FEW-SHOT MULTIMODAL SENTIMENT ANALYSIS BASED ON MULTIMODAL PROBABILISTIC FUSION PROMPTS

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ABSTRACT

Multimodal sentiment analysis is a trending topic with the explosion of multimodal content on the web. Present studies in multimodal sentiment analysis rely on large-scale supervised data. Collating supervised data is time-consuming and laborintensive. As such, it is essential to investigate the problem of few-shot multimodal sentiment analysis. Previous works in few-shot models generally use language model prompts, which can improve performance in low-resource settings. However, the textual prompt ignores the information from other modalities. We propose **Multi**modal **Pro**babilistic Fusion Prompts. which can provide diverse cues for multimodal sentiment detection. We first design a unified multimodal prompt to reduce the discrepancy in different modal prompts. To improve the robustness of our model, we then leverage multiple diverse prompts for each input and propose a probabilistic method to fuse the output predictions. Extensive experiments conducted on three datasets confirm the effectiveness of our approach.

Index Terms— Multimodal Sentiment Analysis, Few-shot Learning, Probabilistic Fusion

1. INTRODUCTION

With the ever-gaining popularity of multimedia platforms, there is an explosion of data with multiple modalities such as text, images, or video. Multimodal Sentiment Analysis (MSA), which has wide applications in market prediction, business analysis, news focus detection, and so on, has become a popular research topic [1, 2, 3]. In this work, we focus on the multimodal image-text sentiment analysis task in social media. Continuous progress has been made in multimodal sentiment analysis. Early works in multimodal sentiment analysis focused on building rich and large-scale datasets [4, 5]. Later works focused on improving the performance of MSA by introducing different effective technology, including MGNNS exploits the global characteristics of the dataset by the Graph Neural Networks to enhance the performance of MSA [6]; CLMLF introduces contrastive learning to the MSA task [7].

However, existing multimodal sentiment models depend on large-scale datasets which are expensive and challenging to annotate. Hence, it is more practical to investigate few-shot learning methods that can perform well in low-resource settings, such as UFO-ENTAIL[8], LM-BFF [9], LM-SC [10], etc. Prompt methods are popular for few-shot learning as prompts enable pre-trained models to generalize to new tasks with little or no training data. Despite prompt tuning being widely used for few-shot text tasks, prompts are rarely used in multimodal scenarios. PVLM [11] directly incorporates image modality into the pre-trained masked language model (MLM) for the few-shot multimodal sentiment analysis (FMSA). However, directly feeding image representations into the language model has to face the discrepancy issue between different modalities since the image encoder is language-agnostic. We find that different prompts contain various amounts of information, and the information conveyed by a single prompt is insufficient. How to design effective multimodal prompts and explore more valuable content of various multimodal prompts is the critical challenge in the FMSA task.

To tackle the above challenge, we propose the **Multi**modal Probabilistic Fusion Prompts (MultiPoint) model for imagetext multimodal sentiment detection in few-shot scenarios. Our method incorporates image and text prompts to enhance the multimodal few-shot performance and formats the finetuning task into a masking language problem that generates the label for a given prompt. Specifically, we first design the multimodal prompt for our task. For the text modality, we exploit automatic template generation to obtain multiple effective textual prompts. For the image modality, we first generate the textual description of each image and encode it as a textual prompt to improve the compatibility between image and text prompts. As shown in Fig. 1, we unify the image and text prompts into a single multimodal prompt. We further find that the information from a single prompt is limited, and different prompts capture more cues. Bayesian Fusion is verified to be robust in increasingly discrepant sub-posteriors scenarios [12]. So we propose a novel probabilistic fusion method to fuse multiple predictions from multimodal prompts to improve the performance of few-shot multimodal sentiment analysis. Our main contributions are summarized as follows:

- We propose a novel Multimodal Probabilistic Fusion Prompts (MultiPoint) model for the FMSA task¹.
- We design the unified multimodal prompt to reduce the

¹The source code of the proposed approach is available at https://github.com/YangXiaocui1215/MultiPoint.

