Exploring Unified Training Framework for Multimodal User Profiling

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Abstract

With the emergence of social media and e-commerce platforms, accurate *user profiling* has become increasingly vital for recommendation systems and personalized services. Recent studies have focused on generating detailed user profiles by extracting various aspects of user attributes from textual reviews. Nevertheless, these investigations have not fully exploited the potential of the abundant multimodal data at hand. In this study, we propose a novel task called *multimodal user profiling*. This task emphasizes the utilization of both review texts and their accompanying images to create comprehensive user profiles. By integrating textual and visual data, we leverage their complementary strengths, enabling the generation of more holistic user representations. Additionally, we explore a unified joint training framework with various multimodal training strategies that incorporate users' historical review texts and images for user profile generation. Our experimental results underscore the significance of multimodal data in enhancing user profile generation and demonstrate the effectiveness of the proposed unified joint training approach.

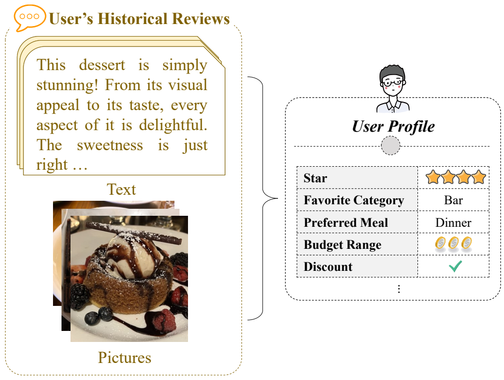


Figure 1: Overview of multimodal user profiling.

1 Introduction

Nowadays, e-commerce platforms and social media have become integral parts of our lives. People frequently shop and share their opinions on these websites, generating a wealth of user data. By analyzing this rich dataset, we can create detailed *user profiles* that assist in developing tailored recommendations and personalized services (Lu et al., 2016; Bertani et al., 2020; Simsek and Karagoz, 2020).

Recent studies on user profiling emphasize the generation of detailed user profiles by extracting multiple aspects of user attributes from textual reviews. These profiles encompass various characteristics, including gender, age, and occupation (Ciot et al., 2013; Alekseev and Nikolenko, 2016; Preoţiuc-Pietro et al., 2015). However, while most previous studies utilizing historical reviews to generate user profiles yield valuable insights, they don't fully harness the potential of the rich multimodal data available to us. Users frequently express their behavior and preferences through diverse channels, encompassing text, images, videos, and other media. To obtain a more comprehensive view of users, it's essential to explore multimodal profiling techniques that integrate data from multiple sources and modalities.

Therefore, we propose a new multimodal user profile dataset and a novel task termed *multimodal user profiling*, which emphasizes the construction of user profiles by harnessing both review texts and accompanying images. This integrated approach takes advantage of the complementary strengths inherent in textual and visual data, enabling the generation of a more comprehensive user profile. As shown in Figure 1, this task involves processing multimodal data, including the user's historical review texts and corresponding product images, to craft a detailed user profile encompassing diverse user attributes.

Integrating product images and text reviews from diverse sources into a cohesive model presents significant challenges due to their inherent disparities. For example, text reviews, being linguistic constructs, have the potential to reveal explicitly key user attributes through descriptive words and phrases. On the other hand, images convey information in a much more implicit and visual manner. They might depict the reviewer's lifestyle, taste, or surroundings, but extracting these insights often requires deeper analysis and interpretation.

To overcome these obstacles, we investigate a unified joint training framework that incorporates both users' historical review texts and images for user profile generation. Specifically, we propose two paradigms for joint training, leveraging these two distinct data types: the Multimodal Paradigm and the Unimodal Paradigm. As illustrated in Figure 3, the Multimodal Paradigm directly integrates multimodal features, exhibiting outstanding performance, especially in scenarios where training data is limited. Conversely, the Unimodal Paradigm extracts valuable image insights from existing multimodal large language models and effortlessly fuses them with textual information.

Our experimental results highlight the crucial role of multimodal data in elevating the quality of user profile generation. Furthermore, they confirm the efficacy of our proposed unified joint training methodology.

