Text Preprocessing in Natural Language Processing

Transforming Raw Text into Actionable Data

Outline

- What is text preprocessing?
- Why is it important?
- Preprocessing techniques

Quick recap of previous lecture

Why text preprocessing is important?

- **Noise Reduction:** Remove irrelevant characters (punctuation, HTML tags).
- **Consistency:** Lowercasing, standardizing formats (e.g., dates).
- **Efficiency:** Smaller vocabulary size = faster model training.
- **Accuracy:** Improves NLP task performance (e.g., sentiment analysis).

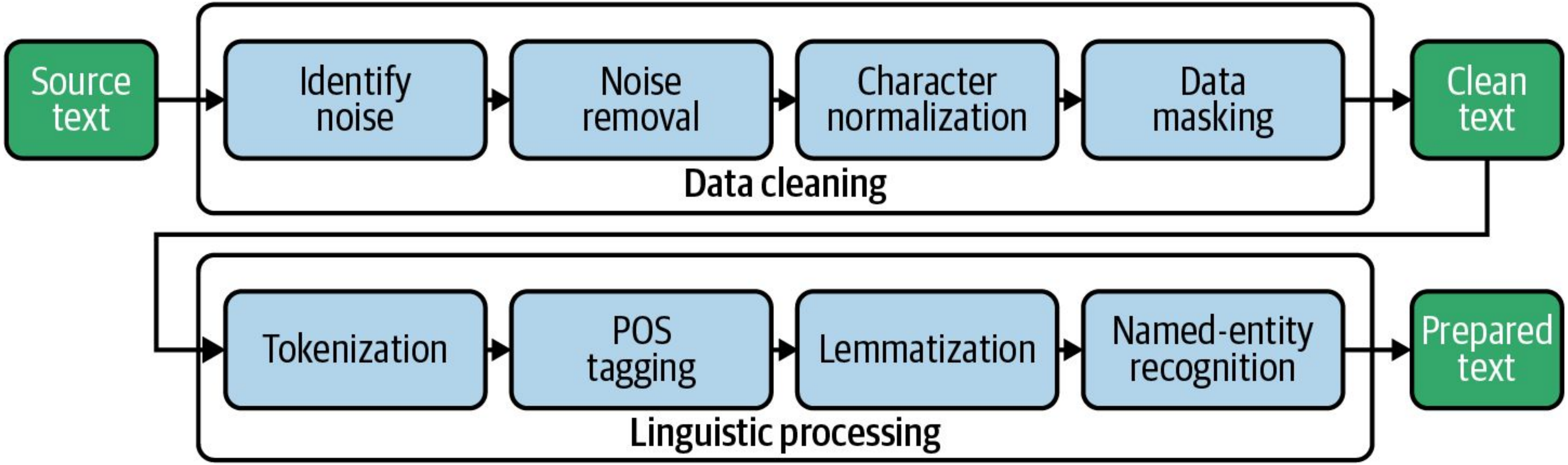
Challenges

- **Ambiguity:** “Apple” (fruit vs. company).
- **Language Differences:** Morphology in Arabic vs. English.
- **Resource Limits:** Lemmatization requires heavy dictionaries.

