The adaptive nature of eye-movement control in linguistic tasks

Michael Shvartsman, Richard Lewis, & Satinder Singh (University of Michigan)
mshvarts@umich.edu

Adaptive control; Reading; Eye-tracking; Lexical decision; English

Overview. We present empirical and modeling evidence that eye-movement control in reading precisely adapts to speed-accuracy tradeoffs imposed jointly by processing architecture and task structure and payoffs. Our experiments provide participants with payoffs at different points on a speed-accuracy tradeoff continuum, and our model optimizes the same payoffs to arrive at quantitative predictions. The work extends existing models of oculomotor control in reading [1, 2] by explicitly identifying loci of strategic adaptation in saccadic control in an architecture capable of performing a simple but complete linguistic task. Architecture and payoff jointly determine predicted adaptive behavior; changes in either can change model predictions because they redefine the adaptive problem. These results extend work on rational analysis of oculomotor control and reading strategies [3, 4, 5] by providing evidence for low-level adaptation of saccadic control to task and architecture. It complements existing empirical approaches to speed-accuracy tradeoff [6] through its focus on deriving behavior as solutions to precisely defined optimization problems that include processing constraints [7].

The task. On each trial of the List Lexical Decision Task (LLDT), participants see six four-letter strings and make one decision as to whether all are words. One nonword appears in a random position in 50% of trials. Participants and model were given feedback in the form of points after each trial; participants were given cash bonuses as a function of total points.

The model and its predictions. The model receives noisy perceptual samples of the fixated string, and performs a Bayesian update of a belief distribution over possible word lists, using priors derived from frequencies in a lexicon of four-letter words. From this distribution the model derives two summary statistics: the probability that the current trial is a word trial, and the probability that the fixated string is a word. The model's decisions are conditioned on these two probabilities: at each time step, the model compares them to two strategically-chosen thresholds to decide whether it should issue a trial (manual) response or program a saccade to the next string. The structure and temporal dynamics of the visuo-oculomotor and manual subsystems are motivated by existing literature (e.g. [8]). Optimal thresholds (found via search and Monte Carlo simulation) yield predictions of faster trial RTs, shorter single fixation durations (SFDs), and lower accuracies in the speed vs. the accuracy payoffs (see table for partial summary). The model recovers and explains both skewed fixation time distributions [9] and the log frequency effect on SFDs [10, 11] as a signature of optimal policies, and furthermore predicts an attenuation of this effect in the speed condition. Many suboptimal strategies do not yield these predictions, and neither do strategies optimal under different architectural constraints (such as changing the eye-brain lag).

Experiments. 48 participants completed 200 trials of the LLDT in one of three conditions specifying per-trial points as function of speed and accuracy. Participants adapted to the payoffs as the model predicted, achieving increased speed at the expense of accuracy via a reduction in SFD accompanied by an attenuation of the frequency effect—despite many other adaptations that were in principle possible, such as changing the number of fixations or regressions or reducing mind-wandering.

	Payoff 1 (speed emphasis)			Payoff 2 (accuracy emphasis		
	Human	Model	Model (no EBL)	Human	Model	Model (no EBL)
SFD (s.e)	224 (9.7)	221 (1.5)	199 (0.9)	250 (6.0)	252 (2.8)	203 (4.9)
Freq. effect	-3.00 (0.6)	-4.08 (0.21)	-5.9 (0.26)	-5.22 (0.62)	-5.68 (0.28)	-5.7 (0.27)
Trial RT	1373	1366	988	1713	1479	1066

References

[1] E. Reichle, T. Warren, and K. McConnell. *Psychon Bull Rev*, 16(1):1–21, 2009.[2] R. Engbert, A. Nuthmann, E. Richter, and R. Kliegl. *Psych Rev*, 112(4):777–813, 2005.[3] K. Bicknell and R. Levy. ACL 2010. [4] B. Tatler, M. Hayhoe, M. Land, and D. Ballard. *J Vis*, 11(5):5, 2011.[5] C. Wotschack. PhD thesis, 2009. [6] B. McElree, S. Foraker, and L. Dyer. *JML*, 48(1):67–91, 2003. [7] A. Howes, R. L. Lewis and A. H. Vera. *Psych. Rev.* 116(4):717-751 2009. [8] V. Clark, S. Fan, and S. Hillyard. *Hum Brain Mapp*, 2(3):170–187, 1994.[9] A. Staub, S. White, D. Drieghe, E. Hollway, and K. Rayner. *JEP:HPP*, 36(5):1280–93, 2010. [10] A. Inhoff and K. Rayner. *Percept Psychophys*, 40:431–439, 1986. [11] D. Norris. *Psych Rev*, 116(1):207–19, 2009.