ASPECT-BASED OPINION MINING USING MACHINE LEARNING MODEL

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Abstract : In modern world the development of web and smartphones increases the usage of online shopping. With the rapid development of E-Commerce, the number of customer reviews that a product received grows rapidly. For a popular product, there are a large number of reviews. This can confuse the customer to make an informed decision on purchasing the product, as well as for the manufacturer of the product to keep track and to manage customer opinions. Accordingly, polarity analysis has become increasingly popular and has emerged as a noticeable research trend. Polarity analysis of reviews based on sentence or document level often cannot show precise results, because of several attributes of the product included in one review sentence. This study uses aspect/feature level semantic analysis to realize the semantic analysis of reviews and propose a framework to focus on the aspect-based sentiment analysis. Experiments on a real-world case studies show that the system is feasible and effective.

***IndexTerms* - Aspect/feature level sentiment analysis, Polarity Analysis, Sentiment Analysis.**

I. INTRODUCTION

Increasing popularity and availability of internet online review sites, blogs, and social networking sites increase the contents rapidly day by day. It allows the users to write the opinions as reviews for various products or services. Sentiment analysis tries to determine the sentiment of a writer about some aspects and also the overall contextual polarity of a document. Sentiment Analysis (SA) or Opinion Mining (OM) is a process for tracking the mood of the people about any particular topic. Online shopping websites like Amazon.com are of specific interest for this task, as hundreds of thousands of user-reviews for tens of thousands of different products are hosted. However, those reviews are currently only of use to users who read them one by one. Using aspect-based sentiment analysis it is possible to analyze these reviews and predict opinions not only for a whole review or sentence, but on an aspect-level [4].

The majority of current sentiment analysis approaches tries to detect the overall polarity of a sentence (or a document) regardless of the target entities (e.g. restaurants) and their aspects (e.g. Food, price). By contrast, the aspect based sentiment analysis task is concerned with identifying the aspects of given target entities and estimating the sentiment polarity for each mentioned aspect.

The big difference between sentiment analysis and aspect-based sentiment analysis is that the former only detects the sentiment of an overall text, while the latter analyzes each text to identify various aspects and determine the corresponding sentiment for each one.

In other words, instead of classifying the overall sentiment of a text into positive or negative, aspect-based analysis allows people to associate specific sentiments with different aspects of a product or service. The results are more detailed, interesting and accurate because aspect-based analysis looks more closely at the information behind a text. Scientists, for example, analyze cells under a microscope so that the components can be better visualized, and aspect-based sentiment analysis follows this principal.

When talking about aspects, it means the attributes or components of a product or service e.g. 'the user experience of a new product', 'the response time for a query or complaint' or 'the ease of integration of new software'. Aspect-based sentiment analysis works in the same way as sentiment analysis. It takes all that data – emails, chats, customer surveys, social media posts, customer support tickets etc. – and automatically structures it so that companies are able to interpret text entries from customers and gain meaningful insights. Not only does this help manager make key decisions based on insights from the customers, it also helps employees become more efficient and less frustrated with time-consuming, monotonous tasks.

Aspect-based sentiment analysis is particularly relevant at the moment because companies need to be more customer-centric than ever. This text analysis model lets businesses read between the lines, and hone in on the specific aspects that make the customers happy or unhappy. By gaining a deeper understanding, businesses are then able to create a seamless customer experience and increase customer retention.

The rest of the article is organized as follows. In Section 2, the research work which related to the aspect based sentiment analysis is summarized. Then, a framework of aspect based sentiment analysis system is designated in Section 3. Section4 has discussed about the implementation of aspect based sentiment analysis system. The case studies and related discussion are described in Section 5 and the work is concluded in Section 6.

II. RELATED WORK

There have already been multiple attempts for aspect-based sentiment analysis, using different approaches, using machine learning [3][6][7], as well as neural networks [2]. Most approaches so far were based on machine learning. In fact, in the annual SemEval competitions on aspect based sentiment analysis since in 2014and 2015, most teams decided to use machine learning techniques like support vector machines (SVM) or conditional random field (CRF) classifiers and scored the best results with those approaches. The aspect based sentiment analysis task was split into two tasks, aspect extraction and sentiment prediction. The winning team of 2015 in the aspect extraction task used CRF and modelled the aspect extraction as a multiclass classification problem and used n-grams and word clusters learnt from Amazon (laptop review task) and Yelp (restaurant review task). The winning team on the sentiment prediction task in 2015 used a maximum entropy classifier in its machine learning approach [1].

