Keywords: Drug; Medicine; Pharmacy; Opinion mining; Rating; Customer review; Social media; Sentiment; Polarity

Introduction

Social media is playing a crucial role in this era nearly in every field like education, health, medical sciences, e-commerce, marketing, finance, travel, demographics, etc. [1]. With the growth of online social networks, everyone can easily interact and engage through different modes and mediums of communication with each other and get the latest updates of information on different fields. One of the major adoptions in a field of information technology is the sentiment analysis which targets to determine the context [2], content and sensitivity of data with respect to any topic or the overall contextual divergence of a text or file. To extract and identify subjective knowledge on huge volumes of digital up-to-date data, Sentiment Analysis (also known as Opinion Mining) is vastly applied in a wide variety of different applications, extending from person to person. This can be well-thought-out as a criterion of judgment and evaluation of a person approach towards subject or topic [3]. Thus, opinion mining or sentiment analysis is used to deal with cost-effective and detailed information [2] related to extracting large volumes of data that helps to determine the product sentiment ratings (also particularly in pharmaceutical industries). The online blogs and reviews are helpful measure for rating the product and its impact day-to-day among people socially.

With the context of health and pharmacological sciences, the patients may also be able to share their reviews and experiences of indications and impact of a medicine so that it can help to rate the medicine according to its usage, cost and chronic effects [4-18]. Several studies carried out to concentrate on the patient’s information and their related matters particularly reviewing patient’s medication data [12] with varying costs and usage of a drug. In this research, we intend to address customer review mining for pharmacy product evaluation and planned a general pattern (based on lexicon-based approach) for mining the customer reviews [17] to evaluate performance measure of a pharmacy product with grading functionalities by analysing different blogs and posts.

The research engaged the individual’s users to show online opinions of other users about medicine potential influence. With the explosion of Web 2.0 platforms [3] such as discussion forums, peer-to-peer networks, blogs, and various other types of social media [13], consumers are able to share their product experiences and opinions, positive or negative reviews, regarding any product or service [2]. Marketers are always needed to observe information related to their products to gain knowledge of sales, popularity according to usage or demand, etc., which must be necessary to improve the quality of the product and market.

Related work

Contextual analysis of health content: Through online social networking, the communication is vastly improved and different interest of information is available on internet easily at the open pace. Different kind of information needs to share to chronic highlights of potential benefits and harms and availability of utilities of certain insights, items, people behaviours, products, etc. [12]. One of the important fields is the medical and health sciences to consider social aspects through online discussions, blogs, reviews, and online surveys, etc. [16]. The health-related content shared through various online feedbacks or reviews contains hidden sentiment [18] patterns that are
need to be identified and extracted through different sources ranging from marketing to service the drugs in a competent way [14]. In this regard, the online mechanism is very popular these days for online shopping, different products through different websites like online purchasing of medicine at door step. After purchases, several websites and blogs offer customers rate their products according to their satisfaction and quality of products and services and also by providing feedback facility by which customer can comment on a particular medicine or on quality of services.

The number of posts available online are analysed to find out responses based on customer reviews available on different online pharmaceutical stores websites in order to detect hidden sentiments on unstructured text data. The information is classified into three forms of orientation as Satisfied, Dissatisfied, and Disinterested based on the result satisfaction obtained by the sentiment classifier from the different datasets [15]. However, the results vary from domain to domain; therefore, a general lexicon is considered using drugs reviews from different sites and blogs related to health, diseases, and drugs [17].

The online reviews area is widespread that provides economical and flexible results by proposing primarily based probabilistic modelling structure [7]. A basic task is to analyse and classify the divergence of a given text at the word, sentence or feature/aspect level related to health content [16]. Several posts are analysed and tested from different online social networking websites like Facebook, Twitter, Google+, etc. [12] showed opinion mining based on customer reviews and ratings is possible with the combination of generalized as well as domain-specific sentiments achieve the desired results.

