Abstract—Event detection using social media streams needs a set of informative features with strong signals that need minimal preprocessing and are highly associated with events of interest. Identifying these informative features as keywords from Twitter is challenging, as people use informal language to express their thoughts and feelings. This informality includes acronyms, misspelled words, synonyms, transliteration and ambiguous terms. In this paper, we propose an efficient method to select the keywords frequently used in Twitter that are mostly associated with events of interest such as protests. The volume of these keywords is tracked in real time to identify the events of interest in a binary classification scheme. We use keywords within word-pairs to capture the context. The proposed method is to binarize vectors of daily counts for each word-pair by applying a spike detection temporal filter, then use the Jaccard metric to measure the similarity of the binary vector for each word-pair with the binary vector describing event occurrence. The top \( n \) word-pairs are used as features to classify any day to be an event or non-event day. The selected features are tested using multiple classifiers such as Naive Bayes, SVM, Logistic Regression, KNN and decision trees. They all produced AUC ROC scores up to 0.91 and F1 scores up to 0.79. The experiment is performed using the English language in multiple cities such as Melbourne, Sydney and Brisbane as well as the Indonesian language in Jakarta. The two experiments, comprising different languages and locations, yielded similar results.

Index Terms—Social Networks, Event Detection, Civil Unrest, Spike Matching, Feature Selection, keyword selection, Twitter

I. INTRODUCTION

Event detection is important for emergency services to react rapidly and minimize damage. For example, terrorist attacks, protests, or bushfires may require the presence of ambulances, firefighters, and police as soon as possible to save people. This research aims to detect events as soon as they occur and are reported via some Twitter user. The event detection process requires to know the keywords associated with each event and to assess the minimal count of each word to decide confidently that an event has occurred. In this research, we propose a novel method of spike matching to identify keywords, and use probabilistic classification to assess the probability of having an event given the volume of each word.

Event detection and prediction from social networks have been studied frequently in recent years. Most of the predictive frameworks use textual content such as likes, shares, and retweets, as features. The text is used as features either by tracking the temporal patterns of keywords, clustering words into topics, or by evaluating sentiment scores and polarity. The main challenge in keyword-based models is to determine which words to use in the first place, especially as people use words in a non-standard way, particularly on Twitter.

In this research, we aim for detecting large events as soon as they happen with near-live sensitivity. For example, When spontaneous protests occur just after recent news such as increasing taxes or decreasing budget, we need to have indicators to raise the flag of a happening protest. Identifying these indicators requires to select a set of words that are mostly associated with the events of interest such as protests. We then track the volume of these words and evaluate the probability of an event occurring given the current volume of each of the tracked features. The main challenge is to find this set of features that allow such probabilistic classification.

Using text as features in Twitter is challenging because of the informal nature of the tweets, the limited length of the tweet, platform-specific language, and multilingual nature of Twitter [14], [23], [29]. The main challenges for text analysis in Twitter are listed below:

1) The usage of misspelled words, acronyms, an non-standard abbreviations make words and expression not understandable.

2) The transliteration of non-Latin languages such as Arabic using the Latin script distorts the feature signal where words with similar spelling have different meaning in different languages (e.g. the term “boss” in English means “manager”, while in Arabic it means...
“look”).
3) The limited length of the tweets makes sentiment analysis and topic modelling pretty challenging.
4) Semantic ambiguity: a single word can refer to many meanings (e.g. “strike” may refer to a lighting strike or a protest or a football strike)

We approached the first and second challenges by using a Bayesian approach to learn which terms were associated with events, regardless of whether they are standard language, acronyms, or even a made-up word, so long as they match the events of interest. The third and fourth challenges are approached by using word-pairs, where we extract all the pairs of co-occurring words within each tweet. This allows us to recognize the context of the word (‘Messi’, ‘strike’) is different than (‘labour’, ‘strike’).

