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

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Motivation

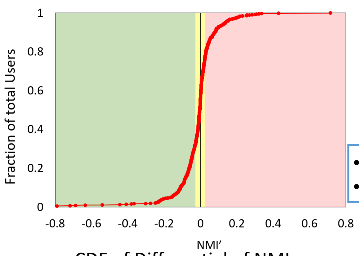
- Patients turn to Online Health Communities not only for information on specific conditions but also for emotional support
- Decreased social interaction and increased negativity could be early indicators of depression
  - claims the lives of 15 -20% of its patients (Sadequeet al.,2016)
- It will be 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
  - $\frac{\partial(NMI)}{\partial t} > 0$ → NMI is increasing with time
  - $\frac{\partial(NMI)}{\partial t} < 0$ → NMI is decreasing with time
  - $\frac{\partial(NMI)}{\partial t} = 0$ → NMI is constant over time



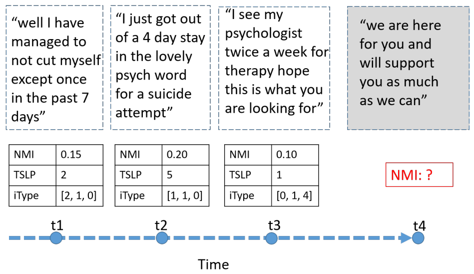
CDF of Differential of NMI

- 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 patients historical posts, can we predict what would her emotional status be in the future?



Model Architecture

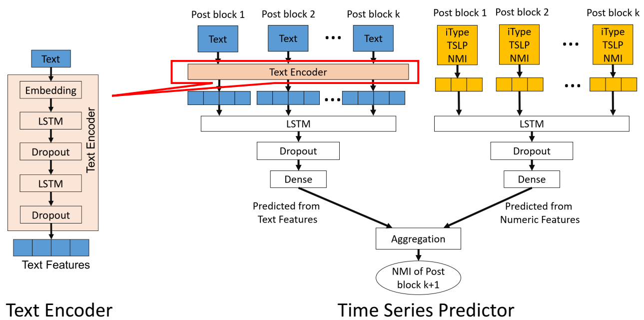
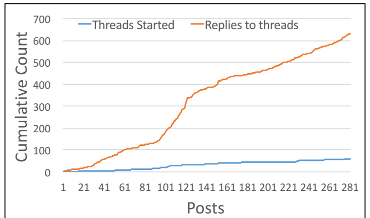


Illustration of model architecture. Each post-block consists of text and numeric features. The text encoder is shown on the left side. The time series predictor, that combines both text and numeric features to predict NMI score of the next post, is shown on the right.

Observed Signals for Last *k* posts

- Post Text
- Interaction Type(iType): A post can be
  - Thread Initiation
  - Reply to someone else's thread
  - Reply to own thread
- Time Since Last Post(TSLP)
  - Difference in days between current post and the last post written by user
- NMI score



Temporal cumulative distribution of interaction types for a sample user in *improving* class. She keeps posting to others' threads instead of starting her own, increasingly with time.

Refer to the full paper for details on the features and parameter settings

Dataset

- Dataset obtained from mental health section of HealthBoards[1]
- 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..

1 www.healthboards.com/boards/mental-health-board

Experimental Results

- Metric: Mean Absolute Error (MAE) for NMI prediction

Model	Numeric Features	Text Features	Numeric + Text Features
Linear Regression	0.2034	8.3553	3.4914
SVM (linear kernel)	0.2022	3.1513	0.2125
SVM (RBF Kernel)	0.2724	0.2072	0.2071
Decision Tree	0.2106	0.2078	0.2106
Random Forest	0.2046	0.2032	0.2031
Our Model	0.0788	0.0802	**0.0781**

- 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 capture 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.
- 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