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Clinical Narratives Context Categorization: The Clinician Approach using RapidMiner

Osama Mohammed[1], Sabah Mohammed[2], Jinan Fiaidhi[2], Simon Fong[3], Tia-hoon Kim[4]

[1]SimBioSys Laboratory, University of Victoria,
3800 Finnerty Road,Victoria, British Columbia V8W 3P6, Canada
[2]Department of Computer Science, Lakehead University,
Thunder Bay, Ontario P7b 5E1, Canada
[3]Department of Computer and Information Science
University of Macau, Av. Padre Tomas Pereira, Taipa, Macau
[4]Department of Convergence Security, Sungshin W. University, Korea

smohamme@uvic.ca, {mohammed,jfiaidhi}@lakeheadu.ca, ccfong@umac.mo,
taihoonn@sungshin.ac.kr

Abstract. For many years natural language processing (NLP) programming tools have been used to process information in various applications areas including medicine. However, most of such systems have been developed by expert programmers and very little or none by clinicians. The subject under consideration in this article is automatic categorization of clinical data. This topic requires great deal of clinical cognition and hence there is a need to let clinicians develop such systems. This article is an attempt in this direction where the RapidMiner environment has been used for this purpose. This article describes how RapidMiner as a visual programming environment can be used for tokenization and categorization of clinical narratives. It also describes how to select the best classifier for categorization. K-NN classifier categorizes clinical narratives with high performance accuracies even for large dataset like the i2b2 smoking challenge data.

Key words: Clinical Narratives Categorization, Tokenization, RapidMiner, Context-Awareness

1 Introduction

Automated categorization of textual clinical narratives is an important research challenge due to the ever-increasing electronic clinical documents. Automatic Text Categorization (ATC) is formally defined as a classification task: given a textual input, the categorizer should return a list of categories, which are supposed to provide non-ambiguous machine-readable information about the input text. ATC assists medical studies by providing statistically relevant data for analysis [1]. The ATC assigns semantic labels to the clinical narratives, such as whether a clinical narrative is a radiology report or a discharge summary. However, the first step to any ATC system

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is the tokenization of the provided text. Tokenization is the process of separating text into individual tokens that each conveys some semantic meaning. For English, in most cases, tokens are equivalent to words. For clinical text, there are often names and symbols of various types of biomedical entities, such as medications, genes, proteins, chemicals, etc. The special characters contained in these names and symbols make it harder to identify meaningful tokens than in normal English text [2]. This means tokenization should manage language related word dependencies, incorporate domain specific knowledge and handle morph syntactically relevant specificities [3]. Literature reveals three types of semantically enriched tokenizers:

(1) Rule-Based Tokenizers [4]: Regular Expressions are commonly used for writing the rules that can identify relevant tokens corresponding to the entity of interest. Tomanek et al [5] have studied tokenization of biomedical texts by using regular expression rules for tokenizing biomedical common text. He concluded that this approach is quite complex, since biomedical authors tend to adopt different, and sometimes inconsistent, notations. The notation used to write biomedical entity names, abbreviations, chemical formulas and bibliographic references conflicts with the general regular expression rules employed for tokenizing common text.

(2) Classification-Based Tokenizers [6]: This tokenization method consists of text classifiers (e.g. Conditional Random Fields (CRF)) to perform mainly two tasks: (i) token boundary detection and (ii) sentence boundary recognition. The classifier is trained by a token sequence when tokens are annotated by single labels. Tokens are represented by their feature vectors. Typical features are binary properties, for example, whether the token matches a pattern. Based on the sequence of labels in training documents and the observed corresponding feature vectors, the classifier learns the relations between labels and features, and builds a discriminative model that is applied to predict the most likely label sequence of unlabeled token sequences. The predictive performance of a classifier model depends heavily on the dataset applied.

(3) Token Disambiguation Tokenizers [7,8]: This tokenization method uses a probabilistic model for token disambiguation which chooses the best sense based on the conditional probability of sense paraphrases given a context.

