

Ordering Effects and Belief Adjustment in the Use of Comparison Shopping Agents

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Abstract

The popularity of online shopping has contributed to the development of comparison shopping agents (CSAs) aiming to facilitate buyers' ability to compare prices of online stores for any desired product. Furthermore, the plethora of CSAs in today's markets enables buyers to query more than a single CSA when shopping, thus expanding even further the list of sellers whose prices they obtain. This potentially decreases the chance of a purchase based on the prices outputted as a result of any single query, and consequently decreases each CSAs' expected revenue per-query. Obviously, a CSA can improve its competence in such settings by acquiring more sellers' prices, potentially resulting in a more attractive "best price". In this paper we suggest a complementary approach that improves the attractiveness of a CSA by presenting the prices to the user in a specific intelligent manner, which is based on known cognitive-biases. The advantage of this approach is its ability to affect the buyer's tendency to terminate her search for a better price, hence avoid querying further CSAs, without having the CSA spend any of its resources on finding better prices to present. The effectiveness of our method is demonstrated using real data, collected from four CSAs for five products. Our experiments with people confirm that the suggested method effectively influence people in a way that is highly advantageous to the CSA.

Introduction

The Internet boom of the late 1990s has created new avenues for merchants to sell their products. The popularity of online shopping is still growing, and today's electronic-markets are populated by thousands of sellers who offer potentially unlimited alternatives to satisfy the demand of consumers. This increase in the number of available options has substantially decreased the cost of obtaining information pertaining to price and other product characteristics, compared to physical markets. Yet, it has posed new challenges, in the form of processing and managing the continuous stream of information one can potentially collect. Naturally, this has led to the emergence of comparison shopping agents (CSAs) such as [PriceGrabber.com](#), [bizrate.com](#) and [Shopper.com](#), offering an easy to use interface for locating, collecting and presenting price-related data for practically any item of interest to consumers. These web-based

intelligent software applications allow consumers to compare many online stores prices at once, saving them much time and money (Pathak 2010).

Naturally, having many CSAs one can use, each offering practically the same functionality, means some competition between them. The 18th annual release of [ShoppingBots and Online Shopping Resources for 2014](#) ([shoppingbots.info](#)) lists more than 350 different CSAs that are currently available online. This rich set of comparison-shopping options that are available over the Internet suggests that prospective buyers may query more than a single CSA, in order to find the best (i.e., minimal) price prior to making a purchase. Indeed, a recent consumer intelligence report (Knight 2010) reveals that the average number of CSAs visited by motor insurance switchers in 2009 was 2.14. This poses a great challenge for CSAs, since the common way for CSAs to generate revenue is through commercial relationships with the sellers they list (most commonly in the form of a fixed payment they receive each time a consumer is referred to the seller's website from the CSA) (Moraga-Gonzalez and Wildenbeest 2012). Therefore, CSAs are forced to differentiate themselves and act intelligently in order to affect the buyers' decision to make their purchases through the CSA's website. If a CSA could influence buyers to avoid querying additional CSAs, it would certainly improve its expected revenue.

There are several methods to affect consumers' decision to terminate their search for a better price. The most straightforward technique is to invest more of the CSA's resources (i.e., time, memory, bandwidth, etc.) in collecting as many prices as possible from different sellers, in order to increase the probability that a highly competitive price is found. However, there is always the risk that other CSAs have succeeded to gather approximately the same set of prices with less resources, thus a CSA should carefully examine whether such resource investment is worthwhile. Alternatively, the CSA may attempt to influence the buyer's expectations regarding the prices she is likely to encounter by disclosing only a subset of all the prices collected by the CSA (Hajaj et al. 2013).

In this paper we take a different approach, which does not alter the set of prices, or requires consuming additional resources in order to increase the set, to influence the probability that a buyer querying a CSA will not continue querying

additional CSAs after. Our method influences human buyers to believe that querying additional CSA is not worthwhile. The method uses known cognitive (psychological-based) biases and is based on two main innovative aspects. First, the method presents the prices to the user in a sequential way, one after the other, unlike the common method of today's CSAs that present all the prices at once, right after the user has specified her query. In addition, the prices are added to the user's display in a specific (intelligent) order.

