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Short Paper

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Abstract

Fast fashion has emerged as a prevalent retail strategy shaping fashion popularity. However, due to the lack of historical records and the dynamics of fashion trends, existing demand prediction methods do not apply to new-season fast fashion sales forecasting. We draw on the Social Contagion Theory to conceptualize a sales prediction framework for fast fashion new releases. We posit that fashion popularity contagion comes from Source Contagion and Media Contagion, which refer to the inherent infectiousness of fashion posts and the popularity diffusion in social networks, respectively. We consider fashion posts as the contagion source that visually attracts social media users with images of fashion products. Graph Convolutional Network is developed to model the dynamic fashion contagion process in the topology structure of social networks. This theory-based deep learning method can incorporate the latest social media activities to offset the deficiency of historical fashion data in new seasons.

Keywords: Social media, fast fashion, social contagion, deep learning

Introduction

Fast fashion, an emerging retail strategy of adapting frequent merchandise assortments, has been widely deployed in the fashion industry (Divita and Yoo 2013). It is becoming prevalent for young customers to quickly meet their needs for the latest fashion trend along with the global e-commerce fashion market size estimated to reach US$ 1 trillion by 2025 (Statista 2021). The leading fast fashion retailers, such as Zara and H&M, have achieved tremendous success by diversifying dynamic fashion popularity in different fashion seasons with their fast merchandise assortments and supply chains (Cameron et al. 2021).

Despite the many benefits of fast fashion and its leadership of seasonal fashion popularity in short life cycle, the emerging industry suffers significantly from demand supply mismatch, making fast fashion the world's second largest polluter and causes retailers suffering from product waste or demand loss (Ekambaram et al. 2020). The industry has adopted standard solutions to pre-season sales prediction for fast fashion new releases. Some studies utilize the time series-based approach using historical sales records (Guo et al. 2018), which is mainly applicable after products are released. However, the time series-based methods suffer from limited historical sales records since we are in a pure pre-season period. The transfer learning approaches match the attributes of new products with the old season product to obtain comparable sales information (Baardman et al. 2017; Ban et al. 2019; Ekambaram et al. 2020). Others attempt to get information cues from external source, such as Google Trend (Skenderi et al. 2021). The transfer learning or information cues-based benchmark methods, including store trial sales or human experts' voting, suffer from the dynamic nature of fast fashion in a short life cycle. They assume a continuing fashion trend from the previous records and ignore the fashion preference is changing significantly, leading to failure to capture the future fashion demand using old-season sales performance.

To tackle the shortcoming of the traditional algorithms, we provide a new paradigm of sales prediction by incorporating social media activities to offset the deficiency of historical data of fast fashion new releases. Social media provide individuals a platform to pose content and reach users over the world. It gradually becomes a channel to product promotion and shape customers' opinions to influence their purchase behavior (Michaela et al. 2015). Some studies explore the successful role of social media marketing in establishing consumer attachment and preference in fashion industry (Wang et al. 2019). Especially, fashion marketing through social media platforms is effective for its direct communication with fans, promoting events, building brand awareness and especially for sharing images which are crucial in fashion industry (Çukul 2015). The existing studies of social media promotion focus on the perceived characteristics of influencers (Casaló et al. 2020; Lou and Yuan 2019) and the relationship with products (Belanche et al. 2021). However, they are not applicable to our context since they are unable to interpret the semantics in fashion image content and mainly examine individual purchase intention rather than aggregated sales volume as the target. Besides, they ignore the early adopters' attitude in product early diffusion stage, which is important for new product's performance (Dedehayir et al. 2020; Robinson 2009). Despite the strong relationship between social media activities and fashion, the underlying mechanism in social media fashion images to collectively and promptly shape the future fashion popularity and improve new-season fashion product sales is yet to be discovered.

We draw on the Social Contagion Theory to examine fashion popularity contagion on social media platforms. Similar to the spread of virus, the Social Contagion Theory suggests the social behaviors spreading among informed sources and exposed individuals lead to a continuous infectious process in social network. It results in infection of a considerable fraction of population. The fashion post spreads in social networks and shapes individuals' fashion preference along the line, which dynamically evolve fashion trend and promote newly released fast fashion product. There are mainly two causes of Social Contagion: the *Source Contagion* and *Media Contagion*. The Source Contagion refers to the internal attractiveness of the social media post that invokes the contained fashion style spread through visual communications. It's similar to the inherent level of infectiousness of the virus, which determines how far the virus can spread without changing the interpersonal interaction in network structures. The contagion media, where the contagion happens through social ties in the network, could be accelerated by various topology structures of contagion media. For example, the virus spread in a high-density network with more sources of infection and more connections among individuals is more likely to lead to a global pandemic. The existing studies mainly examine the network effect in social contagion (Christakis and Fowler 2013; Susarla et al. 2012). Differently, our study provides insights in visual-oriented fashion industry by exploring the role of visual communication and re-conceptualizing the social media fashion images as source contagion that influence the future fashion popularity.

