

Informativeness for Prediction of Negotiation Outcomes

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Abstract. Business negotiations represent a form of communication where informativeness, the amount of provided information, depends on context and situation. This study shows that there are relations between language signals of informativeness and success or failure of negotiations. We support our claim by machine learning experiments. We use linguistic and statistical analysis to acquire language patterns from the data. We apply learning experiments to predict success or failure of negotiations.

1 Communication and Negotiations

Communication, through a variety of forms, conveys messages sent by a speaker and received by a hearer. These messages can be complex and subtly expressed and made up from what is said and what is implied [6]. Success of communication depends on the speaker's ability to produce a message and on the hearer's ability to understand it. Pragmatics, the study of language use, accepts that to be able to infer the meaning of a speaker's message, the hearer expects that the message should satisfy standards of the Grice Maxims [3]: Quantity (informativeness), Quality (truthfulness), Relation (relevance) and Manner (clarity). Not all communications satisfy Grice Maxims. Sometimes a hidden context interferes with the correct understanding of a message. We present examples of situations in which communications and actions come in sharp contradiction. Seemingly successful negotiation given by Table 1 fails because the participant refuses to sign the agreement.

Language plays an important role in communication and its role is critical for situations when people communicate only verbally, e.g., by phone. In exclusively written communication, language is the only tool to deliver a message, whereas in face-to-face communication message can be supplemented by non-verbal body language (gestures,

Communication	Action
<i>Dear XXX, I am YYY, a representative of Such and Such Company. Our company is interested in your [products] . . . Dear XXX, I like your last offer and accept it. Thank you very much for your cooperation.</i>	The participant refuses to sign the agreement.

Table 1. Example of a situation where communicated meaning contradict actions of interlocutors.

movement and so on) and language characteristics (length of pauses, tone of voice and so on). Negotiations in which people negotiate by email or exchange of electronic messages are a form of communication in which language is a fundamental tool for delivering a message.

The amount of information given by a message is called the *informativeness* of a message. For a structured or guided message, the informativeness of a message correlates with the speaker's position revealed by the message or with the speaker's opinion delivered by it [7]. As suggested by Kamakura et al. [4], the relation between informativeness of free text message and the corresponding opinion and position is more subtle. In this article, we consider free text records of electronic negotiations. We study the relation between informativeness of negotiators' communication and negotiation outcomes.

Assessing message informativeness is a complicated task due to the fact that the conveyed information consists of two related parts: said information and implications. *What is said* defines the quality and quantity of possible inference and the message information which is perceived within a given context and established linguistic rules. The combination of the three factors – information, linguistic meanings, context – allows the hearer to infer and recognize *what is communicated*. As a result, informativeness is determined by *what is said* and *what is inferred* and is understood within a context of communication [14].

In this work, we focus on the speaker's ability to deliver a message. We abstract the hearer characteristics, e.g., background knowledge, from consideration. We analyze information exhibited by word categories such as degrees, scalars, comparatives, and that we consider as indicators of informativeness. This representation is then used in statistical and machine learning experiments for establishing relations between informativeness and success or failure of negotiations. Our experiments were run on Inspire data [5].

2 Electronic Negotiations

As a special type of communication between people, negotiation is a dynamic process that is multi-dimensional, irreversible, purposeful [10]. The way negotiators interact depends on many factors, such as

means, face-to-face meeting, email;

topic of discussion, business, personal;

time mode, synchronous or asynchronous;

interaction mode, one-to-one, one-to-many;

speaker-hearer roles, doctor-patient, buyer-seller, presenter-audience.

Convenience of email, instant messaging resulted in a fast-growing number of participants in electronic negotiations. People negotiate through email or negotiation-support systems in legal and economic settings and in research and training. The use of the electronic means changes the way people communicate during negotiations. In Figure 1, we compare sample transcripts of a face-to-face negotiation [8] and an electronic negotiation [12].

The transcripts illustrate how much information during a face-to-face meeting can be gained from non-verbal body language (gestures, movement and so on) and language characteristics (length of pauses, tone of voice and so on). We also see that language plays bigger role in electronic negotiations, covering negotiation issues, e.g., bargaining, introductions and closures, and socializing, e.g., exchange of personal information. This, bigger, role gives us an opportunity to seek additional cues embedded into the language exchange (Table 1).

