Introduction

LING 571 — Deep Processing Techniques for NLP Shane Steinert-Threlkeld

Roadmap

- Motivation
- Language and Intelligence
- Knowledge of Language
- Course Overview
- Intro to Syntax and Parsing



How are you feeling about the start of the quarter and a new academic year generally?

Total Results: 0



Motivation: Applications

- Applications of Speech and Language Processing
 - Call Routing
 - Information Retrieval
 - Question Answering
 - Machine Translation
 - Dialog Systems
 - Spell– and Grammar– Checking
 - Sentiment Analysis
 - Information Extraction
 - ...

Building on Many Fields

- Linguistics: Morphology, phonology, syntax, semantics...
- Psychology: Reasoning, mental representations
- Formal Logic
- Philosophy (of Language)
- Theory of Computation: Automata theory
- Artificial Intelligence: Search, Reasoning, Knowledge Representation, Machine Learning, Pattern Matching
- Probability

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Operationalizing Intelligence: The Turing Test (1950)

- Two contestants: Human vs. Computer
 - Judge: human
 - Test: interact via text questions
 - Question: Can judge tell which contestant is human?

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- Two contestants: Human vs. Computer
 - Judge: human
 - Test: interact via text questions
 - Question: Can judge tell which contestant is human?
- Crucially:
 - Posits that passing requires language use and understanding

• ELIZA (Weizenbaum, 1966) [Try it Online]

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 - Simulates Rogerian therapist:

```
User: You are like my father in some ways
```

ELIZA: WHAT RESEMBLANCE DO YOU SEE

USER: You are not very aggressive

ELIZA: WHAT MAKES YOU THINK I AM NOT AGGRESSIVE

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- Simple pattern matching technique

"On the web, no one knows you're a..."

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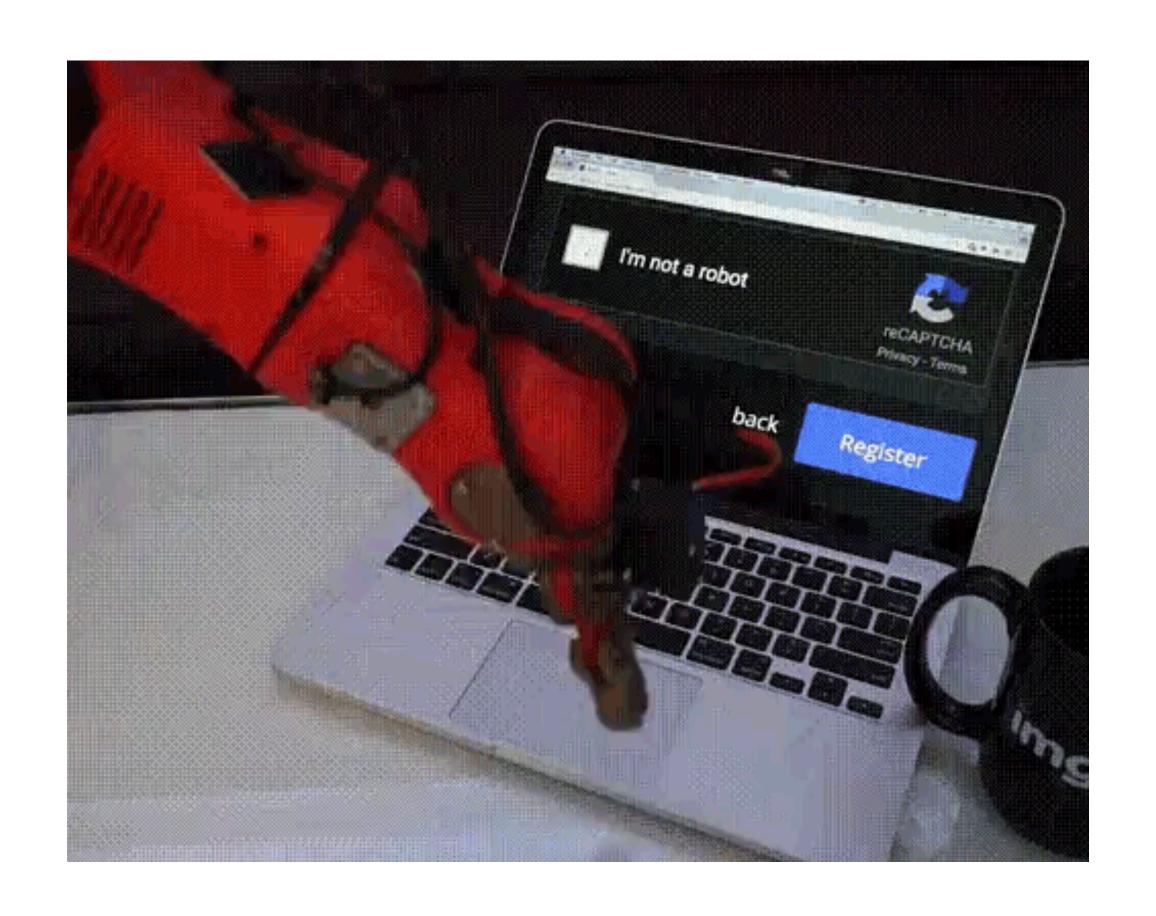
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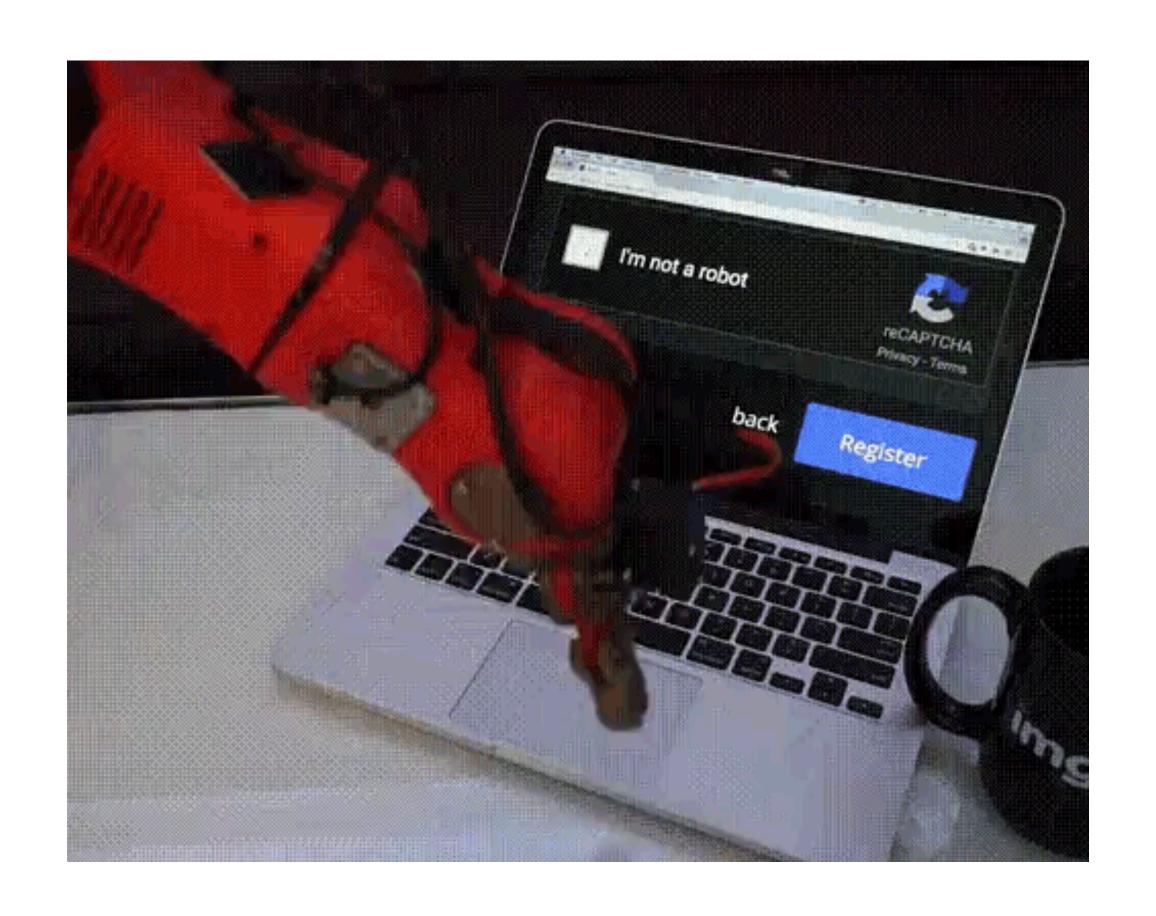
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 - Initially: Distorted images, driven by perception
 - Long-term: Inspires "arms race"

