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ENHANCING ANSWER RANKING IN MARATHI: A MULTI-FACETED APPROACH USING LEXICAL-SYNTACTIC, SEMANTIC, AND CONTEXTUAL SIMILARITY

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Abstract—This paper presents a comprehensive approach to enhance answer ranking in Marathi question answering systems through the integration of lexical-syntactic, semantic, and contextual similarity measures. The goal is to improve the accuracy and relevance of answer selection, advancing Marathi language processing and developing more effective question answering systems. The evaluation is conducted using the Mean Reciprocal Rank (MRR) metric, achieving an impressive MRR value of 0.91 with the weighted combination of similarity measures. These results emphasize the significance of considering multiple dimensions of similarity and utilizing appropriate weights to prioritize different features. The study contributes to the advancement of Marathi question answering systems by demonstrating the effectiveness of integrating lexical-syntactic, semantic, and contextual similarity measures, providing valuable insights for the development of precise and pertinent answer ranking techniques in Marathi language processing.
Keywords— Question Answering, Answer Ranking, Similarity measures, Lexical-Syntactic Semantic and Contextual similarity, Information Retrieval, Natural Language Processing

1. INTRODUCTION

Natural Language Processing (NLP) is widely employed to tackle question answering tasks, which fall under the umbrella of Natural Language Understanding. Question Answering Systems (QAS) leverage NLP techniques to provide answers to natural language questions by searching and traversing multiple online or offline documents. While significant progress has been made in solving reading comprehension-based question answering tasks in English, where answers are extracted from relevant passages, it is crucial to provide relevant passages to the reader module in order to obtain accurate answers to user input questions.

The evaluation and ranking of the relevance and quality of passages in response to a given question play a vital role in natural language processing and information retrieval. Answer ranking is an essential approach utilized in question answering systems, information retrieval, and search engines. It assesses the suitability and accuracy of each answer, ensuring that users are presented with reliable and pertinent information. By employing answer ranking techniques, these systems enhance user experience by delivering precise and relevant answers, thereby improving overall satisfaction and user engagement.

The number of Indian language internet users has significantly increased in recent years due to easy access to smartphones and affordable internet rates. Non-English language users now outnumber English users [1]. Indians prefer local language internet searches, with abundant digital content available in various regional languages for news, events, and government services. Marathi is the official language of Maharashtra state in India with more than 90 million native speakers, it is also in the top ten rank for most native speakers per language [2]. Devanagari script is most widely used for writing Marathi content.

The primary objective of answer ranking is to determine the degree of similarity between a search query and the relevant passages. This process involves analyzing the content of the question and comparing it to potential texts in the paragraphs to identify similarities. To achieve this objective, various methods and techniques are employed to extract and measure similarity. In the context of Marathi question answering systems, it is crucial to incorporate a diverse range of similarity measures. The research highlights the importance of integrating lexical-syntactic similarity measures to capture the intricate structural characteristics and syntactic patterns specific to the Marathi language. This approach allows for more precise and effective matching of question-answer pairs. Semantic similarity measures also play a significant role in capturing the underlying meaning and intent of both questions and candidate answers. By employing semantic analysis, the research aims to identify answers that are semantically equivalent or closely related to the question, thus enhancing the accuracy of answer ranking. Furthermore, contextual similarity measures are employed to leverage the contextual cues present in both the questions and answers. This enables a deeper understanding of the context, leading to the selection of answers that are not only accurate but also contextually relevant.

By combining these various similarity measures, the study aims to provide a comprehensive understanding of the nuances of the Marathi language. This integrated approach is expected to result in substantial improvements in answer ranking and the development of highly accurate and reliable Marathi question answering systems.

