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Large Scale Online Brand Networks to Study Brand Effects

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Abstract

Mining consumer perceptions of brands has been a dominant research area in marketing. The marketing literature provides a well-developed rationale for proposing brands as intangible assets that significantly contribute to firm performance. Consumer-brand perceptions typically collected through surveys or focus groups, require recruitment and interaction with a large set of participants; leading to cost, feasibility and validity issues. The advent of web 2.0 opens the door to the application of a wide range of data-centric approaches which can automate and scale beyond the traditional methods used in marketing science. We address this knowledge area by exploiting social media based brand communities to generate a brand network, incorporating consumer perceptions across a broad ecosystem of brands. A brand network is one in which individual nodes represent brands, and a weighted link between two nodes represents the strength of consumer co-interest in these two brands. The implicit brand-brand network is used to examine two branding effects, in particular, positioning and performance. We use hard and soft clustering algorithms, Walktrap Clustering and Stochastic Block Modelling respectively, to identify subsets of closely related brands; and this provides the basis for examining brand positioning. We also examine how a focal brand's location in the brand network relates to performance, measured in terms of relative market share. For this, a hierarchical regression analysis is conducted between brand network variables and brand performance. While the size of brand community on Twitter does relate to brand performance, the brand network variables like degree, eigenvector centrality and between-industry links help improve the model fit considerably.

Introduction

"Companies with an extensive social media presence reported a return on investment that was more than four times than that of their counterparts" eMarketer (2012). Though a vast majority of companies in North America are increasingly convinced of the benefits of social media to improve organizational performance, half them believe that the major hurdle to social media campaigns is the lack of a reliable and standardized metric to measure return on investment (ROI) (eMarketer, 2012). The rise of '*big data'* technologies has enabled businesses to access and gather limitless information about their customers and ROI without having the need to worry about storage and processing capabilities. Although traditional media offers greater control to the advertiser with a one-way content management approach, the revolution in the digital economy has rapidly changed the way companies and consumers choose to interact with each other. Social media sites such as Facebook and Twitter offer a two-way communicative environment between brands and users; encompassing consumer feedback as a key element of brand management (Nitins et al. 2014).

As increasing number of consumers choose to affiliate themselves with their favorite brands on social media, virtual brand communities have experienced a renaissance in current years. Survey research by Adobe (2014) shows that there is a real monetary value to having Twitter followers; approximate revenue per visit from Twitter is $0.62. Although a few marketing researchers have begun to use these social media based brand communities for understanding value creation (Laroche et al, 2012) and information diffusion (Goel et al. 2012), we believe that we are the first to use a brand's social connections through its communities to examine brand positioning and brand performance. The digital footprints of consumers create a rich data source for marketer's purposes like deconstruction of consumer behavior, and campaign automation and optimization. Our approach, using large scale social media data, contrasts with traditional survey and focus group based methods, which can be expensive and cumbersome, and are also limited in terms of reach across consumers and brands. We collect data on a broad set of social media based brand communities, and use this to generate a large scale brand network. Individual nodes in the network represent brands, and a weighted link between two nodes represents the strength of consumer co-interest in these two brands. The brand network thus reveals brand-to-brand connections based on consumer perceptions across a broad ecosystem.

Brand Positioning is the idea of creating a distinctive place for a brand in the minds of consumers, relative to its competitors and substitutes. This paper examines how tie strength between brands, and centrality measures can help distinguish certain brands over others. The second section of our paper applies network analysis on the consumer-brand interactions data to study brand performance. The extant literature is limited to quantifying social media's financial value for firms, and overlooks brand level success and its contributing factors. For instance, in recent years PepsiCo's carbonated brands have lost value while its noncarbonated ones have gained value. Carbonated drinks such as Mountain Dew, Pepsi and Diet Pepsi have lost 7%, 5%, and 3% of brand value respectively, while noncarbonated drinks such as Gatorade and Tropicana have enjoyed gains, with brand values soaring 10% and 8% respectively, during the same period (Millward Brown's annual BrandZ ranking, 2014). Focusing solely on firm level information, PepsiCo's stock returns, does not give us adequate indication on how individual brands contribute to overall firm success. Given the significant amount of resources expended for building competitive brands, this is a crucial gap in the marketing literature. The brand network that we build embodies consumer perceptions across a broad brand ecosystem; and helps us in understanding brand performance. In the next section, we discuss related work in literature, and explain how our work contributes to this area.

