Constraints on Information Processing in Language Comprehension and Production

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Natural Language as an Information-Theoretic Code

Agent A

Agent B

speaks

comprehends

comprehends

speaks
Natural Language as an Information-Theoretic Code

Intent/ Meaning

Production

Comprehension

Research Program

Models of language processing

Models of how processing shapes language structure
A Nexus Between Fields

- Linguistics
- Cognitive Science
- Information Theory
- Machine Learning
Goals Today

• Develop and test models of language comprehension and language production based on maximizing efficiency subject to constraints.

• Show that a bottleneck on memory yields detailed patterns of comprehension difficulty for nested clauses.

• Show that a bottleneck on control yields accessibility effects in incremental production of words.

• On both sides, a predictive language model ends up playing a central role.
Outline

• Introduction
• Information Theory for Language Processing
• Memory Bottleneck in Language Comprehension
• Control Bottleneck in Language Production
• Conclusion
What is Information?

• The children went outside to…
  \textit{play}
  011101

\textbf{Amount of information \sim Amount of surprise}

• The children came inside to…
  \textit{play}
  011101110001011101
Basic Information Theory: Surprisal

• The **amount of information** in a word (or anything!) depends on how **surprising** it is in context.

• Information content is quantified as **surprisal**: 

  •  \( S(\text{word} \mid \text{context}) = -\log_2 P(\text{word} \mid \text{context}) \)

    (measured in bits)

• Surprisal is also the **length of the shortest binary representation** that encodes the word in context.
A Closer Look at Surprisal

Information content of \( S(\text{play}) \)
The children went outside to **play**…

**Information content** of **play** in **context**

\[ S(\text{play} \mid \text{context}) \]

**A Closer Look at Surprisal**

**Mutual information** between word and context

Remaining information content of the word
Information Theory in Psycholinguistics

- **Surprisal Theory**: (Hale, 2001; Levy, 2008; Smith & Levy, 2013)
  
  - $RT(\text{word} \mid \text{context}) = k \ S(\text{word} \mid \text{context})$.

- **Idea**: Each bit of information content takes a fixed time for processing.
Information Theory in Psycholinguistics

- **Surprisal Theory**: (Hale, 2001; Levy, 2008; Smith & Levy, 2013)
  - \( \text{RT}(\text{word} \mid \text{context}) = k \cdot S(\text{word} \mid \text{context}) \).

- **Idea**: Each bit of information content takes a fixed time for processing.

- Surprisal theory and variants have **high predictive value** for reading times and N400 signals (Smith & Levy, 2013; Frank & Bod, 2011; Frank, 2016; Wilcox et al., 2020; Shain, 2019; Li & Futrell, 2022)

- Predicts classic garden path effects, although underestimating effect size (Hale, 2001; Levy, 2008; but see van Schijndel & Linzen, 2022)
Surprisal and Language Models

• Optimal representations are based on a **predictive language model**

\[
S(word \mid context) = -\log P(word \mid context)
\]

• Fitting a language model to predict words in context *is equivalent to* finding optimal compressed representations of words in context.

• What do you get if you train a giant neural network to minimize surprisal?

As a language model, I don’t have emotions, so I can’t be “stumped” in the way that you mean. But I do have a knowledge cutoff, meaning that I am only aware of information that
Information Theory and Language Processing

• Surprisal Theory is a good start, but...
  
  • It does not account for memory limitations, and often underestimates reaction times.
  
  • It does not say anything about how linguistic structure interacts with processing difficulty.
  
  • It’s not clear what it has to say about production.
  
• What happens when we consider optimal representations under cognitive constraints?
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Memory Effects in Sentence Processing

- Bob threw out the trash. 😊
- Bob threw the trash out. 😊
- Bob threw out the old trash that had been sitting in the kitchen. 😊
- Bob threw the old trash that had been sitting in the kitchen out. 😞

The Dependency Locality Theory (Gibson, 1998, 2000)
Self-Paced Reading Times

none  PP  RC
Embedded

Bartek et al. (2011)
The apartment was well-decorated.

The apartment that the maid cleaned was well-decorated.

The apartment that the maid who the service sent over cleaned was well-decorated.

RT trouble starts here
Memory in Language Comprehension

The children went...
Memory in Language Comprehension

Word

Memory State

\[ x \]

\[ s \]
How to fit a memory bottleneck into Surprisal Theory?

