Moments of Change: Predicting Cognitive Restructuring in Online Mental Health Support Forums

Yada Pruksachatkun,
New York University Center for Data Science
yp913@nyu.edu

Sachin Pendse,
Microsoft Research India,
t-sapen@microsoft.com

Amit Sharma,
Microsoft Research India
amshar@microsoft.com

Introduction

How can we predict if a person feels better in an online, real-time setting? Through data from an online mental health forum, we study patterns of peer support to shed light on how moments of cognitive change happen in online communities. Consistent with psychological literature, we use markers of language associated with moments of change, and explore how temporal changes in sentiment surrounding specific topics can approximate cognitive restructuring processes. In addition, we find that culture mediates the effect of these features. Based on the above findings, we propose a predictive model that can distinguish which conversation thread or a post is associated with a moment of cognitive change, and discuss the implications of our work for forum design and online peer support.

Methods & Materials

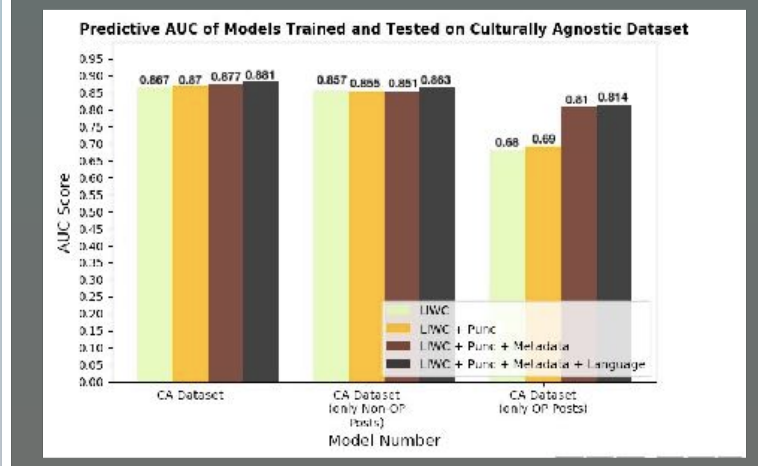
We used data from Talklife, a peer support network for mental health founded in 2012. We gathered a total of 25,537 threads from Indians without a moment of change and 295 threads from Indian users with a moment of change. Among threads started by non-Indians, we obtain 14,604 threads without a moment of change and 6,396 threads with a moment of change.
We derived feature based on four families of features: LIWC based features, punctuation based metadata level features, and mental health language based features.
We then propose a SentiTopic model based on detecting topics in a forum thread across posts and tracing the sentiment of the poster towards those topics. This more accurately shows not only a moment of change, but the pathway in which a person reaches a moment of change.

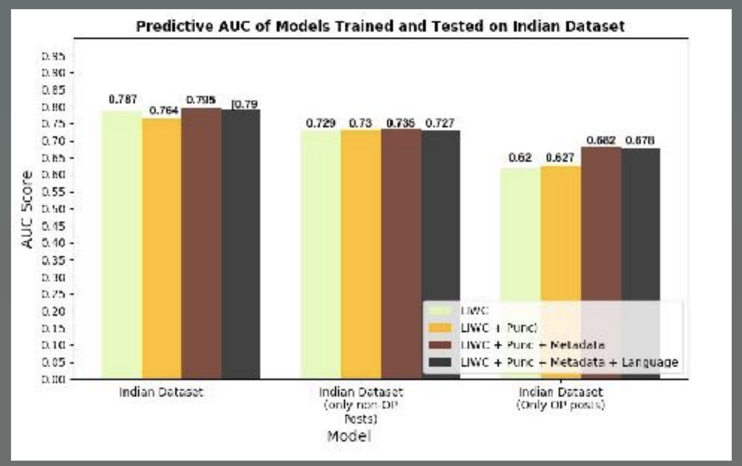
Results

THREAD LEVEL
We first tackled the challenge of predicting whether a mental health forum thread contains a moment of change (MOC).

We used XGBoost on 10-fold cross validation, and report the AUC score. We split the data for both Indian and culturally agnostic datasets with an equal number of data with and without MOCs. We feed into our models three contexts: threads with only posts from posters other than the original poster, only posts from the original poster, and all posts.

Our results are below.

