

Numerical Irony Identification: A Pattern-Based Approach

Isukapalli Sainath Reddy¹, C. Sindhu², Settipalle C Sai Pavan Kumar Reddy³, Isukapalli Pravallika⁴, Lekkala Sai Benerji Naidu⁵

¹UG Student, Department of CSE, SRM Institute of Science and Technology, Chennai, India. Email: isukapallisainath@gmail.com

²Assistant Professor, Department of CSE, SRM Institute of Science and Technology, Chennai, India.

³UG Student, Department of CSE, SRM Institute of Science and Technology, Chennai, India.

⁴UG Student, Department of ECE, Bharath Institute of Higher Education and Research, Chennai, India.

⁵UG Student, Department of ECE, Lovely Professional University, Jalandhar, India.

Abstract

Irony is a type of metaphorical language where the literal meaning of words can't hold, rather the contrary interpretation is planned in a content. This purposeful uncertainty makes irony recognition a significant job of opinion mining. In general irony discovery is viewed as a binary classification issue wherein both rule-based and deep learning models have been effectively worked to foresee wry remarks. These current strategies will in general focus on recognizing irony in a content. However a specific type of irony communicated through numbers stays neglected. In this manner, perceiving numerically ironic statements can be extremely valuable to improve the performance of opinion mining of information gathered from microblogging sites or interpersonal organizations. In this paper, we proposed a pattern-based methodology for recognizing irony communicated through numerical qualities in a tweet. We dissect the difficulties of the issue and present a Machine Learning way to deal with irony in numerical bits of text. Four sets of highlights that cover the various sorts of irony are characterized and used to classify the tweets as ironic and non-ironic. We likewise study the significance of every one of the proposed sets of highlights and assess its additional incentive to the classification. The exploratory outcomes show that our model can clearly beat other cutting-edge strategies and further, we underline the significance of pattern-based highlights for the recognition of ironic statements expressed through numbers.

Keywords: Irony Detection, Opinion Mining, Pattern-based Approach, Social Data, Sentiment Analysis.

DOI: 10.47750/pnr.2022.13.S03.016

INTRODUCTION

The greatest task in sentiment investigation is to precisely decide the veracity of the assertion in a strict sense to characterize text based on the extremity. Sentiment investigation accomplishes fair outcomes on account of strict language as it passes on the normal understanding. Nonetheless, the utilization of metaphorical language that is intrinsically symbolic addresses some different opinions from the solid significance, in this manner making irony investigation a nontrivial problem. Through web-based media individuals regularly use irony to communicate their opinions about products, political events, and more, and is inalienably hard to examine not just for a machine yet in any event, for a human. The presence of ironic remarks importantly affects sentiment investigation assignments. For instance, "It is an awesome feeling to start a week stranded in traffic" is a ironic sentence communicating negative notions about starting a week utilizing good assessment

words like "awesome feeling". In this manner, irony location is critical in improving the efficiency of sentiment analysis. Albeit a few clients demonstrate they are being ironic, the greater part of them don't. So, it's crucial to find an approach to naturally recognize any ironic messages.

Irony discovery can be demonstrated as a paired characterization errand to anticipate the given sentence(s) as snide or non-snide. Programmed irony recognition is regularly a content characterization issue, which depends on an assortment of feature extraction and learning methods. Past methodologies for irony identification report features identified with supposition, creator's verifiable setting, and conversational setting. Blunder examination introduced in large numbers of these works has filled in as an inspiration for our work. Our paper depends on a mistake seen by [Aditya Joshi, Vinita Sharma, & Pushpak Bhattacharyya, 2015] 'Incongruity in numbers, bringing about irony'. Think about the accompanying three tweets:

1. I just love when my canines wake me up at 10 A.M.(Non-Ironic)
2. I just hate when my canines wake me up at 3 A.M.(Non-Ironic)
3. I just love when my canines wake me up at 3 A.M.(Ironic)

From the sentences given above, we saw that irony depends a lot on the semantic connections (and contrast) between singular words and mathematical qualities in a sentence. Nowadays, most individuals love to awaken at 10 A.M while then again prefer not to awaken at 3 A.M. This makes the initial two sentences as non-ironic because of the attestation between the descriptive words and the relating mathematical characteristics. Out of the blue, sentence 3 is ironic as a result of the conflict between the descriptive word and the mathematical worth. This paper figures out how to perceive irony in mathematical pieces of the content, as in the above sentences.

In outline, the significant commitments of this article are as follows:

1. We perceive the key situations in which numerical irony is utilized in informal communities.
2. We propose a capable strategy to recognize numerical ironic tweets, what's more, concentrate on how to utilize this data (i.e., regardless of whether the sentence is snide or not) to improve the exactness of estimation investigation.

The remainder of this article is organized in the accompanying six sections. Section 2 presents our inspiration and groundwork done for this work. Section 3 portrays our proposed approach for finding irony in mathematical portions of the text. Section 4 implements our methodology. Section 5 details our framework. Finally, section 6 closes this work with conclusion and bearings for future work.

RELATED WORK

The developing quest for Internet clients in all types of online media has strengthened specialists' advantage to cleverly mine the substance accessible, both subjectively and quantitatively. Twitter, at present the most acclaimed micro-blogging site has a significant degree of client inclusion. It has continuously arisen as a gigantic wellspring of sentiment rich information [A. Kumar & A. Jaiswal, 2017]. Different organizations and affiliations have been captivated by this information to inspect the evaluation of singular sentiments. The catchphrase "Sentiment Analysis" was at first seen in the distributed work [K. Dave, S. Lawrence, & D. M. Pennock, 2003]. Besides, the writing is well-equipped with studies relating to opinion examination utilizing AI models on explicit text-based clients created online substance via web-based media. [S. Aloufi, & A. El Saddik, 2018] Implemented a model for feeling investigation of football explicit tweets utilizing 3s classifiers, in particular, SVM, Random Forests, and Naive

Bayes. [P. F. Pai, & C. H. Liu, 2018] set forward a model for the forecast of vehicle deals by sentiment examination of twitter information and securities exchange esteems utilizing least squares support vector regression. Examination DL models for sentiment investigation has additionally been reported. [C. W. Tseng, J. J. Chou, & Y. C. Tsai, 2018] dissected text-based sentiments found in instructing assessment polls and applied the investigation results to help the choice of extraordinary training employees utilizing attention-based LSTM. [D. Wu, & M. Chi, 2017] Introduced a model that has quadratic associations of Long short term memory fit of catching perplexing semantic portrayals of normal language messages and assessed on the Stanford Sentiment Treebank.

