Digital Ad Morphing: Using Behavioral Analysis to Increase Response Rates to Online Advertisements

by

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Abstract

This paper details the implementation and testing of a digital ad morphing system, a system which determines user cognitive style based on interaction with a website and serves ads designed to complement that cognitive style. The system is intended to increase click through rates on online advertising such as banner ads. The paper first explains the implementation of an ad morphing system and then describes the process and results of a field study conducted on the CNET.com website in April-May 2011.

Thesis Supervisor: Glen L. Urban
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Chapter 1

Introduction

Online advertising is a vitally important source of income on the internet. Many websites, particularly those that specialize in content or news, depend on advertising to gain enough revenue to continue operation. As a result, many website operators would like to increase their ad click through rates. There have been many previous attempts to increase click through rates, most of them centered around putting the ad in proper context. In this paper, we give another option. The ad morphing system, developed by John Hauser and Glen Urban at MIT, is designed to increase click through rates by varying visual elements of an ad for the same product and serving a version of the ad that complements a particular user's cognitive style. This paper details the implementation and field study of this ad morphing system.

Ad morphing has its origins in trust based marketing, a marketing technique that makes gaining the consumer's trust the first priority. From trust based marketing came the concept of *morphing*. In morphing, the system changes what it shows to the end user in order to maximize the chances that the user will find the system useful. Morphing was first used to design online advisors to build a relationship of trust with a potential customer. These morphing advisor systems were designed and piloted in studies for both Suruga Bank, a Japanese bank, and BT Group, a major British telecom corporation. A newer use of morphing is *ad morphing*, in which the system selects ads to display to the end user based on its current understanding of the user's cognitive style. Ad morphing was first tested in a controlled study for General

Motors, an American automobile company, where it had highly effective results. For this paper, we implement and test ad morphing in a field study on the CNET.com website.

This paper begins by giving more detailed background information about the origins of morphing and ad morphing. Then, it describes the parameters and functionality of a generalized morphing system, giving an overview of the underlying mathematical constructions behind it. Next, it gives the specifics of the ad morphing study carried out in April-May 2011, including implementation details. Then, it summarizes the results to date of the study. Finally, it outlines the author's contribution to the study, lists lessons learned in the process, and discusses possible future work.

Chapter 2

Background

This section gives a brief background of the origins and history of morphing and ad morphing. First, it discusses morphing and its origins in trust based marketing. Then, it discusses previously conducted website morphing and ad morphing studies and their effectiveness.

2.1 Origins in Trust Based Marketing

Morphing as a marketing technique has its origins in trust based marketing. In his 2003 article for the MIT Sloan Management Review, Professor Glen Urban notes that gaining the consumer's trust and truly representing their best interests has replaced previous "push-based" marketing tactics that have been popular in previous decades. To cater to a customer's best interests, a company provides open and complete information about which products best suit the customer's needs, even if that means recommending a competitor. This policy of open disclosure is central to the concept of trust based marketing and consumer advocacy. [4]

2.2 Online Advisors and Website Morphing

In order to provide the best information to a consumer, some companies provide online advisors to assist a consumer in their purchasing needs. To maximize the

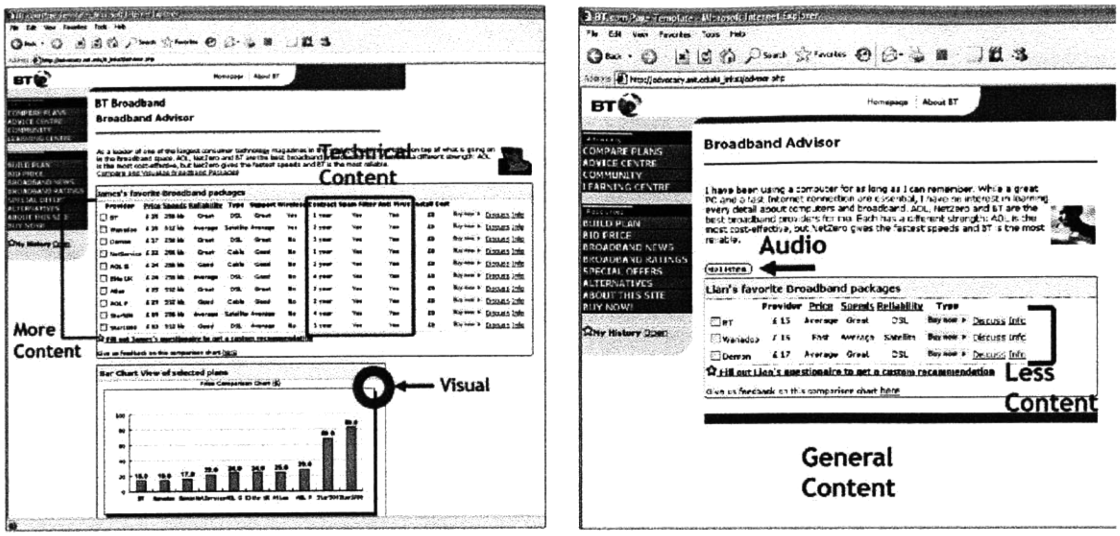

Figure 2-1: BT Website Example Morph: The left morph is aimed at an analytical, deliberative, visual user while the right morph is aimed at a holistic, verbal, impulsive user. Figure from [6]

effectiveness of these advisors, it would be useful if as many consumers as possible found them helpful. Website morphing is a technique that helps with this endeavor. In website morphing, the end user's behaviors are monitored as he interacts with the site. This monitoring allows the system to make an educated guess about the user's cognitive style and consequently present data in a way that this particular user is more likely to find helpful.

Examples of morphing websites include an advisor created for BT Group (formerly British Telecom) comparing broadband plans and an advisor created for Suruga bank comparing card loans. For an example morph from the BT website, see figure 2-1.

In controlled studies, both morphing websites had positive results. The BT website was found to increase BT sales by 20%. The morphing version of the Suruga website was found to be significantly more helpful than a non-morphing version and significantly increased consideration of Suruga products. [2] [1] [3]

Figure 2-2: Example of Rational Deliberative GM Ad

2.3 Ad Morphing

After the success of website morphing, a controlled study was done to apply morphing technology to online advertisements for General Motors. First, user cognitive styles were measured by a survey and they were asked to rate ads. Some time later, the users were asked to browse a simulated version of the Kelley Blue Books site as if they were shopping for a car. On the site, the test group of users were shown their favorite ad while the control group was shown a random ad. In figure 2-2, there is an example of a rational deliberative ad morph used in the study.

In this study, the ad morphing system was found to improve clickthrough rates of GM ads by over 35% and improve Chevrolet consideration by 24%. [5]

Chapter 3

General Morphing System

This section gives an overview of a general morphing system. The first section lists the parameters of the system while the next sections detail the steps required to carry out the morphing process.

3.1 Parameters

3.1.1 Morphs

Morphs are different versions of a system. Different morphs cause differences in various parts of the system such as images shown, format of data presentation, and amount of information provided to the end user. For example, one morph of a web page might have a table with large amounts of data to appeal to a more analytical cognitive style while another would only show basic information to appeal to a more holistic cognitive style.

3.1.2 Cognitive Styles

A user's cognitive style is a r dimensional vector of positive numbers which sum to 1. Each component of the vector is the probability that the user falls into that particular cognitive dimension. Cognitive dimensions are determined by various differentiating factors. For example, the differentiating factors Analytic vs. Holistic, Impulsive vs.

Deliberative, and Visual vs. Verbal form an eight dimensional space of cognitive styles and would be represented by an eight dimensional vector. The eight styles formed by these differentiating factors are Analytic-Impulsive-Visual, Analytic-Impulsive-Verbal, Analytic-Deliberative-Visual, Analytic-Deliberative-Verbal, Holistic-Impulsive-Visual, Holistic-Impulsive-Verbal, Holistic-Deliberative-Visual, and Holistic-Deliberative-Verbal and the eight components of the vector represent the probability that the user is the style corresponding to their respective indices.

It is also possible to use differentiating factors that correspond to cultural styles, such as Individualistic vs. Collectivistic and Egalitarian vs. Hierarchical.

