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The Influence of Customer Churn and Acquisition on Value Dynamics of Social Neighbourhoods

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Abstract. The customers of modern telecommunication service providers implicitly create an interactive social networks of individuals, which both depend on and influence each other through various complex social relationships grown on friendship, shared interests, locality, etc. While delivering services on the individual basis, the social network effects exerted from customer-to-customer interactions remain virtually unexplored and unexploited. The focus of this paper is on customer churn and acquisition, where social neighbourhood effects are widely ignored yet may play a vital role in revenue protection. The key assumption made is that a value loss or gain of a churning or new customer extends beyond the revenue stream and directly affects interaction within local neighbourhoods. The direction and strength of this influence are evaluated experimentally by direct measurements of the total neighbourhood value of the churning customer taken before and after the churn event.

Keywords: social networks, churn, acquisition, social value, social neighbourhood, social network analysis, network dynamics, social position, telecommunication social network

1 Introduction

A social network is one of the many possible representations of a human community, in which people interact and get into relationships with one another. These relationships can be very complex and usually involve our emotions and feelings. Besides, associations within the social network may result from family dependencies or work cooperation. Moreover, a social network continuously evolves and changes its structure. Every second some new communities arise while the others disappear, some relationships reinforce while the other vanish [15]. In the everyday world, people relay on each other. Thus, their choices and behaviour also influence choices and behaviour of the others [5]. This is the fundamental concept of recommender networks [13, 16] or recommender systems [17] and enacts a significant role in marketing [14], in which people spread information and opinion about products through their mutual, personal contacts.

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Capability to predict changes and their consequences is crucial in every business. Apparently, dynamic analysis within the customer network especially in the telecommunication social network is very important. General concept of analysis of dynamic social networks was presented in [1]. In order to forecast such changes and investigate the evolution of social networks even physics and molecular modelling can be utilised [8]. In some other approaches, clustering [4], statistical analyses and visualizations [1] or multi agent systems [2, 19] are used to get an insight into network dynamics. Daspupta *et al.* tried to predict churn based on the analysis of relationship strength in the mobile telecommunication social network [3], whereas Gopal and Meher used typical prediction method – regression to estimate churn time and tenure for the same domain [7].

This paper addresses the question: how much our behaviour, as the customers, influences the others and are we able to evaluate this influence based on the available data about mutual contacts or not? In particular, we analyse the influence of churning or acquired customers on their neighbourhoods after the churn or acquisition, respectively.

2. Telecommunication Social Network

Telecommunication data like voice calls (including residential, mobile and VOIP) contains enormous amount of information about customer activities. Moreover, each phone call can be treated as the evidence of mutual relationship between two subscribers [12].

A telecommunication social network *TSN* is the tuple $TSN=(M,R)$ that consists of the finite set of members (customers, nodes) M and the set of relationships R that join pairs of distinct members: $R=\{r_{ij}=(x_i,x_j): x_i\in M, x_j\in M, i\neq j\}$. Relationships in *TSN* are directed, i.e. $r_{ij}\neq r_{ji}$.

In other words, one member corresponds to one phone number, which, in turn, is assigned to one social entity – a human, group of people or an organisation.

3. Node and Neighbourhood Social Values

Measures are one of the social network analysis tools to describe human characteristic, specific for the given social network and to indicate personal importance of individuals in the community.

Some simple measures and one a bit more complex were used during experiments. All express the social value of a member. In particular, they are: a total number or duration of phone calls initialized (*Out calls* and *Out duration*), a total number or duration of either received or initialized phone calls (*In+Out calls* and *In+Out duration*). The complex measure is Social Position measure, which has been proposed and developed in [9, 11], evaluated for both the duration and number of calls. It can be used to calculate the importance of every single member of the network in an iterative way:

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$$SP^{(n+1)}(x) = (1-\varepsilon) + \varepsilon \cdot \sum_{y \in M} SP^{(n)}(y) \cdot C(y \to x)\ , \tag{1}$$

where:
$SP^{(n+1)}(x)$, $SP^{(n)}(x)$ – social position of node x after n+1th or nth iteration;
ε – the fixed coefficient from the range (0;1);
$C(y \to x)$ – the commitment function which expresses the strength of the relation from member y to x.

The constant ε represents the openness of human social position on external influences, in other words high ε means that the social position is highly influenced by others and low ε means that the social position is more static while others' influence is week [10, 11].