These three tokenization methods as well as many other hybrid methods lack the ability to adapt to the document context due to following strict engineering approach (i.e. one in which developers may focus less (or not at all) on the human factors that result in or otherwise exhibit learning, memory, expertise, and other features; cognitive plausibility is not a major concern in such work) [9]. Tokenization requires several cognitive processing modalities, linguistically-based or otherwise. Our position in this paper is to integrate some human cognition capabilities as part of the process of tokenization and document categorization. This integration requires a promising environment where clinicians can use for implementing, modeling, and studying document categorization. The integration does not mean that document categorization will be semi-automatic as it will only be used during the development process by clinicians. We find RapidMiner as an environment fits this requirement.

2 RapidMiner for Tokenization and Categorization

RapidMiner[1] is a Java framework that can be programmed via Java[2] and R[3] languages. RapidMiner provides many built-in processes for data mining (e.g. Text Processing, Information Extraction) and NLP (e.g. Tokenization, Removal of Stop Words, Part of Speech Tagging and Stemming). The framework became a leading programming environment in the paradigm of business intelligence and recently started to be notable in other fields including in healthcare. The framework offers ease of integration of various operators (i.e. built in or programmed) using very attractive visual designing interface. This interface does not requires programming experience and one can use pipeline and program variety of operators using drag, past and connect approach. This capability allows for the intervention of experts and developers to envision the categorization system as well as enhance it and modify it by changing connections and parameters on the visual interface. Moreover, RapidMiner provides variety of semantic support through three notable plugins (RMonto[4], ISPR[5] and Recommender Systems[6]) that can be used for context awareness. These extensions as well as the programming power of both Java and R, let RapidMiner to be one of the best environments that we would like to start our investigation with on developing a context aware tokenization and categorization approach. The following experiments are an attempt in this direction.

3 Categorizing Clinical Narratives

In order to identify the context of a text written for the purpose of clinical narrative, need to use samples of such clinical narratives from an authentic and reliable source. For this purpose we collected equal number of clinical narratives from the MTSamples.com[7] which is a web repository designed to give you access to a big collection of transcribed medical reports. We collected equal number of samples from eight different clinical categories (Autopsy, Diet, Discharge Summaries, Chiropractic, Cosmetic, Dental, ENT and Radiology). We divided our collected samples into training and testing (80% training and 20% testing) where the textual documents for each category have been assigned to a specific directory. The task is to tokenize these documents and generate a vectored document matrix that can be used for categorizing the context of each of the provided clinical documents. This can be done using the RapidMiner visual interface by dragging the "*Process Document From File*" operator and place it on the design stage. By double clicking this operator, we can start dragging on it generated design stage all the processes required for tokenization, preprocessing (e.g. converting to lower cases), tokens identification, elimination of stop words, stemming and selecting words with min and max number of characters (i.e. NGrams). Figure 1 describes the tokenization process.

