Learning from Peers on Social Media Platforms

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Context of the Study

- A crowdsourced customer support platform of a telecom company

- Company employs this customer-driven platform to help answer customers’ questions
The Emergence of Crowdsourced Customer Support Platforms

Table 1. An Example of Knowledge Seeking and Sharing in Customer Support Forum*

<table>
<thead>
<tr>
<th>Post Type</th>
<th>Author</th>
<th>Time</th>
<th>Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question</td>
<td>A</td>
<td>9:39 PM</td>
<td>I have got a new Sony expert E. I have enter the APN settings and I have connected to 3G but I can't connect to wifi every time I try to use it says 'connecting' and then it just says saved, secured with WAP and it keeps doing that every time I try connecting! HELP!! Please!</td>
</tr>
<tr>
<td>Answers:</td>
<td>B</td>
<td>9:48 PM</td>
<td>This is a quick suggestion based on my experience of the screens on budget routers; enable the tickbox that stores the password as you type instead of stars. It may be that it's triggering some letters twice so the password is saved but incorrect. Once it's right it should join automatically.</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td>9:49 PM</td>
<td>Are you entering your router or the wifi hotspot password in correctly? You should also note that if you are connected to 3G (mobile internet) and wifi, it will try to connect to 3G automatically unless you change this in options on android. (Had to do this for my Galaxy S5)</td>
</tr>
<tr>
<td>D</td>
<td></td>
<td>10:01 PM</td>
<td>Do you have any sort of security set up on your router such as MAC address filtering, or a device access list that might be refusing access to your phone? Can you also confirm that the password is correct by reconnecting another device?</td>
</tr>
<tr>
<td>E</td>
<td></td>
<td>10:50 PM</td>
<td>The wifi settings on your phone have nothing whatsoever to do with the SIM card....You are either trying to connect to your home broadband router, or a public wifi hotspot and the message you're seeing (which is actually &quot;Secured with WEP&quot; (Wired Equivalent Privacy)), and this is possibly why your device will not connect. WEP is not secure and some new devices may refuse to connect to it. Remove the network from your saved network list first, then re-add it but tick the box to show password as you type it, to ensure that you are entering it correctly and not confusing number 0 with a O or number 1 with letters L or lower case l. WEP passphrases use the numbers 0-9 and letters A-F only. You might also check the settings in the router, in case MAC filtering has been enabled. If so, only devices on an approved list can connect to the network.</td>
</tr>
</tbody>
</table>

*Posts source from a thread in a real online discussion forum.
Industry Background

- Anybody can register as a user
- True identities of both knowledge sharer and seekers are revealed
  - Act as quality control in the absence of feedback
- Most of the questions are technical questions
  - "How to insert and retrieve multilingual data using ORACLE NCLOB?"
- Multiple answers are sequenced according to time stamps
- Top management use the forum to identify experts. Active contributors have higher probabilities of receiving bonus or promotion
- We focus on most basic features
Data Description

Table 2. Data Description

<table>
<thead>
<tr>
<th>Variables</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Users</td>
<td>1558</td>
</tr>
<tr>
<td>Number of Periods</td>
<td>30</td>
</tr>
<tr>
<td>Total Number of Questions</td>
<td>3748</td>
</tr>
<tr>
<td>Total Number of Solutions</td>
<td>2684</td>
</tr>
<tr>
<td>Average Number of Questions Asked per User</td>
<td>2.41</td>
</tr>
<tr>
<td>Average Number of Solutions per User</td>
<td>1.73</td>
</tr>
<tr>
<td>Mean of Tenure (Number of Weeks Registered Before Period 0)</td>
<td>25.08</td>
</tr>
<tr>
<td>Average Number of Views per Post</td>
<td>130.59</td>
</tr>
</tbody>
</table>

Learning Mechanism Enabled by Web 2.0

- Seeking knowledge
  - Ask question
  - Everybody can answer
  - Knowledge seeker gains knowledge
  - Whole community gains knowledge

