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LLM Technologies Complex to Reduce Turnover through Improving Workplace Communication

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Abstract. Many companies have suffered from turnover of key workers due to concerns about human relationships in their workplaces. They should enhance relationships that promote all workers to engage in their work pleasantly. The issue can be solved with active listening, where a manager tries to get what a worker feels in the workspace as a listener. However, workers seldom talk frankly. The listener needs to attain listening skills through many experiences. It costs a lot. The study proposes a training method to build LLMs that work as training partners for human listeners to enhance active listening skills. Data for the fine-tuning of the LLMs contains various privacy matters. The method introduces QLoRA to enable LLMs to be trained on-premises, avoiding privacy leaks. The paper discusses the characteristics of the LLMs to improve skills. It compares the emotion recognition performance of the LLMs before and after the fine-tuning to clarify the characteristics. Experimental results reveal that LLMs demonstrate improvement in emotion. It turns out the tuned LLMs have been equipped with higher emotion recognition capability for negative emotions than for positive ones. Through practices using the LLMs, inexperienced listeners acquire skills to extract what workers keep in their minds about issues they face in the workplace.

Keywords. Active listening, Emotional Quotient, Large Language Models, Rapport

1. Introduction

Currently, more than 30% of new graduates entering the workforce turn over within three years in Japan. The Japanese government takes it as a serious problem. The investigation by the government has revealed that relationships in workplaces mainly cause resignation for both men and women [1]. Active listening is one effective method for improving workplace relationships. Active listening is the activity of a listener listening to a speaker's mental problems. Successful active listening helps speakers talk about what they feel frankly. It is known that many speakers who talk to others about most of their problems tend to address the problems in a positive way. Companies have introduced active listening to improve interpersonal relationships in workplaces.

For successful active listening, listeners need to guide the conversation so that speakers talk as much about their problems as possible. The listener must understand the speaker's emotions to gain the speaker's trust enough for the speaker to tell concerns to the listener. The degree to understand emotions is referred to as emotional quotient [2]. Since it takes time for

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speakers to trust listeners enough to talk about their mental problems, active listening requires a significant time cost [3]. It is necessary to improve the skills of listeners in active listening to enhance workplace relationships. Without it, we cannot reduce turnover rates.

The skills of listeners in active listening can be improved only in practices in actual conversations. It requires at least two persons: a speaker and a listener. Speakers in the practices have to pretend to be annoyed with mental problems, which makes it difficult to prepare practice environments. The study proposes a training method for active listening using LLMs.

Rogers' three principles are well-known techniques for successful active listening. They consist of Self-consistency, Empathic understanding, and Unconditional Positive regard [4]. All of these are aimed at getting listeners to pay attention to what speakers talk about. Previous studies[5][6][7] have shown that when others listen attentively to one's conversation, that person's sense of happiness increases. Therefore, active listening is deeply connected to human emotions. A method is proposed for recognizing emotions from voice characteristics [8]. There is also a work that uses body movement instead of voice features [9]. Furthermore, numerous studies have successfully estimated emotions by focusing on specific movements such as actors' actions[10] and dance[11][12][13][14][15][16]. Nemec et al. [17] demonstrate that listeners who exhibit high levels of attentiveness and comprehension during active listening tend to ask questions highly relevant to the content of the conversation. Huang et al. [18] report that listeners frequently paraphrase when they exhibit high levels of attentiveness and comprehension during active listening. Kluger et al.[19] reveal that the more the listener's attention declines, the more the quality of listening perceived by the speaker also decreases. Previous works have examined the conditions conducive to effective active listening and those that hinder active listening. However, there is no study focusing on how to train listeners.

The study proposes a method that utilizes LLMs to enhance human listening skills. The study utilizes LLM to imitate a speaker as a training partner to improve human listening skills. LLM cannot be used online because the content of the listening session is private. To build an LLM in an on-premise environment, the study adopts QLoRA to fine-tune the model with data specific to active listening. QLoRA greatly contributes to the suppression of training costs. It makes the LLM on premise learn the flow of conversations in both successful and unsuccessful active listening instances.

The study evaluates the performance of the LLM in active listening from emotion recognition capabilities after fine-tuning. The results of an experiment reveal that the proposed method improves the emotion recognition capability of the model by approximately 5.2%.

