Sentiment Analysis on Social Media

Conference Paper · August 2012

DOI: 10.1109/ASONAM.2012.164

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2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining

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Abstract

The Web is a huge virtual space where to express and share individual opinions, influencing any aspect of life, with implications for marketing and communication alike. Social Media are influencing consumers' preferences by shaping their attitudes and behaviors. Monitoring the Social Media activities is a good way to measure customers' loyalty, keeping a track on their sentiment towards brands or products. Social Media are the next logical marketing arena. Currently, Facebook dominates the digital marketing space, followed closely by Twitter.

This paper describes a Sentiment Analysis study performed on over than 1000 Facebook posts about newscasts, comparing the sentiment for Rai - the Italian public broadcasting service - towards the emerging and more dynamic private company La7. This study maps study results with observations made by the Osservatorio di Pavia, which is an Italian institute of research specialized in media analysis at theoretical and empirical level, engaged in the analysis of political communication in the mass media. This study takes also in account the data provided by Auditel regarding newscast audience, correlating the analysis of Social Media, of Facebook in particular, with measurable data, available to public domain.

1. Introduction

The Web is a huge virtual space where to express and share individual opinions, influencing any aspect of life, with implications for marketing and communication alike. Reviews and ratings on the Internet are increasing their importance in the evaluation of products and services by potential customers. In certain sectors, it is even becoming a fundamental variable in the "purchase" decision. A recent Forrester study showed that more than 30% of Internet users have evaluated products or services online. Consumers tend to trust the opinion of other consumers, especially those with prior experience of a product or service, rather than company marketing. Social Media are influencing consumers' preferences by shaping their attitudes and behaviors. The influence of the internet, especially via social networking, on people's purchasing behavior has grown over the years. Retailers, who depended on traditional stores to drive sales, have found that the reach of Social Media extends their visibility dramatically. Besides, a friendly, interactive presence on a social network or chat room can greatly improve brand image and help the company gather extremely useful, unstructured data about demand trends, in a nonintrusive way. Monitoring the Social Media activities is a good way to measure customers' loyalty, keeping track of their sentiment towards brands or products, of the impact of campaigns and the success of marketing messages, identifying and engaging the top influencers who are most relevant to the brand, product or campaign. Social Media are the next logical marketing arena. Currently, *Facebook* dominates the digital marketing space, followed closely by *Twitter*. Blogs, *YouTube* and *MySpace* are less preferred, despite obvious benefits these platforms offer.

These factors have led to a burgeoning industry with a plethora of companies offering Sentiment Analysis services in Social Media. Sentiment Analysis and Opinion Mining are established, although nascent, fields of research, development and innovation. The goal is always broadly the same; to know "who" is speaking about "what", "when" and in "what sense".

This paper describes a Sentiment Analysis study performed on over than 1000 *Facebook* posts about newscasts, comparing the sentiment for *Rai* - the

978-0-7695-4799-2/12 $26.00 © 2012 IEEE
DOI 10.1109/ASONAM.2012.164

Italian public broadcasting service - towards the emerging and more dynamic private company *La7*. This study maps study results with observations made by the *Osservatorio di Pavia*, which is an Italian institute of research specialized in media analysis at theoretical and empirical level, engaged in the analysis of political communication in the mass media. This study takes also in account the data provided by *Auditel* regarding newscast audience, correlating the analysis of Social Media, of *Facebook* in particular, with measurable data. The posts have been collected and analyzed by using a content enabling system – *iSyn Semantic Center* - that provides deep semantic information access and dynamic classification features for large quantities of distributed multimedia data.

1.1. The State of Art of Sentiment Analysis

Opinion Mining and Sentiment Analysis are important for determining opinions on brands and services, or understanding consumers' attitude. Given the relentless cascade of information on the Internet, in the last decade the field of automatically extracting opinions has emerged, being not possible to keep up with the flow of new information by manual methods [1]. There is a large body of work on Opinion Mining for English, not for Italian, by automatic means [2][3]. Globally, two techniques are used: Supervised Machine-Learning [3][4] and Unsupervised methods, that use a lexicon with words scored for polarity values such as neutral, positive or negative [5]. Supervised methods require a training set of texts with manually assigned polarity values and, from these examples, they learn the features (e.g. words) that correlate with the value. Chaovalit and Zhou [6] evaluated common implementations for both techniques on movie reviews and concluded that Supervised techniques perform with about 85% accuracy, whereas Unsupervised methods perform about 77%. Supervised techniques have the disadvantage that they require high-quality training data for each type of documents, for each domain and each language. Unsupervised systems are more robust across different types of texts and domains and, once the lexical and semantic resources are developed, can be deployed more easily.

