

Brand Perceptual Mapping by Text Mining Online Product Reviews

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ABSTRACT

Brand perceptual mapping is a visual technique, which displays how a brand is positioned in the mind of customers as well as in relation to its competitors. Building a perceptual map requires information regarding consumer perceptions towards that brand, which usually comes from a comprehensive market study (e.g. by conducting surveys, interviews or similar techniques). However, with rapid growth of e-commerce and abundance of online consumer-generated content, there is no need for marketers to go through time-consuming and error-prone market research to understand customers' opinions. In this study, we propose a method to build a perceptual map automatically by mining customer opinions from online product reviews. We use opinion mining techniques to extract and rank the product aspects that are important to customers while purchasing digital tablets. Then we generate a score for each brand in these aspects and build the perceptual map using clustering the brands by these scores. The proposed method is applied to the online customer reviews for digital tablets extracted from Amazon.com. Our experimental results demonstrate the proposed technique is effective and able to correctly depict the position of a brand in its competitive environment.

Keyword: Brand Position, Perceptual Map, Online Customer Review, Data Mining

INTRODUCTION

In today's competitive world, companies are trying to manage their brands to find and occupy a distinct position in the market. The positioning decision is often a crucial strategic decision for a company because this position can be central to customer's perception and choice decisions (Aaker and Shansby, 1982). To find the best positioning strategy, companies need to be aware of their current position in their competitive environment. One of the best tools is perceptual mapping. Perceptual maps represent the perceptions of customers in a (usually) two-dimensional space so that marketers can visually understand where their brand is placed in the marketplace.

Building a perceptual map requires information regarding product attributes and consumer perceptions towards the brand. This information usually comes from a comprehensive market research study, e.g. by conducting focus groups or surveys. However, with extensive growth of internet and e-commerce, today consumer-generated content is

ubiquitous on the web. For organisations, the analysis to the vast amount of information available on the internet could replace polls, focus groups and similar techniques as effective tools in market research (Marrese-Taylor, Velásquez, Bravo-Marquez, & Matsuo, 2013). Marketers can take advantage of this rich data source to ascertain consumer perceptions and construct a perceptual map.

One of the data sources that have attracted the attention of researchers is the online product reviews. Analysing this kind of source of data, could help marketers monitor customer opinions, attitudes, mood, and preferences and design their product and services accordingly. However, due to the sheer quantity of data, marketers are unable to analyse all the available data manually. To solve this problem, researchers have proposed sentiment analysis approaches that leverage text mining and natural language processing (NLP) to discover the essential information from reviews.

In this paper, relying on text mining and NLP, we propose a method for constructing brand perceptual maps

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by automatically mining online product reviews. We produce a software that downloads a number of online reviews for a product category and analyses the collected reviews to extract consumer opinions. The core of the software consists of two algorithms: Aspect Finder and Opinion Ranking. The Aspect Finder mines the data and determines the aspects that are important to consumers' decision making. The Opinion Ranking mines the data to discover customers' opinions on these aspects and assigns scores to the different aspects accordingly. The final aspect scores are used to construct a visual brand perceptual map. The proposed method is not limited to a specific product category and is able to retrieve customer opinions from any online review data. We have applied the methodology to a database of online reviews for digital tablets extracted from Amazon.com. Our experimental results demonstrate the proposed technique is effective and is able to correctly depict the position of a brand in its competitive environment. The remainder of this paper is organised in the following manner: second section discusses literature review. Third section describes the methodology. In fourth section, we discuss the experimental results; and conclusion comes in fifth section.

LITERATURE REVIEW

Sentiment Analysis

Sentiment analysis (SA) also called opinion mining (OM) refers to the use of NLP and text analysis to identify people's opinions, attitudes, and emotions towards different entities such as products, events and their attributes. SA techniques have been widely used in various applications such as mining newspapers and websites to extract public opinion (Maragoudakis, Loukis, & Charalabidis, 2011), product recommendation (Aciar, Zhang, Simoff, & Debenham, 2006), determining consumers' dissatisfaction with online advertising campaigns (Qiu, He, X., Zhang, F., Shi, Y., Bu, J., & Chen, 2010), stock market prediction (Bollen, Mao, & Zeng, 2011), predicting political election results (Tumasjan, Sprenger, Sandner, & Welpe, 2011) and product feature extraction and ranking (Zhang, Cheng, Liao, & Choudhary, 2011).

