BUILDING AGENT-BASED DECISION SUPPORT SYSTEMS FOR NETWORKED COMMUNICATION

William Rand

In collaboration with Manuel Chica

wrand@ncsu.edu

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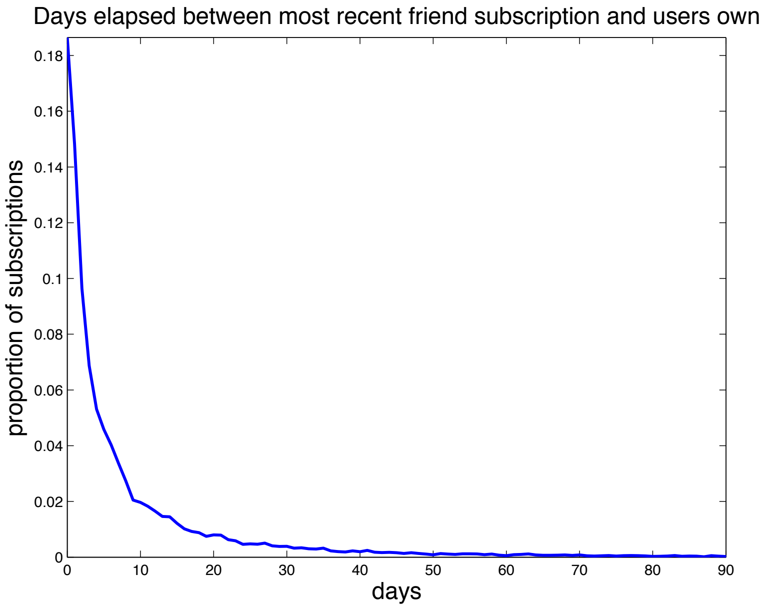
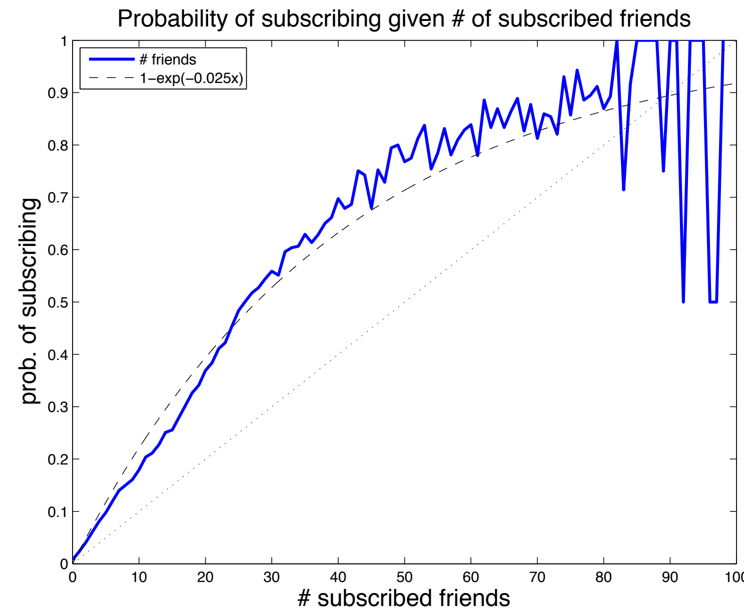
Motivation

- Firm wanted to understand what drove conversions in a massively multiplayer online game (MMOG).
- The original hypothesis was that new content was driving conversions.
- We countered with the idea that the social network drove conversions.

Social Network Effects





- 18.6% of conversions happen *the same day* as a friend's, *Half* happen within 3 days
- <1% of users w/o a premium friend will convert, 0 premium friends → 1: lift is 300%
- New content has no significant impact on conversions, and there was no significant drop in conversions after 20 days without new content

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New Objectives

- Word-of-Mouth became the focus of the research, with the MMOG as an example:
  1. Develop guidelines for the creation of word-of-mouth decision support systems.
  2. Provide a step-by-step framework for the creation of such systems using ABM.
  3. Illustrate the guidelines and framework in a case study of a freemium app.

General Guidelines for DSS Creation

G1. Involve marketers and stakeholders in an iterative and participatory modeling process focused on the adoption of the DSS outputs

G2. Analyze and use available marketing data for all the steps' decisions

G3. Employ data-driven calibration and computational methods with the goal of increasing the model understanding

G4. Minimize number of required DSS parameters to reduce complexity and enable comprehension

Involve Marketers and Stakeholders

- To create “buy-in” for a DSS it is important that the people who use the DSS are involved from the beginning.
- This is a form of Rogers’ Trialability.
- Reduce problems when adopting DSS by practitioners (Lilien, 2011; Little, 1979).

Build Upon Existing Data

- In many cases, there is no reason to start from scratch.
- The model will need to be validated, but if it is constructed from valid data to begin with there is a greater chance that the model will be close to valid at the beginning.
- This is also related to making sure that the inputs to the model are empirically valid.

