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Temporal pattern recognition in retinal ganglion cells is mediated by dynamical inhibitory synapses

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Temporal pattern recognition in retinal ganglion cells is mediated by dynamical inhibitory synapses

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28.06.2023

Neuromod Meeting 2023

Antibes

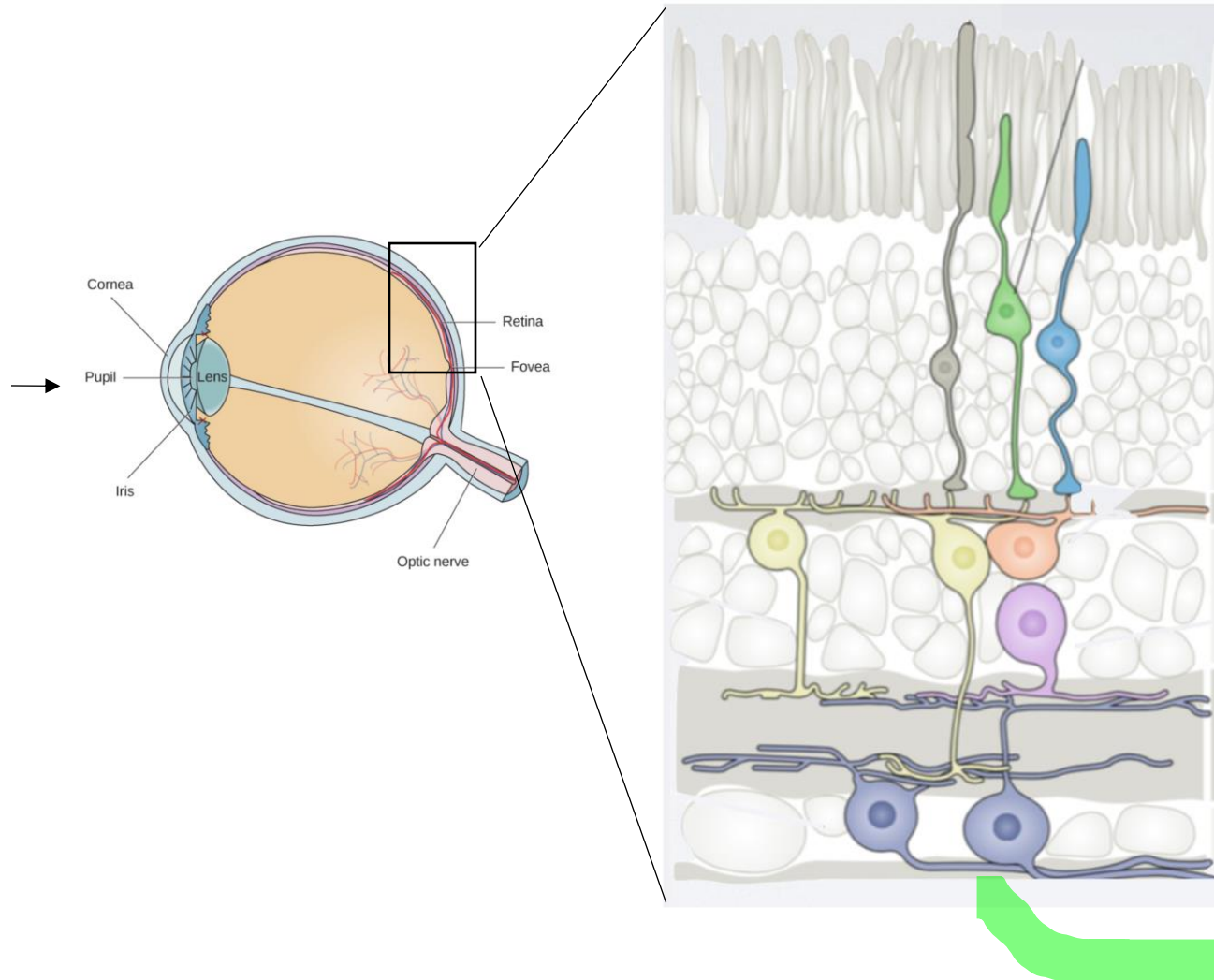
Inria



UNIVERSITÉ
CÔTE D'AZUR



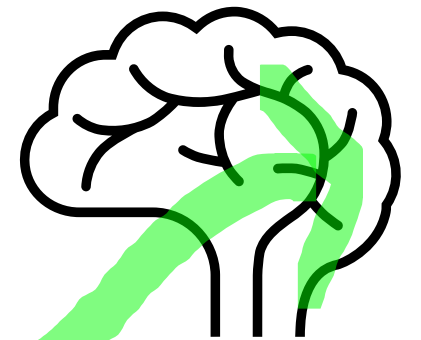
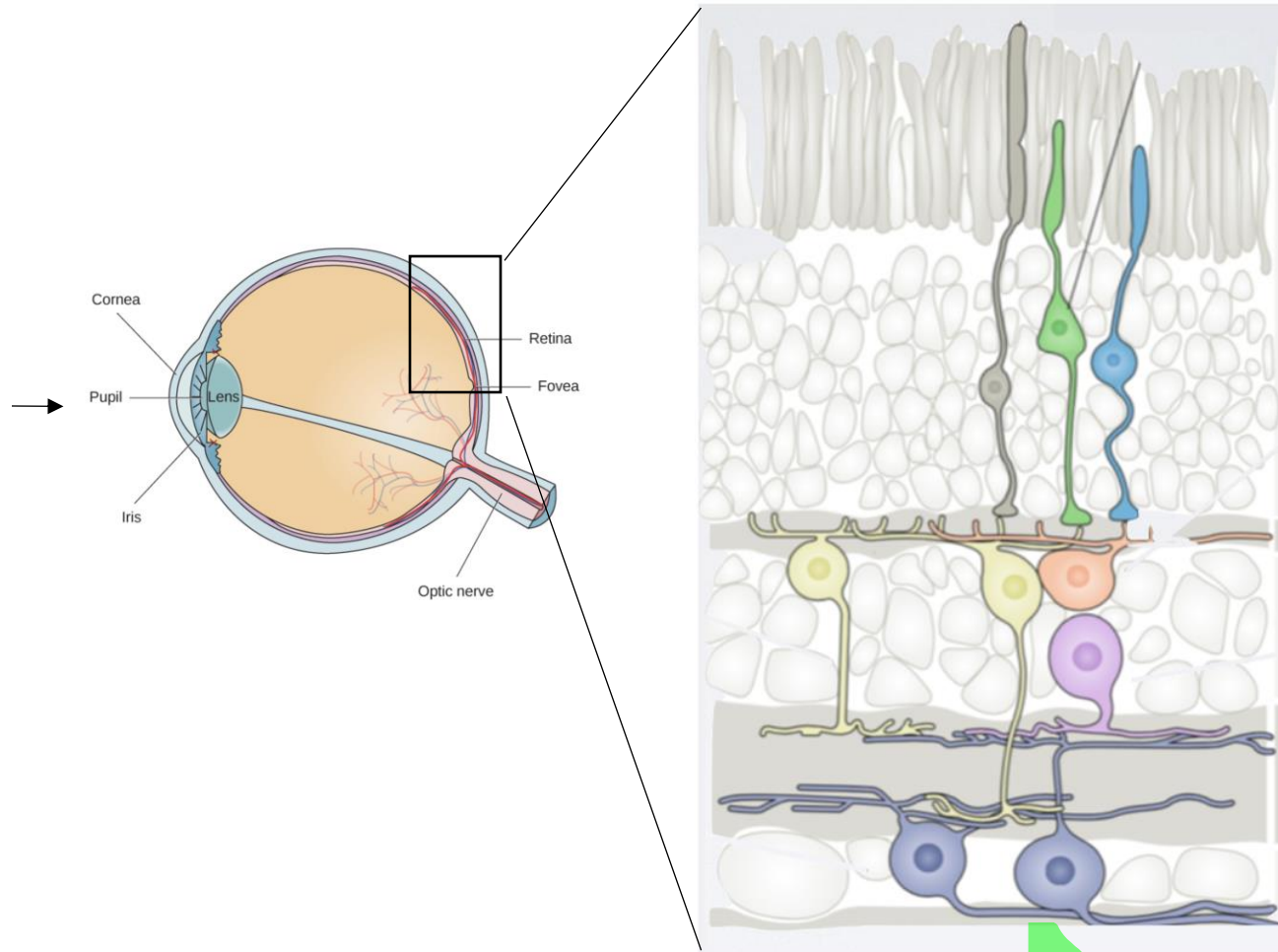
Information Processing in the Retina



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Information Processing in the Retina

- Transforms visual inputs into neuronal responses

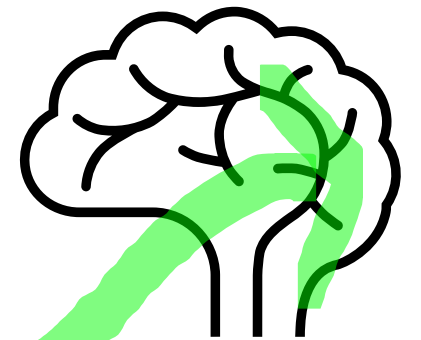
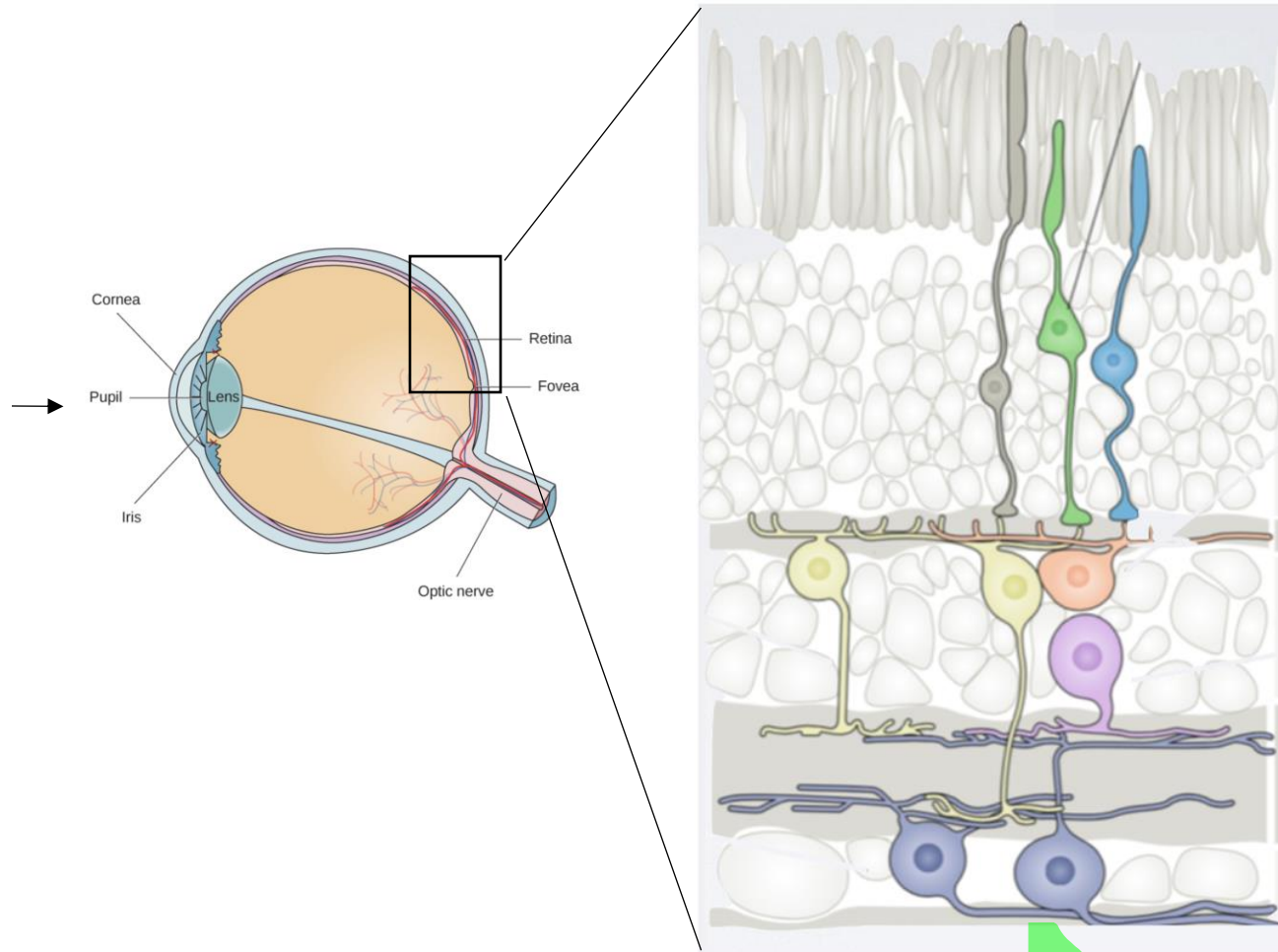


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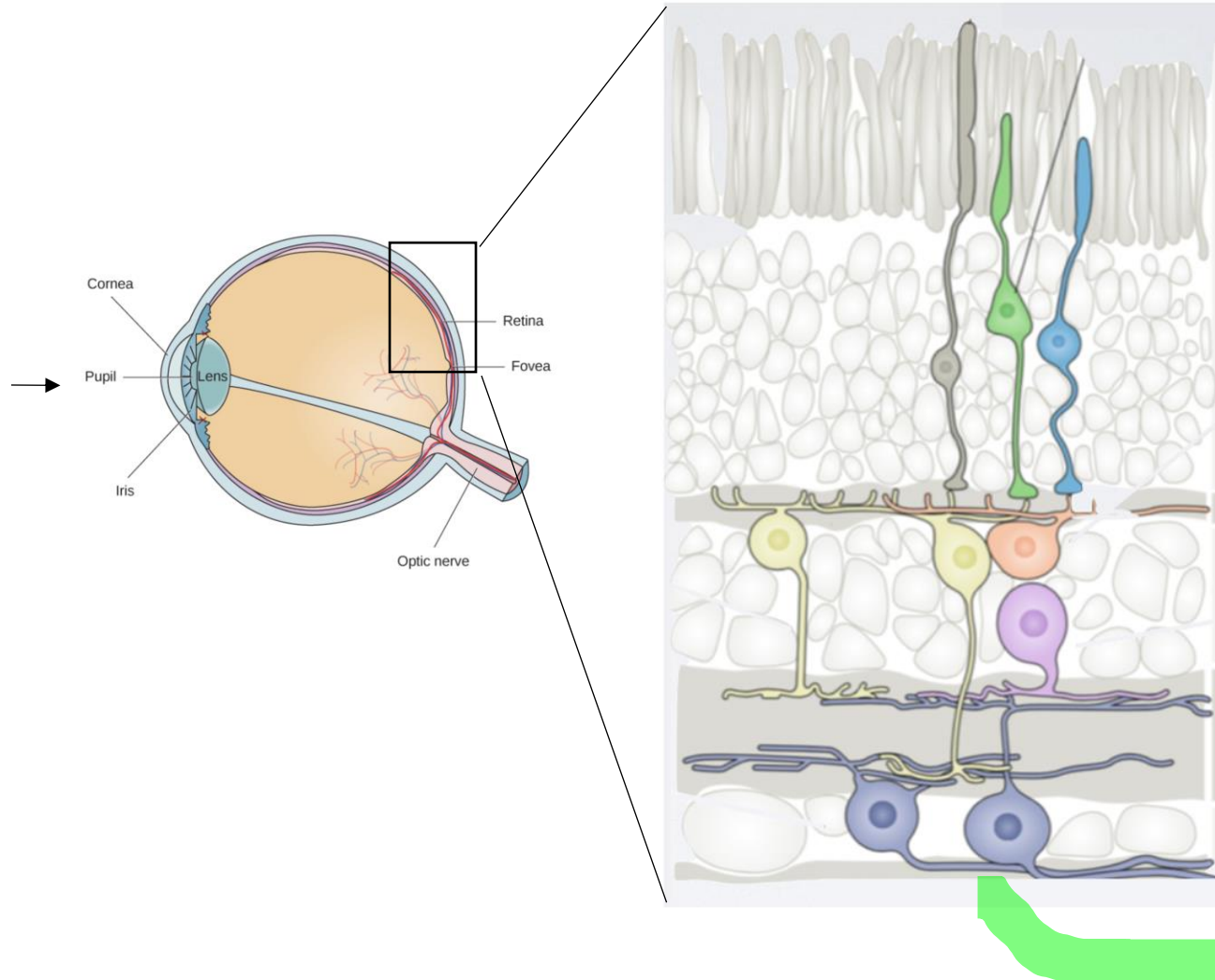
- 3 layered network for analog processing visual inputs



