Optimal Control Approaches to Language

How the Architecture "Shows Through"

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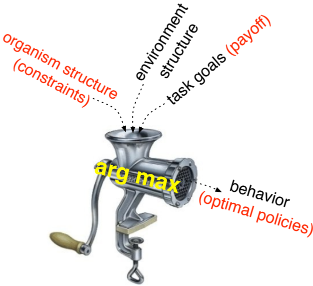
The idea: Applying Newell & Simon's scissors to language (plus utility maximization)

All aspects of linguistic processing and behavior—from parsing strategies to production strategies to control of short and long-term memory to eye-movement control—may be understood as the solution to the constrained optimization problem posed by the external task environment, task structure, and internal processing structure/constraints (e.g. representation noise, knowledge).



Howes, Lewis & Vera (2009, *Psychological Review*)

We'll pursue this via the application of state-of-the-art theoretical ideas . . . from the 1940-60s: optimal control and optimal state estimation.

Overview

1. What determines the nature of eye-movements in linguistic tasks?
   - The task and model
   - Predictions vs. human behavior
   - How architecture shapes adaptation
2. Conclusions and looking ahead

The List Lexical Decision Task

`lead   hilt   robe   helm   guru   east`

Version of this task first used by Schvanaveldt & Meyer (1973); Meyer & Schvanavedlt (1972)

Explicit payoffs: Motivating with cash

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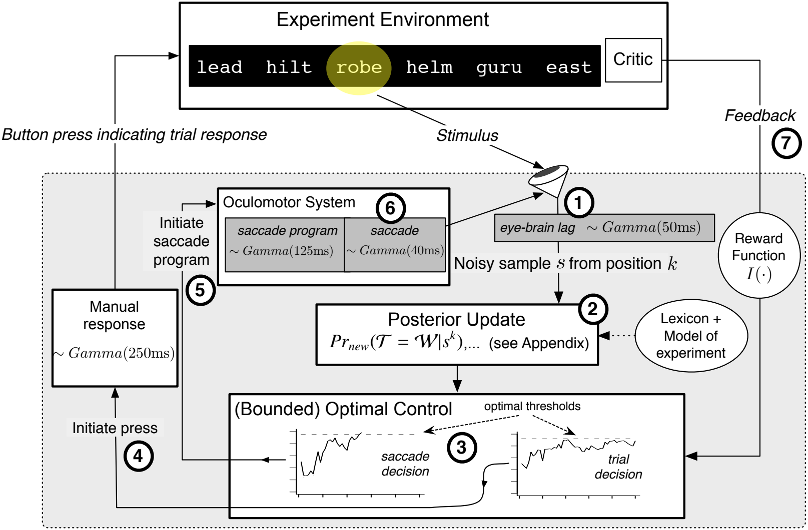
Explicit payoffs: Motivating with cash

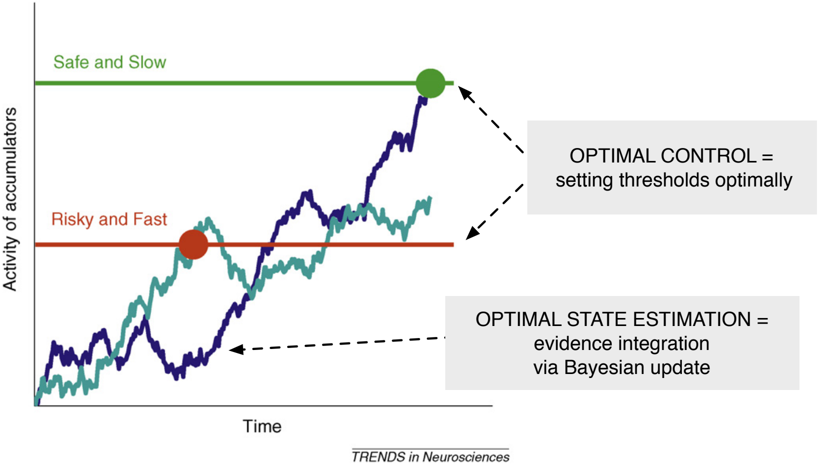
	Accuracy	Balanced	Speed
Incorrect penalty	-150	-50	-25
Speed bonus (per second under 5s)	8	6.7	5.7

An adaptive model that performs the complete task



See Legge et al (1997); Bicknell & Levy (2010); Ratcliff & Mckoon (2008); Norris (2009).

