

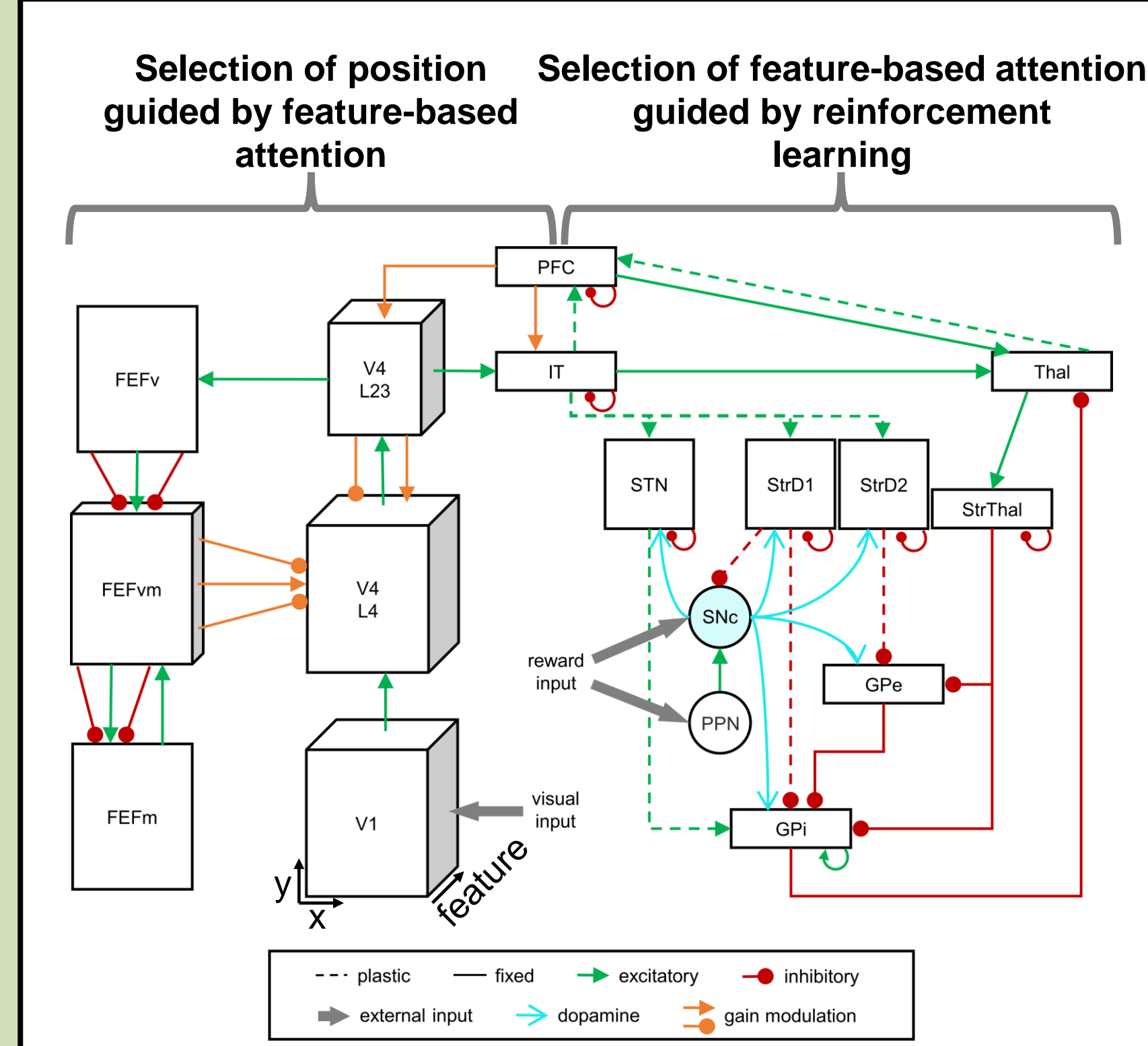
Learning top-down visual attention within a model of a visual cortex-basal ganglia-prefrontal cortex loop

Motivation

Modeling Human-Like Behavior: Through our biologically inspired computational models, we replicate human behavioral tasks, allowing us to explore the underlying neural mechanisms and formulate specific hypotheses regarding system-level functions.

