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Sentiment Analysis of News Articles:
Helping public figures create policy strategies

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Contents

Abstract

In a competitive world, where image is crucial to be successful in the political arena, Sentiment Analysis of news articles is a useful tool that provides accurate information about the media's perception of major political figures. They can benefit from knowing what newspapers, journals, and web sites are publishing about them. This project attempts to provide them with an accurate and powerful program that calculates their popularity based on the Sentiment Analysis of news articles.

Key words - Sentiment Analysis, media, politicians, public opinion

Introduction

In the global market, companies make great efforts to meet their customers' expectations. Business intelligence tools are widely used to predict market changes and reduce financial risks. Because of the enormous amount of information on the internet, companies are focusing their efforts on the analysis of text on websites, specifically news articles.

Sentiment Analysis, also known as opinion mining or emotion AI, is defined as the group of tools and techniques used for inferring the emotions of authors. Companies can used these tools to detect the public's perception of products in a segment of a market.

Sentiment Analysis reports generally provide binary results: positive/negative, like/dislike, good/bad. It can also be applied with multi-class ternary classification tasks. We reported three results: positive, negative and neutral.

Sentiment Analysis has a variety of approaches, techniques and applications that will be discussed below. It uses natural language processing and machine learning methods to extract, identify, and characterize the sentiment content of a text. One of the main challenges of Sentiment Analysis is that humans, who are the authors of the texts, are subjective beings. The task of detecting emotions through an analysis of a text can be difficult, but may yield significant results. Companies use Sentiment Analysis as a business intelligent tool. They can analyze opinions about the price and characteristics of their products and services, as well as those of the competitions'. But subjective data like this may lead to unproductive business decisions. Sentiment Analysis helps companies gather and understand this subjective data, and to create meaningful information for the decision-making process.

Sentiment Analysis is not only applied to business and market decisions, but is also useful in psychology, sociology, law, policy making, and politics. Political Sentiment Analysis is used to analyze trends, identify ideological bias, evaluate voter´s opinions, gauge reactions, and measure popularity. This kind of Sentiment Analysis focuses on analyzing public opinion by studying informal and formal environments. Informal environments refers to personal blogs, social networking services, and feedback sections from online publications, while formal environments refers to news articles and journal publications. An analysis of formal environments can predict political trends, identify market segments for target ads, identify political bias, and evaluate newspapers positions. Politicians and public figures can measure their popularity and make decisions about strategy to win more supporters.

This report uses a number of feature sets and classifiers* to infer sentiment in news articles. The results of our analysis can provide public figures with insight into the level of their popularity in the media. This work is organized as follows: in section 2, we present the related work that was the starting point of our research. Specifically we discuss NLP techniques used with Sentiment Analysis and news articles. In section 3, we describe the representative examples in Sentiment Analysis (approaches, techniques and commercial applications). In section 4, we explain suggested directions for our work. We present our conclusions in section 5.

Related work

Mass media plays a role in shaping the opinions of readers regarding politicians. The vast amount of digital information that is available on the internet makes analyzing this unstructured data challenging. The article "Simple Text Mining For Sentiment Analysis Of Political Figure Using Naïve Bayes Classifier Method" by Yustinus Eko Soelistio, Martinus Raditia and Sigit Surendra describes a way to calculate whether an article expresses a positive or negative opinion.

Three variable are defined. The first is 'who', which is the person that issues the opinion. The second is 'whom', to hold the value of the person about whom the opinion was expressed, and the third is 'what', which is the text. The system stores this information with the polarity of the sentiment of the opinion, and how many times 'who' has expressed it.

The training data is a set of news articles, each of which contains a reference to one or more political figures. The sentiment of the article is determined by this polarity score and by the number of times that it was expressed. The polarity is determined by a unique word in the lexicon that can be either positive or negative. An example of how a score is represented is [3,7]. The left number represents the positiveness or negativeness of a word, and the right number represents the number of times this sentiment was expressed by a particular person towards a particular public figure.

The authors make a list of seven assumptions in the article. The first assumes that every article that is introduced to the system is about politics, whether or not a politician is mentioned or not. The second and third explain that if the identity of the person who is issuing the opinion is not clear, then it defaults to the entity 'news media'. Assumption 4 explains that the system keeps track of any number of the above-mentioned variables. Assumption 5 states that the words 'no' and 'not' reverse the polarity that it modifies. If there is double-negation, then polarity reverses with each negation word. Assumption 6 allows for sarcasm. If the previous word has a negative polarity, and the present word is positive, then the system does not count the positive word's contribution to the final score. The system assumes that a sudden change is not to be taken literally. The last assumption states that the system assumes that every article contains some sentiment.

The steps are as follows. The 'reader' and 'parser' tokenize the words and punctuation. Adverbs and functional words like 'is' and 'the' are removed. Also, a lexicon replaces 'non common pronouns', pronouns and aliases that politicians use with a proper noun. If a 'special word' is found then the system analyzes its polarity, and determines who said the word and about whom it was said. It finds this out by looking at the tokens that occur before the sentiment bearing word 'special word'. The flowchart in the article seems to indicate that the system moves towards the beginning of the sentence token by token. If it finds one that corresponds to a public figure, then it assumes that he or she is the target. But if the token corresponds to an active verb then the system looks at the word that precedes it. If this token is a public figure, then the system assumes that this is the person who is expressing the opinion. If it is not a public figure, then the system uses the default category 'news media'.

The results are checked against a human reader. The authors claim to have a 81.2 accuracy. In the conclusions the authors suggest that this is not the best way to identity the speaker, the target, and the sentiment expressed.