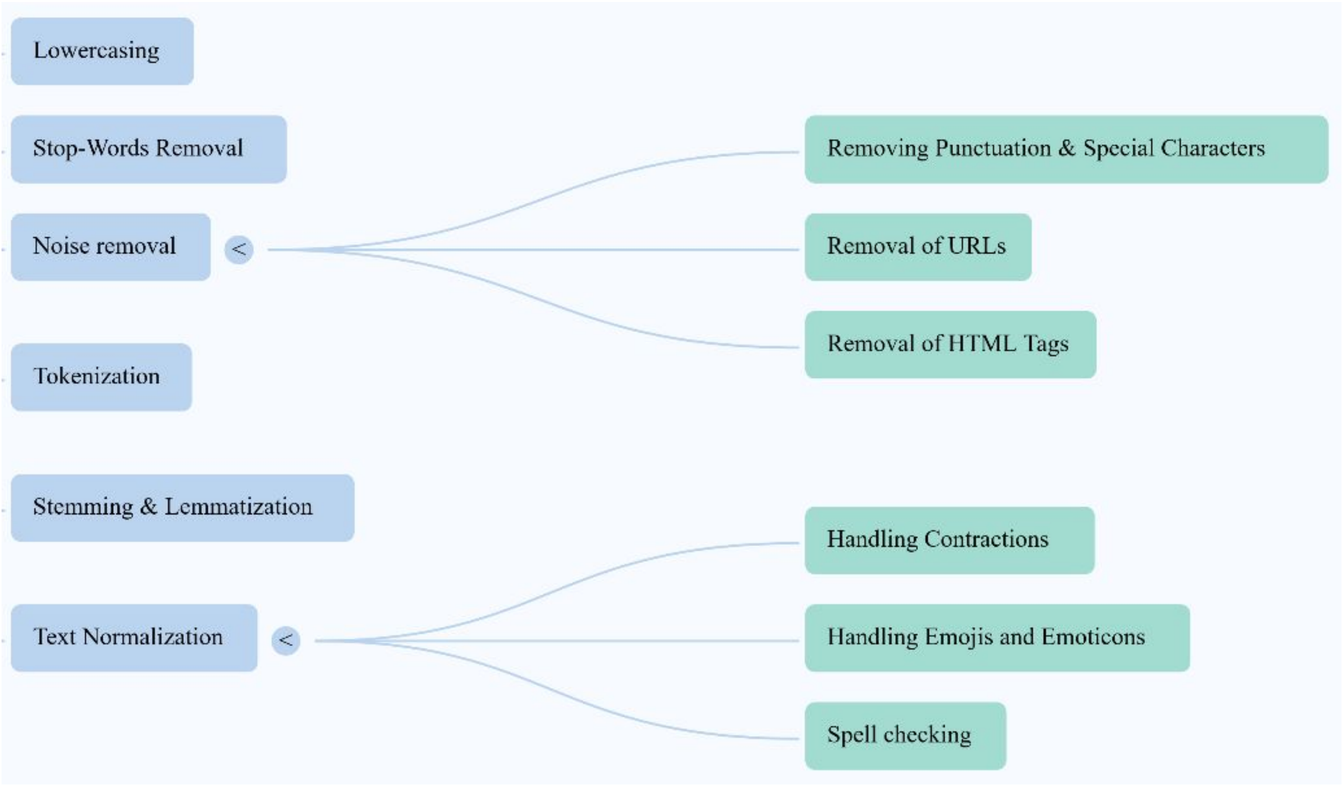
Domain-Specific Preprocessing

- **Social Media:** Emoji handling, slang normalization.
- **Scientific Texts:** Retain equations/symbols.
- **Medical Texts:** Protect sensitive terms (e.g., patient names).

Text preprocessing stages



Common preprocessing steps:



Tokenization

Tokenization is the process of breaking down text into smaller chunks such as words or subwords.

Importance

Foundation for most NLP tasks and models

Tools: NLTK and spaCy toolkits.

Word tokenization

- Splits text into individual words. For example:
- Input: "Tokenization is fun!"
- Output: ["Tokenization", "is", "fun", "!"]

Whitespace tokenization

- Splits text based on whitespace. For example:
- Input: "Tokenization is fun!"
- Output: ["Tokenization", "is", "fun!"]

Subword tokenization

- Breaks words into smaller subword units
- Input: "unbelievable"
- Output: ["un", "believ", "able"]

Character tokenization

- Splits text into individual characters. For example:
- Input: "Token"
- Output: ["T", "o", "k", "e", "n"]

Sentence segmentation

- Splits text into sentences. For example:
- Input: "**Tokenization is fun. Let's learn more!**"
- Output: ["**Tokenization is fun.**", "**Let's learn more!**"]

Regex-based tokenization

- Uses regular expressions to define custom tokenization rules.
- For example, splitting text based on punctuation or specific patterns.

Tokenization

Sentence: Segmentation and Word/Subword: Tokenization

- **Subword Tokenization:** Handle rare/compound words (e.g., BPE in GPT).

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Classes of tokenization algorithms

