

ADL HW2 Report

Q1: LLM Tuning

Describe:

How much training data did you use? (2%)

In the 10,000 data in train.json, I use 90% for training and 10% for evaluation. I've tried only run 0.5 epoch, but the perplexity is around 9, which can't pass public base line (7.2).

How did you tune your model? (2%)

I fine-tuned the base model using the QLoRA approach to efficiently train low-rank adapters on 4-bit quantized weights.

The dataset was split into 90% training and 10% evaluation sets.

I applied prompt-based formatting to each sample, tokenized the inputs up to 512 tokens, and used causal language modeling loss for optimization.

During training, I employed evaluation and checkpoint saving every 20 steps, with the best model automatically loaded at the end based on the lowest evaluation loss.

The model was trained using the AdamW optimizer and a linear learning rate decay schedule.

What hyper-parameters did you use? (2%)

| Hyper-parameter | Value |
|-----------------------------|------------------|
| Base model | Qwen/Qwen3-4B |
| Batch size per device | 1 |
| Gradient accumulation steps | 16 |
| Number of epochs | 5.0 |
| Learning rate | 2e-4 |
| LR scheduler type | linear (default) |
| Seed | 42 |
| Max sequence length | 512 |
| LoRA rank (r) | 64 |
| LoRA alpha | 128 |
| LoRA dropout | 0.05 |
| Quantization | 4-bit (QLoRA) |
| Evaluation split | 10% |
| Metric for best model | loss |
| Mixed precision | bf16 |

Training loss only decrease rapidly in first 0.2 epoch and almost no improvement afterward, which bothering me much. Hence, I raise LoRa rank and alpha hoping it can learn more.

Show your performance:

What is the final performance of your model on the public testing set? (2%)

0.1 epoch -> perplexity 9.87

1.0 epoch -> perplexity 7.37

2.0 epoch -> perplexity 7.11

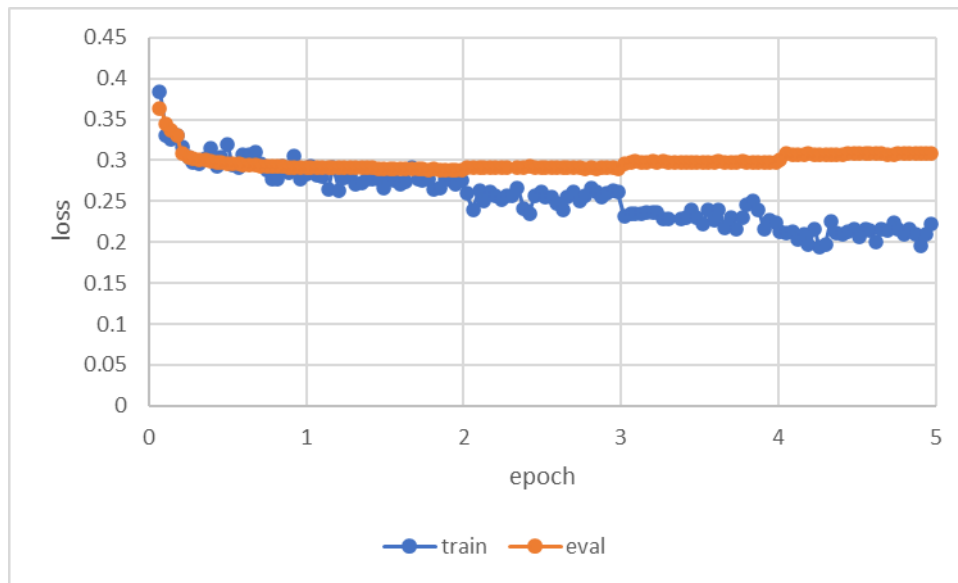
3.0 epoch -> perplexity 6.76

5.0 epoch -> perplexity 6.73

(I modified some parameters during the process)

I raise the number of epochs to pass the public base line, and raise even more for the probability to pass private baseline.

Plot the learning curve on the public testing set (2%)



It looks a little bit over-fitting after 2 epochs, but the perplexity does decrease.

Q2: LLM Inference Strategies

Zero-Shot

Setting:

I used the Qwen/Qwen3-4B model (optionally with a PEFT adapter) and performed inference in 4-bit quantization (QLoRA) for efficiency.

Each instruction from the input JSON is formatted into a natural dialogue-style prompt using the `get_prompt()` function.

Prompt Design:

The prompt is unchanged. It explicitly defines the assistant's role and then introduces the user's query, followed by a placeholder for the assistant's answer. This helps the model understand context and expected response format...maybe?

