Connectionist Language Processing

Lecture 11: Meaning-driven Surprisal and the Electrophysiology of Language Comprehension

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Lecture 11: Our (grand) theory of (nearly) anything some things (?)

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Surprisal Theory

Cognitive effort induced by a word is proportional to the amount of **information** that it conveys in context:

 $difficulty(w_t) \sim Surprisal(w_t) = -log P(w_t|w_{1...t-1},CONTEXT)$

> Surprisal models of linguistic experience (wtlw1...t-1) account for reading times for a broad range of phenomena

(e.g., Hale, 2001; Boston, Hale, Kliegl, Patil, & Vasishth, 2008; Brouwer, Fitz, & Hoeks, 2010; Demberg & Keller, 2008; Frank, 2009; Roark, Bachrach, Cardenas, & Pallier, 2009; Levy, 2008; Smith & Levy, 2008)

> But a word's processing difficulty is affected by the discourse context and world knowledge, above and beyond linguistic experience alone

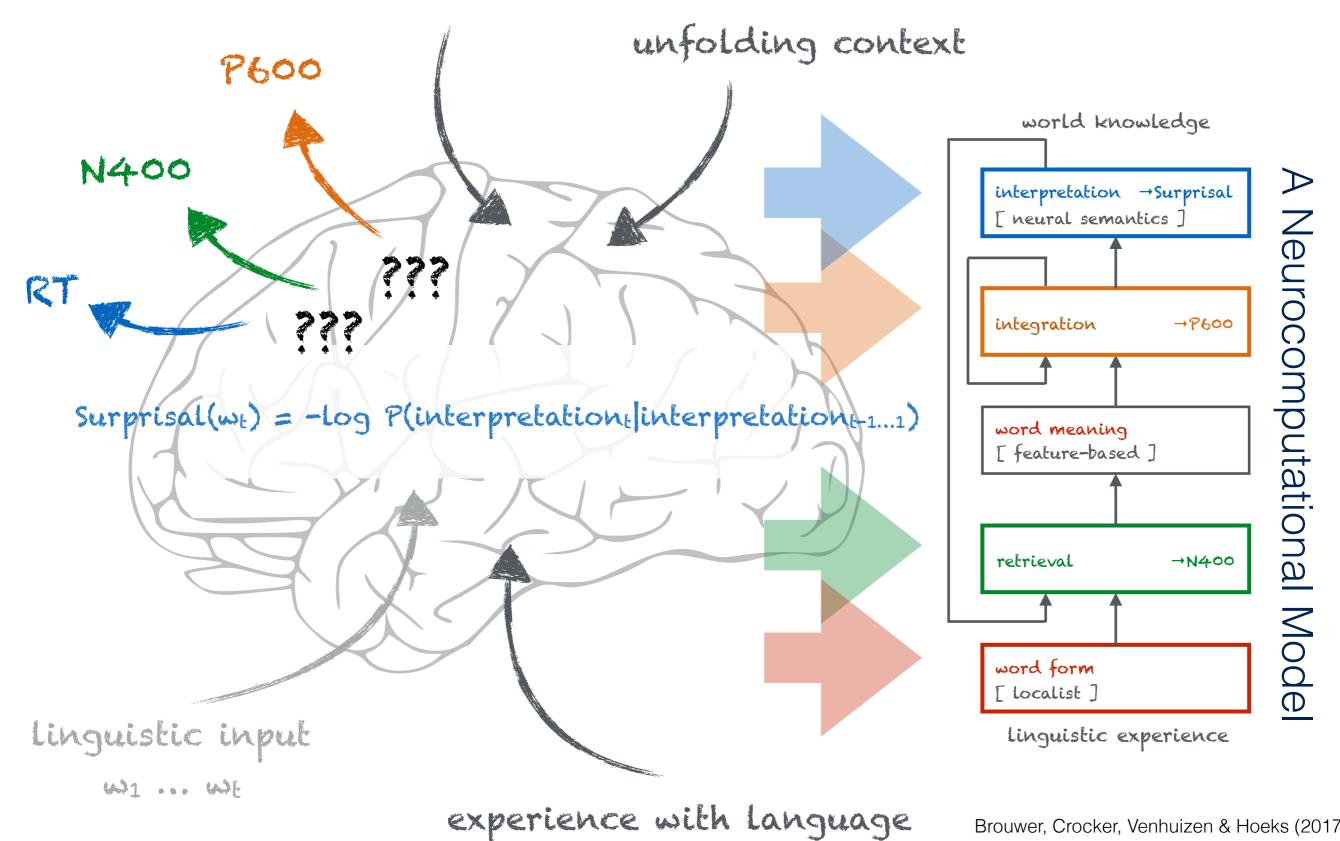
(e.g., Albrecht & O'Brien, 1993; Altmann & Kamide, 1999; Camblin, Gordon, & Swaab, 2007; Cook & Myers, 2004; Garrod & Terras, 2000; Hess, Foss, & Carroll, 1995; Knoeferle, Crocker, Scheepers, & Pickering, 2005; Knoeferle, Habets, Crocker, & Münte, 2008; Kuperberg, Paczynski, & Ditman, 2011; Morris, 1994; Myers & O'Brien, 1998; O'Brien & Albrecht, 1992; Otten & van Berkum, 2008; van Berkum, Brown, Zwitserlood, Kooijman, & Hagoort, 2005; van Berkum, Hagoort, & Brown, 1999; van Berkum, Zwitserlood, Hagoort, & Brown, 2003)

→ Surprisal models need to quantify and factor in 'CONTEXT'

Idea: linguistic experience, discourse context, and world knowledge all interact in the unfolding interpretation that is being constructed

