Social Network Analysis of Facebook Brand Communities

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Abstract

Social Network Analysis (SNA) is used in a broad range of fields. However, its business application is still a relatively new area in marketing field. Meanwhile, social web based on web 2.0 technology has made interaction between people across the world faster and more convenient. Social network has been changing the playing rules in marketplace significantly. To fill the gap of network study in marketing, this research focused on online brand communities to explore their network shapes. In the study, we analyzed the interaction mechanisms and processes behind different network structures; identified key roles and their influence in a network; and examined information-based contagion process.

The research adopted graph-theoretic method which is most widely used in SNA. Data set from the Facebook of eight brands encompassed vertices and arcs. NodeXL program was used to construct graphical networks and provided measure metrics. Statistical analyses were conducted to test the relationship between variables and to identify the significant difference across brand networks.

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Chapter1: Introduction

1.1 Introduction

Network, according to < Oxford Dictionaries>, refers to:

1. An arrangement of intersecting horizontal and vertical lines;
2. A group or system of interconnected people or things

We can find various traces of network in our daily lives, including biological networks (i.e. disease transmission), physical networks (i.e. transportation system) and social networks (i.e. affiliation/acquaintance networks, information exchange networks, broadcast network) (Network Science, 2005). Among the three representative networks, social network is getting more and more attention due to information technology advances. Web 2.0 technologies enable people to contact each other without any restriction. This has made the social web an effective media tool. This technology-enabled person-to-person communication significantly impacts our society, especially the business world.

Many organizations take advantage of social technologies to execute their communication strategies, build customer relations and create reputation. In this study, we explore how social media networks work in marketing field. How are product and marketing information spread on social web? What are the differences in social networks across different industries and brands? By using a social network analysis tool, which gathers vast amount of social network communication data and finds connections and patterns among the data points, we attempt to answer these questions.

1.2 What is a Social Network?

Social network refers to “the articulation of a social relationship, ascribed or achieved, among individuals, families, households, villages, communities, regions, and so on. Each of them can play dual roles, acting both as a unit or node of a social network as well as a social actor” (Laumann & Pappi, 1976).

Under this definition, social network involves two key physical elements: social node (unit) and social tie between units. The social ties generated by interaction are called relationships, such as kinship, friendship, class, ethnic groups and organization, and so on. They are present between individuals, families, households, or any other social roles (nodes). However, not any two units (nodes) must have a relationship in a network. It means members of any pair of groups may have or not have a dyadic relationship. The relationship between members also could be positive or negative, such as friendship or hostility or opposition (Bandyopadhyay, Rao, & Sinha, 2011). In addition, the relationship between a pair of nodes could be one-way or two-way interaction (Rafaeli and Sudweeks, 1997). For example, on Facebook, a celebrity may have a great number of fans but she or he does not know most of them. Compared to one-way interaction, two-way interaction may generate much deeper relationship. In addition, another important attribute behind various networks is similarity among units. The common interests, preferences and other homophilies could attract people to come together and interact with each other (McPherson, Smith-Lovin, and Cook, 2001).

Conclusively, social network encompass two essentials: social nodes and dyadic social ties between the nodes. Interaction among nodes may affect the structure;

ties connecting a node represent the social relationship intersections of the node (Snijdersa, Buntb, & Steglich , 2010).

Refer to table 1 for examples of social networks.

Table 1.1: Examples of Social Networks

Type of Network	Examples
Affiliation/acquaintance networks	clubs, community, business, religious, social media sites, like Facebook, Twitter
Broadcast networks	radio, TV networks
Information exchange networks	Canada mail, telephone service, portal website
Social services network	Social security, Medicare, Medicaid
Business network	Stakeholders network
Group forming networks	eBay, corporate intranets

(Network Science, 2005)

1.3 Social Network Analysis

Social network science started in early twentieth century and grew with the development of the mathematics of graphs and topology. SNA was applied to study human relationship and connections in a broad of range of fields, including sociology, anthropology, communication studies, economics, geography, information science, organizational studies, social psychology, and sociolinguistics. Jacob L. Moreno, psychotherapist, is the pioneer for modern social network analysis. He developed the sociometric method of group analysis in the book *Who Shall Survive* (Moreno, 1934) and provided the first empirical measure of network-level communication. Sociometric use mathematic and other scientific techniques to assess relationship (positive and negative) between persons in a network. Thus SNA developed from studying interactions and relationships in groups (Reis & Sprecher, 2009). During 1971-1972, SNA was applied to sociology study to explore the structural pattern of social relations in rural society in West Bengal (in India) under a sharp inequality in income distribution. The study discovered the varying relationship between parameters of dynamics in the society and economic or traditional sociocultural parameters. (Bandyopadhyay, Rao, & Sinha, 2011).

Social network analysis (SNA) means “analyzing various characteristics of the pattern of distribution of relational ties and drawing inferences about the network as a whole or about those belonging to it considered individually or in groups” (Bandyopadhyay, Rao, & Sinha, 2011).

Social units generated interaction which forms various social structures. SNA provides an access to understand these structures and the relationships behind them. Owing to the high complexity of relations in various social networks, SNA involves multidisciplinary approaches, including sociology, psychology, anthropology, mathematics (combined with graphs and topology), statistics, and computer science. SNA has its own parameters and methodological tools. The methodology of SNA is based on quantitative measures of many qualitative concepts which help in understanding networks. The concepts encompass power, fragmentation, reciprocity, cliques, hierarchy, alliances and cohesion. Visualization is the most important character of SNA. Through visualizing the social network map, SNA can make the relationships and structures visible. Then, analysts can exploit critical components of a network, such as isolated groups and influential participants.

As a theoretical construct, social network varies at largely different sizes from personal network to global interaction. Social networks could be analyzed at three levels: micro-level, meso-level, and macro-level. At Micro-level, SNS focuses on a small group of individuals in a certain social context. Meso level is to explore relationships between micro- and macro-levels. For example, there is significant difference between causal processes displayed by less dense networks and micro-level networks. Macro-level analysis tracks the results of interaction, i.e. the transfer interaction of economic resource over large population (Strogatz, 2001).

1.4 Why marketing people study social network analysis?

Social media dramatically influences marketplace: In the last decade, social technologies have connected people from across the world and facilitated information sharing and influence. Web 2.0 technologies make the interaction faster and convenient by creating an online many-to-many dialogue platform, on which users generate most of the content. Facebook and Twitter are famous examples of these platforms. On these virtual communities, users have the right of voice and strong influence power in the society. These significant characteristics of the social web suggest that it could change the playing rules in the marketplace. For instance, the open access to information allows customers to make purchase decision in a complete information market. It means price between competitive suppliers would be more transparent (it is hard to charge customers more for an identical product or service by a seller than by another seller); word of mouth would impact product sales to a great degree, making mass media communication less effective. Under this situation, marketing people have to research social media networks.

By understanding the structure and mechanism of social networks, they can manage it and use it to work toward a positive direction for their business.

Marketing needs to know people: The role of Marketing is to create, communicate and deliver value to customers. In the process, marketers build long term relationships with customers through satisfying their needs and wants. (Kotler & Kevin, 2012). Marketing people have to know customers, their feedback for marketing activities and then improve them. Compare to traditional media, social media is a two-way communication. The interaction happens not only between users but also between users and companies. Thus it offers a great opportunity for marketers to know well about customers and their relationships. Marketers can utilize the understanding to build social CRM, collective ideation and vendor relationship management.

It is time for marketer to start SNA: As mentioned above, sociologists, organizers, and computer scientists, they already used SNA to gain plentiful valuable findings in their fields and guided meaningful practice in real life. However, in marketing field, the application of social networks analysis was relatively rare. This may be due to the technology constraint, the unapparent form of marketing network, or a weak awareness in new research methodology. Whatever, it is time for marketing people to use SNA to get deep understanding for the social media network and to apply it to real business world in order to improve their campaign efficiency.

1.5 Scope and Objective

The purpose of this research is: (a) exploring the structures of social media network across diverse industries and brands; (b) examining if social networks for brands within a category are similar or different, and if they are different attempting to understand the causes (c) identifying key roles in given networks; (d) content analysis is to find popular content type on Facebook. This research is based on social data (Facebook data) mining and analysis. We look at these questions from network science perspective and marketing perspective. Social network map visualization and statistical test methods would be used to support the two objectives.

1.6 Research Questions

These questions explored by this paper are to address the work mechanism of social media network in marketing field:

What structures do brands' Facebook fan pages display across industries and brands? What are the network mechanisms of these brand Facebook communities? Who play key roles in given networks? How do the key roles influence information diffusion? What kind of information is more likely to be spread more frequently and reach more people?

1.7 Expected Contribution of Research

This study aims to understand how social media propagate brand information. This study would understand how individuals act on social media and how they react to business activities. It also observes how business practices in taking advantage of social media to promote brands. Ultimately we will hope to provide business with valuable guideline in developing social network as a good marketing tool. To the best of our knowledge there has not been an in depth examination of social networks of competing brands. This study aims to address this gap and will contribute to our understanding of brand communities.

To successfully achieve these objectives, this paper will involve a literature review, a research methodology, research analysis and discussion, and suggested future research.

Chapter 2: Literature Review

2.1 Social Networks

Social network is a social structure composed of social nodes and dyadic ties between the nodes (Snijdersa, Buntb, & Steglich , 2010). Ties are social relationships which are achieved in the course of interaction in the processes of various activities. An actor could be a member of families, villages, communities, companies, regions, and so on. The relationships can be positive (friendship) or negative (conflicts or hostilities). However, most of time, we focus on positive relationships. Moreover, not all actors have direct interaction. If there is a relationship between two units, it may follow two-way (reciprocal relationship) communication or only one-direction information flow because social relationship can be symmetric or Asymmetric. Asymmetric relations, for example, on Twitter, A follows B but B does not follow A.

Types of Networks:

(1)Full, Partial, and Egocentric Networks: Full networks contain all the people or entities of interest and the connections among them (Hansen, Shneiderman, & Smith, 2010). A person's egocentric network is a full network including two types of roles: ego and alters. "Ego" is the person staying the centre of attention; "alters" are other people connected to the ego. According to degrees to which a network is extend, egocentric networks can be categorized into "1-degree" ego network (the ego and alters), "1.5-degree" ego network (ego, the alters and the alters' friends who know each other), "2-degree" ego networks (ego, their alters and the alters' all friends), and so on. A full network is able to capture in such system, which works as a hub and involve all connected people. A partial network is a slice of a full network based on a certain rule.

For instance, we choose persons who used the hashtag ”#Ipad 5” on Twitter to form a partial network.

(2)Unimodal, Multimodal, and Affiliation Networks: Networks including one type of node is called unimodal network, such as networks connecting documents to documents or connecting users and users. But, networks can encompass various types of vertexes to create multimodal networks. Networks including two types of vertices are bimodal networks, such as a network with users and posts they wrote (Hansen, Shneiderman, & Smith, 2011).

2.2 Network Structure

Network structure can be analyzed in terms of frequency, content, density and centrality (Giorgos, 2010). Frequency is the level of a person’s engagement. Intensity and centrality indicates the degree of cohesion, solidarity and centralization of a network due to the different involvement of members in these networks (Streeter & Gillespie, 1992).

Dense network: indicates members have strong relationships. People know each other well and interact with each other frequently in a network. This network has high cohesion and solidarity. For example, villagers in a small village are more likely to form a denser network than persons living in a large city because kinship, limited living space and leisure life provide villagers in a small village more opportunities to know each other and develop close relationship. However, far distance and busy work may make neighbours become strangers in large cities, such as New York, Shanghai.

Centralized network: this network is centered on a few focal nodes which generate many edges and connect lots of nodes in a network. High centralization means the entire network can be controlled by managing the central nodes. For instance, in organization behavior, there are two types of organization structures, organic and mechanistic structure. Compared to decentralized organic structure, mechanistic organization display strict hierarchy and centralized controlling power. The report line will be set according to position level and CEO and top managers of departments will form a focal management team. Due to the high efficiency and productivity, mechanistic structure usually is used in manufactory.

Structural holes and central hubs: In a network, not all nodes have direct links. A broker is a node which can bridge other nodes otherwise they don't connect. When groups are not connected, a node could act as a structural hole, which can link the unconnected groups. For example, in organization, the brokers always have more resources and information because they know different departments. Thus, the brokers more possibly achieve better performance and obtained promotion (Hansen, Shneiderman, & Smith. (2011). Central hubs are nodes which connect most others in a network. When the absence of direct links among nodes exists, the efficiency of a network is higher (Lin, Cook, & Burt, eds. 2001). Sparser is the connection ("weak ties") (Granovetter, 1983) between two persons, lower is the redundancy of the information exchange between them. Thus the information is more valuable (Granovetter, 1973).

Robust networks: A network is robust if it performs best against attack. Robust networks can be made of equal size components or be star network. The former structure is not fit for complex tasks and can generate smaller returns from exchanges in the network. If the resources are relatively smaller than the number of nodes in a network, a star structure can be robust network. The force equilibrium is the reason why these networks are robust. There are less weak ties and structural holes in robust networks. The central nodes occupy major resources (Goyal & Vigier, 2009). For example, if most of nodes have strong ties, the network will maintain its function well after some nodes are removed from the system. The network can be called a robust network.

Overlapping and nested community: A node can be a member of more than one clique, so a node can be a member of more than one community. It results in overlapping community structure. Communities are nested if one community contains another. For example a geographic community may contain a number of ethnic communities. (Tropman, Erlich, & Rothman, 2006)

2.3 Community

Many real-world networks display community structure. Communities exist as sub-groups in broad networks. It means a group of nodes which has more connections within the group than outside the group.

In terms of community, there are several conceptions:

Community is “social relationships which individuals have based on group consensus, shared norms and values, common goals, and feelings of identification, belonging and trust”(Booth & Crouter, 1999).

Putnam (2000) operationalized community idea by the conception of social capital, which is the sense of connectedness and formation of social networks. Bridging and bonding capital compose social capital. Bridging capital is the bridges created between social institutions, whereas bonding capital refers to community bonds created within those institutions. Community is one of various social networks which are able to produce social capital. A “Good” community should contain a substantial amount of bridging and bonding capital.

Social capital also can be divided into communal capital and individual capital. Communal capital is a collective good (Putnam 2000), which means what benefit people can derive from social networks. Individual capital (Burt, 1992) refers to the private-good facet, which is about how people’s connections can help them. The concept depends on the cause and effect of participating in a community.

In a real world, due to different motivations and effects, various types of communities include geographic communities (based on location), communities of culture (based on common needs, culture, civilisation), and community organizations (based on more formal incorporated associations) are formed. With technology development, virtual communities are booming. In contrast to physical community, a virtual community relies on information-technology based communication (Crow & Allan 1995).

