Extracting Kansei Evaluation Index Using Time Series Text Data: Examining Universality and Temporality

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Abstract. In recent years, affective needs, such as usability and comfort, have attracted attention, along with conventional manufacturing needs, such as function, price and reliability. Therefore, when designing products, it is necessary to accurately and efficiently reflect user's affective needs on product design. To that end, we clarify the user's emotions and impressions, in terms of the ways that people feel about products. However, they are assumed to be constant regardless of time-series, impressions that are influenced by time-series and impressions that are used universally within a certain period are mixed. As the user's emotions and impressions depend on time-series, it is necessary to deal with them separately, by time-series. In this study, based on time-series changes in the appearance frequency of evaluation words, we classified the Kansei evaluation index, according to whether it changes by time-series or not. In the proposed method, for each evaluation word, a state-space model is first used to extract the information of seasonal and trend variations. Second, by clustering this information, the evaluation terms are separated into several clusters. This method was applied to the fashion field, where time-series effects are believed to exist. The results confirmed that there were two patterns of seasonal variation and four patterns of trend variation in the impression of fashion in general, and eight universal impressions were extracted.

Keywords: Text mining · Time series · Kansei evaluation index

1 Introduction

In recent years, with the diversification of user needs and preferences, products have attracted attention, not only for their value in conventional manufacturing, as with functions and prices but also for their sensibility values, such as usability and comfort [1,2]. The Kansei engineering approach is recognized as the most reliable and effective method to handle affective needs and can be applied to various domains [3]. One specific approach to model Kansei evaluation that expresses the relationship between physical features and impressions of products [4–6]. It is expected that clarifying a user's affective evaluation (impression

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and emotion) of products and providing feedback to their design will improve product's quality and brand image. These studies are based on the assumption that people's impressions of products or services is constant. However, some of the impressions that compose the model include seasonal variation and trend variation; there may be a mixture of those affected by time-series effects and those used universally within a certain period.

As an example of analyzing time-series effects of value, there are some studies about grasping long-term trend information on items and coordinates in the fashion field. With the development of artificial intelligence, research is being conducted actively to predict the future of fashion trends using machine learning tasks [7,8]. As the main focus of these studies is on the future of fashion trends, modeling Kansei evaluation quantitatively is not considered.

Therefore, in this study, we work on the classification of the Kansei evaluation indexes according to whether it changes chronologically, based on the time-series change of the word appearance frequency. In this study, we assume seasonal variation and trend variation as time-series effects, and classify universality and temporality based on how they are affected.

2 Previous Study

In a study to quantitatively model the user's impression using text mining [5,6], a hierarchical structure, consisting of three layers, is assumed: (1) "Emotion" layer that expresses the preference of the product, (2) "Impression" layer that expresses the characteristics of the product, and (3) "Physical element" layer that expresses the physical features of the product. According to this hierarchical structure, the impression structure of the target product field is clarified from the product review text. Specifically, to model the impression structure, words representing the evaluation of the target product (evaluation words) are divided into emotions and impressions, using multiple dictionary information, and topics are extracted for the evaluation words corresponding to the impressions (impression words). However, the user's impressions are thought to be influenced by time series, such as seasonal variation and trend variation. As these factors are not considered in the modeling, we must model the impression structure separately by time-series.

In the case of predicting long-term trends in the fashion field, there are studies to discover trends in realway using the similarity of coordinated images by investigating the relationship between cutting-edge fashion "runway" and general fashion "realway" in fashion shows [7] and to predict the future popularity of styles discovered from fashion images taken in an unsupervised manner [8]. In these studies, time-series modeling of the visual feature of fashion style is possible, but the structure of the impression that causes the trend of the visual feature is not known.

3 Methods

We classify the Kansei evaluation indexes according to whether it changes chronologically, based on time-series changes in the appearance frequency of evaluation words.

The method consists of four steps. First, we collect and select evaluation words, using word classes and Japanese dictionaries of evaluation expressions. Second, we estimate the state-space model that decomposes the appearance of evaluation words into each factor component (seasonal variation and trend variation). Third, we classify the appearance of evaluation words by clustering each factor component. Finally, we cluster evaluation words with small time-series changes using embedding words. In this method, we classify the universal Kansei evaluation indexes according to whether it changes chronologically.

