How Cooperative Game Theory can be utilised to enhance marketing analytics attribution.

MSc Research Project
Data Analytics

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How Cooperative Game Theory can be utilised to enhance marketing analytics attribution.

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MSc Research Project in Data Analytics

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Abstract

Marketing analytics and attribution modelling enable businesses and organisations to measure the true performance of how all online channels work together to generate revenue, sales and increase market growth. The usage of marketing analytics and attribution however remains extremely low, which results in a marginalisation of the marketing industry. As businesses and organisations shift significant amounts of their marketing budget towards digital channel advertising, the necessity for marketing analytics and attribution is ever important.
The marketing industry is currently using Last Click analysis to measure online channel performance which assigns the credit of a conversion and sale to the last marketing channel a customer has interacted with. Research shows Last Click analysis to be an insufficient method to measure campaign effectiveness and performance. Cooperative Game Theory attribution using Shapley Value is shown to be an optimum methodology and technique to employ in order to conduct attribution analysis. An enhanced method of Cooperative Game Theory attribution using a k-order Markov chain can evaluate the online conversion path a user takes prior to purchasing, thus enabling a business to quantify the individual contribution each marketing channel brings in driving conversion and generating revenue.

The author has conducted benchmark analyses that examine the performance of Last Click attribution against that of a Cooperative Game Theory attribution model. The evaluated results show that Cooperative Game Theory attribution out performs Last Click attribution and enhances marketing analytics by unequivocally showing the true added business value that each marketing channel brings in driving conversion and generating revenue.

1 Introduction

The purpose of this dissertation is to examine how Cooperative Game Theory can be utilised to enhance marketing analytics attribution. Marketing analytics is an emerging industry trend whereby businesses and organisations need insight into measuring how their marketing activities and initiatives are performing in terms of revenue generation, sales and increasing market growth.

Attribution modelling enables businesses to measure the true performance of how all online channels work together in driving conversion of business goals. Typically each channel denoted as a marketing touchpoint is assigned a proportional credit or weighted value, through attribution analysis a business can identify which channel mix is informing and influencing the customer journey by generating the most conversions in relation to business goals (Matthews; 2015).

Chapter 2 outlines the related work of a literature review pertaining to the authors research question of how Cooperative Game Theory can be utilised to enhance marketing analytics attribution. The review examines the low adoption rates by businesses and organisations in the measurability of digital advertising and the marginalisation impact this leaves on the marketing industry. The author outlines the approach businesses and organisations are taking by shifting budget from traditional media to digital channel advertising.

Lastly the review examines the important role that attribution plays in measuring the true performance of digital channel advertising and how Shapley Value attribution has been recognised as an optimum attribution methodology. An enhanced approach to attribution is examined, which uses the underlying principles of Shapley Value attribution and a Markovian chain which can calculate the contribution that each individual marketing channel has brought in creating sales/conversions and the generation of revenue for a given business.

Chapter 3 Methodology outlines and defines the objective of the authors benchmark experiment which examines the performance of Last Click attribution against that of the Cooperative Game Theory attribution model.

Chapter 4 Solution Overview details the solution and components of a framework assembled by the author to conduct the attribution benchmark experiment.

Chapter 5 Results & Evaluation Analysis provides a comprehensive analysis and evaluation of findings against the results of the attribution benchmark experiment, with focus on evaluating the limitations and ineffectiveness on business intelligence and marketing operations of the Last Click attribution in comparison to the Cooperative Game Theory attribution model.

Chapter 6 Conclusion & Future Work summarises the overall research findings and concluded results of the benchmark experiment that Cooperative Game Theory can indeed be utilised to enhance marketing analytics attribution. Moreover, future work enhancements that can be made to the framework are proposed.

2 Literature Review

Chapter 2 outlines the fourfold findings and results of the literature review.

2.1 Lag to adoption and usage of marketing analytics

Marketing analytics enables businesses and organisations to firstly track and measure the return on investment (ROI) that has been made into online digital advertising channels in terms of revenue generation, sales and market growth. Secondly, marketing analytics is utilised to conduct analysis into measuring the performance and effectiveness of digital marketing activities and initiatives (Matthews; 2015).

Chaffey and Patron (2012) highlight that there is a lag in adoption in the measurability of digital advertising by businesses and organisations. Moreover Chaffey and Patron discuss the low levels of adoption in relation to analysis techniques being employed by

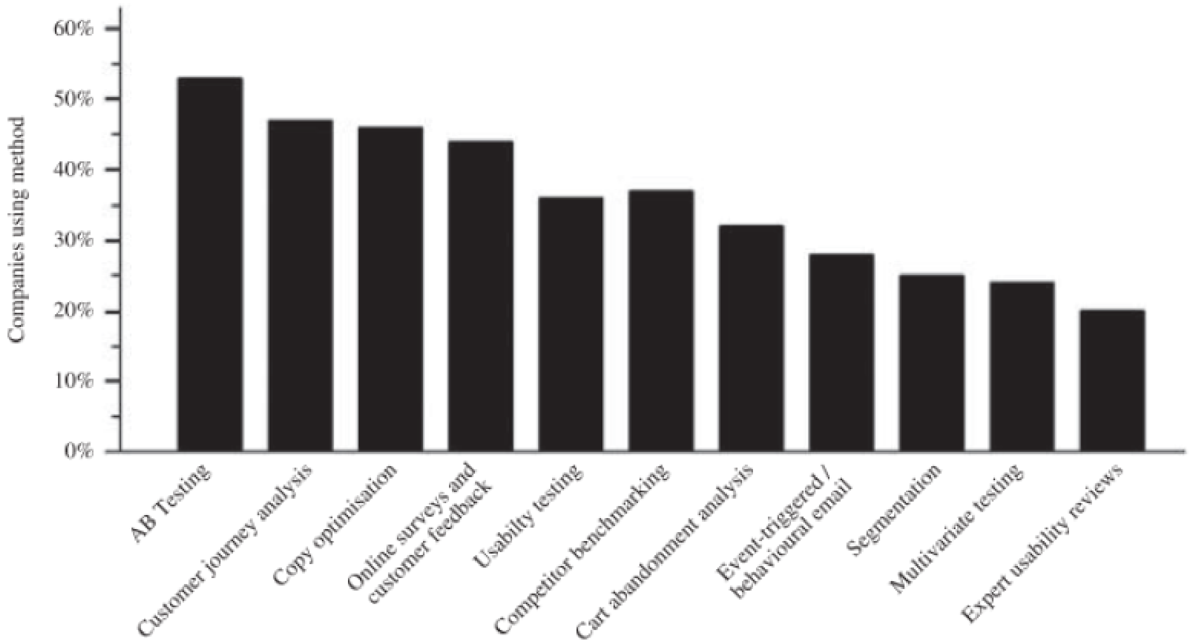


Figure 1: Analytics methods used by companies to improve conversion rates. (Chaffey and Patron, 2012)

businesses and organisations in using marketing and web analytics. In many instances the adoption level of analytics tools is high; however their usage remains extremely low.

