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Sentiment Analysis of Public Opinions: A Case Study on Tesla's Autonomous Electric Cars

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ABSTRACT

In this paper, we wish to address the issues of public concerns on autonomous vehicles. Questions such as how safe the autonomous will be for customers in the long run with such high financial investments. We conducted sentiment analysis on customer reactions towards Tesla's Autopilot Cars. Based on the findings, recommendations would help the autonomous car makers in providing better vehicles which are safe for future buyers as well as other travelers on the road. The systematic way of sentiment analysis can be generalized in helping companies to formulate their marketing goals and expectations.

KEYWORDS: Sentiment Analysis, Public Opinion, Text mining, Autonomous Vehicle

INTRODUCTION

The idea of "Autopilot and Autonomous" vehicles has recently excited public and top tech-innovation firms. Companies such as Apple, Google, Tesla, and Uber are already investing millions of dollars in developing and introducing more autonomous cars to the public (Lafrance, 2015). As one of the major players in autonomous vehicles, Tesla completed development of "Autopilot" hardware by the year 2014 and then by October 2015 this feature was enabled in all models produced by Tesla. Recently in 2016, Tesla made an announcement that all car models produced by it in the future including the upcoming Model 3 will all have more updated Autopilot software. Tesla's Autopilot Car has various features that makes use of sensors, ultrasonic radars, smart cameras and GPS enabled navigation systems to perform better parallel parking, smooth steering as well as changing of lanes on highways (Korosec, 2015). As technology further evolves, Tesla plans to implement "fully-autonomous" functionality in its cars.

Although autonomous cars may seem to be cool and efficient, there have been accidents involving autonomous cars, for example in May 2016, a self-driving Tesla-S model met with an accident which also killed the person in the car because of its failure to judge an adjacent white tractor-trailer. This was a case of concern for people's safety and per a survey conducted by

CarInsuarnce.com from about 2,000 people, 80% of them do not feel safe driving an autonomous car and would not prefer to buy one. Considering above all, it’s highly important to take common reviews, recommendations or feedback from both customers and non-customers by performing sentiment analysis, which will help autonomous car makers like Tesla to come up with safer self-driving vehicles, highly sophisticated autopilot cars which will increase confidence in future buyers. Also, it will help autonomous car makers to fulfill the public demands.
To collect the customer feedback & perform sentiment analysis, we selected Twitter as a major source of data which contains the public opinions about autopilot cars using relevant hashtags.

LITERATURE REVIEW

Sentiment analysis is a text based analysis that utilizes the opinions, sentiments, evaluations, attitudes and emotions of various people for analysis (Liu, 2012). It may make use of natural language processing (NLP), text analysis along with computational linguistics to extract as well as identify subjective information from web data (Ahmed & Danti, 2015). For Sentimental Analysis, data gathering can also be performed by web scraping and text mining in R. Due to the rapid growth of social media platforms, networks, blogs and micro-blogs, sentimental analysis has gained a lot of importance (Bouazizi & Ohtsuki, 2016). Since sentimental analysis based on web-mined data have a growing impact on most studies, it is a popular topic that is increasingly being addressed in the field of text mining and its applications (Seker & Al-Naami, 2013).

Data gathering from websites or web pages is the most crucial part of any text mining study to perform sentiment analysis. In our project, we will be leveraging either of the following techniques based on ease and feasibility: data gathering from a web page can be performed by using a selector gadget in chrome and rvest function in. R language has capable to perform text mining using Tm function (Meyer, et al. 2013). Data extraction from web page can also be done using web crawler using SAS Text Miner (Chakraborty, Pagolu, & Garla, 2013). By using text analysis powered by SAS Text miner (from SAS Enterprise miner), it is possible to use open-ended questions to analyze for sentiments of public opinions from blogs, social sites etc.

In general, sentiment analysis is used in identifying the main subject or problem derived by making an analysis of public opinions. There are several important applications of sentiment analysis. In this paper, we are mainly focusing on the below applications, as we intend to perform analysis on public opinions. Sentiment analysis is helpful in identifying the sentiments expressed by users during disaster events like earthquake or hurricanes. Mainly it captures the user’s concerns, panics, emotional impacts captured through their comments in the social networks, news blogs (Caragea et al., 2014). Sentiment analysis is also helpful in analyzing the public opinions of self-driving cars from social networks, news blogs to derive a summary about the sentiments of buyers, which further helps prospective buyers to decide whether to invest in self-driving car (Kawitkar & Deshpande, 2016).

