Is defectiveness that surprising?

The influence of paradigmatic predictability on token frequency

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Introduction

- The cause of defectiveness is still an open question. Some proposed explanations:
  - Albright (2003)'s uncertainty explanation,
  - Baerman (2011)'s homophony avoidance hypothesis,
  - Sims (2015)'s gaps-as-morphological-objects,
  - Gorman and Yang (2019)'s Productivity Principle.
- Albright (2003) proposing uncertainty about which morphophonological pattern applies as a cause of defectiveness.

  forego ∼ *foregoed?/forewent?*

- In this talk, we aim to explore a generalisation of the intuition behind Albright's claim, showing that uncertainty impacts form frequency in a gradient way.
  - The pattern provides empirical evidence that ties into what we know about paradigmatic structure and frequency effects in language.
  - Our findings + the assumptions behind the underlying intuition can inform how we approach defectiveness.

The plan

- Starting point: the claim that defectiveness results from uncertainty.
- A closer look at Albright (2003): the method, and how the findings relate to defectiveness with the power of hindsight.
- Our contribution:
  - explicitly discussing assumptions about defectiveness
  - rethinking how to quantify uncertainty in the light of information theory
  - scaling up: does uncertainty impact form frequency at all levels?
- Results
- Discussion and conclusion

Defectiveness in Albright (2003)

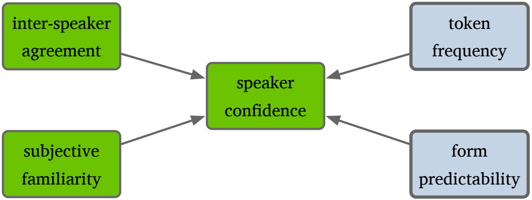
- One of the first attempts to identify a general source for defectiveness. Claim: defectiveness results from uncertainty about what pattern can and should apply

  forego $\sim$ *foregoed?/forewent?*

- To substantiate the claim, he collects the following data:
  - **Behavioural Measures:**
    - **Measure 1**: subjective familiarity ratings for several spanish lexemes.
  - With a cloze reading task ("fill-the-gap": *Ahora yo* ___ *(abolir)*) targeting defective forms in the IND.PRES.1SG:
    - **Measure 2**: confidence ratings on the participant's own production.
    - **Measure 3**: between-speaker agreement on the form in the gap.
  - These are combined with **measures based on linguistic resources**:
    - **Measure 4**: the confidence score of the MGL rule predicting the 1SG IND PRES from the infinitive form (Albright and Hayes, 2003) as a measure of inflectional form predictability
    - **Measure 5**: Log token frequency of the word (as another measure of familiarity)

Defectiveness in Albright (2003)

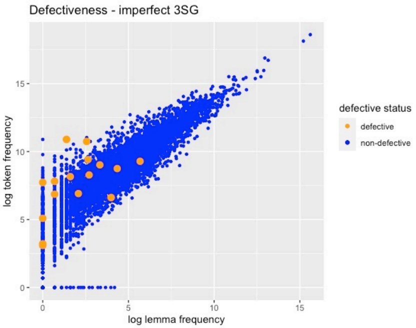
- The question posed is ”does uncertainty create defectiveness?”.
  - Albright assumes that uncertainty is best quantified by speaker confidence and he observes that defectiveness implies uncertainty, but uncertainty doesn’t imply defectiveness
  - He investigates what causes that uncertainty by correlating speakers’ uncertainty with subjective familiarity judgements, token frequency, and confidence scores for applicable rules.



  - He concludes that it’s form predictability + subjective familiarity that cause uncertainty (and hence defectiveness), since those are the best predictors of speaker judgements of uncertainty.
- The research investigates the link between psycholinguistic judgments and systemic measures of uncertainty, but only indirectly addresses the question of defectiveness.

What is defectiveness, anyway?

- The **theoretical definition of defectiveness** characterises the phenomenon as a missing paradigm form, traditionally relying on grammars to tell us which forms are defective. This is not an empirical definition.
- The theoretical definition makes a clear prediction: since a missing form will not be used by speakers, defectiveness should manifest as non-attestation of a form.
- In practice, however, the above is elusive:

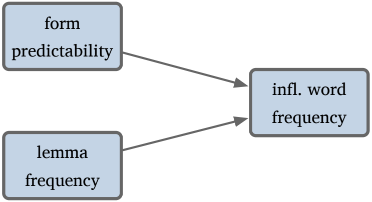


What is defectiveness, anyway?