CAPTCHA arms race



CAPTCHA arms race

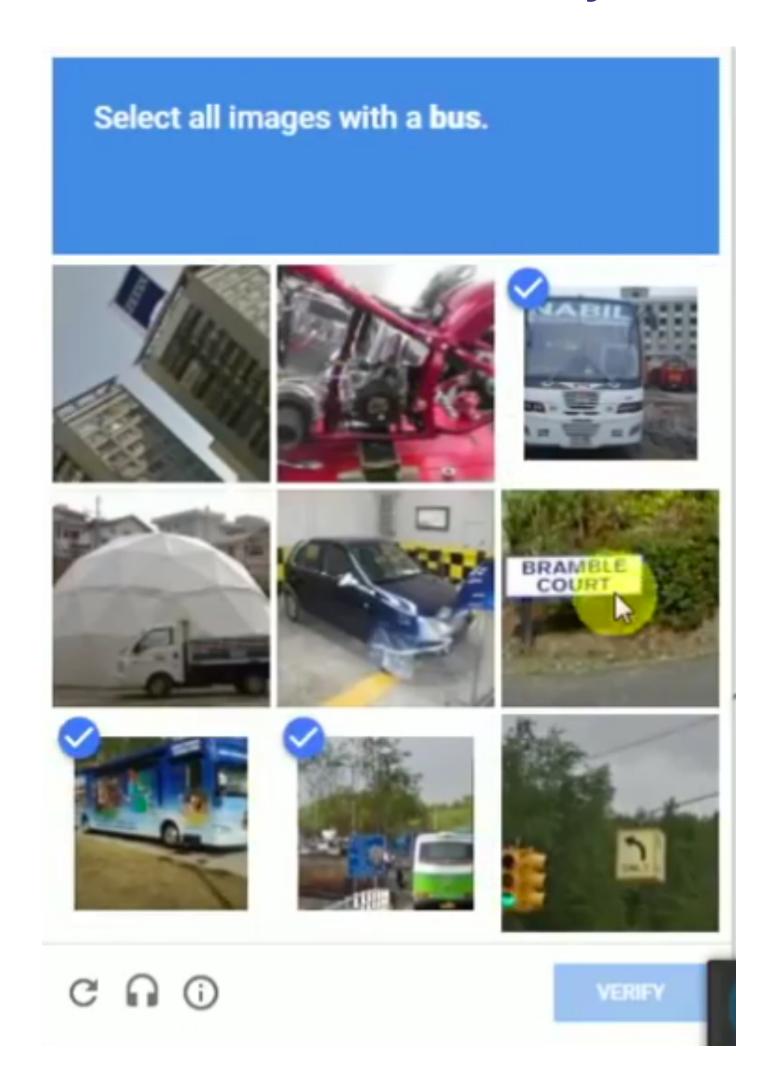


"On the web, no one knows you're a..."

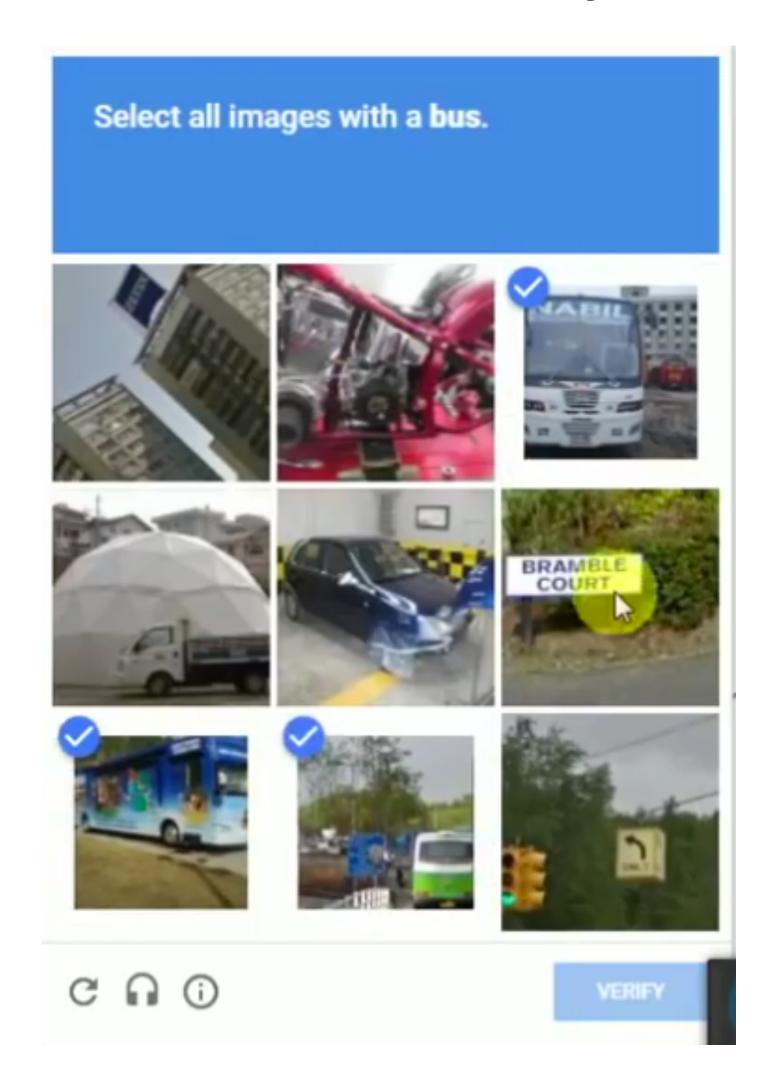
Current Incarnation

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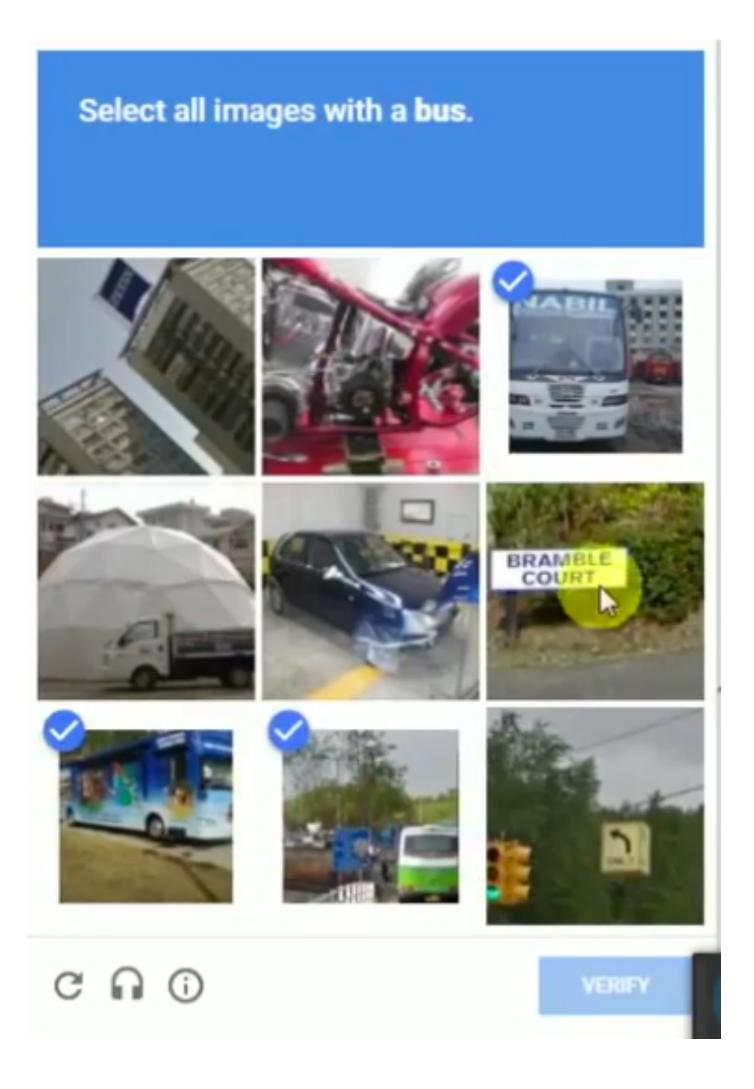
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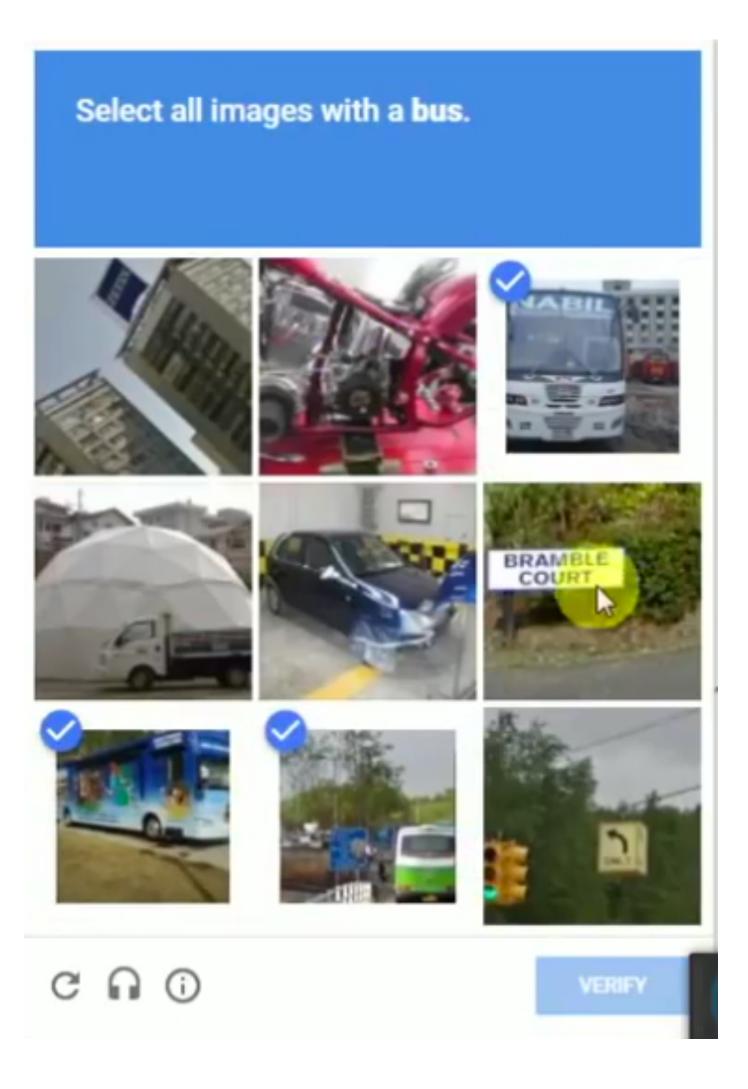
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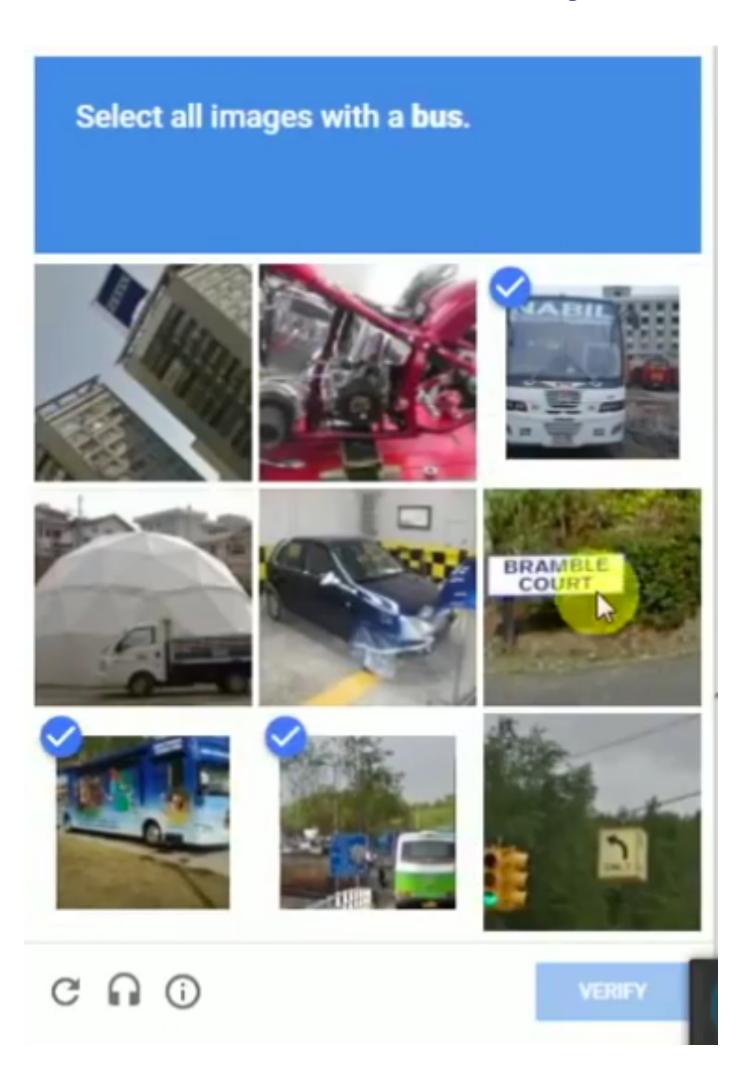
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 - Still perception-based
 - But also relies on world knowledge