- Surprisal: \( RT(w | \text{context}) = S(w | \text{context}) \)
- Lossy-context surprisal: \( RT(w | \text{context}) = S(w | \text{memory representation}) \)

Futrell, Gibson & Levy (2020)
Lossy-Context Surprisal

The maid cleaned...

Objective surprisal: $S(\text{cleaned} \mid \text{The maid})$

Processing difficulty is the number of unpredictable bits.

Memory cost due to memory limitations

Bits predictable given the memory state

$S(\text{word} \mid \text{memory}) = S(\text{word} \mid \text{context}) + \text{Memory cost}$
Uses of Lossy-Context Surprisal

- By constraining memory in various ways, we can account for...
  - Certain dependency locality effects (Futrell, Gibson & Levy, 2020)
  - Cross-linguistic patterns in structural forgetting (Futrell, Gibson & Levy, 2020)
  - General reading times in eyetracking corpora, with neural network implementation (Kuribayashi et al., 2022)
  - Novel patterns in comprehension of nested clauses. (Hahn, Futrell, Levy & Gibson, 2022)
Processing with Constrained Memory

- **Idea**: Only a certain maximum number of words can be retained in memory.
- Predictions about upcoming words are optimal subject to the constraint that not all context words can be represented.

Context
The report that the doctor annoyed the patient… was interesting

Hahn, Futrell, Levy & Gibson (2022)
**Processing with Constrained Memory**

- **Idea**: Only a certain maximum number of words can be retained in memory.
- Predictions about upcoming words are **optimal subject to the constraint** that not all context words can be represented.

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**Lossy Context**
The report ??? the doctor annoyed the patient...

<table>
<thead>
<tr>
<th>Context $c$</th>
<th>$P(c)$</th>
<th>→ was interesting</th>
<th>↔ was interesting</th>
</tr>
</thead>
<tbody>
<tr>
<td>The report that the doctor annoyed the patient...</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The report <strong>by</strong> the doctor annoyed the patient.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The report <strong>about</strong> the doctor annoyed the patient.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Hahn, Futrell, Levy & Gibson (2022)
Predictions about Embedded Clauses

- **Prediction**: The difficulty of multiple embedding depends on the **embedding bias** of the noun.
Predictions about Embedded Clauses

- **Prediction**: The difficulty of multiple embedding depends on the **embedding bias** of the noun.
Model Implementation

True Context \( c^* \)
- The report that the doctor annoyed the patient...

Retention Probabilities
- 0.6
- 0.9
- 0.85
- 0.83
- 0.93
- 0.97
- 0.95
- 0.99

Lossy Representation \( c' \sim P(c' | c^*) \)
- ?? report ?? ?? doctor annoyed the patient...

Next-Word Prediction
\[
P(w | c') = \sum_c P(w | c) P(c | c')
\]

Next-Word Predictions \( P(w | c) \)
- was came yesterday
- End of Sentence

Posterior \( P(c | c') \)
\[
\propto P(c' | c) P(c)
\]
- The report that the doctor annoyed the patient...
- The report by the doctor annoyed the patient...
- A report about the doctor annoyed the patient...

Bayesian Inference
Reading Time Experiment Results

Model

Previous Models

**Surprisal Theory**

**DLT**

\[ \text{Surprisal (bits)} \]

Embedding Bias

\[ -5 \quad -4 \quad -3 \quad -2 \quad -1 \]

\[ -5 \quad -4 \quad -3 \quad -2 \quad -1 \]

**ONE**  **TWO**  **THREE**
Memory Bottleneck in Language Comprehension

- We considered language comprehension difficulty based on surprisal given a lossy memory representation of context.
- Predicts RT better than a less constrained language model.
- Comprehension can be modeled as maximally efficient subject to memory constraints.
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Information Theory and Language Production

- Information-theoretic models of language processing have mostly focused on **comprehension**.

