Annals of the University of Craiova, Mathematics and Computer Science Series
Volume 50(2), 2023, Pages 488–504, DOI: 10.52846/ami.v50i2.1874
ISSN: 1223-6934

Decoding the Impact of Emotions: Machine Learning insights on User Interests in Social Networks

Henda Ouertani

Abstract. This study investigates the correlation that exists between users' emotional states and their expressed interests in the context of social network. By utilizing cutting-edge machine learning methods, we set out to reveal the connections that underpin user behavior. Saudi Arabia is among the nations with the highest usage of X (previously Twitter). Several studies used the analysis of English tweets to determine the topic of interest and whether the user is passive or active. Studies that examined user interaction to ascertain interest have been conducted with reference to Arabic tweets. There are, however, few studies that track how an external factor, like emotions, affects interest over time. To investigate the relationship between interest and emotion, we used two models of supervised algorithms: Support Vector Machines (SVM) and Naïve Bayes. Once the topic of interests and emotions were classified, we discovered that the topic of interest had a higher accuracy than the emotion classifier because it had been applied to a sample of dataset. Furthermore, the SVM outperformed Naïve Bayes in terms of accuracy for classifying both topics of interest and emotions. Finally, the result indicates that the interests for specific user change over time according to the emotions.

2020 *Mathematics Subject Classification.*
Key words and phrases. SVM, Naïve Bayes; Machine Learning; emotion; interest; Twitter.

1. Introduction

Nowadays, users participate in a dynamic interaction of interests and emotions within the vast landscape of social networks, influencing the digital infrastructure of online communication. The explosive growth of online social networks has allowed people to communicate, share comments, express their opinions and spread news with millions of people in a few seconds [1]. There are many social network services available and they are widely used for social communication. X/Twitter is one of the most popular social networking platforms today with nearly 238 million active daily users as of late 2022 [2]. Twitter is a microblogging service that is used to send and read short text messages known as "Tweets". It has an outstanding resource for sharing information, real-time communication and marketing. In addition, January 2023, the nineth highest number of Twitter users (15.5 millions) is in Saudi Arabia according to Statista reports [3]. As the amount of data is growing, this volume of data is becoming an increasingly rich source for researchers to analyze these data in order to develop a variety of applications. Currently, there are many applications that benefit from Twitter data such as customization applications, recommender systems,etc. Indeed, Twitter's users express themselves in all aspects of life, such as, share tweets about their interests and also express their feelings during the day. However, our source of

Received November 11, 2023. Accepted December 5, 2023.

inspiration in this area is that some companies have difficulty to determine the user's interest through their data, for example if a company is advertising sports products, it has a difficulty in identifying targeted sample of Saudi people on social networks who are interested in sports. Since some of interests of users change over time, they must take into consideration some of the external factors that influence their change. Many studies have used Twitter as a resource to identify the topic of user interests [4, 5, 6, 7, 8]. Most of the studies were focused on English language. Few studies identified the user's interest by examining interaction among Arabic users and did not give importance to Twitter content to determine the user' s interest [9, 10].

In another side, emotion analysis is a new field and is a fertile field for research. Most of the research has not achieved any good results compared to the sentiment analysis because of some of the challenges faced by researchers to determine the emotions for each tweets [11].

Finally, after reviewing the previous studies, we notice that there are no studies that explored the topic of interest through the use of Arabic tweets to investigate the effect of some external factors on changing interest. In this work, we will identify the topic of interest for a user and we will apply an emotion analysis in order to investigate the correlation between interest and emotion.

In this research, we will collect tweets for specific users in order to apply the natural language processes and machine learning algorithms in order to determine the topic of interest for each tweet. This research focuses on the observation of one external factor that may affect the change of the topic of interest, namely emotion. Indeed, we will identify the emotion of the named users through their tweets and observe the correlation between the change of interests and emotions. The main goal of this research is to observe the changes of topic of interest for a user over the time and how emotions affect the changes of the topic of interest.

The rest of the paper is organized as follows. The next section presents the methodology and materials. We briefly discuss the five main steps composing our model: data collection, text preprocessing, interest topic classification, emotion classification and finally evaluation. In Section 3, we discuss and interpret the results. The final section concludes this paper.

2. Methodology and materials

Our methodology relies on training the supervised machine learning algorithms [12]. The proposed model is composed of five main steps: data collection, text preprocessing, interest topic classification, emotion classification and evaluation. Figure 1 gives an overview of the proposed model. Below, we will discuss each step in details.

2.1. Data set. In this stage, we follow two steps data collection and data annotation in order to build our data set. Since there is no data set available to apply this research.

2.1.1. *Data collection.* During the data collection process, we faced two challenges. Firstly, the limitation of available resources in Arabic language. Secondly, decide the best way to collect the tweets. Since we aim to observe the dynamic interest of the users, the method of selecting the user has passed through two stages:

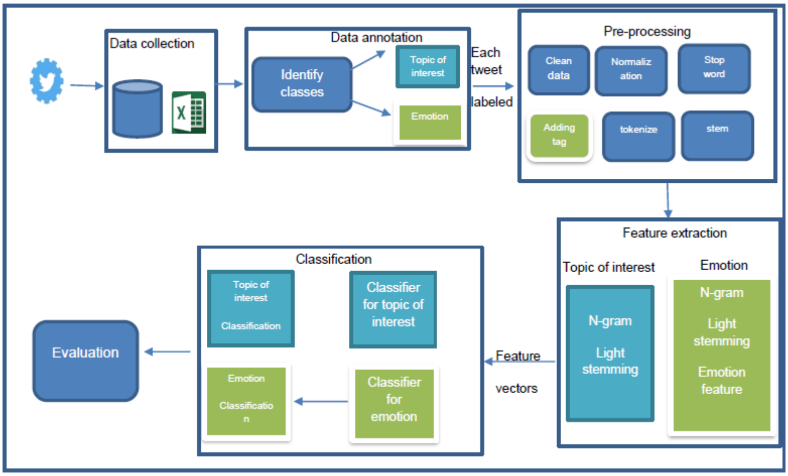

Figure 1. Model Overview.

