

Strategies and language trends in learning success and failure of negotiation

Marina Sokolova · Stan Szpakowicz

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Abstract In negotiation by electronic means, language is an important deal-making tool which helps realize negotiation strategies. Negotiators may use language to request information, exchange offers, persuade, threaten, as well as reach a compromise or find prospective partners. All this is recorded in texts exchanged by negotiators. We explore the language signals of strategies—argumentation, persuasion, negation, proposition. Leech and Svartvik’s approach to language in communication gives our study the necessary systematic background. It combines pragmatics, the communicative grammar and the meaning of English verbs. Language signals become features in the task of classifying those texts. We employ Statistical Natural Language Processing and Machine Learning techniques to find general trends that negotiation texts exhibit. Our hypothesis is that language signals help predict negotiation outcomes. We run experiments on the *Inspire* data. The electronic negotiation support system *Inspire* was gathering data for several years. The data include text messages which negotiators may exchange while trading offers. We conduct a series of Machine Learning experiments to predict the negotiation outcome from the texts associated with first halves of negotiations. We compare the results with the classification of complete negotiations. We conclude the paper with an analysis of the results and a list of suggestions for future work.

M. Sokolova
Département d’informatique et de recherche opérationnelle,
Université de Montréal, Montréal, Canada

S. Szpakowicz (✉)
School of Information Technology and Engineering,
University of Ottawa, 800 King Edward Avenue,
Ottawa, ON, Canada K1N 6N5
e-mail: szpak@site.uottawa.ca

S. Szpakowicz
Institute of Computer Science, Polish Academy of Sciences,
Warsaw, Poland

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1 Introduction

The emergence of electronic markets has profoundly changed the way in which we shop, buy, sell and generally engage in commercial activities. New avenues for research have opened in business studies, information technology, behavioural sciences and many other areas. Another factor is the growing use of electronic means in negotiation. An area that combines several such new directions is electronic negotiations (henceforth, e-negotiations) between people and between software agents. Our focus is on person-to-person e-negotiation.

In this paper we analyze texts of electronic negotiations. The sheer amount of text requires automated methods. We employ Statistical Natural Language Processing and Machine Learning techniques to find general trends that the textual data exhibit. We apply linguistic corpus analysis to the *text data* of business e-negotiations. We investigate how participants in e-negotiations realize negotiation strategies through the language they use. The activities of business e-negotiations are well-defined and structured, so it is feasible to trace and interpret them. At the same time, the use of electronic means influences the communication process; it interferes with the activities which this communication accompanies. We seek two intermingled types of information—about the activity domain, that is to say, e-negotiations, and about people who communicate by electronic means. We next treat the trends thus identified as data for experiments in Machine Learning.¹ This work focuses on the language signals of the *comparison of influence strategies* employed by participants in successful negotiations and participants in unsuccessful negotiations.

We aim to represent text data in a way that captures the significant characteristics of the negotiation process independent of the electronic means. In our case, the use of electronic means comes in a negotiation support system (NSS). We work with the data gathered by the NSS *Inspire* (Kersten et al. 2002–2006). It labels a negotiation based on the system-accepted outcome: a negotiation can be *successful* or *unsuccessful*. A participant in negotiation is either a buyer or a seller. The *Inspire* text data—more than 1,500,000 words—provide enough material for automated analysis and learning.

The work we present here has focussed on the construction of the knowledge-based data features, which pertains to knowledge-based feature generation. In a series of experiments we use the words in language patterns for early prediction of negotiation outcomes. In these experiments, the outcomes of complete negotiations are classified from the text of the first half of a negotiation. The results are compared with the classification of complete negotiations.

Our findings tie into active research topics outside the negotiation studies. Language expressions of strategies and tactics can show attitudes and emotional involvement of negotiators, thus they directly relate to subjectivity and sentiment analysis. Language patterns can be a valuable resource for the prediction of strategies in many forms of electronic communication. Extending patterns to include expressions of threats and

¹ The Appendix briefly explains the Machine Learning techniques we use.

intimidation may help detect a possibility of breakdown of interpersonal electronic communication. Our study continues the research on strategies in the language of negotiators (Sokolova et al. 2004; Sokolova and Szpakowicz 2005).

2 Negotiation strategies and communication

Negotiation is a process in which two or more parties aim to settle what each shall give and take in a transaction between them. This section surveys strategies and tactics which negotiators employ in order to reach their goals. Strategies depend on many factors, including the negotiation protocols, criteria of success, or roles (such as buyer or facilitator). E-negotiation participants employ strategies just like participants in more traditional face-to-face and phone negotiations (Koeszegi et al. 2006; Srnka and Koeszegi 2007). The use of electronic means, however, tends to influence the negotiators' conduct. Researchers have yet to agree how deep this influence is. The behaviour of e-negotiators involves more risk and aggression than in face-to-face negotiations (Cellich and Jain 2004). There is a tendency to adopt an aversive emotional style to achieve negotiation goals. There are suggestions that e-negotiators behave differently if they negotiate within their social group (Thompson 2005). On the other hand, personal power (it includes emotions and adverse behaviour) diminishes when negotiations are conducted electronically (Ströbel 2000). The researchers we cite agree on the "weak get strong" effect of e-negotiations. Due to relaxed social norms, the effect allows some e-negotiators to perform better than they would in face-to-face negotiations.

