Language in Electronic Negotiations: Patterns in Completed and Uncompleted Negotiations

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Abstract

Negotiation is a special and interesting type of interpersonal communication. It occurs in political, business, casual settings. In electronic negotiations, language is the negotiators' principal means of reaching a deal. They use language to persuade, threat and query. An electronic negotiation support system has been gathering textual data. We study these data to identify language patterns that indicate the different roles the negotiators play, and the strategies they apply in negotiation. We observe that role-dependent language patterns do exist. We support this observation by the results of classifying negotiation textual data into role-defined classes and by statistical information.

1 Motivation

Negotiation is a special, and quite interesting, type of interpersonal communication. It occurs in political, business or casual setting, among others. We focus on business negotiations, in which negotiators have well defined roles[1]. The negotiators' behaviour is strongly influenced by the roles they play and by the negotiation environment and available means. Electronic negotiations (e-negotiations), conducted by email or other electronic means [Kersten and Noronha, 1999], are a relatively new phenomenon. Studies of behaviour in e-negotiations [Buddress *et al.*, 2003; Thompson and Nadler, 2002] do not consider roles, although roles are the subject of intensive research on face-to-face negotiations [Brett, 2001; Drake, 2001]. None of these studies apply Natural Language Processing (NLP) or Machine Learning (ML).

Due to the absence of nonverbal communication in e-negotiations, messages that negotiators exchange are the only available source of behaviour disclosure [Brett, 2001]. Our main hypothesis is that the language used in such messages varies according to the roles assigned to the negotiators. To investigate the language, we use NLP, ML and statistical methods to study the texts of messages sent in long-term e-negotiations – up to three weeks – conducted through the Inspire system [Kersten and Noronha, 1999]. It is remarkable that negotiators do not choose their roles: the role of a buyer or a seller is assigned by the system administrators. We look for

[1] In negotiations, the term *role* refers to buyers, sellers, mediators, arbiters, etc.

general language use trends in a collection of messages of more than 1,000,000 words, exchanged by more than 4000 negotiators. We call such trends *language patterns*. We observe that role-dependent language patterns do exist, despite a wide variation in the negotiators' cultural and educational background, current occupations and fluency in English. We support this observation by the results of classifying negotiation textual data into role-defined classes and by statistical information. We present research that has not been attempted yet. This precludes comparison with related work.

Our results are of interest to behavioural and cultural studies. The patterns we find will be employed in building a statistical language model and in developing negotiation support systems. This study continues the research on the language of negotiations [Sokolova *et al.*, 2004] that is part of an on-going major project [Kersten *et al.* , 2002-2004].

2 E-negotiation Systems

Electronic negotiations are conducted through electronic means. Electronic means provide the environment necessary to fulfill negotiation-specific functions based on theories of individual decision-making, communication and negotiation. A negotiation system that is not fully automated allows the negotiators to make the decisions [Kersten and Noronha, 1999]. Such systems are platforms for conducting negotiations: they facilitate communication or offer decision support. We concentrate on the type of data gathered by negotiation support systems (NSS), which combine decision support with electronic communication [Kersten *et al.* , 2002-2004]. We work with data collected by the NSS Inspire[2] [Kersten *et al.* , 2002-2004] since 1996. It is the largest available collection of this kind. In this study we work with 2557 records of negotiations. The negotiations conducted in Inspire have the following characteristics.

- The problem is the purchase of bicycle parts, with four negotiation issues – price, delivery time, payment time, and return policy, each with several possible values.
- There are two participants: a seller (Itex Manufacturing) and a buyer (Cypress Cycles); every negotiator will participate in only one negotiation.
- Upon logging in, the negotiators are instructed to fill a pre-negotiation questionnaire with negotiation preferences and personal and background data.
- The negotiators exchange formal offers (tables with numbers from a small fixed set), and possibly messages that either accompany offers or are exchanged between offers.
- A negotiation is completed only if an offer has been accepted and acceptance registered by Inspire within three weeks; it is uncompleted overwise.