- As Twitter contains many accounts that belong to celebrities or commercial entities, rather than real users, we have first made sure that our targets were standard users. To achieve this, we examined each potential target, know whether the account belongs to a normal user or it is a fake account. The primary criteria are the tweets, the account does not have advertisement tweets, and the user does not use an automatic bot such as some bot that published a pray.

- In addition, we examined each potential target to make sure that the users were active user. The primary criterion is that the users have at least 10.000 tweets and they are active during the last four months. As a result, we collected Arabic tweets written in Saudi dialect over the period 1 November 2022 through 20 February 2023. Following this screening, we were left with a target account set of U= 20 users. We have extracted the Tweets of all the users among this period, amounting to T = 23,578 tweets. Table 1 shows the number of tweets for each user.

Table 1. Number of tweets for each user.

User	Number of tweets	User	Number of tweet	User	Number of tweet	User	Number of tweet
User 1	92	User 6	1072	User 11	308	User 16	791
User 2	1680	User 7	200	User 12	64	User 17	534
User 3	278	User 8	1122	User 13	2074	User 18	1559
User 4	1512	User 9	208	User 14	650	User 19	221
User 5	465	User 10	1920	User 15	838	User 20	790

2.1.2. *Data annotation.* After collecting the tweets, we annotated manually each tweet. This process contains two steps. First step is annotating each tweet with topic of interest class label. The second step is annotating each tweet with emotion class label. For first step, we choose topic of interest labels after reading the tweets and determine which topics that are discussed in our dataset. There are twelve classes, (Sport, Tourism, Restaurant, movie, music, politics, economy, religious, death, shopping, weather and technology). In this step, we created some instructions to identify the class label as shown in Table 2. Then, we asked two human annotators to read the tweets and assign a class label for each tweet and if they disagreed about class label. A third human annotator was asked to determine the final class label. For the second

TABLE 2. Topic of interest labelling instructions.

Label	Instructions	Example
sport	Each tweet includes sports team such as: alhilal, alnasser, aletihad..etc Tweets include name of football players	انا اقول مباراة الاهلي الجاية مع النصر تبطح وتخليهم يناقسون الهلال. مابه رجال والله.
Tourism	Each tweet talks about tourism or cities suitable to travel or hotels	تجربتي في جزر الكي ويست من اجمل الجزر في ولايه فلوريدا عده جزر شاهدت فيها اجمل المنظر الطبيعيه الخلابه الأنشطه البحريه متنوعه وممتعه لعشاق البحر تبعد عن ميامي ساعات ونصف يومين من الاستجمام تكفي شاركني تجربتك فيها محبي السياحه عشاق امريكا
Restaurant	Each tweet talks about restaurant or coffee	مطعم بخاري الحمراء حي العقيق يفوز الا بخاري بالرياض الي ما ذاقه محروم
Movie	Each tweet talks about movies or series.	فلم جاري توتورو من انتاج استديو جيبلي وتسلسل الاحداث فيه رائع
Music	Each tweet talks about singers	قالها عبدالمجيد عبدالله ما ابي غيرك حتى لو غيرك كثير ابيك إنت بالي قلبك شدني
Politics	Each tweet talks about politics topic	فيه اشياء و قوانين بعيد عن مفهوم اسقاط الولايه و تكفل بعض الحريات البسيطه
Economy	Each tweet talks about economy topic	الاقتصاد السعودي الاقتصاد الإيطالي شيء لاحظته امس الحمدله على النعم الي احنا فيها
Religious	Each tweet includes any religious topics such as prayer	سوره الكهف في صفحه واحده و اليوم الجمعه
Death	Each tweet includes death news	يطوب موجه بقضاء اله وقدره إنتقل الى رحمه اله تعالى ظهر اليوم والدي و حبيبي محمد بن علي السليمان و ستكون الصلاه على المرحوم غدا الأحد بعد صلاه العصر ان شاء اله في جامع الملك فهد في حي الإسكان بالخبر و سيوارى جثمان المرحوم الثرى في مقبر الثقبه
Shopping	Each tweet talks about sales ,offers in the shopping	اكبر عرض مغري في تخفيضات البلاك فرايدي
Weather	Each tweet includes news about weather	شاهد العاصمه الرياض السحب ترحم في كل جه ابشرو الخير
Technology	Any tweet includes application issue or new applications	الانستقرام تراجع عن تصميم الجديد ورجع الشكل القديم اما غير جاهز او مايبون يقعون في خطأ سناب شات

step, we faced some challenges to annotate the tweets with emotion classes because the tweets collected for specific user during four months and pervious researches that applied emotion classification collected the tweets that contain emoticons or hashtags such as #joy #sadness [13]. In order to apply our approach, we chose sample from our dataset that contains emoticons to label them to emotion class. We used Ekman's emotion classification of six basic emotions (joy, anger, disgust, fair, sad, surprise) [14]. We used some criteria for labeling the tweets with emotion. First, the meaning of some words that relate to emotion class as shown in Table 3. Second, we used emoji classification used in [13] as shown in Figure 2. When, we face some tweets that include a conflict between the meaning and the emoji indicators, we label it as hybrid. As in [13], we remove each class with hybrid label.