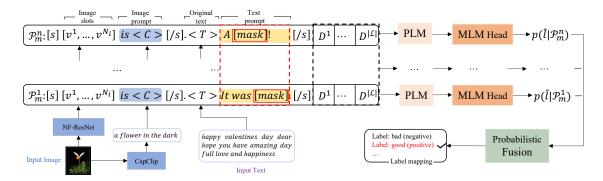


Fig. 1. An illustration of our proposed Multimodal Probabilistic Fusion Prompts (MultiPoint) model for FMSA. A multimodal prompt is composed of multiple slots of representing image, image prompt, and the task-specific text prompt. The red dashed boxes represent different text prompts. PLM represents a pre-trained language model, such as RoBERTa. \mathcal{P}_m^j is the j-th multimodal prompt, [s] and [/s] separately are beginning and ending special tokens in PLM. Like LM-BFF [9], the black dashed boxes represent various demonstrations based on labels. D^i is the i-th multimodal demonstration, and $|\mathcal{L}|$ is the number of labels. \hat{l} is the predicted label for a given text-image pair.

discrepancy from different modal prompts and the Probabilistic Fusion method to aggregate predictions from multiple multimodal prompts to improve the robustness of our model.

 We conduct experiments on three multimodal sentiment datasets to verify the effectiveness of our model.

2. METHODOLOGY

Task Formulation In this paper, we assume access to a pre-trained language model \mathcal{M} , such as BERT [13] or RoBERTa [14], that we wish to fine-tune the sentiment classification task \mathcal{D} with a label space \mathcal{L} . For few-shot multimodal training dataset \mathcal{D}_{train} , we only select K training examples per class, thereby $\mathcal{D}_{train} = \{(t^j, i^j, l^j)\}_{j=1}^{K_{total}}$, where t is the text modality, i is the image modality, i is the sentiment label for a text-image pair, and $K_{total} = K \times |\mathcal{L}|$ is the total number of image-text posts. PLVM [11], which applies the whole development set to fine-tuning parameters, subverts our initial goal of learning from limited data. Different from PLVM, we select the development set \mathcal{D}_{dev} that has the same size as the few-shot training set, i.e. $|\mathcal{D}_{dev}| = |\mathcal{D}_{train}|$. The goal of the model is to generalize to the unseen test dataset $(t_{test}, i_{test}, l_{test}) \in \mathcal{D}_{test}$.

2.1. Multimodal Prompt-based Fine-tuning

Conventional multimodal models are prone to overfitting in low-resource settings. To solve this issue, we propose **Multi**modal **Pro**babilistic Fusion Prompts (MultiPoint) model for Few-shot Multimodal Sentiment Analysis that considers multimodal classification as the cloze-filling task, as shown in Fig. 1. We first separately design prompts for different modalities and then build effective multimodal prompts for

our tasks. For the text modality, motivated by LM-BFF [9], we employ the pre-trained T5 model [15] that automatically generates multiple text templates for our datasets. Then we sort the generated templates and pick top- N_t templates as the candidate textual prompt set \mathcal{T}_t . For the image modality, I, to alleviate the gap between different modalities, we first generate the textual description of the image by ClipCap [16] and use it as the image prompt, C. We further leverage NF-ResNet[17] to extract and project the original image representation into the text feature space.

$$C = ClipCap(I). (1)$$

$$V = W_i Pool(ResNet(I)) + b_i, \tag{2}$$

$$\tilde{V} = reshape(V) = [v^1, ..., v^j, ..., v^{N_i}], v^j \in \mathbb{R}^{d_t}$$
 (3)

where $V \in \mathbb{R}^{d_{nt}}$, $W_i \in \mathbb{R}^{d_v \times d_{nt}}$, $b_i \in \mathbb{R}^{d_{nt}}$. $nt = d_t \times N_i$, N_i that is a hyperparameter, is the number of slots representing initial image representation in a multimodal prompt., and d_t represents the dimension of text embedding in the pre-trained language model.

Last, we design multiple multimodal prompts \mathcal{P}_m , including different text prompts and image prompts. For instance,

$$\mathcal{P}_m = [s] \tilde{V} is C [/s] T \mathbf{It was [mask]}. [/s], \qquad (4)$$

where T is the original text sequence; "It was" is a text prompt, we can randomly replace it with another prompt from \mathcal{T}_t to make a new multimodal prompt, as shown in the red dashed boxes of Fig.1.

Fine-tuning with Multimodal Demonstrations. Motivated by the LM-BFF and GPT-3 [18], we further expand text demonstrations to multimodal demonstrations chosen by the text similarity score, as shown in the black dashed boxes of Fig.1.