According to the distributional semantic hypothesis, event-related words are likely to be used on the day of an event more frequently than any normal day before or after the event. This will form a spike in the keyword count magnitude along the timeline as illustrated in Figure 2. To find the words most associated with events, we search for the words that achieve the highest number of spikes matching the days of events. We use the Jaccard similarity metric as it values the spikes matching events and penalizes spikes with no event and penalizes events without spikes. Separate words can be noisy due to the misuse of the term by people, especially in big data environments. So, we rather used the word-pairs as textual features in order to capture the context of the word. For example, this can differentiate between the multiple usages of the word “strike” within the contexts of “lightning strike”, “football strike” and “labour strike”.

In this paper, we propose a method to find the best word-pairs to represent the events of interest. These word-pairs can be used for time series analysis to predict future events as indicated in Figure 1. They can also be used as seeds for topic modelling, or to find related posts and word-pairs using dynamic query expansion. The proposed framework uses a temporal filter to identify the spikes within the word-pair signal to binarize the word-pair time series vector. The binary vector of the word-pair is compared to the protest days vector using Jaccard similarity index, where the word-pairs with highest similarity scores are the most associated word-pairs with protest days. This feature selection method is built upon the assumption that people discuss an event on the day of that event more than on any day before or after the event. This implies that word-pairs related to the event will form a spike on this specific day. Some of the spiking word-pairs are related to the nature of the event itself, such as “taxi protest” or “fair education”. These word-pairs will appear once or twice along the time frame. Meanwhile, more generic word-pairs such as “human rights” or “labour strike” will spike more frequently in the days of events regardless the protest nature.

To test our method, we developed two experiments using all the tweets in Melbourne and Sydney over a period of 640 days. The total number of tweets exceeded 4 million tweets per day, with a total word-pair count of 12 million different word-pairs per day, forming 6 billion word-pairs over the entire timeframe. The selected word-pairs from in each city are used as features to classify if there will be an event or not on a specific day in that city. We classified events from the extracted word-pairs using 9 classifiers including Naive Bayes, Decision Trees, KNN, SVM, and logistic regression.

In Section 2, we describe the event detection methods. Section 3 states the known statistical methods used for data association and feature selection. Section 4 describes the proposed feature selection method. Section 5 describes model training and prediction. Section 6 describes the experiment design, the data and the results. Section 7 summarizes the paper, discuss the research conclusion and explains future work.

II. EVENT DETECTION METHODS

Analyzing social networks for event detection is approached from multiple perspectives depending on the research objective. This can be predicting election results, a contest winner, or predicting peoples’ reaction to a government decision through protest. The main perspectives to analyze the social networks are (1) content analysis, where the textual content of each post is analyzed using natural language processing to identify the topic or the sentiment of the authors. (2) Network structure analysis, where the relation between the users are described in a tree structure for the follower-followee patterns, or in a graph structure for friendship and interaction patterns.

These patterns can be used to know the political preference of people prior to elections. (3) Behavioural analysis of each user including sentiment, response, likes, retweets, location, to identify responses toward specific events. This might be useful to identify users with terrorist intentions.

In this section, we will focus on textual content-based models, where text analysis and understanding can be achieved using keywords, topic modelling or sentiment analysis.
A. Keyword-based approaches

Keyword-based approaches focus on sequence analysis of the time series for each keyword. They also consider different forms for each keyword, including n-gram, skip-gram, and word-pairs [11]. The keyword-based approaches use the concept of the distributional semantics to group semantically-related words as synonyms to be used as a single feature [19]. In this approach, keywords are usually associated with events by correlation, entropy or distance metrics. Also, Hossny et al. proposed using SVD with K-Means to strengthen keyword signals, by grouping words having similar temporal patterns, then mapping them into one central word that has minimum distance to the other members of the cluster [17].