Related Work

User Brand Affinity

Social Cognition theorists (Shachar et al, 2000; Lydon et al, 1988) have noted the tendency among people to associate with those who are similar to them in socially significant ways. This relationship between similarity and association, also known as the principle of homophily, has been widely observed in sociology, social network analysis, and computational science (McPherson et al, 2001). When users make virtual connections with their favorite brands on Twitter, it provides evidence of their voluntary affiliation with that entity. This user-brand association can be interpreted as an expression of affinity (Kuksov et al, 2013; Naylor et al, 2012). This line of argument is further supported by a stream of studies in Consumer Research (Berger and Heath 2007; Childers and Rao 1992; Escalas and Bettman 2003) that show a strong relationship between brand image and characteristics and identities of the brand's supporters and followers. Thus, mining the social structure of a brand's follower base on social media can help us capture useful information.

Social Media Based Brand Communities

Taking advantage of the user-brand relationships on social media, brand networks incorporate consumer-perceptions across a broad range of brands. User-brand relationships are captured through brand communities on Twitter. Our understanding of brand communities is derived from what Muniz et al. (2001) describe as a "specialized, non-geographically bound community, based on a structured set of social relations among admirers of a brand". Marketers have found that brand communities established on social media lead to value creation through shared consciousness, brand use, brand loyalty and engagement among community markers (Kaplan & Haenlein, 2010; Muniz & O'Guinn, 2001).
Brand-to-brand relationships extracted from data on common consumer interest are an interesting new topic of research. Zhang et al. (2016) find a brand network extracted from brands' Facebook fan pages to be useful for audience targeting. Culotta and Cutler (2016) use associations between a focal brand and specified exemplar brands to mine brand perceptions from brand-followership data on Twitter.

If we solely rely on numbers, Facebook is the most popular social media website with 968 million active daily users compared to 316 million active users on Twitter (Data provided by Facebook and Twitter, 2016). Though the popular microblogging site, Twitter, lacks in overall monthly users compared to Facebook, it makes up for in other areas that are crucial for businesses. First, 49% of monthly Twitter users follow brands or companies, compared to an average of 16% users for other networks (Edison Research, 2016). Second, according to Twitter, 74% of people who follow a brand on Twitter do so to get updates on latest products and discounts. Our work is based on brand community data for a set of brands across industries collected from Twitter.

Community Detection

Two groups of methods for community detection (clustering) on networks have been extensively studied in the literature. The first class of methods involves optimization of some reasonable global criteria such as modularity over all possible network partitions to generate an optimal community structure, such as multilevel modularity maximization or Walktrap clustering (Zhao, Y., et al 2012). Although first proposed in the 80's, the second class of methods - Stochastic Block Models, have recently gained attention due to their ability to handle overlapping community (Airoldi et al. 2008) and varied community structures, which fit real world data sets well (Gopalan and Blei, 2013). Unlike hard clustering algorithms, the stochastic block model is a probabilistic or generative model, which assigns a probability value to every edge in the network. Extensively employed as a canonical model to study community detection, SBMs identify statistically valid similarity relationships in networks, and provide a fair ground to understand the statistical and computational tradeoffs that arise in network and data sciences (Abbe, E. 2017).

Method

Our work on building and analyzing weighted brand network for uncovering branding effects can be divided into four stages: 1. Brand selection 2. Network generation 3. Community detection to study Brand Positioning 4. Brand network variables to examine Brand Performance.

Brand Selection

To test the generalizability of our approach across industries, we collect data on 370 brands from a variety of sectors. We select brands based on the industry-wise directory of brands in social media maintained by the fanpagelist.com website. We manually validate all accounts to check that the selected Twitter handles are verified (marked with a blue badge), and then discard any brands having less than 1000 followers. Twitter's public API is used to collect all followers for each brand in our data set. In total, we collect Twitter user IDs for more than 100M brand followers.

