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Google Analytics based Temporal-Geospatial Analysis for Web Management: A Case Study of a K-12 Online Resource Website

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Abstract

As Google Analytics becomes increasingly popular, more detailed records of users' behaviors can be captured and analyzed to better understand the performance of websites. However, current Google Analytics related research usually draws conclusions from rough estimation based on the observation of the dashboard or other basic statistical processing of the data. This study aims to provide a more accurate and informative analysis from both temporal and geospatial perspectives via clustering and GIS application. The results obtained from a resource website case study demonstrate that the proposed method is able to help web managers better examine the temporal effect on users' visiting patterns based on accurate mathematical computation as well as provides more geographical insight into website performance through the constructed density measure and 3D graphic presentation. By offering in-depth quantitative information relying on mining data from web logs, such a study can help web stakeholders make better decisions on how to maintain and improve the websites, especially adjusting resources by considering temporal fluctuations and inequity in geographical distribution.

Keywords: Google Analytics, Cluster Analysis, Geospatial analytics, Web management

Introduction

Web analytics techniques have become increasingly popular over the past few years. Visitors' mouse clicks and information requests can now be recorded and examined via page tagging and web server log files (Marek, 2011). In this context, Google Analytics is a leading tool for sales, marketing, and advertising arenas, but has received little mention relative to educational websites and information systems. The most frequently used methods to describe users' traffic data on websites use statistics and graphs from Google Analytics dashboards

(Farney & McHale, 2013; Kirk et al. 2012; Pakkala et al. 2012; Kent, 2011).

As a result, interpretations of visitors' traffic data may be oversimplified and subject to limitations endemic to Google Analytics' existing functionalities. Increasingly it is necessary to take these approaches to the next level and use Google Analytics traffic data more strategically (Sen et al., 2006). Jones et al. (2004) have indicated that the employment of more complex methods of analyzing web metrics would be beneficial and must be vigorously advanced. Clifton (2012) concluded that web analytics cannot simply rely on the flood of data alone. Website stakeholders should not only interpret the data, but also fine-tune the metrics to accurately reflect website goals and objectives.

In response to these needs, we investigated a data mining method and a geographical tool, i.e., temporal and a geospatial perspectives, to provide a longitudinal and accurate view as well as a density measure for web stakeholders towards the ultimate goal of strategic improvement of users' experiences. While this study utilizes a particular educational website (eThemes http://ethemes.missouri.edu/) to illustrate a proposed methodological framework, the application of that framework is not restricted to this website or any particular type of site; these procedures may be readily employed with any website. The approach involves transforming Google Analytics data from a somewhat limited and raw state to something that is richer, more accurate, and informative. Compared with rough estimation from Google Analytics Dashboard, the proposed approach, relying on mining log data, is expected to offer more reliable and accurate quantitative results for web manager to make more informed decisions e.g. website maintenance, marketing and strategic planning.

Literature Review

1. Google Analytics and Educational Websites

Google Analytics is a "client-side" data collection system that uses page-tagging techniques in which a line of JavaScript code is embedded into the footer of each page of the website. Because of its strong abilities to provide statistics in great abundance, both researchers and practitioners have used Google Analytics to track users' interactions on websites. However, with a notable exception of academic libraries, Google Analytics has only been used in a handful of studies of educational websites. Of the studies of academic libraries, Farney and McHale (2013) recommended that librarians add Google Analytics to their websites by introducing its history, and major functionalities. Hess (2012) offered specific code instructions on how to configure Google Analytics for academic libraries' better usage, while Turner (2010) proposed a list of key indicators to gauge the performance of academic library websites. Aside from these initiatives, few studies have been conducted on other educational information systems; Kirk et al. (2012) investigated the performance of a health professional education website by directly reporting statistics and figures gathered by Google Analytics. They concluded that Google Analytics could inform approaches to enhancing visibility of the website. Kent et al. (2011) employed bounce rate (percentage of people immediately leaving the site) and the time on site (length of time people spend on the site) to explain the reduction in traffic on an academic website. In sum, most researchers do not further analyze visitor' traffic beyond the figures, graphs, and functionalities residing in Google Analytics. The application of Google Analytics to education information systems is still in its infancy.

2. Temporal Effect and Visitors' Behavior

Khoo et al. (2008) stated that temporal fluctuation has a definite effect on the interpretation of Web traffic metrics. One of the earlier temporal studies (Jansen et al., 2005), examined traffic patterns on a major search engine covering a period of a few years and compared these numbers to those of other search engines. Beitzel et al. (2007) adopted temporal factors to research the quality of web searches, namely search effectiveness and efficiency. Zhang et al. (2009) firmly established search engine transactional logs and time series analysis as viable means of anticipating future web traffic on these sites. Temporal analysis has also been applied to study the fluctuating dynamics of a blog community and detect web bloggers' unique posting behaviors (Chi et al., 2007).

Current time series analysis of Google analytics data is basically following two paths. One of these is merely based on observing the Google Analytics time traffic dashboard to roughly estimate the overall trend of the visits to the website. Kent et al. (2011) discovered that a particular website experienced a decline in usage over time and tried to explain the reasons behind it. Kirk (2012) studied two years' worth of data for a health professional education website. Relying on the visitors' growth trend, he concluded that this particular site would further expand to be a global source on genetics-genomics education. Their conclusions about their websites over time depended on observation and estimation of the Google Analytics dashboard rather than accurate computation.

The second path that has been taken is based on regression analysis of traffic data over a certain period of time and its relationship with other website metrics. Plaza (2009; 2011) examined the effectiveness of entries (visit behavior and length of sessions) depending on their traffic source: direct visit and in-link entries. Basically, the author ran a regression analysis to test the relationship between returning visit behavior and length of sessions over approximately a two-year period. Wang et al. (2011) studied whether users behave differently during weekdays and weekends. They found numerous significant relationships between several key web metrics and traffic variables. Until now, no precise quantitative method has been applied to investigate users' patterns of interaction with a website.

3. Geospatial Effect and Visitors' Behavior

The geographic information or spatial distributions associated with visitor traffic is important for targeting online marketing activities (Clifton, 2012) such as estimation of the website's influence over a particular region. When it comes to the academic world, researchers have already taken advantage of visitors' location information gathered by Google Analytics. Pakkala et al. (2012) used Google Analytics to study visitor use of three food composition websites located in three different countries. Based on the users' geolocation graph provided by Google Analytics, they concluded that the website manager should increase promotion for a particular country over the other two. Similarly, according to the usage of website data in different areas offered by the Google Analytics dashboard, Patton and Kaminski (2010) evaluated the influence of their agency's extension program over their client territories.

