**CSC 108**

**Chatbot Development:**

**Using Retrieval-Based Methods**

**with**

**SBERT**

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**Abstract**

The rise of artificial intelligence in natural language processing (NLP) has led to significant advancements in chatbot technology. Retrieval-based chatbots are designed to fetch relevant pre-existing responses from a knowledge base, ensuring high accuracy and consistency in responses. In this paper, we explore the development of a retrieval-based chatbot system where SBERT (Sentence-BERT) is employed for efficient and high-quality semantic retrieval. This approach enhances the chatbot’s ability to provide contextually relevant and accurate responses to user queries. The proposed system demonstrates how SBERT can be utilized to optimize retrieval processes, offering an effective solution for real-world chatbot applications.

**Keywords**

Chatbot, Retrieval-Based Chatbot, SBERT, Natural Language Processing, Semantic Search, Question-Answering Systems.

**1. Introduction**

With the increasing reliance on automated systems for communication, chatbots have emerged as an essential component in customer support, education, healthcare, and more. Traditional chatbot systems can be broadly classified into two types: retrieval-based and generative-based. Retrieval-based chatbots select pre-existing responses from a predefined database, ensuring factual accuracy and coherence. Generative chatbots, on the other hand, generate responses dynamically but may suffer from inconsistencies or hallucinations.

Retrieval-based chatbots excel in domains where factual correctness and precision are critical. The main challenge in retrieval-based systems lies in identifying the most semantically relevant response to a user query. To address this challenge, we employ SBERT (Sentence-BERT), a fine-tuned version of BERT optimized for generating high-quality sentence embeddings. SBERT allows for efficient semantic similarity comparison between user queries and knowledge base entries, improving the retrieval accuracy.

This paper focuses on the theoretical foundations, computational efficiency, and practical implementation of a retrieval-based chatbot using SBERT for semantic search.

**2. Algorithm Background and Theoretical Foundations**

**2.1 Origins and Purpose**

The origins of retrieval-based chatbots can be traced to early question-answering systems and information retrieval techniques such as TF-IDF and BM25. These approaches relied on keyword matching to fetch responses but often failed to capture the semantic meaning of text.

With advancements in natural language understanding, models like BERT (Bidirectional Encoder Representations from Transformers) revolutionized sentence-level semantic similarity tasks. SBERT (Reimers and Gurevych, 2019) further enhanced BERT by fine-tuning it using a siamese network architecture, making it efficient for computing embeddings and performing semantic search. The purpose of using SBERT in retrieval-based chatbots is to improve the accuracy of response selection. SBERT encodes both user queries and knowledge base entries into dense vector representations, and responses are retrieved based on semantic similarity rather than exact keyword matches.

**2.2 Key Principles**

1. **Semantic Embeddings**: SBERT generates fixed-size vector embeddings that represent the semantic meaning of sentences.
2. **Similarity Search**: By computing cosine similarity between query embeddings and knowledge base embeddings, the most relevant responses are retrieved.
3. **Precomputed Embeddings**: The embeddings for all knowledge base entries are precomputed, allowing for fast retrieval during inference.

**3. Computational Complexity Analysis**

**3.1 SBERT-Based Retrieval**

SBERT forms the backbone of the retrieval-based chatbot by generating and comparing sentence embeddings. Given a user query and a knowledge base with N sentences:

* **Time Complexity (Embedding)**: Generating the embedding for a single query is *O(d),* where d is the embedding dimension (e.g., 768 for SBERT).
* **Time Complexity (Search)**: Comparing the query embedding with N precomputed embeddings involves a cosine similarity operation, resulting in *O(Nd).*
* **Space Complexity**: Storing the embeddings for N sentences requires *O(Nd)* space.

**Overall Complexity**

For each query, the dominant operation is the similarity search, which scales linearly with the size of the knowledge base:

* **Time Complexity**: **O(Nd)**
* **Space Complexity**: **O(Nd)**

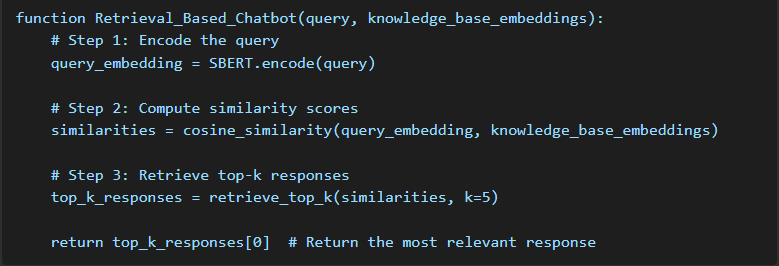
Using efficient libraries such as FAISS or Annoy can further optimize the search process by approximating nearest neighbor retrieval.