FIGURE 2. Set of emoticon with their classification [14].

TABLE 3. Emotion label examples.

Label	Example
Joy	كفو والنصر يفتخر بالعشاق أمثالك
Anger	شيء يقهر والله هجمه وحده يهدف
Disgust	مستوى مسخره
Fair	أنا زاد خوفي من ليستر يوم انهزموا
Sad	عوض سيء طول المباراه وشاهد الدقيقه مثلا النصر عالمي فعلا لأنه قدر يرجع للمباراه وعنده نكبات في الملعب
Surprise	انا مستغرب ان اداره النصر موافقه تلعب في الملز رغم أرضيته الخطره اللعب في ملعب النادي هو الحل حتى يتحرك اتحاد الكره اللي كل همه تحقيق طلبات الهلال فقط
Hybrid	دعواتكم لخالتي بالشفاء لعل من منكم اقرب الى الله منا ❤

2.2. Text Pre-processing. Text pre-processing plays an essential role on Twitter data to clean the input documents by eliminating noise and unnecessary data which reduces the classification performance [15]. It aims to transform the input document to be more consistent with text representation. Based on the studies presented on [13], the pre-processing in this work includes the basic steps: tokenization, stemming, and stop-words removal. Furthermore, the Twitter data required extra step to suit its nature such as adding tags and data cleaning. Figure 3 shows our pre-processing steps that apply for each classification.

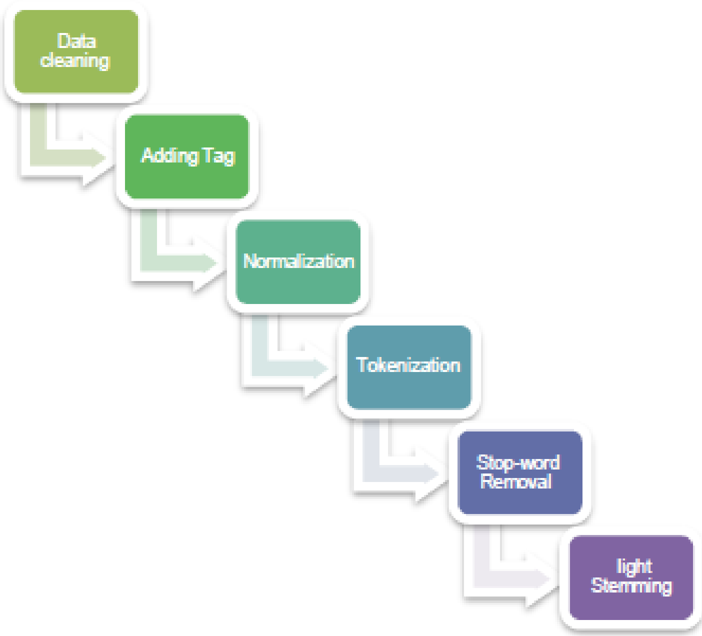

FIGURE 3. Pre-processing Steps.

Data Cleaning: Data cleaning is a critical task for dealing with the noisy nature of Twitter data. There are many noise tokens in Twitter data including references to other users (@Username), URL, and the Re-Tweet (RT) which indicates the sharing of interesting tweets. Besides, we remove numbers, non-letter characters (e.g. + = % $), punctuation marks (except the question mark and exclamation mark) (e.g. . ,: ""; ') and remove all English words.
Normalization: Arabic texts can be formed with the addition of various characters such as diacritics or short vowels and lengthening. Normalization is important in order to manipulate the text and produce consistent word forms. We did some Arabic text normalization which consists of the following steps:
Adding Tags: Emotions in Twitter need special handling. In this step, the emotion symbols were detected and tagged with their corresponding meaningful words, including:

- Stripping diacritics: e.g. " ا لع ر ب ي ة " to " العربية ".
- Replace the letter "ة" by "ه"
- Replace the letter "ى" by "ي"
- Replace the letters " أ-إ-آ " by "ا"
- Normalize repeated letters: e.g. "سعاااادة " to " سعادة "

- The emoji symbols which represent a happy emotion. For example: ":)", will be replaced with the word "فرح " that mean "JOY".
- The emoji symbols which represent a sad emotion. For example: ":(", will be replaced with the word "حزن " that means "SAD".
- Punctuation marks. For example: "!" will be replaced with the word " تعجب" " that means Exclamation Mark" and "?" will be replaced with the word "استفهام " that means "Question Mark".

Tokenization: Tokenization is the process of converting the raw text documents into a sequence of linguistically meaningful units called tokens [15]. In this model, the tweet text is split into a sequence of tokens where each token represents a single word based on white spaces.
Stop-word Removal: In this step, we determine the common words on the dataset that are frequently repeated and they did not provide any information on the text analysis. Removing stop-words helps to have the focus on the most important as well as minimize the dimension.
Light Stemming: Stemming is the process of removing all of word's prefixes and suffixes to reduce words to their stem or root (base form).

