A Framework for Emotion Mining from Text in Online Social Networks

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Abstract— **Online Social Networks are so popular nowadays that they are a major component of an individual's social interaction. They are also emotionally-rich environments where close friends share their emotions, feelings and thoughts. In this paper, a new framework is proposed for characterizing emotional interactions in social networks, and then using these characteristics to distinguish friends from acquaintances. The goal is to extract the emotional content of texts in online social networks. The interest is in whether the text is an expression of the writer's emotions or not. For this purpose, text mining techniques are performed on comments retrieved from a social network. The framework includes a model for data collection, database schemas, data processing and data mining steps. The informal language of online social networks is a main point to consider before performing any text mining techniques. This is why the framework includes the development of special lexicons. In general, the paper presents a new perspective for studying friendship relations and emotions' expression in online social networks where it deals with the nature of these sites and the nature of the language used. It considers Lebanese Facebook users as a case study. The technique adopted is unsupervised; it mainly uses the k-means clustering algorithm. Experiments show high accuracy for the model in both determining subjectivity of texts and predicting friendship.**

Keywords - Online Social Networks, emotion mining, text mining, friendship, emotions.

I. INTRODUCTION

The growth in popularity of online social networks has significantly affected the way people interact with friends and acquaintances nowadays. Indeed, interacting through online social networks and online chatting systems has become ubiquitous, and a major component of a person's life.

Friendships and social relationships can be deduced and observed on these sites since they reflect the continuous interaction between the subjects and are evidently emotionally rich environments.

In this paper, the interest is in mining emotions from texts shared in online social networks in the form of wall posts and comments. The purpose is not to identify specific emotions but rather to tell if the text contains emotions or not; in other words, if the text is subjective reflecting the writer's affect and emotional state or if it is factual and objective where the writer does not express any feelings.

An application of this approach is to predict relationship strength between two individuals based on the affective content of the comments they share online. In this case, the primary interest is whether the individual communicates his emotions in the text or not. The decision to convey emotions in the text is greatly influenced by the strength of the relationship. Thus this technique can be applied to separate the close friends from the acquaintances on online social networks.

A particularity of texts in these environments is the lack of sentence structure and the use of informal language specific to these settings and different from the formal written language. These factors should be taken into consideration when performing any type of text mining.

This paper uses Lebanese Facebook users as a case study, and applies an unsupervised technique to categorize texts based on subjectivity.

The rest of the paper will be divided as follows: section II presents the literature review pertaining to emotion mining from texts. Section III presents the proposed framework. The evaluation of the model is the subject of section IV and the conclusion is included in Section V.

II. LITERATURE REVIEW

A. Emotions

Emotions are mental states accompanied by physiological changes. Ekman identified six basic emotions: happiness, sadness, anger, fear, disgust and surprise [1]. Other approaches do not search to categorize emotions in specific categories, but rather identify them on two scales: the valence of the emotion indicating if the feeling is positive or negative and the arousal level indicating the energy level associated with the emotion [2].

In fact, Thelwall et. al. performed emotion mining from texts retrieved from the online social network MySpace. They argued that studying emotions based on a 2-dimensional scale (i.e. valence and arousal) is more reliable and provides more accurate results than studying emotions on a finer grain [2].

Although emotions are universal, there are huge differences between cultures and between individuals in the way and the extent in which these emotions are expressed. In general, women are more likely to share their emotions and their feelings than men; and this observation was also verified in online social networks [2]. Furthermore, personality is an important factor influencing emotions. Social factors have also an effect on emotions where the expression of emotions is not limited to a person's internal feelings but influenced by the

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society, a person's strategic goals and previous experiences [2].

In the following section, techniques of sentiment mining will be presented.

B. Emotion Mining

Emotion mining can be divided into three categories depending on the purpose for mining emotions. The first category aims at extracting the valence of the text, indicating if the text has positive or negative emotions associated with it. The second category aims at identifying whether the text is subjective or factual (i.e. objective), thus the purpose is to find if the text is emotionally rich or not. The third category aims at recognizing not just the emotion but also its strength or arousal.

An example of the last category is provided by Wilson et al. in [3]. The paper classifies text according to the strength of the emotion, along with the partitioning into subjective and objective texts. The approach is based on a human annotated text corpus, and a major limitation is the difference in strength annotations measures between annotators. Additionally, it relies on syntax clues and thus requires correct sentence structure.

