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OBIM: A computational model to estimate brand image from online consumer review

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ABSTRACT

Brand image is comprehended in consumers' mind through favourability, strength, and uniqueness of brand associations. In this paper, a model is proposed to quantify Online Brand IMage (OBIM) from consumer reviews. We consider the product aspects as a brand association. Natural language processing techniques are used to extract those associations. Favourability, strength, and uniqueness of the extracted associations are computed using sentiment and co-word network analysis. Finally, the multiplicative sum of these values considers as the OBIM score. It can be used as a measure of consumer perception, which apprehends the relation between the association and their changes over time. The proposed model is demonstrated using a dataset of five mobile phones crawled from Amazon. Two applications of OBIM score, Association Based SWOT analysis and Senti-Concept Mapper technique to discover hidden concepts, are proposed. It shows how these techniques can support the decision-making process of marketers.

1. Introduction

In recent times, with high communicational advancements, a brand has to create and sustain its image to maintain market preference (Çifci et al., 2016). Brand image plays a vital role in deciding marketing strategy and empowers the managers to alter or refurbish future marketing endeavours (Böger, Kottemann, Meißner, & Decker, 2017; Faircloth, Capella, & Alford, 2001; Plumeyer, Kottemann, Böger, & Decker, 2019). The network of brand association in consumers' memory reflects brand image (Keller, 1993). In economic terms, the brand image unravels the value consumers derive, implicitly resonating their assessments of the brand associations (Hofmann, Schnittka, Johnen, & Kottemann, 2019). These associations are the features of the product, people, place or occasions which contribute to brand value (Aaker, 2012; Henderson, Iacobucci, & Calder, 1998). The *favourability* (positive or negative sentiments around an association); *strength* (how tightly the associations are attached); and *uniqueness (*the degree of distinctiveness) of an association contributes to brand image (Keller, 1993). Exploration of brand associations help to improve equity and prosperity in the market (Böger et al., 2017; Gensler, Völckner, Egger, Fischbach, & Schoder, 2015; John, Loken, Kim, & Monga, 2006; Keller, 2016). However, venturing into consumers' mind to extract the image they have perceived about a brand is a challenging task (Pournarakis, Sotiropoulos, & Giaglis, 2017).

Various consumer mapping and analytical techniques are adopted by firms to monitor and measure brand association network (John et al., 2006; Schnittka, Sattler, & Zenker, 2012). Such techniques are mostly primary survey-based and costly in terms of time and effort. Moreover, they generate a static and skewed indication of consumer perception (Gensler et al., 2015; John et al., 2006; Pournarakis et al., 2017). The advent of online shopping sites and the growth of textual data in the form of consumer reviews draws the attention of researchers for developing new approaches to gain insight over brands (Chatzipanagiotou, Veloutsou, & Christodoulides, 2016; de Oliveira, Silveira, & Luce, 2015; Keller, 2016). These reviews show the interaction between consumers and firms, influence potential customers, reveal the performance of the product and identify the areas which need further attention (Fronzetti Colladon, 2018). Managers can use these textual data to observe consumers' commentary and their preferences (Gensler et al., 2015). Thus, the evaluation of brand image from online customer feedback has become relevant for brand management.

Text mining techniques are used for perceptual maps, product positioning maps, market structure analysis, and estimating perceptual associations of competing brands from online consumer reviews (Culotta & Cutler, 2016; Lee, Yang, Chen, Wang, & Sun, 2016; Lee & Bradlow, 2011; Moon & Kamakura, 2017; Netzer, Feldman, Goldenberg, & Fresko, 2012). To the best of our knowledge, there is almost no effort on *how to extract brand associations from unstructured*

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consumer reviews; how to identify the most favourable and unique associations of the brand; *how to quantify the brand image from brand associations*; *how to compare competing brands in terms of the brand image*; and *how brand image change over the time.*

To bridge this gap, we propose a computational model, OBIM (Online Brand IMage) to quantify brand image using *favourability*, *strength*, and *uniqueness* of underlying associations. Our approach measures *favourability* in two-steps. First, it extracts aspects from consumer reviews by extending double propagation technique (Qiu, Liu, Bu, & Chen, 2011). Second, it uses a dictionary-based approach to assign sentiment score to each aspect. Considering aspects as brand associations, we estimate *favourability*. Co-word analysis is the basis to calculate *strength*, and *uniqueness* of brand image. The method constructs a co-word network considering words in the review corpus and gives weights to each link. These weights are normalised frequencies of the word co-occurrences. The *strength* of a node in this network is the arithmetic mean of the edge weights, connected to the node (Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004; Duvvuru, Radhakrishnan, More, Kamarthi, & Sultornsanee, 2013; Radhakrishnan, Erbis, Isaacs, & Kamarthi, 2017). The *uniqueness* is determined by extending the degree and importance of lines (DIL) method (Liu, Xiong, Shi, Shi, & Wang, 2016). Finally, OBIM score is computed considering the nodes representing brand associations. We also show two potential applications of OBIM score. The first one, called *Association Based SWOT analysis*. It uses the OBIM scores of competing brands to identify the areas of strengths, weaknesses, opportunities, and threats based on consumers perception for a firm. The second one is a technique to discover hidden concepts called *Senti-Concept Mapper*, by identifying the concepts around related brand associations from a sub-graph of the co-word network.

Two notable work in this area are Gensler et al. (2015) and Fronzetti Colladon (2018). While Gensler et al. (2015) have followed the conceptual model proposed by Keller (1993) and estimated all the three attributes of the brand image; Fronzetti Colladon (2018) propose a model to compute the Semantic Brand Score (SBS). Though these two papers are the primary motivation for us, we differ from them in many ways. The dataset used by Gensler et al. (2015) is semi-structured consumer reviews where the contents are categorized into pros and cons type by the reviewers. Due to such semi-structured data, Gensler et al. (2015) do not use any sentiment analysis technique for favourability assessment. However, most e-commerce sites capture unstructured online reviews. Besides, the analysis of words from pros-cons categorized reviews does not reveal the sentiment of an association efficiently (Lee & Bradlow, 2011). In contrast to Gensler et al. (2015), based upon Keller's model (Keller, 1993) we estimate consumer opinion towards an association using aspect-based sentiment analysis technique (Poria, Cambria, Ku, Gui, & Gelbukh, 2015; Schouten & Frasincar, 2016). We also differ from Gensler et al. (2015) in the computation of *strength* and *uniqueness*. Moreover, Gensler et al. (2015) do not discuss how to combine *favourability*, *strength*, and *uniqueness* to create an indicator for comparing a brand with its competitor. Motivated by Semantic Brand Score (SBS) (Fronzetti Colladon, 2018), we address this gap and propose the idea of OBIM (Online brand image). However, we adopt a multiplicative sum approach in contrast to SBS.

The contributions are mainly methodological in this study. To the best of our knowledge, this is the first attempt to estimate brand image from unstructured consumer reviews using aspect-based sentiment and co-word network analysis techniques. Specific contributions are as follows:

- We consider the aspects present in the online review as a brand association. To extract those aspects, we extend the double propagation-based approach (Qiu et al., 2011) and use an existing library of sentiment lexicon and find brand associations. This our first contribution.
- Earlier literature suggests computing *favourability* from the primary survey (Plumeyer et al., 2019; Schnittka et al., 2012). We are first to propose a model to quantify it from unstructured consumer reviews, which is our second contribution.
- We differ from Gensler et al. (2015) by considering the terms related to product aspects and estimate *strength*. We extend the DIL (Degree and the Importance of Lines) method proposed by Liu et al. (2016) for calculating *uniqueness*. This is our third contribution.
- We probably the first to quantify online brand image. Proposed OBIM score combines the three attributes, *favourability*, *strength*, and *uniqueness*, to provide a numerical measure of brand image. It is our fourth contribution.
- Association-Based SWOT analysis proposed here is a unique attempt for the market positioning of a brand. Unlike the traditional approach of SWOT, we capture this from OBIM value of competing brands. This turns out to be our fifth contribution.
- Our final contribution is a technique called *Senti-Concept Mapper* to discover hidden concepts and associated sentiments from consumer reviews. To the best of our knowledge, we are first to propose the idea of relating brand associations through this process.

The paper is arranged in the order – Section 2 is the literature review. Methodology, demonstration of proposed framework, is described in Sections 3 and 4, respectively. Section 5 covers the application of OBIM score. Section 6 contains the discussion and Section 7 is the conclusion.

