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A Study on the Dynamics of Urban Cultural Image Construction and Symbolic Flow Based on Social Media Data Analysis

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Abstract City image is also the carrier and external manifestation of city culture. Based on the theory of city image communication and social media data, this study constructs the categories of city cultural image and symbol carrier. Taking X city as an example, combining the statistical analysis method and the theme extraction model constructed by TF-IDF, TextRank and LDA algorithm, we analyze the characteristics of the cultural image and symbol dynamics of X city, and further analyze the audience's emotional tendency. The overall city cultural image of X city is positive, with the content of humanistic image and social image as the main content, and the content of humanistic image is mainly the historical attractions and traditional culture, which account for about one percent of the total. The humanistic image is mainly about historical attractions and traditional culture, accounting for 48.3% and 40.8% respectively, and the social civilization style accounts for 91.4% of the content of the social image. The symbols of the city are mainly landscape scenery and food, but lack original music and technological facility symbols. 45.6% of the audience conveyed positive emotions towards the city's cultural image, while 30.2% and 17.6% of the audience conveyed neutral and negative emotions. We should continue to dig deeper into the city's cultural symbols, create high-quality content, and utilize social media platforms to promote the construction and dissemination of the city's cultural image.

Index Terms TF-IDF, TextRank, LDA, theme extraction, city cultural image, social media data

I. Introduction

Urban cultural image is a city's historical lineage, embedded cultural spirit, core values, unique cultural symbols and distinctive temperament characteristics of the centralized display and embodiment of the city's main body of a variety of urban cultural elements, after a long period of comprehensive development of the formation of a potential intuitive reflection and evaluation [1]-[3]. Urban cultural image is the external visible mark that determines the city's taste, which is like the city's “ID card” and “business card”, presenting the city's cultural information in a more intuitive way [4], [5]. The narrow sense of the city's cultural image is the constituent element of the city's image, which together with a number of city images such as the city's functional image, the city's economic image, the city's citizen's image, the city's appearance image and so on constitute the city's image [6]. Broadly speaking, urban cultural image refers to the interpretation of urban image from the perspective of culture, which highlights the importance of culture in urban image, overcomes the weakness of economic orientation of urban image, and represents the concept of a comprehensive and sustainable urban development [7]. The construction of the city's cultural image is an objective requirement put forward by seeking sustainable development after the development of the city to a new historical period [8]. It can not only overcome the major defects of blurred personality differences in regional development and drive the development and revitalization of industries, but is itself an intangible asset [9]. The attractiveness and popularity of the city is increasing, forming intangible assets and spiritual wealth of urban development, enhancing cultural cohesion, forming the core competitiveness of the city, which is conducive to the promotion of the overall progress of the urban society and the overall development of the economy [10], [11].

With the change of the times, the geographical environment in which different cities are located, people's behaviors and lifestyles are constantly changing, and the cultural atmosphere of cities is also constantly changing [12]. Cultural image represents the city image to a certain extent, including material cultural image, behavioral cultural image and spiritual cultural image [13]. Since the birth of the city, the cultural image has been constantly drawing on the essence of the original culture and integrating foreign cultures, so that the city not only has its own characteristics, but also does not lose the opportunity to develop and drive the development of the city's economy

[14], [15]. The tangible wealth and invisible resources nurtured by the urban culture, for the citizens of the city sense of belonging and worship, not only has the effect of increasing, but also able to improve the city's popularity and charm, to attract foreign investment and talent, enhance the development of the city's driving force, the superstructure to promote the development of economic strength [16], [17]. Make the city better “bring in, go out”, better improve the city's cultural image, better create a cultural atmosphere, and better serve the people with human core.

In this paper, we collect the relevant data of the popular short videos of X city on ShakeEn platform through network crawling + manual statistics, as a research sample, and construct a category that includes two levels of content, namely, the city's cultural image and symbolic carriers. The TF-IDF method combined with the TextRank method is used to obtain the document-word and semantic relationship weight matrix, and the LDA model combined with the Random Forest model is used for theme extraction, and the theme division and theme word weights obtained by this model are used to realize the theme extraction model. The model is applied to the analysis of X city's image, and the city's cultural phenomenon shaping is analyzed from five aspects: government image, economic image, social image, humanistic image and environmental image. Then, through the statistical analysis of four types of elements, namely, city music, local food, landscape scenery and scientific and technological facilities, we explore the characteristics of the symbolic carriers of the city's related short videos. Finally, the textual content of the video comments is mined to analyze the audience's emotional attitudes and discussion focuses to explore the communication effect of social media on the city's image.