"Random walk" of Bayesian posterior update



Graph from Bogacz (2009), *TINS*.

Bayesian priors and stimulus representation

Model maintains belief probabilities over:

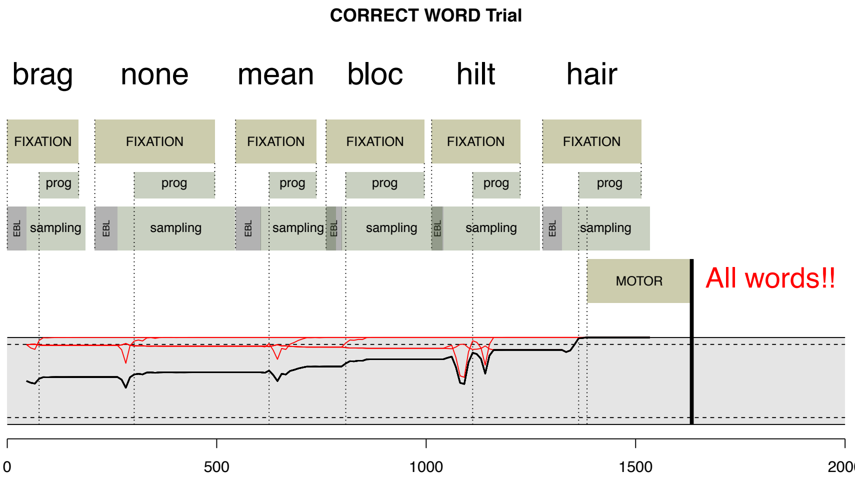
(a) probability distribution over all possible strings in the currently fixated position;

(b) the probability of a nonword in each position; probability current trial is a word trial is $1-$ sum over these.

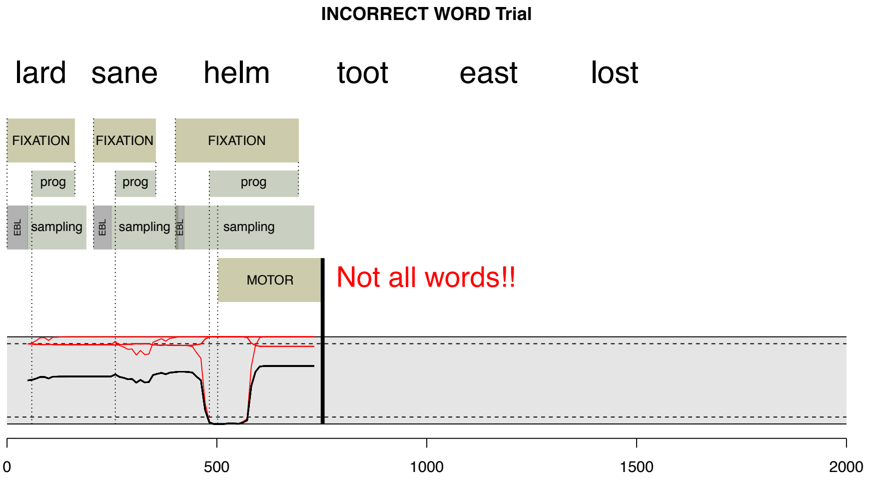
The prior over (a) is based on Brown Corpus frequency; prior over (b) is probability of a nonword trial (0.5) divided by the $\#$ of positions (6).

The string stimulus is represented with a simple indicator vector coding (length 26 $\times$ 4) (Norris, 2009). At each sample (10ms), Guassian noise of mean zero and SD $=$ 1.2 (more on this) is added to the true representation.

Sample model behavior



Sample model behavior



Generating predictions

- Selecting a policy (pair of thresholds) "programs" the machine to perform the task.
- Policy selected through payoff optimization—not data fitting.

