Theory vs. Data-Driven Learning in Future E-commerce

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Abstract
As personalization, adaptation and persuasion are called for in e-commerce and as computational power increases, a question emerges: should companies use theories to develop and run their e-commerce operations or does mere data based optimization do a better job? We explore different types of computer-based learning methods and present two evaluations of primarily data-driven learning applications that advance e-commerce in the direction of interactive e-selling relationships.

1. Introduction
Digital business exchange has developed in the form of e-marketing, e-commerce and e-support/e-automation, but little in the form of actual e-selling. This article investigates how computer based learning can advance the ways in computer-human interactions can manifest adaptations similar to salespeople in traditional offline interactions. We explore different types of computer-based learning and present two evaluations of (primarily) data-driven learning applications that advance e-commerce in the direction of interactive e-selling relationships. The applications—and the detailed descriptions of their implementation methods—serve as exemplars for the increasing shift towards more data-driven learning.

Salesmen—the traditional intermediaries between a product and a purchase—have a diverse set of skills that allow them to bridge the gap between (latent) purchase intentions and the actual purchase. For example, when a customer enters a bookstore a salesman would be able to provide help and guidance on most of the following: (a) determining the right product (e.g. which book suits the customers?), (b) determining the right product pitch (e.g. which Sales Influence Tactics (SIT) should be used to convince the current customer), and traditionally also (c) determining the right price—although this latter one has become relatively standardized in most western countries and thus are not set by the salesmen. Then, if we look at e-commerce, we see that usability engineering and design of e-commerce platforms serve the functions that are attributed to the salesman in the physical store. And, if we look closely, it becomes eminent that a number of the tasks that good salesmen do well seem only remotely be covered by e-commerce platforms. This forces us to distinct e-commerce from actual e-selling [29].

However, applications of artificial intelligence (AI) are more and more filling the gaps between a plain representation of a list of products on a website and actual e-selling: an interactive “dialogue” between the buyer and the selling e-commerce platform. AI applications have lead for example to recommender systems (see e.g. [5]), systems that indeed take over the first of the tasks described for the salesman of selecting the appropriate product for the current customer out of the often large assortment. But, not just product selection has benefited from AI: different product pitches (see e.g. [1,15]) and even a determination of profit maximizing prices have benefited from the applications of AI. Thus, AI is slowly but surely changing e-commerce and e-marketing into e-selling.

This change challenges the current roles of marketing and consumer decision-making theory as opposed to more data-driven reasoning in developing e-selling. So far, the logic and functioning of e-commerce platforms have often been planned according to existing marketing or psychological theories while the data generated from the operations have merely been used to re-engineer them rather than to function as a complete bases for their functioning or design [16,25]. In this paper we try to address this issue by examining the differences between data-driven adaptation of e-commerce to e-selling, and theory-driven adaptation. With the rise of big data and the possibilities to actually analyze such data [22,36] a proper understanding of this divide and the roles of both theory and data in e-commerce and e-marketing is necessary.

2. Data & Theory: How do we inform decisions?
In this section we further detail the conceptual distinction between data- and theory-driven learning. We will do so by examining a specific example—enhancing the effectiveness of an online bookstore—but the results of the examination are general to applications of adaptation and learning in e-commerce.

In social sciences, conceptually there are two alternative ways of using computational power to
optimize business exchanges through adaptive, (dynamic learning) models. Artificial intelligence in this form can be used for both theory-driven and data-driven model building [23]. Traditional theory-driven optimization is based on the assumption that theoretical thinking is powerful in framing an understanding about customers’ responses to given commercial offerings. These theories are then used to, for example, categorize customers their behavior and act upon the categorization in accordance with the theory. Theory-driven, optimization or personalization takes place by a) designing offerings that are theoretically fit for each category; b) evaluating the fit of the end-result to theory and c) using the evaluations to make adjustments to the theory to come up with better offerings.

