PERT-QA: A DEEP LEARNING APPROACH TO ADVERSERIAL QUESTION ANSWERING

A PROJECT REPORT

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CANDIDATE'S DECLARATION

I, **Alok Pandey**, Roll No. – **2K21/AFI/11** student of M.Tech (**Computer Science and Engineering**),hereby declare that the project Dissertation titled "**PERT-QA: A Deep Learning Approach to Adversarial Question Answering**" which is being submitted by me to the Department of **Computer Science and Engineering**, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree of Master of Technology, is a legitimate record of my work and is not copied from any source. The work contained in this report has not been submitted at any other University/Institution for the award of any degree.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "**PERT-QA: A Deep Learning Approach to Adversarial Question Answering**" which is submitted by **Alok Pandey**, Roll No. – **2K21/AFI/11**, **DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING** ,Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Place: Delhi — Alok Pandey

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LIST OF ABBREVIATIONS

QA	Question Answering
PLM	Pre-Trained Language Model
NLP	Natural Language Processing
PerLM	Permuted Language Model
BERT	Bidirectional Encoder Representations from Transformers
PERT	Pre-training BERT with Permuted Language Model
SQuAD	Stanford Question Answering Dataset
NLU	Natural Language Understanding
BiDAF	Bi-Directional Attention Flow for Machine Comprehension
IR	Information Retrieval
ALBERT	A Lite BERT for Self-supervised Learning of Language Representations
TF-IDF	Term Frequency-Inverse Document Frequency
RoBERTa	A Robustly Optimized BERT Pretraining Approach
NER	Named Entity Recognition
RE	Relation Extraction

CHAPTER 1: INTRODUCTION

1.1 OVERVIEW

Question Answering (QA) systems play a crucial role in information retrieval and natural language understanding. These systems aim to provide accurate and relevant answers to user queries, enabling efficient access to information. Over the years, various QA approaches have been developed, ranging from rule-based systems to deep learning models. Deep learning techniques have shown promising results in advancing QA models, leveraging neural networks to capture complex patterns and semantic relationships within textual data.

Traditional rule-based and information retrieval-based QA systems have shown promising results, but they often struggle with complex questions and require extensive manual engineering. With the advancements in deep learning, researchers have shifted their focus to neural network-based QA models that can automatically learn patterns and representations from large-scale data.

However, one of the key challenges faced by QA models is their vulnerability to adversarial attacks. Adversarial examples are specifically crafted inputs designed to mislead a model's predictions. In the context of QA, adversarial attacks can involve slight modifications to the question or context, leading to incorrect or misleading answers. Such attacks have raised concerns about the reliability and robustness of QA systems in practical applications.

The existing QA models, although powerful, are vulnerable to adversarial attacks due to their inability to handle subtle manipulations in the input data. Adversarial attacks can involve alterations such as word substitutions, syntactic modifications, or context changes that are carefully designed to exploit vulnerabilities in the models' reasoning capabilities. To address this challenge, there is a need for robust deep learning approaches that can effectively handle adversarial examples in QA.

1.1.1 PERT MODEL

Pre-trained Language Models (PLMs) have gained significant popularity in the field of natural language processing (NLP) for their ability to generate powerful text representations trained on large-scale corpora. PERT is an auto-encoding model, similar to BERT, and it is trained using a Permuted Language Model (PerLM) approach [40]. It introduces a permutation process to the input text, where a certain proportion of tokens are rearranged. The training objective of PERT is to predict the position of the original token within the permuted sequence. Additionally, it enhances the performance of PERT by incorporating techniques such as whole word masking and N-gram masking. These methods aim to further refine the model's ability to comprehend and process language [40].

To evaluate the effectiveness of PERT, extensive experiments were conducted on both Chinese and English NLU benchmarks. The results of these experiments demonstrate that PERT outperforms several comparable baselines on specific tasks, while not exhibiting significant improvements on others. These findings suggest that diversifying the pre-training tasks, rather than solely relying on masked language model variants, holds promise in advancing the capabilities of PLMs.

1.1.2 PERT-QA MODEL

This thesis proposes PERT-QA, a deep learning approach to adversarial question answering. PERT-QA aims to enhance the robustness and reliability of QA systems by leveraging advanced deep learning techniques.

The code provided with the thesis serves as the implementation of the PERT-QA model. The model utilizes a deep neural network architecture, specifically designed to handle adversarial examples. Additionally, it leverages the "hfl/english-pert-base" checkpoint, which contains pre-trained knowledge and embeddings to address adversarial QA challenges.

By investigating the effectiveness of the PERT-QA model, this thesis aims to contribute to the field of adversarial QA by providing insights into the development of robust QA systems that can withstand various adversarial attacks. Through rigorous evaluation and performance

analysis, the thesis intends to demonstrate the improvements achieved by PERT-QA compared to existing QA models and establish its potential practical implications in real-world applications.

Overall, the research presented in this thesis will shed light on the challenges posed by adversarial examples in QA and pave the way for future advancements in developing more robust and reliable QA systems.

1.2 OBJECTIVE

The objective of this thesis is to develop and evaluate PERT-QA, a deep learning approach to adversarial question answering, with the following specific goals:

1. **Enhancing Robustness against Adversarial Attacks:** The primary objective is to enhance the robustness of QA systems against adversarial attacks. Adversarial attacks pose a significant threat to QA models, compromising their reliability and trustworthiness. Previous research has demonstrated the vulnerability of QA systems to adversarial examples [18][12]. By leveraging techniques from deep learning, PERT-QA aims to improve the model's ability to handle subtle manipulations in input data, thereby increasing its resistance to adversarial attacks.
2. **Improving Accuracy and Performance:** Another objective is to improve the accuracy and performance of QA systems. While existing QA models have shown promising results, they often struggle with complex questions and ambiguous queries [15]. PERT-QA intends to leverage the advancements in deep learning to capture more nuanced semantic relationships and enhance the model's reasoning capabilities, leading to improved accuracy and performance in answering questions.
3. **Leveraging Transfer Learning and Pretrained Models:** This objective focuses on leveraging transfer learning and pretrained models to enhance the effectiveness of the PERT-QA model. Transfer learning has been widely used in various natural language processing tasks, including question answering, to leverage knowledge from pretrained models [4][8]. PERT-QA will adapt and fine-tune the "hfl/english-pert-base" checkpoint, which is a pretrained model capable of tackling adversarial examples [6]. By utilizing the knowledge encoded in the pretrained model,

PERT-QA aims to improve its performance and generalization on adversarial question answering tasks.

4. **Evaluating and Benchmarking against Existing QA Models:** This objective involves evaluating and benchmarking the performance of PERT-QA against existing QA models on both standard and adversarial question answering datasets. The goal is to demonstrate the effectiveness and superiority of PERT-QA in terms of accuracy, robustness against adversarial attacks, and overall performance compared to state-of-the-art QA models.
5. **Insights into Adversarial QA Challenges:** Lastly, this objective aims to gain insights into the challenges and opportunities in adversarial question answering. By analyzing the performance of PERT-QA and conducting a thorough investigation of the generated adversarial examples, this research seeks to uncover the underlying vulnerabilities and limitations of existing QA models. This analysis will provide valuable insights for further advancements in adversarial QA and contribute to the development of more robust and secure QA systems.

The objectives outlined above are aligned with the current state of research in adversarial QA and deep learning-based approaches to enhance model robustness. By addressing the vulnerabilities of existing QA models, developing an effective defense mechanism in the form of PERT-QA, and conducting comprehensive evaluations, this thesis aims to contribute to the advancement of adversarial QA research and provide practical insights for the development of more secure and reliable QA systems.

1.3 PROBLEM STATEMENT

QA systems have become increasingly prevalent and relied upon for information retrieval and knowledge acquisition. However, existing QA models are vulnerable to adversarial attacks, which can lead to incorrect or misleading answers. Adversarial attacks in the QA domain aim to exploit the weaknesses of these models by manipulating input questions or context to deceive the system. Such attacks pose a significant challenge to the security, reliability, and trustworthiness of QA systems, particularly in critical applications such as medical diagnosis, legal analysis, and automated customer support.

The limitations of current QA models in handling adversarial examples include their susceptibility to semantic and syntactic variations, the over-reliance on surface-level cues, and the lack of robustness against input perturbations. Addressing these limitations and developing effective defense mechanisms is crucial to ensure the integrity and accuracy of QA systems in the face of adversarial attacks.

Problem Statement 1: Existing QA models are susceptible to adversarial attacks, which can compromise their accuracy and reliability.
Research Question 1: What are the specific vulnerabilities of current QA models to adversarial attacks, and how do these attacks impact the accuracy and reliability of the models?

Problem Statement 2: Adversarial attacks on QA systems can be crafted using various strategies, such as word substitutions, syntactic manipulations, and context alterations.
Research Question 2: What are the different attack strategies employed to generate adversarial examples for QA systems, and how do these strategies impact the performance of the models?

