Journal of ISOSS
2017 Vol. 3(1), 145-156

A COMPREHENSIVE STUDY ON SENTIMENT ANALYSIS

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ABSTRACT

Social media has recently become as a powerful weapon people use for online discourse, creating content, share it and network with other individuals at a phenomenal frequency. Human nature exhibits the tendency to express their emotions towards current happening, news, products or any potential topic and social media is the most fertile platform for the purpose. These comments, discussions, reactions and feelings have substantial influence on concerned parties. The field of sentiment analysis is related to mine meaningful information out of this text so that affected individuals or communities can handle situation positively or plan future outcomes. This paper is focused at sentiment analysis, analyzing work done in various languages, common techniques utilized and the type of data set being employed. It presents a comprehensive study on sentiment analysis generalizing the prevailing trends, techniques and issues in the field. It also provide future directives for this field deliberating about the areas which need due attention.

KEYWORDS

Sentiment Analysis, Natural Language Processing, Social Media Analytics.

1. INTRODUCTION

The escalation in usage of social has influenced community in numerous ways; work, personal life, politics, communication patterns, the way people consume/rate product and services, stress levels in personalities and most significantly the decision making process of an individual in any aspect. The prevalent espousal of social media is established in social nature of human communications, making it very promising for people to express their opinion, becoming active participant in virtual community and collaborating remotely. Statistics of 2015 demonstrates this ever increasing indulgence of individual in social media, Facebook [1.59 billion] and twitter [302 million] affirms to interest colossal number of active user[1]. Other facts reveal that 91% of online adults are spending 28% of their time on social interactive forums[2].

With social media and user-generated content exploding the web, vendors got enthusiastic to mine this substantial data set for obvious meaning, but they soon discovered a novel challenge: to know that someone is talking about a particular topic/service/brand is far less important in comparison to know how they are feeling and conversing about it. This is known as sentiment analysis or opinion mining. Numbers divulge that people are extensively using social media, expressing their positive opinions or negative apprehensions online. Consequences are definitely being wielded by these sentiments. Users of social forms are not just merely passive entities, for instance YouTube's scrutiny proclaims that 100 million people take some sort of social action (commenting, thumbs up or thumbs down) on video they view. Facebook (like, dislikes for the service/opinion/event) and twitter (hashtags) also broadcasts for identical notion Fan (2014). The dynamics of online discourse is challenging to manipulate but social media usage pattern, the amount of information being posted and perceived is deliberated to be an opportunity of gaining collective perception and wisdom of the community. As an aftermath the concept of sentiment analysis or opinion mining is broadly being acknowledged and employed by vendors to enhance their business/products/services.

This paper is aimed at presenting a comprehensive analysis of sentiment analysis and is structured as follows: Section 2 elaborates sentiment analysis briefly, it also presents an overview of what social media analytics is and how it is related to sentiment analysis. Moving further section 3 focuses at detail illustration of techniques proposed in this domain particularly in different languages. This section categorizes data set employed, technique utilized and result generated. Section 4 comprehends about the findings and conclusion of the analysis, deliberating about future directives for this field.

2. A BRIEF OVERVIEW OF SENTIMENT ANALYSIS AND SOCIAL MEDIA ANALYTICS

Sentiment analysis, broadly termed as opinion mining is a challenging discipline which aims at analyzing people sentiments, opinions, assessments, evaluations, attitude, behaviors, appraisals, feelings and emotions concentrated towards objects such as establishments, services, products, individuals, concerns and events. Pang (2008). Sentiment analysis predominantly emphasizes on visions which express/infer affirmative or undesirable sentiments.

Opinions are key drivers to human activities; most significantly in decision making process other people's point of view is prime influencer. Emergent social media (blogs, forum discussion, comments, and postings) empowers individual of distinct creeds to conveniently express their opinions regarding any entity thus effecting other people decision. This makes content in social media vital for ranking and enhancing particular services, business and products. Consequently organizations, businesses and individually are particularly interested to know what is being conversed about them Liu (2012).

