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Approaching fashion design trend applications using text mining and semantic network analysis

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Abstract

This study aims to identify fashion trends with design features and provide a consumer-driven fashion design application in digital dynamics, by using text mining and semantic network analysis. We examined the current role and approach of fashion forecasting and developed a trend analysis process using consumer text data. This study focuses on analyzing blog posts regarding fashion collections. Specifically, we chose the jacket as our fashion item to produce practical results for our trend report, as it is an item used in multiple seasons and can be representative of fashion as a whole. We collected 29,436 blog posts from the past decade that included the keywords "jacket" and "fashion collection." After the data collection, we established a list of fashion trend words for each design feature by classifying styles (e.g., retro), colors (e.g., black), fabrics (e.g., leather), and patterns (e.g., checkered). A time-series cluster analysis was used to categorize fashion trends into four clusters—increasing, decreasing, evergreen, and seasonal trends—and a semantic network analysis visualized the latest season's dominant trends along with their corresponding design features. We concluded that these results are useful as they can reduce the time-consuming process of fashion trend analysis and offer consumer-driven fashion design guidelines.

Keywords: Fashion trends, Jacket, Text mining, Semantic network analysis, Fashion design application

Introduction

Consumers use smartphones and other devices to search, share, and even create fashion trends in real time (Jennings 2019). The fashion industry uses this flood of data to explore new ways of forecasting trends (Chaudhuri 2018). Several studies have used consumer-driven data approaches through text mining methodology to analyze fashion consumers' preferences (Camiciottoli et al. 2012; Kulmala et al. 2013). Despite recent methodological advances in processing online text data, applying these advances to determine fashion design developments has not yet been discussed. Because of its complexity and various design features, fashion design applications can be difficult to discuss. Previously, fashion collections would be released 6 months before the product was ready for the market. For fashion traders and designers, fashion shows constituted previews that were essential to the collection analysis necessary to understand the latest fashion trends and produce new designs for the upcoming season. However, the current social media environment offers real-time data, and this shortens the traditional fashion cycle and fashion seasons of production (Friedman 2016). Moreover, fashion forecasting methods that use fashion collection image data gathered from human subjective judgment (known as expert advice) have a limited ability to reflect consumers' preferences.

This study, therefore, aims to identify fashion trends with design features and provide a consumer-driven fashion design application by using text mining and semantic network analysis. We focused on fashion blogs' text reflecting consumer demands and analyzed comments about fashion collections. First, we examined the current roles and approaches of fashion trend forecasting. Following, we collected consumer-driven text data. The dataset was drawn from South Korean fashion blog posts from the past decade. We utilized "jacket" and "fashion collection" as the keywords for our search. The jacket was selected because it is a fashion item used in multiple seasons with various features. It can therefore represent fashion as a whole. The design features in jackets reflect seasonal trends and they dramatically change each season (Aldrich 2003). Next, we extracted fashion design trend words and categorized a fashion trend into four clusters of increasing, decreasing, evergreen (consistently popular), and seasonal trends. Finally, we applied semantic network analysis and visualized the latest seasons' dominant trends along with their corresponding design features and interpreted the findings for application in fashion design.

The study thus offers consumer-driven trend analysis and its application for fashion traders and designers. The new approaches in the study contribute to a more in-depth understanding of consumers' fashion preferences and add feasibility and effectiveness dimensions to forecasting techniques, enabling them to reveal previous trends and predict future ones.

Literature review

The current role of fashion trend forecasting

The role of fashion forecasting is recognizing upcoming trends, producing trend reports, and providing methods of implementation to improve fashion design and product sales (Kim et al. 2013). Fashion trend forecasters collect and analyze various references to translate into design concepts, details, colors, and patterns that will be considered fashionable in the next season (DuBreuil and Lu 2020). Notably, fashion collections have played a significant role in the formation of short-run fashion trends that last from months to years (Sproles 1981). Most conventional fashion trend analysis is done through human subjective judgments using the Delphi method to evaluate design variables such as style (e.g., Furukawa et al. 2019), color (e.g., Xiong et al. 2017), fabric (e.g., Yun and Kim 2015), and patterns (e.g., Rhee and Park 2017) in fashion collections. The Delphi method is a principle based on the results of multiple rounds of questionnaires sent to a panel of experts (Gordon 1994). For example, Furukawa et al. (2019) investigated style trends with questionnaires sent to 55 participants educated through a fashion design program. They organized 495 fashion collection images using semantic differentials (SD) Likert scales by constructing a set of eight different pairs of adjectives (i.e., dark–light, casual-formal). Song and Park (2017) investigated the constructed shape of jacket design trends by using 2493 runway images presented in 2000 SS to 2015 FW fashion collections. The frequency analysis showed that the images of hourglass silhouettes, average length, tight sleeve, and natural shoulder appeared in the 2000s fashion collections. Although fashion trend forecasting addressed by expert panels have played a vital role in fashion studies, these methods face limitations. First, expert opinions differ from consumer opinions, which is limited to uncover consumers' preferences. Second, the research process is time-consuming and creates delays between acquiring data and completion, which can be a problem with time-sensitive trends. Third, the criteria used to classify images are ambiguous, which interferes with the ability to compare and contrast studies. Consequently, more innovative and efficient analytics should be coupled with conventional methods.

