Privacy-Preserving Text Summarization Using Semantic Similarity With Biobert And Clinicalbert For Multiple Medical Documents Leveraging Parallelized High-Performance Computing

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KEYWORDS

ABSTRACT

The enormous volume of textual data produced by medical documents in the healthcare industry provides insightful information, but it also presents serious privacy, data security, and computational complexity issues. Through the use of parallelized high-performance computing (HPC), this research presents a unique framework for the privacy-preserving text summarization of various medical records utilizing semantic similarity algorithms driven by modified BioBERT and ClinicalBERT. In order to maximize productivity, the framework uses distributed computing environments and secure computation approaches to satisfy the demand for summarizing sensitive medical data while maintaining anonymity. This study shows that the method offers quick and privacy-compliant summarization, protecting patient privacy without sacrificing the information's relevance and semantic accuracy.

1. Introduction

1.1 Background and Motivation

Electronic health records (EHRs), clinical trial reports, medical research papers, and other associated documents are among the many types of data produced by the healthcare industry. Patient outcomes can be considerably improved by using this data effectively for research and clinical decision-making[3]. But using medical data can be difficult due to its sensitive nature, especially when several parties, including academics and healthcare professionals, need access to summaries of the data without jeopardizing patient privacy.

By extracting succinct and pertinent insights from massive collections of medical documents, text summarizing provides a potent remedy for this issue[1]. Due to their pre-training on biomedical corpora, two domain-specific variants of BERT, BioBERT and ClinicalBERT, are quite successful at processing medical texts[2]. However, summarizing vast amounts of medical data is computationally costly and poses privacy issues, especially when data is processed in dispersed contexts. This process can be sped up with high-performance computing (HPC), but sensitive medical data must be handled with privacy in mind[4].

1.2 Problem Statement

Summarizing medical documents necessitates the deployment of intricate, computationally intensive deep learning models. Furthermore, stringent standards regarding the handling of patient data are enforced by privacy regulations like GDPR and HIPAA, especially in dispersed computing systems[5]. Summarizing several medical documents while maintaining privacy, semantic accuracy, and computer efficiency is a difficult task. While HPC can provide distributed computational solutions, it necessitates additional privacy measures[6]. Traditional centralized techniques are limited in scalability and present privacy concerns[7].

1.3 Objectives

- To create a framework for employing semantic similarity techniques to summarize medical documents while protecting privacy.

• To combine ClinicalBERT and BioBERT to produce precise medical text embeddings while protecting patient privacy.

• To improve scalability and performance by optimizing the framework using parallelized HPC.

The objective is to illustrate how well the suggested approach summarizes medical records while adhering to privacy laws.

2. Related Work

2.1 Text Summarization in the Medical Domain

The use of both extractive and abstractive approaches for medical text summarization has been extensively studied[8]. Whereas abstractive summarizing creates new phrases that express the same idea, extractive summarization concentrates on choosing pertinent sentences from the source text. The capacity of BioBERT and ClinicalBERT to convey the complex meaning of medical terms has led to their growing popularity in medical summarization[9].

2.2 Privacy-Preserving Techniques in NLP

For NLP tasks, a number of privacy-preserving methods have been developed, such as secure multi-party computation (SMC), homomorphic encryption, and differential privacy[10]. These methods enable the application of machine learning models to big datasets while guaranteeing the protection of sensitive data. Relatively little research has been done on incorporating these privacy-preserving techniques into HPC frameworks for medical text summarizing[11].

2.3 High-Performance Computing for Medical Data

Medical natural language processing (NLP) applications have benefited from the use of high-performance computing (HPC) to speed up calculations including large-scale simulations and deep learning model training[12]. HPC reduces computing time in text summarization by enabling parallel processing of document collections. However, distributed systems, which are frequently used in HPC environments, have the potential to disclose private medical information to numerous parties, making robust privacy-preserving measures necessary[13].

