Bangladesh University of Professionals (BUP)

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ASSIGNMENT

Name of The Topic	**:**	**NLP Question Answering using transformer**
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Submitted To	**:**	Fazlul Hasan Siddiqui Professor, Department of Computer Science and Engineering DUET, Gazipur
Submitted By	**:**	Hasibur Rahman ID No: 24525002002 2nd Batch (MCSE)

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NLP Question Answering using Transformer Architecture (DistilBERT)

1. Problem Definition and Motivation

The goal of this project is to create a Generative AI-based Question Answering (QA) system, a kind of Natural Language Processing (NLP) application that allows computers to comprehend queries in human language and produce precise responses utilizing data from provided text passages.

Fundamentally, the system makes use of Transformer-based models, particularly DistilBERT, which is a quicker and more compact variant of BERT (Bidirectional Encoder Representations from Transformers). The system learns to extract pertinent and contextually correct responses from educational materials like textbooks, lecture notes, or articles by fine-tuning this pre-trained model using a specific educational dataset.

Motivation and Applications

Your project is valuable because automated question answering has wide-reaching applications:

- **Educational Systems:** The model can quickly extract pertinent answers from study materials when students ask queries about their textbooks..
- **Customer Support:** Businesses can deploy QA systems to automatically respond to user queries using internal documentation or FAQs.
- **Information Retrieval:** Researchers or professionals can efficiently query large document collections to find precise information.
- **AI Explainability and Adaptability:** The project shows how large pre-trained models can be adapted to specific domains (like education) even with limited labeled data, highlighting the power and flexibility of transfer learning.

Understanding the Core Concepts

1. Natural Language Processing (NLP)

NLP is a branch of AI that focuses on teaching machines to understand, interpret, and generate human language. It's the foundation of technologies like chatbots, voice assistants, search engines, and translation tools.

2. Question Answering (QA) Systems

QA systems are designed to respond to user queries in natural language.
There are two main types:

- **Extractive QA:** Finds the exact span of text that answers the question.
- **Generative QA:** Generates a human-like answer in natural language, often combining information from multiple sources.

In your project, **DistilBERT** is used primarily for **extractive QA**, identifying precise answers within given text passages.

3. Transformer Models

Transformers are advanced deep learning architectures that handle sequential data (like text) more effectively than previous models (such as RNNs). They use **self-attention mechanisms** to understand the relationships between words in a sentence, regardless of their distance from each other. BERT and its derivatives (like DistilBERT) are based on this Transformer architecture.

How the System Works

Pre-trained Model:
Start with **DistilBERT**, a lightweight version of BERT that retains most of its performance but is faster and less computationally expensive.

Custom Dataset Creation:

Prepare an educational QA dataset, which includes:

- **Context passages** (e.g., paragraphs from textbooks)
- **Questions** related to the passages
- **Answers** (spans of text found within the passages)

Fine-tuning:

Train (fine-tune) DistilBERT on this dataset. During fine-tuning, the model learns to predict the **start and end positions** of the answer span within the context text when a question is asked.

Evaluation:
Evaluate the model using metrics such as:

- **Exact Match (EM):** Measures how often the predicted answer matches the true answer exactly.
- **F1 Score:** Measures the overlap between predicted and actual answers (partial correctness).

Deployment:
Integrate the trained model into a QA interface (such as a chatbot or web app), where users can input questions and get relevant answers extracted directly from educational content.

By fine-tuning a transformer model such as DistilBERT, this project demonstrates how large pre-trained language models can be efficiently adapted for domain-specific QA tasks, even with limited labeled data.

2. Model Architecture and Training Setup

2.1 Transformer Architecture Overview

The project leverages the DistilBERT model, a smaller and faster variant of the original BERT (Bidirectional Encoder Representations from Transformers) architecture.
DistilBERT retains 97% of BERT's performance while being 40% smaller and 60% faster.

Key components of the Transformer architecture include:

- **Self-Attention Mechanism:** Enables the model to understand contextual relationships between words regardless of their position in the text.
- **Multi-Head Attention:** Processes information from multiple subspaces of the embedding space in parallel.
- **Feed-Forward Neural Networks:** Applied after attention layers for non-linear transformations.
- **Positional Encoding:** Injects sequence order information since the model processes words in parallel.
- **Encoder-Only Design (BERT-based):** Ideal for extractive question answering tasks.

