2015 48th Hawaii International Conference on System Sciences

Text-Generated Fashion Influence Model: An Empirical Study on Style.com

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Abstract

Various fashion theories have been proposed to explain how fashion works and why it works that way. However, there is little research empirically examining fashion designers' influences even though the benefit of understanding this field is significant. 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. We applied this approach to 6,180 runway reviews collected from Style.com between the year of 2000 to 2014 and constructed hidden influence links and the fashion influence network. Result of our approach is compared to 11 lists of "top fashion designers." We believe this work is one of the first to empirically examine the design influence relationships among fashion designers and to visualize the design influence network. Also, this work explored the way of finding implicit links from textual review data, which may be applied to other fields as well.

1. Introduction

Fashion is everywhere. It can be a way of wearing, a way of living, or even a way of thinking. But most of the time, when talking about fashion, the first thing most people think about is the way people dress in a given context. Outfits, items or persons considered as 'fashionable' are usually because the looks are trendy in that specific season. The notion of being fashionable changes from time to time, making fashion itself an extremely dynamic phenomenon. Designers in the fashion industry keep creating and updating new fashionable elements. But where do their inspirations come from? How do designers influence each other in such a way that they collectively drive the fast-paced fashion trends?

Fashion is a highly subjective industry, where people 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 ones. Is there any scientific way of measuring a fashion designer's influence throughout the fashion industry quantitatively? To address this question, it is important to understand how fashion works and to reveal the insight under all fashion trends. Enough understanding in this domain can serve as a guide for fashion companies to make decisions; being able to foresee how fashion changes in the future can help fashion designer companies minimize the risk when deciding new designs for the next seasons [1].

Existing research has proposed various fashion theories, trying to explain how fashion works and why it works that way. Although conceptual and mathematical models have been proposed to conceptualize fashion trends, there has been limited empirical research conducted to validate these conceptual models with real data due to the reason that data in fashion industry is not highly accessible. Specifically, there is almost no research on examining or even defining fashion designers' innovation and influence. "Fashion is one of the most important creative industries", and yet the topic of examining design influences has not received enough attention in literature. We aim to fill in this gap by proposing a quantitative model of fashion influence network using fashion runway reviews from Style.com. Since "each new fashion is an outgrowth or elaboration of the previously existing fashion [2]", we believe that we can trace the influence flow from earlier designs to later designs by using historical data to analyze silhouettes, shapes, colors, fabrics, and design details of specific objects. We construct a fashion taxonomy based on the domain knowledge and data collection, then derive implicit influence links from our design similarity model and construct a fashion influence network so as to understand the influence of fashion trend within the constructed network.

1530-1605/15 $31.00 © 2015 IEEE
DOI 10.1109/HICSS.2015.438

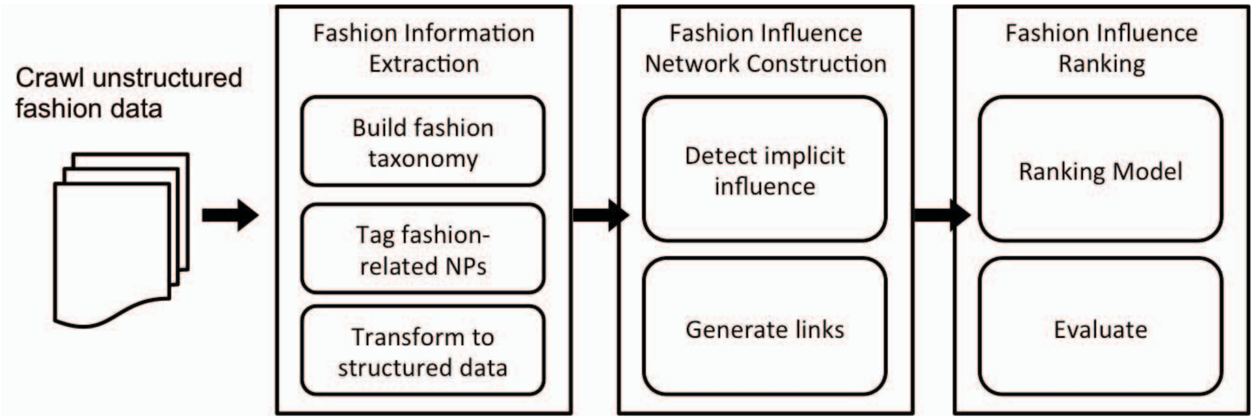


Figure 1. Framework of Text-Generated Fashion Influence Network Model

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. Our work also goes beyond classical literature on citation analysis, which often directly analyze data with explicit relationships. However in this research, we focus on a unique dataset with hidden and implicit relationships derived from textual similarity measure. With the vast availability of textual information, we believe that such methodology can be applied to other fields as well.

