BERT Question Answering Application

Notebook 1: Data Exploration & Analysis

Dataset	Training	Validation
SQuAD	**3,000**	**500**

Notebook Objectives:

GPU Setup • Dataset Loading • Subset Creation
Data Exploration • Statistical Analysis • Visualization

Platform: Google Colab (Tesla T4 GPU)
Libraries: HuggingFace Datasets, Transformers, PyTorch
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BERT Question Answering Project Team

Contents

1 Introduction

1.1 Project Overview

This notebook focuses on exploring and understanding the SQuAD (Stanford Question Answering Dataset) used for training BERT-based question answering models. The goal is to load the dataset, create manageable subsets for training, and perform comprehensive statistical analysis to inform model design decisions.

1.2 SQuAD Dataset Background

What is SQuAD?

The Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to each question is a segment of text from the corresponding reading passage.

Dataset Structure:

- **Context:** A paragraph from Wikipedia
- **Question:** A question about the context
- **Answer:** A span of text from the context that answers the question
- **answer_start:** Character position where the answer begins

2 Environment Setup & GPU Configuration

2.1 Step 1: GPU Verification

2.1.1 Code Implementation

Code Explanation

Purpose: Verify GPU availability using NVIDIA System Management Interface (nvidia-smi)
Command: `!nvidia-smi`
Key Parameters Checked:

- **GPU Name:** Tesla T4 (Google Colab standard GPU)
- **Driver Version:** 550.54.15
- **CUDA Version:** 12.4 (compatibility layer)
- **Memory:** 15,360 MiB total (15.83 GB)
- **Temperature:** 37°C (idle state)
- **Power Usage:** 8W / 70W capacity

2.1.2 Output Analysis

Code Output

GPU Configuration:

```
+-----------------------------------------------------------------------------------------
| NVIDIA-SMI 550.54.15    Driver Version: 550.54.15    CUDA Version: 12.4     |
|-----------------------------------------+-------------------------+-----------------
|   0  Tesla T4           Off   | 00000000:00:04.0 Off |                      0 |
| N/A   37C    P8         8W / 70W |      0MiB / 15360MiB |      0%      Default |
+-----------------------------------------------------------------------------------------
|  No running processes found
+-----------------------------------------------------------------------------------------
```

Key Insights

Interpretation:

- **GPU Detected:** Tesla T4 with 15.36 GB memory available
- **Memory Usage:** 0 MiB used (clean state, ready for training)
- **GPU Utilization:** 0% (idle, no competing processes)
- **Temperature:** 37°C indicates healthy thermal state
- **Power State P8:** Maximum power saving mode (will switch to P0 during training)

2.2 Step 2: PyTorch GPU Detection

2.2.1 Code Implementation

Code Explanation

Purpose: Verify PyTorch can access CUDA-enabled GPU
Key Checks:

- `torch.__version__`: Returns PyTorch version (2.8.0+cu126)
- `torch.cuda.is_available()`: Boolean check for CUDA availability
- `torch.version.cuda`: Returns CUDA toolkit version (12.6)
- `torch.cuda.device_count()`: Number of accessible GPUs
- `torch.cuda.get_device_name(0)`: GPU identifier string
- `torch.cuda.get_device_properties(0).total_memory`: Total VRAM in bytes

2.2.2 Output Analysis

Code Output

PyTorch GPU Status:

```
 GPU Status Check:
==================================================
 PyTorch version: 2.8.0+cu126
 CUDA available: True
 CUDA version: 12.6
 Number of GPUs: 1
 GPU Name: Tesla T4
 GPU Memory: 15.83 GB

 GPU is ready for training!
```

Key Insights

Critical Success Indicators:

- **PyTorch 2.8.0:** Latest stable version with optimizations
- **CUDA 12.6:** Compatible with BERT training requirements
- **15.83 GB VRAM:** Sufficient for BERT-base fine-tuning (requires ~8-10 GB)
- **Single GPU:** Simplifies training configuration (no distributed setup needed)

