Website Morphing 2.0: Switching Costs, Partial Exposure, Random Exit, and When to Morph

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Website morphing infers latent customer segments from clickstreams and then changes websites’ look and feel to maximize revenue. The established algorithm infers latent segments from a preset number of clicks and then selects the best “morph” using expected Gittins indices. Switching costs, potential website exit, and all clicks prior to morphing are ignored. We model switching costs, potential website exit, and the (potentially differential) impact of all clicks to determine when to morph for each customer. Morphing earlier means more customer clicks are based on the optimal morph; morphing later reveals more about the customer’s latent segment. We couple this within-customer optimization to between-customer expected Gittins index optimization to determine which website “look and feel” to give to each customer at each click. We evaluate the improved algorithm with synthetic data and with a proof-of-feasibility application to Japanese bank card loans. The proposed algorithm generalizes the established algorithm, is feasible in real time, performs substantially better when tuning parameters are identified from calibration data, and is reasonably robust to misspecification.

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1. Website Morphing and Its Limitations

Website morphing customizes the look and feel of a website to customers’ cognitive styles. The basic algorithm, developed by Hauser, Urban, Liberali, and Braun (2009, hereafter HULB), combines Bayesian inference of latent cognitive-style segments with dynamic programming optimization to match website designs to customers. Bayesian inference on a customer’s clickstream infers probabilities that the customer belongs to the latent segments. Using these probabilities and data from past purchases, the dynamic program automatically selects the best look and feel for the website for each customer. The “morph” assignment is (near) optimal in the sense that it balances learning about the best assignment for a segment with the profit that can be obtained by exploiting current knowledge of morph-to-segment purchase probabilities. HULB use data from a “calibration study” to simulate what would had happened had the BT Group implemented morphing on its broadband-sales website. HULB estimate that morphing would have increased revenue by $80 million.

Subsequently, Urban et al. (2014) adapted morphing to banner advertising. The only modification in the HULB algorithm was to account for multiple customer visits to the same website. In a field test with over 100,000 customers viewing over 450,000 banners on a CNET website, they report that banner morphing almost doubled click-through rates relative to a random assignment of banners. They also conducted a laboratory test on an automotive information and recommendation website to test the basic concept of morph-to-segment matching. The experiment replaced the automated algorithm with direct measurement in a four-to-five week longitudinal study. Click-through
rates on banners, as well as consideration and preference for Chevrolet-branded vehicles, increased significantly when morphs were matched to customer segments. The Chevrolet application expanded the definitions of customer segments to include the stage of the automotive buying process (collecting data, comparing vehicles, committing to a purchase).

The HULB algorithm, used in the BT Group and CNET tests, assumes that only the customer’s final clicks on the website affect the probability of purchase (or, in the case of banners, click-through rates). The algorithm assumes further that the act of switching the look and feel of a website or banner has no effect on the probability of purchase. And, finally, the algorithm does not take into account that customers might exit the website, sometimes after a relatively few clicks.

This paper proposes an improved algorithm that accounts for three phenomena: the impact of all clicks on a customer’s experience, switching costs, and random exit. We do so by transforming an inherently hard switching-cost problem, with a curse-of-dimensionality computational explosion, into a formulation that accounts for the phenomena and can run between clicks on a real website. We demonstrate that accounting for these phenomena can increase performance dramatically. For example, a counterfactual policy simulation, based on a proof-of-feasibility application to a Japanese bank website, suggests sales would have increased relative to random morph assignment. The increase was 63% of that obtainable by perfect information and over five times the 12% achievable by the HULB algorithm. (Systematic simulations, reanalyzing the HULB application, suggest average improvements of about 1.8× that of HULB.)

The improved algorithm nests the HULB algorithm in the sense that it reduces to the HULB algorithm for specific (and we feel extreme) values of key parameters. When parameters can be identified from a calibration study, the algorithm does at least as well as the HULB algorithm. For many reasonable parameter values, the improved algorithm outperforms the HULB algorithm substantially. The improved algorithm almost always outperforms the HULB algorithm even if parameter values are chosen incorrectly.

We begin by reviewing the HULB algorithm, then present the behavioral model, and propose the improved algorithm. Subsequent sections describe the synthetic-data analyses and policy simulations based on a Japanese bank application. We close with a discussion of unsolved problems.

2. Brief Review of the HULB Website Morphing Algorithm

This section presents an abridged version of the HULB website morphing algorithm. To stay consistent, we adopt the notation used by both HULB and Urban et al. (2014). Appendix A summarizes all notation. Greater details on derivations are available in HULB. A user’s guide, code, pseudocode, example questionnaires, and data are available in the supplemental material to this paper (available at http://dx.doi.org/10.1287/mnsc.2014.1961).

2.1. The Constructs of Morphing: Morphs, Segments, Clickstream, Calibration

We first provide a qualitative overview of the constructs used in morphing. Detailed examples are available in both HULB and Urban et al. (2014) and their online appendices.

2.1.1. Morphs. Morphs refer to alternative implementations of the overall look and feel of a marketing instrument such as a website (HULB) or banners (Urban et al. 2014). For simplicity of notation, this paper focuses on the look and feel of websites. Creating alternative morphs imposes a fixed cost on website or banner design—Urban et al. (2014) report an estimated cost of $250,000 for the many Chevrolet banners tested. This fixed cost (and sample size issues discussed later) means that most applications use a moderate number of morphs. HULB use eight.

2.1.2. Customer Segments. Customers are classified into a set of mutually exclusive and collectively exhaustive segments under the hypothesis that different segments respond differently to the morphs. The BT Group, CNET, and Chevrolet applications classified customers by cognitive styles; in the Chevrolet application customers were also classified by the stage of their buying process. Typically, in a calibration study prior to implementing the morphing algorithm, segment membership can be observed with intrusive measurement. During day-to-day implementation on a website, (latent) segments cannot be observed directly and must be inferred (probabilistically) from the customer’s clickstream. As with morphs, practical considerations require that the number of segments be moderate—16 for the BT Group application, 4 for the CNET application, and 12 for the Chevrolet application. The selection of segments is a modeling decision as discussed extensively in the market segmentation literature.

2.1.3. Clickstream. As a customer explores a website in day-to-day operations, we observe the customer’s clickstream. In particular, on any webpage, the customer must choose among a number of links. Some links are pictures, some are text, some take the customer to another webpage, some open a comparison tool, etc. We call these click alternatives, and we observe the customer’s sequential choice of click alternatives. So that we might use the customer’s sequential choices to infer the customer’s segment probabilities, we code each click alternative by a series of click characteristics.
For example, HULB code each click alternative by 11 characteristics, some of which are based on evaluation by independent judges (e.g., graphs or text), some of which code specific targets (e.g., an analytic tool), and some of which code actions (e.g., post a comment).

### 2.1.4. Outcomes.

Our goal is to maximize an outcome such as sales (BT Group) or click-through (CNET). The algorithm works with other binary outcomes such as 11 characteristics, some of which are based on evaluative alternatives as denoted by $c$. At each click choice, the customer faces denote the vector of clicks up to and including the $t$th click. Let $\tilde{X}$ be the set of the $X_n$ up to an including the $t$th click for all $j = 1$ to $J_n$. Let $\tilde{u}_{ijn}$ be the utility that customer $n$ obtains from clicking on the $j$th click alternative on the $t$th click. Let $\tilde{\omega}_j$ be a vector of click-alternative-characteristic preferences for the $r$th customer segment, and let $\tilde{\epsilon}_{ijn}$ be an extreme value error such that $\tilde{u}_{ijn} = \tilde{x}_{ijn}^{\top} \tilde{\omega}_j + \tilde{\epsilon}_{ijn}$. Let $\Omega$ be the matrix of the $\tilde{\omega}_j$'s.

### 2.2. Calibration of Preferences for Click-Alternative Characteristics.

In the calibration study, we observe the customer’s segment, $r$, the customer’s click-alternative choices, $\tilde{c}_{r,n}$, and the click-alternative characteristics the customer faced at each click-alternative choice, $\tilde{x}_{ijn}$. The extreme value error gives us the standard logit model with the following likelihood for the $n$th respondent in the calibration study:

$$
\Pr(\tilde{c}_{r,n} | r_n = r, \Omega, \tilde{X}) = \Pr(\tilde{c}_{r,n} | r_n = r) = \prod_{t=1}^{T} \prod_{j=1}^{J} \frac{\exp[\tilde{x}_{ijn}^{\top} \tilde{\omega}_j]}{\sum_{r=1}^{R} \exp[\tilde{x}_{ijn}^{\top} \tilde{\omega}_r]}. \quad (1)
$$

The likelihood over all respondents in the calibration study is simply the product of the individual respondent likelihoods. With Equation (1), we obtain estimates (maximum-likelihood methods) or Bayesian posteriors (Markov chain Monte Carlo sampling, with priors) of $\Omega$. (HULB use Bayesian posteriors; Urban et al. 2014 use maximum-likelihood methods.) We denote the estimates (or the mean of the posterior distributions, if Bayesian methods are used) by $\tilde{\Omega}$. Because morph assignments are made in real time, it is not feasible to sample from the full posterior distribution when Bayesian methods are used.

### 2.2.3. Probabilities That a Customer Belongs to Each (Latent) Segment.

In day-to-day website operations, we treat $\Omega$ as known. We observe the customer’s clickstream, $\tilde{c}_{r,n}$, up to the $r$th click, and we observe the relevant click-alternative characteristics, $\tilde{x}_{r,n}$. We seek to estimate the probability that the $n$th customer belongs to segment $r$ for all $r = 1$ to $R$. Denote these probabilities, after the $r$th click, by $q_{r | r_n}$. From the calibration study we know the unconditional prior probabilities, $\Pr_0(r_n = r)$, that the $r$th customer belongs to segment $r$. (Some websites might recalibrate these priors periodically.) Given the observed clickstream, clickstream characteristics, and $\tilde{\Omega}$, we use Equation (1) to obtain $\Pr(r_n = r | \tilde{c}_{r,n}, \tilde{\Omega}, \tilde{X}_{r,n})$. Bayes’ theorem provides the following:

$$
q_{r | r_n}(\tilde{c}_{r,n}, \tilde{\Omega}, \tilde{X}_{r,n}) = \Pr(r_n = r | \tilde{c}_{r,n}, \tilde{\Omega}, \tilde{X}_{r,n})
= \frac{\Pr(\tilde{c}_{r,n} | r_n = r, \tilde{\Omega}, \tilde{X}_{r,n}) \Pr_0(r_n = r)}{\sum_{s=1}^{R} \Pr(\tilde{c}_{r,n} | r_n = s, \tilde{\Omega}, \tilde{X}_{r,n}) \Pr_0(r_n = s)}. \quad (2)
$$
Equation (2) (and the imbedded Equation (1)) runs sufficiently fast on most computers that we obtain the $q_{mn'}(\tilde{c}_{r,n}, \tilde{\Omega}, \tilde{X}_{r,n})$ between clicks on the website.

2.3. Choosing the Optimal Morph If We Knew the Customer’s Segment

Customer $n$’s true segment is latent, but we find it easier to explain the HULB algorithm for a hypothetical case that assumes we know customer $n$’s true segment. We relax this assumption in §2.4. Let $p_{mn}$ be the probability that customer $n$ in segment $r$, who experienced morph $m$, will make a purchase (or other success criterion). We represent our knowledge, prior to customer 1, about $p_{m1}$ with a beta distribution that has parameters $\alpha_{m1}$ and $\beta_{m1}$. Specifically, $f_1(p_{m1} | \alpha_{m1}, \beta_{m1}) \sim p_{m1}^{\alpha_{m1}-1}(1-p_{m1})^{\beta_{m1}-1}$. Define $p_{m1}$, $\alpha_{mn}$, and $\beta_{mn}$ accordingly. After each customer, we update to the posterior distribution, $f_n(p_{mn} | \alpha_{mn}, \beta_{mn}, \delta_{mn})$, where $\alpha_{mn}$ and $\beta_{mn}$ are sufficient to summarize data from customers 1 to $n-1$. Because $\alpha_{mn}$ and $\beta_{mn}$ are used to make decisions about customer $n$, they do not yet include observations for customer $n$.