Motivated by the conceptual framework developed from Social Contagion Theory, we propose a GCN-LSTM model to capture source and media power in fashion popularity contagion and make pre-season sales predictions for fast fashion new releases. Source contagion is measured as the potential popularity of user-generated fashion images, which communicates visually with users and deepens the attractiveness of contained fashion styles. The source contagion power is fed into Graph Convolutional Network (GCN) to model the infectiousness of the fashion styles. Media contagion in GCN then captures the effect in the topology structure of the network, in which the nodes and edges are arranged based on their interactions on social media. Specifically, the graph convolutional operations mathematically simulate the social contagion process, where the infected individuals could become the new source of infection. GCNs from multiple periods are then fed into LSTM, a sequence structure to model the long-term repeating infection among users or short-term viral posts that may induce a temporary sales increase.

We plan to use the preliminary data to empirically explore the mechanisms of fashion popularity contagion. The data includes around 5,500 newly released fast fashion products and around 20,000 social media users per season across six quarterly fashion seasons. Our proposed model investigates the role of visual communication in fashion popularity contagion and model the dynamic fashion trend evolution to predict new-season fast fashion sales. The research framework can also leverage the operational value of social media data by reducing the demand loss and production waste in pre-season production planning for fashion retailers.

Theoretical Background and Model Development

Social Contagion Theory

The Social Contagion Theory is built from the epidemic framework of disease transmission to the spread of social behaviors (Burt 1987; Giddings 1897). It suggests that social behavior spreads in social networks like a pathogen with each exposure by an informed friend potentially resulting in a naive individual becoming infected, causing a global epidemic involving a substantial fraction of the population (Hodas and Lerman 2014). Subsequent studies further extend the phenomenon into diffusion of innovations and new product advertisement (Koçak et al. 2013; Langley et al. 2012). It is commonly believed that the contagion could be due to *Source Contagion* and *Media Contagion*, referring to the inherent characteristics of the spreading sources (Langley et al. 2012), as well as user interactions in social network as the media that may facilitate the intense interactions among individuals (Christakis and Fowler 2013).

The Source Contagion establishes the internal attributes of the object that invoke or enhance the diffusion process (Aral and Walker 2011; Langley et al. 2012; Shin et al. 2020). The source of diffusion has its own characteristics to influence individuals by either suiting their demands for utility (Aral and Walker 2011), attracting attention, or invoking thoughtful considerations of the objects' merits (Shin et al. 2020). It is created by an original individual user who conveys the information to be easily accepted by others, similar to a virus spread among a group with its innate attributes of infectiousness from the source.

The Media Contagion, on the other hand, is established from the contagion process through social ties in a network structure. The repeating and intense exposure of various information increases infection probability in social networks. It's argued that the high-density social network intensifies the reactions among individuals and facilitates the contagion process (Xu et al. 2020). More sources and connections in a high-density social network make the information easier to be received and spread, therefore greatly increasing the potential of a global pandemic (Iacopini et al. 2019). The receiver influenced in previous stages is further turning into the source of contagion in the next stage, expanding contagion networks and the populations to be influenced (Nejad et al. 2014).

Despite the abundant studies in Social Contagion Theory, it remains a challenging task to explore how the mechanisms of Source Contagion and Media Contagion contribute to the dynamic evolution of fashion popularity. The source of fashion popularity contagion is mainly user-generated posts of fashion images. How fashion-related visual factors can serve as the source of contagion in visual communication is not well explored. In addition, the dynamic evolution of the contagion process in a topology structure of social networks renders the prediction of global epidemic of fashion popularity more challenging.

Fashion Popularity Contagion

We draw from the Social Contagion Theory to conceptualize social media influencers' fashion posts and explore its impact on new-release fashion popularity. Specifically, we extend the Social Contagion Theory in fashion popularity contagion by (1) conceptualizing the user-generated fashion posts as the contagion source in visual communication and (2) incorporating the contagion source in a dynamic Graph Convolutional Network to model the contagion process in social network.