2. RELATED WORK

Very little work is done to develop the Marathi Question Answering System. English ontology was used by Chaware et al. [3] to answer Marathi questions. Onto terms extracted from english translated questions were used to extract answers from ontology. Govilkar et al. [4] developed semantic question answering using ontology created using domain experts. Subject, object and verb were extracted from questions which helped in generating onto triples which finally extracted exact answers from ontology. S. Kamble et al. [5] scrapped questions and manually translated them into Marathi to create a Marathi Question Classifier using 1000 questions. The classifier was created using a direct and translation approach and got the best accuracy using a translation approach with 73.5% for coarse-grained class and 47.5% for fine-grained class. Darshan Navalakha et al. [6] created a chatbot system in Marathi language where the system automatically replied to user questions by extracting answers from pdf and images using OCR. Bharat Shelke et al. [7] created a question database for Marathi language. The questions were extracted from the Balbharti book for the 2nd to 4th standard classes. Total 901 questions were extracted from 50 different question types. Around 307 questions were of question type "काय" as the questions were extracted from the student textbook. Aarushi Phade et al. [8] built Marathi language question answering systems by fine tuning Multilingual BERT model on a custom dataset of 1500 questions over wikipedia and new articles and achieved F1-score of 56.7% and Bert-score of 69.08%.

Different authors have conducted experiments to perform answer ranking using various similarity measures for both Marathi and Hindi languages. Shelke et al. [9] investigates the use of similarity measurements in a Marathi Question Answering (QA) system by evaluating the similarity of each candidate answer to the model answer for each model question. The study compares model question answers with candidate answers using four similarity measures: Sequence Matcher Percentage, Jaccard Similarity, Cosine Similarity, and Levenshtein Distance Similarity. For the experiment sixty model question answers were created and compared each model answer with forty candidate answers The experiment collected 9600 candidate answers from the Balbharti Marathi textbook for classes II, III, and IV. The results showed that out of these, 5236 were correct, 1114 were wrong, and 3250 were considered incorrect. The overall similarity results indicated a precision of 82.46, accuracy of 54.54, and an error rate of 33.85. Notably, the Jaccard similarity and sequence similarity measures yielded superior outcomes. Shubhamkar Joshi et al. [10] investigate the effectiveness of different embedding techniques for Marathi question answering (QA) systems. They evaluate multiple sentence embedding algorithms and employ supervised machine learning models to compare their accuracy. The models trained on translated MLQA Marathi Dataset show promising results, with Kernel SVM, XGBoost, CNN, and Multinomial Logistic Regression outperforming the median accuracy. LASER and Word2Vec embeddings, particularly their cosine similarity, outshine other methods. Word2Vec embeddings trained over context exhibit superior semantic understanding of Marathi text. The study suggests that combining cosine similarity with other metrics used for English and Hindi can enhance answer sentence selection accuracy. Devika Verma et al. [11] investigate answer sentence selection in Hindi for Question Answering (QA). They explore the significance of Karaka relations, a crucial syntactico-semantic analysis tool for Hindi sentences. Through empirical experiments, the authors compare various similarity measures, sentence embeddings, and machine learning models. Combining Karaka relation features with cosine similarity, word movers distance, and content word overlap yields the highest accuracy of 64.60%. Using Karaka relations alone achieves an accuracy of 57.22%, outperforming other single-similarity feature sets. These findings demonstrate the potential of Karaka relations as a semantic similarity measure, reducing reliance on large pre-trained language models and enhancing computational efficiency while maintaining accuracy. Manvi Breja et al. [12] tackle the challenge of answering ambiguous "why" questions in English. They propose an answer re-ranking and validation model that considers lexico-syntactic, semantic, and contextual similarities between questions and answer candidates. The importance of each feature type is determined using a proposed algorithm based on Mean Reciprocal Rank (MRR). The re-ranking model achieves an MRR of 0.64, demonstrating the significance of semantic features in answering "why" questions.

3. PROPOSED SYSTEM

To develop a Marathi monolingual question answering system, a retriever-reader approach is employed. The process begins with the question being processed, and relevant features related to the question are extracted. This step aids in understanding the key aspects and requirements of the question. In the retriever module, an efficient semantic matching process is utilized to identify the most appropriate context or passage that is relevant to the question. The purpose of this module is to extract the most pertinent information that has the potential to provide the answer. Once the retriever module identifies the relevant context, it is passed along with the question to the reader module. The reader module's objective is to comprehend the context and accurately locate the specific portion of the passage that addresses the question. It focuses on extracting the correct answer span from the passage, ultimately providing an accurate answer to the question. By combining the retriever and reader modules, the Marathi monolingual question answering system effectively retrieves and processes the relevant information, enabling it to provide precise answers to the given questions.

The primary objective of this study revolves around constructing and evaluating a highly effective answer ranking mechanism. This mechanism plays a critical role in the question answering system, ensuring that the most suitable and accurate answers are identified and presented to the users.

