

Bayesian Parameter Estimation in Green Business Process Management: A Case Study in Online-Advertising

Tobias Blask

Leuphana University
Institute of Electronic Business Processes
Scharnhorststr. 1, D-21335 Lüneburg
Germany
blask@uni.leuphana.de

Abstract: Companies take their responsibilities for a sustainable planet more and more seriously. For online-retail businesses a significant share of all CO₂ emissions is generated by delivering goods to their clients. Now various companies are implementing a greener logistic chain into their business processes. What is a central question for these performance driven companies in this context is whether it pays to invest in additional costs for carbon neutral delivery and if the customers appreciate these steps and prefer retailers that behave in this manner. We develop and perform a non reactive A/B-test that enables us to evaluate the influence of sustainability information on the customers decision to buy a product by clicking on an ad on a search engine results page (SERP). We analyze campaign performance data generated from a European e-commerce retailer, apply a Bayesian parameter estimation to compare the two groups, and demonstrate the advantages of the given Bayesian approach in comparison to the application of Null Hypothesis Significance Testing (*NHST*).

1 Section heading

2 Introduction

Internet search engines like Google, Yahoo! or Bing play an undisputed key role in the modern information society. On the one hand they serve the information needs of their users, on the other hand they represent an important source of customer acquisition for companies in a broad variety of industries and sizes [JM08, AF11]. They also provide the search engine companies with significant amounts of their revenues through Sponsored Search Advertising. While still growing rapidly Sponsored Search Advertising already dominates the online media-spending of companies that advertise on the internet. In this form of advertising, developed in 1998 by Overture, advertisers provide search engines with text-advertisements and a list of keywords, which can consist of one or more terms, they want to be displayed. The advertiser usually also provides attributes to each of these keywords, but at the very least the amount of money he is willing to pay for a click on an ad for this specific keyword (CPC_{max})[JFBY⁺09]. Every time a user types in a query

the search engine generates individual personalized result pages, depending on the users' location, his search history and other factors. If ads are available that could probably satisfy the need of the user, the search engine displays these ads alongside the organic results. If more than one advertiser is willing to pay for the display of an ad the search engine auctions the position of these ads among all interested players typically based on a Generalized Second Price Auction (GSP) [Jan11, Var09]. In each auction only the advertiser that wins the auction by getting a click on an ad is charged by the search engine. The effective Cost-Per-Click (CPC_{eff}) is basically the maximum bid of the advertiser with the subsequent highest bid plus a small additional fee. In practice search engine companies use a more robust mechanism to maximize their profits by rewarding keyword/ad combinations that have a high relevance to users (often referred to as the quality score). Although detailed calculations are not disclosed, the key metric is claimed to be the historic Click-Through-Rate (CTR) where available, otherwise an expected click probability for the specific advertiser-ad-keyword combination is used.



Figure 1: Two variations of an ad, similar to the ones that were used in the A/B test: Carbon Neutral delivery vs. Fast and Reliable delivery

In the present paper we concentrate on the advertisers' perspective and the direct impact of green signals in text advertisements. We evaluate the probability that a user will click on a given Sponsored Search text advertisement containing the promise of Carbon Neutral delivery vs. another one offering generic information on reliable fast delivery and conduct a Bayesian parameter estimation approach to analyze the data. In this context we illustrate the advantages one can get by applying a Bayesian Parameter Estimation analysis compared to conventional Null Hypothesis Significance Testing.

3 Literature Review

There are two streams in literature which are important for the present research. The first is green marketing. The second studies the various influences on Sponsored Search advertising effectiveness.

