Micro-influencer Recommendation by Multi-perspective Account Representation Learning

Shaokun Wang, Tian Gan, Yuan Liu, Jianlong Wu, Yuan Cheng, Liqiang Nie, *Senior Member, IEEE*

***Abstract*—Influencer marketing is emerging as a new marketing method, changing the marketing strategies of brands profoundly. In order to help brands find suitable micro-influencers as marketing partners, the micro-influencer recommendation is regarded as an indispensable part of influencer marketing. However, previous works only focus on modeling the *individual image* of brands/micro-influencers, which is insufficient to represent the characteristics of brands/micro-influencers over the marketing scenarios. In this case, we propose a micro-influencer ranking joint learning framework which models brands/micro-influencers from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. Specifically, to model accounts' *individual image*, we extract topics information and images semantic information from historical content information, and fuse them to learn the account content representation. We introduce *target audiences* as a new kind of marketing role in the micro-influencer recommendation, in which audiences information of brand/micro-influencer is leveraged to learn the multi-modal account audiences representation. Afterward, we build the attribute co-occurrence graph network to mine *cooperation preferences* from social media interaction information. Based on account attributes, the *cooperation preferences* between brands and micro-influencers are refined to attributes' co-occurrence information. The attribute node embeddings learned in the attribute co-occurrence graph network are further utilized to construct the account attribute representation. Finally, the global ranking function is designed to generate ranking scores for all brand-micro-influencer pairs from the three perspectives jointly. The extensive experiments on a publicly available dataset demonstrate the effectiveness of our proposed model over the state-of-the-art methods.**

***Index Terms*—Influencer Marketing, Multi-modal, Social Media Information.**

I. Introduction

Over a period of decades, social media has profoundly affected the way people live, work, and entertainment. Under this circumstance, brands and companies have changed their traditional advertising strategies to influencer marketing [1]. Influencer marketing is defined as a brand that collaborates with a group of suitable social media influencers to promote products or services [2]. Social media influencers are individuals with big followers online who attract a large amount of engagement, and are able to use this popularity for marketing efforts in a specific industry [3]. Figure 1 illustrates an example of a street fashion brand joining hands with an influencer to promote sneakers. Especially, influencer marketing is more accessible and measurable than ever before, and more marketers report finding it effective in achieving their marketing goals[1]. Up to 2021, the influencer marketing is expected to grow to be worth \$13.8 Billion, and three-quarters of respondents are going to dedicate a budget to influencer marketing[2]. Different from traditional influencers, micro-influencers are those who have a small number of followers (i.e., 5K-100K). They usually maintain a real relationship with their audiences and express themselves in a personal way [4]. The most notable characteristics of micro-influencers are high reaction of followers in terms of action, low costs per post published, and being considered trustworthy in certain topics. Moreover, compared with marketing resources being monopolized by a few top influencers (e.g., key opinion leaders), micro-influencer marketing is more beneficial to consumers and brands, and it is helpful to reduce marketing risks and realize the reasonable allocation of marketing resources [5]. Therefore, we focus on the micro-influencer recommendation in this work.

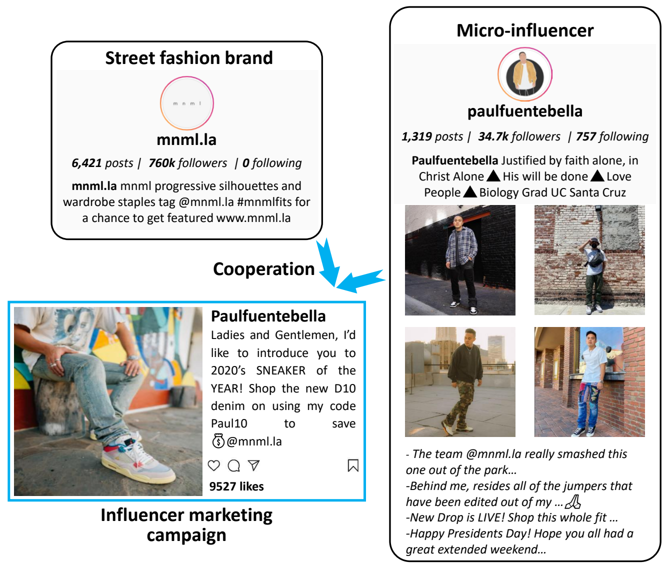

Fig. 1: Example of an influencer marketing campaign designed by a street fashion brand and a micro-influencer.

As a crucial sub-domain of influencer marketing, influencer

This work is supported by the National Natural Science Foundation of China, No.: 62176137, and No.: 62006140; the Shandong Provincial Natural Science and Foundation, No.:ZR2019JQ23 and No.: ZR2020QF106. The associate editor coordinating the review of this manuscript and approving it for publication was xxx. *Tian Gan and Jianlong Wu are the corresponding authors.*

S. Wang, T. Gan, Y. Liu, J. Wu, and L. Nie are with the School of Computer Science and Technology, Shandong University, Qingdao, 266237, China (e-mail: shaokunwang.sdu@gmail.com; gantian@sdu.edu.cn; yuanliu@mail.sdu.edu.cn; jlwu1992@sdu.edu.cn; nieliqiang@gmail.com); Y. Cheng is with the Ant Financial Services Group, Hangzhou, 310013, China (e-mail: chengyuan.c@antgroup.com).

[1]https://www.bigcommerce.com/blog/influencer-marketing-statistics/10-most-important-influencer-marketing-statistics-for-2020.

[2]https://influencermarketinghub.com/influencer-marketing-benchmark-report-2021/.

recommendation is aimed at seeking suitable influencers for brand promotion [6]. In previous works, Sweet *et al.* [7] utilized social media content information (i.e., accounts' profile data) to construct brand/influencer representation, and they trained a k-Nearest Neighbours model to recommend influencers to the target brands. Gan *et al.* [8] proposed a modified listwise learning to rank model, where images and captions in the posts of brands/influencers are leveraged to learn account representation. Wang *et al.* [9] presented a concept-based micro-influencer ranking framework. It models account content information by using high-level marketing concepts, and defines two adaptive learned metrics to learn micro-influencer ranking function. All of these methods focus on utilizing social media content information to model accounts' *individual image*. However, it is far from being enough to represent the characteristics of brands/micro-influencers over the marketing scenarios. A more reasonable way is to take full advantage of abundant social media information, yet how to choose appropriate kinds of data from diverse social media information is always a barrier in this area. It is likely to raise controversy when leveraging some kinds of privacy data [10]. At the same time, the information selection strategy should be supported by related-field theories (i.e., marketing theories)[11].

Driven by these practical needs, we are the first to model *target audiences* and *cooperation preferences* of accounts (i.e., brands and micro-influencers) by making use of social media audiences and interaction information. We propose a micro-influencer ranking joint learning framework (MORNING), where it learns account representations from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. Specifically, in order to model accounts' *individual image*, we extract topics information and images semantic information from historical content information and fuse them to learn the account content representation. Meanwhile, we introduce the *target audiences* as a new kind of marketing role into influencer recommendation. Accounts' audiences information is used to learn the multi-modal account audiences representation. Moreover, we utilize interaction information on social media to mine *cooperation preferences* knowledge between brands and micro-influencers. We define account attributes to describe accounts' traits of interest and occupation. Based on attributes' co-occurrence information which is refined from *cooperation preferences* information, the attribute co-occurrence graph network is built to learn attribute node embedding and to further obtain the account attribute representation. Finally, the global ranking function is defined to rank all micro-influencers for given brands from the three perspectives jointly. To validate the effectiveness of our proposed method, we conduct a series of experiments on the brand-micro-influencer dataset. In summary, the contributions in this work are listed as follows:

- We propose the MORNING by novelly modeling social media accounts from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. Experimental results show that our method achieves state-of-the-art performance.
- We introduce *target audiences* as a new kind of marketing role in the micro-influencer recommendation. Multi-modal audiences information is utilized to learn the account audiences representation. And we collect a social-media-audiences dataset, which can benefit future research.
- We successfully mine *cooperation preferences* from interaction information on social media. Based on account attributes, we build the attribute co-occurrence graph network to capture *cooperation preferences* at the attribute level, and the attribute node embeddings are further utilized to construct the account attribute representation.