The usage of deep learning was mostly based on Wang's and Liu's work on aspect based sentiment analysis [2]. Using deep neural networks, a proof of concept has been provided, showing that deep learning algorithms are capable of potentially outperforming other implementations in aspect-based sentiment analysis. The practice of using word vectors to support machine learning and neural networks have been seen in multiple research papers [2][8][9] [10]. Wang and Liu used word vectors trained using the word2vec algorithm. While word2vec is a predictive model [11] [12] [13], there are other approaches like GloVe, which are count-based models. Baroni, Dinu and Kruszewski found out that predictive models are superior to count-based ones [14].

III. FRAMEWORK FOR ASPECT BASED SENTIMENT ANALYSIS

This section describes the framework of aspect based sentiment analysis using machine learning approach. Before starting any kind of text analysis, it is needed to gather information. Businesses have been collecting colossal amounts of data for years, but have only just started to realize the importance of all this data. There may many sources to gather business data. Internal data is the information that collected from incoming communication, such as emails, social media, reviews, surveys, and customer support tickets. External data is any data that's been made public by other organizations. The web is a hub of external information, and more and more companies are making the datasets public, as well as combining both internal and external data sources to optimize the business processes and influence key business decisions. Text analysis models, like aspect-based sentiment analysis, are intrinsic to handling large amounts of public data since they're able to automatically interpret data easily and quickly at a granular level, and help businesses solve problems.

After gathering data, the next phase is to create models – both sentiment and aspect models – to tag and classify the information that is most relevant to target business. Final Phase is to visualize the results to create an easy-to-understand visual report. Figure 1 shows the proposed framework of aspect based sentiment analysis.

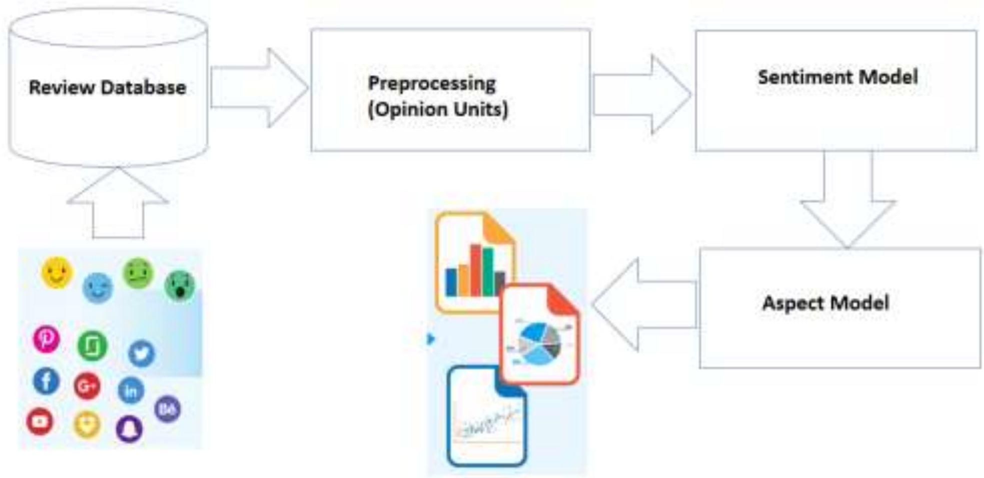

Fig.1. Framework of Aspect/Feature based Sentiment Analysis using machine learning approach.

IV. IMPLEMENTING ASPECT BASED SENTIMENT ANALYSIS

The reviews or opinion is collected from online shopping website or social networking website to mine the data and classifies the overall review into positive or negative categories. The datasets play important role in training of system.

4.1 Preprocessing Data with Opinion Units

Before building models, it's important to understand the mighty process of preprocessing data with opinion units. Opinion units are fragments of text that usually contain one sentiment and multiple aspects. Open-ended survey responses or product reviews, long or short, are likely to contain multiple opinions [15]. As an example of a short review: "I love Slack UX but I wish the pricing was more accessible to small startups." This review has multiple aspects and sentiments. It is a perfect opportunity to use the aspect-based model. But, before starting training the machine learning model, it's a good idea to preprocess data to analyze new data. First, it'll need to separate texts into smaller units, otherwise known as opinion units. It will be used above example can be separated into two opinion units:

"I love Slack UX" – this opinion unit is 'Positive '(sentiment) and is about 'UX '(aspect) "but I wish the pricing was more accessible to small startups "– this opinion unit is 'Negative '(sentiment) and is about 'Pricing '(aspect). Machine models that have been trained to detect opinion units are much more precise when it comes to analyzing data. Why? Well, it's a lot easier for a machine to understand a simple sentence, "I love Slack", which has one sentiment, than a more complex sentence, "I love Slack UX but I wish the pricing was more accessible to small startups", which has multiple sentiments. Heck, even humans will struggle with this; some will classify this sentence as positive, others will tag it as neutral, and others will even say it's a negative expression.

