

Real-Time Adaptation of Influence Strategies in Online Selling

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Abstract

Real-time adjustments in online selling are becoming increasingly common. In this paper we describe a novel method of real-time adaptation, and introduce influence strategies as a useful level of analysis for personalization of online selling. The proposed method incorporates three perspectives on real-time adaptation: the content of the appeal (influence strategies), the context in which the optimization is performed (online selling), and the computational method (a Beta-Binomial model in combination with Randomized Probability Matching). We argue that these three perspectives are in constant interplay in any attempt to dynamically optimize online selling outcomes using personalization. Dynamic learning, adaptation and personalization of influence strategies represents are concluded to be prerequisites for e-selling – using the psychology of personal selling interactions in online marketing.

1. Introduction

With the continuous increase in computing power, real-time adjustments in online marketing are growing increasingly common [217]. Recent research in the field of information systems has produced findings advocating the real-time adjustment of marketing variables based on dynamic learning. From a methodological perspective, a crucial issue in individualizing the online retail experience in real time is the development of lightweight algorithms that are able to learn dynamically [33]. Some real-time adaptation and modeling efforts are reported in the literature, but most of them concentrate on product selection (e.g., [29]) or next-best offers. We argue that adaptation of the online retail experience should be extended beyond product selection to other key marketing variables: promotion, place, and price (e.g., [23]).

To illustrate this proposed change consider the following scenario: once a customer arrives to an online store (say a book store), she will be confronted with a multitude of different books on the initial

product page. Real-time adaptation efforts that focus on product selection make sure that the presented selection of books is one that is likely to sell based on the behavior of previous customers and perhaps a record of interactions with the store of the current customer. However, next to selecting a specific set of product, the pages of the only store often also present distinct promotional appeals: While the page starts with a list of best-selling books, it might also present a short list of books that are discounted, and a collection of books that have been highly rated by (e.g.) the New York Times. These latter three promotional appeals (bestseller, special discount, and recommended by NYT) are distinct from the product in the sense that the list of books presented under each heading could – if reality permits – be interchanged. If the customer chooses to pick an item from the bestselling items, this conveys information about (a) her book preferences, but (b) about her promotional preferences. We refer to the different types of promotions as implementations of distinct influence strategies [10]. The online store could now choose to give the bestseller a more prominent place on subsequent pages knowing that this promotional appeal resonates with the current customer.

While the above scenario is simplified, it describes the essence of the real-time adaptation of online selling that we propose in this paper. We introduce and evaluate a method that facilitates the adaptation of influence strategies [10] to individuals.

2. Optimizing online influence strategies

Professional salespeople have a set of influence strategies at their disposal, and dynamically adapt them to what they experience in their interactions with individual customers [26, 31]. Such strategies facilitate the exertion of interpersonal influence through the pitching of the offering in a tailored, persuasive way: giving a special discount, for example, or arguing that the product has already sold very well or is endorsed by some authority figure in the relevant domain [10]. The literature on influence strategies details several different ways in which a product—irrespective of its price, and perhaps even irrespective of the product at

hand—can be pitched. It has repeatedly been found that such strategies increase the average likelihood of a sale: when salespeople use them, their customers are more likely, on average, to buy the products than when they refrain from using them (e.g., [13, 16]). Thus, the Average Treatment Effect (ATE) of influence strategies is positive.

In addition to the ATEs of influence strategies, social psychologists have analyzed *individual differences* in responses to compliance-gaining tactics. Independently and using a host of different methods, several groups of researchers have reached the conclusion that there is considerable heterogeneity in the effects of these strategies (see e.g., [18, 20, 32]). The large ATEs and significant heterogeneity make influence strategies a key suspect for real-time adaptation and optimization in online marketing.

2.1. Combining the content, context and method of adaptation

The success of methods facilitating the real-time adaptation of marketing variables depends on the *appropriate selection of the variable of interest* (the content), *understanding the context in which the variable is to be adapted*, and having a *suitable method of adaptation* for that content in that context.