The structure of the paper is as follows. Chapter 2 describes the prerequisite technologies. Chapter 3 proposes a method for constructing an LLM as a training partner to enhance human active listening skills. It also analyzes the characteristics of LLMs as training partners for improving human active listening skills. Chapter 4 describes experiments to evaluate the proposed method. Chapter 5 discusses the effectiveness and the applicability of the method.

2. LLM for Emotion Evaluation

2.1. STUDIES Corpus for Rapport

The STUDIES Corpus [20] is an audio dialogue corpus primarily focused on empathy toward Japanese conversation partners. The corpus consists of script text and audio data in simulated dialogue. The dialogue script data consists of lines of dialogue, speaker emotion labels, and phoneme alignments. The simulated dialogue audio data are recorded by one male and two female professional voice actors. One of the women is playing the role of instructor, while the other two are playing the roles of students. Each dialogue is a one-on-one conversation.

Let us train LLMs as training partners for active listening to improve human active listening skills. The training dataset should be acquired from actual active listening sessions. However, active listening differs from ordinary two-way dialogue in that it requires trust from a speaker to a listener. In active listening, a speaker who has no trust in a listener would not tell the listener what is on the speaker's mind. A relationship in which the speaker trusts the listener is referred to as rapport. Due to it, successful active listening data is hard to collect.

For active listening to be successful, rapport is crucial. The listener is required to empathize with the speaker to build rapport. For LLMs to be used as training partners for active listening, it is important that they have the ability to recognize human emotions, especially the ability to empathize. The STUDIES corpus is suitable for achieving it.

2.2. LoRA

The use of data in active listening and the STUDIES corpus requires consideration of privacy issues. It is because active listening sometimes requires the listener to elicit disclosures about highly private matters hidden within the inner thoughts of the person being listened to. The confidentiality of training data is compromised in the fine-tuning of online LLMs like ChatGPT. LLMS for active listening must be fine-tuned in an on-premises environment because the tuning uses highly sensitive data for privacy.

LLMs demonstrate remarkable performance across a wide range of applications compared to traditional machine learning models. The enormous computing resources contribute to the performance. Especially, the training of LLMs requires significant computational resources. The shortage of computational resources in an on-premise environment prevents LLMs from achieving high performance. Even fine-tuning rather than training from scratch requires enormous computational resources.

LoRA[21] is an efficient fine-tuning method. LoRA enables us to reduce the amount of computational resources significantly compared with conventional fine-tuning methods.

LoRA is a technique that saves computational resources by an adapter attached to the original model. LoRA assumes only parts of the whole model contribute to its fine-tuning. The adapter consists of a small number of parameters. In LoRA, only the adapter is trained without updating the parameters of the entire model. Conventional LLM models calculate outputs by applying a weights matrix and inputs. On the other hand, LoRA adds the product of a low-rank matrix and inputs to the outputs of the conventional models to produce the final outputs. Training only the low-rank matrix as parameters, LoRA reduces the computational complexity.

QLoRA[22] improves the memory consumption of LoRA. QLoRA is superior to conventional fine-tuning methods in terms of computational complexity and required memory. It enables the fine-tuning of LLMs in an on-premise environment.

2.3. EQ-Bench

There is no established method for quantitatively evaluating the quality of active listening. Conventional methods have primarily relied on questionnaires for listeners and speakers, resulting in evaluations that remain qualitative. Active listening is an activity to elicit from the speaker matters that are difficult for them to confide in others. Such matters are related to the feelings of the speaker.

EQ-Bench[23] is a benchmark for evaluating the emotional quotient (EQ) of LLMs. EQ-Bench first presents an LLM with a dialogue text along with four specific types of emotion words. Next, the LLM infers whether the speaker in the dialogue is feeling any of the four specified emotion words during the conversation to quantify the intensity of the feeling numerically. Finally, the benchmark evaluates the LLM's emotional intelligence by comparing the correct score with the score predicted by the LLM. Ultimately, the benchmark estimates emotional quotient scores for multiple dialogue exchanges to compute their average.

The emotional quotient of LLMs can be estimated with EQ-Bench. It allows us to know how the listener who is trained with an LLM in active learning improves abilities to lead active listening successfully.

