Research on the Construction of Social Media User Profiles and Resource Aggregation Models (Postprint)

Authors: Xu Hailing, Zhang Haitao, Wei Mingzhu, Yin Huizi

Date: 2023-07-26T00:00:00+00:00

Abstract

[Purpose/Significance] This study creates a social media resource aggregation model based on user profiling to provide a reference for resource aggregation and to enrich and expand its theoretical research framework. [Method/Process] Building upon an in-depth analysis of the connotation and algorithms of user profiling, this research constructs separate models for user profiling and resource profiling based on social media platforms. Employing social tagging system methodologies, it investigates the mapping relationship between user profiling and resource profiling in the context of social media. Drawing upon domain ontology approaches, and through deep-level data mining, it utilizes the principles of resource aggregation to construct both internal and external resource aggregation models for social media based on resource profiling. [Results/Conclusions] In the era of big data, the relevant theories and methods based on user profiling and resource profiling can provide novel insights for resource aggregation in social media.

Full Text

Preamble

Research on the Construction of Social Media User Portraits and Resource Aggregation Models

Xu Hailing[1], Zhang Haitao[1,2], Wei Mingzhu[1], Yin Huizi[1]

[1]School of Management, Jilin University, Changchun 130022
[2]Information Resources Research Center, Jilin University, Changchun 130022

Abstract

[**Purpose/Significance**] This paper creates a social media resource aggregation model based on user portraits, providing a reference for resource aggregation and enriching and expanding its theoretical research system. [**Method/Process**] Based on an in-depth analysis of the connotation and algorithms of user portraits, this study constructs models for both user portraits and resource portraits in the context of social media. Using the social tagging system method, it investigates the mapping relationship between user portraits and resource portraits on social media platforms. Drawing on domain ontology methods and through deep data mining, it constructs both internal and external social media resource aggregation models based on resource portraits. [**Result/Conclusion**] In the era of big data, relevant theories and methods based on user portraits and resource portraits can provide new ideas for social media resource aggregation.

Keywords: user portrait; social media; resource portrait; resource aggregation
Classification Number: G252
DOI: 10.13266/j.issn.0252-3116.2019.09.012

With the advent of the Internet of Things, cloud computing, big data, and artificial intelligence, social platforms have become highly relied upon by people. In an open environment, users are not only consumers of resources but also creators and sharers. As user information behavior trails become easier to capture and user data more accessible, providing precise, objective, and dynamic services based on user needs has become increasingly important, emerging as a frontier and hot topic among scholars. With the rise of social networks, communities such as Weibo, WeChat, and Douban have developed rapidly. Through social websites, users can not only stay informed about world affairs but also find interesting audiovisual information without leaving home. As the number of social media users increases annually, meeting diverse and personalized service needs has become a pursued goal. In light of this, this study attempts to analyze the resource characteristics of social media by drawing on previous experiences and findings. By deeply mining user behavior data, it constructs user portraits and resource portraits for social media. Based on integrating the components of user behavior, it builds a social media resource aggregation model, primarily divided into internal and external resource aggregation models, providing a new approach and attempt for research and application in user information resource aggregation and push services. The logical framework of this paper is shown in Figure 1 [Figure 1: see original paper].

2. Literature Review

With the quiet rise of artificial intelligence and big data, research in the field of user portraits has gradually become a hot topic among scholars, yielding certain research achievements. Yang Fan [1] constructed a big data platform for libraries from the perspective of reader portraits and resource portraits to provide precise services for library users. Wang Shunqing [2] analyzed library user needs and provided differentiated recommendation services based on user interests and hobbies. Yin Xiangquan et al. [3] modeled and analyzed library user data to identify the main factors influencing user behavior. K. Petric et al. [4] developed a mental model of web users based on adaptive knowledge management methods, enabling classification of different user groups. Cheng Quan [5] explored the basic model of digital library information services based on user portraits, providing scientific decision-making for precise digital library information services. Wang Lingxiao et al. [6] constructed user portraits for social Q&A communities from four aspects: user qualifications, user participation, answer quality, and user development trends. Shan Xiaohong et al. [7] built a conceptual model of Ctrip hotel user portraits from three dimensions: user trust attributes, hotel information attributes, and user review information attributes. Huang Wenbin et al. [8] constructed a research framework for data-driven mobile user behavior from several perspectives, including mobile data types, mobile user behavior patterns, construction of mobile user portraits, and deep application of mobile user portraits. Hao Shengyu et al. [9] elaborated on user portrait technology and its important role in enterprise precision marketing from aspects such as target customer identification, target customer scanning, consumption anomalies, and precise push. Pei Guocai [10] designed and implemented a precision marketing model through user portrait methods. Wang Xiaoxia et al. [11] utilized big data technology to precisely cluster users and thereby depict user portraits. Sheng Yijin [12] applied user portrait technology to academic journal reviewer selection and constructed a reviewer portrait model. Xiong Wei et al. [13] collected user information, classified user groups, used LDA to analyze webpage content to establish topic models, and proposed a service redirection method based on user portraits and content. Zhang Shijun et al. [14] proposed a method for constructing customer portraits from power big data based on user portrait theory and technology. Gao Yang et al. [15] constructed talent portraits in the intelligent manufacturing field, revealing the significant characteristics of outstanding talents in this domain.

