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Detecting the Likely Causes behind the Emotion Spikes of Influential Twitter Users for Arabic language

Entesar Eljali,Can Vurdu,Tarik Ahmad
Department of Materials Science and Engineering, Kastamonu University, Turkey
Corresponding Author: Entesar Eljali

ABSTRACT
To our knowledge all the previous researches and studies for extracting the likely cause of emotion spikes was for comments and reviews with non-Arabic languages. Although, According to a study performed by Semiocast , Arabic was the fastest growing language on Twitter in 2011, and was the 6th most used language on Twitter in 2012. While a wide range of Arabic opinionated posts are broadcasted, research in the area of Arabic sentiment analysis remain sparse and show a very slow progress compared to that being carried out in other languages, mainly in English . For that, our work will be to identifying the likely causes of strong and sudden change of emotions within the temporal dimension of influential users' emotion flow in Arabic Twitter we chose twitter because Twitter as a microblogging platform, receives over 500 million tweets worldwide every day as per 2016.These emotion spikes are the reaction of users toward certain events. Hence, our system will try to extracts keyphrases, which associated with each identified emotion spike, and passes them to an analyze step. Then the system will detect the named-entities and events or topics identification since the extracted keyphrases indicate a change on user's emotions, and represent the causes of a particular emotion spike.
Keywords: emotion analysis, spike, social media, keyphrases

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I. INTRODUCTION

It is the end goal of information gathering tasks to find out what people think about a phenomenon or any concept in general. With massive data gathering sites such as Twitter, Facebook and so on, the internet today is littered with this information. This is why it has been the concerns of computational linguists and researchers to develop information technology tools that can automatically extract this information and computationally analyze them to determine the sentiments of the public. Most approaches and literatures in this domain has always been focused on distinguishing between two polarity categories, leaving so much inferable information untapped.

Human emotions have always been a topic of virulent discussion amongst experts due to their variability in definition. Of the major proponents for the meaning of emotions, some have described them as being discrete and constructively different [Paul Ekman, 1992] while others claim they can be characterized on a dimensional basis [Wilhelm Max Wundt, 1897]. Our research is largely based on the view that emotions are discrete due to the latter having lots of ambiguity in meaning, scope and ethnographic universality.

Emotions can be grouped into eight distinctive categories: Anger, Anticipation, Fear, Joy, Disgust, Sadness, Surprise and Trust. While this classification can be subjective enough and the spike detection predictive of the popular emotion based on the processed text entry, another major concern is being able to answer the question: what are the likely causes of these spikes? An attempt at answering this question requires an extensive linguistic analysis of the processed texts.

The emotion spikes from this classification-oriented method of opinion extraction can be used to a large extent to visualize the changes in sentiments of the species under analysis over time. Using this method, it has been shown that the likely causes of such spikes can be inferred and with that, revolutions are inevitable.

The goal of this project is to identify the likely causes of emotion flow (spikes in emotions) within the boundary of information extracted from the timelines of popular Arabic media twitter accounts. Consequently, the most likely causes of these spikes will then be determined by analyzing them both statistically and linguistically. Our technique revolves around the targeted identification of these causes through the extraction of key phrases from the Arabic sentences and robustly filtering the extraction for noise and other redundant data.

We discuss my methods and techniques in this paper and while these strategies are meant to be language agnostic, we have only tested them in the Arabic language with datasets from influential twitter user accounts. The three major issues addressed are:

1. Emotion extraction by relating sentiment, subjectivity, orientation and color association.
2. The identification of emotion spikes by visually representing the flow of timewise fragmented tweets.
3. The extraction of the likely causes of such spikes using key phrase segmentation, POS tagging and other linguistic approaches.

