Lecture 3: Writers' aids: Grammatical errors

LING-351 Language Technology and LLMs

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September 2, 2025

*Acknowledgment: These course slides are based on materials by Lelia Glass @ Georgia Tech (Course: Language & Computers)

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Review

Traditional method: Dictionary + Edit Distance

· Relies on a **dictionary** of correct words, built from a corpus

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- Suggests the closest candidate as the correction
- Adds some weights for more realistic correction

Why context matters in spell-checking

Example: Someone types:

You put the catt before the horse.

- · put the cart before the horse
- · put the cat before the horse

Using N-grams to model context

N-grams are sequences of *n* elements (e.g., words or characters):

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- Trigram = three-word sequence: put the cat

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 Statistical Language Models (n-grams) Use probability of surrounding context e.g., I went to the shcool → "school" is more probable

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- Statistical Language Models (n-grams) Use probability of surrounding context e.g., I went to the shcool → "school" is more probable
- Neural Spell Checkers (Deep Learning) Seq2Seq / Transformer-based models generate corrected text Examples: ChatGPT, Grammarly, Google Docs
- **Hybrid Approaches** Combine edit distance with language models; pick the highest probability candidate

How common are spelling errors?

 About 2–3% of all typed words on a full-size keyboard are misspelled by proficient adults (Flor et al., 2015)

Table 2. Summary statistics for the ETS Spelling Corpus							
	GRE Argument	GRE Issue	TOEFL Independent	TOEFL Integrated	TOTAL		
Total essays	750	750	750	750	3,000		
Essays without misspellings	60	21	18	21	120		
Total Word Count	263,578	336,301	212,930	151,031	963,840		
Average Word Count	351	448	284	201	321		
Total count of Misspellings	5,935	7,962	7,285	5,230	26,412		
Misspellings as % of all words	2.25%	2.37%	3.42%	3.46%	2.74%		

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- On a mobile phone, however, about 40% of words are misspelled (Grammarly, 2019)
- More multi-error misspellings and real-word errors due to auto-complete (e.g., restaurant → typed as restuarnt → auto-corrected to restart)

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- Wrap-up

Key idea: Building a grammar checker begins with understanding key linguistic categories

Grammar

Two viewpoints on grammar

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- Prescriptive Grammar Lays down rules for how language should be used. (Focus: what speakers ought to do)

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- Prescriptive grammar?

Grammar checkers and mixed rules

 Commercial grammar checkers may apply both descriptive rules and prescriptive rules.

Questions (Shared deck)

1. Do you think grammar checkers should allow forms (e.g., "gonna", "ain't")? Why or why not?

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- 1. Do you think grammar checkers should allow forms (e.g., *"gonna"*, *"ain't"*)? Why or why not?
- 2. Do prescriptive corrections (e.g., "less people" → "fewer people"; "He suggested me to go" → "He suggested that I go") really improve clarity, or just follow rules?

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- 2. Do prescriptive corrections (e.g., "less people" → "fewer people"; "He suggested me to go" → "He suggested that I go") really improve clarity, or just follow rules?
- 3. Even without a grammar checker, speakers often recognize what "sounds right." How do you think this internal system of grammar works in your mind?

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- Two key concepts for grammar checkers:
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- · Why this matters for grammar checkers?

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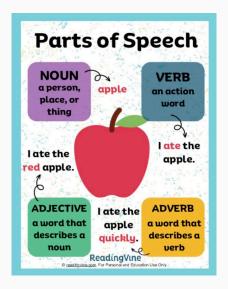
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 - **Distribution:** where a word appears in a sentence (e.g., nouns after articles, verbs after subjects)
 - Morphology: how a word changes form (e.g., verbs mark tense: play → played, sometimes irregularly: go → went)

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- Before deep learning, POS and morphology were essential hand-crafted features (based on the prescribed rules).

Notes. POS tagging: Current NLP



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 - · Noun Phrase + Verb Phrase = Sentence

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- · Syntax is about **structure**, not always meaning.

Phrase structure grammar (Chomsky, 1950s-1960s)

Lexicon:

 $N \rightarrow reindeer, dragon, lunch, game, evening, morning$

 $V(trans) \rightarrow play, eat$

 $V(intrans) \rightarrow run, swim, dance$

Adj → fun, beautiful, interesting

Det \rightarrow the, a, some, many

 $P \rightarrow for$, in, to, at

Phrase structure rules:

 $S \rightarrow NP VP$

 $VP \rightarrow V(trans) NP$

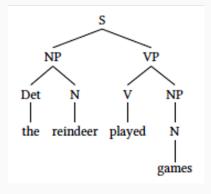
 $VP \rightarrow V(intrans)$

 $NP \rightarrow Det (A^*) N$

 $NP \rightarrow N$

 $NP \rightarrow NP PP$

 $PP \to P \; NP$



Frameworks for analyzing syntax

 Linguists formalize sentence structure using grammar frameworks:

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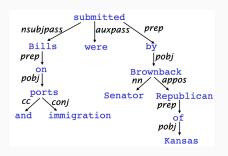
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- Linguists formalize sentence structure using grammar frameworks:
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 - Dependency Grammar (widely used in NLP)

Dependency grammar

Dependency syntax postulates that syntactic structure consists of **relationships** between lexical items, normally binary asymmetric relations ("arrows") called **dependencies**.



