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Question Answering on SQuAD 2.0

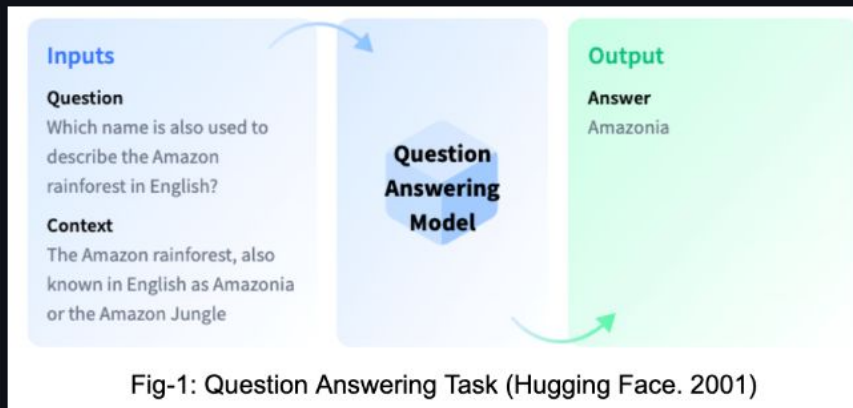
Introduction

In the dynamic realm of Natural Language Processing (NLP), the advent of question-answering (QA) systems marks a significant stride in our ability to interact with and process digital information. This project is dedicated to developing a reading comprehension-based QA system inspired by the comprehensive insights in Speech and Language Processing by Daniel Jurafsky & James H. Martin (2023). We aim to create a system that can interpret and respond to questions posed in natural language, drawing answers from provided text passages.

NLP Task - Question Answering

In the Natural Language Processing (NLP) field, extractive Question Answering (QA) is a pivotal task involving locating the answer to a question within a specified text passage. This task is inherently challenging, as it requires the system to comprehend the posed question and accurately extract the specific text portion that contains the answer. As detailed in Hugging Face's documentation and task library (n.d.), extractive QA demands the capability to sift through extensive text and pinpoint information that precisely responds to the query.

Figure 01



Jurafsky and Martin (2023), in their seminal work, Speech and Language Processing, elucidate the complexities of extractive QA, highlighting the necessity for advanced NLP techniques and models. These models are crucial for understanding the context and semantics embedded in both the question and the passage, thus enabling the identification of the exact text span that answers the question. Extractive QA is particularly vital in scenarios necessitating factual answers directly sourced from the provided text, such as in academic research or specific information retrieval tasks. In our project, we embrace the challenges of extractive QA by training our model on the SQuAD 2.0 dataset. This dataset, encompassing diverse questions and passages, provides a comprehensive framework for the system to learn from varying contexts and question types. The model is meticulously trained to parse the subtleties of language in questions and passages, enhancing its ability to discern and extract the relevant answers accurately. This endeavor underscores the significance of sophisticated text processing and comprehension in NLP, laying the groundwork for more intelligent and adept information retrieval systems.

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Dataset

- **SQuAD 2.0: Stanford Question Answering Dataset 2.0 (SQuAD 2.0)** is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles.
- **Introduction of Unanswerable Questions:** SQuAD 2.0 is enhanced with 53,775 unanswerable questions, created by crowdworkers, in addition to the answerable ones from SQuAD 1.1.
- **Objective of SQuAD 2.0:** It aims to challenge machine learning models in determining when a correct answer is not present in the text, elevating their proficiency in reading comprehension.
- **Increased Complexity:** Unlike SQuAD 1.1, which focused solely on finding the correct text span for a given question, SQuAD 2.0 adds the dimension of identifying unanswerable questions, making it more complex.
- **Public Benchmark:** SQuAD 2.0 is available publicly and serves as the primary benchmark on the official SQuAD leaderboard.

Figure 02

Article: Endangered Species Act

Paragraph: "... Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised."

Question 1: "Which laws faced significant opposition?"

Plausible Answer: later laws

Question 2: "What was the name of the 1937 treaty?"

Plausible Answer: Bald Eagle Protection Act

Figure 03

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Exploratory Data Analysis (EDA)

Statistics about dataset



Select an option:

- ☒ Context Length Analysis Train
- ☐ Context Length Analysis Test
- ☐ Question Length Analysis Train
- ☐ Question Length Analysis Test
- ☐ Answer Length Analysis Train
- ☐ Answer Length Analysis Test
- ☐ Answerable vs Unanswerable Questions Train
- ☐ Answerable vs Unanswerable Questions Test
- ☐ Word Length Analysis
- ☐ Distribution of question type
- ☐ Answer position analysis