Certain study using sentiment analysis of a natural language yielded a success rate of 62%, which is highly correlated to the feature extraction (Seker & Al-Naami, 2013). A study is done on the topic:” A technique to detect favorable and unfavorable opinions toward specific subjects (such as organizations and their products) within large numbers of documents offers enormous opportunities for various applications.” resulted in about 95% precision and roughly 20% recall. However, as they expand the domains and data types, they were observing some difficult data, for which the precision may go down to about 75%. Interestingly, that data usually contain wellwritten texts such as news articles and descriptions in some official organizational Web pages (Nasukawa & Yi, 2014). There was an experiment to make a classifier which can tell: (using microblogging as its data source)

- What do people think about our product (service, company etc.)?
- How positive (or negative) are people about our product?
- What would people prefer our product to be like?

The classifier gave a considerably better result and high accuracy in telling the people's opinion on different things.

There have been a few drawbacks of sentimental analysis reported by previous studies. One of the drawbacks is the difficulty in identifying "slangs" (words or sentences) used in various cultures. A sentence (slang) in one culture may be interpreted differently in other cultures. Also computer algorithms could not be 100% accurate at determining sentiment. In fact, it is not unusual for two humans reading the same content to disagree about the writer's mindset. So, while sentiment analysis is very effective at recognizing trends and identifying outliers, it is still up to humans to parse the fine nuances of human language. Context also plays a big role in understanding a writer's feelings on a subject. "That movie was bad!" is surely a negative sentiment from a 50-year-old film critic, but it might be glowing praise from a 17-year-old boy. Another common drawback of sentiment analysis is the failures in parsing complex sentences that negate the local sentiment for the whole sentence. For example, a complex sentence such as "It's not that it's a bad camera" confuses many sentimental analysis algorithms and can affect software precision altogether (Nasukawa & Yi, 2014).

RESEARCH METHODOLOGY

Data Acquisition

The most important and baseline of any text mining project is its data processing. To perform data processing there should be a data acquisition process to gather data. The following is the data acquisition process we used for our study:

(1) The Twitter has been used as the source of our dataset. We created a developer account/application on twitter apps to have access between R and twitter data. When creating a twitter application account, we could receive access to some credentials like "consumer key", "consumer token" etc. using these we can access twitter data using R. We created an application called "R_mining_ira" to access Twitter tweets and do some data analysis on it.

(2) Our second step was to use various R functions and packages to fetch different tweets about opinions on Tesla's autonomous cars. We used packages like "TwitterR" and "Rcurl". Thereby, using these packages and having access to the twitter application credentials, we could make a connection between R and twitter and able to fetch the tweets successfully.

(3) Our third step was to Export the records in .csv file to form a data set for sentiment analysis. Since this data set has unwanted columns, garbage values, null fields, unwanted special characters so we felt there is a strong need for data pre-processing. Thereby our next step was data pre-processing and this raw dataset in .csv file was our basic dataset for data pre-processing.

Data pre-processing

Since we intend to capture tweets related to Tesla's autonomous cars. First, we performed a keyword search using various hashtags, such as

“#tesla”,
“#Autonomous”,
”#Autopilot”,
“#Selfdriving”,
“#TeslaModelX”

in twitter. The above hashtags were selected based on a number of its usages in comments by the public. We used RiteTag (a chrome extension) to figure-out which hashtags are used highest number of times in comments by the public. So, based on the hashtag results we decided to use above 5 hashtags for data collection. Using these hashtags search we could capture user's views related to autonomous cars. After getting tweets, we performed the data cleansing process on the data set. We removed unwanted data like removed URLs, retweets, mentions, duplicates and any special characters, leading whitespaces, trailing whitespaces etc. These all removals were done using various functions in R.

We successfully fetched total of 14,352 tweets that were collected from ‘10-01-2016’ to ‘12-06-2016’. Final data set contains 6,958 records (tweets) and we included the variables ‘Tweets’, ‘isRetweet’, ‘Date’, ‘Location’. Initially, the “Location” variable did not present in our basic data set. To fetch the location variable, we used user “screen name” variable and fetched location into our base dataset.

SAS Enterprise Miner Models

In this study, we used SAS enterprise Miner for the sentiment analysis. The SAS model is showing in Figure 1