II. Related work

A. Influencer Marketing

With the flourishing of social media platforms such as Instagram and Facebook, social media is not only seen as a communication tool but also an effective marketing channel [1], [12]. For brands, social media provides a great deal of marketing and promotion opportunities that connects them directly with customers. This is why almost all brands from giants like Starbucks and IBM to the local shops are exploring social media promotion projects [13]. Up to 2018, 91% of the Fortune 500 companies were using Twitter with high frequency, and 63% of them created corporate Instagram accounts [14]. At the same time, a series of works about social media marketing are proposed. On the one hand, with the rapid growth of brand-related user posts on social media, how to design the appropriate posts for brands promotion remains an important problem [15]. Mazloom *et al.* [16] utilized engagement parameters such as factual information, sentiment, vividness, and entertainment parameters for predicting the popularity of brand-related user posts. Kim *et al.* [17] proposed a model to examine the influence of brand-related user-generated content on consumers. Gelli *et al.* [18] proposed a tailored content-based ranking method to discover content for target brands. Zhang *et al.* [19] designed a multimodal-based marketing intent analysis scheme to estimate the marketing intent embedded in the social media contents. Zhang *et al.* [20] presented an approach to recommend images that match the brand concept. On the other hand, how to optimize the effects of marketing communication in social networks is also an important issue. Most of the advertisers tend to involve in their campaigns with the most interested users [21]. Bonomo *et al.* [22] proposed a general framework for the recommendation of possible customers (users) to brands based on the comparison between online social network profiles. Zhang *et al.* [14] proposed a new measurement to estimate the similarity between brands via the posts of brands' followers, which can predict the users' interest in brands with a correlation value.

However, fake and irrelevant advertising information everywhere online has destroyed social media users' trust and has caused resistance to them [23]. To address the loss of trust problem, many marketers today are interested in cooperating with social media influencers. Study shows that 92% of consumers will probably be easier to trust brands that promote through influencer channels rather than those who have adopted traditional marketing strategies [24]. And this marketing method is termed as influencer marketing [25]. Influencer marketing is to orient the individuals who have influence over potential customers, and designs marketing campaigns around them [26].

The core challenge of influencer marketing is how to find out right influencers for various brands. There are a lot of works [27], [28], [29], [30], [31], [32], [33], [34] dedicate to find influencers on social media. These works aim to find influential influencers such as users who have lots of audiences. But the effectiveness of influencer marketing is mainly determined by the cooperation between brands and influencers [35], which means that ”influence” is not the most critical factor in influencer marketing. The cooperation effectiveness of brands and influencers mainly depends on *content relevance*, *engagement rate*, and *target audiences similarity*. *Content relevance* is the most basic factor to be considered when a brand chooses influencers. High *content relevance* usually means that influencers are professional in the field of the brand [8]. *Engagement rate* [36] is a metric that measures the engagement level that created content received from audiences. It indicates how frequently people interact with the content [37]. Factors that influence *engagement rate* include users' comments, shares, likes, and so on. *Target audiences* [38] are the intended audiences of the brand's advertisement. In the marketing and advertising domain, it is a particular group of consumers within the predetermined target market, identified as the targets or recipients for specific advertisements. The more clear the *target audiences* of a brand, the more effective its advertising campaign will be in terms of results and cost [39]. For a brand, higher *target audiences similarity* with influencers means that advertisements can be accepted by more *target audiences*. To help marketers to find the right micro-influencers at a large scale, Sweet *et al.* [7] proposed a novel algorithm for matching brands with social media influencers by *content relevance*. Gan *et al.* [8] proposed a modified listwise learning to rank model, which can predict ranking scores based on *content relevance* and *engagement rate* for the given brands and micro-influencers. Wang *et al.* [9] proposed a concept-based micro-influencer ranking framework, which models account content information from the perspective of historical activities and marketing direction, and designs *engagement rate*-based metrics to formulate micro-influencer ranking function. These works focused on *content relevance* and *engagement rate* between brands and micro-influencers, but they did not take the *target audiences similarity* into account.

B. Multiple Information Usage in Recommendation Based on Social Media

With the rapid development of social networks, a large amount of social media information has been generated. It has been shown that multiple kinds of information are valuable for the recommendation based on social media [11], [40], [41], [42], including social media content information, social media relationship information, social media interaction information, and so on.

Georgiou *et al.* [43] used social media content information to extract user communities based on users' interested topics, which can help to recommend more relevant and interesting social media content to users. Ma *et al.* [44] proposed a framework to capture the features from users' off-topic and on-topic content information in social media and introduced them into Matrix Factorization based algorithm. Experiments show that it has positive effects in multi-domain recommendation. Social media relationship information generally contains social media friendship information, follower information, and audiences information. Xiao *et al.* [45] proposed a model called Social Explorative Attention Network for content recommendation, which utilized users' higher-order friend information on social network to improve the recommendation accuracy and diversity. Wu *et al.* [46] proposed a novel method that recommends friends with similar location preferences for LBSN's users, where both online friendship information and offline user behavior information are leveraged. Social media interaction information (e.g., likes, comments, and shares) indicates interaction between users. Rafailidis *et al.* [47] presented an efficient social media recommendation algorithm by using multi-modal user-item interaction information to capture the preferences dynamics that users perform over the time evolution. Li *et al.* [48] proposed an artificial neural network to discover potential bloggers via analyzing social interaction factors (e.g., citations and comments) and other social media information. In our model, we utilized social media content information, audiences information, and interaction information between brands and micro-influencers to model accounts from the perspective of *individual image*, *target audiences*, and *cooperation preferences*.

III. Problem Definition

We indicate $\mathcal{B} = \{\mathbf{b}_1, \mathbf{b}_2, ..., \mathbf{b}_{|B|}\}$ and $\mathcal{M} = \{\mathbf{m}_1, \mathbf{m}_2, ..., \mathbf{m}_{|M|}\}$ as the set of **brands** and **micro-influencers**, respectively. Brands and micro-influencers are both social media accounts. For each brand $\mathbf{b}$ and micro-influencer $\mathbf{m}$, we define its recent H posts with content information (i.e., visual and textual information) as $\mathbf{C}_{b/m}$.

Further, we define $\mathcal{U} = \{u_1, u_2, ..., u_{|U|}\}$ as the set of **audiences** who are the followers of brands/micro-influencers. $\mathbf{U}_{b/m} \subset \mathcal{U}$ indicates the audiences belong to a brand/micro-influencer. Audiences are also social media accounts. Meanwhile, we suppose that each brand/micro-influencer can be represented by a group of attributes, where attributes are the traits of social media accounts. And then, we define $\mathcal{S} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_{|S|}\}$ as the set of all **attributes**. $\mathbf{S}_{b/m} \subset \mathcal{S}$ indicates the attribute-list belongs to a brand/micro-influencer. Based on the definitions above, each brand/micro-influencer can be represented as a triplet:

$$\mathbf{b}_i = \{\mathbf{C}_{b_i}, \mathbf{U}_{b_i}, \mathbf{S}_{b_i}\} \tag{1}$$

or

$$\mathbf{m}_i = \{\mathbf{C}_{m_i}, \mathbf{U}_{m_i}, \mathbf{S}_{m_i}\}. \tag{2}$$

