A. SUPPLEMENTARY OF DATASET CONSTRUCTION

A.1. Data Collection

The detailed information of schema $\mathcal{R}$ is listed in Table 3, where the attribute KR, KR_S, KR_P are required for subsequent data cleaning.

Attribute	Data type	Description
ID	Int	Primary Key, Microblog id from Sina platform
$TEXT$	String	Microblog text
KR	Bool	Whether the microblog text contains the Chinese character '韩'
KR_S	Bool	Whether the microblog text contains the Chinese names of Korean stars
KR_P	Float	Percentage of Korean characters in microblog text

Table 3. Detailed information of schema $\mathcal{R}$.

Algorithm 1 gives the process of microblog data acquisition and storage. Before the algorithm starts, we search with the keyword "Korean stars" through the Baidu engine and collect the first 100 pages of the webpage to get the Chinese name list of Korean stars.

Algorithm 1 Microblog data acquisition and storage

Input: Token list **vocab**, Korean star names list **starlist**, schema $\mathcal{R}$
Output: Microblog table **I**

$\mathbf{I} \leftarrow \phi$
for $token \in$ **vocab do**
  for $page \in [0, \ldots, 100]$ **do**
    $response \leftarrow$ Request($token, page$)
    $r_{json} \leftarrow response$.json()
    for $e \in r_{json}$ **do**
      Create empty tuple $t_i \in \mathcal{R}$
      $t_i.ID \leftarrow$ read_microblog_id(e)
      if $\exists t_j \in \mathbf{I}, t_i.ID = t_j.ID$ **then**
        continue
      end if
      $t_i.TEXT \leftarrow$ read_microblog_text(e)
      $t_i.KR \leftarrow$ False
      if '韩' $\in t_i.TEXT$ **then**
        $t_i.KR \leftarrow$ True
      end if
      $t_i.KR_S \leftarrow$ False
      if $\exists star \in$ **starlist**, $star$ **in** $t_i.TEXT$ **then**
        $t_i.KR_S \leftarrow$ True
      end if
      $t_i.KR_P \leftarrow$ korean_char_num($t_i.TEXT$)
      $t_i.KR_P \leftarrow t_i.KR_P/\text{len}(t_i.TEXT)$
      $\mathbf{I} \leftarrow \mathbf{I} + \{t_i\}$
    end for
  end for
end for

Through the above process, we get the microblog table **I**, where $|\mathbf{I}| = 393,782$.

A.2. Data cleaning

In order to clean **I** by the denial constraint set $\Sigma = \{C_1, C_2, C_3\}$, we set $r = 0.8$ for C_3. After the cleaning process, 64,985 tuples with higher quality are retained, i.e. $|\mathbf{I}'| = 64,985$.

A.3. Annotation

Before annotation, we select volunteers from Yanbian University according to the following rules:
Rule 1: The ethnicity of the volunteer is Korean-Chinese, and the language of the answer sheet when taking the Chinese university entrance examination is Korean-Chinese language.
Rule 2: The volunteer must be a second-year or above student in computer-related field.
Rule 3: The volunteer is required to pass the exam of the machine learning course offered by Yanbian University and have basic knowledge of deep learning and natural language processing.

After selecting the volunteers, we distributed questionnaires to them for annotation. Table 4 demonstrates the available options for the microblog text with index number 222 in the questionnaire.

222. 와 진짜 나에게 이렇게 많은 기회들이 있었구나라는 생각이 드네…
0. The microblog is not written by Korean-Chinese people
1. Positive sentiment
2. Neutral sentiment
3. Negative sentiment

Table 4. Examples of available options for the questionnaire.

After retrieving the questionnaires, we assign the sentiment labels to each microblog text in $\mathbf{I}'$ according to the rules for assigning sentiment labels. Table 5 shows eight example microblog texts after the sentiment label assignment.

B. SUPPLEMENTARY OF PROMPT LEARNING FRAMEWORK

B.1. Korean-Chinese Prompt Template

In order to adapt the prompt learning process to the real Korean-Chinese context and to make full use of the semantic information embedded in PLM in the Korean-Chinese sentiment analysis task, we design six prompt templates suitable for Korean-Chinese sentiment analysis through expert consultation as shown in Table 6.

In the prompt templates, **X** is the location where the original microblog text is filled in. By using our pre-designed prompt templates, PLMs can gain a better understanding of the input text and achieve more accurate sentiment analysis. Meanwhile, the design of the above prompt templates can also help PLMs learn the language patterns better through expert language understanding, thus improving the PLMs' sentiment analysis capability.