Figure 1 illustrates the results of a 700 client-side and digital agency survey conducted by market research leaders Econsultancy and RedEye into the usage of marketing and web analytics techniques on improving conversion rates. Chaffey and Patron highlight the low adoption rates by participants of optimum techniques being in part customer journey analysis, cart abandonment analysis and segmentation (Chaffey and Patron; 2012).

A Forrester report published in 2014 conducted over 500 surveys with marketing decision makers across the US and Europe and shows that there is a distinct lag in the adoption of modern marketing techniques with only 11% of respondents being classified as modern marketers that utilise marketing measurement and attribution (ForresterConsulting; 2014),(Matthews; 2015).

By not utilising marketing analytics effectively or not at all, marketing departments therefore cannot report and or give integral business insights on ROI and marketing campaign performance. This has a knock on effect to marketing management whom in turn cannot demonstrate to boards of directors and C-level executives the true added business value that marketing spend and campaigns bring to driving growth and profitability in a business or organisation (Davies and Ardley; 2012).

Davies and Ardley (2012) describe this as a marginalisation sentiment that is directed towards the overall marketing profession within the business community. By adopting marketing analytics, marketing departments can show their strategic contribution to company performance (Davies and Ardley; 2012).

A framework that measures the capabilities and true value of how all marketing channels work together in driving conversion and in turn business growth is a fundamental necessity. The advertising industry as whole is changing whereby more and more businesses are moving away from traditional advertising mediums and are investing more significantly in terms of budget into digital channel advertising. Section 2.2 "marketing budget shift towards digital channels" outlines the budget shift and investment that is being made by organisations which is weighted towards digital channels.

2.2 Marketing budget shift towards digital channels

The approach in which businesses and organisations are spending and allocating their advertising budgets has changed, with a budget shift from traditional media to digital channel advertising. Jobs et al. (2015) discuss the severity of this budget shift indicating some organisations are shifting between 76% to 100% of their advertising budget towards digital channels (Jobs et al.; 2015).

Jobs et al. (2015) draw attention to the findings of a Nielsen and Interactive Advertising Bureau report from 2012 which surveyed companies whom have made this budget shift and accredit their decision to making the shift to online advertising being deemed to be more cost effective. Furthermore actual consumer behaviour and habits have changed considerably with consumers spending more of their time consuming media in online vs. traditional venues (Jobs et al.; 2015).

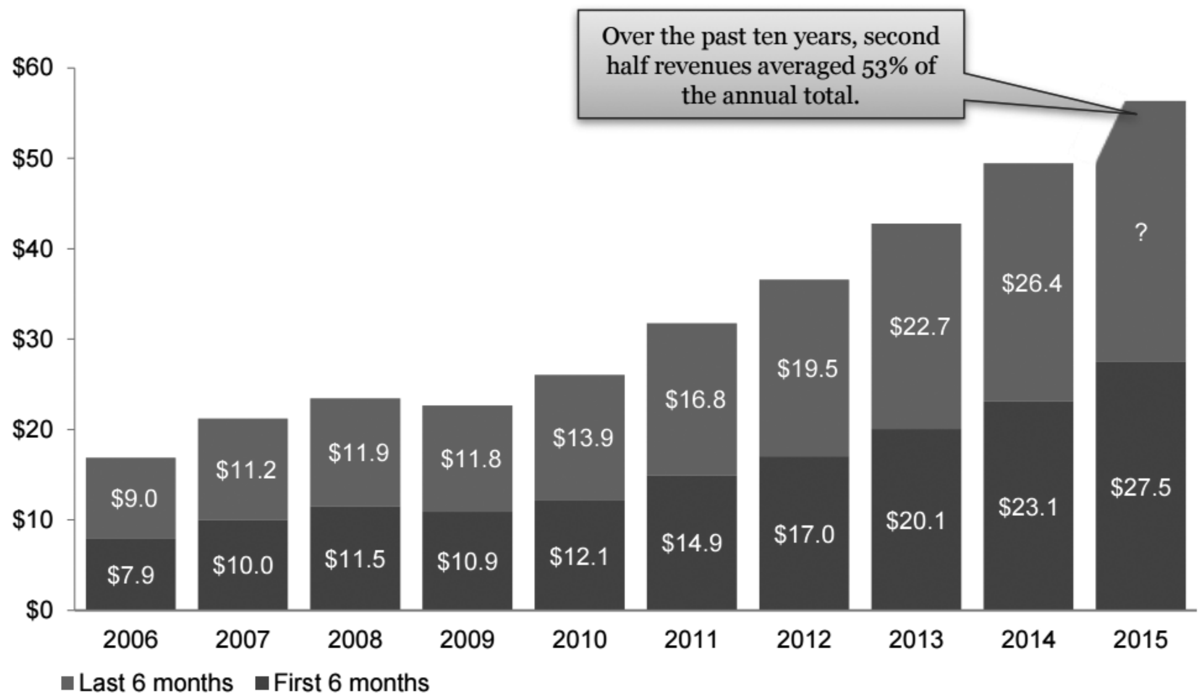


Figure 2: Historical Ad Revenue Spend ($ Billions) Source: IAB/PwC Internet Ad Revenue Report 2015

The domain of digital advertising has seen strong year on year growth over the past ten years as illustrated in Figure 2, an industry based study conducted by PricewaterhouseCoopers on behalf of the Interactive Advertising Bureau shows that in 2014 in the United States alone internet advertising revenues have surpassed $49.5 billion dollars which is a 16% increase on 2013 (PwC; 2015), (Matthews; 2015).

As more businesses and organisations adopt the budget shift approach, marketing analytics has become an emerging industry trend. A marketing analytics framework that has an attribution element would provide value and strategic business intelligence. Section 2.3 "how true performance and value in online advertising is measured through attribution" outlines why attribution is an important element for measuring the true performance of digital channel advertising.

