

Relative entropy, and naive discriminative learning

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in collaboration with

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overview

- ▶ Milin, Filipovic-Durdevic & Moscoso del Prado (2009)
- ▶ Experiment 1: replication with primed self-paced reading
- ▶ Modeling with naive discriminative learning
- ▶ Experiment 2: relative entropy in syntax (lex. dec.)
- ▶ Experiment 3: relative entropy in syntax (eye-tracking)
- ▶ Relative entropy, random intercepts, and stem support

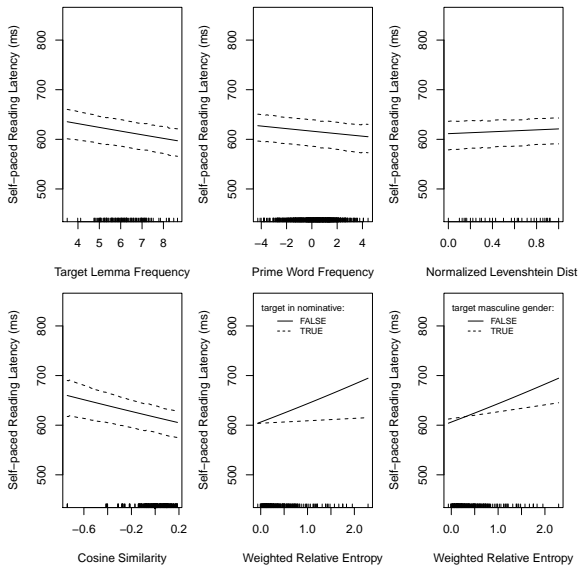
Milin et al. 2009

- ▶ $\{p\}$: the probability distribution of exponents of a given lemma
- ▶ $\{q\}$: the probability distribution of exponents across all lemmata in an inflectional class
- ▶ relative entropy $RE = \sum_i p_i \log_2(p_i/q_i)$
- ▶ **greater relative entropy, longer lexical decision latencies**

Replication study using primed self-paced reading

- ▶ weighted relative entropy: $\sum_i \frac{p_i w_i}{\sum_i p_i w_i} \log_2 \frac{p_i}{q_i}$
- ▶ weights $w_i = \frac{f(\text{target}_i)}{f(\text{prime}_i)}$
- ▶ **a greater WRE predicts longer latencies**
- ▶ but interactions with masculine gender and nominative case

