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Tomáš Komárek

University of Economics, Prague

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Automation in Search Engine Advertising

Author: Tomáš Komárek

Supervisor: doc. Ing. Václav Stříteský, Ph.D.

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Abstract

Automation and smart bidding are currently hot topics. However, the smart bidding performance is lacking a scientific proof. The experiment I conducted on a bookstore account shows that smart bidding works better for Search Network, but not for Shopping Campaigns, which are structured based on a different conversion rate of search terms. The smart bidding was compared with semi-automated manual bidding and evaluated with a Wilcoxon paired test and the Causal Impact analysis. Moreover, the in-depth interviews with 31 PPC experts were conducted. Based on the research, the automated model for manual bidding in combination with smart bidding is the best practice for bidding in Google AdWords. Moreover, an Automated Builder for Campaigns (ABC) framework was created.

Keywords

PPC, Search Engine Marketing, AdWords, Marketing Automation, Smart Bidding, Automated Bidding, Search Term Optimization, Causal Impact

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Table of Content

INTRODUCTION 8

ABBREVIATIONS AND KEY TERMS 9

1 AUTOMATION IN SEARCH ENGINE MARKETING 10

1.1 MANUAL BIDDING 15

1.2 SMART BIDDING 16

1.2.1 THE ADWORDS AUCTION-TIME BIDDING SYSTEM BACKGROUND 17

1.2.2 THE ADWORDS SMART BIDDING STRATEGIES 18

2 OPTIMIZATION AND ADVANCED SET-UP IN ADWORDS SEARCH CAMPAIGNS 22

2.1 SEARCH CAMPAIGNS 22

2.1.1 SEARCH CAMPAIGN STRUCTURE 22

2.1.2 DYNAMIC SEARCH CAMPAIGNS 26

2.1.3 AUTOMATED SEARCH CAMPAIGN CREATION 27

2.1.4 SEARCH CAMAPAING OPTIMIZATION 28

2.2 SHOPPING CAMPAIGNS 31

2.2.1 STRUCTURE 32

2.2.2 FEED OPTIMIZATION 34

3 METHODOLOGY 36

3.1 EXPERIMENT DESIGN 36

3.1.1 CAMPAIGN STRUCTURE AND OPTIMIZATION DESIGN 36

3.1.2 THE PERFORMANCE EVALUATION 41

3.2 QUALITATIVE INTERVIEW DESIGN 43

4 EXPERIMENT 45

4.1 SEARCH CAMPAIGN EXPERIMENT 45

4.2 DSA EXPERIMENT 46

4.3 SHOPPING EXPERIMENT 46

5 QUALITATIVE INTERVIEWS 49

5.1 MEASURING THE PERFORMANCE 49

5.2 STRUCTING THE SEARCH CAMPAIGNS 51

5.3 CAMPAIGN CREATION 52

5.3.1 FIRST INPUTS 52

5.3.2 CREATING RELEVANT ELEMENTS 53

5.3.3 HUMAN CORRECTIONS 55

5.3.4 CAMPAIGN CREATION 55

5.4 SEARCH CAMPAIGN OPTIMIZATION 57

5.4.1 PERFORMANCE CONTROL 57

5.4.2 SEARCH TERMS OPTIMIZATION 57

5.4.3 BIDDING 59

5.4.4 AD TESTING 66

5.5 SHOPPING 68

5.5.1 MANUAL BIDDING 68

5.5.2 SMART BIDDING 70

5.5.3 FEED OPTIMIZATION 70

5.6 FUTURE 72

CONCLUSION 75

Introduction

Marketing automation. Smart bidding. Machine Learning. Are these terms just buzzwords in search engine marketing? Nowadays, every PPC influencer is talking about automation. However, does it really make sense to use such a data-demanding algorithm as machine learning? It is proved that simpler algorithms work much better with a lower volume of data (Sidhu & Fred-Ojala, 2018). Isn't it better to use static rules to manage bids in such small market as the Czech market? Complex models like Machine learning or AI require an enormous amount of inputs (Abadi et al., 2016). Is it enough for the smart bidding to perform well in middle-size accounts with 50 000 keywords or even with only 500 conversions? The algorithm calculates billions of combinations of audiences, devices, locations, and many other inputs. The algorithm is supposedly learning to bid after only 500 conversions. Surprisingly, little research has been conducted to compare the performance of smart bidding algorithms versus the manual bidding. The most relevant study was done by Veurink (2015) on optimal bidding for Shopping campaign without any reference to smart bidding. Therefore, further research is necessary to provide a better understanding of automation in search engine marketing

The objective of this thesis is to compare manual bidding to smart bidding in Google AdWords campaigns for an online bookstore. Furthermore, the aim is to evaluate the results of the experiment with an explanation of the outcome. However, what works for one project is not simply going to work for others. Therefore, the second objective is to understand current practices in the PPC automation of the experts in the field of online marketing. The sub-goals are to find patterns in various approaches for an automated campaign creation and an automated optimization of search and shopping campaigns in Google AdWords. Moreover, to reveal certain patterns in the campaign setup of smart bidding in order to fully use the potential of the algorithm. The last goal is to estimate a future development of PPC automation based on the prediction of experts from the field.

This thesis is intended mainly for the advanced PPC specialists who can use the Automated Builder of Campaigns (ABC framework) for their own automated solutions. Moreover, the current optimization techniques are summarized, and the SEM specialists can decide which approach is the most applicable to their project. Moreover, the scientific researchers can create a better solution in bidding strategy for the low conversion volume datasets based on the outlined bidding structure in combination with smart bidding. Moreover, the results from the in-depth findings deserve further research, such as the impact of product price change on the shopping performance.

The research is divided into two parts. The first part is the experiment of manual vs. smart bidding in Google AdWords Search Network and Google Shopping. I created a framework of bidding rules, which were used for semi-automated optimization through Power Query scripts. The reason was to ensure a certain level of objectivity in the manual bidding. The bidding rules were created based on the literature review. Exactly three bidding experiments were conducted: (1) in search campaigns, (2) dynamic search ads campaigns, and (3) shopping campaigns. The main indicators for better performance are the number of conversions, or alternatively, volume of revenues and the cost per acquisition (CPA) or the return on advertising spend (ROAS). The differences among the smart and manual bidding were analyzed with a Wilcoxon paired test, and the total incremental increase of revenues was analyzed with Causal Impact. The second part of the research is devoted to the in-depth interviews. I interviewed 31 experts with experience in various projects. Based on the research, I created an Automated Campaign Builder framework based on the analysis of the various optimization techniques of automation. Moreover, I gathered the experts' experience to establish eight smart bidding rules. In addition, details regarding smart biding rules, such as the insights from the interviews with the experts, are provided.

Abbreviations and key terms

AOV – Average order value

CPA / (tCPA) – Cost per acquisition / (target cost per acquisition)

CPC / (eCPC) – Cost per click / (enhanced cost per click)

CPM - Cost per mile

CVR – Conversion rate

Conversion lag - Time between when a user interacted with an ad, and when that user converted

CTR – Click through rate

CRM - Customer relationship management

DSA – Dynamic search ads

COS – Cost of sales (also known as Effective revenue share)

GA – Google Analytics

IS - Impression Share

ROAS / (tROAS) – Return on advertising spend / (target return on advertising spend)

Search term/ Search query - combination of words entered into a search engine

Web scraping - Extracting data from websites

Web crawling – Using a bot that systematically browses the websites (URLs) from a domain

SEM – Serach engine marketing

SERP – Search engine result page

USP – Unique selling proposition

1 Automation in Search Engine Marketing

The marketing automation has been studied since 1998. Tracking and analyzing customer behavior helps managers to budget allocation within the purchase funnel (Little, 2001; Bucklin et al., 1998, 2002; Heimbach, Kostyra & Hinz, 2015). Current marketing automation enables much more than budget allocation. Marketing automation is powered by the data stored into CRM. The customer data management platform could send automated personalized messages to the potential or current customers. Such platforms can track users' behavior, and more precisely, score leads and analyze the customers. If such a system is connected also to the Google Analytics (GA) or the AdWords accounts, the SEM specialists could use these insights in their campaigns as well. (Linton, 2012) Marketers can track in Google Analytics the user's behavior on the website, and later also an offline event. The tracking could be done via measure element protocol, which enables one to load any offline events to the GA account. (Brunec, 2017) When the CRM system is connected to the AdWords and GA or even the emailing system, the advanced cross-device tracking is enabled. When the users come from an email for example in a mobile device, we can link the cookie through the CRM to the GA and AdWords audiences. Moreover, if the user buys a product, and then he returns it or does not pick it up, a specific event can be sent to Google analytics and the advertiser can see clear revenues. (Vollmert & Lück, 2018)

The further automation is dependent on the attribution model the marker is using. The attribution model changes the way the marketing channels are scored. The most common way of attribution is the heuristic model last click since it is automatically set in the GA (Vollmert & Lück, 2018). However, this model does not consider the influence of previous users steps. Therefore, many attribution models have been developed and described in various papers (Zhao, Mahboobi & Bagheri, 2017; Papapetrou, Gionis & Mannila, 2011; Sanderson & Guenter, 2006)

Setting the right goal

Many e-commerce businesses set their goals based on ROI analysis. So the business owner can set an estimate to cost of sales (COS), cost per acquisition (CPA), return on advertising spend (ROAS). However, the ultimate goal of most businesses is to maximize profits. The ROI analysis should help the advertisers to get to the ultimate goal. However, the optimization should be made in respect to the profit maximization goal. (Wrodarczyk, 2013; Geddes 2014, p. 451)

The fact that maximizing ROAS does not always maximize profits is seen in table 1 from Geddes (2014). In most cases, the cost of goods, shipping, and other expenses determine the final profit.

Table 1Profit vs. ROAS

Campaign	Average CPC	Conversion rate	Cost per conversion	Revenue per conversion	ROAS	Profit per sale
Chocolate	$1	10%	$10	$20	200%	$10
Flowers	$3	10%	$30	$50	166%	$20

Source: Edited from Geddes, B. (2014). Advanced Google AdWords. INpolis, IN: SYBEX. ISBN: 978-1118819562

As the Witold Wrodarczyk's paper (2013) suggest, the advertisers should set the CPA that reflects their desired revenues. However, it might a challenge for advertisers to calculate the optimum point where the bids should be increased only as long as the profit grows (marginal profit is equal zero). The marginal revenue is shaped by the diminishing returns law (Feldman, 2017; Zainal-Abidin 2010). Based on this we can conclude that bids should increase as long as the profit (not revenues) grows. The optimum point, where the marginal increase of clicks (bids) is equal marginal profit.

$$\frac{dROI}{dCPC} = 0$$

However, the complex problem is how to calculate the marginal profits. If we simplify it that the conversion value is constant (each conversion from various ad position brings exactly the same income) and the conversion rate is constant we can exactly calculate the profit of each conversion just by deducting the cost per conversion.

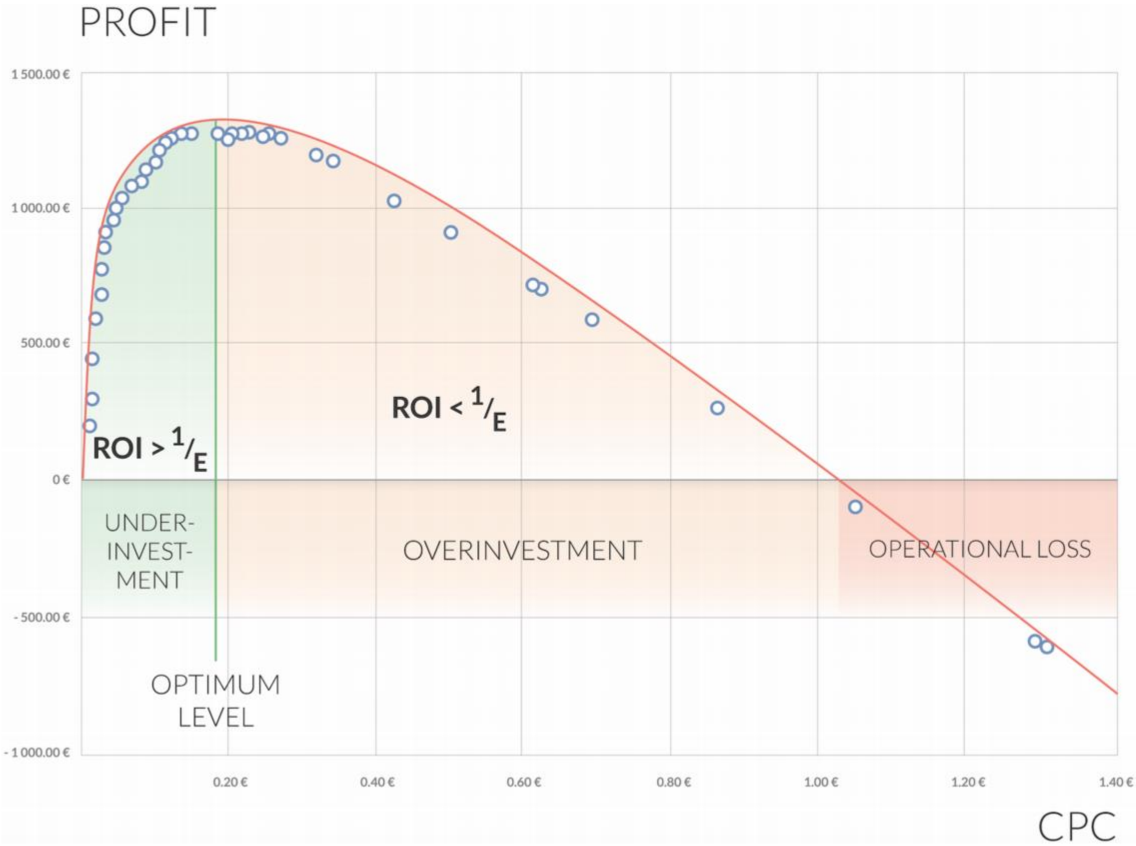
$$\frac{\frac{dCPC}{CPC}}{\frac{cClick}{Click}} < \frac{Conversion\,Value - Cost\ per\ Conversion}{Cost\ per\ Coversion}$$

Which is, as Wrodarczyk (2013) formulated, that the inversed price elasticity is lower than the return on investment.

$$ROI\ < \ {}^{1}/_{E}$$

The profit line is outlined in the following picture 1. The profit is maximized at the optimum level, where the return on investment is equal inversed price elasticity.

Picture 1 Profit curve



Source: Wrodarczyk, W. (2013). Profit Driven Management in PPC Campaigns [PDF]. Warsaw: Adequate Interactive Boutique. Retrieved February 12, 2018, from http://www.adequate.pl/wp-content/uploads/2014/11/Profit-Driven-Management-of-PPC-Campaigns.pdf

The price elasticity can be monitored either by recording every bid change and calculating the outcome. If we visualize the relation beteween Cost and Clicks. It is usually non-linear function with convexly shaped, because the more clicks, the fast CPC increases. Based on the data we can calculate the price elasticity in each CPC point. However, the calculation of every change would be almost impossible. Google created a Bid Simulator, through which the performance of different bid is estimated. This algorithm uses "information such as Quality Score, keyword traffic, and competition in the ad auction" according to the AdWords Help. This data can be downloaded through AdWords API[1] for more advanced bidding systems.

However, the price elasticity in some projects can change dramatically within a short period of time, therefore, advertisers should keep this in mind while defining the target ROAS. Google enables to see the expected elasticity in the Target CPA Bid Simulator The example is in picture 2. This should motivate the advertisers to use smart bidding solutions because they can change the targeted value with one click.

[1] https://developers.google.com/adwords/api/docs/guides/bid-landscapes

Picture 2 Target CPA Bid Simulator

Model and change bids on **Bid strategy 1** for 2 campaigns and 10 ad groups
The combined estimates below represent all campaigns and ad groups using this strategy. Estimates assume sufficient budget for all bid levels.

Download data

Target CPA	Clicks	Cost	Impr.	Top impr.	Converted clicks	Conv.	Total conv. value
$16.90	4,210	$19,238.57	437,000	84,800	1,550	1,670	1,470
$14.30	3,880	$17,623.14	390,000	70,900	1,490	1,590	1,450
$12.70	3,600	$16,123.26	349,000	58,200	1,410	1,510	1,420
$11.60	3,310	$14,590.45	314,000	47,000	1,340	1,430	1,380
$11.25 (current)	3,080	$13,040.93	276,000	40,800	1,260	1,350	1,350
$10.80	2,840	$11,783.76	254,000	35,200	1,160	1,240	1,240
$10.30	2,610	$10,586.80	232,000	30,100	1,070	1,140	1,140
$9.82	2,340	$9,226.26	206,000	24,900	965	1,030	1,030
$9.25	2,060	$7,855.95	176,000	20,100	860	916	916
$8.68	1,800	$6,534.22	155,000	16,300	751	803	803
Use a different bid: $							

Estimated impact for **Apr 20, 2015-Apr 26, 2015**. Estimates don't guarantee future performance and are based on an unrestricted budget. To get this estimated traffic, you may need to increase your budget.

Source: Weckner, A., & Dautaj, D. (2017, March 15). Leveraging Machine Learning - AdWords Smart-Bidding. In OMR 2017. Retrieved January 13, 2018, from https://www.thinkwithgoogle.com/intl/de-de/marketingressourcen/daten-und-erfolgsmessung/omr17-masterclass-leveraging-machine-learning/

Budget constraint

The bidding is mostly influenced by budget. Several researchers tried to solve the bidding in budget constrained campaigns. First, it should be clear what it means. It could be easily interchanged with another problem - campaigns limited by budget. This term explains the problem that if campaigns that have a limited budget and high bids will be spent during the day. So in other words, The advertiser will not enter some auctions. However, not because of bad AdRank, but because the system does not allow to enter some auctions. For illustration, if the system would allow the advertiser to enter all possible auction, the budget would be spent during the day and the ads would not run during the evening. This clearly shows that the budget is ineffectively used when campaigns are limited with a budget. Because if lower bids were set, the lower CPCs would the advertiser pay probably for the same amount of traffic, because the ad would run all day. Advertisers should definitely try to avoid having campings limited by budget in the long run.

The theory the term budget constrained is rather a budget allocation problem. The best possible revenue should be done via setting different goals to different campaigns with different budgets. Imagine a simplified version of this problem. The goal is to get most of the conversions possible with a limit of cost per conversion set to €10. There are 3 campaigns. One has low search volume, however, even with the highest bids to be at the position 1 is the CPA just €5 The second one reaches exactly €10 when it is set to the highest bid. The last campaign is more competitive, and it reaches CPA of €10 when the bid is set to be at the

3rd position. If each of these campings would be set to have €10 CPA than the overall CPA would be lower (because of the first campaign). To keep the goal, the advertiser needs to set the third campaign higher in order to have at the end exactly €10 per conversion. Budget constrained campaigns are therefore rather budget allocation problem.

The understanding of the budget constraint problem and possible solution helps to better analyze and set suitable strategy. This topic is heavily researched from the point of view of the search engine (Mehta, Saberi, Vazirani & Vazirani, 2007; Devenur & Hayes, 2009; Goel, Mirrokni & Leme, 2012; Charles, Chakrabarty, Chickering, Devanur & Wang, 2013). The best solution is to try to motivate the advertisers to spend more. Google made it in practice because the daily budget can double since last year[2].

However, this thesis is focusing on the advertiser's point of view. Many researchers used linear programming to predict the best and fair allocation in order to meet required ROI. (Wang, Suphamitmongkol & Wang, 2013; Wang, Zhang, Shang & Shi, 2013) However, the study from Karande, Mehta & Srikant (2013) showed that linear programming is the least reliable solution. The best solution according to this study is the Optimized Throttling algorithms that analyse data. However, the research has contradicting results. (Borgs et al., 2007; Feldman et al., 2007; Rusmevichientong & Williamso, 2006; Muthukrishnan, Pál & Svitkina, 2009). However, those research do not cover the long-term effect of the bidding decisions. The study from Archak, Mirrokni & Muthukrishnan (2012) shows that the short-term solution, which is perceived as better is, in fact, worse in the long run.

Bid landscapes

Interesting study researching the budget constraint because it is specializing on broad match. In case of broad match campaigns is the bidding even more difficult. Eyal Even Dar and his colleagues (2009) calculated how to bid these keywords. They created a model, similar to Google's bid landscape described above. It shows the curve of marginal volume of clicks based on price for click. The bidding can be set based on the bid landscape even for the dynamic search ads. However, the bidding strategy based on bid landscapes are applicable even for exact match type keywords in the environment, which does not significantly change. In such environment is possible to find market equilibrium based on the price elasticity for the specific keyword or even search terms (Feldman et al., 2007)

In following paragraphs are described the recommended optimization techniques from keyword to the campaign level. The main goal for advertisers is to set the right bid for a certain ad auction so the advertisers get traffic which would convert at their websites. Google enables to bid manually on the right keywords as the lowest level with possibility to use bid modifiers.

Manual bidding is very challenging, since the performance is changing in time, and it is hard to find the right bid at the moment. If advertisers bid high on low converting keywords, then

[2] https://support.google.com/adwords/answer/1704443

the cost per conversion would exceed the budget ineffectively. On the other hand, bidding lower on a highly converting keyword might cause one to lose an opportunity for greater traffic resulting from a better position. Managing bids for broad match campaigns is even more difficult because some queries might perform extraordinarily well, but some queries fired from the same keyphrase might bring much lower, or even negative, profit. (Dar et al, 2009) In the ideal situation, the advertisers set bidding to keywords based on the short historical results. However, most of the keywords do not have enough data to decide which bid is the most suitable for the next day. So, the PPC optimizer needs to decide to either use a longer time frame, where there is enough data, or to cluster the performance of the same keywords with different match types or ad groups, or even to decide on the bid based on whole campaign performance. In case of product campaigns, the groups of ad groups could be promoting a product from the same category, or any similarly performing products. To set a suitable bid, it is important to understand the logic of the general second price auction, which is used by Google. Several studies describe the design of a paid search auction mechanism (Edelman, Ostrovsky, and Schwarz, 2005; Varian, 2007; Xu, Chen, and Whinston, 2011; Zhu and Wilbur, 2011; Chaitanya & Narahari, 2010; Chatterjee, 2013)

Setting up bids for new campaigns is even more challenging. Research from Nadia A. Nabout (2015) tested three different approaches: (1) recommending a bid from the Google Keyword Planner, (2) clustering similar CPCs from already active campaigns, or (3) calculating the recommended bid based on the CR and target CPA. Surprisingly, all the strategies had similar performance, and the simplest (3rd) strategy performed the best.

1.1 Manual bidding

The lowest automated level is complete manual adjustments. Google AdWords enables one to use bid adjustments, automated rules, or even custom scripts for managing the repetitive task in the interface. The scripts enable specified 3rd party tools to make changes in the account automatically. Using such solution might result in cycling and therefore the mechanism should use just a small change in bids. (Borgs et al., 2007) On the market are many tools to professionally manage keyword bids, e.g., EfficientFrontier, IntelliAd, and Omniture. (Klapdor, 2014) Google also created a free tool, AdWords Editor, to manage large accounts with bulk edits.

Unique strategies applicable in manual bidding

The advantage of manual bidding is that the advertiser can test various individual strategies of overbidding to discourage the competitive advertiser or underbid to use the brand power.

In the overbidding strategy, the advertiser's goal might be to primary damage its competitors. The study from Liang and Qi (2007) describes and test vindictive strategies on search advertising. In most of the cases, the malicious strategy leads to Nash Equilibrium. However, the research was done in a time when smart bidding was not available. Several experts argued that purposely increasing bids might disrupt the competitors bidding system. The following study reveals that it is possible to harm the competitor and gain slight profit based on this disruption. However, the bid increase should be done conservatively, otherwise it is contra productive to use vindictive strategy (Tsung, Ho & Lee 2013)

On the other hand, underbidding might be applicable as well. Companies with a strong brand may use a "position paradox" while manual bidding sponsored search auctions. "The paradox is that a superior firm may bid lower than an inferior firm and obtain a position below it, yet it still obtains more clicks than the inferior firm. Under a pay-per-impression mechanism, the inferior firm wants to be at the top, where more consumers click on its link, whereas the superior firm is better off by placing its link at a lower position because it pays a smaller advertising fee, but some consumers will still reach it in search of the higher-quality firm." (Jerath, 2011, p.612) The study from Borgs et al (2007) also confirms this trend and suggest using the perturbed mechanism to randomly decrease the bid to get a lower position. Some studies have shown this effect even on advertisers with brands which has lower awareness. (Du, Su, Zheng & Zheng, 2017; Xu, Chen & Whinston, 2011) A study from Agarwal, Hosangar & Smith (2011) specifies that this evidence of better performance on lower position is due to inefficiency in Google's auction mechanism. The experiment was held on several retailers and the similar outcome was proven. The authors suggest that it is because the auction mechanism does not account for a conversion rate of the advertisers in the top position. This inefficiency might, however, diminish if more and more advertiser would use smart biding strategy provided by Google and the bidding will reflect the predicted CVR.

Bid adjustments

Since 2013, advertisers can use bid adjustments to modify bids with respect to device, location, audience, time etc. The effect was positively proved by Mazen Aly (2017). He provides a statistical method for selecting campaigns that are suitable for bid adjustment with an exact solution for calculating bid adjustments that lead to increased conversion within the set or lower CPA. (Aly, 2017) Another study, analyzing data from 1000 AdWords advertisers, resulted: "The uniform bidding approach guarantees 64% of the optimum on average" (Bateni et al., 2014, p. 19). However, using various bid adjustments at the same time may unexpectedly multiply the effect of several bids and as a result, the system would overbid or underbid due to the combination. This situation is called "multiplicative bidding problem". Mazen Aly stressed that setting bid adjustments is a continuing process and the adjustment value needs to be periodically changed when the bids are changed. He recommends to set bids based on the performance of one base segment (for example location A) and change the adjustments based on the difference with the base segment (for location B and C) to reach the right equilibrium (Aly, 2017)

1.2 Smart bidding

Google uses the Generalized second-price auction for the search engine advertising. (Edelman, 2005) The advantage of smart bidding provided by Google is that the algorithm can adjust the bid on the level of each auction.

1.2.1 The AdWords auction-time bidding system background

Google is trying to help advertisers with data-driven solutions such as automated bidding, which does the adjustments of the campaigns automatically. Nevertheless, an essential part of automated campaigns is the creation of the campaigns – managing the automated bidding strategies. (Newton, 2015) This section describes the optimization strategies and techniques that Google offers.

True auction-time bidding

AdWords automated bidding enables one to set a different bid in each individual auction based on the search context and user. Such granular level of detail creates an ability to increase the precision of each bid. (Google, 2018) There is no other solution of how to optimize a bid so frequently and granularly as for every specified bid. Rules-based bidding changes the bid only when the keyword or ad set meets certain criteria.