In recommender systems [6] - systems which select the right product to present to a customer - the content, the context, and the method are clearly related. The content that is adapted is the choice of product, as opposed to other types of content such as price or the form of promotion. The context of an online store in which recommender systems are employed imposes practical requirements such as the size of the subset and the speed at which it should be served to customers. Finally, the method (e.g., the algorithm used) in itself is dependent on the content and the context: the context constrains the time (or the number of CPU cycles) the algorithms can take, whereas the content determines which types of relationships need to be modeled. In the case of product selection, the set of products ordered by customer A is apparently informative with regard to products that are likely to be bought by customer B, who up to that point has only purchased – or showed an interest in – a subset of those purchased by A. This principle (“*others who bought this product also bought*”) works because there are homogeneous groups of customers with preferences for specific sets of products [19] [25].

Our focus in this paper is on the adaptation of influence strategies in real-time online retail. In the following sections we explain why we chose this

content, describe the limitations arising from the *context*, and discuss the *methods* we chose to employ.

2.2. The content of adaptation: influence strategies

As noted in the introduction, offline sales professionals use a multitude of influence strategies. These strategies have different names in the different streams of literature on personal selling or the psychology of influence, such as influence principles [10], persuasion strategies, or sales influence tactics [26, 31]. Cialdini’s popular taxonomy comprises six influence strategies [10]:

1. *Authority*: When an authority figure tells people to do something, they typically do it [27].

2. *Consensus*: When individuals observe multiple others manifesting the same belief or behavior, they are more likely to believe and behave similarly [1].

3. *Consistency and Commitment*: This strategy refers to people’s striving to maintain consistent beliefs and to act accordingly [10].

4. *Scarcity*: Assumed scarcity increases the perceived value of products and opportunities [10], consequently advertisers and salespeople tend to use phrases such as “limited release”, and “while supplies last” [25].

5. *Liking*: We tend to say, “yes” to people we like, thus if someone we like asks us to do something we are more inclined to do it [10].

6. *Reciprocity*: People are inclined—or actually put in a great deal of effort—to pay back a favor [11].

Although the ATEs of influence strategies have long been known, contemporary social psychology has revealed a number of reasons why they are relevant in the context of adaptation. Empirical investigations have identified several personality traits – such as Need for Cognition (*NfC*) and Preference for Consistency – that moderate the effects of different influence strategies [9, 18]. Previous research has further shown that, although such strategies are effective on average (over a group of customers), they may be ineffective or even counter-effective for individual customers [21]. People who place value on being different, for example, are likely to deviate in their responses to popularity-based influence strategies [20].

The possibility to use influence strategies with multiple products, their substantial ATEs, and the demonstrated heterogeneity in combination, make them a prime target for adaptation. Hauser et al. [17], explain how the cognitive styles of customers differ and have an impact on their decision-making. Hauser et al. [17] propose a method for adapting to the

cognitive styles of customers using a Bayesian approach, and demonstrate its effectiveness. Since this work is currently the only other documented attempt at the real-time adaptation of marketing variables related to promotion in online retail, we compare our context and method descriptions to these earlier efforts.

2.3. The context of adaptation: online selling

It is common to adapt a product or offer to the behavior of an individual buyer ([25, 28, 29] in online selling. This does not, however, hold for influence strategies. Despite the fact that products are frequently advertised as “bestsellers” (the consensus strategy), “promoted by experts” (authority) or “only available today” (scarcity), they seem to be used regardless of the responses of individual consumers or, if optimized, optimized based on group-level effects. There are a number of studies in the fields of electronic selling and information systems on how influence strategies can be applied online. Although some of these indicate that certain effects of promotion are replicated from offline to online [7], the diversity of findings implies that the implementation should be carefully adjusted for digital use. While there are existing examples of how scarcity, authority, and consensus strategies can be implemented in online marketing, strategies which rely on interpersonal relationships (e.g., liking, reciprocity) are not well established.

Second, most online retail applications store relatively little information about their individual customers. Although they might be able to identify customers within a session (e.g., over a number of page views), or even over sessions, information more elaborate than a unique identifier is, in practice, hard to obtain. In contrast to Hauser et al. [17], therefore, we assume that, in practice, real-time online contexts often enforce reliance on clickstream data only, and that associations with (e.g.) questionnaire measures or demographics tend not to be available for real-time optimization.

