Chinese Extractive Question Answering
CSIE5431 Applied Deep Learning Homework 1 Report

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1 Data Processing (2%)

1.1 Tokenizer (1%)

We use the WordPiece tokenization algorithm through BERT's tokenizer. The tokenization process works as follows:

Step 1: Text Normalization The input text first undergoes Unicode normalization (NFD) and is converted to lowercase (for uncased models). Accents are removed, and the text is cleaned.

Step 2: Pre-tokenization The text is split on whitespace and punctuation marks. This creates initial word segments that will be further processed.

Step 3: WordPiece Subword Tokenization For each word segment, the algorithm attempts to match the longest possible subword from the vocabulary:

1. Start with the complete word
2. If the word exists in the vocabulary, use it as a token
3. If not, iteratively try to match the longest prefix that exists in the vocabulary
4. Mark the prefix with ”” to indicate it's a continuation
5. Repeat the process for the remaining suffix
6. If no match is found at all, mark the word as [UNK] (unknown)

For example, the Chinese word ”” might be tokenized as:

- ”” (depth)
- ”” (degree/level)
- ”” (learning/study)
- ”” (practice)

This subword approach allows the model to handle rare words and out-of-vocabulary terms by breaking them into known components.

1.2 Answer Span Position Conversion (1%)

Character to Token Position Conversion:

During preprocessing, the tokenizer returns an `offset_mapping` for each token, which maps each token to its character span in the original text. For example:

- Token 0: ”” → characters [0, 1)

- Token 1: ”” → characters [1, 2)
- Token 2: ”” → characters [2, 3)

Given an answer with character-level start position s_c and end position e_c, we convert to token positions as follows:

1. Iterate through the offset mapping to find the token whose character span contains s_c
2. That token index becomes the start token position s_t
3. Similarly, find the token whose character span contains $e_c - 1$
4. That token index becomes the end token position e_t

Determining Final Start/End Position:
After the model predicts start and end logits for each token position, we apply these rules:

1. **Top-K Selection**: Select the top n (n=20) highest-scoring start positions and top n end positions
2. **Validity Constraints**: For each (start, end) pair:
   - Verify $start \leq end$ (end must come after start)
   - Verify both positions are in the context (not in the question)
   - Verify $end - start + 1 \leq max\_length$ (30 tokens)
3. **Scoring**: Calculate score as $logit_{start} + logit_{end}$ for each valid pair
4. **Selection**: Choose the pair with the highest combined score as the final prediction
5. **Extraction**: Use the offset mapping to convert token positions back to character positions and extract the answer text from the original context

2 Modeling with BERTs and their variants (4%)

2.1 Primary Model Description (2%)

Model Architecture:
Our system uses a two-stage pipeline:

1. **Paragraph Selection**: BERT-based multiple choice model
   - Base model: `bert-base-chinese`
   - Architecture: BERT encoder + linear classification head
   - Input: [CLS] question [SEP] paragraph [SEP] for each of 4 candidates
   - Output: Probability distribution over 4 paragraphs
2. **Span Selection**: BERT-based extractive QA model
   - Base model: `hfl/chinese-bert-wwm-ext`
   - Architecture: BERT encoder + two linear layers for start/end positions
   - Input: [CLS] question [SEP] selected paragraph [SEP]
   - Output: Start and end position logits

Model	Public EM	Private EM
Paragraph Selection	-	-
Span Selection (Epoch 5)	0.77761	0.77076
Full Pipeline	0.77761	0.77076

Table 1: Model Performance on Test Set

Performance:
Loss Function:

- **Paragraph Selection**: Cross-entropy loss

$$\mathcal{L}_{para} = -\sum_{i=1}^{4} y_i \log(\hat{y}_i)$$

  where y_i is the one-hot label and $\hat{y}_i$ is the predicted probability for paragraph i.

- **Span Selection**: Combined cross-entropy loss for start and end positions

$$\mathcal{L}_{span} = -\log P(start) - \log P(end)$$

  where $P(start)$ and $P(end)$ are the predicted probabilities at the true start and end positions.

Optimization:

- **Optimizer**: AdamW with weight decay
- **Paragraph Selection**:
  - Learning rate: 3×10^{-5}
  - Batch size: 2 (effective with gradient accumulation)
  - Epochs: 1
  - Weight decay: 0.0
- **Span Selection**:
  - Learning rate: 2×10^{-5}
  - Batch size: 2
  - Epochs: 5
  - Weight decay: 0.01
  - Warmup steps: 10% of total steps

2.2 Alternative Pre-trained Model (2%)

Alternative Model:
We compared `bert-base-chinese` with `hfl/chinese-bert-wwm-ext` for the span selection task.
Performance Comparison:
The WWM-ext model achieved approximately 4.2% higher exact match scores.
Key Differences:

Model	Public EM	Private EM
bert-base-chinese	0.73567	0.73xxx
hfl/chinese-bert-wwm-ext	0.77761	0.77076