As stated by Liu (2007), SA offers two main approaches, aspect-based and non-aspect based. Aspect-based opinion mining techniques divide input texts into aspects, also called features. The aspect-based approach is very popular and many researchers have developed their own

model. For example, the authors of Mining Reviews for Product Comparison and Recommendation tried to create a product recommendation system by mining product features from online reviews using aspect based SA. The authors of Designing Ranking Systems for Consumer Reviews : The Impact of Review Subjectivity on Product Sales and Review Quality, proposed ranking mechanisms for ranking product reviews by combining econometric analysis with SA techniques and subjectivity analysis. In A holistic lexicon-based approach to opinion mining, the authors have tried to extract and summarize consumers' sentiments from online product reviews related to several electronic products. They used text mining and machine learning methods to summarize the features of the product on which the customers have expressed their opinions, and classified each review into positive or negative opinions. According to Marrese-Taylor, this work is the most representative research in this area, and that is why we used it here as inspiration.

Product Aspect Extraction and Ranking

To construct a perceptual map, we must extract product aspects and consumer opinions from reviews. Aspects refer to every component or attribute of the product such as features, benefits, functions or applications (Liu, 2007). Aspects usually appear as nouns (battery), noun phrases (battery life) or nominal combinations (touch screen) in text. Opinions are the attitude or describer of the aspect, which usually appear as adjectives or adverbs in the text (Decker & Trusov, 2010; Popescu & Etzioni, 2007) . Opinions can be positive or negative and vary in strength. Using the previous assumptions, the problem of extracting product aspects and opinions from texts fall into the following main sub-tasks (Popescu & Etzioni, 2007) :

1. Identifying product aspects by finding most frequent nouns in the text.
2. Identifying opinions regarding product aspects by finding the correlating adjective. For example, in "the size is too big", the "too big" adjective phrase is the opinion on the "size" aspect, which is a noun.
3. Determining the polarity of opinions. Opinions can be positive, negative or neutral.
4. Ranking opinions based on their strength. For example, "horrible" is a stronger indicator than "bad."

Many researches (Decker & Trusov, 2010; Popescu & Etzioni, 2007; Eirinaki, Pital, & Singh, 2012) including this paper have used the aforementioned approach to extract opinions and aspects from texts. However, we have made a small variation to the algorithm. Instead of searching for nouns and then finding the correlating adjective, we search for adjectives that go with a correlating noun. This algorithm, which is called Aspect Finder is based on the high adjective count (HAC) algorithm proposed in feature-based opinion mining and ranking. The main idea behind the algorithm is that the nouns, for which reviewers express many opinions, are most likely to be the important and distinguishing features than those for which users do not express such opinions. We have improved the HAC algorithm by three different ways. First, the HAC algorithm associates each adjective to its closest noun. However, this might not be effective because the aspect might be mentioned far from the opinion in the text. We solved this problem by using grammatical patterns to extract nouns and adjectives. Second, to determine the potential features, in the proposed method, the frequent nouns are filtered and the most frequent English nouns are removed. Third, similar to ‘A holistic lexicon-based approach to opinion mining’, the nouns with the similar meaning are grouped together and then the frequent groups are determined as the potential aspects. The detail of the algorithm is described in third section.

METHODOLOGY

According to Jobber (2001), there are four steps for creating a perceptual map: (1) identify a set of competing brands, (2) identify important attributes that consumers use when choosing between brands, (3) conduct marketing research and determine customers’ opinion on the attributes, and (4) plot the brands on a two dimensional map.

In order to generate the perceptual map, this research follows the same approach. First, we determine the competing brands that we want to plot in the map. Then the product reviews related to these brands are crawled, downloaded and inserted into the review database. After preprocessing the data, an opinion mining engine, determines the most important aspects to customers and extracts the related opinions. Similar to previous researches, we assume that the most important attributes to customers are the ones that they mostly talk about. Therefore, we have determined the most frequently mentioned aspects in the text as the most important attributes to consumers, and then we determine

the consumer opinions on these aspects. Thereafter, the extracted opinions are scored using a dictionary-based method and an opinion score is determined for each (brand, aspect) tuple. The final perceptual map is generated from this data. Fig. 1 gives the architectural overview of our perceptual mapping system. The detail of the architecture is described in the following sections.

