MULTICHANNEL MARKETING ATTRIBUTION USING MARKOV CHAINS

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Abstract

The objective of this paper is to analyze the data of a selected company using Markov chains. The data about online customer journeys were analyzed. The authors found that Markov model decreases the credit assigned to channels favored by last-touch heuristic models and assigns more credit to channels favored by first-touch or linear heuristic models. By using Markov order estimator GDL the authors also found that order 4 was the most suitable for analysis of buyer journeys. Approximately 40% of revenue was generated by journeys with less than 5 interactions and thus indecisive customers have small incremental effect on the overall conversions.

Keywords: attribution modeling, multichannel attribution, Markov chains, digital analysis, web analytics

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Introduction

Approximately 96% of website visitors aren't ready to purchase a product during their first website visit (Bulygo, 2012). On the contrary, since the first visit toward conversion (purchase), the visitors move through the process called the buyer journey. This process represents the sequence of the steps taken by customers during move though the phases of awareness, decision-making and purchases (Roberge, 2015). The modeling of the buyer's journey consists on mapping the customer's interaction with the brand aiming to improve these interactions. This process should result in increase in sales and customer satisfaction (Berg and Pietersma, 2015; Kot et al., 2013; Ślusarczyk and Kot, 2012). Through the progress of digital advertising and technological innovations, companies are able to track digital "footprints" of the customers on a granular level, bringing the knowledge about customer's behavior and, moreover, measure the impact of displaying the particular marketing channels to the customers on conversions (Ghose and Todri, 2015; Smarandache and Vladutescu, 2014). Many researchers such as Peterson (2005), Constantin (2014) or Massara et al. (2010) have tried to model consumers' behavior in order to predict their response. Attribution modeling can be considered to be another point of view to this particular topic. The strategies of Mexican companies tend to focus on the use of resources and capabilities to generate profit. But the results obtained by some of the strongest Mexican worldwide companies are the result of market development and practice of M & A, which are mostly related to areas of its core business. There is no universal strategy that works for all organizations and generates the best profits. Company must also assess favorable and unfavorable conditions for implementation and most importantly, act on that strategy which is most appropriate and effective company in the search to achieve their goals.

Companies usually don’t rely solely on one marketing channel in order to acquire the customers. Several marketing channels are used while working in cohesion to accomplish the company’s goals. The value for importance should be assigned to each of these channels. Attribution modeling is a set of rules based on which the credit for conversion or purchase is assigned to particular marketing channels (Shao and Li, 2011; Clifton, 2015). Ferencová et al. (2015) defined a problem connected to evaluation of utility of marketing channels in sales cycle. In spite of executed surveys for customers, it is often difficult to determine the channels they interacted along their journeys. This issue can be solved by using attribution models where each customer touchpoint with the company can be evaluated. (Szulc et al., 2013) claim that the use of attribution modeling helps optimize the allocation of marketing budget, support marketing budgeting, ensure more precise planning of marketing campaigns, ensure accuracy of cost-per-acquisition calculation and help optimize payments to affiliate partners.

In currently available web analytics tools (such as Google Analytics), there are several Heuristic models implemented in order to determine the merits of each marketing channels, for example Kaushik (2011), Clifton (2015), Shao and Li (2011):

- last touch (100% of the credit is assigned to the channel prior the conversion),
- first touch (100% of the credit is assigned to the first channel that customer got in interaction with),
- linear model (an equal amount of credit is assigned over all the channels that customer interacted with during the journey),
- time-decay (the highest value is assigned to the last channel or campaign, and the assigned value decreases towards first channel),
- position-based (40% is assigned to first and last interaction, the rest of the credit is distributed evenly across the remaining channels),
- custom model (analyst itself assigns the value to the channels based on his own set of rules).

Barajas et al. (2016), Anderl et al. (2014), Anderl et al. (2016), Abhishek et al. (2012) and Bryl (2016) reported that the use of heuristic attribution models are not proper for attribution purposes. Barajas et al. (2016) claim that heuristic models assign value to each displayed and converting channel, however they ignore hypothetical reaction without user being in touch with the advertisement. Abhishek et al. (2012) state that heuristic models are not data-driven. Anderl et al. (2014) discuss that, despite heuristic models are not accurate, the use of more sophisticated attribution approaches found its place in managerial practice. Bryl (2016) claims that heuristic models are not proper for channel attribution, because of their poor quantity, while their selection requires a managerial decision in order to choose the right one that will be suitable for company’s data.