Sayyadi et al. used co-occurring keywords in documents such as news articles to build a network of keywords. This network is used as a graph to feed a community detection algorithm in order to identify and classify events [24]. Takeshi et al. created a probabilistic spatio-temporal model to identify natural disasters events such as earthquakes and typhoons using multiple tweet-based features such as words counts per tweet, event-related keywords, and tweet context. They considered each Twitter user as a social sensor and applied both of the Kalman filter and particle filter for location estimation. This model could detect 96% of Japanese earthquakes [32]. Zhou et al. developed a named entity recognition model to find location names within tweets and use them as keyword-features for event detection, then estimated the impact of the detected events qualitatively [43].

Weng et al. introduced “Event Detection by Clustering of Wavelet-based Signals” (EDCow). This model used wavelets to analyze the frequency of word signals, then calculated the autocorrelations of each word signal in order to filter outlier words. The remaining words were clustered using a modularity-based graph partitioning technique to form events [40]. Ning et al. proposed a model to identify evidence-based precursors and forecasts of future events. They used as a set of news articles to develop a nested multiple instance learning model to predict events across multiple countries. This model can identify the news articles that can be used as precursors for a protest [26].

B. Topic modelling approaches

Topic modelling approaches focus on clustering related words according to their meaning, and indexing them using some similarity metric such as cosine similarity or Euclidean distance. The most recognized techniques are (1) Latent Semantic Indexing (LSI), where the observation matrix is decomposed using singular value decomposition and the data are clustered using K-Means [19]. (2) Latent Dirichlet Allocation (LDA), where the words are clustered using Gaussian mixture models (GMM) according to the likelihood of term co-occurrence within the same context [33]. (3) Word2Vec, which uses a very large corpus to compute continuous vector representations, where we can apply standard vector operations to map one vector to another [24].

Cheng et al. suggested using space-time scan statistics to detect events by looking for clusters within data across both time and space, regardless of the content of each individual tweet [7]. The clusters emerging during spatio-temporal relevant events are used as an indicator of a currently occurring event, as people tweet more often about event topics and news. Ritter et al. proposed a framework that uses the calendar date, cause and event type to describe any event in a way similar to the way Twitter users mention the important events. This framework used temporal resolution, POS tagging, an event tagger, and named entity recognition. Once features are extracted, the association between the combination of features and the events is measured in order to know what are the most important features and how significant the event will be [31].

Zhou et al. introduced a graphical model to capture the information in the social data including time, content, and location, giving location-time constrained topic (LTT). They measure the similarity between the tweets using KL divergence to assess media content uncertainty. Then, they measure the similarity between users using a “longest common subsequence” (LCS) metric. They aggregate the two measurements by augmenting weights as a measure for message similarity. They used the similarity between streaming posts in a social network to detect social events [42].

Ifrim et al. presented another approach for topic detection that combines aggressive pre-processing of data with hierarchical clustering of tweets. The framework analyzes different factors affecting the quality of topic modelling results [18], along with real-time data streams of live tweets to produce topic streams in close to real-time rate.

Xing et al. presented the mutually generative Latent Dirichlet Allocation model (MGE-LDA) that uses hashtags and topics, as they both are generated mutually by each other in tweets. This process models the relationship between topics and hashtags in tweets, and uses them both as features for event discovery [41]. Azzam et al. used deep learning and cosine similarity to understand short text posts in communities of question answering [3]. Also, Hossny et al. used inductive logic programming to understand short sentences from news for translation purposes [16].

C. Sentiment analysis approaches

The third approach is to identify sentiment through the context of the post, which is another application for distributional semantics requiring a huge amount of training data to build the required understanding of the context. Sentiment analysis approaches focus on recognizing the feelings of the crowd and use the score of each feeling as a feature to calculate the probability of social events occurring. The sentiment can represent the emotion, attitude, or opinion of the user towards the subject of the post. One approach to identify sentiment is to find smiley faces such as emoticons and emojis within a tweet or a post. Another approach is to use a sentiment labelled dictionary such as SentiWordNet to assess the sentiment associated with each word.
Generally, sentiment analysis has not been used solely to predict civil unrest, especially as it still faces the challenges of sarcasm and understanding negation in ill-formed sentences. Meanwhile, it is used as an extra feature in combination with features from other approaches such as keywords and topic modelling. Paul et al. proposed a framework to predict the results of the presidential election in the United States in 2017. The proposed framework applied topic modelling to identify related topics in news, then used the topics as seeds for Word2Vec and LSTM to generate a set of enriched keywords. The generated keywords will be used to classify politics-related tweets, which are used to evaluate the sentiment towards each candidate. The sentiment score trend is used to predict the winning candidate [28].

