Machine Learning Models for the Segmentation of eCoaching Text

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Abstract *Machine learning-based models has the potential to to efficiently and accurately identify patient-provider communication behaviors during eCoaching intervention sessions targeting fruit and vegetable intake among young adults age 21-30.*

1) Motivation: Why do we care about the problem and the results?
2) Problem statement: What problem is the paper trying to solve and what is the scope of the work?
3) Approach: What was done to solve the problem?
4) Results: What is the answer to the problem?
5) Conclusions: What implications does the answer imply?

Introduction

Unhealthy eating habits, particularly low fruit and vegetable intake, is a growing, serious public health concern, particularly among young adults age 21-30, referred to as Generation Y (GenY)[1,2]. This generation has adopted a lifestyle that involves eating accessible, "no mess", quick, "grab and go" foods[3,4]. They mainly eat "out" and infrequently shop and prepare food, limiting access to fruit and vegetables (FV)[5,6]. Unfortunately, less than one-third of US adults[1,7] and only 20% of GenY[1,8,9] eat the recommended 5 servings of fruit and vegetables daily. Those in inner city urban and rural settings have among the poorest eating habits[1,2,7–9]. GenY's poor dietary practices placing them at high risk for obesity and many chronic diseases, such as type 2 diabetes, as well as declines in predicted health status and life expectancy. Thus, there is a need to develop effective interventions to improve GenY's eating habits.

GenY is a tech-savvy generation requiring an intervention matched to their mobile lifestyle. Growing numbers use the internet to access health information with the largest increases in internet access among low-income Americans, making the internet well-suited for health promotion intervention[10]. MENU GenY[11] (Making Effective Nutrition Choices for Generation Y) is a technology-based public health intervention to encourage increased fruit and vegetable intake among GenY. A critical component of MENU GenY is personalized eCoaching. eCoaches use email to deliver motivation-enhancing coaching to encourage healthy eating, grounded in the principles of Motivational Interviewing (MI), an evidence-based communication technique to increase intrinsic motivation and self-efficacy for behavior change[12–14]. Patient "change talk", statements of intrinsic motivation about their desire, ability, reasons, need for and commitment to behavior change, is an established mediator of health behavior change[15]. Identifying specific communication strategies linked to behavior change and integrating these strategies into communication-based interventions (e.g., brief, motivation-enhancing interventions delivered in a variety of settings or public health initiatives) can increase these interventions' potency.

A major drawback of this research is the qualitative methods traditionally used to analyze the communication process which are resource-intensive, requiring an iterative process of human (subjective) interpretation of text. Rapidly developing computational technologies, specifically machine learning combined with classification models, offer a unique opportunity to accelerate this process. Our research group has recently applied machine learning-based models to similar communication data[16,17]. A simple communication code scheme was automated to characterize patient communication and achieved accuracy comparable to human coders[16]. The ultimate goal of the research study is to leverage innovative machine learning models to fully automate the communication coding process in eCoach-patient communication to increases in fruit and vegetable intake.

However, a significant barrier of fully automate eCoaching is the unsegmented text data. Developing an automatic

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classification of clinical interactions required segmented text. Nevertheless, eCoaching data comprised of email responses which need to be segmented into group of MI behavior referes to "block of text". Automatic segementation of eCoaching intervention sessions is a challenging task due to the 2 important reasons. First, the email is an unstructured text that contains informal email exchange in non-traditional formats. Second, a text segment not necessarily belongs to the entire sentence or collection of sentences. One sentence can be segmented into several MI behaviors, and vice versa. Figure 1 illustrates that the marked sentence taken from an eCoaching email exchanage, segmented into 2 different MI behaviors, CHT and HUP.

On Mon Nov 10 20:40:02 2014, XXX wrote:

Hi YYY, I haven't had a chance to look through MD 5 or 6, but I've found a few veggies that I like to pack and take with me. I just have to prep them more. Thanks XXX

(Email Date: 2014-11-11 10:29:18)
Hi XXX,

It's good to hear from you. It sounds like you found a plan that works for you as long as you are able to find time to prep veggies for on-the-go snacks. Sometimes people find inspiration for making a change by considering things that are important to them. There is some evidence that behavior change is often easier when it relates to your own values and goals. This might be helpful in finding reasons to keep up with what you are now doing. You stated that being considerate, respected, and responsible are important to you. How, if at all, would you say that eating better and having more energy would help you be considerate and respected? How about to be more responsible?

I look forward to hearing from you again soon,

YYY

Figure 1: Main challenge of text segmentation.