Most studies have drawn conclusions simply based on the Google Analytics geographical dashboard. Their procedures were to insert screenshots of the Google Analytics geographies into their articles and then draw implications from those graphs (Pakkala, 2012; Kirk, 2012; Plaza, 2011; Patton & Kaminski, 2010; Fang, 2007). However, researchers could only obtain location and corresponding number of visits data based on Google Analytics geo-graphs. According to Turner (2010), broad measures of website usage such as virtual visits can be useful; nonetheless, these numbers provide little insight or ability to measure website goals. A more sophisticated measure of the geospatial distribution of visits needs to be developed.

Clifton (2012) introduced the geomap overlay technique for adding other dimensions into visitors' geographical distribution map to deliver information at a glance, and in turn, obtain a more comprehensive picture of the performance of the website. Nevertheless, until now few studies have applied these techniques. Moreover, Clifton's map overlay method has its own limitation in that the dimensions he suggested were limited to the data factors already contained in Google Analytics. For example, geospatial visit distribution data for the United States can be cross-referenced with data from which search engines these visitors are coming (data already collected by Google Analytics) and then displayed in the same graph. This solution does not add outside dimensions into the Google Analytics geographical graph which might have significant impact on website stakeholders' decision-making. For instance, academic websites may need to evaluate usage over different school districts (e.g. Xu et al, 2010) and commercial sites might want to consider a website's influence on different demographics (age, race, or income scale etc.) in different areas (e.g. Kumar et al, 2009). Therefore, Clifton's map overlay methodology is limited by not adding new outside factors to the graph.

Recker et al. (2010) overlaid publicly available datasets with Google Analytics visitors' geographical distribution data to examine the usage of two educational websites. However, this study focused on the relationship between visitors' usage in different areas with the number of school districts or median family income. As a result, the graph they created was still based on the Google Analytics generated geo-location graph and their results were drawn from statistical analysis rather than graph presentation. Their graphical display was in 2D format and therefore limited in presenting multiple metrics in the same picture. Neither did they create any other sophisticated measures besides the number of visits in each location. From an aesthetical perspective, using a screenshot of the Google Analytics dashboard or using the dashboard as a base (Recker et al., 2010) is insufficient because it is merely presents a flat, color-coded graph. Various researchers have indicated that aesthetic pleasure with different display formats could improve the perceivers' information processing dynamics from a design perspective, a psychological perspective, and a practical perspective (Tractinsky, 2013 & 1997, Reber et al, 2004, Petersen et al, 2004).

In summary, current web analytics has three flaws: 1) no precise quantitative method has been applied to examine users' patterns of interaction with a website and especially educational websites. 2) no sophisticated metrics exist; 3) the graphical display is limited in the Google Analytics dashboard. To fill the gaps in the literature, this research explores methods to identify the temporal patterns and create new metrics and graphical presentations for spatial distribution of web visitors for an online resource. Such a study could help stakeholders or web managers make decisions on how to maintain and improve the websites, especially adjusting resources by considering temporal fluctuations and inequity in geographical distribution. Mining data from web logs promises more valuable and in-depth quantitative information as compared to direct screenshots of Google Analytics.

Research Question and Methodology

Research Questions

Two research questions are constructed for this study:

1. How can we precisely identify visitors' behavior patterns over a longitudinal period rather than using a rough estimation procedure through Google Analytics Dashboard?

2. How could we present a more comprehensive and aesthetically pleasing view of visitors' spatial distribution besides graphs based on the Google Analytics Dashboard?

Clustering and ArcGIS based methods are applied to answer the above research questions. Details of this research framework are explained below.

3.2 Cluster Analysis for Temporal Analytics

Users' visiting patterns show significant variations throughout a year. In order for web stakeholders to make decisions effectively, different marketing or maintenance plans should be designed in appropriate intervals that align with the visiting patterns. Cluster analysis, which addresses the problem of data segmentation, belongs to unsupervised learning methods since there is no knowledge of "preferred" clusters (Duda & Hart, 2001). It is a set of techniques used to classify a dataset into groups that are relatively homogeneous within themselves and heterogeneous between each other on the basis of a defined set of variables (Guo & Zhang, 2013). A cluster analysis for pattern identification of the web visits involves the following steps.

State Definition and Matrix Formulation

A significant step in clustering is to define the system scale and select the proper cluster elements. By considering the website log data collected by Google Analytics in different resolution/granularity levels (e.g., daily, weekly and monthly), it is possible to capture the temporal features of website users' behavior with a mathematical method. The system states in our study are defined as follows, assuming there are *M* representative years in the log datasets and yearly visits are recorded into *T* time intervals. For instance, the yearly visit rate (i.e., visits/year) can be subdivided into 52 weekly visit rates (i.e., visits/week) and then *T* is 52.

$$\mathrm{X}\ (t) = (\mathrm{X}_1,\cdots\mathrm{X}_m,\ \cdots\mathrm{X}_M,\ \mathrm{X}_{M+1}\ )$$

Where X (t) is the system state at time *t, t=1, 2, ⋯,T;*

X_m is the weekly website visits in year *#m, m=1, 2,⋯, M;*

X_{M+1} is the time variable indicating the time of visit occurring.

Then the data **X**, a *K (M+1)* × *K (T)* matrix, will have the format as following.

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1M} & x_{1(M+1)} \\ x_{21} & x_{22} & \cdots & x_{2M} & x_{2(M+1)} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{(T-1)1} & x_{(T-1)2} & \cdots & x_{(T-1)M} & x_{(T-1)(M+1)} \\ x_{T1} & x_{T2} & \cdots & x_{TM} & x_{T(M+1)} \end{bmatrix}$$

To deal with the differences in scale between website visits and time variables in different years, the cluster elements should be properly normalized (Guo & Zhang, 2013). This process, which uses Eq. (1), is performed prior to the cluster analysis so as to make original data dimensionless.

$$x'_{tm}=\frac{x_{tm}-\bar{x}_m}{s_m} \qquad (t = 1,2,\cdots,T;\ \ m = 1,2,\cdots,M+1) \qquad (1)$$

Where x_{tm}, $\bar{x}_m$ and s_m represent original, average, and standard deviation of website visits or time variables, respectively, for any particular observation.

Clustering for Temporal Analytics

To identify the patterns of website visitors, K-means cluster analysis—including selection of the number of clusters, clustering algorithms, distance measures and validation of the analysis—is conducted step-by-step.

