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The Creation of an Arabic Emotion Ontology Based on E-Motive

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Abstract

There is an increased interest in social media monitoring to analyse massive, free form, short user-generated text from multiple social media sites such as Facebook, WhatsApp and Twitter. Companies are interested in sentiment analysis to understand customers' opinions about their products/services. Governments and law enforcement agencies are interested in identifying threats to safeguard their country's national security. They are actively seeking ways to monitor and analyse the public's responses to various services, activities and events, especially since social media has become a valuable real-time resource of information. This study builds on prior work that focused on sentiment classification (i.e., positive, negative). This study primarily aims to design and develop a social sentiment-parsing algorithm for capturing and monitoring an extensive and comprehensive range of emotions from Arabic social media text. The study contributes to the field of sentiment analysis (opinion mining) and can subsequently be used for web mining, cleansing and analytics.

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Keywords: ontology, Arabic, social media, emotions, sentiment, sentiment parsing technique.

1. Introduction

Social Media has become an extremely important source of real-time information on a massive number of topics, ranging from the mundane (e.g., what I had for breakfast) to the profound (e.g., political issues around the world). Social media streams represent vast amounts of 'real-time' data streaming daily. Topics on these streams cover every range of human communication, from movies to serious reactions to events and information sharing regarding any imaginable product, item or entity. It has now become the norm for public events to break news over social media streams first, and only then are followed by mainstream media picking up on the news[24].

Detecting, interpreting and monitoring events of interest have a clear economic, security and humanitarian importance. It can affect companies in terms of work-in-progress and competitiveness. It can also monitor conflicts, crimes, natural or manmade disasters and political events (e.g., elections). Those short messages can contain significant amounts of information, and convey useful data.

The use of social media for event detection poses a number of opportunities and challenges as these message streams are: very high in volume; often contain duplicated, incomplete, imprecise and incorrect information; are written in informal style; generally, concern the short-term zeitgeist; and finally, relate to unbounded domains[24]. These characteristics mean that while massive, timely information sources are available, domain-relevant information may be mentioned very infrequently. The scientific challenge is, therefore, the detection of the

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signal within that noise; and exacerbated by the typical requirement that events must be analysed in (near) real-time so that events can be promptly acted upon.

This study will focus on measuring emotions as they are expressed in Arabic within a wide-range of different types of sparse and informal messages in social media. Social media analytical tools will be utilized to analyse this high-volume data by capturing message streams (i.e., tweets) that companies care about, and analysing them to extract the emotion using a complex natural language processing ontology. In this study, we developed a new social media analytical tool that has been borrowed from EMOTIVE—a social media analytical tool developed from research at Loughborough University, which will be extended with a new algorithm to include the Arabic language. The analysis of these emotions can be used to monitor public reaction to events (i.e. event characterization), event clustering or user profiling. It specifically aims to capture how a customer really feels about a product and service of different companies—what people actually say about the product or service.

1. Literature Review

1.1. Sentiment Analysis

Recently, an entire industry of commercial services has grown around the automated monitoring of the crisis-mapping community[29]. Over the recent years, specific tools that help to automate the monitoring of social media content have been developed[25]. The development of commercial services and analytical tools are necessary to analyse the enormous amount of social media content generated daily[14]. No longer is a manual, human-based monitoring feasible. Similarly, the government has also shown interest in similar systems[23]. To the extent that it has become mandatory for governments to monitor, analyse and get involved in social media[15].

Sentiment analysis of user-generated content from social media is now a well-established research area[17, 20]. The research field of sentiment analysis (opinion mining) has developed a variety of algorithms and techniques to automatically detect sentiment in text. Applications range from product and company related sentiment monitoring[20]; generic real-time "polling" on Twitter[19] gauging public emotional response to crises and national security concerns[14] or terrorist attacks[7]. However, the notions of affection and sentiment have been simplified in current state-of-the-art, which is often confined to their assumed overall polarity (i.e. positive, negative). Profile of Mood States (POMS)[6, 16] and Munmun de Choudhury and Counts[8] are exceptions. In this study, sentiment is defined as a positive or negative emotion, opinion or attitude.

Although numerous approaches employ highly elaborates and effective techniques with some success, the sentiment or emotion granularity is generally limited and arguably not always most relevant for real-world problems. Unfortunately, in the field of psychology, social psychology and affective computing there is still much debate over human emotions. Grassi[12] points out that there is no common agreement about which features are most relevant to the definition of an emotion and which are the relevant emotions and their names. In this study, we solely consider emotions expressed in text content, and we specifically consider definitions of emotion taxonomies proposed by[9, 10,13] Plutchik[22]. Although these authors arrived at somewhat different sets of human emotions, we selected a combined set of relevant emotions.

