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Web celebrity shop assessment and improvement based on online review with probabilistic linguistic term sets by using sentiment analysis and fuzzy cognitive map

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Abstract As a representative of the new economy, the web celebrity economy has achieved significant development in China with the rapid development of information technology and the Internet. In this environment, web celebrity shops encounter fierce business competition of peer competitors. Online reviews which imply the consumers' attitudes and sentiments give the web celebrity shops good feedback to improve their competitiveness. Thus, taking milk tea as an example, this paper deeply investigates the assessment of web celebrity shops by mining online review. At the same time, we also discuss the competitive analysis and propose the corresponding improvement advices. In order to obtain the satisfaction assessments of web celebrity shops, on the one hand, we analyze topic extraction with latent dirichlet allocation (LDA) and determine the attributes that customers care about. On the other hand, we utilize long short-term memory (LSTM) and probabilistic linguistic term sets (PLTSs) to more precisely portray customers' sentiment towards different attributes. By using fuzzy cognitive map (FCM) and the association rule, we further investigate the interrelationship among the attributes and construct the relationship graph between attributes for web celebrity

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shops. With the above results, we aggregate the decision information by designing improved extended Bonferroni mean (EBM) and obtain comprehensive evaluations. General speaking, this paper successfully transforms the unstructured data of online reviews into quantitative information and obtain satisfaction evaluations. With the aid of PLTSs and FCM, we further investigate the competitive analysis and propose improvement advices for each shop, which systematically provides us with a data-driven decision-making analysis model.

Keywords Online review · Fuzzy cognitive map · Sentiment analysis · Web celebrity shop assessment · Probabilistic linguistic term sets

1 Introduction

Web celebrity economy refers to a new economic mode that relies on the Internet, especially mobile Internet communication and its social platform promotion. With the development of the Internet economy, the mode gathers much social attention, holds a vast fan base and targeted marketing market, generates various consumer markets around web celebrity intellectual property (IP), and forms a complete web celebrity industrial chain Guan and Wu (2016). With the significant increase in the number of web celebrities, the fields involved in web celebrities are also expanding from the creation of entertainment content and beauty makeup in the early stage to the knowledge popularization and information sharing in the following stage. At present, the emerging vertical fields, such as food and finance, also are explored.

In the field of the web celebrity economy, the web celebrity milk tea is very prevalent Zhou et al. (2018). In practice promotion and operation, web celebrity milk tea can depend on third-party websites (platforms), e.g., Taobao, Jingdong, Douban, Dianping and so on. On the one hand, the independent third-party websites (platforms) can bring network traffic. On the other hand, numerous reviews about different shops are written by customers on these websites. Online reviews not only can be used by consumers to express their attitudes and sentiments, but also can be used by shops to observe consumers' reactions and propose improvement advices. The web celebrity shop's traffic can generate a lot of online review text, which ultimately further boost traffic. The review texts of web celebrity stops contain valuable information, such as the attributes that consumers mostly care about. Such information can not only show the advantages and disadvantages of web celebrity shops, but also help the shops to figure out consumers' satisfaction degree and propose targeted improvement advices. However, online review belongs to a kind of unstructured data. The attributes that consumers care about are not marked, but are implicit in the online review texts. In a competitive environment, the milk tea shops, such as DATONG ICEHOUSE, Nesno, HEYTEA, a little-tea and a yogurt cow, need to make full use of online reviews to improve their competitiveness. With the above background, web celebrity milk tea shops are facing two challenges: (1) Challenge 1: How to extract the customers' satisfaction factors and assessments from online reviews. (2) Challenge 2: How to utilize the assessment results obtained by handling Challenge 1 to design the improvement advices and support competitive analysis.

To counter the challenges above, we pick out attributes that customers care about with latent dirichlet allocation (LDA) in advance. LDA is a topic model which can excavate the critical attributes of consumer satisfaction Blei et al. (2003). To comprehensively assess the web celebrity milk tea shops, LDA can analyze review texts and extract potential attributes that consumers care about in their opinion. After attributes are excavated, it is necessary to understand consumers' attitudes and sentiments towards attributes from the reviews. Long short-term memory (LSTM) Hochreiter and Schmidhuber (1997) evaluates the sentiment polarity of reviews from the perspective of review clauses, which can obtain consumers' sentiments more comprehensively. As a particular form of the recurrent neural network, LSTM can determine the sentiment polarity from the clause-level. Therefore, we use LSTM to translate textual data such as online reviews into structured data, and evaluate customers' sentiment towards different attributes. In this case, we utilize a new concept of probabilistic linguistic term sets (PLTSs) proposed by Pang et al. (2016) to refine the sentiments. The PLTSs have a strong ability to express the vagueness and uncertainty of linguistic information in the real-world applications Liao et al. (2020), Lin et al. (2018), Lin et al. (2019), Wu and Liao (2018), Wu and Liao (2019), Zhou and Xu (2018). In the real decision-making procedure, different attributes may be interrelationships and interact with each other Liang et al. (2018). For example, the improvement of one attribute promotes the improvement of attributes with a positive correlation, and the improvement of one attribute can lead to the decline of attributes with a negative correlation. In order to further mine review texts, we choose fuzzy cognitive map (FCM) Kosko (1986) to excavate and construct the causal relationship between attributes. FCM offers the opportunity to produce better knowledge based on systems applications, addressing the need to handle uncertainties and inaccuracies associated with real-world problems. FCM usually represents systems in a graphical way showing the causal relationships between states-concepts and accomplishes the unification of superposing small subsystems. In this paper, we can construct an overall FCM for all the web celebrity shops, and design an individualized FCM for each shop. More targeted advices can be provided with the combination of these two kinds of FCMs. In the evaluation of consumers' satisfaction with each shop, the causal relationship between attributes should be taken into account to make comprehensive evaluations. Bonferroni mean (BM) Bonferroni (1950) is a kind of aggregation operator for collecting the interrelationship information. The new improved form of extended Bonferroni mean (EBM) of Refs. Dutta et al. (2015), Liang et al. (2018) can meticulously excavate the causal relationship between attributes. In this paper, we further improve EBM and apply it to make a comprehensive evaluation of customers' satisfaction scores towards each attribute. Based on the causal relationships between comprehensive attributes and consumers' satisfaction degree with attributes, we can provide targeted improvement advices for web celebrity shops.

In general, taking milk tea as an example, this paper deeply investigates the value of online review for the web celebrity shops and provides us with a data-driven decision-making analysis mode. There are four innovations of this paper as follows: Firstly, different from traditional construction of attributes based on customer questionnaire or existing models, we use LDA to extract the attributes which customers talk and care most in their online reviews. Secondly, based on these customer attributes, we

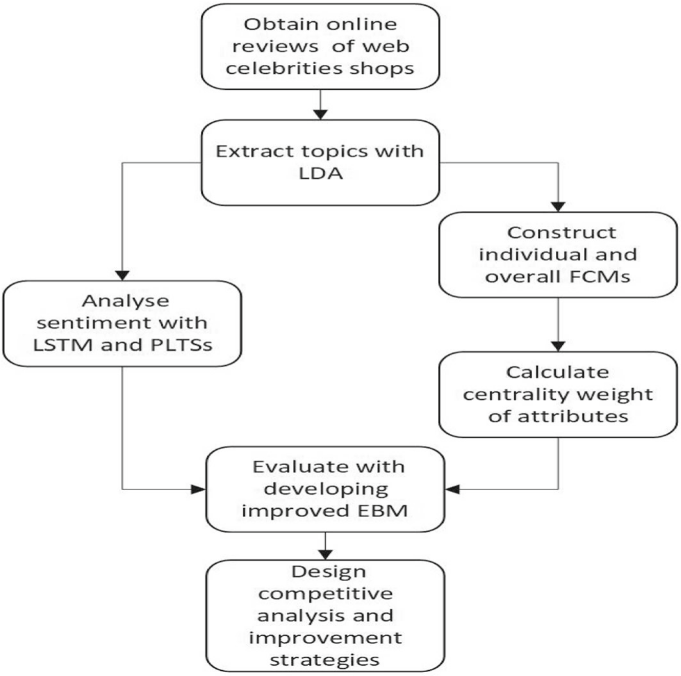


Fig. 1 The framework of decision-making analysis model

use sentiment analysis to determine customers' sentiment towards each attribute with the corresponding PLTSs, which can measure the true reflection of consumer attitudes more precisely. Thirdly, we construct FCM to assess web celebrity shops, which can meticulously describe interrelationships of different attributes, especially the heterogeneity relationship. Fourthly, due to that EBM considers mutual relations between different attributes, we improve and apply it to calculate the satisfaction score of attributes. To more clearly describe the model proposed in this paper, we describe the entire process in Fig. 1.