Interactions with weighted relative entropy

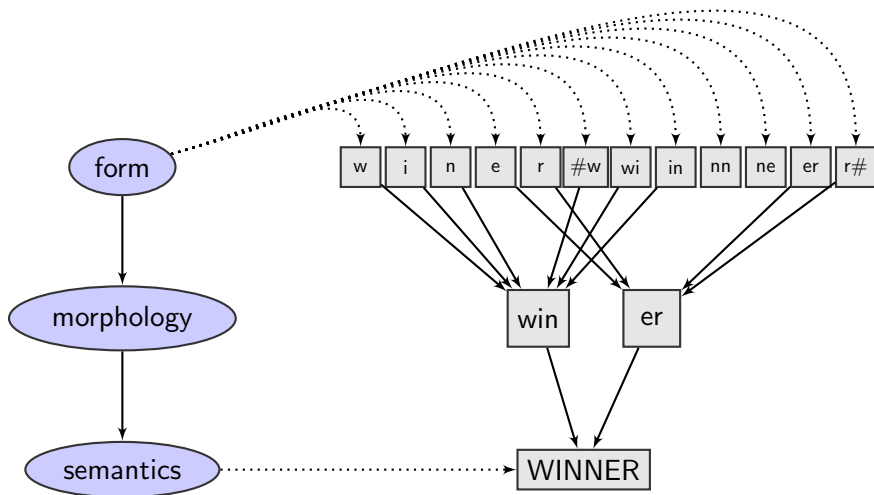


Modeling (weighted) relative entropy effects

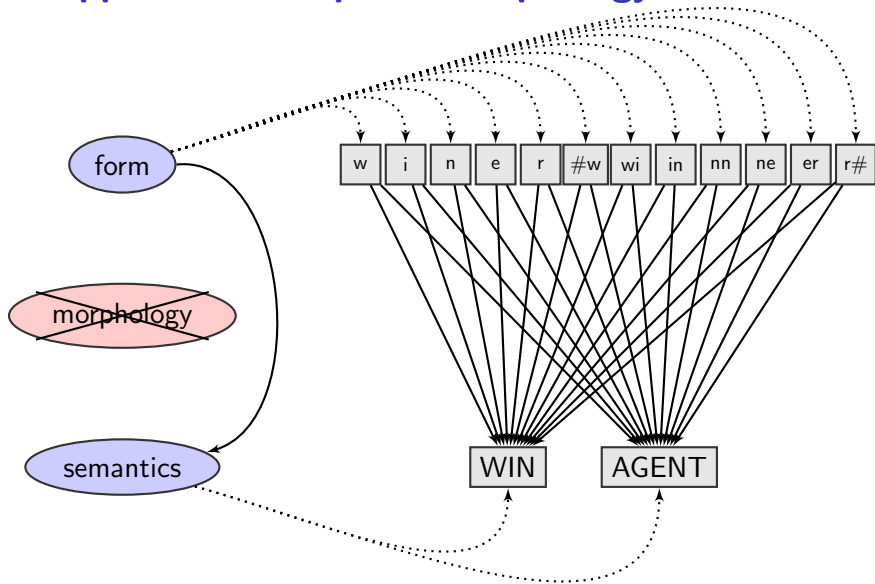
sources of inspiration

- ▶ recent work by Michael Ramscar on the Rescorla-Wagner equations in language acquisition
- ▶ old work by Fermin Moscoso del Prado Martin (PhD thesis, chapter 10)
- ▶ discussions with Jim Blevins

Models of morphological processing: the 'standard' model (Rastle, Davis)



Our approach: amorphous morphology



orthographic cues

- ▶ letters and letter pairs as cues for meanings
- ▶ legal scrabble words beginning with **qa**

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 - ▶ **qanat** (gently sloping underground tunnel for irrigation)
 - ▶ **qat** (leaf of the shrub *Catha edulis*)
- ▶ our model is based on a generalization of this idea

naive discriminative learning

- ▶ Links between orthography (cues) and semantics (outcomes) are established through **discriminative learning**
 - ▶ **Rescorla-Wagner equations** for discriminative learning (Rescorla & Wagner, 1972)
 - ▶ **Equilibrium equations** for the Rescorla-Wagner equations (Danks, 2003)
- ▶ The activation for a given meaning outcome is the sum of all associative links between the (active) input letters and letter pairs and that meaning

Rescorla-Wagner equations

$$V_i^{t+1} = V_i^t + \Delta V_i^t$$

with

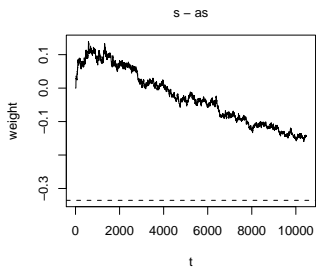
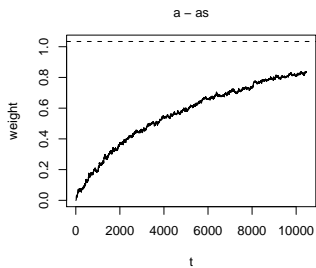
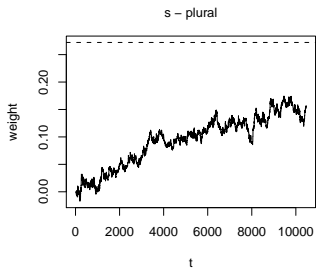
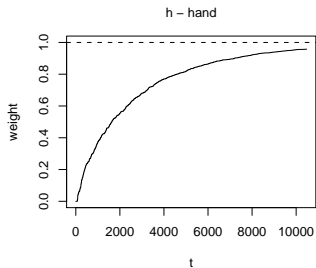
$$\Delta V_i^t = \begin{cases} 0 & \text{if ABSENT}(C_j, t) \\ \alpha_i \beta_1 \left(\lambda - \sum_{\text{PRESENT}(C_j, t)} V_j \right) & \text{if PRESENT}(C_j, t) \ \& \ \text{PRESENT}(O, t) \\ \alpha_i \beta_2 \left(0 - \sum_{\text{PRESENT}(C_j, t)} V_j \right) & \text{if PRESENT}(C_j, t) \ \& \ \text{ABSENT}(O, t) \end{cases}$$

- ▶ if a cue is **reliable**, it's connection strength will increase
- ▶ if a cue is **unreliable**, it's connection strength will decrease
- ▶ if many cues are relevant simultaneously, the contribution of a single cue from the set will be small

Example lexicon

Word	Frequency	Lexical Meaning	Number
<i>hand</i>	10	HAND	
<i>hands</i>	20	HAND	PLURAL
<i>land</i>	8	LAND	
<i>lands</i>	3	LAND	PLURAL
<i>and</i>	35	AND	
<i>sad</i>	18	SAD	
<i>as</i>	35	AS	
<i>lad</i>	102	LAD	
<i>lads</i>	54	LAD	PLURAL
<i>lass</i>	134	LASS	