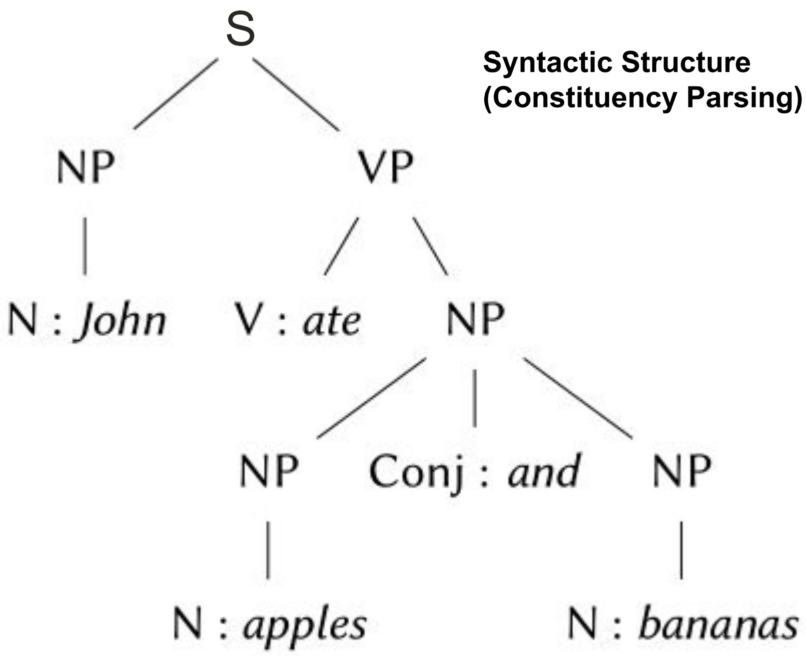
- Top-down tokenization
    - Rule-based (Penn Treebank Tokenizer)
- Bottom-up tokenization
    - Data-driven (Byte-Pair Encoding)

- Speed matters:
    - Tokenization is performed on every input before other language processing steps.
    - Large datasets and real-time systems need tokenizers that are highly optimized for speed.
    - Word tokenizers generally use deterministic (rule-based or algorithmic) logic for reliability and efficiency

Top-down Tokenization

- Involves splitting text based on predefined rules or patterns.
- Focuses on higher-level linguistic units, typically words and sentences.
- Penn Treebank Tokenizer

Syntactic Structure (Constituency Parsing)



Dependency Parsing

```
        ate
      /     \
  John   apple
             \
             and
               \
             bananas
```

Top-down Tokenization

- Involves splitting text based on predefined rules or patterns.
- Focuses on higher-level linguistic units, typically words and sentences.
- Penn Treebank Tokenizer
  - Splits most punctuation from words.
    - Handles contractions and possessives (ownership)
    - e.g., "children’s" → "children" + "’s"; "can’t" → "ca" + "n’t".

```
Input:   "The San Francisco-based restaurant," they said,
         "doesn’t charge $10".
Output:  "␣The␣San␣Francisco-based␣restaurant␣,␣"␣they␣said␣,␣
         "␣does␣n’t␣charge␣$␣10␣"␣.
```

Top-down Tokenization

- Involves splitting text based on predefined rules or patterns.
- Focuses on higher-level linguistic units, typically words and sentences.
- Penn Treebank Tokenizer
  - Splits most punctuation from words.
    - Handles contractions and possessives (ownership)
    - e.g., "children's" → "children" + "'s"; "can't" → "ca" + "n't".
  - Advantages:
    - Fast and deterministic.
    - Designed for structured, well-formed text (e.g., newswire).
  - Deterministic output: Always produces the same tokenization for the same input

Bottom-up Tokenization

- Constructs tokens from lower-level units (characters or bytes), merging them based on data frequencies.
- This data-driven approach is especially useful for handling **rare words** and **diverse language** inputs. [**Finite vocabulary from training data**]
  - NLP algorithm learn some facts from one corpus (**training corpus**) and make decisions on unseen corpus (**test corpus**)
  - By splitting words into smaller, reusable pieces (***subwords***), the model can generalize.
- Most tokenization schemes have two parts: **a token learner**, and **a token segmenter**.
  - Token learner learns the subword vocabulary from the training corpus (e.g., BPE training process).
  - Token segmenter applies the learned vocabulary to segment new (test) data into tokens (possibly splitting unknown words into familiar subwords).

Subword Tokenization (Byte-Pair Encoding, BPE)

- Tokenizers automatically learn a set of tokens smaller than words (called ***subwords***), enabling flexible splitting of both known and unknown words.