Source Contagion in Fast Fashion. The Source Contagion in fast fashion refers to the infectious characteristics of user-generated fashion images that can arouse humans' inherent stimulus of fashion preference. Social media users' visual communication in the infectious fashion posts determines the fluency in transiting the fashion popularity contained in the image, leading to an easily accepted fashion preference by the followers. Existing studies suggest that the image content is impressive in message framing (Seo and Dillard 2019; Seo et al. 2013). Visual communication exhibits its impressiveness through either *sensual* *cues*, which are raw stimulus from nerves transmitted to the brain or *perceptual cues*. It is the concluded meaning after the stimuli is received (Ismail et al. 2013). In fashion posts, the sensual effect in visual communication arouses stronger emotional engagement and cultivate a more emotive media environment to make people more likely to engage in (Joffe 2008), thus leading to easier infection. As an intermediate process, visual communication links the visual-oriented fashion posts and users' interactions, which reinforces the infectiousness of the posts as the source contagion power in fashion popularity contagion.

To capture the direct impact of visual communication, previous studies in marketing images suggest that the model's body postures play an important role by conveying implicit information to enhance the advertising effect (Schroeder and Borgerson 1998) and the postures express the living processes and the feelings widely experienced by the viewers (McDowell 2017). The recent study suggests both the body postures and the selection of the background scenes to highlight the outfit in social media fashion images redefine the influencers' look ages and improve the attractiveness of the post (McFarlane and Samsioe 2020). Meanwhile, the selection of different background can broaden the appeal of the contained fashion products in any scenario. Fashion opinion leaders are more variety-seeking and pursuit the mental stimulation (Workman and Johnson 1993) to meet the expectation of fashion consumers' preference on fashion innovativeness (Park et al. 2007). Hence, fashion influencers are more inclined to pose diversified content to seek acceptance of their followers. We argue that the *posture variety* and *scene variety* from fashion posts have the potential to amplify the infectiousness of user-generated fashion images by accelerating the contagion in visual communication. Besides the direct impact from visual communication in fashion images, *number of likes* further raises the users' perceived likability of the post (Bradley et al. 2019), indicating that audiences are more likely to be attracted by the posts that was already 'liked' by many others. In our context, the fashion post receiving more likes change individuals' fashion preferences by imaginatively persuading them with a new coming fashion trend. To sum up, we integrate the visual impact from *posture variety* and *scene variety* as well as the hint indicator *number of likes* to measure source contagion power of the fashion posts.

Media Contagion in Fast Fashion. The Media Contagion is the infection process from the source of contagion to the potentially infected individuals in a social network after visual communication. The infectiousness of the media depends on the density and size of the follower network (Ghose et al. 2012; Harrigan et al. 2012; Henrich and Gil-White 2001). For example, celebrities with a large follower network and intense user interactions can easily spread product information to their followers who may further spread the information to others. In addition, the collective action that many sources of contagion promote the same or similar product can reinforce the contagion process by repeatedly interacting with individuals, leading to a higher probability of infection (Iyengar et al. 2011; Mønsted et al. 2017). Previous studies examine the Media Contagion by extracting factors directly from network structures, including volume of sources (Iyengar et al. 2011), number of friends as network degree (Aral and Walker 2011) or strong/weak tie centrality of individuals (Venkatesh et al. 2020) as the node level features. These extracted network-related factors lack the ability of modeling the dynamic communications across infected nodes and uninfected nodes in social networks. Therefore, it is desired to directly model the topology structure of social networks as well as the distribution of informed sources of fashion preferences.

With the recent development of the Graph Convolution Network (GCN), some static graph-based networks, such as document citation networks, transportation networks, and knowledge graphs, have been modeled with promising results (Kipf and Welling 2016). GCN learns hidden layer representations that encode both the local graph structure and the features of neighborhood nodes and has been proven to provide a great potential for information diffusion in social networks (Zhang et al. 2019). The GCN model, once constructed for capturing information transmission among individuals for information diffusion in social networks, has the potential of conceptualizing fashion popularity contagion. The GCN is initialized with the infected node set characterizing infectious characteristics of user-generated fashion images from different posts, as well as non-infected node set characterizing the naive individuals who can be infected after visual communication. The visual communication among individuals is modeled as the links connecting individuals with its adjacency matrix characterizing social distance among individuals. The collective actions that infected individuals collectively post similar fashion posts are simultaneously modeled by the GCN structure, from which a non-infected individual is connected to multiple sources of contagion.