Employ Data-Driven Calibration

- This is a cornerstone stage when creating an individual-level WOM DSS.
- When creating a DSS you are by definition pushing beyond the limits of what you know perfectly to make decisions about the unknown.
- To mitigate uncertainty, data-driven methods of calibration should be used.
- *Calibration* is changing the parameters of the model to increase the validity of the output.
- *Validity* means making sure that the output of the model corresponds to the real-world.

Minimize Complexity

- KISS Principle – Axelrod, 1997
- Reducing the complexity of the model:
  - Makes verification (matching the implemented model to the conceptual model) easier
  - Aids validation of the model
  - Enhances the interpretability of the results

Components of a general model

Social network between users

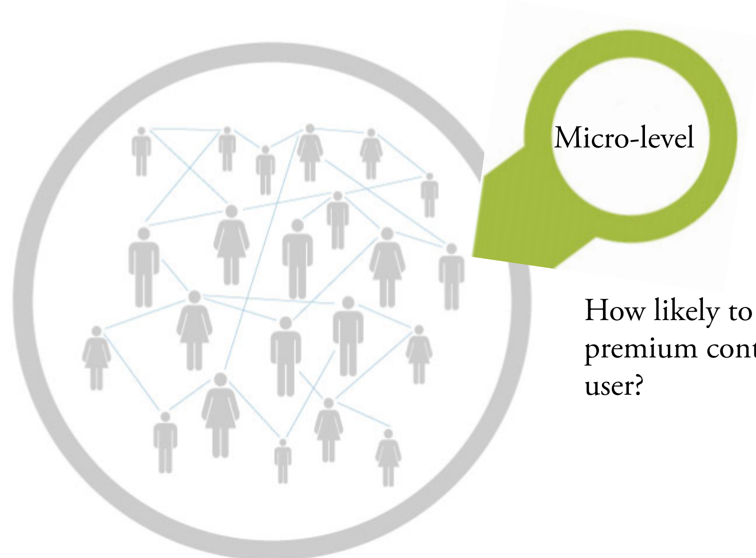
Diffusion dynamics for adopting premium

Seasonality for using the app

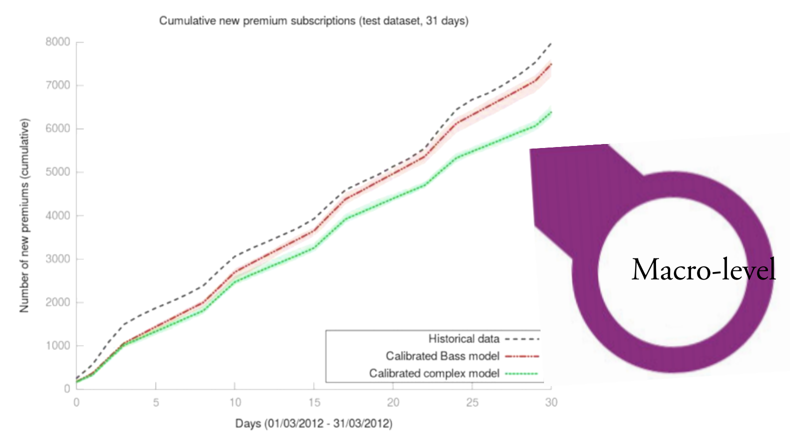
Agent-based modeling simulation

Calibration engine by genetic algorithm

To forecast premium adoption



How likely to adopt premium contents is this user?



What is the forecast of new premium members of the app?

Step S1. Objective and ABM Framework

- **A. Clear objective:** focus the DSS construction to the WOM program setting and policies to explore (targeting, macro-level forecast etc.)
- **B. Initial adoptions and KPIs definition:** study needed agents' properties, initial adopters and KPIs of interest (DSS output).
- **C. Individuals update:** decide whether asynchronous or synchronous update for the individual's state.
- **D. Granularity:** choose granularity of the individuals according to the trade-off between needed details and computational efforts (e.g. mapping, temporal scale).
- **E. Seasonality features:** study the seasonality of the real customers to include this behavior within the model.

Step S2. WOM Dynamics in a Social Network (SN)

- **A. Social network generation:** employ artificial SNs when no information (e.g. scale free, ER). Otherwise, replicate real features of the service/app (e.g. degree distribution).
- **B. Include social influence:** use weighted SNs for bidirectional diffusion when different social influences exist.
- **C. Information diffusion model:** analyze data to see number of friends when adopting. If necessary, add externalities.

Step S3. Data-driven Calibration by Metaheuristics (MHs)

- **A. KPIs optimization:** decide KPIs to calibrate the model in a single or multi-objective way by also including marketers' preferences.
- **B. Hold-out approach:** divide data into training (to find the best model parameters) and test (to validate them).
- **C. Deviation measure:** select it according to data-set and KPIs. Choose single-point or behavior-pattern calculation.
- **D. Knowledge about parameters' values:** if high, local-based and single-solutions MHs (intensification). If low, population-based and stochastic MHs (high diversity).
- **E. Parameters features:** iterative MHs when there are different ranges and types. Use greedy MHs when constraints and dependencies between them exist.
- **F. Automated sensitivity analysis:** high diversification MHs to find design relations (e.g. stochastic population-based).

Objectives and ABM

A. **Clear objective:** focus the DSS construction on the WOM program setting and policies to explore (targeting, macro-level forecast etc.)

