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Thai Twitter Sentiment Analysis: Performance Monitoring of Politics in Thailand using Text Mining Techniques

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Social web-based life involves an enormous amount of data. It is utilised for correspondence reasons. Individuals can impart insights, thoughts, musings, feelings, emotions, proposals, and individual exercises. Twitter is a direct result of basic words. It communicates learned data. It is used by correspondents, well-known government officials, entertainers, and researchers. This legislative issue's theme is the principle issue in numerous nations. Twitter is a functioning site that has numerous devotees, and utilises strategy related tweets in the endeavour to speak with supporters. Estimation or conclusion examination has recently seemed one of the most investigated subjects in Natural Language Processing (NLP), chiefly for destinations like Twitter. This examination proposes a glossy web application in R programming language to act as a passage for the investigation of tweets that depict feelings in a short, focused arrangement. The target tweets incorporate brief feeling depictions and words that are not utilised in a fitting organisation or linguistic structure. There is no solid and usable work done on Thai Tweet assumption examination as a product of customer/web application devices. This examination is an early stage working up subsequent stages.

Key words: *Twitter, sentiment analysis, politics, text mining, Thailand.*

Introduction

Thailand had an extremely delayed general election on March 24, with a new government expected to be in place “by the middle of the year”. Thailand’s Election Commission was announced on Wednesday (Jan 23, 2019) afternoon, hours after a royal decree declaring an election was released. The upcoming election will end military rule that has been in place since 2014, when then army Chief Prayut Chan-o-cha led a coup that toppled the Pheu Thai Party-led government and took over as premier. About 51 million Thais aged at least 18 are eligible to vote in the 2019 election.

sentiment analysis, or opinion mining, portrays a natural language processing issue that endeavours to separate obstinate content from real content. When content is thought to be stubborn, it is considered to communicate a negative feeling, an unbiased conclusion, or a positive one. The point of sentiment investigation or supposition mining is to decide the frame of mind of a speaker or an author regarding an issue or the general logical extremity of a record. An idea, view, or frame of mind dependent on feeling, as opposed to reason, is called supposition. Right now, government officials are progressively worried about conclusions via well-known web-based networking media locales as opposed to criticism given on their websites. Feeling analysis in a general sense takes a gander at sorting the extremity of content, emojis and these days, even symbolisms and recordings. Assessment analysis and opinion mining, an expansion of information mining, is a characteristic form of language preparing and communicating investigative procedures (Pagano and Maalej, 2013). The latter decide individuals' feelings, sentiments or dispositions toward some issue by handling monstrous unstructured online substance.

Conclusion mining removes the assumption or supposition bearing words present in free content while sentiment investigation decides slant extremity, regardless of whether it is positive or negative by dissecting each obstinate word or expression. Dialects that have been examined generally in opinion investigation are English and Chinese. At present, there are extremely few analysts who have researched in different languages like Arabic, Italian, and Thai (Jagdale, Shirsat, and Deshmukh, 2016). Feeling analysis restates the assessment of a creator or speaker about a particular issue. It tends to be done at the word or viewpoint level, sentence level, and record level. Supposition can be sorted in a few different ways: administered arrangement strategies, unaided characterisation procedures, and half-breed grouping systems or by combining two philosophies. We present a Thai Twitter Sentiment Analyser (TTSA) that concentrates conclusions about a political issue from web content archives for checking. Conclusion mining can be characterised as a sub-control of computational etymology that focuses on separating individuals' suppositions from the web. The most recent augmentation of the web urges clients to contribute and communicate by means of websites, recordings, internet-based life locales, and so forth. All these systems' administration locales give a gigantic measure of acknowledged data that we are intrigued to explore.

In this way, the assumption investigations with AI strategies have been extensively applied to content mining from person to person regarding communication locales. In any case, while evaluating the feeling of content information, there are some genuine difficulties that have been examined as the years progress. One point is that passionate responses are different for various individuals. Likewise, in view of various issues, individuals would have distinctive wording to express their conclusions. Another test regarding the enormous information perspective is the way to get continuous, new Twitter information with the goal that government officials can have recharged investigation results. This paper introduces Twitter information recovered online with watchwords, information investigation, and conclusion examination by numerous AI strategies. It also introduces a glossy web application framework to recover information with opinion examination results for checking the voters in Thailand.