1 http://rapidminer.com/

2 http://www-ai.cs.uni-dortmund.de/SOFTWARE/RMD/index.html

3 http://www.e-lico.eu/r-extension.html

4 http://www.e-lico.eu/rmonto.html

5 http://prules.org/doku.php/download:ispr

6 http://www.e-lico.eu/recommender-extension.html

7 http://www.mtsamples.com/

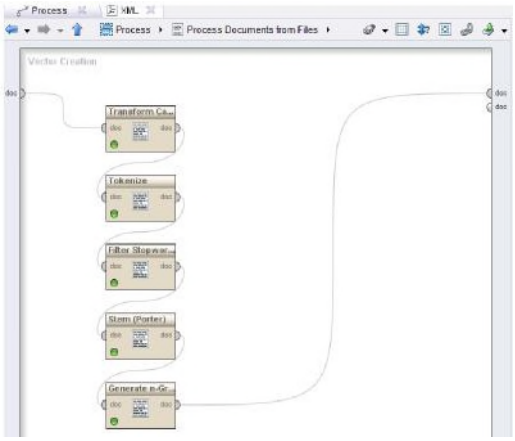

Fig. 7. Tokenization Processes

The upper level parameters for the "Process Documents From File" operator have been set to generate a document victor matrix that identify the important tokens in these clinical documents by calculating their TF-IDF and to optimize the victor document using an absolute pruning method (see Figure 2). The lower level process contains operators like the "Tokenize" where it have variety of options including to use no letters separators, regular expressions, linguistic sentences, linguistic tokens or the use of specific characters as tokens separators. We initially started by using no letter option for the tokenizer. The other operators used in the tokenization are to eliminate the Standard English stop words and to convert the tokens to their stem using the porter dictionary.

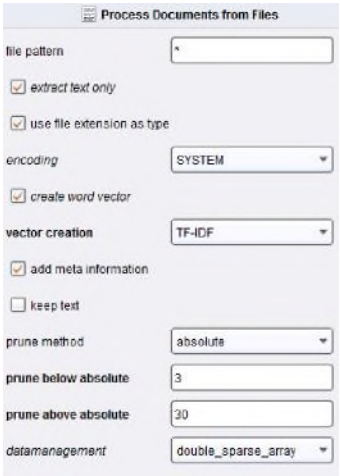

Fig. 2. Parameters used in Converting the Clinical Narratives in Document Matrix.

Once we completed the tokenization process then we can start to experiment with using different classifiers for categorizing clinical documents into the eight selected categories. For this purpose we need to have processes for training the classifiers and

for testing the trained classifier on new provided documents that we need to know its category. Figure 3 illustrates the upper level for the operators required to be dragged onto the design stage. In the training part, we need to store the vectored documents and to use a classification operator container (i.e. the Validation Operator) and to store the resulted model of training into a store. However, the categorization process starts by reading both the vectored documents and the stored model of classification and apply this model on the newly provided clinical document (this requires the use of a "Process Document from File" operator) to predict its category.

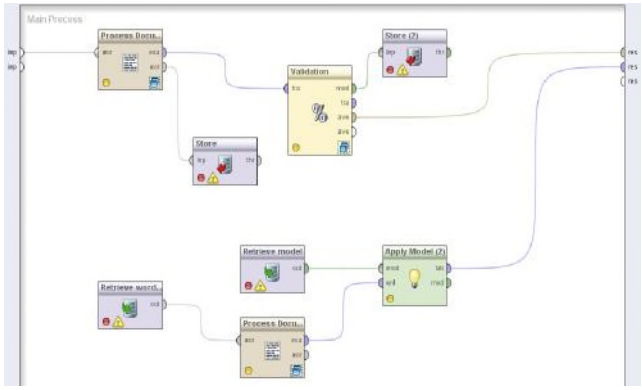

Fig. 3. Training Classifiers and Categorizing New Documents.

The validation operator generates new stage with two windows, one for the including the classifier and the other for applying the classifier on the new provided documents and measure the performance statistics. RapidMiner provides huge number of classifiers (e.g. Naive Bayes, SVM, J48, JRip, ZeroR, Random Tree, K-NN) as well as wide range of performance measures (e.g. Accuracy, Kappa Statistics, Recall, Precision, Absolute Error, Cross Entropy and Correlation). Figure 4 illustrates the classification and categorization container where the K-NN has been used as the classifier.

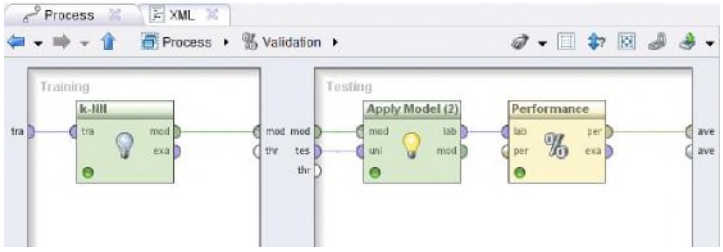

Fig. 4. The Classification and Categorization Process of Clinical Narratives.

