The relation of surprisal and human processing difficulty

Information Theory Lecture

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Information Theory Lecture, Universität des Saarlandes

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Information theory in der Psycholinguistics

Surprisal allows us to estimate a measure of how much information is being conveyed by an utterance.

Psycholinguistic perspective:

▶ Hypothesis: Processing difficulty is proportional to the amount of information conveyed.

▶ i.e., can we measure the difficulty of a sentence using information theoretic concepts?
Syntactic Surprisal

\[ -\log(1.7766 \times 10^{-11}) = 35.712 \]

How to calculate surprisal:

- Calculate prefix probabilities:
  \[ pp_{w_n} = -\log \sum_{T \in Trees} p(T|w_1 \ldots w_n) \]

- Surprisal \( s_{w_n} \) of word \( w_n \):
  \[ s_{w_n} = pp_{w_n} - pp_{w_{n-1}} \]

Example PCFG:

<table>
<thead>
<tr>
<th>Rule</th>
<th>Probability of rule</th>
</tr>
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<tbody>
<tr>
<td>S ( \rightarrow ) NP VP</td>
<td>( p = 0.6 )</td>
</tr>
<tr>
<td>VBD ( \rightarrow ) raced</td>
<td>( p = 0.0005 )</td>
</tr>
<tr>
<td>VBN ( \rightarrow ) raced</td>
<td>( p = 0.000001 )</td>
</tr>
<tr>
<td>DT ( \rightarrow ) the</td>
<td>( p = 0.7 )</td>
</tr>
</tbody>
</table>

sum of both: \( pp_{w_n} = 35.712 \)
Syntactic Surprisal

\[ pp_{w_{n+1}} = -\log(1.06596 \times 10^{-15} \times 0.003) = 58.12 \]

How to calculate surprisal:

▶ Calculate prefix probabilities:

\[ pp_{w_n} = -\log \sum_{T \in \text{Trees}} p(T|w_1 \ldots w_n) \]

▶ Surprisal \( s \) of word \( w_n \):

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Syntactic Surprisal

\[ pp_{wn+1} = -\log(1.06596 \times 10^{-15} \times 0.003) = 58.12 \]

How to calculate surprisal:

- Calculate prefix probabilities:
  \[ pp_{wn} = -\log \sum_{T \in \text{Trees}} p(T|w_1 \ldots w_n) \]

- Surprisal \( s \) of word \( w_n \):
  \[ s_{wn} = pp_{wn} - pp_{wn-1} \]

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<tr>
<td>S → NP VP</td>
<td>( p = 0.6 )</td>
</tr>
<tr>
<td>VBD → raced</td>
<td>( p = 0.00005 )</td>
</tr>
<tr>
<td>VBN → raced</td>
<td>( p = 0.000001 )</td>
</tr>
<tr>
<td>DT → the</td>
<td>( p = 0.7 )</td>
</tr>
</tbody>
</table>

\[ pp_{wn-1} = 35.712 \]
\[ pp_{wn} = 58.12 \]
\[ \text{surprisal}(w_n) = 22.41 \]

- Predictions also depend on parametrization of the grammar, training
Lexical vs. structural surprisal

- $-\log(1.7766 \times 10^{-11}) = 35.712$

- $-\log(1.06596 \times 10^{-15}) = 49.736$

$pp_{w_{n+1}} = -\log(1.06596 \times 10^{-15} \times 0.003) = 58.12$

$pp_{w_{n-1}} = 35.712$

$pp_{w_{n}} = 58.12$

$surprisal(w_{n}) = 22.41$

Some of the surprisal is due to the lexical identity of *fell*, and some of it is due to the syntactic structural information conveyed by that word.
Lexical vs. structural surprisal

\[ S_{wn} = -\log \sum_{T \in \text{Trees}} \frac{p(T|w_1 \ldots w_n)}{p(T|w_1 \ldots w_{n-1})} \]

\[ \text{struct}S_{wn} = -\log \sum_{\text{POS}_n \in \text{POS}} \sum_{T \in \text{Trees}} \frac{p(T|w_1 \ldots \text{POS}_n)}{p(T|w_1 \ldots w_{n-1})} \]

\[ \text{lex}S_{wn} = -\log \sum_{\text{POS}_n \in \text{POS}} \sum_{T \in \text{Trees}} \frac{p(T|w_1 \ldots w_n)}{p(T|w_1 \ldots \text{POS}_n)} \]
<table>
<thead>
<tr>
<th>1</th>
<th>Corpus-based Evaluation of Surprisal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear Mixed Effects Models</td>
</tr>
</tbody>
</table>

| 2 | Surprisal vs. related information-theoretic measures |
Corpus-based results