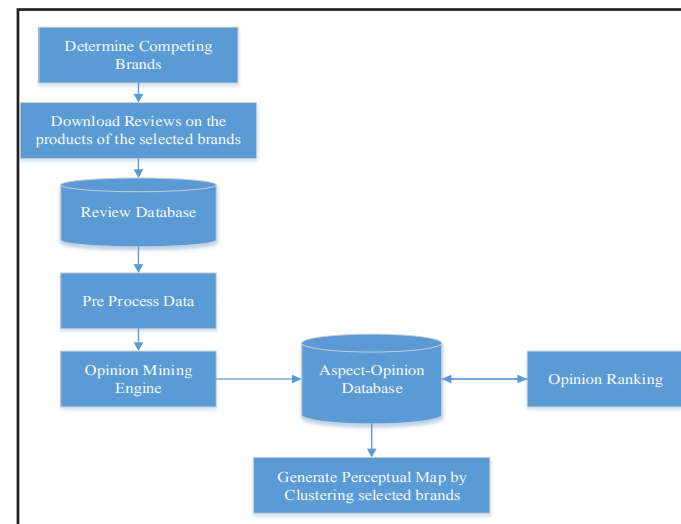


Fig. 1: System Architecture

Preprocessing the data

After crawling and downloading the reviews, the data should be preprocessed to be ready for the opinion mining engine. In this step, duplicate data and the reviews that contain missing fields are deleted from the review database. Then a spell correction algorithm searches the data for possible errors and corrects them. Thereafter, using the Stanford POS (parts-of-speech) tagger module (Stanford Log-linear Part-Of-Speech Tagger, 2015), all of the words in reviews are tagged by their corresponding POS. For example, the sentence: “the camera quality is poor” would be tagged as “<the/DT><camera/NN><quality/NN ><is/VBZ><poor/JJ>”.

Opinion Mining Engine

The opinion mining engine performs the following tasks:

1. Identifying and extracting aspects that have been commented on in each review.
2. Grouping aspects with the same meaning, as different people may use different words to express the same feature.

3. Determining the most frequent aspects.

The core of this engine consists of the “Aspect Finder” algorithm. The Aspect Finder, which is shown in Fig. 2 starts by identifying the adjectives and nouns in each

document collection. First, each review is broken down into sentences. As stated in earlier section, in each sentence, the words, which have a POS tag of adjective, are determined. Adjectives are considered opinions if they are describing a noun, otherwise they are discarded.

```

Aspect Finder (reviews, Frequent_English_Nouns, Noun_Groups, threshold)
noun_score={}
potential_Aspects={}
Foreach review in review database do
{
  Break review into sentences
  Foreach sentence in sentences do
  {
    Foreach adjective in the sentence do
    {
      Noun_Phase = Find the corresponding noun phrase
      If Noun_Phase exists and Noun_Phase is not in Frequent_English_Nouns
      {
        noun_Group = Find the corresponding group in Noun_Groups for Noun_Phase
        noun_score[noun_Group] ++
        negation = FindNegation(adjective, sentence)
        adverb = FindAdverb(adjective, sentence)
        add <noun, noun_Group, adjective, negation, adverb, reviewId> to Aspect_Opinion Database
      }
      Else
        Discard adjective
    }
  }
}

Foreach noun_Group in noun_score
{
  If noun_score(noun_Group) > threshold
  Add noun_Group to potential_Aspects
}

Foreach <noun, noun_Group, adjective, negation, adverb, reviewId> in Aspect_Opinion
{
  If (noun_Group is not in potential_Aspects)
  Remove <noun, noun_Group, adjective, negation, adverb, reviewId> from Aspect_Opinion Database
}

Return potential_Aspects

```

Fig. 2: The Aspect Finder Algorithm

When the algorithm finds an adjective (opinion), it should determine the corresponding noun phrase (aspect). To determine the corresponding noun phrase, we have determined grammatical patterns that are widely used in English language. These patterns help determine, what

noun the adjectives are describing. The patterns are shown in Table 1. If none of the introduced patterns is found in the sentence, then the closest noun to the adjective is considered as the target aspect.

Table 1: Grammatical Patterns for Extracting Nouns

| <i>Pattern</i> | <i>Example</i> |
|----------------------------------|------------------------------------------------------------------------|
| Noun + vb + Adj | <The/DT><camera/NN><is/VBZ><unclear/JJ> |
| Noun + vb + Adj, Adj ... and Adj | <The/DT><camera/NN><is/VBZ><unclear/JJ>, <slow/JJ> and <cheap/JJ> |
| Noun + vb + adv + Adj | <The/DT><screen/NN><is/VBZ><very/RB><bright/JJ> |
| Adj+Noun | <unclear/JJ><camera/NN> |
| Adj + Noun Noun | <short /JJ><battery/NN><life/NN> |
| Adj + Noun Noun ... Noun | <Separate/JJ><micro/ NN ><USB/ NNP><port/ NN > |
| Adj+Noun of Noun | <low/JJ><quality/NN><of/IN><screen/NN> |
| Adj+Noun of the/this/that Noun | <short/JJ><life/NN><of/IN><the/DT><battery/NN> |
| Adj+Noun of the Noun ... Noun | <Recent/JJ><version/NN><of/IN><the/DT><DramaFever/NNP><application/NN> |
| Adj+Noun...Noun and Noun... Noun | <bad/JJ><camera/NN><and/CC><battery/NN><life/NN> |
| Adj+Noun,..., Noun and Noun | <perfect/JJ><size/NN>, <design/NN>, <color/NN><and/CC><thickness/NN> |
| Adj and Adj Noun | <unresponsive/JJ><and/CC><blurry/JJ><screen/NN> |
| Adj,Adj...and Adj Noun | <unresponsive/JJ>, <small/JJ><and/CC><unclear/JJ><screen/NN> |
| Adj,Adj...Adj +Noun | <satisfactory/JJ><beautiful/JJ><professional/JJ><lens/NN> |