Several techniques have been used to automate emotion mining. These can be generally, with some exceptions, classified into four categories:

The first category employs Keyword Spotting; it is based on a lexicon or a dictionary grouping words that have emotional connotations. These techniques predict the emotions of the writer by identifying these affective words from the text. The words are unambiguous and reflect clearly a particular emotion, for instance "happy" reflects happiness and "scared" reflects fear. These techniques are popular because of their simplicity and economical advantage. However, they rely on individual words that is why they perform poorly when the sentence structure is more intricate, (e.g. use of negation). Additionally, their dependence on the text's surface features hampers their ability to uncover underlying emotions from the text.

These techniques rely on available lexicons. One such example is WordNet-Affect [4] which is based on WordNet; the latter is a semantic lexicon where words are grouped into sets of synonyms (called "synsets"); WordNet-Affect further annotates the synsets that have an affective content. Another example is SentiWordNet [5] which assigns WordNet synsets a graded measure with respect to two scales: a positive/negative scale and a subjective/objective scale. It is important to note that the classification is based on synsets, not on words (because a word can have multiple meanings). Unfortunately, due to the large size of the database it is hard to test the accuracy of the measures for all synsets. That is why some approaches have combined multiple lexicons for increasing the accuracy of the results. For instance, a combination of WordNet-Affect and SentiWordNet has been used in [6].

The second category employs Lexical Affinity measures. These techniques are a bit more refined than keyword spotting where they assign for each word a probabilistic affinity for a certain emotion. For example, the word "success" has an 80 % probability of reflecting a positive event. Similar to keyword spotting, lexical affinity techniques perform poorly when facing intricate sentence structures like "This was not a success at all!" (i.e. negation). Additionally, the probability measures may be dependent on the text corpus used in the training. An example of lexical affinity measure is the emotional weight used in [7]. This measure is computed for each word as being the ratio of emotional senses over the total senses the word may have. WordNet and WordNet-Affect are used in order to recognize the total number of senses and the number of emotional senses. This task is easy since it suffices to count in how many synsets the word appears.

The third category uses Statistical Natural Language Processing techniques. These techniques employ machine learning algorithms to learn words' lexical affinities and words' co-occurrence frequencies [3, 8]. Unfortunately, the findings have no predictive value unless a large text corpus is used for training, especially in the social networks domain where the used language lacks proper structure and statistical rules are harder to learn; thus it might not be feasible to use these techniques simply because openly available training data are hard to find.

The last category consists of Hand-crafted Models. These models use deep understanding of the particular text in order to mine for emotions. They are complex systems and their findings are difficult to generalize to other texts. An example of such models is in [9].

An improvement on hand-crafted models is provided by Liu et al. in [10]. The paper uses real world knowledge to extract affect from sentences. It is based on affective commonsense where the text context involving a particular event or situation is examined. Next, knowledge of the feelings invoked by this particular event is used to deduce the affect of the text. The strength of this technique is that it can mine emotions at the sentence level and can provide an accurate result since emotions are evidently context-dependent. However, it is dependent on the particular real-world knowledge database used, and it assumes that all individuals feel the same way about a certain life event. The technique classifies emotions into the 6 basic emotions proposed by Ekman. The above example shows that emotion mining can be done at multiple granularities, it can deal with comments individually, or relate a comment to previous ones, or even extract information about the context of this comment and use real-world knowledge in order to better assess the emotion mined [10].

C. Language in Online Social Networks

Texts in online social networks have their specificity that must be taken into account. Indeed, it is common in these sites for users to use an informal and less structured language to communicate with their friends. Corney et. al. presents in [11] some features of this “online language”. They are presented here in addition to other interesting features:

- Intentional misspelling, in particular the repetition of a letter in the same word, (e.g. “helloooooooo”).
- Interjections and lexical surrogates for vocalizations (e.g. “mwah” indicating a kiss or “hmmmm”).
- Grammatical markers such as the use of upper-case letters and the excessive use of punctuation (e.g. repetition).
- Social Acronyms: Acronyms of popular expressions used in online chatting systems and online social networks. For instance “BRB” denotes the expression “be right back”.
- Emoticons: visual arrangements of characters in order to form facial expressions conveying emotions. For instance “:)” indicates joy and “:(” indicates sadness.

