Assessing the effectiveness of AdWords campaigns on website performance: the case of a tourist SME.

Pilar González, Paz Moral, Beatriz Plaza

Faculty of Economics and Business Studies. University of the Basque Country

Abstract

Making a website findable is critical nowadays, so web analytics tools that monitor website traffic have become key online marketing tools. Our aim is to assess the changes over time in the performance of a website using Google Analytics data and within a statistical framework that enables us to test the effectiveness of online campaigns. A time series econometric methodology is applied based on Structural Time Series Models that take into account the non-stationary behaviour usually displayed by socioeconomic time series. The results show that online campaigns affect traffic volume positively but their effect on its quality is ambiguous. Analyzing paid and unpaid traffic separately, we find that the increase in traffic volume is not always due to the paid keywords and that the lowest quality visits come from paid traffic. This analysis may help webmasters to design successful online advertising strategies to enhance the competitiveness of their firms.

1 Introduction

The application of ICTs has revolutionized tourism marketing and influenced the whole structure of the tourism industry (Law et al., 2010). Tourism sector is basically an SME industry and online marketing is a very useful tool for helping its firms reach wider markets. In this context, making a website findable is critical to its success. Tourist firms strive for maximum exposure on the Internet through the use of search engine marketing. Search Engine Optimization (SEO) is about getting the website, brand, product and dissemination service ranked highly on search engines via organic search results, under the right keywords and phrases, in order to achieve natural visibility and brand recognition. There are also other forms of search engine marketing (SEM) that handle paid inclusion. By contrast with conventional advertising, search engine companies are able to cater to low budget advertisers such as tourist SMEs.

The launch of free web analytic tools, such as Google Analytics, may provide a key online marketing tool with which small players can monitor the performance of their websites. In recent literature the usefulness of Google Analytics as a web analytics tool has been assessed in different fields, e.g., library websites (Bhatnagar, 2009 and Turner, 2010) and medicine (Morgan et al., 2010, Butler et al., 2012). Other authors have proposed different e-metrics based on Google Analytics to analyze the quality of websites (Hasan et al., 2009 and Plaza, 2010).

The aim of this paper is to analyze the visibility and performance of a website and to test the effectiveness of paid campaigns on the quantity and quality of the traffic arriving via search engines using the data provided by Google Analytics. Our interest lies in monitoring the changes over time in these visits and their quality within a statistical framework that enables us to test how great an impact campaigns have on website search traffic. Two specific questions will be
addressed in subsequent order: first, do the AdWords campaigns increase the volume and quality of search traffic? And second, how do paid and unpaid keywords perform during campaign periods?

We propose to achieve these goals via a methodology based on time series econometrics models. We are dealing with time series data, which usually display a high degree of non-stationarity which need to be taken into account, so a structural time series approach is followed (Harvey, 1989). The quality of traffic will be characterized by the e-metrics proposed by Plaza (2010) and Plaza et al. (2011), which consist of five Key Performance Indicators: volume of traffic, number of pages per visit, average length of the visit, bounce rate and return rate. This methodology will be applied to a tourism website: www.aktiba.info. Aktiba (Business Association of the Basque Country Tourism Active Sports) implements Google AdWords campaigns on a yearly basis. In February 2008 the Webmaster started to use Google Analytics to evaluate the performance of the website and to test the effectiveness of the four campaigns carried out so far (May 23 2008 until November 20 2008, May 21 2009 until November 1 2009, August 25 2010 until December 8 2010 and April 11 2011 until October 9 2011).

The article is structured as follows. The new methodology developed is explained in Section 2 and the results obtained for the case study considered are presented in Section 3. The article finishes with some conclusions and suggestions for further research.