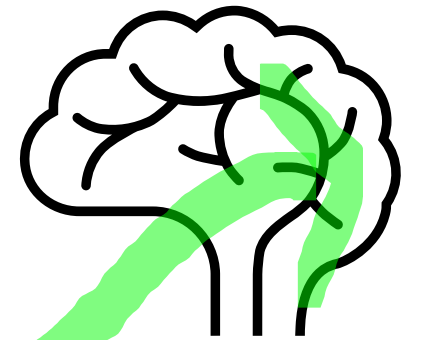
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Information Processing in the Retina

- Transforms visual inputs into neuronal responses
- 3 layered network for analog processing visual inputs
- Complex excitatory and inhibitory interactions to facilitate extraction of relevant information



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Prediction and Surprise in the Retina

- The retina does not encode the visual scene *per se*



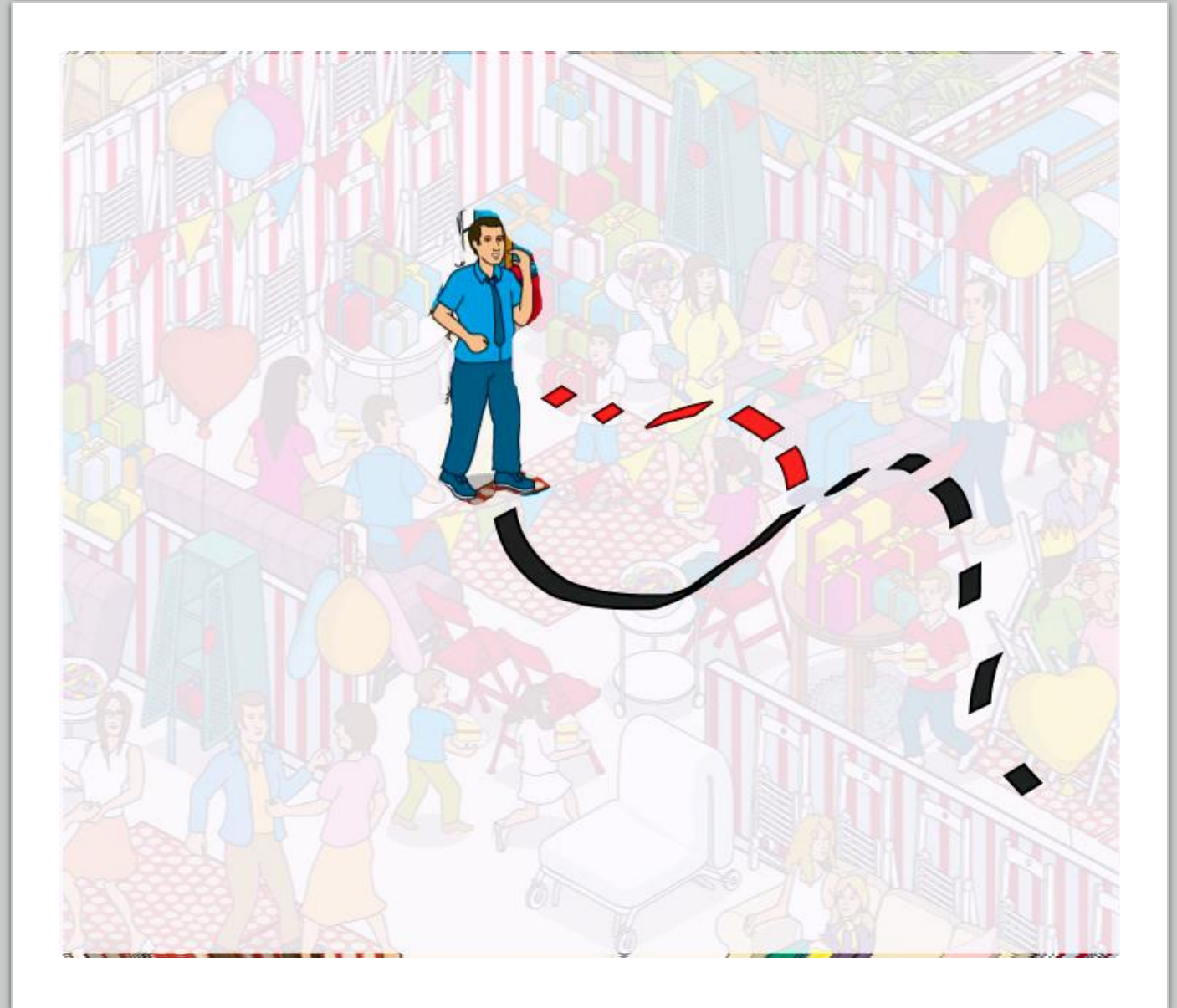
Prediction and Surprise in the Retina

- The retina does not encode the visual scene *per se*
- but forms predictions about future stimuli



Prediction and surprise in the Retina

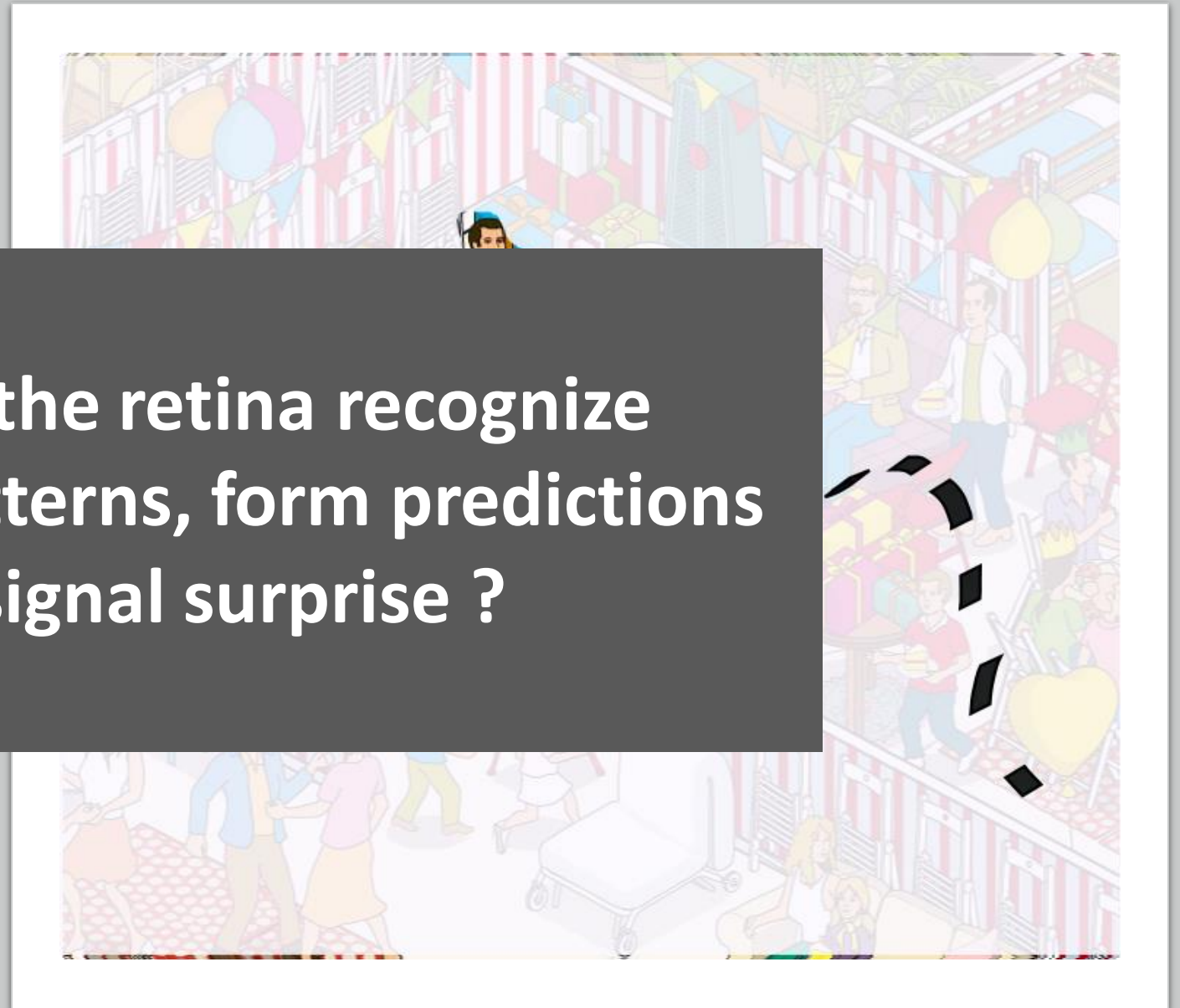
- The retina does not encode the visual scene *per se*
- but forms predictions about future stimuli
- and signals surprise about unpredicted inputs (= error signal)



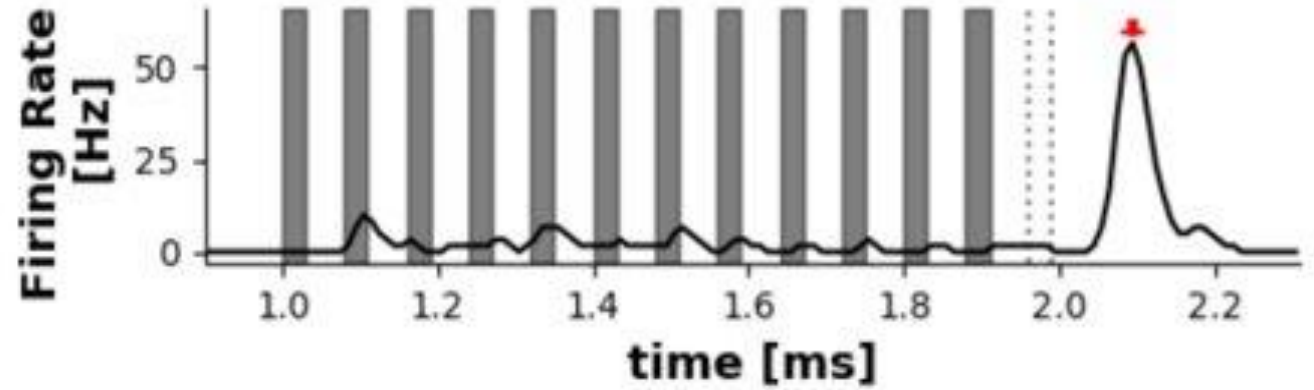
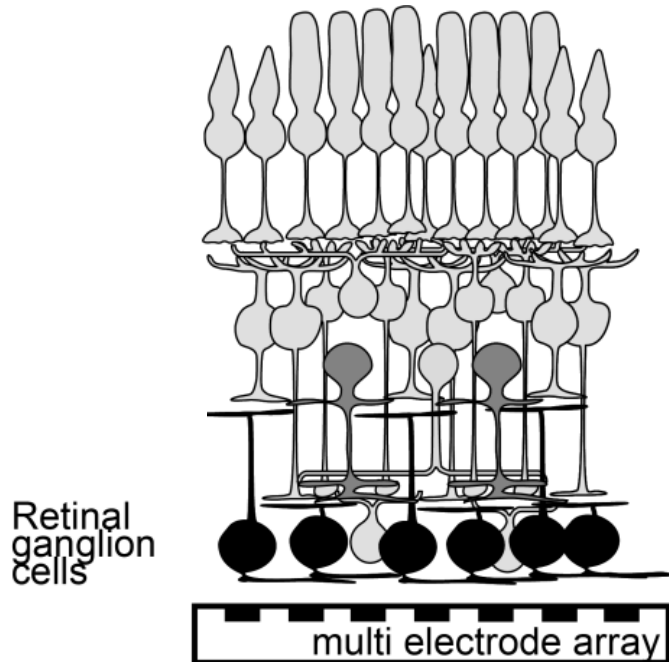
Prediction and surprise in the Retina

- The retina does not just passively receive the visual scene
- but forms predictions about future stimuli
- and signals surprise about unpredicted inputs (= error signal)

How can the retina recognize temporal patterns, form predictions and signal surprise ?