In addition to this informal language, sentences may also lack proper syntax structure and words may be misspelled. Furthermore, specific to the non-English users is the use of non Latin-based languages transliterated into the English Alphabet; the use of other languages such as French and Spanish is also common.

III. Proposed Framework

In this section, we first present the general architecture shown in Figure 1 and then elaborate on each part.

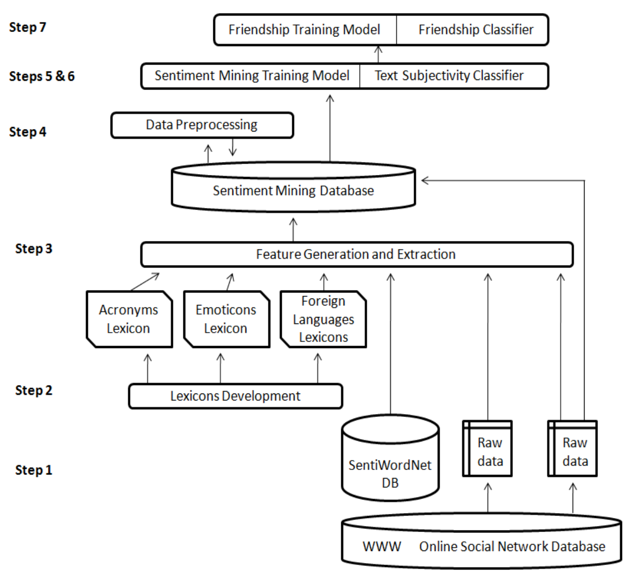

Figure 1: Framework Architecture

A. Architecture

The framework shown in Figure 1 is structured into six steps:

1. **Raw data collection:** This step is concerned in collecting exchanged texts between users. This is done through a social network application which gathers data from the social network and stores them in a custom database.
2. **Lexicons development:** This step deals with the informal language of online social networks. For this purpose, three types of lexicons have to be developed: lexicons for social acronyms, for emoticons and for expressions in foreign languages.
3. **Feature generation:** This step computes new features from available raw data collected in step 1 to assess subjectivity of text. It uses word-matches to existing affective lexicons and employs new lexicons developed in step 2 to handle social acronyms, emoticons and foreign languages transliterated into English. Accordingly, comments collected from step 1 along with the features computed in this step will be stored in the Sentiment Mining Database which is the database used for analysis.
4. **Data preprocessing:** This step is applied on extracted features. It involves removing redundant attributes, discretization by clustering and normalization using Min-Max.
5. **Creating a training model for text subjectivity:** This step generates a model using k-means clustering algorithm with k=3 to categorize texts into three subjectivity levels: neutral, moderately subjective and subjective. The output of the model is the three centroids of the clusters.
6. **Text subjectivity classification:** This step uses the centroids generated in the previous steps and employs the k-nearest neighbor algorithm with k=1 to classify all comments into one of three subjectivity levels.
7. **Friendship Classification:** This step generates an SVM training model and then uses it to predict tie strength between online friends based solely on the subjectivity of the texts they share online. The classification is done by first classifying the subjectivity of the texts exchanged which is performed in step 6 and then taking an average measure. Online friends are classified in one of two classes: close friends and acquaintances.

In what follows, we discuss the steps of the framework proposed.

B. Raw Data Collection

The gathering of training data in step 1 is done through the creation of a social network application communicating with the social network API. The application retrieves relevant user information and stores them in a special database whose schema is discussed below. The owners of the data must be aware of the nature and the purpose of the data collected and must explicitly give consent for the use of their data. In this paper, we consider Facebook users as a case study; consequently we have developed a Facebook application that collects data from Facebook and stores them in a custom database.

