The New Eye of Government: Citizen Sentiment Analysis in Social Media

Ravi Arunachalam
IBM
rarunach@in.ibm.com

Sandipan Sarkar
IBM
sandipansarkar@gmail.com,
sandipan.sarkar@in.ibm.com

Abstract

Several Governments across the world are trying to move closer to their citizens to achieve transparency and engagement. The explosion of social media is opening new opportunities to achieve it. In this work we proposed an approach to monitor and analyze the citizen sentiment in social media by Governments. We also applied this approach to a real-world problem and presented how Government agencies can get benefited out of it.

1 Introduction

Governments across the world facing unique challenges today than ever before. In recent time, *Arab Spring* phenomenon is an example of how Governments can be impacted if they ignore citizen sentiment. It is a growing trend that Governments are trying to move closer to the citizen-centric model, where the priorities and services would be driven according to citizen needs rather than Government capability. Such trends are forcing the Governments in rethinking and reshaping their policies in citizen interactions. New disruptive technologies like cloud, mobile etc. are opening new opportunities to the Governments to enable innovations in such interactions.

The advent of Social Media is a recent addition to such disruptive socio-technical enablers. Governments are fast realizing that it can be a great vehicle to get closer to the citizens. It can provide deep insight in what citizens want. Thus, in the current gloomy climate of world economy today, Governments can reorganize and reprioritize the allocation limited funds, thereby creating maximum impact on citizens' life. Building such insight is a non-trivial task because of the huge volume of information that social media can generate. However, Sentiment Analysis or Opinion Mining can be a useful vehicle in this journey.

In this work, we presented a model and case study to analyze citizen sentiment from social media in helping the Governments to take decisions.

2 Background

2.1 Social Sentiment Analysis

The social media is transforming the way we communicate, the way we form relationships, the way we connect to each other, the way we live and work. Here are some figures that give an idea about the frantic pace in which the social media phenomenon is growing: 1.43 billion people worldwide visited a social networking site in 2012[1]; nearly 1 in 8 people worldwide have their own Facebook page[2]; 3 million new blogs come online every month[3]; and 65 percent of social media users said they use it to learn more about brands, products and services[4].

Mass Communication expert Curtis (2013) divided the history of social media into three phases – *Before the Dawn* (1969 - 1993), *The Dawning* (1994 - 2004) and *After the Dawn* (2005 onwards). The works on social sentiment analysis has started to be reported after the last phase commenced, when the social media has received its maturity.

Around 2007, the researchers and analysts started to take notice of the importance and value of social media monitoring and sentiment analysis as a means to achieve it. An Aberdeen Group

[1] http://searchenginewatch.com/article/2167518/Worldwide-Social-Media-Usage-Trends-in-2012 (Accessed on 6 Jun 2013)
[2] http://ignitevisibility.com/facebook-marketing/ (Accessed on 6 Jun 2013)
[3] http://www.jeffbullas.com/2012/11/28/the-latest-27-social-media-facts-figures-and-statistics-for-2012-infographic/ (Accessed on 6 Jun 2013)
[4] http://www.nielsen.com/us/en/reports/2012/state-of-the-media-the-social-media-report-2012.html (Accessed on 6 Jun 2013)

IJCNLP 2013 Workshop on Natural Language Processing for Social Media (SocialNLP), pages 23–28,
Nagoya, Japan, 14 October 2013.

Benchmark Report (Zabin and Jefferies, 2008) published around same time showed that more than 84% best-in-class companies improved their overall performance, customer satisfaction, risk management and actionable insights from social media monitoring and analysis.

We found the first publication on social sentiment analysis in a most interesting paper by Abbasi (2007), where he proposed an affect analysis approach for measuring the presence of hate, violence, and the resulting propaganda dissemination across extremist group forums. In a similar application, Bermingham et al. (2009) proposed crawling and analyzing social media sites, such as YouTube, to detect radicalism. Martineau and Finin (2009) proposed Delta TFIDF, a new technique to efficiently weight words before classification. Asur and Huberman (2010) proposed an approach to predict real-world outcomes through social media sentiment analysis. Pak and Paroubek (2010) explored the use of Twitter as a corpus for sentiment analysis. Bollen et al. (2011) went ahead and analyzed Twitter content to detect different moods of the microbloggers and linked that with the major events in market, media and culture in time scale. Sindhwani et al. (2011) discussed the architecture of a tool and proposed a new family of low-rank matrix approximation algorithm on TFIDF model for modelling topics in a given social media corpus. Tan et al. (2011) showed that information about social relationship can be used to improve user-level sentiment analysis.