Train Context Lengths



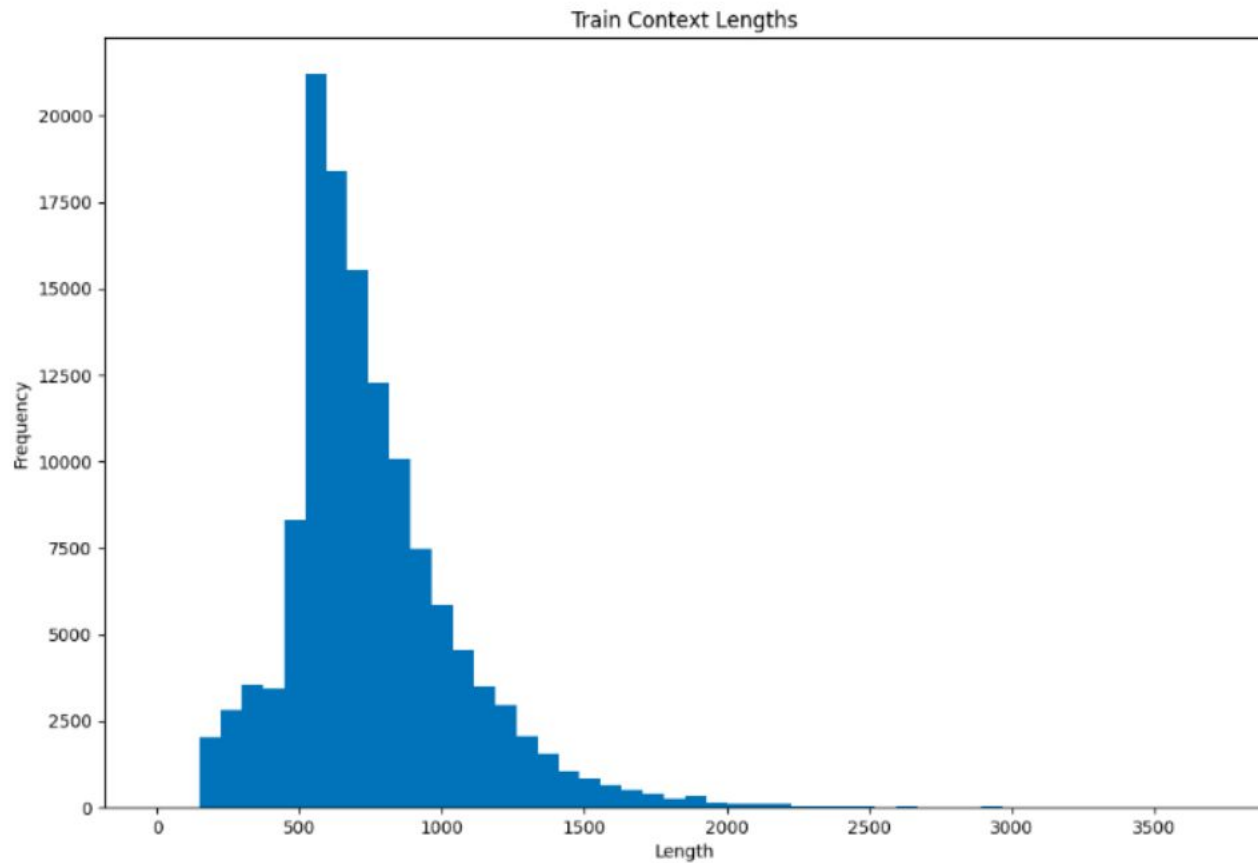
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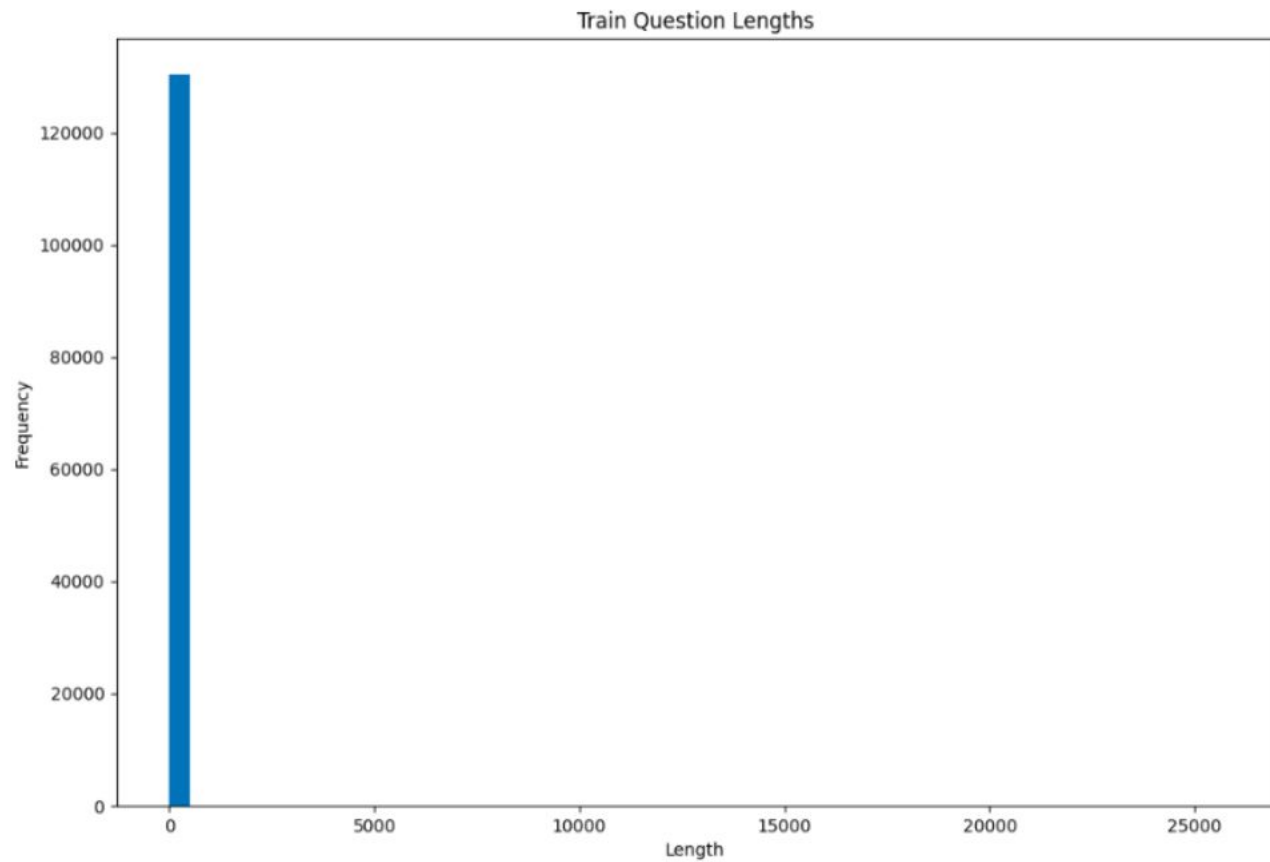