III. Feature Selection Methods

Keywords can be selected as features as a single term or a word-pair or a skip-grams, which can be used for classification using multiple methods such as mutual information, TF-IDF, \( \chi^2 \), or traditional statistical methods such as ANOVA or correlation. Our problem faces two challenges: the first is the huge number of word-pairs extracted from all tweets for the whole time frame concurrently, which make some techniques such as TF-IDF and \( \chi^2 \) computationally unfeasible as they require the technique to be distributable on parallel processors on a cluster. The second challenge is the temporal nature of the data which require some techniques that can capture the distributional semantics of terms along with the ground truth vector. In this section, we describe briefly a set of data association methods used to find the best word-pairs to identify the event days.

Pearson correlation measures the linear dependency of the response variable on the independent variable with the maximum dependency of 1 and no dependency of zero. This technique needs to satisfy multiple assumptions to assess the dependency properly. These assumptions require the signals of the variables to be normally distributed, homoskedastic, stationary and have no outliers [6], [15]. In social network and human-authored tweets, we cannot guarantee that the word-pairs signals throughout the timeframe will satisfy the required assumptions. Another drawback for Pearson correlation is that zero score does not necessarily imply no correlation, while no correlation implies zero score.

Spearman is a rank-based metric that evaluates the linear association between the rank variables for each of the independent and the response variables. It simply evaluates the linear correlation between the ranked variables of the original variables. Spearman correlation assumes the monotonicity of the variables but it relaxes the Pearson correlation requirements of the signal to be normal, homoskedastic and stationary. Although the text signals in the social network posts do not satisfy the monotonicity assumption, Spearman correlation can select some word-pairs to be used as predictive features for classification. Spearman correlation has the same drawback of Pearson correlation that zero score does not necessarily imply no correlation while no correlation implies zero score.

Distance correlation is introduced by Szekely et al. (2007) to measure the nonlinear association between two variables [56]. Distance correlation measures the statistical distance between probability distributions by dividing the Brownian covariance (distance covariance) between X and Y by the product of the distance standard deviations [37], [2].

TF-IDF is the short of term frequency-inverse document frequency technique that is used for word selection for classification problems. The concept of this technique is to give the words that occur frequently within a specific class high weight as a feature and to penalize the words that occur frequently among multiple classes. For example, the term “Shakespeare” is considered a useful feature to classify English literature documents as it occurs frequently in English literature and rarely occurs in any other kind of documents. Meanwhile, the term “act” will occur frequently in English literature, but it also occurs frequently in the other types of document, so this term will be weighted for its frequent appearance and it will be penalized for its publicity among the classes by what we call inverse-document-frequency [30].

Mutual information is a metric for the amount of information one variable can tell the other one. MI evaluates how similar are the joint distributions of the two variables with the product of the marginal distributions of each individual variable, which makes MI more general than correlation as it is not limited by the real cardinal values, it can also be applied to binary, ordinal and nominal values [13]. As mutual information uses the similarity of the distribution, it is not concerned with pairing the individual observations of X and Y as much as it cares about the whole statistical distribution of X and Y. This makes MI very useful for clustering purposes rather than classification purposes [38].

Cosine similarity metric calculates the cosine of the angle between two vectors. The cosine metric evaluates the direction similarity of the vectors rather than the magnitude similarity. The cosine similarity score equals to 1 if the two vectors have the angle of zero between the directions of two vectors, and the score is set to zero when the two vectors are perpendicular [9]. If the two vectors are oriented to opposite directions, the similarity score is -1. Cosine similarity metric is usually used in the positive space, which makes the scores limited within the interval of [0, 1].

