Modeling Temporal Progression of Emotional Status in Mental Health Forum: A Recurrent Neural Net Approach

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Motivation
- Patients turn to Online Health Communities not only for information on specific conditions but also for emotional support
- Decreased social interaction and increased negativity could be early indicators of depression
  - claims the lives of 15 - 20% of its patients (Sadegh et al., 2016)
- It will be immensely beneficial to detect such users early, to be able to
  prevent unfortunate life-critical situations

Our Approach
- By observing the word usage patterns of users in the site over time, we find that there exist different classes of users
  - Some users go through an improvement over time, lessening their use of negative words in their subsequent posts
  - Some users move on a deteriorating slope where increased negative emotions can be observed in their posts
  - Others remain stable over time
- We study the problem of predicting a patient’s emotional status in the future from her past posts and participation history
- We propose a Recurrent Neural Network (RNN) architecture to address it

Capturing Temporal Progression of Emotional Status
- We define a metric, Negative eMotion Index (NMI), obtained from the word usage by a patient as indicator of her mental health status
  - NMI = (NegativeWords - PositiveWords) / TotalWords
  - 1 < NMI < 1
  - High NMI indicates more negativity and vice versa
- We study the change of NMI over time (NMI’) for a patient
  - $\frac{\Delta(NMI)}{NMI} > 0$  $\Rightarrow$ NMI is increasing with time
  - $\frac{\Delta(NMI)}{NMI} < 0$  $\Rightarrow$ NMI is decreasing with time
  - $\frac{\Delta(NMI)}{NMI} = 0$  $\Rightarrow$ NMI is constant over time
- Negativity reduces for ~31%
- Negativity remains constant for ~49%
- Negativity increases for ~20%
- A global trend doesn’t exist
- Important to study at an individual level

Future NMI Prediction Task

Research Question: Given a patient’s historical posts, can we predict what would her emotional status be in the future?

We propose a framework towards understanding temporal progression of users’ emotional status in online mental health forums
- Both LSTM and GRU for sequence encoding produced similar results.
- We did not observe any significant improvement by replacing the RNN with a Bidirectional RNN
- Larger embedding dimensions for words and larger neuron counts in the RNN layers led to over-fitting, possibly due to the dataset size
- Replacing aggregation layer with a Dense layer did not improve the performance

Conclusion
- Presented a framework towards understanding temporal progression of users’ emotional status in online mental health forums
- We identify several forum participation features that are indicative of a user’s temporal emotional progression
- Our proposed neural network architecture uses textual content as well as participation features from a user’s past posts to predict her future emotional status
- In future, we would like to extend the model to capture progression of other long term conditions e.g., ALS, Multiple Sclerosis

Dataset
- Dataset obtained from mental health section of HealthBoards
  - Provides (peer to peer) support to patients with mental health issues
  - Groups (in HealthBoards) include
    - Depression, Stress, Anxiety, Anger Management
    - Self injury Recovery, Addiction and Recovery and so on...

Experimental Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Numeric Features</th>
<th>Text Features</th>
<th>Numeric + Text Features</th>
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<tbody>
<tr>
<td>Linear Regression</td>
<td>0.2034</td>
<td>8.3553</td>
<td>3.4914</td>
</tr>
<tr>
<td>SVM (linear kernel)</td>
<td>0.2022</td>
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- Traditional ML based baseline models yield far less accurate results
  - Both linear regressor model and the SVM regressor with linear kernel model are unable to use the BOW features for the prediction task
- Our architecture leveraging RNNs, is able to capture the temporal progression of emotional status with reasonable accuracy

Discussion on Model Architecture Variants
- Both LSTM and GRU for sequence encoding produced similar results.
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