Hierarchical Agglomerative Clustering Algorithm Based Real-Time Event Detection from Online Social Media Network

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Abstract:-Event detection from online social networks based on the user behaviour has been a research area which has garnered immense attention in the recent years. Many works have been developed for event detection in multiple social media sources like Twitter, Facebook, YouTube, etc. The user updates including short texts, photos and videos can be utilized in detecting the events. However detecting the number of common events from the social media content requires efficient distinguishing as the size of the content and number of users is large, leading to large data. In this paper, a new approach is proposed named as Event WebClickviz that performs the dual functions of visualization and behavioural analysis based on which the events are detected. In this approach, the event detection problem is modelled as clustering problem. Named Entity recognition with Topical PageRank is employed for extracting the key terms in the texts while the temporal sequences of real values are estimated to build the event sequences. The features are extracted by applying the concept of sentiment analysis using term frequency–inverse document frequency (TF-IDF). Based on these features the content is clustered using Hierarchical Agglomerative clustering algorithm. Thus the event is detected with high efficiency and they are visualized better using the proposed model. The simulation results justify the performance of the proposed Event WebClickviz.

Key-Words: Event detection, visualization, Named Entity recognition, Topical PageRank, Hierarchical Agglomerative clustering, term frequency–inverse document frequency.

1 Introduction

Information sharing is a typical component over online social media today from which novel data investigation applications are possible. A prominent technique, known as sentiment analysis, analyses user opinions in order to extract the expressed emotion about products [1], [2], [3], benefits, or even political figures [4]. Marketing found an ideal platform since now organizations can investigate a vast volume of open data and distinguish patterns [5], compelling profiles [6], and specialists [7] or to give customized notices and records [8]. From another point of view, social researchers examine knowledge cascades [9], information propagation [9] or community dynamics [10]. In health care, researchers have been able to track and predict diseases like influenza [11]. From all the above applications, the assignment of event recognition emerges because of its multifaceted nature and social effect. Various event related data is shared through different social media sites like Flickr, Twitter, Tumblr, YouTube, and so forth. This huge user base makes these social media stages a portion of the biggest and quickest data sources [12]. Twitter and Facebook were utilized to spread data amid the counter government challenges in Egypt amid the Arab Spring [13], [14]. Data around an earthquake in Japan was tweeted inside 2 seconds of the quake contrasted with 20 minutes for an alarm to be issued. Social media is likewise generally utilized by open authorities for correspondence and effort to the group [15]. Broadly speaking event detection is the problem of automatically identifying significant incidents by analysing social media data. Such events can be a concert, an earthquake or a strike.

Most methodologies handle event location also to a clustering issue. Clustering can be performed on the printed highlights of users' messages (Topic Clustering) or on their spatio-transient characteristics (Spatio-Temporal clustering). A portion of the recognized bunches relate to genuine events while others are simply gatherings of comparable messages. The distinguishing proof of the event bunches is regularly handled with scoring capacities or machine learning classifiers [16]. Some methodologies use novelty tests [17] while others concentrate on sentiment peaks [18] and keyword bursts [19]. A typical component in numerous techniques is a change identification part important to distinguish that 'something occurred strange'. Change is identified through measurable examination of the messages' substance or the system's structure. The real purpose of research is that the stream of data is gone before by the data significance, interest and importance to it. The characteristics of this data provide us an

opportunity to develop a model to automatically detect the abnormal/important events. The proposed model named as Event WebClickviz is based on the previously developed WebClickviz model [20] for user behaviour analysis based on their clickstream data. In this paper, the Event WebClickviz aims at utilizing the clickstream and message data from the social media and utilizes them to detect the events automatically. The remainder of the article is organized as: Section 2 discusses some the most related research works. The proposed methodologies are discussed in Section 3. Section 4 focuses on the Event WebClickviz performance analysis results. Finally, Section 5 makes a conclusion about the proposed model while also suggesting future directions of research.