2 Methodology

Our aim is to specify an econometric causal model for each of the five KPIs considered in order to measure the effectiveness over time of AdWords campaigns in terms of both quantity and quality of search traffic. The database consists of tourism daily time series, which usually present non-stationary behaviour in the form of trends and cycles that need to be included into the model. Although we are working with daily data, the monthly cycle should be taken into account. Moreover, since AdWords campaigns take place in summer it is very important to distinguish between the effects of the monthly cycle and the AdWords campaigns themselves. On the other hand, daily data usually show a high degree of volatility and present outliers and calendar effects such as Easter, holidays and day of the week effects. These features of the data must be considered and included in the specification of the econometric model:

\[ Y = F(\text{campaigns, trend, monthly cycle, Easter, holidays, day of the week}) \] (1)

One way of dealing with model (1) is to formulate it in terms of a Structural Time Series Model (STSM). Since the early paper by Gonzalez & Moral (1995), STSM has been widely used in tourism research to forecast tourism demand (see Greenidge, 2001, Turner & Witt, 2001, and Song et al., 2011, among others). But the same modelling approach may be useful in much wider contexts since STSM makes it possible to measure how a series responds to external factors while at the same time estimating its components, such as stochastic trends and cycles that help identify important aspects of its trends over time. Furthermore these models take into account the non-stationary behaviour of the dependent variable, so the problem of spurious regression is avoided (Granger & Newbold, 1974).
The specification of the different elements of model (1) is explained below. The four AdWords campaigns staged during the sample period are included in the model by means of four dummy variables \(C_1, C_2, C_3, \text{ and } C_4\). Each of these variables is set to one for the observations related to the corresponding campaign and 0 otherwise.

In STSM the specification of the trend component relies on a stochastic formulation that allows the level, \(\mu\), and the slope, \(\beta\), of the trend to vary slowly over time:

\[
\begin{align*}
\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\
\beta_t &= \beta_{t-1} + \zeta_t
\end{align*}
\]  

(2)

where \(\eta_t\) and \(\zeta_t\) are normally independent white noise processes with zero mean and variances \(\sigma_\eta^2\) and \(\sigma_\zeta^2\), respectively.

The monthly cycle is specified in terms of dummy variables \(M_{it}, i = 1, 2, \ldots, 12\), that take the value 1 for the observations corresponding to month \(i\) and zero otherwise. The specification of this component is deterministic since the sample available is quite short in terms of years.

With respect to calendar effects, let us consider first the outliers. The Aktiba website suffered various attacks between February 18 and 28, 2010, so there are not reliable data for those days. The relevant observations were estimated by interpolation, averaging the data for two weeks before and two weeks after the attacks. Secondly, to include calendar effects in the model, i.e. economic effects related to the calendar such as Easter, local holidays and day-of-the-week effect, the following explanatory variables were constructed:

a. Easter = 1 for Easter days and 0 otherwise.

b. Holiday = 1 for floating local holidays and 0 otherwise.

c. Daily dummy variables, \(D_{it} = 1\) for \(t = i, 2i, \ldots\) and 0 otherwise, with \(i = 1, 2, \ldots, 7\).

Assuming that the functional form in model (1) is linear, the econometric time series model for the KPIs is the following:

\[
Y_t = \mu_t + \sum_{i=1}^{4} \beta_i C_{it} + \sum_{i=1,i\neq 8}^{12} \gamma_i M_{it} + \beta_E \text{Easter}_t + \beta_H \text{Holiday}_t + \sum_{i=1,i\neq 4}^{7} \beta_{Di}D_{it} + \varepsilon_t \]  

(3)

where \(Y_t\) is each of the KPIs considered (number of visits, pages per visit, average time on site, bounce rate and return rate), \(\mu_t\) follows model (2) and \(\varepsilon_t\), the irregular component that captures all the short-term shocks in the series, is a normally distributed error term with zero mean and variance \(\sigma_\varepsilon^2\) which is not correlated with \(\eta_t\) and \(\zeta_t\). Note that the month of August and the day Thursday are not included in the model in order to avoid collinearity problems.

Model (3) can be interpreted as a generalization of the classical general linear regression model. It can be observed that if \(\sigma_\eta^2 = \sigma_\zeta^2 = 0\) the model collapses to a standard regression model with a linear deterministic time trend.
3 Results

The effectiveness of the AdWords campaigns is analyzed in two stages. First, the overall influence of the campaigns on the volume and quality of search traffic is checked. The effect of the campaigns in improving the visibility of a website might be expected to come from the paid traffic. To test this hypothesis, stage two compares the changes over time in paid and unpaid search traffic during campaign periods.