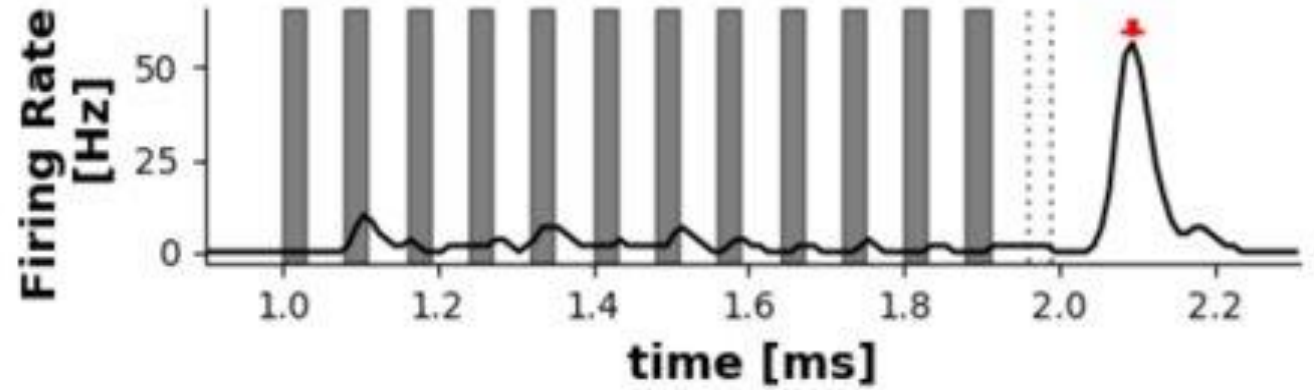
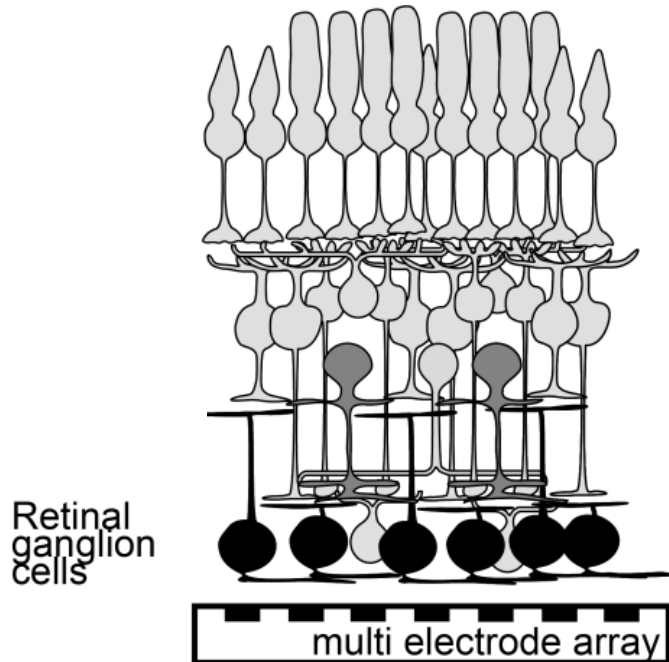
Surprise Response in the Retina



- periodic flash sequence
- omitted flash
- ↓ pulse of activity signaling the missing stimulus

first observed by Schwartz et al, 2007

Surprise Response in the Retina



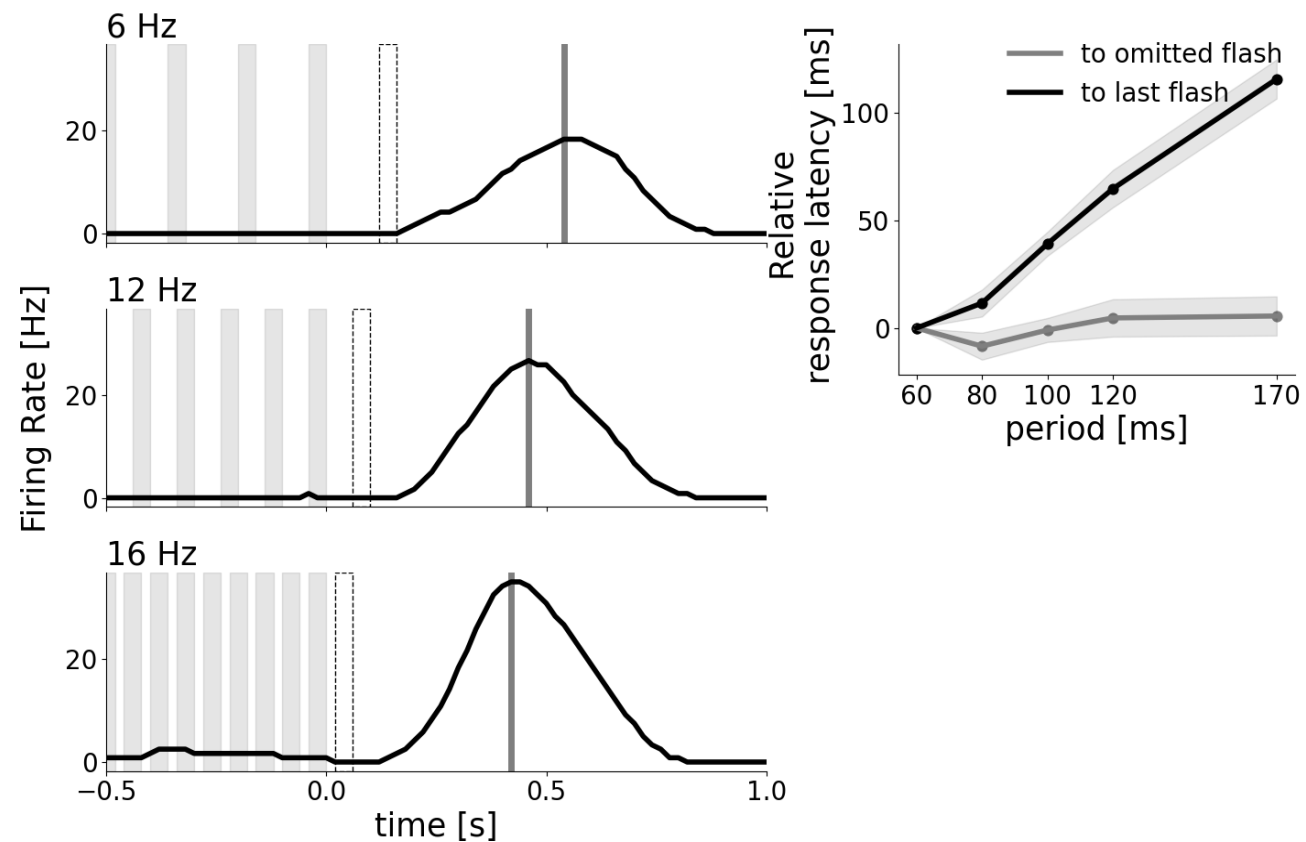
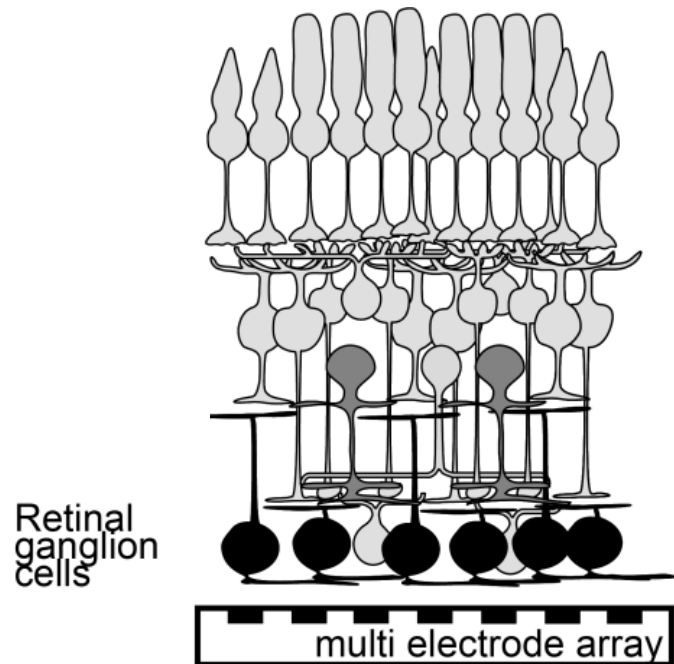
- periodic flash sequence
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The retina emits an **Omitted Stimulus Response** when an expected stimulus in a periodic sequence is missing.

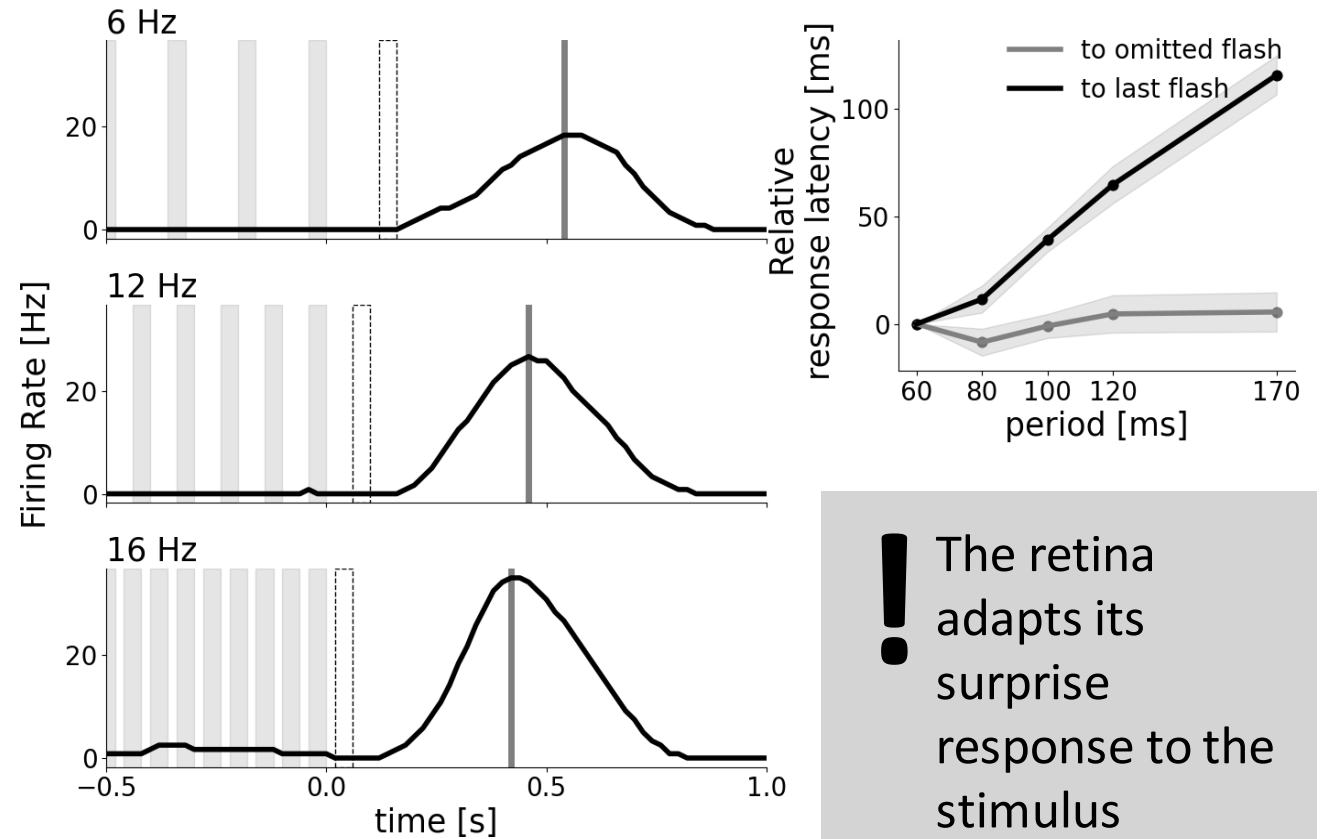
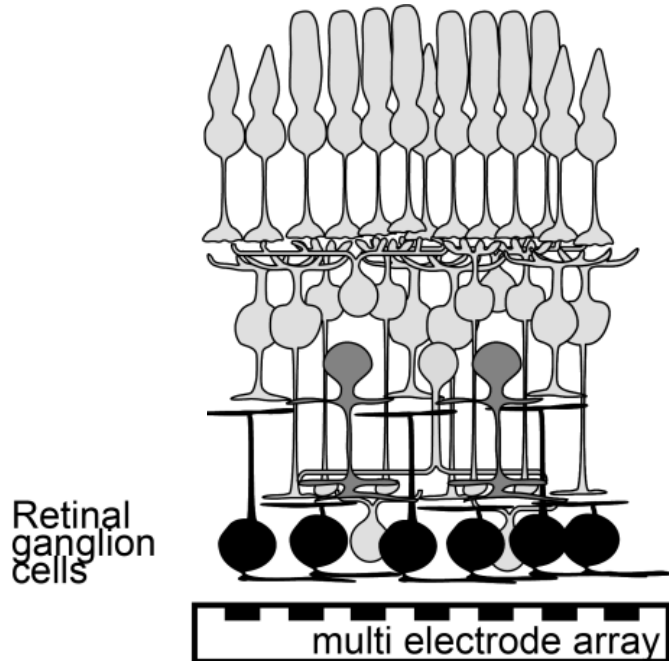
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Response latency shifts with stimulus period



first observed by Schwartz et al, 2007

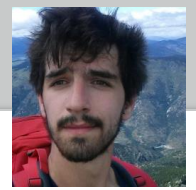
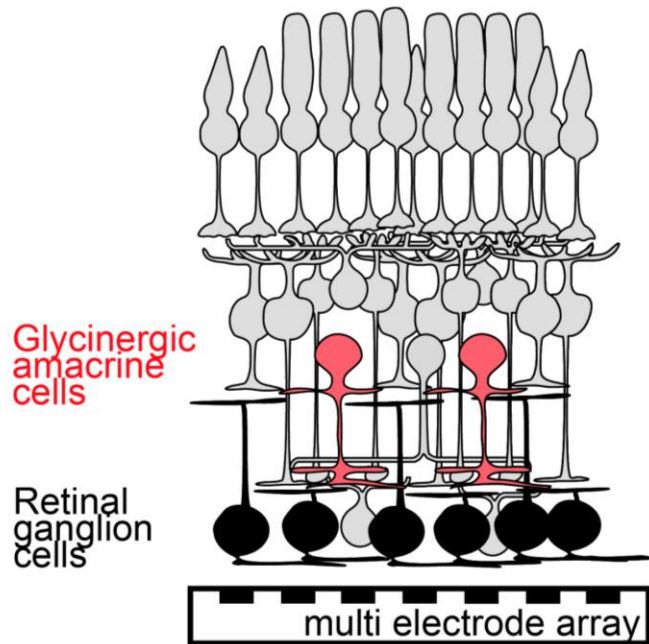
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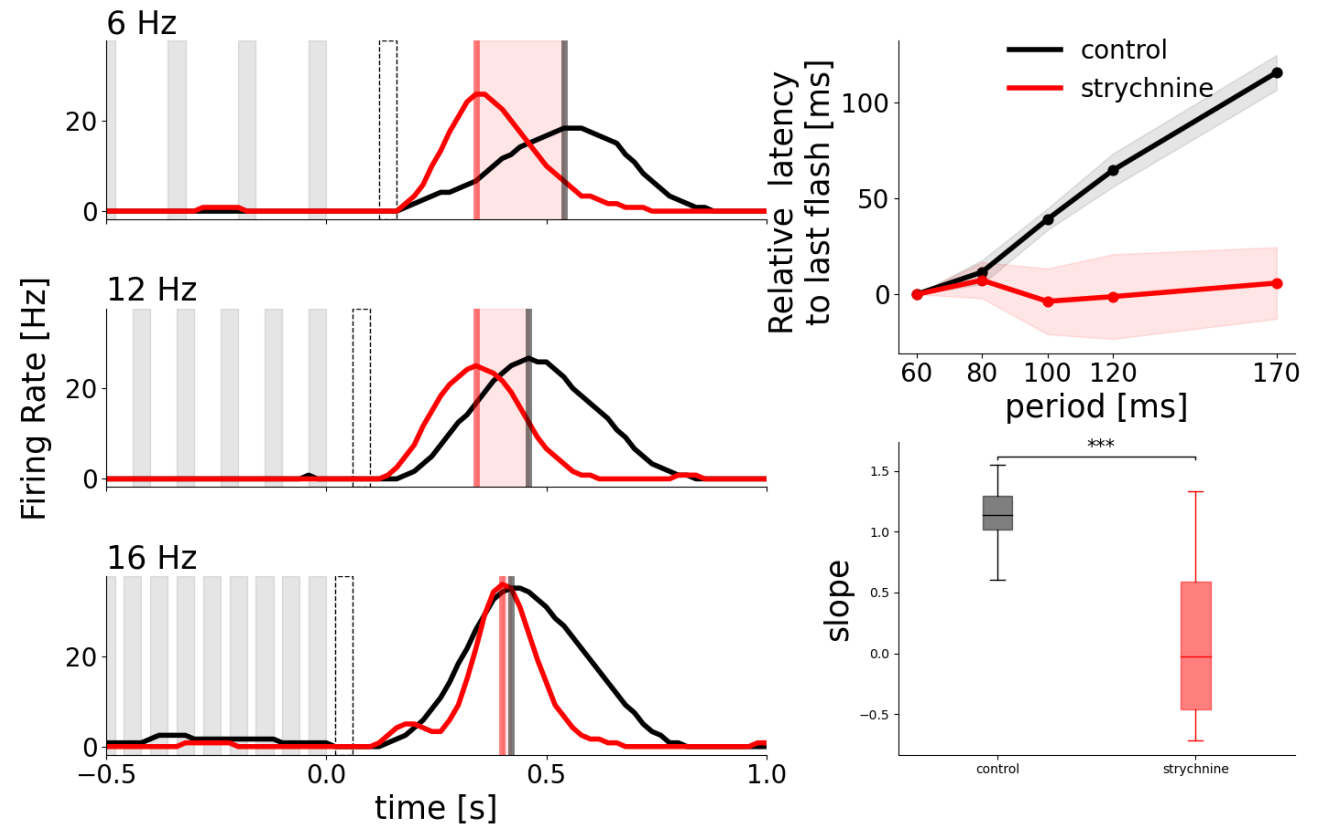
! The retina adapts its surprise response to the stimulus