2.3. Feature extraction. Feature extraction is a process of transforming data from text into numerical features for machine learning process [14]. In this step, different features were extracted. All the features used for each classification topic of interest and emotion. Some features are special for emotion analysis such as emotion feature and punctuating feature. Then, the extracted features from the text will be used to build the feature vectors using TF-IDF weighting scheme; which are the most used schema. TF-IDF (i.e. frequency of occurrence of the term in the collection of documents)[18] is a numerical measure that expresses how relevant a word is for a document in collection. This measure often used a weight factor in information retrieval and text mining. The value of TF-IDF is increasing proportionally to the number of times that a word is appearing in the document, but it is compensated for by the frequency of the word in the document collection, allowing to handle the fact that some words are generally more common than others [10].

• **Uni-gram Features:** In general, a word n-gram is a contiguous sequence of n words from a given sequence of texts. Many variations of n-gram can be produced depending on the value of n. If the value of n=1, it is called uni-gram or BoW, while if n=2, it is called bi-gram, and if n=3 it is called tri-gram, etc. The bi-gram feature preserves the positions between words sequences; it can detect the appearance of phrases in the document such as negation phrases.

• **Emotion feature:** This feature is used in emotion analysis. In Twitter, people express their emotion using different emoticon symbols. In emotion model, we propose to use the emoticon symbols as extra features with the uni-gram model to indicate the emotion.

• **Light Stemming:** Stemming is the process of removing all of word's prefixes and suffixes to reduce words to their stem. the light stemming aims to enhance feature/keyword reduction while retaining the words meanings. Light stemming removes some defined prefixes and suffixes from the word instead of extracting the original root. We used the combination of light stemming and uni-gram as a feature.

2.4. Classification. Our aim is to classify each account into his/her interest topic in order to identify the emotion in this interest topic. We assume the interest topic is the topic that frequently appeared among all the user's tweets. In this process, we split the data into 70% training data, and 30% testing data. In the training phase, the classifier learns from a set of labelled tweets, and then it is used to classify unlabelled tweets in the testing phase. Both classification topic of interest and emotion are classified separately. The dataset has multiclass. We select two different classifiers: SVM (LinearSVC) [16] and multinomial Bayes classifier [17]. In addition, we split the dataset into training and testing sets by using from sklearn libraries, "train test split" package in order to split 70% of the data for training and 30% for testing. Furthermore, we used sklearn libraries in order to import "classification report" to print the evaluation result. However, we used pipeline in order to apply parallel data processing.

2.5. Evaluation. The classifier is evaluated by measuring its effectiveness, i.e. its ability to make the right classification decisions. A variety of measures was proposed for the classifier including accuracy, precision, recall, and F-measure. After applying the classifier model on the testing data, a confusion matrix will result. This matrix shows the number of correct and incorrect samples in each class. The following section will discuss the results for each classifier.

3. Results and discussion

To observe the correlation between the topic of interest and emotion, we investigate the effect of the selected features in both topics classifiers. Furthermore, we examine the results of two classifier models: Support Vector Machine (SVM) and Naïve Bayes for all the features. Finally, we show the results of the correlation between the topic of interest and the emotion.
In the following, we will discuss the results of the topic of interest classifier which includes the feature extraction and classifier compression and the emotion classifier sequentially.

3.1. Topic of Interest classifier. In order to predict the topic of interest, we investigate the selected features (unigram, bigram, trigram, light stemming) in order to predict the topic of interest. We apply two classifier models to determine the best classifier model for topic of interest.
Table 4 shows the result of classifying the topic of interest by using SVM and Naïve Bayes models with each feature. To illustrate the results, we divided the discussion into features extraction and classifier compression. The selected features for Topic of interest classifier are N-gram features (uni-gram, Bi-gram, Tri-gram) and light

Table 4. Topic of interest classification results.

SVM	TF-IDF			
	accuracy	precision	Recall	F-measure
Uni-gram	93.24	61.75	52.88	56.97
Bi-gram	87.5	61.7	53.1	57.078
Tri- gram	74.66	47.57	38.43	42.514
Stemming+ unigram	**93.5**	68.58	62	65.38
Naïve Bayes	accuracy	Precision	recall	F-measure
Uni-gram	90.8	70	69	69.496
Bi- gram	85.6	67	65	65.98
Tri-gram	73	54.33	52.33	53.311
Stemming +unigram	91.03	71	70	**69.5**

stemming feature. The effect of each feature in the interest of topic classifier model is discussed below.

N-gram features

While comparing the results of different n-gram (uni-gram, bi-gram and tri-gram), we found that the uni-gram has the highest accuracy in both of the classifier models as shown in Figure 4. It means that when the feature is a keyword, it will increase the accuracy unlike when two or three keywords are used. In addition, the accuracy decreases when we use three words as a feature in SVM and Naïve Bayes. The best accuracy's result of uni-gram is 93.24 with SVM while the best accuracy's result of Bi-gram is 87.5% with SVM and Tri-gram's best accuracy is 74.66% with SVM also.

Light stemming

We used light stemming as a feature with uni-gram because it gave higher accuracy than other n-gram features. The result shows that the combination of the two features uni-gram and stemming improved slightly the accuracy when compared with uni-gram feature. However, light stemming gave higher accuracy 's result than other feature in both models. This feature gave the highest accuracy with 93.5 with SVM and 91.01 with Naïve Bayes as shown in Figure 5. This result is explained by the fact that the light stemming is about enhancing keywords feature reduction without losing the word's meaning by removing some Arabic suffixes and prefixes. Finally , we notice that the light stemming improves the accuracy in both of SVM and Naïve Bayes.