Investigating "Optimal Tuning of Attention" Mechanisms: Navalpakkam & Itti (2007) suggested that optimal attention is directed to maximize the signal-to-noise ratio between search targets and distractors. They demonstrated that humans focus on features that differ more from distractors than the exact target features. We aim to answer how such attentional control develops and which brain mechanisms are involved. We demonstrate that this can be achieved through a visual cortex-basal ganglia-prefrontal cortex loop. Our hypothesis is that reward-based learning in the basal ganglia modulates the PFC, controlling top-down attentional processes. To test our model hypothesis, we replicate the experimental task from Navalpakkam & Itti (2007).

Replicating Findings from Kerzel (2020): Kerzel (2020) employed a cueing paradigm to study attentional capture by cues in the absence of a relational context, i.e., other features in the scene. Their results show that target-similar cue colors closer to non-target colors captured less attention than target-similar cue colors further away from non-target colors. The target and non-target colors were present in the visual search scene after the cue. This provides evidence for the optimal tuning of attention based on absolute features, as opposed to attentional control guided by relative features. To test the generalizability of our model, we also replicate the cueing paradigm from Kerzel (2020).



Model

- rate-coded model build in ANNarchy (Vitay et al., 2015)

Visual system part key points:

- V1/V4 = retinotopic maps of feature-selective (e.g. orientation, color) cells
- V4->IT = spatial pooling
- V4->FEF = feature pooling
- FEF-V4 loop = spatial competition/selection
- FEFm = selection of position if threshold is reached
- PFC = source of feature-based attention

Basal Ganglia part key points:

- STN/Str = sparse input encoding
- GPe/GPi = selection of feature in Thal (forwarded to PFC)
- SNc = dopaminergic input, modulates plasticity

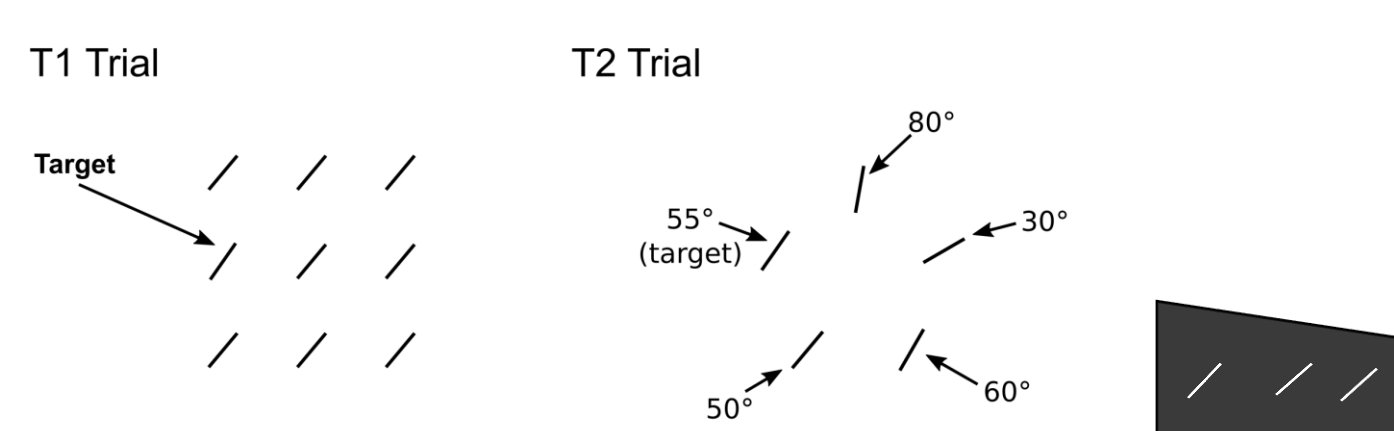
Experiment – Navalpakkam & Itti (2007)