- Sharing knowledge
  - Answer a question
  - Knowledge seeker gains knowledge
  - Whole community gains knowledge

Social network enabled very different learning mechanism

1. **Learning from peers**: learning cannot be achieved without contribution from peers
2. **Externality of learning**: any contribution improves knowledge level of the whole community

Naturally, these properties imply decision process that is

1. Inter-dependent
Core/Periphery Structure

Customer Support Platform Network Structure

How to Improve Knowledge Sharing

- **Concern of the firm**: core/periphery structure might hinders problem solving for consumers

- **Firm proposal**: improving knowledge sharing by anonymizing participants’ identity
Research Questions

• What drives the formation of Core/Periphery structure?

• How does the Core/Periphery structure influence user participation and knowledge sharing on this customer support platform?

• How should we improve the design of the platform to improve knowledge sharing

Summary of Major Findings

• Core/periphery structure implications
  – Discourage individuals with low social status to contribute to the community
  – Hurt knowledge sharing in online social media

• Design intervention
  – Anonymizing knowledge seeker breaks Core/Periphery structure
  – Platform features may be used to prevent formation of core/periphery structure
Flow

- Model
  - Decision variables
  - Formulating utility function
  - State variable updating rules
  - Dynamic game model

- Estimation strategy
- Results discussion
- Policy simulations

Decision Variables

- Decision variables of user $i$ at time $t$,
  - Knowledge seeking
    $$ a_i^t = \begin{cases} 
    1, & \text{if individual } i \text{ asks a question at time } t \\
    0, & \text{otherwise} 
    \end{cases} $$
  - Knowledge sharing
    $$ s_{ij}^t = \begin{cases} 
    1, & \text{if individual } i \text{ answers a question from } j \text{ at time } t \\
    0, & \text{otherwise} 
    \end{cases} $$
  - We allow knowledge sharing to be dyadic
Direct Incentive of Decision Making

- Ask questions
  - Resolve questions
  - Improve knowledge  \rightarrow \text{Knowledge} \ K_{it}

- Answer questions
  - Build social status
  - Recognized by peers  \rightarrow \text{Social Status} \ R_z

- Utility Function

\[ U_{it}(K, R, Z_i, a_{it}, s_{it}, e_{it}) = \alpha_1 K_{it} + \alpha_2 R_{it} + \alpha_3 \sum_j s_{ijt} - C(a_{it}, s_{it}, Z_i) + e_{it}(a_{it}, s_{it}) \]

Knowledge updating rule

\[ K_{i(t+1)} = \beta K_{it} + k_1 I(\sum_{j \in N, j \neq i} s_{j(t-1)} \in \{SN_{it-1}\}) \]
\[ + k_2 \sum_{a \in N, a \neq i} View_{ia(t-1)} \left( \sum_{j \in N, j \neq i} s_{j(t-1)} \in \{SN_{it-1}\} \right) \]

Total number of solutions provided to her question

Total number of answers provided to her peers’ questions

- Inherent interdependency and dynamics:
  - Knowledge seeker needs to predict whether her question will be answered
  - One user’s decision affects knowledge of all peers and hence their future decisions
  - In the long run, she can benefit from higher community knowledge

4/21/16
Measuring Social Status

- Social reputation $R_{it}$
  - It is about
    - Being perceived as an active community contributor
  - High reputation increases utility
    - Social recognition
    - Perceived as valuable in internal labor market
    - Bonus and promotion
  - It depends on
    - Frequency
    - Quality of answer
    - Association
  - Relative ranking of social reputation

