Impact of Customer Networks on Customer Lifetime Value Models

Pavel Jašek[1]
[1]Department of Information Technology, Faculty of Informatics and Statistics, University of Economics, Prague, Czech Republic
pavel.jasek@vse.cz

Abstract: The Customer Lifetime Value (CLV) is believed to be the 21st century marketing strategy approach. The concept of customers viewed as a long-term asset of the company seems to attract proper company resources to the activities related to this asset. The focus on long-term profitability of customers and the selection of the right customers for the future expansion is a key to valuable growth. CLV models alongside with Customer Equity (CE) models, both constitute the core and actionable basis for tactical and strategic marketing of customer-centric companies. Innovations in both concepts of CLV and CE arise from new technological possibilities to empower customer data.

Social network interactions and network structure information signify enormous opportunity for marketers to understand the real value of customer referrals and cooperation, especially in the business-to-consumer industry. Social network analysis techniques are effective to extract individual customer's importance for the company, what subsequently can be compared to the long term profitability and thus used for decisions in reputation management or churn management.

Not only customers form groups on established social networks, but also such groups appear via informal relations in terms of similar behaviour, attitudes, and interactions. Hence a clustering of user behaviour is an important technique for segmented approach to computing future value of a customer base. More precise and subtle input data make CLV models rigorous with deep respect to the heterogeneity of a customer base.

The main goal of this paper is to propose new innovative enhancements of traditional CLV models, with focus on business-to-consumer segment and non-contractual settings of customer relations with a company. Partial goals of the paper include 1) a summarization and discussion of current technological possibilities in social network analysis and clustering for the use in customer retention models, moreover 2) an enhancement of statistical models used for CLV and CE computation and finally 3) an empirical application of these statistical methods on health & beauty e-commerce dataset from the Czech Republic.

The paper focuses on clustering of CLV by marketing channels that are attributed to customers. Clustering of CLV has brought important practical insights to the targeting of marketing campaign. Empirical analysis proved that clusters emphasized actionable insights from CLV estimation in comparison with naïve grouping. Two clusters of customers originated from organic search traffic were found with significantly different CLV predictions and also with overall higher CE than other marketing channels. These clusters of identified customers should be targeted in a different manner.

Keywords: Customer Lifetime Value, Customer Equity, Innovative Marketing Management, Customer Relationship Management, Social Network Analysis

1. Introduction

Companies have to keep in mind the importance of the value of its customers and properly manage the relationship in order to get the maximum from it (Rozek, 2014). This paper researches important links between formal and informal relations among customers and their value for the company. Customer Lifetime Value and Customer Equity, terms that would be defined in next chapter, accentuate the value of an individual customer and of the overall customer base for the company. For non-contractual settings of e-commerce companies, these value models and relations should bring interesting insights for marketing management.

Interactions in a social network among customers can also be used for churn prediction. Work of Oentaryo et al (2012) demonstrate that using collective classification and social features derived from interaction records and network structure yields substantially improved prediction in comparison to using conventional classification and user profile features only. This research studied local features of a user in a chat (interaction metrics e.g. number of chat messages a user has sent, number of times a user joins a community, number of friend adding actions a user has done) and also some relational features (label-independent features e.g. number of neighbours in a node and label-dependent e.g. average cosine similarity of a node and its churn-neighbours). These label-dependent features are quite important: a number of churned neighbours (i.e. churn degree) of a node ties back to the topic of this paper: if one customer ends the relationship with the company, how many other would leave as well?

Oentaryo et al. (2012) concluded that using social interaction and relational features is a crucial facet for improved churn prediction, in comparison to using profile features only. It is important to properly fit churn techniques to non-contractual settings of e-commerce companies discussed in this paper. One of the concerns and distinction of non-contractual settings is described by Fader (2012): the terms "retention" and "churn" apply specifically and exclusively to the contractual setting. A customer buying from company A one time and company B next time, that doesn't mean this customer has undergone churn in company A.

This paper researches Customer Lifetime Value and Customer Equity definitions in chapter 2, analyses various types of customer relations in chapter 3 and thoroughly analyses lifetime value data from the perspective of naïve approach to clustering and hierarchical clustering. The paper also suggests ways of results interpretations. Empirical study of real-world data from one health & beauty online retailer from the Czech Republic provides practical demonstration of proposed analytical technique and points out managerial impacts. Due to length restrictions, the paper does not explain specific steps of CLV modelling and clustering of the dataset.