3.1 Green Marketing

Green marketing has been a widely recognized trend for international firms over the last years. One can clearly identify strong efforts in the development of sustainable brand images in a number of branches. One trend Leonidou et al identify in their review of developments in green advertising research and practice from 1988 to 2007 is a strategy shift from communicating environmental aspects within the production process to the communication of sustainable consumption by the customers themselves. An other important expansion of this field is observed in the intensification of efforts by B2C businesses in communicating green messages in their advertising activities. [LLPH11] The use of ecolabels is a well known tactic is to provide the potential consumer with independent confirmation of the green efforts of the respective advertiser. In fact Rex and Baumann state that there is still lack of empirical knowledge about the consumers reception in this area. [RB07] Recent studies indicate that a number of consumers may be willing to pay higher prices for products they identify as environmental friendly. [HM08] What is still unanswered is the whether these green signals still have an impact direct buying decisions in situations in E-Commerce situations. A first approach to answer this question with a significantly smaller fraction of the given dataset has been made [Bla13]. However, more data is needed to ensure reliable results from the given study setup.

3.2 Sponsored Search Advertising

In published research, Online Marketing and Sponsored Search especially has become an established topic with a variety of high quality publications in Computer- and Information Science as well as in the fields of Operations Research and Marketing. Since 2004, Sponsored Search has become a continuously more and more important topic in the Online Marketing research area [Eva08, Eva09, JM08].

The search engine auctions the positions of the ads on the Search Engine Result Page (SERP) between all advertisers that placed a bid (CPC_{max}) for the given keyword. The ad position is the result of the combined CPC_{max} and so called quality scores of the players. The amount of money a specific advertiser has to pay for the click (CPC_{eff}) depends on the advertisers bid and the ones provided by the other advertisers in the auction as well as the quality score of the ad / query combination.

Many publications in this area have an empirical basis. Basically quantitative research is conducted with three types of datasets: **(a)** Search engine query data **(b)** aggregated media and e-Commerce statistics and **(c)** individual user journeys. Search engine query data is the rarest form of available data for researchers who are not directly affiliated to the search engines as it can only be collected by the search engine companies themselves. Although every search engine company generates masses of this type of data, there are only few datasets available for academic use. One of those is the well known AOL dataset. It consists of about 20 million completely non-censored web queries collected from about 650,000 users over a three month period, arranged by anonymous individual

IDs. This dataset has been extensively examined since 2006 [PCT06, Ada07, SLG⁺07, SPK08, BGA09].

Aggregated media and e-Commerce statistics are generated by the advertisers themselves during their ad campaigns. One way this kind of data is produced is by the campaigning tool itself (e.g. Google AdWords) or the advertiser’s respective software solution. The data is usually aggregated on campaign, adgroup and keyword-level and contains variables like the total number of clicks, impressions, *CTR*, and conversionrate (*CVR*) as can be seen in table 1.

Table 1: typical dataset from Google AdWords (ad level)

Ad	Clicks	Impr.	Avg.CPC	Cost	Avg.Position	Conversions
ad 1	132	2,198	1.32	174.08	2	16
ad 2	421	2,893	2.32	976.72	3	21
...

The third sort of available data enables researchers to understand individual user behavior. User journey conversion datasets include information about all measured touch-points that an individual user has with a specific advertiser. These datasets make the development of attribution-models possible where every conversion success can be allocated to the ad-contacts a user has had. Like the other types of data too, user journey data is always subject to several types of bias, such as caused by media discontinuities.

3.3 Click probability

Click probabilities have been widely studied since the early beginning of the advertising format Sponsored Search. However, due the lack of possibilities to observe the user behaviour while using a search engines, a complete coverage of all factors influencing the *CTR* is no easy task.

Evidence suggests that one of the most influencing factors is the ad position within the Sponsored Search results, which depends among other facts on the advertisers CPC_{max} and the so called quality score. The quality score, used by search engines to determine the quality of an advertisement, is based primarily on the historical *CTR*. A large number of studies has shown the correlation between decreasing position and a decreasing *CTR* and vice versa [RDR07, AHS11]. It should be emphasized, that the highest positions leads to high *CTRs* but not mandatorily to the highest conversion rates. From an advertiser’s perspective, a topic of interest is to predict the future *CTR* of sponsored ads. As argued before, the position has a major influence on the *CTR*, called the position bias. In the course of research, several models have been developed to explain the influence of the position bias on the *CTR*.