- Social reputation updating rule
  - $At$: contribution matrix $A$
    - NxN adjacency matrix
    - $A_{i,j}$: element represents the number of ordinary answers provided by $i$ to $j$’s question
    - Measures intensity of interaction between $i$ and $j$
  - Individual perceived contribution level Nx1
    $$x_t = \beta x_{t-1} + (A_{t-1} - A_{t-2}) \cdot 1_{x \times 1}$$
  - Absolute social reputation weighted by network association
    $$x_t = x_t + \gamma t A_t x_t$$
  - Relative social reputation score
    $$R_u = \frac{x_t - \min (x_t)}{\max (x_t) - \min (x_t)}$$
Cost of Asking and Answering Questions

\[ C(a_{it}, s_{it}, Z_i) = C_a(a_{it}, Z_i) + C_s(s_{it}, Z_i), \]

- Cost of Asking
  \[ C_a(a_{it}, Z_i) = a_{it}(c_{a,0} + c_{a,1} Tenure_i) \]

- Incorporating question quality
  \[ C_s(s_{it}, Z_i) = \sum_j (c_{s,0}(1 + c_{s,1} I(a_{it} = H)) + c_{s,1} Tenure_i) s_{ijt}. \]

Additional cost of answering if question was given kudo

Heterogeneity

- Unobserved heterogeneity
  \[ U_{it}^p(K, R, X_t, a_{it}, s_{it}, e_{it}) = a_{it} K_{it} + a_{it} R_{it} - (C_a(a_{it}, Z_i) + C_s(s_{it}, Z_i)) + e_{it}(a_{it}, s_{it}). \]

- Probability of answers being identified as a solution
  \[ Pr(s_{jit} \in \{SN_{it}\}|s_{jit} = 1) = \frac{\exp(\beta_{j1} + \beta_{j2} K_{it} + \beta_{j3} R_{it})}{1 + \exp(\beta_{j1} + \beta_{j2} K_{it} + \beta_{j3} R_{it})}. \]
User’s dynamic problem

• Individuals are
  – Forward-looking
  – Game

• User’s dynamic problem:

\[ E \left[ \sum_{t=0}^{\infty} \beta^{t-t_{0}} u_{t}(x) \right] | h_{t} \]

• State variables:
  – Knowledge of self and of peers
  – Social reputation score of self and of peers

Oblivious Equilibrium and Estimation

• OE provides an appealing behavioral model
  – Large number of peers
  – Each individual makes nearly optimal decisions based on her own state and the long-run market state.
  – The oblivious value function

\[ \pi(h_{t}, \sigma_{i}, x_{i}) = E \left[ \sum_{t=0}^{\infty} \beta^{t-t_{0}} u_{t}(x) | h_{t} \right] \]

  – Strategy optimizes an

\[ \sup_{\sigma_{t} | h_{t}, \sigma_{i}} v_{t}(h_{t}, \sigma_{i}, x_{i}) = v(h_{t}, \sigma_{i}, x_{i}), \forall i, H \]

• Adopt EM algorithm by Arcidiacono and Miller (2011) to control for unobserved heterogeneity
Estimation Results

<table>
<thead>
<tr>
<th>Utility Function Parameters</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
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<tr>
<td>Impact from Knowledge</td>
<td>0.042***</td>
<td>0.070***</td>
</tr>
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<td>2.927***</td>
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<td>0.069***</td>
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<td>Percentage of Customer in this Type</td>
<td>77.66%</td>
<td>22.34%</td>
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</table>

- Type 1 user derives more utility from knowledge and social status, and less cost of asking and answering questions
- A user would derive higher social status if she solves questions of other high status individuals

Whose Question Gets Solved

- Knowledge seeker with higher social status of more likely to receive a solution
Whether to Participate

- High social status users more likely to ask questions
  - Because high status individuals are more likely to receive solutions to their questions.

