Discover Micro-Influencers for Brands via Better Understanding

Shaokun Wang, Tian Gan, Yuan Liu, Li Zhang, JianLong Wu, and Liqiang Nie, *Member, IEEE*

***Abstract*—With the rapid development of the influencer marketing industry in recent years, the cooperation between brands and micro-influencers on marketing has achieved much attention. As a key sub-task of influencer marketing, micro-influencer recommendation is gaining momentum. However, in influencer marketing campaigns, it is not enough to only consider marketing effectiveness. Towards this end, we propose a concept-based micro-influencer ranking framework, to address the problems of marketing effectiveness and self-development needs for the task of micro-influencer recommendation. Marketing effectiveness is improved by concept-based social media account representation and a micro-influencer ranking function. We conduct social media account representation from the perspective of historical activities and marketing direction. And two adaptive learned metrics, endorsement effect score and micro-influencer influence score, are defined to learn the micro-influencer ranking function. To meet self-development needs, we design a bi-directional concept attention mechanism to focus on brands' and micro-influencers' marketing direction over social media concepts. Interpretable concept-based parameters are utilized to help brands and micro-influencers make marketing decisions. Extensive experiments conducted on a real-world dataset demonstrate the advantage of our proposed method compared with the state-of-the-art methods.**

***Index Terms*—Influencer marketing, interpretable recommendation, multimodal.**

I. Introduction

The rise of a global pandemic is making brands and companies pause and re-evaluate their marketing strategies, from traditional advertisements to influencer marketing. Influencer marketing indicates a brand collaborating with many suitable social media influencers [1] to promote products or services [2], and Figure 1 shows the common workflow of it. In a quest for stronger connections with consumers that lead to long-term sales and customer loyalty, brands are courting influencers and offering them sponsorship deals. According to data from Kantar,[1] social media engagement during the COVID-19 pandemic has increased by 61% over normal usage rates, and the influencer marketing industry is set to grow to approximately \$9.7B in 2020, and nearly 4/5 of the respondents intend to dedicate a budget to influencer marketing.[2] Unlike traditional influencers, depending on their sphere of expertise, micro-influencers make the most engaging social posts on their specialist topics [3]. The above characteristics make micro-influencers easier trusted by consumers.

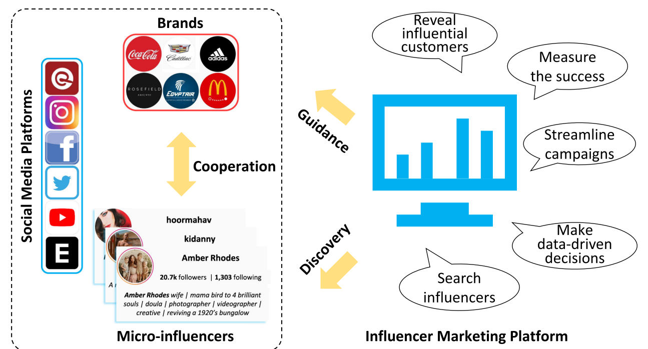


Fig. 1. Illustration of how influencer marketing works.

As a key sub-task of influencer marketing, micro-influencer recommendation has entered its golden development period. Previous works [4], [5] have presented methods to help the given brands to find suitable micro-influencers for better marketing effectiveness, yet most of them ignore the self-development needs of both brands and micro-influencers in marketing activities. In influencer marketing campaigns, there is no question that achieving excellent marketing effectiveness is their *joint objective*. Moreover, through cooperation, brands and influencers are keen to get exposure to the audiences and provide attractive content to optimize their marketing direction and build their self-image [6], [7]. They consider marketing activities as great opportunities for self-development, which are defined as their *individual objectives* in this paper. Whether cooperating with partners is beneficial to meet their self-development needs, is also a determining factor in influencer marketing [8]. Therefore, it is necessary for proposing a method to take both *joint objective* and *individual objective* into account.

Driven by these practical needs, we propose a *concept-based micro-influencer ranking framework* (CAMERA) to address

Manuscript received November 9, 2020; revised March 14, 2021; accepted May 18, 2021. Date of publication June 14, 2021; date of current version May 11, 2022. This work was supported by the National Natural Science Foundation of China, under Grant U1936203. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Abderrahim Benslimane. *(Corresponding author: Tian Gan.)*

The authors are with the School of Computer Science and Technology, Shandong University, Qingdao 266237, China (e-mail: shaokunwang.sdu@gmail.com; gantian@sdu.edu.cn; lizhang.nus2010@gmail.com; lizhang.nus@gmail.com; jlwu1992@pku.edu.cn; nieliqiang@gmail.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TMM.2021.3087038.

Digital Object Identifier 10.1109/TMM.2021.3087038

[1][Online]. Available: https://www.kantar.com/inspiration/coronavirus/covid-19-barometer-consumer-attitudes-media-habits-and-expectations.

[2][Online]. Available: https://influencermarketinghub.com/influencer-marketing-benchmark-report-2020:repeat

marketing effectiveness and self-development needs together in the micro-influencer recommendation task. Specifically, we introduce the social media concepts, which are high-level semantic concepts extracted from social media content information, into our framework, representing the objects, actions, styles, and scenes that appeared in social media accounts frequently. These concepts can be utilized for a fine-grained understanding of the marketing intent in social media accounts. Moreover, in order to achieve the *joint objective*, we propose *a cross-modal social media concept learning network* (COSMIC) to learn social media concept representation, which is leveraged to conduct social media account (i.e., brand and micro-influencer) representation from the perspective of both historical activities and marketing direction. We further model endorsement information and micro-influencer influence information in micro-influencer ranking, where two adaptive learned metrics (*endorsement* effect score and micro-influencer *influence* score) are defined to learn a micro-influencer ranking function. Meanwhile, for achieving the *individual objective*, a *bi-directional concept attention mechanism* (BCAM) is designed to focus on brands' and micro-influencers' marketing direction over social media concepts, and the marketing direction concept weights learned in BCAM are utilized to explain the marketing direction of both partners in cooperation. Based on the interpretable historical activities and marketing direction, brands and micro-influencers can judge whether marketing activities meet their self-development needs, and then help them make decisions. The recommendation performance analysis and the recommendation interpretability analysis validated the effectiveness of our proposed method. To sum up, the contributions of this work are as follows:

- We propose the CAMERA to address marketing effectiveness and self-development needs together in the micro-influencer recommendation task, which successfully understands the marketing intent of social media accounts at a fine-grained level.
- We design the COSMIC and the BCAM to learn social media account representation from the perspective of historical activities and marketing direction. Meanwhile, interpretable concept-based parameters from the two perspectives can be utilized to help brands and micro-influencers make decisions.
- We model endorsement information and micro-influencer influence information in micro-influencer ranking, where two novel adaptive learned metrics (*endorsement* effect score and micro-influencer *influence* score) are defined to learn a better micro-influencer ranking function.
- Recommendation performance analysis and recommendation interpretability analysis demonstrate the advantage of our proposed method compared with the state-of-the-art methods. Especially, we implement a new application scenario of keywords-based micro-influencer search based on our proposed method and demonstrate the effectiveness of it.

II. Related Work

A. Influencer Marketing

Influencer marketing is an emerging form of online marketing, which involves a brand collaborating with an online influencer to market the brand's products or services [9], [10]. Brands are increasingly realizing the value of influencers in reaching their target audience, especially since traditional advertising has a harder time breaking through [11]. As an important task in influencer marketing, influencer recommendation suffers from the insufficiency of related data, due to the sensitivity of the real-world data (e.g., conversion rate, location, and real identity) [12]. Therefore, how to utilize the accessible social media information to model the influencer recommendation is crucial yet challenging.

Influencer recommendation is usually divided into two subtasks: *social media account representation learning* and *influencer ranking*. Various social media information is utilized for *social media account representation learning*. Sweet [4] utilized account profile data to construct social account representation, where a Bag-of-Words approach is used to vectorize the processed account profile data. Gan *et al.* [5] designed a social media content history pooling method, which can leverage social media content information (e.g., visual and textual data in users' posts) to represent brands and micro-influencers. Besides, there are other studies dedicated to account representation learning [13]–[15]. Gelli *et al.* [13] learned the fine-grained brand representation, via the visual information from the brand's posts, where a brand can be mapped into a common latent space by explicitly modeling the brand associations. Zhang *et al.* [14] utilized images and tags from the brand followers to represent the brand, and two kinds of representation are learned by K-means and average pooling method. Bonomo *et al.* [15] constructed the profile tree based on brand content information to represent brands. For *influencer ranking*, social media information is mostly exploited for measuring the influencer impact and cooperation effect of the brand and influencer. Cossu *et al.* [16] employed features processed from users' content information (e.g., user activity, tweets characteristics, and profile) to measure influence. Similarly, Rao *et al.* [17] introduced the Klout score as a metric for measuring the online influence of users, where over two thousand features are extracted from user content information. Social media interaction information (e.g., indegree, retweet, like, mention, etc.) are also commonly used to measure users' influence [18]–[21]. In short, research on influencer marketing is still in its infant stage. Moreover, existing influencer recommendation methods only focus on marketing effectiveness and ignore the self-development needs of brands and influencers.