Byte-Pair Encoding (BPE)

- Process:
  - Start with all characters as initial tokens.
  - Iteratively merge the most frequent adjacent token pairs in the corpus.
  - Build new tokens (subwords/words) with every merge step until ***k*** merges has been done.
    - *k = vocab_size - initial_vocab_size*
- Outcome:
  - Handles arbitrary and out-of-vocabulary words.
  - Produces a compact, efficient vocabulary for downstream models
- Used by: Modern language models like OpenAI’s GPT, Llama.

corpus

5 l o w _
2 l o w e s t _
6 n e w e r _
3 w i d e r _
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w

Vocabulary	#count
e	19
_	18
w	15
r	9
n	8
l	7
o	7
d	3
i	3
s	2
t	2

Vocabulary	#count
er	9
r_	9

corpus

5 l o w _
2 l o w e s t _
6 n e w er _
3 w i d er _
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er

Vocabulary	#count
e	19
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w	15
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n	8
l	7
o	7
d	3
i	3
s	2
t	2
er	9

Vocabulary	#count
er_	9
ne	9
lo	7
w_	7
ow	7
wer	6
wi	3
der	3
id	3
t_	2
we	2
st	2
t_	2

corpus

5 l o w _

2 l o w e s t _

6 n e w er_

3 w i d er_

2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er, er_

Vocabulary	#count
e	19
_	18
w	15
r	9
n	8
l	7
o	7
d	3
i	3
s	2
t	2
er	9
er_	9

Vocabulary	#count
ne	8
w_	7
lo	7
ow	7
wer_	6
der_	3
id	3
we	2
st	2
t_	2

corpus		**vocabulary**
5	`l o w _`	`_, d, e, i, l, n, o, r, s, t, w, er, er_`
2	`l o w e s t _`	
6	`n e w er_`	
3	`w i d er_`	
2	`n e w _`	

corpus		**vocabulary**
5	`l o w _`	`_, d, e, i, l, n, o, r, s, t, w, er, er_, ne`
2	`l o w e s t _`	
6	`ne w er_`	
3	`w i d er_`	
2	`ne w _`	

corpus		**vocabulary**
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne
2	l o w e s t _	
6	ne w er_	
3	w i d er_	
2	ne w _	

merge	**current vocabulary**
(ne, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

function BYTE-PAIR ENCODING(strings C, number of merges k) **returns** vocab V

$V \leftarrow$ all unique characters in C # initial set of tokens is characters
for $i = 1$ **to** k **do** # merge tokens k times
$t_L, t_R \leftarrow$ Most frequent pair of adjacent tokens in C
$t_{NEW} \leftarrow t_L + t_R$ # make new token by concatenating
$V \leftarrow V + t_{NEW}$ # update the vocabulary
Replace each occurrence of t_L, t_R in C with t_{NEW} # and update the corpus
return V

Figure 2.13 The token learner part of the BPE algorithm for taking a corpus broken up into individual characters or bytes, and learning a vocabulary by iteratively merging tokens. Figure adapted from Bostrom and Durrett (2020).

Wordpiece Tokenizer

function BYTE-PAIR ENCODING(strings C, number of merges k) **returns** vocab V

$V \leftarrow$ all unique characters in C # initial set of tokens is characters
for $i = 1$ **to** k **do** # merge tokens k times
$t_L, t_R \leftarrow$ Most frequent pair of adjacent tokens in C
$t_{NEW} \leftarrow t_L + t_R$ # make new token by concatenating
$V \leftarrow V + t_{NEW}$ # update the vocabulary
Replace each occurrence of t_L, t_R in C with t_{NEW} # and update the corpus
return V

$$\text{score} = (\text{freq\_of\_pair})/(\text{freq\_of\_first\_element} \times \text{freq\_of\_second\_element})$$

Exercise for you:

Token learner: Find possible subwords using Wordpiece algorithm

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w
2	l o w e s t _	
6	n e w e r _	
3	w i d e r _	
2	n e w _	

$$\text{score} = (\text{freq\_of\_pair})/(\text{freq\_of\_first\_element} \times \text{freq\_of\_second\_element})$$

Word normalization

Word normalization is the task of putting words or tokens in a standard format.

- Case folding [generalize text to same case (lower case)]
- Normalize [(USA, US), (uh-huh, uhhuh)]
- Morphological analysis [mapping to same root word - (Warsaw, Warszawa)]
  - Stems
  - Affixes
    - Prefix
    - Suffix

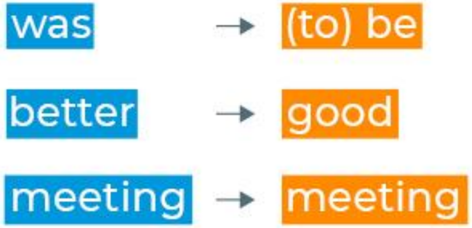
Eg.

- cats - ['cat', 's']
- fox - ['fox']

Lemmatization

Use linguistics to get valid root forms (e.g., “better” → “good”).

