Automated Negotiation and Bundling of Information Goods

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ABSTRACT

In this paper, we present a novel system for selling bundles of news items. Through the system, customers bargain with the seller over the price and quality of the delivered goods. The advantage of the developed system is that it allows for a high degree of flexibility in the price, quality, and content of the offered bundles. The price, quality, and content of the delivered goods may, for example, differ based on daily dynamics and personal interest of customers.

Autonomous "software agents" execute the negotiation on behalf of the users of the system. To perform the actual negotiation these agents make use of bargaining strategies. We present the novel approach of disentangling bargaining strategies into concession strategies and Pareto efficient search strategies. We show through computer experiments that this approach will result in very efficient bargaining outcomes. Moreover, the system is setup such that it is actually in the best interest of the customer to have their agent adhere to this bargaining approach.

1. INTRODUCTION

Personalization of information goods becomes more and more a key component of a successful electronic business strategy [1]. The challenge is to develop systems that can deliver a high level of personalization combined with, whenever possible, a high adaptability to changing circumstances. In this paper we develop a system which can attain these properties through the manner in which it sells information goods.

We consider the novel approach of selling bundles of news items through a system that allows for bargaining over the price and quality of the delivered goods. The advantage of the developed system is that it allows for a high degree of flexibility in the price, quality, and content of the offered bundles. The price, quality, and content of the delivered goods may, for example, differ based on daily dynamics and personal interest of customers.

The system as developed is capable of taking into account business related constraints. More specifically, it tries to ensure that customers perceive the bargaining outcomes as being "fair" by having customers end up with equivalent offers whenever that seems fair. Partly because of this fairness constraint the actual bargaining process is not really one-to-one bargaining between seller and customer but instead is one-to-many (i.e., between seller and customers).

To accelerate the negotiation process customers can initiate concurrent negotiation threads for the same bundle with differences in the quality of the delivered bundles. The thread in which the agreement is reached first determines the final bargaining outcome.

In the developed system pieces of autonomous "software agents" perform (part of) the negotiation on behalf of the users of the system. These software agents bargain over a multi-issue price (the price is actually a tariff with a fixed and variable component).

To enable efficient multi-issue bargaining outcomes, we present the novel approach of disentangling the bargaining strategies into concession strategies and Pareto efficient search strategies. We show through computer experiments that this approach results in very efficient bargaining outcomes (i.e., these outcomes closely approximate Pareto efficient bargaining solutions).

In the system the seller agent uses a Pareto efficient search strategy combined with a concession strategy. Although the customer is free to choose other bargaining strategies the system is set up such that it is actually in the best interest of the customer to have their agent also use a Pareto efficient search strategy combined with a concession strategy.

In Section 2 we discuss the developed system at a more conceptual level. In Section 3 we discuss the customer and seller agent in greater detail. Furthermore, we discuss the type of bargaining strategies these agents use. In Section 4 we present the results of the conducted experiments. In Section 5 we discuss the results of the paper and relate the paper to the relevant literature. Conclusions follow in Section 6.

2. A SYSTEM FOR SELLING INFORMATION GOODS

In this Section, we discuss the developed system at a more conceptual level. This has the advantage that the general framework underlying the system is drawn out more sharply. In Section 3, we give a more detailed description of some of the main components of the system.

2.1 Problem Statement

The goal is to develop a system for selling bundles of news items where customers bargain over the price and quality of the delivered goods. Customers can negotiate a contract either in advance or while the news items become available. The negotiated contract applies to a fixed time interval, which is typically a short period of time, e.g., a single day. The value customers attach to news items may fluctuate heavily due to daily dynamics. Moreover, there may be wide differences in personal interests of customers. The advantage of the developed system is that it allows for a high degree of flexibility in the price, quality, and content of the offered bundles. The price, quality and content of the delivered goods may, for example, differ based on daily dynamics and personal interest of customers.

