Automatic Message Triage: Decision Support from Patient-Provider Messages

Completed Research Paper

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ABSTRACT

Email communication between patients and healthcare providers is gaining popularity. However, healthcare providers are concerned about being inundated with patient messages and their inability to respond to messages in a timely manner. This work provides automated text mining decision support to overcome some of the challenges presented by email communication between patients and healthcare providers.

Keywords (Required)

Text Mining, Classification, Triage, Personal Health Records.

INTRODUCTION

Patient-provider communication plays an important role in patient healthcare and quality of life (Arora, 2003; Street Jr. and Epstein, 2008). Good communication helps patients to better understand relevant medical information (Ye, Ye, Rust, Fry-Johnson, and Strothers, 2010); e.g., instructions they need to follow to improve their healthcare, and facilitating patient motivation to make behavioural changes to improve their health through diet or exercise (Street Jr. and Epstein, 2008). Moreover, effective communication increases patient satisfaction with care (Dutta-Bergman, 2005; Ye, et al., 2010). Communication is traditionally face-to-face, but electronic communication between patients and healthcare providers has become popular due to the advent of the Internet and electronic personal health record (ePHR) systems (Ye, et al., 2010). ePHR systems enable patients to create, access, and manage their health and medical records over the Internet (Archer and Fevrier-Thomas, 2010; Sittig, 2002). These systems support a change to a patient-centered focus, causing a revolution in healthcare delivery strategy (Archer, 2010; Sittig, 2002; Lafky, Tulu, and Horan, 2006). Most ePHR systems enable patients to send messages to their providers through a mechanism like secure messaging (Halamka, Mandl, and Tang, 2008) or email, and more patients are beginning to use web messaging and email to communicate with their healthcare providers (Liederman, Lee, Baquero, and Seites, 2005; Ye, et al., 2010). This can reduce errors in communication, increase the productivity of healthcare providers, enhance patient access to healthcare providers, and boost patient satisfaction (Liederman, et al., 2005; Ye, et al., 2010). Electronic communication increases access to healthcare providers (Rosen and Kwoh, 2007), leads to better health quality (Rosen and Kwoh, 2007), and makes patients feel more comfortable and satisfied (Wakefield, Mehr, Keplinger, Canfield, Gopidi, Wakefield, Koopman, Belden, Kruse, and Kochendorfer., 2010; Ye, et al., 2010). Moreover, it makes it more convenient for them to ask pertinent questions of their healthcare providers (Houston, Sands, Jenckes, and Ford, 2004; Ye, et al., 2010). Electronic communication also eliminates the need for unnecessary visits or phone calls by patients and increases the pace of healthcare delivery (Wakefield, et al., 2010).

Despite these benefits, electronic patient-provider communication has caused many concerns, including the potential for additional unpaid work by providers (Liederman, et al., 2005; Ye, et al., 2010). This may result in overload when healthcare providers are inundated by non-urgent patient messages, while some messages needing an emergency response may be neglected (Ye, et al., 2010). Developments in the field of text mining have opened new doorways to ameliorate these problems.

The advent of the Internet and the resulting explosion of information worldwide (Konchady, 2008) has led to the development of automated text mining techniques to help organize this vast ocean of information into various categories (Weiss, Indurkhya, Zhang, and Damerau, 2004). An important and relevant application of text classification is categorizing text documents such as patient email messages, due to their significance for healthcare providers. Following previous works concerning the use of text and data mining in facilitating healthcare and ePHRs (Sartipi, Yarmand, and Down, 2007) this work proposes decision support, using text mining techniques to triage patient email messages automatically. To the authors' knowledge this is the first work that attempts to analyze patient email messages using text mining techniques. Moreover, this can be a great help to healthcare practitioners in increasing the speed of response to urgent messages and also to handle non-urgent patient email messages in a timely manner.

This paper begins with a review of literature related to text mining and classification algorithms and then discusses the design issues of decision support for message triaging. This is followed by a review of the test results, and finally a discussion of appropriate algorithm choices, related design decisions, and future trends for automatic message triage.