Sourced from:

https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1162/handouts/SLoSP-2014-4-dependencies.pdf

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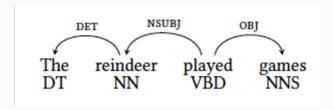
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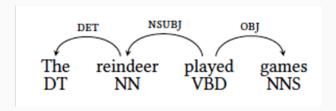
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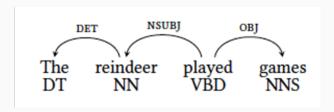
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- · Practice: The reindeer played games.



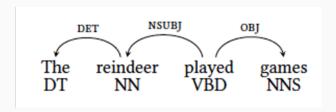
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- the → dependent of reindeer via det
- \cdot reindeer \rightarrow subject of played via nsubj



- the → dependent of reindeer via det
- reindeer → subject of played via nsubj
- games → object of played via obj



- the → dependent of reindeer via det
- reindeer → subject of played via nsubj
- games → object of played via obj
- played = root of the sentence

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- · Practical impact:
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 - State-of-the-art parsers trained on this format work very effectively in many languages (https:
 - //stanfordnlp.github.io/stanza/performance.html)

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Enables cross-linguistic comparison

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- Covers: parts of speech, morphological features, syntactic dependencies
- Open community effort: 600+ contributors, 200+ treebanks, 150+ languages (https://universaldependencies.org/)

· Why it matters:

- · Enables cross-linguistic comparison
- Supports language typology research

 A large multilingual corpus annotated in a consistent dependency format.

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More guides

The secret to understanding the design and current success of UD is to realize that the design is a very subtle compromise between approximately 6 things:

- 1. UD needs to be satisfactory on linguistic analysis grounds for **individual** languages.
- UD needs to be good for linguistic typology, i.e., providing a suitable basis for bringing out cross-linguistic parallelism across languages and language families.
- 3. UD must be suitable for rapid, consistent **annotation** by a human annotator.
- 4. UD must be suitable for computer **parsing** with high accuracy.
- 5. UD must be easily comprehended and used by a **non-linguist**, whether a language learner or an engineer with prosaic needs for language processing. We refer to this as seeking a habitable design, and it leads us to favor traditional grammar notions and terminology.
- 6. UD must support well downstream language **understanding** tasks (relation extraction, reading comprehension, machine translation, ...).

Sourced from: https://people.cs.georgetown.edu/nschneid/p/UD-for-English.pdf

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- · Built using machine learning and large annotated corpora

Grammar checker

From grammar to grammar Checkers

- · So far, we've built a foundation by analyzing sentence structure.
- Now we can apply this knowledge to automatic grammar checking. For example:
- Try to assign a dependency parse.
 - · If parsing fails → likely an error.
 - If parsing succeeds → compare to known grammar rules.

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- · Example:
 - · If the subject (nsubj) is tagged NN (singular noun),
 - Then the verb should be tagged VBZ (3rd-person singular).
 - The dog swim (X) \rightarrow should be The dog swims.

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- · A set of hand-written grammar rules?
- · Confusion sets for commonly misused words?
- · What else?

Rule-Based vs. LLM-Based Grammar Checkers

Rule-Based Checkers

- Use explicit grammar rules and POS/dependency tags
- Rely on parsing + handcrafted logic
- Example: Check for subject-verb agreement via nsubj and VBZ
- Explainable and controllable, but less flexible

LLM-Based Checkers

- Use large neural language models (e.g., GPT, BERT)
- Learn grammar implicitly from vast corpora
- Can handle diverse errors without explicit rules
- Often produce fluent rewrites, but less transparent

Wrap-up

Wrap-up

- In Linguistics, grammar is often studied under syntax.
- Two key concepts for grammar checkers:
 - · Part of Speech (POS) classifies each word
 - Dependency grammar shows how words are connected
- · Why this matters for grammar checkers?
 - · Detect whether words fit together according to rules
 - Spot unusual or incorrect structures

Updates

Syllabus updated

The syllabus has been updated:

2	9/2	Writer's aids: Grammar errors	[LC] Ch.2.5-2.8	
	9/4	Python tutorial 1		Exercise 1
3	9/9	Computer-assisted language learning	[LC] Ch.3	
	9/11	Python tutorial 2		Exercise 2
4	9/16	Text as data		
	9/18	Python tutorial 3		
5	9/23	Word vectors		
	9/25	Python tutorial 4		Exercise 3

So, bring your laptop on Thursday!