B. Interpretable Recommendation Using High-Level Semantic Embedding

The strategies of interpretable recommendation are quite diverse. As the form of interpretability highly depends on the application scenario, the strategies of interpretable recommendation are quite diverse [22]–[28]. One kind of typical solution is that using high-level semantic embedding to enhance the model interpretability. And interpretable high-level semantic embedding with domain-specific background plays a key role in this strategy. In the fashion area, Han *et al.* [29] proposed a prototype-guided attribute-wise interpretable compatibility modeling scheme. They leveraged semantic attributes to provide the interpretation of clothing matching, where attributes are the

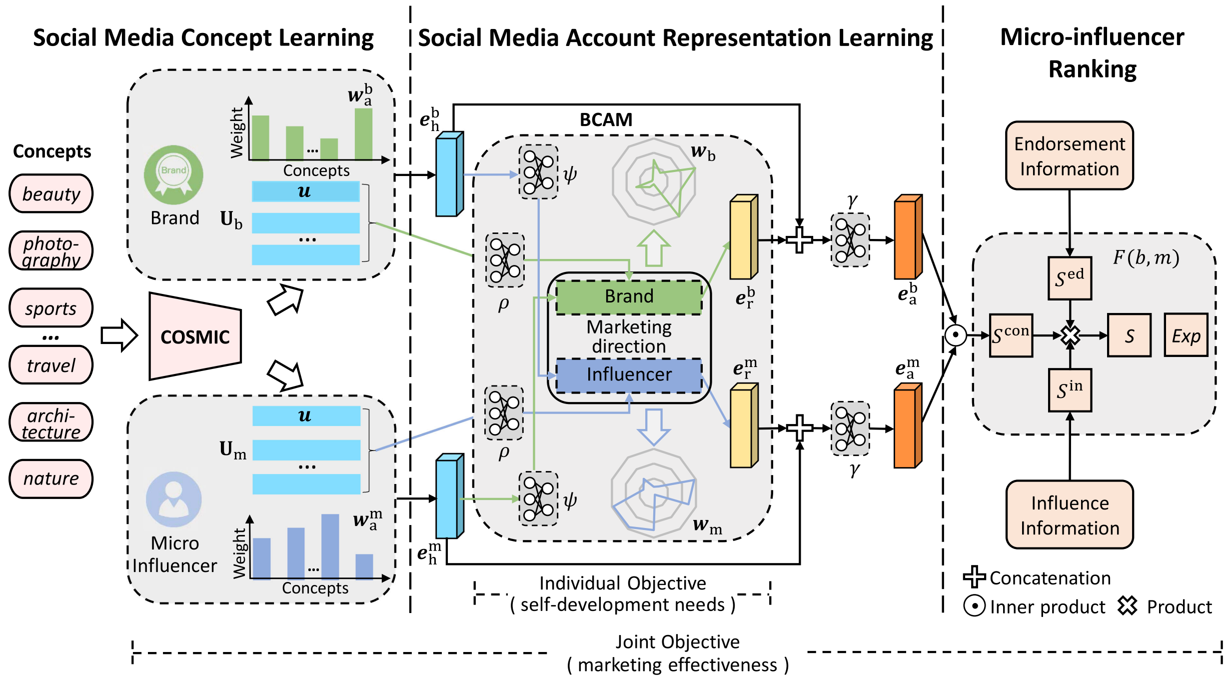


Fig. 2. An overview of CAMERA, which consists of three components, namely social media concept learning, social media account representation learning, and micro-influencer ranking. COSMIC is the *cross-modal social media concept learning network*, where the details are described in Section "Cross-modal Social Media Concept Learning". BCAM is the *bi-directional concept attention mechanism*, which is designed to focus on brands' and micro-influencers' marketing direction over social media concepts.

essential features of fashion items, such as the color, shape, and category. Similarly, Min *et al.* [30] presented a novel fashion recommendation system by utilizing fashion semantic attributes to capture user fine-grained preferences. And this method is able to explain the reason why the clothes are recommended through intuitive fashion attributes. In the area of e-commerce recommendation, Luo *et al.* [31] collected various high-level semantic concepts called e-commerce cognitive concepts, which explicitly represent shopping needs for users, such as "outdoor barbecue" and "gifts for kids". Based on the e-commerce cognitive concept nodes, they built a large comprehensive knowledge graph called AliCoCo, and it can help to generate recommendation reasons when recommending items to customers. Inspired by these works, we introduce a new kind of high-level semantic concept called social media concepts, which represent the objects, actions, styles, and scenes that appeared in social media accounts frequently. And interpretable concept-based radar charts are used to help brands and micro-influencers make marketing decisions.

III. Methodology

In this paper, we focus on micro-influencer recommendation, where the goal of our method is to resolve the problems of marketing effectiveness and self-development needs together. Figure 2 shows the overview of the proposed framework. CAMERA consists of three components, namely social media concept learning, social media account representation learning, and micro-influencer ranking. In social media concept learning, we introduce social media concepts into this task and propose the COSMIC to learn the representations of them. In social media account representation learning, social media concepts are leveraged to learn account representation from the perspective of both historical activities and marketing direction. Meanwhile, the BCAM is designed to focus on brands' and micro-influencers' marketing direction over social media concepts. In micro-influencer ranking, two adaptive metrics (*endorsement* effect score and micro-influencer *influence* score) are incorporated to learn the micro-influencer ranking function.

A. Problem Formulation

We indicate $\mathcal{A} = \{a_1, a_2, \ldots, a_{|A|}\}$ as the set of social media accounts, and both brand b and micro-influencer m are social media accounts. These accounts consist of posts $\mathcal{P} = \{p_1, p_2, \ldots, p_{|P|}\}$ with visual and textual information, and $P_{\mathrm{a}} \subset \mathcal{P}$ indicates the posts of account a. We collect social media concepts $\mathcal{C} = \{c_1, c_2, \ldots, c_{|C|}\}$ to represent brands and micro-influencers at a fine-grained level, where $C_{\mathrm{a}} \subset \mathcal{C}$ indicates the concepts of account a.

If a micro-influencer m has posted an advertisement for a brand b, we define m as a *positive* example for b. For each brand b_x, we use M_x^+ and M_x^- to respectively denote its *positive* and *negative* examples, and $M_x^+ \bigcup M_x^- = M$, where M contains all micro-influencers in our dataset. $\mathcal{H} = \{< b_i, m_j, S_{ij}^{\mathrm{ed}} >\}$ is the endorsement information, where S_{ij}^{ed} is the *endorsement* effect score between b_i and m_j. Meanwhile, we define an *influence* score S_j^{in} for each micro-influencer. At last, the essence of micro-influencer recommendation is to learn a ranking score function

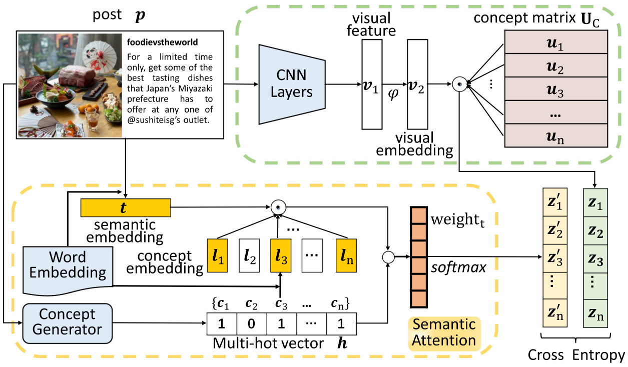


Fig. 3. Illustration of COSMIC. To improve the concept representation learning, we make full use of multi-modal information where concept weight distribution knowledge is transferred from semantic modality to visual modality.

$F(b_i, m_j)$ as:

$$F(b_i, m_j) = F(< b_i, m_j, S^{\text{ed}}_{ij} >, S^{\text{in}}_j) = \{S_{ij}, Exp_{ij}\}, \tag{1}$$

where S_{ij} is the ranking score, and Exp_{ij} consists of interpretability parameters $\mathbf{w}_{\text{b}_i}$ and $\mathbf{w}_{\text{m}_j}$, indicating the marketing direction concept weights of b_i and m_j over their social media concepts, respectively.