E-negotiations give us only written communication between negotiators. As a result, negotiation strategies affect, and are affected by, the interpersonal nature of communication, depend on the negotiation type (e-negotiations are an example) and influence it. At the same time, the scope of written communication affects interpersonal exchange and negotiation; the converse holds as well. Figure 1 summarizes our points.

Negotiators apply strategies to the big picture of negotiations. In interpersonal communications this is done through the influence strategies which employ argumentation, substantiation, appeal and so on. The language signals of influence—*strategic words*—form a feature set that allows Machine Learning methods to link e-negotiation outcomes with the negotiators' strategies (Sokolova and Szpakowicz 2005). More detailed strategy implementations are given by tactics in negotiations (Roloff 1992; Thompson 2005). Tactics are applications of both influence and affective, or emotion-based, strategies. A negotiator delivers tactics using either such moves as commands, requested actions, questions, or

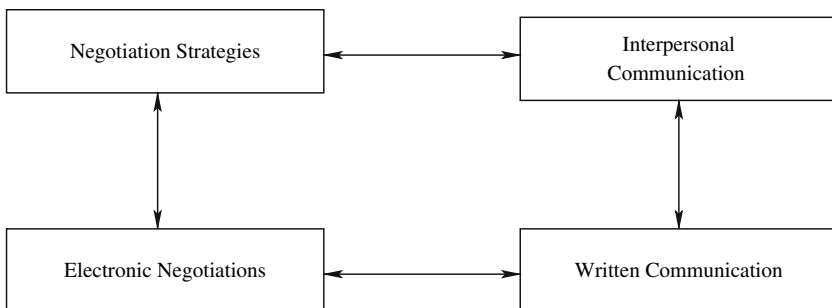


Fig. 1 Strategies and communication

responses to those moves. The negotiator's tactics aim to bring the negotiator closer to a goal. They work on a smaller time scale than strategies and are multi-dimensional. Tactics depend on one's role in negotiation (buyer, facilitator and so on) and in communication (such as speaker or hearer). There may be various initiative or response. In terms of interpersonal communication, tactics correspond to propositions, questions and demands.

Research on negotiations usually describes qualitatively the language representations of propositions, questions, and demands; see Koper and Burrell (1998), Roloff (1992) for further references. Such descriptions tend to be hard to quantify and to turn into an algorithm or procedure. We study the language patterns and look for ways of detecting the outcome of negotiations from pattern-based representations. This work continues research on the language signals of strategies in e-negotiations and on features for electronic negotiation texts (Sokolova et al. 2005; Sokolova and Szpakowicz 2005).

Language discloses information about the e-negotiators' feelings and evaluation of issues (exposing affects) and allows inference about their abilities and intentions (forming impressions). Such disclosure is characterized by five parameters: polarization, immediacy, intensity, lexical diversity, and powerful or powerless style (Roloff 1992). We focus on *immediacy* and on *powerful* and *powerless* language. Immediacy signals a negotiator's desire to move closer to the opponent² who is positively evaluated and to move away from the disliked one. It shows positive or negative directions of the negotiator's affect. High immediacy is more explicit than low immediacy. Powerful language is consistent and direct, but its specific characteristics usually are not defined. In research, powerful language is defined as not having the characteristics of powerless language: hesitation, hedges, tag questions, disclaimers and so on. Powerful language positively correlates with the use of influence strategies. For an overview of these issues, see Koper and Burrell (1998)].

Leech and Svartvik's approach to language in communication (Leech and Svartvik 2002) gives our study the necessary systematic background. It combines pragmatics, the communicative grammar and the meaning of English verbs. Propositions, questions, and demands—the strategy implementations at the level of pragmatics—are conveyed by declarative, interrogative and imperative sentences respectively. Depending on the situation, various grammatical structures and the choice of words allow the implementation of different types of instances: commands, suggestions, prohibitions and so on (Leech 1983, 2004).

3 Influence strategies in negotiations

This section gives background on the strategies and roles in negotiations and e-negotiations. We also discuss how influence strategies are connected with their language implementation. We show how the use of electronic means affects influence strategies.

During negotiation, participants employ influence strategies (Brett 2001; Sjøstedt 2003), intended to make the other party concede. Influence strategies are generally divided into direct and indirect ones, expressed by various types of appeal. Direct influence occurs when the participant says what she wants the other party to do. In indirect influence strategies, requests are implied and often masked by appeals for sympathy. The different types of appeal are connected with the use of pronouns. Influence strategies are exhibited in such negotiation moves as *argumentation*, *persuasion*, *threats* and *substantiation*, and in

² We refer as *opponent* to the other party in bilateral negotiation, though in general negotiations need not be adversarial.

general behaviour such as propositions, reactions, offers and exchange of information (Brett 2001; Donohue and Ramesh 1992). Negotiators are sensitive to strategies employed by the other party, and they adjust their own strategies accordingly (Donohue and Ramesh 1992; Thompson 2005).