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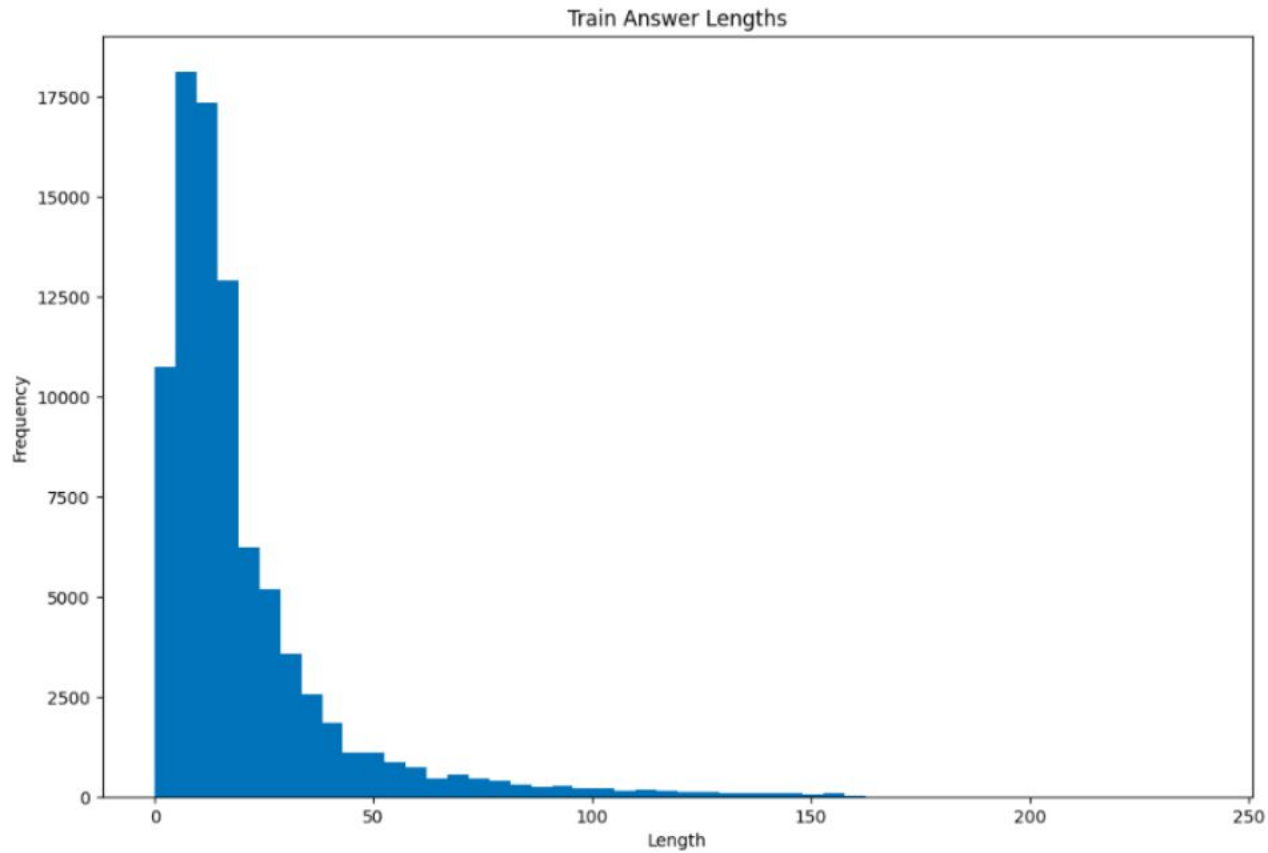
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Selected Option: Answer Length Analysis Train

