The Hidden Influence Network in the Fashion Industry

Completed Research Paper

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Abstract

In this era of big data, even though there exists an abundance of data documenting fashion and fashion trends, there has barely been any quantitative research conducted on the topic of influence or leadership. Unlike many other innovation domains such as patents where citations are explicit, a fashion designer hardly claims that s/he is influenced by others. To trace the hidden fashion influence network, we propose a novel approach to analyze the design influence in fashion industry by comparing similarity between designers in adopting same fashion symbols. Based on text processing techniques, we develop a quantitative model to extract fashion influences from 14-year historical data on fashion reviews. A total of 6,629 fashion runway reviews from the year 2000 to 2014 have been collected for analysis. We compared the performance of our proposed model with the globally published "most influential" lists and calculated a performance of 92.81% area under curve (AUC).

Introduction

In the fast-paced fashion industry, it is fascinating to observe the process of a new design being created and then later becoming a massive fashion trend. It is widely discussed that designers often intentionally or unintentionally inherit designs from other designers. However, how does a design idea flow from one designer to another? What motivate designers to 'learn' a particular design from others in the fashion industry? Are certain designers so influential in the industry that every move they make affects fashion trends in future seasons?

Fashion is a highly creative industry, where designers influence and are influenced by each other because the urge of "following the trend setter" while there is no solid measurement of calculating how influential one is in the fashion industry. There are countless sources announcing the "top designers" without explaining how and why they determine those designers to be the top ones. Is there any scientific way of quantitatively measuring a fashion designer's influence? To address this question, we propose a quantitative model of fashion influence network using fashion runway reviews from Style.com. We develop an approach to model the influence network by using historical data to analyze silhouettes, shapes, colors, fabrics, and design details of specific objects. We believe this work is one of the first to empirically examine the fashion influence relationships among fashion designers and to visualize the design influence network using fashion review data. We focus on a unique and under-studied dataset with hidden and implicit relationships derived from textual similarity measure, which goes beyond classical literature on citation analysis with explicit relationships in their datasets. With the vast availability of textual information, we believe that the method created in this work can be applied to other fields as well. Practically, gaining an in-depth understanding in this domain can guide fashion companies to make decisions on design choices and fashion trends prediction.

Literature Review

Many studies have been done on how ideas and innovations influence and diffuse in networks. For example, studies have analyzed the influence network on the adoption of new drugs within the medical profession (Kempe et al. 2003), and ideas spread among thought leaders (Frick et al. 2013). However, for fashion industry, no work has been done to examine the actual influence network in the industry itself, even though leveraging the abundance of existing data to identify the hidden patterns through data mining techniques seems entirely possible.

In marketing literature, although conceptual and mathematical models have been proposed to conceptualize fashion trends (Miller et al. 1993; Pesendorfer 1995; Tassier 2004), there has been limited empirical research conducted to validate these conceptual models with real data. Some may argue that the stream of literature on patent analysis may potentially apply to our data analysis in the domain of fashion designs. However, we argue that the nature of our data significantly differs from that of patents because of the hidden and implicit relationships among various fashion design innovations. To our best knowledge, there is no quantitative research on examining or even defining trends in fashion designers' innovations and influences. In this study, we aim to fill in the gap by collecting, processing, and analyzing a sufficient amount of textual fashion review data. Based on the idea of detecting co-occurring fashion symbols and similarity measurements, we propose an approach that uses textual data of fashion reviews to study the fashion influence network. We believe this work is one of the first to empirically examine design influence relationships among fashion designers and to visualize the design influence network using 14-year fashion review data.

