Measuring the Effectiveness of Display Adverting: A Time Series Approach

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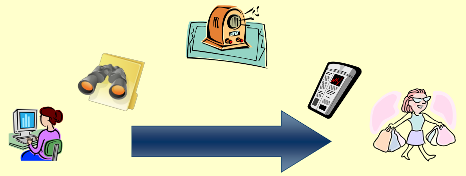
Introduction

- 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 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.

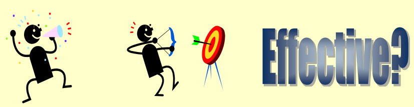


Online display ad shown to a user

User is exposed to multiple advertising channels in time

Eventually, the user performs commercial actions

- Our goal is to measure the effectiveness of display advertising when users are exposed to multiple advertising channels.

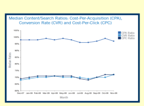


- If a user performs a commercial action, how should the advertiser attribute credit for the conversion across these multiple channels and media impressions?

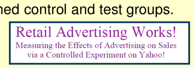
- This is particularly important for the Cost-Per-Action CPA business model when deciding how to allocate resources across advertising channels.

Related Work

- CPA performance on a monthly level [3]. Aggregate study based just on the observed average performance



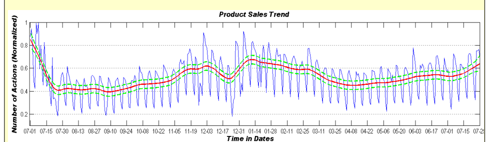
- A study about user features and performance on commercial actions is performed in [4]. However, the study was done with a small set of users and advertisers to have well-defined control and test groups.


Retail Advertising Works!
Measuring the Effects of Advertising on Sales via a Controlled Experiment on Yahoo!

- 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.

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 Dynamic Linear Models based on Kalman filtering and smoothing ideas [5].



$$y_t = F'\theta_t + v_t \qquad v_t \sim N(0,V)$$
$$\theta_t = G\theta_{t-1} + w_t \qquad w_t \sim N(0,W)$$

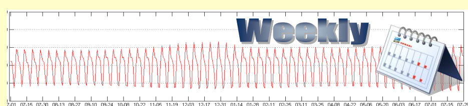
y_t Number of commercial actions at time t

θ_t State evolution of the model components (stochastic process)

- By fixing ***G*** and ***F***, we model the series evolution as a linear combination of a seasonal and a trend component [5]
- Our goal is to deseasonalize the series to associate the trend with a set of marketing campaigns.

$$G_p = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \quad G_T = \begin{bmatrix} \cos(2\pi/T) & \sin(2\pi/T) \\ -\sin(2\pi/T) & \cos(2\pi/T) \end{bmatrix} \quad T=7$$

$$F' = [1,0,1,0,1,0] \quad G = blockdiag[G_p, G_T, G_{T/2}]$$



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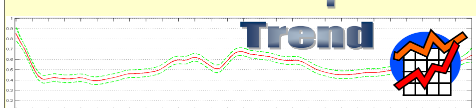

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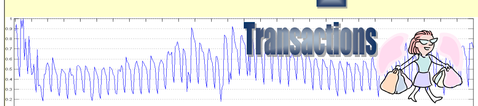


- We find the MLE of the variances Φ = (***V,W***) through the EM algorithm [2] and smooth the series to analyze the trend component.

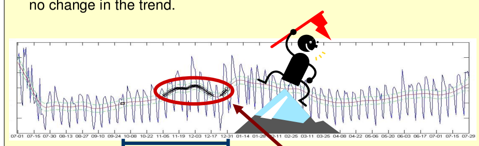
E-step: $Q(\Phi \mid \Phi^{(i)}) = E_{\theta_{1:T} \mid y_{1:T}, \Phi^{(i)}}[\log P(\theta_{1:T} \mid y_{1:T}, \Phi)]$

M-step: $\Phi^{(i+1)} = \arg\max_{\Phi} Q(\Phi \mid \Phi^{(i)})$

$\Phi^{(0)}$ → **Kalman Filtering and Smoothing** $P(\theta_{1:T} \mid y_{1:T}, \Phi^{(i)})$ → $Q(\Phi \mid \Phi^{(i)})$ → **Optimization to update the variances *(W,V)*** → Φ^*; $\Phi^{(i+1)}$

Methodology

- We measure the effectiveness of campaigns by comparing sales occurring during the days of the campaign flight to a baseline.
- We test statistical significance of the change in the trend component against the baseline.
- 95% confidence intervals are used to detect an increase, decrease, or no change in the trend.



Campaign Evaluation

- 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 statistical 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.**

- We estimate the average change of sales during the campaign duration in the trend component.
- We use the delta method to approximate the distribution of the average change in sales respect to the baseline
- The approximation is based on the Taylor series decomposition of the function of the random variables [6].

$$\Delta_c = \frac{\frac{1}{N_c}\sum_{t=1}^{N_c}\theta_{t1} - \theta_{b1}}{\theta_{b1}} \qquad \Delta_c \sim N(E[\Delta_c], \mathrm{var}[\Delta_c]) \qquad E[\Delta_c] = \frac{\frac{1}{N_c}\sum_{t=1}^{N_c}E[\theta_{t1}] - E[\theta_{b1}]}{E[\theta_{b1}]}$$

$$\mathrm{var}[\Delta_c] = \frac{\sum_{t=1}^{N_c}\mathrm{var}[\theta_{t1}] + 2\sum_{t>j}\mathrm{cov}(\theta_{t1},\theta_{j1})}{(E[\theta_{b1}])^2 N_c^2} + \frac{\left(\sum_{t=1}^{N_c}E[\theta_{t1}]\right)^2}{(E[\theta_{b1}])^4 N_c^2}\mathrm{var}[\theta_{b1}] - 2\sum_{t=1}^{N_c}\frac{\sum_{t=1}^{N_c}E[\theta_{t1}]}{(E[\theta_{b1}])^3 N_c^2}\mathrm{cov}(\theta_{b1},\theta_{t1})$$

Results

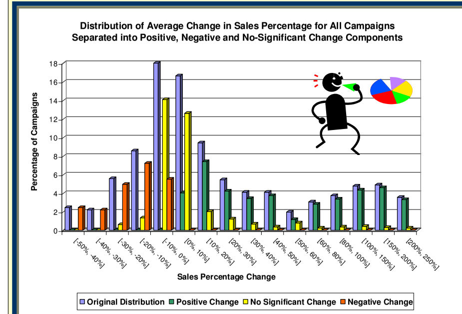
- We analyze **1,635 campaigns** for **429 products** during the period from **July 1st, 2009** to **July 31st, 2010.**

- The following tables presents the successful campaigns according to the above criteria.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4
Succesful Campaigns (%)	43%	65%	73%	84%
Average Increase of Sales: Successful Campaigns	74%	42%	40%	31%

Results

- Distribution of the average change in sales by campaign.
- This is broken down into campaigns with positive, negative and no statistically significant average change.

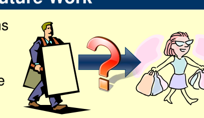


Discussion

- **Main goal:**
  - Measure the impact of advertising on sales near and long term.
- **Difficulties:**
  - 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.
- **Achievements and Gaps:**
  - 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 (the campaign may focus on driving offline sales for instance or launched off-season).
  - Negative sales changes as measured in this study do not necessarily mean that the campaign failed.

Ongoing and Future Work

- Incorporate the number of impressions served as advertising actions in a marketing campaign.
- Does the number of impressions have an impact to predict the number of sales?



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