![Graph showing relationship between Knowledge Seeker Social Status Level and Probability of Asking a Question]

Dynamics of Core/Periphery Formation

Core users:
- Prefer to interact with core users
- Ask more questions

Peripheral users:
- Prefer to interact with core users
- Receive no interact with others
- Ask few questions

Formation of core/periphery
Dynamics of Core/Periphery Formation

<table>
<thead>
<tr>
<th>Randomly adding 500 ties</th>
<th>Adding 500 ties among core</th>
<th>Adding 500 ties among periphery</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network 1</strong></td>
<td><strong>Network 2</strong></td>
<td><strong>Network 3</strong></td>
</tr>
<tr>
<td>Core-periphery Degree</td>
<td>0.0509</td>
<td>0.0641</td>
</tr>
<tr>
<td>Avg Knowledge for Core</td>
<td>13.119</td>
<td>13.418</td>
</tr>
<tr>
<td>Avg Knowledge for Peri</td>
<td>6.655</td>
<td>6.413</td>
</tr>
</tbody>
</table>

- Core-periphery structure leaves knowledge seekers with low social status positions in disadvantageous situations.
- Once a core appears, it reinforces itself through pattern of future interactions.

Sensitivity Analysis

- Anonymizing knowledge seeker's identity

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>Anonymity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Core Knowledge Level</td>
<td>12.712</td>
<td>13.240</td>
</tr>
<tr>
<td>Avg Peripheral Knowledge Level</td>
<td>6.815</td>
<td>7.356</td>
</tr>
<tr>
<td>Avg Community Knowledge Level</td>
<td>8.132</td>
<td>8.670</td>
</tr>
</tbody>
</table>
Sensitivity Analysis

- Decrease the discount factor of individual contribution level to 0.9

<table>
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<th>Faster Decay</th>
</tr>
</thead>
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<tr>
<td>Avg Core Knowledge Level</td>
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<td>15.084</td>
</tr>
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<td>7.173</td>
</tr>
<tr>
<td>Avg Community Knowledge Level</td>
<td>8.132</td>
<td>8.940</td>
</tr>
</tbody>
</table>

Sensitivity Analysis

- Rewarding knowledge seeking behavior by giving reward that equals 10% of the baseline cost of asking questions

<table>
<thead>
<tr>
<th></th>
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<th>Reward Qs</th>
</tr>
</thead>
<tbody>
<tr>
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<td>12.712</td>
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Summary of Major Findings

• Core/periphery structure implications
  – Discourage individuals with low social status to contribute to the community
  – Hurt knowledge sharing in online social media

• Design intervention
  – Anonymizing knowledge seeker breaks Core/Periphery structure
  – Platform features may be used to prevent formation of core/periphery structure

Robustness Check

• Using Absolute social status instead

• Changing discount factors

• Removing reciprocal answers
Is Core-eriphery Network Good for Knowledge Sharing?
-- A Structural Model of Endogenous Network Formation on a Crowdsourced Customer Support Forum

Yingda Lu
Param Vir Singh
Baohong Sun

Cornell
April, 2016

Early Adopters Observe Two Challenges

First Challenge: Slow adoption

Figure 2A. The Total Number of Answers and Questions

Figure 2B. The Number of People Who Participate in the Forum for the First Time in Each Period
Second Challenge: Most activities are generated by a few users

Concentrated Network Structure

Figure 1. The Core/Peripheral Network Structure

a. Individuals are represented by spheres. Lines connecting two individuals represent the presence of a knowledge-sharing relationship between them. The arrow heads point towards the individual who answers the question. More active participants are indicated by larger spheres.

Research Questions

• 1) How the processes of “learning from peers” and “knowledge spill-over” influence the dynamics of individual knowledge seeking and sharing decisions;

• 2) Which drive the formation of core/periphery structure in social media platforms;

• 3) How the core/periphery structure influences user participation and knowledge sharing on a customer support forum;

• 4) How should we improve the design of social media platform to facilitate knowledge sharing on the social media platforms.
Related Literature

- Marketing literature
  - Consumer online decision making
  - Word-of-mouth and social influence
  - Formation of network
    - Narayan and Yang 2007
    - Most assume exogenous network and adopt statistical approach

- Organizational behavior literature on knowledge sharing
  - Knowledge gains through interaction with peers improve productivity
  - Learning from peers
    - Do not directly observe learning