Query-level learning

Machine learning algorithms, that Google uses, are based on the search terms and historical conversion data. However, only a small percent of high volume search terms have enough conversion data for accurate modeling (these search terms are called head terms). The rest low-volume search terms need to take data from other sources. Google uses the modeled performance for a specific search term from other search terms that are within the same keyword. If there is still an insufficient amount of conversion data, the algorithm does "data clustering". That means it takes the performance from the same keyword across match types from other ad groups or campaigns (even from the DSA campaigns, when the portfolio strategy is applied). Thanks to the Bayesian learning, Google still use automated bidding even when the account has only a limited amount of conversions.

Portfolio bidding strategy

The algorithms described in the previous paragraph take the data from the campaign where the bidding strategy is set. Portfolio bidding strategy systems can enlarge the "data clustering" in which different keywords with similar features (conversion rate, level of campaign structure, landing page, etc.) are grouped together. This methodology enables Google's algorithms to make a more precise decision based on these aggregated data, and therefore lower the performance fluctuation and shorten the learning period even for keywords with little or even no data! Wecker & Dautaj (2017) explain that Dynamic clustering to ensure such precisely is done as a pivotal tactic. With a lower volume of conversion, also lowered is the probability of target CPA to estimate the CVR. When a target ROAS is applied, the probability of estimating the AOV and CVR is even lower. Moreover, when the portfolio bidding strategy is created in the shared library, the system enables the advertiser to see the status if the algorithm is still calibrating (learning period) and also shows the predicted conversion lag. The learning period can happen when the goal or any important setting changes in the campaign. Google states that the goal change of 20% should be without the learning period. The learning period usually takes at least one conversion cycle to adjust the performance (Wang, 2015, Google, 2018)

Rich contextual signals

Since smart bidding enables changes in every auction, the algorithms can take into account a specific user or the context of the search action. The algorithm takes the data from each context signal and evaluates correlations of combinations of all signals. In the end, the bid is set by the cross-signal analysis. The most important predictive AdWords smart bidding signals are:

- Device (desktop, tablet or mobile)
- Location (even for on city levels)
- Time of the day and weekday
- Remarketing lists (if the user is already in any advertiser's audience)
- Interface language
- Browser
- Operating system
- Search Network partner
- Actual query (as mentioned above in Query-level learning)
- Ad creative (described below)

In a situation when an advertiser has more ads for a specific keyword, the algorithm optimally chooses an ad with the highest conversion likelihood, and the bidding system evaluates the chosen ad as one of the contextual signals for its analysis. (Wecker & Dautaj, 2017; Google, 2018)

The bidding itself can be done on the product ID or on the product group level. The bid on the product level ID should be set only if the product ID has enough data. If not, the similar product should be clustered together and the bid should be set based on the group performance. The research from Veurink shows that this solution called in the paper called "bucketing" was significantly better. (Veurink p.4) Veurnik suggests that if the products are too heterogeneous, the longer timeframe can be calculated.

1.2.2 The AdWords smart bidding strategies

AdWords provides currently three conversion and revenue-based strategies: (1) Target Cost-per-Acquisition, (2) Target Return-On-Advertising-Spend and (3) Enhanced CPC.

In the past, the AdWords enabled Maximize conversions strategy. This algorithm worked better for budget constrained campaigns because its goal was to spend full budget while trying to get the most conversions. (Feldmad, 2007). However, this bidding strategy is no longer applicable.

All algorithms use "adaptive historical weighting", which means that the more recent the data, the more weight is attributed. However, the recency calculation takes into account the conversion cycle, therefore the bid adaptation is not affected by conversion delays.

However, the algorithm works worse when the conversion lag of 12+ days covers more than 15% of all conversion. The algorithms maximize the impression share till the algorithm reaches the limit of predefined ROAS or CPA.

The best practice in such cases is to have more conversions in the last 30 days than the standardized recommended volume, which is outlined in the following table 2.

Table 2 Differences in recommended number of conversions between Target CPA and Target ROAS

Conversion volume in tCPA	Conversion volume in tROAS	CPA or ROAS Fluctuation	Initial Learning Period
30	50	Medium to High	Slow
60	100	Medium	Medium
100	200	Low	Fast
500	500	Very Low	Very Fast

Modified by author: Google. (2018). Setting Smarter Search Bids: Inside Automated Bidding with AdWords [PDF]. Retrieved from https://storage.googleapis.com/support-kms-prod/rxY9B0H5P418PBlDOBl8inexW7RZqWNEOwhu

Brad Geddes recommends to firstly set the target value which the algorithm is suggesting. In case of tCPA, the recommended CPA level will be the cost-weighted average for the last 30 days, and similarly also for tROAS (Geddes, 2014, p. 437)

Soft-conversions

Unfortunately, the AdWords does not allow one to set different CPA levels for different conversion types, as it is eligible in Double Click Search. But the advertiser can choose which conversion should be counted to the bidding CPA strategy. The best practice to use smart bidding when the account has only a limited volume of conversions is to track more soft-conversions. When the marketer attributes the business value to different types of conversion, the tROAS algorithm can be used. (Glasby, 2018) Brad Geddes noted that the most common soft-conversions are: Contact Us, Any Form Fill, vCard Download, Whitepaper Download, Webinar, Subscription, Save to Cart and Add to Wish List, Send to Friend (or Self) via Email, SMS, Share on social media, Driving Directions, Phone Call, Bookmark, Print page, Coupon Print or even action like copying, scrawling, or being on a certain website more than predefined seconds (Geddes, 2014, p. 212-213)

tCPA - Target cost-per-acquistion[3]

The main goal of this bidding strategy is to get the most conversion within a predefined target cost per acquisition. The system calculates likely conversion rates from contextual

[3] https://support.google.com/adwords/answer/6268632

signals. Afterwards, the maximal bid is calculated based on the predefined tCPA as described in the figure below. The advertiser can also determine the maximal and minimum bid in the settings. If the calculated bid exceeds the maximal inputted bid (or drops below the minimal bid), the predefined maximal (or the minimal) bid enters the auction. This algorithm is not yet available for shopping campaigns. (Google, 2018)

tROAS -Target return on ad spend[4]

The Target ROAS strategy is similar to tCPA. The main difference is that the tROAS algorithm predicts also conversion value per click and its goals are, therefore, to adjust the auction bid to maximize revenues within specific ROAS. Another difference is that tROAS is available also for Display campaigns, Universal App campaigns, and Shopping campaigns.

Shopping tROAS smart bidding used to require a campaign structure that enabled a different tROAS on ad group level where each product group should have a min. 200 clicks per week. So the best practice was to cluster more products into one product group. That is however no more true. The algorithm calculates the predicted performance based on the product ID and predefined parameters like product category etc.

Target ROAS dynamically adjusts a bid according to the revenue of different products and tries to deliver the highest revenues within a set ROAS constraint. (Meretakis, 2015)

eCPC - Enhanced cost-per-click[5]

Enhanced CPC bidding is not a bid type, because the advertiser needs to set the bids manually. This strategy is also aiming to reach more conversions. However, eCPC does not automatically set bids based on tCPA, but just optimizes the manually set max CPC bids to deliver the most conversions. Unlike tCPA, which has a predefined target cost per acquisition, the eCPC goal is to sustain CPA on the campaign level (or portfolio of campaigns). Another constraint of eCPC algorithm is that the average CPC should be below the manual set max. CPC over the last 30 days. ECPC, therefore, offers more manual control over the campaigns and is more eligible for campaigns with a lower number of conversions. Enhanced CPC is suitable to use if the advertiser wants to manage the bids manually, or if a third-party bidding platform is used. Till June 2017, a 30 percent change was the maximal adjustment of the bid. However, now the bid can increase or decrease unlimitedly. (Cloonan, 2017; Geddes, 2014, p. 436; Meretakis, 2015)

[4] https://support.google.com/adwords/answer/6268637

[5] https://support.google.com/adwords/answer/2464964

Other smart bidding strategies

This thesis is focused mainly on conversion and revenue-based goals. Google provides advertisers with awareness-based strategies.

- **Target outranking share** – The goal of this strategy is to outrank, or show more frequently, than a competitor (another domain) in search results. This algorithm is based on auction insights, and therefore not eligible for Shopping Camapigns.
- **Maximize clicks** – This strategy is trying to spend a predefined budget and bring the most clicks. This algorithm doesn't use conversions, therefore, it is necessary to control the quality of the traffic. This strategy will not bring significantly more traffic if the click share is very high. However, it does help to increase visibility for a niche product and can be very beneficial in shopping campaigns to increase clicks on low-traffic products.
- **Target search page location** – This strategy ensures that an advertisers' bids are adjusted to sustain the specific predefined position.

(Google, 2018)

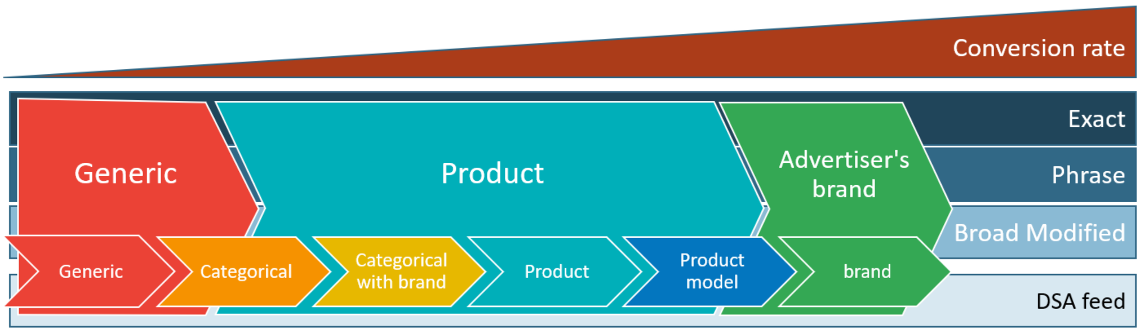
2 Optimization and advanced set-up in AdWords search campaigns

The purpose of this chapter is to introduce the principles of campaign structuring and optimization. The first step in creating an AdWords campaign is to set a goal and campaign structure suitable for a particular project. The most frequent goals in search campaigns are to maximize the revenues within a set ROI or ROAS on goods sold, and to generate a minimum number of acquisition of new customers /sales/ lead/phone calls with specified CPA. A very common goal for publishers is to get new or total visitors per day (Geddes, 2014, p. 379). This thesis focuses only on the goal to maximize the revenues within predefined CPA or target ROAS. Sponsored search campaigns are a great tool for advertisers to show a message to people who are actively looking for information (Hillard et al., 2010). Specifics of different projects, which also play a significant role of the search advertising strategy are outlined in the sixth chapter as result of expert interviews from various fields (transaction e-commerce, service providers, B2B solutions, and others).

2.1 Search campaigns

The general search campaigns have been studied in many papers (Zhou, Chakrabarty & Lukose, 2008; Feldman, Muthukrishnan, P´al & Stein, 2007; Borgs, Chayes, Immorlica, Jain, Etesami, & Mahdian, 2007; Chaitanya & Narahari, 2012; Pin & Key, 2011; Bodin & Oksanen, 2016). Search campaigns can be usually divided into 3 groups by the intention of the user based on the meaning of search terms. Each group (1) Generic, (2) Product, and (3) Brand Campaigns is designed for a different purchase intention. The concept of different purchase stages is similar to Avinash Kaushik's See, Think, Do, Care framework (Kaushik, 2013). The campaign structure is outlined in picture 3 below based on the previous sources.

Picture 3 Serach Network Campaing Structure



Source: Author based on Kaushik (2013) and Kubátová (2017)

2.1.1 Search Campaign Structure

Generic Keywords

The first campaign group targets generic keywords. These keywords have commonly quite a high search volume. On the other hand, the purchase intention and consequently the conversion rate is low. Users are usually at the beginning of the purchase cycle; the search terms are describing the current user's need or categorical search terms (such as 'smart phone'). The importance of advertising on generic search terms are described by several studies (Naik et al., 2008, Rutz & Bucklin, 2011). This stage of consumer behavior is described as Information Search. Users look for the possible solutions to satisfy their needs. (Kotler et al., p. 334, 2016)

Particularly in search campaigns, Oliver J. Rutz and Randolph E. Bucklin confirmed "spillover" effect of generic to branded keywords. Users that used general search term at this stage are very likely to be strongly influenced also in other stages of purchasing decisions. Users, who clicked on an advertiser's page in the early phase of a purchasing decision, had a significantly higher increase in their level of awareness, which resulted in searching for a generic term including the brand name. Rutz and Bucklin used an American major hotel chain to measure its performance. The campaign with generic keywords produced a negative margin, however, the spillover effect increased branded search terms. Therefore, the overall performance was profitable in the end (Rutz & Bucklin, 2011).

Probably that is why Google suggests subdividing the combination of brand and generic keyword, due to its different conversion rate and conversion lag (Kubátová, 2017). Conversion lag is the time between the interaction of a user to an ad and the actual converting action. (Aly 2017, p. 46) Rutz and Bucklin's research shows that in the brand versus generic keywords had an almost 6 times greater CVR (6.03% vs. 1.05%) (Rutz & Bucklin, 2011). A similar effect has brand exposure in an organic listing in Brand search (Xu, Chen & Whinston, 2012).

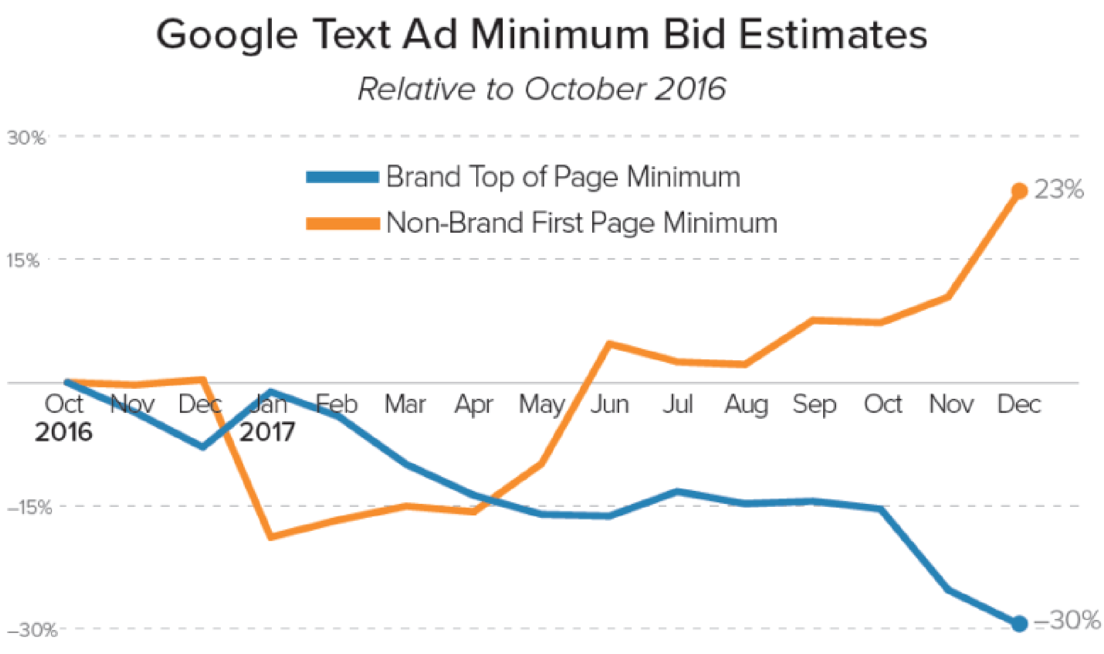
Product Keywords

Product campaigns are trying to capture search terms with higher purchase intent. In most cases, it is a categorical term with the specific brand search term (e.g. Asics running shoes) or even specific product model (e. g. Asic gel 1170 running shoes). These search terms belong to the next stage of purchase cycle called Evaluation of alternatives (Kotler et al., p. 334, 2016). The campaign category is called Product because this naming is probably taken from e-commerce accounts. However, if the advertisers find any group of keywords that significantly performs better, they should separate them similarly as product keyword campaigns.

Brand Keywords

As mentioned earlier, the highest conversion rate usually has search terms, which include the brand of the advertiser. Those search terms are at the very end of the customer's purchase cycle (the Purchase Decision stage). The advertisers are often present in the top organic search result in SERP. However, as a study from Google (Chan, Yuan, Koehler & Kumar, 2011) showed, using sponsored search advertising for branded search terms enhanced the volume of incremental traffic over 89%. The results could be different now due to the changes in Ad Rank algorithm in 2017. The Merkle Digital Marketing Report for Q4 2017 clearly shows that Ad Words system takes the meaning of the queries more into account. Therefore, the cost of the advertiser's branded keywords bids is decreasing as you can see in the picture below. (Merkle, 2018)

Picture 4 Google Text Ad Minimum Bid Estimates



Source: Merkle's Digital Marketing Report for Q4 2017[PDF]. Merkle Inc. Retrieved from https://www.merkleinc.com/thought-leadership/digital-marketing-report

The queries containing the advertiser's brand name should definitely be separated, because as previous studies show, there is a huge difference in performance of those search terms in comparison to any other campaign (Ghose & Yang, 2009; Jansen, Sobel & Zhang, 2011; Rutz & Bucklin, 2007; Klapdor et al. 2014).

Search 2.0 - Single keyword ad groups

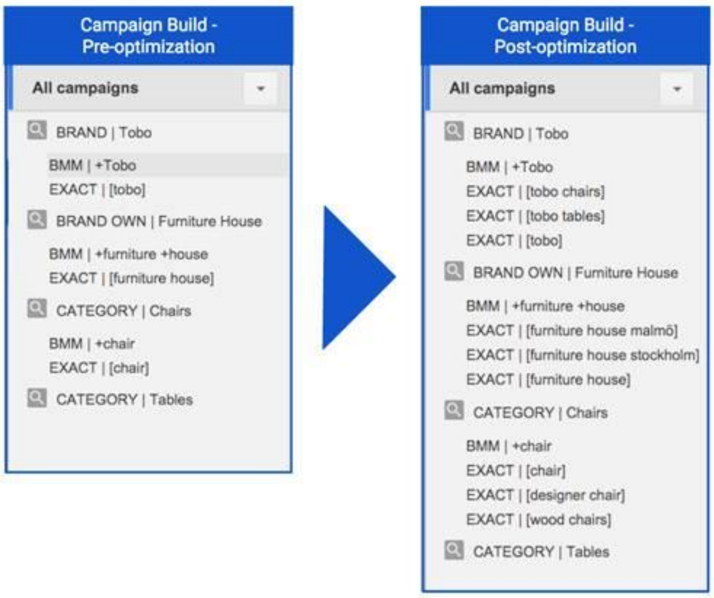
There are several concepts on structuring the search campaigns. The most common approach is the one described above – cluster the keywords with similar meaning into one ad group and the ad groups into campaigns as described above. One of the complex concepts is Search 2.0 or Single Keyword AdGroups (SKAGs). This strategy of structuring keywords is described below.

This strategy is aiming to maximize the impression share for all relevant searches that bring high value to the advertiser. Search 2.0 is a highly systematic keyword-based approach, because each exact keyword has its own ad group. Having such granular campaigns enables one to create highly relevant ads that suit the search term the most. It means that the keyword could appear not only in the headline (as it can be done with dynamic keyword insertion function) but also in the description field. The most suitable landing page and ad extensions could be chosen to improve post-click user experience, increase the quality score, and achieve better positions with the same CPC. This possibility of various ad copies can have a significant impact on the performance, which was proved by several researchers

(Agarwal, Hosanagar, and Smith, 2011; Animesh, Viswanathan, and Agarwal 2011; Jansen and Resnick 2006; Jerath et al., 2011).

The methodology of Search 2.0 suggests dividing the campaigns into 3 groups, similarly as described in the previous chapter. Optimization of such campaign map is done in 2 steps. Firstly, the ad groups containing keywords in the exact match should be highly performing and its quality score should be above average. The keywords with positive performance (ROI) should be boosted to have the highest possible impression share and position. The less performing ad groups should bid lower to a certain point where the performance meets the required KPI. Secondly, the ad groups containing only keywords in broad match modifier are used as a source of inspiration. The advertiser should check the Search term report and find search terms that should be excluded or new queries, which deserve their own exact ad group. The result of such optimization is shown in the picture below.

Picture 5 Serch 2.0 - Campaign Comparison: Pre & Post Campaign Optimization



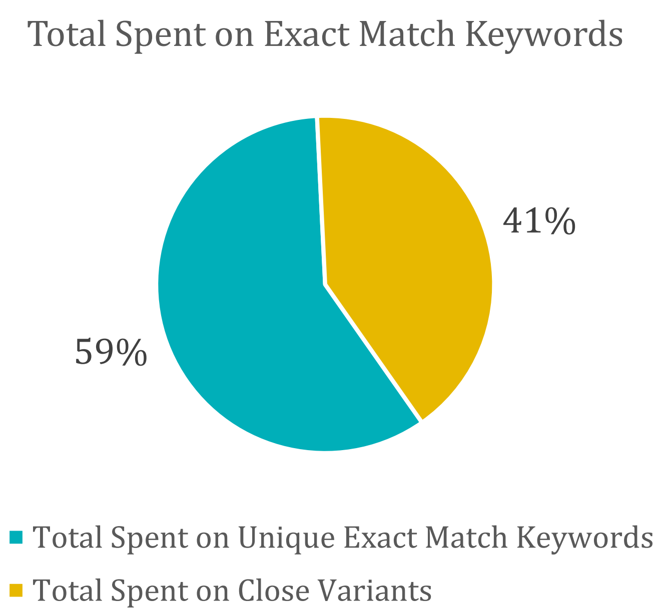
Source: Bodin, T., & Oksanen, K. (2016). Search 2.0: Key concepts on maximising Search advertising. Retrieved from https://www.thinkwithgoogle.com/intl/en-154/insights-inspiration/industry-perspectives/search-20-key-concepts-maximising-search-advertising/

Interestingly, the methodology does not suggest using excluding keywords across the different ad groups, probably due to the matching that Google uses for selecting ad groups and keywords for a specific search term. When several keywords in the ad group, or across more ad groups, match a search query, the preferred keyword for triggering an ad is chosen based on Ad Rank. The keyword with higher Ad Rank is chosen (even though the bid might be lower).

However, there are 2 exceptions. The first exception is when the campaign's budget is restricting the campaign to get all possible traffic, then there is a high probability that other keywords from restricted campaigns will trigger an ad even if it has lower Ad Rank. The second exception is that a specific keyword, which has a low search volume status, cannot trigger any ads. The second reason might be that in the time this framework was published, the exact match type worked differently.

Since March 2017, the exact match now includes “close variants”, which means: “misspellings, singular or plural forms, stemmings, abbreviations, accents and reordered words”. According to the Google internal data, the advertisers should not have noticed this change, because it increases the clicks up to 3% while maintaining comparable CTR and CR (Villalobos, 2017). However, this statement is questionable. Analysis from Allen Finn shows that the effect is significant. 41% of all costs on the exact match keywords were spent on other search terms that do not literary match with the predefined keyword in exact match. (Finn, 2018)

Picture 6 Total spent on exact match keywords



Source: Author, based on: Finn. (2018, March 22). The Impact of Google's New Exact-Enough Match Keywords [Data]. Retrieved from https://www.wordstream.com/blog/ws/2017/04/12/exact-match-keyword-change-data

The Search 2.0 strategy is great to produce a highly performing account with maximal control over all the key optimization aspects. However, it does require frequent control and optimization, and probably works with excluding keywords. Therefore, it makes more sense to use this strategy for segments with a high level of competitiveness and high average CPC. (Bodin & Oksanen, 2016)

2.1.2 Dynamic search campaigns

The role of Dynamic search campaigns (DSA) is to cover search terms that are not yet covered by classical search campaigns and to appear on long tail phrases or other less competitive queries. DSA appears on search terms with an abbreviation, misspelling, or any other similar type of queries. Its benefit is that ads are not blocked by Google for low search volume as they are in classical search campaigns. Therefore, the advertisers can cover completely new search terms, which have a huge portion in Google search. For illustration, Google published in 2008 that 20% of all queries Google receives each day are ones that the system has not seen in at least 90 days. (Kelly, 2008)

DSA campaigns are either generated by website feed or simply by advertisers' URL. In the case of URL targets, Google can recognize website changes, and within 3 days adjust the campaigns. Therefore, the DSA campaign could be used as a "back-up" when an advertiser does not manage to adjust classical search ads. However, these campaigns also have some drawbacks. Google takes more control over advertisers' ads. It generates headlines from the websites, so there is not much space to adjust the titles. Moreover, the bidding system is different, because there is no keyword targeting, so if an advertiser increases bids, it causes higher impressions for new search terms, as well as increasing the ad position. DSA campaigns have therefore a stronger diminishing returns law effect. As the spend increases, the marginal increase of conversions is lower. (Aly, 2017, p. 19) Moreover, it demands on optimization to exclude unrelated search terms, or to add good performing search terms into search campaigns in order to increase bids. Matthew Umbro, the founder of PPCChat recommends increasing DSA bids when at least 75% of website keywords are covered in classical search campaigns. (Umbro, 2014)[6]

2.1.3 Automated Search Campaign Creation

PPC specialists can use predefined solutions or use tools to automate the process of creating and updating campaigns. This is frequently used for large campaigns, either for a granular structure as in Search 2.0 or for large campaign s in terms of promoting products or categories, which have a similar pattern.

Creating ad groups for each product in the company portfolio is sometimes impossible manually. Advertisers can usually use XML feeds of all listed products that they want to promote. This can be done easily by predefined Google sheets rules or in PowerQuery[7]. The executive can also be made by predefined tools that create the campaigns through an AdWords Application programming interface (API), such as PPC Bee, AdBOOST, BlueWinston, ROIminer or even Optmyzr. This solution is often used to create and adjust campaigns with frequently updating products. It allows advertisers to make changes directly in the platform, without the need to manually set these changes. This could be used for creating thousands of product groups and specified ad copies and ad extensions. These tools simply enable creating keywords from custom variables and product feed inputs. Their system resembles the logic of creating the product campaigns via XML feed and Excel. The crucial aspect of such campaign creation is the segmentation and unification of input

[6] There might be a problem of bidding on keywords that are manually set in classical search campaigns. However, this drawback can be easily handled by various scripts taking care of this problem , such as this http://duplicity.igloonet.net/

[7] One of the best solutions to create campaigns without any specialization are described in the excelinppc.com.

data (the XML feed). Therefore, the advertisers need to adjust the data or create specific elements as an extraction from other fields which are already listed in the XML feed. There are several tools and platforms enabling XML feed adjustments: Adalysis, Optmyzr, GoDataFeed or Mergado. These tools have predefined functions of the most used adjustments. Moreover, regular expressions or frequential analysis are possible to use when custom result in XML feed is needed. (Bodin & Oksanen, 2016; Zrůst, 2016; Šmajzrová & Volejník, 2016)

In order to capture traffic from product specific search terms, Dynamic Search Campaigns (DSA) are also used. Ads have automatically generated headlines from the content of website, but they share a common predefined description. The main reason to use an API tool instead of relying on DSA campaigns is the possibility of controlling the performance. The customization in the ads can be also done in the DSA feed campaigns, which currently enables only PPC Bee for frequent updates. However, DSA campaigns do not enable advertisers to create headlines, but only descriptions, where advertisers can show exact prices or discounts for the specific product. As is written at the beginning of this chapter, DSA campaigns should be used mainly as a supplement to classical search campaigns.