There have been several studies that offered more data-driven approaches to the attribution in order to overcome the weaknesses of Heuristic models. Yadagiri et al. (2015) and Nissar and Yeung (2015) use Shapley value in their non-parametric approach to attribution as a game theory based model. In his thesis, Rentola (2014) used two models: binary logistic regression to classify customers to converters and non-converters (purchasers/non-purchasers), as well as logistic regression model with bootstrap aggregation. On the other hand, Shao and Li (2011) used bagged logistic regression and probabilistic model in their study. Li and Kannan (2014) used hierarchical Bayesian model. Geyik et al. (2014) developed their attribution algorithm MTA that was developed to solve two problems: spending capability calculation for a sub-campaign and return-on-investment calculation for a sub-campaign (see more in Geyik et al., 2014). On the contrary, Wooff and Anderson (2015) offer an attribution mechanism based on appropriate time-weighting of clicks using sequential analysis. Hidden Markov Model was used in studies conducted by Abhishek et al. (2012) and Wang et al. (2015).

We can see many approaches to the attribution. However, we incline to Markov chain model proposed by Anderl et al. (2014) discussed in the following parts of our study. Anderl et al. (2014) and the following study by Anderl et al. (2016) use higher order Markov chains model in order to attribute the value of the marketing channels. They propose that for practical reasons, 3rd order is the most proficient when calculating the outcome of particular marketing channels. Anderl et al. (2014) further reported that Markov model meets the following criteria: objectivity, predictive accuracy, robustness, interpretability, versatility and algorithmic efficiency. Anderl et al. (2016) also stated that Heuristic models undervalues display advertising and pay-per-clck campaigns, social media and e-mail activities. On the other hand, Markov chains distribute the value of the channel more evenly. Based on these criteria, we selected Markov chains to be a suitable method for the analysis of our study. We also select this method based on the following criteria:

• The export of customer journeys consisting of marketing channels customers used in order to come to the website prior the purchase is among the standard features of Google Analytics Free that is the most used web analytics tool (Cliffon, 2015). This ensures our analysis might be executed broadly by company of any size and budget.

• Attribution analysis using Markov chains can be easily executed in software The R Project (R, 2016) with couple lines of code using the package ChannelAttribution (Altomare, 2016) and allows users to compare the results in the standard Heuristic models. The data exported from Google Analytics almost exactly suits the structure supported by this package.

Based on the abovementioned claims, we choose Markov chains to be suitable model for our analysis and therefore will be discussed in detail in the forthcoming section.

Markov Chain and Its Use for Attribution Modeling

Formally, a sequence of random variables $\{X_t\}_{t=1}^{\infty}$, $X_t \in S := \{s_1, \dots, s_m\}$, is a Markov chain of order *r* if, for all $(a_1, \dots, a_{t+1}) \in S^{t+1}$, $P(X_{t+1} = a_{t+1} | X_1 = a_1, \dots, X_t = a_t) = P(X_{t+1} = a_{t+1} | X_{t-r+1} = a_{t-r+1}, \dots, X_t = a_t)$

and r is the smallest integer to satisfy it. Essentially, this represents that the probabilities related to X_{t+1} depends only on the last r events, for all t.

In this context, S is referred by the state space, a particular sequence $(a_1, a_2, \ldots) \in S^\infty$ is called by a trajectory, the size of S is the length of state space or number of states, represented by m, and the probabilities of $X_{t+1} = a_{t+1}$ considering that $(X_{t-r+1}, \ldots, X_t) = (a_{t-r+1}, \ldots, a_t)$ are called by the transition probabilities represented by the notation: $p(a_{t+1}|a_{t-r+1}, \ldots, a_t) := P(X_{t+1} = a_{t+1} \mid X_{t-r+1} = a_{t-r+1}, \ldots, X_t = a_t)$. Here, we consider that the Markov chain is stationary, i.e., the transition probabilities don't depend on t. A particular state b is absorbing if the probabilities to leave the state are "0", i.e., $p(c|a_{t-r+1}, \ldots, b) = 0, \forall\, c \neq b$ and, consequently, $p(b|a_{t-r+1}, \ldots, b) = 1$.

A Markov chain can be represented by an initial probability distribution for the first r steps and the m^{r+1} transition probabilities. When r = 1, it is possible to have a graphic representation for the Markov chain. For more details about Markov chains, we recommend (Karlin and Taylor, 1975).

