Czech University of Life Sciences Prague

Faculty of Economics and Management

Department of Information Technologies

Diploma Thesis

Web analytics tools (Google Analytics)

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Faculty of Economics and Management

DIPLOMA THESIS ASSIGNMENT

Daniel Novák

Economics and Management

Thesis title

Web analytics tools (Google Analytics)

Objectives of thesis

The main objective of diploma thesis is devoted to detailed description of the use of Multi-Channel Funnels.
The partial goals of the thesis are:
- Analysis of related issues of Multi-Channel Funnels
- Application of Multi-Channel Funnels within Google Analytics
- Verification of theoretical knowledge in a practical project using Google Analytics and proposal of further recommendations based on Multi-Channel Funnels reports

Methodology

Methodology of the thesis is based on study of literature and analysis of specialized information resources. In practical part of the thesis, a case study of using Multi-Channel Funnels within Google Analytics is demonstrated.

The proposed extent of the thesis

60-80 pages

Keywords

Google Analytics, Multi-Channel Funnels, attribution models, assisted conversions, conversion paths, online marketing, data-driven attribution

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Recommended information sources

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Declaration

I declare that I have worked on my diploma thesis titled "Web analytics tools (Google Analytics)" by myself and I have used only the sources mentioned at the end of the thesis. As the author of the diploma thesis, I declare that the thesis does not break copyrights of any their person.

In Prague on 30 March 2016 ______________________________

Acknowledgement

I would like to thank Ing. Alexandr Vasilenko and all other persons, for their advice and support during my work on this thesis. Special acknowledgement belongs to my family for their patience during my studies.

Webové analytické nástroje (Google Analytics)

Souhrn

Tato diplomová práce je zaměřena na webový analytický nástroj Google Analytics a zhodnocení využití vícekanálových cest a atribučních modelů na konkrétním příkladu v sektoru finančních služeb nebankovního poskytovatele půjček.

Autor se v literární rešerši věnuje důležitým pojmům z oblasti webové analytiky. Zaměřuje se také na způsob sledování digitálních kampaní. Je vysvětlena řada klíčových metrik a jak s nimi pracovat. Autor také poukazuje na případy, při kterých mohou webové analytické nástroje zkreslovat data. Autor pokrývá klíčovou oblast vyhodnocování dat za pomocí vícekanálové atribuce a popisuje atribuční modely používané v Google Analytics.

V praktické části práce se autor zaměřuje na ověření teoretických znalostí a využití vícekanálové atribuce v Google Analytics. Praktická část se skládá z případové studie, v níž autor využívá Google Analytics, aby vyhodnotil konkrétní kampaň na základě vícekanálových cest, atribučních modelů.

Vzhledem ke studijnímu zaměření autora je v praktické části navrženo doporučení k efektivní alokaci investic do marketingových kanálů na základě indikátorů výkonnosti kampaně.

Klíčová slova: Google Analytics, vícekanálové cesty, atribuční modely, konverze, webová analytika, atribuce, konverzní cíle

Web analytics tools (Google Analytics)

Summary

The focus of the diploma thesis is on the web analytics tool of Google Analytics and its Multi-Channel Funnels as well as Attribution to evaluate its use in a specific example within the financial services sector of non-banking lenders.

In the literature part the author describes the core concepts of web analytics. The literature part also underlines the method of tracking digital campaigns. The author explains the concept of key metrics and how to work with them. The literature part of the thesis also points out the cases in which the analytics tool can distort the data. The author extensively covers Multi–Channel Funnels and the Attribution Models used in Google Analytics.

In the practical part of the thesis the author focuses on the verification of theoretical knowledge. The practical part consists of the case study in which the author uses Google Analytics to examine functionality and evaluates a specific campaign based on multi-channel attribution.

Due to the author's field of study, Multi–Channel Funnels and the Attribution Models described in the theoretical part of the thesis are used in the case study to provide insights into the individual channels and how to relocate investments in more effective marketing channels.

Keywords: Google Analytics, Multi–Channel Funnels, Attribution Models, Conversions, Web Analytics, Attribution, Conversion Goal

Table of Content

1 Introduction

The Internet has changed the overall competitive environment for business. To remain competitive in the online world means to apply a completely new approach to marketing and to learn to work daily with data from the Internet. Such an approach should focus strategy and decision making based on data.

Online shopping is also very specific and different from traditional shopping in stores. Online shoppers can easily compare different online retailers. Customers also gain the advantage of the online environment for finding reviews from other customers in terms of the quality of the goods, without having to rely solely on a website description. In addition, customers can search, sort, filter parameters of products, look for sales and browse the history of marketing events.

For these reasons, the role of a website is remarkable, no matter whether referring to an e-shop, a news website or just a corporate website. Online shoppers generate so much data from their visitor/user behaviour that it is worth analysing these.

Not only is the Internet seen as a platform for the realisation of business, it is a very suitable tool for communication and promotion geared towards potential customers interested in the company's services or products. In order to conduct these activities as efficiently as possible and with the knowledge of customer behaviour, we can use digital analytics (Kaushik, 2007).

Kaushik (2007) also points out that digital analytics allow commercial and marketing activities to be targeted as well as the objectives of the company in the Internet environment. It also provides a company with information needed for optimising and shaping online strategies. Moreover, digital analytics focus on the behaviour of the users of a selected website and monitor the functioning of a site in order to support pre-defined commercial goals and needs.

Internet users have many ways of comparing the quality of goods. With the credibility and reliability of the e-shop, they can visit many websites and repeatedly return to a company's website through various online channels. A simple example might be as follows: a customer who initially comes to our e-shop from a commodity catalogue such as Zbozi.cz, then returns via a Facebook post, and eventually clicks through back to our site through PPC advertising.

It is logical to be able to quantify the praiseworthiness of each channel in relation to the costs of advertising for each marketing channel.

This thesis on web analytics tools focuses on the Google Analytics tool and a detailed description of the use of Multi-Channel Funnels.

The author considers the main contribution of the diploma thesis, as the fact that it is not written from the perspective of a web developer attempting to gather more data, but from the perspective of a web analyst attempting to deal with information that enables the use of Google Analytics to extract real business value.

2 Objectives and Methodology

2.1 Objectives

The main objective of the diploma thesis is a detailed description of the use of Multi-Channel Funnels.

The partial goals of the thesis are:

- Analysis of related issues of Multi-Channel Funnels
- Application of Multi-Channel Funnels in Google Analytics
- Verification of theoretical knowledge in a practical project using Google Analytics and proposals for further recommendations

2.2 Methodology

The theoretical part focuses on a study of the literature and the analysis of specialised information resources. It introduces the area of web analytics and explains the most frequently used analytical concepts. The literature part of the thesis covers an important method of campaign tracking. In the theoretical part, the author further points out related isuues, such as the limitations of web analytics tools. The theoretical part also introduces Multi-Channel Funnels, as well as the Atribution Models used in Google Analytics.

The practical part focuses on the usage of the Google Analytics tool and how this web analytical tool can handle the theoretical basis in a practical project. Based on the case study, the author introduces different kinds of attributions and demonstrates the application of Multi-Channel Funnels to selected data. The subsequent goals of the practical part are to comprehensibly interpret the data collected using Google Analytics from the business point of view and to propose further recommendations in terms of advertising budget allocation to more effective channels.

The research method of the diploma thesis is based on retrospective data analysis using Google Analytics and campaign performance indicators such as Return on Advertising Spend (ROAS) and Cost per Acquisition (CPA).

It is necessary to mention that for the discretion of the data of the relevant company, the author cannot present more details of the company’s business or data in any other way than that described in this thesis.

3 Literature Review

Web analytics has its historical roots in the early days of web pages. Initial implementation of measurement have developed from simple hit counters to advanced technologies in order to track customer behaviour in digital environments as well as to facilitate the decision making process.

The initial measurement process consists of recording into a log file. Each time a certain HTML element is requested by a visitor, it is called a hit. A hit might be consisted of a text on a webpage, an image, sound or video file. In addition, when a page receives a hit by a visitor, it is taken for granted by a web server, that a visitor is interested in the entire contents of a page (ClickTale, 2010).

The literature shows consensus that it is a simple way of tracking visitor activity on one's website, but for a time, it possible for webmasters to control how many visitors visit their websites. Eventually, the information gathered through hit counters are assembled and displayed in a dedicated page that shows hit and visit statistics for a website for a given period of time. Hit and visit counts eventually become just part of the overall statistics (Dems, Scudder, 2010).

Gasson (2000) reports that in 1995, the first web analytic tool was released in the form of freeware. It was called Analog. This open-source program analysed log files from web servers, creating thirty-two different reports.

Over the past years more advanced websites have been created. On the logical ground, there were more specific questions asked of how many pages are viewed by a visitor which channels lead visitors to a website, or if a single page comprises of three images, that compiles of four hits for that particular page, but really only one page view.

Currently, it is important to pursue other metrics. Tracking visitor activity on one’s website is a source of economic benefit or other targets of websites. Hits are less significant in current multimedia web (YU HUI, 2008).

YU HUI (2008) also points out that marketers and web analyst started to be more interested in one individual person that interacts with a website. The amount of content that was served up received less priority resulting in greater awareness and arrival of new metrics.

ClickTale.com (2010) also reports that in 1997 webpages began to include other elements beside text such as images. With the help of advanced technologies transferred to the client side instead of measurements on a server side that simplified and accelerated the development of web analytics. JavaScript tagging grew to be used as a new method of data collection. It eliminated the necessity to install and set up a measuring tool on a server as well as on a website. It was sufficient to insert a JavaScript code into the source code of a web page. It helped to precise reports on manifold web traffic and trends.

Moreover, YU HUI (2008) adds that it is more important to understand site activity rather than mere reach. YU HUI demonstrates how marketers demanded more insights. He sees a parallel through a television show that could have 100,000 viewers, but what marketers really want to know is whether those viewers watched the advertisements.

This request to understand site activity rather than mere reach pushed web analytics forward into a stage that made it more useful and relevant.

Another advancement for the popularization of web analytics occurred in March 2005 when Google Inc. bought Urchin Software Corporation. Google subsequently renamed it as Google Analytics. Google offered their web analytic tool free of charge. However, to use Google Analytics, one has to register and accept the general terms of use (Krutiš, 2005).

Over the years, the literature resources have offered all kinds of views on the web analytics industry. Some authors claim that web analytics have an identity crisis (Cutroni, 2011). For this reason, the author focuses on understanding analytics industry in the next chapter.

3.1 Analytics Industry from Today's Perspective

Today's world changes rapidly, some methods that could be used yesterday, are no longer valid today. Currently, there are so many data from analytic tools as never before. We no longer have to rely solely on one's intuition or mediated experience. There is a greater opportunity to support decision-making process due to growing analytics industry.

Renowned analytics specialist Stephen Hamel (2011) claims that it is important to recognize how web analytics is defined. Hamel infers that even the subject matter authority, the Web Analytics Association (WAA), uses a definition of analytics from another era

"*Web Analytics is the measurement, collection, analysis and reporting of Internet data for the purposes of understanding and optimizing Web usage."*

Hamel asks himself in relation WAA's definition what it means to "measure" vs. "collecting data" or why it is in the definition "reporting" after "analysis". According to Hamel, the position of an analyst is to extract data in order to comprehend a business context, understand the constraints the useful outcomes, and provide realistic solutions to the business. Therefore, Hamel puts forward the view that the definition should be as follows (Hamel, 2011):

"Analytics is the process of obtaining an optimal and realistic decision based on existing data."

Kaushik (2007) introduces his own definition of Web Analytics 2.0 as:
"The analysis of qualitative and quantitative data from your website and the competition to drive a continual improvement of the online experience that our customers, and potential customers have, which translates into desired outcomes (online and offline)."

Cutroni (2010) agrees and acknowledges the Kaushik's definition encapsulates three main tasks that every business must make an effort when doing web analytics:

- Measuring quantitative and qualitative data
- Progressively improving a website
- Aligning a measurement strategy with a business strategy

Cutroni (2011) supports both definitions and also emphasizes that we no longer do web analytics. He points out that we deal with many different data sources. From social to mobile applications, the website is not our only source of data. Cutroni states that analytics industry nowadays works with digital data.

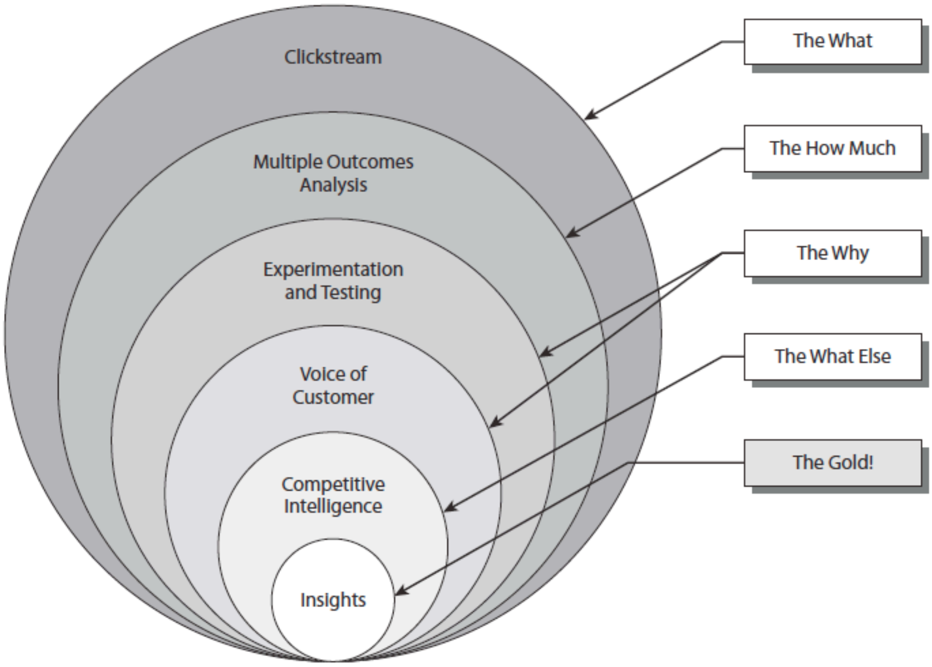
In addition, the author of this thesis suggests referring to the phrase "digital analytics" rather than "web analytics" where appropriate in this paper.

The basic meaning of digital analytics lies deep within these definitions. Digital analytics are designed to assist in a decision making process based on data about behaviour of a user on websites or applications. The purpose of using analytical tools is not only to obtain the data, but far more important is the ability to correctly understand the data and to apply the knowledge in a process of optimization measures. Digital analytics can also help to answer questions such as (Čech, 2010):

- How marketing channels (i.e., sources of traffic to one's website) work together to create sales and conversions
- What marketing channels have the best ration – ROI (return on investment)
- How easily visitors of a website pass through the purchase or other process

Kaushik (2010) goes far deeper in his previous definition of Web Analytics 2.0 to expand the questions that could be answered by rethinking what it meant to do digital analytics, which sources an analyst or marketer could access, and what tools would be put to use. His idea is well depicted on the following Figure 1.