B. Cross-Modal Social Media Concept Learning

The content people uploaded on social media is often informative and complicated, which leads to low-efficiency understanding. An efficient strategy to address this problem is mining high-level semantic concepts to summary the content [32]–[36]. We collect 420 high-level social media concepts, consisting of objects, actions, styles, and scenes that appeared frequently on social media, to help us understand accounts' marketing intent at a fine-grained level. These concepts are learned by exploring the visual and semantic information of its corresponding post. As shown in Figure 3, we construct a concept matrix $\mathbf{U}_{\text{C}} \in \mathbb{R}^{\text{n} \times d_{\text{u}}}$, where each row $\boldsymbol{u}_i$ is a concept representation, n is the length of $\mathcal{C}$, and d_{u} is the length of concept representation $\boldsymbol{u}$. We extract the post visual feature $\boldsymbol{v}_1$ from the post image by utilizing a 5-layer convolutional neural network. Afterwards, a post visual embedding $\boldsymbol{v}_2$ is computed by:

$$\boldsymbol{v}_2 = \varphi(\boldsymbol{v}_1) = leaky\_relu(\boldsymbol{W}^{\text{v}}_1 \boldsymbol{v}_1 + \boldsymbol{b}^{\text{v}}_1), \tag{2}$$

where $leaky\_relu$ denotes activation function, $\boldsymbol{W}^{\text{v}}_1 \in \mathbb{R}^{d_{\text{u}} \times d_{\text{v1}}}$, and $\boldsymbol{b}^{\text{v}}_1 \in \mathbb{R}^{d_{\text{u}}}$. We utilize Word2Vec [37] to extract post semantic embedding $\boldsymbol{t}$ and concept embedding $\boldsymbol{l}$. We further obtain a group of social media concepts by using a pre-trained concept generator, and represent the post as a multi-hot vector $\boldsymbol{h}$. Meanwhile, a semantic attention is introduced to calculate a modified concept weight distribution $\mathbf{z}' = softmax(\mathbf{weight}_{\text{t}})$, where the length of $\mathbf{z}'$ is n, and the $\mathbf{weight}_t$ is defined as $\mathbf{weight}_t = [(\boldsymbol{t} \cdot \boldsymbol{l}_1), (\boldsymbol{t} \cdot \boldsymbol{l}_2), \ldots, (\boldsymbol{t} \cdot \boldsymbol{l}_{\text{n}})] \circ \boldsymbol{h}$, where $\cdot$ is inner product, and $\circ$ is the element-wise product. It is worth noting that there are some posts without text information. In this case, we take the multi-hot vector $\boldsymbol{h}$ as the $\mathbf{weight}_t$.

We expect to utilize the semantic concept weight distribution knowledge to improve the concept representation learning, thus adopting the cross-modality distributions matching techniques [38], [39] to transfer concept weight distribution knowledge from semantic modality to visual modality. For each concept representation $\boldsymbol{u}_i$, we can compute another concept weight distribution $\mathbf{z}$ by utilizing visual information:

$$\mathbf{z} = softmax\{(\boldsymbol{v}_2 \cdot \boldsymbol{u}_1), (\boldsymbol{v}_2 \cdot \boldsymbol{u}_2), \ldots, (\boldsymbol{v}_2 \cdot \boldsymbol{u}_{\text{n}})\}, \tag{3}$$

where $\cdot$ is inner product. Our optimization goal is to update the parameters in the social media concept matrix $\mathbf{U}_{\text{C}} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_{\text{n}}\}$ by fitting these two distributions $\mathbf{z}$ and $\mathbf{z}'$. Therefore, we define a cross-entropy loss $\mathcal{L}_{\text{u}}$ to constrain $\mathbf{z}$:

$$\mathcal{L}_{\text{u}} = -\sum\nolimits_i^{\text{n}} \mathbf{z}'_i \log \mathbf{z}_i. \tag{4}$$

At last, we obtain a trained social media concept representation set $\mathbf{U}_{\text{C}} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_{\text{n}}\}$.

C. Social Media Account Representation Learning

1) Account Historical Activities Representation: We use the social media concepts and the account historical concept distribution to represent each account. The account a's historical concept distribution $\mathbf{w}_{\text{a}}$ is defined as:

$$\mathbf{w}_{\text{a}} = softmax\left(\sum\nolimits_{p_i \in P_{\text{a}}} \mathbf{z}'_{p_i}\right), \tag{5}$$

where P_{a} is the account post set, and $\mathbf{z}'_{p_i}$ is the concept weight distribution of post p_i. Considering that some social media concepts with small weight have little effect but increase the computational burden, we keep the Top-10 weight concept $\mathbf{U}_{\text{a}}$, and define the account historical activities representation as:

$$\boldsymbol{e}_{\text{h}} = \sum\nolimits_{k, \boldsymbol{u}_k \in \mathbf{U}_{\text{a}}} \mathbf{w}^k_{\text{a}} \boldsymbol{u}_k, \tag{6}$$

where $\boldsymbol{e}_{\text{h}} \in \mathbb{R}^{d_{\text{c}}}$, $\boldsymbol{u} \in \mathbf{U}_{\text{a}}$, $\mathbf{U}_{\text{a}} \subset \mathbf{U}_{\text{C}}$, k means the k-th dimension of $\mathbf{w}_{\text{a}}$, and $\boldsymbol{u}_k$ is the corresponding concept representation.

2) Account Marketing Direction Representation: Using only the account historical concept distribution information is insufficient for recommending micro-influencers to brands. When brands/micro-influencers conduct marketing campaigns with different collaborators, marketing directions will be various, which should also be considered in modeling account representation. Therefore, we introduce a *bi-directional concept attention mechanism* to learn marketing direction concept weight, namely, focusing on brands' and micro-influencers' marketing direction over social media concepts. We define the i-th dimension of brand/micro-influencer marketing direction concept weight $\mathbf{w}_{\text{b}/m}$ as:

$$\mathbf{w}^i_{\text{b}/m} = \frac{exp(\psi(\boldsymbol{e}^{\text{m}/b}_{\text{h}}) \cdot \rho(\boldsymbol{u}_i))}{\sum_{\boldsymbol{u}_i \in \mathbf{U}_{\text{b}/m}} exp(\psi(\boldsymbol{e}^{\text{m}/b}_{\text{h}}) \cdot \rho(\boldsymbol{u}_i))}, \tag{7}$$

where $\cdot$ is inner product, both ψ and ρ are 2-layer fully-connected layers, $\mathbf{U}_{\text{b}/m}$ is Top-10 weight concept set of the brand/micro-influencer, and $\boldsymbol{e}^{\text{m}/b}_{\text{h}}$ is the historical activities representation of the target micro-influencer/brand. Moreover, the marketing direction concept weight is used to boost the recommendation performance by constructing account marketing direction representation $\boldsymbol{e}_{\mathrm{r}}$. To be specific, account marketing direction representation $\boldsymbol{e}_{\mathrm{r}}$ is defined as:

$$\boldsymbol{e}_{\mathrm{r}} = \sum\nolimits_{i, \boldsymbol{u}_i \in \mathbf{U}_{\mathrm{b}/m}} \mathbf{w}^i_{\mathrm{b}/m} \boldsymbol{u}_i, \tag{8}$$

where $\boldsymbol{e}_{\mathrm{r}} \in \mathbb{R}^{d_{\mathrm{r}}}$, and d_{r} is the length of $\boldsymbol{e}_{\mathrm{r}}$.

3) Social Media Account Representation: To obtain a more comprehensive account representation $\boldsymbol{e}_{\mathrm{a}}$, we intend to fuse the account historical activities representation $\boldsymbol{e}_{\mathrm{h}}$ and the account marketing direction representation $\boldsymbol{e}_{\mathrm{r}}$ into the same space as:

$$\boldsymbol{e}_{\mathrm{a}} = \gamma(concat(\boldsymbol{e}_{\mathrm{h}}, \boldsymbol{e}_{\mathrm{r}})), \tag{9}$$

where $\boldsymbol{e}_{\mathrm{a}} \in \mathbb{R}^{d_{\mathrm{a}}}$, d_{a} is the length of $\boldsymbol{e}_{\mathrm{a}}$, $concat$ is the concatenation operation, and γ is a 3-layer MLP.

D. Micro-Influencer Ranking

1) Social Media Interaction Information Modeling: In order to produce a more accurate ranking, we leverage social media interaction information on micro-influencer ranking. Due to the sensitivity of real-world data, it is difficult to obtain the information of endorsement effect between brands and micro-influencers. Therefore, we define the endorsement effect metrics by utilizing social media interaction information. We introduce the *engagement rate* [40] to measure the level of engagement that the created social media content is receiving from audiences. The *engagement rate* $E(\mathrm{p})$ of a post p is defined as:

$$E(\mathrm{p}) = \frac{\#(\text{likes}) + \#(\text{comments})}{\#(\text{followers})}, \tag{10}$$

where #(likes) is the number of likes, #(comments) is the number of comments, and #(followers) is the number of followers. For an account, the average *engagement rate* $\overline{E}(\mathrm{a})$ is defined as the average of all posts' $E(\mathrm{p})$, which represents the long-term level of interaction between the account and its audiences. Suppose $\tilde{\mathrm{p}}$ is the post utilized to conduct marketing campaign by a brand and a micro-influencer. Comprehensively comparing the post's $E(\tilde{\mathrm{p}})$ and the brand's $\overline{E}(\mathrm{b})$, we can analyze and quantify the endorsement effect.