2.3 How true performance and value in online advertising is measured through attribution

Last Click analysis is the traditional industry standard method in marketing attribution which assigns all the credit of a conversion to the last touchpoint a user interacted with prior to converting (Lee; 2010). A report published in 2012 by EConsultancy in association with Google indicates that Last Click analysis is no longer a sufficient method from which to measure campaign effectiveness and performance (EConsultancy and Google; 2012),(Matthews; 2015).

The report highlights the importance of marketing attribution in "determining the role that channels play in informing and influencing the customer journey. This research makes it clear that digital channels dont operate independently. Their interplay is unique for every company and every product" (EConsultancy and Google; 2012), (Matthews; 2015).

In the 2015 paper "beyond the Last touch: attribution in online advertising" Berman (2015), benchmarks Last Click analysis against full channel attribution. Bermans findings show that Last Click analysis methods have become highly inefficient and that adopting an attribution model using a Shapley Value is far more accurate and insightful (Berman; 2015).

Berman (2015), denotes that Shapley Value attribution being a "cooperative game theory solution" is an optimum technique that can be utilised for attribution modelling. Shapley Value core functionality accredits value amongst players in a cooperative game and assigns "value for each coalition of players and their contribution of value they created" (Berman; 2015). Shapley Value can be applied to determine what value various marketing channels bring and how they work together in driving conversion.

Nisar and Yeung (2015) conducted an empirical investigation into purchase conversions and attribution modelling in online advertising, with their findings presented at 44th European Marketing Academy conference in Leuven Belgium in May 2015. Similar to Berman (2015), Nisar and Yeung (2015) benchmark Last Click analysis against Shapley Value attribution. Nisar and Yeung (2015) results reveal a far more accurate calculation of the true value of how all channels perform at increasing revenue (Nisar and Yeung; 2015). Nisar and Yeung (2015) show Last Click analysis paid search was accredited 10.92% of revenue and under the Shapley Value attribution this increased by 1.93 percentage points to 12.85%, thus the true value of that channel was recognised.

The findings of Nisar and Yeung (2015) highlight that display advertisements under Shapley Value attribution have a low click through rate of 14.34% down by 4.08% from 18.42% under last click analysis (Nisar and Yeung; 2015). In relation to display advertisements Nisar and Yeung (2015) fail to acknowledge that these display advertisements may well have been severed to a user but that said user did not necessarily click on them, this scenario is known as display exposure. In the 2009 Forrester research paper "a framework for multicampaign attribution measurement" Lovett (2009) recognises the importance frequency exposure to display advertisements and denotes this metric as a frequency lever which "identifies the number of times a customer was exposed to a specific marketing channel" (Lovett; 2009).

In the Marentis (2015) paper "the key to digital marketing attribution" the author outlines the benefits of surveyed advertisers and digital agencies that utilise attribution in their marketing analytics (Marentis; 2015). 72% of participants agreed that "marketing attribution leads to better budget allocations", 64% of participants stated that they have a "better understanding of how digital channels work together" and 58% had "clearer insights into their audience" (Marentis; 2015).

Altomare (2015a), denotes that Last Click analysis fails to take into account multiple interactions that a user may have with different digital marketing channels (Altomare; 2015a). As a result the importance, value and contribution that smaller marketing channels have can be hidden. Altomare (2015a), addresses this failure by adopting an approach that is based upon the underlying principles of Shapley Value attribution, through the use of a Markov chain that analyses the conversion path a given user has taken(Altomare; 2015b). The conversion path contains the interactions a user has made with digital marketing channels. Altomare (2015b), approach can calculate the contribution that each individual marketing channel has brought in creating sales/conversions and the generation of revenue for a given business (Altomare; 2015b).

The benefits and necessity of moving away from Last Click analysis and conducting Cooperative Game Theory attribution modelling is apparent. This approach enables businesses to get a clearer insight into how their marketing activities and initiatives are performing at driving sales/conversion, generating revenue and contributing to market growth.

2.4 Review Conclusions

The research conducted by Chaffey and Patron (2012) show there is a distinct lag in adoption of the measurability of digital advertising by businesses and organisations. The usage of marketing and web analytics techniques is low which prevents marketing management from effectively communicating the true added business value that marketing initiatives and campaigns bring in driving business growth and profitability.

The advertising industry is rapidly changing with more investment being weighted towards digital channels, the domain of digital advertising has seen continual year on year growth over the past ten years. As the industry as whole continues to change marketing analytics has become an emerging industry trend.

With attribution, businesses and organisations can measure the true performance of digital channel advertising and move away from Last Click analysis which has become a non-effective technique for marketing analytics but is still being widely utilised within the marketing industry. The findings from Berman (2015) and Nisar and Yeung (2015) show that Shapley Value attribution is an optimum technique to employ in conducting attribution analysis. Moreover Altomare (2015b) approach based upon the underlying principles of Shapley Value attribution and using a Markov chain can calculate the contribution of each individual marketing on creating sales/conversions and generating revenue.

The objective of this students dissertation is to conduct a benchmark experiment and analyses into performance of Last Click attribution against that of a Cooperative Game Theory attribution model. The results of the benchmark analysis will be evaluated to highlight the limitations and ineffectiveness on business intelligence and marketing operations of the Last Click attribution in comparison to the Cooperative Game Theory attribution model.

3 Methodology

Chapter 3 defines the experiment and methodology that is being applied to address how Cooperative Game Theory can be utilised to enhance marketing analytics attribution. Section 3.2 specifies the dimensions, context and structure of the dataset being utilised in the benchmark experiment. Section 3.3 provides a synopsis on utilising the Mockaroo platform to generate a synthesized and realistic dataset for use in modelling, testing and demoing purposes. Alongside, findings of seminal research that was completed into the use of the Mockaroo platform to generate realistic datasets for use in academia.

3.1 Attribution Benchmark Experiment Defined

The Marketing industry is currently using Last Click analysis to measure online marketing channel performance, which is shown to be an insufficient method to measure marketing channel effectiveness and performance. Shapley Value attribution is shown to be an optimum methodology and technique to employ in order to conduct attribution analysis. An enhanced approach to attribution analysis, combines the elements of Shapley Value attribution in conjunction with a Markovian chain, thus enabling a business to quantify the individual contribution each marketing channel brings in creating sales/conversions and the generation of revenue for a given business. The overall objective of authors experiment is to conduct a benchmark analyses that examines the performance of Last Click attribution against that of the Cooperative Game Theory attribution model. The results of the benchmark analysis will be evaluated to highlight the limitations and ineffectiveness on business intelligence and marketing operations of the Last Click attribution in comparison to the Cooperative Game Theory attribution model.