2.2. Classification

In our task, let $\phi: \mathcal{L} \to \mathcal{V}$ be a mapping from the task label space to individual words in the vocabulary \mathcal{V} of PLM, \mathcal{M} . For each text-image pair d=(t,i), we feed the multimodal prompt from Eq. 4, \mathcal{P}_m , that contains the [mask] token into the MLM head. We can cast our multimodal classification task as a cloze problem, and model the probability of predicting class $\hat{l} \in \mathcal{L}$ as:

$$p(\hat{l}|\mathcal{P}_{m}(d)) = p([mask] = \phi(\hat{l})|\mathcal{P}_{m})$$

$$= \frac{exp(\mathbf{w}_{\phi(l)} \cdot \mathbf{h}_{[mask]})}{\sum_{\hat{l} \in \mathcal{L}} exp(\mathbf{w}_{\phi(\hat{l})} \cdot \mathbf{h}_{[mask]})},$$
(5)

where $\mathbf{h}_{[mask]}$ is the hidden representation of [mask] token and \mathbf{w}_v indicates the final layer weight of MLM corresponding to $v \in \mathcal{V}$. \mathcal{M} can be fine-tuned to minimize the cross-entropy loss in the annotated multimodal posts $\{(t, i, l)\}$.

2.3. Multimodal Probabilistic Fusion

We find that different prompts contain various amounts of information, and the information conveyed by a single prompt is insufficient. We fuse prediction logits from different multimodal prompts based on Bayes Rule [19, 12] to provide more robust detection than a single prompt. For instance, there are n multimodal prompts $\{\mathcal{P}_m^1,...,\mathcal{P}_m^n\}$. Crucially, given one instance d that label is classified as \hat{l} by \mathcal{M} , we assume that different multimodal prompts are conditionally independent.

$$p(\mathcal{P}_{m}^{1},...,\mathcal{P}_{m}^{n}|\hat{l}) = p(\mathcal{P}_{m}^{1}|\hat{l})...p(\mathcal{P}_{m}^{n}|\hat{l}).$$
 (6)

Hence, given different multimodal prompts, the prediction results of the MLM are independent of each other. We perform multimodal sentiment detection given multiple prompts and derive the multimodal probabilistic fusion approach.

$$p(\hat{l}|\mathcal{P}_{m}^{1},...,\mathcal{P}_{m}^{n}) = \frac{p(\mathcal{P}_{m}^{1},...,\mathcal{P}_{m}^{n}|\hat{l})p(\hat{l})}{p(\mathcal{P}_{m}^{1},...,\mathcal{P}_{m}^{n})}$$

$$\propto p(\mathcal{P}_{m}^{1},...,\mathcal{P}_{m}^{2}|\hat{l})p(\hat{l})$$

$$\propto p(\mathcal{P}_{m}^{1}|\hat{l})...p(\mathcal{P}_{m}^{n}|\hat{l})p(\hat{l})$$

$$\propto \frac{p(\mathcal{P}_{m}^{1}|\hat{l})p(\hat{l})...p(\mathcal{P}_{m}^{n}|\hat{l})p(\hat{l})p(\hat{l})}{p(\hat{l})^{n}}$$

$$\propto \frac{p(\hat{l}|\mathcal{P}_{m}^{1})...p(\hat{l}|\mathcal{P}_{m}^{n})}{p(\hat{l})^{n-1}}.$$

$$(7)$$

Therefore, we first train independent classifiers that predict the distributions over the label \hat{l} given the individual multimodal prompt, such as $p(\hat{l}|\mathcal{P}_m^j)$. Lastly, we obtain the fused distribution of label \hat{l} from different n multimodal prompts based on the probabilistic fusion.

$$p(\hat{l}|\{\mathcal{P}_m^j\}_{j=1}^n) \propto \frac{\prod_{j=1}^n p(\hat{l}|\mathcal{P}_m^j)}{p(\hat{l})^{n-1}}.$$
 (8)

3. EXPERIMENTS AND RESULTS

Datasets. We investigate our model on the three image-text multimodal sentiment datasets from social media, such as MVSA-Single, MVSA-Multiple [4], and TumEmo [5]. The label sets, \mathcal{L} , vary across different datasets. For TumEmo dataset, \mathcal{L} is $\{Angry, Bored, Calm, Fear, Happy, Love, Sad\}$; for MVSA datasets, \mathcal{L} is $\{Positive, Neutral, Negative\}$. Like [11], we keep the test set unchanged and randomly sample about $1\%^2$ from the training set to form our few-shot datasets that simultaneously hold a balanced distribution for each category, and $K_{train} = K_{dev}$. The statistics of different datasets are given in Table 1.