Hale (2001), NAACL Levy (2008), Cognition

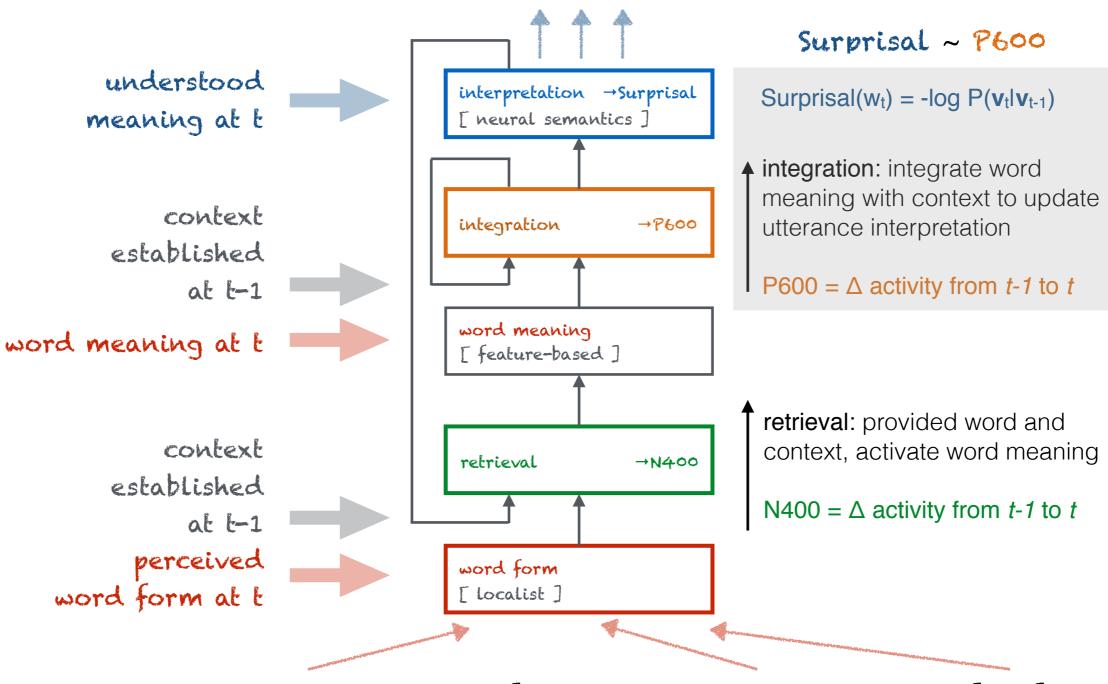
knowledge of the world



Brouwer, Crocker, Venhuizen & Hoeks (2017) Cognitive Sci.

> Venhuizen, Crocker & Brouwer (2019) Discourse Process.

enter(beth,restaurant) ∧ order(beth,champagne)



DP Model — Atomic propositions

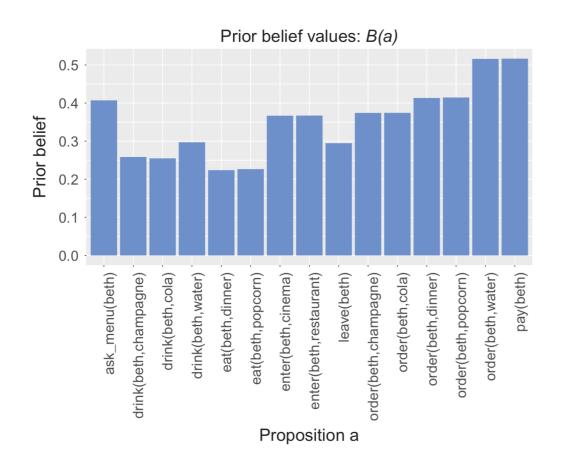
Table 1. Microworld concepts.

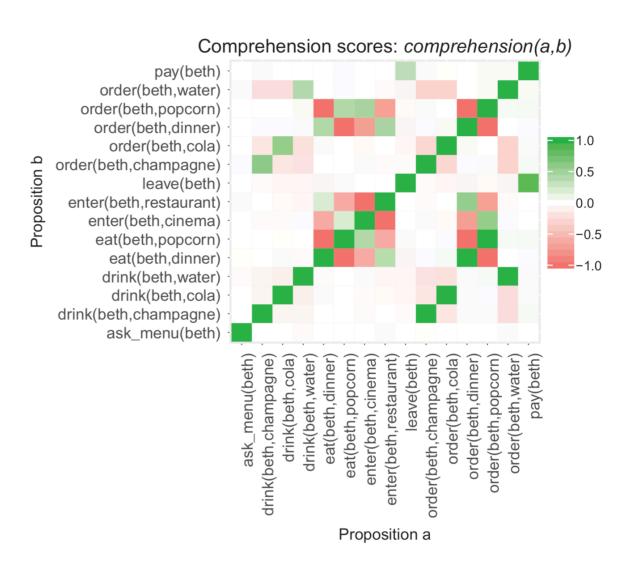
Class	Variable	Class members	
Persons	X	beth, dave, thom	
Places	р	cinema, restaurant	
Foods	f	dinner, popcorn	
Drinks	d	champagne, cola, water	
Predicates	-	enter, ask menu, order, eat, drink, pay, leave	

Table 2. Basic propositions.

Proposition	n
enter (x, p)	6
ask menu (x)	3
order (x, d) , order (x, f)	15
eat (x, f)	6
drink (<i>x</i> , <i>d</i>)	9
pay (x)	3
leave (x)	3
Total	45

DP Model — Meaning space





(only propositions for 'beth' are shown)

DP Model — Grammar

Table 3. Grammar of the language used for training. Optional arguments are in square brackets, and different instantiations of a rule are separatedusing the pipe symbol. Variable $V \in \{enter, menu, order, eat, drink, pay, leave\}$ denotes verb types.

