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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

A Review on Automation of Classification and Summarization of Neurosurvey by Multiclass SVM

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Abstract: NeuroSurvey is conducted to get neurobiofeedback, is a type of biofeedback that uses real-time displays of brain activity most commonly electroencephalography (EEG), to teach self-regulation of brain function. Typically, sensors are placed on the scalp to measure activity, with measurements displayed using video dis-plays or sound. The next phenomenal outcome of the survey system would be brain computer interface, instead of general neuromuscular activities brain com-puter interface acquires direct input from the brain as signals process, analyze and transmit input to the desired output action. The brain computer Interface will be a revolutionary technology for people disabled by neuromuscular disorders. There are numerous hardware devices available to capture the brain waves and process them one such is the EEG (Electroencephalography) device, the EEG registers the ionic current flows within the neurons of the human brain along the scalp. The device has specific electrodes that records the neural oscillations of the brain and converts them into signals. And those signals are analyzed to generate the threshold report.Automation has been the top priority for twenty first century and it ranges from automating spell checking to a complex auto launch rockets. When it comes to neurosurvey classification, automatic classification of large, uncategorized, non summarized collection of data is very much required. Manual classification of neurosurvey may not only need the help of experts from their respective domain and they are also done at the expense of precious time. In this paper we have proposed a novel scheme to classify and summarize neurosurvey based on classification and clustering algorithms. Once summarization is done we can use them to generate a survey of their respective category.

Keywords—Data Mining, Text Classification, Text summarization, Hierarchical Clustering, LSA, Multiclass SVM

I. INTRODUCTION

Text classification [1] and summarization [2] has been one of the longing areas of research where expertise is short. Many researchers have been working on automatic text classification and summarization [3] from 1950's, yet this area requires vast number of techniques in order to find a suitable one for the job. Large numbers of papers are published in research journals every year. Manually classifying all these papers and segregate them into respective domains is a tedious and time consuming task for an average person. Even if one goes to the help of an expert it takes a lot of man-hours to finish the job. Hence automatic classification of neurosurvey's and summarizing them is a need of the moment. In particular, a system that uses its intelligence to accurately divide the papers is of high importance especially for those who are newly diving into research arena.

In a similar way if one can use the text classification method and create a summary based on the input from the classification end, we can generate text summaries of neurosurvey's. These summaries can then be used to quickly get an idea of these papers or even to generate a survey paper on our own. Archaic methods which follow manual labour consist of classifying papers based on keywords and meanings. The biggest problem in these manual classifications is that, the exact research discipline areas of the papers cannot often be accurately designated by the budding research scholars due to their subjective views and possible misinterpretations. In this paper we have proposed a more efficient and suitable method for automatically classifying neurosurvey's and generating summaries.

2.0 RELATED WORKS

2.1 Text Feature Extraction Based on Weighted Scatter Difference

Feature extraction is the process of defining and setting certain text in any given volume of text as important and using the same to analyze other text. If the text feature is present in some other series of text then it is called match and there is high possibility that both the text are similar. In this paper, articles are taken as experimental data set and they are pre-processed in order to remove unwanted and banned data. Then texts are divided using KNN classifier [4] and weighed with respect to the largest value. Scatter difference is measured once after weighting and results are tabulated. Text feature reduction is highly supported by this method which is considered a

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

bottleneck for reducing the efficiency of classification of text.

2.2 Web Page Classification by LS-SVM with LSA

The difference between web page classification and text classification remains humongous. In a text classification the probability of finding an organized content and extracting the feature from that is very low considered to extracting feature from web pages. The web pages have tags like <title>, <h1>,<h2> etc.. These provide an easy way to describe them and classify them. Pre-processing of the web pages is done by segmenting followed by stop word removal [5]. But first the noise is reduced by using the summarisation algorithms [6]. The term document matrix or document term matrix[10] is formed by assigning weight to the keywords found in between tags and obtaining higher frequency keywords set. Then the regularization parameter γ and the Gaussian bandwidth parameter $\xi 2$ are optimized with the help of Bayesian framework to create LS-SVM model. From this model it is proved that LS-SVM provides better accuracy than normal SVM and KNN.