Related Work

There are many more applications and improvements on opinion mining and sentiment analysis algorithms. These surveys give several sentiments or opinion mining techniques and their accuracy is given by authors, as shown in Table 1.

Table 1
Performance index of opinion mining techniques given by different authors

Authors	Opinion mining techniques used	Accuracy rate (%)
Singh and Husain (2014)	Naïve Bayes Multilayer Perception	76 81
Deepthi and Rekha (2014)	Naïve Bayes	84
Sharma, Nigam and Jain (2014)	Dictionary based Approach	67
Mehta and Shah (2014)	Naïve Bayes Genetic Algorithm Naïve Bayes + Genetic Algorithm	91 91 93
Tripathi and Naganna (2015)	Support Vector Machine	85
Singh and Mangat (2015)	Naïve Bayes Maximum Entropy Support Vector Machine K Nearest Neighbour	71 75 81 85
Saha and Ray (2015)	K-means	77
Preety and Dahiya (2015)	Naïve Bayes Support Vector Machine Naïve Bayes + K-means	80 84 89
Umamaheswari, Rajamohana and Aishwaryalakshmi (2015)	Support Vector Machine Support Vector Machine + Particle Swarm Optimisation	68 82

Authors	Opinion mining techniques used	Accuracy rate (%)
Bhadane, Dalal and Doshi (2015)	Support Vector Machine	78
Go, Bhayani and Huang (2009)	NB, MaxEnt, and SVM classifiers.	82.7 83
Anjaria and Guddeti (2014)	NB, SVM, MaxEnt, and ANN classifiers.	88 92
Barhan and Shakhomirov (2012)	NB and SVM classifiers	81 74
Pak and Paroubek (2010)	Multinomial NB and SVM classifiers	65-68
Hamdan, Béchet and Bellot (2013)	NB, SVM	4 2

(Sathyapriya and Akila, 2016)

Data

Improved support of voters depends on the people's opinions. Using these opinions, individuals or parties can find popular voters in cyberspace. People give their opinions on different social networking websites. Many of these sites contain different comments of different politicians, parties, events, issues etc. Twitter is a popular microblogging service where users create status messages called "tweets". These tweets contain users' opinions and thoughts on different issues. Tweets are sometimes used in organising sentiments about particular issues or comments of assumption.

1. Information gathering and pre-handling Twitter channels from twitter.com were acquired. The 10,000 tweets from twitter.com were comprised of assessments about the Thai political race in 2019. The language of the twitter channels was Thai and English. Furthermore, a dictionary of 1,784 words was created with supposition going from negative (-5) to extremely positive (+5), remembering an assortment of notions in-between.

2. In terms of the scoring of the sentiment of tweets for each tweet, an all-out feeling score was determined dependent on the lattice and the dictionary. The all-out opinion score for a tweet was equivalent to the whole notion score of each word times the quantity of the occasions the word was spoken in eq. (1).

$$S_{tweet} \equiv \sum(s_w w_n) \qquad (1)$$

Where S_{tweet} denotes the total sentiment score for a tweet, s_w is the sentiment score of a word n and w_n is the number of times word n appears in a tweet. Equation 1 could be applied to DataTables (DT package version 0.5). As mentioned previously, most words had a sentiment score of 0. For the tweets used to create DataTables, "standwiththanathorn" (Term 6) had a score of +1, "พรรคอนาคตใหม่ (Future Forward Party)" (Term 3) had a score of +1, and "พรรคพลังประชารัฐ (Palang Pracharat Party)" (Term 4) had a score of -4. The all-out supposition score for record 1 would be 0 (0*1 + 0*1 + 0*1), for report 2 would be 1 (1*1 + 0*1 + 0*1 + 0*1), and for archive 3 would be -3 (1*1 + -4*1 + 0*1 + 0*1). From the DataTables, records 1, 2, and 3 would have crude scores of 0, 1, and -3, separately. Under the scoring framework from Equation 1, the assessment scores for a tweet extended from -11 to +11. The crude scores were additionally prepared to create two elective scores.