The Number of Clusters

Before conducting the K-means clustering, the Gap-statistic is used to determine the proper number of clusters (Everitt et al., 2011; Tibshirani et al., 2001). The basic idea of the

Gap-statistic is to find an “elbow” in the plot of the optimized cluster criterion against the number of clusters *K*. In this approach, the graph of log (W_K) against the number of clusters is plotted, where W_K (an overall average within the cluster sum-of-squares) is a cluster criterion that has been minimized for *K* clusters by comparing it with its expectation under an appropriate null reference distribution. For this purpose, letting E_N^* denote the expectation under a sample size of N from the reference distribution, the optimal value for the number of clusters is then the value k for which the “Gap” is the largest.

$$\mathrm{Gap}_N(K)= E_N^* \{\log(W_K)\}\text{-}\log(W_K) \tag{2}$$

In Eq. (2), K is the number of clusters, N is sample size, and W_K denotes an overall average within the cluster sum-of-squares. Those interested in the theoretical details of this method can refer to the original paper (Tibshirani et al., 2001).

Cluster Algorithms and Validation

In cluster analysis, cluster elements are grouped according to their similarities, or more specifically, the distances between them. Therefore, the smaller the distances between the elements, the more similar they are and the more likely they belong to the same cluster. For our study, squared Euclidean distance, as shown in Eq. (2), is implemented for calculating the distance between clusters.

$$d_{ij}^2=\sum_{m=1}^{M+1}(x_{im}-x_{jm})^2 \qquad (i,j=1,2,\cdots,T;\quad m=1,2,\cdots,M+1) \tag{3}$$

Where d_{ij}^2 is the squared Euclidean distance between state elements i and j; x_{im} is the m^{th} element in state i; and x_{jm} is the m^{th} element in state j.

The validation of the optimal number of clusters is one of the most critical steps in the cluster analysis. An insufficient number of clusters would muddle up different users’ visiting patterns, while too many clusters would add unnecessary difficulty of pattern explanation. To validate the efficiency of selected number of clusters, the Silhouette measure is used in this study (Rousseeuw, 1987). The overall average Silhouette width, denoted as the Silhouette Coefficient (SC), is the average of the s(i) for all elements in the dataset as shown in Eq. (4).

$$SC=\frac{1}{N}\sum_{i=1}^{N}s(i)=\frac{1}{N}\sum_{i=1}^{N}\frac{\min\{D_{ij},j\in C_{-i}\}-D_{iC_i}}{\max(\min\{D_{ij},j\in C_{-i}\},D_{iC_i})} \tag{4}$$

Where C_{-i} denotes cluster labels that do not include element i as a member; C_i denotes the cluster label that includes element i; D_{ij} is the averaged distance between element i and all elements in cluster C_{-i} (in other clusters); $\min\{D_{ij}, j\in C_{-i}\}$ is the minimum of average dissimilarity i to all elements in another cluster (in the closest cluster); and D_{iC_i} is the averaged distance between element i and all elements in cluster C_i (in the same cluster).

SC will be a value falling into the range of -1 and 1. If SC is close to 1, it means a state element is assigned to an appropriate cluster and is “well-clustered.” If SC is about 0, it means that the element could be assigned to another closest cluster as well, and the element lies equally far away from both clusters. If SC is close to –1, it means that the element is "misclassified" and is merely somewhere in between the clusters. After cluster analysis, post-processing is conducted to determine the intervals and identify the visits' patterns.

ArcGIS for Spatial Distribution Analysis

Data Preparation

Geographically, Google Analytics allows one to export data to a file according to granularity. For example, if the main target users of the studied website are located in the United States, United States can be selected as the primary study scope to compare the distribution features between different states. The second study scope (e.g., one particular state) can be further selected according to the findings from the study in primary scope.

To conduct spatial density analysis of a resource inventory, Geographic Information System (GIS) is adopted. In undertaking any GIS-based work, additional spatial data should be collected to generate the base map besides the data collected by Google Analytics. The supplemented spatial data includes the data for layer generation and data for computation. In our study, we mainly supplement the TIGER/Line Shape-file data and population information for primary and secondary study scope, respectively. ESRI Data and Maps 10 software package is used to generate basic maps for the following nation-wide and state-wide study.

Density Computation

In additional to the total visits by location directly obtained from Google Analytics, the visits density, representing the number of visits per person at one place, is computed for comparison as well. Assuming there are *m* representative years in the log datasets and website visits are cumulated through the total studied time period for different locations, density of website visits can be computed by the following equation.

$$\mathrm{D_s} = \left(\sum_s \sum_{t=1}^{t=m} V_{ts}\right) / \left(\sum_s P_s\right) \tag{5}$$

Where, $\mathrm{D_s}$ denotes the density of website visits (visits/person) at location s, V_{ts} refers to website visits of the studied time period t at location s, and P_s is the population of location s. Here, s could be nation-wide, state-wide and city-wide etc. ArcGIS outputs provides a way to see the data/information in the form of maps, tables, diagrams, etc. 2-D maps are the most standard display format, and frequently are accompanied by tabular display. Compared with 2-D visualization, 3-D visualization is performed to display a graph with more layers and factors.

Case Study

Study website: eThemes

To illustrate this approach, a K-12 online resource – eThemes – was chosen for the case study. eThemes, hosted by the School for Information Science & Learning Technologies at the University of Missouri, is an online educational resource that is primarily used by K-12 educators (http://ethemes.missouri.edu/). It supports educators by providing themed collections of links to websites relevant to their instructional goals; this saves teachers countless hours that would be otherwise spent searching the Web and culling through lengthy lists of search results, and it frees them to concentrate their efforts on other, more important aspects of teaching. Teachers can request online resources according to a variety of criteria including: subject matter, grade level, type of resource, etc. eThemes currently includes over 2,100 themed collections of over 10,000 total links and is available for anyone to use at no cost via the Internet. The site is maintained and marketed by staff from the University of Missouri with graduate students from the School of Information Science & Learning Technologies serving as internet resource scouts (Wang, 2001). These eThemes resource scouts ensure that the links in the collections are rich in content, age-appropriate, and safe for children. The topics covered range from literature to mathematics, grammar to geography, author studies to teaching tips, and more. eThemes also provides the respective state educational standards that correlate to each themed collection for states such as Missouri, Alabama, Arkansas, Delaware, Texas, and others. eThemes has been in service for more than 12 years.

Data Collection

Temporal data of eThemes website visits

Google Analytics was employed to collect data over three years from 05/30/2010 (last Sunday of May) to 06/01/2013 (first Saturday of June). To better serve the purpose of this study, we selected clickstream data pertaining to time. We downloaded the CSV files containing weekly visits of eThemes website from Google Analytics each year, as shown in Fig. 1.