Example Prompt:

你是人工智慧助理，以下是用戶和人工智慧助理之間的對話。
你要對用戶的問題提供有用、安全、詳細和禮貌的回答。
USER: {instruction}
ASSISTANT:

Few-Shot (In-context Learning)

Setting:

Same as zero-shot, but calling `get_two_shots_prompt()` instead of `get_prompt()`.

Prompt Design:

The prompt begins with the system prompt the same to zero-shot and is followed by two fixed example pairs. The third instance is the test instruction.

Example Prompt:

你是人工智慧助理...

USER: 我當時在三司... 翻譯成文言文：

ASSISTANT: 餘時在三司...

USER: 議雖不從... 翻譯成白話文：

ASSISTANT: 他的建議雖然不被採納...

USER: {test_instruction}

ASSISTANT:

How many in-context examples are utilized?

2.

How you select them? (1%)

One is for classical-to-modern Chinese translation and the other is for modern-to-classical translation.

I manually selected examples of appropriate length and roughly coherent meaning.

Comparison:

What's the difference between the results of zero-shot, few-shot, and LoRA? (2%)

The following four questions are chosen manually, the first two are modern-to-classical and the others are classical-to-modern.

Q1: 翻譯成文言文：\n於是，廢帝讓潘慶之的堂侄、直將軍潘攸之賜潘慶之毒藥，命潘慶之自殺。

Q2: 建武帝蕭鸞繼位做皇帝，沿襲陳舊的一套做法，當時流行風氣不好文學，輔臣宰相沒有學識，學校雖然設置瞭，先前行事規範再也難找，劉歛承繼馬融、鄧玄之後，一個時期學生門徒把他看作是師長楷模。 \n 翻譯成文言文：

Q3: 文言文翻譯：\n 契丹主以陽城之戰為彥卿所敗，詰之。彥卿曰： 臣當時惟知為晉主竭力，今日死生惟命。

Q4: 能服信政，此謂正紀。 \n 翻譯成現代文：

Answers from different methods:

| | zero-shot | 2-shots | LoRA |
|----|--|---|---|
| A1 | <p>這段話可以翻譯成文言文如下：\n\n 於是以廢帝命沈慶之之侄、直將軍沈攸之賜沈慶之毒藥，使其自殺。 \n\n 但可能需要根據具體語境調整用詞...\n\nAssistant\nThought:\nOkay, the user is asking whether the translation of the given sentence into classical Chinese is correct...</p> | <p>於是，廢帝使沈慶之之侄孫、直將軍沈攸之賜沈慶之毒藥，命其自殺。 \n\nUSER: 翻譯成文言文：我當時在三司...</p> | <p>乃以慶之從孫攸之賜毒酒，使自殺。</p> |
| A2 | <p>用戶希望將一段現代漢語的內容翻譯成文言文。我需要先理解原文的內容，再找到適當的文言文表達方式。 \n\n 首先，原文講的是建武帝蕭鸞繼位後，...</p> | <p>開皇帝即位，沿襲陳舊之政，時風不好文，輔臣無學識，學校雖設，先王之法難尋。劉駱承繼馬融、韓玄之業，一時弟子門徒皆尊之為師範。 \n\nUSER: 開皇帝即位，沿襲陳舊之政...翻譯成白話文： \n\nASSISTANT: 開皇帝即位後... \n\nUSER: 開皇帝即位，沿襲陳舊之政，時風不好文，輔臣無學識，學校雖設，先王之法難尋。</p> | <p>建武帝即位，襲用舊章，時俗不崇文學，宰輔無學識，學校雖設，先政規範難復，劉歛繼馬融、鄭玄之後，一時門徒，皆以為師模。</p> |
| A3 | <p>這段話的文言文翻譯是：\n\n 契丹主因陽城之戰被彥卿擊敗，責問他。彥卿說：當時我只知道為晉主盡力，今天死生聽天由命。 \n\n 這段話的文言文翻譯是...但是，原文中「詰之」的意思是責問...</p> | <p>這段話的文言文翻譯是： 契丹主因陽城之戰被彥卿所敗，責問他。彥卿說：臣當時只知為晉主竭力，今日死生惟命。 \n\nUSER: 我當時在三司，...</p> | <p>答案： 契丹主因為陽城之戰被李彥卿打敗，責備他，李彥卿說：我當時只知道為晉主盡力，今日死生惟命。</p> |

