ConversationMoC: Encoding Conversational Dynamics using Multiplex Network for Identifying Moment of Change in Mood and Mental Health Classification

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Abstract

- Mental health encompasses emotional, psychological, and social well-being. Mental illnesses profoundly affect the quality of life, hindering a person's ability to work, maintain relationships, and engage in daily activities.
- Understanding mental health conversation dynamics is crucial, yet prior studies often overlooked the intricate interplay of social interactions [3].
- This study aims to uncover hidden emotional dynamics and understand the impact of social interactions on individual mood shifts.
- This study introduces a framework that incorporates emotional dynamics and social interactions using a graph multiplex model powered by Graph Convolution Networks [1] to encode intricate conversation dynamics.

Main contributions

- A new Reddit dataset, augmented with conversational context and annotations for Moments of Change (MoC) and Mental Health (MH) discourse classification, is now publicly available, offering a novel approach to MoC identification through valence and arousal analysis.
- This study extensively compares suitable baseline models over the new MoC dataset and introduces a multiplex network structure to encode the complex conversation dynamics.
- A comprehensive exploration of the multiplex layers, determining the significance of each layer for conversational MoC and MH classification tasks.

1 Motivation

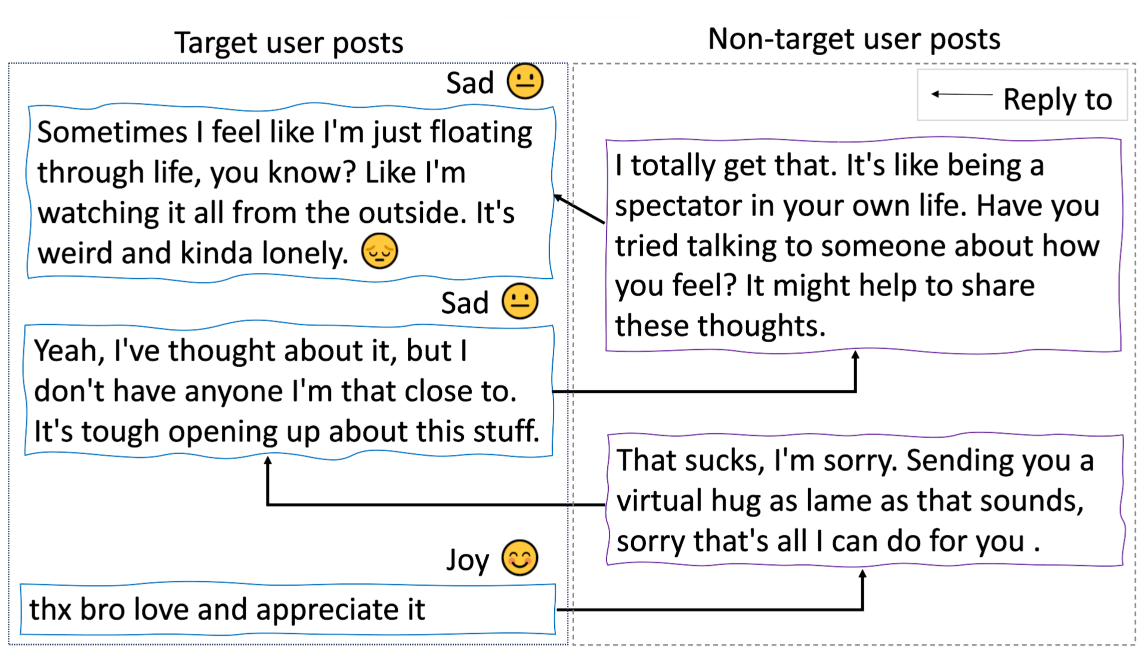

Figure 1: Illustration of emotional dynamics in a conversation. The *target user* initiates, and *non-target users* engage in the conversation.