Figure 1. The model of Web Analytic 2.0



Source: Kaushik, 2010

The model of Web Analytics 2.0 in the Figure 1 explains how each of these four important questions frames the source of elements of the Web Analytics 2.0 strategy.

Kaushik (2010) defines the four elements in this way:

- **The What:** Clickstream – in case of a digital analytics solution hosted externally or hosted by a vendor, The What means simply colleting and analysing the click-level data or so called a clickstream data. A clickstream represents a process of recording virtual trail that a user leaves behind while surfing the Internet. Click-level data is data obtained form free or commercial tools such as Google Analytics, Piwik as open source option to Google Analytics, Spring Metrics, Woopra, Clicky, Mint, Chartbeat, Kissmetrics, Crazy Egg, Open Web Analytics, Clictale, WebTrends, Omniture, Unica NetInsight, Yahoo! Web Analytics, SiteCatalyst, AT Internet analytics suite, CoreMetrics, Lyris HQ or other tools.

- **The How Much:** Multiple Outcomes Analysis – everything that is done on a website should be delivered against three outcomes:
    - Increase revenue
    - Reduce cost
    - Improve customer satisfaction/loyalty

  These outcomes connect customer behaviour to the bottom line of a company no matter of whether a website is designed for ecommerce, tech support, social media, or just general propaganda. In this case of element any click-stream tool already mentioned above plus iPerceptions (to measure task complete rate) or FeedBurner (to track subscribers), enterprise-planning systems, surveys can be used.

- **The Why:**
  Experimentation and Testing – testing a website can be improved based on customer feedback. In this case, tools such as Adobe Target, HP Optimost or SiteSpect can be considered and used to adjust strategy.

  Voice of customers – it is also part of the elements important to exploiting direct feedback from customers on a website or from a target customer base to understand external opinion and focus on customer centricity. Direct feedback can be obtained through surveys, lab usability testing, a remote usability testing or card sorting. Tools such as Ethnio, ForeSee or other can be employed.

- **The What Else:** Competitive Intelligence – Kaushik points out that it is important to see "outside the box" and compare against competitors. He claims that it helps to know how one is performing against their competition. He sees it as precious and thinks that it helps to improve and identify new opportunities.

Understanding today’s role of analytics industry is important not only from a technicall and economic point of view. Today, legal regulations of measurements of customers behaviour is important in order to avoid legal sanctions. In the next subchapter the author focuses legal regulations of measurement technology in the Czech Republic.

3.2 Legal Regulation of Cookies in the Czech Republic

The author considers that it is important to mention at least a basic legal framework under which on-going data collections take place. This sub-chapter may be interesting for website owners as well as digital analysts who work with the data on daily basis.

The term "cookies" in terms of the Internet indicates text files that a server places onto one’s computer while they are browsing the Internet. Cookies can than send information about user’s behaviour back to the server (Kartner et al, 2015).

The term “cookies” and how it is used the author defines more specifically in one of the following chapter.

Original intentions of cookies are to facilitate use of the Internet. Cookies can be used for supporting specific functions of a website to obtain information on user's behaviour and to record the items in one's shopping cart once selected, or for maintaining connection once a user is logged into some online service such as an e-mail account (Governor Technology, 2014).

Currently, cookies are used in great amount for so-called targeted or addressed advertising or marketing campaigns. The European Union (EU) is therefore concerned about negative impact of the use of cookies in terms of privacy of Internet users. Current legislation under the E-Privacy directive sees a consent of a website user in two modes (CHSH Kališ & Partners, 2015):

- **Opt-in mode** – a website user must actively give consent to the use of cookies of a particular website even before cookies are stored on a user's computer or other device
- **Opt-out mode** – some cookies can be stored on a user's computer even without prior consent of a user. Such cookies are mostly known as "session cookies" and are deleted once a user closes a browser

Kartner et al. (2015) also points out that no matter what cookies, a website owner has to fulfil his/her legal obligations to inform a user that cookies are used. Also, the user must be notified about what data is processed in relation to the use of cookies, to what extent and for what purpose, by whom the data is processed and above all, how can a user refuse to be part of the data processing. This information should be provided clearly and understandably eg. using some visual pop-up window.

Specialized legal sources recommend to website owners for using cookies in Opt-in mode to avoid unexpected impositions of a fine by the Office for Personal Data Protection (Kartner et al, 2015).

In the next chapter, the author of the thesis emphasizes on three terms without which it is impossible to circumvent in digital analytics. The following chapters and subchapters are useful for the practical part of the thesis.

3.3 Important Concepts of Digital Analytics

In this chapter, the author focuses on the three basic terms in digital analytics, which are then elaborated on in subchapters.

For proper orientation in digital analytics it is appropriate to clarify three basic terms without which it is almost impossible to understand other related topics in analytics tools and drill down into data to get some business value of using analytics tool. These terms are:

- Dimensions

- Segmentation
- Metrics

3.3.1 Dimensions

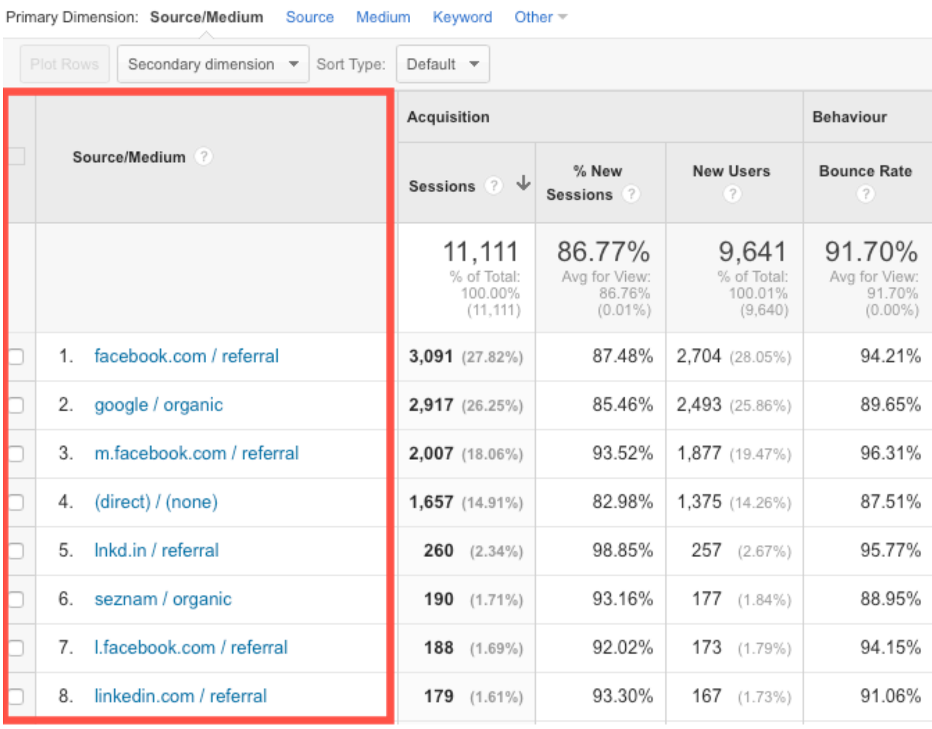
To internalize what dimensions are the author uses Kaushik's (2010) explanations and states that dimensions allow the grouping of data into different buckets. Dimensions are most frequently used to slice and dice the web analytics data.

Burby et al. (2007) defines Dimensions as general source of data that can be applied to define different types of segments, count and refers to a fundamental dimensions of visitors behaviour. There is general consensus on Kaushik's interpretation of Dimension. Burby et al. (2007) confirms that metrics are measured across the Dimensions.

Partially, metrics can be sliced into some of the most frequently used Dimensions (Brindzová, 2016):

- Source/medium
- User type (new vs. returning)
- Key word
- Landing page
- Gender
- Age

Figure 2. Example of Dimensions Source/Media in Google Analytics



Primary Dimension: **Source/Medium** Source Medium Keyword Other

Plot Rows | Secondary dimension | Sort Type: Default

Source/Medium	Acquisition			Behaviour
	Sessions	% New Sessions	New Users	Bounce Rate
	11,111 % of Total: 100.00% (11,111)	86.77% Avg for View: 86.76% (0.01%)	9,641 % of Total: 100.01% (9,640)	91.70% Avg for View: 91.70% (0.00%)
1. facebook.com / referral	3,091 (27.82%)	87.48%	2,704 (28.05%)	94.21%
2. google / organic	2,917 (26.25%)	85.46%	2,493 (25.86%)	89.65%
3. m.facebook.com / referral	2,007 (18.06%)	93.52%	1,877 (19.47%)	96.31%
4. (direct) / (none)	1,657 (14.91%)	82.98%	1,375 (14.26%)	87.51%
5. lnkd.in / referral	260 (2.34%)	98.85%	257 (2.67%)	95.77%
6. seznam / organic	190 (1.71%)	93.16%	177 (1.84%)	88.95%
7. l.facebook.com / referral	188 (1.69%)	92.02%	173 (1.79%)	94.15%
8. linkedin.com / referral	179 (1.61%)	93.30%	167 (1.73%)	91.06%

Source: Extracted from Google Analytics

3.3.2 Segmentation

Segmentation gives the opportunity to find out more about metrics and derive specific information that can have an impact on the business. Using information gained from segmentation, it is possible to make decisions that can more precisely captured reality.

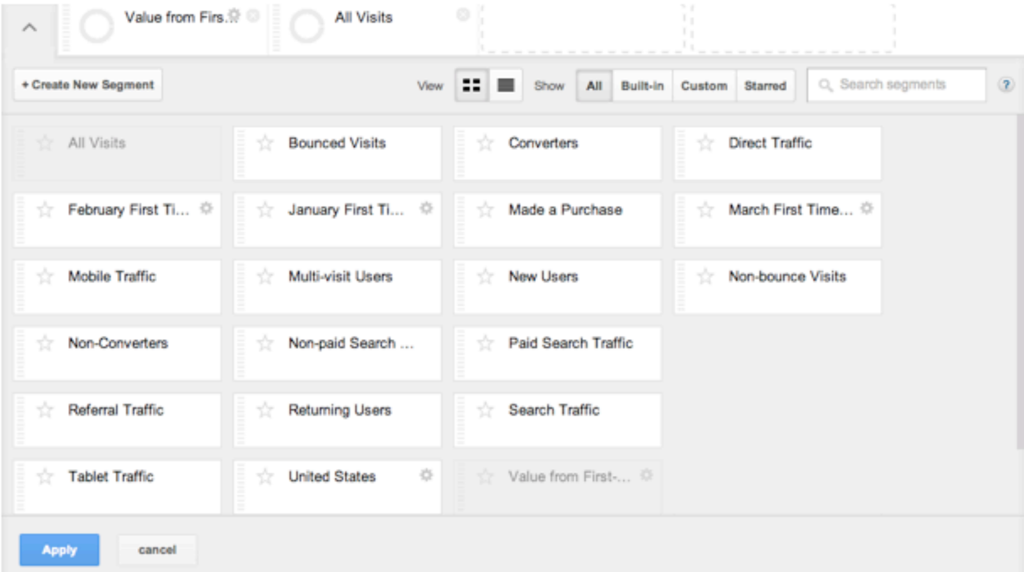
According to Kaushik (2010) segmentation is important part in analytics. There are different people (metric Visitors) coming to a website and each of them has various intentions, trying to solve different problems and looking for solutions.

Xu (2013) emphasizes that by using segmentation it is possible to investigate website audience and evaluate their behaviour based on specific attributes such as:

- Broad attributes – new vs. returning users

- Narrow attributes – users from particular form a particular geographical region who uses specific technology to interact with a website, goals some completed during a visit, revenue some generated during a visit or other cumulative behaviour within period of 90 days in terms of Google Analytics

Figure 3. Segmentation interface in Google Analytics



Source: Own processing

Cutroni (2013) adds that the ability to segment users more effectively is important and provides with three areas of segmentation:

- Simple Segments
- Advanced Segments
- Cohorts

Simple Segments

Generally, user segment provide all of the data connected to a user. It is possible to set up a condition to the user, the visits or hits. In case of the user segment, it is possible to see a user segment which generated 10 000 CZK in terms of revenue.

Or another segment can be applied in terms of revenue but from a visit perspective where there is a visit related segment of 10 000 CZK revenue per visit. Analytics then search for all visits that relate to specified criteria.

It is also possible to segment Pageviews or Events in similar way.

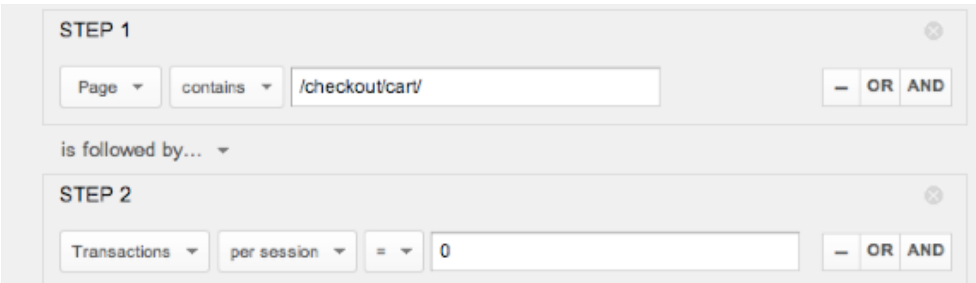
Advanced Segments

Advanced approaches to segmentation allow measuring the impact on long-term behaviour of a user. It is possible to set up segments including multiple visits conditions, multiple user conditions; combining both of the two is necessary to apply filters (Cutroni, 2013).

Other advanced feature that can be used in the Google Analytics segmentation tool is to create own sequence segments. In this case a sequence filters are applied.

Cutroni (2013) adds that Sequence segments provide an analyst with the information of how two actions, either simultaneous or separate, can impact behaviour. In the following Figure 4 there is an example of Filter Visit Sequences to find those who starts the checkout, but do not finish.

Figure 4. Filter Visit Sequences to find those who start the checkout, but do not finish



Source: Own processing

Cohorts

A cohort refers to a segment that consists of some predefined type of data condition. It is possible to set up a cohort that reflects user's first visit to a site but it is necessary to specify the period of time, or a single date, for the first visit (Cutroni, 2015).

Kaushik (2013) agrees and states that Cohorts are helpful when analysing groups of similar people in deeper context of the business.