2 Related Works

For detecting new event occurrences, previous researches usually try to find the abnormality in the collected a data. The collected data may be text, image or any multimedia data, which is made feasible by the developments of wireless multimedia sensor networks [21]. The abnormalities in such data are different going from the unpredictable thickness of significant archives, the tedious utilization of specific keywords, to the adjustments in day by day schedules of data et cetera. As the event discovery is considered as a clustering problem, various calculations have been created for that reason.

He et al [22] utilize a Discrete Fourier Transformation (DFT) technique to discover crests in the frequency space of the catchphrase motions after these were gathered in five element sorts as indicated by the power range quality length and the periodicity. Weng and Lee [23] expand the strategy by utilizing a wavelet change, the creators infer that the transient data of the signs is lost if DFT is utilized despite the fact that it is a critical property. Events are separated from data sources by clustering keywords utilizing modularity-based graph partitioning with respect to the wavelet transformation. Both methodologies investigate the evidence of events as indicated by the unusual instability of the frequency of the keywords; however they have not considered the mix of these keywords in tweets to express the event features. Li et al [24] acquaint an approach with build a framework for extricating events by examining tweets, which are followed from Twitter by utilizing a specific sort of channel. Authors center to distinguish Crime and Disaster related events by group tweets with Social features, for example, Twitter-Specific features and the point's features, yet just substance based features are considered.

Ciglan et al [25] proposed Wikipop, a personalized event detection system based on Wikipedia page view statistics. The Wikipop system presents to the user a set of Wikipedia articles that are popular based on his/her interest. The popularity of an article is based on the increase in page views of the article. The assumption behind their approach is events covered in public sources trigger an increase in the number of visits of corresponding Wikipedia articles. Ahn et al [26] also uses Wikipedia page views to detect events. A set of articles whose daily page views for a fifteen day period substantially increases over the previous fifteen day period are identified. These articles are clustered using k-means and topic modelling to group similar articles together. Each detected cluster corresponds to an event. Based on these methods in literature, the limitations are notified. The limitations of these methods urge the researchers in developing more efficient technique. The proposed Event WebClickviz model is such an attempt.

3 Data Presentation & Event Detection Process

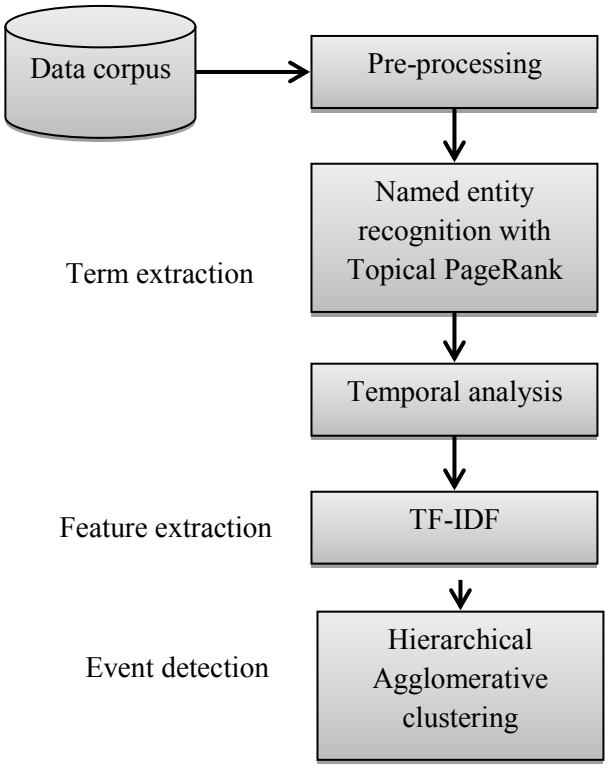

Figure.1. Proposed model Procedure

Figure 1 shows the overall procedure of the proposed model. The textual data from the social media is collected and it is pre-processed followed by the transformation into suitable format. In most cases,

these dataset is transformed into discrete signals for better analysing. Given a temporal corpus of news or messages that are generated by users on a Social network system (SNS), the messages can be distributed in a range of time. The messages are counted with a fixed time rate. The texts, either tweets or messages posted in social media, is represented as

$$txt = x, U_n, v, t \quad (1)$$

Where x is one of the set of users (U_n) who posted messages with v terms in SNS at time t.