3. The first section in your paper

3.1. Method Overview

The study constructs an LLM as a training partner to enhance human active listening skills. First, the study preprocesses the STUDIES corpus. Next, it fine-tunes Gemma3 using QLoRA. Next, the study evaluates the pre- and post-fine-tuning models using EQ-Bench. Furthermore, the study deeply discusses emotional quotient in both the pre- and post-fine-tuning models. Figures 3.1 through 3.6 illustrate the above methods.

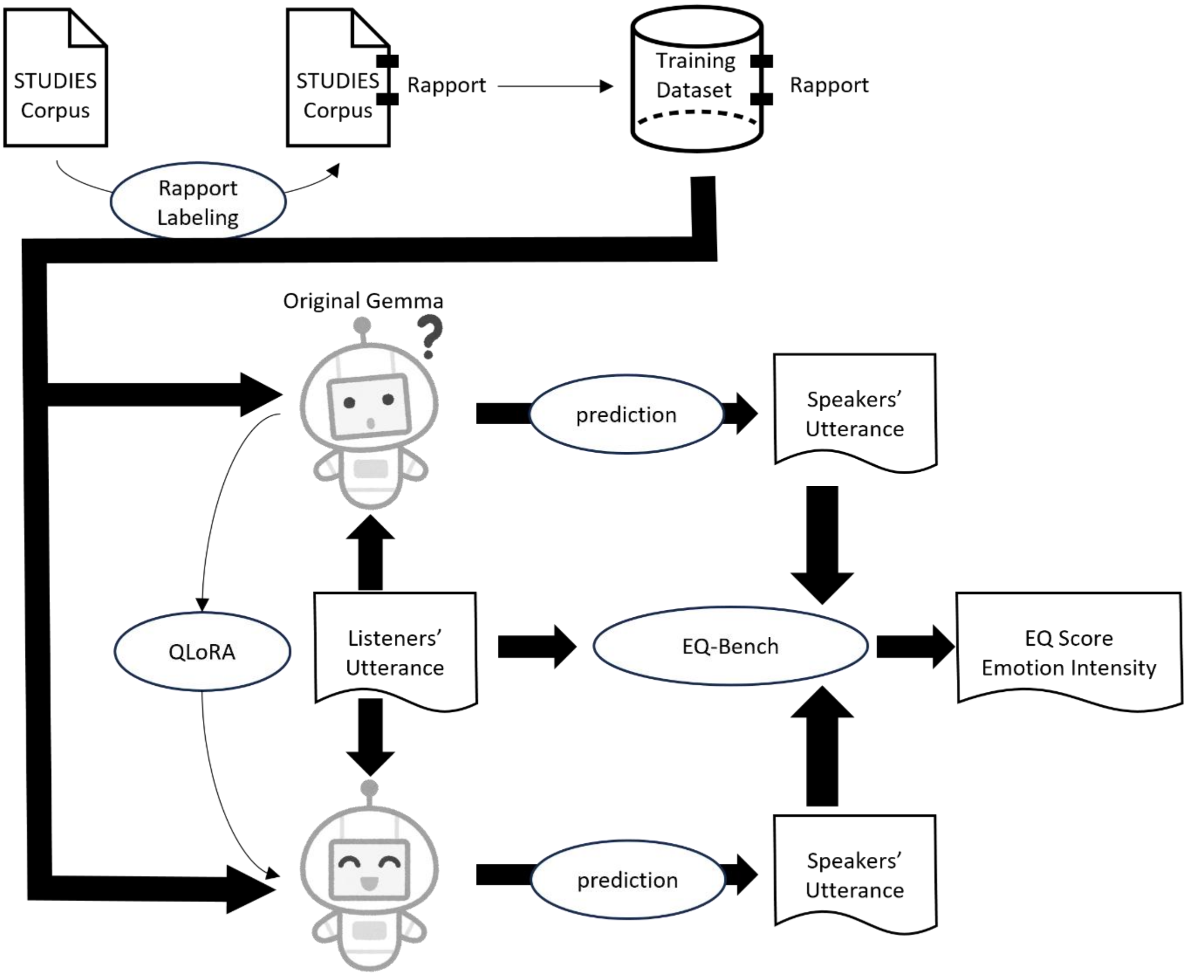

Figure3.1: Method overview chart.

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Figure3.2: Data Preprocessing.