The Rescorla-Wagner equations applied



a shortcut straight to the adult stable state

- ▶ **equilibrium equations (Danks)** when the system is in a stable state, the connection weights to a given meaning can be estimated by solving a set of linear equations

$$\begin{pmatrix} \Pr(C_0|C_0) & \Pr(C_1|C_0) & \dots & \Pr(C_n|C_0) \\ \Pr(C_0|C_1) & \Pr(C_1|C_1) & \dots & \Pr(C_n|C_1) \\ \dots & \dots & \dots & \dots \\ \Pr(C_0|C_n) & \Pr(C_1|C_n) & \dots & \Pr(C_n|C_n) \end{pmatrix} \begin{pmatrix} V_0 \\ V_1 \\ \dots \\ V_n \end{pmatrix} = \begin{pmatrix} \Pr(O|C_0) \\ \Pr(O|C_1) \\ \dots \\ \Pr(O|C_n) \end{pmatrix}.$$

V_i : association strength of i -th cue C_i to outcome O

- ▶ **the association strengths V_j optimize the conditional outcomes given the conditional co-occurrence probabilities characterizing the input space**

from weights to meaning activations

- ▶ the activation a_i of meaning i is the sum of its incoming connection strengths

$$a_i = \sum_j V_{ji}$$

- ▶ the greater the meaning activation, the shorter the response latencies
 - ▶ simplest case:
 $RT_{sim_i} \propto -a_i$
 - ▶ a log transformation may be required to remove the right skew from the distribution of simulated RTs:
 $RT_{sim_i} \propto \log(1/a_i)$

the naive discriminative reader

- ▶ basic engine is **parameter-free**, and driven completely and only by the language input
- ▶ the model is computationally undemanding: building the weight matrix from a lexicon of 11 million phrases takes 10 minutes on my desktop
- ▶ implementation in R

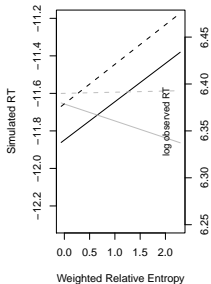
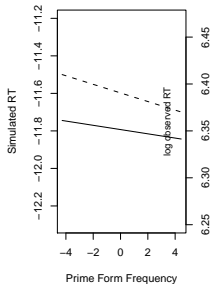
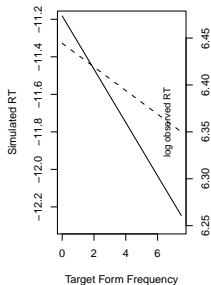
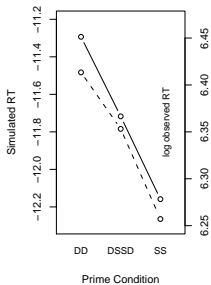
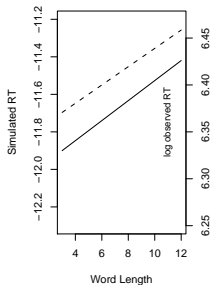
from weights to meaning activations

- ▶ for Serbian case-inflected nouns, sum over lexical meanings and grammatical meanings
- ▶ for priming, we use [Ratcliff-McKoon's compound cue theory](#):

$$S = \sum_{i=1}^{10} (a_{P_i}^w \cdot a_{T_i}^{1-w}) \quad (0 \leq w \leq 0.5) \quad (1)$$

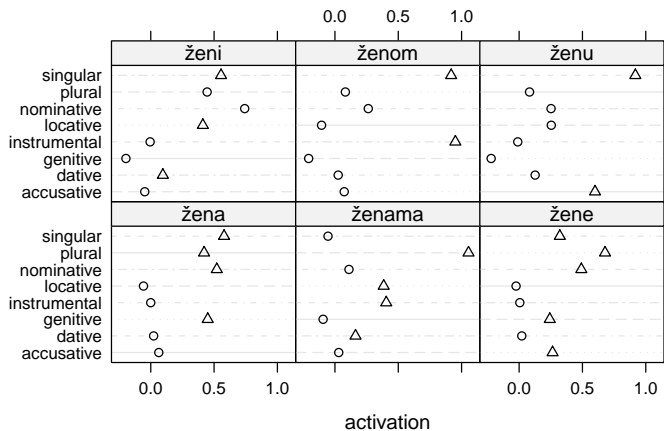
- ▶ this introduces a free parameter for the prime duration
- ▶ we also use one free parameter to model the time required to plan and execute a second fixation for longer words

Observed and simulated latencies ($r = 0.24$)



— simulated
- - - observed

Activation of case meanings



Summary Experiment 1

- ▶ relative entropy effects persist in sentential reading
- ▶ they are modified, but not destroyed by priming
- ▶ the interaction with masculine gender follows from the distributional properties of the lexical input
- ▶ the interaction with nominative case remains unaccounted for (functions and meanings?)
- ▶ frequency effects for complex words and paradigmatic effects can arise without representations for complex words or representational structures for paradigms

