

# Decision-Making Networks using Spiking Neurons



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## Introduction

Decisions often have to be made on imperfect input. For example, in a forced choice task such as random-dot motion discrimination, uncertainty can be added to the task by decreasing the coherence of the moving dots. Hence, a decision-making model needs to function in the presence of noisy input.

A number of computational decision models have been proposed, some of which mirror the architecture of the basal ganglia [Gurney et al., 2001; Bogacz and Gurney, 2007]. The race model [Vickers, 1970] simply integrates the input stream. The multi-hypothesis sequential probability ratio test (MSPRT) computes the relative probabilities of observing each input stream [Bogacz & Gurney, 2007]. However, these methods are usually implemented using firing-rate nodes, and not directly using spiking neurons.

In this study, we implement different models using the Neural Engineering Framework [Eliasmith & Anderson, 2003] and compare their performance on noisy 3-choice decision tasks.

## Neural Engineering Framework

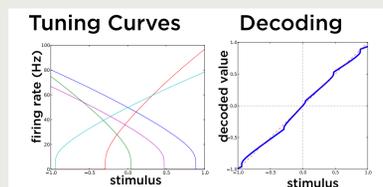
### Leaky Integrate-and-Fire (LIF) Neuron Model

$$x(t) \rightarrow \alpha e^{-x(t) + \beta} \rightarrow \text{input current} \rightarrow \tau \frac{dv}{dt} = RJ(t) - v \rightarrow \text{integrate} \rightarrow \text{activity } a(t) = \sum_p \delta(t - t_p) \rightarrow \text{spike train}$$

$$a(t) = \begin{cases} \frac{1}{\tau_{ref} - \tau \ln(1 - \frac{v_{th}}{v(t)})} & \text{if } v(t) > v_{th} \\ 0 & \text{otherwise} \end{cases}$$

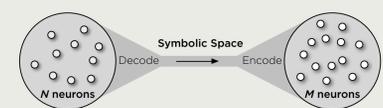
### Population Coding

If we know the tuning curves for a population of neurons, then we can infer the input from the pattern of neural firing rates. We use optimal linear decoding. We can even encode/decode vectors, as well as functions of that data.



### Neural Transformations

We can choose the connection weights from one population to another to transform our data. The weight matrix is the outer product between the encoders and the decoders (for the desired transformation).



### Neural Dynamics

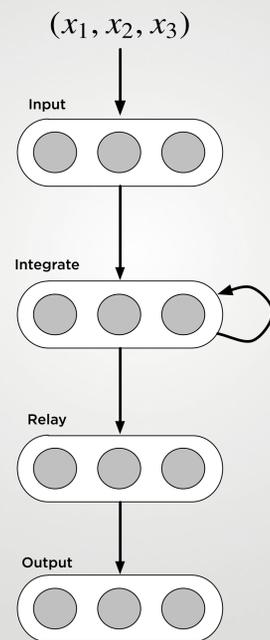
We can also implement dynamics, like a neural integrator, using a recurrently-connected population. It decodes and feeds back the encoded value, and combines it with incoming data.

$$x(t) \rightarrow \text{neural integrator} \rightarrow y = \int x(t) dt$$

## Network Models

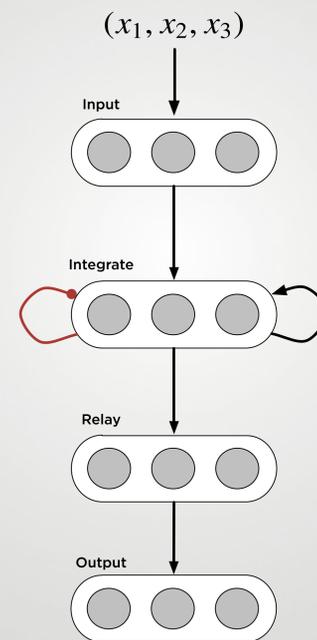
### Race

Based on [Vickers, 1970]. The "Input" layer and "Relay" layer were added to ensure network depths were comparable.



