Using Language to Determine Success in Negotiations: A Preliminary Study*

Marina Sokolova, Stan Szpakowicz, and Vivi Nastase

School of Information Technology and Engineering
University of Ottawa, Ottawa, Canada

Abstract. Negotiation support systems often allow an exchange of messages that help explain better the offers and positions of the negotiators. Collections of such messages can be analyzed using Natural Language Processing techniques. We work with a large collection accumulated by the Inspire system. The messages are unedited and share characteristics with email text data. We use them to classify negotiations as successful or failed, and to find language patterns characteristic of these two classes. The preliminary results show that certain patterns in the language of the messages do predict whether the negotiation will succeed.

1 Texts in Electronic Negotiations

We investigate how language reflects success or failure of electronic negotiations (e-negotiations). We aim to build a language model of texts that accompany fixed-problem negotiations performed via a negotiation support system (NSS). Language models of e-negotiations can help understand how the negotiators' behaviour reflects their strategy and tactics, and balance the negotiators' subjective self-evaluation with an external, and presumably objective, source of evaluation. We seek models that relate success or failure of negotiations to such text characteristics as word statistics and lexical semantics. We report text characteristics discovered as intermediate results in building such a model. This appears to be the first study of e-negotiation textual data that uses Natural Language Processing (NLP) techniques, although other research communities actively investigate such data and the underlying processes [3, 2].

In e-negotiations people do not have visual or acoustic information to evaluate the negotiation process, plan their future actions and further their goals. In free-form *written* messages exchanged, language is essential for understanding the process and outcome of negotiations. To identify language patterns indicative of success or failure of negotiations, we apply statistical analysis to 1482 negotiation texts collected by the NSS Inspire [3]. Inspire is a research and teaching tool used in universities and colleges in more than ten countries. There were over 2500 contributors of texts mostly written in English.

Inspire is a support environment for bilateral negotiations. Every negotiation has a buyer ("Cypress Cycles") and a seller ("Itex Manufacturing") who seek

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agreement on trading bicycle parts. Negotiation issues are fixed (part price, delivery schedule, payment terms, policy on returns) and have pre-specified sets of values, so there can be exactly 180 different offers. Inspire also mediates information exchange during the negotiation: compulsory numerical tables represent offers, optional messages complement offers or are exchanged between offers. Message texts are informal and poorly edited [6]. In this study we keep all orthographic, spelling and grammatical errors. The results show that, while the negotiators' negotiation skills, educational and cultural background and English skills vary, their language shows general trends.

2 Identifying Negotiation Success in Texts

Aiming to determine success from the negotiators' language, we are interested in text data that provide substantial information about negotiations. If messages were absent or were not in English, we ignored the negotiation. This left 1275 negotiations, 761 of them successful. There are 809,584 word tokens and 20,240 word types. This differs from the Brown corpus with 1 million tokens and 53,850 types. We attribute the high token-type ratio to the fixed topic of discussion.

Inspire users discuss a fixed topic, negotiate a fixed problem, and choose among fixed options. We want to know how these conditions affect the growth of the vocabulary and its convergence with respect to the sample size [4]. We add information on rare words based on *hapax legomena* ($V(1,N)$) and *dis legomena* ($V(2,N)$) [9]; $V(i,N)$ is the number of types that occur i times in the text with N tokens. We calculate the growth rate of the vocabulary $P(N) = V(1,N)/N$ and Sichel's characteristic $S(N) = V(2,N)/N$. Table 1 shows that new words are steadily added at every stage; $TT(N)$ is the type-token ratio. Moreover, the vocabulary grows approximately at the same rate through the data, and Sichel's characteristic converges as expected [9]. That is, the Inspire vocabulary grows as the vocabulary of unrestricted languages [4].

Table 1. The lexicon growth rate of the Inspire data.