- Maps words to dictionary roots
- Produces valid words
- Requires POS tagging
- **The algorithm can be complex.**



Stemming

Reduce words to root form (e.g., “running” → “run”).

- Removes word suffixes aggressively
- May produce non-words
- Fast and simple

Text Normalization: Handling Contractions

Convert text to canonical form

Eg. Helloooo → Hello

Expand contractions

Convert shortened forms to full words

Standardize forms

Reduce variations in expression for consistency

Tools: Regex, custom dictionaries.

- can’t
- cannot
- won't
- will not
- isn’t
- is not

Text Normalization: Emojis, Emoticons, and Spell Checking

Handle emojis & emoticons

Convert to text descriptions or remove as needed

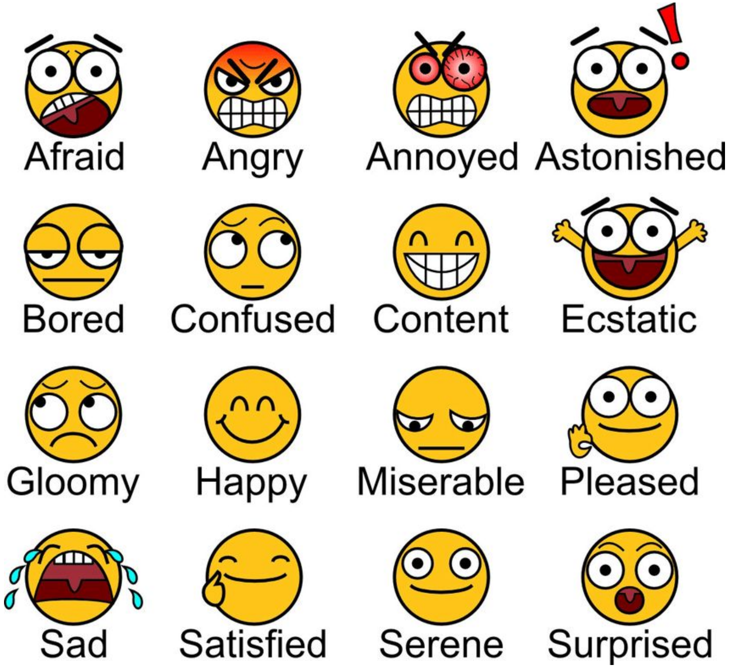
`Toolkit: demoji`

Spell checking

Correct typos to improve data quality

Use Case: Fix typos in social media/text messages.

`Toolkit: pyspellchecker`



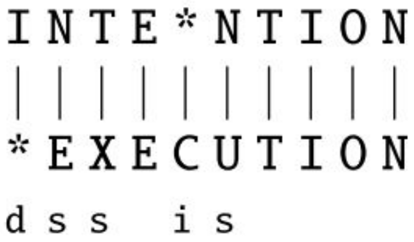
Minimum edit distance

Minimum Edit Distance is the **minimum number of operations** required to convert one string into another.

Edit Operations:

- **Insertion** (add a character)
- **Deletion** (remove a character)
- **Substitution** (replace one character with another)

The gap between **intention** and **execution**



Applications:

- Spell checking
- Machine translation evaluation
- Plagiarism detection
- Speech recognition

Why does it matter?:

- MED quantifies how “similar” two pieces of text are [critical in many NLP tasks].

Minimum edit distance

Minimum Edit Distance is the **minimum number of operations** required to convert one string into another.

Edit Operations:

- **Insertion** (add a character) [("cat" → "cart" by inserting 'r')]
- **Deletion** (remove a character) [("cart" → "cat" by deleting 'r')]
- **Substitution** (replace one character with another) [("cat" → "cut" by substituting 'a' with 'u')]

Applications:

- Spell checking [("recieve" → "receive") distance = 2]
- Machine translation evaluation [Compare translated output with a reference translation]
- Plagiarism detection [Find passages that are almost the same but with small edits.]
- Speech recognition [Align output text with the actual spoken words to score accuracy.]

Why does it matter?:

- MED quantifies how “similar” two pieces of text are [critical in many NLP tasks].

How to calculate MED?

