Consumer Intention Prediction using Twitter

A Report for the Evaluation 3 of Project 2

Submitted By

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BONAFIDE CERTIFICATE

Certified that the project report "**Consumer Intention Prediction using Twitter"** is the bonafide work of **"Charchika Bais (16SCSE101590)"** who carried out the work under my supervision.

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Abstract

- Twitter, the popular microblogging site, has received increasing attention as a unique communication tool that facilitates electronic word-of-mouth (eWOM).
- This broad reach of eWOM provides consumers tremendous clout to influence brand image and perceptions in terms of brand management.
- We present computational models to predict Twitter users' attitude towards a specific brand through their personal and social characteristics. We also predict their likelihood of taking different actions based on their attitudes.
- We aim to analyze the tweets related to a product and identify the purchase intention in it. In this way we can rank the tweets which have high purchase intention and report the name of the person who tweeted as potential customer of product.
- To operationalize our research on user’s attitude and actions, we collected ground-truth data through surveys of Twitter users.
- Brand identification contributes the most to consumer’s retweeting behavior. Brand trust and community commitment are also significant predictors.
- Data from a survey of 315 Korean consumers who currently follow brands on Twitter show that those who retweet brand messages outscore those who do not on brand identification, brand trust, community commitment, community membership intention, Twitter usage frequency, and total number of postings.

Introduction

An important interactive medium among users around the world today is social media. From which Twitter is most accepted social networking platform. It is a social network which is based on microblogging. It has more than 200 million active users who on an average do about 400 million tweets every day. Today, social media is widely accepted as a positive communication channel between the company and its customers. Most of the companies use social media platforms on a regular basis, allowing paper copies or digital copies of part of their work to be made for personal use, provided it should not be made or distributed for making money or commercial advantage, and that copy should have this statement and full instructions on the first page. For other copies, forwards, server postings, or reassignments to the list, you must obtain specific permission and / or fees in advance. The website promotes new products and services and sends messages to customers. Another aspect of the same is that, customers usually submit comments to express their feelings or intentions about services and products of the brand. Utilizing the opportunity of user intention has stimulated a growing interest in the scientific community, which has led to many exciting public challenges and business thanks to the tremendous benefits of marketing and financial forecasting. As an effective method of analyzing social media content, intention analysis has received a lot of attention from the market research community. Some remarkable applications of intention prediction include keeping a track of brands, keeping an eye on brand's activity and competitor SWOT analysis. When this is applied to political comments and products that contain well-framed sentences, including words, manual template syntax methods to extract user intention this has proven very helpful.

Consumers do an in-depth search before buying the essentials. According to consumers, before purchasing, the camera is searched an average of 14 times. Initially, they searched for products based on their need to gain experience and checked them thoroughly before confirming the purchase. Later, target-oriented customers conducted a deeper search to extract deeper information and read reviews to make a final decision. Tracking consumers' online shopping behavior and storing them in a structured way is an exciting task. ComScore is a leading company based in the United States, responsible for this work and stores it as data from the comScore Panel. In recent years, the enormous data from online consumer reviews is becoming an important research area to explore influencing factors in the field of e-commerce. After discovering they asked the question "Is this review helpful to you?" an income increase by $ 2.7 billion (Spool, 2009) was seen. In the audit log of each client. Investigating the impact of consumer feedback data on purchase intent is an important task for consumers to provide an excellent e-commerce platform. Brightlocal.com found that 84% of people followed online reviews before buying. Online reviews will affect consumer confidence to buy products and provide real-life experiences, and product companies will benefit from product reviews to improve product quality.

However, any method of Twitter data faces some challenges. First, because of the widespread use of abbreviations and irregular expressions in tweets, tweet data usually consists of sentences with poor grammatical and syntactic structure. The existing grammatical methods of intention analysis rely mainly on the parts of the text that clearly express the intention, such as polar terms, words and the frequency of their simultaneous appearance. However, intention is usually conveyed implicitly through latent semantics, rendering pure grammatical methods invalid. In this article, we propose a new method for automatically extracting semantic patterns to analyze customer intent on Twitter. From now on, we will refer to these modes as CI modes. Our goal is to explore the possibility of using semantic web technology to add semantics to patterns. In our work, we utilized the natural language processing steps performed by Wordnet, Open NLP and basic OWL ontology.

Our project is a web application that predicts the likelihood/certainty that a customer will buy a product that he is interested in based on his social media posts such as Twitter tweets and user profile data. This will help the company/business target a particular customer more efficiently and boost their sales.

First, we search for Twitter tweets of potential customers wanting to buy a product. And based on those tweets we estimate/predict the likelihood that the customer will buy the product. We then make a model by gathering tweets from users who have already expressed intention to buy the product using their tweet history and if possible, their web search history as well and then training the text analytical model based on those tweets. Using the model, we input potential customers who have tweeted about the product but have not bought it. And based on the training data the model estimates a prediction/likelihood of whether the customer will buy it or not. We have limited the scope of our data on 315 Korean consumers who currently follow brands on Twitter show that those who retweet brand messages outscore those who do not on brand identification, brand trust, community commitment, community membership intention, Twitter usage frequency, and total number of postings.

Step 1- Data acquisition and processing.

Step 2- The Model

Step 3- Predicting Consumer Intensions.

In order to use the concept of intention, it must be formalized according to the formal language. By definition, customer intention is designed by three key components (theme, intention verb, object). In addition, this customer's intention is limited in time and space. In this article, we focus on the first three elements of the customer's intention.

To evaluate and validate our method, we apply a data set and compare the performance of CI mode with the latest technology training method. Our results report that our IQ model is almost superior to all the reference methods, especially in the Twitter dataset, its precision and recovery rate have improved by 3%, 6% and 2%, respectively. The main focus of this article has three parts: -

• Novel method is proposed that helps in automatically extraction pattern to use in twitter client intention analysis.