Anderl et al. (2014) propose the use of Markov chains on channel attributions, considering the state space S as the states "Start" and "Conversion" combined with the set of marketing channels. In this case, the process $\{X_t\}$ represents the possible customer journeys through these channels. They suggest using a removal effect for attribution modeling. The removal effect is defined as the probability to achieve conversion from the "*Start*" state if some of the state (s_i) is removed from the model. As removal effect reflects the change in conversion rate if the given state si is removed, the value (or importance) of the given marketing channel can be determined. If N conversions are generated without the particular channel (compared to the number of conversions in the full model), the removed channel determines the change in the total number of conversion (Bryl, 2016). Markov chain described in this section defines the methodical framework used in our analysis conducted in the following parts of the study.

Objectives and Methods

The main objective of this paper is to define the current state of multichannel attribution and, based on the literature, to analyze the data of a selected company by using the Markov chains approach. The main objective is decomposed on three partial objectives: to determine the current state of use of attribution modeling; to analyze the multichannel paths of a selected company with the use of Markov chains and compare the results with selected heuristic models; to analyze the length of purchasing paths and revenue generated; and to propose the best order for Markov chain.

In order to achieve the abovementioned objectives, we analyzed the data from the e-commerce website of the company SOS electronic s. r. o. based in Slovakia. The company was founded in 1995 and is focused on the distribution of industrial electronic components for manufacturing. The website is adjusted to the countries in which the company has its business affiliations – Slovak Republic, Czech Republic, Hungary, Poland, Romania, Germany and Great Britain. SOS electronic is classified as medium-sized company based on the following criteria by Chapčáková et al. (2010): the number of employees is in the range of 50-249, the turnover of the company is lower than 50 million € and profit is lower than 43 million € (information about company's characteristics was retrieved from Finstat (2016). Website revenues represent 41-60% of the total company revenues. The e-commerce data was retrieved from web analytics platform Google Analytics. Top conversion paths were analyzed using heuristic models and Markov chains, both defined in the previous section. In addition, the elements of descriptive statistics were also used (table, bar chart, pie chart, radar chart). The data was analyzed using The R Project for Statistical Computing (R, 2016), Google Analytics and MS Excel.

The Data

The data were exported from Google Analytics for the date range from 1 April 2016 to 31 August 2016. We analyzed 6,304 conversions representing purchases on e-commerce website of the company. The distribution of the path lengths is presented on the Table 1. More than 75% of customer journeys have at least 2 interactions, so the last-touch heuristic model would not be accurate for the attribution modeling. If only last-touch model was used, there would be missing insights regarding the contribution of marketing channels that appeared in the buyer journey prior the purchasing decision was made. These 75% of customer journeys generated more than 80% of the revenue. It is obvious that it is important to analyze conversion paths on a more granular level and assign the value to the channels which contributed to these conversions. For our analysis we used only conversion paths with more than 1 interaction. In journeys with only 1 interaction, the same value to the channel is assigned by each method – 100% of the credit is assigned to the channel that is responsible for the conversion. In Google Analytics, we set that conversion journey will not be taken for a time period longer than 30 days.

Table 1. The Distribution of Conversions and Revenue Based on the Number of Interactions

Total number of interactions	1	2	3	4	5	6
Number of conversions	2,116	1,131	717	529	377	300
Revenue (in €)	239,350.64	121,487.81	82,595.22	67,365.45	60,398.52	35,979.91
Total number of interactions	7	8	9	10	11	12+
Number of conversions	238	196	183	159	134	2,404
Revenue (in €)	35,431.79	28,331.59	28,248.50	21,592.15	22,695.48	558,662.98

When we exported the data, we were able to determine the set of states *S = {Direct, Organic search, Paid search, Email, Referral, Social Network, Display Advertising}*. Direct traffic represents the users who visited company's website as a result of typing the website URL to the browser or via saved bookmark. Organic search represents users who performed search on Google, Bing, Yahoo or other search engine and landed on the company's website after clicking on the search results. Paid search represents visits from users who clicked on the ads in the search engine results page (consider Google AdWords as an example). Referral traffic is represented by users who visited the company's website by clicking on the link available on another website. Social Network represents visits from users who clicked on links pointing to the company's website on social media such as Facebook, Twitter, LinkedIn etc. Display Advertising represents visits from users who saw banner ads on other websites and by clicking on them, they landed on the company's website. Based on the package ChannelAttribution (Altomare, 2016), we added 2 additional states to the set of states – *Start* (representing the start of the customer journey) and *Conversion* (representing purchase). Thus, the final set of states is the following: *S = {Start, Conversion, Direct, Organic search, Paid search, Email, Referral, Social network, Display advertising}*. We didn't include *NULL* state (the journeys without purchases) as Google Analytics doesn't track these paths and implementation and data collection would take additional amount of time.

