

Making Sense of Web Traffic Data and Its Implications for B2B Marketing Strategies

Analysis with Data Generated from www.beltfurnaces.com Website

Abstract

In the realm of B2B marketing, it is now realized buyers are switching from catalogs and print ads to online sources for manufacturer information. As a result, company website has become an indispensable hub for marketing activities. There are many ways to attract potential customers from the Internet, such as search engine ads, search engine optimization, and building referral sites. With web analysis tools such as Google Analytics, marketers are able to put together a report in a snap. However, it is a more difficult task to find correlations among different data sets. We are interested in ranking the priorities of improving different marketing factors in order to give the company a direction to use the marketing expenditure. This paper focuses on the impacts of different web traffic data on the sales of Hengli furnace of Torrey Hills Technologies. We analyze the historical data on furnace sales and website traffic using generalized linear regression model. The ranks of different impact factors on furnace sales are studied. These statistical results provide a basic guideline in the improvement of future marketing strategies.

Keywords: B2B marketing, furnace, linear regression model, principal component analysis

Introduction

Web traffic is the data flow received and sent by visitors to a web site, and has been the largest portion of Internet traffic since the 1990s [3]. One of the most critical problems is to monitor the traffic and collect the related data in order to help structure sites, highlight security problems, and avoid the unwelcome web traffic [1]. Some companies develop advertising strategies that, with recorded web traffic (visitors' information), pay for screen space on a site or search engine (e.g., Google). Sites also aim to increase the valid web traffic from search engines through search engine optimization (PageRank). There are some famous vendors of web traffic services such as Webtrends, Coremetrics, Omniture, and Google Analytics. However, the web traffics from those vendors are various. It is usually difficult for a company to extract useful data and analyze the relationship between web traffic and its sales. Obviously, some important data sets can reflect boosting impacts on sales, e.g., the average staying time on the company's site (the longer a visitor stays in the site, the more likely that he is interested in the product). Multivariate analysis has been widely used in industrial and business areas [2]. Some efficient tools (linear regression, principal components analysis, factor analysis, etc.) can be applied to deal with the web traffic data. This paper focuses on the web traffic data of Hengli furnace from Torrey Hills Technologies (THT). We obtain the marketing related web traffics from Google Analytics with the permission of THT. The goal is to study the impacts on furnaces sales for different data sets.

Methodology

We collect the valid data from Google Analytics and the records of furnace sales for 27 months. Basically, the data sets consist of nine web traffic factors (e.g., monthly website traffic, unique visitors, etc.) shown in Table 1. Let Y be the column vector that contains the data of furnace sales and $Z = [Z_1, Z_2, \dots, Z_9]$ be the data matrix of website traffic factors. Table 1 presents the normalized data from Torrey Hills Technologies for a proprietary purpose yet without loss of accuracy for the problem.

Table 1 Normalized website traffic and sales data of Hengli furnace

Month	Furnace Sales	Monthly Website Traffic	Unique Visitors	Pages/Visit	Average Staying Time (sec.)	Bounce Rate	New Visits (%)	Traffic from Search Engines (%)	Traffic from Referring Sites (%)	Direct Traffic (%)
	Y	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
1	0.061	0.028	0.030	0.041	0.043	0.038	0.041	0.041	0.031	0.039
2	0.033	0.029	0.029	0.044	0.048	0.034	0.037	0.038	0.033	0.054
3	0.039	0.034	0.033	0.043	0.047	0.038	0.037	0.035	0.050	0.032
4	0.028	0.039	0.032	0.052	0.038	0.034	0.032	0.031	0.056	0.047
5	0.017	0.044	0.037	0.059	0.053	0.026	0.031	0.031	0.051	0.052
6	0.017	0.041	0.034	0.044	0.049	0.033	0.031	0.029	0.059	0.047
7	0.022	0.037	0.033	0.040	0.046	0.037	0.034	0.030	0.061	0.041
8	0.028	0.045	0.039	0.038	0.047	0.039	0.033	0.034	0.055	0.032
10	0.044	0.041	0.041	0.037	0.035	0.041	0.038	0.036	0.047	0.035
11	0.044	0.040	0.041	0.034	0.032	0.041	0.040	0.040	0.035	0.038
12	0.056	0.050	0.046	0.039	0.039	0.039	0.035	0.040	0.032	0.044
13	0.022	0.037	0.036	0.036	0.032	0.043	0.038	0.041	0.032	0.037
14	0.039	0.040	0.042	0.034	0.035	0.041	0.041	0.041	0.029	0.042
15	0.072	0.043	0.040	0.042	0.042	0.037	0.036	0.043	0.026	0.042
16	0.017	0.041	0.045	0.033	0.032	0.040	0.041	0.041	0.029	0.043
17	0.050	0.050	0.051	0.039	0.039	0.036	0.039	0.039	0.034	0.046
18	0.044	0.037	0.038	0.038	0.032	0.036	0.038	0.040	0.038	0.031
19	0.050	0.031	0.033	0.034	0.029	0.038	0.040	0.039	0.038	0.034
20	0.033	0.033	0.037	0.034	0.034	0.039	0.044	0.042	0.033	0.031
21	0.078	0.035	0.035	0.035	0.037	0.042	0.039	0.040	0.032	0.044
22	0.056	0.035	0.036	0.037	0.045	0.038	0.039	0.035	0.044	0.044
23	0.017	0.037	0.041	0.036	0.037	0.040	0.043	0.038	0.042	0.032
24	0.044	0.035	0.037	0.032	0.032	0.039	0.041	0.041	0.036	0.032
25	0.044	0.030	0.033	0.032	0.030	0.041	0.043	0.042	0.034	0.029
26	0.028	0.040	0.045	0.032	0.033	0.044	0.044	0.046	0.023	0.031
27	0.017	0.050	0.055	0.032	0.034	0.046	0.046	0.048	0.023	0.022