Task

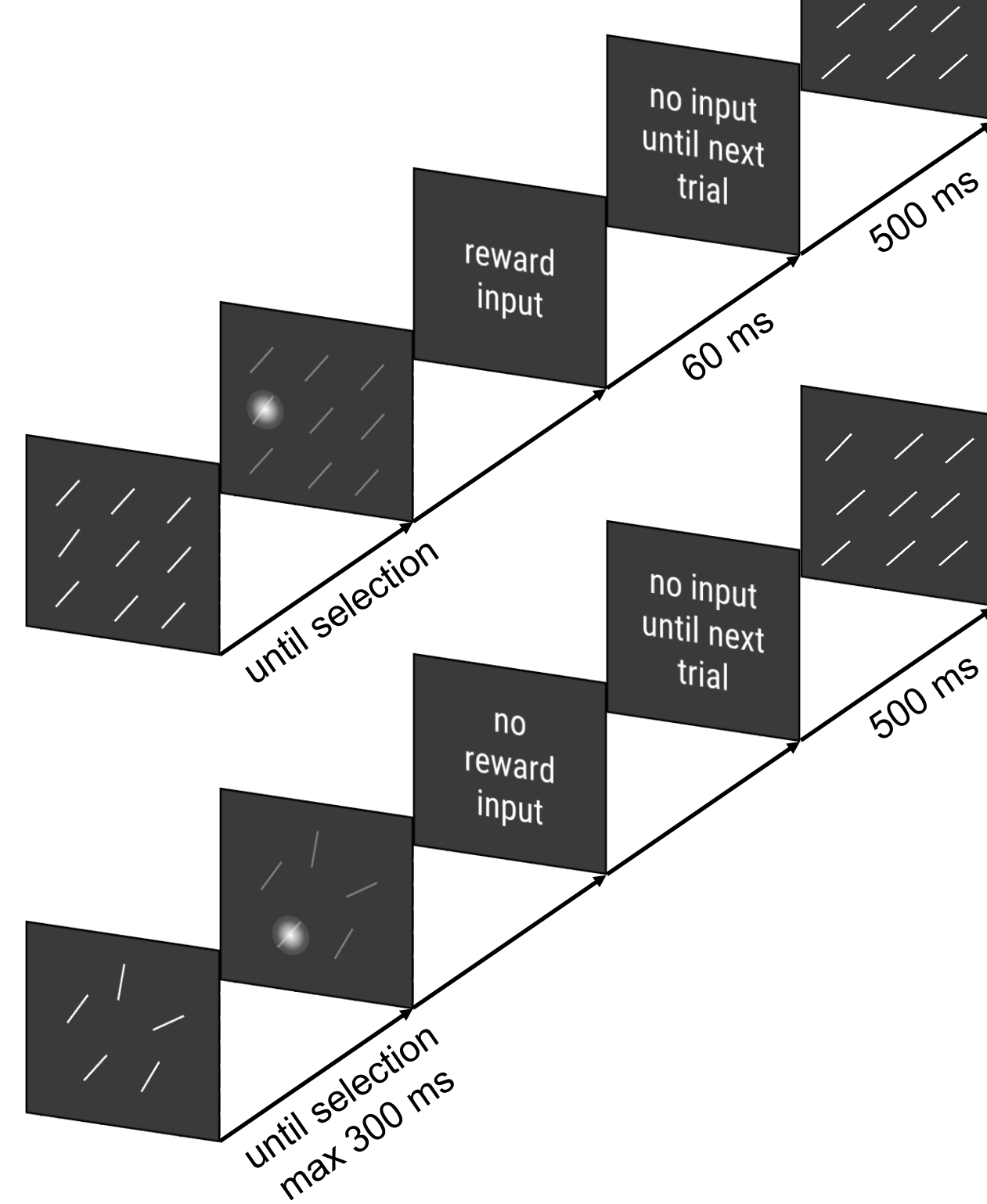
General procedure

- 1st training-block with T1 trials until performance reaches 80%
- 2nd test-block, 340 T1 trials and 160 T2 trials (random order)

