Notes on Intuitionistic Fuzzy Sets
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A reply to Madera et al.'s "A method for optimizing a bidding strategy for online advertising through the use of intuitionistic fuzzy systems"

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Abstract: In 2016, Madera et al. tested the performance of a fuzzy inference system against the Google Ads algorithms for optimizing the number of clicks, the click through rate (CTR) and the average cost per clicks to lower the cost of an advertising campaign [7]. The results of their experiments suggested that the implementation of their fuzzy inference system outperformed the Google Ads algorithms in terms of the obtained number of clicks and cost per clicks. While the research idea is with no doubts an interesting and valuable contribution to the fields of digital marketing research, in the opinion of the authors, their experimental setup was flawed. However, applying a few adjustments can lead to valid findings. This paper reflects on the flaws and suggests enhancements to correct them.

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1 Introduction

In 2016, Madera et al. [7] tested the performance of a fuzzy inference system against the Google Ads algorithms for optimizing the number of clicks, the click through rate (CTR) and the average cost per clicks to lower the cost of an advertising campaign. The results of their experiments suggested that the implementation of their fuzzy inference system outperformed the Google Ads algorithms in terms of the obtained number of clicks and cost per clicks.

While the research idea is with no doubts an interesting and valuable contribution to the fields of digital marketing research, in the opinion of the authors, their experimental setup was flawed. However, applying a few adjustments can lead to valid findings. The suggested enhancements, proposed in this paper differ from their experimental set up in several ways.

Firstly, to minimize day of week bias (time-period bias) the duration of the experiment should be changed from 24 hours to two weeks. Secondly, Madera et al. were running 60 pairwise identical campaigns simultaneously where one member of each pair was optimized via Google's algorithm and the other member via their fuzzy inference system. But pairwise identical campaigns compete against each other during the advertising auction. This is called keyword cannibalization. Consequently, statistical independence of those two campaigns is no longer provided. Therefore, contrary to Madera et al., to obtain statistical independence the authors secondly suggests to randomly choose either Google Ads algorithms or the fuzzy inference system to optimize the performance of a campaign.

Thirdly, to prevent the data from incorrectly appearing to be statistically significant the p-value can be adjusted to reduce the instance of a false positive via the Bonferroni Test.

2 Proposed adjustments

2.1 Time-period bias

Google Ads key performance indicators such as CTR, number of clicks received, and cost per click (CPC) can significantly change over time. So, basically, they are sequences of discrete-time data points and hence fall under the umbrella of time series data.

As with any other time related data those key performance indicators are prone to time-period bias which happens when some decisive changes occur during other periods and as a possible consequence the research results might work during the time frame of the research experiment but might not be valid for extended time periods [8]. This sort of sampling bias is a well-known problem in many research areas [2, 3, 9, 12, 13] and of course applies for days of week in the context of advertising too. For this reason, short time periods such as 24 hours are very likely to paint an inaccurate picture of the performance of an ad campaign and may not be reflective of the longer-term trend. Contrary to Madera et al. the authors propose 14 days instead of 24 hours to ensure that the outcomes of the experiments are independent from unique time periods.

Furthermore, to avoid obtaining market segments specific outcomes a sufficient number of different campaigns from advertisers which come from different industries are to be analysed.

2.2 Ensuring statistical independence

The Google Ads advertising system is an online auction. At any time, t, thousands of marketers are competing to get their keywords placed. The Google Ads auction is a first-price auction, where the closing price is determined by the highest net bid in the auction. Along with the advertisers bid, other factors are used to finally decide whether an ad is shown at auction time or not and at which position.

The most crucial value here is Google's ad rank, a score by which Google's algorithms decide whether your ad is qualified to appear at all as well as the placement position (at the top of the paid results, second slot, third slot etc.). The better the ad rank, the better (higher) the placement.

The ad rank is calculated by incorporating several KPIs. One of those KPIs is the historical click rate [5]. But if one "have multiple keywords from the same account that match to a search, only one will be entered into the auction and eligible to serve" [4]. In other words, if one deploys pairwise identical campaigns such as Madera et al. did in their experiments the campaign that yields the first click always has an advantage over the other campaign in terms of historical click rate and hence got a better ad rank than the other. Hence, the ad rank of the first campaign depends on the ad rank of the second one and vice versa. Therefore, simultaneously running pairwise identical campaigns cannot be statistically independent and thus any *t*-test that runs on that data is invalid, since the assumption of statistical independence of the variables would have been violated.

Deploying A/B split tests instead of running pairwise identical campaigns simultaneously can overcome this problem, if for each of the participating campaigns a simple random number generator randomly chooses either Google algorithms or the fuzzy inference system at the beginning of each of the 14 days to optimize the campaign.

2.3 Reducing the instance of false positive

Finally, to avoid incorrect statistical significance of the A/B test [10] the *p*-value should be adjusted after each day in accordance with the Bonferroni test as follows

$$p_1' = \frac{p_1'}{1},\ p_2' = \frac{p_2'}{2}, \ldots,\ p_{14}' = \frac{p_{14}'}{14}.$$

3 Conclusion

Due to the nature of Google's ad rank, running pairwise identical Google Ads campaigns simultaneously, violates statistical independence of the participating campaigns. Deploying simple A/B split tests can overcome this issue. In addition to avoiding incorrect statistical significance of those A/B test outcomes, p-values can be adjusted by applying the Bonferroni test. Through these simple adjustments plus extending the experiment duration as well as testing campaigns from different industries reliable findings can be achieved when Madera et al.'s fuzzy method is compared with current Google Ads bidding strategies. Moreover, Madera et al. have introduced their method for optimizing a bidding strategy for online advertising using intuitionistic fuzzy systems in 2016. Today, machine learning based smart bidding "a subset of automated bid strategies that use machine learning to optimize for conversions or conversion value in each and every auction" [6] supplanted simple automatic CPC algorithms. However, these improvements go hand in hand with a loss of control and transparency leaving the marketer interacting with black-box algorithms without being able to determine how that algorithm came to its decision [1, 11]. Therefore, fuzzy inference system-based bidding strategies are highly relevant in the ethical context of performance marketing and might become a valuable contribution to the “black-box versus interpretable models” discussion as initiated in 2018 after the Explainable Machine Learning Challenge took place at the Montreal Convention Center during the annual Neural Information Processing Systems (NeurIPS) [11].

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