2. Literature review

Three streams of literature form the basis of the proposed study. It covers the literature related to brand image estimation techniques, aspect-based sentiment and co-word network analysis.

2.1. Estimation of brand image

Brand image is defined as the perception present in the consumers' memory, in terms of a network of associations. As per the associative memory model (Collins & Loftus, 1975; Palm, 1980), associations make a brand more prominent in the network. Moreover, associations shared between competing firms can affect brand preference(Romaniuk & Nenycz-Thiel, 2013). Hence, an association must be favourable, stable and unique (Keller, 1993). Estimation of this association network is necessary to understand brand image (John et al., 2006; Keller, 1993; Schnittka et al., 2012).

Many qualitative and quantitative techniques are available to analyze the brand image. Plumeyer et al. (2019) stated that there are around twelve different techniques available. These techniques include quantification using Likert scale, dichotomous scaling etc. and qualitative methods such as focus groups, in-depth interview, free-choice techniques, and Brand Concept Mapping(BCM) techniques etc. (Plumeyer et al., 2019). Among these methods, Brand Concept Map (BCM), considers the association network. BCM is a combination of three stages (John et al., 2006). The first stage is the elicitation; here, relevant brand associations are collected from market research. In the mapping stage, these associations are given to the respondents for mapping, and in the aggregation stage, these map ingrates into a consensus map (John et al., 2006; Plumeyer et al., 2019; Schnittka et al., 2012). Three issues are associated with BCM technique. Firstly, it does not incorporate the *favourability* of associations (Schnittka et al., 2012). Secondly, respondents are not allowed to insert associations from their mind into the map. Thirdly, the BCM technique involves traditional consumer survey. Later on, Böger et al. (2017) proposed an improved aggregation mechanism for brand association network. However, this mechanism is primary survey-based, and the brand associations are selected prior to the survey. Text Analytic has been used to get brand positioning from consumers' search data, ontology and psychometric analysis (Aggarwal, Vaidyanathan, & Venkatesh, 2009; Moon &

Journal of Business Research 114 (2020) 213–226

Table 1
Some of the Key Literatures.

Paper	Objective	Data Source	Data Type	Techniques	Quantification of Brand Image Score	Use of Keller's construct
(Mostafa, 2013)	Analyze the consumers' sentiment towards famous brands using expert-predefined lexicons.	Twitter	Unstructured Text	Unsupervised sentiment Analysis	No	No
(Berezina et al., 2016)	Study consumers' satisfaction and dissatisfaction on aspects related to service and experience in the hotel along with consumers' behaviour and post-purchase recommendation.	Online hotel review	Unstructured Text	Categorization, text-link analysis	No	No
(Marine-Roig & Anton Clavé, 2015)	Focus on the online image of travel destination Barcelona. Frequency-based analysis and manual understanding have been used to find polarity of word.	Online reviews, blogs	Unstructured Text	Web content mining, Categorization, parsing	No	No
(Pantano et al., 2019)	Sentiment analysis of online user-generated content to improve market intelligence.	Twitter	Unstructured Text	Supervised Sentiment Analysis	No	No
(Klostermann et al., 2018)	Analyzes images posted on social media about a brand. Generate an association network from user-generated text contents.	Instagram	Unstructured Text	Clustering, Unsupervised Sentiment Analysis	No	No
(Moro, Rita, & Vala, 2016)	Focus on performance metrics of a post on a brand's Facebook page. Provide support to the manager to make decision on posting in the brand page.	Facebook	Unstructured Text	SVM classifiers, Data mining approaches	No	No
(Böger et al., 2017)	Propose to improve aggregation mechanism for brand concept mapping technique also present a critical analysis of existing aggregation rules.	Web-based survey and manual survey	Text	Aggregation capability, reliability, stability	No	No
(Nasukawa & Yi, 2003)	Analyzes sentiment of a subject in a sentence based on the semantic relationship of the with the sentiment lexicon.	Online reviews	Unstructured Text	manual lexicon list creation, sentiment analysis	No	No
Our approach	Analysis of *favourability*, *strength* and *uniqueness* of brand associations and combine them into a quantified OBIM score	Online reviews	Unstructured Text	Aspect based sentiment analysis, co-word network analysis.	Yes	Yes

Kamakura, 2017). Lee et al. (2016) propose a method for automatic generation of brand perceptual maps and radar charts from consumer reviews. Marine-Roig and Anton Clavé (2015) estimates online image of a tourist location but it relies upon manual interventions for semantic analysis of words to find the polarity of associations.

Estimation of brand image score from online consumer reviews is rare in the literature. Earlier works are focusing on any particular aspect of the brand image or they do not suggest any method to combine *favourability*, *strength* and *uniqueness* (Gensler et al., 2015; Klostermann, Plumeyer, Böger, & Decker, 2018; Pantano, Giglio, & Dennis, 2019). Gensler et al. (2015) use semi-structured consumer reviews to gain insights about brand image, it does not combine *favourability*, *strength*, and *uniqueness*. Moreover, as the reviews are segregated into pros and cons manner, Gensler et al. (2015) do not explicitly estimate *favourability* of associations using any sentiment analysis approaches. In recent literature, Semantic Brand Score(SBS) model has been proposed which is familiar to the brand equity model (Fronzetti Colladon, 2018), but sentiment related to an association is not considered. Brands are created upon products; hence, it is evident that opinion and aspects of a product represent overall sentiment towards a brand (Gensler et al., 2015; Keller & Lehmann, 2006;).

2.2. Estimation of favourability using sentiment analysis

The *favourability* of brand association is evaluated from the perspective of the consumer and also by the significance of the particular association (Schnittka et al., 2012). It is shown that *favourability* among the brand associations leads to positive brand image (Keller, 1993; Schnittka et al., 2012). Thus sentiment analysis methods can play an essential role in comprehending brand image. Sentiment analysis is a vividly studied field of Natural Language Processing. These techniques are used in business literature to study market structures, consumers behaviour and post-purchase recommendation (Berezina, Bilgihan, Cobanoglu, & Okumus, 2016; Netzer et al., 2012). Mostafa (2013) has applied a sentiment analysis on tweets to estimate brand sentiment. They do not propose any method to extract brand association from tweets and finding *favourability* of those associations. Moreover, it is evident in literature that sentiment analysis of overall textual contents is not capable of addressing polarity of an association (Schouten & Frasincar, 2016; Zhai, Liu, Xu, & Jia, 2011).

Wang et al. (2014) suggests that aspect-based sentiment analysis is more effective than considering the sentiment of the entire corpus to measure customers' choices, preferences, and inclinations towards a product. Aspects are certain functionalities of the product which recognize the associations corresponding to a brand and they are the central point of discussion in a competitive market (Culotta & Cutler, 2016; Decker & Trusov, 2010; Zhang, Xu, & Wan, 2012). Detection and extraction of aspects, along with its corresponding opinionated word pair, determine the accuracy of the process (Schouten & Frasincar, 2016; T. Wang et al., 2014).

Aspect detection techniques are broadly categorized into three groups – Frequency-based, Supervised Machine Learning based and Syntax-based (Schouten & Frasincar, 2016). Frequency-based methods consider frequently occurring noun terms as aspect (Hu & Liu, 2004). However, frequency of a noun does not necessarily make it an aspect (Schouten & Frasincar, 2016). Supervised sentiment analysis approach has been used as a predictor of consumers opinion towards a brand (Cambria, 2016). Pantano et al. (2019) has used such technique on tweets to analyze brand sentiments. The essential requirement of machine learning-based technique is labelled data. It is tedious and expensive task to label online consumer reviews (Lin & He, 2009). In contrast, Klostermann et al. (2018) estimate sentiment using the unsupervised approach. However, for clustering of social media post, Klostermann et al. (2018) use deep learning-based Google Cloud Vision API. Similarly, in recent literature deep learning techniques such as CNN, LSTM and common sense knowledge-based Attentive LSTM are used for aspect-based sentiment analysis (Ma, Peng, & Cambria, 2018; Poria, Cambria, & Gelbukh, 2016). Although deep learning performs well, from a resource utilization perspective, deep learning-based models are costly (Giatsoglou et al., 2017).

The other alternative i.e. syntax-based technique exploits the sentence structure of the document to extract aspects. Qiu et al. (2011) propose double propagation method which interrelates two problems - opinion lexicon expansion and aspect identification. It extracts aspects using a set of rules and dependency parser with a list of known opinion words. This method uses a small set of known opinion word to identify aspects from unlabeled dataset (Feldman, 2013; Qiu et al., 2011; Schouten & Frasincar, 2016). Table1 shows some of the prior literature in the context of brand management using text analysis.