3.1.3 Style Update Matrix

The style update matrix P is a n by q by r matrix where n is the number of places in the system where cognitive style is updated, q is the maximum number of choices at each of the n places, and r is the number of style dimensions.

P_{ijk} is the prior probability that the user is style k given that he is in location i and makes choice j. These prior probabilities are generally obtained with a controlled priming study of some sort. Note that if a particular location i has less than j choices then the remaining entries are set to 0.

3.1.4 Session Definition

The system must have some concept of a session for a given user. The session must have some variable indicating whether it is a success or failure. Session definitions vary by system. One example, is a user interacting with a morphing advisor for an hour who at the end is asked whether he wants to purchase a product from the ones reviewed. If he does, his session is considered a success. Otherwise, it is a failure.

3.1.5 Success Indicator

The success indicator δ is a binary variable that indicates whether a particular session with the system was a success or failure. If it was a success, δ is 1, otherwise it is 0.

3.1.6 Data accumulator matrices

The data accumulator matrices α and β are m by r matrices where m is the number of morphs and r is the number of cognitive style dimensions. These matrices accumulate data from user sessions on the system and are used to determine how future morphs are served. The α matrix accumulates session successes and the β matrix accumulates session failures.

3.1.7 Morph serving matrix

The morph serving matrix G is a m by r matrix where m is the number of morphs and r is the number of cognitive style dimensions. This matrix is derived from the data accumulator matrices α and β by converting the values of α and β to integers and using them to index into the data conversion matrix. It is used by the system to determine which morph to serve to the user.

3.1.8 Data conversion matrix

The data conversion matrix D is a large d by d matrix of values intended to convert the data accumulator matrices into the morph serving matrix. This matrix is generated by approximating a solution to the optimization problem of which morph to serve to a user with a given style with given data accumulator matrices. For more details about how to generate such a matrix, see Hauser et al's 2009 paper. [1]

3.2 Bayesian Loop

The Bayesian Loop runs each time a user makes an interaction with a monitored portion of the site. Each time it runs, the system has a better idea of the user's cognitive style.

3.2.1 Priors

As mentioned previously, a subject's cognitive style is represented as an r-dimensional vector of positive numbers which sum to 1. If a priming study indicates a prior distribution on style dimensions, that distribution can be used as an initial style vector for each subject. In the absence of such information, a flat prior can also be used. For example, if there are four style dimensions, a flat prior would be $\{0.25, 0.25, 0.25, 0.25\}$, indicating no previous information about the user's style. This prior serves as the starting point for each user as he interacts with the system.

3.2.2 Update

When a user makes certain interactions with the site, his cognitive style is updated. This update is made by performing a Bayesian update on the current style using the Style Update Matrix P. Suppose a user has style $\vec{r}$. If a user makes choice j at location i, his style is updated as follows:

$$r_k \leftarrow \frac{P_{ijk} r_k}{\sum_{k=1}^{|\vec{r}|} P_{ijk} r_k}, k = 1, 2, \ldots, |\vec{r}|$$

3.3 Session

After some number of Bayesian updates, the user is served a morph. Then, at some later point, he is presented with a situation in which he must make some sort of decision, for example to click on an ad or to request more information about a product. Depending on the outcome of his decision, the success indicator variable δ is set accordingly. His interactions with the system along with the success indicator variable are stored as a user session.

3.4 Gittins Engine

3.4.1 Priors

The data accumulation matrices, and consequently the morph serving matrix must be set to some initial values. Since the data accumulation matrices α and β represent session successes and failures respectively, they can be initialized with numbers that reflect prior probabilities of success and failure in a given session.

3.4.2 α and β matrix updates

Periodically, recorded user sessions are used to update the α and β matrices. These updates can happen in real time or on a fixed schedule. Updating these matrices requires a success indicator variable δ and cognitive style $\vec{r}$ from each session. Since each session typically has more than one value for $\vec{r}$, we can either take the average of all styles for that session or take the latest recorded style. Then, for each session, α and β are updated as follows where i corresponds to the morph served to the user.

$$\alpha_{ij} \leftarrow \alpha_{ij} + \delta r_j, j = 1, 2, \ldots, |\vec{r}|$$

$$\beta_{ij} \leftarrow \beta_{ij} + (1 - \delta) r_j, j = 1, 2, \ldots, |\vec{r}|$$

Note that since δ is a binary variable, one of δ and $1 - \delta$ will be 1, and the other will be 0. Is essence, this means that successful sessions update the α matrix and failed session update the β matrix.

3.4.3 G matrix generation

Given the two data accumulator matrices α and β and the d by d data conversion matrix D, the morph serving matrix G can be generated. It is obtained as follows. For each α_{ij}, β_{ij}, let

$$a_1 = \lfloor \alpha_{ij} \rfloor$$

$$a_2 = \lceil \alpha_{ij} \rceil$$

$$b_1 = \lfloor \beta_{ij} \rfloor$$

$$b_2 = \lceil \beta_{ij} \rceil$$

for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, |\vec{r}|$.

and

$$f(a,b) = \begin{cases} D_{ab} & \text{if } a, b <= d \\ \frac{a}{a+b} & \text{otherwise} \end{cases}$$

Now,

$$G_{ij} = \frac{f(a_1,b_1) + f(a_1,b_2) + f(a_2,b_1) + f(a_2,b_2)}{4}$$

On a more intuitive level, we wish to index into the data conversion matrix using the values in the α and β matrices. Since these values are generally non-integral, we accomplish this indexing by taking the average of the closest four values in the data conversion matrix.

3.5 Morph Serving

Given the morph serving matrix G, the system serves up the current optimal morph for a user with cognitive style $\vec{r}$ using the following algorithm. Let $\vec{g}$ be a vector of length m that is generated as follows:

$$g_i = \sum_{j=1}^{|\vec{r}|} G_{ij} r_j \text{ for } i = 1, 2, \ldots, m$$

Now, the system serves up the morph corresponding to the index of the maximal element of $\vec{g}$. If there is a tie for maximal element, it chooses a morph uniformly at random from the tied indices.

Chapter 4

Morphing Ad Study Overview

This section describes the system used for the ad morphing field study. The study began on April 12, 2011.

4.1 Study Properties

4.1.1 Platform

The study took place on the CNET.com website, a popular website for technology news and product reviews.

4.1.2 User Identification

The study differentiated users by a unique cookie assigned to them upon entering the CNET.com site.

4.1.3 Test vs. Control

In order to test the effectiveness of ad morphing, users were divided into two groups: test and control. Approximately 30% of recorded users were in the control group and received a randomly chosen ad that disregarded cognitive style. Approximately 70% of recorded users received an ad that was chosen by our system.

4.1.4 Monitored Pages

The monitored pages on the CNET.com website were split into five different page types: Homepage, Product Review, Editor's Choice, Blogs Home, and Blog Post. The Product Review and Blog Post types were actually a set of pages with the same layout while the other three types consisted of only one page.

Each monitored page had up to five monitored sections where the user could click. Clicking on a monitored section of a monitored page resulted in a cognitive style update. For more details about the monitored pages and sections, see appendix B.

4.2 Parameters

This section lists the parameters of the morphing system for this study.

4.2.1 Morphs

The study used eight different ads including five square ads that display on the right hand side of the page and three banner ads that display on the top of the page. The ads featured a refurbished HTC Aria provided by AT&T. The ads and screen placement appear in appendix A.

4.2.2 Cognitive Style

The study used two differentiating factors: Deliberative vs. Impulsive and Analytical vs. Holistic, for a total of four cognitive dimensions. The four dimensions are the probabilities that the user is Deliberative and Holistic, Deliberative and Analytical, Impulsive and Holistic, and Impulsive and Analytical respectively.

4.2.3 Style Update Matrix

The style update matrix was made using results from a priming study conducted in the 2009-2010 school year. In fall 2009, a panel of M.B.A. students looked at various pages on the CNET site and characterized various sections based on cognitive style. For example, some sections were deemed more analytical while others were rated as more holistic. Then in spring 2010, live clickstreams were recorded on the CNET website. If a user clicked on relevant portions of the site, he would be asked to take a survey which asked questions designed to discern his cognitive style. This section of the priming study had 1292 participants. In October of 2010, the information from these two phases was combined to create the style update matrix.