- Learning models
  - Learning through consumption experience, signals contained in price and advertising
    - i.e. Erdem and Keane 1996, Erdem, Keane and Sun 2008
  - Atomistic view of individual experimentation behavior

- Dynamic game

A Dynamic Model

- Decision variables of user $i$ at time $t$,
  - Knowledge seeking
    $$ a_i = \begin{cases} 1, & \text{if user asks question at time } t \\ 0, & \text{otherwise} \end{cases} $$
  - Knowledge sharing
    $$ s_{ij} = \begin{cases} 1, & \text{if user answers question asked by } j \text{ at time } t \\ 0, & \text{otherwise} \end{cases} $$
  - We allow user decisions to be dyadic.
• Per period utility

\[ U_{it} (K, R, Z_i, a_i, s_{it}, \epsilon_{it}) = a_1 K_{it} + a_2 R_{it} + a_3 \sum_{j} s_{ijt} - C (a_i, s_{it}, Z_i) + \epsilon_{it} (a_i, s_{it}) \]

- \( K_{it} \): the knowledge level accumulated up to time \( t \)
- \( R_{it} \): social reputation score
- \( \text{Sum } S_{ijt} \): number of questions answered by \( i \) in \( t \)
- \( Z_i \): observed user characteristics
- \( C(\cdot) \): cost to be estimated
- \( \epsilon_{it} \): private shock, distributed as type-I extreme value

• Knowledge \( K_{it} \)
  - It is about
    - Specific to a product or profession
    - Often related to a technical solution
    - Can saturate slowly over time
  - More knowledge increases utility
    - Better use of the product or find a solution
    - Customer satisfaction and job performance
    - Free time
• Knowledge updating rule

\[ K_{i(t+1)} = \beta_k K_{it} + k_i I \left( \sum_{j \in N, j \neq i} s_{jt-1} \in \{SN_{jt-1}\} \right) + k_j \sum_{m \neq i} View_{i,m,t} \left( \sum_{j \in N, j \neq i} s_{jt-1} \in \{SN_{jt-1}\} \right) \]

where:
- \( s_{jt-1} \in \{SN_{jt-1}\} \) is the total number of answers provided to her peers’ questions (excluding herself).

Inherent interdependency and dynamics:
- Knowledge seeker needs to predict whether her question will be answered.
- One user’s decision affects knowledge of all peers and hence their future decisions.
- In the long run, she can benefit from higher community knowledge.

• Social reputation \( R_{i, it} \)

- It is about:
  - Being perceived as an active community contributor.

- High reputation increases utility:
  - Social recognition.
  - Perceived as valuable in internal labor market.
  - Bonus and promotion.

- It depends on:
  - Frequency.
  - Quality of answer.
  - Association.

- Relative ranking of social reputation.
• Social reputation updating rule
  – \( A_t \): contribution matrix \( A \)
    – NxN matrix
    – \( A_{i,j} \): element represents the number of ordinary answers provided by \( i \) to \( j \)'s question
    – Measures intensity of interaction between \( i \) and \( j \)
  – Individual perceived contribution level Nx1
    \( x_t = x_{t-1} + A_t \cdot x_t \)
  – Absolute social reputation weighted by network association
    \( x_t = x_t + \gamma A_t \cdot x_t \)
  – Relative social reputation score
    \( R_c = \frac{x_t - \min(x_t)}{\max(x_t) - \min(x_t)} \)

• Cost \( C(\cdot) \)
  \[
  C(\hat{a}_{it}, s_{it}, Z_i) = C_a(\hat{a}_{it}, Z_i) + C_s(s_{it}, Z_i),
  \]
  \[
  C_a(\hat{a}_{it}, Z_i) = a_{it}(c_{a,0} + c_{a,2}\text{Tenure}_i)
  \]
  \[
  C_s(s_{it}, Z_i) = \sum(c_{s,0}(1 + c_{s,1}^- l(a_{it} = H)) + c_{s,1}\text{Tenure}_i)s_{ijt}.
  \]
Heterogeneity

