4.2 Case study: Customer retention in social networks

In recent years, in mobile communications as in many other industries, the key focus of customer marketing has shifted from acquiring new customers to retaining customers. This is because many markets have become saturated and nowadays virtually anybody who would like to have a mobile phone contract has one. Industry experts estimate that average acquisition costs per customer are around £150–200. Incurring such high acquisition costs is clearly done in the expectation that there will be some form of customer lock-in and that the customer will produce a stream of revenues through which the company regains their initial subsidies. However, churn rates (the percentage of customers switching providers) in the mobile telecommunications industry are quite high, with industry experts estimating that in advanced economies around 10 to 20% of postpaid and 20 to 30% of prepaid customers are switching operators every year.

One key goal of mobile phone companies is, therefore, to reduce these churn rates and a variety of strategies, such as longer-term contracts and upselling of multiple services, are pursued. At the same time, operators are eager to identify those subscribers who are most likely to leave and to engage them in a way that they stay with the company. This identification is typically carried out by predictive data mining models based on a number of data sources.

Traditionally, predictions have been based on using subscriber characteristics such as demographics, usage behaviour, contract end dates, increases of off-net calls, calls into call centre and so on. Social network analysis offers the opportunity to also include the impact of a subscriber's social network in the modelling. The social network can influence churning decisions for a number of reasons. For example, a friend has had a particular poor service experience with her service provider and tells her friends about it. Likewise, a friend might have changed network because she received an attractive offer from an alternative provider and makes her friend aware of this offer.

There are two main ways in which social network data can be used, which are analogous to the social pressure and social influence concepts from Section 3.2. First, social network analysis can be used to measure the influence that a social network has on an individual's probability to churn, which can be called churn pressure. Secondly,

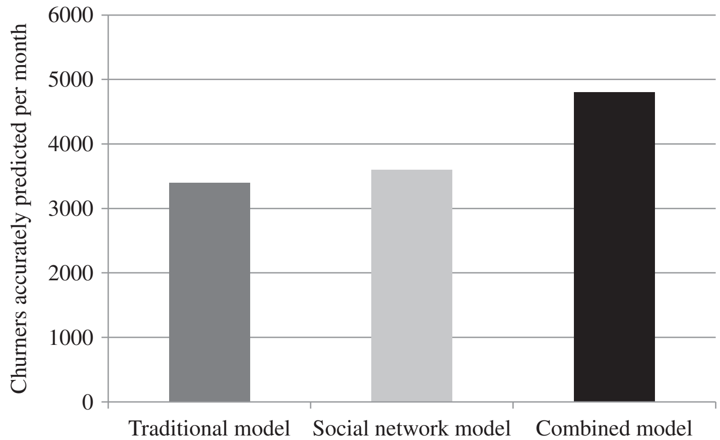

Figure 4.1 Illustrative benefits of combining traditional churn models with social network model.

social network analysis can be used to measure the influence that an individual has on his social network, which can be called churn influence:

1. **Churn pressure:** Subscribers who have other churners in their social network are under pressure to churn as well. One way of including these effects in a churn model is to add variables such as 'number of churned neighbours' into the prediction model. As most companies already have existing churn prediction models, social network information is additive. One way of measuring the success of such models is displayed in Figure 4.1, which shows the number of churners over a three month period in three prediction groups of 20 000 high risk subscribers. While both the traditional and the social network model on their own would have been able to predict circa3500 subscribers correctly as churners, the combined model – combining the highest risk subscribers from both individual models – correctly predicts about 4800 subscribers as churners.

2. **Churn influence:** Influential subscribers are more likely to take other subscribers with them if they churn. Such subscribers might not be more likely to churn at the moment, but it might, nevertheless, make sense to proactively engage them in order to make sure that they don't churn and take their friends with them. One way of identifying such influencers is to identify characteristics of subscribers who have churned and taken a high number of friends with them. Such characteristics typically include measures such as the centrality of the subscriber, the strength of relationship with his social network and the similarity with his peers – the more similar, the stronger his influence with respect to customer churn and product adoption. Afterwards, algorithms can search for similar subscribers who also have these characteristics.