2.4 Social Capital

Social capital is a crucial concept in analyzing community. Bourdieu and Wacquant (1992) define social capital as the total amount of the tangible and intangible resources. The capital can be “aggregated to social actors (individuals or groups) by processing a social network of more or less institutionalized relationships of mutual acquaintance and recognition” (Bourdieu & Wacquant, 1992). For example, friendship is one of social capital. Someone seeking a job may obtain an opportunity because the company of his or her friend is hiring persons. Another social capital definition encompasses various ingredients, including trust, mutual support, goodwill and other shared material, such as responsibilities, ideas, and language and so on. (Huysman and Wulf, 2004). Social capital can exist as a kind of cohesion in a network.

Social capital can be measured and is strongly correlated with community behavior. Putnam introduced many different indicators to measure the trend of social capital in U.S (Putnam, 2001). For example, data came from philanthropy, social trust, and marketing survey over time. The declining ratio of individual charity expense to income reflected falling social capital in U.S. Many surveys about trust also showed steady decline in past forty years in U.S. DDB survey monthly conducted by a marketing firm over twenty-five years included a broad range of questions, such as preferring brands, products, times of going to churches, relationship with friends, and participation for community activities, and so on. The survey indicated each indicator fell over time. Thus, different indicators consistently reflected a falling trend of social capital in the U.S. A community will face increasing social disorder if social capital goes down. For instance, distrust grows between community members. In contrast, commitment to a community and collective work could develop with growing social capital. Generally, the development of a social network is positively influenced by social capital (Helliwell & Putnam, 2004).

Strong and weak ties are major types of relationships in a social network. Strong ties exist among a group of people who regularly and frequently contact each other and maintain close relations. Contrarily, weak ties are weak links between people. People can handle a large number of weak ties because they don't need lots of effort to keep up. Bridge social capital does not provide emotional support, but it is related to weak ties because loose relationship between nodes can provide valuable resource or new ideas for one another (Granovetter 1982). However, bonding social capital always exists in close relations and reflects strong ties including emotional support (Putnam, 2000).

2.5 Social Media

Social media is "a group of internet based applications that builds on the ideological and technological foundations of Web 2.0, and it allows the creation and exchange of user-generated content" (Kaplan & Haenlein, 2010, p.61). Web 2.0-based platform allows users to generate content freely and collaboratively. UGC (user generate content) reflects strong power of users over content on social media. Based on these features, social media become a cost-effective marketing tool (Kaplan & Haenlein, 2010) because it can bring people with similar brand preference together and influence their behavior (Hollenbeck & Zinkhan, 2006). Thus, social media already attracted more and more companies from diverse industries.

Social media can affect consumer behavior due to the following reasons: 1. People form a community owing to the need for belongingness (Sarason, 1974). 2. Social media can meet the need by sharing and exchanging information among people. (Gangadharbhatla, 2008). For example, there is a forum for new mothers so that they can share information and experience about raising children. If someone's bad experience about a product is spread on it, others possibly won't purchase it. Thus social media significantly amplifies consumer's power in the market by unrestricted sharing behavior. The connections in social media are mostly weak ties because it is virtual community and sparse relation can be maintained at low cost (Constant et al., 1996; Granovetter, 1973). Bridge social capital reflects weak ties because it exists among distant relationship and stretches beyond a shared sense of identity. Bridge capital can bring people into a wider network (OECD, 2007). Bridge social capital (Wellman, 1997) can encourage member to engage in community to a close emotional level (Tardini & Cantoni, 2005) because members can obtain useful information or new perspective in such interactions (Granovetter 1982).

2.6 Comparison between Social Media and Traditional Community

As one of various social networks, community should be qualified with communal capital and individual capital. However, Beer (2007) thinks Facebook is individually oriented social networks site on which participants intend to maintain their existing social relationships. Beer (2007) develops “a vision of these sites not as spaces where users are solely preoccupied with forming network around themselves but where they involve themselves primarily in other activities.” It suggests individuals use Facebook for the private benefits (maintaining relationships and articulating their own identity) rather than collective good (Ellison et al), (Baron 2007).

Information technology allows virtual social networking sites to significantly raise weak ties in virtual networks. Information can be diffused in large networks and individuals can draw various resources (Donath & boyd, 2004; Resnick, 2001; Wellman et al., 2001). Thus, users easily develop their holistic relationship at low cost (Boyd 2008). But, the diffusion of weak ties does not improve communal capital (Burt 1992) other than individual capital (Putnam 2000). People use Facebook to maintain relationships rather than to create a community. Golder et al's (2007) findings prove only 15.1 percent of friends actually exchange messages on Facebook. “Friends” on Facebook are different from “friends” in traditional communities.

Evidence also proves the relation between the likelihood of people participating in Facebook and the level of faith in people. People are most likely to participate in Facebook because they hold more faith in people. Lampe et al. (2006) point out that "Facebook members view their audience as peer group members, as opposed to other institutional members like administration and faculty." Although Facebook is different from traditional community, users view it as a community.

The discussion above suggests that Facebook groups are more of individual social capital than a community in a traditional sense. Facebook can be regarded as a homogeneous collection of weak ties. Research shows Facebook users are extremely close (low Closeness) but are not linked to others whom are well-connected (high Eigenvector), compared to a traditional offline community (Dietrich, 2008).

2.7 Brand Community

Brand is an identity for consumers to express their individuality, social status, and preference. Customers with a same brand preference form a brand community. Brand community can be defined as "a specialized, non-geographically bound community, based on a structured set of social relationships among admirers of a brand." (Muniz and O'Guinn 2001). Brand community can positively influence consumers attitude and loyalty on brands (McAlexander, Schouten and Koenig 2002; Algesheimer, Dholakia, and Herrmann 2005) because members can share and exchange information, opinions, and a sense of moral responsibility in the community. (Muniz and O'Guinn 2001; Schau and Muniz 2002; McAlexander et al 2002). Brand community also is a social network connecting marketers and consumers and consumers with other consumers. Based on this platform, marketers can communicate with consumers and improve their feeling of loyalty.

With the growth of information technology, the interactions patterns in a brand community changed. UGC allows consumers to express what they want to say on social media. So consumers' influence is magnified in such virtual communities.

Another attribute of brand community is to form oppositional brand loyalty (Muniz & Hamer, 2001). For example, in brand decision, a form of norm compliance is accomplished through a heuristic process. However, another group people may make choice based on conscious deliberation (Bicchieri, 2006). The two groups will attack each other and defend their own decisions.

These features of brand community offer marketers a great opportunity to learn about consumers and then formulate appropriate marketing strategies..

2.7.1 Brand Community Effects in Brand Loyalty and Trust

Brand community can affect customers' attitude toward brands:

1. Brand community can create values for both members and companies. In the process, brand loyalty of members will be improved because of their growing feelings of belongingness (Laroche, Richard,& Sankaranarayanan, 2012).

2. Practices in brand community can improve members' engagement in the community (Schau et al., 2009) but doesn't significantly influence brand loyalty (Laroche, Richard,& Sankaranarayanan, 2012). Brand use practice refers to member's tendency to help others with newer, improved and enhanced ways to use the focal brand. Impression management practices focus on create favorable brand impression outside the community (Schau, Muniz, & Arnould, 2009, p34). Both brand use practice and

impression management can increase brand trust (Laroche, Richard,& Sankaranarayanan, 2012). The different natures of the three practices may lead to the result. For example, the feeling of belonging to a brand community is different from the feeling of obligations to a community. The former may not be sufficient for individual to take purchase behavior.

3. Online brand communities based on social media have the same effects as offline brand communities. It means both of them can have positive influence on members' attitudes toward brands, including shared consciousness, rituals and obligations. During the process, value creation practices can be improved because the increasing obligations and commitment to society could improve values in brand communities. Members with high commitment and obligations to a society will more actively engage in community to create more values (Laroche, Richard,& Sankaranarayanan, 2012).

4. Based on the findings above, marketers should emphasize brand use and impression management in the management of their brand community. They should make efforts to build strong and positive brand image and actively disseminate product information to help members remember the brand and use the products (Schau et al., 2009).

2.7.2 Brand Congruence in Interpersonal Relations

Brand congruence means that individuals in a social network will have similar brand choices owing to the interactions among them. Research has shown that the type of products, social relationship and social structure will significantly affect brand choice among members in a network (Reingen, Foster, Brown, & Seidman, 1984). The following finds elaborate how the factors affect brand choice.

1. Group cohesiveness is correlated to member brand choice. Brand congruence for multiplex cliques is significantly greater than for single specific-relation cliques. Multiplex cliques encompass at least three social relations (Reingen, Foster, Brown, & Seidman, 1984), such as family business firm including kinship, friendship and employment relationship.

2. But, there is not necessary connection between multiplex cliques and brand congruence. It means that not all multiplex cliques generated brand congruence, and not all brand congruence happened in multiplex cliques. Congruence varied by product in any case (Reingen, Foster, Brown, & Seidman, 1984).

3. People with similarities can form a community. The interpersonal similarity among members may lead to brand congruence (Reingen, Foster, Brown, & Seidman, 1984).

4. The Perceived Influence Studies claimed that tangible and complex products with low testability are more impressionable to individual influence than intangible and simple products with high testability (Park and Lessig,1977). However, the new research showed the opposite result to the previous one (Reingen, Foster, Brown, & Seidman, 1984). Thus, brand congruence may be due to interpersonal similarity rather than personal influence.

2.8 Diffusion Process in Social Networks

Diffusion is a process in which more and more people in a group adopt a new behavior and then form a trend to spread. Rogers pointed out whether a person adopts a new behavior depends on the following factors: “a trade-off between cost and benefit from the adoption, compatibility, complexity, trialability, observability (Rogers, 1983), the type of innovation-decision, the nature of communication channels and social system, and promotion effort for an innovation” (Rogers, 1995). More apparent is the relative advantage of an adoption, the diffusion of an innovation is faster. High compatibility means the existing value, past experiences and needs of potential adopters from an innovation can be highly consistent. High compatibility leads to fast diffusion. Low complexity means an innovation can be understood easily by most people, thus such innovation can be adopted rapidly. If an innovation also can be easily tried and the result is clearly visible, it will attract more adopters fast. The number of people involved in innovation-decision negatively influences dissemination behavior. More decision-makers will slow down the diffusion rate. For example, individual decision-making will be easier than collective decision-making. Communication channel should match the complexity of an innovation. Mass media are efficient for products with low complexity; however, if innovation is difficulty understood, interpersonal channel will provide more elaborate explanation to help adoption. The nature of social system includes the norms of the system and network structures. There is complex relationship between rate of adoption and change agents’ efforts. In the early adoption stage (3-16 percent adoption), change agent effort will receive the greatest response from opinion leaders. Little promotion efforts still will drive diffusion of innovation after a critical mass of adoption is completed.

In contrast, Bass (1969) proposed another diffusion model including a mathematic theory. The Bass model assumes diffusion of a new product is driven by word-of-mouth from previous satisfied adopters. People who earliest purchase a new product are called innovators; those who purchase due to the influence of innovators are imitators. The Bass model principle defined three variables influencing diffusion process: 1.The potential market. New adoption is driven by word-of-mouth of previous adopters. The potential market is represented by the number of members of social network. 2. The coefficient of innovation. According to the Bass Model, the influence outside the social system, such as mass media, government, promotional efforts, will affect adoption. 3. The coefficient of imitation. It refers to internal influence, such as the number of prior adopters. For instance, more previous adopters will lead to more new adopters in the system.

Both models considered the effects of external influence and interpersonal communication in diffusion process. Compared to Rogers' theory, the Bass model has the capability of predicting diffusion process, including the trend, the timing and magnitude of the peak. Moreover, Bass model was based on mathematic theories and supported by accurate prediction across many industries (Wright and Charlett, 1995).

There are three insights for a diffusion process on social networks (Jackson and Yariv, 2006): First, tipping point, the smallest number of previous adopter is sufficient for increasing the spread of a new behavior over time. As the number of adopter beyond tipping point, the new behavior will become more prominent. Second, the speed of adoption decreases as the number of adopters rises to a certain point and then consistently decreases. Third, the social structure changes will lead to the diffusion behavior changes, such as increasing the number of neighbour and connectedness in the population.

2.8.1 Influential Factors in the Diffusion of Innovations

The diffusion of innovations is “the process by which a few members of a social system initially adopt an innovation, then over time more individuals adopt until all (or most) members adopt the new idea” (Ryan and Gross, 1943; Rogers, 1983; Valente, 1993).

Diffusion model: describe a process about how members gradually adopt a new behavior in a network. Threshold model is an important concept in understanding diffusion. It holds that the proportion of people who already engaged in a behavior in a network will influence an individual adoption of the behavior (Granovetter, 1978). People with low thresholds will adopt a new behavior earlier than people with high thresholds.

Exposure: refers to percentage of people who adopt a new behavior in a person’s ego network at a given time.

Both threshold and exposure affect people’s adoption of new behaviors. Sometimes, the people with same threshold may not engage in a new behavior at same time because of their different exposure. High exposure also cannot lead to adoption due to a high threshold. (Marsden and Podolny, 1990).

The categorization of adopters: can be classified into five groups: (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggards (Ryan and Gross, 1943, 1950; Beal and Bohlen, 1955; Rogers, 1983, pp. 245-247). According to the time of adoption, from low to high, they are innovators, early adopters, early majority, late majority and laggards, respectively.

External influences: Early adopters generally have more sources of external influences (cosmopolitan’ actions and communication media). Early adopters can adopt an innovation earlier than others because they have strong external influences, such as abundant and free information resource. (Becker, 1970; Fischer, 1978; Weimann. 1982). By the same token, some are laggards because they have high thresholds and may not receive exposure to the innovation from their ego networks. Individuals with strong external influence possibly are relatively more innovative to the whole network than to their personal network.

Interpersonal persuasion: According to the long-standing theory, interpersonal persuasion plays an important role in convincing individual to adopt. Thus, opinion leadership is crucial in diffusion. Opinion leaders possibly are early adopters in their personal network and have extensive external influence. However, due to different network structure (hierarchy system), there is a special situation. People who adopt early could be opinion leaders in their phase but are not in a whole community, i.e. medical community.

2.8.2 Efficient Diffusion Strategies in Social Media

Marketers are highly interested in influencing people on product and service opinions by taking advantage of word-of-mouth diffusion on social media. Here are some meaningful findings to help improve diffusion efficiency on social media, like Twitter.

First, can "influentials" maximize diffusion? Are individuals who had strong influence or many followers in the past more possible to be influential in the future? It means marketers seed information with certain special individuals to boost increasing diffusion significantly. However, the conclusion is more based on observation rather than convincing research. In fact, portfolio-style strategies only make marketers achieve average performance. Marketers should Target as much audience as possible under the fixed budget in order to amplify influence more efficiently.

