

# COMP4901B LLM ASSIGNMENT 2

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## 1 Single-turn Loss Masking

```
(comp4901b-hw2) lamyekong@DESKTOP-8OJOP65:/mnt/c/Users/lamyekong/AppData/Roaming/Microsoft/Windows/Start Menu/Programs/Python 3.9/COMP4901B_LLM/COMP4901B-LLMs-main$ bash scripts/check_exercises_1.sh
single_turn validation passed. Outputs match the golden answers.
```

Figure 1: Terminal Output 1

- Explanation: First, I get the range of full ids corresponding to assistant by using the prefix lengths with negative indexing. Secondly, I use the range to unmask the part in the labels.

## 2 Multi-turn Loss Masking

```
(comp4901b-hw2) lamyekong@DESKTOP-8OJOP65:/mnt/c/Users/lamyekong/AppData/Roaming/Microsoft/Windows/Start Menu/Programs/Python 3.9/COMP4901B_LLM/COMP4901B-LLMs-main$ bash scripts/check_exercises_2.sh
multi_turn validation passed. Outputs match the golden answers.
```

Figure 2: Terminal Output 2

- Explanation: I loop the messages and pass all the roles except the assistant. Then, I perform similar logic to exercise 1 with additional codes such that loop will break if start  $\geq$  full ids length or end  $\geq$  full id length.

## 3 Reverse Loss Masking (Single-turn with Message Reordering)

```
(comp4901b-hw2) lamyekong@DESKTOP-8OJOP65:/mnt/c/Users/lamyekong/AppData/Roaming/Microsoft/Windows/Start Menu/Programs/Python 3.9/COMP4901B_LLM/COMP4901B-LLMs-main$ bash scripts/check_exercises_3.sh
single_turn validation passed. Outputs match the golden answers.
```

Figure 3: Terminal Output 3

- Explanation: Same as exercise 1. First, I get the range of full ids corresponding to user by using the prefix lengths with negative indexing. Secondly, I use the range to unmask the part in the labels.
- Conceptual Question Answer: The model can predict the user-style query with the assistant's response. In this way, it will be useful for synthesizing the user missing prompt and creating a user simulator. For example, in a non-generative and retrieval-based AI agent, the answer of a question can be used to generate user-style query. In this way, the company can add more keywords. to improve the retrieval recall.

## 4 Reverse Loss Masking (Multi-turn)

```
(comp4901b-hw2) lamyekong@DESKTOP-80JOP65:/mnt/c/Users/lamyekong/AppData/Roaming/Microsoft/Windows/Start Menu/Programs/Python 3.9/COMP4901B_LLM/COMP4901B-LLMs-main/assignment2$ bash scripts/check_exercises_4.sh
multi_turn validation passed. Outputs match the golden answers.
```

Figure 4: Terminal Output 4

- Explanation: Like exercise 2. I loop the messages and pass all the roles except user. Then, I perform similar logic to exercise 3 with additional codes such that loop will break if start  $\geq$  full ids length or end  $\geq$  full id length.
- Conceptual Question Answer: The model can predict the next user-style query based on current user and assistant interaction data, In this way, it will be useful for synthesizing the potential user queries. For example, in an LLM-based AI agent, the user can have a chat with the agent. When the agent replies to the user query every time, the agent can also infer the next user query for the user, allowing the user to have query selection instead of typing manually.

## 5 Cross-Entropy Loss for Language Modeling

```
(comp4901b-hw2) lamyekong@DESKTOP-80JOP65:/mnt/c/Users/lamyekong/AppData/Roaming/Microsoft/Windows/Start Menu/Programs/Python 3.9/COMP4901B_LLM/COMP4901B-LLMs-main/assignment2$ python loss_functions_checker.py
[case 1] passed (num_items=4): loss=1.86005414
[case 2] passed (num_items=2): loss=1.55646694
[case 3] passed (num_items=4): loss=1.08182645

All checks passed!
```

Figure 5: Terminal Output 5

- Explanation of steps: First, I compute the log probabilities with log-softmax.

$$\text{LogSoftmax}(x_i) = \log \left( \frac{e^{x_i}}{\sum_j e^{x_j}} \right)$$

Second, I replace the ignored labels with 0 to prevent indexing errors and choose the log probability of the corresponding given label using gather. Third, I mask the position where the label equals to -100, which leaves the ignored token with no contribution. Lastly, we sum up the valid token and average them by using *num\_items\_in\_batch*.

- Explanation of *num\_items\_in\_batch*: It represent the number of valid token, i.e. non-padding and non-masked token, in a batch. In this way, we can calculate the average loss without a normalized loss value which cannot ensure a magnitude consistence across batches with different valid tokens with gradient accumulation.

