

Forecasting Long-Term Effect of Marketing Actions on the Basis of the Analysis of Incremental Retention of Gross Merchandise Volume

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Abstract:

This paper considers the methodology for forecasting the long-term effect of marketing campaigns in e-commerce service. The research purpose of the study is to develop an approach for predicting the long-term effect of marketing campaigns with the following properties: the approach allows to assess the effect of marketing campaigns, including the return on investment in marketing based on data collected during the first 4 weeks after the end of the campaign; the approach is based on the analysis of actual data on the volume of purchases in groups of buyers participating in the campaign, and their dynamics, both during the campaign, before and after it; the approach has accuracy, which allows us to compare campaigns with statistical significance.

Keywords: e-commerce, marketing efficiency, customer retention

Track: Methods, Modelling & Marketing Analytics

1. Introduction of Paper

1.1 Practical Relevance (a managerial task)

Investments in companies' fixed capital are always measured from a financial point of view, using clear and generally accepted indicators, such as return on investment (ROI) and economic value added (EVA) (Suárez, 2016), this information is provided in detail to shareholders, analysts and investors to enable them to make decisions on the allocation of resources. However, this is not always the case with marketing investments (Wensley, 2016). Typically, they are not sufficiently explained, and due to a lack of transparency, it is difficult for investors to understand whether they create value, and therefore, the investment will make a return to shareholders (Kimbrough, 2009).

1.2 Theoretical base (academic response to the task)

Recently, the focus on the financial evaluation of the effect of marketing campaigns is gaining popularity ((Stewart, 2009). The number of researches on profitability of marketing, lifetime value of the client, payback of marketing actions is growing. The issue of return on investment in marketing in e-commerce, retail and various services is a key growth factor for both companies operating in traditional markets and various startups (Liozu, 2014; Arunachalam, 2019). The gap between marketing and finance is narrowing, marketing becomes financially accountable, and customer profitability becomes a key marketing indicator (Rust, 2004).

The theoretical basis for the study was formed as a review of scientific publications on the following topics: the introduction of tools to work with personalized client experience and technical aspects of working with big data; and the assessment of the effectiveness of investments in personalization. Theoretical papers on the research topic contain the following results:

- in a hypercompetitive business environment, marketers need to understand how different aspects of their marketing activities affect the financial performance of their organization (Hanssens, 2016);
- a particular role in the described area of marketing is played by approaches that determine the lifetime value of a client (Castéran, 2017), and the return on investment in client value (Kreutzer, 2015);
- the paper (Dawes, 2018) demonstrates the drawbacks of traditional econometric approaches for forecasting the effectiveness of marketing investments in advertising and media. It should be noted that these difficulties are inherent not

only in media and advertising, but also extend to more digitized and data-rich marketing channels, such as performance marketing, direct marketing, etc. (Dahana, 2019; Zahay, 2019);

- whereas for traditional loyalty programs based on direct investments of revenue (discounts, bonuses, special offers) the mechanisms of A/B-testing allow to estimate directly the costs and the obtained effect by testing statistical hypotheses about the difference in revenue in the groups of experiment and control (Rowles, 2017), non-monetary marketing actions, such as increased privileges to users, availability of a personal manager, expedited delivery, etc., may not pay off during the period of validity of the shares, but may have an impact on the long-term recoverability.

1.3 Theoretical relevance (research gap)

In (Schamroth, 2019), the authors give an example when short-term solutions to optimize marketing metrics lead to losses in the long run; we will show the opposite example in our work - when investments in marketing are not effective in the short run, but pay off in the long run.

The case that the authors considered in their paper (Schamroth, 2019) is the testing of the interface and placement of advertising on the pages of the site, i.e. it is not directly related to the investment in marketing and their return on investment, however, their idea can be extremely useful in this area as well. The authors note that the use of optimization methods in online media and marketing has become an essential component in every aspect of the customer's life cycle for any website or mobile application, from attracting and retaining customers to monetizing users. Optimization algorithms provide the maximum monetization of the existing audience necessary to take the lead in a competitive environment. However, in each such experiment, one of the biggest dilemmas that is often faced is the question of what metrics should be optimized. (Schamroth, 2019) shows the importance of choosing a metric that focuses on long-term effects over a long period of time. The authors propose a methodology that makes it relatively early to measure and identify differences between the test groups and the focus primarily on controlled experiments in the mobile and web environment related to A/B testing.