Analytical tools, as well as Google Analytics, display the majority of metrics immediately on a home page after login. However, it is important to point out some metrics could be misunderstood by a user of an analytical tool because the analyst, or whoever tends to work with an analytical tool, looks in the metrics for some information which is not there. Therefore the next subchapter focuses on some of the metrics used and how to understand calculations behind those metrics.

3.3.3 Metrics

In order to continue, it is helpful to start of with basic clarifications (Kaushik, 2010):

"A metric is a quantitative measurement of statistics describing events or trends on a website"

" A key performance indicator (KPI) is a metric that helps to understand how you are doing against your objectives. KPI tends to be unique to each company"

The basic prerequisite for the right use and interpretation of data from a selected analytical tool is to clarify what each of the metrics means, where it comes from and what it tells us. Collectively, this area is referred to as the methodology of the selected tool. In order to use the selected analytical tool it is important to get acquainted with the methodology of chosen tool for several reasons (Tichy, 2014):

- To understand the presented numbers and to be able to interpret them.

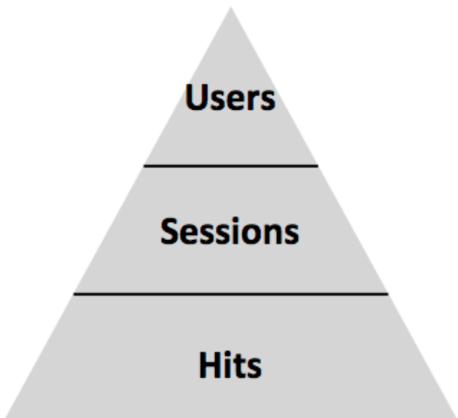
- To avoid wrong decisions based on misunderstanding of report from an analytical tool.
- To prevent incorrect comparing of numbers from various measuring tools.

For a better understanding of how metrics fit together and where they come from, the author provides some explanation from specialized literature sources. Relating to methodology, the author also focuses on explanations of selected metrics in terms of Google Analytics.

The goal of this subchapter is not to present all metrics that exist in the analytics industry.

According to Cutroni (2014) all digital analytics data is systematized into a general hierarchy of users, sessions and hits as shown in the following model.

Figure 5. Hierarchy of hits, sessions and users



Source: Cutroni, 2015

The Figure 5 above presents Cutroni's model of how we should acknowledge the way each piece of the model builds on the other:

- Hits
- Sessions
- Users

Pageviews (Hits)

A hit presents a small piece of data in an analytics tool. It is a way how most analytics tool transfer data to a collection server. Most hits represents actual request by a website or app for an invisible image file which is then transmitted to the data collection server. Most used hits in Google Analytics are represented by (Cutroni, 2014):

- **Pageviews** – this metric is automatically generated and measures a user viewing some part of content
- Events – measure how often a user interacts with a piece of content (clicking on a link, swiping a screen, clicking on a button). It must be manually implemented for measuring desired events
- Transactions - refers to the situation when a user completes an ecommerce transaction. Although it also needs to be implemented it provides additional information into analytics tool such as (ID, color, payment type and more)

It is important to summarize that metric **Pageviews** relates to the situation when every time someone on their web-browser display specific page on a website, in Google Analytics it is counted plus one pageview. The reload of the same page is also counted as plus one pageview. Pageview metric is measured and sent to Google Analytics once the website is loaded to a web-browser (Tichy, 2014).

Visits (Sessions)

According to Kaushik (2010), sessions are referred to as a collection of requests usually pageviews from someone who is on your website. In most analytic tools a session is a period of time of someone actively engaged with one's website, mobile app.

Cutroni (2014) adds that analytics tools, including Google Analytics, group hits together based on certain activity of a user. He carries on and explains that if a user is no longer active after thirty minutes and analytics tool detects the state of a user, it will terminate the session and start a new one as soon as the user is active again.

Cutroni (2014) also provides easy model of sessions.

Figure 6. How a session is measured

Source: Cutroni, 2015

Even though this process is technically called a Session in Google Analytics there is the metric named **Visits**.

Tichy (2014) further explains that the methodology of Google Analytics to determine the end of the visit and the start of another contains three conditions:

- Midnight
- Thirty minutes of the user inactivity – in this case the inactivity referrers to an interval between one pageview to another pageview. It is possible that a user can read an hour lasting article on the same website but because that user does not do any other hit during the period of thirty minutes the visit is declared as ended
- Arrival of the user from another source

Users

Kaushik (2010) emphasizes that the metric Users is simply an approximation of the number of people who come to a website.

Cutroni (2015) agrees and supports Kaushik's argument by saying that users are only labelled by web analytics tools using an anonymous string of characters or mostly use "cookies" as an identifier. A cookie represents a small text file and contains the anonymous identifier that is transferred with every hit done by a user from the website browser back to the analytics server identifier.

According to Jašek et al. (2015), the widely used types of web cookies are:

- First party cookies – cookies are set by the domain of the website that is viewed by a user. Google Analytics uses this type of cookies
- Third-party cookies – cookies are set by third parties, not the website on which a user is currently situated. These identifiers are usually set by advertising systems

Cutroni (2015) adds to Jasek's clarification by stating that third-party cookies can not only be set but also accessed by other domains than those that create it. He also stresses that the core of third-party cookies and their value is in the fact that analytics tools can identify a user as they go from one domain to another. However, he states that this type of the cookie is not permitted by most web-browsers.

Tichy (2014) also explains the weaknesses of such identification and reveals that if one person comes to a website from several computers, and does not login, than there is no simple way to recognize that particular user. Conversely, if ten people visit the website form one computer, there is no way to track them using any analytics tools. He concludes that in reality there are no real persons counting but browsers are measured.

Kaushik (2014) states, that it should not be forgotten that a cookie remains until it expires or in other case is deleted from a web browser.

Cutroni (2015) underlines Kaushik's view and stresses that a user from the perspective of analytics tools can be only understood as so called "*the best-quest of an anonymous person*".

Each type of digital business may require different metrics or performance indicators to measure. When deciding what metrics to use it depends entirely on the type of digital business so it is necessary to define own goals that help to measure the success of a website such as (Kaushik, 2010):

- Average Visit (Session) Duration
- Bounce rate
- Conversions
- Conversion rate
- Cost per acquisition (CPA)
- Return on advertising spend (ROAS)

Some of the metrics above are also calculated in the practical part of the thesis in relation to the case study.

Average Visit (Session) Duration

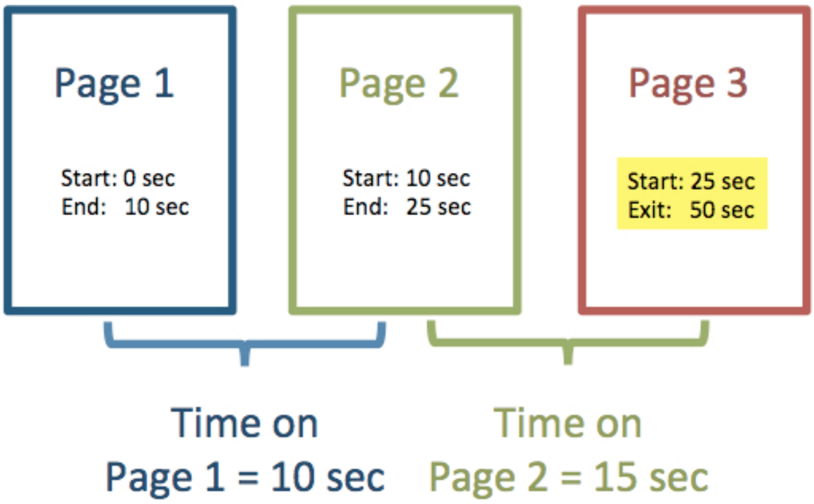
This metric is supposed to represent some basic behaviour of a user once on a website. However, the measurement of this includes some because in most cases this metric does not include time spent on the last page before the end of visit (Kaushik, 2008).

This metric is calculated as total duration of all sessions divide by number of sessions.

Tichy (2014) again points out the fact that not only Google Analytics does not measure and even does not know how long a user spent on an each page. What is measured is the moment when a page is loaded on a web-browser. Analytics tools know the interval (session) between in terms of one visit. So many analytics tools define in their methodology the average visit duration as a time interval between the first and the last hit. Tichy (2014) explains that in reality people might spend more time on particular website than Google Analytics reports.

The Figure 7 on the following page reveals how time on page is calculated. In this example Google Analytics measured 25 seconds in terms of time length a user spent on a website, although the length of the visit surely lasted longer. In reality there only a few people who click on the last page and immediately leave the website (Tichy, 2014).

Figure 7. Understanding Google Analytics Time Calculations



Source: Cutroni, 2012

Cutroni (2012) also adds that Google Analytics tends to use engagement hits such as ecommerce transactions or others on the exit page to get a more accurate measure of time.

Bounce Rate

Kaushik (2010) declares that the metric bounce rate presents the percentage of sessions on one's website with only one page view. He also adds that the bounce rate is measured in two ways (Kaushik, 2008):

- As the percentage of visitors on one's website who see just one page on that website
- As the percentage of visitors on one's website who stay on the website for a small amount of time

This metric also represents the fact that the visited website did not convinced visitors to any other action on our website. For most of the website it could mean bad results. However, Tichy (2014) explains that this approach is not valid for single page websites such as www.cajtydne.cz.

In case users leave immediately from a website, in other words the bounce rate is high on the website, it is worth analysing:

- Whether the website is sufficiently compelling or encourages visitors to visit other pages on the website
- It might be the case the a user has found all necessary information and therefore leaves because the rest of the website is not interesting
- Whether loading of pages does not take too long

The important part of understanding bounce rate metric is the possibility of the segmentation. It is appropriate to segment bounce rate for the following cases (Jasek, 2008):

- Bounce rate of landing pages – as there are more entering pages to a website, it is reasonable to look for the bounce rate on landing pages and if the metric is high then ask ourselves how to improve them
- Bounce rate of marketing campaigns
- Bounce rate of referrals – to know what sources send to our website qualified traffic

At this point, Tichy (2014) reminds the way the time length is measure on page. He carriers on stating that in terms of bounces the first and the last Pageview is the same, if there is only one pageview, Google Analytics counts the time length zero for bounces. This measurement flaw has negative effects on calculation of average visit duration because bounces are also included in calculation of all visits. Tichy concludes that in reality people spent even more time on websites than Google Analytics reports.

Conversions

In digital analytics terminology metric conversions is defined as reaching goals to fulfil the main objectives for which the website was created. Conversion measuring satisfies the main purpose of digital analytics. It does not necessarily mean confirming shopping cart in some e-shop (Tichy, 2014).

Conversion might as well be any user action that indicates that the user aims for some interaction with the website. Tichy (2014) posits that it could be any other following cases done by a user or others:

- Contact form is sent
- Subscription to the newsletter
- User registration
- User goes to contact page
- Vote in a poll
- Watching a video or reading some articles

In other words, conversion can mean a change from one state to another. Google Analytics in its default settings does not measure conversion. This metric needs to be set up manually and sometimes even have it implemented by a programmer.

Conversion rate

The important metric that the author mentions in this part is the conversion rate. It is widely used by marketing specialist to follow fulfilling of goals. The metric conversion rate relates to the percentage of visits to our website, which have converted (Tichy, 2014). To understand the metric conversion rate, the author provides following example:

If there were 1000 visits from which only 50 of them ordered form our online store, then the conversion rate is 5%.

*Conversion rate (%) = number of conversion / total number of all visits * 100*

Cost per Acquisition (CPA)

There exists several ways how to attract people to a website. It is reasonable to be able to track how each of acquisition sources perform.

To monitor performance of acquisition channels it is possible to calculate CPA metric that enables to optimize marketing spends (Wunderdata, 2014).

CPA can be calculated according to the following formula (Kaushik, 2011):

CPA = Channel spend / Number of conversions attributed to the channel

Although, Google Analytics allows importing cost data into the analytics tool, when calculating CPA some data might have to be collected and merged in Excel.

Return on Advertising Spend (ROAS)

Return on Advertising Spend stands for the amount of revenue a company gains for every Czech Koruna on marketing channel. This metric can be calculated in order to measure the effectiveness of online advertising campaigns (Moody, 2015).

ROAS can be calculated using the following formula:

ROAS = Conversion value of particular ad source / Cost of ad source

In case there is a spend of 1,000 CZK on branding campaigns such as AdWords in one month, and revenue of 5,000 CZK generated in the same month, then ROAS would be 5:1 or 500%. In other words there is the return on advertising spend of 5:1. It further explains that there is 5 CZK revenue for every Koruna spent on ad.

In case of the following case study the author calculates ROAS with as total profit of all conversions of the particular add source / total costs of the particular source. This is due to lack of some information regarding revenues of particular ad sources.

There are other key performance indicators that could be used for measuring and making smarter business decisions such as:

- Lifetime Value (LTV) – projected revenue that a customer generates during their entire relationship with a company

This thesis does not intend to cover all metrics that could be calculated. The reason is that in the practical part the author introduces a case study in which he could only work with limited data in terms of costs and revenues. Therefore, only some of those metrics mentioned above are used in the practical part.

3.4 Campaign Tracking

3.4.1 Link Tagging

One of the advantages of Internet marketing is that it allows tracking marketing campaigns to a fine level of details about digital marketing efforts. However, there are still owners of companies, e-shops, or other sites that do not use such features. One of the features is the possibility to track a reference source according to the UTM parameters. This technology can be also found in Google Analytics and is called link tagging.

Link tagging allows adding additional information to URLs that are used in digital adds. Link tagging also enables Google Analytics to gather data from marketing campaigns to support business decisions about marketing spend (Kaushik, 2010).

Tichy (2014) provides an example of link tagging with query string:
http://akademie.medio.cz/?utm_source=sklik&utm_medium=cpc&utm_content=medio-akademie&utm_campaign=brand

In the example above the technical name query string means adding the additional information to the URL used in an ad. In fact, everything after the question mark in URL above is called query string (Cutroni, 2006). Within the query string there are several parameters separated by an ampersand named UTM parameters. In the next subchapter the author suggests how to use UTM parameters.

3.4.2 UTM Parameters

Cutroni (2006) suggests that it is possible to divide each parameter into two parts:

- Variable – as seen in the Table 1.
- Value - as seen in the Table 1.