The social reactions are the reactions performed by the users on posting texts or while seeing the original texts from another user. Based on these texts, the social reactions to the text by the users is represented as

$$R(txt) = txt_i \quad (2)$$

Where txt_i is the smaller portion of the original text.

3.1 Named entity recognition with Topical Page Rank:

The keywords are extracted from the dataset using the Named entity recognition with topical PageRank method. Named-entity recognition is a subtask of data extraction that seeks to discover and categorize named entities in text into pre-defined categories such as the names of persons, organizations, locations, expressions of times, quantities, monetary values, percentages, etc. The model is based on the following assumptions. There is a set of topics in dataset, each represented by a word distribution. Each user has topic interests modelled by a distribution over the topics. When a user wants to write a text, they first choose a topic based on their topic distribution. Then chooses a bag of words one by one based on the chosen topic. However, not all words in a text are closely related to the topic of that text; some are background words commonly used in texts on different topics. Therefore, for each word in a text, the user first decides whether it is a background word or a topic word and then chooses the word from its respective word distribution. Topical PageRank was introduced by Liu et al [27] to identify keywords for future key phrase extraction. It runs topic-biased PageRank for each topic separately and boosts those words with high relevance to the corresponding topic. It is defined as

$$R_t(w_i) = \lambda \sum_{j:w_j \to w_i} \frac{e(w_j, w_i)}{O(w_j)} R_t(w_j) + (1-\lambda) P_t(w_i) \quad (3)$$

Here $R_t(w)$ is the topic specific PageRank score of word w in topic t, $e(w_j, w_i)$ is the weight for edge $(w_j \to w_i)$, $O(w_j)$ is the summation of weight and λ is the damping factor ($\lambda = 0\ to\ 1$). $P_t(w_i)$ is the topic specific preference value of each word. Based on this method, the keywords are extracted from the given dataset with better efficiency. A sliding window T_k is fixed to collect the data of a specific period from the total stream.

3.2 Term Frequency- Inverse Document Frequency (TF-IDF):

In order to determine the significance of the keywords in the dataset, the features such as occurrence based measurements are calculated. For this purpose the TF-IDF [28] is employed, which is a numerical statistic intended for determining the importance of a word in a text or document. Term Frequency $tf_{t,d}$ of term t in dataset d is defined as the number of times that t occurs in d. Similarly Inverse Document Frequency is the estimate of the rarity of a term in the whole data collection. If a term occurs in all the data samples of the collection, its IDF is zero. The tf-idf weight of a term is the product of its tf weight and its idf weight. The samples have temporal characteristic, so the documents are ordered sequences in terms of time. Hence, the score for a given keyword that is computed on the sequence is a variation of its importance indexed by the sample positions. In addition to measuring the score based on tf-idf, occurrence feature of each of the Keywords and diffusion speed of original messages between users is required as well for the analysis.

The keyword score ($S_w(k,i)$) is estimated as the frequency of occurrence of that word in the text based on the context features. The major features are occurrence score and diffusion degree. The occurrence score $S_{w,occurence}(k,i)$ s given by

$$S_{w,occurence}(k,i) = \frac{|B_i^w|}{|B_i|+1} \times log \frac{|U_{B_j} B_j|}{\left|U_{B_j^w} B_j^w\right|+1} \quad (4)$$

Here B_i^w and B_i are the subset of the micro-texts with term word w and all texts that are in the dataset respectively. Based on the occurrence score the frequency of occurrence can be estimated. The Diffusion degree $S_{w,D.Degree}(k,i)$ is estimated as

$$S_{w,D.Degree}(k,i) = \frac{|U_{B_i} R_i(txt_w)|}{|U.R(txt)|+1} \quad (5)$$

Where $R_i(txt_w)$ is the set of user reactions in the collected sample while $R(txt)$ is the set of user

reactions in the whole corpus. Thus the features are estimated based on which the keyword score is computed. These features are also helpful in the clustering process for event detection.