II. Study design

With the help of social media data, this paper analyzes the short videos related to the culture of X city in the short video platform of Jittery Voice, mainly from the two dimensions of the construction of the cultural image of X city and the dynamics of symbolic flow.

II. A. Sample selection

In the Shake video platform, the video play total of the topic of X city is high, the number of videos is large, the communication effect is good, and it is representative, so the short videos under the topic of “X city” are selected as the research samples to study the construction of the city's cultural image and the dynamic characteristics of the symbols. This paper intends to collect short videos with top 200 likes under the topic of “City X”, and the sample collection time is from January 2024 to June 2024. Considering that the ranking is in the state of dynamic updating, and in order to ensure the objectivity and comprehensiveness of the sample collection, the sample collection is divided into 6 months, and the videos with top 250 hotness are collected in each month, and the sample collection time is 6 consecutive months. 250 videos were collected for 6 consecutive months, and duplicates were eliminated (with little change in rankings) and collected in the order of precedence, for a total of 250 videos were collected. 50 irrelevant videos were eliminated and finally 200 videos were obtained as a valid sample.

II. B. Category Construction

In this paper, we intend to categorize the categories into two major categories, namely, urban cultural image and symbol carrier, and make further category subdivisions under the two major categories. The three-level topic coding for the construction of urban cultural image is shown in Table 1. In urban cultural image, it includes government image, economic image, social image, humanistic image and environmental image. On this basis, a secondary subdivision was carried out to subdivide 23 tertiary topics of urban cultural image. The elements of urban image are the identifying symbols and consensus discourses converged based on cultural accumulation, collective cultural memory, and urban material civilization, which can constitute a resource base of narrative personality, narrative material and narrative strategy for urban image communication. Typical elements of city image extracted by scholars in practice include city music, local food, landscape scenery and scientific and technological facilities, which are selected as the symbolic carriers of city image in this paper.

II. C. Reliability test

Reliability testing is an important step in ensuring the validity of research results. It involves testing the consistency of results obtained from repeated testing of the same content by different test subjects. This helps in determining the stability of the results and the higher the consistency, the higher the reliability of the coding design. A total of 20% of the total sample size of 200 short videos, totaling 40 short videos were sampled for the coding test and the results of the reliability test are shown in Table 2. The results show that the reliability of each variable is above 0.80, and the overall reliability coefficient K = 0.875, which meets the coding reliability criteria.

II. D.Research methodology

In this paper, mathematical and statistical analysis methods and text analysis methods are mainly used to study the collected data. In the text analysis method, TF-IDF method, TextRank method and LDA method are used to construct RTF-LDA topic extraction model. The combination of TF-IDF and TextRank methods is used to obtain the text word weight matrix, and this weight assignment strategy makes the text expression consider both word frequency and semantic relationship, so as to comprehensively extract the key information in the document to characterize the corpus document and improve the accuracy of the LDA model topic modeling. Secondly, the document-topic word matrix and topic-keyword matrix obtained from the LDA model are input into the random forest model to obtain the topic classification and the relative importance of different topic words to the topic classification, i.e., the weights, which can improve the classification efficiency and filter out the high-frequency topic words under the topic classification that have low and ineffective weights to improve the quality of the topic words.

