A Structural Model of User Learning and Dynamics in Mobile Phone Content Services

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Mobile Multimedia Content Services Industry

- **$200 billion market** in 2008 worldwide and **CAGR of 23.6 percent** (2008-2013).

- **65% of market is in Asia-Pacific.**

- Mobile content usage rate in S. Korea.

- However, only 36% of customers fully satisfied with mobile multimedia content experiences.
What kinds of content are users creating or accessing via mobile phones?
What kinds of forums are users accessing via mobile phones?

• Two most frequently visited forums for mobile users are 1) regular Internet social networking and community (SNC) sites and 2) multimedia mobile portal sites – *eMarketer 2009*.

  ✓ **Internet SNC websites** like Facebook, MySpace, Cyworld, etc.

  ✓ **Multimedia mobile portal websites** created by the mobile phone companies.

    ❖ Portals allow users to **download and upload** ringtones, wallpapers, videos, screen savers, games, etc.

    ❖ Cingular (USA): Messaging Awards program – Best User-Generated Video and Photo contest.

• Advertisers are grappling with what kinds of forums/websites they can use to **monetize UGC by embedding ads within multimedia content**.
What Drives User Content Generation and Usage Behavior in Mobile Multimedia Settings?

- **Two possible user behavior models**

- **Content match value (taste heterogeneity)** drives usage.
  - Certain kinds of content may appeal more to certain user groups. (e.g., uploading photo to SNC sites appeal more to younger users)
  - *Horizontally* differentiated content service market.

- **Content quality** also drives usage.
  - The perceived quality of a content is the same across users (e.g., downloading ringtone from portal sites).
  - *Vertically* differentiated content service market.
Uncertainty and Learning

• Given the uncertainty in ‘content match value’ and ‘content quality’ and that sampling is costly (e.g., transmission charges), customers learn the value from content-related uploading and downloading activities.
  – Anecdotal evidence of user behavior to explore new content types.

• Two possible sources of learning
  – Direct experience from own activity:
    Costly
  – Indirect experience from social network neighbor activity:
    Less costly, but possibly noisier
Research Questions

• What is the **underlying mechanism of user content generation and usage behaviors** in mobile multimedia settings?
  – Compare “Content match value” model vs. “Content quality” model
  – Which activity (upload/download) and which forum (SNC site/mobile portal) exhibits the highest match value (or quality) of content?

• Between **direct and indirect experience** signals, which one carries more **accurate information** about content match value (or content quality)?
Data Description

• Our data consists of **500 mobile users** (3G) who used the services of the company between March 15, 2008 and June 15, 2008.

• We also have **data on voice calls/text messages/multimedia messages** made by the same users that enables to draw social networks.
  – In the current study, we use only the voice call data.

• Thus we have **70,923 individual-level mobile activity records**
  – Including mobile content activity records for the 500 users and mobile content activity records of network neighbors of the each of the 500 users.

• There are **five options** that a user can choose with respect to activities:

<table>
<thead>
<tr>
<th>Content Uploading</th>
<th>Activity 1</th>
<th>Activity 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Content Downloading</td>
<td>Activity 3</td>
<td>Activity 4</td>
</tr>
<tr>
<td>Internet SNC Sites</td>
<td>Mobile Portal Sites</td>
<td></td>
</tr>
</tbody>
</table>

Activity 5 : Doing Nothing
Figure 1: Plot Showing Variation in Signal Experiences Across Users

- No direct and indirect experience
- Direct experience only
- Indirect experience only
- Both direct and indirect experience
Content Match Value Model [1]

Content match value uncertainty

- Users are imperfectly informed and uncertain about match value with content activity.
- User experiences with respect to content match value vary
  - User $i$, activity $j$, $s^{th}$ event, on day $t$
    
    \[ M_{ij} \sim N(M_j, \sigma_{M_j}^2) \]

  - $M_j$ is the population mean match value of activity $j$ and $\sigma_{M_j}^2$ measures the extent of the taste heterogeneity for match value with activity $j$ across users.

