Deep Sentiment Analysis of Social Network Using Ontology

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Abstract -- **As the Web2.0 rapidly evolves, Web users too are evolving with it. In an era of social connectedness, people are becoming increasingly enthusiastic about interacting, sharing, and collaborating through social networks, online communities, blogs, Wikis, and other online collaborative media. Micro-blogging is one of the most popular Web 2.0 applications and related services, like Twitter, have evolved into a practical means for sharing opinions on almost all aspects of everyday life. Micro-blogging today has become a very popular communication tool among internet user so it becomes rich data sources for opinion mining and sentiment analysis. Analyzing customer's behavior has become very important for the organizations to find new market trends and insights. For the potential customer it becomes really difficult to get the knowledge about a product in the presence of such huge number of reviews and to sort the useful reviews and make good decision. The reviews available on these websites are in heterogeneous form i.e. structured and unstructured form and needs to be stored in a consistent format. Since good decision requires quality information in limited amount of time. This proposed approach first identifies the entities and then sentiments present in the customers reviews related to mobiles are transformed into an attribute table. Towards this direction, text-based sentiment classifiers often prove inefficient, since tweets typically do not consist of representative and syntactically consistent words, due to the imposed character limit. This paper proposes the deployment of original ontology-based techniques towards a more efficient sentiment analysis of Twitter posts. The novelty of the proposed approach is that posts are not simply characterized by a sentiment score, as is the case with machine learning-based classifiers, but instead receive a sentiment grade for each distinct notion in the post. Overall, our proposed architecture results in a more detailed analysis of post opinions regarding a specific topic.**

Keywords: **Sentiment analysis, Opinion mining, Ontology, Micro-blogging, Twitter.**

1. Introduction

With more than 1.5 billion users worldwide, social media offers a treasure trove of information in the form of real-time, interactive communications made available through blogs, tweets, updates, images and videos. Not surprisingly, organizations are growing more and more reliant on social media to understand and work more responsively with employees, vendors and customers, and better gauge the competition. However, mining and analyzing the huge volumes of unstructured data generated by social media is not an easy task. Using social media analytics, organizations can mine and decipher vast amounts of data from various social media platforms to discover customer sentiment about brands, trends, the issues customers' face, the efficacy of marketing campaigns and competitor intelligence.

The growing use of the internet has led to the development of networked interaction environments such as social networks. Social networks have acquired much attention recently, largely due to the success of online social networking sites and media sharing sites. In such networks, rigorous and complex interactions occur among several different entities, leading to huge information networks with outstanding business potential. Researchers are increasingly interested in addressing a wide range of challenges exist in these social network systems.

Social networks are graph structures whose nodes represent people, organizations or other entities, and whose edges represent relationship, interaction, collaboration, or influence between entities. The edges in the network connecting the entities may have a direction indicating the flow from one entity to the other; and a strength denoting how much, how often, or how important the relationship is. Social networks need not be always social in context. Real-world networks like World Wide Web, electrical power grids, the spread of computer viruses, telephone call graphs, and co-authorship and citation networks of scientists, customer networks are instances of technological, business, economic, and biologic social networks.

Epidemiological networks, cellular and metabolic networks, food webs, are some of the examples of biological networks. Social networks are highly dynamic in nature. The network grows and changes quickly over time through the addition of new nodes and edges, signifying the social structure. The number of degrees grows linearly in the number of nodes. It has been experimentally shown that when the network grows, the closeness of the nodes increases, resulting in shrinking diameter of the network. The dynamic, dense, reduced diameter properties of graph show that the social network exhibit heavy-tailed out-degree and in-degree distributions. The dynamic property of such large, heterogeneous, multi-relational social networks has led to an interesting field of study known as Social Network Analysis (SNA). Social network analysis examines the structure and composition of links in a given network and provides insights into its structural characteristics. SNA is the study of the evolution of structures i.e., how the networks change over time, and how information propagates within the networks. SNA assumes that the relationships are important and focuses on the structure of relationships. It also includes understanding of the general properties of networks by analyzing large datasets collected with the aid of technology.