Mechanism of medicine evaluation: Several measures have been taken to find out the favourable and adverse effects of drugs using a classifier. Numerical ratings are used on a drugs data and the data was evaluated using numeric star rating and word count in a particular or number of reviews associated with each medicine to evaluate the performance of a medicine and experience of a customer with that drug. The mechanism to find out the accuracy, quality, effectiveness, limitations, adversaries related to medicine and health was obtained using association rule mining to evaluate correlations among different parameters between drugs and favourable or adverse reactions mentioned in posts online through customer experiences and reviews [1]. A lexicon based manual annotation was developed of user’s posts and equitable accuracy using lexical matching was achieved [17–19]. Comparative product review mining was also done by analysing pros and cons from a big volume of customer reviews online through different pharmaceutical stores websites [3]. Different models were testified to mine valuable customer info intelligently, such as perspectives extraction contrastively, high-quality review recommendation [20], review summarization, etc. CRFs model was used to extract different product information, related reviews in order to evaluate the ranking of a medicine currently and in a near future.

Methods

Data requirement analysis

As previously discussed there are several online platforms (social networking websites, blogs, forums, etc.) are excessively available where people interact and communicate with each other among the social network and usually involves in different activities from chatting to uploading profile pictures or documents, downloading files, liking, disliking posts (like on Facebook, Twitter) [20], giving reviews on certain topics or products. Particularly, in the domain of pharmacy, there are several online websites that deal with large number of customers involved in selling and buying different medicines and customers may place reviews about different pharmaceutical products or the purchases they have made. The customer reviews actually is the symbol of representing their satisfaction or dissatisfaction with the product or service [10]. Therefore, the pharmaceutical reviews in the form of text is required to perform sentiment analysis and computation that would help customer as well as business to identify and improving the quality and features probed by the consumer behaviour (in the form of review) [18].

The research intends to evaluate the quality of drugs of different categories that would be helpful in purchasing decisions. To conduct a research, two online websites reviews data on different drugs are analyzed. Sentiment approach is applied on various customer reviews from the two different websites on different medicines and assesses the reviews either holds positive, neutral, or negative words in order to find out the polarity in the review.

Data collection

The methodology is used in this research is the collection of different online reviews from customers on different medicines to perform sentiment analysis using lexicon-based technique (specifically corpus-based approach that helps in solving different problems of determining opinion words by means of context specific orientations), in order to determine the polarity associated with the sentences or words in the customer reviews [4]. The purpose to identify the polarity in a sentence is helpful to find out customer likes and dislikes towards products. In this way, one can distinguish among good and bad medicines in order to improve the quality and productivity of the medicines based on customer reviews sentiment analysis [16]. Simply, the data containing customer reviews on pharmaceutical products have been gathered from two different online websites. The drugs are grouped into nine different categories of allergy and sinus, children’s healthcare, cough, cold and flu, dehydration, digestive health, eye and skin treatments, pain and fever, sexual wellness and women health. In each category, reviews on approximately three drugs have been analysed for sentiment evaluation. For eight categories, the reviews are collected from livewell.pk [11] and for category “Sexual Wellness” the data is gathered from kaymu.pk [9]. The reviews are then separately analysed for each category. Table 1 contains the list of medicines with nine categories.

Sampling methods

There are various tools and techniques of sentiment analysis to detect hidden emotions in any phrase or a sentence to find out the associated polarity with them. Sentistrength is one of the tools which are used to perform sentiment analysis specifically selected for this research. It basically estimates the strength in a phrase or in a sentence as a positive, neutral or negative sentiment in the text. It practices a sentiment lexicon for assigning scores to positive, neutral or negative phrases in the text [5]. It essentially organizes human -level accuracy for small social web texts in English, except political texts. SentiStrength principally reports two types of sentiment strengths [6].