Experiment 2: Relative entropy in syntax

phrase	phrasal frequency	phrasal probability	preposition	prepositional frequency
<i>on a plant</i>	28608	0.279	<i>on</i>	177908042
<i>in a plant</i>	52579	0.513	<i>in</i>	253850053
<i>under a plant</i>	7346	0.072	<i>under</i>	10746880
<i>above a plant</i>	0	0.000	<i>above</i>	2517797
<i>through a plant</i>	0	0.000	<i>through</i>	3632886
<i>behind a plant</i>	760	0.007	<i>behind</i>	3979162
<i>into a plant</i>	13289	0.130	<i>into</i>	25279478

40 spatial prepositions

prepositional relative entropy

training data

- ▶ the model is trained on 11,172,554 two and three-word phrases from the British National Corpus, comprising 26,441,155 word tokens
- ▶ phrases have as last word one of 24710 monomorphemic words, or any bimorphemic compounds, derived and inflected words containing one of the 24710 monomorphemic words

constructions sampled

PREPOSITION + ARTICLE + NOUN

about a ballet

PREPOSITION + POSSESSIVE PRON. + NOUN

about her actions

PREPOSITION + X + NOUN

about actual costs

PREPOSITION + NOUN

about achievements

X'S + NOUN

protege's abilities

ARTICLE + NOUN

a box

ARTICLE + X + NOUN

the abdominal appendages

POSSESSIVE PRONOUN + NOUN

their abbots

ARTICLE + X'S + NOUN

the accountant's bill

PRONOUN + AUXILIARY + VERB

they are arrested

PRONOUN + VERB

he achieves

AUXILIARY + VERB

is abandoning

ARTICLE + ADJECTIVE

the acute

processing of monomorphemic words

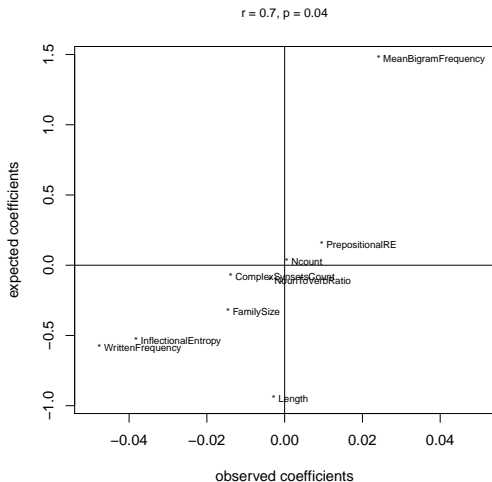
- ▶ stimuli: 1289 monomorphemic nouns
- ▶ lexical decision latencies from the English Lexicon Project
- ▶ simulated lexical decision latencies

- ▶ predictors
 - ▶ Family Size
 - ▶ Inflectional Entropy
 - ▶ Written Frequency
 - ▶ Number of Morphologically Complex Synonyms
 - ▶ Neighborhood Density
 - ▶ Mean Bigram Frequency
 - ▶ Noun-Verb Ratio
 - ▶ Length
 - ▶ **Prepositional Relative Entropy**

results

correlation for the observed and simulated response latencies:

$$r = 0.55, t(1287) = 23.83, p < 0.001$$



Summary Experiment 2

- ▶ lexical paradigmatic effects (family size, inflectional entropy) modeled successfully without representations for inflections and derivations
- ▶ the phrasal paradigmatic effect is also modelled correctly, without representations for phrases
- ▶ the paradigmatic distributional properties of a word can affect single-noun reading

Other results obtained

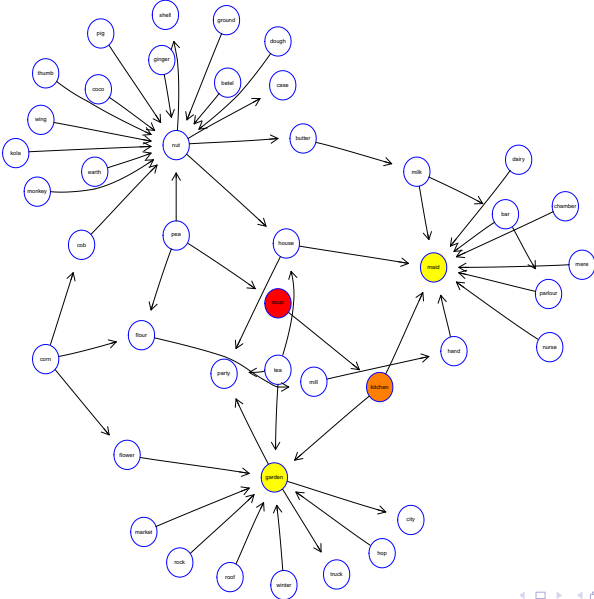
- ▶ phrasal frequency effects
- ▶ phonaestheme effects
- ▶ corn-corner effects (pseudoderived words)
- ▶ family size effects, whole-word frequency effects, and base frequency effects for complex words
- ▶ the interaction between first-constituent frequency and whole-word frequency in compound words (Kuperman et al., 2009)
- ▶ interaction of regularity by tense in English