Social network analysis has emerged as a key technique in modern sociology and has become a popular topic of study in areas like Business and Economics, Geography, Information science, Organizational studies, social psychology, Sociolinguistics. For example, SNA can be used as a tool for market analysis based on opinions about products or brand to market products and services.

2. Social Network Mining

Traditional, social network models were descriptive, rather than predictive. This was mainly due to insufficient data. Fortunately, the growth of World Wide Web has transformed the scenario. Large quantities of data are available on very large social networks from blogs, knowledge-sharing sites, collaborative filtering systems, online gaming, social networking sites, newsgroups, chat rooms, etc. However, handling complex networks with millions of vertices for mining interesting patterns on the network and for a thorough analysis of the properties of the network is not an easy task. The exponential increase in the number of interacting nodes in these networks endow with highly significant challenges for the advanced computing, machine learning and data mining community. Social network mining is a systematic approach used to discover the patterns of relationships among entities in social networks and to make the invisible flows within an organization to be visible. In recent years, social network research has been carried out using large quantity of data collected from online interactions and from explicit relationship links in online social network platforms (e.g., Facebook, LinkedIn, Flickr, Instant Messenger, etc.). Analyzing the properties of the network and understanding the dynamics that drives the evolution of social network is a challenging problem due to a large number of variable parameters. Currently most networks have surpassed the dimensions for which it is feasible to perform accurate analysis with traditional data mining methods. The increased dimension of social network poses critical importance to the success of the social network analysis and mining. Similarly identifying the most influential nodes in the network is an interesting task in social networks because it can exhibit highest business value as these entities can be used for promoting new products. The trend in users' opinion towards a certain product or service that can be discovered through monitoring the growth of network of nodes is another valuable task from a business perspective. Some of the exemplar areas of mining on social networks are link mining, mining customer networks for viral marketing, mining newsgroups, community mining, sub graph detection and opinion mining.

3. Opinion Mining

The web is a wealthy source of information. Web 2.0 provides ample opportunities to express personal experiences and opinions on almost anything at review sites, forums, discussion groups, blogs etc. A research says that consumers generated more than 500 billion impressions about products and services, through social media in 2011. People express their emotions and opinions about various topics like arts, literature, financial markets, about individuals, organizations, ideologies, and consumer goods. When people make decisions to buy products or use services, they search for these opinions instead of searching for facts. 84 percent of millennia's say that user-generated content has at least some influence on what they buy. Organizations also look up to opinions regarding their products to be aware of the market trends and changes. Hence a system to identify and classify opinions expressed in electronic text and to find valuable and interesting information is essential. Sentiment analysis or opinion mining is the computational study of people's opinions, appraisals, and emotions toward entities, events and their attributes. It involves the application of natural language processing, computational linguistics, and text analytics to identify and extract subjective information in source materials.

Applications of Opinion mining

According to the Gartner research, July 2010, a majority of consumers, about 74 percent rely on social networks to guide purchase decisions, proving that word of mouth propagates faster in the web. The applications of opinion mining are huge.

- Some of them are
- Brand affection monitoring and finding the reach of a product, for example how many people have been exposed to Samsung phones.
- Identifying public opinions on a political topic
- Comparing 2 different products, for example, to find the preference between Samsung Galaxy S3 and Apple iphone 5. Businesses can utilize this to improve their market strategies.
- Identifying spam opinions given to boost products sales or to damage a product
- Predicting about the changing society and trends
- Identifying opinion leaders.

4. Ontology

Ontology has been defined as the specialization of the conceptualization by Gruber(1993).The main aim of ontology is to provide knowledge about specific domains that are understandable by both the computers and developers. Ontology improves the process of information retrieval and reasoning thus results in making data interoperable between different applications (Zhou&Chaovalit, 2007). According to Meersman[3](2005), most of the ontologies in the community of information systems are known as data models that are mainly used for structuring a fairly narrow application domain. He claimed that "ontologies" that includes lexicons and thesauri may be a useful first step in providing and formalizing the semantics of information representation. According to Meersman (2005), in near future these ontologies will act as a semantic domain for the information systems and will be very useful. He also predicted with authenticity that:

"It is unmistakable that with the advent of e-commerce, and the resulting natural language context of its related activities, that ontologies, lexicons and the thesauri and research in their use for system design and interpretation will receive a major market driven push"(Meersman,2005, p.02)

According to Meersman, (2005), a lexicon is defined as a language-specific ontology, for e.g English, Polish. Whereas thesaurus is defined as either a domain-specific ontology or an application(s) specific ontology.