Support from reading times in naturalistic texts

- on Dundee Corpus (Demberg and Keller, 2008; Frank, 2009; Fossum and Levy, 2012; Smith and Levy, 2013)
- on English stories with long dependencies (Roark et al., 2009)
- on Potsdam Sentence Corpus (German) (Boston et al., 2008)
- on Brown SPR Corpus (Smith and Levy 2013)

Reading times

linking theory: reading times reflect processing difficulty; if we find a correlation, then surprisal predicts behaviour.
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Support from EEG:

- surprisal predictive of N400 amplitudes (Frank et al., 2013)

N400

N400 has been linked to predictability, difficulty in retrieving / integrating a word.
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Buck did not read the newspapers, or he would have known that
trouble was brewing, not alone for himself, but for every tide-water
dog, strong of muscle and with warm, long hair, from Puget Sound to
San Diego. Because men groping in the Arctic darkness, had found
The Dundee Corpus (Kennedy and Pynte 2005)

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- 51,000 words of British newspaper articles (The Independent)
- 10 subjects read the whole text and answered comprehension questions
- Eye-movements recorded
- Data Cleaning:
  - exclude first and last word of a line
  - exclude words adjacent to punctuation
  - remove tracklosses
  - remove words including numbers
Reading Time Measures

The pilot embarrassed John and put himself in a very awkward situation.

First fixation time = 5
Gaze duration = 5+6
Total time = 5+6+8+10
Second pass time = 8+10
Skipping rate: e.g. put
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Gaze duration = 5 + 6
Total time = 5 + 6 + 8 + 10
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Skipping rate: e.g. put

▶ What are the different measures at “John”? 
▶ Why should we distinguish between different measures?
Use **Eye-tracking Corpora** as complementary evidence to experimental data:

- Sentences are read in *context*
- “real” language, *naturally occurring* text
- Test on many different constructions
- Evaluate *many theories on same data* to obtain better comparability
- But: *less control* over materials
Use **Eye-tracking Corpora** as complementary evidence to experimental data:

► Sentences are read *in context*
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► Test on many different constructions
► Evaluate *many theories on same data* to obtain better comparability
► But: *less control* over materials

**Method:**

► Calculated **Surprisal** for each word in the corpus based on Roark parser [Roark, 2001, 2009]
► Calculated **DLT** Integration Costs (IC) for each word based on MINIPAR [Lin, 1998]
**Correlation between Theories:**

<table>
<thead>
<tr>
<th></th>
<th>Integration Cost</th>
<th>Lexical Surprisal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lexical Surprisal</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>Structural Surprisal</td>
<td>-0.09</td>
<td>0.36</td>
</tr>
</tbody>
</table>
Linear Mixed Effect Models

- All variables and binary interactions entered into a hierarchical linear mixed effects model
- Full random effects structure
- Stepwise removal of variables that decrease model quality (using AIC)
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- All variables and binary interactions entered into a hierarchical linear mixed effects model
- Full random effects structure
- Stepwise removal of variables that decrease model quality (using AIC)

**Random variable:** subject ID

**Dependent variables:**
- first fixation duration
- gaze duration
- total reading time

**Covariates:**
- word length
- log frequency
- word position
- previous fixation
- launch distance
- fixation land position

**Independent variable:**
- integration cost
- lexical surprisal
- structural surprisal
## Broad-Coverage Evaluation on Dundee Corpus