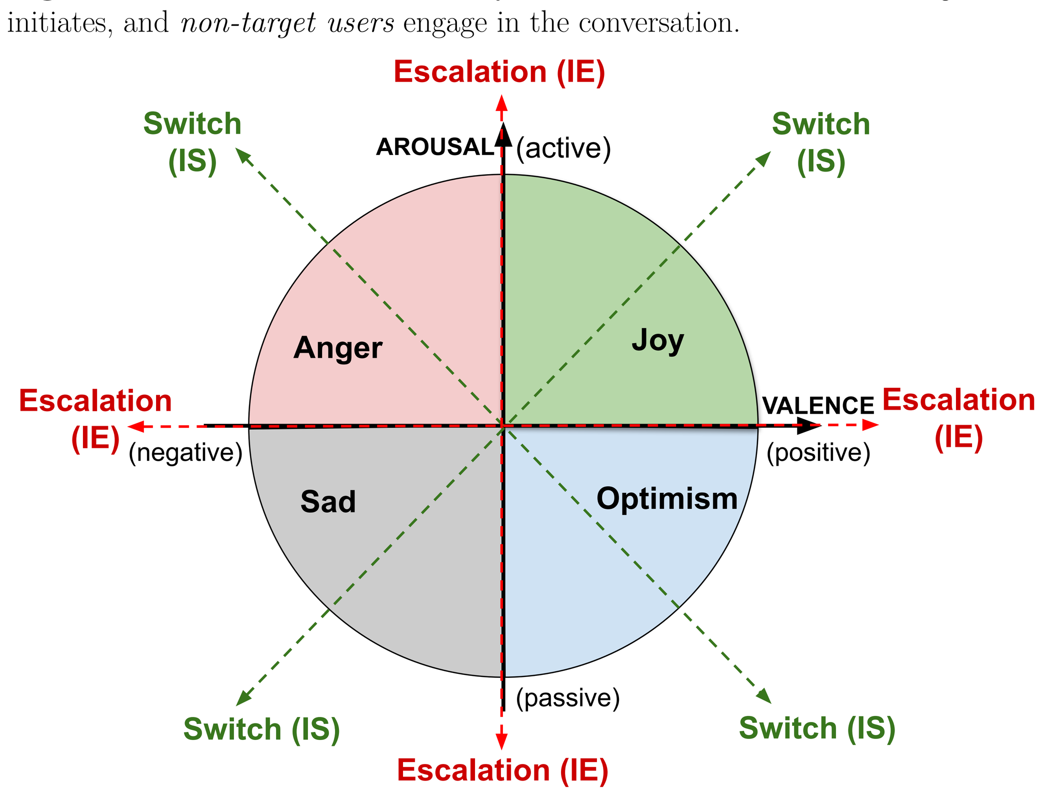

Figure 2: 2D Valency Arousal Space depicting the moment of change in mood reflected through user posts [2].

2 ConversationMoC dataset

Mental Health Topics	Target Users						All Users		
	Convs (#Users)	#Posts	Avg posts /Convs	IS	IE	O	#Users	#Posts	Avg posts /Convs
Addiction	59	385	6.53	15	70	300	591	1381	23.41
ADHD	67	504	7.52	16	84	404	1303	2256	33.67
Alcoholism	65	567	8.72	35	84	448	690	1788	27.51
Anxiety	56	539	9.46	25	84	430	545	1337	23.46
Autism	56	476	8.50	28	49	399	760	1993	35.59
Bipolar	69	649	9.41	40	92	517	742	2082	30.17
BPD	62	843	13.60	43	107	693	895	2117	34.15
Depression	68	697	10.25	41	254	402	898	1982	29.15
Eating Disorder	68	680	10.00	49	89	542	1081	2335	34.34
Health Anxiety	69	635	9.20	49	61	525	674	1759	25.49
Loneliness	69	726	10.52	64	74	588	896	2020	29.28
PTSD	68	565	8.31	38	92	435	771	1804	26.53
Schizophrenia	56	755	13.48	42	94	619	729	2382	42.54
Social Anxiety	67	562	8.15	28	70	464	768	1689	25.21
Suicide	68	638	9.38	22	100	516	763	1734	25.50
Total	967	9221		535	1404	7282	14927	28659	
Unique	#Target users: 963						#Users: 11841		

Figure 3: Dataset statistics of 15 subreddits showing the number of conversations, posts, and users per subreddits.