Given the speed of information technology and social media environments, fashion week runway images are public and searchable in real time. Fashion traders and designers are subscribed to social media around the world, but consumers also examine styles, patterns, and colors on the runway and discuss the performance and design of fashion products (Laurell 2017). Therefore, though fashion collections determine the high-end fashion trends for a coming season (Ræbild and Bang 2017), most fashion researchers, academicians, and designers would agree that the ultimate goal for fashion trend forecasting is to score actual fashion trends selected by a consumer (Beheshti-Kashi et al. 2015).

Text mining analysis

Recently, the fashion industry has used online data to spot upcoming fashion trends (Chaudhuri 2018). On a massive scale, the Google Fashion Trend Report (U.S.) (Zimmer and Horwitz 2015) compiled data on more than six billion searches. The fashion-related searches were compared by applying time-series clustering to categorize trends into six clusters of "sustained growth," "seasonal growth," "rising stars," "sustained decline," seasonal decline," and "falling stars." However, as confirmed by the Google report, it is difficult to determine whether a searcher intended to purchase the product or whether there was some other reason for the search. In addition, design features for a particular fashion item could not be assessed (Sam 2015). Considering additional information, fashion trend forecasting studies using text mining have made small but noticeable strides. Text mining, also known as text data mining, refers to methods for extracting extensive knowledge from unstructured text (Cohen and Hunter 2008). Text mining analysis is completed through natural language processing, a form of machine learning that takes massive amounts of language text and converts it into a useful form for researchers by extracting designated keywords. This is done through several types of analysis techniques, including part-of-speech, degree centrality, and frequency of occurrence analysis (Al-Hashemi 2010; Callon et al. 1983). With the increasing availability of text mining, fashion forecasts are using social media data as an opportunity to improve their insight and guide consumer purchasing decisions (Rousso and Ostroff 2018). Social media discussions about fashion items, colors, fit, and style are clues for understanding consumer fashion design preferences. Casually written consumer opinions can quickly translate into valuable data to help determine design features with consumers' preferences and thus become an asset for forecasting (Huang and Liu 2020). Beheshti-Kashi and Thoben

(2016) integrated text mining analysis with social media applications into the fashion trend analysis process to categorize design features. They analyzed design features by describing words for a jean product and extracted adjective-noun combinations such as "white color," "bootcut style," and "short cut." However, their study does not explain more abstract elements of style concepts such as "casual" and "elegant." Since style is a generic concept that encompasses design features, a specific style can be difficult to explain by a simple combination of features. To address this difficulty, An and Park (2018) proposed integrating methods of text mining and semantic network analysis to visualize the relationships between design features. Following this approach, this study applies text mining analysis with semantic network analysis to explain the correlation among fashion design features within the network.

Semantic network analysis

Semantic network analysis engenders knowledge about semantic relationships between words in a network by representing these in a graph with labeled nodes and edges (Drieger 2013). Principally, any words that can be connected to other words can be considered nodes. In the case of fashion, these nodes are commonly designers, brands, design features, sentiment words, and evaluation words (Zhao and Min 2019; An and Park 2018; Copeland et al. 2019; An and Lee 2016). In semantic network analysis, a matrix is made with rows and columns of entities. A matrix is 1-mode if the rows and columns refer to the same set of entities. In contrast, a matrix can be 2-mode if the rows and columns index different sets of entities (e.g., the rows might correspond to a single concept while the columns correspond to a compound concept) (Borgatti 2009). As nodes represent words, certain design features can quantitatively be characterized by the degree, which indicates the number of relevant nodes (adjacent nodes, connected nodes) and their relationships (links, ties, evaluations). Words with a high degree indicate local hubs in a semantic network. Centrality analysis measures the number and location of a single word that is connected to other words and quantitatively characterizes the dominant words in a network (Wasserman and Faust 1994; Brandes and Erlebach 2005). A few studies have explored the potential application of semantic network analysis in fashion design. An and Park (2018) collected text data from fashion blog posts and extracted design features and corresponding words related to men's striped shirts and visualized consumer preference for design by using semantic network analysis. However, because of a lack of historical data, the study has difficulty identifying seasonal fashion trends. For fashion forecasting, it is necessary to collect all available data for past fashion seasons and consider further extraction of design features.