An example of a theory-driven approach could be based on the popular theoretical divide between utilitarian shoppers and hedonistic shoppers [2]. Utilitarian shoppers search for a specific product, and are assumed to search for the most optimal price-quality trade-off. Hedonistic shoppers value the experience of shopping (and that of experiencing the product) and thus would benefit from a more holistic approach in which the experience of the bookstore is kept into account above and beyond merely functional aspect. Integrating such theory into a bookstore would in practice entail recognizing customers and classifying them into one of the two “types of shoppers” (e.g. based on their initial browsing behavior). Next, the bookstore would adapt according to the theory, providing more graphics and narratives for the hedonistic shoppers while providing a more functional and factual representation of the products for the utilitarian shoppers.

By contrast, the data-driven approach typically starts by gathering data about customers. Next, this behavioral data is used to predict customer responses in a given situation without the involvement of theoretical assumptions on customer decision-making. No holistic properties such as hedonism are assumed nor deemed necessary to map the observed behavior to the target behavior. Recently, sequential Bayesian learning algorithms (cf. [33,15,34,12]) have been developed to be able to optimize offerings with few theoretical assumptions. By measuring the behavior of individuals and building offerings based on real-time adaptation to individual-level responses, the algorithms then adapt the offerings to individuals’ histories and current (real-time) buying situations. This can be done with very limited prior understanding about how customers are theoretically supposed to behave, or how other customers have behaved on aggregate.

<table>
<thead>
<tr>
<th>Theory-driven approach</th>
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<td>Light-weight</td>
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<td>Many conflicting theories to choose from</td>
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<td>Often unclear whether a theory would hold in the application context</td>
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Table 1: Overview of the Pro’s and Con’s of both theory-driven approaches to learning and data-driven approaches to learning.

A fully data-driven analog of the above hedonistic / utilitarian divide on the online bookstore is as follows. The bookstore has two distinct ways of presenting its products, one with lots of pictures and narratives, while the other is merely a factual representation of the product¹. These two versions do not link to any hypothesized features of customer decision-making but rather represent the two technical possibilities that the bookstores e-commerce platform offers. The bookstore could now be made to automatically adapt the representation—e.g. make more likely one or the other ways of presenting products—based on the first few clicks of customers. Given some optimization criterion (e.g. sales) a totally “black-box” algorithm could be trained in which there is no human (or theoretical) involvement but still in real time a choice between the factual and the narrative ways of presenting the product.

Table 1 summarizes the key differences between the data- and theory-driven approaches to e-commerce. While to us these two represents two ends of a continuum, the fully data-driven approach can be characterized by a sort-off black-box thinking that marked the first successes in artificial intelligence. Here mostly algorithms are being trained to predict class membership—whether supervised or unsupervised—of a vector of data points representing different features. These features might be abstract and the modeling can pose functional forms that are hardly tractable by humans. The only concern of such data-driven modeling is a correct class membership specification based on the input features. No effort is

¹ Theory comes in handy to create these two representations, but no assumptions about people or their purchase behavior are necessary to do so.
made to derive additional meaning from the features or their respective importance.

On the other side we can position fully theory-driven adaptation or learning in which no data analysis is present necessarily (although we concur that an assessment of empirical data often is a step in the development of the theory). In this theory-driven approach adaptation choices by systems are made in a heuristic fashion, in which the heuristics are deemed appropriate based on the theory at hand. Consider for example the Elaboration Likelihood Model (ELM) [31]—a strong and well-known theory describing information processing leading to attitude change. The ELM could lead designers of adaptive systems to consider a “high quality” argument in context in which customers have ample room to elaborate, while more “peripheral arguments” can be chosen in situations of restricted elaboration. While a system that adopts its presentation of communication in such a fashion would need some computational reasoning to decide between the high or low elaboration situation, the subsequent action is totally based on the theoretical assumptions behind the ELM and not based on any data collected within the system and context at hand. Frankly, it need not even be the case that the data support the notion that one argumentation form is more effective given a certain elaboration state: this conclusion is taken from the theory without further scrutinizing.

The primary differences between the two approaches are as follows: First, there is a tradeoff between generalizability (often high for theory-driven approaches) and within problem accuracy (high for data-driven approaches). Second, the theory-driven approaches are often computationally lightweight, while the data-driven ones are more demanding in this regard. Next, theory-driven approaches are often interpretable by humans—allowing for usage in offline marketing as well—while the black-box machine learning approaches are often not transparent. Finally, data-driven approaches are often particular to a context, while theory-driven approaches are less context dependent but subsequently less accurate given a context.