- The direct experience provides a noisy but unbiased signal of content match value:

  \[ M_{Eijt}^s = M_{ij} + \zeta_{ijt}^s \quad \text{where} \quad \zeta_{ijt}^s \sim N(0, \sigma_{\zeta_{ijt}}^2) \]

- The indirect experience (WOM) from network neighbors provides a noisy but unbiased signal of population-level content match value:

  \[ M_{WOMijt}^f = M_{j} + \eta_{ijt}^f \quad \text{where} \quad \eta_{ijt}^f \sim N(0, \sigma_{\eta_{ij}}^2) \quad \text{and} \quad f \in N_{WOMijt} = \sum_{k \in n_i} \sum_{h=1}^{N_{Ekt}} w_{ik} d_{kjt}^h \]

: parameters to estimate
Content Match Value Model [2]

User decision

- Forward-looking users: They select the sequence of content activities that maximizes their expected utility.

User utility specification

- User $i$’s utility from activity $j$ at $s^{th}$ event on day $t$:
  \[ U_{ijt}^s = w_g \cdot M_{Eijt}^s + w_g \cdot r_g \cdot (M_{Eijt}^s)^2 - a_g \cdot P_j + \varepsilon_{ijt}^s \]

  - $M_{Eijt}^s$ is direct signal of user $i$’s match value with respect to content activity $j$
  - $w$ is user $i$’s utility weight on match value,
  - $r$ captures the extent of the risk aversion towards variation in match value,
  - $a$ is the price coefficient,
  - $\varepsilon$ captures a taste shock, and
  - $g$ denotes a latent class.

: parameters to estimate
Content Match Value Model [3]

User Updating Content Match Value

- Users update the mean and variance of content match value levels in a Bayesian fashion (DeGroot 1970).

- Users do not know their match value with each content type, but receive signals which allow them to update their beliefs.
  
  - Update from directly engaging in activity \( j \) as well as indirectly via network neighbors WOM.

- Posterior mean of match value with activity \( j \) at time \( t+1 \)

\[
\mu_{ij,t+1} = (\beta_{1ij}^{t+1} * \mu_{ij,t}) + (\beta_{2ij}^{t+1} * \bar{MEijt+1}) + (\beta_{3ij}^{t+1} * \bar{MWOMijt+1})
\]

- \( \beta_{1ij}^{t+1} \): weight for (relative accuracy of) the prior mean of perceived match value
- \( \beta_{2ij}^{t+1} \): weight for (relative accuracy of) the direct experience signal
- \( \beta_{3ij}^{t+1} \): weight for (relative accuracy of) the indirect experience (WOM) signal
- \( \mu_{ij,t} \): prior mean of perceived match value with activity \( j \) at time \( t \)
- \( \bar{MEijt+1} \): sample mean of the realized match value signals from direct experience
- \( \bar{MWOMijt+1} \): sample mean of the realized match value signals from indirect experience
Content Match Value Model [4]

User Updating Perceived Content Match Value

- Posterior variance of match value with activity \( j \) at time \( t+1 \)
  - Weighted sum of accuracy of each source (prior, direct experience and indirect experience)

\[
\sigma_{M_{ij,t+1}}^2 = \frac{1}{\sigma_{M_{ij,0}}^2 + \sum_{\tau=1}^{t+1} \frac{N_{Eij}}{\sigma_{\zeta_j}^2} + \sum_{\tau=1}^{t+1} \frac{N_{WOMij}}{\sigma_{\eta_j}^2}}
\]

- Specifying Initial Conditions
  - 8 weeks for pre-estimation of initial conditions and 5 weeks for estimation

- The user’s optimal decision rule is to choose the option that maximizes the *expected present value* of utility over the planning horizon.
Dynamic Problem and Simulated Estimation

• Solve a **single agent dynamic, discrete choice problem** by DP to derive the value function.
  – 5 state variables ($I_{it}$)
  
  – Bellman’s equation

$$V_{it}(I_{it}) = \max_j E\left[U_{ijt} + \beta \cdot E\left[V_{it}(I_{it+1})|d_{ijt}, M_{ijt}, M_{WOMijt}, N_{WOMijt}\right]I_{it}\right]$$

• We use an iterative approximation method for computing the value function. (Keane and Wolpin 1994)

• Our estimation method is also known as the **nested fixed point algorithm (NFXP)** (Aguirregabiria and Mira 2009).
Empirical Identification

• **Separate the impact of direct experience from the impact of indirect experience on a user’s learning process**
  – Our data includes cases where there are indirect experiences even when there is no/little direct experience, and vice versa.
  – Also a lot of variation within direct or indirect experiences based on four content-related activities.