Besides the computational technique that is used for Opinion Mining, there is a whole gamut of issues that play a role in the quality and usability of the opinion extraction. First of all, opinion mining can be applied to different levels of text: words, phrases, sentences, paragraphs or documents. Words, as the smallest units, can have different polarities in different meanings (e.g. "star" which can be objective as a heavenly body or positive) and or in different domains (e.g. "unpredictable" is good for a movie plot and bad for a car). This requires word sense disambiguation of words in context and domain, or topic detection as prior processing [7]. Furthermore, polarity expressed by a word may be reversed within a phrase through negation. Also, parts of a document may express different polarities. In fact, opinions can be related to topics (what is the opinion about) or associated with different opinion holders (the author, the subject, a citation or quote, etc.).

2. The Logical components

The Sentiment and Knowledge Mining system [8][9][10][11] used in this study is built on the following components:

1. a Crawler, an adaptive and selective component that gathers documents from Internet/Intranet or Database sources.
2. a Semantic Engine, which identifies relevant knowledge in the texts, by detecting semantic relations and facts.
3. a Search Engine that enables Natural Language, Semantic and Semantic-Role queries.
4. a Machine Translation Engine, which enables automatic translation of search results.
5. a Geo-referentiation Engine, which enables an interactive geographical representation of documents.
6. a Classification Engine which classifies search results into clusters and sub-clusters recursively, highlighting meaningful relationships among them, or assigns documents to predefined thematic groups.

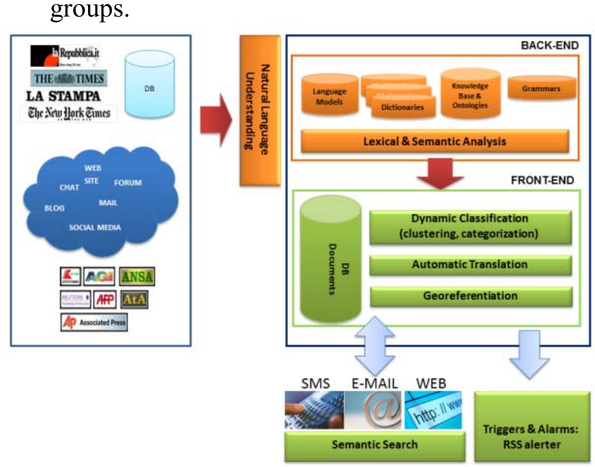

Figure 1 – System architecture

2.1. The Crawler

The crawler is a multimedia content gathering and storing system, whose main goal is managing huge collections of data coming from different and geographically distributed information sources. It provides a very flexible and high performance dynamic indexing for contents retrieval. Its gathering activities are not limited to the standard Web, but also operate with other type of sources like remote databases, other Web sources (HTTPS-FTP-Gopher), Usenet news (NNTP), mailboxes (POP3-POP3/S-IMAP-IMAP/S), file systems and other proprietary source protocols. The crawler provides default plug-ins to extract text from most common types of documents. Even more complex sources, such as audio and/or video files, might be suitably processed so as to extract a textual-based labeling, based on both the recognition of speeches, videos and images [8][13].

2.2. The Semantic Engine

This component identifies the relevant knowledge from the whole raw text, by detecting semantic relations and facts in texts. Concept extraction is applied through a pipeline of linguistic and semantic processors that share a common knowledge [14]. The shared knowledge base guarantees a uniform interpretation layer for the diverse information from different sources and languages [15]. The extracted knowledge and information are indexed, making possible to handle fast semantic searches.