The hedonistic / utilitarian shopper divide provides a compelling illustration of the first trade-off. This theory-driven divide is said to classify shoppers in a holistic manner, allowing generalizations to different product domains or even services. The divide is supposedly informative to decide on different means of representation of products, and to determine price-sensitivities. Such a holistic division of all customers into two distinct groups is however bound to include noise in one way or another and thus to erroneously classify customers in specific situations. The data-driven approach presented above would merely link behavior to representation, and most probably be able to optimize representation more efficiently since only the bookstore (as a situation) is taken into account. However, because of the specificity the choice of representation might be beneficial for the bookstore but not usable in any other context.

The second distinction that is of relevance to transforming e-commerce to e-selling in the future are the operational demands imposed by both learning methods. Theory-driven methods are often fairly lightweight in that no heavy computations are necessary. All possible relationships between customer behavior and subsequent responses of the e-selling platform are derived from the theory and not from an interpretation of the collected data. Thus, no computation is needed. For the data-driven approach on the other hand decisions are made solely on the data. All possible features need to be related to each other, and thus quickly heavy computation becomes necessary.

The third relevant difference between theory-driven and data-driven learning lies not in the learning itself, but in the ability of those using the learning to understand its process. A lot of emergent data-driven learning seems to perform well—in that it optimizes some criterion and indeed performs better than prior to the learning being in place—but is hardly understandable by humans. Thus, while the bookstore does decide between two types of representations of their books, this decision is not meaningful for any other marketing actions since it is unclear to the marketer what the decision is based on. Theory-driven learning is often fully understood by the marketer and its results can thus be off use also outside the specific context.

Finally, we want to emphasize the difference between context specificity and prediction accuracy. While this relates to the previous point we feel that it is important to make clear that data-driven approaches by and large—especially since our ways of dealing with big data have increased—outperform the performance of theory-driven approaches within one specific context. Outside of that context however a fully data-driven approach is meaningless.

Obviously, any sensible transformation of e-commerce into e-selling would be composed of a intermediary point between fully data-driven and fully theory-driven. Fully data-driven methods of learning are to specific and leave marketers no room to exploit the knowledge gained in one setting for other settings. On the other hand, fully theory-driven means of learning are often too general for the specific problem at hand and put too much faith onto the theory: if the data does not match the theory should we stick with a divide introduced in theoretical marketing papers or rather adapt to our specific context?
We believe that both data-driven and theory-driven learning deserve a place in the transformation of e-commerce to e-selling. However, contrary to common approaches we believe that both roles should be made more explicit, and should be combined. While currently some adaptation algorithms are based only on data (such as the recommender system used by NetFlix [8]), and other design choices of e-commerce platforms are made solely on theory, we propose a middle ground that harnesses the strengths of both. This requires a re-evaluation of the position of theory: theory moves to being a starting point of data-driven learning—providing the structure is necessary to ensure generality. Theory, however, is not the end-point of adaptation once data is available.

The next two sections present two case studies in which (a) the selection of Sales Influence Tactics, SITs, and (b) the selection of a profit optimizing sales price are dynamically learned using both theoretical as well as data drive approaches. In both cases a few relatively simple theoretical notions ensure that the learning problem is tractable and even interpretable by humans, while the final adaptation to customers is done purely based on the incoming data.

3. Case 1: Sales Influence Tactics

Currently, sales professionals use a multitude of strategies to increase the chances of an effective sales pitch. While these strategies bear different names in the different branches of the personal selling and influence psychology literature that study them, for example influence principles [6], persuasion strategies or sales influence tactics [24,30], they all share a similar property: these strategies describe ways in which a product pitch can be made more effective, irrespective of the actual product that is being pitched. Thus, sales professionals not only search for the right product to offer to a customer, but also try to optimize the way in which the product pitch is made in order to resonate with preferences of the customer and increase the likelihood of a sale. We will refer to these different types of pitches as different Sales Influence Tactics (SITs) [24,30]. This is the first piece of theoretical knowledge that we introduce into this problem.

