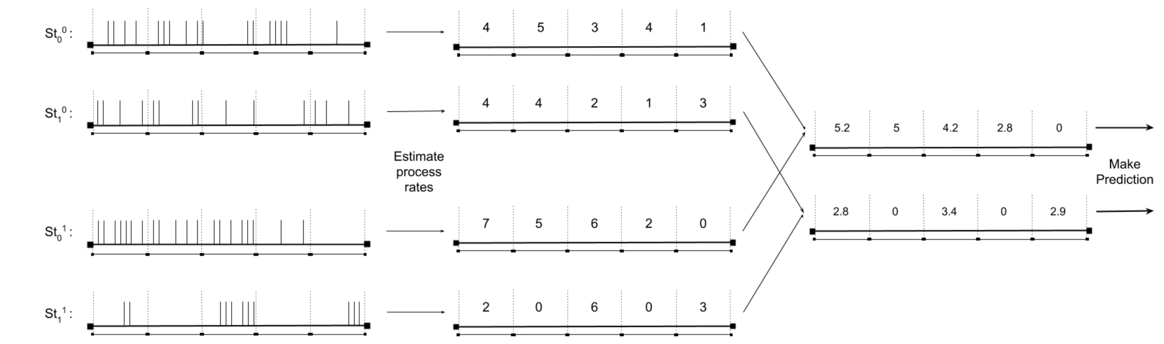
Fig. 3: Comparison of the combination methods

Combining Spiking Predictions

Spikes as class probabilities



Spikes as samples of a Poisson Point Process



Future Work

The results presented are only a sample of the experiments ran. They were chosen to illustrate the fact that a combination method that produces an ensemble with the properties of the central model might exist.
A promising research direction is to investigate the properties of more biologically realistic methods of combining the information from several spike trains, using ensemble learning methods. Such combination methods are widely referred to as Population Coding.

Acknowledgements

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References

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