II. RELATED WORK

Sentiment analysis has attracted much attention in the research community. In its most typical scenario, sentiment analysis aims to detect the sentiment polarity of a given text. The work that has been done regarding Arabic sentiment analysis in Twitter which is one of the most popular microblogging services is limited .The majority of the proposed approaches applied methods from machine learning field to classify a tweet as positive or negative Abdul-Mageed et al.[10], Shoukry et al.[11]. Other researchers proposed lexicon-based approaches that do not require any training data Beltagy et al. [12], Albraheem et al. [13]. While Abdulla et al. [14] they examined both approaches the supervised and the unsupervised. In the unsupervised they built their lexicon manually using SentiStrength website. And enhance it through adding the synonyms of the word. The supervised examination has been done using RapidMinersoftware.Butto our knowledge there are no researches of Arabic language tried to identify the causes behind sentiment spikes.But there is researches done in English Balog et al. [15] used LiveJournal posts which mention the user mood and they extracted unusually common words in order to find the causes of the identified mood changes. These words were then used to search the related events in a news dataset. Tan et al. [16] analyzed sentiment variations and extracted possible causes of such variations. They proposed the Foreground and Background LDA model to extract the foreground topics and the Reason Candidate and Background LDA model to rank the extracted foreground topics according to their popularity within the sentiment variation period. And Montero et al. [6] who tried to identify the likely causes of emotion spikes of influential users. They used empirical heuristics to identify the emotional spikes and keyphrases to extract the causes of the spikes.InGiachanou et al. [7] they tried to observe the sentiment evolution towards the entity of interest and identifying the most important sentiment spikes and extracting the topics that were discussed when the sentiment spike occurred. Then Ranking the extracted topics based on their contribution to the sentiment spike.

III. EMOTIONAL SENTIMENT

As has been established earlier, the study of emotions spans several fields of human study such as psychology, philosophy and sociology. Trying to determine emotions through the analysis of word choices alone has a lot of insufferable shortcomings compared to the much more difficult alternative of trying to do this by first understanding the psychological state of mind of the speaker or writer. In other words, a better wayto accurately extract emotions is by resolving to first understand the mental states – the moods and affects; of the speakers/writers extruding such emotions. [Bing Liu, Sentiment Analysis: mining sentiments, opinions and emotions, 2015].

In the remainder of this section, we'd establish how we've employed the concepts of emotion, affect and mood to show a better way to accurately determine the emotional sentiments of text-based data.

1.1 Emotion, Affect And Mood

An affect is commonly referred to as a neurophysiological state consciously accessible as the simplest raw feeling evident in moods and emotions [Russell, 2003]. In simpler terms, Emotion is an indicator of Affect. Mood, like emotion is a feeling or affective state, but it typically lasts longer than emotion and tends to be more diffused and it is less intense than emotion.

For instance, while watching a scary movie, if you are affected, the movie moves you and you experience a feeling of being scared. Your mind processes this feeling and it is then displayed as an emotion, such as fear or sadness. These emotions may subside and you may feel angry or disgusted for the entire day, now that is mood and it is a consequence of the emotion you felt earlier. In other words, emotions are short-lived while moods which originates due to these emotions may last longer.

How does this apply to our NLP task?

Scientifically, affects are subjective; i.e. they can be classified as negative or positive. Moods can be color coded; as a mood of anger can be termed red and black while that of joy can be purplish, blue and so on.

Following this line of reasoning, what this means is that, to determine emotions from speech; understanding the mental state of the person results in a potentially more accurate extraction of the emotions he's extruding. His mental state is dependent on his mood which can be color-coded, his affective state which is subjective, his mood heat map and time. In essence, emotions are quintuples. [Bing Liu, 2015].

1.2 Emotion Objects

Subsequently, we shall refer to an emotion as an object, a set of five independent variables as represented below.

$$(e, a, m, f, t)$$

Where **e** is the target emotion, **a** is the affective state that is responsible for e, **m**is the mood that's caused by e, **f**is the feeler of the emotione and t is the time when the emotion e is expressed by f.