Through reviewing relevant literature, it is evident that current user portrait research covers a broad range of fields, primarily concentrated in library science, social media, computer science, and marketing, with relatively singular research methods dominated by empirical studies. Therefore, this study attempts to build upon previous research achievements by implementing user portrait and resource portrait characterization based on the social media platform, establishing a mapping relationship between the two, focusing on constructing an internal resource aggregation model within the platform while also creating a cross-platform resource aggregation model across different social media networks. This provides a reference for information resource push on user intelligent terminals and offers theoretical support for related research in this field.

3. Overview of User Profiling Research

3.1 Connotation of User Portraits

As user behavior trails become easier to capture and providing precise, dynamic information becomes increasingly important, the application scope of user portraits continues to expand, gradually extending from the most traditional user personas (persona) in marketing to user profiling in social media and other fields.

3.2 Research Themes, Theoretical Models, and Algorithms

Through reviewing relevant papers on user portraits, current research themes can be broadly categorized into several areas: Weibo [16], mobile libraries [17], enterprise marketing, social Q&A communities [6], e-commerce [18], healthcare, and finance. The primary models for user portraits include the Markov Random Field model and logistic regression model. The main theories encompass Social Identity Theory [16], Complex Adaptive Systems Theory, and Game Theory. Related algorithms consist of Analytic Hierarchy Process [19], clustering algorithms [20], Support Vector Machines, Naive Bayes classification [21], correlation analysis, decision tree analysis, and neural network analysis [22], as shown in Table 1 .

3.3 User Tagging System

The scholar who first proposed user portraits (persona) was Alan Cooper, known as the father of interaction design. He believed that user portraits are virtual representations that truly reflect user data characteristics. By mining user data, extracting user goals, behaviors, and viewpoints, and analyzing typical user features, both static and dynamic user data are tagged to form a target user model. The core task of user portraits is to assign highly precise feature identifiers to users through manual specification. The primary purpose is to enable computers to programmatically process human-related data information, improve information acquisition speed, and construct user portraits based on restored user information, thereby serving information promotion in advertising, marketing, and other fields.

The tagging system for user portraits involves the tagging of user information. Before constructing user portraits, it is necessary to establish a standardized tagging system that comprehensively and multi-dimensionally reflects the basic content of user portraits. The establishment of user portrait tags requires data collection and processing. Based on different data and inconsistent requirements, two primary methods are employed for tag collection: (1) manual induction and annotation of user tags; and (2) semi-automated extraction using machine algorithms. The completeness of the tag indicator system plays a crucial role in the precise construction of user portraits. In the tagging system, each tag represents a specific manifestation of a user characteristic. To some extent, tags must have a certain group nature, capable of summarizing certain attributes and basic features of things. Tags can take various forms in representation, including Chinese symbols or numbers. From raw data collection and processing to business tag generation, and from data cleaning and organization to final machine learning, user attribute features can be classified and processed using computers [17], as shown in Figure 2 [Figure 2: see original paper].

