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"A Study on Impact of Sarcasm In Online Data on Customer Perception Using Data Mining"

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Sarcasm transforms the polarity of word or comment in positive or negative into its opposite meaning. It is very difficult to understand the intention of the person about the comment made online. The higher corporates are also interested in detecting the sarcasm so that they can know the customer perception and behavior about their products. This research will throw light on the impact of sarcasm in online tweets or comments which will help to know the intention of the customer. Furthermore, this will help the corporates to understand the problem occurred in sarcasm which will help the companies to gain knowledge about their product so that they can make better decisions and ultimatelyimprove business performance to forecast economic future of their organization In this examination, we are chipping away at optional information for which we are choosing test size of 100 Tweets for 18 organizations both Sarcastic and Non-mocking organization and breaking down this information by utilizing datamining programming. Tool used in Data Collection are rapid miner and Ms excel.

Keywords: Sarcasm, data mining, Rapid miner, Tweets

1. Introduction

sarcasm (otherwise called verbal incongruity) is a refined type of discourse act where the speakers pass on their message in a verifiable manner. One inborn quality of the mocking discourse act is that it is once in a while difficult to perceive. The trouble in acknowledgment of mockery causes misjudging in regular correspondence and stances issues to numerous NLP frameworks, for example, online audit rundown frameworks, exchange frameworks or brand observing frameworks because of the disappointment of cutting edge notion investigation frameworks to recognize wry remarks. In this paper we explore different avenues regarding a semi-administered system for programmed ID of mocking sentences.

With the progression of shrewd cell phones and the rapid Internet, clients can connect with online

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life administrations like Facebook, Twitter, Instagram, and so forth. The volume of social information being produced is developing quickly. Insights from Global Web Index shows a 17% yearly increment in portable clients with the complete number of one of a kind versatile clients contacting 3.7 billion individuals. Social net-working sites have become an entrenched stage for clients to express their sentiments and assessments on different subjects, for example, occasions, people or items. Web based life channels have become a prominent stage to talk about thoughts and to collaborate with individuals around the world. For example, Facebook cases to have 1.59 billion month to month dynamic clients, every one being a companion with 130 individuals by and large. Likewise, Twitter professes to have in excess of 500 million clients, out of which in excess of 332 million are dynamic. Clients post in excess of 340 million tweets and 1.6 billion inquiry inquiries consistently. With such enormous volumes of information being created, various difficulties are presented. Some of them are getting to, putting away, preparing confirmation of information sources, managing deception and intertwining different sorts of information. In any case, practically 80% of produced information is unstructured. As the innovation created, individuals were given an ever increasing number of approaches to communicate, from basic content informing and message sheets to other all the more captivating and charming channels, for example, pictures and recordings. Nowadays, online networking channels are generally the first to get the criticism about recent development and patterns from their client base, enabling them to give organizations inside significant information that can be utilized topo-segment their items in the market just as assemble quick input from clients.

Model:

(1) From Amazon, may be a real praise in the event that it shows up in the body of the audit. Be that as it may, reviewing the articulation 'don't pass judgment superficially', picking it as the title of the audit uncovers its snide nature. In spite of the fact that the negative supposition is unequivocal in the iPod survey

Displaying the fundamental examples of wry articulations is fascinating from the mental and intellectual points of view and can profit different NLP frameworks, for example, audit rundown. The calculation utilizes two modules: semi administered design obtaining for distinguishing wry examples that fill in as highlights for a classifier, and a characterization arrange that groups each sentence to a snide class. For instance, explore different avenues regarding two profoundly unique datasets: 5.9 million tweets gathered from Twitter, and 66000 Amazon item audits. Despite the fact that for the Amazon dataset the calculation uses organized data, results for the Twitter dataset

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are higher.

Twitter Dataset. Since Twitter is a generally new assistance, a to some degree long depiction of the medium and the information is suitable. Twitter is a mainstream microblogging administration. It enables clients to distribute and peruse short messages called tweets (additionally utilized as an action word: to tweet: the demonstration of distributing on Twitter). The tweet length is limited to 140 characters. A client who distributes a tweet is alluded to as a tweeter and the perusers are easygoing perusers or devotees in the event that they are enrolled to get all tweets by this tweeter. The quantity of unique labels in a tweet is just dependent upon the one hundred forty character limitation. There is no particular sentence structure that implements the area of uncommon labels inside a tweet.

.As of late, online life destinations, for example, Twitter have increased tremendous prevalence and significance. These locales have advanced into huge environments where clients express their thoughts and sentiments uninhibitedly. Organizations influence this extraordinary biological system to take advantage of general conclusion on their items or administrations and to give constant client help. Of course, most enormous organizations have an online life nearness and a committed group for showcasing, after-deals administration, and shopper help through web based life. With the high speed and volume of internet based life information, organizations depend on devices, for example, HootSuite1, to break down information and to give client care. These instruments perform errands, for example, content administration, conclusion examination, and extraction of important messages for the organization's client support agents to react to. Nonetheless, these instruments do not have the refinement to unravel more nuanced types of language, for example, mockery or funniness, in which the significance of a message isn't constantly evident and express. This forces an additional weight on the online life group previously immersed with client messages to distinguish these messages and react fittingly.