For the cumulative sales of furnace, the result shows an approximately linear growing trend (see Fig. 1) which is quite close to a homogenous Poisson process (widely used assumption in modeling customer arrival process). For a long-run perspective, the sales of furnace are increasing in a stable trend.

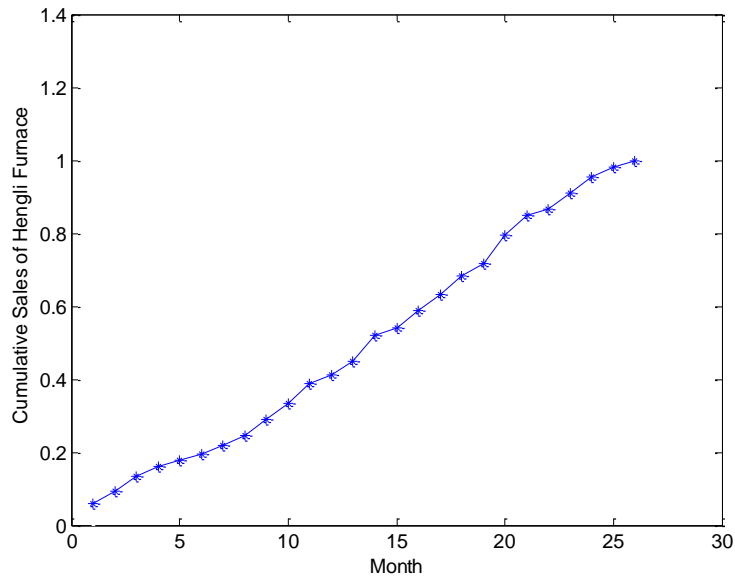


Fig. 1 Cumulative sales of Hengli furnace

However, the monthly sales rate is not so stable based on current marketing strategy. The fluctuation of monthly sales indicates a short term sales variation. Fig. 2 illustrates the monthly sales. It can be seen that the variation of monthly sales is large and is difficult to be predicted. The main problem in this study is to reduce the uncertainty in monthly sales according to the adjustments in current marketing strategy.

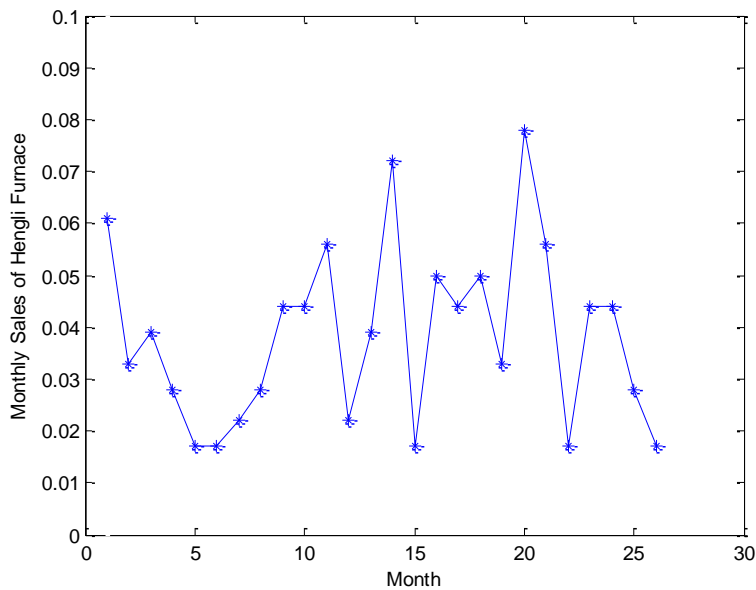


Fig. 2 Monthly sales of furnaces

With the aforementioned problem, we first study the impact of individual factor on the furnace sales. Because the scale-difference of two groups of marketing data is usually very large, this results in the difficulty of interpreting the relationship between them. To investigate the relationships between different groups of the data, we use the normalized data to build the statistical model, as mentioned before, that correlated the data given in Table 1. For an individual factor, e.g., unique visitors, we can see that the impact of it on the furnace sales is nearly positive, i.e., furnace sales increase as unique visitors increases, in Fig. 3. Our interest is to analyze the sensitivity of monthly sales through modifying the different web traffic factors. The goal is to take all of the web traffic factors that affecting the furnace sales into consideration.

