The Optimization of Online Marketing Campaign Performance Leveraging CPM pricing model

Lena Lebecq

Harrisburg University of Science and Technology

Abstract

This paper discusses the optimization of online marketing campaigns under a CPM (cost per impression) pricing model. Today's cookie less world enforcement impacts marketers campaign optimization, which makes any research studying this topic highly relevant. The review from the literature highlighted that the few studies conducted on online marketing pricing models do not focus on a relationship between the cost per impression and performance. This paper covers a potential correlation between CPM and CPA (cost per acquisition), considering real data over last 3 years from a US company, Eaglemoss Inc. Findings from this study highlights that there is a positive correlation between the cost per impression (CPM) and cost per acquisition (CPA) under a CPM pricing model, especially for people that do not have any touchpoint with the brand before-hand (prospecting) and broad (demographic) targeting. This research helps all marketers to optimize their digital campaign by scaling-up their budget when CPM are lower than usual and scale down when CPM are higher than usual to optimize their cost of acquisition performance. The causation effect will need to be studied to fully understand the factors that influence CPM and CPA parameters to find causation in the future and bring additional value to this research.

Keywords: Digital Marketing Optimization; Cost per Impression; Cost per Acquisition

Traditionally, most large and medium-size companies invested on print, television, radio, cinema and outdoor marketing placements to improve their brand and product visibility (Bala and Verma, 2018; Mort and Drennan, 2002). Such advertising placements cost include a fixed fee that vary based on the advertising provider. Those ad placements require a minimum ad fee per placement that most small and medium size businesses cannot afford (Scott, 2015).

The continuous improvements on technology, internet access and development of social networks made over the past few years, allow a seamless online experience for users, that are more and more connected (Alghizzaw, 2019). The apparition of online marketing has impacted the advertising landscape, allowing all companies to buy online ad placements.

The online marketing spectrum contains many advertisers among which the most popular: Google, Facebook, Instagram, Snapchat, TikTok, Bing, Reddit, Amazon, Twitter, Twitch and many more. These advertisers charge online marketing campaigns using either an input-based cost per thousand impressions (CPM) and performance-based cost per click (CPC) pricing model (Asdemir et al., 2012; Zhu and Kenneth, 2011).

Both CPC and CPM pricing models go through an ad auction that determine the best ad to show to a person at a given point in time. Those auctions are based on audience, interest or keywords targeting specificities set-up at the campaign level. Each advertising platform has an algorithm that run those auctions and place ads on its platform accordingly. Although each advertising platform has its own set of rules, most of those include a score-based engagement behavior and initial bid (Asdemir *et al.,* 2012; Zhu and Kenneth, 2011).

Those online marketing platforms allows companies to advertise and reach new potential customers while meeting business goals using defined cost per acquisition target or return on ad spend objective. In addition, online marketing provides measurability and accountability on campaign performance. Online marketing manager are able to access real time data on their campaign performance on self-served platform. This allows companies to optimize spend based on performance track direct conversions from online ads, understand engagement on ads from different audience as well as segmenting offers based on customer behavior (Ramos and Cotta, 2009; Scott, 2015).

From the literature, there is almost no study on online marketing pricing model, whose mostly focuses on online display ads specificities (Cai *et al.*, 2017; Försch and De Haan, 2018). Also, there is no study on how to optimize cost per acquisition performance. This paper intends to research if the cost per impression (CPM) influence cost per acquisition (CPA). Studying a potential correlation is highly relevant. If a relationship is found, this research could lead to significantly improve online marketing campaign performance.

Literature Review

Online Marketing

Internet marketing has been described simply as ‘achieving marketing objectives through applying digital technologies’ (Chaffey *et al.*, 2009). From the literature there is a consensus among researchers regarding the definition of online marketing that encompass a form of marketing using interactive and digital technologies (Chaffey *et al*., 2013; Kotler and Keller, 2007). Earlier research (Koisa-Kanttila, 2004; Rowley, 2008) focused solely on content marketing as the type of online marketing activities, most probably due the fact today’s online advertiser’s platforms did not exist or did not include today’s capabilities, which question the relevance of those papers in today’s modern society.

Mort and Drennan (2002) were among the first authors to introduce digital marketing, emphasizing on the growing importance of mobile interface. However, it was only later that Kotler and Keller (2007) formally introduce the definition of online marketing along with its concept and scope. This field of study is fairly new among researchers, driven by technology improvements on which online marketing is build.