A high psychological intricacy of an individual can be showed on Twitter regarding the language unpredictability of the tweets. Consequently, to pursue an orderly approach, conjecture the center types of mockery utilizing existing mental and conduct contemplates. To create computational highlights to catch these types of mockery utilizing client's present and past tweets. At long last, we join these highlights to prepare a learning calculation to recognize mockery.

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2. Social Media Framework

Snide tweets are not generally made in detachment. When posting mocking tweets, clients attempt cognizant endeavors to express their considerations through mockery. They may choose to utilize mockery as a conduct reaction to a specific circumstance, perception, or feeling. These circumstances, perceptions, or feelings might be watched and broke down on Twitter. It is seen that a few people have more trouble in making or perceiving mockery than others because of social contrasts, language boundaries, and so forth. Interestingly, a few people have a higher penchant to utilize mockery than others. This can be accomplished on Twitter by dissecting the client's past tweets. Utilizing existing examination on mockery and our perceptions on Twitter, we find that mockery age can be portrayed as one (or a blend) of the accompanying:

Sarcasm as an unpredictable type of articulation:

A high psychological intricacy includes understanding and considering, various points of view to settle on apt choices. Moreover, communicating mockery requires deciding whether the earth is reasonable for mockery, making a proper snide expression and surveying if the recipient would be equipped for perceiving mockery. Hence, mockery is an intricate type of articulation requiring more exertion than expected from the client.

Sarcasm as methods for passing on feeling:

Mockery is principally a type of passing on one's feelings. While mockery is at some point deciphered as forceful, humor or verbal animosity, it additionally works as an instrument for self-articulation. Past investigations, perceive that mockery is typically communicated in circumstances with negative feelings and demeanors.

Sarcasm as a potential capacity of commonality:

Companions and family members are seen as greater at perceiving mockery than outsiders. Further, it has been exhibited that the information on language and culture likewise assume a significant job in the acknowledgment and use of mockery.

Sarcasm as a type of composed articulation:

Mockery in brain research has been contemplated principally as a verbally expressed type of

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articulation. In any case, mockery is very common in composed structure too, particularly with the coming of online long range interpersonal communication locales.

3 Scope of the Study

This research aims to evaluate the importance of sentiment and text mining on online data and empirically tested its importance to find out the customer perception about the particular products. It aims to build a model that is based on sentiment mining and Text mining techniques to examine the relationships between customer perception and behavior towards the products

3.1 Objectives of thestudy

- To identify the differentiating features between a sarcastic and non-sarcastic advertisements.
- To analyze the impact of sarcastic and non –sarcastic advertisement on product offering/ tweets using sentiment mining and text mining.
- To classify consumer perception toward online product offerings.

3.2 Measurement and Scaling

The various types of scales used in research fall into two broad categories: comparative and non-comparative. In comparative scaling, the respondent is asked to compare one brand or product againstanother.Withnon-comparativescalingrespondentsneedonlyevaluateasingleproductor brand. Their evaluation is independent of the other product and or brands which the marketing researcher is studying. Study is designed to measure the impact of business intelligence applications on operational efficiency of educationalinstitutions.

In this study, we have worked on the comments or tweets made online about the products by detecting the sarcasm using a software which will fetch the sarcastic words and did sentiment analysis.

H0: Thereis no impact of sarcastic advertisements on consumer perception or behavior.
H1: There is an impact of sarcastic advertisements on consumer perception or behavior.

3.3 Research methodology

Research approach is an orderly method to tackle an issue. It is a study of examining how research is to be done. Basically, the strategies by which specialists approach their work of depicting, clarifying and

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anticipating marvels are called examine strategy. It is additionally characterized as the investigation of techniques by which information is picked up. Its point is to give the work plan of research. It is vital for a specialist to structure a system for the issue picked. It is significant for the re-searcher to know not just the exploration strategies essential for the examination under taken yet in addition the technique. For instance, a scientist not just has to realize how to compute mean, change and dissemination work for a lot of information, how to discover an answer of a physical framework portrayed by numerical model, how to decide the underlying foundations of logarithmic conditions and how to apply a specific technique yet in addition need to know.

Which is an appropriate technique for the picked issue? What is the request for precision of the consequence of a strategy? What is the productivity of the strategy? Etc Consideration of these viewpoints establish an examination approach.

In this investigation, we have taken twenty organizations and isolated it into two sections: Sarcastic and Non-mocking. We have brought least hundred tweets with labels for each organization then we have dissected these tweets with the assistance of information mining programming: Rapid Minor. We have utilized information mining methods like Sentiment mining, Text mining to examine the assumption of the individual. Every movement will be read and reported for its importance in the entire venture. This will fill in as a system that would help recognize the prescribed procedures that would guarantee a fruitful examination.

Information Collection Method

Primary information: Primary information is a kind of data that is acquired straightforwardly from first - hand sources by methods for overviews, perception or experimentation. It is information that has not been recently distributed and is gotten from another or unique research study and gathered at the source, for example, in showcasing.

Secondary information: Secondary information is the information that have been as of now gathered by and promptly accessible from different sources. Such information are less expensive and more rapidly possible than the essential information and furthermore might be accessible when essential information can't be acquired by any means.

In this examination, we have gathered the auxiliary information from person to person communication site (Twitter) which we broke down by the assistance of a product to consider the effect of mockery.

