Dynamical Bayesian models of control in a simple decision making task under changing context

Michael Shvartsman

P6 Meeting

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Agenda

• The task and theoretical goals
• Core inference engine
• Variants of context/target (proactive/reactive) tradeoff
• Cognitive architecture
• Preliminary results (mostly sanity checks)
• Discussion!
The AX-CPT

Cue (Context)

Retention Interval

Target and Response
The AX-CPT

• Stimuli:
  • Cues: A, B(= Q, F, V, S, H, …..)
  • Targets: X, Y(= Z, J, E, O, K, …..)

• Response:
  • Symmetric variant: Left on AX or BY, Right otherwise
  • Asymmetric variant: Left on AX, Right otherwise
The AX-CPT

• Typical trial distribution
  • AX ++++++++ 
  • AY ++ 
  • BX ++ 
  • BY +
AX-CPT as metric of context processing

• AY, BX trials equally probable

• If high uncertainty over context (A/B):
  • ?X most likely == AX -> make BX errors

• If high uncertainty over target (X/Y):
  • A? most likely == AX -> make AY errors

• Schizophrenic patients: more errors on BX trials than healthy controls
Goals

• Descriptive: recover degree of context (vs target) processing from (messy) data
• Explanatory: understand whether, when and how humans adjust context vs. target processing
Solving AX-CPT as an ideal observer

- **Sequential inference:**

\[
P(C = c, T = t \mid e^C_\tau, e^T_\tau) \propto P(e^C_\tau, e^T_\tau \mid C = c, T = t)P(C = c, T = t \mid e^C_\tau, e^T_\tau)
\]

- **Decision variables:**

\[
P(R = L \mid C, T) := P(C = A, T = X) + P(C = B, T = Y)
\]

\[
P(R = R \mid C, T) := P(C = B, T = X) + P(C = A, T = Y)
\]

- **Stopping criterion:**

\[
P(R = L \mid C, T) > z
\]

\[
P(R = R \mid C, T) > z
\]
How to implement context/target tradeoff?

• Serial:
  • Updates based on $e^C_\tau$ until some threshold $z_C$ over posterior is crossed, then updates based on $e^T_\tau$ until response threshold

• Parallel:
  • Updates based on $e^C_\tau$ until target stimulus appears, then updates on both. Tradeoff via relative sampling noise (i.e. drift rate)
Cognitive Architecture

• How to make the model “do the task?”

• Multiply # samples to decision by some sample rate, then...

• Arch.1: add non-decision timing offset ($t_0$)

• Arch. 2: add visual processing delay during which context samples are processed, add motor response delay

• Arch. 3: also add motor response inhibition/cancellation and hysteresis
Visual processing delay

- A.k.a. “eye-brain lag”
- A priori estimates from EEG, MEG evidence:
  - Option 1: earliest visual deflection. ~50ms (C1; Clark et al. 1994).
  - Option 2: earliest stimulus-related deflection. ~125ms for letters (Tarkianen et al. 1999).
  - Option 3: earliest task-related deflection. ~145ms for letters (Tarkianen et al. 1999, but cf. Seeck et al. with 50ms)
Motor planning

- Simplest option: stop-signal response time (~200-250), subtract eye-brain lag (but which one?); no response hysteresis or inhibition
- Better option: sigmoid unit with strong gain (Simen et al. 2006), but how to estimate parameters a priori?
- Better option: motor preparation as nonlinear dynamical system (Erlhagen & Schöner 2002)
Parallel model, Arch. 1

Sequential inference on context

Sequential inference on context, target

Trial type posterior

Response posterior

Non-decision time
\( \sim Gamma(t_0, c_v) \)
Parallel model, Arch. 2

Sequential inference on context

Eye-brain lag $\sim \text{Gamma}(\mu_e, c_v)$

Sequential inference on context, target

Trial type posterior

Response posterior

Motor Plan, Execution $\sim \text{Gamma}(\mu_m, c_v)$

Time
Serial model, Arch. 1

Sequential inference on context

Sequential inference on target

Non-decision time
\[ \sim \text{Gamma}(t_0, c_v) \]
Serial model, Arch. 2

Sequential inference on context

Eye-brain lag $\sim \text{Gamma}(\mu_e, c_v)$

Sequential inference on target

Motor Plan, Execution $\sim \text{Gamma}(\mu_m, c_v)$
Experiment 1

• Design following Henderson et al. 2012:
  • Asymmetric response (L for AX, R otherwise)
  • 5 B stimuli, 5 Y stimuli
  • 68.75% AX, 12.5% AY, 12.5% BX, 6.25% BY
  • Retention interval 2000ms

• Parallel architecture 1:
  • Eye-brain lag mean 50ms, SD 20ms
  • Motor plan mean 250ms, SD 70ms
  • Sample rate: 10ms

• Free parameters:
  • Response threshold: optimize reward rate
  • Context, target noise: sweep
Challenges

- No cue representation degradation during retention interval!
What if retention interval is shorter

- 2000ms —> 200ms