Utility Discounting Explains Informational Website Traffic Patterns Before a Hurricane

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ABSTRACT

We demonstrate that psychological models of utility discounting can explain the pattern of increased hits to weather websites in the days preceding a predicted weather disaster. We parsed the HTTP request lines issued by the web proxy for a mid-sized enterprise leading up to a hurricane, filtering for visits to weather-oriented websites. We fit four discounting models to the observed activity and found that our data matched hyperboloid models extending hyperbolic discounting.

Categories and Subject Descriptors

J.4 [**Social and Behavioral Sciences**]: Economics; J.4 [**Social and Behavioral Sciences**]: Psychology

General Terms

Economics, Experimentation

Keywords

delay discounting, temporal discounting, model comparison, humans

1. INTRODUCTION

In behavioral economics and psychology, researchers use the term "discounting" to describe the phenomenon whereby a subject decreases its valuation of a potential reward as a function of increasing delay or increasing uncertainty. For instance, when presented with a choice between two rewards that differ in delay, human and animal subjects tend to select the reward that is delivered sooner, sometimes even when it has a lower objective utility [5]. In this paper we examine the fit of four common discounting models to our experimental data, which is derived directly from network protocol logs reflecting human-driven behavior on an enterprise network. This data was collecting during the weekend leading up to the local touchdown of Hurricane Sandy, and is an instance of human network usage activity leading up to imminent natural disaster. Hence, our analysis seeks to model human information-seeking behavior leading up to a crisis.

While current hierarchical load prediction models sometimes take a machine learning approach to load prediction [8], we believe a fundamental understanding of the psychological phenomena at work could lead to better predictions about behavior during rare events, such as natural disasters, complementing work that relies on user behavior to detect trends [7]. While hyperbolic discounting has been used previously to describe various economic phenomena [3], we claim novelty in using it to explain network traffic.

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2. METHODOLOGY

2.1 Human data

Hurricane Sandy touched down on the Northeast coast of the United States early in the morning on Monday, October 29, 2012. We collected the HTTP request lines issued by the web proxy for a mid-sized enterprise from 6 pm Friday, October 26, 2012 until 9 am Monday, October 29, 2012. These request lines were attributable to 1207 distinct users of the enterprise network who were active during this time period.

We filtered this corpus of request lines for GET requests to 19 popular weather-related websites. We assume that this filtered corpus is representative of and proportional to the total weather forecast seeking behavior of the enterprise userbase during the observed time period.

2.2 Analysis

We restrict our analysis of the dataset described in Section 2.1 to between 10 am and 11 pm on the days of collection, being the period of greatest activity. For each hour in question, we counted the number of distinct users to issue an HTTP request, and divided by the total number of users. The result is a mean probability that a user will seek out weather information within a particular hour. We interpret this probability as being proportional to the mean perceived utility of learning about the weather at the hour in question. We assume that the users knew that the last chance to do so prior to the hurricane would be late Sunday evening.

A discounting factor $\rho(D)$ at some delay D allows us to compute the subjective value $V(D)$ of a reward A by setting $V(D) = A\rho(D)$. So, if $P(D)$ is the probability drawn from the distribution of our userbase at D, then $P(D) \propto A\rho(D)$. Thus, $P(D) = \mu\rho(D)$ where μ is a constant of proportion-

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Discounting curve	μ	k	s	R^2
Exponential (1)	0.0273	0.9850	-	0.6696
Hyperbolic (2)	0.0288	0.0238	-	0.7242
Green & Myerson (3)	0.0335	0.4434	0.2589	0.8191
Rachlin (4)	0.0337	0.1435	0.5696	0.7984

Table 1: Fit statistics and parameter estimates

ality. This relationship allows us to directly fit μ and $\rho(D)$ to our observations.

2.3 Discounting models

The following discounting equations allow us to compute $V(D) = \mu\rho(D)$. The traditional model used in economics to predict discounting behavior [5] posits time-consistent, exponential discounting:

$$V = \mu e^{kD} \tag{1}$$

Here k parameterizes the discounting rate, and $\rho(D) = e^{kD}$ is the exponential discounting factor. However, more recent experimental results in behavioral economics [3] and psychology [2] suggest that both humans and animals discount rewards in a time-inconsistent manner. Researchers commonly use hyperbolic discounting [4] to model this behavior:

$$V = \mu/(1 - kD) \tag{2}$$

Evidence in the literature suggests that (2) is not sufficiently sensitive to changes in perceived value over differing delays to explain discounting behavior in humans [1]. (3) and (4) are extensions to hyperbolic discounting that introduce a sensitivity parameter s that models the sensitivity to the scaling of delay [1] or the delay itself [6], respectively.

$$V = \mu/(1 - kD)^s \tag{3}$$

$$V = \mu/(1 - kD^s) \tag{4}$$

We fit each of the above models to the dataset described in Section 2.2, providing parameter estimates for equations (1) through (4). Also note that (3) and (4) reduce to (2) when $s = 1$, so deviation from 1 as well as a better coefficient of determination (R^2) in the learned model is needed to justify the added model complexity.

3. RESULTS AND DISCUSSION

Table 1 displays the learned parameters for each of the models, as well as their associated R^2 statistics. Figure 1 plots the best-fit curves for models (1) through (4) against the observed data. Based on a purely qualitative assessment, note that while all of the curves capture the general trend of the observed valuations, (3) and (4) are much more visually successful at capturing the leveling off behavior of the data with increasing delay until 10pm Sunday. Additionally, we see that among the two-parameter models, (2) outperforms (1) according to their R^2 statistics, as well as having a better visual fit to data in Figure 1. However, both three-parameter models (3) and (4) exhibit very similar curves and similar R^2 statistics. This confirms previous research indicating the difficulty in quantitatively deciding between these two models [5]. Whether their better fit is worth their additional complexity is a matter of taste.

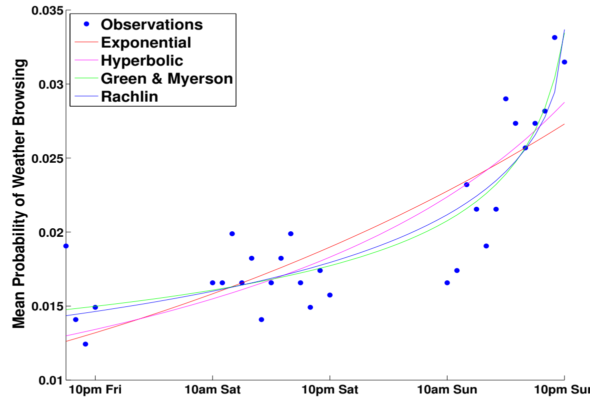

Figure 1: Exponential (1), hyperbolic (2), Green & Myerson (3) and Rachlin (4) discount curves plotted against observed data

These findings support the notion that traffic patterns before important events can be explained by some utility discounting model, though which is best is still uncertain. These results may be extended to predict traffic before deadlines, and be used to anticipate factors such as website load.

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