In this paper, we address this problem by developing several state-of-the-art machine learning based models for the segmentation of eCoaching text to promote the automatic identification of best communication strategies without human interference. More specifically, we develop Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbor (KNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) by utlizing contextual, topic and punctuation mark features, to find the best model for the segmentation of eCoaching text.

Previous studies mainly focus on segemntation of text into sections and headers[18–21] or sentence boundary detection[22–24] in the medical domain. Apostolova et al.[18] applied SVM by utilizing word-vector cosine similarity metric combined with several heuristics to classify clinical report into semantic sections such as demographics, history, exam procedure, finding, impression, etc. After identification of each line in the document, Tepper et al.[20] trained an Maximum Entrophy models for the section classification. In 2009, Denny et al.[19] proposed a SecTag algorithm, which combined natural language processing technique, terminology-based rule, and naive bayesian score for identifying sections and headers that achieved 99% recall with 95.6% precision. On the other hand, SVM exploiting with linear kernel and recurrent convolutional neural networks with posodic, part of speech features and word embeddings, were trained by Kreuzthaler et al.[23] and Griffis et al.[22], respectively, for the detection of sentence boundary. However, segmentation of clinical text, in partiicular, segmentation of MI or eCoaching text into group of MI behavior is ignored while relying on manual hand-coded approach. Therefore, this study introduce an innovative approach and the authors are not aware of any other work this approach has been considered for the segmentation of MI or eCoaching text into "block of text".

Methods

Data collection

The experimental dataset for this work was constructed from the 49 eCoaching sessions, which include a total of 3,138 segmented and annotated MI behaviors. Each session contains an MI intervention involving patient-provider

communications in email. To filter out noise from the dataset, non-ascii characters are removed and then applied stemming to obtain a general form of word from different word representations, such as "eating", "eats", and "eat". We formulate the text segmentation task into a binary classification, as shown in Figure 2. An email text is given as the input, it is partitioned into adjacent word pairs by sliding them. Each pair of them classified into either of the two categories: "boundary" and "not boundary". The text is segmented at position, where an adjacent word pair classified into "boundary" class. If all pairs of word classified into "not boundary", the text is treated as one about a single MI behavior. Totaly, we obtained 95,421 word pairs, which include 3,138 "boundary" and 92,283 "not boundary" instances.
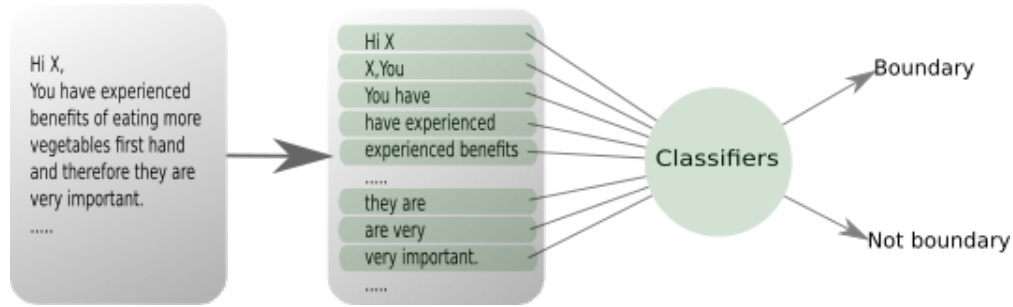
Figure 2: Transformation of text segmentation into text classification.

For the experiment, we utilized three type of features including word, tpoic, and punctuation mark. Each word represented in a binary format, where 1 indicates the appearance of the word and 0 for absence. Topics are considered as features since topic models are very effective[17,25,26] to represent text documents. In this paper, we exploit the Labeled LDA model[17] and represent each word in a vector of 2 topics, where the number of topics is experimentaly determined by the model performance. Punctuation mark containing one of the symbols {'.', ',', '!', '?', ':', ';', '-'} is also employed as feature. This is one of the most important feature as they indicate the boundary of a sentence, clause and phrase.

Segmentation classifiers

Several state-of-the-art classifiers, including Naive Bayes (NB)[27], Support Vector Machine (SVM)[28], K-Nearest Neighbour (KNN)[27], two variant of Recurrent Neural Networks (RNN)[29]: Long Short Term Memory (LSTM)[30] and Gated Recurrent Unit (GRU)[31], are employed to estimate the classification performance.

Naive Bayes: this model is constructed by using the training data and estimate the prior probability of classes, and each feature given the class. Then, posterior probability is computed to predict the class label by applying the bayes theorem with the assumption that features are conditionally independent. This study utilized a specialized version of Naive Bayes called Multinomial Naive Bayes, which is best suitable for discrete features such as word.