The database schema is proposed below:

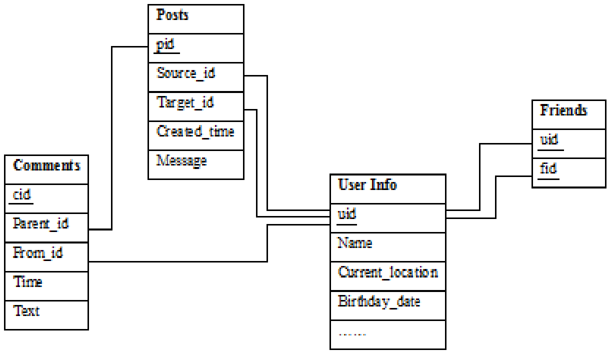

Figure 2: Tables containing raw data

The *UserInfo* table contains the static personal user information that the user has displayed on his profile. The *uid* is a unique identifier assigned to each user and will thus allow the system to locate the user throughout the tables.

The *Friends* table contains all the tuples consisting of a user and his friend.

The tables containing the texts to be mined for emotions are *Posts* and *Comments*.

The *Posts* table contains the messages posted on the user's wall. Each post is assigned a unique number *pid*, a *Source_id* (the id of the user who started the post), a *Target_id* (the target's user id) and the content of the message along with a timestamp.

The *Comments* table contains the user's responses to a wall post. It includes the *Parent_id* (id of the post), the id of the user posting the comment (*From_id*), the time, the text content and the comment's unique id (*cid*).

The above represents the raw data collected. Other features that will be computed from the raw data will also be stored in the database.

C. Lexicons Development

Texts in online social networks are frequently written in an informal language. For this purpose, we developed three types of lexicons in step 2. First, we prepared a lexicon of popular social acronyms used in online social networks and in online chatting. The lexicon is in no way exhaustive as it is impractical to cover all possible social acronyms. Indeed, social acronyms are randomly created and adopted by a small group, and only few of these acronyms are spread to the general online community. The table below illustrates some of the popular acronyms:

Table 1: Social Acronyms

Acronym	*Significance*
B4N	Bye for now
CU	See you
GR8	Great
LOL	Laughing out loud
TTYL	Talk to you later

Similarly, a lexicon has been developed for interjections and for emoticons. The lexicons are not universal but they cover a large percentage of what is globally used in online networks. Tables 2 and 3 illustrate examples of interjections and emoticons respectively.

Table 2: Interjections

Interjections
haha, hehe
waw, wow
oh
hey

Table 3: Emoticons

Emoticons	*Significance*
:) ; :-) ; :> ; :]	Smiling
:(; :-(; :< ; :[	Sad
:* ; :-* ; :-x	Kissing
:P ; :-P	Joking

Similar to the approach in [12], emoticons and abbreviations are related to the actual words they represent, and accordingly are given a subjectivity weight.

It is also necessary to take into consideration the use of foreign languages. The latter practice involves mainly some popular and frequent expressions which can be grouped in lexicons. In the case of Lebanese users, we have to deal with the use of Arabic transliterated into English, this is why we added a small lexicon grouping popular words and expressions used by Lebanese Facebook users. However, since the spelling of this type of words is not universal, the lexicon contains mostly words' roots instead of complete words. The roots are at the same time exclusive with respect to other words, where a root maps to a unique word and inclusive with respect to the different spellings of the same word. Table 4 is an example illustrating the root used for a set of words that denote "I love you".

Table 4: Arabic Transliterated in English Alphabet

Root	*Different Spellings*	*English Translation*
7eb	b7ebbak, b7ebak, b7ebbik, b7ebik, 7ebbak…	I love you

Similarly, we extended the lexicon to contain some popular French words commonly used between Lebanese Facebook users.

D. Feature generation

In order to assess the subjectivity of the text, several features need to be computed. This is done in step 3. These are grouped into three categories:

The first category is based on SentiWordNet, an affective lexicon. Features in this category include the number of affective words, the average subjectivity measure of affective words, etc…

The second category is based on intentional misspelling errors and grammatical markers such as punctuation and capitalized letters. Features in this category include the number of punctuation marks, number of capitalized letters, average number of repeated letters when letters are repeated consecutively at least three times, etc...

The third category is based on social acronyms, interjections and emoticons. Features representing this category include number of interjections, emotional weight of emoticons, etc…

E. Data Pre-processing

After generating several features, some data pre-processing techniques were performed on the data in step 4.

First, feature selection was performed based on a correlation measure to remove redundant attributes. This resulted in nine attributes. They are shown in table 5.