For example: for the emotion expressed in the sentence: هذا الصباح ، كنت غير راضٍ جدًا عن زملائي في الصف ًلأنهم كانوا يدفعونني للتخلي عن سرنا (This morning, I was very unhappy with my classmates because they bullied me into giving up our secret). The target emotion, e can be anger and/or sadness. The affective state is negative, the mood is definitely sadness, the feeler is the speaker and time could be 11/12/2017 8:00. Therefore, the emotion object of the sentence can be represented as follows:

$$(\{\text{anger}, \text{sadness}\}, 0, \{\text{sadness}\}, \text{'I'}, 11/12/2017\ 8{:}00)$$

IV. DATA COLLECTION

Most of the techniques we have used for emotion classification and spike identification are largely based on supervised machine learning algorithms which requires lots of datasets for training purposes. Our data pool consists of automatically downloaded tweets from the twitter handle of 5 major Arabic news accounts.

Using the twitter API, we download the most recent 10,000 tweets of each account and since our approach revolves around changes in these data over time, we perform a fragmentation according to their timestamps after cleaning them of noisy data such as hashes and other irrelevant stop-words. Afterwards, the resulting tweets were stored persistently in a cacheable datastore.

Extraction of emotion objects is achieved using the following lexicons.

1. NRC Emotion Lexicon for emotion classification
2. NRC Word-Color Association Lexicon for mood classification
3. MPQA Subjectivity Lexicon and Bing Liu's Opinion Lexicon for emotion affects classification

Considering this is the first application of its kind in the Arabic language, some of these datasets were in the English language and the Google translate tool was very useful for translation of most of these data into Arabic.

V. EMOTION EXTRACTION AND ANALYSIS

Time-wise fragmented emotions were first classified based on the individual member of the quintuplet set.Using each of the lexicons listed in the preceding section, a sentence was classified into emotion, affect, and mood. Afterwards, a score is then calculated for each of these categories and their average taken to be the emotion score (emotionScore) for the text entry.

The steps taken to achieve this are outlined below.

STEP 1: Emotion Classification

Manually annotated lexicons were used to classify text entries into emotion tags, emotion affects state and color coded moods.

STEP 2: eScore

eScore represents the score of the first member of the quintuplet, the emotion tag score.

$$\text{eScore}_{\text{category}} = \frac{\text{eWords}_{\text{category}}}{\text{eWords}_{\text{all}}}$$

STEP 3: aScore

aScore represents the score of the second member of the quintuplet, the emotion affect state score. Since this represents subjectivity, it is a binary value and shifts towards acting mostly as a statistical weight bias.

$$\text{aScore}_{\text{category}} = \frac{\text{aWords}_{\text{category}}}{\text{aWords}_{\text{all}}}$$

STEP 4: mScore

mScore represents the score of the third member of the quintuplet set, the color-coded affective mood score.

$$\text{mScore}_{\text{category}} = \frac{\text{mWords}_{\text{category}}}{\text{mWords}_{\text{all}}}$$

STEP 5: Average

Lastly, the average of the individual scores is calculated and now the emotionScore for the analyzed text entry.

$$\text{emotionScore}_{\text{category}} = \frac{\text{eScore}_{\text{category}} + \text{aScore}_{\text{category}} + \text{mScore}_{\text{category}}}{3}$$

2. EMOTIONSPIKE IDENTIFICATION

A spike in an emotion flow is defined as a spontaneous change in the average emotion flow of the text entry under analysis. In our research, we give a visualization of the emotion flow based on the emotionScore calculated on tweets from a particular user over time. In other words, for a particular category of emotion, identifying the spikes in such emotion, for instance over a daily basis, is only a matter of looking out for the rise and fall in the values of the relative emotionScoreover such time period.

The following formula describes this process mathematically:

$$\text{emotionSpike}_{\text{category}} = \left(\frac{\text{emotionScore}_{(\text{category},\text{timeRange})}}{\text{emotionScore}_{(\text{category},\text{timeRange}-1)}} > \theta\right) \vee \left(\frac{\text{emotionScore}_{(\text{category},\text{timeRange})}}{\text{emotionScore}_{(\text{category},\text{timeRange}+1)}} > \theta\right)$$

The value θ represents an acceptable threshold for an emotionScore. Depending on the dataset, tweaking this value to an optimal value results in better and less noisy spike identifications.TimeRange represents the time based segment that's represented by the processed text. Mostly due to availability of sufficient data, we've resorted to use days forour timeRange fragment.

