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Towards a neurocomputational model of the actor-strategy in language comprehension

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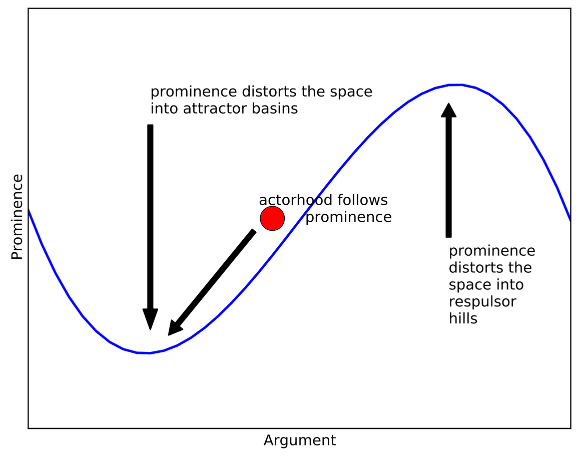
Motivation: The Actor Heuristic

Neurophysiological data from typologically diverse languages provide evidence for an actor-based interpretation strategy in language comprehension[1]. The search for an actor depends on a number of prominence scales: person, case, animacy, position, number and definiteness.

Actor Space The two arguments in a transitive construction are "pulled" toward or "pushed" away from actorhood by the weight of the individual features. Distinctness between arguments corresponds to distance in the actor space.



Weighting Influences Each prominence scale is subject to a language-specific weighting. This weighting serves to distort the actor space, increasing or decreasing the relative influence of specific prominence features. For example, case is stronger in German than word order, while in English the weight of word order is so extreme that the other scales are largely irrelevant.

Aims

Here, we sought to quantify the relative weights of the prominence scales and compare this against various proposed metrics in actor space. We used linear mixed models to examine the predictive power of each metric for fixed factors (prominence scales) for human EEG while compensating for subject and item (lexical) variation.

Computational Model

We implemented an initial quantification of the actor heuristic. Weights were estimated with the help of existing research[2]. There are three metrics for measuring distinctness, or difference in prominence.

metric	formula	description
dist	$\sum_i \lvert NP2_i - NP1_i \rvert$	Manhattan distance (feature overlap)
signdist	$\sum_i (NP2_i - NP1_i)$	pairwise difference (signed, unweighted difference)
sdiff	$\vec{w} \cdot \vec{NP2} - \vec{w} \cdot \vec{NP1}$	scalar difference of weighted prominences

Prominence Hierarchies

Feature	Hierarchy
Person:	First = 1 > Other = 0
Case:	Nominative = 1 > Accusative = -1
Animacy:	Animate = 1 > Inanimate = 0
Position:	Early = 1 > Late = 0
Number:	Singular = 1 > Plural = 0
Definiteness:	Definite = 1 > Indefinite = 0