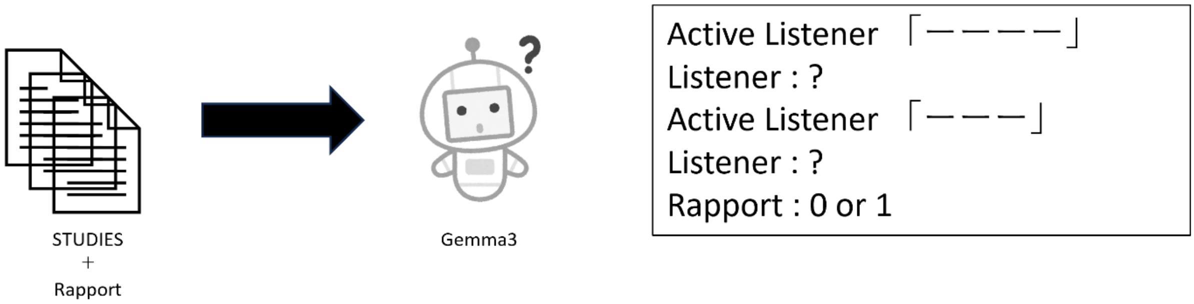

Figure3.3: Fine-Tuning Using QLoRA.

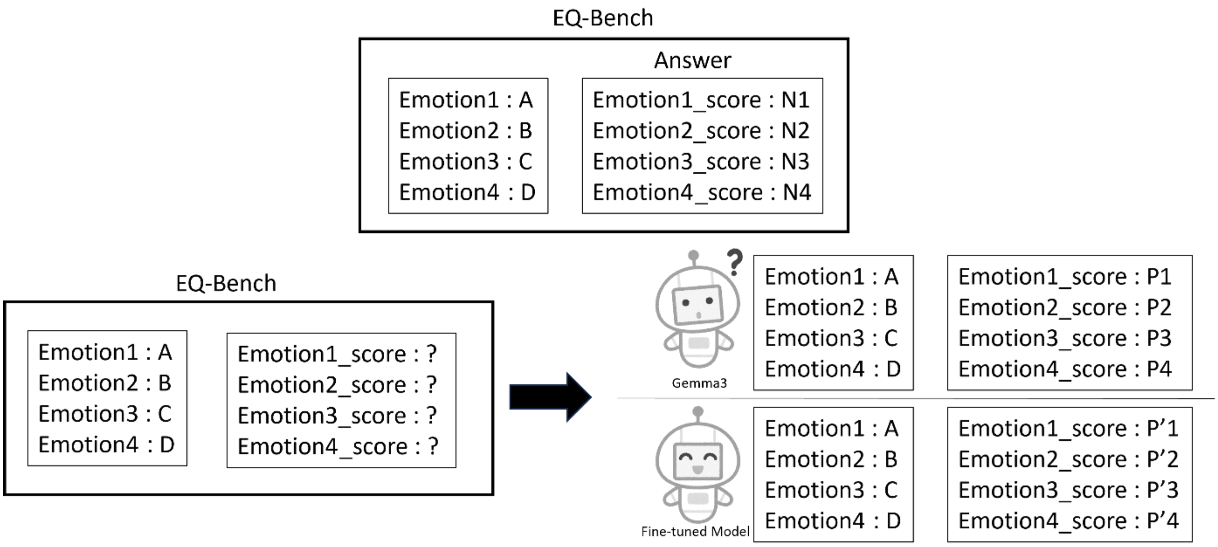

Figure3.4: Evaluation of Emotion Recognition Capability.

3.2. Data Preprocessing

The study preprocesses the STUDIES corpus to use it as training data for fine-tuning. The study regards the teacher role in the STUDIES corpus as the listener side, while the student one as the speaker side. Figure3.2 illustrates the data preprocessing.

The first step is to assign labels to the STUDIES corpus. Self-disclosure of information difficult to share with others indicates that a certain level of trust has been established between the two parties in the conversation. The trust relationship, i.e., rapport, should not be overlooked in active listening. Labels are assigned to each dialogue set in the STUDIES corpus based on whether rapport occurs.