The rest of this paper is organized as follows: Sect. 2 briefly introduces the preliminaries and describes the corresponding references. In Sect. 3, we introduce the LDA method to extract attributes and analyze sentiments with LSTM and PLTSs from online reviews of web celebrity shops. Section 4 proposes the procedure of the construction of FCM and generates evaluations with improved EBM. Based on the results mentioned above, we further investigate the competitive analysis and propose improvement advices for each shop. Finally, the conclusions and prospects are described in Sect. 5.

2 Preliminaries

In this section, we review researches on LDA, LSTM, FCMs and BM and introduce their basic concepts and models.

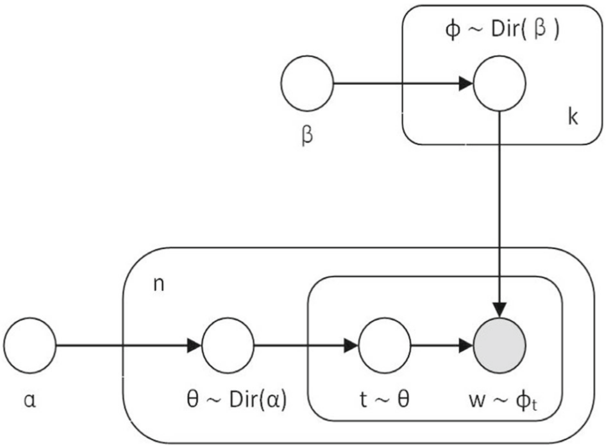


Fig. 2 The basic model of LDA Bíró et al. (2008)

2.1 Latent dirichlet allocation (LDA)

LDA was proposed by Blei et al. (2003). It is a topic model to analyze and extract topics from documents. The LDA has attracted many scholars. Bíró et al. (2008) modified LDA into the multi-corpus LDA technique and built the first web retrieval application of LDA to filter web spam. Krestel et al. (2009) used resources annotated by users with a stable and complete tag set to elicit latent topics and applied LDA to recommend tags of resources in order to improve search.

For the LDA topic model, there is the hypothesis that a person has certain topics in mind for writing a document Krestel et al. (2009). The core idea of this method is that, when creating a document, each word is picked from the word set of a topic with a certain probability and the topic is picked from the topic set with a certain probability. The construction process of LDA can be concluded as finding the mixture topics of each document. The concrete model of LDA is described in Fig. 2.

In Fig. 2, α and β are two smoothing parameters, k means the number of topic t and n means the number of document d. For each topic t, we sample a distribution of word ϕ_t from $Dir(\beta)$. Meantime, for each document d, we sample a distribution of topic θ_d from $Dir(\alpha)$ Bíró et al. (2008). The basic calculation method of LDA model is presented as the following formula Blei et al. (2003):

$$P(w_i|d) = \sum_{j=1}^{T} P(w_i|t_i = j)P(t_i = j|d), \tag{1}$$

where $P(w_i|d)$ means the probability of the ith word in document d, $P(t_i = j|d)$ means the probability of a word i's topic j in document d and T is the number of topic. LDA uses Dirichlet priors and fixation of the number of topic to estimate the topic-word distribution $P(w|t)$ and the document-topic distribution $P(t|d)$. One possible way to achieve this goal is the Gibbs sampling. Gibbs sampling iterates each word w_i in document d_i and samples a new topic j for the word based on the $P(t_i = j|w_i, d_i, t_{-i})$. The iteration stops when the parameters of LDA model converge. The probability $P(t_i = j|w_i, d_i, t_{-i})$ is described as follows Bíró et al. (2008):

$$P(t_i = j|w_i, d_i, t_{-i}) \propto \frac{N^W_{w_i,j} + \beta}{\sum_w N^W_{w_i,j} + W\beta} \frac{N^D_{d_i,j} + \alpha}{\sum_t N^D_{d_i,t} + T\alpha}, \tag{2}$$

where W means the number of word, $N^W_{w_i,j}$ maintains a count of all topic–word assignments, $N^D_{d_i,j}$ counts the document–topic assignments, t_{-i} means the topic-word assignments and document-topic assignments except for current $t_i - w_i$ assignment. The Dirichlet parameters are α and β. We can estimate the posterior probabilities in (1) with the following formulas Bíró et al. (2008):

$$P(w_i|t_i = j) = \frac{N^W_{w_i,j} + \beta}{\sum_w N^W_{w_i,j} + W\beta}, \tag{3}$$

$$P(t_i = j|d_i) = \frac{N^D_{d_i,j} + \alpha}{\sum_t N^D_{d_i,t} + T\alpha}. \tag{4}$$

2.2 Long short-term memory (LSTM)

LSTM is a special form of recurrent neural network proposed by Hochreiter and Schmidhuber (1997). LSTM can overcome the gradient vanishing or exploding problem which RNN has. Sak et al. (2014) used LSTM in large scale acoustic modeling. They proved that LSTM makes more effective use of model parameters and outperforms DNNs. LSTM has also been applied in sentiment analysis. To classify the relation of two entities in a sentence, Xu et al. (2015) proposed SDP-LSTM. They leveraged the shortest dependency path (SDP) between two entities and used LSTM to pick up heterogeneous information along with the SDP. Generally, each component of LSTM model is updated with the following formulas Sak et al. (2014):

$$i_t = \sigma(W_i x_t + b_i), \tag{5}$$

$$o_t = \sigma(W_o x_t + b_o), \tag{6}$$

$$f_t = \sigma(W_f x_t + b_f), \tag{7}$$

$$\widetilde{c}_t = tanh(W_c x_t + b_c), \tag{8}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c}_t, \tag{9}$$

$$h_t = o_t \odot tanh(c_t), \tag{10}$$

where σ means the logistic sigmoid function, W_i, W_o and W_f are weighted matrices $(W_i, W_o W_f \in \mathbb{R}^{d*2d})$, b_i, b_o and b_f are the parameters of input, output and forget gates, which are learned during the training $(b_i, b_o, b_f \in \mathbb{R}^d)$, $\odot$ represents element-wise multiplication, h_t is the hidden layer vector and x_t means the input of LSTM. For clarity, the basic structure of a LSTM is shown in Fig. 3:

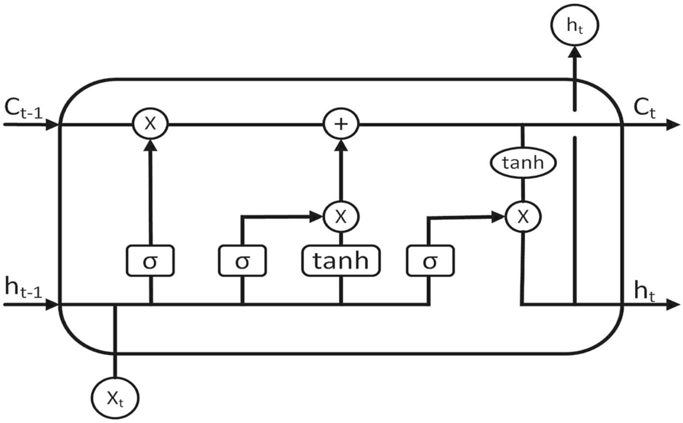
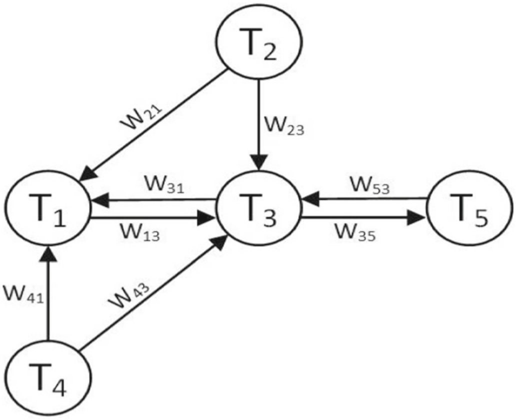


Fig. 3 Basic structure of LSTM Sak et al. (2014)

Fig. 4 Basic structure of a FCM example



2.3 Fuzzy cognitive maps (FCMs)

FCMs are fuzzy-graph structures which represent causal reasoning and relationships. It was proposed by Kosko (1986). FCMs have bright prospects for development and application. For instance, FCMs were applied to support urban design by Xirogiannis et al. (2004). They interpreted the logic-based rules of FCMs to model the disjointed conjuncts of the logic-based rules. Stylios et al. (2008) divided medical decision systems into non-related and related subsystems and used FCMs to construct medical decision support systems.

In what follows, we use an example to illustrate the concept of FCM. The basic structure of the FCM is shown in Fig. 4 and the corresponding adjacency weight matrix is shown in Table 1.

From the results of Fig. 4 and Table 1, there are five nodes, i.e., $T_1 - T_5$. The arrow denotes the causal relationship between two nodes and the weight of the arrow is used to quantify the relationship.

Table 1 Corresponding adjacency weight matrix of Fig. 4

	T_1	T_2	T_3	T_4	T_5
T_1	0	0	W_{13}	0	0
T_2	W_{21}	0	W_{23}	0	0
T_3	W_{31}	0	0	0	W_{35}
T_4	W_{41}	0	W_{43}	0	0
T_5	0	0	W_{53}	0	0

2.4 Bonferroni mean (BM)

BM is a kind of aggregation operator which is capable of excavating the interrelationship between aggregation arguments. Bonferroni (1950) first proposed it. BM has been developed by others during the past decades. Zhu et al. (2012) considered the importance of each argument and the correlations among arguments to build the weighted hesitant fuzzy geometric Bonferroni mean (WHFGBM) and the weighted hesitant fuzzy Choquet geometric Bonferroni mean (WHFCGBM). Liu and Wang (2014) combined BM with the weighted Bonferroni mean (WBM) and the normalized WBM and proposed a single-valued neutrosophic normalized weighted Bonferroni mean (SVN-NWBM) operator to make multiple attribute decision making. The basic BM is defined as follows Bonferroni (1950):

$$
\begin{aligned}
B_{p,q}(a_1, a_2, \cdots, a_n) &= \left(\frac{1}{n(n-1)} \sum_{i,j=1;i\neq j}^{n} a_i^p a_j^q\right)^{\frac{1}{p+q}} \\
&= \left(\frac{1}{n}\sum_{i=1}^{n} a_i^p \left(\frac{1}{n-1}\sum_{j=1;j\neq i} a_j^q\right)\right)^{\frac{1}{p+q}}, \qquad (11)
\end{aligned}
$$

where a_i represents the satisfaction degree with respect to attribute $A_i (i = 1, 2, \ldots, n)$ of an alternative $(p, q \geq 0)$. BM takes the interrelationships among the attributes into consideration and assesses each alternative more comprehensively.

For the EBM, an improved form of BM, the attributes of the set A can be classified into two disjoint sets C and D ($C \bigcap D = \emptyset$ and $C \bigcup D = A$). C is a set of dependent attributes and D is a set of independent attributes. Based on the results of Ref. Dutta et al. (2015), each attribute A_i of C is related to a nonempty subset of attributes $B_i \subset C\backslash\{A_i\}$, while each attribute A_j of D is not related to any other attribute of $A\backslash\{A_j\}$. Let I_i denote the set of indices of the attributes of B_i. Meanwhile, I' denotes the indices of the attributes of D Dutta et al. (2015). By utilizing these assumptions and notations, the EBM of the collection of inputs $(a_1, a_2, \ldots, a_n)$ is defined as follows:

Definition 1 Dutta et al. (2015) For any $p > 0$ and $q \geq 0$, the EBM aggregation operator of dimension n is a mapping EBM: $(R^+)^n \to R^+$, represented as follows:

$$EBM^{p,q}(a_1, a_2, \ldots, a_n)$$

$$= \left(\frac{n - card(I^{'})}{n} \left(\frac{1}{n - card(I^{'})} \sum_{i \notin I^{'}} a_i^p \left(\frac{1}{card(I_i)} \sum_{j \in I_i} a_j^q \right) \right)^{\frac{p}{p+q}} + \frac{card(I^{'})}{n} \left(\frac{1}{card(I^{'})} \sum_{i \in I^{'}} a_i^p \right) \right)^{\frac{1}{p}}, \tag{12}$$

where $card(I^{'})$ means the cardinality of the set $I^{'}$. Note that the empty sum is 0 by convention, i.e., if either $card(I^{'}) = 0$, then this concerns the last sum, or if $card(I^{'}) = n$, then this concerns the first sum and $\frac{0}{0} = 0$.

3 Topic extraction of online reviews of web celebrity shop and sentiment analysis with PLTSs

In this section, we first select Dianping.com as our data source of online review of web celebrity shop and identify our subjects. Then, by using the LDA, we investigate the topic extraction of online reviews of web celebrity shop and further determine the corresponding attributes which customers care about. Finally, we evaluate customers' sentiment towards different attributes more closely by combining LSTM and PLTSs.

3.1 Basic problem description and data source of online review of web celebrity shop

Dianping.com is a leading independent third-party consumption review website in China and the earliest independent third-party consumer review website in the world. Dianping not only provides users with information services such as merchant information, consumer reviews and consumer discounts, but also provides O2O (Online To Offline) trading services such as group purchase, restaurant reservation, takeout and e-membership card. Therefore, this paper chooses Dianping.com as the data source of online reviews. As is shown on Dianping.com, DATONG ICEHOUSE, Nesno, HEYTEA, alittle-tea and a yogurt cow are the five most famous web celebrity shops with plenty of online reviews. In this paper, these five shops are selected as research objects, denoted as $Shop_1 - Shop_5$. In order to facilitate the understanding, we vividly show the online reviews of these shops on Dianping.com, see Fig. 5.

The online reviews are applied as the data source of this paper. Then, we develop a web crawler based on Python software, which is used to capture online reviews of these five web celebrity shops on Dianping.com from March 2017 to March 2019. After removing duplicate, empty and untrue reviews, we obtain a total of 24409 online review texts of five web celebrity shops, as shown in Table 2.

Fig. 5 Shops and reviews on Dianping.com

Table 2 Online reviews general information

Data Source	Review time	Total number of reviews of views
Dianping.com	2017.3–2019.3	24409

3.2 Topic extraction with LDA

After getting the raw data set of online reviews in Sect. 3.1, topic extraction is the first task for us to analyze these unstructured data and understand consumer evaluations. The whole process of topic extraction can be divided into three main steps as follows:

Firstly, it is crucial to preprocess the text review data set. During the analysis, the review sentences need to be divided into some words. The words which have no meanings, e.g., stopwords, and the punctuations will be removed to make the text data more clearly.