To summarize, opinion units break down 'several problems' into more manageable tasks that a machine can resolve faster and more accurately, for example tagging training data and connecting sentiments to specific aspects to gain better insights. There are some tools to get the pertained extractor for retrieving opinion units from text.

4.2 Creating Sentiment Analysis Model

Sentiment Analysis is a field within Natural Language Processing (NLP) that builds systems that try to identify and extract opinions within text [16]. With the help of sentiment analysis systems, this unstructured information could be automatically transformed into structured data of public opinions about products, services, brands, politics, or any topic that people can express opinions about. This data can be very useful for commercial applications like marketing analysis, public relations, product reviews, net promoter scoring, product feedback, and customer service. There are many methods and algorithms to implement sentiment analysis systems, which can be classified as: rule-based systems that perform sentiment analysis based on a set of manually crafted rules, automatic systems that rely on machine learning techniques to learn from data and hybrid systems that combine both rule based and automatic approaches.

• Rule-based Approaches: Usually, rule-based approaches define a set of rules in some kind of scripting language that identify subjectivity, polarity, or the subject of an opinion. The rules may use a variety of inputs, such as the following:

1. Define two lists of polarized words (e.g. negative words such as bad, worst, ugly, etc. and positive words such as good, best, beautiful, etc.).
2. Given a text:
   Count the number of positive words that appear in the text.
   Count the number of negative words that appear in the text.
3. If the number of positive word appearances is greater than the number of negative word appearances return a positive sentiment, conversely, return a negative sentiment. Otherwise, return neutral.

• Automatic Approaches: Automatic methods, contrary to rule-based systems, don't rely on manually crafted rules, but on machine learning techniques. The sentiment analysis task is usually modeled as a classification problem where a classifier is fed with a text and returns the corresponding category, e.g. positive, negative, or neutral.

• Hybrid Approaches: The concept of hybrid methods is very intuitive: just combine the best of both worlds, the rule-based and the automatic ones. Usually, by combining both approaches, the methods can improve accuracy and precision.

4.3 Creating Aspect Model

Creating an aspect-based model is similar to creating a sentiment model. The only difference is that when creating an aspect-based model, it'll need to define a set of tags that are relevant to target business and needs. Usually, when analyzing the sentiment in subjects, for example products, it might be interested in not only whether people are talking with a positive, neutral, or negative polarity about the product, but also which particular aspects or features of the product people talk about. For example,
"The battery life of this camera is too short. "The sentence is expressing a negative opinion about the camera, but more precisely, about the battery life, which is a particular feature of the camera. When analyzing the above example, it can be classifying with two tags: Feature and Ease of use. Then, it will be analyzed by means of the respective confidence. Here, some tools can be used to detect that a review has mentioned.

V. CASE STUDIES AND RELATED DISCUSSION

5.1 Aspect based Sentiment Analysis in Brand Monitoring

Not only do brands have a wealth of information available on social media, but they also can look more broadly across the internet to see how people are talking about them online. Instead of focusing on specific social media platforms such as Facebook and Twitter, it can target mentions in places like news, blogs, and forums –again, looking at not just the volume of mentions, but also the quality of those mentions.

In the United Airlines example, for instance, the flare-up started on the social media platforms of a few passengers. Within hours, it was picked up by news sites and spread like wildfire across the US. News then spread to China and Vietnam, as the passenger was reported to be an American of Chinese-Vietnamese descent and people accused the perpetrators of racial profiling. In China, the incident became the number one trending topic on Weibo, a microblogging site with almost 500 million users. And again, this is all happening within mere hours and days of when the incident took place.

Around Christmastime, Expedia Canada ran a classic "escape winter" marketing campaign. All was well, except for their choice of screeching violin as background music. Understandably, people took to social media, blogs, and forums. Expedia noticed that and removed the ad. Then, they created a series of follow-up spin-off videos: one showed the original actor smashing the violin, and in another one, they invited a real follower who had complained on Twitter to come in and rip the violin away. Though their original product was far from flawless, they were able to redeem themselves by incorporating real customer feedback into continued iterations. Using sentiment analysis (and machine learning), all chatter around the brand can be automatically monitored and detected this type of potentially-explosive scenario while still having time to defuse it.