N	96940	293152	364306	535244	614428	716176	809584
$TT(N)$	0.060	0.040	0.033	0.029	0.027	0.026	0.025
$P(N)$	0.027	0.018	0.015	0.013	0.012	0.011	0.010
$S(N)$	0.008	0.005	0.004	0.0037	0.0035	0.0033	0.0031

For further studies we concatenate all messages that accompany a negotiation and treat it as one entry. This is justified by the nature of bilateral negotiation: in a dialogue, a message depends on or relates to the previous messages. We focus on finding language patterns representative of successful (failed) negotiations, that at the same time cannot represent failed (successful) negotiations. For example, *I can accept* appears almost 3 times more often in successful than in failed negotiations; *you accept my* appears twice as often in failed than in successful negotiations. That is, we look for features frequent in successful and rare or absent in failed negotiation – or conversely. To find such features, we separate the two classes: we construct and investigate two data sets. For both, we build lists of unigrams, bigrams and trigrams, and rank the N-grams by frequency [1]. We compare the ranks of the same N-gram in successful and failed negotiation data, and find N-grams frequently present in one set and rarely present or absent in the other. These N-grams are easily detected when we plot N-grams from successful and failed negotiations; see Fig. 1. The N-grams with a large difference in ranks are depicted as the outliers. Note that the graph for 761 successful negotiations lies, predictably, above the graph for 514 failed negotiations.

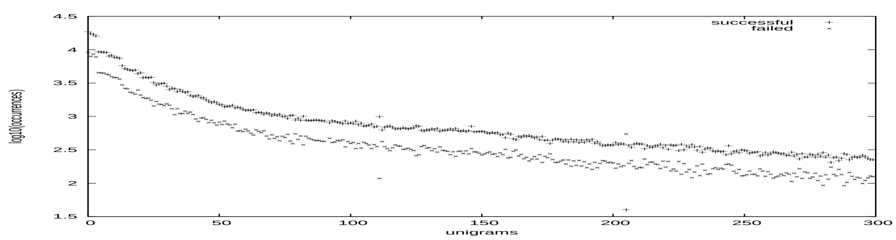

Fig. 1. Successful and failed negotiations

Previous studies on classifying e-negotiations did not consider the language aspect of negotiations [3]. We state our **first hypothesis**: the use of negotiation-related words is relevant to the success of negotiations. To confirm, we run experiments to classify negotiation as successful or failed based on the use of 123 most frequent negotiation-related words. For each negotiation we build a bag of those words [1], counting their occurrences. We add the count of the remaining words to the bag, so each negotiation is represented by a vector of 124 integer-valued features and a binary-valued feature for success/failure. We employ several Machine Learning(ML) classifiers freely available in the Weka suite [10] – AD Trees (ADT), Decision Stumps (DS), Decision Tables (DT), Instance-based using 20-nearest neighbour (IBK), analog of Support Vector Machine (SMO) – and the Decision List Machine (DLM) [5]. We use 10-fold cross-validation. Our experiments give 66-69% overall classification accuracy with the baseline (BL) 60%. Precision and recall are calculated with respect to successful negotiations. See Table 2.

Table 2. Classification of negotiations.

Measure	BL	ADT	DLM	DS	DT	IBK	SMO
Precision	60 %	67.4 %	67.2 %	68.2 %	68.1 %	70.3 %	72.9 %
Recall	100 %	84.2 %	90.5 %	83 %	85.2 %	70.4 %	72.3 %

Simons [8] found that language patterns of the first part of negotiation efficiently predict the negotiation outcome. In our data both company names, *Cypress* and *Itex*, have higher ranks in failed than in successful negotiations. We note that company names mostly appear when the negotiators introduce themselves. The rank difference suggests that the language of successful and failed negotiations differ from the very beginning of the process. Our **second hypothesis**: the starting phases of successful and failed e-negotiations differ.

In a preliminary evaluation of this hypothesis, we find that in successful negotiations *Cypress* and *Itex* together account for 3/4 of the data they account for in failed negotiations. We also compare ranks of frequent bigrams and trigrams containing company names among 500 most frequent bigrams and 700 most frequent trigrams. Their ranks on the list for successful negotiations are r_s, for failed negotiations – r_f. *Cypress* appears in successful negotiations in one bigram ($r_s = 96$) and two trigrams ($r_s = 467, 532$) with 0.0555 % of text covered. In failed negotiations *Cypress* appears in one bigram ($r_f = 55$) and five trigrams (r_f = 359, 391, 420, 474, 625) with 0.1495 % of text covered. *Itex* appears in successful negotiations in one bigram ($r_s = 285$) and no trigrams. In failed negotiations *Itex* appears in one bigram ($r_f = 295$) and no trigrams. The comparison of the N-gram ranks suggests that both in successful and failed negotiations the buyer's name is more frequent than the seller's name. *Cypress* is noticeably more frequent in failed negotiations. *Itex* is more frequent in successful negotiations.