2.2 Bundles of Information Goods

The system sells bundles of news items which become available during a predefined and fixed time interval (e.g., a day). Within the system, prices vary based on the content and the "quality of service" of the bundle. A bundle content defines the number and type of news categories the bundle contains. The system distinguishes between k categories. Within a category the system distinguishes between two quality of service levels: either a customer receives all the headlines of the articles or she receives the complete news articles. In the former case we speak of low quality of service, whereas in the latter case we speak of high quality of service.

A customer bargains with the seller over the bundle tariff. The negotiated tariff is a two-part tariff with a fixed and variable price. The fixed price (p_f) is the price a customer pays for receiving the bundle content with the specified quality of service. Moreover, the variable price (p_v) is the price the customer pays if she wants to read a full article where the quality of service only specifies delivery of the article headline.

Consider, for example, the bundle content religion, culture, and politics, where the category religion has a high quality of service and the other two have a low quality of service. Then the customer pays a fixed price for receiving all the full articles in the category religion and only the headlines of all the articles which do not belong to the category religion but do belong to the other two categories. Moreover, the variable price is the price the customer pays whenever she wants to read the full article of a news item that belongs to the categories culture or politics (and does not belong to the category religion).

2.3 Bargaining with Software Agents

We employ the paradigm of "software agents", where pieces of autonomous software perform (part of) the negotiating on behalf of the users of the system. Customers and seller instruct their agent through a user interface (UI). The agents conduct the actual negotiation. Figure 1 depicts, at a high abstraction level, the bargaining process between a customer and the seller.

2.4 Bargaining Process

Bargaining occurs in an alternating exchange of offers and counter offers, typically initiated by the customer. An offer specifies the fixed price, the variable price (uniform for all low quality of service categories), the bundle content, and also the desired quality of service of the information for each category separately. The bargaining process continues until an agreement is reached or one of the bargainers terminates the process. Based on this bargaining process, figure 2 draws the bargaining protocol the customer agents and seller agent use to do the actual bargaining.

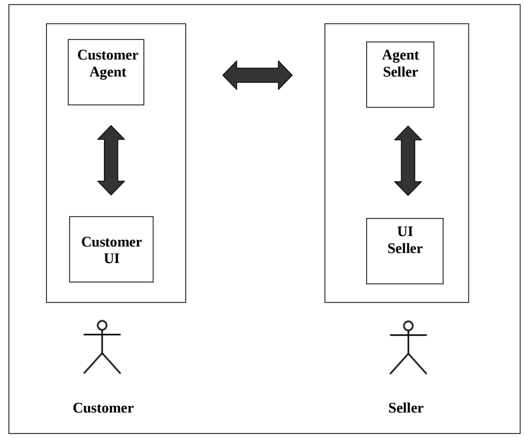

Figure 1: The one-to-one bargaining process

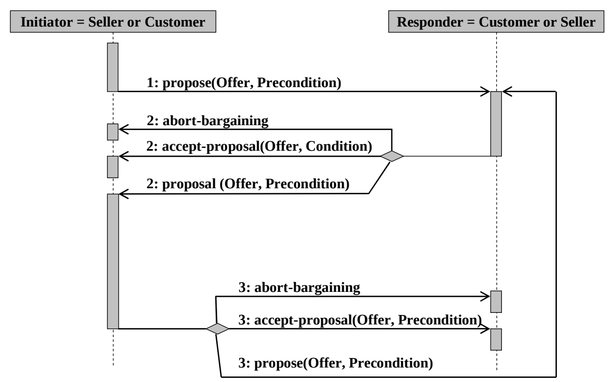

Figure 2: The agents bargaining protocol

To accelerate the negotiation process, we allow concurrent negotiation threads for the same bundle content with different quality of service. The customer can therefore submit several offers at the same time. In order to discern between threads, each thread must have a different quality configuration for the categories where a quality configuration specifies the quality of service for all the bundle categories. The seller can only respond by varying the fixed and variable price. The thread in which the agreement is reached first determines the tariff and quality configuration for the desired categories.

2.5 Fairness & One-to-Many Bargaining

A possible drawback of bargaining is that two customers may end up paying a substantially different price for very similar bundles. Customers may perceive this as unfair. This is an important concern for the seller, since customers may become dissatisfied or stop using the system altogether.