B. **Initial adoptions and KPIs definition:** describe needed agents' properties, initial adopters and KPIs of interest (DSS output).

C. **Individuals update:** decide whether asynchronous or synchronous update for the individual's state and how the individuals will update.

D. **Granularity:** choose granularity of the individuals according to the trade-off between needed details and computational efforts (e.g. mapping, temporal scale).

E. **Seasonality features:** study the seasonality of the real customers to include this behavior within the model.

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WOM and Social Network

A. **Social network generation:** employ artificial SNs information (e.g., scale free, ER) when no other information is available. Otherwise, replicate real features of the service/app to the limit of available information (e.g., degree distribution).

B. **Include social influence:** use weighted SNs for bidirectional diffusion when social influence is heterogeneous.

C. **Information diffusion model:** analyze data to understand the effect of the number of friends when adopting. If necessary, add external influences.

Calibrating the Model

A. **KPIs optimization:** decide KPIs to calibrate the model in a single or multi-objective way by also including marketers' preferences.

B. **Hold-out approach:** divide data into training (to find the best model parameters) and test (to validate them).

C. **Deviation measure:** select an error measure according to data-set and KPIs. Choose single-point or behavior-pattern calculation.

D. **Knowledge about parameters' values:** if high, local-based and single-solutions metaheuristics (intensification). If low, population-based and stochastic metaheuristics (high diversity).

E. **Parameters features:** iterative metaheuristics when there are different ranges and types. Use greedy metaheuristicss when constraints and dependencies between them exist.

F. **Automated sensitivity analysis:** high diversification metaheuristics to find design relations (e.g. stochastic population-based).

Freemium Case Objectives

Understand what drives users to convert to premium memberships in online apps.

Objectives:

- To develop a general model for social adoption of premium levels in a freemium context.
- Identify the best way to model diffusion in this context.
- Forecast premium conversion at the aggregate and individual-level.
- Identify optimal marketing policies.

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Framework

- An overarching agent-based model that represents the users of the online app. They can be either premium or basic users.

- A social network of friends.

- A model of diffusion dynamics to determine adoption at every time step.

- A calibration engine (genetic algorithm) to adjust the parameters of the model to the real data.

Animal Jam data

Online social game for kids: freemium business model.

Understand why users adopt premium contents and the social influence of their friends. Previous analysis showed content drops did not affect conversions.

Real data of the social network (snapshot) and daily premium conversions.

Evaluate the best marketing strategies to expand the market.

ABM and seasonality

The ABM will generate the number of daily premium conversions.

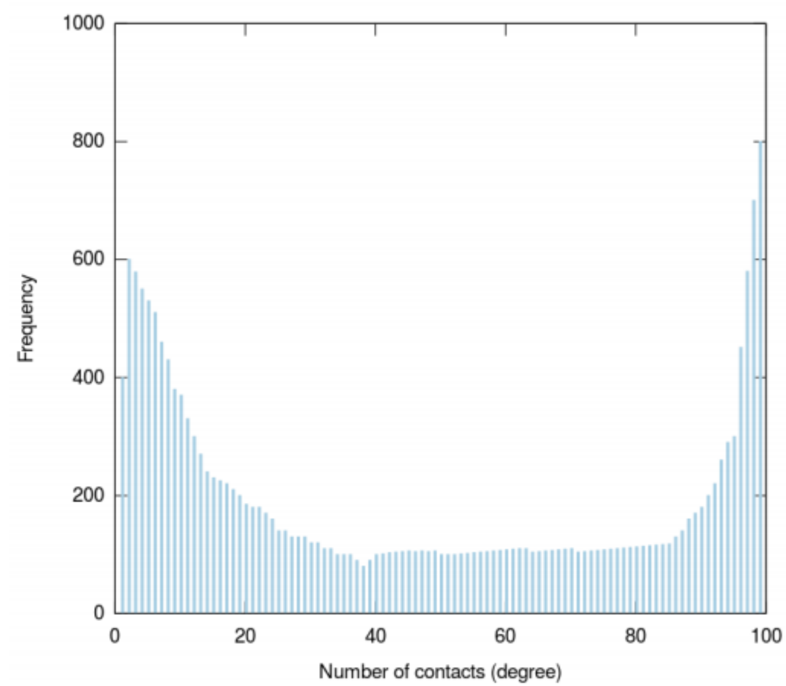
Modeling app use: each agent, before making a conversion decision, has to determine if they are going to play that day

- Primarily affected by playing during weekends and weekdays.
- Every agent can make a decision every day.
- The simulation is asynchronous (actions of an agent at *t* can affect other agents within the same time step *t*).

Social network generation

Agents are linked by a social network. In the case of the Animal Jam, this is limited to a max. of 100 friends.

Instead of using approximated random networks such as SF or ER we use a generalized random network algorithm to create a social network with the same degree distribution.



We have chosen the efficient generator of simple graphs with prescribed degree sequence (Viger and Latapy, 2005)

Bass model diffusion

One of the existing models for diffusion is the Bass model where an agent can adopt the premium content by innovating or by imitating (social network). (Bass, 1959)

$$\frac{F'(t)}{1-F(t)} = p + qF(t)$$

Innovation probability *p* to adopt because of external effects (advertisement or another information outside the social network).