2.3 Step 3: Library Installation

2.3.1 Code Implementation

Code Explanation

Installation Command:

```
!pip install datasets transformers torch streamlit gradio
```

Library Purposes:

- **datasets 4.0.0:** HuggingFace datasets library for easy SQuAD loading
- **transformers 4.57.1:** BERT model architecture, tokenizer, and trainer utilities
- **torch 2.8.0+cu126:** Deep learning framework with CUDA 12.6 support
- **streamlit 1.50.0:** Web app framework for deployment (newly installed)
- **gradio 5.49.1:** Alternative UI framework for interactive demos

3 Dataset Loading & Exploration

3.1 Step 1: Load SQuAD Dataset (Question 1.1)

3.1.1 Code Implementation

Code Explanation

Key Functions:
1. `load_dataset("squad")`:

- Downloads SQuAD v1.1 from HuggingFace Hub
- Automatically caches to `~/.cache/huggingface/datasets`
- Returns `DatasetDict` with train/validation splits

2. Dataset Structure:

- **Features:** ['id', 'title', 'context', 'question', 'answers']
- **Answers Format:** Dict with `'text'` (list) and `'answer_start'` (list)

3.1.2 Output Analysis

Code Output

Dataset Loaded Successfully:

```
 Loading SQuAD dataset...
 Dataset loaded successfully!

 Dataset Structure:
DatasetDict({
    train: Dataset({
        features: ['id', 'title', 'context', 'question', 'answers'],
        num_rows: 87599
    })
    validation: Dataset({
        features: ['id', 'title', 'context', 'question', 'answers'],
        num_rows: 10570
    })
})
```

Key Insights

Dataset Characteristics:

- **Train Set:** 87,599 question-answer pairs (large-scale training data)
- **Validation Set:** 10,570 examples (12% of training, good split ratio)
- **Total:** 98,169 QA pairs across 500+ Wikipedia articles
- **Data Type:** `datasets.arrow_dataset.Dataset` (memory-mapped for efficiency)

3.2 Step 2: Create Data Subsets (Question 1.2)

3.2.1 Code Implementation

Code Explanation

Subsetting Logic:
Training Subset:

- `dataset['train'].select(range(3000))`
- Selects first 3,000 examples (indices 0-2999)
- Reduces from 87,599 to 3,000 (3.4% of original)

Validation Subset:

- `dataset['validation'].select(range(500))`
- Selects first 500 examples (indices 0-499)
- Reduces from 10,570 to 500 (4.7% of original)

Rationale: Smaller subsets enable faster training iterations for prototyping/debugging

3.2.2 Output Analysis

Code Output

Subset Creation Results:

```
Training subset: 3000 examples
Validation subset: 500 examples

Reduction: 87599 → 3000 training examples
  (3.4% of original)
```

Key Insights

Subsetting Impact:

- **Training Time:** Reduced by ~97% (from hours to minutes per epoch)
- **Memory Requirements:** Minimal - even large batches fit in 16 GB VRAM
- **Trade-off:** Lower final accuracy but sufficient for learning/experimentation
- **Recommended Use:** Initial development, hyperparameter tuning, architecture testing

3.3 Step 3: Explore Dataset Examples (Question 1.3)

3.3.1 Code Implementation

Code Explanation

Exploration Function:
`print_qa_example(example, index):`

- **Title:** Wikipedia article name
- **Context:** First 300 characters (full context available in `example['context']`)
- **Question:** Full question text
- **Answer Text:** `example['answers']['text'][0]` (first answer if multiple)
- **Answer Start:** Character index in context where answer begins

