InterNeg Research Papers INR 04/01

InterNeg

Revised version will appear in:

Central European Journal of Operational Research, 2003

Mining Inspire Data for the Determinants of Successful Internet Negotiations *

Gregory E. Kersten and Grant Zhang

J. Molson School of Business, Concordia University, Montreal, Canada
(gregory@jmsb.concordia.ca)

Abstract

1525 bilateral negotiations were conducted over the Internet via a negotiation support system Inspire. In 53% cases the negotiations were successful and the parties achieved a compromise. The data about these negotiations is studied here in order to determine the underlying reasons for successful negotiations. Because of the size of the dataset the knowledge discovery process is modified allowing also testing and comparing the methods' predictive accuracy.

* This work has been supported with grants from the Social Sciences and Humanities Research Council of Canada and the Natural Sciences and Engineering Research Council of Canada.

1. Introduction

Information technology is creating a new opportunity for negotiations and for negotiation support. The Internet offers the possibility for direct contacts of a sophisticated nature among geographically dispersed negotiators in diplomacy (Kappeler 1996; Weisner 1997) and in business (Lo and Kersten 1999; Bichler 2000; Bui, Yen et al. 2001). Already in the mid-nineties, the Internet was used in economic negotiations between governments. At that time several databases containing numerous legal documents were constructed and accessed from remote sites (Studemeister 1998). More advanced tools can provide a comprehensive and active support for conflict resolution based on decision and negotiation support systems and software agents (Guttman, Moukas et al. 1998; Lo and Kersten 1999; Sandholm 1999; Strobel 1999; Kersten and Noronha 2000). Recently, a number of companies developed electronic negotiation tables and support tools to facilitate business negotiations (LiveExchange 2001; Optimark. 2001; TradeAccess 2001).

The paper discusses results of 1525 bilateral negotiations, which involved students, managers and professionals, as well as web surfers. The negotiations were conducted over the Internet via a negotiation support system Inspire (Kersten and Noronha 1999; Kersten and Noronha 1999). The design of the system allowed for detailed logging of the negotiation process itself, as well as for administering of questionnaires to participants before and after the negotiation. Unlike the experimental face-to-face negotiations, which can take only an unrealistically short period of time, Inspire negotiations were scheduled for a three-week period. To make the experiments more realistic the participants were allowed terminate or extend the negotiations.

The Inspire system allows for exchange of both structured and unstructured information. It includes support techniques allowing the participants to evaluate offers and counter-offers, and to view the negotiation history in both textual and graphical formats. The negotiations were carried out anonymously, participants were initially not aware of their partners' cultures, although they could reveal their nationality, if they wished to do so.

The data collected from the Inspire system is unique and describes the first experiment involving a large number of bilateral business negotiations carried out on the Web. Constantly new negotiations are being set up and information about them will eventually be added to the dataset that exceeds now 4,000 cases. This number, however, is only a very small fraction of the total population of Internet users. The dataset is not a statistical sample of the population because we cannot control the access to the system. Most of the users (90%) are students taking university course and managers, lawyer, engineers and other professionals who partake in management training. Their instructors request that they use the Inspire system as part of their training. Other users are mostly web surfers and researchers.

Lack of knowledge of the population, our inability to control of the subjects and to sample the population are drawbacks from the perspective of studying the data with statistical methods. Data mining techniques do not assume the knowledge of the population neither do they require randomized sampling; a dataset is expected to represent a significant percentage of the total population. Although our dataset comprises only a small percentage it is analyzed with several different data mining techniques that are based on well-known statistical models.

Internet-based activities allow for collection of large volumes of data which is similar to the data collected with Inspire. Although large, these datasets include only a small percentage of the population. Another feature is that the data describes unique and describes newly emerging processes and phenomena. Hence there is a need to study such data with the caveat that the results should be seen as tentative and verified with additional data. This is the approach we take here.