3.2 Project Dataset Overview

The project dataset utilised for this dissertation comprises of 20,000 synthesized records generated through the Mockaroo platform (Mockaroo; 2016). The underlying data structure of the dataset is based up the dimensions and metrics of the Google Technology Stack including Google AdWords, Google Analytics and the Google Display Network advertising platform. The dataset represents converting and non-converting conversion paths of commercial transactions on a business that is marketing and selling in a business-to-consumer (B2C) state. A conversion path denotes the various marketing channels a user has interacted with prior to making an online purchase, Table 1 outlines the various online marketing channel names and their associated definitions that are contained within the project dataset.

Marketing Channels	
Channel Name	Channel Description
Direct	Non-Paid Channel, user has directly inputted the website domain name into their browser or visited from a bookmarked link.
Display	Paid Channel, user has been served or interacted with a banner advertisement that has appeared on third party website promoting the business, product and/or service.
Email	Non-Paid Channel, user has clicked on a link contained within an email sent by the business which brings the user to the website.
Organic	Non-Paid Channel, user has completed an online search using generic or branded keyword terms from which the business website address has appeared as a result within Search Engine Result Page Rankings and said user has then clicked on the business website address.
Pay Per Click	Paid Channel, Pay Per Click Advertisements (PPC) promoting the business, product and/or service that are embedded within Search Engine Results Page Rankings from which the user has interacted with.
Social	Paid Channel, Pay Per Click Advertisements promoting the business, product and/or service that are embedded within Social Media platforms like Facebook, Twitter and/or LinkedIn from which the user has interacted with.

Table 1 Marketing Channel Descriptions

Illustrated in Table 2 is an example record taken from the attribution dataset. The conversion path taken by these users overtime show that they have firstly been served/interacted with a Google Display Network banner advertisement, secondly they went on to complete a generic/branded keyword Google search, next they interacted with a Pay Per Click embedded advertisement, after that they came directly back to the website and completed a purchase.

Attribution Conversion Path			
Conversion Path	Sum of Conversions	Sum of Conversion Value	Sum of Null Conversions
Display GDN >Organic Google >PPC >Direct >Purchase	5	1800	2

Table 2 Attribution Conversion Path Example

The Sum of Conversions column in Table 2 shows that a total of five users have taken said conversion path, sum of Conversion Value shows from those five users a total of 1,800 euros in revenue was generated respectively. Sum of Null Conversions illustrates that 2 other uses took the same conversion path but did not purchase.

3.3 Usage of Mockaroo

Mockaroo is an online platform that allows for the generation en masse of synthesized and realistic datasets for use in modelling, testing and demoing purposes. The accompanying user configuration manual documents fully the process involved in generating a dataset through the Mockaroo platform.

Mockaroo generates datasets by utilising a data schema, which is based upon an existing underlying data structure predefined by the user. The Mockaroo data schema has two components in the form of a Field Name and Field Type. The Field Name denotes an attribute name in a given dataset, whilst Field Type being associated with a Field Name contains either a numerical or categorical value. Field Types if numerical are assigned a numeric range that matches the underlying data structure. Moreover, categorical Field Types are assigned all possible characteristic values again based upon the underlying data structure

The data schema is inputted and defined in the Mockaroo platform, alongside the number of required rows needed in the dataset. Mockaroo next generates the dataset based upon the data schema creating the Field Names first and then randomly assigning the categorical Field types with their associated numeric range or characteristic value.

The following three papers have all utilised Mockaroo to create synthesized and realistic datasets.

3.3.1 Adaptive Buffer Resizing for Efficient Streaming Data Anonymization with Minimal Information Loss

Sakpere and Kayem's 2014 paper "Adaptive Buffer Resizing for Efficient Streaming Data Anonymization with Minimal Information Loss" presented at the 2014 IEEE International Conference on Advanced Information Networking and Applications (AINA) in Victoria Canada, utilises the Mockaroo platform in order to generate a dataset that can be utilised as part of their research into speeding-up the real time analysis of data and streaming data (Busayo Sakpere and V.D.M. Kayem; 2014).

Sakpere and Kayem's 2014 generate a realistic crime dataset using the underlying data structure of the Cry-Help App which is a crime reporting mobile application. The attributes and dimensions of the Cry-Help app are passed into the Mockaroo platform, with the end result being a randomly generated and realistic based crime dataset (Busayo Sakpere and V.D.M. Kayem; 2014).

3.3.2 Collaborative Filtering in the News Domain with Explicit and Implicit Feedback

Monsen and Romstads 2014 Master of Science in Computer Science thesis on Collaborative Filtering in the News Domain with Explicit and Implicit Feedback from the Norwegian University of Science and Technology utilise the Mockaroo platform to generate a synthesized dataset as part of their dissertation research into improving the accuracy of collaborative filtering in online recommender systems (Monsen and Romstad; 2014). Monsen and Romstad 2014 generate a realistic and synthesized dataset based upon an underlying data structure of User Study data comprised of explicit feedback, implicit feedback, a wider range of information about documents and topics, and a heterogeneous set of documents (Monsen and Romstad; 2014) (Zhang, 2005).

The attributes and dimensions of Monsen and Romstads 2014 User Study data structure is passed into the Mockaroo platform, with the end result being the generation of a realistic and synthesized dataset containing close to 1 million rows respectively (Monsen and Romstad; 2014).

3.3.3 Enhancing HiveQL Engine Using Map-Join-Reduce

Kulkarni and Dharmadhikari, 2015 paper on Enhancing HiveQL Engine Using Map-Join-Reduce utilises the Mockaroo platform in order to generate a dataset that can be utilised as part of their research into enhancing the data handling of complex joins using MapReduce (Kulkarni and Dharmadhikari; 2015). Kulkarni and Dharmadhikari 2015 utilise Mockaroo and their underlying data structure to generate a test dataset which is then used as part of their benchmarking activities which contains 63,000 rows respectively.

4 Solution Overview

Chapter 4 details a high level overview on the solution and components of the framework assembled by the author to address how Cooperative Game Theory can be utilised to enhance marketing analytics attribution. The accompanying user configuration manual documents fully the functionality of each element of the framework.