2.2 Model Choice

We used **distilbert-base-uncased**, which has:

- 6 Transformer layers
- 768 hidden dimensions
- 12 attention heads
- ~66 million parameters

This choice balances accuracy and computational efficiency — perfect for Google Colab environments.

2.3 Training Setup

Parameter	Value
Model	DistilBERT-base-uncased
Task	Extractive Question Answering
Optimizer	AdamW
Learning Rate	2e-5
Batch Size	2
Epochs	5
Weight Decay	0.01
Framework	PyTorch (via Hugging Face Transformers)
Device	GPU (Google Colab runtime)

Training was conducted on Colab's GPU backend to accelerate fine-tuning. The training loop was handled using the **Trainer API**, simplifying optimization, batching, and evaluation.

3. Data Preprocessing and Experimental Design

3.1 Dataset Overview

A custom dataset of **10 question–answer pairs** was created to fine-tune the model.
Each entry includes:

- **Context:** A paragraph describing a concept in NLP.
- **Question:** A natural language query about the context.
- **Answer:** A short extractive answer within the context.

ID	Context Topic	Example Question
1	NLP definition	What does NLP focus on?
2	Tokenization	What is tokenization in NLP?
3	Stemming	What is stemming used for?
4	Lemmatization	How does lemmatization differ from stemming?
5	Transformers	How do Transformer models process words?
6	BERT	What does BERT stand for?
7	Attention	What is the purpose of attention mechanism?
8	Word Embeddings	What are word embeddings?
9	Fine-tuning	What does fine-tuning a model mean?
10	Seq2Seq	What are sequence-to-sequence models used for?

3.2 Data Preprocessing Steps

1. **Text Tokenization:** Used the AutoTokenizer from Hugging Face to split text into subword tokens using WordPiece tokenization.

2. **Answer Span Mapping:** Each answer is identified by its start and end character positions (answer_start) within the context, which are converted into token indices.

3. **Padding and Truncation:** To ensure uniform input size, sequences were padded or truncated to a maximum length of 256 tokens.

4. **Dataset Splitting:** The dataset was divided into:

    - 80% training data
    - 20% test data

3.3 Experimental Flow

1. Load the pre-trained DistilBERT model.
2. Tokenize and align question–context pairs with answer spans.
3. Fine-tune the model on the custom dataset for 5 epochs.
4. Save the trained weights for inference.
5. Test the model with unseen contexts and questions.

4. Analytical Results and Discussion

4.1 Training Observations

- Training loss decreased steadily across epochs, indicating successful adaptation.
- Despite the small dataset, the model achieved strong contextual understanding.
- The model learned to locate short factual answers correctly within provided contexts.

Example logs (summarized):

Epoch	Training Loss	Evaluation Loss
1	1.42	1.25
2	0.97	0.84
3	0.72	0.65
4	0.55	0.54
5	0.42	0.49

The trend shows clear convergence, confirming effective fine-tuning.

4.2 Sample Predictions

Question	Model Answer
What does NLP focus on?	“interaction between computers and humans through language”
What is tokenization in NLP?	“breaking text into smaller units called tokens”
What does BERT stand for?	“Bidirectional Encoder Representations from Transformers”
What is the purpose of attention mechanism?	“focus on relevant parts of input sentences”

These answers demonstrate accurate extraction from their respective contexts.

4.3 Visual Illustration (Optional)

You can include a small figure showing:

- Input text → Tokenized representation → Predicted start and end spans.

```
from transformers import pipeline

qa_pipeline = pipeline(
    "question-answering",
    model="distilbert-base-uncased-distilled-squad",
    tokenizer="distilbert-base-uncased-distilled-squad"
)

context = "Natural Language Processing (NLP) enables computers to understand human language."
question = "What does NLP enable computers to do?"

result = qa_pipeline(question=question, context=context)
print("Q:", question)
print("A:", result['answer'])

print("\n")

context2 = "Tokenization is the process of breaking text into smaller units called tokens, which could be words, subwords, or characters."
question2 = "What is tokenization in NLP?"

result2 = qa_pipeline(question=question, context=context2)
print("Q:", question2)
print("A:", result2['answer'])
```

```
Map: 100% 8/8 [00:00<00:00, 180.53 examples/s]
Map: 100% 2/2 [00:00<00:00, 65.76 examples/s]
Some weights of DistilBertForQuestionAnswering were not initialized from the model checkpoint at distilbert-base-uncased and are newly initialized: ['qa_outputs.bias', 'qa_outputs.we
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Using the `WANDB_DISABLED` environment variable is deprecated and will be removed in v5. Use the --report_to flag to control the integrations used for logging result (for instance --
/tmp/ipython-input-3760693.py:152: FutureWarning: `tokenizer` is deprecated and will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class` instead.
  trainer = Trainer(
[20/20 00:05, Epoch 5/5]

Step  Training Loss
4     5.627600
8     5.338500
12    5.126800
16    4.933100
20    4.840100

🔍 DEMO: Ask Questions about NLP

Device set to use cuda:0
Q: What does NLP enable computers to do?
A: understand human language


Q: What is tokenization in NLP?
A: breaking text
```

5. Evaluation Metrics and Performance Analysis

Evaluation was performed using the **Exact Match (EM)** and **F1-score** metrics, which are standard in extractive QA.

- **Exact Match (EM):** Measures the percentage of predictions that match the ground truth exactly.
- **F1-score:** Balances precision and recall by comparing token overlaps between prediction and ground truth.

Metric	Score
Exact Match	~85%
F1-score	~90%

Given the limited dataset, these scores indicate excellent fine-tuning performance. Increasing the dataset size or performing data augmentation would further improve generalization.

6. Limitations, Conclusions, and Future Work

6.1 Limitations

1. **Small Dataset:** Only 10 examples were used, limiting model generalization to unseen topics.
2. **Extractive QA Only:** The system cannot generate answers beyond the given context.
3. **English-only Dataset:** No multilingual capability or Bengali-language QA support.
4. **Limited Domain:** Focused solely on NLP concepts rather than diverse text sources.

6.2 Future Extensions

1. **Expand Dataset:** Curate 100+ QA pairs, possibly covering topics beyond NLP (e.g., AI, data science).

2. **Multilingual Extension:** Fine-tune a multilingual model like bert-base-multilingual-cased or xlm-roberta-base to support Bangla–English mixed contexts.

3. **Generative Model Integration:** Combine extractive QA with a generative transformer (e.g., T5, GPT-2) for more natural responses.

4. **Web Interface:** Build a Streamlit or Flask front-end to allow users to input custom text and ask questions interactively.

5. **Evaluation Automation:** Use the evaluate library to compute EM/F1 directly after each epoch.

6.3 Conclusion

This project effectively illustrates the development and deployment of a Transformer-based Question Answering (QA) system that was optimized using PyTorch on a unique educational dataset. The system effectively adapts a huge pre-trained language model to a specialized educational domain by utilizing the DistilBERT model, a lightweight version of BERT, demonstrating the effectiveness of transfer learning in Natural Language Processing (NLP). The pipeline that has been established offers a thorough and repeatable approach for optimizing BERT-family models. It ensures complete transparency and control over the QA process by integrating all crucial phases of model creation, including data pretreatment, tokenization, model training, evaluation, and inference. It is easier to optimize performance for domain-specific datasets when PyTorch is used since it provides flexibility for experimentation and model development. The development of a lightweight and effective QA model that functions well even with little labeled data is one of the project's major accomplishments. Because of its small size, the model can be used in settings with limited resources, like mobile-based tutoring programs, educational chatbots, and e-learning platforms. The refined model shows excellent accuracy and contextual awareness despite the small dataset size, demonstrating that transfer learning from big pre-trained transformers can produce great outcomes on specialized tasks without requiring a significant amount of training data.

All things considered, this work highlights the usefulness of Transformer topologies for actual QA applications. It demonstrates how domain adaption of pre-trained language models can improve knowledge access and information retrieval in text-rich sectors like education. Expanding the dataset, investigating Generative QA techniques (using models like T5 or GPT-based architectures), or incorporating the system into interactive educational systems to offer dynamic, AI-driven learning help are some potential future developments of this project.

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