intermezzo: strong connectivity

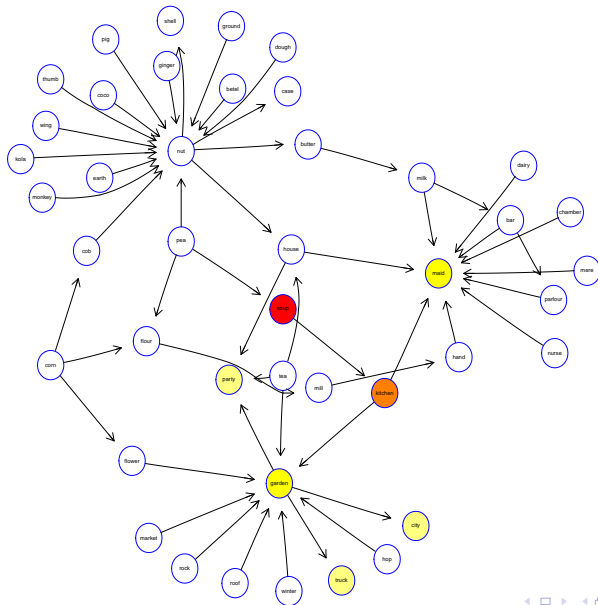
- ▶ **mediated priming** (Balota & Lorch, 1986)
 - ▶ **cat** → cab → **taxi**
 - ▶ **lion** → tiger → **stripes**

- ▶ **priming chains for compounds?**
 - ▶ **tea** trolley → trolley **bus**
 - ▶ **tea** trolley → trolley bus → bus **stop**

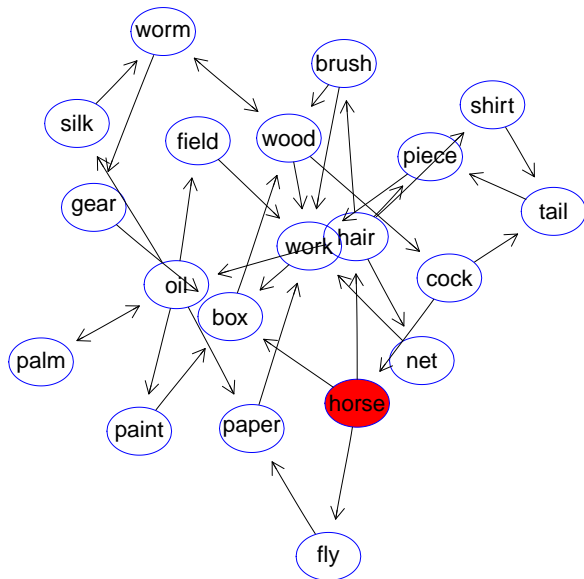
spreading activation: weak connectivity



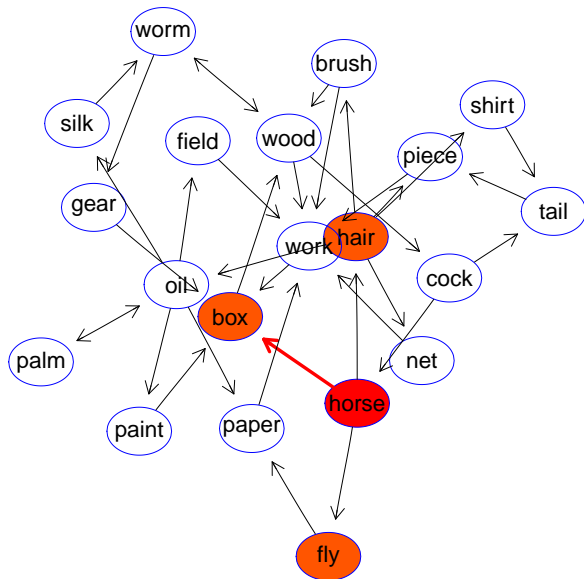
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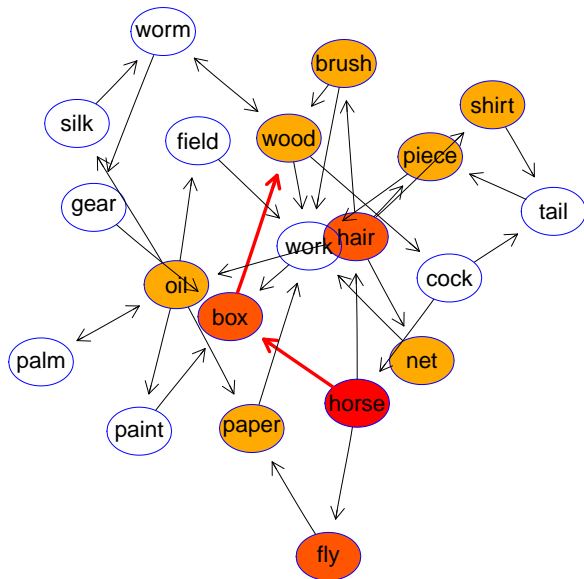
spreading activation: strong connectivity