2. Customer Lifetime Value and Customer Equity

Customer Lifetime Value (CLV) is defined as the present value of the future net cash flows associated with a particular customer (Fader, 2012). Customer Equity (CE) is defined as the sum of the customer lifetime values across a firm's entire customer base (Fader, 2012) or as the lifetime value of current and future customers (Blattberg, Getz and Thomas, 2001, Rust, Lemon and Zeithaml 2004, Gupta and Lehmann 2005).

According to Berger and Nasr (1998) and Blattberg and Deighton (1996), following formula can be used to calculate CE:

$CE = am - A + a * (m - R/r) * [r^n/(1- r^n)]$

where

$r^n = r/(1+d)$,

a is the acquisition rate (proportion of solicited prospects acquired), given a specific level of acquisition costs (A),

m is the margin (in monetary units) on a transaction,

A is the acquisition cost per customer,

R is the retention cost per customer per year,

r is the yearly retention rate, and

d is the yearly discount rate (appropriate for marketing investments).

The parameter m corresponds to estimated CLV as the expected profit.

Rozek (2014) and Rust, Zeithaml and Lemon (2000) take simplified definition of CE: this metric is described as the sum of CLVs of all of the company's current and future customers.

$CE_j = mean_i(CLV_{ij}) \times POP$,

where $mean_i(CLV_{ij})$ is the average lifetime value for firm j's customers i across the sample,

POP is the total number of customers in the market across all brands.

Note that the CLV of each individual customer in the sample is calculated separately, before the average is taken.

More definitions of CLV and CE were broadly researched by Gupta et al (2006).

3. Types of customer relations

In non-contractual settings, various relations of customers with a company and relations among users can be observed:

1. Direct relations in formally or semi-formally defined networks. Traditional business network schemas e.g. multi-level marketing or modern social networks e.g. Facebook and Twitter extensively benefit from interactions between customers. From the perspective of relationship analysis, there are many limitations in proper use of social network interactions, such as data extraction, data integration, privacy and legal concerns etc. that has to be addressed. Research done by Raad, Chbeir and Dipanda

(2010) and Malhotra et al (2012) studied user footprints in different online social networks and compared several publicly available attributes: username, name, profile image, URL, location, gender and description. Oentaryo et al. (2012) studied interactions in social networks for churn predictions.

2. Informal and reciprocal relations. In several cases, there are very weak ties among users that can be observed post hoc only. Typical examples include customer referrals, word of mouth schemas, and user recommendations, sharing gift vouchers or sending discount codes to a friend. Kumar et al (2010) thus find benefits of customer referral value (CRV).

Several of these relations go beyond the scope of this article. These research topics include conventional social network analysis techniques and formal measures, impact of formal and informal relations on customer loyalty and corporate performance, identification of top influencers in a community, classifying customers with high risk of sharing negative feedback, or even discovering customers abusing discounts.

4. Clustering customers for CLV and CE

Two discussed metrics of lifetime value and equity of all customers per se unfortunately lack proper actionability: CLV should be individual-based, yet marketing managers or CRM managers in business-to-customer non-contractual settings don't have enough time to decide on value estimates for each customer. From the other hand, CE is a totally aggregated metric that doesn't give enough context of its components (e.g. what portion of estimated equity comes from new acquisitions).

This paper attempts to bring new approach to the actionability of CLV and CE using clustering. Motivation lies in the hypothesis that some groups of customers share similar behaviour, attitudes, and interactions. Moreover, with the data from direct and indirect social interactions, some informal relations should be observed. Following types of data could be used as an input for clustering:

- User profile attributes.
- User behaviour (on a website, in an application, in a store). Huang et al (2002) presented a cube model to represent Web access sessions. This model used multiple attributes to describe the Web pages visited in sessions. However, as one of Huang's observations indicates, clusters with strong path patterns usually do not contain a large number of sessions due to the complexity of the Web structures and diversity of visitor's interests.
- Time series of user behaviour. Zolhavarieh (2014) presented time series clustering and its taxonomy divided into whole time series clustering, subsequence time series clustering and time point clustering.
- Feature extraction. This technique can be used also on time series clustering. Liao (2005) discussed feature-based clustering approach.
- CLV estimates. Alvandi, Fazli and Abdoli (2012) used k-means clustering and combined CLV with LRFM model.
- Product affinity.
- Marketing attribution. Campaign response history can be shared among many customers.