After determining each tuple of (aspect, opinion), the algorithm searches for two more patterns in the sentence: negation words and adverbs before adjectives. There are a number of words such as “not”, “no”, “but”, and “however”, that give an opposite meaning to the sentence. When these words occur before an opinion word, they negate the opinion word. Thus, when we are searching the sentence for adjectives, we also took the remaining context into consideration and if an inversion word appears, we preserve the negation word along with the opinion. Furthermore, in many English sentences, adverbs occur before the target adjectives and change its strength. For example, “very happy” is a stronger indicator than “happy”. Therefore, the Aspect Finder algorithm, searches for adverbs before the opinions, and saves them alongside the (aspect, opinion) tuple.

Moreover, in any language, there are certain words that are frequently mentioned in any corpora. For example, the word “time” or “thing” are among the most frequently used English nouns. The Aspect Finder algorithm is based on counting the frequency of nouns; therefore, it finds many of the frequent words that are not aspects of the product. In order to fix this problem, we used a database of most frequent nouns from the Corpus of Contemporary American English (wordfrequency.info). This corpus has reviewed documents containing about 450 million words and has determined the top 5,000 frequent words in English. We have only selected the 50 top most frequent nouns and have used them in the Aspect Finder to filter the non-aspect frequent nouns. For each noun that the algorithm finds, if it is in the Frequent_English_Nouns set, then it is discarded and no score will be saved for this noun.

As mentioned above, different people may use different words to express the same feature. For example, the resolution of the screen is referred to by terms such as resolution, screen resolution, display resolution, pixels, etc. These nouns have the same meaning and can be a substitute for one another. Therefore, before counting the frequency of each noun, we should group the nouns with the same meaning. Identifying synonyms is a challenging problem and is beyond the scope of this paper. To simplify the problem, we have used a dictionary-based approach. Similar to ‘A holistic lexicon-based approach to opinion mining’, the synonyms are determined using WordNet Synsets (Miller, 2015). However, WordNet does not contain all of the aspects of a tablet; thus, we have filled this gap by adding the missing aspects of the tablet and their synonyms into this dictionary.

After processing all reviews in our collected data, the set of noun phrase, the correlating adjective, negation, aspect group and adverb are saved as <aspect, aspect group, opinion, negation, adverb, review Id> sets in the Aspect-Opinion database. Then the algorithm assigns scores to each of the extracted noun phrases. This score, which is named noun_score in the algorithm, is equal to the frequency of the noun in the Aspect-Opinion database (Popescu & Etzioni, 2007; Hu & Liu, 2004). The noun scores are used to rank the nouns such that, the higher ranked nouns will be the ones having more adjectives describing them. According to the fact that each review belongs to one opinion holder, if a noun is repeatedly mentioned in a review, its frequency will only be increased by one. Therefore, the noun score shows how many opinion holders have mentioned that specific noun phrase in their review and have expressed an opinion on it. The potential aspects are identified by selecting the nouns, which have a score above a particular threshold. The threshold is an argument of the algorithm and can be chosen by experiment. The pseudo code of the Aspect Finder algorithm is shown in Fig. 2.

Opinion Scoring

In this step, the Opinion Scoring algorithm calculates the sentiment score for each potential aspect of each brand. For example, given a brand like Apple and a potential aspect, e.g. battery life, the Opinion Scoring algorithm finds all the Apple product reviews that have assigned an adjective (opinion) to battery life, and calculates the average sentiment score for all those adjectives as the final sentiment score for Apple’s battery life. The algorithm takes three inputs, which are described in the following paragraphs.

The first input to the algorithm is the MPQA subjectivity corpus. MPQA contains a database of words that are classified into positive, negative or neutral. Each word in this database is also tagged as weak or strong. We calculate the MPQA score for each adjective in the range of [-2, 2]. The MPQA score is calculated using the following formula:

$$\text{Formula (1)} \quad \text{MPQA}(a) = (\text{positivity}_a)(\text{strength}_a)$$

where a is the word from review. The positivity parameter is set to 1 for a positive word, -1 for a negative word and 0 to a neutral word. Strength_a is the strength of the word in the MPQA corpus. The strength parameter is set to two, if the word is a strong subject and it is set to one, otherwise.