Based on this container for classification and categorization template, we selected seven notable classifiers and run them against a sample of 40 clinical narratives for each the eight different clinical categories where the test data represent 24 clinical narratives that we need to predict its category (e.g. Autopsy, Diet, Discharge

Summaries, Chiropractic, Cosmetic, Dental, ENT and Radiology). Figure 4 illustrates the overall accuracy of the seven selected classifiers.

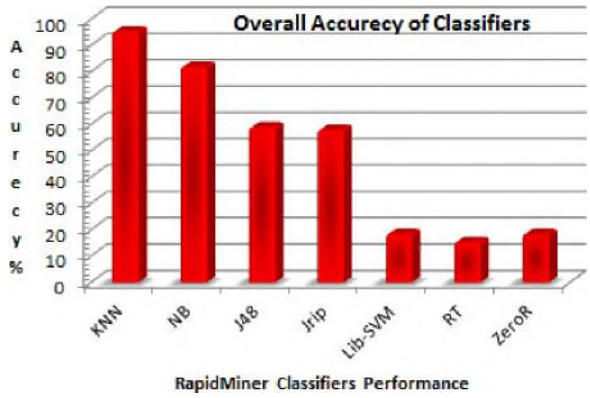

Fig. 4. The Accuracy of the Seven Selected Classifiers.

K-NN proves to provide the highest accuracy (95.5%) compared to the other classifiers. Figure 5 illustrates the outcome of predicting the category of the 24 test sample.

Row N...	label	metadata_file	prediction(l...
1	Test	Autopsy_R6.txt	Autopsy
2	Test	Autopsy_R7.txt	Autopsy
3	Test	Autopsy_R8.txt	Autopsy
4	Test	ChriopracticR6.txt	Chiro
5	Test	ChriopracticR7.txt	Chiro
6	Test	ChriopracticR8.txt	Chiro
7	Test	CosmeticR6.txt	Cosmetic
8	Test	CosmeticR7.txt	Cosmetic
9	Test	CosmeticR8.txt	Autopsy
10	Test	DentalR6.txt	Dental
11	Test	DentalR7.txt	Dental
12	Test	DentalR8.txt	Dental
13	Test	Diet_R6.txt	Diet
14	Test	Diet_R7.txt	Diet
15	Test	Diet_R8.txt	Diet
16	Test	DSR6	DS
17	Test	DSR7	DS
18	Test	DSR8	DS
19	Test	ENTR6.txt	ENT
20	Test	ENTR7.txt	ENT
21	Test	ENTR8.txt	ENT
22	Test	RadiologyR6.txt	Radio
23	Test	RadiologyR7.txt	Radio
24	Test	RadiologyR8.txt	Radio

Fig. 5. Running the K-NN on the 24 Test Data.

The K-NN classifier miss categorized the case test 9 in which the predicted category was Autopsy instead of the real category of Cosmetic. This miss categorization case

may be caused by using ill sensitive tokenization as the no letters separators were used for the purpose of tokenization. However, after using more sensitive tokenization such as identifying tokens based on the linguistic features, the accuracy have been raised to 97.5%. Moreover, one can enhance the accuracy further by choosing more careful document vector pruning such as the absolute pruning instead of the traditional perceptual pruning. The change has raised the accuracy to be 100%. It is also interesting to note the precision of categorizing each class of clinical narrative. Figures 6 and 7 illustrate the precision of categorizing two classes from the eight classes of the clinical narratives (Discharge Summaries and Chiropractic Reports).

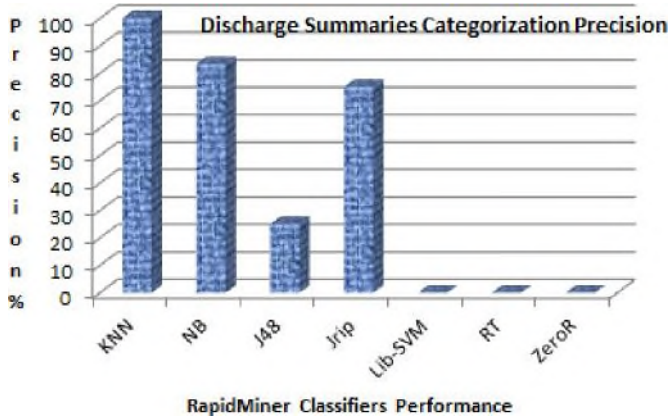

Fig. 6. The Categorization Precision of Distinguishing Discharge Summaries from the rest of Clinical Narratives.

