The typology of veridicality inferences

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Slides available at aaronstevenwhite.io
Data available at megaattitude.io
Introduction
How are a verb’s **semantic properties** related to its **syntactic distribution**? Gruber 1965; Fillmore 1970; Zwicky 1971; Jackendoff 1972; Grimshaw 1979, 1990; Pesetsky 1982, 1991; Pinker 1989; Levin 1993

**Semantic Properties**

- **TELIC**
- **DURATIVE**
- **STATIVE**
  - ...

<table>
<thead>
<tr>
<th>Semantic Properties</th>
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<tbody>
<tr>
<td>+ TELIC</td>
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<td>- STATIVE</td>
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Overarching question

How are a verb’s **semantic properties** related to its **syntactic distribution**? Gruber 1965; Fillmore 1970; Zwicky 1971; Jackendoff 1972; Grimshaw 1979, 1990; Pesetsky 1982, 1991; Pinker 1989; Levin 1993

Diagram:

**Semantic Properties**

- TELIC
- DURATIVE
- STATIVE
- ...

**Syntactic Distribution**

\[
\begin{align*}
\text{[___NP]} \\
\text{[___S]} \\
\text{[___VP]} \\
\text{...}
\end{align*}
\]
Factors claimed to affect the distribution of nominals
Sensitive to event structural properties like stativity, telicity, durativity, causativity, transfer, etc. (see Levin and Rappaport Hovav 2005)
Factors claimed to affect the distribution of **nominals**
Sensitive to event structural properties like **stativity**, **telicity**, **durativity**, **causativity**, **transfer**, etc. (see Levin and Rappaport Hovav 2005)

Factors claimed to affect the distribution of **clauses**
What could matter?

Factors claimed to affect the distribution of **nominals**
Sensitive to event structural properties like **stativity**, **telicity**, **durativity**, **causativity**, **transfer**, etc. (see Levin and Rappaport Hovav 2005)

Factors claimed to affect the distribution of **clauses**

Possibly indirectly, via e.g. neo-Davidsonian event decomposition
Kratzer 2006; Hacquard 2006; Moulton 2009; Anand and Hacquard 2013, 2014; Rawlins 2013; Bogal-Allbritten 2016; White and Rawlins 2016b a.o.
Question
How direct is the relationship between content-dependent properties and syntactic distribution?
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Focus
Two content-dependent properties – factivity and veridicality – that are argued to determine selection of interrogatives & declaratives
Veridicality

A verb $v$ is **veridical** iff NP $v$ $s$ entails $s$ Karttunen 1971a; Egré 2008; Karttunen 2012; Spector and Egré 2015 a.o.

Factivity

A verb $v$ is **factive** iff NP $v$ $s$ presupposes $s$ Kiparsky and Kiparsky 1970; Karttunen 1971b et seq.
Veridicality

A verb $v$ is **veridical** iff $\text{NP } v \text{ S entail } S$ \cite{Karttunen1971a, Egre2008, Karttunen2012, SpectorEgre2015}.

\begin{enumerate}
  \item a. Jo \textit{knew} that Bo was alive $\rightarrow$ Bo was alive
\end{enumerate}
Veridicality

A verb v is **veridical** iff \( \text{NP } v \text{ entails } S \) Karttunen 1971a; Egré 2008; Karttunen 2012; Spector and Egré 2015 a.o.

(1) 

a. Jo **knew** that Bo was alive \( \rightarrow \) Bo was alive

b. Jo **proved** that Bo was alive \( \rightarrow \) Bo was alive

Factivity
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A verb $v$ is **veridical** iff $\text{NP } v S \text{ entails } S$ Karttunen 1971a; Egré 2008; Karttunen 2012; Spector and Egré 2015 a.o.

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(1) a. Jo **knew** that Bo was alive → Bo was alive
   b. Jo **proved** that Bo was alive → Bo was alive

Factivity
A verb v is **factive** iff \( NP \ v \ S \) \( \text{presupposes} \) \( S \) Kiparsky and Kiparsky 1970; Karttunen 1971b et seq

(2) a. Jo didn’t **know** that Bo was alive → Bo was alive
Veridicality

A verb $v$ is **veridical** iff $\text{NP } v \text{ S entails S}$

Karttunen 1971a; Egré 2008; Karttunen 2012; Spector and Egré 2015 a.o.