Network Generation

We define our undirected weighted network as $< b_i, w_{ij} >$ where b_i is an individual brand/node in the network and w_{ij} represents the edge - common followers between any two brands bi and b_j. If F_i and F_j represent the list of followers of brands bi and b_j respectively, then an edge between two nodes is created if and only if $F_i \cap F_j > 0$. Alternatively, the edge list is represented as a weighted adjacency matrix A_{ij} where:

$$A_{ij} = \begin{cases} w_{ij} & \text{Common users between any two brands } b_i \text{ and } b_j \\ 0 & \text{Otherwise} \end{cases}$$

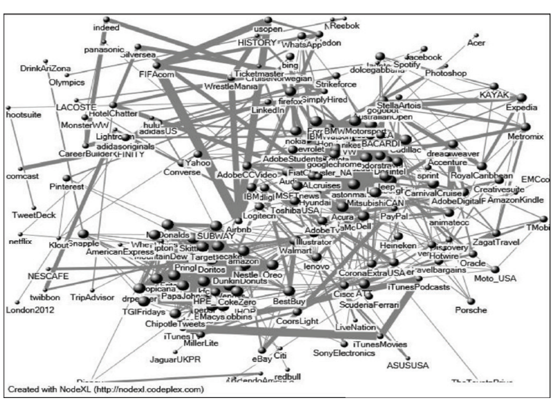

Figure 1 Weighted brand-brand network

Thus, two brands are bridged by common users. Larger the number of common users between two brands, higher the weight of their link in the network. This link can be interpreted as brand-brand affinity based on consumer co-interest.

Normalization of edge weights Highly popular brands such as Disney and Nike have millions of followers, compared to a few thousand followers of small brands such Vizio and Match. We normalize the edge weight by defining the weights as in Zhang, et al. (2014):

Normalized edge weight = $(F_i \cap F_j) / (f_i + f_j)$; where f_i and f_j represent the number of followers of brand bi and b_j respectively. This normalization technique ensures that a few big brands do not dominate our network analysis measures.

Community Detection Algorithms

Walktrap Clustering algorithm (Pons et al. 2005), a hierarchical agglomerative method, is used to identify brand communities in the weighted brand-brand network. The algorithm works on the idea of detecting areas of high density within the graph, through a random walk process. The basic idea is that if two brands lie in the same cluster, the probability of finding the third brand located in the same cluster by a random walk process should almost be the same as for the first two brands. Other popular methods for community detection include: Fastgreedy (Clauset, A., 2004) and Multilevel Modularity Optimization (Blondel, V. D., 2008). To assess the similarity of Walktrap algorithm with these other methods, we use the Normalized Mutual Information (NMI) criterion, proposed by Danon et al. (2005) The value of NMI ranges from 0 to 1, where 0 signifies that the community structures are totally independent and 1 that they are identical (Fortunato, 2010). Table 1 results show strong similarity show strong similarity in brand network clusters obtained with these different techniques.

Community Structure 1	Community Structure 2	Normalized Mutual Information (NMI)
Walktrap	Fast greedy	0.97
Walktrap	Multilevel Modularity Maximization	0.93
Fast greedy	Multilevel Modularity Maximization	0.95

Table 1 NMI for different clustering techniques.

Partitioning of the weighted brand network using Walktrap community detection yields twenty-two significant communities with approximate modularity value of 0.7. Each of the communities can be viewed as a segment of brands with common consumer interests. For instance, the community consisting of brands: Hulu, Netflix, Amazon video and Amazon Kindle represents Twitter users interested in e-videos

Figure 2 One of the communities (out of 22) obtained from Walktrap clustering

/e-reading. Similarly, beer brands such as Budlight, Corona, Millerlite are grouped in one community (see Figure 2).

Stochastic Block Models, are a well-known known class of generative models, used for detecting blocks/communities in a network. Unlike modularity based approaches, these are statistically based models and allow us to use likelihood scores, to compare the fit of models/network structures obtained from different parametrizations. In a simple block model nodes/actors are assigned to blocks and network relations are presented among blocks, rather than among individual nodes (Faust, K., & Wasserman, S. (1992). Unlike traditional community detection algorithms which focus on detecting dense links, block models reveal different block structures which can give a finer grained view of hierarchical communities than Walk trap clustering. To reduce the bias introduced by heavy tailed degree distributions in real world networks, in this paper we use a variant of the traditional SBM, namely degree-corrected SBM to better fit our data (Karrer and Newman, 2011). Hierarchical stochastic block models (Piexoto, 2014) have been found to be effective for their ability to detect smaller sized groups in large networks. We use hierarchical block models on the brand network to obtain finer grained groupings of brands, and thereby discern more nuanced distinctions and similarity for analyses of brand positioning.