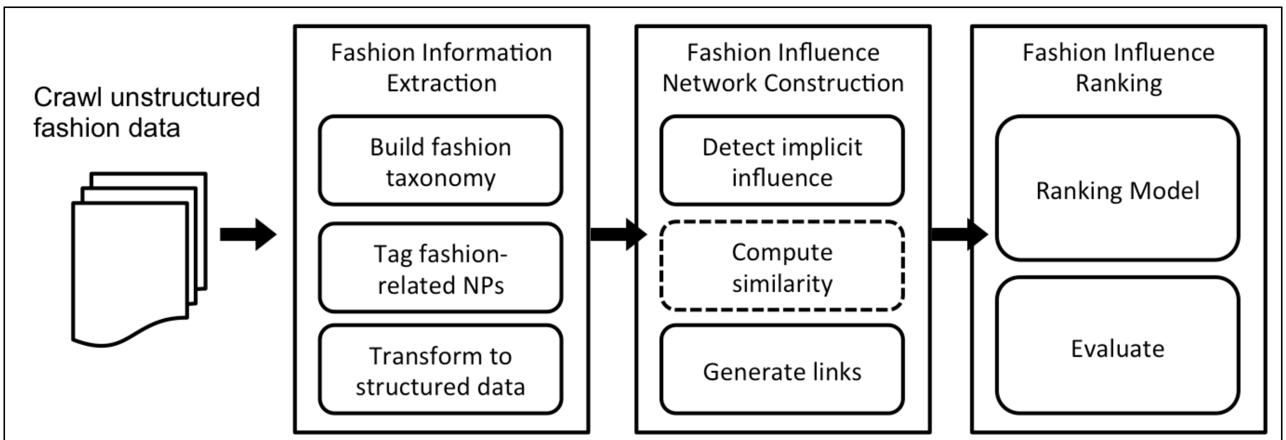

Figure 1. Flow chart of fashion influence network construction

Proposed Framework

As shown in *Figure 1*, we start this research by crawling a total of 6,629 fashion runway reviews from the year 2000 to 2014. A fashion taxonomy was constructed from our dataset; implicit influence links are then derived from our proposed similarity model. This is followed by developing a design influence network in order to better understand the innovation and influence of fashion trends within the network. In this section, we discuss the system component stage-by-stage.

Crawl Unstructured Fashion Data

At present, there is an abundance of fashion data available on the web, including online fashion magazines (e.g., Vogue), fashion runway reviews (e.g., Style.com), fashion online stores (e.g., Neiman Marcus and Saks Fifth Avenue), fashion social networks (e.g., designers' page on Facebook), and fashion blog posts, among others. However, there is barely any publicly available resource that provides a complete and detailed picture of how major fashion labels have evolved over time. Furthermore, some of these fashion resources tend to be ad-hoc, subjective and are written by a small group of writers. Therefore, we focus on the type of data that contains detailed information about fashion in a relatively objective manner — fashion runway reviews from Style.com for each fashion season.

Style.com, formerly the online site for the world's most influential fashion magazine, *Vogue*, contains fashion news and trend reports, as well as extensive galleries and reviews of elite designers' collections. These reviews, written by experts in the fashion industry, are descriptive in nature without an excess of subjective opinions. The typical content of fashion reviews includes descriptions of design inspirations, silhouettes, shapes, colors, fabrics, design details of specific objects, etc.

In the fashion industry, fashion collections are divided into ready-to-wear, couture, resort, pre-fall, and menswear. Read-to-wear, couture, resort, and pre-fall are all descriptive subcategories of womenswear, while menswear does not contain any subcategories, as it has a smaller number of designers and fewer variations of style. We focus on ready-to-wear womenswear in our data collection because it contained the largest numbers of designers and style variations. In addition, collections of ready-to-wear womenswear are typically divided into two seasons per year: Spring and Fall (Calasibetta et al. 2003).

We collected fashion reviews from Spring 2000 to Fall 2014, which included reviews for 816 designers in 30 fashion seasons, represented in 6,629 total reviews. It is important to note that the number of designers included in Style.com's review section has increased over the years, ranging from 97 designers in Spring 2000 to 459 designers in Fall 2014. Only 29 designers have reviews written for all 30 seasons, representing 3.55% of all designers and 13.58% of the entire review dataset. A brief summary of the dataset it shown in *Table 1*.

Table 1. Summary of Style.com fashion runway reviews dataset

Season from	Season until	Total seasons	Total reviews	Total designers	Designers with all seasons' reviews
Spring 2000 (97)	Fall 2014 (459)	30	6629	816	29

Fashion Symbol Extraction

In this stage, fashion-related information is extracted from the collected data. We first built a fashion taxonomy to serve as a tagging reference. Then based on the taxonomy, we extracted all of the noun phrases that include words in the fashion taxonomy from all the collected reviews.