At last, we define a micro-influencer $\mathbf{m}$ as a *positive* example for brand $\mathbf{b}$, if $\mathbf{m}$ has posted an advertisement for $\mathbf{b}$. For each brand $\mathbf{b}_x$, we use $\mathbf{MicroInf}^+_x$, and $\mathbf{MicroInf}^-_x$ to

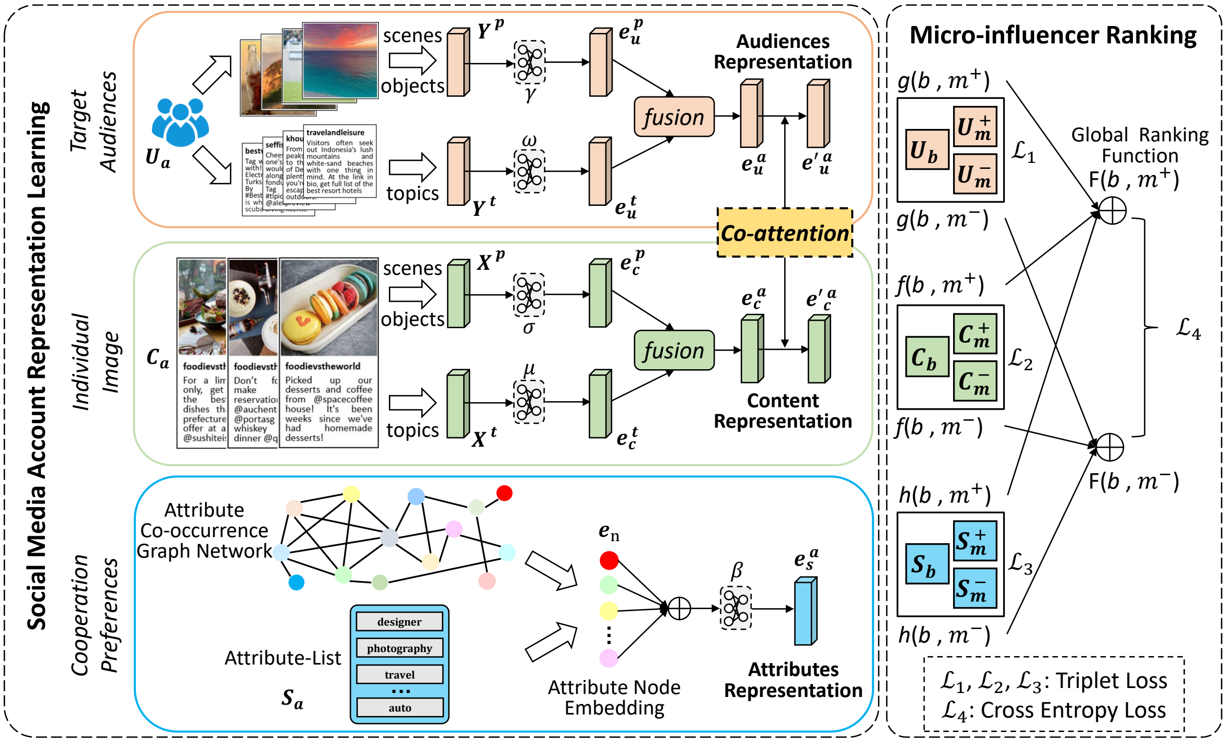

Fig. 2: An overview of MORNING, which learns account representations from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. The global ranking function is designed to rank all brand-micro-influencer pairs from the three perspectives jointly.

respectively denote its *positive* and *negative* examples, where $\mathbf{MicroInf}_x^+ \bigcup \mathbf{MicroInf}_x^- = \mathcal{M}$.

The key problem of our task is to learn a global ranking function $F(\mathbf{b}, \mathbf{m})$ such that for each $\mathbf{b}_x$,

$$F(\mathbf{b}_x, \mathbf{m}_i) > F(\mathbf{b}_x, \mathbf{m}_j), \tag{3}$$

where $\mathbf{m}_i \in \mathbf{MicroInf}_x^+$ and $\mathbf{m}_j \in \mathbf{MicroInf}_x^-$. Notations are summarized in Table I.

IV. Methodology

As shown in Figure 2, we propose our micro-influencer ranking joint learning framework, abbreviated as MORNING. We start by describing three parallel components to learn account representations from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. We then explain how to recommend micro-influencers to brands via our joint learning framework. We decompose the global ranking function $F(\mathbf{b}, \mathbf{m})$ as three ranking sub-functions. Finally, we define a multi-part loss to optimize the global ranking function and three ranking sub-functions simultaneously.

A. Account Content Representation

On social networks, brands and influencers primarily introduce themselves to customers through what they post on their accounts, so accounts' historical content information is an important source to know about their *individual images*. In our model, the account's content information $\mathbf{C}_{b/m}$ consists of visual information and textual information from its posts. Generally, the historical content information of an account is consistent and coherent. Therefore, we represent accounts' *individual image* by mining the common characteristics in its historical content information.

To represent accounts' visual information, we suppose that high-level visual-semantic information frequently appearing can reflect the characteristics of an account. We utilize the Resnet [49] to extract object information vector $\boldsymbol{v}_o$ and the Upernet [50] to extract scene information vector $\boldsymbol{v}_s$ in each post. Each dimension in $\boldsymbol{v}_o$ and $\boldsymbol{v}_s$ represents a kind of high-level visual-semantic information. A confidence threshold is set to filter insignificant high-level visual-semantic information. By this approach, we transform $\boldsymbol{v}_o$ and $\boldsymbol{v}_s$ to $\widetilde{\boldsymbol{v}_o}$ and $\widetilde{\boldsymbol{v}_s}$, respectively. And then, we use a normalization function ψ to obtain the object-semantic vector $\boldsymbol{X}^o$ and the scene-semantic vector $\boldsymbol{X}^s$:

$$\boldsymbol{X}^o = \psi(\sum_{i=1}^{|H|} \widetilde{\boldsymbol{v}_o^i}), \tag{4}$$

$$\boldsymbol{X}^s = \psi(\sum_{i=1}^{|H|} \widetilde{\boldsymbol{v}_s^i}), \tag{5}$$

where H is the number of posts in $\mathbf{C}_{b/m}$. The sum of all elements in $\boldsymbol{X}^o$ and $\boldsymbol{X}^s$ are 1. Further, we define the visual-semantic vector $\boldsymbol{X}^p$ as:

$$\boldsymbol{X}^p = concat(\boldsymbol{X}^o, \boldsymbol{X}^s), \tag{6}$$

where *concat* is the concatenation operation.

To represent accounts' textual information, we analyze the topics that accounts often involve. We utilize the LDA model [51] to train the textual information vector $\boldsymbol{X}^t$, where the value of each dimension means the probability that captions belong to a specific topic. We consider the perplexity [51] and the topic coherence [52] to determine the number

TABLE I: Table of Notation.