3.1 Effect of AdWords campaigns on total search traffic

The sample period chosen to estimate model (3) runs from February 7, 2008 to October 16, 2011. The unknown parameters of the model are given by the regression coefficients $\beta$ and the variances of the unobserved components, $\mu_t$ and $\beta_t$ and of the irregular term, $\varepsilon_t$. Model (3) is estimated for all five KPIs considered in this study. Detailed results are shown only for the "number of visits" indicator while table 1 summarizes the results for the other four quality indicators, focusing on the estimated effects of the campaigns. The results for total search visits are the following:

$$\ln \hat{V}_t = \hat{\mu}_t + 0.1090 C1_t + 0.4003 C2_t + 0.4639 C3_t + 0.2215 C4_t - 0.0194 Ja_t - 0.0206 Fb_t -$$

$$- 0.0581 Mr_t + 0.0195 Ap_t + 0.0168 My_t + 0.0025 Jn_t + 0.0129 Jl_t - 0.0218 Sp_t -$$

$$- 0.0171 Oc_t - 0.1143 Nv_t - 0.1362 Dc_t - 0.1558 E_t - 0.0791 H_t + 0.0474 M_t +$$

$$+ 0.0274 T_t - 0.0088 W_t + 0.3275 F_t - 0.2070 St_t - 0.1342 Sn_t$$

$$\hat{\sigma}^2_\varepsilon = 0.011 \quad \hat{\sigma}^2_\eta = 0.0007 \quad \hat{\sigma}^2_\zeta = 0.0$$

$$r(1) = 0.07 \quad H(448) = 0.20 \quad R^2_d = 0.547$$

The figures in parentheses below the parameter estimates are asymptotic standard errors, $r(1)$ is the first-order autocorrelation coefficient, $H$ is a heteroscedasticity test and $R^2_d$ is a coefficient of determination where the actual observations have been replaced by their first differences.

The effect of the campaigns on traffic volume is seen to be positive and statistically significant, though the size of the impact differs widely from one campaign to another. The first campaign shows the smallest effect which could be explained by the fact that it took place not long after the website was started up. Then after two quite successful campaigns with similar effects, the impact of the fourth campaign is down by half. This result indicates that this campaign has somehow worked differently, a fact that any firm should take carefully into account.

The results show other features of interest in the variation of traffic volume over time. In terms of the monthly cycle the number of visits decreases significantly in November and December. This comes as not surprise since these are the worst months for the type of tourism related to this website. As far as calendar effects are concerned, traffic decreases significantly during vacation periods, at Easter and on local holidays. Some significant differences also appear in the
volume of traffic received within the week: a major increase in traffic on Fridays is followed by a significant decrease during the week-end. Lastly, the estimates of the variances of the stochastic components of the model show that the trend develop very smoothly since its slope is constant over time ($\sigma^2_\zeta = 0$) and the estimated variance for the error term $\eta_t$ is quite small. In this sense, the bigger source of variability comes from the irregular component $\varepsilon_t$.

