Measuring the Effectiveness of Display Advertising: A Time Series Approach

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ABSTRACT

We develop an approach for measuring the effectiveness of online display advertising at the campaign level. We present a Kalman filtering approach to deseasonalize and estimate the percentage changes of online sales on a daily basis. For this study, we analyze 3828 campaigns for 961 products on the *Advertising.com* network.

Categories and Subject Descriptors

H.1.0 [**Information Systems**]: Models and Principles; G.3 [**Mathematics of Computing**]: Probability and Statistics

General Terms

Algorithms, Economics, Management, Measurement

Keywords

Marketing, Online Display Advertising, Time Series

1. INTRODUCTION

Online display advertising is an area of rapid growth and consequently of great interest as a marketing channel. Recent studies show that display advertising often triggers online users to search for more information about commercial products [1]. Eventually, many of these users perform either online conversions at the advertiser's website or offline conversions at a physical store. One key challenge is measuring the effectiveness of display advertising in such cases, in particular when users are exposed to multiple advertising channels. If a user performs a commercial action, how should the advertiser attribute credit for the conversion across these multiple channels and media impressions? This is crucial when the business model is cost per action (CPA).

In this paper, we address the estimation of the effects of display advertising. We first remove the seasonal (weekly) component of sales. We then estimate the percentage change in sales with respect to a base level on a daily basis. We perform this estimation using a Kalman filtering approach. We determine if a change is positive or negative in the trend using hypothesis testing. Finally, we use four success criteria with respect to these results to evaluate the performance of 3828 campaigns on the *Advertising.com* network.

2. RELATED WORK

Previous work has studied CPA performance on a monthly level [3]. A more scientific approach incorporating a few user features and the number of impressions in a controlled experiment is detailed in [4] where resolution is at weekly level. Our main goal is to measure the effectiveness of campaigns on a daily level. This is important for short campaigns and to provide dynamic online performance estimates.

3. METHODOLOGY

We follow a time-series approach to decompose the daily number of sales of a given product into a weekly seasonal component and a trend component using Kalman filtering. Fig. 1 shows an example of the number of sales for a given product over a thirteen month window. As shown, there is a strong weekly seasonal component which should be removed.

Let y_t be the number of sales for a given product at time t for $t = 1, \ldots, T$. Assuming y_t is normally distributed, we assume the evolution of a latent state $\boldsymbol{\theta_t}$ to be a stochastic process describing the true behavior of the series. Then, we can write the Kalman filter as follows:

$$\begin{aligned} y_t &= F'\theta_t + \nu_t & \nu_t &\sim N(0, V) \\ \theta_t &= G\theta_{t-1} + w_t & w_t &\sim N(0, W) \end{aligned}$$

ν_t is the observational noise with variance V and w_t represents the state evolution with covariance matrix W. Given V, W, and the prior mean and variance for θ_1, we perform the state estimation by using Kalman filtering equations.[1] By fixing G and F, we model the series evolution as a linear combination of a seasonal component and a polynomial component (seasonal trend) [5]. Our goal is to deseasonalize the series to associate the trend with the marketing campaigns.

We estimate the Maximum Likelihood Estimate (MLE) of the variances (V, W) through an Expectation Maximization (EM) approach [2]. Assuming known variances, we estimate

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[1]For the full Kalman filtering expressions, see [5] page 103.

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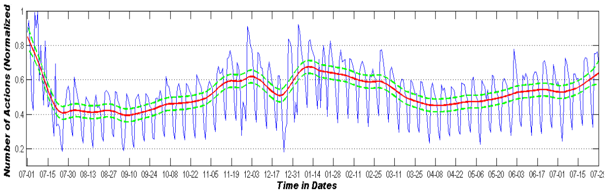

Figure 1: Product sales trend example. X**-axis represents time in dates.** Y**-axis represents number of actions (normalized).**

the distribution of the latent states $P(\theta_t|y_{1:t})$ for $t = 1, \ldots T$ with Kalman filtering equations. We then optimize the likelihood after replacing the expected values for each state.[2] Finally, we smooth the time series by estimating $P(\theta_t|y_{1:T})$ for $t = 1, \ldots T$ [5]. Fig. 1 shows an example of the smoothed stochastic process for the trend component.

We measure the effectiveness of campaigns by comparing sales occurring during the days of the campaign flight to a baseline. We also test statistical significance of the change in the trend component against the baseline. We use 95% confidence intervals to detect an increase, decrease, or no change in the trend. In addition, we estimate the average change during the campaign duration.

4. RESULTS

We analyze 3828 campaigns for 961 products during the period from July 1^{st}, 2009 to July 31^{st}, 2010. We use the previous day of the start of a campaign as the baseline. To evaluate the performance of these campaigns, we define four success criteria:

1. Average positive increase in sales during the campaign
2. Increase or no statistically significant change in sales on every day of the campaign
3. More days with increasing sales than with decreasing sales
4. More days with increasing sales or no significant change than with decreasing sales

Results using these criteria are summarized in Table 1. Notice that 65% of campaigns have no statistically significant decrease in the number of sales for any day during the campaign, thus at least maintaining the same latent sales level. This is the primary objective of many campaigns. Fig. 2 depicts the distribution of the average change in sales by campaign. This is broken down into campaigns with positive, negative and no statistically significant change.

5. DISCUSSION AND FUTURE WORK

Our main goal is to measure the impact of advertising on sales, both near and long term. There are several difficulties we encounter which complicate this goal. First, advertisers typically use all available channels (TV, radio, print, online) and there are many vendors within each channel. Data is typically not integrated across channels or even within channels and thus the idea of following the online click-stream behavior of web users is generally not possible over the whole online channel.

In addition, as this is a high level study across several thousands of campaigns, we do not have a detailed understanding of the exact goals of each campaign. Comparing sales against the sales generated during some period prior to the campaign might not always be appropriate. For instance, the campaign may focus on driving offline sales. Or, if the campaign is launched in the off-season, say after Christmas, then comparing sales against sales generated during the Christmas season is not likely to be the right objective. Therefore, negative sales changes as measured in this study do not necessarily mean that the campaign failed. To select the appropriate baseline for these and similar cases, it is necessary to obtain a detailed understanding of the campaign. This is left for future work.

Finally, in this study we did not incorporate the number of impressions served in total or on a per user basis, nor did we consider advertising targeting in terms of web user attributes and advertising context including campaign and ad features. We propose to incorporate these components in future work.

[2] For details of the optimization see [2].

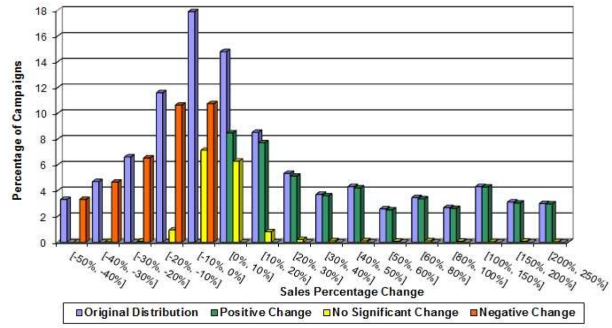

Figure 2: Distribution of average change in sales percentage for all campaigns. X**-axis represents sales percentage change.** Y**-axis represents percentage of campaigns.**

	Criterion 1	Criterion 2	Criterion 3	Criterion 4
Successful Campaigns (%)	55%	65%	73%	84%
Average Increase of Sales: Successful Campaigns	60%	42%	40%	31%

Table 1: Percentage of successful campaigns and average increase for each criterion.

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