We already collected data about trajectories (conversion paths) and defined the set of states. In order to estimate basic Markov model, we removed repeated sequences found in the paths (when customer visited the website by using the same marketing channel more than once in a row during one journey). And therefore, when customer journey was e. g. *Direct > Direct > Social network > Social network > Social Network*, this journey was reduced to *Direct > Social network*. Afterwards, we were able to calculate the transformation matrix in order to find out transition probabilities defining the probabilities of customers moving from one state (marketing channel) to another state (other marketing channel or conversion). The transition matrix is presented by Figure 1.

Channel from \ Channel to	Conversion	Direct	Display advertising	Email	Organic search	Paid search	Referral	Social network
Social network	0.07	0.83	0	0.04	0.04	0.01	0.02	
Referral	0.13	0.7	0	0.06	0.07	0.03		0
Paid search	0.23	0.49	0	0.03	0.23		0.02	0
Organic search	0.1	0.75	0	0.02		0.01	0.02	0
Email	0.05	0.76	0		0.11	0.05	0.03	0
Display advertising	0.03	0.8		-	0.1	0.03	0.03	-
Direct	0.66		0	0.09	0.11	0.06	0.06	0.01
Start		0.7	0	0.06	0.13	0.09	0.02	0

Figure 1. The Transition Matrix

By studying the transition matrix, we came to the following two conclusions:

1. There are only few marketing channels that are responsible for closing the conversion – Direct traffic (p = 0.66), Paid search (p = 0.23) and Referral traffic (p = 0.13).

2. The most probable step from each marketing channel (except Direct) is to

interact with the website directly – via Direct traffic. As we checked the data from Google Analytics, we found out that more than 50% of users visiting website are repeating customers. We assume these users have already company's website on their mind and thus remember the website URL or saved website as a bookmark. As company has also strong offline presence, direct traffic might be a result of potential customers' movement from offline media (e. g. catalogue) to the online environment.

We analyzed the generalized behavior of customers during purchasing process. It is also vital to analyze the revenue generated based on the length of the buyer journey. Figure 2 displays the distribution of the generated revenue based on the number of steps in the buyer journey. It is possible to see that the significant amount of revenue is generated by users presented by path consisting of less than 5 steps. As we weren't able to separate first-time purchasers from repeating purchasers, we assume that this revenue could be assigned to the repeating purchasers. We built this assumption based on the 2 arguments:

1) we assume that repeating customers trust the seller more and thus don't need so many interaction prior repeated purchase;

2) Barker (2017) presents the fact that repeated purchasers spend more during repeated purchases, as the purpose of the first purchase was to test the seller's services.

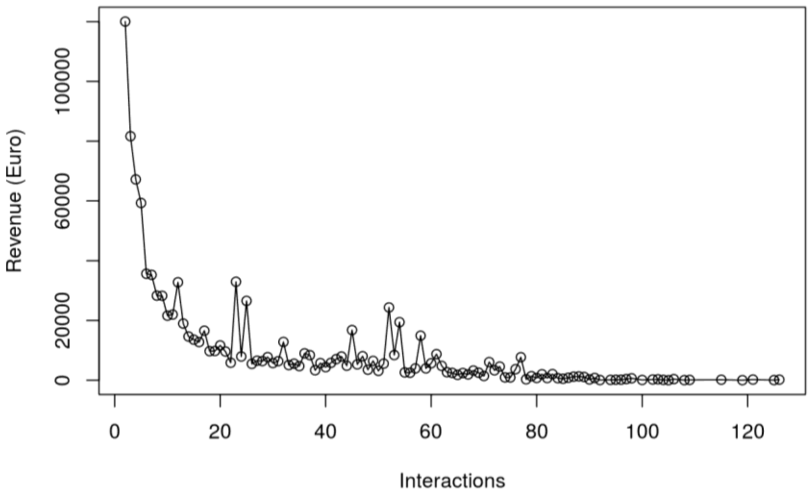

Figure 2. Distribution of Generated Revenue Based on the Length of Buyer Journey

As we can see in Figure 3, buyer journeys consisting of five or less steps are responsible for 40% of company's online revenue. Moreover, buyer journeys consisting of 20 or less interactions are responsible for 60% of overall generated revenue. We can also note that after 60 interactions, there is only small cumulative growth in overall revenue. It is possible to provide a conclusion that indecisive customers have small impact on the revenue growth of the company.