We show a negotiation dialog example from Inspire:
(Buyer) Please make a counter-offer, so that we can proceed a little bit further in our negotiation.
(Seller) would this meet your expectations ?

Compared with other NSSs, Inspire gives the most developed and diverse e-negotiation support [Kersten and Noronha, 1999]. It provides preference assessment in the pre-negotiation phase; offer and message exchange

[2] The Inspire system is available on the Web at http://interneg.org/inspire/

medium, analysis of alternative offers, counter-offer evaluation, access to the on-line manuals and history of the negotiation in the negotiation phase; and assessment of the efficiency of the compromise (Pareto-optimality) in the post-settlement phase. Inspire's main decision-analytical tool is the utility function [Kersten and Noronha, 1999]. The function is calculated for each negotiator considering his preferences for each value of each negotiation issue and balancing preferences for single-issue values with combinations of values. Because the user can change the utility function in the course of the negotiation, it is not an objective measure of the negotiation process or its outcome. Most participants do not answer the post-questionnaires, making the data therein unreliable for generalization. At present, we work with the text data, the offers, the history records, and the pre-questionnaires.

We filtered out 413 negotiations where only one participant was active. Two parties participated in the remaining 2144 negotiations, but did not always exchange text messages. 1434 of these were listed as completed, 710 as uncompleted. From these negotiations we extracted the texts sent by 2113 buyers and 2114 sellers. Table 1 shows how much variety there is in the Inspire negotiators' background. 3125 negotiators identified their first language, 4276 their occupation.

First language	%	Occupation	%
English	28.1	students	82.8
German	22.8	professionals	13.1
Chinese dialects	12.1	managers	1.8
Spanish	9.7	engineers	1.1
Hindi	4.6	teachers	0.6
Russian	3.8	professors	0.4
Finnish	3.4	executives	0.2
Others	15.5		

Table 1: Background of Inspire negotiators

Inspire	Dialogues	Brown	WSJ
to	I	the	the
I	you	of	of
you	and	and	to
the	the	to	a
a	to	a	and
and	ah	in	in
your	a	that	that
offer	it	is	for
we	in	was	one
is	know	He	is

Table 2: 10 most common words in Inspire, Dialogues, Brown , WSJ

We will show that despite this variety in mother tongue and occupation, the language is consistent across negotiations. Furthermore, there are language patterns that characterize negotiators who fill buyer and seller role respectively.

3 Vocabulary Analysis of the Text Data

Concatenating messages exchanged in 2144 Inspire negotiation results in a collection with 1,484,559 word tokens and 24,601 word types. We hypothesize that despite having been collected by an NSS, these data are similar to spoken language data, in particular to dialogues.

We compare our data with face-to-face conversations of upper-level college students (Dialogues) [Allen and Guy, 1974], with the Brown corpus [Francis and Kucera, 1979], and the Wall Street Journal (WSJ) corpus [Paul and Baker, 1992]. We exemplify the commonalities and differences using the 10 most common types in these corpora; see Table 2.

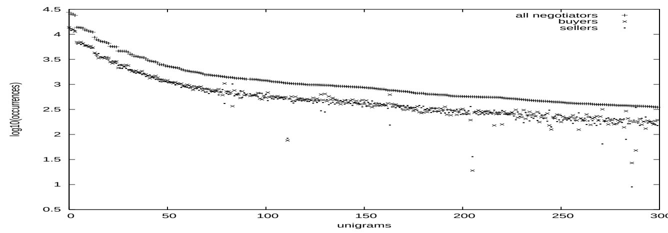

Figure 1: Buyers and sellers, unigrams.