Both Straus and Frost (2009) and Ramos and Cotta (2009) started covering the importance of data analytics to manage online digital campaigns that include SEO (Search Engine Optimization), PPC (pay-per-click) and social networks campaigns, which in addition of content marketing are the most reflective of today’s digital campaigns. Several case studies based on customers engagement towards online campaigns highlighted that social media and mobile ads were driven the best performance and should be used systematically (Ryan and Jones, 2011).

Challenges associated to online advertising includes the challenge for marketers to adapt to new environment driven by new technology, the security problem associated to online purchase and challenge to concenter on the needs of the customer (Munshi, 2012). Although this might have been true at first, marketers have now embraced online marketing environment and with the exhaustive data available are able to better understand the performance of each digital marketing campaign. Also, governments have taken decisions to re-enforce the security problem as the Fair Credit Billing Act in the US or the double identification required at checkout from specific banking institutions.

As online marketing continuously evolves, the challenges mentioned by Munshi (2012) are no longer highly relevant today. As an example, the latest challenge on online marketing campaigns is the potential cookie less world enforcement (GDPR and CCPA regulations, IOS 14 software release) governments and institutions are headed to respect and become more transparent regarding the user's data privacy and remove any type of tracking behavior if the user denies consent on cookies tracking.

This new trend poses challenge to digital marketers as the online campaign optimization highly depends on customer behavior to targeting similar purchasing audience and if this information is no longer available the platform algorithm is automatically performing less accurately. Tucker (2013) research findings on the customer perception toward the control of their personal information used for ads targeting suggest that the more control customers have on their privacy setting, the better personalized ads work. Recent research would be needed to corroborate Tucker's findings.

Consumer Behavior & Digital Marketing

Online marketing campaigns are set to trigger a behavior from the ad displayed (Park and Park, 2016), highlighting that the behavior triggered can be engagement-based (watching video, clicking liking, commenting, tagging the ad), site-based (viewing, add to cart, purchasing product) or both. Depending on the digital campaign objective that include traffic, brand awareness, lead generation or conversion, digital marketers are setting key performance indicators on those objectives to measure how consumers react towards ads and how successful is the marketing campaign (Park and Park, 2016).

As a result, many researchers studied the consumer behavior of people exposed to online marketing to identify a pattern towards their behavior and provide insights to digital marketers. Park and Park (2016) study demonstrates that all visitors to a website are not equally qualified towards a purchase event, and that on-site customer behavior including the size of the visit (average session duration) and visit frequencies indicators impact the conversion rate toward a purchase event. In addition, Alghizzaw (2019) identified that mobile apps, social media platforms and online word-of-mouth were positively impacting the consumer behavior in the tourism industry.

Many studies support the evidence that consumer generated feedback positively impacts conversion rate, up to two times more (Li and Bernoff, 2008; Senecal and Nantel, 2004; Chevalier and Mayzlin, 2006; Stephen, 2016). In addition, online coupon, side-panel ads, and competitive prices with good shipping rates are found to be digital techniques that influence the millennials' purchasing behavior (Smith, 2011). Research also suggests that socio-economic factors such as gender and social attributes tend to significantly impact impulse buying behavior after digital marketing campaigns exposure (Kathiravan *et al.,* 2019). Among which, the 18-39 years old consumers exposed to digital campaigns favors impulse buying on online retail shopping, along with female customers and high disposable income customers (Kathiravan *et al.,* 2019).

Ad relevance, format and placement tends to also impact the customer behavior (Stephen, 2016; Chatterjee, 2008; Edwards *et al*., 2002). There is little agreement in the literature regarding pop-up ads placement. Research supports that pop-up ads create high levels of ad perception, recall and intent to purchase (Chatterjee, 2008) while others research demonstrate that consumers are irritated toward this type of ad which led to rejecting all type of digital advertising afterwards (Edwards *et al*., 2002). A study suggest that consumer prefer internet ad placement despite 40% of them indicating to ignore digital ads without providing reasons why (Ghazie and Dolah, 2018). Because this study was conducted on Malaysia digital advertising only, and before generalizing findings, it is required to verify the consumer ad placement preference from Western countries as ads preference might be different.