We now consider how a negotiator implements in language indirect and direct influence on the other party. We show how these strategies are related to and reflected in the language of negotiators. We consider the strategies and the corresponding semantic and pragmatic use of parts of speech (POS). This is because language is a means of communication, influenced by the process to which this communication belongs (Gries 2003). Pragmatic information exchanged in communication may be associated with language forms in which it was expressed. We look for POS whose uses correspond to *agreement, refusal, exchange of information, argumentation, persuasion, and substantiation*. We concentrate on how influence strategies are exhibited through the use of modal verbs (Johannesson 1976), negatives (Tottie 1991), adjectives (Warren 1984), wh-determiners and personal pronouns (Jurafsky et al. 2000). The resulting correspondence between the strategies and the POS is the following:

- logical necessity—modals, e.g., *can, will, have, may, should, would, could*, and not-negations, e.g., *cannot, haven't, shouldn't, couldn't, wouldn't*;
- appeal—personal pronouns, e.g., *I, we, you, my, your*, no-negations, e.g., *never, neither, no, none, nor, nothing, nowhere*, not-negations, e.g., *not, don't, aren't*, and superlative adjectives, e.g., *latest, best*;
- intention with respect to the subject of discussion—positive volition verbs, e.g., *hope, want, wish, like, prefer, agree, accept, promise, ask, afford, aim, choose, decide, intend, look, plan, propose, make, made, manage, move, proceed, try*, and negative volition verbs, e.g., *decline, refuse, reject, disagree, delay, hesitate*;
- intention with respect to continuation of negotiations—mental verbs, e.g., *know, think, understand, consider* and adjectives, e.g., *new, last, latest*.

The modal auxiliary verbs (modals) have both logical and pragmatic meaning. They express permission, possibility and necessity as the representatives of logic. The modals are divided into two main categories, primary and secondary; see Table 1.

Primary modals *can, will, have, may* are more direct and less hypothetical than secondary modals *should, would, could* (Leech 2004). One of the indicators of argumentation is an openness to the opponent's feedback. In Table 2 we show the most common senses of the primary modals in positive statements (Leech 2004), listed from the most to the least common. The secondary modals tend to be more hypothetical, polite, tentative, formal and indirect than the primary modals (Perkins 1983). The secondary modals refer to the past, whereas the primary modals refer to the present. In general, the difference between the primary and the secondary modals is that the latter are more conditional than the former.

We now point out the uses of the primary modals which we consider the most important in the study of influence strategies. In analyzing the data, we examine how the negotiators apply to their partners, whether they exercise authority openly or prefer the democratic imperative. So, we look for certain characteristic patterns.

Table 1 Modal verbs

Category	Examples
Primary	<i>can, may, must (need), will, shall, have (got) to</i>
Secondary	<i>could, might, ought to, would, should</i>

Table 2 The senses of the primary modal verbs

Verb	Meaning
<i>can</i>	possibility, ability, permission
<i>may</i>	possibility, permission, exclamatory wish
<i>must (need)</i>	obligation or requirement (speaker's authority), logical necessity
<i>will</i>	prediction, willingness, insistence, intention
<i>shall</i>	prediction, intention
<i>have (got) to</i>	obligation or requirement, logical necessity

The modal *can* used with *we* and a third-person subject implies tactful imperative. Such a situation occurs when the speaker does not want to exercise authority openly and suggests that there are certain possibilities. In sentences of the form “*You can VERB ...*”, *can* denotes permission. *May* is mostly used as *can*, with a slight emphasis on factual possibility instead of theoretical possibility. When *must* denotes obligation, this implies that the speaker has authority over the person mentioned in the clause. *I must* and *we must* denote self-obligation, signalling that the speaker has power over herself. The senses of *have to* correspond closely to those of *must*, with more objectivity, as though obligation comes from an outside source. The use of the intentional meaning of *will* is the most interesting for our study. Combined with first-person subjects, it conveys the fact that a decision has been made and the fulfilment of the intention is guaranteed.

The viewpoint of a negotiator can be expressed in positive and negative ways. The indicators of the negative viewpoint include the so-called *fuzzy* and *formally and semantically* negative expressions, or negatives (Tottie 1991). The negatives express rejection including explicit and implicit refusal and denial; see Table 3. Among implicit indicators of negative context there are *any* and *ever*.