4.1 Naïve approach to CLV clustering by marketing attribution

In this paper we present simple approach to clustering customers using their marketing attribution. We use first-touch attribution from a marketing campaign a customer first came to the website of a company. A practical demonstration is done on real-world data from one health & beauty online retailer from the Czech Republic. The data provided consist of 48 thousand transactions by 35 thousand identified, yet anonymized, customers within a period of 232 weeks (18 quarters). The business is clearly non-contractual with business-to-consumer relations. The dataset includes purchase data, but no acquisition and retention costs, therefore some of the values had to be estimated according to the business knowledge.

Table 1 demonstrates data from this retailer, processed with Pareto/NBD models, as described by Gupta et al (2006) and advocated by Fader (2012), to estimate CLV for individual customers. Traffic sources follow the schema of Google Analytics, where organic = search engine non-paid traffic, (none) = direct and unobserved traffic sources, referral = affiliate marketing and traditional referral traffic, cpc = paid traffic from Google AdWords and other pay-per-click campaigns, email = traffic from newsletters.

Table 1: CLV estimates for individual customers of an online retailer. Example of 5 customers. CLV estimated by Pareto/NBD. Traffic medium of customer's first visit comes from Google Analytics. All currency figures are stated in EUR. Source: Author.

Customer ID	CLV	Traffic medium
4867	53.40	organic
5793	7.79	(none)
26909	5.27	referral
19923	0.44	organic
33866	5.94	cpc

Using simple aggregation techniques and following definition of CE by Rozek (2014) and Rust, Zeithaml and Lemon (2000), we get overall figures for each traffic medium. Table 2 includes final figures of CE and average CLV for each group formed by traffic mediums.

Table 2: Simple Customer Equity estimates for each group of customers by traffic medium. All currency figures are stated in EUR. Traffic mediums with less than 10 customers are excluded. Source: Author.

Traffic medium	Number of customers (ratio of total customers)	CE for a group	Average CLV	Standard deviation of CLV
(none)	4 022 (19%)	53 673	13.3	16.3
cpc	351 (2%)	7 239	20.6	21.4
email	22 (0%)	510	23.2	19.1
organic	9 692 (46%)	129 114	13.3	15.3
referral	7 026 (33%)	77 218	11.0	13.1

Interpretation of Table 2 leads us to an important insight that search engine traffic, referral traffic and direct visits to the website form the major group of customers, yet with CLV estimates below the average. We can come to conclusion that pay-per-click campaigns and e-mail newsletters with just a small percentage of newly acquired customers have the highest expectations of future value for such customers. 46% of customers originated from organic search is a very high ratio that should be analysed in further detail.

4.2. Hierarchical Clustering of CLV and marketing data

In this part we study more sophisticated approach of clustering using the same data, this time with hierarchical clustering. The selection of clustering method followed an initial exploratory analysis of the data.

Clustering techniques for CLV were also used by Alvandi, Fazli and Abdoli (2012), who analysed data in banking services using k-means method and explained the data with customer value matrix consisting of customer buying frequency (F) and monetary value (M) with customer relationship length (L) and customer recent transaction time (R). In this paper we chose general dissimilarity coefficient of Gower and Ward's clustering criterion on data consisting of CLV estimates and traffic mediums for individual customers. Similarly to the previous part, following definition of CE by Rozek (2014) and Rust, Zeithaml and Lemon (2000), in Table 3 we get overall figures for each cluster.

The output of Table 3 demonstrates hierarchical clusters with the first step of interpretation: drill-down principle of traffic mediums and CLV aggregations. Table 3 is accompanied by Figure 1 and both outputs will be discussed below.

Table 3: Customer Equity estimates for groups (CE_{group}) formed by hierarchical clustering pruned into 5 clusters. All currency figures are stated in EUR. Traffic mediums with less than 10 customers are excluded. AVG_{CLV} = Average CLV within each cluster. SD_{CLV} = Standard Deviation of CLV within each cluster. Data is sampled to 15 000 customers only due to computational reasons. Source: Author.