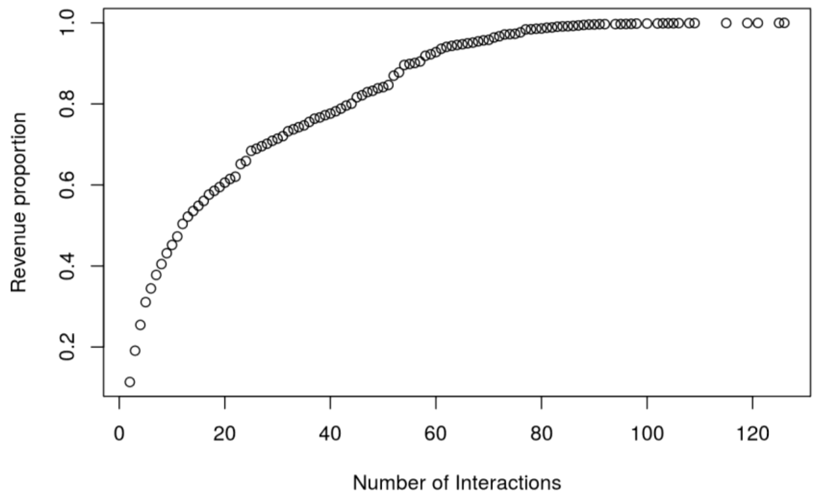

Figure 3. The Proportion of Cumulative Revenue Based on the Number of Interactions

For simplicity, above we considered the order 1 for the Markov chain model. However, it may have a more suitable order for these samples, which can provide a better approximation for the outputs. AIC, BIC and EDC are among commonly used order estimators of Markov chains (Dorea et al., 2015). However, the Markov chain order estimator GDL proposed by (Baigorri et al., 2014) is more suitable to use for our data. Essentially, GDL uses chi-square divergence to compare the probabilities $\{p(b|a_{t-k},\dots,a_1)\}_{b\in S}$ and $\{p(b|a_{t-k-1},\dots,a_1)\}_{b\in S}$ for $k = 1\dots K$, while AIC, BIC and EDC are based on the asymptotic behavior of the log-likelihood function for each $k = 1\dots K$. GDL is more efficient on small samples compared with AIC, BIC and EDC, which is our case. Using the Markov chain order estimator GDL, we could find the order 4 for the reduced data. A Markov chain of order r can be modeled without any loss by a Markov chain of order $k > r$. The problem in choosing an order is to find a short order to avoid large transition matrices. Below we compare removal effects when modeling considering the order $r = 4$ with the models of orders $r = \{1,2,3,5,6,10\}$. The graphic shows that the differences of removal effects when considering orders greater than 4 is substantially small when comparing with orders less than 4. This points out that the order 4 is a good approximation. This finding contradicts to conclusions of study by Anderl et al. (2016) that found order 3 to be the most suitable for their data. In order to determine the right order they computed the average standard deviation of removal effect(s) across ten cross-validation repetitions. We do not consider third Markov order to be the silver bullet in the attribution. However, GDL provides an efficient way to determine the right order easily applicable by companies in general.

As we estimated the right Markov order for our model, it is vital to attribute conversions and value generated by particular marketing channels. We also used commonly used Heuristic models - first-touch, last-touch and linear model – in order to compare the results. Conversions attributed to the particular channels are presented in the Figure 4.