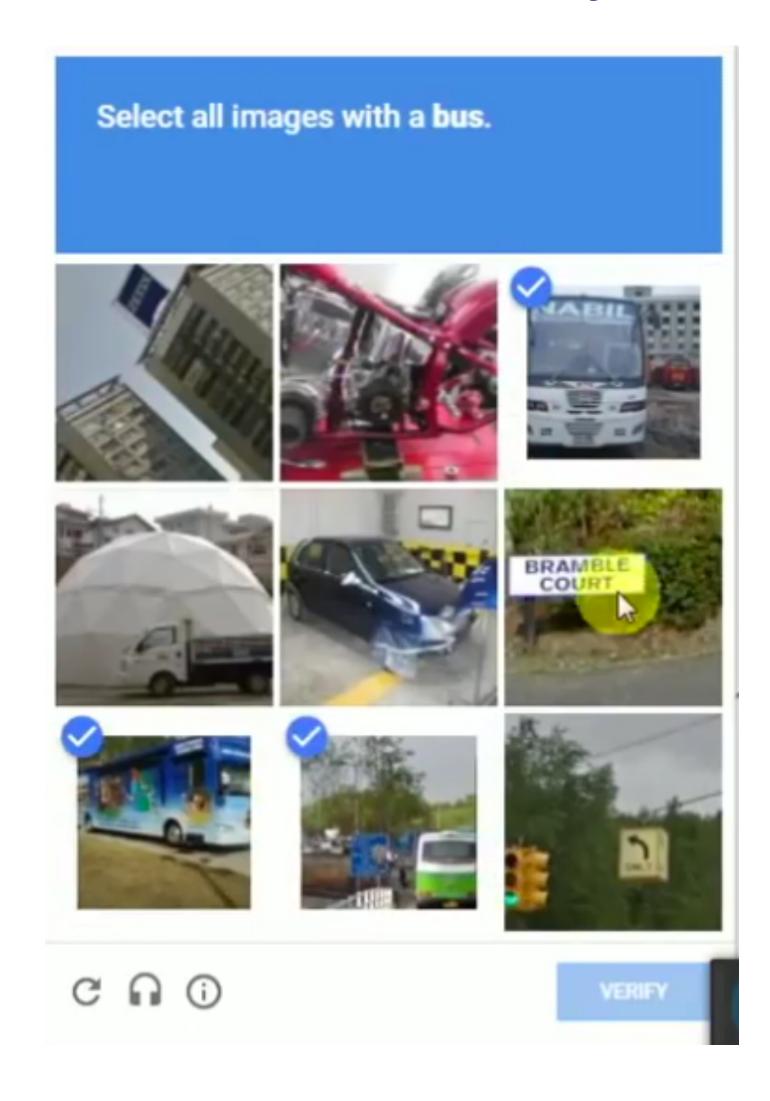
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 - "What is a bus?"

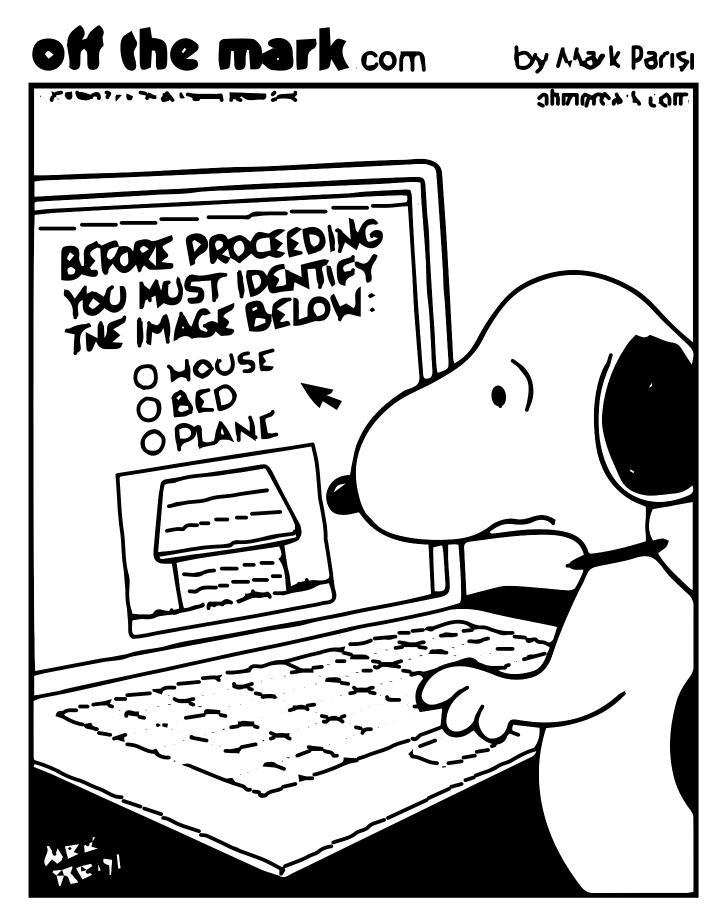


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 - Assumes that the user has extrinsic, shared world knowledge



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The Turing Test in the LLM era

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ChatGPT broke the Turing test — the race is on for new ways to assess AI

Large language models mimic human chatter, but scientists disagree on their ability to reason.

Celeste Biever









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https://www.nature.com/articles/d41586-023-02361-7

Published in Transactions on Machine Learning Research (08/2023)

The ConceptARC Benchmark: Evaluating Understanding and Generalization in the ARC Domain

Arseny Moskvichev

arseny.moskvichev@gmail.com

Santa Fe Institute

Victor Vikram Odouard

vicviod@qmail.com

Santa Fe Institute

Melanie Mitchell

Santa Fe institute

mm@santafe.edu

Reviewed on OpenReview: https://openreview.net/forum?id=8ykyGbtt2q

Abstract

The abilities to form and abstract concepts are key to human intelligence, but such abilities remain lacking in state-of-the-art AI systems. There has been substantial research on conceptual abstraction in AI, particularly using idealized domains such as Raven's Progressive Matrices and Bongard problems, but even when AI systems succeed on such problems, the systems are rarely evaluated in depth to see if they have actually grasped the concepts they are meant to capture.

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Knowledge of Language

NLP vs. Data Processing

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- POSIX command "wc"
 - Counts total number of bytes, words, and lines in text file
 - bytes and lines → data processing
 - words → what do we mean by "word"?

What does HAL (of 2001, A Space Odyssey) need to know to converse?

Dave: Open the pod bay doors, HAL.

HAL: I'm sorry, Dave. I'm afraid I can't do that.

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- Phonetics & Phonology (Ling 450/550)
 - Sounds of a language, acoustics
 - Legal sound sequences in words

• What does HAL (of 2001, A Space Odyssey) need to know to converse?

- Morphology (Ling 570)
 - Recognize, produce variation in word forms
 - Singular vs. plural:
 Door + sg → "door"
 Door + pl → "doors"
 - Verb inflection:
 be + 1st Person + sg + present → "am"

What does HAL (of 2001, A Space Odyssey) need to know to converse?