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>254.07</td>
<td>***</td>
</tr>
<tr>
<td>WordLength</td>
<td>7.36</td>
<td>***</td>
</tr>
<tr>
<td>WordFrequency</td>
<td>-15.80</td>
<td>***</td>
</tr>
<tr>
<td>PreviousWordFrequency</td>
<td>-6.35</td>
<td>***</td>
</tr>
<tr>
<td>PreviousWordFixated</td>
<td>-35.60</td>
<td>***</td>
</tr>
<tr>
<td>LaunchDistance</td>
<td>-0.86</td>
<td></td>
</tr>
<tr>
<td>LandingPosition</td>
<td>-21.39</td>
<td>***</td>
</tr>
<tr>
<td>SentencePosition</td>
<td>-0.28</td>
<td>***</td>
</tr>
<tr>
<td>ForwardBigramSurprisal</td>
<td>2.77</td>
<td>***</td>
</tr>
<tr>
<td>BackwardBigramSurprisal</td>
<td>-1.36</td>
<td>**</td>
</tr>
<tr>
<td>WordLength:WordFrequency</td>
<td>-4.15</td>
<td>***</td>
</tr>
<tr>
<td>IntegrationCost</td>
<td>-2.82</td>
<td>***</td>
</tr>
<tr>
<td>LexicalSurprisal</td>
<td>-0.16</td>
<td></td>
</tr>
<tr>
<td>StructuralSurprisal</td>
<td>1.21</td>
<td>***</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001
Methodological interlude

What is...

- Random intercept?
- Random slope for predictor?
- Full random effects structure?
- “conservative”

Watch out for

- Collinearity
- Model selection
A more problematic example from the literature

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open-class (Intercept)</td>
<td>$2.40 \times 10^{+00}$</td>
<td>$2.39 \times 10^{-02}$</td>
<td>100.4*</td>
</tr>
<tr>
<td>Lexical Surprisal</td>
<td>$-1.99 \times 10^{-04}$</td>
<td>$7.28 \times 10^{-04}$</td>
<td>-0.3</td>
</tr>
<tr>
<td>Word Length</td>
<td>$8.97 \times 10^{-04}$</td>
<td>$4.62 \times 10^{-04}$</td>
<td>1.9</td>
</tr>
<tr>
<td>Bigram</td>
<td>$4.18 \times 10^{-04}$</td>
<td>$5.27 \times 10^{-04}$</td>
<td>0.8</td>
</tr>
<tr>
<td>Unigram Freq</td>
<td>$-2.43 \times 10^{-03}$</td>
<td>$1.20 \times 10^{-03}$</td>
<td>-2.0*</td>
</tr>
<tr>
<td>Derivation Steps</td>
<td>$-1.17 \times 10^{-03}$</td>
<td>$9.02 \times 10^{-04}$</td>
<td>-1.3</td>
</tr>
<tr>
<td>Syntactic Entropy</td>
<td>$2.55 \times 10^{-03}$</td>
<td>$6.19 \times 10^{-04}$</td>
<td>4.1*</td>
</tr>
<tr>
<td>Lexical Entropy</td>
<td>$3.96 \times 10^{-04}$</td>
<td>$6.68 \times 10^{-04}$</td>
<td>0.6</td>
</tr>
<tr>
<td>Syntactic Surprisal</td>
<td>$3.28 \times 10^{-03}$</td>
<td>$9.71 \times 10^{-04}$</td>
<td>3.4*</td>
</tr>
<tr>
<td>Order in narrative</td>
<td>$-1.43 \times 10^{-05}$</td>
<td>$4.34 \times 10^{-06}$</td>
<td>-3.3*</td>
</tr>
<tr>
<td>POS Surprisal</td>
<td>$-6.84 \times 10^{-04}$</td>
<td>$8.11 \times 10^{-04}$</td>
<td>-0.8</td>
</tr>
<tr>
<td>POS Entropy</td>
<td>$1.47 \times 10^{-03}$</td>
<td>$6.05 \times 10^{-04}$</td>
<td>2.4*</td>
</tr>
</tbody>
</table>

Table: Mixed effects models Roark (2009)
### Table: Correlations of predictors for models in Roark (2009)