We further define the *endorsement* effect score S^{ed} as:

$$S^{\mathrm{ed}} = sigmoid(\phi_1(E(\tilde{\mathrm{p}})) + \phi_2(\overline{E}(\mathrm{b}))), \tag{11}$$

where $sigmoid$ maps the S^{ed} between 0 and 1, ϕ_1 and ϕ_2 are MLP which are used to learn the adaptive weights.

$$\phi_1(E(\tilde{\mathrm{p}})) = (sigmoid(E(\tilde{\mathrm{p}})\boldsymbol{W}^{\mathrm{ed}}_1 + \boldsymbol{b}^{\mathrm{ed}}_1))\boldsymbol{W}^{\mathrm{ed}}_2, \tag{12}$$

$$\phi_2(\overline{E}(\mathrm{b})) = (sigmoid(\overline{E}(\mathrm{b})\boldsymbol{W}^{\mathrm{ed}}_3 + \boldsymbol{b}^{\mathrm{ed}}_2))\boldsymbol{W}^{\mathrm{ed}}_4, \tag{13}$$

where $\boldsymbol{W}^{\mathrm{ed}}_1, \boldsymbol{W}^{\mathrm{ed}}_3 \in \mathbb{R}^{1 \times d_{\mathrm{ed}}}$, $\boldsymbol{b}^{\mathrm{ed}}_1, \boldsymbol{b}^{\mathrm{ed}}_2 \in \mathbb{R}^{d_{\mathrm{ed}}}$, and $\boldsymbol{W}^{\mathrm{ed}}_2, \boldsymbol{W}^{\mathrm{ed}}_4 \in \mathbb{R}^{d_{\mathrm{ed}} \times 1}$.

Besides, micro-influencer influence is an important metric in micro-influencer recommendation. Micro-influencer's $\overline{E}(\mathrm{m})$ means the intensity of its influence, and #(followers) means the reach of influence. Considering both $\overline{E}(\mathrm{m})$) and #(followers), we define micro-influencer *influence* score S^{in} as:

$$S^{\mathrm{in}} = sigmoid(\phi_3(\#(\text{followers})) + \phi_4(\overline{E}(\mathrm{m}))), \tag{14}$$

where $sigmoid$ maps the S^{in} between 0 and 1, ϕ_3 and ϕ_4 are MLP which are used to learn the adaptive weights.

$$\phi_3(\#(\text{followers})) = (sigmoid(\#(\text{followers})\boldsymbol{W}^{\mathrm{in}}_1 + \boldsymbol{b}^{\mathrm{in}}_1))\boldsymbol{W}^{\mathrm{in}}_2, \tag{15}$$

$$\phi_4(\overline{E}(\mathrm{m})) = (sigmoid(\overline{E}(\mathrm{m})\boldsymbol{W}^{\mathrm{in}}_3 + \boldsymbol{b}^{\mathrm{in}}_2))\boldsymbol{W}^{\mathrm{in}}_4, \tag{16}$$

where $\boldsymbol{W}^{\mathrm{in}}_1, \boldsymbol{W}^{\mathrm{in}}_3 \in \mathbb{R}^{1 \times d_{\mathrm{in}}}$, $\boldsymbol{b}^{\mathrm{in}}_1, \boldsymbol{b}^{\mathrm{in}}_2 \in \mathbb{R}^{d_{\mathrm{in}}}$, and $\boldsymbol{W}^{\mathrm{in}}_2, \boldsymbol{W}^{\mathrm{in}}_4 \in \mathbb{R}^{d_{\mathrm{in}} \times 1}$.

2) Micro-Influencer Ranking Function: Based on the account representation $\boldsymbol{e}_{\mathrm{a}}$, for each pair of brand b_i and micro-influencer m_j, we can calculate a content-based ranking score S^{con}_{ij}:

$$S^{\mathrm{con}}_{ij} = \boldsymbol{e}^{\mathrm{b}_i}_{\mathrm{a}} \cdot \boldsymbol{e}^{\mathrm{m}_j}_{\mathrm{a}}, \tag{17}$$

where $\cdot$ is inner product. At last, we define a ranking score S by adding social media interaction information, and $F(b_i, m_j)$ can be represent as:

$$\begin{aligned} F(b_i, m_j) &= F(< b_i, m_j, S^{\mathrm{ed}}_{ij} >, S^{\mathrm{in}}_j) \\ &= \{S^{\mathrm{con}}_{ij} \times S^{\mathrm{ed}}_{ij} \times S^{\mathrm{in}}_j, Exp_{ij}\} \\ &= \{S_{ij}, Exp_{ij}\}, \end{aligned} \tag{18}$$

where S_{ij} is the ranking score, and Exp_{ij} consists of interpretability parameters $\mathbf{w}_{\mathrm{b}_i}$ and $\mathbf{w}_{\mathrm{m}_j}$, indicating the marketing direction concept weights of b_i and m_j over social media concepts, respectively.

3) Optimization: We consider the micro-influencer recommendation task as a ranking problem. A commonly used optimization function for ranking is the triplet loss [41]. For each triplet $< b_i, m_j, S^{\mathrm{ed}}_{ij} > \in \mathcal{H}$, we random sample the same amount of micro-influencer m_q to construct $< b_i, m_q, S^{\mathrm{ed}}_{iq} >$, where $m_j \in M^+_i$, $m_q \in M^-_i$, and $S^{\mathrm{ed}}_{iq} = 0$. The optimization goal is to force the $F(b_i, m_j)$ higher than the $F(b_i, m_q)$. Formally, the loss function is defined as:

$$\mathcal{L} = max(F(b_i, m_q) - F(b_i, m_j) + margin, 0). \tag{19}$$

The regularization terms are omitted here for clarity.

E. Interpretability Inference

We leverage social media concepts into social media account representation learning. Based on account historical concept distribution $\mathbf{w}_{\mathrm{a}}$, we can understand the marketing intent of brands and micro-influencers in the past period of time. Moreover, by marketing direction concept weights $\mathbf{w}_{\mathrm{m}}$ and $\mathbf{w}_{\mathrm{b}}$, we can explain brand/micro-influencer marketing direction in the current cooperation. Comprehensive consideration of $\mathbf{w}_{\mathrm{a}}$ and $\mathbf{w}_{\mathrm{b}/m}$, brands and micro-influencers are able to judge whether the marketing campaigns are suitable for self-development strategies, and then make marketing decisions. In short, the explanation consists of two parts: 1) The account historical concept distribution $\mathbf{w}_{\mathrm{a}}$ of all brands and micro-influencers are visualized as radar charts. And 2) in each recommended pair, marketing direction concept weights $\mathbf{w}_{\mathrm{m}}$ and $\mathbf{w}_{\mathrm{b}}$ can also be visualized as radar charts.

IV. Experiments

A. Dataset

We used the brand-micro-influencer dataset [5] as a part of our experiment dataset, which consists of 360 brands and 3748 micro-influencers. Besides, brands are equally divided into 12 categories[3]. For all accounts, this dataset contains their 50 posts (with visual information, textual information, the number of comments, and the number of likes), and their profiles (the number of followers and the bio description). We further split the dataset into training set with 286 brands and testing set with 74 brands. Brands in both training set and testing set cover all the 12 categories.

B. Experimental Setup

Our model[4]. is trained using Adam optimizer. We set a learning rate as 0.001 and a decay as 0.95 for every epoch. We trained our model for 40 epochs and used a batch size of 8. A dropout layer with the rate of 0.6, and a margin score of 7.0 are applied. We initialized all of the neural network parameters with the uniform distribution between -0.1 and 0.1. Both ψ and ρ are 2-layer MLP, with hidden layers' length are 1024 and 512. γ is three-layer fully-connected layer, and the hidden layers' length are 1024, 1024, and 512. ϕ_1, ϕ_2, ϕ_3, and ϕ_4 are all two-layer MLP. d_{ed} and d_{in}'s length are both 64. We used leaky ReLU as the activation function in ψ, ρ, and γ, and sigmoid as the activation function in ϕ_1, ϕ_2, ϕ_3, and ϕ_4. The sizes of $\mathbf{w}_{\mathrm{b}}$ and $\mathbf{w}_{\mathrm{m}}$ are set to 10. We set the dimensions of all $\boldsymbol{e}_{\mathrm{h}}$, $\boldsymbol{e}_{\mathrm{r}}$, and $\boldsymbol{e}_{\mathrm{a}}$ as 100, 100, and 512. We tuned the L1 regularization with the regularization rate of 0.001 in experiments.