4. Construction of Social Media User and Resource Portraits

In recent years, with the rapid emergence of the Internet industry, various types of social media have flourished like mushrooms after rain. For social media platforms, providing precise and personalized push services is crucial for their long-term development. Douban is one of the most representative websites of the Web 2.0 era, with rich online functions. It has evolved from initially providing information on books, movies, and music into a comprehensive social networking platform integrating blogs and commerce. To date, Douban Movie has become China's largest and most authoritative film sharing and online review community, even being called the "IMDb of the Chinese-speaking world." Currently, nearly 3,000 cinemas have joined the platform, and Douban Movie has become the top-clicked submodule of the main Douban website. Therefore, this study uses Douban Movie as an example to construct user portraits and resource portraits, aiming to achieve personalized push services through the mapping relationship between portraits [23].

4.1 Social Media User Portrait Construction

4.1.1 Data Acquisition Taking Douban Movie as an example, this study used Octopus web scraping software to crawl data on popular movies from Douban Movie between 2017 and 2018. The crawling was performed on May 7, 2018. After data screening, cleaning, and processing, the data files were exported to Excel. A total of 221 movie data entries and 7,000 user comment data entries were crawled. These data were categorized and summarized for statistical analysis. The crawled content was primarily classified into two major parts: data related to popular movies from the past two years and data related to users. User data mainly included work title, work ID, comment title, reviewer ID, star rating, recommendation level, comment time, comment summary, comment content, number of useful comments, number of useless comments, follow-up comment time, and follow-up comment content. Resource data mainly included movie title, director, screenwriter, starring actors, genre, production country, release date, movie rating, and movie reviews.

4.1.2 Establishment of User Portrait Tag System Based on user data, the author divided the user tag system into three main aspects: user natural attributes, user behavioral characteristic attributes, and user demand attributes. User natural attributes mainly include user ID and user city. User behavioral attributes primarily include user ratings, user recommendations, user comments, and user sharing. User demand attributes mainly include film actors, directors, genres, release schedules, languages, comment scores, and film rankings, as shown in Figure 3 [Figure 3: see original paper].

4.1.3 User Portrait Construction To display the user tag system more intuitively, the author applied ECharts word cloud software to construct user portraits. The tags primarily focus on user behavioral characteristics and demand characteristics as the core of the research. In the word cloud, larger fonts indicate that the tag occupies a core position in the user's tag system and plays a decisive role, while smaller fonts indicate that the tag is in a non-core position with a relatively weaker role. Using Douban's user community as an example, the constructed user portrait is shown in Figure 4 [Figure 4: see original paper].

4.2 Social Media Resource Portrait Construction

4.2.1 Establishment of Resource Portrait Tag System The resource portrait tag system is roughly divided into three levels: film natural attributes, film feature attributes, and film content attributes. Film natural attributes mainly include film title, release year, and director. Film feature attributes primarily include film rating score, number of reviewers, film reviews, media promotion, topic promotion, and roadshow promotion. The film content category is divided into two major parts: the film's demand tag system for people and the film's own content tag system. The film's demand tags for people mainly include film price, cinema environment, film genre, and film language. Film content tags mainly include film information, ticket purchasing, film rankings, film classification, film reviews, annual film lists, and viewing reports [24], as shown in Table 2 .

4.2.2 Resource Portrait Construction Using ECharts word cloud software and based on the resource portrait tag system, the author constructed resource portraits. Due to the complexity of the resource portrait tag system, duplicate values in resource tags were removed, and the tag word values were set to 1 to generate the data format. The word spacing was set to 0 to ensure moderate gaps between words in the generated data. The constructed resource portrait is shown in Figure 5 [Figure 5: see original paper].

4.3 Mapping Relationship Between User Portraits and Resource Portraits

The social tagging system consists of three different types of sets: users, resources, and tags, forming a complete folksonomy among them. In this system, each data group follows the structure F = {user, resource, tag1, tag2, …, tagt}, where t represents the number of tags assigned by users to different resources.

Define M = {M1, M2, M3, M4, …, Mi}, V = {V1, V2, V3, V4, …, Vj}, and T = {T1, T2, T3, T4, …, Tk}, where M, V, and T represent three different datasets:

M represents the user set, V represents the resource set, and T represents the tag set. i, j, and k represent the quantities of their respective datasets [25].

Simultaneously, each group relationship has corresponding matrices: B, B', and B"', representing user-resource, resource-tag, and user-tag relationships, respectively. In matrix B, if Mi selects resource Tk, then bik = 1; otherwise, bik = 0. Similarly, in matrix B', if Vj is tagged with Tk, then bjk = 1; otherwise, bjk = 0. In matrix B' ', if Mi selects Vj, then bij = 1; otherwise, bij = 0.

