Identifying the related sub-problems in a conversation

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Motivation

A cumulative effect of different social tasks such as hate speech, deception, condescension, trolls, politeness and others in conversations have an overall intended effect on a person's psyche, rather than any individual task.

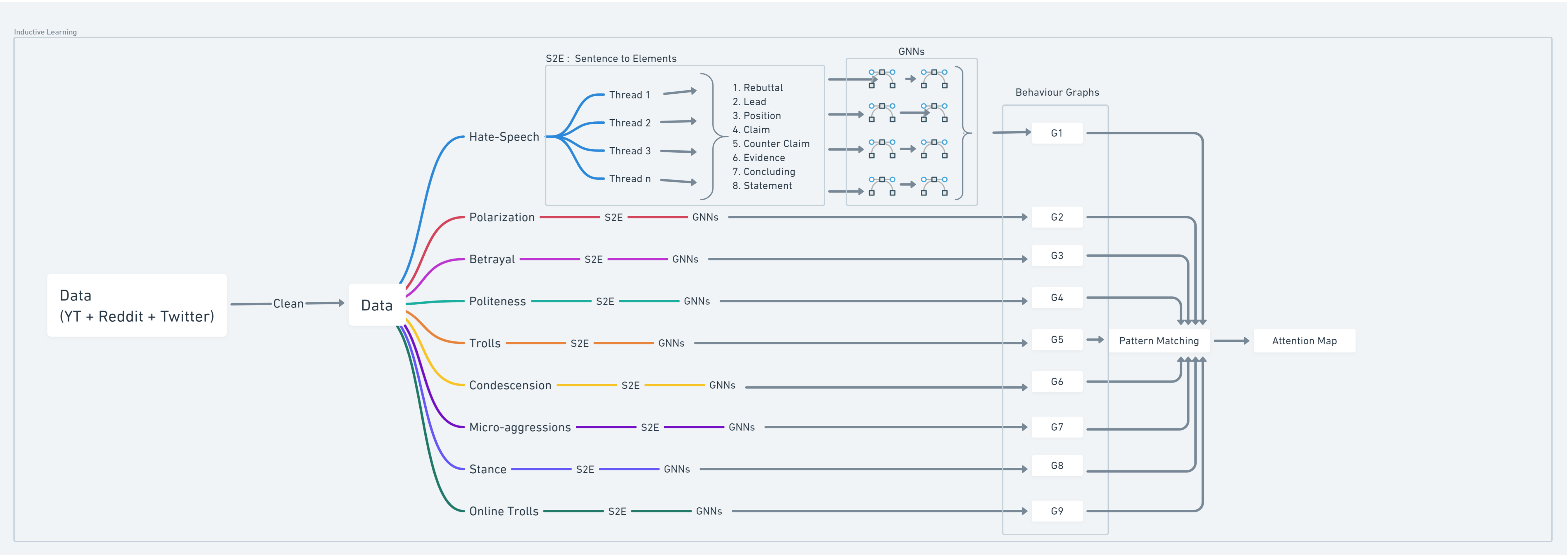
The effect can have positive or negative consequences for a conversation participant or reader, depending upon the interaction patterns observed among these tasks. For eg., polite conversations can conjure positive ideas, whereas conversations interspersed with hate and negative trolling can lead to development of misleading, and possibly, negative ideas.

Objectives

Analyse interactions between these tasks in a social media conversation, and aid in solving issues of social media collaboration, cancel culture and others.

The system development can be accomplished as follows:
1. Extraction of Reddit conversational data to enable the study.
2. Discourse annotation for nodes and edges in the data and for each of the specific tasks.
3. Extraction of discriminative features from conversation utterances and on the basis of proven task-specific heuristics.
4. Conversion of text to knowledge graphs to enable learning of task(s)-based node and edge interactions with the help of Graph Attention Networks (GATs).

Proposed Theoretical Approach



Elements

Edge Types
Asking
Informing
Asserting
Proposing
Summarising
Checking
Building
Including
Excluding
Self-promotion
Supporting
Disagreeing
Avoiding
Challenging
Attacking
Defending
Blocking

Node Types
Agreement
Announcement
Answer
Appreciation
Disagreement
Elaboration
Humour
NegativeReaction
Question

An edge is assumed between two utterances if they are directly related as replies. The node labels would be a result of human annotation. This would act as the common framework that would enable us to compare the various sub-problems.

Task Definition

Let the set of data sources be $D = \{D_1, D_2, D_3, ..., D_N\}$. For our testbed we are dealing with three data sources namely Reddit (D_1), YouTube (D_2) and Twitter(D_3).

Every source D_i an unordered collection of many conversations c_i such that $D_i = \{c_1, c_2, c_3 \ldots, c_N\}$ where N is the total number of conversations from that source.