2. Related Work

Many studies have been done on how ideas and innovations influence and diffuse in networks. There are studies examining the influence network on the use of cell phones among college students, the adoption of a new drug within the medical profession [3] and ideas spread among thought leaders [4]. Increasingly in recent researches, social networks are used as the primary source of data to study the emerging topic detection on Twitter [5], the tracking of influence and opinion on Blogosphere [6] and etc. However, for fashion industry, only a few studies have been done to look at the influence in fashion [7], and no one has looked into the influence network in the industry itself yet.

To date, different theories of fashion trends have been proposed. One view by Miller [8] indicates that fashion design is an internal and self-contained process, which does not involve external information and input. Paul Gregory's view of purposeful obsolescence suggested that fashion industries, regardless of some rare rejections of new products, release new designs in an artificial rate of fashion change, causing the fashion trend to carry on with a fixed pace [9]. Reynolds argued that "fashion is necessarily public [1]" because fashion itself is about how it looks, which is seen by the public once it is shown on runways and worn by consumers.

Lynch once pointed out that "fashion should not be defined by opinion, which is too subjective, but instead should be documented quantitatively by actually counting populations of people wearing particular styles [9]." While information on population of people wearing particular is not available to the public, we aim to find other suitable historical data that allows us to trace fashion influence.

In marketing literature, although conceptual and mathematical models have been proposed to conceptualize fashion trends, there has been limited empirical research conducted to validate these conceptual models due to the lack of real data. Among the proposed mathematical models describing fashion trend, Miller et al.[8] developed a model based on consumers' individual-level conceptual framework. Pesendorfer [10] and Tassier [11], unlike Miller's approach, developed their models based on sales data. Pesendorfer considered that in fashion industry, there exists a monopolist who creates designs, and keeps lowering the prices of products as time goes by, whereas Tassier adopted information cascades [12] into the model, and also took prices as the main consideration. None of them used real data to evaluate their proposed models.

In summary, according to our search of related works, we found that the topic, influence network in fashion industry, hasn't been well studied yet, even though its importance is significant and worth a lot of attentions. Existing studies suffer from not having real world data to examine the proposed methods. With the big data realm, many industries start to utilize online data sources such as Twitter, user reviews, and news articles. The fashion industry will benefit largely from a quantitative method to trace fashion influence using such online dataset. Like other domains, fashion reviews are available on a variety of websites. In this study, we aim to fill in this gap by collecting, processing and analyzing a sufficient amount of fashion textual review data, which we believe carry more information than the commonly used sales data. Based on the idea of the detection of co-occurred fashion symbols and similarity measurements, we propose an approach that uses textual data of fashion to study fashion influence network.

3. Methodology

As shown in Figure 1, we propose Text-Generated Fashion Influence Model (TGFI Model) for building fashion influence networks from unstructured fashion textual data. To develop this model, we first start by crawling unstructured fashion data from the web, then extracting the fashion information from the collected data. This is followed by constructing fashion influence network with the extracted fashion information and then ranking the fashion influence. In this section, we discuss about our system development stage by stage.

3.1 Crawling unstructured fashion data

Nowadays, there is an abundant amount of fashion data available on the web, such as online fashion magazine (Vogue), fashion runway reviews (Style.com), fashion online stores (Nordstrom), fashion social network (designers' Facebook pages) and fashion blog posts. However, no research has done to analyze such rich existing data and to identify the influence network in the fashion industry. It is partially because few of these data sources are structured in a concise manner that one can easily and quickly extract information. Furthermore, there is barely any publicly available resource that provides a complete and detailed picture of how fashion designers evolve throughout a long period of time, say a decade. In addition, fashion reviews tend to be subjective and written by a small group of writers. Therefore, instead of looking for data that explicitly tells us how fashion evolves and how fashion designers influence each other, we target on those data that carry detail information about fashion in a given fashion season.

