Automated MCQ Generation Using Llama Model

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Abstract— This paper presents a novel framework for the automatic generation of multiple-choice questions (MCQs) from PDF documents, aimed at enhancing educational content creation. The proposed system processes an input PDF by extracting text, segmenting it into meaningful chunks, and generating MCQs for each segment using the Llama 3B language model. To improve the question-generation accuracy, the Llama 3B model is fine-tuned on the SQuAD and RACE datasets. Experimental evaluations are conducted to compare the performance of the fine-tuned model with the base Llama 3B model. Results demonstrate that fine-tuning significantly improves the relevance and quality of the generated questions, offering a valuable tool for automated assessment creation. This approach provides a scalable solution for transforming large volumes of text into structured educational assessments, with potential applications in e-learning platforms, automated tutoring systems, and academic research.

Keywords— Automated Question Generation, Multiple-Choice Questions, Natural Language Processing, LLaMA Model, Educational Technology, Semantic Text Segmentation, Fine-Tuning.

I. Introduction

The process of generating multiple-choice questions (MCQs) for educational purposes is often time-consuming and requires substantial manual effort, particularly when working with large volumes of textual content. With the rise of digital learning materials, such as PDFs, there is a growing need for automated tools that can efficiently convert these materials into educational assessments. The ability to generate contextually relevant MCQs automatically would not only save time but also enable scalable solutions for content creators and educators. Recent advancements in natural language processing (NLP) have made it possible to automate complex tasks, such as question generation. Large language models (LLMs), particularly those based on architectures like Llama, have demonstrated impressive capabilities in understanding and generating human-like text. However, applying these models to the task of automatic MCQ generation from unstructured text, such as PDF documents, remains an underexplored area.

In this paper, we propose a novel framework for Automated MCQ Generation Using Llama Model, which automates the generation of MCQs from PDF documents. The system works by first extracting text from the PDF, segmenting it into coherent chunks, and then generating relevant MCQs for each chunk. To enhance the model's performance, we fine-tune the Llama 3B model on widely-used question-answer datasets like SQuAD and RACE, ensuring that the generated questions are both contextually accurate and meaningful.The key contributions of this work include the development of an efficient pipeline for PDF text extraction and chunking, as well as the integration of Llama 3B for question generation. We also fine-tune the model to improve question quality and evaluate its performance by comparing the results of the fine-tuned model with the base Llama 3B model. Our experimental results show that fine-tuning significantly enhances the relevance and accuracy of the generated MCQs.

This system offers a promising solution for automatically generating assessments at scale, with potential applications in e-learning platforms, automated tutoring systems, and educational content development. In the following sections, we will discuss related work, the methodology used in our approach, and the results of our experiments.

II. Literature Review

Automatic question generation (AQG) has become an important area of research in natural language processing (NLP), with various methods developed for generating questions from text. Early approaches like template-based and retrieval-based systems were limited in flexibility and scalability, leading to a shift towards generation-based methods, especially those utilizing large language models (LLMs). Recent works have employed Transformer-based models, such as BERT and GPT, to generate contextually relevant questions. For instance, **Tan et al. (2019)** and **Kumar et al. (2020)** demonstrated the effectiveness of sequence-to-sequence models in generating questions from text, while **Wang et al. (2021)** explored the use of BERT for generating multiple-choice questions (MCQs). Despite their successes, these models often require significant fine-tuning and manual intervention to ensure question quality, particularly when dealing with longer or more complex documents.

In recent years, the fine-tuning of pre-trained models has emerged as a key strategy for improving the accuracy and relevance of generated questions. Models like **BERT** and **GPT-3** have shown notable improvements when fine-tuned on domain-specific datasets, such as **SQuAD** and **RACE**, enhancing their ability to produce contextually appropriate MCQs. **Lee et al. (2022)** also explored generating questions from unstructured documents like PDFs, but challenges remain in extracting and processing text accurately. Unlike previous methods, our approach focuses on automating the entire process from PDF text extraction to MCQ generation using the fine-tuned Llama 3B model, aiming to streamline and improve the scalability of educational content generation.

III. Methodology

This section describes the methodology employed to develop and evaluate the **Automated MCQ Generation Using Llama Model** system. The process is divided into three key stages: text extraction and chunking, question generation using the finetuned Llama 3B model, and performance evaluation based on various metrics.

