Grazing or Staying Tuned:
A Stochastic Dynamic Model of Channel Changing Behavior

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Abstract

Television programs seek to attract and hold audiences in order to show them advertisements. Audience members insist on controlling their media experience by changing the channel. As a result, there is great interest in understanding the factors that lead up to and contribute to the decision to change the channel. Many factors—related to audience individual differences, program content, and media structure—play a role in determining when the television viewer opts out of one program and into another, making it difficult to understand this dynamic behavior. A rigorous mathematical model can help to explain some aspects of this complex phenomenon. Based on the theoretical understanding of channel changing behavior in the current literature, the authors mathematically formalized a stochastic semi Markov choice model of channel changing behavior and submit it to empirical testing.

Keywords: channel choice; viewing duration; semi Markov model; dynamic model

"A tug of war," this is how a popular media programming textbook describes the relationship between television viewers and television program services (Eastman & Ferguson, 2006, p.3). This tug of war becomes more intense with the increase in channel options provided by cable/satellite services and the greater convenience of remote controls along with other new media devices such as Tivo. Channel changing, also called channel surfing or grazing, is one of the largest obstacles that television programmers have to overcome to entice and hold audiences (Eastman & Ferguson, 2006). However, a large range of factors related to both the audience and the channels tangle together, making it difficult to identify the specific processes underlying this behavior. A rigorous mathematical model can help to disentangle this complex phenomenon. One possible avenue for bringing clarity to this process might be through the use of mathematical modeling. Mathematical models are used to rigorously describe and explain existing empirical data, derive corresponding computational models and simulation experiments, and most importantly, generate and test new predictions, and therefore test and develop theories (Bauer & Wade, 1982; Blalock, 1969; Bräten, 1970; Herman, 1967; Luce, 1970; McPhee & Poole, 1982).

A conceptual framework for understanding channel changing behavior was previously developed by Lang (see Fox, Park, Grabe, & Lee, 2005; Lang et al., 2005). In this paper, we mathematically formalize this conceptual framework in terms of a semi Markov choice model and begin to test it using empirical data.

Current Understanding of Channel Changing

Earlier research on channel changing behavior is primarily descriptive, and more recently, Lang and colleagues (Lang et al., 2005, in press) have begun to provide a conceptual framework to explain the underlying cognitive processing of channel changing behavior using the limited capacity theory of mediated message processing (for a review of the theory, see Lang, 2000; for the application to channel changing behavior, see Fox et al., 2005; Lang et al., 2005).

Interaction between Channels and Viewers

The limited capacity framework views media consumption as an interaction between individual audience members, the message content, and the medium's structural features. Factors from both the channel/media side and the audience side have been shown to influence whether a viewer decides to stay or graze.

(1) Program structure format (e.g., pacing and story length), content (e.g., emotion and genres), and context (e.g., air time and alternative channels) can affect channel changing behavior (e.g., Fox et al., 2005; Lang et al., 2005; Patzer, 1991; Walker & Bellamy, 1991). For instance, viewers change the most during sports and the least during pay-cable movies (Eastman & Newton, 1995), and are more likely attracted to messages that are shorter and faster (Bellamy & Walker, 1996; Eastman & Newton, 1995) or with more cutting, short scenes, and shorthand visual techniques (Bollier, 1989; Eastman & Neal-Lunsford, 1993). Experimental studies found that channel changing patterns

are impacted by story length and production pacing (Lang et al., 2005) as well as sensational content and tabloid style presentation features (Fox et al., 2005).

(2) Audiences' individual differences, including age and gender, also play an important role in channel changing behaviors (Fox et al, 2005; Greenberg, Heeter, & Sipes, 1988; Lang et al., 2005; Stafford & Stafford, 1996). For example, viewers' motivational tendencies to approach or avoid affect whether viewers stay tuned to arousing or calm programs (Fox et al., 2005). Younger viewers are found to change channels more frequently than older viewers (Eastman & Newton, 1995; Greenberg et al., 1988) and their viewing pattern are more affected by structure and format compared to older viewers who respond more to content (Lang et al., 2005).

Increased Boredom Leads to Channel Changing

One hotly debated question in this area is whether channel changing is an active or a passive behavior. There are two different views (Ferguson & Perse, 1993). The first view argues that frequent channel changing indicates an active viewer who is constantly evaluating what he or she is viewing and making personal selections based on personal motivations and goals (e.g., Eastman & Newton 1995; Walker & Bellamy 1991). The second view, however, is that channel changing reflects detached, low-involvement viewing and lower levels of attention (Moriarty, 1991; Perse, 1990, 1998).

