Ubiquitous and Mobile Computing CS 528: 
*Designing Content-driven Intelligent Notification Mechanisms for Mobile Applications*

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Outline

- Introduction
- Related Work
- Methodology
- Evaluation/Results
- Challenges
- Future Work
- Conclusions
Introduction

- Notifications can be annoying!
- What if?
- Objective: find the most opportune moment to deliver notifications
Motivation - What is an Opportune Moment?

- Opportune only when the user will answer it immediately
- Aim to reduce response time of the user and the acceptance rate of notifications
The Solution - NotifyMe

![Installed Applications]

- Total apps: 38
- Personalisation: 2
- Tools: 5
- Music & Audio: 1
- Productivity: 2
- Entertainment: 1
- News & Magazines: 1
- Puzzle: 1
- Communication: 5
- Social: 3
- Education: 1

![Select Application Category]

- Total: 58
- Personalisation: 0
- Tools: 9
- Music & Audio: 0
- Productivity: 0
- Entertainment: 0
- News & Magazines: 0

Green indicates accepted notifications and red indicates the notifications with no response.
Related Work

- Similar Studies
  - Contextual factors used to infer interruptibility with
  - Contextual transitions [Ho, et al]
  - Engagements on device [Fischer, et al.]
  - Time of day, location, and activity [Pejovic, et al]
- How is this different?
The Study

- In-the-wild notifications
- 35 users
  - Published on Google Play Store
  - Ages 21-31
  - Advertised at University of Birmingham (UK)
- 3 weeks, 70,000 notifications, 4,096 questionnaire responses

<table>
<thead>
<tr>
<th>Question</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>How would you rate the notification content?</td>
<td>Likert scale rating between 1 and 5 (1 = very annoying and 5 = very interesting).</td>
</tr>
<tr>
<td>Where would you like to receive notifications with similar content?</td>
<td>Home, workplace, other, anywhere and I don’t want.</td>
</tr>
<tr>
<td>When would you like to receive notifications with similar content?</td>
<td>Morning, afternoon, evening, night, anytime and never.</td>
</tr>
<tr>
<td>How are you feeling?</td>
<td>Happy, sad, bored and annoyed.</td>
</tr>
<tr>
<td>Are you busy?</td>
<td>Yes and no.</td>
</tr>
<tr>
<td>Where are you?</td>
<td>Home, workplace, public, other.</td>
</tr>
</tbody>
</table>

Table 2. Questions and their options from NotifyMe questionnaire.
Methodology

● Data collection forms:
  ● Measures notification responses (accept/decline)
  ● NotifyMe notifications
  ● Questionnaires

● Google’s Notification Listener Service to trace notifications, and Activity Recognition API, ESSensorManager to get context info
Dataset

- Classified by info type
  - Work
  - Social
  - Family
  - Other

- Generated label-to-notification map

Figure 2. Percentage of notifications for each category and sub-category. The sub-categories are derived by using the recipient’s relationship with the sender.
Design Tradeoffs

- Tradeoffs
  - Privacy concerns - only access message titles
  - Notification categorization
  - User opt-out
  - “Accepting” a notifications = launching the app
Results

- Collected 70,000 notification samples
- More than 60% notifications were clicked within 10 minutes from the time of arrival

Figure 3. CDF of response time for notifications.
Impact of Context on Response Time

- **Location**
  - home, workplace, the other

- **Surrounding sound**
  - silent or speaking

- **Activity**
  - still, on foot, on bicycle, in vehicle

*Figure 4. CDF of response time for notifications received while performing different activities.*
Impact of Content on Notification Acceptance

- The notification from different categories have a varying acceptance rate
- E.g. Chat Family, System, Tools, Music & Media

Figure 5. Click count percentages for the notifications of each category.
Building the Prediction Model

- Build models for predicting notification acceptance rate by three algorithms: Naive Bayes, AdaBoost, and Random Forest

- Two approaches for building prediction models
  - Data-driven learning
  - User-defined rules
Approaches for building the Prediction Model

- Data-driven learning that relies on the evidences rather than personal intuition
  - without using information type and social circle
  - using only information type
  - using information type and social circle

- User-defined rules that rely on the user's own intuitions
  - notification category
  - best location
  - best time
Evaluation

- **Sensitivity**
  - \( \frac{\text{# of predicted accepted notifications}}{\text{total # of accepted notifications}} \)

- **Specificity**
  - \( \frac{\text{# of predicted declined notifications}}{\text{total # of declined notifications}} \)

Prediction results of the predictors trained by using 3 different set of features for data-driven learning and user-defined rules.
Figure 7. Prediction results of the generic and individual-based models.
Limitations

- Notification might be attended on another device
- Some applications do not require any action taken, just dismiss
Challenges

- Multiple notifications from one application at once
Conclusions

- A user’s activity can impact the time delay in the response to a notification.
- The chat notification, where the sender is a family member or a relative of the user, have the highest acceptance rate.
- The acceptance value of notifications vary for each category.
- The acceptance of a notification within 10 minutes from its arrival time can be predicted with an average sensitivity of 70% and a specificity of 80%.
Future Work

- Increase accuracy of the prediction model
  - Better-defined categories
  - Use Natural Language Processing
- Privacy
References

- http://dl.acm.org/citation.cfm?id=2037402
- http://web.media.mit.edu/~intille/papers-files/HoIntille05.pdf
Questions?