Support Vector Machine: we used this model as one of the state-of-the-art classification technique proven to perform well in text categorisation[32] for its ability to cope with very high dmensional input feature space. SVM finds the best hyperplane in the feature space that maximize the separation between the closest "boundary" and "not boundary" training examples. In this experiment, polynomial kernel is employed to train the SVM model for the segmentation of eCoaching text.

K-Nearest Neighbour: By this model, each training sample represented as a point in the input feature space. For a new test sample, Euclidean distance is calculated to find the k-nearest neighbors. Finally, the test sample is classified into majority class of the k-nearest neighbors. We experimentaly determined that best performance was achieved with k = 3 for the classification of word pairs.

Recurrent Neural Networks: RNN is a neural network architecture designed to capture sequential patterns present in temporal sequence such as text data. When we predict the "boundary" point, adjacent word pair will help to understand

the pattern of the sequence. Long Short Term Memory networks usually reffered as LSTMs[30], are a special type of RNN capable of handling variable size input sequence, contains internal memory. GRU[31] is a variant of LSTM mathematically represented by the following formula:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$

$$\tilde{h}_t = tanh(W_h x_t + r_t \odot U_h h_{t-1} + b_h) \tag{3}$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \tag{4}$$

In Eq. 1-4, σ corresponds to sigmoid function and $\odot$ designates an element-wise product. The update gate z_t and reset gate r_t at time step t are computed by the Eq. (1) and (2), where W_z, W_r, W_h, U_z, U_r, U_h are the weight matrices and b_z, b_h and b_r are bias vectors. The activation h_t of the GRU at time t is a linear combination of previous activation h_{t-1} and the candidate activation $\tilde{h}_t$, which is represented by Eq. (4) and (3). We build our RNN model with one hidden layer, output layer, and input layer which get one hot encoding of word vector as input. We experimentally determined that the best performance is achieved when the number of hidden units=32, batch size=32, optimizer=adam, as well as early stopping is used based on the validation loss.

Evaluation metrics

In this experiment, standard metrics: precision, recall, and F-measure, are applied to evaluate the performance of binary classifiers[33]. However, we didn't report accuracy as a performance metric because accuracy is highly sensitive to the prior class probabilities and does not fully describe the actual difficulty of the decision problem for unbalanced dataset. We conduct the experiment with 5 folds cross-validation and weighted macro-averaging of these metrics over the folds. All models are trained on 80% of the word pairs and remaining 20% of the data is used as a test set for reporting the performance of the model. We also estimated the area under the receiving operating characterstics curve (AUC) metric due to its effectiveness in measuring the quality of binary classifiers for imbalanced datasets[34].

Results

Experimental evaluation of the proposed method is conducted on both under and over-sampled sequences. Predictive performance summary of the proposed methods on under and over-sampled sequences is presented in Table.

1) In general, the pure, unbiased results should be presented first without interpretation (van Wagenen 1990).
2) These results should present the raw data or the results after applying the techniques outlined in the methods section. The results are simply results; they do not draw conclusions.

Table 1: Performance of NB, SVM, KNN, and RNN for identifying segmentation point in eCoaching text. The highest value for each performance metric is highlighted in bold.

Method	contextual features only			contextual + topics + punctuation marks		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Naive Bayes Multinomial	0.594	0.662	0.626	0.590	0.666	0.626
Support Vector Machine	0.742	**0.679**	0.709	0.774	0.696	0.733
K-Nearest Neighbour	**0.808**	0.663	**0.728**	**0.820**	**0.742**	**0.779**
Long Short Term Memory	0.8424	0.8385	0.8381	–	–	–
Gated Recurrent Unit	0.8705	0.8676	0.8673	–	–	–

Predictive performance summary of the proposed methods on under and over-sampled sequences is presented in Table.

Table 2: Performance of NB, SVM, KNN, and RNN for identifying continuous eCoaching text. The highest value for each performance metric is highlighted in bold.

Method	contextual features only			contextual + topics + punctuation marks		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Naive Bayes Multinomial	0.988	0.985	0.987	0.989	0.984	0.986
Support Vector Machine	**0.989**	0.992	0.991	0.990	0.993	0.991
K-Nearest Neighbour	**0.989**	**0.995**	**0.992**	**0.991**	**0.994**	**0.993**
Long Short Term Memory	0.8424	0.8385	0.8381	–	–	–
Gated Recurrent Unit	0.8705	0.8676	0.8673	–	–	–

Table 3: Performance of NB, SVM, KNN, and RNN for the identification of segmentation and continuous eCoaching text. The highest value for each performance metric is highlighted in bold.