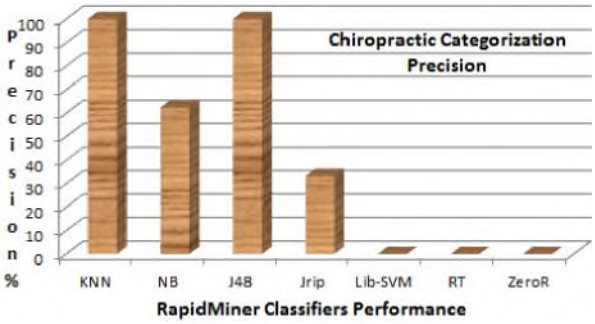

Fig. 7. The Categorization Precision of Distinguishing Chiropractic Reports from the rest of Clinical Narratives.

Moreover, the class recall is another classifier performance measure that provides information on the goodness of a classifier. Figures 8 and 9 illustrated the class recall of two classes (Discharge Summaries and Chiropractic Reports).

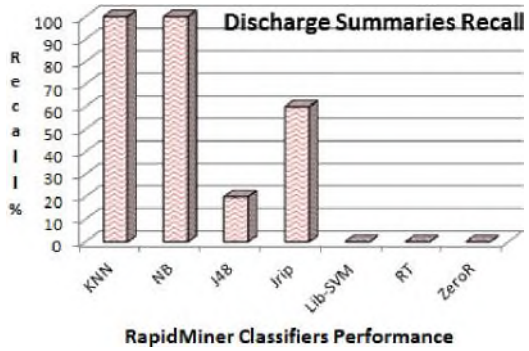

Fig. 8. The Discharge Summary Recall Measure.

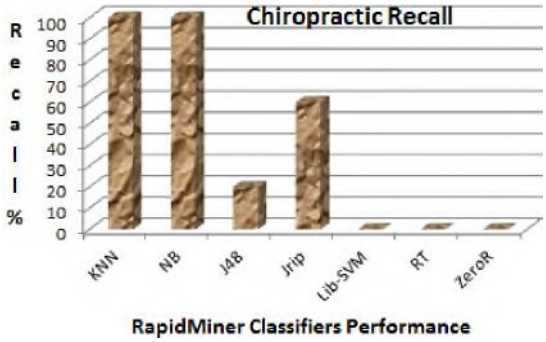

Fig. 9. Chiropractic Recall Measure.

Both the precision and recall identified K-NN to be the best compared to the other classifiers. This is an encouraging result for categorizing clinical narratives. However, one may argue that the classifiers did perform well because there are major differences between the token varieties used by each of the eight different clinical classes. This might be quite true and for this purpose we decided to use the most successful classifier like the K-NN and test its categorization ability when we use rather closely related clinical documents.

4 Validating the Categorizing Ability of the K-NN

In order to validate the ability of any categorization classifier we need to use sound dataset that can be compared to the achievements of other attempts. For this purpose, we used the i2b2 smoking dataset[8] which provides clinical narratives in five different classes as judged by a human expert (Current Smoker, Smoker, Past Smoker,

8 https://www.i2b2.org/NLP/DataSets/Main.php

Non_smoker, Unknown) [9]. The clinical narratives in this dataset share many similar token sets which make it hard for an automatic categorization system to predict the correct category of test data. For simplicity we focused on two categories (Current Smoker and Non-Smoker) and extracted 48 narratives for each of the two categories (see Table 1) as well as 13 narratives test cases (see Figure 10). After running the K-NN classifier on this selected dataset, the performance measures were as follows:

Accuracy: 80.36%
Classification Error: 19.69%
Kappa: 0.616
Average Class Precision: 85.39%
Average Class recall: 81.25%
Absolute Error: 0.196
Relative Error: 19.69
Correlation: 0.661

Table 1: i2b2 Training Smoking Dataset Sample.