2.2 Citizen Social Sentiment Analysis for Government

As established in the facts presented in last section, social media presents itself as a '*big data'* source of citizen voice. If Government agencies can constantly keep a tab on pulse of its citizens, it can pave the way for better governance. Social sentiment analysis can be a very useful tool to achieve the same. It can address the following questions which Government agencies would be very interested to get an answer:

- How do **citizens feel** about the agency's new programmes and policies?
- What are the **most talked about programmes**? Is it **good or bad**?
- What are the **most positively** talked about attributes in the agency's programmes? Can the agency replicate it to other programmes?
- Is there **negative chatter** that the agency should respond to?
- Who are **advocates and sceptics** of the agency?
- Where the agency should be **actively listening**?

Answers to such questions would help agencies to fine-tune their policies to address specific concerns; transform their communication and out-reach programmes to clear any misconceptions; provide with insights on how its programmes and initiatives are perceived by its key stakeholders; identify best practices from positively perceived programmes and replicate it in others; design an effective performance model; and formulate a comprehensive social business strategy.

Interestingly, while it was well established for more than a decade that commercial organizations can get benefited from sentiment analysis (Zabin and Jefferies, 2008), its value for Governments was not very apparent until recent time.

In 2010, Gartner came up with Open Government Maturity Model (Maio, 2010). At 4th level of maturity, Gartner proposed sentiment analysis as a mean to achieve collaboration for Governments.

Echoing to that model, Forrester Research (Gliedman, 2011) observed that the US Federal government was monitoring the citizen sentiment in Twitter. Gartner (Maio, 2011) advised the Governments to use social media for achieving collaborative budgeting and pattern discovery where citizen sentiment analysis in social media can play a significant role. The public safety related works (Abbasi, 2007; and Bermingham et al., 2009) we mentioned in section 2.1, can be seen as early sentiment analysis related works for Government.

3 Approach

We could not find many publications that reported applying the social sentiment analysis in a Government context. Thus, it might be an opportune moment to attempt doing a sentiment analysis in the backdrop of a real-life Government problem. In this section, we proposed an approach to accomplish the same.

3.1 Topic Modelling Problem

Unlike few other type of content, such as movie review, social media is much unstructured and free flowing. Thus it is always a challenge to find out documents or entries that are relevant for the topic we are interested in. This relevance filtering based on topic can be seen as an Information

Extraction (IE) problem, where a large number of documents or entries in social media are analysed to extract some coherent topics out of it before further analysis for subjectivity detection and sentiment classification. This problem is called *Topic Modelling*.

The traditional Term Frequency and Inverted Document Frequency (TF-IDF) model, which is used in Information Retrieval (IR) for calculating relevance, can be adopted here though with some modification as explained below:

Let $X \in \mathbb{R}^{n \times m}$ be the document-term matrix that can be directly used in IR domain, where n = number of documents and m = number of terms. The elements of X can be defined as

$$X_{d,w} = \frac{\log(1 + tf_{d,w}) * idf_w}{C_d}$$

where $tf_{d,w}$ is the term frequency of term w in document d, $idf_w = \log(n / df_w)$, df_w is the document frequency of term w, and C_d is the normalizing factor. Dimensions of X are expected to be large in social media context though X is expected to be very sparsely populated.

If we want to learn k topics, then let $H \in \mathbb{R}^{k \times m}$ be the matrix of topics and terms. Similarly, we can imagine $W \in \mathbb{R}^{n \times k}$ as the matrix of topic distribution among documents. Thus the topic modelling problem can be reduced to be the problem of estimating W and H such that $WH \approx X$.

3.2 Architecture

In our approach, the topic modelling and sentiment analysis is performed by an IBM system – Cognos Consumer Insight (CCI). The architecture of CCI, which runs based on the theoretical foundation above, is presented at Figure 1. The components of this system are described below:

GPFS: The IBM General Parallel File System is a specialized file system targeted for high-performance applications – such as big data analytics.

Hadoop: Apache Hadoop is an open-source software framework for running data-intensive applications in a distributed fashion over commodity hardware.

SystemT: It is a rule-based IE system as proposed by Chiticariu et al. (2010). It uses a declarative rule language, AQL, to define the Natural Language Processing (NLP) rules for information extraction from documents.