Stimuli

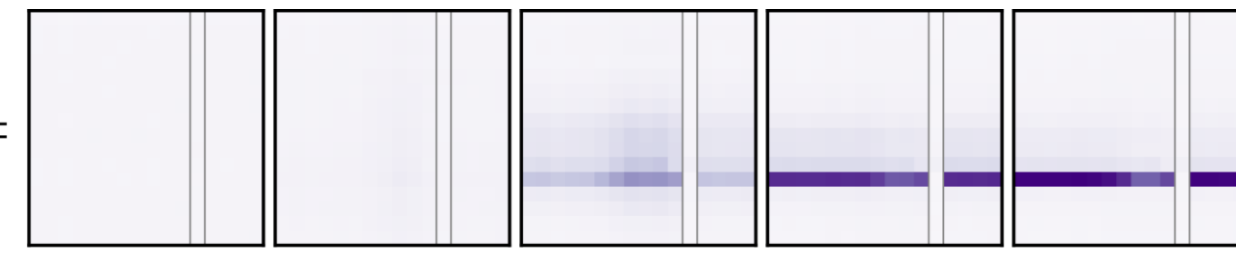


Trials

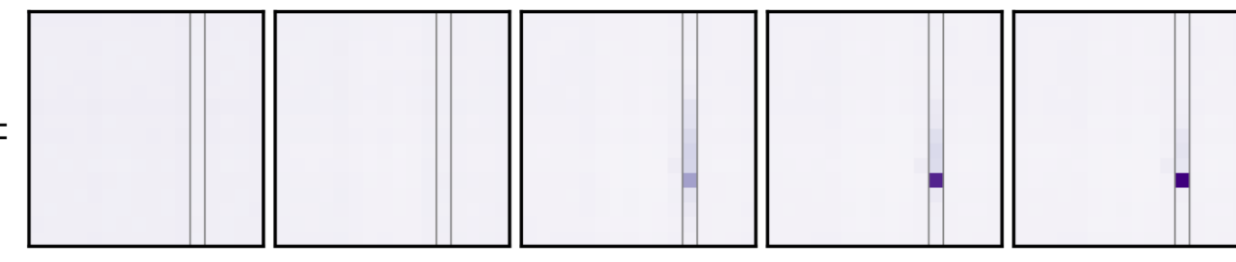


Basal Ganglia learning

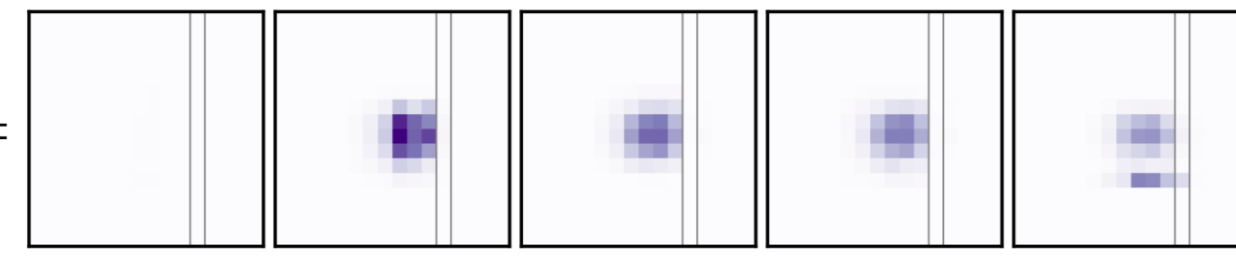
hyperdirect: surround-suppression