2.3 Enhancing GSOM text clustering using LSA

GSOM is an unsupervised machine learning clustering algorithm. It grows depend on the input given from the user at initial stage and later on its own according to the restriction parameter. This parameter is called Spread Factor [9] which helps in controlling the size of the map and at the same time lets us view in different granularity levels. In this paper they have proposed a model in which it starts by pre-processing text data that includes removal of stop words and stemming. This pre-processed text is given to the TF-IDF [9] calculator where the Term Frequencies and Inverse Document Frequencies are computed together producing TF-IDF matrix as final result. This matrix is applied with SVD as transpose thereby reducing the dimensionalities. Then the matrix is fed to the GSOM where it can cluster the text documents.

3.0 PROPOSED MODEL

We propose a model to automatically classify neurosurvey's and summarize them. The first step in this model is to pre-process data. The data can be pre-processed by removal of root words and stemming. Feature extraction is an important process which is achieved by Vector Space Model [10] that produces Term-document matrix [10]. Next is the most important part of the model which proposes to use LSA SVD technique for matrix reduction of term-document matrix. When terms are reduced, the next step is classification and here we use SVM (Support Vector machine)[4]. But instead of single stage, we propose a 2-stage classification system in which each document is classified according to Top Level Domain (TLD) by hierarchical clustering and then sub domain systems are classified. For instance, consider a neurosurvey for Neuro biofeedback arrived and we are about to classify it. The paper belongs to "Neuro disorder". So here, the TLD is "Neuro disorder". Furthermore, it is categorized as, say, "Clustering". So TLDs are categorized first and then they are split according to sub domains. Once all the above processes are successfully completed we need to generate summaries. We use sentence scoring and extraction for generating summaries. General term set is extracted from conclusion, proposed techniques and further similar topics to improve summarization efficiency.

4.0 ARCHITECTURE OF PROPOSED MODEL

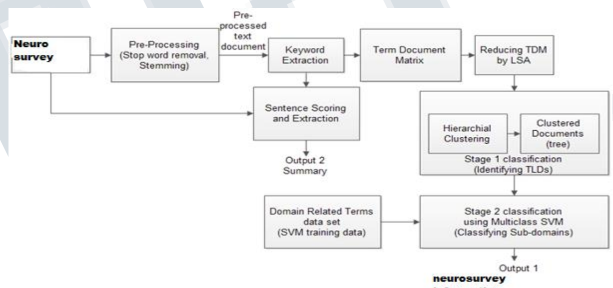

Fig.1 Architecture of Proposed Model

The overall architecture proposes a two step classification method for classifying information and sentence scoring technique to summarize them. The details of the architecture are discussed below.

4.1 Pre-Processing of text documents and Keyword extraction

Pre-Processing is the process of removing stop words and meaningless words. The input to this module is a journal from the data set. The Neurosurvey information is processed to remove stop words and stemming is performed. Stemming is the process of extraction of root words from a given word. We have used Stanford's Maxent POS tagger [11] for tagging the sentences.

E.g This/DT is/VBZ a/DT sample/NN sentence/NN

After tagging the sentences, we remove all the tags except nouns and adjectives like the sample below:

(Noun -> Text mining; Adjective-> Time -Sensitive Matrix)

We use Word-Net to remove proper nouns that are meaningless for example "name->Xang Wu". Stemming is done using either Porter stemmer. Finally the output

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
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will be a set of stemmed words without stop words and meaningless word.
Once pre-processing is done keywords are extracted that describe the entire document. Bi-gram [17] generation is a strategy which is used to generate keywords from extracted words where bi-gram generation is possible. Bi-grams frequency is calculated and keywords for a document are finalized.