3.3Hierarchical Agglomerative Clustering

For this phase, hierarchical agglomerative clustering on a semantic network of texts that is obtained in order to determine the potential clusters. The clusters include adjacent points which are close in terms of time and frequency. Each cluster is a potential candidate depending on the existence condition. Hierarchical agglomerative clustering is the bottom-up approach of the hierarchical clustering. The main motivation behind the proposed algorithm is discovering a structure in text. The event is characterized as the abnormal texts which are different from the normal texts.

The algorithm successively grows "coherent" segments by appending lexically related paragraphs, or by merging larger segments. The result is hierarchical structure, called dendrogram, where text segments correspond to its sub-trees. The dendrogram represents the internal hierarchy of the text discourse, similar to an intention structure. Using sentences as the elementary segments for the algorithm makes sense for a number of reasons. The paragraph is a universal linguistic structure, representing a coherent textual segment. Allowing a boundary in the middle of the sentence is thus counter to the author's intention. In addition, the size of a paragraph, unlike a sentence, contains sufficient lexical information for the proximity test. The proximity test selects the closest pair of segments, based on which the events can be determined. The test is based on repetition of words, a well-recognized indicator for lexical cohesion. The test computes the cosine between the representative term vectors of the segments.

$$Proximity\ (w_i, w_i + 1) = \sum_{k=1}^{n} \frac{e(w_{k,i}).e(w_{k,i}+1)}{\|w_i\|\|w_i+1\|} \quad (6)$$

Where $e(w_{k,i})$ is the weight of word $w_{k,i}$ while $\|w_i\|$ is the vector length. Then the boundary is determined for the coherent text for identifying the abnormal occurrence of the texts. Thus the events are identified.

3.4 Algorithm: Event WebClickviz

Initialize dataset d
Extract txt
Estimate $R(txt)$
Extract key words
Estimate tf
Estimate idf
Multiply tf & idf
Compute $S_w(k, i)$
Partition the keywords to elementary segments
While more than one segment left do
Apply a proximity test to find similar segments $w_i, w_i + 1$
Merge $w_i, w_i + 1$ into one segment
End while
For each node i
Set boundary between two segments
End for
Each segment = event
End

4 Event Webclickviz Performance Analysis

In the experiments, a social media dataset from the FACEBOOK website is employed as the experimental data. There were 5999 records in the raw file from a period of August 2017 to September 2017. After data cleaning, there were 3222 records left from 243 user sessions. There were 8 different kinds of activities during the user sessions in these data. As the primary work of WebClickviz is to visualize the data, the process begins from clickstream data visualization, followed by event detection. The performance of the Event WebClickviz is compared with that of the WebClickviz, Pattern WebClickviz and Social pattern-WebClickviz, to estimate its efficiency.