According to Jerath *et al.* (2014), the consumer behavior on a sponsored ad tend to click more on searches containing less popular keywords (with low search volume) over highly popular keywords (with high search volume). Research indicates that low search volume keywords suggest high relevance for sponsored search advertising targeting due to the increase in search efforts from the customers, and therefore a higher likelihood of interest and purchase (Jerath *et al.,* 2014).

Online Marketing Pricing Models

There is little literature available on online marketing pricing models. While Asdemir *et al.* (2012) research advise digital marketers to choose between CPM (cost per impression) and CPC (cost per click) based on four factors: the interplay of uncertainty in the decision environment, the value of advertising, the cost of mistargeting advertisements and the alignment of incentives, Zhu and Kenneth (2011) argue to choose pricing model based on an optimal spend allocation to cover maximal ad slots exposure while maximizing publishers' revenues. Other studies focusing on real-time bidding or "programmatic buying" on display ads placement founds insights that higher ad frequency and higher ad recency decrease ad engagement (Cai *et al*., 2017; Yuan *et al*., 2013).

There is a gap in the literature as there has been no study on a correlation between CPM (cost per impression) and CPA (cost per acquisition). This paper helps filling the gap into researching a potential correlation, which could significantly improve online marketing campaign performance by optimizing spend accordingly.

Based on the review of the literature review, this paper aims to test if there is a correlation between CPMs (cost per impressions) and CPA (cost per acquisition). In addition, other bivariate correlations will be conducted:

- campaign name (prospecting / retargeting)
- audience (lookalike / interest / demographic / nielsen / others)

Methods

This paper is based on the epistemology philosophy, more precisely, the positivism in the research philosophy. The research strategy is based on data collection and hypothesis development that will be tested. In addition, the research follows a highly structured methodology to facilitate hypothesis testing and replication in the future. The methods include quantitative data from one company, Eaglemoss Inc., due to confidentiality and accessibility issues. This paper uses correlational research to analyze the correlation of CPMs (cost per impression) and CPAs (cost per acquisition).

Data

The quantitative data from the research is collected from Eaglemoss Inc., a worldwide company selling branded memorabilia and collectibles. The data is collected from all media channel (from Facebook Ads Manager, Google Ads…) from April 2019 until April 2021. This research solely focuses on Facebook Ads Manager media source due to its CPM (cost per impression) pricing model and this media source is largely used worldwide by many companies which makes it easy to replicate for other researchers (Asdemir *et al.,* 2012; Zhu and Kenneth, 2011). Data collected includes the following: ad account, campaign name, ad set name, delivery, reach, spend, CPM (cost per impression), link clicks, website purchases, cost per result. The research solely examines conversion campaigns and excludes any lead generation campaigns objective. The data collected also distinguish new prospects (prospecting) to returning prospects (retargeting) audience at the campaign level.

Procedures

Due to confidentiality issues and access restrictions, the data collected only considers the US market and solely examine the subscription stream of Eaglemoss Inc., from April 2019 to April 2021. The data collection involves a daily export from Facebook Ads Manager for all ad accounts. Eaglemoss Inc., has set-up an automated daily export from all media source to a data warehouse platform (Big Query) to ensure that all data collected are secured and easily accessible. Human involvement (compilation of data) in the data collection method of this research is minimal to preserve data accuracy. The data is directly downloaded from the warehouse platform to the researcher analytical tools (RStudio).

Measures

The data collected contains 354,088 observations and 108 variables. From the data collected, we can identify numerical and categorical variables:

- Numerical: reach, spend, CPM (cost per impression), link clicks, website purchases, cost per result
- Categorical: ad account, campaign name (prospecting / retargeting), ad set name (lookalike / interest product / nielsen, demographic, other...)

Excluding the lead generation campaigns from the analysis ensures that the cost per results is the cost per acquisition. The research look at the bivariable correlation between CPMs and CPAs, both in monetary values (in dollars). CPMs represents the cost per impression, meaning that if the CPM value is $1, the advertiser is paying $1 for 1,000 impressions. CPAs represents the cost per acquisition, meaning that amount of advertising spend per purchase event. If the CPA value is $10, this indicates that the advertising cost to have one purchase is $10.