Drawing on the social tagging system model, this study uses M to represent user portraits and V to represent resource portraits, establishing a tag set T between user portraits and resource portraits to create a mapping relationship, as shown in Figure 6 [Figure 6: see original paper].

In this mapping relationship, tags are established between user portraits and resource portraits to enable the mapping. Specifically, M = {user natural attributes, user behavioral attributes, user demand attributes}, V = {film natural attributes, film feature attributes, film content attributes}, and T = {behavior, demand, features, content}. Using clustering algorithms, standard tags serve as cluster centers to calculate the correlation between custom tags from user portraits and resource portraits and the cluster center tags. Custom tags are clustered into the category of the cluster center with the maximum correlation. Clustering stops when the correlation between remaining custom tags and cluster centers is below the threshold. The remaining custom tags are then clustered among themselves, with new cluster centers stored in the standard tag library. The similarity between custom tags and standard tags is recalculated, and custom tag clustering is adjusted to obtain new standard tag clusters. This method achieves mapping between user portraits and resource portraits [26]. Using Douban Movie as an example, the attributes of user portraits and resource portraits on the website were specifically subdivided and tagged, forming a concrete user portrait mapping model, as shown in Figure 7 [Figure 7: see original paper].

5. Construction of Social Media Resource Aggregation Model

5.1 Model Components

Resource aggregation refers to the process of collecting, screening, analyzing, and organizing characteristic information of various resources or different types of data information on the Internet. Through data mining of resources, it analyzes potential relationships between resources and achieves resource aggregation based on attribute relationships between resources, thereby providing users with knowledge resources and information.

5.1.1 User Portraits and Resource Portraits Users are the main subjects of social media resource aggregation and service push, as well as the users of social media resources. They primarily refer to various forms of resource aggregation created by participants through knowledge exchange, sharing, and transmission in social media. User portraits enable the division of user groups, integrating similar features into categories and clustering them to achieve both group push and personalized push services for users. Resources in social media mainly include various forms of information resource aggregation presented digitally in social media, including not only familiar text, images, audio, video, and broadcasts but also intangible resources such as media values and emotional resources. Social media resources exist in diverse forms, and through resource portraits, these resources are integrated to achieve comprehensive documentation of required knowledge.

5.1.2 Domain Ontology Domain ontology refers to the mapping relationships between concepts, determined by the needs of ontology builders. It can be a single discipline domain, a combination of knowledge from several domains, or a scope within a domain. As resource aggregation in the social media domain continues to evolve, organizational structures have undergone significant changes, shifting from original single linear structures to multi-dimensional, multi-space network structures. The forms of social media resource aggregation objectively reflect the relationships between resources across media. Current research in this field shows that domain ontology is no longer limited to traditional attribute structures of existing knowledge but has expanded to multiple integrations of conceptual and attribute relationships, gradually revealing aggregation relationships between diversified information resources [27].

5.2 Resource Aggregation Model

Resource aggregation aims to solve problems such as resource silos, information overload, and redundancy to achieve rapid resource acquisition. Based on the research overview of user portraits, the construction of user portrait models, and the mapping relationship between user portraits and resource portraits, this study constructs a resource portrait-based resource aggregation model by analyzing the concept of resource aggregation. Due to the wide distribution of resources and the diverse needs of user groups, this study focuses on building two resource aggregation models: an internal resource aggregation model based on social media resource portraits and an external resource aggregation model across different social networks, thereby providing precise services for users.

5.2.1 Internal Resource Aggregation Model Based on Social Media Resource Portraits Internal aggregation primarily focuses on aggregating user portraits, resource portraits, and domain ontology within social media. By deeply mining relationships between complex and disordered resources and establishing connections between features, resource aggregation is achieved based on user portraits and the mapping relationship between portraits. The internal resource aggregation model for social media resource portraits is shown in Figure 8 [Figure 8: see original paper].