There is a wealth of examples in the electronic commerce [13,28] how the core psychology in SITs can or could be applied to e-commerce, in essence making it interactive e-selling. However, contrary to everyday practice in face-to-face selling, the usage of SITs in online selling and e-commerce is often static. While the actual product that is offered is frequently adapted to the behavior of individual buyer – think of recommendation systems used on large e-commerce sites like Amazon.com – the SIT that is used to promote the product is not.

The fact that these SITs are largely not adapted to individual customers contradicts not only with current offline sales practice, but also with findings from social psychology on which a number of the SITs are based. In these empirical investigations they have identified several personality traits – such as Need for Cognition and Preference for Consistency – that moderate the effects of different influence strategies [4,14]. There is a recurring phenomenon of groups of people reacting contrary to commonly persuasive messages. E.g., people placing value on being different than everyone else are likely to deviate in their responses to popularity-based influence tactics. The storyline is clear: we should adapt our usage of SITs to individual consumers, not population averages or past or typical performances of others in similar situations. This is the second piece of theoretical knowledge. Thus, (a) there exists SITs—which are effective to increasing sales, and (b) there are individual differences in responses to SITs.

While personalization of SITs was hard in mass-media campaigns in previous decades, e-commerce platforms do provide us with the opportunity to adapt our usage of distinct SITs for individual customers. Furthermore, the effect of SITs in e-commerce platforms can be measured (e.g. does the customer click on the product? Does he add it to the shopping cart? Does he purchase the product?). Advances in machine learning (and most noticeably algorithms for sequential Bayesian learning (see, e.g. [33]) make that it is possible to adapt the usage of SITs dynamically in real-time to the responses of individual customers. Thus, an e-commerce platform can, closely mimicking a face-to-face selling process, monitor the responses of its customers to SITs accompanying a whole range of product offerings, and while browsing adopt the likelihood of distinct SITs being used for an individual customer based on his or her previous responses to the use of that SIT.

3.1 Real-time adaptation and learning of SITs

To realize the adaptation of SIT’s in an e-commerce setting we developed an API (Application Programming Interface) based system that is developed on top of an existing e-commerce website. The chosen website, kinder-kleertjes.com, is an affiliate website that sells children’s clothing primarily to Dutch customers. Users can browse the affiliate website for products. Purchase of products, however, happens at the website of the vendor providing the product feed. The affiliate website receives a share of the revenue that is generated from the lead originating from the affiliate site.

Kinder-kleertjes.com offers a selection of over 1,200 products. Products are offered by two affiliate
programs and the website aims at attracting traffic through search engines and increasing click through to the two final vendors. The site, in its current form, has been running from the beginning of July 2010. The website is rather limited in size, attracting an average of 388 visitors a month on average during from July 2010 to April 2011.

The system for dynamic adaptation of SITs was created on top of the original website. The website kinder-kleertjes.com makes a HTTP call to an external server to request the appropriate SIT to use for the current visitor. The remote server returns the ID of the SIT that should be used and this is presented to the visitor. Finally, after browsing the product that is accompanied by the SIT, kinder-kleertjes.com sends an update to the server to communicate whether or not the SIT was a success (i.e. a click-through to the vendor’s web site).

For each new user, based on their IP address and the current time, a unique User ID is created and sent to the server. To be able to create the adaptive system, the presentation of different SITs to support the product offerings needs to be possible. The home page of the kinder-kleertjes.com presents a “random” selection of the offered products together with pictures of the products 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 SITs were implemented on this product display page. Only two SITs were implemented for this initial trial: a Special offer (with the accompanying text “This clothing item is available today at a special discount rate”), and a Bestseller (“This is one of our bestselling clothing items. This product is popular with many”). The first SIT uses scarcity and the latter one consensus as a mean to influence the customers [7]. By keeping the original “no strategy” product representation the evaluation concerned three product pitch versions that could be used for every product on the site.

To enable sequential learning of the effect of the SITs each product pitch version (the 2 SITs and the neutral version) were modeled independently using a Multilevel Beta-Binomial model. Initially, for each of the three versions of the product pitches, the prior effectiveness was set to a grand-mean of 0.15 (15%). The certainty around this estimate is set relatively low (variance = 0.05). Next, for each new customer on the first day of the field-trial these estimates are “copied” to obtain individual level estimates. We then use randomized probability matching (Scott, 2010) to determine which SIT to use for the current customer. After representing a SIT to a customer the Beta(M,V) distribution for that product pitch for that consumer was updated. Finally, every 24 hours, we batch updated the grand-means: these represent the average success of the different product pitches. Furthermore, we used shrinkage [9] for better estimation of the effects of SITs for previous individual customers2.