Dataset	K _{train} / Train	K _{dev} / Dev	Test
MVSA-Single	96 / 3,608	96 / 451	452
MVSA-Multiple	192 / 13,618	192 / 1,703	1,703
TumEmo	1,344 / 124,432	1,344 / 15,554	15,559

Table 1. Statistics on the different datasets. Train (Dev) represents the original size of the dataset.

Experimental Setup. In the text prompt, for MVSA datasets, we map the label set {negative, neutral, positive} to {terrible, okay, qreat}; due to TumEmo having multiple emotion labels, we use the original label set. We employ NF-ResNet50 to capture the initial image representation and the greedy strategy of ClipCap to generate the text representation of the image. We adopt the RoBERTa-large, \mathcal{M} , to construct our model. It is well-known that fine-tuning on small datasets can suffer from instability, and results may change dramatically, given a new data split [20, 9]. To account for this, we measure average performance across five different randomly sampled \mathcal{D}_{train} and \mathcal{D}_{dev} splits. We argue that sampling multiple splits gives a more robust measure of performance. So we report the mean Accuracy (Acc), Weighted-F1 (F1)³ (and the standard deviation) over five different splits. We set number of templates top- N_t to be 20 for prompt set \mathcal{T}_t . Our model has the best performance in the Acc metric when n=2and $N^i = 2$ in each training, and the learning rate is 8e - 6. We use these hyperparameters unless otherwise specified.

Baselines. We compare two groups of baselines ⁴ with our model for exhaustive comparison. The first group is previous text-based models. **RoBERTa** [14] is the most popular baseline for textual tasks; **Prompt Tuning (PT)** only uses a single textual prompt, such as ([s] < T > It was [mask].[/s]); **LM-BFF** [9] utilizes prompt tuning with demonstrations; **LM-SC** [10] introduces contrastive learning based on LM-BFF. The second group consists of multimodal approaches. **CLMLF** [7],the state-of-the-art model for MSA, uses all training and de-

²MVSA-Single is small so we keep the sample more 1%.

³Since the categories of the MVSA datasets are very imbalanced, the Weighted-F1 value is more reasonable.

⁴Unless otherwise specified, all baselines are based on RoBERTa-large.

Modality	Model	MVSA-Single		MVSA-Multiple		TumEmo	
Modality		Acc	F1	Acc	F1	Acc	F1
	RoBERTa	52.77 (±2.97)	$56.08 (\pm 2.48)$	$56.79 (\pm 2.5)$	$58.79 (\pm 2.29)$	$54.00(\pm0.44)$	$54.03 (\pm 0.43)$
	PT	59.81 (±1.43)	$62.38 (\pm 1.25)$	$59.25 (\pm 1.98)$	$60.81 (\pm 1.66)$	$54.19(\pm 0.81)$	$54.26(\pm 0.77)$
Text	LM-BFF	$58.45 (\pm 2.03)$	$61.65(\pm 1.67)$	$59.15 (\pm 2.34)$	$60.67 (\pm 1.84)$	$54.62 (\pm 0.22)$	$54.78 (\pm 0.33)$
	LM-SC	$57.28 (\pm 2.20)$	$60.51(\pm 1.25)$	$57.94 (\pm 4.73)$	59.82 (±4.31)	$54.31(\pm 1.44)$	$54.38 (\pm 1.58)$
	CLMLF	56.65 (±2.71)	$54.13 (\pm 2.61)$	55.22 (±3.89)	$53.83 (\pm 2.35)$	53.47 (±3.96)	53.45 (±4.27)
Image-	MFN	$55.19(\pm 2.87)$	$57.98 (\pm 2.50)$	$56.79 (\pm 2.50)$	$58.79 (\pm 2.29)$	$53.98(\pm 1.01)$	$53.92(\pm 1.16)$
Text	PLVM	59.03 (±4.50)	$61.94(\pm 3.30)$	$59.11 (\pm 2.90)$	$60.39 (\pm 2.60)$	$54.36(\pm0.48)$	$55.22(\pm 1.75)$
	MultiPoint	62.91 (±2.89)	$65.42 (\pm 2.24)$	61.57 (\pm 1.84)	$62.32 (\pm 1.85)$	56.59 (± 1.01)	$56.68 (\pm 0.94)$

