Predicting is not explaining

targeted learning of the dative alternation in English

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outline

a mathematician and a linguist walk into a lab

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. . . typically, alternations are handled with predictive methods [Bre+07; Baa11]

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- compare the models

example: logistic regression/prediction [Bre+07]

(26) Model B: Relative magnitudes of significant effects

	Coefficient	Odds Ratio PP	95% C.I.
nonpronominality of recipient	1.73	5.67	3.25–9.89
inanimacy of recipient	1.53	5.62	2.08–10.29
nongivenness of recipient	1.45	4.28	2.42–7.59
indefiniteness of recipient	0.72	2.05	1.20–3.5
plural number of theme	0.72	2.06	1.37–3.11
structural parallelism in dialogue	–1.13	0.32	0.23–0.46
nongivenness of theme	–1.17	0.31	0.18–0.54
length difference (log scale)	–1.16	0.31	0.25–0.4
indefiniteness of theme	–1.74	0.18	0.11–0.28
nonpronominality of theme	–2.17	0.11	0.07–0.19

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- linguist: . . .
- linguist: (sobs)

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- explaining:
  - uncovering what drives the choice of one dative form over the other
  - by building upon/targeting the above algorithm

method

targeted learning [LR11, monograph]

- Chambaz and Desagulier [CD15]

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- through causal analysis, we operationalize the set of scientific questions that we wish to address regarding the dative alternation
- we answer these questions by targeting some versatile machine learners borrowing from the latest advances in semi-parametric statistics
- we derive estimates, confidence regions and p-values for well-defined parameters that can be interpreted as the influence of each contextual variable on the outcome PD *vs.* DO

data

the `dative` dataset [Bre+07]

available from the `languageR` package [Baa09]

