Social Networking for Churn Analysis

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Outline of Case Study

• The Project
• The Goals
• Methods
• Findings
The Project

• Mobile Phone Provider with concern about losing subscribers

• Uses Predictive Analysis (Logistic Regression) to target subscribers with increased risk of churn

• Looking for ways to improve prediction and retention

• Pilot Project identified “Social Networking” type data
Goals

• Can Social Networking improve the existing churn model?

• This is a means to an end – The ultimate goal is to reduce churn.
Reducing Churn

• 1) Identify a group of subscribers with high risk of unsubscribe.

• 2) Target effective intervention to this group - without offering expensive incentives to many who will not unsubscribe.

• This can be a high bar!
Predicting Unsubscribe Rate Can Help Target Cost-Effective Interventions
Preliminary Univariate Analysis

• Hypothesis – subscribers who have been calling unsubscribers are more likely to unsubscribe.

• Calling network – who is calling whom?
Social Network Analysis
More Connections found between Cancellers than expected by chance
April 2009
21 customers

Dynamics of cancellation in a selected customer call network
Dynamics of cancellation in a selected customer call network

May 2009
2 deactivations
June 2009
4 deactivations

Dynamics of cancellation in a selected customer call network
July 2009
7 deactivations

Dynamics of cancellation in a selected customer call network
Cancellation Rates Differ for customers calling cancellers

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<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Subscriptions at Start of June</td>
<td>1980582</td>
</tr>
<tr>
<td>Cancellations among this group in June</td>
<td>26294</td>
</tr>
<tr>
<td>Cancellation Rate</td>
<td>1.3%</td>
</tr>
<tr>
<td>Subset with known calls to May churners</td>
<td>35387</td>
</tr>
<tr>
<td>Subset of these churning in June</td>
<td>837</td>
</tr>
<tr>
<td>Cancellation Rate</td>
<td>2.4%</td>
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</tbody>
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And this persists over time...
Social Networking Data

• Association
  – Relatively Stable
  – May be correlated with other predictors
  – How much can it add to existing churn model?

• Influence
  – Related in time
  – May be transient
Variable Selection

• Initial variable selection done using “earth”, the R implementation of Multivariate Adaptive Regression Splines

• Can recognize nonlinear predictors effectively

• Extremely fast algorithm reduces computation by computing the cross products incrementally
Social Network Variables

• Inbound callers “closer” than outbound callees.
• Voice calls are much better measures of association than SMS/texting.
• Counting Calls slightly better than overall length of calls.
Main Social Networking Variable Selected

• Percentage of incoming voice calls in the last 90 days which were from customers cancelling in the last 30 days.

• Those with 10% or higher on this variable were designated as churn-chatters – those speaking with recent unsubscribers relatively frequently.
Generalized Additive Models

• Generalization of Generalized Linear Models

• Using family=“binomial” makes it a generalization of Logistic Regression

• Allows nonlinear predictors (without transformations or binning)
Generalized Additive Models

• Used mgcv::gam – the Implementation in R

• Logit(p) = \sum f(x)

• Automatic plotting of each smooth f(x) term
Smooth Term Example
Days to Contract End
Timeline

• Timing is an essential dimension
  – When can we obtain the data?
  – When will the intervention impact the customer?
  – What time window should we use for evaluating the cancellation rate?

• Prescribed by the client:
  – 60 day lead time
  – 60 day window for measuring resulting churn.
The baseline model predicts seems to predict churn reasonably well when we look at the complete set of subscribers...

Fit 60-120 day churn with no social network data

Each dot represents one semidecile of the subscribers
...but misses the systematic bias when we plot the churn-chatters.

30 days of calls predicting churn over a 60-120 day period

* Churn-chatters are those who have more than 10% incoming calls coming from churners.
The impact of social networking on churn-chatters is larger if we look at the churn window for the immediate next 30 days.
The 4-month window gives us the most comprehensive look at churn-chatters.

30 days of calls predicting next 120 days of churn

Actual Churn Fraction

Predicted w/o Social Networking

Predicted w/o social networking

Actual
There is great value in reacting faster as churn-rate declines rapidly over time – especially in high risk groups identified by model and churn chat.
Impact of Social Networking Highly Dependent on Time to end of contract

Percentage impact on churn propensity

Days to Contract End

Red – churn chatters
Black – all others
Not a Proportional Hazard

- The Social Networking effect is markedly different depending on “Days to Contract End”
- The greatest SN effect is closer to the actual end of contract.
- Additional SN variables are also in the model
Lessons Learned

- Those receiving calls recently are less likely to churn.
Lessons Learned

• Social Networking is composed of at least two effects –

  • Shows affiliation
    • In our model this is an indicator variable with a relatively small value, constant over time.

  • Has influence
    • Immediate influence decays over time
    • Higher at the critical time near end of contract
Lessons Learned

- Adding social networking variables does help identify more churners

- Especially in the high-risk group of churn-chatters: those who get more than 10% of the calls in the last 90 days from people who have churned in the last 30 days.
Lessons Learned

• Time is of the essence!

  • Experimenting beyond the box of current timing constraints reveals new features in the data.

  • SN has the strongest immediate effect (days) and then decays over a longer period (several months)
Time since Caller Churn
Regardless of Association Measure
Lessons Learned

- Time is of the essence!
- Interventions must happen right away or many customers will already be gone.

Comparing Churn Rates Over Time:

- No Social Networking in the Base Model