Let $\delta_{mn} = 1$ if the $n$th customer is in segment $r$ and makes a purchase after seeing morph $m$; $\delta_{mn} = 0$ otherwise. (We temporarily add the $r$ subscript to $\delta_{mn}$ to indicate that the segment, $r$, is known.) Then, because the binomial outcomes are naturally conjugate to beta priors, Appendix B shows that $\alpha_{mn,n+1} = \alpha_{mn} + \delta_{mn}$ and $\beta_{mn,n+1} = \beta_{mn} + (1 - \delta_{mn})$. Normalizing the value of a purchase to 1.0 implies that the immediate reward we expect from the $n$th customer is $E[p_{mn} | \alpha_{mn}, \beta_{mn}] = \alpha_{mn}/(\alpha_{mn} + \beta_{mn})$.

Assigning the optimal morph to the $n$th customer is more complicated than simply maximizing the immediate reward. Whenever we assign a morph $m$ to a customer in segment $r$ and observe an outcome, we update the posterior distribution for $p_{mn}$. The updated distribution enables us to make better decisions in the future. The dynamic decision problem must balance immediate rewards with the knowledge gained that enables better decisions in the future.

HULB demonstrate that this dynamic decision problem, for known $r_{mn}$, is the classic multiarmed bandit problem studied by Gittins (1979). Gittins (1979) proved that the problem is “indexable” and that the optimal solution is to compute an index for each arm and choose the arm with the largest index. (Indexability has a technical definition, but in lay terms, an “arm” of a multiarmed bandit is indexable if, when an index increases, the set of states for which choosing the arm is optimal does not decrease. Indexability implies an index strategy is feasible, although it does not guarantee an index strategy is optimal. Very often an index strategy is near optimal.) Because the detailed derivations are available in Gittins (1979), summarized in HULB, and otherwise widely known, we do not repeat them here. We repeat only the basic equations.

Let $G_{mn}$ be the Gittins index for the $n$th morph assuming the customer is in segment $r$, and we have updated $\alpha_{mn}$ and $\beta_{mn}$ based on all customer purchases up to but not including the $n$th customer. If $a \leq 1$ is the discount rate from one customer to the next and if $V_{Gittins}(\alpha_{mn}, \beta_{mn}, a)$ is the value of continuing with parameters $a$, $\alpha_{mn}$, and $\beta_{mn}$, then $G_{mn}$ solves the following Bellman equation:

$$V_{Gittins}(\alpha_{mn}, \beta_{mn}, a) = \max \left\{ \frac{G_{mn}}{1-a} \alpha_{mn} + \beta_{mn}, \alpha_{mn} + a V_{Gittins}(\alpha_{mn}+1, \beta_{mn}, a) \right\}. \tag{3}$$

Intuitively, the right-hand side chooses the maximum of a fixed “arm” and an uncertain “arm.” The fixed “arm” pays the expected value Gittins index over all future $n$. The uncertain arm pays a unit reward if the outcome is a success and nothing if it is not. A success occurs with an expected probability of $a_{mn}/(\alpha_{mn} + \beta_{mn})$. The uncertain arm also pays the value of continuing to explore optimally for future $n$, but discounted by $a$. The continuation values account for updating the beta distribution.

Equation (3) does not have an analytic solution, but we readily compute the Gittins indices with a simple iterative numeric algorithm. (We reuse code developed by Gittins. Code is available in Gittins et al. 2011.) For a given $a$, we table $G_{mn}$ as a function of $\alpha_{mn}$ and $\beta_{mn}$. If the segment $r$ were known, the HULB algorithm would simply look up the Gittins indices for all $m$ and choose the morph with the largest index.\(^1\) This strategy would lead to the maximum long-term profit taking both exploration and exploitation into account. In the special case where we are limited to using the same website or banner for everyone ($R = 1$), we can use the Gittins index algorithm to choose the optimal website or banner for each $n$.

2.4. Choosing a Morph When Segments Are Partially Observable

2.4.1. Partially Observable Markov Decision Process. When a customer’s segment is not known with certainty, the dynamic program changes. Because the latent segments is only partially observable, the optimization problem requires we solve a partially observable Markov decision process (POMDP). The space state is Markov because the full history is summarized by the $\alpha_{mn}$’s, the $\beta_{mn}$’s, and the latent segments.

\(^1\) As $n$ gets large, $G_{mn} \to \alpha_{mn}/(\alpha_{mn} + \beta_{mn})$. We table $\alpha_{mn}$ and $\beta_{mn}$ up to the point where this difference is small, that is, to a maximum of 3,000. Because the function is smooth, we use linear interpolation for noninteger values. See example in Appendix 3 of HULB.
2.4.2. Expected Gittins Index. Krishnamurthy and Mickova (1999) prove that the POMDP is an indexable decision process. Krishnamurthy and Mickova (1999) establish further that if we compute the expectation of the Gittins index over our uncertainty about the customer’s latent segment and choose the morph that has the largest expected Gittins index (EGI), then, in many cases, the EGI policy will be very close to optimality. More critically, because the EGI is easy to compute, we can select a (near) optimal morph in real time (between clicks on the website). HULB provide simulation evidence that the EGI strategy works extremely well for website morphing.

Specifically, the EGI algorithm replaces the Gittins index with the expected Gittins index, $EG_{mn}$, and chooses the morph with the largest $EG_{mn}$, where

$$EG_{mn} = \sum_{r=1}^{R} q_{mn} \left( \tilde{e}_{T,n}, \tilde{\Omega} \right) \tilde{X}_{T,n} G_{mn}(\alpha_{mn}, \beta_{mn}, a). \quad (4)$$

The HULB algorithm requires that we choose arbitrarily the click on which to morph. HULB use $T = 10$, and Urban et al. (2014) use $T = 5$. Equation (4), with minor modification, also enables us to choose the best starting morph for each customer. We simply replace $q_{mn} \left( \tilde{e}_{T,n}, \tilde{\Omega} \right)$ with $q_{mn}$, our beliefs about the customer’s segment prior to observing any clicks. HULB use $q_{mn} = \bar{P}_0 (r_n = r)$, but it would also be feasible to use periodic updates.

2.4.3. Updating Beliefs When Segments Are Partially Observable. Updating beliefs when the customer’s segment is known is particularly easy because the binomial distribution and the beta distribution are naturally conjugate. When the segments are latent, Appendix B demonstrates that updating is no longer naturally conjugate. However, we can still update if we consider “fractional observations”; that is, if we observe a success, $\delta_{mn}$, conditioned on the customer having seen morph $m$, we consider this as a fractional success for each latent customer segment, $r$. (Note that the outcome, $\delta_{mn}$, is not conditioned on $r$ because the segment is latent.) The fractional success is $q_{mn} \left( \tilde{e}_{T,n}, \tilde{\Omega} \right) \tilde{X}_{T,n} \delta_{mn}$ for each $r = 1$ to $R$. The binomial distribution is well defined for fractional observations and naturally conjugate to the beta distribution. HULB update via

$$\alpha_{mn, n+1} = \alpha_{mn} + q_{mn} \left( \tilde{e}_{T,n}, \tilde{\Omega} \right) \tilde{X}_{T,n} \delta_{mn}, \quad \beta_{mn, n+1} = \beta_{mn} + q_{mn} \left( \tilde{e}_{T,n}, \tilde{\Omega} \right) \tilde{X}_{T,n} (1 - \delta_{mn}). \quad (5)$$

Updating occurs when the customer leaves the website; thus we use all clicks, $\tilde{e}_{T,n}$. Appendix B provides complete derivations as well as arguments that these updating formulae lead to posterior distributions that converge to a mass point at the true values of the $p_{mn,n}$’s as $n \to \infty$. HULB provide simulation evidence that the fractional updating formulae lead to effective and profitable morph-to-segment assignments. These simple formulae enable the morphing algorithm to run in real time between a customer’s clicks on the website. With future, faster computers, one might improve the updating formulae.

2.5. Experience with the HULB Algorithm

Website morphing imposes a high initial fixed cost. The estimated $80$ million in incremental revenue for the BT Group, the observed banner click-through lifts of $80\%$–$100\%$ for CNET’s context-matched banners, and the observed $30\%$ lift in Chevrolet brand consideration justify the initial fixed cost for these high-traffic websites. Morphing also requires high traffic because of its convergence properties.

A sale by the BT Group to the $(n + 1)$st customer is worth almost as much as a sale to the $n$th customer. The HULB example with $100,000$ visitors per annum implies a discount rate of $a = 0.999999$ (HULB, p. 208). When $a$ is close to $1.0$, the optimal strategy includes substantial exploration. With known segments, HULB report that their algorithm explored heavily for the first $1,000$ customers; it did not stop exploring until the $3,000$th customer. They illustrate convergence with their Figure 3 (HULB, p. 209). With $16$ equal-sized segments, the HULB algorithm would likely stabilize around the $50,000$th customer.

Success probabilities for banners are typically much lower than success probabilities for sales on a morphing website—the order of $0.003$ in Urban et al. (2014) versus $0.38$ in HULB. As a result, Gittins indices take longer to stabilize in banner morphing than in website morphing. Nonetheless, the Urban et al. (2014) experience is informative. In their application with $100,000$ customers, the algorithm stabilized for the largest segments, but was still exploring for the smallest segment of approximately $9,000$ customers.

The experience by HULB and Urban et al. (2014) suggest that we should evaluate performance up to approximately $10,000$ customers per segment. Thus, the four-segment synthetic data experiments in this paper examine performance from $1$ to $40,000$ customers per simulation—$10,000$ customers per segment.

3. Behavioral Theory Improvements:

Key Assumptions

The HULB algorithm has no way to determine the click on which to morph. Instead, both HULB and Urban et al. (2014) choose an arbitrary click. This limitation would only be optimal if the morph seen by customers prior to the $T$th click had negligible impact on successful outcomes (sales or click-through). The implications of this implicit assumption were never tested.
Because Gittins’ (1979) solution requires that switching costs are zero (Banks and Sundaram 1994), and because bandit problems with switching costs are often computationally difficult, HULB assumed that customers experienced no switching costs when the website morphed. Indeed, without special structure, switching costs cause the optimization problem to become NP complete (Jun 2004, p. 526; Ny and Feron 2006, Theorem 1).

To address switching costs and the decision of when to morph, we specify a theory of customer behavior. To date, no such theory exists with respect to morphing. We seek a theory that is parsimonious, captures the essence of the phenomena, and is sufficiently “conjugate” that a when-to-morph (WTM) algorithm is feasible in real time between clicks on the website. To the extent that these assumptions can be improved, our tests are conservative. Future elaborations might improve website morphing further.

3.1. Assumption 1: Switching Costs

An extensive literature in psychology and marketing studies the cognitive cost of switching. Papers in psychology, beginning with Jersild (1927), generally study the cognitive cost of completing a task (e.g., Spector and Biederman 1976). Meiran (2000) establishes that switching among methods of response in a computer task imposes cognitive loads on respondents. In marketing, switching costs are well established in many sales contexts (e.g., Weiss and Anderson 1992), appear to apply for cognitive costs (Jones et al. 2000, 2002), and affect purchase intention. For websites, Balabanis et al. (2006, p. 217) suggest that “cognitive search costs in online shopping environments can be significant,” and Johnson et al. (2003, p. 63) report that “perceived switching costs . . . create a cognitive ‘lock-in’” for websites. It is likely that the cognitive costs of switching morphs reduce the benefit of matching a website’s look and feel to a customer segment.

The cost of switching is salient with a hypothetical example. Suppose that the initial morph for the nth customer is graphical and focused. The nth customer experiences this morph and learns to search based on a graphical-focused look and feel. Now suppose that subsequent clicks by the customer suggest instead that the best morph is verbal and general. If we were to switch morphs, the customer might become confused and have to relearn his or her search strategy. Although the verbal-general morph might have been best for the customer had the website had those characteristics from the beginning, it may not be best after the customer has learned to use a graphical-focused website. In general, it is such path dependence that makes switching-cost optimization problems NP complete.