• New representation of customer intention ontology is proposed.

• Using extracted patterns which are differentiating features for pattern matching of tweets, comparison was done between the performances averse to the three state of the art on the basis of 5 different datasets.

Overall Description

We studied the whole model in following six stages which helped us to reach to a result we are publishing in the experiment.

Stage 1- Input from Keyboard

Stage 2-Tweets Retrieval

Stage 3- Data Pre- Processing

Stage 4- Classification Algorithm

Stage 5- Classified Tweets

Stage 6- Sentiment Representation

These 6 stages helped us to produce an accurate result from the analyzed data and it was very good so that we were able to correct the misguided part.

Purpose

This research is primarily conducted in order to know the behavior of a pool of consumers with respect to a particular Brand or personality.

- Through this we will be able to establish a direct relationship between brand and consumers and how much are the effected from the posts related to brand.
- Are the posts for a particular brand or personality affecting the intention of its loyal consumers and do they change their prospective about the brand.
- If the posts are being changed and a healthy content is being provided about the brand then also is the perception of the consumer changing or not or are they liking it or not.

Motivation and Scope

- Twitter is a very vast platform for exchanging information or to see the power of word of mouth.
- On Twitter around 200 million tweets are done on a daily basis and it is a large number to get to know about customer information and customer behavior.
- Twitter provides a list of trending topics in real time, but it is often hard to understand what these trending topics are about.
- An aspect of social media data such as Twitter Messages is that it includes rich and structured information about the individuals involved in the communication.
- It can lead to more accurate tools for extracting semantic information.
- It provides means for empirically studding properties if social interactions.

- Freely available, annotated corpus, Pre-written Classifier Codes in Python using NLTK in order to promote research that will lead to a better understanding of how sentiment is conveyed in tweets and texts.
- Data processing using more Parameters to get best sentiments.
- Updating dictionary for new Synonym and Antonyms of already existing words.
- Web-Application can be converted to Mobile Application.
- Context Sentimental analysis can be implemented in future for accuracy.

Proposed System

This section explains the creation of domain ontology and how to use it to improve the pattern induction process. As mentioned earlier, the primary idea supporting this proposed method is to use domain ontology to improve the learning process patterns for the knowledge obtained from business tweets. When using ontologies in patterns, multiple representations can be described by a pattern. For the adoption of ontology in pattern, our method includes two stages: generation of ontology representation and adoption of ontology repression in pattern learning.

- We aim to analyse the tweets related to a product and identify the purchase intention in it. In this way we can rank the tweets which have high purchase intention and report the name of the person who tweeted as a potential customer of product.
- We will make a model which will analyse step by step and follow persons foot prints on tweeter what the person is re-tweeting in which posts the brand is getting maximum response and what is the customer perception for the brand.
- After knowing all the above data we will see what improvements can be done in the posts and what is the customer expectation and what the company can do for increasing the expectation so that more customer response can be seen on tweets as well as much better shopping behaviour can be seen.
- Theory of planned behaviour (TBP) is a well-recognized attitude behavior model that extends the theory of reasoned action (TRA) by taking into account an individual's perception of voluntary control over their behavior.
- According to this theory, behavioral intentions that reflect three dimensions, attitude toward the behavior, subjective norms, and perceived behavioral control, can help predictions and understanding of future behavior.

- Many researchers have employed the TPB framework to predict behavioral intentions in a variety of contexts, such as acceptance of information technology, online purchasing and shopping behavior, risky credit behaviors of young adults and many more.
- This model have proved to be one of the best model of all times in prediction of customer's intentions and behavior.
- Moreover we will train many text analyst models on tweets and profiles of users those model will be tested on three parameters from them we will choose the best model having the highest measure of performance.
    1. Accuracy
    2. Precision
    3. Recall
- Then we will use that model in predicting the customer intentions towards purchasing the products and ranking customers on the same data in the real time. These results will be shared with the companies so that they can focus on potential customers more precisely.
- There are three components of behavior of a customer on which we will work and try to find out exact behavior of the person for a particular tweet and give prediction according to the behavior which are as follows-
    1. Brand Knowledge
    2. Brand Relationship
    3. Behavioral Outcomes

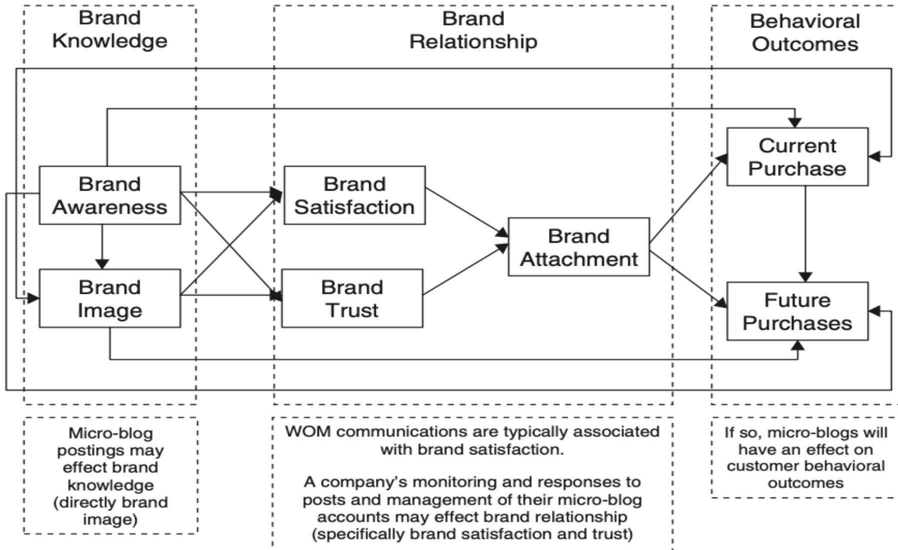


Diagram: General model of branding components and relationship to microblogging

Construct	Items
Prior Product Knowledge	I feel I am very knowledgeable about brands.
	I can give people advice about the type of brands they should buy.
	I feel very confident about my ability to tell the difference between different brands based on their products.
Attitude	I like the brand
	Brand seems satisfactory
	Brand is good
Purchase Intention	It is very likely that I will buy from this brand.
	Whenever I decide to buy a product this brand is on the top of the list.
	I will definitely try to buy this brand.
	Suppose a friend called you last night to get your advice about watching a movie I would recommend buying this brand.