direct: select rewarded orientation



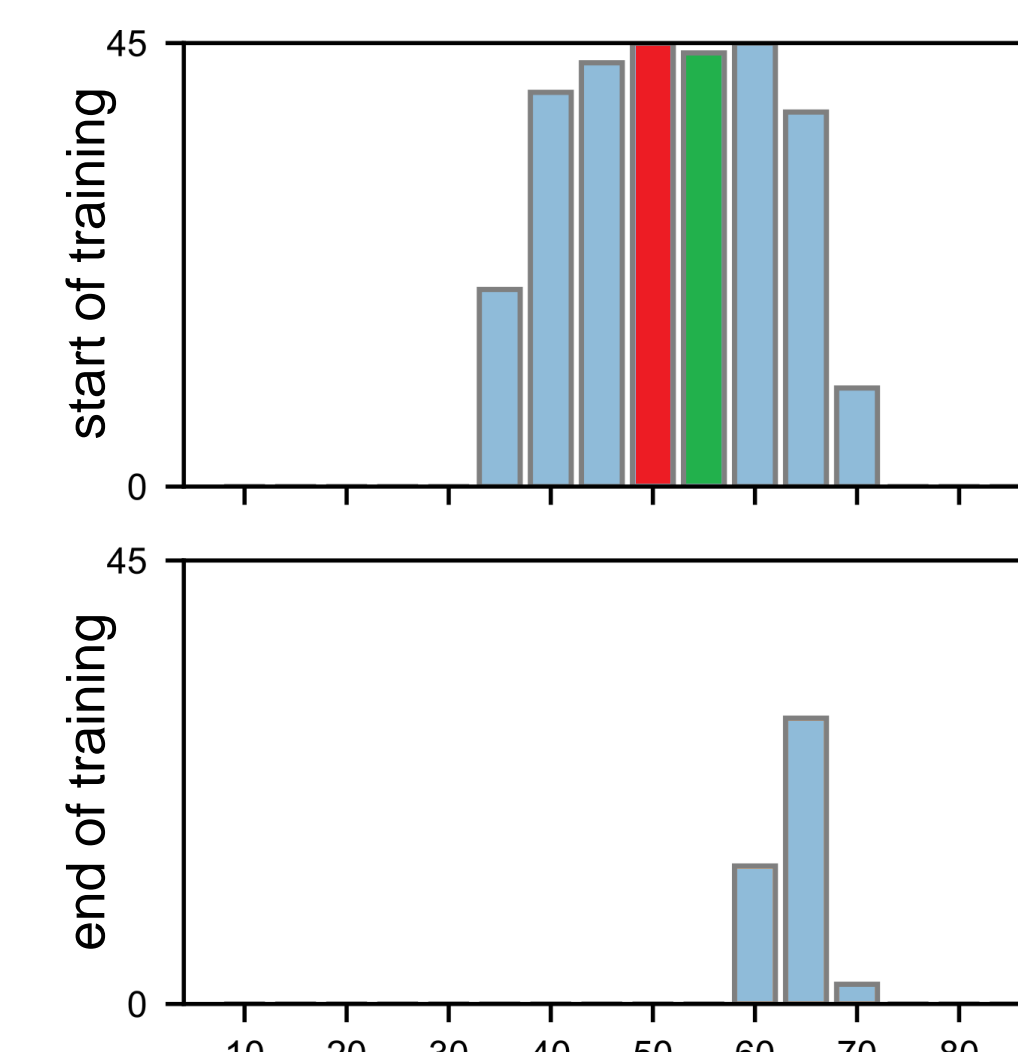
indirect: selective suppression of unrewarded orientations



The Basal Ganglia learn to select orientations that lead to rewarded responses in the visual system.