Imitation probability *q* to become premium by observing her friends where *F(t)* is the fraction of friends already premium.

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Complex Contagion model

We have developed a complex contagion model based on the idea that a contagion requires an individual to have contact with 2 or more sources (initial data analysis). (Centola and Macy, 2007)

The complex contagion is similar to the threshold model. Difference resides on taking into account the sources (not the exposu `

$$\Pr[\text{adopt B}] = \begin{cases} 1 & \text{if } b_i \geq \phi_i, \\ 0 & \text{if } b_i < \phi_i, \end{cases}$$

We also developed a complex contagion with an innovation probability *p* as in the Bass model.

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Calibrating the models

Properties of the ABM:

- A social network (SN) with the degree distribution of the app.
- 20,000 agents linked by the SN and daily steps.
- Parameters for seasonality: probability of playing weekends and weekdays.

Three different diffusion sub-models:
(1)Bass, (2) Complex and (3) Complex with innovation.

Calibration (hold-out approach): 2 months training; 1 month test. Using a genetic algorithm (real-integer seasonality and diffusion parameters). Evaluating individuals by Euclidean error distance.

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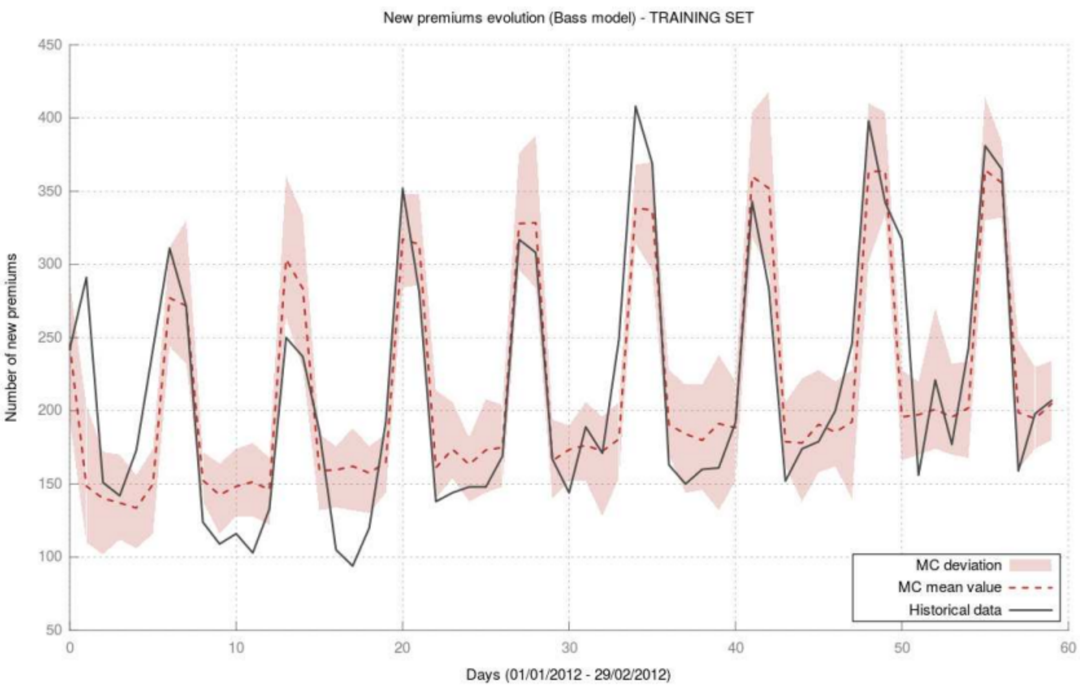
Macro-level forecast results

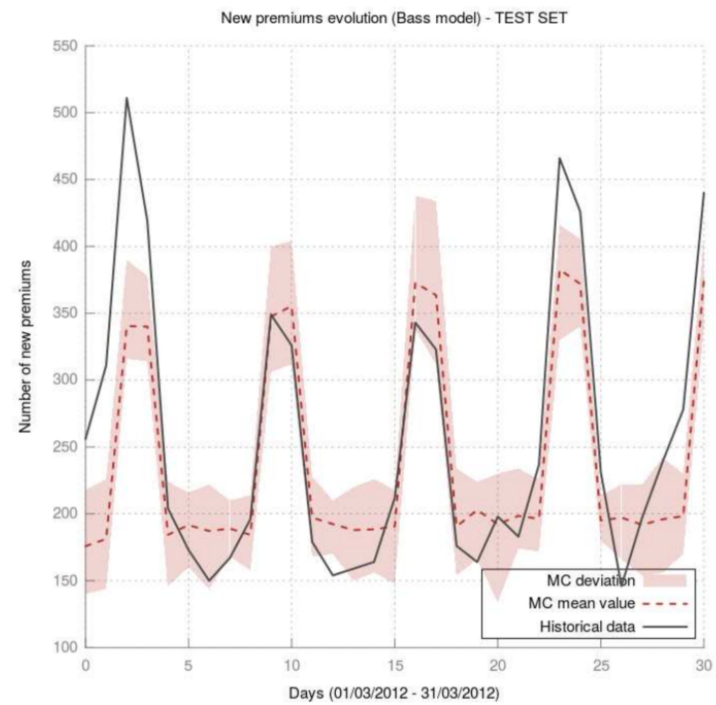
Can we fit the historical data daily and what the best diffusion model is for the problem?