2.2.1. Lexical and Semantic Analyses. The automatic linguistic analysis of the textual documents is based on Morpho-Syntactic, Semantic, Semantic Role and Statistical criteria. At the heart of the lexical system is the McCord's theory of Slot Grammar [16][17]. The system analyzes each sentence, cycling through all its possible constructions. It tries to assign the context-appropriate meaning – the sense - to each word by establishing its context. Each slot structure can be partially or fully instantiated and it can be filled with representations from one or more statements to incrementally build the meaning of a statement. This includes most of the treatment of coordination, which uses a method of 'factoring out' unfilled slots from elliptical coordinated phrases. The parser - a bottom-up chart parser - employs a parse evaluation scheme used for pruning away unlikely analyses during parsing, as well as for ranking final analyses. It builds the syntactical tree incrementally. By including the semantic information directly in the dependency grammar structures, the system relies on the lexical semantic information combined with Semantic Role relations. The Word Sense Disambiguation algorithm considers also possible super-subordinate related concepts in order to find common senses in lemmas being analyzed. Beside Named Entities, locations, time-points, etc, it detects relevant information like noun phrases which comply with a set of pre-defined morpho-syntactic patterns and whose information exceeds a threshold of salience [18]. The detected terms are then extracted, reduced to their Part Of Speech (Noun, Verb, Adjective, Adverb, etc) and Semantic Role (Agent, Object, Where, Cause, etc) tagged base form [8]. 96% of the words in a sentence is normally classified without any ambiguity, while the complete syntactic tree for the sentence is extracted in 77% of the cases. The lemmatization speed is about 300 words per second. Once referred to their lemma inside the multi-lingual Knowledge Base, they are used as documents metadata [8][9]. The Semantic Engine supports English, Italian, German, French, Spanish, Brazilian-Portuguese and Arabic [10][11].

2.2.2. Sentiment Analysis. The Sentiment Analysis is based not only on the negative or positive polarity of words and concepts, but also on the syntactical tree of the sentence being analyzed. The system tries to read between lines, identifying idiomatic or colloquial expressions, giving interpretation to negations, modifying polarity of words basing on the related adverbs, adjectives, conjunctions or verbs, taking in account specific functional-logic complements [19][20][21]. For example, when analyzing the sentence

"*Il Tg di Enrico Mentana piace sempre di più, tanto da superare il record di share di novembre*"

(i.e. "Enrico Mentana's newsbreak program is becoming increasingly popular so that it breaks the audience record in November")

the system automatically gives it a positive polarity (Sentiment Score = positive) (see Figure 2), by identifying as sentiment factors

HOW[piacere, sempre di più]

(i.e. HOW[become,increasingly popular])

OBJ[superare, record]

(i.e. HOW[break,record])

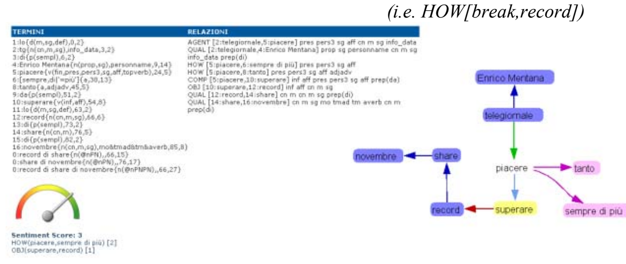

Figure 2 – Linguistic and Sentiment Analyses

2.3. The Search Engine

2.3.1. Natural Language Search. Users can search documents by Natural Language queries, expressed using normal conversational syntax [10][11]. Reasoning over facts and semantic structures makes it possible to handle diverse and more complex types of questions. Traditional Boolean queries in fact, while precise, require strict interpretation that can often exclude information that is relevant to user interests.

2.3.2. Semantic Search. Users can search by conceptual keywords combined by Boolean operators [10][11].

2.3.3. Semantic Role Search. Users can search and navigate by semantic roles, exploring sentences and documents by the functional role played by each concept [10][11]. Users can search by combining concepts into SAO (Subject-Action-Object) triples. By mapping a query to concepts and relations very precise matches can be generated, without the loss of scalability and robustness found in regular search engines that rely on string matching and context windows. The search engine returns as result all the documents which contain the query concepts/lemmas in the same functional role as in the query, trying to retrieve all the texts which constitute a real answer to the query.

2.4. The Machine Translation Engine

The system uses a combination of MT and CAT approaches, enabling the automatic translation of all the pages of interest. It uses a dual feed recursive process, where the reuse of translated text or the re-translation of text continuously improve the quality level [21].