The irony location task is a moderately new territory of examination in NLP and it has become a mainstream territory of exploration lately. The primary methodologies for irony identification have focused on detecting even-minded and lexical features to recognize irony present in a given sentence. A few methodologies have been actualized in writing which displays promising approaches to find fascinating signs to distinguish irony. However, the idea of the characterization and the features utilized change contingent upon the point. [Aditya Joshi, Vaibhav Tripathi, Kevin Patel, Pushpak Bhattacharyya, & Mark Carman, 2016] Utilized the cosine likeness between embedded portrayals of words and augmented word embedding based features and improved F-scores highlighting that these are preferred features for irony identification over simple unigrams. [S. Amir, C. B. Wallace, H. Lyu, P. Carvalho, & J. M. Silva, 2016] show that oral or gestural articulations addressed by emojis and uncommon console characters are valuable pointers of irony.

Critical investigations represent irony as an inconsistency in extremity [E. Camp, 2012], [E. Riloff, A. Qadir, P. Surve, L. De Silva, N. Gilbert, & R. Huang, 2013]. Irony discovery has been accounted for as a non-trivial test for opinion investigation across writings. There have been broad endeavors by specialists to explore irony identification procedures on different web channels as a sub-errand of opinion investigation [E. Cambria, S. Poria, F. Bisio, R. Bajpai, & I. Chaturvedi, 2015]. [M. Bouazizi, & T. O. Ohtsuki, 2016] propose a pattern based methodology to recognize irony on twitter thinking about four arrangements of highlights that cover the various kinds of mockeries. [S. C. I. S. Reddy, & S. C. S. P. K. Reddy, 2021] Developed an approach that can able to tackle the missed sarcasm sentences from pattern-based approach due to the presence of numerical bits in a text. [Le Hoang Son, Akshi Kumar, Saurabh Raj Sangwan, Ashika Arora, Anand Nayyar, & Mohammad Abdel-Basset, 2020] Presented a algorithm that naturally learns arrangements of positive thought articulations and contrasting circumstance (initially, with the seed word 'love'). Accepted that numerous ironic tweets contains the positive action word express and the negative circumstance state.

Deep learning procedures have acquired ubiquity in NLP applications as they are equipped for dealing with information inadequacy in unequal datasets. Studies on harassing and verbal animosity have been accounted for recurrent neural networks for short-text opinion mining [C. Junyi, S. Yan, & K.-C. Wong, 2018]. A couple of such methodologies have been accounted for in programmed irony discovery also. [B. Felbo, A. Mislove, A. Søggaard, I. Rahwan, & S. Lehmann, 2017] Presented a DeepMoji model conditional on the events of the emoticon for recognizing the passionate content on the web. [Yufeng Diao, Hongfei Lin, Liang Yang, Xiaochao Fan, Yonghe Chu, Kan Xu, & Di Wu, 2020] Proposed a novel multidimensional question answering (MQA) network and not just acquaints the bountiful semantic data with comprehending the uncertainty of irony by multidimensional portrayals. Regardless, the above deep learning strategies may disregard the substance data from discussions, and disregard the various depictions to clarify the vulnerability of irony. Here, we need to import the creator setting data and various depictions for recognizing intended irony.

Nonetheless, irony additionally happens because of the discordance between the adjectives and the mathematical qualities. [Lakshya Kumar, Arpan Somani, & Pushpak Bhattacharyya, 2017] present the first report in distinguishing irony in numbers and present Machine Learning, Rule-based, and Deep Learning ways to deal with recognizing irony in mathematical segments of text. Their deep learning approach beats four past methodologies for irony location on a same dataset of tweets.

Recently, with Attention mechanisms and Unequivocal memory organization there is an increase after a period of little activity in computational models which deal with text errands in NLP ([A. Graves, G. Wayne, & I. Danihelka, 2014]&[J. Liang, L. Jiang, L. Cao, L.-J. Li, & A. G. Hauptmann, 2018]). A ceaseless portrayal is the result of encoding the memory network and the procedure on memory units by working on it. These are regularly executed into neural networks. Large number of memory-based ways that work on Natural Language Process Undertakings have been emerged ([P. Chen, Z. Sun, L. Bing, & W. Yang, 2017]&[H. Zhou, M. Huang, T. Zhang, X. Zhu, & B. Liu, 2018]). And on top of that in the place of compositional capacity, attention mechanism could be noticed that can pick where to see by appointing significant loads of various chunks. Favourable exhibitions have been accomplished by these attention based methodologies is meritorious on a miscellany of Natural Language Process Undertakings ([D. Ma, S. Li, X. Zhang, & H. Wang, 2017] & [Y. Diao, H. Lin, L. Yang, X. Fan, D. Wu, D. Zhang, and K. Xu, 2019]).

METHODOLOGY

The test that snide content postures to sentiment analysis

have prompted research interest in computational irony. While a few ways to distinguish irony have been accounted for, for example, [Aditya Joshi, Vinita Sharma, & Pushpak Bhattacharyya, 2015] & [Roberto Gonzalez-Ibanez, Smaranda Muresan, & Nina Wacholder, 2011], they may miss the mark if there should arise an occurrence of irony communicated through numbers. All through this work, we implemented a pattern-based system that plays out the assignment of mathematical irony discovery, a structure moderately simple to actualize, and that shows exhibitions competitive to those of more perplexing ones.