Table 5: List of Attributes

Attribute
Number of affective words
Average subjectivity measure of affective words
Number of capitalized letters
Number of punctuation marks
Number of repeated letters when letters are repeated consecutively at least three times
Number of interjections
Number of social acronyms
Number of emoticons
Average rating of emoticons

Second, the values of the attributes were continuous, and needed to be mapped to discrete values. The mapping to discrete domains seemed intuitive since the goal was to deduce whether the text is subjective or not and knowing for example the exact number of punctuation marks would be irrelevant, whereas knowing whether the writer uses few or many punctuation marks would definitely denote some sort of subjectivity. Accordingly, discretization was done using clustering. The k-means algorithm was performed on each attribute with k=3 or k=4. The values of the attributes were replaced respectively by the centroid of the cluster they belong to.

Finally, the values in each attribute were normalized using Min-Max normalization which mapped them to the range [0;1].

F. Training Model for Text Subjectivity

In studying the subjectivity of text in online social networks, we adopted an unsupervised approach. The training was done in step 5 using the k-means clustering algorithm with k =3. The goal was to cluster the texts into three categories. The first consisted of objective or factual texts, the second contained moderately subjective texts suggesting some kind of friendship between the users and the third consisted of subjective texts suggesting a close friendship between the two users.

The output of the model was the centroids of the three clusters and is used in step 6 for classifying the comments with respect to subjectivity. Step 7 is the application of text subjectivity mining to friends' classification.

IV. MODEL EVALUATION

This section presents the results and discusses the findings of the proposed method. The training data consisted of 2087 comments extracted from Facebook, with the consent of the users.

The evaluation of the model was done at two different levels. First, we tested how accurate the clustering algorithm was in recognizing three different classes of texts with respect to text subjectivity. Second, we tested the accuracy of the model in determining based solely on the subjectivity of the text, the relationship's strength between two Facebook users.

A. Text Subjectivity Classification

This section tested the ability of the model to recognize three different classes of texts, based on the subjectivity of the writer. A sample of 850 comments were extracted from the database and categorized manually into the three classes by three different persons by majority vote. Inter-annotator agreement is reported in Table 6.

Table 6: Inter-Annotator Agreement

	The 3 annotators agree	**Only 2 annotators agree**	**No inter-annotator agreement**
Number of comments	736 (86.6%)	97 (11.4%)	17 (2.00%)

The manual annotation was then compared to the predicted result by the model. A sample example is illustrated below.

Table 7 shows three different comments, one from each class:

Table 7: Example of Comments

Comment ID	**Comment**	**Class**
1	carooooooooooooooooooooooo im going to kiiiillll uuuuuuuuuuuuuuuu... n u know why! but i still looove u (a little bit:P) dont worry :P mwahhh	subjective
2	i love ur profile pic, its much better like this :) best	moderately subjective
3	86 and u how much did u get ?	objective

The above comments are the results of step 1 which is raw data collection.

In what follows, we present the model's output for the three above comments. Table 8 illustrates some of the features generated in step 3 and Table 9 shows the same data after preprocessing (discretization and normalization) in step 4.

Table 8: Data after feature generation

Comment ID	Repeated Letters	Number Emoticon	Rating Emoticon	Number Acronyms	Number affective words	Rating affective words
1	7	2	3	1	5	0.7676813
2	0	1	1.5	0	5	0.7702409
3	0	0	0	0	0	0

Table 9: Data after preprocessing

Comment ID	Repeated Letters	Number Emoticon	Rating Emoticon	Number Acronyms	Number affective words	Rating affective words
1	1	0.01094	1	0.02305	0.45267	0.267515
2	0	0.01094	0.5	0	0.45267	0.267515
3	0	0	0	0	0.04382	0.013532

The training model for text subjectivity is generated in step 5. The output of the model is the centroids of the 3 clusters, shown in Table 10 with only six attributes. The subjectivity weight assigned for each centroid is the Euclidian distance between the centroid and the origin.

Table 10: Centroids of the Three Clusters

Number Punctuation Marks	Repeated Letters	Number Emoticon	Number Acronyms	Number affective words	Rating affective words	Subjectivity weight
0.742402	0.855892	0.3073	0.2093	0.4032	0.3772	1.440489
0.1469	0.120589	0.16317	0.1749	0.2113	0.261	0.889034
0.104403	0.03921	0	0.1159	0.1026	0.1734	0.244849

Table 11 shows the results of the classification using k-nearest neighbor algorithm with k=1 done in step 6. The comment subjectivity weight is the subjectivity weight of the closest centroid.

