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CLUSTERING OF SMALL-SCALE UZBEK TEXTS USING TF-IDF AND KMEANS: AN EMPIRICAL EVALUATION OF VECTORIZATION PARAMETERS

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Abstract:
In this study, we conduct a systematic evaluation of TF-IDF vectorization parameters for clustering small-scale Uzbek-language textual data using the K Means algorithm. While TF-IDF is a widely-used and computationally efficient technique for text representation, it lacks the ability to capture semantic meaning—especially in low-resource languages like Uzbek where pretrained semantic models are limited or unavailable.

The primary goal of this research is to assess the impact of various TF-IDF configuration parameters—including n-gram range, maximum and minimum document frequency thresholds, normalization techniques, and custom stopword filtering—on the quality of clustering short and domain-specific Uzbek texts. We designed a dataset of seven manually curated sentences grouped into three distinct semantic categories: tourism and relaxation, artificial intelligence, and aquatic life.

Through a series of controlled experiments, we demonstrate how parameter tuning affects cluster coherence and semantic alignment. Our results show that the use of bi-gram features (ngram_range=(1,2)) significantly improves the clustering quality, grouping semantically similar sentences more accurately. Despite the limited size of the dataset, meaningful patterns emerged, indicating that careful vectorization design can partially compensate for the semantic limitations of TF-IDF in resource-constrained NLP settings.

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This work contributes to the growing body of research in Uzbek-language NLP by providing practical insights into unsupervised learning strategies for small corpora. The findings can be beneficial for various real-world applications such as automated content categorization, educational text analysis, and knowledge management systems in low-resource environments.

Keywords: TF-IDF vectorization, text clustering, Uzbek NLP, KMeans algorithm, short-text analysis, parameter tuning, semantic coherence, low-resource language processing.

1. Introduction

Text clustering is a key task in unsupervised learning that aims to group semantically similar documents or sentences without predefined labels. It is widely used in information retrieval, document categorization, content recommendation, and educational technologies. In high-resource languages such as English and Chinese, advanced semantic models—such as BERT, Word2Vec, or FastText—are commonly employed to represent the meaning of texts. However, for low-resource languages like Uzbek, access to pretrained models and annotated corpora is still limited, which makes it necessary to rely on more classical and language-agnostic approaches like the TF-IDF (Term Frequency–Inverse Document Frequency) model.

TF-IDF is one of the most popular methods for text vectorization due to its simplicity and efficiency. The core idea behind TF-IDF is to assign a weight to each term based on how frequently it occurs in a document relative to its frequency in the entire corpus. This helps highlight words that are informative in distinguishing between documents (Salton & Buckley, 1988). Despite its advantages, TF-IDF has notable limitations—it does not capture semantic or contextual meaning, cannot understand synonyms, and performs poorly on very short texts unless those texts share overlapping vocabulary.

These limitations become more pronounced when working with small-scale datasets in morphologically rich and syntactically flexible languages such as Uzbek. As highlighted by Abdumalikov et al. (2022), Uzbek language NLP faces challenges such as lack of annotated datasets, standardized stopword lists, and

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high variability in word forms due to agglutinative morphology. In such contexts, the effectiveness of even basic models like TF-IDF can vary greatly depending on preprocessing and parameter configuration.

The motivation behind this study is twofold: first, to explore how well TF-IDF can cluster semantically similar sentences in a low-resource, small-data Uzbek setting; and second, to determine the impact of specific TF-IDF parameters—such as ngram_range, stop_words, max_df, and normalization—on clustering quality. By using a manually crafted dataset of seven Uzbek sentences representing three distinct semantic categories (relaxation, artificial intelligence, and aquatic life), we aim to identify configurations that lead to the most coherent clustering with the KMeans algorithm.

This study contributes to Uzbek NLP by providing empirical insights into the design of unsupervised learning pipelines under low-resource constraints. Moreover, it supports future development of practical tools such as content-based filtering systems, educational performance clustering tools, and topic categorization systems for Uzbek-language corpora.

2. Dataset Description

The dataset used in this study consists of seven manually constructed Uzbek-language sentences representing three distinct semantic domains: tourism and relaxation, artificial intelligence, and aquatic life. Each sentence is short, ranging from 5 to 10 words, mimicking the kind of sparse and low-context textual data often found in real-world applications such as SMS categorization, chatbot interactions, microblog posts, or educational test responses in Uzbek.