Table 1: Estimation results for total search traffic

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pages per visit</th>
<th>Time on site</th>
<th>Bounce rate</th>
<th>Return rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1 $a,b$</td>
<td>0.7569 $^*$</td>
<td>0.2048</td>
<td>-0.0410</td>
<td>0.0025</td>
</tr>
<tr>
<td></td>
<td>(0.3016)</td>
<td>(0.2620)</td>
<td>(0.0263)</td>
<td>(0.0195)</td>
</tr>
<tr>
<td>C2 $a,b$</td>
<td>-0.3858</td>
<td>-0.5974 $^*$</td>
<td>-0.0035</td>
<td>-0.0782 $^*$</td>
</tr>
<tr>
<td></td>
<td>(0.3151)</td>
<td>(0.2685)</td>
<td>(0.0276)</td>
<td>(0.0203)</td>
</tr>
<tr>
<td>C3 $a,b$</td>
<td>-0.1768</td>
<td>-0.3073</td>
<td>-0.0074</td>
<td>-0.0581 $^*$</td>
</tr>
<tr>
<td></td>
<td>(0.3034)</td>
<td>(0.2616)</td>
<td>(0.0265)</td>
<td>(0.0196)</td>
</tr>
<tr>
<td>C4 $a,b$</td>
<td>-0.3384</td>
<td>-0.4522</td>
<td>0.0287</td>
<td>-0.0386 $^*$</td>
</tr>
<tr>
<td></td>
<td>(0.3252)</td>
<td>(0.2990)</td>
<td>(0.0277)</td>
<td>(0.0211)</td>
</tr>
<tr>
<td>$\sigma^2_{\varepsilon}$</td>
<td>1.1096</td>
<td>1.5679</td>
<td>0.0067</td>
<td>0.0049</td>
</tr>
<tr>
<td>$\sigma^2_{\eta}$</td>
<td>0.0059</td>
<td>0.0018</td>
<td>0.00006</td>
<td>0.00002</td>
</tr>
<tr>
<td>$\sigma^2_{\zeta}$</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Notes: a. Asymptotic standard errors in parentheses. b. $^*$, $^*$*, $^*$**: statistically significant at 10%, 5% and 1% levels.

Table 1 shows that the estimated effects of the campaigns are quite different for the KPIs related to the quality of the visits. In general it can be concluded that the campaigns have no strong, significant effect on these indicators. It is true that the average length of visits (measured either by pages or time on the site) is shorter during the campaigns. However, this effect is very irregular in the period analyzed and is not statistically significant for the last two campaigns. With respect to the return rate and the bounce rate the results are quite different: there is no significant difference between campaign and non-campaign periods for the bounce rate, but significant negative effect of campaigns is found on the return rate. Since one of the aims of any AdWords campaign is to attract new traffic, a successful campaign should attract many new visits, and this may entail a reduction in the return rate.

3.2 Effect of campaigns on search traffic by sources

During campaign periods, the traffic arriving through search engines comes from two sources: paid and unpaid keywords. The analysis of the variation over time of these two segments of search traffic is of great interest to the goal of determining the specific factors that originate the changes in total search traffic observed in the data.