Build a Fashion Taxonomy: To find fashion symbols from reviews, we started by constructing a fashion taxonomy based on the words used in the collected runway reviews. *The Fairchild's Dictionary of Fashion* (Calasibetta et al. 2003) was used as the main reference for deciding whether a word should be included or not. We manually picked words that are related to a fashion design element and included them in our fashion taxonomy. In this process, as the size of taxonomy increased, we randomly selected a batch of 100 reviews and used the taxonomy to tag them. Every time after tagging, precision and recall were computed to check whether the taxonomy was able to cover enough fashion-related information. In the end, we stopped including more words when the average precision was 95.08% and the average recall was 94.58%. This resulted in a total of 2,097 words in the taxonomy, with 16 first-level categories: *jargon, time, region, occasion, way of wearing, adjective, style, item, clothes construction detail, body part, material, print, color, shape, hairstyle,* and *makeup*. Some of the first-level categories have subcategories. For example, "item" is considered as a first-level category, which includes tops, bottom, dress, outwear, accessory, etc. And the subcategory "bottom" of "item" includes jeans, pants, shorts, skirt, and leggings.

Fashion-related Noun Phrase Extraction: Intuitively, the more 'similar' two designs are, the more likely it is that the later design will have been influenced by the earlier design. When considering the similarity between two pieces of reviews, a Jaccard score was applied on two sets of bag-of-words, where each document was tokenized based on white spaces; words that are not stop-words are left out. This approach is very intuitive, but the drawback is that it fails to capture the characteristics of fashion designs. For example, *little black dress* and *one-shoulder cocktail dress* are two different types of dresses, but the difference between them will not be detected when we simply compare reviews as a "bag-of-words".

To solve this problem, instead of tagging the fashion reviews by using the fashion taxonomy directly, we chose noun phrases, which carry more information than basic nouns or adjectives. We tokenized each review into sentences and extracted noun phrases based on the sentence structure, leaving only those phrases that included words from the fashion taxonomy. This resulted in a total of 25,354 unique fashion-related noun phrases, such as: *skinny black pants*, *sequin and crystal*, *jeans and T-shirt*. With the ability of carrying more meanings, a fashion-related noun phrase can describe a specific type of design (skinny black pants), a combination of materials used (sequin and crystal), or even ways of pairing clothes (jeans and T-shirt). Therefore, as we mentioned earlier in this section, we are able to use these fashion-related noun phrases as our fashion symbols. In the following sections, we use "fashion-related noun phrase" and "fashion symbol" interchangeably.

Fashion Influence Network Construction

After gathering all the required fashion symbols, we proceed to the stage of constructing fashion influence network. In this stage, all the fashion influences between fashion design collections are detected, and the level of influences are computed based on the similarity measurements we define.

Detecting Fashion Influence: In order to determine the relationships between designers, a fashion influence network is constructed. There are two components in our fashion inspiration network: (1) *nodes* representing designers, and (2) *edges* representing the level of influence between designers. A node can either be an *influencer* or an *influencee*. A designer (*influencer*) first creates or adopts a specific fashion symbol that a second designer (*influencee*) adopts in a later season.

Before we discuss the formation of fashion influence networks, for the sake of clarity, we introduce the notations used throughout this paper: d represents a fashion designer and D is the set of all fashion designers in the analysis. s represents a fashion season (which, as described earlier, is usually Spring or Fall) and S is the set of all the possible fashion seasons in the analysis. A fashion symbol is notated as f and a collection released in season s by designer d is notated as $c_{s,d}$. A fashion collection $c_{s,d}$ consists of a set of fashion symbols, which we notate as $c_{s,d} = \{f_1, f_2, \dots, f_N\}$.

For a fashion symbol f_k, if designer d_e (influencer) adopts in season s_i and another designer d_l (influencee) adopts f_k in a later season s_j, where $s_i < s_j$, we assume that d_l is influenced by d_e in terms of fashion symbol f_k. We therefore connect these two designers with a directed link from d_l to d_e. If there are numerous earlier seasons that also adopt f_k, then, according to this approach, designer d_l links to all of the d_es.