One aim of this study is to apply several different methods in order to compare results and determine their predictive accuracy. We describe an integrative approach to studying data generated on the Internet. The data mining methods applied here are compared in terms of their predictive powers. While the results cannot be generalized to other datasets they may provide a basis for similar studies. The second objective of this paper is to determine the reasons behind successful negotiation, which we consider here to be a negotiation that ends with a compromise.

2. Inspire negotiations

The InterNeg site (http://interneg.org) was initially developed at the Centre for Computer Assisted Management (CCAM) in 1995 and now is hosted at the Concordia and Carleton Universities. The Inspire negotiation support system was the first systems developed by the InterNeg group. It provides support for the negotiation process through electronic bargaining facilities, visualization suites, analytical tools, and quantitative and qualitative models (Kersten and Noronha 1999).

2.1 Simulation

The experiment is a case of a buyer-seller business negotiation for one commodity. The simulation involves representatives of two companies: Itex Manufacturing, a producer of bicycle components and Cypress Cycles, a builder of bicycles. The simulation describes a negotiation problem that users from almost any country are familiar with and therefore no additional explanations are necessary. As the users' language proficiency level may vary the case is fairly simple and well structured. In order to verify the case and the language difficulty, the case was tested with two groups of students (65 in total) taking their first university-level ESL course. The case description fits one and a half pages. There are four issues that both sides have to discuss: the price of the components, delivery times, payment arrangements and terms for the return of defective parts. For each issue there is a given set of options, i.e., issue values. Altogether, there are 180 complete and different potential offers (alternatives) that contain values of all four issues.

Both parties are presented with their side of the case, told that they represent either Itex or Cypress, and that their companies are interested in achieving a compromise. They are also informed that there are other suppliers and buyers; a participant may terminate negotiations and request a new negotiation. That means that a breakdown in negotiations is possible if a good deal cannot be reached.

Inspire negotiators are not given the issue priorities and there is no specification as to what indicates a good deal. Each side, however, is given a clear indication as to the desirability of the options (issue values) but in terms of the direction rather than specific trade-off values. For example, the negotiator representing Cypress, the buyer, is told that Cypress prefers to pay less rather than more and negotiate a shorter rather than longer delivery time. The negotiator has to decide on the trade-offs. For example, s/he has to decide if the price is more important than the delivery time. The negotiator has to determine the specific trade-off values between issues.

In our experiments the preference structure and trade-offs values were kept secret for each party. They were used to provide a rating of each offer that the party considered, and also for offers and counteroffers that were exchanged. Also, each party could modify their preferences during the negotiation.

2.2 Inspire system

Inspire facilitates anonymous bilateral negotiations; the negotiators use aliases and each has his/her own part of the "virtual negotiation table" that is not accessible to any other user. Instructions, glossary and explanations can be accessed at every step of using the system. Other components of the system, for example, the case description, preference specification page and offer construction page can be accessed only in a given sequence.

Exchanges of offers and messages are conducted via the system to protect users anonymity; the negotiators do not know their counter-parts' identity. In addition to the case, the system provides the following key facilities: preference elicitation and utility construction, offer construction and rating, messaging, graph of negotiation dynamics, negotiation history with all offers and messages, and post-settlement efficiency analysis. Upon the completion of the negotiation, users may agree to disclose their utilities which allows each party to view the 'negotiation dance graph'.

2.3 Data

In the Inspire negotiations, data is collected with the use of three instruments: (1) Negotiation transcripts which are automatically generated and contain the participants' preference structure, offers and their ratings, messages and time stamps; (2) The pre-negotiation questionnaire, which every participant fills in after her/his utility function has been constructed and before the negotiation can begin; and (3) The post-negotiation questionnaire, which is not mandatory.

The pre-negotiation questionnaire contains information about the participants' characteristics (e.g., age, gender, profession, country of birth, residence, expected compromise, expected friendliness of the negotiation, negotiation experience). The post-negotiation questionnaire contains information about the participants' perception of the system (e.g., ease of use of its features, help facility, graphs, use of system tools), the counter-part (e.g., her/his perceived honesty, exploativeness, friendliness, persuasiveness, informativeness), and the process (e.g., satisfaction with the settlement, acceptance, learning aspects). The negotiation transcript contains messages, offers, time stamps and graphs depicting the negotiation progress in the individual utility space.

