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Emotion Detection and Recognition from Vietnamese Text

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***Abstract:** the areas of Emotion Detection and Recognition from text have become increasingly interested in finding and exploiting information about people. Various problems have been identified such as product evaluations, emotional recognition and emotional findings in the text. In this paper, we present the application of Support Vector Machine (SVM) to detect emotional states in the Vietnamese sentences. The results of our experiments on datasets extracted from Vietnamese novels show that our proposed SVM classification method has higher accuracy than unsupervised learning methods.*

***Index Terms:** emotion detection, emotion classification, emotions, natural language processing, learning support vector machine.*

I. INTRODUCTION

Emotion is a special feeling that occurs in the life of mankind [1]. It expresses the mood of human beings in the process of communication such as: joy, sadness, anger, fear etc. This is an important factor in understanding human behavior which is studied in psychology [2]. The application of emotional detection can be found in the fields of medicine, sociology, economics, politics, etc. Reliable detected emotion can help developing powerful devices for interacting between person and machine. In recent years, the area of exploring viewpoints and analyzing sentiments has become more and more interested in satisfying the need to search and exploit human information. Many different problems are set up such as product evaluation, emotional detection, sentiment in the text, etc. Emotion detection now has basic technical background. However, emotional classification models, mainly using supervised machine learning methods [3, 4, 5] and non-supervised [6, 7]. For Vietnamese emotional detection, there are also some works done on the detection of Vietnamese emotions by using unsupervised learning method, as described by Nguyen Thi Minh Huyen [8] which is based on the proposed technique describered in [9]. In this paper, we are interested in the problem of detecting emotions in the Vietnamese sentence using Support Vector Machine, a supervised machine learning method. The layout of the paper is as follows. Part II introduces a number of methods for detecting emotions. Part III describes in detail a SVM method for detecting application emotions for the Vietnamese language.

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Section IV discusses the evaluation results of our proposed method. The final section will draw the conclusion of the paper and mention some future work.

II. METHODS FOR DETECTING EMOTIONS

Problem: For a sentence in the text, determine the emotions that the subject expressed in that sentence.

We find that the problem of detecting emotion in the sentence is considered as a classification problem where a sentence is assigned to an emotional label. Emotional detection approaches can be classified into three main categories: dictionary-based, linguistic-based, and machine learning.

A. The uses of Emotional Vocabulary in Dictionary based Approach

The vocabulary of emotions for the process of detecting emotions from the text has been used in the literature [3, 6, 10, 11, 12]. This method has the following limitations: for example, in a sentence, if you separate the semantically related words into separate words, they will have different meanings; in other cases, due to the number of words in the dictionary is fixed, if the word does not appear in the dictionary, then the sentence is considered to have no feelings (for example: “She achieved high scores in the past exam”. We see that this sentence does not contain any emotional words, but in fact this sentence conveyed a strong feeling of happiness).

B. The Approach based on Linguistic Rules

Computational Linguistics uses different rules to define a different language structure. They develop rules based on the emotional vocabularies (eg NEG ('to deceive') & POS ('hope') ⇒ NEG ('to deceive hope')).

Pedro P. Balage Filho and his associates [13] have developed a set of rules related to emoticons for detecting emotions for the Twitter sensation. The ESNA (Emotion Sensitive News Agent) [14] system has been developed to classify emotions on news headlines. Meena et al. [15] studied a combination of syntactic rules and words (such as General Inquirer and WordNet) to analyze sentiment in the sentence. Neviarouskaya et al [16] outlines some approaches that can identify 9 types of emotions. The limitation of this approach is that it depends on the vocabulary list contained in fixed dictionaries and rules that do not cover all the cases. Therefore, it is difficult to apply on different data sets.

Liu and his colleagues [17] have come up with an approach for understanding the basic semantics of language.

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The paper [3] proposes an approach to identifying emotions from rich text in hidden data. These approaches use any emotional set, thus it is showed to be a more practical approach.

C. Machine Learning Based Approach

To overcome the limitations of these approaches the researchers have come up with machine learning -based approach to automatically detect the emotions in the text. They divide the technique into two categories: supervised machine learning and unsupervised learning.