(1)  

a. Jo **knew** that Bo was alive $\rightarrow$ Bo was alive  
   b. Jo **proved** that Bo was alive $\rightarrow$ Bo was alive

Factivity

A verb $v$ is **factive** iff $\text{NP } v \text{ S presupposes S}$

Kiparsky and Kiparsky 1970; Karttunen 1971b et seq

(2)  

a. Jo didn’t **know** that Bo was alive $\rightarrow$ Bo was alive  
   b. Jo didn’t **prove** that Bo was alive $\nrightarrow$ Bo was alive
Our prior work

Question
How direct is the relationship between content-dependent properties and syntactic distribution?

Focus
Two content-dependent properties – factivity and veridicality – that are argued to determine selection of interrogatives & declaratives.
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Prior finding (NELS 2017)
But there are strong empirical reasons to believe they do not.
Our prior work

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Because prior generalizations focus on finite interrogatives & declaratives, prior dataset covered only finite complements.
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But there are strong empirical reasons to believe they do not.

Limitation
Because prior generalizations focus on finite interrogatives & declaratives, prior dataset covered only finite complements.

But there is substantial variability in the veridicality inferences generated with different complements – even for the same verb.
Variability in veridicality

(3) a. \(J_{oi} \) forgot that \(s_{ei} \) bought tofu.
(3)  a. \( \text{Jo}_i \) forgot that \( \text{she}_i \) bought tofu. \( \rightarrow \) Jo bought tofu.
Variability in veridicality

(3)  a. Jo forgot that she bought tofu. → Jo bought tofu.
    b. Jo forgot to buy tofu.
Variability in veridicality

(3)  
   a. $\text{Jo}_i$ forgot that she$_i$ bought tofu. $\rightarrow$ Jo bought tofu.  
   b. Jo forgot to buy tofu. $\rightarrow$ Jo didn’t buy tofu.
Variability in veridicality

(3)  a. Jo$_i$ forgot that she$_i$ bought tofu. $\rightarrow$ Jo bought tofu.
    b. Jo forgot to buy tofu. $\rightarrow$ Jo didn’t buy tofu.

(4)  a. Jo$_i$ knew that she$_i$ bought tofu.
(3)  a.  Jo$_i$ forgot that she$_i$ bought tofu. $\rightarrow$ Jo bought tofu.
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  a. Jo$_i$ knew that she$_i$ bought tofu. → Jo bought tofu.
  b. Jo knew to buy tofu.
Variability in veridicality

(3)  a. Jo forgot that she bought tofu. → Jo bought tofu.
    b. Jo forgot to buy tofu. → Jo didn’t buy tofu.

(4)  a. Jo knew that she bought tofu. → Jo bought tofu.
    b. Jo knew to buy tofu. ∨ Jo {bought, didn’t buy} tofu.
Variability in veridicality

(3)  
  a. Jo forgot that she bought tofu. → Jo bought tofu.  
  b. Jo forgot to buy tofu. → Jo didn’t buy tofu.

(4)  
  a. Jo knew that she bought tofu. → Jo bought tofu.  
  b. Jo knew to buy tofu.  \(\not\rightarrow\) Jo {bought, didn’t buy} tofu.
Question

Is there evidence that this variability correlates with distribution?
Today’s talk

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Empirical contributions
1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
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1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
2. Data-driven typology of inference patterns across comp. types.
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1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
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Analytical contributions

1. Inference pattern typology explains some parts of syntactic distribution reasonably well, but far from perfect.
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Is there evidence that this variability correlates with distribution?

Empirical contributions
1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
2. Data-driven typology of inference patterns across comp. types.