To evaluate the usage of dynamic SIT adaptation on kinder-kleertjes.com a field-experiment was setup. During a 4 month period half of the visitors of the kinder-kleertjes.com website were randomly assigned to the version of the website that implemented dynamic updating of SITs. We will refer to these as the trial condition. The other half of the visitors during that time period was assigned to browse the original website (without any SITs). We will refer to this as the baseline condition.

3.2 Results

During the field-trial 1449 customers visited kinder-kleertjes.com and viewed at least one product page. The average number of product pages visited per customer included in the field-trial was 1.8 (SD = 1.88). Over 30% of the visitors viewed 2 products or more. On average, the click through rate in the Baseline condition was 9.4%, while that in the Trial condition was 13.5% (See Figure 1 Left). This difference in proportions is statistically significant, \( \chi^2 = 6.386, \text{df} =1, p < 0.02 \). So, the dynamic adaptation of SITs indeed outperforms not using SITs in e-commerce. Figure 1 (Right) shows an overview of the individual level estimates of the success of the three different SITs used in the trial over the examination of multiple products for individual consumers. The top panel shows that the Consensus SIT was effective twice for this customer, leading to a consistently higher estimate for this SIT. The bottom panel shows a customer for whom the Scarcity SIT was effective multiple times, while the “no strategy” SIT was found ineffective. Examining the individual level estimates at the end of the trial period found that for around 42% of the customers the Consensus SIT was most effective. 37% of customers responded consistently favorable to the Scarcity SIT, while the no strategy SIT was most effective for 31% of our customers.

Finally, it is interesting to compare the performance of e-selling using adaptive SITs (at an individual level), with e-selling using a SIT that is most effective on average. This comparison is not straightforward since we have not selected one of the three SITs based on previous performance. However, we can estimate the performance of the best performing SIT based on the responses to a first time exposure to the distinct SIT for individual customers in

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2 We have tried to explain the sequential learning algorithm used in this trial without mathematical formalism. The actual algorithm is available from the authors both in [R] as well as PHP.
the trial condition. These first exposures are not yet adapted to individual level responses and thus provide a good estimate for the performance of these SITs on average. We find that the click-through rate of the best performing SIT (the Consensus appeal) for its first appearance in the trial condition is 10.8%, which is significantly lower, $X^2 = 3.854$, df =1, p < 0.05, than the results obtained by the adaptive selling during the full period (13.5%, see previous).

![Comparison of estimated conversion rates for baseline and trial. (Bottom) Estimated effectiveness of the different SITs for two randomly selected users.](image)

### 3.3 Discussion

This first case shows how a very limited theoretical notion—that of the existence of SITs as well as the existence of individual differences in responses to SITs can be used as a basis for further data-driven learning. The data-driven learning, however, is lightweight due to the structure of SITs imposed by the theory. Furthermore, the results of the data-driven learning are humanly interpretable: the estimates of the successes of SITs for individual customers could readily be used in different contexts. Next, we move forward to discuss another example of operating an e-commerce platform and optimizing its revenues, which uses even fewer theoretical assumptions in its approach to learning.

### 4. Case 2: Profit maximizing prices

Sellers are interested in selling their products for the profit maximizing price. Often, this price is set based on an examination of the cost function of the product [26], or it is based on market research querying customer’s price sensitivities for the offered product [32]. Researchers trying to establish profit maximizing sales prices have also focused on setting prices in a competitive market using a game theoretic approach (see, e.g. [18]). This latter form of pricing is highly theory-driven since a large number of assumptions on sellers and buyers dictate the price that is set.

Recently, with the growth of online services, it seems like examinations of the costs functions are relatively uninformative to estimate sales prices (other than setting a lower bound), and market research querying the price sensitivity of customers for online services is often hardly informative of customers actual buying behavior [21]. Furthermore, direct competition for novel services is often limited thus there might be hardly any competitor pricing information available. This combination makes other methods of determining the profit maximizing prices of online services of large applied relevance. Besides the fact that prices are currently hard to estimate for online services, online services also provide us with an opportunity: in online services it is often possible to offer different prices to different customers, and to update the price that is offered to new customers in (near) real-time [19]. Thus, sellers can run “field experiments” on the prices of their services and sequentially learn the profit optimizing price for their online service offering.