Table 1: The three level issue code list for urban cultural image construction

Primary issue	Secondary issue	Tertiary issue
Urban cultural image	Government image	Ruling philosophy
		Official image
		Government policy
		Development planning
		Legal knowledge
	Economic image	Technology level
		Economic development
		Price level
		Public income
		Commercial attractions and activities
	Social image	The style of social civilization
		Social security
		Livelihood guarantee
	Humanistic image	Local food
		Leisure activity
		Historic spot
		Traditional culture
		Festival celebration
		Talent education
	Environmental image	Natural wind
		Environmental protection
		Modern architecture
		Traffic condition
Symbol carrier	City music	Local music
		Non-local music
		No music
	Local diet	Yes
		No
	Landscape	Yes
		No
	Technology facilities	Yes
		No

II. D. 1) Calculation of the TF-IDF matrix

TF-IDF, i.e. Term frequency-Inverse document frequency, is a statistical method to reflect the importance of a word in a document relative to the whole corpus, in which the document consists of a number of sentences, and the corpus is a collection of all the documents.TF-IDF consists of two parts, TF stands for Term Frequency, i.e., the frequency of occurrence of a word in a document. TF-IDF consists of two parts, TF stands for word frequency, i.e., the frequency of a word in a document, and IDF stands for inverse document frequency, which is a quantity that is inversely proportional to the frequency of the word in the whole corpus, that is to say, the more a word occurs in all the corpus, the lower is the value of IDF, and vice versa, the fewer the occurrences, the larger is the value of IDF.

Table 2: Reliability test results

Coding variable		Coding reliability	
Main class	Specific variable	Main class	Specific variable
Urban cultural image	Government image	0.921	0.915
	Economic image		0.934
	Social image		0.918
	Humanistic image		0.866
	Environmental image		0.927
Symbol carrier	City music	0.863	0.828
	Local diet		0.843
	Landscape		0.851
	Technology facilities		0.867

The specific calculation process of TF-IDF is as follows: assuming that d is a document d belonging to the corpus corpus and there is a word t in d, the calculation of TF and IDF is shown in equations (1) and (2):

$$TF_{t,d} = \begin{cases} \dfrac{count(t,d)}{length(d)} & count(t,d) > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

For the TF value, since the word t may occur in different documents d, and the length of different d is different, in order to compute the relative document frequency, we need to divide $count(t,d)$ by the total number of words $length(d)$ in the document d. Since the document will eventually be vectorized, the computation of TF is based on vectorizing the document d based on a list $vocab$ consisting of all the lexical elements in the corpus, and the resulting $TF-IDF$ is a uniquely-hot matrix, with all TF values in the interval $[0,1]$.

For IDF values, N is the total number of documents in $corpus$, and D_f represents the number of articles in $corpus$ in which t appears. The division of N by D_f indicates that the number of occurrences of t in the whole corpus is inversely proportional to the IDF value. To prevent the IDF value from exploding, the IDF value is logarithmized by $\lg$ and the D_f value is smoothed by adding 1 to prevent dividing by 0, as shown in equation (2):

$$IDF_t = \log_{10}\left(\frac{N}{D_f+1}\right) \tag{2}$$

Finally, the two values are multiplied together to obtain a value of $TF-IDF$, as shown in equation (3):

$$TF-IDF = TF \times IDF \tag{3}$$

With the above calculations, the results can be used to determine whether the word is a keyword in the document or not, which in turn selects the non-keyword.

II. D. 2) Calculation of the TextRank matrix

The TextRank algorithm is an improved version of the PageRank algorithm, which can be used to extract keywords and key phrases. In this paper, this algorithm is used to realize automatic text summarization, so here is a detailed description of TextRank to extract key sentences. Unlike the PageRank algorithm, which iteratively calculates based on the bi-directional relationship between nodes, the TextRank algorithm calculates based on the similarity between sentences. TextRank constructs the text as a whole as an undirected graph $G=(V,E)$, where V denotes the nodes in the graph, which correspond to the sentences in the text, and E denotes all the edges in the graph, and the similarity between sentences is used as the weights of the edges, and the scores of sentences are computed by iterative means, and the sentences are sorted in terms of importance according to the size of the scores. The specific algorithm is as follows: 1) Add each sentence in the text to the graph model as a corresponding node in the graph.2) Add the similarity between sentences to the graph model as the weight of the corresponding edges in the graph.3) Iteratively compute sentence scores on the graph model using the TextRank algorithm until it converges.4) Select the summary sentence based on the sorting of the scores of the sentences.