Dave: Open the pod bay doors, HAL.

HAL: I'm sorry, Dave. I'm afraid I can't do that.

- Part-of-speech Tagging (Ling 570)
 - Identify word use in sentence
 - Bay (Noun) Not verb, adjective

What does HAL (of 2001, A Space Odyssey) need to know to converse?

Dave: Open the pod bay doors, HAL. HAL: I'm sorry, Dave. I'm afraid I can't do that.

Syntax

- (566: Analysis, 570: Chunking, 571: Parsing)
- Order and group words in sentence
 - cf. *"I'm I do, sorry that afraid Dave I can't"

• What does HAL (of 2001, A Space Odyssey) need to know to converse?

- Semantics (Word Meaning)
 - Individual (lexical) + Combined (Compositional)
 - 'Open': AGENT cause THEME to become open;
 - 'pod bay doors' → doors to the 'pod bay' → the bay which houses the pods.

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 - Politeness: "I'm sorry, I'm afraid I can't..."

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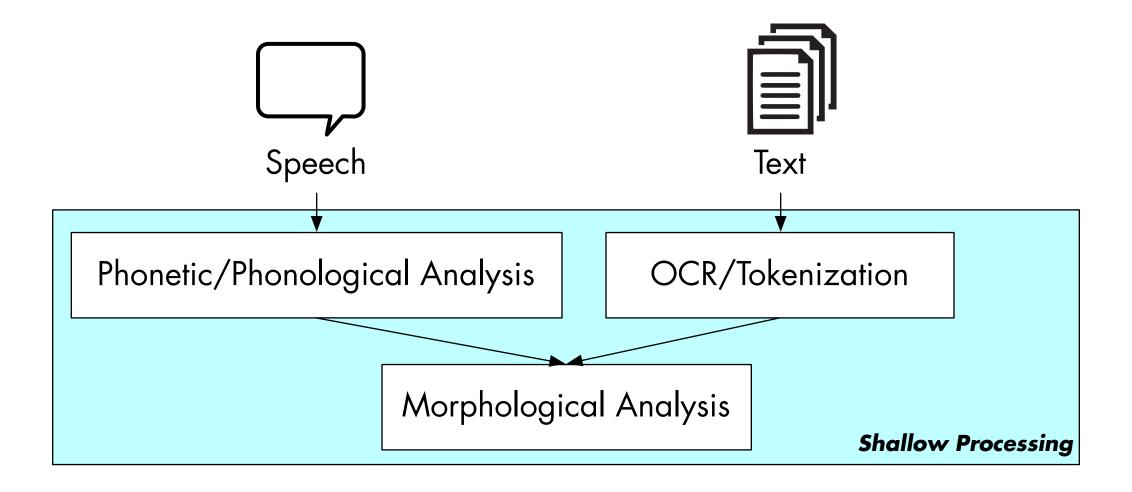
Course Overview: Shallow vs. Deep Processing

- Shallow processing (LING 570)
 - Less elaborate linguistic representations
 - Usually relies on surface forms (e.g. words)
 - Examples: HMM POS-tagging; FST morphology

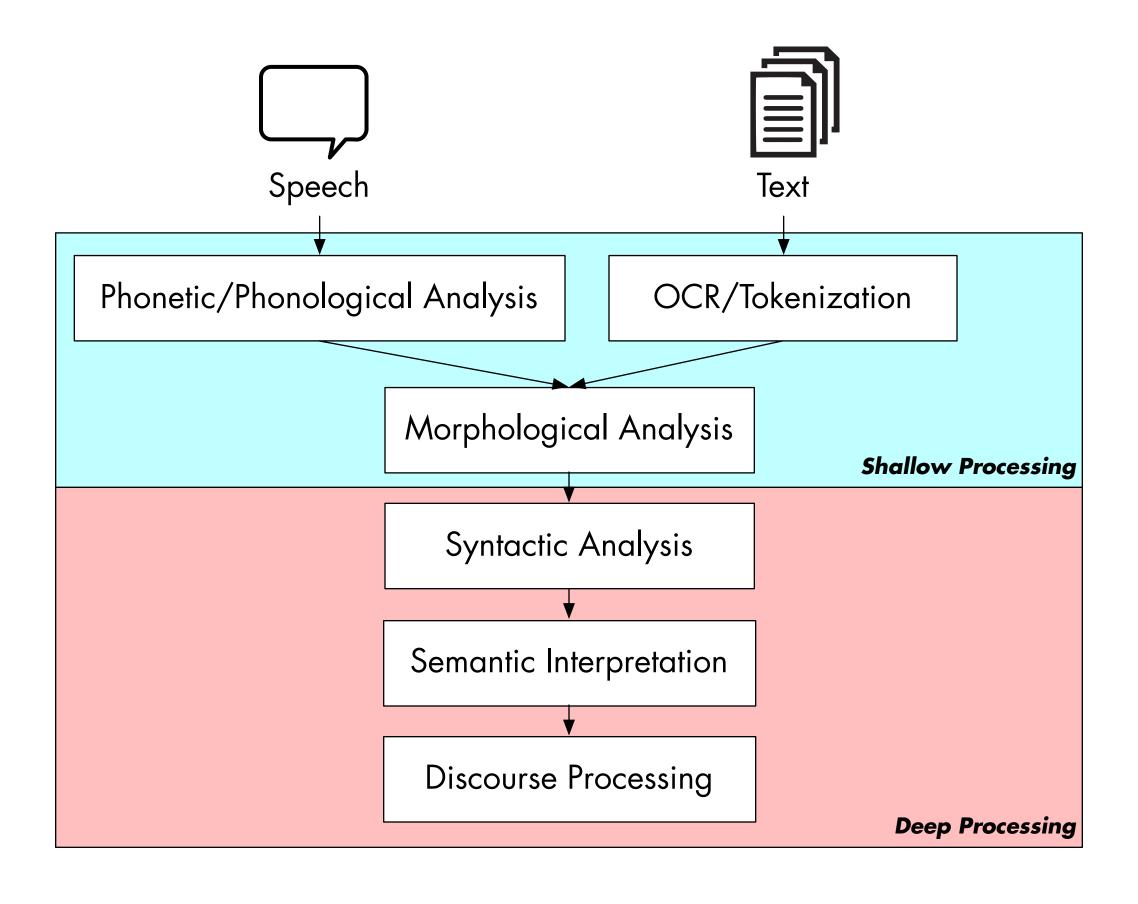
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 - Examples: HMM POS-tagging; FST morphology
- Deep processing (LING 571)
 - Relies on *more elaborate* linguistic representations
 - Deep syntactic analysis (Parsing)
 - Rich language understanding (NLU)