C. Post-Concept Dataset Construction

First, we collected trending social media hashtags from hashtag analysis website,[5] where the hashtags are associated with 12 categories in the brand-micro-influencer dataset. Second, based on these hashtags, we crawled 40 000 posts from Instagram and EyeEm[6]. Third, we used the multi-label generator from EyeEm to generate labels for the 40 000 posts, where 3242 labels were obtained in total and each post has a varying number of labels. Fourth, considering these labels are not all reliable, we conducted a manual tagging to choose the useful social media concepts from these labels. Participants were asked to select the concepts related to the 12 categories mentioned above. Moreover, the chosen concepts must be able to reflect the objects, actions, styles, and scenes of social media content. Fifth, we collected 420 social media concepts to represent the brands and micro-influencers, which are high-level semantic concepts of posts. Finally, after deleting the unselected labels in 40 000 posts, we obtained the post-concept dataset where each post has a group of social media concepts.

[3]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/Micro-influencer-Recommendation

[5]https://hashtagify.me/.

[6]https://www.eyeem.com/.

D. Concept Generation

Based on the post-concept dataset, we trained a multi-label post classification as concept generator. By using this concept generator, all posts in the brand-micro-influencer dataset are labeled with several social media concepts, where each post has an average of 10 concepts, and each account has an average of 20 concepts.

E. Baselines

In order to demonstrate the effectiveness of our proposed method, we adopted the following methods as baselines: 1) RAND is a random score generation method for each brand micro-influencer pair. 2) MIV is a method to evaluate the influence of the influential bloggers in the blogosphere [21]. Considering the task difference, we adopted the activeness-based factors module to evaluate the influence. 3) MIR is a modified listwise learning to rank model, which can predict ranking scores for the given brand [5]. 4) Bp+MR is the combination of a compact bilinear pooling representation learning method [42] and our micro-influencer ranking method. 5) Hp+MR is the combination of a multi-modal history pooling representation learning method [5] and our micro-influencer ranking method. 6) Vl+MR is the combination of a multi-modal fusion representation learning method [43] and our micro-influencer ranking method. 7) C-w/o-SI is CAMERA without semantic attention when learning the social media concept representation. And 8) C-w/o-MR is CAMERA without micro-influencer ranking module.

F. Evaluation Metrics

We introduced AUC, cAUC, Recall@k, MRR, MAP, and MedR to evaluate the recommendation performance. AUC is the probability that a positive example's ranking score is higher than that of a negative example; cAUC is the AUC where the positive and negative examples belong to the same category; R@k is the fraction of positive examples that have been recommended in top k over the total amount of top k examples; MRR is mean reciprocal rank; MAP is mean average precision; and MedR is the median position of the first positive example. The lower MedR is, the better the performance is. It is worth noting that we discarded the metric Precision@k, since this dataset only has 11 positive micro-influencers for each brand in average.

G. Recommendation Performance Analysis

1) CAMERA vs Baselines: As shown in Table II, our proposed CAMERA outperforms C-w/o-SI, verifying the effectiveness of semantic information. CAMERA outperforms C-w/o-MR shows the effectiveness of micro-influencer ranking module. Meanwhile, our proposed CAMERA significantly outperforms RAND and MIV on all metrics, which indicates that simply measuring the influencers' influence for recommendation does not work. Compared to MIR, Bp+MR, Hp+MR, and Vl+MR, our model increases 43.7% in R@10, 59.7% in MRR, 29.1% in MAP, and 3 positions in MedR, while decreases 1.4% in R@50, and 4.5% in AUC. The significant improvement on R@10, MRR, and MedR shows how our model performs in the top

TABLE I
TABLE OF NOTATION

Notation	Description
$\mathcal{A}$	Social media accounts set
a, b, m	Account, brand and micro-influencer
$\mathcal{P}$	Social media posts set
$P_{a/b/m}$	Account post set, and $P_{a/b/m} \subset \mathcal{P}$
p	A post of an account, and $p \in P_a$
$\mathcal{C}$	Social media concepts set
$C_{a/b/m}$	Account concept set, and $C_{a/b/m} \subset \mathcal{C}$
C_p	Social media concept set of a post
c	Social media concept, and $c \in \mathcal{C}$
M_x^+, M_x^-	Positive/negative examples of brand b_x
$\mathcal{H}$	Historical cooperation information set
U_C	Concept matrix belongs to $\mathbb{R}^{n \times d_\mathrm{u}}$
$U_{a/b/m}$	Account concept representation set
$\boldsymbol{u}$	Social media concept representation
S_{ij}^{ed}	*Endorsement* effect score between b_i and m_j
S_j^{in}	*Influence* score of m_j
S_{ij}^{con}	Content-based ranking score of b_i and m_j
S_{ij}	Ranking score of b_i and m_j
$\boldsymbol{e}_\mathrm{h}$	Account historical activities representation
$\boldsymbol{e}_\mathrm{r}$	Account marketing direction representation
$\boldsymbol{e}_\mathrm{a}$	Social media account representation
Exp_{ij}	Interpretability parameters
$\mathbf{w}_\mathrm{a}$	Account a's historical concept distribution
$\mathbf{w}_{\mathrm{b}/m}$	Marketing direction concept weights of b/m

TABLE II
RECOMMENDATION PERFORMANCE ON ALL METHODS

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
Bp+MR	0.806	0.671	0.124	0.383	0.377	0.161	5
Hp+MR	0.812	0.675	0.141	0.416	0.363	0.154	5
Vl+MR	0.808	0.665	0.144	0.420	0.372	0.165	6
C-w/o-SI	0.789	0.653	0.130	0.350	0.368	0.153	7
C-w/o-MR	0.779	0.635	0.073	0.313	0.259	0.098	8
CAMERA	0.810	**0.678**	**0.207**	0.422	**0.602**	**0.213**	**2**

ranked micro-influencers. But the performance on R@50 and AUC shows that mid-ranked micro-influencers are not well differentiated. Considering the improvement in recommendation interpretability, we believe this sacrifice is acceptable.

2) Performance on Different Categories: To study how the proposed method performs with respect to different categories, we further conducted a experiment and reported the recommendation performance based on each category. As shown in Table III, Category Auto and Clothes observe better performance compared to other categories. After analyzing the social media concepts that appeared in these two categories, we found that the high frequent concepts are in line with our speculation of the corresponding brands. For example, concepts *car*, *motorcycle*, and *road* appear frequently in Category Auto; concepts like *fashion*, *beauty*, and *clothes* that appear frequently in Category Clothes. On the contrary, the social media concepts appeared in Category Electronics and Jewelry are relatively ambiguous, since it is difficult to describe the characteristics of such brands. For example, the frequent concepts in Category Electronics are *nature_landscape*, *building_exterior*, and *travel*. Actually, *nature_landscape* and *travel* are related to photography. For Category Nonprofit, the frequent concepts are *nature_landscape*, *sky*, and *sport*, where *nature_landscape* and *sky* relate to environmental organizations. And *sport* is related to social organizations, which provides physical education for kids. But the connection between social media concepts and brands speculation is not straightforward. Similarly, for Category Jewelry, the most frequent concepts are *luxury* and *fashion* rather than *wristwatch* and *ring*. We think it might be the reason why Category Electronics, Nonprofit and Jewelry perform worse than the others. However, the difficulty of generating concepts varies greatly for different categories. How to improve the accuracy of concept generation is of great value for future investigation.

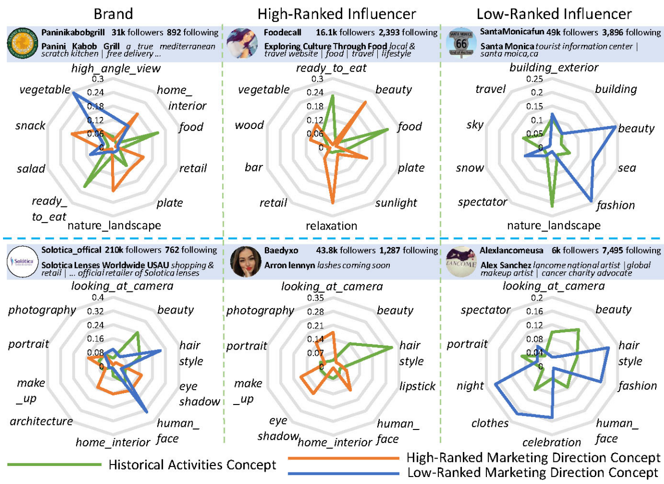
TABLE III
PERFORMANCE ON ALL BRAND CATEGORIES