Third, in order to adapt to the heterogeneity in responses to influence strategies as identified by Kaptein & Eckles [20], every opportunity should be taken to display such a strategy and measure the response of a customer. Hence, it should be possible to change the influence strategies used for a single customer in between page views. Just as computing power has increased tremendously in recent decades, so has the amount of accessible data. For all practical purposes this means that in order to adapt a page within a timeframe that does not hinder the customer (in between page views, e.g. < 0.1 seconds) the algorithm should not (a) revisit (all) historical data to estimate its parameters and thus should be at least

partly “online” (or streaming) , or (b) make extensive use of iterations of (parts of) the dataset to estimate its parameters. Hence, our focus in this paper is on an adaptation algorithm that does not revisit any of the data points and can thus be implemented streaming (or *online* in the statistical literature).

2.4. The method of adaptation: individual profiles

There are various modeling approaches that could be used to adapt influence strategies in real time. In any case, the aim of learning dynamically requires the process to be two-staged. First, estimates of the effectiveness of the different strategies for individual customers need to be determined from the available data. Second, there is a need for a mechanism for choosing which strategy to display given the estimates at hand.

Kaptein & Eckles [20] provide a clear example of modeling heterogeneity in responses to influence strategies. They conducted an experiment in which the responses of individuals to a set of strategies (neutral, scarcity, authority, and consensus) were measured. Using a within-subject design and exposing their respondents to multiple implementations of each strategy they fit a hierarchical model of the following form:

$$y_{jbq} \sim \mathcal{N}(X_{nb} \beta_n + \alpha_b + \dots, \sigma_{err}^2) \quad (1)$$

where $\beta_n \sim \mathcal{N}(\bar{\beta}, \Sigma_\beta)$ for $n = 1, \dots, N$, people, and $\alpha_b + \dots$ is a series of added fixed effects for (e.g.) product categories. In their study $n \times s$ matrix β_n captures the effect(s) of the different strategies, s , on each of the subjects, n , and is bounded by its normal prior with the covariance matrix Σ_β . They inspected the estimated structure of Σ_β and compared these estimates to the fixed average effects of the strategies (vector $\bar{\beta}$) in order to derive their conclusions concerning heterogeneity in the effects.

For our purposes, it is important to determine the main (functional) implications of their model that are useful for estimating the effects of influence strategies on individuals.

1. Estimates of the individual-level effects of influence strategies should be informed by the effect of these strategies on others (as evident in the hierarchical structure).

2. Estimates regarding individuals on whom there is more data should be less and less informed by the behavior of others, and vice versa.

3. Estimates of the effects of influence strategies should be allowed to vary independently: e.g., the relationships between the effects should not be

constrained (This assumes a covariance matrix Σ_β without 0's).

These three implications state that each influence strategy can have a distinct effect on each individual (implication 3) and that the estimate of an individual -- which due to a limited number of observations is inherently uncertain --- should be informed by the estimates of the effects of influence strategies on others (implication 1&2). This latter implication is often counterintuitive: if heterogeneity is present than why should information of the behavior of others inform individual level estimates? However, when true heterogeneity is present the prediction error decreases when “shrunk” towards a grand mean, especially when individual level estimates are uncertain. We thus feel that such shrinkage improves the individual level estimates as long as the group mean is treated as an uncertain first guess of the individual estimate as opposed to a certainty (due to many observations at the group level).

Given our streaming requirements, we do not employ the full multilevel model used by Kaptein & Eckles [20] to estimate heterogeneity. We used a simple Beta-Binomial model in order to estimate the individual-level effects. We are interested in p_{ns} , the (unknown) probability of a click of a given customer, n , on a product presented with strategy, s . Our aim is to learn p_{ns} as an estimate of the effect of an influence strategy s on customer n .

As is well known, it is convenient for reasons of conjugacy to put a beta, $Beta(\alpha_{ns}, \beta_{ns})$, prior on p_{ns} . This allows for the online updating of the posterior distribution of p_{ns} , which is distributed $Beta(\alpha_{ns} + c_{nst}, \beta_{ns} + 1 - c_{nst})$ where c_{nst} is the indicator of the success or failure $\{0,1\}$ of the current product view (at time t) accompanied by strategy s . The above approach would suffice if a lot of data were available for each customer-strategy combination, but this is hardly ever the case in practice. Hence, our estimate of p_{ns} needs to be shrunk towards our estimates of the average effect p_s : the (estimated) probability of success of a strategy averaged over all customers. We used a similar Beta Binomial model to model the average effect of each strategy s , at (overall) page view t .