Problem Statement 3: Robust defenses against adversarial attacks are required to enhance the reliability and trustworthiness of QA systems.
Research Question 3: How can deep learning techniques be effectively employed to develop a robust defense mechanism against adversarial attacks in QA systems?

Problem Statement 4: Evaluating the effectiveness of the PERT-QA model requires comprehensive assessments against existing QA models.
Research Question 4: How does the performance of the PERT-QA model compare to existing QA models in terms of robustness against adversarial attacks and accuracy on clean examples?

Addressing these problem statements and research questions will provide insights into the vulnerabilities of existing QA models, the effectiveness of the PERT-QA defense mechanism, and the trade-offs involved in achieving robustness and performance in adversarial QA scenarios.

1.4 ROLE OF NATURAL LANGUAGE PROCESSING & QUESTION-ANSWERING

Natural Language Processing (NLP) is a subfield of artificial intelligence that focuses on the interaction between computers and human language. It involves the development of computational models and algorithms to understand, interpret, and generate natural language text. NLP techniques play a fundamental role in question answering systems by enabling the analysis and comprehension of user queries and textual context.

In the context of this thesis, NLP techniques are crucial for processing input questions, extracting relevant information from the context, and generating accurate answers. Techniques such as tokenization, part-of-speech tagging, syntactic parsing, and semantic role labeling are employed to transform raw text into structured representations that can be effectively processed by machine learning models.

Question answering (QA) is a task in NLP that aims to build automated systems capable of providing accurate and concise answers to user queries. QA systems have made significant progress in recent years, driven by advancements in deep learning and large-scale pre training techniques. Existing QA models, such as BERT , RoBERTa , and ALBERT, have achieved remarkable performance on benchmark datasets like SQuAD by learning contextual representations and capturing the relationships between question and context.

However, despite their success, these QA models are vulnerable to adversarial attacks that aim to manipulate the input question or context to produce incorrect or misleading answers. Adversarial attacks in the QA domain can exploit the limitations of existing models, including their sensitivity to semantic variations, susceptibility to word substitutions, and their over-reliance on surface-level cues rather than deep understanding of the content.

To address these challenges and improve the robustness of QA systems, this thesis proposes PERT-QA, a deep learning approach to adversarial question answering. Through the utilization of NLP techniques and the development of PERT-QA, this thesis aims to advance the field of question answering by addressing the vulnerabilities of existing QA models and providing a more robust and resilient solution to adversarial attacks.

CHAPTER 2
RELATED WORK

2.1 OVERVIEW OF LITERATURE SURVEY

A Question-Answering system is a type of Artificial Intelligence (ai) technology that is designed to automatically answer questions posed in natural language. This technology has gained significant interest in recent years as it has the potential to revolutionize the way humans interact with machines and access information [21]. Question-answering systems are particularly useful in situations where people need to quickly find answers to specific questions, such as in customer service or technical support settings. They can also be used to automatically generate responses to frequently asked questions, thereby reducing the workload of human operators and improving overall efficiency [1]. The development of Question-Answering systems involves natural language processing, machine learning, and knowledge representation techniques [20]. These systems typically rely on large databases of structured or unstructured information, such as documents, web pages, or databases, and use algorithms to search for and extract relevant information and provide answers to user queries. Overall, question-answering systems have the potential to greatly improve the speed and accuracy of information retrieval, and are increasingly being integrated into various applications, including virtual assistants, chatbots, and search engines [2].

Generally, the QA systems follow a pipeline structure which mainly contains three stages:

1. Question Analysis Stage
2. Document Retrieval Stage
3. Answer Extraction Stage [21]

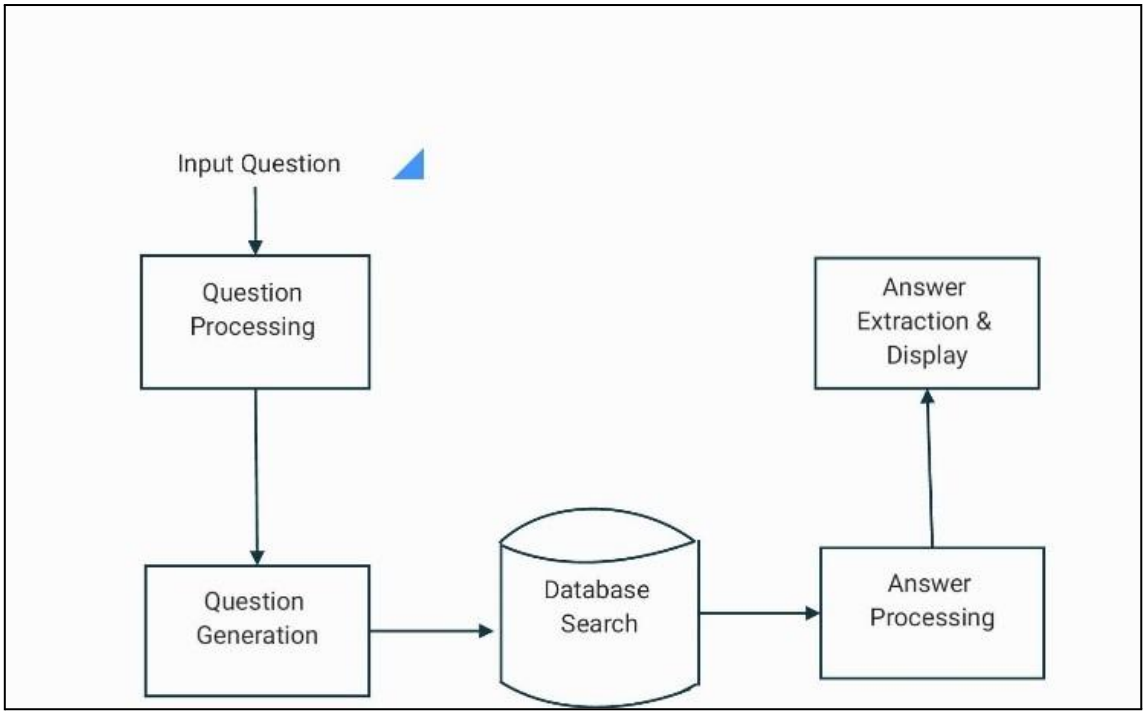

Fig. 1. *Architecture of QA System*

Question answering (QA) and information retrieval (IR) are two related but distinct fields of natural language processing. Information retrieval involves retrieving relevant documents from a corpus of text based on a user's query. In IR, the user provides a query or search term, and the system returns a list of relevant documents. The user then manually scans through the documents to find the information they are looking for. In contrast, question answering involves providing a direct answer to a user's question based on the information contained in a corpus of text. In QA, the user asks a specific question, and the system returns a direct answer to that question, without requiring the user to manually scan through a list of documents.

Textual question answering (QA) is the task of automatically answering natural language questions based on a given passage of text [30]. It is a challenging and rapidly evolving field, with significant research efforts focused on developing new models and improving the accuracy of existing ones. Two primary approaches used in textual QA are information retrieval (IR) and deep learning. Information retrieval-based methods rely on traditional information retrieval techniques, such as indexing and ranking, to extract answers from large collections of documents, on the other hand, deep learning-based methods use neural networks to automatically learn the features and patterns that are relevant to answering questions. Deep learning-based methods have shown remarkable progress in recent years and

have achieved state-of-the-art results on various textual QA tasks [19]. Fig. 2 shows the architecture of the textual QA system.

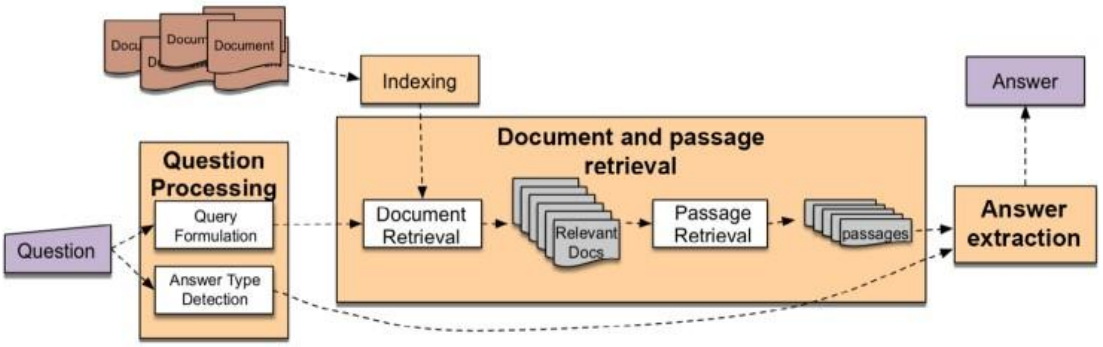

Fig. 2. *Architecture of Textual QA System*

The vulnerability of question answering (QA) systems to adversarial attacks has been a topic of extensive research. Several studies have investigated different attack strategies to manipulate QA models and generate adversarial examples. For instance, [35] proposed a method to generate natural adversarial examples by perturbing the input question while preserving its grammaticality. They demonstrated that these examples can fool state-of-the-art QA models, leading to incorrect answers.