In summary, the rapid growth of online data has attracted considerable attention towards fashion trend forecasting, and techniques have improved. Text mining has technically enabled the extraction of consumer-driven fashion trend words for classification. However, because of a lack of historical data, and the complexity of design features, especially regarding its depth of categorization, fashion design trend applications can be challenging to discuss. Therefore, text mining with semantic network analysis for a more extended period is worth considering as a new approach to fashion trend identification and forecasting.

Methods

Our research question is how to identify fashion trends for specific design features and provide consumer-driven fashion design applications. The study uses a text mining analysis to categorize fashion trends in the past decade and a semantic network analysis to visualize the increasing trends with specific design features for the fashion item; specifically, it focuses on analyzing personal blog posts regarding jacket design in fashion collections. Blogs represent the first domain of fashion social media; fashion bloggers have been shown to operate under the same principles of producing and documenting their styles by combining different fashion information (Laurell 2017). For this purpose, we selected the search keywords of “fashion collection” and “jacket.” This approach is grounded in the characteristic of fashion collections that form the fashion cycle (Sproles 1981). Fashion collection runway showpieces presented by luxury brands in New York, London, Milan, and Paris continue to play a role in the formation of modern fashion trends, and generally provide short-run fashion trends with six-month intervals (DuBreuil and Lu 2020). We also selected “jacket” to produce practical results for analysis as the style of jackets dramatically changes each season (Aldrich 2003). Several researchers have analyzed jacket design in fashion collections based on the designer’s philosophy and concepts (Lee and Lee 2014; Lee et al. 2016) and constructed patterns and details (Song and Park 2017; Kim and Bae 2016). This study intends to illustrate some practical research methods of utilizing consumer-driven data to identify fashion trends for jacket designs in fashion collections.

First, we used selected search keywords to collect blog posts and analyzed the changes in the number of posts per month. Then, a text mining analysis, such as with sentence segmentation, and word removal, was used to refine the collected data. A frequency analysis was conducted to extract fashion trend words. Third, we categorized fashion trends in four clusters applying time-series clustering: increasing, decreasing, evergreen, and seasonal. Each trend was analyzed by the ratio of total frequency to 20 seasons from the 2009 spring/summer through the 2018 fall/winter seasons. Finally, we applied semantic network analysis and visualized the increasing trends with specific design features and sentiment words in the latest season.

In this study we used Textom (version 2.0), provided by TheIMC (http://en.theimc.co.kr), for data collection and text mining. Textom has been utilized on the basis of a Korean text analysis software program, Korean Key Words in Context (KrKwic), and has been developed by Park et al. (2005). In addition, we applied UCINET 6.0 and Netdraw for semantic network analysis and network visualization (Borgatti et al. 2002; Borgatti 2002).

Data collection

The blog posts for analytics were collected from NAVER (http://www.naver.com) and DAUM (http://www.daum.com), the largest Korean portal and search engine, respectively, for the period between January 1, 2008, and December 31, 2018. Over that time, 29,463 posts were collected using a web crawling program, Textom version 2.0 (Park et al. 2005). To classify the periods of the fashion season, spring/summer and fall/winter, we analyzed the changes in the number of posts per month. The monthly number of posts revealed that consumer interest in fashion collections increased between 180

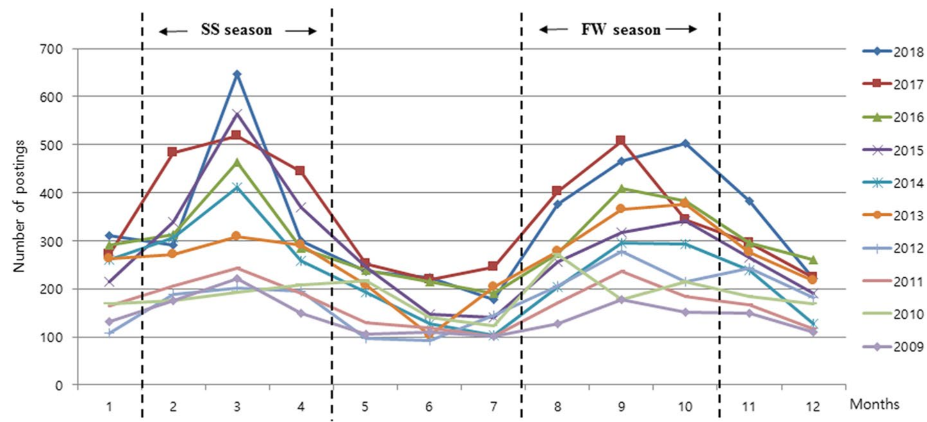


Fig. 1 Number of posts collected between 2009 and 2018. The number of posts is high in the period from February to April (spring/summer season) and from August to October (fall/winter season) in the last 10 years

and 200% between February and April and between August and October in every year we studied. Consumer interest decreased from May through July and from November through January. We observed a high frequency of the words "spring/summer," "SS" during February to April, and "fall/winter," "FW" during August to October. These periods indicate a seasonal focus on sharing information. This shows that there is a time gap between when the season fashion collection is announced and when consumers' full-fledged interest in season fashion begins to trend. Therefore, we identified spring/summer seasonal data from February to April and fall/winter seasonal data from August to October, based on the period during which consumers' interest was highest (Fig. 1). The posts in each 20-season period, from spring/summer 2009 to fall/winter 2018, were grouped as season data.