Style.com, formerly the online site for the world's most influential fashion magazine Vogue, contains fashion news, trend reports, and extensive galleries and reviews of elite designers' collections. These reviews, written by experts in fashion industry, are in descriptive nature without too many subjective opinions. Typical contents of fashion reviews include descriptions of design inspirations, silhouettes, shapes, colors, fabrics, design details of specific objects, and etc (see Figure 2 for a sample review).

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 sub-categories of womenswear, while menswear does not contain any sub-category because it has few numbers of designers and few variations of styles. We focus on ready-to-wear womenswear in our data collection because it contained largest numbers of designers and style variations. In addition, collections of ready-to-wear womenswear are typically divided into two regular seasons per year: Spring and Fall [13].

We collected fashion reviews from the season of Spring 2000 to Spring 2014, which includes reviews for 795 designers in 29 fashion seasons, with 6,180 reviews in total. Note that the number of designers being included by Style.com's review section has been increasing over the years, ranging from 97 designers in Spring 2000 to 408 designers in Spring 2014. Only 29 designers have reviews written for all 29 seasons, which is only 3.65% of all designers and 13.61% of the whole review dataset.

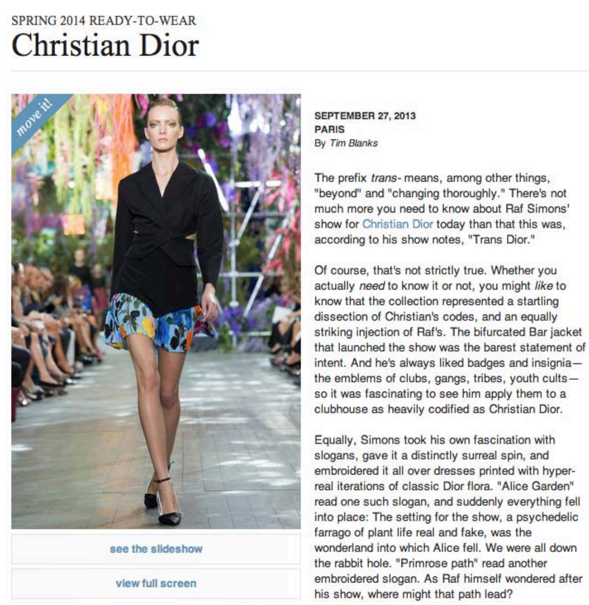


Figure 2. A sample runway review on Style.com

4.2 Fashion Information Extraction

Building fashion taxonomy. To identify fashion symbols from reviews, we started by constructing a fashion taxonomy based on the words used in

Style.com's reviews. In order to have the scope of included words justified, *The Fairchild's Dictionary of Fashion* [13] was used as the main reference for deciding whether a word should be included or not. All of the collected reviews are tokenized and only nouns were left. We manually picked words that are related to fashion, and included them into the fashion taxonomy. In this process, as the size of taxonomy increases, we randomly selected reviews and used the taxonomy to tag them. Every time after tagging, the precision and recall were computed to check whether the taxonomy can cover enough fashion-related information. In the end we stopped including more words when the average precision achieved 95.08% and average recall achieved 94.58%. This results in a number 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 second-level subcategories, such as top, bottom, dress, outwear, accessory and etc. Some of the second-level categories may have third-level subcategories. For example, *bottom* may include jeans, pants, shorts, skirt and leggings. Table 1 is a snippet of the final fashion taxonomy.

Table 1. Example categories and words in fashion taxonomy

Level 1	Level 2	Level 3	Example Words
Item	Top	Sweater	pullover, jumper, ribbed sweater
	Bottom	Trousers	pantaloons, track pants, cargo, bootleg
		Skirt	pencil skirt, sarong, full skirt
Clothe detail	Neckline	-	ruffle neck, lapel, halter neck, boat neck
	Sleeve	-	leg-of-mutton sleeve, puff sleeve
	Sewing	-	smocking, bullion, interlock
Material	Fabric	-	chambray, linen, dupioni
	Leather	-	doeskin, parchment, shearling
Print	Animal	-	zebra, leopard, giraffe
	Stripe	-	chalk stripe, breton stripe, pinstripe
Color	Solid color	-	aquamarine, deep pink, sapphire
	Coloration	-	monochrome, iridescence, fluorescence