first observed by Schwartz et al, 2007

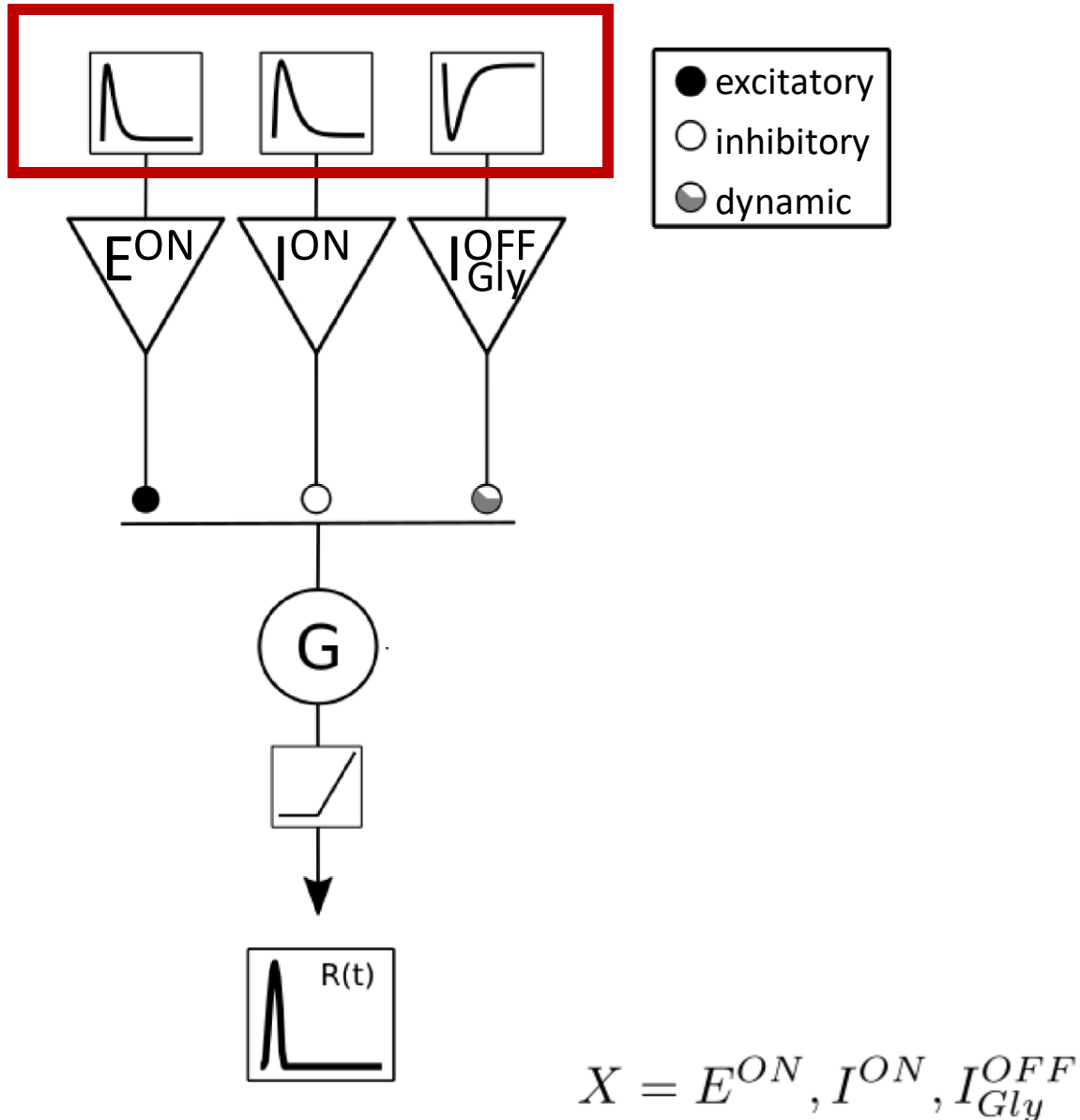
Inhibition is necessary for latency scaling



Thomas Buffet



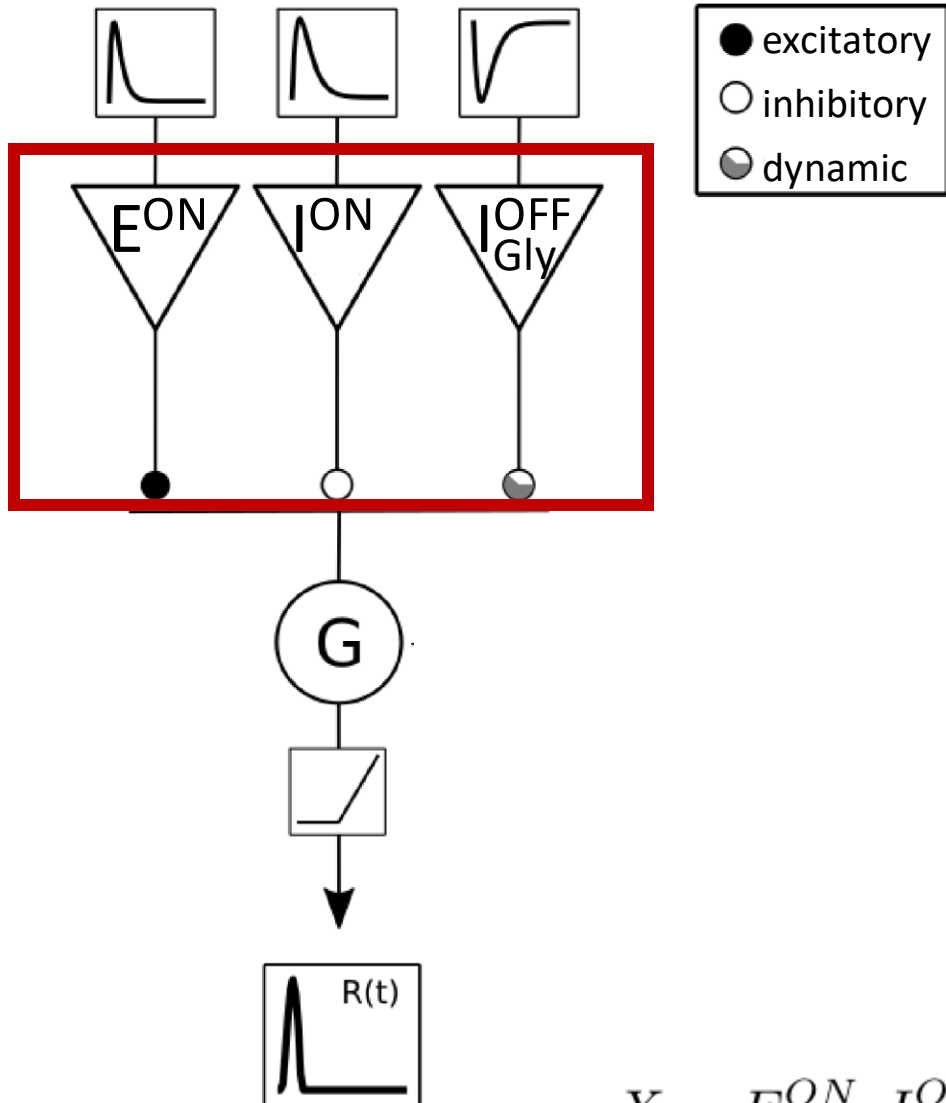
Dynamic Network Model of the Retina



1. Convolution of stimulus and temporal kernel

$$F_X(t) = S_X[\alpha_X * s](t)$$

Dynamic Network Model of the Retina



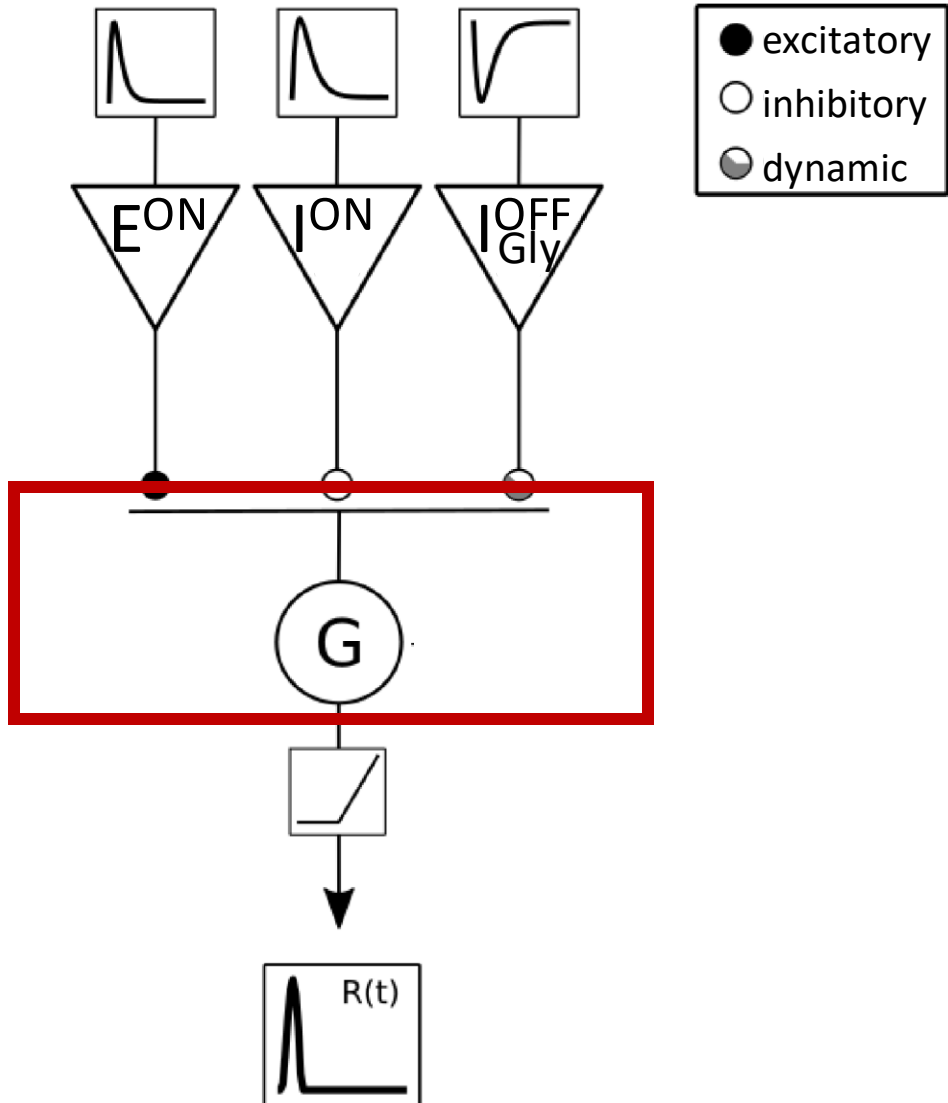
1. Convolution of stimulus and temporal kernel