The question processing module plays a pivotal role in preparing questions for further analysis in a question answering system. This module begins by tokenizing the question, breaking it down into individual tokens, and normalizing it by removing unwanted content or noise. After preprocessing, various features of the question are extracted to gain a deeper understanding of its structure and intent. These features include identifying the type of question, such as "कधी" (When) or "कोणी" (Who), which provides important contextual information. Additionally, the question focus or keywords, typically nouns, adjectives, or verbs, are determined. These keywords help in identifying the key aspects and topics of the question. By extracting these question features, the system gains valuable cues for subsequent processing steps.

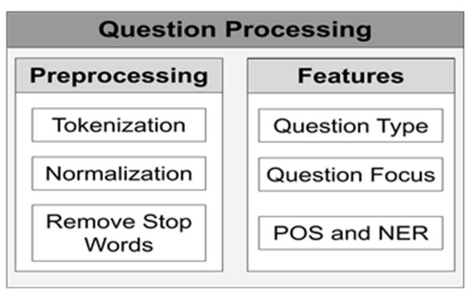


Figure 1: Components of question processing module

Leveraging this information, the system can retrieve relevant passages or contextual information from a larger text corpus. These passages or contextual information serve as the basis for further analysis and enable the system to provide accurate and relevant answers to the user's query. Overall, the question processing module is instrumental in preparing the question for subsequent stages of analysis and information retrieval, ultimately facilitating the accurate retrieval of relevant passages or contextual information for answering the question effectively. Figure 1 depicts the Question Processing Module.

In Figure 2, the answer retriever module has a primary objective of extracting the most relevant passage or context that pertains to a given question. The process begins with the question being searched through a search engine, and the top five results are chosen. From these results, paragraphs are extracted from the corresponding HTML pages. The extracted contexts are then tokenized and normalized, which involves breaking them down into individual units (tokens) and applying standard formatting or transformations to ensure consistency. Additionally, keywords are extracted from the context to capture important terms or phrases. Once these linguistic features are obtained, the answer retriever module selects the top 5 passages based on the maximum number of matching keywords between the question and the extracted contexts. This step helps narrow down the potential answers to those that are most likely to be relevant. The ranking of the selected contexts poses a challenge, but it is crucial to determine the final answer.

