Patterns of Goal-Contingency Learning in Preference Formation
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Abstract
The study investigates learning patterns during goal-directed preference formation. A longitudinal experiment examines formation of attribute importance judgments in the context of contingency relations between a stable consumer goal and alternative product attributes. The results suggest the learning curve in consumers’ attribute importance judgments can be analyzed using nested models to reveal different associative learning systems. Investigating the characteristics of the learning curve, we find that the learning pattern is best represented not by a single learning system, but by a combination of associative learning processes. This combination provides a descriptive basis for modeling representation of goal-directed preference learning.

Introduction
Different associative models imply distinct learning systems according to which consumers can estimate the importance of product attributes over time (van Osselaer and Janiszewski 2001). When the consumer encounters an initially unfamiliar product attribute (such as, rain diffusion windscreen in the car she drives), over time, an associative learning process helps to relate this attribute to achievement of her goal (e.g., safety while driving). The strength of the learned association can be expressed as the importance of the attribute under the Expected Utility framework (Chylinski, Roberts, and Hardie 2008). However, the existence of different associative learning systems suggests that models based on a single learning process may over simplify consumer behaviour. In this article, we develop a model that considers multiple learning systems within a common associative learning framework.

When modeling preference formation, under Multi-Attribute Utility (Keeney and Raiffa 1976), discrimination between different associative learning mechanisms becomes important. van Osselaer and Janiszewski (2001) demonstrate that when products are considered as conglomerates of distinct attributes, contexts exist in which learning of brand associations is not adequately explained by any single mechanism. Human Associative Memory (HAM) models (e.g., Anderson, 1983) suggest that associations are formed when attributes co-occur with goal achievement. Hence, the frequency with which goals are accompanied by product attributes is the key determinant of the associative strength. However, in contexts where the achievement of the goal is motivationally significant, the adaptive (cue interaction) learning models seem to provide better explanation than HAM by suggesting that the strength of the association depends not so much on frequency; but rather on the attribute’s ability to predict achievement of the goal. The HAM and the adaptive models represent distinct associative learning systems that have different implications for establishing associations between attributes and goals. Since the consumer has both systems to estimate the importance of a product attribute, both should be represented by a more general model of associative learning. The model we consider includes the two systems and aims to distinguish which system is dominant, and what the interaction between the two learning systems is.

We verify the performance of our model using a longitudinal experiment, conducted in a motivationally significant scenario, across a range of goal-attribute contingencies. We find
the trajectory of the learning curve in consumer’s attribute importance judgments is consistent with the expectation of the dominant adaptive learning system, but a mixture of the learning mechanisms provides the best representation to the data. We discuss the implication of this result for consolidative application of the two learning mechanisms, where both systems are active and contribute to the overall evaluation of attribute importance.

**Modeling Adaptive Learning of Attribute Importance**

Fundamentally, attribute importance conditioning can be represented as a Markov decision process (MDP) that updates the transition function between alternative states in the environment. In this scenario, the level of attribute \( k \) represents one state, and the level of goal \( Y = y \) represents another state. Each state has its own reward value, denoted by \( U(x_k) \) and \( U(y) \), respectively. Conditioning assumes that initially neutral product features, which have no intrinsic value, acquire utility as the consumer recognizes them as reliable predictors of potential goal achievement (Wasserman and Miller 1997). Focusing only on the predictive relationship between \( x_k \) and \( y \), MDP generates a goal achievement expectation that matches the following expression:

\[
I^t(y) = \sum_{i=1}^{K} I^t_{i+1}(x_k) a(y \mid x_k, C_j),
\]

where \( a(y \mid x_k, C_j) \) defines the transition function between \( x_k \) and \( y \) in the context \( C_j \); \( I(.) \) is the identity function, such that \( I(x_k) = 1 \) when \( X_k \) occurs, and \( I(y) = 1 \) when \( Y \) occurs, but otherwise are 0; and \( v = 1 \ldots T \) is the time horizon for expected goal achievement. To establish the reward value for the product attribute \( x_k \), MDP calculates:

\[
U(x_k \mid C_j) = r_t + \sum_{i=1}^{T} I^t_{i+1}(x_k) a(y \mid x_k, C_j) \gamma(v) U(y)
\]

Existing behavioral literature implies adaptive learning of attribute importance (Kamin 1969; Rescorla and Wagner 1972, Miller, Barnet, and Grahame 1995; Van Hamme and Wassermann 1994). However, a stream of behavioral research also points to HAM models as a plausible alternative learning system (van Osselaer and Janiszewski 2001). To incorporate the two learning systems within our framework, we propose a general autoregressive moving average with exogenous inputs (ARMAX) model (Davidson and MacKinnon 1993). Because ARMAX suggests the possibility of alternative formulations that may lead to monotonic updates of the transition function in equation 2, alternative plausible hypotheses also exist. In the case of contingency learning, ARMAX can be stated as:

\[
\hat{a}_t(y \mid x_k, C_j) = \alpha_0 + \sum_{n=1}^{N} \alpha_n \hat{a}_{t-n}(y \mid x_k, C_j) + \sum_{n=0}^{M} \beta_n a^*(y \mid x_k, C_j) + \epsilon_t.
\]