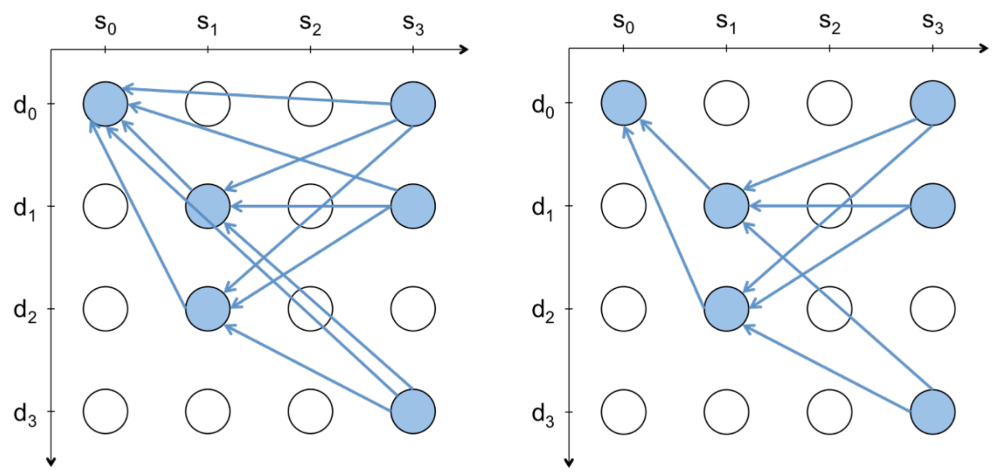

Figure 2. Two approaches to fashion influence network construction: (a) Full influence network, and (b) Nearest influence network

As shown in Figure 2, we use two approaches to construct fashion influence networks: (a) *full influence network (FIN)*, which links all the possible influencers, and (b) *nearest influence network (NIN)*, which links only the nearest possible influencers. *FIN* is an intuitive and safe approach to construct all the possible influence links, because when finding the most influential designers, we naturally look for the designer with the highest indegree. However, this approach has two drawbacks. Firstly, it fails to capture the nature of time distance, meaning that for the same fashion symbol, there is no difference between earlier influencers and later influencers.

Secondly, it's computationally expensive, as the algorithm requires $\frac{1}{2}|D|^2(|S|+1)|S|$ comparisons between collections, which is a complexity of $O(|D|^2|S|^2)$.

To eliminate these two problems, the second approach, *Nearest Influence Network (NIN)*, was introduced. Instead of linking to possible influencers in all earlier seasons and determining the influence of a designer based on its indegree, this approach only considers links pointing to possible influencers in the nearest earlier season. The difference between NIN and FIN is illustrated in Figure 2. As Figure 2 shows, NIN generates less links than FIN and the total number of required comparisons also lowers to $O(|D|^2|S|)$.

As for ranking, PageRank (Page et al. 1999) is used to score the fashion designers. PageRank is a ranking algorithm commonly exploited to find authoritative web pages on the Internet by tracing the hyperlinks from web page to web page. The same idea can be applied to our network, where each web page is a fashion designer and each hyperlink is a fashion influence link. Note that one more benefit of using NIN and PageRank is the ability of capturing the time distance property of the links in the network.

Computing influence similarity/weight: Intuitively, the more common fashion symbols that an earlier collection c_{s_i,d_e} and a later collection c_{s_j,d_l} have, the more 'similar' the two collections are, and the more likely that c_{s_j,d_l} is influenced by c_{s_i,d_e}. When considering the similarity between two fashion collections, we compare their sets of fashion symbols. Traditionally, a Jaccard score is the most commonly used measurement when comparing the similarity between sets. However, because each fashion symbol is a noun phrase that consists of multiple words, when two phrases are only partially overlapped, a Jaccard score fails to detect that. Therefore, we name the simplest Jaccard score as the *Exact Influence Score*.

$$ExactInfluenceScore\left(c_{s_i,d_e}, c_{s_j,d_l}\right) = \frac{\left|c_{s_i,d_e} \cap c_{s_j,d_l}\right|}{\left|c_{s_i,d_e} \cup c_{s_j,d_l}\right|}$$

A finer granularity is used for detecting partially overlapped noun phrases: for two noun phrases, we compare them word-by-word. Therefore, even when two noun phrases are not identical, we can detect the partial overlap. Besides the partial overlap, we also consider the uniqueness of overlapped words. We use *inverse document frequency (idf)* as our method of measurement for word uniqueness. However, unlike the traditional way of applying idf measurement, we add an extra consideration to enable the idf measurement to capture the time factor, i.e. based on the fashion season that the runway review is written on, the scope corpus is changed accordingly. A traditional idf score is defined as:

$$idf(w, D) = \log\frac{|D|}{|\{d \in D: w \in d\}|}$$

where w is the word, D is the corpus, and $|\{d \in D: w \in d\}|$ is the number of documents in D that include the word w. The variable D is frequently viewed as static throughout the computation. However, in our application, as time moves on, the size of corpus increases, i.e. the number of fashion runway reviews increases. So instead of keeping D static, we treat it as a function of the fashion season. Therefore, we can customize and rewrite the *idf* measurement as:

$$idf(w, s_i) = \log \frac{|D_{s_i}|}{\left|\{d \in D_{s_i} : w \in d\}\right|}$$