	Bass model		Complex		Complex with innovation	
Training set (R_{train})						
	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ
Euclidean	**358.72109**	2.00986	447.15797	4.75522	441.52756	5.45638
Correlation	**0.83542**	0.00207	0.74666	0.01341	0.74689	0.01251
Test set (R_{test})						
	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ
Euclidean	**339.01315**	9.09134	420.53968	20.37237	416.76062	19.4957
Correlation	**0.83903**	0.00572	0.82959	0.00766	0.83857	0.00932

Macro-level forecast results

The correlation and fitting of the Bass model using a MC simulation is good for both training and test data (60 and 31 days, respectively).





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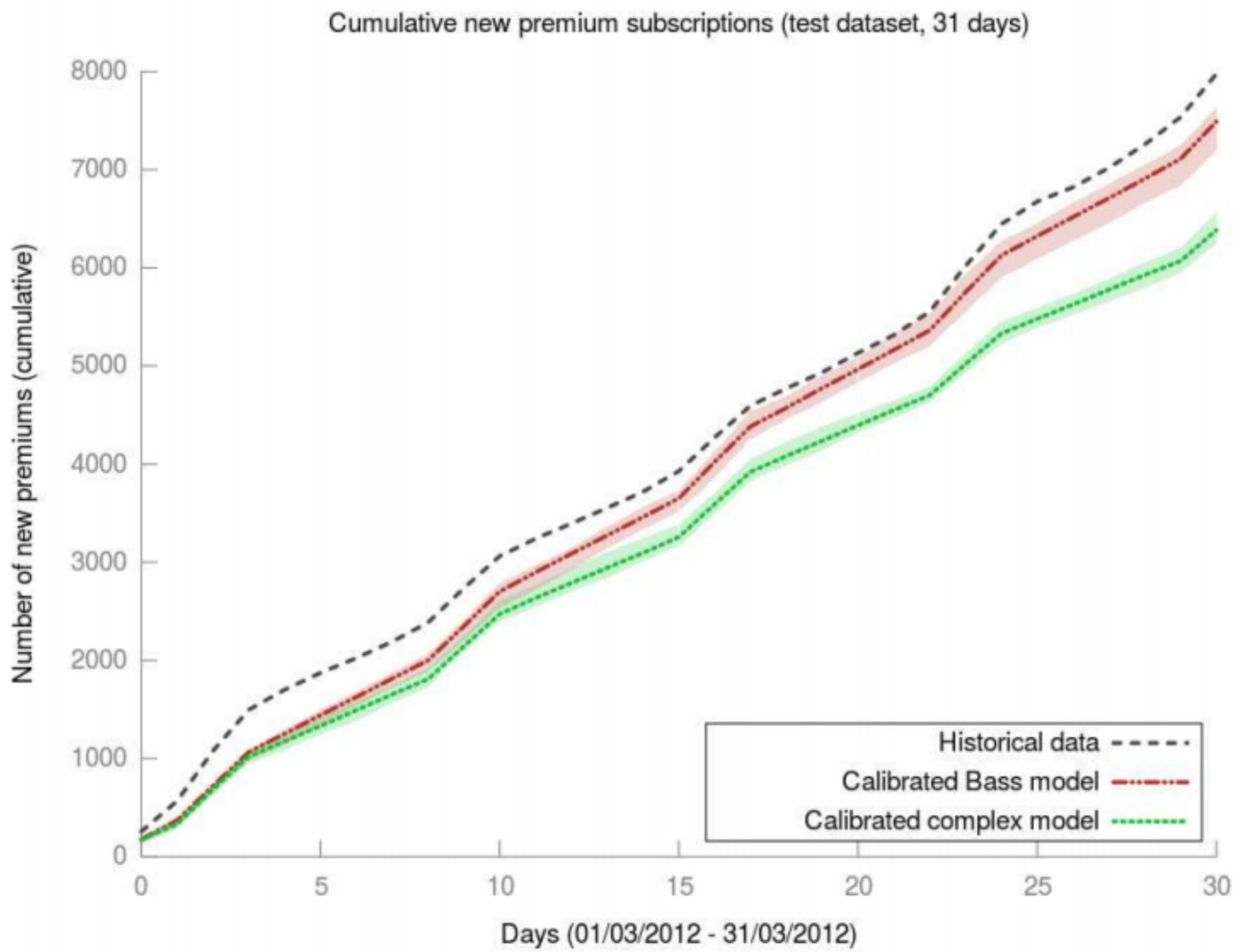
Macro-level forecast results

Also, the cumulative number of premiums adopted in the whole period is much more accurate when using the Bass.