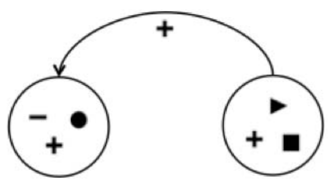
Extracting fashion-related noun phrases. Intuitively, the more 'similar' two designs are, the more likely that the later design is influenced by the earlier design. When considering the similarity between two pieces of reviews, Jaccard score applied on two sets of bag-of-words, where each document is tokenized based on white spaces and words that are not stop words are left. This approach is very intuitive, however, the drawback is that it fails to capture characteristics in fashion designs. For example, a lot of reviews in our data collection include model and designer in the review, while they are not directly related to the fashion design itself. Also, dress is so commonly used that when we find two reviews both including dress, similarity between them should not be considered significant because we have not taken the other word describing dress into account yet. For example, little black dress and one-shoulder cocktail dress are two different types of dresses, and the difference between them will not be detected when we simply compare reviews as bag-of-words.

To solve this problem, instead of tagging the fashion reviews by using the fashion taxonomy directly, we choose noun phrases, which carry more information than simply nouns or adjectives. We tokenized each review into sentences and extracted out noun phrases, based on the sentence structure, left only those including words from the fashion taxonomy. This gives us a total of 25,354 unique fashion-related noun phrases. By doing so, instead of simply finding words such as: pants, sequin and jeans, we are able to find phrases like: 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) and even way of pairing clothes (jeans and T-shirt). Therefore, like we mentioned early in this section, we can use these fashion-related noun phrases as our fashion symbols. In the following sections, we use fashion-related noun phrase and fashion symbol interchangeably.

4.3 Fashion Influence Network Construction

Detecting fashion influence. In order to see 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 be either an *influencer* or an *influencee*. We assume that a designer (influencer) first creates or adopts a specific fashion symbol that another designer (influencee) adopts in a later season.

Before we start getting into the formation of fashion influence networks, for the sake of clarity, we will 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 a 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 it as $c_{s,d} = \{f_1, f_2, \ldots, f_N\}$.



c_{s_i,d_e} c_{s_j,d_l}

Figure 3. Influencer-influencee relationship

We illustrate the influencer-influencee relationship in Figure 3. For a fashion symbol f_k, if designer d_e (influencer) adopts at season s_i and another designer d_l (influencee) also adopts f_k in a later season s_j, where $s_i < s_j$, we assume d_l is inspired by d_e in terms of fashion symbol f_k. So we 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 will link to all of the d_es.

Although there is a well-known saying in fashion that "fashion repeats itself," to simplify our analysis, it is reasonable to assume that "fashion does not repeat itself within x fashion seasons", where x is a safe limitation based on the chosen data.

To summarize our approach of constructing the fashion influence networks, we make the following assumptions:

1. After a designer adopts a fashion symbol x in its design, other designers have the same probability of being exposed to x.
2. When a later designer d_l adopts the fashion symbol f_k in season s_j, other designers d_e, where $e \neq l$, who have adopted f_k in season s_i, where $s_i < s_j$, have the same probability of influencing d_l.

Fashion Influence Detection. Intuitively, the more fashion symbols which an earlier collection c_{s_i,d_e} and a later collection c_{s_j,d_l} commonly have, the more 'similar' 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, Jaccard score is the most common measurement when computing the similarity between sets.

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

However, since each fashion symbol is a noun phrase consisting of multiple words, when two phrases are only partially overlapped, Jaccard score fails to detect that. For example, given two noun phrases cotton shirt and wide cotton skirt, traditional Jaccard score cannot detect the common word cotton, and returns a similarity of 0 instead. To solve this problem, we use a granularity that is smaller than a whole noun phrase: for two noun phrases, we compare them word-by-word. Therefore, even when two noun phrases aren't identical, we can detect the partial overlap.