Given a bunch of tweets, we plan to classify individual one conditional on if it is snide or not. Hence, we separate a bunch of highlights from each tweet, allude to a preparation set, what's more, use ML algorithms to play out the classification utilizing various kinds of highlights as depicted beneath. The highlights are extracted by making use of distinctive segments of the tweet and cover different kinds of irony. The tweets on which the work done is checked and marked physically.

Notion-Related Highlights

An extremely famous kind of irony that is broadly utilized in both normal discussions just as short messages, for example, tweets is the point in which a sincerely positive articulation is utilized in a negative situation. A comparative method to communicate irony is to utilize articulations having conflicting opinions. Such a sort of irony we categorized as "Incongruity as repartee" which is extremely regular in informal organizations and micro-blogging sites where the creator uses irony to be clever; the individual utilizes some uncommon types of speeches, will in general overstate, or then again utilizes a unique tone concerning that when he/she talks typically to make it simple to perceive. In interpersonal organizations, voice tones are changed over into uncommon types of composing: utilization of words having capital letters, outcry, and question marks, just as some irony-related emojis. [A. Kumar & A. Jaiswal, 2017] Presented a novel bootstrapping methodology that naturally attains a list of positive notion expressions and contrary circumstance phrases from ironic tweets (initially, with the seed word 'love'). Presumed that many ironic tweets contain the positive verb phrase and negative circumstance phrase. Notwithstanding, learning all conceivable negative circumstances requires a major and rich source and may be speculative since negative circumstances are erratic.

In this work, we think about any sort of irregularity between notions of words just as different segments inside the tweet. Consequently, to recognize and assess such abnormality, we extricate notion related parts of the tweet and tally them. For this reason, we look after two archives of words categorized as "positive words" and "negative words". These archives are made utilizing the Sentistrength database which contains the list of positive and negative words having scored from 1 to 5 where 1 is given to the almost positive words and 5 to

the extremely positive words and - 1 to -5 where -1 being almost negative and -5 being extremely negative words. Two features cpw and cnw are made utilizing these two archives, where cpw speaks to the count of positive words and cnw speaks to the count of negative words. Describing words have higher emotional content than nouns [M. S. Neethu, & R. Rajasree, 2013]; thus words that have the PoS-tag as shown in table 1 are again checked and made two additional archives. Then again, two more features CPW and CNW are made utilizing these two archives, where CPW addresses the count of highly emotional positive words and CNW addresses the count of highly emotional negative words.

We at that point add three additional highlights by checking the count of negative, positive, and ironic emojis. Ironic emojis are emojis utilized here and there with snide or unexpected explanations (e.g., ":b"). These emojis are utilized at times when the individual is attempting to be entertaining or to show that he is simply making a joke.

Table 1: PoS-tags for words having higher emotional content

Parts of Speech	PoS-tag	Description
Adjectives	JJ	adjective
	JJR	adjective, comparative
	JJS	adjective, superlative
Adverbs	RB	adverb
	RBR	adverb, comparative
	RBS	adverb, superlative
Verbs	VB	verb, base form
	VBD	verb, past tense
	VBG	verb, gerund/ present principle
	VBN	verb, past participle
	VBP	verb, sing. present, non-3d
	VBZ	verb, 3 rd person sing. present

Hashtags additionally have enthusiastic substance. Now and again, they are utilized to disambiguate the genuine goal of the twitter client passed on in his message. For instance, the hashtag utilized in the accompanying tweet: "Going to bed at 8:30 my life is awesome #ihatemylife" tells that the client would truly not like to hit the bed early, he is somewhat censuring himself for being separated from everyone because of which he needs to head to sleep early. To tackle this kind of situation, we check the count of hashtags of both notions.

We at that point characterize 4 highlights that address whether there is a paradoxicality between the various segments which means the conjunction of a negative part and a contrasting one inside a similar tweet. We examine the presence of such paradoxicality among hashtags, among words, among words and hashtags, and words and emojis and utilize these data as additional highlights. The last notion-related highlight vector has 13 highlights.

Punctuation-Related Highlights

Notion-related highlights are not sufficient to distinguish numerous sorts of irony that are available. Additionally, they don't utilize all the segments present in a tweet. Consequently, more highlights are to be extricated. As referred to already, irony is a sophisticated type of discourse: it plays with implications and words, yet also it utilizes conduct perspectives, for example, low tones [S. Attardo, 2000], [P. Rockwell, 2017], facial signals [P. Rockwell, 2003], or distortion. These perspectives are converted into a specific utilization of punctuation or redundant use of vowels. To recognize such perspectives, we separate a bunch of highlights under this category. For every tweet, we calculated the count of dots, exclamation and question marks, capital letter words, semicolons, and single quotations. We at that point characterize one final highlight by including the count of words present in the tweet. Altogether, 7 Punctuation-based highlights are extricated.

Pattern-Related Highlights

Two archives are made using the training set for ironic and non-ironic tweets. The process behind making these archives are as follows. We play out the accompanying strides for each tweet in the training set: Make a pattern vector of the tweet and consider the unit of measurement as the word following the word PoS labeled as 'Cardinal Number'. At last, we add an entry to the archive as per the index of the tweet and as indicated by the ironic comment. The state of every archive in the archive is as per the following:

[Tweet Index No., Pattern Vector, Standard Deviation of Number unit, Unit of measurement].

Likewise, for the wide range of various tweets, the same methodology is used to store them in their individual archives. Numerical irony in a test tweet is anticipated as follows. We separate pattern vector, unit of measurement from the test tweet.