Language Processing Pipeline



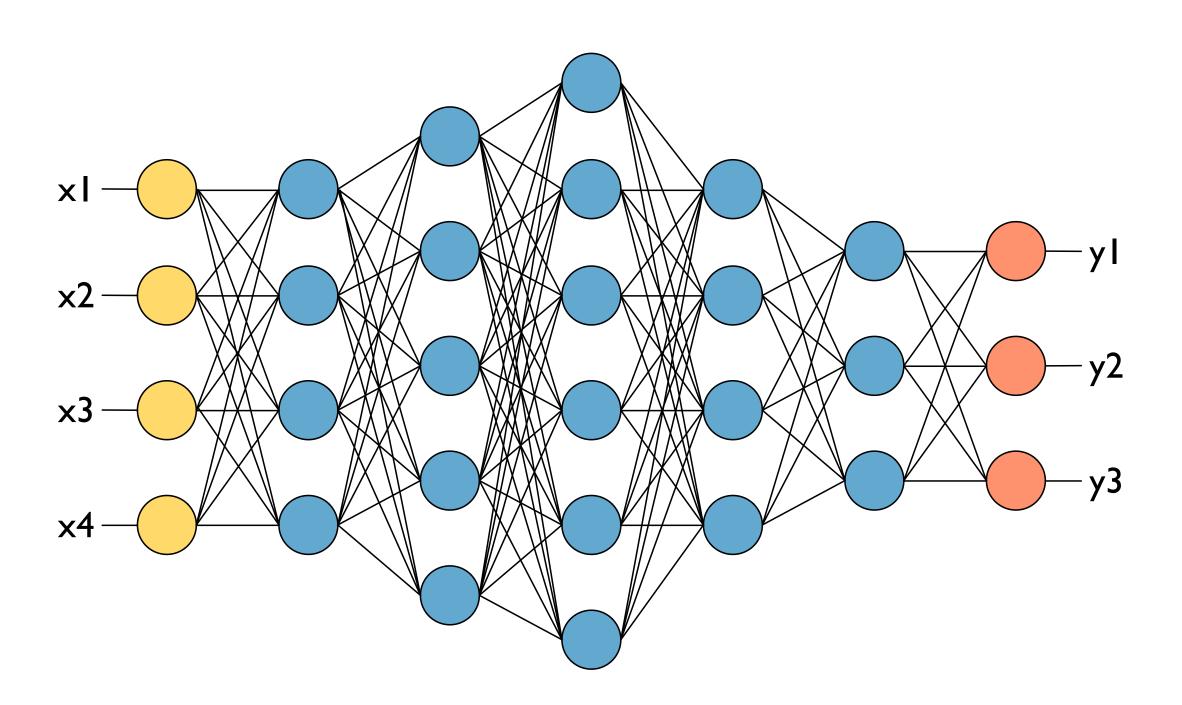
Language Processing Pipeline



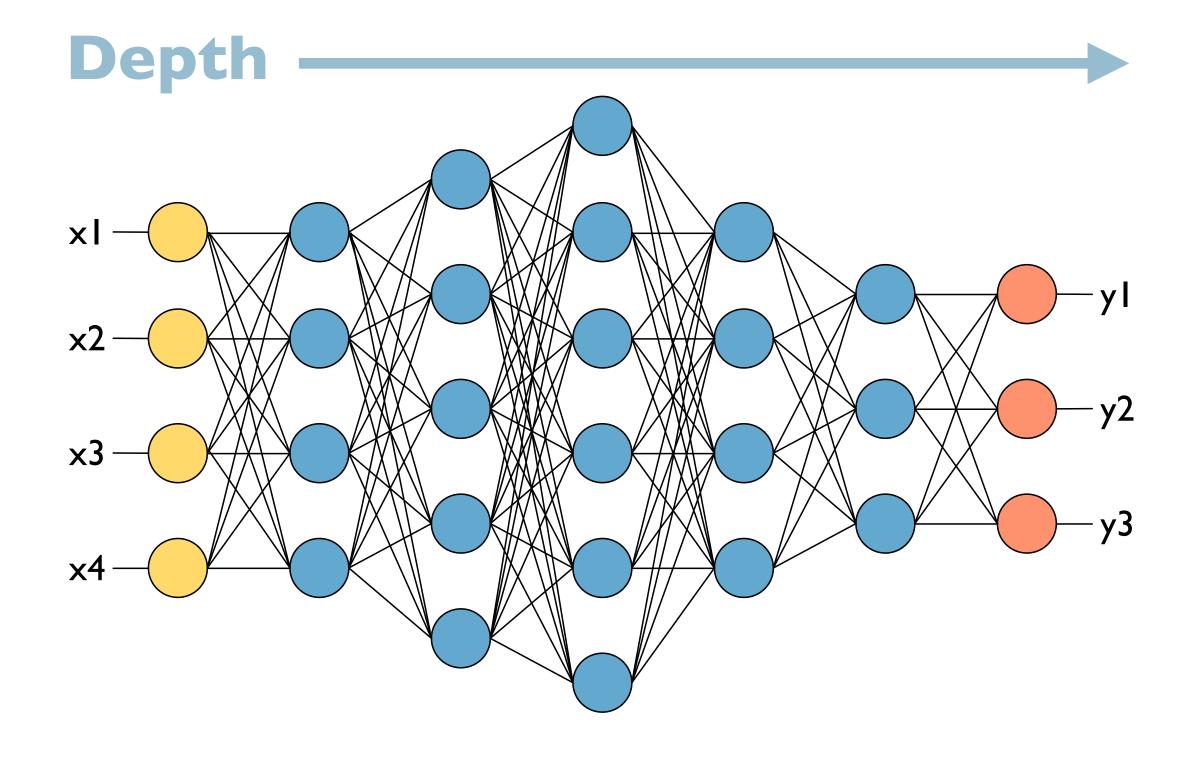
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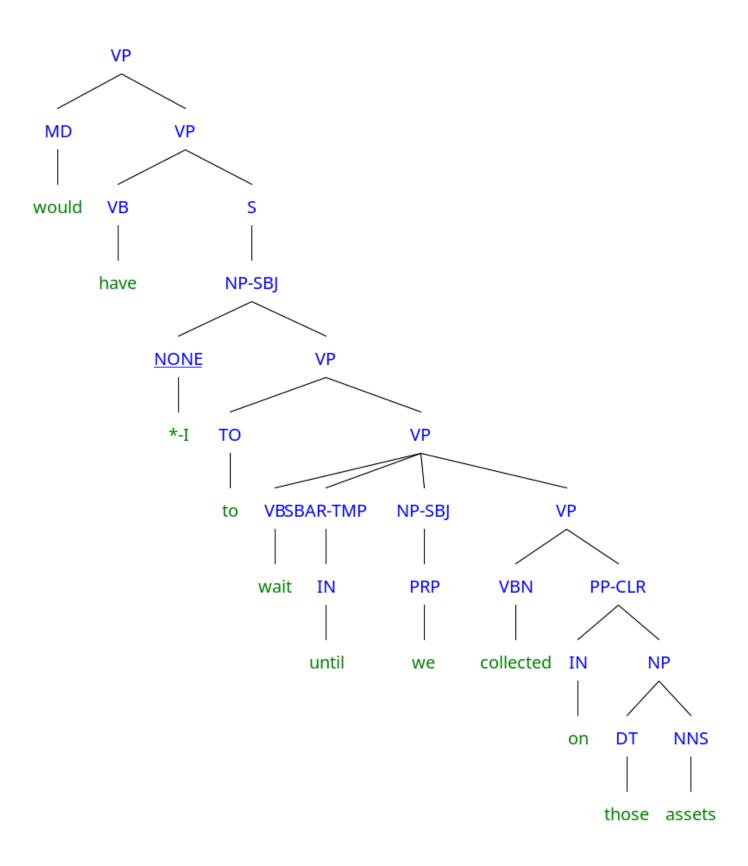
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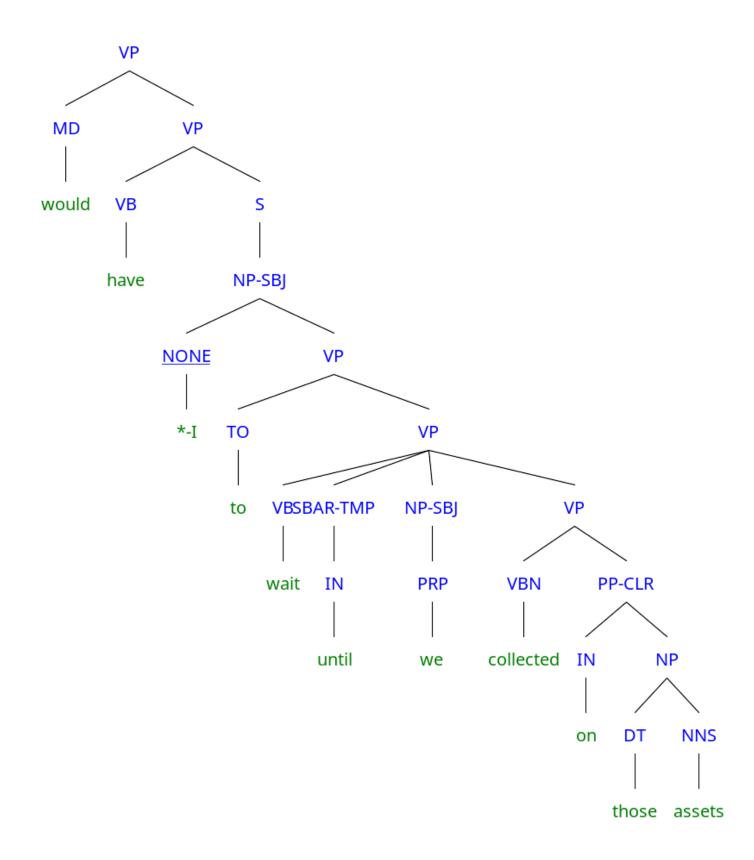
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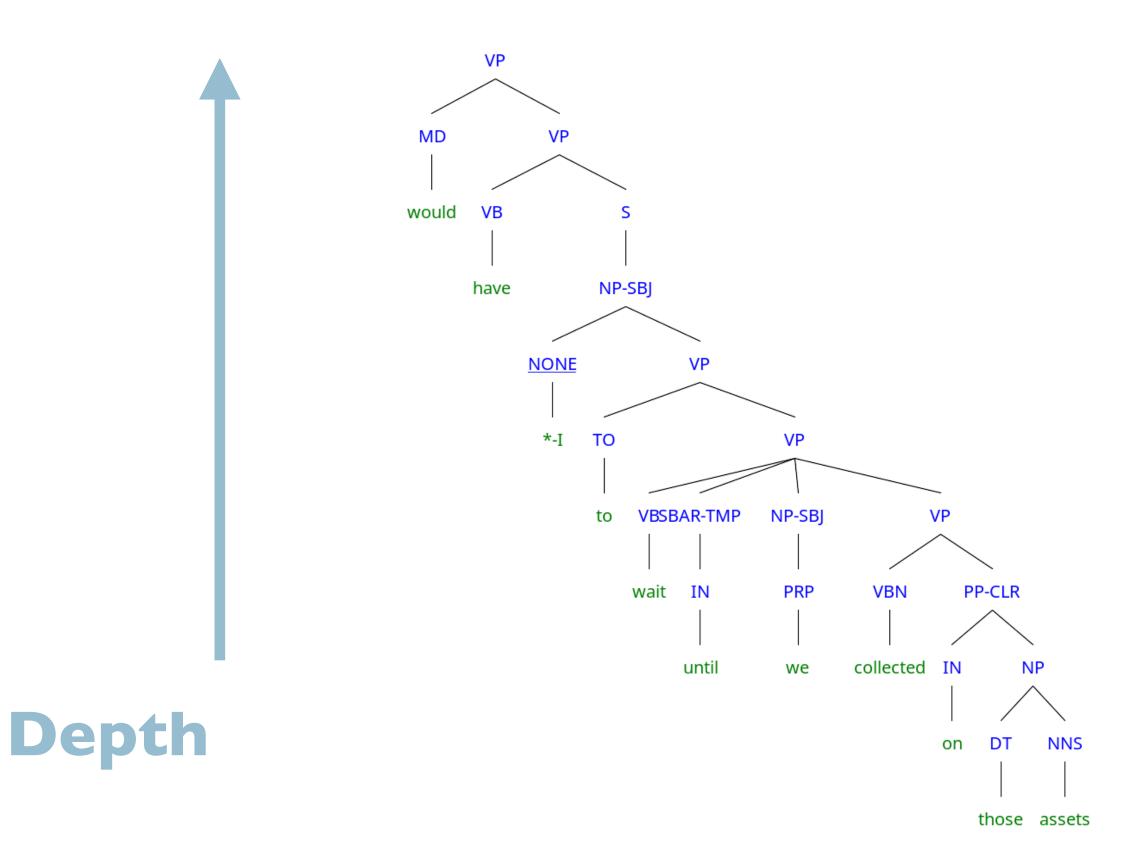
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 - can be used for "shallow" analysis:
 - POS tagging, chunking, etc.
 - Can also be used for "deep" analysis:
 - Semantic role labeling
 - Parsing
- In both paradigms, graph depth aids, but ⇒ abstraction

Cross-cutting Themes

- Ambiguity
 - How can we select from among alternative analyses?