Additive switching cost are common in the literature, and algorithms exist (e.g., Banks and Sundaram 1994, Dushochet and Hongler 2006, Jun 2004), but additive switching costs impose path dependence and make it infeasible to determine when to morph in real time. On the other hand, a multiplicative switching cost can be factored out in a Bellman equation. As we demonstrate below, we can solve a problem with multiplicative switching costs in real time. Specifically, we assume that a switch in the look and feel of the website lowers the customer’s purchase probability. The switch lowers the purchase probability by a factor of $\gamma$, where $\gamma \leq 1$. In this formulation, the HULB algorithm is a special case that assumes $\gamma = 1$.

Fortunately, multiplicative switching costs have descriptive advantages. First, because predicted outcomes, $p_{rmn}$'s, are bounded between 0 and 1, a multiplicative factor does not violate that bound, whereas an additive factor might. Second, although untested, we expect that the amount by which a low probability is lowered by a switching cost will be less than the amount by which a high probability is lowered by a switching cost. For example, suppose a switch lowers $p_{rmn}$ from 0.900 to 0.810. A comparable proportional cost would lower $p_{rmn}$ from 0.090 to 0.081, whereas a comparable additive cost would lower $p_{rmn}$ from 0.090 to 0.000. Likely the former is more realistic.

One might generalize $\gamma$ to assume that $\gamma_{mm'}$ is a function of the morphs from which and to which the customer switches. We leave that generalization to future research because (1) it would introduce severe state dependence that would likely make the dynamic program infeasible, (2) it would introduce a substantial measurement burden requiring a large number of parameters (56 parameters in the BT Group application and 132 parameters in the Chevrolet application), and (3) the HULB algorithm treats morphs as independent. Nonetheless, morph-specific switching costs are an interesting and challenging extension.

3.2. Assumption 2: The Impact of Being Exposed to Multiple Morphs

The HULB algorithm assumes that only the last morph affects purchase probabilities. Implicitly, morphs prior to the switch have zero impact on purchase probabilities. However, suppose that the system morphs after the 10th click and the customer makes a purchase decision after the 20th click. There is no reason to assume that the first 10 clicks have less impact than the last 10 clicks. The last 10 clicks may have more impact (recency), less impact (primacy), or equal impact. To allow various assumptions, we assign weights, $w_t$, to clicks to account for the differential impact of early versus late morphs. Let $\bar{w}$ be the vector of these weights. (Section 3.5 discusses other models.) Setting $w_t = w$ for all $t$ implies equal impact. Setting $w_t$ equal to an increasing (decreasing) function of $t$ assigns greater impact to later (earlier) morphs. The HULB algorithm
assumes a special case for \( \tilde{w} \). In particular, the HULB algorithm implicitly sets \( w_i \) equal to zero for \( t \leq \tau_s \) and \( w_i = w_f \) for \( t > \tau_s \).

In equation form, if customer \( n \) sees morph \( m_{tn} \) at the \( t \)th click (or the \( t \)th observation period), we generalize the HULB assumption to

\[
p_{tn} = \sum_i w_t p_{tn}w_i. \tag{6}
\]

To keep the number of \( w_i \)'s small, we allow \( t \) to index observation periods that may be one click or more than one click. We normalize the impact weights so that they sum to 1.0 over clicks (or observation periods). Switching costs, when relevant, apply for all \( t \) in Equation (6).

3.3. Assumption 3: Variation in the Number of Clicks for Each Customer's Visit

Some customers find the information they need quickly, make a purchase decision, and exit the website. Other customers visit many areas of the website, gather extensive information, and leave later. We cannot assume, nor do the data support, an assumption that all customers stay for all observation periods. The number of clicks does not seem to be particularly correlated with either the morph given or the purchase probability, but rather reflects the (unobservable) information needs of the customer.

Let \( \psi_{tn} \) be the probability that customer \( n \) leaves on the \( t \)th click given that customer \( n \) has already made \( t - 1 \) clicks. For example, before we observe the first click, we expect the customer to leave after that click with probability \( \psi_{1n} \), to leave after the second click with probability \( (1 - \psi_{1n})\psi_{2n} \), to leave after the third click with probability \( (1 - \psi_{1n})(1 - \psi_{2n})\psi_{3n} \), and so on. For each possibility, we normalize the effective impact weights, \( \tilde{w}_t \), to account for the number of clicks before exit. This model generalizes the implicit assumptions of HULB that \( \psi_{tn} = 0 \) for \( t < T_n \) and \( \psi_{tn} = 1 \) for some \( T_n \gg \tau_o \).

The only datum we observe for each customer is the click at which he or she leaves; thus we need a reasonably parsimonious model that balances nonstationarity over \( t \) with heterogeneity over \( n \). In §6.6 we demonstrate how to estimate the parameters of the model from the calibration study. Recall that morphs are assigned randomly during the calibration study. We obtain maximum-likelihood estimates based on the observed times of exit.

3.3.1. Model 1: Heterogeneity over Customers

Model 1 assumes that \( \psi_{tn} \) is beta distributed over customers with parameters \( \alpha_o \) and \( \beta_o \) but independent of \( t \): \( f_{0}(\psi_{tn} | \alpha_o, \beta_o) \sim \psi_{tn}^{a_o-1}(1 - \psi_{tn})^{b_o-1} \). Given this assumption, we can readily calculate the probability that a randomly chosen customer will leave after any given click. We obtain the predicted probability of leaving by integrating out the heterogeneity. For example, simple calculus provides the probability of leaving after the first click as \( \alpha_o/\alpha_o + \beta_o \), the probability of leaving after the second click as \( \alpha_o\beta_o/\alpha_o + \beta_o + 1 \), after the third click as \( \alpha_o\beta_o(\beta_o + 1)/\alpha_o + \beta_o + 2 \), etc. Using these values, we calculate the probability that a customer remains on the website through the \( t \)th click.

3.3.2. Model 2: Homogeneity over Customers, But Nonstationarity over Clicks. Assume \( \psi_{tn} = \psi_t \) for all \( n \).

3.3.3. Model 3: Hybrid Model. Respondents might remain on the website for some initial clicks, but, after those initial clicks, revert to a different \( \psi_{tn} \) that is heterogeneous in \( n \) (as in Model 1).

3.3.4. Model 4: Extensions. We might assume that exit probabilities depend on the customer’s segment, the terminal morph, or the morph history, etc. For example, \( \psi_{trm} \) might be a function of the dissimilarity between morph \( m \) and morph \( m' \). These extensions complicate the optimization challenge and are left to future research.

3.4. Selecting Values of the Tuning Parameters

The switching discount (\( \gamma \)) and the impact weights (\( \tilde{w} \)) are tuning parameters in the more generalized algorithm. They must be selected before the algorithm is used to morph a website (in day-to-day operations). The time of exit is easy to observe in the calibration study. We estimate the parameters of a model for exit probabilities (\( \psi_{tn} \)'s) using standard methods. (Exit seems more tied to the customer’s information needs than the morph given; hence calibration data are likely sufficient for these parameters.)

The tuning parameters, \( \gamma \) and \( \tilde{w} \), require either managerial judgment or experiments during the calibration study. In a calibration study, segment membership is measured directly, therefore the true \( \tau_o \) is known among calibration respondents. Applications to date vary morphs randomly over customers to estimate the priors, \( P_{rm} \). A more complex experimental design might vary morphs randomly over customers and randomly switch morphs within customers. With a sufficient sample size, estimates of the tuning parameters, \( \tilde{w} \), and the \( P_{rm} \)'s are all identified from observed customer outcomes (sales or click-throughs). For example, if there are eight morphs, four segments, and four observation periods, we need to estimate 37 parameters (32 \( P_{rm} \)'s, 4 \( \tilde{w} \)'s, and \( \gamma \)). For each segment, some customers see one morph for all periods. Some customers see two morphs with switches varied over \( t = 1, 2, \) or 3. A full factorial would be \( 8 \times 4 \) (single morph combinations) plus \( 8 \times 7 \times 4 \times 3 \) (two morph combinations) for a total of 704 combinations—more than enough to identify
37 parameters. If a feasible algorithm could be developed to account for different $\gamma_{mn}$'s, they, too, would be identified, albeit with a large sample size requirement.

We might also update the tuning parameters after initial experience on the website, say, after observing 50,000 customers. Although the optimal morph allocations are based on the assumed values of the tuning parameters, we might still identify $\gamma$ and $\bar{w}$ based on the likelihood principle. See related discussions in Hauser and Toubia (2005) and Liu et al. (2007). Basically, in vivo, a morphing algorithm will have assigned various morphs to consumers at various time periods and will have done so based on known rules from known data. We observe $\delta_{mn}$ for every consumer who was so assigned. If the likelihood principle is assumed, it should be feasible to estimate $\gamma$ and $\bar{w}$. Future algorithms might also explore optimal experimentation to learn the tuning parameters while learning about the $p_{mn}$'s.

3.5. Alternative Assumptions
Making the decision of when (whether, how often) to morph is a challenging optimization problem. We must solve the problem optimally or near optimally, and we must do so in real time between customer clicks. Modeling switching costs, impact weights, and exit probabilities with separable functions enables rapid solutions. We believe our assumptions are simple, realistic, flexible, and well matched to the data available in website-morphing applications. However, other assumptions are possible. For example, we might make $\gamma$ an increasing function of the clicks before a switch and a decreasing function of the clicks after a switch, or we might allow $\gamma$ to depend on the number of prior switches. Equation (6) might be replaced by a nonlinear function. Either $\gamma$ or $\bar{w}$ might be modeled as heterogeneous over segments or over customers.

All website morphing applications to date used clicks rather than clock time because clock time adds unobserved variance due to network speed, distractions while browsing, and variations in reaction time. Although clicks are correlated with clock time in our field experiment ($p = 0.57$, $p < 0.01$), future applications might model $\gamma$, $\bar{w}$, and $\psi_{tn}$ as functions of clock time rather than clicks. With experience and new research, we might find one or more of these extensions feasible and profitable. For now, we believe our assumptions are reasonable, robust, and generalize website morphing.

4. When to Morph: Explicit
Endogenous Decisions on Timing
The HULB algorithm identifies the best morph to give to each customer based on a fixed number of customer clicks. We can do better with an algorithm that determines endogenously the number of clicks to observe before morphing. The improved WTM algorithm also allows, but does not require, more than one change in morphs. In this section, $t$ indexes observation periods that may be more than one click.

4.1. Dynamic Decision Problem
Figure 1 illustrates the WTM decision problem for the case where the customer makes a purchase (or leaves the website) after four observation periods. (The theory applies when the number of observation periods is a random variable; four morphs is just an illustration.) Specifically, during observation period $t_{nr}$, the website displays morph $m_{tnr}$. The respondent makes clicks, $c_{tnr}$, while exploring the website, and we update our beliefs about the customer’s segment, $q_{tnr}(\hat{c}_{tnr}, \hat{\Omega}, \hat{X}_{tnr})$. Using the new information, and anticipating more information from subsequent decision periods, we decide which morph, $m_{t+1,nr}$, to display in the next decision period. To keep track of morph changes, we define $\Delta_{m_{n,n-r}}$ as an indicator variable such that $\Delta_{m_{n,n-r}} = 1$ if we change to morph $m_{tnr}$ for customer $n$ in period $t$. With this notation, the total number of morph changes for customer $n$ is $N_{tn} = N_{t-1,n} + \sum_{m_{tn}} \Delta_{m_{n,n-r}}$. We represent the purchase decision by $\delta_{tn} = 1$ if the customer makes a purchase and $\delta_{tn} = 0$ if the customer does not make a purchase. We dropped the $m$ subscript from HULB’s $\delta_{mn}$ to allow for the fact that more than a single morph may have affected outcomes for customer $n$.