The state-space model in this study is indicated by the following formula:

$$y_t = \mu_t + \gamma_t + \epsilon_t \tag{1}$$

$$\mu_t = \mu_{t-1} + \beta + \eta_t \tag{2}$$

where y_t is the evaluation word appearance probabilities vector at time t, μ_t is the trend component, γ_t is the seasonal component with the so-called the four seasons of spring, summer, autumn and winter (In this study, according to the four seasons of the Japan Meteorological Agency, spring is from March to May, summer from June to August, autumn from September to November, and winter from December to February), ϵ_t is the irregular and $\epsilon_t \sim N\left(0, \sigma_\eta^2\right)$, μ_t is a generalization of the intercept term that can vary dynamically across time, β is a generalization of the time-trend that is constant, η_t is the irregular and $\eta_t \sim N\left(0, \sigma_\eta^2\right)$. The seasonal component is modeled as:

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t+1-j} + \omega_t \tag{3}$$

where ω_t is the irregular and $\omega_t \sim N\left(0, \sigma_\eta^2\right)$.

y_t is calculated for each year and the four seasons and standardized to $N\left(0, 1\right)$ for each evaluation word. This model shows what factor y_t is decomposed into and that it changes in x year. In addition, the state-space model consists of two equations: an observation Eq. (1) that determines how an internal state is observed from a certain internal state, and a state Eq. (2) that determines how the internal state changes with time [9].

The clustering of seasonal variation γ_t and potential internal state transition μ_t by k-means method is used to classify the time-series variation of evaluation words. By modeling the time-series relationship of the appearance frequency and bundling the evaluation words with similar models, it can be estimated as an evaluation index with the same time-series tendency.

In the classification results obtained by the above processing, the time-series variation can be interpreted, but evaluation words with different meanings are mixed into the cluster, making them difficult to interpret. For this reason, we interpret each cluster using the distributed representation of words and hierarchical clustering. Word2Vec [10] is used as a learning method for the distributed representation of words. Word2Vec is a technique to obtain a distributed representation of words, using a two-layer neural network, called a Skip-gram model. Next, we calculate the cosine similarity between the evaluation words in each cluster, using the distributed expression of the evaluation words obtained by Word2Vec, calculate the distance based on the cosine similarity, and perform hierarchical clustering by the longest distance method. The number of clusters in this study is determined, such that the evaluation words with a cosine distance in the top 30% of the whole belong to the same cluster.

4 Experiment

4.1 Data

The data included in this study are fashion news articles written at Fashion Press[1] between March 2012 and November 2019, 20,357 pages. There is a structure in which fashion trends are transmitted from top designers and collections in a top-down fashion. Therefore, we analyze fashion news articles that are located in a position that connects users and top designers. Fashion Press has seven categories of news articles: fashion, beauty, gourmet, art, film, music, and lifestyle. In this study, we perform analysis focusing on time-series features in fashion categories.

4.2 The Collection and Selection of Evaluation Words

To extract the evaluation words necessary to extract the evaluation index in the fashion field, we collected and selected evaluation words suitable for expressions to evaluate fashion. First, to extract evaluation words related to the impression, the words with a POS that is a main adjective or noun (adjective base) are collected from all words after morphological analysis. Next, evaluation words of other POS are collected using the following three Japanese dictionaries: (1) EVALDIC ver. 1.0.1 [11,12], (2) Japanese Sentiment Dictionary (Volume of Verbs and Adjectives) ver. 1.0 [11], and (3) Japanese Sentiment Dictionary (Volume of Nouns) ver. 1.0 [13]. The conditions of the collection are as follows: (1) included in EVALDIC; (2) included in the words given the "evaluation" tag in the Japanese Sentiment Dictionary (Volume of Verbs and Adjectives); (3) included in the words given the "evaluation" tag in the Japanese Sentiment Dictionary (Volume of Nouns); and (4) appear in the fashion category more than 0.5% higher than those in the non-fashion categories.

In a related study [5], evaluation terms are classified based on the Japanese Appraisal Dictionary-attitudinal evaluation ver. 1.0. [14] which category information of evaluation expressions is attached. In this dictionary, there are two

[1] https://www.fashion-press.net/.

categories of evaluation expressions: "externalized evaluation" and "internalized evaluation". Internalized evaluation expresses the evaluator's feelings and feelings for the evaluation target, such as "happy" or "fun" and externalized evaluation indicates the characteristics of the evaluation target, such as "soft" or "beautiful." In this study, as in the previous study, evaluation words corresponding to externalized evaluation were selected to clarify the impression factors that lead to the user's emotions.

As a result, 117 evaluation words were selected as evaluation words suitable for expressions that evaluate fashion.

4.3 Time Series Clustering Using State Space Model

As some evaluation words are strongly influenced by trends and seasonal fluctuations, we classify the evaluation indices using a state-space model and the k-means method.

The parameter estimation of the models described in Sect. 3 is performed by the BFGS method, and the potential internal state transition μ_t and seasonal variation γ_t obtained from those models are clustered. The optimal number of clusters was determined using AIC (Akaike Information Criterion). As a result, the number of clusters of potential internal state transition was 4, the number of clusters of seasonal variation was 2, and evaluation indexes with time-series tendency of all 8 patterns were extracted. Figures 1 and 2 show the cluster centroids of potential internal state transitions and seasonal variations, respectively.