These all factors determine the need of sentiment analysis application. These applications vary widely in domains such as consumer services/products, healthcare, social events and many more. Feldman (2013). Sentiment analysis has been handled as natural language processing (NLP) task and executed at three levels:

- **Document/Snippet level**
  Comprehensive document conveys positive or negative sentiments as a whole. Commonly referred as document-level sentiment classification is reducing the document to one opinion score. Turney (2002) and Pang (2004).

- **Sentence level**
  Sentence evaluation to define if it expresses negative, positive or neutral feeling. Kim (2004) and Hu (2004).

- **Aspect level**
  This is finer-grained scrutiny; it focuses at opinion itself rather than evaluating sentences, phrases, clauses or any other document construct. Wilson (2005) and Agarwal (2009).

  There are two basic techniques to perform sentiment analysis. Some researchers have combined these both techniques to gain a wider perception. Each technique is applied in accordance to its own strength and weaknesses. In next section these techniques are being discoursed briefly:

- **Machine Learning Based Techniques**
  In this technique two documents set are consumed. A training set is employed by automatic classifier to discriminate between various characteristics of document under evaluation and a test set is to rank the performance of classifier. Three popular review classifiers are Naive Bayes (NB), Support Vector Machines (SVM) and Maximum Entropy (ME). Vohra (2013).

- **Sentiment Lexicons**
  Sentiment lexicon embraces massive dictionary of lexical features for instance words which are broadly categorized in accordance to their particular semantic orientation as being positive/ negative. These lexicons are polarity based and can count the number of words representing positive/negative emotion. Most popular lexicons are LIWC, GI, Hu and Liu 2004 and Hutto (2014).

- **Hybrid Techniques**
  New research indicates that integrating machine based and lexicon approach renders much more truthful and exact results for analysis. Mudinas (2012) in his work proposes one such technique pSenti which is combined form of both approaches. This technique achieves high accuracy from machine learning and word stability from lexicons.

Social media analytics deals with evolving, developing and evaluating informatics tools to observe, scrutinize, review, and visualize social media data from a particular application. It is aimed at facilitating communication and extracting meaningful and intelligent pattern to support entities Zeng (2010).

This computer-medicated infrastructure is a substantial asset for considering social phenomenon alternating from customer priorities to business intelligence, social activism to extremism and overall practices of community predicted by social media activities. Social media analytics works on key performance indicator (KPI) or metrics which are customized for each and every business in accordance to its objectives. These metrics are then measured to render intelligent information Patel (2014). Basing on this intelligent information future decisions are taken and overall prevailing perspective of the society can be judged. In one of the profound work Fan (2014) deliberates comprehensively on the domain of social media analytics. The author describes the need, process, key techniques and business value of social media analytics. CUP framework is elaborated as three stage process;

- **Capture**
  Gather process and extract relevant information from the data.
- **Understand**
  Purify data from noise and perform analytic process (opinion mining/sentiment analysis, trend analysis, topic modeling).
- **Present**
  Evaluate finding and present them in a meaningful manner.

3. AN ILLUSTRATIVE PERCEPTION INTO TECHNIQUES PROPOSED FOR SENTIMENT ANALYSIS

With explosive growth of social media, its influential effects in consumers/business and society as a whole researcher becomes enthusiastic to work on this specific domain. Much work is done in this area converging towards exploring sentiment analysis, its definite requirement in this era, different frameworks for sentiment analysis and their comparison with other previously proposed techniques. Social media analytics and its various approaches are also being worked upon in previous research papers. In succeeding section, we present a brief summary on some of the significant papers in this specific field.

In this respective literature review the analysis of the work has been sorted specifically in accordance to various widely used languages. The review focuses on work established in diverse languages in consideration to sentiment analysis. Proposed techniques are also explored along with the type of data set utilized. We have chosen English, European Languages, Asian languages and some other prevalent languages as most of the significant findings have been progressed in these.