4.1 Real-time Element for Polling Data

The real-time element of the framework created in the R programming language, utilises the RGoogleAnalytics package. Data is polled from Google Analytics every 120 minutes in order to obtain the most up-to-date conversion path data for use in the attribution model (Pearmain; 2016).

4.2 Attribution Modelling Element

The attribution element of the framework assembled in the R programming language utilises Cooperative Game Theory logic and a Markovian chain via the R ChannelAttribution package. The attribution element analyses the conversion paths taken from Google Analytics and calculates the contribution that each individual marketing channel has brought in creating sales/conversions and revenue for the business (Altomare; 2015a).

The attribution modelling element of the framework outputs conversion volume and value results for each marketing channel based upon Last Click attribution and Cooperative Attribution. These outputted results formulate the overall benchmark experiment results. The comparative differences between conversion volume and conversion value are evaluated and interpreted in chapter 5.

5 Results And Evaluation Analysis

Chapter 5 outlines the results and evaluation of findings on the attribution benchmark experiment. The total number of completed online conversions within the project dataset amounted to 91,338, which in turn generated total revenue of €209,119 Euros respectively. Conversions and revenue is generated through a total of twelve marketing channels.

5.1 Last Click Attribution Model Results

The overall volume of conversions by marketing channel credited to Last Click attribution is illustrated in Figure 3, ranked largest to smallest reading from left to right. Direct is the most effective and best performing marketing channel from which 28,230 or 31% of all conversions was produced from Direct visitors to the website.

Organic-Google is the second best performing marketing channel which produced 25,272 or 28% of all conversions. Pay Per Click Advertising (PPC) follows next, this marketing channel created 15,062 or 16% of all conversions. Combined the top three marketing channels under Last Click Attribution are responsible for 75% of all conversions.

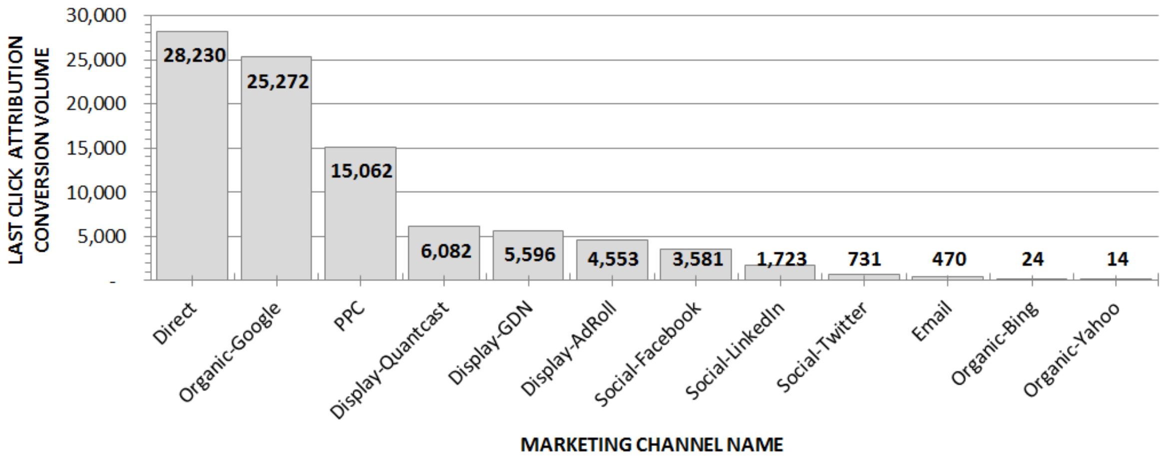


Figure 3: Last Click Attribution Conversion Volume by Marketing Channel

Display marketing channels ranked in order of conversion performance features next in Figure 3. The bar chart shows that the display platform of Quantcast is the best performing third party display platform creating 6,082 conversions followed by Google Display Network (GDN) at 5,596 conversions and lastly AdRoll generated 4,553 conversions. Combined Display marketing channel as a whole is responsible for 16,231 or 18% of all conversions under Last Click Attribution.

Performance of Social Pay Per Click advertisements placed on Facebook, LinkedIn and Twitter produced 6,035 or 7% of overall conversions. Email marketing channel is ranked third lowest amongst all other marketing channels, the results show that email produced 470 or 0.5% of all conversions.

Organic channels of Bing and Yahoo feature next, with Bing being ranked as the second lowest performing marketing channel producing 24 conversions. Yahoo is the lowest performing marketing channel overall producing 14 conversions in total.

The overall conversion value of each marketing channel credited to Last Click attribution is illustrated in Figure 4, ranked largest to smallest by Euro value reading from bottom to top. The conversion value results show the amount of actual revenue that each respective marketing channel has generated for the business.

The most valuable marketing channel is Organic-Google, which generated revenue of €64,613. Direct marketing channel is ranked second most valuable, generating revenue of €60,936. With Pay Per Click Advertising ranked third generating revenue of €36,244. Combined these three marketing channels form the top tier of conversion value and generated a total of €161,794 in revenue.

Display advertising marketing channels of Quantcast, GDN and AdRoll feature next, with Quantcast generating €14,238, GDN €10,998 and AdRoll €8,891. Combined display marketing channels generated total revenue of €34,217 Euros.

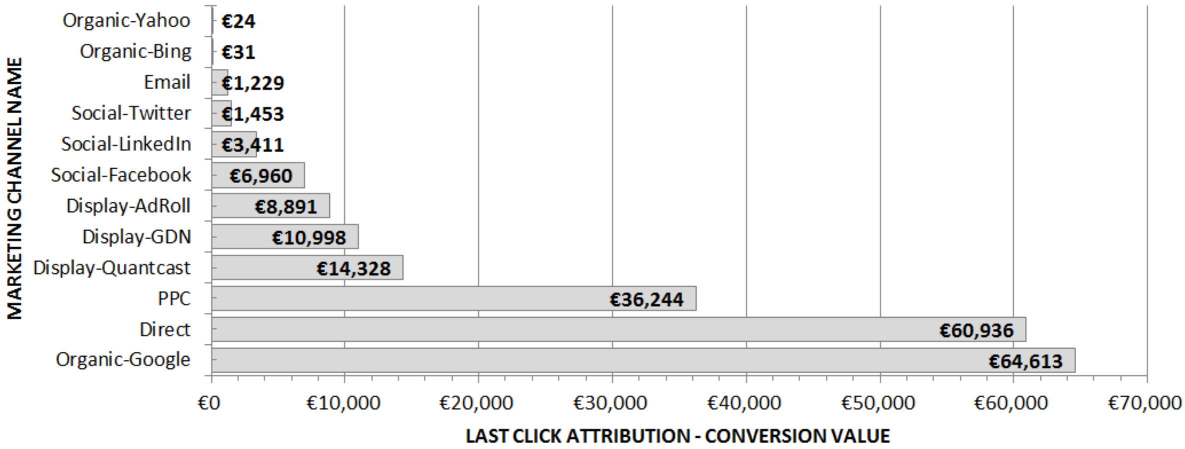


Figure 4: Last Click Attribution Conversion Value by Marketing Channel.