Table 1. UTM parameters - value pairs

Parameter	Variable	Value
utm_source=sklik	utm_source	sklik
utm_medium=cpc	utm_medium	cpc
utm_content=medio-akademie	utm_content	medio-akademie
utm_campaign=brand	utm_campaign	brand

Source: Own processing

Furthermore, Cutroni (2006) provides rules to the variables:

- **UTM_source** – helps to define the name of the website from which the links lead (i.e. Google, Adwords, Seznam.cz, Sklik, Facebok etc.). It is a compulsory variable used in link tagging.
- **UTM_medium** – is the way to define the method used to spread the message, how the message is delivered to the recipient (i.e. email, CPC, banner, , product, link, newsletter etc.). It is also a compulsory variable.
- **UTM_content** – helps to define the name of an add, it can be the next sublevel of ad group. It is not a compulsory variable but it is useful to specify it in order to measure marketing channels more precisely.
- **UTM_campaign** – is used to define the name of the campaign for all marketing activities. It can be useful to tag the campaign variable by date of the campaign. It is again a compulsory variable.

Tichy (2014) provides further overview of using link tagging in terms of source, medium and campaign:

Table 2. Examples of Link Tagging

	Variables		
Origin of a visit	**Source**	**Medium**	**Campaign**
AdWords	adwords	cpc	campaign_123
Sklik	sklik	cpc	campaign_123+add1
Facebook promo post	facebook	cpm	winter_tyres_04_2015
Facebook ads	facebook	cpc	winter_tyres_05_2015
Facebook status	facebook	social	winter_tyres
Twitter status	twitter	social	article_aeroplane
Newsletter or other email campaigns	newsletter	email	winter_tyres_04_2015
Pinterest	pinterest	social	winter_tyres_04_2015
Affiliate partner	"domain name"	affiliate	"campaign name + date"
Paid links, text ads, PR articles	"domain name"	link	winter_tyres_04_2015
Real-time bidding campaign	rtb	cpm	campaign_123

Source: Own processing

Note of the author explaining the abbreviations used in the Table 1.:

CPC – means Cost Per Click

CPM –stands for Cost Per Mille or in other words Cost Per Thousand Impressions

3.5 Limitations of Web Analytics

Current analytical tools reach their technical limits of measurability. Digital analytics tools should not be understood and used as a panacea. Limitations described in this chapter may not be just a problem of one set of analytical tools. It may be valid across many tools. In this part of the diploma thesis, the author would like to point out to some of the functional deficiencies, methodological inaccuracies and data errors in measurements. At the same time, the author attempts to draw up a common limits associated especially with Google Analytics.

3.5.1 Underestimation

One of the measurements error that needs to be taken into account when evaluating some persformace model using a digital analytics tool is an underestimation. This statistical deviation is a technical issue across all digital analytics tools. Google Analytics metrics can differ from the "real world" values. Metrics reported in Google Analytics are simply lower than in reality (Tichy, 2012).

Tichy (2012) also emphasizes that a measurement error in this case is caused due to different methods of measurements. He gives an example of Google AdWords reporting 500 clicks but in Google Analytics we can only see 200 or 1000 visits. Therefore he recommends when someone starts using different tools to become well acquianted with metrics of an each individual tool before making decisions based on such data.

3.5.2 Loss of Attribution

The loss of an attribution significantly undervalues results of advertising campaigns. According to Tichy (2012) this means that it is not always possible to trace the complete path of a website user in terms of the source of visit to the point when the user completes an order on ones website.

Tichy (2014) adds that by presenting a simple example in order to illustrate the problem of Google Analytics while loosing an attribution. A user can come to a website from a Google AdWords campaign. Before the user completes an order, Google Analytics can loose information that the user originally clicked on your AdWords campaign. There are many reasons of such problem.

In most cases loosing attribution happens due to (Kaushik, 2010):

- Users delete cookies stored in their Internet browser
- Cookies may expire due to the long process of decision-making when considering buying more expensive goods

- Using more devices when shopping for some goods eg. computers, tablets, mobile devices

3.5.3 ROPO Effect

The ROPO effect is an abbreviation of Research Online, Purchase Offline. It refers to the behaviour of customers looking for product information on the Internet, but then they purchase goods in a store.

ROPO leads to offline conversions and applies when evaluating marketing investments in online advertising. It is valid especially for companies that follow the principles of performance marketing and also enable online sales as well as purchases at a branch (Kaushik, 2008).

The problem of ROPO effect lies in the fact that customers that visit a website thanks to our online promotion are unidentifiable once at branch. Therefore it is almost impossible to properly allocate investments spent on online advertising.

A typical example of ROPO effect might be (Kaushik, 2008):

- **High bounce rate** related to contact page or a map of branches
- **There is a telephone number on the website** – a customer calls to inquire and after satisfactory answers directly orders by phone
- **A customer does not want to share personal information with a website** – shopping process should be facilitated in such a way that there is no need to register, a website should decrease required in information in shopping process
- **A customer wants to save money on delivery service** – to overcome this obstacle a website can provide free delivery or alternative delivery
- **A customer wants to see and test a product prior to purchase** – the recommendation is to place as much information about the product as possible in clear way (photos, descriptions, 3D views, reviews)

Kaushik (2008) adds that such causes when dealt with appropriately can lower offline conversion and increase website conversion rate.

Tichy (2015) agrees and reasons that consequences of ROPO effect may also be such that at the start of attracting potential customers is a per pay click campaign but eventually Google Analytics only reports small fraction of orders that should be otherwise credited to pay per click campaigns.

Possible measurements of ROPO effect (Adaptic, 2015):

- Questionnaires run when a customer leaves a website
- Reservation of a product at a branch
- Introduction of loyalty cards

3.5.4 Repeated Conversions

Some online stores offer specific goods that can have impact on marketing performance evaluation in terms of repeated conversions and the way such conversions are measured in a digital analytics tool. The problem of repeated conversions complies in the fact that it is only partially possible to measure these conversions using web a web analytics tools (Tichy, 2015).

Tichy (2014) adds that if the e-shop sells goods such as contact lenses, it is possible to measure and evaluate the first order made against its attributed marketing channel eg. Pay-per-click advertising. The problem starts when the same customer orders the same contact lenses in three month’s time again, and this cycle repeats depending on the nature of the goods.

However, a website owner does not expect to target the same customer again using pay-per-click campaign. He/she sends a personalized e-mail, in which the online store offers the selected contacted lenses to the customers who has to buy such contact lenses once again.

Google Analytics can report that there is one order and there exist one click from pay-per-click campaign. But a website owner knowing about the possibility of repeated conversions can expect more orders from the same customer by nature of a product, but those future orders may not be included in an analytical tool. So it cannot measure any attribution. Repeated conversions can eventually lead to the fact that there is no attribution towards marketing channels that caused the initial order. Not taking into account this problem may lead to bad decisions in terms of wrong evaluation of marketing channels based on a web analytics tool (Tichy, 2014).

3.5.5 Extending Tagged Links Beyond Campaigns

Some metrics, especially Visits, can be distorted in an analytical tool when tagged links of our online campaigns get beyond the campaign. Such distortion can happen if are links are tagged by UTM parameters and our campaign happens to grow more than initially expected (Pecka, 2014).

Rostecky (2015) claims that such situations can happen when people start sending the tagged link to each other via emails, using social networks, or posting the link in discussion forums. Clicks from those sources are then credited to the original source for which the link was tagged by UTM parameters. But a digital analytics tool does not take into account the contribution of those channels through which the link was distributed virally beyond the campaign.

In one of the following chapter the author focuses on the possibility of link tagging marketing campaigns.

3.5.6 One Person - Multiple Devices

Currently, when someone visits a website and does research, Google Analytics records them as one visitor but if the same visitor then uses a different device such as a tablet to purchase something, Google Analytics reports the same person as a different user. Consequently, there is one visitor that does a lot of research on their desktop but does not purchase, and one visitor that does not research, but buys on a tablet (Seerinteractive, 2015).

Pecka (2014) assumes that problem of pairing activities of one person on multiple devices can be solved by paring cookies with user identification (user ID).

Cutroni (2014) agrees and offers a solution in defining a user with a unique identifier. When the user ID is defined, Google Analytics then associates the visitor's activity to that unique user ID. The ideal way to do this is to apply some authorization system such as a login. As soon as a user logs in to a website or mobile app it is possible to send the user ID to Google Analytics where the data are processed and grouped. Although such user ID has to be unique and cannot have any personally identifiable information such as an email, phone number for that particular user.

In the next chapter, the author focuses on Multi-Channel Funnels reports and the Attribution Models that can be applied when reporting on customer behaviour as well as advertising budget allocation.

3.6 Attribution in Google Analytics

Many analytics tools tend to give credit for a conversion, or some transaction, to the last touch point that resembles a conversion.

Multi-Channel Attribution across digital channels allows an understanding of how marketing channels work, what customers do, and therefore it enables analyst, marketers or website owners to make better decisions in terms of budget spent (Clifton, 2012). In reality, a visitor comes to one's website many times before they convert. Each visit can be via a different marketing channel. Google Analytics provides reports in order to help understand the full customer path and how the final conversion is impacted by each of the marketing channels.

3.6.1 Multi–Channel Funnels

Online advertising has seen huge growth and innovations in online advertising. Advertisers can now approach customers using a variety of formats such as search advertising, social media, email campaigns, display ads and more.

For this reason, there is an essential need to understand the digital experience of customers. It requires measuring multiple touch points with digital assets such as Google Analytics or others. Such customers experience can consist of any of the following information: paid search, visits to a site, visits directed form other websites, email marketing and social networks and some others. Because of the need to measure customer experience, there is the requirement to attribute credit to the right sources in order to help the company with calculating return on investment (Shannon, Fuentes, 2013).

Although innovation in online advertising enabled marketers to reach their customers considerably, according to Abhishek et al. (2012) such innovation has brought new tasks to be solved. They state that one of the typical challenges that marketers face today is the fact that their potential customers are exposed to multiple formats such as: display ads on websites, mobile phones to search engines, and video advertising on YouTube or email campaigns.

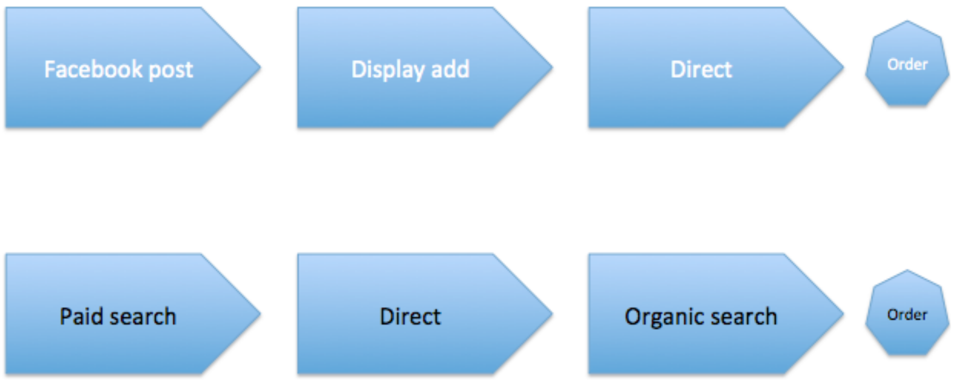
In the case study that is part of this paper, the author verifies theoretical knowledge using Google Analytics. It seems reasonable at this point to mention what Google acknowledges in terms of Multi-Channel Funnels.

Google (2016) explains Multi-Channel Funnels as the way to report how sources of traffic to one's website cooperate to create sales and conversions or in other words how marketing channels contribute to sales.

Cutroni (2012) adds to the latter that analytics tools implicitly assign all credit to the last source of a visit or marketing activity for a conversion. Therefore, Google Analytics can provide website owners with some detailed understanding of what happened prior to that conversion in order to take some further actions in optimizing marketing funnels.

In the Figure 8., it is possible to see an example in which two customers may interact with multiple touch points that contribute to that conversion on one's website. That conversion can stand for various goals that are set up within analytics tool such as Google Analytics.

Figure 8. Example of a Conversion Path



Source: Own processing

Tichy (2014) agrees and states that there is no simply conversion path of a customer coming to a website for the first time from a single source of visit and buying certain product straightaway.

Cutroni (2012) emphasizes that prior to solving any attribution problem, goals must be set to be able to see Multi-Channel Funnels reports in Google Analytics. It is worth acknowledging how marketing channels interact along a conversion path contrary to the contribution of each channel. This can also help to understand in the particular e-shop has any attribution problem.

This can be done applying following analysis (Cutroni, 2012):

- Overview Report
- Assisted Conversion
- Top Conversion Paths
- Time Lag
- Path Length

Overview Report

One of the five types of multi-channel reports is Overview Report. This provides analysts with valuable insight of how various acquisition channels work together. Interactions of channels are showed using a Venn diagram (Cutroni, 2012).

Assisted Conversion

Tichy (2014) explains that assisted conversions represent the interactions that a customer has with a website. Such interactions lead up to a conversion, but not the final interaction. He also adds that there may be channels that contribute more or less to the success of a website. Therefore, Assisted Conversions provide an analysts or marketers with the complete picture of how customers find a website and product that they buy on that particular website.

Google Analytics in Assisted Conversion reports bucket traffic into certain groups. These groups are called Channel Groups. In this report it is possible to see default versions of Channel Groups such as Organic search, Direct Traffic, Paid Advertising, Referrals, Email, Social Networks etc. Such Channel Grouping can be customized according to the specific needs of a company based on campaign's name, keywords, sources and other dimensions already mentioned in the Subchapter 3.3.1 Dimensions.

Figure 9. Overview of Channel Grouping and Assisted Conversions

	Basic Channel Grouping	Assisted Conversions ↓	Assisted Conversion Value	Last Interaction Conversions	Last Interaction Conversion Value	Assisted / Last Interaction Conversions
1.	Direct	819	$100,067.39	2,371	$251,829.39	0.35
2.	Organic Search	382	$35,299.90	3,019	$357,113.68	0.13
3.	(Other)	210	$22,483.28	2,205	$204,825.47	0.10
4.	Paid Search	150	$7,347.24	986	$76,766.61	0.15
5.	Referral	18	$1,068.22	159	$16,184.00	0.11
6.	Display	0	$0.00	2	$151.00	0.00
7.	Social Network	0	$0.00	2	$26.00	0.00

Source: Shannon, Fuentes, 2013

Shannon, Fuentes (2013) shows in the Figure 9 the number of Assisted Conversions. They explain that in this example advertising was underestimated using the Last Click Attribution Model that is set by analytics tools as a default. Comparing the last interaction Conversion Value and the Assisted Conversion Value the Figure 9 demonstrates what channels are undervalued without further segmentation. The example also shows which forms of advertising are prone to immediate conversion.

Top Conversion Paths

Tichy (2014) claims that this report shows all the unique conversion paths that lead to conversions.

Cutroni (2010) agrees and adds that by understanding the conversion path and customers' behaviour using this report can help to make campaign management decisions.

The other literature sources suggest (Bakhos, 2015) that by analysing data of customers behaviour it is possible to check whether a website needs some redesign.