Not-negation corresponds to explicit negation, while *no*-negation corresponds to implicit negation. In general, *not*-sentences are more vague and variable with the focus of negation than *no*-sentences. The verbs that collocate with *no*-negation are the existential and copulative *be*, *have*, the main *do* and *know*, *give*, *make*. *No*-negations sum up a previous discussion, either in the form of an existential sentence such as *there is no need*, or with other indicators. Many negatives co-occur with modals and with verbs that indicate mental processes such as cognition and perception, e.g., *know*, *think*, *want*, *mean*, *suppose*, *like*, *consider*, *understand*. The use of cognition and perception verbs in implicit denials, as in *I don't think I'll ...*, is attributed to the “face-saving” version of negation, which helps continue communication. Another type of implicit denial is a statement that functions as a question, as in *I don't know if you ...*. We want to see how these indicators of cooperativeness correlate with the outcomes of negotiations.

Table 3 Negative expressions

Category	Examples
Not-negations	<i>not</i> , <i>n't</i>
No-negations	<i>never</i> , <i>neither</i> , <i>nobody</i> , <i>no</i> , <i>none</i> , <i>nowhere</i>
Affixal	<i>a-</i> , <i>dis-</i> , <i>in-</i> , <i>non-</i> , <i>un-</i> , <i>-less</i> , <i>-out</i>
Fuzzy	<i>few</i> , <i>hardly</i> , <i>little</i> , <i>rarely</i> , <i>seldom</i>

4 Building language patterns for influence

When the goal is to convince the opponent to perform an action, logical necessity and appeal can be further sub-categorized as *command*, *request*, *advice*, *suggestion*, *tentative suggestion* (positive actions). The categories are listed in the order of decreasing strength with which the negotiators impose their will. When the goal is to prevent the opponent from performing an action, the following categories appear: *prohibition* and *negative advice* (negative actions) (Leech 1983). All the categories for positive actions may involve the speaker. The categories for the speaker's negative actions become *refusal* and *denial*, depending on the main verb.

We build language patterns from personal pronouns and content nouns (for example those denoting negotiation issues), modal verbs and their negations, main verbs and optional modifiers. There are three forms:

- *I/we* μ *ModalVerb* μ *MainVerb* (when the speaker signals involvement by using a first-person pronoun),
- *You* μ *ModalVerb* μ *MainVerb*,
- *ContentNoun* μ *ModalVerb* μ *MainVerb*

ContentNoun can be a noun phrase and μ denotes an optional modifier. Table 4 lists the patterns.

The choice between a personal pronoun and a content noun (or noun phrase) is the choice between high and low immediacy (Roloff 1992). The use of personal pronouns signals higher immediacy. In that case the negotiator explicitly says what she wants the opponent to do. The use of nouns shows a more subtle strategy. The negotiator states what she wants to have, but avoids asking the opponent explicitly.

One of indicators of directness and influence is the category of the main verb in a pattern. We employ a set of categories from (Leech and Svartvik 2002) where the main verbs are categorized by the meaning of the actions they describe. The mental activity verbs such as cognition or perception verbs have a special place in communication. They are common as a face-saving technique and signal influence by politeness (Koper and

Table 4 Tactics and the language patterns

Tactic	Pattern
Commands, Requests involving a speaker	<i>You should/must/will/have to/need to</i> MainVerb ContentNoun <i>should/must/will/has to/needs to</i> MainVerb <i>I/we should/must/will/have to/need to</i> MainVerb
Advice, Suggestion, Tentative Suggestion involving a speaker	<i>You can/could/would/might/may</i> MainVerb ContentNoun <i>can/could/would/might/may</i> MainVerb <i>I/we can/could/might/may</i> Verb
Prohibition	<i>You cannot/do not/have not</i> MainVerb ContentNoun <i>cannot/does not/has not</i> MainVerb
Negative Advice	<i>You could not/would not/should not</i> MainVerb ContentNoun <i>could not/should not/does not</i> MainVerb
Refusal, Denial	<i>I/we cannot/could not/should not/do not</i> Verb

Table 5 Main verbs

Category	Examples
Activity	<i>read, work, negotiate</i>
Communication	<i>tell, say, explain</i>
Cognition	<i>hope, know, suppose, understand</i>
Event	<i>become, reply, agree, pay</i>
Perception	<i>feel, see, hear</i>
Attitude	<i>like, love, hate</i>
Process	<i>change, increase, continue</i>
State of having or being	<i>consist, cost, depend, be</i>

Burrell 1998). Event verbs denote actions that have a beginning and an end, whereas state verbs correspond to actions without defined limits and strong differentiation between them. Activity and process verbs are those that show a goal-oriented action and a series of steps towards a defined end. The verbs of perception and cognition, as well as attitude, are necessarily subjective and more personal than the verbs denoting activity, process, event and state of having or being. The use of perception, cognition and attitude verbs signals the opponent's openness to feedback. Table 5 provides the examples of verbs in all these categories (Leech and Svartvik 2002).