Second, Could different types of content impact the tendency to spread? The type of content will influence its diffusion. If content are more interesting and generate more positive feelings, they will be spread more frequently. For example, UGC tends to diffuse more than content made by marketers. Shareable media can attract more attention than news sites. If people could better understand both the attributes of the seed users and the content being seeded, they can considerably better predict cascade size.

Third, Target**ing strategies:** The ordinary users with average influence and number of followers are the most cost-effective influencers because even strong influencers have many followers but their transition is slow. Because of limited budget, developing ordinary influencers should trade off the number of Target audience and their average level of influence.

2.9 Social Network Analysis

Social network analysis (SNA) is to study society from network perspective. SNA emphasize on the structure of relationship in a social network and view the network as a whole. It means SNA focuses on analyzing social behavior from the whole structure of a network other than individuals alone among it.

SNA can be applied to Social Network Service, Organization Communication and social media. In SNA, we can identify the causes for dysfunctional organizations and understand online behavior and communication. As a result, we can improve communities and their cohesion. In SNA business application in marketing, marketer can learn consumers' perception and decision-making process; improve their products and services; and build positive relationship with customers. (Franke & Shah, 2003; McAlexander et al., 2002).

SNA is different from usual statistical techniques because the data of social network blatantly violate the premise of being statistically independent. Data set in a network encompass vertices and arcs. Graph-theoretic method based on mathematical theory is most widely used in SNA (Foster and Seidman's, 1981, 1983). Graph composed of points (actors) and lines (ties) can reflect social relations among social actors in a network.

SNA include multiple levels of analysis: 1. Dyad (relationship) level is to analyze relationships and distance between nodes. 2. Node (actor) level focuses on aggregating dyads to the node level (e.g., # of friends) or measuring nodes' position in the network. 3. Group (network) level is to aggregate to the group or whole network level (e.g., # of ties or /# of potential ties within group) or measure network shape (e.g., centralization).

2.10 Basic Measure Metrics in Social Network Analysis

SNA is network perspective-based analysis. It emphasizes the importance of relations and structures among a network. To understand a node, we need to understand how the node is embedded in a network of inter-relationships with others.

Measure metrics in SNA:

Edge weights: Edges represent interactions, similarities, or social relations. A strong tie means frequent communications exist between two nodes and the relationship is reciprocal. Other attributes of the nodes or ties and the structure of the nodes' neighborhood also influence edge weights.

Paths and shortest paths: A path connects two different nodes. There are many paths between nodes but the shortest path between them has the smallest number of edges. The length of a path will decide the speed of communication. Shorter is a path, faster is communicating.

Centrality measure:

1. **Degree**: is the number of people who a person can reach directly. In-degree is the number of ties going toward a person. Out-degree is the number of ties coming from a person. Higher values represent high popularity of a person.

2. **Closeness Centrality**: is decided by the average distance of all shortest paths connecting a node and all others in a network. It is a measure of the speed of information disseminations. Lower value means higher diffusion speed.

3. **Betweenness Centrality**: calculates the total number of shortest paths between all nodes and all others which go through a node. It can measure the importance of a node. Great value represents an important node.

4. **Eigenvector**: computes the centrality of a node as a function of the centralities of its neighbors. Higher eigenvector means a person connect to others better.

Reciprocity: is the ratio of the number of reciprocated relations to the total number of relations in a network. It reflects the degree of social cohesion of a network. High reciprocity means high mutuality and reciprocal exchange in the network.

Clustering: is the density of a node's neighborhood. It represents the presence of sub-communities in a network.

Chapter 3: Methodology

3.1 Methods

This study aims to examine the social structures of different brand communities in social media, and then further explore the mechanism of social network in marketing field. In the following we provide information about process of data collection, briefly discussing the sampling design and the techniques adopted to analyze data.

The first step is to prepare data set. We selected brands for the study and collected data from their Facebook fan pages. The data included nodes (fans) and ties (comments). The representative sample and comparable benchmarks are important in this step.

The second step involved use of statistical methods to test whether differences across brands and other variables were significant.

The third step involved constructing a graphical network to show how fans interact with each other in a given brand Facebook. NodeXL program was used for the network formulation. Based on the measure metrics and network visualization, we then compared the structures across different brands and identified key persons within each brand community.

The fourth step is about post analysis. We categorized all posts in the eight brands Facebook into seven groups. Based on the different edge contribution generated by seven groups of posts, we can rank the topic types on Facebook. Thus, we can address the question: What kind of information is more likely to be spread more frequently and reach more people?

3.2 Tools

NodeXL: is a network analysis tool, which supports visuals and analytics, and integrates with ubiquitous Excel spreadsheet software, designed for nonprogrammers. It is easy to manipulate network graphs and draw graphs from various social media, such Twitter, Facebook and YouTube.

SPSS: is a software package designed for statistical analysis. The statistics includes Descriptive statistics, Bivariate statistics, Prediction for numerical outcomes, and Predictions for identifying groups, and so on.

3.3 Sample Design

The selection of brands is according to BrandZ Top 100 Most Valuable Global Brands 2013 (Millwardbrown.com, 2013). We selected two brand categories (Luxury brand and Retail brand) and then chose top four valuable brands under each category. Luxury brand market represents high-end consumption but retail brands generally belong to discount and mass market. The different categories were expected to yield different network structures and behaviors within the network.

3.4 Data Collection

Size: The information of luxury brands is from recent one year (from Aug 11, 2012 to Aug 10, 2013). However, the data of retail brands is just from recent one month (from Sep 6 to Oct 7, 2013) due to the computing problem of mass data. The large data size ensures a good representativeness of the samples. The data set of each brand Facebook page is made of thousands of nodes and ten thousands of ties.

Information: The data included vertex (node) and edges (ties). The basic information of “vertex” included gender, language type (roughly refers to nations), and comment. The information of edge included sender, receiver, and post resource.

Network type: There are two methods to collect data. “Facebook fan page network” is an egocentric network which includes all fans of a certain brand on Facebook. “Facebook group network” is a partial network including people who posted certain content. In this study, we chose “Facebook fan page network”. Furthermore, it also is an users-users unimodal network based on co-comments. It means the network is formed by users who posted co-comments on the brand Facebook. Unimodal network includes one type of node. For instance, a network connecting users and users or post to post is unimodal. If the network encompasses users and posts, it is a Bi-modal network (Hansen, Shneiderman, & Smith, 2011).

3.5 Measure Procedure

NodeXL analysis provides a set of quantitative graph metrics for understanding networks and the individuals and groups within them. Computing and visualizing graph metrics:

1. Overall Graph Metrics summarizes key properties of the entire network. These help characterize the entire networks and allow for comparisons or across different brand networks

2. Vertex Metrics provide a set of centrality properties for each vertex. This metrics can be mapped onto visual attributes so that we can be easy to identify key roles.

3. In Statistical test, we use "univariate" analysis from General Linear Model and conducted parametric statistical test with one dependent variable. We were able to verify if any attributes of vertex influence network structures significantly.

Chapter 4: Results

4.1 Sample Profile

4.1.1 Brand Category and Gender

Table 4.1: Brand Category and Gender

Brand Category	**Brands**	**Male**	**Female**
Luxury brand (data of 1 year)	Hermes	30.45%	69.51%
	LV	22.88%	77.08%
	Prada	36.79%	63.19%
	Michal Kors	8.26%	91.74%
Retail brand (data of 1 month)	Amazon	46.21%	53.79%
	eBay	37.34%	62.71%
	Walmart	35.26%	64.61%
	Target	25.71%	74.24%

1. There are four luxury brands and four retail brands.

2. The gender distribution is significantly different across brands. For example, the majority of customer in most luxury brands is female, especially in Michal Kors.

3. Compared to luxury brands, retail brands have a lower percentage of female fans but the major customers still are female. For instance, in Amazon, the ratio of male to female is 0.8:1.

4.1.2 Country Distribution:

(1) Luxury Brand

Table 4.2: Luxury Brand Country Distribution

Region	**Hermes**	**LV**	**Prada**	**Michael Kors**
U.S	32.72%	34.19%	32.83%	52.90%
South America	10.45%	14.84%	13.29%	23.32%
France	11.77%	5.16%	6.07%	2.91%
UK	7.77%	9.68%	8.18%	6.21%
Italia	7.42%	1.94%	7.76%	0.59%
German	3.56%	2.58%	3.31%	2.32%
Spain	2.37%	4.52%	5.00%	3.93%
Russia	2.33%	0.46%	1.32%	0.25%
Asia	7.69%	13.73%	4.06%	1.08%
others	13.92%	12.90%	18.18%	6.49%

(2) Retail Brand

Table 4.3: Retail Brand Country Distribution

Region	**Amazon**	**Ebay**	Target	**Walmart**
U.S	89.5%	87.0%	91.3%	87.9%
UK	3.6%	4.8%	2.6%	1.7%
South America	2.3%	3.9%	2.9%	7.6%
the rest of Europe	1.3%	3.8%	1.4%	2.2%
Asia	0.4%	0.1%	0.2%	0.1%
Others	2.9%	0.3%	1.5%	0.5%

1. From geographic distribution, U.S has the largest number of fans for the chosen brands on Facebook. The population of fans is relatively low in other continents.

2. This trend maybe is due to two reasons:

- Marketing strategies of different brands: brands have their different marketing strategies, which cause corresponding geography distribution of Facebook fans.

- The data come from Facebook. The overall geographic distribution of Facebook users affects the country distribution of the sample.

4.1.3 Offline and Online Company

Table 4.4: Offline and Online Company Distribution

	Quantity	**%**	**Brands**
Offline company	6	75%	Hermes
			LV
			Prada
			Michal Kors
			Walmart
			Target
Online company	2	25%	Amazon
			Ebay

Online company: The business is built on internet platform and heavily relies on information technology.

4.2 Network Level Analysis- Shape and Cohesion of Entire Network

4.2.1 Basic Information

Table 4.5: Basic Information of Brand Facebook Community

Measures	**Luxury Brands**(data of 1 year)				**Retail Brands**(data of 1 month)			
	Hermes	**LV**	**Prada**	**Michael Kors**	**Amazon**	**Ebay**	**Walmart**	Target
Vertices	2277	3067	4560	9179	2238	2188	5510	2023
Total Edges	47794	76734	123575	242159	51704	51907	124342	43672
Unique Edges%	98.8%	96.6%	82.2%	99.8%	99.9%	99.9%	96.7%	99.7%

Most of brands have low percentage of edges with duplicates except for Prada. Duplicate vertex pairs refer to repeated vertex pairs. For example, A replies to person B on multiple occasionally. Because of the computing issue of mass data, retail brands Facebook have only one month data; however luxury brands have one year data. Thus, for the data samples, the data sizes of luxury brands look larger than of retail brands. But, in terms of complete networks, retail brands Facebook are significantly larger than luxury brands Facebook.

4.2.2 Key Properties of Entire Networks

Table 4.6: Key Properties of Network across Brand Facebook Communities

Measures	Luxury				Retail			
	Hermes	**LV**	**Prada**	**Michael Kors**	**Amazon**	**Ebay**	**Walmart**	**Target**
Connected Components	8	4	3	9	7	5	5	6
Maximum Geodesic Distance (Diameter)	6	6	6	7	8	6	4	5
Average Geodesic Distance	2.9	3.235	2.906	3.101	3.845	3.175	2.253	2.993
Graph Density	0.018	0.016	0.01	0.006	0.01	0.011	0.004	0.011
% edges emanate from the top 10% nodes with the largest edge contribution	32.50%	27.10%	41.40%	31.60%	23.20%	25.20%	36.30%	27.90%
Edge contribution emanate from the node with the largest Degree Centrality	0.94%	0.70%	0.72%	0.33%	0.42%	0.62%	4.38%	1.87%
Median Degree	47	49	47	48	48	48	41	45
Average Betweenness Centrality	2047	3403.31	4317.37	9576.72	2351.7	3887.31	11106.84	3274.74
Median Betweenness Centrality	0	0	0	0	0	0	0	0
Median Closeness Centrality	0.00016	0.0001	0.00008	0.00004	0.00015	0.00016	0.00006	0.00018
Median Eigenvector Centrality	0.00037	0.00021	0.00013	0.00009	0.00023	0.00034	0.00014	0.00034
Median Clustering Coefficient	1	1	1	1	1	0.5	0.5	0.5

We use the measure metrics to compare network structures across different brands Facebook. The detail analysis will be provided later.

4.2.3 Statistical Test

Before we analyze the measure metrics, we verify whether the metrics show statistical significant differences across brands and sexes. In this section, we focus on testing whether statistical differences exist in vertex attributes between the two categories and across different brands in each category; and estimating average level for each attribute. We analyze the difference between genders here but will discuss about how and why the differences exist across industries in the next sections.

4.2.3.1 Luxury and Retail Industry

a. Categorized eight brands into two groups. Group 1 represents retail industry and group two is luxury industry

b. Set significant level=0.05; confidence intervals=95%

a. Statistical Test for Luxury and Retail Industry

Table 4.7: Statistical Test for Vertex Attributes between Luxury and Retail Industry

Dependent Variable	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Degree Centrality R Squared = .004	Corrected Model	205194a	3	68398.1	46.137	.000
	Sex	59494	2	29747.4	20.066	.000
	Industry	118104	1	118104.7	79.667	.000
	Error	46185415	31154	1482.5		
Betweenness Centrality R Squared = .002	Corrected Model	1324370151015a	3	4414567170051	19.583	.000
	Sex	1299996545112	2	649998272556.4	28.835	.000
	Industry	3245544465	1	3245544465.5	.144	.704
	Error	702217149835916	31151	22542363000.7		
Closeness Centrality R Squared = .000	Corrected Model	.001a	3	0.000	0.628	.597
	Sex	0.000	2	0.000	0.391	.676
	Industry	0.000	1	0.000	.746	.388
	Error	18.567	31154	0.001		
Eigenvector Centrality R Squared =.03	Corrected Model	.000a	3	4.122E-05	316.347	.000
	Sex	1.076E-05	2	5.380E-06	41.297	.000
	Industry	.000	1	.000	810.514	.000
	Error	.004	31154	1.303E-07		
Clustering Coefficient R Squared =.502	Corrected Model	1037.375a	3	3.458E+02	10449.471	.000
	Sex	1.235	2	.618	18.667	.000
	Industry	1002.359	1	1002.359	30290.283	.000
	Error	1030.941	31154	3.309E-02		

- Degree, Eigenvector Centrality and Clustering Coefficient have significant difference between luxury and retail industries. However, Betweenness and closeness Centrality didn't show significant difference between two industries.