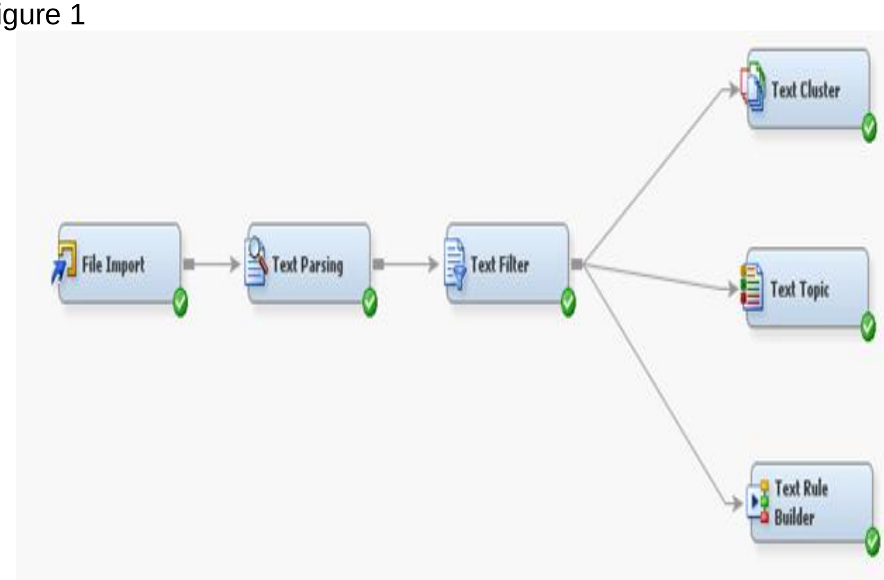


Figure 1. SAS Enterpriase Miner model

We used the file import node to import the cleansed tweets dataset that we achieved through R-Studio. After importing to file import we ran the ‘File Import’ node. In the properties panel of file import node, we set the ‘isRetweet’ variable to target and binary as level using the variable property. We set ‘isRetweet’ as our target variable because we would like to predict the retweets and perform sentiment analysis which contributes to our results. We have used ‘Text Rule Builder’ node to predict the retweets.

Text Parsing

Text parsing was performed on the file import node to further cleanse the data where parts of speech, abbreviations, numbers, punctuations, start list, stop list were removed.

Text Filtering

Text filtering was applied to the output obtained through text parsing where less frequent and irrelevant terms were removed. We also enabled spell check to remove any misspelled words. Best clustering results were obtained through ‘Log’ for frequency weighting when compared to other frequency weights set in the property panel of text filter. We set ‘Mutual Information’ for term weight under property panel as we have text rule builder node for predictive modelling. The minimum number of docs was set to 10. We reached to above settings after running the text cluster with several other parameter combinations.

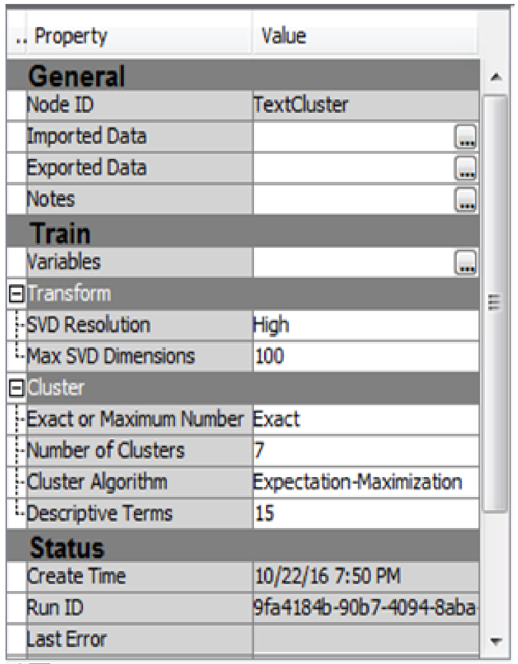
Text Cluster

We applied Text Cluster to the output generated from the text filter. With ‘Number of clusters=5’, we didn’t see much opinions or sentiments that would contribute to our results.

We also tried to ‘Number of clusters=6’, we wanted to see if we are getting all the required opinions in one place. With this cluster, we got the opinions and sentiments regarding the Tesla’s Autopilot cars, but, we still wanted to give a trial by increasing the cluster number to further.

With the number of clusters=8, we saw the clusters showing varied information on Tesla’ Autopilot car, but the frequency in cluster 2 was showing a very less number compared to other clusters. So, at this point we decided to go with Number cluster=7, which even shown the required information about Tesla’s autonomous cars in one place with optimum frequency numbers.

So, with the number of clusters=7, and other best possible combination of parameters we received the best outcome that shown us the required information about the Tesla’s autopilot cars with well distributed frequencies. We decided the cluster number as ‘7’ based on results with various other cluster numbers. With 7 clusters, we saw all the required information in one place which was not the same case with other cluster numbers. Figure 2 shows the settings for Text Cluster.



Property	Value
General	
Node ID	TextCluster
Imported Data	...
Exported Data	...
Notes	...
Train	
Variables	...
Transform	
SVD Resolution	High
Max SVD Dimensions	100
Cluster	
Exact or Maximum Number	Exact
Number of Clusters	7
Cluster Algorithm	Expectation-Maximization
Descriptive Terms	15
Status	
Create Time	10/22/16 7:50 PM
Run ID	9fa4184b-90b7-4094-8aba
Last Error	

Figure 2. Text Cluster settings of the SAS Enterprise Miner model

RESULTS

Sentiment analysis and results from Text Cluster

Clustering results obtained from a text cluster node show the grouping of terms into 7 clusters where each belongs to a certain topic. Clustering uses an expectation-maximization algorithm, which divided the 7 clusters with relatively equally distributed frequencies except for cluster 3.