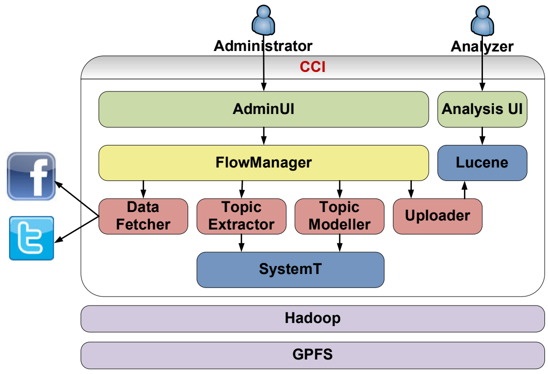

Figure 1: Cognos Customer Insight Architecture

FlowManager: Based on the rules and configurations, this component orchestrates the execution of different tasks across different components in this system.

Lucene: Apache Lucene is an open-source framework for IR applications.

AdminUI: The user interface used by administrators to configure this system and define AWL rules using simple interfaces.

AnalysisUI: The user interface component that enables sentiment analysis execution and rendering using Lucene component.

DataFetcher: The social media interfacing component that interacts with diverse sources, fetches information in different formats and produces JSON representation of them and saves into GPFS.

TopicExtractor: With the help of natural language processing rules in SystemT, this component extracts information from JSON data created by DataFetcher. It computes the $tf_{d,w}$ and idf_w values and produces X matrix. This component runs as a Hadoop job.

TopicModeller: This component computes the estimated matrices W and H. It employs the Proximal Rank-One Residue Iterations (Proximal-RRI) optimization algorithm as proposed by Sindhwani et al. (2011). It also produces JSON documents annotated with topic information. This component also runs as a Hadoop job.

Uploader: This component picks up the annotated JSON documents produced by TopicModeller and uploads them into a staging area. Lucene indexes these documents so that they can be searched and analysed based on extracted information using traditional sentiment analysis techniques for subjectivity detection and sentiment classification.

3.3 Method

We propose the three step method below:

Step I: Define Analysis Model. As first step the analysis model needs to be defined and configured through the AdminUI of CCI. The analysis model comprises of the following:

- **Query**: This defines the scope of baseline data retrieval from social media sources. The DataFetcher would use it. The result of the query produces the document dimension (n) of the W matrix.
- **Topic**: As explained earlier, it is important to define topics to bring the free-form large number of documents into a coherent group. The topics can be configured in CCI in two levels. A set of *Concept* terms are defined and those can be grouped into *Type*. These topics would be used by the analysis engine to create snippets of interest from the base list of documents retrieved from social media. For example, if we are analyzing a social services agency, all the benefit programmes such as Income Support, Employment Support can be identified as Concepts and grouped under the Topic 'Benefits'. This configuration would define the topic dimensions of W and H matrices.
- **Hotword**: Hotwords are the parameters that are common across the defined topics of interest. They can provide additional insight into how sentiments around a particular concept can be perceived in the context of different hotwords. For example, hotword can be a significant process step or a property that is common across multiple Government programmes. Some of the hotwords for a Social Services agency can be '*Claims*', '*Awareness*' etc. '*Income Support*' concept can be perceived in a negative sentiment in the context of *Claims* hotword, but can be perceived in a positive sentiment in the context of *Awareness* hotword.
- **Sentiment Lexicon**: Though CCI provides a sentiment lexicon assigned with prior polarity for different languages, it is necessary to validate that in the context of the rest of the analysis model. This is important since the connotation of a sentiment term can change depending on the context of analysis. Customisation can be done as necessary.

Step II: Perform Analysis. After configuration of the analysis model, the tool can be run and analysis can be performed across different dimensions. Some of them are presented in our *Result* section.

Step III: Root Cause Analysis. Once insights from the analysis are gained, a root cause analysis can be carried out. While this can be done manually by going through all the positive and negative sentiments and analyzing them, there are two ways we can get narrow down the root causes automatically with reasonable accuracy.

- By analyzing the hotwords and their associated overall sentiment that has a closer affinity with a concept. If a particular aspect has an overall negative sentiment and it has a closer affinity with a programme, then one of the root causes for that particular programme to have a negative sentiment is inefficiencies at that particular aspect of that programme.
- By extracting the *Title* of all the documents that contain a particular sentiment separately and by doing a *tag cloud* on the same, we can have some perspective on what discussion item is leading to most of the negative sentiment or a positive sentiment.

3.4 Experiment Setup

We performed Social Sentiment Analysis for one of the major social benefits organizations in the US. The scope included: (a) analysing agency's current social media presence and strategy and compare it with similar agencies in the world; (b) sentiment analysis to understand how agency's various benefit and healthcare programs are perceived by citizens; (c) identify root causes leading to the perceptions; and (d) preparing an actionable roadmap based on the findings.