The second input to the algorithm is the helpful score for the reviews. Amazon.com allows customers to tag a review as helpful or non-helpful. If a review is tagged non-helpful, even for multiple times, then it might be possibly not a valid word or with strong opinion. Therefore, we can assume that this score represents the reliability of a review. The h_score , which is calculated using Formula 2 demonstrates how helpful the review has been to customers.

$$\text{Formula (2)} \quad h_score_r = \frac{\text{Number of users that have rated } r \text{ as helpful}}{\text{Number of users that have rated } r \text{ as helpful} + \text{Number of users that have rated } r \text{ as non-helpful}}$$

The third input of the algorithm is the list of opinion words, which are the adjectives used to express an aspect for each brand. For example, in the sentence “the camera is clear and fast”, if camera is a frequent noun, then the opinion words are clear and fast. For each of the adjectives in the opinion word list, the algorithm needs the negation and the adverb associated with the adjective, which are already in the Aspect-Opinion database. The final sentiment score for each brand aspect is calculated using Formula 3.

$$\text{Formula} \quad \text{sentiment score}_{brand,aspect} = \frac{\sum_{k=1}^n MPQA(adj_k) * n_score_k + MPQA(adverb_k) * h_score_k}{n} \quad (3)$$

```

Opinion Ranking (review helpfulity, Aspect_Opinion database, potential_Aspects, Brands, MPQA)
Aspect_brand_score={}
Opinion_Words={}
Foreach brand in Brands
{
  Foreach aspect in Potential_Aspects
  {
    Opinion_Words = Find the opinion words describing the aspect of the brand in the
    Aspect_Opinion database
    h_score = helpfulity score for the corresponding review
    Foreach opinion_word in Opinion_Words
    {
      total_score+= h_score*MPQA(opinion_word)*negation*MPQA(adverb)
      opinion_word_count++
    }
    Aspect_brand_score [aspect,brand]= total_score/ opinion_word_count
  }
}

```

Fig. 3: Opinion Ranking Algorithm

In this formula, “n” is the number of all adjectives describing the target brand aspect. $MPQA(adj)$ and $MPQA(adverb)$ are the scores of the adjective and its

corresponding adverb, “n_score” is the negativity score and “h_score” is the helpful score for the review that the adjective belongs to. The pseudo code of the Opinion Ranking algorithm is shown in Fig. 3. The output of the Opinion Ranking algorithm is a matrix that contains a score for each aspect of each brand. This matrix is what we need for constructing a brand perceptual map. The following section describes how the map is generated.

Constructing the Perceptual Map

A perceptual map is usually generated in a two-dimensional matrix. Designers, scholars use this method to evaluate or determine the position of a certain brand. But this method fails to compare more than one brand with each other. However, by using the clustering method, we are generating a single multi-dimensional perceptual map, that weighs the performance of many brands. To cluster the brands, the matrix of aspect-brand scores are entered into the K-means algorithm, the clusters are determined and the final perceptual map is generated.

The steps of constructing the perceptual map are implemented using the C# language and Microsoft SQL server. The software crawls the Amazon.com and downloads online reviews automatically. Then it performs the preprocessing tasks, applies the Aspect Finder and Opinion Ranking algorithms to the data and outputs the final matrix of aspect scores in brands. The software’s performance is evaluated in the following section.

EXPERIMENTAL RESULTS

To evaluate the performance of the software, we applied it to the online reviews downloaded from Amazon.com for tablet products. We chose the tablet product reviews because tablet is a very commonly researched product and the aspects that consumers care about are determined in many previous researches; and therefore, we can easily prove that the proposed algorithm has achieved correct results. The following sections describe the results in detail.

Determining the Competing Brands

In the first step, we asked experts to determine eight brands, which are competitors in the category of tablets. The brands are Apple, Microsoft, Acer, Asus, Neutab,

Dell, HP, and Samsung. Thereafter, we crawled and downloaded all the consumer online reviews of the tablets with one of the aforementioned brands. 5230 reviews were downloaded on December 2014 and were inserted

into the review database. After preprocessing the reviews, 5145 reviews were left. Table 2 shows the number of reviews downloaded for each brand.