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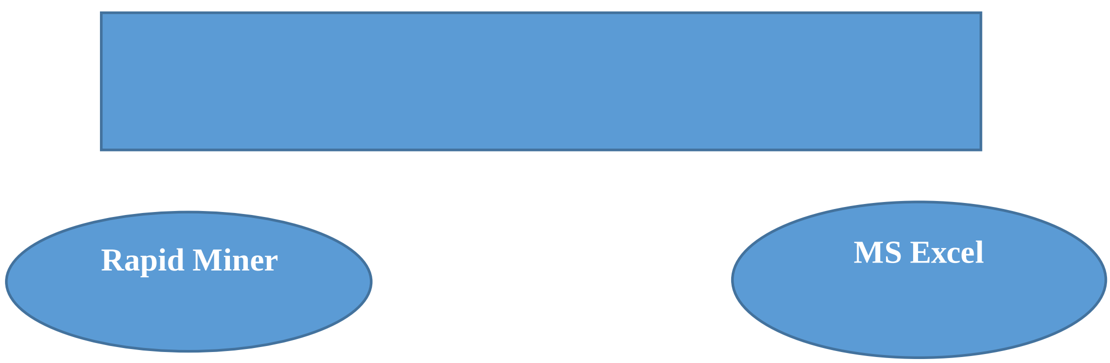
Sample: This includes a particular importance inside quantitative statistical surveying, beginning inside likelihood hypothesis and alluding to the populace that is looked into or examined, drawn from an objective populace. In this unique circumstance, an example ought to speak to the objective populace, with the goal that the outcomes might be summed up to the entire of that populace. Subjective research, then again, doesn't endeavor to infer agent tests. Or maybe, it looks to incorporate individuals or circumstances inside an undertaking that will demonstrate the most prolific, given the idea of the examination question; this is known as a purposive example

Sample size: Sample size, basically characterized, is the quantity of members in a given report. It's a significant part of the insights that go into breaking down the consequences of an examination venture, since it is necessary to computing the entirety of the aftereffects of that review. A few investigations comprise of a solitary example, while others will think about the aftereffects of a few examples. In the last mentioned, test size may allude to any subgroup or to members in the investigation overall.



Rapid Miner:

Rapid Miner is a data science software platform developed by the company of the same name that provides an integrated environment for data preparation, machine learning, deep learning, text mining, and predictive analytics. The tweets are differentiated among positive, negative and neutral based on the detection engine. The tweets that are classified as positive, negative and neutral are further classified as Actual positive, Actual negative and neutral. Actual positive tweets contain the tweets that are actually positive. Actual negative tweets are the tweets that are actually negative and sarcastic tweets are those in which it is difficult to determine whether tweets are actually positive or negative.

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4. Interpretations andAnalysis

We have taken total 18 companies and divided into two groups: Sarcastic and Non-Sarcastic.

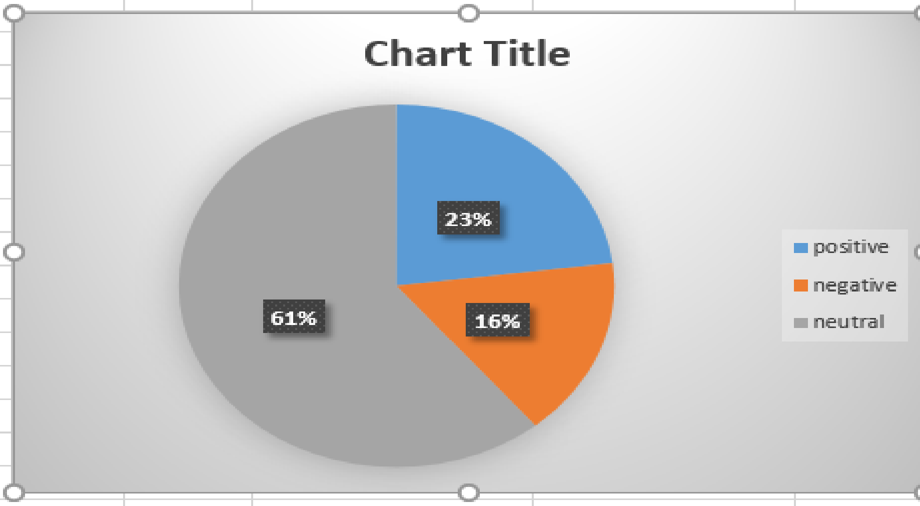
Sarcastic Group

Following are the companies listed in the sarcastic group:

7UP:

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor. We can see that the polarity of tweets is more positive than negative which means that costumer's perception is positive but many of them have neutral perception.