We defined the boundary of our analysis as the user generated content between 1 Jun 2012 and 18 Oct 2012 from Twitter, Facebook, Flickr, YouTube, several blogs, forums and some general websites built around certain community. BoardReader crawler retrieved 41,405 documents based on our configured query and the analysis model extracted 16,954 snippets based on the topics defined. CCI version 1.1 was used to run the analysis.

4 Result

Results from Sentiment Analysis findings are presented below across various dimensions. Our interpretations of the results are also highlighted in the sections below.

4.1 Sentiment Distribution Across Concepts

This analysis is used to compare the perceived sentiments across concepts by citizens. This can be done at two levels:

- including sentiments from snippets that may or may not have hotwords; and
- including sentiments from snippets that has at least one occurrence of a hotword.

The 2nd level gives a much more focused perspective of sentiment analysis since it is relevant to the hotwords of interest.

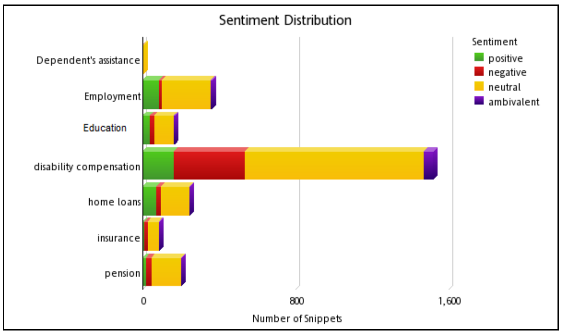

Figure 2: Sentiment Distribution Across Concepts (Regardless of Hotword Presence)

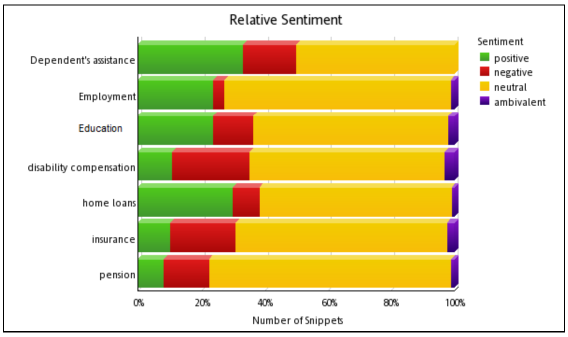

Figure 3: Sentiment Distribution Across Concepts (With Hotword Presence)

It is clearly evident that *Disability Compensation*, *Insurance*, and *Pension* contribute heavily towards negative sentiments, whereas *Employment Benefits*, *Dependent's Assistance*, and *Home Loan Benefits* are talked in positive light.

4.2 Sentiment Distribution Across Hotwords

This analysis gives a perspective on how various aspects of agency's programmes are perceived. The analysis is presented in Figure 4 and Figure 5. We observed the following: (a) *Claims* and *Awareness* are mostly associated with *Benefits and Services* programmes whereas *Quality* and *Helpline* are mostly associated with Healthcare programmes; and (b) *Claims* received most of the negative sentiments.

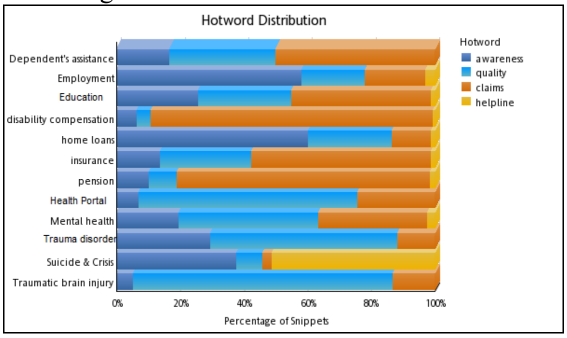

Figure 4: Hotword Distribution Across Concepts

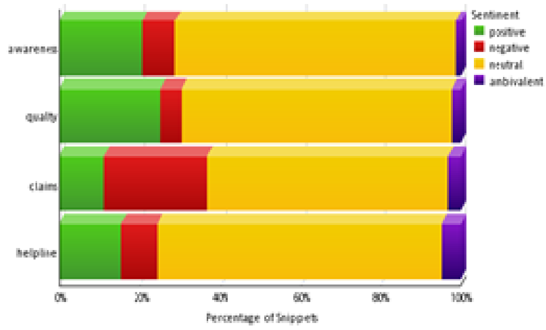

Figure 5: Sentiment Distribution Across Hotwords

4.3 Concept-Hotword Affinity Analysis

The relationship between Concepts and Hotwords is analyzed by measuring the degree of affinity between these two dimensions. It helps us derive which aspects of a particular programme lead to a particular sentiment thus giving some hints towards root cause. Chi-square distribution was used to measure the degree of affinity.