Payoff condition	Optimal Saccade Threshold	Optimal Response Threshold
Accuracy	0.99	0.999
Balanced	0.97	0.999
Speed	0.92	0.99

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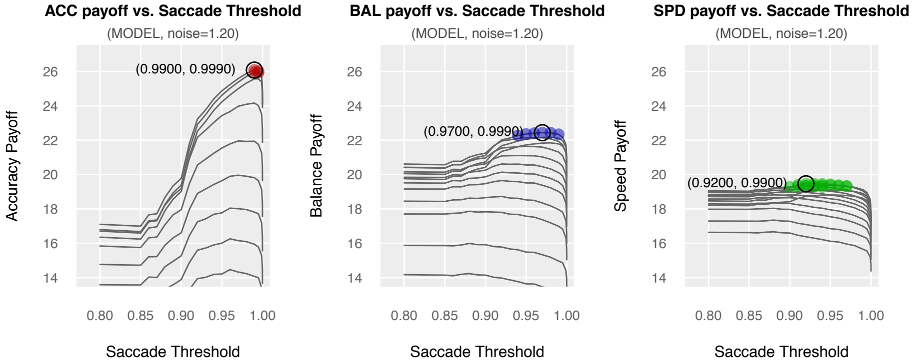
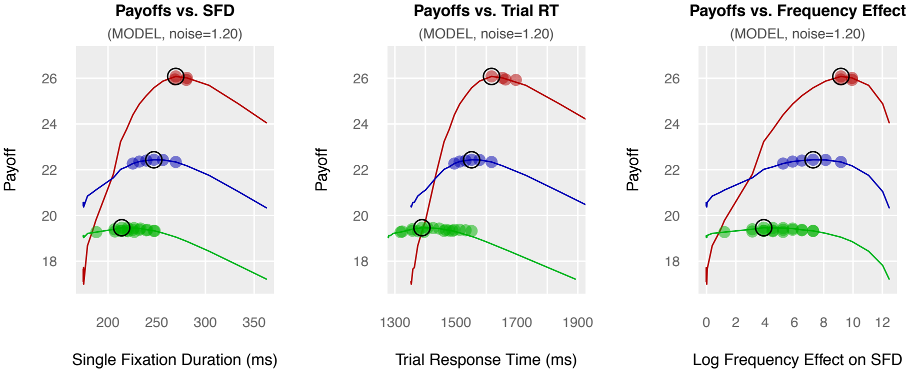
I.e, $\pi^*_{speed} = (0.92, 0.99)$ and so on. With fixed policy, machine generates dozens of behavioral measures (e.g. RTs, errors, RTs for accurate vs./ inaccurate, fixation durations for words, nonwords, frequency effects, . . .)

Finding the sweet spot: Payoff as function of thresholds

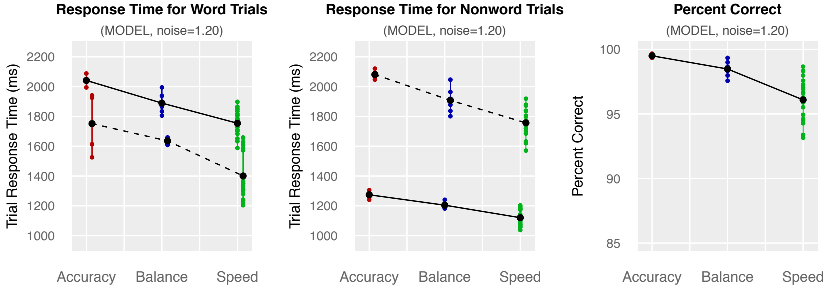
$$\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}_{trial \sim Experiment} U(\pi, trial) \quad (1)$$