- Except for Closeness Centrality, other attributes show significant difference between male and female fans.

b. Estimated Vertex Attributes for Luxury and Retail Industry

Table 4.8: Descriptive Statistics for Significantly Different Vertex Attributes between Luxury and Retail Industry

Dependent Variable	Sex		Mean	Std. Deviation	N
Degree	female	luxury	49.90	27.81	14962
		retail	44.39	26.35	7430
		Total	48.07	27.46	22392
	male	luxury	47.61	32.93	3508
		retail	45.00	22.02	4396
		Total	46.16	27.43	7904
	Total	luxury	49.53	29.65	19160
		retail	45.09	49.51	11998
		Total	47.82	38.59	31158
Betweenness Centrality	female	luxury	6633.00	60516.92	14962
		retail	2738.43	26252.69	7430
		Total	5340.72	51759.72	22392
	male	luxury	5162.00	44435.76	3508
		retail	2321.86	17000.57	4395
		Total	3582.55	32233.94	7903
	Total	luxury	6671.60	59259.49	19159
		retail	4853.91	230308.75	11996
		Total	5971.71	150275.42	31155
Eigenvector Centrality	female	luxury	.00019536	.000261812	14962
		retail	.00034477	.000436754	7430
		Total	.00024493	.000337697	22392
	male	luxury	.00027326	.000377244	3508
		retail	.00030730	.000416696	4396
		Total	.00029219	.000400000	7904
	Total	luxury	.00021177	.000290625	19160
		retail	.00033546	.000452038	11998
		Total	.00025940	.000366389	31158
Clustering Coefficient	female	luxury	0.95436588	0.15547133	14962
		retail	0.56181952	0.19696438	7430
		Total	0.82411314	0.25137253	22392
	male	luxury	0.93971643	0.17540853	3508
		retail	0.59541362	0.22551998	4396
		Total	0.74822413	0.26683895	7904
	Total	luxury	0.94973808	0.16231518	19160
		retail	0.57498801	0.20967068	11998
		Total	0.80543320	0.25765031	31158

Significance level=0.05; Confidence intervals is 95%

- Female fans have higher Degree than male fans in most of luxury brands. However, except eBay, other retail brands' male fans have greater Degree value than female fans. The trends may be related to the different characters of products in two categories. Female fans are more interested in disseminating luxury products.

- The average Betweenness Centrality level of female fans is higher than male fans in both luxury and retail brands. However, in eight brands, except Michael Kors, eBay and Walmart, other brands' male have higher value than female. Thus, the overall level of luxury and retail category may be affected by the larger fan-base brands such as Michael Kors and Walmart.

- In terms of Eigenvector Centrality, female fans are lower than male fans in luxury brands; however female have greater Eigenvector value than male in retail industry. It means female fans link less important nodes than male fans in luxury brands. But, retail industry has the opposite result. The trend may be because high portion of important nodes in luxury brands are female but most important nodes are male in retail brands.

- Female fans have greater Clustering Coefficient than male fans in luxury industry. However, female fans have lower value than male fans in retail brands. It means female nodes' alters know each other better than male nodes in luxury. The situation is reversed in retail brands.

4.2.3.2 Luxury Brands

a. Statistical Test for Luxury brands

Table 4.9: Statistical Test for Vertex Attributes in Luxury Brands

Dependent Variable	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Degree R Squared =.017	Corrected Model	291085.4[a]	5	58217.078	67.372	.000
	Sex	13149.8	2	6574.909	7.609	.000
	brand	274081.5	3	91360.511	105.727	.000
	Error	16551332.1	19154	864.119		
Betweenness Centrality R Squared =.004	Corrected Model	298896687544.2[a]	5	59779337508.842	17.094	.000
	Sex	81580304148.7	2	40790152074.335	11.664	.000
	brand	240815687205.4	3	80271895735.145	22.955	.000
	Error	66978010636042.5	19153	3496998414.663		
Closeness Centrality R Squared =.001	Corrected Model	.018[a]	5	.004	4.659	.000
	Sex	.002	2	.001	1.162	.313
	brand	.017	3	.006	7.191	.000
	Error	15.	19154	.001		
Eigenvector Centrality R Squared =.161	Corrected Model	.000[a]	5	5.212E-05	735.314	0.000
	Sex	4.538E-07	2	2.269E-07	3.201	.041
	brand	.000	3	8.067E-05	1138.117	0.000
	Error	.001	19154	7.088E-08		
Clustering Coefficient R Squared =.010	Corrected Model	4.802[a]	5	.960	36.791	.000
	Sex	1.679	2	.840	32.163	.000
	brand	2.445	3	.815	31.225	.000
	Error	500	19154	.026		

Significance level=0.05; Confidence intervals is 95%

- Each attribute of vertex is significantly different across luxury brands. In other words, the interaction mechanisms and processes of nodes are entirely different across brands.

- Except for Closeness and Eigenvector Centrality, other attributes are significantly different between male and female fans.

b. Estimated Vertex Attributes for Luxury Brands

Table 4.10: Descriptive Statistics for Vertex Attributes across Luxury Brands

Dependent Variable	Sex	Brands	Mean	Std. Deviation	N
Degree	female	Hermes	41.78	24.394	1463
		LV	49.22	18.406	2356
		Michael Kors	52.78	30.705	8435
		Prada	45.92	25.340	2708
		Total	49.90	27.807	14962
	male	Hermes	41.82	24.992	641
		LV	48.70	24.985	688
		Michael Kors	51.02	24.848	606
		Prada	48.18	40.434	1573
		Total	47.61	32.926	3508
	Total	Hermes	41.70	24.935	2278
		LV	49.12	20.639	3108
		Michael Kors	52.93	31.250	9192
		Prada	46.89	32.537	4582
		Total	49.53	29.649	19160
Betweenness Centrality	female	Hermes	1731.557	13163.798	1463
		LV	3273.016	20643.567	2356
		Michael Kors	9636.117	78810.031	8435
		Prada	2850.009	18972.167	2708
		Total	6633.001	60516.919	14962
	male	Hermes	2474.812	9965.221	641
		LV	3340.301	42491.993	688
		Michael Kors	7633.175	42774.755	606
		Prada	6101.798	53513.691	1573
		Total	5162.005	44435.759	3508
	Total	Hermes	2046.102	12638.517	2278
		LV	3358.417	27498.685	3108
		Michael Kors	10114.319	79646.864	9192
		Prada	4311.592	36321.580	4581
		Total	6671.601	59259.492	19159
Closeness Centrality	female	Hermes	0.00379	0.04589	1463
		LV	0.00047	0.00680	2356

Dependent Variable	Sex	Brands	Mean	Std. Deviation	N
		Michael Kors	0.00124	0.03078	8435
		Prada	0.00049	0.00839	2708
		Total	0.00123	0.02758	14962
	male	Hermes	0.00405	0.05734	641
		LV	0.00047	0.00673	688
		Michael Kors	0.00263	0.04314	606
		Prada	0.00090	0.01518	1573
		Total	0.00169	0.03217	3508
	Total	Hermes	0.00360	0.04772	2278
		LV	0.00046	0.00671	3108
		Michael Kors	0.00132	0.03151	9192
		Prada	0.00061	0.01098	4582
		Total	0.00128	0.02800	19160
Eigenvector Centrality	female	Hermes	.00044408	.000428335	1463
		LV	.00033072	.000315948	2356
		Michael Kors	.00010939	.000105901	8435
		Prada	.00021098	.000292079	2708
		Total	.00019536	.000261812	14962
	male	Hermes	.00043477	.000395475	641
		LV	.00033834	.000387948	688
		Michael Kors	.00010883	.000088910	606
		Prada	.00024233	.000401406	1573
		Total	.00027326	.000377244	3508
	Total	Hermes	.00043924	.000417227	2278
		LV	.00033378	.000336989	3108
		Michael Kors	.00010976	.000106377	9192
		Prada	.00022056	.000331976	4582
		Total	.00021177	.000290625	19160
Clustering Coefficient	female	Hermes	0.9500163	0.1601534	1463
		LV	0.9708617	0.1248336	2356
		Michael Kors	0.9537540	0.1592432	8435
		Prada	0.9442700	0.1637759	2708
		Total	0.9543659	0.1554713	14962
	male	Hermes	0.9317415	0.1857306	641
		LV	0.9794966	0.1065303	688
		Michael Kors	0.9516725	0.1622437	606
		Prada	0.9209610	0.1959110	1573

Dependent Variable	Sex	Brands	Mean	Std. Deviation	N
		Total	0.9397164	0.1754085	3508
	Total	Hermes	0.9432618	0.1702073	2278
		LV	0.9726060	0.1216529	3108
		Michael Kors	0.9521603	0.1620761	9192
		Prada	0.9325872	0.1799013	4582
		Total	0.9497381	0.1623152	19160

Significance level=0.05; Confidence intervals is 95%

- In luxury brands, except for Prada, female fans of other brands have greater Degree than male fans. The difference may be because Prada has the largest portion of male in the four brands

- Female fans have high Betweenness than male fans in Michael Kors but the situation is reversed in rest brands. Male have significantly higher value than female in Prada (male: 4311 vs female: 2850), Hermes (male: 2474 vs female: 1731) and LV (male: 3340 vs female: 3273).

- As for Clustering Coefficient, except for LV, other brands' female fans have higher value than male fans.

4.2.3.2 Retail Brands

a. Statistical Test for Retail brands

Table 4.11: Statistical Test for Vertex Attributes in Retail Brands

Dependent Variable	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Degree R Squared =.007	Corrected Model	202271.3[a]	5	40454.256	16.614	.000
	Sex	179361.3	2	89680.659	36.830	.000
	brand	20265.3	3	6755.097	2.774	.040
	Error	29200221.5	11992	2434.975		
Betweenness Centrality R Squared =.007	Corrected Model	4378725229939.8[a]	5	875745045987.950	16.618	.000
	Sex	4338322991920.1	2	2169161495960.040	41.161	.000
	brand	102505116867.4	3	34168372289.124	.648	.584
	Error	631861513827357	11990	52699042020.630		
Closeness Centrality R Squared =.002	Corrected Model	.006[a]	5	.001	4.294	.001
	Sex	.000	2	.000	.490	.612
	brand	.006	3	.002	6.698	.000
	Error	3.5	11992	.000		
Eigenvector Centrality R Squared =.106	Corrected Model	.000[a]	5	5.195E-05	284.272	.000
	Sex	1.465E-05	2	7.326E-06	40.085	.000
	brand	.000	3	7.942E-05	434.535	.000
	Error	.002	11992	1.828E-07		
Clustering Coefficient R Squared =.868	Corrected Model	457.5[a]	5	91.507	15704.458	.000
	Sex	.167	2	.084	14.336	.000
	brand	454.0	3	151.345	25973.912	.000
	Error	69.9	11992	.006		

Significance level=0.05; Confidence intervals is 95%

- Except for Betweenness Centrality, other attributes display significant different across retail brands.

- Except Closeness Centrality, other metrics have significant difference between male and female fans in retail brands.

b. Estimated Vertex Attributes for Retail Brands

Table 4.12: Descriptive Statistics for Vertex Attributes across Retail Brands

Dependent Variable:	Sex	Brands	Mean	Std. Deviation	N
Degree	female	Amazon	45.95	12.991	1173
		Ebay	47.44	18.010	1354
		Target	43.33	22.464	1473
		Walmart	43.11	33.104	3430
		Total	44.39	26.355	7430
	male	Amazon	46.40	13.349	1010
		Ebay	47.19	15.392	809
		Target	43.72	20.116	521
		Walmart	43.78	27.380	2056
		Total	45.00	22.025	4396
	Total	Amazon	46.17	13.413	2241
		Ebay	47.44	17.781	2194
		Target	43.67	27.368	2034
		Walmart	44.23	69.577	5529
		Total	45.09	49.506	11998
Betweenness Centrality	female	Amazon	2218.70	18798.01	1173
		Ebay	4708.33	28631.13	1354
		Target	2380.57	34642.27	1473
		Walmart	2292.23	23062.87	3430
		Total	2738.43	26252.69	7430
	male	Amazon	2345.00	15721.49	1009
		Ebay	2781.56	22715.88	809
		Target	2659.28	16031.58	521
		Walmart	2044.12	15120.55	2056
		Total	2321.86	17000.57	4395
	Total	Amazon	2370.22	18010.95	2239
		Ebay	4259.24	28815.57	2194
		Target	3108.77	42784.13	2034
		Walmart	6737.68	337569.08	5529
		Total	4853.91	230308.75	11996
Closeness Centrality	female	Amazon	0.00182669	0.00659143	1173
		Ebay	0.00218756	0.01305240	1354
		Target	0.00160670	0.01179817	1473
		Walmart	0.00123022	0.02707685	3430

Dependent Variable:	Sex	Brands	Mean	Std. Deviation	N
		Total	0.00157348	0.02009971	7430
	male	Amazon	0.00370052	0.00926823	1010
		Ebay	0.00194623	0.00882816	809
		Target	0.00130716	0.01125726	521
		Walmart	0.00036464	0.01106069	2056
		Total	0.00153384	0.01039237	4396
	Total	Amazon	0.00272176	0.00819066	2241
		Ebay	0.00208861	0.01158448	2194
		Target	0.00162845	0.01279146	2034
		Walmart	0.00089942	0.02237034	5529
		Total	0.00158085	0.01720114	11998
Eigenvector Centrality	female	Amazon	0.00047788	0.00061595	1173
		Ebay	0.00048607	0.00050283	1354
		Target	0.00048919	0.00053237	1473
		Walmart	0.00018145	0.00011217	3430
		Total	0.00034477	0.00043675	7430
	male	Amazon	0.00039665	0.00059609	1010
		Ebay	0.00041715	0.00049373	809
		Target	0.00047647	0.00047542	521
		Walmart	0.00017730	0.00010494	2056
		Total	0.00030730	0.00041670	4396
	Total	Amazon	0.00044882	0.00061235	2241
		Ebay	0.00046147	0.00050103	2194
		Target	0.00049303	0.00056998	2034
		Walmart	0.00018155	0.00016766	5529
		Total	0.00033546	0.00045204	11998
Clustering Coefficient	female	Amazon	0.98508410	0.08809852	1173
		Ebay	0.48422249	0.06400507	1354
		Target	0.49240375	0.04539889	1473
		Walmart	0.47751237	0.07780628	3430
		Total	0.56181952	0.19696438	7430
	male	Amazon	0.98098214	0.10361305	1010
		Ebay	0.49138718	0.04923115	809
		Target	0.48429557	0.06543077	521
		Walmart	0.47509538	0.08077711	2056
		Total	0.59541362	0.22551998	4396
	Total	Amazon	0.98223155	0.09795432	2241

Dependent Variable:	Sex	Brands	Mean	Std. Deviation	N
		Ebay	0.48648385	0.06007958	2194
		Target	0.48980292	0.05322235	2034
		Walmart	0.47638281	0.07942768	5529
		Total	0.57498801	0.20967068	11998

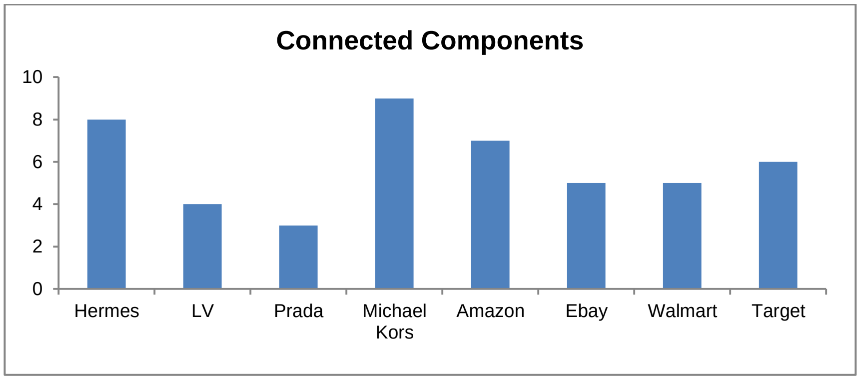
Significance level=0.05; Confidence intervals is 95%

- In retail brands, male fans have greater Degree Centrality than female fans, especially Amazon. The result may be because retail brands have high percentage of male fans or male fans are more interested in retail products.
- On eBay Facebook, female fans (4708.33) have significantly high Betweenness Centrality than male fans (2781.56). It means female fans have higher bridges score compared to male fans in the network. However, Amazon and Target show the contradictory results. Their male fans have larger bridges score than female fans.
- As for Eigenvector Centrality, female fans are higher than male fans in each brand. Because high percentage of important nodes is male in retail brands, these male nodes have low Eigenvector Centrality than other nodes which link them.
- Except eBay, other brands' female fans have high Clustering Coefficient than male fans. It means female fans' alters connect with each other better than male fans' alters.