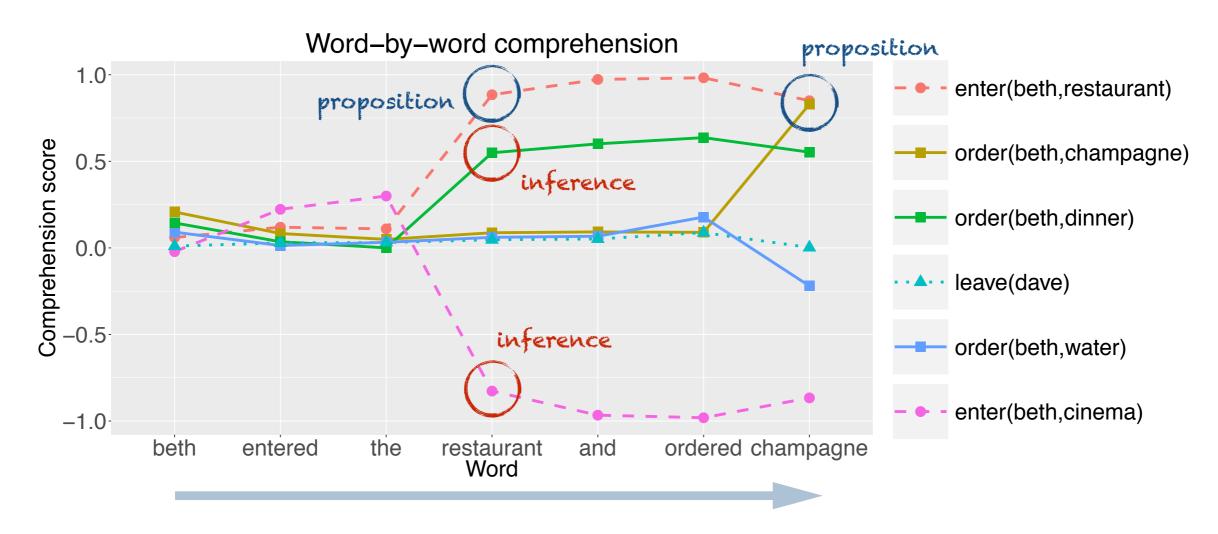
Head		Body
S	\rightarrow	$NP_{person} VP_{V} [CoordVP_{V}]$
NP _{person}	\rightarrow	beth dave thom
NP _{place}	\rightarrow	the cinema the restaurant
NP _{food}	\rightarrow	dinner popcorn
NP_{drink}	\rightarrow	champagne cola water
VP _{enter}	\rightarrow	entered NP _{place}
VP_{menu}	\rightarrow	asked for the menu
VP_{order}	\rightarrow	ordered NP_{food} ordered NP_{drink}
VP_{eat}	\rightarrow	ate NP _{food}
VP_{drink}	\rightarrow	drank NP _{drink}
VP_{pay}	\rightarrow	paid
VP _{leave}	\rightarrow	left
CoordVP _{enter}	\rightarrow	and VP_{menu} and VP_{order} and VP_{leave}
$CoordVP_{menu}$	\rightarrow	and VP _{order} and VP _{leave}
$CoordVP_{\mathit{pay}}$	\rightarrow	and VP _{order} and VP _{leave}

Highly frequent (x9): "NP_{person} ordered dinner," "NP_{person} ate popcorn," "NP_{person} ordered champagne," "NP_{person} drank water";

Relatively frequent (x5): "NP_{person} ordered cola," "NP_{person} drank cola."

Default (x1): All other structures

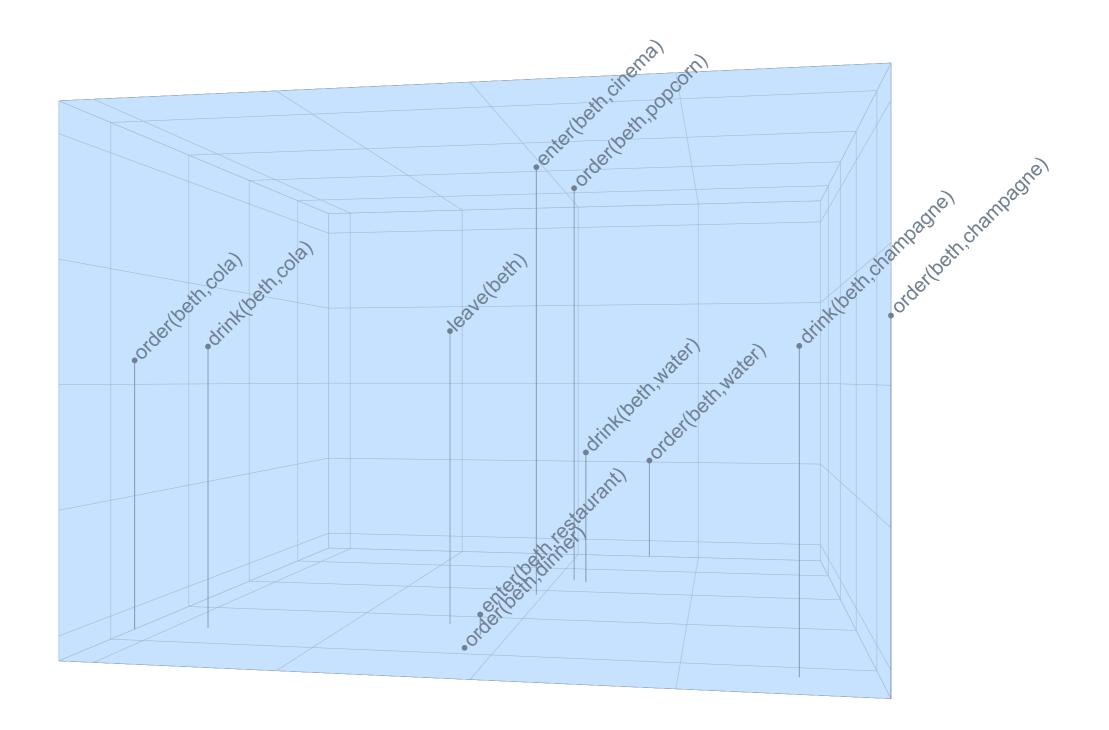
What does the model 'understand'?