The below figure is the comparison of the SQuAD 1.1 and SQuAD 2.0 representing the train, development and test values of the total examples, negative examples, total articles and articles with negatives

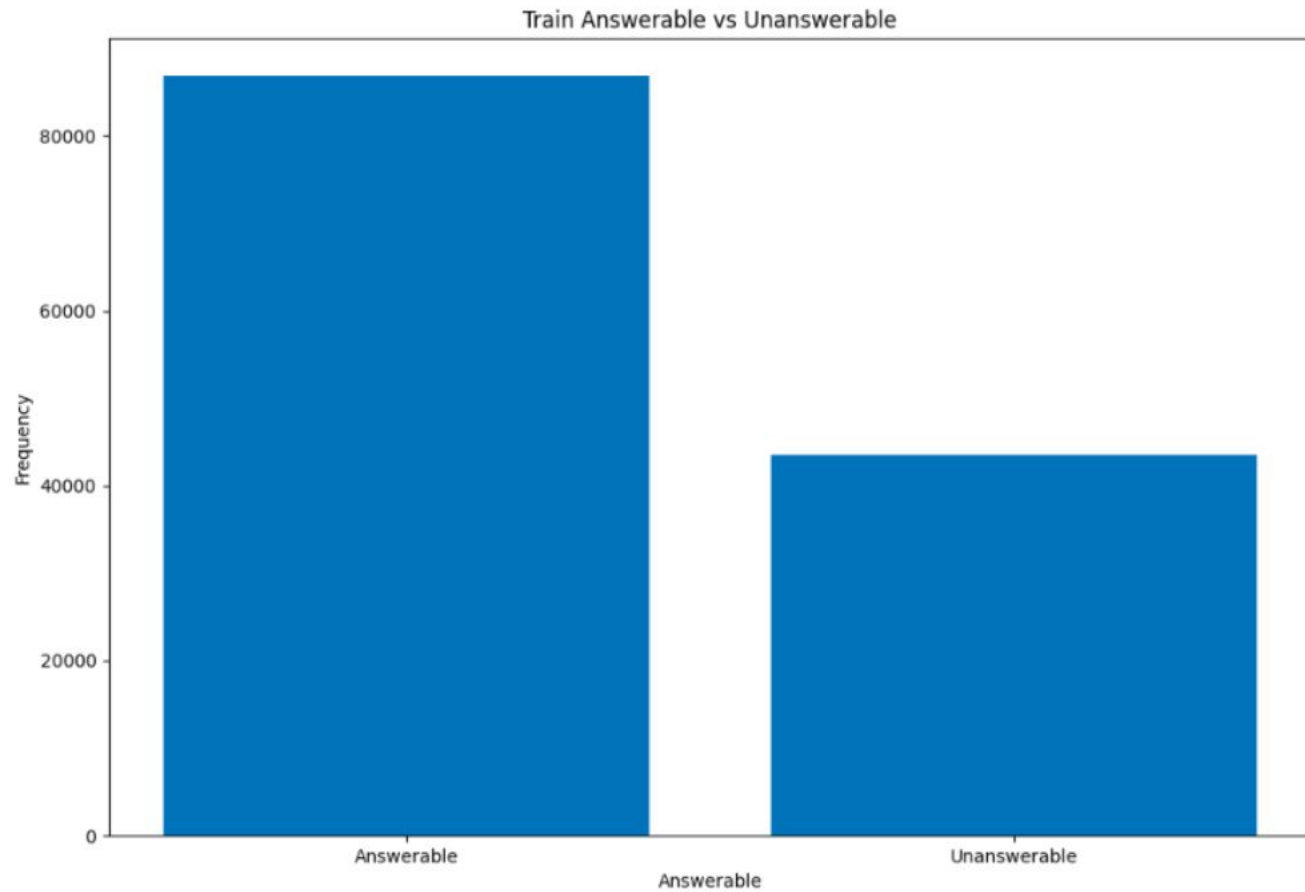
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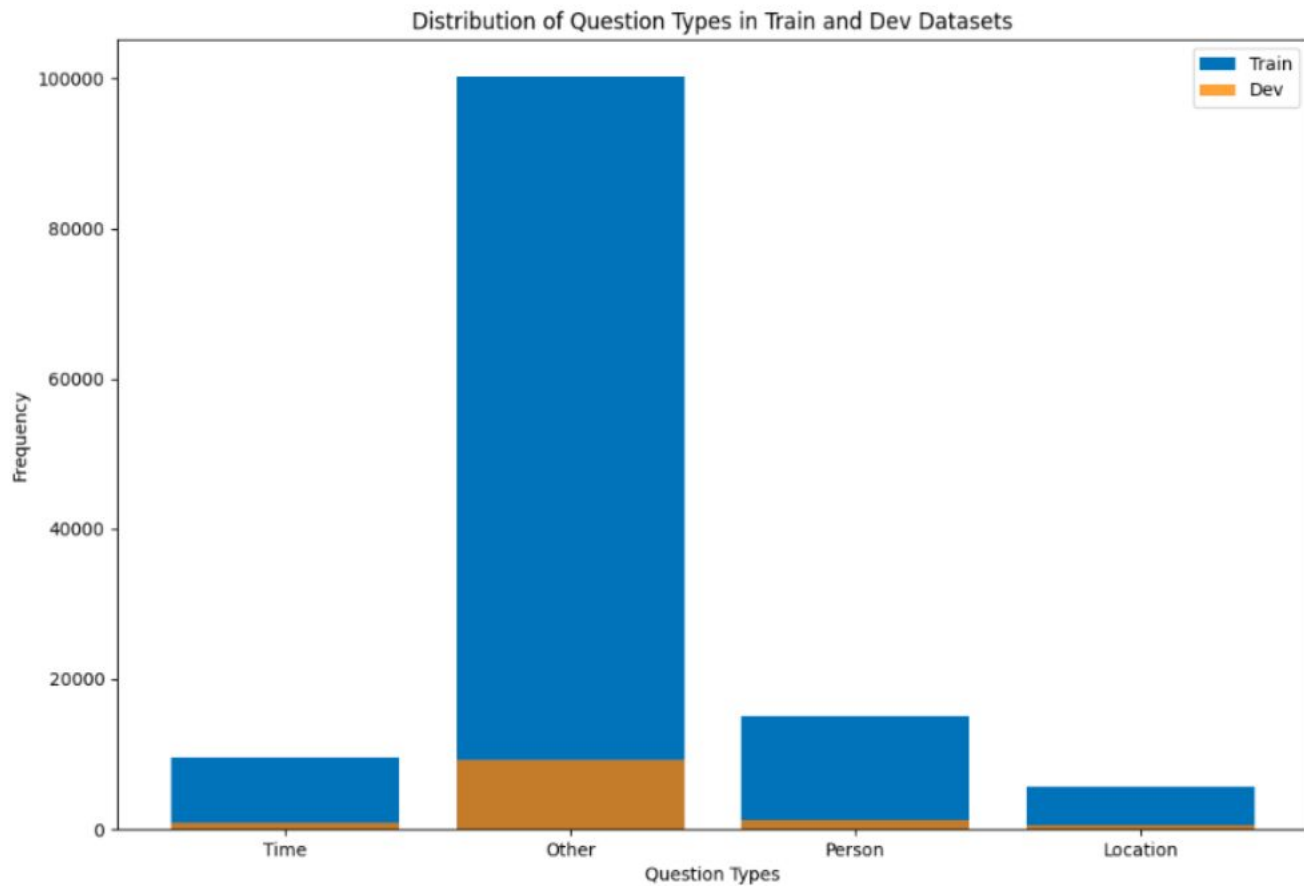
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Selected Option: Distribution of question type



Selected Option: Distribution of question type

The below figure is the comparison of the SQuAD 1.1 and SQuAD 2.0 representing the train, development and test values of the total examples, negative examples, total articles and articles with negatives

	SQuAD 1.1	SQuAD 2.0
Train		
Total examples	87,599	130,319
Negative examples	0	43,498
Total articles	442	442
Articles with negatives	0	285
Development		
Total examples	10,570	11,873
Negative examples	0	5,945
Total articles	48	35
Articles with negatives	0	35
Test		
Total examples	9,533	8,862
Negative examples	0	4,332
Total articles	46	28
Articles with negatives	0	28

Question Answering on SQuAD 2.0

Model Description

ELECTRA

- Two-Component Structure

- **Generator:** Its role is to replace some tokens in the input data with a plausible alternatives.

