# Web Traffic Performance for an Academic Program at a Latin American Graduate Business School


## Abstract

This research aims at determining an optimum model for traffic performance of a web site from the viewpoint of its sources of traffic at an academic program in a Latin American graduate business school between May 2013 and May 2015. The paper analyzes web performance from the viewpoint of web traffic and reviews the tools to determine web traffic performance and its indicators. The methodology adopts a trend-based longitudinal non-experimental research design that uses web page visits to the graduate programs as its unit of analysis for the period between 2013 and 2015. A total 4106 observations were extracted using Google Analytics. The study's techniques and procedures relied on a regression analysis for temporary data using ARMA (Auto-Regressive Moving Average) time series model for estimating and analyzing model errors and data volatility. The general analysis model is based on prior models used in the academic field for an in-depth analytics model (H1), and a new visitor's model (H2-H6). Results are prepared using the in-depth and new visitors' models, where the greatest impact traffic sources are paid social media, displays and direct traffic.  This research contributes to recognizing the web traffic performance model for new visits as a tool to identify the main web traffic sources' role in attracting new quality visits.



*Keywords: Web Analytics, Web Traffic Performance, In-Depth Model, New Visitors Model.*


## Introduction: Web Analytics

Originally, web analytics was developed for the business world to control for commercial web sites' quality and make better strategic decisions (Welling & White, 2006) (Gillaspy, 2005; Phippen, et al., 2004). The business world has used web analytics to study online users' behavior and thereby quickly determine the efficiency of their virtual spaces (Fagan, 2014).

Users increasingly interact with business through digital media. Vendors have identified the need to follow up such interactions and determine their performance (Chaffey & Patrón, 2012). To this end, businesses must use web analytics (WA), defined as the "measuring, gathering, analysis and reporting of Internet data for purposes of understanding and optimizing web use" (Web Analytics Association, 2008).

A recent study (Järvinen & Karjaluoto, 2015) defines WA as a tool to gather browsing data with reference to the web page's traffic source (e-mail, search engines, graphic announcements, social media links and others), browsing routes and website visitors' behavior. WA data are used to understand the online behavior of clients, measure client responses to stimuli, optimize digital marketing components and identify the steps to create benefits for business (Nakatani & Chuang, 2011).

WA is used by over 60% of the 10 million most popular web sites around the world (Encuestas Tecnología Web, 2014). The high value of the data resulting from WA and the high rate of adoption is driven by the fact that some tools, including Google Analytics, are available free of charge (freeware)(Järvinen & Karjaluoto, 2015). Consequently, the key question addressed in the study is ***what is the optimum model for traffic performance measurement for a website from the viewpoint of its sources of traffic at an academic program at a Latin American graduate business school?***

# Web Traffic Performance

Three approaches are available to measure traffic performance.  The first is to ask Internet users about their usage patterns. This is an appropriate approach when rating the users' attitudes toward a website, recognition of website brands, and similar issues. The second approach implies automatically measuring activity, either on the server side or server web records clients' side (PC monitoring). The third approach is to register the server and conduct in large scale measurements. To this end, a group of Internet users are installed a monitoring and registration program that monitors all their PC-based activities and access to the web (Alpar, Porembski, & Pickerodt, 2001).

In addition, three concepts contribute to understanding web traffic analysis: performance strategic measurement, Internet research analysis in marketing and client relationship management (Wilson, 2005).

Determining the performance of the website will depend on the objectives for which the site was developed. Corporate websites' performance will help a business to reach its business objectives (Welling & White, 2006). Understanding the sources of a portal's traffic points to the ability of the search engines to identify the importance of organization's websites and reveal the loyal users' characteristics (Khoo, et al., 2008).

Web analytics generally classifies traffic sources in three categories: written marker or URL traffic, search engines and external reference websites. Previous studies have determined time elements, including peak hours, seasons and holidays, can have an influence on traffic and also on the people dynamics in a website (Wang, et al., 2011). Web traffic is a necessary though not sufficient condition for accomplishing good results in cyber space  (Nikolaeva, 2005). Various authors (Rajgopal, Venkatachalam, & Kotha, 2003) show elsewhere that to enhance future potential revenues, increased web traffic must be based on the ability to attract attention toward the web page, build a network of affiliates and expand business size based on the outfit's ability to retain clients and improve new client capture.