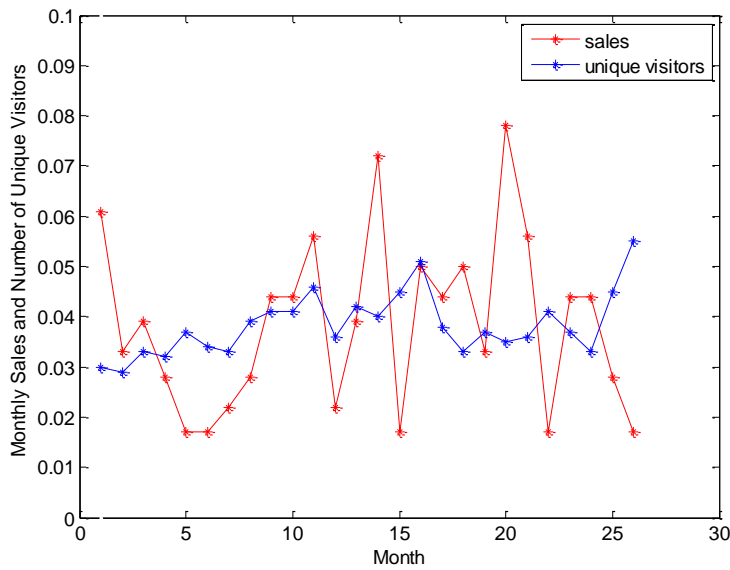


Fig. 3 The relationship between furnace enquiry and unique visitors

Thus, we use multivariate analysis to address this problem (see [2]). Generalized linear regression model (GLM) is utilized to examine the historical data. In this way, we can study the relationships between all of the impact factors and furnace sales. Let $\Phi = [e, \ln(Z)]$ be the design matrix, where $e = [1, 1, \dots, 1]^T$ is an all-ones vector. Denote $\beta = [\beta_0, \beta_1, \beta_2, \dots, \beta_9]^T$ as the coefficient vector for Φ and $\varepsilon = [\varepsilon_1, \varepsilon_2, \dots, \varepsilon_9]$ as the residual vector. The corresponding GLM can be formulated as

$$Y = \Phi\beta + \varepsilon.$$

By using the least squares estimation, the estimated coefficient vector is

$$\hat{\beta} = [1.850, -1.946, -0.128, 0.088, -0.080, 1.494, 1.230, 0.364, 0.215]^T. \quad (1)$$

Based on the result shown in equation (1) and the property of GLM, we can obtain the ranking of significances in furnace sales of those impact factors as

Table 2 Ranking of website traffic factors

Rank	1	2	3	4	5	6	7	8	9
Impact factor	Unique Visitors	Monthly Website Traffic	New Visits (%)	Traffic from Search Engines (%)	Traffic from Referring Sites (%)	Direct Traffic (%)	Pages/Visit	Average Staying Time (sec.)	Bounce Rate

Table 2 gives the priorities of improvement of impact factors and Fig. 4 provides a basic guideline of the priority for improving future marketing strategies.

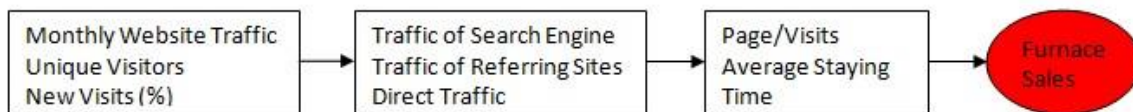


Fig. 4 The improvement priority chart

Conclusions

In this paper, we study some important marketing factors that have significant impact on the sales of a capital-intensive product. The website traffic and sales data of Hengli furnace is analyzed by a multivariate statistical method. A GLM is formulated to obtain the ranking of improvement priorities for different marketing factors. The results suggest that we should first increase the monthly website traffic, unique visitors, and new visits (%) so that we can attract more potential customers. Then, the second step is to improve the marketing strategies in search engine, referring sites, and direct traffic. This helps us to let the true buyers know our product. To ensure the true buyers will be interested in our product and make a quote, we need to redesign our website pages and paste more useful information that make our product become more competitive. Therefore, the future furnace sales will be lifted under this improvement priority.

References

- [1] http://en.wikipedia.org/wiki/Web_traffic
- [2] R. A. Johnson, D. W. Wichern. *Applied multivariate statistical analysis*. Pearson Prentice Hall, NJ, 2007.
- [3] F. H. Campos, K. Jeffay, F. D. Smith. *Tracking the evolution of web traffic: 1995-2003*. University of North Carolina at Chapel Hill.