Data Analytic Plan

The data cleaning process is quite tedious as the dataset contains 108 variables, among which only a few variables is used and renamed to be relevant for the analysis: date, audience names, cost, impressions, conversions, platform, collection, type campaign, marketing channel, Mdate.

The dataset is filtered for the purpose of the analysis by selecting only “social” from the marketing channel variable, the “Delorean” in the collection variable and “Facebook” in the media platform variable. The research paper only examines one collection, the Delorean, as it is the type of product that contains the most historical data, and this ensures that the average of cost per impression and cost per acquisition of all the products do not skew the results. Once filtered with the above criteria, the dataset contains 56,833 observations and 11 variables.

Two new variables are created to calculate the cost per impressions (CPMs) and the cost per acquisition (CPAs), based on variables in the dataset:

- CPMs = 1000 * “spend” / “impressions”
- CPAs = “spend” / “conversions”

Those variables are aggregated from daily to monthly to remove the daily outliers of cost per acquisition calculation. The dataset contains the difference of type of campaign “Prospecting” and “Retargeting” but does not identify the different audience type. For this new variable, value will be determined depending on the audience name variable and separated into 5 categories: “lookalike”, “interest”, “demographic” and “nielsen” if the audience name contains those keywords and “others” if none of those keywords are identified.

The research analysis includes a bivariate correlation of monthly CPA and CPM. Based on the research outcome, the research studies other bivariate correlations on the type of campaign as well as the type of audience correlation of monthly CPA and CPM.

Analysis

A Pearson’s *r* correlation coefficient (Pearson’s *r*) is used to measure the relationship between CPMs and CPAs. In order to use Pearson’s *r*, first the research verifies the assumptions that the Pearson’s *r* can be used; using data interval (continuous variables) and verifying that distribution and variables are normally distributed. To ensure variables follow a normal distribution, the research study plots the density of each variable to confirm and remove any outliers. The bivariate correlations between CPA and CPM will then be assessed to understand which type of variable impacts the potential correlation between CPA and CPM:

- All data (CPA$PnR & CPM$PnR)
- Type of campaign: Prospecting (CPA$P & CPM$P) and Retargeting (CPA$R & CPM$R)
- Type of audience: Lookalike (CPA$Lookalike & CPM$Lookalike), Interest (CPA$Interest & CPM$Interest), Demographic (CPA$Demographic & CPM$Demographic), Nielsen (CPA$Nielsen & CPM$Nielsen) and Others (CPA$Nielsen & CPM$Nielsen)

Results

CPA and CPM correlation

A statistical distribution of the monthly CPA (dependent variable) is conducted using a density plot and the distribution of the data was found somewhat normal (see Figure 1; N= 35, bandwidth = 5.512). The scatterplot representation of the monthly CPM and CPA indicates a correlation between CPA and CPM (see Figure 1). Using Pearson's *r* coefficient of correlation to assess a bivariate correlation, a significant positive relationship between monthly CPA and CPM is found ($r = .40$, $t(33) = 2.54$, $p < .05$).

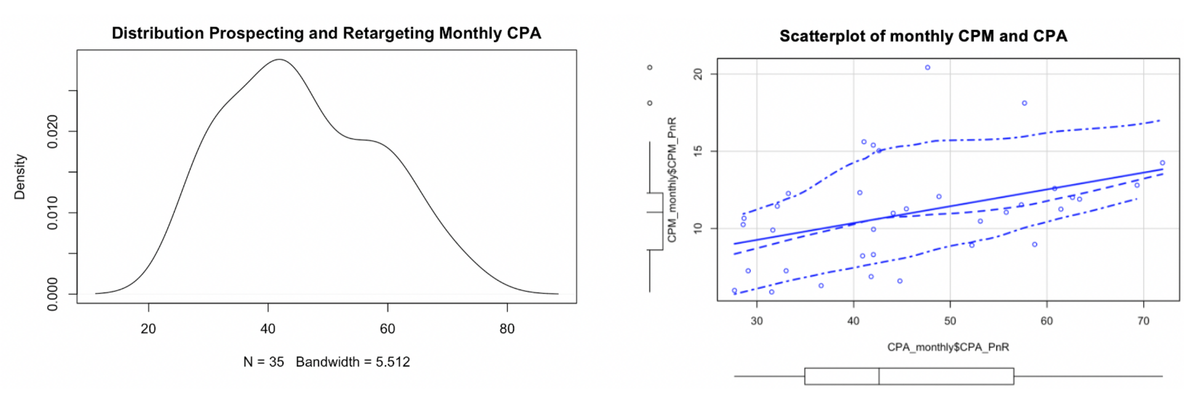

Figure 1 - Distribution monthly CPA and scatterplot representation of monthly CPM and CPA