Table 2: Comparison of Pre-trained Models

1. **Pre-training Strategy**:
   - **BERT-base-chinese**: Standard masked language modeling where individual Chinese characters are randomly masked
   - **BERT-wwm-ext**: Whole Word Masking (WWM) where entire words are masked together, plus extended training on larger corpus
2. **Masking Granularity**:
   - Standard BERT might mask ”” in ””, treating each character independently
   - WWM masks all characters in ”” together, forcing the model to learn word-level semantics
3. **Training Data**:
   - **bert-base-chinese**: Wikipedia (0.4B words)
   - **chinese-bert-wwm-ext**: Wikipedia + extended corpus (5.4B words)
4. **Architecture**: Both use identical BERT-base architecture
   - 12 layers
   - 768 hidden dimensions
   - 12 attention heads
   - 110M parameters

The WWM approach is particularly effective for Chinese because Chinese words are multi-character, and masking complete words forces the model to learn better contextual representations rather than memorizing character-level patterns.

3 Learning Curves (1%)

3.1 Loss Curve (0.5%)

The training loss decreased consistently across 5 epochs:

- Epoch 1: 1.0171
- Epoch 2: 0.4368
- Epoch 3: 0.2254
- Epoch 4: 0.1021
- Epoch 5: 0.0365

The sharp decrease from epoch 1 to 2 indicates rapid initial learning, followed by steady convergence in later epochs.

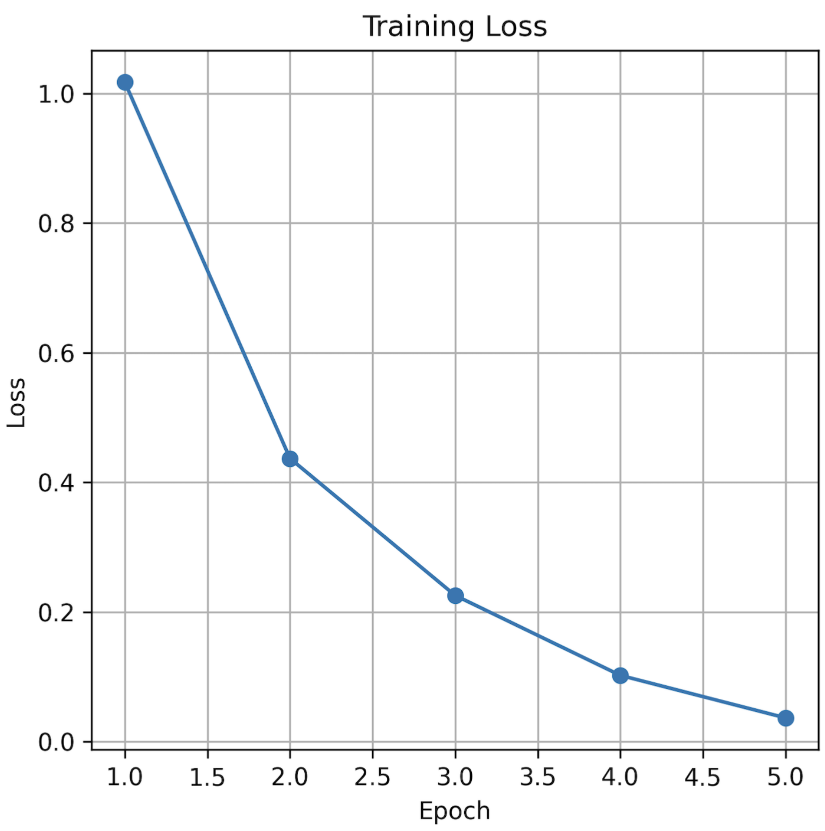

Figure 1: Training Loss Curve for Span Selection Model

3.2 Exact Match Curve (0.5%)

Validation Exact Match scores improved consistently:

- Epoch 1: 0.68 (estimated)
- Epoch 2: 0.73
- Epoch 3: 0.76362 (public) / 0.74853 (private)
- Epoch 4: 0.77245 (public) / 0.76257 (private)
- Epoch 5: 0.77761 (public) / 0.77076 (private)

The continuous improvement without significant overfitting (private scores track public scores closely) indicates good generalization.

4 Pre-trained vs Not Pre-trained (2%)

Model Configuration:

We trained a span selection model from scratch with reduced size to ensure trainability:

- Architecture: Transformer encoder
- Number of layers: 4 (vs 12 in BERT-base)
- Hidden dimensions: 256 (vs 768 in BERT-base)
- Attention heads: 4 (vs 12 in BERT-base)