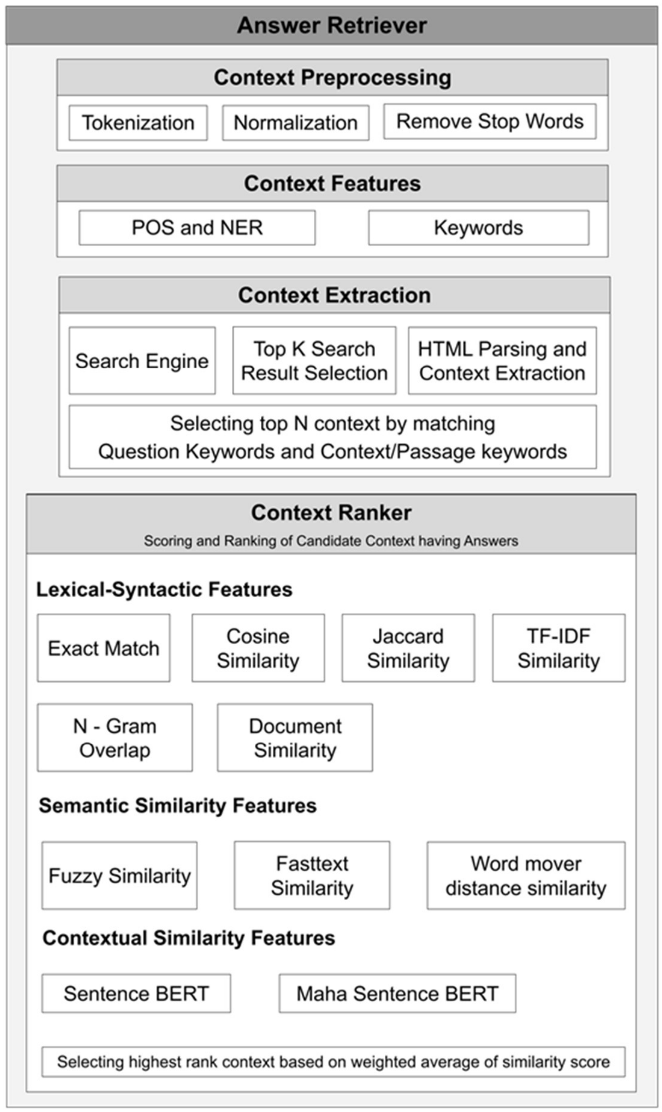


Figure 2: Components of answer retriever module

To rank the relevant contexts, a combination of contextual, semantic, and lexical-syntactic similarity measures is utilized. These measures evaluate the alignment of the context with the question in terms of meaning, word usage, and sentence structure. The objective of the answer retriever module is to identify the most appropriate passage or context that provides the answer to the given question.

Lexical-syntactic features analyze the terms present in both the question and its answer candidates to assess their relatedness. By considering the linguistic properties and relationships of the words, these features help in identifying connections and similarities. Semantic features delve into the meanings and semantic relationships of the words. They evaluate how closely the content aligns with the question and identify relevant information. Contextual features make use of advanced sentence embedding techniques, such as recurrent neural networks (RNNs), transformer models, or self-attention mechanisms. These techniques encode the context of the question and answer sentences into continuous vector representations. The resulting representations capture the semantic relationships and dependencies within the sentences. This means that they can identify the meaning of each word in a sentence, as well as how the words relate to each other. This information can then be used to compare the question to the candidate contexts. The system can determine which context is most relevant to the question by looking at how closely the semantic relationships and dependencies in the context match those in the question.

Lexical-syntactic features are linguistic features that play a crucial role in determining text similarity by focusing on the structure and composition of words and sentences. These features encompass various techniques, including exact keyword matching, cosine similarity, Jaccard similarity, document similarity, TF-IDF similarity, and n-gram overlap.

Exact keyword matching involves comparing the presence of specific words or phrases in both the question and the context. If the keywords from the question are found in the context, it indicates a potential match. Cosine similarity measures the similarity between two documents by calculating the cosine of the angle between their vector representations in a high-dimensional space. It considers the magnitude and direction of the vectors to assess their similarity. Jaccard similarity, on the other hand, compares the overlap and size of two sets of words. It quantifies the similarity based on the intersection and union of words present in both the question and the context. Document similarity examines the similarity between the entire question and the context by considering all the words and their frequencies. It takes into account the distribution of words in both texts to determine their similarity. TF-IDF similarity takes into account the importance of words in a document by considering their frequency in the specific document and across the entire corpus. It assigns higher weights to words that are more discriminative or characteristic of the document. N-gram overlap focuses on matching sequences of n words in both the question and the context. It captures the similarity based on the shared sequences of words, allowing for a more granular analysis. Overall, these lexical-syntactic features provide diverse approaches to assess text similarity, considering different aspects of word usage and composition.

Semantic features aim to capture the deeper meaning and intent behind words, going beyond their surface-level representation. They offer methods such as fuzzy string matching, soft cosine similarity, and word mover distance similarity. Fuzzy string matching compares strings based on their similarity, taking into account character-level differences and patterns. It allows for more flexible matching by considering variations in spelling, punctuation, or word order. Soft cosine similarity utilizes word embeddings, such as fastText embeddings [13], to measure the similarity between documents. This method considers not only the frequency of words but also the semantic relationships between them. By incorporating word embeddings, it captures the meaning and context of words, resulting in more accurate similarity measurements. Word mover distance similarity calculates the minimum distance between the embedded word vectors of two documents. It takes into account both the semantic similarity between words and the overall distance needed to transform one set of word vectors into another. This feature considers the semantic relationships between words and their overall contextual meaning, providing a more comprehensive similarity measure.