In the system a notion of fairness is incorporated into the bargaining strategy the seller agent uses. More specifically, the seller agent makes equivalent offers to customers who are interested in identical bundles. For offers that specify identical bundles, the actual tariff may still differ from customer to customer. Fairness, however, ensures that the expected revenue of these tariffs is identical for all (counter) offers submitted by the seller agent; the expected revenue (r) of a tariff (p_f, p_v) for a particular bundle is defined as follows:

$$r = p_f + p_v \cdot E_r, \quad (1)$$

where E_r denotes the expected number of articles read in the low quality of service categories. The expected revenue can, however, vary through time. The offer equivalence therefore only holds within a limited time frame.

Offers submitted by customers for identical bundles and accepted by the seller could have "unfair" differences in tariffs. Therefore the system has the optional feature of using a more global procedure which ensures that identical bundles will have tariffs with identical expected revenue. The procedure checks all the bargaining outcomes (within a certain time frame) and whenever necessary adjusts an outcome— in favor of a customer— to get equivalent tariffs. Note that beside "fairness" also other business side-constraints may be implemented. The actual way in which side-constraints, such as fairness, are implemented may be important because it can alter the strategic behavior of customers. It is however beyond the scope of the paper to discuss these issues.

The actual bargaining process between seller and customers is not really one-to-one bargaining between seller and customer but instead is one-to-many. On the one hand, the seller can use his experience in other ongoing bargaining processes between customers to adjust his bargaining strategy; under true one-to-one bargaining the bargaining strategy only depends on the moves of the direct opponent. On the other hand, fairness and/or other side-constraints limit the bargaining options of the seller. These limitations do not apply under true one-to-one bargaining. Figure 3 depicts the one-to-many bargaining process and the possibility of parallel negotiation threads between a customer and the seller.

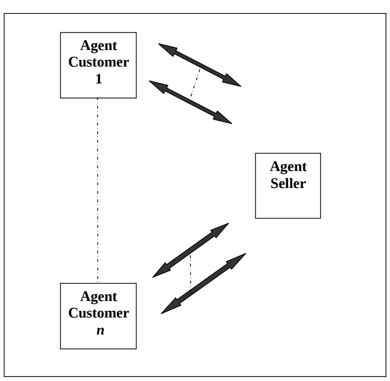

Figure 3: The one-to-many bargaining with parallel threads

2.6 Concluding Remarks

In this Section we introduced a novel system for selling bundles of news items. Through the system, customers bargain with the seller over the price and quality of the delivered goods. Autonomous software agents execute the negotiation on behalf of the users of the system. To accelerate the bargaining process customers can initiate concurrent negotiation threads for the same bundle content with different quality of service. Furthermore, the system is capable of taking into account business related constraints such as fairness. Partly, due to these side-constraints the actual bargaining process is one-to-many.

3. AGENTS & BARGAINING

In this Section we discuss the customer agent and seller agent in greater detail. Additionally, we discuss the bargaining strategies the agent may use. The novelty of these strategies is that— from a system design perspective— they generate good (i.e., closely approximate Pareto efficient) multi-issue bargaining outcomes.

3.1 Agents

3.1.1 Seller agent

The seller agent discriminates between different customers. Due to the fairness constraint discrimination should be based on differences in the preferred bundle content and/or quality of service. In the system, the seller discriminates, for example, by varying the desired expected revenue per article based on the quality of service.

Recall from equation (2.5) that the expected revenue of a tariff (p_f, p_v) for a particular bundle equals $p_f + p_v \cdot E_r$, where E_r denotes the number of expected articles read in the low quality of service categories. The agent can asses the expected number of article read, for example, based on aggregate past sales data. The agent does not need to use individual customer data for the negotiation.

3.1.2 Customer Agent

The customer agent acts on behalf of the customer. The customer can indicate her preferences by specifying, for each information category she is interested in, the amount of articles she expects to read. The customer can furthermore select between several negotiation strategies to be used by the agent and specify a maximum budget b_{max}. The budget provides the agent with a mandate for the negotiation; the total expected costs should not exceed b_{max}. Given a tariff (p_f, p_v) for a particular bundle, customer's expected cost is defined identically to seller's expected revenue (see equation (2.5)). However, E_r the number of expected articles read in the low quality of service categories is now determined differently. It is based on the amounts the customer expects to reed per category.