An ontology can be defined as an ''explicit, machine-readable specification of a shared conceptualization'' (Studer, Benjamins, &Fensel, 1998). Ontologies are used for modeling the terms in a domain of interest as well as the relations among these terms and are now applied in various fields, like agent and knowledge management systems and e-commerce platforms (Gómez-Pérez & Corcho, 2002). Other applications include natural language generation, intelligent information integration, semantic-based access to the Internet and extracting information from texts. However, the most important contribution of ontologies is the key role they play in the development of the Semantic Web. The Semantic Web is an extension of the current Web, where information is given a well-defined meaning, encouraging cooperation among human users and computers (Berners-Lee, Hendler, &Lassila, 2001). Ontologies serve as the primary means of knowledge representation in the Semantic Web. Although various ontology languages have emerged, the currently dominant standards are RDF/S (Resource Description Framework Schema) and OWL (Web Ontology Language).

Other directions of research include the development of ontologies for representing micro-blog posts and relationships between social-network users as for example FOAF (see Brickley & Miller, 2010), SIOC (see Breslin, Harth, Bojars, & Decker, 2005), OPO (see Stankovic, Passant, & Laublet, 2009), SMOB2 (see Passant, Bojars, Hastrup, & Laublet, 2010), or ontologies for representing levels of emotions (e.g. Baldoni, Baroglio, Patti, & Rena, 2012; Francisco, Germans, & Peinado, 2007).

5. Description of the proposed approach

The proposed approach is to take advantage of domain ontology for providing more elaborate sentiment scores regarding the notions contained in a tweet. The aim is to have a system that accepts as input a tweet (or a set of tweets) regarding a specific subject and provides sentiment scores for every aspect/feature of this subject. For example, the sample tweet Tex: ‘‘The screenplay was wonderful, although the acting was rather bad’’. The machine-learning based approaches would return a single quantitative (sentiment score) or qualitative (positive, negative or neutral) result. In this paper, we propose the deployment of ontology-based techniques towards a more fine-grained sentiment analysis of Twitter posts. According to the proposed approach, tweets are not simply characterized by a sentiment score, but instead receive a sentiment grade for each distinct notion in the post. This results overall in a more elaborate analysis of post opinions regarding a specific topic. More specifically, regarding the sample tweet Tex above, our proposed ontology-based approach distinguishes the features of the domain (in this case, screenplay and acting) and assigns respective scores, resulting in a more detailed sentiment analysis of the given statement. The architecture of the system we developed is presented in detail in a following section.

The proposed methodology is divided in five phases: (1) Creation of domain Ontology with FCA or ontogeny tool (section 5.1), (2) Augment attributes from wordnet (section 5.2), and (3) Calculate sentiment score using Semantria (section 5.3).

5.1 Creation of domain Ontology

5.1.1.Formal Concept Analysis

Formal Concept Analysis (FCA) is a mathematical data analysis theory, typically used in Knowledge Representation and Information Management (Ganter & Wille, 1999). Its main characteristic is that is applies a user-driven step-by-step methodology for creating domain models. With the recent emergence of the Semantic Web and the establishing of ontologies as its principal means for knowledge representation (see Section 3), FCA has been accounted as a valuable engineering tool for deriving an ontology from a collection of objects and their properties (Obitko, Snasel, Smid, & Snasel, 2004). Towards this affair, FCA has recently been applied in various occasions (e.g. Fu & Cohn, 2008; Ning, Guanyu, & Li, 2010; Zhang & Xu, 2011) and has been preferred in this work. The main building block in FCA is the concept, which is described via two sets: The extension, which is a set of objects and the intension, which is a set of attributes (Ganter & Wille, 1999). Every object that belongs to the concept has all the attributes in the intension and every attribute that belongs to the concept is shared by all objects of the extension.