- What can we say about **production**?
From Comprehension to Production

- Communicative Goal
- Word
- Memory State
Goal = Picture of Language Production

Word X = cat \sim P(\cdot \mid g, s)^{(Policy)}

State = the
Goal: state the cat

Word: sat $\sim P(\cdot | g, s)$ (Policy)

State: the cat

Picture of Language Production
Picture of Language Production

Goal = the cat on (Policy)

Word \( \sim P(\cdot | g, s) \) (Policy)

State = the cat sat
Picture of Language Production

Goal

State

Word

Picture of Language Production

\[
p(x | g, s) \approx P(x | g, s) \text{(Policy)}
\]

the cat sat on
Optimization Problem for Language Production

- **Goal**: You can only use so much information about the goal per word, due to a constraint on cognitive control.
  - Cognitive control operates under a bandwidth constraint: 50 bits/ms (Fan, 2014; Zénon et al., 2019)
- So, find a policy that
  - Maximizes communicative accuracy
  - Subject to a constraint on the mutual information of $g$ with $x$ in each timestep.

Futrell (2023)
Constrained Optimal Policy

A word is produced if...

- It is low surprisal given the memory state.
- It is communicatively accurate.
- The trade-off of these factors is controlled by the bandwidth of cognitive control, $\alpha$. 

\[
P(\text{word} \mid \text{goal, state}) \propto \exp \left\{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal, state}) \right\}
\]
Uses of the Rate-Distortion Theory of Control

- We can use this production model to explain...

- **Frequency** and **semantic interference** effects in word production (Futrell, 2020; Futrell, 2023, PNAS)

- **Semantic substitution errors** (Upadhye & Futrell, 2022) and use of **filled pauses** (Futrell, 2023, PNAS)

- **Accessibility effects** in use of optional complementizers in English (Futrell, 2023, CogSci)

- **Accessibility effects** in use of Mandarin classifiers (Futrell, 2023, CogSci)
Mandarin Classifiers

- In certain phrases, Mandarin nouns must be preceded by a classifier which can be either specific or generic.

一 台 电脑
one MACHINE computer
‘one computer’

一 个 电脑
one GENERIC computer
‘one computer’

一 只 猫
one ANIMAL cat
‘one cat’

一 个 猫
one GENERIC cat
‘one cat’
An Accessibility Effect in Mandarin Classifiers

A. Zhan & Levy (2019) Experiment
Mandarin Classifier Simulation

- Set up a toy language where every utterance consists of CLASSIFIER + NOUN, where CLASSIFIER can be generic or specific.

- $N=200$ different nouns, each assigned to one of 10 different specific classifiers.

- Probability distribution on nouns is Zipfian.

- Derive the constrained optimal policy.

$$P(\text{word} \mid \text{goal}, \text{state}) \propto \exp \left\{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal}, \text{state}) \right\}$$

Favors generic classifier

Favors specific classifier
Mandarin Classifier Result

A. Zhan & Levy (2019) Experiment

B. Model Simulation

Condition
- quick
- slow

Control gain $\alpha$
- 1.05
- 1.1

$P(\text{specific classifier})$

Log$_2$ Noun Frequency

Log$_2$ Need Probability
Mandarin Classifier Result

- Production of specific classifier is rare when the model has uncertainty about which specific classifier it should use.
- Matches the intuitive idea of “accessibility.”
Control Bottleneck in Language Production

- An information-theoretic model captures 
  **accessibility-based production**
  effects.

- A constrained optimal production policy ends up 
  including a **language model** as a component...

\[
P(\text{word} \mid \text{goal, state}) \propto \exp \{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal, state}) \}
\]

- Really, it’s a language model plus a reward model:
  - As in Reinforcement Learning from Human 
    Feedback (RLHF)

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Natural Language as a Code

Shannon (1948)

Intent/ Meaning

Production

Comprehension
A Nexus Between Fields

Linguistics

Information Theory

Cognitive Science

Machine Learning
Conclusion

- We can model language processing as optimal *subject to constraints*…
  - On incremental memory.
  - On control.
- **Language models** $P(\text{word} | \text{context})$ emerge as a key part of both comprehension and production.
  - **Comprehension**: They define the *information content* of each word to be processed.
  - **Production**: They emerge under a *constraint on cognitive control*.
- Information-theoretic psycholinguistics is an open field!
Acknowledgments

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• Thanks for your attention!
To find out more…

- On **lossy-context surprisal** as a model of human processing difficulty:
  - Michael Hahn, Judith Degen, and Richard Futrell. Explaining patterns of word and morpheme order as an efficient tradeoff of memory and surprisal. *Psychological Review*.

- On **RDC production model**