Time Lag

Cutroni (2012) emphasizes that it is only possible to choose own conversion activity desired to be analysed using Google Analytics and at the same tie apply Time Lag report.

Using Time Lag reports an analyst or website owner can see the amount of time customers take from the first channel interaction to conversion.

Related to the following Figure 10. Cutroni (2012) expresses his understanding of Time Lag report and states that it is good to know whether or not most people buy or do other conversion on an initial day. Additionally, he also stresses that it is reasonable to see how many visits it takes to a customer to convert. He summarizes that such information can help to understand whether there is an attribution problem to be solved.

Figure 10. Time Lag Report

Primary Dimension: Time Lag in Days

Time Lag in Days	Conversions
0	17,974
1	126
2	69
3	59
4	42
5	59
6	42
7	42
8	27
9	30
10	27
11	21
12+	299

Source: Own processing

Tichy (2014) supports Cutroni's view and adds that if majority of visits convert on one visit, than in this case, there may be no attribution problem to tackle on the particular website. He also points out that further segmentation in case of Time Lag report is useful to get deeper insight into customer behaviour.

Path Length

The Path Length report helps to understand the number of interactions visitors have with a website's marketing channels. In such report it is also possible to see if conversions happen because of interactions in marketing funnel or if the last add click is solely responsible for conversions.

Figure 11. Example of the Path Length Report

Viewing: **Path Length in Interactions**

Path Length in Interactions	Conversions	Conversion Value	Percentage of total (Conversions / Conversion Value)
1	**42,328**	**$63,743.92**	87.62% / 68.33%
2	**3,367**	**$18,365.12**	6.97% / 19.69%
3	**968**	**$4,867.79**	2.00% / 5.22%
4	**436**	**$2,150.72**	0.90% / 2.31%
5	**233**	**$1,665.15**	0.48% / 1.78%
6	**155**	**$805.53**	0.32% / 0.86%
7	**103**	**$391.98**	0.21% / 0.42%

Source: Cutroni, 2011

Cutroni (2012) mentions that such a report could be segmented further to get the insight of segments that really matter to the particular business. He stresses that before starting to tackle multi-channels it is important to understand:

- Whether there is a problem in attribution
- Whether the problem applies to all segments that the particular website cares about eg. customers who spend over a certain amount of money, traffic coming from specific type of channel etc.

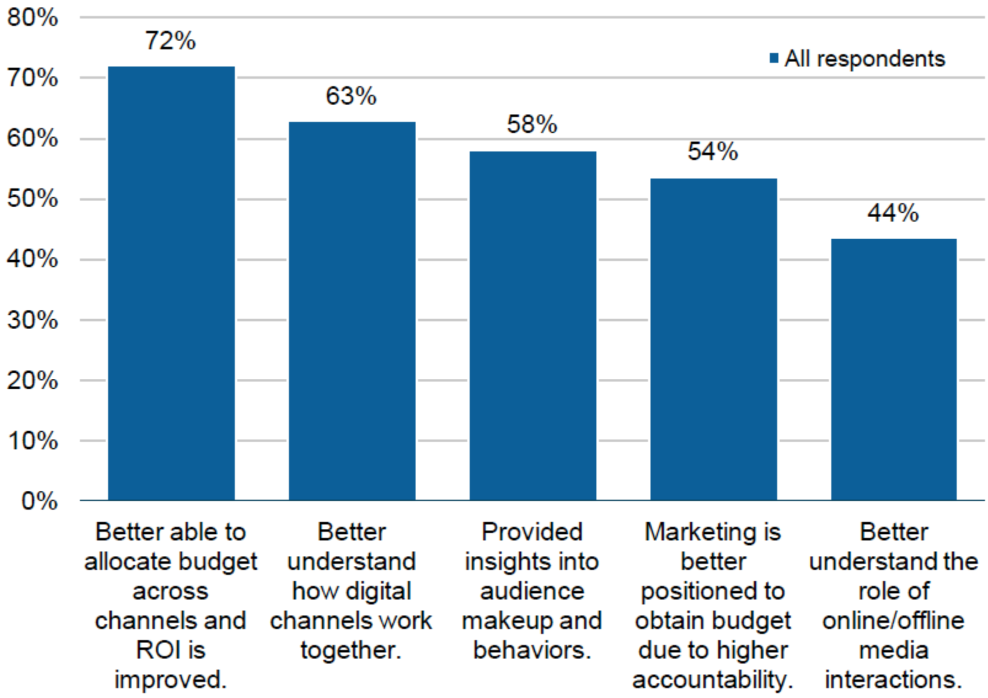
With attributions one always wonders how many times it takes people to come to the website before they convert in order to be able to distribute revenue among all those visits to the particular source of that visit.

For this reason, the next subchapter introduces the Attribution Models that can be applied within Google Analytics.

3.6.2 Attribution Models

Generally, Attribution Models allow us to get acknowledged on how marketing affects the entire cycle of sales, and enables to optimize across it.

Figure 12. Benefits of Attribution



Source: Econsultancy, 2012

According to the study conducted by Econsultacy.com Ltd in 2012 marketer's goals are not only optimizing digital spending, but are also to understanding attribution as the way to see how media perform. The desired outcome is to improve the combination of the company's marketing channels and boost their performance. Marketers also want to improve their knowledge of sales funnel and the sales cycle.

A user can come across a display ad which could have an impact on increase of awareness about some product, then a few days later view an organic search result, then receive a customized email, and finally purchase the product. In this example the email was the last touch point prior to interaction, but all three interactions were likely to happen to have an impact on your customer's decision. Therefore, attribution is the process of deciding how much credit one wants allocating to each of those interactions (Econsultancy.com, 2012).

Key, Honey (2012) claim that there are few perspectives to take around attributions to help to work with attribution models:

- There is no perfect attribution model. Only better ones to improve what some website owners already do today in terms of investment allocation to digital marketing channels
- Attribution models depend on one's business and strategy and customers - in many cases attribution models work in different way depending who is targeted by marketing campaigns, what the prices of our products are and the way to reach potential customers

Kaushik (2013) reveals following Attribution Models that can be used in Google Analytics:

- Last Click Model
- First Click Model
- Last Non - Direct Click Model
- Linear Click Model
- Timey Decay Model
- Position Based Model

Last Click Model

Google Analytics contains a series of options available to digital analysts, marketers or whoever tends to analyse the data. The following Figure 13 shows the Last Click Model that is commonly used by most of the analytics tools. It assigns 100% conversion value to last channel with which customer interacted prior to converting.

Figure 13. Last Click Model

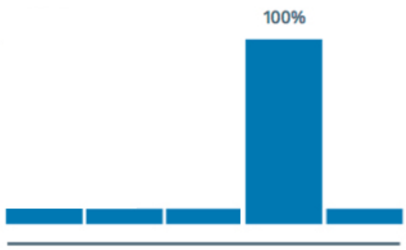
Source: Google, 2012

The model is useful in case ads and campaigns are supposed to attract people at the time of purchase and does not involve a consideration phase (Google, 2016). Cutroni (2012) argues that Last Click Model is as flawed as it ignores all activities that are in the process of conversion.

Last Non - Direct Click Model

Tichy (2014) states that in the Last Non – Direct Click attribution model, all direct traffic gets ignored and all credits are attributed to the last channel that customer clicked through prior to converting.

Figure 14. Last Non – Direct Click Model



Source: Google, 2012

First Click Model

In this case the model gives credit to the first interaction in the customer path. This model allows looking back in time of 90 days and to identifying what was the first channel that introduced the customer (Kaushik, 2013).

Figure 15. First Click Model

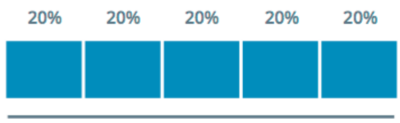
Source: Google, 2012

As Cutroni (2012) states this can be valuable for begging to place a premium on those channels that drive the first interaction with customers and create brand awareness. He also adds that this is not a solution either.

Linear Click Model

As Tichy (2014) adds this model splits the credits evenly across all touch points. This can be useful where there are short customer paths, such as two-step paths. In this case it is possible to allow credit channels evenly.

Figure 16. Linear Click Model



Source: Google, 2012

Cutroni (2012) agrees and says that it can also be useful to apply this model for longer customer paths where it is desired to measure and to get perspective on frequency with which customers interact with certain channels. He also points out that it is important that customers come back over again to learn and research products and suggests that this can be a helpful model to gain insight into customers' behaviour.

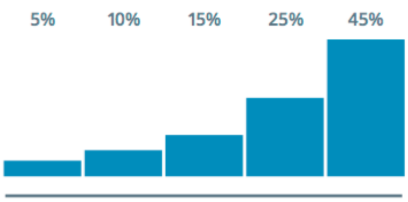
This model is also useful if campaigns are supposed to keep contact and awareness with the customer throughout the entire cycle of sales (Google, 2016).

At this point, Kaushik (2013) argues that it is necessary to take into account that some campaigns are more important than others in terms of timing or might have greater impact on purchase decision of customers. Kaushik (2013) also stresses that this model does not offer a solution to hard decisions to be made that are sometimes overlooked because certain cost, time and effort needs to manage paid searches, manage email campaigns, and social media. Each of these takes a different amount of work.

Time Decay Model

The Time Decay Model interpretation gives more credit to interactions the closer they are to the time of conversion.

Figure 17. Time Decay Model



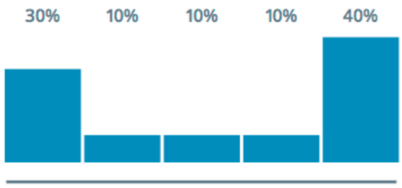
Source: Google, 2012

This model can be useful in case someone sells a product or service for which there is a short decision making process during which conversions happen in a matter of days or a week or two (Google, 2016).

Position Based Model

Position Based Model seen on the following Figure 18 allows a website owner to distribute the attribution based on position in the customer journey, what happens earlier and what happens later.

Figure 18. Position Based Model



Source: Google, 2012

This model recognises that at the beginning of customer's journey there is a lot of work that goes into marketing activities to attract them. There might be a so called "dark period" and at the end of the process there might be more work involved again in marketing activities in order to generate additional customer's interest in buying a product when the purchasing process is very close to being complete (Cutroni, 2012).

4 Practical Part

4.1 Introduction to the Case Study

In order to fulfil the goals of this diploma thesis the author presents a case study. The focus of the case study is on the use of Multi-Channel Funnels in Google Analytics.

The data analysis was carried out for a company that does not wish to be named. Therefore the author cannot present more details of the company's business or data in any form other than that stated in this thesis.

The company is a non-bank financial institution (NBFI) that operates on the Czech market. It offers a wide range of financial products: loans at the point of sale, car loans, cash loans, credit cards and loan consolidation.

At the beginning of the 2015 year the company decided to invest in leads generation. Prior to the start of the campaign which is part of this case study, the company intensively optimised its website which is still an important part of the company 's business in terms of interaction with its potential customers.

In August 2015, the company launched a campaign in order to increase people's interest in its financial products for the purpose of developing a sales pipeline. In this case study, the author uses the term Lead Generation when referring to the business goal of the company.

The author uses Multi-Channel Funnels in Google Analytics in the following campaign.

4.1.1 Campaign Set-up

For the purpose of the case study, the author introduces key points of the company intentions in terms of the lead generation campaign, only with a focus on the online part of the campaign:

- **Business goal:** to increase a lead generation

- **Used platform:** a microsite on a separate domain
- **Target group:** Czech Republic, primary Czech-speaking people, aged 25 – 45 years
- **Campaign data range:** 1st August – 31st December, 2015

The online part of the marketing campaign continued on for 5 months in 2015. The main conversion goal was to obtain valuable leads (lead generation) by convincing people to visit the microsite. The microsite consisted of an online calculator on the following products: car loans, personal loans and loan consolidation.

The digital campaign was executed by a Performance Agency (PA) and all ads in the scope of this campaign were properly and comprehensibly tagged using UTM parameters.

This campaign was executed in the search and content network of two main Czech search engine companies, i.e. Seznam and Google. Part of the media mix consisted of prepaid banners in the display network of certain media houses.

Unfortunately, there was no e-mailing campaign involved to support the campaign. This NBFI did not have any e-mail marketing strategy in place before and during the date range of the campaign.

Campaign Landing Page

For the purpose of the campaign the microsite could be entered on the URL:
http://loan.nbfi.cz

The exact domain name used by the company cannot be provided.

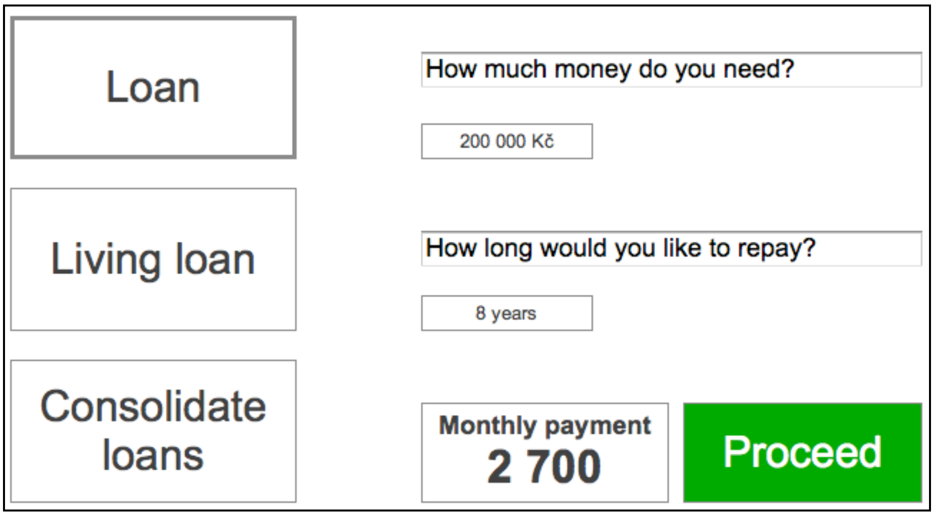
Data Sources

Data for the campaign evaluation were extracted from Google Analytics, Sklik, AdWords and additional spreadsheets containing costs of individual sub-campaigns in pre-paid banners.

4.1.2 Conversion Goal

The following Figure 19 introduces the core part of the landing page that was designed to generate conversion. The full design of the microsite could not be provided.

