

# Have You Made A Decision? Where?

## A Pilot Study on Interpretability of Polarity Analysis Based on Advising Problem

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### Task description

Given a dataset  $D$ , a sample of  $D$  can be represented as  $(c, y)$ . Specifically,  $c = \{U_m\}_{m=1}^{n_c}$  represents the context with  $n_c$  utterances.  $y = \{y_d, Y_u\}$  represents the label set of the dialogue, where  $y_d$  means the overall polarity of the dialogue, and  $Y_u = \{Y_{u_m}\}_{m=1}^{n_c}$  are the meta-polarities for the  $n_c$  utterances. Our goal is to learn a prediction model  $g(c)$  from  $D$  to predict the label set of a dialogue.

$$y_d = \begin{cases} NoSolutionProvided & \forall i, y_{u_i} = Neutral \\ SolutionProvided & \exists i, y_{u_i} \in \{Accept, Reject\} \end{cases}$$

Speaker	Utterance	utterance polarity
	Neutral	
Advisor	the difficulty rating is 2.53.	Neutral
Student	My preference is take a class with 100 people.	Neutral
Advisor	In addition, there are 81 students in the class.	Neutral
Student	This sounds like fun, i'd love to be involved.	Accept
Advisor	Dan, is there anything else that i could do for you?	Neutral
Student	Nope!	Neutral
Overall-Polarity	SolutionProvided	

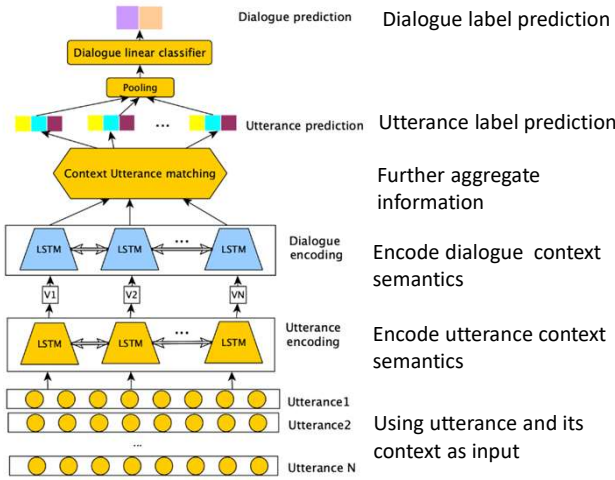
### Challenge

- Compared with previous polarity analysis tasks, dialogue-level polarity and utterance-level meta-polarity in advising result analysis task (ARA) are **interrelated and both need to be identified**.
- Meanwhile, the distribution of meta-polarities are quite imbalanced, and **more than 95% meta-polarities are labeled as Neutral**.

		Train	Old	Dev	Test
Dial	NoSolutionProvided	76,763	5	382	354
	SolutionProvided	28,737	495	118	146
Utter	Neutral	988,941	8,652	4,724	4,539
	Reject	5,996	61	27	36
	Accept	29,712	596	108	146

### Our Solution

- Utterance matching model



- Two-stage progressive training

#### Algorithm 1: Two-stage progressive training

```

1 if In first stage then
    /* Only dialogue loss will be
       used at the 1st training stage
       */
2    $\mathcal{L} \leftarrow \mathcal{L}_{Dialogue}$ 
3 else
    /* Both dialogue loss and
       utterance loss will be
       employed at the 2st training
       stage
       */
4    $\mathcal{L} \leftarrow \mathcal{L}_{Dialogue} + \mathcal{L}_{Utterance}$ 
5 end
    
```

TSPT is proposed to help the model converge better

### Evaluation Metrics

- The **accuracy** of dialogue prediction is considered as the main metric.
- In addition, micro-precision, micro-recall, and micro-F1 score are also evaluated for reference.

### Results

model	Accuracy	Micro-P	Micro-R	Micro-F1
BiLSTM	0.682	0.700	0.636	0.667
DSA	0.710	0.743	0.679	0.710
GP	0.694	0.717	0.651	0.682
BERT	0.708	0.708	0.660	0.683
DA	0.764	0.786	0.774	0.780
HRN	0.780	0.799	0.780	0.789
SUMBT	0.752	0.783	0.743	0.762
HB*	0.802	0.83	<b>0.802</b>	0.817
UCM+TSPT	<b>0.814</b>	<b>0.837</b>	<b>0.802</b>	<b>0.819</b>

Table 2. Comparative study (HB\* is ensemble model and reached top 1 performance in subtask3 of DSTC8).

model	Accuracy	Micro-P	Micro-R	Micro-F1
UCM+TSPT	0.814	0.837	0.802	0.819
-TSPT	0.802	0.834	0.797	0.815
-AgS	0.784	0.811	0.784	0.797
-CE	0.748	0.772	0.744	0.758
-LDAM	0.718	0.728	0.729	0.729

Table 3. Ablation tests by conducting accumulatively.

### Conclusion

- We conduct a pilot study on the task of ARA based on a reformulated large advising dataset.
- We propose an utterance classification model (UCM) to predict both meta-polarities and overall polarity to make our model interpretable.
- A novel two-stage progressive training (TSPT) method is employed to help our UCM performs better on this imbalanced dataset

### Contact

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<https://github.com/TeddLi>