5 Electronic negotiations

As a special type of communication between people, negotiation is a *dynamic process* that is *multi-dimensional, irreversible, purposeful* (Hargie and Dickson 2004). The data of e-negotiations depend on the features of the electronic means supporting the negotiations. Electronic means can be used in quantitative automated negotiation, where the system makes decisions, and in non-automated negotiation support, where negotiators make decisions (Schoop 2003). The latter include process-oriented systems, namely communication systems and NSSs. NSSs combine decision support with electronic communication.

The data gathered by NSSs depend on the decision-support functions of the systems as much as on the communication functions. If decision-support functions of a NSS take care of the pre-negotiation, negotiation and post-negotiation stages, then the data combine the effects of three stages. More elaborate NSSs suggest a starting offer based on the negotiator's pre-negotiation answers, evaluate offers exchanged during negotiations, and propose a settlement when an improvement of the reached agreement is possible for both parties (Kersten 2003).

The largest data set gathered in e-negotiation comes from *Inspire*, a public-domain research and teaching tool mostly used in college and university programmes in numerous countries (Kersten et al. 2002). It allows its users to conduct negotiations over the Web, gives access to on-line manuals, provides automatic evaluation of the negotiation process, and keeps the history of each negotiation. No restrictions are imposed on possible users. Negotiation starts after both negotiators have filled pre-negotiation questionnaires. Negotiators exchange formal numerical offers and may exchange free-form text messages.

Inspire operates in all negotiation phases. In the pre-negotiation phase, it provides preference assessment. In the negotiation phase, it helps analyze alternative offers, exchange offers and messages, and evaluate counter-offers. Finally, in the

post-settlement phase, *Inspire* helps assess the efficiency of the compromise (Pareto-optimality). All offers are monitored and evaluated. Negotiation is bilateral, between a buyer and a seller of bicycle parts, with four issues (price, delivery time, payment time, return conditions), each with only a few fixed numerical values. Negotiators exchange standard offers (tables with numerical values) on forms supplied by *Inspire*. Negotiation, lasting up to 3 weeks, succeeds if a virtual purchase took place within the designated time, and fails otherwise. Exchange of text messages is optional. They either accompany offers or are exchanged between offers. Filling the post-negotiation questionnaires is also optional.

We use *Inspire* as our case study. *Inspire*-mediated negotiations provide us with rich data. First, the negotiations are long enough to allow the participants to develop and apply their strategies. The longer e-negotiation takes, the more complex the structure of the e-negotiation process becomes (Gebauer et al. 1999). Simpler e-negotiation may involve exchange of well-structured business documents (pre-defined contracts, retail transactions). A complex e-negotiation process comprises numerous offers and counter-offers and has a high degree of uncertainty. Next, the number of participants—more than 5500—guarantees that the corpus analysis results are not biased by the personal specifics and that they show general trends exhibited by groups of negotiators. Figure 2 shows an example of text messages (the original spelling has been preserved).

Here are examples of the most frequent patterns (in parentheses, the number of occurrences in the *Inspire* data): *you can accept* (293), *i would be* (272), *you can see* (271), *we can make* (243), *i cannot accept* (230). The distribution of the patterns corresponds to the relations presented by the scheme in Fig. 1. The patterns cover several well-known types of communication. We found that the most frequently used tactical move is suggestion. This move is typical of business communication, including e-negotiations. The prevalence of patterns with personal pronouns is the hallmark of interpersonal communication. The dominance of the event verbs among other verb categories is due to the fact that we are dealing with negotiation processes. Finally, the high number and diversity of the cognition and perception verbs typify written communication.

Kersten and Zhang (2003) analyzed outcomes of negotiations conducted using *Inspire*. They applied a data mining technique to the records of negotiations, working only with the exchange of formal offers. Among their findings the following result on the behaviour of e-negotiators is very interesting: if offer exchanges are made during the early stages of the negotiation, there is a higher possibility of reaching an agreement; offers sent in the last day before the deadline reduce the probability of achieving an agreement.

<p>(Seller) Hi Anles, I have just sent a counter-offer to you. It wasnt such easy, as I thought cause it seemed I made my ratings wrong *g*. Well, now I already asked you, where you are from, cause I did not know that I would have the opportunity to contact you again. I am from Germany. Then, good luck with my offer, I am waiting for your answer. Bye Claudi</p> <p>(Buyer) hi claudi, thank you very much for your offer. I think, the price is acceptable. I totally agree with you. Having informed at a trade fair in Frankfurt/Germany about metal components and comparing some prices and offers from other suppliers all around the world, I came to the conclusion that your offer is the best. It was a pleasure doing business with you. I'll give you a ring this week for more details. Best regards anles</p>
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Fig. 2 A sample from an *Inspire* negotiation

6 Early prediction of negotiation outcomes

Early prediction of negotiation outcomes is an important learning task. So far only the outcomes of complete negotiations have been predicted using either non-textual data (Kersten and Zhang 2003; Nastase 2005) or textual data (Sokolova et al. 2005). In this section we seek the empirical setting in which prediction of the negotiation outcomes from the first part of negotiations is statistically close to the outcome prediction from the complete texts. We use influence-signalling words to represent a complete text T of negotiation. The text and its representation are labelled *positive* (1) if the negotiation is *successful* and *negative* (0) otherwise. The first half of a negotiation is labelled by the outcome of the whole negotiation.