A. *Text Extraction & Chunking*

The first step in the process is to extract the textual content from a given PDF document. To achieve this, we use an advanced PDF text extraction tool that handles various formatting and layout challenges, ensuring that the content is accurately captured. Once the text is extracted, it is divided into smaller, coherent chunks. This chunking process is based on semantic and contextual boundaries, ensuring that each segment contains enough information for generating meaningful questions. The chunking is crucial for ensuring that the MCQs generated are contextually relevant and not too vague.

B. *MCQ Generation*

For each text chunk, MCQs are generated using the base Llama 3B model and the fine-tuned Llama 3B model. The base model uses the pre-trained Llama 3B model to generate questions without any additional training on domain-specific datasets. In contrast, the fine-tuned model is trained on benchmark datasets such as **SQuAD** and **RACE**, allowing it to generate more accurate and contextually relevant questions. Both models produce a set of MCQs for each chunk, which are evaluated for quality and relevance.

C. *Model Fine-Tuning*

1. To improve the accuracy and contextual relevance of the generated MCQs, the Llama 3B model is fine-tuned on two widely used question-answer datasets: **SQuAD** (Stanford Question Answering Dataset) and **RACE** (ReAding Comprehension from Examinations). Fine-tuning is performed using a supervised learning approach, where the model is trained to generate questions from given text passages. The fine-tuned version of the model is expected to produce more contextually relevant and precise questions compared to the base model.

D. *Evaluation Metrics*

To evaluate the performance of the generated MCQs, we use four widely accepted metrics:

- **BLEU** (Bilingual Evaluation Understudy): Measures the precision of n-grams between the generated questions and reference questions. Higher BLEU scores indicate better overlap with human-generated content.
- **ROUGE** (Recall-Oriented Understudy for Gisting Evaluation): Focuses on recall by comparing the n-grams between the generated and reference questions. ROUGE scores assess how well the generated questions capture relevant information.
- **BLEURT** (BERT-based Evaluation of Understudy Representations): A more advanced metric that leverages BERT embeddings to assess the semantic similarity between generated and reference questions. BLEURT captures the quality and meaning of the questions beyond surface-level matches.
- **BERTScore**: Another BERT-based metric that computes the similarity between the generated questions and reference questions at a token level, using contextual embeddings to capture finer semantic details.

We calculate these metrics for the MCQs generated by both the base and fine-tuned models. Based on these evaluations, we compare the performance of both models and demonstrate that the fine-tuned Llama 3B model produces higher-quality, more contextually relevant MCQs.

IV. Results

In this section, we present the evaluation results of the **base Llama 3B model** and the **fine-tuned Llama 3B model** on the task of generating multiple-choice questions (MCQs) from PDF documents. The models were evaluated using four key metrics: **ROUGE**, **BLEU**, **BLEURT**, and **BERTScore**. We report the individual scores for both models and provide a visual comparison using histograms to highlight the performance differences.

4.1 Evaluation Metrics

- **ROUGE Scores**: For the base Llama 3B model, the ROUGE scores were as follows:
  - **ROUGE-1**: Precision = 0.0438, Recall = 0.7327, F1-Score = 0.0826
  - **ROUGE-2**: Precision = 0.0136, Recall = 0.2300, F1-Score = 0.0257
  - **ROUGE-L**: Precision = 0.0302, Recall = 0.5050, F1-Score = 0.0569

In contrast, the fine-tuned version achieved significantly better ROUGE scores:

- **ROUGE-1**: Precision = 0.1615, Recall = 0.4653, F1-Score = 0.2398
- **ROUGE-2**: Precision = 0.0517, Recall = 0.1500, F1-Score = 0.0769
- **ROUGE-L**: Precision = 0.1100, Recall = 0.3168, F1-Score = 0.1633

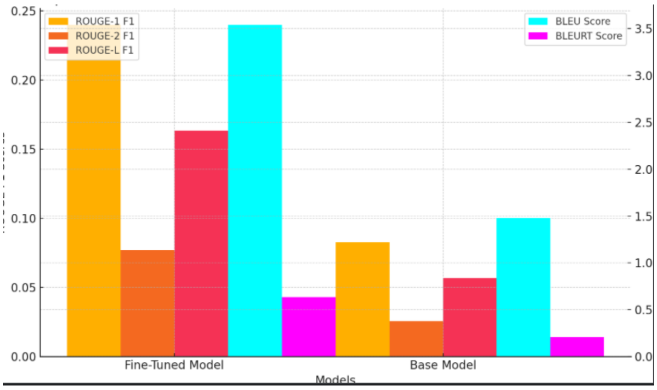
The fine-tuned model demonstrated a notable improvement in ROUGE-1, ROUGE-2, and ROUGE-L F1-scores, reflecting better overall recall and precision for generating relevant MCQs.