3 Model pipeline

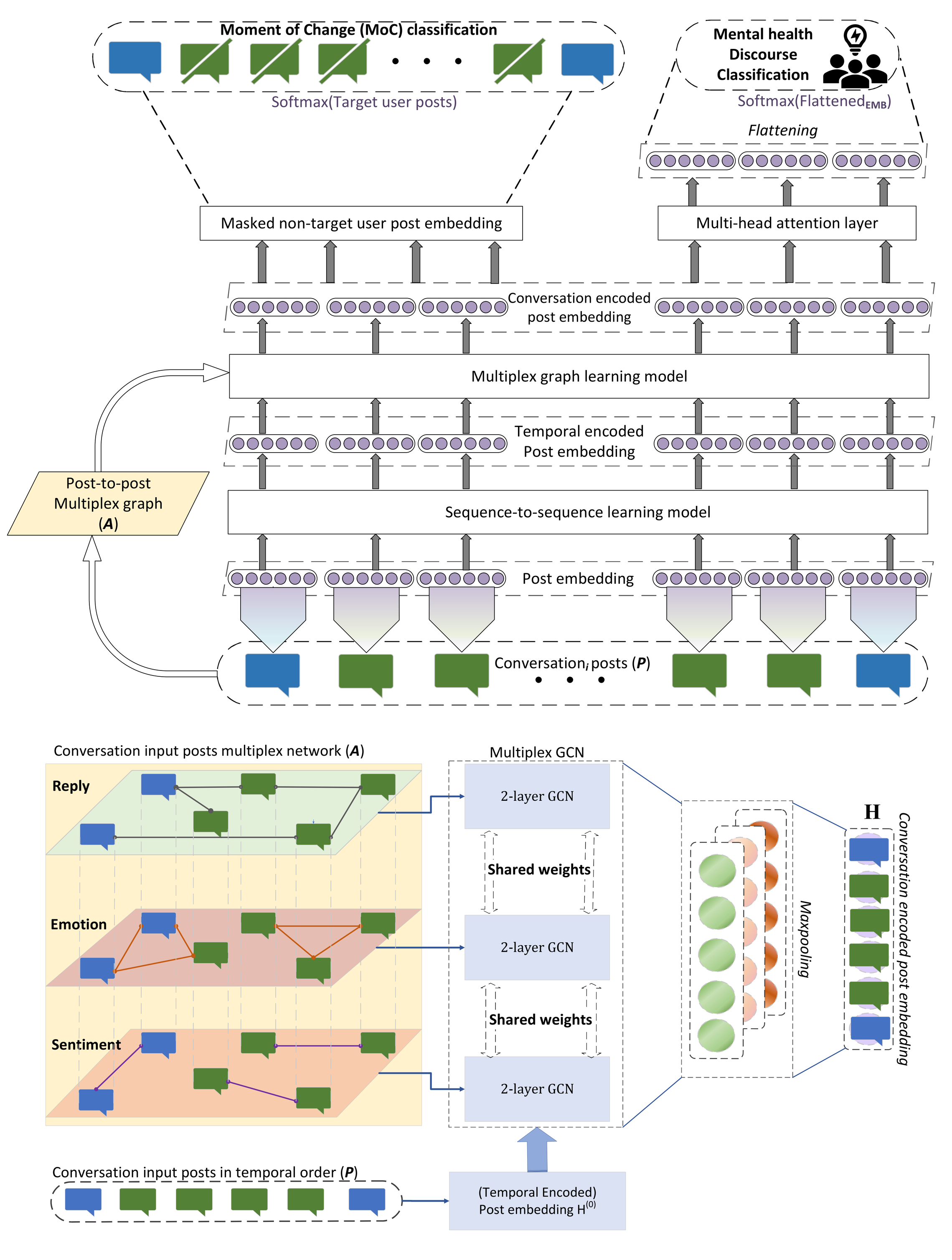

Figure 4: Proposed graph multiplex encoding framework.