The iterative computation of TextRank algorithm is shown in equation (4):

$$WS(V_i)=(1-d)+d\times\sum_{V_j\in In(V_i)}\frac{w_{ji}}{\sum_{V_k\in Out(V_j)}w_{jk}}\times WS(V_j) \tag{4}$$

where: V_i, V_j denote the nodes in the graph, i.e., the sentences in the document, w_{ji} denotes the weights of the edges between node V_j and node V_i, which are expressed as the similarity between the corresponding sentence of node V_j and the corresponding sentence of node V_i, $WS(V_i)$ and $WS(V_j)$ denote the scores of the nodes, and all node scores are initialized to 1. $In(V_i)$ denotes the set of all nodes pointing to the node V_i, and $Out(V_j)$ denotes the set of nodes pointed to by the node V_j. d denotes the damping factor, which represents the probability that a given node randomly points to any node in the graph. Iteration stops when the error at a node is less than 0.0001.

The weights of edges between nodes, i.e., the similarity between nodes corresponding to sentences are calculated by counting the number of co-occurring characters of the sentences, taking sentence S_i and sentence S_j as examples, let sentence S_i consist of N_i characters $S_i=w_1^i,w_2^i,\cdots,w_{N_i}^i$, sentence S_j consist of N_j characters $S_j=w_1^j,w_2^j,\cdots,w_{N_j}^j$, and the similarity between sentence S_i and sentence S_j is calculated as shown in equation (5):

$$Similarity(S_i,S_j)=\frac{\left|\{w_k\,|\,w_k\in S_i\ \&\ w_k\in S_j\}\right|}{\log(|S_i|)+\log(|S_j|)} \tag{5}$$

where: the numerator represents the number of characters in the sentence S_i and sentence S_j, $|S_i|$ and $|S_j|$ in the denominator represent the number of characters in the sentence S_i and sentence S_j, respectively, and the denominator represents the summed value of the logarithmic value of the number of characters in the sentence S_i and sentence S_j.

II. D. 3) Document-Word Frequency and Semantic Matrix

The documents are input to the TF-IDF method to obtain the document-word frequency weight matrix, while the document-keyword weight matrix is obtained by the TextRank method. The TF-IDF and TextRank values of words are weighted and summed to calculate the matrix score of each document in the corpus characterized by words, and obtain the document-word frequency and semantic relationship weight matrix. The first 50 feature words are selected as the TextRank feature words to be combined through relevant literature references and parameter comparison experiments. The calculation formula is shown in Equation (6):

$$score(a)=(1-\alpha)*TFIDF(a)+\alpha*TextRank(a) \tag{6}$$

where α is the damping coefficient in the TextRank algorithm, which is set to 0.85, $TFIDF(a)$ represents the TF-IDF value of a words, and $TextRank(a)$ represents the TextRank value of a words.

II. D. 4) RTF-LDA Topic Extraction Modeling

The document-word frequency and word relationship matrix is obtained through the above steps, so that it replaces the document-word item matrix calculated by the traditional LDA model based on the bag-of-words model. This matrix has both word-frequency characterization and contextual relationship characterization of word relationships, which provides a comprehensive feature representation for the subsequent LDA combined with random forest model for text topic clustering. After inputting this matrix into the LDA model, the parameters of the LDA model are first set, including the number of topics K, the parameter α of the document topic prior Dirichlet distribution θ_d, and the parameter η of the topic-word prior Dirichlet distribution β_k. A topic number is then randomly assigned to each word item in the document-word frequency and semantic relationship matrix. The topic assignment of each word item is updated using the Gibbs sampling algorithm, i.e., for each word item, the probability that the word item is assigned to each topic is calculated based on the topic assignments of all other word items using the Gibbs updating rule, and a new topic number is resampled for it. This is done after continuous iterations until the topic distribution of each document and the distribution of lexical items under each topic converge. At the end of the

Gibbs sampling process, the distribution of lexical items under each topic and the distribution of topics under each document are calculated based on the final topic assignments.

After obtaining the distribution of topics for each document and the distribution of lexical items for each topic through the output of the LDA model, the document-topic word weight matrix is calculated. This matrix is input to the random forest model, and multiple sample subsets are drawn from the training set with put back using the self-sampling method, and each sample subset is used to construct a decision tree, and for each sample subset, the process of constructing a decision tree is split by randomly selecting a portion of the features for each node, instead of using all the features. This method helps to increase the diversity of the model and improve the generalization ability. When all the decision trees are constructed, they are integrated. The topic categorization and the weights of each topic word under each topic are output through the random forest model.