Refining data

After collection, 20-season data were processed. For sentence segmentation, we applied Textom version 2.0 to separate posts into single sentences, and again in every sentence to separate words. Then, we refined the data through correction, control, and removal of the words. The spacing, abbreviation, and plural form of the words were changed in the correction process, while words of similar meaning were unified in the control process. In the word removal process, we examined the part-of-speech of the collected words and extracted nouns and adjectives used with greater than 1% frequency during the coverage period. Verbs such as 'are' and 'is' were removed, which did not play a significant role in expressing the meaning in the context.

Extracting fashion design trend words

To set up design categories, we analyzed the degree centrality of words for fashion design elements (i.e., style, color, fabric, pattern, silhouette, and detail) (Jackson 2007). We applied UCINET 6.0, a comprehensive program for the analysis of semantic network data, to measure the degree of centrality (Borgatti et al. 2002). For style, color, and fabric, the degree centrality was more than 1% for most of the period from 2009 to 2018. In the case of patterns, the degree centrality, which is 0.005 in the 2009 spring/summer season,

Table 1 Extracted fashion trend words

Rank	Style		Color		Fabric		Pattern	
	Word	*f*	Word	*f*	Word	*f*	Word	*f*
1	Retro	600	Black	742	Leather	1036	Checkered	559
2	Chic	539	White	551	Denim	749	Floral	540
3	Classic	551	Blue	295	Padding	482	Stripe	232
4	Military	307	Pink	275	Fur	367	Leopard	180
5	Sporty	245	Red	254	Tweed	296	Animal	91
6	Minimal	164	Grey	137	Lace	168	Dotted	80
7	Punk	123	Orange	118	Suede	101	Geometry	43
8	Feminine	112	Camel	113	Silk	80	Camouflage	37
9	Mannish	105	Brown	111	Linen	76	Lettering	28
10	Futuristic	53	Burgundy	90	Metallic	57	Digital	25

gradually rose to 0.022 in the 2018 fall/winter season, confirming that the number of other words linked to the pattern has grown over the past decade. Other words, such as silhouettes and details, showed a degree centrality of less than 1% over all periods, indicating that they were relatively less influential than other design elements.

Finally, we examined nouns and adjectives with meaning related to influential design elements and categorized the words. On the basis of the frequency of each word during the coverage period, we organized the popular fashion trend words in order. The frequency analysis result of the fashion trend words by categories is shown in Table 1. We established a list of fashion trend words for "jacket" by classifying styles (e.g., retro, chic, or classic), colors (e.g., black, white, or blue), fabrics (e.g., leather/suede, denim, or padding), and patterns (e.g., checkered, floral, or stripe).

Results

Time-series clustering

Time-series clustering was applied to the 20 fashion seasons that occurred during the analysis period of 2009 spring/summer to 2018 fall/winter seasons to classify fashion trends into four types: increased, decreased, evergreen, and seasonal (Fig. 2).

In style trends, Gorpcore, a style characterized by functional outdoor wear, suddenly began to trend at a high frequency during the 2018 spring/summer season. It was introduced on The CUT in 2017 (http://www.thecut.com), which coined the word by combining "Gorp" with "Nomcore" (Chen 2017), as an emerging fashion trend. On the other hand, mannish styles dominated the 2010 spring/summer season, appearing in 26% of the frequent trending style words, but had a consistent decline to 0.7% frequency in 2018 fall/winter. Sporty styles appear to have been popular during the overall period; the trend word "sporty," overall, shows a steadily high language frequency among style trend words. Punk styles appeared as part of 18.4% and 12.2% of style trend words in the 2013 fall/winter and 2017 spring/summer seasons, but except for these seasons, the frequency has continued to be low (see Fig. 2a). Because of their temporary tendency during a season, the punk style ensemble of jackets with ripped and cut-off details in 2013 fall/winter was reported as a "fad," meaning a trend that was unlikely to become evergreen and would not return in 2014 (Hoevel 2014). These results show that over the past decade,