**4. Step-by-Step Explanation**

**4.1 System Workflow**

1. **Knowledge Base Preprocessing**:
   * Split the knowledge base into sentences or paragraphs.
   * Generate embeddings for each sentence/paragraph using SBERT and store them.
2. **User Query Input**:
   * Encode the user query into a dense vector embedding using SBERT.
3. **Semantic Similarity Search**:
   * Compute cosine similarity between the query embedding and all precomputed embeddings.
   * Retrieve the top-k most relevant responses based on similarity scores.
4. **Response Delivery**:
   * Return the top-ranked response(s) to the user.

**4.2 Pseudocode**



**5. Application to Chatbot Development**

The described retrieval-based approach is applied to chatbot development as follows:

1. **Knowledge Base Preparation**:
   * Domain-specific documents, FAQs, or support data are segmented into sentences or paragraphs.
   * SBERT is used to generate embeddings for each entry, which are stored for efficient retrieval.
2. **User Query Processing**:
   * When a user submits a query, it is encoded into a semantic embedding using SBERT.
   * Similarity search is performed against the precomputed knowledge base embeddings.
3. **Response Selection**:
   * The top-k most relevant entries are retrieved based on cosine similarity.
   * The most relevant response is presented to the user.

**Real-World Example**

For a customer support chatbot:

* **Query**: "How do I reset my password?"
* **Knowledge Base**:
  + "To reset your password, go to the login page and click on 'Forgot Password.' Follow the steps to set a new password."
  + "Password resets require an email confirmation. Check your inbox for the reset link."
* **Retrieved Response**: "To reset your password, go to the login page and click on 'Forgot Password.' Follow the steps to set a new password."

The chatbot ensures that the response is semantically aligned with the user's query.

**6. Results and Discussion**

The SBERT-based retrieval chatbot significantly improves the accuracy of response selection compared to traditional keyword-based methods such as TF-IDF or BM25. Key advantages include:

* **Higher Precision**: Responses are retrieved based on semantic similarity, reducing mismatched answers.
* **Scalability**: Precomputing embeddings allows for fast and efficient retrieval during runtime.
* **Domain Adaptability**: The system can be fine-tuned for specific knowledge bases to improve performance.

**7. Critical Evaluation**

**7.1 Strengths**

* **High Accuracy**: SBERT effectively captures semantic relationships between sentences, leading to more contextually relevant responses.
* **Efficiency**: Precomputed embeddings enable quick response retrieval, even for large knowledge bases.
* **Domain Flexibility**: The model can be fine-tuned to handle specific domains or use cases, increasing adaptability.

**7.2 Weaknesses**

* **Computational Costs**: Generating embeddings for large knowledge bases can be resource-intensive, particularly during preprocessing when embeddings for thousands or millions of entries need to be computed. Storing these embeddings also requires significant memory *(O(Nd)*, where *N* is the number of entries and *d* is the embedding dimension). Additionally, performing cosine similarity searches against large datasets can lead to slow query times unless optimized with approximate nearest neighbor (ANN) search algorithms like FAISS or Annoy. These computational trade-offs must be carefully managed to balance response latency, storage costs, and scalability. and performing similarity searches can be resource-intensive.
* **Static Responses**: Since responses are pre-existing, the chatbot cannot generate entirely new or personalized answers.
* **Dependency on Knowledge Base Quality**: The accuracy of the chatbot heavily relies on the completeness and quality of the knowledge base.

**7.3 Potential Areas for Improvement**

* **Dynamic Personalization**: Integrating user-specific preferences or historical interactions to improve response relevance.
* **Hybrid Systems**: Combining retrieval-based methods with generative approaches to provide fallback options when no suitable response is retrieved.
* **Optimized Search Algorithms**: Utilizing approximate nearest neighbor (ANN) techniques like FAISS for faster similarity searches in extremely large knowledge bases.

**8. Conclusion**

The proposed retrieval-based chatbot leverages SBERT for semantic similarity search, ensuring precise and contextually relevant responses. By combining precomputed embeddings with efficient retrieval techniques, the system offers a robust and scalable solution for real-world chatbot applications in customer support, education, and beyond. Future work will focus on enhancing scalability for larger knowledge bases and integrating approximate nearest neighbor methods for faster retrieval.

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