Crasswell, Zoeter and Taylor [CZTR08] present several models for predicting the *CTR*: (a) baseline model, (b) mixture model, (c) examination model, and (d) cascade model . The findings were originally based on organic search results but, they are applicable to

Sponsored Search results as well [AHS11]. The underlying assumption of the (a) baseline model is that a user screens every search result and decides afterwards, which one fits the best to the query. As a consequence, the click probabilities for each individual search result are identically, independently of its position. The (b) mixture model extends the baseline model and divides user behavior into two groups. One group behaves as described in the baseline model, the other group clicks randomly on one of the first search results. The (c) examination model refers to findings from eye tracking studies which state that with declining position, the probability of a click declines as well [JGP⁺05, JGP⁺07]. The (d) cascade model is, owing to the high degree of explanation by click data, one of the most applied explanation approaches. The basic assumption is that the user scans each search result, beginning from the top to the bottom, comparing the relevance of each ad with the relevance of the ad before. The user continuously scans the results until the perceived ad relevance reaches a certain level and the user clicks.

As mentioned above one challenge is to predict the *CTR* of keywords or keyword combinations for potential future Sponsored Search ads. One solution that has been proposed is aggregating historical data from similar keywords [RF]. Here, the *CTR* is represented as a function of position, independent of a bid. In doing so, the developed models do not focus on a certain advertiser. The same clustering approach can be applied in optimizing the search engines' profit [DV10]. There are also models taking the quality score into account [Glu10]. A model developed by Zhu et al. [ZCM⁺10] called General Click Model focuses on the *CTR* prediction of long-tail queries, based on a Bayesian network. Dealing with the position bias mentioned before, Zhong et al. [ZWW⁺10] incorporate post-click user behaviour data from the respective landing page of the clicked ad into the click model to refine the estimation of the perceived user relevance after clicking on a specific ad. A similar approach, using Dynamic Bayesian networks can be found in Chappelle and Zhang [CZ09]. Several models based on historical click data suffer from limitations in terms of lacking consideration of a possible user learning effect. Taking Gauzente's results as an example, it has been shown that past user satisfaction with Sponsored Search results influences the current click behaviour [Gau09]. Besides the incorporation of position data and the perceived relevance of presented ads, the *CTR* of an advertiser is also affected by the relationship between organic and Sponsored Search results. Listing the results of one company at the same time in sponsored and organic search results leads to a higher *CTR* and vice versa [YG10, BFS11].

4 Case Study

This study covers a test period over several weeks in which a single element in selected Sponsored Search text advertisements has been alternated for a number of queries that users type into the Google search engine to eventually buy products in the advertiser's online shop as can be seen in fig. 1. The advertisers' products can be classified as B2C Fast Moving Consumer Goods. The selected keywords include (a) variations of the retailer brand, (b) the brand names of product manufacturers as well as (c) several clear-cut descriptions of selected products in the online-shop. The data was generated directly by

Google Adwords as part of the normal campaign evolution of the advertiser.

Table 2: summary of click-rates of ads in the given dataset

data	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Group 2	0.00000	0.07639	0.14290	0.14490	0.19700	0.42860
Group 1	0.02941	0.10380	0.15000	0.17590	0.19050	0.50000

The test has been carried out in the first half of 2013. The resulting dataset contains a large number of Sponsored Search key performance indicators (*KPI*) for the given period as exemplified in table 1. The content of the unfiltered dataset as well as the exact dates of the test period cannot be revealed to ensure confidentiality for the advertiser and are of no importance for what follows from here. To ensure that only the impact of the specific text alternation is analyzed and to exclude other factors that would blur the results, especially the strong position effects we describe above, we only analyze the advertisements that were displayed above the organic search results and that were part of the described A/B test. The updated dataset, which is only a small fraction of the advertisers’ regular Sponsored Search campaign, includes a total of 110 advertisements of which 49 advertise ”Carbon Neutral delivery” (**Group 1**) while the other 61 advertise ”Fast and Reliable delivery” (**Group 2**) in the third row of the advertisement as illustrated in fig 1. It contains a total number of 42,364 impressions and 5,775 clicks. What is used for the analysis is the aggregated CTR for each ad over the whole test period.

