



An Architecture for a Dialogue System for Depression Detection

ABSTRACTS

The rise of online social network provides unprecedented opportunities for solving problems in a wide variety of fields with sentiment analysis. In our work, we apply sentiment analysis methods to detect depression from posts mined from Social Media platforms. We can summarize our work as:

- A depression detection model is constructed using subject dependent sentiment analysis method which proposes utilizing vocabulary and man-made rules to calculate the depression inclination of each post.

Additionally, we propose to integrate this model in a dialogue-based chatbot for depression detection which would further provide mental health counselling to IIIT-H community.

PROPOSAL

We are working on a dialogue based chatbot which can detect early stages of depression and provide effective counselling. Having implemented a rule-based chatbot similar to Eliza, we plan to make a chatbot which is capable of performing empathetic conversations and provide medical advice for people detected with depression using this model. This dialogue system will be able to sense the conversational context, its intent and the associated emotions.

METHOD

Firstly, a vocabulary fitting for depression detection is constructed, and the sentence structure patterns and calculation rules are derived. The particularity of depression and social media posts are paid special attention to the whole process. The weights of degree modifiers are quantified into six levels according to their intensities. [most(2), over(1.75), very(1.5), more(1), -ish(0.75), insufficient(0.5)]. Next, the part of speech of each word is recognized. The meaning of a sentence could not be decided only by the words it uses, but also by the order of words, named the structure of the sentence. Therefore lastly, linguistic rules based on the proposed vocabulary is constructed by taking the colloquial style of social media into account.

- 1: **Sub-sentence s_i :** I am extremely happy and very glad today.
- 2: **Word segmentation:** I(noun), today(noun), extremely(adverb), happy(adjective), and(adverb), very(adverb), glad(adjective).
- 3: **Keyword extraction in vocabulary:** extremely(adverb)#W_DM, happy(adjective)#W_EW, very(adverb)#W_DM, glad(adjective)#W_EW
- 4: **Structure pattern mining:**
 W_EW+W_EW : happy(adjective)#W_EW+ glad(adjective)#W_EW;
 W_DM+W_EM : extremely(adverb)#W_DM+ happy(adjective)#W_EW;
 W_DM+W_EM : very(adverb)#W_DM + glad(adjective)#W_EW.
- 5: **Polarity calculation of sub-sentence s_i :** $p(s_i) = [\text{weight}(\text{extremely}) \times \text{weight}(\text{happy})] + [\text{weight}(\text{very}) \times \text{weight}(\text{glad})] = [2 \times (+1)] + [1.5 \times (+1)] = +3.5$.

Fig 1. Polarity Calculation Algorithm

Items	Part of Speech	Weight	Notation
Emotion Words	Positive	1	W_EW
	Negative	-1	
Degree Modifiers	Adverb, Adjective	Inherited from WordNet	W_DW
Negative Words	Adverb	-1	W_NW

Fig 2. WordNet Vocabulary

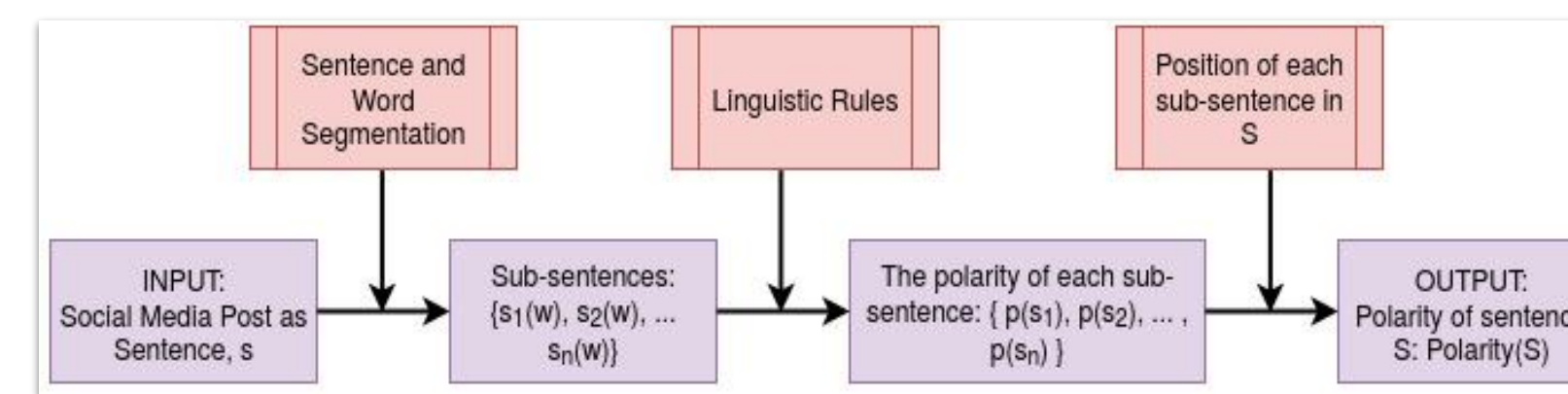


Fig 3. Framework of proposed model