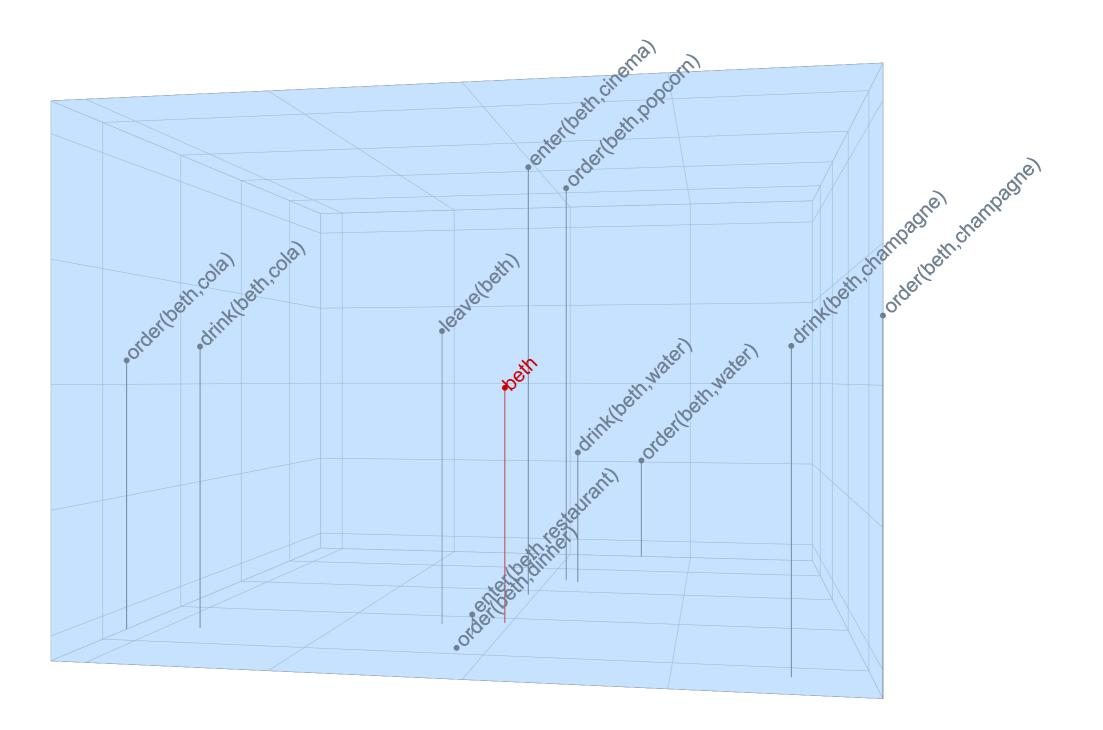
How much is situation a understood to be the case from situation b?

> Representations capture meaning beyond literal propositional content; i.e., model engages in direct knowledge-driven inferencing

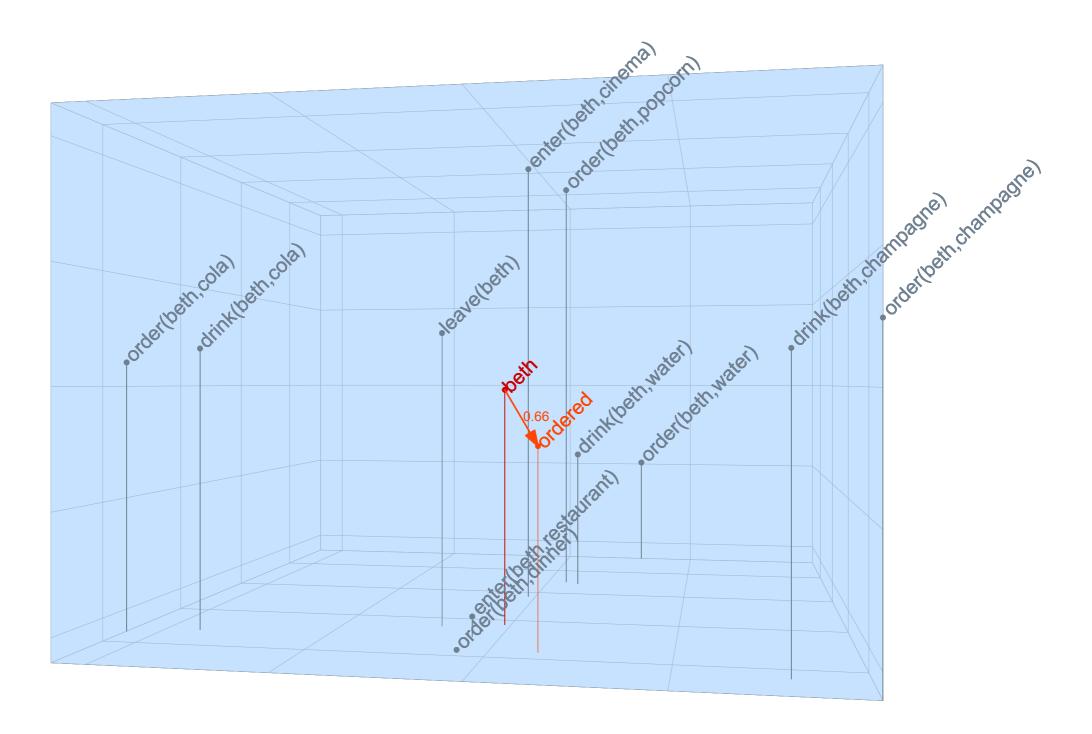
Neural Semantics — Meaning space (multi-dimensional scaling: 150D → 3D)



["beth"]