Secondly, with the aid of Python software, we process text reviews and input them into the LDA model. Each word in review texts is randomly assigned an attribute. We build the text-attribute matrix which is used to represent the distribution of the attributes in review texts, and the word-attribute matrix which is used to represent the distribution of words in each attribute. We traverse all words in review texts, resample and update the attributes distribution of each word according to the Gibbs Sampling formula until the result converges. We get the hidden attributes with their related words. Then, we incorporate similar topics and conclude the name of the attributes. The final result is shown in Table 3.

Thirdly, let $Text_i$ $(i = 1, 2, \ldots, 24409)$ represent a review text and A_j $(j = 1, 2, \ldots, 7)$ denote an attribute. Then, we construct the text-attribute matrix based on LDA model. The result is shown in Table 4.

From the result of Table 4, each value in the text-attribute probability matrix represents the degree that a review text belongs to a specific attribute. For each review text, we can select the max value from its text-attribute probability vector as the main attribute for the text. The result is shown in Table 5.

From the result of Table 5, we can roughly understand the most concerned attributes of the customers. As a whole, the general process of topic extraction with LDA is summarized in Algorithm 1.

Algorithm 1 General process of topic extraction

Input: all online review $Text_n$ and review number N, the number of hidden attributes M, dirichlet parameters α, β
Output: text-attribute matrix

```
for all online review Text_n ∈ [1, N] do
    split Text_n and remove stopwords
end for
for all words in review text do
    randomly assign an attribute to each word
    build the text-attribute matrix
    build the word-attribute matrix
end for
repeat
    for all words in review text do
        resample the attributes distribution with Gibbs Sampling formula
    end for
until converges
```

Table 3 Web celebrity shops' topics (attributes) and key words

Attributes	Related key words			
Service (A_1)	东西(thing)	热情(enthusiasm)	店员(clerk)	不好(bad)
	孩子(children)	香味(fragrance)	服务(service)	广场(square)
	群光(qunguang)	健康(health))	杯子(cup)	夏天(summer)
	服务员(waiter)	关键(key)	品质(quaility)	小哥(young fellow)
	工作人员(staff)	奶香(milk flavor)	喝完(drink off)	客人(guest)
Environment (A_2)	服务(service)	环境(environment)	不错(good)	生意(business)
	装修(decoration)	速度(speed)	般般(general)	面包(breed)
	饮料(drinks)	店面(storefront)	味道(taste)	小姐姐(girl)
	座位(seat)	口味(flavour)	杨梅(waxberry)	干净(clean)
	荔枝(litchi)	风格(style)	舒服(comfortable)	稍微(a bit)
Waiting Time (A_3)	分钟(minute)	排队(queue up)	小时(hour0)	大概(probably)
	20(twenty)	10(ten)	左右(around)	继续(continue)
	结果(result)	时间(time)	取餐 (take drink)	30(thirty)
	40(forty)	时候(moment)	中午(noon)	二十分钟(twenty minutes)
	制作(make)	饮料(drinks)	饮品(drinks)	十分钟(ten minutes)
Price (A_4)	价格(price)	位置(location)	便宜(cheap)	好找(easy find)
	二次(twice)	实惠(affordable	味道(taste)	鸳鸯(mandarin duck tea)
	儿子(son)	评价(review)	15(fifteen)	漂亮(beautiful)
	最近(recent)	消费(consume)	老板(boss)	品牌(brand)
	美团(meituan)	美女(beauty)	块钱(yuan)	热闹(lively)
Sales Promotion (A_5)	团购(group purchase)	划算(cost-effective)	促销(promotion)	最爱(love best)
	简直(virtually)	差评(negative comment)	心情(mood)	三杯(three cups)
	问题(queation)	天气(weather)	忘记(forget)	意思(meaning)
	不值(not worth)	全部(all)	花生(peanut)	蓝莓(blueberry)
	核桃(nut)	冰块(ice cube)	牌子(brand)	完全(totally)
Variety (A_6)	红茶(black tea)	冰淇淋(ice cream)	波霸(pearl tea)	奶茶(milk tea)
	玛奇朵(Macchiato)	三分(three tenth)	珍珠(pearl tea)	外卖(take-out)
	乌龙(oolong)	四季(four seasons flavour)	喜欢(like)	甜度(sweetness)
	无糖(no suger)	布丁(pudding)	奶盖(milk cap)	北京(beijing)
	冰激凌(ice cream)	好喝(taste good)	红豆(ormosia)	奶青(green tea)
Taste (A_7)	奶茶(milk tea)	好喝(tasty)	不错(good)	非常(very)
	推荐(recommend)	味道(taste)	丝袜(silk stockings tea)	服务态度(attitude)
	口感(flavour)	海滨城(seaside city mall)	确实(indeed)	香港(HongKong)
	总体(total)	差不多(almost)	奶味(milk taste)	巴适(comfortable)
	大通(DATONG ICEHOUSE)	必须(must)	浓郁(aromatic)	纯正(pure)

Table 4 Text-attribute probability matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
$Text_1$	0.000462	0.000462	0.320388	0.000462	0.000462	0.676376	0.001387
$Text_2$	0.042114	0.303688	0.194350	0.078734	0.000262	0.105415	0.275438
$Text_3$	0.000344	0.000344	0.176714	0.000344	0.000344	0.769204	0.052704
$Text_4$	0.000657	0.000657	0.001970	0.000657	0.000657	0.842416	0.152987
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Text_{24409}$	0.000285	0.000285	0.003711	0.065944	0.000285	0.828719	0.100771

Table 5 Text-main attribute matrix

	$Text_1$	$Text_2$	$Text_3$	$\cdots$	$Text_{24409}$
Attribute	A_6	A_2	A_6	$\cdots$	A_6

Table 6 Text-sentiment score matrix

	$Text_1$	$Text_2$	$Text_3$	$\cdots$	$Text_{24409}$
Sentiment score	0.980286	0.995816	0.995653	$\cdots$	0.995637

Table 7 Percentage of satisfaction degree towards DA TONG ICEHOUSE with PLTSs

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Very satisfied	0.8198	0.8775	0.8291	0.9191	0.8599	0.8850	0.9515
Satisfied	0.0418	0.0441	0.0586	0.0213	0.0413	0.0525	0.0139
General	0.0156	0.0245	0.0232	0.0234	0.0137	0.0200	0.0112
Unsatisfied	0.0235	0.0098	0.0085	0.0085	0.0082	0.0100	0.0067
Very unsatisfied	0.0992	0.0441	0.0806	0.0277	0.0769	0.0325	0.0167

3.3 Sentiment analysis with LSTM and PLTSs

To dig customers' attitudes toward a specific attribute of a specific shop, we adopt LSTM to analyze the sentiment of each review text and quantize the text information. Before training the LSTM model, we classify about 2000 review texts manually as positive text and negative text as training data. After splitting the train texts and building word dictionary, we train the LSTM model for sentiment classification of online reviews. At the same time, we use the LSTM to analyze the sentiments of web celebrity shops' reviews. The analysis result is shown in Table 6.

In Table 6, each review text of the text-sentiment score matrix has a sentiment score ranging from 0 to 1. In this case, 1 means the most positive sentiment, and 0 means the most negative sentiment. Hence, each score represents the degree of review text's sentiment. With the sentiment score, we can assess customers' satisfaction degree of different web celebrity shops. For the original sentiment analysis, there are only three levels, i.e., positive, negative and neutral. In order to measure the true reflection of consumer attitudes in more detail, we draw on PLTSs to evaluate customers' sentiment towards different attributes. In the framework of PLTSs, we divide the sentiment score into 5 levels, i.e., L_i $(i = 1, 2, 3, 4, 5)$. The five levels are shown as follows: $(1, 0.8)$, $(0.8, 0.6)$, $(0.6, 0.4)$, $(0.4, 0.2)$, $(0.2, 0)$. These levels L_i $(i = 1, 2, 3, 4, 5)$ are respectively correlated with "very satisfied", "satisfied", "general", "unsatisfied", "very unsatisfied". The reviews are sorted by their shops and, after normalization, we get the customers' satisfaction degree matrix towards each shop. Their results are shown in Tables 7–11.