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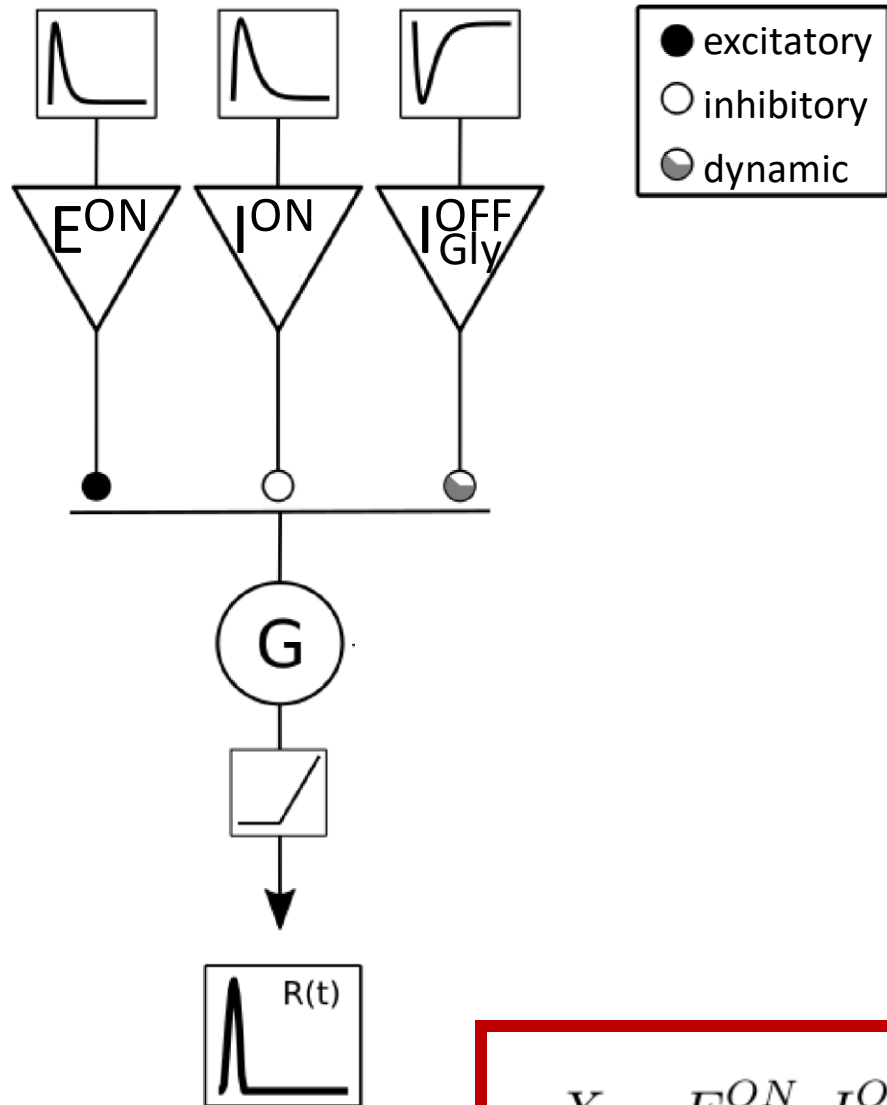
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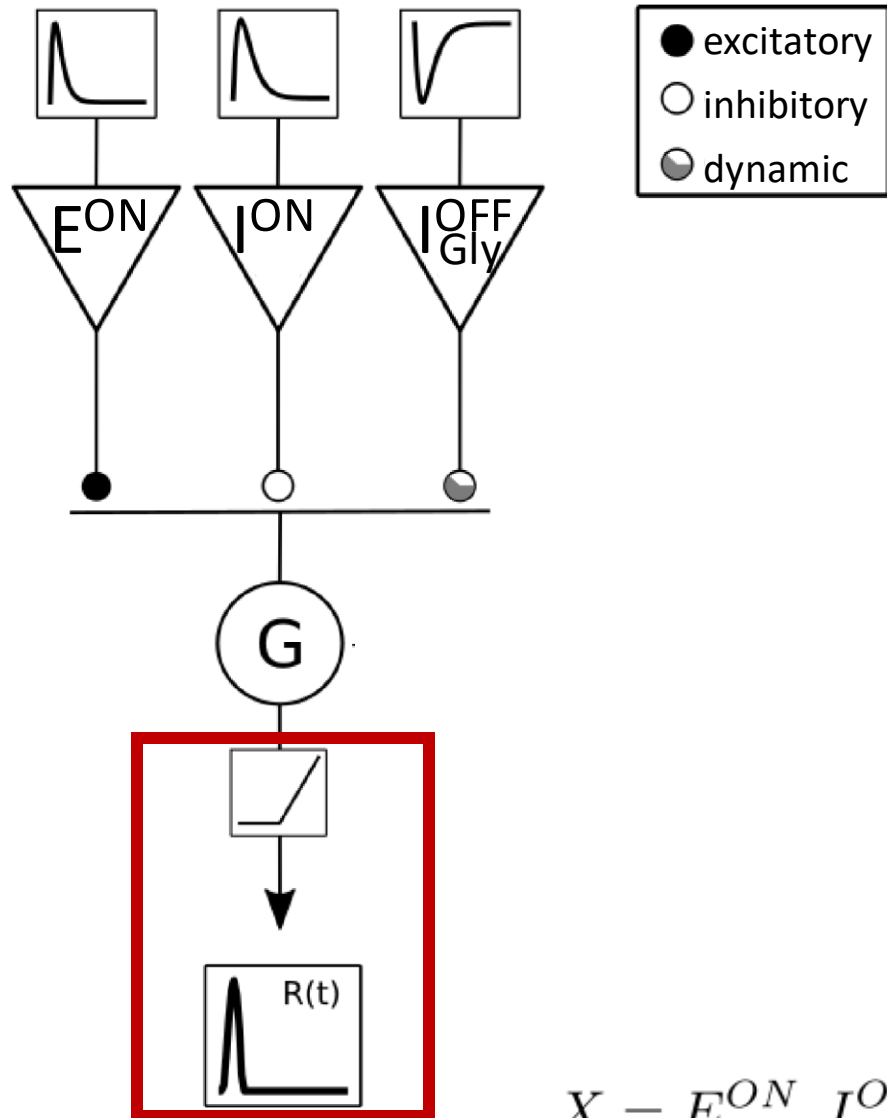
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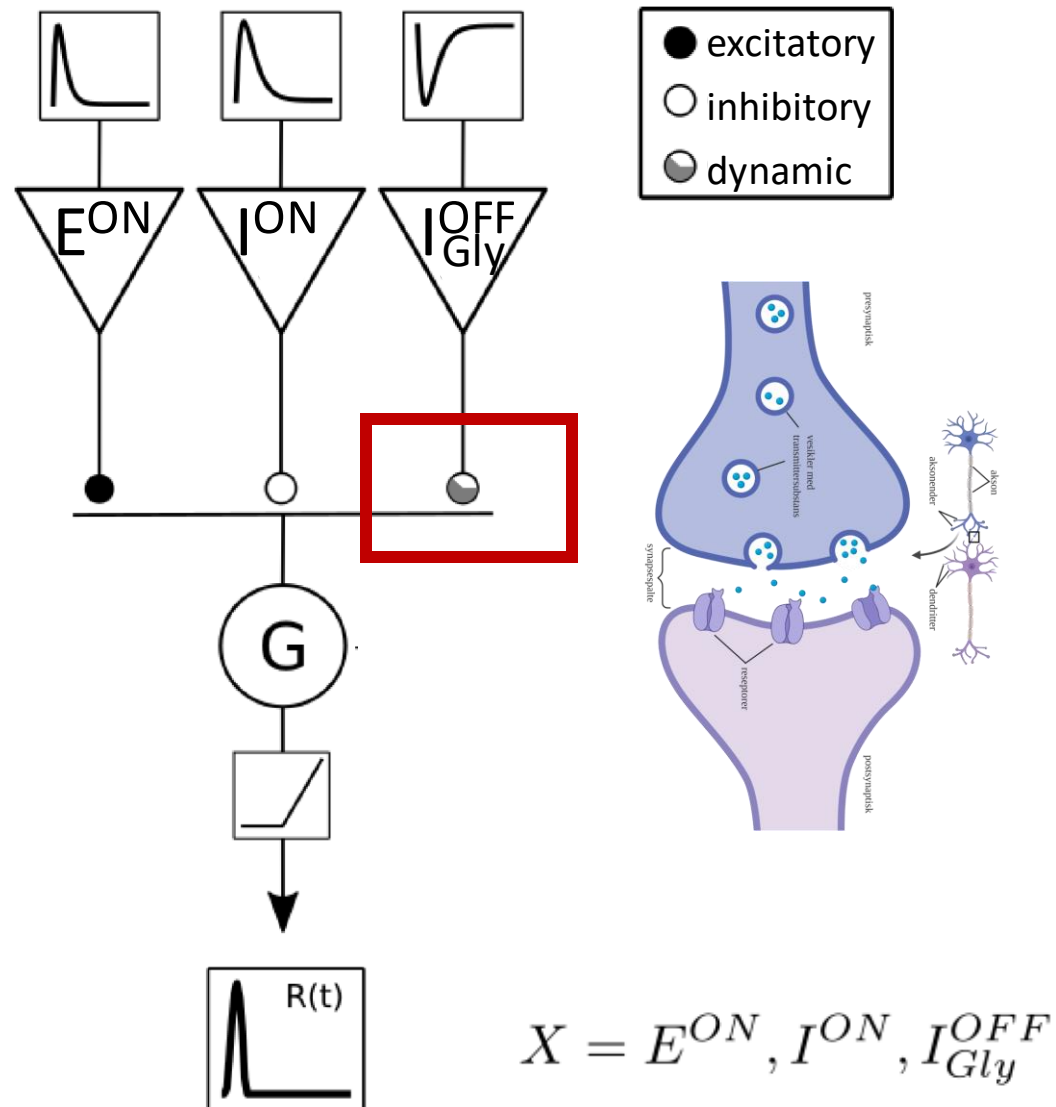
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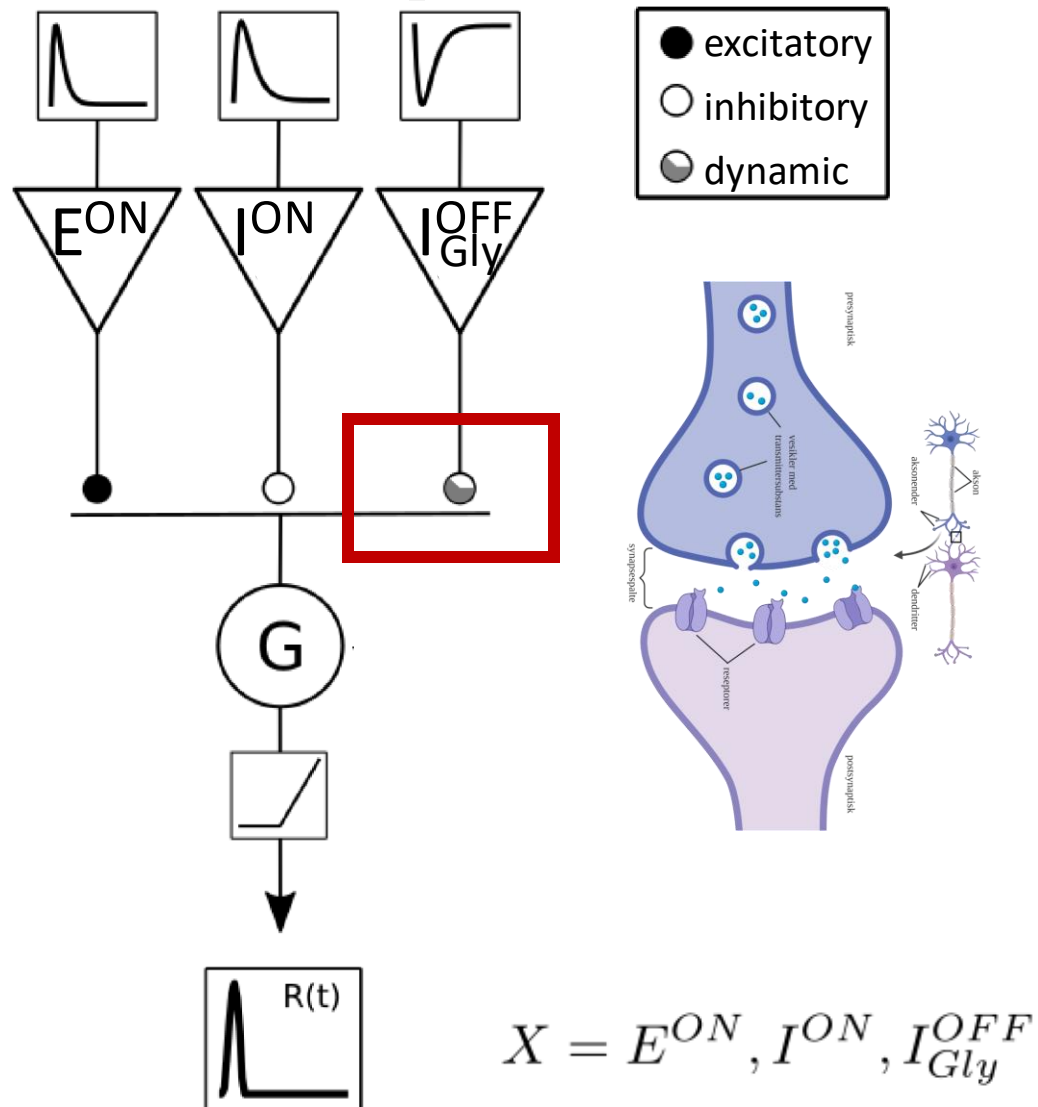
Input-dependent Adaptive Coupling via Short-term Depression



1. The variable n adapts dynamically to the input

$$\frac{dn}{dt} = (1 - n)k_{rec} - \beta k_{rel} p(V_{I^{OFF}_{Gly}}, \theta_{I^{OFF}_{gly}}) n$$

Input-dependent Adaptive Coupling via Short-term Depression

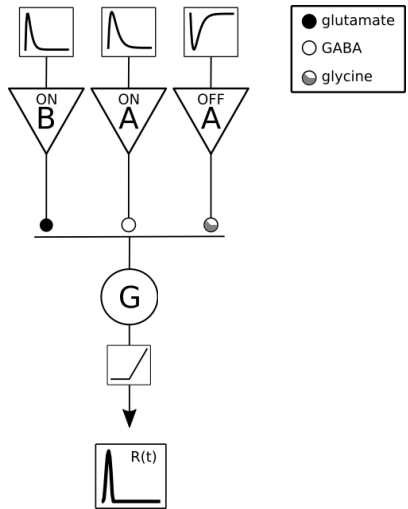


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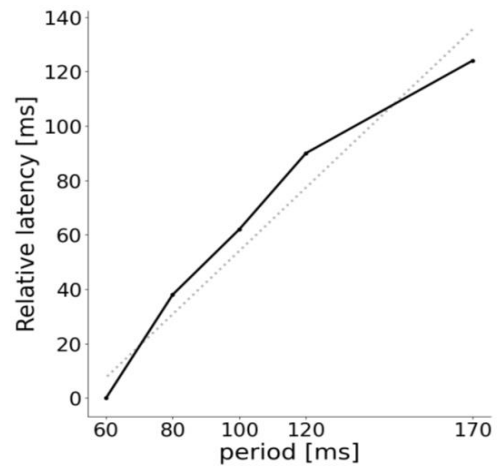
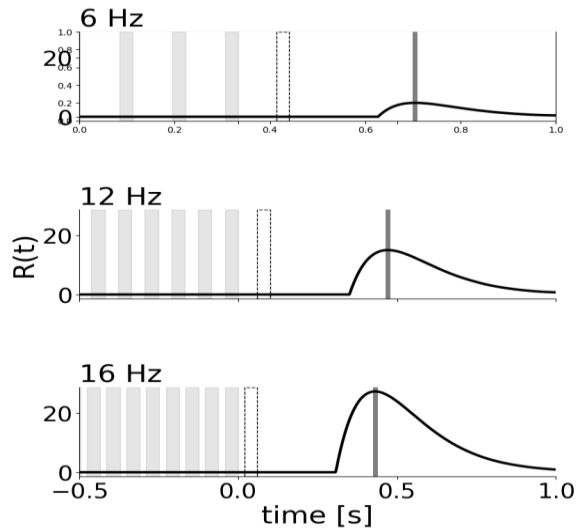
$$\frac{dn}{dt} = (1 - n)k_{rec} - \beta k_{rel} p(V_{I_{Gly}^{OFF}}, \theta_{I_{gly}^{OFF}}) n$$

2. The synaptic weight is scales by n

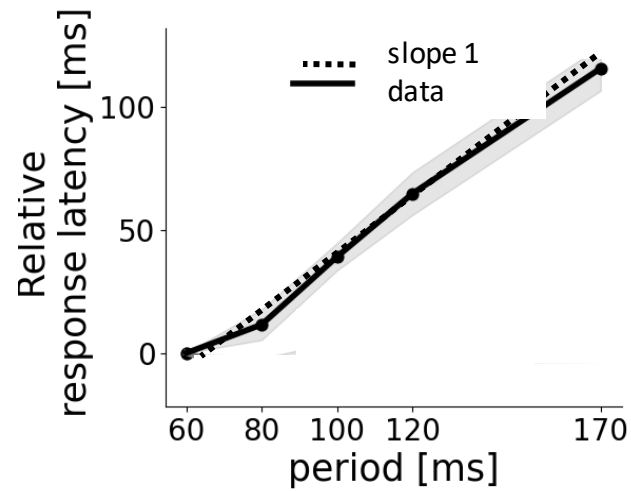
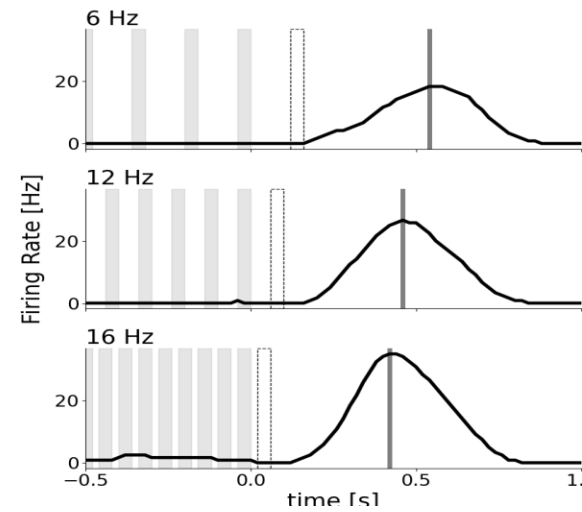
$$w(t) = \bar{w} n(t)$$