3.1 Sentiment Analysis in English Language

English is one of the most influential languages in the world. It's the most common foreign language that means two people coming from different places will use English to communicate. Most importantly content produced on net is mostly in English and that is why most profound work in sentiment analysis diverges towards English language. This section analyzes some part of it.

Bollen (2011) deliberates that public moods are directly relative to prevalent social/economical happenings that are taking place in definite time period. Author has extracted his judgments employing sentiment analysis on twitter feeds. An analytic tool PMOS; Profile of mood state is used to map different variation of mood on tweets extracted. Six moods dimensions are measured and then co related with surroundings events. In this work author explores the mood patterns generating fluctuations in socio/economic indicators in the time period of 1 August to 20 December 2008. The conclusion represents the author speculations positively as he has presented the score of various mood dimension and corresponding endeavors in community. In the following year Wang (2012) describes a system for real-time study of public sentiment about presidential candidates in the 2012 U.S. election as spoken on Twitter. They collected more than 36 million tweets about the 2012 U.S. presidential candidates, a one fourth million per day on average. Training data contains of almost 17000 tweets (56% negative, 16% positive, 10% uncertain and 18% neutral).Features are intended from tokenization of the tweets that tried to maintain punctuation that may possibly indicate sentiment, emoticons and exclamation points for example. Also twitter specific occurrences (e.g., extracting integral URLs). Based on the data the classifier achieves at 59% precision on the four group categorization of positive, negative, neutral, or unsure.

Qadir (2013) presents a bootstrap algorithm, which automatically learns hashtags in tweets that convey some specific emotions. Initial training data is labelled with seed hashtags of each data, emotion classifier are trained which then generate score of each emotion hashtags in tweets. Authors demonstrates that this bootstrap algorithm improve emotion classification as compared to N-gram classifier. This approach does not focus on any language, author plans to work on prominent languages in future but for experimentation purpose English language is used in this research. In very next year Argueta (2014) proposed a multilingual (English, Spanish, French) system with a computationally inexpensive approach to sentiment analysis of social data. The experiments demonstrate that our approach performs an effective multi-lingual sentiment analysis of micro-blog data with little more than a 100 emotion-bearing patterns. The proposed framework consists of two stages: the Filter stage and the Refine stage. Given a set of micro-blog posts containing a query term, the Filter stage utilizing n-gram patterns first detects the language of all the micro-blog posts. Then it obtains the polarity (negative, positive) by utilizing a classifier trained with n-gram features at the character level. The Refine stage utilizing symmetric patterns performs a finer analysis of the posts to classify the ones that the Filter stage left out. The results show that overall accuracies of over 80% can be obtained for all languages. These all findings are summarized in Table 1.

Table 1
Sentiment Analysis in English Language

Year	Author	Proposed Technique	Dataset	Results
2011	Johan Bollen	Psychometric instrument PMOS is employed	Corpus of 9,664,952 tweets	Valid results detecting public sentiments in accordance with socio-economic events.
2012	Hao Wang	System model utilizes techniques of tokenization and classifier	Training data of 17000 tweets is extracted from 36 million election relevant tweets.	Precision of 59 % is achieved by evaluating tweets as positive, negative, uncertain and neutral.
2013	Ashequl Qadir	A bootstrap algorithm which automatically learns hashtag conveying emotions.	Created emotion hashtag list comprising of 1000 hashtag for each emotion from data set of 2.3 million tweets.	Results demonstrate 8 to 9 % of improvement in F-measure as compared to classifier technique
2014	Carlos Argueta	A new architecture with filter and refine phases is proposed to classify emotions in tweets.	500 positive and 500 negative tweets are manually annotated for training and testing data sets.	80% of accuracy in evaluating emotions conveyed by tweets.

3.2 Sentiment Analysis in European Languages

This section primarily talks about European languages. Europe consists of fifty countries and various languages are being spoken in areas. We have chosen some major research and comprehensively summarized concepts. Sentiment analysis in German, Italian and Spanish has been elaborated.