- The question of how defectiveness manifests empirically (behaviourally or in corpora) is currently an open one.
  - Previous attempts to tackle the question (Albright's and ours included) have not yielded empirical properties that uniquely identify the set of defective forms.
  - Is defectiveness not a natural category (contrary to intuition)? Have we not been looking in the appropriate places with the appropriate methods? Is noise preventing us from seeing relevant factors?
  - In any case assuming an empirical quantity to equal defectiveness aside from non-attestation (or, being generous about the amount of noise, low-frequency) is premature.

Our Question

- Albright's intuition makes predictions beyond defectiveness, which are worth testing. This is valuable in itself and may result in additional clues concerning the empirical nature of defectiveness.
- Does form predictability impact token frequency at all frequency levels? If so, how?
  - we opt for a more sophisticated operationalisation of form predictability, relying on paradigm structure
  - we try to remain agnostic about how defectiveness manifests empirically.
- Of interest for defectiveness:
  - If impact of form predictability is gradient, and form predictability correlates with defectiveness, approaches to defectiveness should also be gradient.
  - Defectiveness may correlate with extreme cases of the interaction of form predictability and frequency.

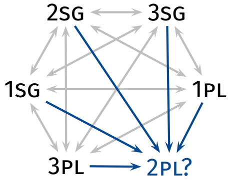


Two aspects of form predictability

- Two aspects of form predictability may be relevant to token frequency:
  1. The particular form filling a cell may be highly unpredictable, in the sense that other options than the actual one are more likely.
     - SG *goose* → PL *geese*
  2. Options for filling a cell may be numerous and comparably likely, leading to difficulty choosing any option.
     - PRS *fling* → PST $\begin{cases} \textit{flung}? \\ \textit{flang}? \\ \textit{flinged}? \end{cases}$
- One of our goals below is to clarify the relationship between these two aspects.

Form predictability as average surprisal I

- We want to derive a quantitative measure of how much confidence a speaker may have that they are producing the appropriate form for a given paradigm cell, given knowledge of the rest of the paradigm.
- This is clearly a variant of the Paradigm Cell Filling Problem (Ackerman, Blevins, and Malouf, 2009; Ackerman and Malouf, 2013).



- We rely on a purely word-based approach to the PCFP of Bonami and Beniamine (2016), using Beniamine's (2018) Qumin package for all computations.

Form predictability as average surprisal II

For each pair of cells (c, c') in the paradigm:

1. Assign each pair to an alternation pattern, optimizing alignments between pairs of words.

Lexeme	PRS.3PL	PRS.2PL
CROIRE	kʁwa	kwaje
BAVER	bav	bave
LEVER	lɛv	ləve
MENER	mɛn	məne
PEINER	pɛn	pɛne
MORDRE	mɔʁd	mɔʁde

⇒

Lexeme	PRS.3PL	PRS.2PL	Alternation
BAVER	bav	bave	π_1 : _ ⇌ _e/X^+C_#
PEINER	pɛn	pɛne	
MORDRE	mɔʁd	mɔʁde	
LEVER	lɛv	ləve	π_2 : _ɛ_ ⇌ _ə_e/X^+_C_#
MENER	mɛn	məne	
CROIRE	kʁwa	kwaje	π_3 : _ ⇌ _je/X^+wa_#

Form predictability as average surprisal III

Lexeme	PRS.3PL	PRS.2PL	Alternation
BAVER	bav	bave	
PEINER	pɛn	pɛne	$\pi_1 : \_ \rightleftharpoons \_e / X^+ C\_\#$
MORDRE	mɔʁd	mɔʁde	
LEVER	lɛv	ləve	$\pi_2 : \_ɛ\_ \rightleftharpoons \_ə\_e / X^+\_C\_\#$
MENER	mɛn	məne	
CROIRE	kʁwa	kwaje	$\pi_3 : \_ \rightleftharpoons \_je / X^+ wa\_\#$

2. Classify predictor cell shapes on the basis of which patterns they are compatible with.

Lexeme	PRS.3PL	PRS.2PL	π_1	π_2	π_3	Predictor shape
BAVER	bav	bave	✓			
MORDRE	mɔʁd	mɔʁde	✓			κ_1
PEINER	pɛn	pɛne	✓	✓		
LEVER	lɛv	ləve	✓	✓		κ_2
MENER	mɛn	məne	✓	✓		
CROIRE	kʁwa	kwaje			✓	κ_3

⇒ Puts words from predictor cell c into classes $\kappa_1, \ldots, \kappa_m$ that share phonological properties relevant for determining what happens in cell c'.