The set $N(x)$ of members y_i which are directly connected to member x is called x*'s* neighbourhood. In real world, it is a set of members, with which member x maintains the closest relationships – nearest neighbours or first-level neighbours. We assume that these closest members from $N(x)$ have the biggest influence on member x and in opposite, member x has big influence on them.

Social value of the neighbourhood of member x – $SVN(x)$ is the sum of social values $SV(y)$ of all x*'s* neighbours y:

$$SVN(x) = \sum_{y \in N(x)} SV(y)\ . \tag{2}$$

Note that the neighbourhood does not include member x. Furthermore, also other churning or just acquired nodes y are excluded from set $N(x)$, see Fig. 1.

In the telecommunication business, members and separately their neighbours can belong to various classes. Two of them are usually distinguished: residential (individuals and their families, acquaintances, friends, etc.) and business (a company, department in the organisation, a position or single employee in the organization).

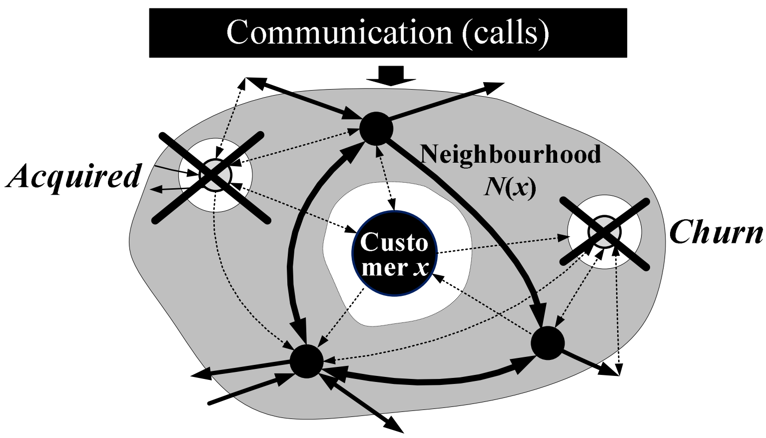

Fig. 1. Churning and acquired nodes from the neighbourhood as well as the central node itself are excluded from social value calculation

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4. Social Effect of Customer Churn and Acquisition

Today's global telecommunication market environment can be characterized by the strong competition among different telecoms and a decline in growth rate due to maturity of the market. Furthermore, there is a huge pressure on those companies to make healthy profits and increase their market shares. Most telecom companies are in fact customer-centric service providers and offer to its customers a variety of subscription services. One of the major issues in such environment is customer churn known as a process by which a company loses a customer to a competitor. Recent estimates suggest that churn rates in the telecom industry could be anything between 25% and 50% [6]. Moreover on average it costs around $400 to acquire a new customer which takes years to recoup [6]. These huge acquisition costs are estimated to be between 5 to 8 times higher than it is to retain the existing customer by offering him some incentives [20]. In this competitive and volatile environment, it makes therefore every economic sense to have a strategy to retain customers which is only possible if the customer intention to churn is detected early enough [18].

4.1. Customer Churn and Acquisition

Nowadays client churn is one of the most important problems in many companies like telecommunication and internet providers [7]. Some analysis indicates that possibility of customer churn strongly depends on the number of neighbours which have already churned from the network. It is extremely challenging task to predict customer churn and prevent it or at lest be able to predict how much this churn affect others network members [3] and how much the company may lose because of particular member's churn.

This paper is trying to deliver the initial intelligence about the impact of customer churn on the dynamics of a service value within a social neighbourhood of the churning customer, such that a decision to retain or rescue a churning customer can be better aligned to the potential value impact. It the intuition says that a churn of an active network member should have an impact at least on his direct network neighbours that could range from fading, redirected or reinvigorated activity up to the follow-up churn in extreme cases. Simultaneously, the acquisition of customers can have a significant influence on other, former customers the new client gets into relationships with. It especially refers the growth or loss in communication between the old customers. For the telecommunication company, the importance of this change lies in individual changes of the neighbours' value streams and can be considered within a generic context of social value and its dynamics

4.2. Social Values Dynamic

Let us consider a social network of customers interacting through telephone calls. Each such customer established his local social network consisted of customers whom he called or who called him at least once during his lifetime. Members of such local social network are customers' first-level neighbours as depicted in Fig 1. Each

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customer generates a dynamic value consisting of a value of his outbound calls as well as value added network component stemming from the fact that his presence drives inbound calls from his neighbours. We refer to such network value added component as social value of a customer.