1.4 Research Purpose

Thus, the purpose of this study was to develop an approach for predicting the long-term effect of marketing campaigns, which has the following properties:

1. The approach allows us to evaluate the effect of marketing campaigns, including ROMI (Return on Marketing Investment) (Farris, 2015) for the first 4 weeks after the end of the campaign;

2. The approach is based on the analysis of actual data of the volume of purchases in groups of buyers participating in the marketing campaign, and their dynamics, during the marketing campaign, before and after it;

3. The approach is accurate, allowing the effects of different marketing campaigns to be compared with each other and separating statistically significant results from statistically insignificant ones.

1.5 Methodology/Design

The data for analysis is represented with information about users of the online taxi-service. In total, from January to February 2018, 5 experiments were conducted. Various privileges were given to users in the series of A/B-test. Privileges included: discounts on services, premium subscription, online support and personal manager. Experimental and control groups were recorded in each of the experiments. In the control group, users were not affected by any marketing offers. In the experimental group various mechanics of additional incentives to purchase the service, retain and increase loyalty were used. The data on the frequency of use of services and their gross cost from February to August 2018 were considered. At the request of the company that provided the data, the data were obfuscated, and the transformation was uniform across all control and experimental groups.

To build the model, we used data on the gross cost of services in each of the groups of each experiment for the first 4 weeks since the start of each marketing campaign. Each campaign lasted from 4 to 7 days. According to the data of the first 4 weeks, we predicted the integral accumulated effect of each campaign on the next 4 months of users' lives.

2. Model & Findings

ROMI (Return on Marketing Investment) is the result of dividing the growth in financial value created by marketing activities by the investment in these activities, less the investment in marketing. For an estimation of increase in financial cost traditionally calculate a difference between volumes of the sales which have been carried out after marketing actions and expected volumes of sales. For an estimation of additional sales control groups of buyers on which marketing actions or the econometric models allowing to construct the forecast of expected sales on historical data can be used.

Next we use the following designations:

II - Incremental Income, - additional revenue;

IVC - Incremental Variable Cost, - additional variable costs;

MI - Marketing Investment, - Investments in marketing;

IMG - Incremental Gross Margin, - additional gross profit;

IR - Incremental Revenue - additional net profit.

$$RoMI = \frac{II - IVC - MI}{MI} = \frac{IMG - MI}{MI} = \frac{IR}{MI}$$

Let's define the function $GMV(t)$ equal to the gross merchandise volume of the company at the moment t (further by t we will understand the number of the week), we'll call $GMV(t)$ turnover function.

Let $GMVR(t) = \frac{GMV(t)}{GMV(t-1)}$ - turnover retention function.

This indicator is analogous to Customer Retention (Rust, 1993). The task of predicting customer retention or retention rate is quite well understood and is now being effectively addressed through machine learning. Note that results such as those suggested in (Vafeiadis, 2015) can be used to improve the accuracy of the approach proposed below.

Note that the turnover retention function is related to the derivative of the turnover function, i.e:

$GMVR(t) * GMV(t-1) - GMV(t-1) = GMV(t) - GMV(t-1) = \Delta GMV$ - an increase in turnover.

Next, let's consider in more detail the mechanics of the A/B experiment (Kaptein, 2015). We would like to remind that A/B testing (Split testing) is a method of marketing research that consists in comparing target metrics (in our case we are interested in gross turnover and its increment) in two groups: a control one, in which the property of the initial system is preserved, and a test one (experimental), which is influenced by the marketing action under study (Bhat, 2019).

Let's record the groups of the experiment "exp" and control - "control". The group sizes are n_{exp} and $n_{control}$. Let's consider the week t_0 - the week preceding the beginning of the experiment and the index $GMV_n(t_0) = GMV(t_0)/n$ - the total cost of the services rendered in the week t_0 in the group of users, normalized by the size of the group (by the number of users in the group). Further, the index n will be omitted and it will be assumed that GMV is a normalized indicator everywhere.

Since the division of users into groups is uniform, the standardised cost of services sold by group size in control and experiment is the same:

$$GMV_{\text{exp}}(t_0) \sim GMV_{\text{control}}(t_0).$$

With the start of the marketing campaign we expect to see an increase in GMV in the experiment compared to control. $GMV_{\text{exp}}(t) > GMV_{\text{control}}(t)$ for $t > t_0$

Note that the uniformity of division into control and experiment also guarantees the equality of return functions between groups at the moment t_0 . Let's assume that the experiment lasted for one week, and after its end (time t_2) the turnover in the groups became equal again (for example, there was an increase in sales due to discounts, and after their end the demand in the groups became equal)

$$GMV_{\text{exp}}(t_2) = GMV_{\text{control}}(t_2).$$

For simplicity, let's denote $GMV_e(t) = GMV_{\text{exp}}(t)$ и $GMV_c(t) = GMV_{\text{control}}(t)$.