We evaluated the effectiveness of our method in experiments with real people, using data collected from real CSAs on real products. The experiments confirmed that our method is highly effective in adjusting buyers' beliefs as it increases the probability that a buyer will not continue querying additional CSAs. Moreover, the results of a complementary experiment that is reported in the paper indicate that both aspects of the new approach are responsible to the improvement achieved; namely, a sequential presentation of prices without the intelligent ordering is not effective. Our method is fast and simple to implement, and does not require the consumption of any other CSAs resources such as communication with additional sellers or complex computations.

We note that the effects of positioning different items in different orders were largely studied in the field of behavioral science (Ullmann-Margalit and Morgenbesser 1977; Nisbett and Wilson 1977; Bar-Hillel 2011). Yet, we are not aware of any work that used positioning of the same item (but with different prices) in order to influence human beliefs. Moreover, the novelty of our approach is neither in the identification nor in the analysis of cognitive biases that are involved in human decision making. Rather, we were able to implement an algorithm that utilizes these biases and experimentally show how an intelligent agent can use this algorithm to its advantage. The encouraging results reported in the paper are a compelling argument for changing the way that today's CSAs choose to present prices to their users.

Market Overview

The method we present in the paper applies to online shopping environments with numerous human buyers, sellers and several CSAs. Buyers typically attempt to find the product in a low price, nevertheless take into consideration the time spent searching. Therefore they usually attempt to minimize their overall expected expense, weighing in somehow the cost of time spent throughout the process. CSAs operate in these environments as middle-agents (Decker, Sycara, and Williamson 1997), collecting the prices that are posted by different sellers and presenting them to the buyers in a compact and organized manner (Bakos 1997; Kephart and Greenwald 2002). Therefore, upon querying a CSA, the buyer needs to decide, based on the results obtained, whether to terminate her price search process and purchase the product or spend more time on querying other CSAs or sellers.

Since CSAs are self-interested fully-rational agents, their goal is to maximize the probability that a buyer querying them will not query another CSA, hereafter termed the "termination probability". This is because the common practice

in today's markets is that the CSAs' revenue is based on fixed payments or commissions obtained from sellers whenever a buyer, referred to their website by the CSA, executes a transaction (Wan and Peng 2010; Moraga-Gonzalez and Wildenbeest 2012). Therefore in order to maximize their own expected profit, CSAs should attempt to reduce further competition once being queried by influencing the buyer to make immediate purchase rather than query additional CSAs.

In the following section we present our method, denoted the "belief-adjustment", for influencing buyers to terminate search and purchase the product upon querying a CSA.

The Belief-Adjustment Method

It is well known that people do not always make optimal decisions and may be affected by psychological properties (Baumeister 2003). Therefore, there is an opportunity for the CSAs to use a belief-adjustment method based on cognitive biases to affect the buyer in a way that encourages her to terminate her search, hence increasing the overall termination probability. The most common method for presenting prices to the buyer in today's markets is to present all the prices that were gathered for a specific product at once, immediately after the buyer has specified her query. This method, which we denote "bulk", is currently the dominating method for CSAs, commonly used by *PriceGrabber.com*, *bizrate.com* and *Shopper.com*, as well as others. We propose a different method which is both sequential and intelligent to in the manner of the prices presentation order.

There is extensive empirical evidence in literature showing that shoppers are mostly sensitive to price (Rao and Monroe 1989; Piercy, Cravens, and Lane 2010). For example, according to a 2013 survey by *dunnhumby.com*, which is based on a database of in-store purchase behavior of over 60 million U.S. households, the price, even more than convenience, is the most important factor determining where consumers decide to shop. In addition, it was found that 52% of American consumers agree that the price of a product is more important than the brand name. For that reason, and similar to all CSAs' implementations nowadays, our method keeps the list of results presented to the buyer sorted according to price in an ascending order, allowing her to focus on the minimum price found at anytime, which is listed first. However, in contrast to most CSAs, our method presents prices in a sequential manner, one after the other, rather than all at once. A sequential presentation of the prices builds an impression that the prices are presented according to the order the CSA finds them when it collects prices from sellers in the market. In addition, our belief-adjustment method chooses the order in which prices are added to the user's display, termed hereafter the "presentation order", making advantage of several known cognitive biases as explained in the following paragraphs.