2.5. The Geo-referentiation Engine

The system allows users to search for information in a geographic map, timely projected. Geo-referencing can be based either on sources, or documents contents: for example, users can navigate into a geographical interactive map basing on the newspapers headquarters, or on the towns mentioned in a news article or post. Then users have the opportunity to understand how news and comments spread throughout the world, or understand what are the primary sources of information; to perceive easily and intuitively which is the original source, or if there’s a coordinated press campaign [21].

2.6. The Classification System

The automatic classification of documents is made fulfilling both the Supervised and Unsupervised Classification schemas. The application assigns texts to predefined categories and dynamically discovers the groups of documents which share some common traits.

2.6.1 Supervised clustering. The categorization model is created during the learning phase, on representative sets of training documents focused on the topics of interest. The Bayesian method is used as the learning method: the probabilistic classification model is normally built on around 100 documents for each thematic category.

2.6.2 Unsupervised clustering. Documents are represented by a sparse matrix, where lines and columns are normalized in order to give more weight to rare terms. Each document is turned to a vector comparable to others. Similarity is measured by a simple cosines calculation between document vectors, whilst clustering is based on the K-Means algorithm, which is a sufficiently robust algorithm for Web Mining interactive applications. The maximum number of clusters is 10. This number has been chosen in order to maximize the coherence of clusters after 5 tests. The application provides a visual summary of the clustering analysis. A map shows the different groups of documents as differently sized bubbles and the meaningful correlation among them as lines drawn with different thickness [8].

3. Monitoring the Social Media

3.1. Collecting the data

Around 1000 posts has been collected, by focus crawling of *Facebook*. Only the textual contributions related to *La7* and *Rai1* news programs have been semantically analyzed and indexed.

3.2. Navigating the data

3.2.1 Search and cluster. Users can search documents by expressing their own interest by Natural Language queries, using normal conversational syntax. In example, when searching for “*gli spettatori vogliono un telegiornale equilibrato*” (namely “*the audience wants a well-balanced newscast*”) (see Figure 3), the system returns as result all the documents talking about sobriety and moderation on news (i.e. journalists and news programmes involved, etc). The Figure 4 shows the efforts made by *La7* to offer a well-balanced news programme, hiliting all the positive comments from *Facebook*.

Figure 3 – Natural Language Search

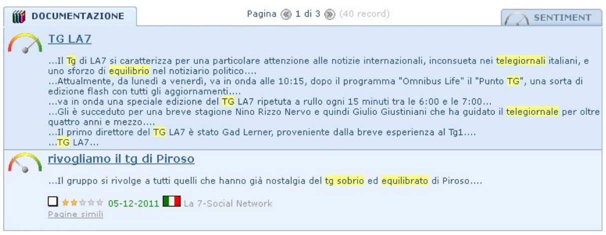

Figure 4 – Results for Natural Language Search

When clustering these results, the system identifies a group of documents dealing with users which follow the *La7* newscast directed by *Enrico Mentana*. Some other documents talk about the special care over sobriety provided by *La7* newscast, when treating the Italian politics; moreover, other clusters deal with the new director *Mentana*, which is found as a true professional journalist in the political arena. Instead, other clusters deal with the slip of approval for *Augusto Minzolini*'s news programme (*Rai1*), being too much factious or dedicating too much time to gossip (see Figure 5).

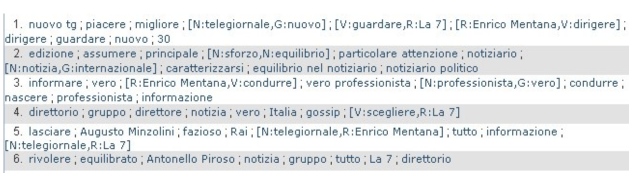
1. nuovo tg ; piacere ; migliore ; [N:telegiornale,G:nuovo] ; [V:guardare,R:La 7] ; [R:Enrico Mentana,V:dirigere] ; dirigere ; guardare ; nuovo ; 30
2. edizione ; assumere ; principale ; [N:sforzo,N:equilibrio] ; particolare attenzione ; notiziario ; [N:notizia,G:internazionale] ; caratterizzarsi ; equilibrio nel notiziario ; notiziario politico
3. informare ; vero ; [R:Enrico Mentana,V:condurre] ; vero professionista ; [N:professionista,G:vero] ; condurre ; nascere ; professionista ; informazione
4. direttorio ; gruppo ; direttore ; notizia ; vero ; Italia ; gossip ; [V:scegliere,R:La 7]
5. lasciare ; Augusto Minzolini ; fazioso ; Rai ; [N:telegiornale,R:Enrico Mentana] ; tutto ; informazione ; [N:telegiornale,R:La 7]
6. rivolere ; equilibrato ; Antonello Piroso ; notizia ; gruppo ; tutto ; La 7 ; direttorio