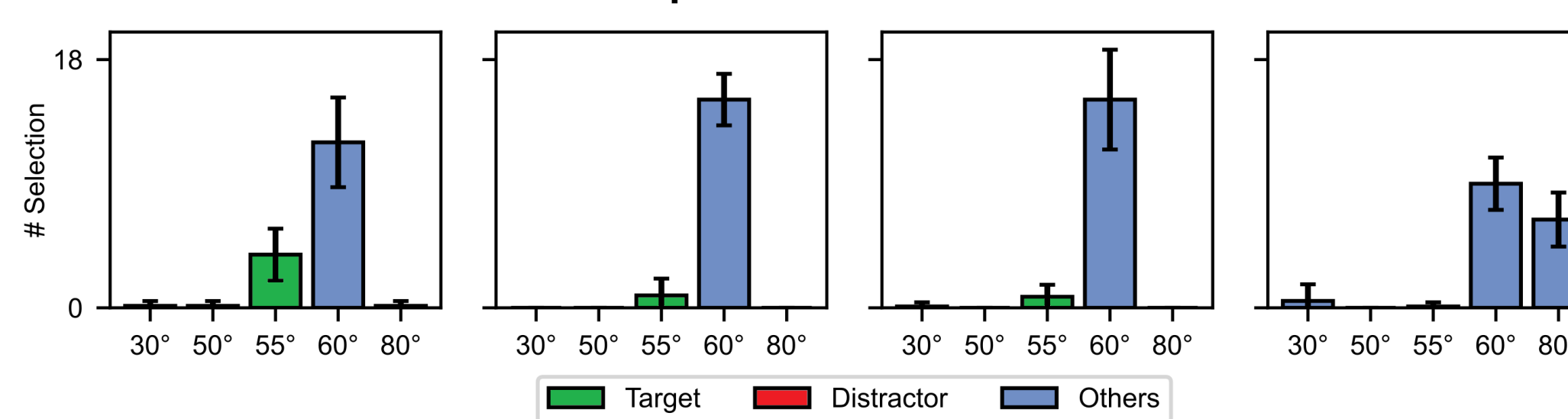
Results

Selected PFC neurons i.e. orientations



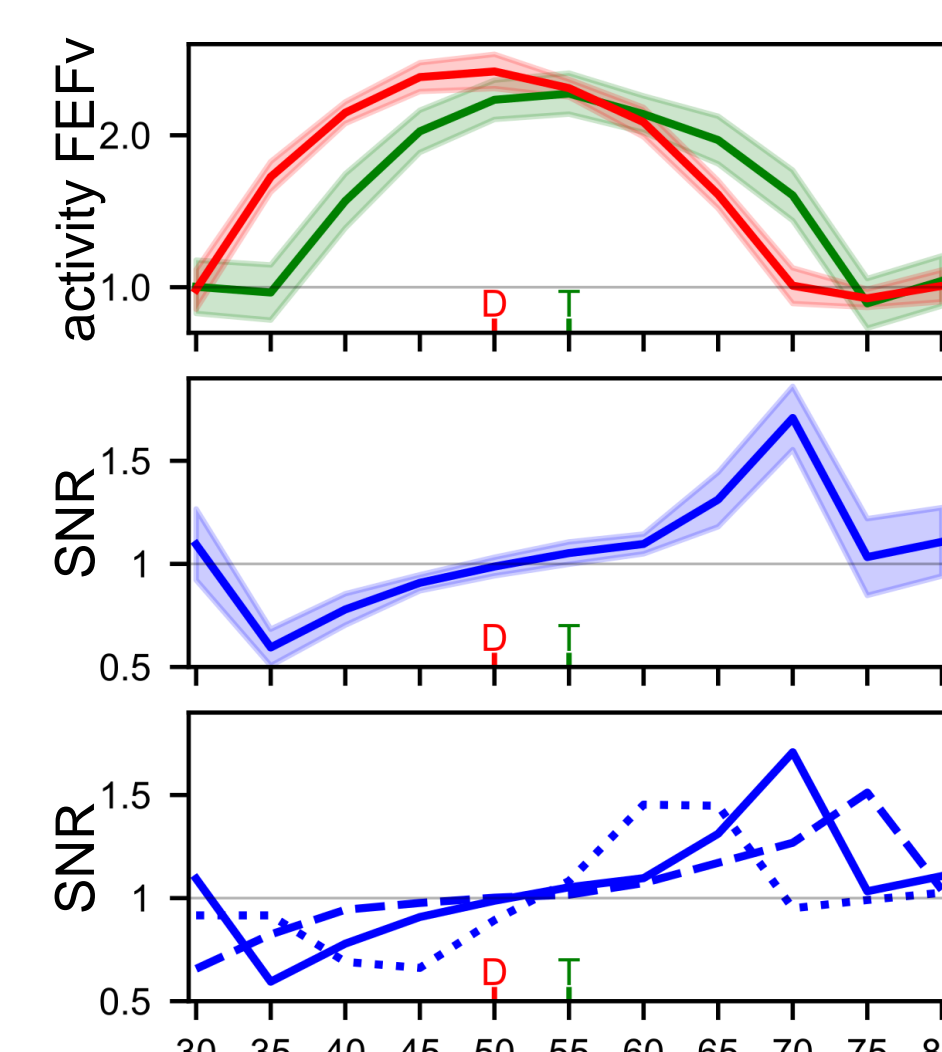
These orientations do not align with the orientation of the target and deviate from those of the distractors.