Polarity	Total
positive	23
negative	16
neutral	61



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polarity	polarity_confidence	subjectivity	subjectivity_confidence
negative	.9	subjective	1.0
negative	.5	objective	.6
negative	.7	objective	1.0
negative	.6	subjective	1.0
negative	.5	subjective	1.0
negative	.4	subjective	1.0
negative	.7	subjective	1.0
negative	.5	subjective	1.0
negative	1.0	subjective	1.0
negative	1.0	subjective	1.0
negative	.8	subjective	1.0
negative	.6	subjective	1.0
negative	1.0	subjective	1.0
negative	.6	subjective	1.0
negative	.5	subjective	1.0
negative	.6	subjective	1.0

polarity	polarity_confidence	subjectivity	subjectivity_confidence
neutral	.4	objective	1.0
neutral	.9	subjective	1.0
neutral	.7	subjective	.6
neutral	.9	subjective	1.0
neutral	.8	objective	1.0
neutral	.5	objective	1.0
neutral	.5	subjective	.8
neutral	.9	subjective	1.0
neutral	.8	subjective	.7
neutral	.7	subjective	1.0
neutral	.9	subjective	1.0
neutral	.6	objective	1.0
neutral	.4	objective	.9
neutral	.6	objective	.9
neutral	.7	subjective	1.0
neutral	.7	subjective	1.0
neutral	.5	objective	1.0
neutral	.6	objective	1.0
neutral	.8	objective	.8
neutral	.6	subjective	1.0
neutral	.6	subjective	.9
neutral	.5	subjective	1.0
neutral	.6	subjective	1.0
neutral	.9	subjective	.7
neutral	.9	subjective	.7
neutral	.9	subjective	1.0
neutral	.9	objective	1.0
neutral	.8	objective	.6
neutral	.9	subjective	1.0

polarity	polarity_c	subjectivity	subjectivity_confidence
positive	.4	subjective	1.0
positive	.7	subjective	1.0
positive	.7	subjective	1.0
positive	.7	subjective	1.0
positive	.5	subjective	1.0
positive	1.0	subjective	1.0
positive	1.0	subjective	1.0
positive	1.0	subjective	1.0
positive	1.0	subjective	1.0
positive	1.0	subjective	1.0
positive	.7	subjective	1.0
positive	.5	subjective	1.0
positive	1.0	subjective	1.0
positive	.6	subjective	1.0
positive	.8	subjective	1.0
positive	.4	subjective	1.0
positive	1.0	objective	1.0
positive	.4	subjective	1.0
positive	.7	subjective	.9
positive	.5	subjective	1.0
positive	.6	subjective	.6
positive	.6	objective	1.0
positive	1.0	subjective	1.0

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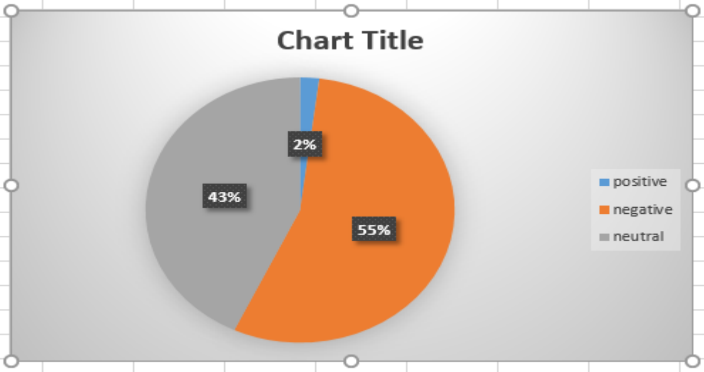
Bisleri:

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is negative which means it has negative impact.

Polarity	Total
positive	2
negative	55
neutral	43



polarity	polarity_c	subjectivi	subjectivity_confid
neutral	.6	subjectiv	1.0
neutral	.9	objective	1.0
neutral	.6	objective	1.0
neutral	.5	subjectiv	1.0
neutral	.4	subjectiv	1.0
neutral	.5	subjectiv	1.0
neutral	1.0	subjectiv	1.0
neutral	.9	subjectiv	1.0
neutral	1.0	objective	1.0
neutral	.9	objective	1.0
neutral	.8	objective	1.0
neutral	.8	objective	1.0
neutral	.8	objective	1.0
neutral	.9	subjectiv	1.0
neutral	.8	objective	1.0
neutral	1.0	objective	1.0
neutral	1.0	objective	1.0
neutral	1.0	objective	1.0
neutral	1.0	objective	1.0
neutral	.7	objective	.8
neutral	.6	subjectiv	1.0
neutral	1.0	subjectiv	.7
neutral	.9	objective	1.0
neutral	1.0	subjectiv	1.0
neutral	.8	objective	1.0
neutral	.5	subjectiv	1.0
neutral	.9	subjectiv	1.0
neutral	1.0	objective	1.0
neutral	1.0	subjectiv	.8
neutral	1.0	objective	1.0

polarity	polarity_c	subjectivi	subjectivity_confiden
negative	.8	subjectiv	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0
negative	.6	objective	1.0

polarity	polarity_c	subjectivi	subjectivity_co
positive	1.0	subjectiv	1.0
positive	.8	objective	1.0

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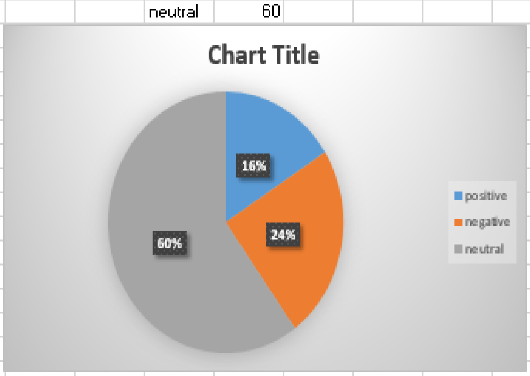
Vodafone

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is negative which means it has negative impact.