Category	AUC	cAUC	R@10	R@50	MRR	MAP	MedR
Airline	0.821	0.605	0.234	0.395	0.523	0.224	2
Auto	0.873	0.591	**0.329**	0.545	**0.857**	**0.323**	**1**
Clothes	**0.915**	**0.826**	0.180	0.487	0.618	0.301	**1**
Drink	0.768	0.697	0.201	0.371	0.589	0.162	**1**
Electr.	0.680	0.641	0.089	0.250	0.282	0.069	9
Entert.	0.803	0.663	0.245	0.419	0.741	0.252	**1**
Food	0.834	0.686	0.256	0.407	0.783	0.276	**1**
Jewelry	0.683	0.607	0.169	0.298	0.467	0.160	2
Makeup	0.878	0.734	0.231	0.565	0.806	0.261	**1**
Nonprofit	0.730	0.624	0.116	0.243	0.356	0.106	3
Shoes	0.819	0.691	0.254	**0.601**	0.722	0.262	**1**
Services	0.827	0.725	0.152	0.469	0.451	0.136	2

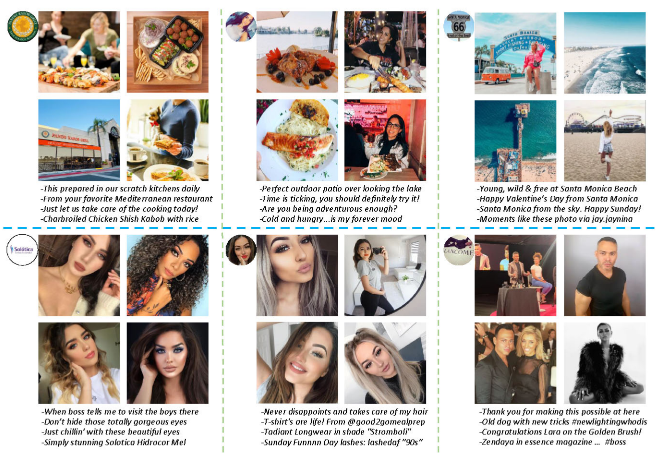
H. Recommendation Interpretability Analysis

1) Case Study: We demonstrated the interpretability of our proposed method with a case study as shown in Figure 4. Figure 4 (a) illustrates two sets of concept-based radar charts, where each row consists of a brand, a high-ranked micro-influencer and a low-ranked micro-influencer. Both brand and micro-influencer have a historical activities concept chart and a marketing direction concept chart. The former shows the historical concept weight distribution in the account, and the latter shows the marketing direction concept weight of the account. According to the two kinds of charts, brands and micro-influencers can judge whether marketing activities are in line with their self-development strategies. Figure 4 (b) shows part of accounts' content with images and corresponding texts to give a better sense of how these concepts related to these accounts.

In Example 1, the highly ranked micro-influencer (8/797) is a beauty who loves food and travel, and the brand is a restaurant. As shown in the brand historical activities concept chart, concepts *food*, *ready_to_eat*, *home_interior*, and *high_angle_view* represent that this account often uploads some posts of customers eating indoors. Similarly, according to the



(a) Concept-based radar charts.



(b) Part of accounts' content with images and corresponding texts.

Fig. 4. Case study for interpretability analysis.

micro-influencer historical activities concept chart, we can observe that this blogger likes to post food she eating when traveling. Besides, concepts *wood*, *sunlight*, and *bar* are some scenes in her travels. Unexpectedly, we find concepts such as *food* and *ready_to_eat* are not the main factors of recommendation. The reason may because she is a beauty who loves vegetables and has a relaxed attitude to life. Such people may be more likely to be trusted by customers, more benefiting the restaurant marketing. For the restaurant, the brand marketing direction concept chart shows that concepts *snack*, *vegetable*, *home_interior*, and *nature_landscape* are the main reason for the recommendation. We think snacks and vegetables are more in line with the blogger's eating preferences. Further, the high weight of *nature_landscape* reflects the style of combining beautiful scenery and food in this restaurant, which matches the blogger's habit. Meanwhile, the low-ranked micro-influencer (164/797) is a tourist information blogger who introduces famous tourist sites to followers. Obviously, the marketing direction concept charts of them are less meaningful, therefore, the blogger is not a good choice for the restaurant. However, it is worth mentioning that this micro-influencer is a positive example of the brand. Thus, it means the useless endorsement information is not adopted in the model learning, which demonstrates the robustness of our model.

In Example 2, a female makeup artist is recommended to a cosmetic brand, and she is the highly ranked micro-influencer (3/797). The concepts *beauty*, *hairstyle*, and *human_face* account for the largest proportion from the brand historical activities concept chart. This is because the brand often uploads posts like the selfie of a woman with makeup. From the brand marketing direction concept chart, we further observed the concepts *human_face*, *portrait*, *eyeshadow*, *home_interior*, and *architecture* have high weights, where *human_face*, *portrait*, and *eyeshadow* are closely related to cosmetics and makeup, which might be the reason why the makeup artist is willing to cooperate with this brand. *home_interior* and *architecture* may indicate the background environment in some selfies with makeup. For the makeup artist, after analyzing the micro-influencer historical activities concept chart, we can know she is a beautiful lady who is good at makeup and likes to upload selfies. According to the marketing direction concept chart, we concluded that she is recommended because she often displays cosmetics and makeup techniques in selfies. The reason why the cosmetic brand and the makeup artist choose each other is quite consistent, which means that such cooperation is beneficial to both parties. Meanwhile, the low-ranked micro-influencer (73/797) is a male makeup artist, whose main job is to do makeup for women. He usually posts pictures of himself, and sometimes posts selfies of himself trying on cosmetics. Therefore, concepts *beauty*, *portrait*, and *look_at_camera* are the mainstream in his historical activities concept chart. From his marketing direction concept chart, we can find that the reason for the recommendation is not sufficient, since concepts *celebration*, *clothes*, *hairstyle*, and *night* are less related to the brand speculation. Although both high ranked and low ranked micro-influencers are makeup artists in this example, different marketing directions show that our model has fine-grained interpretability and discrimination capability.

2) User Study on the Effectiveness of Social Media Concept: We designed a user study to verify the effectiveness of social media concepts on the micro-influencer recommendation. We recruited 30 participants (ages 18 to 30), and all participants are experienced social media users. The whole study lasts 40 to 60 minutes. This study is divided into two tasks. For each task, we assigned 12 choice questions which all have four options. In each choice question, participants should choose one correct answer. Meanwhile, they also need to evaluate the options from "Easy to understand", "Comprehensive" or "Reasonable". And the evaluation is on a five-point scale (very poor, poor, borderline, good, and very good). At the beginning of each task, the participants received a 5-minute tutorial on how to answer.

Task I is intended to test whether social media concepts can well represent the marketing traits of social media accounts. In other words, we would like to figure out whether the concepts of an account are consistent with its historical activities. In each choice question, an account profile is presented to users. And they should pick out the corresponding historical activities concept chart of this account and evaluate all options. With four options, one is the right answer, and another one is an account