The process of the model is as follows:

(1) Read the data and preprocess the cleaned data including word splitting and removing deactivated words.

(2) Calculate the TF value, IDF value and TF-IDF value of each word to generate the TF-IDF weight matrix characterizing each document.

(3) Calculate the TextRank similarity matrix.

(4) Calculate the final document feature matrix: the TF-IDF and TextRank values are weighted and summed to calculate the matrix score for the word representation of each document in the corpus.

(5) Input the obtained weighted fused document-word frequency and semantic relationship matrices into the LDA model for training.

(6) Determine the number k of LDA topics based on the perplexity and consistency discussions.

(7) Multiply the probability of m documents belonging to different topics in the model obtained from LDA training with the word weights of $top\ n$ under k topics to obtain the topic word weight matrix of $m \times kn$, which is computed as shown in Eq. (7):

$$\text{Thematic weighting matrix} = \begin{bmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mk} \end{bmatrix} \times \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{m1} & \cdots & w_{mk} \end{bmatrix} \quad (7)$$

(8) The obtained document-topic word weight matrix is input into the random forest model for training and clustering to obtain the topic classification as well as each feature word weight for word cloud mapping.

III. City cultural image shaping and symbol dynamic analysis

III. A. Presentation of the city's cultural image

In order to study the image of City X presented in the short video of Shake Shack, this paper divides the components of the city's cultural image into five dimensions: government image, economic image, social image, humanistic image, and environmental image. This section will analyze the image of City X shaped by social media from the above five secondary topics and 23 tertiary topics.

III. A. 1) Government image

The frequency and proportion of city government image topics are shown in Figure 1. Among the short videos reflecting the image of X city government, the issue of “official image” accounts for the largest proportion, with a total of 18 articles, accounting for 81.8% of the government image cases, reflecting the distinctiveness of the government's official image display. At the same time, there were 16 topics on “government philosophy”, second only to the official image, accounting for 72.7% of the total, and a total of 5 topics on guidelines and policies, accounting for 22.7%, reflecting the image of the city government in terms of timely communication and continuous improvement of its policy guidelines. In contrast, the development and construction planning and legal knowledge dimensions accounted for the smallest proportion, with content accounting for only 4.50% and 9.10%. According to the proportion of each issue and the content of the issue, social media has constructed a very distinct image of the government.

III. A. 2) Economic image

The frequency and proportion of city economic image topics are shown in Figure 2. Among the 36 short videos reflecting the economic image of City X, those involving commercial attractions and activities are the most numerous, totaling 112 videos, accounting for 73.5%. The topics reflecting economic development and price level totaled 15 and 10, accounting for 30.6% and 20.4%, while the proportion of videos related to the level of science and technology and citizens' income was small in comparison. According to the proportion of each topic and the content of the topics, an image of a modern, fashionable and prosperous city was constructed.