The created matrix gave the probability that a user was each cognitive style, given that he clicked on a given section of a given page. The matrix used for this study was 5 by 5 by 4, reflecting number of pages monitored, maximum number of monitored sections per page, and number of cognitive dimensions respectively.

4.2.4 Session Definition

The study defined a session as all impressions of an ad seen by a given user. A session was supposed to stay within one of the test and control groups and never display more than one of the eight ads. A small number of sessions violated these properties and were consequently removed from the considered data.

4.2.5 Success Indicator

A session was considered successful if the user ever clicked on one of the eight ads. Otherwise, the session was counted as a failure.

4.2.6 Data accumulator matrices

The data accumulator matrices α and β were 8x4 matrices for this study. The dimensions come from the eight morphs and four cognitive dimensions used in the study.

4.2.7 Morph serving matrix

The morph serving matrix G in this study was also a 8x4 matrix.

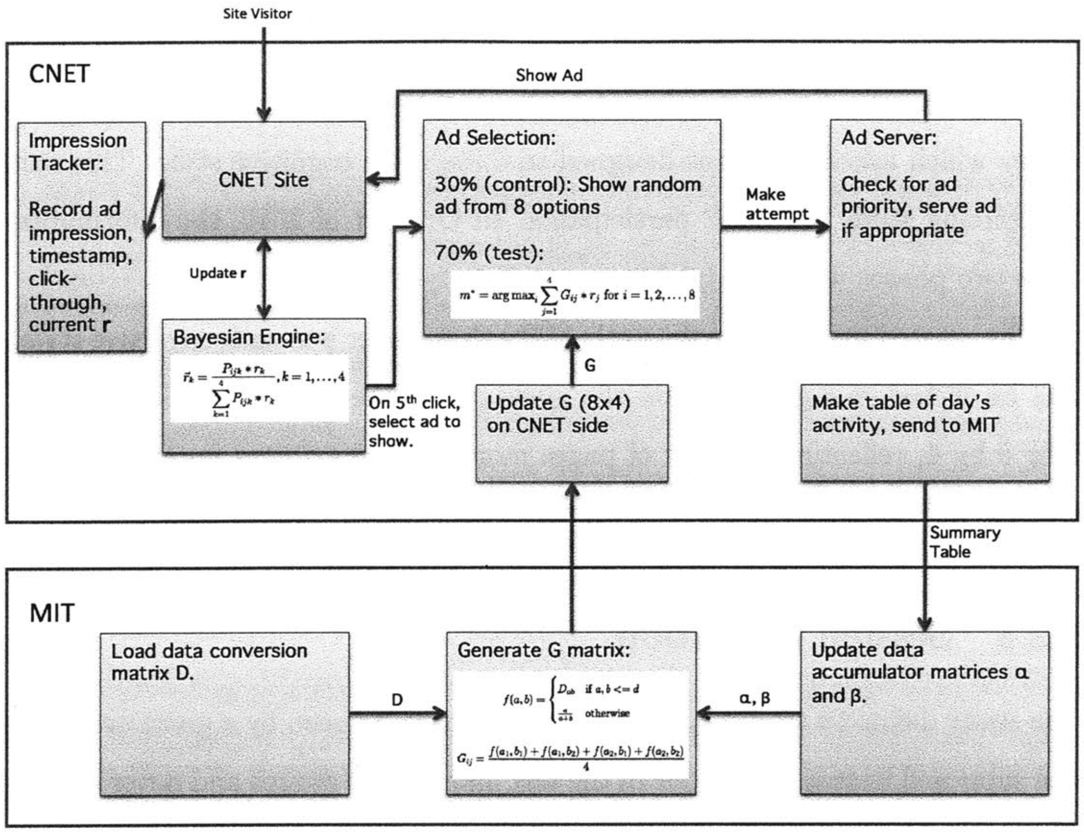

Figure 4-1: Diagram of system for ad morphing study

4.2.8 Data conversion matrix

The data conversion matrix used in this study was a 3000x3000 matrix that was previously generated. The same matrix was also used for the BT Group and Suruga morphing websites to convert α and β to G.

4.3 Visual Overview

Figure 4-1 shows a visual representation of the system.

4.4 Page Monitoring

For this study, there was functionality on the CNET backend to monitor pages viewed by each user cookie and note when an impression of one of the study ads appeared. Each user was assigned a unique cookie, which kept track of his current cognitive style and whether he was in the test or control group. Whenever an impression of our ad was served, CNET recorded the user's cookie id, current cognitive style, inclusion in test or control group, ad served, current timestamp, and whether the user clicked on the ad.

Monitored pages were identified by Java code which ran on the CNET servers. The CNET website has a tag in its URL that corresponds to the section of the referer URL that the user clicked on. The Java code checked for a match in both referer URL to monitored pages and tag to monitored sections. If both matched, the page was one of the monitored pages in our study. For more details on which pages were monitored and which section clicks were tracked, see appendix B.

4.5 Cognitive Style Update

4.5.1 Priors

Using the percentages of each cognitive style from the priming study, we set

$$\vec{r}_{init} = (0.283281734, 0.316563467, 0.254643963, 0.145510836)$$

.

4.5.2 Update

The cognitive style was updated every time the user clicked on a monitored section of a monitored page using the algorithm described in the previous chapter and the style update matrix obtained from the priming study. The style update code was written in Java and ran on CNET's servers.

4.6 Ad Selection

After the user had had five cognitive style updates from clicking on monitored parts of CNET website, the Ad Selection system selected an ad to show him. If the user was in the control group, he would be given one of the eight ads at random and if he was in the test group the system would use the algorithm in the previous section to serve the most optimal ad. The choice of optimal ad depended on the current G matrix and the user's current cognitive style. This system was written in Java and ran on CNET's servers.

4.7 Ad Serving System

After a user made 5 clicks on monitored pages, the system was then supposed to serve him an ad that depended on the morph serving matrix and his cognitive style. However, this ad was not always served because of CNET priorities in balancing different ad campaigns. The ad serving serving system ran on CNET's servers and would decide whether to serve each user the ad recommend by the ad selection system. If other ad campaigns took priority, the user would not receive an impression of one of the study ads at that time.

4.8 Report Generation

Each weekday morning, a CNET employee compiled data for each study ad impression into an Excel file. This report was combined by combining various sources of data on the CNET servers.

4.9 Report Contents

The daily report had one row for each impression of the study ads shown to a user on the CNET website. It had 16 columns in total. Descriptions of each columns are in table 4.1. Later on in the study, we received all attempts to serve a study ad, not

Column #	Name	Description
1	anon_cookie	Unique cookie id for each user
2	is_us	Binary variable indicating whether user was from the United States
3	is_test	Binary variable indicating whether user was in test or control group
4	ad_id	Ranged from 1-8 (test) and 11-18 (control). Indicated which ad was shown to user
5-8	qr1-qr4	Indicated the user's cognitive style
9	is_success	Binary variable indicating whether user click on displayed ad
10	number_all_pages	Number of pages on CNET website the user has visited since acquiring his cookie
11	number_monitored_pages	Number of pages user has visited that are monitored as part of the study
12	exposures	Number of times the user has seen a study ad
13	first_click	Timestamp of first time user clicked on a monitored link
14	first_active	Time when user first acquired his cookie
15	webpage	URL of webpage user was on during current impression
16	current_ts	Timestamp of current impression
17	is_exposure	Binary variable indicating whether attempt to serve ad succeeded

Table 4.1: Report Column Descriptions

just actual impressions. At this point, a seventeenth column, is_exposure was added to the report to indicate whether the attempt had been successful.

Columns 1, 11, and 16 were used to sort the data for processing and columns 1 and 3-9 were used in the G matrix update process. The rest of the columns were included for statistical analysis purposes.

4.10 Report Processing

This section details the report processing step done every weekday on the MIT side of the experiment. The code to update α, β, and G matrices was written in Ruby. The new G matrix was typically sent to CNET by 1pm.

4.10.1 Priors

The data accumulator matrices α and β started as 8x4 matrices consisting entirely of 0.03 and 0.97 respectively. The morph serving matrix G started out as a 8x4 matrix consisting entirely of 0.9807. Thus, the test group initially served ads with the same distribution as the control group.