Table 2. Lists for evaluation of Text-Generated Fashion Influence Model

	List name (publisher)	Focus	Ranked	Length
1	TIMES	Influential	No	45
2	Fashion Merchandising Degrees	Influential	No	10
3	A Celebration of the 20 Most Influential Designers	Influential	No	20
4	ELLE	Popular	No	20
5	International Business Times	Popular	No	10
6	The Richest	Rich	No	10
7	Celebrity Networth	Networth	Yes	50
8	JustLuxe	Best	No	15
9	The Most 10	Famous	No	10
10	Top Tenz	Top	Yes	10
11	AllWomenTalk	Iconic	No	10

4.4 Fashion Influence Ranking

After generating influence links following the proposed algorithm, not only are we able to construct a network graph of fashion influence network, but also are able to rank the influence of fashion designers based on the generated network. According

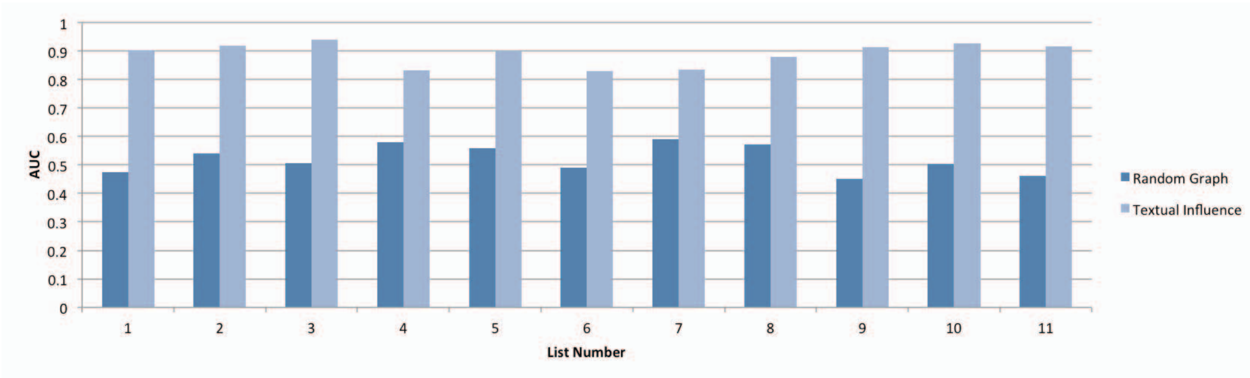


Figure 4. AUC comparison between Text-Generated Influence Model and baseline over 11 lists

to our algorithm, having influence links linking to a node (a fashion designer) means it has influence on other nodes (other fashion designers). Therefore, the simplest measurement to rank the influence of designers is to rank them based on their InDegrees in the constructed fashion influence network.

5. Experiment

According to our proposed framework, in order to construct a fashion influence network, one only has to pick a link construction approach and decide whether to add in the influence score or not. In this section, we implement the framework with a real world data source and evaluate it with published ranked lists.

For our experiment, we compared our proposed framework with a baseline, which is generated by applying the *Erdős–Rényi model* [14] of constructing random graph. We chose random graph as the baseline for its property of treating all the nodes in a graph equally, i.e. for a node i, the probability of connecting to all the node j ($j \neq i$) is equal. In other words, our baseline represents a network in which the designers simply influence and be influenced by others with equal probability (in our experiment, a wiring probability of 5% is set).

Our main comparison are three most influential designer's list from *TIMES*, *Fashion Merchandising Degrees*, and *A Celebration of the 20 Most Influential Designers*. To see how well the result rankings correlate to the real world's opinion, we also included 8 other published ranked lists to evaluate the results. The collected ranked lists and their focuses are presented in Table 2. 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 solid.

6. Result

We use the precision, recall and Area Under Curve (AUC), which are the frequently used measurements in Information Retrieval to evaluate the ranked lists generated by our proposed method.

Firstly, the comparison of AUC between our proposed Text-Generated Fashion Influence Model and Random Graph is presented in Figure 4 and Table 3. Secondly, the ROC curve with the performance of TGFI model on list, A Celebration of the 20 Most Influential Designers, is shown in Figure 5. Lastly, the result fashion influence network constructed with TGFI is presented in Figure 6 along with the InDegree distribution of this network in Figure 7.

Table 3. AUC comparison between TGFI model and baseline over 11 lists

List	Random Graph	TGFI
1	0.4734	0.9043
2	0.5415	0.9181
3	0.5056	0.9402
4	0.5804	0.8332
5	0.5600	0.8991
6	0.4915	0.8307
7	0.5895	0.8359
8	0.5712	0.8783
9	0.4518	0.9148
10	0.5035	0.9272
11	0.4617	0.9152
Average	0.5209	0.8906