## Tools for Web Traffic performance

Although past research (Vaughan & Yang, 2013) has focused mainly on three tools for web traffic measuring, i.e. *Alexa, Compete and Google trends (now Google Analytics),* more tools are now available for comparison. (See Table N° 1). Alexa is the largest free traffic data source while Compete is only partially free of cost (i.e. some types of data are free while others are paid). Google Trends for websites launched in 2008 (Pittman, 2008) was initially available free of cost but not anymore since September 2012 (Matías, 2012).

A popular WA tool now is Google Analytics. Some of its essential characteristics are its friendly browsing, visual display of data summaries, and the way it captures data. Since 2006, Google Analytics has consistently received highly favorable reviews as a Web Analytics tool (Fang, 2007). Google Analytics has adopted an approach to “client data gathering” based on the page labeling technique that includes a JavaScript code line at the bottom of each web page (Wang, et al., 2011). Additionally, it is a free tool used as a web analysis device which in combination with time series creates detailed web page statistics, including web page visits and traffic sources (Plaza, 2009).

Two methods are used for gathering information. *Labeled pages* are identification labels attached to one or more web pages. The visitors’ information is sent to a free software that gathers the data for subsequent analysis. Another approach is to use *Web server record archives*, which consists in collecting a large amount of event information for each of the visitors, without using external services. Given the large amount of information gathered, analysis can be slow and awkward (Pakkalaa, Presserb, & Christensen, 2012).

Using Google Analytics allows webpage owners to know how visitors found the website and how they interact with it. This allows to compare visitors’ behavior by search engine, reference site, e-mail and direct visits and to compare new and recurring visits (Plaza, 2009).

**Table 1. Performance Indicators by Web Traffic Tool.**

| Tools | Indicators |
|---|---|
| Google Analytics | Visitors, Visits, Pages viewed, Average time on site, Rebound percentage, New visitor percentage |
| Yahoo Analytics | Pages viewed, visit path length of visit, demographics, new visitors |
| Alexa | Single daily visitors, number of pages viewed |
| Compete | Single visitors |
| Google Trends | Traffic volume, interest of search on specific issue over time, geographic interest, related interests and comparison with other websites. |

Sources: Google Analytics, Yahoo Analytics, Alexa, Compete y Google Trends
Prepared by the authors.

Given the large amount of information created by web traffic, measuring it requires tools such as Google Analytics, Yahoo Analytics, Alexa and others, which not only allow to measure web traffic but also to use it as a tool for research and market surveys.

The tools most used in prior studies on web traffic performance include Google Analytics, Yahoo Analytics, Alexa, Compete and Google Trends.

## Web traffic performance indicators

The Web Analytics Association (WAA) defines Web Analytics as the measuring, gathering, analysis and reporting of Internet data for purposes of understanding and optimizing web utilization. Additionally, web traffic measurement is performed through the analysis of web metrics. The most representative web metrics analytic entities include the Web Standards Industry Committee (JICWEBS) DTSG, United Kingdom and Europe's ABCe, the US Web Analytics Association (WAA) and to a lesser extent the Interactive Advertising Bureau (IAB) (Dragoş, 2011).

A range of indicators is available for measuring and reflecting web site traffic (Alpar, Porembski, & Pickerodt, 2001). Some frequent web indicators include page visits, views, time and date of each visit, geographic location of IP addresses, traffic sources, destination pages, pages viewed, and others (Alpar, Porembski & Pickerodt, 2001; Khoo, et al., 2008).

Web site performance is directly related to a high rate of rebounds (as measurement of the visit's quality), indicating the website is likely not relevant to visitors (Pakkalaa, Presserb, & Christensen, 2012). The volume of traffic is based on the range of sources and, consequently, web traffic can be used as an indicator of academic quality or business performance (Vaughan & Yang, 2013).