Figure 5 – Clustering

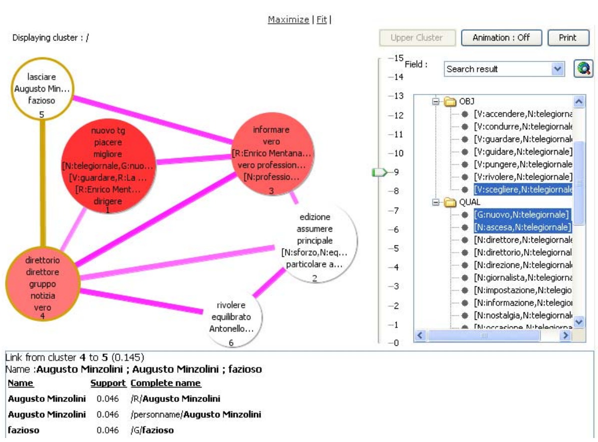

Figure 6 –Thematic map and Semantic Role projection

A map shows the different clusters as differently sized bubbles and the meaningful correlation among them as lines drawn with different thickness. Users can search inside clusters, giving a temporal and functional projection of main concepts they contain, or explore links among topics. In example, when exploring the map, the system suggests that many viewers have left *Rai1*, having considered *Augusto Minzolini* too much factious, giving to analyst an automatic new perspective on cited facts (see Figure 6).

3.2.2 Explore data in depth. When navigating the Space of Concepts, the system suggests that a "*tg libero*" ("*free newscast*") is related to a "*tg normale*" ("*normal newscast*"), "*fazioso*" ("*factious newscast*") to "*Augusto Minzolini*", who is in turn related to "*imbavagliare informazione*" ("*to gag information*"), or "*sobrio*" ("*sober*") to "*equilibrato*" ("*well-balanced*"). This relations chart can be considered a visual investigative component specifically designed to bring clarity to complex investigations. In fact, it automatically enables investigative information to be represented as visual elements, that can be easily analyzed and interpreted [11] (see Figure 7)

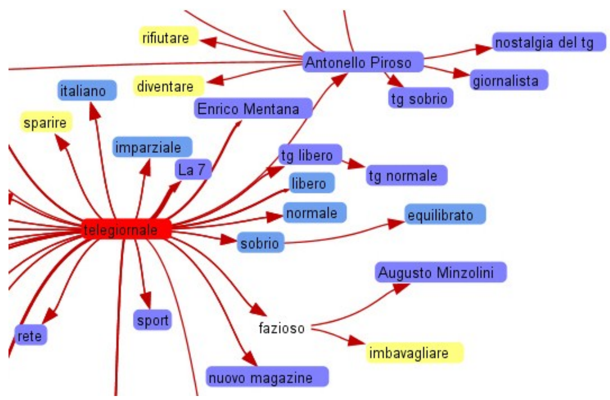

Figure 7 – Space of Concepts

Let's now access the data provided by the *Osservatorio di Pavia* related to the same period of time. The *Osservatorio di Pavia* - together with the *University of Pavia* – has developed a quantitative methodology for the observation and the analysis of political communication in the mass media. The data produced by the *Osservatorio di Pavia* are utilised by the Italian *Parliamentary Commission on Rai*. In may 2010, these data certify that *Tg1* – the *Rai1* newscast - has dedicated more time to goverment and its supporting majority than any other news programme: *Tg1* has reserved 19.6% of the all television spaces to the opposition parties (*Democratic Party*, *UDC* and *IDV* in particular); the rest has been mainly divided between government (43.2%) and majority parties (15%) [23]. Moreover several newspaper articles highlight how