LITERATURE REVIEW

Email communication with patients has been adopted slowly (Ye, et al., 2010), mainly because of the large amount of messages that can lead to certain concerns for patients and healthcare providers, including added workloads for healthcare providers, use of email for improper purposes (Kleiner, Akers, Burke, & Werner, 2002; Ye, et al., 2010), and a lack of compensation for the resulting time demands on healthcare providers (Moyer, Stern, Dobias, Cox, and Katz, 2002; Ye, et al., 2010).

In order to overcome these challenges there have been some suggestions in the literature. For example, Ye et. al (2010) suggest structures like limiting the number of characters in patient emails to reduce the amount of email to be read by healthcare providers. Another solution is to use trained staff to triage messages, responding to low priority messages directly, but sending higher priority messages to the appropriate healthcare providers (Archer, Fevrier-Thomas, Lokker, McKibbon, and Straus, 2011; MyOSCAR Research Team, 2009).

Moreover, literature in other fields suggests using text mining to overcome similar difficulties regarding large amounts of messages. For example, Gartner and Schneider (2012) use text mining to prioritize the end-user feedback based on its content. Alberts and Forest (2012) use text mining to automatically triage email messages that are sent, to avoid email overloads for employees. Bicquelet and Weale (2011) use text mining to handle the large amounts of data generated by the public in public policy analysis projects. Finally, Google's priority inbox which sorts emails based on their importance for the user (Google Research Team, 2010).

Building on these works, the objective of this research was to design a decision support approach that uses text mining to automatically triage messages sent from patients and to potentially manage the patient email challenges mentioned. By automatically classifying patient messages, medium priority messages can be passed along for handling by staff, and urgent messages can be passed directly to the appropriate physician for immediate response. This also opens doors to the design of automated systems that are able to respond directly to low priority requests for information.

AUTOMATIC MESSAGE TRIAGE DECISION SUPPORT SYSTEM

In order to overcome the issues mentioned in email communication between patients and healthcare providers, the authors have designed a text mining decision support to automatically categorize messages according to their importance, to help nurses and physicians to manage patient email messages. System design is elaborated in Figure 1.
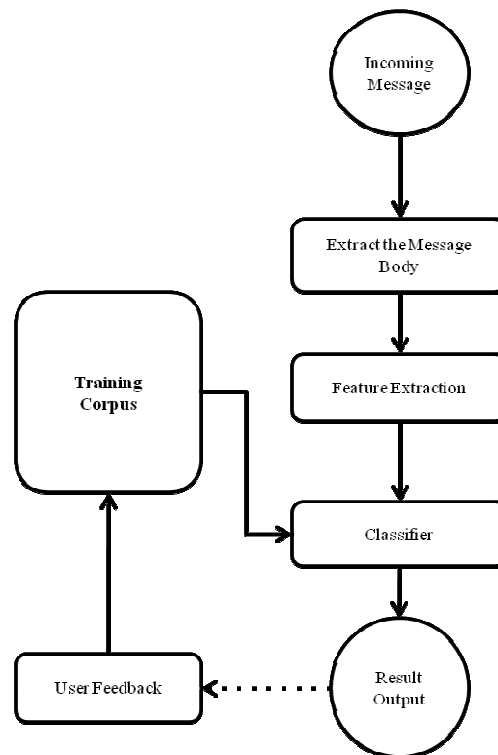
Figure 1 – Overall System Design

The system cleans i.e. *extracts the message body*, which is the main part of the message, from each new incoming message.   Then the *feature extraction* algorithm converts the new message into a vector which contains the important features of the message (known as a feature vector), which is readable by the classifier algorithm. Afterwards, the *classifier* categorizes (i.e. triages) the messages based on their importance, using the *training corpus* already available to it. This requires the classifier to be trained with a training corpus before going live. Then, the system shows the *results* to the user and, if the user provides *feedback*, the message is added to the training corpus to increase the future precision of the classifier. If there is no feedback from the user, the message is just assigned a triage level and will not be used for system improvement. Therefore, for optimal design of the decision support, the best available feature extraction and classification algorithm for this environment must be chosen. Choosing these algorithms is discussed in the next section.