4.2 Classification

4.2.1 Feature Selection and reducing Term-Document Matrix by LSA (Latent Semantic Analysis)

The term LSA is used to denote Latent Semantic Analysis. LSA is a technique to classify text. It is also used for indexing documents. It consists of a concept called Vector Space Model [10]. Vector Space Model provides a way to select features of text within a given document. If documents are to be analyzed by LSA then the result of the analysis exposes semantic closeness of the documents. If the count of common words is high then the documents may be considered as semantically close and if the count is low then it is termed as semantically distant.
LSA compresses the original term-document matrix [10] to reduced matrix. Technically they can described as X=USVT , where X is a matrix with the dimensions of dxt, U is the reduced rank matrix, S is a singular valued diagonal matrix, V is the document matrix. S is mathematically represented as diagonal ( ), in which the elements of S are singular values of X. U and V are dxd, txt matrices respectively. With the help of SVD the matrix X is simplified as Xk=UkSkVkT and the dimensions have been reduced to dxk, kxk, txk respectively.

4.2.2 Stage 1 Classification – Identifying Top Level Domains (TLDs)

Once the term-document matrix is formed, hierarchical clustering can be used to cluster data into one big single set. The reduced matrix from output of LSA contains keywords which are passed as input to hierarchical clustering. Since hierarchical clustering provides deterministic algorithm over K-Means clustering, we go for hierarchical clustering.
The input terms of reduced matrix are clustered in a way such that suppose N items are present in the data set, then each item is calculated the distance to the closest item and they are merged together. The distance calculation and merging continues till a single big cluster is formed. By looping through the same step we finally produce one big cluster identifying the Top Level Domain. The output of this process produces a clustered tree. Software are available for clustering purposes. One such software we used here is Cluster 3.0 [12].

4.2.3 Stage 2 Classification – Classifying Sub-domains

Support Vector Machine [13] is a supervised learning model used for classification and regression analysis. It uses a learning algorithm which predicts, to which class does the given data belongs to. But it requires training data to be fed at first in order completely learn about the data.
Here we have provided Domain Related Terms (DRT) data set for the SVM to learn. One major disadvantage of using SVM is that it is able to predict between only two sets of classes. If further classes are to be classified we should go for Multiclass SVM [14]. In Multiclass SVM, single multiclass problem is reduced to multiple binary class problems. It can be done either by building binary classifiers such as one-versus-all, one-versus-one or by Directed Acyclic Graph SVM [15] or by error-correcting output codes [16]. Here we have used one-versus-all strategy. In this method a single is classifier is trained to distinguish it from all classifiers. Prediction algorithm is used on each binary classifier and the highest probability score provides the required class. Thus sub-domain classification is achieved.

4.3 Summarization by Sentence Scoring

In summarization we extract the most important sentences that thoroughly describe the Neurosurvey. We are using a Sentence Scoring [18] mechanism to summarize the neurosurvey. First step in summarization is to pre-process the incoming paper and extract keywords. After this is done we extract the sentences from the Neurosurvey that contain the keywords alone, this way the number of sentences to score reduces. Once the sentences with the keywords are extracted they are scored in the following way:

F1: Sentence Position
We assume the first sentence of a paragraph is the most important. Therefore we rank a sentence in the paragraph according to their position.
F2 : Frequent keyword in the sentence
Score(S) = [1/ Length(s)] *∑tf i*P
P = #of keyword in sentence / #of keyword in a paragraph
F3: Sentence Relative Length
Score(s) = (#of words occurring in a sentence) / (#of words occurring in longest sentence)
F4: Sentence resemblance to title
Score(s) = (Keyword in S ∩ keyword in title) / (keyword in S U keyword in title)

F5: Sentence inclusion of name entity

Score(s) = #of proper noun in S / Length of S

F6: Sentence inclusion of numerical data

Score(s)= #of Numerical data in S/ Length of S

F7: Term Weight

Score(s)= $\sum$Wi(s)/Max($\sum$Wi(s))

F8: Sentence similarity with other sentence

Score(S) = $\sum$Sim(S,Sj) /MAX($\sum$Sim(Si,Sj))

5.0 EXPERIMENTS AND RESULTS

To validate the proposed approach, several experiments were conducted. The experiments consisted of a dataset of 1000 Neurosurvey information from various domains and they were classified using a machine having Intel Core i7 processor with 8GB RAM. The results and details of the experiments conducted are listed below.