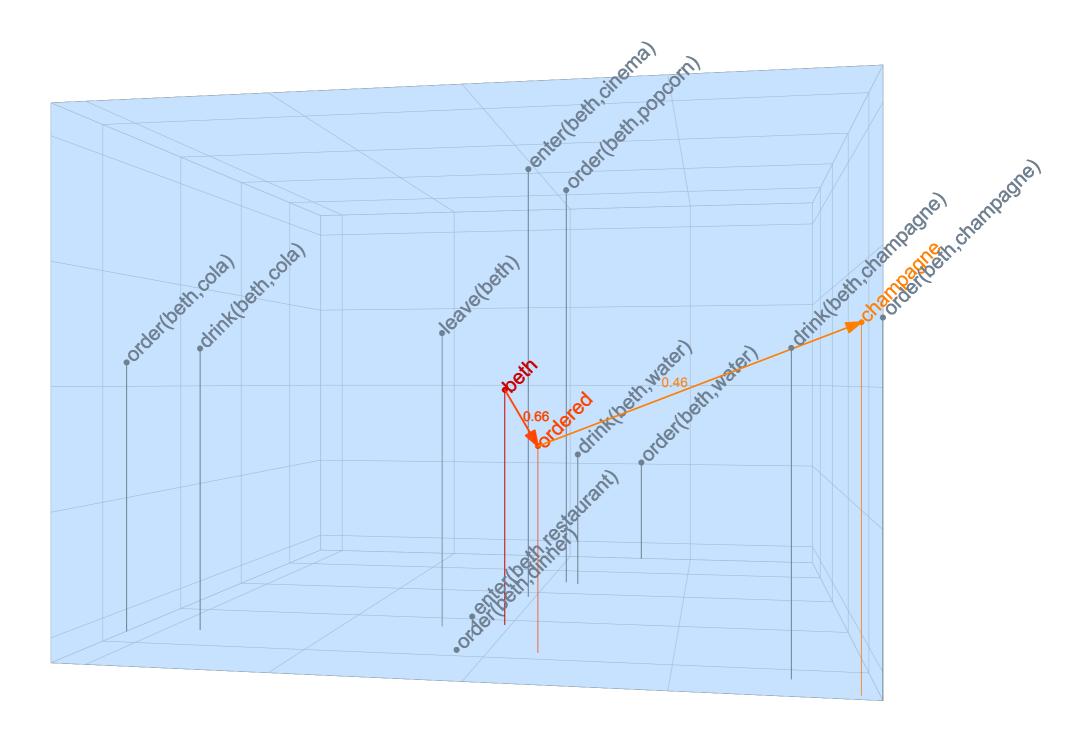


["beth", "ordered"]