Putting the above factors together, we formulate the weighted influence between the earlier collection c_{s_i,d_e} and collection c_{s_j,d_l} as:

$$WeightedInfluenceScore\left(c_{s_i,d_e}, c_{s_j,d_l}\right) = \sum_{k=1}^{|F|} \sum_{m=1}^{|f_k|} idf(w_m, s_j)$$ [1]

where F is the set of overlapped fashion symbols between collection c_{s_i,d_e} and c_{s_j,d_l}, which can be notated as $F = \{f_1, f_2, \dots, f_{|F|}\}$, and ws are the words in the overlapped fashion symbols.

Experiments

In this section, we evaluate the constructed networks by comparing the ranked list, generated by different combinations of network construction methods (Full Influence Network, Nearest Influence Network) and influence scores (Exact Influence Score, Weighted Influence Score), with the collected published ranked lists.

For our experiment, we used three benchmarks to construct different fashion influence networks. We have the following benchmarks to compare with our approach:

1) **Random graph**: Erdős–Rényi model of constructing a random graph is used to serve as the baseline.
2) **Full Influence + Exact Influence Score**: applies the full influence and exact influence score to construct a network, so there is no link weights difference.
3) **Nearest Influence + Exact Influence Score**: exact influence score for link weights, but it applies the nearest influence to construct a network.

Our approach used to compare with the abovementioned three benchmarks is:

4) **Nearest Influence + Weighted Influence Score**: exploits the nearest influence and includes the weighted influence score formula to determine the link weights.

Our main comparison is of the three most influential designer lists published by TIMES, Fashion Merchandising Degrees, and A Celebration of the 20 Most Influential Designers. In our search, there does not exist any gold standard for the most influential designers. And we believe the ones we collected, even though are not completely justified, is a good start to serve as the right answers and real-world opinion for our experiment. To see how well the result rankings correlate to real-world opinion, we also included 8 other published, ranked lists to evaluate the results. However, one should keep in mind that the goal of this work is not to make our results as similar to the published ranked lists as possible. Instead, one should view the evaluation as an examination of whether the published lists are well founded and reflective of our fashion review data.

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[1] Note that the criterion of overlap between two collections here does not require the fashion symbols to be identical. Instead, as long as there is more than one common word, two fashion symbols are considered to be overlapped. Also, when computing the idf score, we consider the corpus regarding the later season s_j.

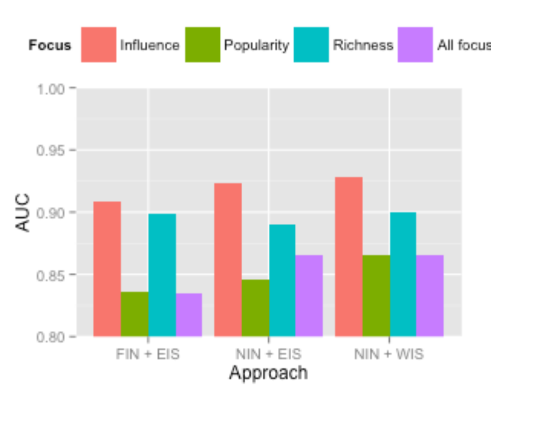

Figure 3. Comparison of average AUC of the four focuses

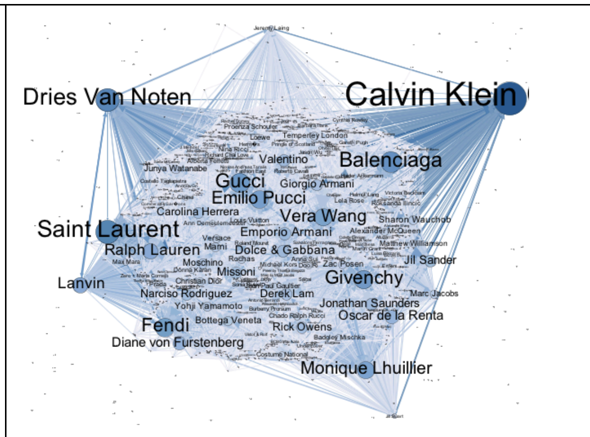

Figure 4. Result of fashion influence network with approach NIN + WIS

Note for Figure 4. *Layout of the network is created by using ForceAtlas algorithm, where the edge weights influence how the nodes spread out. Sizes of nodes are proportional to the level of influence. The dispersed nodes around the network are designers without any influence links going in nor going out.*