In the article "Evaluating Feature Sets and Classifiers for Sentiment Analysis of Financial News" by Pal-Christian S. Njølstad, Lars S. Høysæter, Wei Wei and Jon Atle Gulla, the challenge of detecting implicit sentiment is addressed. The authors believe that this kind of analysis had been limited to domains that are intrinsically sentiment-bearing. Political speeches and blogs are the focus of this analysis. Opinions in newspaper articles are more difficult to detect for three reasons. Unlike blogs and product and product reviews , a news article may not have a clearly defined target. Also, good and bad news is more difficult to separate from positive and negative sentiment. Background knowledge and interpretation are also necessary.

Financial news in Norway is suitable for sentiment analysis, as it does not have the above three limitations. Such news is likely to contain an opinion. Also, the targets are clearly defined. Financial news articles follow patterns in form and style.

The authors define 26 article features and them with five classifiers. These features are grouped into four categories (textual, categorical, grammatical, and contextual). The data set was 1000 articles from the news publisher Hegnor dot no. Each article had a title, a lead, and a main text. When annotating these three parts of the article, the authors used a 'purely textual Sentiment definition', which they assert is represents a 'common denominator of all readers'. The annotators labeled the three parts of the article, and the three as a whole, as negative (-1), neutral/objective (0), or positive (1). If an annotator was not sure how to label a part, he or she labeled it (0).

In engineering feature sets, the authors noticed that both question marks and exclamation marks in articles on the news website were associated with sentiments. Also, the categories 'economics' and 'analyst recommendations' seemed to be prone to contain opinions. The first of the four groups that the authors divided their features into, Textual, contains seven features that describe characteristics that are derived from information about the article. For example, Length_of_Title counts the number of words in an article's title. The second group, Categorical, contains three features, all of which can be extracted from the url of the article. These features are Analysis, Economics, and Stock Exchange, all of which are sections of the website Hegnor dot no. The group Grammatical contains ten features, in which parts of speech and negation are extracted. A POS tagger was used to identify the syntactic categories. The last group, Contextual, has six features. Four of them identify 'clues' that are related to sentiment-laden words only in the title, and the other two are related to 'clues' in the whole article. The term 'clue' in one of the four means a word that expresses a sentiment in the title, and a 'clue' in the other two means a word in the article that is indicative of a recommendation or an analysis.

When creating testing and training sets, the authors used only 12 features. Four groups were formed (Two from Text, two from Category, two from Grammatical, and six from Contextual) and each group was tested individually with each of the five classifiers (Naïve Bayes, Random Forest, Artificial Neural Networks, J48, and Support Vector Machines). Then the first two of these groups were combined and tested with all of the classifiers. After, the first three were tested together. Finally, all four were run against the classifiers. The two Textual features performed the worst, and adding Categorical improved accuracy only a few percent. A jump in performance occurred when the six features in the contextual group were added to the other six. The authors suggested that this added domain-specific knowledge. Also, the group Contextual contains four features that have to do with the title of an article. The authors believe that there is a correlation between the classification of the title and that of the article as a whole.

The best classifier was their own, the J48. This may be due to the small number of documents. Random Forest would excel with a much larger data set. Naïve Bayes scored the highest without the six Contextual features, perhaps because it performs better with low dimensionalities.

The article “Sentiment Analysis in the News” by Alexandra Balahur et al also states that most opinion mining has been done n blogs and product reviews, in which format writers can express their feelings freely. IN contrast, news articles attempt to seem unbiased, and journalists avoid explicitly negative or positive sentiment; identifying opinion that is lexically expressed is less challenging than that which is expressed implicitly. Another difference is that blogs and reviews have a single, concrete target that is the focus of the text. In contrast, a news article is complex in that it can contain a number of targets and detailed description. In opinion mining, it is necessary to associate the sentiment with the right target. For example, a person who is mentioned in an article that describes a disaster may be identified by an opinion mining system as negative, simply because it appeared in that article.

The authors gathered 1592 quotes in English and annotated them. The person who issued the quote, and target or targets, are extracted. Quotes were used because they are usually subjective and more likely to express an explicit opinion. The annotators imposed two criteria on how they estimated opinion. First, they looked for sentiment-bearing words that occurred within a predefined distance from the target. They also ignored sentiment-bearing words that happen to be in the list of words that NewsBrief and Med I Sys use to categorize news articles. These 'category defining' words may or may not be sentiment-bearing. The authors seem to be trying to find a list of words for annotating the quotes that has words that can only express opinion. If the 'category defining' words are removed from the quotations that they have collected, then they have eliminated the 'bad versus good news content'. The authors may believe that there is a set of words that express sentiment, and that are also words that define a category of news. It is the words that form the intersection that they want to remove. Examples of items in this category are 'disaster' and 'crisis'.

In choosing which quotes to use, the authors decided to annotate only the ones that had a clearly expressed opinion. The annotators were asked not to interpret the quote. The authors considered this to be 'news bias'. This is a problem in Sentiment Analysis only to the extent that, for example, word choice or story framing reveals an opinion. The sentiment that is of value is the kind that is explicitly stated.

The score of a quote was computed using the lexicons WordNet Affect, SentiWordNet, MicroWNOp, and the authors' lexicon JRC Tonality. A word and its polarity was taken from these, and its value was converted by the system into one of four scores: positive (1), negative (-1), high positive (4), and high negative (-4). The quote then received a score based on the sum of the values of the words in it.