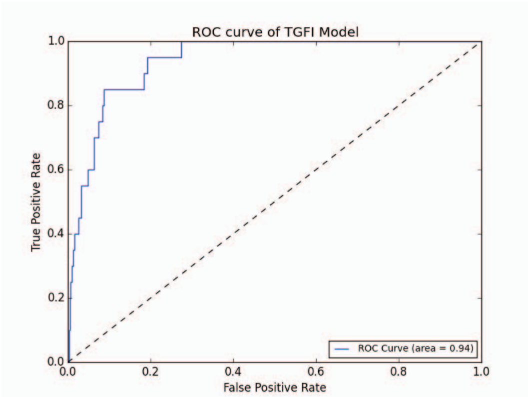


Figure 5. ROC curve of TGFI model with list, A Celebration of the 20 Most Influential Designers

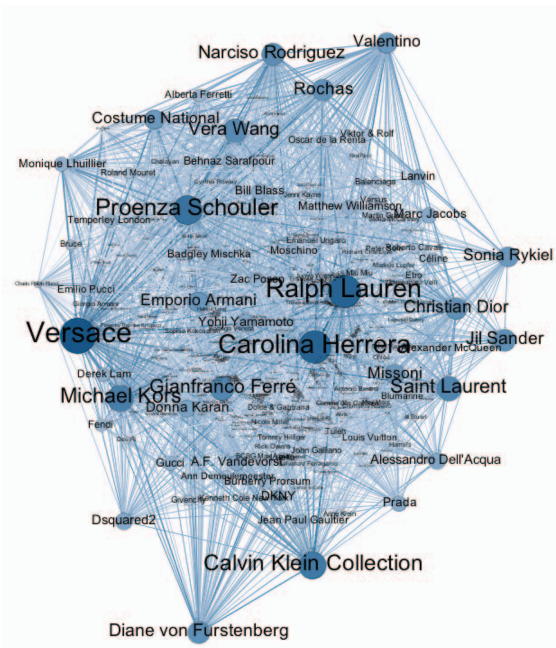


Figure 6. Fashion influence network generated by TGFI model

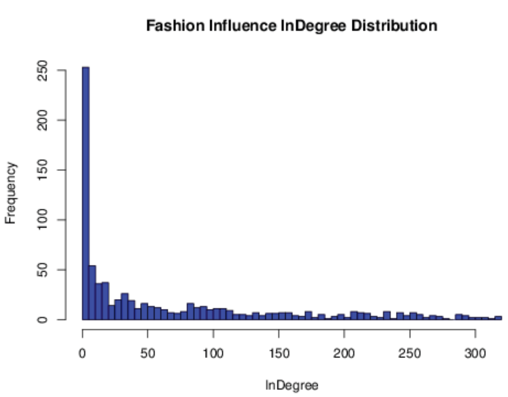


Figure 7. InDegree distribution of the fashion influence network generated by TGFI model

7. Discussion and Conclusion

Performance of TGFI is evaluated by comparing with baseline, Erdős–Rényi's random graph model with 11 collected fashion designer lists from various sources and based on different focuses. Result shows that on average, TGFI performs 1.7 times better than random graph in terms of Area Under Curve (AUC). Also, when grouping the collected lists by focus, influence-based lists give the highest AUCs comparing to lists with other focuses.

As shown in Figure 4 for all of the collected 11 lists, TGFI model outperforms the baseline Random Graph. On average, TGFI's performance is 1.7 times better than Random Graph, which means that when comparing to the scenario where fashion designers are randomly influencing and being influenced by others without any preference, TGFI can show the constructed influence links based on text similarities do capture the designers' tendencies of whom to follow.

On one hand, the list TGFI fits the best is *A Celebration of the 20 Most Influential Designers*[1], which results in an AUC of 0.9402. As we presented earlier, this is one of the three lists based on fashion designers' influences. The list that TGFI doesn't fit the most, on the other hand, is *The Richest*[1], which results in an AUC of 0.8307 and is one of the two lists based on the richness of a fashion designer. With the observed contrast, we can see that TGFI captures the characteristic "influence" better than other characteristics, especially "richness."

To determine the most influential designers we calculate the InDegrees for each designer. Based on our network construction, this captures the number of influence links pointing toward each designer. When looking at the distribution of InDegree in the fashion influence network, one can easily see that a large number, 25.33%, of the fashion designers in the network has no incoming influence links. Also, very few designers, 1.07%, have more than 300 incoming influence links. We can infer that in such a network, fashion influences are led by a small group of fashion designers and followed by the majority in the industry. We found that the designer with the highest InDegree is Versace, followed closely by Ralph Lauren, with only two InDegrees less.