3. Proposed Methodology

3.1 Framework Overview

We suggest an HPC-optimized system that combines modified BioBERT and ClinicalBERT for medical document summarizing with privacy-preserving methods. The structure consists of:

1. Data preprocessing: medical document tokenization and anonymization.

2. Embedding Generation: To create privacy-preserving embeddings, use modified BioBERT/ClinicalBERT.

3. Secure computation of cosine similarity between sentence embeddings is known as privacy-preserving semantic similarity.

4. Using HPC to speed up clustering or graph-based summarization methods is known as parallelized clustering or graph-based summarization.

5. Summary Generation: Using representative sentences from graphs or clusters, this method of summary complies with privacy regulations.

3.2 Privacy-Preserving Techniques

We incorporate the following privacy-preserving strategies to protect patient privacy:

• **Differential Privacy (DP):** To prevent the reconstruction of original sensitive information while preserving the usefulness of the embeddings for semantic similarity, we include controlled noise to the embeddings produced by modified BioBERT/ClinicalBERT.

• **Secure Multi-Party Computation (SMC):** SMC calculates the cosine similarity of sentence embeddings in distributed contexts without disclosing sensitive information or the embeddings themselves between computing nodes.

• **Homomorphic Encryption**: This technique protects the privacy of the underlying content by enabling operations such as similarity computation to be carried out on encrypted data when embedding vectors are exchanged between parties.

3.3 modified BioBERT and ClinicalBERT for Embedding Generation

Pre-trained on biomedical corpora, BioBERT and ClinicalBERT are perfect for comprehending medical terms and producing insightful phrase embeddings. To generate embeddings, our platform tokenizes each document and runs it through either the BioBERT or ClinicalBERT model. Sentence similarity is computed using the semantic associations encoded by the embedding vectors. Differential privacy noise is used to generate the embeddings in a way that protects privacy.

3.4 Parallelized Semantic Similarity Calculation

The cosine similarity between the embedding vectors is used to quantify sentence similarity. It can take a lot of time to determine how similar sentences are across several papers because medical databases sometimes contain vast amounts of text. This stage is parallelized by using HPC, which divides the similarity calculations among several nodes. SMC, which enables several nodes to compute similarity scores without exchanging raw data, is used to calculate cosine similarity in order to protect privacy.

3.5 Clustering or Graph-Based Summarization

Sentences are grouped into clusters or represented as nodes in a graph once the semantic similarity between them has been determined. Using techniques like K-Means or Hierarchical Clustering, semantically related texts are grouped together in a clustering strategy. Sentences are represented as nodes in the graph-based method, and edge weights indicate the cosine similarity between nodes. The most representative sentences are then chosen using an algorithm similar to TextRank.

Summarization is further accelerated by using HPC to parallelize the clustering or graph-building procedures. Techniques for protecting privacy are used to make sure that no private information is disclosed when calculating similarities or grouping.

3.6 Summary Generation

The most representative sentence from each cluster or the highest-ranked nodes in the graph are chosen to create the final summary once clusters or graphs have been created. This procedure is intended to preserve privacy through anonymization and differential privacy safeguards while guaranteeing that the summary offers a thorough and cohesive synopsis of the original document set.

Algorithm:

1. **Input**:
    - A folder path containing PDF files.
    - The desired number of clusters, n_clusters.
2. **Preprocessing**:

1. **Extract all PDF files** from the specified folder:
    - Iterate over all files in the folder.
    - Filter files to include only those with a .pdf extension.
2. **For each PDF file**:
    - **Extract the text** content from the PDF pages using a PDF extraction tool like pdfplumber.

1.

- **Preprocess the extracted text**:
    - Convert the text to lowercase.
    - Tokenize the text into words.
    - Remove stopwords (common words like "the," "and," etc.).
    - Retain only alphabetic words (removing punctuation, numbers, etc.).