Unsupervised Machine Learning: Z. Kozareva and colleagues [7] relied on information theory to calculate the reciprocal correlation between words called PMI (Pointwise Mutual Information) for automatically detecting emotion on the news headlines. Sunghwan Mac Kim et al. [11] also used this method to reduce the number of dimensions to address the problem of detecting emotions with the WordNet-Affect dataset. Ameeta Agrawal et al. [9] also used an unsupervised learning method to calculate the PMI weight between words, while using a syntactic and semantic relationship to enrich their PMI weight for the automatically detecting emotions from the English text.

Supervised Machine Learning: The approach has been used for the problem of auto-detecting emotions and and achieve good results (mostly using the SVM technique - Support Vector Machine) [3, 4, 5]. For each natural language, this method requires the preparation of large, annotated emotion data sets to make training data, test data, and emotion vocabulary specific to each type of emotion.

III. EMOTION DETECTION FROM VIETNAMESE TEXT USING THE SVM

We use SVM to perform training of classifiers for the problem of classifying emotions into different types of topics. This is a multi-layer classification problem. The problem of the multilayered classification is maped into the two-layer classification problem by constructing two classifiers to solve. These common multi-layered classification strategies are: One-against-One (OAO), and One-against-Rest (OAR).

In the OAR strategy (Figure 1), we will use the K-1 binary classifier to construct the K-class. The K class classifier is transformed into a K-1 two layer classifier. The second *i* layer is built on the *ith* class and all the other classes. The *i-th* decision function is used to class *i* and the remaining classes are of the form:

$$y_i(x) = w_i^T(x) + b_i$$

The hyperplane $y_i(x) = 0$ forms the optimal partition superposition, the support vector of class *i* satisfies $y_i(x) = 1$ and the support vector of the other class satisfy $y_i(x) = -1$. If the data vector *x* satisfies the condition $y_i(x)>0$ for only one *i*, *x* will be assigned to *i-th* layer.

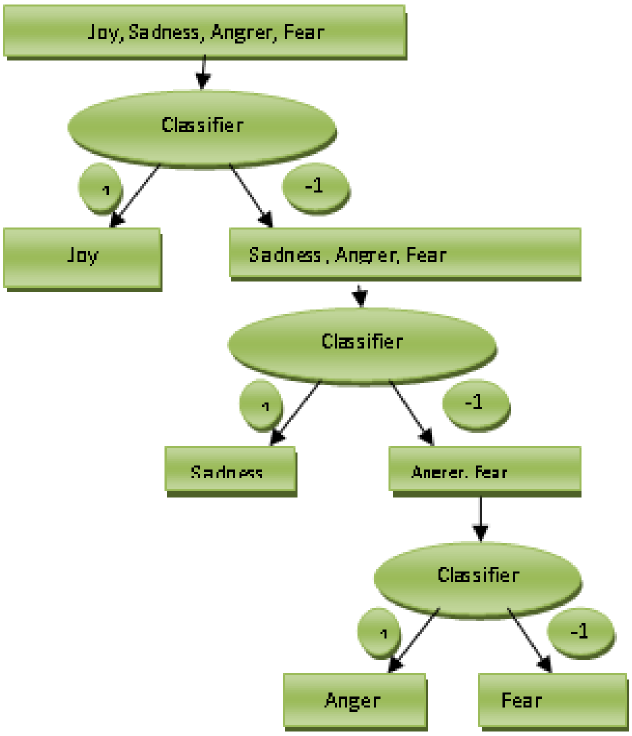

Figure 1: OAR approach

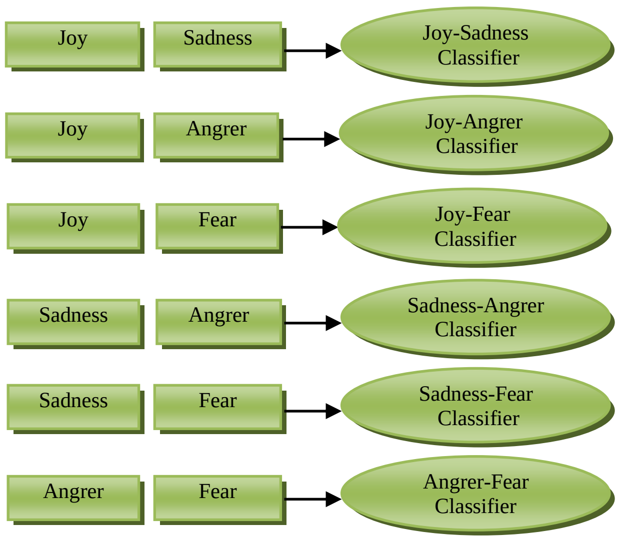

Figure 2: OAO strategy

The OAO strategy (Figure 2), using K (K-1) / 2 binary classifiers, the model was constructed by pairing two classes. Thus, this strategy was also called pairwise and used as the majority method combination between these class members to determine the final classification result. The number of classifiers never exceeds K (K-1) / 2.