B.2. Prompt learning process

Before the prompt learning process, we empirically set K in the Prior Probability Refinement operation to 20.

The prompt learning process combines Equation 8 and the cross-entropy loss function to fine-tune the PLM

No.	Microblog Texts	Sentiment Label
1	한국 식품, 생필품, 주방용품을 도매가로 저렴하게 살수 있습니다.. 한개라도 택포이고 포인트 적립됩니다 (You can buy Korean food, necessities, and kitchenware at low wholesale prices. One item is also free shipping, and points can be accumulated.)	Neutral
2	오랜만에 받는 꽃선물이라 기분이 좋넹 꽃선물 여심저격ㅎㅎ친구야 고마워 (It's been a while since I've gotten flowers and I'm in a good mood. Flowers as a gift haha. Thank you, my friend.)	Positive
3	주말에 서울 가고 싶지만 코시국이라서 지역 이동이 힘들어서 포기ㅠㅠ 진짜 며칠을 고민했었는데 생각하면 생각할수록 아쉽다구 (Although I wanted to go to Seoul for the weekend, I gave up because it was difficult to travel during the COVID-19 period. Really agonized over it for a few days but the more I think about it, the more I feel bad.)	Negative
4	그냥스쳐 지나가는 소나기죠 (It's a passing shower)	Neutral
5	내가 좋아하는 사람이 나를 좋아하게 만들어 주세요 ! (Let my favorite people like me!)	Positive
6	니가 뭔데? 이 나이 되고 제가 왜 너 눈치 봐아돼이제 부터 나 누구의 눈치 다 보기 싫어 (Who are you? At my age, why should I act according to your moods? I don't want to act according to anyone's moods from now.)	Negative
7	누가봐도우린이미사랑	Not written by Korean-Chinese people
8	내가내 생활을 잘 하는충분해	Not written by Korean-Chinese people

Table 5. Examples of microblog texts after the sentiment label assignment.

Template ID	Prompt Template	English Meaning
1	그것은 [MASK] 적이 였다. **X**	It is [MASK]. **X**
2	**X** 전적으로 [MASK] 적이 였다.	**X** It is [MASK] overall.
3	**X** 생각해보면 [MASK] 적이 였다.	**X** Think carefully, it is [MASK].
4	**X** 한마디로 [MASK] 적이 였다.	**X** In a word it is [MASK].
5	**X** 그렇지만 [MASK] 적이 였다.	**X** But it is [MASK].
6	**X** 이에 관하여 나는 [MASK] 적이라고 생각한다.	**X** For that, I think it is [MASK].

Table 6. Prompt templates for Korean-Chinese sentiment analysis.

for the Korean-Chinese microblog sentiment analysis task by minimizing semantic loss. If the training set of the Korean-Chinese Microblog Sentiment Analysis dataset is $\mathbf{C} = \left\{\left(\mathbf{X}^i, \mathbf{Y}^i\right)\right\}_{i=1}^{|\mathbf{C}|}$, where $\mathbf{X}^i$ is the microblog text and $\mathbf{Y}^i$ is the One-Hot sentiment label of $\mathbf{X}^i$. Then the objective function $\mathcal{L}$ for prompt learning is:

$$\mathcal{L} = \Sigma_{i=1}^{|\mathbf{C}|} \left(-\Sigma_{y \in \mathcal{Y}} \mathbf{Y}_y^i P\left(y \mid \mathbf{X}_p\right)\right), \tag{10}$$

where $\mathbf{Y}_y^i$ is the component of $\mathbf{Y}^i$ for sentiment label y. In practice, the process of prompt learning can converge after only a few epochs.

C. SUPPLEMENTARY OF EXPERIMENTS

C.1. Training and Testing set split

As shown in Table 7, we split the KTEA dataset into training and testing sets in the ratio of 8:2. For our KCMSA data, We create the testing set by randomly selecting 100 texts for each sentiment label. The remaining texts are used to form the training set, as indicated in Table 8.

C.2. Details of Baselines

- **SVM** [19] classifying Fasttext [26] word-vector representations of microblog texts via the Support Vector Machine.
- **KNN** [20] classifying Fasttext [26] word-vector representations of testing samples by finding their nearest neighbors in the training set.
- **TextCNN** [21] classifying Fasttext [26] word-vector representations of microblog texts via the TextCNN model.
- **LSTM** [22] classifies the word-vector representation of

Sentiment Label	Training set	Testing set
Positive	153	29
Neutral	460	118
Negative	590	157
Sum	1203	304

Table 7. Detailed information about the KTEA dataset.