While a dynamics of customer value stream is explicitly evident in his outbound calls that translate into telephone bills, the social value remains implicit and is hidden from direct observations. One naïve way of estimating the social value of a customer is to periodically measure the value of his inbound calls. The problem with this method is that it is unclear to which degree the calls made by customer neighbours are driven by the customer presence, or in other words it is not clear if under customer absence his neighbours would call less, redirect calls from the absent customer to other customers or perhaps even get stimulated to grow their neighbourhood and call more.

Customer churn gives a realistic opportunity to evaluate the social value of a customer and explore its dynamics over time. By comparing the value of customer neighbourhood before and after the churn one can truly estimate the impact of churning customer on the change in neighbourhood value which is equivalent o the social value of churning customer, as shown in Fig. 2. A similar case occurs for acquired customers. A new element in the community can influence not only on the communication with this node but also on the information exchange between the old customers, Fig. 3.

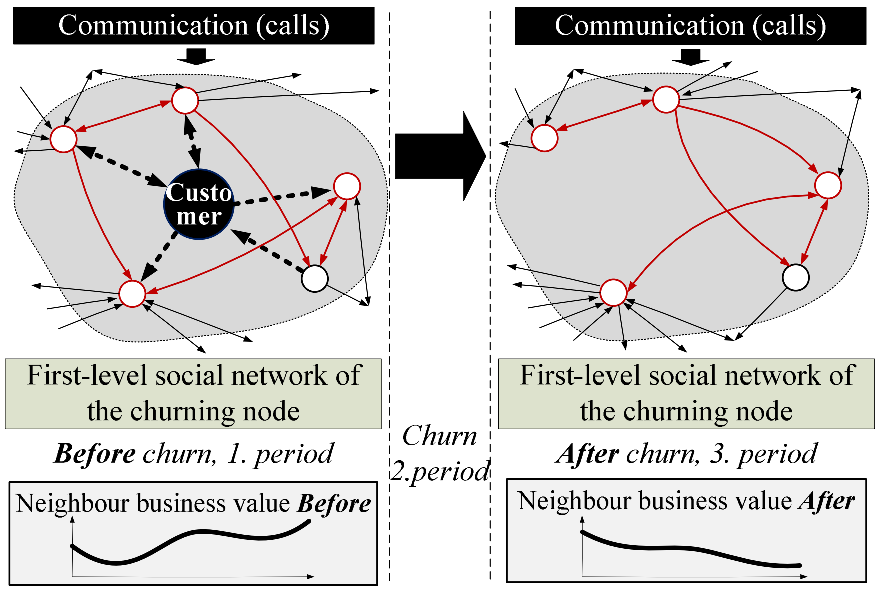

Fig. 2. A churning customer and their first-level (nearest) neighbours

It is important to remember that the neighbourhood value may continue to change at different rates well after the churn or acquisition event until the new equilibrium is achieved. Moreover, it might be very difficult to extract a direct impact of particular customer's churn/acquisition on his neighbourhood value as there may be many other

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concurrent drivers of value dynamics like other customers' churn, acquisition, customer moves and other significant network events. From the global perspective, all these additional processes impacting social value dynamics happen continuously anyway and are part of the ongoing network value fluctuations; hence their impact should be statistically similar before and after the churn/acquisition event.

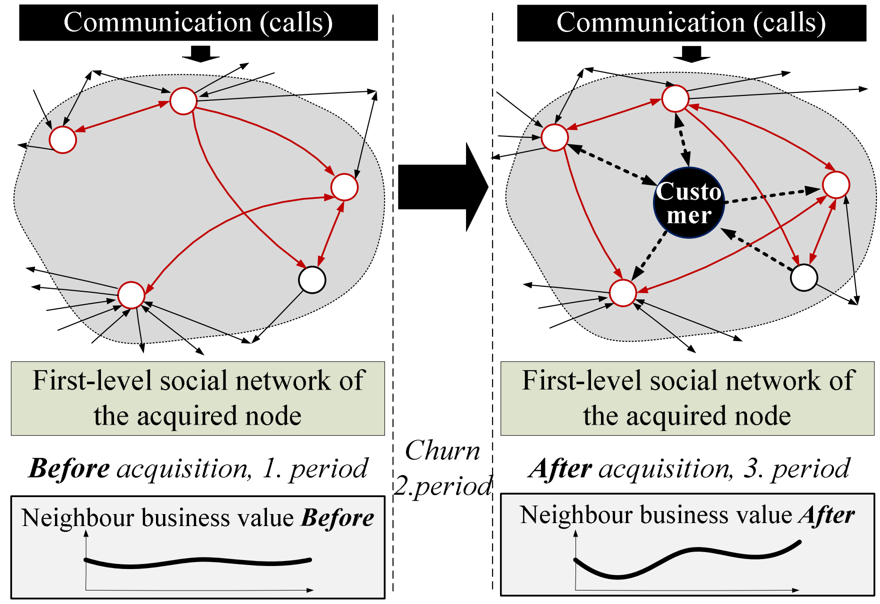

Fig. 3. The neighbourhood of the acquired customer

Note that the process of analyzing the impact of churn on social value dynamics is directly reverse to the process of analyzing the impact of customer acquisition hence the two can be analyzed together possibly even sharing similar observations and conclusions. A diagram illustrating such process is shown in Fig. 4.

