Toward an Automatic Classification of Negotiation Styles using Natural Language Processing

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Abstract. We present a natural language processing model that allows automatic classification and prediction of the user's negotiation style during the interaction with virtual humans in a 3D game. We collected the sentences used in the interactions of the users with virtual artificial agents and their associated negotiation style as measured by ROCI-II test. We analyzed the documents containing the sentences for each style applying text mining techniques and found statistical differences among the styles in agreement with their theoretical definitions. Finally, we trained two machine learning classifiers on the two datasets using pre-trained Word2Vec embeddings.

Keywords: Natural Language, Classification, Virtual artificial agents, Negotiation.

1 Introduction

The effectiveness of intelligent assessment tools and tutoring systems on improving the learner's ability to retain information has been extensively proved in well-defined subjects, but also ill-defined ones, like negotiation [1] and communication skills [2]. Soft skills training, in particular negotiation, has shown to benefit the use of simulation games that include interactions with virtual humans [3]. In most game-based simulations, the user data is collected in the form of multiple choices or non-verbal information like facial expression [4]. While natural language processing (NLP) techniques have been used to generate human-like negotiations, via Wizard-of-Oz or machine learning algorithms (e.g. [3]), these have never been included in the user model. We aim at proposing the first step to fill this gap by presenting a NLP model that allows to map the features of the users' sentences to their predominant negotiation style. We asked participants to interact using natural language with virtual characters and then to complete the Rahim Organizational Conflict Inventory and we built documents of sentences for each style. We show the differences between the styles and then present the results obtained by training two machine learning classifiers on the dataset using Google's Word2vec pre-trained word embeddings.

2 Related Work

Several e-learning technologies have been developed to promote soft skill development. Among the others, Eutopia [5] constitutes an example of a multiplayer platform that provides role-play simulations focused on the development of soft skills. An adaptive tutoring system for communication skills has also been proposed [2]. None of the platforms in literature, however, includes in its user model a NLP architecture that evaluates the learner's soft skills from the user's natural speech.

3 Materials and Methods

The present work is based on Rahim and Bonoma's model [6], which defined five negotiation styles: Integrating (high concern for self and others), Obliging (low concern for self and high concern for others), Dominating (high concern for self and low concern for others), Avoiding (low concern for self and others) and Compromising (intermediate in concern for self and others). This model is supported by the ROCI II (Rahim Organizational Conflict Inventory-II). The virtual characters are taken from Enact [7], a 3D game based on Rahim's model. The game is organized in 5 scenarios, where users can negotiate in conflict situations between peers using verbal and non-verbal cues. In the experiment, participants were asked to fill the consent form and answer to 20 screenshots taken from Enact, 4 for each scenario (2 introductive screens and 2 random interactive screens). Users were asked to answer with their own words in a field under the interactive images using maximum 100 characters. Then, participants were asked to complete the ROCI-II (28 items on a 5–point Likert scale). 173 subjects (mean age = 23.12 ± 9.16) participated and 1730 sentences were collected.

4 Results and Discussion

The user sentences were tagged with the predominant style obtained in the ROCI-II. A reliability test on the ROCI-II items' scores showed a consistent value (Cronbach's alpha = .776, Standardized item's Cronbach's alpha = .797). Participants classified as having two or more predominant styles were excluded from the sample. Five documents were built, each containing sentences belonging to one style. From this dataset (the Full_Dataset), we extracted the sentences provided by users whose predominant style score was at least .4 points above the others. This restricted dataset (Rest_Dataset) consisted of five collections of sentences: 230 Avoiding (words count = 1670, avg. sentence length = 16.40), 210 Compromising (words count = 1885, avg. sentence length = 17.61), 220 Dominating (words count = 1665, avg. sentence length = 16.33), 230 Integrating (words count = 1703, avg. sentence length = 17.42) and 240 Obliging (words count = 1994, avg. sentence length = 18.94). The vocabulary count was of 462 words. We removed punctuation and stopwords, and tokenized using a Porter stemmer. We calculated the similarity using WordNet's Leacock Chodorow algorithm [8] and collected the most frequent pronouns and words (Tab 1).