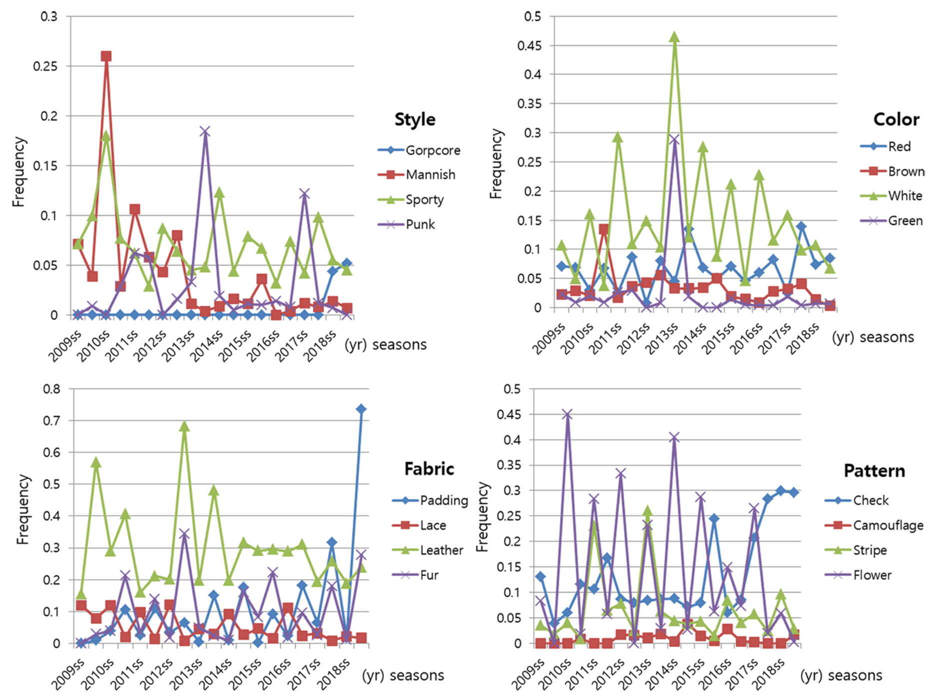


Fig. 2 Time-series cluster results of fashion trend words. Increasing, decreasing, evergreen, and seasonal trends of **a** style trend words, **b** color trend words, **c** fabric trend words, and **d** pattern trend words

style developments have converged for jackets, with sporty styles laying the foundation for the whole, and other styles tending to change dramatically.

Regarding color trends, the color red has consistently increased during the overall period while brown consistently declined from 13.5% frequency in 2010 fall/winter to 0.3% frequency in 2018 fall/winter. Noticeably, the color white increased during the spring/summer seasons and decreased during the fall/winter seasons in an annual recurring pattern. Green, meanwhile, had a temporarily high frequency (28.8%) during the 2013 spring/summer season when Pantone announced emerald green as the official color of the year (Rutherford 2013) (see Fig. 2b). However, the other colors of the year announced by Pantone, such as green with 2017s "Greenery," red-brown color in 2015s "Marsala," and red 2012 with "Tangerine Tango," were presented in high-end fashion collections but not in consumer-driven trend results.[1] The results indicate that consumer-driven color planning for the jacket is necessary as well as analyzing the color trends of official organizations.

In fabric trends, padding fabric was barely mentioned among consumers in 2009, after which it grew slowly, with a high frequency of 73.5% in the 2018 fall/winter season. This shows that padding fabric had a strong growth potential during the upcoming fall/winter season. In particular, leather was classified as an evergreen trend in terms of its consistently high frequency in all seasons. Fur has reflected seasonal demands based on up-and-down graph patterns in the spring/summer and fall/winter seasons (see Fig. 2c).

[1] Past colors of the year, (2020). Pantone. Please see: https://www.pantone.com/color-intelligence/color-of-the-year/color-of-the-year-2020. Accessed 18 February 2020.