Face-to-face negotiations		
Roles	Language exchange	Additional cues
Buyer	<i>It eh what the container eh quan- quantity of each block?</i>	
Seller	<i>Two kilos.</i>	<i>(J outstretches his two arms to indicate a block)</i>
Buyer	<i>Right.</i> <i>And eh ah so you you don't have any propriety of eh the license of the- or another patent, but you have ah know-how to make this</i>	<i>(After clarifying details relating to the size of the product, the Japanese businessman writes a note in his notebook)</i> <i>(lays his pen down)(10 second pause)</i>
Seller	<i>Yeah, yeah, there's many people who have tried to make it</i>	<i>(glances at the first page of his notes)</i>
Electronic negotiations		
Roles	Language exchange	Additional cues
Seller	<i>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</i>	just – degree, as – comparative, thought – scalar
Buyer	<i>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</i>	think – scalar, totally – degree, and – scalar, some – scalar, all – scalar, best – comparative

Fig. 1. Exempts from bilateral business negotiations. Transcripts of face-to-face negotiations are presented at the top, records of electronic negotiations – at the bottom. Language signals of comparativeness are shown in **bold**. The right column shows additional information extracted from communications.

The current study concentrates on *pragmatics* of communications, with focus on comparative comments and estimations that are mapped to degree, scalar and comparative word categories. These word categories include adjectives, adverbs, conjunctions (degrees and comparatives) and cardinal numbers, determiners, cognition verbs, conjunctions (scalars) [1] that are used to compare events and objects. These pragmatic cues substitute for visual information available in face-to-face negotiations.

3 Estimating Informativeness of Negotiation Records

Informativeness of a message is estimated with respect to the context and situation of communication, e.g., its goal, the type of participants’ interaction, communication means and rules. Text of a negotiation is a message of how participants pursue their goals, work on reaching an agreement, and fulfill their negotiation roles. With respect to reaching the agreement, this message is successful if the negotiation succeeds and fails otherwise. This suggests that, from the perspective of negotiators, *informativeness relates to success or failure of negotiations*.

Different information types cause different inferences and vary in their contribution to the message informativeness [14]. Comparative comments and estimations, mapped to degree, scalar and comparative word categories, allow to compare events and objects. The guiding principle underlying such comparison is that a true stronger statement makes all comparable weaker statements true. Thus, words belonging to these categories contribute to informativeness of a message. We used Roget’s Interactive Thesaurus to build the three lists of words shown in Table 2.

Our working assumption is that negotiation results are connected and relate to different types of the information. To find out whether our hypothesis holds on a bigger scale we employ Machine Learning techniques [15]. The use of learning techniques allows to test our assumption on a larger amount of data. Machine learning experiments provide an opportunity to determine what learning model better explains dependencies between informativeness and negotiation outcomes. We seek dependencies with success/failure negotiation outcomes thus perform *qualitative* analysis of the relations. For each negotiation record, we consider that its success or failure corresponds to the negotiation outcome.

We hypothesize that informativeness relates to these outcomes. To prove this, we use *supervised learning*, i.e., a learning algorithm \mathcal{A} constructs a function on training data, a set of input and output pairs (x, y) where x represents a negotiation text through the informativeness language signals and y is the negotiation outcome, and then uses this

Category	Size	Examples
Degrees	65	almost, everywhere
Scalars	34	one, all, some
Comparatives	40	unlike, identical

Table 2. Examples of words in word categories signaling informativeness of a message [9]. The resulting lists include 65 degrees, 34 scalars, 40 comparables.

function to predict outcomes on testing data of previously unseen examples. Learning negotiation success or failure thus defines a *classification* problem that we solve with a variety of learning algorithms.