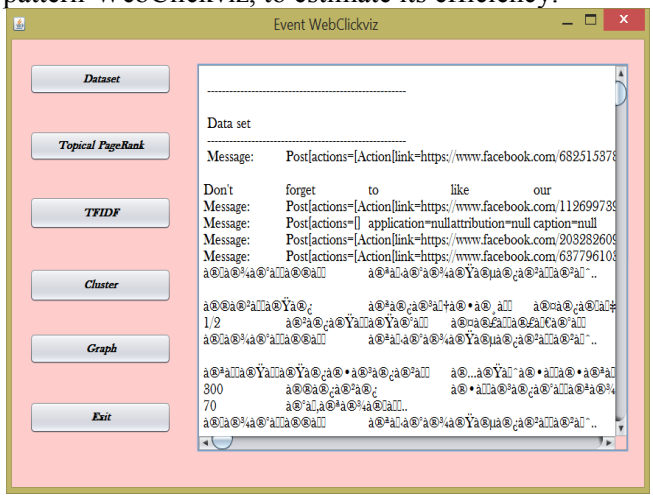

Figure.2. Dataset representation

Figure 2 shows the loading process of the data into the proposed model. The data are represented as texts initiated in the Eq. 1. Figure 3 shows the text extraction results using the Named entity recognition with topical PageRank method. It can be seen that the proposed approach effectively extracts the text from the given dataset.

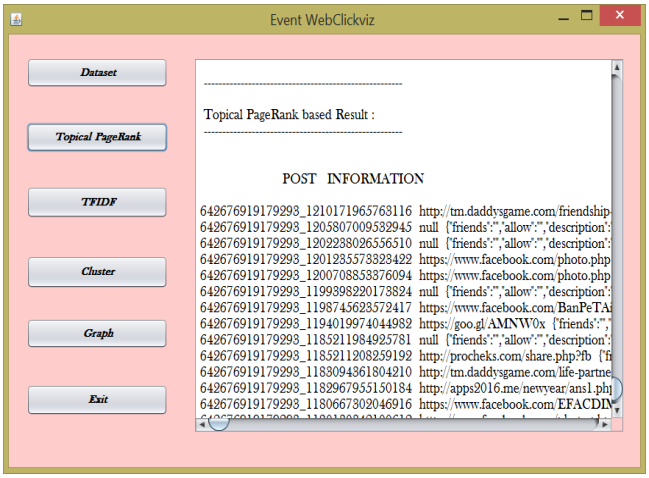

Figure.3. Text extraction

Figure 4 shows the feature extraction process carried out using TF-IDF method. This method is much efficient for the social media data because of its ability extract the features based on the statistical scores.

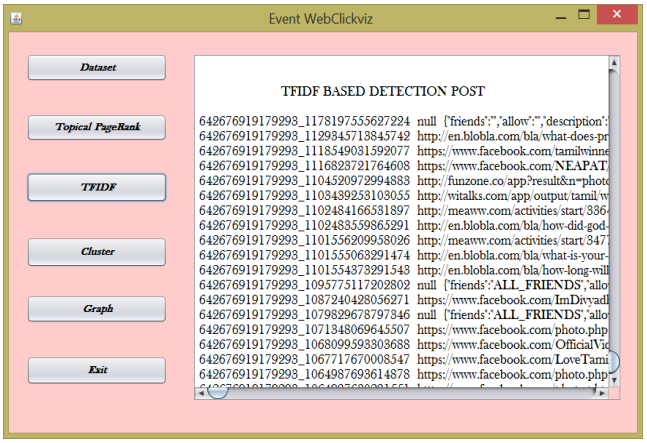

Figure.4. TF-IDF based feature detection

Figure 5 shows the clustering results. It can be seen that the proposed approach has segmented the messages and reactions and utilized them to predict the possible event occurred based on the estimated coherent features.

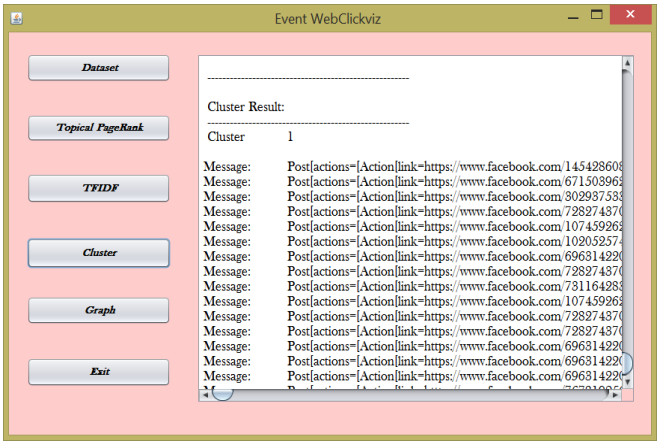

Figure.5. Clustering results

Based on the above clustering results, the events are identified. The refined list of events identified by the proposed model is shown in Figure.6. It can be evident that for the refined form shows fewer actions happened at that time period which means that this event has the highest probability of occurrence.