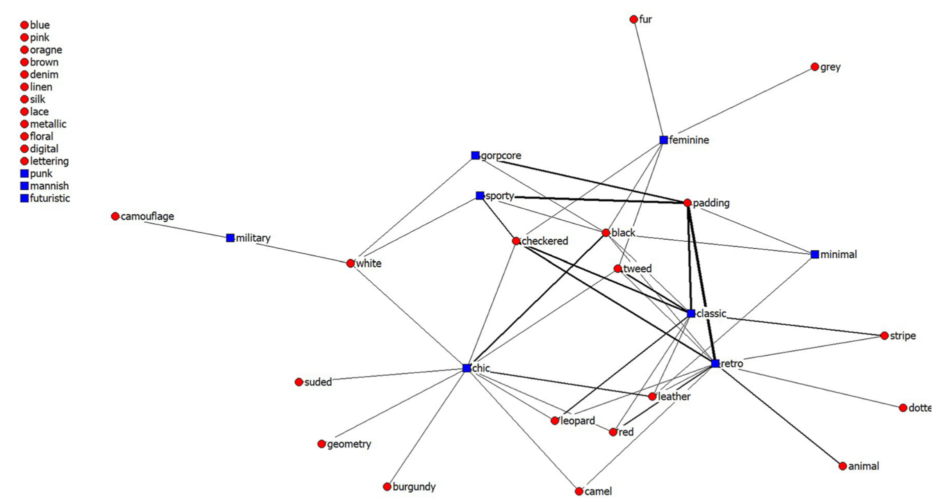


Fig. 3 Semantic network analysis results of 2-mode data on the jacket design feature (2018 fall/winter season). Triangles represent styles, and squares represent other design features (colors, fabrics, and patterns). The thickness of the lines indicates the strength of the links in terms of co-occurrences. Padding has a high degree centrality of 0.455, and it shows strong ties with other design features, considered the dominant fabric trend. Words that could not connect to any design features are shown on the left

In printed pattern trends, checkered patterns had only a 3.9% in 2010 fall/winter but were gradually increasing; during the 2017 fall/winter season, it was at 28.3% frequency. Floral patterns had a total frequency as high as checkered patterns, but the frequency increased during the spring/summer season and showed a strong season-sensitive characteristic (see Fig. 2d).

Semantic network analysis result on 2018 fall/winter

To visualize the increasing trends with specific design features, we applied a semantic network analysis to the latest season. We applied 2-mode data sets as we considered style a generic concept that encompasses various design features, colors, fabrics, and patterns, regarded on equal levels (Borgatti and Everett 1997). We organized 11×30 matrices in terms of co-occurrences; style trend words in Table 1 and rapidly increasing style "Gorpcore" were organized into the rows, and other design features in Table 1 were organized into the columns. NetDraw, a graph visualization software, was utilized for data visualization (Borgatti 2002). Network visualization aims to provide a meaningful visual representation of a network dataset. We interpreted this data with objective criteria. Between these two words, the more often they are mentioned together, the higher the numbers become, and the thicker and closer the line between them (Borgatti and Everett 1997). Figure 3 illustrates the 2-mode data in the network. It infers (1) correlation between design features, such as defining trends in close connections (e.g., checkered pattern and retro style) or trends with fewer connections (e.g., gorpcore style and leather fabric), (2) recognized design trends (e.g., padding fabric and checkered pattern in 2018 fall/winter season), (3) correlation between styles in close connections (e.g., gorpcore style and sporty style were connected to the same color and fabric, suggesting the high relevance of these features).

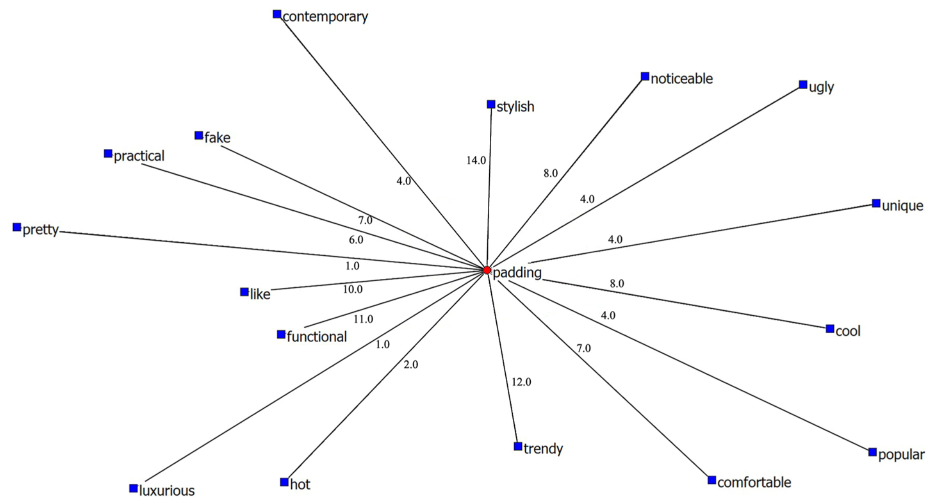


Fig. 4 The ego network of "padding" (2018 fall/winter season). The numbers on the lines indicate the strength of the links in terms of co-occurrences with sentiment words

We applied sentiment words extracted from 2018 fall/winter data, and visualized an ego network built around the increasing trend "padding." Sentiment words describe the overall impression of an item or reactions to design features (Cho and Park 2011). The network in Fig. 4 showed three cases: positive (stylish, trendy, like, cool, comfortable, unique, popular, hot, luxurious, pretty), neutral (functional, noticeable, contemporary), and negative (fake, ugly). However, in the case of the negative reaction "ugly," it was confirmed that the word reflects the new "ugly" trends rather than the negative meaning of the word (Harding 2018).