Figure 1 illustrates the basic dilemma. The longer we wait to morph, the more clicks we observe. More clicks enable us to identify better customer $n$’s segment and, hence, the best morph for customer $n$. However, when the impact weights imply that early morph experience affects purchase probabilities or if the customer is likely to leave early, we want to get to that best morph as rapidly as feasible. The problem is compounded because switches are costly.

4.2. Formulating a Feasible Bellman Equation
Optimizing morph decisions for the problem in Figure 1 is challenging. It is even more challenging when embedded within a dynamic program to learn the best morph to assign for each customer segment (as in HULB). For example, Asawa and Teneketzis (1996, p. 329) caution: “Inclusion of a switching penalty drastically changes the nature of the bandit problem . . . . The optimal policy is not given by an index rule anymore.” Although heuristics exist using multiple indices (e.g., Dusonchet and Hongler 2006), the number of indices explodes exponentially in a morphing problem were there are, potentially, tens of thousands of costly switches (one or more switches for each customer).

The problem is further compounded when Bayesian updating is used to identify customer segments. Each switch presents new click opportunities, which customers choose probabilistically based on their (latent) customer segment and the morph decision. We might anticipate how our decisions in observation period $t$
Figure 1 When-to-Morph Decision Problem (Example Customer, Four-Period Illustration)

---

Notes. Choose morph \( m_n \) at each decision period to maximize sales, \( \delta_n \). The \( q_{rn}'s \) are also a function of \( \hat{\alpha} \) and \( \hat{X}_{tn} \). Some arguments are suppressed in this figure to avoid complexity.

---

affect the observations that update \( q_{rn}(\hat{c}_{tn}, \hat{\alpha}, \hat{X}_{tn}) \) for \( \tau > t \). This problem quickly becomes intractable. We need to finesse the explosion in the number of potential click paths. Finally, any solution must take into account that customers leave stochastically between observation periods.

We address these challenges with an algorithm that runs between a customer’s clicks on the website. Our solution recognizes that the two decisions, morph-to-segment assignment (HULB) and when to morph, are based on learning and optimization that occur over vastly different time scales. The HULB optimization is based on learning from observed outcomes of tens of thousands of customers, whereas the WTM optimization problem is based on learning customer segments based on learning and optimization that occur over periods.

For the purchase \( G \) from clicks \( m_{1n} \), we reduce purchase probability by factor of \( \gamma \) if \( m_{2n} \neq m_{1n} \). This simplification comes from linear impact weights, which enable us to factor them out. The third simplification comes when we recognize that, independently of future clicks, our best estimate at \( t \) of the terminal probabilities, \( q_{rn}(\hat{c}_{T_n}, \hat{\alpha}, \hat{X}_{T_n}) \), is \( q_{rn}(\hat{c}_{t-1,n}, \hat{\alpha}, \hat{X}_{t-1,n}) \). In other words, the \( q_{rn}(\hat{c}_{t-1,n}, \hat{\alpha}, \hat{X}_{t-1,n}) \) represent our expectations over all future clicks. With these simplifications, we write the expected immediate reward, \( EIR(m_{1n}, m_{t-1,n}, \hat{\alpha}, \hat{\alpha}_{t-1,n}) \), as

\[
EIR(m_{1n}, m_{t-1,n}, \hat{\alpha}, \hat{\alpha}_{t-1,n}) = \gamma^t \sum_{\tau=t}^{T_n} q_{rn}(\hat{c}_{\tau,n}, \hat{\alpha}, \hat{X}_{\tau,n}) G_{rn}.
\]

### 4.2.2. Value of Continuing Optimally.

To formulate the value of continuing optimally, we recognize that the evolution of \( q_{rn}(\hat{c}_{tn}, \hat{\alpha}, \hat{X}_{tn}) \) depends on the true customer segment. However, at period \( t \) (and even at period \( T_n \)), we are uncertain about the true segment. We have an expectation over \( r_{true,n} \) for the purchase probabilities, and we have an expectation over \( r_{true,n} \) for the evolution of \( q_{rn}(\hat{c}_{tn}, \hat{\alpha}, \hat{X}_{tn}) \) for \( \tau \geq t \).

To keep track of these expectations, we temporarily write the evolution of the clicks as conditioned on \( r_{true,n} \).
If \( m_{t+1,n}^* (r_{\text{true}}) \) is the morph we would choose at \( t+1 \) if the true segment for customer \( n \) was \( r_{\text{true},n} \), then the continuation value is

\[
V_{t+1}(m_{t+1,n}^*(r_{\text{true},n}), m_{t,n}, \hat{w}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r_{\text{true},n}) = \max \mathcal{F}(m_{t,n}, m_{t+1,n}^*(r_{\text{true},n}), \hat{w}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r_{\text{true},n})
\]

But \( r_{\text{true},n} \) is not known when we are making the decision at \( t \), so we account for this dependence for \( \tau \geq t \) by taking an expectation over this unknown variable at \( t \); that is, we take an expectation over the true segments when we compute the continuation value for \( \tau \geq t \). Going forward to any observation period, \( \tau \), under the assumption that the true segment is \( r_{\text{true},n} \), we would like to anticipate how the \( \hat{w}_{t-1,n} \) will evolve for any future sequence of morphs. However, in practical situations, the state space is so large that we cannot anticipate the future clickstream for \( \tau \geq t \). At the start of the \( t \)th decision period, our best estimate of customer \( n \)'s segment probabilities over all future clickstream paths remains \( q_{\text{true}}(\hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}) \). In other words, \( V_t \) depends on \( \hat{c}_{t-1,n} \) for \( \tau \geq t \). Backward induction does the rest.

Putting it all together enables us to optimize the current period's morph, \( m_{t,n} \), by backward induction using a computationally rapid Bellman equation. Naturally, we keep track of the \( \Delta_{m_{t,n}} \)s for \( \tau \geq t \) when we compute the conditional values, \( V_t(m_{t,n}, m_{t-1,n}, \hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r_{\text{true},n} = s) \):

\[
V_t(m_{t,n}, m_{t-1,n}, \hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r_{\text{true},n} = s) = \max_{m_{t+1,n}} \left\{ \gamma^{m_{t,n}} \mathbb{W}_t s \sum_{r} q_{\text{true}}(\hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}) G_{r_{\text{true},n}} \right. \\
+ \sum_s q_{\text{true}}(\hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}) V_{t+1}(m_{t+1,n}, m_{t,n}, \hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r_{\text{true},n} = s) \left. \right\}. \tag{7}
\]

4.2.3. Variation in the Number of Periods for Each Customer’s Visit. Purely for ease of exposition, we derived the WTM Bellman equation assuming a fixed number of observation periods. It is relatively simple to generalize the Bellman equation for variation in the number of periods for each customer’s visit. The assumption of §3.3 provides the separability necessary. Let \( \Psi_n(S | t-1) \) be the probability that customer \( n \) is still at the website at observation period \( S \) given that customer \( n \) was at the website at observation period \( t-1 \). The expectation over customers is \( \sum_n \Psi_n(S | t-1) \) because we do not know customer \( n \)'s exit probability prior to observing an exit. Using any of the random-exit models in §3.3, we calculate this probability via

\[
\Psi(S | t-1) = E_n[\prod_{s=1}^{S} (1 - \psi_{sn})].
\]

The random exit (r.e.) Bellman equation is then the following equation, where the impact weights are renormalized to reflect the periods in which the customer remains on the website:

\[
V_t(m_{t,n}, m_{t-1,n}, \hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n} | r.e.) = \max_{m_{t+1,n}} \left\{ \gamma^{m_{t,n}} \mathbb{W}_t s \sum_{r} q_{r_{\text{true},n}}(\hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}) G_{r_{\text{true},n}} \Psi(t+1 | t) \right. \\
+ \sum_s q_{r_{\text{true},n}}(\hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}) V_{t+1}(m_{t+1,n}, m_{t,n}, \hat{c}_{t-1,n}, \hat{\Omega}, \hat{X}_{t-1,n}, r.e.| s) \left. \right\}. \tag{8}
\]

4.2.4. Modified Bayesian Updating. The HULB algorithm assumes that only the last morph seen by customer \( n \) affects the probability of a successful outcome for customer \( n \). For real-time computation, HULB treated the observed outcome, \( \delta_{mn} \), as a series of fractional outcomes as determined by the (latent) segment probabilities, \( q_{\text{true}}(\hat{c}_{t,n}, \hat{\Omega}, \hat{X}_{t,n}) \). The WTM algorithm is based on a more general behavioral assumption that allows impact weights for all observation periods. We therefore generalize the updating procedure (Equation (5), §2.4.3). As demonstrated in Appendix B, we can generalize HULB and treat each combination of a period and a latent segment as a fractional observation.

Let \( \eta_{nm} = 1 \) if customer \( n \) saw morph \( m \) during the \( t \)th observation period, and let \( \eta_{nm} = 0 \) otherwise. The fractional observation for period \( t \), morph \( m \), and segment \( r \) is based on the \( \eta_{nm} \), the impact weights \( \mathbb{W}_n \), the switching-cost penalty, and \( q_{r_{\text{true},n}}(\hat{c}_{t,n}, \hat{\Omega}, \hat{X}_{t,n}) \). Appendix B motivates the following (practical) updating equations:

\[
\alpha_{nm} = \alpha_{nm} + q_{r_{\text{true},n}}(\hat{c}_{t,n}, \hat{\Omega}, \hat{X}_{t,n}) \gamma^{\eta_{nm}} \cdot \left( \sum_{t=1}^{T_n} \eta_{nm} \mathbb{W}_n \right) \delta_{nt} \tag{9}
\]

\[
\beta_{nm} = \beta_{nm} + q_{r_{\text{true},n}}(\hat{c}_{t,n}, \hat{\Omega}, \hat{X}_{t,n}) \gamma^{\eta_{nm}} \cdot \left( \sum_{t=1}^{T_n} \eta_{nm} \mathbb{W}_n \right) (1 - \delta_{nt})
\]

4.2.5. Motivation for Expected Gittins Index Decoupling. The WTM optimization (Equations (7) and (8)) is feasible because we decoupled the decision on when to morph for a customer from optimal experimentation between customers. We cannot prove that decoupling retains the near optimality of the expected Gittins index, but we can examine the synthetic-data experiments and the Japanese bank counterfactual. The WTM algorithm does quite well relative to the HULB algorithm and relative to an upper bound of
perfect information. The WTM algorithm achieves a net present value that is 60%+ of that achieved by perfect information. No algorithm could do better than perfect information.

There are intuitive reasons to believe that decoupling will be near optimal. First, the observed $\delta_n$ cannot affect the decision of when to morph for customer $n$. The Gittins indices, $G_{rmn}$’s, and the distributions of the purchase probabilities, $p_{rmn}$’s, are updated after customer $n$ leaves the website. Second, the WTM decision is based on learning about a customer’s segment during a visit, whereas the morph-to-segment decision (HULB) is based on learning about the purchase probabilities using the terminal segment-membership probabilities. Third, learning through Gittins indices happens many orders of magnitudes slower than decisions of when to morph. Empirical evidence (§2.5) suggests that Gittins indices stabilize after 40,000–100,000 customers depending on the number of morphs and segments. On the other hand, decisions about when to morph depend on clickstream observations on the order of fractions of a single customer’s website visit. Fourth, decoupling is analogous (but not equivalent) to the “branching bandits” literature, where researchers have proven that it is often optimal to replace the uncertain outcome of an indexable decision process with its Gittins index (Bertsimas and Niño-Mora 1996, Tsitsiklis 1994). For example, Weber (1992) analyzes a “super process” in which an initial bandit process has rewards that are themselves bandit processes. To solve the superprocess dynamic program optimally, Weber (1992) replaces the outcome of each secondary bandit process with its Gittins index. He then uses those indices as rewards when computing the indices for the arms in the primary bandit process.

At minimum, we expect the WTM algorithm will provide substantial improvements relative to the HULB algorithm. We examine the magnitude of such improvements in §5.