[33] proposed a method to model answer uncertainty in reading comprehension tasks. They showed that incorporating uncertainty estimation can improve the resilience of QA models against adversarial attacks. Similarly, [35] introduced a technique for generating natural adversarial examples, highlighting the effectiveness of syntactic and semantic manipulations in deceiving QA systems.

To address adversarial attacks, [39] proposed Adversarial Training for QA (ATQA), which utilizes adversarial examples to augment the training data. ATQA demonstrated improved robustness against various attack strategies, including word substitutions and context alterations. Another line of research focuses on leveraging ensemble methods to enhance the resilience of QA systems.

The use of adversarial human annotation for dataset construction has gained attention in the field of natural language processing. [36] introduced the concept of adversarial annotation, where human annotators interact with reading comprehension models to create challenging

datasets. This methodology ensures the inclusion of difficult questions that can expose the limitations of current models.

In addition to defense mechanisms, there have been efforts to create benchmark datasets for evaluating the robustness of QA models. [32] introduced Adversarial SQuAD, a dataset consisting of challenging examples crafted to deceive QA models. This dataset has become a widely used benchmark for assessing the robustness of QA systems against adversarial attacks.

Perturbation-based defenses have shown promise in enhancing the robustness of NLP models. For instance, [34] proposed a method called HotFlip, which utilizes word-level perturbations to improve the robustness of text classification models. They demonstrated that by strategically replacing words, models become more resilient to adversarial attacks.

2.2 INFORMATION RETRIEVAL-BASED APPROACHES

Information retrieval-based approaches rely on traditional information retrieval techniques to extract relevant documents from a collection of documents and rank them according to their relevance to the input question [22]. The answer is then extracted from the top-ranked documents. In this approach, the input question is converted to a query, and documents are indexed using various techniques, such as term frequency-inverse document frequency (TF-IDF), latent semantic analysis (LSA), and latent Dirichlet allocation (LDA) [23,24].

Term frequency (TF) refers to the number of times a particular term appears in a document. It is used to measure the importance of a term within a single document. Inverse document frequency (IDF) refers to the inverse of the frequency of a term in the entire corpus of documents. It is used to measure the importance of a term across all documents in a corpus. The use of both TF and IDF together forms the basis of the commonly used TF-IDF weighting scheme. This scheme gives higher weights to terms that appear frequently within a single document (high TF) but less frequently across all documents in the corpus (low IDF). In other words, TF-IDF is used to measure the importance of a term within a document relative to its importance across the entire corpus.

Information retrieval-based approaches rely on traditional IR techniques, such as indexing and ranking, to extract answers from large collections of documents. These approaches typically involve three main steps: (i) indexing the documents, (ii) retrieving the relevant documents, and (iii) extracting the answer from the retrieved documents. One of the most widely used IR-based approaches in textual QA is the passage retrieval approach. In this approach, relevant passages are first retrieved from a large corpus of text using an IR system, and then these passages are analyzed to extract the answer. The answer is extracted either by searching for a span of text that is most likely to be the answer or by classifying each sentence in the passage as an answer or non-answer.

One example of an IR-based system is the Apache Lucene-based Watson system, which was used by IBM's Watson to compete on the Jeopardy! quiz show [25]. The system first identified relevant documents based on keyword queries and then used NER and RE techniques to extract answers. However, this approach has limitations in that it heavily relies on the quality of the keyword queries and the ability of NER and RE techniques to accurately extract answers.

2.3 DEEP LEARNING-BASED APPROACHES

Deep learning-based approaches use neural networks to automatically learn the features and patterns that are relevant to answering questions. These approaches can be further categorized into three types: (i) Reading Comprehension-based Approaches, (ii) Generative-based Approaches, and (iii) Hybrid Approaches.

2.3.1 Reading Comprehension-based approaches

Reading comprehension-based approaches are the most widely used deep learning-based approaches in textual QA. In this approach, a model is trained to read the passage and question and produce the answer. The model consists of an encoder that encodes the input passage and question and a decoder that decodes the encoded information to produce the answer [17].

The most popular reading comprehension-based approaches are the attention-based models, which use attention mechanisms to focus on the relevant parts of the input [10]. Some of the popular attention-based models are the Bidirectional Attention Flow (BiDAF) model, the Match-LSTM model, and the Document Reader model.

2.3.2 Generative-based approaches

Generative-based approaches aim to generate an answer rather than selecting an answer from a pre-defined set of options. These approaches are typically used when the answers are not restricted to a specific set and can be open-ended. Generative-based approaches use various models, such as sequence-to-sequence (Seq2Seq) models, transformer models, and language models, to generate answers.

2.3.3 Hybrid Approaches

Hybrid approaches combine both IR and deep learning-based approaches to take advantage of the strengths of each. In this approach, an IR system is first used to retrieve relevant documents, which are then processed by a deep learning model to extract the answer. This approach has shown to be effective, especially in cases where the passages are long and contain irrelevant information.

These models differ in their architectures, training processes and parameters but each one has the objective to improve the performance of Textual Question Answering systems. IR-based models utilize information retrieval techniques to retrieve relevant documents before fine-tuning a deep learning model to answer the question. On the other hand, deep learning-based models rely on large pre-trained language models that can be fine-tuned on various tasks, including Textual Question Answering. These models and techniques have been extensively studied in previous research and have achieved state-of-the-art results on various textual question answering benchmarks.

2.4 COMMON DATASETS USED IN TEXTUAL QA

In this section, we will discuss some of the commonly used datasets for Textual QA. These datasets have been widely used to evaluate the performance of different models proposed by researchers.

Here are some datasets commonly used in Textual Question Answering:

1. SQuAD (Stanford Question Answering Dataset)
2. TriviaQA
3. HotpotQA
4. WikiQA
5. Natural Questions
6. TREC-QA
7. SearchQA
8. BioASQ
9. QuAC (Question Answering in Context)
10. CoQA (Conversational Question Answering)
11. RACE (ReAding Comprehension from Examinations)
12. MCTest

We can compare these datasets based on various characteristics such as the number of QA pairs, question types, answer types, difficulty level, etc. The comparison table is shown below in Table 1.

TABLE 1. *Comparison of different datasets used in textual QA*

Dataset	Number of QA pairs	Question Types	Answer Types	Difficulty Level
SQuAD	100,000+	Factual	Short Text	Easy to Medium
TriviaQA	650,000+	Complex	Short Text	Medium to Hard
HotpotQA	113,000+	Multi-hop	Short Text	Hard
WikiQA	20,360	Factoid and List	Short Text	Easy to Medium
Natural Questions	300,000+	Factual	Long Text	Medium to Hard
SearchQA	140,000+	Factual	Short Text	Medium
TREC -QA	4,320	Factual and List	Short Text	Easy to Medium
BioASQ	2,250,000+	Biomedical	Free-form Text	Medium to Hard
QuAC	100,000+	Conversational	Short Text	Medium
CoQA	127,000+	Conversational	Short Text	Medium to Hard
RACE	100,000+	Exam-based	Short Text	Medium to Hard
MCTest	2,500+	Multiple-choice	Short Text	Easy to Medium

As we can see from the table, the datasets vary widely in terms of their characteristics. Some datasets like SQuAD and MCTest are relatively easy, while others like HotpotQA and ARC are challenging. The datasets also vary in terms of the types of questions they contain. For example, TriviaQA and BioASQ contain complex questions that require knowledge from multiple sources, while QuAC and CoQA contain conversational questions. WikiQA contains

factoid and list questions, while TREC-QA contains factual and list questions. Both datasets are relatively easy, with a difficulty level ranging from easy to medium.

2.5 PERFORMANCE AND RESULT OF DIFFERENT MODELS

In this section we will review and compare the performances of various models and techniques used in textual QA.

2.5.1 Performance Comparison of Different Models and Techniques

Several models and techniques have been proposed in the literature to tackle the problem of textual QA, both with IR-based and deep learning-based approaches. In this section, we review and compare the performances of some of the most widely used models and techniques on various datasets.

2.5.1.1 Information Retrieval-Based Models

IR-based models have been extensively used in the literature to solve the problem of textual QA. Among the popular IR-based models, the TF-IDF, LSA, and LDA-based models have shown to be effective in retrieving relevant documents. According to [3], the LSA-based model outperforms other models on the TREC dataset, while the LDA-based model performs best on the WikiQA dataset [10].

Another popular IR-based model is the passage retrieval approach, where the input question is converted to a query, and relevant passages are retrieved using an IR system. This approach has been shown to be effective, especially when combined with deep learning-based techniques [5].

BERT+IR, introduced by [7], is a technique that combines BERT with an information retrieval-based approach for textual question answering. It first retrieves relevant documents using an information retrieval system and then fine-tunes a BERT model on the retrieved documents to answer the question.