Form predictability as average surprisal IV

Lexeme	PRS.3PL	PRS.2PL	π_1	π_2	π_3	Predictor shape
BAVER	bav	bave	✓			
MORDRE	mɔʁd	mɔʁde	✓			κ_1
PEINER	pɛn	pɛne	✓	✓		
LEVER	lɛv	ləve	✓	✓		κ_2
MENER	mɛn	məne	✓	✓		
CROIRE	kʁwa	kwaje			✓	κ_3

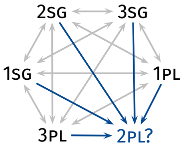
3. Compute the surprisal of the form found in cell c' given the form found in cell c:

$$S = -\log_2 P(\pi_i \mid \kappa_j)$$

Lexeme	PRS.3PL	PRS.2PL	Pattern	Class	p	S
BAVER	bav	bave	π_1	κ_1	1	0
MORDRE	mɔʁd	mɔʁde	π_1	κ_1	1	0
PEINER	pɛn	pɛne	π_1	κ_2	$1/3$	1.585
LEVER	lɛv	ləve	π_2	κ_2	$2/3$	0.585
MENER	mɛn	məne	π_2	κ_2	$2/3$	0.585
CROIRE	kʁwa	kwaje	π_3	κ_3	1	0

Form predictability as average surprisal V

4. Average over predictor cells c to get an overall estimation of how surprising c' is given the rest of the paradigm.



- Ideally, this should be weighted by cell frequency.
- But we do not have quality estimations of cell frequency, because of pervasive syncretism.
- For lack of a better solution we use unweighted frequency.

Form predictability as local entropy

- Instead of asking how surprising the actual form is, we can ask how much uncertainty is associated with the distribution of possible forms.
- To that effect we can use the entropy of the distribution of patterns sharing a class, which we call local entropy. For class κ_j:

$$H = -\sum_{\pi \in \Pi} P(\pi \mid \kappa_j) \times \log_2 P(\pi \mid \kappa_j)$$

Lexeme	PRS.3PL	PRS.2PL	π_1	π_2	π_3	p	S	H
BAVER	bav	bave	✓			1	0	0
MOURIR	mɔʁd	mɔʁde	✓			1	0	0
PEINER	pɛn	pɛne	✓	✓		1/3	1.585	0.918
LEVER	lɛv	ləve	✓	✓		2/3	0.585	0.918
MENER	mɛn	məne	✓	✓		2/3	0.585	0.918
CROIRE	kʁwa	kwaje			✓	1	0	0

Back to predictability and frequency

- (Average) surprisal and (average) local entropy operationalize the two aspects of predictability discussed above:
  1. Average surprisal quantifies the uncertainty associated with the particular form that actually fills the cell.
  2. Average local entropy quantifies the uncertainty associated with making a choice.
- Which of the two should we focus on?
  - Albright confusingly chooses an empirical domain where local entropy seems relevant but uses a measure similar to surprisal.
  - Preliminary work on French adjectives suggests that we focus on surprisal.

French adjectives

- Predicting the M.PL of French adjectives.

Shape in M.SG,F.SG,F.PL	Shape in M.PL	Type frequency	Example
-al /al/	*-aux* /o/	399	*légal* /legal/ ∼ *légaux* /lego/
-al /al/	*-al* /al/	29	*banal* /banal/ ∼ *banals* /banal/
Any other	identical to M.SG	8797	*grand* /gʁɑ̃/ ∼ *grands* /gʁɑ̃//

- French speakers are known to be hesitant as to how to inflect the small class of non-alternating adjectives in *-al*.
  - This is confirmed by frequency data: plurals in *-als* are are comparatively lower token frequency than plurals in *-aux*.
- This is captured by surprisal:

M.SG shape	Alternation	Surprisal	Loc. entropy
-al	*-al*∼*-o*	0.10	0.36
-al	None	3.88	0.36
Any other	None	0	0

- Suggests that the more fine-grained measure of surprisal is of interest to predict frequency.