From the results of Tables 7–11, we can first obtain the percentage of satisfaction degree of each attribute with PLTSs from each shop and its advantage. Meanwhile,

Table 8 Percentage of satisfaction degree towards Nesno with PLTSs

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Very satisfied	0.4926	0.8706	0.7217	0.7589	0.6064	0.9070	0.8136
Satisfied	0.0662	0.0213	0.0361	0.0496	0.0532	0.0210	0.0358
General	0.0221	0.0230	0.0402	0.0355	0.0319	0.0097	0.0251
Unsatisfied	0.0294	0.0160	0.0353	0.0212	0.0425	0.0116	0.0108
Very unsatisfied	0.3897	0.0691	0.1667	0.1348	0.2660	0.0507	0.1147

Table 9 Percentage of satisfaction degree towards HEYTEA with PLTSs

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Very satisfied	0.4832	0.7852	0.6837	0.6577	0.5852	0.8881	0.7490
Satisfied	0.0537	0.0201	0.0586	0.0901	0.0667	0.0250	0.0586
General	0.0537	0.0336	0.0435	0.0180	0.0222	0.0196	0.0251
Unsatisfied	0.0201	0.0403	0.0298	0.0270	0.0444	0.0123	0.0209
Very unsatisfied	0.3893	0.1208	0.1844	0.2072	0.2815	0.0550	0.1464

Table 10 Percentage of satisfaction degree towards alittle-tea with PLTSs

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Very satisfied	0.8427	0.8788	0.7686	0.7179	0.7282	0.9320	0.8404
Satisfied	0.0242	0.0303	0.0406	0.0256	0.0388	0.0127	0.0266
General	0.0081	0.0202	0.0406	0.0385	0.0291	0.0100	0.0186
Unsatisfied	0.0121	0.0000	0.0318	0.0513	0.0388	0.0088	0.0133
Very unsatisfied	0.1129	0.0707	0.1184	0.1667	0.1651	0.0365	0.1011

Table 11 Percentage of satisfaction degree towards ayogurtcow with PLTSs

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Very satisfied	0.7258	0.8421	0.8654	0.8367	0.7623	0.8515	0.9159
Satisfied	0.0565	0.0351	0.0394	0.0000	0.0410	0.0792	0.0291
General	0.0242	0.0351	0.0278	0.0612	0.0164	0.0099	0.0097
Unsatisfied	0.0241	0.0526	0.0093	0.0205	0.0492	0.0000	0.0129
Very unsatisfied	0.1694	0.0351	0.0581	0.0816	0.1311	0.0594	0.0324

we can compare different shops via the percentage of satisfaction degree. For clarity, the general process of sentiment analysis with LSTM and PLTSs is described in Algorithm 2.

Algorithm 2 General process of sentiment analysis

Input: all online review $Text_i$ and number M, the number of training text N
Output: satisfaction degree towards each shop
  for all $Text_i \in [1, N]$ **do**
    classfy sentiment of $Text_i$ manully
    split $text_i$ and remove stopwords
    train LSTM model with manual classified text
  end for
  for all $Text_j \in [1, M]$ **do**
    calculate sentiment score s_j with LSTM model
    divide sentiment score into 5 levels
  end for
  for all web celebrities shops $Shop_k$ **do**
    for all atributes of $Shop_k$ **do**
      normalize the percentage of each sentiment level as satisfaction degree
    end for
  end for

In order to demonstrate the reliability of LSTM, we compare the sentiment analysis results of LSTM with the results of support vector machine (SVM). Based on the online reviews of web celebrity shops, we compute the receiver operating characteristic (ROC) curves of these two methods. Their results are shown in Fig. 6.

The ROC curve can be used to evaluate the accuracy of the analysis method. The closer the curve is to the upper left corner, the better the effect of the method is proved. In Fig. 6, the accuracy of SVM method is 0.71. When LSTM is used in sentiment analysis, there is a significant improvement in accuracy, which is up to 0.96. ROC curves of Fig. 6 fully prove that LSTM has an excellent performance in the sentiment analysis of the online review of web celebrity shops.

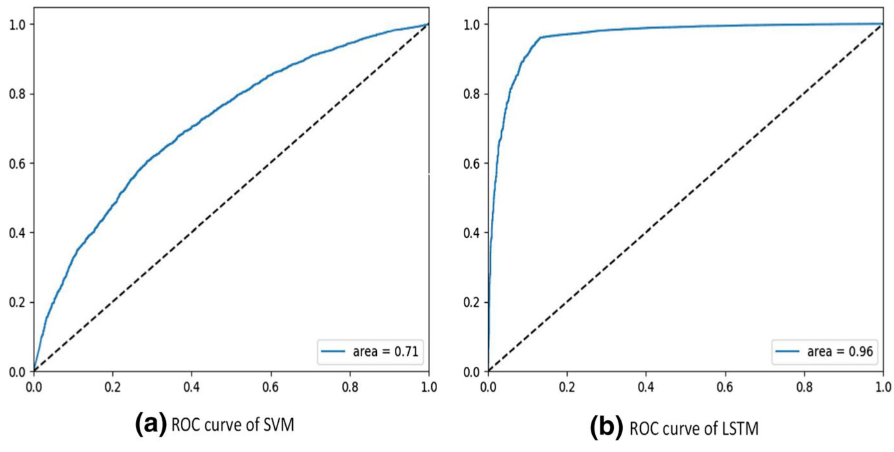


Fig. 6 The comparison of accuracy of LSTM and SVM

4 The comprehensive assessment of web celebrity shop by using FCM and BM

In Sect. 3, we have obtained the evaluation attributes of the customers via topic extraction of online reviews of web celebrity shop. In this section, with the aid of FCM and the result of Ref. Xu et al. (2019), we investigate the interrelationship among the attributes and construct the corresponding cause-effect diagram for web celebrity shops, which can provide us with a new viewpoint for proposing the improvement advices. Finally, we generate the evaluation by designing two improved EBM.

4.1 Construction of individual and overall FCMs

After obtaining the text-attribute matrix of Sect. 3, we start to build FCM model for describing the interrelationship among the attributes. In light of the result of Ref. Xu et al. (2019), we adopt the association rule to measure the interrelationship of attributes. In this situation, we denote $A_n \rightarrow A_l$ as the association rule between the attributes A_n and A_l ($n, l = 1, 2, \ldots, 7$ and $n \neq l$). Let $T = \{t_1, t_2, \ldots, t_{24409}\}$ represent the online reviews, and v_{jl} represent the impact of text t_j towards attribute A_l. The impact value v_{jl} is equal to the probability of text t_j towards attribute A_l. L represents the number of texts. Based on the results of Ref. Xu et al. (2019), we can calculate the support, confidence, and lift of the rule $A_n \rightarrow A_l$ as follows:

$$supp(A_n \rightarrow A_l) = \frac{\sum_{j=1}^{L} v_{jn} \otimes v_{jl}}{L}, \tag{13}$$

$$conf(A_n \rightarrow A_l) = \frac{\sum_{j=1}^{L} v_{jn} \otimes v_{jl}}{\sum_{j=1}^{L} v_{jn}}, \tag{14}$$

$$lift(A_n \rightarrow A_l) = \frac{conf(A_n \rightarrow A_l)}{supp(A_n \rightarrow A_l)}. \tag{15}$$

Support represents the normalized impact of two attributes and denotes the possibility of two attributes appearing together in reviews. Confidence represents the normalized impact of an attribute towards a rule and means the credibility that one attribute affects another attribute. Support and confidence can not reveal the polarity of association rules, so we calculate the lift to decide the polarity.