Macro-level forecast. Testing policies

What is the best policy to expand the market by rewarding the users who convert to premium when they adopt?

Policy 1: 9.95 $

Policy 2: 11.95 $

Policy 3: 22.95 $

Annual membership: 57.95 $

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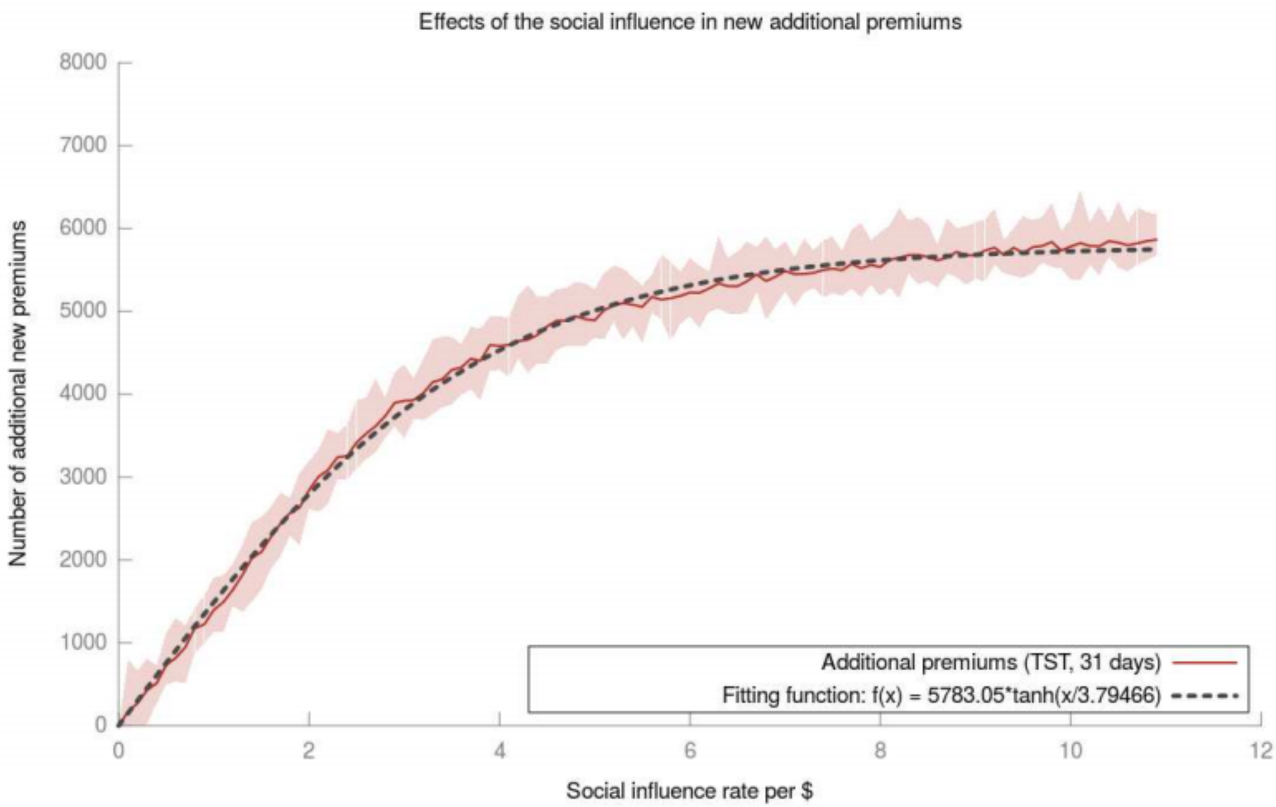
Macro-level forecast. Testing policies

We include a social influence weight for each link. When converting we reward the user and increase their social influence.



The sensitivity analysis shows a non-linear increase in additional conversions when increasing the global social influence.

