

Does information density help?

A Bayesian analysis of *help* + (to) V_{INF} in geographic varieties of English

Natalia Levshina

Leipzig University

DGfS Meeting, Saarbrücken, March 2017

Outline

1. help (to) Vinf:

- Previous research
- Information density hypothesis

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

Alternation

- Mary **helped** John **cook** the dinner.
- Mary **helped** John **to cook** the dinner.

- A rare case when variation is possible between the bare and marked infinitive in PDE.
- Mair (2002) and Rohdenburg (2009): diachronic evidence that the bare infinitive has been gradually taking over, at least since the mid-19th century, with AmE leading.

When marked, when bare?

- Dixon (1991: 199): bare **Vinf** means a more active involvement of the Helper:
 - John **helped** Mary **eat** the pudding (he ate half).
 - John **helped** Mary **to eat** the pudding (by guiding the spoon to her mouth, since she was still an invalid).
- Not all agree with that (e.g. Huddleston & Pullum 2002: 1244).

Complexity

- Principle of cognitive complexity:

“In the case of more or less explicit grammatical options the more explicit one(s) will tend to be favoured in cognitively more complex environments” (Rohdenburg 1996: 151).

- The greater the distance between **help** and **Vinf**, the higher the chances of the marked infinitive.
 - I **helped** (them) as well as I could **to wash** up.
 - ?? I **helped** (them) as well as I could **wash** up. (Rohdenburg 1996: 159).
- Statistical evidence in Lohmann (2011), based on the BNC.

Horror aequi

- Avoidance of identity (repetition in near context)
 - Sorry, but how is this supposed to **help answer** the question?
 - ?? Sorry, but how is this supposed to **help to answer** the question?
- Interacts with formal distance: the greater the distance between **help** and **Vinf**, the weaker the effect (Lohmann 2011).

Presence of Helpee

- the bare infinitive is particularly dominant in the pattern **help** + NP + **Vinf** (Biber et al. 1999: 735; Lohmann 2011).
 - Vegetable soup **helps** you **lose** weight.
 - The mic stand **helps to get** the microphone placed properly for the best sound quality possible.

Inflectional form

- The form **helping** favours **to-Vinf** (Lohmann 2011).
 - I look forward to Vicky **helping** me **to buy** more clothes next season!

Register

- **help** + **bare Vinf** is particularly preferred in informal registers (Biber et al. 1999: 736–737).

Outline

1. help (to) Vinf:

- Previous research
- **Informativity hypothesis**

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

Uniform Information Density

- Information Theory and hypothesis of Uniform Information Density (Jaeger 2010):
 - Less informative/more predictable units tend to require less coding
 - **bare Vinf** in more predictable contexts?
 - More informative/less predictable units tend to require more coding
 - **marked Vinf** in less predictable contexts?

OK, but what is predictability?

- Defining the context: different levels of abstraction

Predictability given the immediate lexical context (words/ngrams), e.g. Piatandosi et al. (2011)