The internal resource aggregation model is divided into three parts: the resource layer, algorithm layer, and portrait layer. The resource layer forms the foundation for resource aggregation and service push. In the database, it mainly includes Douban Movie user data and Douban Movie website resource data. Movie resource data includes digital resources such as films, images, audio, video, and broadcasts, while user data includes basic user information, behavioral information, and demand information. Through organizing and processing this data, required resources are obtained. The algorithm layer cleans and processes Douban Movie website user data. Due to the fine granularity of information concepts, machine learning methods are applied for deep processing of user and resource data to mine essential connotations and information. Douban Movie resources are reorganized to extract resource titles, features, and keywords from numerous data points, classifying movie resource characteristics to establish a tag system. The portrait layer forms similarity matrices among the three elements based on the mapping relationship between user portraits and resource portraits, seeking relationships between ontologies. According to user needs, it provides precise matching results, achieves resource aggregation through resource portraits, and offers valuable push information to users, thereby realizing effective push services.

5.2.2 External Resource Aggregation Model Based on Social Media Resource Portraits As shown in Figure 9 [Figure 9: see original paper], numerous movie-related websites exist outside Douban Movie, such as Youku, Tudou, LeTV, iQiyi, Sohu Video, and Tencent Video. These websites, like Douban, contain large user groups and massive movie resources. By analyzing Douban Movie's resource information and resource portraits, matching and aggregation between resources can be achieved, facilitating exchange and cooperation between different resource websites to provide users with cross-platform resource push services.

Based on in-depth analysis of the connotation, theory, and algorithms of user portraits, this study thoroughly examined social media user portraits. Using Douban as an example, it extracted basic models for social media user portraits and resource portraits. Based on the social tagging system method, it clarified the mapping relationship between user portraits, tags, and resource portraits, constructing a mapping relationship model. Combined with the connotation of resource aggregation and domain ontology knowledge, it deeply analyzed the influencing factors of social media resource portrait-based resource aggregation, constructing both internal and external social media resource aggregation models based on resource portraits to lay the foundation for targeted information push and services. It is hoped that this research can provide a theoretical basis for related studies in this field and enrich and improve user portrait research.

6. Conclusion

Based on the connotation, theory, and algorithms of user portraits, this study conducted an in-depth analysis of social media user portraits. Using Douban as an example, it extracted basic models for social media user portraits and resource portraits. Based on the social tagging system method, it clarified the mapping relationship between user portraits, tags, and resource portraits, constructing a mapping relationship model. Combined with the connotation of resource aggregation and domain ontology knowledge, it deeply analyzed the influencing factors of social media resource portrait-based resource aggregation, constructing both internal and external social media resource aggregation models based on resource portraits to lay the foundation for targeted information push and services. It is hoped that this research can provide a theoretical basis for related studies in this field and enrich and improve user portrait research. The conclusions of this study are as follows: User portraits are virtual representations that truly reflect user data characteristics. By mining user data and analyzing typical user features, a target user model is formed. The social media resource portrait-based resource aggregation model is mainly divided into internal resource aggregation model and external resource aggregation model, which are used to provide personalized services for users.

References

[1] Yang Fan. Library Big Data Based on Portrait Analysis: Taking the National Library Big Data Project as an Example[J]. Library Tribune, 2018(4): 1-9.

[2] Wang Shunqing. Constructing an Intelligent Reading Recommendation System Based on User Portraits[J]. Library Science Research, 2018(4): 92-96.

[3] Yin Xiangquan, Li Shuning, Gong Jianhua. Analysis of University Library Study Room User Behavior Based on System Logs[J]. Modern Information, 2018(1): 115-120.

[4] PETRIC K, PETRIC T, KRISPER M. User Profiling on a Pilot Digital Library with the Final Result of a New Adaptive Knowledge Management Solution[J]. Knowledge Organization, 2011, 38(2): 96-113.

[5] Cheng Quan. Research on Digital Library Information Service Model Based on User Portraits[J]. Library Science Journal, 2018(4): 68-71.

[6] Wang Lingxiao, Shen Zhuo, Li Yan. Construction of User Portraits in Social Q&A Communities[J]. Information Studies: Theory & Application, 2018(1): 129-134.

[7] Shan Xiaohong, Zhang Xiaoyue, Liu Xiaoyan. Research on User Portraits Based on Online Reviews: Taking Ctrip Hotels as an Example[J]. Information Studies: Theory & Application, 2018(4): 99-104.

[8] Huang Wenbin, Wu Jiahui, Xu Shanchuan, et al. Framework and Methodological Analysis of Data-Driven Mobile User Behavior Research[J]. Information

Science, 2016(7): 14-20, 40.

[9] Hao Shengyu, Chen Jingren. User Portraits in the Big Data Era Help Enterprises Achieve Precision Marketing[J]. China Collective Economy, 2016(4): 61-62.