The results show that SentiWordNet overclassified the quotes as positive, while WordNetAffect overclassified them as negative. MicroWNOp and JRC Tonality were the most accurate. Removing the 'category words' improved the accuracy slightly. Also, by limiting the number of words around the target to six, accuracy improved dramatically. Removing this limit, to allow for opinion mining in the entire text, noticeably decreased accuracy.

The article 'Sentiment Analysis on the People’s Daily" by Jiwei Li and Eduard Hovy focuses on Sentiment Analysis in a media outlet that provides information about the policies of the political elite of mainland China. The state that, with time, government policy needs to adapt to events, and the journalists and writers who work at such newspapers adopt a tone and express the change in sentiment. The authors Li and Hovey demonstrate the shift with two sample articles from editions of the People's Daily published in August 1963 and October 2002. The target is the United States, which was prosecuting its wars in Vietnam and Afghanistan. The difference in tone is obvious; the former article is against American intervention in Southeast Asia, while the later article encourages the reader to believe that China and America can cooperate.

Li and Hovy cite two difficulties in extracting opinion from government organs like the People's Daily. The first is processing what they label 'linguistic phenomenon', which includes 'rhetoric, metaphor, proverb, or even nicknames…' The second is creating an algorithm that would allow for the classification documents by the degree of sentiment that is expressed, in contrast to a binary or trinary system (positive, neutral, negative). The algorithms that they suggest could provide these powerful features to their system include 'vector machine / regression' or 'supervised LDA'. A document can contain a variety of opinions, but only one would correspond to a single entity that could be a public figure, a country, or something that a journalist refers to as a 'friend' or as 'an enemy'. For example, a single document refers to US president Trump as an animal, and Mexican president Peña Nieto as long-suffering. The system should associate the target with the appropriate predicate. Algorithms that employ a bag-of-words approach would probably have a low accuracy.

The authors propose that an approach should assume that sentiment that is expressed in an article about an entity is consistent. If the system decides that a newspaper article expresses negative sentiment about an entity, then it cannot be the target of any positive opinion in the article. Also, the program should be able to associate unknown words to the correct entity. The example in the article is the use of the Chinese expression 'tiger made of paper'. The word 'tiger' has positive connotations; however, the system should see that it was associated with an entity that has a negative score, and mark the whole expression negative. The ability to infer this would allow the researchers to start with a relatively small set of seed words, which would reduce the amount of supervision.

The model has six steps. In the first, the opinion-holder, the sentiment, and the target are extracted. The features that are employed at token-level are part of speech, word length, the right and left context words and their POS tags, and others. The second step is notation. The state of the relations between entities is divided into seven categories that range from 'antagonism' to 'brotherhood'. In the third step, a 'Bayesian-Markov framework incorporates 'time information'. It assumes that there is coherence in 'news streams'. Step four is the initialization of the 'target' variable. Steps five and six update the list of 'subjective words' and prevent the damage that 'boot strapping' can cause.

The data set is articles taken from the People's Daily from 1950 to 3010. Each article is tokenized. Those with fewer that 200 words are discarded. A name of a country must appear at least two times in an article. If an article mentions six countries or more, it is discarded. If a sentence is a compound sentence, it is divided into two sentences. If a sentence has fewer than four Chinese characters or more than 50, the sentence is discarded. Sentences with negation are also discarded.

One-hundred of the articles were labeled 1 to 7 (antagonism - brotherhood) by students who were majoring in International Relations at a university in China. From a lexicon the students choose words that describe the label.

The authors compare the results of semi-CRF and CRF. The former is noticeably better, especially on the data set of articles that contain only one target (89.5%), Then the authors compare this to the results obtained with Co-reference+Bootstrap, No-time, SVR-d, SLDA, and SVR-S. The authors' system was better than all of these. No-time came in second place with 80.8%.

The article "Evaluating Sentiment Analysis Methods and Identifying Scope of Negation in Newspaper Articles" by Padmaja et al attempts to perform two tasks related to sentiment analysis. One is to compare the results of three ways to mark negation: Rest of the Sentence RoS, Fixed Window Length, and Dependency Analysis. The data set is news articles about two political parties in India. As in the previous articles here, the authors suggest that it is necessary to identify the target of the opinion. Citing Balahur, they recommend that good and bad news be separated from positive and negative sentiment. Also, the analysis should be limited to sentiment that is expressed explicitly.

The authors gathered 513 documents that contained a total of 1075 sentences. The source of the article was the newspaper websites The Hindu, Times of India, and Economic Times. By analyzing the words that politicians used, the authors attempted to understand how politicians influence public opinion.

Two people annotated each sentence for scope of negation. For example, in the sample sentence 'It was not XYZ', only 'XYZ' is in the negation span. If a negation word precedes a noun phrase, then only the noun phrase is in the scope of negation. The sample sentence in the article is 'People did not expect Sonia to act in such a way'. What the annotators marked as in scope was 'expect Sonia to act in this way'. The system is designed to detect only explicit negation. The scope of negation was tested with three approaches. In Rest of Sentence, if a negation tag is identified by the system, then the values, positive or negative of all token from the negation word to the end of the sentence are reversed. Then, the values of these tokens are summed and returned. The second approach was Fixed Window Length. A length of four was set, so if a negation word was found, the system reversed the polarity of the four words that immediately follow, and then the score of the sentence was calculated. The third approach for negation was more complicated. In dependency Analysis, a negation word is located, and the tokens that are contained in the parent node are reversed, and then the score for the sentence is calculated. This seems to mean that the polarity of the words that are above the negation word are reversed.

Sentences were also POS tagged and parsed with a dependency parser. The POS tagged sentences were input to a Dictionary tagger, which tagged every token with values that were gotten from SentiWordNet (positive, negative, and neutral).