Proposed Methodology and Future Plan

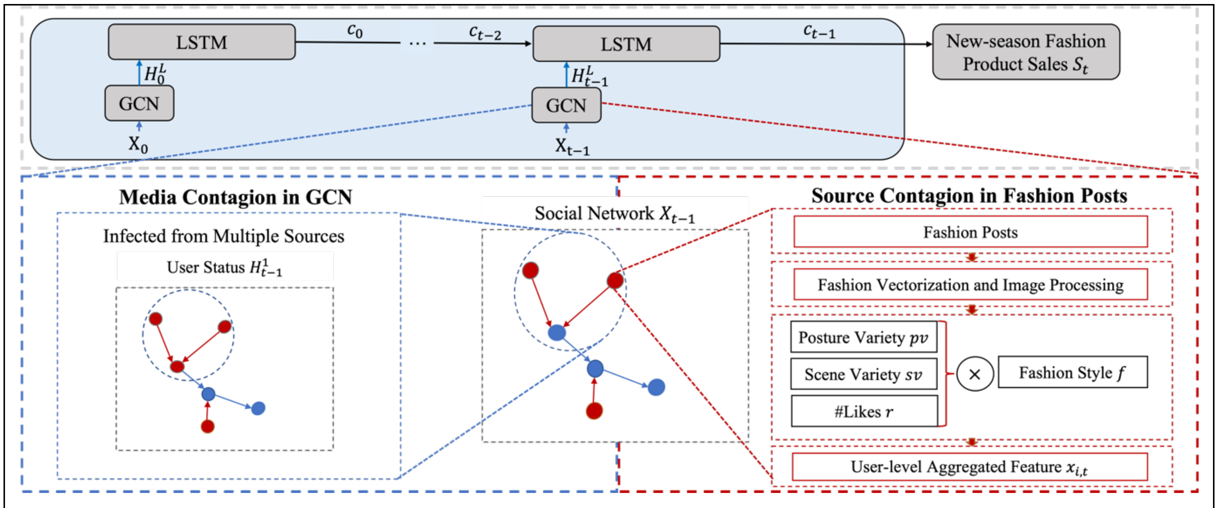

Figure 1. Overall Framework of GCN-LSTM Prediction Model

To model the visual communications in complex topology structures of social networks and the dynamic process of popularity contagion in social media, we propose a GCN-LSTM structure to conceptualize the fashion popularity contagion. Figure 1 presents the overall conceptual framework. The model consists of a Graph Convolutional Network (GCN), which snapshots the distribution of sources of contagions, their fashion-related image posts, and visual communications between infected and uninfected users in a social network. The Long Short Term Memory (LSTM) network is then used to recurrently connect the GCNs snapshots in different periods to model the dynamic evolution of fashion popularity contagion.

Snapshot of Visual Communication in GCN

The bottom panel of Figure 1 presents the detailed GCN structure. We construct the social network at each time period t as a directed graph $G_t = (V_t, E_t)$, where V_t is the set of nodes representing the distribution of infected and uninfected users in period t and E_t is the set of directed edges representing their visual communications through view, comment, and repost.

The source of contagion represented by the red dots in G_t of Figure 1 is characterized using a unified fashion style vector f. It vectorizes the fashion images into a vector of fashion attributes. We identify 1,000 fine-grained fashion attributes in 5 major categories (texture, fabric, shape, part, and style) using the Deep-Fashion model, an advanced computer vision technique developed to extract visual elements from fashion images (Liu et al. 2016).

The spreading of fashion vector f in the source is reinforced by the visual communication from the attractiveness of the post, measured by posture variety pv, scene variety sv, and the number of likes r. The posture of an individual is identified as a set of vectors formed by connecting located significant body points such as shoulders and elbows, which are detected using posture estimation models (Cao et al. 2017). The posture variety is measured for all images that exist within a single post. Specifically, we calculate the average pairwise dissimilarities for all corresponding posture vectors as posture variety. The scene variety is measured in a similar approach by comparing various scene appearances in a single post. One image is considered a binary vector with each entry indicating the existence of identified scene from computer vision-aided scene recognition models (Li et al. 2018). More variety in background scenes and postures meets the variety-seeking expectation of fashion consumers and improve the attractiveness of the posts. Same to visual factors sv and pv, number of likes r also has a positive effect to improve perceived attractiveness. Hence, we use the multiplied value $sv * pv * r$ to measure final aggregated post attractiveness value. It's then normalized as a weight to the fashion style vector f to obtain the contagiousness of each post. Each entry $x_{i,t}$ in node feature matrix X_t is computed as the average source contagion power of the all the posts of user i in period t. The final calculated node feature matrix X_t indicating the initial influential status of individuals is fed into GCN as the original input.