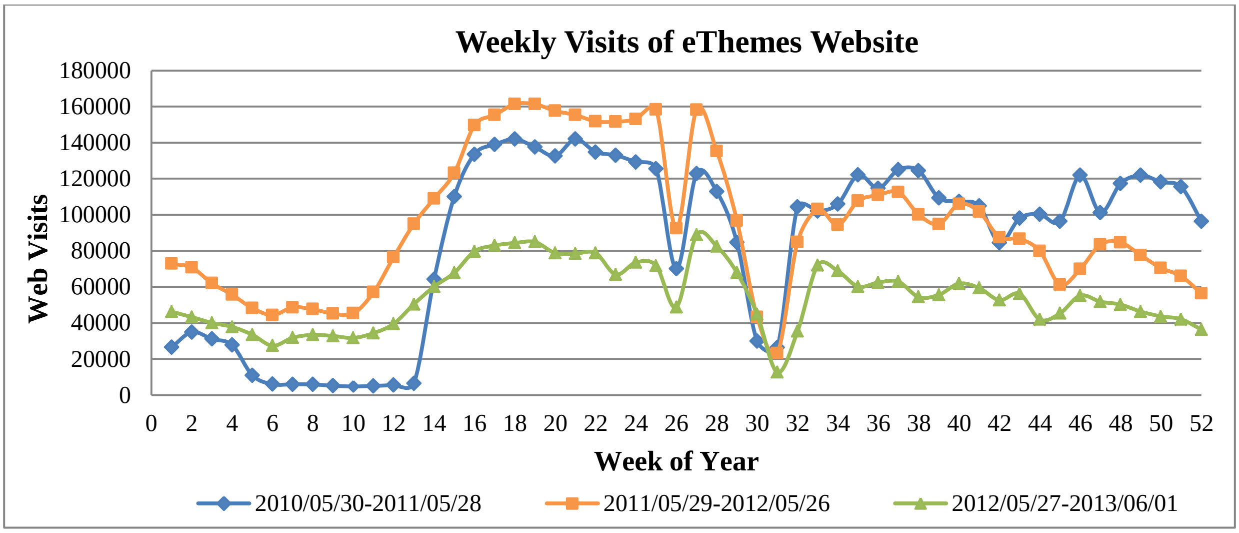


Figure 1: Weekly visits of eThemes website from 2010 to 2013.

Spatial data of eThemes website visits

Similar to temporal data, we exported the CSV files containing visits to eThemes website from Google Analytics over the three studied years by location. Since the main users of eThemes were from the United States, we downloaded the CSV file in the granularity of state to better examine eThemes' influence over states in the US. In addition, we chose Missouri as the study area for state-wide analytics because we wanted to closely examine how eThemes performed in its host state.

In order to compare eThemes' influence over different states, we downloaded the data by state. To compute density of visits, the 2012 population data for each state (except Alaska and Hawaii) of the United States and 2012 population data for major cities in the state of Missouri were collected as well. Moreover, TIGER/Line Shape-files by different layer types (e.g., block groups, census tracts and school districts) were collected from different online open sources. Table 1 lists the selected sources of spatial and population data for this study.

Table 1

Selected sources of spatial and population data

Organization/data provider URL address	Type of data &data description
Federal Geographic Data Committee http://www.fgdc.gov/dataandservices	Geo-Platform and Geography network clearinghouse
TIGER/Line Shapefiles-U.S. Census Bureau http://www.census.gov/cgi-bin/geo/shapefiles2012/main	Line Shape-file Data (nation-wide and state-wide)
U.S. Population by State, 1790 to 2012 http://www.infoplease.com/ipa/A0004986.html	Census Data (nation-wide, year 2012)
Missouri Spatial Data Information Service http://msdis.missouri.edu/data/datalist.html	State-wide Spatial Data

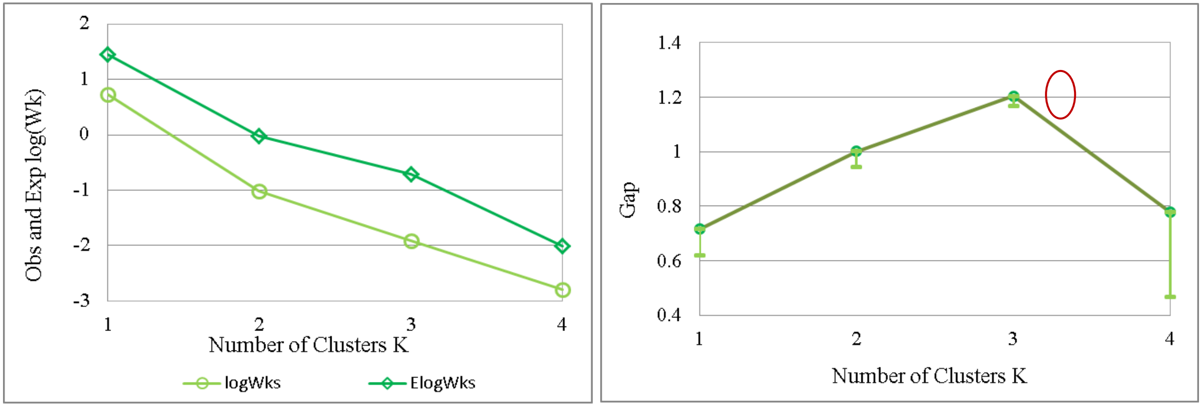
Missouri (USA): State, Major Cities & Places -City Population http://www.citypopulation.de/USA-Missouri.html	Census Data (state-wide, year 2012)
TIGER/Line Shapefiles: School Districts http://www.census.gov/cgi-bin/geo/shapefiles2012/layers.cgi	Layer Data by School Districts (state-wide)

Results of Case Study

Results of Temporal Pattern Identification

Selection of Cluster Numbers

To determine the optimal number of clusters, the Gap statistics measure was conducted by coding in R, a software package for statistical computing and graphics. Fig. 2(a) shows the observed and expected *log* (W_k) and Fig. 2(b) shows the Gap values against the number of clusters in our case study. As shown in Fig. 2(b), the largest Gap value occurs when the number of clusters is three. Thus, we selected three as the number of clusters for further analysis in the next step.