The results section of the article demonstrates that the Dependency Analysis approach for negation returned the best accuracy for both political parties. The authors claim that there is a correlation between the success of Bharatiya Janata Party at the polls and a high accuracy score, which in this case was achieved with SentiWordNet.

Objectives

For this work, we have defined 4 main objectives. We offer a versatile tool for Sentiment Analysis of news articles related to politics and other domains. We allow public figures to gauge public reaction before and after crucial events. The third objective is to implement pioneer feature sets to improve on previous attempts of Sentiment Analysis and the media. Our program allows public figures to redefine and restructure their images and policies to improve their ratings in opinion polls.

Representative examples of Sentiment Analysis

Approaches

Sentiment Analysis can be defined as the integration of text analytics approaches and linguistics techniques that attempt to infer feelings and emotions. It is already widely used by companies to infer market tendencies. One of the most common approach to Sentiment Analysis is knowledge based. In this approach, each word is tagged as positive or negative.

Then, if in a text the frequency of positive class words is higher than negative words, the text is considered positive. SENTIWORDNET 3.0 is a publicly available lexical resource that is designed to supporting sentiment classification and opinion mining applications (Baccianella et al 2010).

The relationship-based approach focuses on different relationships within a text, such as relationships between product features. Depending on the features of a product, words that can be considered negative or positive. Sentiment Analysis is based on these relationships.

Previous research has shown that language model approaches are very accurate for certain types of data. This approach is based on n-grams. Pang et al. found that unigrams worked better for Sentiment Analysis of movies reviews (Pang et al. 2002). Dave et al. found that bigrams and trigrams are more suited for sentiment classification of product reviews (Dave et al. 2003).

Discourse structure and semantics is another approach. Some researchers report that the sentiment of a text appears at the end of a text. In discourse structure the sentiment of a whole text is obtained by determining sentiment among discourse components (Vohra & Teraiya, 2013).

Techniques

Sentiment Analysis can be implemented with supervised or unsupervised methods of classification. Previous works have shown that supervised methods offer better performance than unsupervised methods. The main difference between these two techniques is that supervised methods require the maintenance of labeled training data, which may be prohibitive in terms of time and resources (Vohra & Teraiya, 2013).

Supervised techniques can be implemented by building a classifier. Natural Language Processing Toolkit (NLTK) offers five diverse classifiers: Conditional Exponential, Decision Tree, Maxent, Naïve Bayes and Weka. Previous works have shown that when the dataset for training is small Naïve Bayes presents better results. Some of the most commonly used features for sentiment classifications are:

- Term presence and frequency
  - Unigrams and bigrams have been widely used for sentiment classification. For product-review polarity classification, bigrams have shown better results than unigrams.
- Part of speech
  - part-of-speech tagging is useful to know the lexical category of each word. With this information is easier to identify adjectives and adverbs in sentences, which help researches infer the overall sentiment of a text.
- Negations
  - Negation words can be the key to infer the sentiment of a sentence. For example, in the phrases “Trump is great” and “Trump is not great”, the word 'not' reverses the sentiment.
- Exclamation and Question marks
  - Exclamation and question marks can give a positive or negative sense to a sentence. For example, “Trump is great!” and “Trump is great?” have

different sentiment. Exclamation marks may increase the sentiment of a sentence while question marks can show neutral sentiment.

One of the main disadvantages of supervised techniques is that the accuracy of the results depends on the quality of the training set.

Unsupervised techniques are done by counting the number of negative and positive words in a text. For example, if a text has more positive words, the whole text is tagged as positive. Turney's work is considered the most prominent for opinion mining and sentiment classification. He used "poor" and "excellent" as seed words to calculate the semantic orientation of phrases (Turney 2012). His study of movie reviews scored a 66% accuracy.

Commercial Applications

Enormous amounts of data are produced every day, and access to this data has become simple with digital information sources such as newspapers websites, social media platforms, and public opinion blogs. When creating new, better commercial strategies, companies have found a great resource in digital content.

To have a better insight into the information extracted from digital sites, it is necessary to apply a deep analysis of the text, images, and sources. Sentiment Analysis, the "automated mining of attitudes, opinions, and emotions from text, speech, and database sources through Natural Language Processing (NLP)" (Vohra & Teraiya, 2013), can be used to predict market tendencies and customer preferences. It can also be used in restructuring online commerce strategies and improving the policies for market segmentation ads.

Sentiment Analysis is widely used for various purposes. The most widespread use of Sentiment Analysis is in e-commerce. These websites allow customers to express their opinions of products that they have purchased. For example, after delivery of an item purchased on Amazon, the consumer can express a general opinion about it or rate it on Amazon's website (Figure 1). With these reviews, other customers can make better decisions, and companies can modify the product to increase its acceptance on the market.

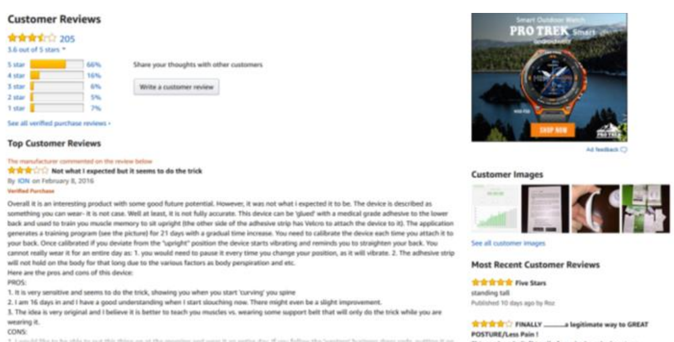

Figure 1. Amazon web site customers reviews

Voice of the market (VOM) is a methodology to collect market feedback, generate practical insights, and establish commercial priorities. In business, time is crucial and Sentiment Analysis provides a deeper understanding of market feedback in real time. When companies have clear and accurate information, it is easier for them to make better decisions about strategic direction. Commercial apps such as Sysomos[1], Radiant6[2], and Cision[3] offer free Sentiment Analysis services in real time. Social Mention*[4] also offers an application that analyses specific digital content, and provides graphic results of Sentiment Analysis (figure 2).