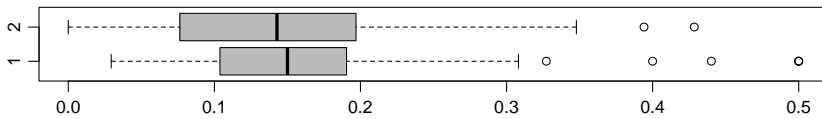


Figure 2: Empirical comparison of CTR’s for Group 2 and Group 1

Analytic approach: Traditionally one makes probabilistic assumptions about the magnitude of the difference between two observed groups by using null hypothesis significance testing (*NHST*). Applying an unpaired t-test, the two-tailed P value equals 0.1420 for the given data. This difference is considered to be not statistically significant. The mean of Group 1 minus Group 2 equals 0.031. The 95% confidence interval of this difference ranges from -0.0105 to 0.0725. In fact this is almost all the information one gets from conventional *NHST* statistics.

We, however, apply a Bayesian approach to answer the question whether there is a positive, negative or zero impact of sustainability information in ad texts in Sponsored Search advertising and await richer information by using Bayesian Methods. To do so, we are comparing the two groups of users that took part in the described A/B test. Even though the applied method possibly influences the behavior of the involved users and could therefore be categorized as reactive in terms of social sciences, it shares common criteria with non-reactive methods since individual users have no knowledge of the investigation of their behavior.

We follow Kruschke and describe the data using mean and standard deviation parameters