Then, we can preliminary construct FCM model with the association rules by comparing the support value of each association rule $A_n \rightarrow A_l$. In this step, we need to set a minimum support value and remove the association rule whose support value is less than the minimum value. Similarly, a minimum confidence value is also needed to set and every association rule with a smaller confidence value can be removed. In the rest of the association rules, we choose the confidence value as the absolute weight of association rules. The degree of the lift value refers to the ratio of the confidence value to the occurrence probability, which can be used to determine the polarity of weight. For each association rule $A_n \rightarrow A_l$, if $lift(A_n \rightarrow A_l) = 1$, then A_n and A_l are independent of each other. If $lift(A_n \rightarrow A_l) > 1$, then A_n and A_l are posi-

Table 12 Confidence matrix under the requirement of the minimum confidence

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
A_1	1	0	0.4185	0	0	0.3870	0.4183
A_2	0	1	0.4145	0	0	0.4455	0.3849
A_3	0	0	1	0	0	0.3764	0.2877
A_4	0	0	0.3997	1	0	0.3505	0.4589
A_5	0	0	0.3792	0	1	0.3585	0.4333
A_6	0	0	0.3012	0	0	1	0
A_7	0	0	0	0	0	0	1

Table 13 Support matrix under the requirement of the minimum support

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
A_1	0.4346	0.3040	0	0	0	0	0.3166
A_2	0.3040	0.4231	0	0	0.3002	0	0.3236
A_3	0	0	0.4755	0.3016	0	0.3009	0.3229
A_4	0	0	0.3016	0.4410	0	0	0.3244
A_5	0	0.3002	0	0	0.4449	0	0.3174
A_6	0	0	0.3009	0	0	0.5277	0.3163
A_7	0.3166	0.3236	0.3229	0.3244	0.3174	0.3163	0.6033

Table 14 Lift matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
A_1	2.3008	0.7049	1.4388	0.4866	0.4475	1.3102	1.3212
A_2	0.5280	2.3635	1.4375	0.5112	0.3506	1.5364	1.1892
A_3	0.3812	0.5085	2.1030	0.3061	0.2661	1.2511	0.8908
A_4	0.5582	0.7829	1.3252	2.2675	0.4795	1.2196	1.4144
A_5	0.5813	0.6079	1.3046	0.5429	2.2479	1.2164	1.3649
A_6	0.2777	0.4348	1.0011	0.2254	0.1985	1.8952	0.6873
A_7	0.2720	0.3268	0.6922	0.2538	0.2163	0.6674	1.6575

tively correlated, and these two attributes appear together more frequently. Likewise, if $lift(A_n \rightarrow A_l) < 1$, A_n and A_l are negatively correlated, namely, these two attributes appear together less frequently. In this paper, we set the minimum confidence as 0.25 and the minimum support as 0.30. Hence, the processed confidence matrix, support matrix and lift matrix between the attributes are shown in Tables 12–14.

Based on the results of Tables 12–14, we further construct the overall FCM of all the web celebrity shops. The result is shown in Fig. 7.

In Fig. 7, w_{nl} represents the weight of association rule from A_n to A_l, which is decided by the confidence value and the lift value. The weight values are recorded in Table 15.

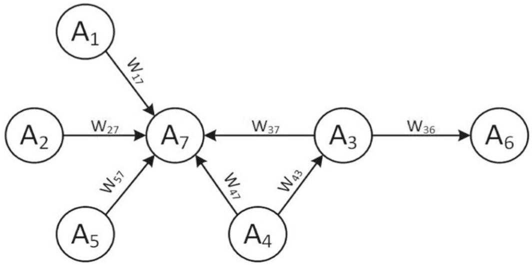


Fig. 7 The overall FCM of all the web celebrity shops

Table 15 Weight of association rule

Rule	Weight	Rule	Weight	Rule	Weight
w_{17}	0.4183	w_{27}	0.3849	w_{36}	0.3764
w_{37}	–0.2877	w_{43}	0.3997	w_{47}	0.4589
w_{57}	0.4333				

For clarity, the decision-making procedure of the overall FCM of all web celebrity shops is summarized in Algorithm 3.

Similar to the result of Algorithm 3, we also can deeply analyze all the online reviews in terms of each shop and construct the corresponding individual FCM. The FCM models of web celebrity shops are shown in Fig. 8.

Algorithm 3 General process of the overall FCM of all the web celebrity shops

Input: all attributes A_j $(j = 1, 2, \cdots, 7)$, text-attribute matrix
Output: weight matrix of association rules
for all attributes $A_n \in [1, 7]$ **do**
  for all attributes $A_l \in [1, 7], i \neq j$ **do**
    calculate $supp(A_n \to A_l)$
    calculate $conf(A_n \to A_l)$
    calculate $lift(A_n \to A_l)$
  end for
end for
for all association rules $A_n \to A_l$ **do**
  set the minimum confidence and the minimum support
  if association rule' confidence is smaller than the minimum confidence **then**
    remove this association rule
  end if
  if association rule' support is smaller than the minimum support **then**
    remove this association rule
  end if
end for
for all remain association rules $A_n \to A_l$ **do**
  if $lift(A_n \to A_l) \geq 1$ **then**
    compute the weight of association rule $w_{nl} = conf(A_n \to A_l)$
  else if $lift(A_n \to A_l) < 1$ **then**
    compute the weight of association rule $w_{nl} = -conf(A_n \to A_l)$
  end if
end for

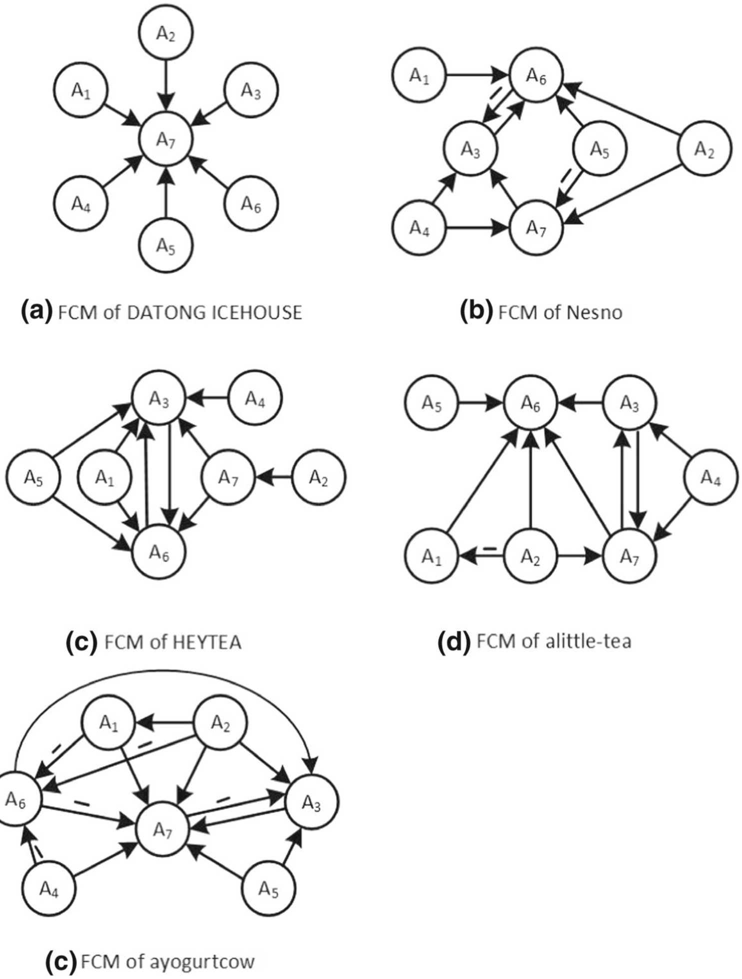


Fig. 8 FCM model of web celebrity shop

4.2 Comprehensive assessment of web celebrity shop with improved EBM

In Sect. 3, we obtain customers' satisfaction degree matrices towards each shop. Following the above results, we assess web celebrity shops by combining the weight information of FCM and the result of Sect. 3. The main process can be divided into three steps: Firstly, based on the matrix of the percentage of customers' satisfaction degree, we can calculate customers' initial satisfaction score. Secondly, we further calculate the degree centrality and centrality weight about all attributes with the help of the weight of association rule. Thirdly, we propose the improved EBM to assess all shops.

