Understanding Happiness by Using a Crowd-sourced Database with Natural Language Processing

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Abstract. In this thesis [1], we conduct two classification tasks on the crowd-sourced database Happy DB, which consists of more than 100,000 descriptions of happy moments collected using Amazon's Mechanical Turk. We apply the state-of-art word embedding algorithm BERT to transform all happy moments to context-sensitive representations and then feed them to a one-layer LSTM to learn two critical concepts of happiness, *agency* and *sociality*. We found that the proposed setup improves performance compared to the previous works.

1 Introduction

Natural language processing has been used to decipher human language. Tasks in this turf such as machine translation, speech recognition, and product recommendation, have vastly improved over the last few years. At the core of these language processing technologies are language models that transform massive amounts of textual information into multi-dimensional vector representations of words or sequences, which are then used as input representations in complex artificial intelligence tasks. This thesis focuses on learning two concepts of happiness, *sociality* and *agency* via two classification tasks. 'Sociality' here refers to feeling happy in the presence of others vs alone, while 'agency' denotes whether the happy moment refers to the participant who reported it or to other people.

Previous work explored diverse methods involving supervised and semi-supervised learning. The former includes a Word Pair Convolutional Model based on the hypothesis that a small set of word pairs were vital for representing the nature of sociality/agency of these happy moments [11], and similar models based on CNNs [12, 2, 15] and RNN/LSTM/Bi-LSTM[10, 13]. The latter comprises learning settings incorporating autoencoders [1] or k-means clustering [14]. Various embedding algorithms were also employed in this task including word2vec [6], GloVe [7], ELMo [8] and word embeddings pre-trained on WikiText-103 corpus[14]. Among all these models, the Elmo-based LSTM proposed by UBC [10] holds the state-of-the-art for prediction on agency(85%) and sociality(92%).

[1] Full thesis: http://spigler.net/giacomo/files/yixia_wang_thesis_2020.pdf

2 Methods

Our proposed method combines LSTMs with a state-of-art word embedding algorithm, BERT. The LSTM used had 60 hidden units and a Tanh activation function, while the output layer. Training was performed using mini-batch gradient descent (size=32) and the Adam optimizer [5] (learning rate $\eta = 0.1$). Early stopping [9] is used in addition to dropout (dropout rate=0.2) to reduce overfitting.
Out of 24 released BERT models, we use the BERT-Base model(Uncased: 12-layer Transformer, 768 dimensions, 12-heads, 110M parameters)[3]. Max sequence length is set at 128. Padding and truncation are used to fix the length of each account of happy moments to 128 tokens. Therefore, for each input text, BERT outputs a tensor of shape (128, 768) with one vector per token. Out of 12 layers, we summed the last four layers as a pooling strategy to obtain a fixed representation for each happy moment description.

We also developed eight baseline models by applying traditional machine learning algorithms, including Support Vector Machine (SVM), Random Forest, Logistic Regression (Log Reg) and Naive Bayes. Each of them is implemented with two sets of word embedding algorithms: Bag of Words (BOW) and Bag of Words with a TF-IDF transformation (BOW tf-idf). As most of the previous works [4] reported their highest accuracy from an architecture equipped with the GloVe word embedding, a further baseline based on LSTM + GloVe is also used.

3 Results

The results of the baseline models show that a linear SVM model with BOW as word representation performs the best overall (sociality accuracy=90.49%, agency accuracy=78.34%), although the classification of agency was found to be marginally higher using Logistic Regression + BOW (accuracy=80.65%). The results of the main evaluation are shown in Table 1. The proposed solution was found to improve all metrices (accuracy, F1 score, and AUC) compared to both GloVe+LSTM and ELMo+LSTM [4].

	Sociality			**Agency**		
Models	**Accuracy**	**F1 Score**	**AUC**	**Accuracy**	**F1 Score**	**AUC**
ELMo + LSTM(publication)	92.00%	93.00%	None	85.00%	90.00%	None
GloVe + LSTM	90.14%	90.89%	95.70%	83.70%	88.55%	89.41%
BERT + LSTM	**93.00%**	**93.49%**	**97.11%**	**86.42**%	**90.42**%	**91.41**%

Table 1. Accuracy of the proposed LSTM+BERT model on Agency and Sociality classification.

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