CPA and CPM type of campaign correlation

To examine if the type of campaign impacts the correlation between CPA and CPM found previously, a statistical distribution of the monthly CPA of the prospecting variable is conducted using a density plot and the distribution of the data was found somewhat normal (see Figure 2; N= 35, bandwidth = 6.19). A statistical distribution of the retargeting variable is also conducted using a density plot and the distribution of the data is found normal (see Figure 2; N= 35, bandwidth = 4.95).

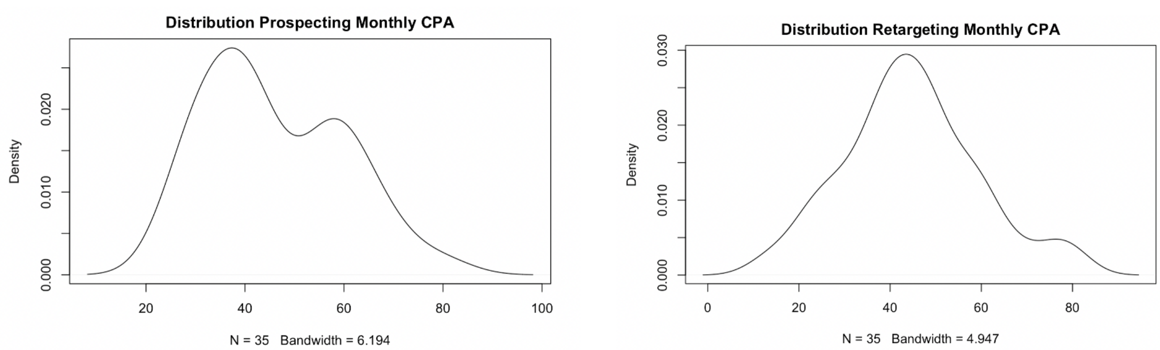

Figure 2 - Distribution prospecting and retargeting monthly CPA

The scatterplot representation of the prospecting monthly CPM and CPA indicates a correlation between prospecting CPA and CPM (see Figure 3). Using Pearson's *r* coefficient of correlation to assess a bivariate correlation, a significant positive relationship between prospecting monthly CPA and CPM is found ($r = .45$, $t(33) = 2.92$, $p < .05$). As for the scatterplot of retargeting monthly CPM and CPA, it indicates there is no correlation between retargeting CPA and CPM. Using Pearson's *r* coefficient of correlation to assess a bivariate correlation, no significant relationship is found between retargeting monthly CPA and CPM ($r = .26$, $t(33) = 1.57$, $p > .05$).

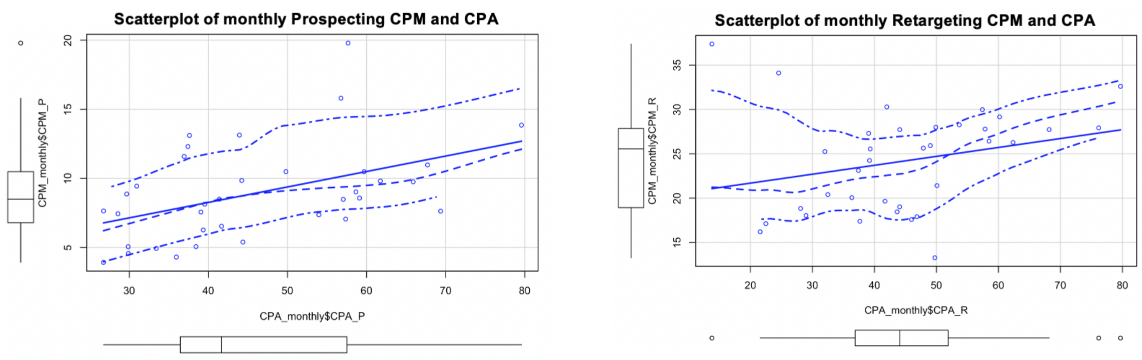

Figure 3 – Scatterplot representation of monthly prospecting and retargeting CPM and CPA

CPA and CPM correlation on type of audience

To understand if the audience type impacts the correlation between CPA and CPM found in prospecting campaigns based on previous results, a statistical distribution of the monthly CPA on the following variables is conducted: lookalike, interest, demographic, nielsen and others. A statistical distribution of the monthly CPA of the lookalike variable is conducted using a density plot. The distribution of the lookalike monthly CPA is right-side skewed. An outlier is removed to get closer to a normal distribution (see Figure 4; N= 34, bandwidth = 6.22).