## 6 Supervised Fine-Tuning

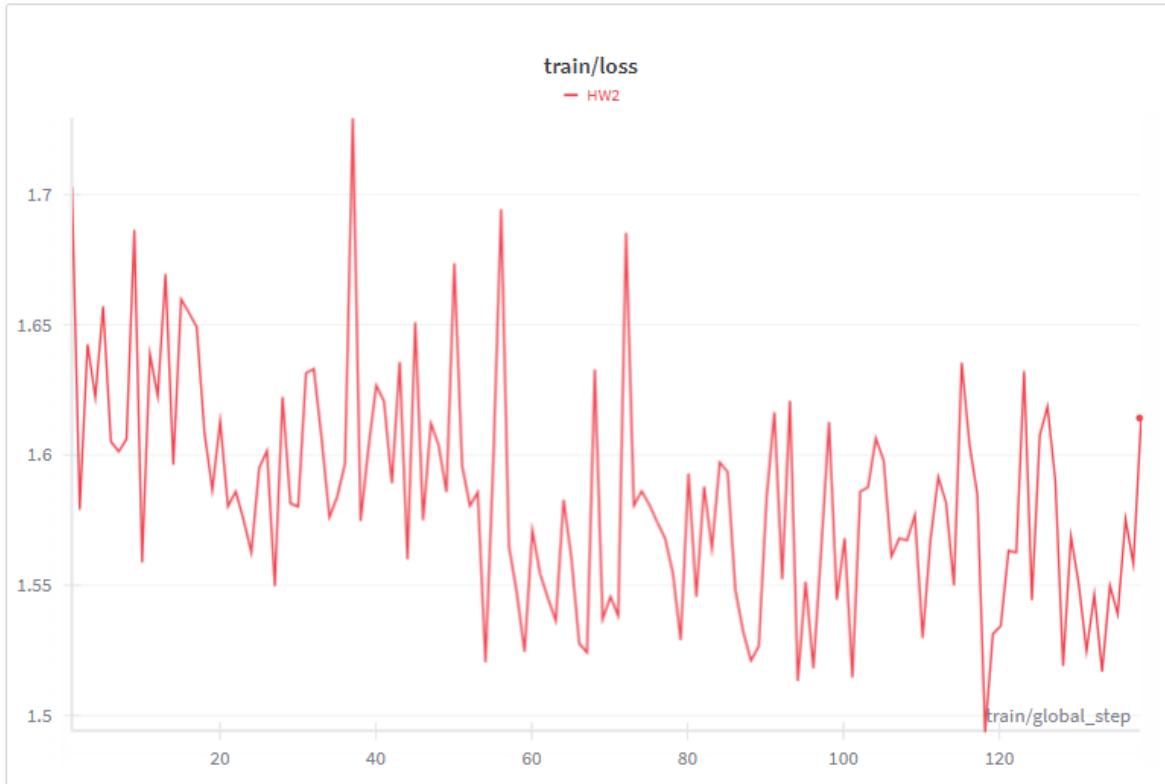


Figure 6: Fune Tune 1

- Training configuraiton:
  - GPU type: L4 GPU
  - Batch size: 128
  - Learning rate:  $2 \times 10^{-5}$
  - Epochs: 3
  - Total steps: 138
- Final checkpoint path: ckpt\FT1\checkpoint-138

```

<|im_start|>user
What is the heat of sublimation of iodine, given that it has a vapor pressure of 10 mmHg at -10°C and a normal boiling point of 184.35°C?<|im_end|>
<|im_start|>assistant
To calculate the heat of sublimation of iodine, we can use the Clausius-Clapeyron equation, which relates the vapor pressure of a substance to its temperature and enthalpy change:


$$\ln(P_2/P_1) = -\Delta H_{\text{sub}}/R * (1/T_2 - 1/T_1)$$


Where:
P1 and P2 are the vapor pressures at temperatures T1 and T2, respectively
ΔHsub is the heat of sublimation
R is the gas constant (8.314 J/mol·K)

We are given:
P1 = 10 mmHg (at T1 = -10°C)
P2 = 760 mmHg (at T2 = 184.35°C, the normal boiling point)

First, we need to convert the temperatures to Kelvin:
T1 = -10°C + 273.15 = 263.15 K
T2 = 184.35°C + 273.15 = 457.5 K

Now we can plug the values into the Clausius-Clapeyron equation:


$$\ln(760/10) = -\Delta H_{\text{sub}}/8.314 * (1/457.5 - 1/263.15)$$


Solving for ΔHsub:

$$\Delta H_{\text{sub}} = -8.314 * \ln(76) / (1/457.5 - 1/263.15)$$


$$\Delta H_{\text{sub}} \approx 62083 \text{ J/mol}$$


The heat of sublimation of iodine is approximately 62,083 J/mol.<|im_end|>
```

Figure 7: Conversation example

- Role of tokenizer.apply\_chat\_template(): The tokenizer.apply\_chat\_template() will standardize the chat format according to the specific format of the language model. In this way, it can prevent the format mismatch and train the data based on the required format. It can be formatted by providing it a list of dictionaries, where each dictionary represent the role and the message. Consequently, it will return with a full\_ids, which represent the full sequence of messages (can be conveyed to token ID) of different role based on the Ninja template. Based on the figure 7, the format for this model is technically <|im\_start|>,role,message,<|im\_end|>.