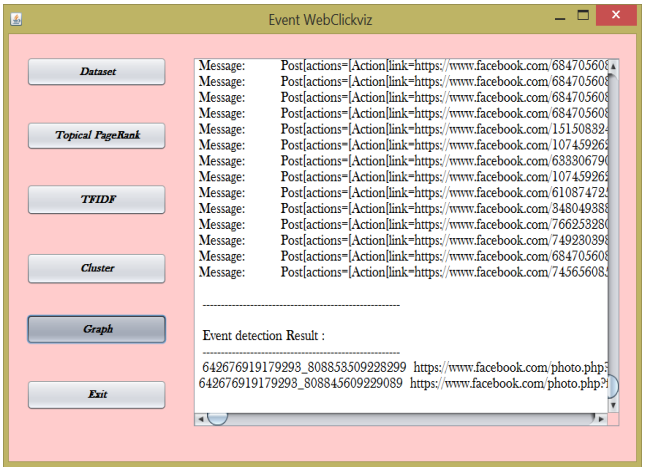

Figure.6. Refined event detection Performance comparison

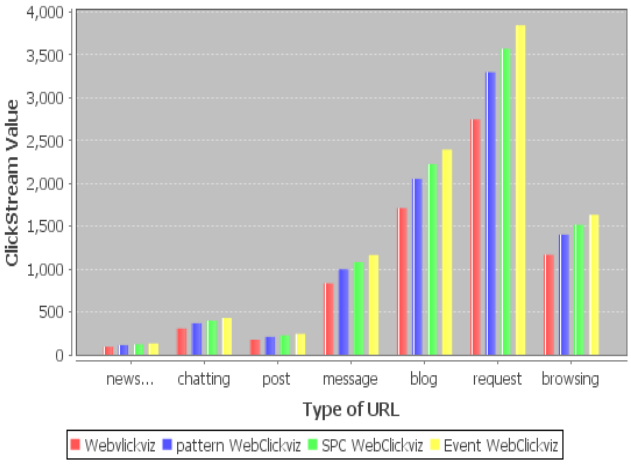

Figure.7. Clickstream value

Figure 7 shows the clickstream value comparison of the proposed Event WebClickviz with the other WebClickviz based models. It is see that the proposed model improves the detection process by identifying the larger actions in the same dataset.