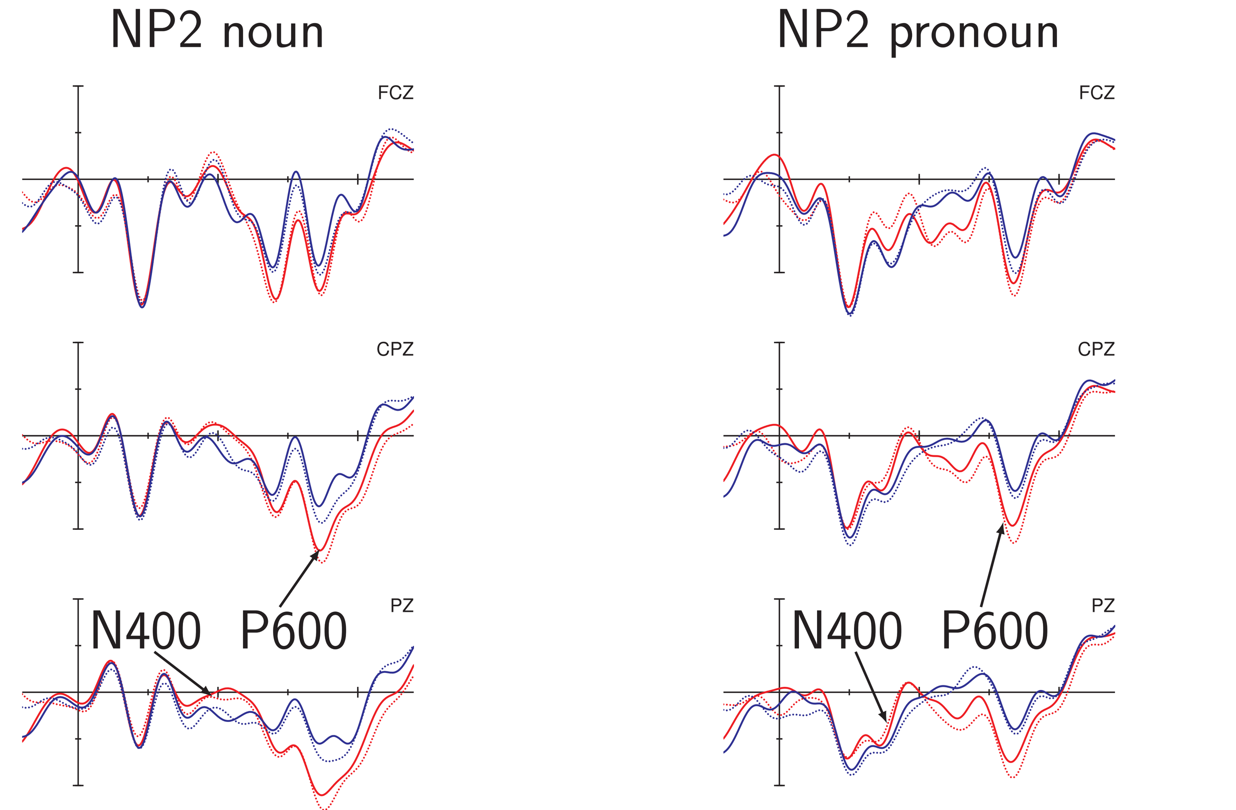
Materials and Design

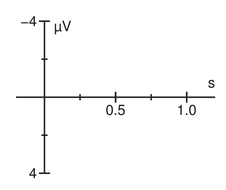
2x2x2x2 design with 60 lexical items; every condition appeared for each lexical item.

Word Order		Ambiguity		NP1-Type		NP2-Type
Subject first Object first	×	Ambiguous Unambiguous	×	Noun Pronoun	×	Noun Pronoun

25 Ag/AgCl electrodes @ 250 Hz
37 German native speakers (20 women)
400ms for single words, 500ms for phrases, 100 ms ISI