Using a highly sophisticated and granular campaign structure is now more difficult to manage, since the close variants have been added to exact match type, but it makes sense for the most important campaigns, which need frequent and detailed control of the quality score. The automated tools for creating campaigns are applicable for not just product campaigns, but also for generic campaigns if the advertiser can get applicable data feed.

2.1.4 Search Camapaing Optimization

The campaign optimization should start with performance check in the respect to the predefined goal. The ad groups that differ from the desired outcome should be adjusted by bidding. This topic is already described in detail in the chapter 1. However, the optimization should not stop just with bidding, because the AdRank can be increased by increasing the quality score as well. The impact of the quality score was studied in 2009 by Craig Danulogg's agency. They found out that the effect of quality score is relatively high, as can be seen in table 3. These numbers are just illustrative since it has been studied only on campaigns of one agency account, but it clearly shows the correlation of quality score on CPC. These results have been confirmed also by other agencies (Roubstov, 2008; Geddes, 2014; Yamaguchi, 2013)[8]

[8] The correlation is undoubtful, the only point of disagreement is whether quality score benchmark is 5 and not 7 (Kim, 2017). This benchmark had become important since September 2016 reported quality score does not show any number if the system does not have enough data. Therefore, the benchmark is necessary for setting substitute value. https://plus.google.com/+GoogleAds/posts/6q25fn3ZLbW

Table 3 Impact of Quality Score on CPC

If Quality score is:	The CPC vs. Quality Score=7 is	
10	Discounted by:	30.00%
9	Discounted by:	22.20%
8	Discounted by:	12.50%
7	-	
6	Increased by:	16.70%
5	Increased by:	40.00%
4	Increased by:	75.00%
3	Increased by:	133.30%
2	Increased by:	250.00%
1	Increased by:	600.00%

Source: Roubtsov, A. (2008, March 19). The Economics of Quality Score. Retrieved February 28, 2018, from https://www.acquisio.com/blog/agency/economics-quality-score

To track quality score can be used third-party tools, such as Optmyzr, PPC Robot, Tenscores or Quality Score Monitor from Hero Pro. There are also several free AdWords scripts to get a report of the quality score (Röttgerding, 2014; Vallaeys, 2014) or scripts that saves these data day by day to see visualize the trend (Kašparů, 2016; Savage, 2013)

The quality score consists of CTR, ad relevance and landing page experience. As many studies already proved. All the aspects of quality score highly depend on the keyword and more specifically the search terms.

Search term analysis

Many researchers tried to develop a system how to optimize the search terms automatically. The research from Klapdor, Anderl, von Wangenheim and Schumann (2014) shows that keyword performance is correlated to frequency of the keyword in the language. (the more it appears, the more different meaning the word have and the worse performance the keyword has). Moreover, the study confirmed the correlation to match type, CTR and CVR of the ad group. The length of keyword was proofed to be uncorrelated factor. However, more patterns could be found in the search terms. The most commonly used is the N-Gram[9]

[9] In computational linguistic context, an n-gram is a contiguous sequence of n items from a given sequence of text (Liddle, Schewe, Tjoa, & Zhou, 2012, p. 41)

report. There are many ways how to create such report automatically. For example, via scripts (Gilbert, 2015) or Power Query (Zrůst, 2018).

Ads and its importance in search advertising

The effect of the ad copy is crucial for effective search advertising, as has been proven by many studies (Agarwal, Hosanagar, and Smith, 2011; Animesh, Viswanathan, and Agarwal 2011; Jansen and Resnick 2006; Jerath et al., 2011) Ad copy, respective CTR, has the biggest portion in Ad Rank according to Google's Chief Economist Hal Varian (2010). To get the best CTR and relevance of the ads, one needs to use the most specific and precise selling point/ call to action, which would be appealing for the users. Therefore, Google is working on tools, like ad customizers[10] and parameters, which help advertisers to reach such desired ads. The customizer can also insert a keyword that triggered the ad in the headline, or a description of the ad. This technique is called "dynamic keyword insertion" (DKI). Another customizer is a countdown, or via IF function, to change the ad copy based on the audience. However, the most important feature of customizers is the possibility of adding a specific attribute into ad through the list in a shared library called business data. Through customizers, specific prices or discounts that correlate with the advertiser's website can be inserted in ads. Similarly, customizers could assign specific ad extensions to predefined campaigns or ad groups. According to PPC Bee (2016), Using a site link list in business data is common in the product campaigns described above. The API tools enable one to automatically ad site link a product category to a product ad group.

Google also helps advertisers to test the ad copies through ad variations[11]. It enables to change only one ad filed. For example, testing two different copies in a second headline. Google also recently introduced Ad Suggestions which automatically generate new ads if an advertiser has less than 3 ads in an ad group. They claim that "Research has shown that ad groups with 3 or more high-quality ads can get up to 5% to 15% more clicks or conversions than ad groups with only 1 ad, provided ad rotation has been optimized. The more ads you provide, the more options you'll have to show the ideal message for each user search." (Google, n.d.)

The important effect of ads on campaign performance has been described above. However, optimizing the ads has its specifics described here. To decide which ad is better, we need to have a sufficient amount of data. According to a Larry Kim analysis, across all campaigns in their agency account, 85% of impressions are made by just 5 % of ads. So it is necessary to optimize primary on that 5 %, and cluster the ad performance from other ad groups in order to have sufficient data. The best way is to set ads to rotate indefinitely, so both ads will evenly enter the ad auctions. From the difference in impressions, we can see which ad won at getting an impression more often, and which ad lost the auction. From the difference in

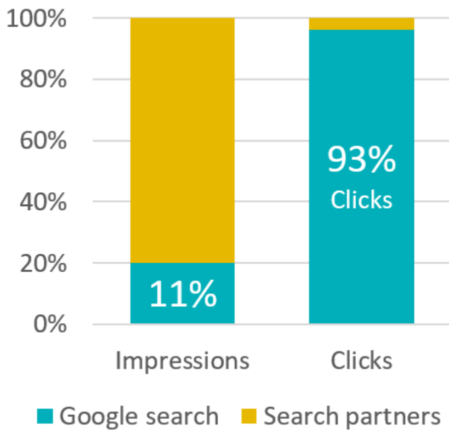
[10] https://support.google.com/adwords/answer/7207341

[11] https://support.google.com/adwords/answer/7438541

impressions, we can see which ad won more often to get an impression and which ad lost the auction. Moreover, the report should be segmented at least to Google.com (excluding search partners). The CTR metric could be misleading, which shows following picture 7.

Picture 7 Misleading CTR in Ad A/B Testing

Ad copy	Segement	Clicks	Impressions	CTR
Ad A	Google search	500	10,000	5.00 %
	Search partners	6	10,000	0.06 %
	Total	**506**	**20,000**	**2.50 %**
Ad B	Google.com	600	10,000	6.00 %
	Search partners	24	40,000	0.06 %
	Total	**624**	**50,000**	**1.25 %**



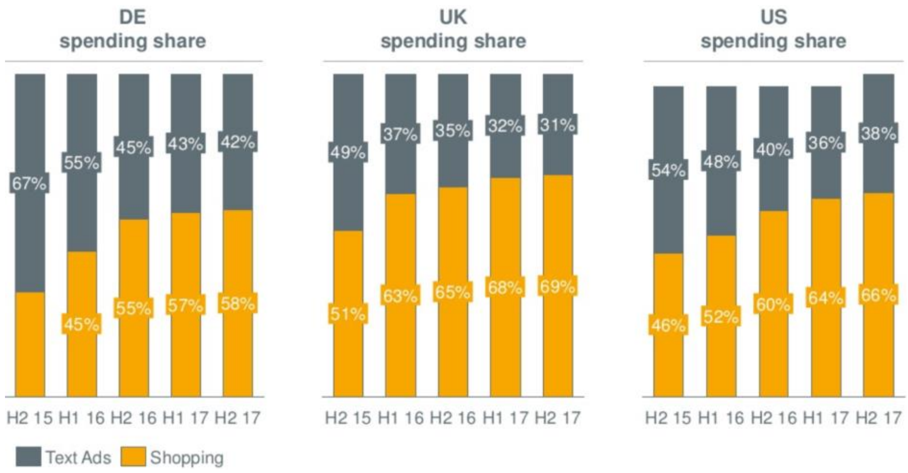
Source: Author, based on: Zdarsa, J. (2017, October 30). Jak vyhodnocuji PPC reklamy pro klienta v 80 zemích - Jan Zdarsa (Google) Retrieved, from https://www.youtube.com/watch?v=gSbwewwHVQo

The second most important segmentation is via ad position, which also differs in performance. However, there are also many other aspects that influence the CTR, such as device, location, and the number of extensions that appeared. (Baker, 2011; Kim, 2018) Senior Analytical Lead at Google, Jan Zdarsa, advises to track the performance in impressions and not CTR, because that algorithm reveals the better ads. (Zdarsa, 2017)

2.2 Shopping campaigns

The importance of shopping campaigns is increasing each year, as can be seen in the picture below. The shopping campaign, also known as PLA, has some differences from search campaigns. The auction system is the same as in classical search (real-time second-price auction), however, Google has not published the AdRank criteria, so advertisers do not know on which components the quality score is based. However, certainly the most important criteria would be the expected CTR. (Veurink, 2015, p.3) Other important factors that influence PLA performance are titles, and advertisers price compared to the competition. (Reiffen, 2015, 2017)

Picture 8 Increasing share of Shopping Investment in Comparison to Search Netwrok Ads



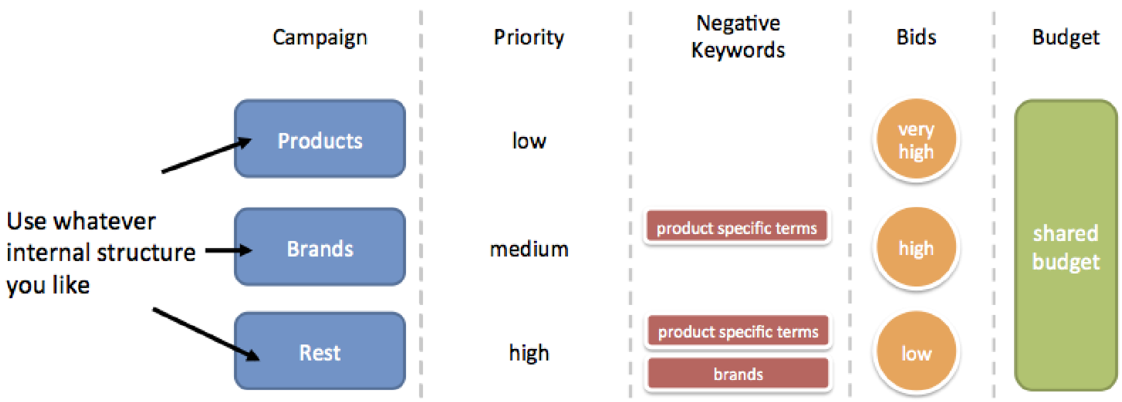
Source: Reiffen, A. (2018, February 16). *Advanced Strategies for Google Shopping Campaigns*. Retrieved from https://www.youtube.com/watch?v=NWVzWwG9DQw

2.2.1 Structure

Bloomarty

Campaign structure needs to reflect the possibilities of targeting in PLA. Shopping campaigns target on products which are in Merchant Centre. Google's algorithm shows ads on search terms that are related to the advertised product. The rules how Google decides which product should be shown for specific search terms are not officially published. There is not possible to target and bid on specific keywords. Martin Roettgerding created a system how to ensure higher bids on higher converting search terms (such as product or brand related search terms). The campaign structure called "Bloomarty" is outlined in the picture below.

Picture 9 "Bloomarty" Campaign Strucutre of Google Shopping Campaigns



Source: Röttgerding, M. (2014, November 2). Taking Google Shopping to the Next Level. Speech presented at Marketing Festival in Czech Republic, Brno.

The advantage of this structure is that the different search term performance is taken into consideration and it enables to set bids accordingly. This approach can be restricted by

AdWords limits[12] the account can have only 20 shared negative keyword lists wich (each can contain 5000 keywords) Moreover, the campaign can have in total only 10 000 keywords. The negative keyword lists can be uses also across many accounts[13]. (Roettgerding, 2014, 2017)

However, the patterns in the search queries need to be managed since they can change over time. This pattern can be found with n-gram report or manually. Some patters are homogenous across the product feed. Most often it could be specific ID model that has high conversion rate and the advertiser wants to usually have it in the higher campaign automatically. Exclude all model IDs manually is impossible in most cases, so the Samuel Ondrišák created specific scripts that are excluding the keywords automatically based on the XML product feed in Merchant Centre. Ondrišák even created a solution how to avoid the AdWords limits. The second script can be linked to several My Client Centers (MCC) that each have 20 negative keyword lists. So the automatical script can "distribute" the excluding keywords into different lists. This is all done automatically as Pavol Adamčák (2016) presented at Marketing Festival.

The main idea, that Roettgerding introduced is that the campaign can be segmented via different patterns in search terms. It does not have to be by brands or product specific terms. In many cases this structure is not applicable, but there are always some patterns that can be found in the search terms, as was discussed in the chapter 2.1.4. For example, Reinhard Einwagner, scores the search terms based on similar aspects as Roettgerding, but with Term frequency–Inverse document frequency – with an adaptive weight of position of word algorithm. This approach is similar to n-gram classification, however, this optimized algorithm can cluster the dataset of search terms with a different element in feed or other metrics. (Chen, Chen, & Liang, 2016; Pitako, 2017)

SPAGs: Single Product Ad Group

Product campaigns can be structured similarly to Search 2.0 structure in the Search Network. Having each product in different Ad Group is probably the most granular system. Recommended structure of Shopping campaigns has recently changed, since it is not possible to set a tROAS for each ad group. The structure can be done automatically in Power Query or even with AdWords Editor. However, the structure needs to be refreshed regularly. Daily changes can be done, however, with 3rd party tools like Optmyzr. (Kirk, 2015; Pitako, 2017; Garcia, 2018)

In order to be able to bid on almost query level, the campaigns should be divided as Roettgerding suggested in the Blomarty method. Moreover, the search terms can be adjusted on the product level, since each product is in specific ad group in each campaign.

[12] https://support.google.com/adwords/answer/6372658

[13] https://support.google.com/adwords/answer/7519927

The bid for the search term can be increased by excluding it in the campaign, so it will skip to get tho the upper campaign with a higher bid. (Garcia, 2018)

Smart bidding structure

On the other hand, Google recommends using smart bidding strategy, which automatically increases bids if users type query with more convertible potential. Structure of PLA campaign, according to Google, does not have to be structured by excluding keywords like in both previous approaches, because the smart bidding deals with impression shares automatically. (Kíč, 2017; Weckner & Dautaj, 2017)

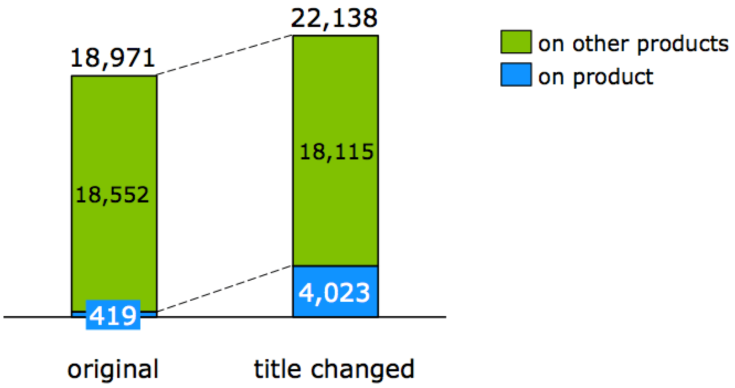
2.2.2 Feed optimization

Very important optimization process in Shopping campaigns is the feed adjustments. The optimization the advertisers can do it directly in the feed itself. The adjustment can be done either with the developers or via external tools, which can extract, adjust or enhance the feed elements based on static rules or regular expressions. The Merchant Center itself has Feed rules function, or there are 3rd party tools like Mergado. Another way how to adjust the current feed is via feed supplement in Merchant Centre. It enables to change specific IDs. This method is great when the advertisers are not able to change anything in the feed. This can be useful for changing pictures etc.

Titles and descriptions

The experiment from Reiffen shows that the title adjustment – categorical term was appended in front of the former title – resulted in higher performance as the picture 10 shows. Wallace (2018) recommends to use on-page SEO techniques for the title or description optimization.

Picture 10 Effect of Product Title Change on the Impressions in Google Shopping



Reiffen, A. (2015, July 16). Advanced Optimization Of Google Shopping Campaigns. Retrieved February 28, 2018, from https://searchengineland.com/advanced-optimization-google-shopping-campaigns-224627

Product price

According to several experiments (Reiffen, 2018; Roettgerding, 2014) the Google's algorithm prioritise the product with lower price. Reiffen's results show that in case of apparel project, the performance drop by 60% when the product price increases by 5%.

Picture 11 Price as an important algorithmic signal

Source: Reiffen, A. (2018, February 16). *Advanced Strategies for Google Shopping Campaigns*. Retrieved from https://www.youtube.com/watch?v=NWVzWwG9DQw

Martin Roettgerding also believes that lowering the price is probably the biggest factor to be shown by Google more often. (Špinar & Roettgerding, 2014)

3 Methodology

The research of this thesis is divided into two parts. The first part is an experiment in a real Google AdWords account of one major bookselling company in the Czech market. The goal of this part is to compare the performance of manually managed campaigns and campaigns using Google smart bidding strategies. However, the outcome of this experiment might be limited only to the specificity of the chosen market. Therefore, the second research part is devoted to in-depth interviews with 31 Czech and Slovak PPC experts from various fields. The first objective of this research is to evaluate the performance and best-practice, while using smart bidding strategies across various projects. The second main goal of these interviews is to summarize the current situation in PPC automation and predict the future trend.

AdWords enables advertisers to reach a very different goal, such as visibility, overrun competitors, and others. (Marshall, P. S., Rhodes, M., & Todd, B.;2017; page 12) This thesis is focused only on the objective of getting the most conversions within a specified CPA or ROAS, without any budget constraint.

3.1 Experiment Design

The aim of the experiment is to compare the different performance of manually adjusted bidding in AdWords search campaigns, with campaigns managed by tCPA or tROAS smart strategy. Many types of research struggle with creating the optimal experiment of smart versus manual bidding. such as a paper from Stefan Veurink, 2015. The main limitation was the subjectivity in manual campaign optimization. This thesis followed predefined optimizing rules in order to avoid such a limitation. These rules are described in paragraphs below. The design of this experiment is divided into three groups, based on the campaign types and different smart bidding strategies: (1) classical search campaigns with tCPA strategy, (2) DSA campaigns also with different tCPA and (3) shopping campaigns with tROAS strategy. All campaigns were not limited by any budget constraint in order to avoid the knapsack problem (Bateni, Feldman, Mirrokni, & Wong, 2014).

3.1.1 Campaign structure and optimization design

The Classical Search Campaigns

Search campaigns were chosen by the volume of conversions and ad spend: Exactly, one campaign targeting author-related keywords, one manual campaign promoting best products and product campaigns. The author-related campaigns were built in Power Query, based on a feed of all authors with ads from 3 templates. The “best product” campaigns were made in Power Query every week, and adjusted every week based on the recommendations from the product manager. These campaigns also have specific ad copy, based on several templates. Both types of campaigns had ad groups divided based on the match type – (1) Exact, (2) Phrase with excluding exact keywords, and (3) Broad Modified with excluding both exact and phrase keywords from previous ad groups. Product campaigns were generated by the tool PPC Bee, based on the 2000 best-selling products in the e-shop. The ads had different ad copies – 2 generally applicable for all products, and 2 specific ad copies displaying in the headline the exact price and discount that the e-shop was promoting. The reason why the PPC Bee was used is due to the fact that the "best products" required more control over the ad copy. Each keyword has been distributed into two specific ad groups – one ad group for exact match type keywords, and a second for keywords with broad match modifiers, with the exclusion of exact keywords from the previous ad group.

All campaigns were set duplicated as draft campaigns, and all have been adjusted to the bidding strategy from manual bidding to target a CPA smart bidding portfolio strategy across all search campaigns. Google AdWords enables users to set a 50:50 split so that both campaigns will enter the ad auction exactly in ratio 50:50. However, this does not mean that the percentage of impressions or clicks for each campaign will be even. The smart bidding algorithm might enter some auctions with much higher bids than manual bidding, and vice versa.

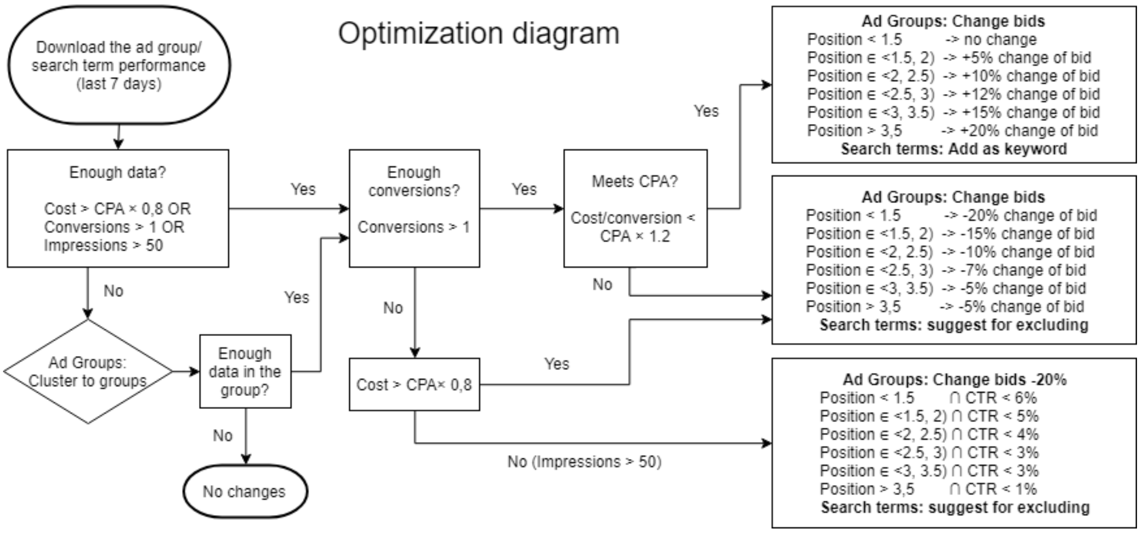
The reason for choosing this portfolio strategy was to gather more inputs, especially conversions, for a machine learning algorithm that Google uses. The campaign was chosen mainly based on customer behavior (conversion rate, conversion lag). This behavior was similar across all chosen campaigns, as you can see in the following table. The general campaign is also in the table, and it was not chosen, mainly due to a different conversion rate and a longer conversion lag. The target CPA was set to €5, based on the previous performance. The reason for choosing tCPA over tROAS was that tCPA required a lower volume of conversions in the past 30 days, as is outlined in the chapter theory 1.2. tROAS requires a higher volume of conversions.

The limitation of this model was that the product campaigns created in PPC Bee were set up for daily updates. However, PPC Bee is not able to work with experimental campaigns, and therefore the campaigns in the experimental part were changed only once a week manually through AdWords Editor.

The optimization of the experimental campaigns was none, except for the updates of product campaigns and adding the new ad groups to the "best product" campaign. The reason was to minimize the changes. The smart bidding should detect inappropriate search terms and bid less, based on the performance of search terms and the n-gram performance of each word in the search term, as described in the chapter 2.1.4. Therefore, no search term optimization, neither were bid adjustments made. The campaigns without smart bidding strategy were optimized similarly. The only optimization for these campaigns were changes in bidding, and excluding/adding keywords based on the search term performance. The bidding was based on the predefined simply rules on the ad group level, as described in the diagram below. In case of product campaigns, the ad groups which did not have enough data were clustered together, and the bid adjustment decision was made on each ad group. These clusters were made by name, because the ad groups from API tool contained features of the products. The change of bid depends highly on the performance and the current average ad position. The exact CPC changes were estimated from experience working with the campaign. This optimization was made primarily in Power Query, and then exported into the AdWords Editor. The reason for that was to provide human control of changes of ad groups in the "best product" campaign, because some new books that were in preorder had a much longer conversion lag. Therefore, I did not decrease the bid for these ad groups, even though the performance from the last 7 days was not optimal.

The second type of optimization was adding or excluding search terms based on the performance. The optimization system is also described in the diagram below. All the search terms were checked by the author, because that provided better control. The system often suggested excluding the exact name of the book, which in some cases made sense only when the product name had also another meaning; for example, the search term "bábovky". This optimization was also made in Power Query because it enables one to automatically adds a new keyword in various match types to specific ad groups.

Picture 12 Optimization diagram: The strategy for bidding rules and search terms optimization



Source: Author

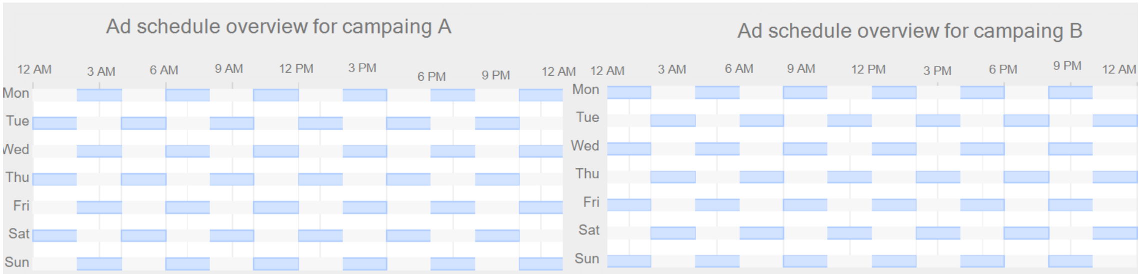
The Dynamic Search Ads Campaigns

The DSA campaigns were made from specific DSA feeds – product feed and category feed. The second campaign was targeting all web pages, based on the advertiser's domain. Both campaigns had a similar conversion lag and conversion rate, therefore, the portfolio tCPA strategy could be applied to campaigns set to smart bidding. In order to minimize the duplicating problem, the target CPA was set 20% lower than the tCPA of classical search campaigns. Manual DSA campaigns were adjusted similarly to the classical search campaigns.