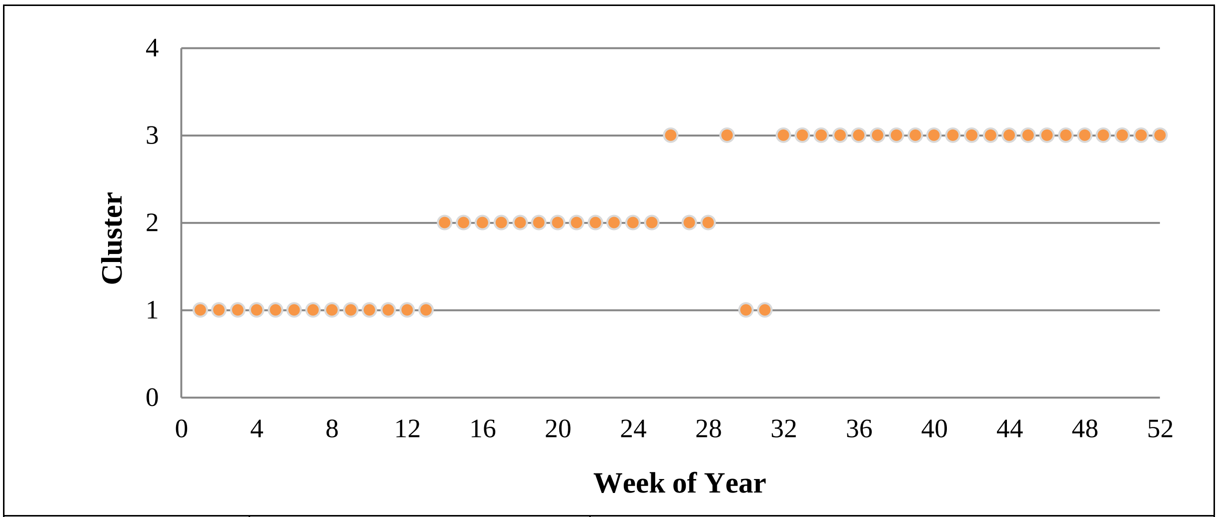


a) Obs and Exp log (W_k) plots of visits b) Gap plots of visits

Figure 2: Gap as a function of number of clusters.

Identification of Patterns

The K-means clustering successfully identifies users' visiting patterns based on the average weekly visits and the time that activity is occurring, as displayed in Fig. 3. Three clusters, as determined in the previous section, were used to find appropriate representation of website visiting groupings over a one-year time period. Fig. 3 provides the results of cluster analysis for pattern identification. In Fig. 3, cluster 1 represents the off-semester pattern, including summer vacations and winter holidays each year; cluster 2 represents the fall semester from September to early December; and cluster 3 represents the spring semester from January to mid-May.



Cluster (K=3)	Pattern Classification	Interval of website visits
Cluster 1	Off-semester	End of May to August, Winter holiday
Cluster 2	Fall semester	September to early of December
Cluster 3	Spring semester	January to middle of May

Figure 3: Results of cluster analysis for pattern identification.

The findings of cluster analysis, shown in Fig. 3, are consistent with existing knowledge (common sense) on eThemes resource website visits where summer vacation (off-semester), fall semester, Thanksgiving week and winter break (holiday seasons), and spring semester are the most commonly observed phenomena/patterns in a year.

Validation of Clustering

To validate how good the number of selected clusters is, the Silhouette Coefficient was calculated by using MATLAB coding. Fig. 4 shows the Silhouette coefficients as a function of number of clusters. The “elbow” occurs when the number of clusters is three, which validates the efficiency of our cluster analysis.

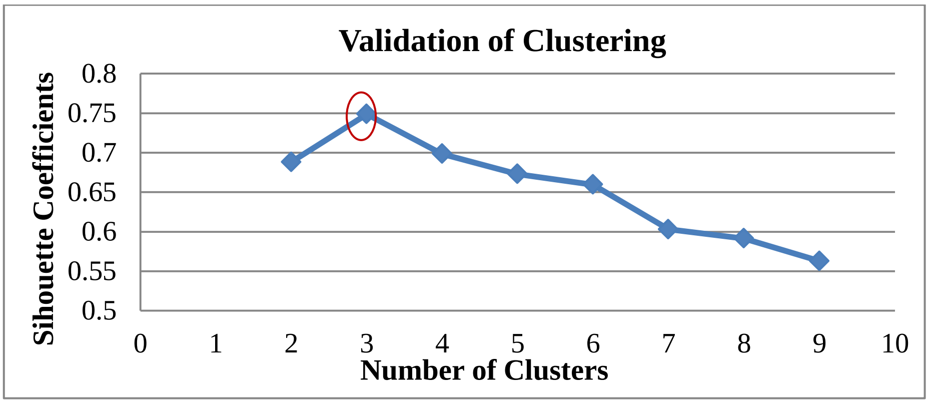


Figure 4: Silhouette coefficients as a function of number of clusters.

The results showed that a larger number of visitors came to the eThemes website during school terms rather than holiday times when schools were not in session. Hence, we inferred that eThemes met the needs of major target audiences—the teachers—because these purposeful users tended to visit the eThemes website frequently during school session periods. The validity of our methodology was attributed to the eThemes real world dataset. Thus, we have provided a more precise way to identify users' behavior patterns over time rather than based on a rough observation of the Google Analytics Dashboard, as illustrated in Fig. 5.

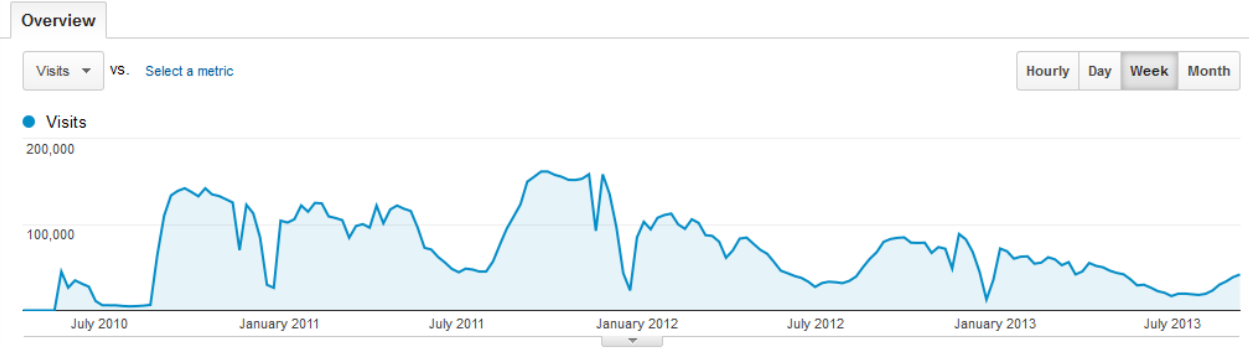


Fig. 5. Google Analytics Dashboard of eThemes website visits.

Results of Geospatial Distribution Analysis

In this case study, two scopes of geospatial distribution analysis were selected: nation-wide study and state-wide study. The base network shape files, both nation-wide and state-wide, were retrieved from TIGER line data, as listed in Table 1. In accordance to state and city boundaries, proper edits (cut, divide, split, and merge) were conducted to meet the requirements.

Nation-wide Geospatial Analytics of eThemes

As stated above, most of the current studies use a screenshot of the visitors' spatial distribution from Google Analytics. To make a comparison to our developed graph, the geograph for the eThemes website was captured from Google Analytics, as shown in Fig. 6. This graph displayed the total website visits from different states by coding in different colors. The states of Texas, California and New York showed the most visits (dark blue) in Fig. 6. This is the only kind of information that website stakeholders can get from to the Google Analytics graph. No other metrics or dimensions can be read from this graph.

