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Using Social Influence to Predict Subscriber Churn

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Abstract—The saturation of mobile phone markets has resulted in rising costs for operators to obtain new customers. These operators thus focus their energies on identifying users that will churn so they can be targeted for retention campaigns. Typical churn prediction algorithms identify churners based on service usage metrics, network performance indicators, and demographic information. Social and peer-influence to churn, however, is usually not considered. In this paper, we describe a new churn prediction algorithm that incorporates the influence churners spread to their social peers. Using data from a major service provider, we show that social influence improves churn prediction and is among the most important factors.

I. INTRODUCTION

The mobile phone industry has seen tremendous growth in the past decade. As the demands of society insist that everyone is reachable anywhere and anytime, mobile phone markets around the world have become saturated with customers. Rather than spend large amounts of resources to capture the remaining small percentage of people who do not have cellular service, operators devote energy towards retaining their existing customers before they *churn*, or leave them to join another. Users churn for a variety of reasons, including non-competitive pricing, network service quality, frequency of service use, and time to the expiry of their service contract. Operators incorporate such factors into machine learning algorithms to help decide which customers should be targeted for retention campaigns [1], [2], [3].

Studies also suggest that users churn out of subscription based services due to social and peer pressures [4]. As an example, users who are given free in-network calling to friends and family may decide to switch service providers if a majority of their friends and family also switch. Users may also decide to switch providers after being influenced by friends that have a popular handset not offered by the current provider. Such peer and social influences, however, are not incorporated as a factor in modern churn prediction algorithms.

In this paper, we examine how to integrate the spread of peer influence among subscribers to enhance churn prediction. We propose a methodology to quantify the strength of ties within a social network composed of subscribers that considers the interaction among users captured in call detail records. These social tie strengths are applied to a novel influence propagation algorithm over the social network. Factors about these interactions, including the total influence from churners propagated to each subscriber, is incorporated into a contemporary churn

prediction algorithm. The results suggest that social factors significantly enhance churn prediction (improving lift from 3.5 to 4 for the top decile of users) and are among the most important factors for prediction.

II. MOBILE CALL GRAPHS AS SOCIAL NETWORKS

A mobile call graph is defined as a simple undirected graph $G = (V, E)$. The set of vertices V of G represent mobile phone users, and an undirected edge $e = (a, b) \in E$ iff $a, b \in V$ and a call was placed between a and b . G thus captures the $|E| = m$ social connections placed between the $|V| = n$ users in the call graph. G is constructed using the information provided in a call detail record (CDR). A CDR captures information about all calls placed between individuals, including the call time, cell towers used, handset identifiers, and call length. The totality of all k calling attributes across calls from two users are captured by the $m \times k$ call attribute matrix \mathbf{E} , where $[\mathbf{E}]_{ij}$ is the value of attribute j for edge i .

A. Quantifying tie strength

The way in which influence propagates from one user to another is directly related to the strength of the social connection that they share, reflected in the calling attributes of \mathbf{E} . For example, if a strong social relationship exists between two users, we expect that an attribute such as the number of calls made between them is high. To measure the strength of social ties, we consider a collection of calling attributes that collectively offer an accurate view of the ties between users.

We combine calling attributes to define social tie strength as follows. Define \mathbf{e}_i as the row vector corresponding to the i^{th} row of \mathbf{E} , $\hat{\mathbf{e}}_i = \mathbf{e}_i / |\mathbf{e}_i|$ as its normalized form, and $\mathbf{\Gamma} = (\gamma_1, \gamma_2, \dots, \gamma_k)$ as a row vector of tunable weights reflecting the importance of each calling feature to determine tie strength. The strength s of the social tie across edge i is given by

$$s(\mathbf{e}_i) = 1 - e^{-\mathbf{\Gamma} \hat{\mathbf{e}}_i^T / \epsilon^2}$$

ϵ is a parameter that controls the rate at which social ties lose strength as call attribute values change. This definition captures the notion that once a strong social connection between two users is manifested, a high proportion of an “idea” (such as churning) will be transferred from one subscriber to another.

B. Influence propagation

Influence propagation algorithms must consider not only the strength of direct relationships, but also the structure of the social network and the distance between a user and the source of influence. There are many different models to represent the flow of influence in a network. We consider a receiver-centric model wherein the receiver of the influence is allowed to “decide” how much influence to retain. The propagation model was designed using the following principles about how users may be influenced to churn:

- 1) A churner initiates the spread of influence immediately after committing to churn.
- 2) The influence retained is proportional to the relative strength of the social tie that the influence comes from.
- 3) When users retain any amount of influence, they replicate that influence and pass it to all neighbors.
- 4) A user will not be influenced by the same information about a churn event.
- 5) The total influence accumulated by a user is the sum of the influences received by all churn events.