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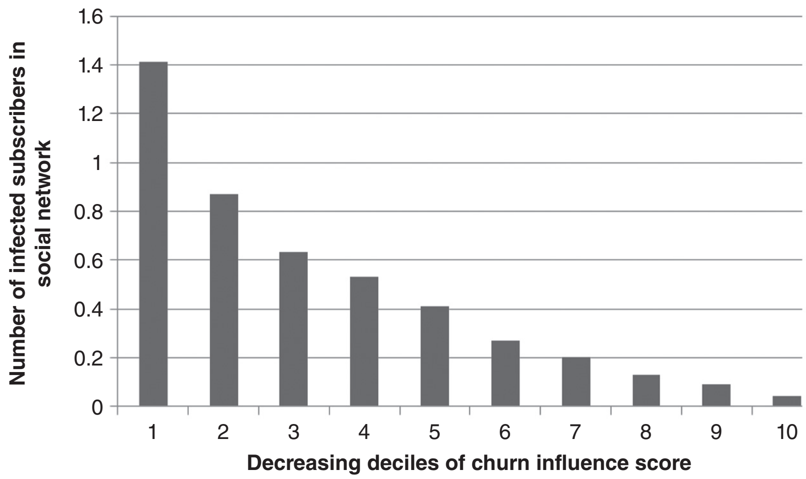

Figure 4.2 Illustrative results from prediction of churn influencers.

Typically churn influencers have been shown to take 1 to 2 additional subscribers with them if they churn. Figure 4.2 shows the impact of influential subscribers on their social network. In this illustrative example the 10% most influential subscribers on average take another 1.4 subscribers with them when they leave, whereas the 10% least influential subscribers on average only take 0.1 subscribers with them.

Across a wide variety of retention campaigns that I have run together with mobile phone companies across the world, the percentage of 'viral' churn was relatively stable at about a quarter of total churn.

However, predicting customer churn is only the first step in saving a customer. In particular, many companies have suffered from unintended consequences in their retention campaigns, as they can remind customers that their contract is coming to an end and they, therefore, have an opportunity to cancel/shop around for a better deal. There are a number of success factors when combating viral churn which will increase the likelihood that a customer can be retained:

- **Respond rapidly:** Most viral churn occurs in relatively quick succession. As a rule of thumb 50–75% of viral churn will occur within one month of the original churn event. A quick prediction and marketing response is, therefore, essential.
- **Understand network value**: Most companies nowadays have some kind of life-time value (LTV) model calculating the value of a customer over his or her lifetime as a customer. Figure 4.2 showed that customers have very different influence over other customers to churn together. LTV models should, therefore, be combined with a network value model (measuring the monetary impact of churn influencers) to derive the true value of a customer to the

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company. This network value should then be used as the basis for treating customers in retention campaigns.

- **Combat causes:** Viral churn can be caused by customer service failures as well as better offers from competitors. If viral churn is caused by a service failure, then this service failure needs to be addressed to stop it.

Case-related questions & problems

1. Discuss various reasons why the social network might influence a consumer's decision to switch mobile operator. In what instances might you ask your friends for their advice on which network to choose? In what instances might your friends talk about the advantages and disadvantages of a particular operator?
2. Discuss in what kind of situations a company would use a churn pressure (CP) model and in what kind of situations it would use a churn influence (CI) model.
3. Discuss how a retention campaign using churn pressure (CP) or churn influence (CI) could take the viral nature of this type of churn into account. Should carriers, for example, make group offers to a connected group of friends? You could frame your answers for example around the following dimensions: CP: cause of initial churn decision, relationship between peers (e.g. family vs. friends vs. work), campaign offer; CI: life-time value of the influential customer, number of peers that might be influenced (few peers with high probability vs. many with low probability), relationship to peers, campaign offer.