Analytical contributions
1. Inference pattern typology explains some parts of syntactic distribution reasonably well, but far from perfect.
2. More likely that the veridicality-distribution relationship is indirect, mediated by fine-grained verb class.
Outline

Introduction
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A new veridicality dataset
Outline

Introduction

A new veridicality dataset

Data overview
Introduction

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Data overview

Predicting distribution using veridicality
Outline

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Data overview

Predicting distribution using veridicality

Conclusion
A new veridicality dataset
Measuring veridicality and distribution

Aim

Measure **syntactic distribution** and **veridicality inferences** across a wide variety of syntactic contexts.
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**MegaAcceptability dataset** (White and Rawlins, 2016a)
Ordinal (1-7 scale) acceptability ratings for **1000 clause-embedding verbs** in **50 syntactic frames**
Measuring veridicality and distribution

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Ordinal (1-7 scale) acceptability ratings for **1000 clause-embedding verbs** in **50 syntactic frames**

**MegaVeridicality dataset** (White and Rawlins, 2018)
Veridicality judgments for **517 verbs** from the MegaAttitude based on their acceptability in the **[NP _ that S]** and **[NP was _ed that S]** frames
61. Someone knew that a particular thing happened.

Did that thing happen?

- no
- maybe or maybe not
- yes

How acceptable is the **bolded** sentence?

- terrible
- 2
- 3
- 4
- 5
- 6
- perfect
Veridicality judgment task

68. Someone didn't know that a particular thing happened.

Did that thing happen?

- no
- maybe or maybe not
- yes

How acceptable is the **bolded** sentence?

- terrible
- 2
- 3
- 4
- 5
- 6
- perfect
Expand MegaVeridicality with **603 verb types** from MegaAcceptability based on acceptability in **7 frames** involving **infinitival complements**:

- \([NP \_ed for NP to VP]\) (184 verbs)
- \([NP \_ed NP to VP [+ev]]\) (197 verbs)
- \([NP \_ed NP to VP [-ev]]\) (128 verbs)
- \([NP was \_ed NP to VP [+ev]]\) (278 verbs)
- \([NP was \_ed NP to VP [-ev]]\) (256 verbs)
- \([NP \_ed to VP [+ev]]\) (217 verbs)
- \([NP \_ed to VP [-ev]]\) (165 verbs)
Stimuli

Expand MegaVeridicality with 603 verb types from MegaAcceptability based on acceptability in 7 frames involving infinitival complements:

- \[NP \_ed \text{for} \ NP \to \ VP\] (184 verbs)
NP _ed for NP to VP

(5)  
  a. Someone wanted for a particular thing to happen.
  b. Someone didn’t want for a particular thing to happen.
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Stimuli

NP _ed for NP to VP

(5)  a. Someone wanted for a particular thing to happen.
    b. Someone didn’t want for a particular thing to happen.

NP _ed NP to VP[+ev]

(6)  a. Someone told a particular person to do a particular thing.
    b. Someone didn’t tell a particular person to do a particular thing.
Stimuli

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NP _ed NP to VP[+ev]

(6)  a. Someone told a particular person to do a particular thing.
b. Someone didn’t tell a particular person to do a particular thing.

NP _ed NP to VP[-ev]

(7)  a. Someone believed a particular person to have a particular thing.
b. Someone didn’t believe a particular person to have a particular thing.
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NP was _ed to VP[+ev]

(8)  a. A particular person was ordered to do a particular thing.
    b. A particular person wasn’t ordered to do a particular thing.
Stimuli

Expand MegaVeridicality with **603 verb types** from MegaAcceptability based on acceptability in **7 frames** involving **infinitival complements**:

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- [NP was _ed NP to VP[-ev]] (256 verbs)
Stimuli

NP was _ed to VP[+ev]

(8) a. A particular person was ordered to do a particular thing.
    b. A particular person wasn’t ordered to do a particular thing.

NP was _ed to VP[-ev]

(9) a. A particular person was overjoyed to have a particular thing.
    b. A particular person wasn’t overjoyed to have a particular thing.
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- [NP _ed to VP[-ev]] (165 verbs)
Stimuli

NP _ed to VP[+ev]

(10)  a. A particular person decided to do a particular thing.
     b. A particular person didn’t decide to do a particular thing.
Stimuli

Expand MegaVeridicality with **603 verb types** from MegaAcceptability based on acceptability in **7 frames** involving **infinitival complements**:

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- \([\text{NP } \_\text{ed to VP}[-\text{ev}]]\) (165 verbs)
Stimuli

NP _ed to VP[+ev]

(10)  a. A particular person decided to do a particular thing.
     b. A particular person didn’t decide to do a particular thing.