We have employed statistical analysis to find language patterns that are characteristic to negotiators' communication. N -gram models are arguably the most widely used models for the language analysis purposes. We construct N -gram models, where $N = 1, 2, 3, 4$, by computing

$$P(w_k|w_1^{k-1}) \approx P(w_k|w_{k-N}^{k-1}) \quad (1)$$

where $P(w_k|w_1^{k-1})$ is the probability of the word w_k appearing after the sequence of words $w_1 \dots w_{k-1}$. Obtaining N -gram frequencies are a necessary and important step in understanding communication data – for each corpus originating from a specific genre or source, the N -gram frequency distribution is one of the essential characteristics. Generalization of the most frequent N -grams helps us to find patterns that correspond to the use of the informativeness words. We use these findings to represent negotiation texts in machine learning experiments.

4 Inspire Data

We support our hypothesis by experiments on data of electronic negotiations. The largest data set gathered in e-negotiation comes from **Inspire**, a public-domain research and teaching tool mostly used in college and university programs in numerous countries [5]. 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 a log of each negotiation. No restrictions are imposed on users. The **Inspire** text data available to us consists of the transcripts of 2557 negotiations, 1427 of them successful (for a sample of the data refer to Figure 1, the record of electronic negotiations). One person can participate in only one negotiation. The number of data contributors is over 5000. We work with raw, unedited data that contain 1,514,623 words (tokens) and 27,055 distinct words (types).

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 formal offers (tables with numerical values) and may send free form messages. Exchange of text messages is optional. They either accompany offers or are exchanged between offers. Negotiation, lasting up to 3 weeks, succeeds if a virtual purchase took place within the designated time, and fails otherwise.

Negotiations mediated by **Inspire** 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. 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.

To find how degree, comparative and scalar words are used, we first search for the most frequently used words. We seek the words that are representative for negotiation data in general and across its possible subsets (e.g., texts of successful negotiations, messages sent by buyers). In order to find such words, we analyze the complete text data and texts of its four subsets, i.e., sent by sellers in successful negotiations, sellers in unsuccessful negotiations, buyers in successful negotiations and buyers in unsuccessful negotiations. We build the unigram model of the data and look for words with occurrence more than 10 in each of the subsets. This gives 67 degree, comparative and scalar words. Five most frequent among the sought after words are *and*, *better*, *only*, *more*, *think*, *than*, listed in alphabetical order.

We then build bigram model of the data, cut-off bigrams with occurrence less than 4 and the so-called stop bigrams, i.e., bigrams containing determiners, articles and prepositions except *and* and *or*. From the remaining set we extract bigrams containing the 67 words. Examples of the most frequent bigrams are *and I*, *better price*, *can only*, *be more*. To obtain more information on the use of the words, we build the trigram model of the data and the four subsets and extract trigrams containing the informativeness words. Examples of the most frequent trigrams are *and I am*, *your offer and*, *the only way*, *know more about*. Although there are no obvious trends in the structure of the trigrams, a common use of personal pronouns has emerged as a pattern, which could be explained by correspondence between bilateral negotiations and dialogue. In the next section we use these results to represent negotiation data in machine learning experiments.

Previously, Inspire data has attracted attention of researchers. Kersten and Zhang [5] analyzed outcomes of negotiations conducted using Inspire. They applied a data mining technique to the history of the exchange of formal offers. Among their findings the following results on the behaviour of e-negotiators are 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. Sokolova and Szpakowicz [13] studied tactical moves and influence strategies of negotiators. They analysed language patterns corresponding to commands, requests, advices, prohibitions, etc. The extracted language patterns have been used to represent negotiations in a set of machine learning experiments. Empirical results obtained on Inspire data showed that language patterns provide better classification of negotiation outcomes than 500 most frequent words appearing in the negotiation records.

5 Prediction of the negotiation outcomes

Early prediction of upcoming events is an important learning task in many domains. We want to know whether text informativeness provides a reliable prediction of the negotiation outcomes from the first part of negotiations. We say that early prediction is *reliable* if the classification results are statistically close to those achieved on complete negotiations. In these experiments we use the extracted 67 words to represent negotiations. Prediction of success or failure of negotiations aims to find whether a text belongs to one of the two categories of negotiation texts. This is a *classification* learning task. We

consider successful negotiations to be a positive class, and unsuccessful negotiations – the negative one.