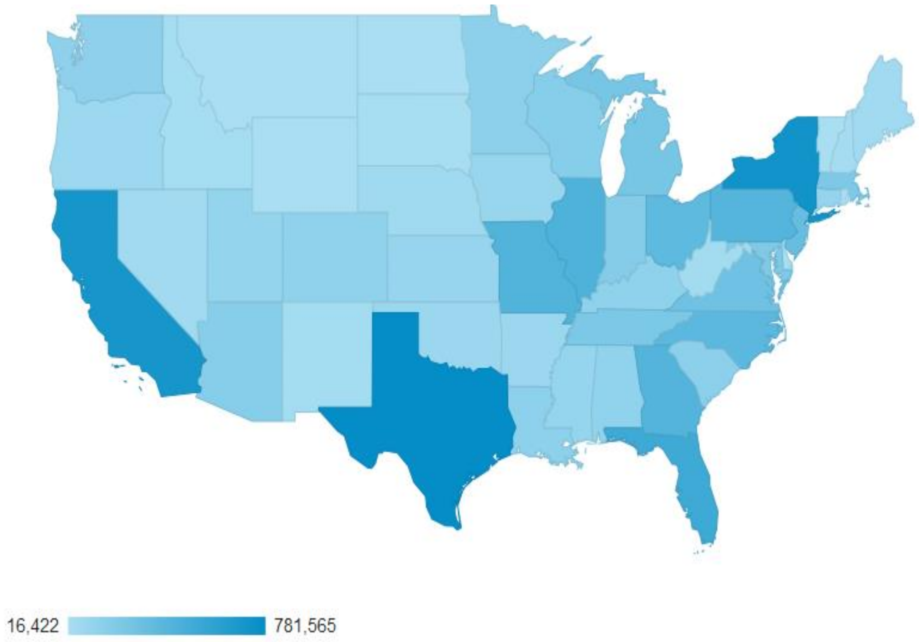


Figure 6: Google Analytics nation-wide spatial distribution of eThemes website visits.

Rather than simply displaying the total number of website visits, we introduced a new metric (i.e., density) to provide more insight into visitors' geospatial distribution. To compute this measure, ESRI's ArcMap was used to perform spatial analytics of website visits for the United States. The new graph added a dimension of density as shown in Fig. 7. We used a star to represent the new layer. The largest star represents the state with the largest website visit density, while the smallest star represents the state with the least density. At the same time, instead of merely using a gradient blue color for the graph, we coded the new graph with different colors to represent different frequencies of visits. This approach achieved the goal of presenting information in a graph with different formats; it communicates better and it is visually pleasing. As a result, the total website visits are displayed by a range of colors, with the blue color representing the smallest visiting number and the red color the largest visiting number.

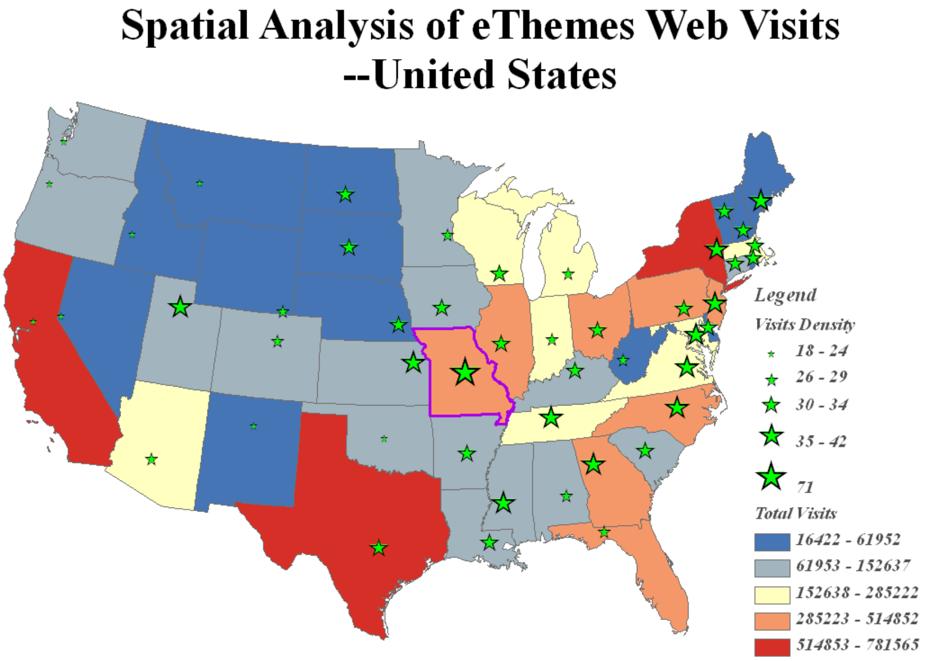


Figure 7: Nation-wide geospatial distribution of eThemes website visits.

State-wide Geospatial Analytics of eThemes

As shown in Fig. 8, we used the two layers of number of visits and density in the analysis. However, in some situations it may be beneficial to add a third or more layers into one graph for a more complete analysis. Building such a comprehensive graph that is both informative and easy to read was explored using the ArcGIS for graph presentation and display using Missouri as the study area for state-wide analytics. In state-wide spatial analytics, ESRI's ArcScene was used to display multiple layers (e.g., city population layer, city density layer, and school districts layer) in one graph. Unlike 50 states in the US, there are hundreds of cities in each state and some of them are very small in region. It was difficult to clearly recognize the city's name just simply based on its location on the map. Therefore, it was necessary to label city name with noticeable density or population features.

To address the challenge of representing all the labels and layers in one readable graph, a 3-dimension format was chosen to present the graph as shown in Fig. 8. Both the upper map and lower map represented the state of Missouri with track grids. For the upper map, the dark-brown region represented elementary levels. The green area depicted secondary levels. The top 12 cities with high visits density were marked by blue round pushpins in the upper map, and the population by city data (green pushpins) were mapped on the lower map. In the upper map, eThemes showed the greatest density in Ballwin and the greater St. Louis area. Columbia was also high in ranking and reasonable since the eThemes website is offered from the University of Missouri in Columbia. When taking the two Missouri state maps together (unlike the national trend) cities with higher populations generally displayed more density in visitors' geographical distribution. In this case study we utilized density metrics for measuring a website's influence over a region rather than merely depending on the numbers of visits to make conclusions. Further, we demonstrated that additional map layers and labels could be overlaid on an existing graph, and thus, present all of this information in one graph to provide a more refined analysis.