Payoff as a function of behavior



Model and human at level of trial



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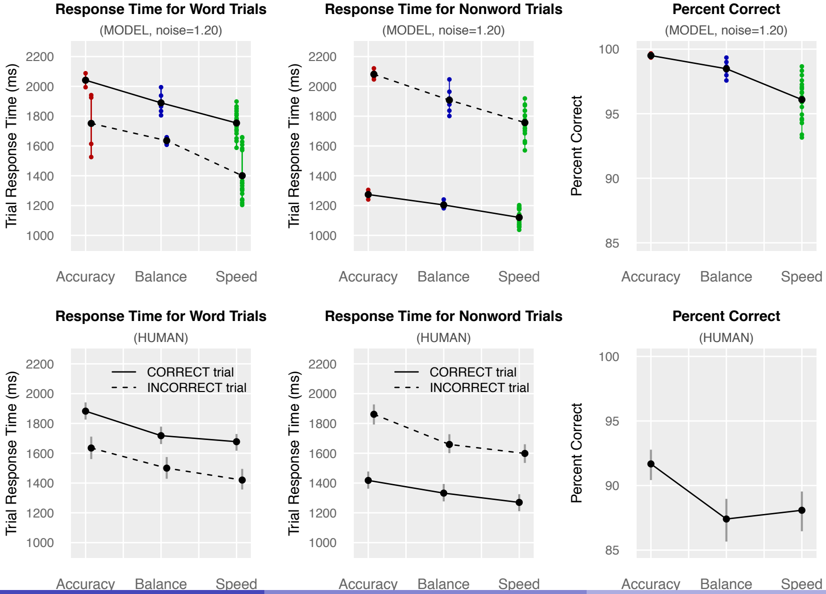
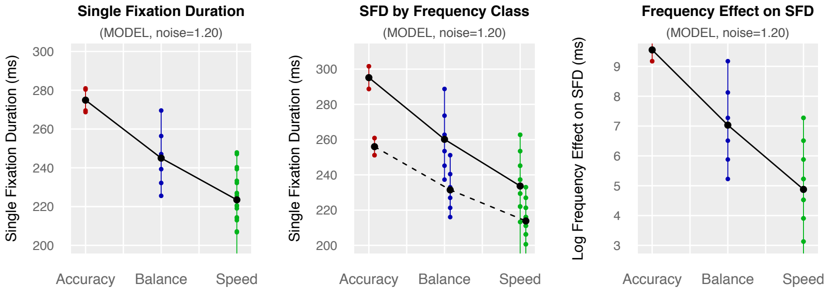


Model and human at level of word/string



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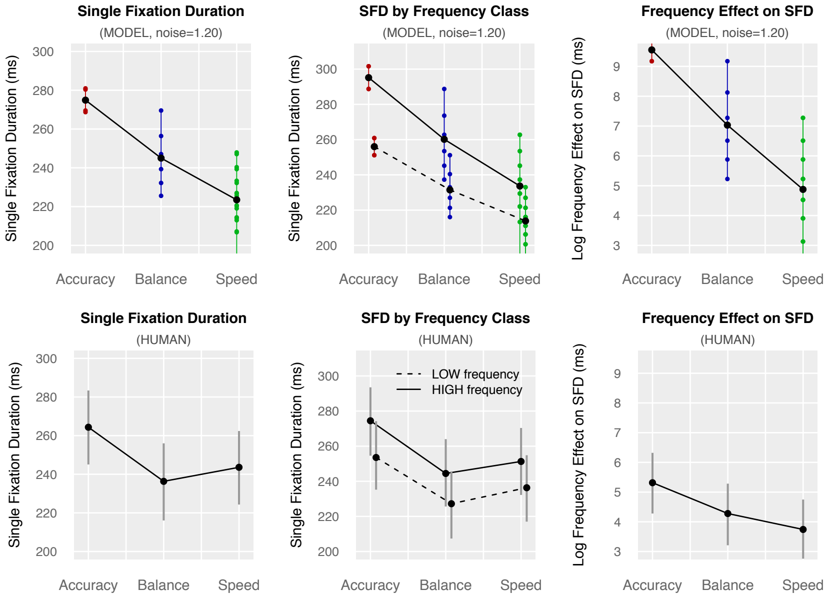
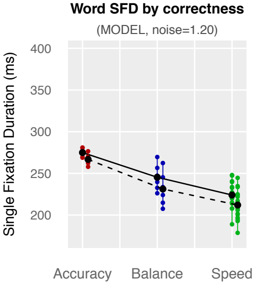
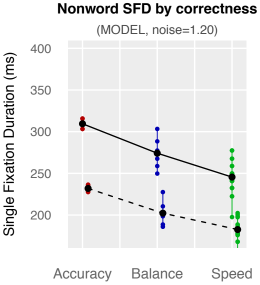