Jaccard index or coefficient is a metric to evaluate the similarity of two sets by comparing their members to identify the common elements versus the distinct ones. The main advantage of Jaccard similarity is it ignores the default value or the null assumption in the two vectors and it only considers the non-default correct matches compared to the mismatches. This consideration makes the metric immune to the data imbalance. Jaccard index is similar to cosine-similarity as it retains the sparsity property and it also allows the discrimination of the collinear vectors.

IV. SPIKE MATCHING METHOD:

The proposed model extracts the word-pairs having a high association with event days according to the distributional
semantic hypothesis and use them for training the model that will be used later for the binary classification task as illustrated in figure. The first step is the data preparation where we load all the tweets for each day, then we exclude the tweets having URLs or unrelated topics, then we clean each tweet by removing the hashtags, non-Latin script and stopping words. Then we lemmatize and stem each word in each tweet using Lancaster stemmer. Finally, we extract the word-pairs in each tweet. The word-pair is the list of n words co-occurring together within the same tweet.

The second step is to count the frequency of each word-pair per each day, which are used as features to classify the day as either event or no-event day. The formulation is a matrix with rows as word-pairs and columns as days and values are daily counts of each word-pair. The third step is to binarize the event count vector (ground truth) as well as the vector of each word-pair. Binarization of the event vector is done by checking if the count of events in each day is larger than zero. The binarization of the word-pair count vectors is done by applying a temporal filter to the time series in order to identify the spikes as explained in equation 1 where the days with spikes are set to ones and days without spike are set to zeros.

\[ f(x) = \begin{cases} 1, & \text{if } x(t)-x(t-1) < \text{threshold and } x(t)-x(t+1) > \text{threshold} \\ 0, & \text{Otherwise} \end{cases} \]

where \( x \) is the count of the word-pair, \( t \) is the time variable, \( dt \) is the time difference, the threshold is the minimum height of the spike. The binarization of the word-pair count vectors is done by applying a temporal filter to the time series in order to identify the spikes as explained in equation where the days with spikes are set to ones and days without spike are set to zeros.

\[ J(\text{word-pair}, \text{GT}) = \frac{WP \cap GT}{WP \cup GT} = \frac{\sum_i \min(WP_i, GT_i)}{\sum_i \max(WP_i, GT_i)} \]  

where WP is the word pair vector, GT is the ground truth vector.

V. TRAINING AND PREDICTION

Once we identify the best word-pairs to be used as features for classification, we split the time series vector of each word-pair into a training vector and a testing vector. Then we use the list of the training vectors of the selected word-pairs to train the model as explained in subsection A and use the list of testing vectors for the same word-pairs to classify any day to event/non-event day B.

A. Training the model:

The third step is to train the model using the set of features generated in the first step. We selected the Naive Bayes classifier to be our classification technique for the following reasons: (1) the high bias of the NB classifier reduces the possibility of over-fitting, and our problem has a high probability of over-fitting due to the high number of features and the low number of observations, (2) the response variable is binary, so we do not need to regress the variable real value as much as we need to know the event-class, and (3) The counts of the word-pairs as independent variables are limited between 0 and 100 occurrences per each day, which make the probabilistic approaches more effective than distance based approaches.

The training process aims to calculate three priori probabilities to be used later in calculating the posterior probabilities: (1) the probability of each word-pair count in a specific day given the status of the day as “event” or “non-event”. (2) the priori conditional probability of each word-pair given event status \( P(\text{word-pair} | \text{Event}) \). (3) The probability of each event class as well as the probability of each word-pair as stated in equations and 4.

\[ P(\text{Event}_c) = \frac{\text{Count(\text{Event}_c)}}{\sum_{c \in \{0,1\}} \text{Count(\text{Event}_c)}} \]  

\[ P(\text{WP}|\text{Event}_c) = \frac{P(\text{WP} \cap \text{Event}_c)}{P(\text{Event}_c)} \]  

where WP is the word-pair, \( \text{Event}_c \) is any class for event occurrence and word-pair is the vector of counts for the word-pairs extracted from tweets.