<table>
<thead>
<tr>
<th>Predictor</th>
<th>SynH</th>
<th>LexH</th>
<th>SynS</th>
<th>LexS</th>
<th>Freq</th>
<th>Bgrm</th>
<th>PosS</th>
<th>PosH</th>
<th>Step</th>
<th>WLen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Syntactic Entropy (SynH)</td>
<td>1.00</td>
<td>-0.26</td>
<td>0.00</td>
<td>0.24</td>
<td>-0.24</td>
<td>0.20</td>
<td>0.02</td>
<td>0.55</td>
<td>-0.05</td>
<td>0.18</td>
</tr>
<tr>
<td>Lexical Entropy (LexH)</td>
<td>-0.26</td>
<td>1.00</td>
<td>0.01</td>
<td>-0.40</td>
<td>0.43</td>
<td>-0.38</td>
<td>-0.03</td>
<td>0.02</td>
<td>0.11</td>
<td>-0.29</td>
</tr>
<tr>
<td>Syntactic Surprisal (SynS)</td>
<td>0.00</td>
<td>0.01</td>
<td>1.00</td>
<td>-0.12</td>
<td>0.08</td>
<td>0.18</td>
<td>0.77</td>
<td>0.21</td>
<td>0.38</td>
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<td>0.24</td>
<td>-0.40</td>
<td>-0.12</td>
<td>1.00</td>
<td>-0.81</td>
<td>0.87</td>
<td>-0.10</td>
<td>-0.20</td>
<td>-0.35</td>
<td>0.64</td>
</tr>
<tr>
<td>Unigram Frequency (Freq)</td>
<td>-0.24</td>
<td>0.43</td>
<td>0.08</td>
<td>-0.81</td>
<td>1.00</td>
<td>-0.69</td>
<td>0.02</td>
<td>0.18</td>
<td>0.31</td>
<td>-0.72</td>
</tr>
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<td>Bigram Probability (Bgrm)</td>
<td>0.20</td>
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<td>0.18</td>
<td>0.87</td>
<td>-0.69</td>
<td>1.00</td>
<td>0.11</td>
<td>-0.11</td>
<td>-0.16</td>
<td>0.56</td>
</tr>
<tr>
<td>POS Surprisal (PosS)</td>
<td>0.02</td>
<td>-0.03</td>
<td>0.77</td>
<td>-0.10</td>
<td>0.02</td>
<td>0.11</td>
<td>1.00</td>
<td>0.22</td>
<td>0.32</td>
<td>0.02</td>
</tr>
<tr>
<td>POS Entropy (PosH)</td>
<td>0.55</td>
<td>0.02</td>
<td>0.21</td>
<td>-0.20</td>
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<td>1.00</td>
<td>0.16</td>
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<tr>
<td>Derivation steps (Step)</td>
<td>-0.05</td>
<td>0.11</td>
<td>0.38</td>
<td>-0.35</td>
<td>0.31</td>
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<tr>
<td>Word Length (WLen)</td>
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<td>1.00</td>
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Note: very high correlations for

- Frequency, Lexical Surprisal, Bigram Prob, (Word Length)
- Syntactic surprisal and POS Surprisal
Watch out for terminology in the literature

- **Lexicalized surprisal** refers to surprisal calculated based on a syntactic parser, combination of both lexical and structural surprisal; used to contrast with “POS surprisal”. (Not what you should use anymore nowadays.)
- **Syntactic surprisal** used ambiguously: sometimes refers to surprisal calculated via a syntactic parser, sometimes only to the structural portion of it.
Conclusion so far:

- Syntactic surprisal is predictive of reading times over and above simple word frequencies and bigram surprisal.
- Syntactic surprisal refers to the portion of surprisal that is caused by syntactic structure, ignoring lexical probability.
- Lexical surprisal is highly correlated with word frequency.
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- Lexical surprisal is highly correlated with word frequency.

Does this relationship between surprisal and reading times hold across the whole range of surprisal values? Or does it just flatten out at some point when the word is not among the very strongly predictable?
Effect of Surprisal on Reading times

Demberg (2010), reading times on Dundee corpus.
Smith and Levy (2013) have a whole paper focussed on this question.
Effect of Surprisal on Reading Times

If you’re using self-paced reading as a measure, make sure you analyse word \( n+1 \)!
Surprisal and ERPs

Can we also correlate surprisal to the event related potentials we observe in EEG studies?

