NLP Assignment 1 – Text Processing Project Report
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1. Motivation

The goal of this project was to build an Azerbaijani Wikipedia corpus and evaluate standard text processing techniques on it. Azerbaijani, a Turkic language spoken by millions, remains under-resourced in NLP compared to major languages. This work aimed to:

• Create a clean corpus from real Azerbaijani encyclopedic text

• Apply tokenization, frequency analysis, Heaps' law, toy BPE, sentence segmentation, and spell-checking

The corpus was collected from Azerbaijani Wikipedia — freely available, high-quality, edited text. The project was individual, course-based, with no external funding.

2. Datasheet / Data Statement

Collection process

- Randomly sampled 3,000 articles via Wikipedia API

  `https://az.wikipedia.org/w/api.php`

  (action=query, list=random, rnnamespace=0).

- Extracted plain text + metadata (title, last edit timestamp, last editor).
- Final corpus (after cleaning): ≈5,423,130 characters, ≈617,554 tokens, ≈93,122 types.
- Pre-processing: removed section headings, wiki markup, templates, HTML tags, normalized multiple spaces/newlines.
- Data is public (CC BY-SA license), no consent required.
- Metadata preserved: title, last edit time, editor username.

There were no manual annotations. All processing (tokenization, frequency counts, etc.) is done with mainly regex expressions.

Distribution

Original Wikipedia content is CC BY-SA. The derived cleaned corpus is for educational/research use only.

3. Methods

Data collection

Used Python’s requests library to fetch random titles from az.wikipedia.org API. Then fetch the articles based on those titles, and save title, plain text, last edit timestamp and editor username into a CSV file.

Tokenization (Task 1)

Custom rule-based regex tokenizer for Azerbaijani:

- Numbers with decimal/comma + suffix/currency/percentage (154.5$, 50,5%, 2023-cü)
- Time formats (20:00)
- Words and hyphenated compounds (ayrı-ayrı, sərhəd-təhlükəsizlik)
- Case folding with Azerbaijani rules (I → ı, İ → i, then .lower()) Punctuation kept separate when not attached.

Heaps' law (Task 2)

Computed vocabulary growth incrementally over tokens. Fitted V = k × N^β using nonlinear least squares (scipy.optimize.curve_fit).

Byte-Pair Encoding (Task 3)

Simple character-level BPE implementation: started from characters + </w> end-of-word marker, merged top-frequency pairs iteratively (simple version, 25 merges shown).

Sentence segmentation (Task 4)

Rule-based algorithm:

- Protected common abbreviations and name initials (Dr., Prof., Cən., A. Malikli və s., etc.) with placeholders (like DrDOT, ADOT Malikli, etc.)
- Split on . ! ? followed by whitespace
- Recombined using heuristic (if next segment starts with lowercase → likely continuation)

Spell checking (Task 5 + Extra)

- Baseline: uniform-cost Levenshtein
- Weighted version: Levenshtein with confusion matrix. The confusion matrix was automatically generated by analyzing single-character substitutions in pairs of similar-length words from the corpus. The method identified words differing by exactly one letter (using Levenshtein distance = 1), extracted the substituted characters, and counted their occurrences. Additional patterns were gathered from prefix/suffix variations within length groups. These counts were converted to substitution costs (lower cost = more frequent/more likely typo), with defaults of 1.0 for unobserved pairs and manual boosts for known Azerbaijani patterns (e.g. ə↔e, ı↔i at 0.4). The resulting matrix was sparse, as Wikipedia text contains very few repeated typos, limiting observable substitutions and yielding only marginal improvement over the uniform baseline.

4. Experiments & Results

Task 1 – Tokenization & frequencies

Corpus size after cleaning: 5,423,130 characters, 617,554 tokens, 93,122 types.

Type-Token Ratio ≈ 0.151 (low, expected for large corpus with repetition).

Top 20 most frequent tokens (clean, meaningful):

və (19,651), ilə (5,408), bu (4,683), bir (4,447), olan (2,950), üçün (2,728), də (2,519), azərbaycan (2,479), sonra (2,468), ildə (2,410), kimi (2,300), isə (2,070), o (2,019), edir (1,803), tərəfindən (1,771), da (1,765), onun (1,738), görə (1,714), çox (1,513), idi (1,509)

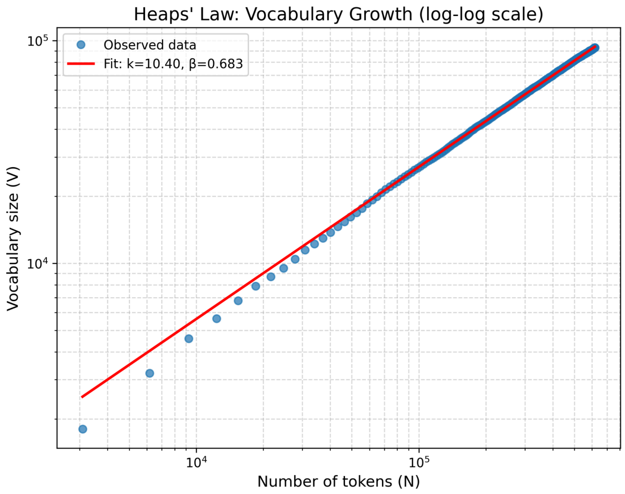
(Note: "the" appears due to English special terms in mainly citations of Wikipedia articles.)