B. Predicting Civil Unrest

Once the priori probabilities are calculated using the training data, we use them to calculate the posterior probability of both
classes of event-days and non-event-days given the values of
the word-pairs using the equation
\[ P(Event|WP_1, WP_2, \ldots, WP_n) = \frac{P(WP_1,\ldots,WP_n) \cdot P(Event)}{P(WP_1,\ldots,WP_n)} \]
\[ = \frac{1}{Z} \prod_{i=1}^{n} P(WP_i|Event) \]  
where \( WP \) is the word-pair, \( Z = P(WP_1,\ldots) = P(WP_1) \cdot P(WP_2) \). As the word-pairs are assumed to be
independent and previously known from the training step.

VI. EXPERIMENTS AND RESULTS

The experiments are designed to detect civil unrest events in
Melbourne on any specific day. In this experiment, we used all
the tweets posted from Melbourne within a time frame of 640
days between December 2015 and September 2017. This time
frame will be split into 500 days for model training and 140
days for model testing on multiple folds. The tweet location is
specified using (1) longitude and latitude meta-tag, (2) tweet
location meta-tag, (3) the profile location meta-tag, and (4)
The time zone meta-tag. The total number of tweets exceeded
4 million tweets daily. Firstly, we cleaned the data from noisy
signals, performed stemming and lemmatization then extracted
the word-pairs from each tweet and count each word-pair per
each day. Example 1 illustrates how each tweet is cleaned,
prepared and vectorized before being used for training the
model. The steps are explained below:

- The data is first cleaned by eliminating the tweets of
  any language other than English, exclude the tweets
  having URLs, remove the hash-tags, non-Latin alphabets,
  punctuation, HTML Tags, and remove the stopping words
  listed by NLTK [21].
- Extract the word-pairs from each tweet by generating
  a list of every two co-occurring words. The number of
  word-pairs extracted from a tweet with size \( m \) equals
  \( m \ast (m - 1) \). Each tweet consists of average 12 words,
  which construct 132 word-pairs per tweet on average.
  The average count of daily different word-pairs exceeds
  10 million after excluding repeated word-pairs and the
  word-pairs with single appearance.
- The words in each word-pair are lemmatized using NLTK
  lemmatizer in order to avoid the morphological effects to
  the word shape (e.g. bought \( \rightarrow \) buy)
- The words in each word-pair are then stemmed by
  Lancaster stemmer in order to return related words to
  their dictionary roots (E.g., Turkish \( \rightarrow \) Turk)
- The word-pairs are then counted per day for all the tweets
  from Melbourne in order to construct the term frequency
  vectors.

As explained in example 1, each word-pair will be trans-
formed from a vector of integer values into a vector of binary
values and denoted as \( B\text{OW} \). \( B\text{OW} \) will be used to calculate
the Jaccard similarity index of the binary vector with the
events binary vector. Each word-pair will have a similarity
score according to the number of word-pair spikes matching
the event days. This method uses the concept of distributional
semantic, where the co-occurring signals are likely to be
semantically associated [22].

Example 1:

Original Tweet:
Protesters may be unmasked in wake of Coburg clash
https://t.co/djjVIfzO3e (News) #melbourne #victoria

Cleaned Tweet:
protest unmask wake coburg clash news

List of two-words-word-pairs: ['protest', 'unmask'],
['protest', 'wake'], ['protest', 'Coburg'],..., ['unmask',
'wake'], ['unmask', 'coburg']..., ['clash', 'news']

['protest', 'unmask'] training : \([x_{1,1}, x_{1,2}, x_{1,3}, \ldots, x_{1,641}]\)