- Unobserved heterogeneity

\[ U_t^e(R, R, x_t, a_t, s_t, e_t) = a^e_t x_t + a^e_t s_t - (c^e_t(a_t, Z_t) + c^e_t(s_t, Z_t) + e_t(a_t, s_t)). \]

- Question heterogeneity

\[ c^q_t(s_t, Z_t) = \sum c^q_{ij}(1 + c^q_{i}(a_t = 1)) + c^q_{i} Z_{it}, \]
\[ c^q_t(a_t, Z_t) = c^q_{ij} + c^q_{i} Z_{it}. \]

- Probability of answers being identified as a solution

\[ \Pr(e_{ij} \in \{SN_t\}|e_{ij} = 1) = \frac{\exp(b_1 e_{ij} x_{ij} + b_2 e_{ij})}{1 + \exp(b_1 e_{ij} x_{ij} + b_2 e_{ij})}. \]

User’s dynamic problem:

\[ E[\sum_{t=1}^{t_T-1} U_t (y)|h_t]. \]

State variables:
- Knowledge of self and of peers
- Social reputation score of self and of peers
Oblivious Equilibrium and Estimation

- OE provides an appealing behavioral model
  - Large number of peers
  - Each individual makes nearly optimal decisions based on her own state and the long-run market state.
  - The oblivious value function

\[ f(h_u, \sigma_t, \sigma_i) = E[\sum_{i=1}^{\infty} \beta^{i-1} u_i(c|h_u)] \]

- Strategy optimizes an

\[ \sup_{\sigma_t} \bar{V}(h_u|\sigma_t, \sigma_i) = \bar{V}(h_u|\sigma_t, \sigma_i), \forall i, \forall \sigma_i \]

- Adopt EM algorithm by Arcidiacono and Miller (2011) to control for unobserved heterogeneity

### Table 3. Parameter Estimation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type 1 Customers</th>
<th>Type 2 Customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility Function Parameters for Type 1 Customers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impact from Knowledge (( \delta_t ))</td>
<td>0.042***</td>
<td>0.107***</td>
</tr>
<tr>
<td>Impact from Social Status (( \eta_2 ))</td>
<td>2.927***</td>
<td>4.644***</td>
</tr>
<tr>
<td>Network Position Effect on Social Status (( \eta_4 ))</td>
<td>0.069***</td>
<td>0.097***</td>
</tr>
<tr>
<td>Constant for Cost of Asking a Question (( \gamma_{da} ))</td>
<td>2.863***</td>
<td>2.166***</td>
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<td>18.975***</td>
<td>11.852***</td>
</tr>
<tr>
<td>Percentage of Customer in this Type</td>
<td>77.66%</td>
<td>22.34%</td>
</tr>
</tbody>
</table>

| Utility Function Parameters for Type 2 Customers | | |
| Impact from Knowledge (\( \delta_t \)) | 0.042*** | |
| Impact from Social Status (\( \eta_2 \)) | 4.644*** | |
| Network Position effect on Social Status (\( \eta_4 \)) | 0.097*** | |
| Constant for Cost of Asking a Question (\( \gamma_{da} \)) | 2.166*** | |
| Constant for Cost of Answering a Question (\( \gamma_{da} \)) | 11.852*** | |
| Percentage of Customer in this Type | 22.34% | |

| Cost Function Parameters | | |
| Impact of Tenure on Cost of Asking Question (\( \gamma_{ta} \)) | 0.045*** | |
| Impact of Tenure on Cost of Answering Question (\( \gamma_{ta} \)) | 0.014 | |

| Other Parameters | | |
| Effect of Knowledge Spill Over (\( \kappa_1 \)) | 0.005 | |
| Additional Cost of Answering a High Quality Question (\( \kappa_2 \)) | -2.371*** | |

- Reputation effect is not trivial
- Cost of answering is higher than cost of asking.
- Benefit cannot compensate for the cost in the current period.
Whose Questions to Answer?