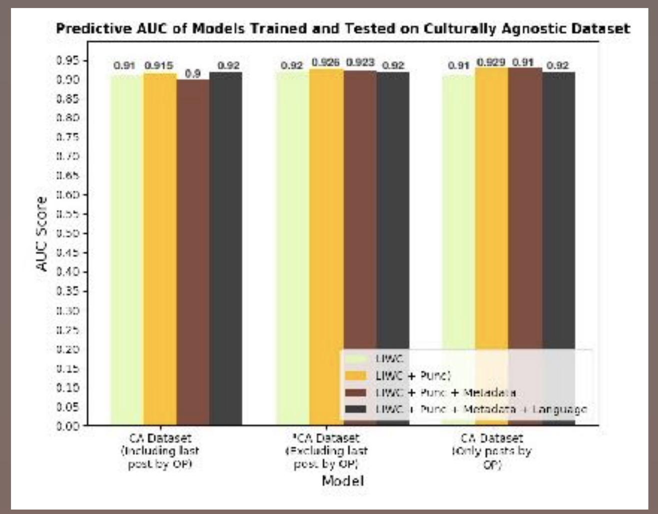


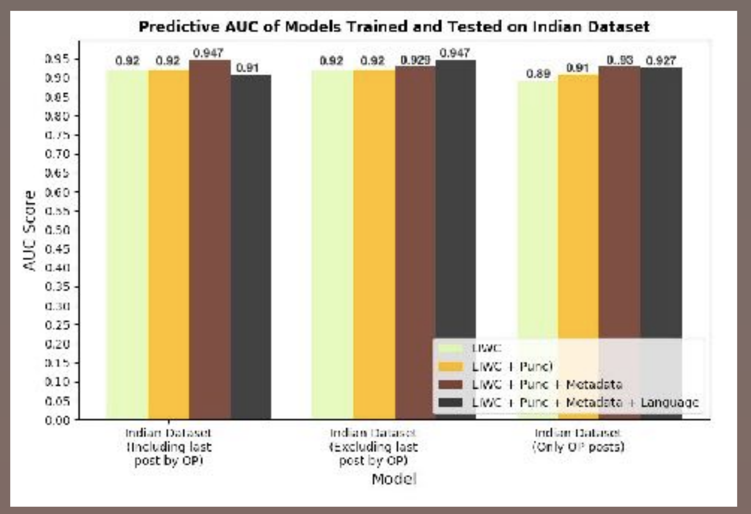


We are able to predict a moment of change to 0.88 accuracy on the Culturally Agnostic dataset and 0.9 for the Indian dataset with all posts included.
While LIWC acts as a good approximation for moments of change under the *Non-OP-only* model, it performs worse under the *OP-only* model. When considering only the posts from the OP, metadata features gain importance, as seen by a bigger increase in AUC score with the addition of metadata features in both CA and Indian datasets.

POST LEVEL
With successful prediction of thread level MOCs, we then racked the challenge of predicting whether a post will contain a moment of change.

First, we test the post level models based on including all posts up to and including an OP-authored post p_j and predicting if p_j has a moment of change. Secondly, we test the post level models after feeding the model all posts up to time X, and predicting if the next post by the OP will contain the moment of change





We were able to achieve an even higher accuracy of 0.947 AUC for post-level predictions, which is due to the granularity of the data fed into the post level as opposed to the thread level. The act of adding features other than LIWC did not impact the model, only marginally increasing the performance.

CULTURAL ANALYSIS
To look at cross-cultural differences in characteristics of threads with a moment of change, we design a classification task where we fit a model on train data from the Indian dataset and test on the non-Indian test set, and vice-versa.

Test set	Trained on Indian train set	Trained on non-Indian train dataset
Tested on Indian test set	0.95	0.55
Tested on non-Indian test set	0.59	0.97

Table 2. AUC score of post-level models in non-Indian and Indian dat. Like for thread-level models, cross-training and testing across cultures leads to a drop in accuracy.

	Trained on Indian train set	Trained on non-Indian train set
Tested on Indian test set	0.9	0.74
Tested on non-Indian test set	0.68	0.86

Table 1. AUC score of thread-level models in non-Indian and Indian data. These models show that cross training results in a significant drop in accuracy, which indicates that predictors of moments of change are dependent on culture

This has the effect of measuring to what extent predictors of moments of change can be transferred between cultures.
We can see that the model performance drops with this cross-training, which implies the importance of culture when making models.

SENTITOPIC MODEL
Although we were able to detect moments of change in post and thread level data with reasonably high accuracy, predictive results do not tell us much about how moments of change happen over the course of a conversation in a thread. In this section, therefore, we construct a model that is derived directly from our definition of a moment of change, rather than the often difficult-to-interpret machine learning models that are commonly used for similar tasks. We use Sense2Vec [1] and a clustering algorithm to create the preliminary SentiTopic model and VADER [2] for sentiment analysi. We created several features from SentiTopic. The first feature is a binary feature that shows if there exists a positive shift in sentiment towards at least one topic, while the second is the difference in sentiment between the first and last post by the OP for each of the detected topics in a thread.

We were able to achieve the below results.

Dataset	Culturally Agnostic Subset	Indian-only Subset	non-Indian only Subset
Pattern-based dataset	0.68	0.7	0.72
Crowdsourced dataset	0.72	0.69	0.76

Table 3. AUC score of post-level models trained and tested on only SentiTopic-level features on various datasets. From these results, we demonstrate that the SentiTopic model performs at a reasonable accuracy using only two features

Although accuracy is lower than our prior models, we only used two features in the model. Furthermore, there were limitations in the use of word embeddings for sense disambiguation of topic related nouns and the granularity of Vader as a suitable sentiment model.

Conclusions

In this work, we examined shifts in perspective through using linguistic, metadata-level, and topical tools to detect these shifts. We developed datasets that allow us to meaningfully distinguish mental health forums that result in a moment of change from those that do not, and developed prediction tools that were able to do exactly that with reasonable accuracy of 0.82 for predicting the presence of a moment of change in a thread and 0.947 for predicting the presence of one in a post. Implications of our work include routing threads without moments of change to expert help and identifying peer responders involved in threads with moments of change. Overall, our study of computationally predicting cognitive shifts opens up the pathway for further questions by allowing a more granular understanding of *if* and *why* online peer-to- peer conversations are effective in helping those who come online to seek help for their distress.

References

[1] Trask, A., Michalak, P., and Liu, J. sense2vec-a fast and accurate method for word sense disambiguation in neural word embeddings. *arXiv preprint arXiv:1511.06388* (2015).

[2] Gilbert, C. H. E. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Eighth International Conference on Weblogs and Social Media (ICWSM-14). Available at (20/04/16) http://comp. social. gatech. edu/ papers/icwsm14. vader. hutto. pdf (2014).

Acknowledgements

Thank you to Microsoft Research for supporting this work as well as Talklife for providing the data to make this research possible and Samantha Bernecker for providing a psychology perspective on the project.