4 Moment of change classification task

Models	O	IE	IS	Macro-F1
Input: Target user posts only				
Heuristic	0.654 (± 0.02)	0.261 (± 0.03)	0.164 (± 0.05)	0.360 (± 0.02)
*BiLSTM (*TU*)	**0.902** (± 0.01)	0.198 (± 0.05)	0.113 (± 0.04)	0.404 (± 0.02)
Input: Entire conversation				
BiLSTM (*All*)	0.895 (± 0.01)	0.264 (± 0.08)	0.056 (± 0.02)	0.405 (± 0.02)
$+GCN (ESR)	0.897 (± 0.01)	0.287 (± 0.01)	0.066 (± 0.02)	0.417 (± 0.02)
BiLSTM+GCN (ESR)	0.896 (± 0.01)	0.250 (± 0.09)	**0.169** (± 0.06)	0.438 (± 0.02)
Graph Multiplex Layer analysis				
BiLSTM+GCN (E)	0.891 (± 0.01)	0.257 (± 0.09)	0.110 (± 0.03)	0.419 (± 0.03)
BiLSTM+GCN (S)	0.885 (± 0.02)	0.219 (± 0.06)	0.164 (± 0.05)	0.423 (± 0.02)
BiLSTM+GCN (R)	0.895 (± 0.01)	**0.396** (± 0.11)	0.085 (± 0.03)	0.459 (± 0.03)
BiLSTM+GCN (ES)	0.889 (± 0.02)	0.257 (± 0.10)	0.127 (± 0.05)	0.424 (± 0.03)
BiLSTM+GCN (ER)	0.891 (± 0.02)	0.299 (± 0.10)	0.123 (± 0.05)	0.438 (± 0.02)
BiLSTM+GCN (SR)	0.891 (± 0.01)	0.372 (± 0.10)	0.146 (± 0.05)	**0.470** (± 0.03)

Figure 5: Performance comparison of the Moment of Change classification task with and without conversation context.

5 Mental Health classification task

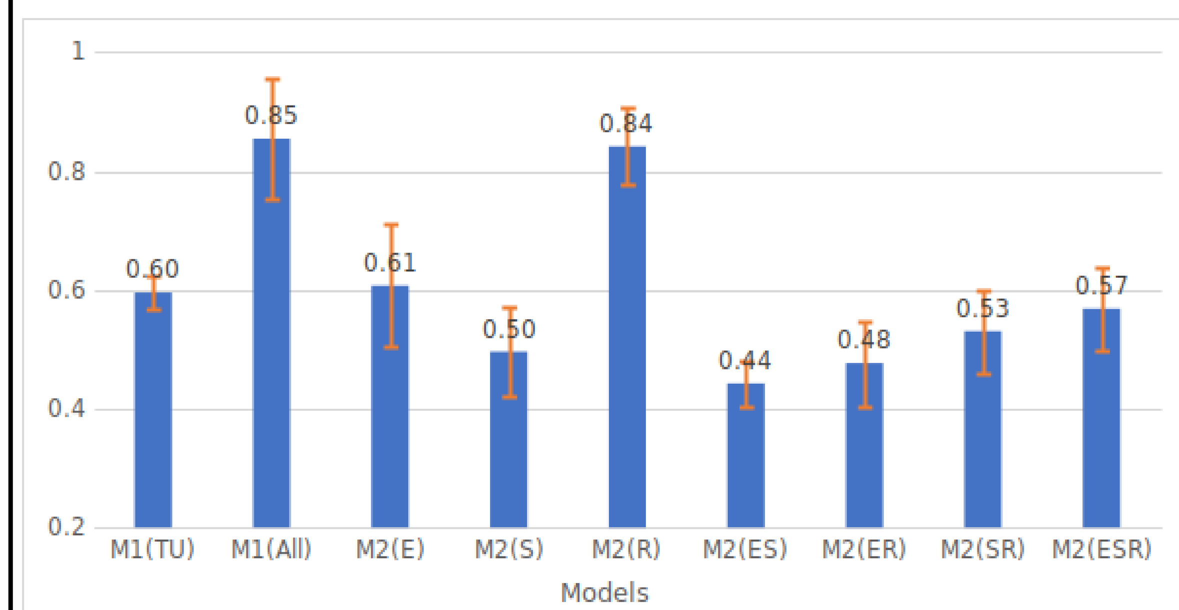

Figure 6: Macro F1-score performance comparison of the Mental Health discourse classification task. M1 and M2 represent the BiLSTM and BiLSTM+GCN models.

6 Conclusions

- Releases a publicly available annotated dataset (**ConversationMoC**) for detecting Moments of Change (MoC) in individual mood and classifying Mental Health (MH) discourse in conversations.
- This study explores the use of BiLSTM and GCN models to leverage conversation data for MoC identification and MH discourse classification.
- Experimental results highlight the importance of incorporating conversation data and how encoding complex social interactions, emotional dynamics, and sentiment patterns in a multiplex network structure boosts classification accuracy.
- The *Reply* network underlines the role of social interactions and user engagement while integrating *Sentiment* and *Emotion* networks further enhances performance, showing the value of analyzing emotional conversations and sentiment

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Ethical statement

Ethical approval for this study was obtained from the University of Southampton ethics board (ERGO).

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