Pattern-related highlights as described give high versatility to improve dependent upon their responsibility and we have the boundary called standard deviation range which must be optimized. To optimize standard deviation, we went after various ranges of standard deviation on training and enhancing sets and the outcomes have appeared in figure 1. The outcomes shows the accuracy of the classification of tweets as ironic and non-ironic. The gotten outcomes showed that the ability of classification for the training set is high for the range of standard deviation from ± 3.1 to ± 3.4 . Be that as it may, the accuracy of classification is high for enhancing set when the range of standard deviation is ± 3.3 . In this manner, we set the range of standard deviation to ± 3.3 .

At that point, the following rules are applied: As shown in

figure 2, We initially turned to the ironic tweet archive. On calculating the cosine similarity between the entry and the test tweet pattern vector, the most comparable entry is chosen from the ironic archive. We at that point compare the unit of measurement of the entry with that in the test tweet. On the off chance that the number unit like hours, days, years, and so on, matches, we utilize an archive of standard

deviations to check whether the numerical value present in the test tweet is inside ± 3.3 standard deviation of the mean and incentive for that unit of measurement. For example Test tweet: 'Love waking up at 11 am. Matched ironic tweet: 'Love waking up at 3.5 am. So, the number 11 is not within the ideal certainty span and the test tweet is non-ironic.

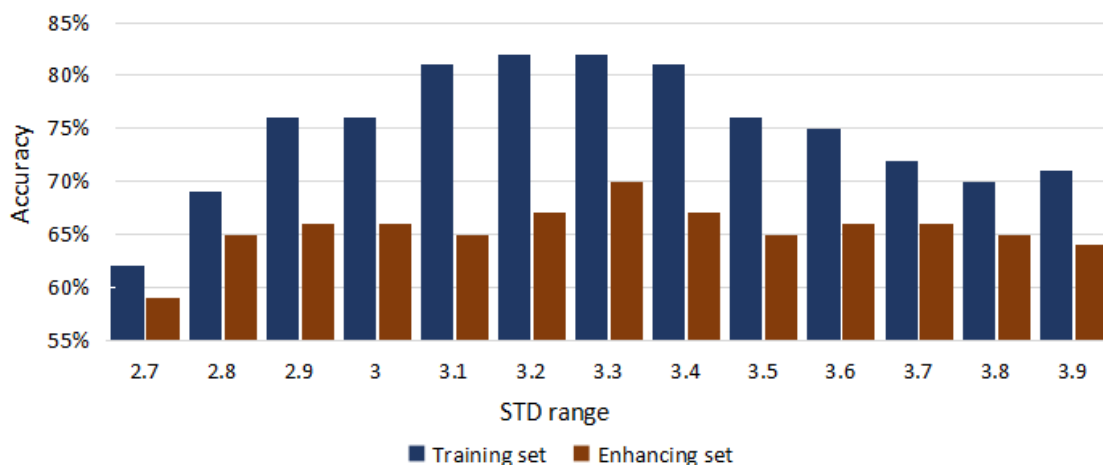


Figure 1: Accuracy per various STD range

If in case the unit of measurement doesn't coordinate, we turn to the non-ironic tweet archive and locate the most comparative entry dependent on the cosine similarity between the pattern vectors of test tweet and entry in the archive. Then we have to check for the unit of measurement matching. If it does then have to examine whether the numerical value present in the test tweet is inside ± 3.3 of the respective standard deviation of non-ironic entry. On the off chance that it lies, at that point foresee the tweet as non-ironic else foresee the tweet as ironic. For instance: Test tweet: 'Today's going to be a great day fml 12-hour shift'. Coordinated non-ironic tweet: 'Today's going to be a great day fml 6-hour shift'. Along these lines, the number 12 isn't inside the wanted certainty stretch and the tweet becomes ironic. **Fall-back label assignment:** At last, in the event that no match is discovered, the test tweet is anticipated as non-ironic.

Pattern vector expansion: We haven't covered all the conceivable pattern vectors from our training set since it is moderately little in size. In this way, to advance our technique and to acquire more patterns, We utilized enhancing set which contains a sum of 8164 tweets and utilizing a similar manner as disclosed above to store all the pattern vectors into their particular archives. Consequently,

we improved the count of patterns. This progression has been done only to get more pattern vectors, hence, none of the different groups of highlights is bothered by the enrichment.

Mathematical Value & Unit-Related Highlights

This highlights concerns about the mathematical worth available in the tweet and the one-hot portrayal of the measurement unit. Illustrations of number units can be an hour, a minute, and so on. Consequently, the respective position in the one-hot vector takes the estimation of one considering the unit present in the tweet and the rest takes the value zero.

IMPLEMENTATION

Since irony is a rare marvel and we manage a particular type of irony (to be specific irony in mathematical content), it is advantageous to assess the number of snide sentences containing numbers. A bunch of roughly 100,000 tweets having 20,164 tweets with numerical values in them, adding up to 20.64%.