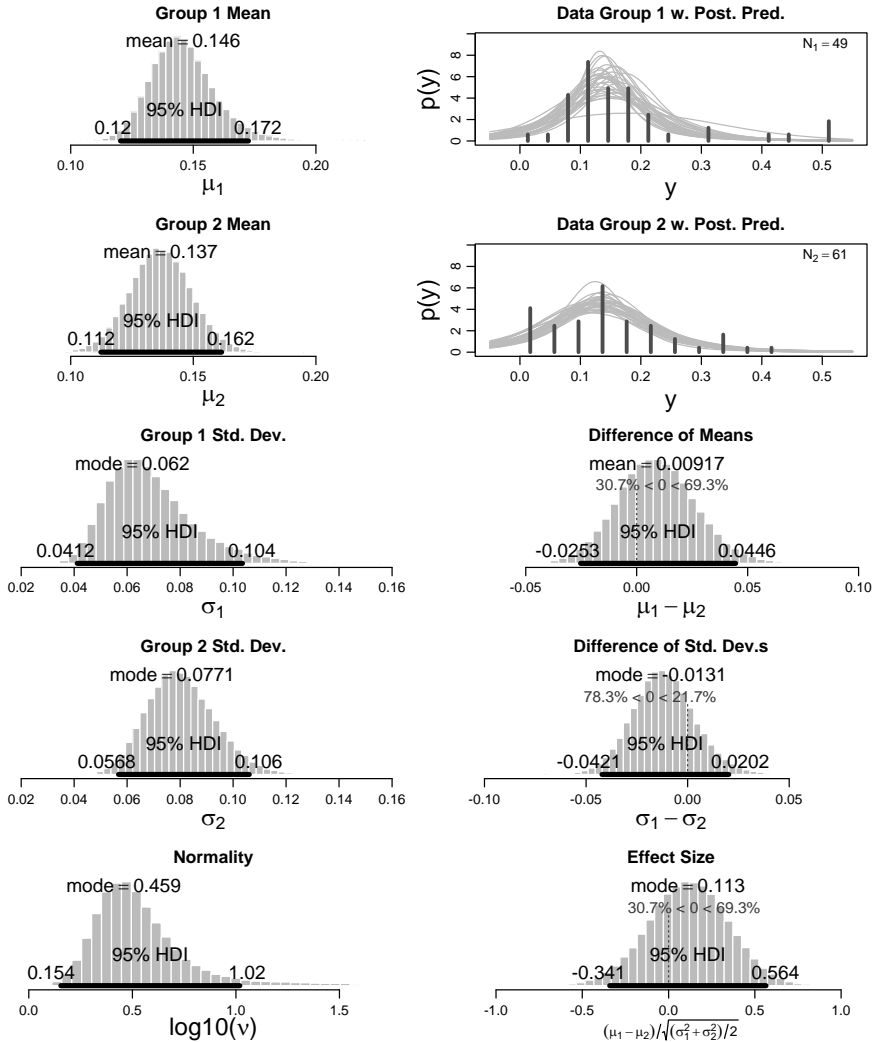


Figure 3: Group 1 = CTR for ads advertising Carbon Neutral delivery, Group 2 = CTR for ads advertising Fast and Reliable delivery.

for t-distributions representing both groups individually and add a normality parameter that is common for both groups. The prior allocation of credibility across the parameters is vague, so that the prior has minimal influence on the estimation, to let the data dominate the inference. Taking the data into account the Bayesian estimation reallocates credibility to parameter values that represent the observed data best. The resulting distribution is a joint distribution across the five parameters, thereby revealing combinations of the five parameter values that are credible, given the data [Kru12]. The two histograms in the top right in fig. 3 are representations of empirical data and display the two observed groups (group 1 = "Carbon Neutral delivery", group 2 = "Fast and Reliable delivery"), with curves of representative examples of posterior predictive t-distributions. In the left column you will find marginals of the posterior distributions of credible values of means of group 1 and 2 as well as the same for the respective standard deviations and a distribution of credible values for the the combined normality parameter. Lower right shows posterior distribution of differences in means and effect size. Fig. 4 displays pairwise plots of the parameters for the given study.

5 Conclusions and Outlook

Taking a first look at the data as displayed in table 2 we find a slightly lower empirical mean *CTR* over all ads on ads that advertise "Fast and Reliable delivery" (14.39%) than on the "Carbon Neutral delivery" ads (15.94%). These values are not to be confused with those in the top left histograms in fig. 3 which represent the simulated mean parameters of t-distributions to fit the empirical distribution. So, in the data we observe a 1.55% higher empirical mean *CTR* for "green" ads which would eventually make us accept the hypotheses that ads with green marketing signals have a higher click probability than their counterparts in the A/B test. What is the central question is whether this result is significant and if it enables us to derive inferences about the "real" long-term distribution.

Table 3: Estimated parameters of the A/B Test results

	mean	median	mode	HDIlow	HDIhigh	pcgtZero
mu1	0.15	0.14	0.14	0.12	0.17	
mu2	0.14	0.14	0.13	0.11	0.16	
muDiff	0.01	0.01	0.01	-0.03	0.04	69.26
sigma1	0.07	0.07	0.06	0.04	0.10	
sigma2	0.08	0.08	0.08	0.06	0.11	
sigmaDiff	-0.01	-0.01	-0.01	-0.04	0.02	21.67
nu	4.23	3.11	2.49	1.22	9.82	
nuLog10	0.54	0.49	0.46	0.15	1.02	
effSz	0.12	0.12	0.11	-0.34	0.56	69.26

To answer this question 100,000 parameter combinations for t- distributions that are credible given the data are generated by Markov Chain Monte Carlo simulation (*MCMC*). One gets a good insight by comparing the distribution of credible values for μ_1 which has