Diagram: Operationalization of the Constructs

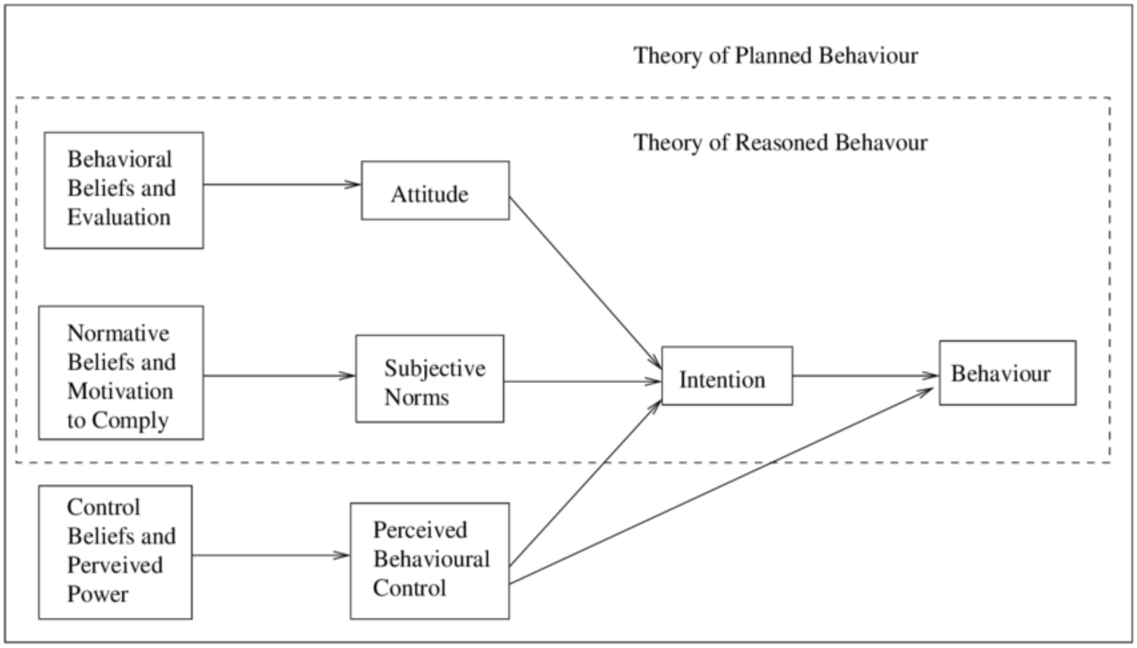


Diagram: Difference between Theory of Planned Behavior and Theory of Reasoned Behavior

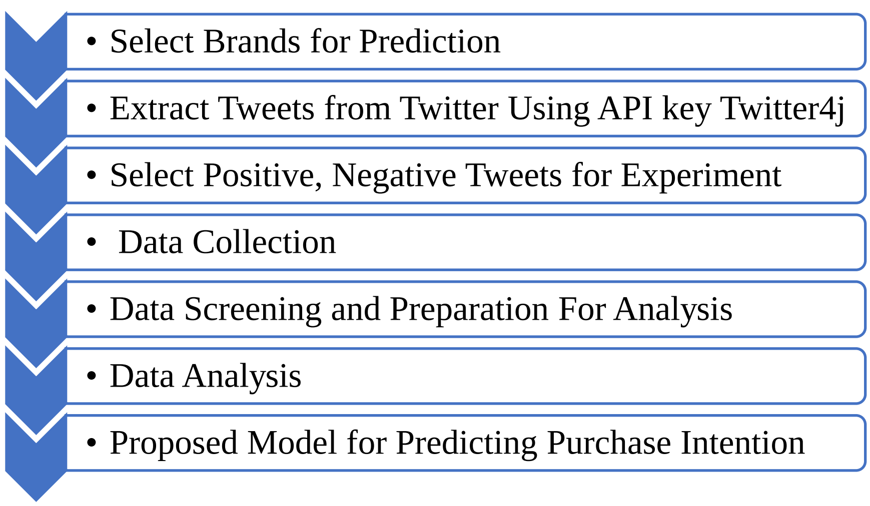


Diagram: Proposed system architecture eWOM sales prediction

Existing System

As the primary objective of our survey study was to find factors responsible for purchase intention we used the product as a brands and extracted tweets about the movie from twitter using an API. In this study used a sentiment analysis tool to identify positive and negative tweets and used it as a treatment to experimental group. The four experimental groups were then subjected to a series of questions to understand their attitude towards the product and intention to purchase the product. The results of the study are presented here.

A. Demographic Profile of the Respondents

Females and males constitute 28.4% and 71.6% of the sample. India being a male dominated society, there appears to be a male bias even in the current survey.

B. Data Screening and Preparation for Analysis

Data screening for out of range values, missing data, outliers, checks for normality and multicollinearity was done prior to proceeding with statistical analysis.

C. Multicollinearity

The correlation matrix for the independent variables was calculated and is shown in Table V. The correlation between the variables does not exceed 0.8, the cut-off prescribed. The data meets the cut-off prescribed in literature for correlation coefficients, tolerance and VIF. Therefore, it was reasonable to assume that the data was not Multicollinear.

Hypothesis Tested Previously

1) Valence

From a marketing perspective, WOM can be either positive or negative. Positive WOM occurs when good news testimonials and endorsements about the product, service or brand are uttered. Negative WOM is the mirror image.