- N400 would be a good candidate, as it’s long been known to respond to predictability
- Smith and Levy (2010) showed that cloze and corpus-estimated surprisal are at least somewhat similar ($\rho = 0.5$)
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**Method:** Linear mixed effects model with

- baseline potential
- log-transformed word frequency
- word length (number of characters),
- word position in the sentence
- sentence position in the experiment
Modelling processing difficulty: Surprisal

This plotting method is very unusual:
it shows the $\chi^2$ from comparing a model with vs. without surprisal as a predictor;
Positive / negative shows the direction of the regression coefficient.
This does not show whether the effect is linear.
No correlation with other ERP measures
Conclusions

- Surprisal is correlated with human reading times and the N400.
- i.e. there is evidence that this notion of the information to be processed has explanatory power for human language processing.
- How surprisal is estimated also matters!
Table of Contents

1. Corpus-based Evaluation of Surprisal
   - Linear Mixed Effects Models

2. Surprisal vs. related information-theoretic measures
Information-theoretic measures

Different accounts of how predictability / uncertainty might affect sentence processing have also been suggested:

- **Surprisal** (aka *pointwise entropy*)
  How unexpected was the word?

- **Entropy Reduction**
  The amount by which a word reduces the uncertainty about the rest of the sentence.

- **Entropy** (one step vs. multi-step)
  The uncertainty about the next word / the rest of the sentence; related to competition models

- **Commitment** (higher difficulty for changing top-ranking analysis)
  Surprisal should have larger effect after highly-contraining contexts.
Entropy Reduction

Hale 2003, 2006:

- Hypothesis: a word is difficult to process if it greatly reduces the uncertainty about the rest of the sentence.

- Uncertainty is quantified as the entropy of the distribution over complete parses of the sentence; that is, if $A_i$ is the set of all possible parses of the sentence after word $w_i$, then the uncertainty following $w_i$ is given by

$$H_{w_i} = -\sum_{a \in A_i} P(a) \log P(a)$$

- Processing load proportional to

$$ER(w_n) = \max\{H_{w_n} - H_{w_{n-1}}, 0\}$$
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  \[
  H_{w_i} = - \sum_{a \in A_i} P(a) \log P(a)
  \]
- Processing load proportional to
  \[
  ER(w_n) = \max\{H_{w_n} - H_{w_{n-1}}, 0\}
  \]
- Extremely hard to calculate for large grammars.
But what about entropy itself as a measure?

- Hypothesis: word is difficult because there is lots of uncertainty about how the sentence will continue
- related to competition hypothesis (McRae et al., 1998; Tabor and Tanenhaus, 1999)
- Uncertainty about what? Complete rest of sentence or next word?
- Has been approximated by calculating the uncertainty about the next word (e.g., Roark, 2009).
- “One-step” vs. “multi-step” entropy

(Beware some sloppyness in use of terms in the literature, there sometimes seems to be some confusion regarding Entropy vs. ER hypotheses.)
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- **Surprisal (aka pointwise entropy)**
  How unexpected was the word?

- **Entropy Reduction**
  The amount by which a word reduces the uncertainty about the rest of the sentence.

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  The uncertainty about the next word / the rest of the sentence; related to competition models

- **Commitment (higher difficulty for changing top-ranking analysis)**
  Surprisal should have larger effect after highly-contraining contexts.
Example (from Linzen and Jaeger, 2014)

Consider “sentences” \( ae \) vs. \( be \):
- Surprisal?
- ER?
- Entropy?
- Commitment?

Figure 1: Example language. Output strings are indicated inside the nodes, and transition probabilities are indicated on the edges. For example, the probability of the sentence \( bf \) is \( 0.5 \times 0.75 \).
Example (from Linzen and Jaeger, 2014)

Consider “sentences” $ae$ vs. $be$:

- Surprisal? $ae = be$
- ER? $b > a$ and $a > b$
- Entropy? $a > b$ and $e = e$
- Commitment? $b > e$ and $e > a$

Figure 1: Example language. Output strings are indicated inside the nodes, and transition probabilities are indicated on the edges. For example, the probability of the sentence $bf$ is $0.5 \times 0.75$. 
Consider “sentences” **ae** vs. **be**:
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Information-theoretic measures

Different accounts of how predictability / uncertainty might affect sentence processing have also been suggested:

- **Surprisal** (aka *pointwise entropy*)
  How unexpected was the word?

