Abstract

Many socio-linguistic cues are used in the conversational analysis, such as emotion, sentiment, and dialogue acts. One of the fundamental social cues is politeness, which linguistically possesses properties useful in conversational analysis. This short article presents some of the brief findings of polite emotional dialogue acts, where we can correlate the relational bonds between these socio-linguistics cues. We found that the utterances with emotion classes Anger and Disgust are more likely to be impolite while Happiness and Sadness to be polite. Similar phenomenon occurs with dialogue acts, Inform and Commissive contain many polite utterances than Question and Directive. Finally, we will conclude on the future work of these findings.

1 Introduction

Conversational analysis can potentially be enhanced with the help of politeness socio-linguistic cues (Danescu-Niculescu-Mizil et al., 2013) along with other linguistic cues. It is also highlighted in the concluding remarks of the PhD thesis Conversational Language Learning for Human-Robot Interaction (Bothe, 2020). This article focuses on a brief extension of the experiments provided in the mentioned thesis, primarily by adding linguistic politeness cues to conversational analysis along with emotion states and dialogue acts.

In this brief experiment, we will explore DailyDialog dataset (Li et al., 2017), a multi-turn dialogue dataset, and it is already annotated with emotion and dialogue act labels. We will find how this dialogue dataset is annotated with a pre-trained politeness recognizer (Bao et al., 2021) that provides values from 1 to 5 on a politeness scale. We discover that the utterances with certain emotion classes are more polite or impolite than others. At least most of the time, it seems natural to use polite utterances in a happy emotional state, whereas to use impolite utterances in an angry state. This phenomenon is precisely the motivation behind this experiment; find some utterance examples given in Figure 1. The conversation in this example shows how an impolite utterance is used in the Anger emotion state and then ends with a polite utterance in the Happiness emotion state. We find out such phenomenon statistically occurring quite often in the given dataset, and the results are also available in the GitHub repository bothe/politeEDAs.

2 Related Work

Perceiving emotions in conversation provides affective information of the conversation partners; similarly, perceiving politeness in conversation pro-
Table 1: Statistics of utterances with Emotion and Dialogue Act classes in the DailyDialog dataset

| Emotions | Ut % total | % Emo | Inform | Question | Directive | Commissive |
|----------|------------|-------|--------|----------|-----------|------------|
| Anger    | 1022       | 1.00  | 5.87   | 615      | 174       | 132        | 101        |
| Disgust  | 353        | 0.34  | 2.03   | 291      | 30        | 18         | 14         |
| Fear     | 174        | 0.17  | 1.00   | 106      | 27        | 21         | 20         |
| Happiness| 12885      | 12.61 | 74.02  | 7830     | 2158      | 1476       | 1421       |
| Sadness  | 1150       | 1.13  | 6.61   | 809      | 190       | 95         | 56         |
| Surprise | 1823       | 1.78  | 10.47  | 1122     | 565       | 72         | 64         |
| no_emotion | 85572    | 83.78 | –      | 36316    | 26549     | 15542      | 7165       |
| Total    | 102979     |       |        | 47089    | 29693     | 17356      | 8841       |

Table 1: Statistics of utterances with Emotion and Dialogue Act classes in the DailyDialog dataset

provides cues about their social manners. The emotional states and dialogue acts have unique relations which is presented by Bothe et al. in Emotional Dialogue Acts (Lakomkin et al., 2017; Bothe et al., 2018b, 2020). For example, Accept/Agree and Thanking dialogue acts often occur with the Joy emotion, Apology with Sadness, Reject with Anger, and Acknowledgements with Surprise. Similarly, politeness and emotion together are evidently discussed a lot in the literature as some of the most critical social cues (Langlotz and Locher, 2017; Renner, 2020; Culpeper and Tantucci, 2021).

Some computational linguistic study shows how machines learn politeness, for example, please and could you words signals on the heatmaps of sentences (Aubakirova and Bansal, 2016).

In fact, Brown and Levinson (1987) mentions that the display of emotions or lack of control of emotions as positive politeness strategies or potentially face-threatening acts. Thus this study fosters analysis of linguistic politeness by understanding how ‘appropriate levels of affect’ are conveyed in the conversational interaction (Langlotz and Locher, 2017). In human-robot interaction, politeness as a social cue plays a vital role to drive engaging social interaction with robots (Steinfeld et al., 2006; Srinivasan and Takayama, 2016; Bothe et al., 2018a). However, this article explores relations between the socio-linguistic cues, finding out how polite the utterances are against their respective emotion and dialogue act classes.

3 Approach

Our goal is to analyze the socio-linguistic cues to find meaningful relations between them, for which we are going to perform the tasks in the following order:

- explore the dataset, DailyDialog, which is already annotated with emotion and dialogue act labels,
- annotate the utterances with politeness values using politeness analyzer, more precisely each utterance with a degree of politeness,
- analyze the annotated utterances with politeness against the emotion and dialogue act classes in the dataset, and
- conclude with the results and findings and provides future conversational analysis work to extend this experiment.