The first three principles encapsulates the receiver-centric design of the influence model. A churner will receive influence as soon as possible after the event, and the sender of the influence will transmit all of the influence that it received to every neighbor. It is then up to the receiver how much of that influence he or she will consider, and will decide based on the relative strength of the social tie they have with the sender. A user may also not be influenced about the same event twice. For example, if information (influence) travels in a cycle in the graph and returns to a user, that person would have already considered this information. If multiple users churn at once, however, the information (influence) relayed from each event is distinct, and a user should combine the information received from different events to influence their decision to churn.

We capture the above principles into our influence propagation algorithm. First we present the following definitions.

- $\mathcal{S} = \{s(\mathbf{e}_i)\}$: The vector of tie strengths.
- $\kappa(a, b)$: The index of \mathcal{S} for the edge connecting a and b . For example, $\mathcal{S}_{\kappa(a,b)}$ is the tie strength of the edge from a to b .
- $\phi_a(b)$: The proportion of influence that node a retains when it receives information from b . It is defined as the tie strength of the incoming edge divided by the sum of the tie strengths along all incoming edges. Let $in(a)$ be the set of all incoming edges to a . Then

$$\phi_a(b) = \frac{\mathcal{S}_{\kappa(b,a)}}{\sum_{j \in in(a)} \mathcal{S}_{\kappa(j,a)}}$$

- $P_\alpha(h)$: The set of all paths of length α starting from h .
- $\hat{P}_\alpha(h)$: The set of all paths of length α starting from h s.t. the path ends at a node with an out degree of 0. In essence, this set excludes all paths that are a subpath of some other path longer than α . For example, the path (a, b, c) is in $\hat{P}_3(h)$ only if c has no outgoing edges. If

c had an outgoing edge, then (a, b, c) must be a subpath of some other path with length > 3 .

- $\mathbb{P}_\alpha(h)$: The set of all paths of length $\leq \alpha$ such that no paths are a subpath of another path in $\mathbb{P}_\alpha(h)$ (i.e. removing cyclic paths). This is defined as

$$\mathbb{P}_\alpha(h) = \bigcup_{i=1}^{\alpha-1} \hat{P}_i(h) \cup P_\alpha(h)$$

- $\mathbb{P}_\alpha(h, a)$: The set of paths of $\mathbb{P}_\alpha(h)$ that vertex a is a member of.

$$\mathbb{P}_\alpha(h, a) = \{p \mid p \in \mathbb{P}_\alpha(h) \wedge a \in p\}$$

The amount of influence that is saved at a node for a specific piece of information is the original amount of influence multiplied by the product of all the influence proportions that were retained along all of the nodes in the path that the information followed. For example, if a is a churner and influence took the path (a, b, c, d) , if a started with Δ units of influence, b would save $\Delta\phi_a(b)$ units of influence and pass the same amount off to c . c would then save $\Delta\phi_a(b)\phi_b(c)$ units of influence, passing that amount off to d , and d saves $\Delta\phi_a(b)\phi_b(c)\phi_c(d)$ units.

A node a will pick up information across all of the paths that it is a member of in $\mathbb{P}_\alpha(h)$. This sets up the expression. Let Δ_i be the amount of influence that churner i starts with. The total amount of influence that a node a will receive due to the spread of influence by the set of churners \mathcal{C} is

$$\mathcal{N}(a) = \sum_{c \in \mathcal{C}} \sum_{p \in \mathbb{P}_\alpha(c, a)} \Delta_c \prod_{i=1}^{|p|-1} \phi_{p_{i+1}}(p_i).$$

III. EXPERIMENTAL RESULTS

We tested the use of social influence to predict customer churn using a dataset provided by a large telecom service provider. The data set consists of subscriber contract information for over half a million subscribers, customer churn dates, and CDRs for calls made across a large geographic area for two months. To derive \mathbf{E} we considered three calling metrics: (i) the number of calls placed between two users; (ii) the total duration of calls between two users; and (iii) the neighborhood overlap to two connected users. Neighborhood overlap is defined as the proportion of neighbors that two users have in common with each other. If a node a has the set of neighbors $N(a)$ and b has the set of neighbors $N(b)$ then the neighborhood overlap of a and b is $\mathbb{N}(a, b) = |N(a) \cap N(b)| / |N(a) \cup N(b)|$. Every feature was considered equally important (i.e. $\Gamma = (1, 1, 1)$).