Table 2: Number of Downloaded Reviews for Each Brand

| <i>Brand Name</i> | <i>Acer</i> | <i>Apple</i> | <i>Asus</i> | <i>Dell</i> | <i>Hp</i> | <i>Microsoft</i> | <i>Neutab</i> | <i>Samsung</i> |
|-------------------|-------------|--------------|-------------|-------------|-----------|------------------|---------------|----------------|
| Number of reviews | 166 | 368 | 1303 | 110 | 103 | 254 | 196 | 2645 |

Finding the Most Important Aspects

To determine the most important aspects to the customers, the data from the previous step was put to the Aspect Finder. As stated in the algorithm, the first looks for the adjectives, which have a correlating noun. 38665 sets of <noun, adjective, negation, adverb, reviewId> was detected in the reviews. In the second step, the algorithm groups the nouns that have similar meanings and then counts the frequency of each group to determine the potential aspects. In order to determine the most frequent

nouns, according to previous researches (Eirinaki *et al.*, 2012) we set the threshold to 0.5 percent. This means that if a noun is repeated more than 193 (0.005×38665) times, then the noun is considered to be a potential aspect. The resulting potential aspects are shown in Table 3. From the ten potential aspects, only the first one (tablet) is not an aspect of a tablet. Although, opinions on this word can provide an insight about consumer perceptions towards the tablet as a whole, we eliminated this word because it is not an aspect for constructing the perceptual map.

Table 3: Potential Aspects Extracted from Online Product Reviews

| <i>Aspect</i> | <i>Frequency</i> | <i>Aspect</i> | <i>Frequency</i> |
|---------------|------------------|---------------|------------------|
| tablet | 1974 | battery life | 294 |
| screen | 779 | resolution | 278 |
| application | 554 | camera | 247 |
| price | 364 | processor | 246 |
| review | 309 | design | 210 |
| size | 299 | Total | 5554 |

Price, size, battery life, resolution, camera, processor, and design are obvious features/benefits of a tablet. The screen aspect, describes the screen of the tablet. It is different from screen resolution. The screen resolution specifically reviews the resolution of the screen while most of the reviews describing the screen aspect evaluate other attributes of the screen. For example, “The screen is quite bright, colourful and contrasty. NO, it’s not a retina screen, but it’s clear and crisp” shows that the user cares about the clarity and colour of the screen.

Moreover, the “application” aspect is mostly about the available applications on the tablet. For example, “With a wide range of available applications from the App Store and also through my company, I have everything I need to stay productive” and “The Android Market doesn’t distinguish between phone applications designed for a

small screen and tablet applications” show that the users significantly care about the possibility of installing and using applications on the tablet.

Finally, the “review” aspect is about the previous online product reviews. When consumers are buying online, they usually read many of the available online reviews. This study shows that the previous reviews are a determinant factor for consumers while buying tablets online. For example, in the following review the user has clearly mentioned that the previous reviews has affected his/her judgment about the product: “reading the bad reviews about the quality issues and service problems for the TF701t make me think that ASUS is going somehow downhill”. The following review also proves that previous reviews are very important to customers, especially when they do not have enough time to compare

various products.

“I originally thought I’d get another Nexus because I’ve been really pleased with it. But then I remembered it’s 20 days until Christmas and I have 6 children to buy gifts for and looked for something that had good reviews, was a brand that I recognised and was in my price range.”

Evaluation of algorithm

To evaluate the algorithm, we compare the performance of this algorithm to three other algorithms in the area of extracting frequent aspects from reviews. The three algorithms are High Adjective Count (HAC) (Eirinaki *et al.*, 2012), the well-known TF, and TF*IDF. We perform this task the same as feature-based opinion mining and ranking. We compare the precision of the top-N results given by the four algorithms for various values of N. Precision in this context is defined as follows:

$$\text{Formula (4) Precision} = \frac{\text{number of relevant aspects}}{N}$$

An example of the comparison of the top-10 features for the review data set between the four algorithms is as follows:

Table 4 shows that the proposed method has performed better than the other three models. In the potential aspects found by TF*IDF, which has performed better than the other two, iPad and Samsung are brand names, tablet and device point to the product itself and time is not an aspect of a tablet. It is clear that the potential aspects found by the Aspect Finder are better suited as aspects of a tablet. As it is shown, the precision of Aspect Finder is a bit higher than the other algorithms. Moreover, when we lower the threshold and compare algorithms in the top 20 nouns, the precision of Aspect Finder is much better than the other algorithms.