4.10.2 Pre-Processing

Upon receiving the report, all rows that had a 0 in the is_exposure column (indicating that the ad impression was attempted but not served) were removed. The report was then sorted in Excel by anon_cookie, then by current_ts, then by number_all_pages which caused impressions to be sorted in approximate chronological order for each user. The report was then saved as a CSV and used as input for the update code to obtain the new G matrix.

4.10.3 Data Accumulator Matrices Update

The update code first loaded the current versions of the data accumulator matrices α and β. It then proceeded to read the sorted report line by line and update these matrices accordingly. We consider a session to be all of the interactions by a given user with the website. Hence, our updating rules work as follows:

1. For each user in the report, check whether that user was previously processed.
   - If he was previously processed as a success, move on until we see a new user
   - If he was previously processed as a failure, check to see if a success appears in the current report. If there is no success, move on until we see a new anon_cookie. If there is a success, remove the previous failure recorded from this user, then process the user as a success.
2. If the user was not previously processed, check to see if there was a success with

that user in the report. If so, process the user as a success. Otherwise, process him as a failure.

To process the user as a success or failure, we simply update either α or β as described in the previous chapter. If we have previously recorded a failure for that user, we remove it using the stored value of $\vec{r}$ and then process the success using the latest value of $\vec{r}$ from columns 5-8 of the report. After processing each user, we record the user's cookie id, whether he is in the control or test group, his ad_id, and his current cognitive style for possible recall later. By using these steps, we ensure that the data accumulator matrices are only updated once for each user.

4.10.4 Morph Serving Matrix Update

After we finish the updates to α and β, we load the data conversion matrix and use it along with the data accumulator matrices to obtain a new G matrix. This G matrix is then sent to CNET and updated in their system. The new values for α, β, and G are saved for use in the next update.

Chapter 5

Study Results

This section details the study results from April 12, 2011 to May 5, 2011. The study is still ongoing at this time.

Figure 5-1 shows the eight ads used in the study, included here for convenience.

5.1 User Cognitive Styles

Tables 5.1 and 5.2 show average cognitive styles by ad and overall. As expected, both the test and control groups have similar overall average cognitive style. Furthermore, the cognitive style distributions by ad in the control group are very similar to each other, since ads were assigned randomly to the control group. However, there is significant differentiation by ad in the test group.

Overall, the most popular style was Deliberative-Analytical, which might be expected given that CNET.com is a technology news website. Deliberative-Holistic was the least popular style by a significant margin, and Impulsive-Holistic and Impulsive-Analytical were roughly equally probable. This posterior cognitive style distribution is quite different from the priors we started with, possibly because of changes in monitored sections between the priming study and the field experiment.

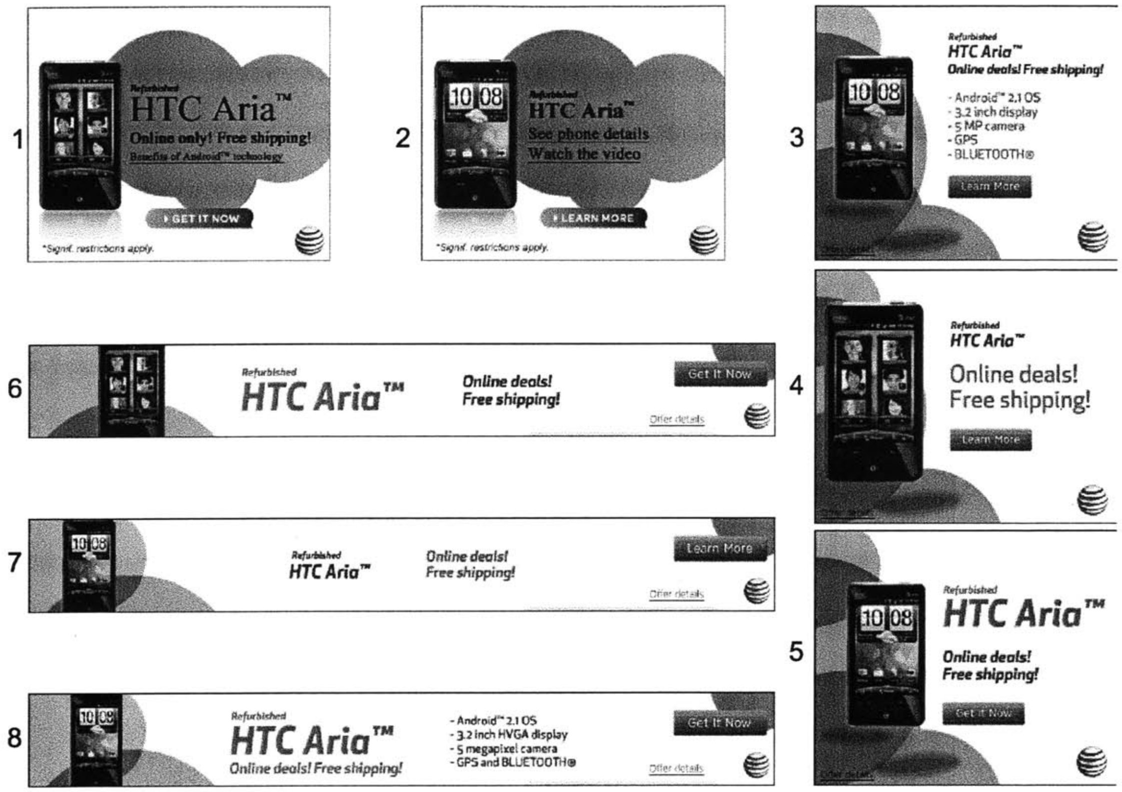

Figure 5-1: Ads used for the study

Table 5.1: Average cognitive styles by ad for the test group

	Average	1	2	3	4	5	6	7	8
Deliberative-Holistic	0.09	0.05	0.07	0.03	0.14	0.2	0.03	0.04	0.15
Deliberative-Analytical	0.42	0.74	0.27	0.59	0.28	0.24	0.45	0.34	0.41
Impulsive-Holistic	0.23	0.12	0.11	0.16	0.4	0.34	0.2	0.3	0.22
Impulsive-Analytical	0.27	0.09	0.55	0.23	0.18	0.22	0.32	0.33	0.22

Table 5.2: Average cognitive styles by ad for the control group

	Average	1	2	3	4	5	6	7	8
Deliberative-Holistic	0.08	0.07	0.08	0.08	0.08	0.09	0.06	0.08	0.06
Deliberative-Analytical	0.45	0.46	0.45	0.48	0.47	0.43	0.44	0.44	0.46
Impulsive-Holistic	0.22	0.23	0.19	0.22	0.22	0.18	0.25	0.23	0.24
Impulsive-Analytical	0.25	0.25	0.29	0.21	0.23	0.3	0.25	0.25	0.24

Table 5.3: Ads assigned by cognitive style for the test group

	1	2	3	4	5	6	7	8
Deliberative-Holistic	0.07	0.1	0.04	0.2	0.28	0.04	0.06	0.21
Deliberative-Analytical	0.22	0.08	0.18	0.08	0.07	0.14	0.1	0.12
Impulsive-Holistic	0.06	0.06	0.09	0.22	0.18	0.11	0.16	0.12
Impulsive-Analytical	0.04	0.26	0.11	0.08	0.1	0.15	0.15	0.1

Table 5.4: Ads assigned by cognitive style for the control group

	1	2	3	4	5	6	7	8
Deliberative-Holistic	0.12	0.13	0.13	0.13	0.15	0.1	0.13	0.1
Deliberative-Analytical	0.13	0.12	0.13	0.13	0.12	0.12	0.12	0.13
Impulsive-Holistic	0.13	0.11	0.13	0.13	0.1	0.14	0.13	0.14
Impulsive-Analytical	0.12	0.14	0.1	0.11	0.15	0.12	0.12	0.12

5.2 Ads Assigned to Each Cognitive Style

Tables 5.3 and 5.4 show the ad assignment to each cognitive style in the test and control groups respectively. As expected, the control group has relatively flat distribution for all styles while the test groups shows a nonuniform distribution, indicating preference for one ad over another in cognitive style.