4.3. Summary of the Algorithmic Improvements

The HULB algorithm has proven successful on calibration-study-based synthetic data representing the BT Group website and for a field experiment morphing banners on CNET. However, the HULB algorithm assumes that only the last morph matters, that there are no switching costs, and that customers do not leave the website randomly. Our proposed WTM algorithm generalizes the HULB algorithm to address those issues. The algorithm is based on a series of behavioral assumptions that we feel are reasonable and capture the relevant phenomena. The WTM algorithm runs in real time between clicks on a website and identifies when to morph while retaining the ability to allocate the best morph to each customer. The WTM algorithm requires “tuning” parameters for impact weights and switching costs. The tuning parameters can be estimated with a sufficiently large sample in the calibration study. Lacking a calibration study, the parameters can be set by managerial judgment. We now examine the WTM algorithm with synthetic data and with a counterfactual policy simulation based on a proof-of-feasibility application.

5. Synthetic Data Experiments

If customers are described accurately by the behavioral assumptions, the principle of optimality suggests that the WTM algorithm will outperform the HULB nested algorithm. We use synthetic data experiments to examine the amount of the improvement. We also examine robustness by comparing the HULB algorithm to the WTM algorithm when the WTM algorithm uses incorrect values of the tuning parameters.

5.1. Reanalysis of the HULB BT Group Simulations

HULB tested their algorithm with synthetic data chosen to mimic behavior on the BT Group website. In particular, they used the $\hat{p}_{rm}$ estimated from the calibration data to create $p_{rm, true}$’s. If morph $m$ was assigned to a customer in segment $r$ after the first $\tau_o$ clicks, HULB drew a binomial outcome based on $p_{rm, true}$ and updated accordingly. To simulate Bayesian segment identification, HULB drew customer click-alternative choices with Equation (1) using the $\hat{\Omega}$ estimated from the calibration data (up to 20 webpages and 16 click alternatives per webpage). The $q_{rm,j}(\tilde{r}_{r,n}, \tilde{\Omega}, \tilde{X}_{r,n})$ were based on the simulated clickstream and Equation (2).

We begin by reexamining the HULB BT Group simulations. We examine a hypothetical world in which there are four observation periods of five webpages each (20 webpages as in the HULB simulations). Data are generated with $\gamma = 0.95$ and $\tilde{w} = (0.25, 0.25, 0.25, 0.25)$. We compare the proposed WTM algorithm with the HULB algorithm, which implicitly assumes $\gamma = 1$ and $\tilde{w} = (0, 0, 0, 1)$. This example illustrates that there exists at least one case where the WTM algorithm substantially improves revenue. Because the calculated rewards include switching costs, the rewards in Table 1 are smaller than those reported by HULB.

We select four customer segments and simulate 10,000 customers from each segment (a total of 40,000 synthetic customers per simulation). Visual inspection of the $G_{rmn}$ plots indicates that 10,000 synthetic customers per segment are sufficient to observe performance for finite $n$ and at (or near) convergence. Although the variance over simulations is small, we simulate each algorithm 10 times and take the average.

Table 1 summarizes the relative improvements. We report the net present value of the rewards using the discount factor from HULB, $\alpha = 0.999999$. We also report the rewards over the last of 40,000 synthetic customers as an indication of the rewards after the $G_{rmn}$’s have
We examine whether the WTM algorithm improves WTM over the HULB algorithm is worth approximately $25.5 million. The improvement of the BT Group website is worth approximately $4 million in revenue. Based on this valuation, the improvement is even larger at convergence (60.0% for WTM versus 33.4% for HULB).

HULB (p. 212) report that a 1% increase in sales on the BT Group website is worth approximately $4 million in revenue. Based on this valuation, the improvement due to the HULB algorithm over random allocation is approximately $25.5 million. The improvement of the WTM over the HULB algorithm is worth approximately $17.5 million.

5.2. Systematic Comparisons Using a Full-Factorial Design for Tuning Parameters

We now compare projected revenues when the WTM algorithm performs better than the HULB algorithm—algorithms perform identically. In all other cases, the WTM algorithm performs better than the HULB algorithm—sometimes substantially better. Improvements in the net present value average 1.78 times higher. They vary from 1.19 at \( \gamma = 1 \), \( \bar{w} = (0.02, 0.05, 0.18, 0.75) \) to an almost fourfold increase of 3.89 at \( \gamma = 0.80 \), \( \bar{w} = (0, 0, 0, 1) \). Increases at convergence are less dramatic, but still substantial. Ratios vary from 1.17 to 2.17 with an average of 1.59.

Table 2 provides insight on when the additional complexity of WTM has the largest impact. The relative increase is most sensitive to switching costs, with the largest increase when switching costs are largest. The effect of impact weights varies and interacts with switching costs. For modest switching costs, the relative increase is largest for equal impact weights. For large switching costs, the relative impact is largest when the impact weights favor the last period. Overall, the effect of impact weights is less than that of switching costs.

5.3. Robustness Tests When the WTM Tuning Parameters Differ from True Values

Table 2 and Figure 2 compare the net present value of projected revenues and the values of revenue at convergence, for the WTM algorithm compared with the HULB algorithm. We report comparisons for all 20 (5 \( \times \) 4) combinations of \( \gamma \) and \( \bar{w} \). Projected revenues are averaged over 10 replications—a total of 400 simulations and 16 million synthetic customers.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Reanalysis of BT Group Website Morphing (with Switching Costs and Impact Weights)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reward at convergence</td>
<td>Percent improvement in reward (%)</td>
</tr>
<tr>
<td>Baseline for no morphing</td>
<td>0.3171</td>
</tr>
<tr>
<td>Website morphing</td>
<td></td>
</tr>
<tr>
<td>Website morphing (HULB)</td>
<td>0.3392</td>
</tr>
<tr>
<td>Website morphing with improved algorithm</td>
<td>0.3567</td>
</tr>
<tr>
<td>Perfect information (( n \to \infty ))</td>
<td>0.3831</td>
</tr>
</tbody>
</table>

Notes. For these comparisons, switching costs are \( \gamma = 0.95 \). Impact weights are \( \bar{w} = (0.25, 0.25, 0.25, 0.25) \).

*Rewards for the last 400 customers out of 40,000 customers.

*(Reward due to algorithm — reward at no morphing) / (reward due to perfect information — reward at no morphing).

*Net present value of the rewards divided by the number of periods.

*NPV due to algorithm — NPV at no morphing) / (NPV due to perfect information — NPV at no morphing).

*This is the upper bound. Applications do not have perfect information on either customer segments or purchase probabilities.

In Figure 2, the vertical axes are the projected revenue per customer with the revenue for a success normalized to 1.0. The horizontal axes are the number of synthetic customers reported every 400th customer. In all cases, both algorithms converge smoothly. By 40,000 synthetic customers, convergence is usually complete. (For some values of the tuning parameters, revenues are still increasing slowly at 40,000. It is unlikely we would gain further insight beyond 40,000 synthetic customers per experimental cell.) The case where the WTM algorithm matches the HULB algorithm, \( \gamma = 1 \) and \( \bar{w} = (0, 0, 0, 1) \), is shown in the lower right. As predicted, the WTM and HULB algorithms perform identically. In all other cases, the WTM algorithm performs better than the HULB algorithm—sometimes substantially better.

We examine whether the WTM algorithm improves outcomes for a wide range of switching costs and impact weights. We vary switching costs systematically from \( \gamma = 0.80 \) to \( \gamma = 1.0 \). We choose \( \gamma = 0.80 \) as a lower value because HULB report an improvement of approximately 20%. Such an advantage would not be sufficient if \( \gamma < 0.80 \). The upper value corresponds to the HULB implicit assumption. We vary impact weights systematically from equally valuing all observation periods (\( \bar{w}_t = \bar{w} \forall t \)) to favoring only the last observation period (\( \bar{w}_t = 0 \forall t < T_{cr}, \bar{w}_{T_{cr}} = 1 \)). Specifically, we vary \( \bar{w} \) over the following values: (0.25, 0.25, 0.25, 0.25), (0.10, 0.15, 0.25, 0.50), (0.02, 0.05, 0.18, 0.75), and (0, 0, 0, 1).

We plot performance for \( n = 1 \) to 40,000 at increments of 400 to illustrate both small-sample properties and properties near the convergence of the \( G_{r_{mn}} \)’s. We do not test sensitivity to random exit (\( \bar{u} \)) because the tuning parameters for random exit are easy to infer from the calibration data (as in §6.6). The discount rate, \( a \), is determined directly from the firm’s discount rate and the number of website visitors per year.

Table 2 and Figure 2 compare the net present value of projected revenues and the values of revenue at convergence, for the WTM algorithm compared with the HULB algorithm. We report comparisons for all 20 (5 \( \times \) 4) combinations of \( \gamma \) and \( \bar{w} \). Projected revenues are averaged over 10 replications—a total of 400 simulations and 16 million synthetic customers.

We now compare projected revenues when the WTM algorithm assumes incorrect values of the tuning parameters. Our synthetic data experiments are illustrative. A full-factorial crossing all misspecifications with all true values would require (4 \( \times \) 5) \( \times \) (4 \( \times \) 5) = 400 cases for a total of 2,000 simulations and 320 million synthetic respondents. Such a large number of simulations would...
Tables 2

Table 2 Proposed When-to-Morph Algorithm vs. the HULB Algorithm as Switching Costs ($\hat{w}$) Vary

| $\hat{w}$'s | $\gamma = 0.80 \; \gamma = 0.90 \; \gamma = 0.95 \; \gamma = 1$ |
|-------------|------------------|------------------|------------------|
| $(0.25, 0.25, 0.25, 0.25)$ | $0.25$ | $0.20$ | $0.15$ | $0.10$ |
| $(0.10, 0.15, 0.25, 0.50)$ | $0.20$ | $0.15$ | $0.10$ | $0.05$ |
| $(0.02, 0.05, 0.18, 0.75)$ | $0.15$ | $0.10$ | $0.05$ | $0.00$ |
| $(0.00, 0.00, 0.00, 1.00)$ | $0.10$ | $0.05$ | $0.00$ | $0.00$ |

The next four plots hold $\gamma$ constant, match $\hat{w}$ to the implicit assumptions of HULB, and vary $\gamma$. We set $\gamma_{\text{true}} = 0.95$. In all cases, the WTM algorithm outperforms the HULB algorithm. Finally, the last three plots favor the HULB algorithm. Whereas $\gamma_{\text{true}}$ and $\hat{w}$ match the HULB assumptions, $\gamma$ and $\hat{w}$ in WTM are misspecified. The HULB algorithm does slightly better, as anticipated, but not by much. The loss due to using a misspecified WTM algorithm is much smaller than the loss due to ignoring switching costs and impact weights.

The 12 plots are indicative. If $\gamma_{\text{true}}$ and $\hat{w}_{\text{true}}$ differ from the values assumed in the WTM and HULB algorithms, then the WTM algorithm does substantially better than the HULB algorithm. If $\gamma_{\text{true}}$ and $\hat{w}_{\text{true}}$ match the HULB algorithm, but $\gamma$ and $\hat{w}$ are misspecified in the WTM algorithm, then the HULB algorithm does only slightly better. These results suggest that the WTM algorithm is likely robust to misspecification. This is likely the case because the HULB algorithm assumes extreme values for the tuning parameters: the HULB algorithm assumes no switching costs ($\gamma = 1$) and ignores all but the last observation period ($\hat{w}_{\text{true}} = 0$ for all but $t = T_n$). As is often the case in modeling, it is better to attempt to model phenomena, even if done so imprecisely, than it is to ignore the phenomena altogether (e.g., Little 1966, 1970).