Given the customer's instructions specified above, the agent is able to translate the customer's preferences into offers and also respond to the seller's offers as to reach efficient deals.

The negotiation protocol allows for multiple negotiation threads for the same bundle content (see Section 2.4). Given a bundle content with n categories, in principle 2^n threads are possible (by varying the quality of service for each category). The customer agent, however, selects only a limited number of combinations based on the customer's preferences, to reduce the amount of communication. In the current system the customer agent initiates $n+1$ threads. In the first thread the quality of service for all categories is set to low. In the second thread, only the quality of service for the category with the highest expected articles read is set to high. In the third thread, this is done for the two categories with the first and second highest expected articles read, and so on. Within a thread, a fixed price and a variable price are negotiated.

3.2 Disentangling Bargaining Strategy

The customer agents and seller agent contain various bargaining strategies to do the actual bargaining over the two-part tariff. These strategies make use of the notion of a utility function to represent the bargainers' preferences for the various tariffs. We introduce the novel approach of disentangling bargaining strategies into concession strategies and "Pareto search" strategies.

Concession strategies determine what the desired utility level of an offer will be given a particular sequence of offers and counter offers. Algorithms that implement Pareto search strategies determine, given a particular utility level and a particular history of offers and counter offers, what the multi-issue offer will be, i.e., the fixed price p_f and the variable price p_v of the two part tariff. In terms of a multivariable utility function a counter offer entails both a movement off the iso-utility line and a movement along the iso-utility line. (Given a specified utility level, an iso-utily line specifies all the p_f and p_v points which generate identical utility.) Concession strategies determine the movement of an iso-utility line; Pareto search strategies determine the movement along an iso-utility line.

Pareto search strategies aim at reaching agreement as soon as the respective "concession" strategies permit this. Therefore it may be good for both parties to use it. In more economic terms a negotiated tariff is called Pareto efficient if it is impossible to change the tariff without making one of the bargainers worse off, i.e., one of the bargainers will always attach a lower (or equal) utility to the adjusted tariff. From a system design perspective Pareto efficiency of the negotiated tariffs is clearly desirable.

In Section 3.3 we introduce a particular class of Pareto search algorithms. The experiments in Section 4 show that if the seller agent uses this Pareto search algorithm and customer agents use a similar Pareto search algorithm, then the bargaining outcome will closely approximate a Pareto efficient solution given a wide variety of concession strategies.

In the system the seller agent uses an instance of the Pareto efficient search algorithms combined with a concession strategy. Although a customer is free to select other bargaining strategies the system is set up such that it is actually in the best interest of customers to have their agents use Pareto search strategies combined with a concession strategy. We elaborate on this issue in the discussion in Section 5.

3.3 Orthogonal Strategy & DF

Both customer agent and seller agent may use— what we call— an orthogonal strategy as the Pareto search algorithm. This strategy is probably best explained through an example. Suppose, the customer (with whom the seller bargains over the tariff) placed the t^{th} offer of $(p_f(t), p_v(t))$. Moreover, the seller's concession strategy dictates an *aspiration level* of $U_s(t+1)$: i.e., in utils the (counter) offer should be worth $U_s(t+1)$. Based on this information the orthogonal strategy determines $(p_f(t+1), p_v(t+1))$, the counter offer of the seller, by choosing a (p_f, p_v) combination that generates $U_s(t+1)$ utils and lies closest (measured in Euclidean distance) to the point $(p_f(t), p_v(t))$. Figure 4 gives the graphical representation of the orthogonal strategy.