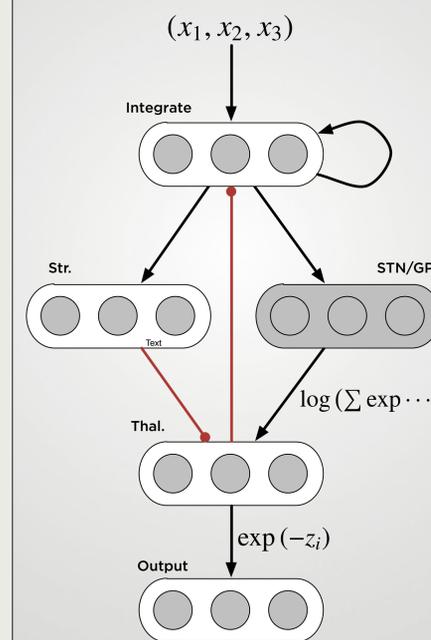
### Inhibitory Race

The same as the Race network, except each integrator inhibits each of the others [Usher & McClelland, 2001].



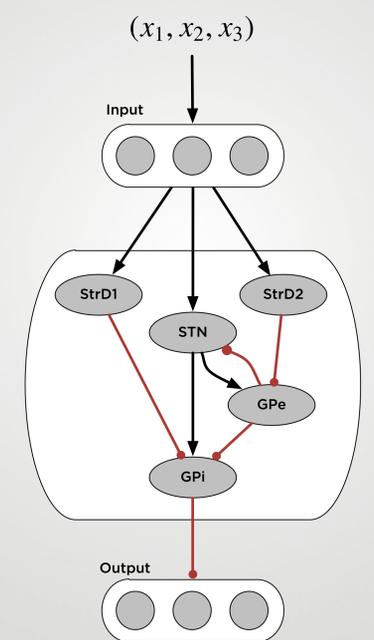
### MSPRT

The Multi-hypothesis Sequential Probability Ratio Test is based on [Bogacz & Gurney, 2007].



### GPR

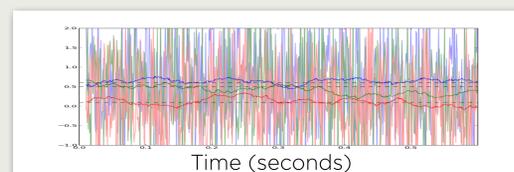
The Gurney-Prezcott-Redgrave model is based on [Gurney et al, 2001], as implemented by [Stewart et al, 2010].



## Experiments

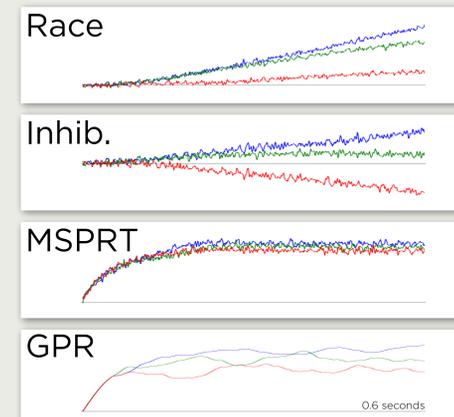
### Input

Three Gaussian input signals:  
 $N(0.6, 1)$   $N(0.5, 1)$   $N(0.1, 1)$



Faint lines show actual input.  
Solid lines show low-pass filtered input.  
Dotted lines show input means.

### Sample Run

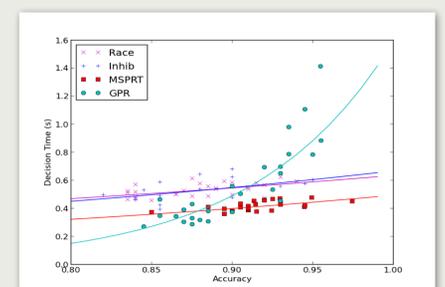


### Results

For a chosen threshold, each method was run on 100 different inputs.

For each run, we recorded:  
**Selection:** which signal reached the threshold first.  
**Decision Time (DT):** when the first signal reached the threshold.

After 100 trials, we computed:  
**Accuracy:** % where selected signal had highest affinity (0.6).  
**Average DT:** average time to decision.



Decision Time (ms)	Accuracy		
	85%	90%	95%
<b>Race</b>	508	547	590
<b>Inhib. Race</b>	498	550	607
<b>MSPRT</b>	360	400	445
<b>GPR</b>	273	491	885

### References

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