Topic of interest's classifier compression

Table 4 above shows the result for each classifier with different features. It can be clearly seen that the SVM outperforms the Naïve Bayes with 93.5 %. In addition, SVM always outperforms Naïve Bayes with all features that have been used. The best result was obtained when SVM was applied with light stemming and uni-gram for the same reason that light stemming enhances keywords feature reduction. The

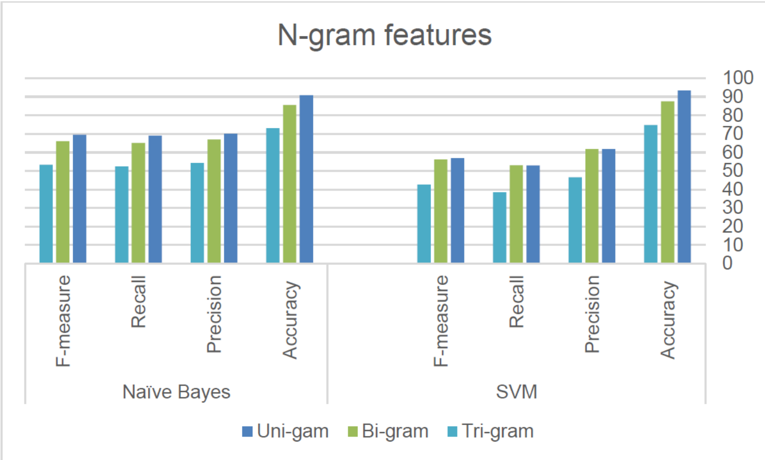

FIGURE 4. Different n-gram results for topic of interest.

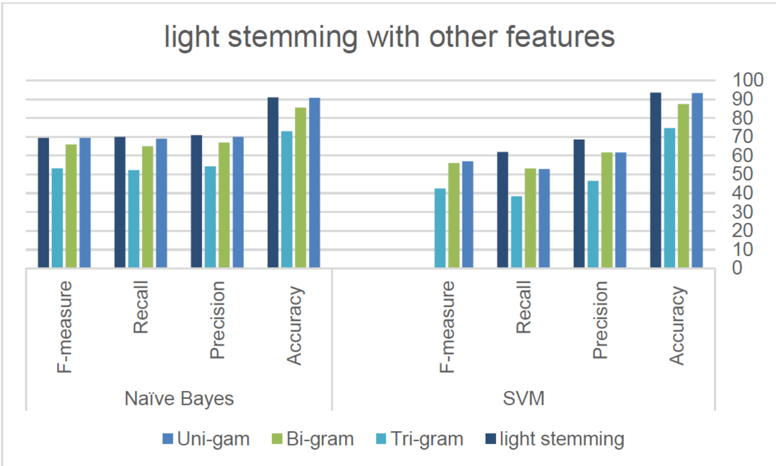

FIGURE 5. Compression of Light stemming with other features.

accuracy means that SVM can predict correctly 93.59% of tested data. However, F-measure gave the best result for instance 69.5%, when using Naïve Bayes with Bi-gram feature. In addition, we observe that Naïve Bayes gave higher result in the recall and the precision than SVM. We notice that the accuracy decreases when two keywords (bi-gram) and three keywords (tri-gram) were used with both classifiers. The least accuracy, 73%, was obtained when applying Naïve Bayes with Tri-gram.

3.2. Emotion classifier. After applying the Topic of interest classification, the same steps were applied to build the emotion classifiers with the addition of particular feature: the emoticon feature. Below, we discuss the effect of each feature in order to predict the emotion. As we did with the topic of interest, two classifier models SVM and Naïve Bayes were applied. Table 5 shows the results of emotion classifier models with all the features.

Table 5. The emotion classification results.

SVM	TF-IDF			
	accuracy	precision	recall	F-measure
Uni-gram	59	48.8	44	46.23
Bi-gram	50	36	33.2	34.54
Tri- gram	47.5	23	25.2	12.02
Emoticon+uni-gram	65.8	56.6	51.8	54.9
Light Stemming+ unigram	60	50.6	45	47.63
Light Stemming +emoticon+ uni-gram	**67.08**	57.8	52.2	55.8
Naïve Bayes	accuracy	precision	recall	F-measure
Uni-gram	50.6	35.33	41	37.96
Bi- gram	47.5	40.5	54.95	43.7
Tri-gram	45.3	32	50	39.02
Emoticon +uni-gram	54.9	46	58	51.3
Light Stemming +unigram	51.24	36.33	41.33	38.66
Light Stemming +emoticon + unigram	55.42	42.67	45	42

Many features were tested in emotion classifier: n-gram features (uni-gram, bi-gram, tri-gram), stemming with uni-gram, emoticon with unigram and combination of emoticon, stemming and uni-gram features.

N-gram features

As mentioned above, the use of uni-gram increases the accuracy in both of the classifier models (SVM, Naïve Bayes). Table 5 shows the accuracy which is slightly low and where the best accuracy is 59 % when applying uni-gram with SVM. In addition, the other n-gram features gave a low accuracy. This could be due to the fewer number of dataset compared to the topic of interest and the data set is unbalanced.

Light stemming feature

As shown above, the light stemming slightly increases the accuracy of the two classifier models (SVM, Naïve Bayes) for the same reason that light stemming reduces the feature keywords. However, SVM has higher accuracy than Naïve Bayes. Furthermore, when combining the light stemming with emoticon the accuracy is slightly improved. In addition, we observe the light stemming also in emotion classifier improved the accuracy results. When we compare between the results of uni-gram and light stemming with unigram, we find that the accuracy is improved slightly from 59% to 60% with SVM and from 50.6% to 51.24% with Naïve Bayes.