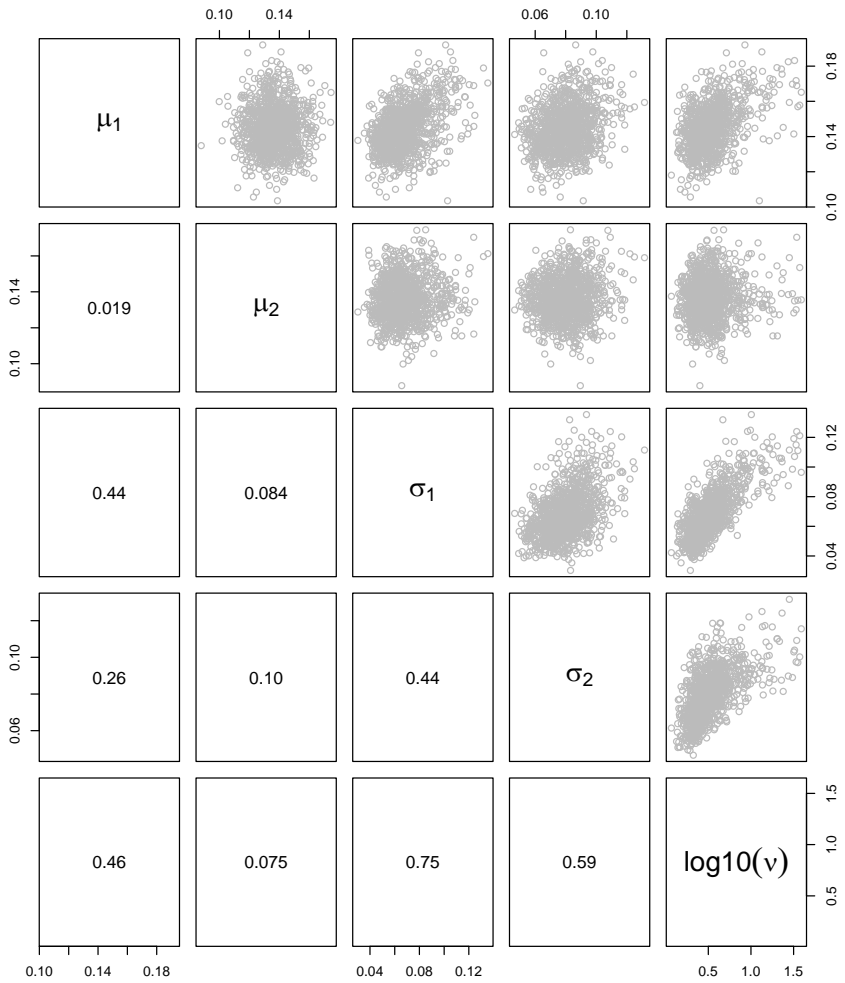


Figure 4: Posteriors for Bayesian Parameter Estimation

a mean of 0.146 and a 95% Highest Density Interval (*HDI*) from 0.120 to 0.173 with μ_2 which has a mean of 0.136 with a 95% *HDI* from 0.112 to 0.161 as can be seen in tab. 3. The exact difference $\mu_1 - \mu_2$ is 0.009 on average as can be found in the plot in the middle of the right column of fig. 3. One can see that 69.3% of the 95% *HDI* for $\mu_1 - \mu_2$ is positive. What is even more relevant for the analysis is that all computed values within the 95% *HDI* fall into the Region of Practical Equivalence (*ROPE*) which spreads from -0.1 to 0.1. So, these results imply that there is a 69.3% chance that the "real" mean of group 1 is greater than the "real" mean of group 2. Nevertheless the difference of means is so small that there is a high probability that the groups are not credibly different from each other in this aspect. Comparing the distribution of credible values for σ_1 and σ_2 one can see that these groups do not credibly differ too. This can be seen in the respective histogram in fig. 3 where all computed values for $\sigma_1 - \sigma_2$ are found in the *ROPE* with 78.3% being negative and 21.7% being positive. This suggests that there is a 78.3% probability that the standard deviation for group 2 is greater than for group 1.

The lower right panel of fig. 3 shows the distribution of credible effect sizes, given the data. For each combination of means and standard deviations, the effect size is computed. The histogram of 100,000 credible effect sizes has a mode of 0.123 and the zero included in the 95% *HDI*. 69.3% of all computed outcomes are positive while 30.7% are negative.