2) Volume

The volume of reviews and the effect it has on sales have been tested in several markets. Thus, more reviews have high probability in increasing the perceived usefulness than fewer reviews and as a result to increase in total the usefulness of the contribution.

3) Prior Product Knowledge

In past studies prior product knowledge used to be examined under the spectrum of familiarity, expertise and experience, considered to influence all the stages of the consumers decision process.

For this study the dimension of the self-assessed knowledge has been chosen for the following reasons. According to self-assessed knowledge is an indicator of objective knowledge as well as a self-confidence indicator. Additionally, it was found that subjective knowledge offers a better insight to the attitudinal evaluations than the other types of knowledge.

4) Attitude

An attitude is an individual's disposition to respond favourably or unfavourably to an object, person, institution, or event, or to any other discriminable aspect of the individual's world.

Since this study is using one sided arguments for both positively and negatively valence reviews, the following hypotheses can be made: H1a: Positive online reviews will have a positive relationship with attitude toward the product.

H1b: Negative online reviews will have a negative relationship with attitude towards the product.

H2: The effect of online reviews on attitude is correlated with the volume of online reviews read by the consumer.

H3: Prior product knowledge will have a direct effect on attitude.

5) Purchase Intention

Strong beliefs are held by consumers for various products and brands. These beliefs were generated by various factors like advertisement, previous experience, WOM, prior knowledge etc. As per the above mentioned factors, various hypotheses can be developed as follows:

H4a: positive online review bears a positive impact and relationship with the customer's behaviour towards the product

H4b: negative online review possesses a negative impact on the customer’s attitude for the product

H5: The effect of online reviews on purchase intention is correlated with the volume of online reviews read by the consumer.

H6: Prior product knowledge will have a direct effect on purchase intention.

H7: Prior product Knowledge will have an indirect positive effect on purchase intention through attitude.

H8: Attitude will have a direct positive effect on Purchase Intentions.

Hypotheses Tested	
H1a	Positive online review bears a positive impact and relationship with the customer's behaviour towards the product.
H1b	Negative online review possesses a negative impact on the customer’s attitude for the product.
H2	The effect of online reviews on attitude is correlated with the volume of online reviews read by the consumer.
H3	Prior product knowledge will have a direct effect on attitude.
H4a	Positive online reviews will have a positive relationship with purchase intention of the product.
H4b	Negative online reviews will have a negative relationship with purchase intention towards the product.
H5	The effect of online reviews on purchase intention is correlated with the volume of online reviews read by the consumer.
H6	Prior product knowledge will have a direct effect on purchase intention.
H7	Prior product Knowledge will have an indirect positive effect on purchase intention through attitude.
H8	Attitude will have a direct positive effect on Purchase Intentions.

Architecture

The main background of this project work is on the ground of sentiment analysis, since there are many comments from web logs, comment web pages and micro blogging social networking sites, this is an area of extensive research. On one aspect, data analysts have studied, explored and examined the user's intention for web search queries. On other point of view, proposes to classify the intentions expressed by the creators of web content and classify them as navigation or information. The same author published a follow-up study that bridges the gap between link intent and query intent, and how this gap can improve the quality of web search. In the business field, user intentions have also been extensively studied, examining the relationship between search intentions, quality of outcomes and search engine's contribution in online shopping, and how can it optimize these interactions to more effectively detect search engine targets. Currently there are some researches related to our paper which introduces a new wish identification task. He built and studied in detail a corpus of wishes consisting of political reviews and product reviews. The manual template and SVM-based text classifier are mixed and used in the desired corpus, and the method for identifying more templates is also discussed. There are two specific desires: suggestions for existing products and the author's intention to buy the product. The work restricts its research to product review. They believe that most strong desires include key word phrases involving some of the modal verbs, such as "will," "can," "should," etc. Therefore, rules based on the same are manually extracted and studied. With this they are automatically identifying desires in product reviews. These wishes or desires are sentences where the author makes suggestions about the product or indicate the intention or will to buy the product. Therefore, the desire for analysis can provide a deeper understanding of consumer's desires and to help product makers, advertisers and others seeking to discover the real needs of customers. This paper first proposes a keyword based strategy to find the candidate's hop beans, then extracts sequential patterns from these manually labeled sentences and eventually uses user’s footprints as features to train the classifier to identify the desired beans in tweets related product reviews.

Language Used

1. Python: Python is an object oriented, high level programing language with Dynamic semantics. Python is used for backend web development, scientific computing, data analysis and artificial intelligence. It’s built in high-level data structures combined with dynamic binding and typing makes Python very attractive for Rapid Application Development. Python is most widely used programing language because of its easy to learn syntax which makes readability simple resulting in the reduction of cost for program maintenance. Debugging of programs written in Python are easy and a segmentation fault will never occur from a bug or bad input. Instead if an error is found by interpreter it will be raised as an exception.

2. Django: Django is a free and open source web framework, which follows the model-template-view architectural pattern. Django is one of the framework written in Python programming language. Django is neither a frontend nor a backend development tool it is only a framework. Whole framework of Django is maintained by the Django Software Foundation. Main function of Django is to ease the creation of complex database driven websites. Django is one of the most popular Python framework and it is quite easy to learn. Syntax used in this are simple and clean they are close to actual English so it is easy to read. Django is used in rapid development and of websites because in this a developer can use pre saved sources instead of starting everything from scratch which makes it even more reliable for development and writing any program.

Following tools were used for making this project

1. Naive Bayes Classifiers: Classifiers are machine learning models which can discriminate between different objects based on specific features. In machine learning Naive Bayes classifiers are simple probabilistic classifiers or a collection of classification algorithm based on Bayes Theorem. It is a family of algorithms where there share common principle which is every pair being classified is different from each other. These are mostly used in sentiment analysis, recommendation system, filtering spam. They can be implemented fast and easily they just have one limitation that they don't work well if predictors are not independent. In real life predictors are dependent this hinders classifier performance.