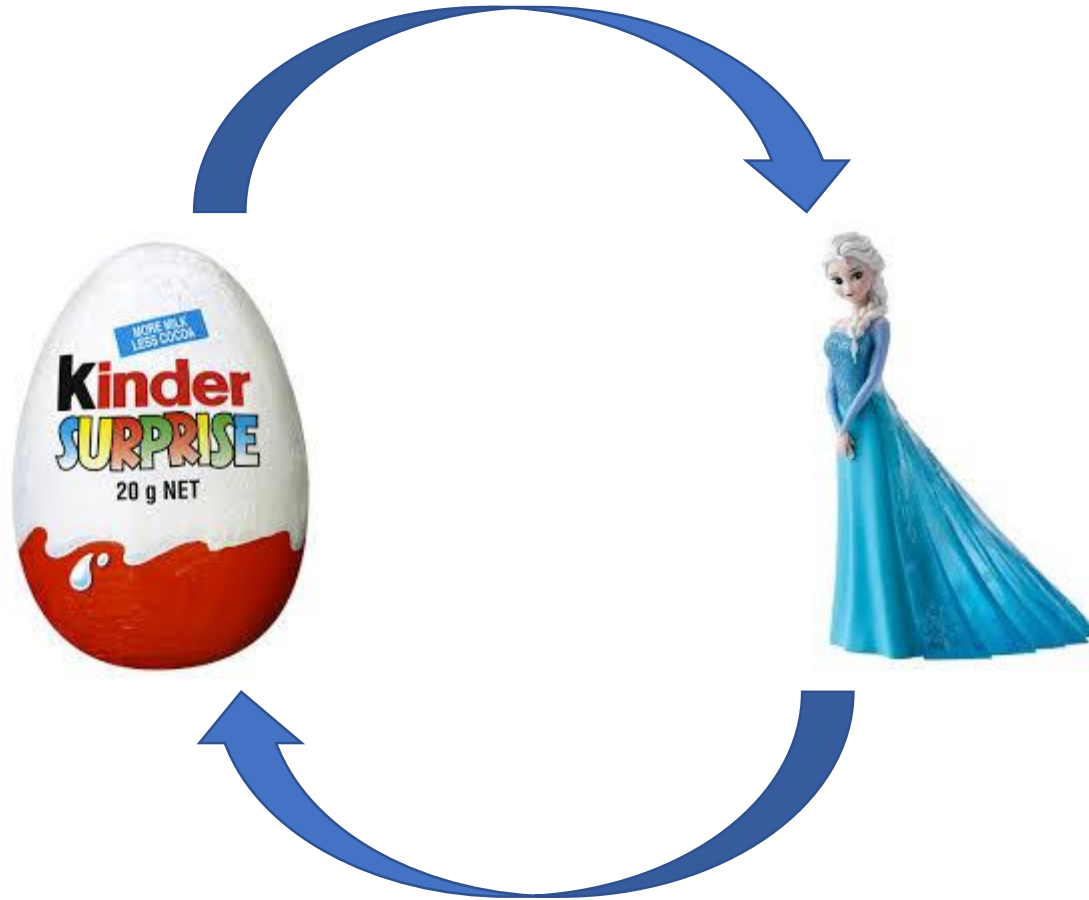
or

Predictability given syntactic information, e.g. Jaeger (2010): predictability of complement clauses given matrix verbs helps predict the use or omission of *that*, e.g. *I know he did it vs. I read that he did it.*

OK, but what is predictability?

- Left of right context (in case of ngrams)?
 - E.g. Bell et al. (2009): left context is more important for phonetic reduction of function words, while right context is more important for reduction of content words.
- Direction of predictability:
 - predictability of **Vinf** given the context? Or predictability of the context given **Vinf**?

Recall the intro talk...



Research questions

- Does information density help in general to model the variation of help of **help**?
- Which types of informativity/predictability are (more) important wrt. this variation?
- Do we find similar tendencies in different varieties of English?

Outline

1. help (to) Vinf:

- Previous research
- Informativity hypothesis

2. GloWbE corpus

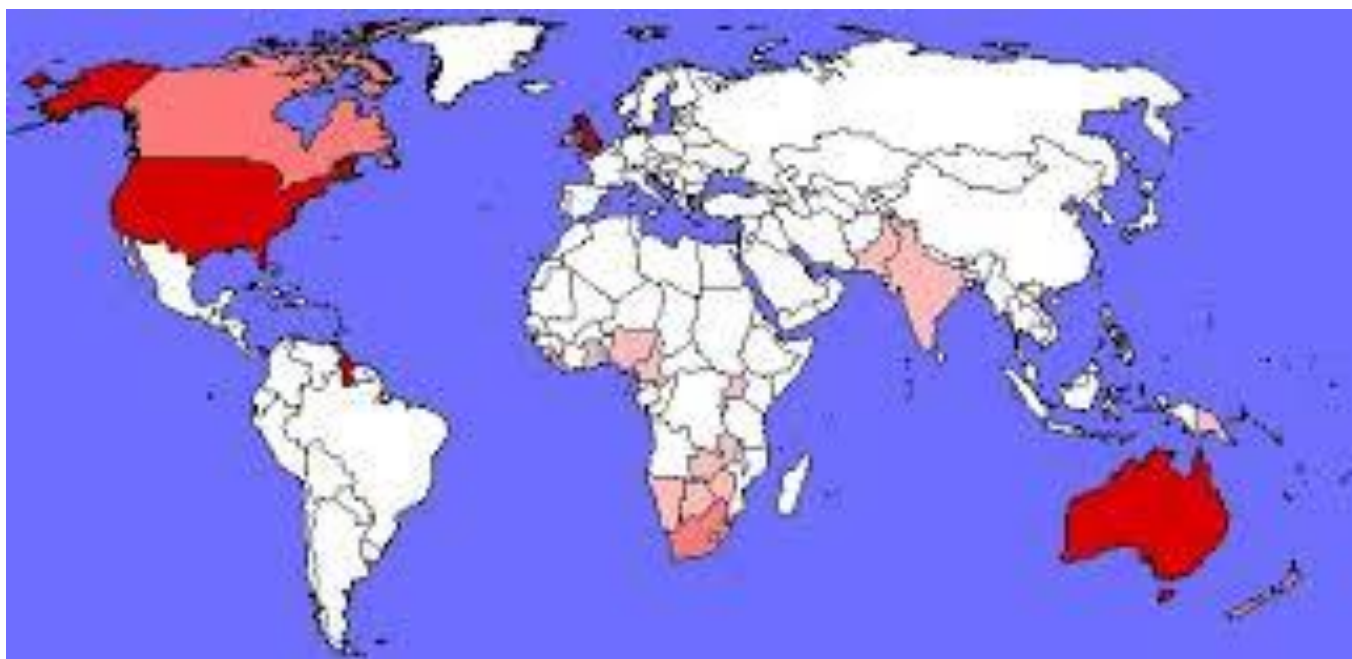
3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

GloWbE corpus (Davies 2013)



Data

- Online English from 20 countries
- Created by Google Advanced Search [Region] for highly frequent ngrams from COCA
- 1.9 Bln words
- 1.8 Mln web pages
- Lemmatized, POS-tagged
- See special issue *English World-Wide* 36(1), 2015