Table 11: Classifier Output for the three sample examples

Comment ID	Comment Subjectivity Weight	Class
1	1.440489	subjective
2	0.889034	moderately subjective
3	0.244849	objective

Evaluating the model was done by applying the same above procedure on the sample of 850 comments. In general, the model predicted the right class 88% of the time. Table 12 illustrates the results.

Table 12: Model's Clustering Results

Type of text	Predicted as objective	Predicted as moderately subjective	Predicted as subjective	Total
Objective	119 (88 %)	14 (10 %)	3 (2 %)	136 (16 %)
Moderately subjective	38 (8 %)	432 (90 %)	11 (2 %)	481 (57 %)
Subjective	5 (2 %)	31 (13 %)	197 (85 %)	233 (27 %)
Total	162 (19 %)	477 (56 %)	211 (25 %)	850 (100%)

The model was more likely to mildly underestimate the subjectivity when predicting a wrong class. This was probably due to the fact that the lexicons were not exhaustive and that many other symbols and words are used to express subjectivity, more specifically, the extensive usage of foreign languages (such as French, Armenian, etc…) and of Arabic transliterated in English Alphabet.

An interesting observation was that the model predicted that nearly 81% of Facebook comments contained some sort of subjectivity. The result was similar to the number of comments rated as subjective manually, which was 84%. It was also analogous to the result found in [2], which was 83%.

B. *Friendship Classification*

Another way to evaluate the model was to test its results when it comes to using it for friends' classification. In other words, the model was used to predict relationship strength on Facebook. Indeed, a way to evaluate friendship between two Facebook users is to examine the comments shared on the site between these users. We expect that the relationship is stronger when the average subjectivity measure of the comments is greater.

Accordingly, using the same data collected from Facebook. We collected the comments shared for 1213 pairs of users. For each pair, we used the output of step 6 which is text subjectivity classification in order to get the subjectivity measure of all comments shared between the pair. Finally, the subjectivity measure for each pair of friends was computed as the average of the subjectivity measures of all the pair's comments.

Based solely on the subjectivity measure for each pair, an SVM algorithm was used to predict whether the pair consists of close friends or just acquaintances. The relationships were assessed by the users themselves: every user reported a list of his/her close friends. Using 10-fold cross-validation, the SVM model reported an accuracy of 87%.

V. Conclusion and Further Work

This paper discusses a novel sentiment mining technique for texts in online social networks. It presents a new perspective for studying friendship relations and emotions' expression in online social networks where it deals with the specific nature of these sites and the nature of the language used. The purpose was to identify whether the writer conveys his emotions and feelings in his writings. The processed data was then used to identify tie strength between two persons based on the subjectivity of the texts they share online. The main challenge for the model proposed is the unstructured language of online social networks; in this perspective, we developed new lexicons that cover common expressions used by online users, including emoticons, social acronyms, Arabic expressions transliterated into English, etc…

Texts were grouped into three categories using a k-means algorithm. The first category consisted of objective or factual texts, the second contained moderately subjective texts suggesting some kind of friendship between the users and the third consisted of subjective texts suggesting a close friendship between the two users. Experiments run on the data showed high efficiency of the method. The model predicted the right class with 88% accuracy. Additionally, when the resulting model was used to predict relationship strength between two users, the prediction reported an accuracy of 87% based solely on the subjective content of comments shared online.

An interesting observation was that the model rated 81% of Facebook comments as containing some sort of subjectivity. This result affirms that online social networks are highly emotionally-rich environments and that exploring the social interactions on these sites can give great insight on social relationships and social behavior.

We propose as future work to first test if considering sentence structures and syntax cues extracted using a parser would yield better results. Second, an important aspect to explore is to extract the comment's context and use real-world knowledge to assess the emotion of the comment. The comment's context in addition to a thorough understanding of the comment itself can provide more insight for understanding the nature of the relationship between two persons. Finally, one of the challenges was to deal with the variety in the language the used in online social networks. That is why it is important to develop new and creative ways to learn and cope with the changes of the language used in chatting and on online social networks.

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