- **Entropy Reduction**
  The amount by which a word reduces the uncertainty about the rest of the sentence.

- **Entropy** (one step vs. multi-step)
  The uncertainty about the next word / the rest of the sentence; related to *competition* models

- **Commitment** (higher difficulty for changing top-ranking analysis)
  Surprisal should have larger effect after highly-constraining contexts.

High or low Surprisal / ER / Entropy / Commitment?
The horse raced past the barn fell.
Information-theoretic measures

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The children went inside to **play**.
The children went outside to **play**.
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---

High or low Surprisal / ER / Entropy / Commitment?

The children went inside to **look**.
The children went outside to **look**.
Comparison

Examples

The men **forgot** the waterfall **had** dried up
The men **heard** the waterfall **had** dried up
The men **claimed** the waterfall **had** dried up
The men **sensed** the waterfall **had** dried up

sent. comp. surpr. subcat entropy
Comparison

Surprisal at had?
Subcategorization frame entropy at the verb?

Examples

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<table>
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NP = noun phrase; Inf = infitive;
PP = PP completion; SC = sentence complement
Comparison

Surprisal at had?
Subcategorization frame entropy at the verb?

Examples

| The men | verb | object | had | action | entropy
|---------|------|--------|-----|--------|---------|
| forgot  | the waterfall | had | dried up | 3.46
| heard   | the waterfall | had | dried up | 3.22
| claimed | the waterfall | had | dried up | 1.15
| sensed  | the waterfall | had | dried up | 1.55

NP = noun phrase; Inf = infitive; PP = PP completion; SC = sentence complement
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NP Inf PP SC
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Methods:

- Self-paced reading via Mechanical Turk
- 128 participants (4 excluded)
- 8 verbs in each condition (32 verbs total); 64 fillers
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Results

- no differences on *the men* or *discovered*
- significantly higher RTs for high SC surprisal on *the island* only in unambiguous sentences (*that* present); (spill-over from *that*).
- significantly faster RTs for unambiguous conditions on *had been invaded*.
- RTs on same region significantly higher for high SC surprisal in ambiguous condition.
- no significant effects of subcat frame entropy (expected on verb)
Results

Discussion:

- Evidence for subcat frame surprisal: reading times higher when evidence for unexpected subcategorization frame is encountered.

- But did we calculate / conceptualize entropy in the right way when considering subcat frame entropy??
Discussion: single vs. multistep entropy

Subcat frame entropy is like “single step entropy”.

*Figure 3: Entropy calculation example: the single step entropy after *discover* is 1 bit; the overall entropy is $1 + 0.5 \times 14 + 0.5 \times 50 = 33$ bits.*

- Single step entropy can be very different from full entropy.
- Linzen and Jaeger calculate the full entropy using an adapted parser.
Model predictions

Sentential complement surprisal
- Low
- High

Subcategorization entropy
- Low
- High
Surprisal effects as seen in data

- Entropy / ER driven by SC surprisal, not much affected by Subcat entropy.
- Entropy and ER make opposite predictions on main verb:
  - Entropy: verbs that typically take complements are harder to process.
  - ER: verbs that typically take complements are easier to process.
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  - Entropy: verbs that typically take complements are harder to process.
  - ER: verbs that typically take complements are easier to process.

Result: ER was a significant positive predictor of RTs on main verb in lme model.
Overall predictions not comparable due to *partial* lexicalization of PCFG model.

- computational modelling was chosen to estimate full entropy compared to just single step entropy (subcat frame entropy).
- experimental design controlled for subcat frame entropy but not full entropy, therefore, needed mixed effects model to estimate effect of full entropy.
- no evidence in Linzen & Jaeger expt for single step entropy
- but RTs on verb were longer for verbs that don’t take complement, i.e. when post-verb entropy is lower. This is consistent with entropy reduction.
Overall results / discussion

- Surprisal is not the only way in which information-theoretic concepts have been linked to processing difficulty.
- Surprisal doesn’t exclusively explain all effects.
- Other studies have found additional effects of, e.g., level of constraint, entropy reduction (Frank, 2011).
- Distinguish: Entropy vs. Entropy Reduction
- Estimating entropy of complete sentence can be very different from entropy of next step