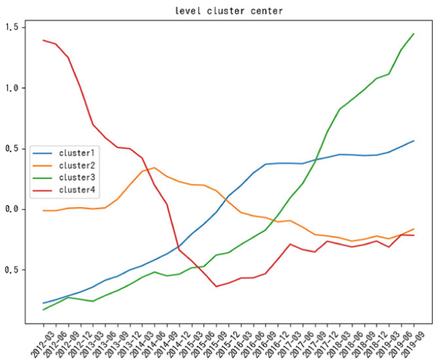

Fig. 1. Potential internal state transition

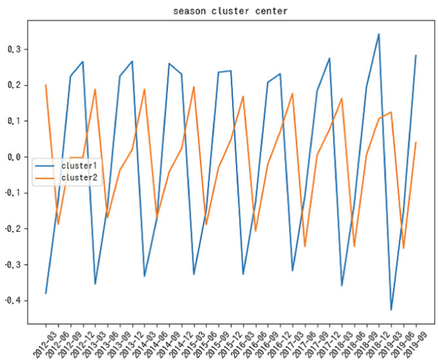

Fig. 2. Seasonal variation

Looking at Fig. 1, it is possible to estimate that there are clusters 1 and 2, which have relatively small fluctuations and are relatively stationary, as well as cluster 3, which has an upward trend, and cluster 4, which has a downward trend. Looking at Fig. 2, it is possible to interpret cluster 1, which has a strong seasonal variation, and others.

4.4 Interpretation of Evaluation Index by Word2Vec

Clustering was performed on the evaluation words belonging to cluster 2, which is a group of evaluation words with small seasonal variation in Fig. 2, among the relatively stationary clusters 1 in Fig. 1. Table 1 shows the results of these interpretations. It was possible to extract eight universal evaluation indices, except for clusters containing fashion-specific words like cluster 3 and clusters with only one word in the cluster, such as cluster 10, which are difficult to interpret.

The clusters obtained from this result are: (1) impression on services and assortment (Clusters 1, 2); (2) impression on physical characteristics (Cluster 4); (3) impression on comfort (Clusters 5, 7); (4) tactile impressions (Cluster 6); and (5) visual impressions (Clusters 8, 9). It was possible to interpret all clusters as a set of evaluation words related to fashion, so reasonable results were considered to have been obtained.

Table 1. Interpretation result

Cluster	Interpretation	in Japanese	Impression Words	in Japanese
Cluster 1	Sense of security	安心感	prepare, comfortable, stable, enhanced	備える，快適だ，安定，向上
Cluster 2	Richness	豊富さ	rich, prepared	豊富だ，備える
Cluster 3	noise	ノイズ	best, down	ベストだ，ダウン
Cluster 4	Feeling of size	サイズ感	big, long, short	大きい，長い，短い
Cluster 5	Feeling of wearing	着こなし感	rough, can handle	ラフだ，こなせる
Cluster 6	Soft feeling	ソフト感	soft, supple, soft	柔らかだ，しなやかだ，ソフト
Cluster 7	Active feeling	アクティブ感	casual, light, active, effective, sporty, hard, neat, elegant	カジュアルだ，軽やかだ，アクティブだ，効く，スポーティーだ，ハード，端正だ，上品だ
Cluster 8	Presence	存在感	presence, attract, glow	存在感，惹く，光る
Cluster 9	Pop feeling	ポップ感	vivid, pop, pale, shines	鮮やかだ，ポップだ，淡い，映える
Cluster 10	noise	ノイズ	reminiscent	彷彿たる

From these results, we extracted eight types of evaluation indices (sense of security, richness, feeling of size, feeling of wearing, soft feeling, active feeling, presence, and pop feeling) that are commonly used in fashion during the target period.

5 Conclusion

In this study, we propose a method to classify the Kansei evaluation index, which is influenced by time series, from the fashion news articles existing on the web and the Kansei evaluation index, which is universal within a certain period. In the proposed method, evaluation words were first collected and selected, based on the category information and the evaluation expression dictionary. Next, we modeled the time-series changes in the appearance frequency of evaluation words using the state space method, and clustered seasonal changes γ_t and potential internal state transitions μ_t using the k-means method. Finally, the validity of this method was verified by interpreting the evaluation index using Word2Vec.

In this experiment, we analyzed fashion news articles for 9 years and applied this method. As a result, it was confirmed that there were two patterns of seasonal variation and four patterns of trend variation in the overall impression of fashion. We extracted clusters with small fluctuations in internal state and small seasonal fluctuations, and performed clustering to interpret their semantic information. As a result, we were able to confirm the evaluation indices that are universally used in the evaluation of eight fashions.

Future tasks include improving the accuracy of the state space model, modeling the relationship with emotions and improving the diversity and usefulness of the information obtained by investigating clusters that were not used in the interpretation in Figs. 1 and 2.

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