The Shopping Campaigns

Google does not allow to use experiments for PLA, therefore, another approach was used to experiment the bidding strategy for this campaign type. In the literature are various ways how to do this experiment. The methodology was discussed with Google's performance manager, Matouš Ledvina, and performance team leader in Zoot, Martina Bakičová, in order to design the most suitable model for this research. The most common solution is to divide the campaigns by the Ad schedule. So, the manual would run from 1 am to 3 am and then the smart bidding would run till 5 am, whet it would again run the manual from 5 am to 7 am and so on. In the middle of the experiment period would be the set-up switched as outlined in the picture 13. (Malafová, 2016) The drawback, according to both experts, is that the Google's campaigns are not adjusted for such settings, and such a set-up would limit the smart bidding strategy. Moreover, the differences in the times might be significant, and the external result might play a much higher role than it might seem from the outside.

Picture 13 A/B Test of Smart Bidding Strategy Based on Ad Schedule



Source: Atuhor, based on: Malafová, M. (2016, July 13). Automatická optimalizace kampaní [Video file]. Retrieved from https://www.youtube.com/watch?v=ldJjt5QJSh8

Another approach is to run a manually adjusted campaign and then set the smart bidding strategy. It would mean waiting after the learning period is done, and comparing the performance of the period after the learning phase with the control one. Another approach is to calculate the incremental value based on a time series analysis, such as Causal Impact. (Brodersen et. al, 2015) However, the outcome would be influenced by external influences, which change in time (seasonality, special promotion etc.).

The final experimental design was to divide the products into two groups by its ID. The products with even IDs were in the manually managed bids and the products with odd IDs were in the campaign with smart bidding. Both groups are similar in terms of a number of clicks, cost, revenues or number of conversions. Therefore, the external influence would influence both groups similarly and there will not be any limitations for Google's smart bidding. Even the high, best-selling books will not influence the results, because of the great volume of products (over 100 000 eligible products for shopping campaigns).

The structure of manually adjusted campaigns is based on the same logic as the methods from Martin Roettgerding, outlined in the theoretical part of this thesis, well-known as "Bloomarty". The method was adjusted because the product does not have attributes similar to shoes. The logic behind it is that keywords are distributed among the campaigns based on different conversion rates and performance rather than strict naming rules.

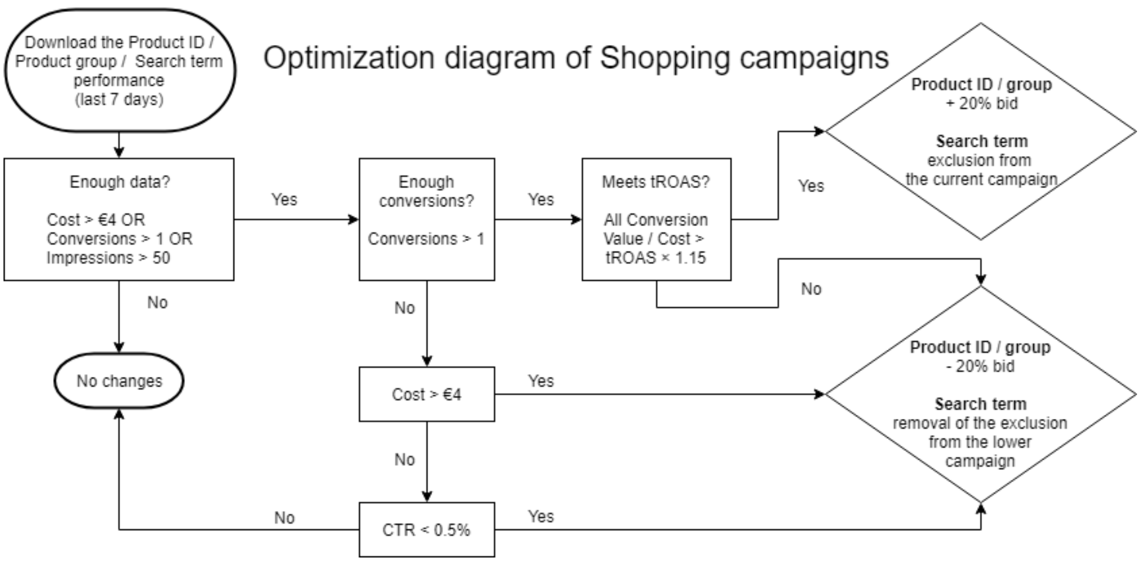
The campaign with the highest priority and lowest bids has excluded keywords that should be fired from the other campaigns (with higher bids). This triggers the product listing an ad on search terms with a low conversion rate. If there are some outperforming search terms, then they are excluded from the low-bid campaign. Afterward, the ad from the middle-bid campaign enters the ad auction when the search term is performed. Only the top performing search terms, which have an extraordinary conversion rate are initiated from the last campaign with the highest bid and lowest priority. The goal is to capture most of the traffic from the specific search query.

This structure is further divided into ad groups based on custom labels: Best-sellers, Year of publication, Discount level and the availability of the product, and the last level is divided into product IDs. However, subgroups are not created for each product, but aggregated as Item ID=*. Only products with enough impressions are added as a specific subgroup with the individual bid. The system of separating these products is described in the following paragraph.

The manual optimization is done also via Power Query (PQ) rules. The inputs for the PQ rules are the performance of each product from last 7 days, and campaign structure in AdWords Editor format. The weekly performance is exported as a .csv file via custom AdWords script. When data are loaded, the PQ rules filter the products, based on similar simple rules as in search campaigns as described in the following diagram. Only several products have enough data to be optimized specifically. Therefore, if the product is not subdivided with a specific product ID, the PQ automatically creates a new subdivision in AdWords Editor format. The bid is based on the bid that was in Editor, predefined for the "upper" level and adjusted by either +20% or -20%, as described in the diagram.

However, the bigger impact on the performance was optimization of product groups rather than specific products. Therefore, after the product ID optimization, a similar approach is applied even to the product groups. Power Query rules prepare the product group structure with adjusted bids, and several new product ID subdivisions. Finally, this output is copied and pasted to AdWords Editor and posted to the account.

Picture 14 Optimization diagram of Shopping campaigns: The strategy for bidding rules and search terms optimization



Source: Author

The campaigns are structured into 3 campaigns so different bids can be set, based on search queries. Therefore, the last optimization was the search term exclusion. For keywords, exclusion is used for Campaign negative keywords lists from the shared library. The decision process is using the same logic as the product ID or Product group optimization rules, to determine which search terms should be excluded, in order to be featured in campaign with the higher bid. The evaluation was done also via Power Query rules, and checked by the author before posting the changes in the AdWords account through AdWords Editor.

3.1.2 The performance evaluation

The goal of the experiment is to decide which bidding strategy performs better, based on predefined goals. To validate, each bidding used a Welch Two Sample t-test, because it can evaluate the sample even with low volume data. In case that the data were not in normal distribution, the Wilcoxon rank sum tests with continuity correction applied. This test enables the evaluation of the difference, even for non-noramal distributed datasets, because it calculates the left and right side separately. However, this approach requires much larger samples to achieve 95% confidence interval coverages.

Skewness and kurtosis factors were used to validate the distribution. The normal distribution was validated when the skewness was in the range of (-1.5,1.5) and the kurtosis in the range of (-3;3) to be 0,95 statistical probability. (George & Mallery, 2010)

The main metrics that were used to validate the performance were the 'conversions' and 'CPA' for campaigns in Search Network, and 'revenues' and 'ROAS' for Shopping campaigns. In case that data for 'conversions' were statistically insignificant, the 'revenue' metric was used instead of this metric, and vice versa. There is also the possibility that the performance of classical search campaigns and dynamic search campaign would not have enough data to have validated the model with 95% probability. Therefore, to re-validate, the data will use an aggregation of both campaign types and evaluated by the result on conversions and CPA.

The winning bidding solution would be chosen with certainty when the bidding significantly increased the volume of conversions or revenue, and at the same time decreased the CPA[14] when compared with the second bidding style. However, in most of the cases the profitability ratio, such as CPA or ROAS, deteriorates when the volume of revenues increases (as described in the first chapter). The manager should afterward choose the strategy based on the real profit that the campaigns attributed. This profit analysis is not incorporated in this research due to the fact that such confidential information of margins, was not provided by the organization.

Causal Impact analysis could provide a more precise estimation of the overall increase of incremental revenue and conversions generated by the switch of half of the campaigns into the smart bidding. Causal Impact helps to assess to what extent did an Intervention influenced the performance and it enables to calculate an incremental lift of sales. Causal Impact is a regression model that predicts the counterfactual outcome (generated revenues

[14] In case of shopping camapings, the increase the return on advertising spend.

or conversions) that would have occurred had no intervention taken place. The model conjectures temporal impact of an event. (Brodersen et al., 2015)

The synthetic control groups (later described as predictors) are evaluated using a Markov chain Monte Carlo simualtion to find a statistical correlation with the campaign data. Afterwards the predictors are incorporated as time-varying influence factors into the prediction by using a fully Bayesian treatment. The author, Kay H. Brodersen, recommends using from 5-10 predictors, however, the more predictors the better. (Brodersen, 2016)

The predictors in this research were these types of traffic: (1) Organic traffic from Google search, (2) Organic traffic from Seznam.cz, (3) Paid traffic from Heureka.cz, (4) Traffic from Google Brand Search campaigns, (6) Traffic from Seznam.cz Brand Search campaigns and (7) Paid non-brand traffic from the Seznam.cz.

If the causal impact would be significant, the difference between the incremental revenues and the incremental cost would be compared. This method estimates the causal effect of a designed intervention on a time series-based o the historical dataset and the sysntetic control predictors.

In case the causal impact would be used, the tracking system need be kept same for the whole time series that are used in the analysis. The cross-device tracking would change the attribution and could influence the evaluation. Moreover, the study from Aly, using aggregating data from campaigns, did not show the significant effect on the total number of conversions. (Aly, 2017, p. 45) Therefore, cross-device tracking was not enabled, and the attribution model was kept at last-click to increase preciseness of causal impact validation. The data were downloaded from AdWords system. All calculations were made in R Studio.

Experiment timing

The evaluation period for the experiment of Search and DSA campaigns was 47 days (5.3. - 30.4.). However, the smart bidding was applied prior, on 28.2. The learning period (28. 2. – 4.3.) was not considered in the evaluation in order to increase the validity of the results. Moreover, the evaluation was done two weeks later, 15. 5., in order to collect most of the conversions that happen after the day of interaction, as suggested by Aly (2017, p. 46) Therefore, the data collected shows 88% of all conversions in search campaigns and 86% in DSA campaign based on the pre-test sample. The detailed conversion lag analysis is in Appendix 2.

The experiment in the Shopping campaign was designed differently. The change to smart bidding was done already 15.2. to follow the recommended transfer to smart bidding. First, the target ROAS was set to 300% as it was recommended by the system in the AdWords interface. Exactly after 4 weeks (13.3.) was the system adjusted for the tROAS that was chosen for the experiment 400%. The evaluation period is however from 18. 3. Since the system needed some time to readjust to a new target. The data set for our research is still 30.4. for the same reason of conversion lag as in the search campaigns. The data were retrieved from the system 15.5. and the evaluation should cover 92% of all conversions.

The data for Causal Impact evaluation was downloaded for period 1.1. 2017 – 30.4. also for the predictors. However, the invention day is set to 28. 2., because that day was changed the smart bidding algorithm and as the recommendation of this method in R-package suggests, the intervention should be set as the first day, otherwise, the prediction would take into account the trend from the learning phase and the whole calculation would be misleading. Moreover, the prediction is calculated based on several predictors as described above in order to refine the prediction from noise variables.

3.2 Qualitative interview design

The objective of this research was to find a deep understanding of the automation techniques that are used in the market. More specific goals were: (1) what methods do experts use to create and optimize the search campaigns, (2) how do respondents structure the shopping campaigns and what are the benefits and disadvantages of chosen structure. (3) how do experts optimize the shopping campaigns and what are the main elements that require the most attention. (4) Understanding of differences between manual vs. smart bidding from the respondents' experience. Furthermore, the goal is to summarize the aspects that influence the success rate of smart bidding. (5) The last subgoal is to predict the future trends in PPC.

Methodology

The chosen methodology is qualitative in-depth interviews based in conversation (Kvale 1996) It enables one to derive interpretations from the respondent talk (Mishler, 1986), and find local idiographic correlations, thanks to the flexibility, and attentively to react to each respondent individually. (Hendl, 2016)

The disadvantage is that the outcome cannot be generalized or predict any quantitative estimations. However, the research is representative of the issue of automation. Conducting and evaluating the process is time-consuming, and the results could be influenced by the conductor. (Hendl, 2016)

I used the semi-structured interview in informal settings because it enables one to take into account the individual differences of projects that experts experienced. This approach enables one to react to this distinction, however, it also makes it harder to assess the interview and moderate the interview, as Hendl points out (2016). It enables to ask to follow up questions that are to clarify answers, requests further examples or to explain the implications (Rubin & Rubin, 1995, p.145-6) Preparation was conducted prior to each interview, summarizing the companies/projects that the expert managed, and which methods the expert uses, if he or she shares his/her know-how publically during conferences or via blogging. The interview was divided into 5 parts with respect to the structure of research goals.

The interview duration was scheduled for 90 minutes, however, the duration fluctuated from 50 to 130 minutes. Except for two cases, the interviews were audiotaped. During the interviews were taken field notes. However, immediately after the interviews were done the proper coding based on the system that recommends Chytková (2017). Afterward, I analyzed together with results from previous interviews. Each extra interview in comparison to the previous interviews opens new in-depth questions, which were used for the next interview. However, the main structure of the interview (that was set at the beginning of the study) was kept in each interview. Afterward, the conclusions leading from the interviews were confirmed with the interviewees in case that clarity was needed.

The analysis of the interviews was done by the coding method described in Hendl (2016). Isolation of each subtopic was done at the end of an analysis of each interview which was analyzed and coded as a whole in order to keep the whole picture of context and references to various subtopics of the interviews (Hendl, 2016).

Sample of participants

I chose theoretical sampling strategy to contact only respondents that was matching my predefined analytical to have a diverse sample that view the problematics from a different point of view as suggested in Glaser and Strauss (1967). The design of selection had the features as stratified sampling in the way that the contacted experts were chosen by the predefined subcategories, which are described below. This personalized approach leads to a high response rate of selected experts. As Hendl (2016) recommend the precise number of respondents should not be predefined or crucial for the methodology since the qualitative research is shaped by the outcome of each interview and the decision of the researcher (Hendl, 2016). The research required a diverse sample, therefore, the higher variability resulted in the higher sample volume. The size sample with similar design usually consists of 8-10 interviews according to McCracken (1988). The respondent sample was successful, because after the tenth interview the theoretical saturation did not occur. Therefore, the respondent sample was at the end 31 experts, when I concluded that more respondents would not contribute significantly to the research. The list of the respondents is in appendix 5.

The criteria for the theoretical sampling were as follows:

- Diverse project type experiences: different sizes of account, airlines, arbitrary projects, services, events, B2B or transaction e-commerce.
- Different background of the experts: several experts are former web developers, several data scientists, and web analysts. Moreover, the experts that actively share their advanced scripts were chosen to understand the different thinking behind the campaign structure and optimization in comparison to the experts without the technical skill..

4 Experiment

The experiment is calculated with the Wilcoxon pair test as the methodology suggests. When the dataset had the normal distribution, the results from the Wilcoxon test were validated also with the Welsch paired t-test. The percentage increase or decrease was calculated with the confidentiality range of 95%. In case of Wilcoxon, the estimated location shift of control group (manual bidding) was compared with the median. The reason is that the Wilcoxon test calculates the confidence interval from the pseudomedian[15]. On the other hand, the percentual change for the t-test was calculated from the mean. Because the t-test calculates the difference in means.

4.1 Search campaign experiment

The results from search campaigns managed are as follows: The campaign of "best product" had significantly lower CPA -37,3% according to Wilcoxon test bidding W(1.89) = 2302, p < .001, 95% CI [0.99, 2.77] and by t-test -34% t(103.4) = 3.96, p < .001, 95% CI [0.98, 2.94]. However, the test for conversion change was not valid (p = .78)

The CPA of the "**best product"** campaign, which has the most custom approach, has dropped by 38.4% with smart. The cost plummeted by 37%, W(3) = 2608, p < .001, 95% CI [1.98, 4.18] while the change in conversion volume was not statistically possible to prove (p = .788). The main reason is, in this case, that the campaign with higher priority (the best product) were overbidded due to its importance for the business owner.

The biggest difference in performance was seen in the **product campaigns** generated by the API tool, PPC Bee. The conversions increased by 216% t(72) = -16.9, p < .001, 95% CI [-20, -16], while the cost increased by 209% W(-16.9) = 0, p < .001, 95% CI [-19, -15].

However, the biggest opportunity has the algorithm on campings that are bidded low. In the case of the **author** campaigns (which promote over 5000 unique authors) the bids were historically set low. The semi-automated bidding system had enough data to change the bids only in case of few ad groups every week. So there was a huge potential in the ad groups with low bids, which the smart bidding revealed. The increase of conversions was however, not possible to calculate (p = 1). But the cost increased by 376% W(-12.4) = 0, p <.001, 95% CI [-13.6, -11.2] while the CPA did increase only by 43% W(-1.4) = 549, p <.001, 95% CI [-1.96, -0.78]. The overall performance of search campaigns was unable to compute since the volatility of dataset was high (p >.25 for all datasets).

[15] The pseudomedian of a distribution F is the median of the distribution of $(u+v)/2$, where u and v are independent, each with distribution F. If F is symmetric, then the pseudomedian and median coincide. See Hollander & Wolfe (1973), page 34.

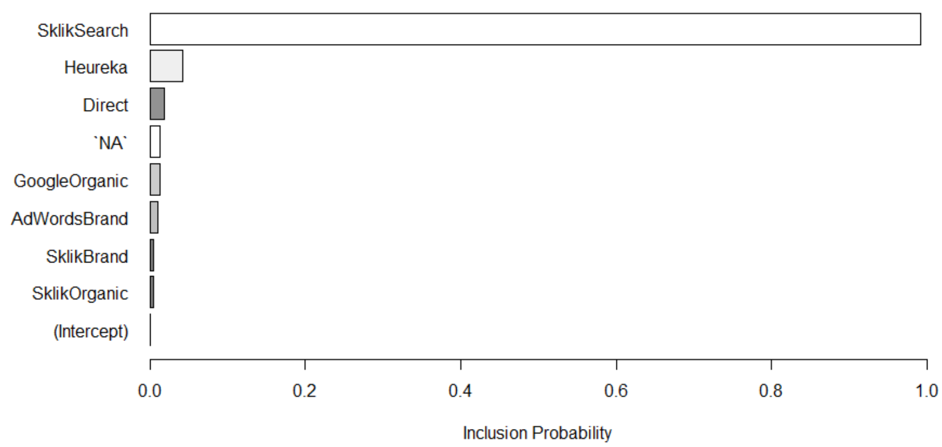
4.2 DSA experiment

The analysis of DSA campaigns shows that the smart bidding is very efficient. The conversions volume increased by 50% W(-1)=1239, p = .024, 95% CI [-1,0]. And the CPA lowered by 22% W(83) = 2.4, p = .019, 95% CI [0.23, 2.4].

4.3 Shopping experiment

The smart bidding resulted in the increase of cost, by 118.47% W(-32.73) = 91, p <.001, 95% CI [-37.64, -25.96] . Similar results could be seen even with the t-test: t(64) = -11.45, p < .001, 95% CI [-0.45, 1.1] in comparison to the control group. However, the revenues increased only by 69% W(-86.27) = 575, p < .001, 95% CI [-136.89, -35] the t-test calculated increase by 59% t(85) = -3.46, p = .001, 95% CI [52.83, 59.74] and there was only a 42% increase in conversions, W(-86) = 575, p < .001, 95% CI [-136.89, 35.32]. ROAS was insignificantly lower by 22.5% W(1.22) = 1196, p = .057, 95% CI [0, 2.572]. The conclusion might seem to be better for the manual bidding, which delivered the conversions with much better ROAS than smart bidding. The Causal impact methodology was used to better calculate the incremental increase in revenues which was caused by the smart bidding. From the predictors, described in Methodology 3.1.2, Sklik Search corelated the traffic most, when compared with the branded search campaign in Sklik, as shown in the picture below.

Picture 15 Predictors used in the Causal Impact calculation



Source: Author

The analysis from CausalImpact shows following results. During the post-intervention period, the response variable had an average value of approx. 496.83. In the absence of an intervention, we would have expected an average response of 399.32. The 95% interval of this counterfactual prediction is [216.02, 580.31]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 97.51 with a 95% interval of [-83.48, 280.81]. For a discussion of the significance of this effect, see below.

Table 4 Incremental increase of revenues caused by smart bidding in Google Shopping

	Average	Cumulative
Actual	18	796
Prediction (s.d.)	23 (1.4)	1025 (59.6)
95% CI	[21, 26]	[907, 1143]
Absolute effect (s.d.)	-5.2 (1.4)	-228.9 (59.6)
95% CI	[-7.9, -2.5]	[-347.1, -111]
Relative effect (s.d.)	-22% (5.8%)	-22% (5.8%)
95% CI	[-34%, -11%]	[-34%, -11%]
Posterior tail-area probability p:	0.00267	
Posterior prob. of a causal effect:	99.73333%	

Source: Author

During the post-intervention period, the response variable had an average value of approx. 18.09. By contrast, in the absence of an intervention, we would have expected an average response of 23.29. The 95% interval of this counterfactual prediction is [20.61, 25.98]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -5.20 with a 95% interval of [-7.89, -2.52]. For a discussion of the significance of this effect, see below.

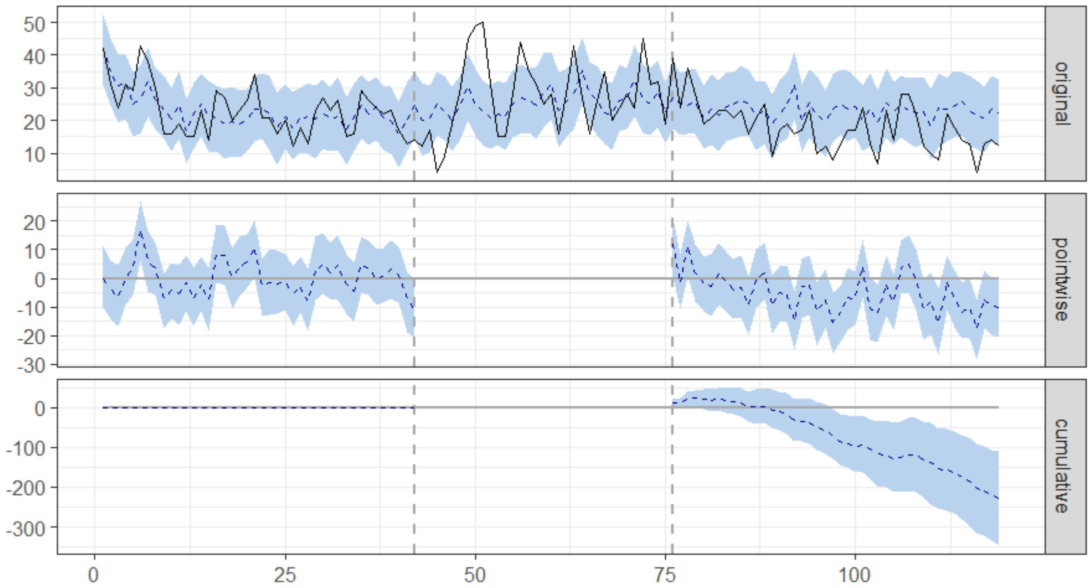
Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 796.00. By contrast, had the intervention not taken place, we would have expected a sum of 1024.88. The 95% interval of this prediction is [906.96, 1143.05].

The above results are given in terms of absolute numbers. In relative terms, the response variable showed a decrease of -22%. The 95% interval of this percentage is [-34%, -11%].

This means that the negative effect observed during the intervention period is statistically significant. If the experimenter had expected a positive effect, it is recommended to double-check whether anomalies in the control variables may have caused an overly optimistic expectation of what should have happened in the response variable in the absence of the intervention.

The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.003). This means the causal effect can be considered statistically significant. The incremental increase can be seen in the following picture 16.

Picture 16 The Causal Impact



Source Author

The limitations of this experiment can be that the shopping campaign in smart bidding was set with high priority. Therefore, general search terms were used, where the algorithm could fire either of the campaign groups (the manual and the smart bidding). Moreover, another limitation is that one major competitor during the evaluation period suddenly increase its bids and was hitting the maximal impression share. This could have created inaccuracies for the smart bidding algorithm (see Appendix)

The manual adjustments may have performed better, however, the smart bidding is perceived as a strategy which requires less optimization, and therefore it should be preferred even though it performs slightly worse. Therefore, the objective rule-specific methodology of manual bidding was used to ensure a higher level of objectivity in optimization, and at the same time, more-or-less the same time devoted to optimization as is requires with the smart bidding strategy.

5 Qualitative interviews

Most of the advertisers are trying to increase the volume of sales while trying to minimize the cost per each transaction. However, the PPC managers need to know if the client chooses to maximize revenue or maximize profit. The PPC strategy reflects this attitude, which differs among various projects. When the company aims to become a market leader, a highly data-driven approach usually needs to be chosen. The structure of big projects also depends on the business intelligence capability to use the internal information, create customized feeds, and advanced event tracking and performance evaluation with respect to attribution. Dalibor Klíč stressed that an important aspect is also the number and skill of SEM specialists.

5.1 Measuring the performance

The first and the most crucial step of creating a campaign structure is to set the right tracking. Generally, the tracking is done via importing conversions from GA or AdWords tracking. However, this needs a more sophisticated tracking. Usually, the performance from GA or AdWords needs to be compared with an internal database in order to calculate the CLV, or score the leads in the future. The key to link the users from various channels and the CRM is to label every visit with some identifier, which will be called "session ID" in this thesis. It could be any similar identifier (timestamp, cookie ID, lead id,…). This tracking enables Dan Zrůst, the Digital Marketing Specialist at Avast Software, and author of ExcelinPPC.com, to calculate the CLV several years from the first interaction (installing the antivirus). This calculation could be made on a very granular level in terms of Campaign, or even a specific keyword. Another example is Michal Voskár, Founder of Inevio agency, who developed a custom connector for lead scoring. It works similarly to the previous case. Every visit is tracked with a session ID, and when a user coverts – e.g. send a form with a phone number – the email enriched with the session ID is stored in the CRM. At the same time, the measurement protocol sends to GA an empty custom dimension that is linked to the session ID. Afterward, when the salesperson made a sale or failed to make a sale, he types the value of the sale, or just 0, in the CRM. The CRM sends this lead value automatically to the custom dimension, which was created earlier in Google Analytics The measurement protocol "rewrites" the empty slot, and adds either the value or data from the salesperson. Because the dimension is linked to the session ID, the marketer can see which source of traffic brings the most valuable leads and can attribute to this channel higher budget for example. The steps of this system are as it follows: (1) the system works with 2 dimensions in GA. First is the session ID and the second it the lead value. (2) the CRM works also with 2 dimensions – the session ID and the lead value. (3) When the user converts (sends the contact form) the session ID is sent to both systems (GA and CRM). (4) When the lead score is known, the CRM and GA can link the value based on the session ID.