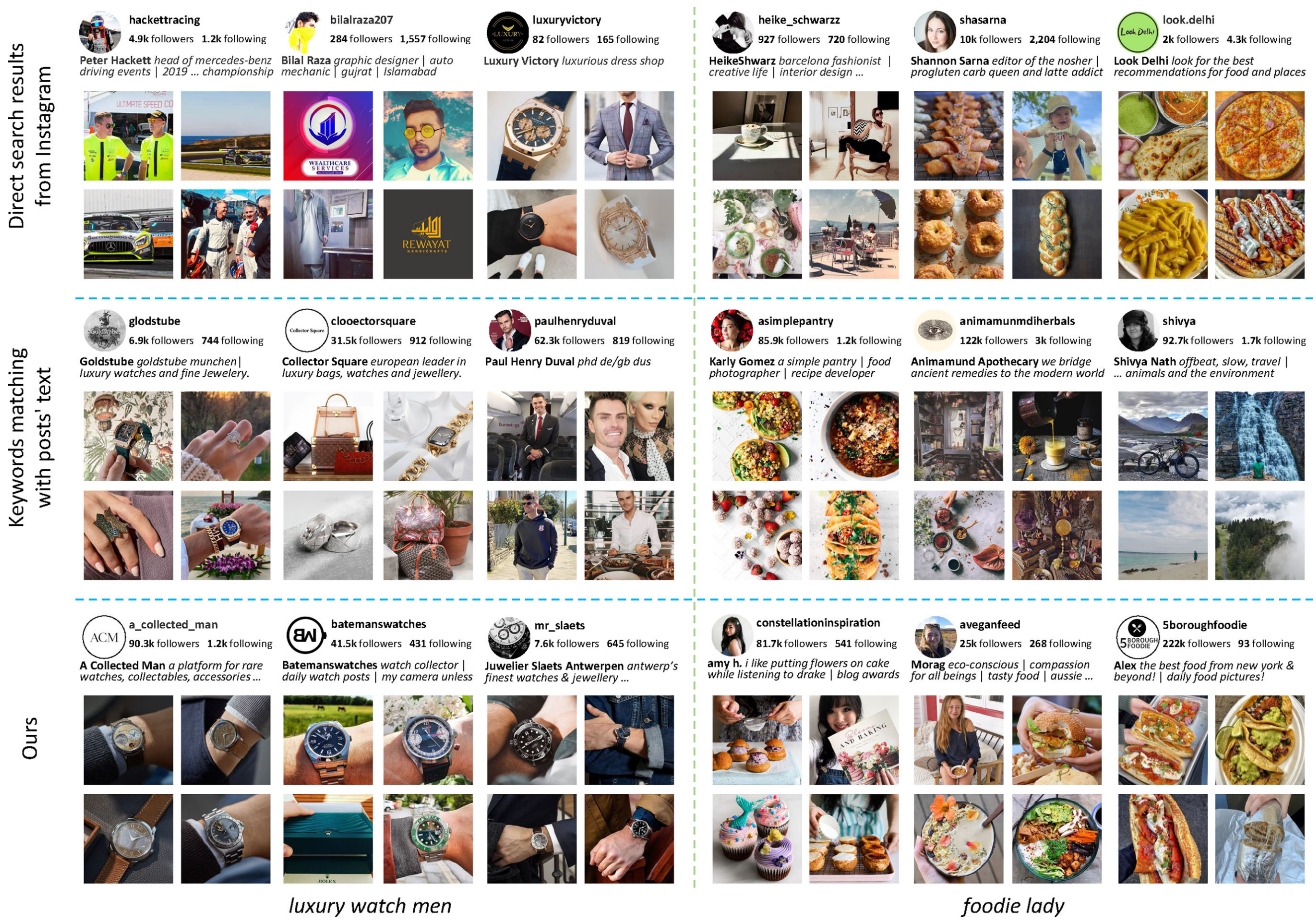


Fig. 5. A demonstration of the keywords-based micro-influencer search.

TABLE IV
USER STUDY ON THE EFFECTIVENESS OF SOCIAL MEDIA CONCEPTS. ACC: "ACCURACY"; ACC*: "ACCURACY" OF THE CONTROL GROUP; COMP: "COMPREHENSIVE"; ETU: "EASY TO UNDERSTAND"; REAS: "REASONABLE"

Task	Acc	Acc*	Comp	ETU	Reas
I	0.947	-	4.311	3.861	-
II	0.886	0.736	-	3.944	3.886

that belongs to the same category with the right answer. The others are accounts that belongs to different categories. As shown in Table IV, the "Accuracy" of Task I is 0.947, and the average rate of "Comprehensive" and "Easy to understand" of the right answers are 4.311 and 3.861, respectively, which proves that historical concept distribution weights can represent accounts' historical activities successfully in most cases.

Task II is intended to figure out whether social media concepts are helpful for users to understand the marketing direction. Profile and historical activities concept chart of a brand/micro-influencer are presented to users in each choice question. The experimental group and the control group are set in this task. In the experimental group, four marketing direction concept charts of micro-influencers/brands are given. The correct answer is the highest-ranked candidate. Users are asked to choose one of four candidates which is the most suitable to cooperate with the given brand/micro-influencer. Meanwhile, they should evaluate all options from "Reasonable" and "Easy to understand". In the control group, four marketing direction concept charts of the candidates are replaced by their profiles, and all other data are the same as the experimental group. Especially, users are not told that the candidates in the experimental group are the same as those in the control group. Experiment results show that the "Accuracy" of the experimental group increases 0.150 compared to that of the control group. Besides, the "Easy to understand" average rate and "Reasonable" average rate of the right answers are 3.944 and 3.886, respectively. By controlling variables, we found that marketing direction concept chart is helpful to recognize the higher-ranked recommendation result. Therefore, we concluded that marketing direction concept weights provide a reliable basis for users to make the right marketing decisions.

3) Keywords-Based Micro-Influencer Search: Searching for specific micro-influencers based on brands' needs is a critical function, while traditional social media platforms did not well-support this operation. For example, searching directly from Instagram may result in several unrelated private accounts. Meanwhile, multi-keyword search usually returns empty results. As a byproduct, we implemented the function of searching for micro-influencers with keywords. Specifically, we calculated the word similarity between the keywords and the social media concepts for each micro-influencer, and returned a weighted score for the matching. We also compared our method with two baselines: "direct search results from Instagram" and "keywords matching with posts' text". Two sets of keywords are used for this experiment: {*luxury, watch, men*} and {*foodie, lady*}.

We showed the Top-3 retrieved micro-influencers in Figure 5. The results of the retrieved micro-influencers in our method are highly consistent with the keywords. For example, the Top-3 retrieved micro-influencers of {*luxury, watch, men*} are male wristwatch-lovers who often share pictures of the wristwatch. And the Top-3 retrieved micro-influencers of {*foodie, lady*} are beautiful ladies who like to share food on social media. In comparison, the results of the two baselines are not satisfactory: there is a female wristwatch-lover and a sportscar-lover when searching for {*luxury, watch, men*}; a travel-lover and a fashion designer are retrieved when searching for {*foodie, lady*}. Moreover, when the number of keywords increases to add more constraint to the query, the two baselines returns empty results (e.g., {*food, tasty, delicious*} and {*cosmetic, eye, shadow, eyelash*}).

V. Conclusions and Future Works

In this work, we proposed the CAMERA to address the problems of marketing effectiveness and self-development needs together in the micro-influencer recommendation task. In order to improve marketing effectiveness, social media concepts are leveraged to learn social media account representation from the perspective of historical activities and marketing direction. And we employed social media interaction information on defining two adaptive learned metrics, which are utilized to learn a micro-influencer ranking function. Meanwhile, to meet self-development needs, we also designed the BCAM to focus on brands' and micro-influencers' marketing direction. Brands and micro-influencers can use interpretable historical activities and marketing direction parameters to make marketing decisions. At last, we proposed a new scenario of using our proposed model to search for specific micro-influencers with keywords. The extensive evaluation demonstrates the effectiveness and satisfying interpretability of our method. In the future, we will dedicate to generate high-quality concepts by overcoming the semantic gap between different brand categories. Also, we want to model social media information in a more comprehensive way. For instance, audience information is beneficial for us to gain a better understanding of social media accounts.

References

[1] Q. Fang, J. Sang, C. Xu, and Y. Rui, "Topic-sensitive influencer mining in interest-based social media networks via hypergraph learning," *IEEE Trans. Multimedia*, vol. 16, no. 3, pp. 796–812, Apr. 2014.

[2] C. Ashley and T. Tuten, "Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement," *Psychol. Marketing*, vol. 32, no. 1, pp. 15–27, 2015.

[3] N. Zietek, "Influencer marketing: The characteristics and components of fashion influencer marketing," Ph.D. dissertation, University of Boras, Faculty of Textiles, Engineering and Business, 2016.

[4] T. Sweet, A. Rothwell, and X. Luo, "Machine learning techniques for brand-influencer matchmaking on the instagram social network," 2019, *arXiv:1901.05949*.

[5] T. Gan *et al.*, "Seeking micro-influencers for brand promotion," in *Proc. ACM Int. Conf. Multimedia*, 2019, pp. 1933–1941.

[6] N. Michaelidou, N. T. Siamagka, and G. Christodoulides, "Usage, barriers and measurement of social media marketing: An exploratory investigation of small and medium b2b brands," *Ind. Marketing Manage.*, vol. 40, no. 7, pp. 1153–1159, 2011.

[7] R. Dolan, J. Conduit, J. Fahy, and S. Goodman, "Social media engagement behaviour: A uses and gratifications perspective," *J. Strategic Marketing*, vol. 24, no. 3-4, pp. 261–277, 2016.

[8] L. G. Gilbert, C. Childers, and B. Boatwright, "Fyre festival: the good, the bad, the ugly and its impact on influencer marketing," Chancellor's Honors Program Projects, 2020. [Online]. Available: https://trace.tennessee.edu/utk_chanhonoproj/2320

[9] I. M. Hub, "The state of influencer marketing 2019: Benchmark report," *Influencer Marketing Hub*, 2019. [Online]. Available: https://influencermarketinghub. com/influencer-marketing-2019-benchmark-report/

[10] R. Felix, P. A. Rauschnabel, and C. Hinsch, "Elements of strategic social media marketing: A holistic framework," *J. Bus. Res.*, vol. 70, pp. 118–126, 2017.

[11] S. Woods, "# Sponsored: The emergence of influencer marketing," Chancellor's Honors Program Projects, 2016. [Online]. Available: https://trace.tennessee.edu/utk_chanhonoproj/1976

[12] A. Narassiguin and S. Sargent, "Data Science for influencer marketing : feature processing and quantitative analysis," 2019, *arXiv:1906.05911*.

[13] F. Gelli, T. Uricchio, X. He, A. D. Bimbo, and T. Chua, "Beyond the product: Discovering image posts for brands in social media," in *Proc. ACM Int. Conf. Multimedia*, 2018, pp. 465–473.