polarity	polarity	subject	subjectivity_confidence
positive	.9	objective	1.0
positive	.7	subjectiv	1.0
positive	.9	subjectiv	1.0
positive	.5	subjectiv	1.0
positive	.8	objective	1.0
positive	.7	subjectiv	1.0
positive	.9	objective	1.0
positive	.6	subjectiv	1.0
positive	.5	subjectiv	1.0
positive	.6	subjectiv	1.0
positive	.9	objective	1.0
positive	.8	objective	1.0
positive	.8	objective	1.0
positive	.5	subjectiv	1.0
positive	.8	objective	1.0
positive	.8	objective	1.0

polarity	polarity	subject	subjectivity_confidence
neutral	.8	objective	.6
neutral	.9	subjectiv	1.0
neutral	.7	objective	.7
neutral	.6	subjectiv	1.0
neutral	.6	subjectiv	1.0
neutral	.7	objective	1.0
neutral	.7	objective	1.0
neutral	1.0	objective	1.0
neutral	.9	objective	1.0
neutral	.8	objective	1.0
neutral	.8	subjectiv	1.0
neutral	.7	objective	1.0
neutral	.8	objective	1.0
neutral	.7	objective	1.0
neutral	.6	objective	.9
neutral	1.0	objective	1.0
neutral	.6	subjectiv	1.0
neutral	.7	objective	1.0
neutral	.9	subjectiv	1.0
neutral	.9	subjectiv	1.0
neutral	.9	objective	.9
neutral	.7	objective	.8
neutral	1.0	objective	1.0
neutral	1.0	objective	1.0
neutral	1.0	subjectiv	.8
neutral	.9	objective	1.0
neutral	1.0	objective	1.0
neutral	.7	objective	1.0
neutral	.6	objective	1.0
neutral	.7	objective	1.0
neutral	1.0	objective	1.0
neutral	.9	objective	1.0

Polarity	total
positive	16
negative	24
neutral	60



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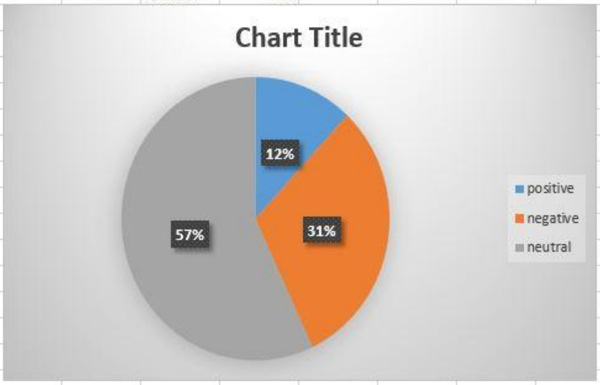
Non-Sarcastic Group

Following are the products listed in the sarcastic Group: -

Aquafine

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is negative which means it has negative impact.

positive	12
negative	31
neutral	57



polarity	polarity_c	subjectivi	subjectivity_confidence
negative	1.0	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.6	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	.5	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.7	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.8	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	.4	objective	1.0
negative	.8	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	.5	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	.5	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	.5	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	1.0	subjectiv	1.0
negative	.9	subjectiv	1.0
negative	1.0	subjectiv	1.0

polarity	polarity_c	subjectivi	subjectivity_confic
neutral	.6	objective	1.0
neutral	.9	objective	1.0
neutral	1.0	subjectiv	1.0
neutral	.8	subjectiv	1.0
neutral	.8	subjectiv	.9
neutral	.8	subjectiv	.6
neutral	.5	subjectiv	1.0
neutral	.9	objective	1.0
neutral	.4	subjectiv	.9
neutral	.7	objective	1.0
neutral	.8	objective	1.0
neutral	.6	subjectiv	1.0
neutral	.7	objective	1.0
neutral	.9	subjectiv	1.0
neutral	1.0	subjectiv	1.0
neutral	.7	subjectiv	1.0
neutral	.6	subjectiv	1.0
neutral	.5	objective	1.0
neutral	.5	subjectiv	1.0
neutral	.8	subjectiv	1.0
neutral	.6	subjectiv	1.0
neutral	.5	objective	1.0
neutral	.7	subjectiv	1.0
neutral	.5	objective	1.0
neutral	.5	subjectiv	1.0
neutral	1.0	objective	1.0
neutral	.6	subjectiv	1.0
neutral	.9	objective	1.0
neutral	1.0	objective	1.0
neutral	1.0	objective	1.0
neutral	.9	subjectiv	1.0
neutral	1.0	subjectiv	1.0
neutral	.9	subjectiv	1.0

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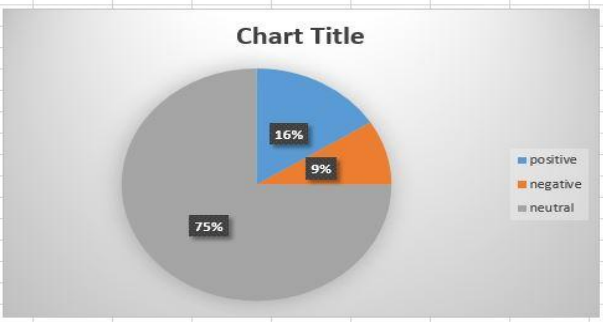
polarity	polarity_confi	subjectivity	subjectivity_confidence
positive	.6	objective	1.0
positive	.9	subjective	1.0
positive	.9	subjective	1.0
positive	.9	objective	1.0
positive	.5	subjective	1.0
positive	.5	subjective	1.0
positive	.8	subjective	1.0
positive	.7	subjective	1.0
positive	.8	subjective	1.0
positive	.9	subjective	1.0
positive	.8	subjective	1.0
positive	1.0	subjective	1.0