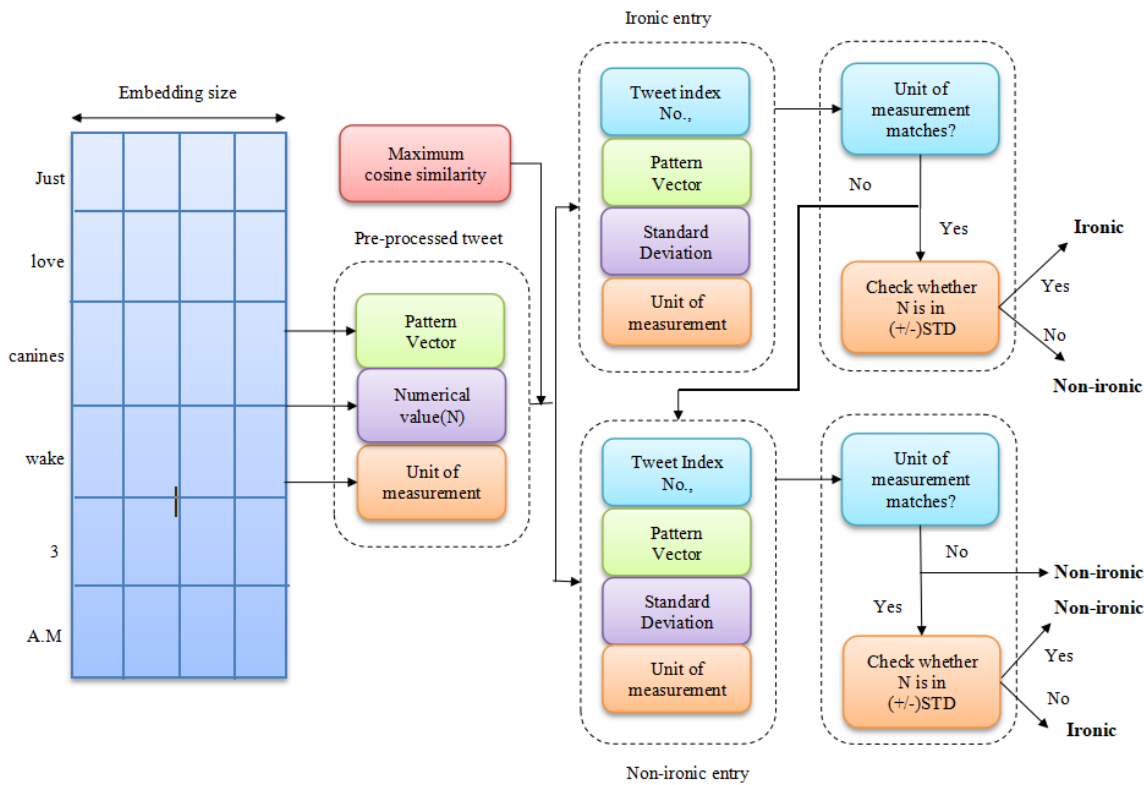


Figure 2: Cycle behind Pattern-based Approach

Data

We utilize three datasets in our work and their creation subtleties are as follows. We download tweets containing hashtags related to irony furthermore, we gathered tweets dealing with various points and ensured they have some passionate content under non-ironic utilizing the Twitter-API. We dispense with copy tweets, retweets, eliminate uniform resource locators, usernames, and hashtags present in the tweets. We got a dataset that contains a sum of 100,000 tweets. From these gathered tweets, We arranged 3 datasets for our framework as explained beneath:

Training set: This dataset contains a sum of 12000 tweets which are taken from the sum of 20,164 tweets we stated before, out of which 5000 are ironic and staying 7000 are non-ironic. These tweets are labeled relying upon their emotion as either ironic or non-ironic. This dataset is utilized to prepare our model. Subsequently, Thusly, it will be alluded to as the "training set" in the remainder of this work.

Enhancing set: This dataset contains a sum of 8164 tweets which are taken from the sum of 20,164 tweets we stated before, out of which 4100 are ironic and staying 4064 are non-ironic. These tweets are labeled relying upon their emotion as either ironic or non-ironic. However, no manual check is done making it a noisy dataset. This dataset is utilized during our testing cycle to advance the boundaries we characterized for our work. Thusly, it will be alluded to as the "enhancing set" in the remainder of this work.

Test set: This dataset comprises an aggregate of 1000

tweets, out of which 500 are ironic and the remaining 500 are non-ironic. We checked these tweets manually and guaranteed that at least 300 out of 500 ironic tweets are ironic because of the presence of numbers and the same with non-ironic tweets. This dataset is utilized to assess the exhibitions of our approach. Thusly, it will be alluded to as the "test set" in the remainder of this work.

Tools

To play out the distinctive NLP tasks, we utilized Apache OpenNLP. However, OpenNLP PoS tagger exhibits ineffectively with the offered model to label tweets, because of the immaterial content and the utilization of slangs, and so on. So we utilized Gate Twitter PoS tagger [L. Derczynski, A. Ritter, S. Clark, & K. Bontcheva, 2013]. This PoS-tagger arrives at a precision of 90.5% on Twitter information. We utilized the toolkit weka for the task of classification which presents an assortment of classifiers. We utilized libsvm for classification using SVM.

Once the preprocessing is done, we continue to our analyses. The Key Performance Indicators(KPI's) used to assess our methodology are Accuracy, Precision, and Recall. Furthermore, we characterize the fourth one to the previously mentioned Key Performance Indicators, which is the F Measure characterized as follow:

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \quad (1)$$

It consolidates the precision and recall, accordingly it addresses a more dependable Key Performance Indicators to collate various methodologies.

We utilized "Support Vector Machine"(SVM), "Random Forest" and "K Nearest Neighbours"(K-NN) for the classification task. The exhibitions of the classifiers on our dataset have appeared in table 2. The overall precision arrives at 96.2% utilizing the classifier Support Vector Machine for a low F1-score equivalent to 32.6%. From the rate acquired for precision, we can say that the tweets that are named ironic are ironic. However, it identified fewer ironic tweets. From this, we can say that yield acquired from SVM can be utilized to refine sentiment analysis. Yet in a

genuine series of tweets, the quantity of ironic tweets is lesser than that in the dataset utilized; in this manner, the outcomes acquired imply that just one out of five ironic tweets will be identified. Then again, the Random forest classifier presents an accuracy equivalent to 84.2% for an F1-score equivalent to 82.4% on setting the boundaries as follows: Count of features: 18, count of trees:120, seeds: 15 lastly max_depth is 0 which implies limitless. Classifier K-NN presents a higher exactness and F Measure, nonetheless, the exhibitions of Random Forest are the most noteworthy. So for the remainder of our work, the outcomes utilized are those obtained from the classifier Random Forest.