NP _ed to VP[-ev]

(11)  a. A particular person hoped to have a particular thing.
     b. A particular person didn’t hope to have a particular thing.
Stimuli

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2,850 items randomly partitioned into 50 lists of 57
Note
Mixed-effects ordinal model-based normalization to control for variability in how participants use the response scale. (see Agresti, 2014)
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Applied to both veridicality and acceptability judgments.
Results

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Mixed-effects ordinal model-based normalization to control for variability in how participants use the response scale. (see Agresti, 2014)

Applied to both veridicality and acceptability judgments.

Intuition
Like z-scoring, but better models response behavior.
Data overview
Results

that S for NP to VP NP to VP[+ev]

¬p ← ¬V(p) → p
¬p ← V(p) → p

NP to VP[−ev] to VP[+ev] to VP[−ev]
Example: \textit{x-axis}

A particular person didn’t forget to do a particular thing.
Results

\[ \neg p \leftarrow \neg V(p) \rightarrow p \]
Example: $x$-axis
A particular person didn’t forget to do a particular thing.
Example: \textit{x-axis} \\
A particular person didn’t forget to do a particular thing.

Example: \textit{y-axis} \\
A particular person forgot to do a particular thing.
Results

\[ \neg p \leftarrow \neg V(p) \rightarrow p \]

that S for NP to VP NP to VP[+ev]

NP to VP[−ev] to VP[+ev] to VP[−ev]

\[ \neg p \leftarrow \neg V(p) \rightarrow p \]
Results
<table>
<thead>
<tr>
<th>that S</th>
<th>for NP to VP</th>
<th>NP to VP[+ev]</th>
</tr>
</thead>
<tbody>
<tr>
<td>know</td>
<td></td>
<td></td>
</tr>
<tr>
<td>forget</td>
<td></td>
<td></td>
</tr>
<tr>
<td>remember</td>
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<td></td>
</tr>
<tr>
<td>think</td>
<td></td>
<td></td>
</tr>
<tr>
<td>hope</td>
<td></td>
<td></td>
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\[
\neg p \leftarrow \neg V(p) \rightarrow p
\]
Results

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Results

NP to VP

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<td>think</td>
<td>hope</td>
<td>think</td>
</tr>
<tr>
<td>pretend</td>
<td>order</td>
<td>pretend</td>
</tr>
<tr>
<td>want</td>
<td>hope</td>
<td>pretend</td>
</tr>
<tr>
<td>order</td>
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<td>pretend</td>
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</tbody>
</table>

NP to VP[−ev]

<table>
<thead>
<tr>
<th>to VP[+ev]</th>
<th>to VP[−ev]</th>
</tr>
</thead>
<tbody>
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<td>bother</td>
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\[-p \iff \neg V(p) \rightarrow p\]
Results

\[ \neg p \leftarrow \neg V(p) \rightarrow p \]
Predicting distribution using veridicality
Goal

Extract patterns of inference – e.g. factive, veridical, or implicative.
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**Approach**
Use an automated method to discover inference patterns across verbs by decomposing veridical data into underlying factors.
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Use an automated method to discover inference patterns across verbs by decomposing veridical data into underlying factors.

Method
Regularized censored factor analysis with loss weighted by normalized acceptability and scores constrained to \((-1, 1)\).
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Regularized censored factor analysis with loss weighted by normalized acceptability and scores constrained to (-1, 1).

Selected number of factors (12) using cross-validation procedure.
Preliminaries

Goal
Extract patterns of inference – e.g. factive, veridical, or implicative.

Approach
Use an automated method to discover inference patterns across verbs by decomposing veridical data into underlying factors.

Method
Regularized censored factor analysis with loss weighted by normalized acceptability and scores constrained to (-1, 1).

Selected number of factors (12) using cross-validation procedure.