Compared to the OAR strategy, this strategy has the advantages of reducing the unclassified area. It also increases the accuracy of classification. The OAR strategy requires only K-1 classifiers for the K classes, while the OAO strategy requires K (K-1) / 2 classifiers. However, the number of training samples for each classifier in OAO is lower and classification model is simpler.

Thus, the OAO strategy is more accurate but the cost of rebuilding the model is equivalent to that of OAR strategy.

The class decisive function of class *i* for class *j* in the OAO method is:

$$y_{ij}(x) = w_{ij}^T(x) + b_{ij}$$

However, both approaches lead to ambiguous areas in the subclass (see Figure 3). We can avoid this problem by constructing a K-based linear function K of the form $y_k(x) = w_k^T x + b_{k0}$. And one point x is assigned to class C_k when khi $y_k(x) > y_j(x)$ for every $j \neq k$.

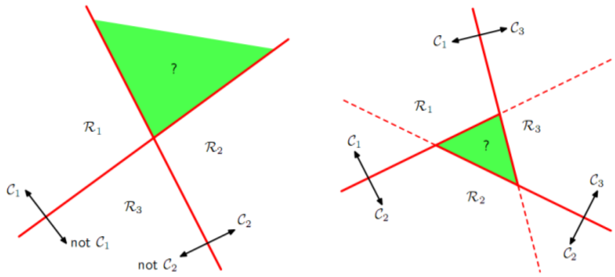

Figure 3: The vague region in subclass

Table 1: Labling by emotions

Subject	Label
Joy	1
Sadness	2
Anger	3
Fear	4

<class$_i$><label$_1$>:<value$_1$><label$_2$>:<value$_2$>... <label$_n$>:<value$_n$>

Where:

Class$_i$ là nhãn phân loại của mỗi chủ đề với i = 1 ÷ 4 (table 1).

Label$_j$ là chỉ số của từ đặc trưng thứ *j* trong không gian từ đặc trưng có xuất hiện ở các câu văn cảm xúc huấn luyện với j = 1÷ n.

*Value$_j$*là trọng số của *index$_j$* được tính bởi công thức *TF.IDF*, nếu value$_j$ = 0 thì không cần phải ghi đặc trưng đó.Định dạng này tuân thủ đúng theo định dạng dữ liệu đầu vào của chương trình SVM$^{\text{Multiclass}}$ [18].

A. Specific steps in the training of the classifier:

Step 1: Training data is obtained from rich emotional sources such as emotional novels, facebook.

Step 2: Preprocessing: Extract words (using VnTokenize) according to [19] and removal of specific stop words [3] (will be covered in detail in Section 4, Experiment and Evaluation).

Step 3: Express each sentence in the form of a vector as follows:

<class$_i$><label$_1$>:<value$_1$><label$_2$>:<value$_2$>... <label$_n$>:<value$_n$>

where:

Class$_i$ is the classification label of each topic with i = 1 ÷ 4 (see Table 1).

Label$_j$ is the index of the jth feature word in the word feature space from the one that appears in the training emotion sentences with j = 1 ÷ n.

Value$_j$ is the weight of *index$_j$* calculated by the TF.IDF formula, if value$_j$ = 0, then no such attribute is required. This format conforms to the input format of the SVM$^{\text{Multiclass}}$ [18].

Step 4: Training the classification model based on the multilayer SVM algorithm using the OAO strategy with optimal model parameters (empirical and using some methods such as GrisSeach, Genetics, etc)

B. Specific steps in the classification phase are as follows:

Step 1: Allows the user to type in an emotional statement.

Step 2: Take the word separation (integrate VnTokenize) and remove the stop word from the text. Then vectorize the text in the input format of the SVM algorithm.

