Criterion learning in an orientation-discrimination task

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Introduction

Signal detection theory describes detection and discrimination decisions as a comparison of stimulus "strength" to a *fixed* decision criterion[1].

We need to make decisions in situations we have never before experienced and adapt to changes in the environment.

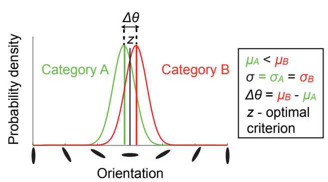
We designed a novel paradigm in which we overtly measure trial-by-trial criterion placement.

Q1: How is criterion set in a novel environment with static uncertainty?

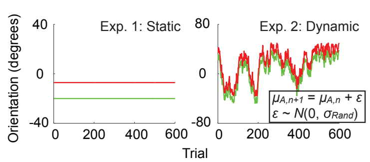
Q2: How is criterion set in a novel environment with dynamic uncertainty?

Stimuli

Two categories of ellipses with mean orientations chosen randomly at the beginning of each block



Example of category means across a block



Procedure

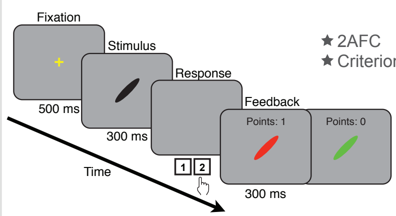
Calibration task → Overt-criterion task → Covert-criterion task

Calibration task → Covert-criterion task → Overt-criterion task

Calibration task

- ★ 2IFC orientation-discrimination
- ★ Estimated sensory uncertainty (σ_v)
- ★ Set $\Delta\theta = \sqrt{2(\sigma_v^2 + \sigma^2)}$ for use in the covert- and overt-criterion tasks

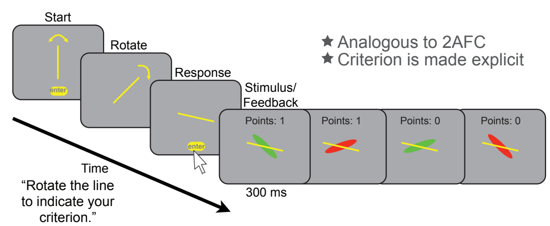
Covert-criterion task



- ★ 2AFC
- ★ Criterion is implicit

"To which category does the ellipse belong?"

Overt-criterion task

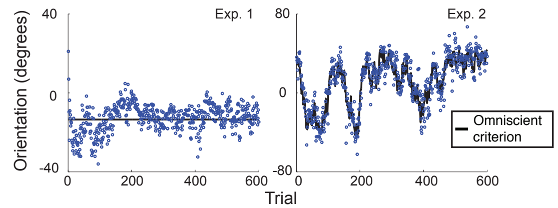


- ★ Analogous to 2AFC
- ★ Criterion is made explicit

"Rotate the line to indicate your criterion."

Results

Overt-criterion placement for representative observers



Models

Ideal Bayesian (IB)

- ★ Sets criterion to maximize p(correct), given the sample history and all possible criteria.

Model selection (MS)

- ★ Sets criterion between the best estimates of the category means.

Exponential moving-average (EMA)

- ★ Computes a weighted average, giving more weight to recently experienced stimuli.

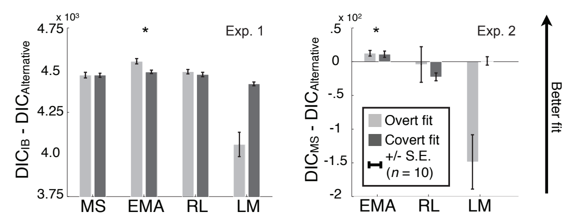
Reinforcement-learning (RL)

- ★ Updates criterion when receiving negative feedback by a proportion of the error.

Limited memory (LM)

- ★ Sets criterion between the last observed sample from each category.

Model comparison: Relative DIC scores



*Best fit: Deviance information criterion (DIC) differences > 6 indicate strong evidence[2].

Summary & Conclusions

When uncertainty was static, observers converged on the optimal criterion over many trials.

When uncertainty was dynamic, observers adapted to the changes in the environment with a lag rate ranging from 1 to 4 trials.

Similar strategies were used in the covert- and overt-criterion tasks.

A model in which the history of recently viewed samples determines a belief about category means (the exponential moving-average rule) fit the data best for both experiments.

Criterion placement is dynamic, even after prolonged training.

References

[1]Green, D. & Swets, J. (1966). Signal detection theory and psychophysics *(Wiley, New York).*

[2]Spiegelhalter, D. J., Best, N. G., Carlin, B. P. & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistics Society, B 64*, 583–639.

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