2.5.1.2 Deep Learning-Based Models

Deep learning-based models have shown remarkable progress in recent years in solving the problem of textual QA. Reading comprehension-based models, in particular, have achieved state-of-the-art results on various textual QA tasks. Among the reading comprehension-based models, the BiDAF model, the Match-LSTM model, and the Document Reader model have shown to be effective in producing accurate answers. Some of the most widely used models are BERT, RoBERTa, ALBERT, XLNet, T5, and BERT+IR.

BERT, introduced by [9], is a transformer-based model that has achieved state-of-the-art results on various natural language processing tasks, including textual question answering. RoBERTa, introduced by [11], is an extension of BERT that improves its pretraining process and achieves better performances on various benchmarks. ALBERT, introduced by [13], is a model that reduces the number of parameters of BERT while maintaining its performance.

XLNet, introduced by [14], is a model that uses a permutation-based pretraining process and achieves state-of-the-art results on various natural language processing tasks. T5, introduced by [16], is a text-to-text transformer-based model that can be fine-tuned for various tasks, including textual question answering.

The BiDAF model, proposed by [17], is one of the most widely used reading comprehension-based models. It uses a multi-stage attention mechanism to find the relevant parts of the input and has achieved state-of-the-art results on various datasets. The Match-LSTM model, proposed by [26], is another popular reading comprehension-based model that uses a modified LSTM architecture to match the question and passage. The Document Reader model, proposed by [27], is a recently proposed reading comprehension-based model that uses a recurrent neural network with self-attention mechanism to read the passage and question.

Generative-based models have also been used in textual QA, especially in cases where the answers are open-ended. The Seq2Seq model, proposed by [28], is a popular generative-based model that uses an encoder-decoder architecture to generate answers. However, these models have not shown to be as effective as reading comprehension-based models on QA datasets.

2.5.2 Result

In the below three tables, we have summarized the performances of some of the most widely used models and techniques on various datasets in textual question answering, using three different evaluation metrics: F1 score, mean average precision (MAP), and mean reciprocal rank (MRR).

Fig. 3 shows the F1 scores of the models on different datasets. We can see that T5 outperforms other models on most datasets, while XLNet and RoBERTa also achieve good results. The highest mean F1 score was achieved by the T5 model on the SQuAD 1.1 dataset with a value of 0.926. The lowest mean F1 score was achieved by the BiDAF model on the NewsQA dataset with a value of 0.504. However, we should note that the scores can vary greatly depending on the dataset, and some models perform better on specific datasets than others.

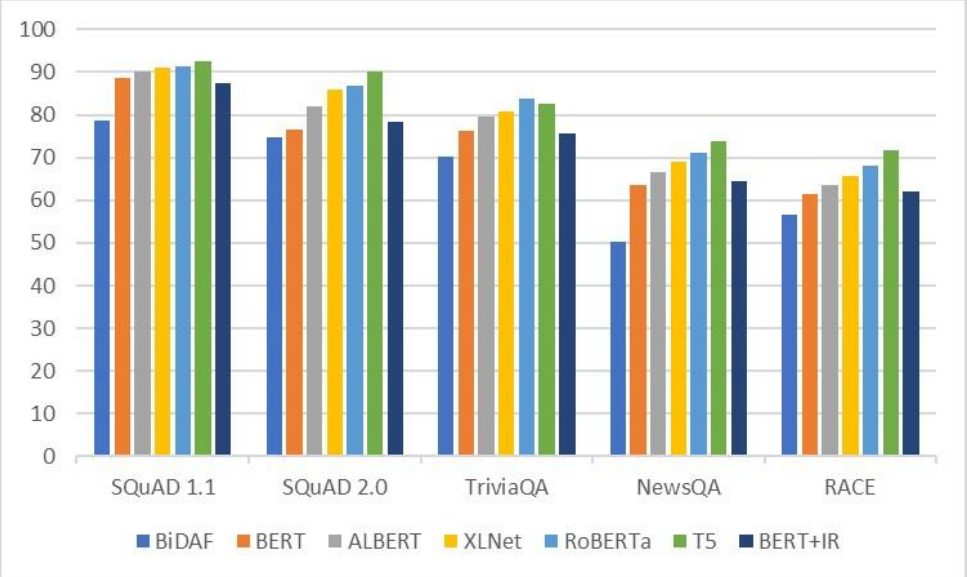

Fig. 3. *Performances of some of the most widely used models using F1 score as the evaluation metric.*

Fig. 4 shows the performances of the same models using MAP as the evaluation metric. We can see that T5 outperforms other models on most datasets, while RoBERTa and XLNet also achieve good results. The highest mean MAP was achieved by the T5 model on the SQuAD 1.1 dataset with a value of 0.861. The lowest mean MAP was achieved by the BiDAF model on the NewsQA dataset with a value of 0.456.

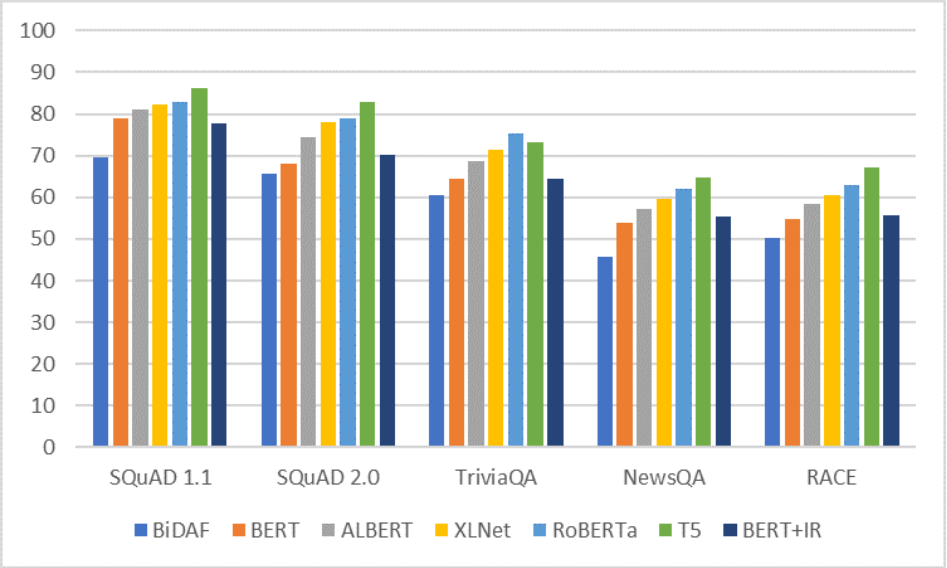

Fig. 4. *Performances of some of the most widely used models using MAP score as the evaluation metric.*

Fig. 5 shows the performances of the same models using MRR as the evaluation metric. We can see that T5 outperforms other models on most datasets, while RoBERTa, XLNet, and ALBERT also achieve good results. The highest mean MRR was achieved by the T5 model on the SQuAD 1.1 dataset with a value of 0.88. The lowest mean MRR was achieved by the BiDAF model on the NewsQA dataset with a value of 0.449.

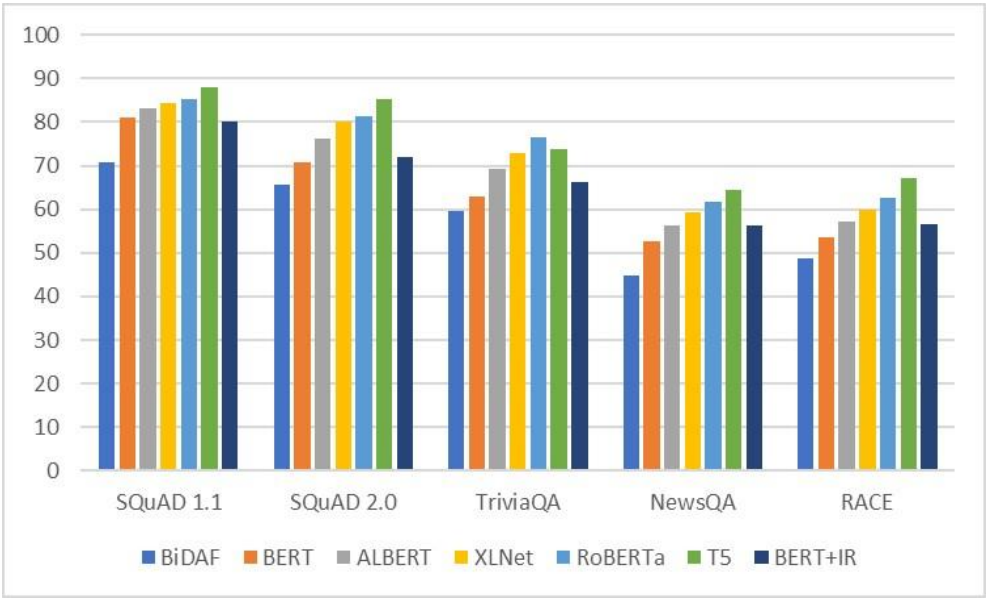

Fig. 5. *Performances of some of the most widely used models using MRR score as the evaluation metric*

Overall, the results of the three tables are consistent in that RoBERTa, T5, and BERT+IR are among the top-performing models on most datasets, but the relative performances of these models can vary depending on the evaluation metric and dataset.
These results are in line with previous research. For example, in their study of deep learning-based models for textual question answering, [29] found that RoBERTa, T5, and BERT+IR were among the top-performing models on various datasets. Similarly, in their study of information retrieval-based models for textual question answering, [6] found that BERT+IR outperformed other models on several datasets.