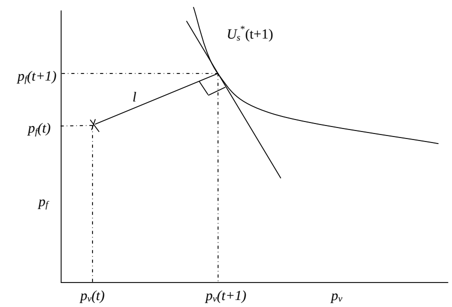

Figure 4: Example of Orthogonal Strategy

The use of the orthogonal strategy by both parties results in a mapping f from a bargainer's aspiration level at t to the aspiration level at $t+2$. Given convex preferences (cf. [12]) and fixed aspiration levels the mapping f can be shown to satisfy the Lipschitz condition $||f(x) - f(y)|| \leq ||x - y||$ for all x and y in the domain of f.[1] Thus, given fixed aspiration levels and convex preferences, the orthogonal strategy does imply that consecutive offers do not diverge. Figure 5 illustrates the use of the orthogonal strategy by both parties in the case their iso-utlity lines intersect. It draws a sequence of two offers and counter offers with convex preferences and a fixed aspiration level. (U_s and U_c denote the iso-utility lines of the seller and shop, respectively.)

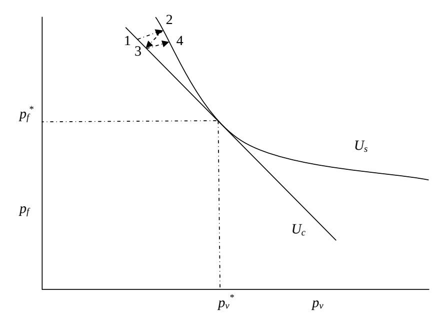

Figure 5: Sequence of two offers and counter offers with fixed aspiration levels and convex preferences, where (p_f^*, p_v^*) denotes a Pareto Efficient tarrif.

The use of just the orthogonal strategy by both parties may lead to very slow converge to Pareto efficient bargaining outcomes. To speed up the convergence process we can

[1]The proof is a straightforward application of convex analysis (cf. [15]) given that without loss of generality we can assume that the preferences are bounded, i.e., negative and extremely high $(p_f(t), p_v(t))$ combination can, without loss of generality, be discarded.

add an amplifying mechanism to the orthogonal strategy. As the amplifying mechanism we use the derivative follower with adaptive step-size (ADF). (Henceforth we will call this the orthogonal-DF.) The derivative follower (DF) is a local search algorithm (cf. [8, 7, 10]). It adjust the variable price p_v found by the orthogonal strategy by either subtracting or adding δ to it, where δ is called the step-size of the DF. Consequently also the fixed price p_f changes because the adjusted offer still needs to generate the same utility level (specified by the concession strategy). The difference between ADF and DF is that the step-size δ becomes adaptive [4, 14]; this allows for quicker searching by "amplification" of the step-size if searched in the proper direction (see below). We use the ADF proposed by [14] because it has nice convergence properties.

The direction of the step-size— i.e., subtracting or adding $\delta(t)$— is determined based on the last two offers of the opponent. The direction changes whenever the (Euclidian) distance of the opponent's last offer decreases compared to the previous offers. Otherwise, the direction remains unchanged.

Consider one of the bargainers, let $(p_f(t-2), p_v(t-2))$ and $(p_f(t), p_v(t))$ denote the opponent's last two offers. The distance of an offer is then computed as follows. First, the orthogonal strategy computes the corresponding "response" offers $(p'_f(t-2), p'_v(t-2))$ and $(p'_f(t),\ p'_v(t))$ on the bargainer's *current* utility function corresponding to the utility level $U(t+1)$. That is, $(p'_f(t-2),\ p'_v(t-2))$ and $(p'_f(t),\ p'_v(t))$ are points that generate $U(t+1)$ utils and lie closest (measured in Euclidean distance) to the points $(p_f(t-2),\ p_v(t-2))$ and $(p_f(t),\ p_v(t))$, respectively. Then the distance of an offer is the (Euclidian) distance between the original offer and the corresponding offer in the (p_f, p_v) plane (e.g., the distance between the points $(p'_f(t), p'_v(t))$ and $(p_f(t), p_v(t))$.