Methodology

- We set out to confirm that surprisal has a negative effect on token frequency throughout the lexicon
- Case study: French verbal cells

Methodology

- For the items within each cell, we constructed a model of the shape
  - *token frequency* $\sim$ *surprisal* + *lemma frequency* + *surprisal:lemma frequency*
- Why separate models for each cell?
  - It would be worth having by-cell random effects if we had information from the whole system, rather than just pockets of it.
  - (...also, difficulties fitting the data this way, and time-consuming to test different alternatives, so for the moment this is not a priority)
- The value of surprisal we employ is the average surprisal of the given form based on each of the other forms in the paradigm.
- Lemma frequency is included as a control variable (= familiarity)
- The interaction between the two predictors is included to test the intuition that for high values of lemma frequency, surprisal matters less (words with a strong representation in memory don't need to be predicted)
- Separate bayesian poisson regressions with minimally-informative priors were fitted to the data in each cell.

Methodology

- Resources used:
  - Frequency counts: FrCoW (Schäfer & Bildhauer, 2016) for token and lemma counts.
  - Paradigms & excluding homographs: GLàFF (Hatout, Sajous & Calderone, 2014)
  - Surprisal: values computed using Qumin (Beniamine, 2018) on the Flexique verb dataset (Bonami, Caron, and Plancq, 2014)

Data selection

- Which cells in the paradigm of French verbs can we work with?
- Working with our dataset, we exclude...

Finite forms

	1SG	2SG	3SG	1PL	2PL	3PL
IND.PRS	2	3	183	2	5	14
IND.IPFV	0	0	5083	10	10	5076
IND.PST	4484	4448	4694	5116	5116	5101
FUT	5211	5207	5213	5190	5212	5221
SBJV.PRS	0	250	2	8	7	13
SBJV.IPFV	4701	4725	5119	4726	4738	4740
COND	0	0	5220	5212	5212	5215
IMP	—	0	—	2	2	—

Nonfinite forms

INF	PRS.PTCP	PST.PTCP			
		M.SG	F.SG	M.PL	F.PL
5006	4311	3935	3055	2903	3199

Number of verbs from Flexique with no homograph documented in the GLÀFF, by paradigm cell

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  - cells with high numbers of homographs according to the GLÀFF;
  - cells out of current usage (i.e. most attestations are likely to be archaic);
  - past participle cells, for which tagging is inherently unreliable.

Finite forms

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IND.PRS	2	3	183	2	5	14
IND.IPFV	0	0	5083	10	10	5076
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		M.SG	F.SG	M.PL	F.PL
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Number of verbs from Flexique with no homograph documented in the GLÀFF, by paradigm cell

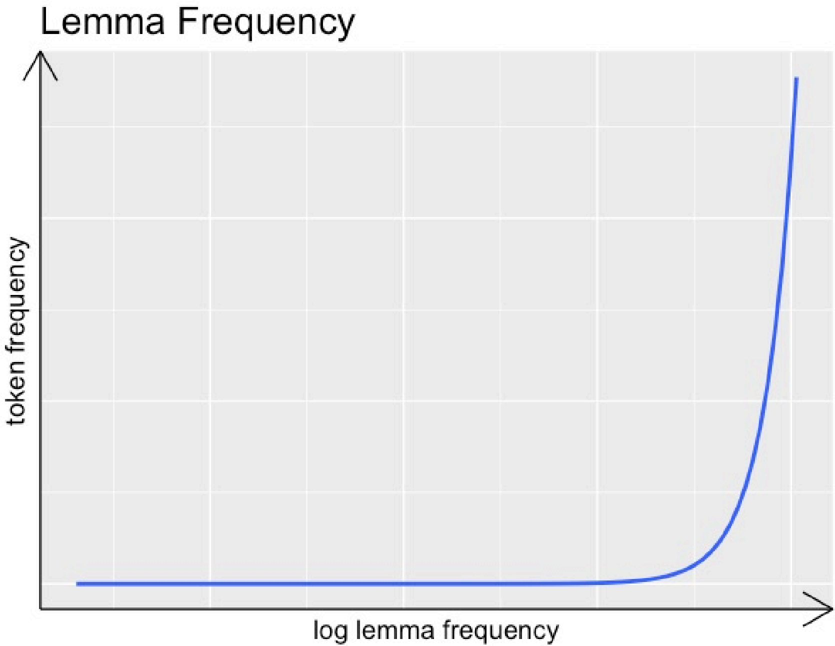
Properties of the selected cells

- The selected cells correspond to 3 areas of high interpredictability.