These semantic features offer techniques that enable a deeper understanding of text by capturing the underlying meaning and intent. By considering character-level differences, semantic relationships, and contextual distance, they contribute to a more nuanced assessment of semantic similarity between documents. Contextual features are employed to capture the overall context and meaning of sentences. These features utilize sentence embedding techniques such as sentence BERT, and MahaSBERT to represent sentences as continuous vector representations. Through these embeddings, the semantic and syntactic information of sentences is captured, enabling more accurate similarity comparisons. By applying sentence embedding techniques, sentences are transformed into vector representations that encode their semantic and syntactic properties. These embeddings capture the underlying meaning and contextual nuances, allowing for a more comprehensive understanding of sentence similarity. The vector representations facilitate comparisons between sentences based on their semantic and syntactic similarity rather than relying solely on surface-level features. Utilizing techniques such as sentence BERT, and MahaSBERT, contextual features enhance the accuracy of similarity assessments by considering the broader context and meaning of sentences. The continuous vector representations obtained through these techniques enable more precise comparisons, taking into account the semantic and syntactic relationships between sentences. Due to the low resource nature of Marathi as a language, there is limited availability of transformed-based models specifically designed for tasks like text similarity extraction. To overcome the challenges posed by the low-resource nature of Marathi as a language, this research incorporates the Sentence BERT multilingual model [14] and the MahaSBERT monolingual Marathi model [15] for text similarity extraction.

In the ranking process, all the scores of contextual, semantic, and lexical-syntactic similarity measures are combined using a weighted average. This approach assigns different weights to each type of similarity measure based on their relative importance. By assigning appropriate weights, the ranking algorithm can prioritize certain features over others, reflecting their significance in determining the overall similarity between the question and the contexts.

Once the most relevant context is identified, it is passed on to the answer reader module to extract the answer from it. This process ensures that the context with the best match is selected, increasing the likelihood of retrieving an accurate answer for the given question using the answer reader module.

4. EXPERIMENT AND RESULTS

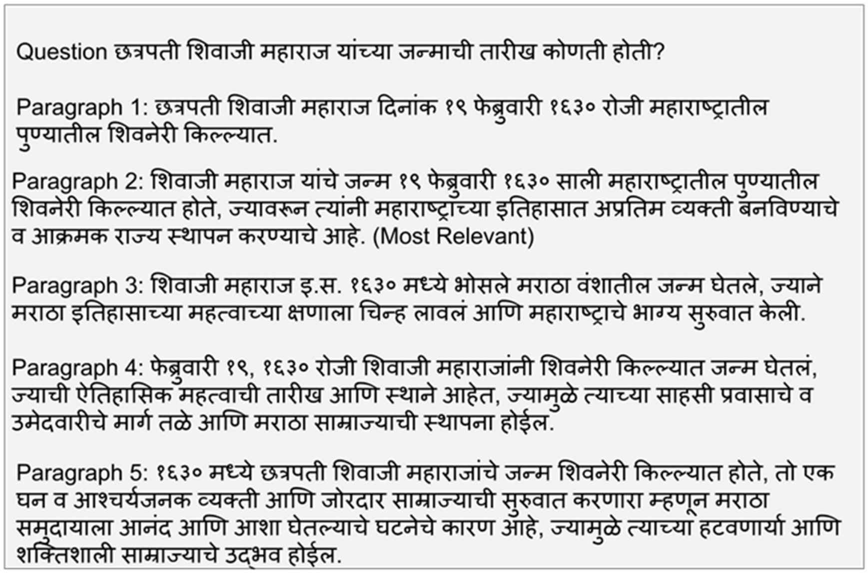
In the field of information retrieval (IR), the Mean Reciprocal Rank (MRR) serves as a widely employed metric for evaluating the effectiveness of ranking algorithms. It primarily focuses on assessing how well a ranking algorithm places the first relevant item within a ranked list of results. The MRR achieves this by calculating the reciprocal rank of the first relevant item, which is essentially the inverse of its position in the list. To compute the MRR, the reciprocal ranks of all queries within an evaluation set are averaged.

A higher MRR score indicates a ranking algorithm's superior performance, implying that the relevant items are typically positioned closer to the top of the ranked list. Essentially, a higher MRR signifies that the algorithm exhibits an enhanced capability to identify the most relevant information for a given query. Thus, the MRR metric plays a crucial role in evaluating and comparing the effectiveness of ranking algorithms in the field of information retrieval.