What can we derive from that? What is true is that there is some probability that there is absolutely no effect caused by the different signals in the advertisements as we do not observe strongly significant unambiguous results. If any effect is presumed, it will have a higher probability of being positive for "green signals" in Sponsored Search ads, given the observed data. How can this outcome be explained? One argument could be that ad texts do not influence users on SERPs at all. Although we know about various other effects, like the strong position bias described above, that do affect the user there are too many indications that ad texts do have influence on click decisions to let this be true.

In fact, these results need to be interpreted with caution. One possible explanation for this is that users might not be as green in their decisions as marketers would like them to be. In this case the promise of "Fast and Reliable delivery" seems to lead to a slightly lower motivation to click on an ad than the green signals the advertiser sends out to his potential customers. This A/B test should be repeated over a number of various branches before one can derive implications for the whole e-Commerce industry. What is an even more interesting outcome of this paper is that more future research should be conducted on the general impact of texts in Sponsored Search ads considering a variety of branches and containing more diversity in texts to make sophisticated assumptions on the impact of text-details on click probabilities.

References

- [Ada07] E. Adar. User 4xxxxx9: Anonymizing query logs. *Proc of Query Log Analysis Workshop, International Conference on World Wide Web - WWW '07*, 2007.
- [AF11] T. Alby and B. Funk. Search Engine Marketing in Small and Medium Companies: Status Quo and Perspectives. In M. Cruz-Cunha and J. Varajão, editors, *E-Business*

Managerial Aspects, Solutions and Case Studies, pages 206–221. igi-global, 2011.

- [AHS11] Ashish Agarwal, Kartik Hosanagar, and Michael D Smith. Location, Location, Location: An Analysis of Profitability of Position in Online Advertising Markets. *Journal of Marketing Research*, 48(6):1057.1073, 2011.
- [BFS11] T. Blask, B. Funk, and R. Schulte. Should Companies Bid on their Own Brand in Sponsored Search? In *Proceedings of the International Conference on e-Business (ICE-B 2011)*, pages 14–21, Seville, Spain, 2011.
- [BGA09] David J. Brenes and Daniel Gayo-Avello. Stratified analysis of AOL query log. *Information Sciences*, 179(12):1844–1858, 2009.
- [Bla13] Tobias Blask. Applying Bayesian Parameter Estimation to A / B Tests in E-Business Applications : Examining the Impact of Green Marketing Signals in Sponsored Search Advertising. In *Proceedings of the International Conference on e-Business (ICE-B 2013)*, 2013.
- [CZ09] Olivier Chapelle and Ya Zhang. A dynamic bayesian network click model for web search ranking. In *Proceedings of the 18th international conference on World wide web - WWW '09*, page 10, New York, New York, USA, 2009. ACM Press.
- [CZTR08] Nick Craswell, Onno Zoeter, Michael Taylor, and Bill Ramsey. An experimental comparison of click position-bias models. In *Proceedings of the international conference on Web search and web data mining - WSDM '08*, page 8, New York, New York, USA, 2008. ACM Press.
- [DV10] Kushal S. Dave and Vasudeva Varma. Learning the click-through rate for rare/new ads from similar ads. In *Proceeding of the 33rd international ACM SIGIR conference on Research and development in information retrieval - SIGIR '10*, number July, page 897, New York, New York, USA, 2010. ACM Press.
- [Eva08] David S Evans. The Economics of the Online Advertising Industry. *Review of Network Economics*, 7(3):pp359–391, 2008.
- [Eva09] David S Evans. The Online Advertising Industry: Economics, Evolution, and Privacy. *Journal of Economic Perspectives*, 23(3):37–60, August 2009.
- [Gau09] Claire Gauzente. Information search and paid results proposition and test of a hierarchy-of-effect model. *Electronic Markets*, 19(2-3):163–177, June 2009.
- [Glu10] Ilya Gluhovsky. Forecasting Click-Through Rates Based on Sponsored Search Advertiser Bids and Intermediate Variable Regression. *October*, 10(3):1–28, 2010.
- [HM08] DL Haytko and Erika Matulich. Green advertising and environmentally responsible consumer behaviors: Linkages examined. *Journal of Management and Marketing Research*, 1:2–11, 2008.
- [Jan11] Jim Jansen. The Serious Game of Bidding on Keywords. In *Understanding Sponsored Search Core Elements of Keyword Advertising*, chapter 8, pages 176–201. Cambridge University Press, 2011.
- [JFBY⁺09] Bernard J. Jansen, Theresa B. Flaherty, Ricardo Baeza-Yates, Lee Hunter, Brendan Kitts, and Jamie Murphy. The Components and Impact of Sponsored Search. *Computer*, 42(5):98–101, May 2009.