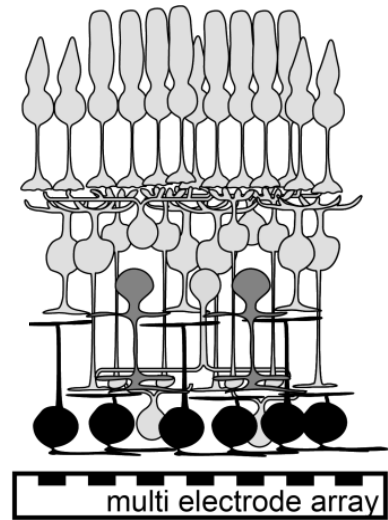
Model

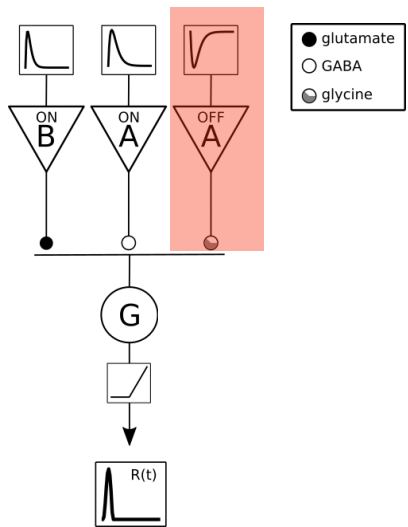


Experiments

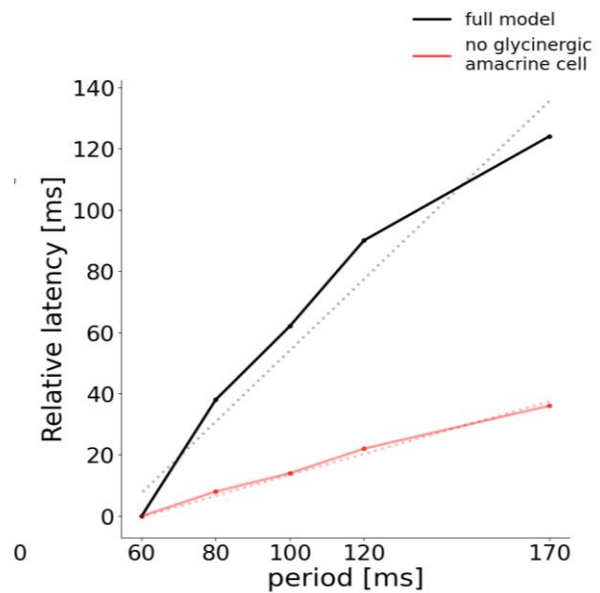
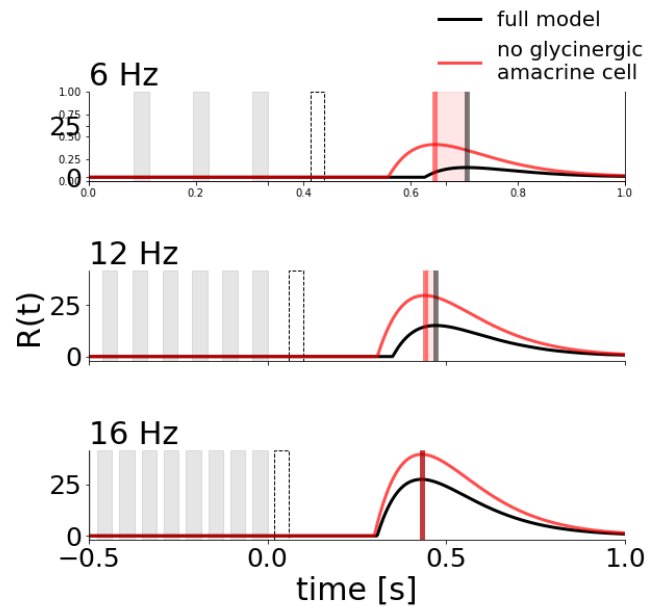


Retinal ganglion cells

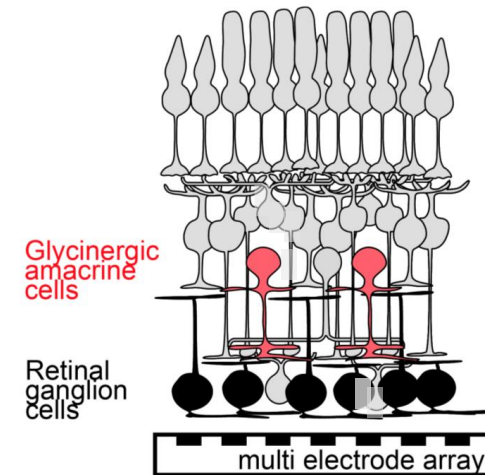
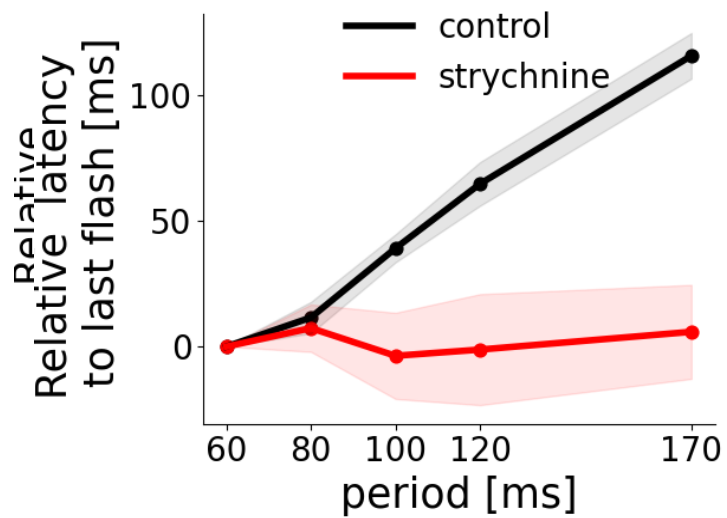
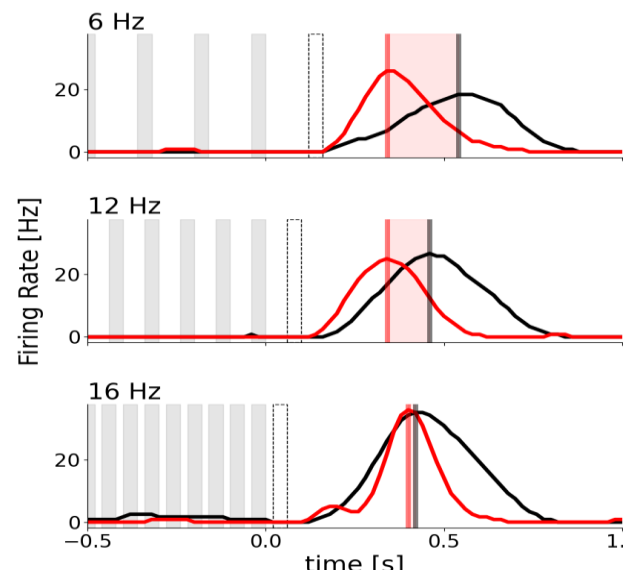




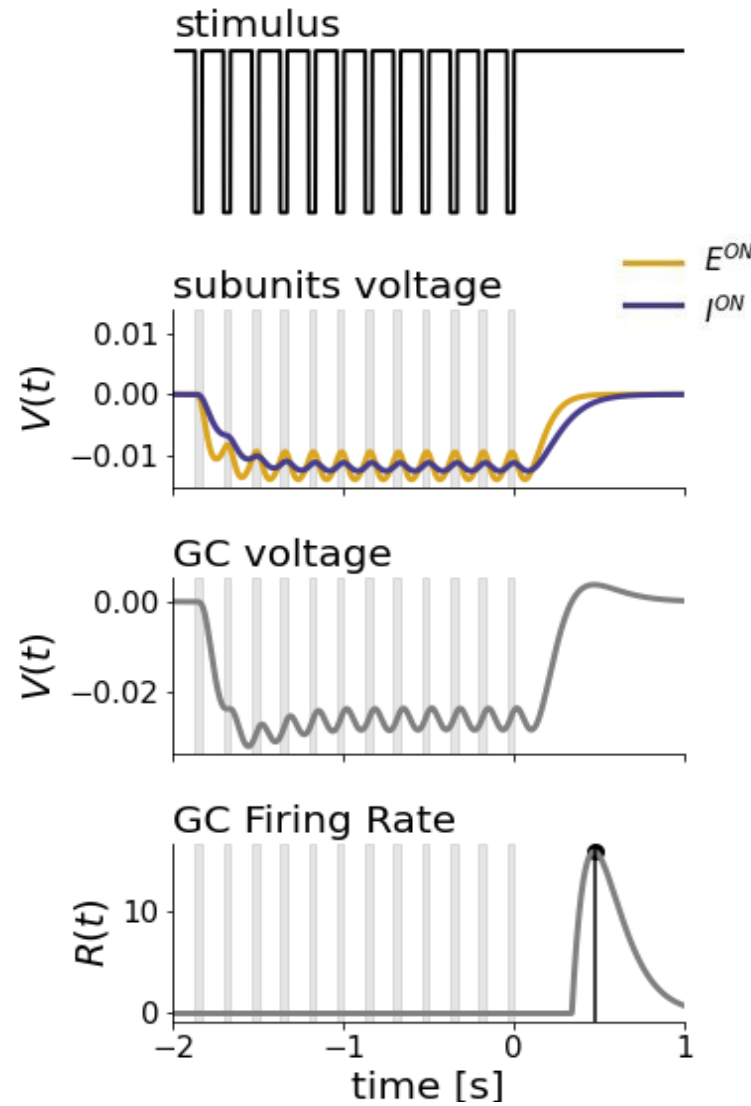
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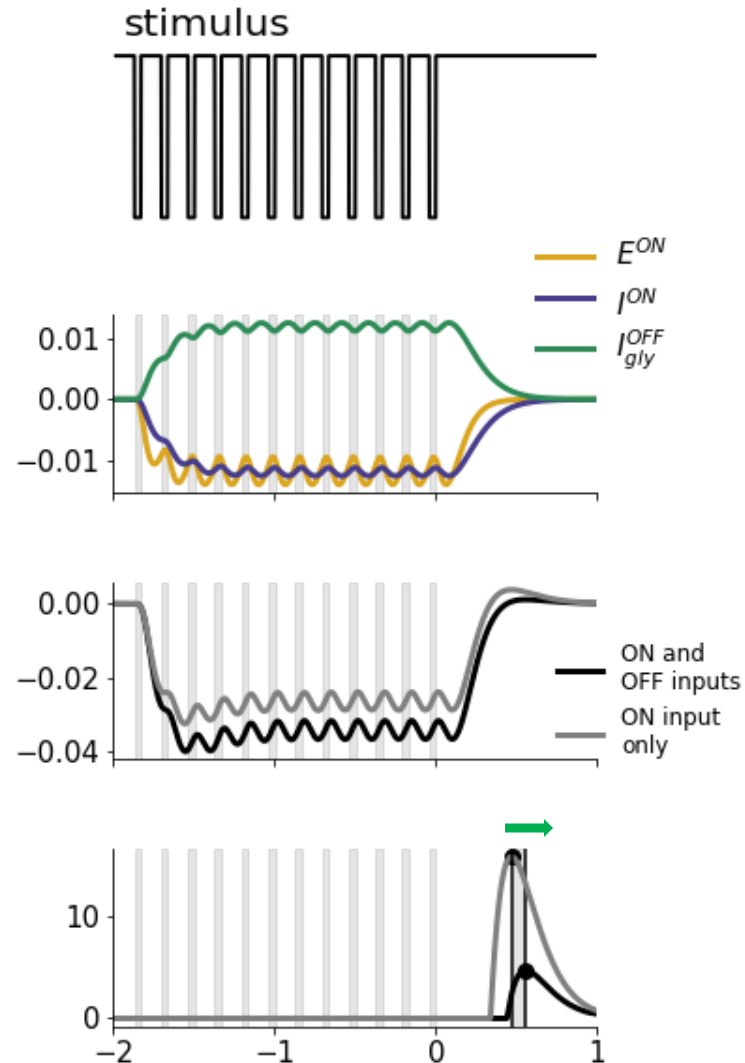
Model produces **error signal** via excitation and slower inhibition



$$\frac{dV_G}{dt} = -\frac{V_G}{\tau_G} + w_{EON} V_{EON} + n w_{I_{Gly}^{OFF}} p(V_{I_{Gly}^{OFF}}, \theta_{I_{Gly}^{OFF}}) + w_{ION} V_{ION}$$

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Additional inhibition **shifts the latency**



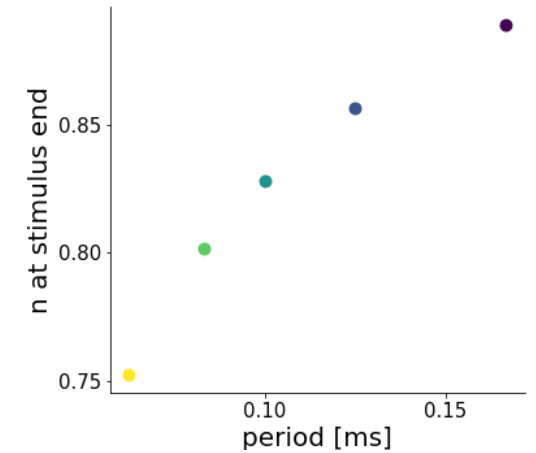
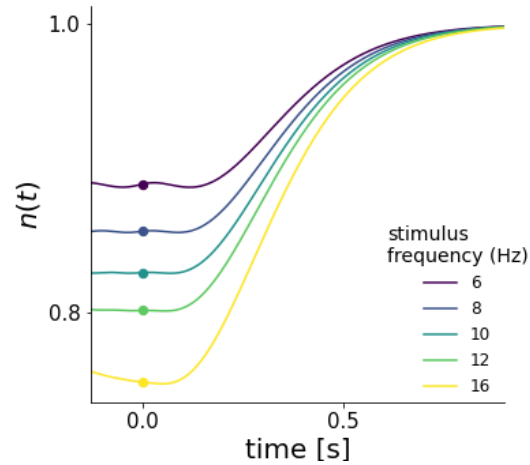
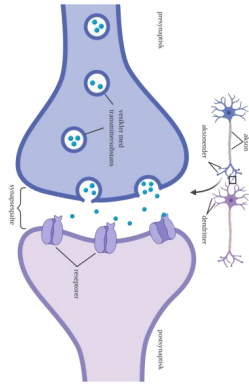
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Plasticity scales latency **shift to frequency**

$$\frac{dn}{dt} = (1 - n)k_{rec} - \beta k_{rel} p(V_{I_{Gly}^{OFF}}, \theta_{I_{gly}^{OFF}}) n$$