This tracking system is applicable even for e-commerce projects. Ondřej Švarc, PPC specialist at Alza.cz, links the session ID with the Google click ID (gclid)[16] altogether in Alza's CRM. This enables their attribution system to send back to AdWords the exact revenue attributed to the exact gclid. Afterwards, Ondřej Švarc can optimize the campaigns to the data in AdWords without the necessity of calculating the revenue from internal systems. Moreover, Ondřej Švarc uses a ValueTrack parameter[17] that enables linking even more information to the database: which product appeared in the ad which the user with the session ID clicked, and afterwards evaluating which product the user really bought, or what the complement products were. However, this tracking has a disadvantage in that the PPC specialists see only data from yesterday and older because of a one day import delay. Advanced tracking is not only for market leaders. On contrary, smaller players need to track the soft-conversions to be able to optimize their campaigns when they have a low volume of hard conversions. Jiří Mařík, web analyst with specialization on performance, said that every project should track the soft-conversions. The question is which events later result in sale and the analyst should attribute a specific business value to each of these soft-conversions. It could be filing a form, downloading a price list and more. Michal Blažek, founder of Marketing Makers agency, found a significant correlation of copying on the website in the B2B sector. The arbitrary projects, like Heureka or Glami, have as conversion an exit click from their websites. Therefore, they send in the revenue from each click to the system and also a provision from each generated sale if the e-shop is in the Heureka košík[18] program or in the Glami COS pricing system[19].

Many experts believe that optimizing for margins is the right solution. tROAS now prefers low margin products with a high AOV. It is a very strategical decision because it can radically change the product sold. Some products, such as mobile phones, have almost no margin, and with optimizing on the cost of margin would probably be less visible. There needs to be an analysis of product attribution and complement products before such a step could be made. Plus, there is the necessity is of knowing how to incorporate the CLV calculations.

When the tracking is set, it is up to the advertiser how he will use it. Most of the experts use the AdWords data for campaign automation, and data from Google Analytics for reporting. The data in the platform interface are usually higher, in some cases it could be a 20% percent difference. Two specialists disclaimed that they create a new dimension in AdWords, and multiply the revenues by the difference they report to the client (such as Total AdWords Revenues * 0.8)

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[16] https://support.google.com/ds/answer/7342044

[17] https://support.google.com/adwords/answer/6305348

[18] https://sluzby.heureka.cz/napoveda/kosik/

[19] https://glami.info

5.2 Structuring the search campaigns

The campaign structure starts with a mind map to consider if the structure is manageable. It helps to reflect the differences in the key segments, set individual budgets, and also improves the ease for reporting. Jan Zdarsa, senior analytical lead at Google, uses mind mapping to better estimate the sizes of the campaigns with respect to the AdWords limits. In most cases advertisers use the campaign's structure described in the theoretical part: (1) brand, (2) generic/categorical, and (3) product campaigns. But it is important to create a new group of (4) top campaigns. These top campaigns are usually managed individually due to high revenues, or the keywords are extremely competitive and searched heavily. E-commerce projects such as Alza or Mall need to separate the campaigns of products that are prioritized due to contracts with vendors. Besides the campaigns mentioned above, there were mentioned campaigns targeting a competitor's brand. Moreover, the experts separate the keywords by the keyword match types, targeting locations, audiences, and some even by device. Such a granular structure can be linked with external data, according to Milan Merglevský, senior e-commerce consultant and founder of Ecommerce-architects.com. Afterward, an automated bidding strategy powered with a sophisticated mathematical model can be used, with cross analysis for better attribution. Around a third of the experts create a small keyword analysis for PPC purposes. All of them use OpenRefine to cluster the possible keywords from Google keyword planner and similar tools (keyword.io, soovle.com, answerthepublic.com and others), or from historical search terms from the AdWords account, or from an organic search. This analysis enables them to prepare clusters of keywords applicable for campaigns, and also potential excluding keywords.

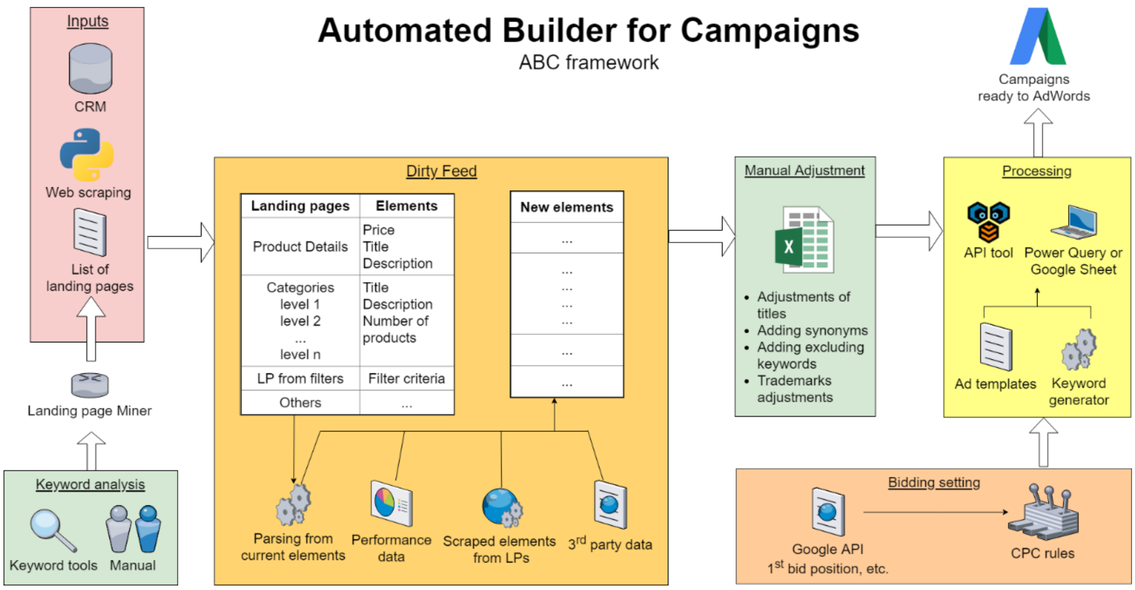
Search 2.0

The Search 2.0 method, which is described in chapter 2.1.1, is used by several experts. All of them have tools to automatically create the structure and also the optimization. Most of the experts use this method for the top campaigns. This method enables maximizing the ad relevance to improve the quality score, and at the same time bidding exactly on the right keywords. Some experts like Markéta Kabátová, founder of the UnicornsLab agency, and Dalibor Klíč, Industry Manager for e-commerce at Google, are against this approach because it is complex to manage it and, in the long-term, when the campaigns reach a certain volume, it is not manageable, and just top campaigns could be managed like this. Jakub Hermann, the founder of Placement.cz, agrees that the process of creating the automation tools is difficult, especially the proper system of excluding keywords. However, he says, it truly pays off, and he some optimization techniques are much more efficient in this structure than in the classical one. Jiří Mařík adds that this structure or methodology is not applicable for everyone. However, if the advertiser can automatize it, then it makes sense to use Search 2.0 it this way from the business perspective. It does not have to be just Search 2.0. If any automation or new approach would generate business profit, then the specialists should try it. The level of automation should be discussed – How much would the investment need to be to develop and maintain such an automation tool? In most cases, semi-automated solutions are used, like PQ etc. The level of automation should reflect the return on investment.

5.3 Campaign Creation

The research showed that there are 2 groups of people doing campaign creation. The first devotes a lot of time creating "perfect" campaigns, but saves time during optimizing and managing such campaigns. The second group of experts create most of the campaigns automatically, even with automated ads to cover all product/services that the client sells, and then optimize the campaigns based on the priority of their performance. Some experts told that they are trying to keep less structured campaigns, because the smart bidding would perform better. However, this solution is made for the less prioritized campaign, when the experts have only limited time to optimize it. They say that there does not have to be a decrease in ad relevance by using ad customizer. This approach would theoretically have same effect by separating the campaign into several ad groups. However, none of the experts really use ad customizers to keep the campaign less structured. Jan Zdarsa said that he has never seen an account that would use the ad customizer in this way, because it would not even make sense. The specialist would completely lose the control of the ads, and even ad testing would be much more difficult. Separating the ad groups is still perceived as the best practice by the majority of experts. Therefore, this chapter is devoted to the automated creation of campaigns. There are many various methods and tools for automated campaign creation. However, among all are various similarities, and they are outlined in the Automated Builder for Campaigns (ABC framework) – see picture 16. Different ways how to build the search campaigns automatically are described in the following paragraphs.

Picture 17 Automated Builder for Campaigns (ABC framework)



Source: Author

5.3.1 First inputs

The most convenient way for building campaigns is to have a prepared feed generated from CRM, which automatically updates and include all necessary elements. However, in real practice, PPC specialists need to be able to create the campaigns even without help from IT.

There are two main approaches: 1) finding useful landing pages, and 2) finding relevant keywords.

The most manually demanding way is to go through the sitemap or websites, and by using scraping browser extensions[20] to just download the relevant subcategories or collections of URLs with titles. To go through a great website structure, the PPC masters can use the web crawling software like free Xenu or Scremingfrog. The outcome from the crawling tool will be landing page structure, which needs to be manually adjusted because, for example, not all URLs generated from website filters might be applicable for the PPC campaigns. With this tool, the descriptions and headlines can also be downloaded. Pepa Folta, PPC freelancer, uses this outcome, and recommends that the client change to less appealing meta descriptions, which Pepa Folta uses further in the ad creation process.

Another approach is to create a list of keywords and by Marketing Miner's keywords miner tool finds the most accurate URL to the keyword according to the Google SERP. This approach enables us to cover all the keywords at which the advertiser wants to be present. The advantage is that this approach reveals missing landing pages and the client can create new pages that help to even increase the organic traffic. However, if the client does not have the capacity for creating specified websites, the links leading to internal search needs to be used, which is not a very nice solution. This approach is done mainly by those experts that use Search 2.0 campaign style. Lukáš Král, the co-founder of Placement.cz, stressed that the benefit of his custom tool is to create campaigns automatically for any keywords they want to have in the account

All the URLs or feeds should be differentiated to the groups or categorical levels. Usually, the category is divided into several levels, which very often copy the breadcrumb navigation. For example the product level 1 "iPhone 7" than product level 2 "iPhone 7 32 GB" and level 3 "iPhone 7 32 GB gold". Each of these levels needs to have a different landing page, ad copy and keywords. Ondřej Švarc put emphasis on this diversification because later on, it would enable to add automatically all negative keywords from upper levels for each specific ad group. Matěj Slavík, head of PPC in Notino, uses the specific feed for each category level.

5.3.2 Creating relevant elements

The next step is to add more relevant elements into the predefined feed. According to Jiří Homola, PPC specialist at Besteto agency, stressed that this is the most important part. Product landing pages are usually accompanied with CRM data like a tag for bestsellers/low-sellers, the discount, inventory status, etc. They are only limitedly also used for competitive analysis. Lukáš Hvizdoš, the co-founder of a 6clickz agency, Product miner

[20] Scraper, Linkclump

from Marketing Miner[21]. Ondřej Švarc recommended a similar tool, Azor[22], for price competitiveness. Usually, preparing suitable elements for a further keyword generator is the most time consuming process. Most experts need to parse the titles or descriptions to get the model id, or the clean name of the product. To use the parsing method specifically for every product category is heavily time-consuming. Some experts like Matěj Slavík, head of PPC in Notino, have CRM which enables them to add very specific custom elements. However, the feed is not always so editable. Martin Zítek, therefore, uses advanced statistical analysis to detect important elements that should be extracted. The most accurate system to detect a specific model ID which is unique for the whole product feed, is a frequential analysis[23]. Afterwards, this word will be used as a keyword. Some experts do not use single-word keywords because of the higher possibility of mistakes in showing irrelevant search terms. Among them is Michal Blažek, who believes that it is almost impossible to "win" with automatic creation of one-word keywords ad sets. However, Martin Zítek did manage to win. He tested that single keywords (specifically for the product models) and found that it can double the revenue while maintaining the same level of ROAS.

Another solution to avoiding the parsing problems is to scrape the websites. This strategy was developed by Adam Šilhan, Google Partners Trainer and Head of Marketing at igloonet. The logic is to add an element that would be relevant for the users, and to increase the ad copies to get higher CTR and conversions. The list of URLs from the previous step is enriched by the HTML or JS elements from the websites. These elements are: (a) static, such as material, unique collection, or (b) dynamic elements, like dynamical free shipping or changing a number of products in a category, or number of product in the internal search. These dynamical elements need to be later treated as ad customizers. The scraping tool checks the URLs every day, and saves all the elements that were specified. This can be done by classical python scraping tools, which are available online[24]. The benefit is that it is not a heavy-loading solution. Adam Šilhan even adjusted the python script so that it scrapes each unique landing page once, even though the web page is used for more ad groups so it is very light on the server CPU.

Jan Matějček, the PPC specialist at Glami, uses the most advanced solution to add very relevant feed tags. A custom machine learning algorithm detects all the pictures from cooperating e-shops and adds the tag based on category, style, length of sleeves, and much

[21] https://www.marketingminer.com/en/miners/by-data/product

[22] https://www.dataweps.com/cs/azor/

[23] Frequential analysis calculates how many times is any word contained in the feed and based on the results creates elements containing the specific word.

[24] The scraping can be via several scripts, like this one from Sidhu & Fred-Ojala: https://github.com/afo/dataXprague/blob/master/05b-webscraping/notebook-webscraping_v4.ipynb However, the most demanding part is to mange to change the ads through API documentation.

more features. Jan Matějček uses solution form Rossum, however, even Google Vision offers a similar solution[25]. However, the advantage of Rossum is that the algorithm takes into consideration also the product descriptions and headlines.

5.3.3 Human Corrections

The feeds often need a human correction. The category titles may need adjustments. It could be done in Google Sheets, special tools like Mergado, or within the CRM system that generates the feeds. Jiří Homola validates the parsed phrases from the last step with the real search terms. If he finds that people use synonyms, he adds all elements. If the system creates more general keywords, he adds negative keywords. He adjusts the element for keyword generation very precisely, so that all the keywords he is targeting are relevant and he can bid each ad group to a 1.5 position. Matěj Slavík said that this is usually the case for some more general brands, or collections like "summer". That is the advantage of their CRM that can synchronize the excluding logic even for the campaigns in all countries.

5.3.4 Campaign creation

Big transaction e-commerce projects are using API tools to create automated campaigns. The best API tool, according to most experts, is PPC Bee. Jan Zdarsa stated, that in Dubai it is most common to use a Double Click search, which enables creating campaigns based on feed. However, it does not have as many features or as much flexibility as PPC Bee, by far. He personally uses custom python scripts that are more flexible than the PPC Bee. On the market are also other solutions such as Ad Boost, which uses only one expert, Ondřej Švarc from Alza.cz. However, predefined rules in Power Query can do the same work in specified Google Sheets macros or python scripts.

The first step is to generate the keywords. Most of the interviewed experts create one exact match campaign, and a second with keywords in a broad modified match with excluded exact keywords. Lukáš Hvizdoš also automatically creates a DSA ad group with excluding exact and broad keywords. The excluding keywords are more complicated, according to Jakub Hermann. If the advertiser wants to use the Search 2.0 method, the "cross exclusion[26]" needs to be performed. Some experts add in the feed an extra labeling system, which enables the automated Power Query to do this excluding system. The rules take the keywords from all ad groups containing the same label tag as excluded keywords in exact match. Afterwards, from these keywords are deleted those that exactly match the positive exact match keywords. Jakub Herman confirms that this labeling system for excluding the keywords truly pays off, and after the creation, the system of search term optimization in Google Sheets enables them to quickly create a new ad group with relevant ad and keywords, and to exclude the keywords from "neighboring" ad groups. Jakub Kašparů,

[25] https://cloud.google.com/vision/

[26] Cross exclusion is a style of useing excluding keywords from similar adgroups that might cause that specifi search term might fired from both ad groups.

founder of Lynt services and author of PPC Robot and ppc-scripts.eu, has another approach. He spotted a high difference in performance after Google launched the new exact match type as described in the chapter 2.1.1 The close variants match to completely different search queries with poor CTR and CR. This is extremely important for keywords with extreme search volume and competitive level. Honza Zdarsa said that in some cases with these head keywords, it is wise to set a stand-alone campaign to also manage the budget. Kuba Kašparů manages accounts targeting the whole world, so several thousand keywords need special treatment. He says to focus to increase impression share only on the best performing search queries. He developed a script that downloads the search term report from exact campaigns, and hourly excludes the search terms that are not exactly matching the keyword. So, the search term is shown in broad match ad groups with a lower bid. However, the script requires a lot of time to manage all the search terms for an enormous volume of keywords. Therefore, Jakub Kašparů created another script that is run during the process of creating the Exact ad groups. The Google sheet script connects to Google keyword planner API, and excludes every suggested query from a specific keyword. The script performs this excluding process with every new keyword in the exact ad group.

Dynamic search ads

Martin Zítek will even use only the exact and DSA ad groups for product campaigns. Jiří Mařík warns away from a strategy of having only Exact and DSA campaigns. The DSA triggers different search terms than Broad Modified match, and the advertiser can lose control since the Broad campaigns can be more segmented, based on different keywords. However, most specialists do not realize that the broad campaign can bring more relevant traffic from new search terms, and play a similar role to DSA to pick the best performing search terms. The Broad campaigns can be targeted at similar problems the target group can have, or a substitute product, which would not be targeted with DSA.

For all the experts (except Pavel Erfányuk), the DSA plays a role of an extra campaign that covers the low volume search terms, or catches some phrases that were forgotten while creating the standard search campaigns. The DSA is like a KW generator. Moreover, Ondřej Švarc also uses DSA feed campaigns for categories that are not yet incorporated into product or category campaigns. These are usually less performing or new smaller categories, with a relatively small volume of conversions. A few experts are creating the DSA ad groups together with the product or category campaigns in a search network. Dalibor Klíč says that DSA campaign is a “must-have”, because these campaigns are necessary extensions to verify that the search campaign strategy is correct.

The exception is Pavel Erfányuk from Heureka, where the DSA campaigns are generating 80-90% revenues for all Search Campaigns. It is interesting that 90% of all DSA campaigns are generated by one generic DSA campaign. He believes that it is due to the high level of On-page SEO. Moreover, the products are changing so fast that DSA is almost the only way to have updated campaigns

The last important task is to calculate the right bid for the ad groups. Lukáš Hvizdoš uses the estimated CPC for the first-page bid, which is in AdWords API. Jakub Kašparů warns that the estimated CPC is not always correct, and they developed a system that calculates the optimal bid based on the estimated CPC and CR of the current LP from GA data. Lukáš Hvizdoš also uses competitive metrics to see the right bid level.

Afterwards, Zrůst uploads the changes through DoubleClick. The AdWords Editor is impractical, since the Avast accounts are so huge. DoubleClick, unlike the AdWords Bulk import, can automatically ask for request" if an ad pops up the notification that it needs to be checked. David Choleva, the PPC specialist at Mall Group, stresses the importance of extra control in the first few weeks after the completing all the ad groups and ads with ad customizers and site links. He uses the automated rules or scripts to detect abnormal performance of the ad groups generated from PPC Bee. For example, it sends him an e-mail if some ad group has a significantly higher volume of impressions and low volume of clicks. If there are some irrelevant keywords, the peaks can be easily spotted, or it would not have any impressions. For ad groups promoting LP with only one e-shop or a low volume of product in the specific category, Jan Matějček sets AdWords script pause. But the more detailed optimization is described in the following chapter.

5.4 Search campaign optimization

The most important optimization by almost all expert is to have different views on campaign performance, and possibility to see that some aspects deteriorate the performance, and some improve it. Those views could be differentiated as (1) overall performance check, (2) search terms performance, (3) ad testing, and (4) keywords level quality score and its development. Peter Pleško, Performance & Branding Specialist at Fragile, pointed out that some of these insights are now also in the new AdWords interface in the opportunity tab.

5.4.1 Performance control

Performance check is the most important view that all the specialists use. Most of them not only check a monthly performance, but also compare it with different time frames to see the development. Among these views are the cost, revenues, and ROAS on a level of campaign groups. Several experts need to combine the performance with internal systems to validate the outcomes. Most of the time they need to change the targets. Matěj Slavík is trying to eliminate any possible human mistake with alerting notifications or predefined views that reveal any potential problem. The essential is a Link checker script to reveal 404 or redirects. Almost every expert told me that they are using the scripts from Stanislav Jílek, like a budget guard, impression control and other available scripts[27]. They also use other custom reports like HI report from Google, or paid solutions like Roiminer or Optmyzr.

5.4.2 Search terms optimization

The search term optimization is, according to most respondents, the most time-consuming activity. They have often predefined scripts that download the search terms with

[27] https://www.standajilek.cz/

performance into Google sheets, where they cluster into groups of top/low performing search terms and manually check them based on the priority. Markéta Kabátová uses, for example, a view, which sorts, on a weekly basis, the search terms with the highest weekly difference in search volume. Many respondents have a system where they need to check unique search terms just once. They store the checked search terms in another Google sheet. When the new search term report is downloaded, the script automatically filters them, and only new, unchecked search terms are displayed in a new sheet. Hana Kobzová, PPC freelancer recommended by Russell Savage for AdWords Scripts, uses the AdWords interface for the search term analysis. She always excludes or adds the whole search term in exact match type. She can later filter, in an AdWords interface, only the search queries that are not labeled as added or removed. Matěj Slavík, is, on the other hand, trying to adjust the search terms on the feed level as described above. The main reason that method is used are the similarities in all the 9 countries where Notino is present.

Another view detects a search term that was fired from 2 different ad groups. Most of the experts use a free script[28]. The advertisers set a priority level where the search term should be fired, and if the Google chooses an ad from a lower level ad group, the search term is automatically added as an excluding keyword in exact match type. However, Jakub Kašparů warns that SEM specialists should check why, for example, the DSA campaign with a lower bid was preferred in an ad action to a manually created ad group. Jan Zdarsa recommends checking how the better performing ad looked, and using it also in the search ad. Other interesting views, that Jakub Kašparů developed, are comparing the Search keywords and queries with (1) organic search results and also with (2) the search terms with conversions from shopping campaigns and (3) the search terms with conversions from search campaign of other platforms (Sklik or Bing).

The most sophisticated and efficient way to manage the search terms uses Lukáš Vožďa and Jan Zdarsa. Lukáš Vožďa is web analyst at Proficio agency, and Jan is testing a similar tool from his colleague at Google. Jan Zdarsa developed a python script that creates clusters and word aggregation. This script separates each word from the search terms, and checks the performance of the words across all search terms in the account or campaign. The script prepares the insight of which words deteriorate the performance or which words improved it. Based on these patterns, not just a new ad group structure should be made, but it also recommends creating new keywords using the better performing pattern. Lukáš Vožďa explained the logic behind his script. Firstly, he ran a script that highlighted the search terms that are very similar to the original keyword, based on several open-source scripts such as N-Gram Fingerprint, Phonetic Fingerprint or kNN[29]. Later on, he found out that it's more suitable to use the Levenshtein Distance to calculate the differences between two text strings. Currently, Lukáš is testing a python script using machine-learning algorithms based on TensorFlow to spot the differences more precisely. There is a very similar script

[28] Such as this one http://duplicity.igloonet.net/

[29] https://github.com/OpenRefine/OpenRefine/wiki/Clustering-In-Depth

developed by Jan Zdarsa's colleague, a system[30]. It downloads search terms and the keywords structure of the account. The algorithm calculates the differences of the search terms of the keywords and recommends adding the search term into a specific ad group of the structure as just another keyword in the predefined ad group, or creating a new ad group based on the structure. This suggestion is also made based on the quality score and other metrics. The PPC managers later need to only check that the keywords to make sense and to let the system add it to the campaign structure. This approach would save plenty of time, according to the Jan Zdarsa. Both of the scripts are, however, currently being adjusted based on testing on different accounts, so they are still a long way from the final versions.

The smartest way of search term optimization uses Michal Blažek, who weekly sends the search term report to the client to be checked. This is done especially for German campaigns where the insight from a native speaker is needed. In the case of small accounts, they just check the search terms that are prioritized by the advertising spend. Michal Blažek is trying to automatize most of the repetitive tasks in PPC. However, he is against a solution where the scripts manage the search terms, because it can exclude some search terms which might have potential for the advertiser. According to Michal Blažek, the search term analysis is very crucial, and the automatized solutions mostly failed in the optimization of search terms.

5.4.3 Bidding

The bidding strategy is according to the vast majority of experts the most important aspect of optimization. The manual bidding is still used by vast majority of respondents. The reason is that the Czech market is rather small, and marketers do not have enough data to use the power if smart bidding. Machine learning algorithms require a vast amount of data, as explained Ikhlaq Sidhu and Fred-Ojala from UC Berkley at the Data-X Master class (2018) He believes that small data sets could be performing much better with some predefined rules rather than ML. Surprisingly, many respondents do not understand the logic of smart bidding or the basic rules of machine learning. They are convinced that because Google has more inputs to choose from, their smart bidding algorithms simply must perform better. But in the Czech market, it is not always the case. Jan Zdarsa stressed that the volume of conversions, which recommends Google, are highly dependent on the size of the account. The algorithm works differently for a single keyword that has 30 conversions than it does for conversions are spread among thousands of keywords. However, there is a way to use the smart bidding solution even with a low volume of conversions. The way, as described also in the chapter 1, is to track soft-conversions. Michal Blažek assigns a specific business value that is attributed to each type of soft conversion in order to differentiate the more important conversion events, as described in the chapter 1.2.2 It is not just for the bidding algorithm, but more importantly for the PPC manager, who should take the types of soft conversions into consideration. Jan Zdarsa agrees, and predicts that soon the AdWords

[30] Googles machine learning tool that was opened to public.

interface will enable setting different weights to the soft-conversions pro tCPA. It is currently possible with DoubleClick Search.