2.3. Co-Word networks and analysis

As per cognitive psychology, people frame associative networks in their memory that associate disconnected things in the form of structured knowledge (Palm, 1980). In marketing literature, associative memory networks have great importance (Gensler et al., 2015; Keller, 1993; Keller & Lehmann, 2006; Netzer et al., 2012). Co-word analysis is used as a tool to create an association network (Fronzetti Colladon, 2018). This technique is introduced to improve the investigation of semantic relations in the scientific literature (Callon, Courtial, Turner, & Bauin, 1983). Co-word analysis uncovers patterns and estimates the *strength* of association among the used words (Leydesdroff, 1989; Small, 1988). Organizations utilize such analysis to increase their competitiveness and business (Delecroix & Epstein, 2004).

Online consumer reviews are qualitative in nature, which increase the noise in the data. Co-word network analysis is a solution to this problem (Netzer et al., 2012). Netzer et al. (2012) analyze the market structure considering co-occurrence frequency among the words and establish Brand Association Network. Since the Association Network reflects top-of-mind associations, it can be used to measure overall brand image and can give opportunities to compare competing brands (Gensler et al., 2015; Netzer et al., 2012). In a co-word network, the *strength* of association represents the semantic connectedness of nodes (Farquhar, Herr, Aaker, & Biel, 1993).

3. Methodology

Proposed Online Brand Image (OBIM) model uses unstructured consumer reviews to extract the *favourability, uniqueness,* and *strength* of associations. In online reviews exist noise in the form of HTML tags, special characters, repetitive characters, words of other languages, etc. Therefore, as shown in Fig. 1, data pre-processing is an essential step before model building. There are three building blocks, outlined by dotted boxes to compute *favourability*, *strength*, *uniqueness* and finally online brand image (OBIM) score. Each of these processes is discussed in next subsections.

3.1. Computation of favourability

This part of the model deals with the identification of brand associations and the sentiment of those associations. We propose a two-step approach for the same: (1) extraction of aspects from the online reviews, (2) detecting the polarity of each aspect. We consider aspects as brand associations. The polarity of associations is captured in a scale of −1 to +1. The average of these polarities is the *favourability* score of the association.

3.1.1. Aspect extraction

In earlier works considers all the words present in the review as potential brand associations (Gensler et al., 2015; Netzer et al., 2012). We perceive that this approach may capture words which are not directly related to the brand as a whole, rather to specific aspects of the product. For example, consider the sentence: *"Nice phone with amazing performance"*. Here, if we consider all words, except the stop words, "*nice*", *"phone", "amazing"* and "*performance*" are treated as associations. However, close observation reveals, *"nice"* is the associations with the phone as a whole, "*amazing*" is the association concerning its "*performance*". Consumer analyses the important aspects of the product separately to make purchase decision (Häubl & Trifts, 2000; Zhang et al., 2012). Therefore, we suggest taking product aspects as the associations for each brand. Besides that, considering aspects as association decreases the number of association and makes the computations faster. To extract the aspects, we first enlist the opinion words from VADER sentiment dictionary because of its accessible and elaborate list of the gold standard lexicon (Yang, Callaway, & Atwater, 2015). Next, syntactic structure of a sentence is explored using the dependency parsers (Chen & Manning, 2014). Fig. 2 shows the dependency relation between the words of a sentence. For example, "*nice*" and "*amazing*" turns out to be the modifiers for "*phone*" and "*performance*" respectively. Now, aspects are those nouns for which opinion words act as the modifier. We follow a rule-based approach adopted from double propagation approach for aspect extraction (Feldman, 2013; Qiu et al., 2011). Table 2 presents these rules. Since we are not concerned with the domain lexicon expansion task; we only consider two out of five rules

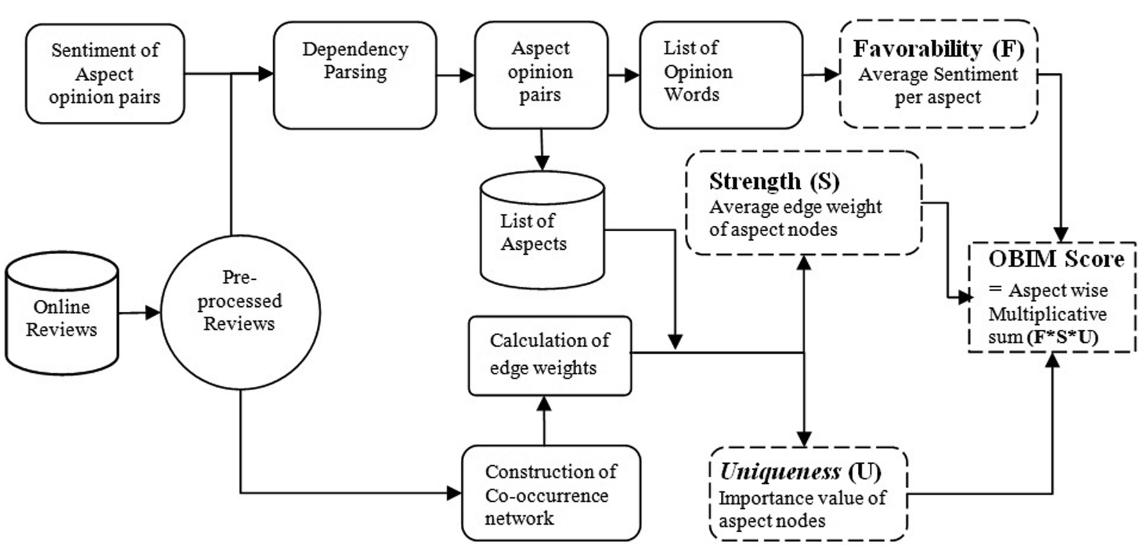

Fig 1. Computational Model of Online Brand IMage (OBIM).

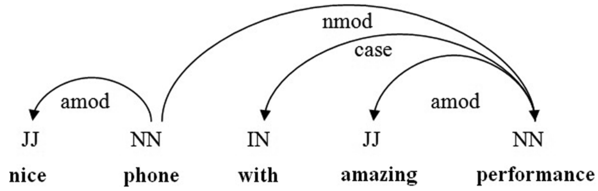

Fig 2. The output of Dependency Parser.

suggested by Qiu et al. (2011). Fig. 3 shows the algorithm for aspect extraction. The algorithm starts with an empty aspect set and keeps on adding aspects following the rules specified in Table 2. It is noted that, the noun phrases in the singular (NN) or plural (NNS) in a parsed sentence are potential candidates for an aspect. If an opinion word is related to a noun by adjective modifier (amod), noun modifier (nmod) then the noun is considered as an aspect. The opinion and aspect pairs are kept for sentiment analysis.

3.1.2. Sentiment polarity detection of aspects

We use an unsupervised lexicon-based sentiment analysis approach due to the absence of labelled dataset. We use VADER (Valence Aware Dictionary and sEntiment Reasoner). VADER which analyzes opinion in the range of -1 to $+1$; the value nearer to -1 suggests negative and toward $+1$ implies positive sentiment. Now, a list of positive and negative sentiment score has been generated for each opinion aspect pairs. Finally, the arithmetic mean of these values has been taken as the *favourability* score for the aspect. Fig. 4 shows a running example of *favourability*, *strength*, *uniqueness* and OBIM score calculation procedure for two reviews given in step (a). Step (b) to (d) shows dependency parsing, aspect extraction, and *favourability* calculations. Finally, the *favourability* scores are shown in the last column of (d).

3.2. Computation of strength

Co-word network analysis focuses on extracting knowledge and relationship among keywords (He, 1999). It has been used for finding the relation between different themes in word community identification (Jia, Carson, Wang, & Yu, 2018), marketing structure analysis (Netzer et al., 2012) , measure semantic brand scores (Fronzetti Colladon, 2018) and *strength* of brand associations (Gensler et al., 2015). Co-word network is constructed with a set of vertices$G = \{w_1, w_2, \ldots.w_n\}$ where $\{w_1, w_2, \ldots.w_n\}$ are the words appearing in the entire corpus. Along with, a set of edges $E = \{e_{11}, e_{12}, e_{13}. \ldots e_{nn}\}$ where e_{ij}exists if both $i^{th}$and j^{th}words appear in the same context of the corpus. Here, the context is a set of consecutive words in a sentence (Bullinaria & Levy, 2012). Gensler et al. (2015) use co-word network analysis to find the *strength* of brand association. We improve upon this and find association at the aspect level. Therefore, as discussed in Section 3.1 we have to find the aspects before carrying out the following steps to compute the *strength* of an association.