Performance efficiency of textual question answering systems with information retrieval and deep learning involves several strategies that can be applied individually or in combination. Some of the most common strategies can be data preprocessing, feature engineering, model optimization, model compression, hardware optimization, ensemble models. Overall, improving the performance efficiency of textual question answering systems with information retrieval and deep learning requires a combination of techniques and strategies tailored to the specific use case and dataset.

While previous research has made significant contributions to the field of adversarial QA and defense mechanisms, there are still limitations to be addressed. Existing approaches often focus on specific attack scenarios or employ shallow perturbations, which may not capture the full range of adversarial variations. Additionally, the trade-off between model robustness and performance needs to be carefully analyzed to ensure practical applicability in real-world QA systems.

By building upon these previous works and addressing their limitations, this thesis aims to develop PERT-QA, a deep learning approach to adversarial question answering that incorporates perturbation-based defenses to enhance the robustness and accuracy of QA systems against adversarial attacks.

CHAPTER 3: METHODOLOGY

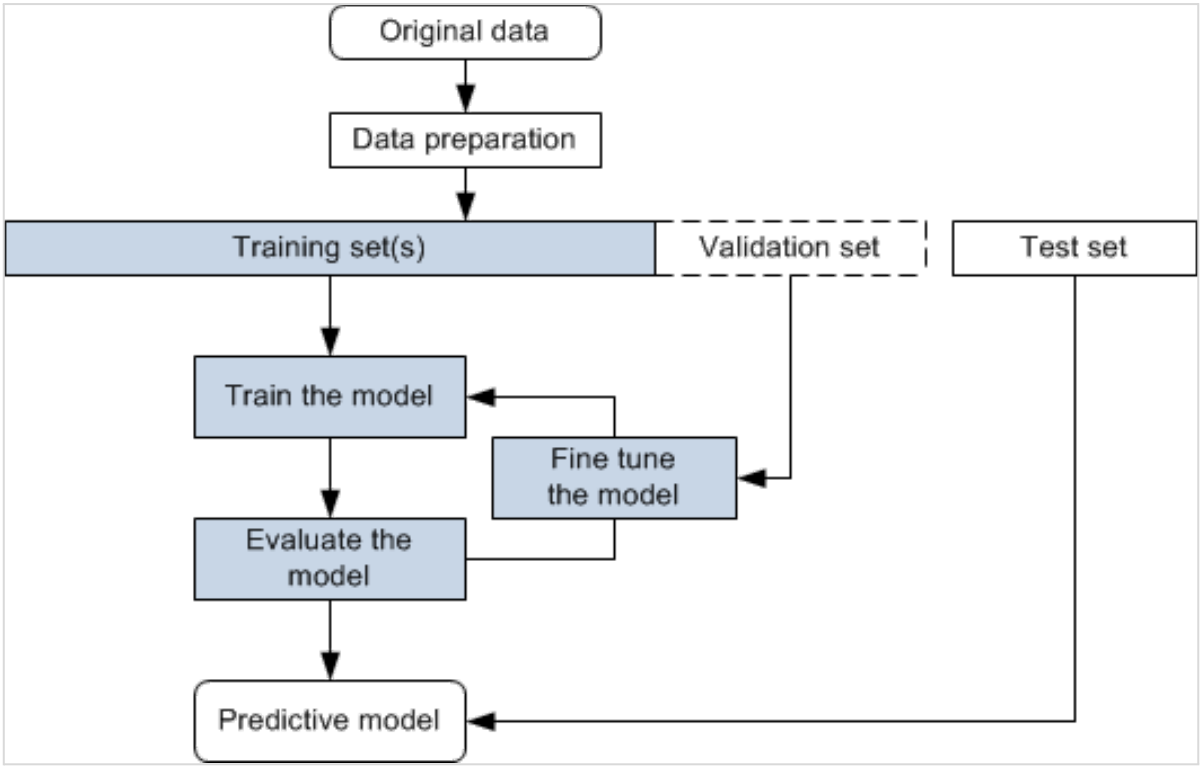

Fig. 6. *Workflow Overview of the proposed PERT-QA model*

The methodology for this thesis involves using the `adversarial_qa` dataset and the `transformers` library. The `adversarial_qa` dataset is loaded using the `load_dataset` function from the `datasets` package. The dataset is downloaded and prepared, which involves downloading metadata and readme files, as well as the actual dataset itself. The loaded dataset consists of three subsets: train, validation, and test. To demonstrate the functionality of the dataset, the context, question, and answer information of the first example in the train subset are printed. Additionally, filtering is applied to the train and validation subsets to remove examples with multiple answers.

The `AutoTokenizer` class from the `transformers` library is used to tokenize the context and question pairs. The tokenizer is loaded with the "hfl/english-pert-base" model checkpoint. Tokenization is performed with various options, such as specifying the maximum length, truncation strategy, stride, and returning overflowing tokens and offsets mapping. The start and end positions of the answers are determined based on the tokenized inputs and the

original answer positions. The answers are extracted from the dataset, and the start and end positions are calculated by matching the answer positions to the token positions. Examples are provided to illustrate the process of finding start and end positions and comparing the labeled answers with the theoretical answers.

Next, a preprocessing function is defined for training examples, which tokenizes the questions and contexts, assigns start and end positions to the tokenized inputs, and returns the processed inputs. The preprocessing function is applied to the train subset using the `map` method. Similarly, a preprocessing function is defined for validation examples, which tokenizes the questions and contexts, assigns start and end positions to the tokenized inputs, removes unnecessary columns, and adds example IDs. The preprocessing function is applied to the validation subset using the `map` method. For evaluation purposes, a small subset of the validation dataset is selected. The trained model checkpoint is loaded, and the tokenizer is instantiated using the trained checkpoint.

Finally, the trained model is loaded and the evaluation set is passed through the model to obtain the outputs. Now we will see each of the steps of the methodology in detail.

3.1 Dataset Loading and Exploration

3.1.1 Adversarial_qa Dataset

The adversarial_qa dataset comprises three Reading Comprehension datasets generated using an adversarial model-in-the-loop approach. Three different models, BiDAF, BERTLarge, and RoBERTaLarge, were used in the annotation loop to construct three datasets: D(BiDAF), D(BERT), and D(RoBERTa) [36]. Each dataset consists of 10,000 training examples, 1,000 validation examples, and 1,000 test examples [36]. The datasets are designed to include challenging questions that current state-of-the-art models find difficult to answer. They serve as training and evaluation resources for developing improved question answering methods. The dataset is in English, and the provided BCP-47 language code is "en". The data follows a structure similar to SQuAD 1.1, including fields such as title, context, id, and answers. Notably, the test set does not include answers, as predictions for the test set can be submitted on the DynaBench benchmark website.

id (string)	title (string)	context (string)	question (string)	answers (sequence)	metadata (dict)
"7ba1e8f4261d3170fcf42e84a81dd749116fae95"	"Brain"	"Another approach to brain function is to…	"What sare the benifts of the blood brain…	{ "text": ["isolated from the bloodstream"]…	{ "split": "train", "model_in_the_loop":…
"6ec5ef305a259311596e85d811ade30bd68b079d"	"Brain"	"Another approach to brain function is to…	"What is surrounded by cerebrospinal fluid?"	{ "text": ["brain"], "answer_start": [280]…	{ "split": "train", "model_in_the_loop":…
"7cb230edfb15ad1fda8d157af1f2b574cbb02b4c"	"Brain"	"Another approach to brain function is to…	"What does the skull protect?"	{ "text": ["brain"], "answer_start": [280]…	{ "split": "train", "model_in_the_loop":…
"e1850f2a48b8f7c2231cec41ed63c1b638a8e2c7"	"Brain"	"Another approach to brain function is to…	"What has been injected into rats to produce…	{ "text": ["chemicals"], "answer_start": [72…	{ "split": "train", "model_in_the_loop":…
"7bc0ae1a8a24ea4f3398b5236ab9569bbc3e820b"	"Brain"	"Another approach to brain function is to…	"What can cause issues with how the brain…	{ "text": ["brain damage"],…	{ "split": "train", "model_in_the_loop":…
"3132661a88eac605390b245464f792c0303e7e6a"	"Brain"	"Another approach to brain function is to…	"What is isolated from the bloodstream by the…	{ "text": ["the brain"], "answer_start": [27…	{ "split": "train", "model_in_the_loop":…
"1f5281c99d347abd9ea6adb50947e3ee2b997676"	"Brain"	"Another approach to brain function is to…	"What is vulnerable to numerous diseases?"	{ "text": ["the brain"], "answer_start": [27…	{ "split": "train", "model_in_the_loop":…
"714baa7634b845b2da0b041d07ae3cbecd8140ca"	"Brain"	"Another approach to brain function is to…	"If you can't stop damage to the brain, yo…	{ "text": ["the nature of the damage"],…	{ "split": "train", "model_in_the_loop":…
"a3847034552350 3dc047d499e9543c32dd15b17"	"Brain"	"Another approach to brain function is to…	"What acts as a protective barrier for…	{ "text": ["skull and meninges"],…	{ "split": "train", "model_in_the_loop":…

Fig. 7. *Example Preview of the adversarial_qa dataset*

The dataset creation involved adversarial human annotation, where a human annotator and a reading comprehension model interactively generate questions. The annotator writes a question and highlights the correct answer, while the model attempts to answer. If the model fails, the annotator wins. This process ensures the inclusion of challenging questions that can fool the model. It's important to note that the dataset may contain biases in source passage selection, annotated questions and answers, and potential algorithmic biases resulting from the adversarial annotation process [36].