The Inspire data and face-to-face dialogues exhibit a frequent use of first and second person singular pronouns **I, you**. This differs from the general texts (Brown and WSJ), and is consistent with the view of Inspire negotiations as interpersonal communication. The high frequency of the negotiation-related word **offer** suggests that this communication has a specific topic – negotiating a purchase with an exchange of mandatory offers. The Spearman's Rank Correlation Coefficient (SRCC) [Oakes, 1998], a common measure for comparing corpora with different sizes [Kilgarriff, 2000], calculated on the intersections of the Inspire list with the other lists, also indicates that the Inspire data is more similar to the dialogue data (SRCC = 0.7227) than to the Brown (SRCC = 0.0681), or the WSJ (SRCC = 0.1409) corpus.

Communication via the Inspire system does not resemble regular dialogue. In e-negotiations people do not always communicate in turns. Some negotiators, considerably more active than their partners, send several messages before receiving a reply, while others rely on the system's tables of offers and choose not to send accompanying messages. Also, unlike people involved in generic dialogues, negotiators fill specific roles in a negotiation. In our case, one is a seller, the other is a buyer. We are interested in verifying if this difference in roles translates into a difference in language use. We separate the data into two classes, corresponding to the two roles, and we look for language patterns. The Buyer data consists of a collection of messages sent by 2113 buyers, the Seller data – messages sent by 2114 sellers.

In the first step we compare the two classes using unigram frequencies. Although for a deeper comparison of two corpora we could consider other features, such as part-of-speech (POS) distribution and lexical semantics, the reliability of word frequencies makes the statistical results a trustworthy measure [Kilgarriff, 2000]. We have compared the occurrences of 300 most frequent unigrams in our data when they are used by all negotiators, only by buyers, and only by sellers. These unigrams are mostly stop words, negotiation-related words such as **offer, price, delivery, agree, accept**, and process-related words such as **send, receive**. The similarity in the distributions of these unigrams in the two classes is shown in Figure 1.

To compare POS distribution in the corpus, we use Brill's tagger [Brill, 1995] to tag the two collections of messages with parts of speech. The messages contain many misspelled words [Sokolova *et al.*, 2004], so we apply *ispell*, an off-the-shelf spell checker, in automatic correction of the most frequent negotiation-related words such as **negotiation, delivery, receive, agreement**. The POS tagging was performed on the corrected data. The distribution of word classes over the two sets of data (buyer and seller) is very similar.

For a more detailed comparison, we split each of the two sets of data into two subsets, according to the negotiation outcome (completed or uncompleted negotiation). This results in four classes: buyers-completed (BC) with messages from 1424 negotiations and 544961 tokens; buyers-uncompleted (BU) with 689 entries and

209025 tokens; sellers-completed (SC) with 1426 entries and 525049 tokens;, and sellers-uncompleted (SU) with 688 entries and 205524 tokens. The variations in word classes over these four sets are small, ranging from **0.27** (for nouns) to **0.003** (for comparative adjectives and interjections).

4 Classification of Negotiation Roles

We have hypothesized that the textual data in negotiations allow us to distinguish buyers and sellers. While the statistical comparison of the buyers' and sellers' messages show that some differences exist, we need to use ML methods to automatically discover the underlying patterns.

Each of 4227 entries concatenates in chronological order all messages sent by one buyer or seller. We represent an entry as a bag of words. We seek words that will be useful for further interpretation and can be identified automatically. Words with significant relative frequency between the two corpora [Rayson and Garside, 2000] satisfy our conditions. We compute the log-likelihood statistics LL for each word w:

$$LL(w) = 2 * ((a * log(\frac{a*(a+b)}{c})) + (b * log(\frac{b*(a+b)}{d})))$$

a and c are the number of occurrences of w and the number of word tokens in the first corpus; b and d – in the second corpus. The higher $LL(w)$ is, the larger the difference between the frequencies of the word w in the two corpora [Rayson and Garside, 2000]. We call the words with the highest LL values *indicative* words. To compare the representativeness of the indicative words with the negotiation-related words [Shah *et al.*, 2004], we cut off after the first 123 most common indicative words[3], and use them as the features that represent our data. For each entry a bag of 124 attributes is built, with the counts of appearances of each indicative word and the count of appearances of non-indicative words in the entry.