In the first part of machine learning experiments presented here, the data consists of the texts of the first half of negotiations. This segment is labelled by the outcome of the whole negotiation. In the second part of the experiments, the data consists of the texts of complete negotiations. For each data entry we assign 67 attributes, one attribute for each of the degree, scalar and comparative distinct words (types). An attribute is binary: it is 1 if the word appears in the entry and 0 – otherwise. This data representation captures whether a comparative event happens in a negotiation or not. The binary attributes do not capture how persistent are negotiators. Persistency partially can be estimated by attributes that show how many times each word appears in the negotiation. We leave this research avenue for future work.

We use classification algorithms available from Weka, an open source software [15]. We applied:

- decision-based algorithms, ALTERNATING DECISION TREE(ADT) and DECISION TREE (DT): DT estimates *InformationGain* of the attributes to discriminate between classes; ADT alternates prediction estimates, which are generated by boosting of DECISION STUMPS, and *InformationGain* of the attributes to split data; both algorithms output models for analytical analysis;
- a learning algorithm NEAREST NEIGHBOR(KNN) that evaluates the class label of an entry based on the labels of entries closest to it; closeness is evaluated by calculating distance between representations; the algorithm’s output shows a level of similarities among data entries;
- kernel-based methods RADIAL BASED FUNCTION NETWORKS(RBFN) and SUPPORT VECTOR MACHINE(SVM), known for high accuracy of classification of texts, serve as empirical estimate of the goodness of results.

Quality of classification can be assessed using a confusion matrix, i.e., records of correctly and incorrectly recognized examples for each class. Table 3 reports on binary classification, where *tp* are true positive, *fp* – false positive, *fn* – false negative, and *tn* – true negative counts.

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>

Table 3. A confusion matrix for binary classification

To estimate how the classification algorithms work, we calculate

$$Accuracy = \frac{tp + tn}{tp + fn + fp + tn}, \quad (2)$$

Classifiers	First half				Complete			
	<i>Acc</i>	<i>F</i>	<i>Pr</i>	<i>Rec</i>	<i>Acc</i>	<i>F</i>	<i>Pr</i>	<i>Rec</i>
KNN	0.66	0.67	0.73	0.62	0.66	0.68	0.72	0.65
ADT	0.70	0.74	0.71	0.76	0.70	0.75	0.69	0.83
DT	0.68	0.73	0.69	0.77	0.69	0.75	0.69	0.81
RBFN	0.68	0.75	0.68	0.83	0.68	0.75	0.67	0.86
SVM	0.70	0.74	0.70	0.78	0.70	0.76	0.70	0.83

Table 4. The algorithms’ best classification results of success or failure of negotiations. Negotiation texts are represented by degree, scalar and comparative words. The left part presents classification of the first part of negotiations; the right part presents classification of complete negotiations. For each of data representations, we show the best value of each measure (in **bold**).

and measures commonly used in text classification [2]

$$Precision = \frac{tp}{tp + fp} \quad (3)$$

$$Recall = \frac{tp}{tp + fn} \quad (4)$$

$$Fscore = \frac{(\beta^2 + 1)tp}{(\beta^2 + 1)tp + \beta^2 fn + fp} \quad (5)$$

We evaluate the algorithm’s performance with respect to the results the classifiers obtained on the dominant class (i.e. successful negotiations). Table 4 reports the best results obtained by exhaustive search of the algorithm’s parameters. The results are estimated by tenfold cross-validation. We calculate *Fscore* for $\beta = 1$. *Acc* equals 0.55, when all negotiations are classified as positives. Corresponding *F* is equal to 0.71.

The empirical results show the reliability of the early prediction of the negotiation outcomes when negotiation texts are represented by the informativeness signals. However, conclusion differs for classification of successful and unsuccessful negotiations. Increase of *Recall* shows that informativeness of complete negotiations assists in a better classification of successful negotiations. This holds for the five classifiers. *Precision* has decreased for NEAREST NEIGHBOR and ALTERNATING DECISION TREE and is steady for the other classifiers. This trend implies that informativeness is more important in the first part of unsuccessful negotiations than for complete negotiations.