To rank answers based on a question and a set of relevant passages, the Mean Reciprocal Rank (MRR) is computed by averaging the reciprocal ranks of the relevant passages for each question. The reciprocal rank of a passage is determined by counting the number of passages that are ranked lower than the specific passage in the overall list of passages. For instance, if a passage is ranked first among all the passages, its reciprocal rank would be 1/1. If a passage is ranked second, its reciprocal rank would be 1/2. In general, a higher reciprocal rank score signifies that the passage is more pertinent or relevant to the given question. Therefore, when calculating the MRR, the reciprocal ranks of the relevant passages are considered, and the average of these reciprocal ranks is taken. This metric helps assess the effectiveness of the ranking system by measuring how well the most relevant passages are positioned in relation to the other passages in the list.

The evaluation of the proposed answer ranking technique is performed using the Mean Reciprocal Rank (MRR) as the assessment metric. To conduct this evaluation, a dataset consisting of Marathi questions and their corresponding sets of five relevant passages or contexts is gathered. The dataset comprises a total of 3,134 questions, with each question accompanied by five relevant passages or contexts. In total, the dataset encompasses 15,670 distinct question and relevant passage pairs.

Within the dataset, a single passage is designated manually as the most pertinent passage among five passages that pertain to a given question. Each question-passage pair is assigned a similarity score, which quantifies the degree of similarity between them. These similarity scores are then employed to rank all five passages with respect to their relevance to the question. The question-passage pair exhibiting the highest similarity score is assigned a rank of 1, while the pair with the lowest score is assigned a rank of 5. In order to optimize the Mean Reciprocal Rank (MRR), various weight combinations are experimentally tested to identify the most suitable weight for each type of similarity score.



Question छत्रपती शिवाजी महाराज यांच्या जन्माची तारीख कोणती होती?

Paragraph 1: छत्रपती शिवाजी महाराज दिनांक १९ फेब्रुवारी १६३० रोजी महाराष्ट्रातील पुण्यातील शिवनेरी किल्ल्यात.

Paragraph 2: शिवाजी महाराज यांचे जन्म १९ फेब्रुवारी १६३० साली महाराष्ट्रातील पुण्यातील शिवनेरी किल्ल्यात होते, ज्यावरून त्यांनी महाराष्ट्रांच्या इतिहासात अप्रतिम व्यक्ती बनविण्याचे व आक्रमक राज्य स्थापन करण्याचे आहे. (Most Relevant)

Paragraph 3: शिवाजी महाराज इ.स. १६३० मध्ये भोसले मराठा वंशातील जन्म घेतले, ज्याने मराठा इतिहासाच्या महत्वाच्या क्षणाला चिन्ह लावलं आणि महाराष्ट्राचे भाग्य सुरुवात केली.

Paragraph 4: फेब्रुवारी १९, १६३० रोजी शिवाजी महाराजांनी शिवनेरी किल्ल्यात जन्म घेतलं, ज्याची ऐतिहासिक महत्वाची तारीख आणि स्थाने आहेत, ज्यामुळे त्याच्या साहसी प्रवासाचे व उमेदवारीचे मार्ग तळे आणि मराठा साम्राज्याची स्थापना होईल.

Paragraph 5: १६३० मध्ये छत्रपती शिवाजी महाराजांचे जन्म शिवनेरी किल्ल्यात होते, तो एक घन व आश्चर्यजनक व्यक्ती आणि जोरदार साम्राज्याची सुरुवात करणारा म्हणून मराठा समुदायाला आनंद आणि आशा घेतल्याचे घटनेचे कारण आहे, ज्यामुळे त्याच्या हटवणार्या आणि शक्तिशाली साम्राज्याचे उद्भव होईल.

Figure 3: Question and relevant passage related to question

The MRR values have been calculated for each type of similarity score, as depicted in Figure 4, Figure 5 and Figure 6.