**Table 2. Web Traffic Performance Indicators**

| Variables | Description |
|---|---|
| Visits | Number of sessions or visits |
| Users | Number of users |
| Pages viewed | Number of pages viewed in the website. |
| Depth of visit | Pages viewed/number of sessions: a measure of the quality of a visit. A large number of pages viewed reveal visitors interact in depth with the website. |
| Average duration of session | Average duration of session by site users. |
| % rebound rate | Rebound percent: the percentage of visits that arrive at a site and leave it without moving to other subpages. |
| % new sessions | % new sessions |
| Paid searches | Number of sessions per page search |
| Organic search- Search engines | Number of sessions per organic search (search engine): key words point to the type of information visitors are looking for. |

| | |
|---|---|
| Direct traffic (source of traffic) | Number of sessions per search – direct visit: visits by persons that click in known bookmark; number of visits by persons clicking a known bookmark as favorites. These are webpages stored in our browser or directly linked by writing the webpage's URL or use it as a home page. |
| Referred visits | Number of sessions per referred visits (links from other pages): Visits of persons clicking a webpage link through another website. |
| Display | Number of sessions per display (advertisement). |
| Email | Number of sessions coming from an email |
| Social media | Number of sessions from social media. |
| New visits | New visits: a large number of new visitors points to a high visitor enrollment. |
| Returning visits | Returning visits: a high number of returning visitors points to the website's relevance for and interest by visitors. |
| Single visitors | Estimated number of persons visiting a site. |

Prepared by the authors.

# Research methodology

## Research design

This research was designed following a non-experimental longitudinal approach using regression analysis for temporary data in an ARMA (Auto-Regressive Moving Average) time series model. Data were used without deliberately manipulating the variables, and phenomena were observed in their natural environment before their analysis.

A **non-experimental longitudinal research** is based on studies gathering data at various points in time to infer their evolution pattern, and cause and effect relations. For purposes of the study, a trend design was used to analyze changes over time (in categories, concepts, variables and their mutual relations), for a given segment of the general population. As the study focuses on a segment of the population, such changes seem peculiarly relevant (Sampieri, Fernández, & Baptista, 2013).

The purpose of this study is to analyze changes in web traffic sources, when visitors try to choose a graduate studies' program. The choice of traffic sources is measured daily. For purposes of this research, the relevant period was from May 2013 to May 2015. This provides an appropriate time frame for examining the traffic sources' evolution.

The study aimed at examining and measuring the entire visitor population. However, samples were taken to observe and measure certain variables and their mutual relations.

It is important to mention the study's participants did not remain unchanged over time, although the population at large does. Website visitors from the graduate program change, although there is a stable population of new enrollees become potential visitors as they join the graduate business school's student body.

## Sampling and variables

To delimit the research sample we must first determine the analysis unit and the population. The analysis unit will be the number of visits to the business school's website. The population has been identified as the number of visits to the school's graduate program website during a given period.

The sample under analysis is the number of visits made to the graduate program's website from 2013-2015. The purpose is to determine the main sources of traffic (paid and not paid) creating greater page traffic, and their quality. Google Analytics was used to create a database comprised of 4106 observations.

**Table 3. Main variables statistics**

| Indicators | Page views | Aver. page views x visit | Average session durationseconds | Average Bounce Rate | New visits | Returning visits | Bound visits | Average new visits | Average returning visits |
|---|---|---|---|---|---|---|---|---|---|
| Average | 1591 | 2,02 | 125 | 58% | 446 | 407 | 543 | 50% | 50% |
| Median | 1326 | 2,04 | 127 | 57% | 299 | 329 | 391 | 49% | 51% |
| Minimum | 214 | 1,47 | 55 | 34% | 48 | 42 | 43 | 39% | 32% |
| Maximum | 4106 | 2,82 | 205 | 78% | 1835 | 1073 | 1959 | 68% | 61% |

Source: Google Analytics
Prepared by the authors

Our research focuses on a specific graduate program, the Marketing Master's Degree, as the program where most of the indicators examined in this research can be identified. The variables under analysis all correspond to the same period and therefore allow a better understanding of the users' online behavior and determining the sources of traffic and their relationships.