Cross-cutting Themes

Ambiguity

How can we select from among alternative analyses?

Evaluation

- How well does this approach perform:
 - On a standard data set?
 - As part of a system implementation?

Cross-cutting Themes

Ambiguity

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Multilinguality

- Can we apply the same approach to other languages?
- How much must it be modified to do so?

• "I made her duck."

- "I made her duck."
- Could mean...
 - I caused her to duck down.
 - I made the (carved) duck she has.
 - I cooked duck for her.
 - I cooked a duck that she owned.
 - I magically turned her into a duck.

NOUN

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Ambiguity: POS

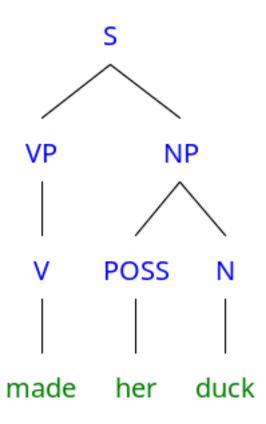
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PRON

POSS

Ambiguity: Syntax

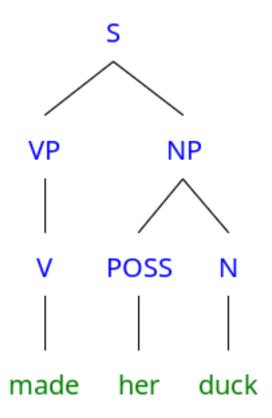
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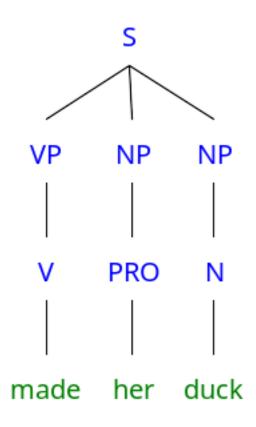


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"I made her duck."

32

"I made her duck."

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I cooked the duck she owned

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| Cooked duck for her | made = [AG] cook [TH] for [REC]
| Cooked the duck she owned | made = [AG] cook [TH]
| Cooked the duck she owned | made = [AG] cook [TH]
| Made the (carved) duck she has | duck = duck-shaped-figurine
```

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| Cooked the duck she owned | made = [AG] cook [TH]
| Cooked the duck she owned | made = [AG] sculpted [TH]
| Cooked the duck she owned | duck she has | made = [AG] sculpted [TH]
| duck = duck-shaped-figurine | duck = [AG] transformed [TH]
| duck = animal
```

Pervasive in language

33

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- "I believe we should all pay our tax bill with a smile.
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- Pervasive in language
- Not a bug, a feature! (<u>Piantadosi et al 2012</u>)
- "I believe we should all pay our tax bill with a smile.
 I tried—but they wanted cash."
- What would language be like without ambiguity?

Challenging for computational systems

- Challenging for computational systems
- Issue we will return to again and again in class.

Course Information

Course Information

- Website is main source of information: https://www.shane.st/teaching/571/
 - slides, office hours, resources, etc
- Canvas: lecture recordings, homework submission / grading
 - Communication!!! Please use the discussion board for questions about the course and its content.
 - Other students have same questions, can help each other.
 - May get prompter reply. The teaching staff will not respond outside of normal business hours, and may take up to 24 hours.

Course Information

- Grading, policies, etc: see link under "Policies" on course page
 - Shared policies for 570, 571, 572, 574
- Office hours:
 - Shane: MW 230-330 (GUG 415K + Zoom; see website)
 - Saiya: TBA
- Homeworks:
 - 9, released on Wednesday, due the following Wednesday
 - With a pause during Thanksgiving week
 - [NB: also no class the Wednesday before Thanksgiving]

Course Content

- Syntax
 - (Probabilistic) Context-Free Grammars
 - Parsing algorithms (CKY, Earley)
 - Dependency Parsing
- Semantics
 - Logical / event semantics, lambda calculus
 - Distributional semantics, lexical semantics
 - Semantic Role Labeling
- Pragmatics / Discourse
 - Reference, Co-reference, structure / discourse parsing

W What are you most looking forward to in 571 this quarter?

Total Results: 0



Syntax Crash Course

LING 571 — Deep Processing Techniques for NLP Shane Steinert-Threlkeld

Roadmap

- Sentence Structure
 - More than a bag of words
- Representation
 - Context-free Grammars
 - Formal Definition

Applications

- Shallow techniques useful, but limited
- Deeper analysis supports:
 - Grammar checking and teaching
 - Question-answering
 - Information extraction
 - Dialogue understanding
 - ...

Grammar and NLP

- "Grammar" in linguistics is NOT prescriptive high school grammar
 - Explicit rules
 - "Don't split infinitives!" etc.

Grammar and NLP

- "Grammar" in linguistics is NOT prescriptive high school grammar
 - Explicit rules
 - "Don't split infinitives!" etc.
- "Grammar" in linguistics IS:
 - How to capture structural knowledge of language as a native speaker would have
 - Largely implicit
 - Learned early, naturally

More than a Bag of Words

- Sentences are structured
- Choice of structure can impact:

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 - Meaning:
 - Dog bites man. vs. Man bites dog.

More than a Bag of Words

- Sentences are structured
- Choice of structure can impact:
 - Meaning:
 - Dog bites man. vs. Man bites dog.
 - Acceptability:
 - Colorless green ideas sleep furiously.
 - * Colorless sleep ideas furiously green.
 - * Dog man bites

Constituency

- Constituents: basic units of sentences
 - Word or group of words that act as a single unit syntactically

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- Phrases:
 - Noun Phrase (NP)
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- Phrases:
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- Single unit: type determined by "head"
 - e.g. N heads NP

Representing Sentence Structure

- Basic Units
 - Phrases (NP, VP, etc...)
 - Capture constituent structure

Representing Sentence Structure

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 - Phrases (NP, VP, etc...)
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- Subcategorization
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 - Capture <u>argument</u> structure
 - Components expected by verbs

Representing Sentence Structure

- Basic Units
 - Phrases (NP, VP, etc...)
 - Capture <u>constituent</u> structure
- Subcategorization
 - (NP-SUBJ, VP-INTRANS, etc...)
 - Capture <u>argument</u> structure
 - Components expected by verbs
- Hierarchical

Representation: Context-free Grammars

- CFGs: 4-tuple
 - A set of terminal symbols: Σ
 - [think: words]
 - A set of nonterminal symbols: N
 - [think: phrase categories]
 - A set of productions *P*:
 - of the form $A \rightarrow \alpha$
 - Where A is a non-terminal and $\alpha \in \{\Sigma \cup N\}^*$
 - A start symbol $S \in N$

Representation: Context-free Grammars

- Altogether a grammar defines a language L
 - $L = \{ w \in \Sigma^* \mid S \Rightarrow^* w \}$
 - The language *L* is the set of all words in which:
 - $S \Rightarrow^* w$: w can be derived starting from S by some sequence of productions

CFG Components

Terminals:

- Only appear as leaves of parse tree (hence the name)
- Right-hand side of productions (RHS)
- Words/morphemes of the language
 - cat, dog, is, the, bark, chase...

CFG Components

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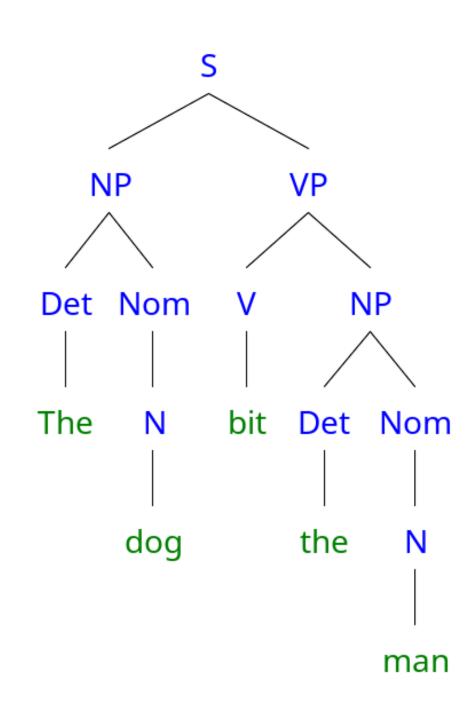
Non-terminals

- Do not appear as leaves of parse tree
- Appear on left or right side of productions
- Represent constituent phrases of language
- NP, VP, S[entence], etc...