Naturally, results might change for different $\hat{p}_{\text{rm}}$'s and other values of $\gamma_{\text{true}}$ or $\hat{w}_{\text{true}}$. We expect WTM to perform particularly well when the website is designed so that we learn the customer’s segment substantially faster than $\tau_s$. The effect would be particularly strong when there are substantial differences by segment in the effects of the morphs on outcomes. We see such case in the next section. The website was designed so that segments could be identified quickly.
Figure 2  Proposed Algorithm (WTM) vs. HULB as Switching Costs, $\gamma$, and Impact Weights, $\vec{w}$, Vary

Figure 3  Representative Sensitivity Analyses

Note. This figure shows the results when true values of switching costs, $\gamma$, and impact weights, $\vec{w}$, do not match assumptions in the WTM algorithm.
6. Proof-of-Feasibility Implementation to a Japanese Bank Website

The WTM algorithm requires that we solve a dynamic program between clicks (or observation periods) while customers are actively using a website. In this section, we use data from a Japanese Bank website to examine whether evaluating when to morph is feasible in real time on a real website. We also examine whether the WTM-versus-HULB comparisons using BT Group data would meet the needs of many customers. Suruga’s were Orix, which spent ¥13.6 billion, mostly on banner advertising (¥95 in that time period). The terms of card loans vary among banks and are often confusing. Some banks offer low interest and high limits, but a more difficult screening process, whereas other banks offer higher interest and lower limits, but an easier screening process. In 2006–2007, the leading card loan banks were Orix, which spent ¥13.6 billion, mostly on banner advertising, and Acom, which spent ¥10.9 billion, mostly on television advertising (¥1 ≈ ¥95 in that time period).

Suruga Bank is a Japanese commercial bank in the greater Tokyo area. Unlike most commercial banks, it focused on retail banking for more than 20 years. Suruga began a virtual bank in 1999, one of the first Japanese banks to do so. By 2008, its online presence had grown to 10 virtual branches and 8 virtual alliances (Tokoro 2008, p. 7). In that time period, Suruga was less well-known than other Japanese banks, spending approximately 1/10th that of Acom and Orix on advertising (¥1.4 million; Tokoro 2008, p. 17). As part of an overall strategy to reach more customers, Suruga developed a customer advocacy website on which it presented the best products from all competitors. By using a strategy of openness and honesty, Suruga sought to demonstrate that its products (low interest rates, high limits, but a careful screening process) would meet the needs of many customers. Suruga’s managers found website morphing intriguing and authorized a small-scale field experiment.

6.3. Website Design

Website designers (native Japanese speakers) developed four morphs that varied on the number of graphs, the amount of technical content, the number of options and alternatives presented, the amount of content on popular trends, the amount of “you-directed” content, formal versus informal Japanese language, and hierarchical versus
egalitarian images. Although the designers did their best to develop morphs that would be more effective for specific segments, the best morph for each segment is determined automatically by the morphing algorithm. The website designers also developed click alternatives that would help identify segment membership. For example, on the opening page (Figure 4, first panel), customers enter the site by choosing one of two pictures. The pictures are designed to appeal to different customer segments. In another example, customers choose from six ways to obtain information (Figure 4, second panel) with the hope that different segments will choose different paths. To avoid an obvious demand artifact, the website was not identified as a Suruga Bank website. We expected that these design features would enable the Bayesian engine to identify customer segments more rapidly than was possible with the BT Group website.

6.4. Outcome Measure and Tuning Parameters

Because we were unable to sell card loans in the experiment, the algorithm maximized customers’ requests for more information. In particular, $\delta_2 = 1$ if the customer clicked on “send me more information.” The tuning parameters were set conservatively by managerial judgment ($\hat{\gamma} = 0.99$, $\hat{\psi} = \psi \forall t$).

6.5. Sample Used in the Suruga Proof-of-Feasibility Application

In November–December 2009 Suruga recruited customers from the Interface Asia panel. Screening and incentives were similar to those in the calibration study—the initial response rate was 22.1%. After screening on interest in card loans and age requirements, 10,182 out of 13,696 potential respondents were declared not eligible for the study. The remaining 3,514 were directed to the card-loan site, of which 1,997 explored the website for at least 2\(1/2\) minutes and 10 clicks (56.9%). Of these customers, 1,395 completed pre- and postvisit questionnaires providing valid data (70.1%). This is a net completion rate of 39.7% and an overall completion/response rate of 8.8%. The market research provider, Applied Marketing Science, Inc., reports that such overall rates are typical of complex Web-based studies. Of the 1,395 completions, 1,061 respondents experienced website morphing (a when-to-morph algorithm, test condition), and 334 experienced a static website (control condition). This was not a sufficient sample for either the HULB algorithm or the WTM algorithm to converge. However, it was sufficient to establish that it was feasible to decide when to morph within a customer’s visit. On measures such as ease of use, providing relevant information, helpful to decisions, trustworthy, and recommendation, the morphing website did as well as the static website (no significant differences on 15 evaluative scales). Had the sample size been larger, perhaps the morphing website would actually have done better.

6.6. Analysis of the Random Time to Exit

We use the Suruga experience to examine which random-exit model would have fit the data best. For each respondent we observe the observation period in which the respondent left the website. These data are plotted in Figure 5 as a solid black line. The dashed red line plots the performance of a homogeneous model ($\psi_{tn} = \psi$ for all $t, n$, where $\psi$ is determined by maximum-likelihood estimation). The homogeneous model explains 79.6% of the uncertainty ($U^2 = 0.796$), but visual inspection suggests a kink for the first observation period. To model the kink, we fit a hybrid homogeneous model ($\psi_{tn} = \psi$ if $t = 1$, but $\psi_{tn} = \psi$ otherwise) as shown by the green fine-dashed line in Figure 5(a). The fit is significantly better ($\chi^2 = 58.0, p < 0.01$) and explains almost all of the uncertainty ($U^2 = 0.968$).

We next examine the heterogeneous model described in §3.3.1. Using the functional invariance property of maximum-likelihood estimation, we reparameterized the model to estimate $E_t[\psi] = \alpha_\psi / (\alpha_\psi + \beta_\psi)$ and $Z_\psi \equiv (\alpha_\psi + \beta_\psi)$. The maximum-likelihood estimate of
\( E_n[\psi] \) is 0.346, however, the maximum-likelihood estimate of \( Z_\psi \) appears to diverge. The likelihood was still increasing at \( Z_\psi > 50,000 \). The resulting heterogeneous model is indistinguishable from a homogeneous model (\( \chi^2 = 0, \ p > 0.90 \)). We also fit a hybrid heterogeneous model with \( \psi_t = 0.3027, E_n[\psi] = 0.425 \), and \( Z_\psi > 50,000 \) for \( t > 1 \). The hybrid heterogeneous model was significantly different than the heterogeneous model (\( \chi^2 = 58.0, \ p < 0.01 \)) and indistinguishable from the hybrid homogeneous model (\( \chi^2 = 0 \)). The heterogeneous models are plotted in Figure 5(b).

In the Suruga data, a hybrid homogeneous model of random exit appears to fit the data best. A fully time-varying model (\( \psi_{tn} = \psi_t \)) is significantly better than a hybrid homogeneous model (\( \chi^2 = 11.0, \ p = 0.03 \)), but the slight increase in \( U^2 \) on a sample of 1,395 respondents may not be worth the sacrifice in parsimony. We estimated these models a posteriori to demonstrate that future applications could readily fit descriptive models using only the calibration data.

### 6.7. Descriptive Statistics for the Time to a Morph Change

If initial morphs were assigned randomly, then we would expect the initial morph to be optimal for roughly 25% of the respondents. However, both the HULB and WTM algorithms assign the initial morph based on the expected Gittins indices using the prior probabilities that customer \( n \) belongs to each segment. If an algorithm works well, we expect the initial morphs to be optimal for more than 25% of the respondents, especially when one segment is larger than the others. (For Suruga, the largest segment was approximately 43.2% of the respondents.) Furthermore, to avoid switching costs, the WTM algorithm may keep the initial morphs if the expected improvement in the expected Gittins index is small.

Performance was consistent with these expectations. The implemented WTM algorithm stayed with the initial morph roughly half of the time. Of those respondents who experienced morph changes, most experienced a single change; very few experienced three or more changes (Figure 6). Figure 6 also suggests that, empirically, the WTM algorithm was able to identify the morph changes rapidly. The majority of morph changes were made after the first period, with decreasing numbers in subsequent periods. This is consistent with a website designed explicitly to identify customer segments rapidly.
6.8. Attempted Comparison Between a WTM Algorithm and a Static Website
To evaluate performance, we collected measures that were not maximized by the algorithm: consideration, preference, and purchase likelihood. Consideration was a binary consider-or-not measure, preference was a 100-point constant sum scale, and purchase likelihood was measured on an 11-point scale as in Juster (1966). All measures reflect that a customer will not prefer or purchase from Suruga Bank if they do not first consider Suruga Bank. We also attempted to correct for premeasures, but because Suruga Bank was not known for card loans at the time of the application, only 70 respondents considered Suruga Bank in the premeasures. Unfortunately, because the sample size was small relative to the synthetic-data experiments and Urban et al. (2014), none of the measures were significantly different between the test and control cells. The results are available in the supplemental material.

6.9. Counterfactual Policy Simulations with Suruga Morph × Segment
Purchase Probabilities
Although the Suruga Bank experiment ran for only 1,395 customers, we can run a counterfactual policy simulation in which there are 40,000 customers in each of three experimental cells—WTM, HULB, and random assignment. We use the same code that reproduced the HULB simulations (Table 1, §5.1) except that we use the \( \tilde{p}_{rm} \) from the Suruga Bank implementation. Table 4 reports the results. HULB is substantially better than random assignment, and WTM is substantially better than HULB. In this case, the improvement due to WTM (63%) is almost 5 times that of HULB. WTM does well because, for the counterfactual policy simulation, it is better to morph much earlier than the HULB default. The \( \tilde{p}_{rm} \) differ among morphs more for the Suruga Bank website than they do for the BT Group website. Although a devil’s advocate might argue that a revised earlier-morphing HULB might perform better than the tested HULB, such an insight was made possible by the dynamic program in the WTM algorithm and would be hard to know a priori without the analyses in this paper.

7. Summary and Challenges
The HULB website-morphing algorithm has proven to increase outcomes with both synthetic data (BT Group application) and in the field (Urban et al. 2014), but it ignores switching costs, the impact of premorph clicks, and random exit. The WTM algorithm generalizes the HULB algorithm to allow more realistic assumptions. The WTM algorithm runs in real time between clicks on a website. Synthetic data analyses of two data sets suggest that the WTM algorithm can improve outcomes substantially if the tuning parameters are set properly. The algorithm appears to be reasonably robust to misspecification of the tuning parameters. Furthermore, the Suruga Bank application suggests that it is feasible on a real-world website to determine when to morph in real time.

There remain many challenges. (1) Large-sample empirical applications might (a) parse the incremental value of the WTM algorithm relative to the special case of HULB and (b) calibrate the values of the switching-cost and impact-weight tuning parameters. (2) Improved theory might (a) establish optimality properties for the linkage between the morph-to-segment and when-to-morph optimizations and (b) improve “fractional-observation” updating of the posterior distributions of the \( p_{rm} \)‘s. (3) Improved algorithms might (a) relax assumptions of multiplicative switching costs, additive impact weights, and independent website exit; (b) model network externalities such as the ability of customers to share knowledge of a website’s look and feel; (c) allow for switching costs that depend on the multiple morphs (\( \gamma_{rm} \)); and (d) allow exit probabilities that depend on segments, final morphs, or morph history (\( \psi_{trm} \), \( \psi_{trm} \), etc.).

<table>
<thead>
<tr>
<th>Segment Probabilities</th>
<th>Reward at convergence</th>
<th>Percent improvement in reward(^a) (%)</th>
<th>Net present value (NPV)(^b)</th>
<th>Percent improvement in NPV (\xi) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline for no morphing</td>
<td>0.0632</td>
<td>0</td>
<td>0.0619</td>
<td>0</td>
</tr>
<tr>
<td>Website morphing (HULB)</td>
<td>0.0688</td>
<td>13</td>
<td>0.0667</td>
<td>12</td>
</tr>
<tr>
<td>Website morphing with improved algorithm</td>
<td>0.0912</td>
<td>66</td>
<td>0.0882</td>
<td>63</td>
</tr>
<tr>
<td>Perfect information (( n \rightarrow \infty ))(^c)</td>
<td>0.1055</td>
<td>100</td>
<td>0.1034</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes. Switching costs are \( \gamma = 0.95 \). Impact weights are \( \vec{w} = (0.25, 0.25, 0.25, 0.25) \). \( \xi \) is as in Table 1. \(^a\) Rewards for the last 400 customers out of 40,000 customers. \(^b\) (Reward due to algorithm − reward at no morphing)/(reward due to perfect information − reward at no morphing). \(^c\) Net present value of the rewards divided by the number of periods. \(^d\) (NPV due to algorithm − NPV at no morphing)/(NPV due to perfect information − NPV at no morphing). \(^e\) This is the upper bound. Applications do not have perfect information on either customer segments or purchase probabilities.
Supplemental Material
Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.1961.