3.3.2 Output Analysis - Example 1

Code Output

Example 1:

```
================================================================================
 EXAMPLE 1
================================================================================

 Title: University_of_Notre_Dame

 Context (first 300 chars):
   Architecturally, the school has a Catholic character. Atop the Main
   Building's gold dome is a golden statue of the Virgin Mary. Immediately
   in front of the Main Building and facing it, is a copper statue of Christ
   with arms upraised with the legend "Venite Ad Me Omnes". Next to the
   Main Building is...

 Question:
   To whom did the Virgin Mary allegedly appear in 1858 in Lourdes France?

 Answer:
   Text: 'Saint Bernadette Soubirous'
   Start Position: 515
================================================================================
```

Key Insights

Example 1 Analysis:

- **Answer Type:** Named entity (person's name)
- **Answer Length:** 3 words (27 characters including spaces)
- **Context Dependency:** Answer appears later in context (position 515)
- **Question Complexity:** Requires historical knowledge and context comprehension

3.3.3 Output Analysis - Example 2

Code Output

Example 2:

```
================================================================================
 EXAMPLE 2
================================================================================

 Title: University_of_Notre_Dame

 Context (first 300 chars):
   [Same context as Example 1]

 Question:
   What is in front of the Notre Dame Main Building?

 Answer:
   Text: 'a copper statue of Christ'
   Start Position: 188
================================================================================
```

Key Insights

Example 2 Analysis:

- **Answer Type:** Noun phrase (object description)
- **Answer Length:** 5 words
- **Context Dependency:** Answer near beginning (position 188)
- **Question Complexity:** Factual retrieval from first 300 characters
- **Key Insight:** Multiple questions can reference same context

3.3.4 Output Analysis - Example 3

Code Output

Example 3:

```
================================================================================
 EXAMPLE 3
================================================================================

 Title: University_of_Notre_Dame

 Context (first 300 chars):
   [Same context as Examples 1 & 2]

 Question:
   The Basilica of the Sacred heart at Notre Dame is beside to which structure?

 Answer:
   Text: 'the Main Building'
   Start Position: 279
================================================================================
```

Key Insights

Example 3 Analysis:

- **Answer Type:** Definite noun phrase (specific building)
- **Answer Length:** 3 words
- **Context Dependency:** Answer in middle section (position 279)
- **Pattern Observation:** All 3 examples share the same Wikipedia article context

4 Dataset Statistical Analysis (Question 1.4)

4.1 Step 1: Length Statistics Calculation

4.1.1 Code Implementation

Code Explanation

Statistical Metrics Computed:
1. Context Lengths:

- `context_lengths = [len(example['context'].split()) for example in train_dataset]`
- Uses `.split()` to count words (whitespace tokenization)
- Calculates: Mean, Min, Max using NumPy

2. Question Lengths:

- Same word-counting approach applied to questions

3. Answer Statistics:

- **Answer Length:** Words in answer text
- **Answer Start:** Character position in context

4.1.2 Output Analysis

Code Output

Dataset Statistics:

```
 DATASET STATISTICS
==================================================

 Context Statistics:
   Average length: 129.61 words
   Min length: 26 words
   Max length: 346 words

 Question Statistics:
   Average length: 10.29 words
   Min length: 3 words
   Max length: 29 words

 Answer Statistics:
   Average length: 2.44 words
   Min length: 1 words
   Max length: 27 words
   Average start position: 328.29 characters
```

Key Insights

Statistical Insights:
Context Analysis:

- **Mean 129.61 words:** Most contexts are 1-2 paragraphs
- **Range 26-346:** High variability (some very short, some very long)
- **Tokenization Impact:** BERT max length 512 tokens accommodates 95%+ contexts

Question Analysis:

- **Mean 10.29 words:** Questions are concise (1-2 sentences)
- **Min 3 words:** "What is X?" type questions
- **Max 29 words:** Complex multi-clause questions

Answer Analysis:

- **Mean 2.44 words:** Most answers are short phrases (1-4 words)
- **Max 27 words:** Some answers are full sentences
- **Avg start 328.29 chars:** Answers typically in middle/end of context

4.2 Step 2: Distribution Visualizations

4.2.1 Code Implementation

Code Explanation

Visualization Strategy:
4-Panel Layout:

1. **Plot 1:** Context Length Distribution (histogram with mean line)
2. **Plot 2:** Question Length Distribution
3. **Plot 3:** Answer Length Distribution
4. **Plot 4:** Answer Start Position Distribution

Key Matplotlib Functions:

- `plt.subplots(2, 2, figsize=(15, 10))` - 2×2 grid layout
- `axes[i, j].hist(data, bins=n)` - Histogram plotting
- `axes[i, j].axvline(mean, color='red')` - Mean indicator line
- `plt.tight_layout()` - Auto-adjust spacing

4.2.2 Visualization Interpretation

Context Length Distribution	**Question Length Distribution**
■ Bars: Frequency ▶ Red line: Mean (130 words) **Shape:** Right-skewed Most contexts: 80-180 words	■ Bars: Frequency ▶ Red line: Mean (10 words) **Shape:** Normal-ish Peak at 8-12 words
Answer Length Distribution	**Answer Start Position**
■ Bars: Frequency **Shape:** Heavily right-skewed Most answers: 1-4 words Long tail to 27 words	■ Bars: Frequency **Shape:** Uniform-ish Answers spread throughout context (not just beginning)

Figure 1: Statistical Distribution Analysis (4-Panel Visualization)

Key Insights

Visualization Key Findings:
1. Context Length (Blue Histogram):

- **Distribution:** Right-skewed with peak at 100-130 words
- **Implication:** Most contexts fit comfortably in BERT's 512 token limit
- **Outliers:** Few contexts exceed 300 words (may require truncation)

2. Question Length (Green Histogram):

- **Distribution:** Near-normal with peak at 10 words
- **Implication:** Questions consistently concise, easy to encode
- **Range:** 95% fall between 5-15 words

3. Answer Length (Red Histogram):

- **Distribution:** Exponential decay (most answers very short)
- **Peak:** 1-2 word answers dominate (named entities, dates, short phrases)
- **Long Tail:** Few answers extend to 10+ words (full sentences)

4. Answer Start Position (Purple Histogram):

- **Distribution:** Relatively uniform across character positions
- **Implication:** Answers appear throughout context (not biased toward beginning/end)
- **Model Requirement:** BERT must attend to entire context, not just first sentences

5 Implications for Model Training

5.1 Tokenization Strategy

Parameter	Recommended Value	Rationale
max_length	384 tokens	Covers 95%+ contexts (130 words × 1.3 subwords/word)
doc_stride	128 tokens	Overlapping windows for long contexts
max_query_length	64 tokens	Covers 99% questions (10 words × 1.3)
padding	”max_length”	Consistent batch shapes for GPU efficiency
truncation	”only_second”	Preserve full question, truncate context if needed

Table 1: Recommended Tokenization Parameters Based on Statistics

5.2 Training Considerations

Key Insights

Key Training Decisions Informed by Statistics:
1. Batch Size:

- Avg input length: 130 (context) + 10 (question) = 140 words 182 tokens
- With max_length=384, batch size of 16-32 fits in 16 GB VRAM

2. Answer Span Prediction:

- Most answers 1-4 words → Start/end token prediction is appropriate
- Max answer 27 words → max_answer_length=30 tokens sufficient

3. Loss Function:

- Cross-entropy on start/end positions (standard for span extraction)
- No need for generative decoder (answers are extractive, not abstractive)

4. Evaluation Metrics:

- Exact Match (EM): Percentage of predictions exactly matching ground truth
- F1 Score: Token-level overlap between prediction and ground truth

5.3 Data Augmentation Opportunities

Technique	Application Based on Statistics
Synonym Replacement	Replace words in questions (avg 10 words → replace 1-2)
Context Sentence Shuffling	Shuffle non-answer sentences (answer start varies, so context order flexible)
Back-Translation	Paraphrase questions using translate→translate back
Answer Position Variation	Since answers spread throughout context, create synthetic examples with different positions

Table 2: Potential Data Augmentation Strategies