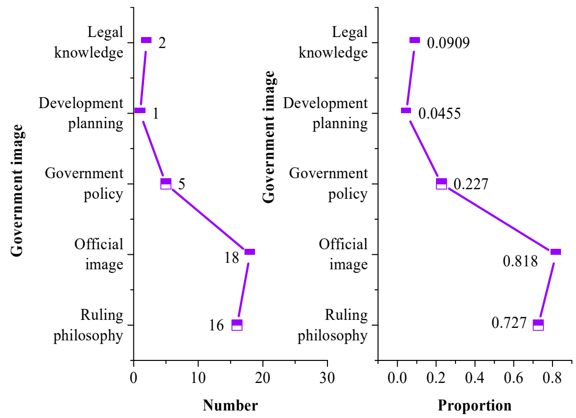

Figure 1: The issue frequency and proportion of urban government image

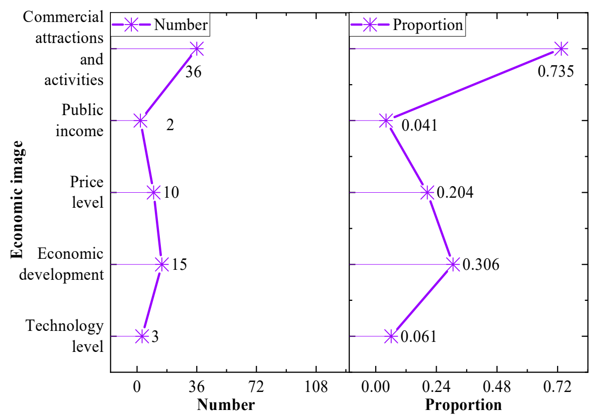

Figure 2: The issue frequency and proportion of urban economic image

III. A. 3) Social image

The social image of X city is mainly presented through 3 aspects, namely, social civilization style, social security, and livelihood protection. Statistically, the number of appearances and percentage of each three-level topic are shown in Figure 3. Among them, the videos showing social civilization have the highest number and proportion, with a total of 74 videos, accounting for 91.4% of the social image short video samples, which intuitively reflects the distinctive social civilization image of City X. The next highest proportion is the videos showing social governance, and livelihood protection. The next highest proportion is videos reflecting the content of social security, with a total of 17 videos accounting for 21.0%. Lastly, there are 11 videos related to people's livelihood and security, which account for a smaller proportion of the social image, but are still reflected. In the video samples of the three-level topic of social civilization style, the number of positive video content is predominant, accounting for 82.4% of the overall. It presents the image of the city's people's work with love and dedication, their life with diligence and courage, and their interpersonal interactions with sincerity and friendliness.

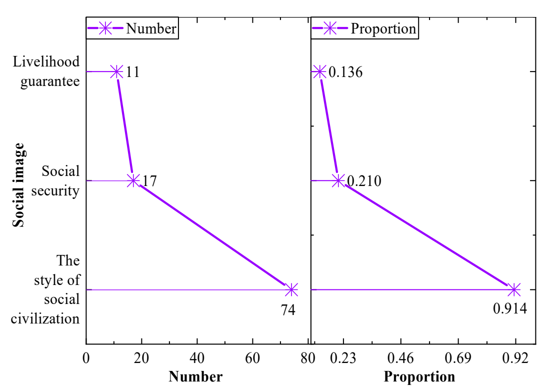

Figure 3: The issue frequency and proportion of urban society image

III. A. 4) The human face

Figure 4 shows the frequency and proportion of topics on the humanistic image of the city. The videos involving historical landscapes are the most numerous, with a proportion of 48.3%. Culture is the soul of a city, and 49 of them are about traditional culture, with a proportion of 40.8%, second only to historical landscapes, but both historical attractions and cultural activities directly or indirectly show the city's heritage. Local food and leisure activities accounted for more than 20% of the videos, and a small portion of the content about festivals, accounting for 2.50%, showing the colorful and rich local characteristics of X citizens' recreational activities and a strong festival atmosphere. To summarize, it shows a diversified humanistic image with a wide range of cuisines and a rich culture.

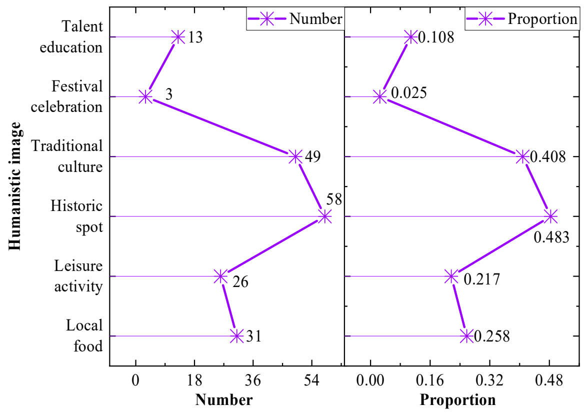

Figure 4: The issue frequency and proportion of urban humanism image

III. A. 5) Environmental image

Environmental image is mainly portrayed through four three-level topics, i.e., natural scenery, environmental protection, modern architecture, and transportation conditions, and the frequency and proportion of environmental image topics are shown in Figure 5. Among the videos reflecting environmental image, the videos showing modern architecture in X city have the highest number and proportion, 40.7%, which is an important symbol to capture the characteristics of the city's environmental image. The next highest proportion of videos is those reflecting transportation conditions, accounting for 39%. Natural scenery and environmental protection videos accounted for 30.5% and 8.5% respectively.