1. Create a word co-occurrence matrix Cconsidering all the words in the reviews. The matrix elements $C(i, j)$contain the frequency of co-occurrences of words $i$and$j$. Create an occurrence vector where each element $WC(i)$indicates the total number of times the word $i$occurs in the corpus. Let Vbe the total number of unique words present in the corpus
2. The matrix elements $C(i, j)$are normalized as follows.

$$NC(i, j) = \begin{cases} \frac{1}{V} \; if \; \frac{C(i,j)}{WC(i)} = 1 \\ \frac{C(i,j)}{WC(i)} \text{ otherwise} \end{cases} \tag{1}$$

$NC(i, j)$ is considered as the weight of the edge connecting the nodes$i$and j. Please note that the value $NC(i, j)$ will be between 0 and 1. A close look at Eq (1) reveals, in case j co-occurs whenever $i$appears then $NC(i, j)$ is severely penalized. The reason is as follows: First, even if both the words occur only once, the edge weight becomes ‘1’ which is not desirable as the actual frequencies are low. Secondly, occurring together sometimes makes the combination trivial and information gain from such combination is very less. The example includes the occurrence of *“Los”* and *“Angeles”* collectively. Under such circumstances, the weight is smoothed out, and its dominance is decreased by distributing it on all the words$V$present in the corpus.

3. The average of all the weights$NC(i, j)$edge attached to a word i represents the *strength*$S_i$of the word.

$$S_i = \frac{\sum_{j=1}^{n} NC(i, j)}{n_i} \tag{2}$$

Here, n_i is the degree of the node.

In the running example, Fig. 4 (e) shows the co-word network generated from both the reviews. It may be noted that the edge weights are computed using step 1 above. The *strengths* for aspect words (highlighted in red) are shown in Fig. 4 (f) the second column.

3.3. Computation of uniqueness

Cognitive psychological study suggests, distinctive properties of products boost uniqueness and lead to consumer preferences (Zhang & Markman, 2001). Moreover, *Figure-Ground Principle* suggests, a consumer is capable of perceiving an item by its distinctive qualities (Kyei & Bayoh, 2017). We propose that distinctiveness of aspects can be considered as the *uniqueness* within the co-word network. In order to quantify distinctiveness, network theory-based measures like *degree, betweenness and closeness centrality* are often used (Gao, Wei, Hu, Mahadevan, & Deng, 2013; Gensler et al., 2015). *Degree centrality* gives equal importance to all the node having the same degree (Liu et al., 2016). We feel it is not an appropriate measure in co-word networks as we consider only the aspect word as relevant. The *betweenness centrality* expects the information to flow through the shortest path (Liu et al., 2016). Similarly, the disadvantage with *closeness centrality* is it does not work with disconnected graphs (Gao et al., 2013). In the co-word network of a large corpus, there may be certain words which occurred only in the context of a few selected peers and make the network disconnected. To overcome this situation, we extend the DIL (Degree and the Importance of Lines) method proposed by Liu et al. (2016). DIL uses local information such as the neighbourhood of a node, degree of a node, weight of the edge to find the significance of a node. This method has two steps. Firstly it calculates the importance of an edge. Secondly, it finds the contribution of the nodes which are attached to that edge. It is proposed for unweighted graphs. We have extended the concept and

Table 2
Rules for Aspect Extraction (Qiu et al., 2011).

#Rules	Observed Pattern	Examples
Rule 1	If the opinion word directly related to the target word with an adjective or noun modifier, then the target word has been taken.	The phone has a great “sound”. (*great* → *mod* → *sound*)
Rule 2	If the opinion word directly related to a word with an adjective or noun modifier and Target word also associated with the same word, then the target word has been taken.	The phone has the best camera (best → mod → camera ← subj ← phone)

Input: Opinion Word List {O}, Review data D
Output: Aspects of the Product {A}
Function:
1. *{A} = Ø*
2. *for each parsed sentence in D:*
3. *if (extracted aspect not in {A}):*
4. *Extract aspect {Ai} using Rule1 and Rule2 depending on Opinion words in {O}*
5. *end if*
6. *Set{A} = {A}+{Ai}*
7. *Repeat 2 till all sentence in D are Executed*

Fig 3. Algorithm for Aspect Extraction.

used it for weighted graphs. In our network, edge weights can be a measure for the importance of nodes. So, the contribution of a node over an edge can be written as –

$$\mu_{i,j} = \begin{Bmatrix} NC(i,j) * \frac{n_i - 1}{n_i + n_j - 2} \\ NC(i,j) \text{ if } n_i = 1 \text{ or } n_i + n_j = 2 \end{Bmatrix} \quad (3)$$

Where $NC(i, j)$ denotes the importance of an edge between the node i and j. n_i, n_j degrees of the corresponding nodes. Now, if n_i is 1 then the $n_i - 1$term becomes zero. This happens when a word appears only once in the corpus. For example, in Fig. 4 (d) aspect *camera* is such a node which is having degree one. Similarly, if n_i and n_j both are 1 then the denominator $n_i + n_j - 2$becomes zero, this situation arises when two rare words occurred together in the same context and in the co-word network, these two words create a disconnected component. For example, in Fig. 4 (e) *display* and *impressive* creates such a component. These two problems are addressed by considering the edge weight as their contribution. Finally, the importance of i^{th}node can be estimated by using Eq. (4)

$$I_{node} = \bar{n}_i + \sum_{j \in N} \mu_{i,j} \quad (4)$$

Where$N$is the set of a neighbour ofi^{th} node and $\bar{n}_i$ is the normalized degree of i^{th} node. I_{node} is proposed as the *uniqueness* of a node in the co-word network. The last column of Fig. 4(f), shows the *uniqueness* score for the aspect words. For example, the score corresponding to the aspect *camera* is 0.44 which is obtained as follows. Degree of the node *camera* is 1. Hence, the second condition of Eq. (3) will be applicable. The total contribution of the node *camera* on its attached edge is the edge weight = 0.33. By applying Eq. (4) we get: $I_{camera} = 1/9 + 0.33 = 0.44$.

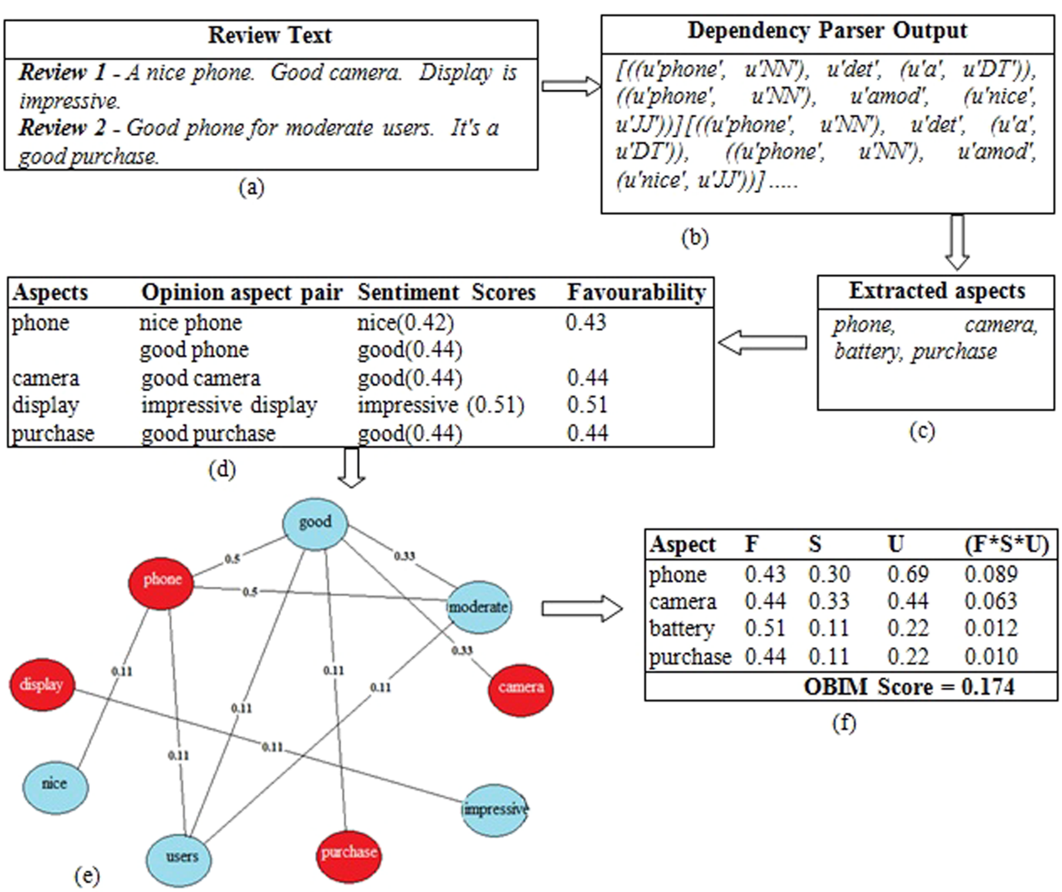

Fig 4. Estimation of OBIM Score from Reviews. F, S, and U represent *Favourability*, *Strength* and *Uniqueness* respectively.