The extraction of the sequence according to which the prices the CSA has in hand will be added to the user display is divided to three main phases. In the first phase (denoted "**anchor**"), the method attempts to affect the user's

expectation regarding the possible price range of the product in the market, in order to create an initial reference point/anchor (Kahneman 1992). The motivation for this psychological bias is based on the well-known anchoring-and-conservative-adjustment estimation method by (Tversky and Kahneman 1974). We note that the best price known to the CSA is not included in this initial set of prices, intentionally, to increase the best price’s attractiveness in the next phase. In the second phase (denoted “**effort**”), the method attempts to affect the user’s expectation regarding the intricacies in finding the best price. The method builds the impression that there is need for an extensive sellers’ search in order to further improve the best finding, which takes a considerable amount of time. In addition, the “effort” phase attempts to affect the user’s belief that even after an extensive sellers’ search, most of the new prices that are found are higher than the prices in the set of reference point prices. The final phase (denoted “**despair**”) is meant to build the impression that querying another CSA is worthless. The method demonstrates that investing additional time in querying the prices from the remaining set of sellers does not yield a better price, thus the set of best prices that were already found by the CSA is rare and unique. To summarize, the first phase creates an initial expectation regarding the prices in the market, the second phase creates a belief regarding the hardness of finding low prices and the last phase forms a belief regarding the non-attractiveness of querying competing CSAs, given the information from the previous phases. The above concepts were implemented as described in Algorithm 1, and the division of prices into different phases is illustrated in Figure 1 for a specific set of prices.

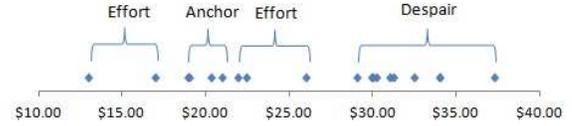


Figure 1: Division of prices into different phases for a Lexmark Black Ink Cartridge. Prices were sampled from Bizrate.com.

is the set’s lowest price followed by the set’s highest price. The second tuple is the second lowest price followed by the second highest price and so on. This fluctuation is intended to create the impression that the prices converge to a specific price and that the overall price range in the market is probably similar to the range of the anchor prices.

In the “effort” phase (steps 3,4,8-10), the algorithm adds two sets of prices to the sequence: *effortMin*, which contains the best prices known to the CSA, and *effortMid*, which is twice the size of *effortMin* and contains prices that are a bit more expensive than the anchor prices. It thus creates the belief that the CSA managed to find few prices that are better than the usual prices in the market, even though there is not much room for improvement.

Finally, the “despair” phase of the method (steps 5,11) aims to convince the user that additional search does not result in any better prices than those found so far. Hence, the CSA adds all the remaining prices to the sequence, and each of these prices is higher than any of the prices put in the sequence in the previous two phases.

Since there is need for a considerable amount of prices for the “despair” phase, the top half of prices known to the CSA ($sp_7 - sp_{12}$) is reserved for that phase, and the bottom half of prices ($sp_1 - sp_6$) is divided equally between the “anchor” and the “effort” phases. In addition, the prices of “effort” are divided into two sets of prices, *effortMid* and *effortMin*, where *effortMid* is twice the size of *effortMin*. Therefore, the algorithm divides the set of prices into twelve equal parts (step 2-5).¹