2. Decision Tree: Tree like model used by a decision support tool for identifying possible consequences of a particular program and there outcomes written in Python programming language. It is one of the supervised machine learning took in this data which is being entered continuously splits related to some particular parameters. This model contains two aspects which are decision nodes and leaves. Mostly end results or final outcomes are always demoted by leaves. Places where the data split are termed as decision nodes. It can contain two types of trees which are Classification trees which show results for yes/no type queries second type of tree are Regression Tree in these the data is continuously analysed till the program is ends completely.

3. Support Vector Machine (SVM): This is a supervised machine learning model this model is ideally used for two group classification algorithm problems. This tool best performs when it is used with regression problems. In other words both classification and regression can be performed by this with ease. Kernel trick technique is used in this. Kernel trick transforms data and optimal boundary is drawn along possible outcomes. Extremely complex transformation of data is done and results are spread according to the labels or outputs defined by the user. Best part of using this tool is much complex relationship can be established and recorded between the data points without actually performed separately by the user.

4. Logistic Regression: It is another form of machine learning and mainly done for Performing mathematical functions such as statistics. There are two types of logistic regression Binary and Multi linear logistic regression. Based on results obtained and mixed with probability it can predict the outcomes. It us very much easy to apply and results obtained from this are very reliable as they are obtained using probability and sigmoid function. In today's world it is widely used in filtering useful and non-useful information like weather an email is spam or not spam and many more.

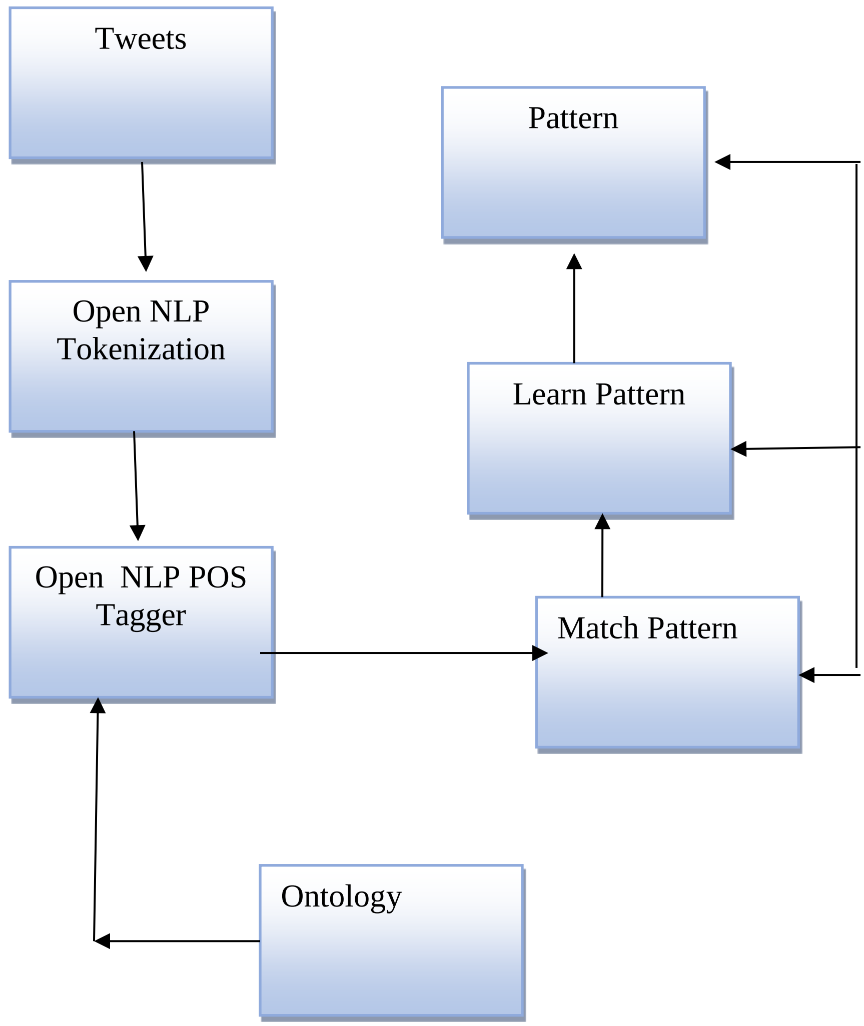


Fig1 proposed flow chart

Methodology

Customer Intention Ontology. This section explains the creation and use of domain ontology to improve model awareness processes. As mentioned earlier, the main idea behind the proposed method is to use domain ontology to improve model learning methods for knowledge contained in business tweets. Ontology as a model, a pattern can determine many manifestations. For the ontology to design the process consists of two steps: (a) the representation of ontology (b) the formation of ontology in the form of learning and design ontology to represent knowledge. The representation of the intended ontology we use as follows. The concepts of ontology were developed during the implementation of the presentation process. Simple list of keywords that illustrates the similarity among concepts. Mood, and POS coding is ontological representation. From syntactic selection creates semantic representation. The latter uses the energy contained in the semantic workbook Wordnet [11] to find regional synonyms and substitutions for verbs, and the latter returns a series of syllables and earphones (assemblies -company or partnership) for each given word. . Then each synonym is combined with the ontological and is associated with the original verb. In Greek with the OWL form of ontology, OWL: similar classes and OWL: SubClass were developed to represent the organization. According to our definition, the model exists. Three topics, topics, and things to consider. The verb seeking determines the relationship between the subject and the subject of the two concepts: For example, when using the verb "intention": a class or example of the class organization) to the subject (which may be examples of product or class). n category is "intention", the category of verbs is: desire, hope, search, etc.

Table 1. For evaluation purposes, commercial domain connection is used.