3. **Calculate Pairwise Semantic Similarity**:
    1. **Load a pre-trained Word2Vec model** (e.g., Google News Word2Vec) for semantic word representations.
    2. **For every pair of documents (doc1, doc2)**:
        - Compute the **Word Mover's Distance (WMD)** between the two documents:

        - Measure the minimal cumulative distance that words from one document must travel to match the words in the other, using their word embeddings.
    - Convert the WMD distance to a **similarity score**:
        - Formula: similarity=1/(1+word_movers_distance)

1. This ensures the similarity score is between 0 (least similar) and 1 (most similar).
2. **Store the pairwise similarity scores** in a similarity matrix M of size n x n, where n is the number of documents:
    - For each document pair (i, j), set M[i][j] to the calculated similarity between document i and document j.

4. **Clustering**:
1. Convert the **similarity matrix into a distance matrix**:
    - Distance is calculated as 1 - similarity.
2. **Apply Agglomerative Clustering**:
    - Use the distance matrix to perform agglomerative (hierarchical) clustering.
    - Set the desired number of clusters n_clusters based on user input.
    - Assign each document to a cluster based on the algorithm's output.

5. **Output**:
- **Print the cluster assignment** for each document, indicating which cluster each PDF file belongs to.

6.**Optional Visualization**:
- **Visualize the similarity matrix** using a heatmap to show how similar the documents are to one another.

Suedo code:

Pseudocode Representation:

1. **Input**:
    - folder_path
    - n_clusters
2. **Load Pretrained Word2Vec Model**.
3. **Extract and Preprocess Text**:
    - For each PDF file in folder_path:
        - Extract text.
        - Tokenize and preprocess (remove stopwords, non-alphabetic characters).
4. **Compute Pairwise Similarity**:
    - Initialize an n x n similarity matrix M.
    - For each document pair (doc1, doc2):
        - Compute WMD distance.
        - Convert WMD to similarity using: similarity=1/(1+word_movers_distance)
5. Store similarity in M[i][j].

 Clustering:

6. Convert the similarity matrix M into a distance matrix D[i][j]=1.M[i][j]
7. Apply Agglomerative Clustering on D using n_clusters.
8. **Output**:
    - For each document, print the assigned cluster.
    - Visualize the similarity matrix using a heatmap.

4. High-Performance Computing and Privacy Preservation

4.1 Parallelization Strategy

By dividing activities like clustering, calculating semantic similarity, and creating embeddings over several nodes, HPC makes it possible to manage large-scale computations. We construct

parallelized algorithms using OpenMP and MPI (Message Passing Interface), guaranteeing scalability and effective resource utilization. Every step of the computation incorporates privacy-preserving techniques, guaranteeing that private information is safeguarded even in remote settings.