We observed the following: (a) *Disability Compensation* and *Pension* had a close affinity with *Claims*, which in turn had a negative sentiment due to high number of backlogs; (b) *Suicide and Crisis Prevention* had a high affinity with *Helpline* which had a positive sentiment; (c) *Mental Health* and other healthcare programmes had high affinity with *Quality* and were positively perceived; and (d) Many benefit programmes had close affinity with *Awareness*. There seemed to lot of out-reach activities done by the agency which boosted the positive sentiment around *Awareness*.

4.4 Root Cause Analysis

We performed a root cause analysis with the aid of affinity analysis and formation of tag cloud as shown below:

Figure 6: Tag Cloud

We discovered some of the major reasons behind negative sentiments: (a) the agency was suffering from huge backlogs in claims processing; (b) awareness of benefits and services was little among its clients and the agency needed to transform its outreach activities; and (c) agency had a poor social media strategy. This analysis provides key information to draw an actionable roadmap for the agency which can result in reducing negative perceptions and accentuating the positives.

5 Conclusion

In this work we chose a particular tool and proposed a method to apply social sentiment analysis in the context of Government. We went ahead and applied the technique and method to a real-life problem. In the process of doing so we gained valuable insights, which can be converted into actionable roadmap for the Government.

The success of this application can be taken as an encouragement to apply this approach to more such issues, such as – *Lokpal Bill* discussion in India or *Universal Credit* controversy in UK. Such analysis would be able to provide a conclusive sentimental insight from the mind of the citizens.

Another interesting problem that can be taken up is to apply this method in a multi-lingual country like India, where generating content in a mixture of languages (e.g. English and Bengali) is a common practice in social media.

References

A. Abbasi. 2007. *Affect intensity analysis of dark web forums*. Proceedings of Intelligence and Security Informatics (ISI), pp. 282–288

Sitaram Asur, and Bernardo A. Huberman. 2010. *Predicting the Future With Social Media*. Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on. Vol. 1. IEEE

Adam Bermingham, Maura Conway, Lisa McInerney, Neil O'Hare, and Alan F. Smeaton. 2009. *Combining Social Network Analysis and Sentiment Analysis to Explore the Potential for Online Radicalisation*. International Conference on Advances in Social Network Analysis and Mining (ASONAM'09), IEEE

Johan Bollen, Alberto Pepe, and Huina Mao. 2011. *Modeling public mood and emotion: Twitter sentiment and socioeconomic phenomena*. Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media.

Laura Chiticariu, Rajasekar Krishnamurthy, Yunyao Li, Sriram Raghavan, Frederick R. Reiss, and Shivakumar Vaithyanathan. 2010. *SystemT: an Algebraic Approach to Declarative Information Extraction*. Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, pp.128-137

Anthony R. Curtis. 2013. *The Brief History of Social Media*. University of North Carolina at Pembroke, [Online] Accessed on 1 Jun 2013 at http://www.uncp.edu/home/acurtis/NewMedia/SocialMedia/SocialMediaHistory.html

Chip Gliedman. 2011. *Industry Innovation: US Federal Government*. Forrester Research Report

Andrea Di Maio. 2010. *Gartner Open Government Maturity Model*. Gartner Report

Justin Martineau, and Tim Finin. 2009. *Delta tfidf: An improved feature space for sentiment analysis*. Proceedings of the 3rd AAAI International Conference on Weblogs and Social Media. 2009.

Alexander Pak, and Patrick Paroubek. 2010. *Twitter as a Corpus for Sentiment Analysis and Opinion Mining*. Proceedings of LREC. Vol. 2010

V. Sindhwani, A. Ghoting, E. Ting, and R. Lawrence. 2011. *Extracting insights from social media with large-scale matrix approximations*. IBM Journal of Research and Development, 55(5), pp.9:1-9:13

Chenhao Tan, Lillian Lee, Jie Tang, Long Jiang, Ming Zhou, and Ping Li. 2011. *User-level sentiment analysis incorporating social networks*. arXiv preprint arXiv:1109.6018

J. Zabin, and A. Jefferies. 2008. *Social media monitoring and analysis: Generating consumer insights from online conversation*. Aberdeen Group Benchmark Report