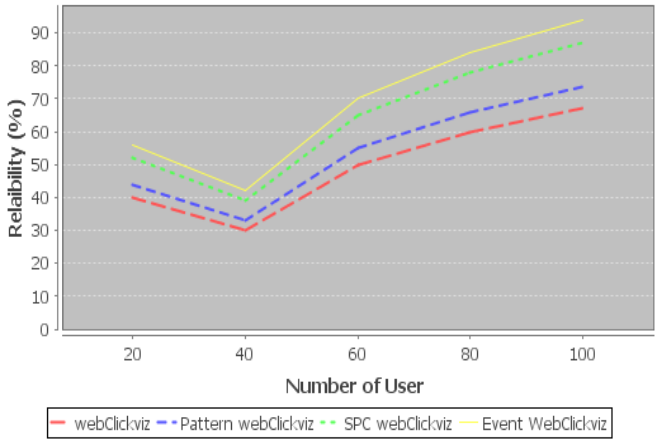

Figure.8. Reliability

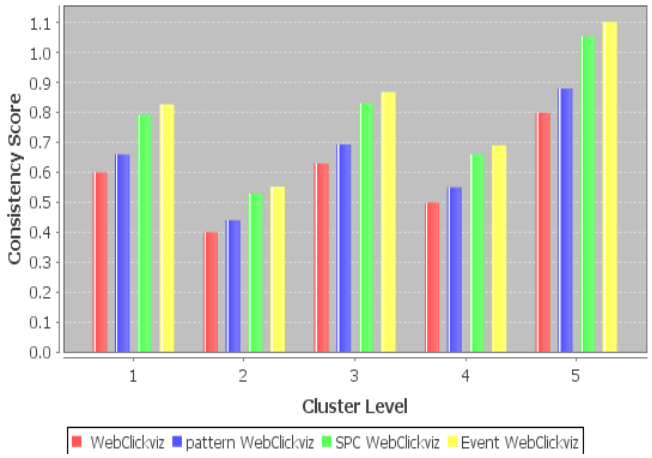

Figure.9. Consistency score

Similar to clickstream value, the reliability and consistency score comparisons are shown in Figure 8 and 9 respectively. It is found that the proposed Event WebClickviz has better values in both the cases, thus justifying its performance efficiency.

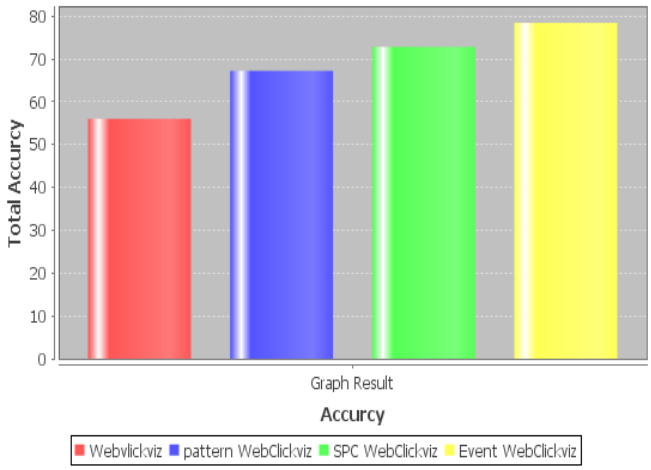

Figure.10. a) Accuracy

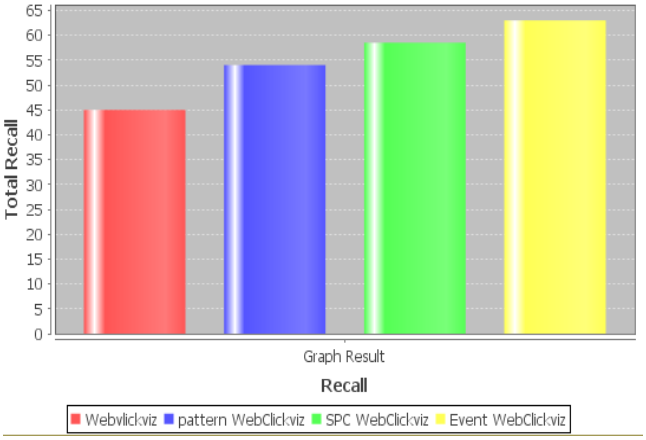

Figure.10. b) Recall

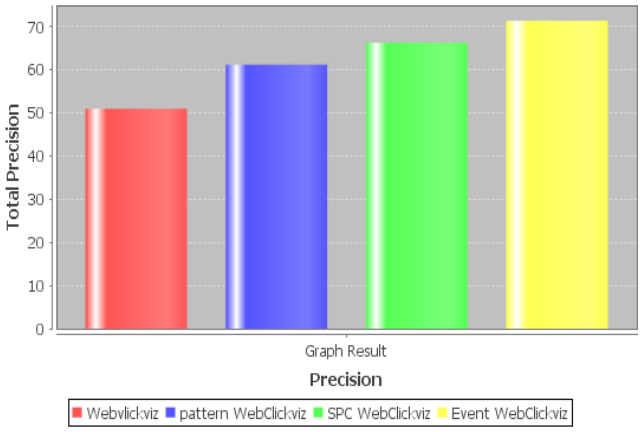

Figure.10. c) Precision

Figure 10 shows the a) accuracy, b) recall and c) Precision comparison of the Event WebClickviz with the other WebClickviz based models. As in the other performance metrics, Event WebClickviz outperforms the other models with higher values of accuracy, recall and precision. This is due to the novel process of the proposed approach in extracting the texts and features from the data corpus.