Object	Relation	Item
Individual	want	Commodity
Individual	Has desire	Commodity
Individual	Search for	Commodity

Datasets to examine the results of the performed CI state, we used 4 data sets for the benchmark methods added in the prior art. (How to choose Epines.com and MouthShut.com). Among them, we selected a collection of comments on the Apple iPod (Data1), digital camera (Data2), TV (Data3) and bank comments for the five previous banks in the United States (Data4). also used the TREC Microblog Dataset2011.

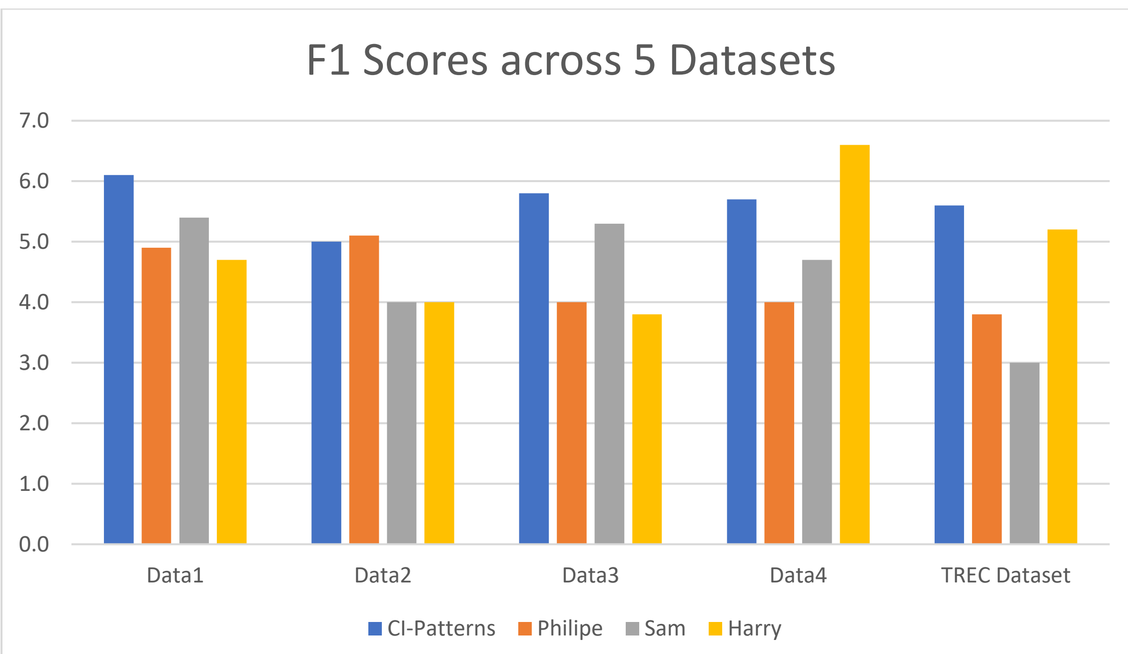


Fig 2 f1 score for different data set

Evaluation Objectives In our experiments, we compared the performance of the CI model and the baseline method in terms of accuracy, recall, and F1 goals. These measures are appropriate because our goal is to determine the intended position. These relationships are given below

$$\frac{P \ = \ |Relevant \ \Omega \ F \ ound|}{lFound|}$$

$$\frac{R \ \ = \ |Relevant \ \Omega \ F \ ound|}{lFound|}$$

"Relevant" is a set of related intention positions, and "Found" is a set of intention positions found. There is a trade-off between accuracy and recall, so we can calculate the F1 metric. The F1 metric is used to calculate the uniform combination, that is, the average harmonic value of accuracy and recall:

$$\text{R} = \quad \frac{2 \times P \times R}{P + R}$$

Table 2 P and R results across datasets

Datasets	Total of Posts	#Intentions	Harry		Sam		Philipe		CI-Patterns	
			P	R	P	R	P	R	P	R
Data1	23421	95	65%	38%	60.20%	48%	49%	44.30%	52.30%	73%
Data2	5750	205	50%	55%	35%	65%	33%	61%	59%	44%
Data3	1369	375	48%	52%	80%	48%	44%	48%	81%	46%
Data4	2456	22	55.50%	45%	63.10%	41%	77%	67%	59%	57.80%
TREC DataSet	5500	3100	38%	28.90%	39%	29%	51%	52.20%	54%	52.35%