2 Related Works

In recent years, user profiling has garnered increasing attention in various fields, including recommendation systems and e-commerce. This task aims to deduce user attributes by analyzing social media data (e.g., Twitter, Facebook, Sogou) (Al Zamal et al., 2012; Dong et al., 2014; Hu et al., 2017; Li and Dickinson, 2017; Liang et al., 2018; Liu et al., 2023) and e-commerce platforms (e.g., JD, Alibaba) (Cao et al., 2019; Chen et al., 2019, 2021; Liu et al., 2023).

Conventional approaches often formulate user profiling as a multi-class classification problem, primarily concentrating on inferring specific user attributes like gender (Rao et al., 2011; Liu et al., 2012; Ciot et al., 2013; Sakaki et al., 2014), age (Rosenthal and McKeown, 2011; Alekseev and Nikolenko, 2016; Mac Kim et al., 2017), occupation (Preoţiuc-Pietro et al., 2015), and preferences (Cambria et al., 2022).

Recently, Wu et al. (2019) approached user profile inference as a generation task. They trained a two-stage extractor specifically designed to extract user attributes from dialogues. Li et al. (2021) mapped visual and textual modalities into a shared semantic space, integrating them with the original representations. More recently, Liu et al. (2023) introduced a joint user profiling model that incorporates hierarchical attention networks. Lastly, Wen et al. (2023) presented a prompt-based generation method. They innovatively employed attribute names as prompts within the input sequence, aiming to generate comprehensive user profiles.

In this study, we propose a novel multimodal user profiling task along with a new real-world user profile dataset. Unlike previous work, the proposed task is more challenging, requiring the simultaneous prediction of multiple multi-label user attributes. Additionally, our dataset offers multimodal data, facilitating joint training for enhanced accuracy.

	Amount
Users	14,821
Avg. Reviews Per User	24.3
Avg. Words Per Review	58.7
Avg. Images Per User	13.7

Table 1: Statistics of the dataset.

3 Multimodal User Profile Dataset

In this study, we introduce a new multimodal user profile dataset designed to explore the integration of visual knowledge in generating comprehensive user profiles. To compile this dataset, we sourced data from Yelp.com, a popular review platform. Initially, we filtered reviews to eliminate those that were excessively long or unusually short. This filtering process ensured the quality of the review text. Subsequently, we removed users with fewer than 30 historical reviews to bolster the precision of user profile creation.

Since not all reviews are accompanied by corresponding images, we selectively use only those reviews that include at least one image. This ensures that the reviews and images for a user originate from the same products, maintaining consistency and relevance in our analysis. The statistics of our dataset can be found in Table 1.

Then, we tallied the attributes of restaurants visited by users to discern their preferred restaurant types and attributes. Additionally, we filtered out low-frequency attributes and eliminated those with

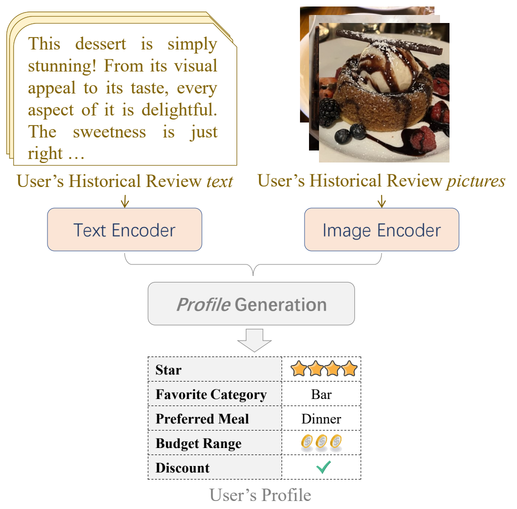


Figure 2: Example of the basic multimodal user profile generation model.

highly imbalanced categories. The remaining high-quality attributes then constituted the user profiles. Therefore, user's *Stars*, *Favorite Category*, *Preferred Meal*, *Budget Range*, *Discount Preference*, *Service Preference* are used as attributes to describe user's profile. The detailed discussion and statistics of these attributes can be found in Appendix A.

4 Basic Multimodal User Profile Generation Model

In this study, we introduce a novel task termed *Multimodal User Profiling*. This task aims to construct a comprehensive user profile by leveraging the user's historical reviews and the corresponding product images associated with those reviews.

Formally, the input to our model consists of a user's historical reviews R and related product images I, where $R = \{r_1, r_2, ..., r_n\}$ represents the collection of reviews and $I = \{i_1, i_2, ..., i_m\}$ denotes the set of accompanying images. The output Y of our model is a detailed user profile, including user's *Stars*, *Favorite Category*, *Preferred Meal*, *Budget Range*, *Discount Perference*, and *Service Perference*.