-1 (not negative) to -5 (extremely negative) 1 (not positive) to 5 (extremely positive). SentiStrength can also report binary (positive/negative), trinary (positive/negative/neutral) and single scale (-4 to +4) results [6]. SentiStrength was originally developed for English language and optimized for general small social web texts but can be configured for other languages and contexts by changing its input files [6].
trinary methodology is basically applied in this research on different medicine reviews. The review on each medicine in each category was analysed by splitting sentences or phrases into parts separately (with respect to full stop). Each sentence is then drastically given a trinary test to detect whether the text hold the positive (+1), neutral (0) or negative (-1) sentiment. The (+1) indicates the positive sentiment, (0) indicates the neutral sentiment and (-1) indicates the negative sentiment as a result in a customer reviews [3]. The positive, neutral or negative score of each sentence in a review is computed by averaging the scores together. Thus, the sentiment of a given review is measured by averaging the trinary results of all sentences within that review or comment individually medicine wise and category wise separately.

Results

The medicine wise and category wise average polarity (trinary results) are presented in Table 2. All the nine categories are presented as major evaluation metric for the medicines based on customer reviews. Each term or word in a sentence is analysed by parsing lexicon based trinary sentiment method to classify the sentence as positive, neutral or negative sentiment [5]. The sentiment term hold the sentiment score according to the strength. There are three cases to compute sentiment score in each sentence in a review. In first case, the overall result (+1) is determined by positive > (3) if possible score. terms are greater than negative score terms, the overall polarity of a sentence is (+1) i.e., positive. In second case, the overall result (0) is determined by positive =1 negative = (-1) if positive score terms and negative score terms are equal means no sentiment term is detected or found, the overall polarity of a sentence is (0) i.e., neutral [6]. Likewise, in third case, the overall result (-1) is determined by positive < negative if positive score terms are lesser than negative score terms, the overall polarity of a sentence is (-1) i.e., negative [6].

The graph in Figure 1 illustrates the category wise result of medicines with comparison to the number of reviews in each category with respect to positive, neutral and negative polarity. The result presented graphically, clearly specifies the categories with totally positive reviews, positive and neutral reviews, negative and neutral reviews and mixed reviews among different medicines in each category according to the polarity distribution.

The precision is defined as a metric for the evaluation of medicines based on customer reviews for individual category as follows [4]:

Precision = Number of Positive Reviews for each Medicine Category/Total Number of Reviews for each Medicine Category

All nine medicine categories have been presented to extract positive reviews from each category [19]. The customers have posted their reviews on medicines belonging to different categories [4]. The positive reviews particularly have been selected in order to determine the most popular category of medicines evaluated with respect to customer satisfaction in terms of product quality, price, usage, and impact. Category 6 and 8 has been positively evaluated by determining the most accurate sentiment rating mechanism and the research can extend to more pharmaceutical categories from several resources.

Figure 1: Polarity Distribution among Medicine Categories with comparison to the Number of Reviews.

Figure 2: % Precision of Medicine Categories.

Conclusion

In this paper, the sentiment analysis using lexicon-based approach is presented on various pharmaceutical products from two different websites based on customer review mining. Nine distinguished categories of medicine were chosen to apply corpus-based sentiment method using SentiStrength tool and trinary results were obtained from the customer reviews on medicines and polarity was found as positive, neutral or negative by breaking sentences in a review and applying sentiment method to detect sentiment related with the sentences in a review. Then, finally averaging the scores of sentences in a customer review about medicines were computed. The high percentage of precision implies the most satisfactory and consistent medicine category in terms of usage, quality, price and frequency of purchases. However, in some reviews, the sentences are not fully analyzed for sentiment detection.

