

# Automatic Spelling Correction

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# What is Spelling Correction?

- Identifying and correcting misspelled words.
- Applications: search engines, text editors, chatbots.
- Two key tasks:
  - **Error Detection:** Identifying incorrect words.
  - **Error Correction:** Finding the most likely correct word.

- **1950s-1980s: Rule-Based Systems**

- Dictionary-based lookups.
- Edit distance (Levenshtein, 1965).

- **1990s-2000s: Statistical Methods**

- Noisy Channel Model (Bayesian inference).
- N-gram models for contextual spelling correction.

- **2010s-Present: AI-Based Approaches**

- Neural networks (RNNs, LSTMs).
- Transformer-based models (BERT, T5).

# Basic Approach: Rule-Based

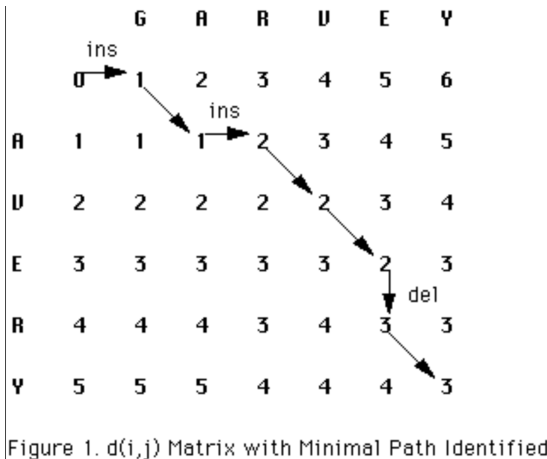
- Uses predefined rules and dictionaries.
- Detects misspelled words that are not in the dictionary.
- Uses **edit distance** to find the closest correct word.
- Example:
  - Input: hte
  - Correction: the (Edit distance = 1)

**Dataset:** Webster's Dictionary, WordNet, Aspell Dictionary.

**Model:** Levenshtein Distance, Wagner–Fischer algorithm

# Wagner-Fischer Implementation

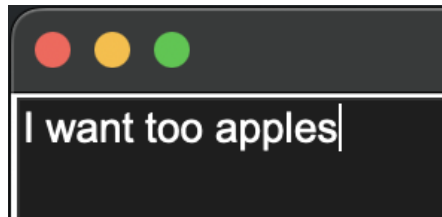
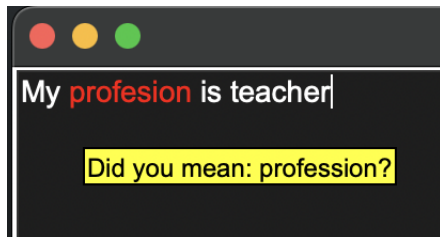
- **Key Features:**
  - Computational efficiency



# Wagner-Fischer Implementation

- **Downsides:**

- Lack of context awareness
- No tolerance for new words



# Enhanced Wagner-Fischer Implementation

- **Key Features:**

- Keyboard distance weighting
- Context-aware scoring
- Phonetic similarity (Metaphone)
- Word frequency consideration



- **Scoring Formula:**

$$Score = 0.4 \cdot \frac{1}{1 + d_{edit}} + 0.3 \cdot s_{phonetic} + 0.2 \cdot f_{word} + 0.1 \cdot s_{context} \quad (1)$$

Where:

- $d_{edit}$ : Enhanced edit distance
- $s_{phonetic}$ : Metaphone similarity
- $f_{word}$ : Word frequency
- $s_{context}$ : Context score

## • Key Components:

- Word frequency dictionary from training corpus
- Edit distance generation (1 and 2 edits)
- Probability-based candidate selection

## • Correction Algorithm:

- 1 Generate all possible edits:
  - Deletions: `hello` → `helo`
  - Transpositions: `hello` → `hlelo`
  - Replacements: `hello` → `hallo`
  - Insertions: `hello` → `helloo`
- 2 Select most frequent candidate:

$$correction = \arg \max_{c \in candidates} P(c) \quad (2)$$

## • Advantages:

- Simple yet effective implementation
- No complex language models needed
- Training requires only text corpus

- **Features:**

- N-gram language model for context
- Metaphone phonetic matching
- Log-scaled frequency weighting
- Confidence threshold ( $score > 1.0$ )

- **Implementation Details:**

- Uses NLTK for n-gram modeling
- Phonetic similarity via Metaphone algorithm
- Contextual analysis with 2-word window
- Preserves original capitalization

- **Scoring Formula:**

$$Score = 2.0 \cdot E_1 + 1.0 \cdot E_2 + 0.5 \cdot \log(f + 1) + 1.5 \cdot P + 0.3 \cdot C \quad (3)$$

Where:

- $E_1$ : Edit distance 1 match
- $E_2$ : Edit distance 2 match
- $f$ : Word frequency
- $P$ : Phonetic match
- $C$ : Context score

# AI-Based Approach: Deep Learning

- Context-aware spelling correction.
- Models:
  - **Seq2Seq** (LSTMs).
  - **Transformers** (BERT, T5).
- Example:
  - Input: "I am going too the store"
  - Output: "I am going to the store"
- Used in Google Search, Grammarly, and ChatGPT.

**Dataset:** TypoCorpus, Common Crawl Dataset, Lang-8 Learner Corpus.

**Model:** BERT, T5.

## Evaluation Metric: BLEU Score

- Measures similarity between the corrected text and the reference text.
- Formula:

$$BLEU = \exp \left( \sum_{n=1}^N w_n \log p_n \right) \quad (4)$$

# Comparison of Approaches

Method	Accuracy	Speed	Context Awareness
Rule-Based	Medium	Fast	Low
Statistical	Medium	Medium	Medium
AI-Based	Very High	Slow	High

# Conclusion

- Spelling correction evolved from rule-based to AI-based methods.
- Statistical and ML approaches improve accuracy.
- AI-based models can handle complex, context-dependent errors.