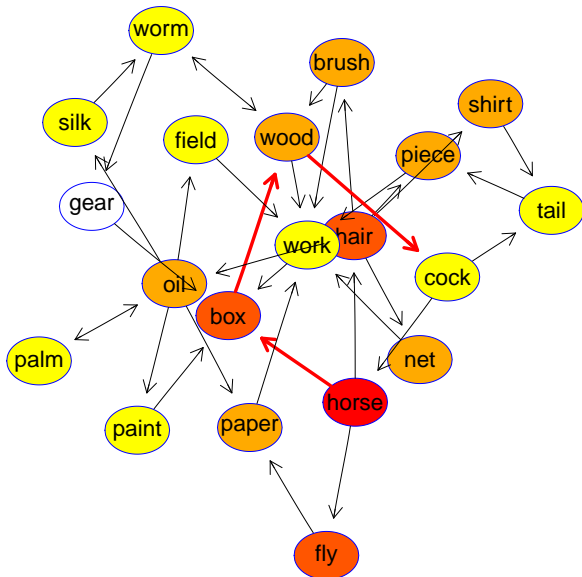
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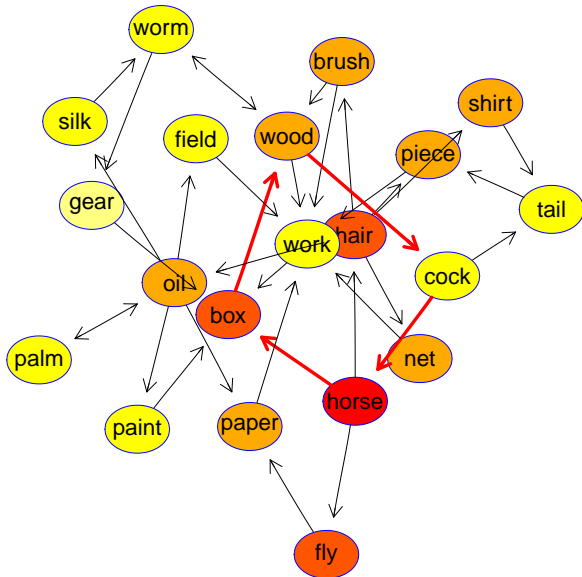
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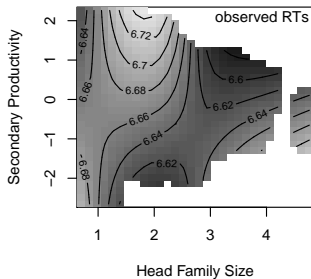


is strong connectivity advantageous?

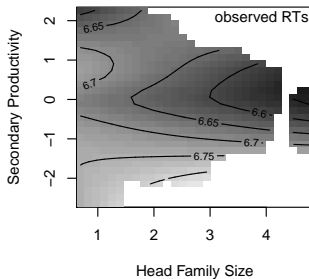
- ▶ is strong connectivity advantageous?
 - ▶ possibly yes — more integrated learning
 - ▶ possibly no — might cause confusion secondary family size
- ▶ this kind of connectivity should be beyond what the naive discriminative reader can handle — but it isn't