Notation	Description
$\mathcal{B}$	Brands set, and all brands are social media accounts
$\mathcal{M}$	Micro-influencers set, and all micro-influencers are social media accounts
$C_{b/m}$	Content information of a brand/ micro-influencer
$\mathcal{U}$	Audiences set, and all audiences are social media accounts
$U_{b/m}$	Audiences information of a brand/ micro-influencer
$\mathcal{S}$	Social media attributes set
$S_{b/m}$	Attribute-list of a brand/ micro-influencer
$\mathbf{MicroInf}_x^{+/-}$	Positive/ negative examples of brand b_x
$\boldsymbol{X}^o, \boldsymbol{X}^s$	Object/ scene-semantic vector
$\boldsymbol{X}^p, \boldsymbol{Y}^p$	Visual-semantic vector
$\boldsymbol{X}^t, \boldsymbol{Y}^t$	Textual information vector
$coocf$	Co-occurrence frequency function
$\mathcal{G}$	Attribute co-occurrence graph network
$\boldsymbol{e}_c^p, \boldsymbol{e}_u^p$	Visual-semantic representation of content/ audiences
$\boldsymbol{e}_c^t, \boldsymbol{e}_u^t$	Textual information representation of content/ audiences
$\boldsymbol{e}_{c/u/s}^a$	Account content/ audiences/ attribute representation
$\boldsymbol{e}_f^a$	Affinity representation
$\boldsymbol{w}_{c/u}$	Attention weights of $\boldsymbol{e}_c^a$ and $\boldsymbol{e}_u^a$
$\sigma, \mu, \gamma, \omega, \beta$	Multilayer perceptrons
F	Global ranking function
f, g, h	Ranking sub-functions

of topics. Through compressing multiple historical content information into one representation, we obtain the visual-semantic vector $\boldsymbol{X}^p$ and the textual information vector $\boldsymbol{X}^t$. We denote visual-semantic representation as $\boldsymbol{e}_c^p$ and textual information representation as $\boldsymbol{e}_c^t$, respectively.

$$\boldsymbol{e}_c^p = \sigma(\boldsymbol{X}_c^p), \tag{7}$$

$$\boldsymbol{e}_c^t = \mu(\boldsymbol{X}_c^t), \tag{8}$$

where $\boldsymbol{e}_c^p \in \mathbb{R}^{d_1}$, $\boldsymbol{e}_c^t \in \mathbb{R}^{d_2}$, d_1 is the length of $\boldsymbol{e}_c^p$, d_2 is the length of $\boldsymbol{e}_c^t$, μ is 2-layer multilayer perceptron, and σ is 4-layer multilayer perceptron. In order to learn the multi-modal account content representation, we adopt a low-rank bilinear pooling method [53] to fuse $\boldsymbol{e}_c^p$ and $\boldsymbol{e}_c^t$. Formally, the final account content representation $\boldsymbol{e}_c^a$ is defined as:

$$\boldsymbol{e}_c^a = (\boldsymbol{e}_c^p \boldsymbol{W}_1^p + \boldsymbol{b}_1^p) \circ (\boldsymbol{e}_c^t \boldsymbol{W}_1^t + \boldsymbol{b}_1^t), \tag{9}$$

where $\circ$ is the element-wise product, $\boldsymbol{W}_1^p \in \mathbb{R}^{d_1 \times d_a}$ and $\boldsymbol{W}_1^t \in \mathbb{R}^{d_2 \times d_a}$ are weight matrices, $\boldsymbol{b}_1^p \in \mathbb{R}^{d_a}$ and $\boldsymbol{b}_1^t \in \mathbb{R}^{d_a}$ are bias vectors, and d_a is the length of $\boldsymbol{e}_c^a$.

B. Account Audiences Representation

When brands choose influencers, *target audiences similarity* between them should also be regarded as an important reference factor. Higher *target audiences similarity* means that advertisements by influencers can be accepted by more *target audiences*. In our model, audiences u consists of both visual information (images) and textual information (captions) from the same amount (L) of posts. For each brand/micro-influencer, it has a corresponding audiences subset $U_{b/m}$, where $U_{b/m}$ has a fixed amount (Q) of audiences. Audiences information can be utilized to obtain the unified audiences view of accounts that help us to understand exactly who their audiences are, and what their audiences are interested in. Unified audiences view has usages as follows: (1) describe exactly what audiences love to focus their strategy; and (2) filter out influencers that do not match the interests of a brand's audiences. Therefore, we define account audiences representation $\boldsymbol{e}_u^a$ to represent unified audiences view of an account. The low-rank bilinear pooling method [53] is used to fuse the audiences' visual-semantic representation $\boldsymbol{e}_u^p$ and the audiences' textual information representation $\boldsymbol{e}_u^t$:

$$\boldsymbol{e}_u^t = \gamma(\boldsymbol{Y}^t), \tag{10}$$

$$\boldsymbol{e}_u^p = \omega(\boldsymbol{Y}^p), \tag{11}$$

where $\boldsymbol{e}_u^p \in \mathbb{R}^{d_3}$, $\boldsymbol{e}_u^t \in \mathbb{R}^{d_4}$, d_3 is the length of $\boldsymbol{e}_u^p$, d_4 is the length of $\boldsymbol{e}_u^t$, ω is 4-layer multilayer perceptron, and γ is 2-layer multilayer perceptron. $\boldsymbol{Y}^p$ and $\boldsymbol{Y}^t$ are the visual-semantic vector and the textual information vector which are obtained as the same as $\boldsymbol{X}^p$ and $\boldsymbol{X}^t$. Finally, the account audiences representation is defined as:

$$\boldsymbol{e}_u^a = (\boldsymbol{e}_u^p \boldsymbol{W}_2^p + \boldsymbol{b}_2^p) \circ (\boldsymbol{e}_u^t \boldsymbol{W}_2^t + \boldsymbol{b}_2^t), \tag{12}$$

where $\circ$ is the element-wise product, $\boldsymbol{W}_2^p \in \mathbb{R}^{d_3 \times d_a}$ and $\boldsymbol{W}_2^t \in \mathbb{R}^{d_4 \times d_a}$ are weight matrices, $\boldsymbol{b}_2^p \in \mathbb{R}^{d_a}$ and $\boldsymbol{b}_2^t \in \mathbb{R}^{d_a}$ are bias vectors, and d_a is the length of $\boldsymbol{e}_u^a$.

C. Account Attribute Representation

Social media interaction information contains the *cooperation preferences* between various brands and micro-influencers, which is helpful to guide the micro-influencer recommendation. We design a data-driven method to mine *cooperation preferences* knowledge from interaction information. Our original inspiration is to figure out what kind of micro-influencers brands tend to work with. We suppose that each brand/influencer can be represented by a group of social media attributes. These high-level semantic attributes are the marketing-related interests and occupations of brands and micro-influencers, which can accurately and briefly describe the traits of accounts. By introducing social media attributes, the *cooperation preferences* knowledge can be understood at the attribute level. Specifically, the *cooperation preferences* are refined into the co-occurrence knowledge between attributes. And then, attributes' co-occurrence knowledge is utilized to learn the account attribute representation.

First, an attribute selection method guided by external knowledge is designed: (1) A series of high-frequency keywords are collected from accounts' biographies which describe

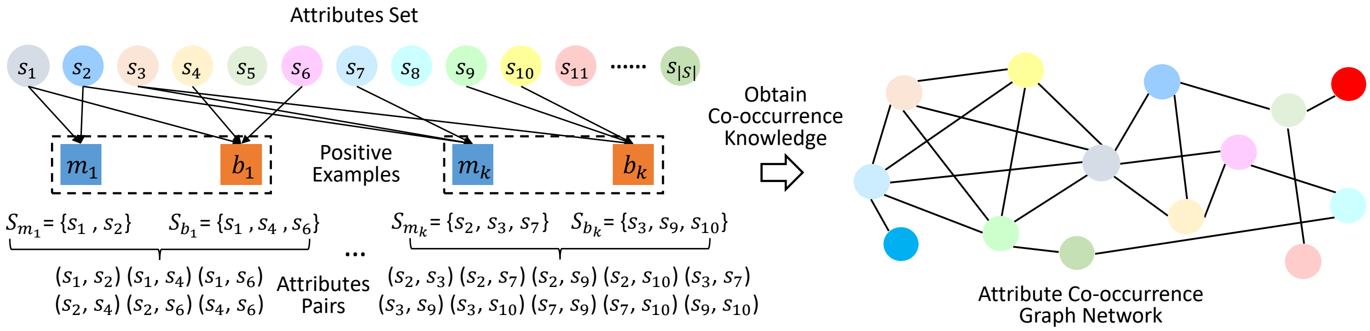

Fig. 3: Illustration of how to build the attribute co-occurrence graph network. We obtain the co-occurrence frequencies of all attributes pairs by using cooperation records. In the attribute co-occurrence graph network, nodes represent social media attributes and edges' weights are calculated from co-occurrence frequencies.