The STUDIES corpus contains numerous simulated dialogues performed by voice actors. The length of each turn varies depending on the conversation set. The length of a turn here refers to the length of the dialogue exchange. One turn is defined as a sequence where the listener speaks and the speaker responds. If turns are too long, it is more likely to run into computational resource shortages during fine-tuning. Conversely, when turns are too short, information specific to dialogue is likely to be less reflected in the model. Dialogue is fundamentally based on the content of the immediately preceding turn. The study sets the time window size of the fine-tuning to two turns.

In the corpus, the listener and the speaker repeat their utterances sequentially. The data format is arranged so that the utterance starts from the listener in all datasets. The study extracts two-turn dialogues in a manner that makes one turn overlap, namely, when the next two turns are extracted from a dialogue, the second turn of the previous becomes the first turn of the latter.

3.3. Fine-Tuning Using QLoRA

The study uses the dataset prepared in Section 3.2 to fine-tune Gemma3-1b with QLoRA. The fine-tuning should take place in an on-premises environment because privacy must be protected. It holds for any dataset on active listening.

Figure3.3 illustrates fine-tuning using QLoRA. The study aims to develop an LLM as a training partner to enhance human listener skills for active listening. In other words, it trains an LLM to act as a speaker in active listening sessions. Using the dataset prepared in Section 3.2 as a training dataset, the LLM predicts the student's response. The LLM is expected to present the most appropriate subsequent utterance based not only on the previous teacher's utterance but also on labels reflecting the success of active listening and the relationship between teacher and student.

3.4. Evaluation of Emotion Recognition Capability

The rapport labels are assigned manually to the STUDIES corpus. They lack objectivity. We need to introduce a way to evaluate how accurately the model objectively captures each kind of emotion.

The study uses EQ-Bench to evaluate the performance of fine-tuned LLMs as training partners for active listening tasks. Since EQ-Bench evaluates LLMs from diverse emotional perspectives through numerous dialogue examples, it achieves a comprehensive assessment of their emotion recognition capabilities. Figure3.4 illustrates the evaluation method for emotion recognition capability.

EQ-Bench is entirely composed in English. However, the study assumes active listening in Japanese. The data used for the fine-tuning is also represented in Japanese. The study adjusts EQ-Bench to Japanese environments. Only the simulated dialogue portion in EQ-Bench is localized into Japanese. The adjustment enables us to know how LLMs work well as training partners for Japanese listeners in active listening.

The ability to empathize with the person LLMs are talking to is a crucial element for successful active listening. The foundation of the ability to empathize with a conversation partner lies in understanding their emotions. The study regards the evaluation of LLM's emotion recognition ability will lead to an assessment of its performance as a training partner for active listening.

In operations, utterance generated by both the fine-tuned Gemma3 model and the original Gemma3 model are fed to EQ-Bench to compare their performance. A significant difference between them means the proposed method succeeds in constructing an LLM that works as a training partner to improve the skills of human listeners empathising with speakers.

3.5. Grouping of Emotions Represented by Words

Let us examine for which kind of emotion the LLM constructed with the proposed method has better recognition capabilities compared to other LLMs. Figure 3.5 illustrates the grouping of emotions expressed by words.

