BERT-based Document Clustering: Unveiling Semantic Patterns in 20News Group, Reuters, and BBC Sports Corpora

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Abstract

Document clustering plays a pivotal role in structuring and analyzing vast textual datasets. In this paper, we leverage the Bidirectional Encoder Representations from Transformers (BERT) algorithm, a cutting-edge natural language processing model, to perform document clustering on three distinct datasets: the 20News Group dataset, Reuters dataset, and BBC Sports dataset. BERT’s contextualized embeddings enable a deeper understanding of document semantics, enhancing the clustering process. The objective is to investigate the efficacy of BERT-based document clustering across diverse domains, shedding light on its performance and potential applications. We implement BERT for document clustering, utilizing its pre-trained contextual embeddings to capture intricate relationships within textual data. Our study aims to assess how well BERT adapts to the unique characteristics of each dataset, offering insights into the model’s generalizability and effectiveness across various domains.
Similarity Matrix
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Abstract

Document clustering plays a pivotal role in structuring and analyzing vast textual datasets. In this paper, we leverage the Bidirectional Encoder Representations from Transformers (BERT) algorithm, a cutting-edge natural language processing model, to perform document clustering on three distinct datasets: the 20News Group dataset, Reuters dataset, and BBC Sports dataset. BERT’s contextualized embeddings enable a deeper understanding of document semantics, enhancing the clustering process. The objective is to investigate the efficacy of BERT-based document clustering across diverse domains, shedding light on its performance and potential applications. We implement BERT for document clustering, utilizing its pre-trained contextual embeddings to capture intricate relationships within textual data. Our study aims to assess how well BERT adapts to the unique characteristics of each dataset, offering insights into the model’s generalizability and effectiveness across various domains.

Keywords: Document Clustering, BERT (Bidirectional Encoder Representations from Transformers), Natural Language Processing (NLP), Contextual Embeddings, Dataset Generalizability.
1 Introduction

The burgeoning growth of digital content underscores the critical need for advanced
document clustering techniques to manage and interpret vast textual datasets
effectively[1],[2]. Traditional clustering methods, while foundational, often fall short
in addressing the intricate semantics inherent in natural language. The absence in
capabilities has spurred a shift towards advanced models like Bidirectional Encoder
Representations from Transformers (BERT), celebrated for its adeptness in produc-
ing intricate contextual word embeddings[3],[4]. This introduction expanded with a
literature review, delves into the evolution of document clustering methodologies, the
emergence of Document Clustering Techniques Document clustering
has historically leveraged a range of algorithms, from k-means and hierarchical meth-
ods to advanced probabilistic models like Latent Dirichlet Allocation (LDA) (Blei,
Ng, & Jordan, 2003)[6]. These techniques, while effective in rudimentary clustering
tasks, often struggle with the nuanced understanding of language, particularly in cap-
turing contextual meanings (Xu & Wunsch, 2005)[7].
The advent of word embeddings,
such as Word2Vec (Mikolov et al., 2013) and GloVe (Pennington, Socher, & Manning,
2014)[8], marked a significant improvement by providing dense, semantically rich rep-
resentations of words. However, these static embeddings could not still capture word
meanings in varying contexts. The emergence of deep learning techniques, such as
Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs),
and Convolutional Neural Networks (CNNs), in the realm of natural language process-
ing opened up novel avenues for delving into and comprehensively processing language
(Hochreiter Schmidhuber, 1997; Kim, 2014)[9],[10]. These models showcased remark-
able success in capturing sequential and hierarchical patterns in text. Despite these
advances, the challenge of fully grasping context-dependent word meanings persisted,
setting the stage for the introduction of transformer-based models like BERT[11].

BERT and Its Impact on NLP

Developed by Devlin et al. (2018), BERT rev-
olutionized NLP by employing a transformer architecture to generate contextualized
embeddings. Unlike prior methods, BERT takes into account the entire context of a
word, analyzing both preceding and succeeding words within a sentence, thus enabling
a nuanced comprehension of language. This capability to produce profound contextu-
alized embeddings has rendered BERT notably proficient across diverse NLP tasks,
including document clustering[12].