Model and human: Words vs. nonwords, position effects

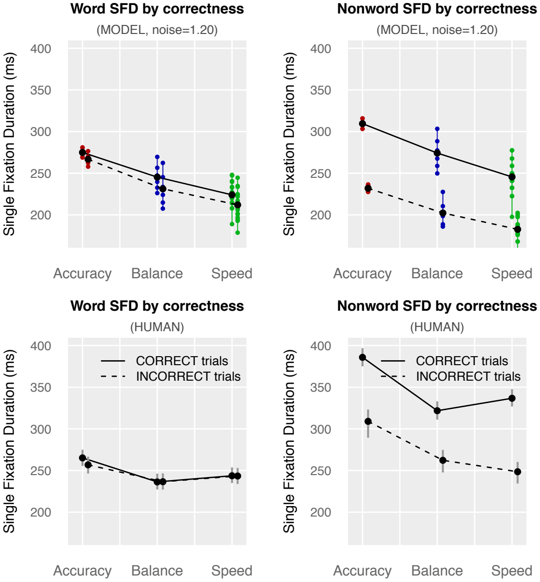




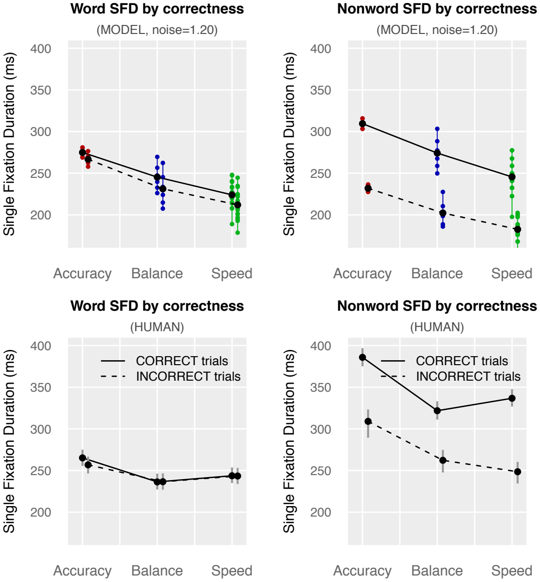
Word SFD by correctness
(HUMAN)

Nonword SFD by correctness
(HUMAN)

Model and human: Words vs. nonwords, position effects



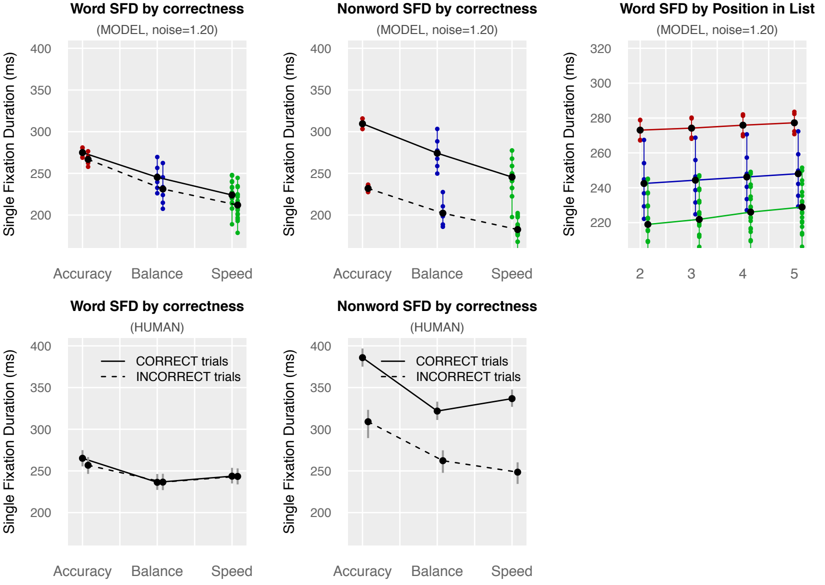
Model and human: Words vs. nonwords, position effects