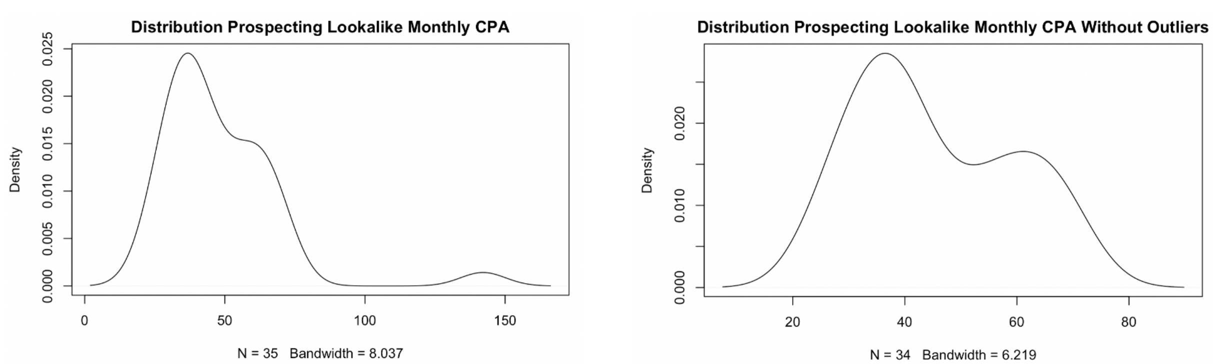

Figure 4 – Distribution prospecting lookalike audience monthly CPA before and after removing outliers

A statistical distribution of the monthly CPA of the interest variable is conducted using a density plot and the distribution is slightly right-side skewed. The outlier is removed to get closer to a normal distribution (see Figure 5; N= 28, bandwidth = 5.91).

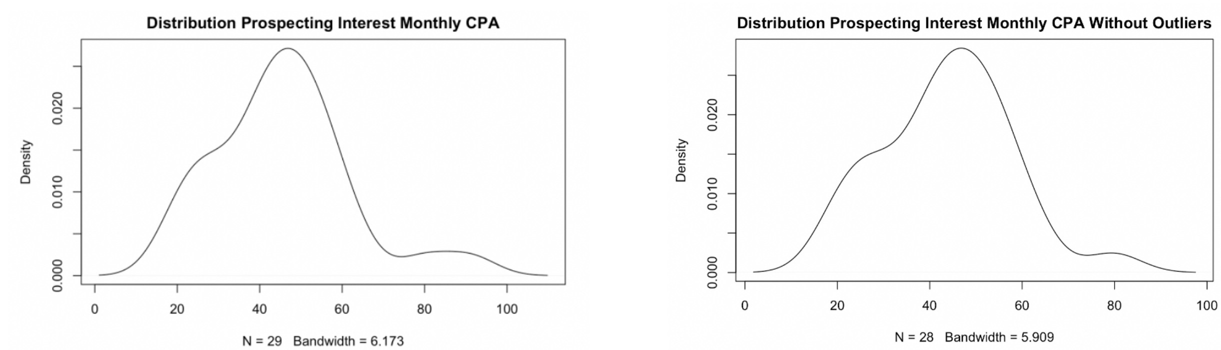

Figure 5 – Distribution prospecting interest audience monthly CPA before and after removing outliers

A statistical distribution of the monthly CPA of the demographic variable is conducted using a density plot and the distribution is right-side skewed. The outlier is removed to get closer of a normal distribution (see Figure 6; N= 17, bandwidth = 6.36).