Mathematical Identification

• **We impose a scale normalization restriction**
  – Setting the mean match value for any one activity to 1 (Erdem et al 2008).
Evidence of Learning from Data

Figure 3: Variation in Types of Activities Within a User

Note: Percentile is determined by the total number of activity-related prior experience in the pre-estimation period.
Evidence of Learning from Data

50 percentile

Content download from mobile portal sites
Content download from SNC sites
Content upload to mobile portal sites
Content upload to SNC sites

75 & 95 percentile

Note: Percentile is determined by the total number of activity-related prior experience in the pre-estimation period.

Figure 3: Variation in Types of Activities Within a User (Cont’d)
Model Comparisons

- Multiple latent classes to incorporate unobserved heterogeneity
- Comparison of simulated and “in-sample” observed frequencies for both models.
- **“Content match value” model better explains the in-sample data.**
  - Selection criteria comparison for “content match value” model

<table>
<thead>
<tr>
<th></th>
<th>One latent class</th>
<th>Two latent classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood</td>
<td>-28108.1</td>
<td>-27926.4</td>
</tr>
<tr>
<td>AIC</td>
<td>56258.2</td>
<td><strong>55902.8</strong></td>
</tr>
<tr>
<td>BIC</td>
<td>56435.9</td>
<td><strong>56114.4</strong></td>
</tr>
<tr>
<td>Num. of Parameters</td>
<td>21</td>
<td>25</td>
</tr>
<tr>
<td>Sample size</td>
<td>35047</td>
<td>35047</td>
</tr>
</tbody>
</table>

- Selection criteria comparison for “content quality” model

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</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood</td>
<td>-29171.4</td>
<td>-29044.8</td>
</tr>
<tr>
<td>AIC</td>
<td>58376.8</td>
<td><strong>58131.6</strong></td>
</tr>
<tr>
<td>BIC</td>
<td>58520.7</td>
<td><strong>58309.3</strong></td>
</tr>
<tr>
<td>Num. of Parameters</td>
<td>17</td>
<td>21</td>
</tr>
<tr>
<td>Sample size</td>
<td>35047</td>
<td>35047</td>
</tr>
</tbody>
</table>
Parameter Estimates for Content Match Value Model

- Content download from mobile portal sites has the highest match value.
- Content download from SNC sites has the lowest match value.

<table>
<thead>
<tr>
<th>Homogenous parameters</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match Value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$M_1$ Mean match value of uploading to SNC sites</td>
<td>1.124</td>
<td>1.11E-4***</td>
</tr>
<tr>
<td>$M_2$ Mean match value of uploading to portal sites</td>
<td>1.327</td>
<td>1.16E-4***</td>
</tr>
<tr>
<td>$M_3$ Mean match value of downloading from SNC sites</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>$M_4$ Mean match value of downloading from portal sites</td>
<td>1.834</td>
<td>1.19E-4***</td>
</tr>
<tr>
<td>$\sigma_{M1}$ Std. dev. of match value of uploading to SNC sites</td>
<td>0.110</td>
<td>7.00E-4***</td>
</tr>
<tr>
<td>$\sigma_{M2}$ Std. dev. of match value of uploading to portal sites</td>
<td>0.086</td>
<td>7.11E-4***</td>
</tr>
<tr>
<td>$\sigma_{M3}$ Std. dev. of match value of downloading from SNC sites</td>
<td>0.085</td>
<td>7.01E-4***</td>
</tr>
<tr>
<td>$\sigma_{M4}$ Std. dev. of match value of downloading from portal sites</td>
<td>0.083</td>
<td>7.35E-4***</td>
</tr>
<tr>
<td>$\varphi_0$ Constant utility from doing nothing</td>
<td>3.249</td>
<td>1.18E-4***</td>
</tr>
</tbody>
</table>

Notes: These estimates are based on two latent segment model (g=2). *** denotes significant at 0.01
Parameter Estimates for Content Match Value Model

- **Direct signals about content download from SNC sites are the most accurate.**
- **Direct signals about content download from mobile portal sites are the least accurate.**
- **Learning based on direct experience is more reliable.**