A tweet score was changed over to a basic positive/negative scoring framework (-1, 0, +1) in light of the complete positive, nonpartisan, and negative scores. Tweets with an absolute score of -10 or -3 were both viewed as negative tweets and the extent of the negative or positive score was overlooked. Additionally, a tweet score was changed over to a scaled score (-2, -1, 0, +1, +2). Scores of -11 to -5 were reassigned a score of -2, scores of -4 to -1 were reassigned a score of -1, scores of 1 to 4 were reassigned as score of 1, and scores of 5 to 11 were reassigned a score of 2. This scoring separated the exceptionally negative or positive scores. The straightforward positive/negative scoring framework for reports 1, 2, and 3 would be 0, 1, and -1, individually. The scaled scores for archives 1, 2, and 3 would likewise be 0, 1, and -1, individually. These two prepared scores (positive/negative and scaled) were utilised as the reaction variable for the regulated arrangement step.

There is one technique to gather an enormous number of tweets in TTSA: by recovering information utilising Twitter APIs (Twitter, 2019) using the "twitteR" bundle (form 1.1.9). All the while, we requested the questions by watchword to gather tweets for the days having feeling news impact. Ten thousand tweets were filtered for 5 months from January to May 2019. We picked this time span since it speaks to a period that starts with the declaration of the Thailand political decision (January 23, 2019) and closes with the most recent day for the inquiry tweet (May 25, 2019). It is worth mentioning that we didn't expel retweets and tweets containing URLs from our dataset, yet "rt" and URLs were expelled from the gathered tweets. Figure 2 shows an example of tweets that are identified with the political decision and casting ballot issues utilising the #เลือกตั้ง62 (#thailandelection2019) inquiry.

Methodology

The scoring dataset is utilised in wistful examination to score the model and get nostalgic circulation in the information. For sentimental analysis, the joked feed was classified into positive and negative groupings. This example was utilised to prepare the factual model in the wistful examination bundle.

Sentimental analysis

After grouping the information, we cleaned it by expelling some irregular good for nothing images and keeping just Thai content information. Our notion examination framework depended on controlling concerning highlights, conclusion lexicons, emoji records, slang records, and other internet-based, life-explicit highlights. We didn't utilise a particular language examination program. Moreover, the language occupied with Twitter had specific qualities. For example, the increase of tweets that were reposted by different clients had "RT", the increase of themes utilised the "#" (hash sign) and different clients utilised the "@" sign. Every one of these angles must be considered at the hour of preparing tweets. Independent from anyone else, before applying directed calculation of how to sort the supposition of the tweets, we pre-processed them to standardise the language they encase.

The pre-handling step incorporated the accompanying advances:

Stage 1: Repeated accentuation sign standardisation

In the primary phase of the pre-handling, we identified duplications of accentuation signs (".", "!" and"?"). Various rational accentuation signs are supplanted with the names "multi-stop". For the full stops, "multi outcry" were involved on account of shout sign and "multi-question" involved the question mark and spaces previously and after the fact.

Stage 2: Lower packaging and tokenisation

Therefore, the tweets were lowercased and isolated into tokens, in view of spaces and accentuation signs.

Stage 3: Word standardisation

In this stage, the tokens were contrasted with passages in the Thesaurus. In the event that no match was discovered, rehashed letters were diminished in grouping to two or one until a match was found in the word reference. The words utilised in this structure were set apart as "pushed".

At long last, the clients referenced in the tweets, which were set apart with "@", were supplanted with "Individual" and the subjects, which the tweets allude to, were set apart with "#" and supplanted with "Point".

At the start we loaded the positive and negative words' datasets. Iteratively, we got the tweets about products given by the various users. Tweets can be segmented into a number of words.

Segmented keywords can be forwarded through training datasets to compute positive and negative values and compute positive and negative probability with respect to all the words. This maintains the key value pairs for the scores of the various tweets and integrates them for the final scores of the tweets. In this scenario, for an experimental analysis, we used "shiny" package (version 1.3.2) as a web application framework for R to create a TTSA shiny web application as a testing sample. The key thought for the mapper was that we were taking the tweet, normalising the content, searching for a political watchword of enthusiasm and checking the positive and negative catchphrases. We subtracted the proportion of negative words from the proportion of positive words.