Experimental Design

In order to test the effectiveness of our method we compared the termination probability achieved when presenting the prices according to our belief-adjustment method with the one achieved when presenting the prices according to the bulk method, which is the common method for CSAs’ implementation nowadays. For this purpose, we conducted online experiments using Amazon Mechanical Turk (AMT), a platform in which it has been well established that participants exhibit the same heuristics and biases as in lab experiments and pay attention to directions at least as much as subjects from traditional sources (Mason and Suri 2012). The experimental infrastructure developed for the experiments is a web-based application that emulates an online CSA website. In order to ensure that our results are applicable to real markets, we sampled, for the

Algorithm 1: Belief-Adjustment Method

Input: *sampledPrices* - Set of sorted known prices

Output: *order* - An ordered vector of the prices

- 1 Divide *sampledPrices* to 12 equal parts $\{sp_1, \dots, sp_{12}\}$
 - 2 $anchor \leftarrow \{sp_2, sp_3, sp_4\}$
 - 3 $effortMin \leftarrow sp_1$
 - 4 $effortMid \leftarrow \{sp_5, sp_6\}$
 - 5 $despair \leftarrow \{sp_7, sp_8, sp_9, sp_{10}, sp_{11}, sp_{12}\}$
 - Phase I : Anchor
 - 6 **for** $i \leftarrow 1$ **to** $|anchor|$ **do**
 - 7 $\left\{ \begin{array}{l} \text{Iterate between moving the minimal and the} \\ \text{maximal price from } anchor \text{ to } order. \end{array} \right.$
 - Phase II : Effort
 - 8 **for** $i \leftarrow 1$ **to** $|effortMin|$ **do**
 - 9 $\left\{ \begin{array}{l} \text{move two random prices from } effortMid \text{ to } order. \\ \text{move a random price from } effortMin \text{ to } order. \end{array} \right.$
 - Phase III : Despair
 - 11 move a random permutation of *despair* to *order*
 - 12 **return** *order*
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The algorithms divides the set of sorted prices into twelve equal subsets (the reason for this specific division will be explained below). For the “anchor” phase (steps 2,6,7), it uses the second best subset of prices, and orders the prices in that set in the following manner: The first tuple of prices

¹The size of each part is rounded to the nearest integer if the total number of prices does not divide evenly by twelve.

sake of the experiments, the prices of five different products from four well-known CSAs: PriceGrabber.com, Nextag.com, Bizrate.com and Amazon.com as depicted in Table 1. The sampled prices of the products ranged from \$13 to \$350, and as can be seen from the table, the products picked highly vary in their essence and the number of prices available for them if querying the CSAs.

Product	Sampled from	# of prices
Logitech Keyboard & Mouse ("Combo")	Nextag.com	10
Garmin Portable GPS Navigator ("GPS")	PriceGrabber.com	19
Lexmark Ink Cartridge ("Cartridge")	Bizrate.com	19
64GB Firma Flash Drive ("Flash")	Amazon.com	20
HP Laser Printer ("Printer")	PriceGrabber.com	29

Table 1: List of products and CSAs sampled.

Once accessing the experiments' web-based application, an opening screen with a short textual description of the domain and the experiment was presented. The participants were told that their goal is to minimize their expenses in purchasing five different products. The experiment started with a practice session, where the participants had the opportunity to become familiar with the experiment's environment. They then had to answer three questions regarding the infrastructure and the prices presented, to verify their understanding of the experiment's environment. After the participants answered all of the questions correctly, they were directed to the actual experiment. We initially divided the participants into two groups. For each product, the first group immediately obtained the full list of sellers and their prices, in order to imitate a CSA that uses the bulk method. The second group obtained the prices according to the belief-adjustment method as described in Algorithm 1, where a new price (and the seller associated with the price) was added to the participant's display every second. To prevent any learning effect from one product to another (since each participant experimented with five different products), we randomized the order of the products which were presented to the participants (e.g., the first product that the i -th participant experimented with was not necessarily the first product that the j -th participant experimented with).

As claimed before, buyers are sensitive to prices. Therefore, the emulated CSA always presented the seller that offered the product for the lowest price along with its price on the right side of its interface. In addition, for the belief-adjustment method, the new price that was added to the user's display appeared in red for half a second (in contrast to the other prices that appeared in black), to ensure that every participant noticed each new price added.