Subjectivity and sentiment analysis (SSA) aims to determine the attitude of the Twitter's user with respect to a topic or the overall contextual polarity of an utterance[24].

Deep emotional analysis of public data such as tweets could reveal interesting insights into human behaviour. Substantial work has been done in the field of emotion extraction to distinguish the subjective portion in text and find sentiment orientation. However, harvesting emotions from tweets in real-time remains to be very challenging. The use of mining technique was one way to find out if the text is an expression of the writer's or not. Refaee & Rieser[24] suggested that one approach was to create a set of search queries to obtain tweets that convey emotions, behaviours and opinions towards specific events for a month, analyse them, and then retrieve them through a dataset for nine days to get certain information. Although the techniques of sentiment analysis are advancing, many challenges remain unsolved such as complexity of sentences, dealing with negotiation expression and using other languages[1].

There has been limited literature about this research in Arabic despite having more than 3.7 million Arab users on Twitter[1]. This underserved population of users makes this work important so that both companies and governments can focus on analysing those tweets and make sense of them.

Belkredim & El Sebai[4] mentioned that the Arabic language is structured into nouns, verbs and particles, and those are collected and derived from the original roots. Usually, roots are composed of three or four letters, and there is a large number of words that are derived from their roots. Derivations come from using nouns and verbs, where verbs use different tenses. Those nouns and verbs follow certain patterns and those further deliver morphological, semantic and contextual information[4]. One of the problems with the Arabic language is that there are so many different combinations of syntax (i.e., classical Arabic, modern standard Arabic, and also the dialectal Arabic) [24]. There is also a growth in the users who use English letters to write Arabic sentences mixed with numbers to denote some of the Arabic characters (e.g. 5aled, 7amed, 3bdallah). Additionally, we also have regional differences within the language that distinguish it from others (e.g., Gulf Arabic, Jordanian Arabic, Egyptian Arabic, Algerian Arabic) [2]. Therefore, varieties in the Arabic language makes it difficult to come up with one common algorithm or technique that will cover all differences.

Arabic ontology is proved to be delivered in different applications and fields such as information search and retrieval, where it helps provide precision and better quality of results. Furthermore, it offers machine translation and word disambiguation. This feature helps with defining terms to their exact meanings. Moreover, data integration uses the Arabic ontology as a semantic reference for different information systems. Also, in the semantic web, it is used to clarify meanings in websites[5].

1.2. EMOTIVE Technique

EMOTIVE is a technique developed at Loughborough University to monitor and analyse social media traffic reactions based on eight different key emotions: anger, disgust, fear, happiness, sadness, surprise, confusion and shame[27]. This technique was implemented on selected time frames and events. They used Twitter to aggregate data that was connected to the events using hashtags and words. All the data was further analysed according to the emotions that were associated with particular words.

EMOTIVE used the lexicon/linguistic approach. This particular approach is limited with three main problems along with it. First, notions of effect and sentiment are more simplified in current state-of-the-art and restricted to overall polarity. Second, polarity-centric sentiment classifiers, in general, include an obscure idea of extremity that packs together emotion, states and opinion. Third, there could be multiple disagreements regarding which features are related to certain emotions and what these emotions are. Only clear emotions are accepted, and other vague expressions are left ignored. Fourth, EMOTIVE ontology can identify negations, intensifiers, conjunctions and interjections, and measure the strength and activation level of people’s emotions, whether they are in slang or used in standard English and associated POS (Parts-of-Speech) tags. All of the aforementioned could help solve the uncertainty[27].

The EMOTIVE technique has a number of limitations. First, there is spam on social media streams and misusing of hashtags or words. Second, data would be only filtered if emotions were explicit. Third, profiling the users and determining their age, gender or income level proves to be difficult. To overcome these limitations, they further organized the data by agglomerative clustering to help generate a dendrogram. The dendrogram helps reveal the events so that it becomes easier to observe them. Thus, some events are not very related and close to specific emotions, which means that even after clustering, some results are not 100% connected to the emotions.

Loughborough University also introduced a system called ReDites that detects real-time events, track, monitor and visualizes them. The system was designed to mainly focus on security-relevant events. Once a related event is detected, it will be tracked, geo-located, summarized and then visualised to be delivered to the end users. ReDites monitors the changes of emotions over those events through detected tweets. The Westgate shooting incident from 2013 was used to experiment the ReDites potentials. However, detecting events and emotions through social media streams is challenging as the high volume of streams could contain erroneous data that is vague and indirect and might be irrelevant. Such systems are challenged to pick up the message from the flawed data, and process that data in a real-time manner[1].