their marketing-related traits. These keywords are mainly related to interests (e.g., *makeup*, *food*, and *driving*) and occupations (e.g., *makeup-artist*, *food-blogger*, and *sporter*); (2) We leverage the Microsoft Concept Graph [54] to summarize and integrate these keywords as social media attributes. This knowledge graph consists of over 5 million concepts and 85 million "IsA" relations (e.g., dog IsA animal). With the guidance of this knowledge graph, similar categories of attributes are merged into their "father" attributes. For example, *lipstick*, *foundation*, and *eyeshadow* are merged into *cosmetic*; *cake*, *ice-cream*, and *chocolate* are merged into *dessert*; (3) After attributes filtering and merging, we can get an attribute-list for each account. As shown in Figure 3, we also obtain the attributes set $\mathcal{S} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_{|S|}\}$, where $\mathcal{S}$ consists of 572 attributes. For each attribute $\mathbf{s}_i$, $\mathbf{s}_i \in \mathbf{S}_{b/m}$, and the attribute-list of account $\mathbf{S}_{b/m} \subset \mathcal{S}$. Second, based on the cooperation records between brands and influencers (positive examples), we can calculate the co-occurrence frequencies between all attributes. For each attributes pair ($\mathbf{s}_i$ and $\mathbf{s}_j$),

$$coocf(\mathbf{s}_i, \mathbf{s}_j) = \sum\nolimits_{k=1}^{|K|}(q_b + q_m + q_{bm}), \tag{13}$$

$$q_b = \begin{cases} 1, & \text{if } \mathbf{s}_i \text{ and } \mathbf{s}_j \in \mathrm{S}_{b_k} \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

$$q_m = \begin{cases} 1, & \text{if } \mathbf{s}_i \text{ and } \mathbf{s}_j \in \mathrm{S}_{m_k} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

$$q_{bm} = \begin{cases} 1, & \text{if } \mathbf{s}_i \in \mathrm{S}_{b_k/m_k} \text{ and } \mathbf{s}_j \in \mathrm{S}_{m_k/b_k} \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

where $|K|$ is the amount of positive examples in the training set, and q_b, q_m, and q_{bm} are co-occurrence frequencies of $(\mathbf{s}_i, \mathbf{s}_j)$ that appeared in one positive example. Third, after getting the co-occurrence frequencies of all attributes pairs, we build the attribute co-occurrence graph network $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where $\mathcal{V}$ is the set of attribute nodes n and $\mathcal{E}$ is the set of edges between attribute nodes. Each edge is associated with a weight $w_{ij} > 0$, indicating the strength of the co-occurrence frequency between two attribute nodes:

$$w_{ij} = \sqrt{coocf(\mathbf{s}_i, \mathbf{s}_j)/\eta}, \tag{17}$$

where η is a scaling factor. Finally, we utilize the node2vec [55] to train the attribute node embedding $\boldsymbol{e}_n$. For each account, the account attribute representation is defined as:

$$\boldsymbol{e}_s^a = \beta(\sum_{\mathbf{s}_i \in \mathbf{S}_{b/m}} \boldsymbol{e}_n^i / |\mathbf{S}_{b/m}|), \tag{18}$$

where $\mathbf{S}_{b/m}$ is the attribute-list of accounts, and β is 2-layer multilayer perceptron.

D. Micro-influencer Ranking Joint Learning Framework

We have learned the account content representation $\boldsymbol{e}_c^a$, the account audiences representation $\boldsymbol{e}_u^a$, and the account attribute representation $\boldsymbol{e}_s^a$, which represent social media accounts from different perspectives. Afterwards, we construct a joint learning framework to generate ranking scores for given brands and all micro-influencers on these three perspectives. We have defined a global ranking function $F(b, m)$ in Section III to make a mathematical description of the ranking problem. As mentioned in Section III, each brand/micro-influencer can be represented as a triplet. Therefore, $F(b, m)$ can be formulated as the sum of three ranking sub-functions:

$$F(b, m) = f(\mathrm{C}_b, \mathrm{C}_m) + g(\mathrm{U}_b, \mathrm{U}_m) + h(\mathrm{S}_b, \mathrm{S}_m). \tag{19}$$

Since $\boldsymbol{e}_c^a$ and $\boldsymbol{e}_u^a$ are learned from homologous and complementary data, we design a co-attention mechanism to improve the recommendation performance. The co-attention mechanism starts with defining the affinity representation $\boldsymbol{e}_f^a$, and the element of it means the similarity between $\boldsymbol{e}_c^a$ and $\boldsymbol{e}_u^a$. Specifically, $\boldsymbol{e}_f^a$ is defined as:

$$\boldsymbol{e}_f^a = \phi(\boldsymbol{e}_c^a \boldsymbol{W}_f^1 + \boldsymbol{b}_f^1) \circ \phi(\boldsymbol{e}_u^a \boldsymbol{W}_f^2 + \boldsymbol{b}_f^2), \tag{20}$$

where $\circ$ is element-wise product, ϕ denotes a sigmoid function, $\boldsymbol{W}_f^1$ and $\boldsymbol{W}_f^2 \in \mathbb{R}^{d_a \times d_a}$ are weight matrices, $\boldsymbol{b}_f^1$ and $\boldsymbol{b}_f^2 \in \mathbb{R}^{d_a}$ are bias vectors. And then, we calculate the attention weights of $\boldsymbol{e}_c^a$ and $\boldsymbol{e}_u^a$ as follows:

$$\boldsymbol{w}_c = softmax(\boldsymbol{e}_c^a \circ \boldsymbol{e}_f^a) \times |d_a|, \tag{21}$$

$$\boldsymbol{w}_u = softmax(\boldsymbol{e}_u^a \circ \boldsymbol{e}_f^a) \times |d_a|, \tag{22}$$

where $\circ$ is element-wise product, and $|d_a|$ is the magnitude of $\boldsymbol{e}_f^a$. Based on the attention weights, the weighted vectors $\boldsymbol{e'}_c^a$

and ${e'}_u^a$ could be represented as:

$$ {e'}_c^a = e_c^a \circ w_c, \tag{23} $$

$$ {e'}_u^a = e_u^a \circ w_u, \tag{24} $$

where $\circ$ is element-wise product.

Finally, we can represent the three ranking sub-functions as:

$$ f(\mathrm{C}_b, \mathrm{C}_m) = \langle {e'}_c^b, {e'}_c^m \rangle, \tag{25} $$

$$ g(\mathrm{U}_b, \mathrm{U}_m) = \langle {e'}_u^b, {e'}_u^m \rangle, \tag{26} $$

$$ h(\mathrm{S}_b, \mathrm{S}_m) = \langle e_s^b, e_s^m \rangle, \tag{27} $$

where $\langle \cdot, \cdot \rangle$ is inner product.

E. Loss Function

We define a multi-part loss to learn the global ranking function $F(\mathbf{b}, \mathbf{m})$. For each pair of brand b_i and micro-influencer m_x, random sampling is used to get the same amount of micro-influencers m_y to keep balance of data distribution, where $m_x \in \mathbf{MicroInf}_i^+$ and $m_y \in \mathbf{MicroInf}_i^-$. We define three triplet loss functions to optimize $f(\mathrm{C}_b, \mathrm{C}_m)$, $g(\mathrm{U}_b, \mathrm{U}_m)$, and $h(\mathrm{S}_b, \mathrm{S}_m)$, respectively:

$$ \mathcal{L}_1 = max(f(C_{b_i}, C_{m_y}) - f(C_{b_i}, C_{m_x}) + margin1, 0), \tag{28} $$

$$ \mathcal{L}_2 = max(g(U_{b_i}, U_{m_y}) - g(U_{b_i}, U_{m_x}) + margin2, 0), \tag{29} $$

$$ \mathcal{L}_3 = max(h(S_{b_i}, S_{m_y}) - h(S_{b_i}, S_{m_x}) + margin3, 0). \tag{30} $$

Moreover, we define a cross-entropy loss to constrain $F(b, m)$, which can be seen as a global optimization:

$$ \mathcal{L}_4 = -y \ln F(b_i, m_x) - (1 - y) \ln F(b_i, m_y), \tag{31} $$

where the positive example label y is 1 and the negative example label $(1 - y)$ is 0.