The second disadvantage of smart bidding, perceived by the interviewed experts, is its slow reaction to seasonal peaks, or to some promotions that highly influence the conversion rate. However, Double Click Search enables tracking these changes in Business Data, and two respondents are already using Beta for AdWords. So, it will hopefully roll out officially to all AdWords account soon. Martin Zítek believes that it will be adjusted for this year's Black Friday. All of the experts use manual bidding in brand campaigns for its specificity and relatively small size. The ways to optimize manual campaigns, are described in the first part. However, vast campaigns with thousands of keywords are almost impossible to manage without any automation. Therefore, semi-automated manual bidding is described by the second part of this chapter, and lastly, more experiences with smart bidding are described in the third part of this chapter.

Manual bidding

Undoubtedly, the biggest advantage of manual bidding is that this approach does not require a vast amount of data as does machine learning. Every responding expert uses manual bidding to manage the brand campaigns, because they want to ensure the full impression share.

Hana Kobzová uses the manual bidding even for the generic campaigns in AdWords. The logic is that if the whole ad group does not have enough data, the bids are set to the whole ad group. When considering the ad group reach and its' a certain search/cost volume, the bids are set to the keyword level or divided into two ad groups in order to be able to create more relevant ads (or single keyword Ad Group for exact match with high volume. Daniel Kotisa, Google Partners Trainer and online marketing freelancer, stressed that adjusting the bids in the AdWords interface enables to quickly change the timeframes. To increase the efficiency of this manual bidding, Hana Kobzová uses several tool and extensions to speed up the work. She said that she cannot imagine the optimization without Usability booster extension to the AdWords interface[31] that speeds up search terms revision. She also has predefined macros in Notepad++, several extensions for Excel, such as RJ tools[32] but these tools are rather used for keyword list expansion and creating new campaigns. However, by the end of 2018, the old AdWords interface will not be possible to use[33], and all the tools will have to be adjusted. Papa Folta uses another approach. Instead of adjusting the bids and creating new ad groups right away in the AdWords interface, he adds labels that change what should be done. When he finishes this labeling process, the script automatically processes all the predefined actions in the label, deletes the old label, and creates a new

[31] http://hanakobzova.cz/usability-booster-rychlejsi-prace-v-google-adwords

[32] https://www.rjurecek.cz/excel/rj-tools/

[33] https://adwords.googleblog.com/2018/05/adwords-transition-new-experience.html

label containing the date and type of action. Folta can afterwards see all the changes he has performed in a format of labels.

According to Michal Blažek, many PPC specialists extremely prioritize optimization that leads to only a minor change in performance – such as too much search terms optimization, or over-sophisticated bidding strategies. The automated rules in AdWords are sufficient, and the human control is always needed.

Semi-automated manual bidding

Ondřej Švarc, however, needs a more automatized approach to handle campaigns for the various categories he manages, and around 200 000 promoted products multiplied by number of countries Alza is active in. (And that is just a portion of all their product). They developed scripts handling manual bidding. The main reason for manual bidding is that, since they an advanced business intelligence team, they have managed to link all the AdWords performance with all other sources of traffic, and they have a custom attribution model, which make more business sense than the classical platform data. The bidding system that Ondřej uses is based on the margins, the price of the product. And, in some countries, they also use third-party data about competition as input to the bidding system. Probably that is the reason why the manual bidding was, in past experiments, better than the tROAS. However, Ondřej admitted that because of the poor results of the tROAS, they didn't do the experiment after the tROAS algorithm was adjusted. Currently, they are testing the tROAS again at a specific segment. This thesis categorizes the bidding strategy, which is based on the calculations or rules in Google Sheets, Excel (Power Query) or via scripts – either the AdWords/Google App script in JSON or custom python scripts, as included in the semi-automated method. The ways to automate bidding are various, however, the logical rules are similar across the methods. For example, Marek Mašek, Performance & Branding Specialist, uses Google Sheets rules to suggest bid changes, and afterwards he checks the suggested bids, and applies them only to the ad groups that make sense to him. Lukáš Hvizdoš adds that the recommended bids can be too high, and the PPC specialist should use the expert estimate based on experience with the account, as to which bid level should be preferable. On the other hand, some experts change the bids through scripts on daily bases.

The first step is to differentiate the campaigns by objectives. Some campaigns are optimized on ROAS and some on high visibility. Moreover, usually camping's in one account have different targets across the campaigns. The bidding is similar to the strategy I used in for the experiment (see chapter 3.1.1) Jakub Kašparů uses the same script for several clients in order to maintain only one script. As Jiří Mařík stressed, the PPC managers should also calculate the cost of maintaining the scripts regarding changes in the AdWords features or the API documentation. The best practice among interviewed experts is to have one Google sheet or table with variables that can be adjusted based on the project-specific or the season. Among these variables are: (1) the threshold what is considered as enough data, (2) the time frames and (3) the targets to evaluate the performance of the ad groups with sufficient data.

To decide exactly what "enough data" means differs among the campings – usually, it is how many impressions, conversions or cost, and what are the time frames he uses for the calculations, for example (7 days, 30 days and 2-3 months). Adam Šilhan stressed the importance of time frames. Not all ad groups have the same "starting" conditions, and due to some short-term imbalance in performance, the PPC specialist could easily remove potentially good performing keywords that are not yet in the season. The timeframes for bid adjustments should be based on the purchasing process and conversion lag of the specific product. However, even within a single account can be products with completely different purchasing behaviors, and it needs to be taken into account for bid management. Adam Šilhan said that the biggest bidding problem he sees currently is too frequent bid changes.

The ad groups without sufficient data are being kept at the first page on desktop devices, and script should wait till the data are collected, at least in the longest time frame. The ad groups with enough data are separated into two groups – (1) good performers and (2) bad performers. The good performers need to increase the bid. Milan Merglevský explained the logic, saying that he first needs to estimate how broad the space is that he is able to capture by any increase of bids, and at which point would the marginal increase of click/revenues not be profitable. So, the bidding program calculates the weighted Conversion rate and AOV from the predefined time frames. It also checks the estimated bid for the 1st page bid and for the 1. position bid from AdWords API and calculates the maximal affordable bid to capture the missing impression share. To explain it in a more simplified way, the lower IS or position, the more aggressively the bid can be increased, if the performance from last 30 days is positive. Jakub Kašparů would like to include into this prediction the data from bid landscapes through API to increase the accuracy of the model. However, he is still testing how big an influence it should have on the prior calculation. Dan Zrůst from Avast used an approach similar to what Kašparů intends to test. Zrůst tested it on tCPA smart bidding, since the manual bidding would be too time consuming. However, setting the right target for this smart bidding is as challenging as is setting the right bid for keyword. He was changing the set target of ± 10-20%. Then he calculated the tCPA elasticity, which is a similar approach to the manual bidding. He calculated how much the revenues will increase if he changed the target by 1%. From this calculation, he could set the target CPA, which brought the best balance between cost and revenues. He found out that he is already hitting the level when increasing spend brings almost no extra revenue, due to the diminishing return law as explained in the chapter 1. AdWords API enables users to get this info by calling bid landscape. However, Zrůst ran several experiments which resulted in a very worse performance than the bid landscape predicted. Therefore, he built his own solution of the bid landscape. He downloads the AdWords change history from 2 years. Filters only changes of bids (in his case target CPA), and parses the exact bid changes, because all inputs are in text format. Afterwards, he creates a timeline where each day has a value of the set bid (or tCPA), by adding dates where were no bid changes was made. Afterward he can analyze on real data how much did conversions increase when bid increased. Most of the time he sees that the conversions do not increase by even small percent, so he returns the CPA back. However, some experiments result in acceptable increase and he can let the target on lower level. This approach of goal setting is possible only in stable industries as antiviruses or for the top performing keywords with sufficient volume.

Stanislav Jílek uses another approach to increase the accuracy of the model, without using such a sophisticated solution as Dan Zrůst uses. Jílek includes the average position from the previous day into the bidding rule. In a case where the ad group is performing badly, the estimated decrease of the bid could also be similarly calculated, but all the experts sets a percentage decrease of the ad group. This approach enables keeping low performing ad groups with a very low bid, and when the performance increases, the ad groups can be lifted to the first page again. This very important reason is why Lukáš Král uses this bidding strategy together with the Search 2.0 structure. Several times he has experienced where low performing keywords, that would be normally excluded, start to generate a profit, probably because of changes in the pricing strategy, and this bidding strategy enabled him to capture this opportunity.

In a standard season, the bidding scripts change bids based on a longer time period. It might be a month with the higher weight on the last week. In the seasonal peaks, for example, Black Friday, the script could easily be adjusted to make a decision based on a much shorter time period (eg. 1 day back, if the campaign has enough data). Therefore, the bidding will be highly influenced by the current trend. However, Standa Jílek found out that at the seasonal borderline, the bids require more aggressive adjusting, and "shorting" the time frame was not enough. So, if the bid is under some level (which is also a variable in the Google Sheet), the script increases the bids by an absolute number, so as to quickly return to top bid positions and to capture the starting season conversions. This approach is used also for Black Friday, some promotion event, or any other expected change in the conversion rate. For product campaign optimization, Milan Meglevský even uses 3rd party tools to predict an increase in CR. The tools like Azor compare the price competitiveness of the products. So, if the competitors' product is suddenly more expensive or temporarily out of stock, the bids can be increased, because the conversion rate will logically increase. If the ad groups have enough data, but a low volume of conversions or no conversions, the problem is usually in a low quality score. The Search terms in the broad match need to be checked better, and the exact campaigns usually need new ad copy. If the adjustments will not change the performance, than the bid is significantly decreased. Lukáš Hvizdoš also checks the click assisted conversion before decreasing the bids. The weight, which should be attributed to the assisted conversions, is also one of the variables to the script that is adjusted to the specifics of the client.

In order to differentiate the performance, Milan Mergelvský structures the campaigns by device. Jakub Kašaprů, on the other hand, uses a second script that runs after the first bid adjusting script. All the adjustments of the first script are only based on the data from a desktop device. The second script changes the bid adjustment on a campaign level, based on the difference in performance compared to the desktop. Samuel Ondrišák, PPC & technology leader at UI42 and Google Partners trainer, is using Magic script to adjust the bids, based also on the day and hour of the week, but many experts discourage using this solution, since a bid adjustment problem as described in the theory chapter2.1 might occur.

The advantage of Magic script is that the tool is already created, and the advertiser without the skill to create his own scripts, or to prepare the Google sheet workflow that estimates the bids, can use it immediately. There are also possibilities for directly connecting CRM systems, or adjusting the bidding based on the Google Analytics data, which might be very useful for apparel projects, since the cancelled orders could be as much as 40% of all orders.

Lukáš Vožda is the only expert, who uses machine learning algorithms in his scripts. He believes that ML is applicable even for custom scripts, especially since Google has opened its machine-learning algorithm Tensor Flow. The algorithm will manage the bids as static rules outlined above and when the ad group reach a certain level then the bidding would be based on the ML algorithm. The reason for this is clear. Almost all experts stated that 80% of all conversion is brought by just 20% of ad groups (or keywords). So those 20 most important percent have potential to be managed with ML since it has enough data and the rest with classical static rules. This seems to be a good transmission between the manual the smart bidding. Most of the experts predict that in future, which the development of ML will be possible to adjust the smart bidding more accurately even with low datasets.

On the other hand, Jakub Kašparů believes that current capabilities of ML require a much higher volume of conversions to use it. It is proved that simpler algorithms work much better with a lower volume of data (Sidhu & Fred-Ojala, 2018) So he does not devote his time in the ML algorithmization of his current scripts.

Adam Šilhan said that they devoted loads of time to create a custom auto bidding solution. However, he soon realized that it is a dead project. None system can compete with Google with a general solution. It makes sense only if you find a pattern that Google cannot learn from the inputs but it significantly changes the behavior and CR of website users and also has an impact on a global level (across all the client's campaigns, not just a minor segment). These patterns should be backed by real statistical evaluation in order to get a coefficient, which could be used to adjust the bids. Those should be either internal/external factors unknown to the Google. e. g. massive repeated internal promotion with significant influence on sales (stronger first few days, local maxima in the middle of promotion with strong ascending last days of promotion); bit overhyped influence of weather on sales. Even Milan Merglevský who has experience from highly data-driven projects, said it makes sense to test some segments to switch to smart bidding, because the algorithms behind ML are constantly evolving.

Smart bidding

By smart bidding, many respondents understand only it to mean tCPA or tROAS strategy. Surprisingly many experts did not count eCPC as smart bidding, since the bidding needs to be adjusted the same way as manual bidding. The vast majority of interviewed experts use eCPC for almost all search campaigns. Michal Blažek remarked that in most of his campaigns, the enhanced algorithm does not play a much different role, since the campaigns do not have enough data. They usually claimed that the ML algorithm of eCPC helps them to tune the final bid based on the audience and time for each auction. However, almost none of them indicated they had tested the performance of eCPC, so it is just their belief. Karel

Rujzl, PPC freelancer, has seen a decrease in performance of the new eCPC algorithm, which can increase or decrease the bid without limit. On the other hand, the experiments that Samual Ondrišák did prove that eCPC works across accounts and various campaigns. Matěj Slavík who uses a static weekly script system to manage bids that are then "adjusted" by eCPC strategy, sees a better response to seasonality trends than he does with the classical CPC strategy. Jan Zdarsa perceive the new eCPC as a "light version of tCPA". It does not have boundaries, but the algorithm is not as aggressive as the target CPA. Michal Voskár compares it to automated bid adjustments.

Many experts told me that the tROAS or tCPA did not work because they chose the wrong timing, setting, or simply chose the wrong campaign for smart bidding. In the following paragraph describe the 8 most important features the campaign or project had when the smart bidding worked well. (1) relatively stable conversion rate above 3%, (2) the conversion lag should be low. David Choleva stated that the campaign should not have more than 15% of conversions performed after the twelfth day after an ad click. Martin Zítek recommends having (3) stable feed more than 2 years to let the algorithm calculate the seasonal peaks. Marek Mašek recommends choosing a campaign with (4) lower impression share than 80%, because then the tROAS is set to maximize the IS till it reaches the predefined ROAS. So, if the algorithm does not have space to grow, the bidding solution will not have a much more significant effect. Michal Blažek believes that if the project has (5) a niche segment or, in the case of Google, a very distinctive target group, the algorithm works better. Also, (6) if the domain is a website specialized to only one product, the algorithm can more easily find the correlation, since a unique group of people visit the website. Moreover, (7) the larger the campaign structure is, the larger the volume of conversions needs to be that is available to the algorithm. (8) Google recommends having at least 50 conversions in the past 30 days, stable all the year, and 500 conversions total to ensure a fast learning period and stable performance. However, if some of these criteria are missing, it's important that the dataset of conversions be bigger, and the volume of conversions, higher. The recommended volume of conversions across the spectrum of interviewed experts is 200-500. However, they stress that smart bidding should at least be tested. I have heard from many great examples that smart bidding works perfectly with even 50 conversions.

The most crucial aspect of the smart bidding performance is patience. All of the experts explained that it is always painful to wait through a learning period to see some improvement. Many clients stop the experiment even within the learning period. The smart bidding's learning phases are extremely expensive, therefore the main thing is to set it up correctly, and create a long-term strategy in order not to fall into learning phase again (changes ±10-20%). This is especially true when the advertiser is switching to smart bidding on huge campaigns. Pavel Erfányuk, the head of PPC at Heureka, said that they have almost no other choice but to use smart bidding, since they have over 27 million products, and they experienced a hugely unpleasant situation during the learning period because the spending increase was extreme. Therefore, he recommends setting some alerting notifications and predefined budget constraints that would limit the learning periods huge spending.

Another important problem might be the start of smart bidding. It is necessary to start smart bidding during the standard e-shop season (not during Christmas, or when some unusual peaks may influence the learning period).

The minor drawbacks, in addition to the necessity of huge volume of conversions, are that marketers could not add more inputs to the algorithm (such as competitiveness in terms of product pricing) and that smart bidding is just a black box. Dalibor Klíč said that Google will soon incorporate the prices of the competitors into the matching algorithm. Moreover, it will add many features that are now available in Double Click Search (DCS), enabling it to add context to the algorithm through the business events. Some of these tools will probably be in AdWords as well. Another common disadvantage mentioned during the interviews was that the smart bidding over/under bids some search queries. Martin Zítek analyzed the histogram of average CPC search queries, and checked the distribution, as to whether the smart bidding strategy set analogically high bid search terms. He found out that the bids correlate to the normal distribution. The obvious overbidding happened in only 5% of all search terms. Dan Kotisa also mentioned that the machine learning algorithm is not that well developed in getting the meaning of the search queries, and therefore it requires an even higher data volume than is usual for machine learning algorithms.

The tCPA works similarly as tROAS. The difference, as stated by the experts, is that it requires a lower volume of conversions. However, Jan Matějček experienced that, in the case of Glami, the tCPA works better than tROAS. He believes that it is due to highly volatile conversion rate. The tCPA strategy can more precisely estimate the conversion rate than tROAS. So Matějček uses this smart bidding solution, and adjusts the targets for tCPA through a custom script that changes the target CPA level based on average exit click costs for each subcategory. The average exit click is, in this case, AOV because Glami is an arbitrary project.

Apart from the smart bidding strategies that this thesis is focusing on, Markéta Kabátová, Marek Mašek and Michal Voskár experienced that, by maximizeing clicks, smart bidding delivered higher revenue with a similar cost-per -onversions than the tCPA strategy. It was always a case of lead generating projects.

Several experts told me that while testing smart bidding strategies, they found that they deteriorated the campaign performance. When the bidding model was set back, the performance could not be reached ever after.

5.4.4 Ad testing

Jan Zdarsa perceives that nowadays Google offers the best tool for advertisers to test the ads with ad variation and experiments. However, the SEM specialists do not consider it as important as they used to perceive it to be. That is the hidden potential the advertisers are omitting. So it proved during the interviews. Experts rather spend the time adding specified elements into the feed to automatically create the ads with the best USP for the users. They believe that the most effort should be put in creating the ad copy. Advertizers need to be finding the real selling-points, either through discussion with clients, or via the more sophisticated way of scraping discussion forums or reviews at website comparison pages. However, the interviewed experts do not test which of the ad copies is better. Most of the experts told me that they almost never test new ads. Their main excuse was that they set an even ad rotation, but it did not show the ad evenly. They said that, especially with tROAS, the system was still showing the old "preferred version" much more than the new ad. Also, another problem is in deciding which ad works better, since CTR simply cannot choose, as described in the chapter 2.1.4. To omit the "problem" of not-even distribution of ads, Dan Zrůst is using campaign experiments. He creates an empty draft in AdWords interface, then editor-copies all the campaigns in AdWords, where tests the ads to the draft campaign. Afterwards, he changes the ads in the chosen draft campaigns, and the Google experiment will show the total impact on the campaign performance. In the end, Zrůst disclosed that the problem of suspicly unequal ad rotation is still apparent even with the campaign experiments.

One of the experts who tests the ads, Matěj Slavík also uses campaign experiments for ad testing. However, the importance of ad copy will increase in the near future. They are now already trying to include a specific element to feed-convey the most appealing selling point. The ideal situation is that the brand itself convey e-shop specific selling points – trust, quality of customer care, logistic quality, etc.-- and the specific USP of the product should be stressed in the ad. Then the ad will tell everything the user needs within the first few words that fit in the ads. However, they still let smart bidding choose their ad copy. Most of the responding advertisers are trying to have at least 3 ads, because it truly helps the performance. And they are doing ad testing in a way that they just add new ads and let Google to decide which performs better. They usually add new ads when the ad relevance is low in the campaign level. Markéta Kabátová does not even set the ad rotation to evenly. She labels the new ads and she believes that if the new ad copy is really better than the previous, Google will prefer it over the old one even with smart bidding strategy. The other extreme is Lukáš Hvizdoš's approach. He has the even rotation always set in all his campaigns, even when he has no A/B test running. His reason is that the accounts are small, and the machine learning solution from Google frequently preferred an ad that was perceived as better simply because immediately after the ad started, someone converted. The system did not change to the other ads, and the algorithm decision was clearly inaccurate, since the second ad could have performed better. When Lukáš Hvizdoš does the A/B test, it is a longitudinal experiment. He checks the performance of the ads based on the labeling system. This approach can ensure that even small Ad Groups have enough data and moreover, he can see the trends and the patterns that change in time. Therefore, he can adjust or create new ads based on the insights from the A/B test.

An interesting ad copy approach that is worth mention is from Samuel Ondrišák. He is using specific promotion codes in the headlines. The CTR is higher, but the increase in the conversion rate is remarkable, Samuel called it a "unicorn conversion rate".

5.5 Shopping

Many experts use smart bidding with shopping products, because they have much more dataset eligible for smart bidding. The experts estimate that the average e-commerce players spend around 60-70 percent on shopping campaigns. Campaign structure reflects most of the time is given to the applied bidding system. Interviewed experts still believe that for smart bidding strategies, it is better to keep the campaigns together. Hana Kobzová found out that if the campaigns are more segmented, the amount of impressions is higher, even though how the campings are structured should be irrelevant since December 2017, when the tROAS started using only product ID performance. However, manual bidding is still applied, especially for the top performing products, because the conversion rate is usually much higher than at the rest of the products. The best practice appears to be to use manual bidding at the beginning, with the so-called "Bloomarty" logic as described in the theory chapter 2.2.1 When the campaign reaches a certain level, it is wise to test the smart bidding solution, and to use the tROAS strategy if it performs better. Matěj Slavík is using a "Bloomarty" structure, even though he has a tROAS portfolio enabled to keep the search terms overview. It helps him to estimate the potential change if the target for ROAS is changed, and to be exposed to possible opportunities, such as the different behavior of different cohorts, etc.

The shopping campaigns for website comparisons works differently. Heureka is only promoting the "cart" products which can be directly purchased without leaving Heureka's site. Pavel Erfányuk said that they add the feeds from the cooperating e-shops directly to the Merchant center in order to keep the highest accuracy of the feeds. They have more then 200 different input feeds. On the other hand, Honza Matějček got accepted for CSS certification[34] with Glami, so they can use the shopping service even though they do not sell any product directly.

5.5.1 Manual bidding

The most crucial problem of manual bidding is that the some of the advertisers do not separate the campaigns in order to distinguish the differences in the search queries. They have one campaign and set the bidding on the product group level. Even if they know about the "Bloomarty" style, they do not know how to use the logic if the project is different from the one that Martin Roettgerding showed at the Marketing Festival. Some these specialists stick strictly to the presented structure – Products, Brands and Rest campaign-- and when the products do not have such attributes, they do not use any method that would differentiate between the varied performance of search terms. Dalibor Klíč confirmed that the PPC specialists do not really understand the shopping campaigns, and they are not able to use the "Bloomarty" or similar methods as well. The problem described above, the issue of an inadequate quantity of data for ML is also applicable for shopping campaigns. When

[34] Comparison Shopping Service - https://comparisonshoppingpartners.withgoogle.com/

smart bidding is not working, then it is suitable use methods for manual optimization and structures, which can be applicable, for example, the "Bloomarty".

Search term optimization

Those who know and use this methodology in shopping campaigns face the obstacle of limitations in excluding keywords. Ondřej Švarc needs to have 9 accounts for shopping just in the Czech Republic, mainly because he is using the list of negative keywords. This problem also faced Samuel Ondrišák, who solved it by creating more MCC accounts that are linked to a specific account, and, via script, he is able to add or remove specific excluding keywords in MCC level lists without the necessity of creating more accounts. Undoubtedly a strategy is needed for excludeing keywords. Karel Rujzl pointed out that if this method is used for a long time (+2 years), the campaigns might contain excluded keywords that might be profitable. There might be keywords excluded 2 years ago because of poor performance, but now they might be performing well. Matěj Slavík is including the excluded keywords in a broad match type, and only uses words that are brand or model specific, like "100ml". This structure provides an overview of the search term characters, and how they are evolving in time. The rest of the search terms are, in his case, handled via the tROAS anyway.

Bidding

Most of the experts that are using semi-automatic bidding in search campaigns use similar approaches in shopping campaigns. However, there are some differences. The shopping campaigns only enable the sharing of impressions to predict whether the bid should be increased or decreased. Jakub Kašparů also checks the products with the high benchmark CTR and the low CTR, and tries find the reasons for their respective performance, and, based on this insight, tries to change the titles or pictures. But he found out that the product price plays an unexpectedly huge importance in ad performance, and with one client he suggested changing the price and that was successful, because the higher volume and lower marketing spend increased the client's profits even though the margin was lower. Ondřej Švarc found that it is very efficient to adjust the bid more "aggressively" for better performing categories, but not for less performing ones. Several experts said that another disadvantage is that the first broad campaign could be too narrow, since the bids could be set too low. Lukáš Vožďa uses an interesting approach to handle this issue. He splits a broad campaign in two, based on the different conversion rate behavior of the audiences. One only targets the current database of customers, and in the second campaign, this audience is excluded. This solution enables him to more precisely track the bids, and more interestingly, also the search terms that appear in the campaign using that audience. Pepa Folta also uses the label strategy to do bid changes. He has a script that structures his product group into an ad group. Moreover, he labels the ad groups with a notification to change bid, and the script adjusts the bids on the product group level. The result is that the bidding changes are performed, and Folta sees a record of them in the labels.

Another relatively common way of bid optimization is to use Optmyzr. This tool enables product group refreshing to adjust the structure that corresponds to the actual product ID, and changes bids frequently for the different products. The bid changes can be done based on the same rules other experts use in their scripts, because the tool works with custom labels. The benefit, according to Martin Zítek, is that Optmyzr labels each change, and it does not change bids for some time till the next bid change is performed. Jirka Homola most appreciates the predefined views on different aspects of campaigns, and he changes the most important aspects based on the patterns that can be easily spotted in the Optmyzr.

Product structure

Adam Šilhan and Michal Blažek stressed that whenever the smart bidding is enabled at Google shopping, the structure of sold products changes. Google prioritizes some categories, and the impressions increase. On the other hand, some categories are promoted less. Adam Šilhan recommends doing the analysis of the product structure before and after enabling the smart bidding strategy. Ondřej Švarc tried to push the product with the highest margin in a generic search term campaign. However, it was very time consuming to exclude the specific search terms related to other products, and the effect was very small. It happens very often that people that click on a product using a generic search, and end up purchasing a different product. Product attribution is more important in shopping campaigns, so the analytical team at Alza set up Value Tracking, as described in the first chapter of this thesis.