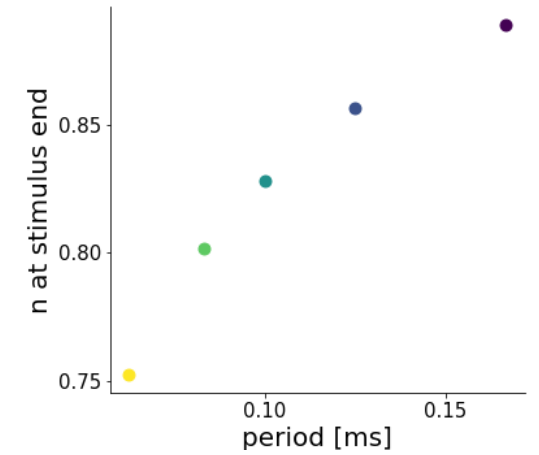
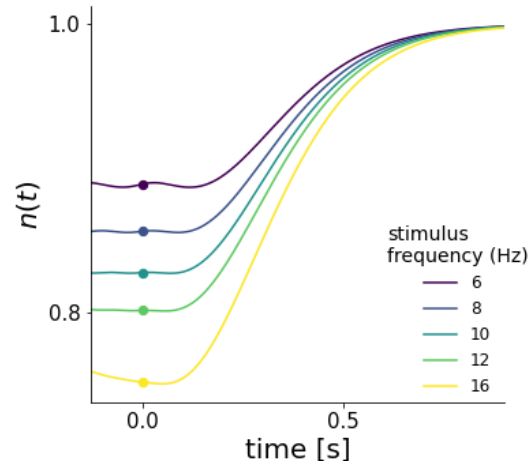
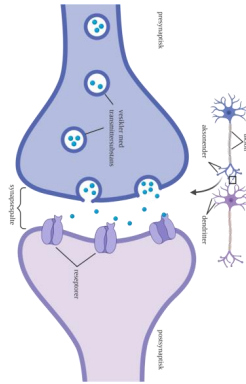
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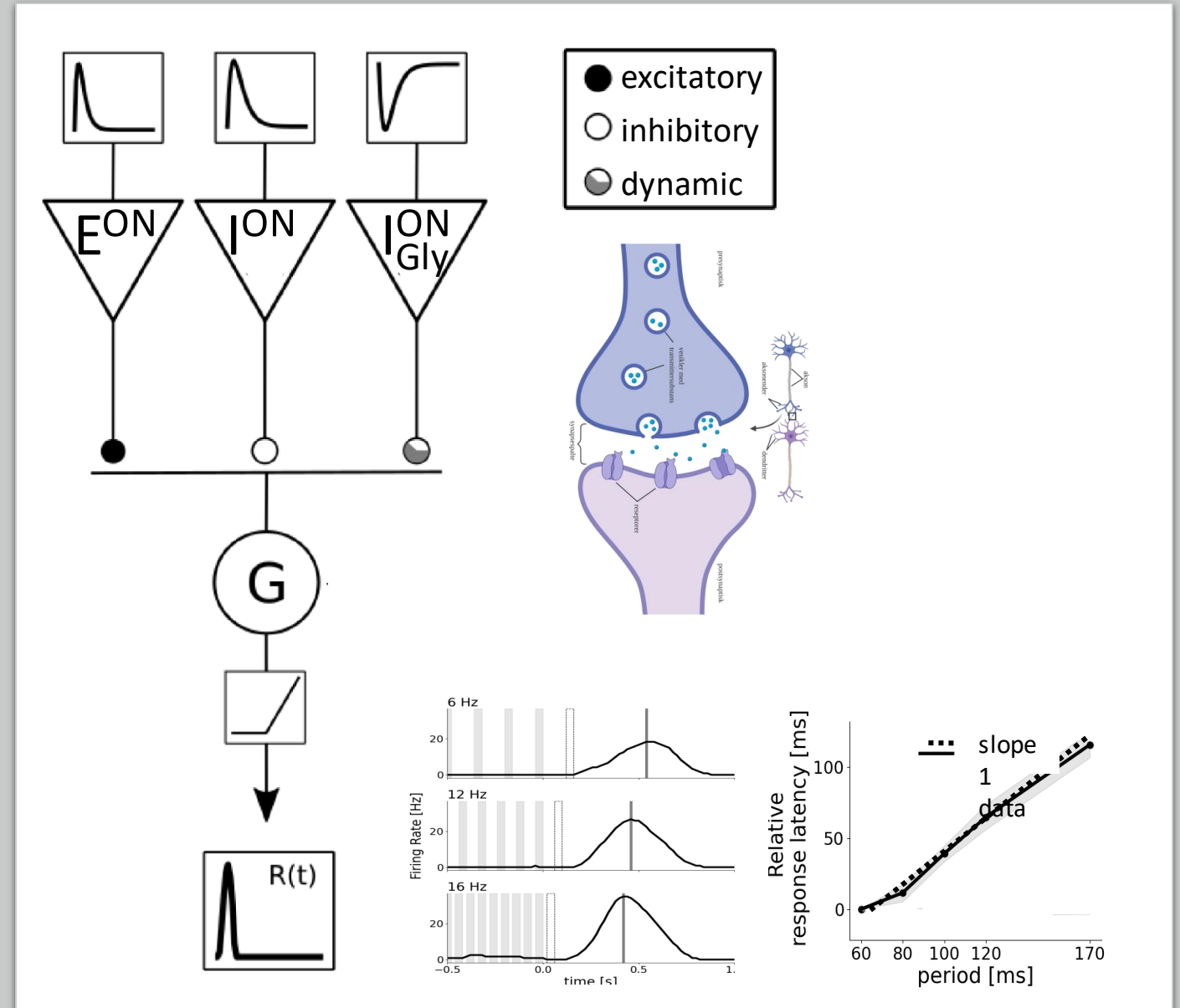
Conclusion

- Retina forms **predictions** about its future inputs and signals **surprise** when they are violated



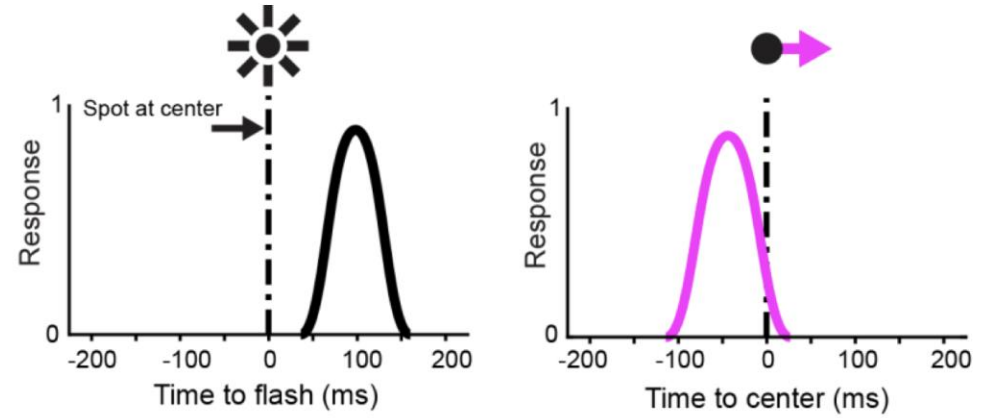
Conclusion

- Retina forms **predictions** about its future inputs and signals **surprise** when they are violated
- We show how this may be implemented via excitatory-inhibitory interactions
- temporal precision arises from **dynamic synaptic adaptation**



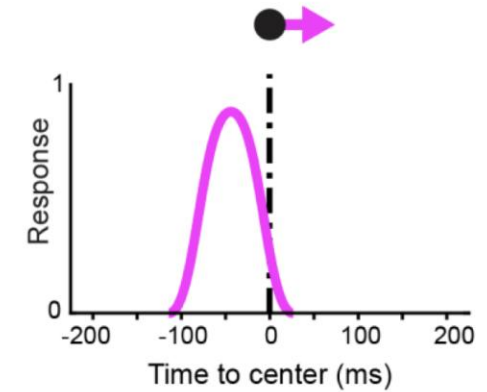
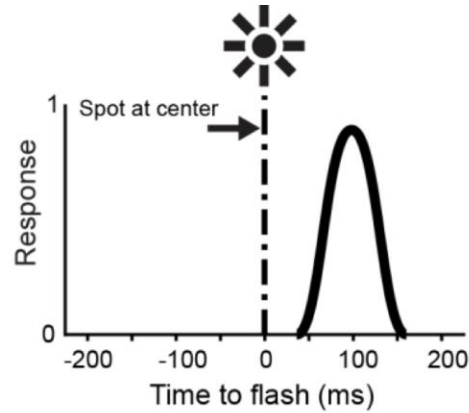
Outlook

- **Anticipation of motion trajectories**

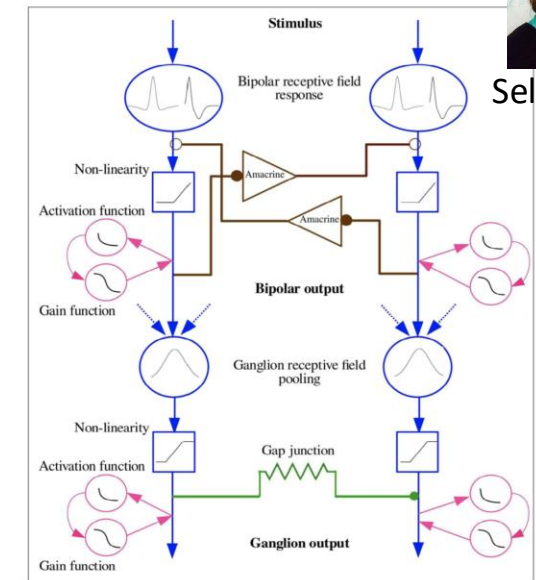


Outlook

- **Anticipation of motion trajectories** via inhibitory network



Selma Souihel

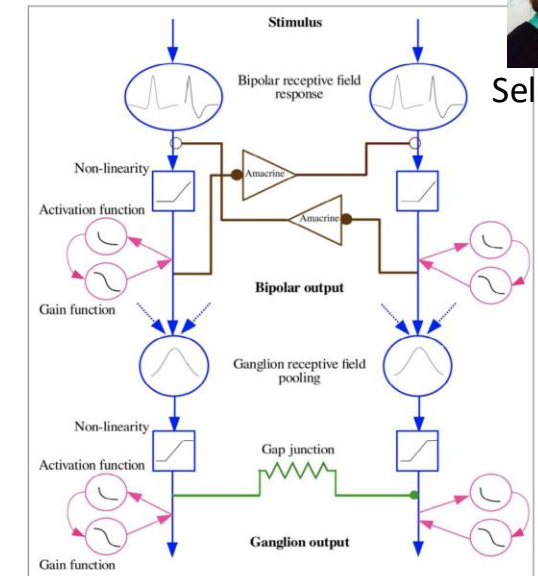
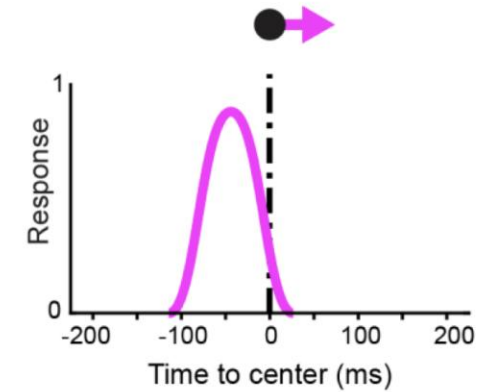
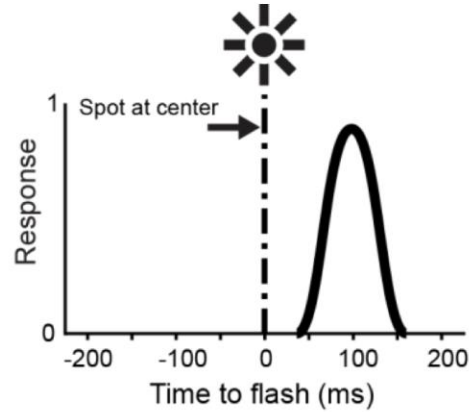
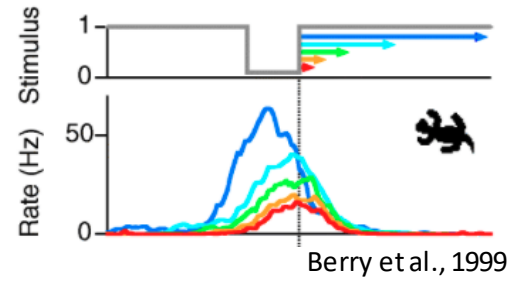


Souihel et al., 2021

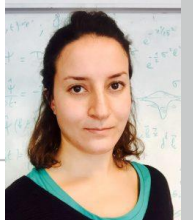
Outlook

- **Anticipation of motion trajectories** via inhibitory network

? **Dynamic adaptation** for **speed** representation



Souhail et al., 2021



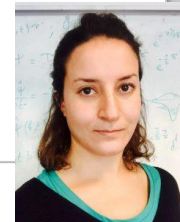
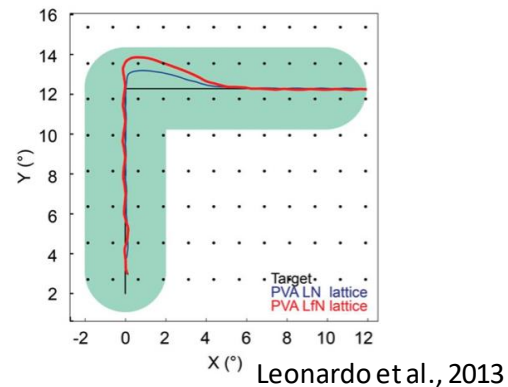
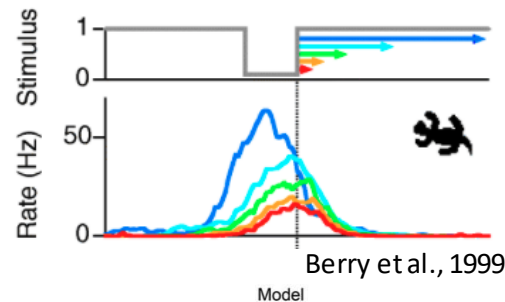
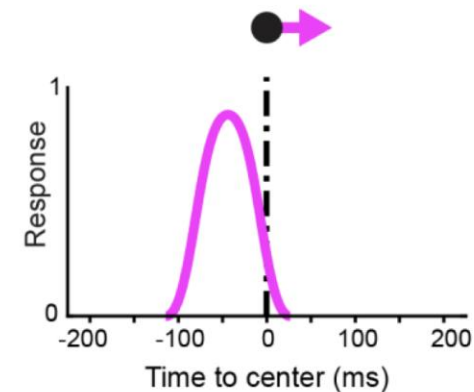
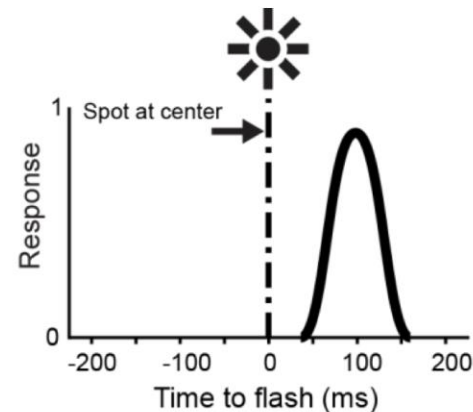
Selma Souhail

Outlook

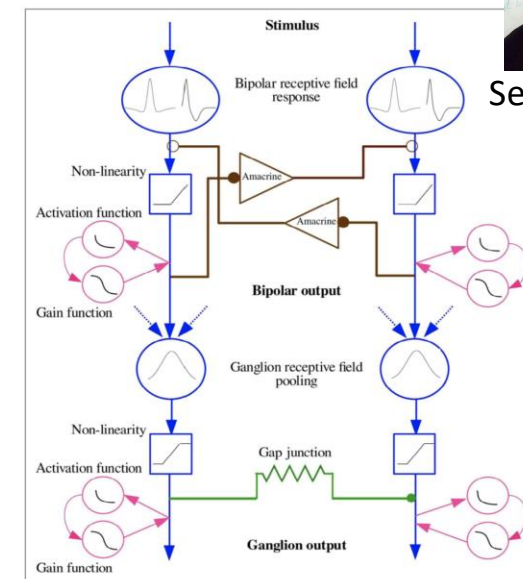
- **Anticipation of motion trajectories** via inhibitory network

? Dynamic **adaptation** for **speed** representation

? Surprise to sudden **changes** in trajectories



Selma Souihel



Souihel et al., 2021

Thank you !