We present a method of sequentially learning optimal sales prices based on a heuristic called randomized probability matching. This method rests only on very limited theoretical assumptions, only those necessary to structure the problem. After the structure is imposed, a data-driven approach is used to converge to the profit maximizing sales price. As a comparison, we test the efficiency of our method against a “batch”-learning procedure based on comparisons of the overall learning costs of both methods.

### 4.1 Sequential learning

The opportunity provided by online services to sequentially learn the about the behavior or consumers is making its way into marketing literature (see, e.g. [15]). The sequential learning of the profit maximizing sales price of a service can be treated as a variation of the multi-armed bandit problem [33]: for each possible price a seller wants to learn her pay-offs (probability of a sale) to be able to determine the sales maximizing price. While the multi-armed bandit is notoriously resistant to analysis [11], optimal solutions are available in certain cases [11,38]. The problem of finding the profit maximizing sales price of an internet service compares to the multi-armed bandit problem in the sense that the seller wants to learn the respective
probabilities of a sales (success) given different prices (arms). Contrary to the standard formulation of the multi-armed bandit problem however is the fact that the pay-offs for each successful sale given different prices are not equal but depend on the price offered.

Methods that have been put forward to solve the multi-armed bandit problem range from the use of the Gittins Index [11] to multiple heuristic strategies. One heuristic that corresponds well to the tradition of conducting market research to set optimal sales prices would be to use a batch learning approach: The seller randomly allocates the first $N$ customers to each of the possible prices $p$ of the product and observes the willingness to buy given a certain price. After this learning phase the seller has sufficient information to compute the optimal price. In this batch learning the size of $N$ is critical but cumbersome to determine: Large $N$ will lead to a correct estimation of willingness to buy given a price, but will also lead to incurred losses by selling the product too cheap to a number of customers.

Another, more recent, heuristic to approach the multi-armed bandit problem is the use of randomized probability matching [33]. Here, each of the “arms” of the bandit are treated as independent and their respective success probabilities are modeled using a Bayesian approach. Next, one performs a random draw of the posterior probability distribution of each arm, and selects the arm with the highest draw. Finally, the probability distribution describing the estimated success of that arm is updated based on the observed success or failure.

4.2 Maximizing profit

The theoretical specification of the profit-maximizing price of an online service can be derived from a few very simple theoretical notions. These present all the theory we impose to structure the problem:

- Prices, $p$: These are easily rescaled: $\{p \in \mathbb{R} | 0 \leq p \leq 1\}$
- Probability of a sale given a price, $\alpha = P(\text{Sale} | p)$
- (Potential) market volume, $M$
- Expected number of units sold given a price, $U$: $U = f(p, \alpha, M)$
- Expected revenue, $R$: $R = U \times p$
- Costs, $C$: Consisting of fixed costs ($C_f$) and variable costs ($C_v$)
- Profit, $\Phi$: $R - C$

One wants to set the optimal price such that profit, $\Phi$ is maximized. Note that the only theoretical assumption that is put up is that the profit is a convex function of the price that is set. We try to find its maximum.

Suppose the probability of a sale, $\alpha$, is known and given by: $\alpha = 1 - p$. Thus, $\alpha$ is a strictly decreasing function from 1 to 0 given the range of $p$. The number of units sold is then given by $U = M \times (1 - p)$, where $M$, the potential market size, is assumed to be constant. The expected revenue is, $R = U \times p = M \times (p - p^2)$, and the total costs, are given by: $C = C_f + U \times C_v$. If one assumes no fixed costs, $C_f$ and linear variable costs, the total costs, $C$, are $U \times C_v = M \times (1 - P) \times C_v$, where both $M$ and $C_v$ are chosen to be constant in this example. Now, determining the sales price that maximizes profit is easy: The profit $\Phi$ is given by:

$$\Phi = R - C = M \times (p - p^2) - M \times (1 - p) \times C_v = p - p^2 - (C_v - pC_v) = -p^2 + (1 + C_v)p - C_v$$

which is maximized by setting its derivative ($\Phi' = (1 + C_v) - 2p$) to zero. Thus, the profit maximizing price $p = (1 + C_v)/2$