Method	contextual features only			contextual + topics + punctuation marks		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Naive Bayes Multinomial	0.975	0.974	0.975	0.976	0.974	0.975
Support Vector Machine	0.981	0.982	0.981	0.983	0.983	0.983
K-Nearest Neighbour	**0.983**	**0.984**	**0.983**	**0.986**	**0.986**	**0.986**
Long Short Term Memory	0.8424	0.8385	0.8381	–	–	–
Gated Recurrent Unit	0.8705	0.8676	0.8673	–	–	–

We took the inspiration for the representation of behavior codes from the idea of word embeddings. Word embedding is a representation of words in low-dimensional space by vectors, which contain the features of the words. In our study, we employed embedding in place of one-hot vectors for representation of behavior codes as input to LSTM and GRU, since one-hot vectors are high-dimensional and sparse.
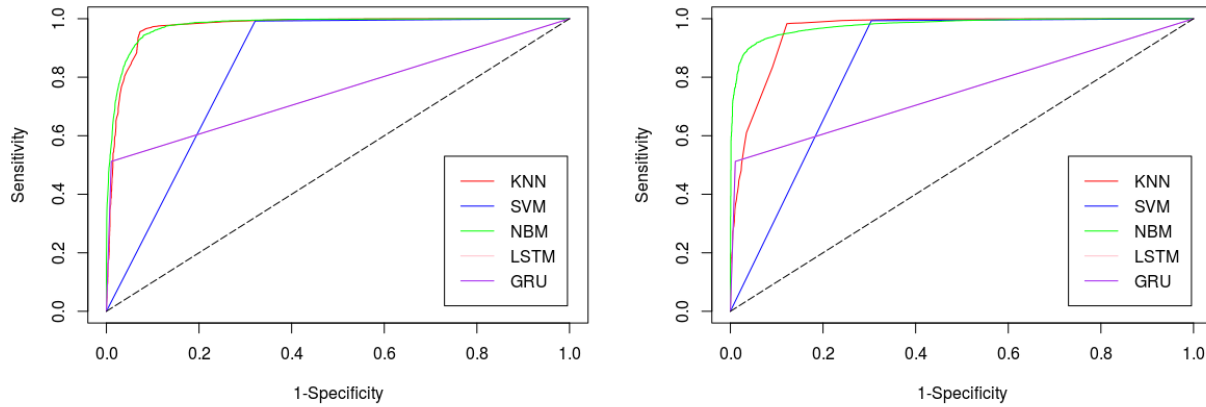
Figure 3: ROC curves compared the performance of different models.

Discussion

By analyzing the experimental results of different communication sequence outcome prediction methods proposed in this paper, we arrived at the following conclusions. First, the overall predictive performance of RNN models is substantially better than probabilistic models. In particular, the RNN-based method achieves near-human accuracy for predicting the

1) What, specifically, did you learn from comparing these algorithms or data structures?
2) What do your results say about the problem or question you were investigating?

3) Was your hypothesis confirmed or disproved?
4) Are the results what you expected?
5) If you obtained anomalies or other unexpected results, can you explain them? If not, how could you set about in the future to identify what caused them?
6) How do your results compare to past findings? Are they consistent? Different?Why?
7) How would you respond to objections or questions that other researchers might have about your methods, results, or interpretations?
8) What is new and significant?

Conclusion

Segmentation of eCoaching text is an integral part of developing an automated eCoaching intervention. Although several studies have done for the segmentation of clinical text into sections and sentences, none of them are used for the segmentation of text into a group of MI behavior in the setting of discourse analysis with email under the principle of motivational interviews. In this paper, we compared the performance of machine learning models for the task of segmentation of e-coaching text. We found out that k-nearest neighbour provides the best performance for the segmentaion of text in terms of all performance metrics. Manual segmentation of e-coaching data is very resource-intensive and time consuming task, which can significantly decrease the time and effort required to develop effective behavioral interventions. Our proposed methods can help to identify individual text segments, which can be annotated directly with a classification model and increase the effectiveness of behavioral interventions. This approach will help for developing fully automated eCoaching and also accelerate the pace of identifying effective communication strategies linked to healthy eating. As our future work, we plan to evaluate our approach on other datasets involves in discourse analysis for enhancing our proposed method.

Acknowledgments

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