Partitioning of the weighted brand network using degree corrected Stochastic Block Modelling yields seven levels of hierarchy. Communities at the third level of hierarchy (see figure 3), consisting of 25 blocks, closely resemble the 22 communities obtained by Walktrap clustering previously.. Majority of the brands are noticed to organize into communities by industry, like for example, the auto brands and beer brands. At the lowest level, the model yields 71 blocks, giving a more fine-grained view of the communities, for example, subgroups of automotive brands, which are not detected in the Walktrap clusters.

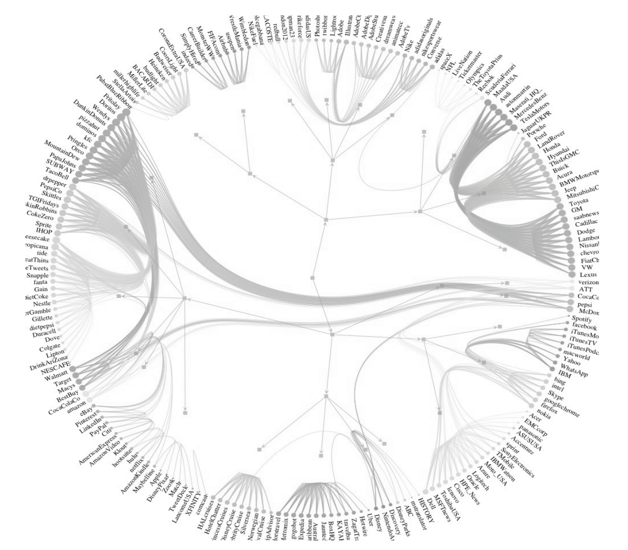

Figure 3 Communities obtained from Stochastic Block Modelling

As another example, iTunesTV, iTunesPodcasts, iTunesMovie and macWorld are in the same cluster at the lowest level; at the next higher level, they group together with brands like IBM, Bing, Facebook, etc, and at the further higher level, with a broader set of computing-related brands. The SBM model also shows interesting connectivity between clusters – for example, in Figure 3, the cluster of McDonalds, Pepsi and CocaCola (on the middle right), showing strong connections to the cluster of fast-food brands like Dominos, KFC, Pizzahut in the upper left of the figure.

Brand network variables to examine Brand Performance

Network Metrics as Independent Variables A stream of research in graph theory (Proctor and Loomis, 1951; Sabidussi, G., 1966; Freeman, 1977; Bonacich, P., 1972), have reported a positive relationship between node centrality, a collection of measures that describe a node's position in a network, and node performance. In this paper, we examine whether Degree and Eigenvector centrality of brands in the network carry information relevant to brand performance.

Degree centrality of a node is the number of immediate connections it has with other nodes. Our second network measure, eigenvector centrality, is based on topological features alone and focuses on the neighborhood structure of the node in question. Based on the idea that links to higher quality nodes contribute more to the quality of the node in question, this measure assigns relative scores to nodes in the network. Our third measure, between-industry weighted links, is calculated as the sum of weights incident on the node from brands of different industries. For instance, the between-industry weighted links for Microsoft is calculated as the sum of weights incident on it from all other non-technology brands.

The eigenvector centrality distribution for our brand network is shown in figure 4. The distribution is seen to roughly follow the Pareto principle (law of the vital few) as 20% of the brands account for 80% of the total centrality scores.