Finally, our loss function $\mathcal{L}'$ is:

$$ \mathcal{L}' = \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + \mathcal{L}_4 + \lambda ||\theta||_1, \tag{32} $$

where θ is the set of all the weights of the model, and λ controls the importance of the regularization terms.

V. Experiments

A. Experimental Setup

We split the brand-micro-influencer dataset into training set (286 brands) and testing set (74 brands). There are 12 categories of brands[3] in both training set and testing set.

We trained our model by using Adam optimizer with a mini-batch size of 16. Our model is trained for 100 epochs. The learning rate begins with 0.002 and the decay rate is 0.95 for every epoch. We set dropout layers with the rate of 0.5, and L1 regularization with the regularization rate λ of 0.001.

In our model, we initialized all neural network parameters with the uniform distribution between -0.1 and 0.1. We set the number of an account recent posts (H) as 50, the number of an account's audiences (Q) as 25, and the number of an audience posts (L) as 2. We set the scaling factor η as 2. The confidence threshold is set to 0.1. We set σ and ω as 4-layer multilayer perceptrons where the layers length are 1,024, 1,024, 1,024, and 512. We set μ and γ as 2-layer multilayer perceptrons where the layers length are 128 and 512. We set β as 2-layer multilayer perceptron where the layers length are 1,024 and 512. We used leaky ReLU as the activation function in σ, ω, μ, and γ. The lengths of $\mathbf{v}_o$ and $\mathbf{v}_s$ are 1,000 and 365. Both the sizes of $\mathbf{X}_c^p$ and $\mathbf{Y}_u^p$ are set to 1,365. The sizes of $\mathbf{X}_c^t$ and $\mathbf{Y}_u^t$ are set to 22 and 21. The dimensions of e_c^a, e_u^a, and e_s^a are 512, 512, and 512. margin1, margin2, and margin3 are 4.0, 2.0, and 2.0, respectively.

TABLE II: Statistics of the brand-micro-influencer dataset and the social media audiences dataset. #(Accounts) is the number of accounts, and #(Posts) is the number of posts.

Dataset	Brand	Micro-influencer	Audience
#(Accounts)	360	3748	102700
#(Posts)	18000	187400	205400

B. Dataset

Brand-micro-influencer dataset [8] is an open source multi-modal dataset of micro-influencer recommendation, and it consists of 360 brands and 3,748 micro-influencers. Each brand/micro-influencer in this dataset has an Instagram account. Besides, 360 brands are equally split into 12 categories. For all accounts, this dataset contains 50 posts (with visual information, textual information, the number of comments, and the number of likes), and profile information (the number of followers and the bio description) of them.

However, there is no audiences information of brands and micro-influencers in this dataset. Therefore, we extended the brand-micro-influencer dataset by supplementing a social-media-audiences dataset[4]. Audiences information is a useful kind of data that can help brands choose suitable influencers via *target audiences similarity*. It provides a more comprehensive perspective for influencer recommendation. Therefore, based on the brand-micro-influencer dataset, we selected all active audiences of each account from their crawled 50 posts, which are defined as the users who have given comments under accounts' posts. From these candidates, we selected 25 active audiences for each brand and micro-influencer. Finally, we crawled 10 posts for each active audience, which contains visual information (images) and textual information (captions). Afterward, we selected 2 posts from the 10 posts randomly. In short, for all brands and micro-influencers, we collected 25 active audiences with their biography information, visual information, and textual information.

C. Baselines

In order to demonstrate the effectiveness of our method, we compared MORNING with the following methods:

- **RAND**: a random ranking score method for all brand-micro-influencer pairs.

[3]These 12 categories are Airline, Auto, Clothes, Drink, Electronics, Entertainment, Food, Jewelry, Makeup, Nonprofit, Shoes, and Services.

[4]The code and data to replicate our experiments are available at https://github.com/Mysteriousplayer/20210106.

- **MIV**: a method to evaluate the influence of micro-influencers [48]. Considering the differences between this task and influencer recommendation, we adopted the activeness-based factors module.
- **MIR**: a multimodal learning to rank method, which can predict ranking scores for the given brands and micro-influencers [8].
- **HPTR**: the combination of a multi-modal history pooling representation learning method [8] and a triplet loss ranking method.
- **CATR**: the combination of a concept-based social media account representation learning method [9] and a triplet loss ranking method.
- **CAMERA**: a concept-based micro-influencer ranking framework [9].

Ablation experiments are designed for comparison:

- **MORNING$^{\text{c-only}}$**: only use account content representation with our micro-influencer ranking function.
- **MORNING$^{\text{au-only}}$**: only use account audiences representation with our micro-influencer ranking function.
- **MORNING$^{\text{att-only}}$**: only use account attribute representation with our micro-influencer ranking function.
- **MORNING$^{\text{c+au}}$**: our model without adopting account attribute representation.
- **MORNING$^{\text{c+att}}$**: our model without adopting account audiences representation.
- **MORNING$^{\text{au+att}}$**: our model without adopting account content representation.

D. Evaluation Metrics

We adopted AUC, cAUC, Recall@k, MRR, MAP, and MedR to evaluate the performance.

- **AUC** is the probability that a positive example's (micro-influencer) ranking score of a brand is higher than a negative one's ranking score.
- **cAUC** is the AUC where the positive and negative examples in a same category. cAUC is harder than AUC.
- **R@k** is the recall rate at k micro-influencers.
- **MRR** is the average of the reciprocal ranks of micro-influencers for a sample of brands.
- **MAP** is mean average precision.
- **MedR** is the median position of the first positive example. The lower is the better.

It is noteworthy that we discarded the Precision@k. Because in the brand-micro-influencer dataset, there are only 11 positive micro-influencers for each brand in average.

E. Recommendation Performance Analysis

First, we compared our model to all baselines. According to Table III, we can observe that MORNING has great advantages over baselines. Compared to MIR, CATR, HPTR, and CAMERA, our model increases 4.1% in AUC, 7.2% in cAUC, 2.4% in R@10, 28.7% in R@50, and 11.2% in MAP. The significant improvement on R@50 show how our model performs on the mid-ranked positive examples. Particularly, the performance of MIV is only slightly better than RAND. We think the reason is that the methods of only measuring influence are insufficient for influencer recommendation.

TABLE III: Comparison of MORNING (short as MOR.) with the baselines.

Method	AUC	cAUC	R@10	R@50	MRR	MAP	MedR
RAND	0.494	0.489	0.005	0.054	0.038	0.019	54
MIV	0.499	0.498	0.019	0.079	0.057	0.027	49
MIR	0.849	0.675	0.135	0.428	0.368	0.153	6
HPTR	0.804	0.647	0.090	0.311	0.269	0.101	7
CATR	0.781	0.633	0.073	0.313	0.256	0.099	8
CAMERA	0.811	0.678	0.208	0.422	**0.602**	0.214	**2**
MOR.	**0.884**	**0.727**	**0.213**	**0.551**	0.565	**0.238**	**2**

TABLE IV: Ablation experiments of MORNING (short as MOR.).