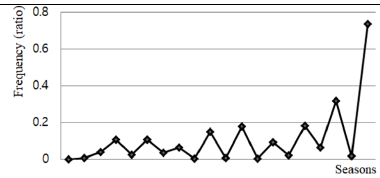
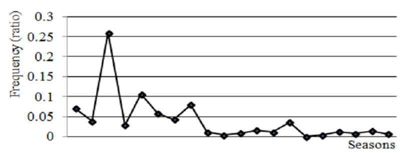
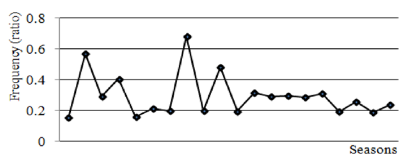
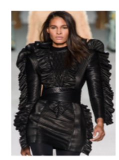
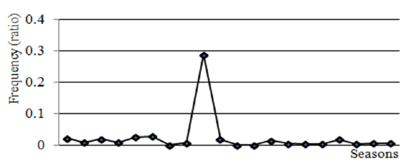
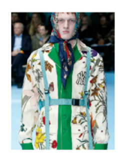
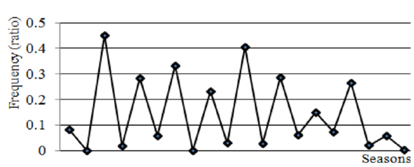
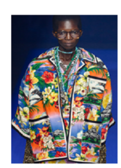
Discussion

This study processed consumer text data to examine fashion trends. Besides the extraction of fashion trend words and categorization, the study visualized a network of design features and sentiment words. This is the first step toward identifying consumer-driven fashion trends. In this study, we clustered decades of consumer-driven text data to categorize increasing, decreasing, evergreen, and seasonal fashion trends in a reasonable way. Table 2 illustrates four clusters of fashion trends and matches them to design features of the jacket.

Stable increasing trends (such as padding fabrics) and rapidly increasing trends (such as Gorpcore style) revealed whether a trend was continuing from the previous season or emerging (Yotka 2018). On the other hand, decreasing trends (such as the mannish style) revealed a low level of frequency of words in recent online comments. Notably, in the 2018 fall/winter season, the mannish, futuristic styles and silver jackets were introduced by the Balmain fashion collection.[2] However, the results show that consumers are not attracted to some designs even if they have been presented in fashion collections, suggesting that a consumer-driven trend analysis is needed.

[2] Monica Feudi (Indigital.tv), (2018). Look 3, Fall 2018 ready to wear, Balmain. Vogue. Please see: https://www.vogue.com/fashion-shows/fall-2018-ready-to-wear/balmain/slideshow/collection#3. Accessed 18 February 2020.

Table 2 Time-series cluster result on the jacket design feature (since 2009 spring/summer to 2018 fall/winter seasons)

Category		Design features	
Increasing	**Stable increasing trend**	 **Padding fabric**	 **Gucci 2018 SS**
	Rapidly increasing trend	 **Gorpcore style**	 **Valentino 2018 SS**
Decreasing	**Consistently decreasing trend**	 **Mannish style**	 **Balmain 2018 FW**
Evergreen	**Consistently popular trend**	 **Leather fabric**	 **Balmain 2018 FW**
Seasonal	**Temporarily favored trend**	 **Green color**	 **Gucci 2018 FW**
	Particularly favored trend in either SS or FW	 **Floral pattern**	 **Gucci 2018 SS**

The evergreen trends were considered a stable trend because of consumers' continued demand. In particular, leather, which has been popular for jackets regardless of season (Davis 2018), is noteworthy in that it can be used in many different ways by designers or brands in a fashion collection. During the 2018 pre-fall season, Gucci introduced a cowboy western leather jacket with fringe,[3] and during the 2018 fall/winter season, Balmain applied frilly decorations to sleeves and presented a leather jacket emphasizing the feminine silhouette via a belted waist.[4] Evergreen trends can successfully be mixed with unique design details and applications for fashion brands aiming for innovative products or new design attempts.

Seasonal trends were considered temporary when popularity peaked and fell at particular times, whereas season-sensitive trends had high frequency in either spring/summer or fall/winter but continued over time. Temporarily favored trends are difficult to predict. However, color trends can be predicted even though they are temporarily favored because they are announced 24 months before the season starts. The results of this study showed that consumers are interested in some of the trend colors that are released by the Intercolor Congresses. The season's color trend should be considered in design development, and out-of-trend colors should be used as accents. For example, Gucci's 2018 fall/winter collection presents a jacket with green accents only on the braided edges; green had been the 2013 trend color.[5] Season-sensitive trends were notable in fabrics and patterns (such as fur and floral).