As presented in this research through experiment, the medicine categories: eye and skin treatments and sexual wellness gives the highest and satisfactory precision as compared to other categories based on the evaluation of online customer reviews. A future challenge is to fully analyse the sentences and phrases in reviews in order to develop proper accurate sentiment rating mechanism and the research can extend to more pharmaceutical categories from several resources.
| Category 'Allergy & Sinus' | Telfast BD Fexofenadine HCI Tablets |
|--------------------------|-----------------------------------|
|                          | Kestine Ebastine Tablets          |
|                          | Senergy-OD Tablets                |
| Category Calpol 6 Plus Suspension Syrup | Calpol 6 Plus Suspension Syrup |
|                          | Disprol Paediatric Suspension Syrup |
|                          | Tempol 6+ Suspension Syrup        |
| Category 'Cough, Cold and Flu' | Strepsils Original Lozenges |
|                          | Actifed-P Cold Tablets            |
|                          | Fexet Fexofenadine HCl Tablets    |
| Category 'Dehydration'   | Orazaf Powder                     |
|                          | OEM Orange Powder                 |
|                          | Peditra Lemon Powder              |
| Category 'Digestive Health' | Mucaine Suspension Syrup          |
|                          | Dicaine Suspension Syrup          |
| Category 'Eye & Skin Treatments' | Xyzal Levocetirizine Dihydrochloride Tablets |
| Category 'Pain & Fever' | Polyfax Skin Ointment For External Use Only Antiseptic |
|                          | Paracetamol Suspension Syrup      |
|                          | Panadol Extra (Paracetamol with Caffeine) Tablets |
|                          | Voltra Emulgel Gel                |
| Category 'Sexual Wellness' | Pfizer Viagra Pills              |
|                          | Fertilex (For Men)               |
| Category 'Women Health'  | Fertile Fast Conception Capsules  |
|                          | Nutrifaxor Evening Primrose Oil   |

Table 1: Medicines with Nine Categories are listed below.

| Categories with Medicine Listing | Medicine wise | Category wise |
|----------------------------------|--------------|--------------|
|                                  | Average      | Average      |
|                                  | Polarity     | Polarity     |
|                                  | (Trinary Results) | (Trinary Results) |
| Category 'Allergy and Sinus'    |              |              |
| Telfast BD Fexofenadine HCI Tablets | (0) Neutral | (1) Positive |
| Kestine Ebastine Tablets        | (1) Positive | (1) Positive |
| Senergy-OD Tablets              |              |              |
| Category 'Children's Healthcare' |              |              |
| Calpol 6 Plus Suspension Syrup  | (0) Neutral | (0) Neutral |
| Disprol Paediatric Suspension Syrup | (-1) Negative | (1) Positive |
| Tempol 6+ Suspension Syrup      | (1) Positive | (1) Positive |
| Category 'Cough, Cold and Flu'  |              |              |
| Strepsils Original Lozenges     | (0) Neutral | (-1) Negative |
| Actifed-P Cold Tablets          | (-1) Negative | (1) Positive |
| Fexet Fexofenadine HCl Tablets  | (0) Neutral |              |
| Category 'Dehydration'          |              |              |
| Orazaf Powder                   | (0) Neutral | (1) Positive |
| OEM Orange Powder               | (1) Positive |              |
| Peditra Lemon Powder            | (0) Neutral |              |
| Category 'Digestive Health'     |              |              |
| Eno Lemon Powder                | (1) Positive | (-1) Negative |
| Mucaine Suspension Syrup        | (-1) Negative |              |
| Dicaine Suspension Syrup        | (-1) Negative |              |
| Category 'Eye and Skin Treatments' |              |              |
| Xyzal Levocetirizine Dihydrochloride Tablets | (1) Positive | (1) Positive |
| Polyfax Skin Ointment For External Use Only Antiseptic | (1) Positive | |
| Category 'Pain and Fever'       |              |              |
Conflicts of Interests

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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| Table 2: Average Polarity Results. |
|-----------------------------------|
|                                    |
| Allergy and Sinus | Children’s Healthcare | Cough, Cold and Flu | Dehydration | Digestive Health | Eye and Skin Treatments | Pain and Fever | Sexual Wellness | Women Health |
| Number of Positive Reviews | 2 | 1 | 0 | 1 | 1 | 2 | 1 | 2 | 1 |
| % Precision | 67 | 33 | 0 | 33 | 33 | 100 | 33 | 100 | 33 |

| Table 3: Number of Positive Reviews with precision (in %). |
|----------------------------------------------------------|
|                                                          |
| Allergy and Sinus | Children’s Healthcare | Cough, Cold and Flu | Dehydration | Digestive Health | Eye and Skin Treatments | Pain and Fever | Sexual Wellness | Women Health |
| Number of Positive Reviews | 2 | 1 | 0 | 1 | 1 | 2 | 1 | 2 | 1 |
| % Precision | 67 | 33 | 0 | 33 | 33 | 100 | 33 | 100 | 33 |