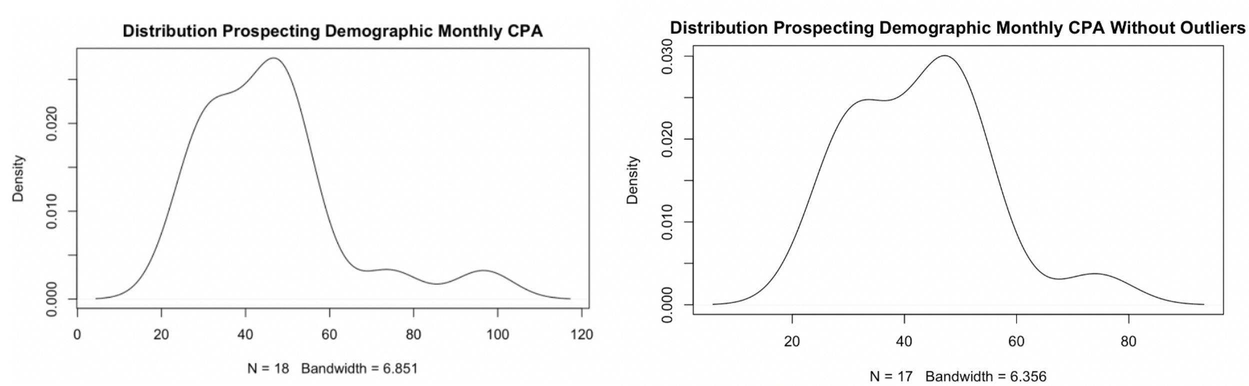

Figure 6 – Distribution prospecting demographic audience monthly CPA before and after removing outliers

A statistical distribution of the monthly CPA of the nielsen variable is conducted using a density plot and the distribution is normally distributed (see Figure 7; N= 10, bandwidth = 17.07). A statistical distribution of the monthly CPA of the other variable is conducted using a density plot and the distribution is normally distributed (see Figure 7; N= 15, bandwidth = 5.30).

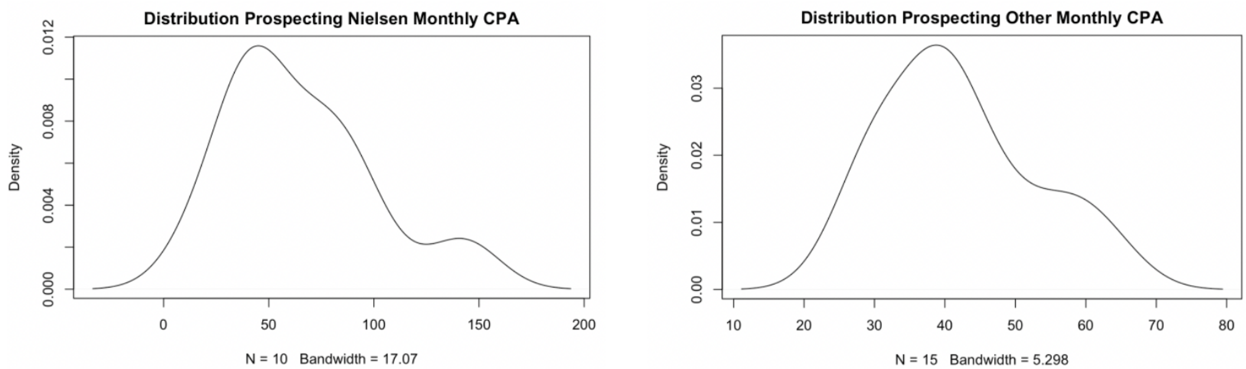

Figure 7 – Distribution prospecting nielsen and other audience monthly CPA

The scatterplot representation of prospecting lookalike, interest, nielsen and other monthly CPM and CPA audiences indicates there is no correlation between CPA and CPM (see Figure 8). Using Pearson's *r* coefficient of correlation to assess a bivariate correlation, no relationship between lookalike monthly CPA and CPM is found ($r = .24$, $t(32) = 1.41$, $p > .05$). No relationship is also found between interest monthly CPA and CPM ($r = -.24$, $t(26) = -1.27$, $p > .05$), nielsen monthly CPA and CPM ($r = .11$, $t(8) = .31$, $p > .05$), and other monthly CPA and CPM ($r = .03$, $t(13) = .09$, $p > .05$). However, a significant positive relationship between prospecting demographic monthly CPA and CPM is found ($r = .56$, $t(15) = 2.63$, $p < .05$).