In a multi-issue bargain situation there is a whole set of Pareto efficient solution. As a result of the concessions during bargaining this set shrinks. Ideally, bargaining will eventually result in a skeleton set of Pareto efficient solution which represents the bargaining outcome. Due to this dynamics the search strategy needs to be response enough and yet have sufficiently nice convergence properties such that the offers lie closer and closer to the current set of Pareto efficient solutions. The intuition underlying the orthogonal-DF is that it combines these two properties.

4. EXPERIMENTS

In this section we show by means of computer experiments the effectiveness of the orthogonal and derivative follower approach to find Pareto-efficient solutions. Furthermore, we evaluate the robustness of the search strategy by experimenting with various concession strategies on the customer side. First we discuss the experimental settings in subsection 4.1, followed by the concession strategies in subsection 4.2. The results are discussed in subsection 4.3.

4.1 Settings

We simulate the negotiation with a variety of customer and seller preferences. Although concurrent negotiation threads can significantly speed up the negotiation process, within a thread the Pareto search strategy operates independently from the other thread. For researching the efficiency and robustness of Pareto efficient search strategies it, therefore, suffices to consider only a single negotiation thread in the experiments. Furthermore, the bundle content consists of a single category with a low quality of service. The experimental results generalize to negotiations involving multiple categories. Only the shape of the iso-utility curves is affected by the number of categories. In the experiments the shape is varied using different parameter settings.

Customer's utility is based on the total expected costs of reading all the desired articles in a bundle. The customer agent's expected clicks (i.e., the number of articles the customer expects to read) for the category is randomly set between 1 and 20. This results in a linear iso-utility curve in the (p_f, p_v) plane (see Fig. 5). The seller agent uses an aggregate measure of expected clicks, which is fixed for the duration of the experiment. The expected clicks for the seller is a linear function of the variable price p_v with slope α; customers with a very high variable price are more likely to click less than customers with a low variable price (i.e. we assume the law of demand holds cf. [12]). As a result, the seller's iso-utility curve is convex (towards the origin). We vary the slope α in the experiments. Furthermore, we vary the customer's initial desired utility level randomly.

4.2 Concession strategies

The concession strategy can be selected by the customer and the seller. Although the seller's concession strategy in the main system can depend on the behavior of all customers (i.e., one-to-many), in the simulation the seller agent simply uses a strategy with a fixed concession per round. However, we implemented four classes of concession strategies on the customer side to test the robustness of the Pareto search strategy:

- *Hardhead.* The customer agent does not concede when this strategy is used; the desired utility remains at the same level during the negotiations.
- *Fixed.* A fixed amount c in utils is conceded each round.
- *Fraction.* The customer concedes the fraction γ of the difference between the current desired utility level and the utility of the opponent's last offer.
- *Tit-for-tat.* This strategy mimics the concession behavior of the opponent, based on subjective utility improvement. If the utility level of the seller's offers increases, the same amount is conceded by the customer. Note that it is the increment in the utility level perceived by the customer. The seller's actual concession is shielded from the customer agent, as an improvement could also occur when the seller moves along his iso-utility curve. Furthermore, note that the perceived utility improvement could also be negative. To make the concession behavior less chaotic, no negative concessions are made by the customer.

4.3 Results

The seller and the customer in the experiments negotiate until an agreement is reached. The efficiency of the agreement is then evaluated based on the distance of the final offer from a Pareto-efficient solution. We measure an offer's distance from a Pareto-efficient solution as the maximum possible utility improvement for the customer if a Pareto-efficient offer was made, all else remaining equal.

Concession strategy	Random search	Orthogonal/DF search	DF/DF search
hardhead	18.92 (±23.56)	**8.03** (±11.44)	18.63 (±32.81)
fixed ($c = 20$)	26.52 (±34.49)	**10.43** (±17.34)	28.82 (±46.71)
fixed ($c = 40$)	38.91 (±49.72)	**16.21** (±23.84)	44.29 (±69.76)
fixed ($c = 80$)	42.12 (±56.88)	**25.61** (±38.72)	48.84 (±72.12)
fraction ($\gamma = 0.025$)	30.26 (±38.37)	**10.07** (±15.03)	32.25 (±52.81)
fraction ($\gamma = 0.05$)	31.53 (±40.00)	**11.52** (±16.16)	28.52 (±52.13)
fraction ($\gamma = 0.1$)	37.81 (±48.82)	**16.91** (±30.80)	26.28 (±42.20)
tit-for-tat	72.78 (±121.35)	**59.60** (±113.27)	56.64 (±116.82)