The ML tool we use is C5.0, a decision tree learner that classifies entries by separating them into classes according to information gain of the attributes [Quinlan, 1993]. In our experiments we employ tenfold cross-validation and exhaustive search among the adjustable classification parameters. We run experiments on classifying buyers' and sellers' data for three subsets of the Inspire data: all negotiations (B and S), completed negotiations (BC and SC), and uncompleted negotiations (BU and SU). For each classification problem, we run two sets of experiments, representing data by bags of words.

In one set we use indicative words (IND), in the other a set of negotiation-related (NR) words[4]. As a baseline (BL) we consider a classifier that classifies everything as buyers' data. Table 3 shows the smallest average classification errors obtained for each bag of words. The precision (P), recall (R) and F-score (F), corresponding to the results in the column IND, are reported in table 4. BL, B and S, BC and SC, BU and SU mean the same as in table 3.

Unigrams and trigrams tend to give the best classification results [Manning and Schutze, 1999]. While the experiments using unigrams were quite successful, the ones using trigrams did not give good results, due to the sparsity of the data.

[3]We used 123 negotiation-related words to represent the data in previous experiments.

[4]The most frequent 300 unigrams are manually tagged with semantic information [Shah *et al.*, 2004], and we extract from these the negotiation-related words.

Data	BL %	NR %	IND %
B and S	49.98	27.3	**23.5**
BC and SC	49.96	29.2	**26.3**
BU and SU	50.03	29.8	**27.5**

Table 3: Buyers and sellers, classification error

Data	BL %	P %	R %	F %
B and S	66.6	76.90	75.81	76.35
BC and SC	66.3	72.76	75.77	74.23
BU and SU	66.9	72.27	73.00	72.63

Table 4: Buyers and sellers, classification with bags of indicative words

The classification results show that the ML system detects differences between messages written by buyers and sellers. The results also show that the indicative words differentiate classes reasonably well. This supports our hypothesis that language use by people playing different roles in a negotiation exhibits these roles. We are especially interested in the indicative words with high frequency that correspond to common negotiation behaviour, such as persuasion, threats, querying [Brett, 2001]. Such indicative words are **best, can, must, will**. The next section discusses their use and corresponding patterns.

5 Negotiation Trends

We look for language patterns that may signal the use of common negotiation tactics that, in the verbal mode, include substantiation, argument, persuasion and appeal [Brett, 2001]. Our working hypotheses:

1. Buyers and sellers employ negotiation tactics in different ways; this difference could be found through language patterns.
2. The use of negotiation tactics and the use of corresponding language patterns vary in completed and uncompleted negotiations.

As the seeds for those patterns, we use the superlative adjective **best** and the modal verbs **can, must, will**. The numbers of their occurrences are reported in Table 5 where $||BC||=1.03*||SC||=2.6*||BU||=2.63*||SU||$. Mutual information MI relates two corpora and a word w [Church and Hanks, 1989]:

$$MI(w) = log(\frac{a*(c+d)}{c*(a+b)}),$$

where a, b, c, d are the same as in Section 4. It was calculated for each word for two cases: BC and SC, BU and SU. Its value ranges from **0.19** (for **best** in BU and SU) to **0.02** (for **will** in BC and SC). The small MI values correspond to small variations in the data (see the end of section 3). We apply the MI measure because the words have high frequencies. Although MI overemphasizes rare events [Kilgarriff, 2000], it is a reliable measure for common words.

Word	BC	SC	BU	SU	Word	BC	SC	BU	SU
best	1440	1610	530	668	must	422	370	195	165
can	3647	4030	1536	1596	will	3952	3929	1544	1582

Table 5: Distribution of the indicative words

The superlative adjective **best** is used primarily as the attribute of nouns and pronouns, as in **the best** *offer* or *It* **is the best**. They indicate "the sole feature of the referent" [Warren, 1984] for someone who uses them; this indication is, or should be, “evident to one’s interlocutor” [Warren, 1984]. While it appears only marginally more often in completed than uncompleted negotiations, the adjective **best** is used in different contexts in the four classes. In completed and uncompleted negotiations, sellers use it more often than buyers in negotiation-related contexts, in the patterns **the best** *offer/price/deal PersPron* **can** *make/do/give* or *offer/price/time* **is the best** *that/for*. In the literature on language use in negotiations [Brett, 2001], such patterns are considered indicative of substantiation and persuasion. Referring to the identifying function of the superlative adjective **best**, we say that sellers tend more than buyers to emphasize that their offer cannot be improved and that this should be obvious to their partners.