The relationships between the set of objects and the set of attributes are represented by a formal context. A formal context K(O;A; I) is a triple where:

- O is a set of formal objects,
- A is a set of attributes, and,
- I is a binary incidence relation between the objects and the attributes; $I \subseteq O \times A$, where $(o,a) \in I$ is read as ‘‘object o has attribute a’’.

A formal context can be represented as a cross-table, where the rows represent O, the columns represent A and the incidence relation I is represented by a series of crosses as shown in Table 1.

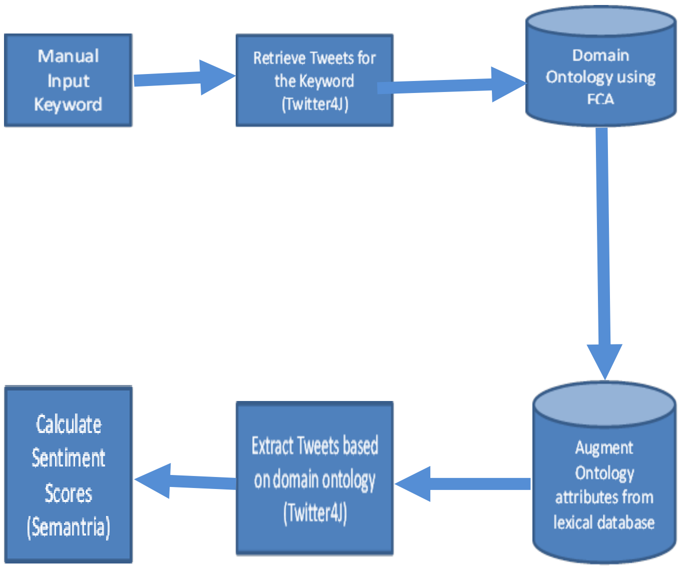

FIG.1 Architecture of proposed system

Algorithm: Create ontology

Input: concept (C)
Variables: An initially empty set of tweets (W)
An initially empty set of object (O)
An initially empty set of attributes (A)
Output: Across-table, filled with object and attributes (T)

```
W ← retrieve tweets(C);
For each  w ∈ W do
     o← retrieve object (w);
     If o ≠ NULL then
        O := o U {o}
        A’ ← retrieve attributes (w);
        For each  a ∈ A’  such that  (o, a) ≠ ∅  do
                    A := A U {a};
 T← populate Table (O, A);
 Return T
```

Table 1
Smartphone ontology.

Model	Properties				
	Android Display	Camera Processor		Battery	
Apple		+	+	+	+
samsung	+	+	+	+	+
HTC	+	+	+	+	+
Nokia		+	+	+	+

Populating the concept cross-table. According to FCA, the aim is to create the concept cross-table that corresponds to the domain ontology. As mentioned previously, the table corresponds to the incidence relation I ∈O×A; thus, it is essential to determine sets O and I. These sets can be derived via the algorithm.

The algorithm accepts as initial input a concept parameter (e.g.‘‘#smartphone’’), determined manually by the user. The retrieve Tweets method retrieves the first N tweets (default value for N is 100) that belong to the result set corresponding to the concept parameter. Towards this affair, Twitter4J4 was utilized, a Java library that gives access to the Twitter API and assists in integrating the Twitter service into any Java application. The retrieve Object method subsumes that every tweet is inspected for references to objects and, if any such reference is detected, the corresponding attributes are retrieved via method retrieveAttributes. For every attribute associated to the object, the attribute is appended to the existing set of attributes. The latter two methods are currently performed manually by an ontology engineer. Eventually, the final concept table is populated with the detected objects and attributes. Table 1 displays the resulting cross-table for analyzing 100 retrieved tweets for the concept ‘‘smartphone’’.

5.1.2. Ontology learning

An alternative to the manual FCA methodology presented above is offered by the various existing semi-automatic ontology learning techniques (e.g. Cimiano & Völker, 2005; Hazman, El-Beltagy, & Rafea, 2009). Ontology learning, also known as ontology extraction, ontology generation or ontology acquisition, refers to the task of automatically creating an ontology, via extracting concepts and relations from a given data set. Nevertheless, the task of creating an ontology in a fully automated manner still remains elusive to a great degree. In this work, we resorted to OntoGen (Fortuna, Grobelnik, & Mladenic, 2007), a semi-automatic, data-driven ontology editor. The software deploys text-mining techniques via an efficient user interface that reduces development time and complexity. Overall, the tool attempts to bridge the gap between complex ontology editors and domain experts, who do not necessarily possess ontology engineering skills.