2. Research Methodology

The research field of sentiment analysis has developed a variety of algorithms and techniques to automatically detect sentiment in text and sentiment analysis of user-generated content from social media, but there is limited research about automatic detection sentiments algorithm for Arabic texts analysis of user-generated content from social media. The structure of the ontology algorithm will require knowledge of the Arabic language, preferably a native Arabic speaker with training in linguistics and discourse analysis to be able to go through hundreds of tweets and come up with keywords and terms that been commonly used in certain events.

In order for the system to be able to monitor certain words of interest or certain events occurring, an efficient extracting method is required based on emotions, locations, organizations or certain keywords. Especially when it comes to security, it is important to filter tweets to be able to report and present a rich dataset.

The problem with Arabic tweets is the different Arabic dialectics and how to extract certain keywords from tweets. For this reason, the following steps are required:

1. Keyword/Key phrase monitoring or event detection, filtering and extraction.
2. Accurate geolocation detection, as this will help when choosing the different dialectics.
3. Emotion detection and evaluation.
4. Tone of tweet message detection, further semantic enrichment and organization.
5. User-interface visualization.

The EMOTIVE system focuses on fine-grained emotion detection, geolocations and simple tone detection. Table 1 provides examples of multiple ways to say the same phrase in Arabic based on the dialect:

Table 1: A Comparison of Different Arabic Dialects

Dialect/ Language	Example
English	I don't know what to do
Jordanian Arabic	مش عارف شو اعمل
Palestinian Arabic	شو بدي اعمل
Emirati Arabic	معرف شو اسوي
Modern Arabic	لا اعلم ماذا افعل
Egyptian Arabic	مش عارف اعمل ايه
Tunisian Arabic	منعرفش
Algerian Arabic	ما على بالي
Kuwaiti Arabic	ما ادري شو اسوي

This study first translates emotions found in English into Arabic in order to make sense of the tweets. Table 2 below shows a subset of the translations used in this study. It then uses this as an input to the EMOTIVE tool to analyse Arabic tweets. It is used to find the relationship between the words in the tweets in terms of negations, intensifiers, conjunctions and interjections. The visualization tool was useful in making sense of the data.

3. Research Analysis, Discussion and Findings

In this section, the results of the research and data analysis are presented. Two fundamental steps drove the collection of the data and the subsequent data analysis. Those goals were to develop a base of knowledge about the key emotion categories in Arabic and the Arabic dialects of each emotion. The basic emotions categories in addition to the dialects from several Arab countries have been identified as shown in Table 2. More categories like sadness, joy, contempt, fear, surprise and others will be added to the list of the categories and their Arabic dialects.

Table 2: Samples of the Work

Key Emotion		Country	Dialects
English	Arabic	General	احْتِدام ¸ إِضْطِراب ¸ إِمْتِعَاض ¸ إِنْفِعَال ¸ إِهْتِيَاج ¸ بَغْضَاء
Anger	غضب	(UAE) الإماراتي	معصب ، محرج ، مقهور، مغيّض ، مفوّل ،
		(Kuwait) الكويتي	امشلوط ، ماد برطمه / براطمه ، امكشر ، مستعسر ، تحرمص ، محنق
		(Egypt) المصري	متنرفز ، متنشن ، متعصب
		(Palestine) فلسطيني	زعل ، غضبان ، طفران ، طلعت روحو
		(Tunisia) تونسي	غش / متغشش ، تنرفيز / متنرفز
		(Algeria) جزائري	زعفان
		(Jordan) اردني	معصب
		(Lebanon) لبناني	غضب ، طالع خلئو ، معصب ، مسكر راسو ، مأنقرا معو ، مضوا راسو ، عايف حالو
		(Morocco) مغربي	طايرلي ، معصب
		(Sudan) سوداني	فرحان ، سعيد
Confusion	حَيْرَة	General	إبْهام ؛ إخْتِلاط ؛ إضْطِراب ؛ إلْتِباس ؛ تَحْيِير ؛ تَرَدّد
		(UAE) الإماراتي	متخربط ، متردد ، محتار، متحير، متلخبط ، مضيّع
		(Kuwait) الكويتي	محتار ، متردد ، متحير ، متعومس ، متبلعم
		(Egypt) المصري	مستغرب ، متلخبط ، قلقان
		(Palestine) فلسطيني	متحير
		(Tunisia) تونسي	داخل بعذي / بعضي، محتار، متردد،
		(Algeria) جزائري	محير
		(Jordan) اردني	محتار ، مشعارف
		(Lebanon) لبناني	مخربط ، ضايع ، برم راسي
		(Morocco) مغربي	دوخه
		(Sudan) سوداني	ملخبط ، حيران
Disgust	إشْمِئْزاز	General	تَأَفّف ؛ تَقَزّز ؛ تُخْمَة ؛ جَفَاء ؛ جَفْوَة ؛ سَأم ؛ ضَجَر
		(UAE) الإماراتي	لوعة جبد ، منقرف ، متلوّع ، منسده نفسه ، فضل عنهم ، يعطا عنهم، جبدي لايعه
		(Kuwait) الكويتي	لوعة جبد ، يلوع ، متبلعم
		(Egypt) المصري	أرفان / قرفان
		(Palestine) فلسطيني	أرفان / قرفان ، مقزز ،
		(Tunisia) تونسي	عايف روحي ، تعيف ، تقزز / قززتني ،
		(Algeria) جزائري	معجبنيش الحال ،
		(Jordan) اردني	مقرف ، بقزز ،
		(Lebanon) لبناني	ارفان ، نياع ، عايف حالو ، شي بيأرف ، شو هيدا ، العما
		(Morocco) مغربي	قبيح
		(Sudan) سوداني	رفان