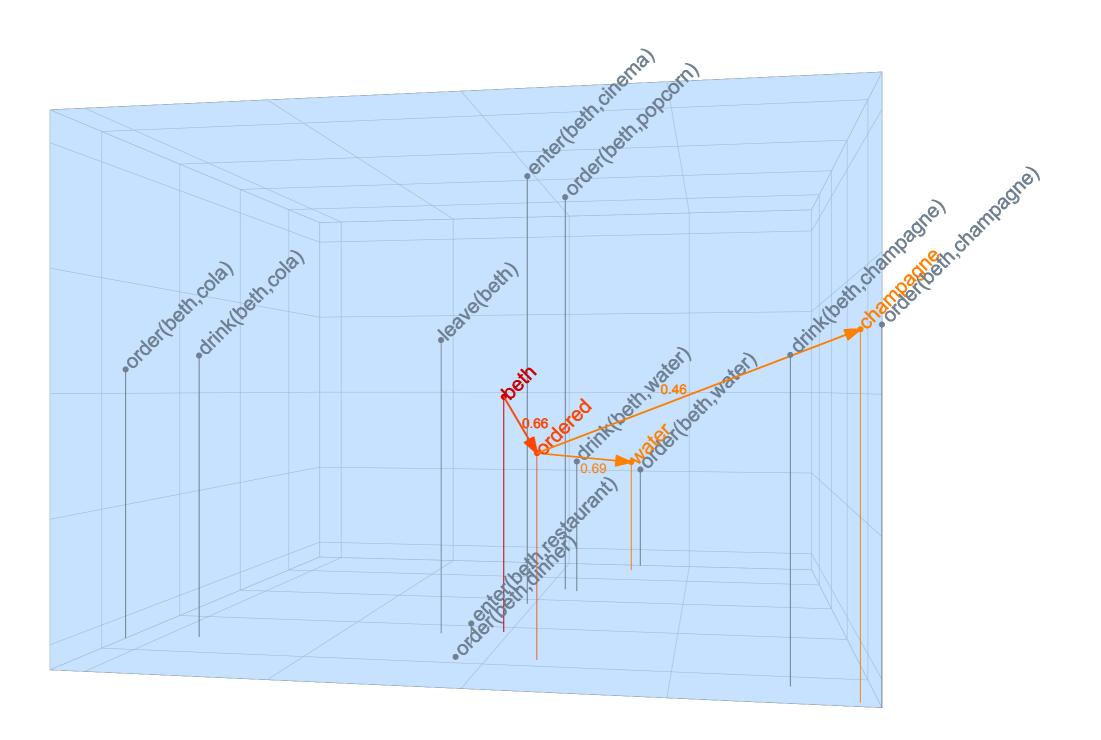


Surprisal ∝ distance

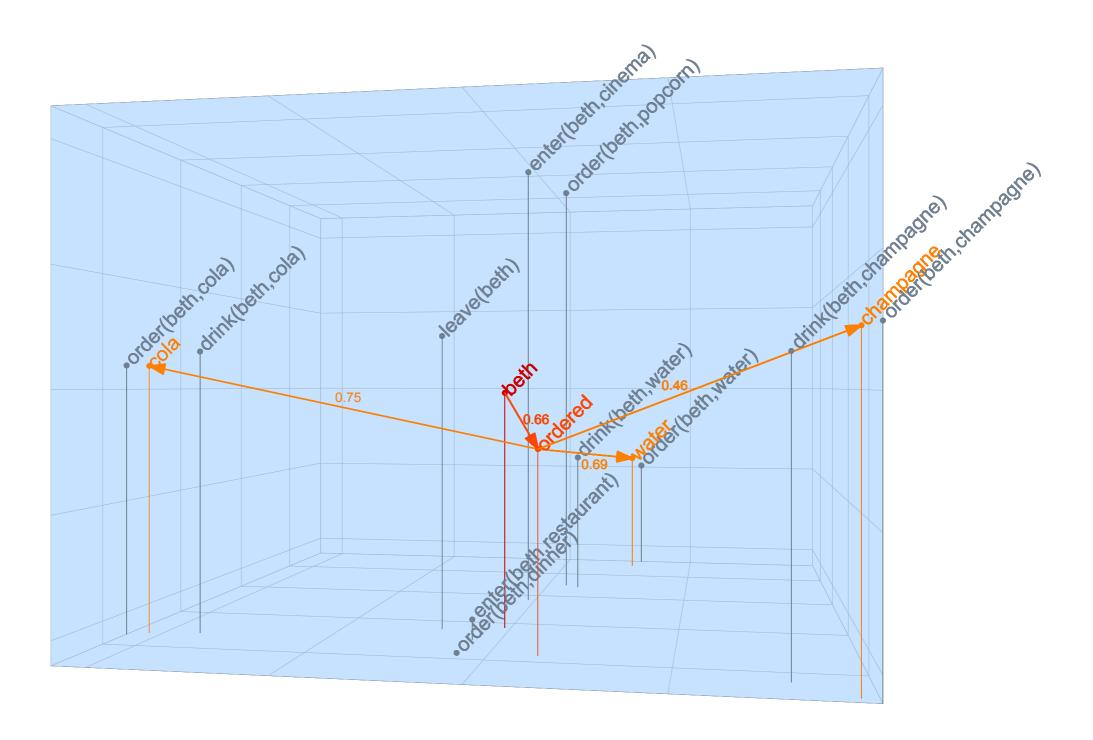
["beth", "ordered", "champagne"]



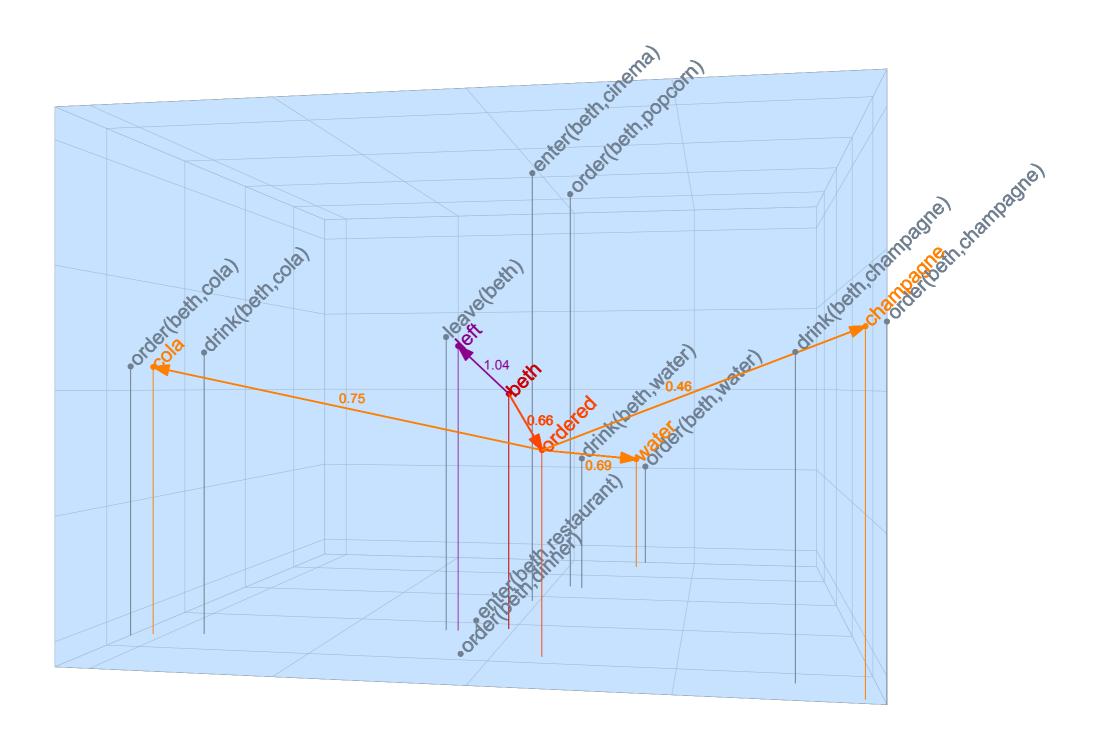
Surprisal ∝ distance



Surprisal ∝ distance



Surprisal ∝ distance



Surprisal ∝ distance

Surprisal in comprehension

Meaning-level Surprisal

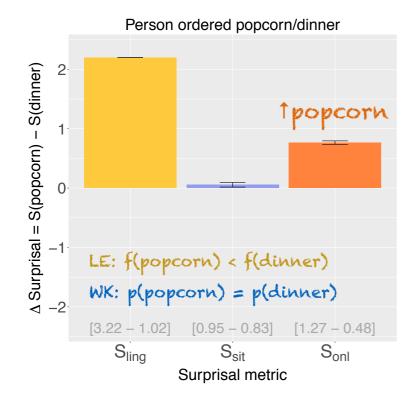
difficulty(w_t) \propto Surprisal(w_t) = -log P($\mathbf{v}_t | \mathbf{v}_{t-1}$)