The contagion media represented by the edges connecting the infected individuals (represented by the red dots) and uninfected individuals (represented by the blue dots), is characterized by an adjacency matrix A_t. The basic element $A_{t,(i,j)} \in A_t$ indicates the strength of social ties from source node i to target node j, which is measured by the interaction frequencies between the two nodes. When influencers collectively post similar fashion styles, the connected individuals will receive accumulative influence from these sources. As a result, information of fashion popularity is reinforced, leading to a higher probability of status change. Besides, the users' status updated in the current layer may continue to infect the surrounding users becoming the new source of contagion.

The GCN models social contagion at time t by taking the node feature X_t as input, which propagates along the adjacency matrix A_t through L layers of graph convolution and generates a hidden status H_t^L as output. Formally, the construction of l-th layer in the GCN model is formulated as follows:

$$\tilde{A}_t = A_t + I_N \tag{1}$$

$$H_t^l = \sigma(\widetilde{D}^{-\frac{1}{2}}\tilde{A}_t\widetilde{D}^{-\frac{1}{2}}H_t^{l-1}\Theta) \tag{2}$$

where $I_N \in \mathcal{R}^{N\times N}$ appears as the identity matrix and $\widetilde{D}$ is the diagonal node degree matrix with each diagonal element $\widetilde{D}_{ii}$ counting the number of edges for the corresponding node i. Θ is the learnable parameters of GCN and σ is a non-linear activation function which takes the role as the updating the user's status when they receive visual communications from connected nodes. The layer-wise contagion in (2) computes the impact of visual communication origin from the input layer $H_t^0 = X_t$ to the output H_t^L, indicating potential changes in infection status of uninfected individuals within each period t.

Dynamic Evolution of Fashion Popularity Contagion

To capture the temporal dependencies from a temporal sequence of GCNs snapshot in different periods, we propose an LSTM sequence to capture the short-term and long-term fashion popularity contagion to predict the sales of new-season fashion products. The top panel of Figure 1 presents the sequence of LSTM structures. Each LSTM cell at t takes the output of the GCN unit H_t^L as input, which is the final updated infectious status of users in the social network.

The LSTM sequence is directly connected to new-season product sales in a many-to-one structure, which integrates cell states in multiple periods for prediction. The LSTM processes the updated infectious status from GCNs in different periods into a higher-level cell status, which re-examines the infectious status of the social network by remembering long-term status and filtering out the non-important information in the current period. The repeating interactions among individuals from multiples periods in a long-term can be easily captured and the vulnerable users who are easier to be infected will be differentiated through the LSTM structure. Meanwhile, it's also capable of identifying the viral popularity contagion and intensive user infection within a short period, such as an extremely viral post may induce a temporary sales increase.

Preliminary Data and Future Plan

We have collected data from major social media platforms including Weibo and RED, and fashion product sales information from the leading e-commerce platform Tmall.com. The time period covers six quarterly fashion seasons from Dec 2019. The sales data includes 7 major clothing categories from 11 major fashion retailers in China. On average, we have collected sales information of around 5,500 newly released fast fashion products and related social media activities from about 20,000 social media users per season. Our ongoing work focuses on the validation of the effectiveness of the two mechanisms: Source Contagion and Media Contagion by evaluating their predictive power in a GCN-LSTM model. Further, we will evaluate the prediction accuracy and deliver a fast-fashion new releases sales predictor preseason when the historical sales information is limited.

Intended Contributions

The paper proposes a theory-based deep learning model for new-season fast fashion sales prediction. It incorporates social media activities to offset the deficiency of historical data and dynamic nature of fast fashion in a short life cycle. Theoretically, the proposed model extends Social Contagion Theory in Source Contagion and Media Contagion within the context of fashion popularity contagion and offer a more nuanced understanding of the role of visual communication in social contagion. Practically, the research framework leverages the operational value of social media data in understanding the fashion content and the fashion trend evolution to capture consumers' future fashion preference. Besides, our model takes a step forward to the sustainability of the fashion industry by reducing textile pollution with accurate preseason sales forecasting. It can be extended to other retail industries similar to fast fashion, where the existing methods of transfer learning or information cues are not applicable to the newly released products.

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