Table 2: Key Performance Indicators (KPIs) of different classifiers

KPIs →	Accuracy	Precision	Recall	F1-Score
Classifiers ↓				
SVM	74.4%	96.2%	25.4%	32.6%
Random Forest	84.2%	93.4%	75.7%	82.4%
k-NN	79.6%	88.7%	69.7%	75.5%

Exhibitions of Various Extracted Highlights

First and foremost we checked the ability of classification for a different set of highlights and presented the exhibitions of different highlights underneath.

- **During Cross-Validation**

The classification performances during cross-validation have appeared in figure 3. Exceptionally better performances are noticed for Pattern-related highlights during cross-validation. Because of low accuracy and recall, mathematical value and unit-related highlights seem not a lot productive whenever utilized alone for the classifying task. The reason for this is the mathematical worth isn't the only one adequate to choose the incongruity

in a sentence however whenever joined with notion-related features, the ambiguity can be recognized. Punctuation-related highlights and Notion-related highlights have superior estimation rates. They are more productive still their exhibition is lower than pattern-related highlights. Accuracy acquired for the two of them is almost 60%. Besides, the precision of Notion-related highlights is surprisingly better than the accuracy. In different terms, from the tweets that are classified as ironic, the rate of prediction is prominent. This can be clarified by the way that sentences having differentiating notion substance are probably going to be ironic. In this manner, whenever identified, they would be named ironic.

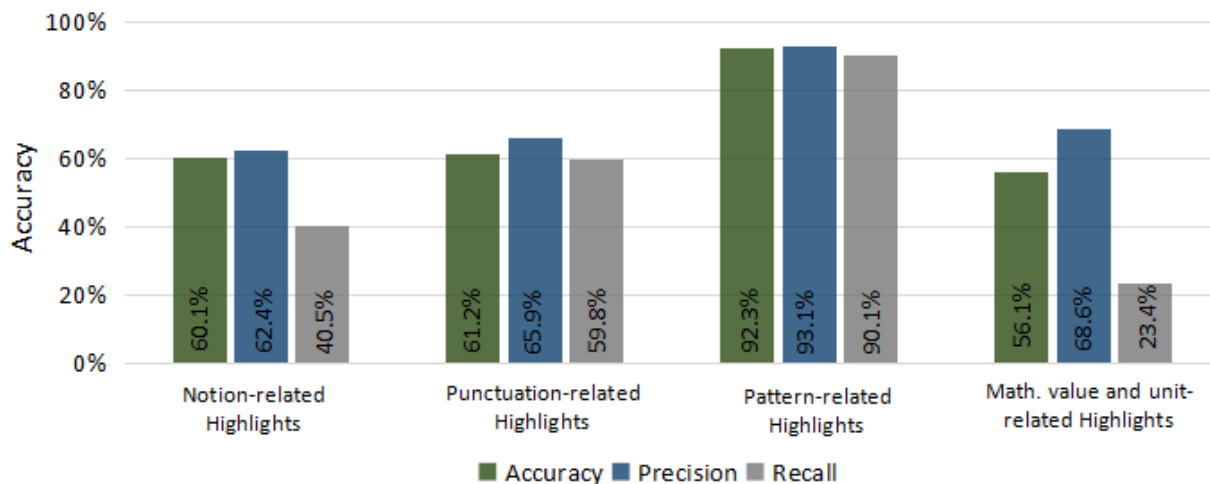


Figure 3: Classifying accuracy for each set of highlights in the time of cross-validation

• On a Test Set

The exhibitions of our approach on test set have appeared in figure 4. As we as a whole know about the way that the capacity of characterization is unquestionably low for a

piece of unknown information than during cross-validation. However, one can observe that the group of highlights that are having good classifying ability during cross-validation are the one having higher classifying ability on the test set.

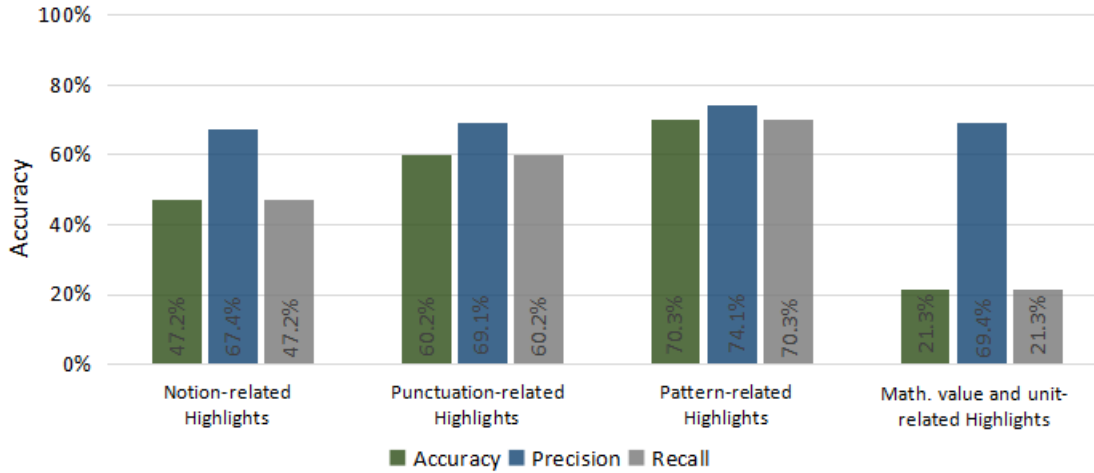


Figure 4: Classifying accuracy for each set of highlights on the test set

EXPERIMENTAL RESULTS

The performance of the classifier is better when all the features are utilized together rather than one itself. The performance of the proposed classifier when all highlights are utilized has appeared in figure 5. Although we got higher accuracy and precision i.e greater than 90% during cross-validation. Strangely, the gotten accuracy with the test set before the enhancement of patterns, surpasses 78% with a precision greater than 75% indicating that the performance is better when all highlights are consolidated rather than utilizing one itself. The process of enhancement add-on more potential to the methodology and improved the accuracy and precision of the categorization perceptibly. Increased precision mirrors that the tweets that are classified

as ironic are indeed ironic. Recall, then again has a lower estimate, however still better than before enhancement. A lower value of recall indicates that the ironic tweets are not classified correctly. While we are preparing datasets for our work, we found that the majority of the tweets are not having a unit of measurement. Since we are using the unit of measurement as a key for identifying numerical irony, the tweets without a unit of measurement are delegated non-ironic due to fall-back labeling. However, this can be advanced if we use bigger training or enhancing sets.