Notion examination unveils the general emotions inside content information (Taboada et al., 2011). Learning-based and vocabulary-based techniques are two fundamental methodologies for assumption examination (Khan, Atique and Thakare, 2015). The first approach utilises AI classifiers when there is earlier information about information classifications. The subsequent methodology, a savvy one, finds the recurrence of a predefined lexicon of positive and negative terms to reveal the notion in the information when there isn't any earlier information about its classes (Medhat, Hassan and Korashy, 2014). We didn't have any earlier information about the classifications of the tweets in this exploration. In this manner, we applied the second way to deal with finding positive and negative tweets.

Results

This explorative paper advances an investigation dependent on the notions of the tweets during the 2019 Thailand political decision. The internet-based life stage chosen for this investigation is Twitter. The goal was to perform persistent observation and assessment of individuals in Thailand so as to distinguish potential tweets or posts progressively or even ahead of time as for the customary news media.

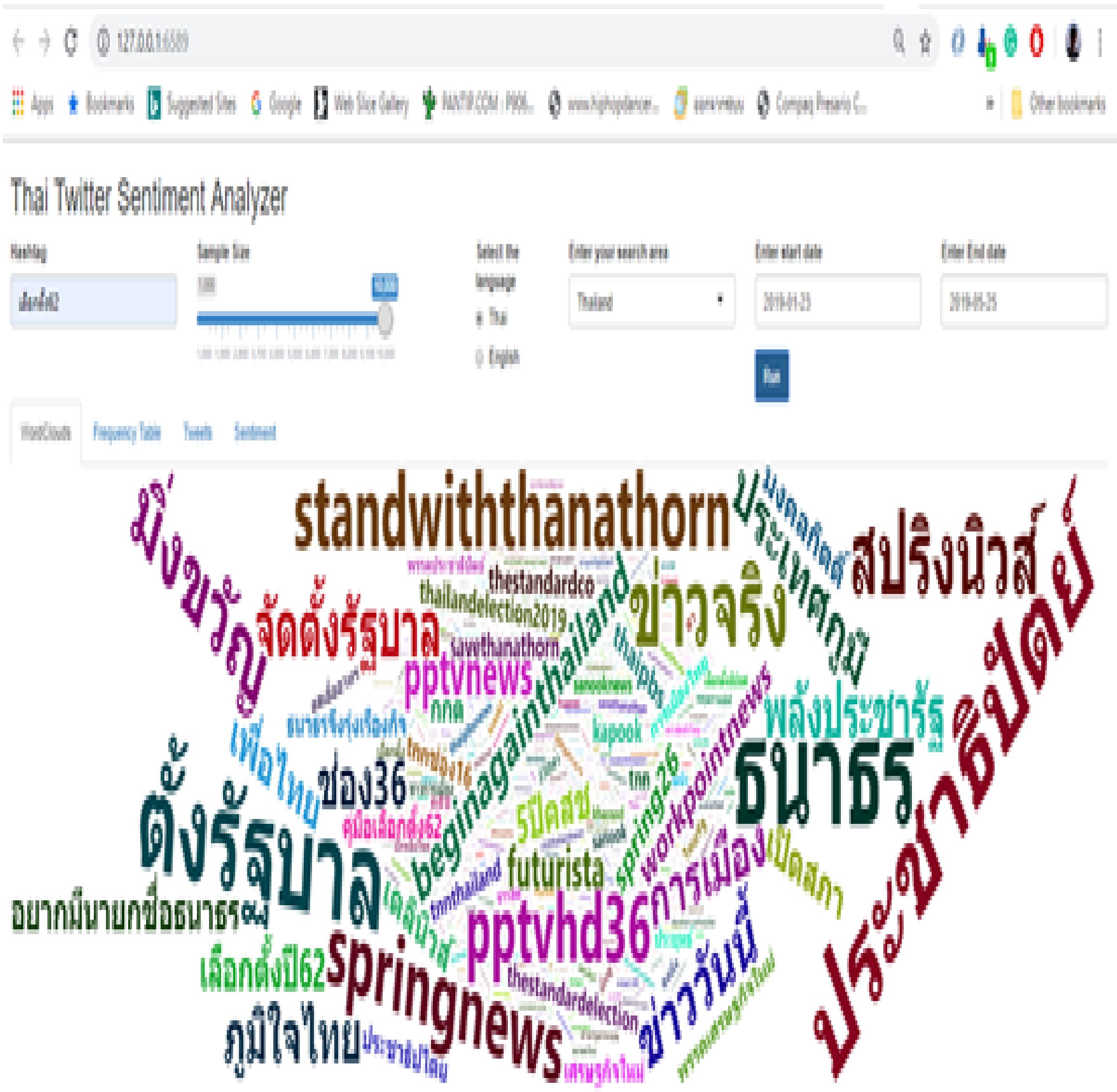
Shiny app: Thai twitter sentiment analyser