Where \( a^*(.) \) is the relative frequency-based contingency; Equation 3 is useful as a general formulation of the transition function in equation 2 because it nests many commonly estimated specifications that correspond to other descriptive models discussed in consumer behavior literature. Therefore, it can serve to test the adaptive learning model relative to other commonly analyzed learning patterns (see Table 1).
### TABLE 1
ALTERNATIVE LEARNING PROCESSES BASED ON RESTRICTIONS OF EQUATION 3

<table>
<thead>
<tr>
<th>Type</th>
<th>Process</th>
<th>Restriction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. General associative</td>
<td>$\hat{a}<em>t(.) = \alpha_0 + \alpha \hat{a}</em>{t-1}(.) + \beta_0 a_t^<em>(.) + \beta_1 a_{t-1}^</em>(.) + \epsilon_t$</td>
<td>None</td>
</tr>
<tr>
<td>2. Adaptive</td>
<td>$\hat{a}<em>t(.) = \alpha_0 + \alpha \hat{a}</em>{t-1}(.) + \beta_0 a_t^*(.) + \epsilon_t$</td>
<td>$\beta_1 = 0$</td>
</tr>
<tr>
<td>3. Connectionist</td>
<td>$\hat{a}_t(.) = \alpha_0 + \beta_0 a_t^*(.) + \epsilon_t$</td>
<td>$\alpha_1 = \beta_1 = 0$</td>
</tr>
<tr>
<td>4. No learning</td>
<td>$\hat{a}_t(.) = \epsilon_t$</td>
<td>$\alpha_1 = \beta_0 = \beta_1 = 0$</td>
</tr>
</tbody>
</table>

### Method
To test the process of attribute importance learning, respondents faced with different attribute–goal contingencies provide estimates of their attribute utility at different levels of exposure to goal and attribute information. Eleven conditions appear across the contingency spectrum. In each condition, 12 replications of the experiment enable an analysis of the dynamics of attribute importance learning, at low and high levels of random noise. A simulated Internet share trading scenario enabled respondents to sample the information about product attributes and consumer goals sequentially while making natural repeated attribute utility judgments and decisions. This scenario also features a decision support software agent that provides recommendations about which shares to purchase at any given point in time. The software agent operates on the basis of two salient, but initially unfamiliar, algorithms (product attributes), neural net ($X_1$) and temporally continuous ($X_2$). The presence or absence of either attribute affects the accuracy of the agent’s recommendations in terms of capital gains from each transaction. Respondents attempt to choose the most profitable equity stock (the one with the greatest capital gain) out of four possible options shortlisted by the Internet site. The value of goal achievement equals $100 (based on the pricing strategy that pays $100 for choice of stock with greatest capital gain, but absorbs any gains/losses from any other choices). The choice of stocks is followed by feedback about which stock resulted in greatest capital gain, which stock the respondent chose, and which stock the agent recommended.

### Results and Discussion
Three hundred and thirty subjects from a population of undergraduate and MBA students at a leading university participated in the experiment in exchange for $20, plus a chance of winning a $500 prize. Willingness to pay indicates attribute utility at different levels of contingency and exposure to product attributes.


<table>
<thead>
<tr>
<th>Model Type</th>
<th>Condition</th>
<th>Low Random Noise</th>
<th></th>
<th>High Random Noise</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj. $R^2$</td>
<td>AIC</td>
<td>SBC</td>
<td>Adj. $R^2$</td>
<td>AIC</td>
</tr>
<tr>
<td>1. General associative*</td>
<td>.903</td>
<td>-13213</td>
<td>-13188</td>
<td>.848</td>
<td>-9855</td>
</tr>
<tr>
<td>2. Adaptive*</td>
<td>.893</td>
<td>-12814</td>
<td>-12795</td>
<td>.838</td>
<td>-9649</td>
</tr>
<tr>
<td>3. Connectionist*</td>
<td>.770</td>
<td>-9775</td>
<td>-9764</td>
<td>.733</td>
<td>-8034</td>
</tr>
<tr>
<td>4. No learning*</td>
<td>n/a</td>
<td>-3961</td>
<td>-3955</td>
<td>n/a</td>
<td>-3759</td>
</tr>
</tbody>
</table>

* All model parameters statistically significant ($p < .05$).

Model performance in Table 2 relates inversely to the normative properties. That is, the full information assumption of no learning (null model 4) is clearly dominated by preference formation over time (models 1, 2, and 3). The normatively correct process of connectionist judgment updating (model 3) is outperformed by the adaptive process (model 2). However, the adaptive process is marginally surpassed by the general associative model that suggests a more distributed lag structure to reflect a mixture of both the adaptive and the connectionist components in attribute importance judgments over time. Hence, our model distinguishes between the alternative associative learning systems that guide preference formation over time, and highlights the consolidative application of the different learning mechanisms.

The findings presented herein have several significant managerial implications. By focusing on the value of consumer goals, managers may trace the pattern of utility development on the basis of established learning models in psychology. This ability offers them clues into the possible acceleration of preference formation using the known properties of different associative conditioning mechanisms (see van Osselaer and Janiszewski 2001). The distinct monotonic convergence of attribute importance judgments, at a diminishing rate over time, confirms that accumulated experience with product attributes results in stable preferences. Applying our model to this expected empirical result enables managers to predict the eventual value, and hence position, of products at equilibrium. Yet, more importantly, our model also distinguishes between the alternative associative learning systems that guide preferences formation over time. Because, different learning systems imply different actions needed to accelerate preference formation, a model that distinguishes the dominant learning system using a pattern of utility judgments is a useful tool.

References