Second FT: divide step size by 4 Third FT: warmup\_ratio change from 0.1 to 0.15, epoch change from 3 to 4, batch size change from 128 to 248 Fourth:

## 7 Instruction-Following Evaluation and Hyperparameter Tuning

### 7.1 Comparison table before and after SFT

Accuracy	Before SFT	After SFT
Strict accuracy	0.16	0.22
Loose accuracy	0.18	0.25

Table 1: Comparison Table

## 7.2 Hyperparameter tuning summary

	Train epoch	lr	Warmup	Batch size	Strict Accuracy	Loose accuracy	Training loss
SFT/FT1	3	2e-5	0.1	128	0.22	0.25	1.584
FT2	3	4e-6	0.1	128	0.28	0.32	1.631
FT3	4	4e-6	0.15	248	0.28	0.32	1.632
FT4	4	2.5e-6	0.15	256	0.27	0.31	1.635
FT5	4	4e-6	0.05	256	0.31	0.35	1.633

Table 2: Hyperparameter Tuning Summary

Conclusion: Final strict accuracy of the best model: FT5 according to figure 2. Analysis: THe most impactful parameter will be learning rate. By only dividing the learning rate by 4, the strict accuracy increases evidently from 0.22 to 0.28. Later, by adjusting the epoch, batch size and warmup ratio, the accuracy still vary around 28. However, once the warmup ratio is changed from 0.1 to 0.05 while following the learning rate from FT2 and increase the epoch and batch size, the strict accuracy is increased from 0.28 to 0.31. Hence, the warmup ratio will be the second impactful parameter.

### 7.3 Example outputs







## 7.4 Analysis of instruction-following capabilities

	instruction_id_list	accuracy_base	accuracy_best	accuracy_diff	improve
7	detectable_format:constrained_response	0.000000	1.000000	1.000000	True
6	detectable_content:postscript	0.166667	1.000000	0.833333	True
3	combination:repeat_prompt	0.000000	0.777778	0.777778	True
4	combination:two_responses	0.000000	0.666667	0.666667	True
12	keywords:existence	0.250000	0.750000	0.500000	True
11	detectable_format:title	0.166667	0.666667	0.500000	True
0	change_case:capital_word_frequency	0.142857	0.571429	0.428571	True
18	length_constraints:number_paragraphs	0.000000	0.400000	0.400000	True
19	length_constraints:number_sentences	0.200000	0.600000	0.400000	True
20	length_constraints:number_words	0.285714	0.571429	0.285714	True
15	keywords:letter_frequency	0.500000	0.625000	0.125000	True
1	change_case:english_capital	0.000000	0.000000	0.000000	False
5	detectable_content:number_placeholders	0.333333	0.333333	0.000000	False
2	change_case:english_lowercase	0.000000	0.000000	0.000000	False
10	detectable_format:number_highlighted_sections	0.000000	0.000000	0.000000	False
8	detectable_format:multiple_sections	0.000000	0.000000	0.000000	False
16	language:response_language	0.000000	0.000000	0.000000	False
22	startend:end_checker	0.000000	0.000000	0.000000	False
9	detectable_format:number_bullet_lists	0.000000	0.000000	0.000000	False
17	length_constraints:nth_paragraph_first_word	0.000000	0.000000	0.000000	False
23	startend:quotation	0.000000	0.000000	0.000000	False
14	keywords:frequency	0.272727	0.181818	-0.090909	False
13	keywords:forbidden_words	0.500000	0.300000	-0.200000	False
21	punctuation:no_comma	0.812500	0.375000	-0.437500	False

Figure 8: Instruction statistics comparison

Analysis: According to the figure 8, almost half (11/24) of the instructions have improved, while only 3 instruction result are worsen. Thus, the model now can follow the formatting instruction better.

In addition, the instructions that require semantic or stylistic understanding rather than formatting are still struggling, especially the part that is related to context-sensitive keyword constraints, like *keywords\_forbidden\_words* and *keywords\_frequency*.

In the fine tuning, I believe that the enhancement of epoch number allow model to learn more from the data, which enable a better convergence. Besides, by reducing learning rate, it allows the training to be more stable and avoid overshooting local minima. Furthermore, the enhancement of batch size allow enable the training to estimate better for the gradient and help the update to be more consistent. What's better, by lowering the warmup ratio, it allows the model to reach effective learning earlier since small model can converge in a quicker time.