IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

MARKETING CHANNEL ATTRIBUTION WITH MARKOV CHAINS IN PYTHON

M. Annapurna
Department of Computer Science and Engineering
Vignan's Institute of Engineering for Women
Visakhapatnam, India

K. Leelavathi
Department of Computer Science and Engineering
Vignan's Institute of Engineering for Women
Visakhapatnam, India

M.Uma Maheswari
Department of Computer Science and Engineering
Vignan's Institute of Engineering for Women
Visakhapatnam, India

K. Hema
Department of Computer Science and Engineering
Vignan's Institute of Engineering for Women
Visakhapatnam, India

Mr. A. Maheswararao
Assistant Professor
Department of Computer Science and Engineering
Vignan's Institute of Engineering for Women
Visakhapatnam, India

Abstract- Customers get exposed to advertisers through various channels. A series of such interactions made with the customers through these ads results in the conversion or sale. In this scenario, we are left with a key question of attribution: which ads get credit for the conversion and how much significance each of these ads have in conversion of a Lead. Though the issue is not newly produced, the solutions are often simplistic and unreliable. For e.g., attributing the sale to most recent ad exposure.
In this project, we integrate the customer data taken from an organization which includes various touch points with the customers through campaigns conducted by the company to create a customer journey also called as "CUSTOMER 360".This integrated data then can be used to calculate the significance of each campaign by applying Markov chain analysis. These metrics can be used to calculate Return on Investment on each campaign.

Keywords – marketing strategies, marketing channel, digital platform, channel attribution model, Markov analysis, web analytics

I. INTRODUCTION

The use of digital technologies for the purpose of advertisements has been growing tremendously since past decade. This growth made it possible for the advertisers to reach their customers in several innovative ways through various formats. Though this laid a new bridge between the marketers and customers, it also raised several problems to solve. One among them is to know the return what we get after spending on each channel in a sale. This problem arises because a typical customer may be exposed to advertiser across multiple channels ranging from advertisements on various websites to sponsored ads on search engines. These repeated interactions with an advertiser's campaign are termed "multi-touch" in the popular press (Kaushik, 2012), and they jointly affect a customer's behavior. When a user buys a product or signs up for a service, his decision to do so may be influenced by a series of exposures with ads on various platforms. Advertisers wish to access to what extent each channel influences a customer through a reliable process. This information helps them in optimal allocation of the budget in ads.
This problem of attribution is not a new one, but then with the advancements in the technology and with the availability of individual level data in the online channels, we can now have more detailed view of the trends and patterns followed by users. This granular data

from the advertisements can be used to build rich models to analyze customer journeys and to measure the significance of each channel in driving a lead to a customer.

Due to the lack of proper awareness and technological advancements many marketers still depend on rule-based techniques for attribution like last touch attribution (LTA). In this technique all the credit for the customer conversion is given to the most recent ad after which the user has converted. But this technique is often misleading as no credit was given to the all the previous ads the lead the user to the conversion. Forexample a user may see a display ad which lead him to a website. In LTA all the credit was given to website which is a false attribution and may move the funding from efficient channel. This incorrect attribution not only impacts the company in long term but also increases inefficiency in the marketplace. First touch attribution, Linear attribution are some other heuristics which suffer similar problem.

In this project we propose a data driven model for attribution using Markov Chain analysis and thus give a technique to calculate Return on Investment of each channel. Here we use the concept of customer 360 to get the customer behavior, then based on impact it has on customer's probability to convert, we assign return on investment to various channels using Markov chain analysis.

The rest of the paper is organized as follows. Literature servey is explained in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

II. LITERATURE SURVEY

There are many ways to calculate the return on investment on attribution modelling. Attribution modelling is the method used to measure the monetary impact a piece of communication has on real business goals like sales, profit and revenue. It means defining a system of analysis that can be used to measure marketing metrics against business results. This means using metrics like Turnover, Profit, Customer retention and Volume of sales. Attribution models are typically categorized as single-touch or multi-touch. Attribution models are typically categorized as single-touch or multi-touch.