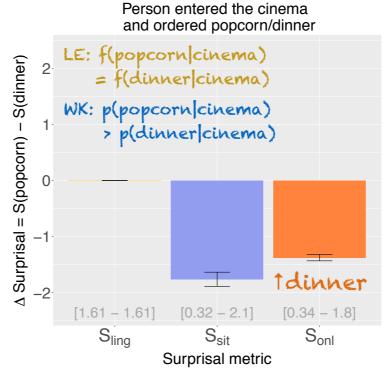
Venhuizen, Crocker & Brouwer (2018)

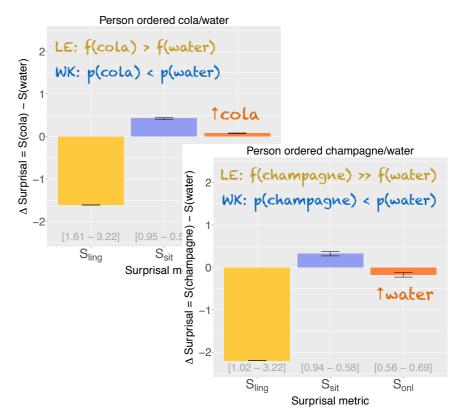
Discourse Process.

Beyond context, there are two sources for Surprisal in the model:

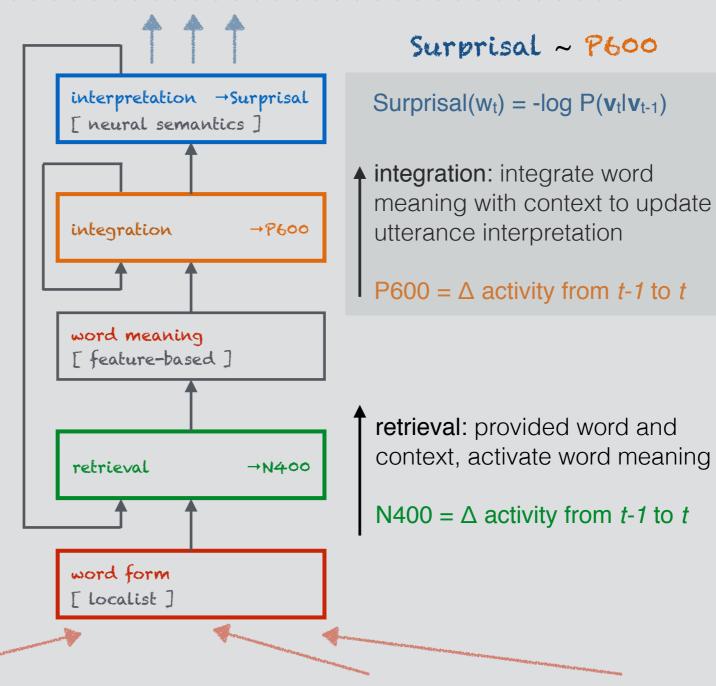
- > Linguistic Experience (LE) the model's linguistic input history
- > World Knowledge (WK) the model's probabilistic knowledge of the world







enter(beth,restaurant) ∧ order(beth,champagne)



Testing Surprisal ~ P600

Baseline:

John entered the restaurant.

Before long he opened the menu and ...

Event-related:

John left the restaurant.

1 Integration/P600 1 Surprisal

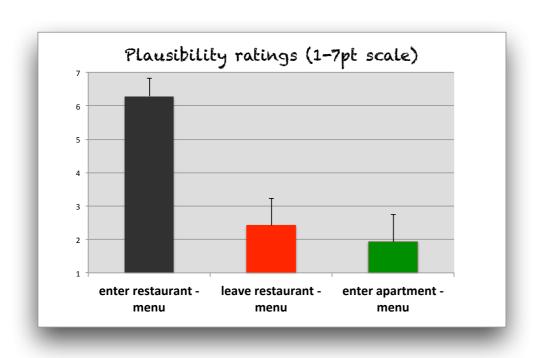
Before long he opened the menu and ...

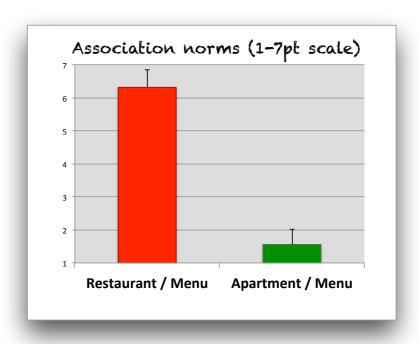
Event-unrelated:

John entered the apartment.

†Retrieval/N400 †Integration/P600 †Surprisal

Before long he opened the menu and ...





ERP Model — World specification

- Events: enter, leave, open
- Referents: (colours indicate objects that are 'presupposed' by places)
 - persons: john, mary
 - places: apartment, restaurant
 - openable objects: mail, menu, umbrella
 - other objects: bed, couch, table, waiter
- Preferred combinations: (WK ≈ 5:1, LE = 4:1)
 → plausibility
 - enter(x,apartment) & open(x,mail)
 - enter(x,restaurant) & open(x,menu)
 - leave(x,apartment/restaurant) & open(x,umbrella)

ERP Model — Training sentences

NP_{person} V the $N_{location}$ and he/she opened the N_{object}

Condition	V	N _{location}	Nobject	Effect
Baseline (×4)	entered	apartment restaurant	mail menu	
Event Related (×1)	left	apartment restaurant	mail menu	P600
Event Unrelated (×1)	entered	apartment restaurant	menu mail	N400 + P600
Control Fit (×4)	left	apartment restaurant	umbrella umbrella	
Control No Eit (v.1)	entered	apartment restaurant	umbrella umbrella	
Control No Fit (×1)	left	apartment restaurant	menu mail	

ERP Model — Sentence semantics

- Sentence statistics: types = 24, tokens = 48
- Word statistics: types = 14, tokens = 432

Word frequencies

john	24	and	48
mary	24	he	24
entered	24	she	24
left	24	opened	48
the	96	mail	14
apartment	24	menu	14
restaurant	24	umbrella	20