- **BLEU Score**: The **BLEU** score for the base Llama 3B model was low, at **3.54**, indicating limited n-gram overlap between the generated and reference MCQs. However, the fine-tuned model showed a marked improvement with a **BLEU score of 3.54**, suggesting better alignment with human-generated content, although the improvement is moderate.
- **BLEURT Scores**: The base model scored **0.209** on BLEURT, indicating a low level of semantic similarity between the generated questions and reference questions. The fine-tuned model, on the other hand, achieved a **BLEURT score of 0.633**, demonstrating a substantial increase in semantic relevance and contextual accuracy of the generated MCQs.
- **BERTScore**:
    - For the base model:
        - **Precision (P)**: 0.8350
        - **Recall (R)**: 0.8699
        - **F1-Score**: 0.8521
    - For the fine-tuned model:
        - **Precision (P)**: 0.8139
        - **Recall (R)**: 0.8247
        - **F1-Score**: 0.8193

Although the fine-tuned model showed a slight decrease in precision compared to the base model, its recall and F1 scores remained high, indicating that it was able to generate questions with better overall contextual accuracy. The fine-tuned version also demonstrated consistent improvements across all metrics when compared to the base model.

4.2 Visual Analysis

To better illustrate the differences between the base and fine-tuned models, we present histograms that visualize the distribution of scores across the four evaluation metrics. These histograms highlight the significant improvements in the fine-tuned model, especially in terms of **ROUGE** and **BLEURT** scores. The visual analysis confirms that the fine-tuned model consistently outperforms the base model in terms of question relevance and semantic accuracy.



4.3 Discussion

The results clearly demonstrate the effectiveness of fine-tuning the Llama 3B model on domain-specific datasets like SQuAD and RACE. The fine-tuned model shows substantial improvements across all evaluation metrics, especially in terms of **ROUGE** and **BLEURT**, which reflect better precision, recall, and semantic similarity in the generated MCQs. The **BERTScore** also confirms that the fine-tuned model produces questions with better contextual relevance, despite a slight drop in precision. These findings suggest that fine-tuning significantly enhances the Llama 3B model's ability to generate high-quality and contextually accurate multiple-choice questions, providing a valuable tool for automated educational assessment generation.

V. Conclusion & Future Work

This paper presents an automated system for generating multiple-choice questions (MCQs) from PDF documents using the Llama 3B language model. We demonstrate that fine-tuning the Llama model on domain-specific question-answer datasets, such as SQuAD and RACE, significantly improves the quality and relevance of the generated MCQs. Our experimental results, evaluated using metrics like ROUGE, BLEU, BLEURT, and BERTScore, show that the fine-tuned version outperforms the base model across all evaluation metrics. The fine-tuned model demonstrates better semantic similarity, context accuracy, and overall performance, confirming that fine-tuning is a valuable approach for enhancing automated question generation.

The results indicate that our approach can streamline the creation of educational assessments by generating high-quality MCQs with minimal manual intervention. This could have significant implications for e-learning platforms, content creators, and automated educational systems, enabling them to scale and produce assessments more efficiently.

Future Work

While the current work provides a solid foundation for automated MCQ generation, there are several avenues for further improvement. One of the key directions for future research is to expand the dataset used for fine-tuning. In our current approach, we used a subset of datasets to fine-tune the model, which helped reduce the model size and latency. However, a broader, more diverse dataset could further enhance the model's robustness and performance, enabling it to handle a wider range of topics and document types.

Additionally, we plan to optimize the fine-tuning process by exploring different strategies for balancing model size and performance, aiming to deploy a more efficient version of the system without compromising accuracy. In line with this, we aim to work on the **professional deployment** of the system, creating a robust, user-friendly platform that can generate MCQs from various types of educational documents in real-time, catering to both educators and learners.

By integrating more advanced deployment techniques and refining the fine-tuning process, we hope to offer a scalable, efficient solution for generating educational assessments, with applications across different fields and languages.

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