- Questions from high social status users are more likely to be answered
- High status users are more likely to share knowledge

Implication: high status users are likely to answer each other's questions and thus form a cohort.

Individual Optimal Decision Rules
- Whether to Participate?

Figure 2A. Probability of Receiving a Solution to a Question given Knowledge Seekers’ Social Status Level

• Prob of K seeking increases with reputation

Figure 2B. Probability of Posting a Question given Social Status Level

• Prob of K sharing increases with reputation
Explain “Free Riding” Behavior

Findings:
- Slow start: low overall knowledge level
- Low increasing rate: formation of cohort discourage users with low position from participating

Managerial implications:
- Some users are “forced” not to participate
- The adoption does not really take off

Formation of Cohort Affects Effectiveness of Knowledge Sharing

Findings:
- Only centralized users benefit from the formation of cohort.

Managerial implication:
- New users do not get help
Better Design to Align with User Behavior

• Three Alternative Policies
  – Rank based on recency
  – Hide the identity of knowledge seeker
  – Reward knowledge seeking

• Simulation takes into account ripple effect in the community
  – i asks or answers a question
  – The state variables of everybody in the whole community change
  – All peers alter their decisions about asking and answering questions
  – ……
  – The whole process continues

Breaking the Cohort and Reward Knowledge Seeking

Findings:
• Individual benefits more than the community
• Higher knowledge increment when asking than answering questions

Managerial implications:
• It is not about donation, it is about learning.
• Proactive learning is more effective than reactive learning

Finding:
• Hiding identity of knowledge seeker can improve knowledge sharing by 36%.
Managerial Implication

- Higher knowledge increment when asking than answering questions
- Hiding identity of knowledge seeker can improve knowledge sharing by 36%.
- It is not about donation, it is about learning.
- Proactive learning is more effective than reactive learning
- Encourage competition for reputation, but break the cohort
- Alternative design: periodically reset the record, financial incentive to encourage individuals to answer questions from users with low social status

Summary of Major Findings

- (1) Knowledge seeking and sharing are strategic decisions driven by knowledge and network position of herself and those of the community: users choose to seek and share knowledge for future rewards reciprocated by her peers.
- (2) Users are more likely to seek and share knowledge when her peers are more knowledgeable.
- (3) While both knowledge and reputation motivate users to share knowledge, a cohort is formed over time that has the privilege to obtain help from each other and in the meanwhile, exclude other users from participating.
- (4) “Free-riding” behavior of inactive contributors could be an equilibrium result: the earlier low community knowledge level and the later formation of cohort “force” low ranked users from participating.
- (5) Proactive learning by asking is much more effective than reactive learning by observing
- (6) Current design of the open forum is not aligned with dynamic, interrelated and inter-dependent user decision process. An alternative design that breaks the cohorts can improve the knowledge sharing by 36%. 

Conclusion

- Formally investigated knowledge seeking and sharing decisions
  - A new learning mechanism: learning from peers
  - Endogenize the formation of social network structure
  - Rationalize a seemingly altruism behavior: “reciprocal altruism”
  - Using observed decisions to integrate some economic, social and psychological behavior
  - Provide explanations to the two observed challenges

- Some suggestions for adaptors
  - Recognize the conspicuous nature of platform adoption
    - Knowledge Sharing Day (possibly?)
  - Build a formal reward system to recognize reputation building
    - It is a double sided sword
  - Top management should change the mind set
    - It is not a platform for donation
    - Proactive knowledge seeking behavior should be motivated
  - Be aware that silos typically formed offline also form online.
    - Modified designs that encourage competition for reputation, but break the cohort

Innovative Research

- Dynamic consumer decision making

- Technology enabled dynamic consumer decisions

- Firms act on customer information
THANK YOU!