4.2.4 Interpretation of Overall Metrics of Networks

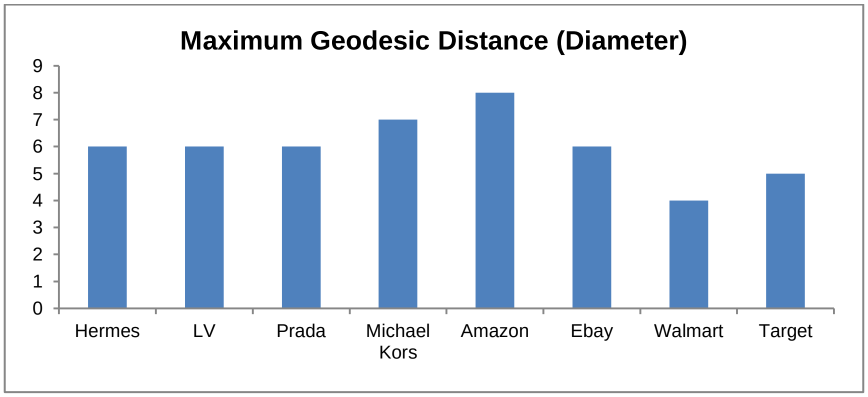
Connected components: The number of connected components indicates how many isolated clusters exist in an entire network. These clusters are composed of vertices that are connected to each other but not to the rest vertices in the network. Hermes (8) and Michael Kors (9) have more clusters than LV (4) and Prada (3). However, the numbers of cluster in retail brands are similar (about 6). The quantity of cluster is irrelevant to the number of vertex. For instance, Hermes and Amazon have relatively few vertexes, they have more connected components.

Figure 4.1: Number of Components in Brand Communities



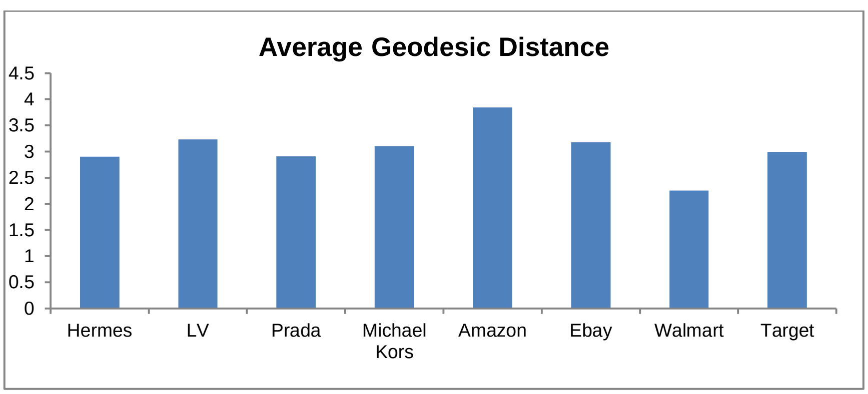
Maximum Geodesic Distance: is the diameter of a network. The geodesic distance is the length of the shortest path between two nodes. The maximum geodesic distance is the largest one of the geodesic distance between all vertices pairs. The average diameter of luxury brands is roughly 6. The diameters of Facebook networks significantly vary in retail brands. Unlike Amazon with the largest diameter of 8, Walmart and Target have smaller “Maximum Geodesic Distance”, respectively 4 and 5.

Figure 4.2: The Diameter of Network in Brand Communities



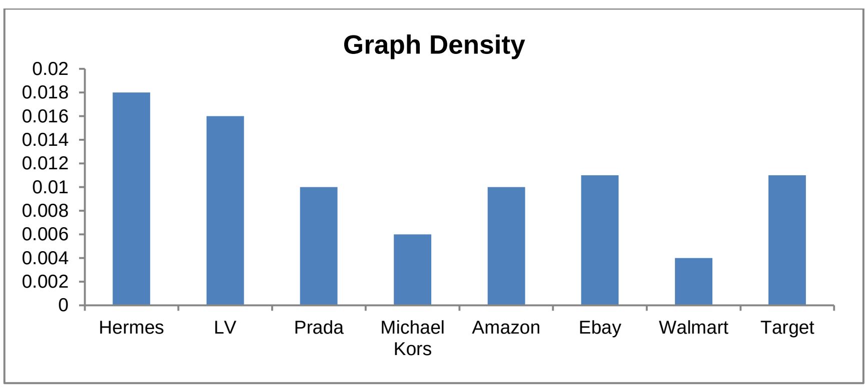
Average Geodesic Distance: measures how "close" community members are from one another. Walmart has the lowest Average distance score which means most people know one another either directly or through a mutual friend in Walmart. However, in Amazon Facebook, many people do not directly know each other. In luxury brands, from small to large distance, the brands are respectively Hermes, Prada, LV and Michael Kors. In retail brands, from high to low, they are Amazon, Ebay, Target and Walmart. Luxury brands have smaller distance than retail brands because the former market size is smaller than the latter.

Figure 4.3: Average Geodesic Distance of Network in Brand Communities



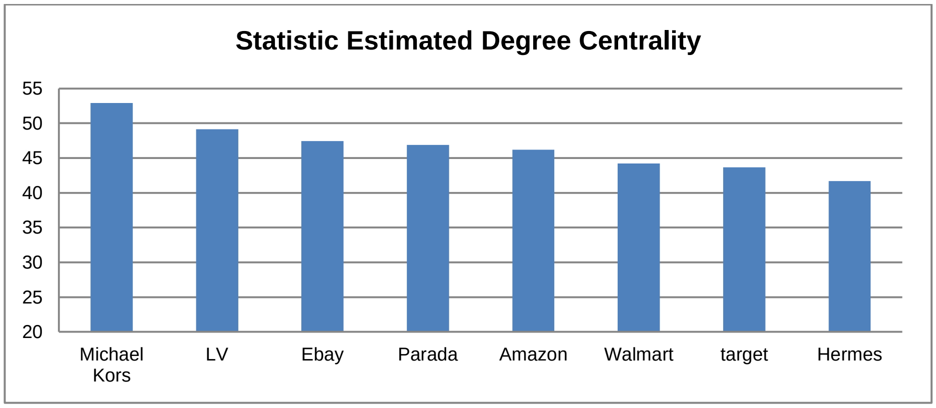
Graph Density: indicates how interconnected the vertices are in the network. Greater graph density refers to more interaction among nodes. Graph density seems negatively relevant to the quantity of vertex. If a network has more nodes, it is less likely that everyone interacts with each other. Thus, we found the largest networks, Michael Kors and Walmart, have the smallest density. As an extremely expensive brand, Hermes has the densest Facebook. From high to low density, other luxury brands are LV, Prada and Michal Kors. The density of retail brands is lower than luxury brands. The larger Facebook size of retail brands makes fans more difficultly know each other. In retail brands, from high to low density, the brands are Amazon, eBay, Target and Walmart.

Figure 4.4: Graph Density of Network in Brand Communities



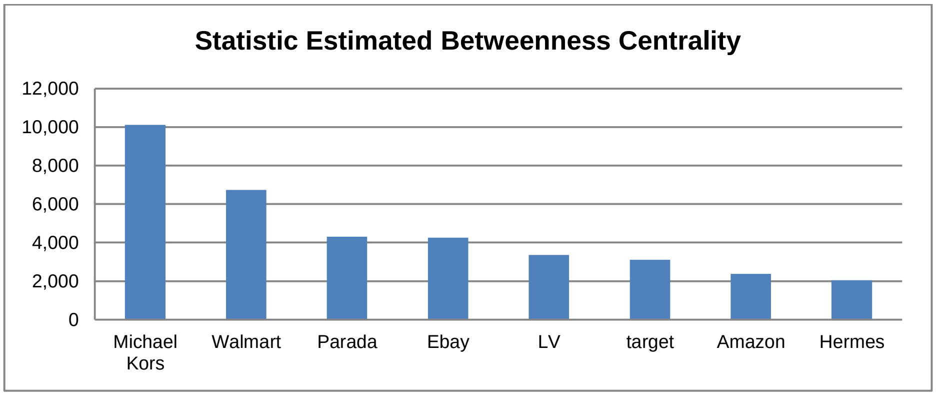
Degree: It is a popularity measure. High value refers to a person connected to many other people in a network. The average Degree Centrality level of Luxury brand is higher than retail brands. Luxury brands focus on emotion appeal rather than retail brands emphasize discount, thus they built closer relationship with customers. Luxury brands also may develop opinion leader strategy to positively influence fans. In Luxury brands, Michael Kors and LV fans have the largest popularity score and are followed by Prada and Hermes. In retail brands, eBay has the highest Degree Centrality and is followed by Amazon, Walmart and Target. In Walmart, there is an extremely large central node connecting 84 percent of vertexes.

Figure 4.5: Degree Centrality of Network in Brand Communities



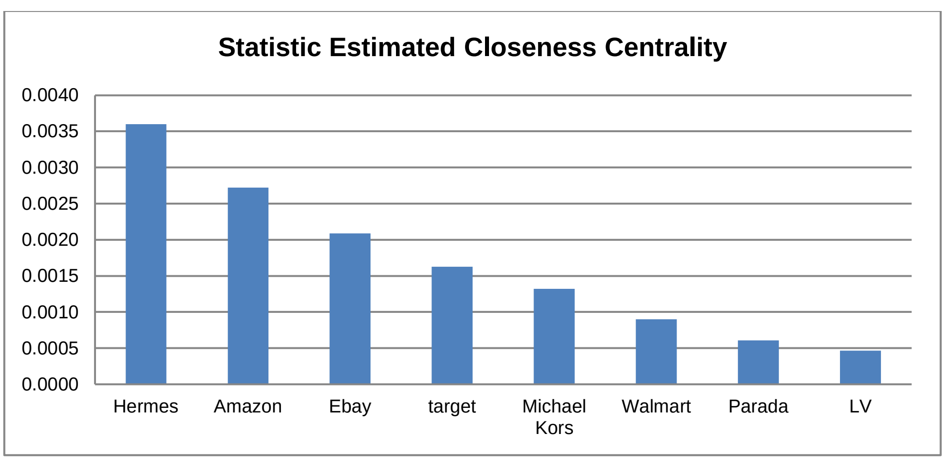
Betweenness Centrality: It is bridge score for boundary spanners. It measures how much removing a person would disrupt the connections between other people in the network. Luxury industry has significantly high Betweenness Centrality than retail industry. Michael Kors have extremely large “average betweenness”. It implies more percentage of nodes have high Betweenness Centrality in Michael Kors than in other brands. In luxury brands, from high to low Betweenness Centrality, the brands are Michael Kors, LV, Prada and Hermes. As statistical test mentioned above, retail brands don’t have significant difference on this parameter.

Figure 4.6: Betweenness Centrality of Network in Brand Communities



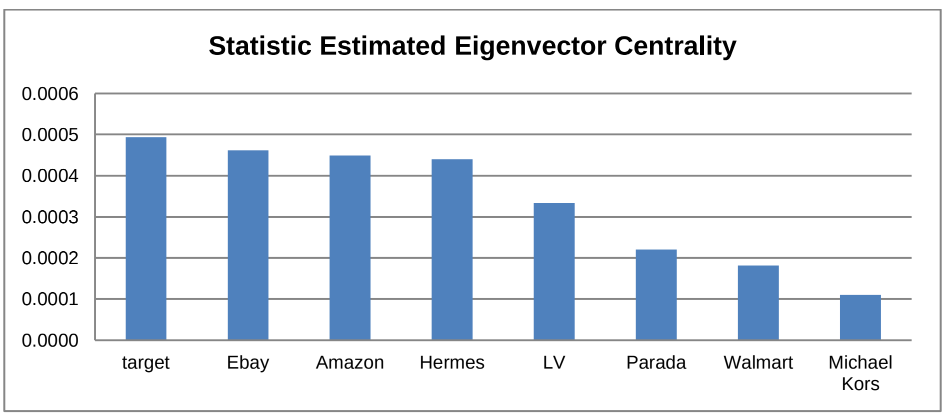
Closeness Centrality: It is distance score for broadly connected people. The low score means short distance between two persons, so information can be spread fast. Significant difference doesn't exist between two categories. In luxury brands, LV has the most efficient Facebook and is followed by Prada, LV, Michael Kors and Hermes. In retail brands, from low to high Closeness Centrality, the brands are respectively Walmart, Target, eBay and Amazon.