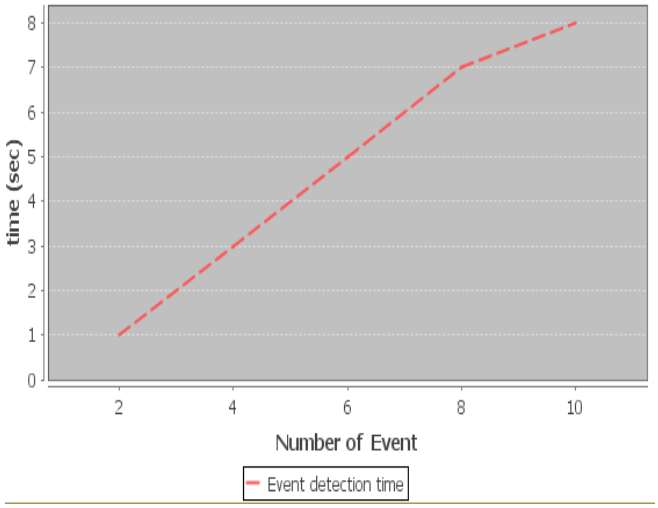

Figure.11. Event detection time

Figure 11 shows the event detection time of the Event WebClickviz model. It is evident that the proposed model has less time for detecting the events which is in seconds. Thus the proposed approach is not only accurate but it is also very faster in performance.

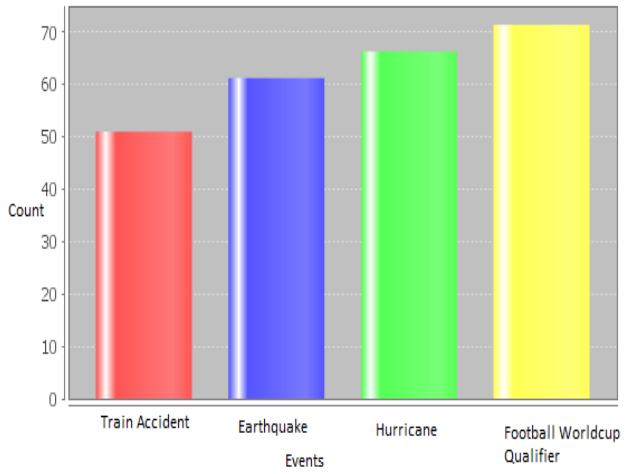

Figure.12. Major Event detection

During the specified duration of analysis, the major event which has higher count value is shown in Figure 12. It can be seen that from the data collected the event of football match has higher count in that particular period from August 2017 to September 2017. The main reason behind this result is that maximum number of users who posted messages during that period was fond of football matches. Thus similar to this, the behaviour of mass crowd cab also be analysed with this approach.

4. Conclusion

In this paper, an approach for detecting events from social media is presented. The proposed model which was developed on the basis of WebClickviz was named as Event WebClickviz efficiently detects the events with higher accuracy. The experiments conducted on Facebook dataset justify the claim. It is worth noting that this model has been developed not only for Facebook but suitable for text based social media like Twitter. It is also possible to utilize descriptions from images used in multimedia social networks for event detection. In the future, multiple source data will be combined to test the diverse performance of the vent detection model. Similarly instead of collecting data from social networks and utilizing it is planned to extend for collaborative collection of data and proceesing in parallel systems.

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