Table 16 Initial satisfaction score matrix

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
$Shop_1$	0.8919	0.9402	0.9094	0.9519	0.9198	0.9495	0.9753
$Shop_2$	0.6485	0.9216	0.8222	0.8553	0.7383	0.9444	0.8846
$Shop_3$	0.6443	0.8617	0.8055	0.7928	0.7259	0.9358	0.8485
$Shop_4$	0.8944	0.9293	0.8618	0.8154	0.8252	0.9590	0.8984
$Shop_5$	0.8290	0.9193	0.9290	0.8980	0.8508	0.9327	0.9566

4.2.1 Calculation of initial satisfaction score

To match with 5 levels of satisfaction degree, we set basic score vector as $B = (1, 0.8, 0.6, 0.4, 0.2)$ based on the result of Ref. Chen and Hwang (2000). $P_{ij} = (p^i_{jk})_{5\times 1}$ represents the satisfaction degree percentage matrix of $Shop_i$ with respect to the attribute A_j ($k = 1, 2, \ldots, 5$). Each p^i_{jk} in the matrix p_{ij} means the percentage of satisfaction level L_k of the attribute A_j. The basic satisfaction score s_{ij} of $Shop_i$ under the attribute A_j can be calculated as follows:

$$s_{ij} = B \cdot P_{ij}. \tag{16}$$

The initial satisfaction score matrix of web celebrity shops is displayed in Table 16.

4.2.2 Centrality weight of attributes

In FCM, the centrality is used to describe a measure for determining the attribute importance Xu et al. (2019). According to the result of Ref. Xu et al. (2019), the weight information is calculated by using the sum of indegree and outdegree value of an attribute. Thus, the degree centrality of the attribute A_j is defined as follows Xu et al. (2019):

$$Degree\ centrality(A_j) = Outdegree(A_j) + Indegree(A_j). \tag{17}$$

In this case, the indegree value is equal to the sum of the weight of all association rules point to this attribute, and the outdegree value is equal to the sum of the weight of all association rules point out from this attribute. If an attribute has a higher degree centrality, it should play a more critical role in the FCM. Then, we further normalize the degree centrality of the attribute A_j and compute the centrality weight as follows:

$$c_i = \frac{Degree\ centrality(A_j)}{\sum_{i=1}^{7} Degree\ centrality(A_i)}. \tag{18}$$

Finally, we can obtain the centrality weight of attributes A_j ($j = 1, 2, \ldots, 7$) as follows:

$$C = (c_1, c_2, c_3, c_4, c_5, c_6, c_7) \\ = (0.0958, 0.0881, 0.1118, 0.1966, 0.0.0992, 0.0862, 0.3223). \quad (19)$$

4.2.3 Evaluation by developing improved EBM

As a kind of aggregation operator, BM is capable of excavating the interrelationship between aggregation arguments. In Sect. 2, we have introduced the basic form of BM. Although the basic form considers the interaction between attributes, the interaction is non-directional. With respect to the FCM, each association rule represents the causal relationship between attributes. Fortunately, EBM of Ref. Dutta et al. (2015) provides us with a new aggregation. Therefore, for a specific $Shop_i$, we develop two cases of improved EBM to measure the satisfaction score by utilizing the multiply and addition properties.

Case 1 (Bmmultiply) EBM can assess the object with the casual relationships between attributes taken into consideration. Based on the result of EBM, we separately evaluate each attribute A_j with the multiply property as follows:

$$B^i_{FCM}(A_j) = \sqrt{I_{ij}(\sum_{k=1}^{7} I_{ik} \cdot v_{kj} \cdot w'_{kj})}, \quad (20)$$

where I_{ij} is $Shop_i$'s initial satisfaction score of A_j, w_{kj} is the weight of association rule from A_k to A_j. Let $v_{kj} = w_{kj} + 1$, which can range from 0 to 2. Normalize all rules' weights which point to A_j and the result is w'_{kj}. $B_{FCM}(A_j)$ is $Shop_i$s' final satisfaction score of A_j. Then, by combining $B_{FCM}(A_j)$ with the centrality weight C, we can obtain the final satisfaction score of $Shop_i$ as follows:

$$B^i_{FCM} = \sqrt{\sum_{j=1}^{7} c_j \cdot I_{ij}(\sum_{k=1}^{7} I_{ik} \cdot v_{kj} \cdot w'_{kj})}. \quad (21)$$

With the aid of (20) and (21), the satisfaction score matrix of all web celebrity shops under the attributes and the final evaluation are shown in Tables 17–18.

Case 2 (BMplus) Based on the EBM, this case combines it with the additional property and aggregate the decision information. Hence, for a certain $Shop_i$,

Table 17 Attribute score of web celebrity shops by using improved EBM of Case 1

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
$Shop_1$	0.9444	0.9696	1.1049	0.9794	0.9591	1.0902	1.0852
$Shop_2$	0.8053	0.9600	0.9921	0.9248	0.8592	1.0338	0.9601
$Shop_3$	0.8027	0.9283	0.9454	0.8904	0.8520	1.0186	0.9180
$Shop_4$	0.9457	0.9640	0.9918	0.9030	0.9084	1.0666	0.9972
$Shop_5$	0.9105	0.9588	1.0806	0.9476	0.9224	1.0921	1.0466

Table 18 Web celebrity shops final score by using improved EBM of Case 1

	$Shop_1$	$Shop_2$	$Shop_3$	$Shop_4$	$Shop_5$
$Score$	1.0328	0.9402	0.9091	0.9686	1.0039

Table 19 Attribute score of web celebrity shops by using improved EBM of Case 2

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
$Shop_1$	0.8919	0.9402	0.9848	0.9591	0.9198	0.9878	1.1397
$Shop_2$	0.6485	0.9216	0.8894	0.8553	0.7383	0.9790	1.0243
$Shop_3$	0.6443	0.8617	0.8678	0.7928	0.7259	0.9697	0.9804
$Shop_4$	0.8944	0.9293	0.9259	0.8154	0.8252	0.9952	1.0470
$Shop_5$	0.8290	0.9193	0.9996	0.8980	0.8508	0.9718	1.1087

Table 20 Web celebrity shops final score by using improved EBM of Case 2

	$Shop_1$	$Shop_2$	$Shop_3$	$Shop_4$	$Shop_5$
$Score$	1.0107	0.8987	0.8621	0.9365	0.9742

each attribute score $D_{FCM}(A_j)$ and its final score D^i_{FCM} can be calculated as:

$$D^i_{FCM}(A_j) = I_{ij} + (\sum_{k=1}^{7} I_{ik} \cdot w_{kj} \cdot w'_{kj}), \tag{22}$$

$$D^i_{FCM} = \sum_{j=1}^{7} D_{FCM}(A_j) \cdot c_j. \tag{23}$$

With the aid of (22) and (23), the satisfaction score matrix of all web celebrity shops under the attributes and the final evaluation are shown in Tables 19–20.

4.3 Competitive analysis and improvement advices of web celebrity shop

For competitive analysis, we perform the corresponding visual analysis in this section. Comparing web celebrity shops' initial score and two kinds of improved EBM scores of Sect. 4.2, we can obtain the same rank, i.e., $Shop_1 > Shop_5 > Shop_4 > Shop_2 > Shop_3$. Note that the initial score is computed based on the independence scenario in order to the comparison analysis. For clarity, the detailed rank results of different methods are shown in Fig. 9.