The dataset comprises 1525 bilateral negotiations and contains descriptive information about 3050 participants. The data was collected by the Inspire system from September 1996 to November 2000. Each negotiation case is recorded in two separate records, one for each negotiator. Each record contains 82 attributes describing one participant's demographics and activities.

3. Data mining

Data mining techniques have been contrasted with confirmatory statistical methods (Pregibon 1998; Weiss and Indurkhya 1998). The latter are difficult to use in situations when the underlying distribution of data is unknown or complex (Glymour, Madigan et al. 1996), and the population cannot be defined and samples obtained. In statistics, the issue of generalization involves the definition of a population to which one can generalize and bring in issues of sampling. Without restrictions on the sampling method one cannot guarantee the statistical significance of the models. In data mining the population that is not described by a set of given data is ignored. It is assumed that the data set is either the whole population or that it comprises a sufficiently large fraction of the population so that the generalization is justifiable. Hence the sampling is done from the database rather than the population (Fayyad 1996; Mahadevan, Ponnundurai et al. 1999).

3.1 Procedure

Most data mining software requires a minimum amount of cases to conduct effective mining results, for example, SAS Enterprise Miner (SAS version 8.1 and Enterprise Miner version 4.1 were used in this study) (SAS 2001) needs a set with at least 2000 cases to implement data mining effectively. In very large datasets this set is sampled from the whole database, regarded as the population. Since we have 3050 cases and between 25% and 35% (depending on the variable) of them have missing values, we applied data mining on the whole set. This required a modification of the SEMMA approach to data mining that has been proposed by SAS.

In the next step the data is partitioned into three subsets. The first subset is used for training, the second for validation, and the third subset is used for testing. The training and validation subsets are used at the same time and the results from each subset are compared with each other. These rules or predictors that have the lowest error rate in both subsets are selected as the final results. The test subset is used for testing the rules or predictors generated from the training and validation subsets.

The Inspire dataset was partitioned into 1220 cases (40%), 1220 cases (40%), and 610 cases (20%) each comprising respectively training, validation and test subsets. We randomly partitioned the selected data five times and therefore obtained five different partitionings of data. Each dataset is different from another, but they all contain the training, validation and test subsets with respectively 1220, 1220 and 610 cases.

We applied three known data mining methods: (1) Logistic regression analysis (LLR), (2) Tree and rule induction (TRI), and (3) Artificial neural network (ANN). For each method several models were selected. Logistic regression was conducted using three algorithms: stepwise, backward and forward. In tree and rule induction methods three algorithms Chi-square, entropy reduction and Gini reduction were used. The level of significance of a variable on the target variable (negotiation success) was measured with the T-score and the variables ranked according to the T-score value.

Artificial neural network methods were differentiated according to the number of hidden layers and number of units in each layer. Specifically, we used five models, which had from one and five hidden layers each with three units; and five models which had from one to five hidden units each with two hidden layers.

Taking the above into account we used 16 algorithms: three based on LLR methods, three based on TRI methods, and 10 ANN models. Each method and model was tested on five datasets partitioned from the Inspire 3050 cases.

3.2 Prediction

Discovering rules and patterns from data allows making predictions. One may expect that information obtained from the application of different methods has different predictive powers. An aspect of this study was to obtain a preliminary assessment of the prediction accuracy of the selected methods and algorithms for the type of data that is obtained from Inspire negotiations.

Prediction accuracy can be obtained with the use of a separate data set that does not contain cases used to obtain the results. That is, the data is sampled and divided into two sets: a set used for data mining and a set used to determine prediction accuracy. Because of the size of the current dataset we resorted to the sampling of the same dataset that was used for the data mining purpose. The database was sampled five times and five subsets were obtained with each having 1221 cases. These five data sets were used to make predictions and then they were compared with the actual negotiation results.