- [JGP⁺05] Thorsten Joachims, Laura Granka, Bing Pan, Helene Hembrooke, and Geri Gay. Accurately interpreting clickthrough data as implicit feedback. In *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval - SIGIR '05*, page 154, New York, New York, USA, 2005. ACM Press.
- [JGP⁺07] Thorsten Joachims, Laura Granka, Bing Pan, Helene Hembrooke, Filip Radlinski, and Geri Gay. Evaluating the accuracy of implicit feedback from clicks and query reformulations in Web search. *ACM Transactions on Information Systems*, 25(2):1–26, April 2007.
- [JM08] B.J. Jansen and T. Mullen. Sponsored search: an overview of the concept, history, and technology. *International Journal of Electronic Business*, 6(2):114–131, 2008.
- [Kru12] John K Kruschke. Bayesian Estimation Supersedes the t Test. *Journal of experimental psychology. General*, July 2012.
- [LLPH11] Leonidas C. Leonidou, Constantinou N. Leonidou, Dayananda Palihawadana, and Magnus Hultman. Evaluating the green advertising practices of international firms: a trend analysis. *International Marketing Review*, 28(1):6–33, 2011.
- [PCT06] Greg Pass, Abdur Chowdhury, and Cayley Torgeson. A picture of search. In *Proceedings of the 1st international conference on Scalable information systems - InfoScale '06*, pages 1–es, New York, New York, USA, 2006. ACM Press.
- [RB07] Emma Rex and Henrikke Baumann. Beyond ecolabels: what green marketing can learn from conventional marketing. *Journal of Cleaner Production*, 15(6):567–576, January 2007.
- [RDR07] M. Richardson, E. Dominowska, and R. Ragno. Predicting clicks: estimating the click-through rate for new ads. In *Proceedings of the 16th international conference on World Wide Web*, pages 521–530. ACM New York, NY, USA, 2007.
- [RF] Moira Regelson and Daniel C Fain. Predicting Click-Through Rate Using Keyword Clusters. In ACM, editor, *EC'06*.
- [SLG⁺07] M. Strohmaier, M. Lux, M. Granitzer, P. Scheir, S. Liaskos, and E. Yu. How do users express goals on the web?-An exploration of intentional structures in web search. *LECTURE NOTES IN COMPUTER SCIENCE*, 4832:67, 2007.
- [SPK08] Markus Strohmaier, Peter Prethenhofer, and Mark Kröll. Acquiring Explicit User Goals from Search Query Logs. In *2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, volume 8, pages 602–605. Ieee, December 2008.
- [Var09] H.R. Varian. Online ad auctions. *American Economic Review*, 99(2):430–434, 2009.
- [YG10] S. Yang and A. Ghose. Analyzing the Relationship Between Organic and Sponsored Search Advertising: Positive, Negative, or Zero Interdependence? *Marketing Science*, 30(1):1–22, April 2010.
- [ZCM⁺10] Z.A. Zhu, W. Chen, Tom Minka, Chenguang Zhu, and Zheng Chen. A novel click model and its applications to online advertising. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 321–330. ACM, 2010.
- [ZWW⁺10] Feimin Zhong, Dong Wang, Gang Wang, Weizhu Chen, Yuchen Zhang, Zheng Chen, and Haixun Wang. Incorporating post-click behaviors into a click model. *Annual ACM Conference on Research and Development in Information Retrieval*, pages 355–362, 2010.