Bruno Cessac

Pierre Kornprobst

Hui-Yin Wu

Johanna Delachambre

Franz Franco Gallo

Alexandre Bonlarron

Jerome Emonet

Florent Robert

Clement Bergman

Jeremy Termoz-Masson

Erwan Petit

Sebastian Gallardo Diaz

Sebastian Vizcay

Olivier Marre

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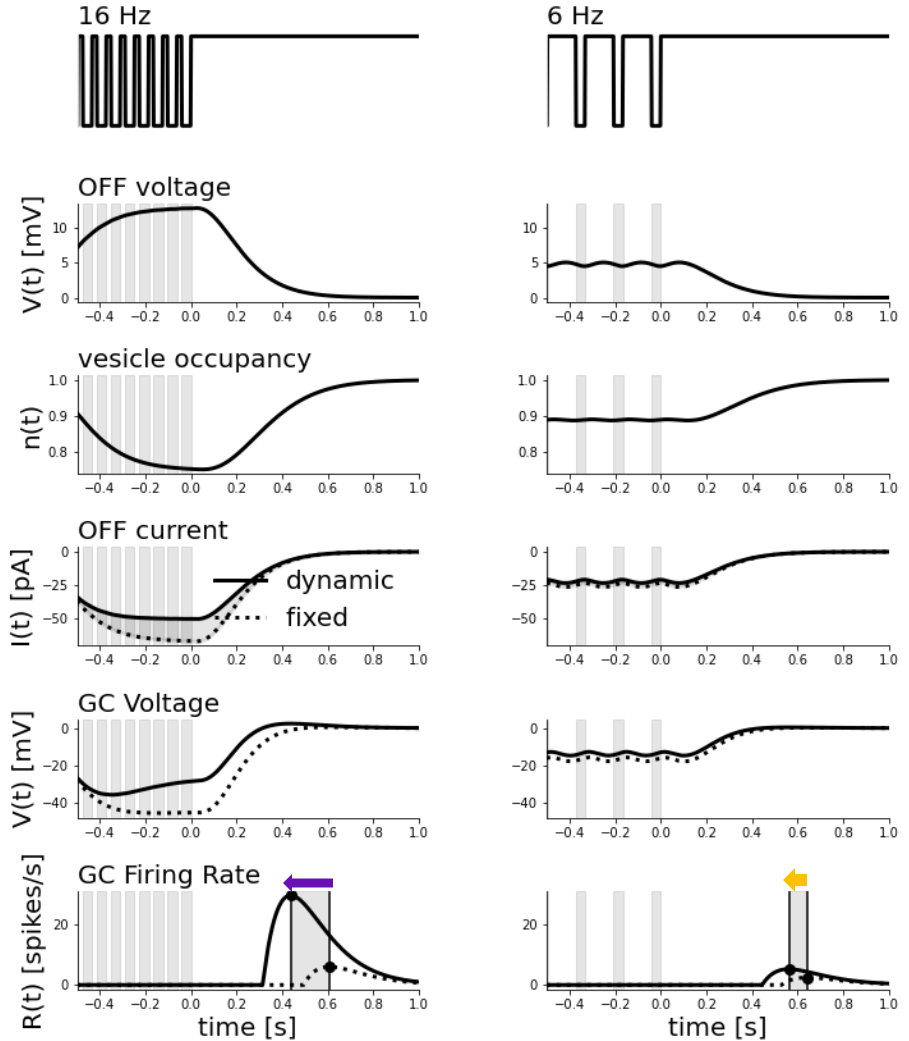
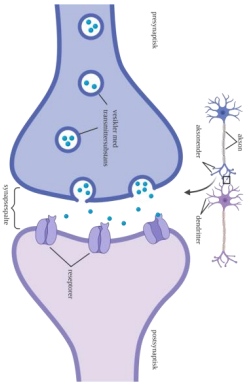
Ebert et al., 2023,
in review



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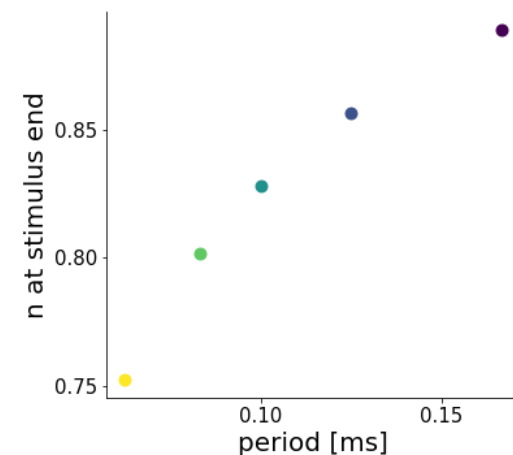
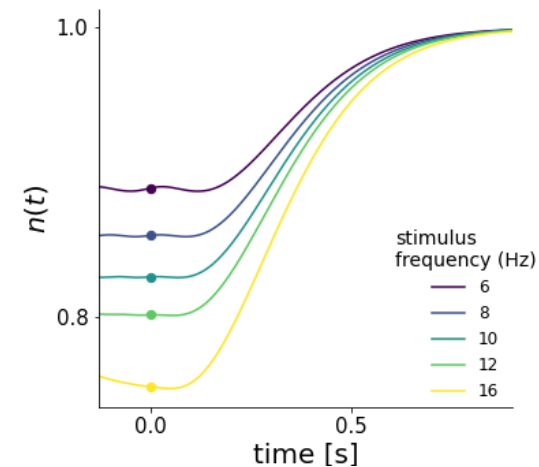
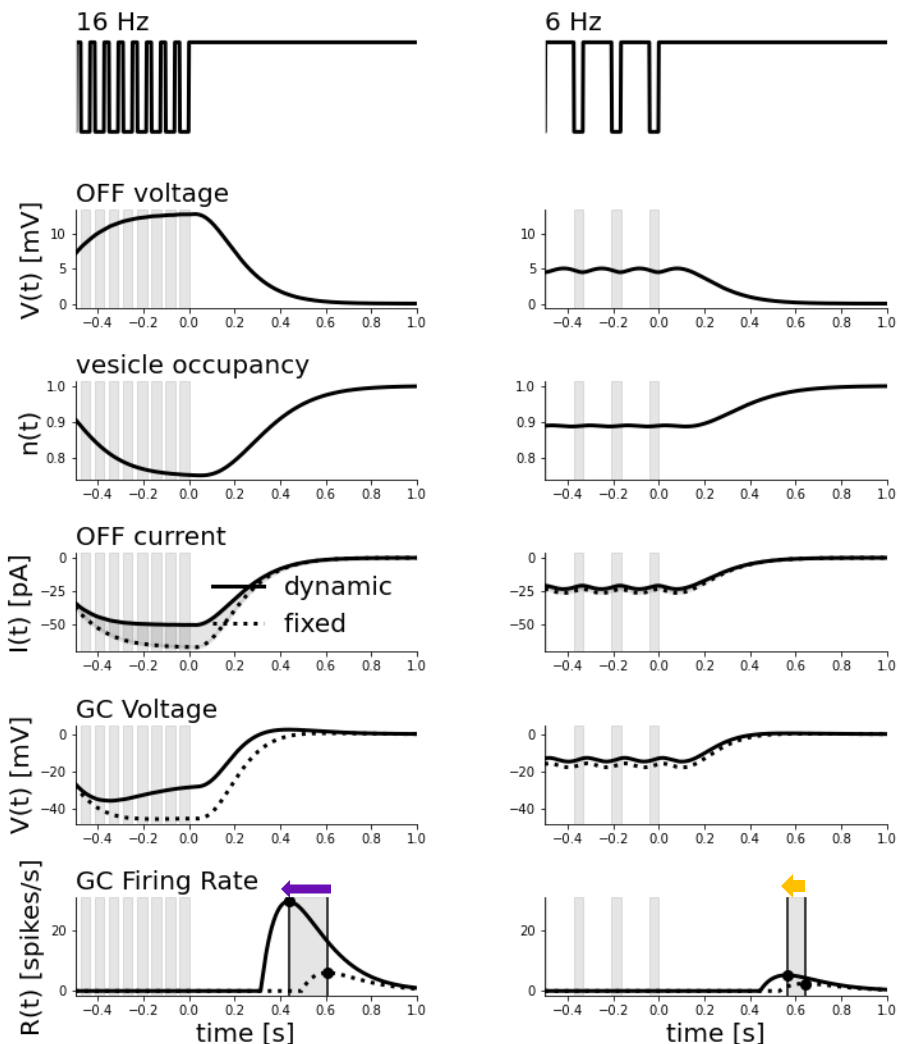
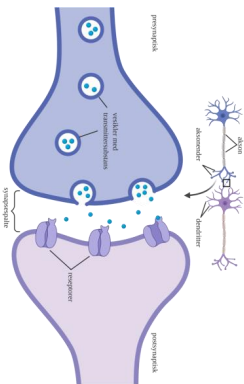


$$\frac{dV_G}{dt} = -\frac{V_G}{\tau_G} + w_{EON} V_{EON} + nw_{I_{OFF}^{Gly}} p(V_{I_{OFF}^{Gly}}, \theta_{I_{OFF}^{Gly}}) + w_{ION} V_{ION}$$

Model produces **error signal** via excitation and slower inhibition

Additional inhibition shifts the latency

Plasticity scales latency shift to frequency

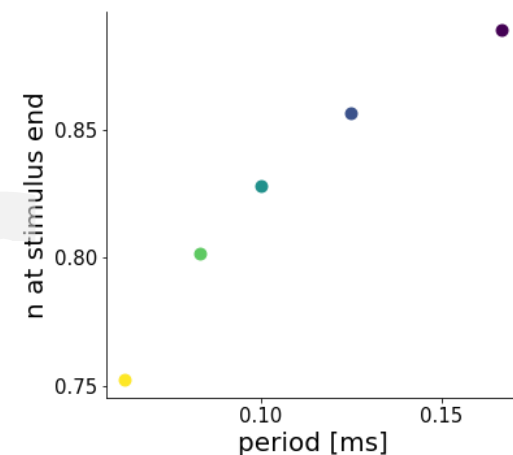
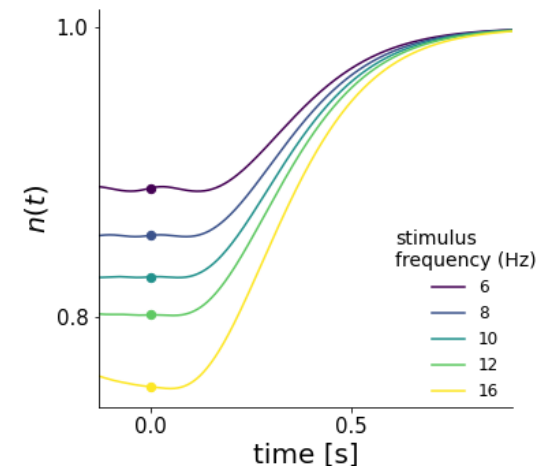
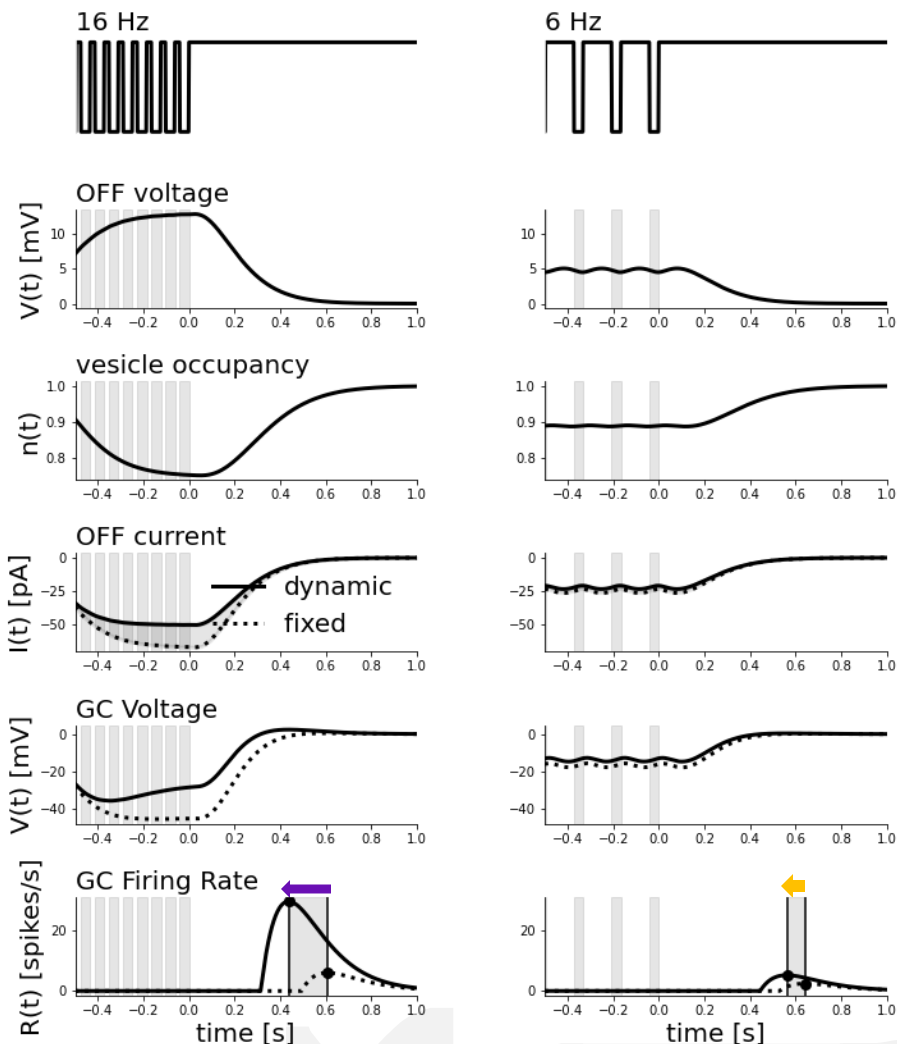
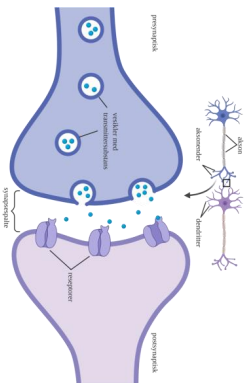


$$\frac{dV_G}{dt} = -\frac{V_G}{\tau_G} + w_{EON} V_{EON} + nw_{I_{OFF} Gly} p(V_{I_{OFF} Gly}, \theta_{I_{OFF} Gly}) + w_{ION} V_{ION}$$

Model produces **error signal** via excitation and slower inhibition

Additional inhibition shifts the latency

Plasticity scales latency shift to frequency



$$\frac{dV_G}{dt} = -\frac{V_G}{\tau_G} + w_{EON} V_{EON} + nw_{I_{Gly}^{OFF}} p(V_{I_{Gly}^{OFF}}, \theta_{I_{Gly}^{OFF}}) + w_{ION} V_{ION}$$