5.5.2 Smart bidding

The rules described in chapter 2.1.4 can also be applied for smart bidding in PLA. Karel Rujzl explained that the difference is in the aggressivity in changes. Target ROAS in shopping campaigns can be changed monthly changed by 20% because the change in performance is much faster. Sometimes happen to him that a learning period starts again, but the period is always short. David Choleva uses tROAS for almost every shopping campaign at Mall Group with the exception of the top products. The structure of campaigns is the same as the BI structure. So it enables him to compare product categories across different countries, where Mall Group is active. Kamil Kotraba, the performance specialist at Bonami, said that tROAS tripled the shopping performance and the growing trend is still apparent. Kamil Kotraba assumes that it is due to the fast-changing products that can smart bidding handle better than any script. They tried for instance magic script, but it didn't increase the performance. Kamil also seen that tROAS can very efficiently work with segment promotions that are in Bonami common. The tROAS spot quite early high increase in conversion rate and the products are more often sold out so there are not very big problems in overbidding when the promotion is over.

5.5.3 Feed optimization

According to many experts, it is the most important part in optimizing shopping campaigns are as follows: (1) main categories and titles, (2) product price change and (3) pictures.

Main categories and titles

The essential is to edit all products into to the right categories and other detailed product description fields that help Google to categorise the products and also not to hide the products that are not available. Matouš Ledvina, agency performance manager at Google, confirmed that custom labels are not taking as inputs for the smart bidding algorithm. The title and description optimization is a controversial theme. Some experts did not find any correlation with a title or description improvements and the performance change. Some did improve the performance after adjusting the titles. They believe that highly depends on the optimization style. The adjustment should follow the recommendation in AdWords help. Matěj Slavík did several experiments in changing the order of elements in the title. The goal was to find the best way the users want to see the product name order. After they have everything in the title, the descriptions don't convey much extra information. However, they have customized descriptions on the website. Jan Matějček enhances the feeds from the e-shops with more information containing the characteristic of the product from the machine learning tool as described previously.

Pictures

Onřej Švarc tried to differentiate their pictures from the competition. For example, put their mascot Alzák in desktop or TV screens in the product pictures. However, the effort with creating such pictures didn't bring the expected effect on performance. It is very important even for Matěj Slavík, said that they put always all the 3 possible pictures and let Google's AI pick the best. They stress the importance of a unique picture because it works better not just in the shopping campings but also the product is more appealing in retargeting formats and the landing page itself as well. Michal Blažek said that after various of experiments he found out that the closer the product is to the camera lens and the zoomed the products are, the better performance they had.

Price

According to many experts, the product price has the highest influence on performance. The more competitive price cause higher CTR. The conversion rate is better since the people know they need not compare prices anywhere, so it enables to increase bids. Higher CTR results in higher QS which together with higher bid improves the AdRank and the result is in better positions. According to Martin Zítek the experiments with pricing, adjusting margin and will have an influence on performance across all channels. The main goal should be to find where lowering the margin would save the marketing costs and also generate more revenues due to higher volume sold. He believes that especially shopping performance depends more on price than on bidding. Peter Pleško also mentioned that if the price is discounted it is better to use the new tag <g:sale_price>. Google will show the price drop directly in the ad.

Pavel Erfányuk doesn't agree, at least not for his project. He believes that people know Heureka and it is a natural pillar in purchasing cycle. For example, the search ads are not displaying any price and in Google shopping are promoted only e-shop from the Heureka cart, which is not the cheapest.

5.6 Future

The vast majority of experts believe that the future in online advertising will be influenced by the development of AI, especially the linguistic part of machine learning. If the algorithm would be able to understand the meaning of search terms than the search advertising will be much easier automated than now.

Most PPC experts predict that the work they are currently doing will not be needed in the future (10-20 years from now). Many specialists predict that PPC specialist will not be needed. Jakub Kašparů said that the PPC specialist who is now between Google and the client, will not be needed. PPC specialist themselves will help Google to make this transmission. Currently, they are like ambassadors explaining the clients the advantages of smart bidding tools. Some experts believe that Google will not even enable to set up and optimize campaigns as we can today. Dan Zrůst simplifies that in future, Google will just let advertisers insert domain of their website, set the target and credit card number. These opinions are based on the past changes that Google did, such as disabling to manage the app campaigns in the new Universal App campaigns. Shopping campaigns combine with the retargeting campaign[35]. It is only a matter of time when the Universal campaigns will roll also for shopping campaigns. Zrůst expressed that it would be interesting, how Google will handle projects which have almost “untrackable” conversions - e. g. industries where the volume of online micro online events (web forms, calls) could be high while only small portion of leads is good enough to be considered as a proper "conversion" (e.g. some sort of contract signing). Sample industries could be various insurance/utilities comparison site where real human being needs to talk to the lead and evaluate it's quality first..

According to most experts the manual adjustments, that SEM specialists do nowadays, will disappear. It will be either automated directly via AdWords features or as a minority of experts believe via 3rd party tools. The only tools that would be applicable for bidding can be cluster the performance of more channels like AdWords/Bing and Sklik. Another tool that would increase the effectiveness would be the competitors checking tool. However, most of the bidding tools nowadays just download the data from GA or AdWords and they simply cannot compete with Google if they will not use something extra.

The “future PPC specialists” will do less manual and repetitive work and they will be either more analytical and business strategy roles or focus on the creative side of PPC. The analytical thinking is crucial for decisions in AdWords campaigns. Jan Zdarsa can see that people with data science background can be much more successful than other colleagues that do PPC for decades. It is the way people think. The future PPC master will need to be able to get the important data from the system and find the patterns or hidden logic to scale up the campaigns. Stanislav Jílek emphasized: “We will manage the robot”[36]. According to

[35] https://adwords.googleblog.com/2018/05/drive-sales-and-reach-more-customers.html

[36] Translated by the author

Dan Zrůst and Ondřej Švarc, the most important skill for future PPC specialist will be in connecting the internal databases with AdWords data and find insights from this enhanced dataset. The only PPC skill that will be necessary is to understand the possibilities of each platform and understand how the algorithms work and how the performance could be adjusted. Milan Merglevský predicts that UML[37] will develop and be used much more in the future. Even though some experts predict that the strategy will also be done on the Google because the algorithm could better allocate budget based on Google Data-Driven Attribution. The machine learning may optimize the budget, however, the long-term vision of the company needs to be set by a human. Moreover, the Google Attribution is still a very disguised product, and nobody knows when it will actually properly work. In the near future, according to the Adam Šilhan, the PPC specialists should realize that the repetitive task will be automated. They should try to automate it with current solutions to be used to "control" robots and proactively try to automate these tasks and create culture of experimenting. Most of the experiments will not result in some great outcome, but it keeps the account ahead from the competitor's. Since the manual work on campaigns will shrink, the experiments will make the difference. The SEM specialist should focus on the insights that are hidden in search data. They can predict the demand, estimate the inventory and optimize the pricing strategy. According to all experts the more importance will be on conversion rate optimization and more website optimization.

The creative branch of online marketers will create the ad copies and visuals and according to Daniel Kotisa tonality of all channels, understand the logic and position of each channel in the purchasing decision will be necessary to create the storytelling experience. Adam Šilhan stressed that the search ads are alike already. There is untapped opportunity to increase performance by ad copy experiments. Some experts are not sure whether the creative part of search campings will be necessary in the future since Google is now testing automatically generated ads. But Jan Zdarsa stresses, that Google will never use data from other advertisers to generate better ads of another. The machine learning might create the ads but only based on the ads that are already in the account.

The only skeptics are Markéta Kabátová and Pepa Folta. Folta thinks that still in next 15 years, the PPC specialists will still need to optimize and create the campaigns structures manually. However, the main optimization will be in his opinion, the website adjustments. Michal Blažek is afraid that the PPC channel will deteriorate due to increasing regulations and higher usage of Ad Blocking users as is seen in Asia. The companies should not be so dependent on traffic from paid channels. The importance of branding is growing.

Small vs. Big Players

The automation will lead to higher bids and perfect competition. All experts stressed that the difference will not be in PPC management but in the whole customer service. Firms will try more differentiated and improve the logistic, inventory management or pricing

[37] unified modeling language

strategies. The big companies will have much more data that can help the algorithm to work better. The small companies will be able to compete in terms of AdWords in local search. Ondřej Švarc, on the other hand, believes that big companies will attract more efficiently new customers buy their brand. From experiments with branding, he really could see higher CTR among specific product segments. Matouš Ledvina predicts that as the fast-growing companies reach a size level that makes their decision rigid, the smaller players will be able to attract niche segments back. Google is enabling the same technologies for everyone.

Conclusion

The lack of scientific proof of the smart bidding performance on the relatively small market led to the goal of this thesis, which is performance comparison of manual versus smart bidding. The experiment was conducted on search, DSA and shopping campaigns of a middle-sized account. Specifically, it was a bookstore in the Czech market. All the campaigns were separated into two parts, so no external effect should have influenced the results and the results were analyzed with Wilcoxon paired test and validated with other statistical analysis. I optimized the manual control group with the semi-automated approach with is based on the main rules. The reason for this approach was to make the optimization as objectively as possible for further re-application of this research in the future. Moreover, the optimization itself required only a short period of time each week.

The results show that the Search campaigns are performing differently depending on campaign segment. The campaign with the highest priority for the advertiser was slightly overbid in manual setting and the total volume of conversions was significantly higher in manual setting. However, the smart bidding lowered the CPA. On the other hand, another insight from the experiment can be seen in a semi-automated campaign targeting over 5000 authors. The smart bidding enabled to differentiate the performance and increased the conversions by 216% within the predefined CPA. The performance of DSA campaigns was significantly better since the conversions increased and CPA decreased. The overall outcome is that smart bidding works better in Search Network. This result strongly shows how beneficial it can be to test the smart bidding strategy.

The design of Shopping experiment was done differently. The product feed was divided into two same size groups and on one half was run tROAS and the second half was the control group optimized manually with the semi-automated approach. The increase in revenues was significantly higher, however, the drop in ROAS did not prove that smart bidding performs better, rather the opposite. The data were analyzed with Causal Impact to more precisely identify the incremental increase of revenues, which was negative. Compared to the volume of manual campaigns and its efficiency, the manual bidding was better than the smart bidding. Because the extra cost that was spent did not result in the increase in revenues that would make sense for the business. However, it also depends on the business goals. This experiment will continue in the future with higher target ROAS to see whether the algorithm could be at least as effective as the semi-automated manual bidding.

The second part of the research was conducted to find how the experts really use the automation in creating search and shopping campaigns and what do they use to optimize them. I conducted 31 in-depth interviews, which took on average 90 minutes. The respondents were experts from various projects, in order to cover many approaches in AdWords automation. This diverse group enabled me to create Automated Builder of Campaigns (ABC) framework, which enables the advertisers to use the most appealing USPs that are relevant to the specific landing page in the Search Network campaigns. Moreover, the different ways of ad testing are outlined. The research revealed that many PPC specialists omit the ad testing, which is still very important part of campaign optimization.

However, even more surprising outcome of the research is that many interviewed experts do not realize the logic of separating the shopping campaigns based on different conversion rate of search terms. All of them claim that they know the concept called among PPC specialists "Bloomarty" presented at Marketing Festival. However, the in-depth interviews revealed that they use it only when it precisely meets the example presented by Martin Roettgerding at Marketing Festival. However, the essential logic of the method is applicable to any project in shopping campaigns.

Furthermore, I summarized the various approaches of bidding. The best practice across various projects is to start with manual bidding using a predefined semi-automated style of bidding. After the campaign volume reach a level when the smart bidding test is applicable, the advertisers should test it. In case of shopping campaigns, the structure should be differentiated by the search term logic. When the portfolio strategy of tROAS proves to be better in the test, the structure can be kept the same because the smart bidding does not take the campaign structure into consideration. Moreover, the research outlined 8 main characterizes that influence the smart bidding efficiency.

Some experts revealed their automated tools that run on Google's ML system for example for search term optimization. These tools might be implemented in the AdWords in near future and in the 10 or 15 years, the role PPC specialists will not exists based on the research results. The clients will not need a specialist, because Google will make the AdWords system more intuitive and the campaign setting will be highly restricted as we can see nowadays with Smart App campaigns. The only necessary roles will be a "creative producer", who prepares the ad templates and banners and the analytical role. The analytics would calculate the targets and performance of all the marketing channels. When this transmission will happen highly deepens on the ML development in the word and text analysis.

The further research would be needed in estimating the impact on the marketing efficiency based on the price change of the product. Especially in the Shopping campaigns, because most of the advertisers believe that the marketing cost would drop since the lower priced product perform better on PLA. Especially if the future prediction is true and AdWords will become "black box". The price of a product will be the only way how to "optimize" the performance.

I want to conclude this paper with the quote from Brad Geddes that summarise the approach the advertisers should have. "As the industry is ever-changing, those who can continuously evolve their marketing can find great success." (Geddes, 2014, p.17)

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List of tables

Table 1Profit vs. ROAS 11

Table 2 Differences in recommended number of conversions between Target CPA and Target ROAS 19

Table 3 Impact of Quality Score on CPC 29

Table 4 Incremental increase of revenues caused by smart bidding in Google Shopping 47

List of pictures

Picture 1 Profit curve 12

Picture 2 Target CPA Bid Simulator 13

Picture 3 Serach Network Campaing Structure 22

Picture 4 Google Text Ad Minimum Bid Estimates 24

Picture 5 Serch 2.0 - Campaign Comparison: Pre & Post Campaign Optimization 25

Picture 6 Total spent on exact match keywords 26

Picture 7 Misleading CTR in Ad A/B Testing 31

Picture 8 Increasing share of Shopping Investment in Comparison to Search Netwrok Ads 32

Picture 9 "Bloomarty" Campaign Strucutre of Google Shopping Campaigns 32

Picture 10 Effect of Product Title Change on the Impressions in Google Shopping 34

Picture 11 Price as an important algorithmic signal 35

Picture 12 Optimization diagram: The strategy for bidding rules and search terms optimization 38

Picture 13 A/B Test of Smart Bidding Strategy Based on Ad Schedule 39

Picture 14 Optimization diagram of Shopping campaigns: The strategy for bidding rules and search terms optimization 40

Picture 15 Predictors used in the Causal Impact calculation 46

Picture 16 The Causal Impact 48

Picture 17 Automated Builder for Campaigns (ABC framework) 52

Appendix 1

The normal distribution

	Eligible for t-test	Skewness		Kurtosis		Standard Deviation	
		manual	smart	manual	smart	manual	smart
Search Campaings							
cost	Yes	0.257	0.956	-0.891	0.998	10.063	10.965
conversion	Yes	1.282	0.814	2.287	0.425	3.964	3.552
revenue	No	4.357	1.297	23.505	1.336	171.340	112.968
CPA	No	1.934	1.383	4.908	2.358	2.507	2.111
DSA Campaigns							
cost	Yes	0.828	0.257	-0.230	-0.782	5.619	2.969
conversion	No	2.324	1.100	7.767	1.263	2.290	1.744
revenue	No	1.988	1.328	3.993	1.273	55.210	52.054
Total Search Network Camapings (DSA + Classical search)							
cost	Yes	0.559	0.598	-0.689	0.224	12.499	11.743
conversion	Yes	1.118	0.556	1.550	-0.378	4.450	3.652
revenue	No	3.623	0.802	17.535	0.044	178.872	116.072
CPA	No	1.784	1.026	4.680	0.634	2.176	1.553
Shopping Campaigns							
cost	Yes	0.154	-0.296	-0.114	-0.619	8.204	16.022
conversion	No	1.438	0.105	3.271	-0.608	4.234	4.648
revenue	Yes	1.015	0.373	0.699	-0.648	104.049	131.456
ROAS	No	0.753	2.106	-0.537	6.480	3.886	2.738

Appendix 2

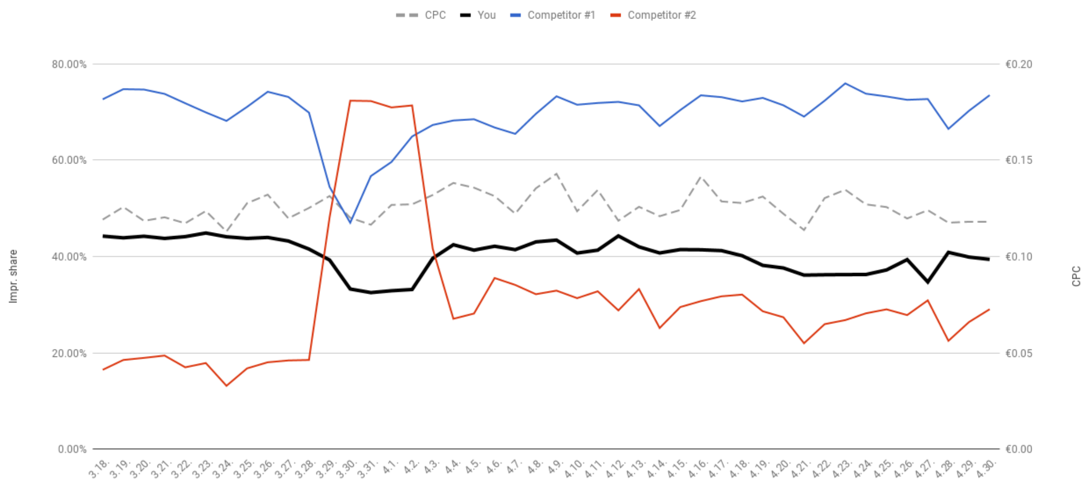
Time DSA a SEA: 15. 1. - 27. 2. 2018 a Shopping: 15. 1. - 13. 2. 2018

Conversion lag

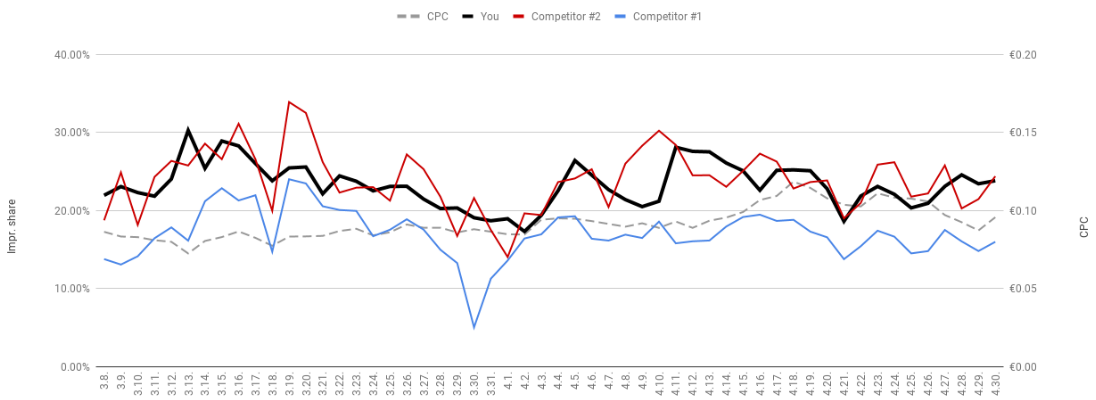
Days to conversion	Shopping	Search	DSA
<1 day	81%	78%	70%
1-2 days	2%	1%	5%
2-3 days	2%	2%	3%
3-4 days	2%	2%	1%
4-5 days	1%	1%	2%
5-6 days	1%	0%	2%
6-7 days	0%	1%	0%
7-8 days	1%	1%	1%
8-9 days	1%	0%	0%
9-10 days	1%	1%	0%
10-11 days	0%	1%	0%
11-12 days	1%	0%	1%
>12 days	8%	12%	14%
12-13 days	0%	1%	1%
13-14 days	1%	2%	0%
14-21 days	2%	4%	2%
21-30 days	5%	5%	10%
Conversion rate	5%	2%	2%

Appendix 3

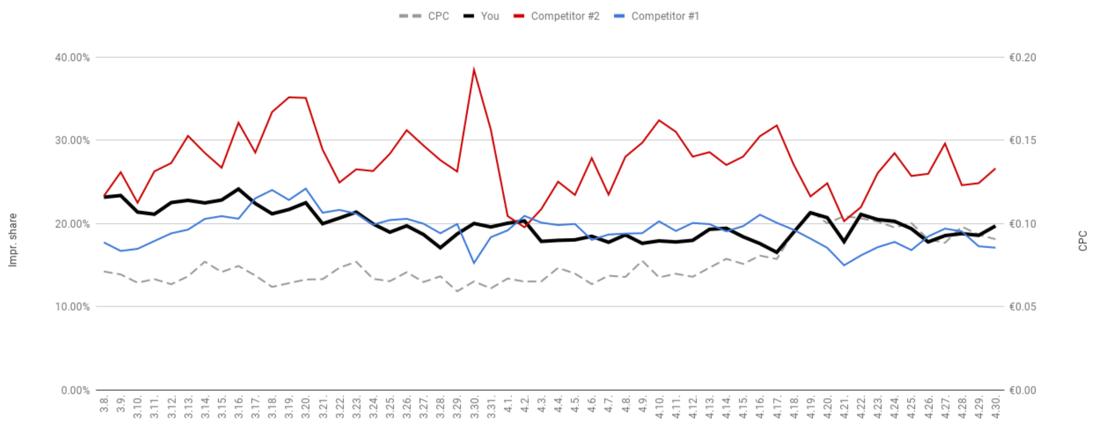
Shopping campaigns Auction Insights



Search Campaings Auction Insights

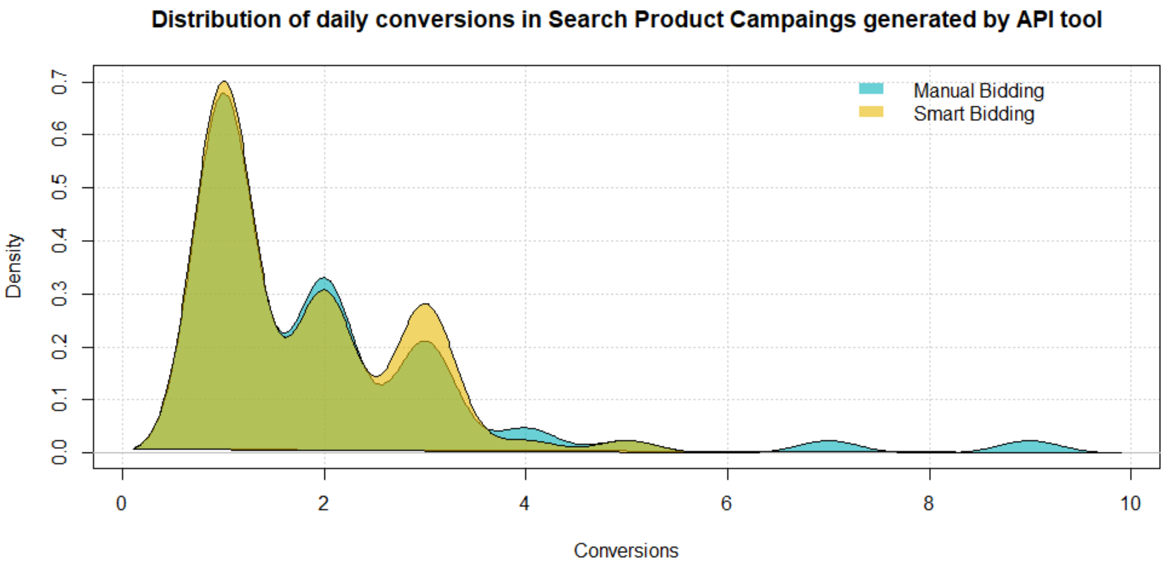


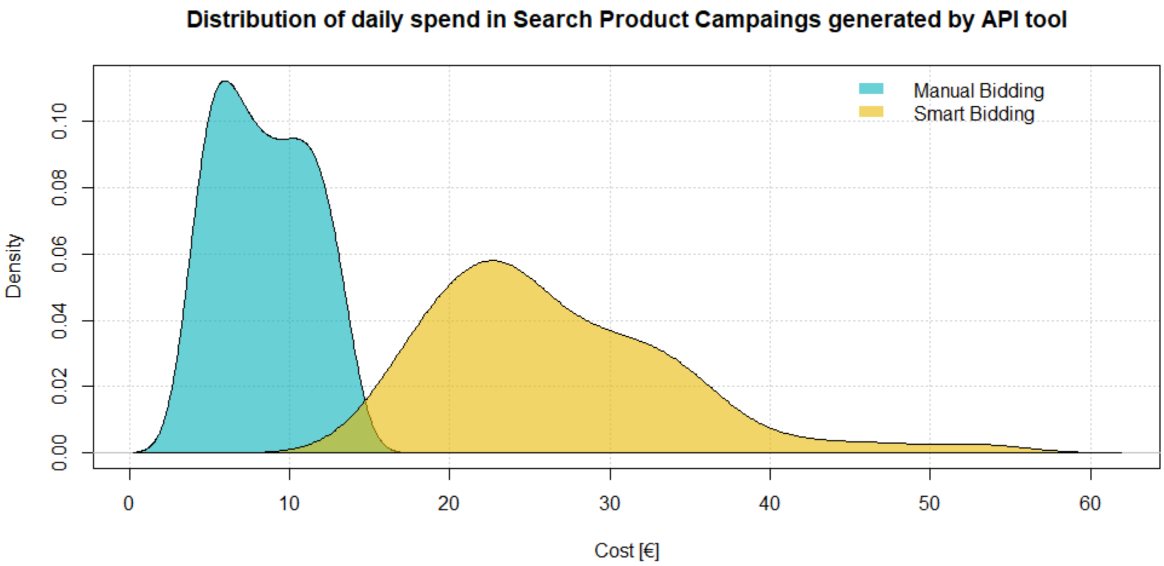
Dynamic search ads Auction Insights

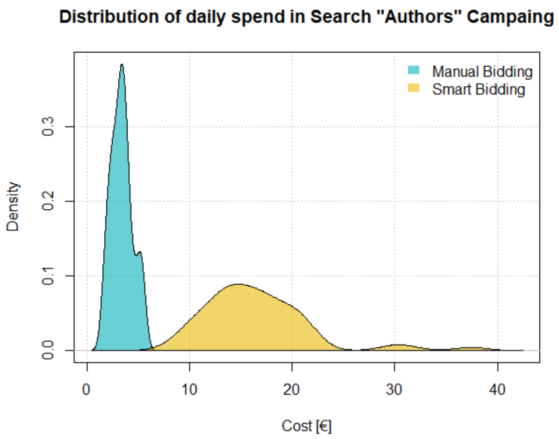


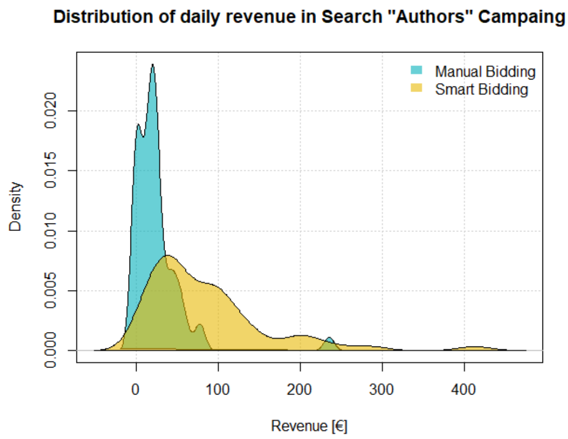
Appendix 4

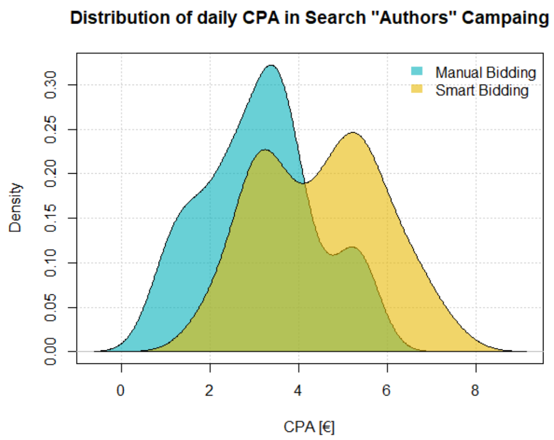
The visualization of densities from important datasets from the experimental research.