OntoGen interactively offers assistance during the development of domain ontologies, by suggesting concepts and relations and by automatically assigning instances to the concepts. The user can accept or reject the suggestions or perform manual adjustments. Most of the aid provided by the system is based on the provided underlying data. In our case, the role of this data set is played by the initial set of retrieved tweets (see previous subsection), which is fed to OntoGen as a set of named line-documents (i.e. each tweet is stored as a separate text file, with the first word in the line serving as the document title/ID). Fig. 2 illustrates the resulting ontology visualization via OntoGen, after examining the same set of 100 retrieved tweets for the concept ‘‘smartphone’’.

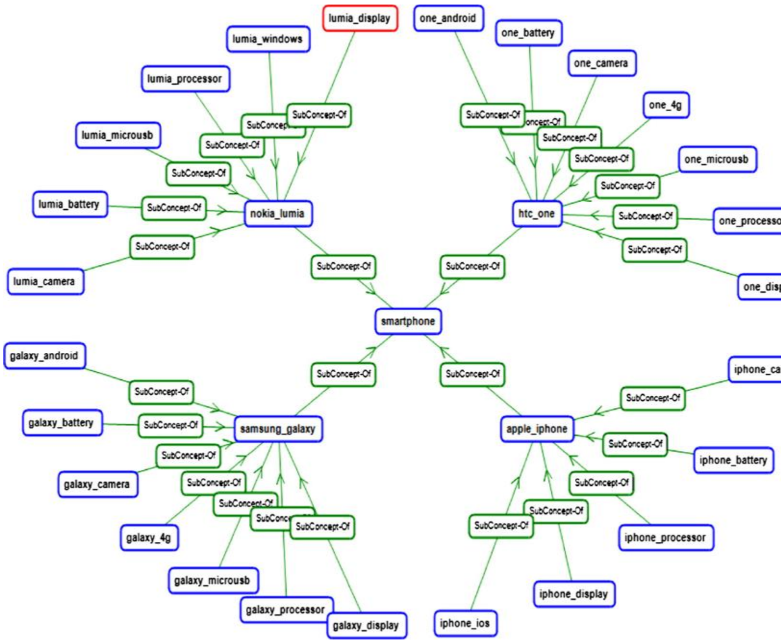

Fig. 2. Ontology visualization via OntoGen.

5.2. Augmenting the semantics

The ontology created via FCA (Section 5.1.1) or Ontology Learning (Section 5.1.2) is in essence a simple taxonomy of concepts and attributes. In order to augment the underlying semantics, the ontology is enriched with synonyms and hyponyms (subordinate notions) of the detected attributes. For example, in the ‘‘smartphone’’ universe used throughout this paper, the ‘‘display’’ attribute could also be expressed as ‘‘monitor’’ or ‘‘screen’’, which are synonymous words.

For appending the sets of synonyms and hyponyms to the ontology, we used the popular WordNet lexical database (Miller, 1995), which retrieves synsets (groups of synonymous words or collocations) of the synonyms and hyponyms of every given word. Each synonym and hyponym is then added to the ontology and associated with the initial attribute. Syntactically, in the OWL DL representation of the ontology, these associations are expressed via the owl:equivalentProperty and rdfs:subPropertyOf constructs, respectively.

5.3. Calculate sentiment score using Semantria.

The overall process involves retrieving a set of tweets that correspond to entities in the ontology and performing sentiment analysis on each of the retrieved tweets. There are three distinct steps in the procedure: (1) querying the ontology for the corresponding attributes of each object, (2) retrieving the relevant tweets, and (3) performing the sentimentanalysis.

5.3.1. Step#1: Taking advantage of the ontology

In order to take advantage of the domain ontology created during the previous steps, the retrieved tweets have to contain information regarding the objects and attributes of reference. This is achieved via JENA (Rajagopal, 2005), a Java API for processing RDF/S and OWL ontologies. Having an ontology-based structured hierarchy of classes and properties, JENA assists in retrieving object-attribute pairs (oi,aij). More specifically, for every object/class oi, all attributes/properties aij are retrieved via processing RDF/S triples of the form: <aij rdfs:domain oi>.