3.4. Computation of brand image score

Multiplicative models are used in estimating consumers' brand choice behaviour (Papatla, 1996), finding advertising response patterns from marketing mixes (Grover, Vriens, & Tellis, 2011) and evaluation of association density of a network (Vriens, Chen, & Schomaker, 2019). As per the multi-attribute attitude model, perception of a brand can be estimated by finding the attitude towards the brand multiplied by its importance. Schnittka et al. (2012) use the multi-attribute attitude model and compute multiplicative sum to represent overall *favourability* of the brand association network. Motivated by these works, we propose OBIM as a sum over the product of *favourability*, *strength*, and *uniqueness* of each association of a brand–

$$= \sum_{k=1}^{n} F_k * S_k * U_k$$

Here, F_k, $S_k$and$U_k$represent the *favourability*, *strength*, and *uniqueness* of the association$k$. Multiplying these values for the k^{th}association is called the OBIM value, while the sum over all the OBIM value is called OBIM score. Here, $n$is the total number of associations extracted from the review corpus. In Fig. 4 (f) in the fifth column, we show the brand image score of each association and combine all of them with summation to produce the final OBIM score.

4. Demonstration of the proposed framework

4.1. Description of the dataset

We use a consumer review dataset of five mobile phone brands from Samsung, Coolpad, Lenovo, Motorola, and Huawei (Dey, Jenamani, & Thakkar, 2019). These brands are within the range of budget phones. The dataset is crawled from Amazon.in website from January to May 2017. Some reviews are concise and not expressive enough. Hence, extracting consumer perceptions and brand associations from these would have been difficult. To eliminate this issue, we put a threshold and consider only those reviews with three or more sentences. From this, we sample 500 reviews for each brand such that the average rating range between 3 and 4. We utilized the standard text pre-processing steps like- changing characters to lowercase and removal of stop words. Table3 shows the description of the dataset.

4.2. Computing favourability strength and uniqueness scores

We generate an arrangement of triplets showing the linguistic connection between the pair of word from each sentence using Stanford dependency parser. Initially, all singular and plural nouns are considered as potential aspects. We follow the algorithm described in Fig. 3 with the rules presented in the Table2. From these opinion-aspect pairs, the noun phrases are extracted as a brand association. In Table3 we have shown the average count of unique opinion aspect pairs and the average count of unique aspects for each month.

Favourability of extracted aspects is represented by the positive and negative orientation of the opinion words paired with them. Since, the procedures for *strength* and *uniqueness* we generate values between 0 and 1; to maintain uniform scaling we normalize the aspect sentiment values to the range of 0 to 1, where 0 is the most negative and 1 is the most positive sentiment towards an association. The mean sentiment of an aspect is considered as the *favourability* of the association.

Table 3
Description of the Dataset.

Brand	Average Rating	Unique Opinion Aspect-Pairs (avg/month)	Unique Aspects (avg/month)
A	3.84	261	42.6
B	3.80	336	51.2
C	3.20	287	49.2
D	3.60	310	66.1
E	3.43	299	70.2

We formed a network using the word co-occurrence matrix of all the reviews. In this co-word network, an edge between two nodes indicates that those two words have appeared in the same context window of five words. We normalize weights using Eq. (1) and calculate the *strength* of word using Eq. (2). The *uniqueness* of an association has been calculated by implementing the concept of the importance of a node in a co-word network. Eqs. (3) and (4) is used to calculate *uniqueness*. Among these, only the words representing aspects, identified while calculating *favourability* score, are taken as the associations. When the nodes other than these are removed, the resulting network we call as association network. In this process, some of the nodes in this network may remain disconnected from the rest. These nodes are the association which is essential in the brand context but do not co-occur with any other aspects. These disconnected nodes have their *strength* (which come from other non-aspect words), *uniqueness* and *favourability* scores.

4.3. Comparison based on brand image attributes

The customer perception towards a brand can be analyzed from the three attributes of brand image - *favourability*, *strength*, and *uniqueness*. These three attribute values, when viewed across the months for a specific brand or in a month among the competitive brands can help to compare market performance. For example, Fig. 5 (a-h) shows a 3D-scatter plot to compare between Brand A and other brands based on *favourability*, *strength* and *uniqueness* values. Fig. 5 (a-d) compare the scores for January and Fig. 5 (e-h) for March. It is evident from the plots that associations of Brand A are more favourable and strong but less unique in comparison to others. For Brand D and Brand B, the *favourability* is spread from low to high indicating mixed reaction from the customers. Attribute values for Brand A remain unchanged in March when compared with January. In comparison to A, the *uniqueness* of Brand B and C drops. On the contrary, the *uniqueness* of Brand D and E are higher than Brand A.

Sometimes it may be beneficial to compare the brands across a few selected associations. The *favourability*, *strength*, and *uniqueness* measure of few such selected associations have been shown in Appendix A. The following are some representative observations. For Brand A “performance” (0.7693) shows the highest *favourability* score in January and remain high till May (0.7502). The same attribute in case of Brand B remains high till March and falls down from April (0.5821). Which may indicate that marketer should analyze the reason and take corrective actions. Another attribute “camera” of Brand A shows a similar increase in *strength* and *uniqueness*. It may be noted that people are not much concern about “feature” and “experience”, hence do not explicitly express their opinion towards it, till April for Brand A. Another observation is, *favourability* of “quality” for Brand E in March is low (=0.4036) whereas *strength* and *uniqueness* of the attribute is high. This may indicate that people are talking negatively regarding “quality”. Another insight from the *favourability* scores is none of these mid-range brands achieves consumers' reliance in terms of “quality”.

4.4. Calculation of OBIM score

It is worth noting from the above discussion that the comparison using three attributes can be completed which is further simplified using the OBIM score. As discussed earlier, OBIM score is the multiplicative sum of *favourability*, *strength*, and *uniqueness* of a brand. It brings the convenience of comparing the brands based on the perception of the online community over time. Table4 shows the OBIM score calculated using the Eq (5). The OBIM score of Brand E is the maximum (=0.6297) in February, considering all other brands across five months. OBIM score of Brand E shows an uprising trend up to March and reached 0.8772 then indicates a gradual decrease. Except for Brand