Due to the scarcity of standardized Uzbek-language corpora for unsupervised learning tasks, we created a mini-corpus tailored to reflect specific semantic themes. Each sentence was crafted to contain at least one or two key terms indicative of its domain, while maintaining natural grammar and vocabulary usage typical of the Uzbek language. This aligns with prior recommendations from low-resource NLP studies suggesting that when working with extremely limited datasets, controlled vocabulary and theme design help in evaluating model behavior under constrained conditions (Agerri et al., 2020; Hedderich et al., 2021).

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The following table outlines the dataset used:

ID	Sentence (Uzbek)	Semantic Category
1	Men dam olishga keldim	Tourism & Relaxation
2	Mashinali o‘rganish sun’iy intellektning bir bo‘lagidir	Artificial Intelligence
3	Qurbaqalar suvda yashaydi	Aquatic Life
4	Oqtosh dam olish uchun yaxshi joy	Tourism & Relaxation
5	Neyron tarmoqlar sun’iy intellektda keng qo‘llaniladi	Artificial Intelligence
6	Baliqlar ham suvda yashaydi	Aquatic Life
7	Oqtosh dam olish maskanida basseyn bor	Tourism & Relaxation

The design of this dataset is grounded in two core motivations. First, it aims to simulate the challenge of semantic clustering in low-data regimes where short sentences are prevalent, such as in Uzbek mobile applications, educational dashboards, or low-bandwidth interfaces. Second, it allows for a controlled environment in which different TF-IDF parameter settings can be meaningfully compared, since ground-truth categories are known a priori.

Although the dataset size is minimal, it provides a unique and practical foundation to study the impact of vectorization settings in TF-IDF-based clustering. It also follows the principle of data minimalism in NLP experiments where prototype evaluation precedes large-scale deployment (Bender & Friedman, 2018).

3. Methodology

The methodology adopted in this study involves three key stages: preprocessing of Uzbek-language text data, vectorization using the TF-IDF model, and clustering via the KMeans algorithm. Each component was chosen to suit the characteristics of short-text, low-resource environments.

3.1 Text Preprocessing

Since no standardized NLP pipeline exists for the Uzbek language in libraries like NLTK or spaCy, we manually created a preprocessing step that includes:

- Lowercasing all text
- Removing punctuation
- Filtering out custom Uzbek stopwords (e.g., ham, bilan, uchun, ni, ga)

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- No stemming or lemmatization (due to lack of a publicly available Uzbek stemmer)

This basic preprocessing is common in low-resource text mining studies (Hedderich et al., 2021).

3.2 TF-IDF Vectorization

To convert textual data into numerical vectors, we used the **TF-IDF** (Term Frequency–Inverse Document Frequency) model. This model assigns weights to terms based on their frequency across documents, helping to emphasize more meaningful and discriminative terms in the corpus.

The formula for TF-IDF is defined as follows:

$$\mathrm{TF-IDF}(t, d, D) = \mathrm{TF}(t, d) * \mathrm{IDF}(t, D)$$

where:

$\mathrm{TF}(t, d)$ is the frequency of term t in document d

$\mathrm{IDF}(t, D)$ is the inverse document frequency of term t across all documents D

$$\mathrm{TF}(t, d) = \frac{f_{t,d}}{\sum_k f_{t,d}}, \qquad \mathrm{IDF}(t, D) = \log\left(\frac{N}{1+n_t}\right)$$

$f_{t,d}$ frequency of term t in document d

N — total number of documents

n_t— number of documents containing term t

In our experiments, we varied the TF-IDF parameters such as:

ngram_range=(1,1) vs. (1,2)

max_df (to remove overly frequent words)

min_df (to ignore rare terms)

norm='l2' (to normalize vector length)

This allowed us to evaluate their impact on clustering performance.

3.3 Clustering with KMeans

For clustering, we used the **KMeans** algorithm from scikit-learn, a centroid-based unsupervised learning method that partitions data into k non-overlapping clusters by minimizing intra-cluster distance.