As shown in Figure 3, the basic multimodal user profile generation model comprises three main modules: (1) *Text Encoder* is responsible for encoding the user's historical reviews into textual feature representations. (2) *Image Encoder* encodes the user's related product images into image feature representations. (3) *Profile Generation* integrates the text and image feature representations from the previous two modules to generate a comprehensive user profile. This profile encapsulates the user's historical review data and visual preferences, providing a holistic view of their interests and behaviors.

4.1 Text Encoder

We initialize our text encoder using the encoder of the pre-trained Flan-T5 model (Chung et al., 2024). The text input consists of the user's historical reviews, which we tokenize into words, creating an input sequence X composed of tokens. We then feed this input sequence into the text encoder, and the output from the encoder is H_{txt}.

$$H_{txt} = \{T_1, T_2, ..., T_N\} = T5(R, \theta^{t5}) \quad (1)$$

where N denotes the length of the sequence. T_i denotes the hidden state of each token. θ^{t5} denotes the parameters of the Flan-T5 model.

4.2 Image Encoder

We utilize a pre-trained Vision Transformer (ViT) (Dosovitskiy et al., 2020) model as our image encoder, which shares a similar structure with the Transformer (Vaswani et al., 2017) and exhibits good initial performance. To encode images using the image encoder, we divide product images I into m flattened 2D patches. We then feed the image sequence into the image encoder, using the hidden state of the [CLS] token as the output H_{img} of our model.

$$H_{img} = \{\mathbf{I_C}, I_1, I_2, ..., I_M\} = ViT(I, \theta^{vit}) \quad (2)$$

where M denotes the length of the image representation. θ^{vit} denotes the parameters of the ViT model.

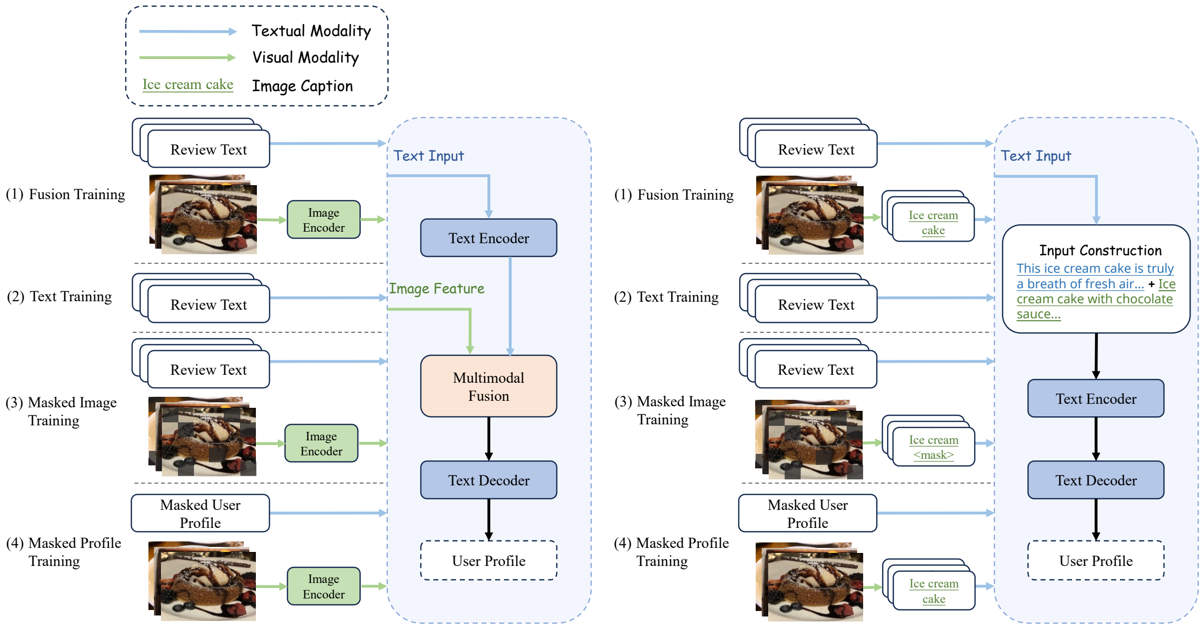
4.3 Profile Generation

We utilize the decoder of the Flan-T5 model to generate user profiles. We concatenate the text and image feature representations as a fused feature representation H_{fused}, which is then used as the input for the text decoder:

$$H_{fused} = [H_{txt}; H_{img}] \quad (3)$$

The text sequence outputted by the text decoder ends with </s>. The conditional probability of the whole output sequence $p(y|I, R)$ is progressively combined by the probability of each step $p(y_t|y_{<t}, I, R; \theta)$:

$$p(y|I, R) = \prod_{t=1}^{|y|} p(y_t|y_{<t}, I, R; \theta) \quad (4)$$



(a) Multimodal-Paradigm

(b) Unimodal-Paradigm

Figure 3: Overview of proposed user profile generation model with unified joint training framework.

$$p(y_t|y_{<t}, I, R; \theta) = \sigma(W^o O_{L,t} + b^o) \quad (5)$$

where $O_{L,t}$ is the hidden state of the L-th decoder layer at the t-th decoding step, $\{W^o, b^o\}$ are trainable parameters, $\sigma(\cdot)$ is a softmax function, $y_{<t} = y_1 ... y_{t-1}$ and $p(y_t|y_{<t}, I, R; \theta)$ are the probabilities over target vocabulary V normalized by softmax.

5 User Profile Generation with Unified Joint Training Framework

In this study, we explore a unified joint training framework that incorporates both users' historical review texts and images during the model's training process for user profile generation.

Specifically, we introduce two paradigms for joint training with historical review texts and images: the *Multimodal Paradigm* and the *Unimodal Paradigm*. These paradigms exhibit distinct characteristics. The Multimodal Paradigm integrates multimodal features and excels in scenarios with limited training data. Conversely, the Unimodal Paradigm leverages high-quality image knowledge extracted from existing multimodal large language models and fuses it with textual information. Review texts and images are organized according to two paradigms and then fed separately into the model's text and image encoders.

Figure 3 illustrates these two paradigms, and we will delve into the details in the belowing of this section.

5.1 Multimodal Paradigm

In this subsection, we design four training methods to learn how to harness visual knowledge for user profile generation effectively. By employing these diverse training techniques, we enhance the model's versatility and accuracy in generating comprehensive user profiles, leveraging both textual and visual data effectively.

Fusion Training represents a standard multimodal training approach that leverages both users' historical reviews and images to train the user profile generation model. An example is illustrated in Figure 3a(1).

Text Training is a fundamental training technique that solely relies on users' historical reviews to train the user profile generation model. This method is exemplified in Figure 3a(2).

Masked Image Training is aimed at reducing the visibility of images to mimic an intermediate phase between text and fusion training. As shown in Figure 3a(3), it captures all pixels in the images and masks each pixel based on a pre-defined probability, effectively turning the pixel black.

Masked Profile Training involves masking attributes in the user profiles and using them as inputs alongside users' historical images. An example of masking attributes is as follows: "Stars: 4 $\xrightarrow{\text{Mask}}$ Stars: <mask>". This approach challenges

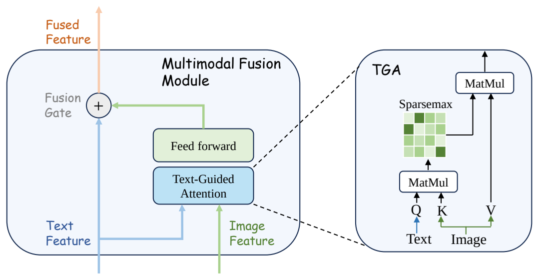


Figure 4: Example of text-guided attention module with user's historical reviews and images.

the model to complete the user profile solely based on product images and the masked user profiles. An instance of this method is shown in Figure 3a(4).

5.2 Unimodal Paradigm

Different from the multimodal paradigm, we utilize image captions to bridge the divide between the user's historical reviews and images within an unimodal framework. Specifically, we employ the BLIP2 model (Li et al., 2023) to generate captions for users' historical images. Then, we craft prompts from review texts and these captions to train the user profile generation model.

The training process is outlined in Figure 3b. The key difference between the unimodal and multimodal paradigms lies in the unimodal approach's use of captions converted from images to train the user profile generation model. This method allows us to integrate visual information indirectly through textual representations, maintaining an unimodal processing flow. It should be noted that in the unimodal paradigm, *masked image training* masks the image captions rather than the images.