Our assumption is that AdWords campaigns may have a two-fold effect on search traffic: a direct effect - since they represent a new source of visits - and an indirect effect due to the probable influence of the campaigns on unpaid traffic. It has to be taken into account that AdWords are online marketing tools geared towards making the website and its products known. Therefore, they are a source of new customers who will probably use other keywords, such as the website or company names, for subsequent visits, which will be then considered as unpaid visits. Our goal is to determine which of these two effects is responsible for the impact of the campaigns on the quantity and quality of search traffic, or whether both are responsible.
The indirect effect is analyzed first, by means of the estimation of model (3) for unpaid search traffic indicators. Table 2 summarizes the estimation results. In particular, the first block test the relevance of the effects of AdWords on this kind of traffic. It should be noted that only the first campaign seems to have a statistically significant positive impact on the quality indicators. Once long term movements and calendar effects have been accounted for the estimated return rate of unpaid search traffic increased 4 percentage points (pp) in the first campaign, the bounce rate decreased 5 pp and the average number of pages per visit increased by 0.78. It can be concluded that the data do not show any indirect effect of AdWords campaigns on unpaid searches, although there is some evidence that the campaigns could have helped to improve their quality at first. The estimates for the variances of the stochastic unobserved components of the models are shown in Table 2. The main source of volatility is the irregular component while the trend slope, an indicator of underlying growth, is quite stable over time for all series.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>Visits (logs.)</th>
<th>Pages per visit</th>
<th>Time on site</th>
<th>Bounce rate</th>
<th>Return rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNPAID TRAFFIC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(C_1^{\ a,b})</td>
<td>0.0985</td>
<td>0.7810**</td>
<td>0.4086</td>
<td>0.0548*</td>
</tr>
<tr>
<td></td>
<td>(0.1249)</td>
<td>(0.3763)</td>
<td>(0.3397)</td>
<td>(0.0295)</td>
<td>(0.0165)</td>
</tr>
<tr>
<td></td>
<td>(C_2^b)</td>
<td>0.0423</td>
<td>0.2335</td>
<td>0.0617</td>
<td>0.0220</td>
</tr>
<tr>
<td></td>
<td>(0.1295)</td>
<td>(0.3922)</td>
<td>(0.3510)</td>
<td>(0.0310)</td>
<td>(0.0163)</td>
</tr>
<tr>
<td></td>
<td>(C_3^b)</td>
<td>0.0083</td>
<td>0.2264</td>
<td>0.1560</td>
<td>0.0228</td>
</tr>
<tr>
<td></td>
<td>(0.1248)</td>
<td>(0.3769)</td>
<td>(0.3399)</td>
<td>(0.0298)</td>
<td>(0.0163)</td>
</tr>
<tr>
<td></td>
<td>(C_4^b)</td>
<td>0.0637</td>
<td>0.0990</td>
<td>0.0153</td>
<td>0.0073</td>
</tr>
<tr>
<td></td>
<td>(0.1215)</td>
<td>(0.3973)</td>
<td>(0.3802)</td>
<td>(0.0310)</td>
<td>(0.0185)</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\varepsilon)</td>
<td>0.0509</td>
<td>1.4647</td>
<td>2.0690</td>
<td>0.0082</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\eta)</td>
<td>0.0041</td>
<td>0.1111</td>
<td>0.0043</td>
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</tr>
<tr>
<td></td>
<td>(\sigma^2_\zeta)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\varepsilon)</td>
<td>0.0817</td>
<td>6.3587</td>
<td>2.9688</td>
<td>0.0225</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\eta)</td>
<td>0.0007</td>
<td>0.0000</td>
<td>0.0532</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\zeta)</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\varepsilon)</td>
<td>0.0114</td>
<td>0.7040</td>
<td>0.6459</td>
<td>0.0043</td>
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<td></td>
<td>(\sigma^2_\eta)</td>
<td>0.0020</td>
<td>0.0000</td>
<td>0.0000</td>
<td>2.8E-05</td>
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<tr>
<td></td>
<td>(\sigma^2_\zeta)</td>
<td>1.3E-06</td>
<td>0.0000</td>
<td>0.0000</td>
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<tr>
<td></td>
<td>(\sigma^2_\varepsilon)</td>
<td>0.0111</td>
<td>0.1458</td>
<td>0.2547</td>
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<td></td>
<td>(\sigma^2_\eta)</td>
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<td>0.0000</td>
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<tr>
<td></td>
<td>(\sigma^2_\zeta)</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\varepsilon)</td>
<td>0.0063</td>
<td>0.1452</td>
<td>0.1858</td>
<td>0.0030</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\eta)</td>
<td>0.0072</td>
<td>0.0041</td>
<td>0.0093</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2_\zeta)</td>
<td>0.0000</td>
<td>8.6E-06</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Notes:  
a. Asymptotic standard errors in parentheses.  
b. *, **, ***: statistically significant at 10%, 5% and 1% levels.

Secondly, consider what we have called the direct effect. Unpaid search traffic does not seem to be affected by the campaigns, so it can be used as a benchmark to analyze in detail the behaviour of search traffic coming from AdWords. To that end a graphic analysis is performed in Figure 1, comparing the variation over time in paid and organic traffics. In the graphs of this
Organic traffic and the unpaid entries fluctuate, following a yearly cycle, on an almost constant level. Given the significance of the seasonal component for tourist activity, we use the sum of the trend and monthly cycle components here as the indicator of the underlying level of the KPIs. To estimate these components the following STSM is specified:

\[
Y_t = \mu_t + \sum_{i=1,i\neq 8}^{12} \gamma_i M_{it} + \beta_E \text{Easter}_t + \beta_H \text{Holiday}_t + \sum_{i=1,i\neq 4}^{7} \beta_{Di} D_{it} + \varepsilon_t \tag{4}
\]

where all the elements on the right-hand side of the equation are defined as in model (3). This model is estimated for all five KPIs for unpaid search traffic and for each of campaign subsample periods (see Table 2).