Figure 19. Landing Page Design Example



Source: Own processing

Logic behind Lead Generation

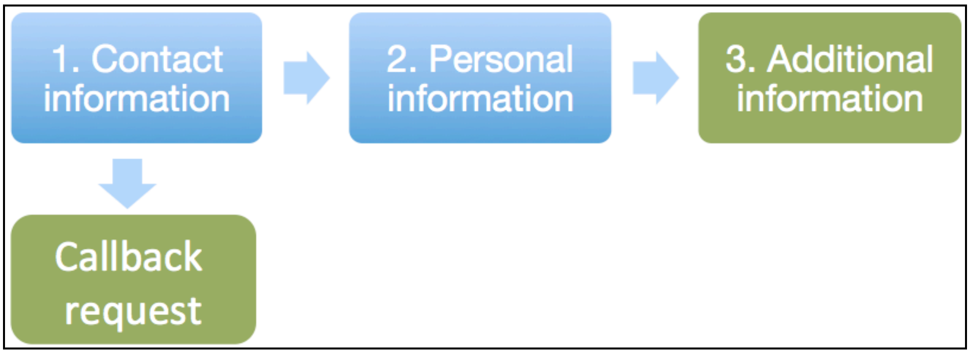
A visitor can submit a loan application by completing the three-step form. The landing page provides the visitors with the possibility of viewing an estimation of monthly payments based on custom loan configuration. In the event that a visitor finds any of the financial products of the company interesting, it is necessary to proceed to the three-step form.

In the first step (Contact information), the visitor fills in contact information: name, surname, telephone and e-mail address. Before proceeding to the next step, the visitor is obliged to check the agreement for personal information processing and to agree. This step is crucial for the company in order to be able to contact the visitor after completion of the form.

The other option in the first step is a call-back request if the visitor is not willing to complete the online form. Both the form submit in the third step as well as the call back request in the first step are considered as being equal.

The process of lead generation is demonstrated on the following Figure 20.

Figure 20. Lead Generation Mechanics



Source: Own processing

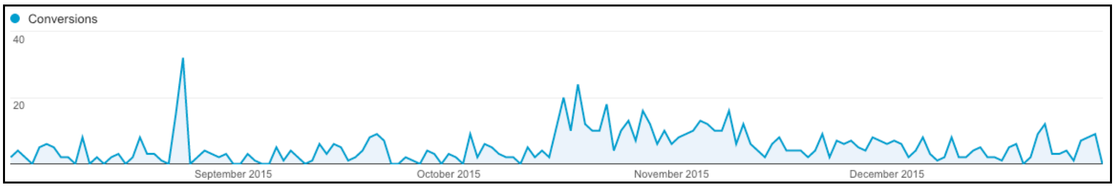
Number of Conversions

The digital part of the campaign generated 784 leads. There were 357 assisted conversions out of 784.

It is important to mention in this part of the case study that the company has a very strong team of sales people in its Call Centre. The average success rate of the sales team is 75 %. The percentage shows the success rate for selling financial products over the phone. Out of 784 leads there were 588 loans confirmed by customers.

The following Figure 21 shows how people converted over time. The most conversions took place during November and December 2015. This seems quite obvious because people tend to spend more money before Christmas Time.

Figure 21. Development of the number of conversions during the campaign



Source: Extracted from Google Analytics

Table 3 below introduces the number of sessions that were generated during the campaign as well as the number of completed conversions. The Table also shows that the most visits came from the Display channel, which consisted of ads the financial products placed in exclusive banner positions on Seznam.cz or other premium websites. Even though this channel tends to show the highest number of visits, it is possible to see that the most conversions took place thanks to the Organic Search channel. This channel was mainly successful thanks to optimisations that were carried out prior to this campaign.

Table 3. Overview of Conversions and Conversion Rate

Channel	**Sessions per Channel**	**Conversion completed**	**Conversion Rate**
Paid Search	17,000	102	0.60 %
Display	39,000	112	0.29 %
Social Network	3,000	23	0.77 %
Organic Search	24,000	314	1.31 %
Direct	16,000	177	1.11 %
Referral	11,000	56	0.51 %

Source: Own processing

The Referral channel surprisingly reached a high conversion rate of 0.51 %, although it was not a part of the controlled marketing campaign. The Display channel seems to perform a weak conversion rate of 0.29 % in further comparison of the cost of the channel.

4.1.3 Demographic Data

One of the interesting insights that Google Analytics can provide an analyst with is the possibility of segmenting data according to several dimensions such as Age or Gender. In terms of the case study, this demographic information is valuable for the marketers in the company. Marketers need to know if their campaign is reaching the desired group of people in terms of productive age.

In this part of the thesis, the author firstly segments and compares, general demographics in terms of age. Secondly, the author segments only those visitors who converted during the campaign:

- Segmented sessions according to Age and Gender
- Segmented sessions that led to conversions

Demographic reports are also part of the Google Analytics service, and can provide valuable information about a company. However, it is important to acknowledge that such reports are an estimate that is based on a sample of visitors to the microsite. The page span of this thesis does not allow the author to describe in more detail the method whereby Google collects data for age or gender and how accurate these estimates are. Nevertheless, studies have been carried out to show that Google is efficient in making accurate estimations of visitors' profiles (Ridder, 2014).

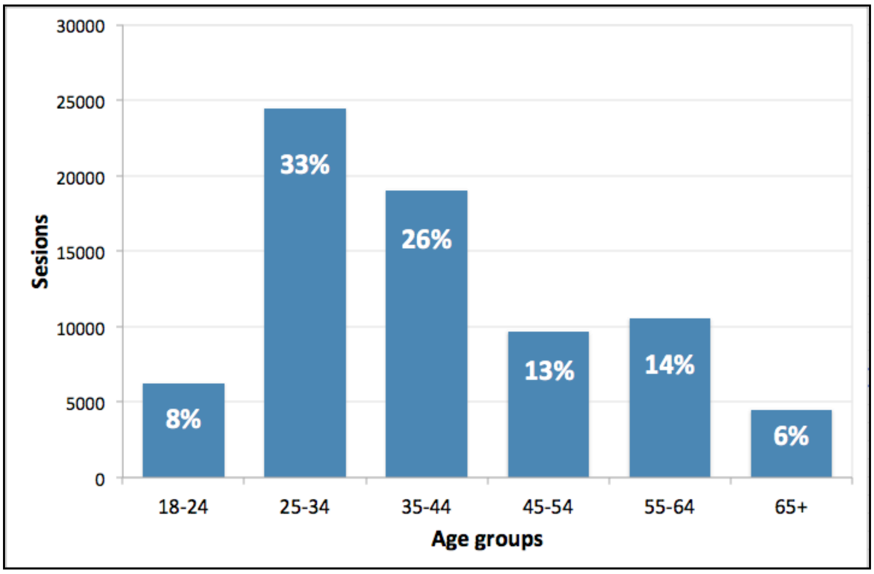
Segmented Sessions according to Age

The following report was generated using Google Analytics, based on a data sample of 68 % of all sessions during the campaign period.

Number of all sessions during the campaign period = 110,000 sessions over the duration of 5 months time.

According to the following Table 4, the largest group of visitors is the 25 – 34-years age group, which comprised of 33 % of all the sessions for which it was possible to determine their age based on Google's data sampling. The second largest group of visitors was between 35 and 44 years old. According to the initial target group, these two largest groups of visitors fall within the desired age group predetermined by the company.

Table 4. Demographics of all sessions



Source: Own processing

Segmented Sessions according to Gender

According to data analysis, the most frequent group in terms of gender is female, with a prevalence of 8.8 % compared to the male group. The male population of visitors comprised 45.6 %.

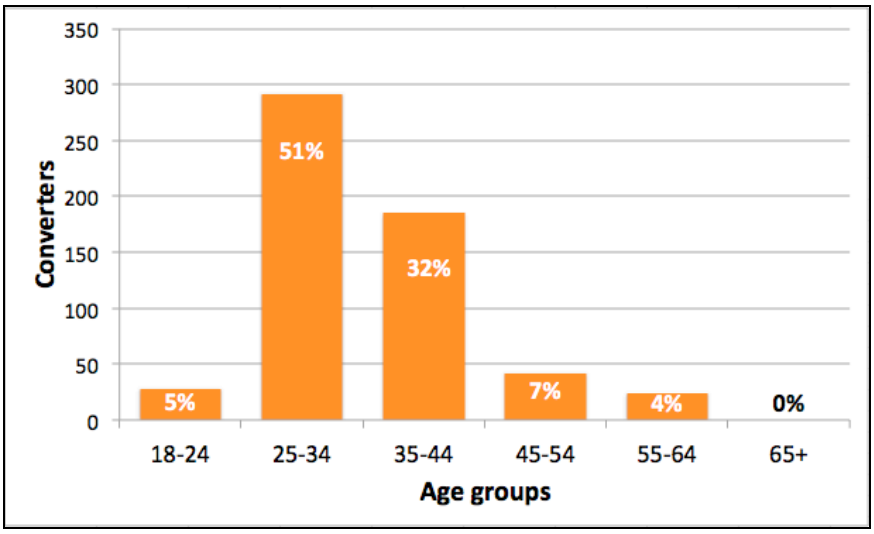
This information could be important to know when marketers prepare certain brand campaigns in terms of banners to appeal either to men or women.

Segmented Sessions that Led to Conversions

The following reports presenting Age and Gender were compiled only from users who had converted.

The Table 5 shows that more than half of all converts were aged between 25 and 34 years. This age group again falls within the target group of the company. The second most frequent age group is represented by users of their aged 35 – 44 years.

Table 5. Age Structure of Converting Microsite Traffic



Source: Own processing

Comparing the results from the previous Table 4, it is possible to see that the use of segmentation in Google Analytics provides the company with a comparison of the structure of converting users. It also shows that there are no people aged 65+ years. The age group of 65+ people is not a target, generally speaking, as they are not of a productive age. The company sees potentially higher risks in terms of their ability to repay all the borrowed money.

From the two above Tables, the author points out that the there is a 7 % difference between the 25–34-year and the 35–44-year age groups. At the same time, the segment report represented by the Table 5 shows an even greater difference between these age groups. There is a 19 % difference between these age groups, representing 250 users who had converted.

Demographics related to the campaign and provided by the Google Analytics tool are very similar to the data from the company's customer Relationship Management system. The author states this evidence on the basis of a personal discussion with the company.

4.1.4 Campaign Spend

During the entire digital campaign there was a total spend of CZK 1,750,000 for some of the following channels that brought traffic to the microsite:

- **Paid Search** – in Google Analytics, this refers to visits resulting from ads that show up on Google Search results pages. The tools responsible for results and budget spend in this case study are called Google AdWords or Sklik.
- **Display** – this is also part of Google paid advertising in the form of banners. In the case of the campaign, it mainly refers to display banners placed in exclusive banner positions on Seznam.cz or other premium websites or media houses.
- **Social Network** – In this category, Google Analytics categorises many social sites such as Facebook and Twitter, However, in this case study the budget was allocated only for Facebook.
- **Organic Search** – this channel relates to any search on a search engine that brings a visit to the microsite from non-paid results thanks to the brand name or other search engine optimisation activity performed on a website.
- **Direct** – in the case of this channel, it is assumed that visitors directly type a URL into a web browser and reach the microsite. In the case of the channel, visitors seem to be familiar with the company prior to visiting. There were no costs related to this channel.
- **Referral** – in the case of this channel, visitors can get to know the specific website from some other website, such as a blog post related to the company or a particular financial product, a press release, etc. There were no costs associated with this channel.

For a better overview of the total campaign costs, the author provides the following Table 6.:

Table 6. Monthly Channel Spend in CZK During the Campaign

Channel	August	September	October	November	December	Total Campaign Cost per channel
Paid Search	40,000	45,000	70,000	50,000	45,000	250,000
Display	125,000	125,000	150,000	200,000	150,000	750,000
Social Network	15,000	15,000	15,000	15,000	15,000	75,000
Organic Search	20,000	20,000	20,000	20,000	20,000	100,000
Direct	-	-	-	-	-	-
Referral	-	-	-	-	-	-
Total Spend per month	200,000	205,000	255,000	285,000	230,000	1,175,000

Source: Own processing

Table 6 above represents the overall cost for the online campaign with the goal of lead generation. In terms of Organic Search, the costs represent a monthly fee for a contractor who optimises the microsite for search engines. There were no costs associated with Direct and Referral channels. Any conversions associated with the Direct channel could relate to the impact of offline campaigns for which the author has no specific data, figures or information.

The Display channel shows the highest spend in the 5-months duration of the campaign. The reason for the higher cost is that the company paid for exclusive banner positions on top Czech websites such as Seznam.cz

In Chapter 4.3 and Chapter 5.1, the author introduces other economic points of view in terms of the Cost per Acquisition (CPA) and Return on Advertisement Spend (ROAS).

4.2 Data Analysis using Multi–Channel Funnels

In this chapter of the case study the author analyses data using specific reports that can be generated in Multi-Channel Funnels in Google Analytics. Some reports provide valuable insight into how those marketing channels functioned together in the specific campaign. These reports are:

- Overview Report
- Assisted Conversion
- Top Conversion Paths
- Time Lag
- Path Length

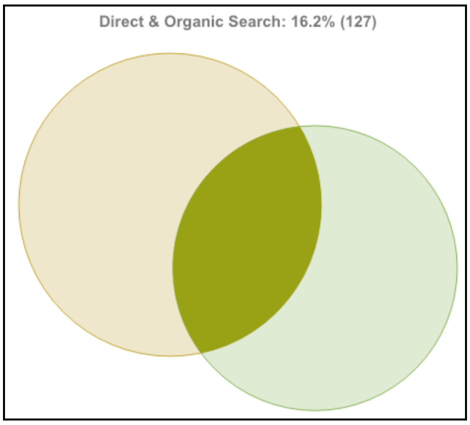
4.2.1 Overview report

Based on the analysed data, it is not necessary to identify one universal conversion path that users follow in the conversion process. More valuable insight can be gained from Multi-Channel Funnels using Overview Report and built in Multi-Channel Conversion Visualiser.

Based on the data provided by the company, this visualiser enables the creation of the following Venn diagram to show how each channel, through which users converted, overlaps.

The Figure 22 below shows that there is a significant overlap of 16.2 % between the multiple channels of Direct and Organic Search. It means that these two channels show a higher relationship. There were 127 conversions that took place due to the combination of these channels.

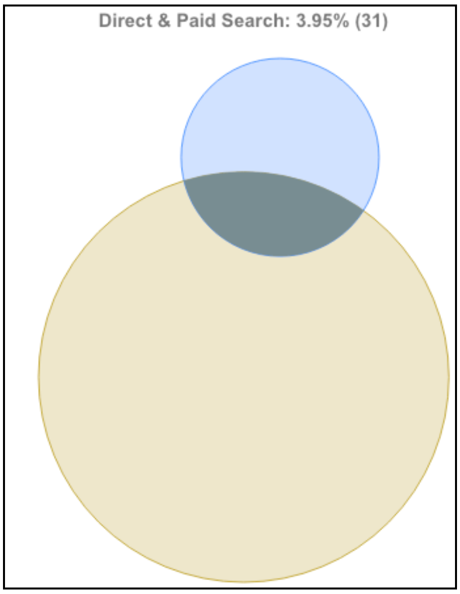
Figure 22. Conversion Visualiser – Combination of Two Channels



Source: Extracted from Google Analytics

Figure 22 shows that the brand awareness of the company's financial products works in favour of direct visits as well as the Organic search. Small overlap with the Paid Search also means the budget for pay-per-click does not get burned by visitors who would otherwise came via the Direct or the Organic search.