Revenue generated by Social media Pay Per Click advertisements, rank 7th, 8th and 9th overall, with Facebook generating €6,960, LinkedIn €3,411 and Twitter €1,453.

The conversion value of Email is ranked 10th, generating total revenue of €1,229. Lastly Organic channels of Bing and Yahoo are ranked 11th and 12th overall, with Bing generating €31 and Yahoo €24.

5.2 Cooperative Attribution Model Results

The results from the Cooperative Attribution Model are formulated based upon all interactions users have had with multiple marketing channels along their conversion path, prior to making a purchase. In comparison, Last Click attribution only focuses on one marking channel being the Last, within a conversion path prior to making a purchase.

The results presented in Figure 5 from Cooperative attribution model show the influence and contribution that each marketing channel brings in driving overall conversion and secondly the ranked importance of each marketing channel in driving said conversion.

The Direct marketing channel is ranked 1st in terms of conversion and collective channel importance, producing a total of 16,128 conversions. PPC marketing channel features next and is ranked 2nd collectively and influenced 15,775 conversions. Organic-Google is ranked 3rd collectively influencing 15,314 conversions overall.

Display marketing channels of GDN, AdRoll and Quantcast feature next, with their collective importance and contribution on conversion being, GDN ranked 4th prompting 13,897 conversions, AdRoll ranked 5th prompting 10,010 conversions and lastly Quantcast ranked 6th prompting 7,857 conversions.

Social Pay Per Click advertisements from Facebook, Twitter and LinkedIn are placed next, with Facebook ranking 7th with 4,980 conversions, Twitter ranking 8th with 3,483 conversions and LinkedIn ranked 9th with 2,639 conversions.

Email marketing channel is ranked 10th overall in terms of conversion and collective channel importance having prompted 1,212 conversions. Organic marketing channels of Bing rank 11th influencing 38 conversions and lastly Yahoo ranks 12th overall having influenced 5 conversions respectively.

The overall collective conversion value in terms of revenue generated for the business by each marketing channel and credited by Cooperative attribution is illustrated in Figure

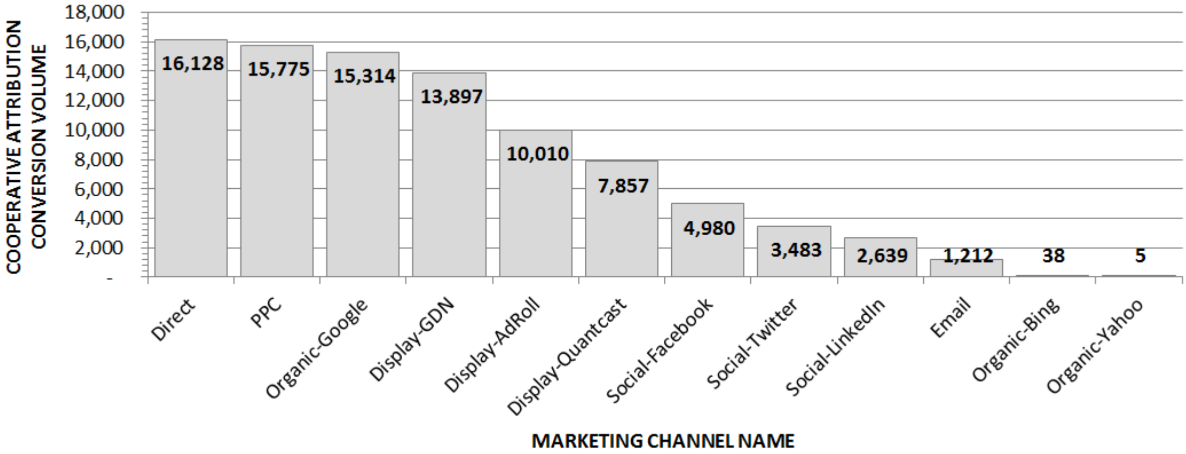


Figure 5: Cooperative Attribution Conversion Volume by Marketing Channel

6, ranked by importance in terms of Euro value reading from bottom to top.

The Direct marketing channel is ranked 1st overall having generated revenue of €36,292, followed closely by PPC with €36,389 ranking it 2nd, alongside Organic-Google ranked 3rd with revenue of €36,029.

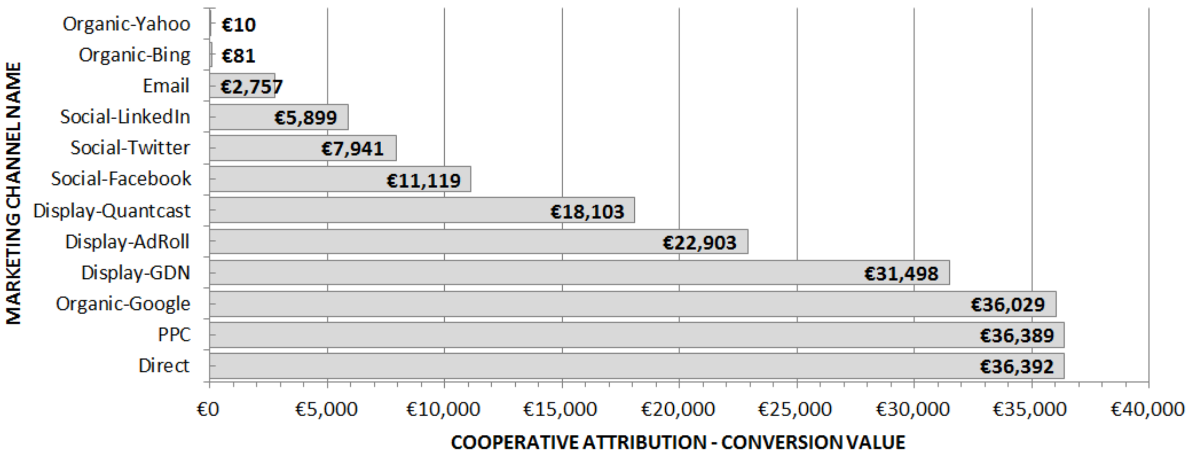


Figure 6: Cooperative Attribution Conversion Value by Marketing Channel

Display marketing channel of GDN features 4th having delivered revenue of €31,498. The other display marketing channel platforms of AdRoll and Quantcast rank 5th and 6th respectively, with AdRoll producing revenue of €22,903 and Quantcast with €18,103.