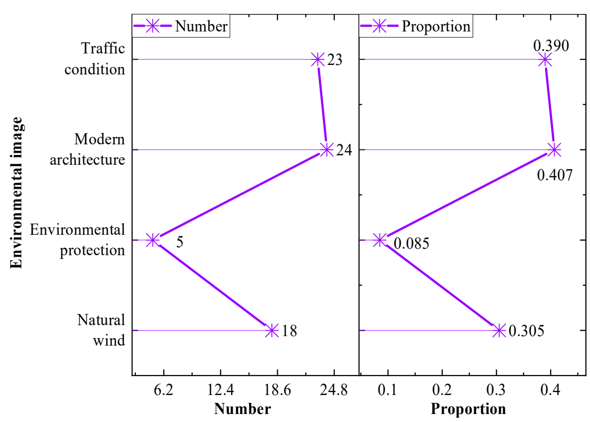

Figure 5: The issue frequency and proportion of urban environment image

III. B. Symbolic flow dynamics

This section statistically analyzes short videos related to the culture of City X as a way of exploring the symbolic dynamics of the city's image, which is characterized by the data of the city's symbolic carriers as shown in Figure 6. The spirit related to the city's culture is manifested behind the city's music. In the relevant short videos, the percentage of using local music is 8%, the percentage of non-local music is 87.5%, and the percentage of without any music is 4.5%. Local music also includes a very small number of dialect-based original music. Original music usually includes local food and drink, and the use of original songs enhances the sense of belonging to the city's culture and strengthens the unique personality of the city's image, but the number of original music compositions that incorporate the local dialect is relatively small. The percentage of relevant short videos that include the symbol of local food is 28.5%, and the variety of local food symbols is still lacking. The proportion of presentations of landscape scenery is 23.5%, and the number of presentations of technological facilities is very small at 7.5%.

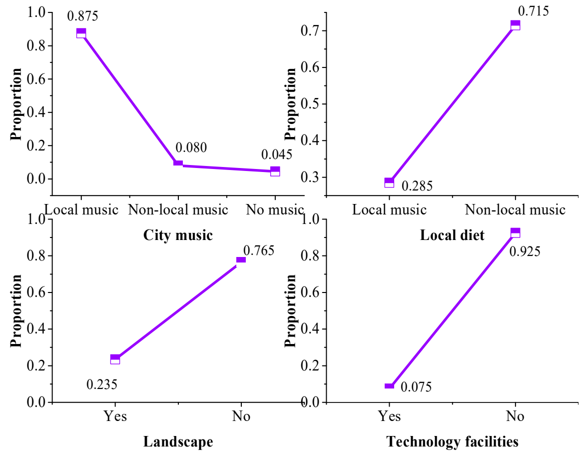

Figure 6: The city's symbol carrier data feature

III. C. Comment text analysis

The shaping and dissemination of city image is not only in the content display of city short videos only, but it is also deeply rooted in every part of the short video dissemination process, especially the interactive feedback between users, which also constructs the city image step by step. In order to explore the audience's interpretation of the short video images of City X, this paper selects the top 10 comments with the highest liking in the comment section of each of the 200 popular short videos studied, totaling 2,000 comment texts as samples for the analysis of the audience's attitudes and communication interactions.

III. C. 1) Sentiment of audience comments

The selected comment texts are classified into four categories according to the emotional attitudes of netizens: favorable, neutral, critical and other. The statistics of netizens' comment emotional tendencies are shown in Figure 7. Netizens' attitudes towards short video content related to City X are largely favorable and supportive, but the proportion is less than one-half, 45.6%. Neutral and opposing attitudes accounted for 30.2% and 17.6% respectively. By analyzing the attitudinal tendency of netizens' comments, it can be seen that netizens generally approve of the image of City X presented in the short video images, both in terms of renewing their understanding and appreciation of City X, and also in terms of comparing their own perceptions, but some netizens show their skepticism and sarcasm towards the image of City X presented in the short video images should not be ignored.