**Table 4. Relationship between website performance variables**

| Variable | Definition | Relationship |
|---|---|---|
| Average pages viewed per visit | Average number of pages viewed by a group of visitors during a visitor session. The indicator is number of page views/ number of total visits | This variable relates to the visit's depths. It measures the visit quality, as a large number of page views reveal visitors engage in extensive interactions with the websites. |
| Sessions and visits | Total number of sessions or visits to a website. A visitor may access a website, leave it and come back. This is counted as two visits | |
| Page views | Number of pages seen by visitors during their website visits. | This variable is related to the webpage's efficiency. |
| New visits | Number of visitors who had never visited the website and visit it only once in a given period of time. | A large number of new visitors points to a high visitor enrollment. |
| Recurrent visits | Number of visits returning to the website. | This variable related to the visitors' loyalty and the website's retention efficiency. It reveals the website content is relevant and attractive to visitors. |
| Direct visits (direct traffic) | Number of visits per direct search. This is a visit for individuals that have directly written the URL or clicked a bookmark. | Variable related to the website page awareness's efficacy. The target audience is made more aware of the web page. |

| | | | |
|---|---|---|---|
| Referred visits | E-mail referrals (e-mail) | Number of visits from e-mails including communication by e-mail which provides an alternative way to contact in a less invasive manner. This is regarded as a less intrusive delayed communication option. | |
| | Paid social media referrals | Number of visits from paid social media. | |
| | Organic social media referrals | Number of visits from organic social media. | |
| | Website referred visit | Number of visits from individuals from a homepage | |
| | Referrals (not social media) | Number of sessions from referred visits (links to other pages other than social media) | |
| | Display referrals | Number of visits per Display (advertisement) | |
| Search engines | Paid Search | Number of visits per paid search | |
| | Organic Search (Organic search-Search engine) | Number of visits per organic search where key words point to the information visitors look for. | Variable related to website performance. The greater number of visitors to a website using a search engine, the more popular will the website be. |

Prepared by the authors

## Techniques and procedures

Taking as a basis the prior studies' techniques and procedures (Plaza, 2009) (Budd, 2012), and since the model aims at examining how much variables change as a response to changes in other variables, this study will adopt a time data regression analysis approach. The prognosis and analysis of model mistakes and the data volatility uses an ARMA type (Auto-Regressive Moving Average) times series model for multiple regression. The **Auto-Regressive Moving Average ARMA (p, q)** process is a natural extension of auto-regressive models **AR(p)** and moving averages **MA(q)** (Pérez, 2012). This is represented by the following equation:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + .. + \varphi_p Y_{t-p} + u_t - v_1 u_{t-1} - v_2 u_{t-2} - \ldots - v_q u_{t-q},$$

Which can also be written as:

$$Y_t - \varphi_1 Y_{t-1} - \varphi_2 Y_{t-2} - .. - \varphi_p Y_{t-p} = u_t - v_1 u_{t-1} - v_2 u_{t-2} - .. - v_q u_{t-q}, \text{ or:}$$

$$\left(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p\right) Y_t = \left(1 - v_1 B - v_2 B^2 - .. - v_q B^q\right) u_t.$$

Consequently, the ARMA process is stationary if the auto-regressive component also is stationary, and invertible if its moving average component is as well. Consequently, an ARMA (p, q) model is invertible if the B polinomy roots defined by $1 - v_1 B - v_2 B^2 - \cdots - v_q B^q$ falls outside the unit circle. This condition is equivalent to the $y^q - v_1 y^{q-1} - v_2 y^{q-2} - \cdots v_{q-1} y - v_q = 0$ equation's roots being all below 1 in the module. Likewise, ARMA (p, q) is stationary if the roots of the polinomy defined by $1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$ fall outside the unit circle. This condition is equivalent to the roots of the: $y^p - \varphi_1 y^{p-1} - \varphi_2 y^{p-2} - \cdots - \varphi_{p-1} y - \varphi_p = 0$ equation falling all below one in the module.