Emoticon feature

When comparing the results of all the features with the emoticon one, we noticed that using emoticon improved the accuracy. When comparing the combination of two features (unigram and emoticon) with the uni-gram feature, we can see that the emoticon improved the accuracy from 59 % to 60.8%. Moreover, when comparing the result of the combination of three features (emoticon, stemming and uni-gram features) with the feature including unigram and light stemming, we find that the emoticon improved the accuracy from 60% to 67.08%. The combination of three features (emoticon, stemming and uni-gram features) has higher accuracy than the feature that includes unigram and emoticon only. For both classifier models, we notice that combining three features increases the accuracy. The highest accuracy reaches 67.08 when using SVM.

The emotion's classifier compression

For the emotion classifier model, we applied the same process as for the topic of interest. Table5 shows the result for each classifier with different features. It can be clearly seen that the SVM gave the highest accuracy compared to Naïve Bayes with 67.08%. In addition, SVM always gave higher accuracy than Naïve Bayes with all used features. The best result was obtained when SVM is applied using a combination of three features: light steaming, uni-gram and emoticon. In addition, we observe the tri-gram feature gave accuracy less than 50% in both of SVM and Naïve Bayes so this feature does not fit well in emotion classifier. As for Bi-gram feature which gave low accuracy also. However, the accuracy of emotion classifier is lower than the topic of interest due to the fact that the number of the dataset of the topic of interest is greater than emotion. In addition, emotion dataset has unbalanced classes. The annotation of emotion was challengeable because the topic of interest comes down to keywords while the emotion relies on the meaning of the tweets which need more features such as part of speech to improve the accuracy results. Finally, we apply two classifications one for the topic of interest and the other for the emotion. There are common features between the two classifications such as N-gram and light stemming. We observe that the uni-gram gave higher accuracy results than bi-gram and tri-gram for both of topic of interest classification and emotion classification. Also, the results show that the use of two keywords as a feature (bi-gram) decreasee the accuracy by not less than 5%. Furthermore, the tri-gram (three keywords) is considered to be less accurate than the other n-gram features. In addition, the combination between the light stemming and uni-gram improved slightly the accuracy by at least 1% in each classification (topic of interest and emotion). There is a special feature for emotion classifier which is emoticon. This feature generally increases accuracy by 5% whether used with light stemming or not. However, the two supervised learning algorithms SVM and Naïve Bayes have been tested for a topic of interest and emotion. We can see the SVM gave higher accuracy than Naïve Bayes for both classifications (topic of interest and emotion).

3.3. The correlation between topic of interest and emotion. This subsection is dedicated to observe the correlation between the topic of interest and emotion. We chose four users to carry out this experiment. The selection of users was based on

the number of their tweets as well as the data that contains indication of emotion in order to apply this experiment. However, we conducted some analysis to understand much more the data. We found that the time between 15-18 (from 3:00 till 6:00 PM) is considered as the peak activity for all users, although the user's activity varies. This result demonstrates the importance of determining the most appropriate time for advertising to reach the most significant number of users.
However, the variation of interests for all users was observed during the days. In the following, we discuss for each user the results and we conclude by the final finding.

Figure 6 shows the topic of interest and emotion for the first user. The sport was the most topic of interest that appeared in this user's tweet, but he also posts about shopping at 5:00am then tourism at 8:00am, politics at 9:00am and religion appeared at different times. However, when we see the chart that contains emotion, we observe that differences of emotions appeared. Anger takes a higher proportion than other emotions when we exclude the neutral class. Also, when the user post about tourism, the joy appeared unlike when he posts about the religion. Neutral appeared for the majority of tweets that deal with religion. Figure 7 shows the second user's results.

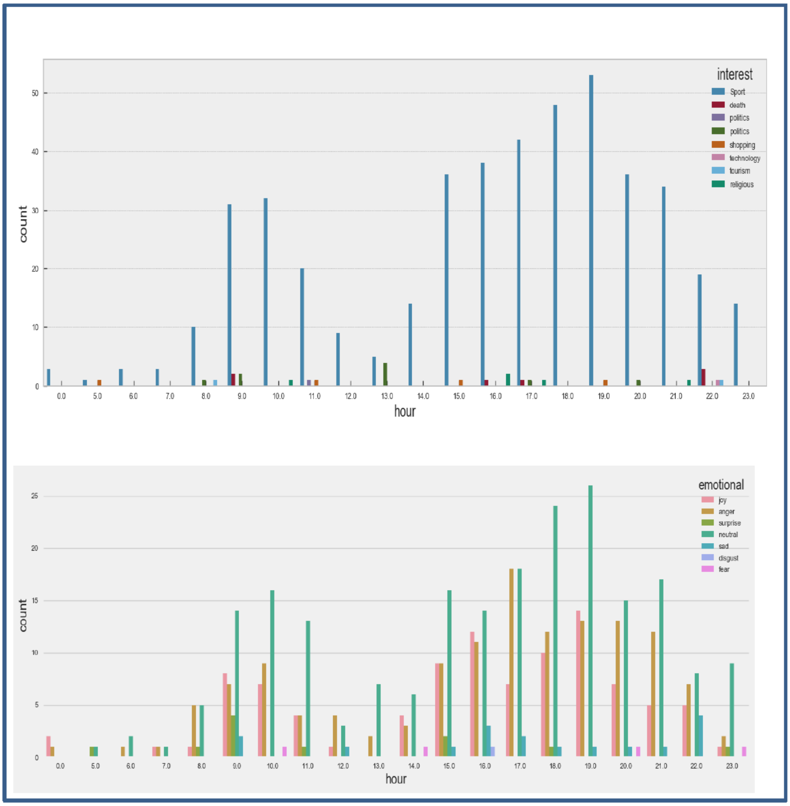

FIGURE 6. The first user results.