[14] Y. Zhang, X. Wang, Y. Sakai, and T. Yamasaki, "Measuring similarity between brands using followers' post in social media," in *Proc. ACM Multimedia Asia*, 2019, pp. 1–6.

[15] M. Bonomo, G. Ciaccio, A. D. Salve, and S. E. Rombo, "A semantic approach for user-brand targeting in on-line social networks," 2019, *arXiv:1907.01326*.

[16] J.-V. Cossu, N. Dugué, and V. Labatut, "Detecting real-world influence through twitter," in *Proc. IEEE Eur. Netw. Intell. Conf.*, 2015, pp. 83–90.

[17] A. Rao, N. Spasojevic, Z. Li, and T. Dsouza, "Klout score: Measuring influence across multiple social networks," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, 2015, pp. 2282–2289.

[18] M. Cha, H. Haddadi, F. Benevenuto, and K. P. Gummadi, "Measuring user influence in twitter: The million follower fallacy," in *Proc. Int. AAAI Conf. weblogs social media*, vol. 4, no. 1, 2010, pp. 10–17.

[19] N. Segev, N. Avigdor, and E. Avigdor, "Measuring influence on instagram: A network-oblivious approach," in *Proc. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval*. ACM, 2018, pp. 1009–1012.

[20] I. Anger and C. Kittl, "Measuring influence on twitter," in *Proc. Int. Conf. Knowl. Manage. Knowl. Technol.*ACM, 2011, pp. 1–4.

[21] Y.-M. Li, C.-Y. Lai, and C.-W. Chen, "Discovering influencers for marketing in the blogosphere," *Inf. Sci.*, vol. 181, no. 23, pp. 5143–5157, 2011.

[22] Y. Zhang and X. Chen, "Explainable recommendation: A survey and new perspectives," Found. *Trends Inf. Retr.*, vol. 14, no. 1, pp. 1–101, 2020.

[23] J. Gao, X. Wang, Y. Wang, and X. Xie, "Explainable recommendation through attentive multi-view learning," in *Proc. AAAI Conf. Artif. Intell.*, 2019, pp. 3622–3629.

[24] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Comput. Surv.*, vol. 52, no. 1, pp. 5: 1–5:38, 2019.

[25] L. H. Gilpin *et al.*, "Explaining explanations: an approach to evaluating interpretability of machine learning," 2018, *arXiv:1806.00069*.

[26] M. T. Ribeiro, S. Singh, and C. Guestrin, "Model-Agnostic Interpretability of Machine Learning," 2016, *arXiv preprint arXiv:1606.05386*.

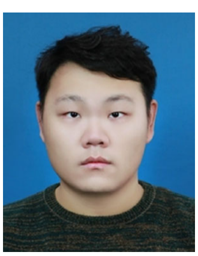
[27] G. Peake and J. Wang, "Explanation mining: Post hoc interpretability of latent factor models for recommendation systems," in *Proc. ACM Int. Conf. Knowl. Discov. Data Mining*, 2018, pp. 2060–2069.

[28] M. Du, N. Liu, and X. Hu, "Techniques for interpretable machine learning," *Commun. ACM*, vol. 63, no. 1, pp. 68–77, 2020.

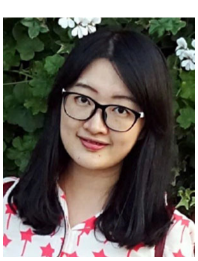
[29] X. Han, X. Song, J. Yin, Y. Wang, and L. Nie, "Prototype-guided attribute-wise interpretable scheme for clothing matching," in *Proc. Int. Conf. Res. Develop. Inf. Retrieval*. ACM, 2019, pp. 785–794.

[30] M. Hou *et al.*, "Explainable fashion recommendation: A semantic attribute region guided approach," in *Proc. Int. Joint Conf. Artif. Intell.*, 2019, pp. 4681–4688.

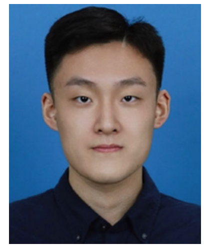
[31] X. Luo *et al.*, "AliCoCo: Alibaba e-commerce cognitive concept net," in *Proc. Int. Conf. Manage. Data*. ACM, 2020, pp. 313–327.
[32] Q. Fang, J. Sang, C. Xu, and M. S. Hossain, "Relational user attribute inference in social media," *IEEE Trans. Multimedia*, vol. 17, no. 7, pp. 1031–1044, Jul. 2015.
[33] H. Wu *et al.*, "Mining unfollow behavior in large-scale online social networks via spatial-temporal interaction," in *Proc. AAAI Conference Artificial Intelligence*, 2020, pp. 254–261.
[34] Y. Gao, Y. Zhong, D. Preotiuc-Pietro, and J. J. Li, "Predicting and analyzing language specificity in social media posts," in *Proc. AAAI Conf. Artif. Intell.*, 2019, pp. 6415–6422.
[35] Q. Fang, C. Xu, J. Sang, M. S. Hossain, and G. Muhammad, "Word-of-mouth understanding: Entity-centric multimodal aspect-opinion mining in social media," *IEEE Trans. Multimedia*, vol. 17, no. 12, pp. 2281–2296, Dec. 2015.
[36] Z. Hussain *et al.*, "Automatic understanding of image and video advertisements," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 1100–1110.
[37] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," in *Proc. Int. Conf. Learn. Representations, ICLR*, 2013, *arXiv:1301.3781*.
[38] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, Oct. 2010.
[39] H. Chen, G. Ding, Z. Lin, S. Zhao, and J. Han, "Cross-modal image-text retrieval with semantic consistency," in *Proc. ACM Int. Conf. Multimedia*. ACM, 2019, pp. 1749–1757.
[40] L. Hollebeek, R. Srivastava, and T. Chen, "S-D logic-informed customer engagement: Integrative framework, revised fundamental propositions, and application to crm," *J. Acad. Marketing Sci.*, vol. 47, pp. 161–185, 2019.
[41] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," 2015, *arXiv:1503.03832*.
[42] A. Fukui *et al.*, "Multimodal compact bilinear pooling for visual question answering and visual grounding," 2016, *arXiv:1606.01847*.
[43] M. Ren, R. Kiros, and R. S. Zemel, "Image question answering: a visual semantic embedding model and a new dataset," 2015, *arXiv:1505.02074*.



Shaokun Wang received the B.Eng., degree in 2018 from Shandong University, Jinan, China, in 2018, where he is currently working toward the master's degree. His main research interests include social media marketing and multimedia computing.



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



Yuan Liu is currently an Undergraduate Student with the School of Computer Science and Technology, Shandong University, Jinan, China. He is also a Research Assistant with Intelligent Media Research Center, Shandong University. His research interests include recommendation system and natural language processing.

Li Zhang received the Ph.D. degree from the School of Computing, National University of Singapore, Singapore, in 2015, major in machine learning and related application in computer vision and natural language processing. He is currently leading a R&D team in Alibaba, working on user content, POI and products understanding for search optimization using computer vision and NLP technology.

Jianlong Wu received the B.Eng., and Ph.D. degrees from the Huazhong University of Science and Technology, Wuhan, China, in 2014 and Peking University, Beijing, China, in 2019, respectively. He is currently an Assistant Professor with the School of Computer Science and Technology, Shandong University, Jinan, China. He has authored or coauthored more than 20 research papers in top journals and conferences, including IEEE TRANSACTIONS ON IMAGE PROCESSING, ICML, NeurIPS, and ICCV. His research interests include computer vision and machine learning, especially weakly supervised learning. He is a Senior Program Committee Member of IJCAI 2021, the Area Chair of the ICPR 2020, and a Reviewer for many top journals and conferences, including IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, *International Journal of Computer Vision*, ICML, and ICCV.

Liqiang Nie (Member, IEEE) received the B.Eng., degree from Xi'an Jiaotong University, Xi'an, China, in 2009 and the Ph.D. degree from the National University of Singapore, Singapore, 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, Jinan, China. Meanwhile, he is the Adjunct Dean of Shandong AI Institute. He has authored or coauthored about 100 papers in the top conferences or journals, with more than 9600 Google Scholar citations. His research interests include multimedia computing and information retrieval. He was the recipient of various awards, including the SIGIR 2019 Best Paper honorable mention, the ACM SIGMM Rising Star 2020, the Green Orange Award 2020 of Alibaba DAMO Academy, the AI 2000 the most influential scholar in artificial intelligence and MIT TR35 China. He is an Associate Editor for the *IEEE TRANSACTIONS ON MULTIMEDIA*, *IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING*, *ACM TRANSACTIONS ON MULTIMEDIA COMPUTING, COMMUNICATIONS, AND APPLICATIONS*, and *Information Science*. He is the PC Chair of ICIMCS 2017, PCM 2018, and ChinaMM 2020 and the Area Chair of ACM MM 2018-2021.