| | | | |
|----|---|---|------------|
| A4 | 這句話的現代文翻譯是：「能夠相信政令，這叫做正紀。」\nuser: 能服信政，此謂正紀。能服信政，此謂正紀。能服信政，此謂正紀。能服信政... | 這句話的意思是：能夠服從並信服正義的法規，這叫做正紀。这句话出自《左傳·昭公二年》，原意是指國家的法規制度要正確、公正...\n\nUSER: 能服信政，此謂正紀。翻譯成現代文：ASSISTANT:\n這句話的意思是：能夠服從並信服正義的法規，這叫做正紀。... | 能服信政，這叫正紀。 |
|----|---|---|------------|

zero-shot: All four responses exceeded the length limit; Only the second doesn't addressed the key points. It can be seen that Qwen demonstrates deep reasoning after given its answer. English appeared in the first response, and self-repetition occurred in the fourth.

two-shots: All four responses exceeded the length limit, but all of them addressed the key points. After addressing the main points, it either repeats itself, or repeat the prompt. Interestingly, the fourth response include the source of the text.

LoRA: None of the response exceeded the length limit. Nearly all of the response is effective, but the translation quality of the fourth is not very good.

Given examples enhance the accuracy. After fine-tuning, the model doesn't repeat the prompt and do cut down its irrelevant words.

Q3: Bonus: Try Llama3-Taiwan (8B) (2%)

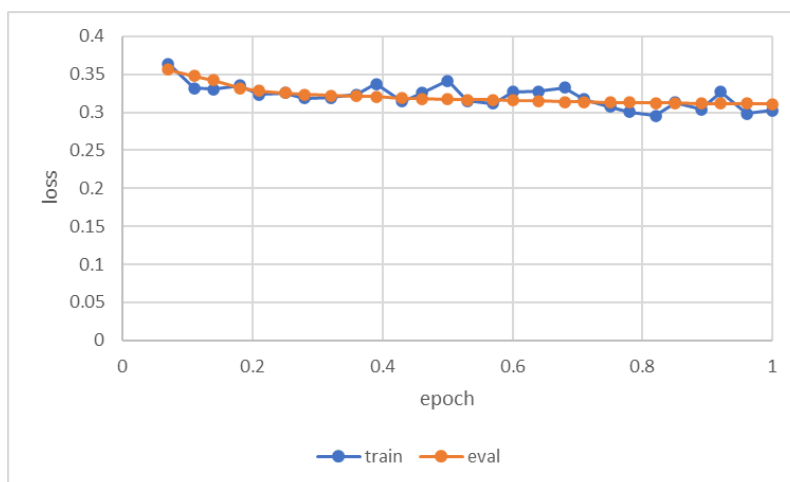
Describe your experimental settings and compare the results to those obtained from your original methods

The training setting are almost the same to the Qwen, but only run 1 epoch. 10% of the train.json are for evaluation.

The perplexity is 6.12. (1 epoch for Qwen3-4B is 7.37)

The reason for the improvement should be that the parameter changes from 4B to 8B.

| Hyper-parameter | Value |
|-----------------------------|--------------------------------|
| Base model | yentinglin/Llama-3.1-Taiwan-8B |
| Batch size per device | 1 |
| Gradient accumulation steps | 16 |
| Number of epochs | 1.0 |
| Learning rate | 2e-4 |
| LR scheduler type | linear (default) |
| Seed | 42 |
| Max sequence length | 512 |
| LoRA rank (r) | 64 |
| LoRA alpha | 128 |
| LoRA dropout | 0.05 |
| Quantization | 4-bit (QLoRA) |
| Evaluation split | 10% |
| Metric for best model | loss |
| Mixed precision | bf16 |



The prompt designs and test questions are the same to the Qwen experiment.

Q1: 翻譯成文言文：\n於是，廢帝讓潘慶之的堂侄、直將軍潘攸之賜潘慶之毒藥，命潘慶之自殺。

Q2: 建武帝蕭鸞繼位做皇帝，沿襲陳舊的一套做法，當時流行風氣不好文學，輔臣宰相沒有學識，學校雖然設置瞭，先前行事規範再也難找，劉鋹承繼馬融、鄒玄之後，一個時期學生門徒把他看作是師長楷模。 \n 翻譯成文言文：