Cluster	Number of customers (ratio of total customers)	Number of customers by traffic medium					CE_{group}	AVG_{CLV}	SD_{CLV}
		(none)	cpc	Email	organic	referral			
1	2 208 (15%)	0	0	0	2 208	0	62 146	28.15	18.47
2	4 618 (31%)	0	0	0	4 618	0	27 452	5.94	3.52
3	4 969 (33%)	0	0	0	0	4 969	54 016	10.87	12.26
4	2 941 (20%)	2 941	0	0	0	0	39 393	13.39	16.68
5	259 (2%)	0	242	17	0	0	5 296	20,45	21,20

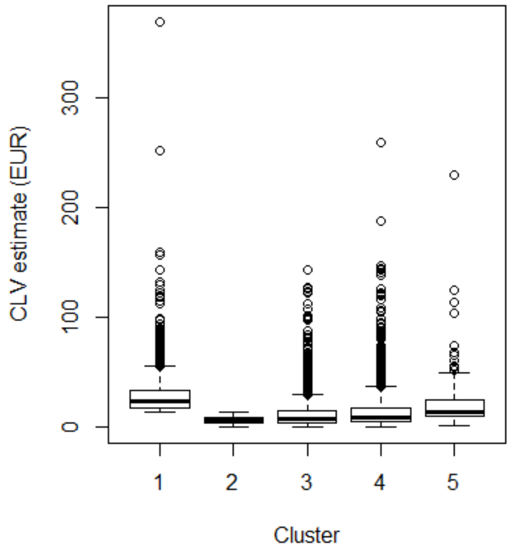

Figure 1: Box plots of CLV estimates within each cluster. Data is sampled to 15 000 customers only due to computational requirements of pairwise dissimilarities between observations in the data set. Source: Author.

Figure 1 visually explains differences in CLVs within each groups that could be observed in Table 3 only in matter of group averages. Table 3 confirms that these clusters differ significantly both in terms of mean value and standard deviation. Both clusters 1 and 2 originate in organic traffic sources, yet differ by average CLV (28.15 EUR and 5.94 EUR, respectively) and Figure 1 also explains the lower variability of Cluster 2 (SD of 3.52 EUR) in comparison with Cluster 1 (SD 18.47 EUR). Cluster 1 is estimated with the highest group CE of 62 146 EUR. Clusters 1 and 2 are very useful for the company as the higher priority lies in Cluster 1 that has five times higher CLV than Cluster 2. Cluster 3 consists of referral traffic only and Cluster 4 of direct visits. Cluster 5 with high average CLV of 20.45 carries only 2% of sampled customer base, mainly from paid campaigns.

5. Conclusion

The main goal of this paper was to propose new innovative enhancements of Customer Lifetime Value (CLV) models, with focus on business-to-consumer segment and non-contractual settings of customer relations with an online retailer. This goal was fulfilled mainly in part 4 by incorporating clustering techniques in alignment with an approach by Alvandi, Fazli and Abdoli (2012) into CLV computations, with several social network analysis techniques discussed.

The motivation for focus on clustering lies in its clear interpretation. In this paper we demonstrate an analysis of 35 thousand customers. Besides cluster averages we also calculate mean CLV estimates for each group and visualize the data using interactive tools. These methods are suitable for marketing managers for clear interpretation. As an ultimate goal for each group we calculate the sum in order to get CE for each group. The data shown in this paper bring important managerial impacts with practical applications to marketing campaign targeting. The goal of clusters in this case was also to emphasize actionable insights for CLV computation, 1) comparing CLV within just a several groups, and 2) bringing more details into CE by simplified aggregating CLVs by groups.

This paper followed an approach of elementary computation of CE discussed in Rozek (2014) and Rust, Zeithaml and Lemon (2000). Taken approach can be considered useful after the empirical study in part 4 found that a small percentage of 15% customers form 33% of Customer Equity.

Future research should aim at 1) incorporating social interactions as described by Oentaryo et al (2012) into customer datasets used for clustering of CLV, and 2) more advanced methods of CE than the basic computation of Rust, Zeithaml and Lemon (2000).

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