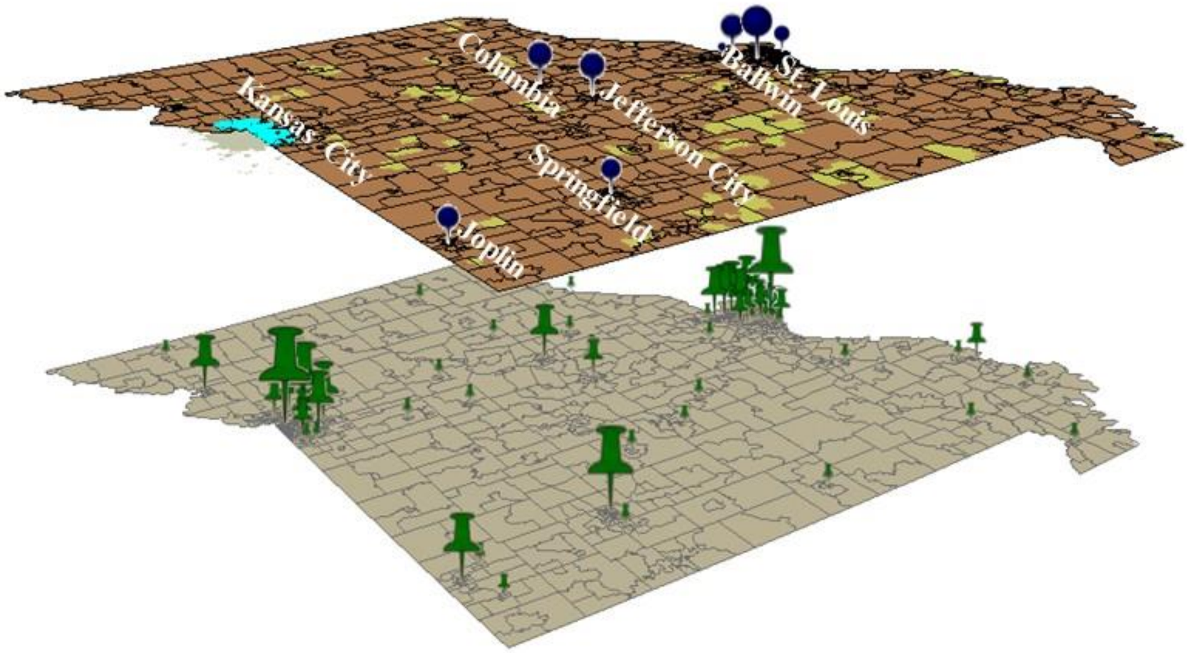


Figure 8: State-wide spatial analytics of eThemes website visits (Missouri).

Discussion

Web users' behaviors, such as temporal patterns and geospatial distribution, are common factors considered by a website. Findings in this study, therefore, have the potential to be implemented in practice. The basic premise behind website management is the development of maintenance plans that are best suited for expected website visiting conditions for particular dates or times. Considering the usage pattern variations, it is necessary to determine appropriate breakpoints, where different maintenance tasks can be implemented during the time periods between two consecutive breakpoints. Transition costs will occur when changing database maintenance plans, because it takes additional costs (both time and human resources) for web managers to adjust time/task efforts and allocate human resources. For example, in the busy season (e.g., in spring term), the web manager may need to ask the employee to work overtime or hire temporary workers to help update the database. Conversely, the web manager can reduce the operating costs during the non-peak time. Therefore, the determination of breakpoints needs to balance the efficiency of website management and the consequent transition costs. In practice, management plans can be quantified/determined based on the temporal analytics developed in this study. It can help the web manager to estimate the annual operating budget as well.

Moreover, this method provides a precisely quantified and longitudinal point of view, and thus, has the potential to be applied in different contexts and for different usages. Currently, the most popular temporal metrics to describe website visits are the times when it has the highest or lowest visits based on Google Analytics Dashboard; average visits per day, week or month etc. Nevertheless, it is insufficient to make strategic plans based on those metrics because it lacks a longitudinal view of website usage. For instance, suppose the 28th week, 2011 has the highest visits of the three-year period; one cannot simply assume the 28th week of 2014 or 2015 would also have relatively higher hits and use this projection in website management decisions. However, based on our proposed method, website stakeholders could utilize information from a longitudinal view of whether 28th week is in the highest cluster over the years. If yes, then it might be a good decision not to schedule adjustments or do maintenance during that time. Otherwise if it is in the lower clusters, the 28th week might be just a random fluctuation; other times, the visits to the website might be very low and therefore, it might be the best time period to make adjustments or do maintenance. Our methodology offers a method to do a longitudinal analysis of the pattern of website visits and then utilize those data to improve the quality of decision making.

In terms of geospatial analytics, we create a new metric – density to more accurately reflect the influence of the website over a particular area. To illustrate, the states of Texas, California and New York in Fig. 7 still showed the most visits (red color) when comparing the total website visits. However, when it comes to visit density, the state of Missouri shows the largest density, while the star symbols of California and Texas are relatively small. This finding is in line with both our website strategy and the fact that Missouri includes more eThemes member schools than any other state. Thus, a count of the frequency of visits in each location directly from Google Analytics does not appear to be the best measure to describe visitors' geospatial distribution as it does not take density into consideration. It is not necessarily true that a website has the most influence in a location with the largest number of visits. In fact, we argue that the constructed new measure—density—is a better indicator when analyzing a website's influence within a particular region.

On the other hand, we demonstrated both 2D and 3D graphical presentations for spatial distribution of web visits. These displays outperformed normally used Google Analytics Dashboard not only in aesthetical perspective such as different shapes (e.g. stars) and colors in the graph but also have the capacity to hold more measures and dimensions on them. Our methodology is expected to show a more accurate picture of the website usage and influence over a region and also easily for web managers to obtain and understand the information. In sum, by offering in-depth quantitative information based on mining data from web logs, this study provides an evaluation and decision support tool for web stakeholders to make better decisions on how to maintain and improve the websites.

Conclusion

As Google Analytics becomes more popular, more detailed records of user activities can be captured and analyzed, and in turn, offer feedback to website administrators, design teams, and domain experts to better understand their users and users' interactions with website resources. As an exploratory study, this research presented an experiment undertaken with time series and geographically distributed click steaming data that Google Analytics collected for an educational website. A new methodological framework based on advanced analytical techniques was developed to more accurately examine the visitors' behavior patterns over time. To better measure a website's influence over a particular region, the authors introduce the density measure to give more insight into website performance geographically. Additionally, our study filled the gap for current Google Analytics research on map overlay procedures, and expanded the graph representation format both aesthetically and functionally. Data aggregation, manipulation and presentation strategies were also provided. From an applied perspective, this study contributes methodologically to website analytics in the education field.