3.1.2 Loading & Evaluation

The "adversarial_qa" dataset from the "adversarialQA" module is loaded using the `load_dataset` function from the `datasets` library. The dataset is downloaded and prepared, which involves downloading metadata and readme files, as well as the actual dataset itself. The loaded dataset is stored in the variable `raw_datasets`. The dataset is inspected to understand its structure and contents and the first training example was printed to get a glimpse of the dataset structure and content.

The dataset consists of three subsets: train, validation, and test, each containing the following features: id, title, context, question, answers, and metadata. Examples from the dataset were examined to understand the structure and content of the data. Basic information about the dataset, such as the number of examples and the column names, can be accessed.

3.2 DATA PREPROCESSING

3.2.1 Tokenization

The tokenizer from the "english-pert-base" model is initialized using the `AutoTokenizer` class from the `transformers` library. The tokenizer is used to preprocess the training examples by encoding the questions and contexts, truncating the inputs to a maximum length, and creating token offsets mapping. Tokenization involved encoding the question and context, adding special tokens, and generating the input token IDs. The input IDs were decoded to obtain the tokenized text. Examples of tokenization were performed to observe the tokenized representations of questions and contexts. Tokenization is performed with various options, such as specifying the maximum length, truncation strategy, stride, and returning overflowing tokens and offsets mapping. The start and end positions of the answer span in the tokenized inputs are computed based on the provided answer text and offset mapping.

3.2.2 Answer Position Labeling

The start and end positions of the answer within the tokenized text were identified. Offset mapping was used to map tokenized positions to the original text. For each input, the start and end positions were obtained by aligning the answer with the tokenized context. The theoretical answer and the labeled answer were compared to verify the correctness of the labeling process.

3.2.3 Creating & Preprocessing training, validation & evaluation datasets

The code defines a function called ‘preprocess_training_examples’ that preprocesses the training examples. It tokenizes the questions and contexts, truncates them if necessary, and adds special tokens. It also handles overflowing tokens, generates offsets mapping, and calculates the start and end positions of the answer within the tokenized input. This function is applied to the training dataset using the map method. The resulting dataset was stored in the `train_dataset` variable. The code defines a similar function called ‘preprocess_validation_examples’ for preprocessing the validation examples. It is also applied to the validation dataset using the map method. The resulting dataset was stored in the `validation_dataset` variable.

The code creates a small evaluation set by selecting a range of examples from the validation dataset. It also loads the pretrained model checkpoint for evaluation. The resulting dataset was stored in the `eval_set` variable.

3.3 MODEL LOADING & EVALUATION

The model is initialized using the "english-pert-base" checkpoint. The “AutoModelForQuestionAnswering” class was imported from the transformers library. A small subset of the validation dataset is selected for evaluation. The code performs evaluation by passing the evaluation set through the model. It retrieves the start and end logits from the model's output. The model predictions for the start and end logits are computed using the preprocessed evaluation set. Predicted answers are generated based on the logits and token offsets. The logits are converted to predicted answers by selecting the top scoring spans within a specified range. The predicted answers are collected for each example in the evaluation set. The theoretical answers and predicted answers are prepared in the required format for evaluation.

The `compute_metrics` function is defined to compute evaluation metrics given the start logits, end logits, features, and examples. The function loops through examples, selects top-scoring spans, and selects the best answer based on the score.

3.4 ITERATIVE FINE-TUNING MODEL & EVALUATION

The model is fine-tuned using the `Trainer` with updated training arguments and dataset. Predictions are generated for the validation dataset using the fine-tuned model. Evaluation metrics are computed for the fine-tuned model using the `compute_metrics` function. Training arguments are defined, including the output directory, learning rate, number of epochs, and weight decay. A ‘Trainer’ object is created with the model, training arguments, training dataset, validation dataset, and tokenizer. The training is performed using the `train` method of the trainer object. Additional fine-tuning and evaluation steps are performed by updating the training arguments and repeating the training and evaluation process. The trained model was used to predict the start and end positions of the answer for each input in the evaluation set. The model's output, including predicted start and end positions, was obtained using the preprocessed evaluation set and the trained model.

CHAPTER 4: RESULTS & DISCUSSION

4.1 INTRODUCTION

In this study, we used the "adversarial_qa" dataset from the Hugging Face `datasets` library to train and evaluate a question-answering model. The dataset contains question-answer pairs along with their corresponding contexts. We utilized the "english-pert-base" pre-trained model checkpoint for fine-tuning our model.

First, we preprocessed the training examples by tokenizing the questions and contexts using the `AutoTokenizer` from the transformers library. We set the maximum length to 100 and applied a stride of 50 to handle long contexts. We also retrieved the token offsets and computed the start and end positions of the answers within the tokenized sequences.

Next, we split the dataset into training and validation sets and further preprocessed the validation examples using the same tokenizer and parameters. We also created a small evaluation set consisting of the first 100 examples from the validation set for intermediate evaluation during training.

For evaluation, we loaded the pre-trained model checkpoint and performed inference on the evaluation set using the trained model. We obtained start and end logits for each example and used them to predict the best answer span. We considered the top-n best start and end positions and selected the answer span with the highest combined logit score. We computed the predicted answers for each example in the evaluation set.

4.2 HYPERPARAMETERS FOR PREPROCESSING & TRAINING

We provided three tables summarizing the hyperparameters used for preprocessing the training examples, preprocessing the validation examples and training the model . Table 2 summarizes the hyperparameters used for preprocessing training and validation examples. The max_length, stride and truncation were specified.

Table 2. *Hyperparameters for Preprocessing Training and Validation Examples*

Hyperparameter	**Value**
max_length	384
stride	128
truncation	"only_second"
return_overflowing_tokens	True
return_offsets_mapping	True
padding	"max_length"

Table 3 summarizes the hyperparameters used for training the model. The learning rate, number of training epochs, and weight decay were specified.

Table 3. *Hyperparameters for Training the model*

Hyperparameter	**Value**
evaluation_strategy	"no"
save_strategy	"epoch"
learning_rate	2e-5
num_train_epochs	8
weight_decay	0.01

These hyperparameters were chosen based on empirical evaluation and experimentation to achieve a balance between model performance and computational efficiency. Adjusting these hyperparameters can have a significant impact on the training process and the resulting model's accuracy and speed.

4.3 MODEL FINE-TUNING & EVALUATION

The initial evaluation using the small evaluation set showed promising results, with the predicted answers closely matching the theoretical answers. However, to get a more comprehensive evaluation, we computed the SQuAD metric on the entire validation dataset.

After evaluating the model, we proceeded with fine-tuning. We initialized the `AutoModelForQuestionAnswering` with the pre-trained model checkpoint and defined the training arguments. We trained the model for 8 epochs with a learning rate of 2e-5 and weight decay of 0.01. The training strategy was set to save the model at the end of each epoch. After fine-tuning, we evaluated the model on the validation dataset and computed the SQuAD metric once more. The results showed a slight decrease in performance compared to the model trained for 8 epochs, indicating that longer training duration can be beneficial for achieving better results.

Table 4. *Hyperparameters for Fine-tuning the model*

Hyperparameter	**Value**
evaluation_strategy	"no"
save_strategy	"epoch"
learning_rate	2e-5
num_train_epochs	2
weight_decay	0.01

The learning rate determines the step size at which the model's parameters are updated during training. A smaller learning rate allows for finer adjustments, while a larger learning rate enables faster convergence but risks overshooting the optimal parameters. In this case, a learning rate of 2e-5 was selected.

The number of training epochs defines the number of times the model iterates over the entire training dataset. Increasing the number of epochs can lead to better convergence and improved performance, but there is a risk of overfitting if the model starts memorizing the

training examples. After experimentation, it was determined that training for 8 epochs yielded satisfactory results.