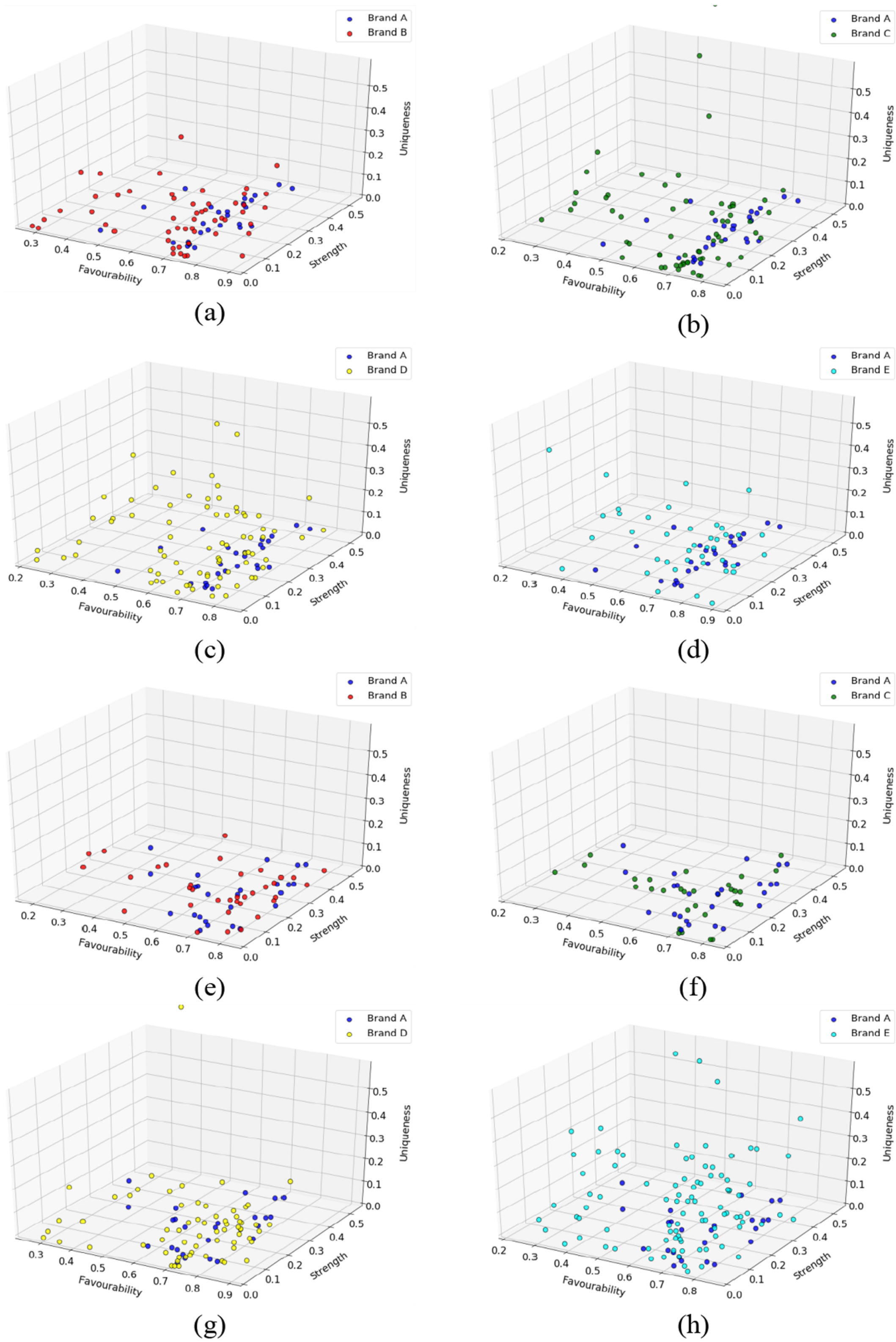

Fig 5. 3D Scatter Plot of *Favourability*, *Strength* and *Uniqueness* of Brand A with respect to Brand B, Brand C and Brand D. (a)-(d) is for January and (e) to (h) is for March.

Table 4
OBIM Scores for five mobile brands across five months.

Brand	January	February	March	April	May
A	0.0525	0.0744	0.1336	0.1582	0.3118
B	0.0885	0.1010	0.0966	0.2664	0.1631
C	0.1548	0.1388	0.0678	0.0560	0.0971
D	0.2894	0.6218	0.2111	0.1936	0.2703
E	0.1726	0.6297	0.8772	0.3967	0.2070

A and Brand B; there is a fall in the OBIM score in April.

OBIM Score and its contributing factors if analyzed with sales and marketing efforts of a firm, may reveal the success or failures of existing strategies, in comparison with the approach of the competitors. It helps to build new strategies. However, in the absence of such data, OBIM score can reveal many facts about consumer perception. In Section 5, we will discuss two such tools for strategy building using these values.

5. Applications of OBIM scores

The *favourability*, *strength* and *uniqueness* values construct the OBIM score. These values provide ways to identify – strong and weak points of a brand, hidden concepts, and comparison between competitive brands based upon their *favourability*, *strength*, and *uniqueness*. Some of the introductory analysis has been applied in this section.

5.1. Association based SWOT analysis: A technique for market positioning

SWOT (Strengths, Weaknesses, Opportunities, and Threats) is an essential tool for strategy formulation and development in the competitive market structure (Chang & Huang, 2006). It is used to reveal the strengths, explore the opportunities, and counteract threats to minimize weaknesses of the organization. Phadermrod, Crowder, and Wills (2019) suggests, a SWOT analysis should include consumers perceptions.

In this work, OBIM scores represent the consumers' perspective for a brand. We use this score for SWOT analysis on Brand A. Firstly; the associations are arranged in ascending order with respect to their OBIM values into high and low OBIM category. For Brand A "camera" having the highest OBIM value, which is 0.02197. We have considered top 5 associations as the point of strength in SWOT analysis. Similarly, five least OBIM valued associations are categorized into low OBIM category. Among these associations "screen" having the least OBIM value of 0.00167.

The associations under high OBIM category are considered for strength and associations with low OBIM are considered for weakness quadrant in SWOT. The associations like - "camera", "performance", "product", "service", "features" are the strength for Brand A whereas, associations like – "storage", "battery" etc. are in weakness quadrant. Associations of all other brand are also categorized into a strong and weak set.

External opportunities are analysed by looking into weak associations of all brands except Brand A. Here, the association "experience" is in weakness quadrant for both Brand A and Brand E which reveals from the analysis of the high low category of OBIM values. Hence, for Brand A, improvement in the "experience" is better for internal strength and

Table 5
SWOT analysis of January for Brand A.

Strength	Weakness
camera, performance, product, service, feature	storage, battery, resolution, experience, screen
Opportunities	**Threats**
experience, camera, performance	money, price, screen, battery

external opportunities. Moreover, some associations under the strength quadrant may reveal its potential to be included in strategy formulation. For example, "camera" and "performance" of Brand A is stronger in OBIM category with respect to Brand D and Brand B respectively. In Table 5 the SWOT analysis is shown.

The terms related to financial issues like "money" and "price" are at high OBIM category for all brands except Brand A. It can be conclude that Brand A is not perceived as value for money which is a threat to the overall brand image. On the other hand, "battery" is in high OBIM category in Brand C and Brand D. Hence, "battery" usage is a threat for Brand A. Brand managers can use this analysis to set more relevant and achievable goals. Moreover, as the analysis comes from the OBIM score, it embeds the consumer perspective as well. Table6 shows the list of associations as per the high and low category for all the brands.

5.2. Senti-Concept Mapper: A technique to analyze the sentiment of hidden concepts

In the network of brand associations, there is an edge between the co-occurring aspects. With a closer observation of this network, managers can identify the concepts constructed by the brand associations. We propose a technique, *Senti-concept Mapper*, which uncovers concepts emerge from functionally interrelated and connected aspects in the association network. It also estimates the sentiment of the revealed concept. Identification of concept by visual analysis and finding the sentiment of that concept – both are executed in *Senti-Concept Mapper*. This technique can be used to analyze the change in the sentiment of a concept over time. The longitudinal analysis of the sentiment, going around a concept enables the managers to coin strategies to address the improvements passively demanded by the consumers and make the brand more prominent in the market. Fig. 6 (a-d) shows the association network and extracted concept. We have analyzed the concept involving the quality of the camera for Brand A. Here; we considered the subgraph constituting the related associations. The whole network of January, February of Brand A has considered initially. To notice the change in sentiment association network of April and May is also analyzed.

5.2.1. Concept identification

Visual analysis extracts the concepts from the final association network. In Fig. 6(a) we mine the concept revolve around "performance" of the "camera" by taking into account "resolution", "performance" and "battery". The corresponding *favourability* scores are also shown beside the nodes. Here, "resolution" is connected with "camera" as well as "screen". However, we consider it with "camera" to represent the quality of the image taken by the "camera". Moreover, as there is no restriction for including an association in more than one concept, the association "resolution" can be included in some other concept such as - "screen". The association "battery" addresses the power consumption caused by the "camera" and flash. It is worth noting that a concept may evolve by involving newer associations. It is visible in February where "price" has come under consideration concerning the concept "camera". Similarly, it may so happen that in a set of reviews there is no explicit mention of "camera". However, the concept of "performance" of the "camera" still be identified by other related associations such as – "images", "quality" etc. Such identification has been applied for April in Fig. 6(c). In Fig. 6(d) the concept builds around "camera" has been considered for May.

5.2.2. Sentiment of identified concepts

Once the identification of concepts complete, we take the arithmetic mean of the *favourability* scores to represent the overall sentiment of the concept. The average sentiment score for the performance of camera is 0.72. Whereas, in February, the opinion has come down to 0.58. It may be due to the low *favourability* score of "photos", and "quality" or consumers may not be happy upon specific modification of the product

Table 6
Top and Bottom five Associations based on OBIM values.