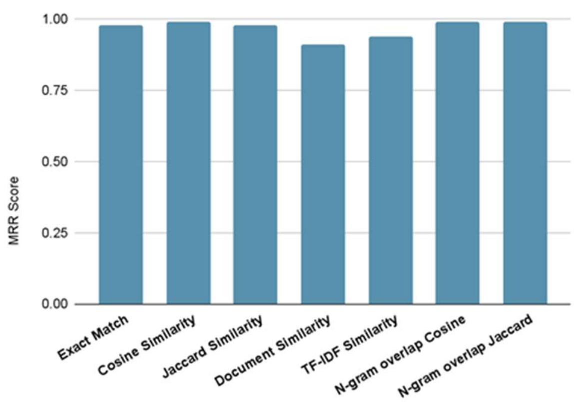


Figure 4: Comparison of MRR Score for Lexical-Syntactic similarity

In order to determine the ideal weight for each type of similarity score, we conducted experiments with various weight combinations. Initially, we assigned equal weights of 0.33 to each type. This resulted in an MRR of 0.49. Subsequently, we adjusted the weights, increasing the values for lexical-syntactic and contextual similarity scores to 0.4, while reducing the weight of semantic similarity scores to 0.2. Consequently, the MRR improved to 0.54. Notably, we observed that the semantic similarity score had a notable impact on the overall MRR when considering the weighted average of the three types of scores.

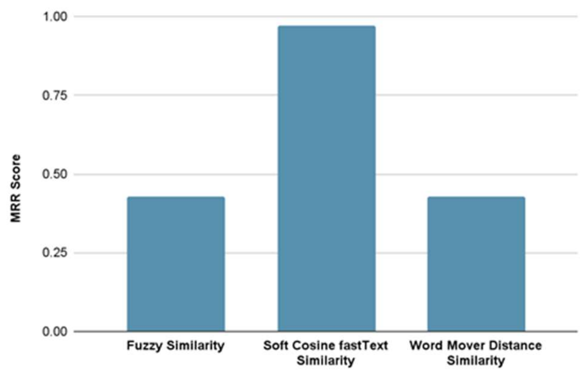


Figure 5: Comparison of MRR Score for Semantic similarity

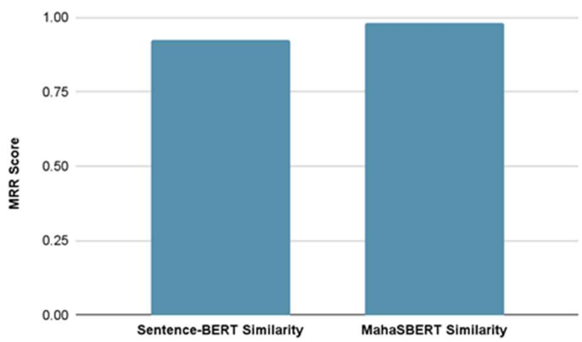


Figure 6: Comparison of MRR Score for Contextual similarity

By systematically exploring different weight combinations, we identified the optimal weights for achieving the highest MRR. Specifically, we determined that assigning a weight of 0.35 to lexical-syntactic similarity scores, 0.05 to semantic similarity scores, and 0.60 to contextual similarity scores yielded an impressive MRR value of 0.91. Table 1.1, illustrates the weights used for different combinations and their corresponding MRR values.

TABLE 1: MRR value based on different weights for lexical-syntactic, semantic, and contextual similarity score

Weight for Lexical-Syntactic	**Weight for Semantic**	**Weight for Contextual**	**MRR value**
0.33	0.33	0.33	0.49
0.40	0.20	0.40	0.54
0.45	0.10	0.45	0.71
0.47	0.06	0.47	0.86
0.60	0.05	0.35	0.88
0.50	0.05	0.45	0.89
0.40	0.05	0.55	0.90

0.35	**0.05**	**0.60**	**0.91**

5. CONCLUSION

The study focused on enhancing answer ranking in Marathi question answering systems by adopting a multi-faceted approach that incorporated lexical-syntactic, semantic, and contextual similarity measures. By leveraging these different aspects, the research aimed to improve the accuracy and relevance of answer selection. The use of lexical-syntactic features allowed for precise matching of question-answer pairs by analyzing language structures. Semantic similarity measures captured the underlying meaning and intent, enabling the identification of semantically equivalent answers. Contextual similarity helped in understanding the context and selecting contextually relevant answers. With the utilization of a weighted average of similarity scores, incorporating weights of 0.35, 0.05, and 0.60 for lexical-syntactic, semantic, and contextual measures respectively, the achieved MRR value reached an impressive 0.91. The results show that lexical-syntactic and contextual similarity measures are more important than semantic similarity measures. This approach successfully prioritized specific features, leading to substantial enhancements in answer ranking. By combining these different facets of similarity, the overall answer ranking process was enhanced. This comprehensive approach contributed to the advancement of Marathi language processing and the development of more effective question answering systems in Marathi.

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