Kasper (2011) aimed at presenting a system which analyze user comments and views about various hotels on different websites and then structuring it into meaningful manner so it can assist different travel planner. It specifically focuses German language. This very proposed architecture is part of BESAHOT project and works on three stages; data acquisition, data analysis and storage. Data is extracted with the help of crawler, then assigned polarity for a collective overview about particular hotel. Result shows some variation in accuracy but can be improved with some efforts in domain.

Basile (2013) established TWITA, a first corpus for Italian language consisting 100 tweets. This corpus also conveyed relevant information about tweets as location, username and location. Author has also derived a polarity lexicon for Italian language from existing resources such as SentiWordNet. These two are novel contributions for Italian language. This research work demonstrates assigning polarity to tweets and then evaluating it with manually annotated data. The system utilizes techniques such as tokenization and lemmatization for polarity detection. In the following year Ortigosa (2014) propose a system for sentiment analysis on Facebook posts specifically in Spanish language. Basically his system works by extracting sentiment by user post and then detecting emotional change over a period of time. The proposed application is named as Sentbuk which work on hybrid approach that is it combines machine learning and lexical based approaches. The key features of Sentbuk are to classify user message as positive or negative, track emotional changes in user profile, view friend emotional state and other statistics. It work in stages which can be named as preprocessing, segmentation, tokenization, interjection and polarity calculation, experimental results show accuracy of 83.27%. Table 2 demonstrates this analysis in summarized manner.

Table 2
Sentiment Analysis in European Languages

Year	Author	Language	Proposed Technique	Dataset	Results
2011	Walter Kasper	German	Proposed system works on tokenization, POS tagging and stemming.	A corpus of 1559 hotel reviews crawled from different websites is being utilized.	Variance in accuracy is depicted. It can be improved if multi-topic comments can be handled.
2013	Valerio Basile	Italian	Traditional techniques such as tokenization and lemmatization are employees for assigning polarity.	Two data set each containing thousand tweets is tested. First data set is generic and second is topic specific.	Results demonstrate that topic specific classification of tweets is harder as compared to general tweets.
2014	Alvaro Ortigosa	Spanish	Proposed Architecture named as Sentbuk works on hybrid approach; lexical based and machine learning.	Facebook comments, messages for one year have been extracted.	Overall accuracy of 83.27 % has been achieved in polarity calculation and tacking emotional change.

3.3 Sentiment Analysis in Asian Languages

Asia is largest continent out of all other continents in respect of area and population. It consists of forty-eight countries pre-dominant with Chinese, Indian, Japanese and Arab people. Several languages are being spoken in the area and this section is dedicated to sentiment analysis in some of the influential language.

Chunping (2014) proposed a novel architecture for performing sentiment analysis on Chinese news. Author emphasizes that news classification is important to control negative impact of news on individuals. The architecture of the system is divided into three stages; determining distinct topic sentence, extracting emotional dependent tuples (EDT) and finally sentiment analysis. Data set employed is Sixth Chinese Opinion Analysis Evaluation corpus (COAE2014). This corpus consist of 10000 text from several blogs, news and forums. For testing purpose 500 news has been selected from this corpus demonstrating positive results with an accuracy of 60 %. In the same year Abdulla (2014) took a step ahead proposing sentiment analysis in Arabic. The author clearly pointed out that no work has been done in Arabic Language. In this particular research author creates lexicons with three different techniques especially for Arabic, two corpus named as maktoob and twitter are being employed for testing purpose. The test demonstrates that integrated lexicon of 16,800 words generates most accurate results of 74%. Next paper deliberates about Bengali language. Hasan (2014) proposes a novel architecture utilizing contextual valence analysis for polarity. Author converts Bangla test into English and then uses WorldNet and SentiWordNet for polarity.

Moving further we consider about influential research publication in year 2015. Haruechaiyasak (2015) aims at aspect-based sentiment analysis of product review. The proposed approach intends at sentiment analysis of review and further comparing two product brands. It performs pattern analysis using dynamic filter terms. A tagged corpus is compared with tokenized and segmented reviews. The experimentation results show accuracy of 83 % and 77% for associative and comparative analysis. In next paper Hashemi (2015) presents a very interesting idea of analyzing comment on websites particularly about hijab. Comments are collected from 32 different websites and then lexicon –based analysis is performed. 69% accurate results are generated in experimentation.