- **Discriminator:** Its role is to determine whether the replaced tokens are real or fake.

- **Joint Training:** Both the generator and the discriminator are trained simultaneously. (It contrasts with GANs.)

- **Final Model Utilization:** After training, only the discriminator is used for downstream tasks. (It contrasts with the traditional approach.)

- **Efficiency and Scaling:** ELECTRA shows that it's more efficient than models like BERT in terms of computational resources needed for training.

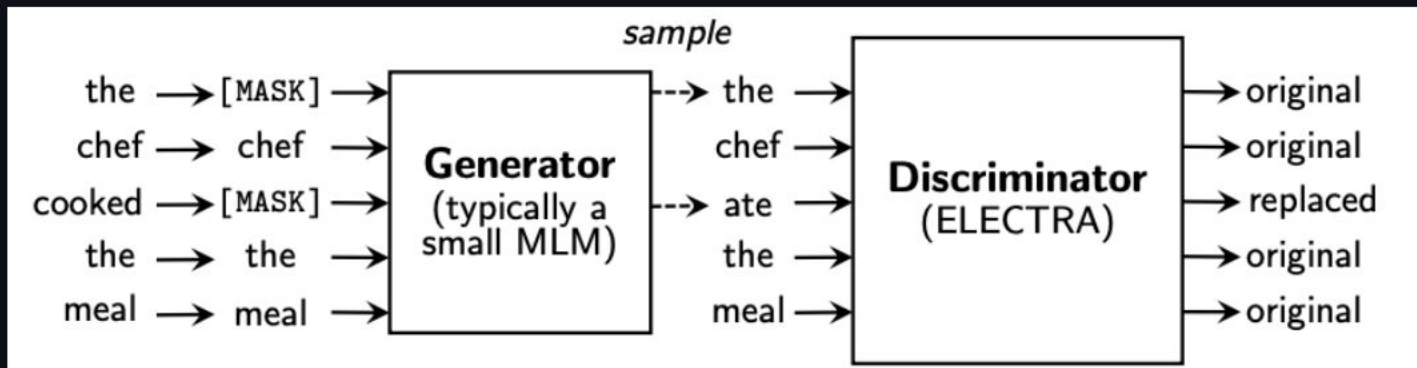
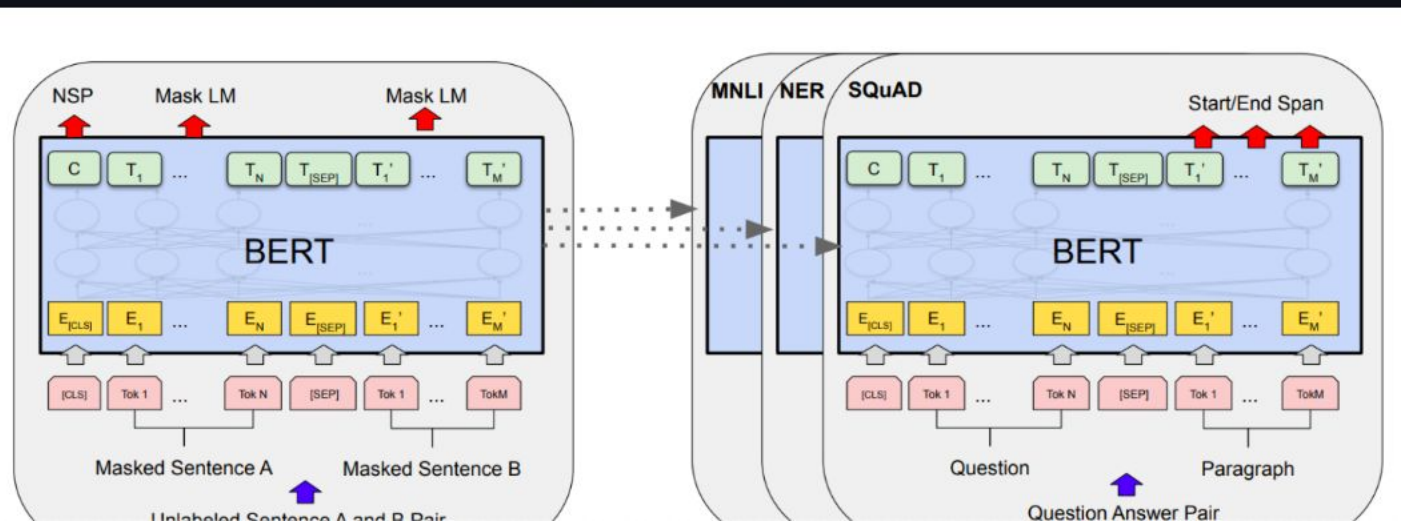