We employ the language patterns and their variations to investigate the effect on the classification results. First, the patterns discussed in Sect. 5 are used as a base for text representation. It is interesting that, according to the Information Gain estimation (Witten and Frank 2005), the use of the following patterns in the first part of negotiations influences the negotiation outcome (in the order from the most to the least important): *you should not be*, *we must be*, *I cannot accept*, *I should do*, *you cannot/can't accept*, *we cannot/can't agree*, *I cannot/can't make*. The patterns, however, are very sparse, i.e., they scarcely appear in the texts. In order to overcome sparsity, in the next representation we use all word types (that is to say, distinct words) that appear in the patterns. For example, the pattern *you should not be* counts as four words *you*, *should*, *not*, *be*.

In the next representation, we want to assess the effect of conditionality on the negotiation results. To represent texts, we use both the words from the patterns and the condition words that often appear before the patterns. The construction of two representations is based on pragmatic and linguistic knowledge, and that is why we call them *knowledge-based* representations. To see whether they give us an advantage over a straightforward statistically motivated representation, we represent texts by 500 most frequent word types of the *Inspire* data. Their total occurrence is 1,255,445, or 81% of the data. This is the most dense of the three representations. We consider it as a baseline representation. In further experiments we use:

- I the word types that constitute the language patterns;
- II the pattern word types and condition words, for example, *as*, *if*, *whatever*;
- III 500 most frequent word types of the *Inspire* data.

For the representations, their attributes have binary values: 1 if a word or a pattern appears in the first part of a negotiation, and 0 otherwise.

We seek methods that (almost) eliminate manual intervention. The automatic learning algorithms Support Vector Machines (SVM), Decision Trees (DT) and Naive Bayes (NB) satisfy the requirement (Witten and Frank 2005) (for an overview of Machine Learning concepts refer to the Appendix). The algorithms predict a text label, either 1 or 0, that is to say, perform classification of texts. The quality of classification is assessed using a *confusion matrix*, whose general form for a two-class problem appears in Table 6: tp is the number of correctly classified positive examples, fp —incorrectly classified positive examples, fn —incorrectly classified negative examples, and tn —correctly classified negative examples.

Table 6 A confusion matrix for binary classification

Class	Classified	
	as <i>pos</i>	as <i>neg</i>
<i>pos</i>	<i>tp</i>	<i>fn</i>
<i>neg</i>	<i>fp</i>	<i>tn</i>

We assess an algorithm’s performance by calculating four measures:

$$Accuracy = \frac{\text{correctly classified examples}}{\text{all examples}} \tag{1}$$

$$Precision = \frac{\text{correctly classified positive examples}}{\text{all examples classified as positive}} \tag{2}$$

$$Recall = \frac{\text{correctly classified positive examples}}{\text{all positive examples}} \tag{3}$$

$$F\text{-measure} = \frac{(\beta^2 + 1) * Precision * Recall}{\beta^2 * Precision + Recall} \tag{4}$$

F-measure is the weighted harmonic mean of *Precision* and *Recall*. In our work these two are equally important, so β is set to 1.

We use tenfold cross-validation to estimate the algorithms’ performance. In *K*-fold cross-validation the data entries are randomly divided into *K* mutually disjoint sets of approximately equal size. An Algorithm builds a function on the examples from *K*–1 sets and tests it on examples from the remaining set. This is repeated *K* times, once for each set (that is to say, each set is used once as a test set). The average *Accuracy* over all *K* sets is the cross-validated *Accuracy*. The same holds for other measures. Ten-fold cross-validation was chosen because of the reliability of results (Cherkassky and Muller 1998).

We say that prediction is *reliable* if the classification results are statistically close to those achieved on complete negotiations. When we classify the *Inspire* data, the accuracy on the binary attributes of the complete negotiations is 71.2% ± 2.6 and the equally-weighted *F-measure*-74.1% ± 4.8 (Sokolova et al. 2005). Mean and standard deviation are calculated for the results of NB,³ SVM and DT on four feature sets. Table 7 reports the results of early prediction. Column *Attr* shows the number of attributes in each representation. Columns *Acc* and *F* list the classifier’s best *Accuracy* and corresponding *F-measure* obtained by adjusting its parameters.⁴ Column *Gap* reports the gap between the highest and the lowest *Accuracy* across the algorithm’s adjustable parameters. For each representation, the highest *Accuracy* and *F-measure* are in *italics*.

Our results show that the knowledge-based representations provide reliable prediction, *more steady* when contrasted with the classification *Accuracy* and *F-measure* on complete negotiations (70.8% ± 1.6 vs. 71.2% ± 2.6 and 75.4% ± 2.0 vs. 74.1% ± 4.8, respectively).