BERT in Document Clustering: Recent studies have explored the application of
BERT in document clustering, highlighting its potential to significantly improve the
clustering quality by leveraging contextualized embeddings. For instance, research has
shown that BERT outperforms traditional clustering methods and static embeddings
in grouping documents with nuanced semantic similarities (Lee et al., 2019). The
effectiveness of BERT-based clustering has been examined across various datasets,
demonstrating its versatility and adaptability to different domains and linguistic
challenges[13].

Challenges and Opportunities in Diverse Datasets

The 20News Group [14],
Reuters [15], and BBC Sports datasets[16] represent a broad spectrum of topics, lan-
guages, and styles, presenting unique challenges for document clustering. The 20News
Group dataset, with its wide range of discussion topics, tests the ability of algorithms to distinguish between diverse subjects. The Reuters dataset, rich in financial jargon and specific language use, challenges the semantic understanding of domain-specific terms. Lastly, the BBC Sports dataset, with its dynamic and varied sports-related content, requires the clustering algorithm to adapt to frequently changing contexts and terminologies.

**Contributions and Future Directions:** This study aims to bridge the gap in the literature by systematically evaluating the performance of BERT in document clustering across these diverse datasets. By analyzing BERT’s effectiveness in capturing semantic relationships and facilitating meaningful document clusters, this research offers insights into its adaptability and potential for future applications in information retrieval, content organization, and knowledge discovery[17].

### 2 Methodology

We initiated our study by selecting three distinct textual datasets: the 20News Group dataset, the Reuters dataset, and the BBC Sports dataset, each representing diverse domains of information. Before applying algorithms, thorough preprocessing was carried out on the datasets to eliminate noise, which involved removing stopwords, punctuation, and special characters. Furthermore, text normalization techniques such as stemming or lemmatization were utilized to achieve consistency in textual representations[18].

For the document clustering task, we adopted the Bidirectional Encoder Representations from Transformers (BERT) algorithm, renowned for its capability to capture contextual information effectively. Utilizing BERT’s pre-trained contextual embeddings, we encoded each document into dense vector representations, thereby encapsulating semantic meanings and nuances within the text. Furthermore, fine-tuning of the BERT model was performed specifically for the document clustering task to adapt to the unique characteristics of our datasets[11],[19].

The clustering of documents was executed using algorithms such as K-means or hierarchical clustering, with the number of clusters determined empirically or through evaluation metrics like the silhouette score or the elbow method to ensure the formation of meaningful clusters. Evaluation of cluster quality was conducted using standard metrics such as silhouette score, Davies–Bouldin index, or purity, providing insights into cluster cohesion and separation[20].

Cross-dataset evaluation was carried out to assess the generalizability of the BERT-based document clustering model across all three datasets, examining its adaptability to diverse domains and its consistent performance. Furthermore, benchmarking against baseline methods such as traditional vector space models (e.g., TF-IDF) or word embeddings (e.g., Word2Vec, GloVe) facilitated the assessment of the relative advantages of employing BERT for document clustering tasks[21]. Sensitivity analysis was performed to evaluate the robustness of our BERT-based document clustering approach to variations in parameters such as clustering algorithm hyperparameters or BERT fine-tuning configurations, ensuring the reliability and reproducibility of results[22].
**Algorithm 1 BERT Algorithm**

Input text \( x = (x_1, x_2, ..., x_n) \)

1. Tokenize input text into subwords
2. Apply Word-Piece tokenization
3. Add [CLS] token at the beginning and [SEP] token at the end
4. Feed tokenized text into BERT model
5. Obtain contextual embeddings for each token
6. Perform task-specific fine-tuning

**Output:** Task-specific predictions

---

**Fig. 1 BERT System Architecture**

The self-attention mechanism in BERT can be represented as:

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V
\]

where:

- \( Q, K, \) and \( V \) represent matrices corresponding to query, key, and value.
- \( d_k \) denotes the dimensionality of the key vectors.
- The function softmax normalizes the scores row-wise.

The transformer encoder is structured as a series of identical layers, each containing two primary sub-layers: a multi-head attention mechanism and a fully connected feed-forward network[23].

Initially, the input to the transformer encoder is a sequence of words, which undergo conversion into word embeddings. Subsequently, these embeddings traverse a positional encoding layer, augmenting them with positional information, crucial for preserving word order[24].

The output from the positional encoding layer then enters the initial encoder layer. This encoder layer comprises two sub-layers:

- The first sub-layer integrates a multi-head attention mechanism. This mechanism enables the model to selectively focus on various segments of the input sequence while
processing specific words, akin to how humans attend to different parts of a sentence during reading[25].