categorical contextual information variables

variable	*vs.*	estimate	CI	*p*-value
Modality	written%spoken	0.0277	[-0.0031,0.0585]	0.0776
AnimacyOfRec	inanimate%animate	0.0938	[0.0549,0.1327]	0.0000
DefinOfRec	indefinite%definite	0.0395	[0.0102,0.0688]	0.0083
PronomOfRec	pronominal%nonpronominal	-0.1398	[-0.2171,-0.0624]	0.0004
AnimacyOfTheme	inanimate%animate	0.0843	[0.0337,0.1348]	0.0011
DefinOfTheme	indefinite%definite	-0.0568	[-0.0865,-0.0272]	0.0002
PronomOfTheme	pronominal%nonpronominal	-0.1168	[-0.1377,-0.0959]	0.0000
AccessOfRec	new%accessible	-0.3824	[-0.5458,-0.2189]	0.0000
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SemanticClass	t%a	0.1152	[0.0548,0.1755]	0.0002
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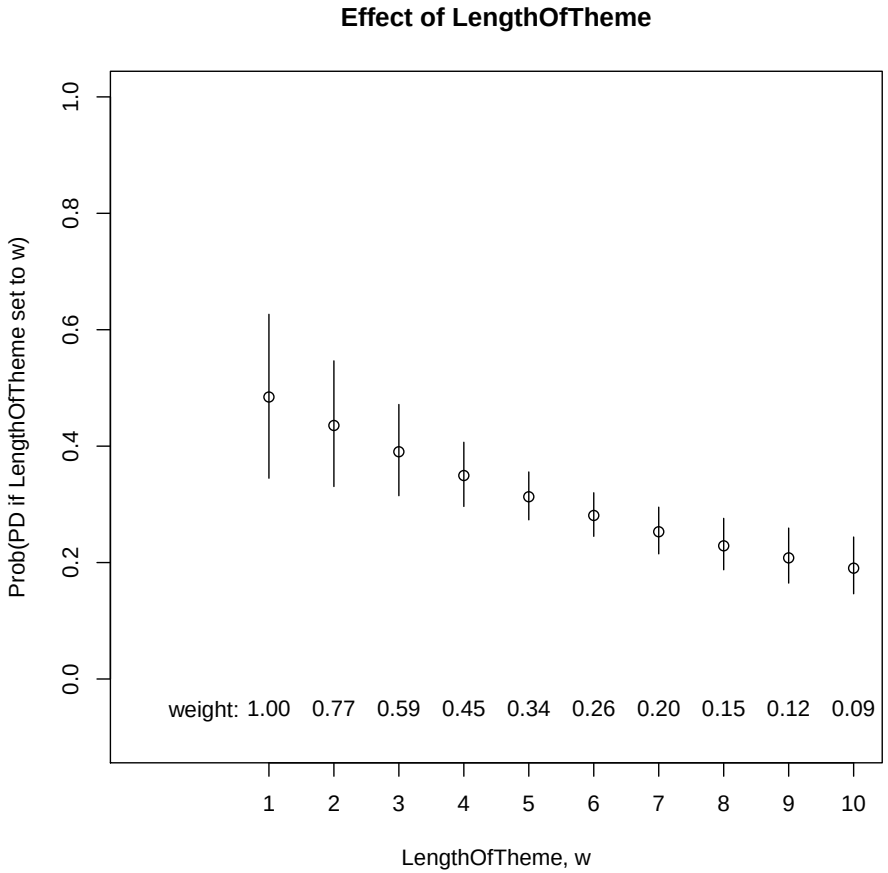
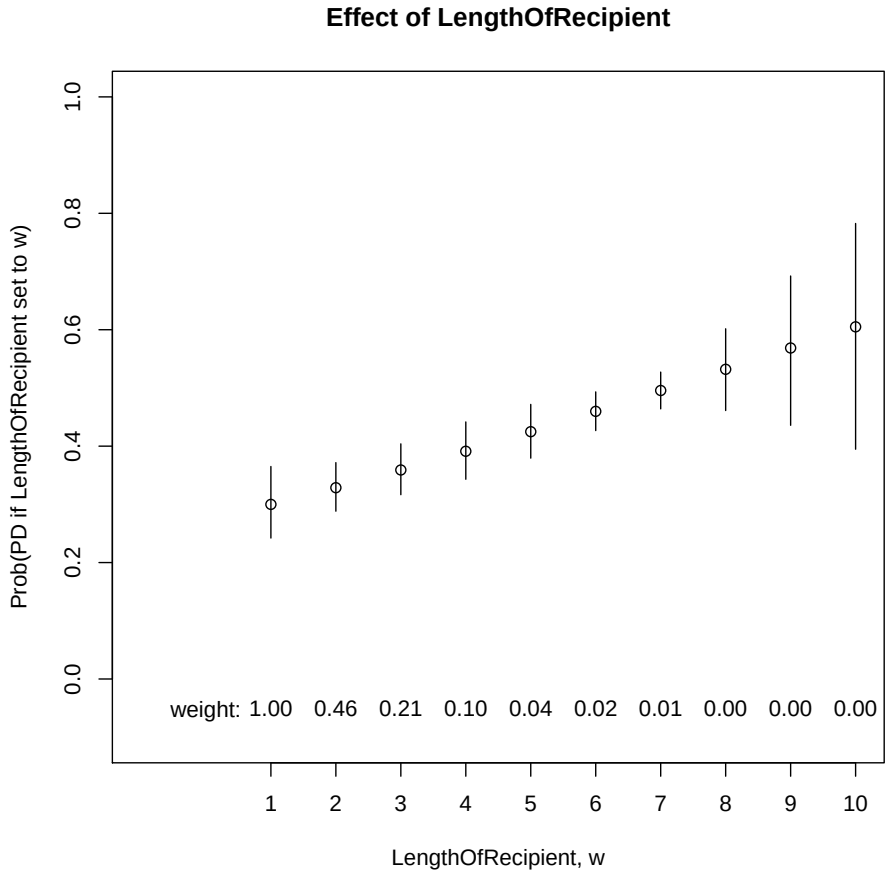
integer valued contextual information variables

(using a working model)





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- further illustrates that the parameter matching pronominality of theme in a logistic regression model is an awkward function of the law of data