Compared with the performance on the 500 most frequent words, all three classifiers marginally improve the prediction *Accuracy* and narrow the gap between the best and the worst *Accuracy*. Parallel increase of *F-measure* indicates that this is due to the increase of

³ High standard deviation is due to the poorer performance of NB compared with other classifiers.

⁴ Acc equals 55.8% when all negotiations are classified as positives. Corresponding *F* is equal to 71.6.

Table 7 *F-measure, Accuracy, and the Accuracy gap; first half of negotiations*

	Attr	NB			SVM			DT		
		<i>F</i>	<i>Acc</i>	<i>Gap</i>	<i>F</i>	<i>Acc</i>	<i>Gap</i>	<i>F</i>	<i>Acc</i>	<i>Gap</i>
I	124	73.9	70.5	0.1	77.9	72.8	1.2	74.5	69.3	1.9
II	137	73.2	69.7	0.1	77.8	72.7	1.5	74.9	69.8	1.5
III	500	71.3	68.9	0.4	75.1	70.6	7.1	73.1	68.4	2.6

Table 8 *Precision and Recall, first half of negotiations*

	Attr	NB		SVM		DT	
		<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>	<i>Recall</i>	<i>Precision</i>
I	124	75.1	67.9	85.9	66.2	80.2	64.5
II	137	74.1	67.3	85.5	66.1	80.7	64.6
III	500	69.4	68.6	81.8	65.8	77.1	64.4

true positive rates. The higher *Accuracy* and *F-measure* of SVM can be attributed to its overall ability to perform well on the binary data. *Recall* and *Precision* rates show how the classifiers work on the positive class; see Table 8.

The results in Table 8 demonstrate that the language signals of influence tactics assist in the correct prediction of successful negotiations. For all three classifiers, *Recall* has been improved compared with the baseline results. The correct prediction of unsuccessful negotiations, however, diminishes when knowledge-based representations are used. We conclude that the language implementations of strategies are more easily detected in successful negotiations than in unsuccessful negotiations.

The accuracy results support our hypothesis that negotiation outcomes can be predicted during the first part of negotiations. The prediction is based on appeal, logical necessity, and the indicators of intentions towards the subject of the negotiations and the negotiation process. In language, these strategic tools are exhibited in persuasion, substantiation, exchanges of offers, agreement and refusal; they reflect the reasoning, opinions and emotions of the participants.

7 Future work

In this section we list directions for future work on corpus analysis of text data of e-negotiations. We are interested in the use of personal power in negotiations.

Ströbel (2000) studied the influence of electronic means on the negotiation power. The following sources of power are used in negotiations: resource control, information power, personal power (attractiveness, emotion, integrity, persistence and tenacity). The general assumption for highly transparent markets, including electronic markets, is that both parties always have the same level of information, so neither party can benefit from excessive information power. Language is the negotiators' main means of exercising personal power in e-negotiations. Power is expressed through the direct or indirect influence strategies that include persuasion, argument, substantiation, threats and appeal (Brett 2001). Our hypothesis is that buyers and sellers use different influence strategies, reflected in the messages they exchange.

After analyzing the semantic characteristics of the vocabulary of e-negotiation data we conclude that the data provide a solid foundation for future research on the use of emotions, threats and opinions in e-negotiations. We suggest four directions for analysis.

- Find language patterns in which participants express their emotions, threats and opinions.
- Analyze how emotions, threats and opinions, expressed in language, are connected and related to negotiation moves and exchange of formal information.
- Investigate the effect of emotions, threats and opinions on the negotiation process and outcome.
- Study how emotions, threats and opinions are exhibited using restricted electronic means.

Emotions and personal opinions are important aspects of personal power. They are studied by Machine Learning and Natural Language Processing methods in research on emotion detection (Cowie et al. 1999), opinions (Nigam and Hurst 2004), sentiment analysis (Nasukawa and Yi 2003), in particular monologues and dialogues (Devillers et al. 2003). We propose to use such methods to recognize emotions, threats and opinions in e-negotiations. We could begin by identifying agreement-disagreement pairs in e-negotiation interaction (Galley et al. 2004).

After analyzing the semantic characteristics of the vocabulary of e-negotiation data we conclude that the data provide a solid ground for future research on the use of personal power in e-negotiations. We suggest three directions.

- Find *language patterns* by which participants express threats; in e-negotiations threats can be related to the actual process (delay of replies, inability to connect with the system), to imaginary events (receiving manager's approval, finding another supplier), or to personal life.
- Learn how *expressions of personal power* depend on and affect negotiation moves and exchange of formal information; such a study can combine textual and non-textual data and concentrate on the moves of the sender of emotions, threats and opinions.
- Explore *the effect of emotions, threats and opinions* on the negotiation process and outcome; this study can connect emotional and strategic choices and concentrate on sender-receiver dialogue and on the recipient's reaction to the sender's emotions, threats and opinions.