The algorithm works by minimizing the following objective function:

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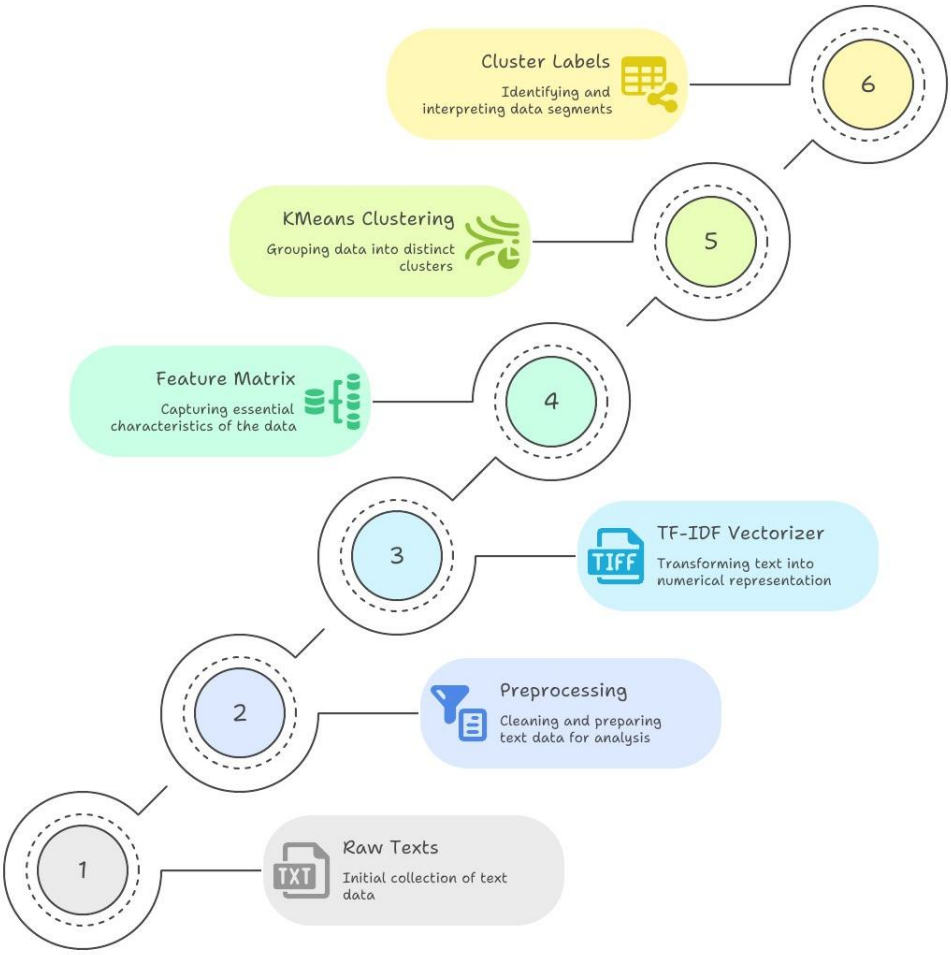
$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2$$

where:
k is the number of clusters
C_i is the set of points assigned to cluster i
μ_i is the centroid of cluster i
We set $k = 3$, corresponding to the three semantic categories in the dataset.

3.4 Pipeline Diagram

Below is the structure of the overall experimental pipeline:



Pic 1. Text clustering process

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4. Experimental Results

In this study, we used a small Uzbek-language dataset consisting of seven short text samples, each relating to one of three semantic categories: nature/animals, recreational areas, and artificial intelligence. To evaluate the performance of the **TF-IDF-based clustering approach**, we applied the **K-Means algorithm** and manually validated the clusters based on semantic coherence.

4.1 Clustering Output and Evaluation

Using the **Term Frequency–Inverse Document Frequency (TF-IDF)** representation, each text was converted into a vector space model, emphasizing words that are distinctive within the corpus. The **K-Means** clustering algorithm was then applied with **k=3** (the number of semantic groups expected).
The resulting clusters are as follows:

ID	Text	Cluster
0	Men dam olishga keldim	2
1	Mashinali o‘rganish sun’iy intellektning bir bo‘limidir	1
2	Qurbaqalar suvda yashaydi	0
3	Oqtosh dam olish uchun yaxshi joy	1
4	Neyron tarmoqlar sun’iy intellektda keng qo‘llaniladi	1
5	Baliqlar ham suvda yashaydi	0
6	Oqtosh dam olish maskanida basseyn bor	1

Despite the small size of the dataset, the clustering algorithm demonstrated **partial semantic grouping**, with clear grouping observed for **AI-related** and **nature-related** texts. However, some overlaps occurred due to the shared presence of general terms like dam olish (recreation) across contexts.