The most significant fact that can be observed in the upper left graph of Figure 1 is the failure of the last campaign: indeed, the large increase in the number of visits that took place from April 2011 onwards came from unpaid traffic. Given that the dummy variable for this campaign was not significant in the model for unpaid visits (see Table 2) the increase in these flows must be due to reasons other than the campaigns, captured by the trend component. This is not the case for the previous campaigns, when the jump in the volume of visits is given by the paid traffic and the unpaid entries fluctuate, following a yearly cycle, on an almost constant level.

Figure 1: Key Performance indicators

In terms of the effectiveness of the keywords, the return rate for unpaid searches is getting slightly worse, with an annualized average decay in the trend of 0.36 percentage points (see lower right graph of Figure 1). Moreover, it can observed that the effectiveness of unpaid visits
is higher throughout the whole period, so the advertising campaigns clearly have a negative direct effect on return rates. An increase in new visitors and a consequent increase in their share in the total number of visits at the expenses of return visitors is an obvious feature of AdWords campaigns. Therefore, the key question is whether the new visitors spend some time looking at the information given by the website. At this point, the bounce rate, the number of page views and the length of stay are the best indicators of campaign success.

The bounce rate for both segments of search traffic displays a general upward trend: for example the trend in unpaid traffic is up 6.9 pp per year (see lower left graph of Figure 1). The variation over time in the bounce rate for paid search traffic is quite similar to the unpaid search bounce rate, so the direct effect is small. The variation over time of the bounce rate shows transitory deviations from the aggregate results for the whole period. The main difference between the two flows of traffic took place during the last campaign C4, when the bounce rate of the paid AdWords search was notably higher, especially from August onwards, when the deviation from the unpaid traffic was more than 4 pp.

The average time on site shows a decreasing trend for both segments of search traffic (see upper right graph of Figure 1). For example, the estimated trend shows that the time spent by unpaid visitors is down by an average of about 20 seconds in annualized terms. Over the whole period, visitors via AdWords spend less time on the site.

In summary, the AdWord campaigns increased the volume of traffic, but the quality of this traffic was worse than that of organic traffic. Furthermore, the last campaign seems to have failed, especially in terms of volume of traffic, with a trend lower than the level of unpaid visits.

4 Concluding remarks

This work presents an experiment done with a structural time series model with Google Analytics data. A new methodology is developed to analyze the effectiveness of Google AdWords campaigns. Google Analytics provides a huge amount of daily data for analyzing the traffic that arrives at a website. These data can be used to monitor the effectiveness over time of AdWords campaigns on both the volume of traffic and quality (length of visit, return rate, bounce rate, etc.). A time series econometric methodology based on structural time series modelling is proposed here to achieve this goal. This methodology allows the impact of campaigns and all the specific features of the time series data, such as changes in trends to be modelled simultaneously.

The results of applying this methodology to the Aktiba website suggest that AdWord campaigns improve the visibility of a website and increase the volume of traffic, but the quality of that traffic worsens. This result is quite clear for the return rate, but it may also be true for the bounce rate, the length of stay and page views. If search traffic is split into paid and organic, it can be concluded that the paid AdWords are responsible for the increase in the number of visits. Note that the last campaign examined seems to have failed in this sense since the volume of paid traffic is lower than unpaid traffic. A comparison of the quality of the two traffic sources shows that the quality of paid visits is worse in terms of the return rate and length of visit indicators. The bounce rate is quite similar for the two segments of traffic except for the last campaign.
The case study analyzed shows that the methodology proposed in this paper can be very useful in monitoring the effectiveness of online campaigns. The results obtained are very detailed and enable the webmasters to assess the success of their online strategies.

5 References