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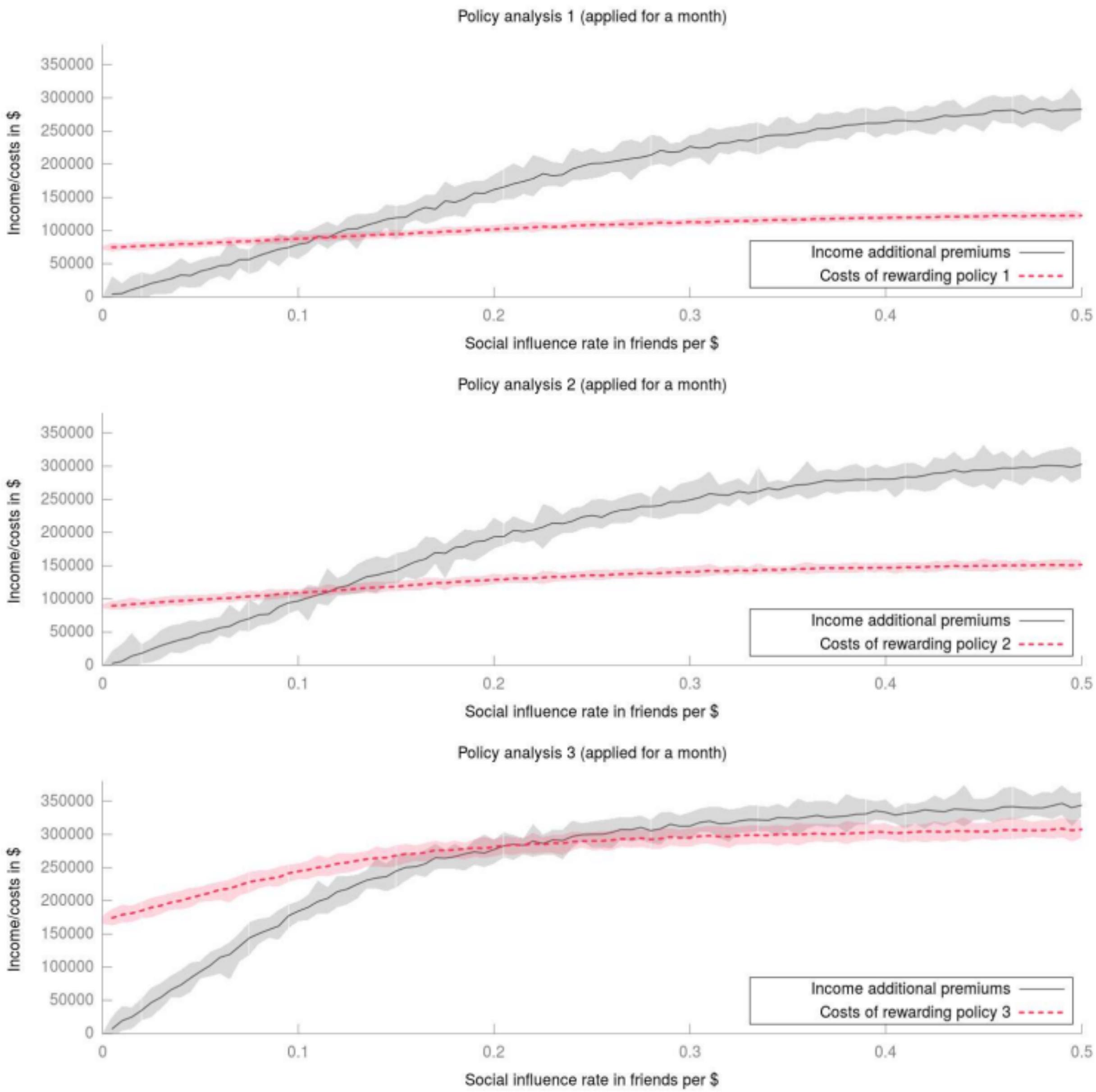
Macro-level forecast. Testing policies



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Experimentation: micro-level

The goal is to try to predict the exact users who are going to convert by using the same models: the Bass and Complex contagion.

We use a sampled dataset of 10,798 freemium users and count the premium conversions after one month (we do not care when in this month).

We use ROC analysis to compare the behavior of the models:

True Positives: 718 users (around 6% conversions)

True Negatives: 10,080 users

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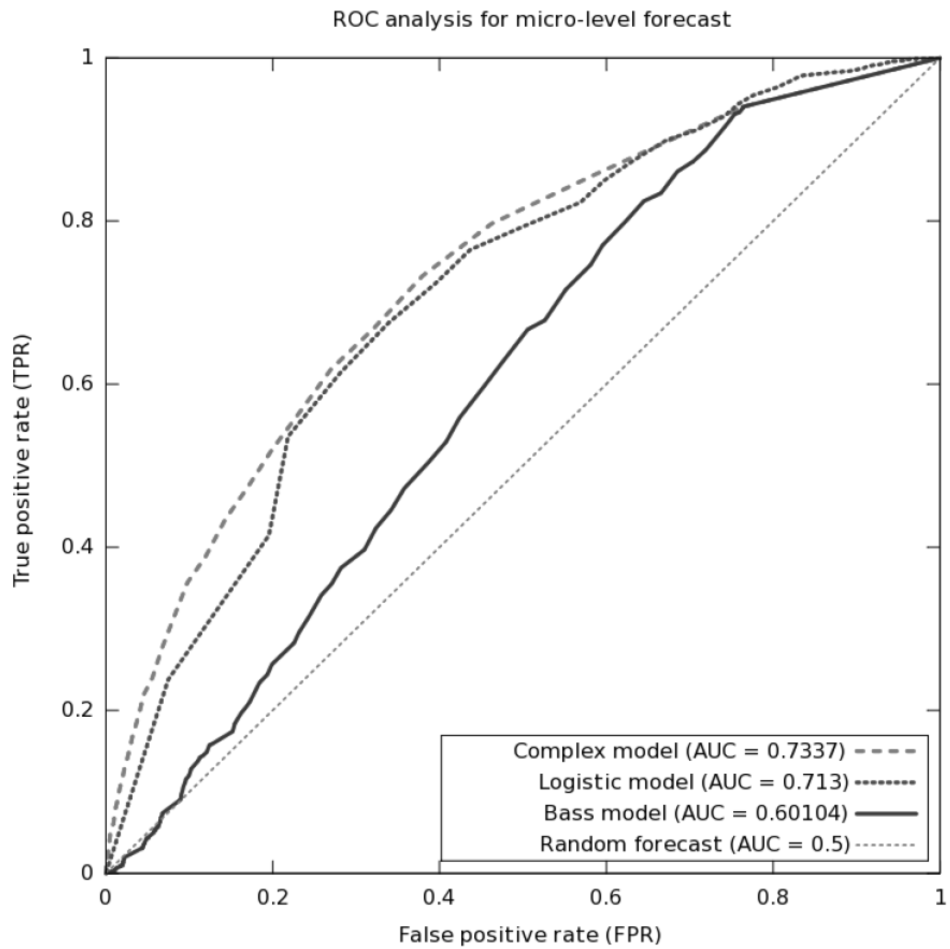
Micro-level forecast. Results