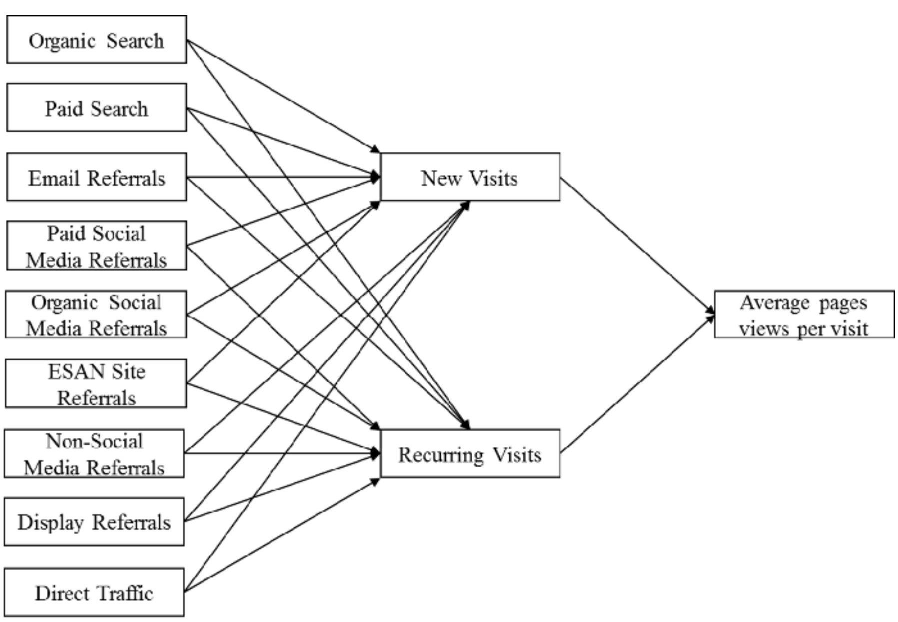
Various authors have already used the above models in web traffic research, including Plaza (2011) who measured a tourism web site performance and Budd (2013) who applied these models to measure website performance for social media and examine the efficiency of traffic sources.

The methodological procedure is comprised of the following steps: (1) The data to be used must meet the norm. (2) The data must be stationary. Compliance with these requirements will allow to use the data for the temporary data regression model. (3) A regression analysis is used. The ARMA model is used for better error modeling and create the most significant variables to explain the elements under assessment. (4) The following model validation tests were used: Breusch Godfrey Autocorrelation Test, White Heteroscedastikity Test and Jarque-Bera Normality Test. This last is validated if the model is right for using its outcomes.

# Analysis Model

A web traffic performance general model is proposed examine traffic sources of the website at a Latin American business school's graduate program, with a focus on traffic and quality of visits. We analyze the visitors' behavior sent from traffic sources captured using Google Analytics' organic searches, paid searches, referrals from paid social media, referrals from organic social media, referrals from business schools' sites, referrals not from social media, direct traffic, email and display.

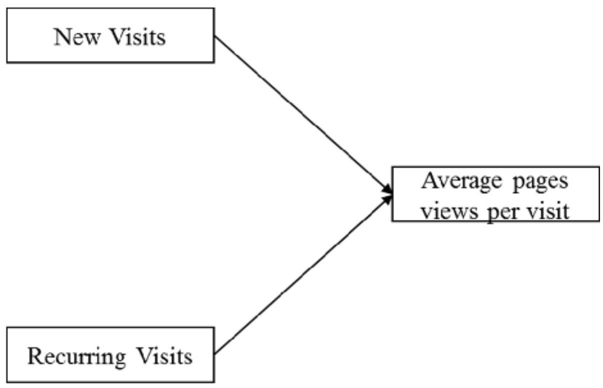
**Figure 1. Web Traffic Performance General Model**




Prepared by the authors.