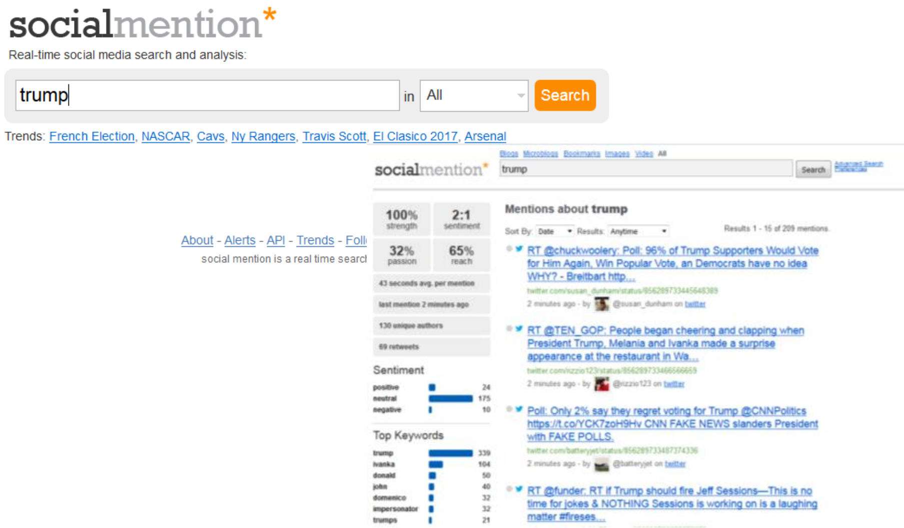

Figure 2. Social Mention, Sentiment Analysis on real time

Voice of customer (VOC) is a term used in business analytics to describe what individual customers are saying about products or services. This process captures the customer´s expectations, preferences and dissatisfaction. It is too costly for companies to have direct communication with each of its customers in order to know their personal preferences. With Sentiment Analysis of reviews, comments and suggestions, companies can have a better understanding of what the preferences of their customers are, and offer better service.

Sentiment Analysis is also used for "brand reputation management." This is strategies that a company implements to improve its reputation. With Sentiment Analysis of opinions and reviews, companies can know how its brand is perceived by the market. With this information, the company can restructure its marketing strategy to improve its public image.

Finally, Sentiment Analysis helps governments assess their strengths and weaknesses by analyzing public opinion. They can detect to what degree public policies have been accepted. Also, it can help individual politicians measure their popularity and, if necessary, restructure their campaigns.

Suggested directions for Sentiment Analysis of news articles.

As mentioned above, we use supervised techniques with a diverse set of features in this project. One of the main disadvantages of this technique is that the accuracy of the classifier depends on the quality of the dataset. W gathered 1,000 news articles about Trump,

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[1] https://sysomos.com/solutions/customer-experience/

[2] https://www.marketingcloud.com/products/social-media-marketing/radian6/

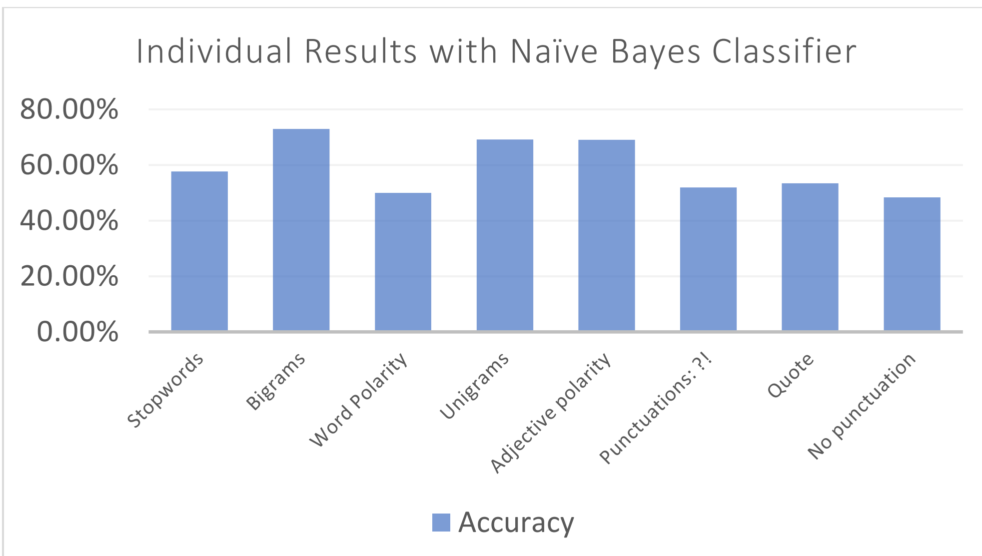
[3] http://www.cision.com/us/pr-software/?nav_location=main_menu