Method	AUC	cAUC	R@10	R@50	MRR	MAP	MedR
MOR$^{\text{c-only}}$	0.861	0.699	0.158	0.472	0.391	0.173	3
MOR$^{\text{au-only}}$	0.773	0.634	0.069	0.286	0.201	0.086	13
MOR$^{\text{att-only}}$	0.805	0.682	0.164	0.410	0.364	0.156	4
MOR$^{\text{c+au}}$	0.874	0.699	0.161	0.490	0.393	0.177	4
MOR$^{\text{c+att}}$	0.882	0.715	0.205	0.540	0.559	0.234	**2**
MOR$^{\text{au+att}}$	0.845	0.695	0.174	0.471	0.409	0.168	3
MOR.	**0.884**	**0.727**	**0.213**	**0.551**	**0.565**	**0.238**	**2**

TABLE V: Performance for different brand categories.

Category	AUC	cAUC	R@10	R@50	MRR	MAP	MedR
airline	0.885	0.670	0.217	0.510	0.329	0.191	5
auto	0.902	0.626	0.217	0.611	0.574	0.267	2
clothes	0.925	**0.861**	0.160	0.587	0.415	0.259	3
drink	0.880	0.834	0.264	0.618	0.366	0.226	3
electr.	0.823	0.751	0.151	0.373	0.279	0.119	4
entert.	0.867	0.722	0.219	0.486	0.654	0.240	**1**
food	0.836	0.646	0.172	0.396	0.436	0.209	2
jewelry	0.836	0.735	0.165	0.417	0.451	0.182	2
makeup	**0.951**	0.706	0.194	0.701	0.694	0.255	**1**
nonprofit	0.852	0.673	0.250	0.475	**0.753**	0.298	**1**
shoes	0.939	0.678	**0.280**	**0.754**	0.569	**0.318**	2
services	0.840	0.783	0.183	0.408	0.354	0.136	5
all	0.884	0.727	0.213	0.551	0.565	0.238	2

Second, we designed ablation experiments to verify the effectiveness of each component in our model. Table IV shows the results of ablation experiments. Comparing each component individually, we found that MORNING$^{\text{c-only}}$ has the best performance. MORNING$^{\text{c-only}}$ decreases 2.6% in AUC, 3.9% in cAUC, 25.8% in R@10, 14.3% in R@50, 30.8% in MRR, 27.3% in MAP, and 1 position in MedR compared to MORNING. As far as we know, all existing methods are based on modeling social media content information. Comparison of MORNING$^{\text{c-only}}$ and baselines shows the effectiveness of our account content representation learning method. MORNING$^{\text{att-only}}$ is slightly weaker than MORNING$^{\text{c-only}}$, which reflects the necessity of introducing social media interaction information. We think it also proves that characterizing social media accounts by using attributes is a feasible technical route. MORNING$^{\text{au-only}}$ performs not well. However, we observed that the overall performance of MORNING$^{\text{c+au}}$ is better than that of MORNING$^{\text{c-only}}$, and the overall performance of MORNING$^{\text{au+att}}$ is better than that of MORNING$^{\text{att-only}}$. It might be that audiences information plays an auxiliary but indispensable role in the micro-influencer recommendation. At last, the performance of MORNING

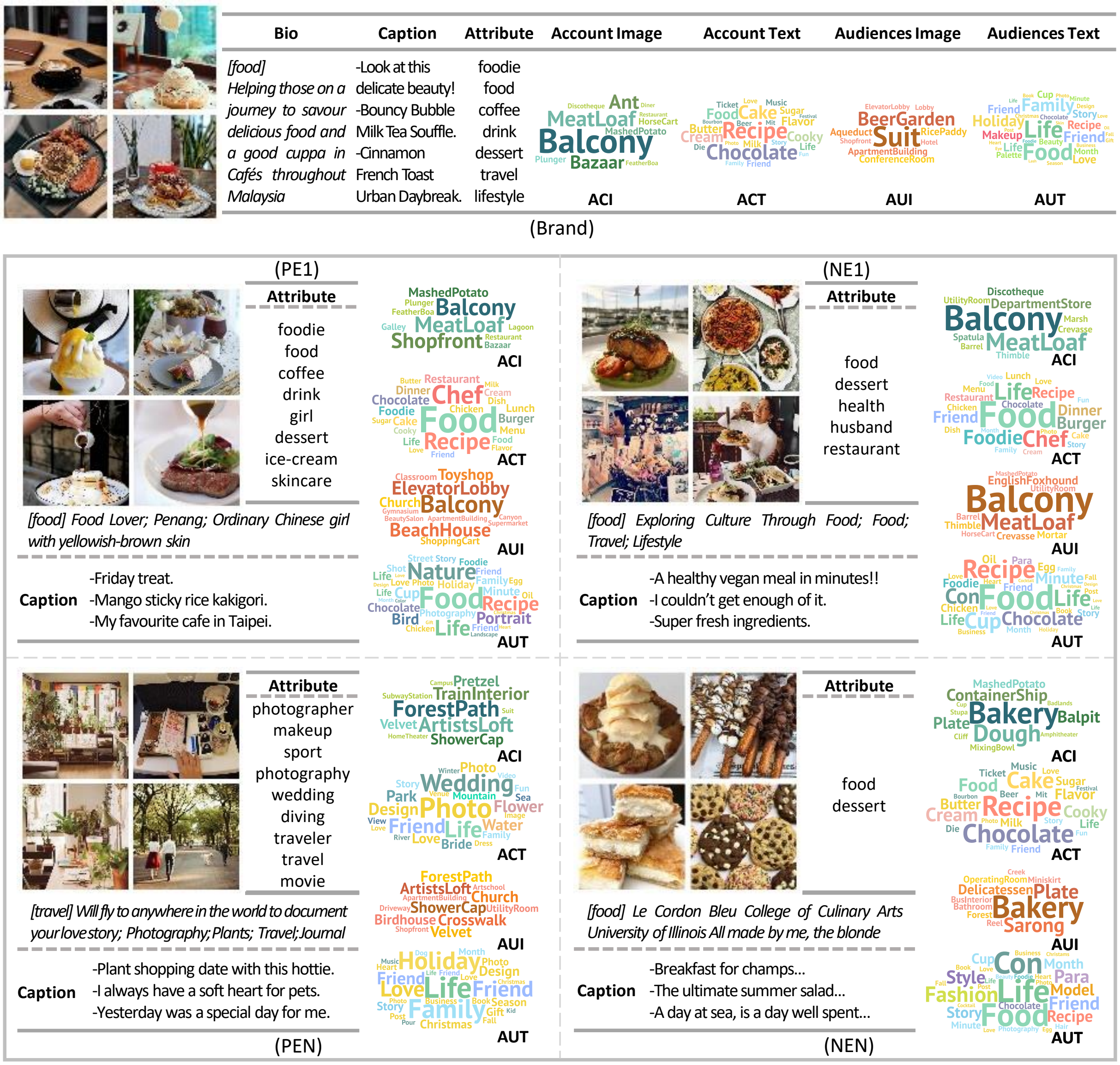

Fig. 4: Case study for a brand with four representative micro-influencers.

shows these three components are mutually reinforcing.