Figure 1: ELECTRA Architecture (Source: Electra Paper)

BERT with LORA

- **Transformer, an attention mechanism :**
- **Encoder:** Its target is to process the input text and understand the context of each word or token within it.
- **ATTENTION Mechanism:** It gives the model ability to weigh the importance of different words in the sentence relative to each other.
- **Embedding Layers:** Find the Embedding Representation of Each words (Word Embedding, Positional Embedding, Segment Embedding)
- **Pretraining:** Masked Language Models/ Next Sentence Prediction
- **Fine-Tuning on QA:** Start Vector/ End Vector
- **Why using LORA?** Base BERT model: 110 millions parameters
- **A method to learn a lower-dimensional, task-specific representation of the layer's weights.**



- **Pretraining: Masked Language Models/ Next Sentence Prediction**
- **Fine-Tuning on QA: Start Vector/ End Vector**
- **Why using LORA? Base BERT model: 110 millions parameters**
- **A method to learn a lower-dimensional, task-specific representation of the layer's weights.**

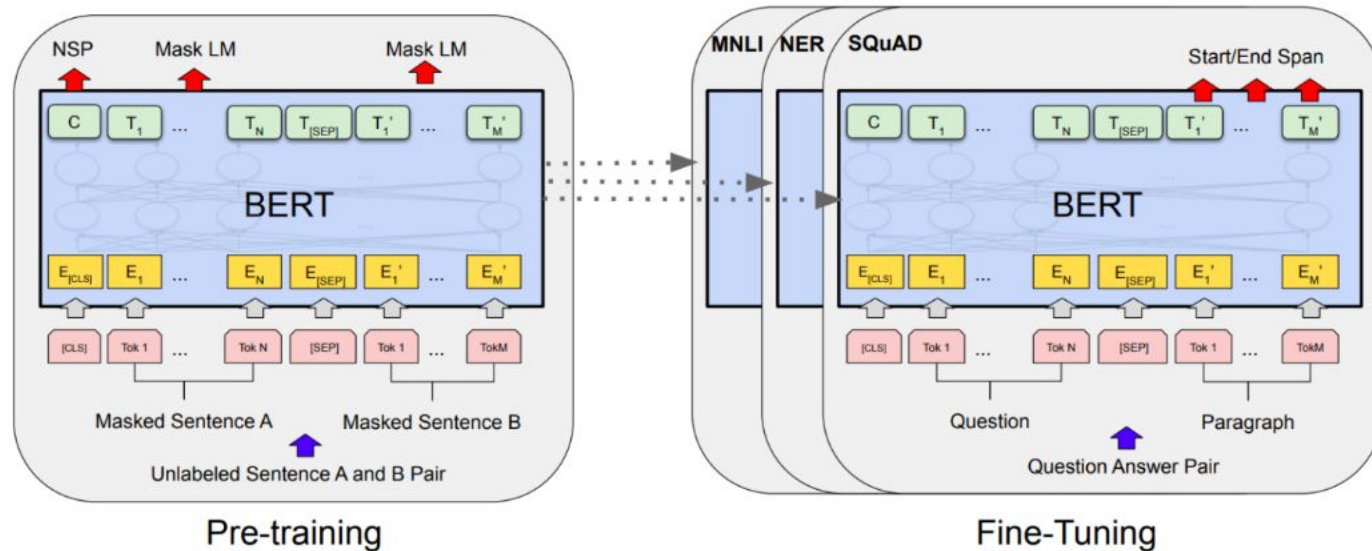


Figure 2: BERT Architecture (Source: Google AI Language)