Dominozz

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is Positive which means it has positive impact.

positive	16
negative	9
neutral	75



polarity	polarity_c	subjectivi	subjectivity_confidence
positive	.9	objective	1.0
positive	.9	objective	1.0
positive	.9	objective	1.0
positive	.9	objective	1.0
positive	.8	subjectiv	1.0
positive	.9	subjectiv	1.0
positive	.7	subjectiv	1.0
positive	.5	subjectiv	1.0
positive	.8	subjectiv	1.0
positive	.8	subjectiv	1.0
positive	.6	subjectiv	1.0
positive	.6	subjectiv	1.0
positive	1.0	objective	1.0
positive	.8	objective	1.0
positive	.8	objective	1.0
positive	.7	subjectiv	1.0

polarity	polarity_confidence	subjectivity	subjectivity_confidence
negative	.9	subjective	1.0
negative	.5	subjective	1.0
negative	.9	subjective	1.0
negative	.7	subjective	1.0
negative	.4	subjective	1.0
negative	.7	subjective	1.0
negative	.6	subjective	1.0
negative	.8	subjective	1.0
negative	.7	subjective	1.0

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polarity	polarity_confidence	subjectivity	subjectivity_confide
neutral	.7	subjective	1.0
neutral	.9	subjective	1.0
neutral	.9	objective	1.0
neutral	.9	subjective	1.0
neutral	.9	objective	1.0
neutral	.8	objective	1.0
neutral	.6	subjective	1.0
neutral	.9	subjective	1.0
neutral	1.0	objective	.7
neutral	1.0	subjective	1.0
neutral	.8	objective	1.0
neutral	.9	subjective	.9
neutral	1.0	objective	1.0
neutral	.5	subjective	1.0
neutral	.4	subjective	1.0
neutral	.8	objective	1.0
neutral	.9	subjective	1.0
neutral	.9	subjective	1.0
neutral	1.0	subjective	1.0
neutral	.9	objective	.8
neutral	.8	subjective	1.0
neutral	.9	subjective	1.0
neutral	.9	subjective	1.0
neutral	.7	objective	1.0
neutral	.6	subjective	1.0
neutral	.5	objective	1.0
neutral	.8	objective	1.0
neutral	1.0	subjective	1.0
neutral	.9	objective	1.0
neutral	.7	objective	1.0
neutral	.9	objective	1.0
neutral	.8	objective	.9

I. Eclairs

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is Negative which means it has negative impact.

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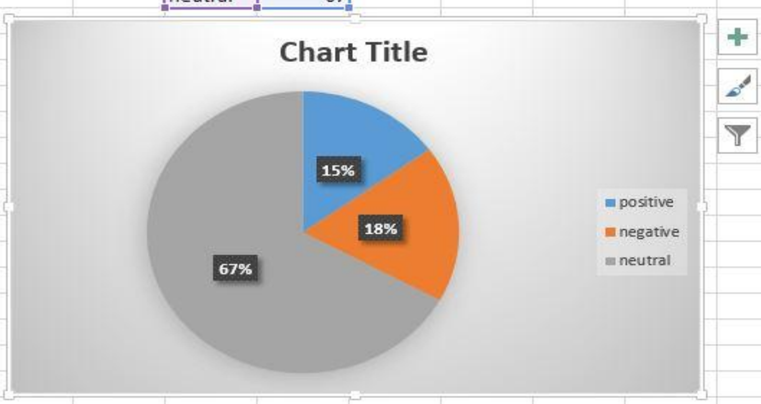
polarity	polarity_confidence	subjectivi	subjectivity_confidence
negative	.5	subjective	1.0
negative	.6	subjective	1.0
negative	.8	subjective	1.0
negative	.8	subjective	1.0
negative	.9	subjective	1.0
negative	.6	subjective	1.0
negative	.8	subjective	1.0
negative	.9	subjective	1.0
negative	.9	subjective	1.0
negative	.5	objective	.8
negative	.5	subjective	1.0
negative	.8	subjective	1.0
negative	.9	subjective	1.0
negative	.4	subjective	1.0
negative	.5	subjective	1.0
negative	.9	subjective	1.0
negative	.7	subjective	1.0
negative	.5	subjective	1.0

positive	15
negative	18
neutral	67



polarity	polarity_confidence	subjectivity	subjectivity_confidence
positive	.6	subjective	1.0
positive	.8	subjective	1.0
positive	.5	subjective	1.0
positive	.7	subjective	1.0
positive	1.0	subjective	1.0
positive	.6	subjective	1.0
positive	1.0	objective	1.0
positive	.4	subjective	1.0
positive	.6	subjective	1.0
positive	.5	objective	1.0
positive	.6	subjective	1.0
positive	.5	objective	1.0
positive	.4	objective	.7
positive	.8	subjective	1.0
positive	.9	subjective	1.0

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Strepsills

For this product, we have collected 100 Tweets from the internet and analyzed these tweets by using rapid minor which shows the polarity of this product is negative which means it has negative impact.