Our **third hypothesis** is that politeness characterizes successful negotiations. To support it, we find the unigram ranks of such indicators of polite speech as *Thank* ($r_s = 69$, $r_f = 83$), *Thanks* ($r_s = 108$, $r_f = 109$), *thank* ($r_s = 250$, $r_f = 315$), *thanks* ($r_s = 420$, $r_f = 379$). We deliberately preserve case-sensitivity, to enable further studies of negotiators' attitude towards the negotiation process and negotiation partners. The combined percentage of the orthographic variations of the words *thank* and *thanks* is 2.5 times higher in successful than in failed negotiations.

We employ bigrams and trigrams to find more language differences between successful and failed negotiations. We are looking for trigrams that show the negotiators' goal (win by any means, reach a compromise, do away with the assignment), their attitude to partners (friendliness, aggressiveness, indifference), and behaviour in the negotiation process (flexibility, stubbornness). The same trigrams must be noticeably present in either successful or failed negotiations. We notice that in the trigrams from the failed negotiations there is a trace of aggressive behaviour (**you will accept, you will agree, you are not**), which is absent from the corresponding trigrams in the successful negotiations (**you can accept, agree with your, it is not**). Tracing the trigrams with "you", we found that in successful negotiations they correspond to politeness, in failed negotiations – to aggressiveness. See [7] for more on the methods used and language patterns found.

3 Conclusions and Future Work

We presented a procedure for identifying language patterns indicative of the outcome of negotiations. Using NLP and ML techniques, we showed how text messages exchanged by the users of an NSS are relevant to the outcome of e-negotiations. We related language with the success of negotiations by arguing in favour of three hypotheses. We showed that e-negotiations can be classified correctly if they are represented by bags of words built from negotiation-related words. We showed some ways in which language differs in successful and failed negotiations, in particular in initial phases. Also, politeness is a factor in successful negotiations.

We did not emphasize differences between the language patterns of buyers and sellers. Role-dependent patterns are a promising direction of ongoing work. We will use ML methods to find language patterns. How ML methods are implemented poses questions about different mappings of negotiations to bags of words. This is closely linked to the question how the use of words not related to negotiation relates to negotiation outcomes. Finally, there is the issue of how noise in text affects the e-negotiation process, also left for future work. Preliminary experiments show correlation between text data not related to negotiation, noise level and the negotiation outcomes.

References

1. D. Jurafsky and J. H.Martin. *Speech and Language Processing.* Prentice Hall (2000).
2. G. E. Kersten. "The Science and Engineering of E-negotiation: An Introduction". InterNeg Report 02/03, 2003. interneg.org/interneg/research/papers/
3. G. E. Kersten, G. Zhang. "Mining Inspire Data for the Determinants of Successful Internet Negotiations", *Central European J. of Operational Research*, **11**(3), 297-316, 2003.
4. M. P. Oakes. *Statistics for Corpus Linguistics.* Edinburg University Press, 1998.
5. M. Sokolova, M. Marchand, N. Japkowicz, J. Shawe-Taylor "The Decision List Machine", *Advances in Neural Information Processing Systems*, **15**, 921-928, The MIT Press, 2003.
6. M. Sokolova, S. Szpakowicz, V. Nastase. "Automatically Building a Lexicon from Raw Noisy Data in a Closed Domain". INR01/04, 2004. http://interneg.org/interneg/research/papers/
7. M. Sokolova, S. Szpakowicz, V. Nastase. "Language Patterns in Text Messages of Electronic Negotiations: A Preliminary Study". INR05/04, 2004. http://interneg.org/interneg/research/papers/
8. T. Simons. "Speech Patterns and the Concept of Utility in Cognitive Maps: the Case of Integrative Bargaining". *Academy of Management J.*, **38**(1), 139-156, 1993.
9. F. J. Tweedie, R. H. Baayen. "How Variable May a Constant be? Measures of Lexical Richness in Perspective". *Computers and the Humanities*, **32**, 323-352, 1998.
10. I. Witten, E. Frank. *Data Mining*, Morgan Kaufmann, 2000. http://www.cs.waikato.ac.nz/ml/weka/