[4] http://www.socialmention.com/

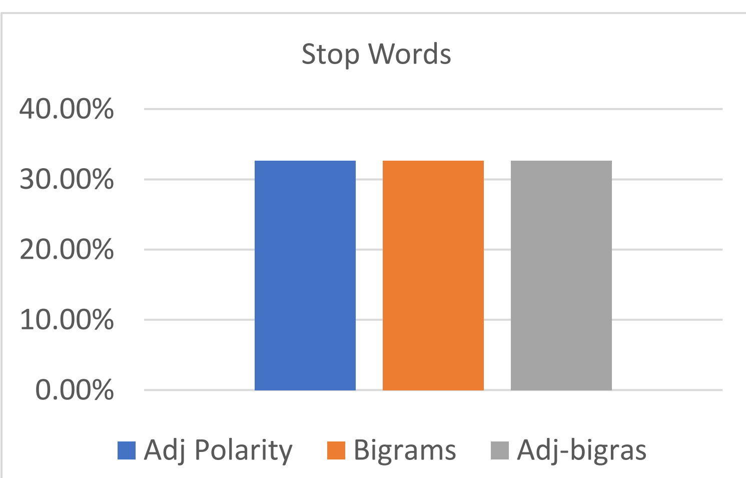
500 before his inauguration and 500 after. After processing the dataset and labeling 20% manually, we used the followed feature sets for training the Naïve Bayes classifier:

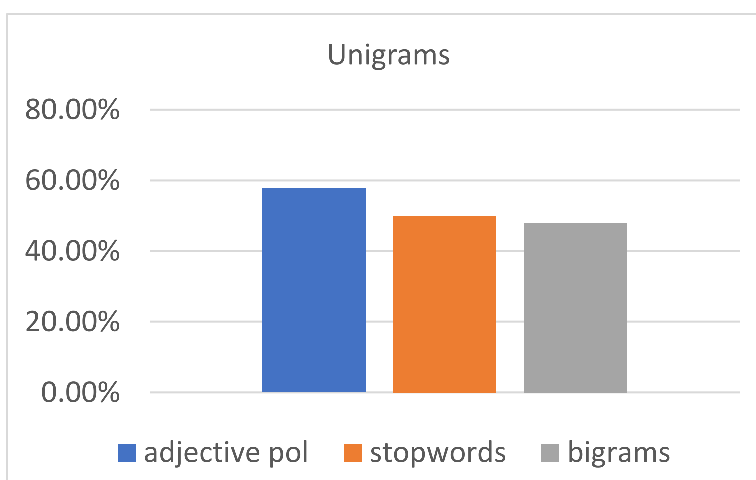
- Quote: counts the number of quotations in the data
- No Punctuation: removes all punctuation
- Punctuation: creates a dictionary of exclamation marks and question marks
- Word Polarity: retrieves the strength, POS tag, whether it is stemmed, and the polarity of a word from a lexicon
- Adjective Polarity: retrieves the strength, POS tag, whether it is stemmed, and the polarity of an adjectives from a lexicon
- Stopwords: removes stopwords that are in the NLTK stopword corpus
- Bigram: extracts two consecutive words
- Unigram: extracts the most common the 2000 words

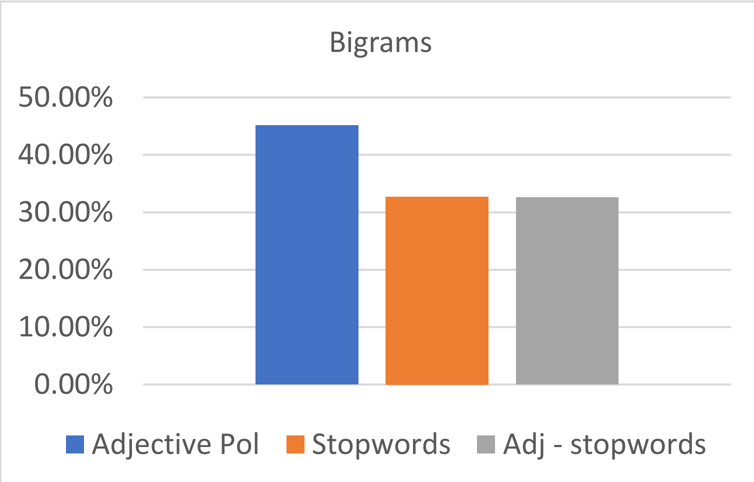
Below are the results that we obtained with these features:

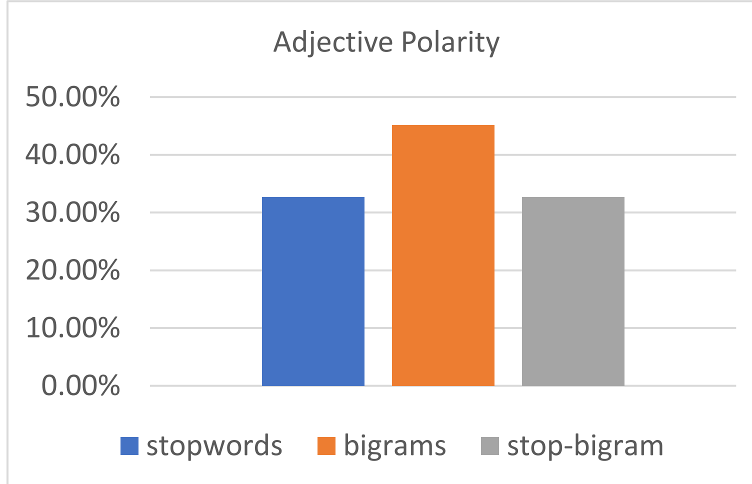


We decided to combine the features that scored the highest accuracy, and got the following results:









Because the feature combinations reported lower accuracies than the individual results, we decided to use bigram features to build the following commercial prototype:

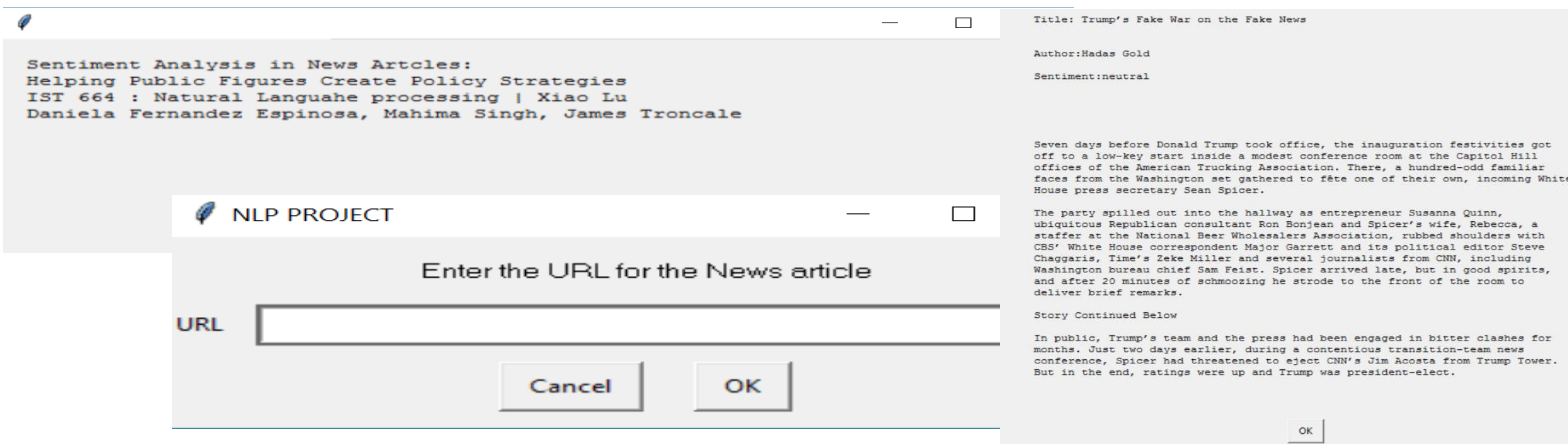


Figure 5. Sentiment Analysis report

In the future, we expect to increase the functionality of our prototype. We would like to offer our model as a commercial intelligence business tool to help public figures manage policy strategies. We plan to apply our model not only to the analysis of news articles, but also to magazines, social media, blogs, and journals. This offers a public figure a comprehensive understanding of the media's perception of him or her.

In this improved prototype (figure 6), our customers chose from categories such as sports, entertainment, culture, and influential people. Then, they apply the analysis to social media, newspapers, or blogs, whose perceptions of the public figure are presented in a visual representation.