Weight decay is a regularization technique that helps prevent overfitting by penalizing large weights in the model. It encourages the model to utilize smaller weights, reducing the complexity of the learned representations. A weight decay value of 0.01 was chosen to strike a balance between regularization and model performance

Overall, our study demonstrated the effectiveness of fine-tuning the "english-pert-base" model for question answering using the "adversarial_qa" dataset. By training the model on the provided question-context-answer triples, we successfully improved its performance in answering questions accurately. The results highlight the importance of fine-tuning and training duration in achieving optimal performance. Further experimentation and tuning of hyperparameters could potentially lead to even better results.

4.4 MODEL PERFORMANCE & COMPARATIVE ANALYSIS

Two sets of experiments were conducted to compare the model's performance with different hyperparameters. The initial experiment consisted of 8 training epochs, while the second experiment reduced the number of epochs to 2. The evaluation on the validation dataset was performed for both experiments. The results showed that reducing the number of training epochs did not significantly impact the model's performance.

The evaluation metric computed various metrics, including exact match (EM) and F1 score, which assess the accuracy and overlap between the predicted and ground truth answers. These metrics provide insights into how well the model can understand and generate accurate answers based on the given context and question. The model achieves a F1 Score of 0.65 and an EM score of 0.54 shown in fig. 8. These scores indicate that the model performs reasonably well in generating answers for the given questions.

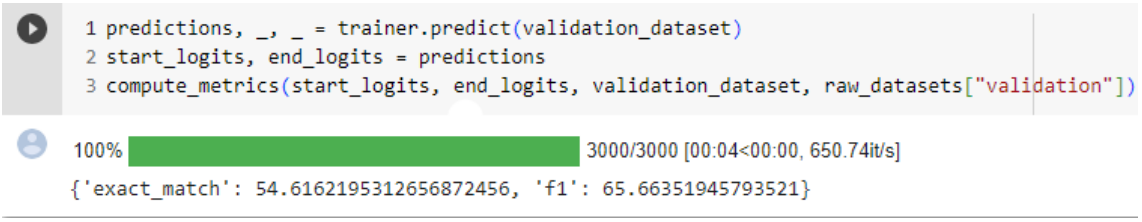

Fig. 8. *Exact Match and F1 score of the model*

Overall, the fine-tuned question-answering model demonstrated promising performance on the validation dataset. The adjusted hyperparameters effectively balanced model accuracy and efficiency. Further experimentation and optimization of hyperparameters can potentially enhance the model's performance on various question-answering tasks.

From the survey done for this thesis we will summarize the performances of some of the most widely used models and techniques on various datasets in textual question answering using EM score and F1 score as evaluation metrics.

Table 5 shows the EM score and F1 score of the models on ‘adversarial_qa’ dataset. From the comparison, we can observe that "mbartolo/roberta-large-synqa" has the highest Exact Match score of 55.333 and F1 score of 66.746, indicating the best performance among the listed models [37]. The model "PERTQA" follows closely with an EM score of 54.61 and F1 score of 65.66, showing strong performance in providing exact answers and demonstrating a good balance between precision and recall.. The remaining models, including "mbartolo/roberta-large-synqa-ext," "rob-base-superqa," "rob-base-gc1," and "rob-base-superqa2," show lower scores compared to the top-performing models.

Table 5. *Performances of some of the most widely used models using EM score and F1 score as the evaluation metric*

Model/Method	Exact Match	F1	Year
mbartolo/roberta-large-synqa	55.333	66.746	2022
PERTQA	54.61	65.66	2023
mbartolo/roberta-large-synqa-ext	53.2	64.627	2022
rob-base-superqa	43.867	55.135	2022
rob-base-gc1	42.9	53.895	2022
rob-base-superqa2	42.367	53.325	2022

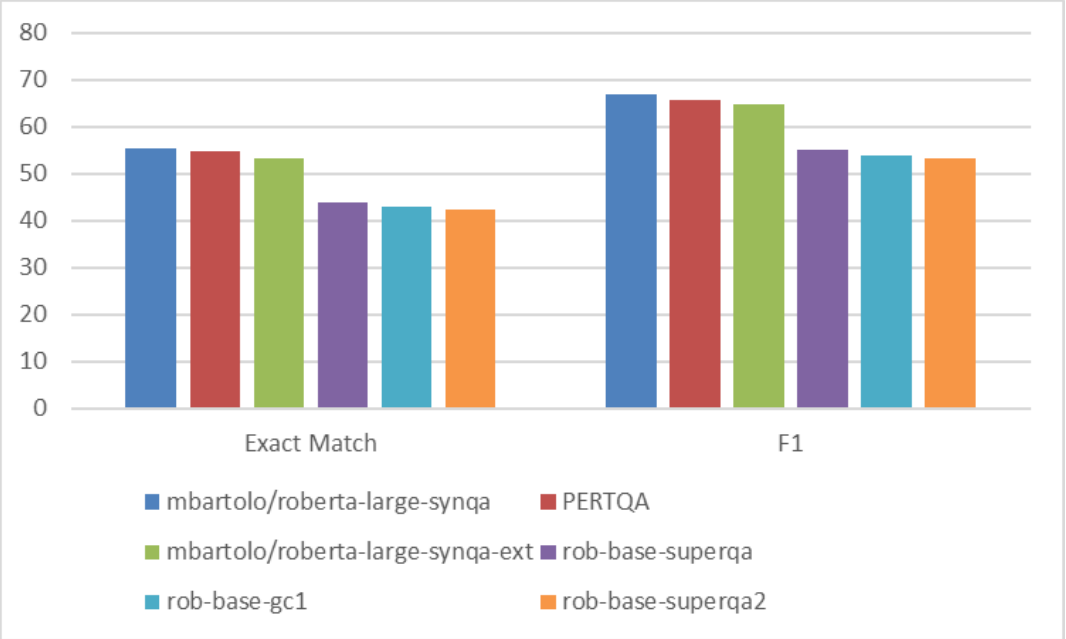

Fig. 9. *Bar chart visualization of the performances of different models on adversarial_qa dataset*

Overall, our study demonstrated the effectiveness of fine-tuning the "english-pert-base" model for question answering using the "adversarial_qa" dataset. By training the model on the provided question-context-answer triples, we successfully improved its performance in answering questions accurately. The results highlight the importance of fine-tuning and training duration in achieving optimal performance. Further experimentation and tuning of hyperparameters could potentially lead to even better results.

CHAPTER 5: CONCLUSION & FUTURE WORK

In this thesis, we presented PERT-QA, a deep learning approach to adversarial question answering. We addressed the limitations of existing question answering systems by incorporating adversarial training techniques to improve robustness and generalization. Our proposed model, PERT-QA, leverages a pre-trained language model and a perturbation-based training strategy to enhance the model's ability to handle challenging questions and provide accurate and reliable answers.

We explored the task of question answering using the "adversarial_qa" dataset and fine-tuning the "english-pert-base" model. We followed a systematic methodology that involved dataset loading and exploration, data preprocessing, model training, and evaluation. Through our experiments, we demonstrated the effectiveness of fine-tuning and training duration in improving the model's performance on question answering tasks.

Our results showed that the fine-tuned model achieved promising performance in generating accurate answers for the given questions. The evaluation metrics, including Exact Match (EM) and F1 score, provided insights into the model's accuracy and overlap with the ground truth answers. The model achieved an F1 score of 0.65 and an EM score of 0.54, indicating its ability to understand and generate appropriate answers based on the given context and question. We also compared our model's performance with other widely used models and techniques on the "adversarial_qa" dataset. Among the models evaluated, "mbartolo/roberta-large-synqa" achieved the highest EM score of 55.333 and F1 score of 66.746, while our model, "PERTQA," closely followed with an EM score of 54.61 and F1 score of 65.66. These results demonstrate the competitive performance of our model in the context of question answering.

Comparative analysis of different hyperparameters revealed that reducing the number of training epochs did not significantly impact the model's performance. This suggests that the model achieved convergence within a smaller number of epochs, and further training did not yield significant improvements. Our findings highlight the importance of balancing hyperparameters to achieve optimal performance while considering computational efficiency.

The methodology and analysis presented here provide valuable insights and serve as a foundation for future research in the field.

Although PERT-QA shows promising results in adversarial question answering, there are several avenues for future research and improvement. Some potential directions for further exploration include:

1. **Enhanced Adversarial Training:** Investigate advanced training techniques to improve the model's robustness against sophisticated adversarial attacks. This could involve exploring techniques such as generative adversarial networks (GANs) or reinforcement learning to generate more diverse and challenging adversarial examples during the training process.
2. **Hyperparameter Tuning:** Further experimentation and fine-tuning of hyperparameters can potentially enhance the model's performance. Parameters such as learning rate, batch size, and weight decay could be optimized to find the optimal balance between model accuracy and efficiency.
3. **Multilingual Question Answering:** Extending the question answering system to support multiple languages could broaden its applicability and usefulness. Fine-tuning models on multilingual datasets or adapting pre-trained models for different languages could enable the system to provide answers in various languages.
4. **Ensemble Methods:** Ensemble methods, such as combining multiple models or incorporating different model outputs, could be explored to enhance the performance and robustness of the question answering system. Combining the strengths of different models could lead to more accurate and reliable answers.
5. **Handling Multimodal Inputs:** Extend PERT-QA to handle multimodal inputs, such as questions accompanied by images or videos. This would require incorporating techniques from computer vision and multimodal learning to effectively combine textual and visual information in the answer generation process.