For applications of fashion trends, in the study, we visualized a network of design features of the 2018 fall/winter season. Here, we focused on an increasing trend that can lower the risk when designing new products for next season (Hastreiter 2016). Semantic network analysis of 2-mode data presents the structure of style and design feature networks for the upcoming season. This method complements previous studies on fashion forecasting that use text mining analysis, in that it successfully identifies various design features connected to style trends that have not been explained. Further, semantic network analysis with sentiment words derived consumer-direct responses to the increasing trend. Since consumers do not favor all styles presented in a fashion collection, the result of sentiment network analysis may reflect consumer preferences more accurately and enable designers to make more reasonable decisions.

Currently, fashion trends move faster than ever, and new styles emerge every season. Time-series clustering, semantic network analysis, and trend forecasting can offer fashion traders and designers the possibility to market specific items on a tri-monthly basis, along with decade fashion trends. Using semantic network analysis with design features and sentiment words, designers can easily point out key trends and monitor positive or negative feelings of consumers to meet their demands swiftly. The "luxury" and "ugly" sentiment results derived from this study have presented new demands for the padding jacket, and are confirmed to be the same as the subsequent market results (Ferrier 2019). Although many clothing companies have trend forecasting reports based on sales records, fashion design trends are not created by business but by consumers' demand and preferences (Greenwood and Murphy 1978). Keywords that are repeatedly extracted in the consumer-driven text data can represent specific necessary features for

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[3] Peter Schlesinger-Courtesy of Gucci, (2018). Look 8, Pre-fall 2018, Gucci. Vogue. Please see: https://www.vogue.com/fashion-shows/pre-fall-2018/gucci/slideshow/collection#8. Accessed 18 February 2020.

[4] Monica Feudi (Indigital.tv), (2018). Look 28, Fall 2018 ready to wear, Balmain. Vogue. Please see: https://www.vogue.com/fashion-shows/fall-2018-ready-to-wear/balmain/slideshow/collection#28. Accessed 18 February 2020.

[5] Marcus Tondo (Indigital.tv), (2018). Look 21, Fall 2018 ready to wear, Gucci. Please see: https://www.vogue.com/fashion-shows/fall-2018-ready-to-wear/gucci/slideshow/collection#21. Accessed 18 February 2020.

the fashion item. Continuously building a keywords dictionary for design features can create an academic database of consumer-driven fashion analysis that can reduce time-consuming processes and give designers real-time guidance to find out how one trend has changed and in which direction it will move forward.

Conclusion

This study attempted to establish a consumer-driven fashion analysis to extract fashion trends. Text mining with a semantic network analysis was used to analyze 29,436 fashion blog posts using the keywords "fashion collection" and "jacket" during a ten-year study period. The main contributions of this study are as follows:

1. This study employed text mining methods and analyzed fashion trends quantitatively. We extracted keywords from the past decade online data boost to pinpoint popular design features of the jacket. We concluded that these results are useful as they can reduce time-consuming processes and effectively analyze consumers' preferences in fashion design.
2. This study established data on 20 fashion seasons based on consumer interest and determined dominant fads and real trends more reliably and accurately through time-series clustering. Decade fashion trends were categorized into the four clusters of increasing, decreasing, evergreen, or seasonal trends. We concluded that these four clusters could be used as academic criteria for fashion trend analysis research.
3. The study visualized the network of trend words for the 2018 fall/winter season. We established a correlation between fashion design features that focus on an increasing trend that can lower risks when designing new products for the next season. We confirm that the combinations of the methods we used in this study could offer consumer-driven fashion design guidelines to invigorate the fashion industry.

Control over fashion trends has shifted from producer to consumer, and reliable fashion trend analysis and forecasting based on consumer data is essential for the future of the fashion industry. This might encourage prospective designers to collaborate with digital information and computer support specialists to simultaneously enhance their competitiveness and creativity. In this study, we used text mining and semantic network analysis and found a feasible and effective way to identify consumer-driven fashion trends. The advent of global online communications, social networking, and the ubiquity of mobile phone technologies have increased consumers' power to influence trends in the fashion industry. Designers need a fashion trend calendar that identifies increasing trends regarding specific design features relevant to the fashion item they are creating. This allows them to plan ahead and create items that attract consumers while maximizing profits and influence.

This study has the limitation that demographic variables do not apply in terms of utilizing blog posts. Additional consideration of the characteristics of the user population needs to be made to analyze trends for the specific market.

Abbreviations

SS: spring summer; FW: fall winter.

Authors' contributions
HA originated the research idea. HA carried out the research and drafted the first manuscript. MJ helped with interpretation and improvement of the manuscript. Both authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request. The photos analyzed during the current study are available at the Vogue Runway website: https://www.vogue.com/fashion-shows.

Competing interests
The authors declare that they have no competing interests.

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