RTify: Aligning Deep Neural Networks with Human Behavioral Decisions

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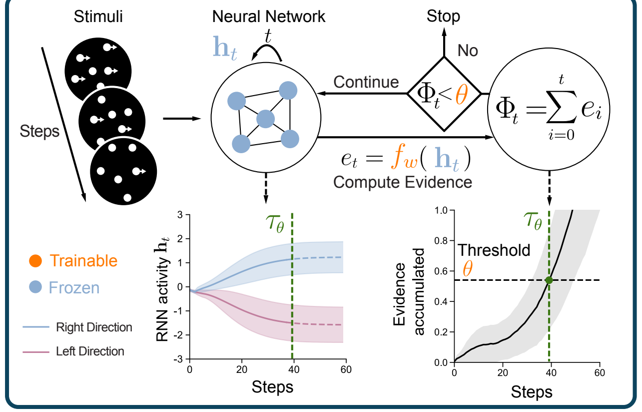
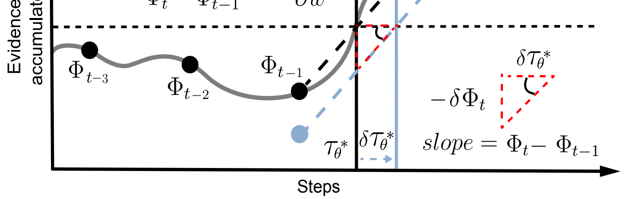
- Current **neural network models** of primates primarily replicate **behavioral accuracy** but overlook **reaction times (RTs),** a key indicator of **visual perception dynamics**.
- **Decision-making models** (e.g. DDM, LBA) have focused on explaining how visual information gets integrated over time, **but cannot handle more complex, natural stimuli** apart from parameterized stimuli (e.g. Gabor).
- **Recurrent neural networks (RNNs)** hold great promise since they **are temporally dynamic, image-computable, and have a notion of RT** via recurrence steps.



$$\frac{\partial L(\tau_\theta)}{\partial w} = \frac{\partial L(\tau_\theta(\Phi))}{\partial \tau_\theta(\Phi)} \cdot \frac{\partial \tau_\theta(\Phi)}{\partial w} \approx \frac{\partial L(\tau_\theta(\Phi))}{\partial \tau_\theta(\Phi)} \cdot \frac{\partial \tau^*_\theta(\Phi)}{\partial w}$$

$$\frac{\partial \tau^*_\theta}{\partial w} \approx \frac{\delta \tau^*_\theta}{\delta w} \approx -\frac{\delta \Phi_t(\frac{1}{\Phi_t - \Phi_{t-1}})}{\delta w} \approx \frac{1}{\Phi_t - \Phi_{t-1}} \cdot \left(-\frac{\partial \Phi_t}{\partial w}\right)$$



- We present RTify, a novel computational approach to optimize the recurrent steps of RNNs to account for human RTs.
- With this framework, we **successfully fit an RNN directly to human behavioral responses**.
- Our framework can also be extended to an ideal-observer model whereby the RNN is trained without human data via a penalty term that **encourages the network to make a decision as quickly as possible.**
- Under this setting, **human-like behavioral responses naturally emerge from the RNN.**

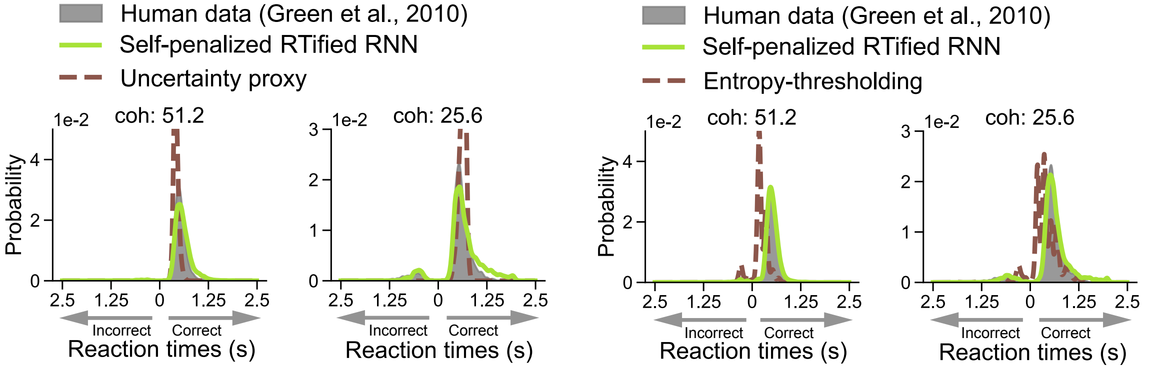
Extracting RTs with supervision (fitting human RTs)

$$Loss = \|\mathcal{D}_{\text{human RT}} - \mathcal{D}_{\text{model RT}}\|_2$$

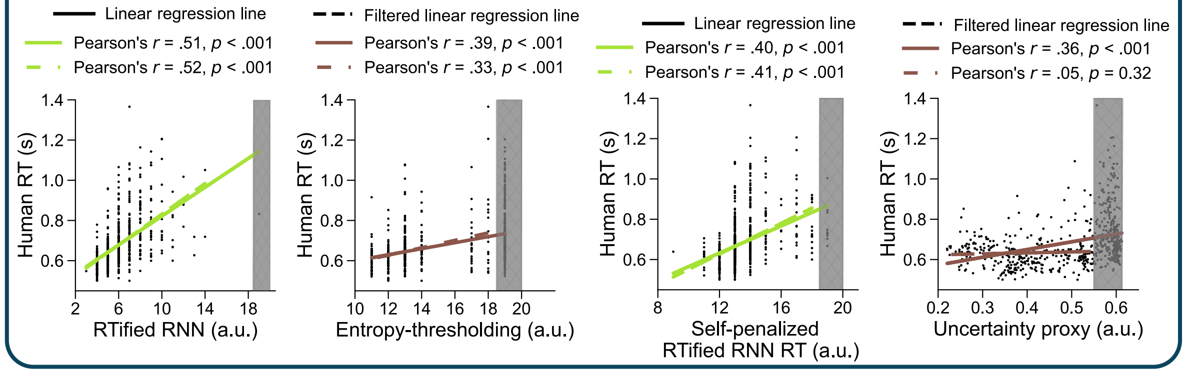
Extracting RTs via self penalty (leveraging RNN dynamics)

$$Loss = CCE + \lambda \cdot l_y \cdot \mathcal{T}_\tau$$

Model Evaluation on Random Dot Motion Task



Model Evaluation on Object Recognition Task



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