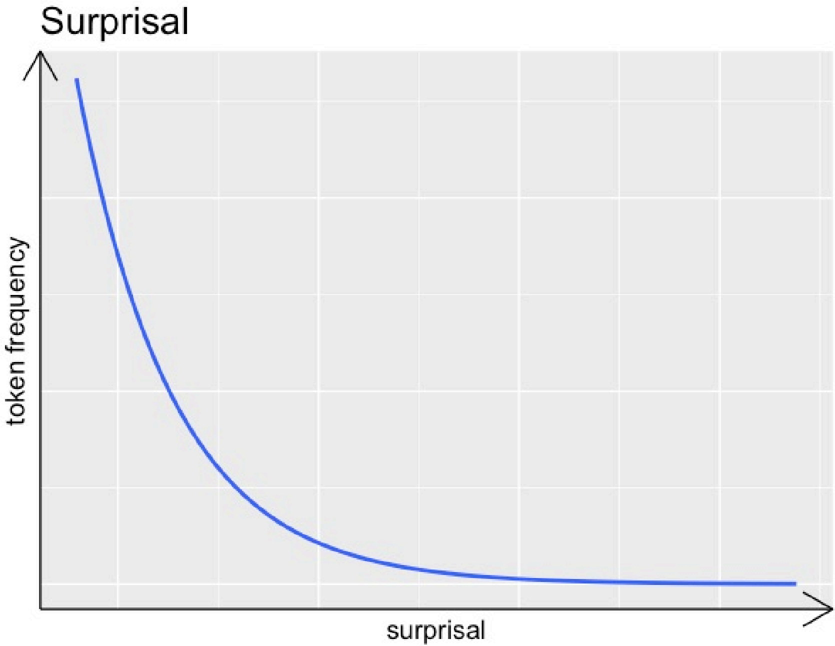
	FUT.1SG	FUT.2SG	FUT.3SG	FUT.1PL	FUT.2PL	FUT.3PL	COND.3SG	COND.1PL	COND.2PL	COND.3PL	IPFV.3SG	IPFV.3PL	PRS.PTCP	INF
FUT.1SG	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
FUT.2SG	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
FUT.3SG	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
FUT.1PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
FUT.2PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
FUT.3PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
COND.3SG	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
COND.1PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
COND.2PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
COND.3PL	0	0	0	0	0	0	0	0	0	0	0.24	0.24	0.24	0.23
IPFV.3SG	0.35	0.34	0.34	0.34	0.35	0.34	0.35	0.33	0.33	0.35	0	0	0.0004	0.34
IPFV.3PL	0.35	0.34	0.34	0.34	0.35	0.34	0.35	0.33	0.33	0.35	0	0	0.0004	0.33
PRS.PTCP	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.33	0.33	0.34	0	0	0	0.32
INF	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.076	0.077	0.074	0

Implicative entropy (Bonami and Beniamine, 2016) between selected cells

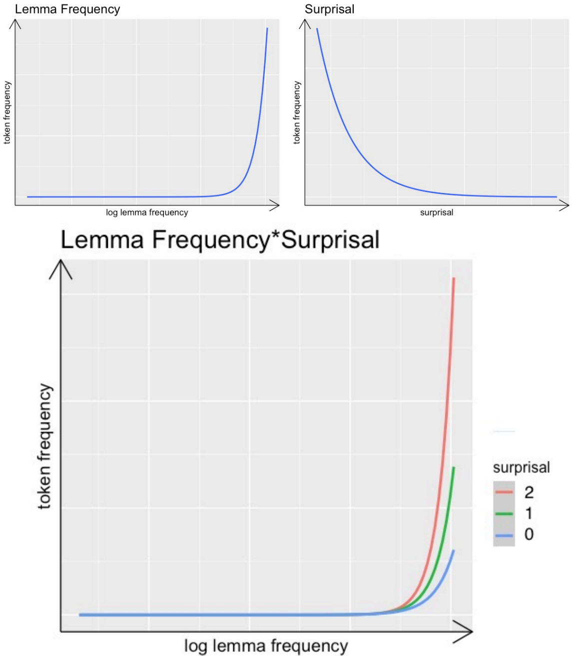
Predictions



Predictions



Predictions



Results

- Lemma frequency has a uniform positive effect on token frequency in all cells.
- Surprisal had a negative effect in 12/14 cells, an effect indistiguishable from 0 in 1/14, and an unexpected positive effect in 1/14.
- The interaction between surprisal and lemma frequency had a positive coefficient in 11/14 cells and an effect indistiguishable from 0 in 1/14. 2/14 have unexpected negative coefficients.
- Overall, 11/14 cells behaved exactly as predicted, two behaved counter to expectations and one showed non-significant impact for surprisal and surprisal:lemma