The second sub-layer features a fully connected feed-forward network. This network, a straightforward neural architecture, is adept at capturing non-linear associations among the words within the sequence[26].

The output of the first encoder layer is then fed into the second encoder layer, and so on. Each encoder layer further refines the representation of the input sequence[27].

The final output of the encoder stack is a sequence of vector representations, one for each word in the input sequence. These vector representations capture the meaning of each word in the context of the entire sentence[28].

3 Results

Data Preprocessing Techniques:

Data preprocessing is a crucial step in preparing textual datasets for analysis. Here, we outline several common techniques employed in data preprocessing:

3.1 Noise Removal
- **Stopword Removal**: Removing frequently occurring words (e.g., "the", "is", "and") that lack substantial semantic significance.
- **Punctuation Removal**: Removing punctuation marks from the text to emphasize the core content.
- **Special Character Removal**: Omitting special characters like symbols and emojis that might not contribute to the analysis.

3.2 Text Normalization
- **Stemming**: Normalizing variations by reducing words to their root form (e.g., "running" to "run").
- **Lemmatization**: Similar to stemming but guarantees that resulting words are valid linguistic forms (e.g., "went" to "go").

3.3 Tokenization
- **Word Tokenization**: Segmenting text into individual words or tokens.
- **Sentence Tokenization**: Segmenting text into sentences for further analysis.

3.4 Normalization
- **Lowercasing**: Converting all text to lowercase to ensure uniformity.
- **Encoding Conversion**: Converting text encoding to a standardized format (e.g., UTF-8).
3.5 Spell Checking

- **Spell Checking**: Detecting and rectifying misspelled words through the use of dictionaries or algorithms.

These preprocessing techniques help in cleaning and standardizing textual data, making it suitable for subsequent analysis tasks such as document clustering, sentiment analysis, and topic modeling.

**Similarity Matrix Calculation:**

To calculate the similarity matrix for a set of documents, we can employ various methods, such as cosine similarity or Jaccard similarity. Below is an algorithmic representation of calculating the similarity matrix using cosine similarity:

```
Algorithm 2 Cosine Similarity Matrix Calculation
1: procedure CosineSimilarity(X)
2: Initialize S as an empty matrix with dimensions n × n, where n is the number of documents.
3: for i = 1 to n do
4:    for j = 1 to n do
5:        S[i][j] ← cosine_similarity(X[i], X[j])
6:    end for
7: end for
8: return S
9: end procedure
```

Here, X represents the matrix of document embeddings or feature vectors. The cosine similarity between two vectors \( \mathbf{a} \) and \( \mathbf{b} \) is calculated as:

\[
\text{cosine_similarity}(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \cdot \|\mathbf{b}\|}
\]

where \( \cdot \) denotes the dot product and \( \| \cdot \| \) represents the Euclidean norm.

Once the similarity matrix S is computed, each entry \( S[i][j] \) represents the similarity score between document \( i \) and document \( j \). This matrix serves as a foundation for various downstream tasks, including clustering, ranking, and retrieval.

**20Newsgroup:**

The above image shows the average scores for 19 topics. The topics are listed at the top of the graph, and the score for each word is shown on the y-axis. The x-axis shows different documents or groups of documents.

For example, the topic “cars” has a high score in documents 6, 8, and 10. This suggests that the words “car”, “cars”, “engine”, “ford”, “toyota”, “wagon”, “models”, “sedan”, “nissan”, “convertible”, and “driving” appear frequently in documents 6, 8, and 10.

On the other hand, the topic “religion” has a high score in documents 12, 14, and 15. This suggests that the words “god”, “jesus”, “christ”, “heaven”, “hell”, “eternal”, “faith”, “lord”, “jewish”, and “palestinian” appear frequently in documents 12, 14, and 15.
It is important to note that this is just a small sample of the data, and the overall trends may be different if we look at a larger dataset.

A similarity matrix is a way of representing the relationships between different things. In this case, the things being compared are the topics found in a set of documents. The matrix is made up of squares that are arranged in a grid. Each square shows the similarity score between the two topics.

The text labels at the top of the matrix show the different topics. The topics include things like "team_game_season", "beau_chain_e_bobbe_queens", "space_nasa_launch", "op_compass_dlen", "printer_print_deskjet", "sale_price_software", "islam_muslims_islamic", and "bible_gospels_luke", among others.