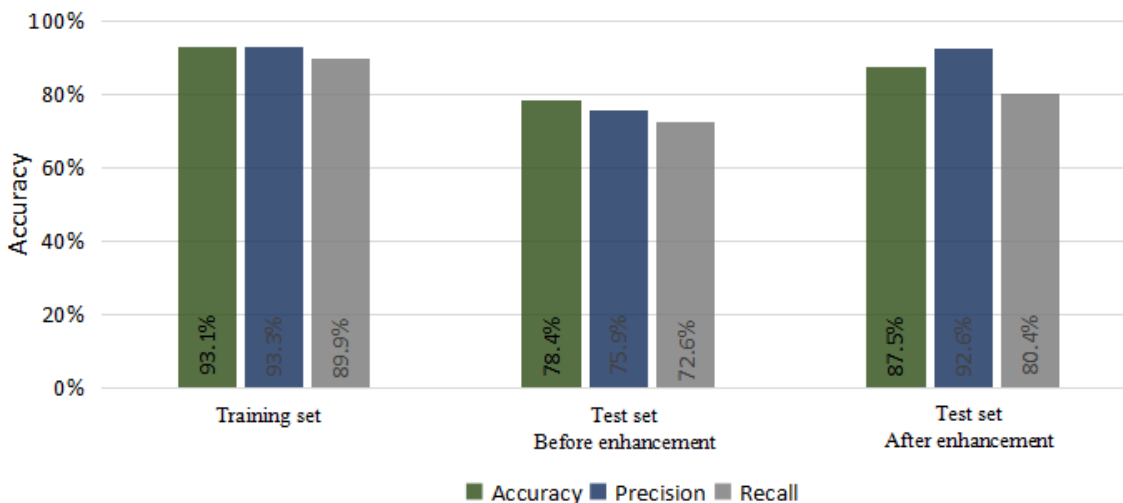


Figure 5: Classifying accuracy on training and testing set by consolidating all highlights

To gauge the capability of our technique, we consider the methodology proposed by [Lakshya Kumar, Arpan Somani, & Pushpak Bhattacharyya, 2017] and n-gram based methodologies as our reference. The divergence of our methodology with the references are shown in table 3. From the obtained accuracy and precision we can say that our

methodology beats the past techniques and the F Measure is conveniently improved when contrasted with the references. Compared to more perplexing methodologies our methodology presents competitive outcomes even though it doesn't need a larger data set for training, or a knowledge base of the clients.

Table 3: Key Performance Indicators of our methodology contrasted with the previous methodologies

KPIs →	Accuracy	Precision	Recall	F Measure
Methodology ↓				
[18]	85.3%	88.2%	71.2%	79.1%
n-grams	65.9%	82.2%	40.6%	65.9%
Proposed Methodology	87.5%	92.6%	80.4%	86.0%

CONCLUSION

Extensive utilization of slang, deformed words, short structures, informal articulations, concoction words, and so on in web-based media enhances the equivocalness in the content of social web making the assignment of investigating nonexclusive and explicit feeling computationally troublesome. We presented a new methodology in our work to sort out the mathematical incongruity present in the tweets by utilizing various segments of the tweet and got the intriguing outcomes on the equivalent datasets when contrasted with the baseline ones. However, the outcomes may be stunningly better if we utilize more tweets in our preparation since the patterns and numerical units we extracted from the current one probably won't cover every conceivable pattern and numerical unit.

REFERENCES

- S. C. I. S. Reddy, & S. C. S. P. K. Reddy. (2021). Consolidating Pattern-Based Approach for Detecting Sarcasm in Numerical Portions of the Text. 2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WISPNET). pp. 230-234.
doi: 10.1109/WISPNET51692.2021.9419430.
- S. K. Bharti, B. Vachha, R. K. Pradhan, K. S. Babu, & S. K. Jena. (2016). Sarcastic sentiment detection in tweets streamed in real time: A big data approach. *Digit. Commun. Netw.*, vol. 2, no. 3, pp. 108–121.
- Aditya Joshi, Vinita Sharma, & Pushpak Bhattacharyya. (2015). Harnessing context incongruity for sarcasm detection. In *ACL (2)*, pages 757–762.
- A. Kumar & A. Jaiswal. (2017). Empirical study of Twitter and Tumblr for sentiment analysis using soft computing techniques. In *Proc. World Congr. Eng. Comput. Sci.*, pp. 1–5.
- K. Dave, S. Lawrence, & D. M. Pennock. (2003). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *Proc. 12th Int. Conf. World Wide Web*, pp. 519–528.
- S. Aloufi, & A. El Saddik. (2018). Sentiment identification in football-specific tweets. *IEEE Access*, vol. 6, pp. 78609–78621.
- P. F. Pai, & C. H. Liu. (2018). Predicting vehicle sales by sentiment analysis of Twitter data and stock market values. *IEEE Access*, vol. 6, pp. 57655–57662.