We can see the sport was the most frequent topic, but he posted more about politics in different times from morning till afternoon. Restaurant, music, and movie appeared

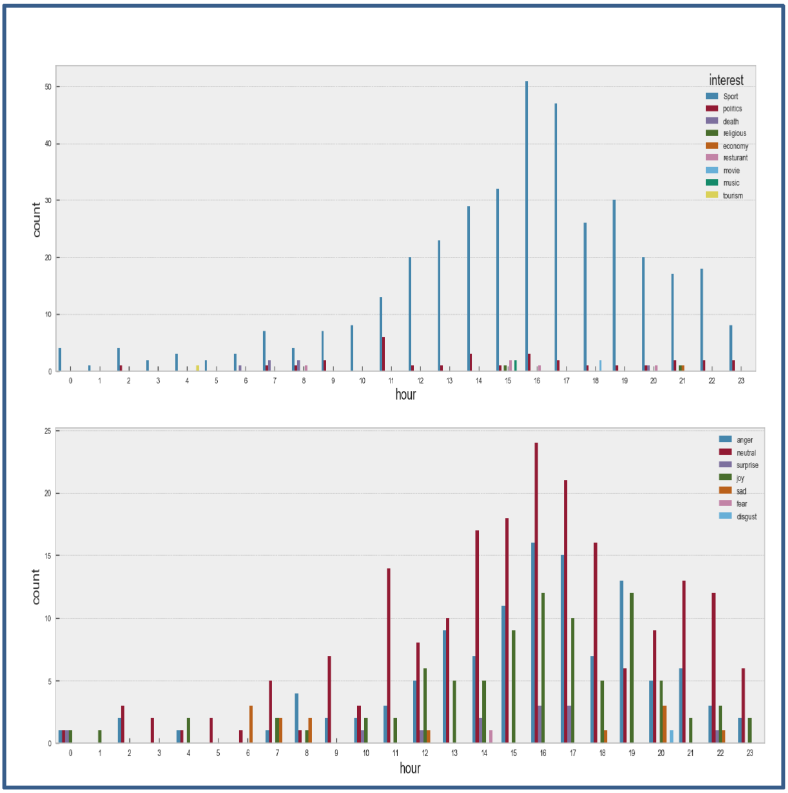

FIGURE 7. The second user results.

also. When we see the emotion chart, we observe that when a user posted about politics three different emotions were expressed (anger, joy, sad) in addition, the restaurant topic appeared mostly with joy similarly to music and movie topics. The results of the third user are shown in the Figure 8. This user, unlike the other users has a more diverse topic of interest. The interests vary from Politics and Tourism. He was also interested in shopping at 11am and 4pm. Furthermore, tweets about the economy was posted from the afternoon till the evening. We can see in emotion chart, the appearance of politics linked with neutral because each tweet contains news which does not express any emotion. While the presence of shopping and tourism, the expression became more joy. The last user posted about sport only as shown in the Figure 9. While the emotions were varying from joy to anger and sad during the different periods.

After observing and discussing the situations related to the four users, we found that the changes of interest for the first three users were accompanied by changes in emotions. However, it was not the case for the last user. His topic of interest does not vary all the time even though he expressed different emotions. We conclude, from the experiment that the user interest may change through the time. These changes can be related to the user emotion. Indeed, some topics of interests are associated with specific emotion such as tourism is associated with joy; sport is associated with anger, and restaurant, movie, music are associated with joy. However, some other topics of interests such as politics, religious are challenging to determine their emotions.

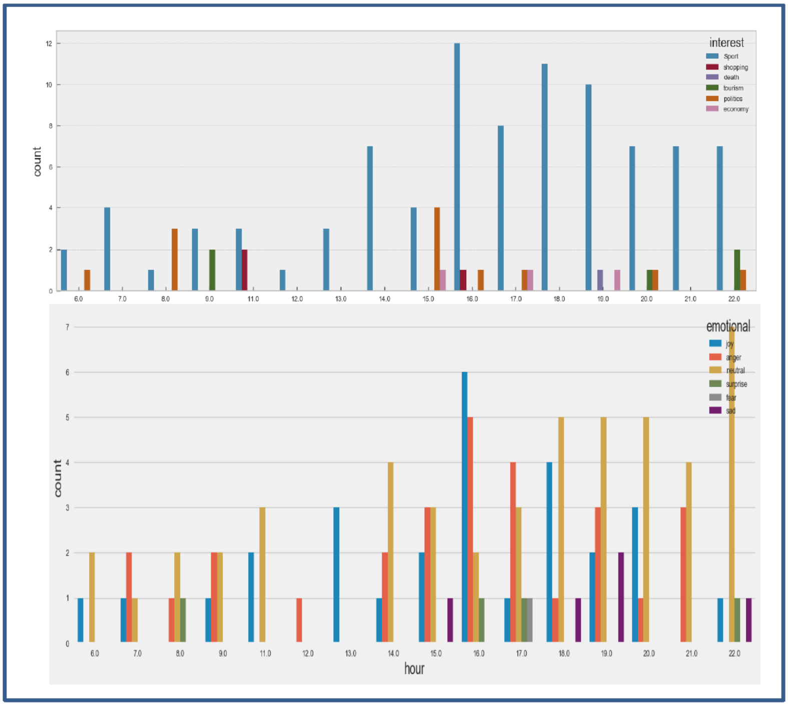

FIGURE 8. The third user results.