Lang's limited capacity theory of media processing, suggests that active viewers would show a consistently high level of cognitive effort while viewing television. That is, they would be attending to the content and continuously making decisions about whether to stay with the old or switch to something new. Passive viewers, on the other hand, would display a different pattern of cognitive effort, where viewers watch a program until they lose interest or their boredom increases to some threshold at which point they change the channel. Thus, if people view passively, we might see attention and arousal levels decreasing monotonically up to some point which, when reached, leads to a channel change at which point attention and arousal should increase as the viewers orient themselves to the new content (Lang et al., 2005). A recent experimental study using psychophysiological measures to study viewers' levels of cognitive effort (indexed by heart rate) and physiological arousal (indexed by skin conductance), and using recognition to measure information encoding, supported the passive viewing model (decreasing attention and arousal) rather than the active model (continuously high levels of attention and arousal) (Lang et al., 2005).

Modeling Channel Changing Behavior

The significance of channel changing behaviors to industry practice is obvious from the intensive competition between channels in the current hypercompetitive media environment. The most popular audience analysis measures provided by media research companies (e.g., ratings, shares, average quarter-hour audience, and cumulative audience estimate) are mostly interested in two variables that are related to channel changing—channel choice and viewing duration. As introduced earlier, previous research has tried to draw a picture of who watches what channels and why they watch or change. The model proposed here attempts to define the passive viewing model in a rigorous mathematical theorization to bridge our existing scholarly understanding of channel changing behavior to the two most interested variables in the industry: channel choice and viewing duration.

The model, called ChaCha, after the first three letters of "channel" and "changing" is based on a semi-Markov Model (Bhattacharya & Waymire, 1990; Cox & Miller, 1965), this model conceives of different channels as states of the Markov chain and of switching between channels as transitions between states, which are driven by individual viewer's interest or boredom in each channel. A strength of the semi-Markov Model is that it provides a model of not only the choice probabilities, but also the distribution of time between transitions (Böckenholt, 2005). This flexibility is necessary for modeling channel changing behavior where time durations between channel switches vary extensively. The model mathematically formalizes channel attraction and strength, boredom with a channel, learning from a channel, and finally predicts the choice of channel and viewing duration for a given channel.

Choices of Channel

The probability of choosing any "new" channel during a switch is given by a logistic ratio of strength model, which is commonly used to model choice behaviors (Böckenholt, 2005). Table 1 demonstrates a sample of data to be modeled. The left column lists channels that a viewer sequentially watched and the right column shows the duration of watching each channel.

Table 1: Channel choice and time durations.

Channel	Time
C_0	t_0
C_1	t_1
…	…
C_k	t_k
C_{k+1}	t_{k+1}
…	…
C_N	t_N

The logit model of probabilities of choosing any "new" channel is defined as the following. First, we define $x_j(k)$ as the attractiveness of channel j for the *k-th* row of the above table, which is the attraction score used to predict the *k-th* switch after viewing *k-1* previous channels. The logit model uses a ratio of strengths of the states to compute choice probabilities, and the strengths must be positive to guarantee that the ratio is a probability, which ranges between zero and one. Therefore channel attraction scores (on a positive—negative scale) are transformed into strength scores (from zero to infinity) by exponential transformation, $v_j(k) = \exp[x_j(k)]$, which defines the strength for the channel j to predict the *k-th* switch.

If a viewer is watching channel i and decides to switch, then the viewer must switch to some other channel $j \neq i$. Suppose the *i-th* channel is the current channel before the *k-th* switch, which is denoted $C_{k-1} = i$. The probability of choosing channel j for the *k-th* switch is

$$\Pr_k = \Pr[C_k = j \mid C_{k-1} = i] = \frac{v_j(k)}{\sum_{l \neq i} v_l(k)}. \qquad (1)$$

Here, $\Pr_k$ is a conditional probability—the probability of choosing channel j on the *k-th* switch, given channel i is the channel viewed before this switch. The numerator is the strength of the channel j, and the denominator is the sum of strengths of all channels except for currently viewed channel i. That is, the probability of choosing a "new" channel depends on how large the strength of the "new" channel is compared to the sum of strengths of all channels except for the currently watched channel.