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Appendix A. Notation Used in This Paper and in Appendix B

\( a \) The amount by which we discount a sale to customer \( n + 1 \) relative to customer \( n \)

\( B(\alpha, \beta) \) Beta distribution with parameters \( \alpha \) and \( \beta \)

\( c_{t_0} \) Indicator variable to indicate whether customer \( n \) chooses click alternative \( j \) at \( t \)

\( c_{t_0} \) Number of customer \( n \)'s clicks in the \( t \)th observation period; \( n \) may be suppressed

\( \bar{c}_{t_0} \) Customer \( n \)'s clicks up to and including the \( t \)th observation period, \( \{c_{t_0}, c_{2n}, \ldots, c_{tn}\} \)

\( EG_{rn} \) Expected Gittins index for \( m \)th morph for customer \( n \)

\( EIR \) Expected immediate reward (used in the when-to-morph Bellman equation)

\( f(\cdot | \cdot) \) Posterior distribution; specific distribution when parameters are specific; sometimes subscripted by \( n \)

\( G_{rn} \) Gittins index for \( r \)th segment and \( m \)th morph for customer \( n \); \( n \) may be suppressed

\( HULB \) Hauser, Urban, Libenali, and Braun (2009)

\( j \) Indexes click alternatives (links)

\( j_n \) The number of click alternatives faced by customer \( n \) on the \( t \)th click

\( m \) Indexes morphs

\( m_n \) Morph that customer \( n \) sees in observation period \( t \)

\( m_{tn} \) Optimal morph for customer \( n \) in observation period \( t \)

\( M \) Number of morphs available from which to choose

\( n \) Indexes customers

\( n_{\alpha} \) Number of customers in an observation period; used in Appendix B

\( n_{\alpha, rm} \) Number of customers in an observation period who were in segment \( r \) and saw morph \( m \)

\( p_{rm} \) Probability that customer \( n \) is in segment \( r \) when shown morph \( m \)

\( Pr_n(r_n = r) \) Prior probability that customer \( n \) belongs to segment \( r \)

\( q_{rn}(\bar{c}_{t-1,n}, \bar{\Omega}, \bar{X}_{t-1,n}) \) Probability that customer \( n \) is in segment \( r \)

\( q_{rn} \) Shorthand for \( q_{rn}(\bar{c}_{t-1,n}, \bar{\Omega}, \bar{X}_{t-1,n}) \); used in Appendix B

\( q_{rn}(s) \) Shorthand for \( q_{rn}(\bar{c}_{t-1,n}, \bar{\Omega}, \bar{X}_{t-1,n} | r_{true} = s) \); used in Appendix B

\( r \) Indexes customer segments

\( R \) Number of customer segments

\( r_{true,n} \) Customer \( n \)'s true segment (used derive the when-to-morph dynamic program)

\( s \) Used in summations

\( S \) Observation period (used in random exit equation)

\( S_j \) Set of customers in the last \( n_{\alpha} \) customers whose true segment is \( s \); used in Appendix B.

\( t \) Indexes observation periods

\( T_n \) Number of observation periods for customer \( n \)

\( \tilde{u}_{tnj} \) Utility customer \( n \) obtains from clicking on the \( t \)th click alternative on the \( n \)th click

\( V_{\text{crit}}(m_{tn}, m_{t-1,n}, \bar{c}_{t-1,n}, \bar{\Omega}, \bar{X}_{t-1,n}, N_{t-1,n}) \) Continuation value function for when-to-morph decision

\( V_{\text{crit}}(\alpha_{\beta n}, \beta_{\gamma n}, a) \) Continuation value function when calculating the Gittins index

\( w_t \) Impact weight for the \( t \)th observation period

\( \bar{w} \) Vector of the \( w_t \)'s; \( \bar{w} \) if estimated from the calibration data

WTM When-to-morph algorithm; proposed generalization of the HULB algorithm

\( \tilde{x}_{tnj} \) Vector of characteristics of the \( t \)th click alternative up to the \( t \)th click of customer \( n \)

\( \tilde{x}_{tnj} \) Set of all \( \tilde{x}_{tnj} \)'s for all clicks up to an including click \( t \), \( \{\tilde{x}_{tnj}, \tilde{x}_{2tnj}, \ldots, \tilde{x}_{tnj}\} \) \( \forall j = 1 \) to \( J_n \)

\( Z_{\phi} \) Equal to \( \alpha_{\phi} + \beta_{\phi} \)

\( \hat{Z}_{\phi} \) Maximum-likelihood estimate of \( Z_{\phi} \)

\( \alpha_{\beta n} \) Parameter of the beta distribution used to model uncertainty over \( p_{rn} \)

\( \beta_{\gamma n} \) Parameter of the beta distribution used to model uncertainty over \( p_{rn} \)

\( \alpha_{\phi} \) Parameter of a beta distribution used to model heterogeneity in exit probabilities

\( \beta_{\phi} \) Parameter of a beta distribution used to model heterogeneity in exit probabilities

\( \gamma \) Discount for switching from one morph to another; after a switch, the probability of a purchase is reduced by a factor of \( \gamma \) (if estimated from the calibration data)

\( \delta_{n} \) Indicator variable to indicate whether customer \( n \) makes a purchase; used in the when-to-morph algorithm when multiple morphs (might) affect outcomes

\( \delta_{\alpha n} \) Indicator variable to indicate whether customer \( n \) makes a purchase given that customer \( n \) saw morph \( m \) after a switch; used in HULB

\( \delta_{\alpha n} \) Indicator variable to indicate whether customer \( n \) makes a purchase given that customer \( n \) is in known segment \( r \) and saw morph \( m \); used in Appendix B.

\( \Delta_{\alpha n} \) Indicator variable to indicate if we change morph \( m_{tn} \) in period \( t \) for customer \( n \)

\( E_{\psi} \) Maximum likelihood estimate of \( \alpha_{\phi} / (\alpha_{\phi} + \beta_{\phi}) \)

\( \hat{e}_{tnj} \) Extreme value error; used to model customer \( n \)'s preference for click alternatives
Appendix B. Full-Probability Model and Updating Formulæ

B.1. Review of Updating for Gittins Indices

Notation follows the text. If we knew the customer’s segment, \( r \), and the customer saw the same morph, \( m \), for the entire visit, then the relevant posterior probability after customer \( n \) would be \( p_m \), the probability that customer \( n \) in segment \( r \) who saw morph \( m \) would make a purchase. We assume that the prior distribution for \( p_m \) is beta as given by

\[
f_n(p_m | \alpha_m, \beta_m) = \frac{p_m^{\alpha_m - 1} (1 - p_m)^{\beta_m - 1}}{B(\alpha_m, \beta_m)}, \tag{B1}
\]

where \( \alpha_m \) and \( \beta_m \) are parameters of the beta distribution, and \( B(\alpha_m, \beta_m) \) is the beta function.

We now observe whether or not customer \( n \) makes a purchase. Let \( \delta_{mn} = 1 \) if customer \( n \) in known segment \( r \) made a purchase and \( \delta_{mn} = 0 \) otherwise. The data likelihood is then given by a binomial distribution:

\[
f_n(\delta_{mn} | p_m) = p_m^{\delta_{mn}} (1 - p_m)^{1 - \delta_{mn}}. \tag{B2}
\]

Combining Equations (B1) and (B2), the posterior distribution for \( p_{m,n+1} \) is proportional to

\[
f_{n+1}(p_{m,n+1} | \alpha_{m,n+1}, \beta_{m,n+1}, \delta_{mn}) \sim p_m^{\delta_{mn} + \alpha_{m,n+1} - 1} (1 - p_m)^{\beta_{m,n+1} + (1 - \delta_{mn}) - 1}. \tag{B3}
\]

Equation (B3) is again a beta distribution. Thus we have the updating equation as given by

\[
\alpha_{m,n+1} = \alpha_m + \delta_{mn},
\beta_{m,n+1} = \beta_m + (1 - \delta_{mn}). \tag{B4}
\]

We easily extend the formal updating to the case where we observe \( n_{ob} \) additional customers before we update (read \( n_{ob} \) as “\( n \) observed”). In this case we have a binomial data likelihood and we allow a more general definition of \( \delta_{m,n_{ob}} \) as the number of purchases made by the \( n_{ob} \) customers that follow the \( r \)th customer. Following similar steps, the posterior distribution is also a beta distribution with parameters given by

\[
\alpha_{m,n+n_{ob}} = \alpha_m + \delta_{m,n_{ob}},
\beta_{m,n+n_{ob}} = \beta_m + (n_{ob} - \delta_{m,n_{ob}}). \tag{B5}
\]

Because updating for the Gittins index is naturally conjugate, computations are simple and rapid. It is feasible to update after every customer or observation period. Furthermore, by comparing Equations (B4) and (B5) it is obvious that we obtain the same posterior distribution at the \((n + n_{ob})\)th customer whether we update sequentially using Equation (B5) or update all \( n_{ob} \) customers at one time.

B.2. Review of Updating for the HULB Hidden Markov Model

HULB extend Gittins updating to a situation where we do not know the customer’s segment, but rather have estimates, \( q_{rmn}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) \), that customer \( n \) belongs to segment \( r \) for each possible segment. HULB continue to assume that the customer saw a single morph, \( m \), for a sufficient fraction of the visit that we need only consider the effect of morph \( m \) on customer \( n \)’s purchase. With these assumptions, the probability, \( p_{mn} \), that customer \( n \) who saw morph \( m \) makes a purchase is given by

\[
p_{mn} = \sum_{r=1}^{R} q_{rmn}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) p_{m}. \tag{B6}
\]

HULB assume a beta prior distribution as in Equation (B1). For indexability, HULB assume that each \( r,m \)-arm of the bandit process is independent. Independent arms imply that the prior distributions are independent over \( r \) and \( m \). The joint prior distribution generalizes Equation (B1) to become Equation (B7) prior to observing \( \delta_{mn} \). For simplicity of notation, we let \( \alpha_{mn} \) and \( \beta_{mn} \) be the vectors of parameters (over \( r \)):

\[
f_n(p_m | \alpha_{mn}, \beta_{mn}) = \prod_{r=1}^{R} B(\alpha_{mn}^r, \beta_{mn}^r p_m^{\alpha_{mn}^r - 1} (1 - p_m)^{\beta_{mn}^r - 1}. \tag{B7}
\]

The data likelihood is binomial and generalizes Equation (B2):

\[
f_n(\delta_{mn} | p_m) = p_m^{\delta_{mn}} (1 - p_m)^{1 - \delta_{mn}} = \left( \sum_{r=1}^{R} q_{rmn}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) p_{m} \right)^{\delta_{mn}} \cdot \left( 1 - \sum_{r=1}^{R} q_{rmn}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) p_{m} \right)^{1 - \delta_{mn}.} \tag{B8}
\]

We extend the analysis to allow updating after \( n_{ob} \) customers. Unlike in the single-armed case, the analysis does not simplify. Specifically, each customer has a different set of \( q_{rmn}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) \) values based on that customer’s unique clickstream. Thus, the data likelihood is now given by Equation (B9), where \( \xi \) is notation for use in the product so that it does not conflict with \( n \) or \( n_{ob} \):

\[
f_{n+n_{ob}}(\delta_{m,n_{ob}} | p_m, n_{ob}) = \prod_{\xi=1}^{n_{ob}} \left[ \sum_{r=1}^{R} q_{\xi \xi_{T_{rmn}}}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) p_{m,n+n_{ob}} \right]^{\delta_{mn}} \cdot \left( 1 - \sum_{r=1}^{R} q_{\xi \xi_{T_{rmn}}}(\hat{\xi}_{T_{rmn}}, \hat{\Omega}, \hat{X}_{T_{rmn}}) p_{m,n+n_{ob}} \right)^{1 - \delta_{mn}.} \tag{B9}
\]
We first note that the binomial distribution, a probability mass fraction, allows for fractional outcomes to become

equivalent to ratios for fractional observations. We then interpret the outcome of Website Morphing as a numerical definition, even when

the online activity is not known with certainty, the posterior distribution becomes

natural conjugate, as proven by Hauser, Liberali, and Urban (Website Morphing 2.0, pp. 1–23, © 2014 INFORMS.