Figure 23. Conversion Visualiser – Combination of Direct & Paid Search

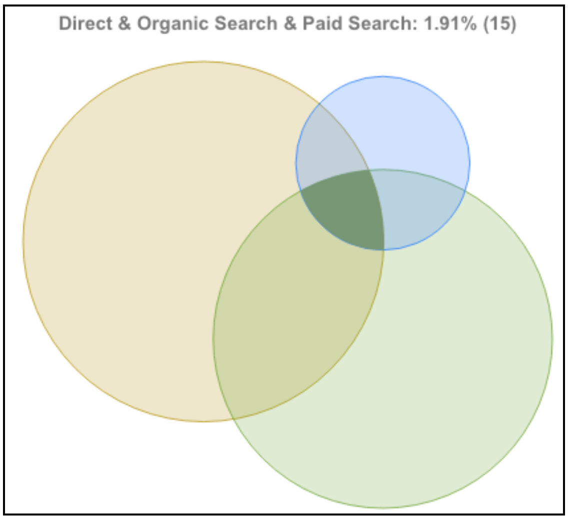


Source: Extracted from Google Analytics

A slightly larger overlap is achieved when combining Direct and Paid Search. The Figure 23 above shows that this combination of these channels was responsible for 31 conversions. Such information can be valuable in order to see conversions that were influenced at least by those two channels.

In addition, in the following Figure 24, the author adds one more channel to observe how one channel impacts another. In this case, the Figure shows that there is a low overlap of only 1.91 %. This overlap of the three marketing channels indicates that only 15 conversions were influenced by a combination of these 3 channels.

Figure 24. Conversion Visualiser – Combination of Three Channels



Source: Extracted from Google Analytics

Furthermore, marketers than should test changes in conversions soon after company reallocates money for one of these channels and to analyse changes in each individual channel.

In addition, if there were two channels in the campaign that function well together towards conversions, the author suggests that the company may plan a coordinated campaign or spend in both channels simultaneously to gain the most from all parts of the conversion funnel.

4.2.2 Assisted Conversions

Many users usually do not convert to any website immediately. It depends on the conversion goal of the particular website. Normally, users gather and compare information from different websites. Typical user behaviour represents several interactions with a website. Initially, they may be attracted by a banner ad on Seznam.cz and click through to the website. Having found enough information, they leave the website. Later the same user may spot a post or recommendation from his/her friend on a social network and return to the website via a Facebook post. Again, the user exists the website to discuss the financial product with family or others. Eventually, the user enters the same website by typing the web address in the web browser and goes directly to the website to convert.

Therefore, such user behaviour results in multiple visits to a website before converting. Assisted conversions are attributed to the display ad, as well as to the social network. It is most likely that the conversion would not have taken place without the prior two interactions.

In the following Table 7 the Assisted Conversion Report presents the column Assisted / Last Click or Direct Conversion. This ratio is important to understand, as it compares the number of assisted conversions to the last-click or direct conversions

This is one of the ratios that represent valuable insight for the company. The closer the ratio is to zero, the more likely the channel interacts with the user as the last channel in the conversion path, rather than in assisting in the conversion. With regard to this thesis, the more the value of the ratio exceeds 1, the more the channel is prone to assist in conversions.

As the ratio Assisted / Last Click or Direct Conversion summarises a channel’s overall role, this case study reveals that the ratio of particular channels tend to be very similar in value.

Table 7 shows that the Referral channel assisted the most in conversions in comparison to the other channels with the value of 1.26. In reality, there could be some websites, such as blogs or specialised financial websites, that publish articles advising on a choice of financial product such as a loan. If the company wants to maintain a Referral channel it should consider hiring copywriters or paying those financial websites for publishing the company's own articles. This channel also has the potential for an overlap with Direct or Organic Search, as people first search for information, read some articles and then visit the NBFI domain directly or via other channels.

Surprisingly, the Social Network channel tended to be the closest the conversion path.

Table 7. Custom Channel Grouping Tailored to Match Campaign Tagging

Custom Channel Grouping	Assisted Conversions	Assisted Conversion Value	Last Click or Direct Conversions	Last Click or Direct Conversion Value	Assisted / Last Click or Direct Conversions
1. Direct	185 (35.24%)	$0.00 (0.00%)	328 (41.84%)	$0.00 (0.00%)	0.56
2. Organic Search	154 (29.33%)	$0.00 (0.00%)	235 (29.97%)	$0.00 (0.00%)	0.66
3. Paid Search	71 (13.52%)	$0.00 (0.00%)	83 (10.59%)	$0.00 (0.00%)	0.86
4. Display	54 (10.29%)	$0.00 (0.00%)	76 (9.69%)	$0.00 (0.00%)	0.71
5. Referral	54 (10.29%)	$0.00 (0.00%)	43 (5.48%)	$0.00 (0.00%)	1.26
6. Social Network	7 (1.33%)	$0.00 (0.00%)	18 (2.30%)	$0.00 (0.00%)	0.39
7. (Other)	0 (0.00%)	$0.00 (0.00%)	1 (0.13%)	$0.00 (0.00%)	0.00

Source: Extracted from Google Analytics – Multi Channel Funnels

From the above Table, Multi-Channel Funnels enable the observation that the most frequent channel during the campaign was the Direct channel. This means that users visited the microsite either after typing the web address directly into their web browsers, used the whispering option of a web browser, or could use web bookmarks in their web browser.

The author suggests that the company should take into account that in this type of channel and conversions attributed to this channel there are hidden costs that were not associated in Table 6 presented in sub-chapter 4.1.4, and those costs were incurred due to the offline part of the campaign. This means that the cost of spotting the link to the microsite by people was due to an outdoor advertisement, advertisement in public transport, or a radio spot heard, and cannot be attributed to the actual channel.

Based on the previous description of the campaign set-up, this part of the digital campaign was designed for the subdomain name: loan.nbfi.cz. However, the second-level domain of the company is: nbfi.cz.

Using Google Analytics, it was found that many users had visited the second-level domain of the company prior to converting to the subdomain that was designed for the campaign. The company claims that the design of the microsite could not be placed on the homepage, second-level domain, due to technical limitation and not having a flexible content management system (CMS). Such limitations place some barriers into a clear conversion path. It is likely that people who came across the offline part of the campaign could remember the name of the NBFI or the name of the financial items such as NBFI loan. Such behaviour could cause the higher organic search on Google or Seznam search engines, which consisted of 154 assisted conversions as shown in Table 7 above.

In addition to the Multi-Channel Funnels and attribution of particular channels, Google Analytics can provide a valuable insight into user behaviour. The author suggests that, for the future campaigns similar to the one that has already been carried out, the company should place the online calculator on its second-level domain in order to increase leads as the conversion goal.

4.2.3 Top Conversion Paths

The author also wants to analyse the data in terms of the most common combinations of channels that visitors interact with to find the website used in this particular case study.

The Top Conversion Paths report tends to answer the question: What does the typical conversion paths look like from the first interaction to the conversion?

Based on the data analysis using Multi-Channel Funnels in Google Analytics, the author generates the following Table 8. The Table shows that Organic Search traffic in this particular campaign was ranked in 1st position, accounting for 149 conversions. This means that the most typical source of conversion is a one-time visit from Organic Search.

Table 8. Top Conversion Paths

	Custom Channel Grouping Path	Conversions
1.	Organic Search	149 (19.01%)
2.	Direct	113 (14.41%)
3.	Display	62 (7.91%)
4.	Paid Search	54 (6.89%)
5.	Organic Search > Direct	37 (4.72%)
6.	Referral	36 (4.59%)
7.	Direct × 2	24 (3.06%)
8.	Organic Search × 2	24 (3.06%)
9.	Display > Direct	18 (2.30%)
10.	Direct × 3	14 (1.79%)

Source: Extracted from Google Analytics – Multi Channel Funnels

On the 5th position in the above Table, it is possible to see the 2 separate visits from Organic Search and Direct. This position also indicates that 37 users initially came to the website from Organic Search. Then they left and visited the website directly after some time, having typed the specific URL into their web browser and then converted.

Despite, this report tending to suggest that it is possible to follow one specific marketing activity based on the most frequent conversion paths, the author claims based on a study of specialised literature sources and examples, that users convert in many different ways.

The following Table 9, the author continues by showing more complicated sources of visits that were not so frequent prior to conversions. The following Table also supports the author's point of view that there are no universal conversion paths of visitors.

Table 9. Top Conversion Paths – lower position

35.	Paid Search > Direct > Organic Search	2 (0.26%)
36.	Paid Search > Direct > Organic Search > Direct > Display	2 (0.26%)
37.	Paid Search > Display > Referral > Organic Search > Paid Search	2 (0.26%)

Source: Extracted from Google Analytics–Multi Channel Funnels

4.2.4 Time Lag

A Time Lag report generated using Multi-Channel Funnels in Google Analytics can provide a business owner or analysts with valuable insight. This report enables the viewing of a breakdown of how many days it takes for a user from the first channel interaction to conversion.

Based on the following Table 10, it shows that 69 % of all conversions took place during the first day of a user's visits. This means that marketers had done great work in terms of designing a webpage where all conversions took place. It could also mean that the financial product was clearly understood by visitors when visiting the website.

Table 10. Time Lag Report

Time Lag in Days	Conversions	Percentage of total: Conversions	Percentage of total: Conversion Value
0	542	69.13%	0.00%
1	31	3.95%	0.00%
2	12	1.53%	0.00%
3	10	1.28%	0.00%
4	3	0.38%	0.00%
5	12	1.53%	0.00%
6	4	0.51%	0.00%
7	13	1.66%	0.00%
8	14	1.79%	0.00%
9	6	0.77%	0.00%
10	11	1.40%	0.00%
11	8	1.02%	0.00%
12-30	118	15.05%	0.00%

Source: Extracted from Google Analytics – Multi-Channel Funnels

On the other hand, the above Table also reports that 118 conversions appeared within an interval of 12–30 days after the first visit. Those users were able to take their time to evaluate other possibilities related to the financial product of the particular company.

4.2.5 Path Length

In relation to analysed data, the Path Length Report provides valuable insight into the number of visits it takes to convince visitors to a particular website to convert. This allows analysts to understand how channels interact along the conversion path.

The following Table 11 shows that approximately 55 % of all conversions took place within the first user interaction and almost 20 % of all conversions occurred during the second visit. The latter means that the visitors needed at least two visits before they left their contact details. In addition, the report shows that a significant portion of website visitors visited the site once, converted immediately or, after leaving, further considered their decision. Some came back later and left their contact information.

Table 11. Path Length Report

Path Length in Interactions	Conversions	Percentage of total: Conversions / Conversion Value
1	427	54.46% 0.00%
2	155	19.77% 0.00%
3	79	10.08% 0.00%
4	49	6.25% 0.00%
5	28	3.57% 0.00%
6	9	1.15% 0.00%
7	3	0.38% 0.00%
8	15	1.91% 0.00%
9	4	0.51% 0.00%
10	3	0.38% 0.00%
11	1	0.13% 0.00%
12+	11	1.40% 0.00%

Source: Extracted from Google Analytics – Multi Channel Funnels

Given the nature of the defined conversion type – a Lead – it is expected that people could convert relatively soon in terms of the number of interactions that lead to a conversion. Having used the calculator and leaving their contact information, the visitor would expect a phone call from a sales team.

In relation to the client's business and the design of the microsite, the report can satisfy a business owner or a marketer, because the microsite seems to facilitate visitors adequately with an online loan calculator and contact form or other related information, so it is easy for them to convert on a first visit.

Because Table 11 still shows that not all conversions occurred during the first visit, it is interesting to analyse the data in a further subchapter and to suggest further recommendations.

It is important to understand that no company can capture its audience with just one perfectly placed advertisement. There are additional steps before the marketing efforts of any company convince their customers to buy or achieve another conversion goal such as in this case study.

In the next chapter, the author compares Attribution Models in relation to the campaign of the company. In further sub-chapters, the author evaluates the performance of the campaign using Multi-Channel Funnels and Attribution Models.

4.3 Comparison of Attribution Models

In this chapter, the author presents the use of Multi-Channel Funnels in terms of built-in Attribution Models and a comparison of those models in the campaign. Each Attribution Model provides a different approach to measurement. Therefore it is interesting to compare them in Table 12 to see what changes there are when attributing credit to particular sources of conversions.

The following comparison consists of four models:

- Last Non–Direct Click model
- First Click model (First Interaction)
- Last Click model (Last Interaction)
- Time Decay model

Table 12. Comparison of Attribution Models

Channel	Total Costs	Last Non - Direct Click		First Interaction		Last Interaction		Time Decay	
		Conversions	CPA in CZK	Conversions	CPA in CZK	Conversions	CPA in CZK	Conversions	CPA in CZK
Paid Search	250,000	102	2,451	108	2,315	83	3,012	87	2,874
Display	750,000	112	6,696	109	6,881	76	9,868	85	8,824
Social Network	75,000	23	3,261	17	4,412	18	4,167	17	4,412
Organic Search	100,000	**314**	318	**274**	365	235	426	255	392
Direct	-	177	-	206	-	**328**	-	**286**	-
Referral	-	56	-	70	-	44	-	54	-

Source: Own processing

Part of the above Table 12 is also a key performance indicator CPA (Cost Per Acquisition). The indicator signifies the cost of reaching one conversion. This performance indicator was established on the basis of the previous campaigns to:

- Cost per Acquisition (CPA) < CZK 3,500

4.3.1 Last Non – Direct Click

Based on the Table 12 above, the model of Last Non–Direct Click is a clear indication in favour of Organic Search. Comparing the Attribution Models, there were 314 conversions credited to this channel, which seems to work the most efficiently for the company in terms of CPA. CPA for Organic Search is only CZK 318.

In the case of Organic Search, many users converted by specifying one set of relevant keywords using a search engine. The merit of success of this channel lies in prior web optimisation at the beginning of 2015. This result is also consistent with the Top Conversion Path analysis in sub-chapter 4.2.3. The Top Conversion Path was reported as the most frequent channel that was responsible for the highest number of conversions.