(Ask about specifics after the talk.)
Inference patterns

**Inference polarity**

**Matrix polarity**

- **negative**
- **positive**
Inference patterns

NP was \_ed to VP\[−ev\]
NP \_ed to VP\[−ev\]
NP was \_ed to VP\[+ev\]
NP \_ed to VP\[+ev\]
NP \_ed NP to VP\[−ev\]
NP \_ed NP to VP\[+ev\]
NP \_ed for NP to VP
NP was \_ed to VP\[+ev\]
NP \_ed to VP\[−ev\]
NP was \_ed to VP\[−ev\]
NP \_ed that S
NP \_ed that S
NP \_ed for NP to VP
NP \_ed NP to VP\[+ev\]
NP \_ed NP to VP\[−ev\]
NP was \_ed to VP\[+ev\]
NP \_ed to VP\[−ev\]
NP was \_ed to VP\[−ev\]

Inference polarity

Matrix polarity

Pattern 0     Pattern 1     Pattern 2     Pattern 3

Pattern 4     Pattern 5     Pattern 6     Pattern 7

Pattern 8     Pattern 9     Pattern 10    Pattern 11

Inference polarity

Matrix polarity

negative positive
Inference patterns

Pattern 5

Pattern 3
Inference patterns
Inference patterns: factivity/veridicality
Inference patterns: factivity/veridicality
Inference patterns: factivity/veridicality

Pattern 3

Pattern 5
Inference patterns

<table>
<thead>
<tr>
<th>Inference patterns</th>
<th>Pattern 0</th>
<th>Pattern 1</th>
<th>Pattern 2</th>
<th>Pattern 3</th>
</tr>
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</table>

**Matrix polarity**

- **negative**
- **positive**
Inference patterns
Inference patterns

Pattern 3

Pattern 7
Inference patterns: factivity/veridicality

Pattern 7

Pattern 3

- amaze
- bother
- surprise
- find out
- realize
- prove
- know
Inference patterns: factivity/veridicality
Inference patterns

Pattern 0

Pattern 1

Pattern 2

Pattern 3

Pattern 4

Pattern 5

Pattern 6

Pattern 7

Pattern 8

Pattern 9

Pattern 10

Pattern 11

Inference polarity

Matrix polarity

negative positive

53
Inference patterns

Pattern 0
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 1
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 2
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 3
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 4
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 5
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 6
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 7
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 8
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 9
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 10
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 11
NP _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
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Inference polarity
Matrix polarity negative positive
Inference patterns: implicatives
Inference patterns: implicatives
Inference patterns: implicatives
Inference patterns

Pattern 0
NP was _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
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NP _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 1
NP was _ed to VP[−ev]
NP _ed to VP[−ev]
NP was _ed to VP[+ev]
NP _ed to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed NP to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 2
NP was _ed that S
NP _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
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NP _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]

Pattern 3
NP was _ed to VP[−ev]
NP _ed to VP[−ev]
NP was _ed to VP[+ev]
NP _ed to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed NP to VP[+ev]
NP was _ed to VP[+ev]
NP _ed to VP[−ev]
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Pattern 4
NP was _ed that S
NP was _ed that S
NP _ed for NP to VP
NP _ed NP to VP[+ev]
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NP _ed to VP[−ev]
NP was _ed to VP[−ev]
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Pattern 5
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
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NP _ed to VP[−ev]
NP was _ed to VP[−ev]
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Pattern 6
NP _ed for NP to VP
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NP _ed to VP[−ev]
NP was _ed to VP[−ev]
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NP was _ed to VP[−ev]
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Pattern 7
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
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Pattern 8
NP _ed for NP to VP
NP _ed NP to VP[+ev]
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Pattern 10
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
NP _ed to VP[−ev]

Pattern 11
NP _ed for NP to VP
NP _ed NP to VP[+ev]
NP _ed NP to VP[−ev]
NP _ed to VP[+ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
NP _ed to VP[−ev]
NP was _ed to VP[−ev]
NP _ed to VP[−ev]

Inference polarity

Matrix polarity
negative positive
Inference patterns

Inference polarity

Matrix polarity

Pattern 0

Pattern 1

Pattern 2

Pattern 3

Pattern 4

Pattern 5

Pattern 6

Pattern 7

Pattern 8

Pattern 9

Pattern 10

Pattern 11

Inference polarity

Matrix polarity

negative

positive
Question
Can we predict **syntactic distribution** directly from **veridicality inference patterns**?
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Approach
Learn optimal mapping from veridicality inference patterns to syntactic distribution using cross-validated ridge regression.
Predicting distribution from inference

Question
Can we predict syntactic distribution directly from veridicality inference patterns?