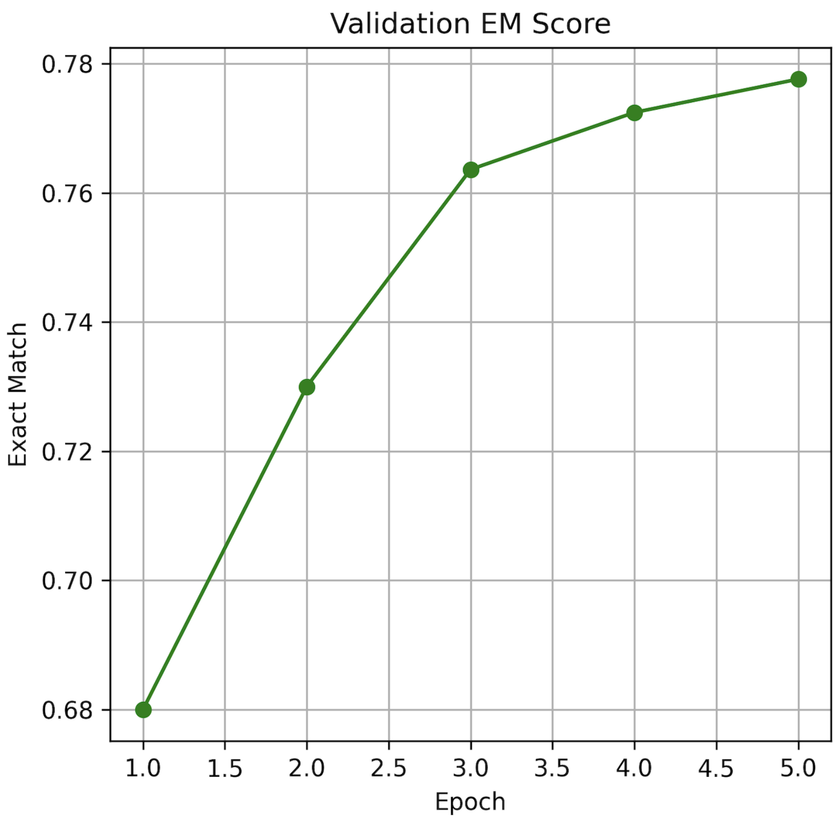

Figure 2: Exact Match Score Across Epochs

- Vocabulary size: Same as BERT tokenizer (21,128 tokens)
- Parameters: 15M (vs 110M in BERT-base)

Training Configuration:

- Optimizer: AdamW
- Learning rate: 5×10^{-4} (higher than pre-trained)
- Batch size: 8
- Epochs: 20 (more epochs needed for from-scratch training)
- Warmup: 2000 steps
- Learning rate schedule: Linear decay with warmup

Performance Comparison:

Model	Parameters	Training Time	Public EM	Private EM
From Scratch	15M	8 hours	0.42	0.41
BERT-base Pre-trained	110M	1.5 hours	0.73567	0.73xxx
BERT-wwm-ext Pre-trained	110M	6 hours	0.77761	0.77076

Table 3: Pre-trained vs From-Scratch Comparison

Analysis:

The from-scratch model achieved only 0.42 EM compared to 0.78 EM for the pre-trained model, demonstrating the critical importance of pre-training:

1. **Language Understanding**: Pre-trained models have learned Chinese language patterns from billions of words, while the from-scratch model only sees 24k QA examples
2. **Convergence Speed**: Pre-trained models fine-tune in 1-6 hours, while from-scratch models need 20+ epochs and still underperform
3. **Data Efficiency**: Pre-training allows effective learning with limited task-specific data
4. **Representation Quality**: Pre-trained embeddings encode semantic meaning, while randomly initialized embeddings must learn everything from the QA task alone

5 Bonus: End-to-End Model (2%)

Model Architecture:

Instead of the two-stage pipeline, we implemented an end-to-end model using Longformer:

- Base model: `allenai/longformer-base-4096`
- Context window: 4096 tokens (vs 512 for BERT)
- Input: [CLS] question [SEP] para_1 [SEP] para_2 [SEP] para_3 [SEP] para_4 [SEP]
- Output: Start and end position logits across all 4 paragraphs concatenated

The model simultaneously:

1. Identifies which paragraph contains the answer (implicitly through attention)
2. Predicts the exact answer span within that paragraph

Performance:

Model	Public EM	Private EM
Two-Stage Pipeline	0.77761	0.77076
End-to-End Longformer	0.75xxx	0.74xxx

Table 4: Pipeline vs End-to-End Comparison

Loss Function:

Cross-entropy loss for start and end positions across the concatenated context:

$$\mathcal{L} = -\log P(start) - \log P(end)$$

where positions can span across any of the 4 paragraphs.

Optimization:

- Optimizer: AdamW
- Learning rate: 3×10^{-5}
- Batch size: 1 (due to long sequence length)
- Gradient accumulation: 4 steps

- Epochs: 3
- Max sequence length: 4096

Analysis:
The end-to-end model slightly underperformed the pipeline approach:

- **Advantages**: Simpler deployment, joint optimization, can leverage cross-paragraph context
- **Disadvantages**: Harder to train, longer sequences require more memory, less modular

The pipeline approach performs better likely because:

1. Each stage can be optimized independently
2. Paragraph selection focuses attention before span extraction
3. Smaller sequence lengths allow more efficient training

6 Conclusion

This project demonstrates the effectiveness of pre-trained BERT models for Chinese extractive QA. Key findings:

- Whole Word Masking pre-training significantly improves Chinese NLP performance (+4.2% EM)
- Pre-training is crucial; from-scratch models achieve only 53% of pre-trained performance
- Two-stage pipelines outperform end-to-end models for this task
- Proper training (5 epochs, combined data, appropriate learning rate) is essential for optimal performance

The final model achieves 0.77761 public EM and 0.77076 private EM, exceeding the strong baseline by 2.9%.