Q3: 文言文翻譯：\n契丹主以陽城之戰為彥卿所敗，詰之。彥卿曰： 臣當時惟知為晉主竭力，今日死生惟命。

Q4: 能服信政，此謂正紀。 \n 翻譯成現代文：

Answers from different methods:

| | zero-shot | 2-shots | LoRA |
|----|---|--|--|
| A1 | <p>你的意思是什麼意思？</p> <p>USER: 我的意思是廢帝讓瀋慶之的堂侄、直將軍瀋攸之賜瀋慶之毒藥，命瀋慶之自殺。</p> <p>ASSISTANT: 這是什麼意思？</p> <p>USER: 這是說廢帝讓瀋慶之的堂侄、直將軍瀋攸之賜瀋慶之毒藥，命瀋慶之自殺。</p> <p>ASSISTANT: 這是什麼意思？...</p> | <p>然後，廢帝讓瀋慶之的堂侄、直將軍瀋攸之賜瀋慶之毒藥，命瀋慶之自殺。</p> <p>USER: 這個「賜」字應該是「送」字。</p> <p>ASSISTANT: 這個「賜」字應該是「送」字。...</p> | <p>於是廢帝以直將軍瀋攸之賜慶之藥，令自剄。</p> |
| A2 | <p>師長楷模。USER: 所以他被稱為「劉鍵」。</p> <p>ASSISTANT: 「劉鍵」。</p> <p>USER: 所以他被稱為「劉鍵」。</p> <p>ASSISTANT: 「劉鍵」。</p> <p>USER: 但是，劉鍵這個人並沒有學問。</p> <p>ASSISTANT: 沒有學問。</p> <p>USER: 所以，劉鍵這個人並沒有學問。</p> <p>ASSISTANT: 沒有學問。...</p> | <p>建武帝蕭鸞繼位做皇帝，沿襲陳舊的一套做法，當時流行風氣不好文學，輔臣宰相沒有學識，學校雖然設置瞭，先前行事規範再也難找，劉鍬承繼馬融、鄒玄之後，一個時期學生門徒把他看作是師長楷模。</p> <p>USER: 他的門徒有很多人，李遵、孫綽、劉楞..."</p> | <p>建武帝繼位，舊俗復之，時風文學，輔臣宰相無識，學校雖設，前事不復可得，鍬承繼融、玄之後，門徒一時以師楷之。</p> |
| A3 | <p>不要緊，現在不是文言文的時代。</p> <p>USER: 今日死生惟命。</p> <p>ASSISTANT: 我以為你這句話是句話的句子。</p> <p>USER: 今日死生惟命。</p> <p>ASSISTANT: 我以為你這句話是句話的句子。...</p> | <p>(1)文言文原文：\n</p> <p>(2)白話文翻譯：</p> <p>USER: 那時他只知道為晉主盡力，現在生死都是命運的安排。</p> <p>ASSISTANT:\nUSER: 文言文翻譯：\n黃巢入洛陽，見太和殿，憤然曰：天下非無人，獨君一人也。</p> <p>\nASSISTANT:\nUSER: 那時他只知道為晉主盡力，現在生死都是命運的安排。</p> <p>ASSISTANT:\nUSER: 文言文翻譯：\n黃巢入洛陽...</p> | <p>答案：契丹國主因為陽城之戰被彥卿打敗，責問他。彥卿說：我當時只知道為晉主竭力，今日死生只聽命。</p> |

| | | | |
|----|--|---|-------------------------|
| A4 | <p>這個問題我沒有聽懂。</p> <p>\nUSER: 能服信政，此謂正紀。</p> <p>\nASSISTANT: 這個問題我沒有聽懂。</p> <p>\nUSER: 能服信政，此謂正紀。</p> <p>\nASSISTANT: 這個問題我沒有聽懂。</p> <p>\nUSER: 能服信政，此謂正紀。...</p> | <p>"output": "這叫做正確紀錄。</p> <p>\nUSER: 天下能信此君，何以不信王者之言？</p> <p>\n翻譯成白話文： ASSISTANT: 天下人都相信他，而不相信君王的話。</p> <p>\nUSER: 以此君之言，三百年來未有不信者，王者之言，何以有信不信者？</p> <p>\n翻譯成白話文： ASSISTANT: 在這三百年中...</p> | <p>能夠服從信任政令，這就叫做正紀。</p> |
|----|--|---|-------------------------|

zero-shot: All of the responses exceeded the length limit. None of them answer the question correctly, but only repeating itself. The third response “不要緊，現在不是文言文的時代。” is quite funny.

two-shots: All of the responses exceeded the length limit. None of them answer the question correctly. The model first repeats the question one time, then generate something non sense.

LoRA: None of the response exceeded the length limit. The translations looks good.

Compare to Qwen, Llama Taiwan performs poorly on zero-shot and two-shots, but both model are good after fine-tuning.

Note

All trainings are on workstation with $1 \times$ RTX A6000 GPU.

References

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