In carrying out this process we followed two principles: first, when a new customer arrived at the affiliate store we “copied” the current posterior distribution of p_s to inform p_{ns} . However, since at the average level the certainty of the estimate p_s becomes very large, we choose to increase the variance of the prior for p_{ns} . Second, after each update of p_{ns} upon the arrival of a new data point we shrink the estimated expected individual-level effect μ_{ns} towards the average effect using the standard hierarchical Empirical Bayes estimation. Finally, by modeling each strategy

independently we assured that the estimates of the strategies can vary independently.

2.4.1. The selection of content based on the estimates. After obtaining an estimate of the posterior distribution of p_{ns} we have to decide on which strategy to display to each customer upon viewing a new product. If p_{ns} were known with perfect certainty, one would resort to selecting strategy s for which p_{ns} was highest. However, given uncertain estimates of p_{ns} one seeks a method to optimize the so-called explore-exploit trade-off.

According to explore-exploit trade-off, updating one's knowledge about a p_{ns} will not inform one's knowledge about $p_{ns'}$ (the prime indicating a different strategy). If $p_{ns} > p_{ns'}$, but both estimates are uncertain, then it might be feasible to *explore* the actual density of $p_{ns'}$ instead of *exploiting* the (uncertain) knowledge that $p_{ns} > p_{ns'}$, and thus offering strategy s' to customer n .

The canonical version of the problem described above is coined the multi-armed bandit problem [33]. In this formulation of the problem the multiple influence strategies that can be selected for an individual are regarded as arms of a multi-armed-bandit slot machine. Each arm produces its own pay-off every time a coin is entered into the slot machine. The aim of the gambler is in this case not necessarily to estimate the pay-off for each arm, but rather to win as much money as possible given his budget.

This optimization problem is generally difficult to resolve. Hauser et al. [17] use the Gittins index to solve their explore-exploit problem, albeit at a different level of analysis. The Gittins index [15] [35] assumes geometrically discounted future rewards, thereby providing an algorithm for computing the value of playing arm k , assuming optimal play in the future. The resulting quantity is the Gittins index, and the optimal solution to the problem is to play the arm with the highest index. The index suffers from logical and computational difficulties (cf. [33]), however, the latter being the reason why Hauser et al. resorted to pre-computed values. In terms of logic the challenge is that it displays incomplete learning: one is led at some point to choose one arm, and there is an above-zero probability that this arm is suboptimal [8]. Moreover, if the discounting is not geometrical the Gittins index is no longer optimal [33].

Because of the above difficulties we adopted a more recently devised flexible solution to the explore-exploit tradeoff, and used Randomized Probability Matching (RPM) as presented by Scott [33]. RPM is based on the idea that for many explore-exploit problems one can compute - or sample from - the posterior $p(\theta|y_t)$. If this is indeed possible then the

RPM algorithm states to take a single draw from the posterior θ and select the arm for which $a = \operatorname{argmax}_a \mu_a(\theta(t))$. In the simple case of the binomial bandit this entails playing the arm, j , for which the posterior draw of θ_j is highest over all j . In our implementation RPM entails taking a draw for each beta posterior density d of strategies $1, \dots, s$ for customer n . This gives draws d_1 to d_s , which are then ordered and the highest is selected. Strategy s of $\max d_s$ is then selected and displayed to the current customer.

2.4.2. Putting it together. We based our algorithm for adapting influence strategies to individuals in real-time on the estimation procedure and the selection procedure described above, as follows:

1. An event (success or failure) of a certain strategy s for a specific customer n is received.
2. P_s , the average success of that strategy is updated by updating its associated $\text{Beta}(a_s, b_s)$ prior.
3. Depending on whether customer n is already known:
 - a. If the customer exists (e.g., P_{ns} exists) then:
 - i. Update the $\text{Beta}(a_{ns}, b_{ns})$ prior
 - ii. P_{ns} is "shrunk" towards P_s
 - b. If the customer does not exist:
 - i. P_{ns} is copied from P_s .
4. Take a draw d_s from each $\text{Beta}(a_{ns}, b_{ns})$ for each s .
5. Select the highest draw.
6. Display the strategy s associated with that draw.