Data from the D_i's will then combined and segregated on the basis of their relevance with respect to the set of Sub-Problems $S \in \{S_1, S_2, S_3, ..., S_Z\}$. Once separated based on heuristics, each sub problem S_i gets its own data, which is an unordered set of conversations c_i' s from the combined data $D_{Si} = \{c_1', c_2', c_3' \ldots, c_N'\}$

Each of the conversations $c_i \in D_{Si}$ are ordered collections of utterances u_i to a post $p_i \mid c_i = \{p_i, \{u_1, u_2, u_3 \ldots, u_n\}\}$
Where n is the total number of utterances.

Each of the c_i are converted into a graphical representation $G_{ci} = (V, E, V_f, E_f)$ where V are the nodes, E the edge relations between.
Each node and edge can have a set of features associated with it and they are represented using the Node feature matrix V_f and E_f respectively

Sub-problems

Table 3.1: Reddit External Data Information

Subreddit	2020	2021	2018
r/unpopularopinion	16234	26196	8514
r/roastme	6994	7070	5772
r/unexpected	63700	10034	7643
r/askreddit	45644	50118	55484
r/FreeCompliments	27444	8063	255
r/funny	18597	10857	20266

Listed above are some of the subreddits that are bound to have a certain kind of behaviour. However, for some sub-problems need special attention like trolls, considering they are not limited to a particular sub-reddit.

Which node-node pairs and edges are more likely?

		A	B	C	D	E	F	G	H	I
	Table 7	Agreement	Announcement	Answer	Appreciation	Disagreement	Elaboration	Humour	NegativeReaction	Question
A	Agreement	AA								
B	Announcement	BA			BD	BE	BF		BH	BI
C	Answer	CA			CD	CE	CF	CG	CH	CI
D	Appreciation				DD					
E	Disagreement	EA				EE				EI
F	Elaboration	FA			FD	FE	FF			
G	Humour							GG		
H	NegativeReaction									
I	Question	IA		IC				IG		II

Figure 5.4: All the node pairs

Approach 1: Analysing Nodes based on entire conversation

- Look at the distribution of the labels based on the entire conversation and pick the node types that comprise more than 2/3 of the utterances.
- However, this lead to counting some relations many times because the transitive relations were not taken in account. Say, ("Announcement", "Question") and ("Question", "Answer") were found related, we also got a ("Announcement", "Answer") transitive relation while analysing each of them independently.
- This is taken care of by approach 2.

Table 8	Asking	Informing	Asserting	Proposing	Summarizing	Checking	Building	Including	Excluding	Self-promotion	Supporting	Disagreeing	Avoiding	Challenging	Attacking	Defending	Blocking
AA			✓					✓			✓					✓	
BA			✓				✓				✓						
BD							✓	✓			✓						
BE			✓			✓			✓			✓		✓	✓		✓
BF			✓	✓			✓	✓			✓						
BH			✓						✓			✓	✓	✓	✓		
BI	✓					✓	✓	✓									
CA			✓				✓	✓			✓						
CD			✓					✓			✓						
CE			✓							✓		✓		✓	✓		
CF			✓				✓			✓	✓					✓	
CG																	
CH			✓			✓			✓			✓		✓	✓		
CI	✓		✓			✓						✓		✓			
DD			✓				✓	✓			✓						
EA			✓			✓	✓	✓			✓						
EE			✓			✓			✓			✓		✓	✓		
EI												✓		✓			
FA			✓				✓				✓						
FD							✓				✓						
FE						✓			✓			✓		✓	✓		
FF				✓		✓	✓	✓			✓						
GG												✓			✓		✓
IA	✓										✓						
IC		✓		✓			✓										
IG													✓		✓		✓
II	✓			✓		✓	✓					✓					

Figure 5.5: Proposed edge pairs on the basis of contextual clues

Approach 2: Reply – wise

- We are analysing the number of direct replies to a particular discourse component. After getting the total count of replies, we check how these replies are divided at each post depth.
- For instance, a total of 31,884 utterances are of "Answer" type at post depth 1, out of which 31,813 are direct replies to questions at post depth 0 i.e. more than 90%.

So, for a node pair to exist we have kept a threshold of 33%. Therefore, for the question component, ("Question", "Answer") , ("Question", "Humour") , ("Question", "Question") and ("Question", "Agreement") pairs can be formed.

Fig 5.4 depicts the results of this approach for node-node interactions whereas 5.5 is the contextually plausible edge options once we have reduced the node-node interactions.

Future Work

1. This analysis was done on a small sample of data and hence we need a bigger human annotated data that can be used to statistically signify these relations or observe if these change with this new data.
2. Inculcate these finding to explore these graphs for recurring patterns in the sub-graph structures based on spatial graphical features. (GNNs in the approach diagram)
3. Use these structures as the basis for behaviour models for these sub-problems (Behaviour Graphs in the approach diagram)
4. Test the hypotheses by observing the "Attention" that the combined model pays to a new conversation of a certain group based on their structural similarity to the Behaviour graphs.

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