5.1 Confusion matrix for classification

The performance of our system can be demonstrated by confusion matrix which is a specific table layout that allows visualization of the performance of our system. It contains information about the actual and predicted classification done by classification system. The following domains are taken testing our experiment: Domain A represents Classification, Domain B represents Clustering, Domain C represents Summarisation, Domain D represents Pattern Recognition, Domain E represents Semantic Analysis, Domain F represents Miscellaneous, and Domain G represents Visual mining.

Domains Under Data Mining	A	B	C	D	E	F	G	Total
A	196 (98%)	4 (2%)	0	0	0	0	0	200
B	8 (4%)	192 (96%)	0	0	0	0	0	200
C	0	0	200 (100%)	0	0	0	0	200
D	0	0	0	95 (95%)	0	5 (5%)	0	100
E	0	0	0	5 (10%)	44 (88%)	1 (2%)	0	50
F	0	0	0	8 (4%)	8 (4%)	184 (92%)	0	200
G	0	0	0	0	0	0	50 (100%)	50

Fig.2: Confusion Matrix

In the above Fig.2, the left plot shows the confusion matrix C where C(i ,j) is the number of data in domain i being classified as domain j. The right plot is the corresponding recognition rates for each class. From the confusion matrix ,the recognition rates for domain A,B,C,D,E,F,G are 98%, 96%, 100%, 95%, 88%, 92% and 100% with an overall recognition rate of 95.58%.

5.2 Standard measures

We selected both quantitative and qualitative criteria as points for evaluation for summary. The quantitative measures included precision, recall, compression and time required for assessments which are commonly used in informal retrieval evaluations. The qualitative measures addressed preferred length, intelligibility and usefulness of the summaries. Quantitative measure:-The summaries based on each document were judged to be either relevant or non-relevant to the same topic. These relevance judgments of the summaries fall into four distinct classes, as indicated in table below. For e.g. we have taken sample documents with their summary and conducted a survey to judge those summaries based on the manual (variable length) summary. The results are shown in the table below:

Table 1: Quantitative measure

Human	**Proposed**	**Results**
Relevant	Relevant	True Positive
Non relevant	Relevant	False Positive
Relevant	Non relevant	False Negative
Non relevant	Non relevant	True Negative

Table 2: Results of content evaluation measures

	TP	**FP**	**FN**	**TN**	**Accuracy**	**Precision**	**Re-call**	**F-Measure**	**Time**
Proposed	175	34	66	75	0.68	0.83	0.72	0.77	6 sec
Human	176	33	61	80	0.67	0.84	0.74	0.78	-

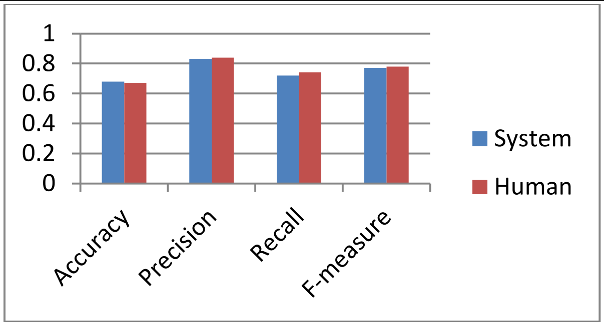

Fig.3: Measures on accuracy, precision, recall, f-measure.

5.2.1 Accuracy

Accuracy is the sum of the correct hits (true positives, i.e., those correctly judged relevant) and the correct misses (true negatives, i.e., those correctly judged irrelevant) over the total number of judgments. From the Table.2, system has a accuracy rate of 0.68.