[10] Pei Guocai. Research on Telecom Precision Marketing Model Based on User Portraits[J]. Information Communications, 2017(12): 240-241, 24.

[11] Wang Xiaoxia, Liu Jingsha, Xu Dandan. Practice of Operator Big Data User Portraits[J]. Telecommunications Science, 2018(5): 127-133.

[12] Sheng Yijin. Application of User Portrait Technology in Academic Journal Reviewer Selection[J]. Publishing Research, 2018(8): 54-58.

[13] Xiong Wei, Hang Bo, Li Bing, et al. An Integrated Service Redirection Method Based on User Portraits and Content[J]. Small Microcomputer Systems, 2017(12): 2762-2765.

[14] Zhang Shijun, Chen Feng, Wang Zhiying, et al. Research on Construction and Application of Customer Stereoscopic Portraits Based on Power Big Data[J]. Electrical Applications, 2018(8): 18-25.

[15] Gao Yang, Chi Xuehua, Zhang Chengzhi, et al. Research on Constructing Precise Talent Portraits: Taking the Intelligent Manufacturing Field as an Example[J]. Library Tribune, 2018(9): 1-8.

[16] Lin Yanxia, Xie Xiangsheng. Weibo Group User Portraits Based on Social Identity Theory[J]. Information Studies: Theory & Application, 2017(3): 142-148.

[17] Chen Tianyuan. Empirical Study on Constructing User Portraits for University Mobile Libraries[J]. Library and Information Service, 2018, 62(7): 38-46.

[18] Lu Donglei. User Portrait Analysis Based on E-commerce[J]. Computer Knowledge and Technology, 2018(22): 1.

[19] Hu Yuan, Mao Ning. Construction of User Model for Digital Library Knowledge Community Based on User Portraits[J]. Library Theory and Practice, 2017(4): 82-85, 97.

[20] Li Bing, Wang Yue, Liu Yongxiang. User Portrait Construction Based on k-means in Big Data Environment[J]. Modern Computer (Professional Edition), 2016(24): 11.

[21] Zhang Xiaoke, Shen Wenming, Du Cuifeng. Research on Bayesian Networks in User Portrait Construction[J]. Mobile Communications, 2016(22): 22-26.

[22] Zhang Jun. Research on Library Knowledge Discovery Services Based on User Portraits[J]. Library and Information, 2017(6): 60-63.

[23] Wang Xiang. Research on the Relationship Between Movie Website Ratings and Box Office: Taking Douban Movie as an Example[D]. Nanchang: Nanchang

University, 2016.

[24] Xue Huanxue. Process of Creating User Portraits for University Library Subject Services[J]. Library Science Research, 2018(13): 67-71, 82.

[25] Sun Hongfei, Wu Huijuan, Zhou Lanping. Research on Theoretical Model of Personalized Information Recommendation Based on Tags[J]. Information Science, 2013, 31(4): 24-27.

[26] Yang Jing, Cheng Weiqing, Guo Changzhong. Research on User Interest Model Based on Standard Tags[J]. Computer Science and Technology, 2013(10): 208-211.

[27] Liu Jian. Research on Digital Library Resource Aggregation and Service Recommendation[D]. Changchun: Jilin University, 2017.

Author Contributions

Xu Hailing: Paper writing and revision
Zhang Haitao: Proposed research proposition and research framework
Wei Mingzhu: Collection of English literature and translation of abstracts
Yin Huizi: Data collection and processing

Abstract: [Purpose/significance] This paper creates a social media resource aggregation model based on user portraits, provides a reference for resource aggregation, and enriches and expands its theoretical research system. [Method/process] Based on the in-depth analysis of the connotation and algorithm of user portraits, and mapping relationship between them, the models of user portraits and resource portraits are constructed based on social media. The social media based user portraits and resource portraits are studied by using the social labeling system method. Based on the domain ontology method, through the deep mining of data and the principle of resource aggregation, a social media internal resource aggregation model and an external resource aggregation model based on resource portraits are constructed. [Result/conclusion] In the era of big data, relevant theories and methods based on user portraits and resource portraits can provide new ideas for resource aggregation of social media.

Keywords: user portrait; social media; resource portrait; resource aggregation

Note: Figure translations are in progress. See original paper for figures.