The system had a relatively strong preference for giving Deliberative-Holistic users ad 5 and giving Impulsive-Analytical users ad 2. However, since users were often split between different styles, they might also receive a different ad, depending on how the split happened. Since users were given the ad that maximized the dot product of their cognitive style with each column of these tables, they were quite likely to get a different ad than their most probable cognitive style would indicate.

5.3 Click Through Rates

Table 5.5 shows click through rates at both the impression and cookie level for our entire data set while table 5.6 shows this data for pages where our ad was in proper context. Proper context in this case was defined by the URL containing either the word "phone" (but excluding "headphone") or "HTC". These pages were mostly product review pages and blog posts.

Table 5.5: Overall Click Through Rates

	Test (Morphing Ads)			Control (Random)			Differences		
	CTR	n	clicks	CTR	n	clicks	diff	p	Lift
Impression	0.17%	170,107	285	0.15%	97,038	147	0.02%	0.284	11%
Cookie	0.18%	52,014	95	0.16%	23,280	38	0.02%	0.533	12%

Table 5.6: Contextual Click Through Rates

	Test (Morphing Ads)			Control (Random)			Differences		
	CTR	n	clicks	CTR	n	clicks	diff	p	Lift
Impression	0.211%	12,801	27	0.118%	6,783	8	0.093%	0.066	79%
Cookie	0.248%	8,873	22	0.116%	4,296	5	0.132%	0.054	113%

From the tables we see that overall, even though the test group did slightly better than the control group, the difference was not significant. However, in the proper context, the effects from morphing were quite dramatic. At the cookie level, click through rate was 113% better for the test group than the control group, and the p values indicate a strong trend. Given that the learning algorithm is still being updated, we hope to see decisive significance of results by the end of the experiment.

Chapter 6

Contribution, Reflection, and Future Work

In this section, I outline my contribution to this project, describe lessons I learned from working on it, and give suggestions for future work that could be done in the same subject.

6.1 Contribution

My primary contribution was to design, implement, and test a morphing ad system capable of being deployed to a live website. The subparts of this system include the code running on the website to update the cognitive styles and select the optimal ad for each user as well as the update code that ran each day on the MIT side. Assuming similarity in format for the daily report, both subparts could easily be reused for a similar study.

In addition to designing, implementing, and testing the system, I also ran the daily update code to update the data accumulator matrices and generate the new morph serving matrix. I also wrote functionality to make a record each time the data accumulator matrices updated, in order to show the evolution of the morph serving matrix over time. With this data, we could examine the the evolution of the morph serving matrix and make sure it was converging properly.

6.2 Reflection and Lessons Learned

This project was a new experience for me, both in doing research in the field of digital marketing and in taking on a project of such large scope and with so many involved parties. Looking back, I learned several lessons from this project, which I detail here.

The main lesson I learned from this study was the difficulty of conducting field studies of this scope and the importance of good documentation. In order to get the study off the ground and running smoothly, it was necessary that many different people in CNET be informed of study specifics. One person was responsible for loading the new morph serving matrix each day, while another was responsible for compiling the daily reports and sending them, and a separate person handled the ad campaign priorities and could give insight about when ad serving attempts were made but not fulfilled. These people had to be separately briefed and kept on the same page about study related information. It turned out to be really helpful to put together a common document with relevant information and distribute it to all of the parties involved.

In addition to keeping everyone at CNET properly informed, it was also challenging to coordinate between involved parties on the MIT side. Since my primary collaborator in day to day operations for the project was located in the Netherlands, we had to keep communication up through a combination of Skype and email. In doing this, I learned to be more careful and precise about my statements, because even video chat transmits less information than face to face meetings. It was also helpful to put together formal documents to communicate complicated ideas, where in person a collaboration session with a whiteboard would have sufficed.

Another lesson learned was to analyze the data sooner rather than later. We noticed rather late in the experiment that our weekend data was quite different from weekday data and perhaps should not have been considered equivalently. If we had been more through about data analysis earlier in the experiment, we may have been able to adapt our data processing method to account for these differences.

On the technical side, I discovered that due to Ruby's dynamic allocation of memory, it can sometimes produce difficult to debug errors when loading large amounts of data into memory. In particular, the gem Excelsior, used to parse CSV files, starts throwing `malloc` errors on large files, something that can't be fixed without actually going in and editing the underlying C code. I solved this problem by switching to using the ruby built in functions to parse most CSVs. Though they were slightly slower, they did not seem to have the same memory allocation problems. If I were to do this project over again, I would not have used Excelsior and would have done more research about CSV parsers' abilities to handle large amounts of data.

In addition to learning about the importance of careful research of technology tools, I also learned about the importance of testing. In the study, we ran a couple days of the study with a few users in the beginning in order to make sure the data from the CNET website looked good. In addition, I extensively tested both the code that ran on the CNET server and the update code I ran locally using sample data and examining it for errors. By doing this testing, I was able to uncover several errors I had made initially which would have significantly compromised the study. In addition, at my collaborator's request, I added code to make a record every time the data accumulator matrices updated, which uncovered a previously undiscovered boundary problem with our starting values for the α and β matrices.

6.3 Future Work

This study represented a major step forward in the field of ad morphing. Previously, morphing experiments had been done only in controlled studies, which can give less accurate results because of their contrived conditions. Testing the ad morphing system in the field caused some number of problems, mainly in coordinating data between many parties and keeping everyone on the same page. Our experiment will run for a couple more weeks than the data reported here (until May 23), but we don't expect substantial changes in results from what we've reported here. Now that we've nearly finished a successful field study for this system, we have a few ideas for future work to learn more about the effectiveness of ad morphing.

Our results were significantly different between weekend and weekday data. In particular, the weekends had fewer visitors, fewer clicks, and less differentiation between the test and control groups. We theorize that this might be because the user population of the CNET website differs substantially between weekdays and the weekend, and because people tend to have different interactions with the site if they're looking at it during the work day. In a future study, we might want to update the morph serving matrix separately for weekends and weekdays and consider the resulting data sets in isolation.

In addition, given that CNET is a technology news site, our users were quite biased in most probable cognitive style. We would like to conduct future study on websites aimed at different cross sections of society to get a better sense of how ad morphing performs in different contexts.

In the results, we noted that the morphing ad system performed much better given appropriate context. The ads we used for the study were for phones, and the morphing ad system worked far better than random ad assignment if the user was browsing a page that had something to do with phones or HTC. It would be interesting to do another study that further explored this context-dependent effect, perhaps using different sets of ads and learning separately depending on page context.

In our study, we updated the morph serving matrix each day, continually learning from clicks in the system. Given more time, we would have also wanted to observe what happened without the continuous updates. A future study might be done to evaluate when to halt the learning process and to discover how well just the Bayesian system performs once sufficient learning has been done. Continuously updating the matrix is a somewhat time and computationally intensive process, so it would be useful to figure out how long it must be done in order to get good results.

One final piece of future work concerns figuring out how to estimate the effect of client side adblockers in this work. Currently, there is no good way to tell which users are using adblockers, given that we can't control what processing the user's browser does to a page before displaying it to them. Consequently, it could be true that a significant percentage of our users never see banner ads at all, a phenomenon which is not reported on in our data. If at some point it becomes possible to detect the presence of adblockers on the server side, it would be interesting to repeat this study taking this information into account.

In conclusion, this study represents an exciting first step in evaluating the effects of ad morphing systems which serve ads based on cognitive style. In the future, we hope to test the system on other platforms, further evaluate its effectiveness when coupled with proper context for ads, and gain more data about best practices for both construction and deployment for such a system.

Appendix A

Ads and Ad Placement

A.1 Ads

Eight ads were used for the study. They appear in figures A-1 through A-8, scaled to fit the page.

A.2 Ad Placement

Figure A-9 is a screenshot of the CNET website that shows where ads are placed.