For political worth, recovering ongoing information is basic since parties need to settle on political choices dependent on what's going at the present moment. This is not founded on prior information or experience. In this examination, we made a glossy application connected with ongoing information so individuals can have new outcomes. In this application, the tweets were be naturally refreshed at regular intervals and all information was classified as negative or positive. Under every class, we constructed a word cloud to exhibit mainstream words. Note, once in a while the word cloud was too enormous to show in every classification.

Plotted word cloud

We used the “wordcloud2” package (version 0.2.1) to create a word cloud with an 'htmlwidget' library. We utilised the "content" section from the tweet_doc article to make a word lexicon of the tweets subsequent to evacuating accentuation and undesirable characters. The size of the words increments involved their recurrence of appearance in the tweets. The picture below shows such a word cloud with featured words demonstrating high-recurrence phrases.

Figure 1
Popular words word cloud



Frequent terms and associations

We analyse the association between frequent terms (i.e., terms which correlate) using the findAssocs function.

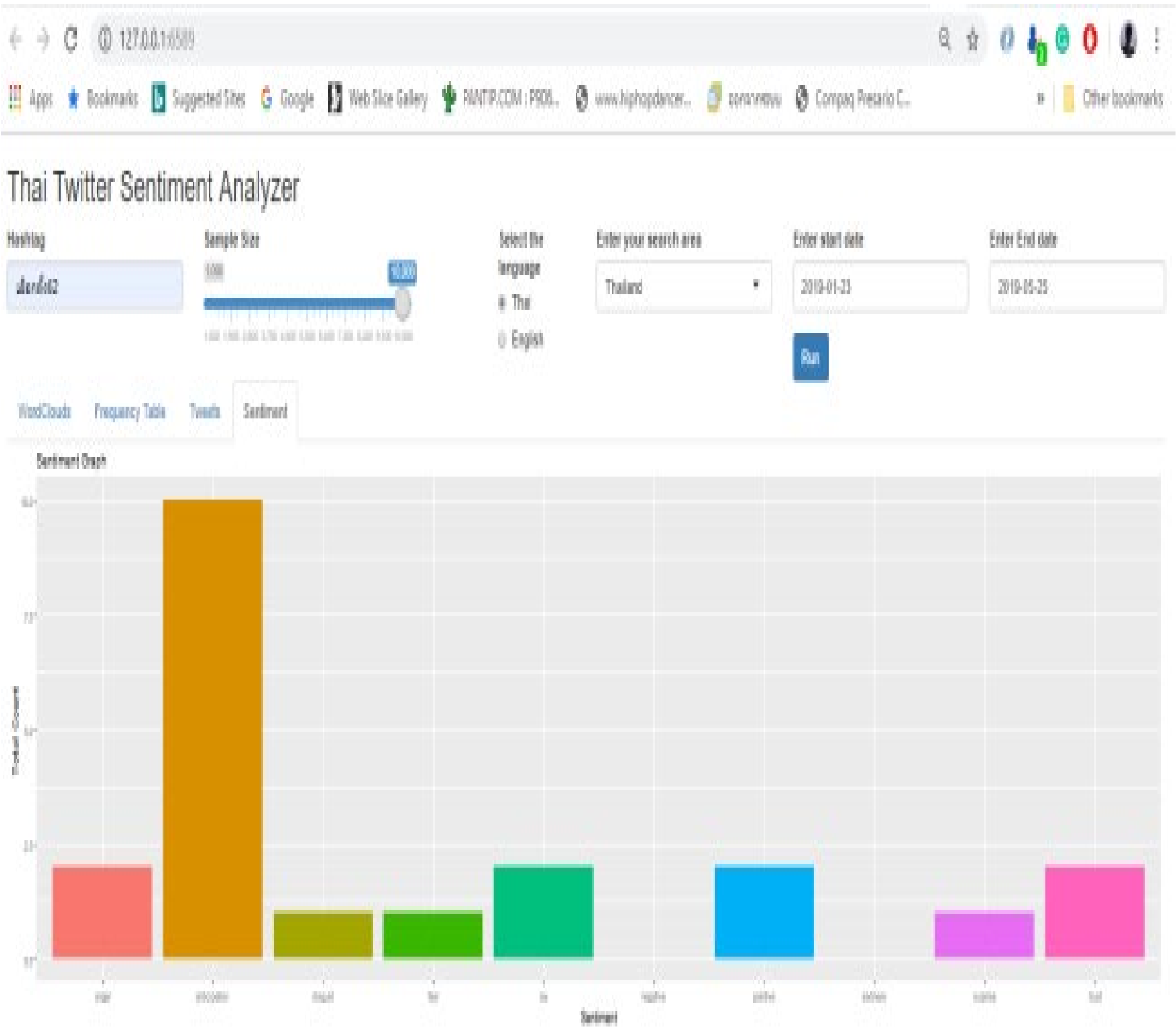
Figure 2
Word frequency table list

Plot sentiment graph

We used the "syuzhet" package (version 1.0.4) to extract sentiments and sentiment-derived plot arcs from text and assigned emotional values to each of the 10,000 tweets we extracted. This was done using the get_nrc_sentiment function (Mohammad, Kiritchenko and Zhu, 2013; Kiritchenko, Zhu and Mohammad, 2014; Zhu, Kiritchenko and Mohammad, 2014). This appoints a numeric incentive to each tweet to show different feelings communicated in the tweet: outrage, expectation, dread, euphoria, and so forth. Then we added these qualities back to the tweet_doc protest and process segment sums to infer the general load for every feeling. We can likewise utilise the scores to check whether positive or negative feelings change with the time of day or date.

Figure 3

Sentiment analysis



Its application of text mining techniques

Feeling mining and slant examination involves a wide scope of utilisations. 1) Argument mapping of sparkling web applications sorts out (in a consistent manner) these strategy proclamations by identifying the legitimate connections between them. Under the exploration field of Online Deliberation, devices like Compendium, Debatepedia, Cohere, and Debate Diagram have been created to give legitimate structure to the quantity of arrangement explanations and to interface contentions with the proof to back them up. 2) Voting advice applications help voters to understand which ideological groups (or different voters) have nearer positions to theirs. For example, SmartVote.ch requests that voters proclaim their level of concurrence with various arrangement proclamations and afterward coordinates its situation with ideological groups. 3) Robotised content investigation forms tremendous measures of subjective information. There are numerous devices available that consolidate measurable calculations with semantics and ontologies, just like AI with human supervision. These arrangements can distinguish applicable remarks and relegate positive or negative undertones (of the supposed supposition).