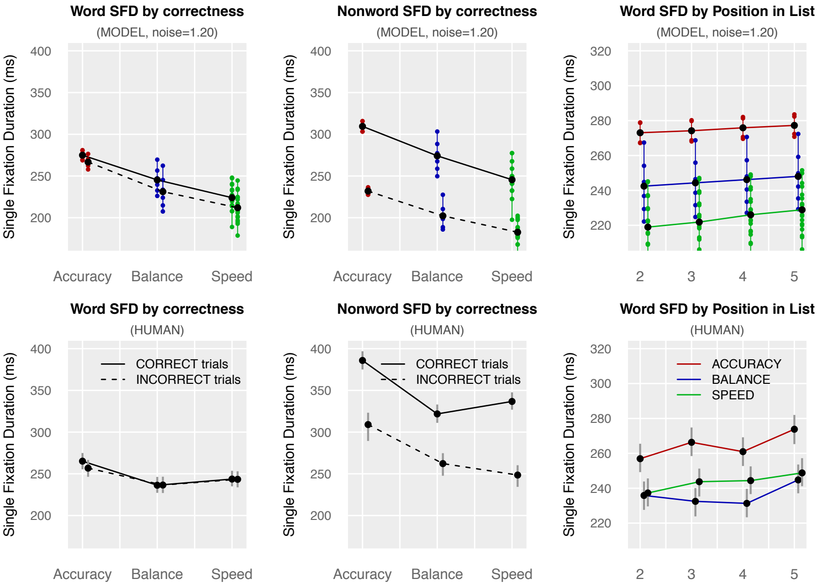
Word SFD by Position in List

(MODEL, noise=1.20)

Model and human: Words vs. nonwords, position effects



Model and human: Words vs. nonwords, position effects



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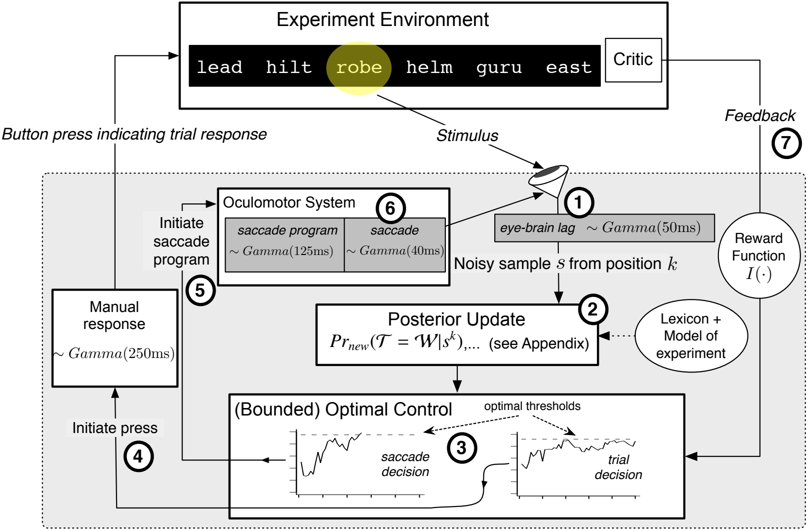
Does the processing architecture matter?

The theoretical claim here is that eye-movement control is jointly shaped by both task payoff *and* architecture. What is the evidence for this?

Through modeling we can explore adaptation to *different architectures* than the one hypothesized for the human oculomotor system.