Choosing Appropriate Algorithms

To build the appropriate decision support, the first step is to extract the message body and choose the right feature extraction algorithms. Extracting the message body involves removing the unwanted part of the message which is dependent on the data structure of the message. For example, the structure of email messages is considerably different from SMS text messages; as a result this requires a different algorithm for extracting the message body. We will describe the algorithm used in the method section.

After extracting the message body, an appropriate feature extraction method needs to be used. To extract the important features, the first step is to break text into words or "tokens" (known as "tokenization") (Weiss, et al., 2004). An appropriate data representation for the text documents must be chosen, with the most common data representation known as the spreadsheet model or "bag-of-words" (Weiss, et al., 2004). In the spreadsheet model the text document is represented as a "feature vector" consisting of document token frequencies. Examples are depicted in Table 1.

		Tokens		
		CN Tower	*Celebration*	*Toronto*
Documents	doc_1	1	0	5
	doc_2	0	2	1
	doc_3	1	0	1
	doc_4	2	4	0

Table 1 – Example Spreadsheet Representation of Text Documents

Another well-known technique in text representation is the multiword feature (Weiss, et al., 2004) or n-grams (Konchady, 2008) in which groups of tokens (words or characters) that are related to each other (occur together frequently such as 'CN Tower' in Table 1), are treated as one token in the document vector. In this work, both of these methods (bag-of-words and n-gram) have been used to find the most appropriate approach.

When the right data representation techniques have been chosen, these approaches may result in a huge number of tokens in each document. To filter these tokens and choose only the most important ones, algorithms for feature reduction have been developed. For example, removing stop words, like "to" or "for", from a document is a commonly used feature reduction technique (Feldman and Sanger, 2007; Weiss, et al., 2004). Another method for reducing the number of features is to remove words that are the most frequent (ibid). But just removing the words that are most frequent can be risky in most cases because these words can be rare in other documents, making the words more valuable (ibid). To overcome this deficiency different methods have been suggested, with a well-known one being TF-IDF which stands for Term Frequency - Inverse Document Frequency (ibid). In TF-IDF words are weighted based on their importance, so the only words chosen are the words that have greater importance (thus greater weight) (Feldman and Sanger, 2007; Weiss, et al., 2004). In this work, both of these methods (removing stop words and TF-IDF) have been used to find the most appropriate approach.

There are several "classification algorithms" that can be used to build a model based on a set of text documents and then to use the model to classify a new and unknown text document. Some of these classifiers, used in this work, are discussed in the following.

K Nearest Neighbor

The K Nearest Neighbour (KNN) classification method is based on similarities between documents (Weiss, et al., 2004). The KNN classifier converts any new document it is given into a feature vector and calculates the distance between the new vector and the previously calculated feature vectors. The K nearest neighbours of the new document is then selected and the new document is classified into the most frequent category appearing among its K nearest neighbours (Konchady, 2008; Weiss, et al., 2004).

Language Model Classifier

The Language Model (LM) classifier has been widely used in many other areas like speech recognition (Carpenter, 2010; Tenenboim, Shapira, and Shoval, 2008). A LM classifier uses a comparison of the n-grams in the new unknown document with those in the training documents of a certain category (Carpenter, 2010; Konchady, 2008). If an n-gram has appeared in the training corpus it will have a higher chance of belonging to that category of n-gram in the training corpus (Carpenter, 2010).

Naive Bayes Classifier

The Naive Bayes (NB) classifier categorizes text documents based on the Bayes theorem of probability (Feldman and Sanger, 2007). NB classifier calculates the probability that a new document belongs to each category, and classifies the new document in the class with the highest probability. The NB classifier is based on the rigorous assumption that all features are probabilistically independent, so this classifier is known as "naive" (Feldman and Sanger, 2007). Because of the naive assumption, this classifier does not perform as well as many other classifiers, and is mostly used as a classifier in comparing classifier performance.