In the future, the results from this study can be compared with other case studies. In addition, Clifton (2012) proposed that the comparison of visitors' key performances by advanced segmentation would contribute to a more comprehensive informational view of visitors. We recommend the investigation of visitors' behavior patterns from different traffic sources (direct, reference or search engine) as well as return visitors' navigation in comparison with that of new visitors. To identify the loyal users of a website, behavior characteristics can be further explored in the extended study as well. On the other hand,

References

Beitzel, S.M., Jensen, E.C., Chowdhury, A., Frieder, O. & Grossman, D. (2007). Temporal analysis of a very large topically categorized web query log, *Journal of the American Society for Information Science and Technology, 58*(2), 166-78.

Chi, Y., Zhu, S., Song, X., Tatemura, J. & Tseng, B.L. (2007). Structural and temporal analysis of the blogosphere through community factorization, *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. Available at: http://portal.acm.org/citation.cfm?doid=1281192.1281213

Clifton, B. (2012). *Advanced web metrics with Google Analytics*. John Wiley & Sons.

Duda, R.O., Hart, P.E., & Stork, D.G. (2001). *Pattern Classification, 2nd ed.* John Wiley& Sons, Inc., New York.

Everitt, B.S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis, 5th ed*. John Wiley & Sons, Ltd., 2011.

Fang, W. (2007).Using Google Analytics for improving library website content and design: A case study. *Library Philosophy and Practice, 9*(3), 1–17.

Farney, T. & Mchale, N. (2013). Data Viewing and Sharing: Utilizing Your Data to the Fullest. *Library Technology Reports 49*(4), 39-42. American Library Association.

Guo, R., & Zhang, Y. (2013). Identifying Time-of-Day Breakpoints Based on Non-intrusive Data Collection Platforms. *Journal of Intelligent Transportation Systems*.

Hess, M. R. (2012). Web Analytics: Using Evidence for Improvement-Über analytics: Customizing Google Analytics to track multiple library platforms.

Jansen, B. J., & Spink, A. (2005). How are we searching the World Wide Web? A comparison of nine search engine transaction logs. *Information Processing & Management*, *42*(1), 248–263.

Jones, C., Giersch, S., Sumner, T., Wright, M., Coleman, A. & Bartolo, L. (2004). Developing a web analytics strategy for the National Science Digital Library, D-Lib Magazine, *10*(10). Available at: www.dlib.org/dlib/october04/coleman/10coleman.html.

Kent, M. L., Carr, B. J., Husted, R. A., & Pop, R. A. (2011). Learning web analytics: A tool for strategic communication. *Public Relations Review, 37*(5), 536-543.

Khoo, M., Pagano, J., Washington, A. L., Recker, M., Palmer, B., & Donahue, R. A. (2008). Using web metrics to analyze digital libraries. In*Proceedings of the 8th ACM/IEEE-CS joint conference on Digital libraries* (pp. 375-384). ACM.

Kirk, M., Morgan, R., Tonkin, E., McDonald, K., & Skirton, H. (2012). An objective approach to evaluating an internet-delivered genetics education resource developed for nurses: using Google Analytics™ to monitor global visitor engagement. *Journal of Research in Nursing*, 17*(6)*, 557-579.

Kumar, C., Norris, J. B., & Sun, Y. (2009). Location and time do matter: A long tail study of website requests. *Decision Support Systems*, 47*(4)*, 500-507.

Marek, K. (2011). Chapter 2: Getting to Know Web Analytics. *Library Technology Reports, 47*(5), 11-16.

Pakkala, H., Presser, K., & Christensen, T. (2012). Using Google Analytics to measure visitor statistics: The case of food composition websites. *International Journal of Information Management*, *32(6)*, 504-512.

Patton, A. J., & Kaminski, J. E. (2010). Tracking the impact of your web-based content. *Journal of extension*, *48*(4), 4TOT1.

Petersen, M. G., Iversen, O. S., Krogh, P. G., & Ludvigsen, M. (2004). Aesthetic Interaction: a pragmatist's aesthetics of interactive systems. In *Proceedings of the 5th conference on Designing interactive systems: processes, practices, methods, and techniques* (pp. 269-276). ACM.

Plaza, B. (2009). Monitoring web traffic source effectiveness with Google Analytics: An experiment with time series. In *Aslib Proceedings* 61*(5)*, pp. 474-482). Emerald Group Publishing Limited.

Plaza, B. (2011). Google Analytics for measuring website performance. *Tourism*

Management, *32(3)*, 477-481.

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: is beauty in the perceiver's processing experience? *Personality and social psychology review*, 8*(4)*, 364-382.

Recker, M., Xu, B., Hsi, S., & Garrard, C. (2010). Where in the World? Demographic Patterns in Access Data. In *EDM* (pp. 337-338).

Rousseeuw, P.J. (1987). Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics 20*(1), 53–65.

Sen, A., Dacin, P.A. and Pattichis, C. (2006), “Current trends in web data analysis”, *Communication of the ACM*, *49*(11), 85-91.

Tibshirani, R., Walther, G., and Hastie, T. (2001). Estimating the Number of Clusters in a Data Set via the Gap Statistic. *Journal of Royal Statistical Society*, B63, Part 2, 411–423.

Tractinsky, N. (1997). Aesthetics and apparent usability: empirically assessing cultural and methodological issues. In *Proceedings of the ACM SIGCHI Conference on Human factors in computing systems* (115-122). ACM.

Tractinsky, N. (2013): Visual Aesthetics. In: Soegaard, Mads and Dam, Rikke Friis (eds.). *The Encyclopedia of Human-Computer Interaction*, 2nd Ed. Aarhus, Denmark: The Interaction Design Foundation. http://www.interaction-design.org/encyclopedia/visual_ aesthetics.html.

Turner, S. J. (2010). Website statistics 2.0: Using Google Analytics to measure library website effectiveness. *Technical Services Quarterly*, *27*(3), 261-278.

Wang, F.K. & Wedman, J.F. (2001) eThemes: An Internet instructional resource service. *Information Technology and Libraries*. *20*(4), 179-184.

Wang, X., Shen, D., Chen, H. L., & Wedman, L. (2011). Applying web analytics in a K-12 resource inventory. *The Electronic Library, 29*(1), 20-35.

Xu, B., Recker, M., & Hsi, S. (2010). The data deluge: Opportunities for research in educational digital libraries. *Internet Issues: Blogging, the Digital Divide and Digital Libraries. Nova Science Pub Inc., New York.*

Zhang, Y., Jansen, B. J., & Spink, A. (2009). Time series analysis of a Web search engine transaction log. *Information Processing & Management*, *45*(2), 230-245.