Figure A-1: Ad 1

Figure A-2: Ad 2

Figure A-3: Ad 3

Figure A-4: Ad 4

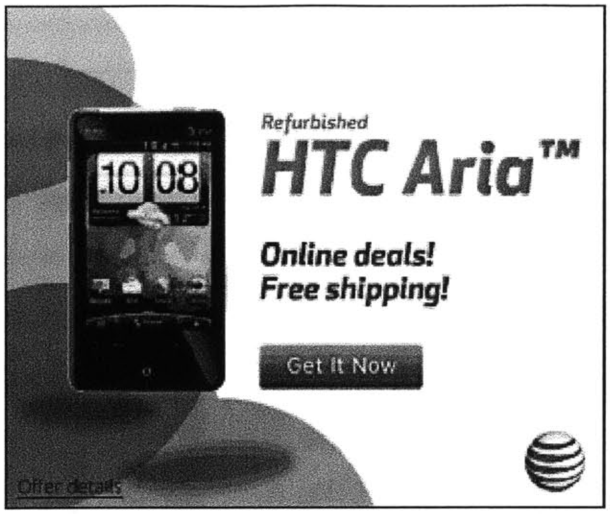

Figure A-5: Ad 5

Figure A-6: Ad 6

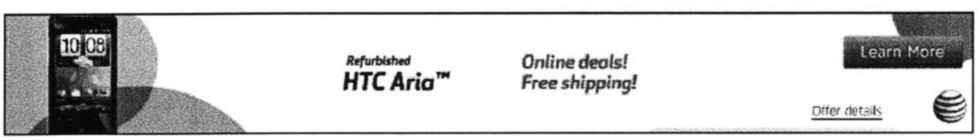

Figure A-7: Ad 7

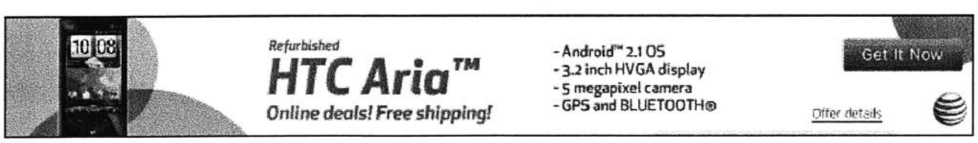

Figure A-8: Ad 8

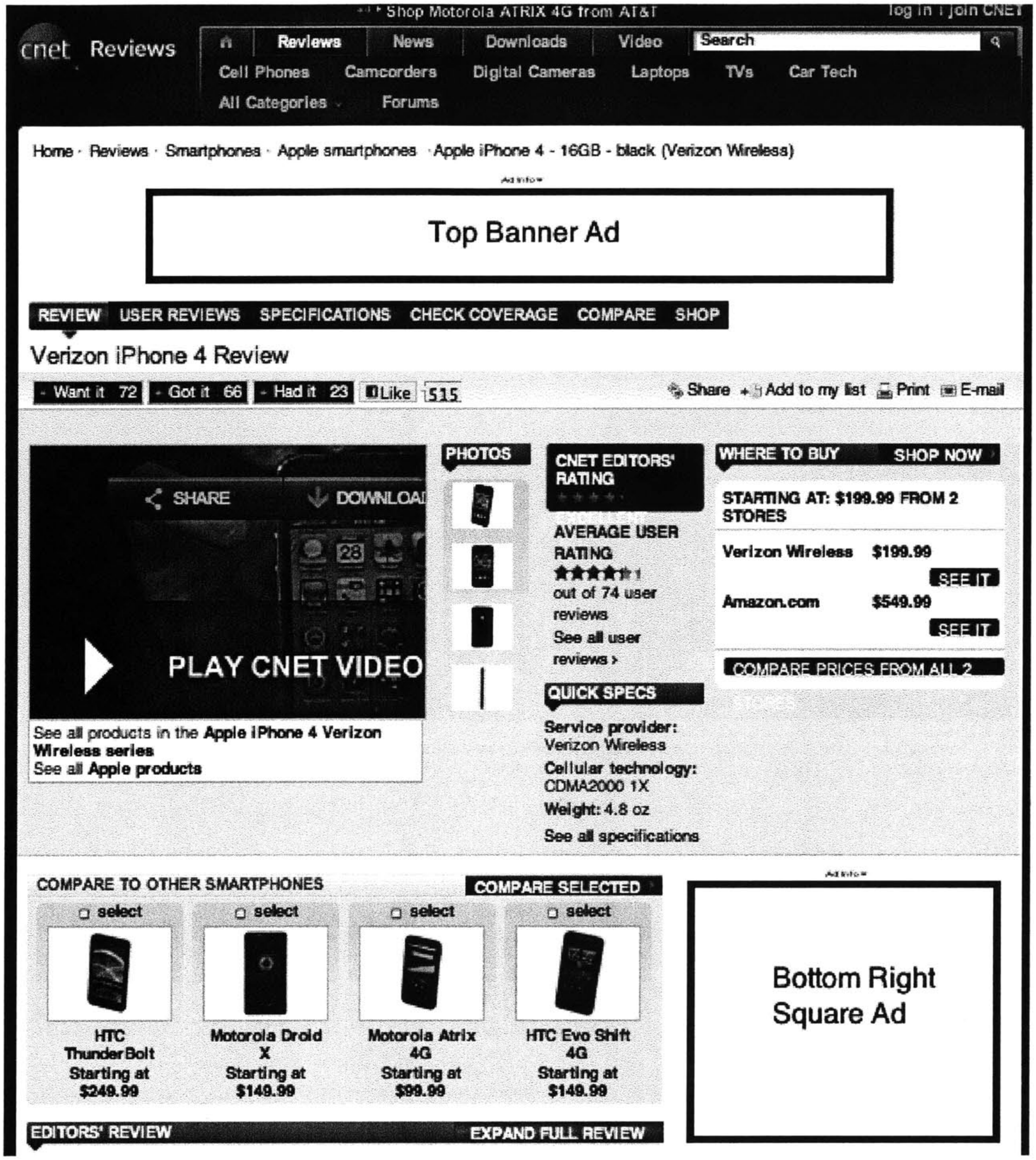

Figure A-9: Screenshot showing placement of top banner and bottom right square ads

Appendix B

CNET Monitored Pages and Links

B.1 Homepage

The homepage had five monitored sections: `TOCleftColumn.0`, `TOCcarouselMain.0`, `TOCmoreStories.0`, `epicStories`, and `ftr`. These sections are shown in figures B-1 and B-2.

B.2 Product Review

The Product Review page had four monitored sections: `hdr;brandnav`, `hdr;snav`, `contentBody;similarProds`, and `doormat`. The `doormat` section was divided up into three separate tags: `doormat;rnav`, `doormat;component.0`, and `doormat;component.1`. This change occurred between the priming study for cognitive styles in Spring 2010 and the experimental period in April-May 2011. These sections are shown in figures B-3, B-4, and B-5.

B.3 Editor's Choice

The Editor's Choice page had three monitored sections: `latestWinner;latestProduct`, `contentEdChoice;recentWinners`, and `moreWinners`. The `moreWinners` section was divided up into three separate tags: `moreWinners;more1`, `moreWinners;more2`,