Table 1: Average distance from Pareto-efficient solution for various customer concession strategies (rows) and customer/seller search strategies (columns). Results are averaged over 500 experiments with random parameter settings. Standard deviations are indicated between brackets. Best results (see column 3) are obtained if the customer and the seller use orthogonal search, and the seller's search is amplified with a derivative follower (DF).

Table 1 shows the results for various concession strategies of the customer and various search strategies. The second row of Table 1 shows the outcomes when both seller and customer use a random search strategy. This strategy selects a random point on the iso-utility curve[2]. The distance of the final offer when random search is used, lies between 1 and 3 percent of the total costs.

Although the inefficiency with random search is only a small fraction of the total costs, even better results are obtained when one bargainer uses orthogonal search and the other uses orthogonal-DF (i.e., orthogonal search combined with a derivative follower). The distance of the final offer as a percentage of total costs lies then, for almost all concession strategies, between 0 and 1. Only for the tit-for-tat strategy the distance lies between 1 and 2 percent. The third column in Table 1 shows the results when the customer uses the orthogonal search strategy and the seller uses orthogonal search amplified with a derivative follower. The improvements are considerable. Notice that this search strategy combination is also robust, as it works good relatively independently of the concession strategy selected by the customer.

Table 1 also shows the results if both customer and seller use an amplified orthogonal search (row 4). These results are very similar to random, however. The derivative follower relies on a consistent response from the opponent to signal the right direction. If both use a derivative follower, this signal is distorted.

Notice that the distance also depends on the concession strategy used by the customer. Particularly *tit-for-tat* results in a relatively high inefficiency. Recall that tit-for-tat uses a subjective measure of the opponent's concessions. In practice, the perceived utility increments are sometimes quite large, resulting in bursts of large concessions. If this occurs near the agreement point, the concession is much larger than necessary, resulting in inefficient outcomes. A similar effect occurs with a fixed concession strategy when the concession c is high.

[2]Only the downward sloping part of the seller's iso-utility curve is used.

5. DISCUSSION

5.1 The System Revisited

In the paper, we focus on the problem of selling bundles of news items. Clearly, other types of (information) goods can also be sold through the developed system. A key question for extending the use of the system to other application areas is, however, if customers and (to a lesser degree) sellers are willing to have (autonomous) agents do the actual bargaining for them. A prerequisite would be that the traded goods have a relatively low value and transactions are conducted frequently. Consequently, the risks are low and an agent has a lot of opportunities to learn from past experience and gradually improve performance. Note that the negotiation procedure of the system does not require both seller and customer to use the same level of automation. Depending on the particular application of the system, it may be desirable for the customer to rely more or less on the assistant of the software agent.

An additional important aspect of the relevance to other application areas is the potential benefit of using such a system. The developed system appears particular suitable for selling (bundles) of goods with a high degree of personalization given relatively rapidly changing preferences (as is the case with the news items). More specifically, in the system personalization entails discriminating between customers based on the bundle price and the quality of service. Second-degree price discrimination is the economic term for this type of personalization.

In second-degree price discrimination the price depends on the quantity and/or quality of the purchased good (cf. [16]). The distinguishing aspect of second-degree price discrimination is that customers can *self-select* the best purchase. Traditionally, customers are offered a menu of options where a tariff assigns a price to the option in the menu. The work of [3, 9] discusses algorithms which— given a particular tariff structure— learn the best tariffs on-line. They conclude that (especially in a dynamic environment) complex tariffs are generally not the most profitable strategy.