Table 2. Our main results for few-shot experiments on three datasets. The standard deviation is in parentheses.

velopment datasets and introduces contrastive learning; **Multi-modal Fine Tuning (MFN)** employs the representation of [s] token to classification; we reproduce the **PLVM** [11] model based on RoBERTa-large model; **MultiPoint** is our model that introduces multiple multimodal prompts with demonstrations and probabilistic fusion to improve the performance of FMSA.

Main Results. The performance comparison of our model (MultiPoint) with the baselines is illustrated in Table 2. Our model outperforms other robust models, including the SOTA multimodal baseline (CLMLF), text-only prompt tuning model (LM-BFF, LM-SC, and PT), and multimodal prompt tuning models (PLVM). MultiPoint outperforms the existing multimodal model PLVM by more than 2-3\% on different datasets. The effectiveness is because we leverage image prompt to bridge the gap between text and image modalities and utilize a probabilistic fusion module to capture more practical information from multiple multimodal prompts. Similar to the previous study, the related prompt-tuning approaches outperform standard fine-tuning models (RoBERTa, MFN, and CLMLF). Models that perform well on the full dataset perform poorly in the few-shot scenario. It is mainly because a model with numerous parameters overfits a small amount of training data. We also find an interesting phenomenon that LM-SC introducing contrastive learning underperforms PT on the MVSA datasets. We speculate that the imbalance of the MVSA dataset may limit the performance of the contrastive learning module.

Ablation Study. We conduct ablation experiments on the MultiPoint model to demonstrate different modules' effectiveness and list related results in Table 3. We remove the image prompt (w/o Cap) that directly introduces the initial image representations to the pre-trained language model. We further remove the Probabilistic Fusion Module (w/o PF) and Multimodal Demonstration (w/o D) to verify the effectiveness of multiple multimodal prompts and multimodal demonstrations, respectively. The removal of the different modules adversely affects the model results, which indicates that these modules are significant for FMSA. Multimodal Prompt Tuning with Demonstrations (MPTD) leverages only a single multimodal

Datasets	Model	Acc	F1
MVSA- Single	w/o Cap w/o PF w/o D MPTD + R-base	61.26 (±0.98) 62.43 (±2.48) 62.09 (±2.08)	62.41 (±1.34) 63.90 (±2.08) 65.54 (±1.80) 63.88 (±2.18) 62.92 (±2.28)
MVSA- Multiple	w/o Cap w/o PF w/o D MPTD + R-base	60.82 (±2.81) 60.33 (±3.19) 60.02 (±2.99)	62.17 (±1.66) 62.02 (±2.43) 61.48 (±2.72) 61.50 (±2.44) 60.89 (±4.05)
TumEmo	w/o Cap w/o PF w/o D MPTD + R-base	$55.95 (\pm 1.10)$ $55.93 (\pm 0.98)$ $56.21 (\pm 1.33)$	$54.79 (\pm 0.61)$ $55.97 (\pm 1.01)$ $55.90 (\pm 0.94)$ $56.08 (\pm 1.53)$ $54.81 (\pm 1.71)$

Table 3. Ablated experimental results.

prompt with demonstrations. The competitiveness of MPFD with w/o PF shows that simply adding prompts does not necessarily improve model performance. We also verify the effectiveness of large-scale PLM by replacing RoBERTa-large with Roberta-base (+ R-base). Our model's performance degrades severely, demonstrating that the larger PLM with more knowledge benefits the FMSA task.

4. CONCLUSION

We propose a novel Multimodal Probabilistic Fusion Prompts model for the FMSA task. To reduce the discrepancy in prompts from different modalities, we design a unified multimodal prompt which is comprised of the image description prompt and textual prompt. We further exploit the probabilistic fusion module to fuse multiple predictions from different multimodal prompts. We demonstrate the effectiveness of our model on three datasets in the FMSA task. In future work, we will design a more effective prompt for FMSA.

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