And the turnover retention is to be seen $R(t) = GMVR(t)$.

Then the additional revenue can be estimated as follows (remember that the turns in the zero week - week before the experiment - coincide due to the correctness of the A/B-test):

$$II = GMV_e(t_1) - GMV_c(t_1) = (R_e(t_1) - R_c(t_1)) \times GMV_c(t_0)$$

In this case, $R_e(t_2) < R_c(t_2)$, - at the moment of the end of the action, the turnover returned to the previous level, and the retention rate is respectively lower than in the control. In this case, the calculation of ROMI completely coincides with the traditional models and is not difficult. We will consider a case when $R_e(t_1) > R_c(t_1)$, a $R_e(t_2) = R_c(t_2)$.

In this case, $GMV_e(t_2) > GMV_c(t_2)$, - the turnover in the first week after the action in the experimental group remains higher than it was before, and there is a long-term effect. To estimate it, it will be necessary to integrate the difference between $GMV_e(t_2) - GMV_c(t_2)$ with correction for the retention of the turnover. Since we are interested not in the final effect on a fixed point in time in the future, but in the effect on the entire life cycle of users, it is impossible to limit the consideration of the final amount, more precisely, it is necessary to find the sum of an infinite series of II_{∞} .

$$II_{\infty} = \sum_{t=t_1}^{\infty} GMV_e(t) - GMV_c(t) = \sum_{t=t_1}^{\infty} R_e(t) \cdot GMV_e(t-1) - R_c(t) \cdot GMV_c(t-1)$$

Let's consider the first summand of this sum, it exactly represents the additional revenue for the week of the experiment, we will designate, as before:

$$II_1 = GMV_e(t_1) - GMV_c(t_1) = (R_e(t_1) - R_c(t_1)) \times GMV_c(t_0)$$

Now let's consider additional revenue II_2 - the week following the week of the experiment:

$$II_2 = GMV_e(t_2) - GMV_c(t_2) = R_e(t_2) \cdot GMV_e(t_1) - R_c(t_2) \cdot GMV_c(t_1)$$

Now let's notice that after the experiment the retention in the control and experiment should coincide, besides, the retention in the model as a whole can be accepted as a constant, which characterizes the retention of users in each of the groups. Therefore, for all weeks except the week of the experiment $R_e(t) = R_c(t) = R, t \neq t_1$.

So we're getting $II_2 = R \cdot GMV_e(t_1) - R \cdot GMV_c(t_1) = R \cdot II_1$, and the whole row can be written down as:

$$II_\infty = II_1 + R \cdot II_1 + R^2 \cdot II_1 + R^3 \cdot II_1 + \dots = II_1 \cdot \sum_{t=0}^{\infty} R^t$$

Note that being the share of turnover returned in the user group, the retention coefficient is by definition less than 1, and the specified series has a final sum:

$$II_\infty = (GMV_e(t_1) - GMV_c(t_1)) \cdot \frac{1}{1 - R}$$

That's where the theoretical model ends. Next, we will apply this approach to practical experiments to assess its accuracy for ROMI evaluation and decision making on the effectiveness of marketing actions.

2. Validation Results and Experiments

The data for analysis were data about users of the online taxi-service. In total, from January to February 2018, 5 experiments were conducted. They gave users in the A/B-test various privileges, from discounts on services to premium subscription, including online support and personal manager. Experimental and control groups were recorded in each of the tests. In the control group, users were not affected by any marketing offers. The experimental group used various mechanics of additional incentives to purchase the service, retain and increase loyalty. The data on the frequency of use of services and their gross cost from February to August 2018 were considered. At the request of the company that provided the data, the data were obfuscated, and the transformation was uniform across all control and experimental groups.

To build the model, we used the data on the gross cost of services in each of the groups of each experiment for the first 4 weeks since the start of each campaign. Each campaign lasted from 4 to 7 days. According to the data of the first 4 weeks we predicted the integral accumulated effect of each campaign on the next 4 months of users' lives.