5.3 Combination of Multimodal-Paradigm and Unimodal-Paradigm

To integrate the different training processes in the above two subsections, we design the text-guided attention module to learn to assign attention scores between user's historical reviews and images. As shown in Figure 4, we normalize the attention weights using Sparsemax (Martins and Astudillo, 2016), where the weight of the redundant visual features will be set to 0.

$$H_{\text{img}} = \text{FFN}(\text{TGA}(H_{\text{txt}}, H_{\text{img}}, H_{\text{img}})) \quad (6)$$

where H_{img} denotes the visual representation of [CLS] token. We expand H_{img} to be consistent with the sequence length using broadcasting.

Then, we employ a gate λ to determine how much visual information is retained.

$$\lambda = \text{Tanh}(W^T H_{\text{txt}} + W^I H_{\text{img}}) \quad (7)$$

where W^T and W^I are trainable parameters.

Finally, we add the visual information to the original textual feature using the gate module to obtain the multimodal fusion representation.

$$H_{\text{fused}} = H_{\text{txt}} + IF(img) \cdot \lambda \cdot H_{\text{img}} \quad (8)$$

where $IF(img)$ denotes whether the product image is available. When the product image is unavailable, $IF(img)$ will be set to 0.

It is worth noting that we do not use the traditional Sigmoid function (Li et al., 2022), but the Tanh function. The advantage of this is that the Tanh function is centered at zero, so when the sum of image and text features approaches zero, the value of the Tanh function is also nearly zero. So training methods for which product images are unavailable can be considered as a special case of Equation 8 (i.e. $IF(img = unavailable) = Tanh(0) = 0$), thus enabling it to be incorporated into the unified training framework.

Furthermore, since the multimodal and unimodal paradigms are not mutually exclusive, they can be used simultaneously under the same framework without modifying the model. We then utilize Equation 8 for multimodal feature fusion, the only difference is that we concatenate the image captions from the unimodal paradigm into the text input. In this way, the two methods can take advantage of their respective strengths, thus further enhancing the performance of the model.

6 Experiments

In this section, we introduce the datasets used for evaluation and the baseline methods employed for comparison. We then report the experimental results conducted from different perspectives.

6.1 Setting

In this study, we construct the multimodal user profile dataset by ourselves, the detailed discussion and statistics can be found in Section 3. In particular, we randomly split it into training, development, and test sets, with sizes of 3,000, 500, and 500 respectively.

We utilize Flan-T5 [1] and ViT [2] as our base models. We randomly selected three reviews and cor-

[1] https://huggingface.co/google/flan-t5-base
[2] https://huggingface.co/google/vit-base-patch16-224

Methods	User Profile						
	Stars	Category	Budget Range	Service	Meal	Discount	Average
Unimodal Methods							
OD-TUP	40.56	22.86	56.99	53.68	56.05	52.55	47.11
Flan-T5	50.60	19.76	53.43	49.07	57.46	45.77	46.01
BART	44.39	25.18	**60.19**	45.00	60.88	45.36	46.83
LLaMA	22.69	21.02	57.42	48.24	57.80	50.99	43.03
ChatGLM	32.73	19.44	38.12	35.51	36.83	32.85	32.58
Multimodal Methods							
COOPNet	41.78	22.24	56.48	54.37	58.78	55.12	48.12
LLaVA	41.60	22.55	52.42	49.46	57.86	56.28	46.69
SelectAtt	45.03	24.60	55.25	52.59	60.39	51.57	48.24
VLP-MABSA	45.52	21.41	56.21	56.02	59.25	56.89	49.22
AoM	45.37	21.13	55.74	55.89	58.94	56.13	48.87
Ours	**53.44**	**28.19**	58.16	**63.93**	**61.55**	**58.23**	**53.91**

Table 2: Comparison with baselines. “Category” denotes Favorite Category. “Meal” denotes Preferred Meal. “Service” denotes Service Preference. “Discount” denotes Discount Preference.

responding images as inputs for the model. We set the batch size to 4, the learning rate to 5e-5, the number of epochs to 10, and the maximum input text length to 600. We employ Adam (Kingma and Ba, 2014) as the optimizer to finetune our model parameters. During inference, we do the beam search with beam size 5. All our experiments are conducted on an NVIDIA Tesla V100S 32G GPU.