Responses in T2 trials



In T1 trials, performance exceeds 80%, while in T2 trials, non-targets are selected significantly more frequently than the target, consistent with the findings from Navalpakkam & Itti (2007).

Amplification by PFC activity

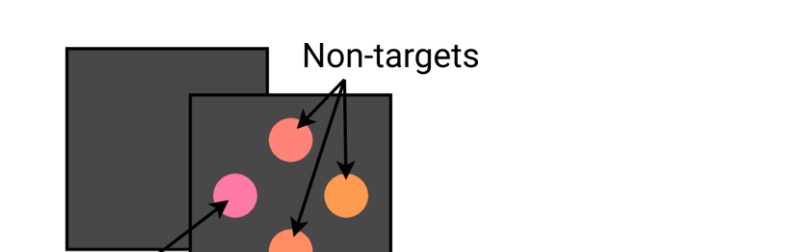


The reason for this is that attending orientations differing from the distractors leads to a larger signal-to-noise ratio between the target and distractors within the visual system, consistent with the optimal tuning of attention proposed by Navalpakkam & Itti (2007). The shift of the SNR peak depends on the bandwidth of the orientation-selective V1 cells (dotted: narrower, solid: default, dashed: wider).

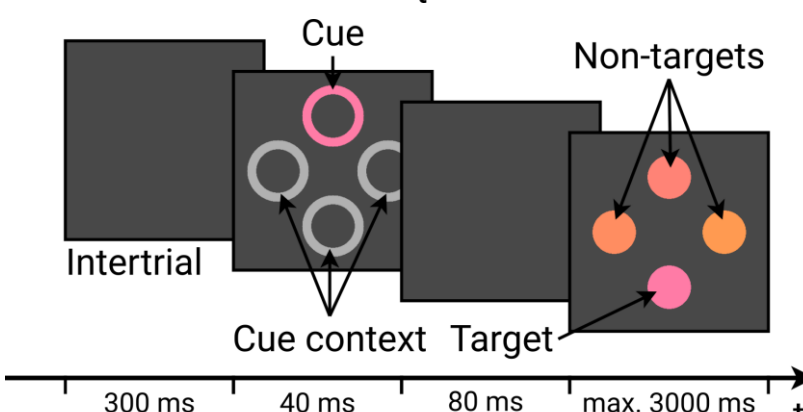
Experiment Kerzel (2020)