5.3.2. Step #2: Retrieving the relevant tweets

For every property aij of an object oi a relevant query is submitted to Twitter via the Twitter4J library described previously. The query has the form ‘‘oi aij’’, where different terms are separated by whitespaces, resulting in an intersection query. Alternatively, one could execute a hashtag intersection query, like e.g. ‘‘#oi #aij’’, which would nevertheless drastically reduce the result set, without necessarily increasing the precision.A predefined number of tweets t1i, . . . , t1n is retrieved (default number is 100) that contain the relevant keywords. A secondary phase of preprocessing takes place on the retrieved set of tweets.

The preprocessing phase involves removing characters or sequences of characters that cannot assist during the subsequent sentiment analysis phase, in order to reduce the noise in the data set. More specifically, for each retrieved tweet, the following items of text constitute representative examples to be removed:

1. Replies to other users’ tweets, represented by strings starting with ‘@’.
2. URLs (i.e. strings starting with ‘http://’).
3. Hashtags, which are strings starting with ‘#’ used for categorizing messages are not removed

as a whole. Instead, only the ‘#’ character is removed, since the rest of the string often forms a legible word that contributes to better understanding the tweet. The remainder of each tweet is added into a collection of sentences.

5.3.3. Step #3: Sentiment analysis

After going through the preprocessing phase during the previous step, the retrieved tweets are submitted to Semantria for sentiment analysis. Semantria is a web service that tags the opinions and sentiments detected in a textual corpus, based on the subject domain, as well as the intensity of the sentiment expression. A sentiment score s is assigned to each tweet, where s 2 [10, 10], depending on the appreciation level of the submitted sentence.

On the other hand, deploying a third-party sentiment analysis service like Semantria may be considered as a drawback, since the exact process of extracting the sentiment from a sentence cannot be verified – the source code and methodology behind Semantria are not publicly available. Thus, an imminent goal for the future is to integrate a custom sentiment analysis methodology in our approach and compare the resulting sentiment scores.

6. Evaluation

The purpose of the current subsection is twofold: (a) to estimate the recall ratios for the two versions of our proposed architecture as well as for the custom-built system (which has been introduced for evaluation purposes only) and (b) to evaluate whether the observed differences in the way the selections are performed by each method can be characterized as qualitatively analogous or not. The two versions of our proposed architecture are: (a) the full-fledged ontology-based semantically-enabled system (SEM), and, (b) the same system without the synonym/hyponym augmentation, but still with ontology support (ONT). The custom-built system is stripped of any ontology- based domain representation and, thus, cannot retrieve tweets referring to specific object-attribute pairs; it is limited to retrieving tweets regarding the superclass of the domain, which is associated to the ‘‘#smartphone’’ tag (CUS). The introduction of the CUS method is attributed to the fact that our approach adopts an utterly novel path and therefore it is not feasible to identify other methods that can be used as a comparison base. Additionally, there is no point in evaluating the returned sentiment results, since the Semantria sentiment classifier used in this work does not constitute a contribution of ours.

Given a random sample of T observations, the recall ratio for a particular methodology is defined by the ratio of the total number of relevant selected tweets over the sample size.

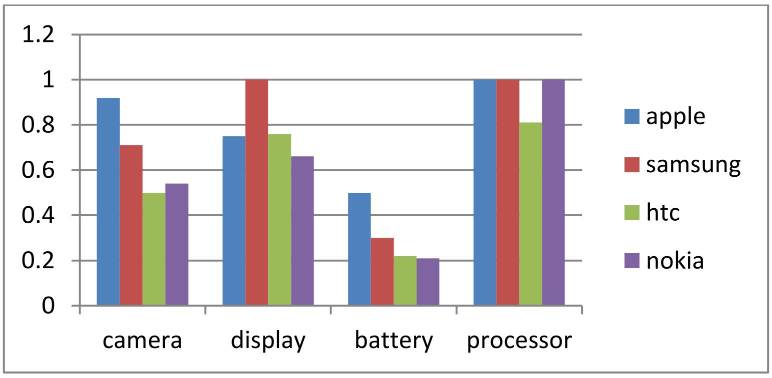

Fig. 6. Sentiment values corresponding to the smart phone attributes in the scenario.