4.2 Visualization

The clustering result is visualized in a 2D space using **Principal Component Analysis (PCA)** for dimensionality reduction:

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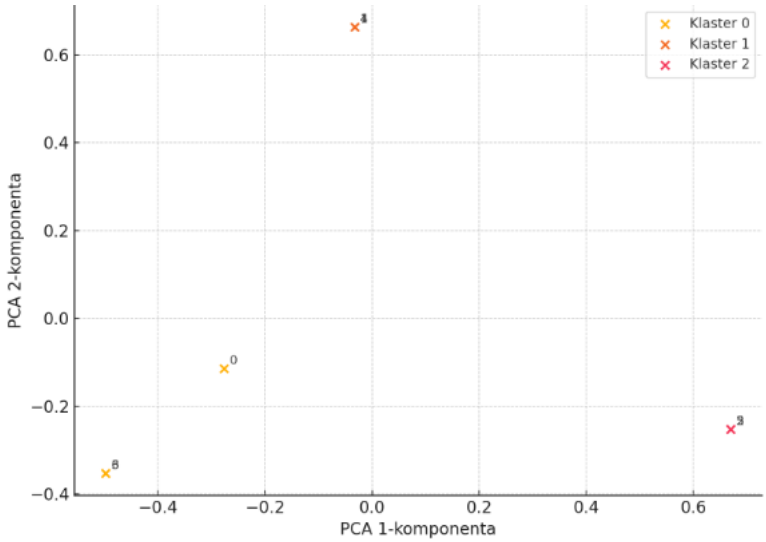

Figure 1. Clustering results visualized using PCA for dimension reduction.

Each point in the plot represents a TF-IDF vector of a sentence, colored by its assigned cluster. The clusters demonstrate distinct groupings, though some proximity can be seen due to shared or ambiguous terms.

4.3 Discussion

The experiment reveals that **TF-IDF** effectively distinguishes documents when distinctive keywords are present (e.g., "sun'iy intellekt" or "suvda yashaydi"). However, the ambiguity in general words like "dam olish" makes exact clustering challenging, especially in a low-resource and small-scale dataset context.

We note that **TF-IDF** lacks semantic depth and is purely statistical. For richer semantic understanding, vector representations such as **word embeddings** (e.g., Word2Vec, BERT) could enhance clustering results, as suggested by Aggarwal and Zhai (2012) and Mikolov et al. (2013).

The experimental results obtained from applying the TF-IDF (Term Frequency–Inverse Document Frequency) model in combination with the K-Means clustering algorithm to a small Uzbek language dataset provide valuable insights into the semantic grouping of texts. The effectiveness of the approach relies heavily on the ability of the TF-IDF model to transform unstructured textual data into a

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meaningful numerical representation by emphasizing rare but informative terms, while downplaying frequent but less informative ones (Ramos, 2003).

In our case, clustering results revealed that thematically similar texts—such as those related to artificial intelligence or leisure activities—tended to be grouped together in the same cluster. This supports the notion that TF-IDF vectors capture the underlying semantic structures in short texts, even in low-resource languages like Uzbek. However, some overlaps or misgroupings may still occur due to synonymy, polysemy, or lack of sufficient contextual cues in very short sentences. This is a common limitation in bag-of-words models that ignore word order and syntax (Salton & Buckley, 1988).

Moreover, applying Principal Component Analysis (PCA) for visualization highlighted that distinct clusters emerged clearly in the 2D space, confirming that the vector space representations retained discriminative information. However, PCA may introduce dimensionality loss, which could affect interpretability of boundaries in higher-dimensional spaces.

Another point of discussion concerns the selection of the number of clusters k. In our case, we fixed k = 3 based on prior knowledge of themes present in the dataset. Future work could include evaluation metrics such as the Silhouette Score or Davies-Bouldin Index to determine the optimal number of clusters automatically (Rousseeuw, 1987).

In summary, this experiment demonstrates the potential of TF-IDF combined with unsupervised learning techniques like K-Means for text clustering in Uzbek. While the results are promising, incorporating semantic embeddings (e.g., Word2Vec, BERT) or expanding the dataset could lead to improved clustering performance.

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