In the case of the company looking for the most expensive channel to shift investments away from, the author definitively suggests considering the Display part of the campaign for subsequent campaigns. This channel was the most expensive in terms of CPA CZK 6,696. This is almost twice as much as the initial CPA value < CZK 3,500.

4.3.2 First Interaction

This model tries to identify what was the first channel that introduced the customer. For this reason, the company's strategy was to place a premium on those channels that drive the first interaction with customers and create brand awareness. Unfortunately, the Table 12 above reveals that, when comparing four Attribution Models, CPA is shown to be the highest for Display channel. In addition, Paid Search and Display channels can hardly compete with Organic Search, which is credited for 274 conversions resulting in CPA of CZK 365.

It is important to mention that the Organic Search channel only consists of the costs related to continuing search engine optimisation of the website which is in the form of a monthly agency fee and represents a cost of CZK 100,000 during the campaign.

The logic behind this model is based on the idea that if there was no interaction, there would be no conversion. In case there is a similar campaign in the future, the author suggests the company allocates a greater budget to Paid Search, rather than showing a banner on exclusive websites such as Seznam.cz.

4.3.3 Last Interaction

This model completely ignores channels that, prior to conversions, were mainly paid channels or channels that were present at the first interaction. The Table 12 above reveals that the most credited channel tends to be Direct. It generates the highest number of conversions. Unfortunately, this model ignores the fact that a user might see an expensive banner placed high in an exclusive position and he/she comes back to the microsite having typed the URL straight into the web browser. This might not happen without remembering the brand that display banners drive. In this case the model shows the highest CPA of CZK 8,824 in relation to the Display channel.

According to the author, this model completely ignores the overall conversion path and deliberately disadvantaged channels featured in the conversion paths.

4.3.4 Time Decay

The author mentions in the literature review that the Time Decay model gives more credit to interactions the closer they are to the time of conversion.

Taking into account the gradual degradation of the importance of a particular channel in time, Table 12 above shows that similar CPA values compare to the Last Interaction model. According to the author, this model is slightly better in the sense of crediting the channels. However, it is still not very suitable from the company point of view, as there is a short conversion path and many conversions took place within the one or two days as seen in sub-chapter 4.2.4 Time Lag.

The tool for multi-channel attribution helps to reveal what brings people to the website and how many times they interact with the website prior to conversion. The Time Decay model does not contribute any new valuable insight by the gradual weakening of the attribution of individual channels.

5 Results and Discussion

5.1 Performance Evaluation in Multi–Channel Attribution

In this chapter, the author summarises results data that there were possible to be analysed by using Google Analytics and its Multi-Channel Funnel and Attribution. The author also presents results in terms of selected performance indicators and measured channels. These results also serve as part of the Chapter 5.2 in which the author proposes further recommendations in terms of future campaigns.

Cost per Session (Visit)

Over the period of the campaign there were 110,000 visits. The largest number of visits came from the Display channel, as seen in the following Table 13, which includes banners on individual websites such as Seznam.cz

Table 13. Cost per Session

Channel	Total Channel Cost in CZK	Sessions	Cost per Session in CZK	
Paid Search	250,000	17,000	14.7	
Display	750,000	39,000	19.2	
Social Network	75,000	3,000	25	
Organic Search	100,000	24,000	4.2	
Direct	-	16,000	-	
Referral	-	11,000	-	
Total	**1,175,000**	**110,000**	-	
			15.8	**Average Cost per Session in CZK**

Source: Own processing

The above Table also shows that the company was able to generate 24,000 visits while continuously optimising the particular microsite. This approach pays off the most effectively in terms of the Cost per Session at CZK 4.20.

Given the highly competitive sector of non–banking loans, the Average Cost per Session shows the value of CZK 15.8. The Social Network channel, which mainly consists of Facebook management and posts, shows the cost per session of CZK 25. This represents a value of almost 6 times higher than Organic Search. However, company's Facebook profile was not primarily created to get people to visit the loan calculator, but with the intention of providing information on various news items and building the brand awareness of financial products.

Furthermore, the author provides an evaluation of customer behaviour in terms of the metric Bounce Rate. The following Table 14 shows that the Display channel tends to have the highest bounce rate of 61.2 %, which at the same time generated the highest number of sessions. It could be a signal for the company to pay attention towards the Display channel in terms of either optimising either ads that were displayed or the landing site of the campaign. Google Analytics also recorded a reasonable number of sessions which can be credited mainly to continuous search engine optimisations towards the main Czech search engines such as Seznam and Google. It is also worth pointing out that Paid Search shows 44.3 % of bounce rate. However, when comparing the performance of Display and Paid Search, the latter performed better overall in this campaign.

Table 14. Bounce Rate

Channel	Sessions	Bounce rate
Display	39,000	61.2 %
Organic Search	24,000	22.3 %
Paid Search	17,000	44.3 %
Direct	16,000	34.1 %
Referral	11,000	51.7 %
Social Network	3,000	35.3 %

Source: Own processing

Key Performance Indicators

Multi-Channel Funnels and Attribution Models allow for an understanding of how marketing channels function together to create conversions or sales if applicable to other websites.

With the use of Multi-Channel Funnels, it is possible to gain insight based on the following indicators provided by the company:

- Conversions
- Conversion Rate
- Cost per Acquisition (CPA)
- Return on Advertising Spend (ROAS)
- Profit

To calculate ROAS, it is necessary to know the profit. The company provided the author with the information of CZK 14,000 of profit for one conversion.

All business cases were closed by the sales team of the company. The success rate for closing a deal is reported by the company and reaches up to 75 %, generating overall 588 various type of sold loans out of 784 leads.

- Success Rate = 75 %
- Number of Loans = 588

The settings of performance indicators and their targets should precede results evaluations using Multi–Channel Funnels. Such targets must be measurable. Therefore, it is necessary to determine the values of selected indicators that the company wants to reach. These values may be based on previous campaigns

In this case study on the use of Multi–Channel Funnels, the following targets were identified:

- Cost per Acquisition (CPA) < CZK 3,500
- Return on Advertising Spend (ROAS) > 0

The CPA is based on previous campaigns and the value should ideally be lower than CZK 3,500. The value represents the cost incurred to obtain a Lead. This threshold should not exceed the profit that is generated by one conversion of one conversion.

ROAS is another indicator that can provide the company with valuable insights in terms of evaluating the effectiveness of the campaign. This indicator suggests the return on advertising spend and shows the return on 1 Czech Koruna invested in the marketing channel. If the indicator is below zero, the investments in the marketing channel have not been returned.

An equally important indicator considered in this diploma thesis by the author is the number of conversions that could be tracked by the company to the source of the marketing channel (Loans contracts tracked to the channel) as seen in Table 15. If the source generates relatively expensive conversions, it is not always necessary to eliminate such a marketing channel. Therefore, it is important to know how many conversions took place. In the case of this study, it is also important as well as interesting to know how many loans were the subject of the deal.

Table 15. ROAS of Individual Channels

Channel	Conversions "Leads"	Loan contracts tracked to the channel	Average Profit per One Conversion in CZK	Total Costs in CZK	Total Profit in CZK	ROAS in CZK
Paid Search	102	77	14,000	250,000	1,078,000	4.31
Display	112	85		750,000	1,190,000	1.59
Social Network	23	9		75,000	126,000	1.68
Organic Search	314	147		100,000	2,058,000	20.58
Direct	177	**249**		-	3,486,000	-
Referral	56	21		-	294,000	-
Total	784	588		1,175,000	8,232,000	

Source: Own processing

In above Table 15, the author shows that there were 314 conversions credited to Organic Search. In reality, the company signed up only 147 loan contracts. As was mentioned earlier in this case study, the greatest responsibility in terms of closing a deal goes to the sales team of the company. Nevertheless, the Organic Search channel contributes a large portion of leads generated during the campaign, as well as the profit generated. Despite the Social Network channel mainly consisting of working for the company as its brand ambassador, it still generates a profit of CZK 126,000 and a cost of CZK 75,000 during the campaign. Based on the ROAS indicator, this channel is even more effective than the Display part of the campaign.

The highest return on 1 Czech Koruna invested is credited to Organic Search. The above Table reports ROAS of CZK 20.58 to Organic Search. The second most effective source seems to be the Paid Search channel with ROAS of CZK 4.31

A large portion of the overall profit tends to fall into the Direct channel. There were 249 loan contracts signed and the above Table shows a profit of CZK 3,486,000. However, the Direct channel could not be part of the campaign management.

5.2 Recommendations

It is viable to use the Google Analytics and Multi–Channel Funnels web analytics tool for the analysis of data from marketing campaigns. Such campaigns should be monitored continuously. Evaluations of campaigns should be conducted through regular analyses and reports on at least a monthly basis. The author suggests that any analyst or marketer responsible for management of these campaigns should record changes applied to campaigns or the particular websites that are responsible for conversion goals. Thanks to this procedure it should be possible to track changes in indicators or other metrics that might be affected and the company can decide whether to undergo similar changes in the future.

The core of using Multi–Channel Funnels and Attribution Models in Google Analytics focuses on finding whether the money that the company invests in online marketing can be effectively allocated. The company should analyse its campaigns on a regular basis and check and test the redistribution of funds between channels. The author suggests that the company should ascertain whether its investments in specific marketing channels are returned in the form of profit and it should also examine how different marketing channels interact.

Moreover, the author suggests that the company takes into account the possibility of importing costs related to particular channels as well as the conversion value that was missing in this case study into the Google Analytics. Then this particular analytics tool can support the company in a more efficient way in the process of crediting the channels.

Based on previous analysis, the author suggests that the company tests decreasing campaign spend for future campaigns in relation to those channels that have lower ROAS in favour of the channel that has a lower CPA than the target value. In particular, the author recommends the redistribution of investments from the Display channel in favour of the Paid Search channel. The Display channel has a very high CPA of a minimum of CZK 6,696 according to the Last Non–Direct Click model. In all Attribution Models, Table 12 shows almost the same number of conversions. Whereas the Paid Search channel reaches the CPA in all the compared models the value of between CZK 2,451 and CZK 3,012 that is still below the target CPA value of CZK 3,500

The above recommendations are necessary to be tested and evaluated again by the company to see changes in the number of conversions as well as the improvement of ROAS and CPA of both the Display as well as Paid Search channels. These recommendations are made in order to effectively reallocate the investments, not to increase the campaign spend. If the changes take place towards the desired targets, the company may consider designing its own Attribution Model to reflect the importance of individual channels.

Based on the data analysis, the author also recommends the company keeps up the same intensive work on the optimisation process of the company website which reflects the external and internal time of SEO consultants, programmers and copywriters who incorporate the recommended changes in terms of optimisation. This recommendation is based on Table 12. In most of the model this channel represents the highest number of conversions and at the same time the lowest CPA. Looking at ROAS value for this channel, Organic Search tends to be the most effective channel in the campaign

Moreover, search engine optimization (SEO) usually tends to have higher initial costs compared to the paid online advertising, but the positive outcome is apparent in the long term. With reference to this case study, as was previously mentioned, the company hugely optimised its website at the beginning of the 2015 year, prior to the start of the analysed campaign.

It is likely that the absence of the E-mail channel had an impact on the final campaign performance because emailing tools and a high-quality client database can currently provide extensive opportunities for maintaining customer relationships, as well as for selling a financial product. The author suggests that the company develops its e-mailing strategy.

The author also suggests that the company takes a few extra steps in order to use Multi–Channel Attribution in an advanced approach. The company may consider combining click stream data from a web analytic tool, such as Google Analytics, social network data from Facebook, data from CRM systems and other data that could drive the data-driven decision more precisely.

6 Conclusion

This thesis summarises the essential information on the use of Multi–Channel Funnels in Google Analytics. The author also analyses related issues such as Attribution Models.

In the literature part, the author focuses on describing the core concepts of web analytics. The literature part also underlines the method of campaign tracking in order to be able to measure online marketing activities using Google Analytics. The author explains the concept of key metrics and how to work with them. The literature part of the thesis also covers the cases in which the analytics tool could distort reality in terms of the data reported by the analytics tool. The author widely covers Multi–Channel Funnels and Attribution Models used in Google Analytics.

In the practical part of the thesis, the author focuses on the verification of theoretical knowledge. The practical part consists of the case study in which the author used Google Analytics to examine the functionality and evaluated a specific campaign based on Multi-Channel Attribution. This campaign was conducted by a non-bank financial institution (NBFI) prior to this diploma thesis.

Due to the author's field of study, Multi–Channel Funnels and Attribution Models described in the theoretical part of the thesis are used in the case study to provide insights into the individual channels and how to relocate investments in more effective marketing channels.

Based on the practical part of the thesis, the author suggests that the company to relocates part of its future investments from the Display channel in favour of the Paid Search channel that had a relatively low performance in terms of CPA

Based on previous analysis, the author suggests that the company to decreases campaign spend for future campaigns in relation to those channels that have higher ROAS in favour of the channel that has a lower CPA than the target value. In particularly, the author recommends redistributing investments from the Display channel in favour of Paid Search channel, which still showed a higher performance indicator of ROAS CZK 4.31

In the event of the NBFI launching a similar campaign in the future with the same conversion goal, a lead generation to sell non-banking loans, the author assumes that the Last Non–Direct Click seems to be an optimal model.

The mindset behind the recommendation is based on the results of the thesis which show that the decision-making process of those users who converted was relatively quick and the customer path across all channels was short in the number of interactions leading to conversions as well as the number of days it took for users to convert. The author also assumes that the Last Non–Direct Click model could absorb more changes in the way that future campaigns might be managed. If the company starts using its e-mail database, the performance of channels might change. As the author already mentioned, all changes need to be tested on regular basis. Only then can the company experiment in modeling its own customised Attribution Model and in testing it across all online channels.

Moreover, the author states that the Last Non–Direct Click model is still the standard in the industry. In the context of the campaign that was retrospectively analysed, and which recorded small number of touch points, the model seems sufficient and meets the requirements of the company to evaluate the effectiveness of the channels.

The author would like to point out that there is no perfect Attribution Model, as was mentioned in the literature review. There are only better ones to improve investment allocation to digital marketing channels. In addition, it is worth stating that Attribution Models depend on the type of business as well as on the strategy under which a particular company operates.

Google Analytics can provide the company with valuable insights. Knowing the limitations of Google Analytics, the author states that the approach to the utilisation of any analytical tool is also limited by the mindset of the company's goals and strategy.

The main goal and partial goals of the thesis were fulfilled in the literature review, as well as in the practical part of the thesis.

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List of Abbreviations

NBFI – Non Bank Financial Institution

PA – Performance Agency

URL – Uniform Resource Locator

SEO – Search Engine Optimization

CMS – Content Management System

CRM – Customer Relationships Management systems