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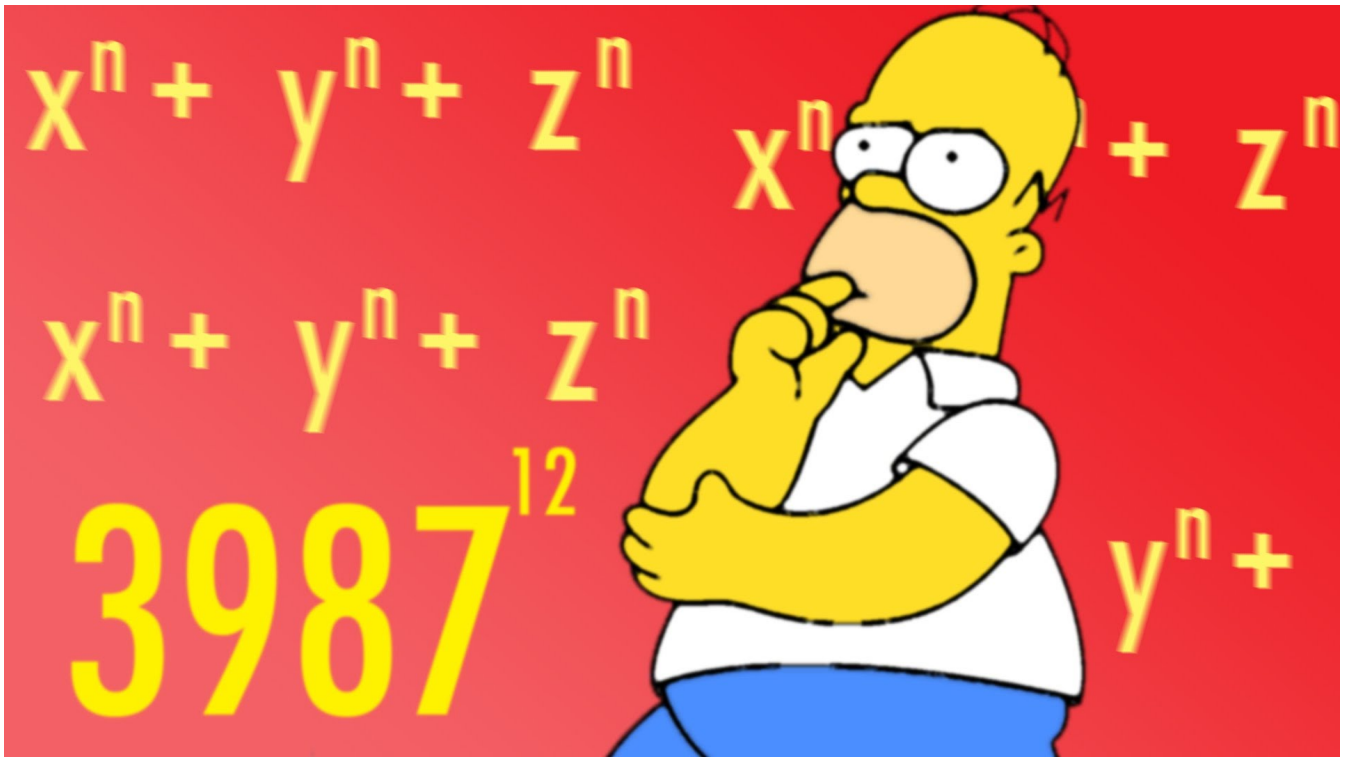

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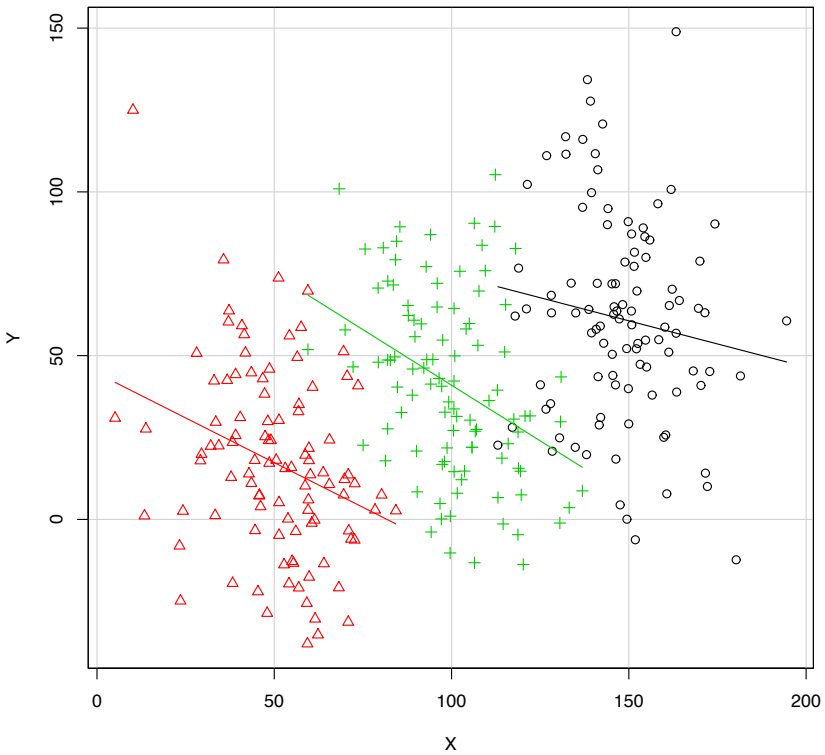