Combination of Classifiers

In everyday life if several experts give their suggestions on a subject it is more likely to result in a better decision than a decision based on single expert judgment. Results from a combined classifier are also more likely to be precise than a single classifier. The simplest form of combining classifier results is known as voting. In this method the new document is classified into the category which most individual classifiers have voted for (Li and Jain, 1998). Another common method for classifier combination is known as adaptive classifier combination (ACC). ACC combines the results of various classifiers in order to get better results (Li and Jain, 1998).

In this work simple voting and ACC were used to combine classifiers. All of the combination classifiers combine the results from all of the three linear classifiers mentioned (KNN, LM, NB). The implementation of ACC is mostly inspired by (Li and Jain, 1998). Steps in this method are:

1 – Find the k nearest neighbourhood of the newly given document using standard neighbourhood algorithms like Euclidean or cosine distance methods.

2 – The given document is classified using all of the 4 individual classifiers mentioned.

3 – For all categories a measure called ACC is calculated by multiplying the cosine distance of the newly given document and the located neighbourhood by the probability that the new document belongs to that category, as calculated by the classifier.

4 – The document is classified in the category that has the highest ACC measure.

Nonlinear Classifiers

Two nonlinear classifiers are also used for testing their performance in this environment: Neural Networks (NN) and Support Vector Machines (SVM). In NN, the first step is designing an NN that can be trained using data from known documents and their classification, and then using the trained network to classify new documents (Feldman & Sanger, 2007). For text classification, mostly feed-forward back-propagation neural networks are used, in which weights are determined by propagating error through the networks (ibid). In SVM, an optimal hyper-plane is found in a high dimensional vector space which separates documents that belong to a category and those that do not belong to that category (ibid).

METHOD

Data Collection

Messages used for this study were obtained from the My Blood Pressure (MyBP) study (MyOSCAR Research Team, 2009), which evaluated the effects of ePHRs on patient hypertension self-management. In this study, patients had access to a customized version of MyOSCAR, which is an online, open source, secure electronic personal health record (ePHR) system (ibid). In the MyBP study, patients could record their blood pressure, see their blood pressure charts and drug prescriptions, and contact their healthcare providers through a secure email system (MyOSCAR Research Team, 2009). The patients were instructed to send messages to the healthcare providers whenever they had a very high blood pressure or when they had technical or health related question (MyBP Research Team, 2010). A sample of one patient message asking his or her healthcare provider for rescheduling an appointment is provided here:

> "Hi I'm sorry I won't be able to attend the meeting tomorrow. I've just received a call giving me a cancellation for a specialist I have to see. The date I had was September so I really want to keep this appointment. Can you reschedule for me please?
>
> Thanks"

The email messages mentioned were used to design and test the automatic triage system developed in the current work. In the MyBP study, a triage person read and redirected incoming messages to the appropriate healthcare providers (pharmacists, dieticians, nurse practitioners, and primary care physicians).

During the study 1460 email messages where exchanged between patients and healthcare providers (MyOSCAR Research Team, 2009). 1296 of these were general email messages, (e.g. reminders), sent by the nurse as reminders to patients. The remaining 164 email messages were used in designing and testing the automatic message triage system. These email messages could concern clinical subjects or technical issues. Based on the subject and importance, they were answered in a time ranging from immediate up to at most 72 hours. All the email messages were responded to, even if the response was a simple thank you. Table III shows the email message categories and their response times.