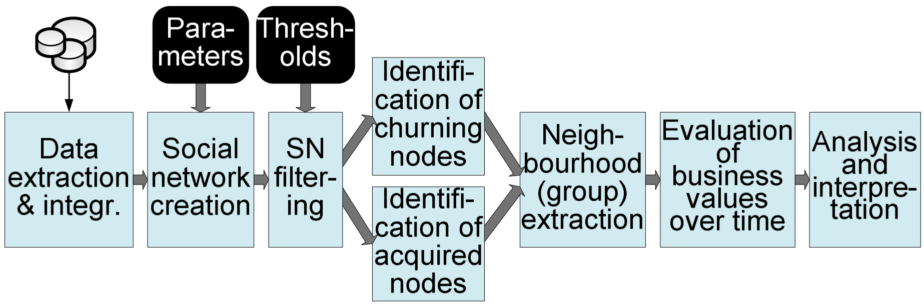

Fig. 4. Process of analysis of social neighbourhood for churning and acquired customers

The first part of this process is the identification of relationships in social network which allows establishing the neighbourhood of any particular customer. The next step is finding customers for which we want to analyse the social value dynamics, and

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those would be the customers who churn or are acquired preferable during the middle part of the period the analysis is conducted for. Then the key part involves establishing the neighbourhoods of such customers (prior- for churn and post- for acquisition) and measure the time series of their total business values from before the event until the point after the event for which the neighbourhood value time series attains again stationary. Note that as illustrated in Fig. 1, the value of churned or acquired customer is excluded from the neighbourhood value both before and after the churn/acquisition event and thus social value of a customer is a measure of customers ability to drive business value from the rest of the social network

5. Experiments

The experiments were performed for two real telecommunication social networks only for churning customers, Fig. 2. The first data set with several dozens of thousand of residential customers (*Residential*) and a few hundred of churning customers. The second one with several hundreds of thousands of business and residential (*Busines+Residential*) clients and a few thousand of churning clients and in line with the process shown in Fig. 4. The data came from 1-month period that has been split into three 10-day slots. The second slot was used to identify churning members, the first one to extract their neighbourhoods and calculate neighbourhood values "*Before*", whereas the last slot was utilised to evaluate values "*After*" and relative change: "*After*" compared to "*Before*". During the experiments, measures described in section 3 were utilized.

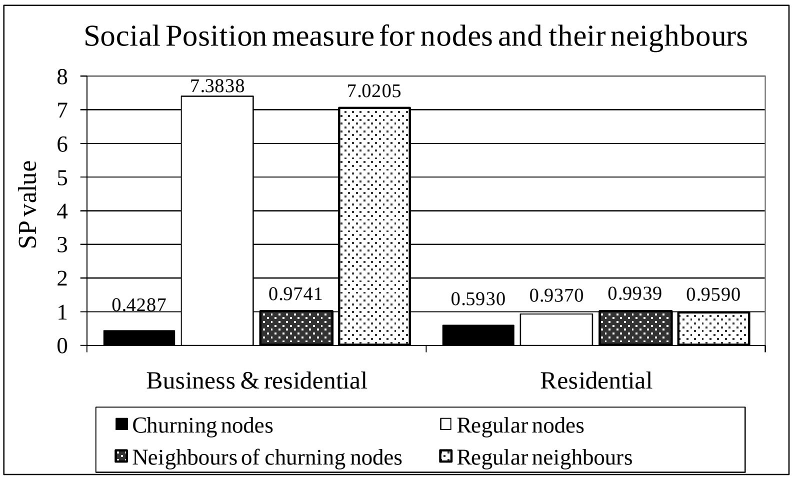

Fig. 5. Average social position value for members in the first time slot

The average social position of the churning nodes turned out to be about 40% for the *Residential* network and 57% for the *Business+Residential* network lower than the average social position of all other network members, Fig. 5. It suggests that churning customers lower their activities within the network before they leave it. Moreover,

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weaker social position of the churning customer also affects his neighbourhood although the average neighbours' social position is only 2.3% smaller than the average neighbour of the non-churning customer. However this is happening only in the *Residential* network, in case of the *Business+Residential* network average social position is about 5% higher than the average neighbour. Anyway, if we look into the dynamics of social position over the three time slots, the impact of churn on the entire neighbourhood is becoming more apparent.