After observing all the prices of a given product, the participants were awarded their show-up fee (i.e., the "hit" reward promised in Mechanical Turk) and a bonus of a few

cents. The participants were offered to give up the bonus, in exchange for sampling a new random CSA for additional prices. The participants were told that if the querying of the random CSA results in a better price (than the current minimum), they would obtain the difference (i.e., the savings due to the better price) as a bonus. Therefore, each participant faced the same tradeoff captured by querying an additional CSA, where the bonus she needed to forgo was equivalent to the search cost (i.e., the time it takes to query the additional CSA) and the alternative bonus in the form of the improvement achieved in the best price obtained is the savings on the product cost obtained from querying the additional CSA.

In order to determine the bonus for each product properly, we followed the principle given in Hajaj et al. (2013): We first measured the mean time it takes for an average user to find the minimal price of a product given the url of the CSA's website and the product's name (60.9 seconds). Then, we multiplied this time by the average hourly salary of a worker at AMT (\$4.8) to find the (average) cost of time to query a CSA. However, the suggested calculation is applicable only for a bulk-based CSA, and we thus had to adjust it for calculating the bonus for the sequential-based CSAs. The participants did not know which method (bulk or sequential) the random CSA would choose to present its prices. Therefore, we set the initial bonus to the average between the bonus for a bulk-based CSA and a sequential-based CSA (e.g., for the "Combo" product the initial bonus was set at 9 cents).

We also wanted to test the hypothesis that an improvement in termination probability may result merely from switching the presentation type from bulk to sequential. This is important, as it can shed light on the role of proper price sequencing when it comes to improving the termination probability. Therefore, a third group was recruited for a complementary experiment. Each of the participants in this group obtained the prices in a sequential way, but with random presentation order of the prices (i.e., the order in which prices were added to the user's display was randomly chosen).

Overall, 266 participants participated in our experiments, divided into groups of 76 participants for the bulk method, 86 for the random-sequential method and 104 for the belief-adjustment method.

Results

In the first experiment we compared the termination probability that resulted from presenting the prices according to the belief-adjustment method with the termination probability that resulted from presenting the prices according to the bulk method. As depicted in Figure 2, presenting the prices according to our suggested method resulted in a higher termination probability than with the bulk method for every product tested.

The maximum improvement in the termination probability was achieved with the first product (the "Combo"), where our method increased the termination probability from 30.26% to 59.62%, which is almost twice the termination probability achieved with the bulk method. Overall, for all the products, we achieved an average improvement of 78.32% in the termination probability, (new probability - old probability)/old probability.

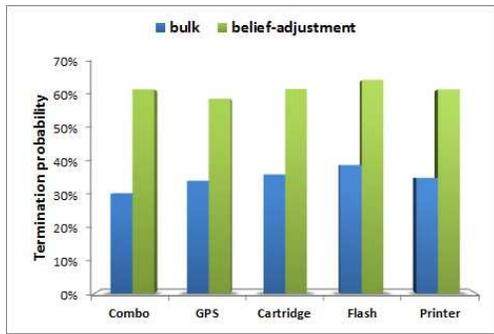


Figure 2: Comparison of the termination probability, bulk vs. belief-adjustment.

To test the statistical significance, we arranged the results in contingency tables and analyzed them using Fisher’s exact test. The increase in the termination probability is statistically significant for each of the products ($p < 0.01$), thus we conclude that our suggested belief-adjustment method is more effective than the commonly used bulk method.

Based on the above findings, one may wonder if it is possible that the improvement is an implication of the presentation of the prices in a sequential way and not a direct result of the CSA’s intelligent presentation ordering. In order to refute this hypothesis, we conducted a complementary experiment, which aims to differentiate between the presentation type effect (bulk vs. sequential) and the presentation ordering effect (random vs. belief-adjustment). We thus compared the termination probability that resulted from presenting the prices according to the belief-adjustment method with the termination probability that resulted from presenting the prices in random order. As depicted in Figure 3, presenting the prices according to the belief-adjustment method results in an higher termination probability than with the random-sequential method for every product tested.