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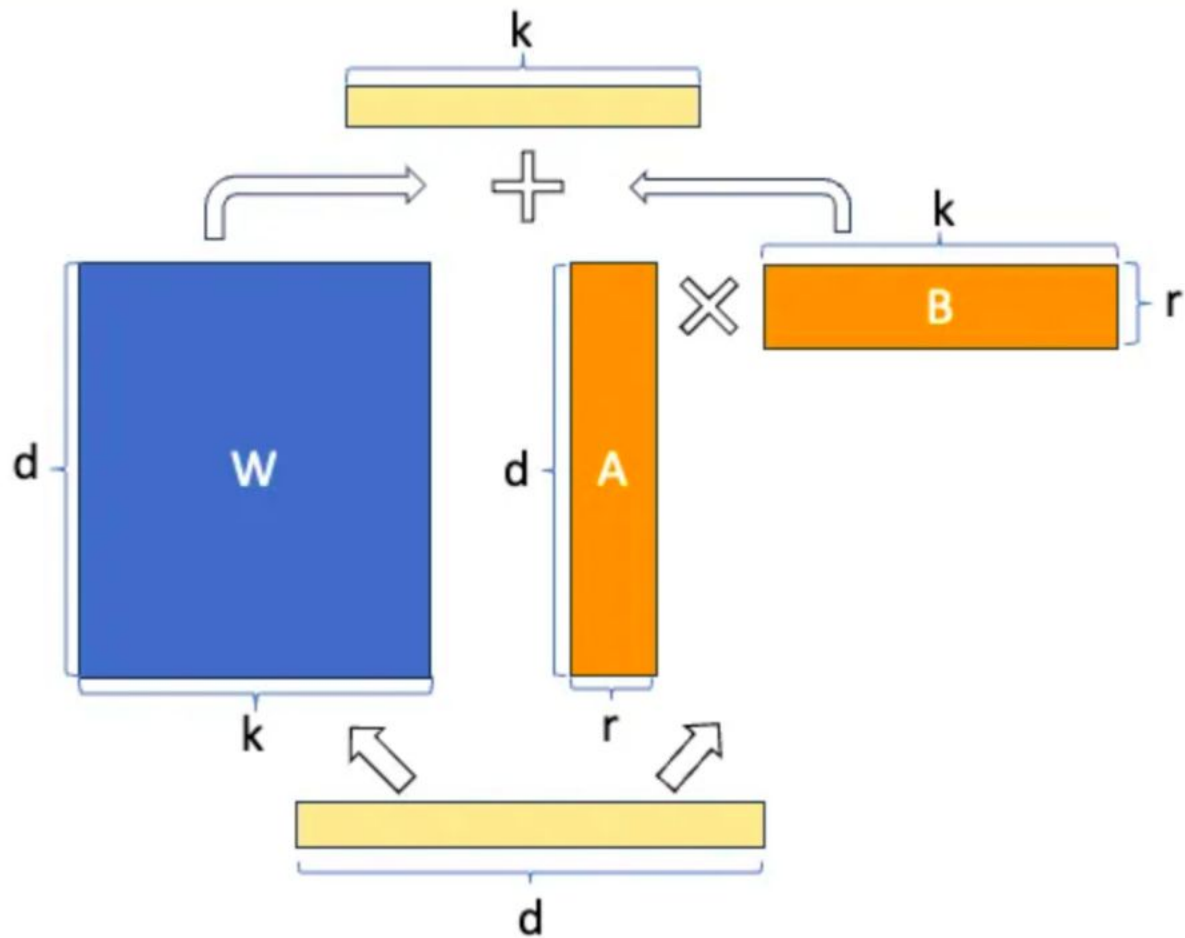
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Training Setups

- **Dataset:** Utilized the SQuAD 2.0 dataset with 130,319 training, 11,873 development examples.
- **Preprocessing:** Tokenization, sliding windows, padding, and answer localization.
- **Evaluation Metrics:** Exact Match (EM) and F1 score.

ELECTRA Model Fine-Tuning for SQuAD 2.0

Hyperparameters:

- **Maximum Sequence Length:** 384
- **Stride:** 128
- **Number of Predictions to Generate:** 20
- **Maximum Answer Length:** 30

Training Parameters:

- **Learning Rate:** $5e-5$
- **Batch Size:** 32
- **Number of Epochs:** 3 (Training duration: 1.5 hours)

The model is fine-tuned using HuggingFace's implementation with an AdamW optimizer.

BERT Model Fine-Tuning for SQuAD 2.0

Hyperparameters:

- **Model:** bert-base-uncased with optional LoRA configuration.
- **Maximum Sequence Length:** 512

Learning Rate: $5e-5$

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Training Parameters:

- Learning Rate: $5e-5$
- Batch Size: 32
- Number of Epochs: 3 (Training duration: 1.5 hours)

The model is fine-tuned using HuggingFace's implementation with an AdamW optimizer.

BERT Model Fine-Tuning for SQuAD 2.0

Hyperparameters:

- Model: bert-base-uncased with optional LoRA configuration.
- Maximum Sequence Length: 512
- Learning Rate: $5e-5$
- Batch Size: 16
- Number of Epochs: 3 (Training duration: 2 hours)

LORA Parameters:

- r: 16
- lora_alpha=32
- lora_dropout=0.05

The model is fine-tuned using HuggingFace's implementation with an AdamW optimizer.

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Evaluation / Results

ELECTRA

- **F1 Score: 0.50071**
- **Exact Match: 0.50071**

BERT with LORA

- **All params : 109,484,548**
- **Trainable Parameters: 54% 591,362**
- **Training Loss(epoch 1 -3): 2.6399 1.6731 1.4301**
- **Valid Loss(epoch 1 -3): 1.7555 1.3669 1.2309**
- **F1 Score: 0.50989**



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Model Selection:

Select Model

BERT



Question Answering on SQuAD 2.0

Demo: Free Question Answering

Context:

Question:

Predict

Clear