Revenue generated by Social media Pay Per Click advertisements, rank 7th, 8th and 9th collectively, with Facebook producing €11,119, Twitter €7,941 and LinkedIn €5,899.

Email Marketing channel is ranked 10th overall having delivered revenue of €2,757. Lastly Organic channels of Bing and Yahoo are ranked 11th and 12th overall, with Bing creating €81 and Yahoo €10.

5.3 Evaluation of Results

In evaluating the results of the attribution benchmark experiment, it is evident that there are varying and conflicting differences on Marketing channel performance and effectiveness between Last Click and Cooperative attribution. The significance and impact to the business on yielding actionable insights and basing business intelligence upon the Last Click attribution results could potentially cause adverse effects to both conversion volume and revenue generation.

Under Last Click attribution we can infer from the results that the Direct Marketing channel responsible for 31% of all conversions is the most effective channel at driving conversion for the business. Alongside, Google-Organic responsible for 28% of all conversions and is ranked the most valuable revenue generating channel under Last Click attribution. Both Direct and Google Organic Marketing Channels are non-paid, meaning no marketing spend is allocated to said channels.

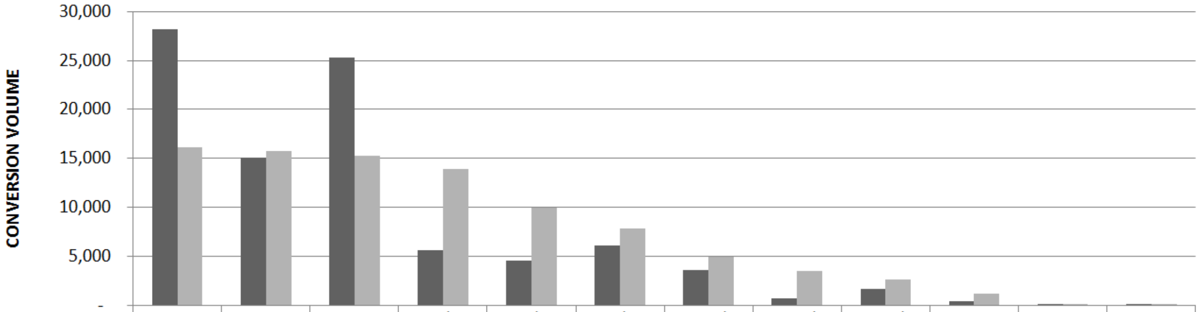
From a Marketing Operations perspective to the business, one can derive from Last Click attribution that Brand Awareness is already high as most customers come directly to the website to purchase or find the business on Google Search under a generic or branded keyword search term.

Evaluating the performance and effectiveness under Last Click attribution for the paid marketing channels, all appear to be under performing in comparison to the non-paid channels of Direct and Organic-Google. Last Click attribution results show that PPC, being ranked third overall for conversion, is under performing against Direct by -47% and Google-Organic by -40% in terms of conversion. The under performance of PPC extends to conversion value, again with PPC generating less revenue than Direct by -41% and Google-Organic by -44%.

The same under performance trend is apparent with the Paid Display marketing channels of Quantcast, GDN and AdRoll ranked in order of both conversion volume and value under Last Click attribution 4th through to 6th overall. The Display marketing channels individually are producing fewer conversions and in turn less revenue in comparison to Direct and Organic-Google. The conversion volume and value footprint of the paid Social marketing channels under Last Click attribution is shown to have a minimal impact. The Last Click attribution results formulate a basis to reduce marketing spends on paid channels as non-paid channels of Direct and Organic-Google are out performing said paid channels by achieving the most conversions and revenue for the business. Moreover, under Last Click attribution there is a footing to perhaps remove the paid under performing marketing channels from the overall channel mix therefore reducing the marketing budget and in turn saving the business operating revenue.

However, Cooperative attribution results provide a counter argument for the reduction of spend on paid marketing channels and/or for the removal of any paid marketing channel from the overall channel mix. Under Cooperative attribution through analysing the entire user conversion path, the results show collectively the individual contribution each marketing channel has brought in producing the total volume of completed conversions of 91,338 and in generating revenue of €209,119.

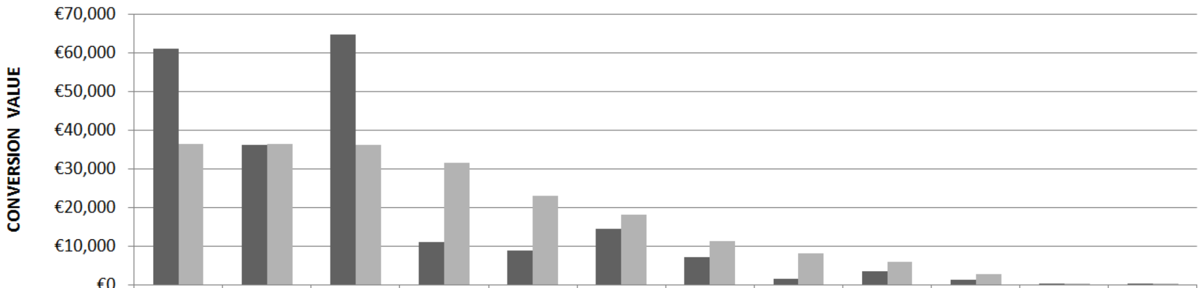
The comparative conversion volume of Last Click and Cooperative attribution is illustrated in figure 7, which shows that combined non-paid marketing channels of Direct, Organic-Google, Email, Organic-Bing and Organic-Yahoo under Last Click attribution accounted for 54,010 or 59% of all conversions. The true value of non-paid marketing channels under Cooperative attribution is shown to be actually only 32,697 or 35% of all conversions. Moreover, the resulting delta between paid channels of PPC, Display and Social under Last Click and Cooperative attribution is discernible, with Last Click accounting for 37,328 or 41% of all conversions in comparison to the true value under Cooperative attribution of 58,641 or 64% of all conversions.