Step 3: Perform classification (by four types of emotions) and save the results to the database;

IV. EXPERIMENTS AND EVALUATION

A. Pre-processing of data and training classification model

We selected high frequency sentences for expressing emotions from Vietnamese literary works, from short stories and from social networks involving four emotional labels (Joy, Sadness, Anger, Fear), and then label the feelings for each sentence. The job of labeling the sentences has been completed manually. Then, the elimination of stop words in the preprocessing steps are performed as step 2 in the training phase shown in section 3. After word separation, the words will be weighted according to the formula (1) and then sorted in descending order of weight to make the selection of the feature words for the feature vectors represention. Each text in the dataset is represented by an n-dimensional vector, each corresponding to a feature word. The expression of the emotional sentences is described in step 3 of section 3.1

The value *i* of the *ith* word in the emotion vector *j* is the weight of the word that is calculated by the formula (1)

$$\text{weight}(i,j) = \begin{cases} (1+\log(tf_{ij}))\log\left(\frac{N}{df_i}\right) & \text{If } tf_{ij} \geq 1 \\ 0 & \text{If } tf_{ij} = 0 \end{cases} \quad (1)$$

where:

dfi< cfi and $\sum_j tf_{ij} = cfi$

tfij (Term frequency): The number of occurrences of the word wi in the sentence dj.

Dfi (Document frequency): Number of document containing the word w*i*

Cfi (Collection frequency): The number of occurrences of the word w*i* in the entire collection

If value $value_J$ = 0 then no such feature is required

The data set for training and testing have totals 2198 emotional statements in which 2000 sentences will be selected in the training data set and the other 198 will be the test data set. Table 3 lists the number of training and test data sets for each topic.

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Table 2 Number of training dataset and evaluation data sets

Emotion label	Training dataset	Evaluation dataset
Joy	343	58
Sadness	897	79
Anger	447	41
Fear	313	20

To conduct a selection of values for the four types of emotions (Joy, Sadness, Anger and Fear) for the vector space we choose from two sources of data:

Based on WordNet_affect English [20, 21] combined with Vietnamese dictionary to build for Vietnamese. The translation of words expressing emotions in English into Vietnamese is completely manual. We translate based on the the meaning of English words to select the corresponding Vietnamese words in semantics.

Based on the frequency of occurrences of the words in the sentence after removing the stop words, the choice based on how the inverse frequency of the text is calculated will eliminate the low frequency words in each emotion label, keeping only high frequency words which have an unique emotional label. The number of words by type of emotion in feature space is shown in Table 3.

Table 3. Feature space

Emotion label	Wordnet_affect	Selected High-frequency words
Joy	158	595
Sadness	81	974
Anger	58	513
Fear	93	687

B. Classification and Evaluation Experiments

Experimental results were evaluated by measurement of F (F measure), which was determined by three indicators: Prec (precision), Rec (recall) and Fscore

$$\text{Prec} = \frac{\text{Input}_i \cap \text{Output}_i}{\text{Output}_i} \quad (2)$$

$$\text{Rec} = \frac{\text{Input}_i \cap \text{Output}_i}{\text{Input}_i} \quad (3)$$

Where:

Input i: the number of input sentences for emotion *i*

Output i: the number of output sentences of emotion *i*

In this experiment use four basic types of emotions: e = {Joy, Sadness, Anger and Fear}.

To automatically categorize news on the web, the authors create an automated classified application with four themes: Joy, Sadness, Anger, and Fear by using SVM model with the dimensionality of the feature vectors selected in section 4 of Section A. The application has been built based on three specific steps which are described in Section 3, Section B.

The evaluation results of SVM classifier with different feature dimension vectors on training and evaluation data sets are shown in Table 4. The the accuracy is evaluated using formular (2) (3).

Table 4. Results From the Evaluation of the Classification by Emotion.

Emotion label	SVM	
	Prec	Rec
Joy	82.14%	48.93%
Sadness	39.08%	73.91%
Anger	75%	29.03%
Fear	73.33%	68.75%

V. CONCLUSION

This paper describes a method for automatically classifying emotions in Vietnamese text using two layler learning methods, a multiple layer support vector machine (SVM).

Our experimental results on a dataset extracted from Vietnamese novels show that the proposed SVM classification method has higher accuracy than unsupervised learning methods. To be able to apply this model in practice the model needs to be trained on larger dataset.

In the further research, we aim to improve this classification method to increase the accuracy of classification for different emotions.

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