A. *Single-Touch Attribution Models*

Single-touch Attribution models attribute a conversion to a single touchpoint, often the first or last one engaged with by the consumer. This neglects to look at the wider customer journey and touchpoints engaged with.

B. *Multi-Touch Attribution*

Multi-touch attribution models look at all of the touchpoints engaged with by the consumer leading up to a purchase. As a result, these are considered more accurate models.

C. *Types of Attribution Models*

As noted earlier, there are two main categories of attribution: single touch, and multi touch. Within these categories there are several core models which each provide different insights:

D. *Single-Touch Attribution First-Touch Attribution*

First-touch attribution assumes that the consumer chose to convert after the first advertisement they encountered. Therefore, it gives full attribution to this first touchpoint, regardless of additional messaging seen subsequently.

E. *Last-Touch Attribution*

Conversely, last-touch attribution gives full attribution credit to the last touchpoint the consumer interacted with before making the purchase, without accounting for prior engagements.
Drawback:

Each of these methods fails to factor in the broader customer journey, as such marketers should avoid relying solely on these methods.

F. *Multi-Touch Attribution*

These models are largely differentiated by how they divide credit between touchpoints on the path to purchase.

G. *Linear*

Linear attribution records each touchpoint engaged with by the consumer leading to purchase. It weighs each of these interactions equally, giving each message the same amount of credit toward driving the conversion.

H. *U-Shaped*

Unlike linear attribution, the U-Shaped attribution model scores engagements separately, noting that some are more impactful than others on the path to purchase. Specifically, both the first touch and lead conversion touch are each credited with 40 percent of responsibility for the lead. The other 20 percent is divided amongst the touchpoints engaged with between the first and lead conversion touch.