Sentiment Label	Training set	Testing set
Positive	1155	100
Neutral	1584	100
Negative	654	100
Sum	3393	300

Table 8. Detailed information about our KCMSA dataset.

texts by the hidden layer vectors output from the bidirectional LSTM model.

- **GRU** [23] classifying word-vector representation of microblog texts using the hidden layer vectors produced by the bidirectional GRU model.
- **Attention-based LSTM** [24] is based on the bidirectional LSTM model, the weight of token corresponding to the output vector is adjusted according to the attention mechanism between the hidden layer and the output vectors. The weighted sum of the output vectors is utilized to classify the word-vector representations of microblog texts.
- **BERT Fine-turning** [6] applies KLUE-BERT to the Korean-Chinese language sentiment analysis task in a classical fine-tuning manner. The method uses the representation vectors of '[CLS]' tokens after KLUE-BERT processing for microblog text classification.
- **BERT Prompt-learning** [13] is the regular prompt learning method [14] for PLM pre-training. We only use "긍정" to form the label word set for the Positive sentiment label, "중성" for Neutral, and "부정" for Negative.

C.3. Details of KAP Implementation

In our experiments, we set the learning rate to 5e-5, the prompt learning epoch number to 3. We also set the training batch size to 64. Since microblogs usually have less characters, we set the maximum length of a single text to 160, and we truncate any text that exceeds this length. In addition, we use the first prompt template in Table 6 by default.

C.4. Hyperparameter Evaluation

We discuss the impact of two key hyperparameters for our KAP framework: learning rate and epoch for prompt learning, on the experimental results by performing parameter sensitivity analysis over our KCMSA dataset.

First, we set the epoch to 3 and adjust the learning rate in $\{5e-4, 1e-4, 5e-5, 1e-5, 5e-5, 1e-5, 5e-6, 1e-6\}$. It can be observed through Figure 2 that the sentiment analysis of our KAP is best when the learning rate is 5e-5. When the learning rate is too large, the model is difficult to converge. At the end of training, the loss of objective function is still large and cannot produce good results for sentiment analysis. When the learning rate is too small, the training of the model will be under-fitting due to the fixed epoch, affecting the effectiveness of sentiment analysis.

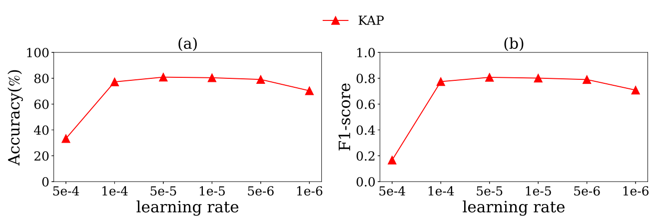

Fig. 2. Varying learning rate of our KAP framework over KCMSA dataset.

Then we set the learning rate to 5e-5, and varying the epoch for prompt learning in $\{1, 2, 3, 4, 5, 6\}$. As shown in Figure 3, KAP's sentiment analysis is best when the epoch is set to 3. When the epoch is set to other values, KAP still produces better sentiment analysis results. This result suggests that the epoch setting is not too stringent.

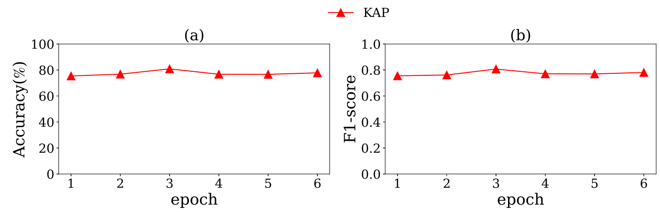

Fig. 3. Varying epoch of our KAP framework over KCMSA dataset.

C.5. Effects of Prompt Templates

As shown in Table 6, we designed a variety of prompt templates suitable for sentiment analysis of Korean-Chinese texts in order to apply the prompt learning method to the Korean-Chinese sentiment analysis task. To evaluate the impact of different prompt templates on the effectiveness of sentiment analysis, in this section, we conduct experiments with the six prompt templates shown in Table 6, respectively.