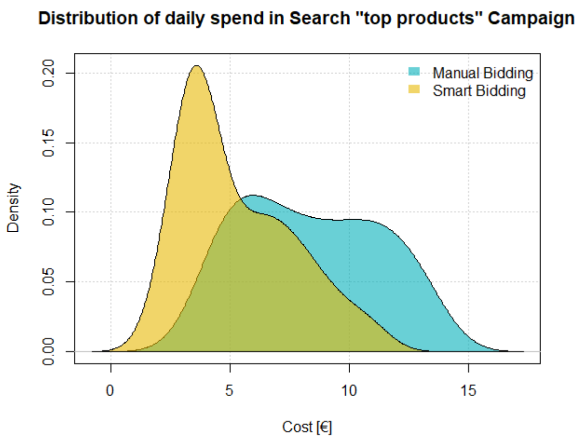


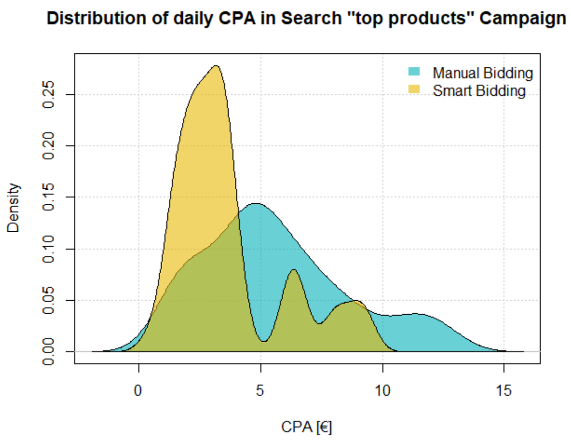


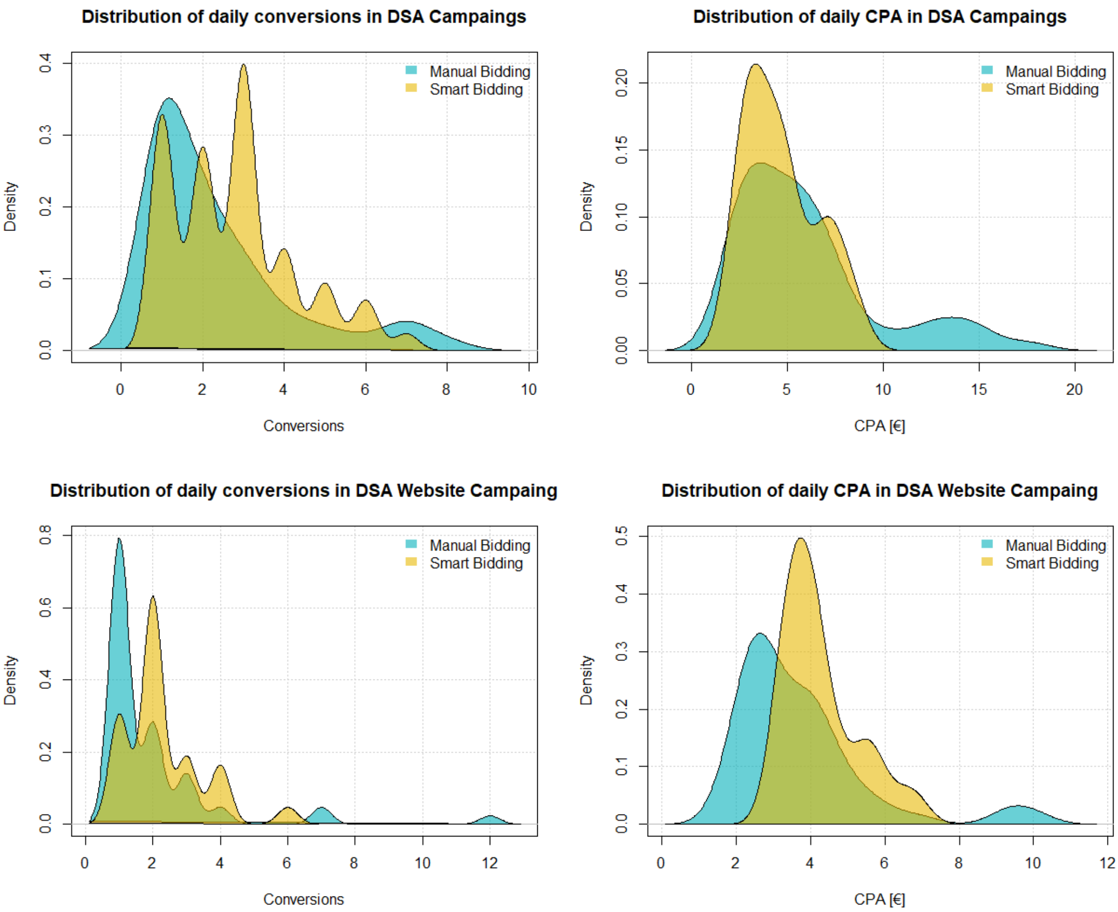

Distribution of daily spend in Search "Authors" Campaing
Manual Bidding
Smart Bidding
Density
0.0
0.1
0.2
0.3
0
10
20
30
40
Cost [€]


Distribution of daily revenue in Search "Authors" Campaing
Manual Bidding
Smart Bidding
Density
0.000
0.005
0.010
0.015
0.020
0
100
200
300
400
Revenue [€]

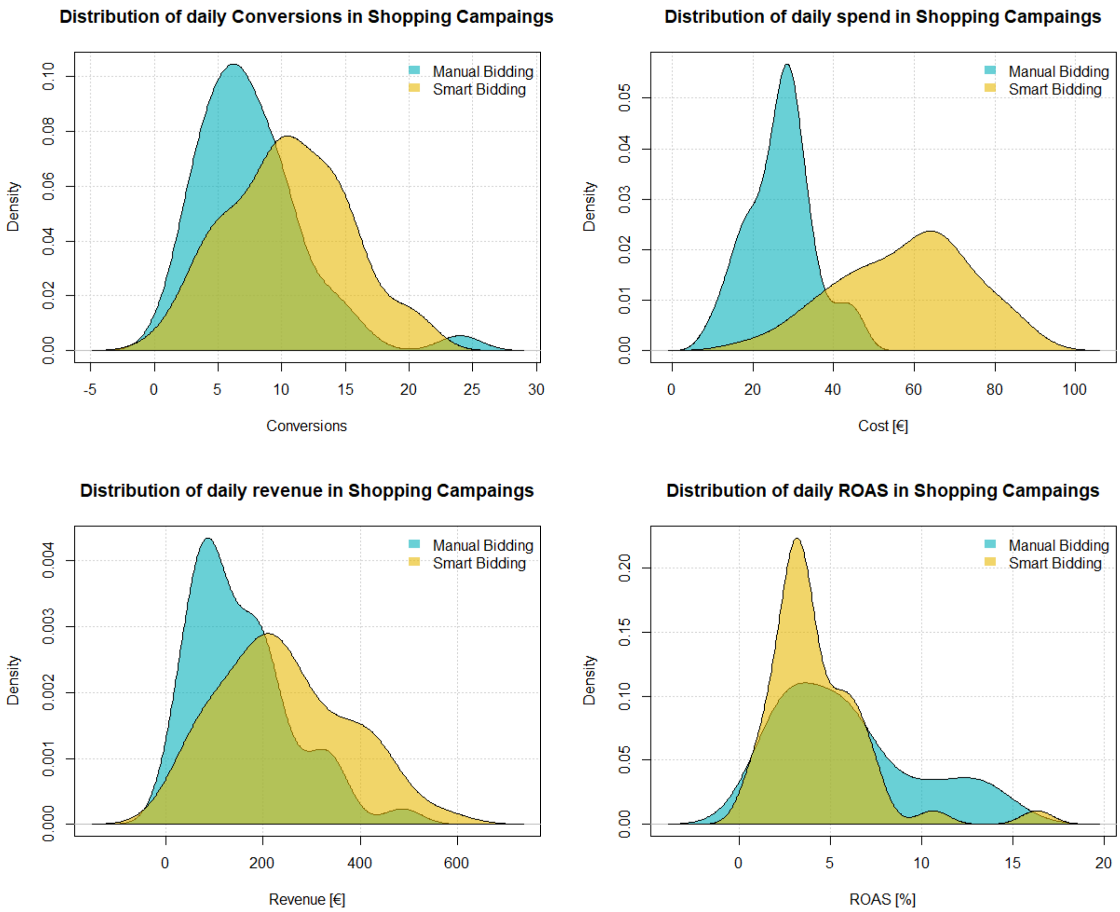

Distribution of daily CPA in Search "Authors" Campaing
Manual Bidding
Smart Bidding
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
CPA [€]


Distribution of daily spend in Search "top products" Campaign
Manual Bidding
Smart Bidding
Density
0.00
0.05
0.10
0.15
0.20
0
5
10
15
Cost [€]

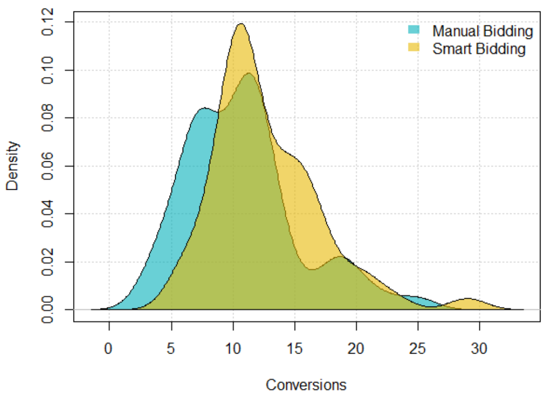

Distribution of daily CPA in Search "top products" Campaign
Manual Bidding
Smart Bidding
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
5
10
15
CPA [€]



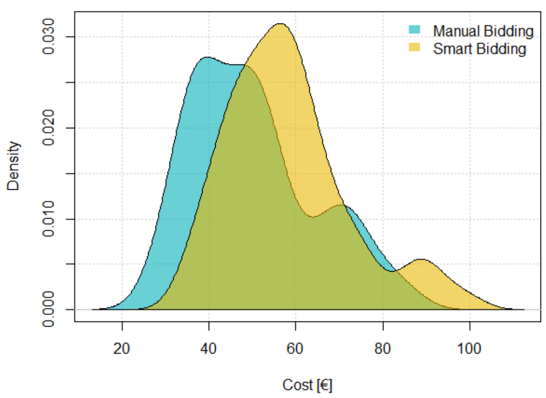
Distribution of daily conversions in DSA Campaings
Manual Bidding
Smart Bidding
Density
Conversions
Distribution of daily CPA in DSA Campaings
Manual Bidding
Smart Bidding
Density
CPA [€]
Distribution of daily conversions in DSA Website Campaing
Manual Bidding
Smart Bidding
Density
Conversions
Distribution of daily CPA in DSA Website Campaing
Manual Bidding
Smart Bidding
Density
CPA [€]


Distribution of daily Conversions in Shopping Campaings
Manual Bidding
Smart Bidding
Density
0.00
0.02
0.04
0.06
0.08
0.10
-5
0
5
10
15
20
25
30
Conversions
Distribution of daily spend in Shopping Campaings
Manual Bidding
Smart Bidding
Density
0.00
0.01
0.02
0.03
0.04
0.05
0
20
40
60
80
100
Cost [€]
Distribution of daily revenue in Shopping Campaings
Manual Bidding
Smart Bidding
Density
0.000
0.001
0.002
0.003
0.004
0
200
400
600
Revenue [€]
Distribution of daily ROAS in Shopping Campaings
Manual Bidding
Smart Bidding
Density
0.00
0.05
0.10
0.15
0.20
0
5
10
15
20
ROAS [%]

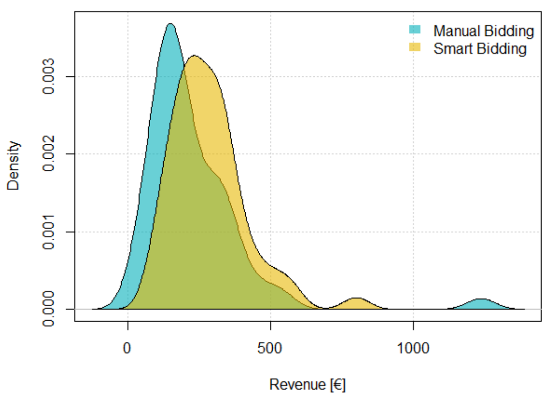
Distribution of daily conversions in Search Network Campaings



Distribution of daily spend in Search Network Campaings



Distribution of daily revenue in Search Network Campaings



Appendix 5

The respondents from the in-depth interviews.

name	company	position	comment
Adam Šilhan	igloonet	Head of Marketing	Google Partners Trainer
Dalibor Klíč	Google	Industry Manager for e-commerce	
Dan Zrůst	Avast	Digital Marketing Specialist	author of ExcelinPPC.com
Daniel Kotisa	freelancer		Google Partners Trainer
David Choleva	Mall Group	Performance Marketing Manager	
Hana Kobzová	freelancer		recommended by Russell Savage for AdWords Scripts
Jakub Herman	Placement.cz	co-founder	
Jakub Kašparů	Lynt services	co-founder	author of PPC Robot and advanced scripts at ppc-scripts.eu
Jan Matějček	Glami	PPC specialist	
Jan Zdarsa	Google	senior analytical lead	
Jiří Homola	BESTETO	PPC specialist	
Jiří Mařík	freelance web analyst with specialization on performance		PhD. student at the University of Economics, Prague
Josef Folta	freelancer		former web developer
Kamil Kotraba	Bonami	performance specialist	
Karel Rujzl	freelancer		
Lukáš Hvizdoš	6clickz	PPC specialist	
Lukáš Král	Placement.cz	co-founder	
Lukáš Vožda	Proficio	web analyst	
Marek Mašek	Fragile media	Performance & Branding Specialist	
Markéta Kabátová	UnicornsLab	co-founder	organizer of the PPC Camp
Martin Zítek	Mall Group	Performance Marketing Manager	
Matěj Slavík	Notino	Head of PPC	
Matouš Ledvina	Google	performance manager	
Michal Blažek	Marketing Makers	co-founder	
Michal Voskár	Inevio	co-founder	former performance manager at Google
Milan Merglevský	H1.cz	senior e-commerce consultant	founder of Ecommerce-architects.com
Ondřej Švarc	Alza	PPC specialist	author of advanced scripts at OndraSvarc.cz

name	company	position	comment
Pavel Erfányuk	Heureka	Performance Marketing Specialist	
Peter Pleško	Fragile media	Performance & Branding Specialist	
Samuel Ondrišák	Ui42	PPC & technology leader	Google Partners trainer for Export
Stanislav Jílek	Onio	PPC specialist and data analysts	author of advanced scripts at Standajilek.cz

Appendix 6

The complete results from the experimental research

Dataset	Kurtosis Manual	Kurtosis Smart	Skewness Manual	Skewness Smart	Max manual	Max Smart	Min manual	Min max	sd Manual	sd Smart	median manual	median smart	normal distribution
DSAConversions	1.587	-0.072	1.548	0.737	8.000	7.000	1.000	1.000	1.816	1.524	2.000	3.000	no
DSACost	-0.168	-0.590	0.784	0.595	25.580	17.120	4.230	6.610	5.110	2.781	8.800	9.920	yes
DSACPA	1.094	-0.886	1.342	0.562	17.510	8.670	2.184	2.119	3.695	1.873	4.980	4.315	yes
DSARevenue	2.340	0.269	1.698	1.086	255.340	221.100	0.000	0.000	59.176	56.430	21.980	40.030	no
DSAWebConversions	13.431	1.517	3.384	1.217	12.000	6.000	1.000	1.000	1.879	1.164	1.000	2.000	no
DSAWebCost	8.516	2.199	2.559	1.247	26.650	21.630	2.230	3.900	4.202	3.588	4.710	8.430	no
DSAWebCPA	3.758	0.114	1.894	0.994	10.100	7.010	1.676	2.890	1.795	1.006	3.150	4.003	no
DSAWebRevenue	7.867	4.032	2.660	1.907	255.340	221.100	2.100	0.000	48.775	44.030	12.590	30.720	no
PLAConversions	3.271	-0.608	1.438	0.105	24.000	20.000	1.000	1.000	4.234	4.648	7.000	10.000	no
PLACost	-0.114	-0.619	0.154	-0.296	45.930	85.720	9.140	19.130	8.204	16.022	27.630	61.440	yes
PLARevenue	0.699	-0.648	1.015	0.373	486.470	568.530	13.040	14.880	104.049	131.456	123.825	225.325	yes
PLAROAS	-0.537	6.480	0.753	2.106	15.112	16.300	0.700	0.778	3.886	2.738	5.430	3.447	no
Search_totalConversions	0.676	2.049	0.892	1.193	25.000	29.000	3.000	6.000	4.613	4.354	11.000	11.000	yes
Search_totalCost	-0.552	0.441	0.655	0.869	83.680	98.680	28.980	36.740	14.215	14.086	48.370	56.480	yes
Search_totalCPA	5.889	1.052	2.016	1.060	14.166	9.515	1.554	2.771	2.092	1.505	5.010	4.658	no
Search_totalRevenue	15.552	2.695	3.292	1.324	1237.930	800.830	25.690	91.700	178.849	131.700	175.480	262.470	no
SearchAPIConversions	7.621	0.479	2.498	1.044	9.000	5.000	1.000	1.000	1.518	0.964	1.000	1.000	yes
SearchAPICost	-1.261	1.505	0.145	1.126	13.830	53.160	3.710	15.300	2.890	7.579	8.100	24.710	yes
SearchAPICPA	-0.367	0.340	0.625	1.085	12.710	14.245	1.154	2.195	2.999	3.037	4.930	5.433	no
SearchAPIRevenue	3.213	1.198	1.697	1.295	172.760	111.750	7.290	8.380	33.117	23.205	23.380	20.420	no
SearchAuthorConversions	1.790	1.790	1.485	1.485	4.000	4.000	0.000	0.000	0.901	0.901	1.000	1.000	yes
SearchAuthorCost	-0.647	3.828	0.347	1.581	5.530	37.450	1.600	8.480	1.033	5.212	3.340	15.920	no
SearchAuthorCPA	-0.773	-1.004	0.117	0.059	5.530	7.453	0.805	1.944	1.273	1.389	3.280	4.687	yes
SearchAuthorRevenue	21.868	4.695	4.094	1.931	235.530	413.070	0.000	10.950	34.363	75.981	20.100	59.010	no
SearchBestConversions	7.621	0.479	2.498	1.044	9.000	5.000	1.000	1.000	1.518	0.964	1.000	1.000	no
SearchBestCost	-1.261	-0.522	0.145	0.767	13.830	10.930	3.710	2.000	2.890	2.326	8.100	4.370	yes
SearchBestCPA	-0.367	0.344	0.625	1.154	12.710	9.390	1.154	0.500	2.999	2.229	4.930	3.090	yes
SearchBestRevenue	3.213	1.198	1.697	1.295	172.760	111.750	7.290	8.380	33.117	23.205	23.380	20.420	no
SearchConversions	1.365	1.175	1.164	1.082	26.000	23.000	4.000	3.000	4.414	4.012	10.000	9.000	yes
SearchCost	1.957	0.387	1.166	0.956	94.270	82.290	25.410	29.960	13.403	12.679	48.580	45.830	yes
SearchCPA	0.338	2.398	0.781	1.388	10.810	12.553	1.839	2.311	1.857	2.102	4.813	4.848	yes
SearchRevenue	15.521	1.614	3.457	1.334	1290.420	622.940	42.080	29.540	188.793	122.705	175.060	206.290	no

T-test	t value	df	p-value	CI +	CI + [%]	CI -	CI - [%]	mean x	mean s	difference in means	change [%]
DSACost	-0.0296	86.5057	0.976	-1.5546	15%	1.50899	-14%	10.5184	10.5412	0.02281	-
DSACPA	2.39906	82.9872	0.019	0.22503	-4%	2.40782	-40%	5.98115	4.66472	-1.316426	-22.0%
PLACost	-11.45	64.0992	0.000	-36.492	136%	-25.65	95%	26.9134	57.9846	31.07114	115.4%
PLARevenue	-3.4572	81.6921	0.001	-137.66	89%	-37.096	24%	155.249	242.627	87.378	56.3%
Search_totalConversions	-2.3806	111.628	0.019	-3.6647	34%	-0.3353	3%	10.7193	12.7193	2	18.7%
Search_totalCost	-3.0018	111.991	0.003	-13.209	26%	-2.7049	5%	50.1251	58.0819	7.95684	15.9%
SearchAPICost	-16.884	71.9451	0.000	-20.282	242%	-15.999	191%	8.38737	26.5277	18.140351	216.3%
SearchAPICPA	-0.7467	111.982	0.457	-1.5425	27%	0.69806	-12%	5.6279	6.05011	0.422204	-
SearchAuthorConversions	0	112	1.000	-0.3346	24%	0.33458	-24%	1.38597	1.38597	0	-
SearchAuthorCPA	-5.0072	86.2675	0.000	-1.9208	61%	-0.8291	27%	3.12459	4.49955	1.374955	44.0%
SearchBestCost	6.32726	107.11	0.000	2.1349	-25%	4.083	-49%	8.38737	5.27842	-3.108947	-37.1%
SearchBestCPA	3.96139	103.391	0.000	0.97909	-17%	2.94218	-52%	5.6279	3.66727	-1.960635	-34.8%
SearchConversions	0.5329	110.993	0.595	-1.1446	11%	1.98673	-19%	10.6316	10.2105	-0.42105	-
SearchCost	0.82171	111.657	0.413	-2.8341	6%	6.85024	-14%	50.3207	48.3126	-2.00807	-
SearchCPA	-0.0496	110.323	0.961	-0.7547	14%	0.71784	-14%	5.25787	5.2763	0.018422	-

Wilcoxon test	W value	p-value	CI +	CI + [%]	CI -	CI - [%]	location parameter	change [%]	Final Results
DSAConversions	1239.0	0.024	-1.000	50%	0.000	0%	-1.000	50%	increase (50%)
DSACost	1436.0	0.287	-2.250	26%	0.820	-9%	-0.930	11%	-
DSACPA	1855.0	0.192	-0.230	5%	1.580	-32%	0.532	-11%	decrease (-11%)
DSARevenue	1277.5	0.049	-27.140	123%	0.000	0%	-12.630	57%	increase (57%)
DSAWebConversions	1077.0	0.001	-1.000	100%	0.000	0%	-1.000	100%	increase (100%)
DSAWebCost	691.5	0.000	-4.370	93%	-2.280	48%	-3.340	71%	increase (71%)
DSAWebCPA	1008.5	0.000	-1.207	38%	-0.413	13%	-0.848	27%	increase (27%)
DSAWebRevenue	1182.5	0.012	-19.940	158%	-2.400	19%	-10.300	82%	increase (82%)
PLAConversions	576.5	0.001	-5.000	71%	-1.000	14%	-3.000	43%	increase (43%)
PLACost	91.0	0.000	-37.640	136%	-25.960	94%	-32.735	118%	increase (118%; 115%)
PLARevenue	575.0	0.001	-136.890	111%	-35.320	29%	-86.270	70%	increase (70%; 56%)
PLAROAS	1196.0	0.057	-0.033	1%	2.572	-47%	1.222	-23%	-
Search_totalConversions	1199.5	0.015	-4.000	36%	0.000	0%	-2.000	18%	increase (18%; 19%)
Search_totalCost	1073.5	0.002	-13.080	27%	-3.300	7%	-8.130	17%	increase (17%; 16%)
Search_totalCPA	1809.0	0.297	-0.234	5%	0.774	-15%	0.270	-5%	-
Search_totalRevenue	1065.0	0.002	-112.250	64%	-28.670	16%	-71.290	41%	increase (41%)
SearchAPIConversions	1668.5	0.788	0.000	0%	0.000	0%	0.000	0%	increase (216%)
SearchAPICost	0.0	0.000	-19.070	235%	-14.980	185%	-16.940	209%	increase (205%)
SearchAPICPA	1511.5	0.524	-1.303	26%	0.697	-14%	-0.322	7%	-
SearchAPIRevenue	1822.0	0.264	-2.350	10%	9.260	-40%	2.924	-13%	-
SearchAuthorConversions	1624.5	1.000	0.000	0%	0.000	0%	0.000	0%	-
SearchAuthorCost	0.0	0.000	-13.630	408%	-11.180	335%	-12.400	371%	increase (376%)
SearchAuthorCPA	549.0	0.000	-1.965	60%	-0.777	24%	-1.422	43%	increase (42.9%; 44%)
SearchAuthorRevenue	510.0	0.000	-63.890	318%	-29.020	144%	-44.450	221%	increase (193%)
SearchBestConversions	1668.5	0.788	0.000	0%	0.000	0%	0.000	0%	-
SearchBestCost	2608.0	0.000	1.990	-25%	4.180	-52%	3.010	-37%	decrease (-46.0%; -37%
SearchBestCPA	2302.0	0.000	0.988	-20%	2.770	-56%	1.893	-38%	decrease (-37.3%; -34%
SearchBestRevenue	1822.0	0.264	-2.350	10%	9.260	-40%	2.924	-13%	-
SearchConversions	1681.0	0.750	-1.000	10%	2.000	-20%	0.000	0%	-
SearchCost	1824.0	0.259	-1.830	4%	6.280	-13%	2.300	-5%	-
SearchCPA	1671.0	0.794	-0.580	12%	0.718	-15%	0.083	-2%	-
SearchRevenue	1460.0	0.353	-50.780	29%	19.790	-11%	-16.020	9%	-