Table 4: Comparing the Performance of to TF, TF*IDF and HAC Algorithms

| <i>Algorithm</i> | <i>Top 10 extracted aspects</i> | <i>Precision</i> |
|------------------|---------------------------------------------------------------------------------------------------------------|------------------|
| Aspect Finder | Tablet, Screen, Application, Price, Review, Size, Display Resolution, Battery life, Camera, Processor, Design | 9/10 |
| HAC | Tablet, Thing, Application, Time, Screen, Product, Device, Price, Year, Review | 4/10 |
| TF | Tablet, Screen, iPad, Application, Device, Android, Time, Samsung, Battery, Thing | 4/10 |
| TF*IDF | Screen, iPad, Application, Device, Battery, Android, Time, Samsung, Thing, keyboard | 5/10 |
| Common words | Screen, Application | 2/10 |

Determining the Opinion Score for each Frequent Aspect

In this step, the Opinion Scoring algorithm assigns scores to each aspect of the eight selected brands. The final score of each brand in each aspect is shown in Table 5. As it is shown in the table, the maximum average score

in all the selected aspects belongs to the Apple brand and it has achieved the highest scores in the aspects of “screen”, “design”, and “processor”. However, Apple has scored very low in the camera aspect. This shows that customers love the Apple brand but they are not much satisfied with the camera. Many negative adjectives such as “insufficient”, “not so great”, and “disappointing” have been used to describe iPad’s camera.

Table 5: Brand Scores in Each Aspect

| <i>Brand</i> | <i>battery life</i> | <i>size</i> | <i>processor</i> | <i>application</i> | <i>screen</i> | <i>resolution</i> | <i>price</i> | <i>camera</i> | <i>design</i> | <i>review</i> | <i>Average</i> |
|--------------|---------------------|-------------|------------------|--------------------|---------------|-------------------|--------------|---------------|---------------|---------------|----------------|
| Acer | 0.75 | 0.78 | 0.94 | 0.54 | 0.6 | 0.46 | 1.05 | 1.23 | 1.05 | -0.13 | 0.73 |
| Apple | 0.95 | 0.75 | 1.36 | 0.77 | 1.1 | 0.68 | 0.82 | -0.03 | 1.35 | 0.1 | 0.78 |
| Asus | 1.03 | 0.65 | 0.79 | 0.26 | 0.93 | 0.58 | 0.53 | 0.98 | 0.9 | 0.25 | 0.69 |
| Dell | 0.28 | 0.62 | 0.3 | 1.04 | 0.77 | 0.42 | 0.37 | 0.99 | 1 | -0.06 | 0.57 |
| Hp | 0.17 | 0.12 | 0.55 | 1.05 | 0.58 | 0.02 | 0.31 | 0.16 | 1.3 | 0.97 | 0.52 |
| Microsoft | 0.72 | 0.48 | 1 | 0.62 | 0.9 | 0.76 | 0.49 | 0.67 | 0.75 | -0.38 | 0.60 |
| Neutab | 0.4 | -0.08 | 1 | 0.84 | -0.12 | 0.14 | 0.66 | -0.59 | 1 | 0.009 | 0.33 |
| Samsung | 0.95 | 0.86 | 0.73 | 0.7 | 0.95 | 0.66 | 1.04 | 0.62 | 1.14 | 0.2 | 0.78 |

The following reviews clearly depict this result:

-“The rear facing camera is pretty low quality. As a camera intended to be used for actually taking pictures, it’s pretty inexcusable.”

-“The quality of these cameras are nowhere near the standards that one expects to see from a piece of technology, especially at the price that Apple charges.”

Following Apple, the second top average score belongs to Samsung tablets. Samsung Galaxy tabs are among the most wished ones for tablets in Amazon.com. This brand has scored first in the “size”, second in “price” and “screen”. The lowest score for Samsung is in the “review” aspect. Although customers love it, many negative reviews have been written about this product. However, some consumers have stated that the negative reviews on Samsung products are bogus. For example, one user said: “Product arrived on time and in perfect condition. Need I say more. All the previous reviews are bogus”. However, classifying reviews as bogus or truthful is outside the scope of this study.

Constructing the Perceptual Map

The final step of the perceptual map is the part when the maps are generated. We can easily draw two-dimensional maps for each 2-combination of the aspects and show the brands in that map. For example, Fig. 4 and Fig. 5 are perceptual maps for price-design and camera-review combinations.

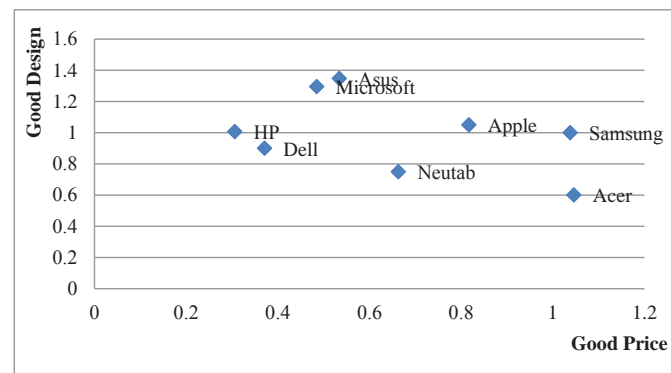


Fig. 4: Perceptual Map for Price and Design Aspects

As mentioned in earlier section, we used a K-means clustering method to put the brands in clusters based on all the important aspect scores. In order to determine the best number of K for the clustering task, we used the Silhouette Index. Silhouette Index shows how well each object (brand) lies within its cluster. The best K was determined as 3 and the clustering was performed using Matlab 2010. The results are shown in Table 6.