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}}$$

5.2.2 Precision

Precision measures the percentage of correctness for the total number of summaries judged by the summary assessors to be relevant. That is, it measures the percentage of relevant sentences in a set retrieved as a result of a summary. Clearly, this measures the preciseness of the system. From the Table.2, system has a precision of 0.83.

$$P = \frac{\mathrm{TP}}{\mathrm{TP + FP}}$$

5.2.3 Re-Call

In an IR evaluation, re-call measures how many relevant sentences of the total sentence set a system is able to retrieve. This is clearly an important measure for IR systems which, in combination with precision, gives a workable measure of a system's effectiveness. From the Table.2, system has a re-call rate of 0.72.

$$R = \frac{\mathrm{TP}}{\mathrm{TP + FN}}$$

5.2.4 F-Score

F-Score is a composite score that combines precision and recall measures in the equation from the Table.2, system has an F-score of 0.77.

$$F = \frac{(2 * \mathrm{P} * \mathrm{R})}{(\mathrm{P + R})}$$

5.2.5 Compression Ratio

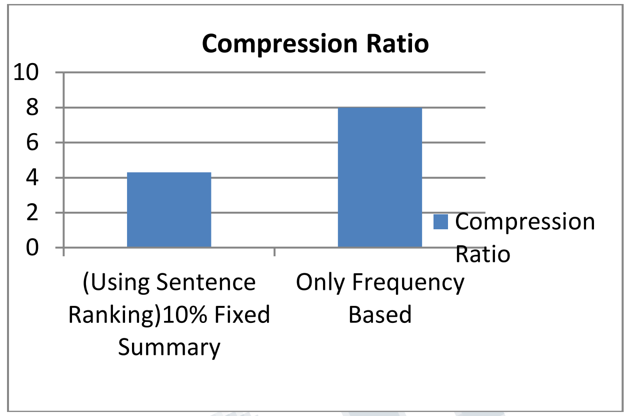

Fig.4: Compression ratio

It shows how precise the generated summary is compared to the original document. Compression Ratio= (Number of words in generated summary)/(Number of words in original document). From the graph in Fig.4, it is evident that optimal compression ratio has been achieved by our system due to the extraction based summary using sentence ranking (Relative length, resemblance to title, term weight, etc.) to identify significant sentences.

5.2.6 Non Redundancy Method

Non-redundancy measure describes the amount of uniqueness of summary without repetition. Our system attains the Non Redundancy Measure of 95 percent against frequency based method which has a measure of 91.5 and cue phrase method which has a lower measure of 90.The increase in evaluation parameter as indicated in the graph in Fig.5 is the result of including our idea of extraction based sentence ranking using sentence relative length, sentence resemblance to title, term weight, etc.

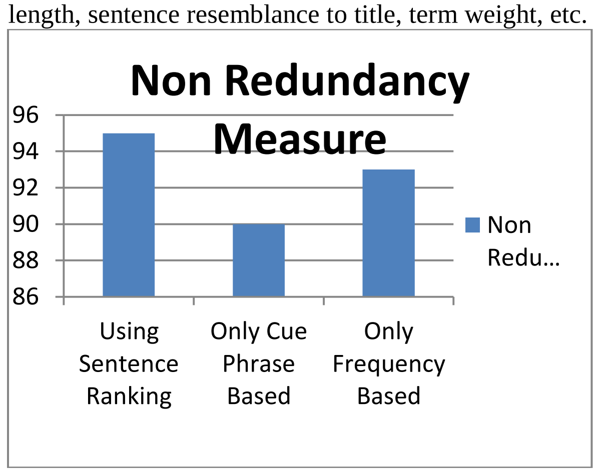

Fig. 5: Non-redundancy measure

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

6.0 CONCLUSION AND FUTURE WORK

This paper has presented an automation method for classification and summarisation of neurosurveys. A cluster of neurosurveys is constructed to categorize the concept terms in different discipline areas and to form relationships among them. The experimental results showed that the proposed method improved the similarity identification in neurosurvey corpus. Also, the proposed method promotes the efficiency in the neurosurvey classifying process. This paper also provides an efficient and quick approach for extraction based summarization of neurosurveys. Future work may include multithreading of the classification process and parallel classification of neurosurveys with map reduce framework. Another future work, in which summaries generated may be further enhanced to generate survey papers, is proposed.

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