Third, to deep dive into how our method performs in different categories, we reported the results of 12 categories in Table V. We can see that *makeup*, *shoes*, and *clothes* have good performance in AUC, which shows that micro-influencers who work with brands in these categories may have a high degree of similarity. For example, the *makeup* micro-influencers often upload their selfies with makeup and introduce a lot of cosmetics. The *clothes* micro-influencers often upload photos of themselves in different outfits. The *shoes* micro-influencers often upload close-ups of various shoes and shoes introductions. Moreover, we observed that AUC is closely related to recommendation metrics(i.e.,R@k, MRR, MAP, and MedR). When the performance of a category is below average in AUC, the recommendation metrics are also significantly lower than average, such as *electronics*, *food*, *jewelry*, and *services*. And then, *clothes* and *drink* perform particularly well in cAUC, which might be the brands in these categories have very diverse influencers choosing strategies. In contrast, *auto* and *food* have poor performance in cAUC. It seems that the brands in these categories tend to choose similar micro-influencers. Further, R@10, MRR, and MedR indicate how our model performs on the top-ranked micro-influencers. *shoes* and *nonprofit* achieve good performance in this area. Besides, we found some categories such as *makeup* and *auto* perform well in R@50 and MAP. It also proves the model's recommendation ability in these categories. Finally, the R@10, R@50, MAP, MRR, and MedR of *shoes* are better than or equal to the average. Especially, R@10, R@50, and MAP are the highest of all categories. Therefore, we think *shoes* achieves the best recommendation performance.

F. Case Study

We designed a case study to make intuitive explanations of our model's recommendation results. We presented a set of examples with the visualization results of their social media information. This set of examples is a *food* brand with four representative recommended micro-influencers, namely the Top-1 ranked positive example (PE1), the Top-1 ranked negative example (NE1), the lowest-ranked positive example (PEN), and a low ranked negative example who is still similar to positive example (NESN). They are ranked 1st, 4th, 200th, and 65th of 798 micro-influencers. As shown in Figure 4, each account contains four representative posts, biography information, social media attribute-list, visualization results of the visual-semantic vector of accounts (ACI), textual information vector of accounts (ACT), the visual-semantic vector of audiences (AUI), and the textual information vector of audiences (AUT), respectively.

As we can see from the posts, biographies, and social media attribute-list, the brand belongs to a Malaysian restaurant specializing in Western food, dessert, and coffee. According to the ACI, we can observe that scenes (e.g., balcony and restaurant) and objects (e.g., meatloaf and mashed potato) account for a large proportion, which are obviously related to food displaying. From the ACT, we found that it usually talks about various foods, and sometimes talks about life and friendship. And then, according to the AUI and AUT, the interests of this brand's audiences are diverse. Various scenes and objects are included in their posts. Their daily topics cover a wide range, such as makeup, food, family, life, and so on.

The PE1 is a food lover, who often shares delicious food, desserts, and drink on Instagram. From its ACI and ACT, we got the conclusion that this account's content is consistent with the brand. Besides, there are many food-related elements in its AUI and AUT. We concluded that this influencer's audiences are also very passionate about food, who are similar to the brand's audiences. The micro-influencer PE1 is ranked 1st among all micro-influencers, which proves that our method can accurately find suitable positive examples. The NE1 is ranked 4th among all micro-influencers. This account belongs to a couple who like to share life experiences and food on Instagram. NE1 and PE1 are very similar in content information, audiences information, and social media attributes. It means our method tends to give a high ranking to the micro-influencers who have a lot in common with the good positive examples. The PEN is a travel blogger who loves photography. This account mainly shares photographic works in traveling. According to ACI and ACT, we observed that there are few food-related elements in its content, and its audiences have little interest in food. Although the brand and the PEN have cooperated in the past, it might not be a good choice. Finally, the results of NESE reveal the model's ability to make a fine-grained distinction among micro-influencers. Compared to NE1, the NESE is also a food blogger who loves baking desserts and sharing desserts on social media, but it is just ranked at 65th. It might be that its interest is only focused on desserts, which is obviously shown in ACI. In addition, this micro-influencer prefers cooking to food marketing. Thus, the NESE is not a very appropriate candidate.

VI. Conclusions And Future Works

We proposed the MORNING by modeling brands/micro-influencers from the perspective of *individual image*, *target audiences*, and *cooperation preferences*. To be specific, we introduced *target audiences* to the micro-influencer recommendation. Audiences information and content information of accounts are utilized to learn two kinds of multi-modal account representations, where the co-attention mechanism is designed to boost recommendation performance. Moreover, in order to mine *cooperation preferences* from interaction information, we built the attribute co-occurrence graph network based on account attributes, which can capture *cooperation preferences* at the attribute level. Attribute node embeddings are further used to construct the account attribute representation. Finally, we designed the global ranking function to calculate the ranking scores for given brands and all micro-influencers from the three perspectives jointly. We evaluated our model on the brand-micro-influencer dataset, in terms of performance comparison, ablation study, and case study. A future research direction is to build knowledge graphs by using domain knowledge in influencer marketing, which is helpful to better understand the cooperation preferences between various brands and micro-influencers.

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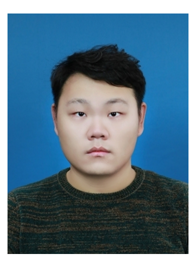
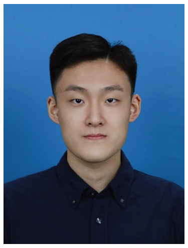


Shaokun Wang received his B.Eng. degree from Shandong University in 2018 and the M.S. degree from Shandong University in 2021. He is currently a Ph.D. candidate at Xi'an Jiaotong University. His main research interests include social media marketing, multimedia computing, and incremental learning.

Tian Gan is currently an Associate Professor with the School of Computer Science and Technology, Shandong University. She received her B.Sc. from East China Normal University in 2010, and the Ph.D. degree from National University of Singapore, Singapore, in 2015. She was a Research Scientist in Institute for Infocomm Research (I2R), Agency for Science, Technology and Research (A*STAR). Her research interests include social media marketing, video understanding, and multimedia computing.



Yuan Liu is currently a Ph.D. student at the Institute of Computing Technology of the Chinese Academy of Sciences and the University of the Chinese Academy of Sciences. He is a member of the Key Laboratory of the Network Data Science and Technology, Chinese Academy of Sciences. His research interests include recommendation system, information retrieval and natural language processing.

Jianlong Wu received his B.Eng. and Ph.D. degrees from Huazhong University of Science and Technology in 2014 and Peking University in 2019, respectively. He is currently an assistant professor with the School of Computer Science and Technology, Shandong University. His research interests lie primarily in computer vision and machine learning, especially weakly supervised learning. He has published more than 20 research papers in top journals and conferences, such as TIP, ICML, NeurIPS, and ICCV. He serves as a Senior Program Committee Member of IJCAI 2021, an area chair of ICPR 2020, and a reviewer for many top journals and conferences, including TPAMI, IJCV, ICML, and ICCV.

Yuan Cheng is a staff algorithm engineer at Ant Group. He received his PhD degree from National University of Singapore, and Bachelor's degree from Fudan University. His research interests include video analysis, biometrics, affective computing and medical image analysis. He was awarded tens of patents and published more than ten papers in conferences.

Liqiang Nie received the B.Eng. degree from Xi'an Jiaotong University in 2009 and the Ph.D. degree from the National University of Singapore (NUS) in 2013. After Ph.D., he continued his research in NUS as a Research Fellow for more than three years. He is currently a professor with the School of Computer Science and Technology, Shandong University. Meanwhile, he is the Adjunct Dean with the Shandong AI Institute. His research interests lie primarily in multimedia computing and information retrieval. He has published around 100 papers in the top conferences or journals, with 9,600 plus Google Scholar citations. He was granted several awards like SIGIR 2019 best paper honorable mention, ACM SIGMM Rising Star 2020, Green Orange Award 2020 of Alibaba DAMO Academy, AI 2000 the most influential scholar in artificial intelligence and MIT TR35 China. He is an Associate Editor of *IEEE Transactions on Multimedia* (IEEE TMM), *IEEE Transactions on Knowledge and Data Engineering* (IEEE TKDE), *ACM Transactions on Multimedia Computing, Communications, and Applications* (ACM TOMM) and Information Science. He serves as a PC Chair of ICIMCS 2017, PCM 2018, ChinaMM 2020 and an Area Chair of ACM MM 2018-2021.