Besides the InDegree, we also calculated the average path length in this network, which is 2.069. This means that, on average, a fashion design idea is

[1] Both lists, *A Celebration of the 20 Most Influential Designers* and *The Richest* are presented in Appendix A.

not directly taken from the original designer. Instead, the idea will be taken from an intermediate designer.

The designer that has the highest betweenness is Ralph Lauren. This suggests that Ralph Lauren is the central point of this network, which means most of the shortest paths between every two designers have to go through Ralph Lauren. This position in the network allows Ralph Lauren to have the most power to control what fashion symbols to adopt or discard. This can be seen in the network graph in Figure 6.

In summary, we proposed a method of detecting, tracing fashion influence and, further more, constructing a fashion influence network. Because the proposed method leverages highly accessible textual data, we named it *Text-Generated Fashion Influence Model* (TGFI Model). A fashion taxonomy consisting 2,097 words with an average precision of 95.08% and average recall of 94.58% is constructed to assist the process of fashion symbol detection. TGFI Model is intuitive while powerful for capturing the essence of fashion influence in the fashion industry.

By understanding the real fashion influence network, one can benefit from it for the following perspectives: for a manufacturer who wants to maximize their newest fashion design material, such as fabric, targeting on those more influential fashion designers as the customers can possibly lead to the maximum fabric adoption spread; for a fashion designer who wants to keep his/her design line on trend, knowing who are the influential designers brands to follow is also crucial.

For future work, we want to incorporate more data sources, such as other runway review websites, fashion magazines and social network's discussion on fashion. We then want to refine the network construction, and explore the reasons behind the fashion influence network, not only on the ready-to-wear, but also resort and couture. We also aim to study the trends of fashion symbols: analyze how they evolved in the past and predict how they will become in the future with the abundant textual data.

7. Acknowledgements

Heng Xu is supported by the U.S. National Science Foundation. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the U.S. National Science Foundation.

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Appendix A: Two lists for evaluation of Text-Generated Fashion Influence Model

A Celebration of the 20 Most Influential Designers[2]
Miuccia Prada
Marc Jacobs
Ralph Lauren
Giorgio Armani
Domenico Dolce & Stefano Gabbana
Christopher Bailey
Frida Giannini
Nicolas Ghesquière
Stefano Pilati
Alber Elbaz
Rei Kawakubo
Martin Margiela
Vivienne Westwood
Karl Lagerfeld
John Galliano
Alexander McQueen
Jean Paul Gaultier
Donatella Versace
Helmut Lang
Hedi Slimane
The richest
Calvin Klein
Donatella Versace
Valentino Garavani
Giorgio Armani
Coco Chanel
Ralph Lauren
Tom Ford
Kate Spade
Betsey Johnson
Marc Jacobs

Appendix B: The 50 Most Influential Fashion Designers Generated by TGFI

Rank	Designer
1	Versace
2	Carolina Herrera
3	Ralph Lauren
4	Proenza Schouler
5	Calvin Klein Collection
6	Michael Kors
7	Saint Laurent
8	Gianfranco Ferré
9	Vera Wang
10	Narciso Rodriguez
11	Diane von Furstenberg
12	Jil Sander
13	Christian Dior
14	Rochas
15	Emporio Armani
16	Valentino
17	Sonia Rykiel
18	Missoni
19	Costume National
20	Donna Karan
21	Alessandro Dell'Acqua
22	Dsquared^2
23	Yohji Yamamoto
24	A.F. Vandevorst
25	DKNY
26	Marc Jacobs
27	Prada
28	Bill Blass
29	Lanvin
30	Gucci
31	Matthew Williamson
32	Monique Lhuillier
33	Behnaz Sarafpour
34	Zac Posen
35	Alexander McQueen
36	Badgley Mischka
37	Burberry Prorsum
38	Derek Lam
39	Jean Paul Gaultier
40	Moschino
41	Alberta Ferretti
42	Fendi
43	Temperley London
44	Emilio Pucci
45	Céline
46	Oscar de la Renta
47	Ann Demeulemeester
48	Viktor & Rolf
49	Blumarine
50	Etro

[2] Designers included in this list are designers as individuals instead of fashion designer brands. Therefore, for our analysis, we transformed each designer into the designer brand s/he works for before comparing to our generated results.