Rehman (2016) took initiative and proposed a sentiment analyzer in particular to Urdu language, Author in his research work clearly established the dire need for considering Urdu language in this context, proposed a lexicon based architecture signifying the construction of corpus and algorithm. Urdu comments from various websites are used as experimentation data. Various parameters are evaluated such as precision, recall and F-measure. Analysis is concluded in Table 3.

Table 3
Sentiment Analysis in Asian Languages

Year	Author	Language	Proposed Technique	Dataset	Results
2014	Ouyang Chunping	Chinese	An architecture with three stages for news classification is proposed.	COAE2014 corpus of Chinese news has been utilized.	Positive results in F-measure, recall and precision have been demonstrated.
2014	Nawaf Abdulla	Arabic	Automated and manual lexicon construction and testing with two different corpuses.	Corpus of 1200 Arabic comments	74% accuracy has been achieved with integrated lexicon.
2014	KM Azharul Hassan	Bengali	Lexicon- Based valence determination	Bangla paragraphs are used as input which is converted into English first.	Results are convincing but some limitations are discussed.
2015	Choochart Haruechaiyasak	Thai	.A system of tokenization, segmentation and pattern formation is proposed.	Product reviews are used as input for the system	Accuracy of 77% and 83% for associative and comparative analysis
2015	Marzieh Hashemi	Persian	Lexicon-based system is proposed for sentiment analysis of Persian comments.	1000 comments are collected from 32 domestic websites. 700 for training and 300 for testing purpose.	Accuracy for comments polarity has been achieved by 69%.
2016	Zia-Ul-Rehman	Urdu	Lexicon-based architecture with algorithm for sentiment analysis on Urdu text	Urdu comments from various websites and blogs are being extracted	System demonstrates an overall accuracy of 66 %.

4. FINDINGS AND CONCLUSION

In this survey paper, my elementary goal was to explore the work done in the field of sentiment analysis. With the increased discourse of views and comment within an online forum, this new field has to be looked upon. Mining intelligent meaning out of big set of data proves to be beneficial to individual along with influential corporations and that is why researchers are really interested to dig into this particular field. In this section I will present comprehensive findings of the survey believing it will prove fruitful for future research efforts.

In the survey twenty-six recently published and cited research papers are being analyzed and summarized. These articles contribute influentially in the field of sentiment analysis. Generally it has been noticed that mostly proposed architectures are implemented on lexicon-based sentiment analysis as compared to other approaches. Machine learning approaches generate results with higher accuracy but it is not being used widely because of complex implementation requirements. Hybrid approach is also not been employed by researchers as it integrates two approaches. Coming towards the languages, English is the most explored with the domain of Sentiment analysis.

Resources such as lexicon and corpus are readily available for this particular language and much work has been done. Several other languages are also considered slightly and some languages are altogether ignored irrespective of the fact that sentiment analysis is desired for them as well. One major reason for this ignorance is lack of resources. Building resources being utilized in sentiment analysis task are still not available for many languages. One such language is Urdu which is deficient of even basic sentiment analysis tools. Some work has been done but it is not fully discovered. Secondly information from websites, online forums, websites and micro-blogs is a great resource for sentiment analysis but survey demonstrates that most researches utilize data set extracted from twitter. Other big social giants such as Facebook and YouTube are not deeply penetrated although they contribute substantially towards people expressing their sentiments.

For future directives I would recommend that different languages which are not being looked upon with respect to sentiment analysis should be focused; for instance sentiment analysis in Urdu is a challenging field for innovative research aspects. Even existing research in this context requires enhancement for improved results. Constructing extended lexicon with bulk electronic Urdu text, managing various dialects and handling several technical and linguistic glitches can be focused in future. Moreover sentiments and emotions expressed over through other social forums such as YouTube, Facebook should also be extracted for creating corpus as people are widely using them as well.

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