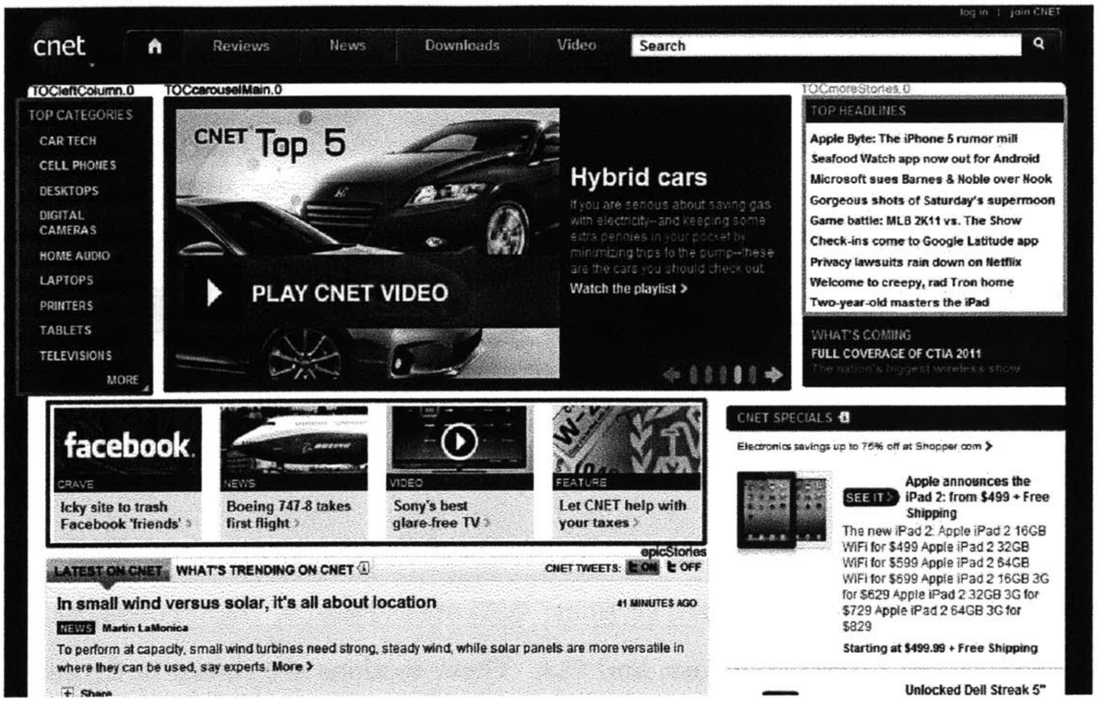

Figure B-1: Monitored sections on homepage

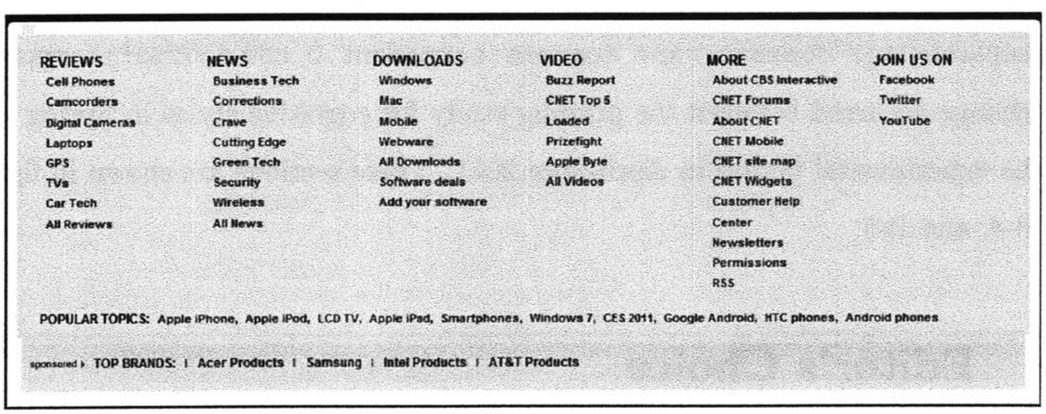

Figure B-2: Monitored sections on homepage

Figure B-3: Monitored sections on product review page

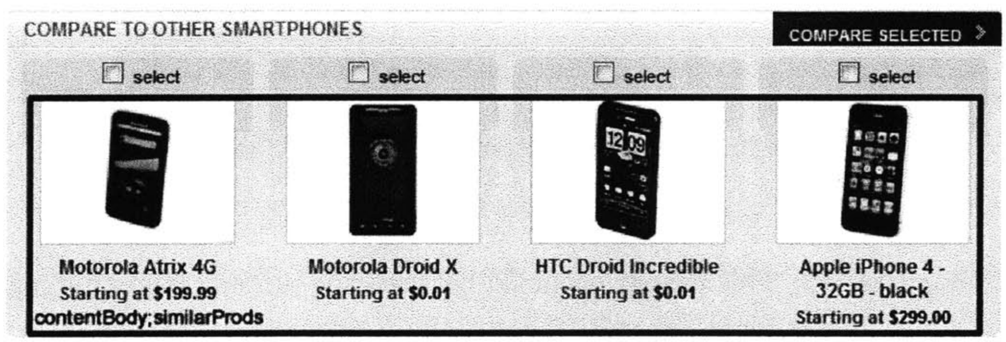

Figure B-4: Monitored sections on product review page

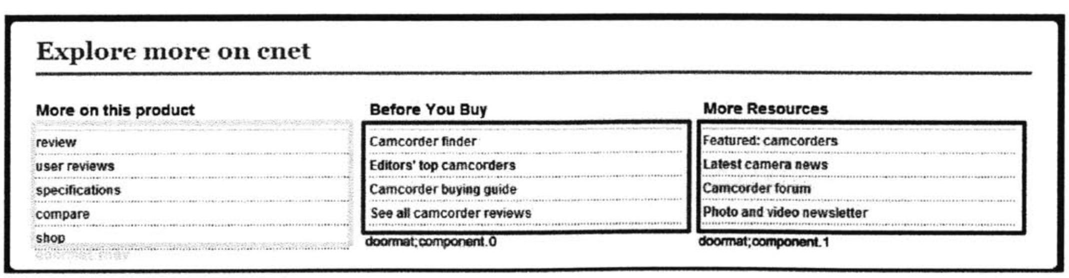

Figure B-5: Monitored sections on product review page

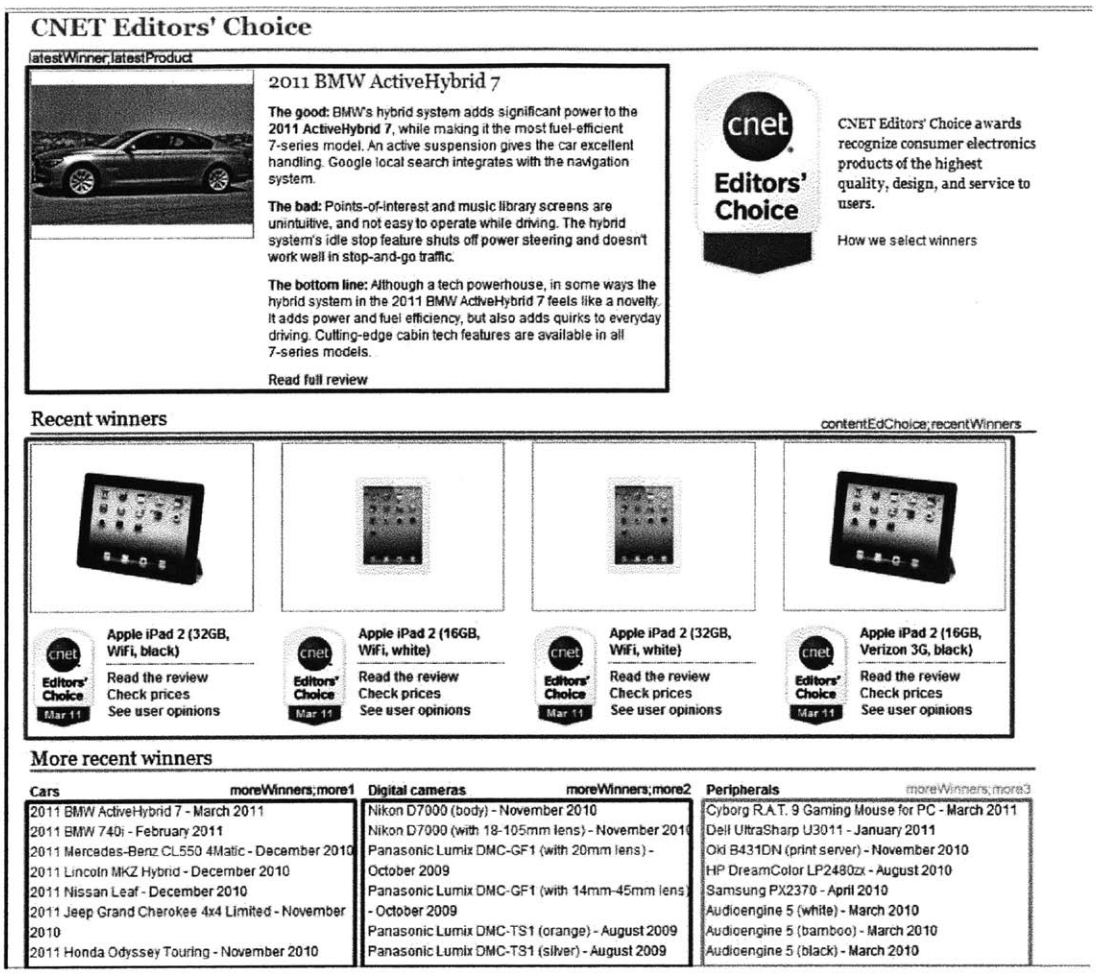

Figure B-6: Monitored sections on Editor's Choice page

`moreWinners;more3`. This change occurred between the priming study for cognitive styles in Spring 2010 and the experimental period in April-May 2011. These sections are shown in figure B-6.