lexical connectivity

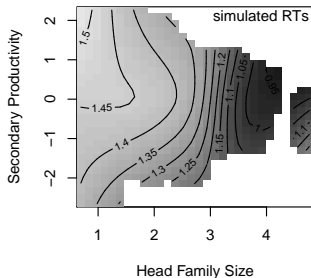
not in Strongly Connected Component



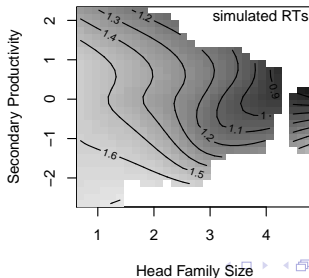
in Strongly Connected Component



not in Strongly Connected Component



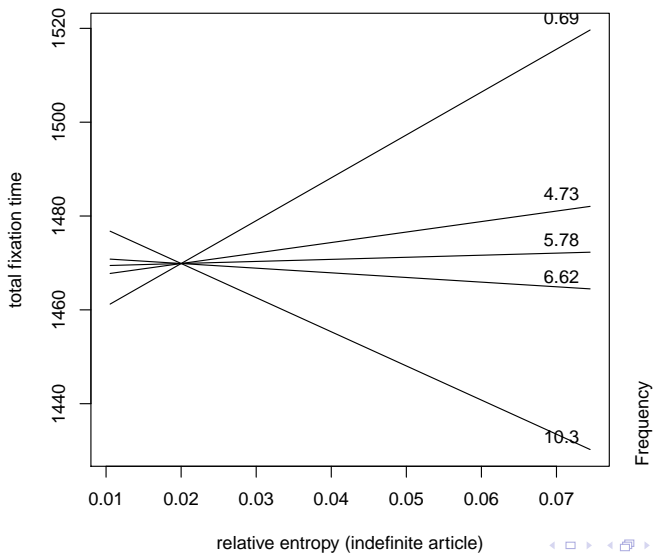
in Strongly Connected Component



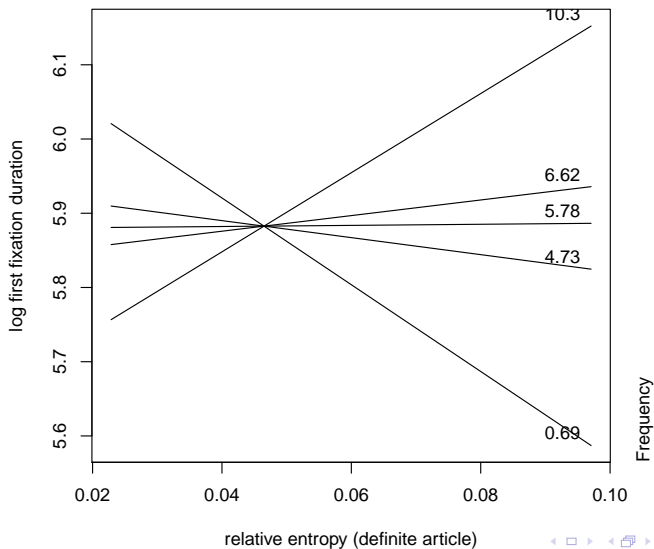
Experiment 3: More on relative entropy in syntax

- ▶ reading aloud combined with eye tracking
- ▶ first experiment: reading aloud single words
(e.g., *table*)
- ▶ second experiment: reading aloud prepositional phrases
(e.g., *on the + table*)

Experiment 3: single words, total fixation time



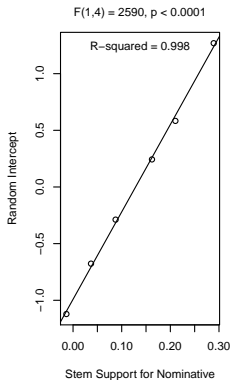
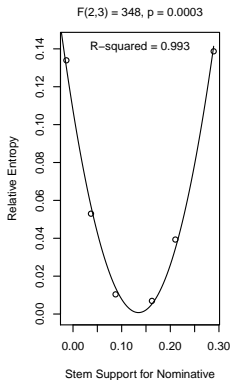
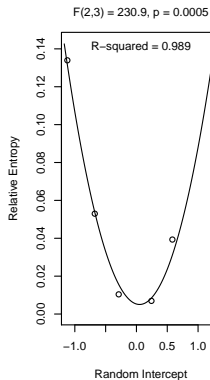
Experiment 3: phrases, total fixation time



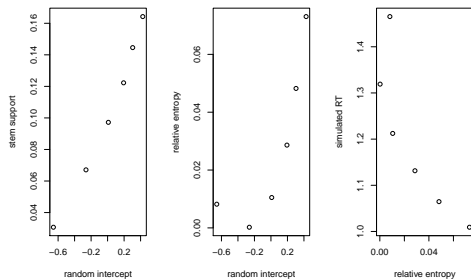
Naive discriminative and mixed-effects classifiers