3. Empirical evaluation

In order to test the effects of the adaptation of influence strategies in online selling we endowed an affiliate online retail platform with the ability to dynamically adapt its usage of two such strategies. We set up an evaluation process comparing the performance of the online retail platform in a version of the affiliate store that used adaptive influence strategies (from now on referred to as *Adaptive*) against its performance in one that did not implement any influence strategies (*Baseline*).

We specifically chose to compare a version of the site that did not use influence strategies at all with a version that used adaptive influence strategies because the comparison would give the most direct estimate of the applied contribution of our work: it constitutes the combination of content—influence strategies—as well as adaptation. Other cells could have been added to the experiment, however: (e.g.) comparisons with a version of the online retail website that used static implementations of influence strategies (preferably the strategy with the highest ATE), or even a random

selection of strategies. These comparisons would test different hypotheses, however: comparison to the strategy with the highest ATE would estimate the increase obtained through the *adaptation* of influence strategies, not the increase in their use to begin with. A comparison with their *random* use (e.g., for any product each strategy has an equal probability of being displayed) would partially test the usage effect as well as the effect of altering content during the visit of a customer. Given our focus on introducing the adaptation of influence strategies—combining the type of content and the adaptation—the current comparison should favor adaptation over the baseline to warrant any further investigation.

3.1. Method

During a 73-day trial period in January-April 2011 we endowed the affiliate website www.kinder-kleertjes.com with our proposed method of adapting the use of a set of influence strategies. Kinder-kleertjes.com offers a selection of over 1,200 children's clothing products and the website aims at attracting traffic through search engines and increasing clicks-through to the two final vendors. The site, in its current form, has been running since the beginning of July 2010. During the trial, the site was rather limited in size, attracting an average of 388 visitors per month between July 2010 and April 2011.

The affiliate store setup, in which a customer leaves the website upon actual purchase, only allows the measurement of click-through behavior. We therefore considered any presentation of an influence strategy followed by a click on the product to see more information or to pay for the current product a successful influence attempt. We had access to these clicks, in combination with a unique customer ID (see below) and the ID of the strategy that was displayed.

3.1.1. Customers participating in the evaluation.

Half of the visitors to the kinder-kleertjes.com website during the period of the field trial were randomly assigned to the baseline condition, and the other half to the adaptive condition. Once the customers had been assigned to the condition we placed a cookie containing a customer ID based on the customer's IP address and the current timestamp to allow tracking of the customer ID. We used the customer ID to track (a) users within the session (e.g., over multiple page views during one visit to kinder-kleertjes.com), and (b) the assignment of customers to the condition over the session. Hence, assignment to the two conditions was between subjects.

3.1.2. Implementation of the influence strategies.

The home page of kinder-kleertjes.com presents a ‘random’ selection of the products on offer, together with pictures and single-sentence descriptions. Once a visitor clicks on one of the products (or enters the site using a search term directly pointing at a product page), the product is displayed using a large image and a textual description.

The consensus and the scarcity influence strategies were implemented, both of which are frequently used online: messages such as “Bestseller” and “Other people who bought this also bought” represent the former, whereas “Only 3 items left” and “Limited time offer” represent the latter. Having chosen implementations of the respective strategies that are familiar to most online shoppers and are relevant to current online selling practice due to their prevalence in the field, we implemented them on the product-display pages of the affiliate store. These pages show a large image of the product, and give a description. The scarcity strategy was implemented through the use of a button that stated: ‘Special offer’ (with the accompanying text “This clothing item is available today at a special discount rate”), and the consensus strategy through the designation of the product as a ‘Bestseller’ (with the text: “This product is very popular”). We kept the original product representation—not implementing a strategy—as one of the display options, thus the evaluation concerned three distinct product-pitch versions.

3.2. System design

The system for the dynamic adaptation of influence strategies was created on top of the original website. The kinder-kleertjes.com website makes an HTTP call to an external server to request the appropriate social-influence strategy for the current visitor. The remote server returns the ID of the strategy that should be used, and this is presented to the visitor. Finally, when the visitor - identified by his or her unique customer ID - finishes browsing the product-display page, kinder-kleertjes.com sends another HTTP request to the external server to update whether or not the influence strategy was a success.