Model Output - Coefficients

Cell	Lemma freq.	Surprisal	Interaction
FUT.1SG	0.9935	–0.3783	0.0675
FUT.2SG	1.0771	–0.2306	0.0447
FUT.3SG	1.1764	–0.0261	0.0073
FUT.1PL	0.9693	–0.1932	0.0415
FUT.2PL	1.1072	–0.3368	0.0647
FUT.3PL	1.1466	–0.0040	0.0088
COND.3SG	1.2509	–1.0392	0.1835
COND.1PL	1.2544	–1.7739	0.2876
COND.2PL	1.2583	–2.7622	0.4486
COND.3PL	1.2312	–1.3889	0.2404
IPFV.3SG	1.1707	–0.0441	–0.0010
IPFV.3PL	0.9352	–0.5588	0.0959
PRS.PTCP	0.5916	0.0545	0.0053
INF	0.9438	0.0620	–0.0089

Unexpected coefficient sign
95% Credible interval overlaps with zero

Outlier Cells

- Cells that didn't conform to predictions: infinitive, imperfect 3sg, present participle.
- It is notable that these are by far the three most frequent cells in the dataset. The most frequent is the infinitive, followed by imperfect 3sg and present participle.
- We propose that the effect of surprisal is therefore nullified by the high frequency of the cell beyond very high lemma frequency items.
- This fits in with the data: while the coefficients for surprisal and the interaction have unexpected monotonicity, their value is much smaller compared to other cells, and very close to 0 (for pres. part. it is indistinguisheable from 0)

Discussion

- The data presented provides evidence that token frequency is impacted by form predictability beyond low values alone.
  - The pattern (form hard to predict → low token frequency) is reversed for items of high lemma frequency. High frequency lexemes are more familiar to speakers, so they do not need to rely on paradigmatic information to realise them
- The method performs well on 11/14 cells, and the exceptions exist for principled reasons.
  - Showcases the usefulness of paradigmatic information in predicting frequency.
  - Adds to our knowledge on paradigmatic frequency effects.
- The results further support a gradient understanding of defectiveness: defectiveness is an extreme case of form predictability, but form predictability affects token frequency at all levels.
  - The finding that form predictability affects token frequency at all levels, together with the observation that it correlates with (but does not uniquely identify) defectiveness, could lead us to investigate whether defectiveness is the result of low form predictability in conjunction with a second factor.

What next?

- Obtaining a good estimate of cell frequency (existing resources yield poor estimates, especially for the person dimension)
  - It would allow a weighed average of surprisal to be used
  - It would help interpret outlying results.
- Expanding our sample size by looking at other large inflectional systems (ideally featuring less homography).
- Testing the general effect of surprisal psycholinguistically.

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Model Output - Coefficients & Cell Frequency

Cell	Lemma freq.	Surprisal	Interaction	Cell Frequency	Freq. Rank
FUT.1SG	0.9935	-0.3783	0.0675	1345435	10
FUT.2SG	1.0771	-0.2306	0.0447	303754	13
FUT.3SG	1.1764	-0.0261	0.0073	6575463	5
FUT.1PL	0.9693	-0.1932	0.0415	789963	11
FUT.2PL	1.1072	-0.3368	0.0647	1506039	9
FUT.3PL	1.1466	-0.004	0.0088	4069211	6
COND.3SG	1.2509	-1.0392	0.1835	7394571	4
COND.1PL	1.2544	-1.7739	0.2876	255317	14
COND.2PL	1.2583	-2.7622	0.4486	365173	12
COND.3PL	1.2312	-1.3889	0.2404	1848943	8
IPFV.3SG	1.1707	-0.0441	-0.001	19020206	2
IPFV.3PL	0.9352	-0.5588	0.0959	3726892	7
PRS.PTCP	0.5916	0.0545[1]	0.0053[2]	14297764	3
INF	0.9438	0.062	-0.0089	112986370	1

[1] 95% Credible interval overlaps with zero.

Illustrating Defectiveness