Dative Ordering Preferences in English: Productive Constraints, Item-Specific Experience & Frequency

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Language presents speakers with ordering choices: for example, they can use a dative verb in a double object (DO) form, *give the man an apple,* or a prepositional phrase (PP), *give an apple to the man.* These choices are partly driven by rule-based, productive constraints: e.g., longer constituents are preferred later [1]. But item-specific information also plays a role: some verbs and VPs are strongly preferred in one order (**give the creeps to me*). Previous work on binomial expressions has shown productive constraints tradeoff with item-specific knowledge, with higher frequency items relying more on item-specific knowledge than lower frequency items [3,4]. We ask whether this tradeoff replicates in syntactically complex constructions, like the dative, which may involve different planning processes than NPs. Many dative verbs occur in non-dative, ditransitive structures that superficially resemble dative PPs (e.g. *push the box to the wall,* analyzed as a spatial goal), which raises a second question: How do speakers learn item-specific ordering preferences for a specific construction (the dative), given their experience of the language as a whole? Do they learn from every ditransitive example of that verb (including spatial goals), only dative instances, or some combination of the two?

Methods: We parsed 6.15 billion words of English web text [5], extracting examples of dative-alternating verbs which had two objects [2]. We sampled and annotated examples of each verb for productive constraints previously shown to affect ordering preferences, discarding spatial goals [1]. The final dataset contains 107 verbs and 23,488 sentences, of which 7,403 were dative. We fit a Bayesian logistic mixed-effects model using BRMS (Model 1) predicting argument order of dative examples (DO or PP) from productive constraints (outlined in [1] and modeled by fixed effects) and item-specific experience (a random intercept for each verb).

Results: 1) Observed ordering preferences were not captured by the fixed effects: a large portion of verbs with extreme PP preference, and a smaller portion with a DO preference, were not predicted from fixed effects (Figure 1). This suggests verb-specific experience is crucial for modeling the full distribution of dative preferences.

2) More frequent verbs were associated with a larger difference between their observed and fitted preferences (Figure 2), suggesting that the more a verb's ordering preference differs from the productive constraints, the more item-specific experience is required for speakers to learn it. The verbs which were least-captured by the fixed effects were high-frequency verbs, and had an observed preference for the DO structure (verbs which used the DO structure in more than 50% of datives are shown in red). We hypothesize that learning a preference for the DO structure requires more item-specific experience than learning a PP preference, perhaps because a larger number of dative lemmas prefer the PP structure (Figure 1). As a result, speakers may consider the PP form the default.

3) Finally, we asked whether verb-specific preferences (as captured by the random effects of Model 1) were better predicted by the distribution of PP and DO structures among datives or non-datives. If knowledge of similar non-dative structures (like spatial goals) supports speakers in learning the PP preference, this may also explain why mostly frequent verbs have a DO-preference. We fitted a linear regression (Model 2), and found that the distribution of forms among only datives, not non-datives, was predictive of verb preference. This suggests that speakers implicitly recognize the dative as a mental category and can learn dative-specific preferences without regard to superficially similar structures.

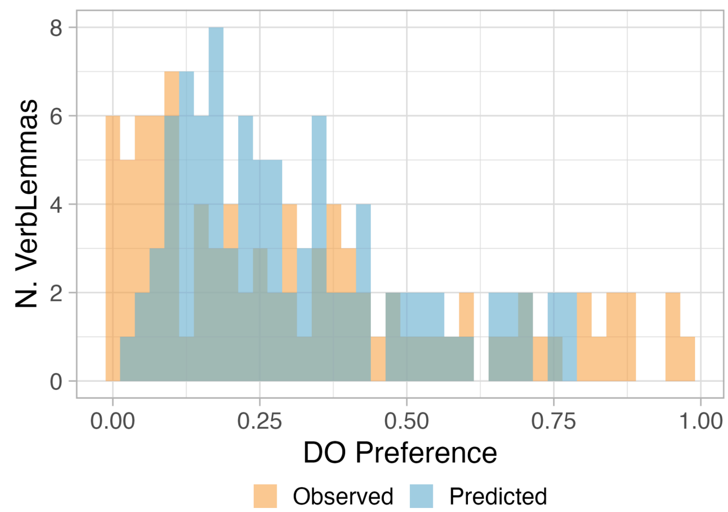

Figure 1: The distribution of observed ordering preferences (proportion of dative instances in the DO structure for each verb) and predicted ordering preferences from the fixed effects of Model 1 (which capture the productive constraints but not item-specific knowledge).

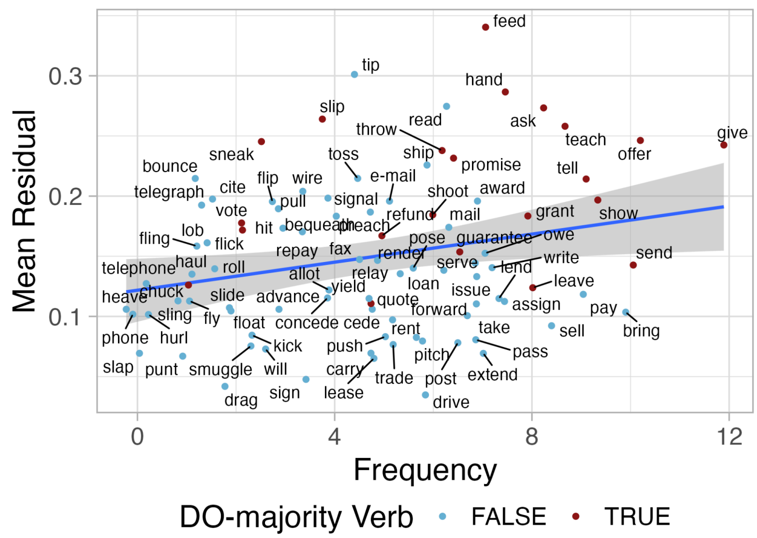

Figure 2: The difference in observed vs predicted preference for each verb, as a function of the log frequency of the verb in a dative structure (measured per billion words of corpus data).

Model 1: structure ~ themeDefinite + themePronominal + themeGiven… + (1|verbLemma)

Model 2: randomEffectValue ~ nonDativeDO_preference + dativeDO_preference

Model 2 Results:

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	-1.8321	0.1334	< 2e-16 ***
nonDative_DO_skew	0.7050	.4764	0.143
dative_DO_skew	5.2571	.4293	< 2e-16 ***

References

[1] Bresnan, Cueni, Nikitina & Baayen. (2005). *Predicting the Dative Alternation*. [2] Levin. (1993). *English Verb Classes and Alternations: A Preliminary Investigation*. [3] Morgan & Levy. (2015). Modeling idiosyncratic preferences: How generative knowledge and expression frequency jointly determine language structure. *Proceedings of the 37th CogSci*. [4] Morgan & Levy. (2016). Abstract knowledge versus direct experience in processing of binomial expressions. *Cognition*, *157*. [5] Qi, Zhang, Zhang, Bolton & Manning. (2020). Stanza. *Proceedings of the 58th ACL: System Demonstrations*.