<table>
<thead>
<tr>
<th>Signals</th>
<th>Description</th>
<th>Std. dev.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{\xi_1}$</td>
<td>Std. dev. of direct signal of uploading to SNC sites</td>
<td>0.054</td>
<td>1.27E-4***</td>
</tr>
<tr>
<td>$\sigma_{\xi_2}$</td>
<td>Std. dev. of direct signal of uploading to portal sites</td>
<td>0.091</td>
<td>1.26E-4***</td>
</tr>
<tr>
<td>$\sigma_{\xi_3}$</td>
<td>Std. dev. of direct signal of downloading from SNC sites</td>
<td>0.024</td>
<td>1.35E-4***</td>
</tr>
<tr>
<td>$\sigma_{\xi_4}$</td>
<td>Std. dev. of direct signal of downloading from portal sites</td>
<td>0.197</td>
<td>1.17E-4***</td>
</tr>
<tr>
<td>$\sigma_{\eta_1}$</td>
<td>Std. dev. of indirect signal of uploading to SNC sites</td>
<td>0.217</td>
<td>1.16E-4***</td>
</tr>
<tr>
<td>$\sigma_{\eta_2}$</td>
<td>Std. dev. of indirect signal of uploading to portal sites</td>
<td>0.325</td>
<td>1.20E-4***</td>
</tr>
<tr>
<td>$\sigma_{\eta_3}$</td>
<td>Std. dev. of indirect signal of downloading from SNC sites</td>
<td>0.374</td>
<td>1.19E-4***</td>
</tr>
<tr>
<td>$\sigma_{\eta_4}$</td>
<td>Std. dev. of indirect signal of downloading from portal sites</td>
<td>0.332</td>
<td>1.23E-4***</td>
</tr>
</tbody>
</table>

Notes: These estimates are based on two latent segment model (g=2). *** denotes significant at 0.01
Policy Simulations

• Changes in usage share from 20% increase in the population mean match value by user characteristics (age, gender, geographic mobility, etc.)

The impact of an increase in match value on the propensity to download content from mobile portal sites is higher in the more mobile segment.

<table>
<thead>
<tr>
<th>Base Case (%)</th>
<th>Increase in Match Value for Uploading to SNC Sites (%)</th>
<th>Increase in Match Value for Uploading to Portal Sites (%)</th>
<th>Increase in Match Value for Downloading from SNC Sites (%)</th>
<th>Increase in Match Value for Downloading from Portal sites(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>Less Mobile</td>
<td>Mobile</td>
<td>All</td>
<td>Less Mobile</td>
</tr>
<tr>
<td>0.42%</td>
<td>0.00%</td>
<td>0.42%</td>
<td>5.15%</td>
<td>1.27%</td>
</tr>
<tr>
<td>0.59%</td>
<td>0.12%</td>
<td>0.47%</td>
<td>0.49%</td>
<td>0.10%</td>
</tr>
<tr>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>83.89%</td>
<td>53.68%</td>
<td>30.21%</td>
<td>80.87%</td>
<td>52.88%</td>
</tr>
<tr>
<td>15.10%</td>
<td>8.71%</td>
<td>6.40%</td>
<td>13.50%</td>
<td>8.25%</td>
</tr>
</tbody>
</table>
Conclusion

• First paper to build a dynamic structural model of learning behavior in user-generated content.
  – Direct experience signals more accurate than indirect experience.

• Impact on user behavior from direct/indirect experience varies by content.
  – Most accurate in the case of download from mobile portal sites.

• “Content match value” model better explains the observed data than “content quality” model

• Policy simulations suggest insights for targeting strategies.
  • The impact of an increase in match value on the propensity to download content from mobile portal sites is higher in the more mobile segment.
Managerial Implications

• Develop **effective mobile advertising** strategies
  – Embed advertisements in multi-media content on **mobile portal sites** (higher content match value and quality).
  – Marketing channel decisions (mobile portals vs. social networking/community sites) to promote ads to increase user views and click-through rates.

• Incentivize customers by **providing explicit monetary rewards**
  – *Whom* to target and *how* to motivate them to contribute high quality content through mobile devices (more mobile versus less mobile users).
  – **Design programs or contests** that lead to more frequent and high quality user-generated content updates on online social networking sites.