The data-driven learning is easily specified. For sellers offering online services $\alpha$ is not known. One thus wants to find the profit-maximizing price by finding $\alpha$ as efficiently as possible. We define efficient in this setting as minimizing the learning costs $\theta$. The learning costs are defined to be given by the difference in expected profit one would have obtained if $\alpha$ was known, $\Phi_{\text{max}}$, and the profit, $\Phi_{\text{search}}$, obtained while using a learning algorithm. To address the problem of sequentially learning the optimal sales price we propose the following algorithm:

- Split up the possible price range into a number of possible categories $j$.
- Specify a relatively uninformative diffuse prior for each category (e.g. $P(\text{sale} | \text{price}) \sim \text{Beta}(1, 1)$)
- Next, for each customer in the market $M$:
  - Perform a random draw from the beta-binomial for each price range
  - Weight the value of the draw by the profit given that the unit is sold for that price
  - Select the highest weighted draw
  - Offer the respective price to the customer
  - Observe response and update the posterior of that price category

To compare the performance of the proposed weighted randomized probability matching algorithm...
with a batch estimation algorithm we perform $S = 100$ simulations testing both algorithms. The market size $M$ is set to $10,000$, and $\alpha = 1 - p$ and thus linearly decreasing from $1$ to $0$ over the range of $p$. Costs are defined to consist only of variable costs $C_v$ of $0.05$. The price range for the simulation is split up into $j = 10$ equal size categories, $p = 0.05, 0.15, \ldots, 0.95$. Hence, the discretized price category closest to the profit maximizing price is $0.55$ and the max profit, $\Phi_{\text{max}}$, given that $\alpha$ is known would be: $0.55 \times (1 - 0.55) \times 10,000 = 2.475$.

The “batch” algorithm “offers” each of the price categories to $500$ customers. For each category a random draw from a binomial with success probability given by $\alpha$ is drawn to determine the success of the offer. Based on this “field experiment” $\alpha$ is estimated and the $\alpha$ with the profit maximizing price is selected for the remaining $5,000$ customers of that simulation run. The weighted randomized probability matching algorithm starts with a Beta$(1,1)$ prior for each of the price categories. Next, a random draw of the Beta$(\alpha, \beta)$ for each category is weighted by the profit obtained when selling a product for the price in the respective price category. Finally, a random draw from a binomial with success probability given by $\alpha$ for the respective price category is drawn and the Beta$(\alpha, \beta)$ prior for that category is updated based on the value of the draw $1$.

Figure 2 shows the search costs of the weighted randomized probability matching compared with the search costs of batch estimation. Averaged over the simulation runs the mean costs $\Theta$ of the weighted randomized probability matching algorithm is $291.88$, giving a profit of $88.2\%$ of $\Phi_{\text{max}}$, and the costs of the batch estimation are $364.37$ (85.3% of $\Phi_{\text{max}}$).

![Figure 2: Search costs per simulation run. In black the results for weighted randomized probability matching, in gray those for batch estimation.](image)

Weighted randomized probability matching significantly outperforms batch estimation, $t = -5.338$, $p < 0.001$. Perhaps even more interesting than the results on average over the training runs, however, is the stability of the weighted randomized probability matching: The costs of the estimation are relatively stable and decrease over increasing market size $M$. For batch estimation this is often not the case: If a suboptimal price category is chosen based on the batch experiment the incurred costs increase as market size $M$ grows.

### 4.3 Discussion

We described the problem of setting profit maximizing prices for online services. In practice, traditional means of setting optimal prices are hardly possible for online services or they lead to suboptimal results. Online services, however, do provide sellers with novel ways of “learning” the profit maximizing price of the service they are offering. We presented a data-driven learning method that is based on only minor theoretical assumptions about people’s responses to differing prices. However, introducing such theory into the learning process outperformed an even more data-driven approach (batch estimation). Furthermore, the results—the estimated probabilities of a sale given a certain price—are readily interpretable by marketers and can thus be generalized outside of the specific context. Weighted randomized probability is computationally lightweight and can thus be implemented in real time (and online).