To be able to use the beta binomial model in practice we need to specify a prior beta distribution, thus we chose α_s, β_s for each s . In this trial we set $\alpha_s=0.12$ and $\beta_s=0.48$. Hence the initial estimate of the success of each of the strategies was $\mu_s=0.2$ (thus $p_{is}=0.2$) and the associated variance was $\sigma_s^2=0.1$.

4. Results

During the field trial 1,449 customers visited kinder-kleertjes.com and viewed at least one product page. The average number of product pages visited per customer included in the trial was 1.8 (SD = 1.88). Over 30 percent of the visitors viewed two products or more, and the average click-through rate during the trial period (averaged over both conditions) was 11.4 percent. further investigation.

4.1. The average effects of using SITs online

In order to test the effects of the usage of adaptive influence strategies we first compared the average performance of the online store between the Adaptive condition (customers browsing the online store that implemented dynamic influence strategies) and the Baseline condition (in the store that did not). Figure 3 shows the estimated success (proportion) of the Baseline and the Adaptive condition—as well as the 95-percent confidence bounds on the average success in both conditions—over the period of the field trial.

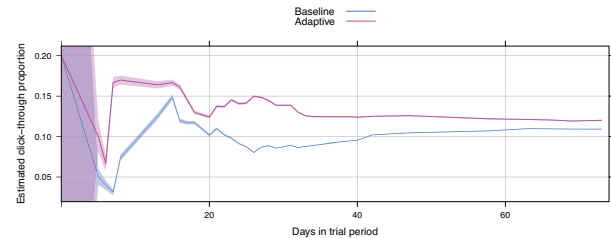


Figure 1. A comparison of the estimated conversion rates between baseline and in the trial condition.

On average, the click-through rate in the Baseline condition was 9.4 percent, and 13.5 percent in the Adaptive condition. This percentage difference is statistically significant ($X^2=6.386$, $df=1$, $p < 0.02$), such that dynamic adaptation indeed achieved better results in online selling than no adaptation. Furthermore, even though the algorithm only optimizes click-through rates, subsequent analysis showed that, on average, the revenue created for the affiliate store (which is a proportion of the money customers end up spending at the online store of the vendor) was higher per customer in the Adaptive condition (€0.041) than in the Baseline condition (€0.034).

4.2. The effects of individualized profiling

We were interested not only in the average performance of individualized profiling compared to the default version of the affiliate store, but also in how the adaptation of influence strategies compared to their static usage in online commerce. Such a comparison is

not straightforward given that our selection of the Baseline comparison was not based on previous performance. We could, however, (roughly) estimate the performance of the best-performing influence strategy based on the responses of individual customers to first-time exposure in the Adaptive condition. These first exposures are not yet adapted to individual-level responses and thus provide a relatively good estimate of the average performance of the influence strategies. The click-through rate of the best performing strategy (Consensus) at its first appearance in the trial condition turned out to be 10.8 percent, which is significantly lower ($X^2=3.854$, $df=1$, $p < 0.05$) than the results obtained from adaptive selling during the full period (13.5%).

A large number of customers visited the website multiple times during the trial period, and examined multiple products. Thus, they were presented with different influence strategies, the effectiveness of which (in terms of click-through rates) was directly modeled. This allowed us to create for each customer a *unique* profile of the estimated success of the different strategies. Figure 3 gives an overview of the individual-level estimates of the success of the social influence strategies used in the trial over the examination of multiple products. The plot makes clear how both the estimated success as well as the certainty around these estimates varied over time among individuals.