Subsequently, the general model was split into two submodels, i.e., the in-depth model to confirm which types of visits determine the optimum performance model, and the new visits traffic model, to determine which sources of traffic are more significant in the optimum model.

**Figure 2. Web traffic performance model – In depth**




Prepared by the authors.

Plaza (Plaza, 2009) found the number of pages per arrival grew more in each recurring visit, while new visits have no impact. Therefore, recurring visits are the main engine to extend session length.

Additionally, another study (Budd, 2012) mentions recurring visits are a measure of retention increasing the number of times a page is viewed, compared to new visits.

However, in the academic environment, new visitors to a website require from the onset a more careful review of pages, to draw more information. The following hypotheses are suggested:

***H1:*** *"The effect of* ***New Visits*** *is the main engine to increase the average number of pages viewed per visit".*

Although previous studies focus on recurring visits (Plaza, 2009) (Budd, 2012), their authors did not directly examine new visits. However, they mention there may be a dependency relationship through their direct relation with traffic sources under study, such as direct traffic, referrals and searches. For that reason, to confirm the new visits model, the hypothesis compares the main traffic sources mentioned in the literature.

***H2:*** *"****Display Referral visits*** *are more effective than* ***Direct Traffic*** *in creating new visits to the graduate program's website".*

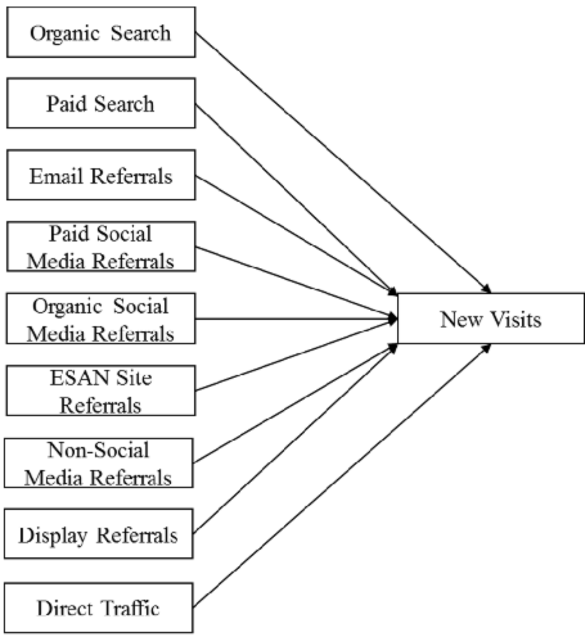
***H3:*** *"****Paid social media referral visits*** *are more effective than* ***Direct Traffic*** *in creating new visits to the graduate program's website".*

***H4:*** *"****Display Referral*** *visits are more effective than* ***Paid Search*** *in creating new visits to the graduate program's website".*

***H5:*** *"**Paid Social Media Referral** visits are more effective than **Paid Search** in creating new visits to the graduate program's website".*

***H6:*** *"**Paid Search** are more effective than **Direct Traffic** in creating new visits to the graduate program's website".*

**Figure 3. Web Traffic Performance Model – New visits**

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# Findings

Results from our study show the data meet the Normality and Stationarity Tests. This section focuses principally on the in-depth and new visits model, within the proposed hypotheses.

## Web traffic performance model – In Depth

The first model measures changes in new visits and recurring visits to the website and their impact on the average number of paid views per visit (depth).