- The space of all possible edits is enormous, so we can’t search naively.
- We could just remember the shortest path to a state each time we saw it.
- Dynamic programming - a table-driven method to solve problems by combining solutions to subproblems. (Eg. Viterbi algorithm)
- MED base cases:
  - D[i,j] = The edit distance between X[1..i] and Y[1.. j]
  - D[i,0] = i (requires i deletes)
  - D[0,j] = j (requires j deletes)

How to calculate MED?

$$D[i,j] = \min \begin{cases} D[i-1,j] + \text{del-cost}(source[i]) \\ D[i,j-1] + \text{ins-cost}(target[j]) \\ D[i-1,j-1] + \text{sub-cost}(source[i], target[j]) \end{cases}$$

Levenshtein Distance

$$D[i,j] = \min \begin{cases} D[i-1,j] + 1 \\ D[i,j-1] + 1 \\ D[i-1,j-1] + \begin{cases} 2; & \text{if } source[i] \neq target[j] \\ 0; & \text{if } source[i] = target[j] \end{cases} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9
	Src\Tar	**#**	**e**	**x**	**e**	**c**	**u**	**t**	**i**	**o**	**n**
0	**#**	0	1	2	3	4	5	6	7	8	9
1	**i**	1	2	3	4	5	6	7	6	7	8
2	**n**	2	3	4	5	6	7	8	7	8	7
3	**t**	3	4	5	6	7	8	7	8	9	8
4	**e**	4	3	4	5	6	7	8	9	10	9
5	**n**	5	4	5	6	7	8	9	10	11	10
6	**t**	6	5	6	7	8	9	8	9	10	11
7	**i**	7	6	7	8	9	10	9	8	9	10
8	**o**	8	7	8	9	10	11	10	9	8	9
9	**n**	9	8	9	10	11	12	11	10	9	8

Figure 2.18 Computation of minimum edit distance between *intention* and *execution* with the algorithm of Fig. 2.17, using Levenshtein distance with cost of 1 for insertions or deletions, 2 for substitutions.

	#	e	x	e	c	u	t	i	o	n
#	0	← 1	← 2	← 3	← 4	← 5	← 6	← 7	← 8	← 9
i	↑ **1**	↖←↑ 2	↖←↑ 3	↖←↑ 4	↖←↑ 5	↖←↑ 6	↖←↑ 7	↖ 6	← 7	← 8
n	↑ 2	↖←↑ **3**	↖←↑ 4	↖←↑ 5	↖←↑ 6	↖←↑ 7	↖←↑ 8	↑ 7	↖←↑ 8	↖ 7
t	↑ 3	↖←↑ 4	↖←↑ **5**	↖←↑ 6	↖←↑ 7	↖←↑ 8	↖ 7	←↑ 8	↖←↑ 9	↑ 8
e	↑ 4	↖ 3	← 4	↖← **5**	← **6**	← 7	←↑ 8	↖←↑ 9	↖←↑ 10	↑ 9
n	↑ 5	↑ 4	↖←↑ 5	↖←↑ 6	↖←↑ 7	↖←↑ **8**	↖←↑ 9	↖←↑ 10	↖←↑ 11	↖↑ 10
t	↑ 6	↑ 5	↖←↑ 6	↖←↑ 7	↖←↑ 8	↖←↑ 9	↖ **8**	← 9	← 10	←↑ 11
i	↑ 7	↑ 6	↖←↑ 7	↖←↑ 8	↖←↑ 9	↖←↑ 10	↑ 9	↖ **8**	← 9	← 10
o	↑ 8	↑ 7	↖←↑ 8	↖←↑ 9	↖←↑ 10	↖←↑ 11	↑ 10	↑ 9	↖ **8**	← 9
n	↑ 9	↑ 8	↖←↑ 9	↖←↑ 10	↖←↑ 11	↖←↑ 12	↑ 11	↑ 10	↑ 9	↖ **8**

At each step:

- If you follow ↖ **(diagonal)**, you either substitute (if letters differ) or match (if same).
- If you follow ↑ **(top)**, you've deleted a character from the source.
- If you follow ← **(left)**, you've inserted a character into the source.

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
d s s   i s
```

When to Skip Preprocessing?

- **Context:** Tasks needing case sensitivity (e.g., NER).
- **Models:** Modern LLMs (BERT, GPT) handle raw text better.

Impact on Model Performance

- Text preprocessing improves NLP system performance
- **Case Study:** Sentiment analysis accuracy improves by 15% after stop word removal.

Key Takeaway: Preprocessing tailors text for NLP tasks.

Wider reading

Tokenization:

- Wordpiece: https://huggingface.co/learn/llm-course/chapter6/6
- Unigram: https://huggingface.co/learn/llm-course/en/chapter6/7

References:

- Chapter 2: https://web.stanford.edu/~jurafsky/slp3/ed3book.pdf