Data Collection

The current study was approved by the McMaster Faculty of Health Sciences/Hamilton Health Sciences Research Ethics Board. To prepare the MyBP messages for this study, the bodies of all the messages were extracted from the 1460 available raw XML messages. All header data including senders, receivers, subject lines, etc. were deleted. Any personally identifiable data was also deleted from all of the email messages to protect patient privacy. Because there were a large number of messages, a text mining program called GATE (Cunningham et al., 2011) was used to detect and delete names and other personal data in the email messages. The final message set was reviewed by the authors to ensure that all personal data had been removed. The remaining 164 email messages were grouped into four triage levels based on their required response time, with the help of two nurses who worked with the MyBP study team. To ensure the correctness of the triage levels, the nurses triaged the messages independently. The few disagreements in assigned triage levels were resolved by the authors before the resulting triage assignments were used. The triage levels are shown in Table 2.

| Triage Level	Description	Num. Msg. Available
Level 0	*Immediate action* – probable emergency. *Personal messages that required immediate response.*	*0*
Level 1	*Immediate action* – to be handled by the triage person. *Personal messages that required immediate response.*	*0*
Level 2	*Response within 24 hours* – to be handled by triage person. *Personal messages that required response in 24 hours.* Examples: Patient appointment times; anything to do with non-urgent elevated / potentially blood pressure readings	*19*
Level 3	*Response within 72 hours* (since the aim is that all messages will be addressed within 3 days). *Personal messages that required response in 72 hours.* Example *C*: Issues with personal blood pressure monitors Examples *D*: Medication changes to be updated; updates to other online personal health record Examples *E*: Issues accessing different aspects / components of online personal health record; difficulties with survey completion; lost passwords; etc.	*69*
Level 4	*Duplicate message* – not used for classification	*74*

Table 2 – Triage Levels for email Messages

The messages were categorized, based on the response time needed for the most urgent issue and not based on the time needed to provide a solution to all the problems if the message addressed more than one issue. Other similar

studies have shown that most email messages address only one issue (White, Moyer, Stern, and Katz, 2004; Ye, et al., 2010).

Column 3 of Table 2 shows the number of messages available in each section. Because there were only 28 patients in the MyBP study and the length of the study was relatively short (1 year), there were no level 0 messages and only one level 1 message, in agreement with other similar studies (Rosen and Kwoh, 2007). Therefore, the study only considered available messages from the patients used in triage levels 2 and 3.

There is no way to estimate the appropriate size of a corpus for training and testing a text mining algorithm (Weiss, et al., 2004). In the real world it is common for the number of messages in each category for training and testing to be different (Weiss, et al., 2004). The only way to check whether there are enough messages in each category is to check the performance of the system. Since the final results from the system that was designed were satisfactory for this study which is at its initial stages, it can be argued that there were enough messages in each of the sample sets. A related issue is that differing numbers of messages in each triage category may increase the likelihood of bias in the classifier toward a certain category (Konchady, 2008), but it is difficult to overcome such potential bias without eliminating valuable training messages. Therefore, since this study is the initial step in designing the system the number of messages was not considered in this study. Figure 2 shows the process of data preparation discussed.
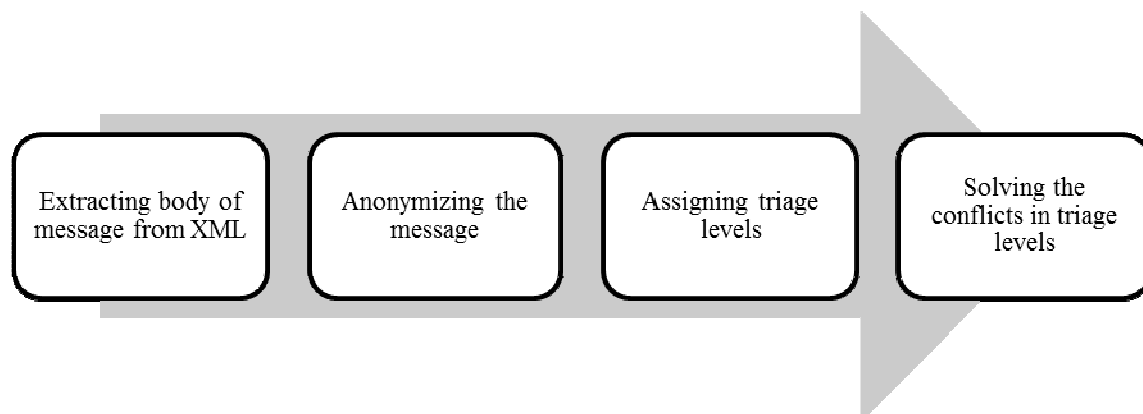
Figure 2 - Data preparation process