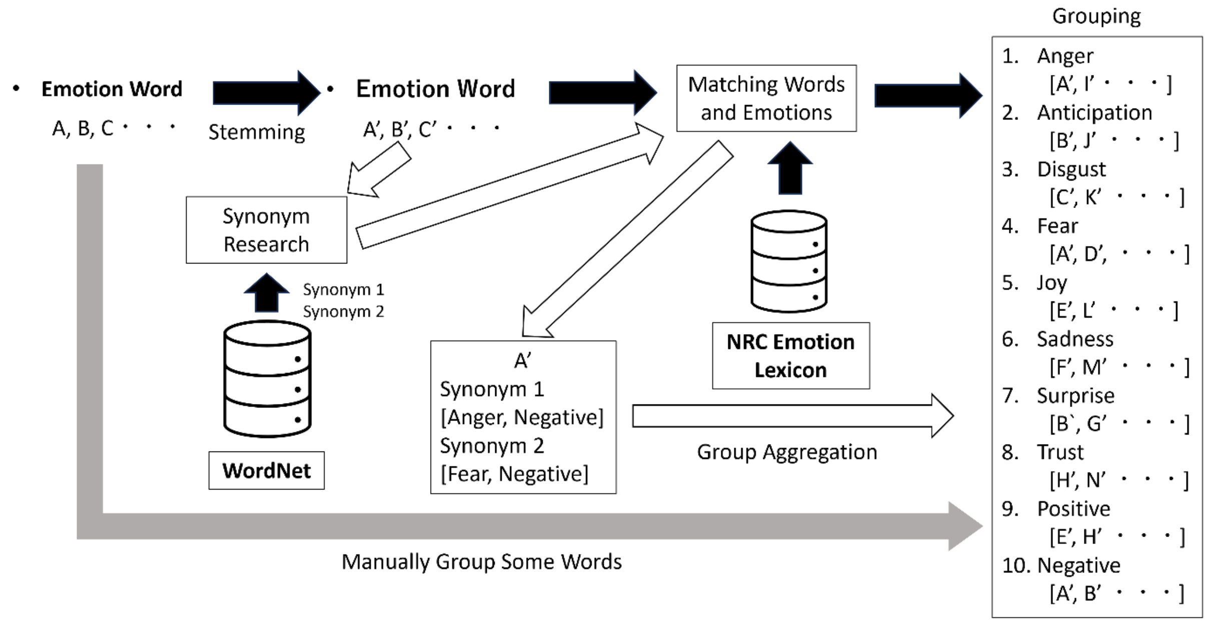

Figure3.5: Grouping of Emotions Represented by Words.

EQ-Bench consists of a set of prompts containing dialogue and specific emotional words of four types, along with their scores. There are a total of 171 dialogue sets in EQ-Bench. Each dialogue set contains four specified emotional words. There are 201 distinct types of emotional words in the benchmark. It is hard to analyze the 201 types due to the fine granularity. The study analyzes emotional words after dividing them into several groups. The study stems all words for grouping because many of the emotional words in EQ-Bench are derived words.

The study uses the NRC Emotion Lexicon [24] as its dictionary database. NRC Emotion Lexicon is a resource developed by the National Research Council Canada that maps English words to emotion categories. NRC Emotion Lexicon includes ten categories of emotion. The study categorises all emotional words in the EQ-Bench into the ten categories. Each emotional word must belong to at least one category. Among the 201 stemmed emotional words, 129 are classified.

The study classifies the remaining 72 words based on their synonyms found using WordNet [25]. WordNet is an English lexical database developed by Princeton University, in which words are organized by semantic units. The next step is matching with the NRC Emotion Lexicon for synonyms. If any synonym contains a term registered in the NRC Emotion Lexicon, the study classifies the remaining emotional word into the category of the synonym. Though the procedure above categorizes most terms, 17 emotional words remain uncategorized. They are manually assigned to categories.

3.6. Group-Based Evaluation of Emotion Recognition Capability

EQ-Bench contains 171 dialogue sets, each of which is equipped with four types of emotional words together with their scores as labels. Additionally, EQ-Bench independently predicts the four types of emotion scores from the dialogue presented by the target LLM. If the error between the prediction and the label for a specific emotion decreases in the fine-tuned model compared to the original model, we can say the fine-tuned model has higher recognition capability for the emotion. Figure3.6 shows the group-based evaluation of emotion recognition capability.

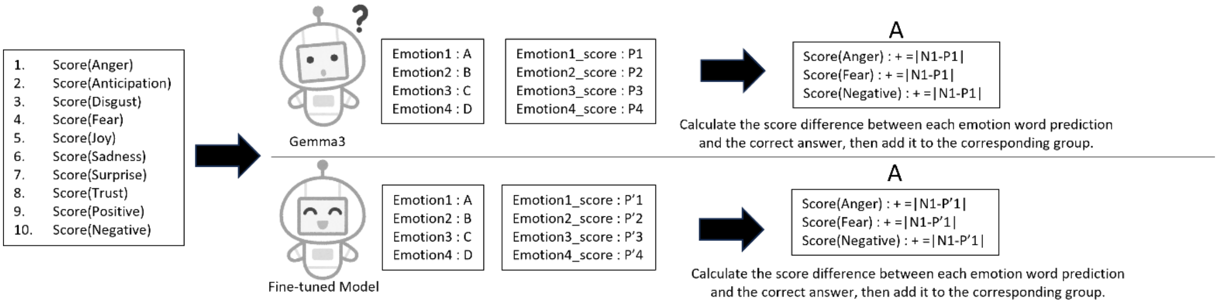

Figure3.6: Group-Based Evaluation of Emotion Recognition Capability.