VI. EXTRACTING LIKELY CAUSES FOR EMOTION SPIKES

An emotion is an effect produced by a cause. All emotions have causes and are usually at least one of internal or external events. For instance; in the sentence: عملية المدير غير الناجحة التي أدت إلى وفاته ، تسببت لهم في البكاء طوال اليوم(the manager's unsuccessful surgery which resulted in his death, caused them to cry all day).Sadness is a good candidate for the emotion expressed by this sentence and the reason(s) for this sadness is hidden within the text, the manager's unsuccessful surgery and his death.

The second phase of our research aims to answer the question: what are the likely causes of the emotion spikes that were identified in the first phase? The answer to this question orients towards a linguistic and a statistical domain and we have used techniques from these two branches of machine learning to approach this problem.We provide an overview below.

Subjectively, the reasons/causes of outbursts and emotional write-ups are always represented by the choice of words and usually, the schema used in making up the text. This is the ideology we have based our application on; analyzing the input text to search for the likely causes of the emotion objects represented in such text.This was achieved by linguistically extracting keyphrases from the texts and filtering them on an established heuristic to select the most viable keyphrase chunks.

VII. KEYPHRASE EXTRACTION

STEP 1 – Normalization:

Reducing the inflectional forms and the derivationally related forms of words to a common base form was the first step in our attempt to extract keyphrase chunks. For grammatical reasons, removing the different forms of a word helps to reduce redundancy of selected phrases and improves the efficiency and effectiveness of the filtering algorithm.

A canonical approach was taken to achieve this, first the words in the sentences were first lemmatized to leniently filter out inflectional forms and reduce most words to their base forms. Lastly, the lemmatized words were then stemmed.

STEP 2 – POS Tagging:

In order to generate a tagged text based on a set of lexical categories, the system performs part of speech tagging on the normalized words.

we have employed a cyclic dependency network using HMMs (Hidden Markov Models) based on the work of Kristina Toutanova and Christopher Manning [Kristina Toutanova, Feature-Rich Part-of-Speech Tagging with a Cyclic Dependency Network, 2013) to achieve this.

STEP 3 – Chunking:

A set of L manually defined syntactic rule patterns were used to extract keyphrases from the POS tagged texts. These syntactic patterns are created to be general enough to include keyphrases of named-entities, actions and noun phrases. (NP, ADJP, VP). Given a set of lexical categories C, a pattern X is a syntactic rule of the form:

$$X = Y_1 Y_2 \ldots Y_n$$

Where $Y_i \in C$andX $\in L$.

An alternative to this approach is shallow parsing using n-grams and other statistical methods. We have taken this path since the linguistic analysis that were done in previous steps were shown to give more meaningful phrases. On average, the length of a chunk after extraction using the defined syntactic rules varies from three to nine words.

VIII. KEYPHRASE FILTERING

The final step after chunking of the extracted keyphrases is to filter them statistically to reduce redundancy and improve causality accuracy. This was achieved by selecting the longest keyphrase in a situation where a keyphrase is a string subset of another and then scoring them by frequency.

STEP 1 – Filtering using Raita Algorithm:

To remove shorter phrases from the phrase pool, we employed the Raita string searching algorithm due to its soft complexity of $O(m) + O(mn)$ time where m is the length of a phrase that's been searched for and n is the length of the phrase that's been searched.

After extensive testing, on average, about 60% of the original phrases were always filtered out and redundancy was greatly reduced.