Figure 4.7: Closeness Centrality of Network in Brand Communities



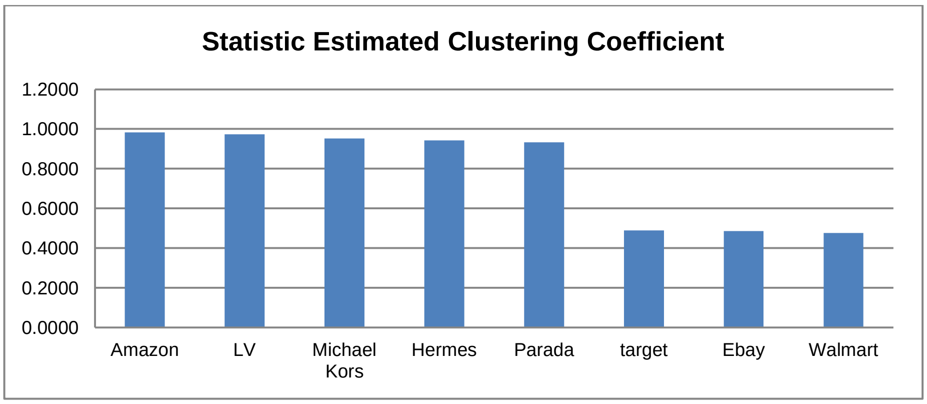
Eigenvector Centrality: is based on the assumption that a connection to a popular individual is more important than a connection to a loner. High value represents most connections are linked to popular, important and central nodes. Retail brands have higher Eigenvector Centrality than luxury brands. It indicates more fans connected to influencers in retail brands than in luxury brands. In luxury brands, Hermes has the largest value. It means the relation with important nodes and connections between “alters” of a node are better in Hermes than in other brands. From high to low value, the brands are respectively LV, Prada and Michael Kors. Although Michael Kors has the largest Facebook, the quality of relationship between fans is lower than other brands. In retail brands, Target has the largest value and is followed by eBay, Amazon and Walmart. The quality of ties of Target Facebook is better than Walmart.

Figure 4.8: Eigenvector Centrality of Network in Brand Communities



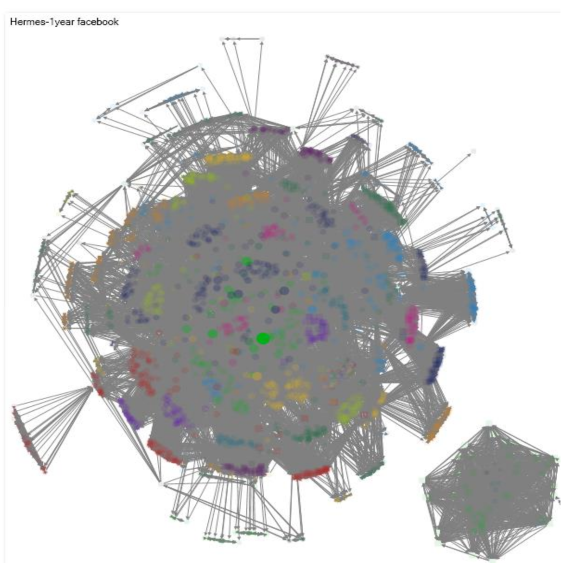
Clustering Coefficient: measures how connected a vertex’s neighbors are to one another. The high Clustering Coefficient indicates a node’s alters know well each other in its 1.5-degree egocentric network. Luxury brands (0.94973) have significantly high value than retail brands (0.57498). It means fans have closer relationships in luxury brands Facebook than in retail brands. Luxury brands focus on emotion appeal rather than retail brands emphasize discount, thus they built closer relationship with customers. In luxury brands, some brands Facebook have well-connected 1.5-degree networks. They are LV, Michael Kors, Hermes and Prada. In retail brands, Amazon (0.98) has the significantly higher value than other brands (about 0.48). The following brands from high to low value are Target, eBay and Walmart.

Figure 4.9: Clustering Coefficient of Network in Brand Communities



4.2.5 Visualization of Brands Facebook: (Map degree to vertex size and betweenness to vertex opacity; collapse group according the value of "Group")

Figure 4.10: Network Graph – Hermes (Left) and LV (Right)



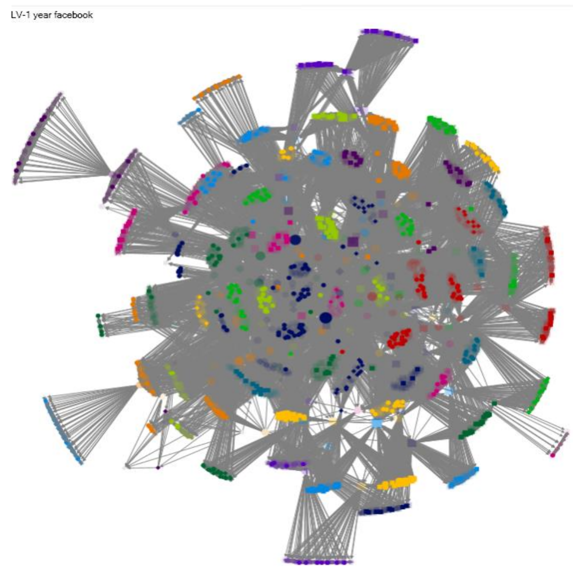
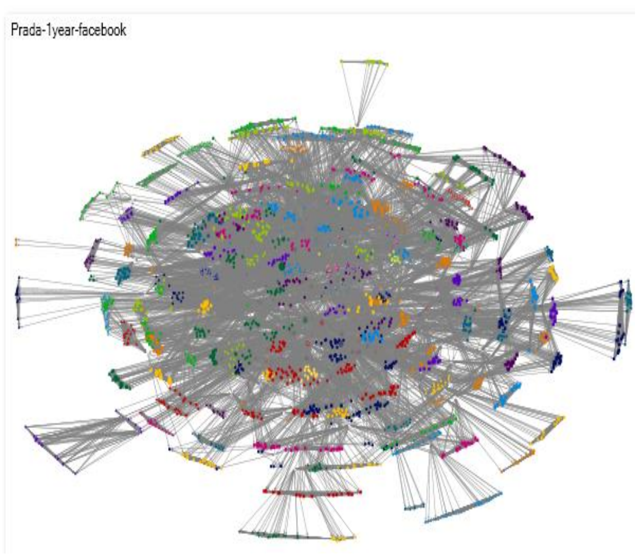


Figure 4.11: Network Graph – Prada (Left) and Michael Kors (Right)



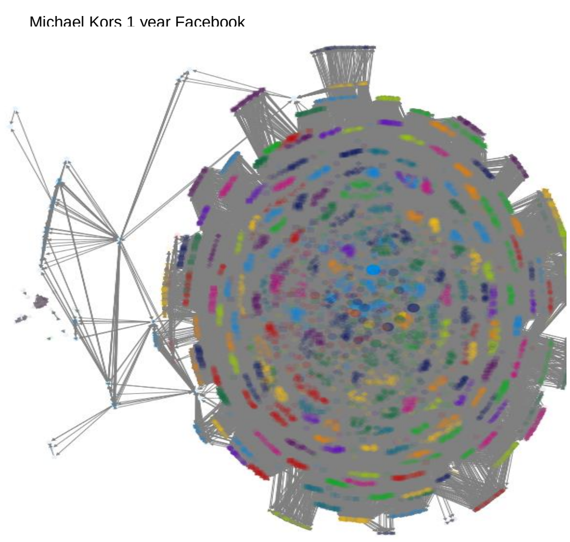


Figure 4.12: Network Graph – Amazon (Left) and eBay (Right)

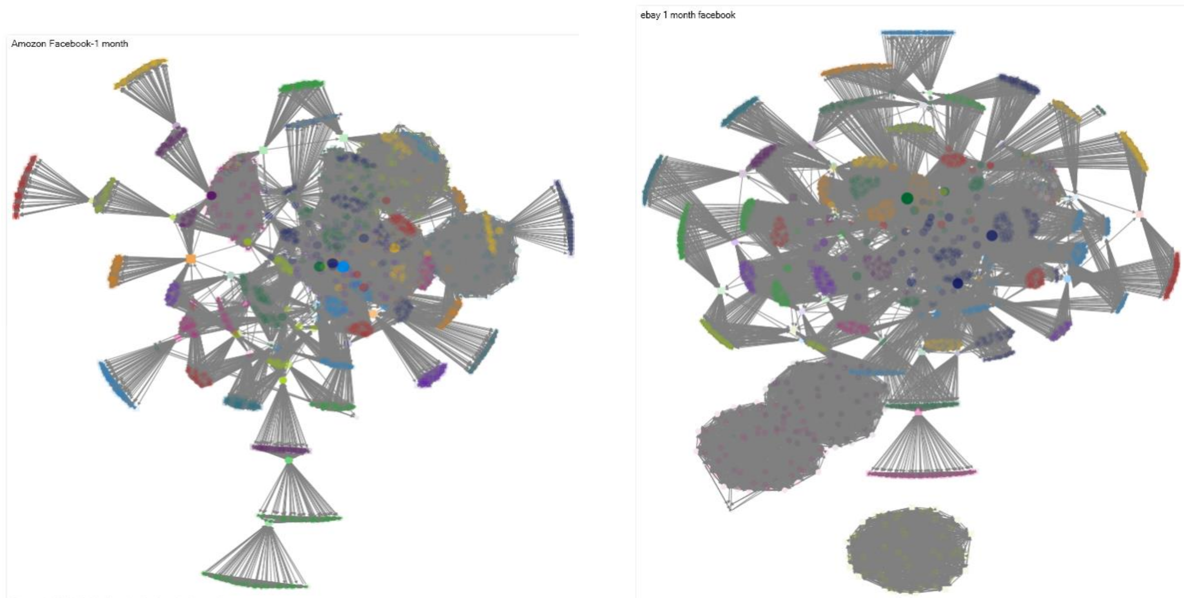
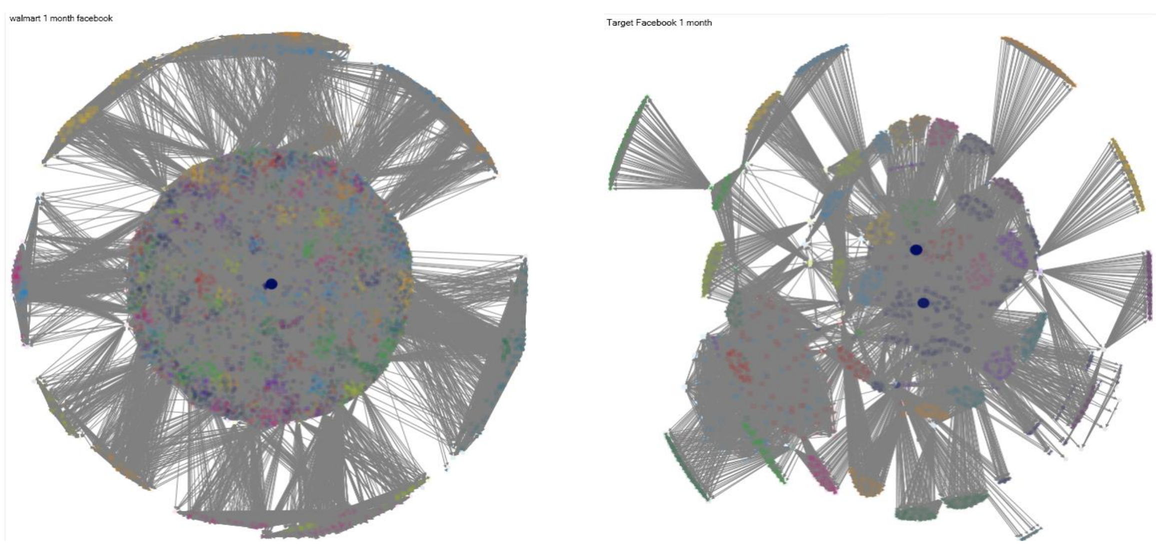


Figure 4.13: Network Graph – Walmart (Left) and Target (Right)



4.2.6 Conclusions: Network structure comparison across brands Facebook

- **Density- Aggregate Network Metrics**: the measures include "Graph Density", "Clustering Coefficient" and "Average Geodesic Distance"

1. Generally speaking, the density of luxury brand network is higher than retail brand. It means luxury brands Facebook are highly cohesive and solid. Tight relationship exists among fans of luxury brand Facebook. For example, in terms of Hermes, not only fans of its Facebook connect each other but neighbors of fans know well each other. In contrast, retail brands Facebook, especially Walmart, display looser networks. The relationship among vertices is weak. A dense network also is a robust network which can perform well against attack.

2. In luxury brands, the densest network is Hermes Facebook. Sequentially, the networks from high to low density are Prada and Michael Kors Facebook. Although of Michael Kors Facebook has the largest sizes, its fans don't connect with each other frequently and the density is fairly low.

3. In retail brands, Amazon, eBay and Target Facebook have similar density. Similar to Michael Kors, Walmart has the largest Facebook in retail brands (in this study). But Walmart network displays a lower density than Michael Kors Facebook. Walmart Facebook is a two-layer structure, including a solid ball and a scattered circle. The inside structure is dense but the nodes sitting at the periphery of the network are scattered. It indicates the relationships between the two groups are entirely different. The inner nodes have strong ties but the outer vertices keep weak ties.

- **Centralization- An aggregate metric that characterizes the amount to which the network is centered on one or a few important nodes.**

We calculated edge contribution generated by each node in a network. From high to low, we respectively chose top 0.5 percent and top 1 percent of nodes in each network. Finally, we analyze how much edge contribution generated by the top 0.5% and 1% nodes in each network. If the given percentage of nodes can generate the greatest number of edges in a certain network, the Facebook is the most centralized.

Figure 4.14: Edges contribution generated by important nodes- Top 0.5% of nodes

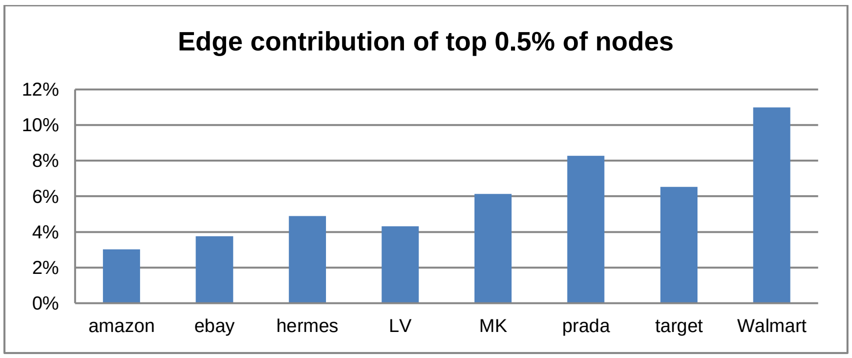
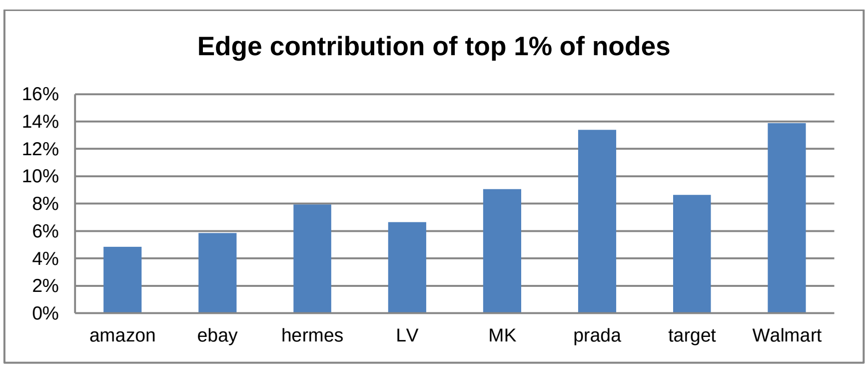


Figure 4.15: Edges contribution generated by important nodes- Top 1% of nodes



Centralized networks have many edges which come from a few important vertices. The charts show the edge contribution capability of nodes across brands. Walmart Facebook is the most centralized network and followed by Prada, Target and Michael Kors Facebook. According to network graphs of brands Facebook, Walmart also displays a concentric circle composed of two parts, a compact central ball and an incompact peripheral circle. The inside ball represents a group of nodes which actively interact with each other and keep strong relationship with core nodes. The peripheral nodes don't directly connect focal persons; instead keep touch with bridge nodes to obtain information. This diffusion pattern can reach people as many as possible by spreading information radially. Unlike Walmart, another centralized network of Prada doesn't have a few extremely central nodes but it organizes other nodes into a Quasi-circular structure by managing a variety of bridge nodes. The most decentralized network is Amazon Facebook and secondary one is eBay. According to the charts above, we find online company Facebook pages are more decentralized than offline company Facebook pages. Online company Facebook lack of central nodes and the forces are equally decentralized into many clusters. But this conclusion is based on the limited number of samples, so its reliability should be verified by more online and offline brands Facebook.