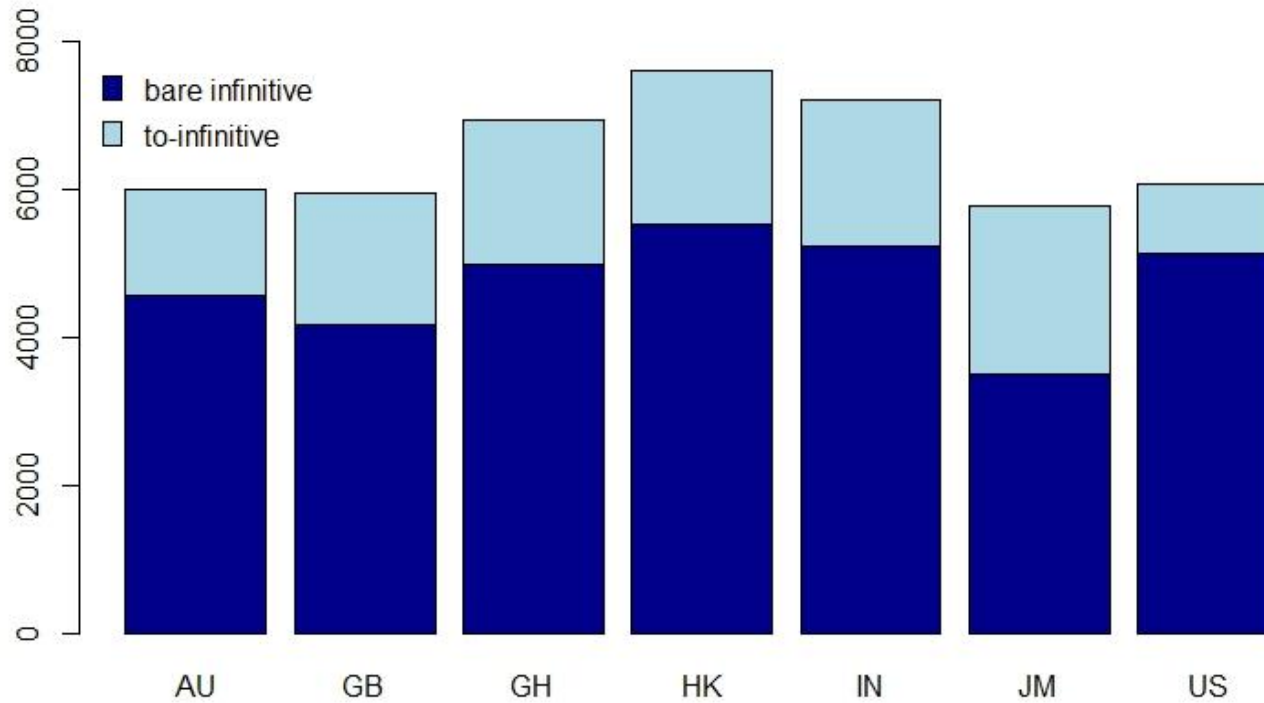
Varieties for this case study

- Australia
- Ghana
- Great Britain
- Hong Kong
- India
- Jamaica
- USA

Data set

- This study: 18 Mln. words for each country
- Any form of **help** followed by a **Vinf** somewhere in the same sentence, a stop list (he, is, where, etc.)
- Decent recall and precision + manual cleaning

Frequencies



Outline

1. help (to) Vinf:

- Previous research
- Informativity hypothesis

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

“Traditional” variables

- Valency of **Vinf** (Trans + Pass, Intrans, Clause)
- Helpee: Animate, Inanimate, Implicit
- Formal distance (in words) between **help** and **Vinf** (excluding to) (principle of complexity)
- Is there **to** before **help**? (Horror aequi)
- Morphological form of **help** (help, helps, helping or helped)
- Mean word length in the text: a proxy for formality

Outline

1. help (to) Vinf:

- Previous research
- Informativity hypothesis

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

Ngram-based measures

- Informativity of **Vinf** given the word on the left/right:
 - $-\log P(\text{Vinf} \mid \text{word left})$
 - $-\log P(\text{Vinf} \mid \text{word right})$
- Informativity of the word on the left/right given **Vinf**:
 - $-\log P(\text{word left} \mid \text{Vinf})$
 - $-\log P(\text{word right} \mid \text{Vinf})$
- Expectation: the greater the scores, the greater the chances of the **to-Vinf**

NB: the frequencies of word X with the bare and marked infinitive are added up! I.e. the bare and marked infinitives are treated as 1-gram.

Example: AU

- She also took the lead in solving the problems caused by a deconstructionist artist who got hold of an alien power wand and turned the whole city into abstract art, helped an all-female group of **superheroes** **to** **battle** the deadly shapeshifting Chimaera, and generally pulled her weight in the team.
 - Frequency **superheroes** + **(to)** **battle** = 1
 - Frequency **superheroes** = 22
 - Frequency **(to)** **battle** = 105
 - $P(\text{battle} | \text{superheroes}) = 1/22 = 0.045$
 - **Informativity Vinf given word left** = $-\log(0.045) \approx 3.1$
 - $P(\text{superheroes} | \text{battle}) = 1/105 = 0.009$
 - **Informativity word left given Vinf** = $-\log(0.009) \approx 4.6$

Syntactic directional measures

- a) Informativity of **Vinf** given **help** as governing verb:
-log P(Vinf|help)
- b) Informativity of **help** as governing verb given **Vinf**
-log P(help|Vinf)

Expectation: the greater the scores, the greater the chances of the **to-Vinf**

NB: the frequencies of constructions with the bare and marked infinitive are added up!