['protest', 'unmask'] testing : \([x_{2,1}, x_{2,2}, \ldots, x_{1,641}]\)

Assuming a time frame of 20 days
word-pair: \([2,3,3,4,5,2,3,8,3,3,1,3,9,3,1,2,4,5,1]\)

Spikes \( B\text{OW} \): \([0,0,0,1,0,0,1,0,0,0,0,0,0,1,0,0,1,0,1,0,1,0,0,1,0]\)

Events \( GT \): \([0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,0,1,0,1,0,1,1,0,1,1,0,0,0,0]\)

\[ J(B\text{OW}, GT) = \frac{\sum_{i} \min(B\text{OW}_i, GT_i)}{\sum_{i} \max(B\text{OW}_i, GT_i)} = \frac{3}{5} \]

Once we selected the most informative word-pairs as fea-
tures, we will use the raw values to train the Naive Bayes
classifier. The classifier is trained using 500 days selected
randomly along the whole timeframe, then it is used to predict
the other 140 days. To ensure the robustness of our experiment,
We applied 10-folds cross-validation, where we performed the
same experiment 10 times using 10 different folds of randomly
selected training and testing data. The prediction achieved an
average area under the ROC curve of 90%, which statistically
significant and achieved F-score of 91%, which is immune
data imbalance as listed in table [I]. Figure 4 shows the
ROC curves for the results of a single fold of Naive Bayes
classification that uses the features extracted by each selection
methods. The classification results of the proposed method
outperformed the benchmarks and state of the art developed
by Cui et al. (2017), Nguyen et al. (2017), Willer et al. (2016),
and Adeyoyin-Olowe et al. (2016) as illustrated in the table
[IV] [40, 8, 39, 10, 11, 25].

The same experiment has been applied to Sydney, Brisbane
and Perth in Australia on a time frame of 640 days with
500 days training data and 140 days testing data and the
results were similar to Melbourne results with average AUC
of 0.91 and average F-Score of 0.79. To ensure that the
proposed method is language independent, we used the same
method to classify civil unrest days in Jakarta using the
Indonesian language, the classification scores were lower than
the average scores for English language by 0.05 taking into
consideration that we did not apply any NLP pre-processing
TABLE I: Event detection results for 10 randomized folds using the metrics of accuracy, precision, recall, F1, Area under ROC curve and area under PR curve

| method             | AUC ROC | F1s | AUPR | Precision | Recall | Accuracy |
|--------------------|---------|-----|------|-----------|--------|----------|
| Pearson correlation| 0.759   | 0.517 | 0.457 | 0.658     | 0.431 | 0.758    |
| distance correlation| 0.831   | 0.677 | 0.564 | 0.687     | 0.669 | 0.807    |
| Mutual_Information | 0.552   | 0.426 | 0.321 | 0.328     | 0.613 | 0.504    |
| Jaccard similarity | 0.894   | 0.794 | 0.676 | 0.727     | 0.788 | 0.862    |
| Cosine similarity  | 0.651   | 0.397 | 0.358 | 0.431     | 0.405 | 0.655    |
| Spike matching     | 0.913   | 0.793 | 0.689 | 0.770     | 0.821 | 0.875    |

TABLE II: A comparison of classification AUCs using word-pairs extracted by different feature selection methods

| method             | NB  | SVM | MLP | LDA | GPC | LR  | RF  | DT  | KNN  |
|--------------------|-----|-----|-----|-----|-----|-----|-----|-----|------|
| Pearson Correlation | 0.759 | 0.555 | 0.778 | 0.565 | 0.598 | 0.784 | 0.740 | 0.720 | 0.614 |
| Distance correlation| 0.831 | 0.589 | 0.874 | 0.713 | 0.667 | 0.673 | 0.866 | 0.814 | 0.637 |
| Mutual Information | 0.556 | 0.554 | 0.509 | 0.525 | 0.502 | 0.539 | 0.559 | 0.531 | 0.511 |
| Jaccard Similarity  | 0.894 | 0.659 | 0.951 | 0.795 | 0.598 | 0.955 | 0.934 | 0.921 | 0.691 |
| Cosine Similarity   | 0.651 | 0.561 | 0.591 | 0.527 | 0.497 | 0.670 | 0.528 | 0.600 | 0.523 |
| Spike Matching      | 0.913 | 0.517 | 0.963 | 0.759 | 0.891 | 0.966 | 0.965 | 0.929 | 0.657 |