Figure 3. Distribution of the seven clusters from the results of the SAS Enterprise Miner model

We identified a few key characteristics in each cluster and they are explained as follows:

Cluster-1: In this cluster, people are basically excited about the Innovation that Tesla has come up with and the advancements have been achieved due to the power of solar energy.

Cluster-2: In this cluster, people are expressing their astonishment which has arisen because of Tesla's superior functionality and configuration which is making it popular all over the world.

Cluster-3: In this cluster, people have expressed their experiences of driving the Tesla Autopilot Car along with their interaction with its new functionalities.

Cluster-4: In this cluster, people have compared the Tesla's autopilot cars to cars in a similar category built by competing car manufacturers.

Cluster-5: In this cluster, people discuss how Tesla as a company is progressing and the direction in which its founder Elon Musk plans to take it.

Cluster-6: In this cluster, people react to Tesla setting up one of its manufacturing factory in Europe and also discuss how it will perform against European rivals.

Cluster-7: In this cluster, people talk about the Super Charging Stations that Tesla has set up in different parts of the country and how it will be convenient for people.

Based on the clustering results, we also found that most tweet locations were from Massachusetts, Washington DC, California regarding opinions about Tesla Autopilot cars.

Sentiment analysis and results from Text Topic

Text topic node has been used for the analysis sake to understand the topics that are most intriguing to the users (twitter users) relative to Tesla X model. The multiple topic term attribute has been set to 20. For the project's sake top 5 topics have been selected based on the most frequent number of occurrences of that topic. The screenshot below illustrates the results of the Text Topic node and the top 5 selected topics:

First topic: The topic that has top most priority is the model x which was a new topic by the time the tweets were collected. This topic emphasizes and discusses the tesla car models and their properties specially the model x.

Second topic: The next topic that is most famous with the tweeters is tesla's model x cars which give a general overview of model x car designed by tesla

Third topic: The topic here is autonomous cars where the generic view towards automated cars had been expressed and was emphasized more on the automated cars and their use and in specific features of this autonomous model developed by tesla compared with others.

Fourth topic: Here the topic doesn't hold significance relative to tesla model x but the importance is a comparison of tesla model x with other such automated devices and applications such as autopilot or a robot
Fifth topic: This topic throws light on technology used for model x and the same technology is used to run an entire island (island ref)

Sentiment analysis and results from Text Rule Builder

After finding out the most important topics the next step would be to analyze the tweets that have gained retweets since retweets imply interest from the user's end. For this purpose, the

Text Rule Builder node has been used which analyses the opinions of each tweet. The most popular retweets were collected based on the retweets prediction factor which is isRetweets-T/F (this is a column from the input table) and are obtained from the Text Rule Builder results.

We found the most predicted retweets include:

- The public expectations for lithium solar cells gigafactory
- The public recommending self-driving AI specialists to introduce IoT in its cars
- The public appreciation of the Vector Ltd partnership with Tesla to provide renewable solar powered batteries etc.

CONCLUSIONS

Based on the results obtained from the above analysis the conclusions can be drawn as follows. Sentiment analysis of public opinions about Tesla's autopilot model shows: the public's excitement of its specialized features, the tweets unmistakably suggest encouragement towards the setup of the solar energy island, the users shared their driving experiences with the autopilot version of Tesla through tweets.

Also from the test topics and retweets predictions it can be said: Apart from people's comparison about the Tesla's product with its competitors there have been several recommendations made like supercharging station to be set up in several locations making convenient to people for access. There has been general excitement towards a Tesla's plan to set up its manufacturing company in Europe, which will face competitions from European rivals.

There are several innovative ideas the user has come up such as the necessity of lithium solar cell gigafactory, to introduce IoT devices in its autopilot models were recommendations from the public which illustrates the severity of the impact of Tesla technology on the public.

The above results may help Tesla or other Car makers to formulate its goals and expectations to renew its autopilot cars with more superior features and to meet the other expectations of public.

Also, Tesla may focus on introducing IoT enabled devices in its autopilot models to make it more superior and safer. It is good to follow the recommendations and innovative ideas from the public to improve the business value and the economy of the company. If Tesla can implement the above recommendations and ideas to its future autopilot cars and existing models, it will increase the confidence of the future buyers and thus there can be more customer base in Tesla's Autonomous car market.

In the Future, we would like to perform text mining and sentiment analysis on other social media websites such as Facebook, news blogs to confirm or compare with the findings in this study. We would like to perform the word cloud in R, and provide analysis of more appropriate results in terms of frequency and importance.

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