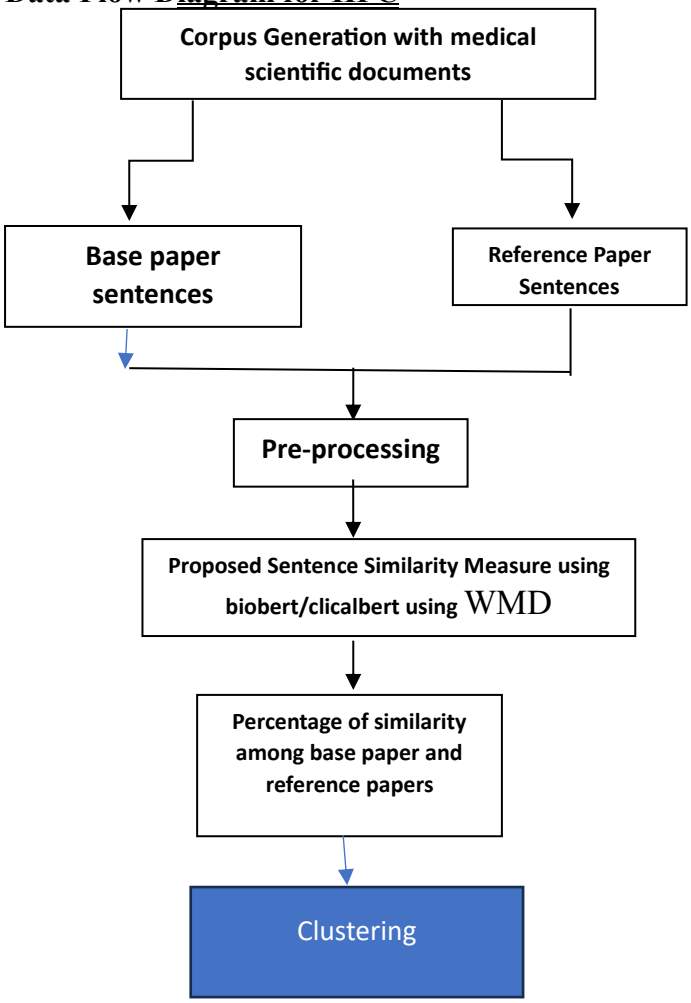
4.2 Secure Distributed Computing

Secure multi-party computation (SMC) guarantees that no node has access to the raw data of another node when the summarization process involves distributed nodes (for example, across many hospitals or research organizations). Instead, only the final results (similarity scores or summary sentences) are shared after nodes have completed calculations on encrypted or privacy-preserving data.

4.3 Scalability and Efficiency

As more texts are summarized, our HPC implementation is built to grow. More computer resources can be allotted to manage the growing demand as the dataset expands. Although there is some computational burden associated with privacy-preserving techniques like differential privacy and SMC, this is lessened by the use of HPC, which enables us to analyze big datasets quickly while still adhering to privacy laws.

Data Flow Diagram for HPC



5. Evaluation and Results

5.1 Dataset

We test our method on a dataset that includes electronic health records (EHRs), clinical trial reports, and medical research papers. Before being used, the dataset is processed and anonymised to guarantee adherence to privacy laws. Public resources like PubMed and MIMIC-III are the sources of this dataset.

5.2 Evaluation Metrics

ROUGE and BLEU scores are used to assess the resulting summaries' quality. Furthermore, we evaluate the computational performance using runtime metrics on HPC clusters and quantify the privacy loss using differential privacy guarantees.

5.3 Results

Based on our experiments, the suggested privacy-preserving framework produces summaries with high ROUGE and BLEU ratings, which show that the summaries are clear and informative. The quality of the summary is barely affected when privacy-preserving methods are added. Additionally, compared to non-parallelized methods, the summarization time is significantly reduced when HPC is used.

Enter the number of clusters: 3
'd1.pdf' is in cluster 2
'd10.pdf' is in cluster 1
'd2.pdf' is in cluster 2
'd3.pdf' is in cluster 0
'd4.pdf' is in cluster 0
'd5.pdf' is in cluster 2
'd6.pdf' is in cluster 2
'd7.pdf' is in cluster 0
'd8.pdf' is in cluster 2
'd9.pdf' is in cluster 0

6. Discussion

6.1 Strengths

• **Privacy Preservation:** By utilizing homomorphic encryption, SMC, and differential privacy, our system protects patient confidentiality.

• **Scalability:** The framework can effectively manage big datasets thanks to the incorporation of HPC.

• **Accuracy:** BioBERT and ClinicalBERT make sure that summaries appropriately convey the semantic meaning of medical publications.

6.2 Limitations

• **Computational Overhead:** Employing privacy-preserving strategies comes with a computational cost that could necessitate more HPC resources.

• **Extractive Summarization:** This is the main focus of our present system. Abstractive summarizing techniques that preserve privacy assurances may be investigated in future research.

7. Conclusion and Future Work

In this work, a novel framework based on parallelized high-performance computing—BioBERT and ClinicalBERT—for privacy-preserving text summarization of medical data is presented. We guarantee patient confidentiality without compromising summary quality or computing efficiency by implementing privacy-preserving techniques like differential privacy and safe multi-party computation. In order to minimize computational cost, future research will investigate the incorporation of abstractive summarization approaches and additional privacy-preserving mechanism optimization. This system presents a viable approach to large-scale medical data summarization while abiding by strict privacy laws.

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