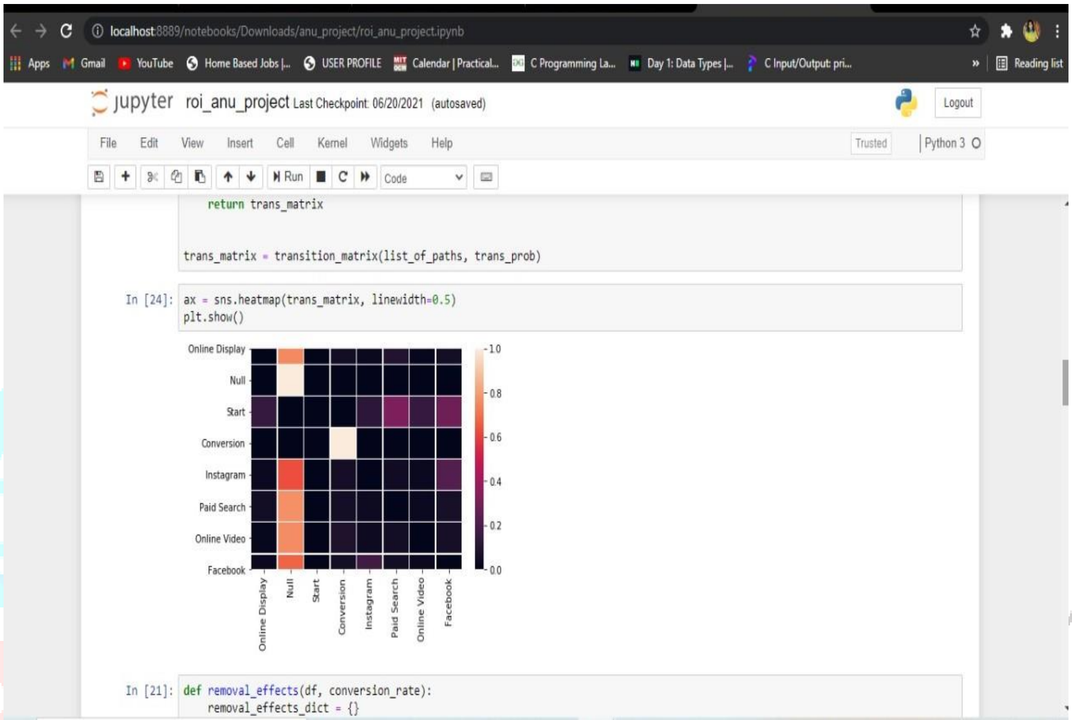
I. *Time Decay*

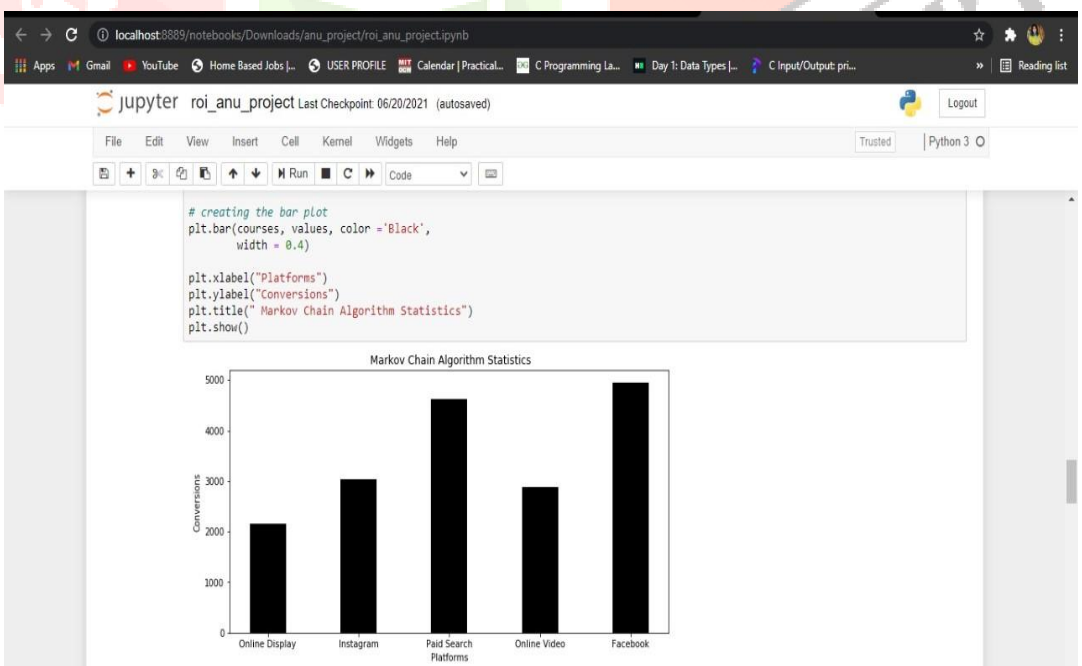
The time decay model also weighs each touchpoint differently on the path to purchase. This model gives the touchpoints engaged with closer to the conversion more weight than those engaged with early on, assuming those had a greater impact on the sale.

2.2Why Markov chains?

Traditionally, channel attribution has been tackled by a handful of simple but powerful approaches such as First Touch, Last Touch, and Linear. However, the limitations with these 3 approaches is that they are oversimplified. This may lead to overconfidence of the results driven by the marketing channels. This oversight can be detrimental — misguiding future business / marketing decisions. To overcome the oversight we may have to consider employing a more advanced approach: Markov chains. Markov chains, in the context of channel attribution, gives us a framework to model user journeys and how each channel factors into the users traveling from one channel to another toeventually purchase (or not).

III. Experiment and Result





IV.CONCLUSION

The Markov chain shows the behaviour of the customer which is modelled based on customer funnel. In a stochastic manner, the customers move through the states of the Markov chain model when exposed to advertising activity. Customer being in a certain state, he can move to another with certain probability which is a function of present state. This model is estimated on customer data of GEEKL company.

