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Identifying Emotional Support in Online Health Communities

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Abstract

Extracting emotional support in Online Health Communities provides insightful information about patients' emotional states. Current computational approaches to identifying emotional messages, i.e., messages that contain emotional support, are typically based on a set of handcrafted features. In this paper, we show that high-level and abstract features derived from a combination of convolutional neural networks (CNN) with Long Short Term Memory (LSTM) networks can be successfully employed for emotional message identification and can obviate the need for handcrafted features.

Introduction

Online health communities (OHCs) provide a user-friendly environment for patients, and their families and friends to share thoughts and socialize with each other on various topics such as therapeutic processes, prescribed medicines, side effects, mental and emotional health. Patients who suffer from life-threatening diseases (e.g., cancer or AIDS) feel supported when they interact with their peers who experience similar problems (Qiu et al. 2011). Emotional support is considered the principal function of OHCs that brings better feelings and fewer mortality rates to patients (Holt-Lunstad, Smith, and Layton 2010). Table 1 shows an example message (i.e., the *reply*) that contains emotional support, which improves the mood of the originator.

Thus, identifying messages that contain emotional support presents an insightful view of the users' characteristics, dynamics, and behavior. For example, analyzing emotional messages provide the main constituents required for learning the emotional states of patients through therapeutic process.

Prior studies (Wang, Kraut, and Levine 2012; Biyani et al. 2014) proposed computational models for analyzing social support of thousands of messages in OHCs by handcrafting a set of features extracted from patients' messages. Examples of such features include bag-of-words, linguistic features, lexicon-based features and word patterns. Biyani et al. (2014) showed that the lexicons that include subjectivity-analysis-based words, drugs' names, side effects and therapeutic processes are among the most effective features in emotional vs. informational message classification.

–**Originator:** When my oncologist did the muga scan my heart went from 68 to 63. I have never had a problem with my heart at all. I'm Very nervous.
–*Reply:* I had much the same problem while doing chemo [...]. Try not to worry too much! [...] Blessings to you...
–**Originator:** Thanks so much I feel allot better now. [...]

Table 1: A sample of an emotional comment.

However, despite the success of lexicon-based features, building comprehensive lexicons in different health domains (e.g., cancer and diabetes) requires medical experts on each domain to contribute intensively in a way that makes the process almost impractical. In this work, we propose a computational model for identifying *emotional messages* in OHCs that eliminates the need for handcrafting features or building expensive lexicons that require experts' knowledge. Our proposed model called *deep convolutional LSTM*, or *C-LSTM* for short, is described in the next section.

Deep Convolutional LSTM (C-LSTM)

We propose a combination of CNN and LSTM-based models that use the final feature vectors from CNN as the input vectors for LSTM to improve the performance of previous works in emotional support identification in OHCs. CNN is used to extract high-level (abstract) features that capture the semantic part of the text (Lai et al. 2015), whereas the feature transfer task allows the LSTM network to represent the function learned by the CNN model. The proposed C-LSTM captures both high-level and sequential information without adding extra complexity as is the case with the memory or attention mechanisms (Bahdanau, Cho, and Bengio 2014).

Our proposed classification model is similar to that described in Kim et al. (2016). However, Kim et al. (2016) applied a character-level CNN to extract high-level features, whereas our model works at word-level. We use the word-level input to CNN to take advantage of applying embedding vectors, which are trained on health data from OHCs.

Data Collection and Annotation

We used two datasets for evaluating our model. The first dataset is provided by Biyani et al. (2014), which contains 1066 messages from the breast cancer discussion board, denoted as B-DS. For building the second dataset, we ran-

Method	B-DS			L-DS		
	Pre. (%)	**Rec.(%)**	**F-1 (%)**	**Pre. (%)**	**Rec (%)**	**F-1 (%)**
C-LSTM	**88.7**	**94.3**	**91.4**	**82.7**	**84.5**	**83.6**
Kim et al. (2016)	89.5	88.6	89.04	80.8	80.9	80.84
LSTM	88.4	91.5	89.92	82.3	79.8	81.0
CNN	84.6	92.8	88.51	80.1	81.3	80.7
EMO2014	85.1	91.1	88.0	74.0	83.2	78.33
BoW-POS	85.5	85.8	85.7	72.9	80.8	76.6
Lexicon-based model	66.7	92.0	77.4	64.3	97.3	77.4

Table 2: Emotional messages classification results using 10-fold cross validation.

domly selected 225 comments from 21 discussion threads in the lung cancer discussion board in the Cancer Survivors' Network (CSN) of the American Cancer Society. We denote this second dataset as L-DS with 1041 messages. We followed Biyani et al. (2014) in annotating L-DS.

Experimental Setting and Results

We conducted experiments for classifying emotional messages by using various deep neural networks: CNN, LSTM, word-level C-LSTM, and the character-level combination of CNN and RNN (Recurrent Neural Network) as described in (Kim et al. 2016). The results are shown in Table 2 (along with baseline results).

In our experiments, for the word-level C-LSTM, we used word embeddings as input to the neural networks. In particular, we used the CSN dataset that contains user's comments from June 2000 to June 2012, as our resources for generating word vectors. We set hyper-parameters for each deep neural network (i.e., CNN, LSTM, and C-LSTM) via a grid search over combinations of important parameters. We estimated hyper-parameter values using a development set, which consists of removing 10% of instances from the training set in 10-fold cross validation experiments. The experiments using Wikipedia for generating word vectors showed lower performance as compared with CSN.

Results: From Table 2, we observe that all deep neural networks achieve a better performance than the state-of-the-art model EMO2014 by Biyani et al. (2014) and the BoW baseline and the lexicon-based model. C-LSTM achieves the best performance with an F-1 score of 91.4% and 83.6% on B-DS and L-DS, respectively. C-LSTM outperforms EMO2014 (Biyani et al. 2014) by 3.4% and 5.27% on the B-DS and L-DS, respectively. Also, it can be seen that the word-level C-LSTM outperforms the character-level model of Kim et al. (2016), which supports our hypothesis that using word embeddings trained on OHC health data yields better model performance than character-level.

The results presented in Table 2 show that all classifiers achieve substantially better Precision, Recall and F1 score on B-DS compared with L-DS. The F1 score decline in L-DS can be explained by the fact that in B-DS, commentators express their emotions using more explicit emotional words compared to L-DS; for example, consider the messages: *"I haven't gotten depressed from it"* and *"I have no idea what the future holds."* In the former message from B-DS, the commentator used the word *depressed* reflecting a rather similar situation (this judgment is based on reading the whole related threads) as in L-DS, but the commentator in L-DS did not use any explicit emotional words. This is an interesting observation since, intuitively, women typically use more emotional words as compared to men. A manual investigation of our B-DS and L-DS datasets (based solely on the text of the messages) revealed that 79% of messages were written by women in B-DS, whereas only 55% of the messages were written by women in L-DS.

Conclusion

In this work, we proposed a model for identifying emotional messages in online health communities. Unlike prior works, our model does not need any external knowledge such as expensive lexicons and generates high-level and effective features through the training process in a combination of CNN and LSTM. Our model improves prior works that use handcrafted features on emotional message identification.

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