Other contexts in which **best** appears frequently are **best regards**, **all the best** and **best wishes**. They are typical of the closing part of a polite conversation. For buyers and sellers, these contexts appear more often in completed than in uncompleted negotiations.

An interesting difference comes from the use of **can** versus **will** and **must** in sellers’ and buyers’ data. While both BC and BU use **will** and **must** slightly more often than **can**, for SC and SU the reverse is true: **can** is used slightly more often than **will** and **must**. In their most common use, **can** expresses the possibility and ability of doing something, **must** – obligation, requirement or logical necessity of some actions; **will** means prediction or volition [Leech, 1987; Johannesson, 1976]. In the negotiation process, the use of modal verbs partially corresponds to argument and appeal [Brett, 2001].

The pattern **you can** *Verb* is used more by sellers than by buyers in completed negotiations. Note that *Verb* in patterns **you can/must/will** *Verb* does not include the verb **be**, because in the Inspire data such patterns mostly correspond to the personal exchange of information. The reverse is true in uncompleted negotiations: the buyers use **you can** *Verb* more often than sellers. We do not specify the verbs in these patterns because of their variety. As to the use of the patterns *I/we* **can** *Verb* and **you can** *Verb* within the same class, the ratio is 2.9 for SC, 2.6 for BC, 3.3 for SF, and 2.4 for BF. Although the use of the impersonal pattern **it can** is infrequent in both completed and uncompleted negotiations, it is worth noting that it appears 3.5 times more often in completed than uncompleted negotiations.

As it was shown before, buyers use the modal **must**, that is, express requirements and logical necessity in their arguments, more often than sellers. However, different trends in its use appear when we compare completed and uncompleted negotiations. Buyers and sellers in completed negotiations apply **must** to themselves relatively more often than in uncompleted negotiations. BC use **must** in the patterns *I/we* **must** *say/tell/inform* and *I/we* **must** *insist/change/make* 4 times more than in the patterns **you must** *consider/understand/think* and **you must** *send/pay/change*. For BU the ratio is only 2. SC use the patterns *I/we* **must** *say/tell/inform* **(***inform/change/make* 2.5 times more than the patterns **you must** *consider/understand/think* **(***send/pay/change***)**. SU use the former patterns only 1.3 times more than the latter ones.

The modal **will** appears most often in the same patterns as **must**, which corresponds to its most common use [Leech, 1987]. Its use varies in completed and uncompleted negotiations.

The comparison of the patterns shows that buyers and sellers in *completed* negotiations use **must** and **will** more with self-obligation and self-intention [Leech, 1987] than to express insistence or authority over their partners. As for the modal **can**, self-referring happens more often in all four classes. In completed negotiations the impersonal pattern *it can/must/will*, perhaps a sign of indirect influence [Brett, 2001], appears more often than in uncompleted negotiations.

The results on the dependence of the negotiation outcome on the intensity of offer exchange [Kersten and Zhang, 2003] have stimulated us to test the use of language patterns with the superlative adjective **latest**, for example, **the latest** *offer/price/delivery PersPron* and *PossPron* **latest** *offer/price/delivery*. Such patterns correspond to a reaction either to their own or the partner's move. Buyers and sellers in completed negotiations use them more often than buyers and sellers in uncompleted negotiations. We conclude that in completed negotiations buyers and sellers react more often. This supports the results – obtained from the non-textual Inspire data – that positively correlate the frequency of offers and the negotiation outcome [Kersten and Zhang, 2003].