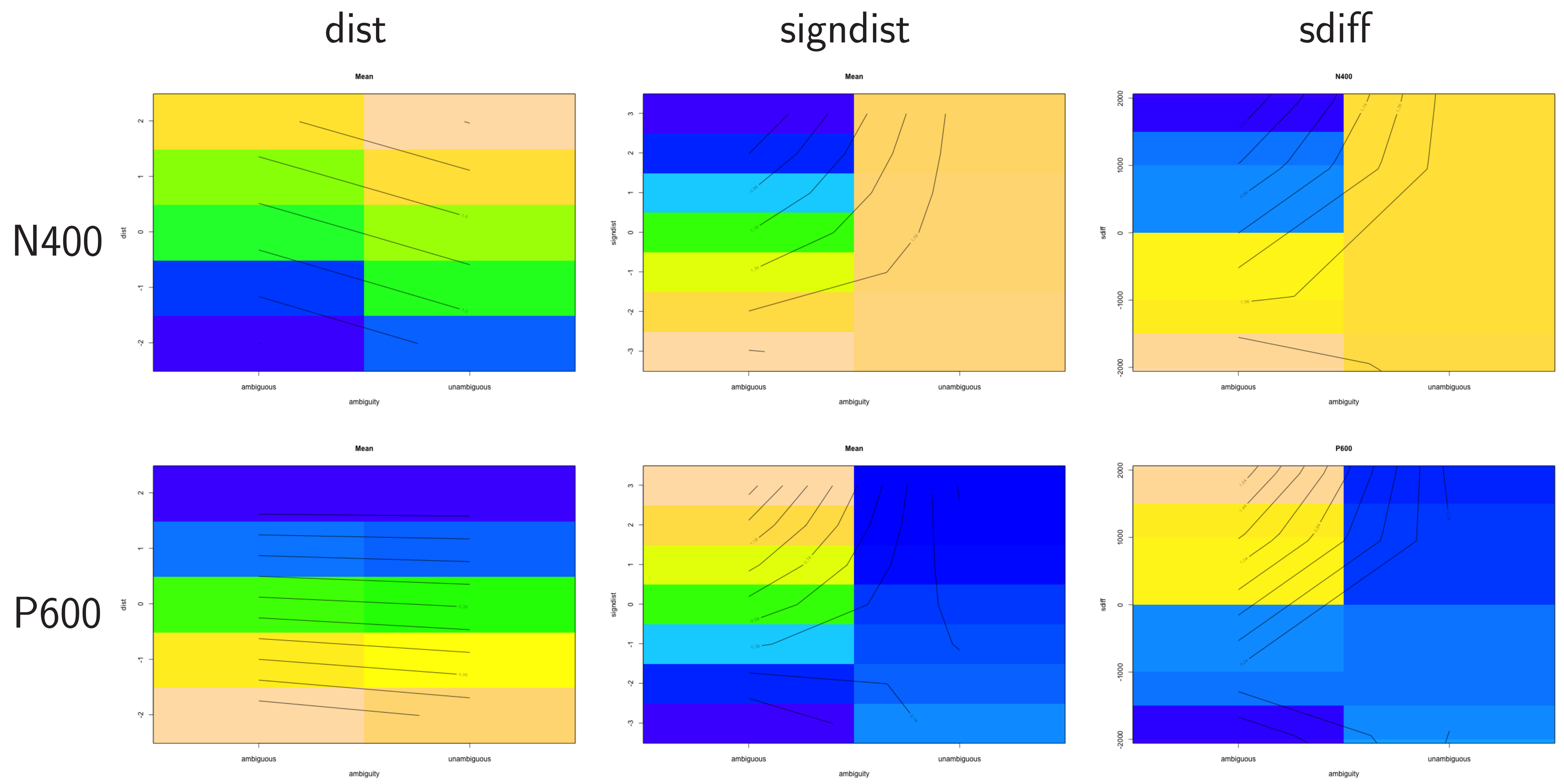
EEG Data





Grand average ERPs triggered at the onset of NP2 for the ambiguous condition. Blue = subject (actor) initial, Red = object initial; solid = noun, dashed = pronoun for NP1.

Model Data



Mean EEG (restricted to the left posterior ROI) in each time window as a function of the different metrics (centered) and its interaction with ambiguity. The colors indicate the "height", i.e., a range of (predicted) values of the mean EEG. More color indicates more variation.

Metric Performance

Likelihood ratio test for models in the N400 time window with NP1 ambiguous. A linear mixed model of the form

```
mean ~ c.(metric) + (1 | item) + (1 | subj),
```

was calculated with `lme4`[3].

	Df	AIC	logLik	Chisq	Chi Df	Pr(Chisq)
dist:	5	197812	-98901.48			
signdist:	5	197740	-98865.21	0.00	0	1
sdiff:	5	197596	-98793.06	216.84	0	<2.2e-16***

Discussion

All three metrics show some potential; however, `sdiff` performs significantly better than `signdist` (which performs better than `dist`). The signedness of `signdist` allows for conditional prediction — hence the different color scale in the ambiguity condition above. The gradience of `sdiff` allows for much more precise predictions, which is reflected in the subtlety present in the respective color scale.