Another interesting conclusion can be drawn when we look at the parameters of the best classifiers built by the algorithms. It is important to remember that the structure of models built by each algorithm remains the same on the first half and complete negotiations. NEAREST NEIGHBOR classifies unsuccessful negotiations better than the other algorithms. For each data entry, the algorithm needs 15 entries, closest to it with respect to the Euclidean metric, to find its class label. This holds for the first half of negotiations and a complete negotiation. This implies a *high level of similarity* among occurrences of the informativeness signals in unsuccessful negotiations. Although ALTERNATING DECISION TREE and DECISION TREE performed relatively close on both data, their parameters differ substantially. For example, to classify the first part of negotiations ALTERNATING DECISION TREE builds 3 layers with 31 nodes, including 21 leaves,

Classifiers	First half				Complete			
	<i>Acc</i>	<i>F</i>	<i>Pr</i>	<i>Rec</i>	<i>Acc</i>	<i>F</i>	<i>Pr</i>	<i>Rec</i>
KNN	0.71	0.74	0.72	0.77	0.69	0.73	0.71	0.76
ADT	0.70	0.75	0.70	0.82	0.70	0.75	0.69	0.83
DT	0.68	0.74	0.69	0.79	0.69	0.75	0.69	0.81
RBFN	0.69	0.75	0.68	0.83	0.69	0.76	0.68	0.86
SVM	0.70	0.76	0.69	0.85	0.71	0.78	0.69	0.89

Table 5. The algorithms’ best classification results of success or failure of negotiations. Negotiation texts are represented by personal pronouns, degree, scalar and comparative words. The left part presents classification of the first part of negotiations; the right part presents classification of complete negotiations. For each data representation, the best measure values are shown in **bold**.

whereas DECISION TREE constructs 15 layers with 109 nodes, including 55 leaves. The same tree structures were obtained while classifying complete negotiations. SUPPORT VECTOR MACHINE’ best performance is obtained when it uses linear polynomials and $C = 0.01$ to separate classes. RADIAL BASED FUNCTION NETWORKS first clusters the data into a small number of classes and then uses logistic regression to model them

Personal and possessive pronouns, e.g. *we*, *ours*, *you*, *yours*, commonly present in the patterns with the informativeness words. We conduct a set of experiments in which 10 attributes corresponding to personal and possessive pronouns are added to the data representation. Table 5 presents the results.

For most algorithms, adding pronoun attributes to the data representation either did not change or marginally changed the overall accuracy of classification. Only NEAREST NEIGHBOR substantially improved its classification results. ALTERNATING DECISION TREE and SUPPORT VECTOR MACHINE improved classification of successful negotiations while their correct classification of unsuccessful negotiations diminished. This holds for the first part of negotiations and complete negotiations. NEAREST NEIGHBOR significantly improved classification of successful negotiations without losing accuracy of classification of unsuccessful negotiations, although now it requires 25 neighbors to classify a data entry. DECISION TREE slightly decreased the number of nodes – to 95, including 48 leaves – when it classifies the first half of negotiations. Other tree structures remain the same.

6 Conclusion

In this study, we have shown that *informativeness* of messages exchanged by negotiators correlates with negotiation success or failure. The analysis has been done for free text records of electronic negotiations. Previously, studies of *free text* message informativeness [1] have been conducted on a smaller scale, involving manual analysis of a restricted number of examples. In our work, Machine Learning methods allowed the analysis of a significantly larger number of examples. We analyzed language signals of informativeness provided by the presence or absence of degree, scalar, and comparative word categories. This representation was used in machine learning experiments to

establish relations between informativeness and the negotiation outcomes. Using machine learning experiments on the first half of negotiations, we have shown that the informativeness signals may provide early prediction of the negotiation outcomes.

In the future, we intend to analyze correlation between informativeness of messages and numerical values of the negotiation offers. In order to perform a *quantitative* analysis of relations between informativeness and negotiation outcomes. Studying relations between factual and implied information and between explicit and implicit information are other promising venues for future research.

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