polarity	polarity_confidence	subjectivity	subjectivity_confidence
positive	.9	subjective	1.0
positive	.5	subjective	1.0
positive	.5	subjective	1.0
positive	.8	objective	1.0
positive	.5	subjective	1.0
positive	.4	subjective	1.0
positive	.8	objective	1.0
positive	.8	subjective	1.0
positive	.4	subjective	1.0
positive	.6	subjective	1.0
positive	.4	subjective	1.0
positive	.4	subjective	1.0
positive	.8	objective	1.0
positive	.5	objective	1.0
positive	.5	subjective	1.0
positive	.6	subjective	1.0
positive	1.0	objective	1.0

polarity	polarity_confidence	subjectivity	subjectivity_confidence
negative	.5	subjective	1.0
negative	.6	subjective	1.0
negative	.9	subjective	1.0
negative	.9	subjective	1.0
negative	.9	subjective	1.0
negative	.6	subjective	1.0
negative	.9	subjective	.5
negative	.8	subjective	.8
negative	1.0	subjective	1.0
negative	.8	subjective	1.0
negative	.8	subjective	1.0
negative	1.0	objective	.9
negative	.4	subjective	1.0
negative	.6	subjective	1.0
negative	.8	subjective	1.0
negative	1.0	subjective	1.0
negative	1.0	subjective	1.0
negative	.7	subjective	.8
negative	1.0	objective	1.0
negative	.6	subjective	1.0
negative	.6	objective	1.0
negative	1.0	subjective	1.0
negative	.7	subjective	1.0
negative	.7	subjective	1.0
negative	.8	subjective	1.0
negative	1.0	subjective	1.0
negative	1.0	subjective	.8
negative	1.0	subjective	1.0
negative	1.0	subjective	1.0
negative	.5	objective	1.0

polarity	polarity_confidence	subjectivity	subjectivity_confid
neutral	.9	objective	.5
neutral	.5	subjective	1.0
neutral	.9	subjective	1.0
neutral	.7	objective	1.0
neutral	.9	objective	.9
neutral	.6	objective	1.0
neutral	.4	objective	1.0
neutral	.7	objective	.6
neutral	.7	subjective	.6
neutral	.8	objective	1.0
neutral	.9	subjective	1.0
neutral	.4	objective	1.0
neutral	.5	subjective	1.0
neutral	.5	subjective	1.0
neutral	.5	subjective	1.0
neutral	.4	subjective	1.0
neutral	.6	objective	1.0
neutral	.5	objective	1.0
neutral	.7	subjective	1.0
neutral	.4	objective	1.0
neutral	.8	subjective	1.0
neutral	.8	objective	1.0
neutral	.8	subjective	1.0
neutral	.5	subjective	1.0
neutral	.7	subjective	1.0
neutral	.6	objective	1.0
neutral	.5	subjective	1.0
neutral	.4	subjective	1.0
neutral	.9	subjective	1.0
neutral	.7	objective	1.0
neutral	.5	objective	1.0

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polarity	polarity_confidence	subjectivity	subjectivity_confidence
neutral	.9	subjective	1.0
neutral	.9	subjective	1.0
neutral	.7	objective	1.0
neutral	.9	objective	1.0
neutral	.9	subjective	1.0
neutral	.9	objective	.6
neutral	.6	subjective	1.0
neutral	.7	subjective	1.0
neutral	.6	subjective	1.0
neutral	.9	objective	.9
neutral	.6	subjective	1.0
neutral	.8	subjective	1.0
neutral	.8	objective	1.0
neutral	.4	subjective	1.0
neutral	.9	subjective	1.0
neutral	.5	subjective	1.0
neutral	.7	objective	1.0
neutral	.4	subjective	1.0
neutral	.9	objective	1.0
neutral	.9	subjective	1.0
neutral	.7	subjective	1.0
neutral	.5	subjective	1.0
neutral	.5	objective	1.0
neutral	.5	subjective	1.0
neutral	.9	objective	1.0
neutral	.9	objective	1.0
neutral	.9	objective	1.0
neutral	1.0	subjective	.9
neutral	.7	objective	.7
neutral	.9	objective	1.0
neutral	.5	subjective	1.0

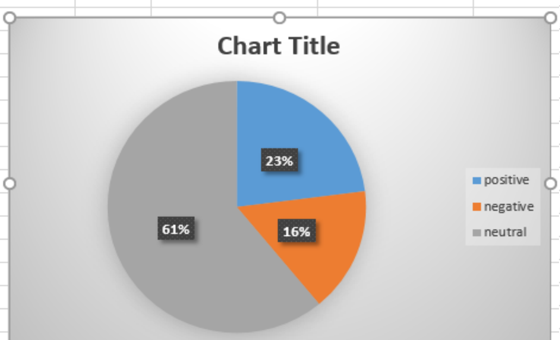
Comparison of Sarcastic and Non-Sarcastic advertisements

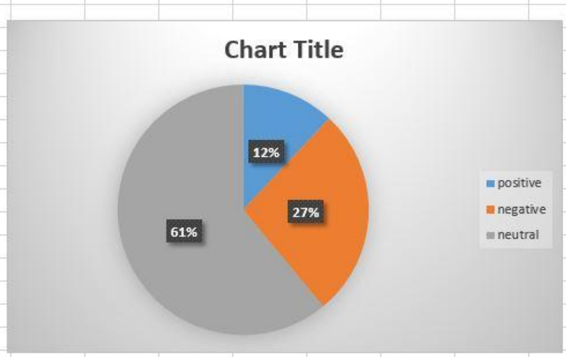
7up Vs Sarsaparilla

In this comparison, Neutral polarity of both the products are similar but there is slight difference in the positive and negative polarity. As we can see that the positive polarity of sarcastic product is more than other product but the negative polarity of non-sarcastic product is more than other product which means that people have positive impact of sarcastic product but they have negative impact of non-sarcastic product.