Brand	High	Low
A	*camera, performance, product, service, features*	*storage, battery, experience, resolution, screen*
B	*camera, features, device, lags, heating*	*contacts, performance, expectation, experience, note*
C	*service, sim, hardware, buy, money*	*color, downloading, network, weight, grip*
D	*usage, battery, performance, backup*	*repair, weight, segment, camera, patch*
E	*camera, features, gb, screen, price*	*experience, sound, rating, brightness, device*

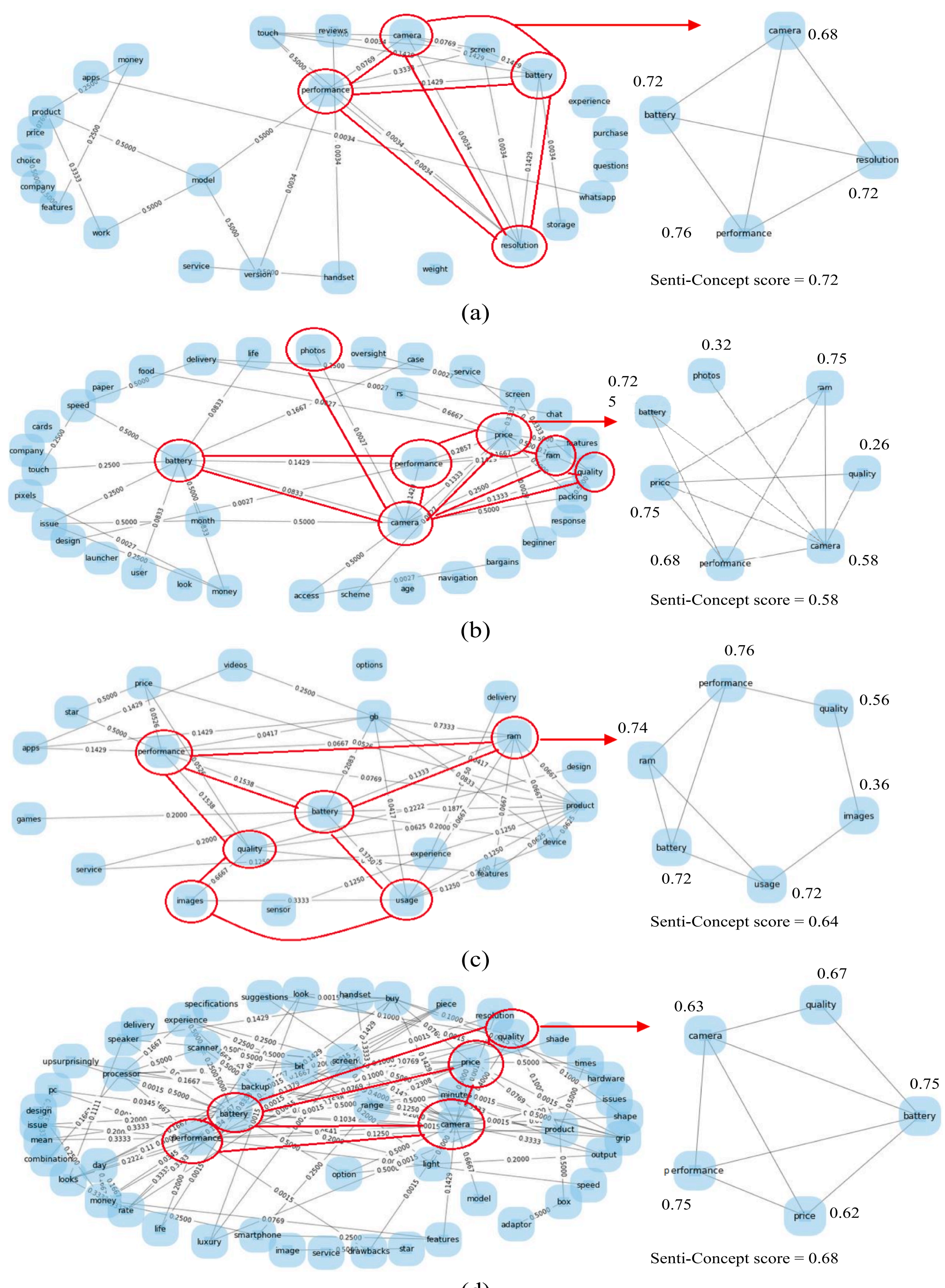

Fig 6. Senti-Concept values for Brand A for January.

etc. On the other hand, from April, the sentiment score (0.64) increases and reaches 0.68 in May.

6. Discussion

In this study, we presented a novel model called OBIM to quantify Online Brand IMage (OBIM) from consumer reviews of individual brands in combination with aspect-based sentiment analysis and co-word network analysis. *Favourability, strength,* and *uniqueness* of the extracted associations are computed using sentiment and co-word network analysis. Finally, the multiplicative sum of these values represents the OBIM score. Two applications, *Association Based SWOT analysis* and *Senti-Concept Mapper* technique are proposed to discover hidden concepts. OBIM score is relevant to the managers as it helps in tracking the market performance of the brand, identify beneficial associations and compare their brands in a competitive environment. In earlier studies, the primary survey is the only source for gaining knowledge about the brand image (John et al., 2006; Schnittka et al., 2012). We use online consumer reviews, which makes the entire process faster than primary surveys (Gensler et al., 2015).

We estimate the OBIM score based on *favourability, strength,* and *uniqueness* of brand associations. In many of the prior studies, there is no distinct analysis of these three attributes of brand image (Lee et al., 2016; Moon & Kamakura, 2017; Mostafa, 2013; Pantano et al., 2019). In this study, we focus on each of these attributes and estimate their respective values around an association. Moreover, we combine the attributes of the brand image into a confined OBIM score, which remain unattempt in earlier works (Gensler et al., 2015; Lee & Bradlow, 2011). We have demonstrated a temporal analysis across five months, which can be essential for the managers to monitor their brand's performance over a period of time.

To mine consumers opinion towards a brand, document-level sentiment analysis has been applied (Mostafa, 2013; Pantano et al., 2019). In our approach, we use aspect-based sentiment analysis to capture the favourability of brand associations. This technique firstly extracts aspects from reviews, which represents brand associations. Later on, the sentiment orientation of each of these associations describes favourability. With the use of aspect-based sentiment analysis, we differ from prior researches, where the polarity of the entire document is defined as an indicator of consumer perception towards the brand (Mostafa, 2013; Pantano et al., 2019). The use of automatic aspect extraction eliminates the need for conducting interviews and market researches to identify relevant brand associations and pre-defined attributes which is convenient for the managers to use in the competitive market. It is an improvement over prior studies (Culotta & Cutler, 2016; John et al., 2006., Netzer et al., 2012). Besides that, in most of the shopping sites, consumer feedback is maintained in an unstructured format. As per studies, around 80% of data in many firms possession is unstructured and the growth of such data is 15 times faster than structured data (Balducci & Marinova, 2018). OBIM is implemented for unstructured reviews which is significant in the current scenario and a contribution over existing literature (Gensler et al., 2015; Lee & Bradlow, 2011).

We use the co-word network analysis to produce the brand association network. This network helps in the estimation of strength - and uniqueness of brand associations. This approach generates brand association maps more quickly and efficiently for more than one brand. We use the node importance as measurement technique to show the *uniqueness* of an association. This technique measures the significance of an association based upon the locally connected nodes. Hence, the knowledge extracted from the network is dependent upon the context of the association, which is relevant in extracting consumers' perceptions. The application of network theory model is prevalent in the OBIM model. From the information-theoretic point of view, OBIM utilizes the knowledge shared in the unstructured consumer reviews for managerial decisions making.

6.1. Managerial implications

In the quick-paced internet and business world, with numerous brands under ambush, marketing managers need to make marketing strategies based on the ground reality of their product performance (Faircloth, Capella, & Alford, 2001). In such a scenario, consumer perception revealed through online reviews become highly relevant to the managers to make marketing decisions. These reviews are so useful that many firms are hosting reviews on their websites (Filieri, 2015).

Comprehension of the brand image from online reviews is faster than manual survey techniques. In a competitive market environment, OBIM approach can be applied, in line with the development of marketing strategy and product performance analysis. OBIM apprehends consumers' perception through estimating their favourable, significant and distinctive brand associations. OBIM can, therefore, be generalized further and seen as a metric of the brand's market performance. With less human intervention, OBIM can track the dynamic changes in the marketing scenario when deployed over time.