Results obtained from the 16 models were used to make predictions on the predicted data. The results obtained from different models but the same training data were used to make predictions on the same dataset. The predicted results were compared with the actual results and the prediction accuracy of each model was thus obtained. This process was repeated five times for a different sample of the dataset used for prediction. One-way ANOVA method of mean comparison was employed to assess the presence of significant differences between the 16 models measured with their prediction accuracies.

4. Indicators of successful negotiations

4.1 Results from LLR models

The key indicators are related to the number of exchanges between the parties and their timing. The available data allows to distinguish between an offer, a message, and an offer accompanied by a message. One variable (Ofr) represents the number of offers with and without messages. It is this variable that has a significant impact (using the *t* test) on the negotiation success; the more offers (with and without messages) are sent, the greater the probability that the agreement will be reached. Variable Ofr was found to have positive effect on the target 8 times out of 15 LLR models (3 methods run 5 times); six times it was identified as a strong predictor.

The number of offers sent without messages and messages sent without offers does not have a significant impact on the success.

The timing of offers (with and without messages) is also significant. Variable Off_1 describes the number of offers sent during the last day before the deadline and variables Off_2 and Off_4 describe the number of offers (with and without messages) sent respectively during the last two and four days before the deadline. Variable Off_all describes the number of offers (with and without messages) sent before the last four days (Ofr = Off_4 + Off_all).

Variables Off_1 and Off_2 were found to be significant predictors but they have a negative effect on achieving a compromise. Out of 3050 negotiators only 268 (9.8 %) sent one or more offers during the last day before the deadline. Only 80 negotiators, out of 268, reached an agreement. The frequency of successful negotiations among the negotiators sending offers on the last day is 29.85%, almost half of the average frequency of 53%.

Variable Off_all also has a significant but positive effect on the negotiation, reinforcing the importance of exchanges during early stages of the negotiation. Seven times, the LLR methods found that Off_all has a strong positive effect on reaching agreement; 4 times it was identified as a strong predictor.

We also found that males were less likely to reach agreements than females. Gender was identified as an effective predictor in five LLR models. In these five models Gender_M and Gender_F were identified together; with negative and very close to each other rating. Gender_M was found to have stronger negative effect on target than Gender_F, however the difference is not large. This implies that male participants found it somewhat more difficult to reach and agreement than females.

4.2 Results from TRI models

From the application of the three tree and rule induction methods (TRI) a number of different trees and corresponding rules were obtained. Comparing the prediction accuracies obtained for these trees we found that: (1) two groups of trees can be identified with each group having the same trunk and main branches (top-level rules), and (2) the values of prediction accuracies were similar for different trees. Using the Games-Howell post-hoc, we found that there is no significant difference between the prediction accuracy for trees with and without many branches (the *p*-value for trees with and without trunks is the same and equals 0.75). Hence we could reduce 15 trees to two trees. These two trees are depicted in Figure 1 and 2 respectively and they describe the whole Inspire dataset.