Nonsmoker	Current Smoker	Nonsmoker	Current Smoker
696	641	761	130
710	681	764	223
714	704	766	236
716	757	777	241
718	786	794	260
742	872	799	265
759	874	823	284
839	535	552	346
862	540	570	352
212	543	571	370
249	563	573	85
879	564	577	130
888	565	586	845
896	585	600	515
899	602	603	562
907	626	614	633
913	643	617	906
519	681	627	109
530	25	628	1
542	133	629	220
547	328	630	151
551	406	639	202
640	31	9	214
27	43	36	73

Figure 10 illustrates how the K-NN performs in predicting the 13 unknown cases.

Row No.	label	metadata_file	prediction(l...
1	STest	R643_S.txt	Smoker
2	STest	R704_S.txt	Smoker
3	STest	R757_S.txt	Smoker
4	STest	R865_N.txt	Nonsmoking
5	STest	R868_N.txt	Nonsmoking
6	STest	R872_S.txt	Nonsmoking
7	STest	R874_S.txt	Nonsmoking
8	STest	R888_N.txt	Nonsmoking
9	STest	R896_N.txt	Nonsmoking
10	STest	R899_N.txt	Nonsmoking
11	STest	R906_S.txt	Smoker
12	STest	R907_N.txt	Nonsmoking
13	STest	R913_N.txt	Nonsmoking

Fig. 10. Categorizing the Class of the 13 Cases.

Only two cases were miss categorized by our K-NN. This result represent a good one although it was weaker than the results on the eight clinical categories dataset. However, since the i2b2 smoking dataset is a public one, there are many attempts to use classifiers for categorizing clinical documents for the categories related to smoking. Ozlem Uzuner [10] published these attempts and their accuracy measures. Figure 11 illustrates the comparison of the average precision and recall in categorizing two different classes (Current Smoker vs Non_Smoker) using our K-NN method and 11 other attempts. Interestingly, our K-NN categorization method showed higher precision and recall than any other approach.

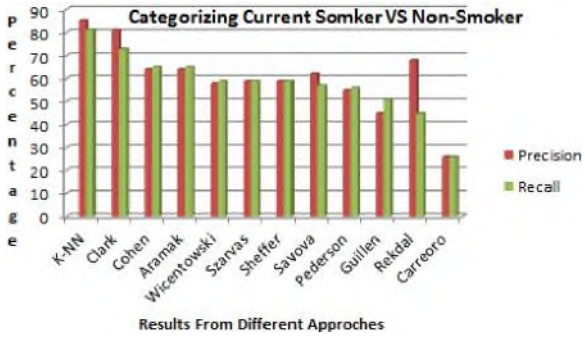

Fig. 11. Comparing K-NN with Other Notable Approaches in Categorizing Clinical Narratives for Current Smoker and Non-Smoker.

5 Discussion and Conclusion

This article demonstrates how clinicians can use visual programming tool like the RapidMiner to tokenize and categorize clinical narratives. Clinicians can flexibly drug

and past variety of visual operators and change their behaviors' via parameterizations even for complex processes like tokenization and classifications. Several experiments have been conducted for this purpose that reveal major findings for categorization of clinical narratives. For example K-NN classifier outperform other classifiers in categorizing diverse clinical reports including those narratives that include high degree of similarity like the smoking vs nonsmoking discharge summaries. However, this work is only our initial attempt as we are intending to enrich the categorization process with higher sense of context-awareness. The next step that we are currently experimenting with is to enable clinicians through RapidMiner to incorporate ontologies in the process of tokenizing and categorizing clinical narratives. This extension is quite possible with the RMonto plugin for RapidMiner. Clinicians can develop their own ontologies as well as to use an existing one. This work is left to our next research work.

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