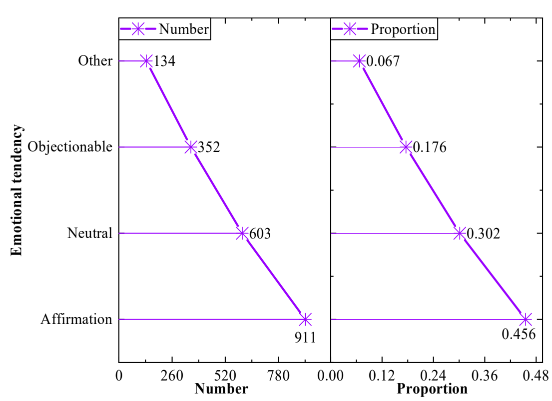

Figure 7: The emotional tendency of netizens' comments

III. C. 2) Highlights of audience discussions

The focus of netizens' discussion is on the one hand related to the specific content of the popular videos, which is a symbolic feature more often presented in short videos and a reflection of the high-frequency content perceived by netizens. In order to better understand and analyze the focus of netizens' discussion in the popular short videos of the city, the word frequency analysis of 2000 popular comment texts combined with the RTF-LDA model was carried out, and the high-frequency keywords that ranked in the top 15 were selected, and the Top15 high-frequency words of netizen's comment texts are shown in Table 3. keywords such as X city and X city man ranked in the top 2, and they were also talked about by netizens the most, which indicates that the comments of netizens have a good relationship with the city. The netizens' comments have a good correlation with the city. Emoticons such as [rose], [sobbing], [applauding], [smile], [tears] and the exclamation [ah ah] are also included in the ranking in the table, which show positive or neutral attitudes on the whole. For example, emoticons such as [rose], [applauding], and [smile] are generally used when praising or recognizing the content, and the specific meaning conveyed by other symbols depends on the context, but they do not embody negative sentiments on the whole. Finally, an overall observation of the word frequency distribution of comments shows that food, city architecture, and beautiful scenery are the content that netizens focus on discussing under short videos.

Table 3: The high frequency word for the comment text

Sort	Key words	Word frequency	Sort	Key words	Word frequency
1	X city	134	9	Beauty	72
2	X city man	131	10	[funny]	50
3	[rose]	129	11	uh-oh	49
4	[applause]	125	12	Good-looking	46
5	[weeping]	119	13	Culture	35
6	[smile]	114	14	City	33
7	[tears]	113	15	Wages	24
8	Yummy	90			

IV. Conclusion

This study takes short videos related to City X as the main research object, combines the text analysis methods constructed by TF-IDF, TextRank and LDA to construct the city's cultural image and symbol carrier categories, conducts quantitative analysis, and explores the audience's affective tendencies and discussion focuses on the city's image.

Humanistic image and social image have the most relevant videos. Historical attractions and traditional culture accounted for the largest proportion of the humanistic image, at 48.3% and 40.8%. And the social image is dominated by the content of social civilization style, accounting for 91.4%. Through statistical analysis, it is found that social media has constructed the image of X city as a service-oriented government that is friendly and active, the image of a harmonious society that is industrious and friendly and has sound protection, the image of an economy that is fashionable, modern and energetic and innovative, the image of a diversified humanistic culture that is rich in food and culture, and the image of a livable environment that is full of high-rise buildings and convenient transportation. In the use of the four major symbols, non-local music accounted for 87.5% of the city's music, and the two major symbols of original music and technological facilities were neglected, with landscape scenery and cuisine dominating the use of the four major symbols. 45.6% of the audience approved of the overall cultural image of City X, while 30.2% and 17.6% of the audience had a neutral attitude and an opposing attitude.

Overall, the cultural image of City X in social media is positive, but there is still room for improvement in the communication content. It is necessary to make full use of social media networks, deeply excavate the city's cultural symbols and turn them into cultural capital, grasp the rules of the platform, deeply cultivate the content to create high-quality products, and promote the city's cultural communication to form a benign cyclic interaction with its image shaping.

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