For all experiments, we evaluate each attribute in the generated user profiles using Macro-F1 and finally calculate the average as a reference for model performance.

6.2 Main Results

In this subsection, we compare our proposed model with both unimodal and multimodal models in all the attributes from user profiles.

In particular, **OD-TUP** (Wen et al., 2023) proposes a generation method based on prompts, which can generate a more comprehensive user profile compared to extraction methods. **Flan-T5**, **BART** (Lewis et al., 2019), **LLaMA** (Touvron et al., 2023), and **ChatGLM** (Du et al., 2022) are pre-trained language models used for NLP tasks. In the multimodal approaches, **COOPNet** (Li et al., 2021) is an image-text collaboration framework that predicts user profiles in a multimodal regression manner. **SelectAtt** (Li et al., 2022) proposed a selective attention model to explore the patch-level contributions of images. **LLaVA** (Liu et al., 2024) is an end-to-end trained large multimodal model, connecting vision encoders with LLM to achieve general visual and language understanding. **VLP-MABSA** (Ling et al., 2022) and **AoM** (Zhou et al., 2023) are unified multimodal sentiment analysis frameworks based on the BART model, we modify the input-output format of the model to adapt to our proposed task.

As shown in Table 2, Large language models (LLMs) struggle to achieve acceptable performance, they are even lower than the basic generative pre-trained models (i.e., BART, Flan-T5). This is probably because LLMs have good performance for most tasks, but are powerless against specific tasks. We also find that multimodal models generally outperform unimodal models, suggesting that relying solely on text is insufficient for generating accurate user profiles. Utilizing multimodal information allows models to analyze and construct user profiles from multiple perspectives, thereby enhancing model performance.

Besides, the performance of our proposed model outperforms all baseline models significantly ($p < 0.05$). It indicates the effectiveness of multimodal information for user profiling and also shows the effectiveness of the proposed model with the unified joint training framework.

6.3 Impact of Unified Joint Training Framework

We then investigate the impact of the proposed unified joint training framework for multimodal

Methods	Macro-F1
Ours	53.91
-Uni	52.96
-Multi	53.07
-Multi -Uni	48.53

Table 3: Impact of different paradigms in unified joint training framework. "Uni" denotes the unimodal paradigm. "Multi" denotes the multimodal paradigm.

Methods	Multi	Uni
Text-Only	46.01	
+Fusion	48.53	47.49
+Text	52.05	52.21
+MaskImage	49.12	48.75
+MaskProfile	49.91	49.76
+Text, MaskProfile	52.55	52.57
Ours	52.96	53.07

Table 4: The effects of training methods on the multimodal and unimodal paradigm.

user profile generation.

As shown in Table 3, both unimodal(-Uni) and multimodal(-Multi) training paradigms are effective for learning the correlations between reviews and images, if we remove one of them, the performance drops to 52.96% and 53.07% respectively. In addition, if we remove the whole unified joint pretraining framework (-Multi -Uni), the performance drops to 48.53%, which indicates that this framework is very important for the proposed multimodal user profile generation task.

We further investigate the impact of the four kinds of training methods in the two paradigms in Table 4. In particular, we use the Flan-T5 model trained solely on text as the baseline (Text-Only) and then gradually add different training methods for joint training.

The performance of the *Text-Only* approach falls behind other methods, highlighting that mere reliance on textual data is inadequate for building a comprehensive user profile. *Fusion*, which denotes standard multimodal training, demonstrates superior performance. Subsequently, when we incorporate additional training methodologies for joint training, the model's performance is enhanced to various extents. This indicates that all these training techniques complement *Fusion* in learning cross-modal interactions. Moreover, these training strategies prove effective in both multimodal and unimodal training paradigms. Our proposed model, incorporating all training methods across both paradigms, achieves the highest level of performance. A more detailed discussion of these training methods can be found in Appendix B.

7 Analysis and Discussion

In this section, we will conduct a comprehensive analysis and discussion on a unified joint training framework to investigate the various factors. Furthermore, we explore the potential applications of the generated user profiles in other fields.

7.1 Influence of Numbers of Historical Reviews and Images

Since we propose to use multimodal information to generate user profiles, we first investigate whether historical reviews and images can contribute to the construction of user profiles.