The "minimal model"



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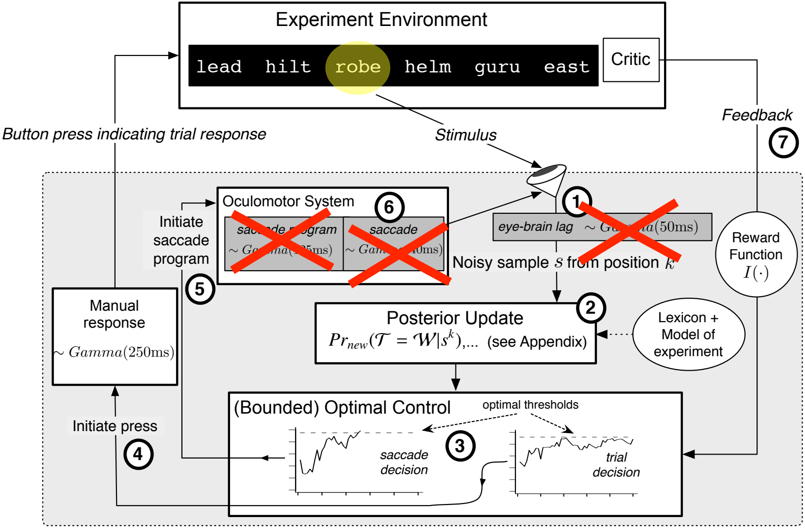
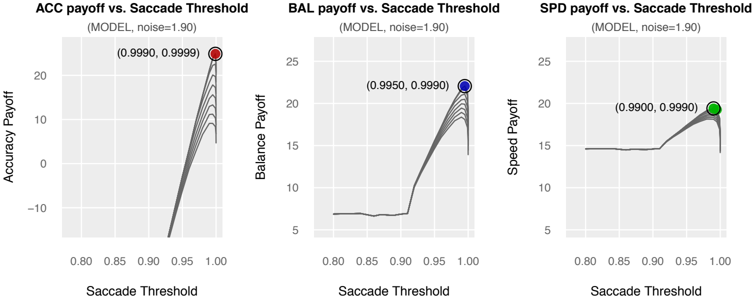


Payoff structure & predictions for the minimal model



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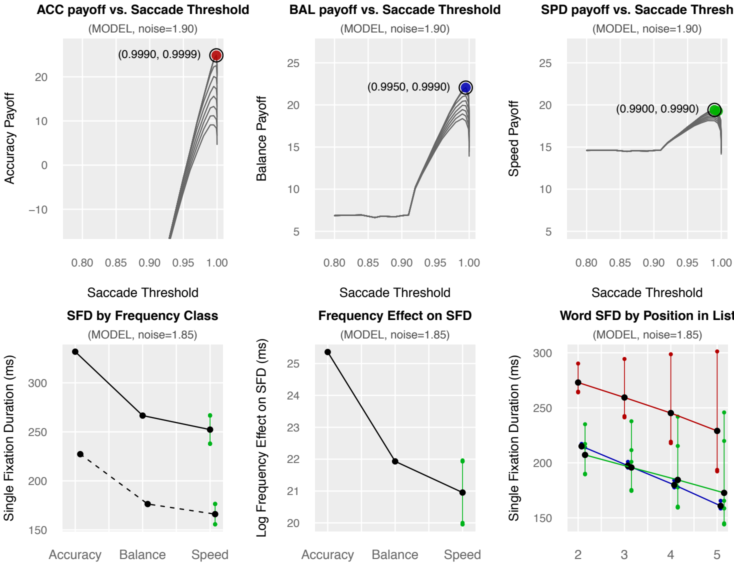
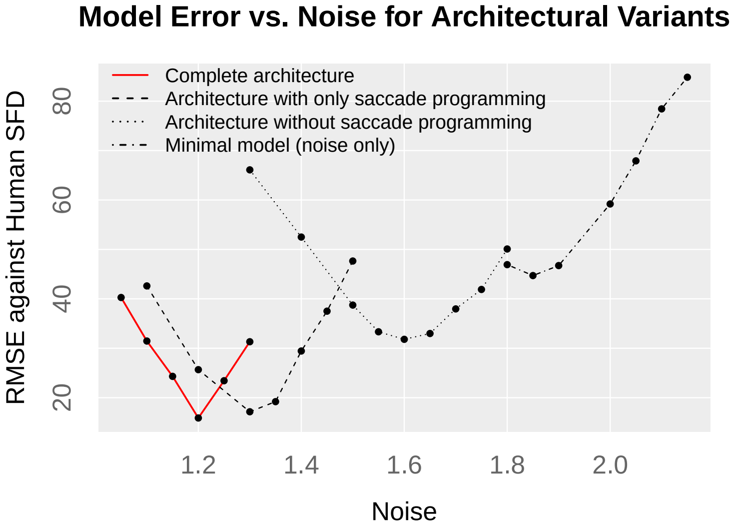