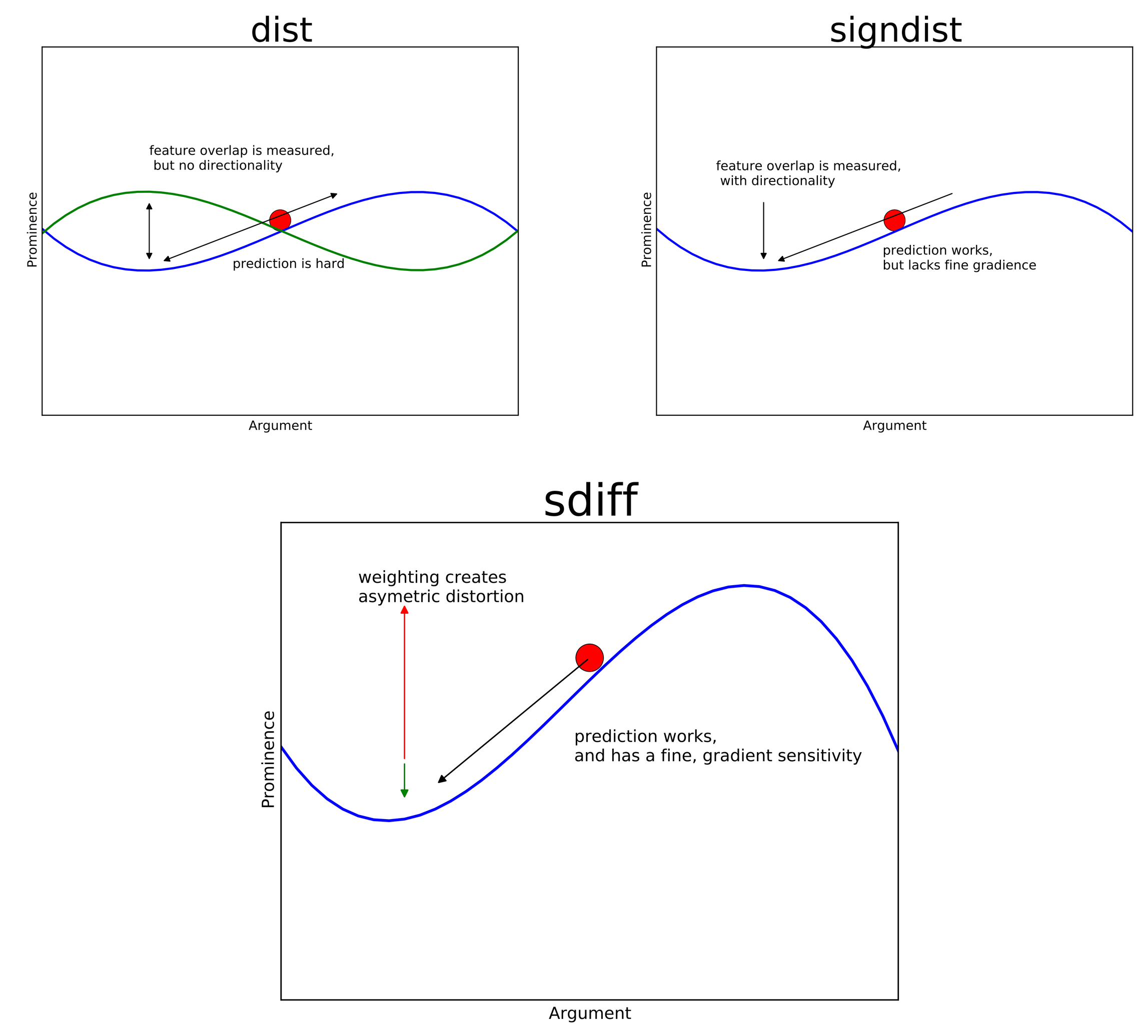
Sample processing

Die Bettlerin bedrängte den Kommissar auf der Straße.
"The beggar hassled the commissioner in the street."

Partial analysis:

Feature	NP1	NP2	W
Case	0	-1	1000
Animacy	1	1	10
Person	0	0	100
Number	1	1	10
Definiteness	1	1	1
Position	1	0	100
Simple	5	2	
Weighted	121.0	-979.0	

metric	value
dist	2.0
signdist	+2.0
sdiff	−1100.0



Conclusions

The power of the `sdiff` metric comes from both its directionality (signedness) and its gradience. While a simplistic measure of feature overlap, `dist`, as used in working memory models[4, 5], provides some insight, an immediate benefit is apparent from adding a directionality (or direction of drift to and from actorhood), as seen in `signdist`. The gradience of `sdiff`, achieved via feature weighting, allow for much finer tuned modelling.

Literature

[1] I Bornkessel-Schlesewsky and M Schlesewsky. The role of prominence information in the real-time comprehension of transitive constructions: A cross-linguistic approach. *Language and Linguistics Compass*, 3(1):19–58, 2009.

[2] V Kempe and B MacWhinney. Processing of morphological and semantic cues in russian and german. *Language and Cognitive Processes*, 14(2):129–171, 1999.

[3] D Bates, M Maechler, and B Bolker. *lme4: Linear mixed-effects models using S4 classes*, 2011. R package version 0.999375-42.

[4] J Jonides, R. L Lewis, D. E Nee, C. A Lustig, M. G Berman, and K. S Moore. The mind and brain of short-term memory. *Annual Reviews*, Jan 2008.

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