This study evaluates which types of emotions the fine-tuned model using labels indicating rapport can recognize, i.e., which types of emotion is closest to human sensibilities. The result enables us to identify which types of emotions are most important for LLM as a training partner for active listening.

4. Experiments

4.1. Evaluation Using EQ-Bench

The study fine-tunes the LLM consisting of Gemma3 and QLoRA with the STUDIES corpus labelled with rapport states. EQ-Bench is used to evaluate the emotion recognition capability of each LLM before and after fine-tuning. Table 4.1 and Table 4.2 show the EQ-Bench results before and after fine-tuning, respectively. The study runs EQ-Bench five times on each model before and after fine-tuning to calculate the scores.

Table 4.1: EQ-Bench Results for the Model Before Fine-Tuning.

	1	2	3	4	5	Mean
Score	26. 87	27. 7	28. 01	26. 36	28. 49	27. 486
Parse able	155. 0	153. 0	154. 0	152. 0	151. 0	153

Table 4.2: EQ-Bench Results for the Model After Fine-Tuning.

	1	2	3	4	5	Mean
Score	28. 95	28. 81	28. 85	28. 88	29. 06	28. 91
Parse able	169. 0	168. 0	168. 0	168. 0	168. 0	168. 2

The row indicated with "Score" represents the emotion recognition capability of the models evaluated by EQ-Bench. The higher the value, the greater the model's emotion recognition capability. The row of "Parse able" indicates how many of the 171 dialogue sets in EQ-Bench the LLM can generate a speaker's utterance according to EQ-Bench's instructions. The two tables show that the model after fine-tuning with QLoRA achieves an average score

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increase of approximately 1.4 points compared to the model before fine-tuning. It means that fine-tuning with QLoRA using the STUDIES corpus can improve emotion recognition capability. Furthermore, the model after fine-tuning with QLoRA shows an increase of approximately 15 points in parse able dialog sets compared to the model before fine-tuning. It implies that fine-tuning of QLoRA using the STUDIES corpus can enhance its ability to recognize emotion following EQ-Bench instructions.

4.2. Emotion Category Recognized by Trained LLM

Table 4.3 shows the evaluation of emotion recognition capabilities for each model before and after fine-tuning, grouped by the categories defined in Section 3.5. The columns "Base" and "QLoRA" show emotion recognition error, which is the difference of the prediction score by the LLM from the correct answer score presented in EQ-Bench. The smaller the error, the higher the LLM's emotion recognition capability for the emotion category. Columns "Base" and "QLoRA" represent the emotion recognition error of the model before and after fine-tuning, respectively. Column "Difference" shows the difference between the two errors.

Table 4.3: Model Classification Performance by Emotion Group Before and After Fine-Tuning.

	Base	QLoRA	Difference
Anger	6. 202	2. 927	3. 275
Anticipation	5. 028	3. 497	1. 531
Disgust	5. 792	2. 848	2. 944
Fear	5. 870	2. 510	3. 359
Joy	3. 971	3. 172	0. 799
Negative	6. 002	2. 766	3. 236
Positive	4. 523	3. 537	0. 985
Sadness	5. 617	2. 542	3. 074
Surprise	5. 692	3. 505	2. 188
Trust	4. 736	3. 968	0. 768

Table 4.3 shows that the model before fine-tuning recognizes emotions closely related to the category "Positive," such as trust and joy, slightly better than other categories. After fine-tuning, the model exhibits slightly higher emotion recognition performance for negative categories, such as anger, disgust, fear, and sadness, compared to other emotion categories. The model after fine-tuning demonstrates higher emotion recognition performance across all groups. Furthermore, the improvement is greater for the negative emotion group than for the positive emotion group. It is interesting that the degree of improvement for categories semantically intermediate between positive and negative emotion, such as anticipation and surprise, falls between those of positive and negative emotion categories.

5. Discussion

5.1. LLM to Improve Active Listening Skills

The experiments provided certain guidelines for constructing an LLM as a training partner to enhance active listening skills.