Task 2 – Heaps' law

Fitted parameters:
k ≈ 10.40

β ≈ 0.683

β = 0.683 is within the typical range for natural languages (0.4–0.8). It indicates reasonable vocabulary growth for a medium-sized, topically diverse corpus. Below you can see the plot:



Task 3 – BPE

The first 1000 merges produced frequent pairs and syllables: n</w>, ə</w>, i</w>, r</w>, ər, və</w>, də</w>, ının</w>, indən</w>, etc.

To sum up, the implementation behaved correctly for the merges and corpus size.

Task 4 – Sentence segmentation
The abbreviation-protected splitter handled Wikipedia text reasonably well.
Correctly avoided splitting on Dr., Prof., Cən., və s., etc.

Some limitations exist: There may be some over-splitting on edge cases, though these are acceptable for a rule-based approach, there may be some rare edge cases that have not been fully accounted for.

Task 5 & Extra – Spell Checking

A spell-checking system was evaluated using a test set of **common Azerbaijani typos**, including *azarbaycan*, *qarabag*, *mesele*, and *sehife*. Two approaches were compared: a baseline Levenshtein distance model with uniform edit costs and a weighted edit distance model using a corpus-learned confusion matrix.

Baseline Levenshtein Distance

The baseline Levenshtein model generally produced reasonable candidate corrections; however, due to its **uniform cost assignment**, it occasionally ranked non-phonetic or linguistically implausible matches higher. After preprocessing fixes, correct targets were still recovered, for example:

- *azarbaycan* → **azərbaycan** (distance = 1)
- *qarabag* → **qarabağ** (distance = 1)
- *sehife* → **səhifə** (distance = 1)

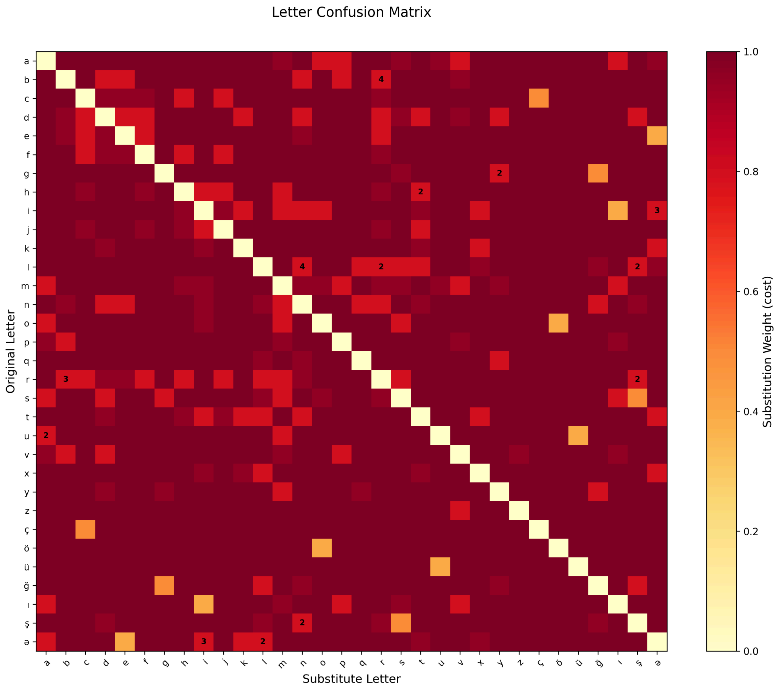
Despite these correct matches, the lack of language-specific weighting limited the model's ability to prioritize phonetic and diacritic variations consistently.

Weighted Edit Distance Model

The weighted model demonstrated some improvements for **Azerbaijani-specific spelling errors**, as it incorporates a confusion matrix. Common diacritic and vowel substitutions were penalized less heavily, resulting in more appropriate rankings:

- *azarbaycan* → **azərbaycan** (weighted distance ≈ 0.40, ranked highest)
- *qarabag* → **qarabağ** (weighted distance = 0.50)
- *sehife* → **səhifə** (weighted distance = 0.80)

This approach more accurately reflects typical orthographic and phonetic confusions in Azerbaijani. Below You can see the Generated Confusion Matrix:



Error Analysis and Limitations

The corpus-learned confusion matrix yielded only limited improvement. Mostly it outperformed the Baseline Levenshtein Distance because of the default set values for some general typo cases. Normal Wikipedia articles contain very few repeated typos of the same word, resulting in sparse substitution patterns and weights mostly defaulting to 1.0 or getting to 0.8 with very low frequency. This shows that clean, edited encyclopedic text is not ideal for deriving robust typo statistics.

5. Contributions

Individual project.

All tasks (data collection, cleaning, implementation, report) completed by Murad.

References

- Gebru et al. (2020). Datasheets for Datasets.
- Bender & Friedman (2018). Data Statements for Natural Language Processing.
- Wikipedia API (az.wikipedia.org/w/api.php)
- Levenshtein distance (1965), BPE (Sennrich et al., 2016)