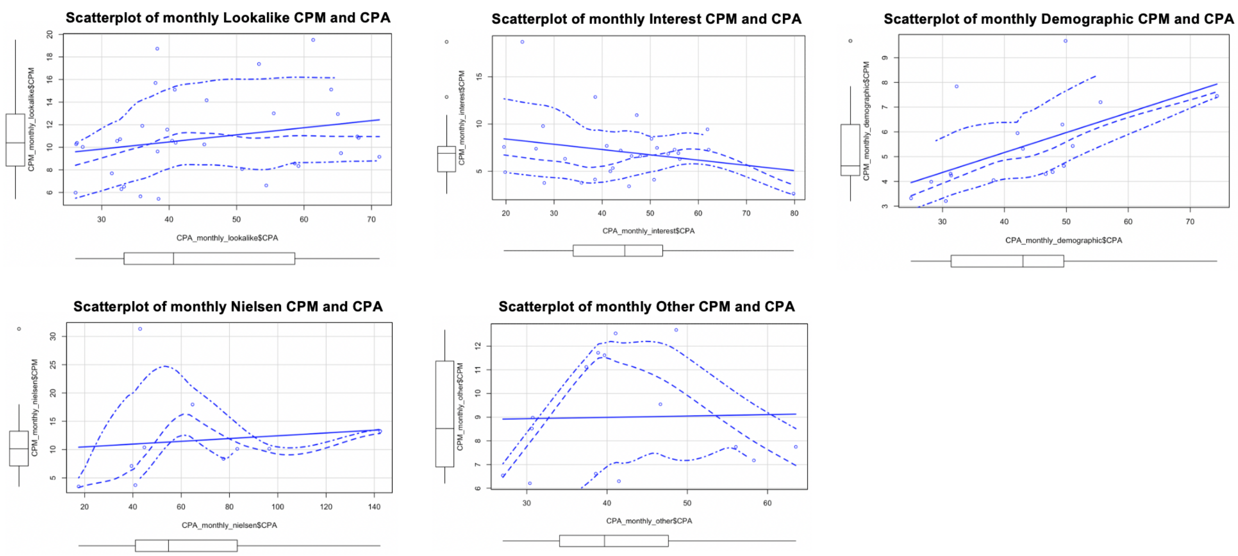

Figure 8 – Scatterplot representation of monthly prospecting of lookalike, interest, demographic, nielsen and other CPM and CPA audience

Discussion

The research found that there is a positive correlation between the cost per impression (CPM) and cost per acquisition (CPA) under the CPM pricing model studied at Eaglemoss Inc. The research also found that there is a positive correlation between CPM and CPA for prospecting campaigns, targeting people that do not have any touchpoint with the brand before-hand. However, there is no correlation found between CPM and CPA for the retargeting campaigns, designed to reengaged customers that were exposed previously to marketing content.

Narrowing the type of audience in the prospecting campaign where there is a positive correlation between CPM and CPA, only the demographic audience is significant. All the other audience types had no correlation between their CPM and CPA.

The above findings help all digital marketers in their campaign optimization. By knowing this relationship exists, marketers can scale-up their digital marketing budget when CPM are lower than usual and, on the opposite, scale-down budget when CPM are high, especially towards prospecting campaigns and demographic targeting audience where the correlation is stronger.

Conclusion

This research found a positive correlation between the cost per impression (CPM) and cost per acquisition (CPA) under a CPM pricing model on digital marketing campaigns. The correlation is particularly significant for people that do not have any touchpoint with the brand before-hand (prospecting) and broad (demographic) audience.

The main limitation of this research is causation. Further research is needed to investigate what are the factors that influence both CPM and CPA parameters to find the causation. Tests that include increasing the monthly digital marketing budget when CPM are lower than average and examining how CPA evolves is particularly relevant.

By facing digital marketing industry core updates such as the IOS 14 cookie consent tracking in 2021 and the sunset of certain detailed targeting in March 2022 in Facebook Ads, marketers must analyze their historical data and find pattern to boost their digital campaign performance. This research is a steppingstone in global digital marketing campaign optimization. Finding a significant correlation between CPM and CPA allows every marketer and researcher to explore and apply correlation analysis to validate, refine and improve the research findings on this topic. This research adds value to the current literature review on online marketing pricing models topic, that contains a limited number of studies and findings despite its relevance.

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