At the start of the share we see an increase in the incremental return rate in the experimental group compared to the control group, while at the end of the share, on the contrary, we see a decline. When no additional promotions affect the users, the incremental

returns in the control and experiment are equalized, and the return functions themselves may now differ.

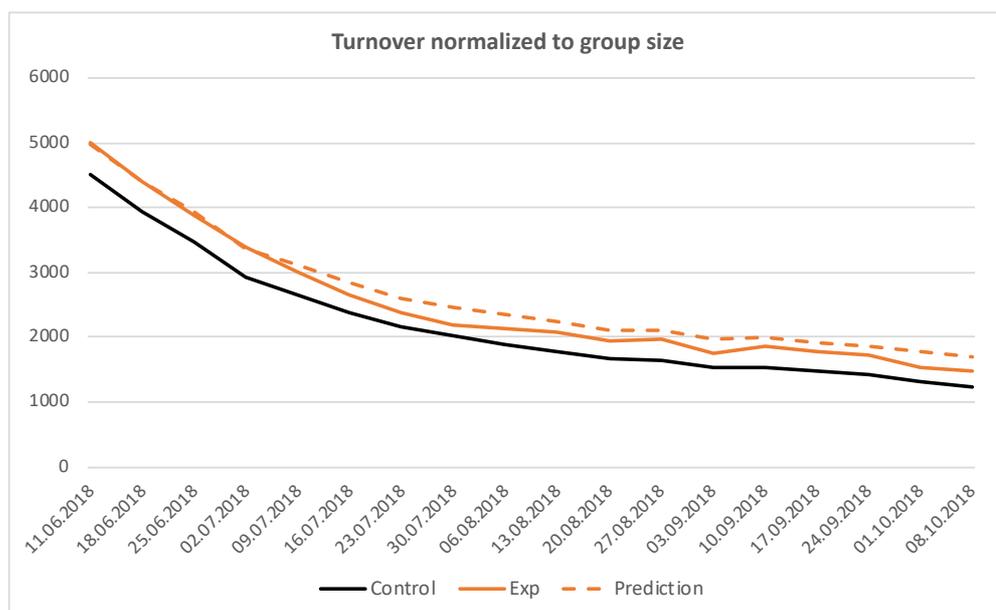


Fig. 1. GMV normalized to group size.

Estimating the return coefficients for the first 4 weeks (in this particular case the least squares method was used), with the help of the model described above, we get the value by which the turns in the experiment and control at each moment t differ. If we sum up these values, we get the cumulative effect of the stock for any number of periods in advance.

Here we use the fact that the differences in incremental returns after the end of the share are not statistically significant, in general this may not be the case.

The least-squares return coefficients selected in this experiment can be used in similar experiments to predict the long-term effect of new campaigns.

ID акции	exp_1	exp_2	exp_3	exp_4_mon	exp_5_mon
Increase in turnover per first week of experiment	10,69%	10,69%	10,69%	24,38%	27,11%
Increase in turnover over 17 weeks	12,95%	12,95%	12,95%	1,79%	2,17%
Model error of 4 weeks of training	0,67%	2,13%	1,94%	1,95%	2,36%
Error in the value at week 17	14,20%	12,92%	24,14%	7,68%	5,26%
Error in accumulated effect for 17 weeks	4,86%	5,29%	9,23%	1,42%	1,24%

Table 1. Results of model forecast validation

The error of the model in estimating the long-term effect is quite large, but we can see that even such accuracy allows us to separate statistically significant effects from statistically insignificant ones. We can also see that the experiments with discounts do not give a significant increase on the horizon of 17 weeks (the increase in turnover is observed only in the week of the experiment).

3. Conclusion, Limitations & Future Research

The described approach allows us to evaluate the long-term effect from the marketing campaign and its payback in the first weeks after the end of the experiment. In this paper we do not predict the full lifetime value of the client (LTV), as it depends on the pricing parameters and can vary depending on changes in the marketing strategy of the company, as well as changes in the competitive environment. However, the conducted analysis allows us to estimate with good accuracy the total growth of revenue for the period of 4 to 6 months, which we can expect, and to give a lower bound of revenue for the long-term. This allows us to evaluate the ROMI of marketing campaign and make a decision on the profitability of marketing campaign as well as it also allows us to compare marketing campaigns among themselves.

Shortcoming & Future Research: in future works it is desirable to carry out more experiments from different branches of e-commerce, to analyze factors influencing accuracy of model, to carry out comparison with more difficult methods of forecasting on the basis of machine learning and to give recommendations on practical use of the approach.

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