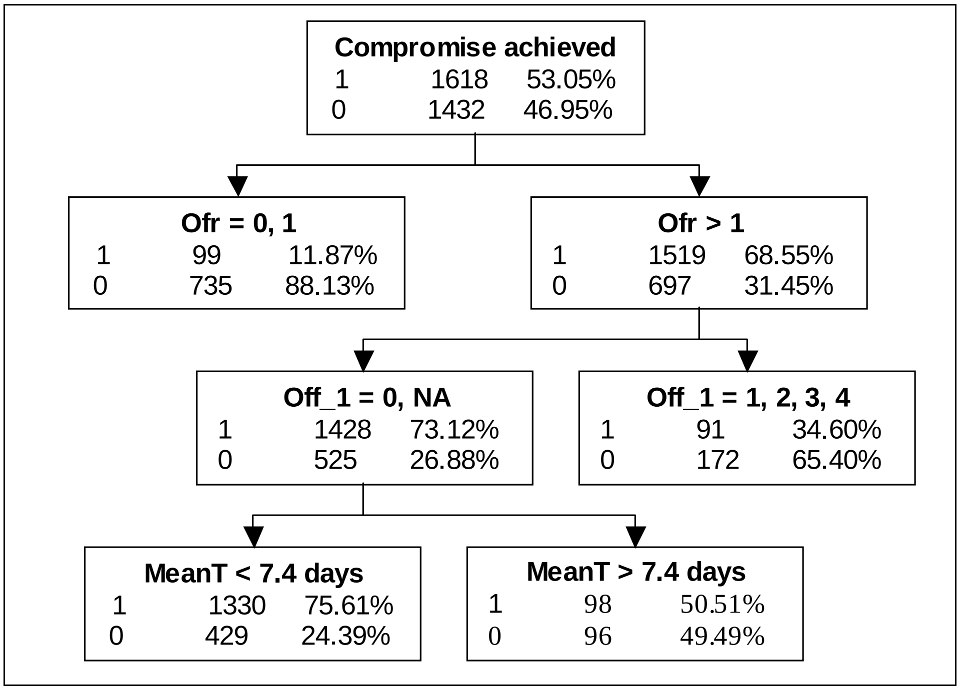

Figure 1. Tree 1

From the first tree, depicted in Figure 1, we obtain the following rules:

1. If the number of offers (with and without messages) is less than two, then the probability of reaching an agreement is very low (11.87%). Sending two or more offers increases probability of reaching a compromise by 15.5% (i.e., from 53.05% to 68.55%).
2. If two or more offers (with and without messages) are sent, and at least one offer is sent on the last day before deadline, then the probability of reaching an agreement drops from 53.05% for the population, to 34.60%. On the other hand, if no offers are sent (or their number is unknown-NA), then the probability increases to 73.12%.
3. If the negotiator sent two or more offers (with and without messages) and all of them were sent earlier than on the last day before deadline and the mean time between the offers (MeanT) is less than 7.4 days then the probability of achieving a compromise is high (75.61%). On the other hand, if the mean time between offers exceeds 7.4 days the probability of a compromise is slightly lower than for the population (50.51% vs. 53.05%).

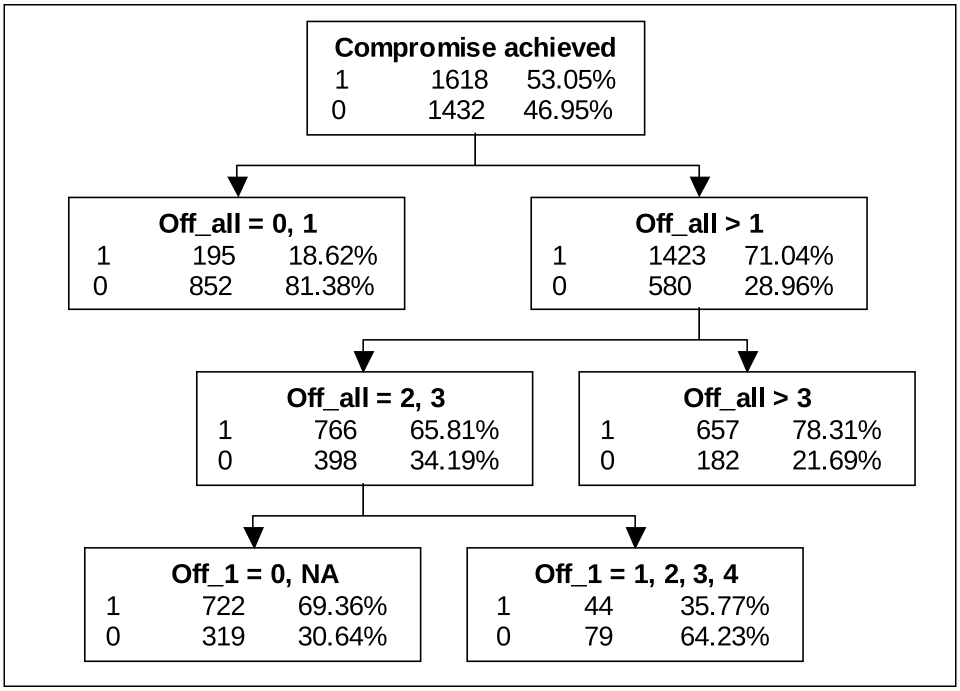

Figure 2. Tree 2

From the second tree, depicted in Figure 2, we obtain the following rules:

1. If the negotiator sent fewer than two offers (with and without messages) between the beginning of the negotiation and the fourth day before the deadline, then the probability of reaching an agreement is very low. Out of 1047 participants (i.e., 34.33% of the population) who sent less than two offers during this period only 195 (18.62%) have reached an agreement. On the other hand sending 2 or more offers 4 days before the deadline increases the probability of a compromise from 53.05% for the whole population to 71.04%.
2. Sending more offers (with and without messages) in the early stage, increases the probability of achieving a compromise; if the negotiator sent more than three offers, the probability increases to 78.31% as opposed to 65.81% for negotiators who sent two or three offers.
3. If two or three offers are sent four days before the deadline, and no offer is sent (or their number is unknown-NA) on the last day before the deadline, then the probability of reaching an agreement is 69.36%. However, if one or more offers are sent during the last day then the probability drops to 35.77%.

4.3 Comparison of LLR and TRI results

Both the three logistic linear regression methods (LLR) and three tree and rule induction (TRI) models provide similar results that are summarized in Table 1. Negotiation literature recognizes that communication is necessary for negotiations and our results reinforce this requirement (Kennedy 1998; Lewicki, Saunders et al. 1999). Interestingly, the relevant communication is one that involves offers; message exchange has no statistically significant impact on the achievement of a compromise.

Table 1. Key indicators of successful negotiations

No.	Rules	LLR	TRI
1	If the parties continue negotiations on the last day before the deadline, the probability of reaching a compromise decreases.	Yes	Yes
2	The more offers (with and without messages) the parties exchange the greater is the probability that they will reach an agreement.	Yes	Yes
3	The offers (with and without messages) that are sent in early stage of the negotiation have stronger impact on reaching agreements than the offers sent at the later stage.	Yes	Yes
4	Males are somewhat less likely to reach agreements than females.	Yes	No
5	If the time between offers (with and without messages) that the parties exchange, exceeds one week, the possibility of reaching an agreement is significantly reduced.	No	Yes

Exchange of offers with and without messages is an obvious requirement. What is less obvious is that the success of the Internet negotiation also depends on the number and timing of these exchanges. One possible explanation is that the narrow bandwidth of the Internet as opposed to the face-to-face negotiation requires compensation in the volume of communication. This may also conform to the need for early exchanges and the negative impact of the exchanges just before the deadline. The parties may need to get acquainted and may be able to change their perspectives without being pressured to reach a compromise at the last moment. This has probably more to do with the relationship aspects of the negotiation than the negotiation problem. There are neither cognitive nor technical difficulties in the understanding and control of the problem process. The problem is fairly simple and well structured, and the analytic and process visualization tools allow evaluating and controlling both the individual issues and the overall progress.

5. Prediction accuracy

Inspire negotiations were successful in 53% of the cases, that is, the parties achieved an agreement. This means that without data analysis and search for information about the influence of particular variables on the negotiation success, the prediction accuracy for this data set is on average 53%.

Every data mining method allows increase in prediction accuracy but there are differences among these methods.

For each method (LLR, TRE and ANN) and each of the 16 models within the methods five prediction accuracies were calculated. In each of the five runs, the 16 models were determined using the same training and validation datasets, and the prediction was also done on the same dataset. In order to analyze the differences between accuracies for different models and methods the Games-Howell post hoc test of the one-way ANOVA was used to compare their means.