Review word-level results

Model fit for the alternative architectures

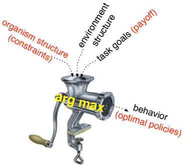


1. What determines the nature of eye-movements in linguistic tasks?

2. Conclusions and looking ahead

Summary

We applied *optimal control* and *state estimation* techniques to pursue, computationally, an interesting theoretical idea. Doing so yielded two things:



1. What determines the nature of eye-movements in linguistic tasks? *Answer:* Eye-movement control is the solution to a constrained optimization problem posed by task structure and payoff, linguistic knowledge, and oculomotor processing architecture.
2. A novel empirical demonstration: Humans adapt their oculomotor control at the level of single fixation durations to maximize payoff in linguistic tasks, and do so in ways sensitive to the specific contingencies of the task at hand.

Stronger ties between psycholinguistics and linguistics and other areas of cognitive science?

Bayesian memory & perception

reinforcement learning

decision making

rational analysis

bounded rationality

psycholinguistics:

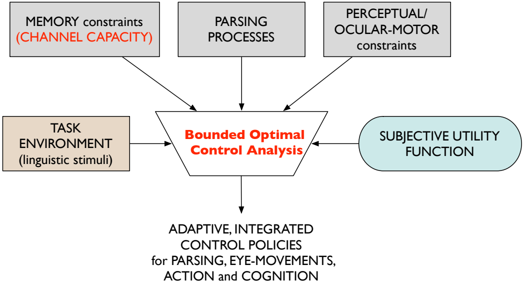
classic parsing strategies

rational approaches

language-as-action

syntactic theory

language evolution



Optimal control and syntactic theory and evolution??

The question we can pose is: What optimization problem (specifically, bounded optimal control problem) is human language the solution to?

- This offers a perspective on language evolution/emergence that complements existing approaches by placing emphasis on how *the details of cognitive architecture and utility* shape language, abstracting away from processes of evolution.
- It *perhaps* offers another way to pursue the "Strong Minimalist" thesis of optimality in language (recent work by Chomsky).

For more, see Bratman, Shvartsman, Lewis & Singh (2010) on my web site.

Grammar as bounded optimal policy

Bratman, Shvartsman, Lewis & Singh (2012)

Environment	Agent memory	Lexicon size (S)	Properties of emergent linguistic system
Two Rooms	one symbol working memory + one symbol long-term memory	3	Association and systematic order, where in addition single symbols uttered in isolation denote specific box-key combinations. Can only achieve 75% success.
		4	Association and systematic symbol order. SPEAKER first describes the box, then the key (see Figure 2b).
		8	Highly context-dependent and idiosyncratic symbol meanings. For example *key 2* is represented by *symbol 4* if uttered before box, but *symbol 5* after.
		16	Each symbol denotes a box-key combination. For example symbol 5 means *key 1* and *box 1*.
Two rooms	two symbol working memory (no long-term memory)	3	Similar to case with 3 symbols above.
		4	Complex lexical forms. Describes entire box-key combination with two symbols which can be observed simultaneously by LISTENER effectively creating a 2-symbol length word (see Figure 3b).
One room	one symbol working memory + one symbol long-term memory	3	Symbols act as direct orders to LISTENER, but otherwise policy is similar to the cases of 3 symbols above.
		4	Association and symbol order, but no storing or retrieving from long-term memory is necessary because LISTENER can act immediately upon hearing a symbol

Collaborators and sponsors

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