Table 2. Properties of constructed networks

	Random Graph[2]	FIN + EIS	NIN + EIS	NIN + WIS
Total number of edges between collections	-- [3]	494,506	43,554	62,463
Total number of edges between designers (K)	16,845	51,185	37,479	24,968[4]
Average distance between nodes (L)	2.487	2.069	2.164	2.271
Average clustering coefficient (C)	0.025	0.324	0.221	0.163
Average indegree (D)	20.643	62.727	45.93	82.574
Global Efficiency (E)	0.007	0.244	0.234	0.301

Note. FIN = full influence network; EIS = Exact Influence Score; NIN = nearest influence network; WIS = Weighted Influence Score.

By following the method for each combination of network construction methods and link weight assignments, we get a different number of total links. The network statistics of each network is shown in *Table 2*.

We used area under curve (AUC), a frequently used measure in Information Retrieval, to evaluate the ranked lists generated by the baseline, as well as the benchmarks. The result

[2] Initialize with 816 nodes and wiring probability 0.05. No link weights and all links are directed.

[3] The random graph used as a baseline is generated directly from 816 designer nodes instead of 6,629 fashion runway reviews. Therefore, the total number of edges between collections does not apply to random graph.

[4] Due to the low threshold of having influence between two designs (designers) in NIN + WIS, a huge portion of influence links represent fashion words with low idfs, such as *fabric* and *dress*. In order to analyze a small world network, we only leave a 50% quantile (score = 1.3653) of the influence links between designers.

performances were presented in *Table 2*. We also made a comparison between the three approaches among four different focuses of lists; those results are shown in *Figure 3*. Finally, we presented the final fashion influence network of the benchmark with the best AUC performance in *Figure 4*.

Discussion

As shown in *Table 2*, the combination of the Full Influence Network and the Exact Influence Score (FIN + EIS) leads to the highest number of edges, both between collections (11.35 times more as compared to NIN + EIS) and between designers. We can argue that even though the Full Influence Network provides the most conservative method of building the network, once the data scales up, such as social network data, the storage of edge files and the time it takes to compute influences becomes unsupportable. Also, the performance of FIN + EIS on average is not better than the other two combinations (NIN + EIS and NIN + WIS).

In terms of performance, all of the approaches outperform the baseline, Erdős-Rényi's random graph. They outperform it by an average of 1.6 times when compared with all of the 11 published lists, and 1.8 times when compared with the three influence-based lists. In particular, the combination of the Nearest Influence Network and the Weighted Influence Score performs the best on average. When capturing different focus of lists three approaches perform better on lists that are influence-based. This shows that our model does represent how influential a designer is, rather than reflecting other characteristics, e.g. popularity, fame, richness, etc.

More network statistics have been calculated to examine the constructed networks and are shown in *Table 2*: average distance between nodes, average clustering coefficient, and average efficiency. All of the approaches have higher average clustering coefficients than the random graph method. This is seen in the constructed networks: designers have more "neighbors" in terms of receiving influence, inspiration, and ideas from other designers than from a random network. The average distances between nodes are not too different from the random graph results, which are approximately 2. We can infer that in the fashion industry network, all designers are indirectly influenced by other designers from two hubs away, even though they are not their direct neighbors. In other words, even if they do not directly share common fashion symbols, the overall design ideas for a collection evolve and spread for on average two hubs.

Conclusion

In the present era of big data, many industries have started to utilize online data sources, such as Twitter, user reviews, and news articles to gain more insight into trends. The fashion industry will significantly benefit from a quantitative method to trace fashion influence using this sort of online dataset. In this work, we proposed a quantitative model to construct a fashion influence network by extracting influence relationship information from historical fashion data on Style.com with the help of text-processing techniques. Two approaches of connecting influence links and a unique, time-sensitive fashion influence score measure are presented. Results showed that our model could adequately capture the influence of fashion trends and the influence between fashion designers as compared to the published fashion designer ranked lists.

For future work, we plan to scale up the data to include more data sources in our analysis. We also plan to conduct further studies about what factors make a fashion designer influential.

Finally, based on all the frameworks and methods that we crafted, we want to predict and extrapolate future fashion trends through the use of historical data.

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