Approach
Learn optimal mapping from veridicality inference patterns to syntactic distribution using cross-validated ridge regression.

Finding
Across all frames in MegaAcceptability, this mapping explains about 20% of the variance in the acceptability judgments.
Predicting distribution from inference

Variance explained

Syntactic structure

62
Predicting distribution from inference

Variance explained

Syntactic structure
Predicting distribution from inference

Variance explained

Syntactic structure
Points

1. Some amount of information about syntactic distribution carried in veridicality inferences.
Points

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   1.1 **Caveat:** It’s hard to tell how much explanation is driven by syntactic information encoded in the patterns.
Inference patterns

Inference polarity

Matrix polarity

negative positive
Predicting distribution from inference

Points

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   1.1 Caveat: It’s hard to tell how much explanation is driven by syntactic information encoded in the patterns.
Points

1. Some amount of information about syntactic distribution carried in veridicality inferences.
   1.1 **Caveat:** It’s hard to tell how much explanation is driven by syntactic information encoded in the patterns.

2. Not nearly enough information to base a generalization on.
Exploratory analysis

Question
What drives the relationship between veridicality and distribution?
Exploratory analysis

Question
What drives the relationship between veridicality and distribution?

Possibility
The relationship is *indirect*, mediated by underlying features that explain both distribution and veridicality.
Exploratory analysis

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Possibility
The relationship is indirect, mediated by underlying features that explain both distribution and veridicality.

Motivation
Relationship may be mediated by non-contentful properties of contentful events Kratzer 2006; Hacquard 2006; Moulton 2009; Anand and Hacquard 2013, 2014; Rawlins 2013; Bogal-Allbritten 2016; White and Rawlins 2016b a.o.
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Approach
Use Uniform Manifold Approximation and Projection (UMAP) to visualize the topological structure of the distribution and veridicality data. McInnes and Healy 2018
Exploratory analysis
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Exploratory analysis
Exploratory analysis
Conclusion
Conclusion

Question
How do inference patterns in clause-embedding verbs relate to syntactic distribution?
Conclusion

Question
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Empirical contributions

1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
Conclusion

Question
How do inference patterns in clause-embedding verbs relate to syntactic distribution?

Empirical contributions

1. Dataset capturing the variability of **factivity** and **veridicality** across **finite and infinitival complement types**.
2. Data-driven **typology of inference patterns** across comp. types.
Conclusion

Question
How do inference patterns in clause-embedding verbs relate to syntactic distribution?

Empirical contributions
1. Dataset capturing the variability of *factivity* and *veridicality* across *finite and infinitival complement types*.
2. Data-driven *typology of inference patterns* across comp. types.

Analytical contributions
1. *Inference pattern typology* explains some parts of *syntactic distribution* reasonably well, but far from perfect.
Conclusion

Question
How do inference patterns in clause-embedding verbs relate to syntactic distribution?

Empirical contributions
1. Dataset capturing the variability of factivity and veridicality across finite and infinitival complement types.
2. Data-driven typology of inference patterns across comp. types.

Analytical contributions
1. Inference pattern typology explains some parts of syntactic distribution reasonably well, but far from perfect.
2. More likely that the veridicality-distribution relationship is indirect, mediated by fine-grained verb class.
Big remaining question
How are inference patterns represented in the lexicon?
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How are inference patterns represented in the lexicon?

Possibility 1
Verb class-specific rules (possibly sensitive to content-dependent properties, like veridicality and factivity).
Future directions

Big remaining question
How are inference patterns represented in the lexicon?

Possibility 1
Verb class-specific rules (possibly sensitive to content-dependent properties, like veridicality and factivity).

Possibility 2
More abstract semantic properties relevant to thematic roles – e.g. affectedness, existence, creation/destruction, ...
Thanks!
For discussion of this work, we are grateful to audiences at JHU, University of Rochester, UMD, NELS 2017 in Reykjavik, as well as Valentine Hacquard, Rachel Rudinger, and Ben Van Durme.

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Data available at megaattitude.io


Aaron Steven White and Kyle Rawlins. Question agnosticism and change of state., September 2016b.