The recall ratios for the three examined selection methods are estimated by using 10 randomly taken samples, each comprised of 100 observations. The estimation results, for all taken samples, reveal that SEM achieves steadily higher recall ratios from ONT and both present steadily higher recall ratios from CUS (See Table 2). Solely based on the recall ratio as a comparison criterion a first round conclusion is that SEM performs better than ONT and both outperform CUS

Table 2

Sample	Recall ration		
	SEM ONT	CUM	
Sample 1	0.93	0.72	0.26
Sample 2	0.86	0.72	0.40
Sample 3	0.89	0.60	0.26
Sample 4	0.90	0.67	0.27
Sample 5	0.79	0.60	0.32
Sample 6	0.90	0.69	0.29
Sample 7	0.85	0.65	0.26
Sample 8	0.80	0.53	0.26
Sample 9	0.88	0.60	0.36
Sample 10	0.89	0.61	0.28

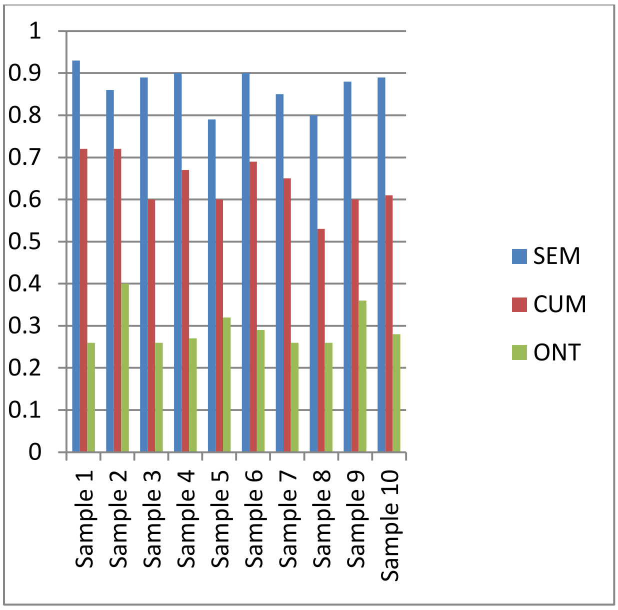

FIG 3 Comparision of SEM, CUM, ONT

7. Conclusions and future work

The paper argued that sentiment analysis constitutes a rapidly evolving research area, especially since the emergence of Web 2.0 and its related technologies (social networks, blogs, wikis etc.) The recent explosion in the usage of micro-blogging services, and particularly Twitter, has shifted attention to sentiment analysis of micro-blogging posts and tweets. There exist various machine learning-based approaches that perform sentiment analysis on tweets, with the drawback that they treat each tweet as one uniform statement and assigning a sentiment score to the post as a whole. This paper proposes the deployment of ontology-based techniques for determining the subjects discussed in tweets and breaking down each tweet into a set of aspects relevant to the subject. The result is the assignment of a sentiment score to each distinct aspect. A baseline scenario is also presented that deals with the domain of a popular product (smartphones) and results in comparatively evaluating the distinct features of each model series.

Our goals for future improvements of the proposed approach initially involve the integration of a custom-built sentiment classifier that will substitute Semantria in our architecture. A further aim is to integrate a fully automatic ontology-building functionality, potentially through a combination of ontology learning techniques. Nevertheless, keeping the manual and semi-automatic ontology creation approaches still remains useful, as they offer a more controlled means for building the domain vocabulary. Exploring various methods for visualizing the resulting sentiment is an additional direction for providing more thorough information to the user. Finally, provided that investors (or consumers) are prone to exogenous sentiment waves, an interesting research direction would be the development of time-series sentiment indexes for a range of investment (or consumer) goods. In case these developed indexes contain useful predictive power with respect each time to the future price movements of the investigated good, they may act as valuable tools in forming efficient strategies for all market participants.

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