4 Resources

4.1 Dataset: DailyDialog

As the name suggests, the DailyDialog dataset contains conversation topics of daily life ranging from ordinary life to financial topics. It contains bi-turn dialogue flow such as Question-Inform and Directive-Commissive; thus, the dataset is annotated with those four fundamental dialogue acts to follow unique multi-turn dialogue flow patterns (Li et al., 2017). This dataset is manually labelled with six emotion classes and no_emotion class. The statistics of the dataset is presented in Table 1, we can see that the no_emotion class dominates the total number of utterances. However, Happiness dominates within emotion classes, whereas Fear contains the least number of utterances. Table 1 also presents the number of utterances for the dialogue act classes in the dataset for their corresponding emotion classes.

4.2 Politeness Analyzer

We will use a politeness analyzer from the recent work of Bao et al. (2021), where they combine two datasets from Danescu-Niculescu-Mizil et al.
(2013) and Wang and Jurgens (2018). The politeness regressor model is obtained on these datasets by pre-training a BERT-based model (Devlin et al., 2019) on Reddit data using masked language modelling. The final model is obtained at an average Pearson of 0.66 with human judgments from both the datasets and made available online by authors. The model provides a degree of politeness on the scale in [1, 5], where around 3 indicates neutral.

5 Results and Analysis

We annotate all utterances in the DailyDialog dataset for politeness values in the range [1, 5] using the politeness analyzer mentioned above. Then we plot histograms of the politeness values of the utterances against the emotion categories shown in Figure 2. As we can see in these histograms, utterances in the emotion classes Anger and Disgust are neutral and impolite on the politeness scale. On the other hand, many utterances in the Happiness and Sadness emotion classes are polite. Fear and Surprise classes are mostly neutral on the politeness scale than other emotion classes.

We also plot the histograms of the politeness values of the utterances against the dialogue act classes shown in Figure 3. We can see that most of the utterances are neutral or polite on the politeness scale for all the dialogue acts. However, we find that the Inform and Commissive dialogue act classes contain many polite utterances compared to Question and Directive dialogue acts. Interestingly, we discovered that speakers often tend to use polite utterances when answering, thanking, and agreeing (and the utterances that come under Inform and Commissive). Whereas when asking, guiding, directing, ordering (under Question and Directive), the utterances are primarily neutral or polite.

Table 2 presents top polite, neutral and impolite utterances from the DailyDialog dataset annotated

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3https://github.com/wujunjie1998/Politenessr/
with the politeness analyzer. There are five exam-

Table 2: Examples from the DailyDialog dataset showing 5 utterances extreme DoP (degree of politeness)

| DoP  | Dialog Act | Emotion  | Utterances |
|------|------------|----------|------------|
| Polite utterances | | | |
| 4.63  | INFORM    | HAPPINESS | OK! Thank you very much! |
| 4.63  | INFORM    | HAPPINESS | Sure, that would be great! Thank you! |
| 4.63  | COMMISSIVE| HAPPINESS | That would be great! Thanks a lot! |
| 4.62  | INFORM    | HAPPINESS | Thank you, thank you, thanks again. |
| 4.62  | INFORM    | HAPPINESS | This is exciting! Thank you so much! |
| Neutral utterances | | | |
| 3.34  | INFORM    | HAPPINESS | I went to the tutoring service centre on campus today. |
| 3.34  | INFORM    | HAPPINESS | I never knew there were so many fun things to do on a farm. |
| 3.34  | INFORM    | no_emotion | Just a minute. It’s ten to nine by my watch. |
| 3.34  | INFORM    | no_emotion | You may check out books or videos. |
| Impolite utterances | | | |
| 1.59  | INFORM    | DISGUST | Don’t dress like that. You’ll make fool yourself. |
| 1.51  | COMMISSIVE| ANGER    | Make it work, Geoff. You would say that, wouldn’t you. |
| 1.47  | DIRECTIVE | no_emotion | Get up, you lazybones! |
| 1.46  | DIRECTIVE | SURPRISE | You idiot! Don’t say that! Do you want this job, or not? |
| 1.37  | DIRECTIVE | ANGER    | Get out of my store, you jerk! |

Figure 4: Polite Emotional Dialogue Act labels from the DailyDialog dataset focused on Surprise and Sadness emotion utterances, the utterance with Surprise shows an immediate reaction which becomes impolite, interestingly most of the Sadness utterances are polite.

6 Conclusion

Recognizing politeness in conversation is an essential aspect of conversational analysis, and we discover how politeness flows in a dialogue. Moreover, socio-linguistics features relatedness provide an additional dimension for behavioural analysis of conversation partners and their use in the virtual assistant and human-robot interaction fields.

In this short paper, we discover how politeness is related to emotions and dialogue acts in the given dataset. Specifically, we discover that the utterances are mostly polite in Happiness and Sadness emotion classes and Inform and Commissive dialogue acts. Similarly, the utterances are primarily neutral or impolite in Anger and Disgust emotion classes. We find that the utterances in the Question and Directive dialogue acts are mostly neutral; however, many are also polite.
The continuing work under this experiment is planned to extend to other dialogue datasets to prove the discovered phenomenon. The politeness analyzer used in this experiment provided fair annotations for the degree of politeness linguistically. However, the next step would be to use more than one analyzer for more robust detection of politeness or annotate the utterances manually. Future work could also be extended to learn the social behaviours using analyzed linguistic cues with the help of deep learning techniques.

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