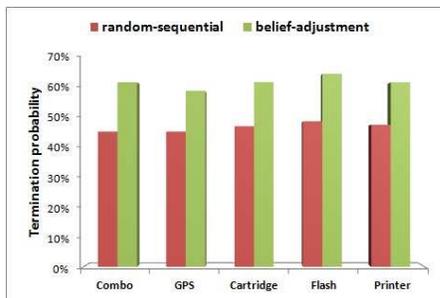


Figure 3: Comparison of the termination probability, random-sequential vs. belief-adjustment.

The maximum improvement in the termination probability was achieved with the second product (the “GPS”), where our method increased the termination probability from 45.35% to 62.50%. Overall, for all the products, we achieved an average improvement of 33.52% in the termination probability. The increase in the termination probability is statistically significant for each of the products ($p < 0.05$)

in this case as well, thus we conclude that our suggested belief-adjustment method is more effective than the presenting the prices at random-sequential manner.

In summary, we conclude that our belief-adjustment method affects peoples’ decision of whether to query additional CSAs or not. We note that there is no statistically significant difference between presenting prices according to a random-sequential order and according to the bulk method.

Related Work

The domain of comparison shopping agents has been studied extensively by researchers and market designers in recent years (Krulwich 1996; Decker, Sycara, and Williamson 1997; He, Jennings, and Leung 2003; Sarne, Kraus, and Ito 2007; Sarne 2009; Tan, Goh, and Teo 2010). CSAs are expected to reduce the search cost associated with obtaining price information, as they allow the buyer to query more sellers in the same time (and cost) of querying a seller directly (Wan, Menon, and Ramaprasad 2009; Pathak 2010). Consequently, the majority of CSA research has been mainly concerned with analyzing the effect of CSAs on retailers’ and consumers’ behavior (Johnson et al. 2004; Karat, Blom, and Karat 2004; Xiao and Benbasat 2007) and with the cost of obtaining information (Markopoulos and Kephart 2002; Waldeck 2008). Our paper deals with the ability of a CSA to influence the belief of its buyers.

The properties, benefits and influence of belief revision has been widely discussed in AI literature (Icard, Pacuit, and Shoham 2010; Shapiro et al. 2011; Dupin de Saint-Cyr and Lang 2011). In particular in the multi-agent systems domain, works such as Elmalech and Sarne (2012) and Azaria et al. (2012; 2014; 2014) investigate the ability to influence the user’s beliefs. Nevertheless, these works require learning the user or the development of peer-designed agents (PDAs) for this specific purpose. Moreover, Azaria et al. (2013) designed a recommender system which may be sub-optimal to the user but increase the system’s revenue. However, they do not consider providing these recommendations in sequential order as we do. Our recent work (Hajaj et al. 2013) suggests a computational method to influence buyers’ beliefs by a CSA, which termed “selective price-disclosure”. The idea is that by disclosing only a subset of all the prices collected by the CSA one can influence the buyers expectations regarding the prices she is likely to encounter if she queries additional CSAs. The selective price-disclosure method was experimentally shown to be effective both for fully-rational agents and people. However, this approach requires pre-processing for each product in order to choose which prices to present, and it also requires fine tuning of several parameters (e.g., the expected number of new results the buyer will obtain from the next CSA she queries, and the minimal number of prices that are reasonable to present).

The method presented in the paper utilizes cognitive biases of people to affect their decision making. The identification and analysis of cognitive biases is a fundamental research subject in the social science literature, which has attracted the attention of many researchers. In particular for the Internet domain, it has been shown that users’ initial experience with a website affects their subsequent

choices (Menon and Kahn 2002), that electronic retailers can alter the background of their website to bias choices in their favor (Mandel and Johnson 1999), and that a specific use of colors in websites can affect the user's choices (Bonnardel, Piolat, and Le Bigot 2011).