These metrics helps to assign the contribution made by each channel in conversion of a lead to a customer. This further allows us to select the profitable channels and invest on the same. In addition, it also helps marketers to target customers based on their current state in the model. This model increases the revenue which increases the efficiency of the advertising market.

Finally, every company must include a model to assess return on investment we get on channels, as if there is a hardship in a company, advertising investment is the first thing to cut-off. So, each organisation should properly assess channels and invest on them which are profitable using a reliable and accurate model

V. REFERENCE

1. Abhishek, V., Fader, P. and Hosanagar, K. (2012), "Media exposure through the funnel: A model of multi-stage attribution", available at: https://ssrn.com/abstract=2158421 (accessed December 20, 2017).
2. Altomare,D.(2016),"Package'ChannelAttribution'",available at: https://cran.rproject.org/web/packages/ChannelAttribution/ChannelAttribution.pdf, (accessed 25 September 2016).
3. Anderl, E., Becker, I., Wangenheim, F.V. and Schumann, J.H. (2014), "Mapping the customer journey: A graph-based framework for online attribution modeling", available at: http://ssrn.com/abstract=2343077 (accessed December 20, 2017).
4. Anderl, E., Becker, I., Wangenheim, F.V. and Schumann, J.H. (2016), "Mapping the customer journey: Lessons learned from graph-based online attribution modeling", International Journal of Research in Marketing, Vol. 33 No. 3, pp. 59457-474.
5. Baigorri, A.R., Gonçalves, C.R. and Resende, P.A.A. (2014), "Markov chain order estimation based on the chi-square divergence", Canadian Journal of Statistics,Vol. 42 No. 4, pp. 563-578.
6. Barajas, J., Akella, R., Holtan, M. and Flores, A. (2016), "Experimental designs an estimation for online display advertising attribution in marketplaces", Marketing Science, Vol. 35 No. 3, pp. 465-483.
7. Barker, D. (2017), "Important ecommerce metrics nobody mentions #1: First to second order rate", MeasureCamp London, Vol. 10, pp. 10-11.
8. Berg, G.V.D. and Pietersma, P. (2015), 25 Need to Know Management Models,Pearson, Harlow.
9. Bryl, S. (2016), "Attribution model with R (part 1: Markov chains concept)", available at: http://analyzecore.com/2016/08/03/attribution-model-r-part-1, (accessed December 20, 2017).
10. Bulygo, Z. (2012), "What The Highest Converting Websites Do Differently", available at: https://blog.kissmetrics.com/what-converting-websites-do, (accessed accessed December 20, 2017).
11. Chapčáková, A., Hečková, J. and Huttmanová, E. (2010), Podnikanie v malých a stredných podnikoch, Fakulta manažmentu Prešovskej univerzity v Prešove, Prešov.
12. Clifton, B. (2015), Successful Analytics: Gain Business Insights by Managing Google Analytics, Advanced Web Metrics, West Sussex.
13. Constantin, C. (2014), "Principal Component Analysis-A Powerful Tool in Computing Marketing Information", Bulletin of the Transilvania University of Brasov, Economic Sciences, Series V, Vol. 7 No. 2, pp. 25-30.
14. Dorea, C.C., Resende, P.A. and Gonçalves, C.R. (2015), "Comparing the Markov Order Estimators AIC, BIC and EDC". in Kim, H., Amouzegar, M., Ao, S. (Eds) In Transactions on Engineering Technologies, Springer, Dordrecht, pp. 41-54.. Ferencova, M., Jelenova, I. and Kakalejcík, L. (2015), "Social Media Usage in ProductInformation Searching", Applied Mechanics and Materials, Vol. 795, pp. 69-76. Finstat (2016), "SOS electronic s. r. o.", available at: http://finstat.sk/31703186, (accessed December 20, 2017).