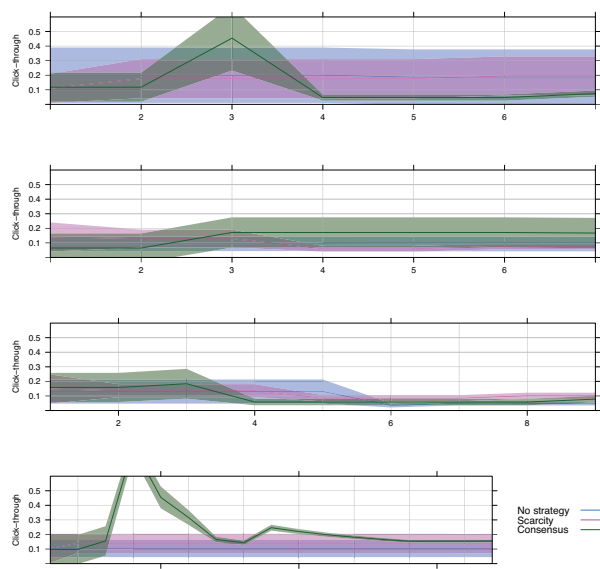


Figure 2. The estimated effectiveness of the different persuasive strategies for four randomly selected users (of those who viewed seven products or more). The transparent regions are 1.96 S.E. above and below the p_{ms} based on the posterior beta.

Depending on their start time in the experiment, the initial certainty in the estimates differed. In the last plot in particular—an early user of the system hence its large variance in the initial estimates—it is clear that the consensus strategy outperformed the other strategies and was thus selected for this customer. An analysis of the individual-level estimates at the end of the trial period showed that the consensus strategy was most effective for around 42 percent of the customers, whereas 37 percent responded consistently favorably to the scarcity strategy. These estimates emphasize the *heterogeneity* in responses to different influence strategies.

5. Discussion

The personalization of influence strategies in online retail will increase revenues. Our results show how a system that dynamically adapts its usage of different influence strategies to the responses of individual customers over time outperforms a system that does not use such strategies. Influence strategies are a prime subject for personalization given their large but heterogeneous effects on customer behavior. Our affiliate-store context allowed us to model the clickstream of customers exposed to certain influence strategies, and our method enabled us to quickly generate real-time “next best strategy” advice for each individual customer while optimizing explore-exploit thinking. We show that such an approach not only improves the aggregate performance of an online retail platform, but also allows for the creation of individual-level estimates of the effect of distinct strategies: estimates that can be of use for subsequent interactions.

In addition to changing the focal level of analysis to individual consumer responses to influence strategies, the current work makes a significant contribution in theoretically formalizing the implementation of some aspects of face-to-face selling in online retail. Table 1 summarizes how prior methods have facilitated the development of interactive selling behavior in computer-to-human online retail, how the present method contributes and which challenges remain unresolved.

Although online retail has largely caught up with individual product selection, online promotion still differs considerably from the dynamic real-time promotion of products in face-to-face selling. The dynamic adaptation of influence strategies based on individual profiles provides the means for implementing the dynamic process of face-to-face selling in online retail, thereby creating a rudimentary form of e-selling. This adds to our understanding of the

effects of message framing in online retail: effects that have also been successfully demonstrated in different online retail applications [7].

Table 1. Advancements in selling behaviors in computer-to-human online retail

Prior advancements	Current contribution	Unresolved issues
Optimization of product recommendations	Personalization and optimization of the use of influence strategies (optimization of promotion)	Ability to deal with individual price sensitivity in real time.
Aggregate-level optimization based on click-stream data and A/B testing: Optimizing for average treatment effects.	Real-time optimization without questionnaires, iterations or CRM data	Implementation of more social influence strategies (e.g. liking, reciprocity)
Optimization of promotional styles based on in-depth customer data.		

5.1. Managerial and technical implications

Many online retail platforms use recommender systems, but none of them currently tailor all of Kotler's (e.g., [23]) four Ps (product, price, place, promotion) to an individual based on his or her behavior. Although personalization is already commonplace [24], its extension to promotion through influence strategies is a significant step forward in online business. Such an extension requires three technical possibilities. First of all, it must be possible to uniquely *identify* consumers online. The identification does not have to be personal, as long as it is unique to each customer. Many customer relationship management (CRM) systems are already moving in this direction, and are tying cookies and other means of tracking unidentified customers to subsequent logins or email addresses that are less error-prone. This unique ID is necessary in order to store the customer's estimate and use these for the subsequent selection of influence strategies or other persuasive contents. Some CRM systems also track and feed individuals' web behavior into the offline sales funnel. Arrangements that do not tie the customer ID to personal information are obviously easier to manage from a privacy perspective.