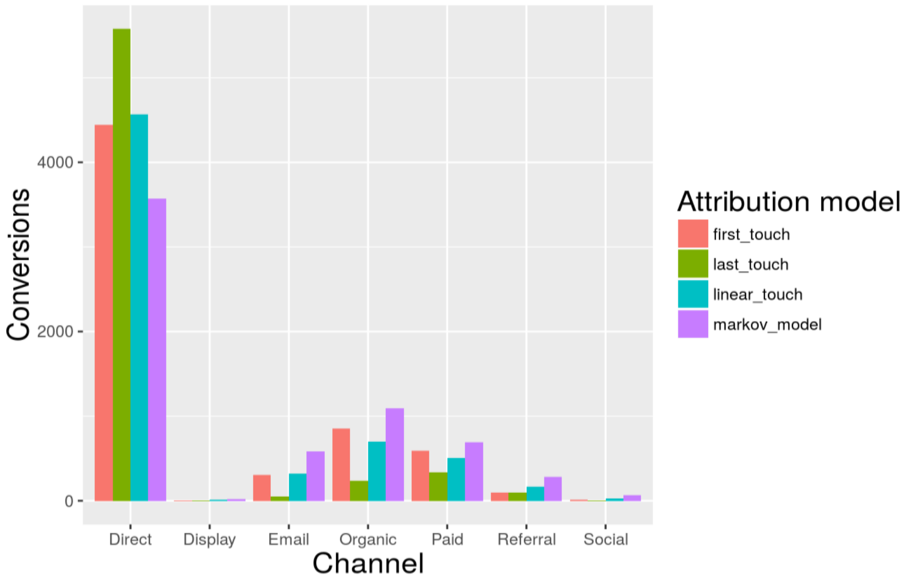

Figure 4. Conversions Assigned to Marketing Channels

The results shows that Direct is the most valuable marketing channel for the analyzed company by all means. This result proves that strong branding really affects the behavior of the customers towards purchase. In our case, it is also possible to conclude that purchases from direct visits might be a result of repeated customers who were already familiar with the company domain name or have bookmark created in their web browsers. We also need to take cross-device effect into account (more in the limitations of the study). This result contradicts with Abhishek at al. (2014), Zheng et al. (2017) and Anderl et al. (2016) in whose studies the paid search was the most productive marketing channel. We note that in the abovementioned studies, direct visits were not analyzed. However, in case of Li and Kannan (2014) the results regarding the direct traffic are the same. In general, we can conclude that Markov model assigns less credit for conversions from direct traffic compared to Heuristic models, however, assigns more conversion credit to other channels such as organic search, paid search, email, referral traffic and social media traffic to which first-touch and linear heuristic models assigns more conversions than to last touch model.

Limitations of the study:

• There is no presence of NULL state. As we didn't include journeys that didn't end up with purchase, the model wasn't fully optimized for the accuracy – especially if generally there are more buyer journeys without the purchase. On the other hand, journeys that have not end up as conversions now, might end up as conversions in the future.

• We took into account only touch points resulting in the visit of the company's website. Some of the customers might be displayed to the advertisements they didn't click on, however, they remembered them. On the other hand, direct traffic could be affected by saved bookmarks or offline advertisement.

• Cross-device analysis was not applied in order to analyze purchase paths. This could result in more direct conversions as user could browse the offer at one device, remembered the website and accessed it directly via other device.

• For customer journey, we only analyzed data including only 30 days prior the conversion. However, there might be existing customer journeys that are longer than 30 days.

• We didn't take ROPO effect (research online, purchase offline) by Seitz (2014) and vice versa into account. This limitation might be solved by importing offline data about customer journeys into the existing conversion paths.

Conclusions

Multichannel attribution helps companies assign the value to each marketing channel in order to select the profitable ones. The main objective of this paper was to define the current state of multichannel attribution and based on the literature study analyze the data of selected company using Markov chains. Attribution modeling has already been the focus of the study of several authors. Some of them have already focused on Markov chains. To accomplish the main objective of our study, we analyzed top conversion paths from the e-commerce website of the company SOS electronic s. r. o. We found that the evaluation of marketing channels differs comparing Markov chains and heuristic models. First of all, we found direct traffic to be responsible for the majority of the purchases. Afterwards, we found that almost 40% of conversions are generated by users with less than 5 steps in their buyer journey. In addition, we found that indecisive customers (those who have many interactions with company's website) have small incremental effect on the overall conversions. In order to evaluate the customers' behavior and predict it more precisely, we focused on the determination of the right Markov order using GDL. We found that order 4 is the most suitable for our data. By analyzing conversions and revenue with the new model, we found one important implication of Markov model. Markov model decreases the credit assigned to channels which are favored by last-touch heuristic models, on the other hand assigns more credit to channels who are more favored by first-touch or linear heuristic models. The methodology and results might be used by companies whose customers need more than one interaction with the company to purchase a product. Moreover, the results and methods can be also used by companies that don't generate online sales to evaluate other types of conversions. Our future work will focus on removing the limitations mentioned in the results of the study.

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