

Lecture 2: Writers' aids: Spelling errors

LING-351 Language Technology and LLMs

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August 28, 2025

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

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Review

- Language

- Language
- Writing

Language, writing, encoding

- Language
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- Language = writing?

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 - Syllabic → syllables
 - Logographic → meanings

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- Bit (0/1 signal): the smallest unit of digital information
- Byte (8 bits): a bundle of 8 bits, the basic unit of storage
- Character encoding (UTF-8): rules that map bytes to code points

Lesson plan

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- Wrap-up

Key idea: ~~Spelling errors are annoying~~

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Key idea: ~~Spelling errors are annoying~~

Spelling errors vary by types (and even by languages);
there is no one-size-fits-all solution.

Spelling problems in writing



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- Standardized spelling came much later...

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Willm Shakp, William Shaksper, Wm Shakspe, William Shakspere, Willm Shakspere, William Shakspeare

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*To what extent do the **spelling errors** in this **setnence dirsupt** your **undersanding**?*
- Readers often focus on **word shape**, not letter-by-letter decoding

What if everyone spelled freely?

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- Imagine replacing English spelling with **IPA** (phonetic spelling).

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Question

What are the benefits and drawbacks of having a standardized spelling system?

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- Enables searching and record-keeping

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- How often do you use tools to check the spelling errors?

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Group discussion

- *(Put into the shared deck)* Come up with at least one example
- How often do you use tools to check the spelling errors?
- Which one do you rely on the most?
- Do they ever create problems (instead of solving them)?

Breaking down the problem

Not all spelling errors are the same.

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Not all spelling errors are the same.
To solve them, we need to consider **error types**.

Different types of spelling errors

Spelling error types

- 1. Non-word errors
- 2. Real-word errors
- *Notes.* How common?

1. Non-word errors

- True confusion:



1. Non-word errors

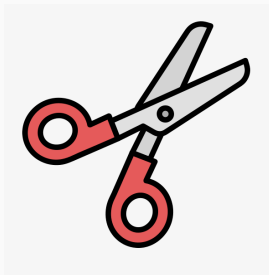
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 - Word *not found* in **dictionary** of correct spellings

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- Measures how “far apart” two strings are
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- Minimum number of operations to transform one word into another

Each operation = 1 unit of cost

- Insertion: *aquire* → *accquire*
- Deletion: *arguement* → *argument*
- Substitution: *calender* → *calandar*
- Transposition: *concsious* → *conscious*
 - Sometimes counted as two substitutions

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- Substituting a nearby key on the keyboard may cost less than a distant one
 - e.g., *friemd* \rightarrow *friend* (substitution: $m \rightarrow n$, keys are adjacent \rightarrow low cost)
 - vs. *friemd* \rightarrow *fried* (deletion of m , more disruptive \rightarrow higher cost)

Traditional method: Dictionary + Edit Distance: How it works

- Relies on a dictionary of correct words

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Q. What happens if the misspelled word is still a real word?

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 - Surrounding **context** must be considered

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*)

Building a simple spell-checker

- Generate all candidate words within 1-2 edits

Baseline spell checker (Peter Norvig)

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 - Input: *langage*
 - Candidates: *language*, *lineage*
 - Output: **language**

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 - Transpositions (e.g., *teh* → *the*)
- Baseline only looks at **frequency**, not how errors happen
- We need a better model: **noisy channel**

Formula

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- Example:
 - Input: *recieve*
 - Candidates: *recipe*, **receive**
 - Baseline (frequency only) \rightarrow *recipe*
 - Noisy channel (frequency + typo likelihood) \rightarrow **receive**

Thinking about a more complex
spell-checker

Why context matters in spell-checking

Example: Someone types:

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 - **put the cat before the horse** is not

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- `put the cart` is more frequent than `put the cat`

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Other approaches

- **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

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Real-Word Errors and Grammar

- Not all mistakes are spelling errors → some are **real-word errors**.
 - Example: *I want to by a book* → “by” is valid, intended: *buy*
- Real-word errors often overlap with **grammar errors**.
 - Example: *Their going to school* → all words exist, but grammar is wrong (*They're*)
- Modern systems therefore blur the line between spell checking and grammar checking, using **context-aware models** to handle both (which we'll talk about in the next class).

Wrap-up

Key idea: Spelling errors are annoying

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Spelling errors vary by types

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Spelling errors vary by types More questions to think about:

- What about the spacing errors?
- What about in other languages that have different encoding systems?