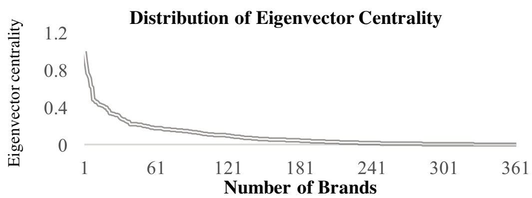

Figure 4 Eigenvector Centrality Distribution of Brand network

Brand Performance as Dependent Variable To describe brand performance across industries, we collect brand shares data from EuroMonitor Passport (formally known as Global Market Information database) for the year 2016. Data includes retail value sales trend for 100 brands across ten industries: 1) Chained Consumer Fast-food 2) Beer 3) Carbonates 4) Apparel and Footwear 5) Cars 6) Technology 7) Retail 8) Cosmetics 9) Watches 10) Snacks. To ensure comparability for analyses of brands across industries, these values are normalized by the total retail sales price for that industry. Also, to ensure consistency of our results we compare our brand performance measure with market share data, provided by Euromonitor, and find a high correlation of 0.75.

Results

Brand Positioning

The first step in brand positioning (Keller et al, 2002) is to identify a 'frame of reference' which signals to consumers the goal they can expect to achieve by using a brand. The choice of frame of reference is generally determined by the product's stage in the life cycle. When a new product is launched, its frame of reference comprises of competing brands to penetrate the target market easily. Eventually as the brand evolves, growth opportunities arise, and broadening the competitive framework may be necessary (Keller et al. 2002). Choosing an appropriate competitive frame of reference is important because it determines the types of brand associations that will function as points of parity (POP) and points of difference (POD). *PODs are strong, favorable and unique perceptions that consumers strongly associate with a brand and use them to differentiate the brand from other firms that offer similar services. POPs, on the other hand, are not necessarily unique to a brand and represent associations that consumers view as essential within a certain product or service category (Keller, K. 2014).*

Aligning with Keller's (2014) notion of a competitive framework, two brands share a common frame of reference if they belong to the same industry or compete for customers. Community detection of the weighted brand network helps us in determining brand positioning by highlighting POPs and PODs between two brands. For hard clustering algorithms like Walktrap clustering, *links within community (internal edges) can be used to highlight points of parity between two brands whereas links across communities, (external edges) can highlight points of difference between two brands*. Similarly, for block models, being in the same block can indicate POP; however, this may not necessarily involve greater internal edges since block may define dis-assortative structures. In the hierarchical block structure, two brands in the same community may be assigned to different blocks at deeper hierarchy levels, indicating POD's between these brands.

Given space limitations, we provide two examples of competitive brand positioning. Brand positioning strategy can be evaluated for any two brands in the network like Amazon and Macys, which share a common frame of reference as 'e-retailers'. Their points of parity are highlighted by the fact they share the same community with Target, Walmart, Best-Buy and other food/beverages brands. Also, their unique brand perceptions (PODs) are highlighted by their cross-community links; Amazon is linked to the e-video and technology clusters whereas Macys is linked to the set of cosmetics related brands. Similarly with the hierarchical block model, Amazon and Macys are in the same block at higher level, indicating their POP; at lower levels, they separate out in different blocks.

We also propose another measure, betweenness-centrality, to evaluate points of difference between two or more brands. A vertex with a high betweenness centrality score acts as a bridge between two densely knit communities, removal of which may hamper the 'communication' between these two groups of vertices. For instance, though Amazon and Netflix share the same frame of reference with respect to video streaming, Amazon has a much higher betweenness score than Netflix in the network. This signals that Amazon would have more influence over the network, as it appeals to a broad range of consumers across different communities. This argument is strengthened by the fact that Amazon is linked to multiple brands from different industries: Walmart, Bestbuy, eBay, Paypal, Netflix, Target etc. Netflix, on the other hand, is linked to Hulu and Amazon, restricting its connections to providers of online video streaming services. So, this reflects that the Netflix brand's perception is relevant primarily for online video streaming whereas Amazon's brand carries broader association with retail and ecommerce brands.

Brand Performance

A Hierarchical Regression Analysis is conducted to examine the relationship between brand network variables and brand performance. This method shows if certain variables of interest explain a statistically significant amount of variance in the dependent variable, after accounting for all other variables. We build several regression models by adding variables at each step, and results are shown in Table 2.