	Direct	PPC	Organic-Google	Display-GDN	Display-AdRoll	Display-Quantcast	Social-Facebook	Social-Twitter	Social-LinkedIn	Email	Organic-Bing	Organic-Yahoo
Last Click	28,230	15,062	25,272	5,596	4,553	6,082	3,581	731	1,723	470	24	14
Cooperative	16,128	15,775	15,314	13,897	10,010	7,857	4,980	3,483	2,639	1,212	38	5

Figure 7: Comparative Conversion Volume Last Click and Cooperative Attribution

The true performance of the Display Marketing channels under Last Click Attribution is ambiguous; Figure 7 shows that Display marketing channels were responsible for 16,231 conversions, whilst under Cooperative attribution the true performance is shown with Display Marketing channels influencing 31,763 conversions respectively.



	Direct	PPC	Organic-Google	Display-GDN	Display-AdRoll	Display-Quantcast	Social-Facebook	Social-Twitter	Social-LinkedIn	Email	Organic-Bing	Organic-Yahoo
Last Click	€ 60,936	€ 36,244	€ 64,613	€ 10,998	€ 8,891	€ 14,328	€ 6,960	€ 1,453	€ 3,411	€ 1,229	€ 31	€ 24
Cooperative	€ 36,392	€ 36,389	€ 36,029	€ 31,498	€ 22,903	€ 18,103	€ 11,119	€ 7,941	€ 5,899	€ 2,757	€ 81	€ 10

Figure 8: Comparative Conversion Volume Last Click and Cooperative Attribution

The comparative conversion value of Last Click and Cooperative attribution is illustrated in figure 8 Under Last Click attribution Display GDN is ranked the second best performing display channel responsible for 5,596 conversions and revenue of €10,998, the true performance of Display GDN is that said channel actually influenced 13,897 conversions and revenue of €31,498 respectively.

The top three marketing channels under Cooperative attribution being Direct, PPC and Organic-Google have minimal variances in terms of their conversion value with all three being within €36,000 range in comparison to the stark variances of under Last Click attribution.

The minimal conversion volume and value footprint of Social marketing channels under Last Click attribution has altered; from figure 7 and figure 8 we can ascertain that Social marketing channels do in fact have a bigger influence in relation to both conversion volume and value under Cooperative attribution. The results indicate that under Cooperative attribution Social marketing channels influenced 11,102 conversions in comparison to Last Click attribution of 6,035. The conversion value of Social marketing has increased under Cooperative attribution to €24,959 in comparison to Last Click attribution of €11,825.

Whilst the notion that Brand Awareness appears high under Last Click attribution, within Cooperative attribution paid marketing channels as whole act as a major influencer in growing said brand awareness.

Providing the business with actionable insights and business intelligence derived from the Cooperative attribution model around marketing channel performance can indeed enhance marketing analytics. The Cooperative attribution results allow for the marketing operations department to easily identify and allocate their marketing budget accordingly to the best performing marketing channels, said finding is in accord with Marentis (2015) that marketing attribution leads to better budget allocations.

The results from Cooperative attribution model unequivocally show the true added business value that each marketing channel brings in driving conversion and generating revenue. This finding is in agreement with Berman (2015) and Nisar & Yeung (2015) that Cooperative Game Theory attribution is a more accurate calculation of denoting the true value of how all channels perform at increasing revenue.

Finally upon completion of evaluating the overall results of the attribution benchmark experiment this authors findings support that of Berman (2015) that Last Click analysis methods are indeed highly inefficient and that adopting an attribution model using a Cooperative Game Theory is far more accurate and insightful method.

6 Conclusion and Future Work

6.1 Conclusion

Research conducted by the author shows there is a distinct lag in adoption of the measurability of digital advertising by businesses and organisations, with marketing analytics becoming an emerging industry trend. To measure digital channel performance in driving online conversion and sales, businesses and organisations use a method know as Last Click analysis, which is shown to be a non-effective technique for marketing analytics but is still being widely utilised within the marketing industry.

Shapley Value attribution is shown to be an optimum methodology and technique to employ in order to conduct attribution analysis. An enhanced approach to attribution analysis, combines the elements of Shapley Value attribution in conjunction with a Markovian chain, this approach enables a business to quantify the individual contribution each marketing channel brings in creating sales/conversions and the generation of revenue for a given business.

The author conducted a benchmark analyses that examines the performance of Last Click attribution against that of the Cooperative Game Theory attribution model. The evaluated findings of the benchmark experiment show that there are varying and conflicting differences on Marketing channel performance and effectiveness between Last Click and Cooperative Game Theory attribution.

Under Last Click attribution non-paid marketing channels of Direct and Organic-Google outperformed paid marketing channels of PPC and Display in both conversion volume and generated revenue. Moreover, the Last Click attribution results formulate a basis to remove under performing paid channels from the marketing channel mix and minimise budget wastage by reducing marketing spends on paid channels as non-paid channels are achieving the most conversions and revenue for the business.

Cooperative attribution results provide a clear and concise counter argument for the reduction of spend on paid marketing channels and/or for the removal of any paid marketing channel from the overall channel mix. The Cooperative attribution results show collectively the true value, importance and individual contribution each marketing channel brings in creating sales/conversions and the generation of revenue for a business, thus supporting Marentis (2015) finding that marketing attribution leads to better budget allocations.

The results from the benchmark experiment also acknowledge and support the findings of Berman (2015) and Nisar & Yeung (2015) that Cooperative Game Theory attribution is a more accurate calculation of denoting the true value of how all channels perform at increasing revenue. Finally, the authors findings support that of Berman (2015) that Last Click analysis methods are highly inefficient and that adopting an attribution model using Cooperative Game Theory is far more accurate and insightful method.

6.2 Future Work

The solution framework assembled by the author is targeted towards enterprise and small medium businesses that are utilising the Google Technology stack. The solution can be replicated and adapted to work against instances of Google Analytics that have completed the perquisites customisation steps outlined in the user configuration manual. As an area of future work, the solution framework could be trialled and benchmark analysis run against real world data sources, from varying industries in the enterprise and small medium business space.

As a future work enhancement, there is scope within the solution framework to add additional functionality in the form of a Return on Investment (ROI) calculator. This component would receive as input additional data sources of marketing spend and product pricing data points. The ROI calculator would utilise output from the Cooperative attribution model as base data to delineate ROI metrics on marketing channel and overall marketing spend.

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