MA and AR roots were 0.89 and 0.58 (below 1) and point to a stationary ARMA model. This process is reversible and thereby it points to the need for further research. New visits and recurring visits have significant impacts on the average number of pages per visit, with the highest impact from returning visits (absolute value of the beta coefficient =0.44 higher than the 0.27 value for new visits). In both types of visits, the average page views per visit falls below 2.34, and, consequently, recurring visits serve less pages on average. Consequently, recurring visits are less deep than new visits.

| Variable | Coefficient | Coefficient Beta | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|---|
| C | 2.3415 | | 0.0870 | 26.9098 | 0.0000 |
| NUEVAS_VISITAS | -0.0002 | -0.2768 | 0.0001 | -2.1010 | 0.0393 |
| VISITAS_RECURRENTES | -0.0005 | -0.4444 | 0.0002 | -2.8679 | 0.0055 |
| AR(1) | 0.8946 | | 0.1002 | 8.9319 | 0.0000 |
| MA(1) | -0.5836 | | 0.1689 | -3.4547 | 0.0009 |

| | | | |
|---|---|---|---|
| R-squared | 0.744344 | Mean dependent var | 2.017886 |
| Adjusted R-squared | 0.729523 | S.D. dependent var | 0.286418 |
| S.E. of regression | 0.148959 | Akaike info criterion | -0.905117 |
| Sum squared resid | 1.531022 | Schwarz criterion | -0.749437 |
| Log likelihood | 38.48934 | Hannan-Quinn criter. | -0.843015 |
| F-statistic | 50.22336 | Durbin-Watson stat | 1.907664 |
| Prob(F-statistic) | 0 | | |

| | |
|---|---|
| Inverted AR Roots | 0.89 |
| Inverted MA Roots | 0.58 |

| | | | | |
|---|---|---|---|---|
| Breusch-Godfrey Serial Correlation LM Test | F-statistic | 0.020987 | Prob. F(1,68) | 0.8852 |
| White heterocedasticiy Test | F-statistic | 0.445046 | Prob. F(20,53) | 0.9754 |
| Jarque bera Test | | 29.71058 | Probability | 0 |

Source: Eviews 8
Prepared by the authors.

The model adjusted for errors using an ARMA (1, 1) model. The adjusted determination coefficient for the model showed it explains 73% of data variability.

Breusch Godfrey's test demonstrates the null hypothesis shows no residues' serial auto-correlation and likelihood above 0.05. As a consequence, the hypothesis is accepted. White's test shows the null hypothesis of homoscedasticity in residues has a likelihood greater than 0.05 and therefore the null hypothesis is also accepted, pointing to homoscedastic residues. Jarque-Bera's test demonstrates the null hypothesis's normality of residues has a probability under 0.05. Therefore, the null hypothesis is rejected as no normality in the residues can be demonstrated. The above confirm the hypothesis **H1:** "The effect of **New Visits** is the main engine to increase the average number of pages viewed per visit".

## Web traffic performance model – New visits

The following regression demonstrates the impact of traffic sources to create large number of new visits. Paid social media have the greatest impact on this type of visits. Display and direct traffic come next and Paid Search create the least impacts.

| Variable | Coefficient | Coefficient Bet | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|---|
| PAID_SEARCH | -0.506 | -0.108 | 0.238 | -2.124 | 0.038 |
| REFERIDOS REDES SOCIALES PAGADAS | 0.877 | 0.687 | 0.058 | 15.209 | 0.000 |
| REFERIDOS DISPLAY | 1.004 | 0.217 | 0.203 | 4.951 | 0.000 |
| TRAFICO DIRECTO | 2.150 | 0.195 | 0.369 | 5.830 | 0.000 |
| DUMMY_11_14 | 712.161 | | 55.678 | 12.791 | 0.000 |
| DUMMY_16_14 | 526.364 | | 77.156 | 6.822 | 0.000 |
| DUMMY_17_14 | 500.755 | | 76.742 | 6.525 | 0.000 |
| AR(1) | 0.787 | | 0.104 | 7.578 | 0.000 |
| MA(2) | -0.549 | | 0.141 | -3.888 | 0.000 |
| R-squared | 0.960472 | | Mean dependent var | | 450.3562 |
| Adjusted R-squared | 0.955531 | | S.D. dependent var | | 344.7755 |
| S.E. of regression | 72.70515 | | Akaike info criterion | | 11.5257 |
| Sum squared resid | 338306.5 | | Schwarz criterion | | 11.80809 |
| Log likelihood | -411.6881 | | Hannan-Quinn criter. | | 11.63824 |
| Durbin-Watson stat | 1.852178 | | | | |
| Inverted AR Roots | 0.79 | | | | |
| Inverted MA Roots | 0.74 | -0.74 | | | |
| Breusch-Godfrey Serial Correlation LM Test | | F-statistic | 0.7689 | Prob. F(1,63) | 0.3839 |
| White heterocedasticiy Test | | F-statistic | 2.3054 | Prob. F(45,27) | 0.0116 |
| Jarque bera Test | | | 34.4290 | | 0.0000 |

Source: Eviews 8
Prepared by the authors.