Style	Words similar to "You"	Words similar to "I"	Most frequent pronouns	Most frequent words
Avoiding	Me, I, We	You, We, Give	You, it, I	Take, Don't
Compromising	I, We, Watch	You, We, It	You, I, it	Get, Take
Dominating	I, What, Us	You, Later, It	You, it, I	Let, Go
Integrating	I, We, It	You, We, Time	You, I, it	Take, Let
Obliging	It, Then, I	Go, When, Ok	You, it, I	Let, Take

Table 1. Words similar to the pronouns "I" and "You" for each style calculated with the Leacock Chodorow algorithm, most frequent words and pronouns for each style

Compromising and Integrating styles show a use of "We" comparably to that of "I" and "You" and showed "You" and "I" as the most frequent pronouns. This is in accordance with the styles' definition (interest for self and for other). Obliging style, whose self-concern is the lowest, used the pronoun "I" comparably to the word "Ok" showing a more condescending attitude. Then, we trained two classifiers, Multinomial Naive Bayes (MNB) [9] and Support Vector Machine (SVM) [10] on the datasets using Google Word2Vec word embeddings for the initialization [11] and compared the accuracy measured by F score using 10-fold cross validation for the train/test split. Rest_dataset was trained for 1000 iterations, Full_dataset for 3200 iterations (Fig 3).

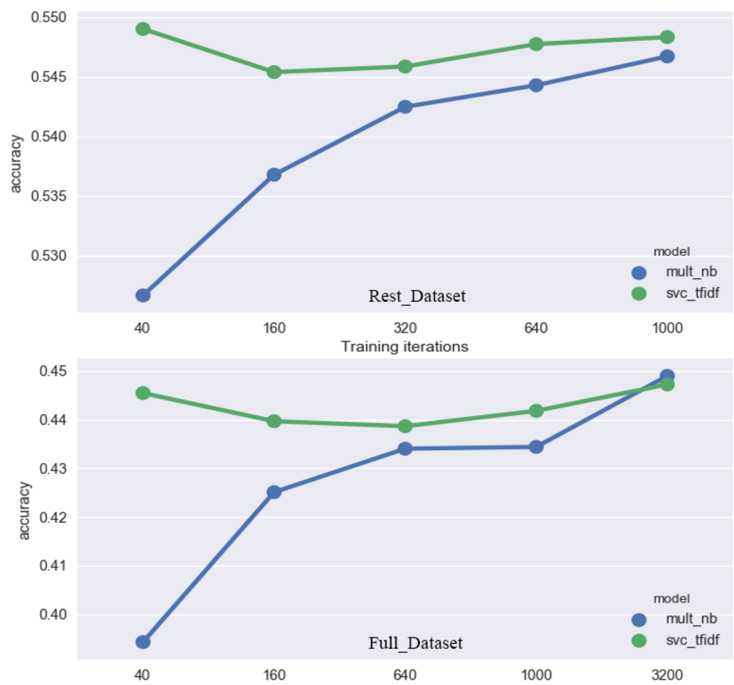

Fig. 1. Accuracy obtained by the two classifiers for the Rest_Dataset and the Full_Dataset.

Both the models reached an F score higher than 0.5, with MNB scoring slightly higher (0.552). The Rest_Dataset, even if smaller, gained a maximum accuracy 0.10 higher than the Full_Dataset. This measure proves that the score obtained with ROCI-II correlates with the accuracy with which the user's negotiation style can be predicted.

5 Conclusion

We presented a NLP model for the automatic categorization of the user negotiation style. We collected natural sentences used in the interactions with 3D virtual humans and associated their negotiation style using the ROCI-II test. We analyzed the corpus applying text mining techniques and found differences among the styles consistently with our theoretical framework. We trained machine learning classifiers (Multinomial Naive Bayes and Support Vector Machine) on the full dataset and on a dataset containing only the most representative sentences using Word2Vec embeddings, and reached a significantly higher accuracy in the case of the more representative dataset.

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