Word Form	Frequency	Case	Lemma	Relative Entropy	Ranef	Stem Support Nominative	Stem Support Genitive	Exponent Support
AQeA	10	nom	A	0.134	-1.121	-0.014	0.260	0.353
AQeI	20	gen	A	0.134	-1.121	-0.014	0.260	0.740
AQeU	30	acc	A	0.134	-1.121	-0.014	0.260	0.595
AQeA	40	acc	A	0.134	-1.121	-0.014	0.260	0.127
ABCa	15	nom	B	0.053	-0.676	0.037	0.260	0.353
ABCI	22	gen	B	0.053	-0.676	0.037	0.260	0.740
ABCu	28	acc	B	0.053	-0.676	0.037	0.260	0.595
ABCa	35	acc	B	0.053	-0.676	0.037	0.260	0.127
APQa	20	nom	C	0.010	-0.288	0.087	0.260	0.353
APQi	24	gen	C	0.010	-0.288	0.087	0.260	0.740
APQu	26	acc	C	0.010	-0.288	0.087	0.260	0.595
APQa	30	acc	C	0.010	-0.288	0.087	0.260	0.127
ZPEa	30	nom	D	0.007	0.243	0.162	0.260	0.353
ZPEI	26	gen	D	0.007	0.243	0.162	0.260	0.740
ZPEU	24	acc	D	0.007	0.243	0.162	0.260	0.595
ZPEa	25	acc	D	0.007	0.243	0.162	0.260	0.127
EPBa	35	nom	E	0.039	0.583	0.210	0.260	0.353
EPBI	28	gen	E	0.039	0.583	0.210	0.260	0.740
EPBu	22	acc	E	0.039	0.583	0.210	0.260	0.595
EPBa	20	acc	E	0.039	0.583	0.210	0.260	0.127
DPBa	40	nom	F	0.139	1.269	0.289	0.260	0.353
DPBI	30	gen	F	0.139	1.269	0.289	0.260	0.740
DPBu	20	acc	F	0.139	1.269	0.289	0.260	0.595
DPBa	10	acc	F	0.139	1.269	0.289	0.260	0.127

stem support, random intercepts, and unsigned relative entropy



the main trend depends on the balance



$c(10, 20, 30, 40) * 20,$

$c(15, 24, 32, 40) * 10,$

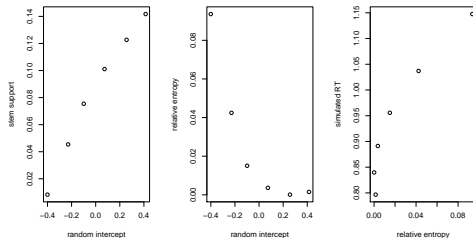
$c(20, 28, 33, 40) * 3,$

$c(25, 32, 35, 40) * 2,$

$c(30, 34, 37, 40) * 1,$

$c(35, 37, 38, 40) * 1$

trend depends on position prototype



c(10,20,30,40)*1,
c(15,24,32,40)*1,
c(20,28,33,40)*2,
c(25,32,35,40)*3,
c(30,34,37,40)*10,
c(35,37,38,40)*20

trend depends on position prototype

- ▶ in a complex system, the same measure can have slopes with opposite signs depending on the distributional properties of the language input
- ▶ this may help explain the changes in sign of RE in the eye-tracking+naming study
- ▶ **our distributional measures provide partial and potentially distorting views on the complex structure arising from simple principles of learning**

Discussion

- ▶ Our model shows morphological effects in the absence of morphological representations, including paradigmatic effects
- ▶ This is consistent with a-morphous views on morphology (e.g.: Anderson, 1992; Blevins, 2003)
- ▶ The model is a classifier (for the dative alternation, it outperforms mixed models)
 - ▶ relative entropies are functionally equivalent to unsigned random intercepts in a mixed-effects model
 - ▶ relative entropies capture the total association strengths from stems to grammatical meanings

Discussion

- ▶ Our model is similar in spirit to the reading part of the triangle model (Seidenberg & Gonnermann, 2000)
- ▶ Both models map orthography onto semantics without morphological representations
- ▶ Our computational engine, however, is much simpler than that of the triangle model: we do not assume hidden layers or use back-propagation to estimate connection weights.
- ▶ Furthermore, our model is more radically a-morphous in that there is no hidden layer that can covertly represent morphology.

Discussion

- ▶ Our model is also similar in spirit to the Bayesian Reader (Norris, 2006)
- ▶ Both models map forms onto 'central' representations without intercession by morphemes
- ▶ Our computational engine, however, is much simpler than that of the Bayesian reader: the complexity of the Bayesian reader is quadratic in the number of orthographic 'units', whereas our model is linear in the number of elementary meanings

Summary

- ▶ Discriminative learning provides a good fit to a wide range of experimental data
- ▶ The model is trained on realistic input, it is as sparse as possible in its number of representations, and it is computationally efficient
- ▶ The model does not make an a priori distinction between phrasal learning and morphological learning, and therefore can straightforwardly handle gradient phenomena at the interface of morphology and syntax (cf. construction morphology, Booij 2010)