STEP 2 – Tf-Idf Scoring:

Given that keyphrases containing rare words are considered more informative than common ones, a second filter was applied to the spikes based on an adaptation of the tf-idf algorithm. As a statistical measure, tf-idf provides scored weights to evaluate how important a keyphrase is to a spike within a set of detected spikes. We employed the tf-idf algorithm because it has been shown to achieve better performance than other algorithms.

With tf-idf, we aim at scoring and ranking the extracted keyphrases in order to sort them by causality accuracy. An adaptation of the algorithm used is shown below:

$$\mathrm{tf}-\mathrm{idf}(\mathrm{K_i}) = \mathrm{tf_{ki}} * \mathrm{idf_{ki}}$$
$$= \mathrm{tf_{ki}} * \log\frac{|S|}{|\{s \in S : K_i \in s\}|}$$

Where$\mathrm{tf_{ki}}$ is the number of times $k_i$occurs in emotion spike s, |S| is the total number ofspikes, and $|\{s \in S : k_i \in s\}|$ is the number of spikes in which $k_i$occurs.

IX. EXPERIMENTS AND RESULTS

In this section we illustrate our methods with some examples and provide a preliminary analysis of their effectiveness.

2.1 The tweets

Using the twitter API, Our data pool consists of automatically downloaded tweets from the twitter handle of 5 major Arabic news accountslisted below (10,000 recent tweets of each account).

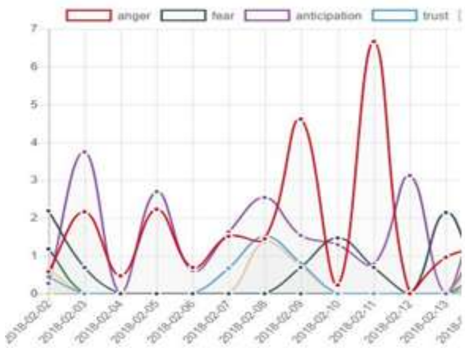
- Bbcarabialerts.
- Libyalaan.
- Agarabic.
- Euronewsar.
- Skynewsarabia.

2.2 Emotion extraction

Using each of the lexicons listed in section (4) and the formula in section (5) we extract the emotion for each tweet for each accounts.

2.3 Emotion spike identification

A spike is a sudden change in an average emotion flow of the text entry under analysis.



The emotion flow chart above has been generated from the tweets of the bbcarabicalert twitter account from the month of February 2018. It shows how the emotions expressed in their tweets changes on a daily basis.

2.4 AN OPTIMAL VALUE FOR θ

From the analysis of bbcarabicalerts tweets, an emotion flow chart was generated with a threshold value of 1.5 as shown above.On the 11th of the processed month, anger really soared up and on the 17th of the same month, anticipation and sadness went up instead. Changing the value of the threshold to 1.0, anger was still prevalent but it was shown that there was no spike for anticipation and sadness.

The significance of the θ value lies in the fact that it represents a threshold for identifying good spikes and an optimal value for it can only be determined by trial. For our application, 1.5 represented a good optimal value and with it a lot of noisy spikes can be filtered out as was the case. This value was determined after an analysis of about 3200 tweets within a space of five months.

2.5 Extracting Likely Causes For Emotion Spikes

In this stage we used a combined linguistic and statistical analyses approach (see section 9) to uncovering the causes of a spike in the emotion flow.

Going back to the chart in the previous section, the keyphrases extracted using this technique for Anger and Fear On the 18th of the processed monthare shown below:

2.6 Failure analysis

Evaluation of the methods described here is non-trivial. We found that our peak detection method is effective despite its simplicity. Anecdotal evidence suggests that our approach to finding explanations underlying the spikes is effective. We expect that it will break down, however, in case the underlying cause is not written in standard Arabic language but, for instance, they written in Egyptian Dialect.

X. CONCLUSION

We described a method for discovering the likely cause of emotion flow in a large number of tweet, and labeling them with a natural language explanation. Our method shows that simple techniques based on combined linguistic and statistical analyses with large quantities of data, are effective for identifying the cause underlying changes in emotion flow.

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