The Algorithm implementation in Java is as follow:

- Read sample tweets (sample: فرحان و سعيد بعملي ،افضل العمل نهارا،انا احب العمل في الجامعه، انا اعشق العمل في الجامعه، لكن اكره العمل ليل)
- Pre-process the tweets: remove strange characters/text, and exclude all unnecessary words
- Extract the sentiment words from the text by comparing each word in the text with the built-in dictionary
- Get from the built-in dictionary the score sentiment description of the word, i.e., the words will be classified in the code as positives and negatives
- Calculate the positivity of the topic as follows: # of positive words / (# of positive words + # of negative words) * 100 %
- The result of the previous sample is: Positive sentiment: 83.33333333333334 %

4. Contribution of the Study

The goal of this study is to develop an Arabic social sentiment-parsing algorithm. The Arabic social sentiment-parsing algorithm will be used to analyse sentiments in Arabic message streams. It provides a practical contribution to the field of data analytics by coming up with a new algorithm that makes sense of ontology to analyse diverse message streams in Arabic. This algorithm can subsequently be used for web mining, cleansing and analytics.

The study was initially applied to understand the wide variety of information limited a particular event with a limited number of tweets. It applied the social sentiment-parsing algorithm to analyse the sentiments in the tweets and form associations with the words based on the frequency of the words and co-location of the words to emphasize the sentiments of the phrases. These were then associated with certain rules. To verify the accuracy, the manual review of the phrases was made before continuing to build more dictionary words.

5. Conclusion

The study found that by using the EMOTIVE technique, a rough translation of sentiment allowed us to look at streams of social media in Arabic on Twitter to understand the sentiment of users on a particular event.

Future research would benefit from analysing events that are of interest to corporations or government agencies. As such, further research on data analytics can cover two main areas. The first area will use big data analytics, using EMOTIVE to analyse Twitter accounts for sentiments that impact product launches. The sentiment analysis of social media message streams will help product/service vendors access real-time information about their product launches and other related events. It provides them with the ability to respond to market trends promptly. The second area can cover those relevant to security and national issues that are of interest to government entities. The sentiment analysis of social media relevant to security and national issues allow governments to respond quickly to issues that may arise. The latter being an area that could include an Arabic Smart EMOTIVE for smart government services in UAE.

Additionally, future research may include identifying emotions from tweets with the implementation of an emoji-detecting algorithm. A great volume of users, especially of a young audience, typically chooses to include smiley emoticons, or 'emojis,' into their tweets. Some users may utilize this feature to express thoughts, opinions and reactions with or without the usage of textual language. Moreover, the utilization of this feature by Twitter users can be beneficial towards future research as some users are able to portray their thoughts more accurately, or at least feel that they do so, using emojis. Similar to analysis of text-only tweets, tweets using emojis can be analysed for valence, polarity and energy levels. To elaborate, there are several variations and versions of a happy or smiley emoji. The different versions of the emoji could portray various levels of happiness. As the same applies to other emotional icons, they can, too, be identified for levels of energy and polarity. The aim for this potential research is to collect the ideas and opinions of Twitter users' on events, products, and ideas and so forth on a greater level of sentiment.

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