We compare the use of patterns in Tables 6 and 7. In Table 6 we compare the BC and SC collections, and the BU and SU collections. In Table 6 we compare the BC and BU collections, and SC and SU collections. "+" means that the pattern is used more frequently in this class than in the opposite one, "-" means that the pattern is used less frequently, and "=" means that the frequency is the same in both classes. In both tables *Noun* means offer/price/deal/time/delivery and their spelling versions. Recall that *Verb* in patterns **you ...** does not include the verb **be**.

Pattern	BC	SC	BU	SU
the best *Noun PersPron*				
can *Verb*	-	+	-	+
Noun **is the best** *Prep*	-	+	-	+
I/we **can** *Verb*	-	+	-	+
you can *Verb*	-	+	+	-
it can *Verb*	=	=	+	-
I/we **must** *Verb*	+	-	+	-
you must *Verb*	=	=	-	+
it must *Verb*	=	=	+	-
I/we **will** *Verb*	+	-	+	-
you will *Verb*	=	=	-	+
it will *Verb*	=	=	+	-

Table 6: Distribution of patterns, buyers/sellers

Pattern	BC	BU	SC	SU
best regards	+	-	+	-
all the best	+	-	+	-
best wishes	+	-	+	-
the latest *Noun PersPron*	+	-	+	-
PossPron **latest** *Noun*	+	-	+	-
it can *Verb*	+	-	+	-
I/we **must** *Verb*	+	-	+	-
you must *Verb*	+	-	+	-
it must *Verb*	+	-	+	-
I/we **will** *Verb*	+	-	+	-
you will *Verb*	-	+	-	+
it will *Verb*	+	-	=	=

Table 7: Distribution of patterns, completed and uncompleted negotiations

The average deviations of the specific mutual information [Oakes, 1998] of patterns over four sets are small, ranging from **0.516** (for **you will ...**) to **0.403** (for **you must ...**).

6 Following the Leads

Drake [Drake, 2001] shows in a series of experiments that the buyer's or seller's role affects the relationship between a negotiator's opening bid and final profits and that participants may be sensitive to the competitive or cooperative climate established by the counterpart. We plan to analyze negotiators' strategic reaction to their partners. We hypothesize that buyers and sellers use different negotiation strategies [Brett, 2001], reflected in the messages they exchange.

We work on identifying language expressions that indicate strategies, especially "cause-effect" relations reflected in phrases like "if - then". We apply parsing to see how such phrases, through clauses, are distributed in

Pattern	BC	SC	BU	SU	Pattern	BC	SC	BU	SU
If you	502	525	232	235	If we	80	66	39	36
As you	262	273	121	86	So I	132	144	38	45
But I	112	172	57	54	As we	47	37	32	20
As I	97	103	43	40	But we	48	56	28	16

Table 8: Distribution of most frequent starting patterns in negotiation-related clauses

four classes of data. We run the Xerox Incremental Parser [Chanod *et al.*, 2001] to extract clauses, group them by the starting patterns, and analyze using unigram counts to identify their topic – negotiations or personal information. In Table 8 we report the numbers of most frequent starting patterns. It is obvious that sellers use more self-referring phrases than buyers. We leave for the future a study, based on information theory, of the relationship between “cause - effect” phrases and the negotiation outcomes.

7 Conclusion

We have presented a method of recognizing and identifying language patterns that correspond to well-established roles in e-negotiations. To represent the data, we have developed and implemented a fully automated procedure of feature selection. Our methodology applies to other types of data coming from activities with well-established roles, such as court procedures, legal and medical consulting or job interviews. We have shown that different patterns exist for different role bearers. We report empirical results of data classification and statistical analysis. The patterns found highlight differences between buyers and sellers, between buyers in completed and uncompleted negotiations, and between sellers in completed and uncompleted negotiations.

To be more specific in our results and to investigate negotiation trends in more detail, we need to incorporate the numerical information. One of the promising directions is to analyze how the offer values correspond to substantiation, persuasion and argument.

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