In Fig. 9, the rank of 3 kinds of scores of 5 milk tea shops is the same from the general point of view. However, our proposed improved EBMs can portray the interrelationship among the attributes in detail from a microscopic point of view. The scores of 5 milk tea shops calculated by Bmmultiply are higher than the scores obtained by BMplus. Then, in order to figure out each shop's strengths and shortcomings, we

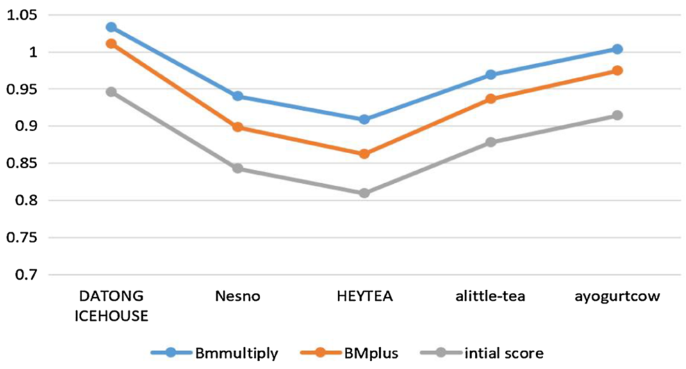


Fig. 9 Score rank of all web celebrity shops

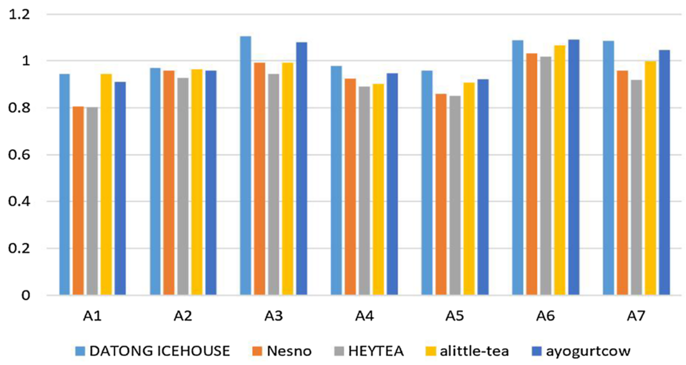


Fig. 10 Attribute score of different shops

deeply investigate the attribute score of 5 milk tea shops with Bmmultiply method, see Fig. 10.

In Fig. 10, it shows the attribute scores of different shops, respectively. More specifically, we use the results of improved EBM method to conduct competitive analysis on attributes of 5 milk tea shops. The results are represented in Fig. 11.

In addition to the above visualization analysis method, we also combine each web celebrity shop's individual FCM and the overall FCM of Figs. 7 and 8 to have further analysis. For the overall FCM presented in Fig. 7, we can easily find that A_3 and A_7 are two key attributes that the customers of web celebrity shops are more concerned about. The overall FCM reveals the universal association rules between attributes. The universality and particularity should be taken into consideration when we search for improvement advicess which will have a more considerable influence on web celebrity shop's competitiveness.

Then, we conduct specific competitive analysis on the five milk tea shops based on the above results and methods and further propose corresponding improvement advices. The $Shop_3$ HEYTEA has the highest popularity on online social platforms. However, its satisfaction score rank is fifth. All attributes have the lowest scores, especially in A_1, A_3 and A_7. Although the high popularity may bring more customers,

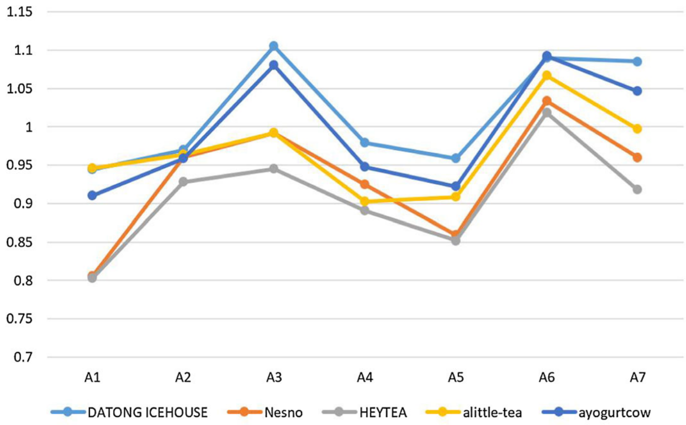


Fig. 11 Attribute competitiveness of each shop

a large number of customers cause the reduction of service quality and the growth of waiting time that may lead to the customers unsatisfied. From the FCM of *Shop*$_3$, we know that A_3, A_7 and A_6 are the first three most important attributes for HEYTEA. Thus, the advice for *Shop*$_3$ HEYTEA to improve its competitiveness is concentrating its effort on A_7 and A_3.

The second-lowest satisfaction store is *Shop*$_2$ Nesno. *Shop*$_2$ Nesno is also popular in young people. It has the problem that a large number of customers cause the reduction of service quality and its obvious disadvantages are A_1 and A_5. The FCM of *Shop*$_2$ shows that both A_1 and A_5 can promote A_7 and A_6 which are key attributes in the FCM of *Shop*$_2$. Thus, it is wise for *Shop*$_2$ Nesno to improve A_1 and A_5. *Shop*$_2$ needs to maintain the level of A_2, which is the higher level of the milk tea industry.

Shop$_4$ alittle-tea is the third of satisfaction score. It ranks the first in A_1. For *Shop*$_4$, A_1 and A_2 are its advantages and its weaknesses are A_3 and A_4. Based on its FCM, A_2 and A_4 have obviously positive correlation with A_3, A_7, A_6, which has the lead roles in FCM of *Shop*$_4$. If *Shop*$_4$ wants to promote customer satisfaction score, it should maintain its advantage in A_2 and give priority to the development of A_4. This advice can drive the growth of key attributes A_3, A_7 and A_6.

For *Shop*$_5$ a yogurt cow which is the runner-up of satisfaction score rank, its A_3 and A_6 have strong competitiveness, while A_1 and A_5 may be catched up and even exceeded by other shops and have relatively low scores. In its FCM, A_1 has a positive effect on A_6 and A_6 has a positive effect on A_3. Therefore, there is no doubt that the primary task of *Shop*$_5$ ayogurtcow is keeping enhancing A_1 to boost overall development. Meanwhile, A_5 should be developed to widen the gap with others.

Shop$_1$ DA TONG ICEHOUSE wins the highest score. *Shop*$_1$ has the risk of being exceeded by other shops in A_1, A_2 and A_6, and A_1 and A_2 have relatively low scores. A_7 is not in the lead. In its FCM, A_1 and A_2 have a positive effect on A_7. A proper advice for *Shop*$_1$ DA TONG ICEHOUSE to keep leading position is vigorously developing A_1 and A_2 and paying attention to A_6 at the same time.

5 Conclusions

In this paper, we deeply explore the value of online reviews for the assessment of web celebrity shops and competitive analysis. Based on the online reviews, we extract the attributes which customers care about by using the LDA. With the aid of LSTM, we further quantize the online reviews. Meanwhile, we evaluate customers' sentiment towards different attributes in the framework of PLTSs, which can precisely measure the true reflection of consumer attitudes. Under the guidance of the association rule, we further investigate the interrelationship among the attributes and construct FCM of web celebrity shops, which can provide us with a new viewpoint for proposing the improvement advices. Compared to the existing literature, we consider a general-purpose scenario, i.e., there is a heterogenous interrelationship among attributes. Hence, we severally investigate the extensions of EBM for aggregating the comprehensive evaluations. This paper not only successfully extends the scope of application of PLTSs, but also provides us a data-driven decision-making analysis mode. Future research work may focus on extending our results to some complex applications and improving the computational efficiency and aggregation of PLTSs.

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