![ROC curves for Naive Bayes classification using features extracted by different selection methods](image)

Fig. 4: ROC curves for Naive Bayes classification using features extracted by different selection methods

TABLE III: The average results of event detection in multiple cities using multiple metrics after cross validating the results on 10 folds

| City     | Accuracy | Precision | Recall | F1   | AUC PR | AUC ROC |
|----------|----------|-----------|--------|------|--------|---------|
| Melbourne| 0.873    | 0.770     | 0.820  | 0.793| 0.688  | 0.913   |
| Sydney   | 0.860    | 0.707     | 0.770  | 0.719| 0.640  | 0.897   |
| Brisbane | 0.855    | 0.514     | 0.612  | 0.528| 0.449  | 0.791   |
| Perth    | 0.903    | 0.605     | 0.797  | 0.686| 0.574  | 0.886   |
| Jakarta  | 0.762    | 0.816     | 0.706  | 0.705| 0.735  | 0.860   |

VII. CONCLUSIONS

In this paper, we proposed a framework to detect civil unrest events by tracking each word-pair volume in twitter. The main challenge with this model is to identify the word-pairs that are highly associated with the events with predictive power. We used temporal filtering to detect the spike within the time series vector and used Jaccard similarity to calculate the scores of each word-pair according to its similarity with the binary vector of event days. These scores are used to rank the word-pairs as features for prediction.
Once the word-pairs are identified, we trained a Naive Bayes classifier to identify any day in a specific region to be an event or non-event days. We performed the experiment on both Melbourne and Sydney regions in Australia, and we achieved a classification accuracy of 87% with the precision of 77%, Recall of 82%, area under the ROC curve of 91% and F-Score of 79%. The results are all achieved after 10-folds randomized cross-validation as listed in table III.

The main contributions of this paper are (1) to overcome twitter challenges of acronyms, short text, ambiguity and synonyms, (2) to identify the set of word-pairs to be used as features for live event detection, (3) to build an end-to-end framework that can detect the events likely according to the word counts. This work can be applied to similar problems, where specific tweets can be associated with life events such as disease outbreak or stock market fluctuation. This work can be extended to predict future events with one day in advance, where we will use the same method for feature selection in addition to time series analysis of the historical patterns of the word-pairs.

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| Author et al. (2017) | Ref | Method | F-score | Accuracy |
|---------------------|-----|--------|---------|----------|
| [10] Cui et al. (2017) | used a graph based key-phrase extraction algorithm (TextRank) to extract the key-phrases matching the events. | 0.79 | 0.65 |

| Author et al. (2011) | Ref | Method | F-score | Accuracy |
|---------------------|-----|--------|---------|----------|
| [40] Weng et al. (2011) | EdGCW: Clustering of Wavelet-based Signals followed by discrete wavelet analysis for each term | 0.43 |

| Author et al. (2012) | Ref | Method | F-score | Accuracy |
|---------------------|-----|--------|---------|----------|
| [8] Crodeiro et al. (2012) | WATIS: Wavelet Analysis Topic Inference Summarization | 0.43 |

| Author et al. (2016) | Ref | Method | F-score | Accuracy |
|---------------------|-----|--------|---------|----------|
| [11] Adedoyin-Olowe et al. (2016) | Transaction-based Rule Mining to extract worthy hashtag words | 0.77 |

| Proposed method | Keyword volume and spike matching approach | 0.79 | 0.87 |

TABLE IV: The classification scores compared to benchmarks
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