Implementation of Algorithms

For the implementation of classification algorithms there are several open-source customizable packages, including R (R Core Team, 2012), GATE (Cunningham, et al., 2011), WEKA (Witten and Frank, 2005), and LingPipe (Alias-I 2008, 2013b) . LingPipe was chosen for the linear classifiers (KNN, LM, NB, ACC classifiers) in this work since it is flexible and relatively easy to use. R was used to test the non-linear classifiers (NN and SVM) in this work.

Feature Reduction Algorithms

Email messages are usually brief (Sittig, 2003; White, et al., 2004; Ye, et al., 2010), so any reduction in the number of features can reduce classifier performance. In fact, testing in this environment showed that use of TF-IDF feature reduction on all classifiers actually reduced their precision significantly. Consequently, for this work only common feature reduction algorithms like changing the words into lower case, removing white spaces and removing English stop words was used.   No other specific feature reduction or selection algorithm was used. Table 3 summarizes the technical specifications of each classification method implementation.

Classifier Type	Data Model	Feature Reduction
KNN	Bag-of-words	All letters lowercased, Whitespace removed, stop words removed
LM	n-gram based on characters	All letters lowercased, Whitespace removed, stop words removed
NB	Bag-of-words	All letters lowercased, Whitespace removed, stop words removed
NN	Bag-of-words	All letters lowercased, Whitespace removed, stop words removed
SVM	Bag-of-words	All letters lowercased, Whitespace removed, stop words removed

Table 3 – Summary of Classification Algorithms Implementation Details

Benchmark Conditions

To choose the most suitable classification algorithm, all of the classification algorithms were tested on the messages. In order to optimize the parameters and testing, the classifier K fold cross-validation technique with K=5 was used (Friedman, Hastie, and Tibshirani, 2008; Stone, 1974). Moreover, for this work "accuracy" was used to measure classifier performance. Accuracy is the percentage of documents which are properly classified (Weiss, et al., 2004).

Classifier Optimization

For each of the classifier algorithms mentioned proper parameters (e.g. K which is number of neighbours in KNN) should be chosen to minimize the error for the current corpus. Therefore, several tests were run by the authors to find these proper parameters. The details of these tests and the code for the classifiers are available from the first author upon request.

RESULTS

This section discusses the results of different algorithms using the benchmark conditions discussed.

Comparison of classifiers

Algorithm	Accuracy
NB Classifier	0.76
LM Classifier	0.76
KNN Classifier	0.76
Simple Voting Classifier	0.76
ACC Classifier	0.81
NN Classifier	0.81
SVM Classifier	0.81

Table 4 – Classifier performance comparison

Table 4 compares classifier performance for the different classifiers tested using the parameters described. The results are the average of 5 fold cross-validation. The ACC with the new distance algorithm classifier proved to have the best classifier performance of all the algorithms tested.

DISCUSSION AND CONCLUSION

The results indicate that ACC and nonlinear classifiers (NN and SVM) have the best performance. However, since ACC is a combination of linear classifiers which are faster than nonlinear classifiers, ACC is the best choice for

triaging email messages sent from patients to healthcare providers. Moreover, it was found that since these messages are brief, any reduction in the number of features can reduce classifier performance. Further, since the current system shows 81% accuracy it is recommended to send the priority 1 and 2 messages with a very high priority flag to a nurse before sending them to a physician for further emergency actions. Furthermore, these linear algorithms are readily available through open-source packages like LingPipe (Alias-i, 2008). Therefore, the findings of this work are easily implementable in ePHR systems. As a result, these findings can open the doorway for future development of ePHR systems. These findings can have several other business applications. For instance, classifying the messages sent from customers in CRM systems or sorting user opinions regarding a firm's products.

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