Predictor Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Size of B.C	1.8E08***	2.86E08***	3.0E-08***	2.9E-08***	2.9E-09
Industry					
Carbonates		0.0063	0.012	0.0171	0.009
Apparel /footwear		-0.0214	0.002	0.0090	-0.001
Beer		0.0286	0.0932*	0.101*	0.117**
Cosmetics		0.0633	0.0962*	0.105*	0.118**
Home care		0.0944	0.108*	0.119*	0.139**
Premium cars		0.0186	0.027	-0.0067	0.104
Retailers		0.0401	0.051	0.0570	0.051
Snacks/tea		0.0229	0.047	0.0494	0.060
Technology		-0.0978	-0.097	-0.0850	-0.046
Watches		0.0727	0.181*	0.1849*	0.1959**
Degree Centrality			0.201***	0.170**	0.154*
Eigenvector Centrality				0.0873	-0.131
Between-Industry links					0.0309***
Adjusted R^2	0.07	0.164	0.264	0.26	0.388
R^2 change		0.094*	0.1**	-0.004	0.128***

Table 2 Hierarchical Regression Analysis to examine the effect of brand network variables on brand performance

Model 1 shows that the size of brand community (i.e., number of Twitter followers) is a significant predictor of brand performance, with the model explaining less than 0.1 variation in the data. In Model 2. we add the industry dummies, to account for the variation in model attributes seen across different sectors; this results in significantly higher model fit (adjusted R^2). Model 3 adds degree centrality of a brand to the model, and this is seen to have a significant positive effect ($\beta = 0.201$, $p < 0.001$) on brand performance. This implies that having connections to a larger number of other brands in the network relates to brand success. Thus for a brand manager, having an actively engaged brand community, with interests across other brands, can indicate higher profit margins. This is an important finding and justifies the increased resources that brands invest in managing consumer communities in social media.

In step 4, weighted eigenvector centrality of a brand is added to the model. This variable does not have a significant effect ($\beta = 0.087$, $p > 0.01$) on brand performance. Thus, or a brand of interest, an audience coming from powerful players in the network (high quality nodes in terms of weighted degree) does not influence brand performance. In other words, common followership with the more connected brands (typically, the larger, more popular brands) does not correspond to higher performance.

Our final network measure, between-industry links is added in Model 5, and is seen to have a significant positive association with the dependent variable. Thus, brands receiving high consumer co-interest across different industries perform better than the others in the brand ecosystem. Higher cross-industry links imply a diverse brand image as it appeals to a broad range of consumers across different communities.

Conclusion and Future Work

Our paper applies network analysis on a brand network obtained from large scale data on consumer-brand interactions to study brand effects, in particular, positioning and performance. This is one of the first studies to our knowledge that explores Brand Positioning using a large social media data set; compared with traditional survey based methods, this data-mining and network analysis approach provides a flexible and scalable way to monitor brands relative to other competing brands. With the ability to incorporate consumer perceptions across a broad brand ecosystem, brand networks have the potential to make future advances in areas of branding such as segmentation and co-branding. Our work highlights the potential for novel methods based on large-scale data and network analysis for marketers and brand managers to effectively manage brands.

To our knowledge, this is also one of the first studies that relates brand-brand affinity on social media to brand level performance. While size of brand community on Twitter does relate to brand performance, the brand network variables (degree, eigenvector centrality and between-industry links) carry significantly more information and help improve the model fit considerably. This confirms the relevance of consumer-brand perceptions as powerful indicators of brand performance.

Large scale data focused methods for brand management are relatively new, and present many opportunities for future research. . Given space limitations, this paper presents brief findings on how a brand network can inform brand positioning and value. In continuing work, we are investigating how mixed membership SBM's, primarily used for overlapping community structures, can be used to better inform about PODs and POP's between brands. Though we use Twitter brand communities for our analysis, it will be interesting to compare with Facebook and Instagram "fan" relationships. Future research can also explore second degree connections of brands along with text analyses of UGC to gain deeper understanding of consumer-brand relationships on social media. Community detection techniques on brand networks employed to generate competitive market structures can help study brand associative networks (Henderson et al. 1998, Netzer et al. 2012, Urban et al. 1984). Clustering brands may aid in finding communities of consumers with similar brand preferences, similar to the marketing strategy of segmentation.

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