Representation: Context-free Grammars

Partial example:

- Σ : the, cat, dog, bit, bites, man
- N: NP, VP, Nom, Det, V, N, Adj
- \bullet P:
 - S→NP VP;
 - NP→Det Nom;
 - Nom→N Nom I N;
 - VP→V NP;
 - $N \rightarrow cat$; $N \rightarrow dog$; $N \rightarrow man$;
 - Det→the;
 - V→bit; V→bites
- S: S



Parsing Goals

- Acceptance
 - Legal string in language?
 - Formally: rigid
 - Practically: degrees of acceptability

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 - Legal string in language?
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 - What structure produced the string
 - Produce one (or all) parses for the string

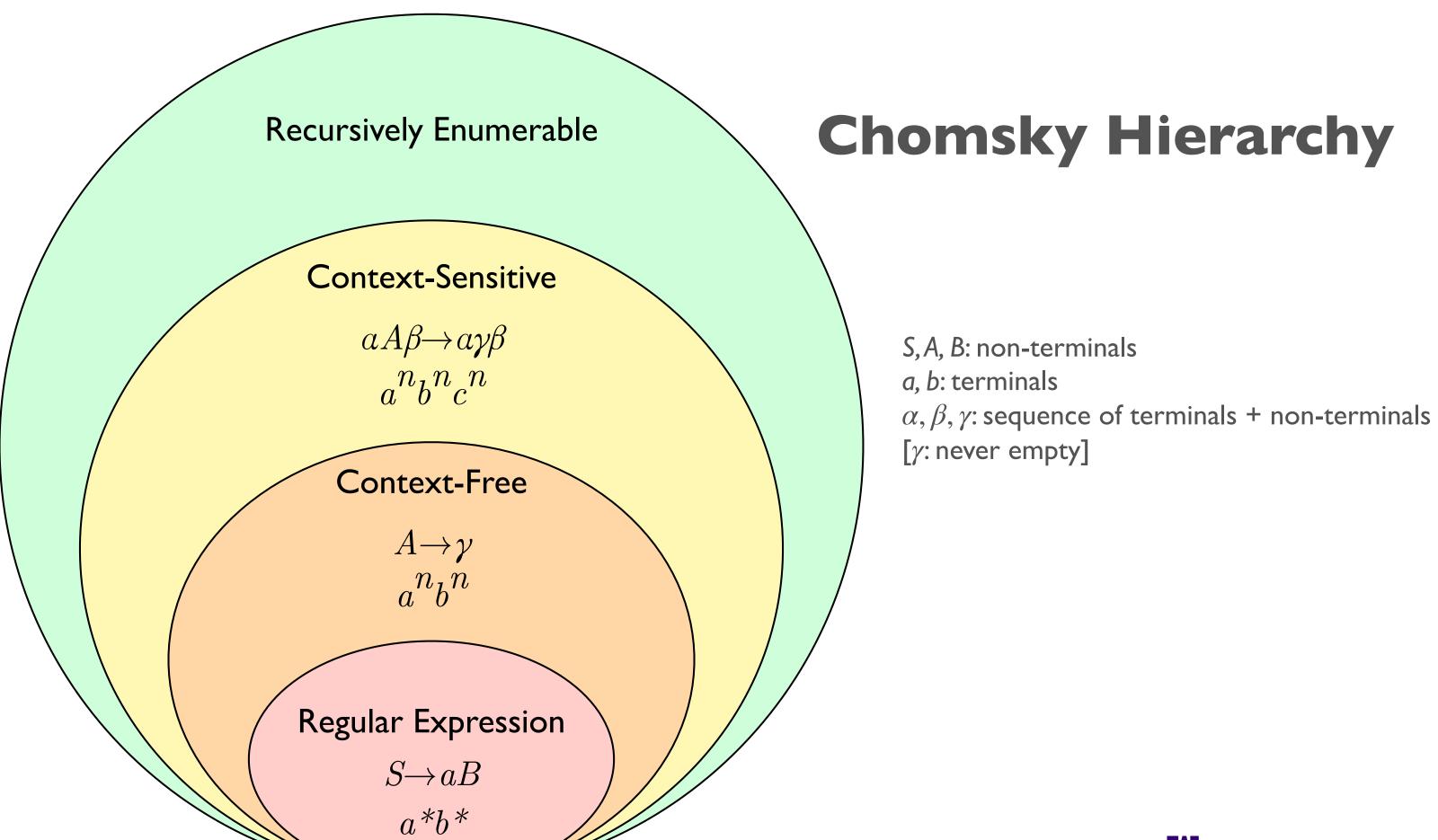
Parsing Goals

- Acceptance
 - Legal string in language?
 - Formally: rigid
 - Practically: degrees of acceptability
- Analysis
 - What structure produced the string
 - Produce one (or all) parses for the string
- Will develop techniques to produce analyses of sentences
 - Rigidly accept (with analysis) or reject
 - Produce varying degrees of acceptability

Sentence-level Knowledge: Syntax

• Different models of language that specify the expressive power of a

formal language



Representing Sentence Structure

- Why not just Finite State Models (Regular Expressions)?
 - Cannot describe some grammatical phenomena
 - Inadequate expressiveness to capture generalization

Representing Sentence Structure: Center Embedding

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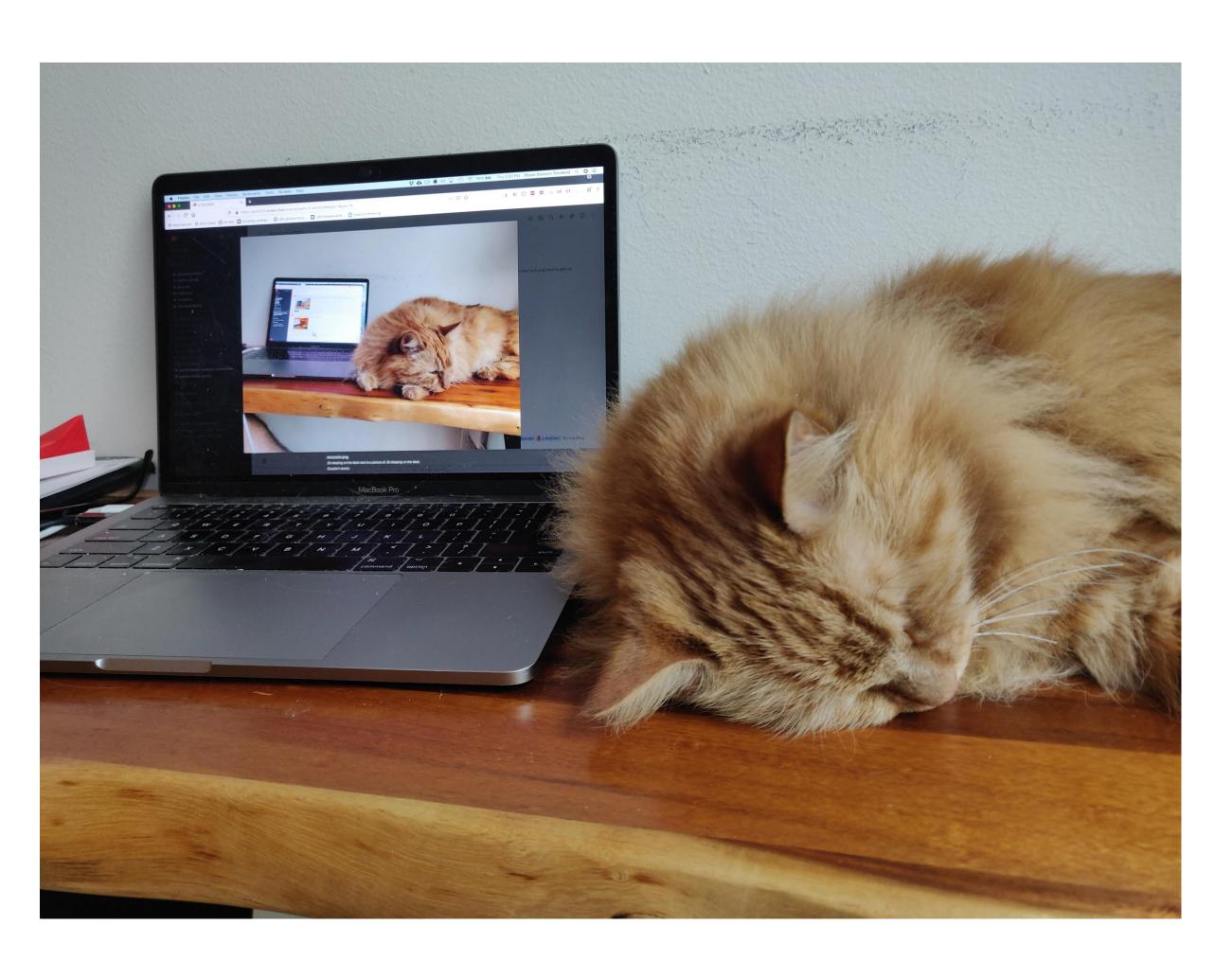
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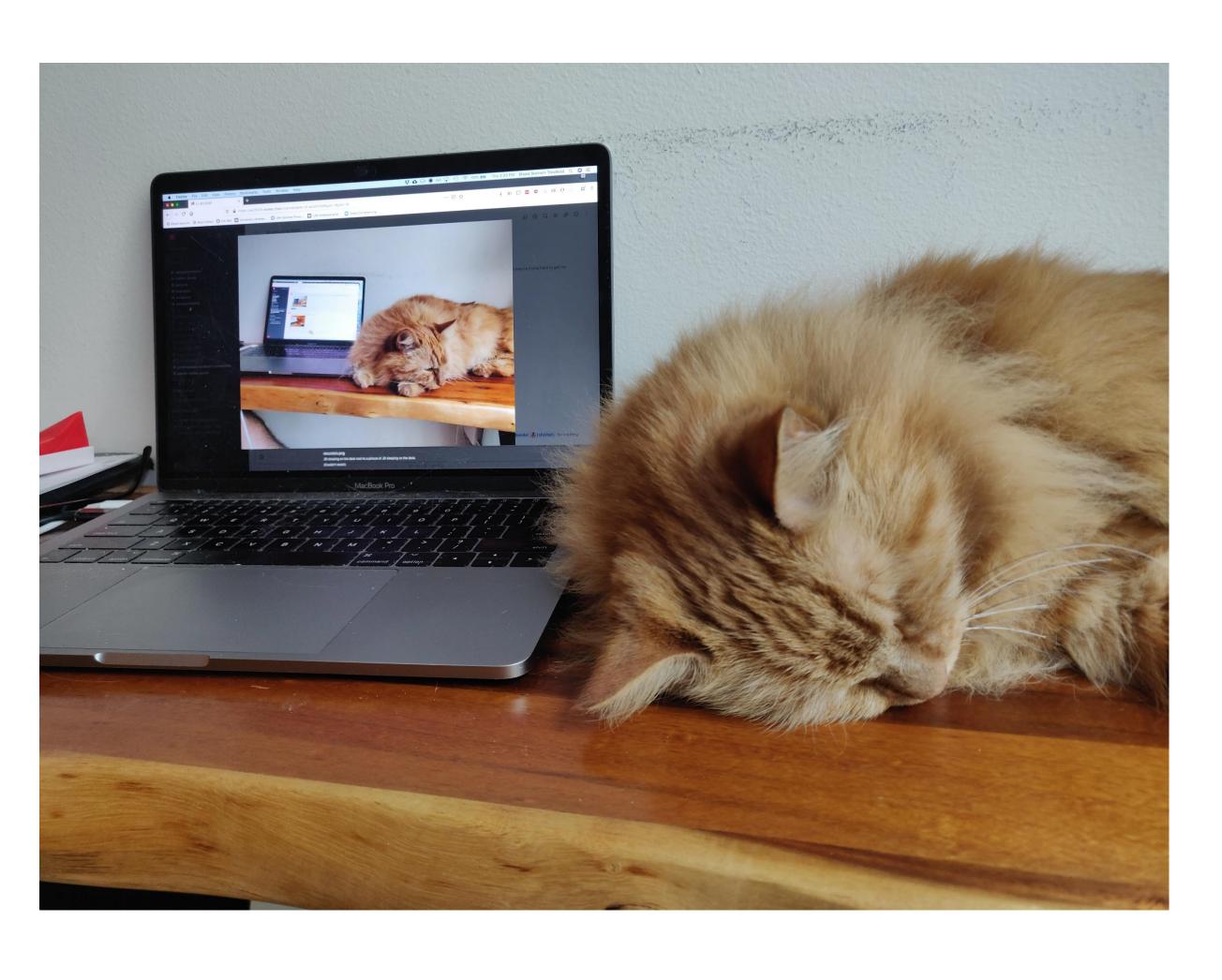
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Recursion in Grammar