Tg1 describes the political facts with a mono-cultural perspective [24]: "*È incredibile il flusso di utenti raminghi da un canale all'altro, quasi immediata la fuga a La7, ma il particolare curioso è il numero di gente che chiude Rai1 durante l'editoriale di Minzolini*" ("*It's amazing the flow of users wandering from one channel to another, almost immediately the flight to La7, but it's awesome the number of people that closes Rai1 during Minzolini's editorial*") [26].
Besides, in April 2010, compared to April 2009, the *Tg1* has lost 11,3% of its audience. During the first twelve days of April of 2010, *Tg1* achieves an average audience of 5.9 million people (27,1 % of share). In the same period of 2009 – being director *Gianni Riotta* – *Tg1* was followed by 6.7 million viewers (30% of share) [22]. In November 2011, *Tg1* reaches the bottom in share, having an average 16,1% in audience [23]. On November 2011, the 8th, *Tg La7* exceeds its share record, having an average share of 14,6% in audience [24]. Besides, during *Minzolini*'s mandate, *Tg1* loses all the population segments, women and men, young and old, rich and poor, with and without tertiary education [22].

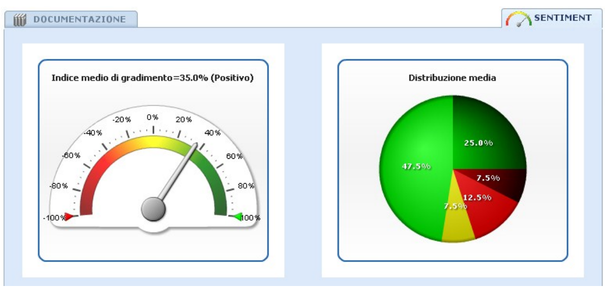

Figure 8 – Distribution of consensus for La7

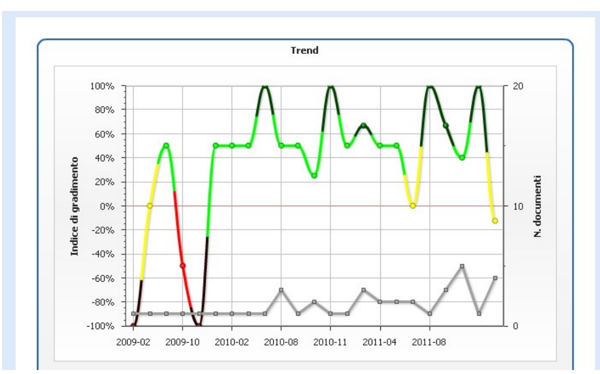

Figure 9 – Time distribution of consensus for La7

The overall performance measures used on Sentiment Analysis used Recall and Precision: in our tests, they are normally above 87% and 93% respectively.

3.2.3 Explore the consensus for La7. The system allows users to explore statistical – time and frequency – distributions for concepts, taken in account basing on their Part Of Speech (Noun, Verb, Adjective, Adverb, etc) and Semantic Role (Agent, Object, Where, Cause, etc). Adjectives, adverbs, nouns or even sentences can be labeled as subjectly positive/negative, or objective, giving indications about perception people may have about persons or facts [19]. When analyzing the time projection for consensus for *La7*, analysts can note that it is costantly positive, apart a few negative comments published in November 2009 (see Figure 9).

4. Acknowledgements

This work is partially funded by the European Commission (CAPER project, 261712 FP7-SECURITY SEC-2010.1.2-1).

5. Conclusions

This paper describes a Sentiment Analysis study performed on over than 1000 *Facebook* posts about newscasts, comparing the sentiment for *Rai* - the Italian public broadcasting service - towards the emerging and more dynamic private company *La7*. It maps Sentiment Analysis on Social Media with observations and measurable data. Its results accurately reflect the reality as described by the *Osservatorio di Pavia* and *Auditel*, highlightening the importance of *Facebook* as a platform for online marketing. Monitoring the social media activities is a good way to measure customers' loyalty and interests, keeping track of their sentiment towards brands or products. This study has been performed by a Knowledge Mining system used by some security sector-related government institutions and agencies in Italy to limit information overload in OSINT and Web Mining. The linguistic and semantic approaches implemented in this system enable the research, the analysis, the classification of great volumes of heterogeneous documents, helping documental analysts to cut through the information labyrinth, analysts to take account of complexity of public views, assigning automatically a sentiment polarity, rapidly accessing all the potential texts of interest.

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