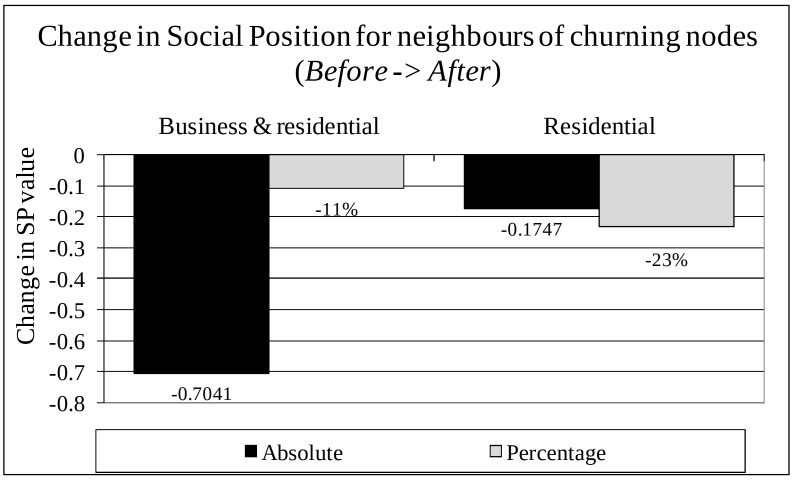

Fig. 6. Average change of neighbourhood social position value for churning members compared to regular members; the third time slot (*After*) compared to the first one (*Before*)

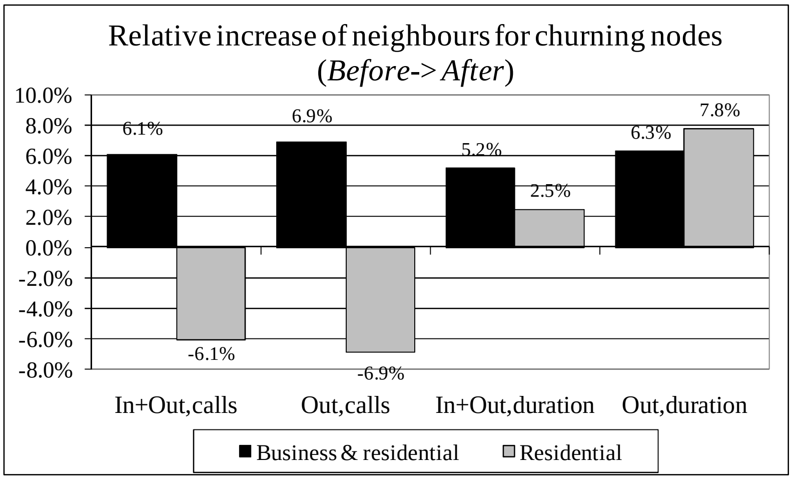

Fig. 7. Average change of neighbourhood value for churning members compared to regular members; the third time slot (*After*) compared to the first one (*Before*)

The average social position of churner's neighbourhood decreased by 23% for the *Residential* network and 11% for the *Business+Residential* network after the churn event compared to regular members as shown in Fig. 6. It shows how big influence

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the customer churn has on his neighbourhood. Because of customer churn, the network loses both the member and big part of the member's neighbour's activities. In order to present churn influence the trend, describing general change of customer activities between the third and the first period, was removed.

The similar studies were carried out using four other measures described in section 3 and the conclusions are the same.

6. Conclusions and Future Work

People influence one another and this principle can be used to analyse and understand customer behaviour especially in retail companies. This impact can be observed by means of social network analysis and changes in social value of nearest neighbours.

The preliminary experiments presented in the paper revealed that the churning customers influence their neighbourhoods. In particular, social position of the neighbours drops significantly after the churn. Smaller values of social position also point to the churning customers before they churn.

However, to indicate why it happens and to verify the extent of the presented phenomena and to build a dynamic profile of the social value change additional studies on larger data set stretching along longer periods is necessary. Once these observations are validated and formally described the next step could be to try to predict the magnitude of the change in network's activity based on the local properties of the node that triggers the change.

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