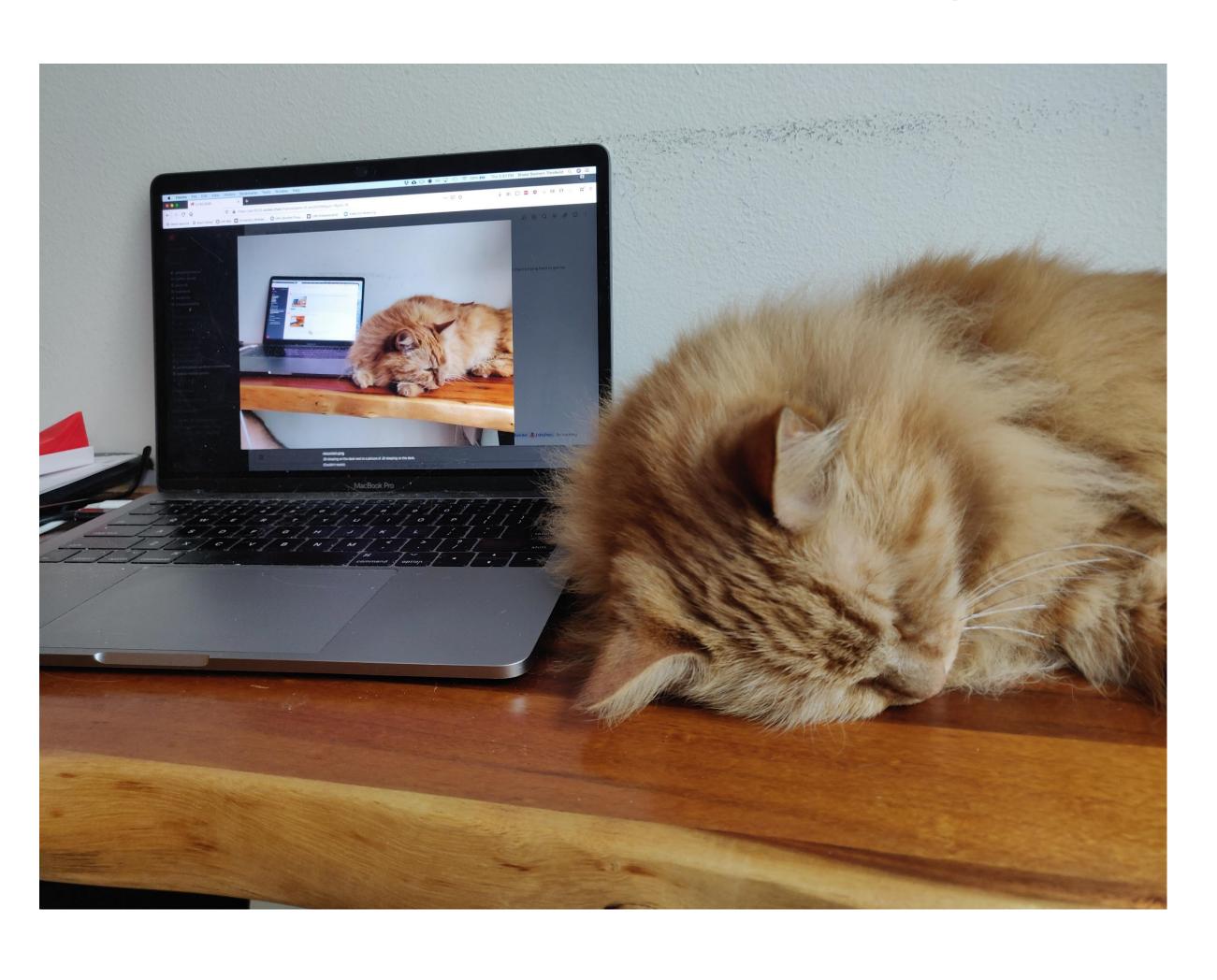


Recursion in Grammar



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Recursion in Grammar



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Exercise: write a toy grammar for producing this sentence! Is context-freeness required?

Is Context-Free Enough?

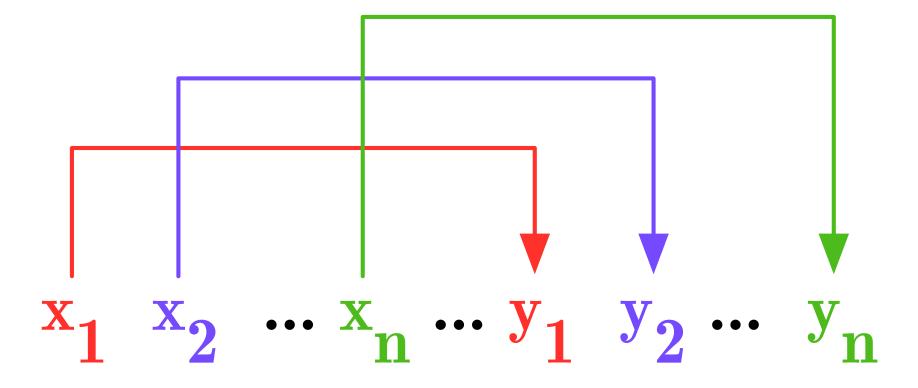
Natural language not finite state

Is Context-Free Enough?

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- ...but do we need context-sensitivity?
 - Many articles have attempted to demonstrate we do
 - ...many have failed.

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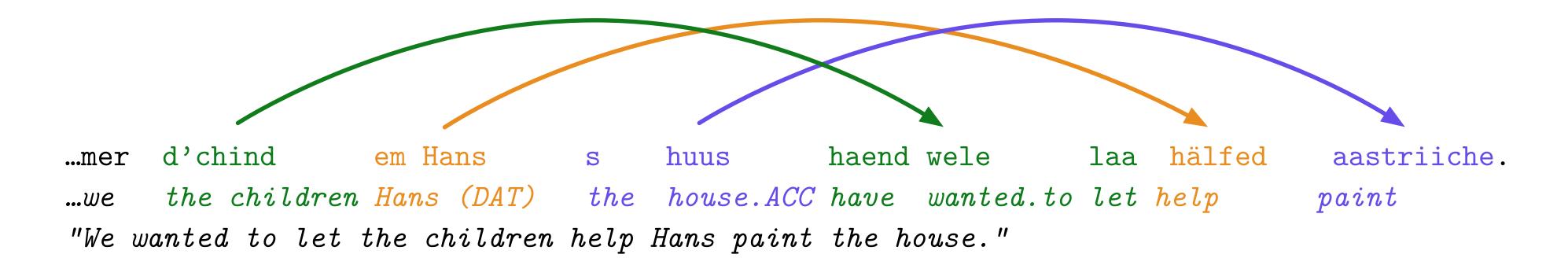
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 - ...many have failed.
- Solid proof for Swiss German: Cross-Serial Dependencies (Shieber, 1985)
 - aibicidi



Context-Sensitive Example

- Verbs and their arguments must be ordered cross-serially
 - Arguments and verbs must match

```
...mer em Hans s huus hälfed aastriiche.
...we Hans (DAT) the house.ACC help paint
"We helped hans paint the house."
```



What questions do you have?