Tables 4.1 and 4.2 show that the fine-tuned model demonstrates better performance in both “Score” and “Parse able.” Empathy is essential for success in active listening. In other words, it is important for active listening to understand the other person's feelings and be empathetic. This active listening characteristic is presumed to account for the difference in emotion recognition capability between models before and after fine-tuning.

Table 4.3 shows that the fine-tuned model exhibits greater improvement in emotion recognition capability for the Negative emotion group compared to the Positive emotion group than the pre-fine-tuned model. Let us investigate the STUDIES corpus to explain the experiment result.

Approximately 55% of the data used for fine-tuning on QLoRA contributed to successful active listening. For each label related to active listening, human classification of the STUDIES corpus dialogues into four categories of emotions (joy, anger, sadness, and happiness) revealed that data leading to successful active listening had the following proportions: approximately 1.5% for joy, 36.8% for anger, 57.4% for sadness, 4.4% for happiness, and 4.4% for neutral. Furthermore, for data not leading to successful active listening, the proportions of joy, anger, sadness, and happiness were approximately 34.1%, 2.4%, 2.4%, and 61.0%, respectively.

Active listening primarily involves eliciting information about matters that are difficult for others to disclose. When the content is positive for oneself, people often share it with others without needing active listening. These characteristics are thought to have been reflected in the data through the labelling performed during preprocessing.

Table 4.3 shows that the improvement in emotion recognition capability was greater for the Negative emotion group than for the Positive emotion group. Furthermore, the pre-fine-tuning model shows higher emotion recognition capability for positive emotions than for negative emotions, whereas the post-fine-tuning model demonstrates higher emotion recognition capability for negative emotions than for positive emotions. These findings suggest that when building LLMs as training partners to improve human active listening skills, prioritizing the emotion recognition capability for negative emotions over positive ones may lead to better results.

5.2. Limitation

Let us discuss the limitations of the proposed method in terms of its applicability to actual situations.

The study primarily uses text data to construct an LLM as a training partner to improve active listening skills. The dialogue audio data is used solely for labelling related to active listening. In essence, the success of active listening depends not only on the content of the conversation but also significantly on the tone of voice, eye contact, nodding, and other body movements appropriate to the dialogue. The words in other voice tone or attitude would convey quite different meanings to partners in active listening sessions.

To improve the performance of LLM to enhance the listening skills of human listeners, it is necessary to incorporate nonverbal information into the data used for fine-tuning. For example, audio information such as voice tone can be incorporated into the training data by converting dialogue audio data into spectrograms. Fine-tuning using the data would enable

LLMs to realize the features of human speakers. Such LLMs would enhance the skills of human listeners.

It is crucial to discuss how much diversity of human speakers' emotions the proposed method can address to examine its limitations. The method uses QLoRA to reduce the number of trained parameters. The number of parameters determines the extent to which it addresses the diversity of speakers' emotions. The research should clarify the criteria for the number of parameters suitable for a given diversity. Meanwhile, the diversity to be addressed is a trade-off with reducing computational costs through on-premise training. On-premise training is essential to protect privacy in active listening. It is impractical to train a huge number of parameters on-premises. The study introduces EQ-Bench to evaluate the ability of LLMs to recognize emotion. It is worth examining whether the diversity covered by EQ-Bench is practical.

6. Conclusion

The study proposes a method for constructing an LLM as a training partner to enhance human active listening skills. It also evaluates LLM characteristics from the viewpoint of emotion recognition capability to establish guidelines to construct an LLM as a training partner to enhance human active listening skills.

The method fine-tunes a general LLM, Gemma, with the STUDIES corpus, which is a dataset simulating actual active listening. To avoid privacy leaks, LLMs should be fine-tuned on premises, where the tuning cost should be suppressed. The method introduces QLoRA to reduce the cost.

The study has verified the effectiveness of LLM through a well-known benchmark, EQ-Bench. It turns out that the proposed method enhances the performance for the LLM to recognize emotions. Furthermore, analyzing the experimental data for both pre- and post-fine-tuning models reveals the characteristics of LLMs improving active listening skills.

Active listening is a two-way communication involving the exchange of both verbal and nonverbal information. The current training method, primarily based on text information, has limitations in case LLMS should recognize emotions in actual dialogues that contain not only verbal but also nonverbal information. The use of audio information and other modalities will be addressed to promote recognizing emotions expressed in various ways.

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