Consumer sentiment affects product sales (Lee & Bradlow, 2011). Aspect based sentiment analysis of the product reviews represents the favourability of vital associations that can mediate consumers' choices over rival brands. Favourability construct and its interpretation over time reveal consumers' needs and expectations from the brand. These aspects can be recognized by managers to take the necessary action to make their brand relevant compared to other brands.

In the context of favourable association, we propose *SentiConcept Mapper* and *Association based SWOT* tools to gain managerial insights in a comprehensive way. *SentiConcept Mapper* identifies favourable concepts latent in the brand association network. This tool reveals the association clusters and gives an idea about the significant concepts rolling in consumers' perception. Repurchase intention assessment is another critical task for a manager. As per literature, aesthetics, social, cultural utilitarian factors affect repurchase intentions (Filieri & Lin, 2017). Clubbing associations into concepts enable managers to identify these factors. Hence, *SentiConcept Mapper* can be used as a tool for perceiving repurchase intention. On the other hand, *Association based SWOT* analysis on temporal data, points out the associations which play a pivotal role in consumers' purchase decision and identifies associations which can be a potential threat to the brand image.

Furthermore, managers can tally their brands with rivals upon favourability, *strength* and uniqueness of individual association. Managers can take precautionary and developmental measures to boost the brand image. Moreover, the co-word network gives an in hand visualization of the entire association network. Brand image is a predominant factor in Consumer Based Brand Equity (Keller, 1993). Therefore, the proposed approach to measure brand image can be used to gain insights on brand equity.

7. Conclusion

Consumer perception revealed through online reviews has become highly crucial for managerial decision making. The computational model proposed in this paper is an attempt to quantify the brand image from such reviews. The OBIM score, a numeric representation of spontaneous consumer reactions, integrates three pivotal attributes of the brand image, *favourability*, *strength*, and *uniqueness* of the underlying associations. This score and the related applications, Association Based SWOT analysis and Senti-Concept mapper can help the managers to comprehend brand image.

However, there exists certain limitations in our study. Typically, consumer reviews consist of both textual contents as well as a rating. The proposed model is limited to use only textual contents. Though we primarily focus on product reviews, social media data such as Twitter can also be utilized to refine the OBIM score. In the present study, we do not assess the quality of online reviews. If reviews are filtered based on their quality, the result may be improved. The proposed model may be calibrated using the actual sales data, which is not publicly available. Specific efforts in this regard may be made when both consumer review and sales data are available during a particular period. Currently, both *Association Based SWOT* and *Senti-Concept mapper* techniques require manual interventions. Automatic approaches for these tools can also be proposed. The inclusion of emotional effects around a word in the sentence, external factors such as existing social, political, and economic ups and downs, if included, may affect OBIM score. Finally, consumer views may be biased by marketing efforts such as promotions and advertisements. Capturing such biases in the model may bring further improvements.

Appendix A. Selected associations and monthly *Favourability*, *strength* and *uniqueness* Scores: "X" denotes missing associations in the following month's review

Brand A

Associations		January	February	March	April	May
camera	*Favourability*	0.6894	0.6537	0.61	X	0.6364
	Strength	0.0986	0.0992	0.14	X	0.0915
	Uniqueness	0.0632	0.0618	0.05	X	0.1456
performance	*Favourability*	0.7693	0.6814	0.7202	0.7663	0.7502
	Strength	0.1692	0.1323	0.4586	0.1638	0.0874
	Uniqueness	0.0300	0.0466	0.0146	0.0796	0.1260
features	*Favourability*	X	X	X	0.5852	0.7898
	Strength	X	X	X	0.1093	0.1298
	Uniqueness	X	X	X	0.0753	0.0452
experience	*Favourability*	0.2289	X	X	0.8125	0.7981
	Strength	0.0034	X	X	0.1835	0.2436
	Uniqueness	0.0010	X	X	0.0655	0.0516
quality	*Favourability*	X	0.2617	X	0.5642	0.6700
	Strength	X	0.1788	X	0.1563	0.1157
	Uniqueness	X	0.0230	X	0.1060	0.0546

Brand B

Associations		January	February	March	April	May
camera	*Favourability*	0.7693	0.7148	0.7859	0.7202	0.7387
	Strength	0.2471	0.1070	0.0425	0.2000	0.1835
	Uniqueness	0.0337	0.0493	0.0020	0.1424	0.1293
performance	*Favourability*	0.7108	0.7500	0.7202	0.5821	X
	Strength	0.0833	0.2130	0.3495	0.1073	X
	Uniqueness	0.0010	0.0356	0.0052	0.0307	X
features	*Favourability*	0.7616	0.7869	X	0.7202	X
	Strength	0.3593	0.2747	X	0.1638	X
	Uniqueness	0.0214	0.0123	X	0.0629	X
experience	*Favourability*	0.7378	0.5371	0.8155	0.8125	X
	Strength	0.0099	0.3344	0.2147	0.0016	X
	Uniqueness	0.0030	0.0231	0.0301	0.0050	X
quality	*Favourability*	X	0.5418	0.2617	0.5061	0.7368
	Strength	X	0.1508	0.1467	0.1804	0.1049
	Uniqueness	X	0.0461	0.0748	0.0382	0.0660

Brand C

Associations		January	February	March	April	May
camera	*Favourability*	0.6807	0.6203	0.6726	0.6533	0.6846
	Strength	0.0594	0.0852	0.0826	0.1286	0.1096
	Uniqueness	0.0974	0.0862	0.0705	0.0468	0.0695
performance	*Favourability*	X	0.7202	0.7202	X	0.6347
	Strength	X	0.1055	0.2363	X	0.1719
	Uniqueness	X	0.0156	0.0262	X	0.0173
features	*Favourability*	0.8125	X	0.7827	0.7202	0.8185
	Strength	0.2018	X	0.1659	0.2267	0.3401
	Uniqueness	0.0198	X	0.0253	0.0188	0.0083
experience	*Favourability*	X	X	0.2289	X	0.2289
	Strength	X	X	0.3160	X	0.2449
	Uniqueness	X	X	0.0065	X	0.0054
quality	*Favourability*	0.5674	X	0.4909	0.7202	0.6008
	Strength	0.0697	X	0.1456	0.0386	0.2160
	Uniqueness	0.0885	X	0.0444	0.0060	0.0319

Brand D

Associations		January	February	March	April	May
camera	*Favourability*	0.8125	0.6012	0.7734	0.7045	0.7333
	Strength	0.0220	0.1647	0.1331	0.0928	0.0648
	Uniqueness	0.0060	0.0268	0.1648	0.1640	0.2028
performance	*Favourability*	0.7513	0.7571	0.6945	0.6667	0.7541
	Strength	0.1865	0.1291	0.1673	0.1044	0.1040

	Uniqueness	0.0732	0.1650	0.0451	0.0535	0.0640
features	*Favourability*	X	X	X	0.7751	0.7287
	Strength	X	X	X	0.1236	0.1567
	Uniqueness	X	X	X	0.0190	0.1079
experience	*Favourability*	X	X	X	0.7470	0.7155
	Strength	X	X	X	0.2230	0.0547
	Uniqueness	X	X	X	0.0034	0.0122
quality	*Favourability*	X	0.7422	0.6521	0.4871	0.5517
	Strength	X	0.1173	0.1248	0.1152	0.1169
	Uniqueness	X	0.1247	0.0952	0.0265	0.1105

Brand E

Associations		January	February	March	April	May
camera	*Favourability*	0.6613	0.6786	0.7544	0.72450	0.7086
	Strength	0.1974	0.1442	0.1458	0.1184	0.0810
	Uniqueness	0.1684	0.2680	0.3892	0.2149	0.1799
performance	*Favourability*	X	0.6226	0.6761	0.6937	0.6356
	Strength	X	0.1677	0.1673	0.1493	0.1360
	Uniqueness	X	0.1276	0.1007	0.0696	0.0717
features	*Favourability*	X	0.6425	0.7280	0.6355	0.7101
	Strength	X	0.1854	0.2069	0.1896	0.1873
	Uniqueness	X	0.0354	0.0812	0.0398	0.0129
experience	*Favourability*	0.5973	0.2288	0.2289	0.5163	0.2288
	Strength	0.1454	0.0010	0.2862	0.2052	0.2153
	Uniqueness	0.0104	0.001	0.0640	0.0428	0.0141
quality	*Favourability*	0.6591	0.7157	0.4036	0.5852	0.7332
	Strength	0.4770	0.0864	0.1418	0.1425	0.1428
	Uniqueness	0.0487	0.1630	0.2396	0.1105	0.0607

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