5.2 Aspect based Sentiment Analysis in Customer Feedback

Social media and brand monitoring offer people immediate, unfiltered, invaluable information on customer sentiment. In a parallel vein run two other troves of insight –surveys and customer support interactions. Teams often look at their Net Promoter Score (NPS), but this analyses can also be applied to any type of survey or communication channel that yields textual customer feedback. NPS surveys ask a few simple questions – namely, would you recommend this company, product, and/or service to a friend or family member? and why? –and use that to identify customers as promoters, passives, or detractors. The goal is to identify overall customer experience, and find ways to elevate all customers to "promoter" level, where they theoretically will buy more, stay longer, and refer other customers. Numerical survey data is easily aggregated and assessed, but we want that same ease with the "why" answers as well. A regular NPS score simply gives a number, without the additional context of what it's about and why the score landed there. Sentiment analysis takes it that step further.

5.3 Aspect based Sentiment Analysis Customer Support

All people know the drill: stellar customer experiences is equal to the more probable returning customers. Particularly in recent years, there's been a lot of talk (rightfully so) around customer experience and customer journeys. Leading companies have begun to realize that oftentimes how they deliver is just as (if not more) important as what they deliver. Nowadays, more than ever, customers expect their experience with companies to be immediate, intuitive, personal, and hassle-free. In fact, research shows that 25% of customers will switch to a competitor after just one negative interaction.

Some analysis has been done on how the four biggest US phone carriers (AT&T, Verizon, Sprint, and T-Mobile) handled customer support interactions on Twitter. Tens of thousands of tweets mentioning the companies (by name or by handle) were downloaded, and ran through a sentiment model to categorize each tweet as positive, neutral, or negative. Then new Insight Extractor was used, which reads all text as one unit, extracts the most relevant keywords, and returns the most relevant sentences including each keyword.

- Here's some insights:
- T-Mobile had far and away the highest percentage of positive tweets.
- Verizon was the only company with more negative tweets than positive ones.
- Top keywords for positive tweets at Verizon included typical terms such as "new phone," "thanks," and "quality customer service." Key sentences were typical, formal, somewhat dry interactions between the team and followers.
- Top keywords for positive tweets at T-Mobile included names of people on their customer support team, because their team runs higher engagement, back-and-forth about anything type conversations with followers.

To sum up, this could imply that a more personal, engaging take on social media elicits more positive responses and higher customer satisfaction.

5.4 Sentiment Analysis in Product Analytics

In our agile world, we've learned that products are best built by prototyping early, soliciting feedback frequently, and continuing to iterate and improve. But for many product teams, soliciting frequent feedback can be the trickiest part. How do you narrow down which customer segment to ask? How do you sort through and weigh all their feedback? This is exactly where sentiment analysis can change the game. Whether by analyzing surveys, customer support interactions, or social media, machine learning enables to assess huge amounts of product feedback at once.

Sentiment analysis on customer support interactions have executed and used those insights to empower everyone in company – not just the support agents. So when a customer mentions that they're having difficulty with X or that they'd like to see Y, the information directly to the people who make and manage the products. Real feedback come from the customers, directly reaching the ears of the people to whom it mattered most. As any great product team listens to the customers and meets their needs. All too often, all it takes is simply equipping the team with the right insight.

5.5 Sentiment Analysis in Market Research and Analysis

And as a final use case, sentiment analysis empowers all kinds of market research and competitive analysis. Whether you're exploring a new market, anticipating future trends, or keeping an edge on the competition, sentiment analysis can make all the difference.

An analysis was conducted about how people feel about hotels in several major cities around the world, more than one million reviews from TripAdvisor was scraped and analyzed. Hotels in London, Paris, New York, Bangkok, Madrid, Beijing, and Rio de Janeiro were looked.

Here's some insights:

- Reviews were mostly positive –on average, 82% of the things people wrote were tagged with a positive sentiment:
- London hotels got the worst reviews.
- London was reviewed as dirtier than New York and with the worst food overall.

The keyword extraction module was used to analyze the actual content of the positive/negative reviews, and found a few more interesting insights:

- "Cockroaches" appears only in Bangkok –watch out!
- "Croissants" appears only in Paris (as it might be expected). Shockingly, though, they appear to be a letdown –reviewed almost exclusively in a negative context. With a closer dive, it can be seen that was more a reflection on the subpar hotel breakfast food than on the city itself.

VI. CONCLUSION

Aspect based sentiment analysis is a widely explored research area and lot of applications are associated with it. The accuracy is still a major issue which affects the classification of reviews and rating. In this work, we have shown that our proposed approach of improving the performance of aspect-based sentiment analysis by using machine learning methodology. Aspect-based sentiment analysis can be used to make sense of all business review such as understanding specific aspects that customers like and dislike about your brand, getting valuable, granular-level insights from customer feedback, analyzing service and product reviews to discover the successes and failures of your brand, and compare them to your competitor's, tracking how customer sentiment changes toward specific features and attributes of a service or product and determining if customer segments feel more strongly about a specific feature, for example an older demographic might find a travel website harder to navigate than a younger demographic.

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