For each model the average prediction accuracy of 5 runs is given in Table 2. We notice that the method providing the highest average accuracy is the tree and rule induction method followed by logistic linear regression. Artificial neural networks have low prediction accuracy; it is less than 6% higher than the 53% of the negotiations that ended with an agreement.

5.1 LRA and TRI models

Both the stepwise linear regression model and the forward linear regression model have the same prediction accuracies (*p*-value is 1.0 with 0.95 confidence level). These two models have better prediction accuracies than the LRA backward model (p-value is 0.081 and 0.144 respectively with 0.85 confidence level).

The LRA stepwise model with average prediction accuracy of 62.39% and the LRA forward with average of 1.93% have respectively 3.11% and 2.65% more correct predictions on average than LRA backward model. The latter model has 59.28% average prediction accuracy.

Table 2. Average prediction accuracy of 5 runs

Logistic linear regression		Tree and rule induction		Neural network (1-5 layers, 3 units)		Neural network (1-5 units, 2 layers)	
LR_Step	62.40	Tree_Chi	75.14	N_1layer	57.83	N_1unit	57.87
LR_Back	59.28	Tree_Entr	75.33	N_2layer	57.67	N_2unit	59.28
LR_Frwd	61.93	Tree_Gini	75.26	N_3layer	57.76	N_3unit	57.69
				N_4layer	57.53	N_4unit	57.84
				N_5layer	57.63	N_5unit	57.94

All three tree and rule induction models have the same prediction accuracy; their *p*-values equal 1.0. No model was found more accurate at prediction than others; the TRI Chi-square, TRI entropy reduction and TRI Gini reduction have respectively an average of 75.14%, 75.33% and 75.14% prediction accuracy.

5.2 ANN models

The prediction accuracy of the five ANN models that differ in the number of hidden layers, is the same. For each model the *p*-value is equal to 1. This implies that the layer number had no impact on the prediction accuracy. Similarly, the differences between the prediction accuracies of models with different number of the hidden units is statistically insignificant, implying that the number of units has no impact on prediction accuracy of an ANN model with two hidden layers.

5.3 Comparison of LRA, TRI and ANN models

The differences in prediction accuracy of models within TRI and ANN methods are statistically insignificant. LRA The prediction accuracy of LRA backward model is significantly lower than that of the LRA forward and step-wise models. Accuracies for models from different methods are different (see Table 2). To test the hypothesis that these differences are significant we used one-way ANOVA test. The result is that, at the 95% confidence level, the TRI methods have significantly higher prediction accuracy than the LRA methods which, in turn, has higher accuracy than the ANN models. If this result remains when we mine the larger Inspire dataset then it means that it is sufficient to employ TRI and LLR methods. Not only do these methods provide higher prediction accuracy but they also specify the predictors that can be observed during the negotiations.

6. Conclusions

In this paper three data mining methods available in SAS Enterprise Miner were applied to determine the key reasons behind successful Inspire negotiations. Although the results are tentative and more studies are needed several observations can me made. We found that the statistical models embedded in data mining methods that have explanatory powers, specifically the logistic linear regression and the tree and rule induction models have also higher prediction accuracy than the “black box” type methods such as artificial neural networks. We plan to undertake more studies with different data sets, including the new Inspire dataset that would include negotiations conducted between September 1996 and June 2001.

The indicators of successful negotiation conform to the main postulates of the negotiation literature, namely that effective and substantiated communication is very important. What we found being significant is perhaps as important as the variables that were not found significant. The latter include messages that are sent solely to establish rapport, persuade, present ones perspective. Their role in the Internet negotiation appears to be much less important than the role of messages sent together with offers. We also found that the culture, education and profession have no significant impact on negotiations. Similarly the differences in one position (buyer or seller), in the understanding of the case, negotiation expertise, use of the Internet and the ease of use of the Inspire system are not statistically significant.