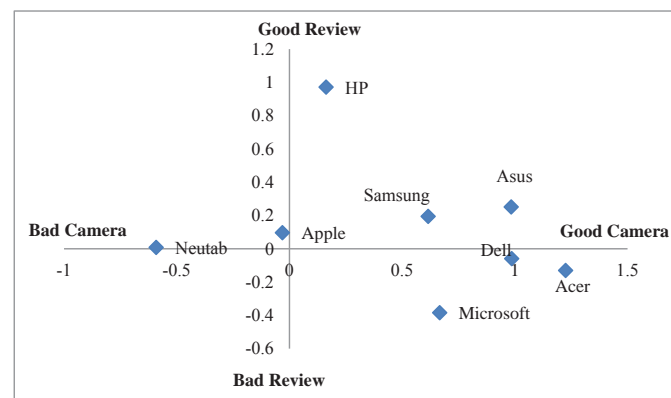


Fig. 5: Perceptual Map for Camera and Review

Table 6: Results of Brands Clustering

| Cluster | Brands in cluster | Average of aspect sentiment | Number of Most Bought | Percent of most bought | Number of Most Wished for | Percent of Most Wished for |
|---------|-----------------------|-----------------------------|-----------------------|------------------------|---------------------------|----------------------------|
| 1 | Apple, Samsung, Acer | 0.76 | 35 | 0.35 | 35 | 0.38 |
| 2 | Asus, Microsoft, Dell | 0.62 | 7 | 0.7 | 8 | 0.8 |
| 3 | HP, Neutab | 0.42 | 4 | 0.4 | 5 | 0.5 |

The first cluster consists of Apple, Samsung, and Acer brands. The average sentiment score for all the aspects of

these three brands is higher than other clusters. Therefore, we can say that this cluster contains the brands that have

the best perception by the customers. In order to evaluate the clusters, we have used two lists from Amazon.com: the “mostly bought tablets” and the list of “most wished for” tablets. Each of the two lists contains a hundred tablet models. We have counted the number of tablets in these two lists, which have a brand the same as the brands in the three clusters. As shown in Table 6, the percent of the most bought and wished for tablets comply with our clustering method. The brands in the first cluster, which has the highest score, has been purchased more than other clusters, and a higher percent of them are among the most wished for tablets. This result shows that the proposed technique is effectively constructing the perceptual map and is showing the brand positions correctly in the maps.

CONCLUSION

The availability of online product reviews on the web has brought new opportunities for marketers to gain information of consumers’ opinions, attitudes and perceptions without going through time-consuming and expensive surveys. The process of extracting consumer opinion from text data is called opinion mining and is currently one of the most challenging research topics in this area. Opinion mining is concerned with analyzing the opinions of users towards a particular subject expressed in the form of natural language. In this paper, we have proposed an innovative methodology based on opinion mining techniques to build a brand perceptual map using online product reviews. The process consists of four stages: (1) selecting the competing brands, (2) mining reviews to discover product aspects that are important to customers using the Aspect Finder algorithm, (3) determining customer sentiment score for each aspect of each brand using the Opinion Ranking algorithm, and (4) constructing the perceptual map by clustering the brands using the aspect scores.

We applied the algorithm to the data of the tablet reviews downloaded from Amazon.com. The most important aspects found by the Aspect Finder algorithm are screen, application, price, review, size, display resolution, battery life, camera, processor, and design. Results show that the proposed technique is very efficient in finding the most important aspects. Furthermore, comparing the clustering results to the data of most wished for and most bought products from Amazon.com itself, we can conclude that the final perceptual model constructed by the method complies with the real customer’s opinions.

Despite all the advantages of the proposed approach, it has several limitations. First, this study has used basic sentiment analysis techniques based on MPQA dictionary. In the future, the research could be improved by incorporating machine learning techniques. Second, the validation of the proposed method is not wide enough. Future research can apply this method to other domains such as services, tourism, etc.. Third, we have established out research on the hypothesis that all the available reviews are truthful. However, it is known that bogus reviews exist on websites like Amazon.com. Future research can be performed to detect and remove bogus reviews.

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