Network centralization can be analyzed according to Vertex Centrality attributes, including "Degree Centrality", "Betweenness Centrality" and "Closeness Centrality".

Centralized network should have a few nodes with high Degree Centrality. It emphasizes on two requirements: 1. Nodes have high Degree Centrality; 2. The number of core nodes is small. Therefore other nodes can form a concentric cycle to encircle the focal vertices. Under this structure, the efficiency of a network would be high. For instance, the network can spread information quickly and reach a large number of people.

- **Summary**

As for network density, luxury brands are tighter and more solid than retail brands. More fans in these luxury brand Facebook pages interact with each other more frequently. In terms of network centralization, offline retail brands, Walmart and Target Facebook, are relatively more centralized. A centralized but incompact networks means nodes concentrate on a few focal nodes and don't know well each other. The centralized network structure allows a few influencers to affect the entire networks. The focus of a centralized network is control. Through effectively managing key roles, a centralized network can spread information in a broad scope. In contrast, the structure of online companies Facebook is sparser and more decentralized. In such networks, forces are decentralized into lots of ordinary vertices, called "grassroots" in a real world. "Grassroots" refers to "common or ordinary people in a society, especially as contrasted with the leadership or elite of a political party, social organization, etc." (Online Dictionary, 2013) Thus, in Amazon and eBay Facebook, numerous grassroots dilute the power of a few core people. The networks are composed of a variety of clusters with equal force. Unlike centralized network, it is difficult to manage a whole network by controlling a few focal influencers.

4.3 Node (actor) Level Analysis-Role Identification

In identifying the role of a node, we take account into three factors, including Degree, Betweenness and Eigenvector Centrality. Here, X and Y axes are determined by a node's Degree and Betweenness Centrality, respectively. Another dimension is Eigenvector Centrality which decides the size of a node. We hide the edges if their weight is less than two.

There are three types of influencers:

First type: These nodes have extremely high Betweenness, Degree and Eigenvector Centrality. They are popular and large network brokers who bridge unconnected sub-groups composed of a great many of vertices. Moreover, these nodes keep connected with some important and central vertices.

Second type: these nodes have medium Degree and Betweenness Centrality. They are secondary influencers.

Third type: these nodes are not very popular but bridge some isolated groups.

4.3.1 Luxury Brands

Figure 4.16: Node-level Analysis for Hermes Facebook

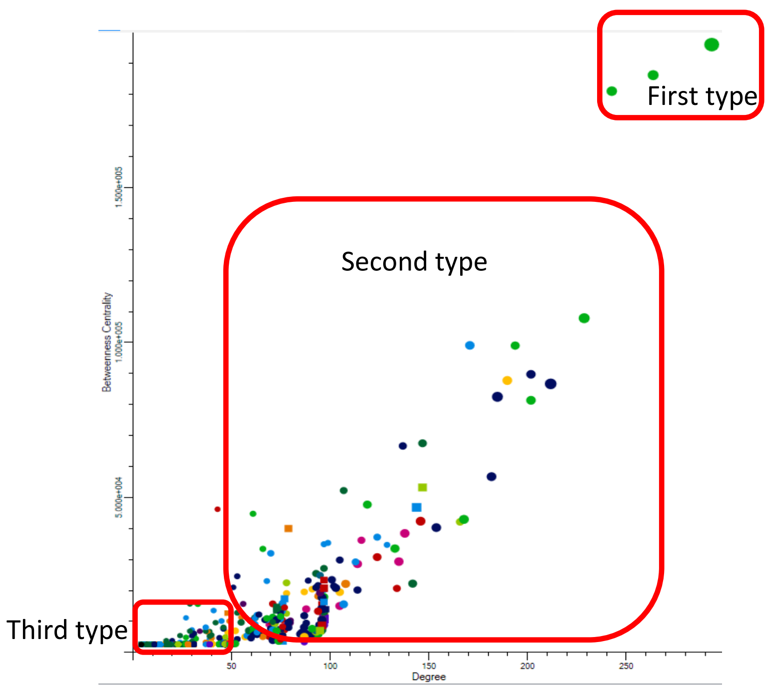


Figure 4.17: Node-level Analysis for LV Facebook

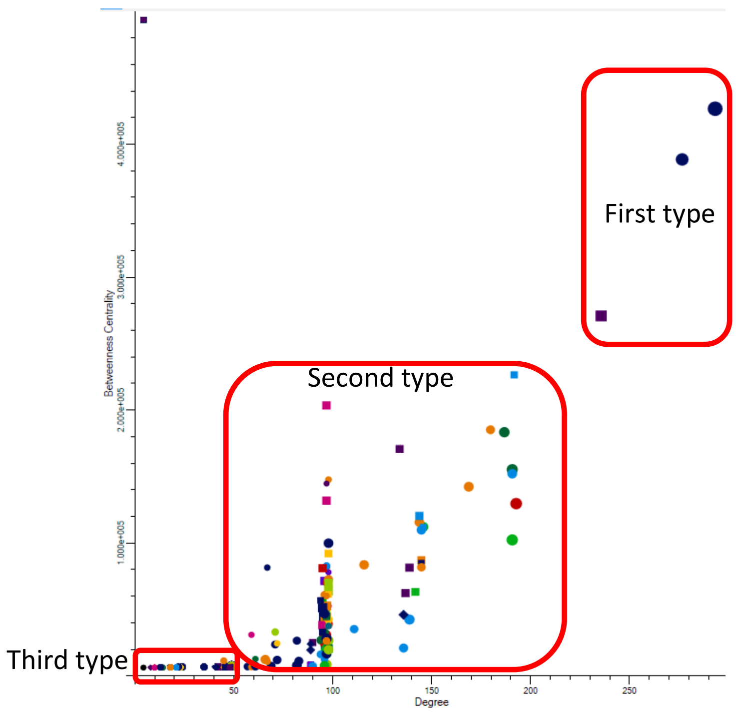


Figure 4.18: Node-level Analysis for Michael Kors Facebook

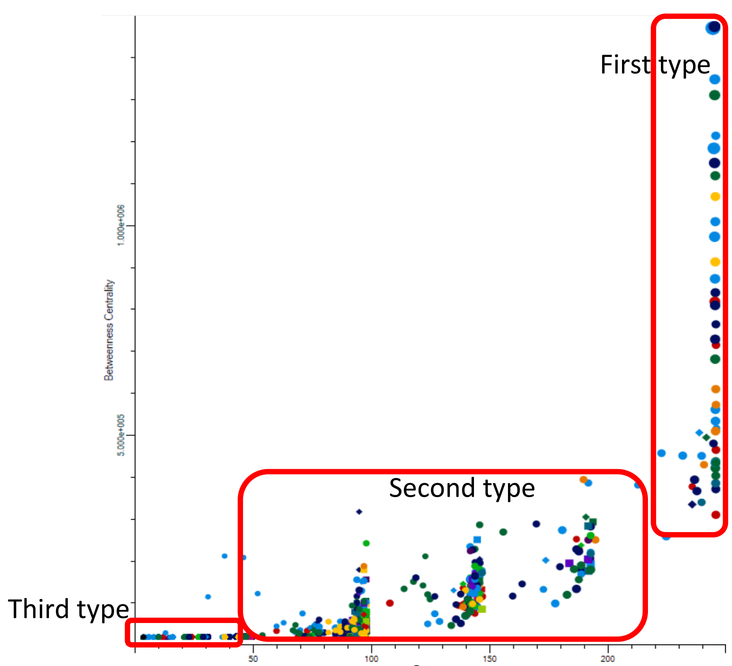
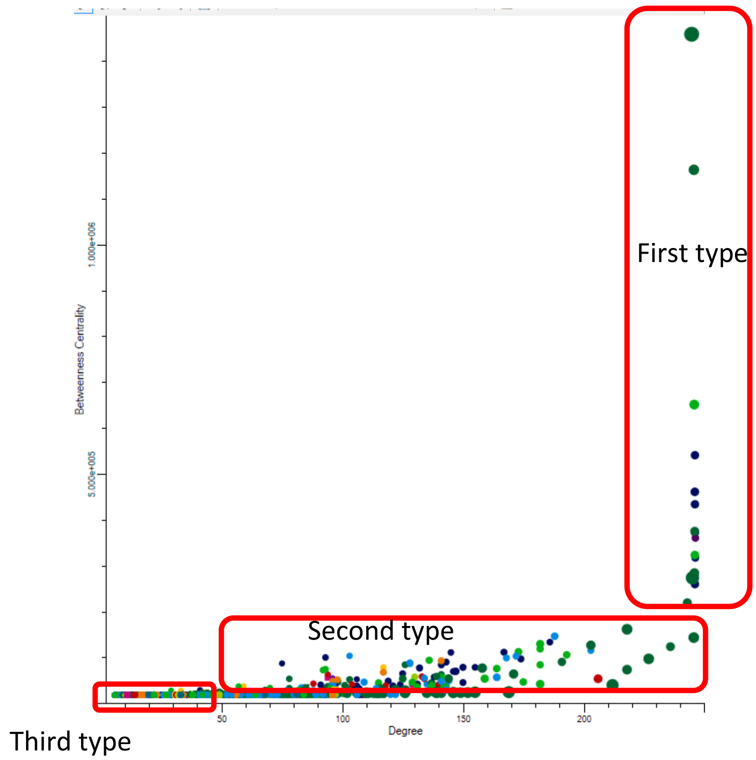


Figure 4.19: Node-level Analysis for Prada Facebook



- First type nodes are extremely popular and link many unconnected groups to spread information. Michael Kors has the largest percentage of first type nodes and Prada has the second large percentage. LV and Herms don't have lots of extremely popular nodes or nodes with high bridge score.

- In sum, Michael Kors Facebook has a great many of important nodes which have high Degree and Betweenness Centrality. Michael Kors also has the largest Facebook in the four luxury brands. As for the two aspects, Prada ranks at the second place and is followed by LV and Hermes. The attribute of vertex are significantly different across luxury brands because their unique marketing strategies, especially social media strategies. In contrast to Hermes and LV, Michael Kors is more popular because of its lower price and fashion style. Prada also achieved significant performance in last five years. Prada ranked the sixth place in the most valuable luxury brands in 2012. It is the first time for Prada to rank in top 10 luxury brands. Michael Kors and Prada developed a great number of fans and foster high percentage influencers who connect many persons and unconnected groups. Compared to other brands, Hermes has the smallest Facebook, low percentage of influencers but the largest density. From another point of view, Hermes Facebook is a relative robust network because nodes have strong ties and removing some nodes may not influence the whole network. It is related to the market positioning of Hermes. Hermes is the extremely expensive luxury brand and possesses a particularly high-end niche market compared to the other three brands. Thus its Facebook reflects the trend.