- C. W. Tseng, J. J. Chou, & Y. C. Tsai. (2018). Text mining analysis of teaching evaluation questionnaires for the selection of outstanding teaching faculty members. *IEEE Access*, vol. 6, pp. 72870–72879.
- D. Wu, & M. Chi. (2017). Long short-term memory with quadratic connections in recursive neural networks for representing compositional semantics. *IEEE Access*, vol. 5, pp. 16077–16083.
- Aditya Joshi, Vaibhav Tripathi, Kevin Patel, Pushpak Bhattacharyya, & Mark Carman. (2016). Are word embedding-based features useful for sarcasm detection?. In *EMNLP, PP:1006–011, ACL*.
- E. Camp. (2012). Sarcasm, pretense, and the semantics/pragmatics distinction. *Noûs*, vol. 46, no. 4, pp. 587–634.
- E. Riloff, A. Qadir, P. Surve, L. De Silva, N. Gilbert, & R. Huang. (2013). Sarcasm as contrast between a positive sentiment and negative situation. In *Proc. Conf. Empirical Methods Natural Lang. Process*, pp.704–14.
- S. Amir, C. B. Wallace, H. Lyu, P. Carvalho, & J. M. Silva. (2016). Modelling context with user embeddings for sarcasm detection in social media. In *Proc. CONLL*.
- Le Hoang Son, Akshi Kumar, Saurabh Raj Sangwan, Ashika Arora, Anand Nayyar, & Mohammad Abdel-Basset. (2020). Sarcasm Detection Using Soft Attention-Based Bidirectional Long Short-Term Memory Model With Convolution Network. *IEEE Translations, Volume 7*.
- C. Junyi, S. Yan, & K.-C. Wong. (2018). Verbal aggression detection on Twitter comments: Convolutional neural network for short-text sentiment analysis. *Neural Comput. Appl.*, pp. 1–10, doi: 10.1007/s00521-018-3442-0.
- E. Cambria, S. Poria, F. Bisio, R. Bajpai, & I. Chaturvedi. (2015). The CLSA model: A novel framework for concept-level sentiment analysis. In *Proc. Int. Conf. Intell. Text Process. Comput. Linguistics*. London, U.K.: Springer, pp. 3–22.
- M. Bouazizi, & T. O. Ohtsuki. (2016). A pattern-based approach for sarcasm detection on Twitter. *IEEE Access*, vol. 4, pp. 5477–5488.
- Yufeng Diao, Hongfei Lin, Liang Yang, Xiaochao Fan, Yonghe Chu, Kan Xu, & Di Wu. (2020). A Multi-Dimension Question Answering Network for Sarcasm Detection. *IEEE Access, Volume : 8*.
- Lakshya Kumar, Arpan Somani, & Pushpak Bhattacharyya. (2017). Having 2 hours to write a paper is fun!?: Detecting Sarcasm in Numerical Portions of Text. *arXiv:1709.01950v1 [cs.CL]*.
- Roberto Gonzalez-Ibanez, Smaranda Muresan, & Nina Wacholder. (2011). Identifying sarcasm in twitter: A closer look. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: Short Papers - Volume 2, HLT '11*, pages 581–586, Stroudsburg, PA, USA.
- B. Felbo, A. Misllove, A. Søgaard, I. Rahwan, & S. Lehmann. (2017). Using millions of emoji occurrences to learn any-domain

- representations for detecting sentiment, emotion and sarcasm. [Online]. Available: <https://arxiv.org/abs/1708.00524>.
- A. Graves, G. Wayne, & I. Danihelka. (2014). Neural turing machines. arXiv:1410.5401.
[Online]. Available: <https://arxiv.org/abs/1410.5401>.
- J. Liang, L. Jiang, L. Cao, L.-J. Li, & A. G. Hauptmann. (2018). Focal visualtext attention for visual question answering. In Proc. IEEE Conf. Comput. Vis. Pattern Recognit., pp. 6135–6143.
- P. Chen, Z. Sun, L. Bing, & W. Yang. (2017). Recurrent attention network on memory for aspect sentiment analysis. In Proc. Conf. Empirical Methods Natural Lang. Process., Pp. 452–461.
- H. Zhou, M. Huang, T. Zhang, X. Zhu, & B. Liu. (2018). Emotional chatting machine: Emotional conversation generation with internal and external memory. In Proc. 32nd AAAI Conf. Artif. Intell., pp. 730–738.
- D. Ma, S. Li, X. Zhang, & H. Wang. (2017). Interactive attention networks for aspect-level sentiment classification. arXiv:1709.00893. [Online]. Available: <https://arxiv.org/abs/1709.00893>.
- Y. Diao, H. Lin, L. Yang, X. Fan, D. Wu, D. Zhang, and K. Xu. (2019). Heterographic pun recognition via pronunciation and spelling understanding gated attention network. In Proc. World Wide Web Conf. New York, NY, USA: ACM, pp. 363–371.
- M. S. Neethu, & R. Rajasree. (2013). Sentiment analysis in Twitter using machine learning techniques. In Proc. 4th Int. Conf. Comput., Commun. Netw. Technol., pp. 1–5.
- S. Attardo. (2000). Irony markers and functions: Towards a goal-oriented theory of irony and its processing. *Rask*, vol. 12, no. 1, pp. 3–20.
- P. Rockwell. (2017). Vocal features of conversational sarcasm: A comparison of methods. *J. Psycholinguistic Res.*, vol. 36, no. 5, pp. 361–369.
- P. Rockwell. (2003). Empathy and the expression and recognition of sarcasm by close relations or strangers. *Perceptual Motor Skills*, vol. 97, no. 1, pp. 251–256, Aug. 2003.
- L. Derczynski, A. Ritter, S. Clark, & K. Bontcheva. (2013). Twitter part-of speech tagging for all: Overcoming sparse and noisy data. In Proc. Int. Conf. RANLP, pp. 198–206.
- Ibrahim, S., & Koksai, M. E. (2021). Commutativity of sixth-order time-varying linear systems. *Circuits, Systems, and Signal Processing*, 40(10), 4799-4832.