Word co-occurrences

apartment & mail	10
restaurant & menu	10
apartment & menu	4
restaurant & mail	4

→ association

Model predictions

Baseline ("entered restaurant - menu")
 Event-related ("left restaurant - menu")

Event-unrelated ("entered apartment - menu)

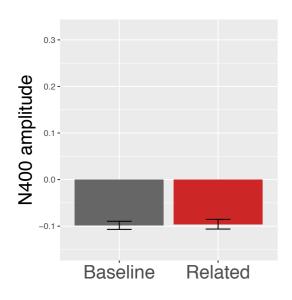
Surprisal

inguistic	Semantic	Online
0,4	0,19	0,11
1,79	1,6	2,28
1,79	2,32	2,36

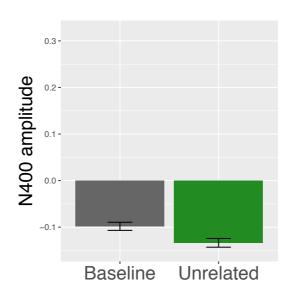
ERP effects

N400	P600
_	_
No	Yes
Yes	Yes

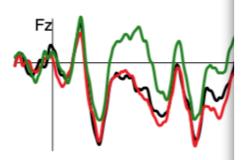
Event-related / Baseline

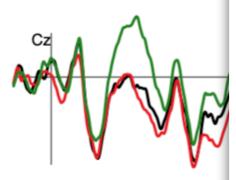


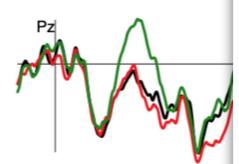
Event-unrelated / Baseline



ERP res







Baseline ("entered re Event-related ("left re Event-unrelated ("en



OPINION

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omponent

overlap?

On the Proper Treatment of the N400 and P600 in Language Comprehension

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Keywords: N400, P600, event-related potentials (ERPs), language comphrension, component overlap, task dependence

Event-Related Potentials (ERPs)—stimulus-locked, scalp-recorded voltage fluctuations caused by post-synaptic neural activity—have proven invaluable to the study of language comprehension. Of interest in the ERP signal are systematic, reoccurring voltage fluctuations called *components*, which are taken to reflect the neural activity underlying specific computational operations carried out in given neuroanatomical networks (cf. Näätänen and Picton, 1987). For language processing, the N400 component and the P600 component are of particular salience (see Kutas et al., 2006, for a review). The typical approach to determining whether a target word in a sentence leads to differential modulation of these components, relative to a control word, is to look for effects on mean amplitude in predetermined time-windows on the respective ERP waveforms, e.g., 350–550 ms for the N400 component and 600–900 ms for the P600 component. The common mode of operation in psycholinguistics, then, is to tabulate the presence/absence of N400- and/or P600-effects across studies, and to use this categorical data to inform neurocognitive models that attribute specific functional roles to the N400 and P600 component (see Kuperberg, 2007; Bornkessel-Schlesewsky and Schlesewsky, 2008; Brouwer et al., 2012, for reviews).

Here, we assert that this Waveform-based Component Structure (WCS) approach to ERPs leads to inconsistent data patterns, and hence, misinforms neurocognitive models of the electrophysiology of language processing. The reason for this is that the WCS approach ignores the *latent component structure* underlying ERP waveforms (cf. Luck, 2005), thereby leading to conclusions about component structure that do not factor in *spatiotemporal component overlap* of the N400 and the P600. This becomes particularly problematic when spatiotemporal component overlap interacts with differential P600 modulations due to task demands (cf. Kolk et al., 2003). While the problem of spatiotemporal component overlap is generally acknowledged, and occasionally invoked to account for within-study inconsistencies in the data, its implications are often overlooked in psycholinguistic theorizing that aims to integrate findings across studies. We believe WCS-centric theorizing to be the single largest reason for the lack of convergence regarding the processes underlying the N400 and the P600, thereby seriously hindering the advancement of neurocognitive theories and models of language processing.

WHY THE DATA ARE INCONSISTENT

ERP studies examining the processing of semantic incongruity sometimes report contradictory results. To shed light on these contradictions, Van Petten and Luka (2012) (henceforth VP&L) conducted a systematic review on semantic incongruity effects. VP&L selected studies comparing incongruent to congruent sentence-final words—e.g., "He spread the warm bread with socks/butter" (Kutas and Hillyard, 1980)—in healthy adults, using sentences that were otherwise syntactically felicitous, and procedures that did not have an explicit by-item acceptability or judgment task. As these studies were mostly targeted at the N400 component, statistics for the P600

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Discussion

- > Surprisal models typically focus on **linguistic experience** and offer no direct **performance** ↔ **representations/processes** link (**causal bottleneck**)
- > Integrated comprehension model predicts close link between Integration/P600 processes and interpretation-level Surprisal
- > ERP data support this link between Surprisal and Integration/P600
- > Model offers a more direct link between representations, surprisal (meaning-conditional probabilities) and processes (integration)

What's next? Investigate P600 ~ Surprisal/RT (combined EEG and eyetracking), component overlap (using MVPA, rERPs)

Surprisal

Offline syntactic (linguistic) Surprisal:

$$s_{syn}(w_{i+1}) = -\log P(w_{i+1}|w_{1,...,i})$$
$$= -\log \frac{P(w_{1,...,i+1})}{P(w_{1,...,i})}$$

Offline semantic (situation) Surprisal:

$$s_{sem}(w_{i+1}) = -\log P(\text{sit}(w_{1,...,i+1})|\text{sit}(w_{1,...,i}))$$

 $\approx -\log B(\text{sit}(w_{1,...,i+1})|\text{sit}(w_{1,...,i}))$

Online Surprisal:

$$s_{onl}(w_{i+1}) = -\log P(\overrightarrow{DSS}_{i+1}|\overrightarrow{DSS}_i)$$