B.3. Extending the HULB Updating Formula to Switching Costs, Impact Weights, and Multiple Morphs

Once we accept the concept of fractional observations as a practical means to retain the structure of expected Gittins index updating, we can extend Equation (B13) to account for switching costs, impact weights, and multiple morphs. No new derivations need to be introduced. We simply substitute the new fractional observations into Equations (B12)–(B15). The new concepts are that the switching costs, impact weights, and multiple morphs may affect customer n’s purchase probabilities.

First, customer n does not see morph m for the entire website visit; customer n sees morph m for those periods in which the morphing algorithm selects morph m. The effect on purchasing is proportional to the impact weights for the periods in which morph m was shown. As defined in the text, \( \eta_{mt} = 1 \) if morph m is shown to customer n in observation period t, and \( w_t \) is the impact weight for observation period t. The probability is also affected by whether or not a switch in morphs occurs in the period as summarized by \( \Delta_{mnt} \). The new fractional observation becomes

\[
\hat{q}_m(C_{t,n}, \hat{X}_{t,n})^{\sum_{t=1}^{T} \gamma_{mtn} \eta_{mt} w_t}.
\]

With the revised definition of a fractional observation, the revised updating formula becomes Equation (B14), which is Equation (9) in the text. The data likelihood and the posterior distributions generalize Equations (B11) and (B12) as expected:

\[
\begin{align*}
\alpha_{rm,n+1} &= \alpha_{rm,n} + \hat{q}_m(C_{t,n}, \hat{X}_{t,n})^{\sum_{t=1}^{T} \eta_{mt} w_t} \delta_{nt} \\
\beta_{rm,n+1} &= \beta_{rm,n} + \hat{q}_m(C_{t,n}, \hat{X}_{t,n})^{\sum_{t=1}^{T} \eta_{mt} w_t} (1 - \delta_{nt}).
\end{align*}
\]

Using this interpretation and the shorthand notation \( q_{rn} = q_{rnT}(C_{t,n}, \hat{X}_{t,n}) \), the data likelihood becomes

\[
\hat{f}(\eta_{rn} | p_{rn}) = p_{rn}^{\eta_{rn}} (1 - p_{rn})^{(1 - \eta_{rn})}.
\]

We continue to use Equation (B1) as the prior distribution, which gives Equation (B12) as the posterior distribution:

\[
\begin{align*}
\alpha_{rm,n+1} &= \alpha_{rm,n} + q_{rnT}(C_{t,n}, \hat{X}_{t,n}) \delta_{nt} \\
\beta_{rm,n+1} &= \beta_{rm,n} + q_{rnT}(C_{t,n}, \hat{X}_{t,n}) (1 - \delta_{nt}).
\end{align*}
\]

B.2. Practical Solution: Fractional Observations. To obtain a feasible solution, HULB makes a heroic independence assumption and use the concept of fractional observations. We first note that the binomial distribution, a probability mass function, can also be interpreted as a probability density function for fractional observations. We then interpret the outcome variable, \( \delta_{nt} \), as a combination of fractional outcomes for each potential customer segment, r, and treat the fractional outcomes as if they were independent over r. In particular, the fractional outcomes become

\[
\delta_{nt} = \hat{q}_{rnT}(C_{t,n}, \hat{X}_{t,n}) \delta_{nt} \forall r.
\]

We examine in §B.4 why the updating formulae are still likely to converge, and we present evidence of convergence from the synthetic data experiments.
B.4. Motivation of Why Fractional Observations Are a Good Approximation

The trick of fractional observations requires that we assume a level of independence that we know is violated. Despite this assumption, both the HULB algorithm and the WTM algorithm improve outcomes substantially with synthetic data—the HULB algorithm relative to a static website and the WTM algorithm relative to the HULB algorithm. In this section we motivate why that is likely that fractional observations are a good approximation. Our arguments are not a formal proof, and they do not rule out the algorithms getting trapped in local minima; rather they suggest why we expect the fractional-observation updating formulae to converge to \( p_{rm, true} \).

For simplicity of notation, consider the HULB assumptions of \( \gamma = 1 \) and \( \bar{w} = (0, 0, 0, 1) \). We are interested situations where the data overwhelm the priors; that is, assume we observe \( n_{ob, m} \) customers where \( n_{ob, m} \) is sufficiently large: \( n_{ob, m} \gg \sum_{r=1}^{R}(\alpha_{rn, m} + \beta_{rm, m}) \). Let \( S_m \) be the set of customers whose true segment is \( r \) and who saw morph \( m \). We continue to use the shorthand notation, \( q_{rm} = q_{r|T_n}(e_{r|T_n}, \tilde{\Omega}, \tilde{X}_{r|T_n}) \), and define \( q_{rn}(s) = q_{s|T_n}(e_{s|T_n}, \tilde{\Omega}, \tilde{X}_{s|T_n} | \text{true} = \delta) \). Under the conditions that the data overwhelm the priors, the HULB updating formulæ (Equation (B13)) become (for all \( r \) and \( m \))

\[
\alpha_{rm, m} = \sum_{n=1}^{n_{ob, m}} q_{rm} \delta_{mn} = \sum_{s=1}^{R} \sum_{n \in S_m} q_{rn}(s)\delta_{mn},
\]

\[
\beta_{rm, m} = \sum_{n=1}^{n_{ob, m}} q_{rn}(1 - \delta_{mn}) = \sum_{s=1}^{R} \sum_{n \in S_m} q_{rn}(s)(1 - \delta_{mn}).
\]

We now take expected values:

\[
E_n[\alpha_{rm, m}] = \sum_{s=1}^{R} \sum_{n \in S_m} q_{rn}(s)p_{rm, true},
\]

\[
E_n[\beta_{rm, m}] = \sum_{s=1}^{R} \sum_{n \in S_m} q_{rn}(s)(1 - p_{rm, true}).
\]

Under the assumption that customers are homogeneous within true segments such that \( q_{rn}(s) = q_{r}(s) \), we recognize that

\[
E_n[\alpha_{rm, ob, m}] = \sum_{s=1}^{R} q_{r}(s)n_{ob, m}p_{rm, true} = q_{r}(n_{ob, rm}p_{rm, true} + \sum_{s\neq r} q_{r}(s)n_{ob, m}p_{rm, true},
\]

\[
E_n[\beta_{rm, ob, m}] = \sum_{s=1}^{R} q_{r}(s)n_{ob, m}(1 - p_{rm, true}) = q_{r}(n_{ob, rm}(1 - p_{rm, true}) + \sum_{s\neq r} q_{r}(s)n_{ob, m}(1 - p_{rm, true}).
\]

If the first term dominates (the term containing \( q_{r}(r) \)), the beta posterior will converge to a point mass at \( p_{rm, true} \) as \( n_{ob, m} \) gets large. It will converge to a point mass because both \( E_n[\alpha_{rm, m}] \) and \( E_n[\beta_{rm, m}] \) are the order of \( n_{ob, m} \). Furthermore, \( p_{rm, ob, m} = E[\alpha_{rm, ob, m}]/[E[\alpha_{rm, ob, m}] + E[\beta_{rm, ob, m}]] \), which approach \( p_{rm, true} \) when the first term dominates (because \( q_{r}(r)n_{ob, rm} \) drops out).

There are two forces that make it likely that, as \( n_{ob, m} \) gets large, the first term is much larger than the remaining terms for the morphs that are chosen for segment \( r \). First, if \( \Omega \) is well estimated and the logit model does a good job in predicting customer segments, then \( q_{r}(r) \gg q_{r}(s) \forall s \neq r \). Second, as the algorithm gets better at identifying the best morph for segment \( r \) (and if there is sufficient variation in morphs that different morphs are best for different segments), then \( n_{ob, rm} \gg n_{ob, sm} \) for \( s \neq r \). \( m^* \) is the best morph for segment \( r \). If the algorithm is indeed close to optimal, \( m^* \) will be chosen for segment \( r \). Convergence will be best for optimal segment \( x \) morph matches, and especially for those morphs that are shown many times. (Because it is likely that \( p_{rm, true} \leq p_{rm, true} \), we can also argue that convergence will be from below. Details are available in the supplemental material.)

It is an empirical question whether these two forces are sufficiently strong so that fractional updating converges. Fortunately, synthetic-data experiments and empirical experience suggest that the HULB algorithm and the generalized algorithm, which also relies on fractional-observation updating, lead to improved outcomes and the ability to match morphs to segments. For the synthetic-data experiments in §5, we can compare the true purchase probability values, \( p_{rm, true} \), to the posterior means. With \( \gamma = 1 \) and \( \bar{w} = (0, 0, 0, 1) \), we test the HULB updating formulæ in Equation (B13). For this case, the mean absolute percent error is approximately 0.028, which is 8.7% of the average true probability. As the number of customers gets large, the algorithm tends toward identifying the optimal morph for each segment; hence we gain the most information about optimal segment \( x \) morph matches (\( r \) and \( m^* \)). When we look at optimal segment \( x \) morph matches, the error reduces to 5.8% of the average true probability. This reduces to 0.5% when we require a morph to have been shown to customers at least 2,000 times.

We examine Equation (B14) with \( \gamma = 0.95 \) and \( \bar{w} = (0.25, 0.25, 0.25, 0.25) \). For this case, the mean absolute percentage error is approximately 0.0318, which is 10.0% of the average true probability. When we look at the optimal morph for each segment, the error reduces to 7.3% of the average true probability. This reduces to 3.4% when we require a morph to have been shown at least the equivalent of 2,000 times (i.e., 2,000T_n total periods). The mean absolute error decreases further when morphs are shown even more often. We see similar patterns for \( \gamma = 0.80 \) and \( \bar{w} = (0.25, 0.25, 0.25, 0.25) \).

Appendix C. Supplemental Material Available at http://dx.doi.org/10.1287/mnsc.2014.1961

C.1. Synthetic Data and Counterfactual Code and Pseudocode (Tables 1, 2, 4; §§5, §6.9)

- Pseudocode and R code with which to run the 40,000 synthetic-customer simulations using specified values for \( \hat{p}_{rm} \), \( \gamma \), and \( \bar{w} \).
- Spreadsheet with the values of \( \hat{p}_{rm} \) for the BT Group simulations and the Suruga Bank counterfactual policy simulation

C.2. WTM Code for Suruga Bank Application (§6)

- R code (that reproduces original PHP code) that was called by the Suruga Bank website to determine the morph-to-segment match and when to morph
C.3. Data from Suruga Bank Experiment (Figure 6, §6)
- Table comparing insignificant measures of consideration, preference, and purchase likelihood
  - Excel spreadsheet for comparison table
  - Excel spreadsheet that produced the descriptive statistics (Figure 6)
- Excel spreadsheet for site-evaluation measures

- Japanese with English translation of the questionnaire used in the calibration study
- Japanese with English translation of the questionnaire used to obtain evaluative measures for the Suruga Bank experiment

C.5. Demonstration That Fractional Updating Will Likely Converge from Below (Appendix B)
- Short derivation to illustrate why fractional updating will likely converge from below

- A user's guide on how to implement morphing including both morph-to-segment assignment and the decision on when to morph; user's guide relies on citations to this paper, HULB, and Urban et al. (2014) to provide a practical roadmap to morphing.

References