4. Conclusion

The correlation between the topic of interest and emotion has been investigated in this work. The experiment shows that the user's interests in majority of time are changing during the day according to the emotions. We notice that the interests of three of the four users on the dataset changed during the day according to their emotion. In addition, we find that some topics of interest are associated with specific emotion such as restaurant, music, movie are associated with joy whereas sport is more likely associated with anger or sad. The result of this experiment proves that the change of user's interest is mostly associated with changing their emotion. Certainly, we suggest that the advertisement and the recommender systems should take the emotions into consideration. For instance, if a company is advertising a tour package, for example, it should take the emotion into consideration with a topic of interest because the emotion may change the user interest. Therefore, we consider that determining the user's interest is not sufficient on its own since it changes over time and should be studied and determined related to the emotion of the user.

FIGURE 9. The fourth user results.

Acknowledgements

The authors extend their sincere appreciation to Deputyship for Research and Innovation, "Ministry of Education" in Saudi Arabia for funding this research (IFKSUOR3-232-1).

References

[1] A. Abdel-Hafez, Y. Xu, A Survey of User Modelling in Social Media Websites, *Computer and Information Science* **30** (2022), no. 3, 5–20.

[2] N. Reimann, Twitter Hemorrhaging Its Most Active Users, Report Says, https://www.forbes.com/sites/nicholasreimann/2022/10/25/twitter-hemorrhaging-its-most-active-users-report-says/?sh=e34ed5e6e5e1

[3] Statista Search Department, Countries with the most X/Twitter users 2023. Statista, https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries (Accessed September 13th, 2023.)

[4] T.S. Sai Kumar, K. Arunaggiri Pandian, S. Thabasum Aara, K. Nagendra Pandian, A Reliable Technique for Sentiment Analysis on Tweets via Machine Learning and BERT, *Asian Conference on Innovation in Technology (ASIANCON)* 27 August (2021).

[5] R. Abbasi, G. Rehman, J. Lee, F. M. Riaz, B. Luo, Discovering temporal user interest on twitter by using semantic based dynamic interest finding model (TUT), *2017 IEEE 2nd Information*

Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chengdu, China, 2017, 743–747. DOI:10.1109/ITNEC.2017.8284832

[6] N. Nimita Mangal, S. Sartaj Kanwar, R. Rajdeep Niyogi, Prediction of Twitter Users' Interest Based on Tweets, In: (J. Mandal, S. Satapathy, M. Sanyal, V. Bhateja (Eds.)) *Proceedings of the First International Conference on Intelligent Computing and Communication. Advances in Intelligent Systems and Computing*, **458** (2016), pp. 167–175, Springer, Singapore. DOI:10.1007/978-981-10-2035-3_18

[7] Ma. Cebral-Loureda, A. Hernandez-Baqueiro, E. Tamés-Munoz, A text mining analysis of human flourishing on Twitter, *Scientific reports* **1**3 (2023), Article number 3403.

[8] A.P. Logan, P.M. LaCasse, B. Lunday, Social network analysis of Twitter interactions: a directed multilayer network approach, *Soc. Netw. Anal. Min.* **1**3 (2023), Article number 65.

[9] M.A. Al-Hagery, M.A.Alassaf, F.M. Al-kharboush, Exploration of the best performance method of emotions classification for arabic tweets, *Indonesian Journal of Electrical Engineering and Computer Science* **1**9 (2020), no. 2, Article number 1010.

[10] M. Abdullah, M. AlMasawa, I. Makki, M. Alsolmi, S. Mahrous, Emotions extraction from Arabic tweets, *International Journal of Computers and Applications* **4**2 (2020), no. 7, 661–675.

[11] M.N.M. Shelke, Approaches of Emotion Detection from Text, *International Journal of Computer Science and Information Technology* **2** (2014), 123–128.

[12] S.B. Kotsiantis, Supervised Machine Learning: A Review of Classification, *Informatica (Slovenia)* **3**1 (2007), 249–268.

[13] I.D. Wood, S. Ruder, Emoji as Emotion Tags for Tweets, *Proceedings of LREC, Workshop, Emotion and Sentiment Analysis* (2016), 76–79.

[14] P. Ekman, An argument for basic emotions, *Cognition and Emotion* **6** (1992), no. 3–4, 169–200.

[15] M. Ikonomakis, S. Kotsiantis, V. Tampakas, Text Classification Using Machine Learning Techniques, *WSEAS TRANSACTIONS on COMPUTERS* **4** (2005), 966–074.

[16] sklearn.svm.LinearSVC - scikit-learn 0.20.3 documentation. https://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html

[17] sklearn.naive-bayes.MultinomialNB - scikit-learn 0.20.3 documentation. https://scikit-learn.org/stable/modules/generated/sklearn.naive-bayes.MultinomialNB.html

[18] D. Kim, D. Seo, S. Cho, P. Kang, Multi-co-training for document classification using various document representations: TF-IDF, LDA, and Doc2Vec, *Information Sciences* **477** (2019), 15–29.

(Henda Ouertani) Information Technology Department, College of Computer and Information Sciences, King Saud University, P.O. Box 2455, Riyadh 11451, Saudi Arabia.
E-mail address: houertani@ksu.edu.sa