Comparing variables that are the determinants with those that are not we find that no technological or methodological variable that appears because the negotiation are conducted via the Internet and with the use of an negotiation support system is significant. The significant variables are the same that characterize every negotiation, including face-to-face. Testing the role of communication and spacing of massages in time in the traditional setting, that is face-to-face negotiation, is difficult because it requires that the parties meet over a long period of time.

References

Bichler, M. (2000). "A roadmap to Auction-based Negotiation Protocols for Electronic Commerce". Proceedings of the Proceedings of the 33rd Hawaii International Conference on Systems Sciences.

Bui, T., J. Yen, et al. (2001). “A Multi-Attribute Negotiation Support System with Market Signalling for Electronic Markets.” Group Decision and Negotiation((to appear)).

Fayyad, U. M. (1996). “Data Mining and Knowledge Discovery: Making Sense Out of Data.” EEE

Expert **11**(5): 20-25.

Glymour, C., D. Madigan, et al. (1996). “Statistical Themes and Lessons for Data Mining.” Data Mining and Knowledge Discovery **1**(1): 25-42.

Guttman, R. H., A. G. Moukas, et al. (1998). “Agent-mediated Electronic Commerce: A Survey.” Knowledge Engineering Review **13**(3).

Kappeler, D. (1996). The Impact of Information Technology on Preparation and Support of Small State Participation in Economic Negotiations. Institute of International Relations, http://hostings.diplomacy.edu/iirt/conf/Dipl2000/Text/kapp1.htm. Accessed: Aug. 20, 1999.

Kennedy, G. (1998). Kennedy on Negotiation. Brookfield, VA, Gower.

Kersten, G. E. and S. Noronha (1999). “Negotiations via the World Wide Web: A Cross-cultural Study of Decision Making.” Group Decision and Negotiations **8**: 251-279.

Kersten, G. E. and S. J. Noronha (1999). “WWW-based Negotiation Support: Design, Implementation, and Use.” Decision Support Systems **25**: 135-154.

Kersten, G. E. and S. J. Noronha (2000). Modeling Integrative and Distributive Negotiations. InterNeg, INR03/00, http://interneg.org/interneg/research/papers/. Accessed: June 2000.

Lewicki, R. J., D. M. Saunders, et al. (1999). Negotiation. Boston, MA, McGraw-Hill.

LiveExchange (2001), http://www.moai.com/solutions/LiveExchange. Accessed: May 2000.

Lo, G. and G. E. Kersten (1999). "Negotiation in Electronic Commerce: Integrating Negotiation Support and Software Agent Technologies". Proceedings of the 5th Annual Atlantic Canadian Operational Research Society Conference (CD ROM & http://interneg.org/interneg/research).

Mahadevan, A., K. Ponnundurai, et al. (1999). "Knowledge Discovery in Databases for Decision Support". Decision Support Systems for Sustainable Development in Developing Countries. G. E. Kersten, Z. Mikolajuk and A. Yeh, (Eds.). Boston, Kluwer.

Optimark. (2001)., http://optimark.com. Accessed: May.

Pregibon, D. (1998). Data Mining: What's at Stake for the Field of Statistics. Ottawa, Canada, Statistics Canada.

Sandholm, T. (1999). “Automated Negotiation. The Best for All Concerned.” Communication of the ACM **42**(3): 84-85.

SAS (2001). SAS Enterprise Miner, http://www.sas.com/products/miner/. Accessed: May 2001.

Strobel, M. (1999). On Auctions as the Negotiation Paradigm of Electronic Markets. Zurich, BM Zurich Research Laboratory**:** 7.

Studemeister, M. S. (1998). “The Impact of Information and Communications Technologies on International Conflict Management.” ASIS Bulletin **24**(3).

TradeAccess (2001)., http://www.tradeaccess.com.

Weisner, M. (1997). "Virtual Tools for Real Diplomacy". Proceedings of the Virtual Diplomacy Conference of the United States Institute of Peace. US Institute of Peace. **2000**.

Weiss, S. M. and N. Indurkhya (1998). Predictive Data Mining: A Practical Guide. San Francisco, CA, Morgan Kaufman Publishers.