Substances in administration text mining applications are essential in the plan of huge scale agreeable policymaking. They have the benefit of comprehending a large number of intercessions. They help to identify the early cautioning arrangement of conceivable disturbance in an auspicious way by recognising early criticism from residents. Generally, impromptu reviews are utilised to gather criticism in an organised way. Be that as it may, this sort of information gathering is expensive, as it merits an interest in plan and information assortment. This is troublesome, as individuals are not keen on noting overviews. Additionally, it isn't entirely significant, as it recognises "known issues" through pre-characterised questions and interviewees but neglects distinguishing the most significant issues (the popular and "obscure"). Content mining steadily orders issues by tuning in instead of by asking. In this manner, it guarantees an increasingly honest impression of the real world. A TTSA is then valuable to guarantee that approach discourses are coherent and proof-based and don't rehash similar contentions. These applications would be valuable for legislators as well as for residents who could more effectively comprehend significant thoughts and exchanges and take part in the gathering process.

The findings show that this examination underpins situational mindfulness in certain ways. The first one gives a colossal picture of harms and open concerns. Contrasting with different examinations, this investigation has various benefits. In the first place, TTSA is a quick, ongoing, and financially savvy structure. The second benefit is joining notion investigation and point demonstrating strategies. While different investigations have utilised the two strategies independently without an association between them in TTSA examination, this exploration gives a flexible structure that can possibly install different systems (i.e. using profound learning for estimation examination and LDA). Another benefit is concentrating on unpalatable or negative encounters rather than all encounters. The third favourable position is presenting new issues (i.e. the intensity of netizens) that were not considered in different examinations and confirmed by official reports (Kitchin, 2014). The following has a powerful point of view in investigating the political race issues during a time span. Notwithstanding, online life clients produce a gigantic measure of information that should be abridged to give a major picture in a political circumstance.