Other works, such as (Ariely and Zakay 2001), show that the decision making process is affected by time. The authors indicate that people's decision is prone to change when time passes. That is, the decision that a decision-maker makes at a given time is not necessarily the same decision that she will make a couple of seconds later. In our work, we use the time to shape and update the user's beliefs by means of the three phases comprising our belief-adjustment method.

Another bias that we use for adjusting the user's belief is ordering. It was previously shown that presenting the same information but changing the order of the pieces of information can lead to a different decision (Entin and Serfaty 1997). In contrast to our work, the goal in their work was to provide confirming and disconfirming evidences of previous information that is already known. The effects of positioning different items in different orders has been largely studied in the field of behavioral science (Ullmann-Margalit and Morgenbesser 1977; Nisbett and Wilson 1977; Bar-Hillel 2011). Our work uses positioning of the same item (but with different prices) to adjust human beliefs. Hogarth and Einhorn (1992) suggests a general theory of how people handle belief-updating tasks. They claim that the order of information affects people decisions, since the current opinion is repeatedly adjusted by the impact of succeeding pieces of evidence. Our work is inspired by their ideas and provides an actual algorithm that utilizes an ordering effect. The work most related to ours is the study by Bennet, Brennan, and Kearns (2003), which shows that when prices of the same product are ordered in descending order, the price the buyers are willing to pay for the product is higher than the price they are willing to pay if the prices are ordered in ascending order. This finding, however, has no meaning in the CSAs domain where prices are always ordered ascending.

Extending Our Results - Discussion

In this paper we focused on the domain of CSAs, and presented a specific method that affects the buyer's decision. In a more general context, our belief-adjustment method can be of use in any situation where there is a user who needs to choose from multiple opportunities, and there is an entity that provides the different opportunities to the user.

For example, consider a buyer wishing to buy a used car. After visiting a dealer the buyer needs to decide whether to stop the search and buy the best car so far or to continue her exploration by visiting another dealer. Since exploration is costly, the buyer needs to consider the probability of finding better cars in the market in her decision-making process, and the buyer's beliefs are affected by the options already observed. In this case, our approach can be used by the dealer, who determines the way in which she presents the cars to the buyer. The dealer can use our method to affect the buyer's decision, hence increasing the probability of the buyer buying from her.

Conclusions

In this paper we introduced a method that affects buyers' decisions of whether to terminate their search for the best price. We experimentally showed that our method increases the termination probability of people compared to the commonly used bulk method and compared to a random-sequential approach, without changing the set of prices. The prices for our experiments were sampled from a variety of CSAs for five different products, and in all cases our method demonstrated an (statistically significant) improvement. We propose a method that is fast and simple for implementation by any CSA, which does not depend on the number of prices that are known for the product, and succeeds in increasing the CSA's expected revenue without investing much resources.

We note that our experimental design assumes that the CSA knows all the prices a-priori. This assumption is aligned with the architecture where CSAs hold a database with the different sellers' prices (Clark 2000). There is a recent alternative approach for an architecture that consists of real time querying. For example, *Kayak.com* runs an on-line search for every buyer's query. This CSA simply presents the prices as they are gathered, rather than wait until collecting the full set. With this architecture, our method has further advantages as the CSA can potentially disclose some of the prices even before all the prices are collected.

We foresee a variety of possible extensions of our work. First, in this work we fixed the number of prices that the CSA presents to the buyer at each time step to one. However, it is possible to present more than one price at each time step, which is useful for cases where there are many prices to present. It would be interesting to develop a heuristic for determining how many prices to present at each time step and in which order, and compare its performance to our method. In addition, our method divides the prices into groups based on a pre-defined ratio (i.e, a fourth of the prices each to the "anchor" and to the "effort" steps and half of the prices to the "despair" step). It is possible to treat this ratio as a parameter which will depend on the number of prices the CSA knows or on specific buyer's properties. Lastly, in this paper we exemplify the effectiveness of our suggested method in the domain of comparison shopping agents. As discussed earlier, our method can be easily and effectively used in many other domains where opportunities are provided to the user by a self-interested entity.

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