AR and MA inverted roots are lower than one and allow to interpret our findings. Paid social media sources, displays and direct traffic have positive effects on new visits. However, paid searches have a negative effect, which may harm new visits. In addition, an ARMA (1, 2) model was used to study residues including dummy variables to control for outliers in weeks 11, 16 and 17 of year 2014.

The Breusch Godfrey test, which demonstrates in its null hypothesis that there is no serial auto-correlation between the residues with probability greater than 0.05 confirms the hypothesis and therefore no autocorrelation exists. White’s test which proves in the null hypothesis the homoscedasticity of residues with a probability under 0.05 rejects the null hypothesis and consequently, residues are found to be heteroscedastic. Jarque-Bera’s test which proves in the null hypothesis the normality of residues with a probability under 0.05, rejects the null hypothesis and therefore shows the absence of normality in residues. Consequently, the results from **H2, H3, H4** and **H5** are supported while only **H6** is rejected.

# Discussion

This research has contributed to identify the main sources of traffic for a website, with the endpoint goal of attracting new quality visits. An examination of how new visits are generated shows a priority must be placed on using social media, direct traffic and displays. Paid social media create poor quality traffic and must therefore be avoided when looking for quality and preventing rebound visits.

The main research constraints are the lack of broken rebound information for key performance indicators for each traffic source and that traffic is only analyzed for a single university, which advises caution in generalizing findings. The importance of this research lies in its ability to determine the performance of traffic sources by enforcing a proven methodology for accomplishing its findings.

Likewise, our analysis focused on a specific graduate program. A future research agenda should replicate this experiment with other graduate programs' websites and by comparing results from various studies provide a more accurate understanding of the efficacy of various traffic sources. Academic organizations could then use web analyses of this type to reshape their strategies and improve their websites' performance and effectiveness.

In addition, drawing on this study's findings, subsequent surveys could explore the type of connectivity used for the visits as a mediating variable for visits per page and expand the impact of web traffic performance to include the analysis of businesses' performance.

## Conclusions

Our research shows that between 2013 and 2015, recurring visits had a lower impact on the depth of visits to a graduate program's page reflecting the fact that recurring visitors' behavior is mainly driven by the search of specific information during their visit without engaging in further exploration. However, the objective of a website is to attract new users (new visits) to get them familiarized with the site and thereby deepen the visit, and incite them to return. This would show the visited page has met the users' expectations.

During the period of research focusing on the graduate program's website it became clear that increasing new visits' traffic (number of users that visit the page for the first time) should prioritize the use of referred visits, such as paid social media and displays, because of their positive impact on new visits, followed by direct traffic. The opposite is true of paid searches.

Findings also confirm the hypothesized users' online behavior, as they increasingly visit social media when searching for topics of their interest and then pay a first visit to the pointed website page. This is a good indicator of how promoting the website can attract new visitors. A similar phenomenon takes place although to a lower degree, with displays (online advertisements) users see and eventually lead them to visit the website (Vélez & Pagán, 2011).

As a consequence, display is regarded as a more effective source than direct traffic because online advertisements are likely more easily seen during users' sessions. They typically grab the users' attention and lead them to visit the website. A display campaign increases the potential for visibility. These displays appear in many websites and are more effective than direct traffic-prompted visits which happen only when visitors arrive at a website by directly typing a URL, which requires prior familiarity with the graduate program's website. It is noteworthy that our analysis showed paid searches should be avoided, as this traffic source does not create new visits.

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