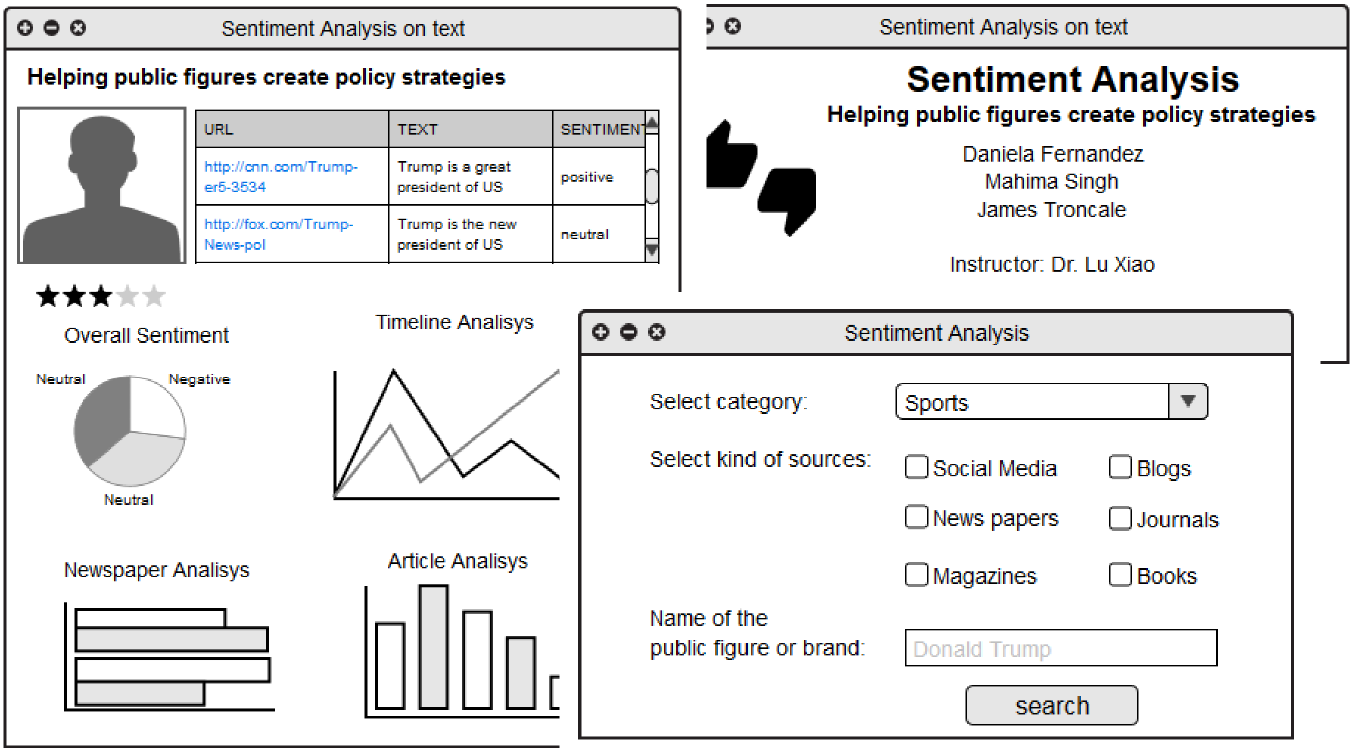


Figure 6. Improved prototype

Conclusion

After analyzing the results, our team concluded that bigrams with the Naïve Bayes classifier is the most accurate. We observed that Decision Tree classifier in NLTK is not appropriate for complex feature sets and large amounts of data. Our accuracy is comparable or better than that of related articles. As any Sentiment Analysis is subjective, this model is limited by the taggers' interpretation of polarity.

If we want to extend our model to include public figures in other domains, it is necessary to process news articles from those domains as well

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Appendix

A visual representation of our methodology

Step 1

Collect 1000 articles

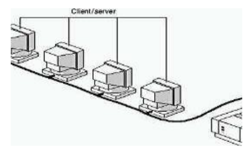
Step 2

Tag 20% of the corpus for training and testing

Step 3

Wrote python code to process all the data

Step 4



Created different feature sets

Step 5

Applied a variety of feature sets to *different classifiers

Step 6

Selected the ones that presented the highest accuracy

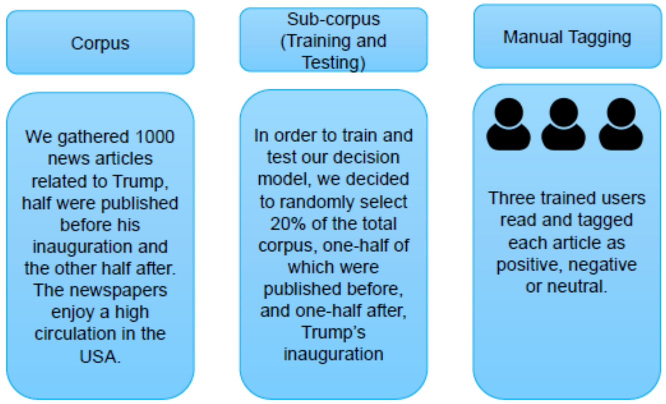
Step 7

Created a prototype for commercial use

Step 8

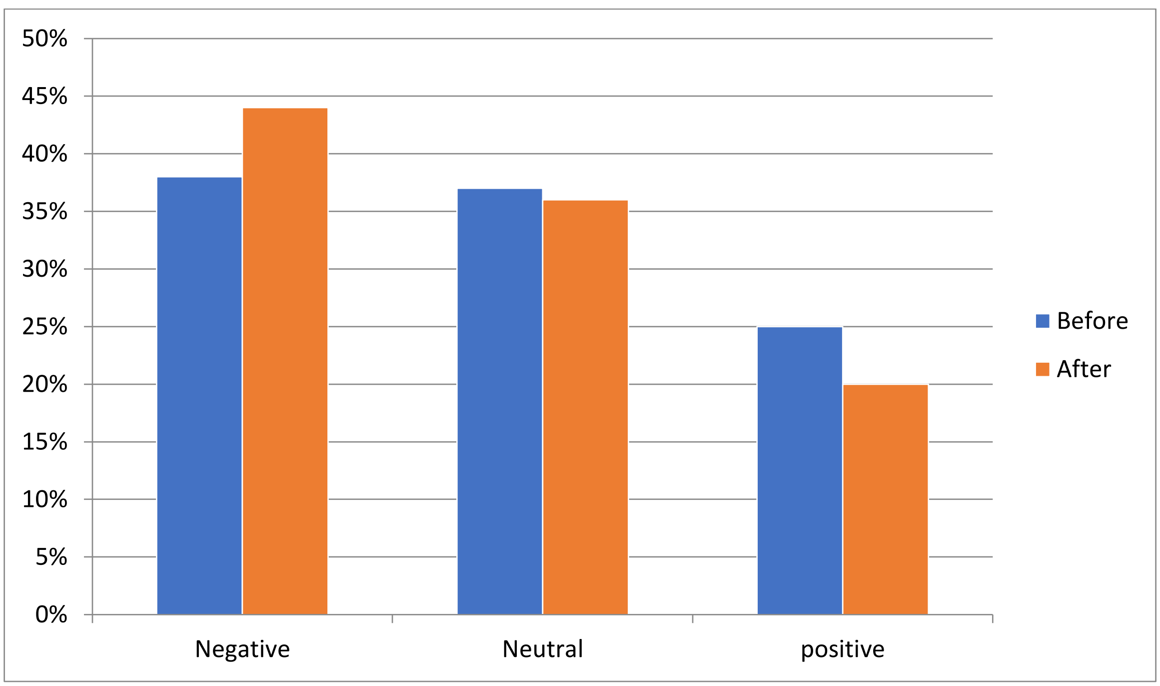
Processed the corpus and got the comparative results for Trump

Description of the dataset



Our analysis of Trump

After we decided on the final classifier, we ran our remaining 800 articles through ours program and yielded the following results



The final results did confirm our hypothesis that after his inauguration, Trump's perception in the media declined. The percent of negative articles went up while the percentage of positive articles in our data went down.