B.4 Blogs Home

The Blogs Home page had two monitored sections: `mncol` and `rtcol;latest`. These sections are shown in figure B-7.

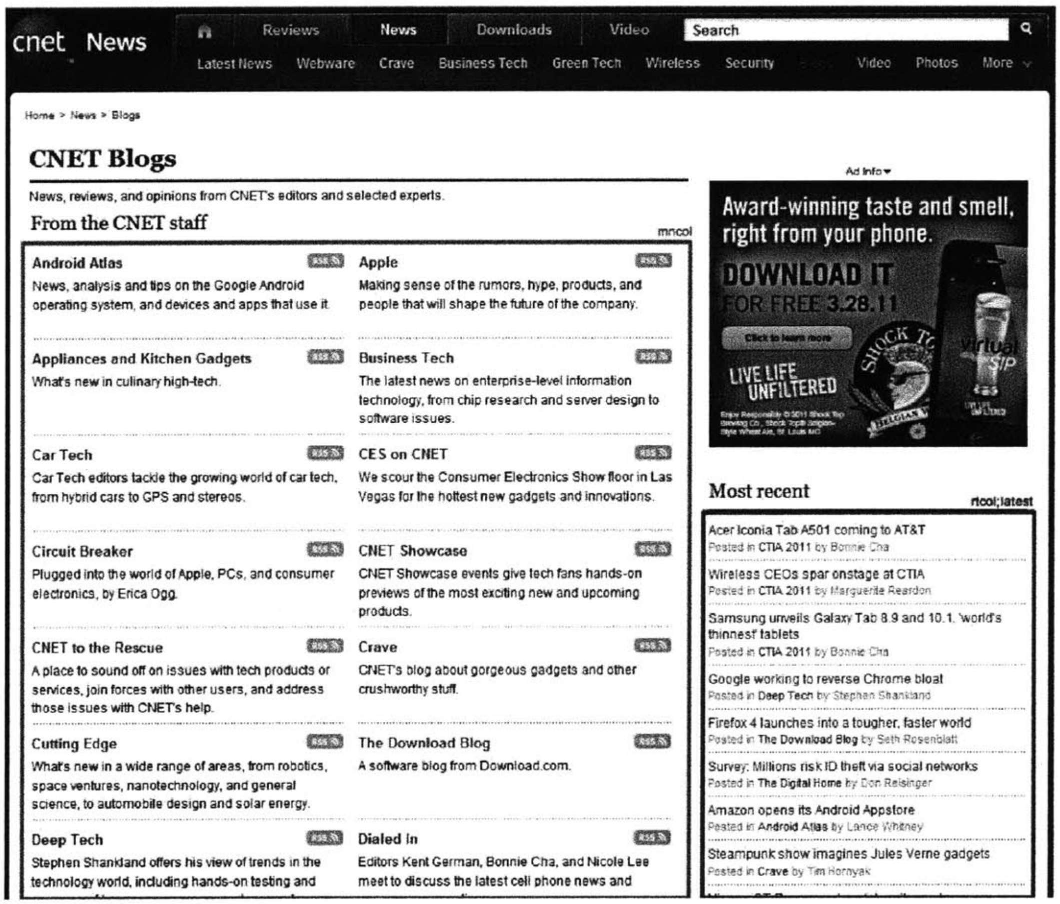

Figure B-7: Monitored sections on Blogs Home page

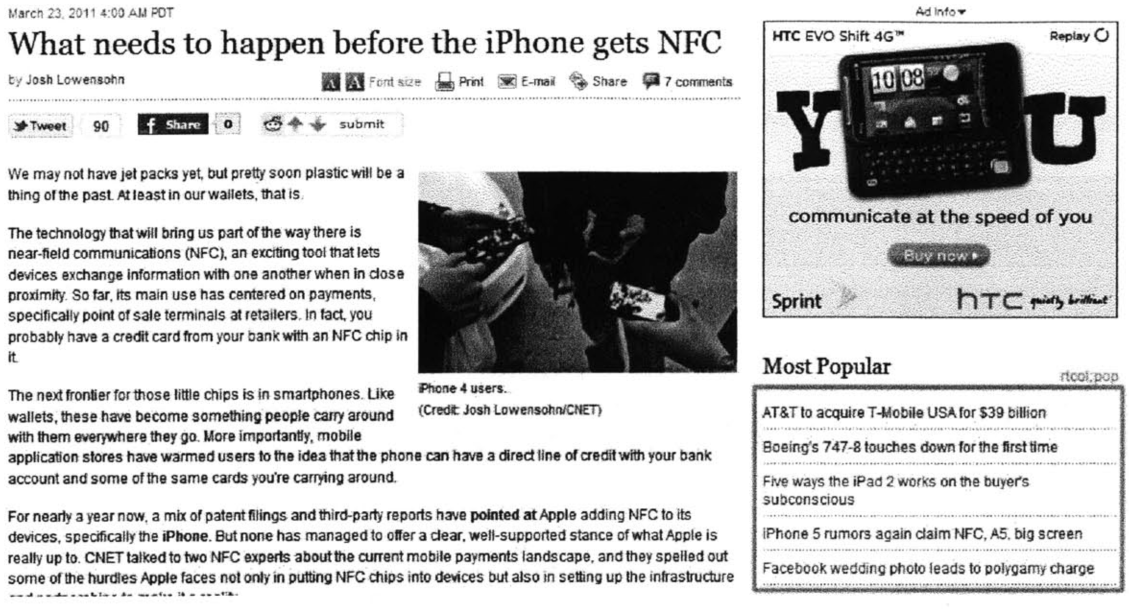

Figure B-8: Monitored sections on Blog Post page

B.5 Blog Post

The Blog Post page had two monitored sections: `rtcol;pop` and `rtcol;inTheNewsNow`. These sections are shown in figures B-8 and B-9.

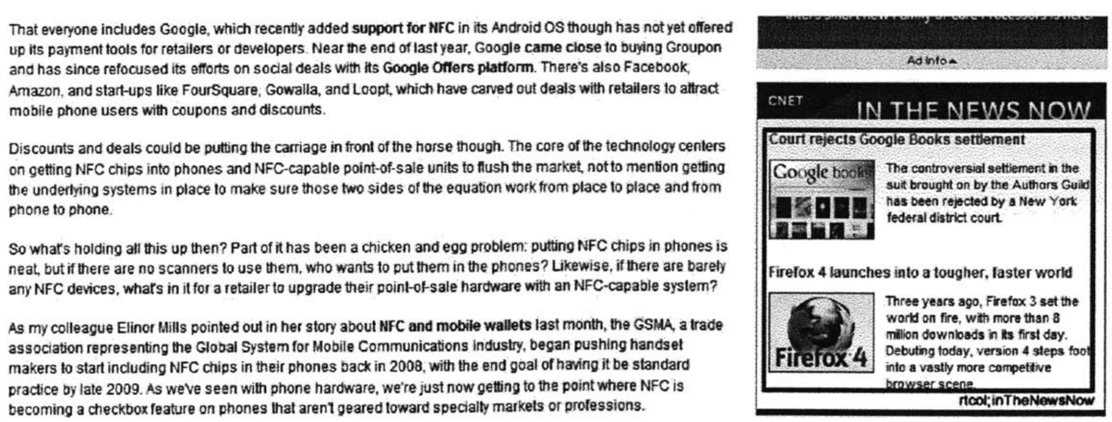

Figure B-9: Monitored sections on Blog Post page

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