The distinguishing aspect of the developed system is that instead of having explicit tariffs customers can bargain for the most appropriate bundle tariff combination. This can result in a similar (or even higher) degree of discrimination between customers as with explicit complex tariff. In the absence of an explicit tariff structure the seller is, however, more flexible in the degree to which she discriminates. The seller does not have to a priori limit the complexity of the tariff structure. Whenever bundles of (information) goods are being offered, an additional advantage is that, by initiating the negotiation process, customers can explicitly express their interest in a particular bundle of goods. This may facilitate the process of offering customers the appropriate bundles (and consequently it may facilitate the discrimination between customers).

Possibly, bargaining leads to price discrimination based on customers' bargaining skills and not on their preferences. In the developed system this possibility is, however, reduced significantly by the fairness constraint in particular and the fact that bargaining is actually one-to-many in general.

5.2 Bargaining & Pareto Efficiency

In the system the seller agent uses the orthogonal-DF as the Pareto search strategy combined with a concession strategy. The concession strategy determines the next concession relatively independently of the ongoing bargaining process with a particular customer. The idea is that, on the one hand, bargaining with a particular customer should lead to finding the best possible deal for both parties, given the seller's desired utility level. That is, the bargaining outcome should closely approximate a Pareto efficient solution. On the other hand, the one-to-many aspect of the bargaining process (i.e., bargaining with more than one customer) should guide the updating of the concession strategy. Thus the seller uses the disentanglement of the bargaining strategy (in a concession and Pareto search strategy) to distinguish explicitly between the one-to-many and one-to-one aspects of the bargaining process.

The experiments in Section 4 show that if a customer agent uses an orthogonal strategy as the Pareto efficient search strategy then the bargaining outcomes will closely approximate a Pareto efficient solution. The experiments are conducted for a variety of (customer) concession strategies, customer preferences, and seller preferences. Based on the experimental results we can conclude that any other strategy choice of a customer will probably result in less efficient outcomes. Moreover such a strategy will not influence the concession strategy of the seller (due to the independence of the concession strategy). Consequently, any alternative bargaining strategy of the customer is probably at most as good as the orthogonal strategy combined with a concession strategy that mimics the concessions of the alternative strategy. Thus, given the seller's choice of the orthogonal-DF combined with a relatively independent concession strategy, it is in a customer's best interest to choose the orthogonal search strategy combined with a concession strategy. Moreover, this choice results in (a close approximation of a) Pareto efficient solution.

Rather than via direct negotiation, another way to find (Pareto) efficient solutions for multi-issue problems is through a mediator, see for instance [5, 11, 13]. Both parties need to reveal their preferences to the mediator. With a mediator, however, trust becomes an important issue. Furthermore, additional costs are often involved.

Related to our work, in [6] a heuristic approach to finding win-win trade-offs between issues is introduced. Contracts which are similar to the opponent's offer are selected based on fuzzy similarity criteria. Their approach, however, is applied to additive utility functions with independent issues. The orthogonal search method, on the other hand, operates on a more general class of utility functions, which is widely accepted in the economic literature as a reasonable representation for ones preferences.[3] Additionally, with an orthogonal search method no (domain-specific) similarity function needs to be specified.

[3]More specifically, with convex preferences the approach works particularly well.

6. CONCLUDING REMARKS

We developed a novel system for selling bundles of news items. Through the system, customers bargain over the price and quality of the delivered goods with the seller. The advantage of the developed system is that it allows for a high degree of flexibility in the price, quality, and content of the offered bundles. The price, quality, and content of the delivered goods may, for example, differ based on daily dynamics and personal interest of customers.

The system as developed can take into account business related side-constraints, such as "fairness" of the bargaining outcomes. Partly due to these side-constraints (especially fairness) the actual bargaining process between seller and customers is not really one-to-one bargaining between seller and customer but instead is one-to-many (i.e., between seller and customers).

Pieces of autonomous software agents perform (part of) the negotiation on behalf of the users of the system. To enable efficient negotiation through these agents we present the novel approach of disentangling the bargaining strategies into concession strategies and Pareto efficient search strategies. We show through computer experiments that this approach will result in very efficient bargaining outcomes. Moreover, the system is setup such that it is actually in the best interest of the customer to have their agent adhere to this approach of disentangling the bargaining strategy into a concession strategy and Pareto efficient search strategy.

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