An individuals' sentiment overview is a customary system to examine general feeling; be that as it may, this costly technique ought to be actualised after the celebration of a political decision. What's more, a low number of individuals take an interest in the information assortment, and information investigation steps take a lot of time (Urcan, 2012).

The development of online networking has given an extraordinary chance to follow popular supposition. Enormous continuous online networking information can help the head of gatherings to build up a superior TTSA during a political race. This examination proposes an expository system to recognise and follow the process of driving open worries about informal communities. For example, Twitter gives a superior open connection in a political race in Thailand. TTSA consolidates slant investigation and subject demonstration to deal with a grasped number of tweets and to unveil positive and negative open concerns.

This exploration affirmation (that internet-based life is acknowledged information) aims to find individuals' worries during a political decision in Thailand. The TTSA can help gatherings' supervisory groups to find open interests in the quickest manner to build up a superior constant regarding a well-known vote and executive plan. The proposed system can be utilised during political race season as well as after a political race as post-occasion strategy and audit capability for future mainstream voting opportunities. This exploration has applications for policymakers and well-known vote chance administration specialists in building up a superior methodology for examining online networking substance and reacting to it. It additionally helps social scientific inquiry about creating a Public Service Announcement (PSA) and divulging popular sentiments (US Department of Commerce, 2015).

Our future headings focus on limiting the effect of crusades, data missing and investigating positive and negative tweets. A potential impediment of our methodology is that the TTSA glossy web application instrument doesn't typically recognise feelings, incorrect spellings, sayings, remote words, mockery, and shortened forms. Another restriction is identified with the tweets containing incorrectly or off base data and spams (Najafabadi, 2017). LDA identifies significant points (few out of every odd single theme) in a corpus. In this manner, we expected a gigantic number of tweets in the Thai language. While we accept that the Thai language doesn't have a significant influence on the outcomes, we will use a few strategies to deal with decreased potential impacts of the Thai language. The first approach is evacuating retweets and tweets containing URLs to keep away from spams. The subsequent methodology distinguishes disconnected or off base subjects and afterward takes out the tweets whose essential points are among the immaterial or off base themes. The essential subject is the point that has the most elevated likelihood to be tweeted about. The following methodology involves utilising bot location apparatuses. For example, Botometer (Ferrara et al., 2016) is used to evacuate social bots spreading missing data. We accept that the likely arrangement will deliver these impediments to give more excellent information and new bits of knowledge to improve the TTSA.

Conclusion

Twitter tools reveal different opinions on a number of issues and topics. They provide keen insight into topics. This may be the best space for analysis and for making decisions in different areas. This paper shows that the TTSA shiny web application framework performs very well regarding the arrangement of the feelings of client tweets with high precision. It executed fluffy capacities to imitate the impact of different etymological fences. For example, dilators, concentrators, and invalidation of obstinate expressions help the framework to accomplish more precision in conclusion arrangement and the rundown of clients' remarks in different angles and different zones. Conclusion mining or estimation examination is a significant job in content mining applications. It involves to breaking down pearls of information from a huge volume of individual input and about remarks or tweets of any article, political decision or vote. A great deal of work has been examined and directed to remove assumptions. For example, records, sentences, and angles highlight level supposition investigation. The information sources from social sites, microblogs, news stories, and gatherings are for the most part utilised in supposition examination daily. These information sources are utilised in communicating individuals' emotions or criticism about specific articles or themes.

This paper offered numerous assessments or sentiments in terms of mining strategies, levels, and sorts. These are applied by the creators and exactness is delivered. One principle challenge in Thailand's legislative issues is to fabricate innovation to recognise and outline a general slant within specific subjects. In this last venture, we basically considered the opinion investigation with various AI strategies and contrasted the precision of every technique and tweeted information. We physically planted a few words with this theme as positive or negative seeds. Afterward, we utilised a course of action to portray the Twitter information. Along these lines, all parties in Thailand can quickly get results and create campaigns, policies, and strategies of value using our TTSA shiny web application.

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