Example: *get* in GB

- Frequency of **get** with **help** (as bare and to-Inf): 303
- Total frequency of **help** + **Vinf** in GB: 5950
- Total frequency of **get** in GB: 49738
- Informativity of **get** given **help** = $-\log(303/5950) \approx 2.98$
- Informativity of **help** given **get** = $-\log(303/49738) \approx 5.1$

Syntactic bidirectional measures

- Represent the mutual attraction between **Vinf** and **help** as governing verb (cf. Levshina 2015: Ch. 10)
 - log odds ratio
 - Collostructional Strength (Gries & Stefanowitsch 2005)
 - Minimum Sensitivity (Pedersen & Bruce 2006)
- Expectation: the greater these measures, the higher the chances of the **bare Vinf**.

Outline

1. help (to) Vinf:

- Previous research
- Informativity hypothesis

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

Technical details

- Mixed logistic models: **to/bare Vinf** as the response variable, random intercepts for specific **Vinf** and textID
- All variables centred (sum contrasts for categorical)
- 4 chains, 2000 iterations in each (50% initial discarded)
- Flat priors (as in frequentist)
- Good mixing (diagnostic plots)
- R package brms (a wrapper for Stan in C++)

Posterior probabilities of effect pro *to*-Vinf: only ‘traditional’ var.

| Variables | AU | GB | GH | HK | IN | JM | US |
|-------------------------------------|--------------|-------------|--------------|--------------|--------------|--------------|--------------|
| Helped vs. help | 0.03% | 0% | 84.9% | 1.4% | 0.03% | 4% | 0% |
| Helping vs. help | 100% | 100% | 100% | 100% | 99.7% | 100% | 100% |
| Helps vs. help | 87.9% | 91.4% | 84.7% | 98.4% | 100% | 62.5% | 78.1% |
| Tr. Vs. Intr. Vinf | 41.3% | 17.2% | 63% | 94.1% | 84.9% | 82.6% | 64.1% |
| Clause vs. Intr. Vinf | 54.3% | 57.8% | 79.6% | 20.4% | 13.6% | 10.7% | 14.4% |
| Inanim. Helpee vs. anim. | 92.4% | 7.9% | 15.5% | 14.7% | 1.1% | 13.7% | 86.3% |
| Implicit Helpee vs. explicit | 96.2% | 100% | 99.3% | 100% | 100% | 100% | 96.2% |
| to help | 0% | 0% | 0% | 0% | 0% | 0% | 0% |
| Ling. distance | 100% | 100% | 100% | 100% | 100% | 100% | 99.8% |
| To help x ling. distance | 100% | 100% | 100% | 100% | 100% | 100% | 100% |
| Mean word length | 97.6% | 100% | 41.2% | 93.4% | 0.1% | 90.6% | 70% |

The percentages show the posterior probabilities of a parameter having a **positive** effect on the chances of **to**-Vinf.

How to compare IT measures?

- Problem: strong correlations between some IT measures.
- Fit a model with 'traditional' variables + one information-theoretic for each variety ($9 \times 7 = 63$ models)
- Compute the posterior probabilities of a positive effect wrt. **to-Vinf**
- LOOIC as the criterion for model comparison (predictive accuracy + parsimony)