Task

1st: training-block



2nd: test-block



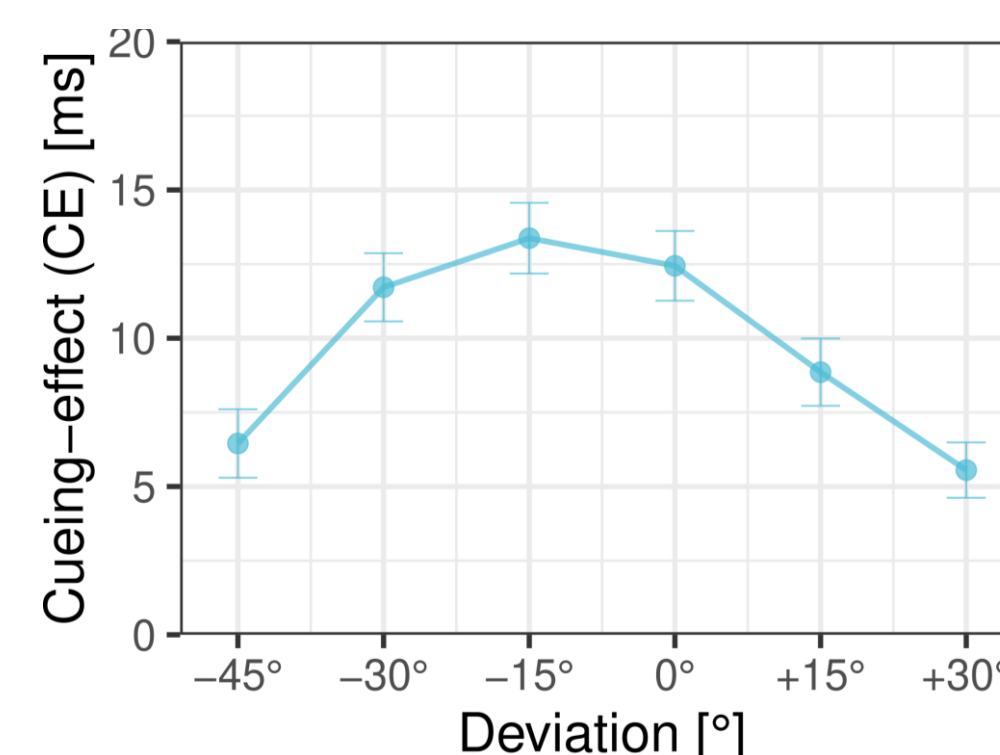
two experiments in test-blocks:

cue variation: cues varied from -45° to $+30^\circ$; non-targets = $+30^\circ$, $+45^\circ$, $+60^\circ$ relative to target

near vs. far: only 2 cues -15° and $+15^\circ$, additional non-targets „far“ = $+60^\circ$, $+75^\circ$, $+90^\circ$

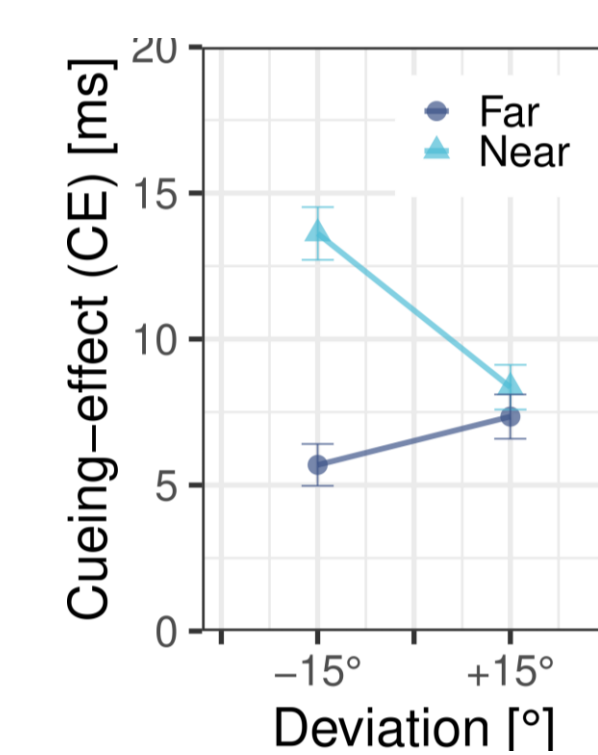
Results

cue variation



the cueing-effect depends on the similarity to the target hue and is shifted away from the non-targets

near vs. far



the shift does not occur when the non-target hues are far from the target hue

References

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