Web 2.0 and Knowledge Sharing

• An increasing focus on social software applications and services to
  – Break the silos
  – Encourage knowledge sharing across department and locations

• 90% are building the culture
  – IBM, CISCO, Infosys, Dell, Sun, Oracle
  – Knowledge sharing, idea generation
  – Customer service
    • Customer help each other
    • Significant savings of service costs

• Many discussions about how Software/Media revolutionizing the working world of the future
Marketing Applications of Knowledge Sharing

• Customer service
  – Adobe and Oracle
  – OSI saw 22% decrease in time to solve customer support issue

• Manage business process
  – 3 months less to complete project

• Production innovation (Crowdsourcing and ideation)
  – 36% decrease in time to enact key business changes based on customer feedback

• Prediction market

Knowledge Updating is Different from Reputation Updating

• Reputation is directly affected by own decisions.
• Reputation ranking can go up or down
• Compete for reputation ranking.

• Thus,
  – High reputation users may not have high knowledge
  – Low reputations users may have high knowledge
Our Study …

- Explicitly model the dynamic and interdependent decision process
  - rationalize the key driving forces behind knowledge seeking and sharing decisions
  - not altruism but future reward reciprocated by peers

- Endogenize formation of a social network
  - demonstrates the formation of social network as a result of strategic interaction.

- Recognize the unique learning mechanism enabled by social media platform
  - Treats knowledge sharing as consequence of dynamic interactions of individuals.
    - learning from peers vs learning by doing
    - interdependent vs. dependent
  - Integrate social psychology, information system and marketing

Managerially, we evaluate current design of web 2.0.

Timeline of Decisions

- Everyone observes their own states as well as the states of everyone else in the community.
- Everyone receives their private shocks on the decision of asking question.
- Everyone makes predictions on their peers’ decisions based on equilibrium strategy given their information others’ states in current period. Using this prediction everyone simultaneously makes decisions on whether they are going to ask question.
- Everyone observes the outcomes of asking question decisions—they know who ask questions in current period.
- Everyone receives their private shocks on the decision of answering question.
- Given information on who ask questions in current period and the predictions on others’ decisions of answering questions, everyone simultaneously makes decisions on whether to provide answer for each one of the questions proposed.
- State variables, Accumulated Knowledge and Reputation Status, are both updated.
## Model Comparison

### Table 3. Model Performance Comparison

<table>
<thead>
<tr>
<th>Variable</th>
<th>Actual Statistics</th>
<th>Full Model</th>
<th>Benchmark 1</th>
<th>Benchmark 2</th>
<th>Benchmark 3</th>
<th>Benchmark 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Num of Questions per User per Period</td>
<td>0.082 (0.009)</td>
<td>0.081 (0.000)</td>
<td>0.085 (0.001)</td>
<td>0.076 (0.015)</td>
<td>0.079 (0.017)</td>
<td>0.086 (0.021)</td>
</tr>
<tr>
<td>Avg Num of Solutions per User per Period</td>
<td>0.059 (0.021)</td>
<td>0.060 (0.024)</td>
<td>0.058 (0.038)</td>
<td>0.059 (0.036)</td>
<td>0.062 (0.036)</td>
<td>0.056 (0.020)</td>
</tr>
<tr>
<td>Probability a Question Received</td>
<td>0.728 (0.096)</td>
<td>0.7453 (0.087)</td>
<td>0.689 (0.083)</td>
<td>0.778 (0.104)</td>
<td>0.785 (0.093)</td>
<td>0.656 (0.093)</td>
</tr>
<tr>
<td>Hit Rate</td>
<td>95.33%</td>
<td>94.83%</td>
<td>93.69%</td>
<td>94.08%</td>
<td>92.35%</td>
<td></td>
</tr>
</tbody>
</table>

*We estimate the models with different number of individual types, and choose the best fitting model based on the Bayesian Information Criterion. We find that a two-segment model fits the best for all benchmark models.*

Benchmark model 1: replace relative ranking by absolute ranking

Benchmark model 2: remove forward-looking decision making