Channel Attraction

A viewer's interest in a channel continuously changes based on information about what is shown on alternative channels. This process basically can be viewed as a simple learning from experience—to learn what is shown on channels and pick the one that is interesting. Our model adopts one of the most established and commonly used learning models in psychology— the reinforcement learning model (Busemeyer & Myung, 1992; Erev & Roth, 1998). Format features of channels (in our data, pacing and story length) have corresponding parameters and can affect the learning rate, that is, the update of interest in a channel. The learning process is defined as the following:

On one hand, if channel i is watched before the *k-th* switch, it produces a change in the attraction of that channel:

$$x_i(k) = x_i(k-1) + D_1\beta_1 + D_2\beta_2 + D_1D_2\beta_3, \qquad (2)$$

where β_1, β_2, and β_3 are the change of attraction of channel i produced by the features of the channel. In our case, two features (pacing and story length), dummy coded by D_1 and D_2, are included. The items of $D_1\beta_1$ and $D_2\beta_2$ are the main effects of these two channel features on channel attraction. The interaction effect is also considered by including the $D_1D_2\beta_3$. On the other hand, if channel j is not watched before the *k-th* switch, then this produces a change in the attraction of channel j too, where α is the change:

$$x_j(k) = x_j(k-1) + \alpha \qquad (3)$$

Boredom and Viewing Duration

This is assumed to be determined by a diffusion process, which is commonly used in cognitive psychology to model response time (Busemeyer & Johnson, 2004; Ratcliff & Rouder, 1998; Ratcliff & Smith, 2004). The viewer begins with some initial interest in a channel, but then starts to drift and lose interest in that channel. This loss of interest (i.e., boredom) increases stochastically across time until it reaches a threshold at which point of time the viewer decides to switch to another channel. The process is stochastic because of continuing variations of television program content or structure across time (e.g., emotional scenes, personal relevant information, and production effects). The mean rate of increase in boredom is inversely related to the strength of the channel.

Suppose that the i-th channel is being viewed and it has strength v_i. Let *t(0)* denote the beginning of a viewing period and let *B(0)* = 0 represent the boredom at *t(0)*. Define time t as the viewing duration on a channel, and let *B(t)* represent the boredom after time t. Let h represent a small unit of time. Then, the random walk model (Luce, 1986) has

$$B(t+h) = B(t) + h \cdot v_i^{-1} + \varepsilon(t+h), \qquad (4)$$

where $\varepsilon(t+h)$ is an independent error with a variance equal to $h \cdot \sigma^2$. The random walk process continues to drift until the boredom crosses a threshold θ. The process stops as soon as the threshold is reached and then the channel is changed. This process is illustrated in Figure 1.

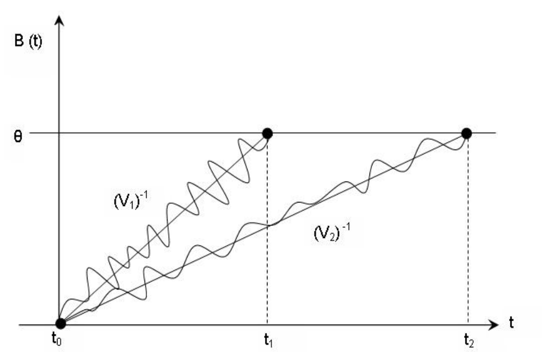

Figure 1: View durations differ for channels with different strengths.

If the small time step h is allowed to approach zero to produce a continuous time diffusion process, then the distribution of stopping times or the viewing durations, as described above, are a Wald distribution, with its probability density function defined as

$$f(t) = \left(\frac{\lambda}{2\pi t^3}\right)^{\frac{1}{2}} \exp\left[-\frac{\lambda}{2\mu^2 t}(t-\mu)^2\right], \qquad (5)$$

where μ is the mean of the distribution, λ is the threshold for change divided by the standard deviation units of noise, and the probability density is defined as a function of time duration t (Luce, 1986, p.509).

What is worth mention is, the mean of the distribution of viewing durations, μ, can be interpreted in terms of the strength of the currently watched channel (v_i) and the threshold bound for changing channels (θ). To see this, consider a simpler case in which the variance of the error is set to zero, $\sigma^2 = 0$. Then the random walk model is not random anymore, and the boredom increases linearly across time like a car traveling at constant speed for some fixed distance to a destination. In this simple example, calculating the time to reach the destination is familiar: time = distance/speed. To draw an analogy between the channel changing process and car traveling, the time to travel is identified with the mean of viewing durations, μ, the distance to travel is just the threshold bound θ, and the speed of travel is the mean rate of increase in boredom which is inversely related to the strength of channel i, that is, v_i^{-1}. Thus we have the following relationship between μ, θ, and v_i^{-1}, as illustrated in Figure 1:

$$\mu = \frac{\theta}{v_i^{-1}} = v_i \cdot \theta \cdot \quad (6)$$

This equation is intuitive. If a channel is attractive and has large strength, then the boredom grows slowly and viewers stay on the channel longer, and if a channel is not attractive and has small strength, then boredom grows quickly and viewers change channels more frequently. Thus the mean of the distribution of viewing durations is directly related to the attractiveness and strength of the channel. As shown in Figure 1, suppose there are two channels, 1 and 2, and channel 1 is less attractive and has smaller strength than channel 2 ($v_1 < v_2$). Then, the boredom experienced while watching channel 1 grows more quickly than while watching channel 2. According to equation (6), the time it takes to reach the same threshold θ are $t_1 = v_1 \cdot \theta$ for channel 1 and $t_2 = v_2 \cdot \theta$ for channel 2, which is not the same, $t_1 < t_2$, as shown in Figure 1.

In addition, in the ChaCha model, the Wald distribution parameter is the threshold bound in standard deviation units of noise, $\lambda = (\theta / \sigma)^2$. With others equal, individuals with a larger value on this parameter will tend be more persistent and stick to a channel longer even in the face of boredom. Increasing λ (i.e., higher θ) produces longer viewing durations. This is portrayed by Figure 2. Even with the same channel strength ($v_1 = v_2 = v$), a viewer with higher threshold θ_2 ($\theta_2 > \theta_1$), stays on the channel longer t_2 ($t_2 > t_1$).

Therefore, in addition to rigorous predictions and tests, another benefit of this modeling effort is to provide a theoretically based individual difference measure. The model can be fitted to each individual's data by finding the model parameters that maximize the likelihood of the observed choices and viewing durations. These parameters include the learning rate parameter and the threshold parameter for each individual. It is then possible to examine how these parameters vary across age, gender, and other specific populations.

The Dynamic Process

The meaning of being "dynamic" is twofold for this model. First, *within* one channel, attraction and strength of the channel continuously changes, and boredom of the viewer changes correspondingly. That is, learning about a channel is dynamic and stochastic, which is modeled as a diffusion process and is defined by the updating formulas of channel attraction (equations (2) and (3)) and illustrated by Figure 1 and 2. Second, the processing *across* channels is also dynamic. This is formalized by continuous changes of boredom across channels. A viewer can be bored by a channel and switch to other channels. After comparing with other channels, the viewer may find that the previous channel actually is more interesting than other options, and switch back to it. Additionally, cross different channels, a viewer can have different thresholds. This difference of boredom cross channels also dynamically changes over time, as illustrated in Figure 3.

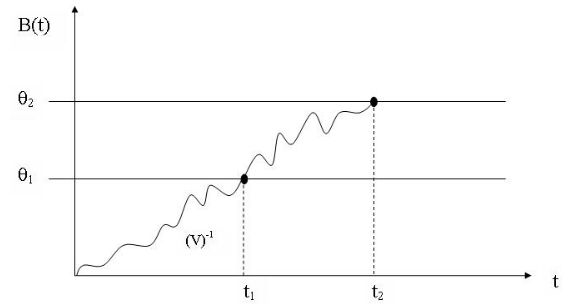

Figure 2: Viewing durations differ for viewers with different thresholds.

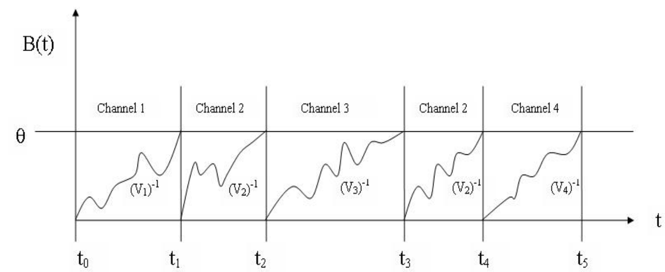

Figure 3: Dynamic changes of boredom across channels.

Alternative Models

In this paper, we compare proposed models to find out: (1) Whether the time distribution should be Wald distribution. Another possibility would be to assume an exponential, rather than a Wald, distribution of viewing durations: $f(t) = e^{-t/v_i} / v_i$; (2) Whether the learning process is necessary. Basic models without and without learning process are compared; and (3) Whether the interaction effect of the channel features should be included.

Crossing these two features (presence vs. absence of the learning process and Wald vs. exponential distribution) yields four different models to be compared to one another. Models without the learning process will be called basic models, those with it learning models. The preferred model from the four will be tested for its alternative by excluding the interaction effect parameter β_3.