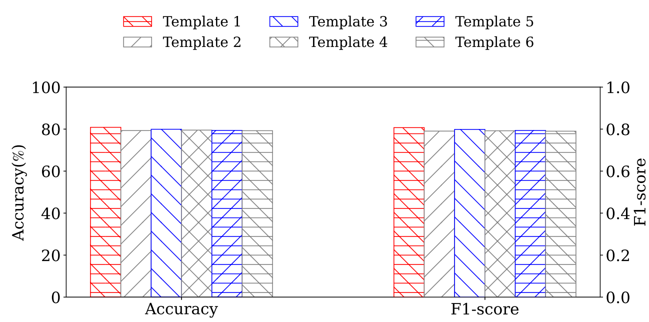

Fig. 4. Varying prompt templates for our KAP framework over KCMSA dataset.

The experimental results are shown in Figure 4. The prompt template index number shown in the figure corresponds to the "Template ID" in Table 6. The experimental results show that all the six prompt templates produce better sentiment analysis results, and the results produced by different prompt templates do not differ much, which reflects that KAP has a better sensitivity to the prompt templates. In addition, since the sentiment analysis results obtained by utilizing the first prompt template are slightly better than the other prompt templates, we adopt the first prompt template by default.

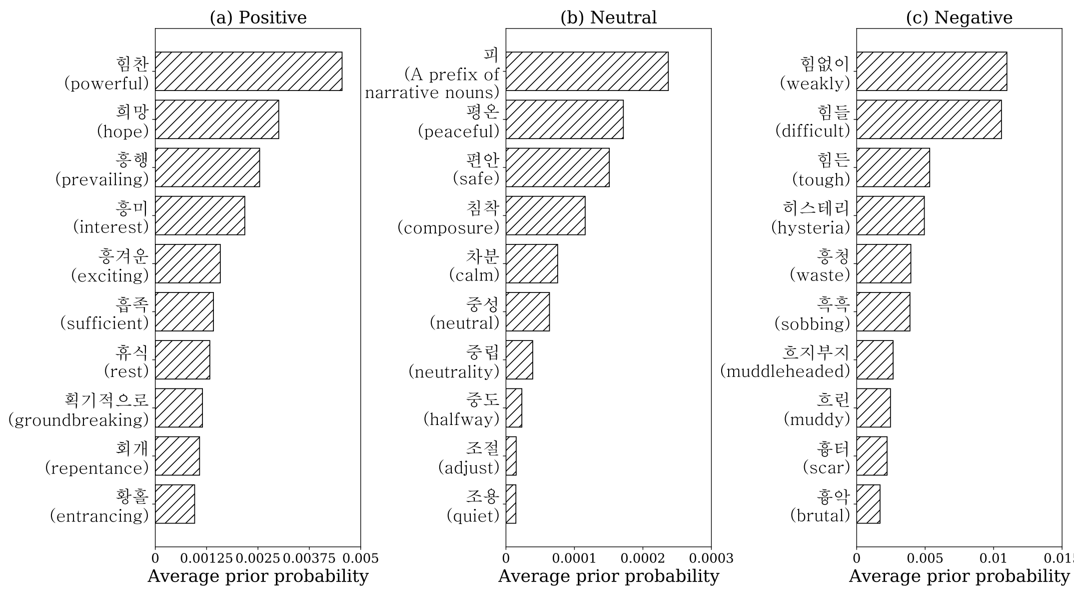

Fig. 5. The Top-10 sentiment words with the largest prior probabilities in the Korean sentiment knowledge base.

C.6. Visualization of Maximum Prior Probability Sentiment Words

The ablation experiments in Section 4.3 have demonstrated that the Prior Probability Refinement operation is able to effectively refine the sentiment words in the knowledge base and enhance the subsequent sentiment analysis. To further reflect the role of this operation, we obtained the corresponding prior probabilities of the sentiment words from [17] of each sentiment label through the KLUE-BERT [6] PLM model according to Equation 6, and selected the Top-10 sentiment words with the largest prior probabilities to visualize with their corresponding prior probabilities in Figure 5.

After consulting with experts in Korean linguistics, we find that after introducing the Korean sentiment knowledge base, the label words corresponding to sentiment labels are able to cover a wide range of real-life scenarios. Additionally, the prior probability rankings align with human intuition in the context of Korean-Chinese. This suggests that the knowledge-aware verbalizer incorporating the Korean sentiment knowledge base can better estimate the probability of sentiment label words in real-life scenarios, reducing the likelihood of deviation.