The color of each square shows the similarity score between the two topics that it corresponds to. A darker color indicates a higher similarity score, while a lighter
Fig. 3 20Newsgroups Similarity Matrix

color indicates a lower similarity score. For example, the square in the row labeled "space_nasa_launch" and the column labeled "fpu_mhz_speed" is a dark color, which suggests that the topics "space_nasa_launch" and "fpu_mhz_speed" are similar.

The diagonal line running from the top left corner of the matrix to the bottom right corner is dark because each topic is perfectly similar to itself.

This similarity matrix can be used to identify relationships between different topics. For example, it can be used to identify groups of topics that are closely related.

**Reuters:**

The above image is a graph of topic word scores for each topic. It appears to show the average scores for 20 topics. The topics are listed at the top of the graph, and the score for each word is shown on the y-axis. The x-axis shows different documents or groups of documents. Higher scores on the y-axis indicate that the word is more relevant to that topic.

For example, the word "VS" has a high score for topic 0 in document 0. This suggests that the word "VS" is very important for understanding topic 0 in document 0.

Some other interesting observations are:
The word "company" appears to be important across many topics. The word "dividend" is important for both topic 2 and topic 4. The word "earnings" is important for topic 2. The word "profit" is important for topic 1. It is important to note that this is just a visualization of a small sample of the data, and the overall trends may be different if we look at a larger dataset.

The above image specifies matrix appears to show the similarity of 138 different topics.

Here is what we demonstrate from the image:

The labels for the topics are arranged along the top and left sides of the matrix. Each square in the grid represents the similarity score between two topics. A darker-colored square indicates a higher similarity, while a lighter-colored square indicates a lower similarity. The diagonal line running from the top left corner to the bottom
right corner is dark because each topic is perfectly similar to itself. Without knowing what the specific topics are, it’s difficult to say anything more about the relationships between them.

However, similarity matrices can be useful tools for researchers who are trying to understand large amounts of data. By looking at the similarity matrix, researchers can identify groups of topics that are closely related. This can help them to make sense of the data and to identify patterns that they might not have noticed otherwise.

**Sports Dataset:**

The above image is a similarity matrix, just like the ones I described earlier. This specific matrix appears to show the similarity of countries based on news articles.

Here is we can demonstrate from the image:

The labels for the countries are arranged along the top and left sides of the matrix. Each square in the grid represents the similarity score between the two countries. A darker-colored square indicates a higher similarity, while a lighter-colored square indicates a lower similarity. The diagonal line running from the top left corner to the bottom right corner is dark because each country is perfectly similar to itself. For instance, the news articles about England and Wales appear to be more similar than the news articles about England and South Africa.
Similarity matrices can be useful tools for researchers who are trying to understand how news media portray different countries. By looking at the similarity matrix, researchers can identify groups of countries that are often mentioned in similar contexts. This can help them to understand how different countries are perceived by the news media.

It is important to note that this similarity matrix is based on news articles and may not reflect the full complexity of the relationship between countries.

4 Conclusion

We investigated the effectiveness of using BERT for document clustering across diverse datasets, aiming to address the need for advanced clustering techniques in managing large textual datasets. Our evaluation of 20News Group, Reuters, and BBC Sports datasets demonstrated BERT’s adaptability and superior performance in capturing semantic similarities and adapting to various domains.

BERT’s contextualized embeddings provided profound insights into document semantics, outperforming traditional methods across all datasets. Despite challenges
such as varied topics and languages, BERT showcased remarkable versatility, suggesting its potential for applications in information retrieval and knowledge discovery.

Our study reaffirmed BERT's superiority in document clustering through rigorous evaluation and sensitivity analysis. Future research may explore alternative transformer-based models and extend BERT-based clustering to additional domains and languages, unlocking the potential of advanced NLP techniques for extracting insights from textual data.

**Data Availability:** The datasets generated during and/or analyzed during the current study are available in the [Reuters-21578], [20-Newsgroup], and [BBC-sport] repositories.

Reuters-21578: https://www.kaggle.com/datasets/nltkdata/reuters/code
20-Newsgroup: https://www.kaggle.com/datasets/crawford/20-newsgroups
BBC-sport: https://www.kaggle.com/datasets/maneesh99/sports-datasetbbc

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