Second, it will be necessary to *create content that can be dynamically adapted* in the content management system (CMS). Product presentations should focus not only on product features, price, and pictures but also on the specific implementation of the various influence strategies that are applicable. Hence, one should be able to separately identify whether, for example, customer ratings are available or special discounts can be given, and whether there are expert sources recommending the products.

Finally, it should be possible to *keep track of the effect* of the different influence strategies by measuring the responses of customers to presentations of their implementation. We tracked click-through behavior in our field experiment, but other means of classifying success or failure (e.g., time on site or customer-level turnover) would be equally (or even more) appropriate.

If these three requirements are met, thus constituting a change in at least CMS systems and sometimes CRM systems, dynamic adaptation based on individualized profiling will find their way into online channels.

5.2. Limitations and future work

There are still a number of unanswered questions with regard to the methods surrounding adaptive influence strategies. First of all, because the field trial spanned the original version of the online retail site and the fully adaptive version, it is unclear exactly what differences in the two systems actually increase conversion rates. It would be worthwhile setting up an evaluation system that would also explicitly compare the use of the "best" (between-user) influence strategy (consensus in our evaluation) as opposed to the adaptive system, or of a randomly selected influence strategy versus the adaptive e-selling system, for example. These kinds of evaluations would make it possible to reliably rule out the mere effects (a) of influence-strategy optimization at an average (between-user) level and (b) of changing product representations within a session.

Second, the system design as detailed in this paper represents a rudimentary approach to developing an adaptive persuasive system. Not only does it implement just two strategies out of a possible larger set (six according to Cialdini [10]), it is also restricted to one specific implementation that is identical for each product presentation. Systems that employ a broader range of tactics and subsequent implementations will probably support a larger visitor base.

Third, the chosen measure of success – customer click-through—might not be the best predictor for subsequent purchases. Possibly training an algorithm based on a combination of success measures (e.g.

click-through, time on site, recurrence, purchase amount) will aid in faster and more accurate estimation of individual level effects of influence strategies.

Beyond further development of the algorithm and improvements in its implementation, there are a number of ways in which to strengthen and extend the idea that optimized content, the method of optimization and the context need to match. Different psychological variables—such as cognitive style (e.g., [17]) - could be used as the prime content of personalization. Second, various types of electronic exchange, such as auctions, could be chosen as content and would provide practitioners with different constraints than those mentioned here. Finally, given the content and context, different types of models might be appropriate: for some content it might be worthwhile modeling the relationships between different variables—in our case between influence strategies—explicitly. Future studies should investigate whether the explicit modeling of relationships between strategies to borrow strength between estimates might lead to increased effectiveness.

In terms of developing methods for optimizing real-time online influence strategies, it would be useful to test a larger variety of strategies in order to enhance understanding of how and to what extent they benefit from dynamic adaptation and profiling. Studies following the use of multiple strategies separately, in bundles and/or sequentially would provide relevant information about their different roles and interdependences. Some influence strategies are likely to have more of a foot-in-the-door role, some work well in combination, and others work best alone. Even though Barry and Shapiro [5], as well as Kaptein and Duplinsky [19], have shown in experiments that combinations of influence strategies tend to be less effective than well selected single strategies, it is still an empirical question whether sequences of strategies could improve compliance. This area is largely unexplored. The persuasiveness of different strategies introduced gradually and in various combinations would be an interesting future research avenue that online retail systems would be capable of analyzing and optimizing in different permutations.

Finally, it would be interesting to further explore how the real time optimization of the use of influence strategies in online marketing could also benefit offline marketing efforts. While scholars have studied how presenting online product information can – in some cases – contribute to offline sales [30], the idea of using individual level estimates obtained online for subsequent use in offline retail is as far as we know novel. We believe that individual level estimates of the effect of influence strategies which are obtained online could also be beneficial for a sales people in

subsequent offline interactions. Similarly, the individual level estimates of the success of influence strategies could be used across multiple channels. The participation of offline sales personnel in online communities and e-commerce service processes is one obvious avenue. Offline salespeople could also be given information on how customers have responded to different psychological approaches online, particularly in the information-seeking phase. Restaurant or in-store personnel, for example, would benefit enormously from knowing, which influence strategy struck a chord when a specific customer chose to book a table or reserve an in-store pick-up online.

6. References

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