Polarity	Total
positive	23
negative	16
neutral	61

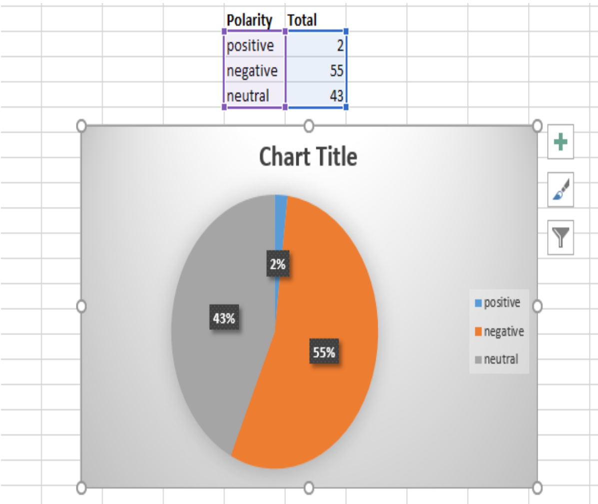
positive	12
negative	27
neutral	61

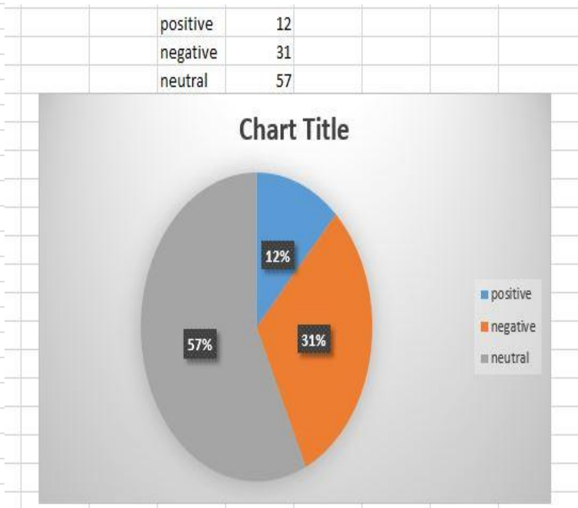




Bisleri Vs Aquafina

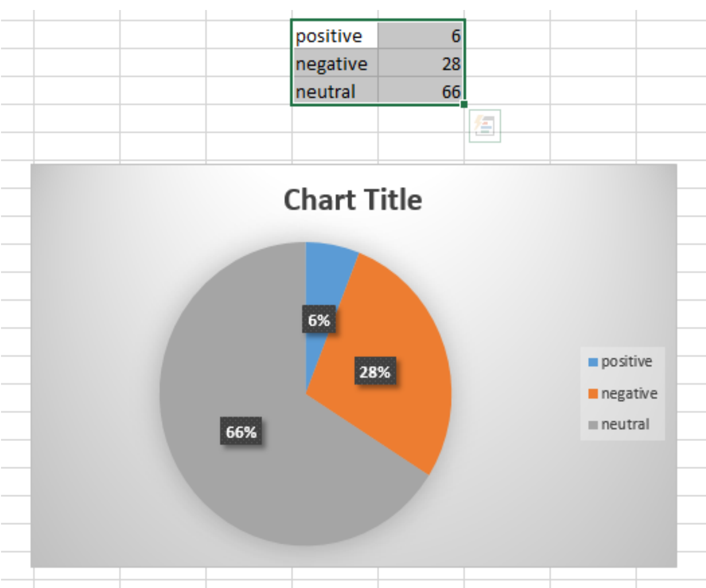
In this comparison, if we ignore the neutral polarity we can see that both the products have more negative polarity which means the impact is negative but there is slight positive impact of non-sarcastic product on customer's perception.





Kurkure Vs Haldiram

In this comparison, neutral polarity of both the products is almost similar but there is difference in the positive and negative polarity. As we can see that the negative polarity of sarcastic product is more and positive polarity of non-sarcastic product is more which means that people have negative impact of sarcastic product but they have positive impact of non-sarcastic product.



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5. Conclusion

In this project, we have studied some of the online tweets for the products having sarcastic and non-sarcastic advertisement and described the impact of these advertisements on customer's perception.

In this study, we analyze the sarcastic and non-sarcastic products individually than we find out that there is fluctuation in the impact on customer's perception, but if we consider the whole sarcastic and non-sarcastic products then we find out that the products having sarcastic advertisements have negative impact on costumer's perception and the products having non-sarcastic advertisements have positive impact on costumer's perception.

Hence, the sarcastic advertisements having negative impact but people likes to discuss these advertisements with other which makes these kinds of advertisements very popular. That's why, the higher corporates used these type of advertisements for the marketing.

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