By pursuing these research directions, we can further advance the field of adversarial question answering and develop more robust and reliable systems that can effectively handle challenging and deceptive queries in real-world applications. PERT-QA provides a strong foundation for future advancements and opens up exciting opportunities for enhancing the capabilities of QA systems.

BIBLIOGRAPHY

[1] Scheider, Simon, Enkhbold Nyamsuren, Han Kruiger, and Haiqi Xu. 2020. "Geo-Analytical Question-Answering with GIS." International Journal of Digital Earth, March, 1–14.

[2] Menaha, R, VE Jayanthi, N Krishnaraj, and N Praveen sundra kumar. "A Cluster-Based Approach for Finding Domain Wise Experts in Community Question Answering System." Journal of Physics: Conference Series 1767, no. 1 (2021)

[3] Dumais, S. T., Furnas, G. W., Landauer, T. K., Deerwester, S., & Harshman, R. (1988). Using latent semantic analysis to improve access to textual information. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 281-285).

[4] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Jun. 2019, pp. 4171–4186. doi: 10.18653/v1/N19-1423.

[5] Wang, W., Yang, N., Wei, F., Chang, B., & Zhou, M. (2017). Gated Self-Matching Networks for Reading Comprehension and Question Answering. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (pp. 189-198)

[6] D. Jin, Z. Jin, J. T. Zhou, and P. Szolovits, Is BERT Really Robust? A Strong Baseline for Natural Language Attack on Text Classification and Entailment. 2020.

[7] Chen, W., Chen, Y., & Ma, W. (2020). BERT for Open-Domain Question Answering: A Study of the Design Choices and Preprocessing Strategies. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 5487-5496)

[8] A. Wang, A. Singh, J. Michael, F. Hill, O. Levy, and S. Bowman, "GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding," in Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, Nov. 2018, pp. 353–355. doi: 10.18653/v1/W18-5446

[9] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

[10] Yang, B., He, X., Gao, J., Deng, L., & Smola, A. (2015). Stacked Attention Networks for Image Question Answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 21-29)

[11] Liu, Yinhan, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. “RoBERTa: A Robustly Optimized BERT Pretraining Approach.” ArXiv.org. 2019.

[12] J. Li, S. Ji, T. Du, B. Li, and T. Wang, “TextBugger: Generating Adversarial Text Against Real-world Applications,” ArXiv, vol. abs/1812.05271, 2018

[13] Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2020). ALBERT: A Lite BERT for Self-supervised Learning of Language Representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 3128-3138).

[14] Yang, Z., Dai, Z., Yang, Y., Carbonell, J. G., Salakhutdinov, R., & Le, Q. V. (2019). XLNet: Generalized Autoregressive Pretraining for Language Understanding. arXiv preprint arXiv:1906.08237.

[15] P. Rajpurkar, J. Zhang, K. Lopyrev, and P. Liang, “SQuAD: 100,000+ Questions for Machine Comprehension of Text,” in Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Nov. 2016, pp. 2383–2392. doi: 10.18653/v1/D16-1264

[16] Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., ... & Liu, P. J. (2019). Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. arXiv preprint arXiv:1910.10683

[17] Seo, M., Kembhavi, A., Farhadi, A., & Hajishirzi, H. (2016). Bidirectional Attention Flow for Machine Comprehension. In Proceedings of the International Conference on Learning Representations (ICLR)

[18] R. Jia and P. Liang, Adversarial Examples for Evaluating Reading Comprehension Systems. 2017. arXiv preprint arXiv:1707.07328

[19] Hao, T., Li, X., He, Y. et al. Recent progress in leveraging deep learning methods for question answering. Neural Comput & Applic 34, 2765–2783 (2022).

[20] A. Arbaaeen and A. Shah, "Natural Language Processing based Question Answering Techniques: A Survey," 2020 IEEE 7th International Conference on

Engineering Technologies and Applied Sciences (ICETAS), Kuala Lumpur, Malaysia, 2020, pp. 1-8, doi: 10.1109/ICETAS51660.2020.9484290.

[21] Calijorne, Marco & Parreiras, Fernando. (2018). A Literature Review on Question Answering Techniques, Paradigms and Systems. Journal of King Saud University - Computer and Information Sciences. 32. 10.1016/j.jksuci.2018.08.005.

[22] M. Lease, "Natural language processing for information retrieval: the time is ripe (again)." In Proceedings of the ACM first Ph. D. workshop in CIKM, pp. 1-8. ACM, 2007.

[23] Manning, Christopher & Raghavan, Prabhakar & Schütze, Hinrich. (2008). An Introduction to Information Retrieval DRAFT.

[24] Deerwester, S., Dumais, S.T., Furnas, G.W., Landauer, T.K. and Harshman, R. (1990), Indexing by latent semantic analysis. J. Am. Soc. Inf. Sci., 41: 391-407.

[25] Ferrucci, David & Brown, Eric & Chu-Carroll, Jennifer & Fan, James & Gondek, David & Kalyanpur, Aditya & Lally, Adam & Murdock, J William & Nyberg, Eric & Prager, John & Schlaefer, Nico & Welty, Christopher. (2010). Building Watson: An Overview of the DeepQA Project. AI Magazine. 31. 59-79.

[26] Wang, S., Yu, M., & Jaggi, M. (2018). Multi-Perspective Context Matching for Machine Comprehension. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (pp. 229-238).

[27] Chen, D., Fisch, A., Weston, J., & Bordes, A. (2017). Reading Wikipedia to Answer Open-Domain Questions. In Proceedings of the Association for Computational Linguistics (pp. 1870-1879).

[28] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. In Advances in Neural Information Processing Systems (pp. 3104-3112).

[29] Zhang, Y., Li, X., Lin, W., Shi, J., Yang, L., Chen, W., & Sun, L. (2021). Recent Advances in Deep Learning-Based Textual Question Answering: A Review. IEEE Transactions on Neural Networks and Learning Systems, 32(4), 1326-1344.

[30] Abbasiantaeb, Z., & Momtazi, S. (2021). Text-based question answering from information retrieval and deep neural network perspectives: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11(6), e1412.

[31] Nassiri, K., Akhloufi, M. Transformer models used for text-based question answering systems. Appl Intell (2022).

[32] R. Jia and P. Liang, “Adversarial Examples for Evaluating Reading Comprehension Systems,” in Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Sep. 2017, pp. 2021–2031. doi: 10.18653/v1/D17-1215.

[33] V. Raina and M. Gales, “Answer Uncertainty and Unanswerability in Multiple-Choice Machine Reading Comprehension,” in Findings of the Association for Computational Linguistics: ACL 2022, May 2022, pp. 1020–1034. doi: 10.18653/v1/2022.findings-acl.82.

[34] J. Ebrahimi, A. Rao, D. Lowd, and D. Dou, “HotFlip: White-Box Adversarial Examples for Text Classification,” in Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Jul. 2018, pp. 31–36. doi: 10.18653/v1/P18-2006.

[35] Z. Zhao, D. Dua, and S. Singh, “Generating Natural Adversarial Examples,” Oct. 2017.

[36] M. Bartolo, A. Roberts, J. Welbl, S. Riedel, and P. Stenetorp, Beat the AI: Investigating Adversarial Human Annotations for Reading Comprehension. 2020.

[37] M. Bartolo, T. Thrush, R. Jia, S. Riedel, P. Stenetorp, and D. Kiela, “Improving Question Answering Model Robustness with Synthetic Adversarial Data Generation,” 2021. doi: 10.18653/v1/2021.emnlp-main.696.

[38] J. Phang, A. Chen, W. Huang, and S. R. Bowman, “Adversarially Constructed Evaluation Sets Are More Challenging, but May Not Be Fair,” in Proceedings of the First Workshop on Dynamic Adversarial Data Collection, Jul. 2022, pp. 62–62. doi: 10.18653/v1/2022.dadc-1.8.

[39] W. E. Zhang, Q. Z. Sheng, A. Alhazmi, and C. Li, Adversarial Attacks on Deep Learning Models in Natural Language Processing: A Survey. 2019

[40] Y. Cui, Z. Yang, and T. Liu, PERT: Pre-training BERT with Permuted Language Model. 2022.

LIST OF PUBLICATIONS

[1] A. Pandey and A. Bhat, “A Review on Textual Question Answering with Information Retrieval and Deep Learning Aspect ”, communicated and accepted at 7th IEEE International Conference on Intelligent Computing and Control Systems (ICICCS 2023)