4.3.2 Retail Brands

Figure 4.20: Node-level Analysis for Amazon Facebook

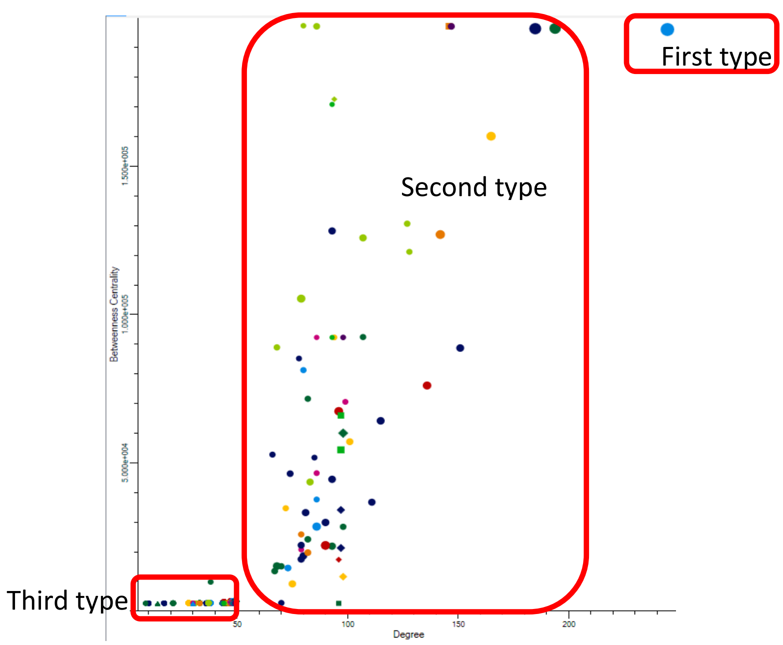


Figure 4.21: Node-level Analysis for eBay Facebook

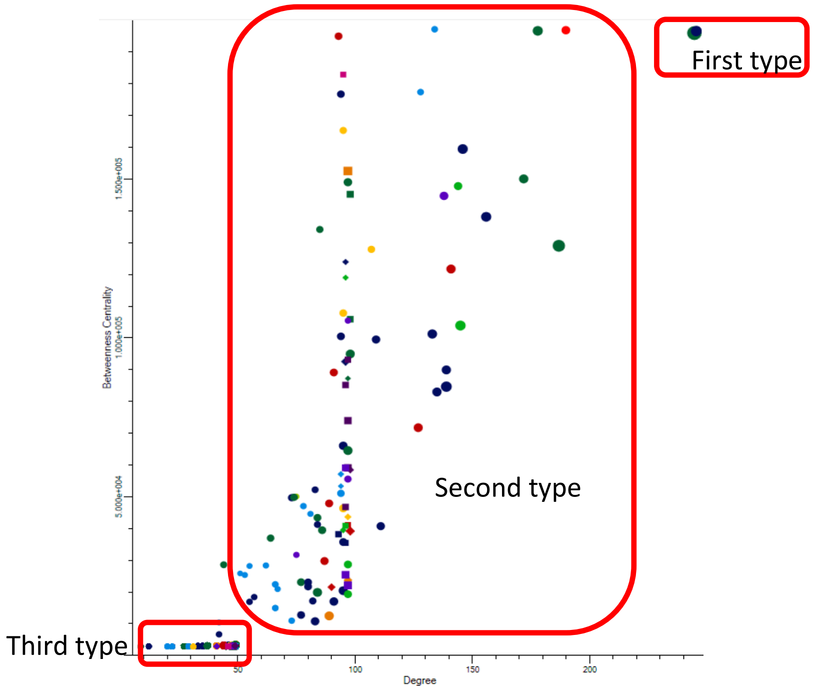


Figure 4.22: Node-level Analysis for Walmart Facebook

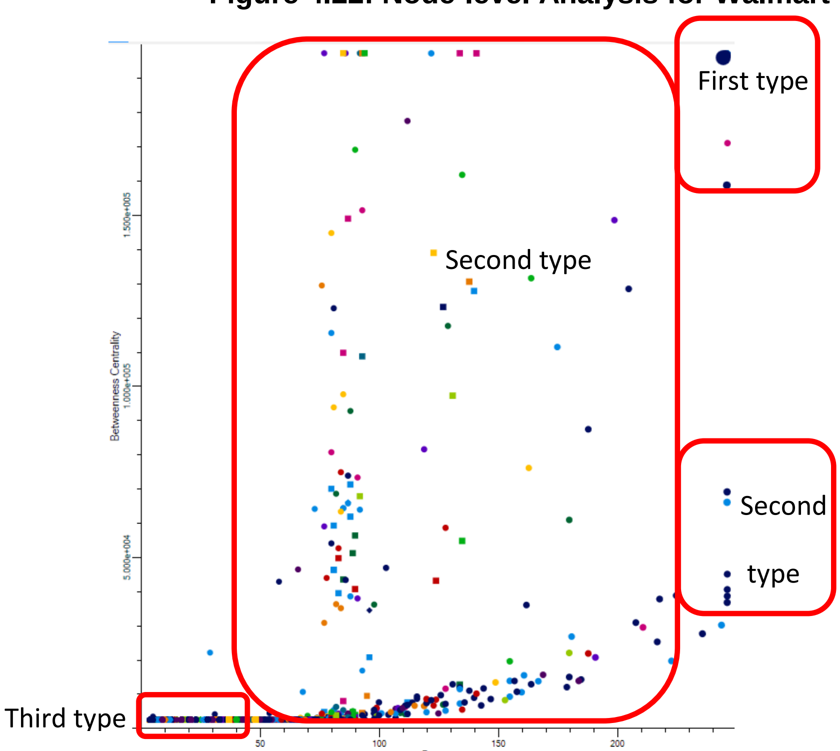
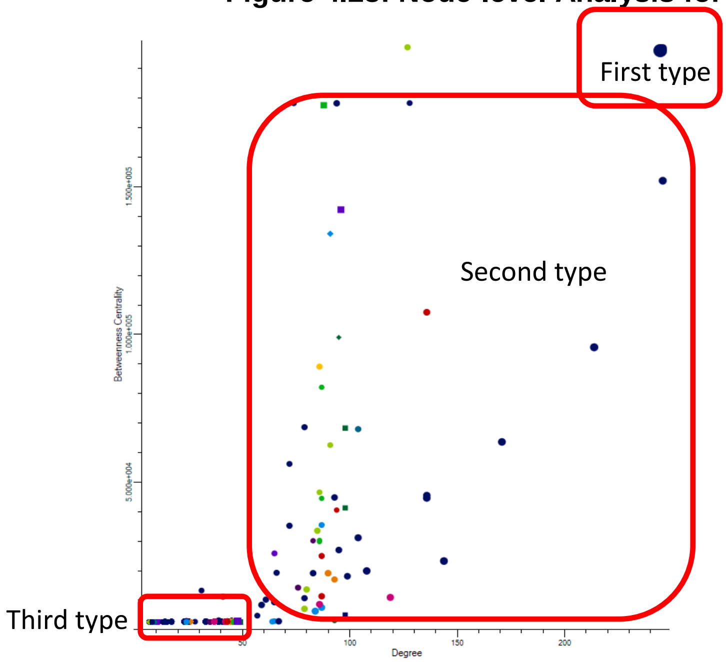


Figure 4.23: Node-level Analysis for Target Facebook



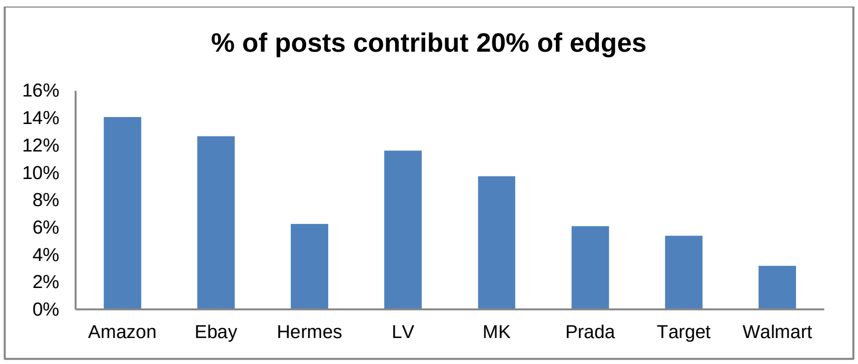
- Walmart has the largest portion of first type of nodes. In second type nodes group, the fans of Walmart Facebook have higher Degree and Betweenness Centrality than other brands. In terms of network size, Walmart Facebook is the largest in the four retail brands. The network structure is due to the two reasons: 1. Walmart is the largest retailer and has considerably mass market. 2. Walmart actively develops its social media strategies. Compared to Target, Walmart more successfully developed a large network and many influencers on its Facebook. But due to the large size, the ties between nodes are weak and most relationship occurs between ordinary and central fans.

- Compare to offline retailers, Walmart and Target, Amazon and eBay have lower Betweenness Centrality, however the Degree centrality of their nodes is relatively higher. It indicates Amazon and eBay have few central nodes but the average popularity level of all nodes is higher. It may be because online companies provide broader communicating platforms.

4.4 Content Analysis

4.4.1 The diffusion scope of posts

Figure 4.24: The Diffusion Scope of Posts



The chart represents how many posts can generate a given proportion of edges (top 20%). According to the chart, we find in Walmart, 3.2% of posts generated 20% of edges. It indicates the network has strong control power over their fans. In other words, the network maybe has a high fans coverage rate. In a diffusion process, it can reach a great many of people. From high to low coverage rate, other networks are Target, Prada and Hermes Facebook, respectively. The diffusion pattern possibly correlates with the centralization of networks. If the centralization is high, it is possible to spread information more efficiently into a broader scope.

4.4.2 Content type

We calculated edge contribution generated by each post and chose top 20 percentage of posts in each brand. We categorized these posts into seven groups (Greeting, Survey, Game, New product, Event, New, Video) based on their topics. Then we aggregated edge contribution by the seven topic categories. The category which generated the largest edge contribution is the most popular content on Facebook.

Table 4.13: Content Category Distribution in Brand Communities

Content Type	Hermes	LV	Michael Kors	Prada	Target	Walmart	Amazon	Ebay	Total
Greeting	12.50%								0.8%
Survey	12.50%		2.8%	4.8%	100.0%	31.6%			11.8%
Game	62.50%	8.3%		4.8%		26.3%	44.4%	44.4%	16.8%
New product	12.50%	75.0%	97.2%	23.8%		15.8%	55.6%	55.6%	52.9%
Event				9.5%		26.3%			5.9%
News				57.1%					10.1%
Video		16.7%							1.7%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%

The table shows the most popular topic is about new product. The secondarily popular post is game and then followed by survey questionnaire and news. The popularity trend of post on Facebook indicates:

- For companies, the most valuable function of Facebook is to promote new products or services.

- User engagement in content will increase information diffusion. The content which can encourage people to participate will be spread more. It is similar to UGC theory (user generated content). UGC is more prevalent than traditional authorized content provided by companies.

Chapter 5: Conclusion

In this part, we will review our initial study purpose and questions, business practical implication, the limitation of this research project and further research to address some limitations.

5.1 Initial Research Purpose and Questions

The purpose of this research is: (a) exploring the structures of social media network across two categories and four brands within same category; (b) identifying key roles in given networks; (c) content analysis is to find popular content type in Facebook.

5.1.1 What network structures do companies Facebook display across industries and brands?

The research indicates that the Facebook from two industries and four brands in each industry display disparate network shapes.

Luxury and Retail industry: luxury brands have higher density than retail brands because the former is more niche market and the latter is mass market. Moreover, luxury brands more emphasize emotional appeal but retail brands focus on discount. Thus fans may have stronger ties on luxury brand Facebook than retail brand Facebook.

Luxury brands: Hermes and LV Facebook have relatively high density compared to Michael Kors and Prada. Michael Kors is the largest and Prada is the most centralized in the four luxury brands. From marketing operation, the most popularity of Michael Kors brand positively influenced its Facebook size. In recent years, Prada made efforts to raise its rank in the most luxury brands. Hermes, as an extremely high-end brand, is niche market and has the smallest and dentist Facebook.

Retail brands: As the largest retailer in the world, Walmart has the largest and the most centralized Facebook in the four retail brands. Due to the large size, Walmart has relatively weaker ties among fans than other brands. Compared to eBay, Amazon is less centralized and more scattered Facebook. Both of them are the most decentralized networks in retail brands. There are many equal size parts instead of a few central nodes in the both Facebook.

5.1.2 What are the network mechanisms of these brands Facebook?

Our research indicates:

A dense network requires strong ties among its nodes. It encompasses three meanings: 1. People interact each other. 2. The interactions are frequent. 3. There are not apparently central nodes. These features can be found in Hermes and LV Facebook. Dense network can diffuse information fast.

A centralized network need to satisfy two criteria: 1. Focal nodes which are firmly at the center of a network and directly connect to most other nodes. 2. The number of central nodes is limited. Walmart and Prada are typical examples. Centralized network can spread information widely.

Based on the comparison between the two structures, we can infer that they are incompatible structures. Dense network with strong ties allows nodes to exchange information freely, thus centralization control is hard to build through a few focal nodes.

5.1.3 Who play key roles in given networks? How do the key roles influence information diffusion?

Our research indicates key roles in a network should be equipped with: 1. High Degree Centrality; and 2. High Betweenness Centrality.

According to the score of Degree Centrality, we can identify popular nodes which directly connected many other nodes in a network. For instance, in Walmart and Target Facebook, we find the both companies are members of their own Facebook and become the central nodes in the networks. Central nodes can help spread information relatively easily in a whole network.

Some nodes with low Degree still are important roles because they bridge structural holes in a network. Bridge nodes maybe know only a few people but they come from different and unconnected groups. Information can be spread from a few bridge nodes to a broader audience. For example, Prada Facebook has a certain percentage of nodes with high Betweenness Centrality. Content analysis indicates that information can be spread widely in Prada network. Although its density is not high, the low Closeness centrality shows its diffusion speed is still high. Thus, we think bridge nodes are meaningful in efficiently (more quickly and broadly) diffusing messages.

5.1.4 What kinds of information are more popular and spread by more people on brand Facebook?

Our research indicates the most popular post is about new product information. From high to low popularity, the posts are about game, survey questionnaire and news. It reflects two possibilities: 1. Company prefer to release new product in their Facebook. 2. Users favor content with high interaction. High user engagement also increases information diffusion.

5.2 Managerial Implications

In the process of delivering value to customers, marketers have been making efforts to explore how the interaction mechanisms among people influence the adoption of product and service in society. However, in traditional marketing period, it is difficult to capture and quantitatively analyze the process. Nowadays, the development of digital marketing and network theories offers an access to explore the value delivering process. Internet-based brand community allows data collection through computer software. SNA provides a new analysis perspective focusing on social behavior in the structure of a network rather than in the individuals alone. Based on the understanding of inter-relationships in a community, marketers can:

Know how the structure of a network and how it impacts its members' behavior through network structure-level analysis. For example, a centralized network has a few focal nodes which emanate a large proportion of edges. If a brand community is centralized network, marketers should identify these core nodes and manage them to spread information broadly. If a community is decentralized, it means the relationships between members are strong. People are familiar with each other rather than a few central members. As for such a network, marketers can encourage active user engagement to create more cohesive and solid community.

Identify key roles in a network. A few key roles can influence a great many of people in a network. According to crucial attributes of nodes, such as Degree Centrality and Betweenness Centrality, marketers can identify important nodes with high popularity or bridge score. In order to make cost effective marketing strategies, marketers should build positive relationship with them and take advantage of them to influence more people.

Capture the diffusion model of new product and service. Why people adopt a new product or service? Which factors will affect people's adoption? What is the trend of innovation diffusion? The findings from network analysis also can be applied to advertising and communicating practices. For instance, early adopters have low threshold but much resource of external influence. In diffusing an innovation, marketers should identify the early adopters and motivate them to diffuse new product and service.

Conclusively, relationship-focused network analysis provides marketers with a new perspective to know customers. It fosters more positive relationship in brand community and more precise marketing strategies.

5.3 Limitations

The major limitations of the research are due to data restriction. Owing to privacy concern, NodeXL don't provide other detailed demographic and personal relationship information of Facebook fans except for their sex and locale through. The data limitation increased the difficulty in understanding inter-relationship among members. We know the network shape but cannot explain the reasons behind the structure.

Another data deficiency is regarding to response time information. The data of edge describes the interaction process, including senders, receivers and discussion topic information. However, data doesn't provide the time when the interaction occurs.

Therefore, it is difficult to calculate a diffusion model describing how information is spread among people over time.

Finally, the research is based on the data sample of eight brands Facebook. The limited sample size and the characteristics of Facebook may affect the representativeness of conclusion partly. It is more meaningful to apply the methodology to broader samples to verify the conclusion.

5.4 Further Research

Firstly, the further research should involve more background information (age, occupation, interest, relationship, etc.) of members in a network. The background information could be collected by survey and data mining. So we can understand the reasons for different interaction mechanism and process across networks as well as find the similarities within a sub-group and dissimilarities among sub-groups.

Secondly, this research shows the information diffusion result but not the process. We know who participated in discussion and what topic they talked about but don't know how these topics were spread from person to person. If we can collect time information, further research can know more about an entire contagion process. It is benefit for innovation diffusion and cost-effective advertising strategies.

Finally, because this research only focuses on Facebook community of certain brands, it is meaningful to enlarge the research sample. For instance, we cannot only compare Twitter, Facebook, and offline communities but also cover more industries and brands in the research. Thus, we can know more types of network structure and shape as well as their operation mechanisms. It is helpful for marketers to build healthy brand communities.

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