### 5. The new e-marketing

We introduced the distinction between methods of data-driven learning to transform e-commerce into e-selling and methods of theory-driven learning. By and large traditional marketing focuses on theory-driven learning in which a learning problem is highly structured based on marketing theory and several heuristics are used to facilitate decisions. On the other hand, AI applications focus primarily on data-driven learning with a black-box approach and very limited theoretical structure. We set apart the advantages and disadvantages of both methods of learning. Next, we presented two cases which—in our opinion—combine both methods in a way that is relatively novel. We used minor theoretical guidance, guidance about SITs and about the general responses to different sales prices, as inputs for our data-driven approaches to learning. We showed how such learning outperformed theoretical learning (based only on the best SIT according to theory in case 1) and data-driven learning (based only on relatively dumb batch-estimation in case 2). We also highlighted how marketers can interpret the results derived from this hybrid form of learning and thus generalized outside of their respective domains.

The time has come to not just trade-off data-driven and theory-driven learning but rather to use theory as a starting point to enable structured data-driven learning. Theory is meaningful to overcome the cold start
problem usually experienced in data-driven approaches, and it is useful to provide generality outside of the chosen domain. This latter property enables an integration of computer and human learning activities. This means that subsequently computer learning can be integrated in all marketing efforts, also in those initiated by salesmen. On the other hand, data-driven learning serves a function to dynamically falsify theory, and adapt accordingly.

The applications presented in this paper represent a shift towards data-driven learning. However, the imposed structure enables understanding and generalizing beyond standard AI applications. Importantly, both of the applications introduce a probabilistic rather than deterministic selection of content to individual consumers. This reflects the idea of theory functioning as a guideline, but not the definite answer, to applied marketing problems. Probabilistic decisions, besides enabling optimization of the explore-exploit trade-off, will become more and more common as lightweight Bayesian algorithms sequentially learn a simple number of theoretical rules.

The proposed integration of data-driven learning and theory-driven learning also impacts the separation of “human” and “computer” tasks. Computers will be devised to do what they do best: log and analyze large datasets. Humans, however, deserve a strong place in the transition from e-commerce to e-selling: it is humans who design the actual content (e.g. the implementations of the SITs in case 1) and it is humans who setup the structure of the learning problem so as to provide generality outside of the specific domain.

Both of our cases result in differing content and product pitches to individual consumers. At the most, theory-driven approaches would create batches of customers and accordingly tailored offerings. However, more data-driven approaches will result in individual dialogues between the e-commerce platform and the customer. This creates both practical problems and ethical considerations. For example, it is important to be able to retrieve an individual conversation after an offering has been made. Consider case 2 and suppose a customer visits an online store and subsequently calls a customer representative. At that time her or his individual dialogue needs to be known: What price was offered to this particular customer? Thus, data-driven approach will place even greater demands on cross-channel information exchange. However, this approach will also provide new opportunities for sales persons. Consider case 1 and the customer calling to a sales representative after an online store visit. If the inter-channel information exchange works, the sales person knows, which SIT was effective to this particular customer and adapt her sales pitch on phone, too.

A final note is the importance of the level of analysis that is addressed by the theory and by the data-driven learning. These often do not correspond. Many customer decision-making theories are based on the analysis of aggregate behavior and thus concern only average effects. The effects identified in case 1 are conditional effects (on the individual) that might cause effects to be different from those predicted by theory. Data-driven learning will enable the creation of theories on the level of individual customer decision making.

6. Conclusions

Our two cases operating in a data-driven mode can be desirable to create dynamically learned interactions that outperform theoretically justified interactions. Theory-led approaches are not necessarily most useful for optimizing offerings but they can be invaluable in designing content. We argue that in the emerging day and age of dynamically adapted systems—systems that close in on true e-selling—both types of adaptation have their place. The examples and the distinction between data-driven and theory-driven have significant implications on the division of labor between humans and computers in digitalized business exchanges. In businesses requiring learning and adaptation at the customer interface, computers have predominantly only had the role of back-end computation and, to some extent, informing human sales people. The examples show how computers can learn without human involvement and adapt to customers. A detailed understanding about the division of labor between humans and computers is needed.

7 References