In our experiments, we use the Text-Only scenario as a benchmark (w/o images). As shown in Figure 5, when the number of images is zero, all models perform at their lowest. This indicates that relying solely on review texts to generate user profiles is insufficient. Then, as we gradually increase the number of images, an evident improvement in model performance can be observed. This suggests that images provide rich information that allows for a more accurate construction of user profiles. Moreover, We find that both reviews and images are equally effective in enhancing model performance. However, when the number of reviews reached a certain level, the improvement diminished or even had a negative impact, whereas images do not exhibit this issue. This suggests that compared to review texts, there is less redundant information among images, thereby providing a stable contribution to the model. This guides us not to blindly increase the number of reviews, as this could lead to a saturation of effective information and bring meaningless training costs. Increasing the number of images to compensate for the reduction in reviews might be a good choice.

7.2 Effect of Historical Review Images

In this subsection, we conduct ablation experiments on historical review images to determine whether they truly made a contribution in our model. In particular, we use unpaired data to check the importance of these images. In addition, we observe whether model performance is negatively affected

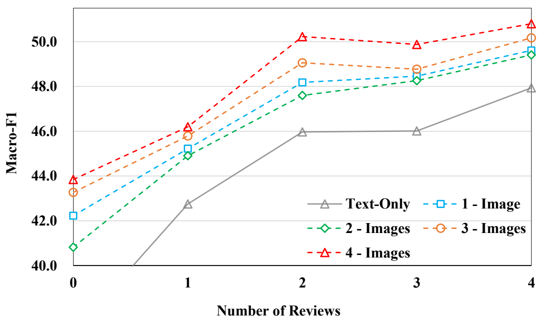


Figure 5: The effect of the numbers of reviews and images.

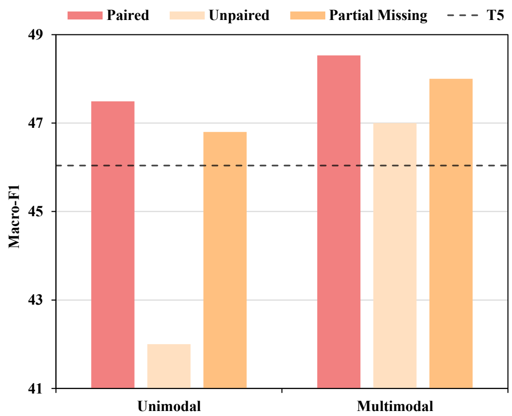


Figure 6: The performance of our model under Paired, Unpaired, and Partial Missing scenarios. **Paired** indicates that the historical review texts and the image correspond to each other. **Unpaired** indicates that the historical review texts and images do not correspond. **Partial Missing** means that the review texts and images are paired, but the number of images has been reduced.

by reducing the number of images. We provide the performance of the Flan-T5 model as a reference.

As shown in Figure 6, both unimodal and multimodal paradigms show different degrees of performance degradation after the number of historical images is reduced. This indicates that our model is capable of obtaining effective information from historical images. In the case of unpaired historical images, both paradigms' performances show a significant decrease, and the performance of the unimodal paradigm is even lower than the baseline. This shows the dependence of our model on image information. It is worth noting that the multimodal paradigm performance is still higher than the baseline performance although it shows a significant drop. This indicates that historical images in the model not only provide multimodal information but also act as a regularization term, improving the robustness of the model.

Model	Text	Text+Profile
BERT	55.4	57.6
T5	64.8	66.8
BART	57.0	59.4
LLaMA	66.4	69.0
ChatGLM	59.2	61.4

Table 5: The results of sentiment classification with user profiles.

7.3 Application of User Profiling

In this subsection, we aim to explore the effectiveness of generated user profiles. To achieve this, we choose the *sentiment classification* task as a means of integrating and evaluating the profiles. Subsequently, we concatenate the generated user profiles as additional information along with the review text and input this combined data into the model. The user profiles are generated using our proposed model.

The experiment is conducted on our proposed dataset, where we randomly select some users and choose one historical review as training data. The review text and user profile served as inputs for the model, with the review's rating being used as a reference for sentiment classification. As shown in Table 5, the generated user profiles (Text+Profile) are truly effective for sentiment classification across various classification methods. This suggests that constructing a user profile composed of multiple attributes can significantly enhance the accuracy of sentiment classification. The results clearly demonstrate the value of incorporating rich user profiles in sentiment analysis tasks.