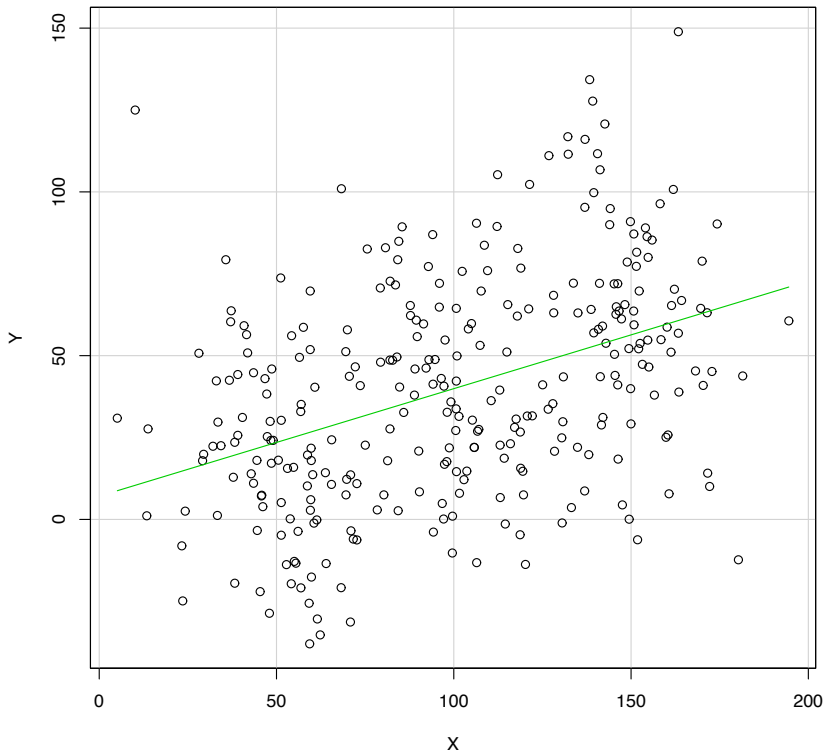

Simpson's paradox

"a trend appearing in different data groups may reverse once these groups are combined"

numerical example: "all other things being equal, switching theme from definite to indefinite yields a 5% decrease of the probability of PD"

theme	definite	indefinite
PD	63	378
DO	28	858

uncontextualized data

- $\mathrm{ER}(P_n) = \frac{63}{63+28} - \frac{378}{378+858} \approx 38\%$
- $\Psi(P_n^*) \approx -5\%$ (significant difference)

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when explanation is sought, prediction is only a means to an end

- the take-home message on the dative alternation cannot be provided in the form of a fitted prediction model
- *e.g.*,
  - we observed a significant decrease of the probability of obtaining PD when, all other things being equal, the theme is switched from nonpronominal to pronominal
  - a crude measure of statistical association such as the excess risk would have indicated a significant increase
  - this is an illustration of Simpson's paradox

what we did

what we provide instead is two-fold:

- we framed our account of the dative alternation in a causal model
  $\neq$ prediction model
- we investigated the effect of each available, contextual information variable on the choice of PD over DO, resulting in a table of estimates, confidence intervals, and *p*-values

our approach is based on causal inference, machine learning, and semi-parametric statistics

- we operationalized the effect of any given element of context on the dative alternation as a functional evaluated at the true, unknown law of the data
- we also showed how to estimate this effect in a targeted way, under the form of that functional evaluated at an empirical law built specifically to estimate the corresponding effect

future work

our method can be applied to case-studies involving contrasts or alternations, such as

- the choice of the predeterminer *vs.* preadjectival position of intensifiers (*e.g.*, *quite* and *rather*),
- the choice of one word over a near-synonym (*e.g.*, *almost/nearly*, *big/large*, *broad/wide*, *freedom/liberty*, . . . the sky is the limit)

thanks for your attention!

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