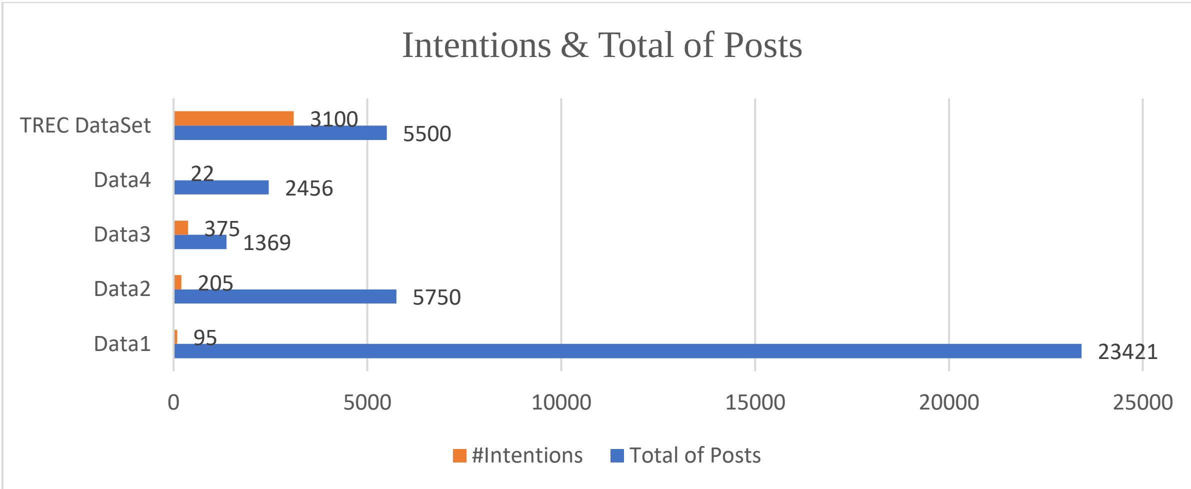
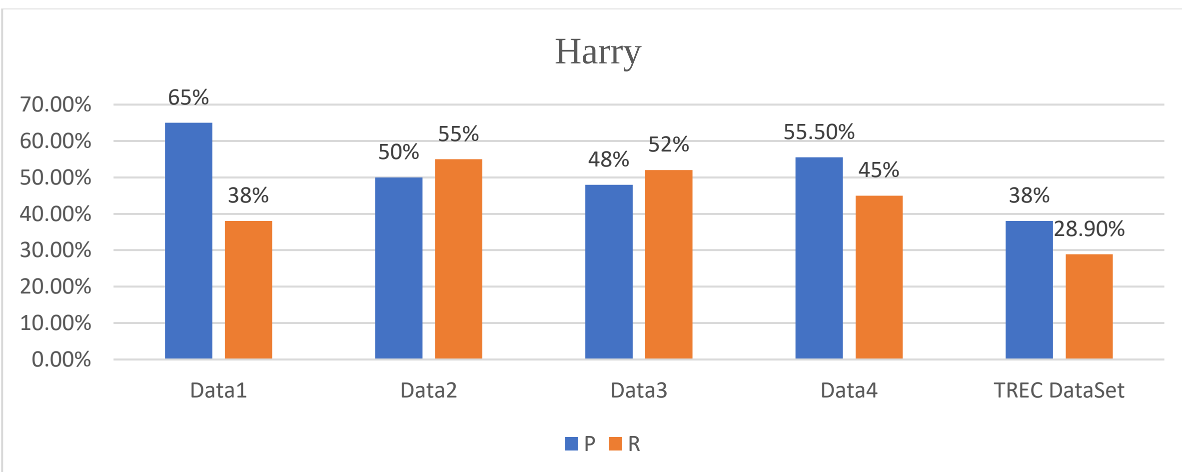