Method and Results

The model along with competing models are implemented using MATLAB (MathWorks, Inc., Natick, MA) and fitted to empirical channel changing data from an study by Lang et al. (2005)[1]. Because the entire viewing time is short (15.5

[1] The experiment is a 2 (Story Length: long vs. short) × 2 (Production Pacing: fast vs. medium) × 2 (Age: adolescents vs. adults) design. Age was the only between-subject factor. Participants watched television through which they could use a remote-control to choose among the four local news channels. Viewers' channel choice and viewing durations were recorded by computers.

minutes per participant) in the experiment, the number of data points of each participant is small. Hence, the models are fitted to observations of all participants all at once, instead of individually.

Table 2: Model comparisons.

Model	β_1	β_2	β_3	α	σ	θ	*BIC*
Exponential basic	0.83	0.77	-0.82	—	—	—	40437.20
Exponential learning	-0.10	-0.08	0.10	0.52	—	—	31836.60
Wald basic	-0.04	-0.06	0.06	—	25.64	60.30	18580.00
wb 1 (no length)	-0.01	—	—	—	24.94	58.51	18575.00
wb 2 (no pacing)	—	-0.04	—	—	25.09	58.92	18569.00
wb 3 (no interact)	-0.01	-0.04	—	—	25.27	59.37	18576.60
Wald learning	-0.03	-0.06	0.05	-0.02	29.60	69.83	18585.41
wl 1 (dif learning)	-0.03	-0.06	0.05	0 adolescents; -0.02 adult	28.29	66.72	18587.81

The parameters that maximize the log likelihood for each model when it is fitted to the data are used to make model comparisons. Because the models vary in the number of parameters and all are not nested, Schwartz Bayesian Information Criterion (BIC) is calculated for each model to select the preferred model. Generally, the model with the lowest value of BIC is selected. As shown in Table 2, Wald models perform much better than the exponential models. The Wald basic model performs slightly better than the Wald learning model, but the difference of BIC is very small (18580.00 vs. 18585.41), further tests need to be conducted to decide whether the learning process is needed to be included in the ChaCha model at the expense of adding one parameter α.

Our data were collected from two age groups: adolescents and adults. It is intuitive that different age groups would demonstrate different learning rate α, but is this difference large enough to be considered in this model? To find out this, two models are compared: One is with the α being the same for both age groups (the Wald learning model in Table 2); and the other estimates different learning rate α for the two age groups (the wl 1 model in Table 2). As shown in Table 2, both the best fitted parameters and the BIC values are very similar for these two models, with the Wald learning model having a slightly smaller BIC (18585.41 vs. 18587.81). Therefore, based on current data, the learning process described in early sections may not contribute significantly to the channel changing behaviors.

Based on this data set, the Wald basic models are preferred because they perform better than the exponential models and are more parsimonious than the Wald learning models, producing relatively smaller BIC. Further tests on Wald basic model alternatives found that when excluding the effects of story length (the wb1 model in Table 2), the effects of pacing (the wb 2 model in Table 2), and interaction effect between length and pacing (the wb 3 model in Table 2), the model with only the main effect of story length performs best, although all the best fitted parameters and BIC values generated by those alternatives are similar to the more complete Wald basic model. This suggests that story length may have a larger effect on channel changing behavior compared to the other program feature, pacing, modeled in this study.

Discussion

The proposed ChaCha model helps to test and develop theories about channel changing behavior. It also demonstrates the strength of modeling in media psychology theory building: (1) Any media use behavior is a result of complex combination of processes and the model helps untangle these subprocesses and allow them to be taken apart and studied in depth. (2) The model's parameters provide potential measures of audiences' individual differences. (3) The model's parameters also can test and predict the effects of various treatment conditions of media content and format features. (4) A model provides deeper scientific understanding of the mechanisms, which can be used to design new programs or treatments. In this paper, the pattern of channel changing behavior of television viewers is precisely descried by our model.

Constrained by the available empirical data, the present paper only illustrates, to a very limited extend, these potentials. For example, the model fitting procedure found that learning rates for different age groups did not vary. This may be the case in real mediated environment since watching television is a passive activity and learning, which is generally active, may not be a significant part of the viewing experience. However, the absence of different learning rates may due to the factor that we are not able to fit the data individually. Due to the limited data available, the model testing results are tentative. Refined models should be developed and tested by carefully designed experiments with longer viewing time.

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