We modify the probability of the Bass model and the threshold of the complex contagion to see the TP and FP rates. Complex contagion does much better:



Combined model: rewarding seed users

The goal is to identify the best group of seed users to be rewarded in advance in order to maximize adoption.

3 group of 1,000 seed users:

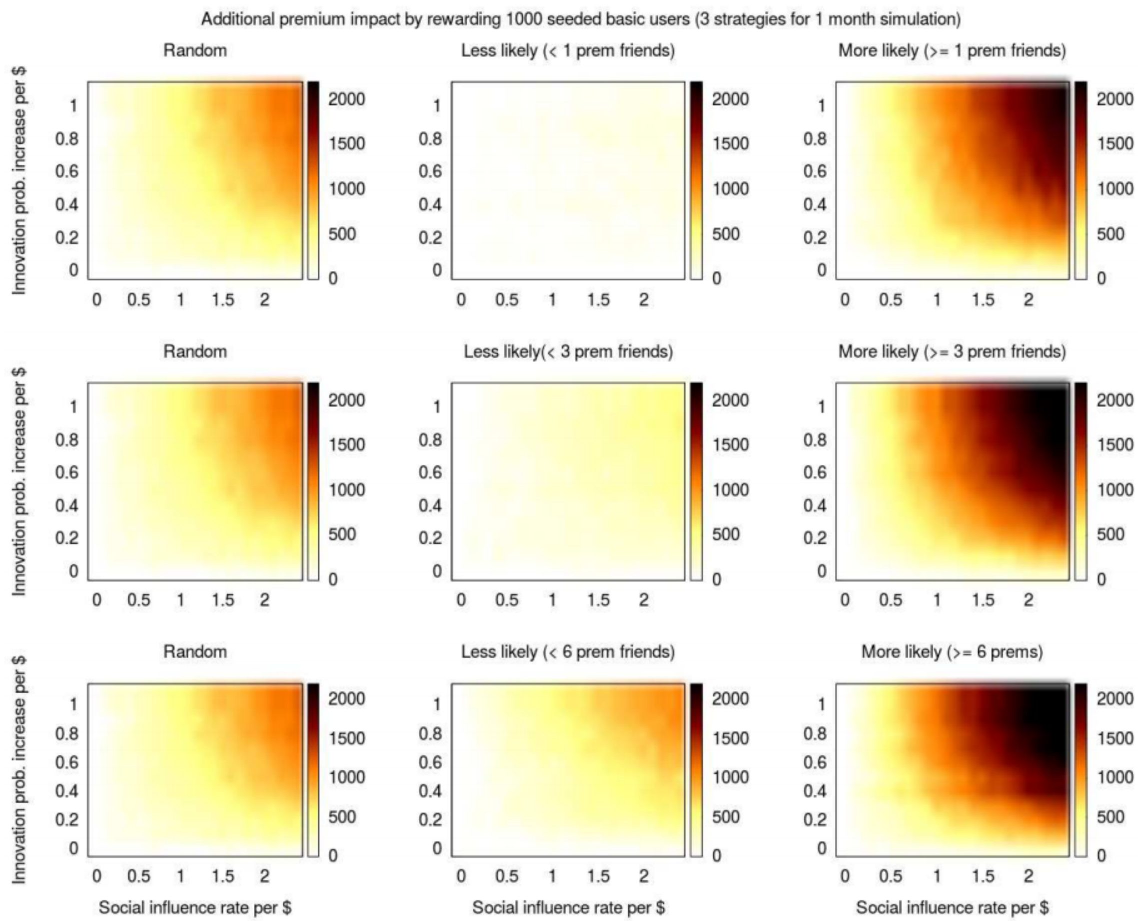
① Random users

② Users who are most likely to adopt

③ Users who are least likely to adopt

Combined model. Results

The best option is to seed the most likely users to convert. It is not worthwhile to focus on the least likely to convert since it does not produce additional income. Random would be better.



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Final thoughts

We develop a general model to understand why users of social apps purchase premium contents.

We have applied this general model to the Animal Jam data and tested different marketing scenarios both micro and macro levels.

In general, the goal of this presentation is to convince you that ABM + Networks not only gives you interesting insights about the world, but can also be used to drive actual business decisions.

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Thanks!

- Any Questions?

- wmrand@ncsu.edu
- twitter: @billrand
- billrand.org

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