IT variables + 'traditional' (not shown)

| | IT measures | AU | GB | GH | HK | IN | JM | US |
|---------------------|------------------------|-------|-------|-------|-------|-------|-------|-------|
| Ngrams | Info Vinf Word left | 70.9% | 13.5% | 25.3% | 24% | 18.4% | 36.4% | 59.4% |
| | Info Vinf Word right | 5% | 0.3% | 17.8% | 6.5% | 1.6% | 74.4% | 46.1% |
| | Info Word left Vinf | 100% | 99% | 100% | 100% | 98.4% | 100% | 88.6% |
| | Info Word right Vinf | 99.5% | 98.7% | 70.5% | 42.8% | 70.7% | 60.5% | 22.8% |
| Synt. directional | Info help Vinf | 100% | 98.1% | 99.4% | 100% | 100% | 99.7% | 99% |
| | Info Vinf help | 77.9% | 7.6% | 83.8% | 84.7% | 33.5% | 51.2% | 88% |
| Synt. bidirectional | Log Odds Ratio | 0.3% | 1% | 1.2% | 0.05% | 0% | 0.9% | 1.2% |
| | Coll. Strength | 12.7% | 64.2% | 2.4% | 4.6% | 27.2% | 6.6% | 6.4% |
| | Min. Sensitivity | 29.2% | 67.4% | 14.7% | 20% | 30.7% | 26.6% | 31.7% |

The percentages show the posterior probabilities of a parameter having a **positive** effect on the chances of **to-Vinf**.

Examples from GB

High informativity of **help** given **Vinf**

- think
- leave
- apply
- know
- come
- describe
- publish
- tell
- use
-

Low informativity of **help** given **Vinf**

- defray
- detoxify
- identify
- burnish
- regrow
- rewire
- legitimate
- demystify
- personalize
- ...

An effect of hapax legomena? No! If remove, the results remain the same.

All directional IT measures together + 'traditional' (not shown)

| | IT measures | AU | GB | GH | HK | IN | JM | US |
|-------------------|------------------------|-------|-------|-------|-------|-------|-------|-------|
| Ngrams | Info Vinf Word left | 54.5% | 30% | 0.7% | 10.1% | 52.8% | 22% | 58.3% |
| | Info Vinf Word right | 13.3% | 2.4% | 26.7% | 20.9% | 15.2% | 91.2% | 64.2% |
| | Info Word left Vinf | 98.8% | 93% | 100% | 99.7% | 68.9% | 99.6% | 63.4% |
| | Info Word right Vinf | 98% | 94.1% | 44.9% | 14.8% | 30.5% | 36.1% | 12.5% |
| Synt. directional | Info help Vinf | 80.2% | 50.9% | 4% | 92.6% | 99.6% | 82.6% | 97.2% |
| | Info Vinf help | 90.8% | 44% | 99.7% | 94.1% | 44.3% | 58.2% | 78.5% |

The percentages show the posterior probabilities of a parameter having a **positive** effect on the chances of **to-Vinf**.

Outline

1. help (to) Vinf:

- Previous research
- Informativity hypothesis

2. GloWbE corpus

3. Variables:

- Traditional
- Information-theoretic

4. Bayesian mixed-effect logistic regression models

5. Discussion

Summary of the results

- There are some information-theoretic measures that play an important role in each variety.
- The estimates of other semantic and syntactic variables change little: the effects are independent.
- Overall, the higher information content, the more frequent the *to-Vinf*.
- Strikingly, it is informativity of a context given *Vinf* that matters in all varieties, rather than informativity of *Vinf* itself given the context.
- In particular, predictability of *help* as the governing verb given *Vinf* and/or that of the word on the left are important in each variety.
- Bidirectional measures do not add much in terms of predictive power to the unidirectional measures.

Discussion

- Hypothesis of UID in Levy & Jaeger (2007): maximization of uniformity of **upcoming**-event probabilities.
- Here: longer coding **after** more informative contexts given the infinitive!
- Not so strange: *to* signals the reader that **Vinf** belongs together with **help** and Helpee, not with some other construction. If **Vinf** is a 'promiscuous' verb, it tends to be marked with *to*. If it is 'faithful' to **help** and Helpee, the particle will be omitted.

Thanks for your attention!

natalia.levshina@uni-leipzig.de

The slides are available at

www.natalialevshina.com/presentations.html