Churners during the month in which the CDRs were collected were marked on the call graph. We simulated the spread of influence from these churners using our algorithm, limiting the propagation to a maximum of three hops. The users were rank-ordered by the total influence accumulated and this list was compared against the list of users who churned in the subsequent month. Figure 1 compares the percentage of users who are in the top percentile of this rank ordered

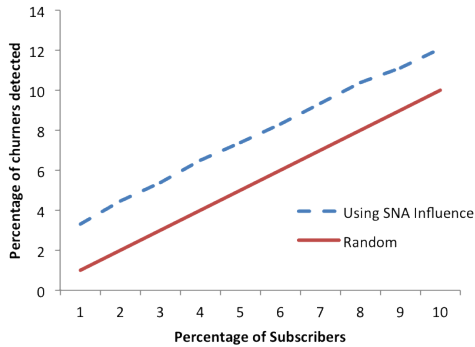


Fig. 1: Influence-based prediction vs. random sampling

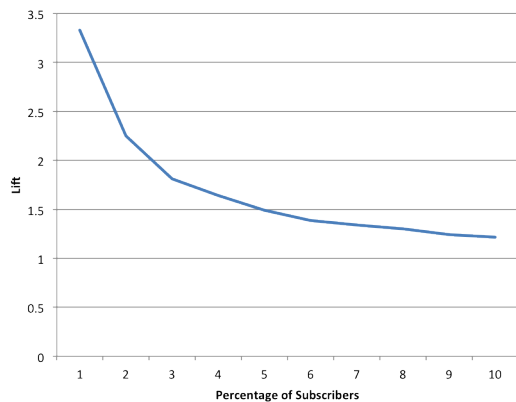


Fig. 2: Lift curve using social influence

list who are churners compared to taking a random selection of a percentage of subscribers. By using the accumulation of influence alone, we are able to identify significantly more churners compared to a random sample. Figure 2 presents the *lift curve*, defined as the multiplicative factor between the random and influence curves in Figure 1. This figure shows how if an operator could only afford to target 1% of its users with a marketing campaign, selecting the 1% of users with greatest accumulated influence would reach 3.3x more churners compared to if the operator sent the campaign to random users.

Next, we integrated the accumulated influence into a boosted decision tree churn prediction algorithm that also considers traditional churning factors such as service usage and user demographic data. Figure 3 compares the overall lift provided by the churn prediction algorithm with and without including social influence. For identifying churners among the highest scoring 10% of users, social influence adds a substantial boost in performance. Table I lists the five most important predictor variables in the decision tree algorithm. Social influence was found to be the third most important predictor, outranked only by whether or not the users' contract had expired and for how long the user had been a subscriber. It is understandable that most users choose to keep their service

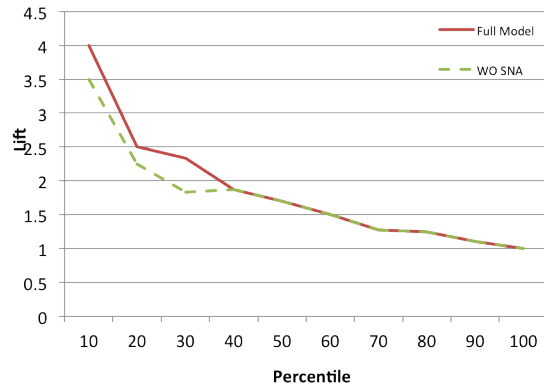


Fig. 3: Churn prediction performance

1	Whether user is on a service contract
2	Number of days subscribed
3	Social influence
4	Number of calls placed to churners
5	Number of calls placed per month

TABLE I: Most important predictor variables

while still on contract to avoid early termination penalties, or if they have been a satisfied long time customer no matter how much social pressure they weather. If a user is out of contract and is not a long time customer, however, peer influence is the strongest factor that drives them to churn.

IV. CONCLUSIONS AND FUTURE WORK

This paper integrated the spread of social influence into churn prediction algorithms over cell phone network subscribers. We combined features about calls placed reflecting the presence of a social tie to describe how much influence a user retains. We devised a model for the total amount of influence a user accumulates due to churning events, and applied the churn prediction algorithm to real data. We found that peer influence is a major factor causing users to churn.

Future research seeks to enhance the tie strength and diffusion models for better targeting over different applications and services. This includes modeling the decay of influence over hops, the directionality of information propagation, and asymmetrical tie strength values across edges.

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