8 Conclusion

In this study, we introduce a novel task termed Multimodal User Profiling, which focuses on creating comprehensive user profiles by analyzing both user review texts and associated product images. To facilitate this task, we have constructed a new multimodal user profile dataset that incorporates users' historical review texts and corresponding images. To capture cross-modal interactions effectively, we have explored a joint training framework, offering two distinct training paradigms. Through rigorous experimentation, our results emphasize the crucial role of multimodal data in significantly improving the quality of user profile generation. Furthermore, they validate the effectiveness of our proposed unified joint training methodology.

Limitations

The limitations of our work lie in two aspects: 1) due to the design of four types of training methods for joint training in our training paradigm, it is inevitable that the overall time complexity is high; 2) we have primarily focused on testing with English datasets and have shown promising results, but the performance of the model on Chinese datasets remains unknown.

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A Attributes of User Profile

Then, we tallied the attributes of restaurants visited by users to discern their preferred restaurant types and attributes. Additionally, we filtered out low-frequency attributes and eliminated those with highly imbalanced categories. The remaining high-quality attributes then constituted the user profiles. Therefore, we describe these attributes in the below:

- **Stars** represents the average rating given by users. The value of this attribute is an integer ranging from 1 to 5. Average scoring can help us understand users' evaluation tendencies and their level of inclusiveness.

- **Favorite Category** refers to the type of restaurant preferred by the user. This attribute comprises 10 distinct categories, from which we

User Profile					
Attribute	**Amount**	**Attribute**	**Amount**	**Attribute**	**Amount**
Stars	**4,000**	**Favorite Category**	**8,000**	**Budget Range**	**4,000**
1	1	Automotive	199	Low	2,113
2	74	Shopping	1,333	High	1,887
3	645	Event planning & services	1,883	**Discount Preference**	**4,000**
4	2,987	Pizza	1,899	True	3,285
5	293	Coffee & tea	1,631	False	715
Preferred Meal	**4,000**	Active life	272	**Service Preference**	**4,000**
Lunch	1,620	Beauty & spas	499	True	2,939
Dinner	2,380	Local services	77	False	1,061
		Health & medical	99		
		Home services	108		

Table 6: The distribution of user attributes.

identify two as the user's favorite restaurant types. This can help us understand users' taste preferences.

- **Preferred Meal** specifies the meal type in which the restaurant specializes. This attribute has two potential values, indicating the restaurant's primary meal focus. This can infer the user's lifestyle patterns and dining habits
- **Budget Range** represents the cost bracket of the restaurant frequently visited by users. This attribute also consists of two values: low and high, reflecting the spending capacity of users.
- **Discount Preference** indicates whether the restaurants that users like to visit offer promotions. This attribute is binary, with possible values of True and False. This can also reflect the consumption level of the users.
- **Service Preference** denotes whether the restaurant provides takeaway or banquet services. This attribute is also binary, marked as True or False, depending on the availability of these services. This can help us understand the lifestyle habits of users.

Detailed statistics on the attributes of user profiles can be found in Table 6. By analyzing these attributes, we can gain a deeper understanding of users' dining preferences, enabling more precise recommendations and personalized services within the restaurant industry.

B Performance of Training Framework On Other Models

We propose a unified joint training framework that has significantly enhanced our model. To verify that our framework is widely applicable and not designed for a specific model, we conducted experiments on other models. We selected several models from both unimodal and multimodal approaches for validation and set up two scenarios: one is a basic multimodal user profile (**Basic**), and the other applies our joint training framework based on the former (**Basic + Joint**).

Model		**Basic**	**Basic+Joint**
Unimodal	BART	46.83	50.80
	LLaMA	43.03	46.54
	OD-TUP	47.11	52.06
Multimodal	Selective	48.24	49.63
	LLaVA	46.69	49.27
	Ours	48.53	53.91

Table 7: The performance of joint training framework on other models.

As shown in Table 7, in the **Basic** scenario, the multimodal model maintains a lead over the unimodal model. In the **Basic+Joint** scenario, after applying our joint training framework, the performance of all models has been significantly improved. This demonstrates the effectiveness and general applicability of our framework. Moreover, our model shows the largest improvement, which is due to our interaction module that allows the model to utilize all training methods for joint training. Additionally, we found that even the basic pre-trained model (i.e., BART) can outperform the multimodal models. Considering the scarcity of multimodal annotated data in the real world, we believe that using non-standard multimodal training methods for joint training is more important for multimodal user profiling.