Fig 3 Intensions & Total of Posts



Fig

4 precision and recall results across for Harry

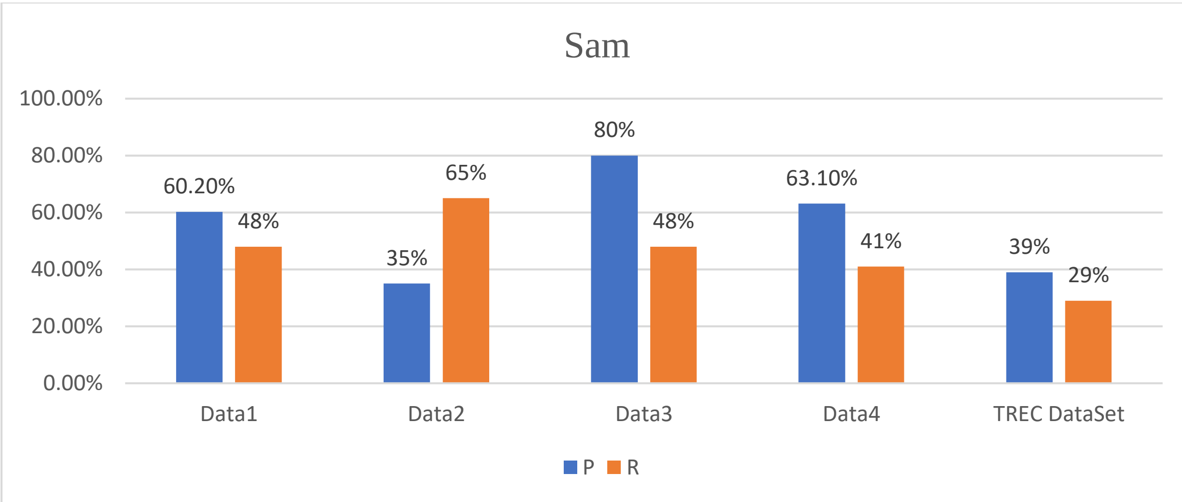


Fig .5: precision and recall results across for Sam

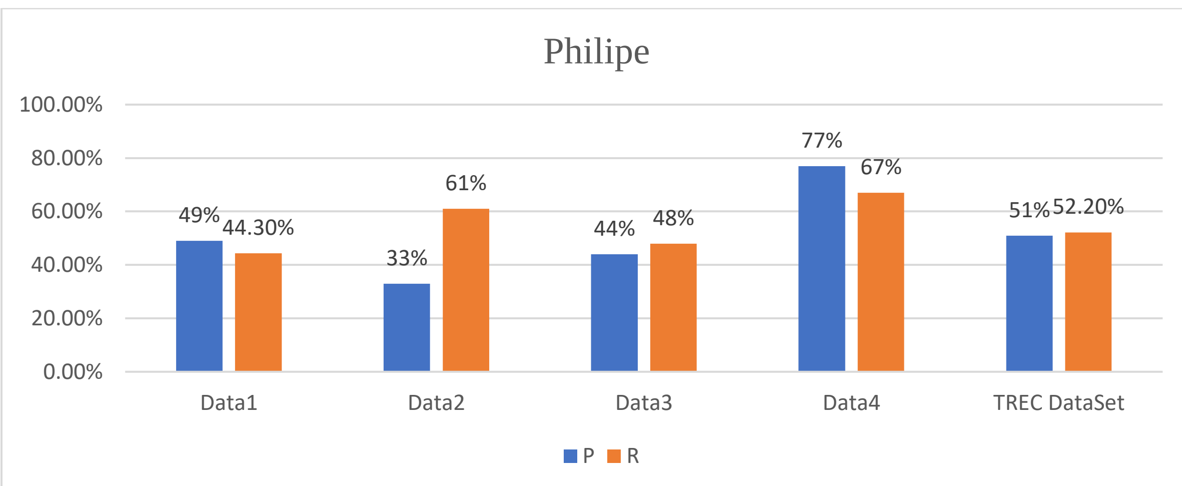


Fig .6: precision and recall results across for Philipe

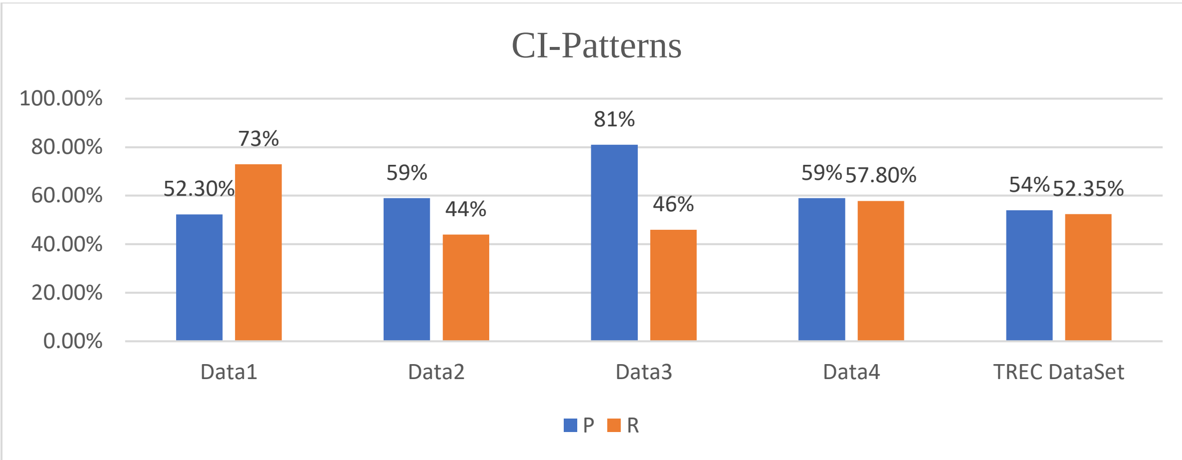


Fig 7: precision and recall results across for CI

Results

To recap, our fundamental question is whether the Twitter textual data can be used to predict any variation and changes and sentiments of consumers towards any brand. But the deeper question raised in this is how effective it is after all?

This study offers important insights into microblogging as eWOM communications, with implications for branding for corporations, organizations, and individuals. There are also implications for the social effects that social communication services (like Twitter) are having, in terms of fostering new relationships in the commercial sector, specifically in gauging marketplace reactions (i.e., sentiment), external communication (i.e., information providing), and gathering marketplace information (i.e., information seeking). These implications are the same for both corporations and individuals. First, of the entire population of tweets, ≈19% mention an organization or product brand in some way. This is good percentage and indicates that the microblogging medium is a viable area for organizations for viral marketing campaigns, customer relationship management, and to influence their eWOM branding efforts.

Second, about 20% of all microblogs that mentioned a brand expressed a sentiment or opinion concerning that company, product, or service. Microblogging is a social communication channel affecting brand awareness and brand image, that managing brand perception in the microblogging world should be part of an overall proactive marketing strategy, and maintaining a presence on these channels should be part of a corporation's branding campaign. It is apparent that companies can receive positive brand exposure via followers and others who microblog about the company and products. Twenty percent of this fast-growing market is substantial. Additionally, with 80% of tweets mentioning a brand but expressing no sentiment suggests people are also seeking information, asking questions, and answering questions about brands via their microblogs. Thus, company microblogging accounts are probably a smart idea to both monitor brand community discussions and to push information to consumers. This information seeking and brand and product commenting seems to open the door for some type of advertising medium. Similar to search advertising, where relevant ads are triggered via key terms in queries, it would appear that there could be a tweet advertising medium where relevant ads are triggered by keywords in tweets.

Conclusion

Our work involved semantic patterns removal for Twitter consumer thirst analysis. Our approach is not to rely solely on free grammar or word definitions, but rather uses the relation of ontological concepts and word formulation. We have included 5 different data sets, product releases and brand or product related Twitter posts, and the model taken as a work of classification to justify the patterns taken. Three base methods were used to see the performance of this method. The CI status of the method we presented shows a longer and better performance than the methodology, especially on the TREC dataset. In this research we examined the use of microblogging and suggestions, considering the rapid growth and of eWOM branding. Examining several datasets from clarity of microblogging, companies should come up with a variety of angles, our research has shed light on critical systematic way to handle customers on microblog sites to aspects of this phenomenon. The implications of this research influence brand image. It would seem that microblogging include that microblogging is a potentially rich avenue for can be used to provide information and draw potential companies to explore as part of their overall branding start custotomers to other online media, such as Websites and blogs. Customer brand perceptions and purchasing decisions such, monitoring and leveraging microblogging sites appear increasingly influenced by Web communications and one's own brand and the brand of competitors is a social networking services, as consumers increasingly use valuable competitive intelligence. Companies can get near these communication technologies for trusted sources of real-time feedback by setting up corporate accounts. Information, insights, and opinions. It is apparent people who follow their corporate accounts. Finally, companies that microblogging services such as Twitter could become key companies can leverage contacts made via microblogging services applications in the attention economy. Given the ease further their branding efforts by responding to comments, storing any brand's sentiment, one can view microblogging suggestions, or comments about the company brand. The essence of eWOM communicating and customer examined microblogs from only one microblogging site. Relationship management is knowing what customers and Users of other microblogging services might differ in their potential customers are saying about the brand.

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