8 Conclusion

We have explored how influence strategies are reflected in the language of e-negotiations. We have shown that the language signals and their representation by parts of speech are correlated with the negotiation outcomes. We have presented a method of building language patterns for the tactical moves of influence strategies. A pattern consist of a modal verb, a main verb, and a personal pronoun or a content noun. The modal defines which move corresponds to the pattern and the power of language. The main verb contributes to the power of language, and the pronoun or noun—to the immediacy of disclosure.

In our empirical study, we acquired the patterns from the data of electronic negotiations. The patterns and words used in them have been employed to learn the negotiation outcomes in Machine Learning experiments. We have considered their influence on the

correct early prediction of the negotiation outcome. The results have shown that the language signals of influence strategies and their tactics give a reliable prediction of the negotiation outcome from the first half of the negotiation. This should be useful in the study of the behaviour of negotiators and in the development of electronic means to support electronic negotiations. Our recommendation would be text analysis which focusses on the representation of strategies. A reliable forecast of the negotiation outcome may result from the use of language patterns that indicate requirement, obligation, intensity of negotiations and so on.

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Appendix

We present a brief overview of Machine Learning techniques employed in this paper.⁵ According to (Witten and Frank 2005), algorithms “learn when they change their behaviour in a way that makes them perform better in the future”. To assess an algorithm’s performance, we need *performance measures* (how good learning is) and *model selection* (how to find a learning system that appropriately models the problem—e-negotiation in our case). A learning algorithm \mathcal{A} has a *training* phase (it learns) and a *test* phase (it is assessed), each with its own data. In a binary classification problem (success or failure of e-negotiation in our case) data consist of positive and negative examples. On *training data*, \mathcal{A} builds a set of functions $F(\mathcal{A}) = \{f(\mathcal{A})_j\}, j = 1, \dots, m$. One of $f(\mathcal{A})_j$ is then applied to *test data*, and the results are used to estimate the algorithm’s performance.

In *supervised* learning, training data consist of a set of input and output pairs $(\bar{x}_i, y_i), i = 1, \dots, N$, where \bar{x}_i is the data entry representation and y_i is its given label (positive/negative in our study of e-negotiation). During training, \mathcal{A} has access to data labels.⁶ During testing, \mathcal{A} gets data entries without labels. $f(\mathcal{A})_j$, constructed and selected during training, determines the label values, some of them perhaps incorrectly.

Generally, a learning algorithm’s performance is estimated via the number of errors it makes on test data. Such estimations could be balanced with respect to errors on positive and negative examples, e.g., *Accuracy*, or emphasize performance on one class, e.g., *F-measure*. The latter have been historically used in text classification.

Data can be collected specially for Machine Learning, but this is far from a common practice. Real-life observations (records of e-negotiations in our case) are made with little concern for learning algorithms. In particular, the proportion of negative and positive examples is not a typical consideration.

The way in which data are split into training and test sets defines model selection. Two most popular approaches are *validation* and *K-fold cross-validation*. We described the latter in Sect. 6. The former means dividing data into three sets, for training, validation and

⁵ For more information on Machine Learning theory and practice refer to (Alpaydin 2004) and (Witten and Frank 2005), respectively.

⁶ In *unsupervised* learning, an algorithms does not have access to data labels during training.

testing. A validation set is used to choose among the algorithm's parameter values found during training. This model selection is useful when an algorithm can easily overfit training data (when it works very well only on training data). An oft-cited *leave-one-out* method is $m-1$ -fold cross validation applied to m data entries. An algorithm is trained on all but one example and then tested on the remaining example. Repeated m times, each time for a different example, this gives us the average accuracy.

There are generative and discriminative learning algorithms. Generative algorithms produce functions, usually probability distributions, that approximately generate data. Discriminative algorithms produce functions that discriminate among data entries.

This work employs supervised learning. A learning algorithm is applied to a text's representation to predict its label. The label value is binary—we solve a *classification* learning problem: given an input vector $\vec{x} = (x_1, \dots, x_n)$, make a prediction \hat{y} of the output $y \in \{0, 1\}$. 0 indicates negotiation's failure and 1 indicates success—see Sect. 6.

In the Machine Learning setting, e-negotiation texts are analyzed under the umbrella of *non-topic classification* that establishes whether the text satisfies a pre-determined criterion (Sebastiani 2002), for example, whether it bears the characteristics of *successful* or *failed* negotiations. In text categorization Machine Learning methods often employ the seeds of manually labelled data. We do not have access to manually labelled text data, nor do such data exist in large amounts.

We use Support Vector Machines (SVM), Decision Trees (DT) and Naive Bayes (NB). SVM and DT are discriminative algorithms. SVM uses quadratic optimization to separate positive and negative examples, DT calculates information gain of the data attributes to do the same. NB is a generative algorithm often used as a discriminative one. It outputs two probability distribution functions—one for positive examples and one for negative examples. Example separation is based on the values of these distributions.

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